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Electricity Demand Evolution Driven by Storm Motivated Population Movement

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Abstract

Managing the risks to reliable delivery of energy to vulnerable populations posed by local effects of climate change on energy production and delivery is a challenge for communities worldwide. Climate effects such as sea level rise, increased frequency and intensity of natural disasters, force populations to move locations. These moves result in changing geographic patterns of demand for infrastructure services. Thus, infrastructures will evolve to accommodate new load centers while some parts of the network are underused, and these changes will create emerging vulnerabilities. Forecasting the location of these vulnerabilities by combining climate predictions and agent based population movement models shows promise for defining these future population distributions and changes in coastal infrastructure configurations. In this work, we created a prototype agent based population distribution model and developed a methodology to establish utility functions that provide insight about new infrastructure vulnerabilities that might result from these new electric power topologies. Combining climate and weather data, engineering algorithms and social theory, we use the new Department of Energy (DOE) Connected Infrastructure Dynamics Models (CIDM) to examine electricity demand response to increased temperatures, population relocation in response to extreme cyclonic events, consequent net population changes and new regional patterns in electricity demand. This work suggests that the importance of established evacuation routes that move large populations repeatedly through convergence points as an indicator may be under recognized.

Keywords: Infrastructure dynamics models; Department of energy; Climate change; Electric power demand; Electricity

Introduction

New demands for increased energy and power in new and different locations will challenge the power grid as it evolves over the next decades. Climate change and resulting extreme weather events will affect these challenges as electricity demand will rise with temperature rise [1] and population will move in response to extreme weather events to locations less vulnerable to environmental hazards [2-4].

Migration in response to extreme weather events occurs in part as a result of individual decisions to relocate to less vulnerable regions [5,6] and in part as a result of businesses closing and rebuilding elsewhere after natural disaster [7]. Although these decisions can significantly affect regional electricity demand, the implications of these shifts are little studied because the character of the influence of natural disaster on migration flow remains uncertain. Modelings of migration flow and the changes these flows create in the power grid topology require integration of disparate fields and theories and only recently have data from these fields at the required scale become available. Permann [8] and Amal [9] surveyed past attempts to connect people movement, power topology changes and their combined effect on the robustness and resilience of the resulting power grid.

To provide a testbed for the interaction and interdependencies of these forces, Oak Ridge National Laboratory (ORNL) developed a suite of tools including Visualizing Energy Resources Dynamically on Earth (VERDE) [10], Energy Awareness and Resiliency Standardized Services (EARSS) [11], Homeland security Extreme weather Awareness Tool (HEAT) [12] and Connected Infrastructure Dynamics Models (CIDM) [13].

This suite provides a common spatial scale for climate-infrastructure-population migration modeling by coupling high-resolution climate models with the neighborhood-scale infrastructure modules. Integration of the models provides a framework for placing existing high-resolution climate modeling output, [13] ORNL infrastructure model data and population movements in a common reference grid so these domains can operate on the same spatial and temporal scales.

Methodology

Projections of changing electricity demand

The US Energy Information Administration (EIA) makes historical electricity demand tables available by state for each year [14]. Comparison of the demand over several decades shows the effects of various economic and demographic characteristics of a population such as changes in household size, increases in personal electronic devices, changes in efficiency of heating, cooling and appliance technology, and the effect of energy prices on demand. There are large demand differences evident between years, however, which could represent outmigration from environmental or economic disaster areas and significant increases in population in other locations. Characterizing these changes over time is important for accurate prediction of changes in production and transmission necessary for the adaptation of the electrical grid to the changing climate.

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Electric power demand is projected by the EIA by state for future years. For the projections, changes in power demand are calculated using broadly-defined determinants of energy consumption for the commercial and residential sectors. While economic and demographic effects of consumption are considered in each of these sectors, changes in these effects due to migration, and especially large migration due to cataclysmic events, is not included. We examine the additional effects of migration on electricity demand using LandScan population data at 1km resolution aggregated to the county level, along with by-county annual changes in migration as reported by the US Census.

Calculation of electrical customer demand

As population relocates and businesses rebuild in new locations, electricity demand shifts. To calculate the electrical customer demand it is necessary first to convert the population count into electricity customer count using a conversion factor that varies geographically. This Bailey Young [15] correction factor is derived for a given county as the population for a given decennial year (in this case, 2000) divided by the sum of the households and the firms in the county.

Datasets and approach

We use population migration and growth projections to estimate energy demand resident within CIDM developed as part of the LandScan population suite. Natural population fluxes such as births and deaths and new businesses moving into an area change the customer electricity demand in a somewhat predictable way, but the most startling and less predictable changes occur after a disaster of some kind for which the effects can last for at least a decade [16,17]. These migration models are agent based models allowing agents to move from cell to cell based on balance between attractors and repelling forces upon which the climate drivers act. The modeling framework allows stochastic examination of different migration theories and assumptions about adaptation options. We derived relationships between historical population data and energy demand data at the same spatial resolution as climate data and extrapolate to relative change in energy demand as future populations migrate. This relationship consequently estimates future energy demand levels and their spatial distribution.

To develop the utility functions upon which the agents in the models act we examine existing data from a variety of sources and derive a relationship based upon multiple linear regression scored by information complexity criteria. Selection of the data is based upon the decision-making metrics given in recognized social theory. Decisions by households as to whether to remain in the same location or to relocate tend to be economically and culturally motivated [5]. It is reasonable, then, to assume that individuals' economic, social and cultural characteristics influence their mobility. To some extent, both early and later gravity models captured this idea as communities' "attractiveness" based on factors such as low unemployment and per capita wages [18,19] earning potential and social interaction opportunities among individuals of the same race [20,21]. Our approach uses an expanded set of these same variables, but is evaluated to take into account the decision making of composite individuals.

Raphael and Riker [21] show, however, that there are demographic types who perceive themselves to be mobile in the face of unexpected displacement from work whom we might expect to seek a livelihood elsewhere. These individuals include more men than women, more Caucasian than other races, more military households [22] than civilian, and households with fewer than average occupants.

We took as our model a linear equation to examine the tendencies of individuals to stay or move to a chosen destination based upon their own demographic characteristics.

The basic equation is of the form:

$$Y = \beta X + \varepsilon$$

and is generated via least squares regression analysis and evaluated by four Information Complexity Criteria [23]. The difference between the evaluation of this equation and those used for traditional single-equation regression migration models is the preprocessing stage. We do not use **Y** as a vector of values associated with a subset of all possible destinations but as a vector that represents agents associated with a single destination—namely a vector of ones and zeroes that represent the percentage of the population that moved from the origin to the specific destination [24]. The length of the vector is determined by the amount of computing available for the regression process. We have arbitrarily chosen that number to be 1000.

Likewise, the **X** vectors are each random distributions of ones and zeroes representing the demographic attributes of the parish of origin. These demographic attributes are listed in Table 1. As agents were developed from these attributes, care was taken to represent mutually exclusive data as such during the stochastic process—that is, because citizens reporting race identified as either black or white alone, then the stochastically assigned ones for blacks did not overlap those for whites. Citizens reporting mixed race are counted implicitly as "other" by their absence. The decision to include only two racial choices was made to limit the number of independent variables and because blacks and whites make up at least 95% of the population in 2005 in most parishes. Studies [25] have indicated an increase, however, in Hispanic residents from 3.2% in 2005 to 6.6% in 2007 driven by migration into the affected areas. Likewise, as reported by the Bureau of Labor employed civilian population counts, individuals work in only one sector of the economy, so there is no overlap of career. Thus the employment categories were partitioned among the thousand agents and stochastically assigned each within its own partition. Data were compiled from several sources: US Census (population, gender, married households, education, race, and veterans), Internal Revenue Service (IRS) (to and from migration), Louisiana State Government (employed civilian population), and Louisiana Department of Revenue (poverty rates). Since migration

Model Ref	Type	% Jeff	% Orlea	% Plaqu	% St B	% St C	% St T
1	Gender female	52%	53%	49.9%	51.5%	51%	51.1%
2	Married	34%	34%	58%	54%	65%	65%
3	College Education	18%	18%	18%	18%	18%	18%
4	Below Poverty Level	13.7%	27.9%	18%	13.1%	11.4%	9.7%
5	White	70%	28.9%	71%	88.1%	72.2%	86.8%
6	Black	25%	67.6%	22.8%	9.0%	25.9%	10.6%
7	Ag/forest/fish Career	1.9%	1%	12.2%	1.9%	1.6%	2.6%
8	Construction Career	7.7%	4.9%	7.2%	9.2%	9.9%	9.1%
9	Manufacturing Career	8.3%	5.2%	9.0%	10.8%	17.9%	7.8%
10	Retail/Trade Career	4.7%	9.8%	3.7%	12.4%	10.5%	13.0%
11	Transportation/ Utilities	5.9%	5.9%	10.6%	7%	8.1%	4.9%
12	Finance Career	6.9%	2.4%	4.1%	6.8%	4.9%	6.9%
13	Professional/ Scientific	10.2%	9.9%	8.1%	8.1%	7.3%	10.1%
14	Education Career	19.4%	25.7%	15.1%	17%	18.1%	20.2%
15	Artistic Career	10.2%	15.3%	8.2%	9.7%	6.5%	8.5%
16	Military Veteran	9.0%	8.0%	7.9%	9.5%	8.3%	10.6%

Table 1: Demographics of Origin Populations.

rates were taken from IRS tax records, we chose to focus on the working population and therefore did not consider age (such as retirees) among our explanatory variables.

Results

Regional demand map after hurricane-induced redistribution

In order to demonstrate how this methodology might work, we examined county-by-county changes in electricity demand for the years surrounding the hurricane season of 2005. We downscaled the state by state electricity sales data for the years 2004-2006 provided by the Energy Information Administration (EIA) using LandScan population counts for 2004 aggregated to the county level and converted to customer counts using the Bailey Young conversion factors (Section 2.2). To obtain population counts for subsequent years, by-county proportional changes in population as recorded by the US Census were used to convert population counts from 2004 to those in subsequent years. Figures 1-4 show the results as energy use in million kilowatt-hours by county in nine southeastern states.

A comparison of Figures 1 and 2 indicated little change in electricity demand occurred during this period because only marginal population shifts occurred (-7% to 20% per county). Much larger differences appear between 2005 and 2006 as Figure 5 illustrates changes in population ranged between -76% and 13%. Most notable in the plots is the reduction in demand in south Florida; Plaquemines, Jefferson, St. Bernard (-76%) and Orleans due to migration in response to Hurricane Wilma Parishes in Louisiana in response to Hurricane Katrina; and in Cameron Parish Louisiana and several southeastern Texas counties in response to Hurricane Rita. Significant increases in demand as a result of Hurricane Katrina are evidenced in the largely populated areas of in which even a small percent increase produces a significant increase in power usage, Harris, Bexar, Dallas, Tarrant, Collin and Denton, TX as well as Harrison County, MS and East Baton Rouge and Lafayette, LA. Increases in demand shown in Caddo, Louisiana are due to influx of Rita evacuees.

Power demand increases *Correlate with evacuation routes*

Hurricane Katrina (August 23, 2005-August 30, 2005) made

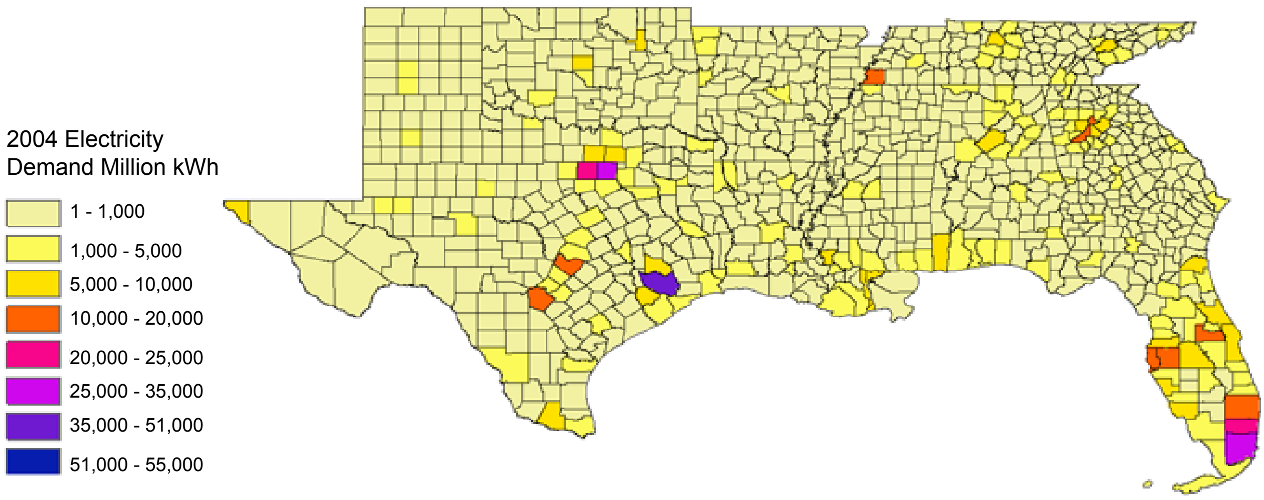

Figure 1: Electricity demand for southeastern states, 2004 in million kWh.

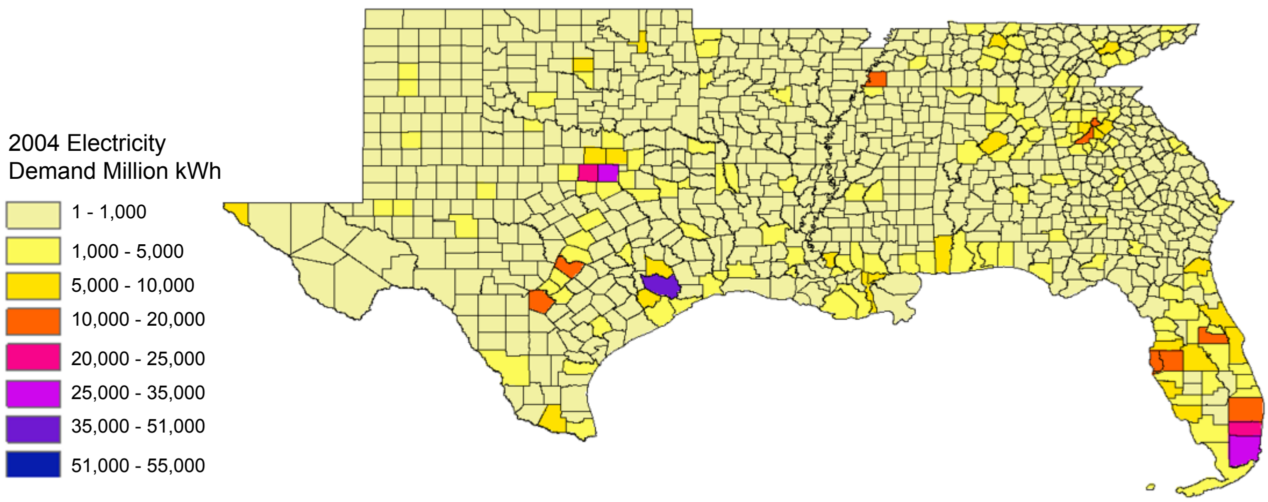

Figure 2: Electricity demand for southeastern states, 2005 in million kWh.

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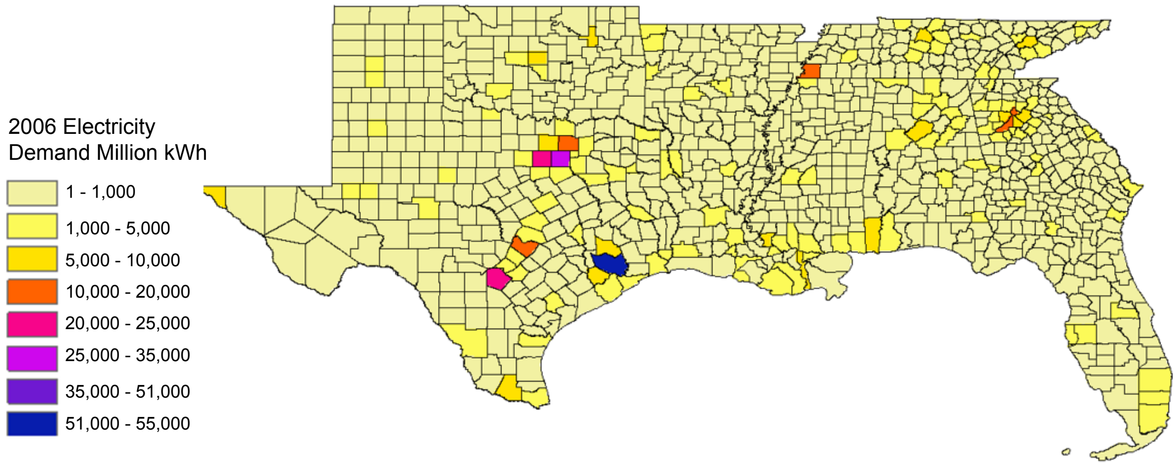

Figure 3: Electricity demand in southeastern states for the year 2006, shows large decreases in southeast Florida due to population losses from Hurricane Wilma. Large decreases in southeast Louisiana and southwest Mississippi are indicative of population losses due to Hurricane Katrina. Increases are shown in Harris, Bexar, Dallas and Tarrant counties in Texas, and to a lesser but significant extent in Shelby County, TN and Fulon County, GA. These were counties that provided the most refuge for Katrina evacuees.

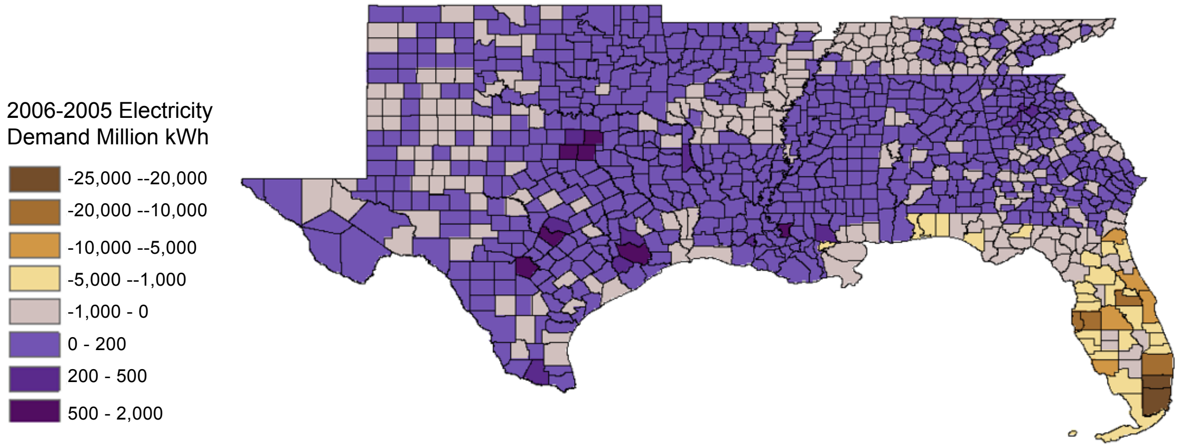

Figure 4: Differences in demand in the southeast from 2005 to 2006 reveal gains and losses in population due to hurricane events.

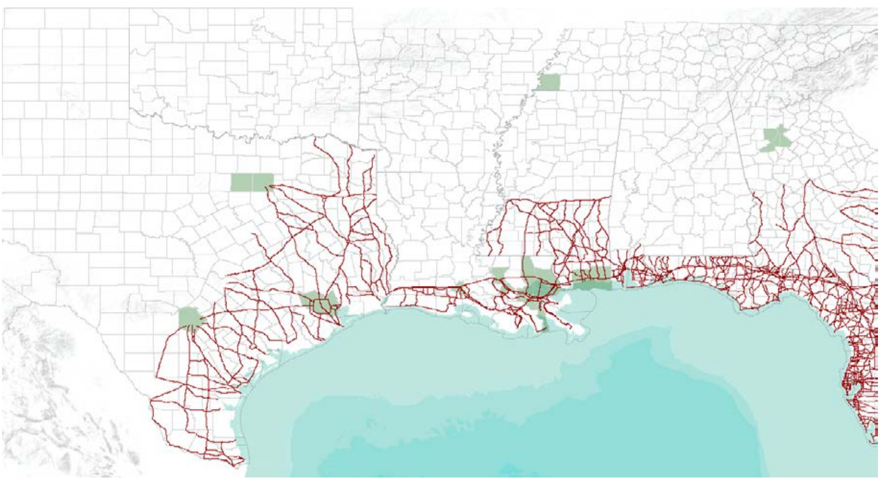

Figure 5: Contraflow Routes for Gulf Coast states take outflow to nearest habitable areas on the designated routes and their highway extensions. 15 of the top 20 receiving counties of Katrina refugees are located on the contraflow routes.

landfall along the U.S. Gulf Coast on August 29, 2005, sustaining 110 knot winds, which extended 205 miles outward from the center of the storm. Extensive flooding in the City of New Orleans, Louisiana, resulted due to storm surge from adjacent Lake Pontchartrain and several levee failures. Damage from the storm displaced more than 1,000,000 Gulf Coast residents from their homes.

Hurricane Rita (September 19, 2005-September 25, 2005) made landfall along the Gulf Coasts of western Louisiana and eastern Texas one month later on September 24, 2005. Sustained winds were reported above 140 knots with extent 80 miles from the center of the storm. Storm surge flooding reached 15 feet in Cameron Parish. New Orleans experienced additional flooding and levee failures from Hurricane Rita, and 600,000 households in that city remained displaced [17]. According to the Cable News Network (CNN) and the American Red Cross in 2005, evacuees resided predominantly in 2 states during this time: 55,000 evacuees in LA and 56,000 evacuees in TX. Forced evacuations, destroyed homes, disruption of economic activity, and the ruin of community infrastructures ($145 billion in damages) in the wake of these storms led to population shifts in the Gulf Coast Region.

The population shifts resulting from the hurricanes' damage recorded in the IRS data shows that the most attractive destination for the refugees was Harris County, TX. Tables 2 and 3 show the counties that received the most migrants from parishes affected by the storms for the years 2005-2006 and 2006-2007. Table 4 indicates the difference between population in 2005 and population in 2007.

The tables illustrate that between the years of 2005 and 2006, population moved out of Katrina- and Rita-impacted areas and predominantly into three Texas counties. East Baton Rouge, Jefferson, St. Tammany and Tangipahoa Parishes, however, were the most popular in-state destinations. Between the years of 2006 and 2007, as counties recover, population begins to move back to pre-hurricane locations. By 2007, numbers of in-migrants are nearing pre-Katrina/Rita values.

Rank	To State (FIRS)	To County (FIPS)	County Name	Migrants
1	22	51	Jefferson,LA	11820
2	22	71	Orleans, LA	7707
3	22	103	St. Tammany, LA	5751
4	28	47	Harrison, MS	2780
5	28	59	Jackson, MS	2225
6	22	95	St. John Baptist, LA	1816
7	48	201	Harris, TX	1809
8	22	89	St. Charles, LA	1732
9	22	87	St. Bernard, LA	1611
10	22	33	E Baton Rouge, LA	1509
11	28	45	Hancock, MS	1351
12	22	105	Tangipahoa, LA	1280
13	28	109	Pearl River, MS	1240
14	22	75	Plaquemines, LA	983
15	1	97	Mobile, AL	824
16	6	73	San Diego, CA	586
17	48	113	Dallas, TX	555
18	22	117	Washington, LA	553
19	48	439	Tarrant, DC	464
20	22	55	Lafayette, LA	451

2004-2005

Tables 2: Between the years of 2005 and 2006, population moved out of Katrina-devastated areas and predominantly into three Texas countries. East Baton Rouge, Jefferson, St. Tammany and Tangipahoa Parishes were the most popular in-state destinations.

Rank	To State (FIPS)	To County (FIPS)	County Name	Migrants
1	48	201	Harris, TX	37933
2	22	51	Jefferson, LA	26113
3	22	33	E Baton Rouge, LA	14148
4	22	103	St. Tammany, LA	13484
5	48	113	Dallas, TX	10143
6	48	439	Tarrant, TX	5683
7	22	105	Tangipahoa, LA	4630
8	22	71	Orleans, LA	4549
9	48	29	Bexar, TX	3642
10	28	59	Jackson, MS	3413
11	28	109	Pearl River, MS	3387
12	22	95	St. John Baptist, LA	3328
13	22	55	Lafayette, LA	3255
14	47	157	Shelby, TN	3085
15	22	89	St. Charles, LA	2997
16	13	89	DeKalb, GA	2966
17	28	47	Harrison, MS	2922
18	13	121	Fulton, GA	2922
19	22	5	Ascension, LA	2693
20	13	67	Cobb, GA	2684

2005-2006

Tables 3: Between the years of 2005 and 2006, population moved out of Katrina-devastated areas and predominantly into three Texas countries. East Baton Rouge, Jefferson, St. Tammany and Tangipahoa Parishes were the most popular in-state destinations.

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12	22	95	St. John Baptist, LA	3328
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15	22	89	St. Charles, LA	2997
16	13	89	DeKalb, GA	2966
17	28	47	Harrison, MS	2922
18	13	121	Fulton, GA	2922
19	22	5	Ascension, LA	2693
20	13	67	Cobb, GA	2684

2005-2006

Table 4: Between the years of 2006 and 2007, as countries recover, population begins to move back to pre-Katrina parishes.

Orleans and St. Bernard parishes show increases in numbers of in-migrants from 2005 to 2007 indicating recovery of the parishes.

Influence of evacuation routes on migration: The state of Louisiana has published directions for phased evacuation in the event of a hurricane, and in which contraflow routes are established to allow traffic to use all lanes available to exit the impacted area. Planning models and logistics include the determination of the fuel required for all vehicles, the designation of public transit to evacuate disabled population, and mobilization strategies for emergency response personnel and emergency medical equipment. Evacuation routes direct traffic away from potential areas of congestion and toward maximum flow. They are also routed toward emergency shelters that have been preselected based on estimates of flooding potential for at-risk geographic areas in storm scenarios [26]. For the most intense evacuation procedures, busses carry those without transportation to designated shelters. Those with personal transportation drive to the nearest safe area and take cover until the storm has passed, waters recede and cleanup has completed. As the nearest hotels reach capacity, evacuees must continue along a given route to find the next nearest hotels with vacancies. Thus, nearest hotels fill up first and more distant hotels reach occupancy later.

Implicit in Groen and Polevka [25] about decisions of evacuees to return to affected counties after Katrina is that the alternative is to remain in the location of displacement. The IRS data show that of the top twenty locations to which Katrina refugees migrated in 2006, only five were not located on branches of the evacuation routes (Figure 2). One of these counties, Tarrant County, TX is adjacent to Dallas County, TX, which is a terminus. The other four (Shelby, TN; DeKalb, Fulton and Cobb, GA) are located on the extensions of the major highways designated as contraflow routes for the initial exodus from Louisiana. Thus, perhaps the longer a population remains displaced, the more likely it is to settle in place, finding and retaining employment in the temporary location.

Influence of demographics on relocation choice: Results of the multi-agent regression indicate several key findings. First, there was no one model that could be applied to every parish's population relocation. For each parish, county-specific demographics sets were selected to represent the characteristics of the individuals who chose to locate in the counties they did following the hurricane. Second, those who returned, those who relocated, and the counties to which they relocated were determined primarily by economics in some parishes, and in others by race, gender or educational attainment. As noted in [7] the economic sector to make the fastest recovery among the affected parishes was that of the Professional, Scientific and Technical. In many cases these companies were the largest and the most lucrative in the area, so they were the companies that could afford rapid recovery efforts. Our study supports this finding as this group had the highest tendency to return especially to the parishes of St. Tammany and St. Bernard. Those in agricultural, fishing and wildlife also tended to stay or to return quickly to their origins.

The model that best fit the Orleans Parish to Bexar Country (San Antonio), TX flow included only construction and retail workers. Correspondingly, city data for Bexar County reports the number of new house construction building permits for the county in 2005 as 10, 298 buildings at an average cost of $146,700 and in 2006 as 9219 buildings at an average cost: $156,000. Numbers of similar permits in previous and subsequent years was approximately half those levels.

Individuals living below the poverty level moved mostly to the suburbs [27]. Models showed that parish citizens living below the poverty level moved from Orleans to Jefferson, Jefferson to Tangipahoa and St. Charles, and St. Charles to East Baton Rouge. For poverty-level households from Jefferson, models best describing the population flux included four demographics, the poverty demographic was associated with a slightly negative (on the order of 10^{-2}) coefficient, whereas if the poverty demographic was one of fewer than four explanatory variables, the coefficient was positive. Plyer and Ortiz [27] show that one of the results of this migration is the change in poverty per parish from the year 1999 to the years 2008-2010 (average). In Tangipahoa, this number is statistically higher for the later period. This type of shift in parish income demographic profile has an additional effect on electricity demand [28].

If we track population moves from a single parish outward, Plaquemines, for example, we note that black and white households moved to different places. White households moved from Plaquemines to Jefferson, St. Tammany, Tangipahoa, Lafayette and St. Mary parishes. Black households did not return to their original parishes [25] but moved to Orleans (the parish with the highest black population before Hurricane Katrina) from other parishes.

Our results also suggest that women-led households moved farther from their original residences than other groups did. For example, these households moved from St. Tammany and Orleans to Dallas and to Tarrant Counties in Texas. Longer in-state moves for females were from St. Bernard to Ascension Parish. Groen and Polevka [25] report that in high-damage areas, evacuees with children were less likely to return than those without children.

Heads of Households with a college education (along with a Professional/Scientific/Technical career) stayed in St. Bernard Parish and moved to Parishes with large universities such as East Baton Rouge. These households also moved to Washington, St. Charles and Ascension Parishes.

Veterans favored parishes or counties with military facilities such as Jefferson (Coast Guard, US Air Force Department, Patrician military housing (Naval Base)), St. Tammany (Coast Guard, National Guard, Arm and Navy facilities), Ascension (National Guard and Louisiana National Guard), St. Mary (National Guard, Army Base, Civil Air Patrol), Terrebonne (Coast Guard and National Guard), and Fulton County in Georgia (Fort McPherson).

Framework for long-term evacuation evaluation

In order to explore the balance of the influence of evacuation routes and of the demographics of a population on relocation, we developed FLEE (Framework for Long-term Evacuation Evaluation), an agent based model that moves the evacuating population along the established routes. As each agent approaches a possible relocation parish or county, it makes a "decision" as to whether to stay (relocate there) based upon its demographic components (as determined by the method described in section 2.4). The model ran for each of nine parishes of origin: five for response to Hurricane Katrina and four for response to Hurricane Rita. The four Rita parishes were those which experienced intense impacts from both Hurricane Rita in 2005 and Hurricane Gustav in 2008. Model results obtained for the Hurricane Rita parishes were then compared to the same parishes' responses to Hurricane Gustav in 2008.

Previous research [29] suggests that the sequence in which evacuees approach locations with hotel or motel availability significantly affects an individual's choice of location of temporary refuge. That is, the sequence of opportunities to choose shelter site is sensitive to the direction of evacuation relative to the path of the storm. Apparent from the simulations was that the starting location determined initial evacuation destination decisions for the agents. This observation led to the simulation of agent evacuation based upon random movement along the flow routes in the direction of the contraflow mandated by state emergency procedures. Next, simulations with the full model, including weighted demographics were run. Results from these simulations are shown in Table 5.

Table 5 indicates that the FLEE model does well (0-20% error) at predicting destination parishes for long-term evacuees, but not as well for return population projections for storm-affected parishes of origin. In fact, the more intensely a parish suffered from each storm, the less accurate the model population projection was for long-term relocation to that parish. Figure 6 illustrates this idea showing wind swaths from both Katrina and Rita along with the percentages by which FLEE under- or over-estimated 2006 population counts (as indicated by the legend). The red shading in the hurricane swaths represents the areas which sustained 59-74 knot winds. The yellow shading indicates 40-58 knot winds, and the blue shading 39 knot winds.

Because the model employs geographically sequential decision-making for choice of destination, it tends mostly to underestimate the return of the population to the parish of origin. The model also tended to predict better the long-term relocation for Rita evacuees than it did for Katrina evacuees. Additionally, since long-term relocation patterns after Gustav for 2009 were similar to those after Rita for 2006, the model used for Rita showed good agreement with relocation figures after Gustav.

Using values generated by FLEE, calculations using the Connected Infrastructure Dynamics Model (CIDM) of the values shown in Figure 5 matched reasonably well with the EIA actual figures, except for those in the most heavily affected areas. Differences between the FLEE model results and the EIA data are shown in Figure 7.

Robustness and resilience

In determining a population's likelihood to stay or to leave an area affected by extreme weather events, it is useful to evaluate a community's robustness to these events and its resilience once subject to them. Infrastructure is robust to extreme climate activity if it is capable of withstanding stress. For example, a robust power plant may withstand a 100 year storm and continue to provide full service without interruption indicating a probability of reduced service equal to zero, even though the probability of the climate stressor is 1 percent [17]. Infrastructure is resilient if, once exposed to a stressor, it is capable of repair and renewal within a short time. Different regions have different amounts of robustness and resilience, and these differences among regions can be quantified using fragility curves.

Fragility curves

Fragility curves provide a powerful approach for understanding total environmental damage potential and the number of outages observed for a particular area during an extreme weather event. These curves depict the relationship between a weather variable (wind speed, gust speed, ice accumulation, precipitation rate) and the observed outages for a targeted infrastructure network [29]. The ability to predict such outages based on the robustness of the local power grid against environmental damage potential given the outages observed for a particular area during an extreme weather event, and the capability of the operators of that local system to bring the power back online, can become a measure of both robustness and resilience of the community's infrastructure as a whole.

Issues affecting the fragility of the grid from location to location include physical and structural, informational, geospatial, procedural and societal components, but the prediction of fragility relies solely on customer outage and atmospheric data. Fragility, expressed as the bivariate relationship between wind speeds and number of observed power outages at time periods for a large (multi-county) region, follows an exponential curve, the extremity of which can vary empirically, but which is closely approximated by that developed by the Electric Power Research Institute (EPRI). Using this curve, counties with increased or decreased robustness can be characterized by terrain more or less susceptible to persistent flooding in areas where above ground poles have located their foundations. This information, then, can be applied to the calculation of the proportion of people expected to return to an area affected by severe flooding, and the timing of their return (Table 6) [7,25].

Time to restoration

Once an outage has occurred, the number of crew members per county available for repair may be estimated according to local resources, and the amount of time to restoration calculated as a result. This provides a measure of resiliency within a community to electrical outage, and represents a first step toward complete restoration of a community's infrastructure.

Influence of county resilience on population return

A major influence on the rapidity with which the population returns to a county after a disastrous event is the resilience of the county [7,22,25] Comparison of the population between Hurricane Katrina in 2005 and Hurricane Isaac seven years later supports this observation [30]. In the time intervening, the Army Corps of Engineers completed a Risk Reduction System [31] and a mandatory evacuation for Hurricane Isaac was not issued. While the storm caused more damage than expected, and more than a million people were without power from three to six days, the costs to New Orleans citizens was far less than it was in the aftermath of Katrina and the city resumed its normal activity in much less time [7]. Migration patterns for this year did not exceed typical outflow). Because of this response, we can posit that the vulnerability of its power transmission and distribution system, along with the length of time it takes for the utility to restore

Rank	To State (FIRS)	To County (FIRS)	County Name	Migrants
1	22	51	Jefferson, LA	8653
2	22	71	Orleans, LA	7991
3	48	201	Harris, TX	4508
4	22	103	St. Tammany, LA	3787
5	22	33	E. Baton Rouge, LA	2796
6	22	87	St. Bernard, LA	2395
7	28	47	Harrison, MS	2097
8	28	59	Jackson, MS	1946
9	22	105	Tangipahoa, LA	1889
10	22	89	St. Charles, LA	1634
11	22	95	St. John the Bap, LA	1588
12	28	109	Pearl River, MS	1249
13	48	113	Dallas, TX	1224
14	22	5	Ascension, LA	1055
15	1	97	Mobile, AL	1041
16	48	439	Tarrant, TX	868
17	22	63	Livingston, LA	801
18	28	45	Hancock, MS	741
19	48	157	Fort Bend, TX	720
20	22	75	Plaquemines, LA	712

2006-2007

Table 5: Between the years of 2006 and 2007, as countries recover, population begins to move back to pre-Katrina parishes.

Parish	Hurricane	LS+IRS Pop 2005	FracTo	ABM Pop 2006	LS+IRS Pop 2006	Difference	Pcnt Diff
Beauregard, LA	Rita	34645	0.214	9581.886381	35235	-25653.11	-72.81
Calcasieu, LA		185496	0.036	179802.5101	185311	-5508.49	-2.97
Vernon, LA		48737	0.227	56601.415	46966	9635.42	20.52
Allen, LA		25375	0.115	30503.463	25582	4921.46	19.24
Harris, TX		3711496	0.038	3715487.997	3833176	-117688.0	-3.07
Lafayette, LA		197439	0.003	197571.932	203930	-6358.07	-3.12
Jeff Davis, LA		31312	0	30623.136	31537	-913.86	-2.90
E. Baton Rouge		412029	0.004	426575.695	431397	-4821.30	-1.12
Rapides, LA		128404	0.03	129628.846	130727	-1098.15	-0.84
Orange, TX		85253	0.005	86180.48	84497	1683.48	1.99
Jefferson, TX		247585	0.001	247770.496	244309	3461.50	1.42
Cameron, LA		9635	0.002	9103.666603	7811	1292.67	16.55
Vermilion, LA		55485	0	55485	56242	-757.00	-1.35
Acadia, LA		59368	0	59461.936	60580	-1118.06	-1.85
Jefferson, LA	Katrina	452553	0.704	342406.359	432799	-90392.64	-20.89
Orleans, LA		455286	0.05	466113.455	224927	241186.46	107.23
St Tammany		220024	0.007	22130.15	230825	-208694.9	-90.41
Dallas, TX		2312519	0	2312739.024	2349871	-37131.98	-1.58
St Charles, LA		50744	0.02	59795.06	52959	6836.06	12.91
St John, LA		46340	0.013	52223.189	48737	3486.19	7.15
Tarrant, TX		1623670	0.001	1624180.547	1675427	-51246.45	-3.06
Tangipahoa, LA		106550	0.038	163151.238	113561	49590.24	43.67
Evangeline, LA		35726	0	35726	36178	-452.00	-1.25
St. Landry, LA		90129	0.005	90285.56	92027	-1741.44	-1.89
Bexar, TX		1519552	0	1519552	1558634	-39082.00	-2.51
Fulton, GA		840041	0	840041	863210	-23169.00	-2.68
DeKalb, GA		686803	0	686803	696352	-9549.00	-1.37
Shelby, TN		910530	0.003	911895.858	916294	-4398.14	-0.48
Plaquemines	Katrina	28997	0.223	6466.331	22585	-16118.67	-71.37
Terrebonne, LA		107729	0.027	108511.919	109996	-1484.08	-1.35
St Mary, LA		51515	0.001	51543.997	52173	-629.00	-1.21
St Bernard, LA	Katrina	65165	0.234	15248.61	15518	-269.39	-1.74
Pearl River, MS		52576	0.053	65490.777	57227	8263.78	14.44
Livingston, LA		108906	0.005	109231.825	114750	-5518.18	-4.81
Ascension, LA		90773	0.003	90968.495	97686	-6717.51	-6.88
Washingtn, LA		44487	0.028	50647.672	44962	5685.67	12.65
Montgmry, TX		378410	0	378410	397641	-19231.00	-4.84

Table 6: Differences between 2006 population migration results from FLEE model and US Census counts for parishes of origin and destination.

power to its residents is an indicator of the robustness and resilience of its infrastructure and the overall resilience of the community to extreme events [32]. Because of the extreme ire that Katrina provoked, however, little outage information is available for hindcast predictions of its fragility or its resilience.

Resilience indicators

Li et al. [22] demonstrated that school reopenings played a major role in indicating the ability of a community to rebound and to signal its citizens that the community was operating again. Groen and Polivka [25] confirm this finding. Other socioeconomic resilience indicators investigated by Li include employment rate increase, increase in sales tax earnings, and severance taxes (levied on production of natural resources taken from land or water) as indicators of a returning economy. Before any of these indicators can take effect and be recognized, however, basic infrastructure and places of employment must be repaired and in place. The demographic attributes that best described the population who returned within eight months is employment. As Li and Fernandez [33] show, the most easily rebuilt businesses are those whose workers return first. In Plaquemines Parish, this business was manufacturing. St. Bernard also included agriculture, retail, professional/scientific, and artistic careers. Jefferson's returning employees were in transportation, finance, education, and artistic careers. The most likely to stay in St. Tammany were those living below the poverty level, while no variables had positive coefficients indicating that they stayed in Orleans or St. Charles Parishes.

Conclusions and Future Work

In this work, we created a prototype agent based population distribution model coupled to infrastructure models to anticipate emerging power grid vulnerabilities. If, as projected in climate models, the frequency of storms increases in the coming decades, populations will continue to shift in response to these extreme weather events. These shifts in turn will place new power consumption demands on the electrical infrastructure. We coupled these agent based models to Department of Energy (DOE) Connected Infrastructure Dynamics

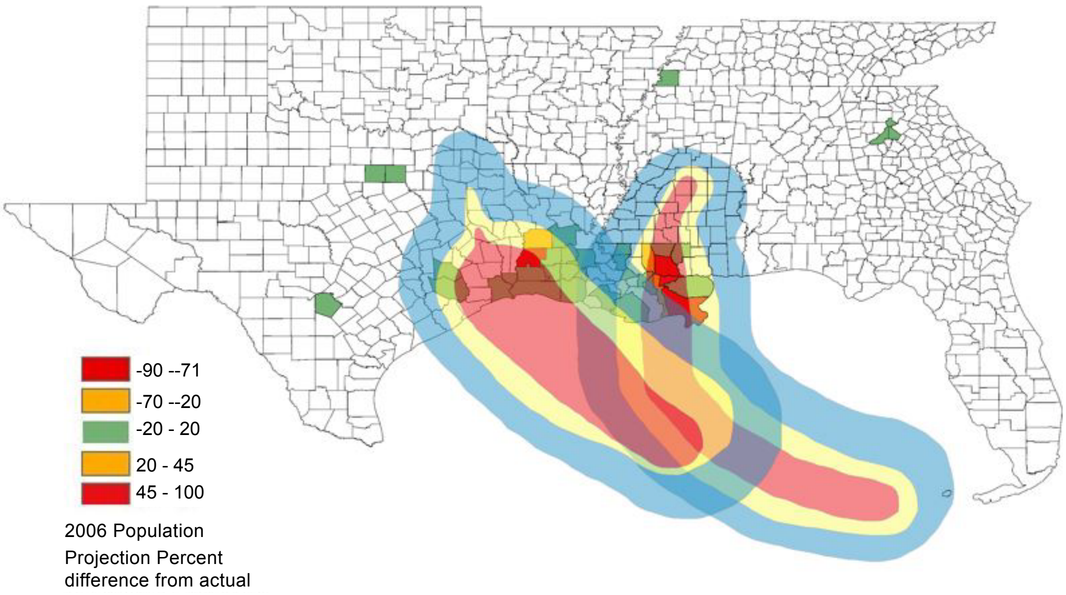

Figure 6: Uncertainty for population relocation is greatest for locations experiencing the highest intensities of the storms. Wind swath shading: Red=59-74 knot winds, Yellow=40-58 knot winds, Blue=39 knot winds.

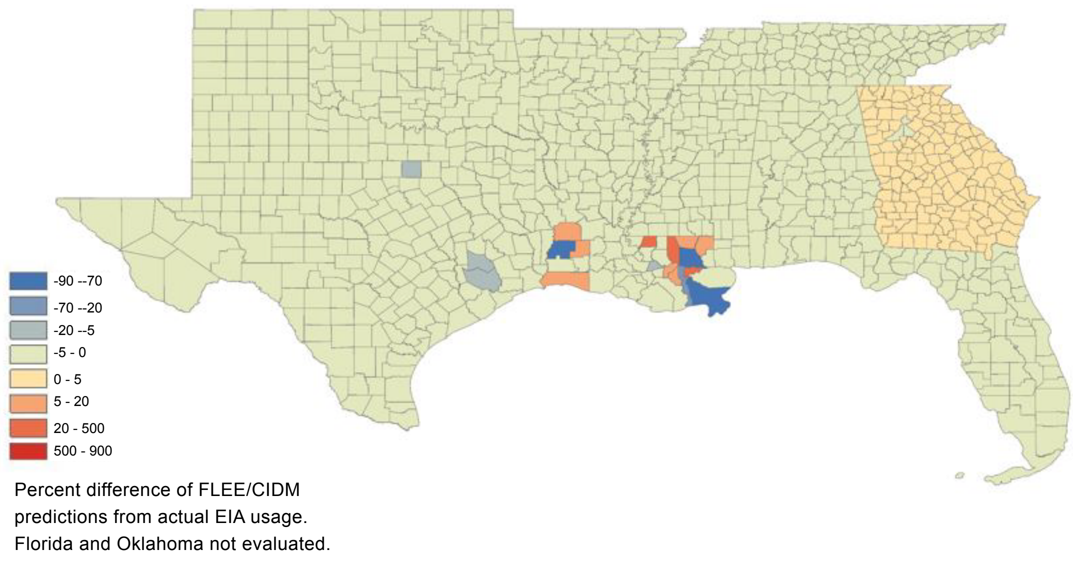

Figure 7: Percent difference between model calculations of by-county energy demand for 2006 and EIA values.

Models (CIDM) to examine electricity demand response to increased temperatures, population relocation in response to extreme cyclonic events, consequent net population changes and new regional patterns in electricity demand. This work suggests that the importance of established evacuation routes that move large populations repeatedly through convergence points as an indicator may be under recognized.

Additional studies of repeated evacuations is required before anticipatory models can be used to assess the impact on the nation's critical infrastructure including an examination of the response of populations in counties that have experienced hurricanes in close succession. These models may allow key studies on future states of critical infrastructure resulting from increasing frequency of extreme events at vulnerable locations.

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