Impacts of Climate Change on Sub-regional Electricity Demand and Distribution

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Abstract
New tools are employed to develop an electricity demand map for the southeastern United States at neighbourhood resolution to serve as a baseline from which to project increases in electricity demand due to a rise in global and local temperature and to population shifts motivated by increases in extreme weather events due to climate change. We find that electricity demand increases due to temperature rise over the next 40 years have a much smaller impact than those due to large population influx. We also find evidence that some sections of the national electrical grid are more adaptable to these population shifts and changing demand than others are; and that detailed projections of changing local electricity demand patterns are viable and important for planning at the urban level.

Introduction
Communities have begun to experience the realization of climate change predictions of increases in storm intensity, flooding, inundation, heat waves and wildfires; the risk they pose to infrastructure and neighbourhoods; and the disruption they cause to the energy supply and its dependent infrastructure. Direct effects have included damage to power plants, roads, bridges, and communication towers; and resultant interruption of electrical energy, transportation, and communications sectors in cities.[1]
As climate conditions continue to change, local communities and the infrastructure on which they depend will necessarily respond, adapt and evolve. Population will shift in response to sea level rise and increased intensity of extreme weather events,[2,3] for example, and services that generate new economic activity in more environmentally stable locations will attract new workers and associated households. This shift will force demand locations for power to change. As a result, networked infrastructures may be required to accommodate new load centres and to minimize vulnerability to natural disasters.[4] To provide information about the complex interactions among climatic conditions, population shifts, and energy supply and use, new tools informed by consistent spatially disaggregated data are needed.[5] For instance, little research has been conducted to quantify potential climate-related impacts on the operating limits of electrical substations within the power grid. Two reasons for this gap are first, that until recently, climate projections at high enough resolution to be compatible with infrastructure modelling have been unavailable; and second, that population migration data and analysis techniques capable of providing estimates of future energy demand have been missing and/or difficult to characterize.

We address these issues by extending the current state of the science in three significant ways. 1) We employ a spatial methodology for electric load forecasting for grid planning in which a cost distance algorithm based on regional population is used to determine the service area for a given substation. 2) We apply satellite population observations (LandScan) and predictions based upon Census and Internal Revenue Service (IRS) data to project spatial shifts in electricity demand in the southeastern US region and we incorporate several sudden redistributions of population in response to a 2005-like hurricane season at the predicted return period for such events in the region based on recent climate science. 3) To analyse further the effect of increases in global temperature and resulting regional electricity demand consequences, we calculate local per cent change in electricity demand given temperature changes from dynamically downscaled (12km resolution) climate model projections for the region. From this analysis, we make a substation-service-area-level projection of substation capability in the southeastern US to support changes in demand due to temperature rise and sudden population shifts in response to intense storms, and demonstrate a viable tool for making high-resolution predictions in the absence of address-specific data regarding electricity use.

Background

Vulnerability to climate impacts is a function of exposure, the sensitivity and adaptive capacity of the system being exposed.[6] Climate change will present a variety of environmental symptoms, two of which are a focus here: changes in regional temperature[7], and increases in landfilling hurricane intensity.[8,9] As both temperature maxima and duration of heat waves increase in various locations, electricity demand for cooling will also increase.[10,11] Also, because damage rises by about a factor of four for every hurricane category increase, population stresses associated with hurricanes are likely to increase with the increase in hurricane intensity[12].

Previous research has predicted increases in electricity demand in response to increases in global temperature expected with climate change. For instance, using the Electricity Information Administration National Energy Modelling System (NEMS), Hadley et al.[10] showed that for most US locations, the savings of electricity in the winter months due to fewer cooling degree days do not offset the added expenditures on electricity in the summer for the increase in heating degree days. The climate inputs used in the Hadley study, however, were global model output at 2.5-degree resolution, so while the study was able to capture electricity customer response to some general trends in future temperature, it was unable to resolve regional differences in temperature in both base and future cases. To improve upon such predictions, the California Energy Commission[13] employed a Constructed Analogues method for statistically downscaling global climate model output at coarse resolution (2.5 degrees) to fine (~13km) resolution, using analogues from present regional climate. With this method, along with electricity utility billing data, and demographic information, they made projections regarding increases in residential electricity use according to geographic and economic boundaries of the population in the state.

Our study improves upon the previous methodologies for forecasting temperature-related electricity demand increases. For instance, while the Constructed Analogues method may provide some enhanced information regarding regional temperature projections, the results from this type of downscaling are less than physically, chemically and temporally robust. To address these deficiencies, we use a Coupled Model Intercomparison Project, Phase 5 (CMIP5) ensemble member's temperature projections (RCP 8.5) dynamically downscaled to 12km resolution with the Weather Research and Forecasting (WRF) model.[14] This method is shown to produce much better agreement with extreme temperature observations for representative locations than global model results (at 1x1.25 degree resolution) in representative locations of the southeastern states in the US examined here (Ref. Sheffield CMIP5 evaluation). It also takes into account the climate non-stationarity embedded in the Representative Concentration Pathway prescribed by the 8.5 W m^{-2} by year 2100 scenario.

Much research regarding population movement (both typical and that in response to environmental stress) has been conducted and weaknesses in various methods identified. Batty[15], for instance, notes that the growth of every small area is linked to causes and forces located elsewhere in the region and by demographic and economic interactions; thus, the process of regional growth and resulting electricity demand changes is hard to characterize. Yet strides have been made in relating population changes to changes in electricity demand. A variety of commercial models for forecasting electric load based on land use projections have been used in the past to generate scenarios for long range planning. Among the first were linear urban models based on Ira Lowry's[16] gravity model for population movement and generalized by Garin[17] to a set of matrix computations. While these models take into consideration the projected development of various types of electricity customers (residential, commercial, industrial), they do less well at predicting the ways in which re-development of land use will occur. Therefore, the US Geological Survey[18], Duke Energy[19] and the California Energy Commission[20], among others, have added development to such models that incorporate economic and demographic weights for the determination of various redevelopment types using agent based modelling. For each of these models, the critical components are those of the spatial distribution of the population among their places of residence and their places of business, and the way changes in those distributions are projected for the future. However, these models do not evaluate electricity usage by customers as organized within utility service areas.

We instead apply high-resolution (1km) satellite-observation-informed population data (LandScan) for average 24-hour population locations, along with customer correction factors[21] and a cost-distance algorithm to determine electricity customer service areas at neighbourhood scale. To project future customer service areas and demand, we use this satellite data as a base case, coupled with cohort-component population projections and appropriate land use predictions[22] to provide reasonable customer inputs to the cost distance evaluation to determine future service areas yielding more reliable planning scenarios. Population projections include methods for modelling suitability, service area planning, consequence assessment, mitigation planning and implementation, and assessment of spatially vulnerable populations. Finally, to these population projections we add, at hypothetical return periods suggested by Keim et al.,[23] population response to a 2005-like hurricane season.

Electricity Supply and Demand Modelling

Datasets used for the determination of changes in electricity demand due to changes in population include substation location (Ventyx)[24], measured capacity (see Supplementary Material S.1), LandScan population data sets for 2011 and projections for 2030 and 2050[22], Energy Information Administration (EIA) State Energy Data System (SEDS, 1960-2012 Complete[25]) state by state total annual electricity consumption records for 2011 and the Annual Energy Outlook (2013) predictions to 2040, and Internal Revenue (IRS) Data sets[26] for by-county in- and out-migration for the years 2004-2007.

The 2011 LandScan[27,28] data set is built using a dasymetric mapping approach in which a source layer is converted to a surface and multiple ancillary indicator data layers are used to derive density level values for input to a weighting scheme that allocates population to 1 km grid cells. The source data layer surface comprises the sub-national level census counts. Ancillary datasets include primary geospatial data such as land cover, roads, slope, urban areas, village locations and high-resolution imagery analysis; all of which are key indicators of population distribution. Calculation of error in the dataset is made by imagery analysts using high-resolution imagery to create a set of population likelihood coefficient modifications to correct or limit input data anomalies. Population projections for 2030 and 2050 are made in a similar manner, but also incorporate cohort-component and urbanization projections as outlined by the US Census.[22] An example of anticipated changes in population density anticipated for mid century is shown in Figure 1. (This and the following figures were created using the Environmental Systems and Research Institute (ESRI) ArcGIS software). Projections indicate overall population growth along with movement away from rural areas and larger concentrations in cities and suburbs.

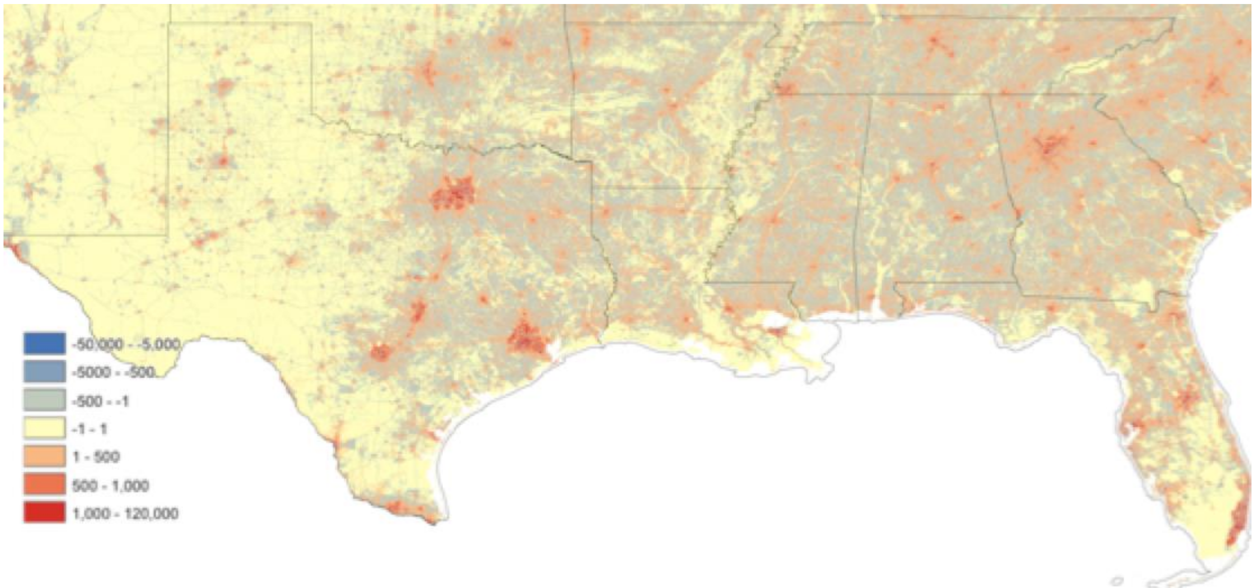

Figure 1. Change in population from 2004-2050. The map shows population growth and prediction of more urbanization by mid-century.

To determine the amount of stress placed on substation capacity in an area and to estimate the service area for each substation based on its location and its capacity, we used a two step process: 1) convert LandScan population count to customer count and 2) employ a cost-distance algorithm to allocate customers to the substations most likely to serve them.

For each county, a customer correction factor was obtained by adding together the number of households and the number of firms within the county as given by the US Census for the year 2000, and then dividing the total population in the county for that year by this sum[21]. To convert the population in a given 1km cell to customers, then, the population was divided by the customer correction factor. While this calculation does not represent a perfect relationship between population and customers, in that it does not account for the differences in electricity use characteristics among residential, industrial and commercial customers (nor the change in number of residences and firms through time), it does offer a simple means for disaggregating average use across all sectors with a representative case. The cost-distance algorithm employed to determine customer service areas was the Power Distribution Model (PoDiuM) developed by Omitaomu[29]. PoDiuM is an algorithm that compares cost units to geographical units to determine the maximum distance to customers served. In this approach, the lower the demand, the higher the cost, and the greater the transmission distance, the greater the cost. Further details can be found in Supplementary Material S.1.

To project the total average customer instantaneous demand per service area for the future, we take as a base average per-customer demand value the total consumption in GWh/year per state divided by the number of customers in the state and then further divided by the number of seconds in a year (365.25*24*3600) and multiply by 1000 to convert gigawatts to megawatts. Once the average customer instantaneous demand is calculated, we calculate the total customer demand per substation service area by multiplying this value by the number of customers within the service area. Substation capacity for a service area is estimated using measurements of the instantaneous aggregate peak load (real and reactive power) at the substation for a typical summer day to obtain the instantaneous aggregate apparent power at each substation and assuming that it is approximately 80% of the total capacity (further details in Supplementary Material S.1).

For an electric utility company, peak demand is defined as the single half hour or hour-long period during which the highest amount of customer consumption of electricity occurs. Since the amount of electricity over a certain threshold must often be purchased from additional providers during this time, the cost to provide that electricity is much more than that produced up to that threshold. Therefore, the utility companies calculate a peak-to-average demand ratio to be used in assessing their own costs to provide the electricity and the costs they pass on to the consumers. Linear trends were fit to time series of annual peak-to-average demand ratios from the Electric Reliability Council of Texas (ERCOT) and the Southeastern Reliability Council (SERC) for the years 1993–2012 in order to project peak to average demand ratios for future years, 2030 and 2050, for each of the states included in our southeastern study region. It should be understood that the years 2030 and 2050 are only representative years for those decades, and thus a more exact fit to the more cyclical nature of the peak-to-average demand ratios is not necessarily required for the approximation. (Procedure and results are outlined in Supplementary Material S.2).

Demand Change in Response to Temperature Rise and Population Migration

Increased electricity demand in response to rising temperatures has been well established by the utility industry, and it has a latitudinal dependence. The per cent increase in electricity demand for a county due to temperature rise for this study is calculated according to Toole, et al.[30] (Supplementary Material S.3), derived from empirical data for the latitudes spanning the state of California. (Although the California data may not provide a direct latitude temperature correlation to the much hotter and more humid southeast, its constituent climate zones follow a similar latitudinal progression to those in the southeastern region.[31])

While the United States Census and others[32] have made viable projections of population distribution for future years, the projections do not include changes due to environmental stresses caused by climate change (sea level rise, drought, increases in extreme weather events (storms, wildfires)), yet recent studies[33] have shown that not only have significant numbers of people migrated away from locations affected by extreme storms such as hurricanes making landfall on the Gulf Coast in 2005, these migrations have caused large changes in electricity consumption by counties of both origin (decrease) and destination (increase). For this study, we investigate the impacts of further population redistribution on the spatial and overall electricity demand by including in those projections an adjustment for a 2005-type hurricane season applied at a hypothetical 20-year return period for such a season.[3,4,5] (Supplementary Material S.4). To simulate this impact, we apply by-county migration rates from 2005-2006 and 2006-2007 to the study region as a hurricane migration component. Our procedure for representing this component is in Supplementary Material S.5.

It should be noted that the authors do not attribute hurricanes Katrina, Rita and Wilma to climate change, they only use these events as an example scenario to show population changes that could occur under extreme storm circumstances along the US Gulf Coast (a situation that could occur more often in the future due to predicted increases in intensity of storms), and how these might be represented in a methodology for predicting these changes. (It should also be noted that globally, the largest population redistributions in response to environmental circumstances are projected to occur in the least developed countries, as those with the most robust economies are more likely to have the means to rebuild.[34])

Resulting Development of a New Demand Map for the Southeastern United States

While projections of future energy capacity and use are made by the Electricity Information Administration for each National Energy Reliability Council (NERC) region for each year from 2011 through 2040, these predictions have been unable to predict stresses at specific locations where local demand may, either on average or during peak hours, exceed the peak load of substation capacity causing, in extreme climate cases, potential for blackouts. Each NERC region is projected by the EIA to sustain a demand of between approximately 40%-50% of the generating capacity available for each region (Figure 2). Our results improve upon these predictions at the resolution of the electricity service area. The new demand maps from our simulations show current and future potential vulnerabilities at representative service area locations for individual substations, and demand-to-capacity what-if scenarios for sudden population shifts that result from storm motivated migration. Additionally, we show the impact of an overall rise in temperature on average customer demand.

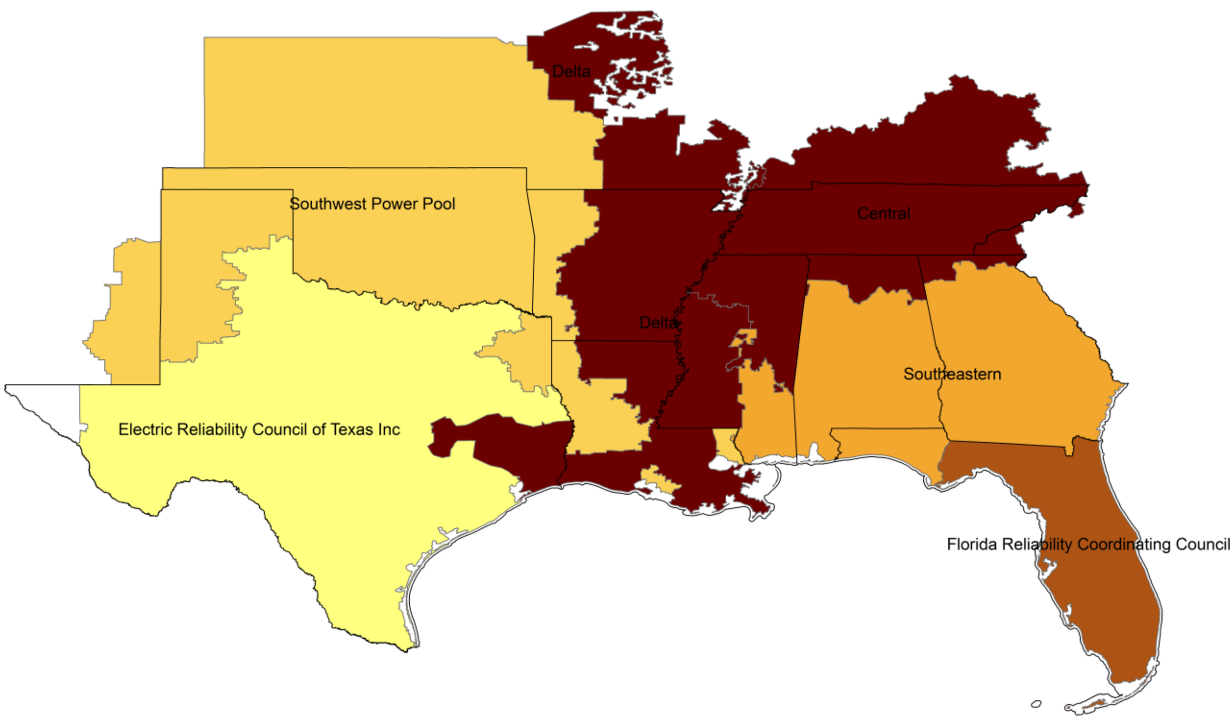

Figure 2. EIA Substation Demand Predictions, 2030.

To establish a baseline for these predictions, we first generated a demand map for the southeastern United States that outlines potential service areas based on the spatial pattern of the location of the population (discussed in Section 2.1). We then determined the per cent of capacity of the substations that is used on average by customers in a service area, based on 2011 average state-wide electricity consumption as reported by the EIA. Figure 3 shows the results for average customer demand. Additionally, because it is in the interest of electricity providers to retain enough capacity to serve its customers during peak demand hours, we also produced a baseline map that shows the per cent of capacity used for peak demand (Figure 4). The maps show that if service areas were distributed as the Power Distribution Model suggests, there would be several service areas in the state of Texas that are operating at 80% or greater substation capacity for the service areas. These areas increase with the added demand for peak hours.

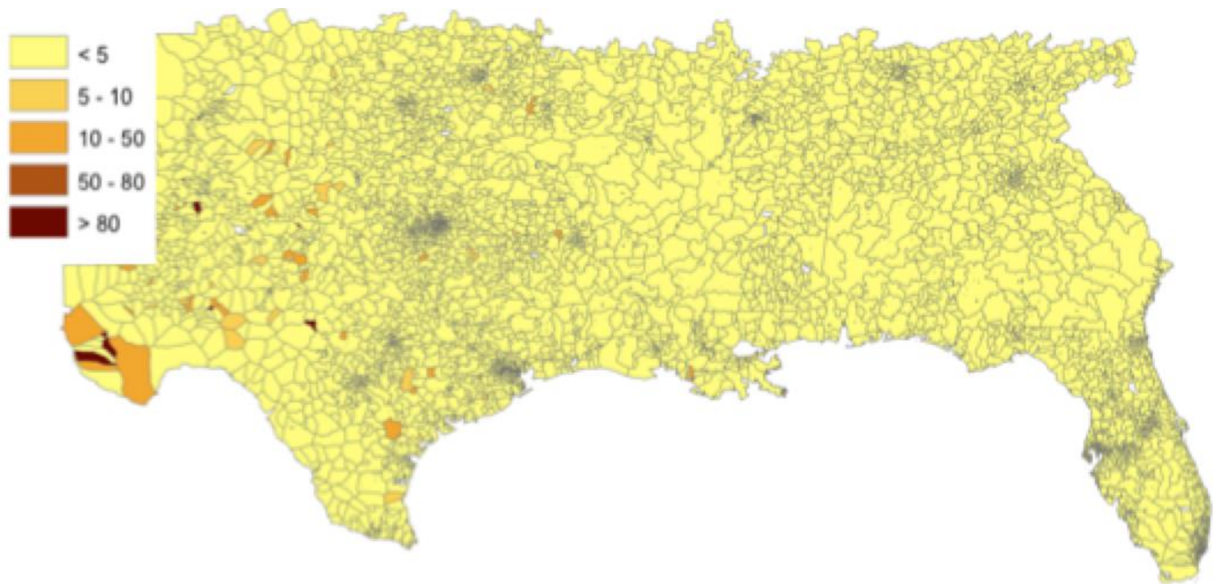

Figure 3. Per cent substation capacity used on average by model-determined customer service areas in the year 2011.

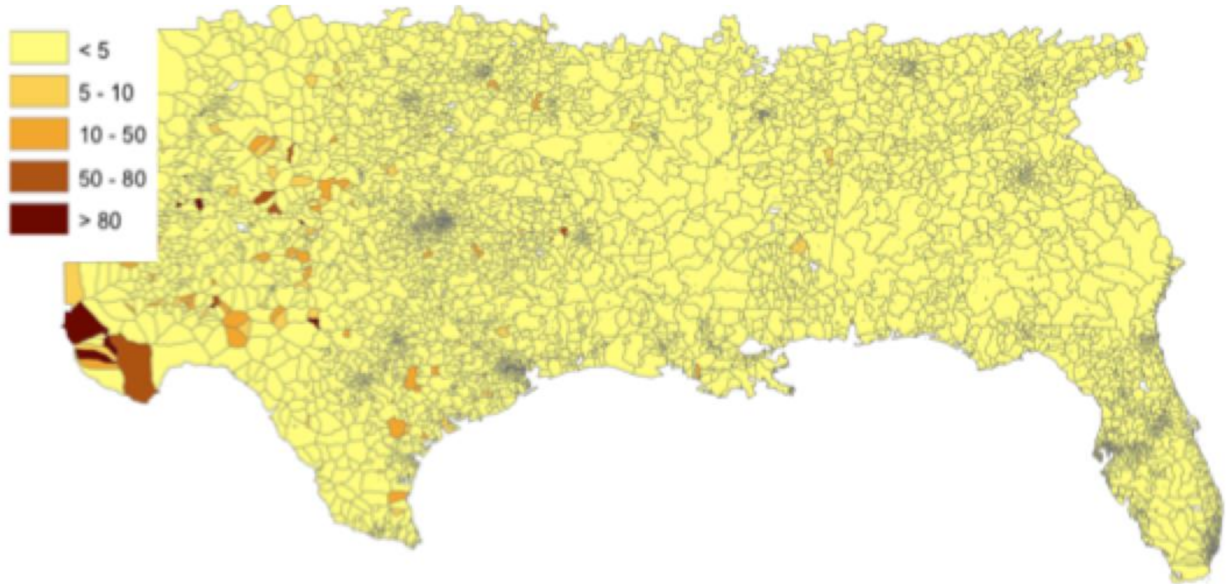

Figure 4. Per cent substation capacity used at peak demand by model-determined customer service areas in the year 2011.

Next, service area demand and capacity were evaluated for future years 2030 and 2050. Service areas were recalibrated based on the new distributions of population for the 2030s and 2050s before calculating the demand to capacity percentages (2030 shown in Figure 5) so that the excesses in the demand due to growing populations were distributed more evenly among the substations available. Typical population growth and migration causes little stress to the existing electrical grid because it can adapt in a timely manner even with no additional substation capacity.

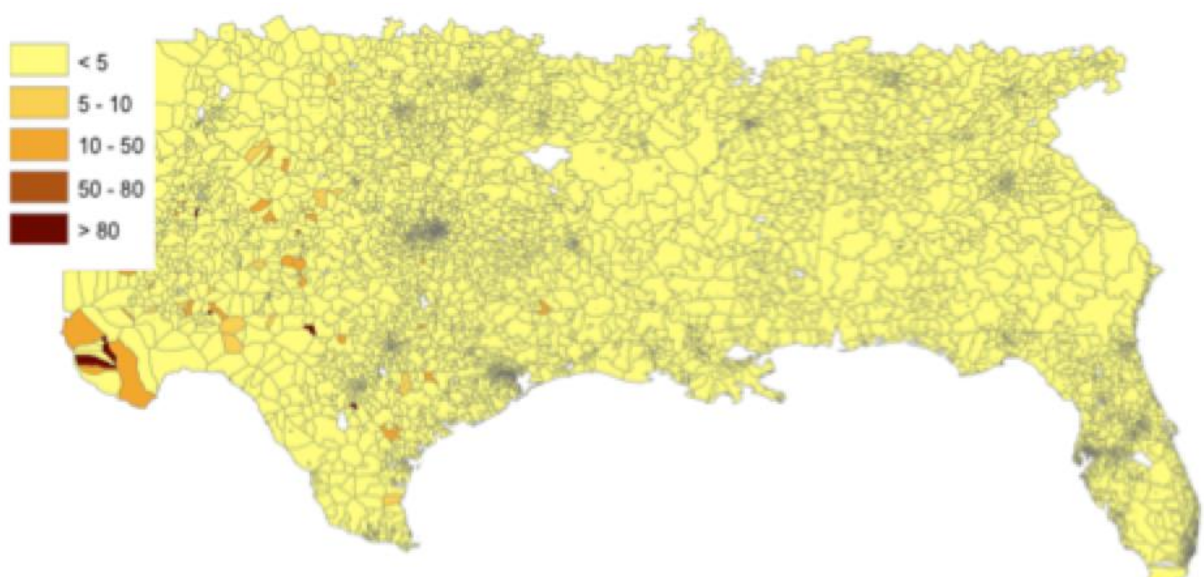

Figure 5. Per cent of substation capacity of average electricity demand by service area in 2030 if service areas are redistributed to match 2030 population distributions.

A few service area locations stand out in Figure 5 including one spanning the sparsely-populated counties of Menard, Kimble and Mason in Texas; one in Atascosa County, south of San Antonio; and several in the extreme western counties of Jeff Davis and Presidio, both with very low population. In both average and peak situations, these areas show the largest percentages in demand vs. capacity. This may be due in part to the very low substation capacity in these areas. These substations can become particularly vulnerable when overall demand spikes[35].

For the decades of both the 2030s and the 2050s, the population distribution effects of a 2005-type hurricane season were simulated, and results for peak demand in the 2050s for two years following the hurricane season were determined (Figure 6). Here it is assumed that for each county, the approximate ratio of population to the total of residences and firms is maintained. Service areas in Dickens, King, Kent, Stonewall, Childress, Cottle and Hardeman are now operating between 50 and 80 per cent capacity at peak when population growth and shifts due to hurricane displacement are taken into account.

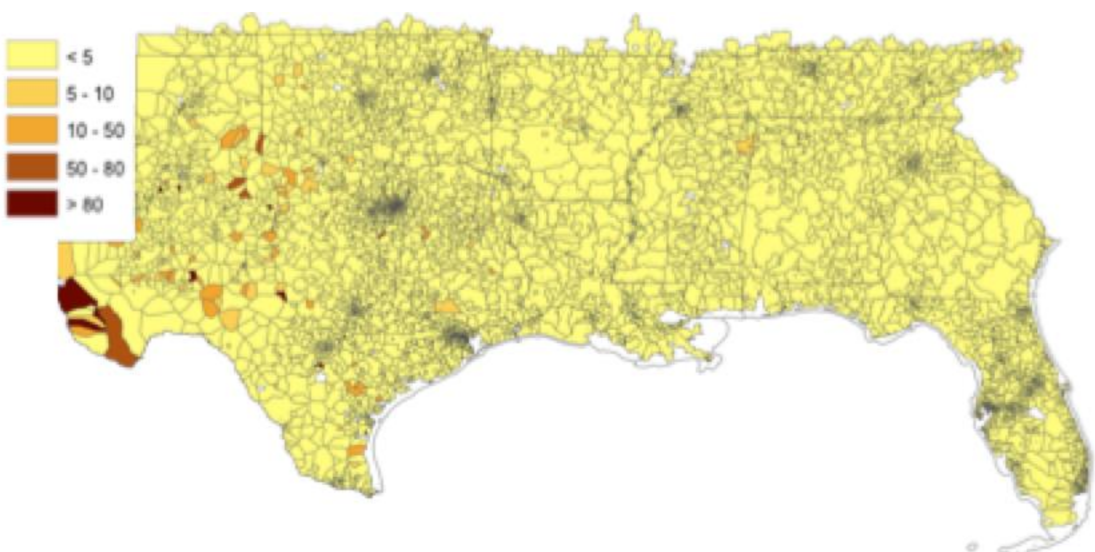

Figure 6. Per cent of substation capacity of peak electricity demand by service area in the 2050s two years after a 2005-like hurricane season.

Finally, calculations for increase in electricity demand due to temperature increase predictions were made according to the procedure described in Section 2.2. Temperature predictions were at 12 km resolution for the base case and for the 2030s and 2050s. Temperatures in Fahrenheit from both periods were averaged for each service area. The differences in temperature from 2004-2057 in each of the service areas, normally distributed and ranging from -0.7 to 16.6 degrees Fahrenheit, had a much larger impact on per cent demand of available capacity at peak than it did on average demand. This is seen most prominently in the service areas identified above as having substations operating at 50-80 per cent capacity during peak load. With the increase in temperature, the demand on the substations increases to over 80% of capacity.

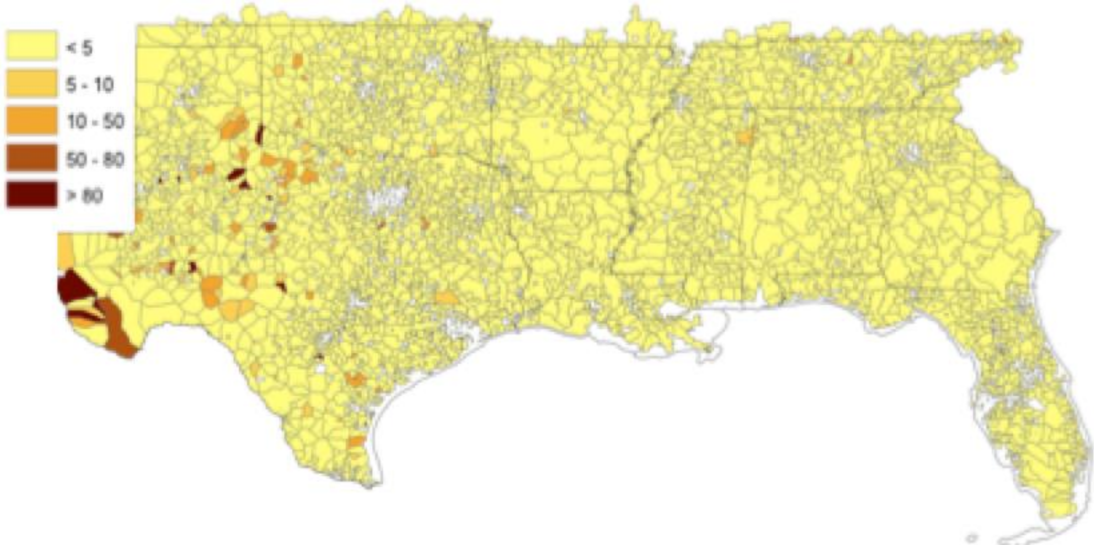

Figure 7. Per cent of substation capacity of peak electricity demand by service area in the 2050s two years after a 2005-like hurricane season and including added demand due to rise in maximum July temperature.

Figure 8 shows the demand difference due to temperature change and population growth and movement. Large decreases in demand next to large increases are shown for several service areas in locations of low population in Texas. The larger cities in Texas, Dallas, San Antonio, and Houston show little change. Various locations in Oklahoma, Mississippi, Alabama, Tennessee, Georgia and Florida show up to 10% increase in demand. Only one small service area in the centre of Arkansas shows an increase in demand. This is likely due to the combination of a low capacity substation and the pattern of population growth projected for that region.

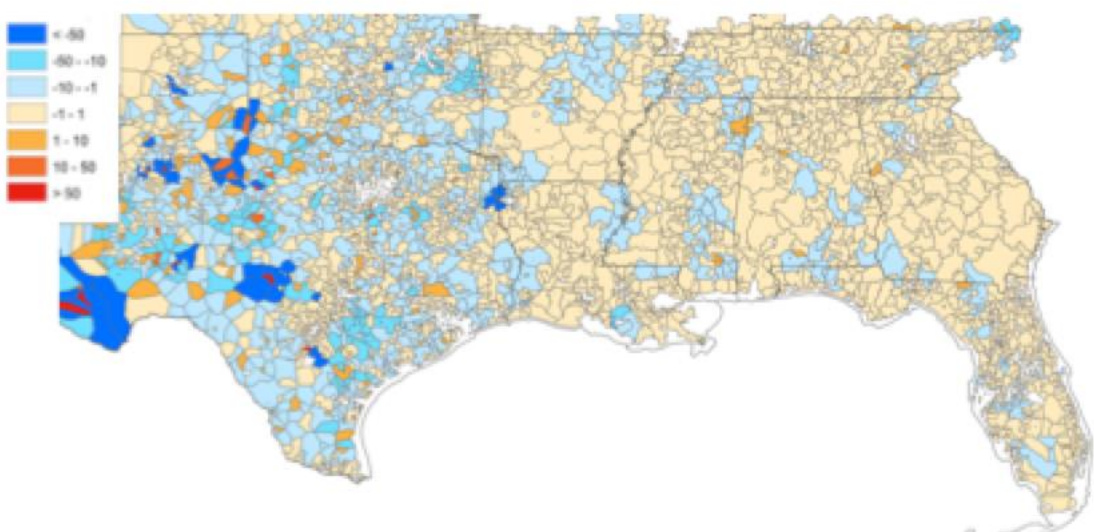

Figure 8. Difference between predicted 2050 percent capacity used during peak demand with temperature rise due to climate change two years after 2005-like hurricane event and 2011 peak demand.

Combining Climate and Infrastructure Models Provides Planning Insight

The use of high-resolution population distribution data and dynamically downscaled climate projections with electricity demand modelling provides an improved method for identifying specific locations of electrical grid vulnerability to increased electricity demand due to regional temperature changes as a result of global climate change, and to population shifts in response to typical (e.g., economic) drivers and to extreme weather events. Results show that electricity demand increases due to temperature change are less than those due to the effect of large population influx into a service area, but that in the areas most affected, the grid will be stressed. It is also evident that some sections of the national electrical grid are more adaptable to population shifts and changing demand than other sections are; and that detailed projections of changing local electricity demand patterns are important for planning at the urban level.

The findings from this study show that information at this scale, not previously achieved, is now possible. The methodology applied to the study can serve planning for regional utilities regarding reorganization of substation service areas, addition of capacity to existing substations and the addition (or removal) of substations to existing service areas as the grid begins to evolve in response to a variety of climate change drivers.

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Author Contributions
M.A. and S.F. designed the study. M.A. collected the population, migration and electricity consumption data and performed the service area and per cent demand calculations. J.F. provided the climate and WRF-downscaled temperature data. M.O. acquired and archived and documented the substation capacity data. All participated in drafting, reviewing and revising the manuscript.

Additional Information
Competing financial interests
The authors declare no competing financial interests.

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