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Spatially heterogeneous effect of temperature on electricity consumption in Shenzhen, China

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ABSTRACT

The relationship between electricity consumption (EC) and temperature (T) influences the energy supply-demand balance within cities, and a nonlinear EC-T relationship has been widely documented at the city scale for this case, while the within-city spatial heterogeneity of the EC-T relation has been overlooked. Using Shenzhen, China, as a case study, this study aims to investigate the spatial variations in the relationship between electricity consumption and temperature at the intraurban scale. We first examined the EC-T relation by sector at the city scale using segmented regression models, and then further extrapolated this relation to the grid scale of 12 m using a population and floor area weighting method. Specifically, we assumed that EC by sector was associated with different functional zones and is equally proportional to population and floor area, so the local EC can be estimated by multiplying the sectorial EC by the mean ratio of local population and floor area. We found that the rate of change in EC with T per land area varied from 0 to 4.7 kWh/m^2/°C, with a mean value of 0.01 kWh/m^2/°C and a coefficient of variation (CV) of 3.0. Among function zones, the largest value of the rate of EC was observed in commercial areas, with a mean value of 0.05 kWh/m^2/°C. The proportion of the temperature-sensitive electricity consumption to the total electricity consumption (TECP) varied from 9.7% to 49.3% in space, with the highest mean value of 40.5% occurring in residential areas. These findings provide effective strategies for reducing energy use through cooling measures, showing great practical implications for urban planning and energy management policies adapted to the local environment to ensure equitable and sustainable urban development.

1. Introduction

Climate change seriously affects social development and human health, posing a major challenge to natural and human systems [1–3]. It alters biogeochemical cycles and leads to frequent extreme weather events [4–6], contributing to an increase in water resources and energy consumption [7–9]. In particular, urban areas are likely to experience more heat waves due to the synergistic effects of global warming and the urban heat island effect (UHI) [10–12], as this effect is one of the ecological problems caused by increasing urban population and changes in land cover and it is reflected by higher temperatures in urban areas compared to suburban areas [13–16]. Consequently, the city's demand for energy, especially electricity, will continue to increase [17–19], putting the energy security and sustainability of cities at risk [20,21].

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Exploring the impact of temperature on electricity consumption (EC) is therefore essential to mitigate the energy crisis, combat climate change and increase the resilience of cities [22–24].

Numerous studies have documented the nonlinear relationship between air temperature (T) and EC, and it usually conforms to a U- or V-shaped curve [25–27]. When T is higher than a certain degree, the increase in temperature leads to an increased EC for cooling. Meanwhile, elevated temperature can save the electricity used for heating in cold weather [28]. For example, domestic electricity consumption swings slightly over 13–25 °C in Shanghai and increases by 2.8% and 14.5% for 1 °C cooling and warming beyond the above temperature range, respectively [29]. The threshold temperature and response rate of EC vary across climate, economy, and sector [30–32], due to the unbalanced heating and cooling needs in diverse climate zones, the unevenly distributed energy sources at different economic levels, and the disparate dependence on temperature among sectors [33,34]. In Europe, the average critical temperature ranges from 14.7 °C in cold countries to 22.4 °C in warm countries with a mean value of 16.1 °C [35], while it is 14 °C, 17 °C or 21 °C in different parts of America [36]. A global-scale study finds a balance temperature of 14.6 °C, and it is higher in more urban and industrial areas [37]. Electricity consumption in buildings is the main source of total EC in urban areas, and is influenced by multiple factors such as urban form, population density, building type and building stock, in addition to the temperature factor [38–40]. Therefore, the impact of temperature on EC is different from country to country, from city to city, and even from building to building within a city depending on the local climate and socioeconomic characteristics [31,38,41,42].

The majority of current studies have focused on developed countries and regions, such as the United Kingdom, the United States, and Japan [35,43–45]. Less attention, however, has been given to developing countries such as China and India, which are considered hot spots for future urban warming and energy consumption [46–48]. The limited number of studies conducted for these regions mostly focus on the total or domestic EC, with insufficient research on the EC of different sectors [29,49,50]. Additionally, most of these studies were conducted at a coarse spatial scale, typically focusing on the entire city, or even using the province as the analytical unit [51], but few studies discussed the spatial differentiation of the EC-T relationship at the intraurban scale [52]. As a pioneering effort, Nakajima and colleagues revealed a large spatiotemporal variation in the EC-T relationship on a city block-scale using EC data for 1290 substations and weather data from seventeen weather stations in the Tokyo Metropolitan Area [53]. However, such fine-scale data are typically unavailable in most cities, especially in developing countries. As a hybrid social and ecological ecosystem, cities exhibit high spatial heterogeneity in terms of population distribution, land cover, building patterns, and temperature, and this could potentially lead to large spatial differences in electricity demand [54–57]. Quantifying the EC-T relationship at a finer scale can help cities locate priority areas in terms of cooling and energy savings and achieve urban sustainability from the perspective of social equity and environmental justice.

To bridge the above research gaps, we choose Shenzhen, China, as a case study to investigate the spatial patterns of EC-T at the intraurban scale (Fig. 1). First, we quantified the nonlinear relationship between temperature and electricity consumption by sector at the city scale using segmented regression models. Second, we constructed an electricity consumption coefficient (ECC) at the grid scale using a spatial resolution of 12 m to estimate the spatial electricity consumption and its relationship to temperature. Here, we assumed that the sectorial electricity consumption was exclusively distributed over the corresponding function zone in space, and that local EC was positively correlated with local population and floor area, thus apportioning the city's total EC to fine grids by population and building weighting. Finally, we calculated the temperature-sensitive electricity consumption and its proportion to total electricity consumption (TECP) at the grid scale to compare the impact of local climate on local EC across the city. The higher the proportion is, the greater the impact of local temperature on electricity consumption. The findings are of great significance for cities in terms of addressing the issue of increased energy consumption in addition to addressing the intensified urban heat stress [58–60].

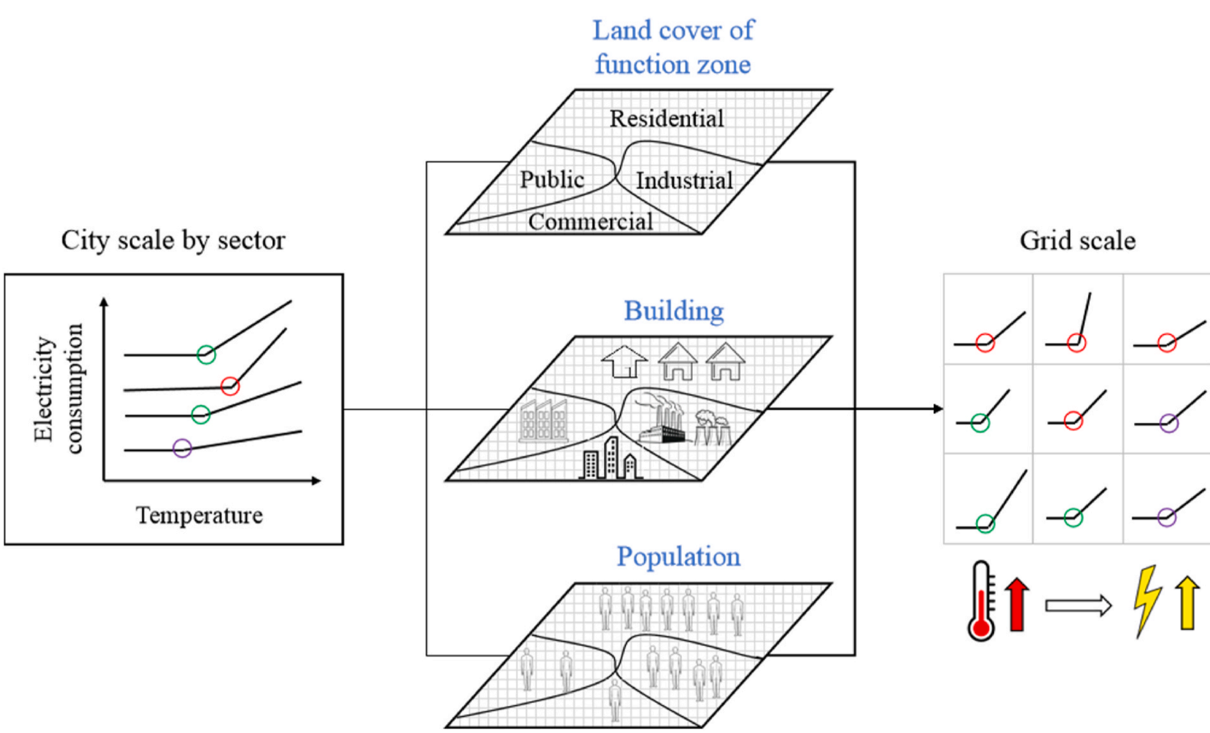

Fig. 1. Overview of research on the relationship between electricity consumption and temperature from the city scale to the grid scale.

2. Materials and methods

2.1. Study area

This research focuses on Shenzhen, China, a densely populated megacity with a total population of 17.56 million in 2020, a total area of 1997 km^2 and a built-up area of 927.96 km^2. Shenzhen is an ideal case for studying the impact of temperature on energy consumption for the following reasons. First, the total energy consumption in Shenzhen increased from 3711 (10 000 tons of Standard Coal Equivalent/SCE) in 2014 to 4413 (10 000 tons of SCE) in 2020 [61]. In particular, residential consumption showed a continuous growth trend from 582 (10 000 tons of SCE) to 845 (10 000 tons of SCE), while industrial consumption decreased from 1685 (10 000 tons of SCE) to 1580 (10 000 tons of SCE). With the continuous increase in population and rising living standards, the future incremental pressure on energy consumption will likely mainly come from residential consumption, and this would significantly be affected by climate [29,30,62]. Second, Shenzhen is located in the southeastern coastal region with a subtropical monsoon climate, and thus hot and humid weather makes it necessary to cool and dehumidify for more than half of the year. As global warming and the urban heat island effect intensify, the future energy demand will continue to rise, posing a grand challenge for Shenzhen to move toward becoming an energy-efficient city. Third, Shenzhen's energy consumption per unit of GDP and carbon dioxide emissions per unit of GDP in 2020 were 1/3 and 1/5 of the national average, with a five-year decline of 19.3% and 23.2%, respectively. As one of the first national low-carbon pilot cities, Shenzhen has a very strong motivation for energy consumption reduction and exploring its path to a net-zero carbon city can provide a reference for other cities.

2.2. Data and processing

2.2.1. Quantifying the relationship between temperature and electricity consumption by sector at the city scale

We investigated the relationship between the daily mean temperature and electricity consumption in Shenzhen by sector in 2020 at the city scale. Temperature data were quality-controlled historical records of the Shenzhen National Weather Station (ID: 59493), and the data were downloaded from the China Meteorological Data Service Center (http://data.cma.cn/), representing the typical climate of the region. Electricity consumption data were obtained from the State Grid Corporation of China and then clustered into four categories, namely, domestic, industrial, commercial, and public (Table S1, Fig. S1), corresponding to four function zones in space, and thus we arrived at the subsequent spatialization of the relationship between temperature and electricity consumption (Fig. S2). We checked the electricity consumption data using an interquartile range (IQR) method of outlier detection, and excluded the outliers for industrial electricity consumption from the 22nd of January to the 16th of February 2020, as such data were affected by the breakout of the COVID-19 epidemic.

Using the package *segmented* in R software version 3.6.1, segmented regression models were utilized to quantify the relationship between the daily mean temperature and energy consumption [63]. This package uses an iterative method to estimate the piecewise linear relationships between the response and explanatory variables, namely, a representation of two or more straight lines connected at unknown values [64]. We selected the number of breakpoints based on the Bayesian information criterion (BIC). The BIC is a measure of model fit that balances the complexity of the model (number of parameters) and the goodness of fit (likelihood). It penalizes models with more parameters, encouraging the selection of simpler models that explain the data well. The segmented package uses a search algorithm to find the optimal number of breakpoints that minimize the BIC value, starting with one breakpoint and adding more breakpoints until the BIC value stops decreasing or reaches the user-specified maximum number of breakpoints. Consequently, the "segmented" package finds the most parsimonious model that explains the data well and avoids overfitting. In addition, standard errors for all model variables (i.e., intercept, slopes and breakpoints) are provided along with the estimates. Although regression splines can also be used for fitting nonlinear models, the locations of the knots are prespecified, e.g., placed in the equally spaced quantile position, so we chose the more flexible segmented regression models [29].

2.2.2. Estimating electricity consumption and its relationship to temperature at the grid scale

We estimated electricity consumption and its relationship to temperature at the grid scale based on the land cover of function zones, population count, and floor area. The function zone data consist of 4 types of zones: residential, commercial, industrial and others, with a spatial resolution of 12 m (Fig. S2), and this was categorized based on the attribution of building usage [56]. The population count data were obtained from WorldPop in constrained individual countries, and the data are the 2020 UN adjusted version (https://www.worldpop.org/). We downscaled the data from 100 m to 12 m and adjusted the values using the seventh national census population data for each district (Fig. S3). The floor area data were obtained from a building census in 2015 that was conducted by the Bureau of Planning and Natural Resources, and the data consist of 594,823 polygons of building footprints with attributes such as building height, the number of floors, and floor area. The accuracy of the data was greater than 95%, which can be verified by comparing the number of floors and the ratio of floor area to building area. If the number of floors obtained from the survey is basically equal to the ratio of floor area to the building area calculated in the ArcGIS software, the building information can be considered in accordance with the actual situation. We extracted the floor area values based on a fishnet of 12 m × 12 m aligned with the function zone layer (Fig. S4). Hence, for simplicity, we made a few assumptions before estimating electricity consumption and its relationship to temperature at the grid scale. First, all electricity consumption in a given category comes from the corresponding function zone, and all electricity consumption in a given function zone only belongs to the corresponding category of electricity consumption. For example, all domestic electricity consumption is distributed in the residential zone, and the sum of the electricity consumption in the residential zone is equal to the domestic electricity consumption. Second, electricity consumption is positively correlated with population and floor area, and this correlation has been demonstrated in previous studies [49,65,66]. The more people there are, the more electricity is used; the larger the floor area is, the more electricity is used. Finally, we assume that population and floor area have an equal impact on electricity consumption because no study has yet given the relative impact of population and floor space on electricity consumption.

Based on the above assumptions, we constructed an electricity consumption coefficient (ECC) to estimate electricity consumption and its relationship to temperature at the grid scale. The ECC_{ij} of grid j in function zone i was equal to the average value of the ratio of the population and floor area of each grid to the total population and total floor area of the function zone to which it belongs, as shown in Eq. (1) and Fig. 2A. Therefore, the electricity consumption of each grid (EC_{ij}) is equal to the coefficient of that grid (ECC_{ij}) multiplied by the total electricity consumption of the function zone to which it belongs (EC_i) (Eq. (2) & Fig. 2B). Similarly, the rate of change of electricity consumption with temperature of each grid ($slope_{ij}$) is equal to the coefficient of that grid (ECC_{ij}) multiplied by the slope of the function zone to which it belongs ($slope_i$) (Eq. (3) & Fig. 2C). The breakpoints of each grid (bp_{ij}) were consistent with the breakpoints of the function zone to which it belongs (bp_i), with the insignificant slopes equal to zero (Eq. (4) & Fig. 2D). Analyses in this section were performed in ArcGIS™ software and R version 3.6.1.

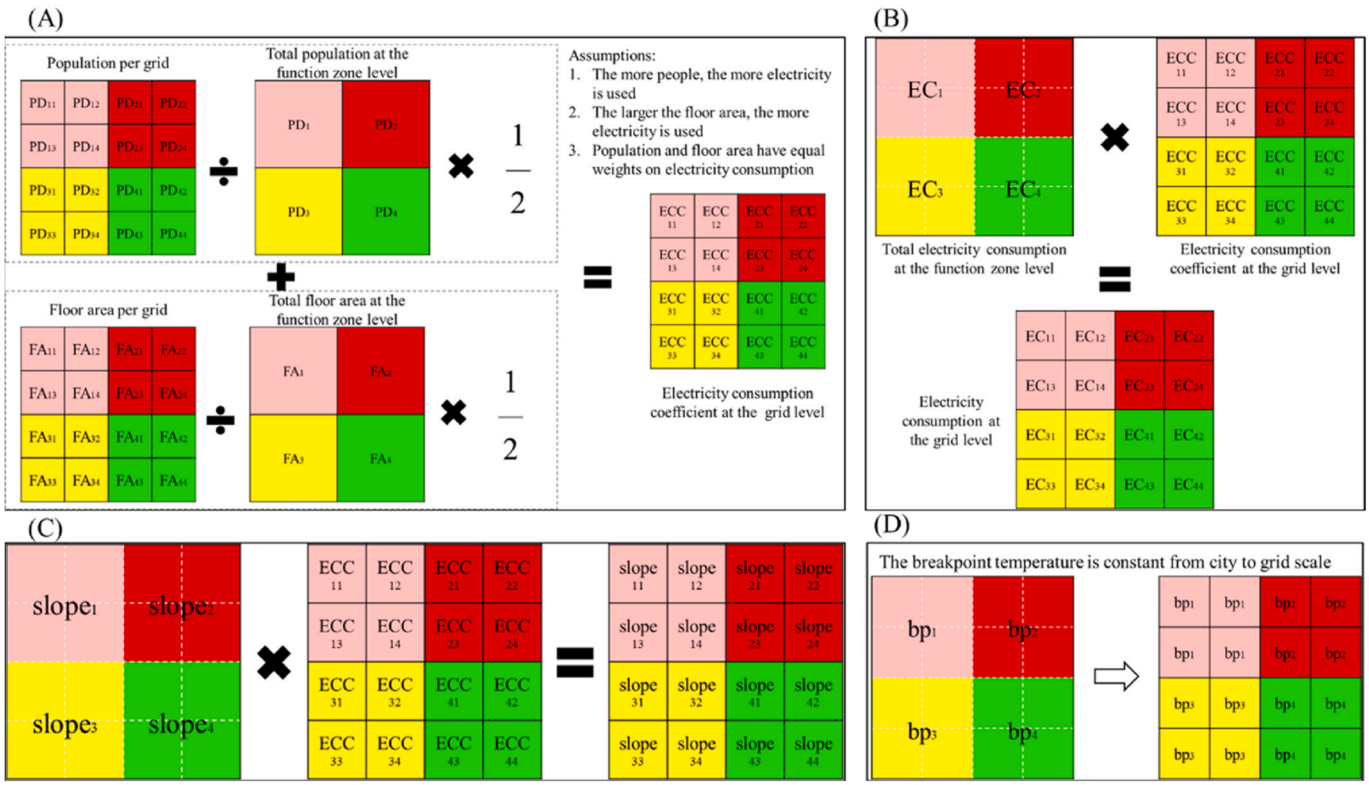

Fig. 2. Schematic diagram of estimating electricity consumption and its relationship to temperature at the grid level.

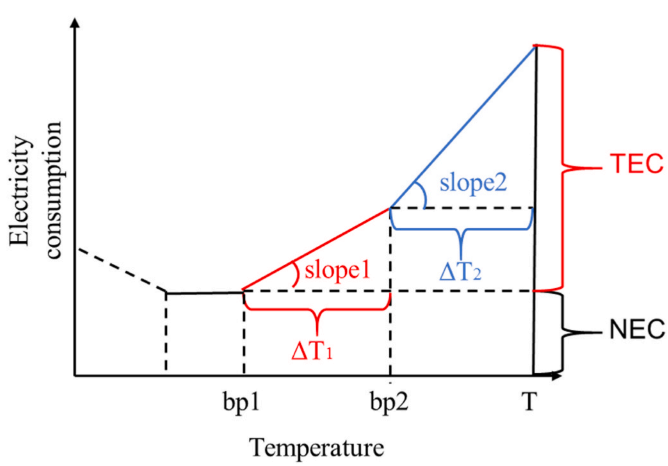

Fig. 3. Conceptual diagram of the effect of temperature on electricity consumption in Shenzhen. There is no temperature range in which electricity consumption decreases with increasing temperature, and one or more breakpoints can exist.

$$ECC_{ij} = \left(\frac{Population_{ij}}{\sum_{j=1}^{n} Population_{ij}} + \frac{Floor\ area_{ij}}{\sum_{j=1}^{n} Floor\ area_{ij}} \right) \bigg/ 2 \tag{1}$$

$$EC_{ij} = EC_i * ECC_{ij} \tag{2}$$

$$Slope_{ij} = Slope_i * ECC_{ij} \tag{3}$$

$$bp_{ij} = bp_i \tag{4}$$

2.2.3. Calculating the temperature-sensitive electricity consumption and its proportion to total electricity consumption at the grid scale

As shown in Fig. 3, total electricity consumption consists of two components. One is the nonweather sensitive energy consumption (NEC), determined by local attributes such as function zone type, population, floor area, etc., and the other is the temperature-sensitive electricity consumption (TEC), which is not only influenced by local socioeconomic attributes but also regulated by temperatures. We defined a temperature-sensitive electricity consumption coefficient (TECP), that is equal to the proportion of temperature-sensitive electricity consumption to total electricity consumption, to compare the impact of local climate on local energy consumption across the city. The formulas for calculating TEC (Eq. (5)) and TECP (Eq. (6)) are as follows:

$$\mathrm{TEC}_0 = \begin{cases} 0, T < bp1 \\ (T - bp1) * slope1, bp1 < T < bp2 \\ (T - bp2) * slope2 + (bp2 - bp1) * slope1, bp2 < T \end{cases} \quad \mathrm{TEC} = \min(\mathrm{TEC}_0, \mathrm{EC}) \tag{5}$$

$$TECP = \frac{\mathrm{TEC}}{EC} \times 100\% \tag{6}$$

where T is the actual temperature on a given day, bp1 is the threshold temperature at which the first statistically significant linear segment begins; when the temperature is lower than bp1, the change in electricity consumption with the temperature is not statistically significant and can be considered equal to 0; slope1 represents the rate of change in electricity consumption with temperature within the first linear segment; bp2 is the second threshold temperature at which a new linear segment with a different slope from slope1 begins, and slope2 represents the rate of change in electricity consumption with temperature within the second linear segment. TEC_0 is the calculated temperature-sensitive electricity consumption in a certain day, and EC is the actual electricity consumption for that day. The EC is used to correct TEC_0 to ensure that the simulated temperature-sensitive electricity consumption does not exceed the total electricity consumption, and thus we can obtain the corrected temperature-sensitive electricity consumption (TEC) that is equal to the smaller one of the two variables (TEC_0 & EC).

We calculated the daily temperature-sensitive electricity consumption and its proportion of total electricity consumption at the grid scale based on daily gridded temperature data and the relationship between electricity consumption and temperature (i.e., bp and slope). Daily gridded temperature data were obtained by spatial interpolation based on records from 59 automatic weather stations in Shenzhen (Fig. S2), and IDW method was adopted out of Kriging and Spline methods according to the minimum root mean square error (RMSE) criterion. Before applying automatic station data, we performed climatic range checks, temporal consistency checks, spatial location checks, etc., to improve the reliability of the data. We obtained the annual TEC by summing the results for each day of the year and compared the yearly TEC and TECP to the daily TEC and TECP on a hot day since the spatial pattern of temperature differs from the annual average on hot days (Fig. S5). We selected July 14th, 2020 as a typical hot day, as it was one of the hottest days in Shenzhen, with a daily mean temperature reaching 30.5 °C, and it was also the day with the highest electricity consumption of 366 GWh. This date is also in the middle of a heat wave where the daily mean temperature did not fall below 30 °C for six consecutive days from July 11 to July 16. All analyses in this section were performed using ArcGIS™ software.

3. Results

3.1. The EC-T relationship by sector at the city scale

The results showed a nonlinear effect of the daily mean temperature on all types of electricity consumption, but the number of breakpoints, threshold values, and slopes varied across sectors (Table 1 & Fig. 4). Domestic electricity consumption had the strongest correlation with temperature, with the adjusted R^2 of the model reaching 0.92, indicating that the daily mean temperature could explain 92% of the variation in domestic electricity consumption. There were 2 breakpoints and 3 stages of the daily mean temperature, namely 23.6 °C and 28.8 °C (Fig. 4B). For daily temperatures below 23.6 °C, a statistically insignificant negative correlation was found between electricity consumption and temperature. As temperatures continued to rise, domestic electricity consumption increased with the increase in temperature at a rate of 6.1 GWh/°C. When the temperature exceeded 28.8 °C, the electricity consumption increased sharply with an average rate of 14.3 GWh/°C, leading to a 24.9% increase in energy consumption per degree increment.

In contrast, industrial electricity consumption was much less affected by temperature, with a minimum adjusted R^2 value of 0.37, but the breakpoint temperature occurred at the earliest of approximately 20 °C (Fig. 4 C). Industrial electricity consumption would increase by 4.1 GWh for every 1 °C increase in temperature when the temperature was higher than 20 °C, and this was equivalent to 3.9%/°C. Although the proportion seems small, the increased energy consumption is substantial because the industrial electricity consumption in Shenzhen accounted for nearly half of the total. The effect of temperature on commercial and public electricity consumption was different from that on the first two sectors, with moderate adjusted R^2 values of 0.75 and 0.76, and the same breakpoint of temperature at 20.8 °C (Fig. 4D and E). Both electricity consumption slightly increased with higher temperatures before the temperature reached 20.8 °C, but the trend was not significant. Then the rates of increase in electricity consumption were 4.5 GWh/°C and 1.5 GWh/°C, or 9.5%/°C and 10.9%/°C for the commercial sector and public sector, respectively.

Table 1
Results of the EC-T segmented regression models.

Electricity sector	Total	Domestic	Industrial	Commercial	Public
Proportion (%)	100	16.8	48.4	26.8	7.8
Number of breakpoints	1	2	1	1	1
Adjusted R^2	0.70	0.92	0.37	0.75	0.76
Intercept (GWh)	105.7	27.0	103.6	37.2	12.6
slope1 (GWh/°C)	4.0[a]	−0.04	0.04	0.5	0.04
breakpoint1 (°C)	21.8	23.6	20.0	20.8	20.8
slope2 (GWh/°C)	16.9[a]	6.1[a]	4.1[a]	4.5[a]	1.5[a]
breakpoint2 (°C)		28.8			
slope3 (GWh/°C)		14.3[a]			

[a] Indicates significant indices at the 0.01 level.

3.2. The electricity consumption and its relationship to temperature at the grid scale

ECC exhibited a pattern of high in the south and low in the north due to the spatial patterns of population and floor area in Shenzhen, leading to a large spatial heterogeneity of EC within the city (Fig. 5 A&B). EC varied from 0 to 25.0 MWh/m^2 (per land area) in 2020, with a mean of 45.8 kWh/m^2 and a standard deviation (SD) of 165.0 kWh/m^2, resulting in a coefficient of variation (CV, =SD/mean) of 3.6. High values were mainly found in commercial grids, with a mean value of 248.6 kWh/m^2, followed by industrial grids with a mean of 142.7 kWh/m^2. This was because commercial zones consumed 26.8% of the total electricity with 5.0% of the land area and industrial zones consumed 48.4% of the total electricity with 15.6% of the land area. In comparison, residential and public zones consumed 16.8% and 7.8% of the total electricity with 17.7% and 61.8% of the land area, respectively. Hence, the mean value of EC of residential grids was 43.7 kWh/m^2, and was only 5.8 kWh/m^2 of public grids due to the wider and more dispersed distribution.

Similarly, there were spatially heterogeneous characteristics of the EC-T relationship (i.e., bps and slopes). The spatial pattern of breakpoints was consistent with the distribution of function zones, with a bp of 20.0 °C in industrial zones, a bp of 20.8 °C in commercial and public zones, and a bp1 of 23.6 °C and a bp2 of 28.8 °C in residential zones (Fig. 5 C&D). The spatial variation of slopes went beyond the pattern of function zones, varying both across the city and within function zones (Fig. 5 E&F). Slope1 and slope2 decreased from southwest to northeast, ranging from 0 to 4.7 kWh/m^2/°C citywide, with mean values of 0.008 and 0.01 kWh/m^2/°C, and SDs of 0.03 and 0.04 kWh/m^2/°C, respectively. Among the four function zones, the greatest variation was found within the public zone, with a mean of 0.001 kWh/m^2/°C and a CV of 4.0, and the smallest variation was found in the industrial zone, with a mean of 0.001 kWh/m^2/°C and a CV of 1.1. The commercial zone had the largest mean slope and a greater degree of variation, which were 0.05 kWh/m^2/°C and 2.4, respectively. The coefficient of variation for residential areas hardly changed from the first slope to the second slope, but the mean value of the slope doubled from 0.02 to 0.04 kWh/m^2/°C.

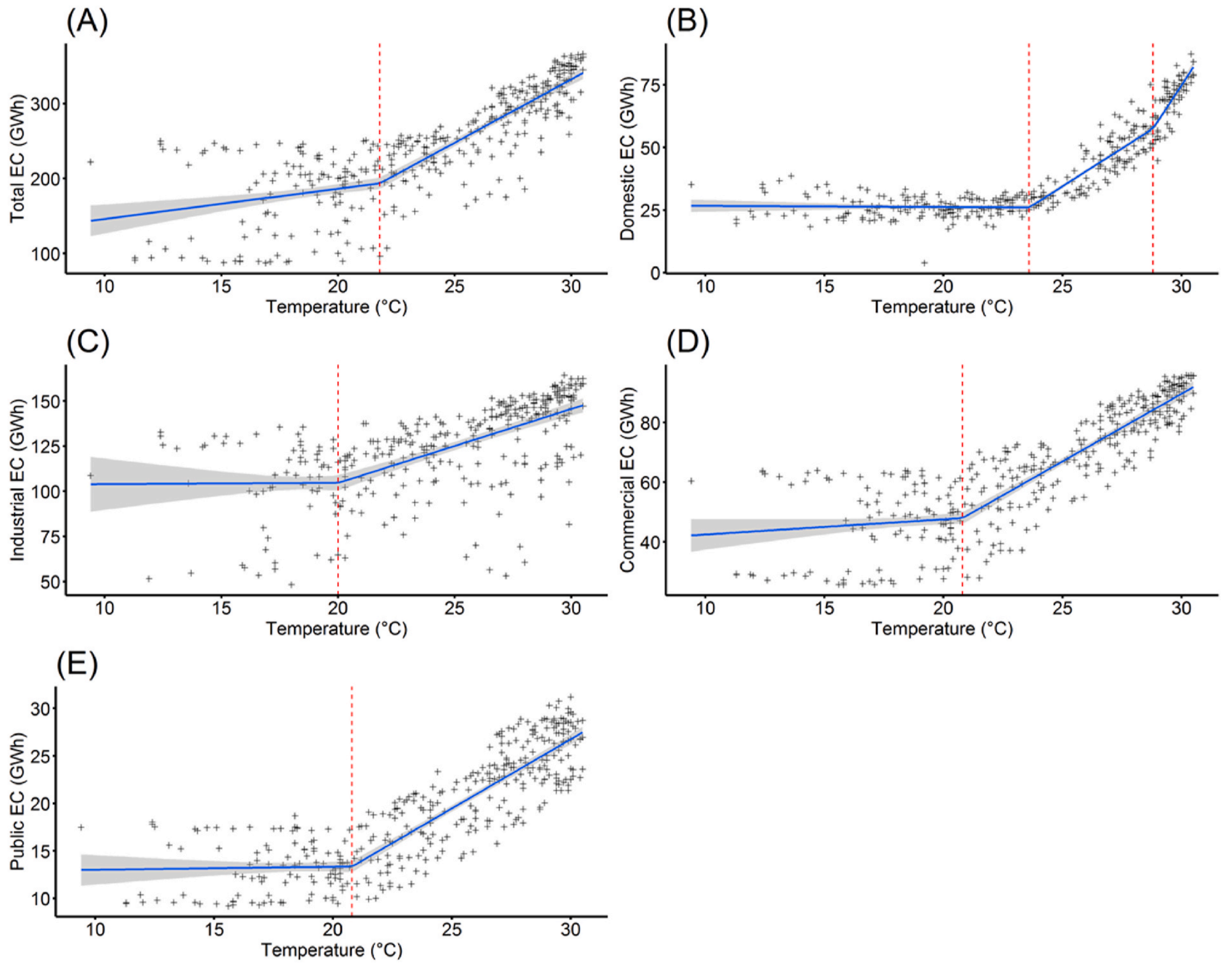

Fig. 4. The segmented relationship between (A) total, (B) domestic, (C) industrial, (D) commercial, and (E) public EC and T. The blue solid lines are the segmented regression lines, the gray shading is the 95% confidence interval, and the red dotted line indicates the location of the threshold temperature. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

3.3. The spatial pattern of temperature-sensitive electricity consumption and its proportion of total electricity consumption

The spatial distribution of TEC throughout the year was similar to that of EC, with a mean value of 11.5 kWh/m^2 and an SD of 44.7 kWh/m^2, showing large spatial variations (Fig. 6 A). The maximum value of the yearly TEC reached 7.4 MWh/m^2, but in the high-value area, it was small and concentrated in the south-central part of Shenzhen. Approximately 25% of the land had above average values (>11.5), and the value of half of the area was equal to 0. Among the four function zones, the average TEC was 17.9, 23.4, 71.9, and 1.8 kWh/m^2 for residential, industrial, commercial, and public grids, respectively. TEC on a hot day had a similar but more homogeneous spatial pattern, i.e., clustered high value areas and dispersed low value areas, with a CV of 3.5 in space, which was slightly less than the CV of 3.9 throughout the year (Fig. 6 B). The mean and SD of TEC on a hot day across the city were 0.09 and 0.3 kWh/m^2, respectively, and commercial grids had the largest average value of TEC (0.50 kWh/m^2), followed by industrial (0.16 kWh/m^2), residential (0.20 kWh/m^2), and public grids (0.01 kWh/m^2).

TECP throughout the year varied from 9.7% to 49.3%, with a mean of 29.8% and an SD of 9.9% across the city (Fig. 6 C), and the TECP on a hot day varied from 20.8% to 99.6%, with a mean of 57.5% and an SD of 23.9%, nearly twice the yearly TECP (Fig. 6 D). Unlike EC and TEC, TECP showed less variation within function zones, with CVs of 0.3, 0.1, 0.05, 0.06, and 0.08 for yearly TECP values in residential, industrial, commercial, and public grids, respectively. Quantitatively, the yearly TECP was distributed with three peaks in frequency at approximately 15%, 30%, and 40%, and these were related to different function zones (Fig. 6 E). Specifically, the yearly TECP of residential grids was normally distributed with a mean value of 40.5% and an SD of 4.1%, and those of industrial grids were concentrated at approximately 16.3% with an SD of 0.9%, while the mean values of commercial and public grids were close, with a bimodal distribution of approximately 30%, but slightly larger for public grids than for commercial grids (30.7% ± 2.5% vs. 28.6% ± 1.8%). The histogram of the hot day TECP was also unevenly distributed, with the values greater than 60% mostly falling in residential grids, whose mean was 87.5% and SD was 9.5% (Fig. 6F). Likewise, the distribution of TECP in public, commercial and industrial zones was 52.7% ± 3.4%, 49.9% ± 2.6%, and 29.2% ± 1.2%, respectively (mean ± SD).

4. Discussion

4.1. Different paradigm of the relationship between temperature and electricity consumption

In contrast to a U-shaped or V-shaped relationship [25–27], our study in Shenzhen revealed a J-shaped relationship, exhibiting a steeper curve for high temperatures and a flatter curve for low temperatures, and this pattern was associated with narrow temperature fluctuations and relatively high temperatures year-round (Fig. S6). According to current research, the lower breakpoint usually appears at 10–15 °C

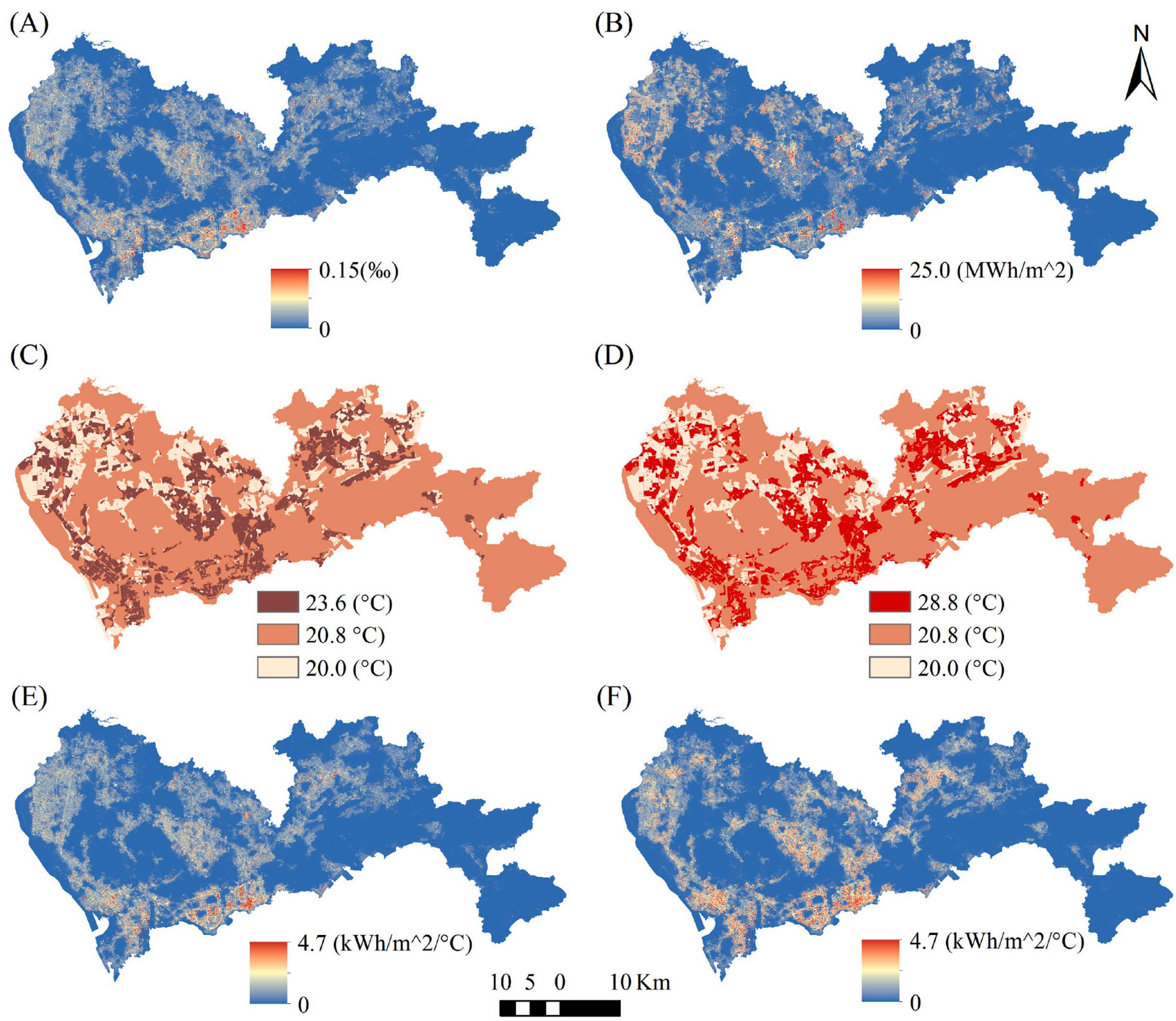

Fig. 5. The spatial distribution of (A) ECC, (B) EC, (C) bp1, (D) bp2, (E) slope1, and (F) slope2.

accompanied by a comfort zone with a temperature as large as 7 °C; therefore, no heating effect can be observed when most daily mean temperatures are greater than this range [63]. Similar results have been found in tropical cities such as Abidjan, Accra and Mindelo [67]. In addition, the upper breakpoint of 23.6 °C in Shenzhen for the residential sector is higher than the results in other high-latitude regions, such as 16 °C in London and 20 °C in Athens, but lower than the 26 °C in the central and southern Vietnam [35,68]. This phenomenon is a result of acclimation [69] and is influenced by the temporal resolution of the data because coarse data will sacrifice information on the temporal variations in electricity use and temperature [28,67]. Taking Shanghai as an example, the thresholds are 22 °C and 25 °C when using monthly and daily data, respectively [29,70]. Therefore, the threshold temperature for estimating electricity use must be obtained by calculation based on local measurements and cannot be determined by prior knowledge, such as the value of 18 °C, which has been widely used in the cooling degree days/heating degree days method [71,72]. In addition, the rate of change in EC of Shenzhen ranks among the top in the world [52]. Compared with Hong Kong, a neighboring megacity, EC increases at rates of 9.2%, 3.0%, and 2.4% in the domestic, commercial, and industrial sectors, respectively, for every 1 °C increase [62]. The explanation for this remarkably rapid growth remains unclear and can be explored in depth in terms of the age structure and lifestyle of the residents, including a relatively high proportion of migrants, young people, and solitaries. These findings demonstrate the urgency of cooling in subtropical cities like Shenzhen, where it is unlikely to save energy by reducing heating consumption to offset cooling consumption.

4.2. Spatial differences in the relationship between temperature and electricity consumption

Beyond the city-scale relationship between electricity consumption and temperature, our analysis revealed large spatial variations in the relationship at the intraurban scale, with $\Delta EC/\Delta T$ varying from 0 to 4.7 $kWh/m^2/°C$. Consistent with the results found in the Tokyo Metropolitan Area, we found that the rate of change of EC with T was higher and more variable in commercial areas than in residential areas, implying that commercial areas have a greater potential for energy savings for the same cooling magnitude (Fig. 5 E&F, and Fig. S7) [53]. However, there are large differences in the data and methods used in the two studies. The work by Nakajima and colleagues described the relationship between electricity consumption and temperature, as well as its uncertainty, by leveraging high spatial- and temporal-resolution metered EC data [53]. Our study, by comparison, developed a conceptual framework that related sectoral EC to urban functional zones, estimated local EC based on open data such as population distribution and building footprints, and then extended the city-scale EC-T relationship to the local scale. As opposed to the prevailing methodologies on urban building energy modeling, our approach is more concise, comprehensible, and computationally expedient. Specifically, numerous studies use

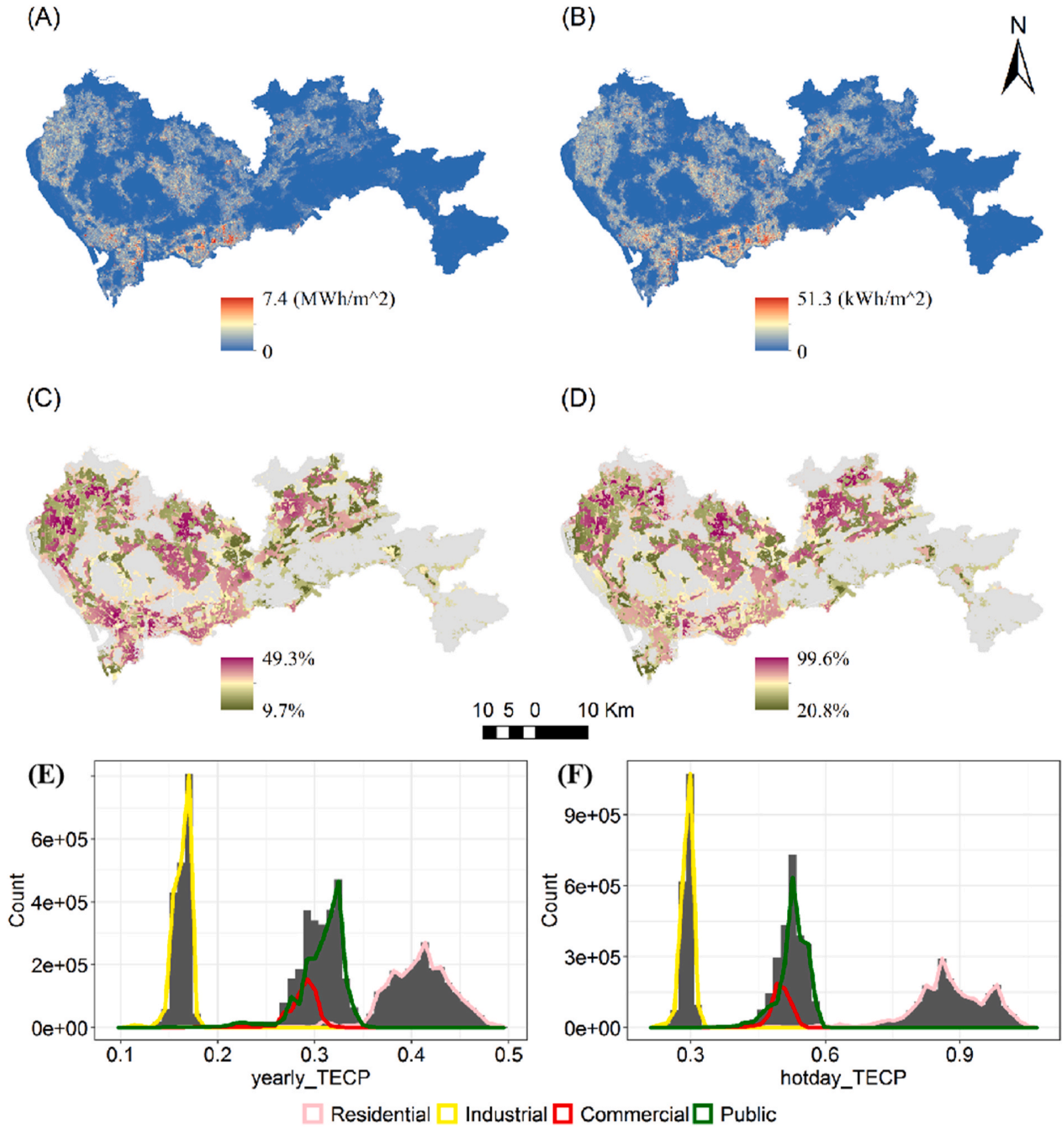

Fig. 6. The spatial distribution of (A&B) TEC, (C&D) TECP, and (E&F) the corresponding histogram of TECP throughout the year and on a hot day, respectively.

machine learning algorithms to estimate building energy consumption based on a data-driven framework [73–75]. This necessitates the input of copious auxiliary data and the calculation process is opaque, rendering the results challenging to elucidate in layman's terms [65,76,77]. Conversely, studies that employ numerical models to simulate building electricity consumption can be explicated through rational physical processes, but the applicability is circumscribed due to exact computational demands [39,78,79]. Therefore, despite the lack of verification of the spatialized results, our work makes a valuable contribution by offering new insights and possibilities for future research.

In addition, we explored the impact of urban heat island effects on electricity consumption patterns by mapping the proportion of temperature-sensitive electricity consumption to total consumption (TECP). Research has shown that there is a significant fine-scale spatial heterogeneity in the UHI intensity, with temperatures exhibiting large differences within close proximity, especially during hot weather conditions [57,80–82]. In Shenzhen, the temperature difference was found to be more than 7 °C [57]. As a result, the increase in cooling loads due to urban warming varies spatially with the local UHI and cannot be solely measured by the value of ΔEC/ΔT [44,83,84]. For example, the growth of cooling loads in Rome is 12% in the suburbs and up to 46% in the city center; and it varies from 15% to 50% in Athens [85,86]. Similarly, our research found that the TECP in Shenzhen varied from 9.7% to 49.3%, and thus is equivalent to a relative change in EC between 11% and 100%. The TECP in residential areas was much higher than that in other areas, reminding city managers to pay more attention to the energy security of residential electricity, because the health of residents will be at risk when the energy supply is insufficient [3]. Therefore, it is crucial to mitigate urban warming in such regions, especially in the context of increasing urban heat island intensity and expanding urban heat island extent in the urban agglomerations of the Guangdong-Hong

Kong-Macao Greater Bay Area [11,87,88].

In general, the study findings have important implications for urban planning and energy management in cities. The spatial variations in the relationship between temperature and electricity consumption suggest that targeted interventions, such as the implementation of cooling measures in areas with higher rates of EC with T, could yield more substantial energy savings. This information can be used to inform decision-making around urban design and energy policies, with the aim of reducing energy demand and improving the sustainability of the city. In addition, the use of population and floor area weighting methods at a fine spatial scale could provide valuable insights for building-level energy management strategies, enabling more efficient allocation of resources and reducing energy waste. Overall, the study highlights the importance of considering spatial variations in both urban heat island effects and energy consumption patterns when developing effective energy management strategies for urban areas.

4.3. Limitations and opportunities for future studies

There are some limitations in this study. First, we focused on the impact of daily mean temperature on electricity consumption without considering potential confounding factors such as humidity, wind speed, wind direction, and air pollution, as these may have an effect on electricity consumption to a greater or lesser extent [89–91]. For example, the results of Pearson correlation analysis indicated that high levels of humidity could increase cooling needs and therefore lead to higher EC, while air pollutants were negatively correlated with temperature as well as EC (Fig. S8). Then we tested the overall effects of various factors using generalized additive models, showing a higher degree of explanatory power for variations in EC, particularly in the case of industrial electricity consumption (Fig. S9). Furthermore, there was a holiday effect on the relationship between EC and T, with EC changing at a faster rate on workdays than on holidays (Table S2, Fig. S10). Therefore, it is important to comprehensively consider multiple factors in future studies to better understand the complex interactions between weather conditions and energy consumption [63].

Second, we spatialized EC from the city scale to the grid scale based on an electricity consumption coefficient, assuming equal effects of population count and floor area on electricity consumption within the same function zone. However, other factors such as income, building patterns and blue-green infrastructure interactively affect electricity consumption with temperature [34,92–95]. Research has found that reduced accessibility to green spaces and water bodies can increase household energy consumption [96]. Residents living in areas with more urban tree canopy can cool down by seeking shade, while residents in areas lacking tree canopy have to rely on cooling facilities such as air conditioners, causing different electricity consumption sensitivity to temperature [97]. Meanwhile, high-income populations tend to lead a greater energy consumption intensity, even though they usually live in greener neighborhoods, further increasing the uncertainty of the electricity consumption-temperature relationship. Consequently, the interaction of these demographic and socioeconomic factors on the relationship between EC and T is complex and warrants future studies.

Finally, considering the impact of the COVID-19 pandemic on global climate and energy use, the results of this study may underestimate the rate of change in EC with temperature due to the restricted human activities during lockdown periods. Comparing the differences in the EC-T relationships before and after the pandemic can reveal the effectiveness of human behavioral changes as a means to alleviate energy crises in the context of climate change [98–100]. In addition, the relationship between EC and T could change over time with economic development, technological innovation, policy intervention, and population acclimation [9,30,71], and its spatial pattern can also change due to the uneven distribution of infrastructure, spatial heterogeneity of the urban heat island effect, and intercity and intracity population movements [27,101]. It is important to conduct more retrospective or longitudinal long time-series studies of the relationship between temperature and electricity consumption by collecting historical data on electricity consumption and temperature, and using advanced statistical techniques such as machine learning, and forecasting future electricity consumption patterns by combining scenarios such as shared socioeconomic pathways (SSPs) and representative concentration pathways (RCPs) with energy system models [19,25,102].

5. Conclusion

In this study, we quantified the relationship between electricity consumption and daily mean temperature in Shenzhen at the city scale using segmented regression models, and then extrapolated it to the grid scale based on the land cover of function zone data, building footprint data, and population count data. We found that electricity consumption increased with temperature along the J-shaped curve, but the relationship varied by sector and in space. Domestic electricity consumption increased late but quickly, by 23.4%/°C and 24.9%/°C after 23.6 °C and 28.8 °C, respectively. Industrial electricity consumption increased early but slowly, by 3.9%/°C starting at 20 °C. The responses of commercial and public electricity consumption to temperature were similar and in the middle, growing at rates of 9.5%/°C and 10.9%/°C when the temperature exceeded 20.8 °C. At the grid scale, the rate of change in energy consumption with temperature ranged from 0 to 4.7 kWh/m^2/°C, leading to large spatial differences in electricity consumption increments for the same temperature change. We compared the proportion of temperature-sensitive electricity consumption to the total electricity consumption (TECP) across the city, showing a large spatial heterogeneity annually, with a mean of 29.8% and even a greater mean value on a hot day, equivalent to a 57.5% increase in electricity consumption due to extreme heat. This study contributes to the basis of the impact of climate change on urban energy consumption by underscoring the need for managing energy use influenced by temperature at the local scale. The findings will allow the local government to establish an eco-friendly and energy-conserving environment through functional renovation and cooling measures, showing great practical implications for urban planning and energy management. In the future, exploring the long-term trends of the relationship between temperature and electricity consumption, considering the influence of other factors, or examining the effectiveness of specific cooling and energy-saving interventions remain priorities for achieving urban sustainability.

CRediT authorship contribution statement

Jie Cao: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Weiqi Zhou:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Weimin Wang:** Resources, Data curation. **Xuelian Pan:** Resources, Data curation. **Chuanbao Jing:** Methodology. **Yuguo Qian:** Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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