

# Differential Sensitivities of Electricity Consumption to Global Warming Across Regions of Argentina

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## Research Article

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# Abstract

The description of the relationship between temperature (T) and electricity consumption (EC) is key to improve our understanding of a potential climate change amplification feedback and, thus, energy planning. We sought to characterize the relationship between the EC and daily T of different regions of Argentina and use these historical relationships to estimate expected EC under T future scenarios. We used a time series approach to model, remove trends and seasonality of EC accounting for breaks and discontinuities. EC and T data were obtained from Argentine Wholesale Market Administrator Company and global databases, respectively. We evaluated the T-EC model for the period between 1997 and 2014 and two sub-periods: 1997–2001 and 2011–2014. We used modelled temperature projections for the 2027–2044 period based on the Representative Pathway Concentration 4.5 together with our region specific T-EC models to predict changes in EC due to T changes. The shape of the T-EC relationships was quite stable between periods and regions but varied according to the temperature gradient. We found large increases in EC in warm days (from 40 to 126 Wh/cap/°C) and a region specific response to cold days (from flat to steep responses). The T at which EC was minimum varied between 14 and 20°C and increased in time as mean daily T also increased. Estimated temperature projections translate into an average increase factor of 7.2 in EC with contrasting relative importance between regions of Argentina. Results highlight potential sensitivity of EC to T in the developing countries.

## 1 Introduction

For centuries energy use was associated to human well-being (Ahuja & Tatsutani, 2009). However, this relationship might have been recently levelled off due to the extensive environmental impacts of energy generation. To meet material needs, societies use energy and impact ecosystems by changing land use-land cover (e.g., for roads, oil and gas seismic exploration grids, transmission lines, dams, etc.), emitting greenhouse gas and consequently, intensifying global warming (Dale et al., 2011). In parallel, changes in air temperature alter patterns of energy consumption, as the rise and fall of temperature increases demand for cooling and heating respectively (Dale et al. 2011; Auffhammer & Mansur, 2014). The International Energy Agency (IEA) in the World Energy Outlook (2016) (IEA, 2016) estimated that electricity accounts for 30% of residential energy consumption, but due to the rapid uptake of appliances and cooling systems it is expected to rise more than 40% in 2040. In addition, electricity integrates different sources of primary energy and therefore its consumption can be used as an estimator of the total energy consumption (IEA, 2019). Understanding of the energy-climate relationship, and more precisely the relationship between temperature and electricity consumption along a mean annual temperature gradient, is a critical requirement to improve energy planning within a context of a potential climate change amplification feedback.

Relationships between air temperature and electricity consumption (T-EC) are, in general, non-linear as both, temperature increases and decreases result in higher electricity consumption (Moral-Carcedo & Vicens-Otero 2005; Bessec, & Fouquau 2008; Apadula et al. 2012; Santamouris et al. 2015; Gupta 2016; Shaik, & Yeboah 2018, Li et al. 2019). T-EC relationship has been characterized by means of three

attributes: i) the shape (Bessec, & Fouquau 2008; Auffhammer & Aroonruengsawat 2011; Apadula et al. 2012; Davis & Gertler 2015, Li et al. 2019), ii) the threshold temperature – TT (Moral-Carcedo & Vicens-Otero 2005; Santamouris et al. 2015; Auffhammer & Aroonruengsawat 2011; Psiloglou et al 2009), and iii) the response of EC to temperatures below or above the TT (Moral-Carcedo & Vicens-Otero 2005; De Cian et al. 2007; Bessec, & Fouquau 2008; Psiloglou et al 2009; Auffhammer & Aroonruengsawat 2011; Apadula et al. 2012; Santamouris et al. 2015; Gupta 2016; Thornton et al. 2016; Shaik, & Yeboah 2018). (see Appendix A). The shape of T-EC relationships describes qualitatively how EC changes when T varies and it ranges from linear (increasing or decreasing) to U-shape (where in both extremes of temperature range the EC increases strongly) to hockey stick-shape (where the EC increases strongly with only high or only low temperature values). TT is the value (or range of values) of air temperature at which the qualitative behavior of electricity consumption changes and the electricity consumption is minimum, known as the inflection point of electricity consumption. Finally, the response of EC to temperature above or below the TT is generally quantified by means of the slope of a linear model fitted to T and EC values above and below the TT (i.e. warm temperature regimes –WTR-, and cool temperature regimes –CTR).

Previous studies found that the T-EC relationship differs across climate zones (i.e countries or regions). Bessec & Fouquau (2007, 2008) described warmer zones with U shaped pattern and colder ones with hockey stick shape. Linear negative or positive responses of EC to temperature were found in zones where the temperature ranges were constrained to high or low temperatures (e.g Finland or Sweden in Bessec & Fouquau 2007). Several authors found lower values of TT at colder regions: Auffhammer & Aroonruengsawat (2011) comparing different regions in California; Santamouris et al. (2015) analyzed fifteen studies around several northern hemisphere countries; Moral-Carcedo & Vicens-Otero (2005) at different locations in Spain; Psiloglou et al. (2009) comparing different countries in Europe. Bessec & Fouquau (2008), Santamouris et al. (2015) and Shaik & Yeboah (2018) found that the responses of EC to temperatures depends mainly on characteristics of the zone, like the infrastructure, energy sector and the type of energy used.

There are several reasons to study the T-EC relationship in a developing country like Argentina. First, most studies focused on developed countries from the Northern hemisphere (Moral-Carcedo & Vicens-Otero 2005; Bessec, & Fouquau 2008; Psiloglou et al 2009; Auffhammer & Aroonruengsawat 2011; Apadula et al. 2012; Thornton et al. 2016; Shaik, & Yeboah 2018, Li et al. 2019) however for exceptions see De Cian et al. (2007) and Santamouris et al. (2015). Davis and Gertler (2015) and Gupta (2016) worked in developing countries but in the Northern hemisphere. Second, Argentina's steep climatic gradient allows the characterization of regional T-EC relationships minimizing the effects of different regulations. Third, Argentina provides a relevant case-study because it is representative of a set of Southern hemisphere upper/middle-income countries under-represented in the literature. Argentina is one of the largest economies from Latin American countries with a marked cultural, social and demographic diversity, depicted of countries with constant economic and political instability. Data from The World Bank Group (2019) showed that in the last two decades, Argentina underwent smooth and abrupt changes that make it an interesting -as well as challenging- case to study. For example, the average density population doubled from 1990-2014 (The World Bank Group, 2019). The pump price for gasoline was non-linear,

doubling from 1990-2014 but had two peaks, one in 2000 of 1.07 US\$ per liter, a fall of 30% in subsequent years and a maximum peak in 2014 of 1.52 US\$ per liter (The World Bank Group, 2019). The Gross Domestic Product (GDP) amounted to ca. 140 billion current US\$ in 1990 and doubled by 2001 then it decreased markedly to 98 billion current US\$ during the 2002 crisis and by 2014 it reached 530 billion current US\$ (The World Bank Group, 2019). In conclusion, to study the T-EC relationship in Argentina approaches should account for abrupt changes associated with modifications in legal regulations, prices, or due to economic crises that countries may experience.

The study of the T-EC relationship is still incipient in Argentina. For example, Legisa and Reali (1989) showed that daily EC increased up to 2 GWh per unitary increase in the difference between daily temperature and the mean temperature for all the country. Moreover, Beyrne et al. (2015) analyzed the T-EC relation for all the country using annual econometric model and determined that an increased in EC per unit change in T was slightly less than double in summer compared to winter (6.99 GWh and 3.78 GWh average, respectively). Most recently, Margulis et al. (2016) analyzed the T-EC relationship in winter in Buenos Aires between 1998-2015 and found that it was a negative relationship, that is, the lower the temperature, the higher the EC and vice versa. In addition, Margulis et al. (2017) analyzed the T-EC relationship in summer in 3 different administrative units of the country and found a semi-elasticity of 1.5% reached for the Gran Buenos Aires area (the biggest city in the country). However, for the rest of the administrative units (i.e. Santiago del Estero and Chubut Provinces, and Trelew city) the impact of T on EC was much lower (from 0.3% to 0.6%) (Margulis et al., 2017). In relation to these last publications, Mastronardi et al. (2016) analyzed the T-EC relation in different regions during 2010-2016 and found an increment in the EC between 1.8% and 3.2% when mean daily temperature increased by 1°C during summer. Chévez et al. (2018) found that the highest EC in warm regions were associated to the use of air conditioning equipment. Finally, Zaneck et al. (2019) proposed a model to forecasts the residential EC of the City of Salta (city in the north of Argentina) using surveys and interviews to characterize EC. Therefore, we still lack a quantitative long-term description of spatial patterns in T-EC relationship across Argentina. Such regional characterization for the rest of the country would shed light on the potential underlying mechanisms and its temporal dynamics.

Climate change is projected to have impacts on EC across the world (Auffhammer et al., 2017; Wenz et al., 2017; Li et al. 2019; van Ruijven et al., 2019). These potential effects of climate change on the electric power system is an issue of growing interest and important for decision-making (Franco & Sanstad, 2008). Future EC is likely to increase due to climate change, but the magnitude depends on many interacting sources (van Ruijven et al., 2019). Locally, Franco & Sanstad (2008) estimated that a 3% increase in EC in California by 2020 due to global warming would translate to about \$930 million (2000 dollars) in additional annual electricity expenditures. At a larger scale, Auffhammer et al. (2017) found an average EC increase of 2.8% across the United States by end of century under a business as usual scenario. In China, Li et al. (2019) found that annual EC will increase by 9.2% per +1°C in annual global mean surface temperature. More extensive study from Wenz et al. (2017) found a significant increase on the overall EC in Southern and Western (~3 to ~7% for Portugal and Spain) countries and a significant decrease in Northern European countries (~-6 to ~-2% for Sweden and Norway) due to future warming.

Finally, van Ruijven et al., (2019) combined socioeconomic and climate scenarios to estimate EC around the world and found that EC will rise by more than 25% in the tropics and southern regions of the USA, Europe and China.

Here we sought to characterize the relationship between EC and T at a daily time step at different regions of Argentina, assess its temporal changes and use these historical relationships to estimate expected EC under two different T scenarios. The main questions guiding our work were: (1) How does the T-EC relationship vary along a temperature gradient? (2) How did the electricity consumption-temperature relationship change between 1997 and 2014? And (3) How will future temperature translate into EC across different region of Argentina? To address these issues we performed a time series and regression analysis based on spatially explicit meteorological, electricity consumption databases and different temperature scenarios.

## 2 Methodology

We restricted our analysis to Continental Argentina, a total area of 2.79 Mkm<sup>2</sup> inhabited by 40.1 Mhab in 2010 and that displays a marked latitudinal and altitudinal temperature gradient from 7 to 22 °C of mean temperature (18-year daily average) (Argentine National Geographic Institute, 2019). We used electricity consumption data collected by Argentine Wholesale Market Administrator Company (CAMMESA acronym in Spanish). Data from CAMMESA included the total hourly supplied electricity consumption from 1997 to 2014 for 9 regions in which the country is subdivided by the Argentinean Secretary of Energy dominated by different thermal regimes (Figure 1 a and b). It is the net consumption between the total demanded and the losses by region. These regions were: Patagonia, Comahue, Cuyo, Buenos Aires (BAS), Centro, Noroeste, Gran Buenos Aires (GBA), Litoral and Noreste. Tierra del Fuego, Antarctica and South Atlantic Islands were not included in our analysis because they are not connected to the national power grid (Sistema Argentino de Interconexión, SADI acronym in Spanish). Due to the aggregated EC data that was available, residential, commercial or industrial electricity consumption could not be discriminated. Nevertheless, residential and commercial represent on average almost 80 % of total EC (Mastronardi, et al., 2016). According to data from CAMMESA and the National Energy Ministry (MINEM 2021) between 2012 and 2014, only Patagonia had 40% more industrial consumption than residential and commercial (see Appendix B). Daily EC was calculated as the sum of hourly EC between 9 pm of the day before to 9 pm of the following day to match meteorological data daily time-step. We excluded holidays or weekends from the analysis to avoid including days with altered economic or residential activity.

The study of T-EC relationships is complex because EC covariates with several social, economic and environmental factors that operate at different time scales (Psiloglou et al., 2009). Two approaches have been frequently use to minimize confounding effects on the T-EC relationship: a time series analysis – where long term and seasonal trends are removed- or a multivariate regression analysis including time (Psiloglou et al., 2009). However, these approaches do not fully account for abrupt changes associated with modifications in legal regulations, prices, or due to economic crises that countries may experience. Therefore, we here performed a time series analysis coupled with a breakpoint detection using BFAST

(Breaks for Additive Seasonal and Trend) (Verbesselt et al., 2010) and characterized daily EC with the residuals of the model (i.e. Residual EC). Residuals were obtained from the difference between the modeled and the observed data. As many other time series analyses BFAST models and removes trends and seasonality using an additive decomposition model (Verbesselt et al., 2010). Changes in the trend component are often associated to variations on the population or economic activity (e.g. GDP or fuel or electricity price) while changes in the seasonal component can be related to changes in the seasonal temperature. Therefore, we regressed BFAST residuals to daily temperature values in order to characterize the T-EC relationship with minimum influences from long-term trends and/or seasonal variability. However, BFAST additionally seeks for breakpoints (i.e. abrupt changes) (Verbesselt et al., 2010) which make it particularly suitable to study the T-EC relationship in Argentina due to the numerous disrupting events (economic crises, sudden changes in relative prices, etc.) that have taken place during the study period (e.g. the 2001 economic crisis).

BFAST requires several user-defined parameters including the expected number of breakpoints. To avoid user bias, we performed several runs with all possible breakpoints (i.e. from 0 - without breakpoints- to 18) and chose the number of breakpoints that minimized the standard deviation (SD) of residuals as a measure of the spread of a data distribution. The general model is of the form (Eq. 1):

$$SD = \sqrt{\frac{\sum |x_i - x_{avg}|^2}{n-1}} \quad (\text{Eq. 1})$$

Where  $i=1, \dots, 18$ ;  $X_i$  – the average residual in one year,  $X_{avg}$ – the arithmetic mean of the average residual in the period analyzed,  $n$  – 18 years

We also evaluated the minimum root-mean-square error (RMSE) of residuals as a measure of goodness of fit. Thus, for each region daily EC time-series, we performed 7 BFAST runs (ranging from 0 to 5 breakpoints plus the maximum number of breakpoints detected for the region under consideration). We did not consider more than 10 breakpoints to avoid over-fitting the model. Results showed that in most cases, models with 5 breakpoints minimized the SD (or the RMSE) and therefore from here on we base our results on these models (see appendix C).

Daily temperature data were obtained from WATCH Forcing Data ERA-Interim (WFDEI) (Weedon et al., 2014). This database has a 0.5 x 0.5° spatial resolution for all the globe and daily temporal resolution from 1979 to date. The selection of this database was the result of a per region comparison of 7 data sources (Table1) using the indices proposed by Toté et al. (2015). For each of the 7 databases we calculated 5 statistics (i.e. Pearson correlation coefficient (r), Relative Mean Absolute Error (RMAE), Nash-Sutcliffe Efficiency coefficient (Eff) and Bias) that relate each database daily temperature value with an independent meteorological stations dataset. To that end, we assembled 315 meteorological station data provided by the National Institute of Agricultural Technology (INTA, acronym in Spanish) and the National Meteorological Service (SMN, acronym in Spanish) from 1980 to 2016. From each spatially explicit global database, we selected the cells that contained the meteorological station from which we had data.

To order the 7 databases for each region we used the sum of the ranking for the 5 statistics. The final ranking was weighed by the area of each region. Finally, we chose the explicit spatial database with the lowest ranking for all the regions (see appendix D).

For each of the 9 regions, daily temperature was calculated from WFDEI cells containing urban areas under the assumption that rural electricity consumption is negligible. To define the extent of urban areas at each region we used monthly average radiance composite images of 2014 using nighttime data from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) (Mills et al., 2013). Based on visual interpretation we assumed that VIIRS pixels with radiance values higher than  $12 \text{ nanoWatts.cm}^{-2}.\text{sr}^{-1}$  corresponded to urban areas (Shi et al., 2014). To obtain temperature values for each region we calculated the daily mean temperature values of WFDEI cells weighted by urban areas in each cell. All analyses and image processing were done mostly on R (R Core Team, 2018.) and Google Earth Engine (Gorelick, et al., 2017).

To analyze the T-EC relationship we fitted linear, quadratic, cubic spline and natural cubic spline models and selected the best one compared by means of the Akaike criterion. We evaluated three attributes to characterize the T-EC relationships for each region along different periods between 1997 and 2014: (1) the shape, (2) the TT and (3) the slopes. To decide the shape (U-shaped or hockey stick-shaped) of the T-EC relationship of each region we calculate the quotient between slopes of the warm temperature regimes (WTR) and the cool temperature regimes (CTR), if this quotient was higher than 0.5 we considered a U-shaped relation and less than 0.5 was a hockey stick-shaped relation. TT was determined from searching when the first derivative of the function chosen by the Akaike criterion was equal to zero. For the slopes we calculated linear models for the T-EC relationship below or above the TT and analyzed the change on the response to WTR (Wh/cap/°C) and CTR (Wh/cap/°C). Similarly, the temporal changes were evaluated by assessing the T-EC relationship for two separate periods: initial (1997-2001) and final (2011-2014). Residual EC is shown on a per capita basis to allow comparisons among regions.

Finally, to estimate the response of EC to climate change we used temperature predictions from Commonwealth Scientific and Industrial Research Organisation (CSIRO) (Gordon et al., 2002, 2010) based on the Representative Pathway Concentration 4.5 and 8.5 (Moss et al. 2010; Pachauri et al. 2014). These two emission pathways represent an intermediate and an extreme scenario where emissions peak around 2040 (RCP 4.5) or continue to rise throughout the 21 century (RCP 8.5). As done previously, regional T predictions for the period 2027-2044 were estimated from urban areas only. Thus, mean daily temperature for the period 2027-2044 was calculated as (Eq. 2):

$$MDT_p = MMT_h - (MMT_p - MDT_h) \quad (\text{Eq. 2})$$

Where  $MDT_p$  is the predictive mean daily temperature for scenarios,  $MMT_h$  is the historical mean monthly temperature,  $MMT_p$  is the predictive mean monthly temperature and  $MDT_h$  the historical mean daily temperature.

To quantify the response of EC to climate change we subtracted the per capita residual EC (Wh/cap) estimated using future expected T according to the different climate change scenarios to the observed temperature of the 1997-2014 period. We also expressed these results as the ratio between expected residual EC (under the two RCP scenarios) and observed residual EC. In addition, we analyzed the difference in EC comparing the difference between mean temperatures from the T scenarios and the measured T with WFDEI database (see appendix E).

## 3 Results And Discussion

### *3.1 How does the electricity consumption-temperature relationship vary along a temperature gradient?*

The shape of the T-EC relationship during the period 1997-2014 differed across regions that encompass a marked temperature gradient (Figure 2 and Table 2). Warm regions such as Centro, Noroeste, Gran Buenos Aires and Noreste showed a U-shaped pattern while cold regions such as Comahue, Cuyo, Buenos Aires and Litoral displayed a hockey stick- type where EC increased only with warmer temperatures. No clear saturation of EC at low or high temperatures was noted. For all regions cubic splines functions described best the observed T-EC relationship (see appendix F) indicating that the response of EC to changes in daily temperature are not constant along the temperature range. Given that there was no significant T-EC relationship in Patagonia we excluded the region from the results – although we included in Figure 2 (a) for the readers to judge.

Our results have some similarities with the findings of Bessec & Fouquau (2007, 2008) who also showed that warm regions, like Southern European countries, had a U-shaped relationship between T and EC and a hockey stick-shaped relation at cold regions like Northern European countries. However, their hockey stick shape implied that EC increased at cold temperatures, just opposite to our hockey stick shape, which increased only at high temperatures. We hypothesize that this contrasting result stems from three main differences between European countries and Argentina: temperature range, relative prices of alternative energy sources and heating devices. On average European countries are colder than Argentina and winter temperatures are particularly colder. In addition, since 1947 –when large natural gas reserves were found at Loma de la Lata fields (Neuquén, Argentina) - the use of natural gas has increased markedly due to infrastructure development and relatively low prices. Residential heating in Argentina has generally relied on natural gas, as electrical heating devices are not widespread used. In colder regions, such as Comahue, the availability of network gas according to the 2001 and 2010 census exceeds 80% of the population (INDEC, 2012). The opposite happened in warmer regions where the availability of network gas was below 20-25 % (e.g Noreste, Noroeste and Litoral) (INDEC, 2012) (Table 3). Nevertheless, Margulis (2014) analyzed the association between EC and natural gas availability among different regions of Argentina and found that the lack of availability of natural gas through networks for heating in Noreste and Noroeste represents a 10 % decrease in EC. While a thorough explanation of the causes of household heating choices is out of the scope of the study, the findings of Bessec & Fouquau (2007, 2008) are consistent with our hypothesis because, at country level, their results implies the extensive use of electric devices for heating and favorable electricity prices compared to other energy sources.

Additional support comes from a study by Auffhammer (2013) where the lack of response of EC to low temperatures in California was associated to the generalized use of natural gas for heating. Overall, these results coarsely suggest that low summer temperatures restrain European countries from a general U shape pattern while in Argentina it is due to a mixture of availability of natural gas at low prices together with the extensive use of gas fed heating devices.

Connected to the overall shape of the T-EC described above, we found that EC increased when daily temperatures were higher than the TT (i.e. WTR) at every region while the opposite did not occur. EC in cold regions with higher access to natural gas –i.e. Comahue, Cuyo and Buenos Aires- did not increase while in warm regions without access to natural gas it did increase. Given this confounded effects, here on we will focus on the response of EC to WTR. The slope of the linear relationship between EC and WTR –a simple estimator of the response- ranged from 40 to 126 Wh/cap/°C -that is more than a twofold variation- between cold and warm regions. This variability in the response of EC to warm daily temperatures together with the lack of a saturation threshold -i.e. daily temperature above which EC does not increase- suggest that future increases in temperature may have significant and heterogeneous impacts on electricity demand. Clearly, a one-degree increase in daily temperature will not translate into similar per capita electricity consumptions across regions of Argentina. Whether this increase occur in a warm or cold region, with extensive availability of electric cooling devices will be key to anticipate future demand. This is key given the ongoing adoption of residential electrical equipment (Margulis 2014), particularly since 2018 (Table3). In addition, access to alternative energy sources for heating will also play a significant role, as the increase in cooling demand will not be balanced by a decrease in the heating demand of electricity.

The temperature threshold (TT) for the country was on average of 17°C but varied between 14 and 20°C closely matching the mean daily temperature (MDT) range –from 12.7°C to 21.6°C- across regions (Table 2). Indeed, we found a positive linear relation between MDT and TT (Eq. 3):

$$TT = 1.76 + 0.89MDT \text{ (Eq. 3)}$$

$$(\text{adjusted } r^2 = 0.93 \text{ and } p \text{ value} \ll 0.001)$$

This relation has the ability to predict an aspect of the T-EC relationship behavior with climatic data. It suggests an adaptive and predictable behavior, where people´s perception of what is cold or warm is context dependent. Intuitively, people that live in warm regions apparently sense hot conditions at higher temperatures than people that live at colder regions and vice versa. In addition, this behavioral adaptation had seemingly occurred to the modal situation, that is, the MDT. Only in Noreste, Buenos Aires and Comahue regions TT differed by more than 1°C from MDT. Additionally, as could be expected from the T-EC shape, TT could be found at a single or at range of daily temperatures. In conjunction, these results agree with the findings of Santamouris et al. (2015) comparing fifteen Northern hemisphere countries (i.e. average TT=18°C and varied between 12°C and 23°C) and Bessec & Fouquau (2008) (i.e. average TT=16.1°C, and varied between 22.4 °C for warm countries and 14.7 °C for the cold countries).

### ***3.2 How did the electricity consumption-temperature relationship change in time?***

The shape of the T-EC relationships was quite stable between periods with only two regions – i.e. Noroeste and Litoral- changing from the initial hockey stick-shaped response to a U-shaped at the final period (Figure 3 and Table 4). That is, in recent years both regions showed higher sensitivity of EC to low temperatures than in the initial period. This finding is consistent with the low (ca. 25% of households) access to the natural gas network at these regions (INDEC, 2012) whereas electricity would represent the major energy source for heating. Implicit in the higher sensitivity of EC to low temperatures that we found is the increase in electrical heating devices availability such as heating or cooling air conditioners (ACs).

At regions where the shape of the T-EC relationship did not change the main difference between 1997-2001 and 2011-2014 was the intensification of the U-pattern. That is, the response of EC to warm or cold temperatures increased between periods. In particular, the slope for WTR in 1997-2001 ranged from 20 to 75 Wh/cap/°C and in 2011-2014 ranged from 54 to 177 Wh/cap/°C, a 2 to 3 fold increase (Table 3). We associate this increase in the EC with warm temperatures to the increase development and adoption of electric devices – a concept named as extensive margin in the literature- and particularly of ACs. After the Argentinian 2001 economic crisis, there was a marked increase in sell of ACs in part due to pro-internal market policies and frequent summer daily temperature records among other causes (Table 3). In fact, according to the National Survey of Household Expenditures (ENGHo) in 2012 in almost every region more than 30% of households had air conditioners and in 1996/97 only 4% had (Chávez et al., 2018). Alternatively, the intensive margin – i.e. the increase in the use of already available electric devices when temperature increases – could be put forward as an explanation. However, the magnitude of the increase in the sensitivity of EC to warm days and the fact that the intensive margin has a limit -the use of electric devices cannot be increased infinitely- suggest that its impact, though not irrelevant, would be limited. In another developing country – Mexico- Davis & Gertler (2015) found residential EC increases of up to 3.2% per month for each day with temperatures above 32°C compared to one baseline day of 19°C. While not directly comparable, Davis & Gertler (2015) and our results highlight potential sensitivity of EC to climate change in the developing countries where population income is expected to increase and thus the extensive margin.

The threshold temperature (TT) changed between periods at every region (Figure 3 and Table 4). These differences were, in general, positive meaning that TT at the final period was higher than at the initial period, with the exception of a cold region, Comahue. Differences ranged from 0.03°C to 3.2°C at Litoral and Buenos Aires respectively, but mostly every region increased around 1°C. However, when TT was plotted against MDT the slope of this relationship was not significantly different between periods. That is, a unitary increase in MDT translates into a similar increase in TT along the MDT gradient. In other words, the increase of EC when MDT increases by, for example, 1°C would be similar irrespectively of a change from 18 to 19°C or from 35 to 36°C. This may suggest a context dependent acclimation of human behavior to changes in temperature. For example, if there were physiological limits to temperature acclimation, surpassing such thresholds would translate into a more than proportional increase in EC. However, the lack of such thresholds points to a relative perception of ambient temperature, where

changes in behavior may be triggered more by the comparison to a reference situation than to an absolute temperature.

### ***3.3 How will future temperature translate into EC across different region of Argentina?***

Climate change will likely increase EC in Argentina. This issue is central to decision making because the country should increase the electrical power if the T predictions of the RCP 4.5 scenario are accomplished. Both scenarios, RCP 4.5 (Table 5) and RCP 8.5 (see Table 7 appendix) had similar results. From now on, assuming a stabilization for GHG emissions we will focus only the RCP 4.5 scenario results. In the RCP 4.5 scenario the predicted country average for 2027-2044 increase in temperature will be of 0.5°C ranging between -3.2°C and 3.0°C at Cuyo and Centro regions respectively (Table 5). Combining the expected warming of the RCP 4.5 scenario with our T-EC models results into an average increase of 109.8 Wh/cap in the mean daily residual EC oscillating from -41.5 Wh/cap in Noroeste and 302.5 Wh/cap in Litoral. This means that EC would grow or be reduced by a factor of -2 to 26.8 depending on the region. Translated into power facilities, the increase in EC only due to the expected warming would demand a small power plant of 150 Mw. However, this is a conservative calculation, as we did not take into account the expected population increase and neither income growth among other variables known to impact energy consumption. Future research should carry out the study as Franco & Sanstad (2008) to estimate the additional annual electricity expenditures that global warming would generate for Argentina.

The large differences in the expected EC increase can be traced to two intertwined variables: the average change in the expected daily temperature and the shape of the T-EC relationship. As calculated here, the average change in the expected temperature will define the shift in the daily temperature distributions, together with the sensitivity of EC to daily temperature -that is, the shape of the T-EC relationship- will determine the expected EC. Thus, the larger the increase in average daily temperature at regions where the T-EC relationship has a hockey stick shape -with a steep WTR slope- the larger the EC increase will be (eg. Litoral region- see Figure 2 (h) and Table 2). In addition, due to the size of the CAMMESA residual mean EC some ratios show very high values however this disappears when we expressed these results as a difference in EC.

The marked differences in the expected residual EC among regions reported here suggest that site-specific policies will be needed to secure future electricity access. However, policy interventions require more information than the one provided here and thus these results should be taken with caution. Future EC not only depends on the expected temperature but also on many other factors such as future population size and wealth. A recent global comprehensive study (van Ruijven et al., 2019) reported small -less than 10%- energy demand increases for Argentina mainly due to increases in the northern regions in partial agreement with our findings (Noroeste region has the highest EC increase factor of 26.8). In any case, our results, bundled with other studies, point to an increase in the EC due to climate change; the magnitude of which may represent a significant challenge to some Argentinean regions.

## **4. Conclusions**

Using a time series approach we analyzed the relationship between T and EC across space and time. Our study provided a qualitative and quantitative description of three parameters of the T-EC relationship with important implications for energy planning. We found large increases in electricity consumption in warm days, -a pattern that has intensified in time- with a region specific response to cold days. Moreover, the temperature at which electricity consumption is minimum (i.e. TT) differed among regions closely tightly associated to the mean daily temperature gradient, and increased similarly in time as mean daily temperature also increased. These results point to an extensive change in behavior with remarkable consequences in electricity consumption. Our findings suggest that the shape of the T-EC relationship varied across regions depending on the temperature range, relative prices of alternative energy sources and electric heating devices availability. Future temperature scenarios will translate into an average increase of 109.8 Wh/cap [by a factor 7.2] in residual EC with contrasting relative importance between regions of Argentina.

Energy planning deals with the anticipation of energy demand. Forecasting energy demand due to changes in temperature can coarsely be approached by substituting time for space. That is, modeling the T-EC relationship to infer future trajectories of electricity consumption at a site from contemporary spatial patterns. This approach, frequently used in ecological studies (Blois et al., 2013), assumes that drivers of the T-EC relationship in space holds when considered in time. Our results suggest that this assumption is valid for TT but not for the response of EC to cold days. Intuitively, the drivers of human behavior when temperature change seem more consistent in space and time than those that control electricity use such as income and adoption of electric devices. Nevertheless, these results highlight the importance of a specific site approach to anticipate the impacts of global warming on EC and thus improve energy planning in Argentina. Further, the linear relation model between TT and MDT might be an approach to predict an aspect of the T-EC relationship and anticipate the EC for specific sites with expected change in temperature

Finally, our results should be used with caution. We are aware that our data encompasses all electricity uses and not only residential. However, in Argentina 80% of the EC is mostly residential and commercial (Mastronardi et al., 2016) except for Patagonia -the region not included in our analyses- where industrial EC was more important than the residential and commercial sectors. Additionally, we might have not removed completely other effects in addition to daily temperature on EC, though the use of a time-series approach that accounts for abrupt changes due to, for example, economic crises or changes in regulations, must have minimized these confounding effects.

## **Declarations**

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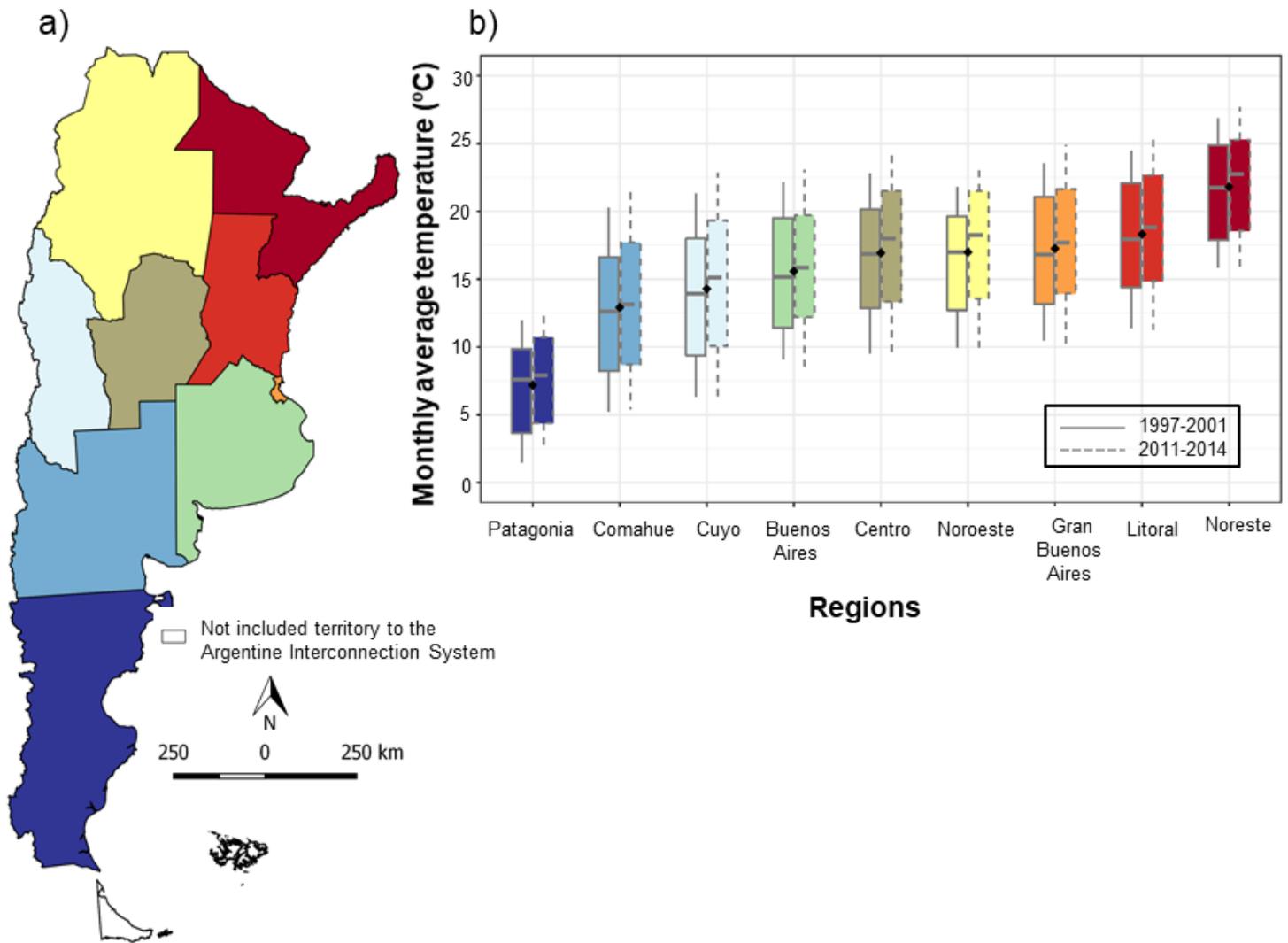
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## Tables

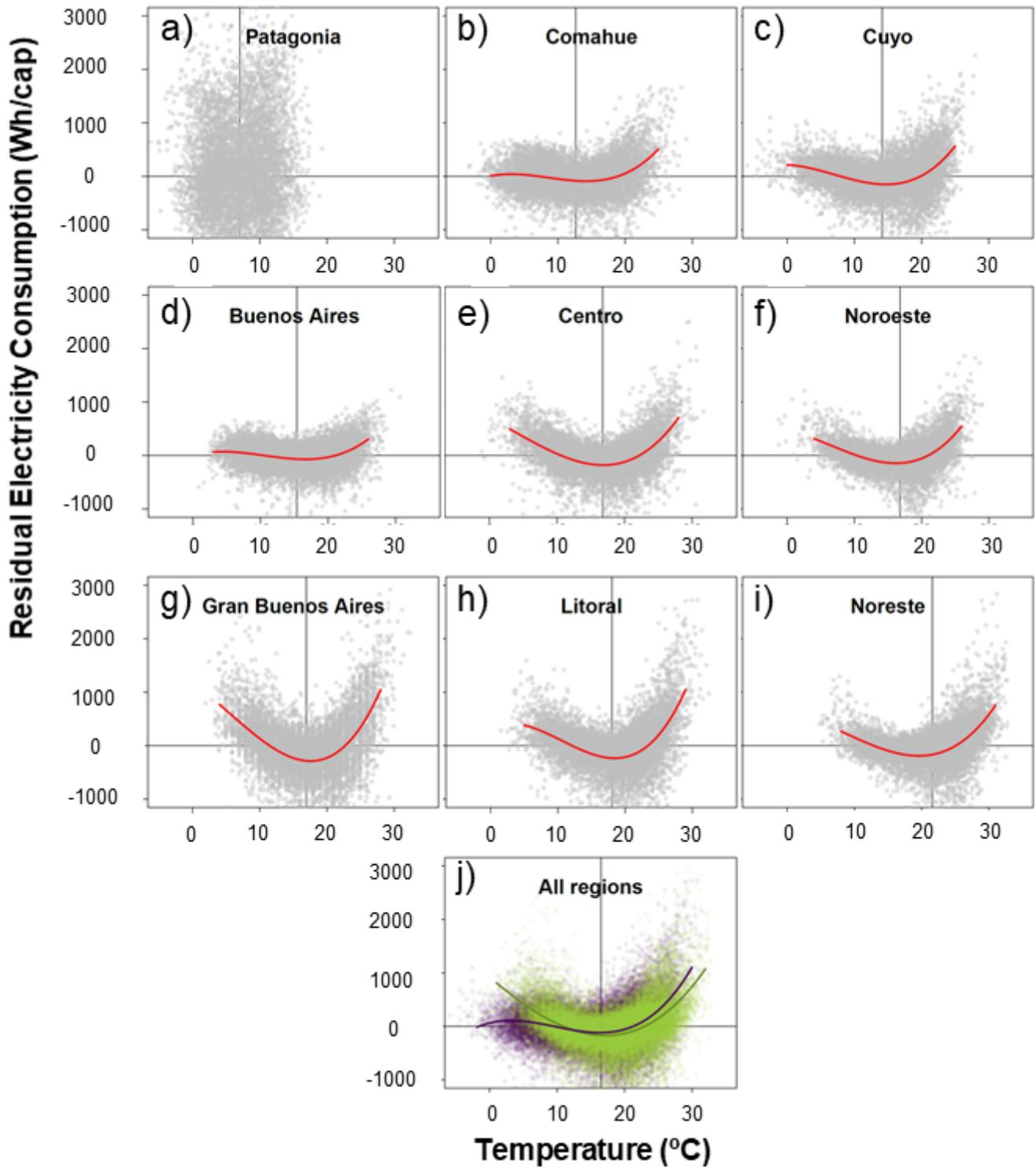
Due to technical limitations, table 1-5 is only available as a download in the Supplemental Files section.

## Figures



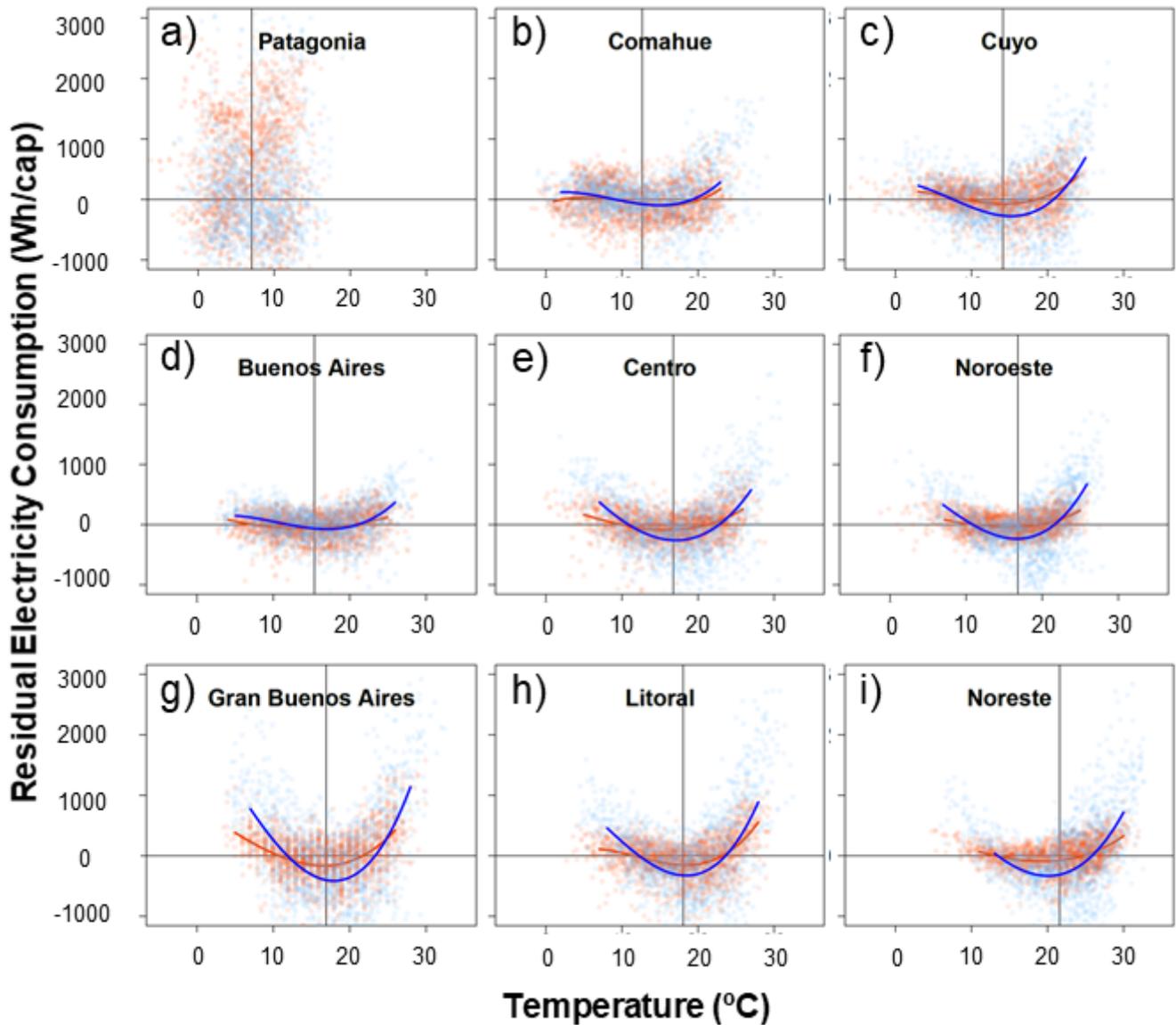
**Figure 1**

Argentine Wholesale Market Administrator Company (CAMMESA acronym in Spanish) regions (a) and box plot monthly average temperature for each region for all the period (black point) and the initial (full line) and final (dash line) periods (b). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.



**Figure 2**

Relationship between per capita residual electricity consumption (Wh/cap) and temperature (°C) for nine regions of Argentina for 1997-2014 (grey points, red line is the best model adjusted). Vertical line represents the mean daily temperature of the region. The order of the figures follows from lower to higher mean daily temperature. In panel j, U shaped regions are depicted in green and hockey stick shaped regions in purple and Patagonia was not included.



**Figure 3**

Relationship between per capita residual electricity consumption (Wh/cap) and temperature ( $^{\circ}\text{C}$ ) for each region for two different periods: 1997-2001 (red points) and 2011-2014 (blue points) (colored by period, lines are the best model adjusted). Vertical line represents the mean temperature for the complete period (1997-2014) of the region. The order of the figures follows from lower to higher the mean temperature of the regions.

## Supplementary Files

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