University of Michigan’s School for Sustainable Systems

Residential cooling load impacts on Brazil’s electricity demand

Master’s Opus

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Abstract

Brazil's growing middle class, electrification rates, and urbanization has led to a significant uptick in residential appliance adoption. Air conditioner usage, increasingly relevant to both average and system peak demand, will have strong environmental and economic impacts to the country as a whole. With nearly every Brazilian household connected to the centralized electricity grid, increasing temperatures, higher incomes, and vulnerability from reduced energy supply; residential cooling demand will have a large impact on Brazilian electricity grid reliability and whether or not the country will be able to meet both environmental and efficiency goals. Though Brazil's air conditioner impacts have been referenced anecdotally, most detailed studies of cooling demand are focused on countries such as the U.S. This study increases temporal resolution to hourly grid impacts as well as improving spatial granularity to municipality-level climate and air conditioner adoption predictions. The paper is split into two parts with separate models. The first outlines a econometric model that utilizes census data (municipality urbanization, household density, household income) and downscaled global climate model results (humidity, temperature) to project each municipality's household air conditioner adoption rate showing an increase of 44.6% between 2000 to 2010 in households with air conditioners, specifically in municipalities with hot climates and high average incomes. The second part aggregates adoption numbers up to five regional levels to match each region's hourly grid data with three-hourly climate data to closely study how the climate variables impact grid requirements at various temporal levels, showing an increase in usage for every degree-increase in heat index and daily peaks shifting to later hours in the day. Though this paper is specific to Brazil, it highlights a potential future for other fast-developing countries in warm regions pertaining to energy demand, grid reliability, and environmental consequences.

Acknowledgements

Big thanks to my thesis advisor, Jeremiah Johnson (North Carolina State University) for all of the help and guidance. Also a thank you to Roberto Schaeffer and Cenergia (Universidade Federal de Rio de Janeiro) for lending me some guidance and desk space for a month. Another thank you to the International Institute, Rackham, and Latin American and Caribbean Studies- Brazil initiative for funding my travel and work while with Cenergia.

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1. Introduction

1.1 Overview

In 2016, the top four non-OECD consumers, China, India, Russia, and Brazil, made up 36.1% of global electricity consumption.[1] This trend will likely persist into the future, leading to an overall increase of global energy consumption, due to non-OECD countries' increasing access to energy, improving economies, and urbanization.[2]

The residential sector drives over 27% of total global electricity demand and exhibits larger seasonal demand swings than commercial and industrial sectors,[1,3,4] increasing load coincident with system peaks.[5] Growing middle class populations and urbanization in non-OECD countries have contributed to a strong increase in residential appliance adoption for goods such as refrigerators and air conditioners. Studies of appliance adoption trends, known as the "extensive margin," show dependence on purchasing power and income along with others such as migration, policy and personal purchasing decisions.[6–10] Lighting, television, and refrigeration are often the first household electronics adopted, in that order. As those markets reach saturation and economies grow in hot and humid areas, air conditioners are likely the next appliance to see strong growth.[7] While air conditioner adoption is still fairly low in developing countries, global sales increased 13% in just one year between 2010 and 2011.[11]

Studies focusing specifically on air conditioners introduce relationships with climate factors,[12–18] which become especially important when analyzing how appliance use intensity, known as the "intensive margin", changes.[3,5,19–22] Consequently, more cooling degree days have proved to be a significant predictor of increased energy usage[1].[23–29] Though fewer heating degree days may offset part of an increased cooling load,[12,19,20,24] this offset is not sufficient to deter a net load increase.[14,21] Overall, demand for cooling may increase three to five times by 2050, with adoption and use intensity likely concentrated in quickly-developing, populous, warm countries.[12,30]

Increased residential cooling load will have economic impacts on a country-wide scale down to power system ratepayers. Since AC use is often coincident with summertime system peak load, it has direct impact on the amount of generating capacity required on the grid.[5] Without adequate capacity, energy rationing or blackouts may occur and impair economic and social conditions. Moreover, even with sufficient generating capacity, spot market prices may rise due to increased demand during these times, forcing high compensation oftentimes for inefficient thermoelectric generation.[31] This would, in turn, impact rates and energy affordability for customers.

[1] Cooling degree days are often measured by measuring the difference between a day's higher temperature and some set base temperature. For example, using a base of 25 deg. C, one day of 30 deg. C temperatures would be 5 cooling degree days [deg. C]. A week of them would be 35 cooling degree days [deg. C]. Heating degree days are similarly measured between some base and the day's lower temperature.

Additionally, the construction of new generating facilities and the use of peaker plants (inefficient generators used for infrequent hours of very high demand) will have adverse environmental consequences. Resulting greenhouse gas emissions may contribute to a positive feedback loop, accelerating a changing climate and increased cooling demand.

Understanding changes in air conditioner market saturation is complicated and impacted by data scarcity. Moreover, large sensitivity variation prevents the ability to generalize adoption trends across wide regions or timescale.[3,6,15,21] Regardless, a deeper understanding at more granular spatial and temporal levels is critical to better grid planning as well as energy efficiency policy design to ensure system reliability, affordability, and economic development.

1.2 Brazil's Power Sector

As a large country experiencing increases in both ambient temperature and household income, Brazil's increasing air conditioner saturation may reach the point at which it impacts system peak demand. Brazil used 575 TWh of electricity in 2017, making it the fourth-largest non-OECD electricity consumer and eighth-largest worldwide[1,32]. States in Brazil are nested into four grid regions served by the National Interconnected System (SIN): South, Southeast/Midwest, North, and Northeast. Due to differences in climate, socioeconomic, and other factors, consumption is unevenly distributed throughout regions. For example, while the Southeast, with cities such as Rio de Janeiro and Sao Paolo, contains 48% of residential customers, it represents 54% of residential usage. In contrast, the Northeast makes up 25% of residential customers, but only represents 15% of usage.[33] An additional 237 isolated grids, located primarily in the Amazons and Northwest portion of the country, make up less than 1% of total demand.[34] While the SIN annual peak most often falls on a summertime workday between 2 PM and 4 PM,[32] residential cooling demand in the evening is starting to increase during these summer months and may soon dictate system peak in wealthier and warmer regions.[8,9,23,35]

For over three decades, Brazil's residential demand has grown at an average annual rate between 3.5% and 6% due in large part to increased grid interconnections, urbanization, increasing incomes, and falling electricity tariffs.[8,33] In 2003, *Luz para Todos* was established to enable universal electricity access to electricity. Before the program in 2000, the country-wide electrification rate was 93%, with only 69% of rural households connected.[36] By 2010, Brazil had achieved 98.6% electrification, leading to electricity demand in communities where there had previously been none. With near full electricity access today, near-term annual growth is projected to persist at levels between 2.9% and 4.7% due to Brazil's increasing population, economic activity, and urbanization.[37]

Most of Brazil's demand is met from the country's large hydroelectric resource, which makes up 65% of installed capacity.[2,32] This has provided Brazil with large amounts of low-carbon generation, but has also exposed the country to shortages due to a changing climate. In recent decades, droughts have led to significant economic contraction that have impacted the country as a whole. For example, Brazil's 2001 drought led the government to demand 20% load curtailment, stalling development.[38] During the next large drought of 2013-2015, reservoirs were at levels 17% below those in 2001, but Brazil was able to avoid country-wide curtailment through the use of fossil fuel-run thermoelectric plants. Even so, there were smaller-scale economic impacts as temporary electricity cuts affected large cities such as Rio de Janeiro and, and spot market prices hit historic highs ten times those in preceding years.[31,38] Additionally, the heavy use of these thermoelectric generators, constructed as far back as the 1960's with efficiencies below 20%, increased costs, fuel consumption, and emissions[31] Anticipating further issues with reliability, Brazil is working to diversify grid resources primarily through new wind installations and imported natural gas.[31] Moreover, various studies show that climate introduces large levels of uncertainty for generator performance into the future, predicting that rising temperatures may negatively impact both thermoelectric and large hydro generators, but may benefit wind.[20,31,39–49] To combat aging infrastructure, growing demand, and climate uncertainty, planners seek to supplement capacity expansion with energy efficiency, revising plans annually.[50]

Brazil's Energy Efficiency National Plan (PNEf) set a goal of 10% (107 TWh) reduction in electricity consumption by 2030.[50] The government has suggested that 38% of projected savings through 2022 would come from the residential sector alone, which only accounts for a quarter of total load.[37,50] Direct energy efficiency gains of residential air conditioners along with other appliances have stemmed primarily from the mandatory minimum energy performance standards (MEPS) created in 2001, and secondarily through voluntary Selo PROCEL labeling.[35] These measures generated an estimated savings of 334 GWh of savings in 2007, 6.8% of total air conditioner load, and a 114 MW peak reduction compared to business as usual.[35] However, Brazil's MEPS coefficient of performance requirements are still less than requirements in similar markets like China, where most of Brazil's units originate.[35]

Appliance adoption studies in Brazil are often generalized over large temporal and spatial ranges, but consistently show large projected load growth in the residential sector primarily due to socioeconomic improvements.[8,9,51] Using 30-year average temperatures, capital cities' household consumption was significantly and positively correlated with the interaction term between high income and warm temperatures.[51] Air conditioners are still considered a luxury item for many in Brazil. In 2012, air conditioning represented 5% of total residential electricity consumption and, in 2015, were only present in 18% of households.[50] Nevertheless, annual household adoption grew 21% in 2014 and was estimated to grow an additional 12% in 2015.[52] With increased adoption, air conditioners will have a large impact on overall grid demand.

1.3 Study Objective

Electric load growth has often been estimated through top-down models that account for economic and population growth indicators along with other large-scale trends such as those in industry. While climate can be considered, it is often treated as a constant over time, and averaged across large ranges temporally and spatially. Recently, literature has started to focus on bottom-up models that disaggregate the residential sector.[53] In understanding residential load growth, research has focused primarily on factors that impact appliance adoption, known as the extensive margin, and on those that impact use intensity, known as the intensive margin. Due to difficulty obtaining longitudinal data across granular regions in non-OECD countries, most literature focuses on OECD countries, or solely in urban areas of developing countries.[12,23] Unfortunately, due to the nature of adoption patterns and diversity across markets, resources, climate, and population, it is difficult to generate universal understanding of appliance adoption and residential consumption across multiple locations.

This thesis aims to analyze the impact of household income, climate, and household distribution on air conditioner adoption at the municipality level; understand the consequent impact on regional hourly electricity demand; use predictions to understand the point at which residential air conditioner load may dictate annual peaks; and relate the results back to Brazil's capacity expansion goals and energy efficiency policies. This will be done using both temporal and spatial data to study the extensive margin (i.e., appliance adoption) and intensive margin (i.e., usage) of air conditioners in Brazil. While there are industry estimates for air conditioner adoption and data on urban adoption rates, there have been no data on household penetration of air conditioners at the municipality level since the 2000 Census. Currently, studies estimate usage and potential efficiency savings regionally by appliance stocks, the number of hours above a specific temperature, and efficiency/capacity of the average unit[35,54] However, by taking hourly impacts on the grid and municipality-level impacts of air conditioner adoption and climate, this study estimates adoption and savings at a more granular level that remains inclusive of rural communities. With nearly every Brazilian household connected to the centralized electricity grid, increasing temperatures, higher incomes, and vulnerability from reduced energy supply, residential cooling demand will have a large impact on Brazilian electricity grid reliability and whether or not the country will be able to meet both environmental and efficiency goals of 10% reduction by 2030.[50]

To address the central research question, a two-step approach is deployed. First, the extensive model utilizes climate and census data to project each municipality's household air conditioner adoption rate. Second, the intensive model aggregates air conditioner adoption values up to a regional level and, coupled with load and climate data, offer novel findings on increases to residential electricity consumption. This allows better understanding of how residential cooling demand may impact overall grid reliability at various temporal levels, which may serve to better inform future energy efficiency policy and grid design. Though the data and findings are specific to Brazil, the approach can be broadly applied and the results underscore the importance of this issue to energy demand, grid reliability, and environmental consequences for other fast-developing countries in warm regions.

2. Extensive Model: Data and Methods

The extensive model determines each municipality's household air conditioner adoption using census data at the municipality level for household distribution, urbanization levels, and household income as well as climate data from a downscaled regional climate model. Since air conditioner usage can only occur in households with the appliance, understanding the number and distribution of household ownership is critical to better understand the magnitude and timing of electricity demand.

Climate Data

In order to obtain the spatial and temporal granularity required for this analysis, Princeton Hydrology Center's reanalysis data proved to be the most complete and consistent with the Climatic Research Unit TS3.0.[55] The downscaled data provided values at a 0.25x0.25 degree level at three-hour intervals for specific humidity [kg water/kg air] and ground level temperature [K] for years 1990 through 2010. Temperature and specific humidity were combined to one heat index value as per the United States' Weather Service's guidelines (Equation 1: Heat index as a function of temperature and relative humidity).[55]

Equation 1: Heat index as a function of temperature and relative humidity

$$\begin{aligned} Heat\ Index = &-42.379 + 2.049 * T + 10.143 * rh - 0.225 * T * rh - 6.838E-3 * T^2 - 5.482E-2 * rh^2 + 1.228E-3 * T^2 * rh \\ &+ 8.528E-4 * T * rh^2 - 1.99E-6 * T^2 * rh^2 \end{aligned}$$

The resulting heat index at a spatial level of 0.25x0.25 degrees was then aggregated up to Brazil municipalities (Figure 1). To then convert heat index values to CDD values, a 25 deg. C base was used and 3-hourly values were combined, by day to create a CDD value (Equation 2). 25 deg. C was selected due to the common base value of 18 deg. C being too cold. A behavioral study showed residents in Brazil turning on their air conditioner unit at temperatures closer to 30 deg. C, and another study showed that some considered 26 deg. C "chilly"[54,56,57]. To accurately account for differences in perceived temperature, a base of 25 deg. C was used. This was done for each year over the course of the decade preceding 2000 and 2010, respectively and averaged (i.e. 1990-2000 for AC ownership in 2000). By taking a decadal average, outliers would not skew data and the final values would more accurately reflect the overall perceived climate over a time period that more closely matches the lifespan of an AC unit.

Equation 2: Calculating CDD values for municipality i and day j from eight individual three-hourly heat index values

$$CDD_{i,j} = \sum_{k=1}^{8} \left(HI_{3hr,j} - CDD_{base}\right) * 3\ hours * \frac{day}{24\ hours}$$

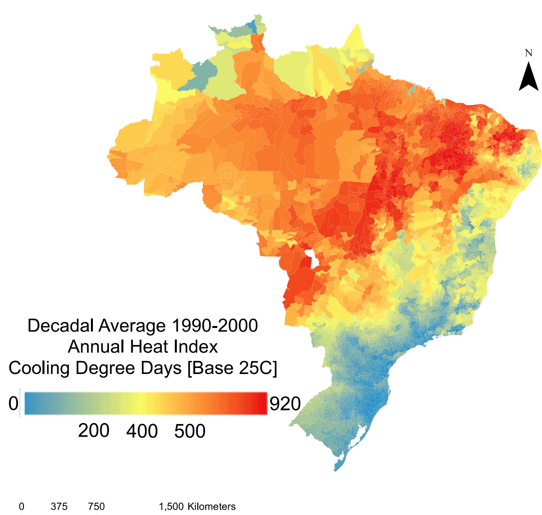


Figure 1: 1990-2000 Decadal average annual heat index CDD [base 25 deg C] by municipality

Using 25 deg. C as a base, decadal average annual CDD values across municipalities increased from 360 to 382 between the 1990s and 2000s (Figure 2a). Using a higher base of 30 deg. C, it becomes clear that temperature increases are concentrated in more extremely hot days. In the 90's, 73% of municipalities had average CDD values less than 50; by 2010, only 36% of municipalities were in this low range for cooling loads (base 30 deg. C) (Figure 2b). As the frequency and intensity of extreme heat events increase, the adoption of air conditioners will likely increase, along with their use intensity.

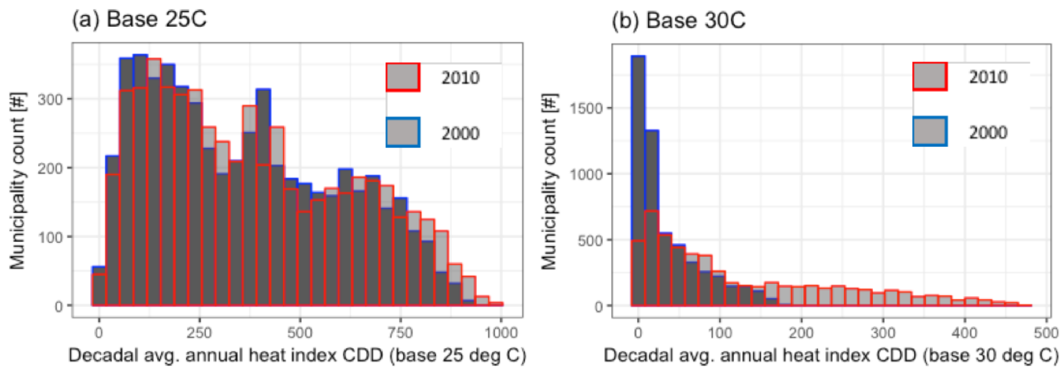
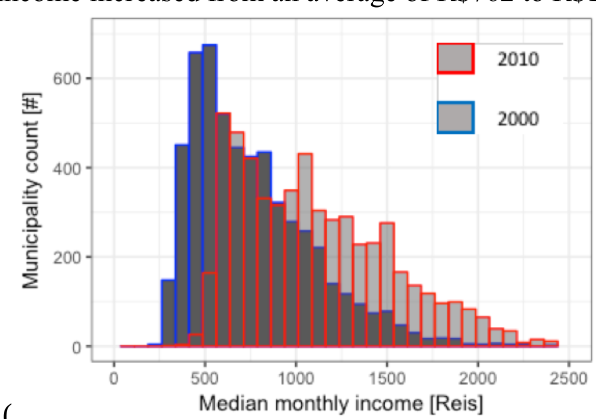


Figure 2: Changing Decadal Average Heat Index Cooling Degree Days from 1990's to 2000's, by municipality: (a) Base 25 deg. C represents the temperature at which consumers turn on the air conditioner (Procel); (b) *Base 30 deg. C represents increased number of extreme heat events*

Household Data

This paper utilized the Brazilian government's Institute of Geography and Statistics' (IBGE) municipality data (n = 5,564) from the national census in 2000 and 2010 to fully capture information from all households in Brazil, including those in rural areas.[58] For the extensive air conditioner adoption model, monthly median income (adjusted to 2010 values to account for inflation) and the number of households, both urban and rural, were used as inputs. Overall, census data show that municipalities' monthly household income increased from an average of R$762 to R$1,111 from



2000 to 2010, adjusted for inflation (
Figure 3). As incomes increase across municipalities, energy usage may do so as well.[33]

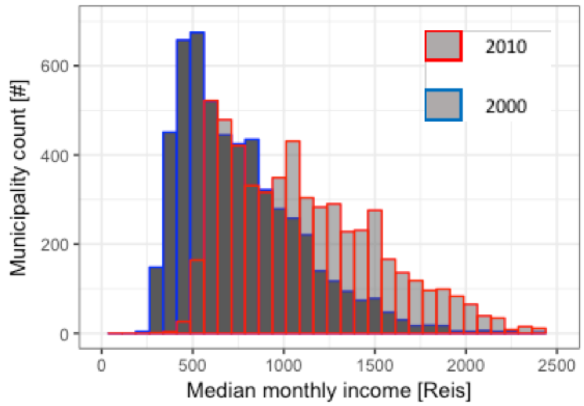


Figure 3: Median monthly household income [R$ 2010] histogram, by municipality in 2000 and 2010

The most recent, complete dataset for household air conditioner adoption at the municipality level is from the 2000 census.[58] As shown in Figure 4, adoption rates for air conditioners varied greatly, ranging from 0% to 50% penetration. High penetration was most often determined by locations with high average monthly incomes (e.g., Rio de Janeiro, Sao Paulo).

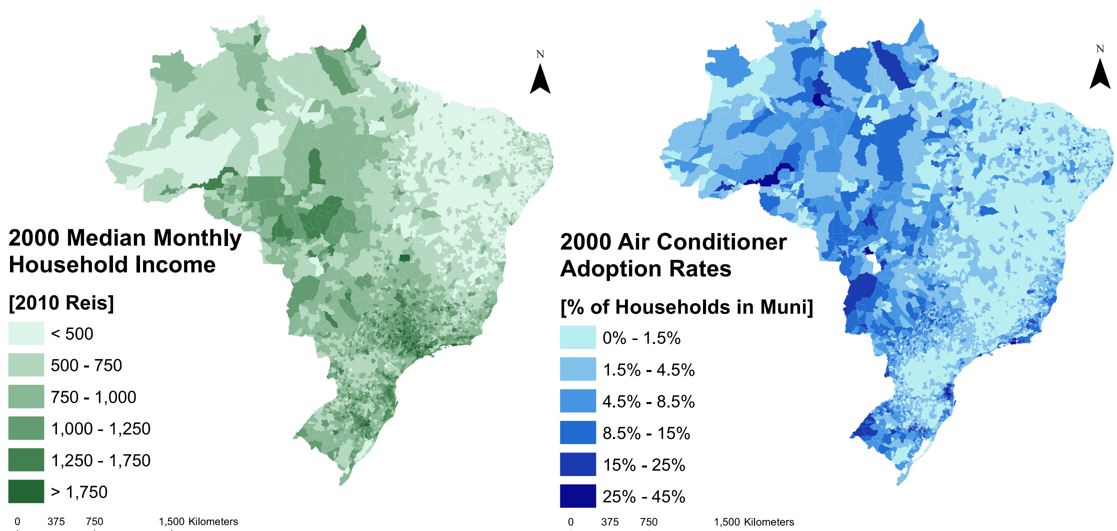


Figure 4: (a) Income, and (b) AC Adoption Rates across Brazil municipalities in 2000

Climate factors also played a part in adoption for locations with more cooling degree days (e.g., Northwest) (Figure 1: 1990-2000 Decadal average annual heat index CDD [base 25 deg C] by municipality). However, peak adoption often requires a combination of the two. In areas with lower income, such as the Northeast, adoption remained low despite high temperatures and high humidity.

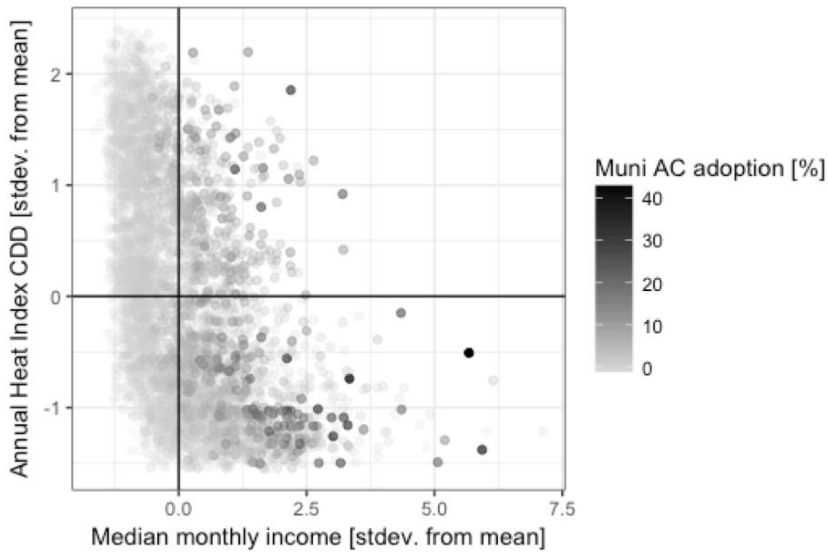


Figure 5: AC adoption by municipality's climate and income, organized into quadrants separated by mean values

Considering climate and household data together, Figure 5 shows municipalities split into quadrants by average heat index values and monthly income across the country show households with above-average incomes have air conditioner adoption rates averaging 11.3% in warmer-than-average municipalities and 8.6% in colder-than average municipalities. For municipalities with below-average incomes in warmer and cooler locations, average adoption rates drop to 2.0% and 1.8%, respectively (Figure 5).

To model air conditioner adoption at a municipality level, multiple models were considered and analyzed for their predictive power. The linear mixed model selected treated urban and rural households separately due to different factors affecting adoption rate including electrification rates, cultural norms, and income. Both models, while separate, controlled for random effects both at the state and regional levels. Fixed effects included urbanization level, total households, and the interaction between the median monthly income and average decadal specific heat index (Equation 3). While the random effects, urbanization level, and decadal specific heat index were the same for both models, the total household and median monthly income varied between urban and rural models (e.g. the urban model uses total urban households and urban median monthly income). Appendix 2 describes the different models considered along with why they were ultimately rejected.

Equation 3: Linear mixed model for municipality i, state j, region k, number of households, urbanization level, heat index cooling degree day value, median household income, and income/heat index cooling degree day interaction. This model was run separately for urban and rural household populations in each municipality.

$$ACHH_i\ [\%] = \beta_0 + \beta_{0j} + \beta_{0k} + \beta_1 HH_i + \beta_2 Inc_i + \beta_3 UrbLvl_i + \beta_4 Clim_i + \beta_5 Inc_i | Clim_i + \varepsilon$$

3. Intensive Model: Data and Methods

The intensive model analyzes households' air conditioner usage patterns in the larger context hourly regional electricity demand. Brazil is made up of 5,564 municipalities nested into 26 states and one federal district, which are subsequently nested into 5 regions, two of which combine to form 4 regional subsystems. Distribution of household air conditioner adoption from the extensive model are used to give each municipality a weight that goes towards aggregating climate factors from the 5,564 municipality levels to the 4 regional substations. Supporting data include the same climate and census variables with additional GDP and population data from the census bureau and hourly load data from the system grid operator.[32,58]

Climate Data

Using the same dataset and methods for calculating heat index values as the extensive model, three-hourly data were used for 2009-2011. These three-hourly data were linearly interpolated to hourly heat index values in order to match hourly load data for each municipality. Municipality weights represented the percentage of households with air conditioners as a fraction of total air conditioners in a municipality's respective regions. These weights were used to aggregate hourly heat index values up to regional levels to match hourly load data.

Table 1: Descriptive characteristics of regions in 2010

Region	Tot. Households [#]	Households with AC [#]	Households with AC [%]	Monthly Household Income [2010$R]	Avg. Heat Index [C]	Heat Index CDD [Base 25C]
Midwest/Southeast	28,270,338	3,458,156	12.23%	$ 1,800	22.4	791
Northeast	14,172,976	870,001	6.14%	$ 959	25.2	1531
North	3,678,930	1,182,357	32.14%	$ 1,194	26.2	2084
South	8,661,473	942,088	10.88%	$ 1,843	18.4	269

Electric Load Data

Hourly load data by region were provided by the National Electricity Grid Operator (ONS) for 2009 through 2011.[32] We analyzed a period of three years to reduce bias of any single year's climate or usage variability, but small enough such that 2010 air conditioner adoption levels could be assumed as constant. These three years are both sufficiently close to 2010 and occur before drought conditions that began in 2013, which led to grid failures.[8] The years surrounding 2000 were left out due to concerns that consumption would not be representative of current trends due to significant changes in appliance adoption, consumer behavior, and electrification rates resulting from *Luz Para Todos*. Additionally, the drought of 2001 and subsequent electricity rationing would introduce confounding effects and prediction error.

Due to differences in population, climate, income, industry, and other factors, each of the four regional grids vary. Each of Brazil's regions make up a subsystem with the exception of the Southeast and Midwest, which are blended into one. As a result, the country's interconnected system (SIN) is composed of four regions: North, Northeast, Southeast/Midwest, and South.

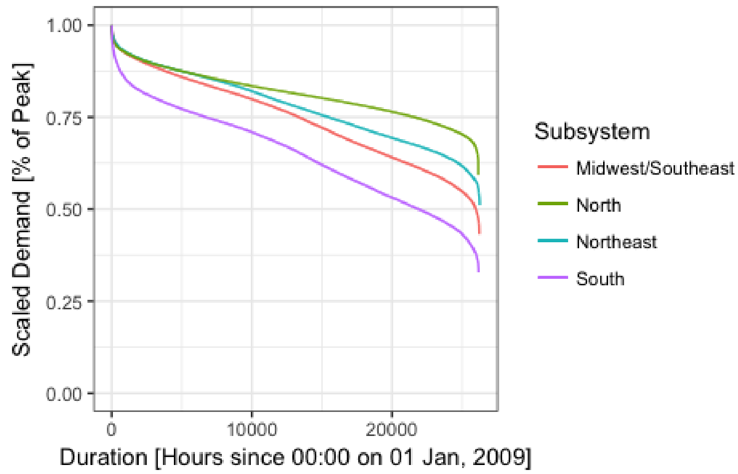


Figure 6: Three-year normalized load duration curves, by subsystem

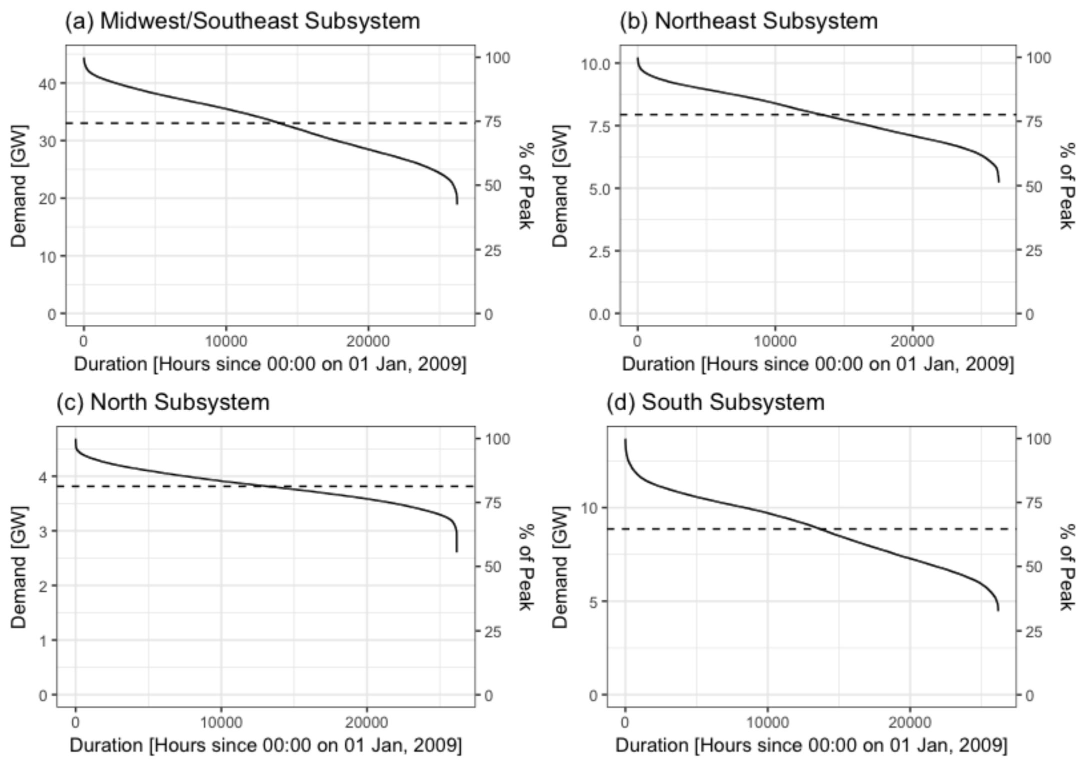


Figure 7: Subsystems' three-year load duration curves using hourly data from Jan 01, 2009 through Dec 31, 2011. Dotted line represents the three-year average demand.

Figure 6 and Figure 7 show the load duration curve for each subsystem. The Midwest/Southeast subsystem accounts for the great majority of SIN load, as it holds the majority of the population and has higher household incomes. Looking at the slope of each line shows the potential that load shifting would have on reducing maximum demand. Currently, the peaks in each system occur at the middle of a workday around 3 pm (Figure 8). With the exception of the North, each subsystem's peak demand day generally falls during a warm month. More information on how hourly demand changes by month and hour of the day for each subsystem is illustrated further in Appendix 3.

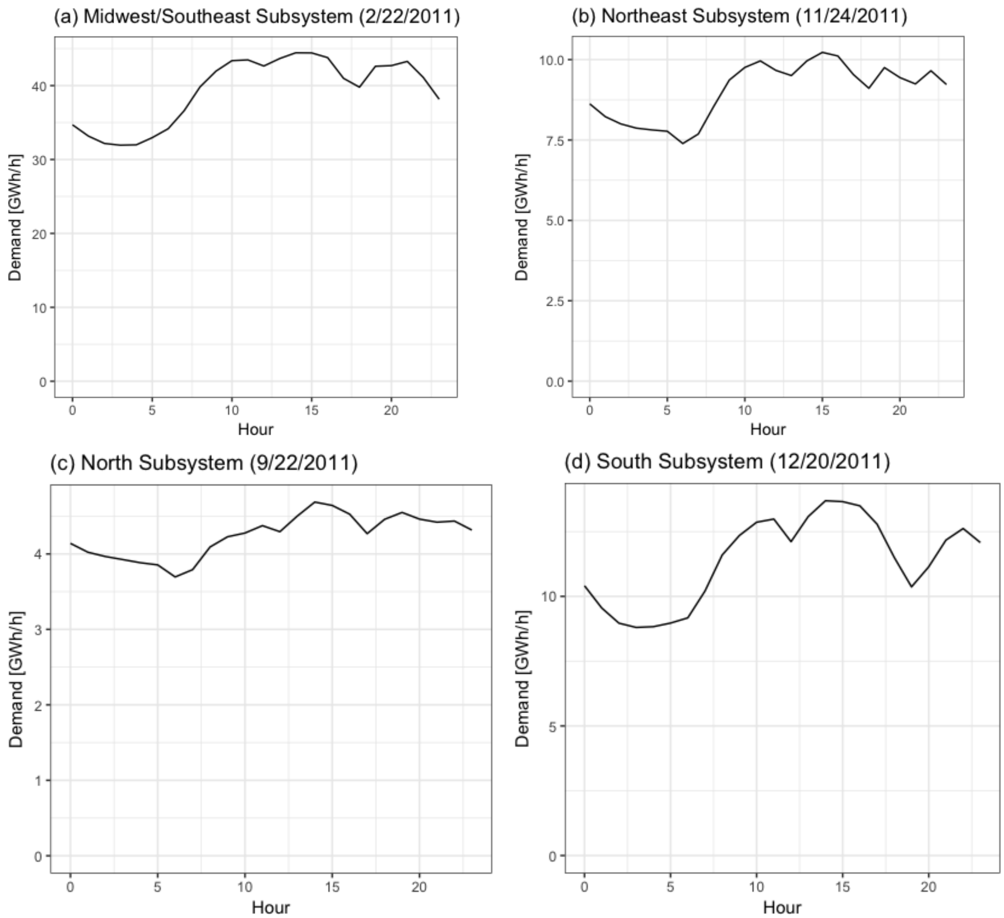


Figure 8: Hourly electricity demand for each subsystem's peak demand day

During the warmest days, the impact of air conditioners become more apparent. Figure 9 shows the differences in the hourly load curves' shapes and magnitudes between the coldest and warmest day of each region. During the warmest days, usage begins to increase around 8 and 9 pm. Patterns and levels of change depend on each region's climate and socioeconomic factors (Table 1). For example, the South and Southeast experience the largest differences in temperatures and thus have the most variation in seasonal shapes. The two regions have winter peaks in electric shower use in the evenings (due to electric water heaters in showerheads), and a summer air conditioner peak in the summer. On the other hand, the North and Northeast subsystems are relatively warmer year-round, and have relatively lower incomes. This may translate to more inflexible demand. While the residential air conditioning contribution during the evening hours does not yet play a role in setting the maximum system demand, it is growing in each subsystem with increasing incomes, appliance adoption, and ambient temperature.

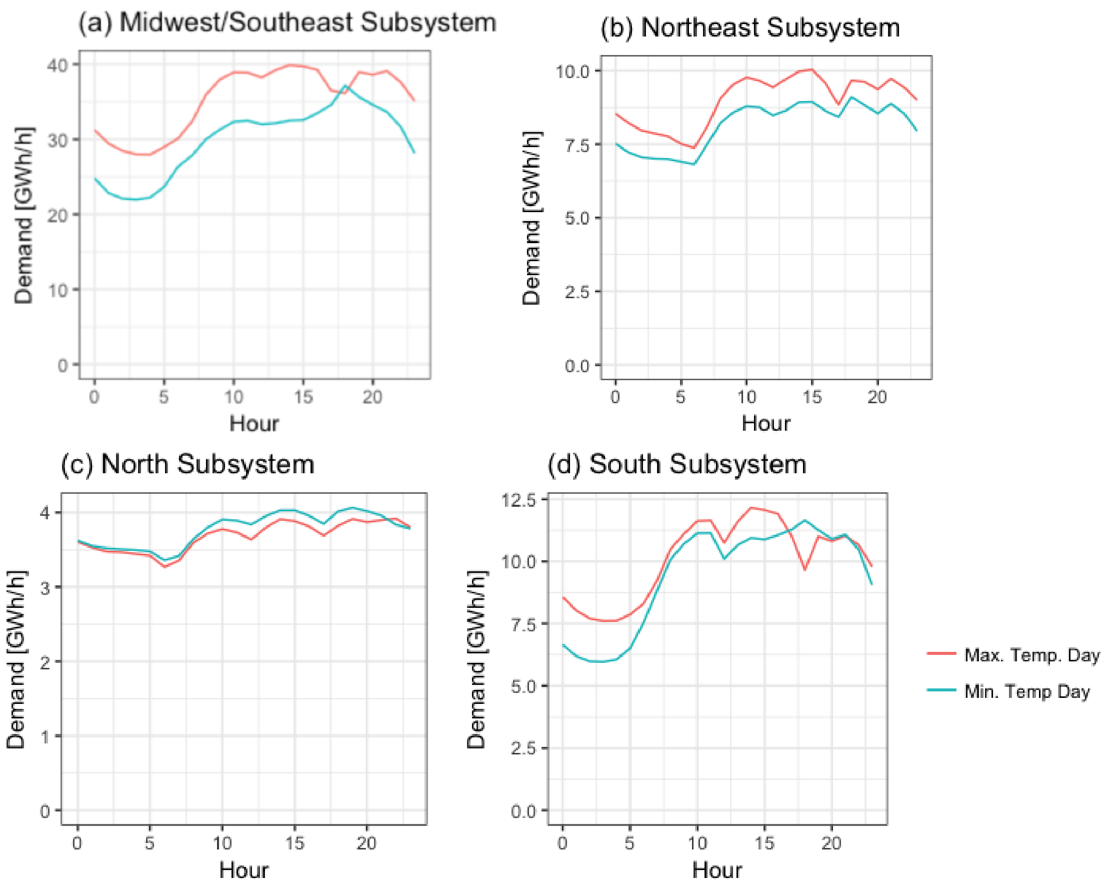


Figure 9: Hourly load curves for each subsystem's day of maximum and minimum temperatures

The three-hourly air temperature and specific humidity data were combined as in Equation 1 to create three-hourly heat index values for each municipality between 2009 and 2011. The extensive model's 2010 air conditioner adoption levels, by municipality, were then used to weight climate data for the intensive model as a percentage of the region's total number of households with air conditioners. This allowed for the final regional three-hourly heat index values to better capture climate factors that would impact air conditioner usage, specifically. To match the hourly regional load data, three-hourly heat index values were linearly interpolated to hourly values. The dataset was cleaned of any days where significant faults may have tripped off significant load by finding outliers in hourly ramp-down rates. Outage-affected data points represented only 0.3% of the initial data set.

With each hour's per-capita load [Wh/h per capita] as a response variable, predictors included the region, hour of the day, whether or not it was a workday, the hour's heat index value, annual regional GDP adjusted to 2010 $R values, and the minimum heat index value from the previous 24 hours. Non workdays were considered to be any weekend day or Brazilian national holiday. The minimum heat index value from the previous 24 hours was included to account for the solar heat gain stored in a home from preceding days. For example, if the prior day was warmer, given the same climate profile for the following day, usage would likely be higher.

The behavior of load is non-uniform and non-linear. As such, a random forest mixed model approach was used. Separating out 80% of the data to train and 20% to test, the median error value across the test data was 2.5%, demonstrating high predictive capabilities.

4. Results and Discussion

For both urban and rural household extensive models predicting adoption rates, all fixed effects (i.e. number of households, income level, urbanization level, heat index cooling degree day, and income/heat index cooling degree day interaction found in Equation 3) had significance. The addition of random effects narrowed the respective model's variance considerably, demonstrating meaningful contribution. A more detailed model summary can be found in Appendix 1.

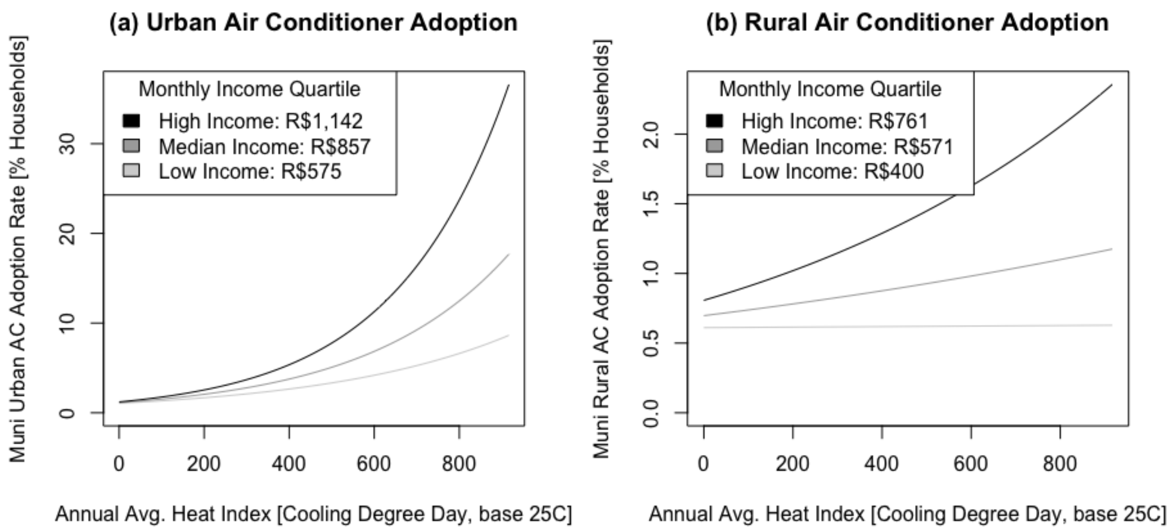


Figure 10: Interaction plots between annual average heat index CDD (base 25 degrees C) and average median monthly household income for municipalities with non-zero air conditioner adoption (a) urban extensive model, (b) rural extensive model

Overall, rural households are far less likely than urban households to adopt air conditioners, and income must reach a higher value before significant adoption begins (Figure 10). This could be due to various factors such as relatively lower incomes or fewer appliances given that electrification has occurred only recently.[2] Across income levels, adoption remains fairly low until heat index cooling degree day values reach ~ 500 (Figure 10). Upon reaching a heat index cooling degree day of about 500 C, adoption levels increase across households in hotter municipalities (apart from rural households in the first income quartile). Only when the income barrier is overcome does adoption rate depend heavily on climate factors, with the slopes of adoption curves far steeper for households in the upper income quartile. On two ends of the extreme, for households with lower incomes in warmer climates, an air conditioner is a luxury regardless of ambient temperature. For households with higher incomes in cooler areas, air conditioners may be affordable, but are not useful. Thus,

[2] In 2000, median monthly income levels across municipalities were R$838 for urban households and R$613 for rural households (values inflated to 2010 R$ values)

adoption is highest for wealthy, urban households in warm municipalities. These results are consistent with literature finding that high adoption rates in hotter, fast-developing countries were heavily reliant on both higher incomes and higher perceived temperature.[12] Referring to Table 1, the North and Northeast subsystems have heat index values far above 500 C, but relatively low household incomes. On the other hand, the Midwest/Southeast and South subsystems experience lower heat index values, but higher incomes. In the future, the increasing incomes in the Northern regions will have the largest impact on country-wide adoption with increasing temperatures in Southern regions having a significant secondary effect.

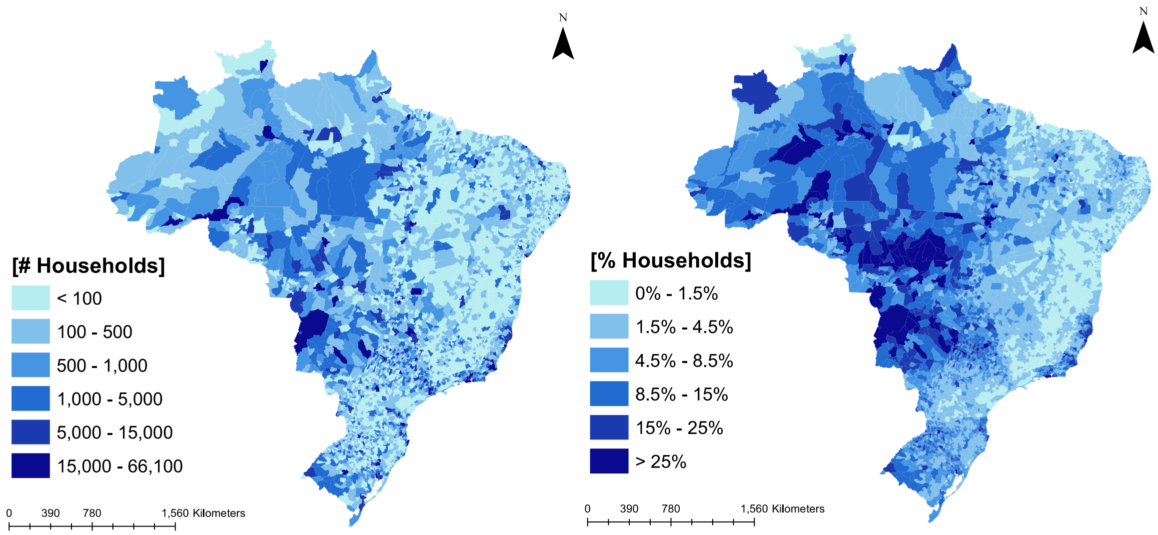


Figure 11: Air Conditioner Adoption Rates, by Municipality: (a) Number of households with at least one AC unit and (b) Fraction of households with at least one AC unit predicted in 2010

Brazil's total household adoption rate for 2010 was predicted at 11.8% up from 7.4% in 2000 (Figure 4b, Figure 11b), which is consistent with available country-level information. Similar to in 2000, most of the households with air conditioners can be found in locations with higher incomes and warmer climates (Figure 11a). While there are no data for 2010 municipality-level adoption rates, Brazil's HVAC industry group ABRAVA and other sources have estimated country-wide adoption rates for comparison (Table 2). ABRAVA announced a household adoption rate of 15% nationwide for residential mini-split and window air conditioner units four years later in 2014.[59] Consistent with our model's results, Euromonitor 2010 numbers put adoption rates close to 11%.[60]

Moreover, when comparing the results in terms of distribution of total AC stocks, the model put most of the air conditioner units in the wealthier Southeast and less in the hotter, but less wealthy Northeast. Actual stocks and sales information indicate that the model may have overestimated penetration in the Southeast, and underestimated penetration in the Northeast. However, it is important to note that this is not a direct comparison, as the model presented in this paper estimated the number of households with at least one air conditioner unit, while ABRAVA data account for each individual unit. Additionally, distribution in 2010 may have been different than 2014 due to increased immigration to Brazil, especially in the North and Northeast regions.[59]

Table 2: Distribution of air conditioners, a comparison

Distribution of Households with Air Conditioners Across Brazil

Region	2010 (Predicted, authors)	2014[59]
Northeast	13%	18%
North	18%	12%
Midwest	16%	21%
Southeast	38%	32%
South	15%	17%

Creating a predictive model that takes five data points including, and between, each region's hourly median and maximum heat index value, the Wh per capita increase per degree increase was quantified for each subsystem. Focusing on weekday consumption, The Midwest/Southeast and South subsystems had the largest sensitivities to changes in climate factors (Figure 12). This is consistent with results from the extensive model in that the wealthier regions are more sensitive to climate when it comes to their electricity usage patterns.

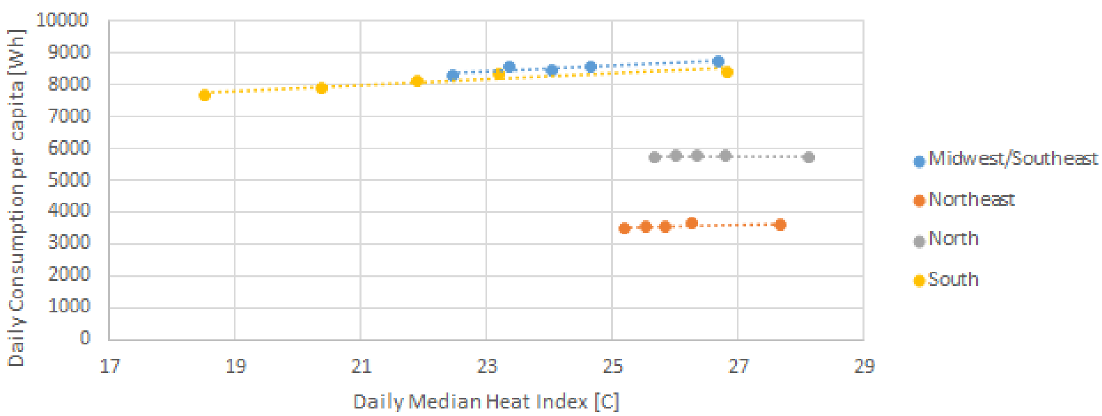


Figure 12: Per-capita weekday daily consumption sensitivity to climate, by subsystem

With the exception of the North subsystem, which showed a slightly positive, non-significant relationship, each subsystem showed an increase of overall load as daily median heat index increased. Though appearing to be relatively flat, when taking population into consideration, each degree-increase in daily median heat index has a sizable impact on total demand, especially in the wealthier and more populous regions where electricity demand is more flexible (Table 3).

Table 3: Daily Wh per capita and total GWh increase per 1 C increase in heat index, by subsystem

Region	Wh per cap. increase per 1C	GWh increase per 1C
Midwest/Southeast	98.85	9.37
Northeast	~ 0	~ 0
North	56.66	0.87
South	91.06	2.52
Total	**246.57**	**12.77**

Another consequence of increasing temperatures was the timing of each daily peak in addition to the overall increase in magnitude. In the case of the Midwest/Southeast and South subsystem, the peak shifted from being determined by an early evening (likely electric showers) peak at median temperatures to a midday peak at higher temperatures, likely driven by commercial and/or industrial cooling loads. On the other hand, the North and Northeast subsystem saw peaks shift from midday commercial loads at median temperatures to late evening residential peaks, likely driven by residential air conditioners (Appendix 4). As the North and Northeast regions gain purchasing power, and as the Southeast, Midwest, and South get warmer, air conditioner adoption will increase far more rapidly and begin to impact total and peak consumption at the grid level

Limitations

While the extensive model produced very reasonable results, there were a few limitations to the study. The main limitation arose due to data availability and quality. Since municipality-level data for household ownership of air conditioners only existed for 2000, creating a predictive model for 2010 assumes that the same adoption behavior and trends that existed in 2000 were still drivers a decade later and does not account for migration. This is likely a good assumption for urban households in 2010, but rural households likely behave far differently now that electrification rate has increased due to Luz Para Todos. Additionally, household income is quickly growing, and the extensive model can only interpret values that it has seen before so as not to extrapolate. This limits the potential for future projections once incomes reach levels that were beyond the upper limits in 2000. The beginning of this was seen in 11 municipalities that experienced quick increases in both CDD and income when predictions indicated full urban household penetration of air conditioners, which is not likely. Note that this is a small fraction of the 5,564 total municipalities and that this was not an issue for rural households, whose predicted adoption rates remained relatively low.

For the intensive model, the model was able to track with very low error, however, there is very limited information regarding load disaggregation in Brazil. Disaggregation by sector is available publicly only by month and year as opposed to by day or hour. Additionally, load disaggregation by appliance to isolate an air conditioner peak requires data from a smart meter or other sensor, which was not available. A 2005 study done by Procel interviewed households and created load curves by region for a typical household, but information on usage patterns and sensitivity to seasons was more general and qualitative[3].

Future studies could project this model into the near future to align with Brazil's proposed grid expansion plans, and could include methods to disaggregate appliance load to more definitively understand consumption patterns and behavior. This would be valuable to plan and prioritize grid expansion, but would require additional data that may not be available. This study could be further expanded to include more information on air conditioner unit efficiencies and how this may change over time to impact the intensive model.

5. Conclusion

Brazil's total household adoption rate for 2010 was predicted at 11.8% up from 7.4% in 2000 (Figure 4b, Figure 11b). The country is experiencing increasing temperatures and wealth, distributed asymmetrically around the country at the same time it is experiencing challenges from aging infrastructure and dwindling hydro capacity. With increasing wealth, households become more sensitive to a warming climate when making purchasing decisions about air conditioners. As such, growing temperatures in the wealthier Southeast, Midwest, and South regions will have a large impact in air conditioner adoption country-wide. These regions have higher household incomes and larger population numbers and are thus more climate-sensitive. However, due to a relatively mild climate, adoption has remained low, indicating large adoption potential in the future as these regions warm. On the other hand, the North and Northeast regions represent a smaller number of households and air conditioner adoption. Due to lower buying power, household adoption has remained flat and electricity demand inflexible. As households gain buying power in these regions, sensitivity to their warm surroundings will likely increase and spark higher rates of air conditioner adoption. While there is not much literature at this level of granularity for Brazil, specifically, these results are consistent with similar findings in Mexico and other warm, fast-developing countries.[12]

Even at 2010 levels, climate has an impact on overall consumption, peak demand magnitude, and time of daily peak consumption. For the Midwest/Southeast, North, and South, a change in daily median temperature of 1C resulted in a per-capita weekday daily usage increase of around 99 Wh, 57 Wh, and 91 Wh, respectively. This results in a total subsystem impact of 9.37 GWh, 0.87 GWh, and 2.52 GWh increase, respectively. This amounts to a 0.9, 1.1, and 1.2 percentage point increase in average daily load per each degree of temperature increase, respectively.

Disaggregating load by sector and/or by appliance would provide more information on how climate impacts air conditioner usage intensity. Though one can assume that the late-evening peak that shows up only on warm days can be attributed to residential air conditioners, it is hard to know for sure. With this information, Brazil may be able to target programs such as demand response or energy efficiency standards to ensure that this evening peak does not increase to the point where it is dictating system peak during warm days. This in turn would benefit emission reductions, economics, and grid reliability, alleviating some need for increased generation capacity or reliance on expensive and inefficient peaker plants.

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[3] Procel

With non-OECD countries outside of Brazil experiencing similarly increasing wealth and temperatures, trends such as those found in Brazil may be replicated across the globe. With a better understanding of air conditioner adoption and use intensity, countries may be able to implement mitigation strategies in a proactive manner so as to remain aligned with environmental, development, and other goals.

6. Appendices

Appendix 1: Extensive model R outputs

To predict log-normal air conditioner adoption rates for each municipality, rural and urban households were considered separately. A log transform was applied in order to account for over-dispersion of the municipality's number of households with air conditioners.

Predictor	Estimate	Std. Error	Degrees of Freedom	t-value	P Value
	Urban Households				
(Intercept)	-0.4109	0.3003	5.187	-1.368	0.2275
Total Households [log(1000 HH)]	0.1507	0.0173	3153	8.709	4.87E-18
Median Monthly Household Income [log(100 $R)]	0.02334	0.008314	3155	2.808	0.005016
Average Decadal Heat Index CDD [100 CDH]	0.003491	0.001039	3112	3.361	0.0007848
Urbanization Level [percentage]	0.002396	0.00103	3154	2.327	0.02003
Income/Heat Index Interaction	0.001051	0.0001051	3154	9.998	3.45E-23
	Rural Households				
(Intercept)	-1.234	0.1353	313.4	-9.116	9.61E-18
Total Households [log(1000 HH)]	-0.1878	0.03669	1632	-5.119	3.44E-07
Median Monthly Household Income [log(100 $R)]	0.07703	0.01411	1531	5.459	5.58E-08
Average Decadal Heat Index CDD [100 CDH]	-0.005114	0.001178	856.2	-4.342	1.58E-05
Urbanization Level [percentage]	0.009761	0.0008975	1633	10.88	1.20E-26
Income/Heat Index Interaction	0.001311	0.0001783	1242	7.355	3.46E-13

Appendix 2: Extensive Model Comparison

A mixed model linear model was ultimately selected for this study, however, a mixed model poisson, quasi-poisson, negative binomial, two-step model approach were initially considered.

The two-part mixed model consisted first of a binomial model to first predict whether or not a municipality would have at least one household with air conditioner. If a municipality was predicted a non-zero adoption rate, a linear model was fit to estimate magnitude of the adoption rate. In 2000, across all municipalities, air conditioner penetration was zero (i.e. no household in the municipality had an air conditioner unit) in 44.5% of rural households and 16.7% of urban households. Ultimately, the binomial model was not used because, while the accuracy of the urban binomial model was fairly high at 86.01% (95% CI: (83.82%, 88.01%), it did not surpass the no information rate of 90.37%. Thus, for 2010, all municipalities assumed presence of at least one household with an air conditioner. On the other hand, the rural logistic model, while lower with an accuracy of 67.21% (95% CI: (64.35%, 69.98%), was much higher than the no information rate of 58.04%. However, this value was still fairly low and led to a wide 95% confidence interval for predicted values. Additionally, low adoption rates in rural areas could have been due to confounding effects of low electrification rates. As such, the initial binomial model was omitted in the final analysis.

Count models such as poisson and negative binomial models were considered so as to not separate the process to logistic and linear mixed model regression while still including municipalities with zero urban and/or rural households with air conditioners. Unfortunately, due to over-dispersion of the households with air conditioners' counts, models failed to converge. While a quasi-poisson distribution fit the data, the inability to account for random effects at a regional and state level led to even higher error. This over-dispersion led to similar convergence challenges for the binomial model estimating air conditioner adoption rate. Using 5-fold cross validation, the poisson, quasipoisson, and binomial models had mean squared errors 5.2, 9.8, and 5.0 times higher, respectively, when compared to the linear model ultimately selected.

Appendix 3: Average load magnitude by month and hour for each subsystem 2009 - 2011

	(a) Midwest/Southeast											
Hour	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0	30,960	32,444	30,791	29,286	28,034	27,277	28,311	29,101	30,055	30,298	31,330	32,260
1	28,988	30,544	28,867	27,432	26,204	25,492	26,447	27,176	28,098	28,273	29,272	30,076
2	27,823	29,440	27,818	26,426	25,232	24,558	25,414	26,174	27,057	27,162	28,170	28,882
3	27,262	28,903	27,372	26,015	24,870	24,230	25,002	25,774	26,660	26,698	27,698	28,305
4	27,150	28,838	27,427	26,104	25,008	24,392	25,111	25,900	26,783	26,768	27,706	28,220
5	27,666	29,478	28,362	27,076	26,134	25,464	26,008	26,954	27,655	27,410	28,489	28,819
6	28,473	30,686	29,347	28,209	27,805	27,353	27,519	28,487	28,719	28,629	29,425	29,390
7	29,708	31,957	31,171	29,804	29,152	28,608	29,054	30,054	30,810	30,492	31,099	31,094
8	32,085	34,400	33,862	32,224	31,371	30,734	31,352	32,351	33,310	32,913	33,552	33,630
9	33,828	36,085	35,632	33,796	32,794	32,192	32,891	33,879	34,884	34,570	35,298	35,419
10	34,867	37,083	36,715	34,778	33,795	33,170	33,825	34,911	35,988	35,652	36,466	36,449
11	34,756	37,072	36,862	34,975	33,973	33,307	33,713	35,080	36,159	35,803	36,641	36,400
12	34,568	36,649	36,355	34,493	33,505	32,840	33,418	34,543	35,647	35,414	36,215	36,083
13	35,238	37,262	36,783	34,818	33,758	33,027	33,920	34,847	35,950	35,702	36,598	36,501
14	35,549	37,706	37,141	35,112	33,999	33,190	34,175	35,182	36,331	35,966	36,948	36,769
15	35,574	37,701	37,117	35,130	34,060	33,229	34,238	35,242	36,368	35,983	36,982	36,770
16	35,423	37,394	36,960	35,177	34,396	33,704	34,628	35,502	36,449	35,951	36,903	36,629
17	34,549	36,093	35,692	34,998	35,620	35,465	35,450	35,460	35,936	35,460	36,220	35,962
18	33,161	35,124	37,539	38,591	38,845	38,624	38,987	39,285	39,321	36,646	35,058	34,728
19	33,223	36,195	39,079	38,196	37,445	37,182	37,947	38,731	39,252	37,911	36,575	35,226
20	36,606	38,314	38,392	37,238	36,376	36,063	36,741	37,784	38,486	38,100	38,769	38,416
21	36,765	38,342	37,997	36,616	35,713	35,259	35,998	37,062	37,905	37,339	38,044	38,251
22	36,051	37,330	36,183	34,779	33,734	33,133	34,008	35,111	35,969	35,869	37,119	37,439
23	33,936	35,063	33,578	31,965	30,742	30,100	30,975	32,034	33,040	33,001	34,403	34,931

	(b) Northwest											
Hour	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0	7,900	7,929	7,854	7,560	7,379	7,226	7,162	7,200	7,477	7,988	8,143	8,299
1	7,511	7,571	7,576	7,298	7,122	6,979	6,902	6,942	7,214	7,647	7,748	7,880
2	7,262	7,344	7,410	7,141	6,970	6,833	6,771	6,810	7,067	7,450	7,503	7,613
3	7,105	7,215	7,318	7,044	6,890	6,757	6,700	6,751	7,002	7,335	7,359	7,459
4	7,011	7,143	7,274	7,016	6,865	6,736	6,691	6,746	7,005	7,291	7,289	7,371
5	6,976	7,031	7,010	6,778	6,676	6,600	6,595	6,614	6,718	7,051	7,225	7,316
6	6,579	6,763	6,803	6,586	6,518	6,410	6,406	6,500	6,722	6,873	6,754	6,806
7	6,452	6,809	7,338	7,100	7,042	6,932	6,934	7,059	7,327	7,245	6,930	6,875
8	6,999	7,392	8,051	7,757	7,685	7,563	7,550	7,677	7,986	7,901	7,575	7,515
9	7,651	7,942	8,407	8,081	8,008	7,882	7,864	8,007	8,332	8,403	8,249	8,189
10	7,975	8,212	8,583	8,245	8,156	8,030	8,014	8,177	8,502	8,640	8,588	8,517
11	8,117	8,304	8,532	8,216	8,119	7,987	7,957	8,116	8,433	8,682	8,752	8,659
12	8,048	8,211	8,370	8,068	7,962	7,828	7,800	7,939	8,230	8,551	8,668	8,560
13	7,886	8,142	8,529	8,187	8,086	7,935	7,908	8,048	8,363	8,528	8,501	8,393
14	8,048	8,316	8,680	8,309	8,218	8,053	8,053	8,218	8,551	8,694	8,706	8,585
15	8,191	8,388	8,634	8,269	8,190	8,019	8,042	8,205	8,530	8,748	8,865	8,727
16	8,086	8,221	8,342	8,063	8,027	7,868	7,876	7,993	8,280	8,560	8,749	8,611
17	7,859	7,957	8,088	8,300	8,492	8,260	8,090	8,073	8,358	8,528	8,445	8,320
18	7,476	8,047	9,116	9,105	9,065	8,942	8,921	9,002	9,229	9,035	8,419	8,055
19	8,481	8,691	9,028	8,873	8,770	8,665	8,664	8,747	8,957	9,276	9,340	9,162
20	8,750	8,768	8,833	8,654	8,543	8,421	8,391	8,475	8,689	9,018	9,140	9,189
21	8,530	8,689	9,021	8,754	8,631	8,493	8,456	8,556	8,801	8,970	8,894	8,959
22	8,671	8,725	8,749	8,437	8,288	8,148	8,084	8,193	8,475	8,866	9,022	9,106
23	8,356	8,370	8,319	7,975	7,802	7,661	7,577	7,659	7,949	8,433	8,645	8,747

	(c) North											
Hour	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0	3,775	3,767	3,774	3,771	3,810	3,770	3,732	3,818	3,896	3,920	3,963	3,958
1	3,658	3,661	3,688	3,685	3,740	3,692	3,664	3,744	3,822	3,829	3,848	3,844
2	3,588	3,589	3,627	3,625	3,686	3,637	3,618	3,695	3,769	3,774	3,784	3,779
3	3,545	3,539	3,584	3,589	3,650	3,602	3,586	3,661	3,733	3,732	3,739	3,738
4	3,518	3,509	3,564	3,572	3,632	3,582	3,565	3,636	3,711	3,703	3,705	3,705
5	3,498	3,501	3,561	3,572	3,624	3,574	3,547	3,610	3,672	3,659	3,680	3,677
6	3,477	3,473	3,466	3,480	3,513	3,463	3,413	3,467	3,504	3,545	3,607	3,627
7	3,366	3,422	3,514	3,535	3,558	3,504	3,452	3,504	3,569	3,519	3,461	3,483
8	3,429	3,512	3,712	3,705	3,730	3,707	3,653	3,706	3,765	3,654	3,557	3,569
9	3,618	3,657	3,811	3,796	3,814	3,807	3,747	3,816	3,861	3,787	3,760	3,766
10	3,705	3,730	3,863	3,840	3,857	3,859	3,798	3,876	3,906	3,852	3,844	3,848
11	3,747	3,756	3,840	3,833	3,848	3,851	3,776	3,858	3,899	3,860	3,885	3,891
12	3,725	3,723	3,800	3,793	3,804	3,805	3,725	3,813	3,854	3,828	3,869	3,873
13	3,671	3,715	3,876	3,853	3,875	3,879	3,808	3,912	3,956	3,855	3,823	3,825
14	3,747	3,792	3,940	3,907	3,938	3,950	3,893	4,003	4,057	3,955	3,930	3,910
15	3,807	3,834	3,932	3,901	3,935	3,945	3,892	4,007	4,055	3,995	4,005	3,986
16	3,780	3,809	3,876	3,854	3,884	3,891	3,829	3,926	3,964	3,933	3,981	3,964
17	3,734	3,759	3,811	3,825	3,855	3,836	3,756	3,828	3,878	3,864	3,917	3,902
18	3,662	3,755	3,940	4,050	4,089	4,057	3,946	4,011	4,100	3,967	3,854	3,839
19	3,765	3,878	4,099	4,135	4,147	4,142	4,073	4,152	4,197	4,120	4,098	4,024
20	3,986	4,010	4,068	4,095	4,103	4,083	4,016	4,096	4,151	4,116	4,152	4,174
21	3,963	3,989	4,059	4,081	4,086	4,060	4,004	4,087	4,150	4,100	4,117	4,133
22	3,952	3,964	4,017	4,026	4,036	4,013	3,961	4,051	4,126	4,094	4,115	4,123
23	3,896	3,887	3,905	3,901	3,924	3,891	3,844	3,932	4,018	4,027	4,074	4,073

	(d) South											
Hour	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0	8,427	8,756	8,223	7,493	7,085	7,139	7,210	7,275	7,301	7,571	8,125	8,589
1	7,838	8,208	7,704	6,999	6,598	6,610	6,647	6,705	6,765	6,968	7,537	7,924
2	7,471	7,868	7,404	6,728	6,339	6,339	6,350	6,411	6,476	6,655	7,212	7,545
3	7,305	7,715	7,282	6,630	6,257	6,260	6,255	6,319	6,390	6,548	7,089	7,370
4	7,243	7,671	7,284	6,646	6,289	6,295	6,284	6,354	6,422	6,564	7,083	7,324
5	7,399	7,858	7,544	6,922	6,584	6,579	6,569	6,648	6,720	6,820	7,334	7,496
6	7,692	8,257	7,991	7,522	7,338	7,363	7,317	7,373	7,245	7,303	7,738	7,713
7	8,177	8,856	8,729	8,143	8,004	8,142	8,168	8,146	8,108	8,152	8,510	8,384
8	9,128	9,802	9,704	8,959	8,778	8,896	8,975	8,991	8,966	9,025	9,465	9,333
9	9,642	10,295	10,194	9,383	9,171	9,310	9,420	9,420	9,371	9,437	9,946	9,847
10	10,002	10,650	10,589	9,736	9,496	9,638	9,767	9,778	9,723	9,798	10,334	10,222
11	10,020	10,648	10,645	9,759	9,501	9,621	9,697	9,764	9,719	9,822	10,363	10,257
12	9,410	9,926	9,848	9,022	8,707	8,805	8,900	8,951	8,931	9,074	9,630	9,632
13	9,922	10,453	10,350	9,426	9,037	9,144	9,303	9,311	9,263	9,409	10,034	10,033
14	10,227	10,800	10,708	9,713	9,268	9,339	9,499	9,530	9,504	9,655	10,338	10,342
15	10,183	10,755	10,682	9,687	9,260	9,316	9,456	9,498	9,490	9,631	10,322	10,319
16	10,085	10,649	10,607	9,671	9,371	9,492	9,591	9,599	9,553	9,631	10,277	10,241
17	9,703	10,174	10,134	9,504	9,683	9,981	9,868	9,639	9,488	9,446	9,947	9,926
18	9,146	9,473	9,613	10,047	10,415	10,614	10,556	10,315	9,881	9,363	9,472	9,439
19	8,542	9,442	10,697	10,183	9,850	9,996	10,135	10,278	10,240	9,710	9,071	8,846
20	9,340	10,041	10,280	9,580	9,302	9,481	9,588	9,735	9,678	10,008	10,257	9,748
21	9,937	10,272	10,261	9,521	9,232	9,412	9,533	9,626	9,547	9,651	10,002	10,163
22	9,931	10,133	9,869	9,105	8,818	8,971	9,076	9,186	9,106	9,320	9,896	10,137
23	9,364	9,532	9,043	8,231	7,887	8,002	8,062	8,206	8,171	8,424	9,118	9,477

Appendix 4: Daily total and peak load sensitivity to climate, by region

Day's Med. Heat Index	Daily Consumption	Daily Consumption2	Day's Peak Load	Time of Peak	Region
C	[Wh/day/cap]	[GWh/day]	[GWh/h]	Hour	
22.45241793	8262.1151	783.336974	37.35448718	18	CWSE
23.36921438	8574.103562	812.9168206	39.42111863	15	CWSE
24.01803544	8472.543258	803.2878163	38.41029992	16	CWSE
24.63835549	8582.572136	813.7197321	39.67062043	14	CWSE
26.67724032	8745.177343	829.1364467	38.59270028	13	CWSE
22.45241793	7069.68984	670.282292	35.59101605	19	CWSE
23.36921438	7372.077909	698.9519186	33.38852853	20	CWSE
24.01803544	7162.787101	679.1089092	34.57060834	21	CWSE
24.63835549	7960.338144	754.7252874	36.16304587	20	CWSE
26.67724032	8463.468373	802.4274201	38.36565022	14	CWSE
25.17378504	3477.2223	186.3485053	8.605420485	20	NE
25.5260166	3538.275669	189.6204284	8.981265128	19	NE
25.84503971	3540.46105	189.7375456	8.755032523	15	NE
26.25037905	3656.553969	195.9591041	9.375965519	15	NE
27.66324593	3625.07188	194.2719412	9.061940041	20	NE
25.17378504	3335.763979	178.7675846	8.943263677	19	NE
25.5260166	3138.522522	168.1971788	8.520296622	19	NE
25.84503971	3192.169211	171.072169	8.915059779	19	NE
26.25037905	3178.92385	170.3623343	8.743649113	19	NE
27.66324593	3271.110633	175.3027343	8.816805772	20	NE
25.65709031	5701.375224	87.5708885	3.872590042	20	North
26.01054583	5760.73378	88.48261266	3.89927855	14	North
26.35470438	5780.750177	88.79005666	3.929632136	15	North
26.80024898	5802.429679	89.12304531	3.972747737	15	North
28.10880095	5734.350353	88.07737356	3.865803546	21	North
25.65709031	5285.366391	81.1811559	3.848883654	19	North
26.01054583	5573.77753	85.61103794	3.97605498	20	North

26.35470438	5496.86958	84.42976198	3.886956751	20	North
26.80024898	5371.253687	82.5003511	3.806230773	20	North
28.10880095	5572.702172	85.59452086	3.929845243	21	North
18.52227321	7660.801599	212.3506635	10.23654435	15	South
20.37826757	7923.694122	219.6378124	10.77951472	14	South
21.88561754	8119.056791	225.0530932	11.15985153	14	South
23.17298248	8339.517316	231.1640645	11.37281556	16	South
26.83397471	8406.955883	233.0334021	11.52579068	15	South
18.52227321	6028.390419	167.1016654	9.014370914	18	South
20.37826757	6422.789415	178.0340577	8.992229961	19	South
21.88561754	6165.303899	170.8967863	9.170577668	20	South
23.17298248	6841.061727	189.6281973	9.181283101	21	South
26.83397471	6982.502321	193.5488058	9.211095683	21	South

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