Climate Change Scenarios for Paraguayan Power Demand 2017-2050*

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Abstract

Although Paraguay has a surplus of electricity generation capacity, an underdeveloped electricity transmission and distribution infrastructure has constrained economic growth. The trajectory of future electricity demand is therefore important for planning purposes. We create electricity demand scenarios for Paraguay between 2017 and 2050 for two climatic scenarios, the Representative Concentration Pathways (RCPs) 4.5 (medium atmospheric CO_2 concentration) and 8.5 (high atmospheric CO_2 concentration), in combination with three socio-economic scenarios, the Shared Socio-economic Pathways SSP1, SSP3 and SSP5. Using historical climatic and socio-economic data from 1985 to 2010, we estimate an autoregressive distributed lag model for Paraguayan power demand with an in-sample Symmetric Mean Absolute Percentage Error (sMAPE) of 2.3% and an out-of-sample (2011-2016) *ex-post* sMAPE of 4.6%. We re-estimate the parameters on the full dataset 1985-2016 and produce electricity demand projections until 2050 for the selected scenarios. The scenarios show an increase in power demand until the period 2045, after which two of the six scenarios show a decline and the remainder continue increasing at a slower rate. The SSP1- and SSP5-based scenarios reach an annual demand of 65-80 TWh/year around 2045-2050, and the scenarios based on SSP3 reach an annual demand of 100-115 TWh/year around 2050. In addition to aid in energy planning, these scenarios may provide input to negotiations with neighbouring countries regarding Paraguay's surplus generation capacity.

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1 Introduction

This study investigates the drivers of electricity demand in Paraguay, and presents six scenarios for future electricity demand under conditions of climatic change, based on combinations of Representative Concentration Pathways (RCPs) (Smith and Wigley, 2006; Fujino et al., 2006; van Vuuren et al., 2007; Clarke et al., 2007; Riahi et al., 2007; Hijioka et al., 2008; Wise et al., 2009; Moss et al., 2010; van Vuuren et al., 2011) and Shared Socio-economic Pathways (SSPs) (van Vuuren et al., 2011; Moss et al., 2010; O'Neill et al., 2014; Kriegler et al., 2014).

The energy sector is of great importance to many economies and the well-being of a large part of the world population (for a small selection of recent studies reinforcing this importance, see for instance the literature reviews by Payne (2010) and Ozturk (2010)). As noted in these reviews, most studies identify a strong relationship between energy consumption and economic growth. This relationship underlines the importance of a comprehensive approach to energy planning.

Understanding the impact of different factors on the electricity demand is important for effective planning in the electricity sector. Socio-economic, demographic and climatic factors have been found to be the main drivers of electricity demand (Dryar, 1944; Parkpoom et al., 2004; McSharry et al., 2005; Isaac and van Vuuren, 2009; Hyndman and Fan, 2010; Trotter et al., 2016a; Steinbuks, 2017). According to the Intergovernamental Panel on Climate Change (IPCC) (2009), the climate will experience large changes over the coming decades. In a review of the literature on the impacts of climate change on the electricity market, Mideksa and Kallbekken (2010) identify the need to study the impacts of climate on electricity demand for Latin American countries, as this is not well covered in the existing literature. Another literature review by Cronin et al. (2018) claims that studies on the impact of climate change on the energy systems in developing countries are scarce, and recommends greater research effort in this area. The present study helps fill this gap in the existing literature.

Gaps in the literature notwithstanding, Paraguay represents a particularly interesting case. Despite a surplus of generation capacity, the country has experienced electricity outages and frequency fluctuations, as demand growth has outpaced investments in transmission and distribution infrastructure. Reinstein (2009) claims that this has hampered economic growth, since the country has been unable to take full advantage of the hydroelectric potential of the Paraná river. By creating scenarios for future electricity demand for Paraguay, this study provides information that may aid electricity planning and policy decisions, and may ultimately help remove barriers to economic growth and welfare in Paraguay.

In addition, the 1973 treaty between Paraguay and Brazil that resulted in the Itaipu power plant expires in 2023, and renegotiations are scheduled to begin in 2019. This study provides information that could be relevant to the negotiations.

To generate future electricity demand scenarios, we first estimate an autoregressive distributed lag (ARDL) model for electricity consumption using historical GDP, population, and heating/cooling degree days. This model captures both long-run relationships and short-run dynamics in a single-equation model. We subsequently validate the model using the bounds testing procedure developed by Pesaran et al. (2001) and investigate the forecasting accuracy of the model. Finally, we combine the estimated model with projections of the exogenous explanatory variables – GDP and population from SSPs and heating/cooling degree days from RCPs – to generate scenarios for future electricity demand.

Section 2 presents an overview of the Paraguayan power sector. Section 3 provides details on the methodology used for creating electricity demand scenarios for Paraguay under climatic change, and discusses the data sources and the pre-processing. Section 4 discusses the results, whereas section 5 summarises the key findings and draws conclusions.

2 Overview of the Paraguayan Electricity Sector

Paraguay's electricity is mainly supplied by three hydroelectric power plants on the Paraná river: Itaipu (7GW installed capacity), Yacyretá (1.6 GW), and Acaray (0.2 GW) (Administración Nacional de Electricidad, 2018). In addition, there are four thermal power plants with a combined generation capacity of approximately 25 MW. The total installed generation capacity in 2014 was 8.825 GW.

According to Administración Nacional de Electricidad (2018), average electricity demand in 2014 was 2.5 GW, less than 30% of the installed generation capacity. Peak demand in 2009 was 1.8 GW, approximately one-fifth of the installed generation capacity (Reinstein, 2009). There is, therefore, a surplus of generation capacity compared to the demand, which has existed since the Itaipu dam was completed in 1984. Electricity accounted for 15.7% of final energy consumption in 2017, with petroleum derivatives supplying 40.1% and biomass (mainly firewood) accounting for 44.2% (Viceministerio de Minas y Energía, 2018). As for residential electricity consumption, 6.7% of homes used electricity for heating in 2017, whereas 42.7% of homes used electricity for cooling, thus temperature may impact electricity consumption through residential cooling.

The electricity sector is dominated by a monopolistic, state-owned, vertically integrated utility – the National Administration of Electricity (ANDE) – which is responsible for the generation, transmission, distribution and sale of electricity in the country. The tariffs are comparatively low due to the abundant water resources and installed generation capacity (Reinstein, 2009).

Historically, insufficient investment in transmission and distribution, combined with rapid demand growth, has resulted in electricity outages and frequency fluctuations. This has been considered an impediment to realising the full potential of the abundant energy in the country (Reinstein, 2009). Large investments have recently been made in order to improve the transmission and distribution infrastructure. The transmission and distribution problems, as well as the recent investments in transmission and distribution infrastructure, further highlight the importance of creating scenarios for future electricity demand in Paraguay, in order aid the energy planning process and guide future infrastructure improvements.

3 Methodology

In this study, we create scenarios for electricity demand in Paraguay in the period 2017-2050, considering different climate change scenarios. The scenarios are based on internally consistent scenarios for meteorological/climatic scenarios, GDP and population.

We first estimate an econometric model using historical data for electricity demand, weather, GDP, and population. We account for annual seasonality in electricity demand, and estimate both short-run dynamics and long-run relationships. The model is then used to create scenarios for future electricity demand by incorporating internally consistent projections for the independent variables, based on combinations of drivers from Representative Concentration Pathways (RCPs) (Smith and Wigley, 2006; Fujino et al., 2006; van Vuuren et al., 2007; Clarke et al., 2007; Riahi et al., 2007; Hijioka et al., 2008; Wise et al., 2009; Moss et al., 2010; van Vuuren et al., 2011) and Shared Socio-economic Pathways (SSPs) (van Vuuren et al., 2011; Moss et al., 2010; O'Neill et al., 2014; Kriegler et al., 2014). Beyond ensuring internal consistency in the results, using standardised scenarios for the exogenous variables ensures that the results are more easily understood and comparable across studies.

3.1 Electricity Demand Drivers

Climatic variables affect power demand directly through heating and cooling needs (Mideksa and Kallbekken, 2010). Therefore, the model includes Heating Degree Days (HDD) and Cooling Degree Days (CDD): the number degrees below or above a certain cut-off temperature, respectively, accumulated over a certain period. This allows heating and cooling needs to be accumulated separately over a period, rather than cancelling each other out (Quayle and Diaz, 1980).

GDP is the main socio-economic variable considered in the analysis. Chontanawat et al. (2008) identified a unidirectional causal relationship between GDP and electricity demand in the case of Paraguay, and we therefore consider GDP exogenous in the electricity demand model.

Population is the main demographic variable we consider: we expect that the greater the population, the greater the electricity demand. This is consistent with other electricity demand studies (for instance Hor et al. (2005)).

Finally, dummy variables will capture seasonal demand variations that may not be adequately captured by other variables.

We do not, however, include price as an independent variable in the model. There are several reasons for this. Firstly, price elasticity in the electricity sector has been shown to be fairly low – at least in the short term. Although we are not familiar with studies that investigate this for Paraguay, Andrade and Lobão (1997), as well as de Mattos and de Lima (2005), confirm the low price elasticity for the neighbouring country of Brazil. Due to the low electricity price and abundant generation capacity in Paraguay, we expect the price elasticity of electricity demand in Paraguay to be even lower than in Brazil. Secondly, demand and price are usually mutually dependent, as discussed by Trotter et al. (2016a): demand is a component of the price formation, and price is at the same time a determinant of demand. Estimating price in the various scenarios, however, also requires considering the supply situation – this is beyond the scope of this work. For these reasons, we have omitted price from the model.

3.2 Model, Estimation and Scenario Generation

We expect that the marginal effect of GDP and population on electricity demand is linear in terms of percentage changes, as implied by the model specifications in Eskeland and Mideksa (2010), Hyndman and Fan (2010) and Trotter et al. (2016a). We therefore formulate the model in the *logarithms* of electricity consumption, GDP and population. Electricity demand also exhibits autoregressive characteristics (see, for instance, Vu et al. (2017)), and changes in independent variables may have effects beyond the current period. Therefore, we propose the following Autoregressive Distributed Lag (ARDL) model:

$$\begin{aligned}\ln(\mathrm{Cons}_t) =& \beta_0 + \beta_1 t + \sum_{i=1}^{p} \beta_i^{\mathrm{Cons}} \ln(\mathrm{Cons}_{t-i}) + \sum_{i=0}^{q_1} \beta_i^{\mathrm{GDP}} \ln(\mathrm{GDP}_{t-i}) \\ &+ \sum_{i=0}^{q_2} \beta_i^{\mathrm{POP}} \ln(\mathrm{POP}_{t-i}) + \sum_{i=0}^{q_3} \beta_i^{\mathrm{HDD}} \mathrm{HDD}_{t-i} + \sum_{i=0}^{q_4} \beta_i^{\mathrm{CDD}} \mathrm{CDD}_{t-i} \\ &+ \sum_{m=2}^{12} \alpha_m \mathrm{MTH}_{m,t} + \varepsilon_t.\end{aligned} \tag{1}$$

The variables in equation 1 have the following meaning:

- Cons_t represents electricity consumption in period t.
- GDP_t represents Gross Domestic Product in period t.
- POP_t represents population at time t.
- HDD_t represents the number of Heating Degree Days accumulated over period t.
- CDD_t represents the number of Cooling Degree Days accumulated over period t.
- $\mathrm{MTH}_{m,t}$ is a dummy variable which equals one if the number of the month represented by t is equal to m, and zero otherwise. January is omitted, as it serves as the base value.
- $p \in \mathbb{N}$, $q_1, q_2, q_3, q_4 \in \mathbb{N}_0$ indicate the number of lagged terms of each respective variable.
- β_0 is a constant and β_1 is the coefficient of a linear trend, whereas $\{\beta_1^{\mathrm{Cons}}, \ldots, \beta_p^{\mathrm{Cons}}\}$, $\{\beta_0^{\mathrm{GDP}}, \ldots, \beta_{q_1}^{\mathrm{GDP}}\}$, $\{\beta_0^{\mathrm{POP}}, \ldots, \beta_{q_2}^{\mathrm{POP}}\}$, $\{\beta_0^{\mathrm{HDD}}, \ldots, \beta_{q_3}^{\mathrm{HDD}}\}$, $\{\beta_0^{\mathrm{CDD}}, \ldots, \beta_{q_4}^{\mathrm{CDD}}\}$ and $\{\alpha_2, \ldots, \alpha_{12}\}$ are coefficients to be estimated.

Table 1: Stationarity test p-values for the variables included in the analysis. For the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979), lag lengths were selected using the Bayesian Information Criterion (BIC), and the maximum lag length was chosen as suggested by Schwert (1988). The number of lagged terms selected by the BIC is indicated in parenthesis after the p-value. The ADF and Phillips-Perron (PP) tests (Phillips and Perron, 1988) check if a series is non-stationary, whereas the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests (Kwiatkowski et al., 1992) check if a series is stationary.

	ADF			**PP**	**KPSS**		***Conclusion***
	Random Walk	Drift	Trend		Level	Trend	
$\ln(\text{Cons}_t)$	0.9981 (16)	0.0296 (16)	0.6289 (16)	< 0.01	< 0.01	< 0.01	$I(1)$
$\Delta\ln(\text{Cons}_t)$	0.0554 (15)	< 0.01 (15)	< 0.01 (15)	< 0.01	> 0.1	> 0.1	$I(0)$
$\ln(\text{GDP}_t)$	0.9999 (13)	0.9620 (13)	0.8495 (13)	0.0336	< 0.01	< 0.01	$I(1)$
$\Delta\ln(\text{GDP}_t)$	< 0.01 (12)	< 0.01 (12)	< 0.01 (12)	< 0.01	> 0.1	> 0.1	$I(0)$
$\ln(\text{POP}_t)$	0.9904 (13)	0.1245 (13)	0.7872 (13)	> 0.99	< 0.01	< 0.01	$I(1)$
$\Delta\ln(\text{POP}_t)$	0.1247 (12)	0.08914 (12)	0.4511 (12)	> 0.99	< 0.01	< 0.01	$I(0)$
HDD_t	0.4208 (11)	< 0.01 (11)	< 0.01 (11)	< 0.01	> 0.1	> 0.1	$I(0)$
CDD_t	0.4743 (11)	< 0.01 (11)	< 0.01 (11)	< 0.01	> 0.1	> 0.1	$I(0)$

- ε_t represents a random error term.

We first test the variables for stationarity to ensure that the estimation results will be valid. Table 1 reports the results of three different stationarity tests: the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979), Phillips-Perron (PP) (Phillips and Perron, 1988), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) (Kwiatkowski et al., 1992) tests. The tests indicate that electricity consumption ($\ln(\text{Cons}_t)$), GDP ($\ln(\text{GDP}_t)$) and population ($\ln(\text{POP}_t)$) are $I(1)$, whereas heating- and cooling-degree days are $I(0)$. However, one the ADF tests for $\ln(\text{Cons}_t)$ and the PP test for $\ln(\text{POP}_t)$ contradict this conclusion, and the conclusions from the stationarity testing are somewhat uncertain. There is no indication, however, that any of the variables are $I(2)$ or higher.

Since the variables are a mixture of $I(0)$ and $I(1)$, and there is uncertainty about the order of integration of some variables, the bounds testing procedure of Pesaran et al. (2001) can be used to ensure the validity of the model. This approach is common in the electricity forecasting literature (see, for instance, Khalifa et al. (2019), Adom and Bekoe (2012), Zachariadis (2010) and Fatai et al. (2003)), and allows both short-run dynamics and long-run relationships to be estimated, regardless of whether the independent variables are $I(0)$, $I(1)$ or mutually cointegrated. The ARDL model can incorporate seasonality using dummy variables, which is not as easily implemented in alternative cointegration techniques. The inclusion of lagged terms is important for capturing the dynamics of electricity consumption and incorporating autocorrelation properties. The ARDL/bounds testing approach is also known to have better small-sample properties than alternative cointegration techniques.

Following the bounds testing procedure of Pesaran et al. (2001), we first estimate a conditional unrestricted equilibrium correction model (ECM) using OLS:

$$
\begin{aligned}
\Delta \ln(\text{Cons}_t) = &\mu_0 + \sum_{i=1}^{p} \mu_i^{\text{Cons}} \Delta \ln(\text{Cons}_{t-i}) + \sum_{i=0}^{q_1} \mu_i^{\text{GDP}} \Delta \ln(\text{GDP}_{t-i}) \\
&+ \sum_{i=0}^{q_2} \mu_i^{\text{POP}} \Delta \ln(\text{POP}_{t-i}) + \sum_{i=0}^{q_3} \mu_i^{\text{HDD}} \Delta \text{HDD}_{t-i} + \sum_{i=0}^{q_4} \mu_i^{\text{CDD}} \Delta \text{CDD}_{t-i} \\
&+ \theta_0 \ln(\text{Cons}_{t-1}) + \theta_1 \ln(\text{GDP}_{t-1}) + \theta_2 \ln(\text{POP}_{t-1}) + \theta_3 \text{HDD}_{t-1} + \theta_4 \text{CDD}_{t-1} \\
&+ \sum_{m=2}^{12} \alpha_m \text{MTH}_{m,t} + \varepsilon_t.
\end{aligned} \tag{2}
$$

The lag structure of this model, represented by p, q_1, q_2, q_3 and q_4, was determined by the Bayesian Information Criterion (BIC), considering up to 12 lagged terms of each variable.

The Pesaran et al. (2001) bounds test determines if there exists a long-run relationship between the variables, in which case we can infer both their short-run dynamics and long-run relationship. Using projections of the exogenous variables for the future, we can then generate corresponding scenarios for electricity demand that reflect both the adjustment dynamics and the equilibrium relationship. Technically, the model in equation 2 model is interchangeable with equation 1 (although the coefficients differ – for details on the transformation of coefficients between the models, see Hassler and Wolters (2006)), and, as noted by Fatai et al. (2003), the approaches produce equal forecasts[1].

To assess the accuracy of the model, we divide the historical dataset into a training sample and a verification sample. The lag structure and coefficients will initially be determined using the training sample. Using these coefficients together with the independent variables from the verification sample, we create an *ex-post* out-of-sample forecast for the electricity demand, which can be compared to the true electricity demand in order to evaluate the model performance out-of-sample.

The model accuracy will be assessed primarily by the Symmetric Mean Absolute Percentage Error (sMAPE). The sMAPE is frequently recommended for electricity demand studies (e.g. Steinbuks (2017)). In addition to being intuitive, this choice allows the results to be easily compared across studies. Given forecasts $\hat{y}_t$ and outcomes y_t for the T periods $t \in \{1, \ldots, T\}$, the sMAPE is calculated as follows:

$$
\text{sMAPE} = \frac{1}{T} \sum_{t=1}^{T} \frac{|y_t - \hat{y}_t|}{(|y_t| + |\hat{y}_t|)/2}. \tag{3}
$$

After investigating the out-of-sample accuracy, we re-estimate the coefficients using the entire historical dataset, which presumably increases the accuracy of the coefficients, and generate scenarios for future electricity demand using future scenarios for the independent variables.

[1] We have verified that the results of forecasting with equation 1 and 2 are equal, allowing for floating-point rounding errors.

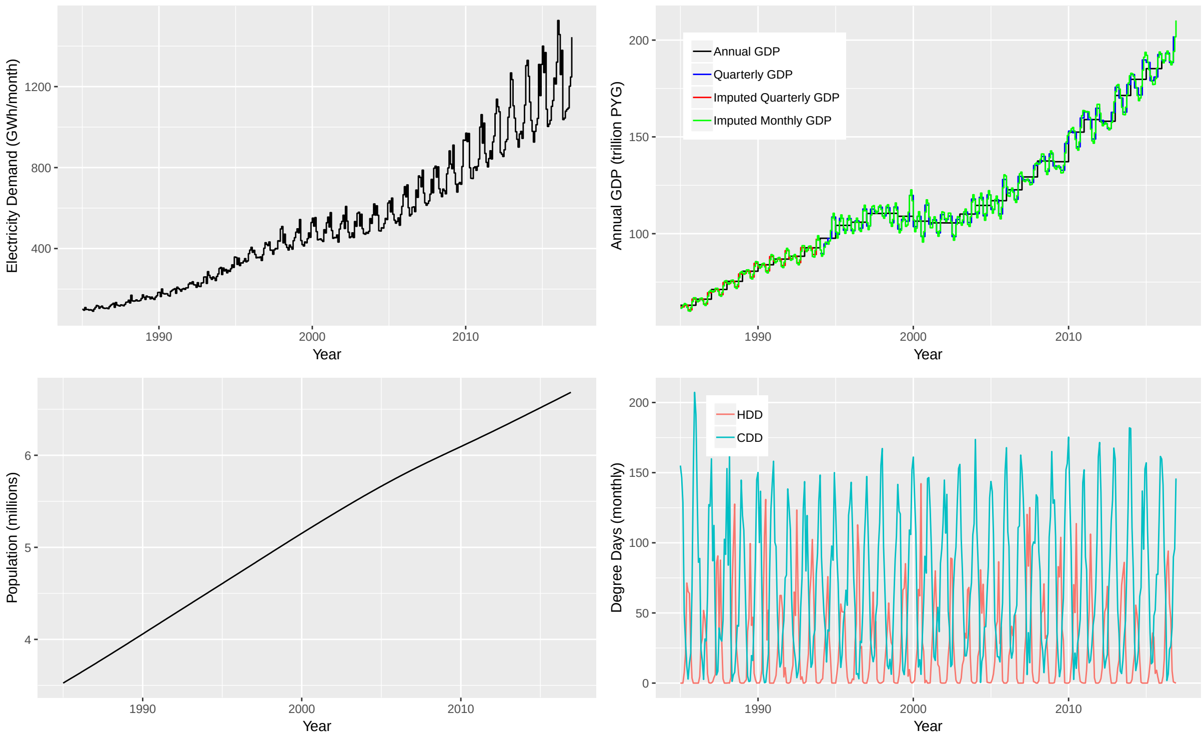

Figure 1: Electricity demand and its main drivers: GDP, population, Heating Degree Days (HDD) and Cooling Degree Days (CDD). Electricity demand includes transmission and distribution losses. GDP is given in real terms, with a reference year of 2014. Quarterly and monthly GDP in this figure have been annualised. HDDs/CDDs represent a population-weighted mean of seven weather stations.

3.3 Data Sources and Preprocessing

3.3.1 Historical Data

Gross total monthly electricity consumption in Paraguay between 1985 and 2016, including transmission and distribution losses – shown in Figure 1 – has been provided by the Paraguayan national electricity company, Administración Nacional de Electricidad (ANDE).

Annual GDP from 1950 and onwards, and quarterly GDP from 1994 and onwards, were obtained from the Paraguayan central bank, Banco Central del Paraguay (BCP) (Banco Central del Paraguay, 2018b,a). Both are available in real terms, using 2014 as the reference year, denominated in Paraguayan guaraní (PYG). Since the dependent variable is available at a monthly resolution, we up-sample the independent variables to monthly resolution. For GDP, this is done in two steps: first, we up-sample the data for 1985 to 1993 to a quarterly resolution by calculating the average share each quarter contributes to the annual GDP in the period 1994 to 2016 and applying these shares to annual GDP from 1985 to 1993. Secondly, we use quarterly GDP to estimate monthly GDP for the entire period 1985 to 2016 by generating a maximum smoothness interpolating quartic spline with C^2 continuity, then integrating over each month, as described by Trotter et al. (2016b). This results in estimates of monthly GDP that are consistent with the quarterly and annual GDP figures, which are all shown together in Figure 1.

Annual population data was obtained from the General Directorate of Statistics, Survey and Census (DGEEC) (Dirección General de Estadística, Encuestas y Censos (DGEEC), 2018). Monthly estimates were generated by linear interpolation, thereby generating estimates of the population in the same resolution as electricity demand. Figure 1 shows the historical population figures.

Meteorological observations were obtained from the Department of Meteorology and Hydrology of the National Directorate of Civil Aeronautics (DINAC), which is responsible for the collection of meteorological data in Paraguay. Data from only seven of the twenty available meteorological stations were used. These seven stations were selected because they have a complete historical record for the period of interest, and they are sufficiently distant from each other to present significant differences in meteorological conditions. For these seven stations, we obtained average daily temperature in degrees Celsius (°C) for the period 1985 to 2016.

Electricity consumption reacts non-linearly to temperature, so we transform the average daily temperature T_d, $d \in \{1, \ldots, D\}$, into Cooling Degree Days (CDD) and Heating Degree Days (HDD), using cut-off temperatures of 22°C and 18°C, respectively, as follows:

$$\mathrm{CDD}_d = \max\{\ 0,\ T_d - 22°C\ \}$$
$$\mathrm{HDD}_d = \max\{\ 0,\ 18°C - T_d\ \}.$$

The sum of CDDs and HDDs over each month was calculated for each station, and subsequently a population-weighted average of the stations was calculated. The locations of the stations and their weights are illustrated in Figure 2, whereas the resulting CDD and HDD series are shown in Figure 1.

3.3.2 Climatic and Socio-economic Scenarios 2017-2050

In order to generate electricity demand scenarios for Paraguay from 2017 to 2050, we require future scenarios for GDP, population, and temperatures – all of which must be internally consistent within each scenario.

We construct the scenarios using the scenario framework described by van Vuuren et al. (2014), creating a matrix by combining scenarios for the radiative forcing of the climate (Representative Concentration Pathways) and scenarios for global socio-economic development (Shared Socio-economic Pathways). By relying on existing climatic and socio-economic scenarios that are well-explored and frequently used in the literature, we ensure that the underlying climatic and socio-economic assumptions are well understood and that the results are compatible and comparable across studies.

For future projections of temperature, we utilise RCP4.5 (Thomson et al., 2011) and RCP8.5 (Riahi et al., 2011). RCP4.5 scenario is considered a stabilisation scenario, in which the radiative forcing stabilises at 4.5 W/m^2 in the year 2100, corresponding to a CO_2e concentration of approximately 650

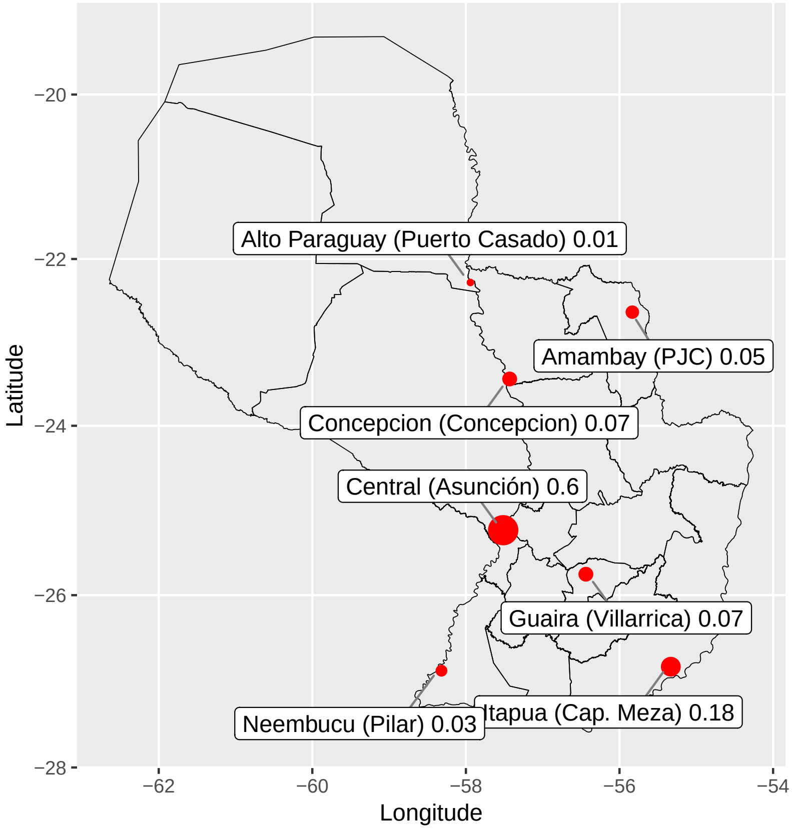

Figure 2: Map of the geographical locations of the meteorological stations used calculating CDDs and HDDs. The population-based weights of the stations are indicated in the labels and by the size of the point.

ppm. Additional details on a set of assumptions consistent with RCP4.5 are described by Clarke et al. (2007). RCP8.5 assumes a radiative forcing of 8 W/m^2, which corresponds to a high concentration of greenhouse gases. More details on the assumptions consistent with such a scenario have been described by Riahi et al. (2007) and Riahi et al. (2011).

For future projections of GDP and population, we use drivers from Shared Socio-economic Pathways (SSPs). Each pathway represents a distinct, internally consistent, global development scenario. A summary of the pathways is provided by Riahi et al. (2017), whereas a more detailed review is provided by O'Neill et al. (2017). We use three of the five scenarios:

SSP1: "Sustainability – Taking the Green Road" features low population growth and relatively high economic growth, reduced inequality, and a rapid shift away from fossil fuels.

SSP3: "Regional Rivalry – A Rocky Road" is characterised by relatively high population growth and low economic growth, high inequality, and low environmental sustainability.

SSP5: "Fossil-fuelled Development – Taking the Highway" represents a pathway with low population growth and high economic growth, featuring reduced inequality and low environmental sustainability.

We use only the driving forces of the SSPs (GDP and population time series), and assume that their relationship with electricity demand remains stable in the future, in line with the historical relation obtained by the econometric estimation on data from 1985-2016. Other aspects of the storylines do not directly enter the model, such as jumps in efficiency due to climate policy, changes in consumption habits (proliferation of electric vehicles, for example), and so forth: the observed historical relationships between the variables are assumed to hold for the future. In particular, consumption habits and the relative price of electricity are presumed stable, and projected efficiency gains are based on historical observations.

Characteristics of the different combinations of climatic and socio-economic scenarios are summarised as a scenario matrix in Table 2.

The population and GDP projections were obtained as output of the OECD-GDP model, available from the SSP Database hosted by the International Institute for Applied Systems Analysis (IIASA) (2018). As the database provides population projections for every fifth year, monthly figures were obtained by exponential interpolation. GDP projections are provided for every fifth year: first, annual GDP figures were created by exponential interpolation, then a quarterly profile was applied to the annual figures to create quarterly GDP figures, and finally monthly numbers were generated by integrating under a maximum smoothness interpolating quartic spline adjusted to the quarterly GDP figures. This treatment mirrors that for historical GDP, described in section 3.3.1, and recreates the annual seasonality in GDP that was observed in the historical data, which we assume is based on the inherent seasonality of economic activities (e.g. agriculture), differences in the number of working days (e.g. public holidays),

Table 2: The scenario matrix: a brief overview of the main characteristics of the scenarios considered in this study.

Socio-economic Scenarios	**Climatic Scenarios**	
	RCP4.5	RCP8.5
SSP1	• Medium radiative forcing • Low population growth • Medium economic growth	• High radiative forcing • Low population growth • Medium economic growth
SSP3	• Medium radiative forcing • High population growth • Low economic growth	• High radiative forcing • High population growth • Low economic growth
SSP5	• Medium radiative forcing • Low population growth • High economic growth	• High radiative forcing • Low population growth • High economic growth

and the cyclical consumer or worker behaviour (e.g. holidays) over the calendar year – all of which are assumed to continue in a similar manner into the future. The population and GDP projections were scaled to match observed values for 2016, avoiding abrupt breaks in the data. The resulting population and GDP projections are shown in Figure 3.

Temperature projections for RCP4.5 and RCP8.5 were obtained from the MIROC5 Global Circulation Model (Watanabe et al., 2010), provided by the National Aeronautics and Space Administration (2018). From the gridded dataset, maximum and minimum daily temperatures for the location of each weather station were obtained by bilinear interpolation. From these, cooling and heating degree days were calculated as described in section 3.3.1, with the mean of the maximum and minimum daily temperature substituting the observed mean temperature in the calculation. The resulting CDD and HDD scenarios are illustrated in Figure 3.

The climatic and socio-economic projections were then combined according to the scenario matrix in Table 2 to create six scenarios, which were fed into the electricity demand model in order to generate electricity demand scenarios for the period 2017-2050. Although we have not explicitly attached probabilities to the different scenarios, some scenarios are considered to be more likely than others: SSP1, which is characterised by a rapid reduction in GHG emissions, is not likely to lead to a high radiative forcing scenario such as RCP8.5, and SSP3, which is characterised by low economic growth, may also be less likely to occur in combination with RCP8.5. However, scenarios that are unlikely to play out at a global scale might still apply to individual countries, as there may be significant heterogeneity between countries even within each global trend. In addition, increased climate sensitivity might also lead to a higher chance of improbable combinations of socio-economic and climatic scenarios occurring. Furthermore, scenarios that could be considered less likely may still be informative and help assess the impacts of the various drivers within the scenarios.

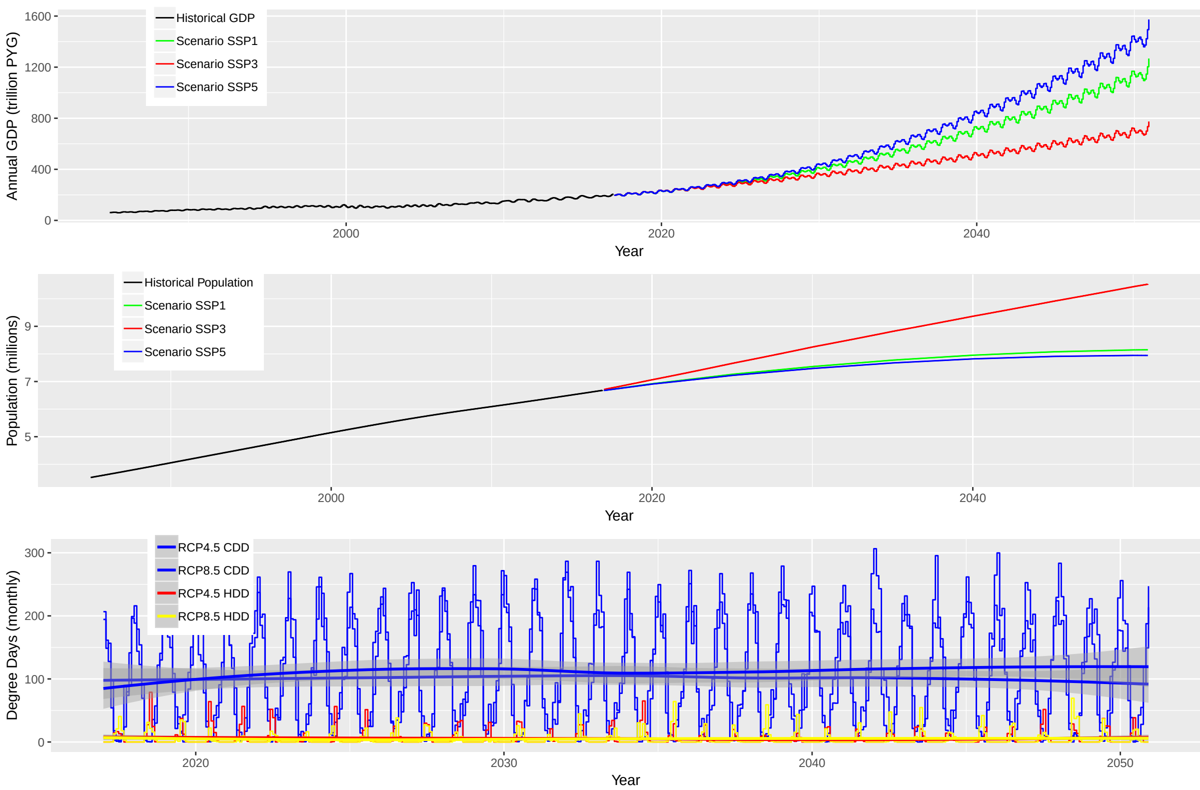

Figure 3: Scenarios for the electricity demand drivers: GDP and population scenarios based on the Shared Socio-economic Pathways (SSP): SSP1, SSP3 and SSP5. HDD and CDD scenarios based on the Representative Concentration Pathways (RCP): RCP4.5 and RCP8.5. The smooth HDD/CDD curves were generated using a Loess filter.

4 Results and Discussion

4.1 Model Validity

We validate the ARDL model using the bounds testing procedure of Pesaran et al. (2001). When estimated on the training sample 1985-2010, the F-statistic of the model in equation 2 is 10.13, which exceeds the 1% upper bound critical value with unrestricted intercept, unrestricted trend, and six regressors (4.90), as tabulated by Pesaran et al. (2001). Using the full sample 1985-2016, the corresponding F-statistic is 15.78. Therefore, the null hypothesis of no long-term relation can be rejected, and the corresponding ARDL model is valid. In addition, we have verified that there is only insignificant serial correlation remaining in the residuals, that the residuals are normally distributed, and that the model is dynamically stable. The values of the coefficients of the ARDL model are shown in Table 3, estimated both on the training sample and the full sample. We also extract the long-run relationships and the short-run dynamics, shown in Table 4.

Thus, the resulting model is considered valid, and can be used for generating the scenarios for future electricity demand, provided that the historical relationships estimated by the model continue holding in the future.

4.2 Model Accuracy

The coefficients of the ARDL model are shown in Table 3, which displays the results both from the training sample (monthly data from 1985 to 2010, 312 observations) and the full sample (1985 to 2016, 384 observations). Firstly, the R^2 suggests the models account for approximately 99.8% of the observed variance in the *logarithm* of the electricity consumption, indicating a good fit. Secondly, the coefficients of the two estimations are close, suggesting that they are at least somewhat robust.

Figure 4 shows predicted electricity demand, together with historical electricity demand and the absolute value of the residual. The observations to the left of the vertical line at the start of 2011 were used for estimating the coefficients, and the observations to the right of the line were used as a verification sample. As expected, the absolute value of the residuals post-2011 are generally higher than those pre-2011. However, the demand model appears to underestimate the demand on the verification sample, especially in the summer months (October to March).

Table 5 shows statistical error indices for the model, calculated both on the training sample and the full sample. The error indices for the model estimated on the training sample were calculated both for the training sample itself (in-sample) and for the verification sample (out-of-sample *ex-post* forecasts, that is, calculated with the actual observed values for the independent variables), in order to provide an indication of the out-of-sample performance of the model. For the model estimated on the full sample, only in-sample error indicators can be calculated. The Symmetric Mean Absolute Percentage Error

Table 3: Regression results from estimating the Autoregressive Distributed Lag (ARDL) model.

	Dependent variable:	
	$\ln(\text{Cons}_t)$	
	Training Sample (1985-2010)	Full Sample (1985-2016)
Constant	-1.6749***	-2.0909***
	(0.2908)	(0.2901)
Trend	-0.0012***	-0.0014***
	(0.0003)	(0.0002)
$\ln(\text{Cons}_{t-1})$	0.6797***	0.5609***
	(0.0546)	(0.0501)
$\ln(\text{Cons}_{t-2})$	0.0751	0.1398***
	(0.0479)	(0.0431)
$\ln(\text{GDP}_t)$	-0.3782*	-0.0586
	(0.2015)	(0.1944)
$\ln(\text{Quarterly.GDP}_t)$	0.4050*	0.1377
	(0.2214)	(0.2156)
$\ln(\text{Annual.GDP}_t)$	-0.3174	-0.2843
	(0.2257)	(0.2443)
$\ln(\text{Annual.GDP}_{t-1})$	0.6002***	0.5946***
	(0.2090)	(0.2241)
$\ln(\text{POP}_t)$	1.1353***	1.3618***
	(0.2300)	(0.1914)
HDD_t	0.0000	0.0001
	(0.0001)	(0.0001)
CDD_t	0.0015***	0.0018***
	(0.0001)	(0.0001)
CDD_{t-1}	-0.0007***	-0.0005***
	(0.0001)	(0.0001)
$\text{MTH}_{02,t}$	-0.0673***	-0.0594***
	(0.0141)	(0.0147)
$\text{MTH}_{03,t}$	0.1021***	0.0832***
	(0.0144)	(0.0151)
$\text{MTH}_{04,t}$	-0.0112	0.0105
	(0.0159)	(0.0168)
$\text{MTH}_{05,t}$	0.0263	0.0332*
	(0.0191)	(0.0200)
$\text{MTH}_{06,t}$	0.0178	0.0431*
	(0.0206)	(0.0220)
$\text{MTH}_{07,t}$	0.0654***	0.0895***
	(0.0203)	(0.0217)
$\text{MTH}_{08,t}$	0.0110	0.0493**
	(0.0193)	(0.0206)
$\text{MTH}_{09,t}$	-0.0023	0.0166
	(0.0166)	(0.0177)
$\text{MTH}_{10,t}$	0.0462**	0.0645***
	(0.0184)	(0.0193)
$\text{MTH}_{11,t}$	-0.0047	0.0015
	(0.0155)	(0.0160)
$\text{MTH}_{12,t}$	0.0259*	0.0201
	(0.0139)	(0.0144)
Observations	310	370
R^2	0.9979	0.998
Adjusted R^2	0.9977	0.998
Note:		*p<0.1; **p<0.05; ***p<0.01

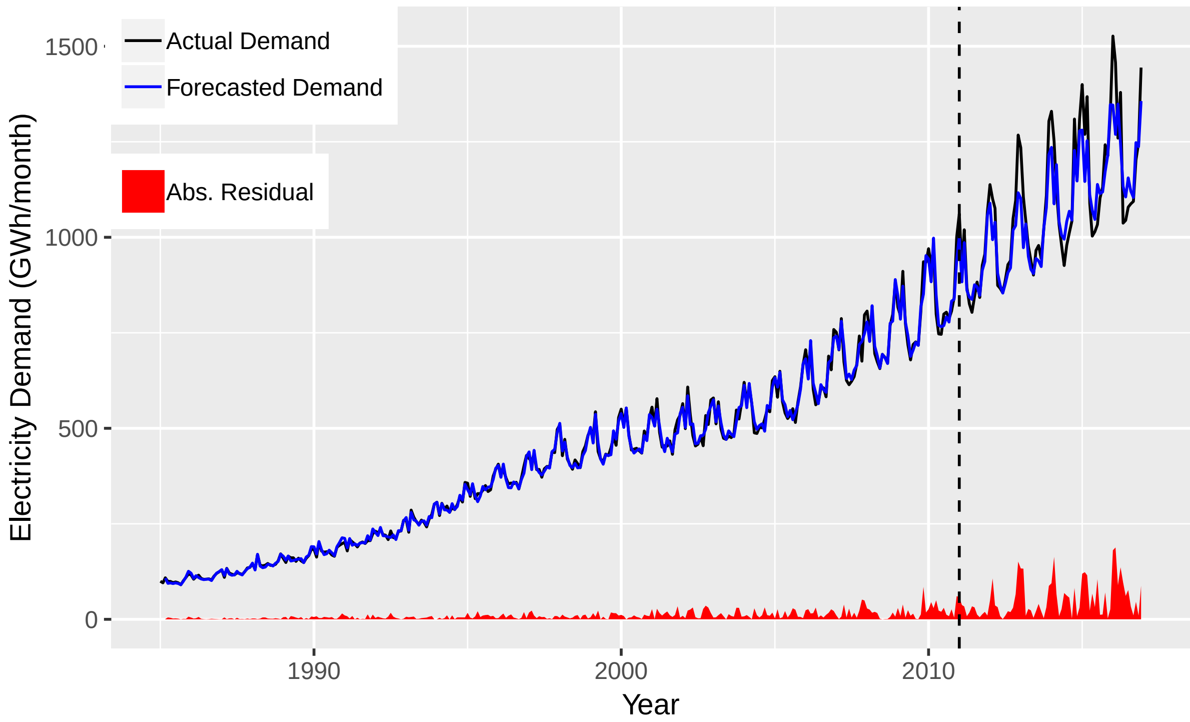

Figure 4: Monthly actual and forecasted electricity demand for Paraguay, 1985-2016, together with the accompanying absolute residual. The vertical line marks the division between the training sample and the verification sample: to the left of the vertical line, the forecasted demand is an in-sample forecast, whereas to the right the forecasted demand is an *ex-post* out-of-sample forecast.

(sMAPE) is highlighted in Table 5, showing an in-sample error of 2.27% on the training sample and 2.57% on the full sample. The magnitude of the in-sample sMAPEs are similar to those reported in comparable studies, for instance by McSharry et al. (2005) (around 1.9%), Hor et al. (2006) (around 2%), Hyndman and Fan (2010) (around 2%), Ziser et al. (2012) (about 2.4%) and Trotter et al. (2016a) (1.6%). The out-of-sample sMAPE (4.56%) is greater than the in-sample sMAPE (2.27%). All the error indices indicate that the out-of-sample error is greater than the in-sample error, which is expected. However, the Mean Bias Error (MBE), also shown in Table 5, is negative, which suggests that the model may tend to underestimate the electricity demand rather than overestimate it. This tendency is also visible in Figure 4.

The statistical error indices appear to be in-line with those reported in the existing literature and the estimated coefficients appear robust, although we note that the model appears more likely to underestimate electricity demand than overestimate it.

4.3 Electricity Demand Scenarios 2017-2050

The electricity demand scenarios for Paraguay 2017-2050 generated by the proposed methodology are shown in Figure 5, and summarised in Table 6. The scenarios based on SSP1 and SSP5 show an increase in electricity demand until approximately 2045, followed by a slight decline in 2050 in the RCP4.5 scenarios

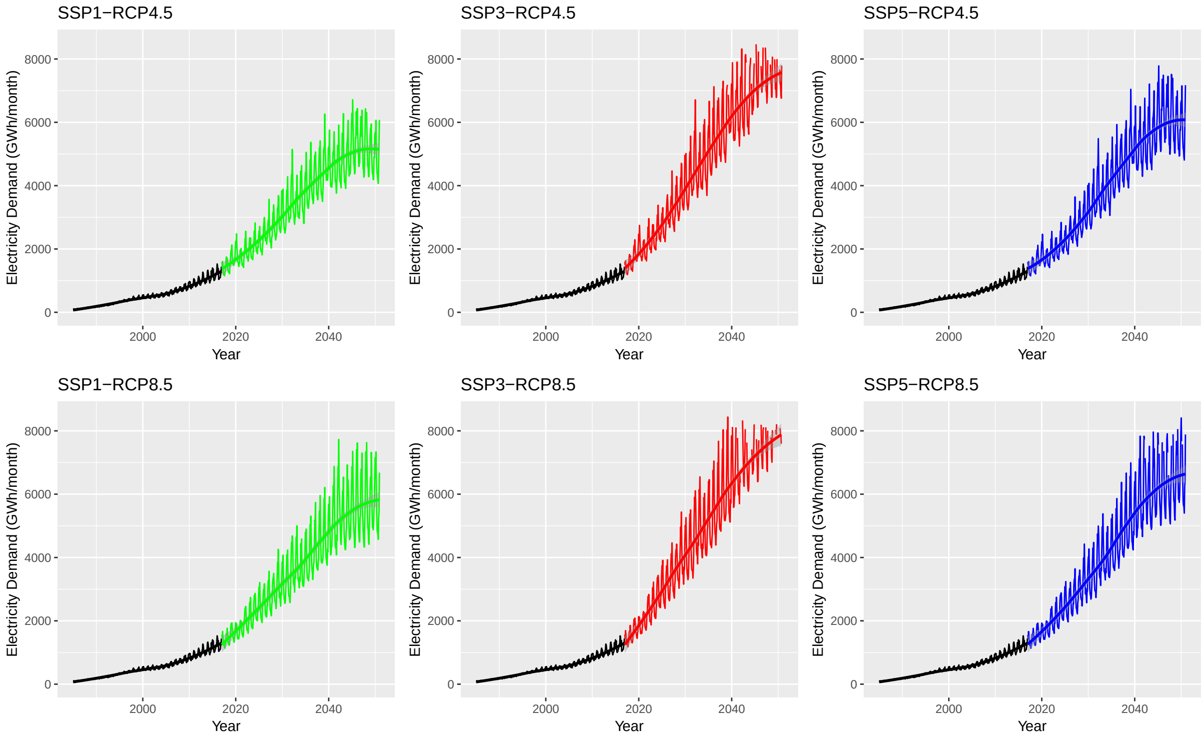

Figure 5: Electricity demand scenarios for Paraguay for the time horizon 2017–2050, with combinations of three different Shared Socio-economic Pathways (SSP) – SSP1, SSP3 and SSP5 – and two different Representative Concentration Pathways (RCP) – RCP4.5 and RCP8.5.

and a stabilisation in the RCP8.5 scenarios. The scenarios based on SSP3, however, show a sharper increase that continues until the end of the forecasting horizon in 2050. The general shape of the electricity demand scenarios resembles those presented by Trotter et al. (2016a) for Brazil. The electricity demand in the SSP3-based scenarios is significantly higher than in the corresponding SSP1- and SSP5-based scenarios: since SSP3 features a greater population growth and lower economic growth, this illustrates the importance of population as a driver of electricity demand. The SSP1- and SSP5-based scenarios are comparatively close to each other, despite significant differences in the economic growth between these two scenarios, which again highlights the importance of population as an electricity demand driver.

Although the RCP8.5 scenarios consistently present a higher electricity demand than those based on RCP4.5, the direct impact of the climatic variables on electricity demand appears to be lower than the impact of the socio-economic variables. Comparing the RCP8.5 scenarios to those based on RCP4.5, the RCP8.5 scenarios not only appear to show a consistently higher electricity demand, but also a greater amount of annual variability in the electricity demand, and a greater difference between the electricity demand in the highest and lowest months.

Paraguay has historically had a large surplus of installed generation capacity: the installed generation capacity in Paraguay in 2009 (8.766 GW) was nearly five times greater than peak electricity demand (1.81 GW). The current installed capacity of 8.825 GW could be capable of generating about 77.3 TWh of power if run at maximum capacity for a year. Only the two scenarios based on SSP3, and the scenario based on SSP5 and RCP8.5 exceed this value until 2050. The results therefore imply that Paraguay will be able to generate sufficient power to supply its own annual demand in two out of three scenarios with a lower radiative forcing, but only in one out of three scenarios (the one which, as mentioned, is less likely to occur) with higher radiative forcing. This suggests that the level of radiative forcing may be, in the balance, key to whether or not Paraguay will continue to be self-sufficient with the current installed generation capacity.

The relationship between peak electricity demand and generation capacity is also interesting. We do not have access to historical peak electricity demand figures, so we are unable to explicitly model peak demand. However, we have a single observation: peak electricity demand in 2009 (1.81 GW, according to Reinstein (2009)), which was 39.23% above the mean electricity demand in November 2009, the month in 2009 in with the highest total electricity demand (1.3 GW). If we assume that the annual peak electricity demand is 39.23% above the mean demand of the month with the highest total electricity demand, we find the peak demand of all the scenarios exceed the installed capacity at some time between 2032 and 2045. Therefore, Paraguay may be required to invest in new generation capacity within the next two decades to ensure it will be self-sufficient, despite the current large surplus.

5 Conclusion

In this study, we created scenarios for the monthly electricity demand in Paraguay for the period from 2017 to 2050 under different climatic and socio-economic assumptions.

An ARDL model for electricity demand was proposed, estimated and validated, which incorporated GDP, population, seasonality, HDDs/CDDs and a trend component. The model is able to explain a significant amount of the variability in historical electricity demand. The coefficients were estimated on a training set of historical data from 1985 to 2010, and the model accuracy was assessed both on an in-sample and out-of-sample (ex-post, historical data from 2011 to 2016) forecast: the in-sample Symmetric Mean Absolute Percentage Error (sMAPE) of about 2.27% is in-line with similar studies, and the *ex-post* out-of-sample sMAPE was about twice as high (4.56%). A negative Mean Bias Error (MBE) suggests that the model may underestimate the demand. Overall, the model appears adequate for the purpose of generating future electricity demand scenarios when projections of future socio-economic and climatic variables are given.

The model was used to create six electricity demand scenarios for Paraguay under different socio-economic and climatic assumptions: combinations of three SSPs (1, 3 and 5) with two different RCPs (4.5 and 8.5). The scenarios imply that the population size and, to a slightly lesser extent, the GDP will greatly affect electricity demand. The included weather variables (CDD and HDD) are less important for determining the level of electricity demand, but will greatly influence the short-term variation. All the scenarios show an increase in power demand until about the middle of the century, after which demand growth appears to slow down somewhat or even decrease. The magnitudes, however, differ substantially between the socio-economic scenarios. Scenarios based on SSP1 and SSP5 are relatively close, showing a steady growth up to 55-80 TWh/year around 2045-2050. The scenarios based on SSP3 show a high growth rate up to 100-115 TWh in 2050. These large differences between the SSP1/SSP5 scenarios and the SSP3 scenario are mainly caused by differing assumptions about the population growth, implying that electricity demand is highly sensitive to the population size.

These scenarios for future electricity demand may provide useful input for policy decisions and energy planning in a region which has been neglected in the existing literature. Furthermore, improved energy planning in Paraguay may remove barriers to greater economic growth and welfare, as well as provide important information for the renegotiation of the Itaipu Treaty. Considering peak electricity demand, the scenarios suggest that the current situation of surplus generation capacity will only last until around 2030-2040, which implies that the country should start considering generation capacity expansions, despite the large current surplus generation capacity.

We suggest that future studies on electricity demand for Paraguay focus on the impact of extreme weather events, create an electricity demand model with a higher granularity, and analyse and quantify uncertainties in both the model and in the underlying independent variables. Another natural continuation of this study would be an analysis of the energy supply situation in Paraguay: the current study could provide a starting point for studies on the impact of climatic changes on the energy supply situation of Paraguay, which would need to evaluate not only how climatic changes impact electricity demand, but also how they might influence the hydrological situation of the country.

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Table 4: The long-run and short-run coefficients from the Autoregressive Distributed Lag (ARDL) model.

Long-Run Coefficients. Dependent variable is $\ln(\text{Cons}_t)$.

	Estimate	Std.Err	Z value	Pr(>z)	
$\ln(\text{GDP}_t)$	-0.1959	0.0838	-2.3381	0.0194	*
$\ln(\text{Quarterly.GDP}_t)$	0.4600	0.0641	7.1775	0.0000	***
$\ln(\text{lAnnual.GDP}_t)$	1.0368	0.0489	21.2130	0.0000	***
$\ln(\text{POP}_t)$	4.5500	0.0463	98.1938	0.0000	***
HDD_t	0.0003	0.0002	1.7804	0.0750	.
CDD_t	0.0043	0.0001	37.0631	0.0000	***
$\text{MTH}_{02,t}$	-0.1985	0.0212	-9.3866	0.0000	***
$\text{MTH}_{03,t}$	0.2781	0.0211	13.1536	0.0000	***
$\text{MTH}_{04,t}$	0.0352	0.0211	1.6664	0.0956	.
$\text{MTH}_{05,t}$	0.1108	0.0211	5.2385	0.0000	***
$\text{MTH}_{06,t}$	0.1440	0.0212	6.7982	0.0000	***
$\text{MTH}_{07,t}$	0.2992	0.0213	14.0493	0.0000	***
$\text{MTH}_{08,t}$	0.1648	0.0212	7.7831	0.0000	***
$\text{MTH}_{09,t}$	0.0556	0.0211	2.6317	0.0085	**
$\text{MTH}_{10,t}$	0.2155	0.0211	10.1902	0.0000	***
$\text{MTH}_{11,t}$	0.0051	0.0211	0.2405	0.8100	
$\text{MTH}_{12,t}$	0.0673	0.0211	3.1894	0.0014	**

Short-Run Coefficients. Dependent variable is $\Delta \ln(\text{Cons}_t)$

	Estimate	Std.Err	Z value	Pr(>z)	
Constant	-1.0175	0.1858	-5.4778	0.0000	***
$\Delta \ln(\text{Cons}_{t-1})$	-0.1145	0.0413	-2.7723	0.0056	**
$\Delta \ln(\text{GDP}_t)$	0.1712	0.1671	1.0243	0.3057	
$\Delta \ln(\text{Quarterly.GDP}_t)$	0.1010	0.1480	0.6823	0.4950	
$\Delta \ln(\text{Annual.GDP}_t)$	-0.3740	0.2585	-1.4470	0.1479	
$\Delta \ln(\text{POP}_t)$	121.5122	20.8439	5.8296	0.0000	***
ΔHDD_t	0.0003	0.0001	2.8517	0.0043	**
ΔCDD_t	0.0016	0.0001	15.1618	0.0000	***
$\text{MTH}_{02,t}$	-0.0541	0.0168	-3.2138	0.0013	**
$\text{MTH}_{03,t}$	0.0922	0.0190	4.8550	0.0000	***
$\text{MTH}_{04,t}$	-0.0749	0.0178	-4.2064	0.0000	***
$\text{MTH}_{05,t}$	-0.0364	0.0201	-1.8087	0.0705	.
$\text{MTH}_{06,t}$	-0.0339	0.0177	-1.9202	0.0548	.
$\text{MTH}_{07,t}$	0.0152	0.0149	1.0221	0.3067	
$\text{MTH}_{08,t}$	-0.0404	0.0156	-2.5856	0.0097	**
$\text{MTH}_{09,t}$	-0.0578	0.0175	-3.3048	0.0010	***
$\text{MTH}_{10,t}$	0.0136	0.0229	0.5908	0.5547	
$\text{MTH}_{11,t}$	-0.0596	0.0164	-3.6329	0.0003	***
$\text{MTH}_{12,t}$	0.0104	0.0155	0.6715	0.5019	
z_{t-1}	-0.1064	0.0187	-5.6926	0.0000	***

Significance: '***' 0.1% '**' 1% '*' 5% '.' 10%

Table 5: Statistical error indices for the electricity demand model.

	Training Sample		**Full Sample**
	In-Sample (1985-2010)	Out-of-Sample (2011-2016)	In-Sample (1985-2016)
sMAPE	**2.27%**	**4.56%**	**2.57%**
MAPE	2.27%	4.48%	2.57%
MAE	9.80	51.95	15.41
MBE	-0.30	-21.17	-0.58
RMSE	14.71	70.04	28.40

Table 6: Annual electricity demand for selected years for the different scenarios. Figures are in TWh/year. To place the scenarios in context, the shaded portion provides historical electricity demand figures.

	RCP 4.5			RCP 8.5		
Year	**SSP1**	**SSP3**	**SSP5**	**SSP1**	**SSP3**	**SSP5**
1990	2.23	2.23	2.23	2.23	2.23	2.23
1995	4.12	4.12	4.12	4.12	4.12	4.12
2000	5.75	5.75	5.75	5.75	5.75	5.75
2005	7.00	7.00	7.00	7.00	7.00	7.00
2010	10.19	10.19	10.19	10.19	10.19	10.19
2015	14.22	14.22	14.22	14.22	14.22	14.22
2020	21.72	24.22	21.59	19.7	21.98	19.58
2025	26.26	32.2	26.51	29.9	36.66	30.18
2030	36.75	47.57	38.58	38.37	49.66	40.28
2035	46.45	61.41	51	46.32	61.24	50.85
2040	54.79	75.3	62.14	59.11	81.26	67.04
2045	65.28	96.67	75.74	67.09	99.33	77.83
2050	60.04	99.31	70.83	69.32	114.63	81.78