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Impacts of climate change on energy consumption and peak demand in buildings: A detailed regional approach

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ABSTRACT

This paper presents the results of numerous commercial and residential building simulations, with the purpose of examining the impact of climate change on peak and annual building energy consumption over the portion of the EIC (Eastern Interconnection) located in the United States. The climate change scenario considered includes changes in mean climate characteristics as well as changes in the frequency and duration of intense weather events. Simulations were performed using the BEND (Building ENergy Demand) model which is a detailed building analysis platform utilizing EnergyPlus™ as the simulation engine. Over 26,000 building configurations of different types, sizes, vintages, and characteristics representing the population of buildings within the EIC, are modeled across the three EIC time zones using the future climate from 100 target region locations, resulting in nearly 180,000 spatially relevant simulated demand profiles for three years selected to be representative of the general climate trend over the century. This approach provides a heretofore unprecedented level of specificity across multiple spectrums including spatial, temporal, and building characteristics. This capability enables the ability to perform detailed hourly impact studies of building adaptation and mitigation strategies on energy use and electricity peak demand within the context of the entire grid and economy.

1. Introduction

Building energy demand will change in response to future climate change, with cooling and heating demand generally going in opposite directions. Net increases or decreases largely depend on a region's cooling or heating demand dominance. Much of the literature on building energy demand modeling is oriented toward simply forecasting future demand or increasing energy efficiency. While it may address the impact of weather or climate sensitivity of demand or the impact of current climate on demand, it does not address the impact of future climate change (e.g., [24,37,38,50,55,56]). The extant literature projecting the effects of climate change on future building energy overwhelmingly has emphasized changes in overall annual energy consumption. Most analyses of the impacts of climate change on building energy demand distinguish between heating, cooling, and other end uses (e.g. [13]), but nearly all the existing literature discusses annual energy consumption, with only a few taking on the question of peak demand (for a nice review see Ref. [26] and specific papers [12,27,32]). However, peak demand is a critical element in the long-term planning for energy system capacity which for developed countries generally consists of electricity (the mix and spatial distribution of generation technologies, transmission, and distribution) and natural gas (production, transmission, distribution, and storage).

In most prior analyses, climate change has been expressed as changes in annual or monthly HDD (heating degree-days) and CDD (cooling degree-days) (generally using 65 °F/18.3 C) (see for example Ref. [4] and the survey of approaches in Ref. [20]) instead of the true building balance point or simulation approach (see however, Refs. [2,6,15,19,20,41]). Energy consumption is generally correlated with changes in HDD or CDD in the same periodicity (i.e., monthly or annual). Methodological approaches include multiple regression (e.g., [1,19,29,33,39,40]), simulation of individual buildings (e.g., [51]), and combining the two approaches (e.g., [52]). These analyses conclude that the impact of climate change is generally benign or at least not seriously deleterious as demonstrated by the following results:

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- Annual cooling energy consumption (almost always electricity) is likely to increase by a few percent,
- Heating energy consumption (by a variety of fuels) to decrease by a few percent, and
- Net total energy consumption to decrease by a lesser percentage in colder regions and increase in warmer regions.

Generally there is a note that cooling demand increases strongly in most regions, but the consequences for utility investment are not pursued. Some analyses have relied on detailed building models (see, for example, Refs. [7,17,23,43]) but, to date, no climate analysis has attempted to take into account the great diversity of buildings that actually would be affected by climate change. Instead, these papers have derived their conclusions concerning future energy consumption based on the energy response of only one or two building types, which is assumed to be representative of the entire building stock (e.g., [10,23,28,30,42,57]). One interesting exception that uses a group of buildings for forecasting, but for planning rather than forecasting with climate change, is Ref. [5]. How would the energy forecast answers change if the diversity of building types was taken into account directly, and in particular, how would peak loads be affected? These are the primary questions we address in this paper.

This paper presents the results of a comprehensive commercial and residential building simulation study, with the purpose of examining the impact of climate change on peak and annual building energy consumption over the portion of the Eastern Interconnection located in the United States. The climate change scenario considered (IPCC (Intergovernmental Panel on Climate Change)) A2 scenario as downscaled from the CASCaDE dataset—[9] has changes in mean climate characteristics as well as changes in the frequency and duration of intense weather events. This investigation examines building energy demand for three annual periods – 2004, 2052, and 2089. These years were chosen because they are representative of the overall climate trend in the CASCaDE A2 dataset. Simulations were performed using the BEND (Building ENergy Demand) model which is a detailed building analysis platform utilizing EnergyPlus as the simulation engine. EnergyPlus is a well known and highly validated model that is the industry standard. EnergyPlus has been validated in numerous tests from ASHRAE, ANSI, and IEA (for a complete listing of EnergyPlus testing and validation please visit: http://apps1.eere.energy.gov/buildings/energyplus/energyplus_testing.cfm).

BEND was developed in collaboration with the PRIMA (Platform for Regional Integrated Modeling and Analysis), a modeling framework designed to simulate the complex interactions among climate, energy, water, and land at decision-relevant spatial scales, which will be briefly discussed in Section 3. Over 26,000 building configurations of different types, sizes, vintages, and, characteristics which represent the population of buildings within the EIC (Eastern Interconnection), are modeled across the three time zones using the climate from 100 locations within the target region resulting in nearly 180,000 spatially relevant simulated demand profiles for each of the three selected years. In this study, the building stock characteristics are held constant based on the 2005 building stock in order to isolate and present results that highlight the impact of the climate signal on commercial and residential energy demand. Results of this analysis compare well with other analyses at their finest level of specificity. For example, some studies offer a high degree of variation within building types but have limited spatial variation and are not focused on climate change [5,43] while others offer wider spatial and temporal coverage yet lack detailed the detail simulation necessary to explore full impacts of climate change on building energy consumption [3,13]. This approach, however, provides a heretofore unprecedented level of specificity across multiple spectrums including:

- Spatial—Modeling geographic areas down to a one-eighth degree grid with the ability to aggregate up to any larger geographic area
- Temporal—annual, monthly, weekly, hourly, and sub-hourly modeling are possible
- Building Type—an array of building types possible; five residential and eleven commercial were used for this analysis.
- Building Vintage—multiple vintage classes possible for each type of building; seven categories used here.
- Building Size—limitless building size capability; six size bins were used.

This capability enables the ability to perform detailed hourly impact studies of building adaptation and mitigation strategies on energy use and electricity peak demand within the context of the entire grid and economy.

2. Models and methods

2.1. The BEND model

The Building ENergy Demand (BEND) model simulates climate-dependent hourly building energy demands for populations of buildings at various spatial scales with resolution as fine as a one-eighth degree grid and an ability to aggregate up to any size geographic area including counties, states, utility control area, and census regions. BEND combines DOE's EnergyPlus™ [46] model of individual building energy use with a geospatial analysis of regional climate, population, building types, and technologies to provide this scale-flexible characterization of regional building energy demand.

EnergyPlus is a highly detailed building thermal load simulation program that relies on detailed user inputs. EnergyPlus calculates heating and cooling loads, and energy consumption, using sophisticated calculations of heat gain and heat loss including transient heat conduction though building envelop elements. It also accounts for heat and mass transfer that impact sensible and latent thermal loads due to ventilation and infiltration. Additionally, the model has detailed calculations of heat transfer to or from the ground and comprehensive models of solar gain through the fenestration and opaque envelop components.

The BEND model is applied by developing a “population” of statistically representative buildings (see Section 5) for a geographic region (see Section 4) based on data from the Commercial Building Energy Consumption Survey [47] and the Residential Energy Consumption Survey [49]. Starting estimates for the number of each type of representative building are typically modified through a calibration exercise whereby actual historical weather is used to simulate energy consumption for the building population, which is compared to actual energy consumption for the same time period. The calibrated model can then be used to project energy consumption under specific climate and technology scenarios. BEND estimates of future building energy demand can then be used by other models in the PRIMA framework as described in the next section.

In addition to the statistically representative building population and flexible spatial scale just described, BEND also provides an ability to resolve the temporal character of building power demands. This capability is critical for understanding the way that electricity generation capacity requirements will need to change in the future and how a changing climate may influence the evolution of electricity system planning and operation. Finally, the richness of building modeling that BEND delivers provides the ability to explore myriad building adaptation and mitigation strategies within the context of the entire grid and economy.

2.2. Platform for Regional Integrated Modeling and Analysis

BEND is one of the component models of the Platform for Regional Integrated Modeling and Analysis (PRIMA), developed by Pacific Northwest National Laboratory [22]. PRIMA provides a regional scale capability to explore the interactions between human and environmental systems under climate change. It is intended as a decision support tool to understand the opportunities for and potential tradeoffs associated with climate change mitigation and adaptation decisions. As shown in Fig. 1, PRIMA provides a flexible capability to couple the following types of component models according to stakeholder decision support needs: 1) a regional earth system model that simulates regional climate at high temporal and spatial resolution, 2) a regional integrated assessment model that simulates the interactions between socioeconomic change, the energy economy, water supply and demand, and agriculture/land use change, and 3) sector models representing building energy demand (BEND), electricity infrastructure, water availability, land use, and crop productivity. The sector models provide higher resolution detail than is feasible to include in the integrated assessment model where some accuracy and resolution are necessarily traded off for increased computational speed.

2.3. Overview of analysis methodology

The general analysis process is as follows:

1. For the geographic area of interest determine the number of Climate Similar Regions to be evaluated balancing accuracy with computation time.
2. Determine the number of buildings and characteristics of those buildings, again balancing greater accuracy simulating more buildings with increased processing time. These building characteristics may change over time or be held constant as they were in this analysis.
3. Develop climate data in the appropriate format for calibration (actual historic weather) and simulated data that are consistent with the climate change scenario under consideration.
4. Collect actual historical energy consumption data for calibration regions and calibrate the model. (Note that for expediency in this particular effort, the uncalibrated model was used because the analysis was investigating relative changes rather than absolute magnitudes.)
5. Run the future climate data through the model (calibrated if available) to determine future building energy consumption and peak electricity demand under the climate scenario being evaluated.
6. Using the weights (calibrated if available) aggregate the building consumption profiles to the geographic subareas of interest (e.g., states).

3. Model setting—BEND region of evaluation

This analysis models the impact of climate change on building demand within the U.S. portion of a geographic region known as the Eastern Interconnection (EIC). The EIC represents one of three electrically interconnected regions in the United States. These interconnections create the logical boundaries for power grid modeling within North America. Large intraregional differences in annual and seasonal temperature and humidity signatures under the current climate, as well as the widely varying impact of the IPCC A2 climate scenario also make this area an excellent choice for investigation of the impacts of climate change on a static building stock.

To reduce the computational overhead associated with representing small-scale spatial climate variability while still maintaining an operating procedure that can accurately model sub-state level building energy demand, a process was developed to identify climate similar regions. These climate similar regions are developed using data on a one-eighth degree grid over the United States retrieved from the phase two NLDAS (North American Land Data Assimilation System-2) [35,54] for the period 1979–2005 together with the locations of weather stations across the US that record data that is of sufficiently high quality.

The NLDAS one-eighth degree grid cells that contained known Class I [36] weather stations (or Class II for some states with no or

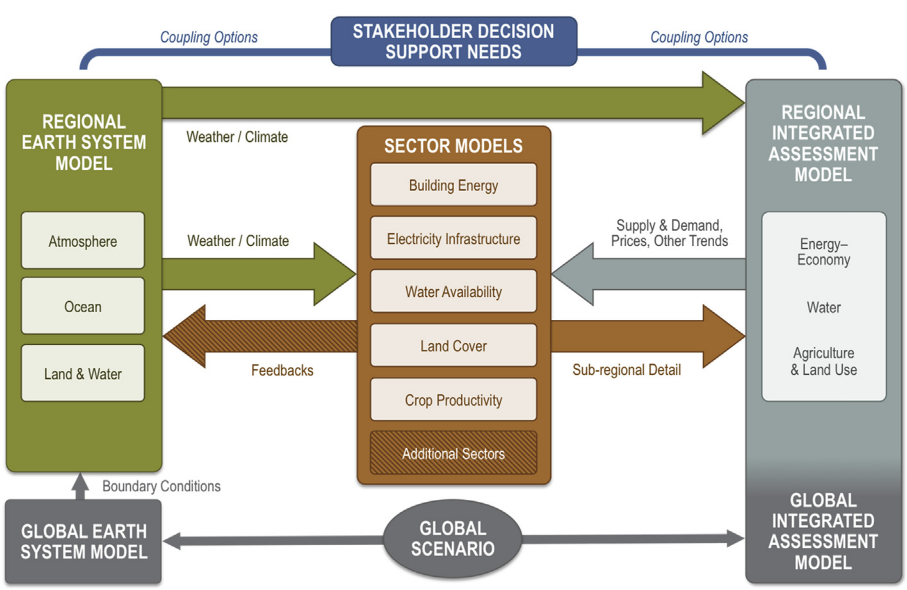

Fig. 1. Platform for Regional Integrated Modeling and Analysis (PRIMA) Architecture [22].

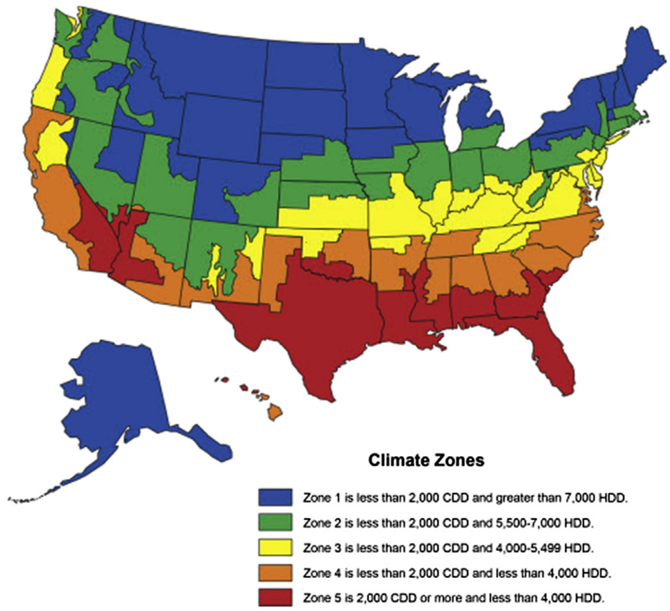

Fig. 2. EIA climate zones [48].

limited Class 1 weather stations) were used to define the 250 reference cells, which are referred to as weather station locations. The 53,746 grid cells within the U.S. were then compared to each weather station location using a goodness-of-fit procedure developed by Ref. [11] across nine different climate variables in a manner similar to the methods used to generate TMY (typical meteorological year) data [53]. This procedure provides a CSS (climate similarity score) of each weather station location to each of the 53,746 grid cells. These CSSs can then be used to assign each of the one-eighth degree grid cells to the most similar weather station [14].

Within the EIC there are 23 unique intersections of EIA climate zone (Fig. 2), census region, and time zone that are used to develop building characteristics as described in the next section. Rather than simulate the climate in every grid cell in each one of these 23 intersections, climate similar regions are selected within each intersection. For this paper, an optimal set (minimizes the population weighted CSS over the grid cells in the target area) of 100 stations was selected that is the most representative of the 29,621 grid cells in the EIC, based on the CSS described above and the constraint that climate similar regions do not extend across intersections. Fig. 3 shows the U.S. portion of the EIC and the 100 climate similar regions.

4. Climate impacted building energy demand analysis—data and results

4.1. 2005 EIC building characteristics

The year 2005 was selected as the base year for the building characteristics for 3 reasons:

1. This analysis was being conducted as part of a larger PRIMA analysis (Section 3) and several of the models that we were integrating with use 5-year time steps with 2005 as the starting year.
2. For calibration purposes we use real weather data and actual consumption data. NOAA stopped producing a type of cloud cover data that is necessary to produce the EnergyPlus weather files in September 2009 so the starting year needed to be prior to that. While we did not calibrate for this analysis, as it was a relative analysis and therefore not necessary, these building instances are also be used as part of other work under PRIMA where calibration is necessary.
3. A good share of the statistical data that is used to infer the commercial building characteristics are derived from CBECS

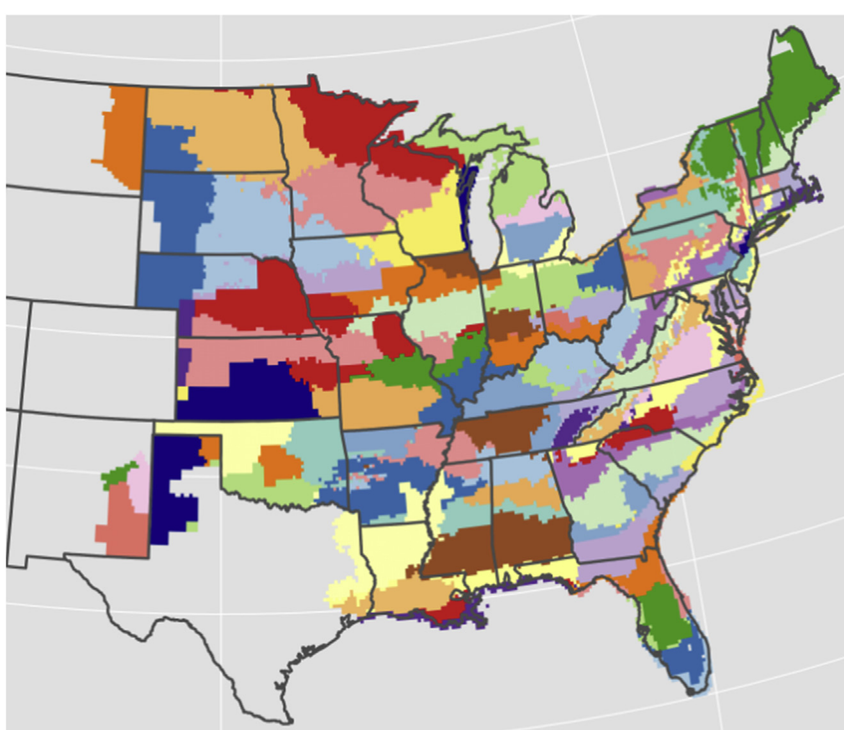

Fig. 3. Climate similar regions for the EIC.

Table 1
Estimated floor area and number of buildings in 2005 by building type and census division.

Million square meters (thousands of buildings)		Census divisions						
		New England	Middle Atlantic	East North Central	West North Central	South Atlantic	East South Central	West South Central
Residential	Single family detached	938.7 (2931.9)	2631.2 (8218.0)	3742.8 (13118.0)	1586.5 (5562.5)	3831.4 (14165.0)	1211.2 (4477.9)	902.2 (3342.1)
	Single family attached	127.9 (603.0)	358.5 (1690.2)	252.9 (1056.1)	107.2 (448.3)	145.3 (1029.3)	45.9 (325.4)	34.8 (245.5)
	2–4 unit buildings	72.5 (221.7)	203.2 (621.3)	135.5 (356.1)	57.4 (151.1)	75.8 (335.6)	24 (106.1)	18.1 (80.0)
	5 or more unit buildings	83 (86.8)	232.5 (243.2)	181.9 (225.3)	77.2 (95.6)	263.8 (266.5)	83.4 (84.2)	62.2 (62.9)
	Mobile homes	9.6 (112.2)	26.8 (314.6)	52.3 (536.8)	22.3 (228.7)	192.9 (1978.8)	60.9 (625.6)	45.5 (466.4)
Commercial	Assembly	42.6 (30.2)	119.6 (84.7)	147.2 (115)	62.3 (48.8)	142.0 (130.6)	44.9 (41.3)	33.4 (30.7)
	Education	40.3 (8.1)	112.9 (22.6)	156.4 (44.3)	66.3 (18.8)	200.2 (81.2)	63.3 (25.7)	47.1 (19.3)
	Food sales	6.9 (10.4)	19.1 (29.2)	20.1 (39.9)	8.5 (16.9)	28.3 (49.2)	8.9 (15.6)	6.7 (11.6)
	Food service	5.6 (9.8)	15.5 (27.5)	33.9 (61.4)	14.4 (26.0)	39.5 (66.4)	12.4 (21.0)	9.3 (15.6)
	Health care	14.7 (6.5)	41.2 (18.3)	68.6 (26.5)	29.1 (11.3)	75.6 (30.3)	23.9 (9.6)	17.7 (7.2)
	Lodging	19.0 (5.9)	53.1 (16.6)	57.5 (19.6)	24.4 (8.3)	59.6 (23.6)	18.9 (7.5)	14.1 (5.6)
	Mercantile and service	57.5 (55.2)	161.2 (154.9)	217.2 (260.3)	92.1 (110.3)	293.1 (257.2)	92.6 (81.3)	69.0 (60.4)
	Office	56.9 (40.7)	159.3 (114.0)	181.2 (162.1)	76.8 (68.7)	152.0 (130.4)	48.0 (41.2)	36.0 (31.0)
	Other	23.5 (10.4)	65.8 (29.2)	80.8 (61.3)	34.3 (26.0)	64.8 (58.3)	20.5 (18.4)	15.2 (13.6)
	Public order/safety	7.8 (6.0)	21.8 (16.8)	14.8 (13.9)	6.2 (5.9)	16.4 (8.0)	5.2 (2.5)	3.8 (1.9)
	Warehouse and storage	29.1 (16.5)	81.5 (46.3)	161.7 (111.1)	68.6 (47.1)	185.0 (141.0)	58.5 (44.6)	43.4 (33.1)

Note: West North Central includes some buildings from Montana and East South Central includes some buildings from New Mexico that are part of the EIC.

(Commercial Buildings Energy Consumption Survey) [47] and it was last updated in 2003. Hence, an accurate representation of the 2005 could be made and characteristics data for a later date are not available.

In 2005, there were roughly 22.6 billion square meters of residential and commercial floor space in the approximately 112 million buildings in the EIC. A breakdown of the floor area and number of buildings by census division and building type is provided in Table 1. Similarly, a breakdown of the floor area and number of buildings by vintage category and building type is provided in Table 2.

The buildings in Table 2 (16 different building types and seven vintage categories) are further sub divided into six size categories and multiple HVAC system combination categories. Building features needed for implementation in EnergyPlus, roughly 500 per building, were inferred by varying the high-level characteristics of construction vintage (7 levels), building use type (16 levels), and HVAC system type. Numerous HVAC system types are considered and those that represent the most common systems for buildings of that vintage, size, type, and location are simulated. Similarly, lighting, equipment, and other building characteristic were inferred based on statistical data from CBECS [47], RECS (Residential Energy Consumption Survey) [49], and FEDS (Facility Energy Decision System) [8]. The specific building features resulting from each high-level characteristic were unique to the spatial location of the building as defined by EIA climate zone and census region. This process resulted in over 26,000 unique building configurations that are intended to represent the population of buildings in use. These unique building representations are then evaluated at the 100 different climate regions over the three selected climate years resulting in a total of nearly 180,000 simulated energy demand profiles for each of the three selected years.

4.2. Climate data

4.2.1. The CASCaDE dataset and its transformation

In order to understand changes in building energy consumption and demand in response to future climate conditions, the Computational Assessments of Scenarios of Change for the Delta Ecosystem (CASCaDE) dataset (http://cascade.wr.usgs.gov) was retrieved and transformed to drive the BEND model. In the CASCaDE dataset, daily precipitation, maximum and minimum temperature from GCMs (General Circulation Models) were statistically downscaled using the constructed analogs method [16,31] to a 1/8° grid over the US, consistent with the NLDAS-2 dataset used for deriving the climate similar regions in Section 4. Downscaled products from multiple GCMs are available from the CASCaDE

Table 2
Estimated floor area and number of buildings in 2005 by building type and vintage category.

Million square meters (thousands of buildings)		Vintage Category						
		Up through 1945	1946–1960	1961–1973	1974–1979	1980–1986	1987–1996	1997–2005
Residential	Single family detached	2225.8 (7804.6)	3052.1 (11233.1)	1840.7 (6229.6)	2100.0 (7305.6)	1839.9 (6245.1)	2306.6 (8184.3)	1479.0 (4813.1)
	Single family attached	172.3 (859.5)	184.1 (920.7)	101.3 (514.3)	166.9 (843.4)	251.8 (1235)	124.7 (636.9)	71.3 (387.9)
	2–4 unit buildings	232.5 (655.2)	109.2 (324.9)	63.3 (208.2)	61.6 (225.2)	59.8 (206.5)	36.6 (144.5)	23.3 (107.5)
	5 or more unit buildings	116.6 (122.2)	95.6 (122.5)	125.6 (142.5)	249.5 (231.0)	197.2 (192.8)	138.2 (155.7)	61.1 (97.6)
	Mobile homes	8.9 (96.2)	10.8 (121.1)	15.5 (176.5)	105.8 (1087.9)	119.2 (1219.8)	120.3 (1228.8)	30.0 (332.8)
Commercial	Assembly	227.3 (122.7)	122.5 (84.7)	63.8 (64.0)	34.3 (47.0)	43.4 (52.9)	55.6 (57.6)	45.1 (52.3)
	Education	69.6 (22.2)	170.2 (46.3)	160.1 (46.3)	29.7 (15.8)	61.2 (24.3)	93.0 (31.9)	102.8 (33.3)
	Food sales	23.6 (29.3)	8.1 (21.2)	17.5 (27.3)	5.3 (17.1)	7.2 (20.2)	23.4 (32.5)	13.7 (25.4)
	Food service	33.3 (43.8)	13.9 (30.1)	12.0 (28.2)	10.2 (26.1)	12.8 (28.1)	25.2 (37.2)	23.1 (34.2)
	Health care	40.2 (15.8)	40.3 (16.2)	11.0 (9.4)	33.7 (14.4)	13.8 (9.2)	62.7 (21.6)	68.8 (23.1)
	Lodging	35.3 (11.2)	37.0 (13.0)	55.4 (17.6)	12.7 (7.2)	19.4 (8.7)	69.4 (20.8)	17.6 (8.5)
	Mercantile and service	217.3 (173.5)	122.5 (139.3)	200.5 (162.2)	57.3 (104.8)	110.4 (130)	164.3 (147.9)	110.6 (122.0)
	Office	242.7 (123.5)	56.2 (70.8)	130.4 (94.6)	38.3 (65.8)	111.3 (87.2)	82.6 (76.1)	48.7 (70.1)
	Other	111.6 (52.8)	71.1 (41.4)	30.9 (28.0)	6.0. (17.0)	39.2 (27.2)	35.0 (30.2)	11.1 (20.7)
	Public order/safety	7.3 (6.8)	5.2 (5.7)	8.7 (7.3)	2.9 (4.9)	3.2 (5.7)	31.5 (14.6)	17.4 (9.9)
	Warehouse and storage	72.2 (54.7)	35.1 (43.1)	45.6 (50.3)	25.6 (37.8)	96.7 (62.8)	136.1 (82.8)	216.3 (108.1)

Note: West North Central includes some buildings from Montana and East South Central includes some buildings from New Mexico that are part of the EIC.

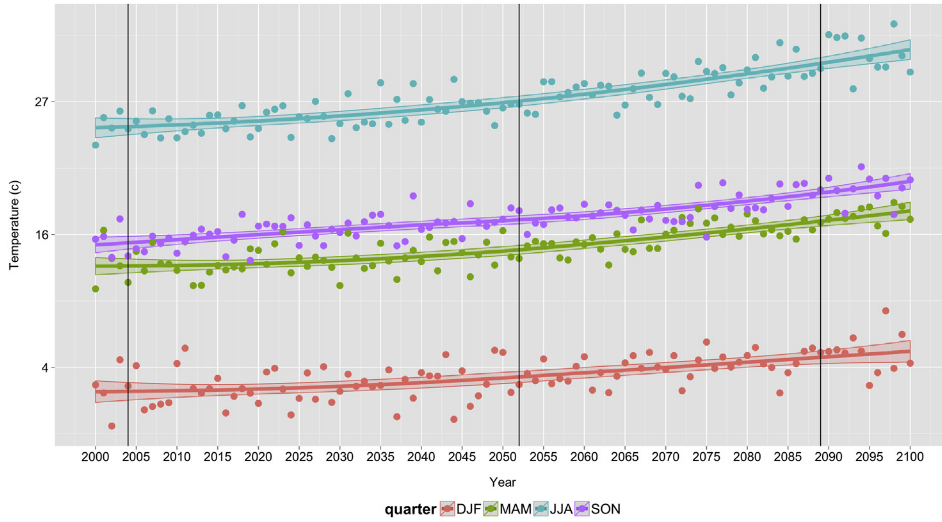

Fig. 4. Expected and actual quarterly temperatures for CASCaDE GFDL A2 scenario.

dataset. In this study, we chose to use the one downscaled from NOAA's GFDL (Geophysical Fluid Dynamics Laboratory) coupled ocean-atmosphere GCAM (CM2.1) in response to the A2 greenhouse-gas emissions scenario from the Intergovernmental Panel on Climate Change (IPCC) [34], which is representative of middle-of-the-road climate projections.

The daily precipitation and temperature time series over the period 1975–2100 from the CASCaDe GFDL historical period and A2 scenario were then fed into the VIC (Variable Infiltration Capacity) [18,25] by using it as a meteorological forcing disaggregator (see at http://www.hydro.washington.edu/Lettenmaier/Models/VIC/Documentation/VICDisagg.shtml) to generate hourly precipitation, temperature, short- and long-wave radiative fluxes, dew point temperature, and relative humidity using the MTCLIM (Mountain Climate Simulator) 4.2 algorithm [44,45]. Due to the lack of information for deriving wind speed, the climatological mean daily wind speed averaged over the period of 1979–2005 for each 1/8° grid cell were calculated and used to supplement the variables described above.

4.2.2. Selection of climate simulation years

Our objective was to run the BEND model at three trend representative years well-spaced across the 100-year period; nominally, we were hoping to select years near 2005, 2050, and 2095. The 100-year annual time series in Figs. 4 and 5 documents the significant year-to-year variation around the mean trend and shows that our target years were highly unrepresentative of the underlying trends. Hence, these plots highlight the necessity of a process to optimize the selection of trend-representative years. Fig. 4 shows the expected temperature (population weighted average) across the EIC for each of the four seasons. Within the climate change community, seasons are generally defined as, December to February, May to March, etc. [21]. While the trend is clear in all seasons, it is equally obvious that there is significant

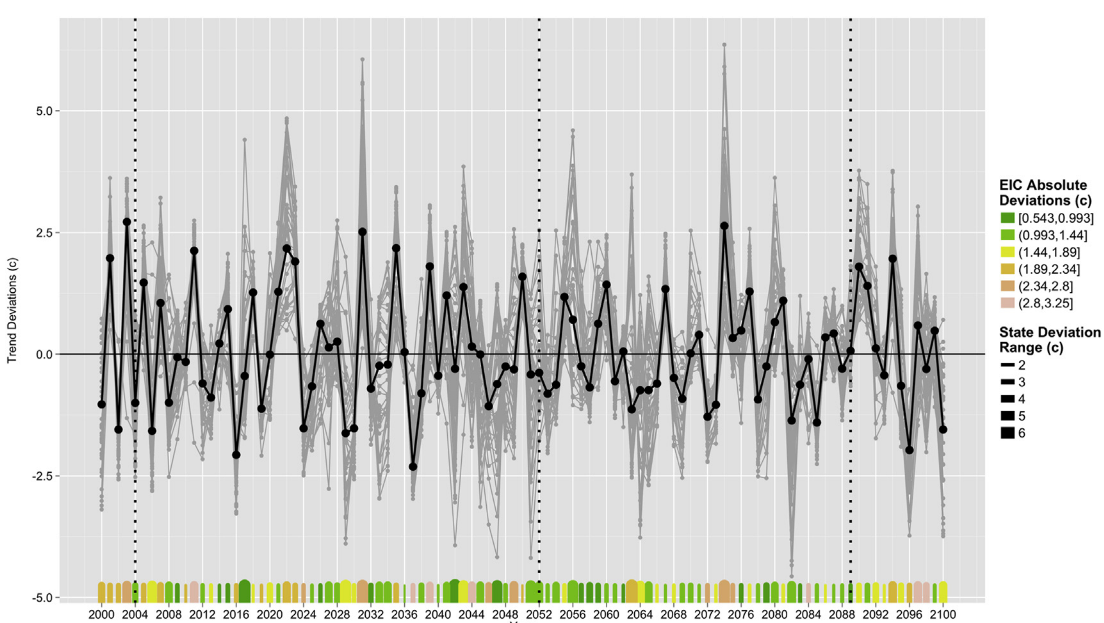

Fig. 5. CASCaDE GFDL A2 scenario seasonal averaged annual deviations from the 100-year trend for the EIC and individual states.

Table 3
Quarterly average temperature by census division for simulation Years.

Temperature (°C)	DJF			MAM			JJA			SON		
	2004	2052	2089	2004	2052	2089	2004	2052	2089	2004	2052	2089
New England	-2.0	-0.5	1.7	6.6	8.4	11.3	21.7	22.2	26.3	10.3	14.2	15.9
Middle Atlantic	-0.3	1.1	3.2	7.7	9.9	13.3	22.9	23.8	27.7	11.8	15.8	17.3
East North Central	-2.1	-1.3	1.4	7.1	9.7	12.7	21.3	24.7	28.3	11.1	14.8	16.7
West North Central	-2.2	-2.5	0.9	9.1	11.5	13.3	22.5	27.3	29.8	11.3	14.3	17.3
South Atlantic	9.6	8.9	11.2	17.1	18.2	21.6	27.3	28.1	30.7	17.6	21.3	22.7
East South Central	6.7	5.5	9.0	15.7	17.8	21.1	27.8	29.9	31.5	15.6	20.1	21.6
West South Central	9.3	7.5	12.0	18.5	21.5	23.4	28.8	32.4	33.4	17.7	21.7	23.7

All comparisons are across years. Minimum is white, maximum is red, intermediate values are relative shades of pink.

annual variation around the mean and most of the observed annual values lie outside the statistical error bounds on the mean trend. Fig. 5 shows the seasonal averaged annual deviations from the 100-year trend. Beyond the general EIC annual trend (Black line), each state has its own trend and annual deviation and we calculated the same seasonal averaged annual deviations for each state's trend (gray lines). The rug plot along the *x*-axis is colored to represent the absolute annual EIC deviation from the trend. The width of each rug line summarizes the spread of state deviations about their respective trends. The simulation years (2004, 2052, and 2089—marked with the vertical lines in each figure) were selected to meet the expectation that deviations of the annual observation from the trend for the EIC and each state were small while spreading the three simulation years across the 100-year period.

4.2.3. Climate summary

In addition to the temporal variation that drove the selection of the simulation years there is also significant spatial variation away from the central trend line within the target region. Tables 3 and 4 show this spatial variation for census divisions and selected states. States were selected to be geographically distributed and relatively high in population. Inspection of Table 3 reveals that the winter quarter of 2052 is cooler than in 2004 for all of the southern census divisions and one of the northern divisions as well. Similarly, in Table 4, half of the states show the same trend.

Fig. 6 provides average temperature data for the winter and summer quarters for each state. Here it is easy to see some overall trends as well as diversity across the region. For example, parallel to the census division of Table 3 it is clear that during the winter quarter the warmer regions (near the top of the list) are cooling between 2004 and 2052 and then rising in temperature for 2089. Whereas the colder regions (near the bottom of the list) are generally warming over the entire timeframe.

Population weighted average peak temperatures (Fig. 7) demonstrate a somewhat different pattern than the average temperatures with some winter temperatures increasing and some decreasing over both time periods. Summer quarter peak temperatures also show a significant amount of variation with some states showing little to no change and others increasing dramatically; additionally, many mid-century peak temperatures are substantially below the 2004 values. Finally, Table 5 demonstrates that at the winter 10th percentile and summer 90th percentile the trends are very similar to the average temperature trends. The combination of the average, 10th and 90th percentiles, and peak temperature indicate generally increasing temperatures with increased variation.

4.3. BEND energy and peak demand results

This section covers three areas of results from this analysis. The first area is electricity use and includes the changes in total annual consumption, electric cooling consumption, and peak electric demand. The next area covers annual energy consumption changes for cooling, heating, and the entire building. The final part presents resulting changes in consumption associated with specific building types.

4.3.1. EIC electricity usage changes

Tables 6 and 7 show the spatial variation of total annual electricity use, cooling electricity use, and peak electricity demand for census divisions and selected states within the EIC. Mid-century changes in total electricity consumption range from a modest decrease of 4% to an increase of 19% while end of century increases range from 9% to 30%. Selected state level values do not show significant differences from these values.

More dramatically, annual cooling energy use doubles (South Atlantic and East South Central) to more than triples (East North Central and West North Central) across the census divisions of the EIC by the end of the century. For the selected states, as one would expect, the variation is even greater with cooling changes ranging from doubling to a nearly nine fold increase in Minnesota (in an absolute sense the increase is rather modest when compared to states like Florida, however, given that Minnesota started with a

Table 4
Quarterly average temperature of selected states for simulation Years.

Temperature (°C)	DJF			MAM			JJA			SON		
	2004	2052	2089	2004	2052	2089	2004	2052	2089	2004	2052	2089
Florida	18.0	17.0	18.5	23.5	23.6	26.4	28.6	29.6	31.8	23.5	25.7	27.3
Louisiana	12.7	11.0	15.2	21.2	23.2	25.6	29.0	31.6	33.0	19.7	23.5	25.6
Minnesota	-7.7	-6.4	-4.0	5.0	6.7	8.1	18.9	23.2	27.0	8.2	10.4	14.6
Missouri	2.4	1.3	5.3	12.4	15.2	17.7	25.4	30.3	31.7	13.8	17.7	19.7
New York	-0.6	0.9	2.9	7.2	9.4	12.5	22.5	23.4	27.3	11.7	15.6	17.2
Virginia	3.7	4.1	6.3	12.0	13.5	17.6	25.2	26.1	29.4	13.9	18.2	19.3

All comparisons are across years. Minimum is white, maximum is red, intermediate values are relative shades of pink.

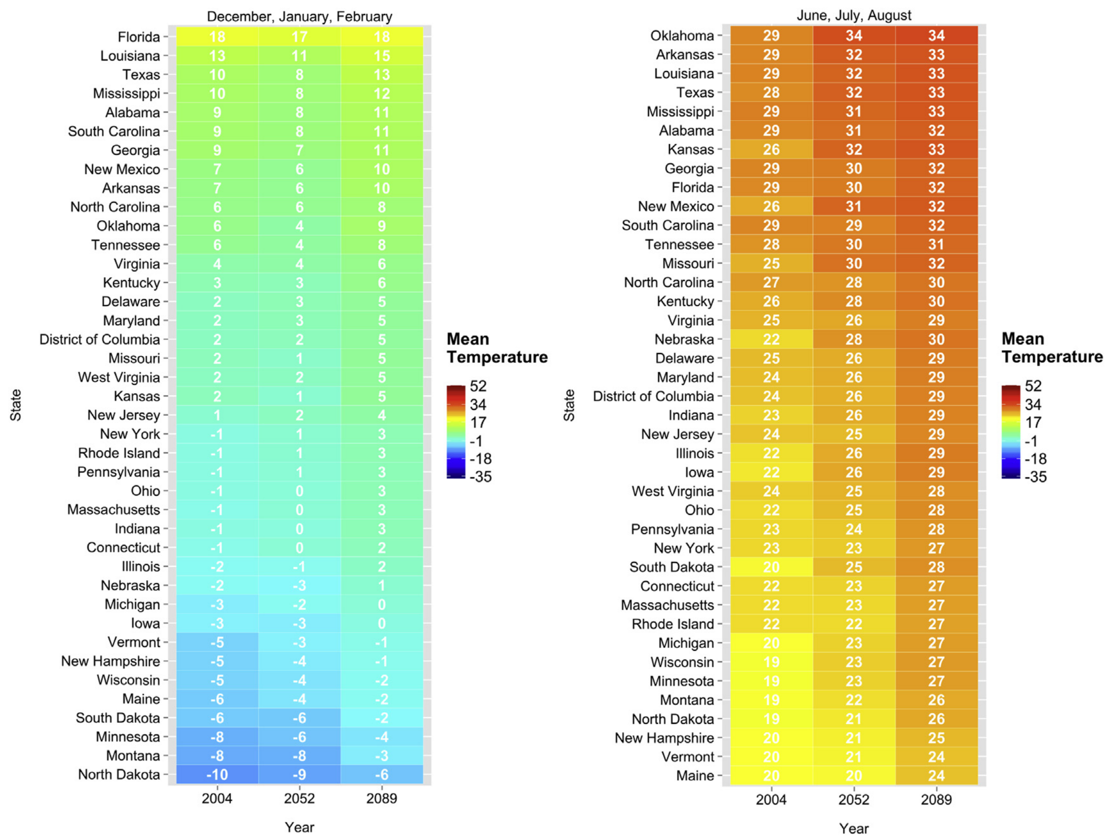

Fig. 6. DJF and JJA average temperatures (°C) by state for simulation years.

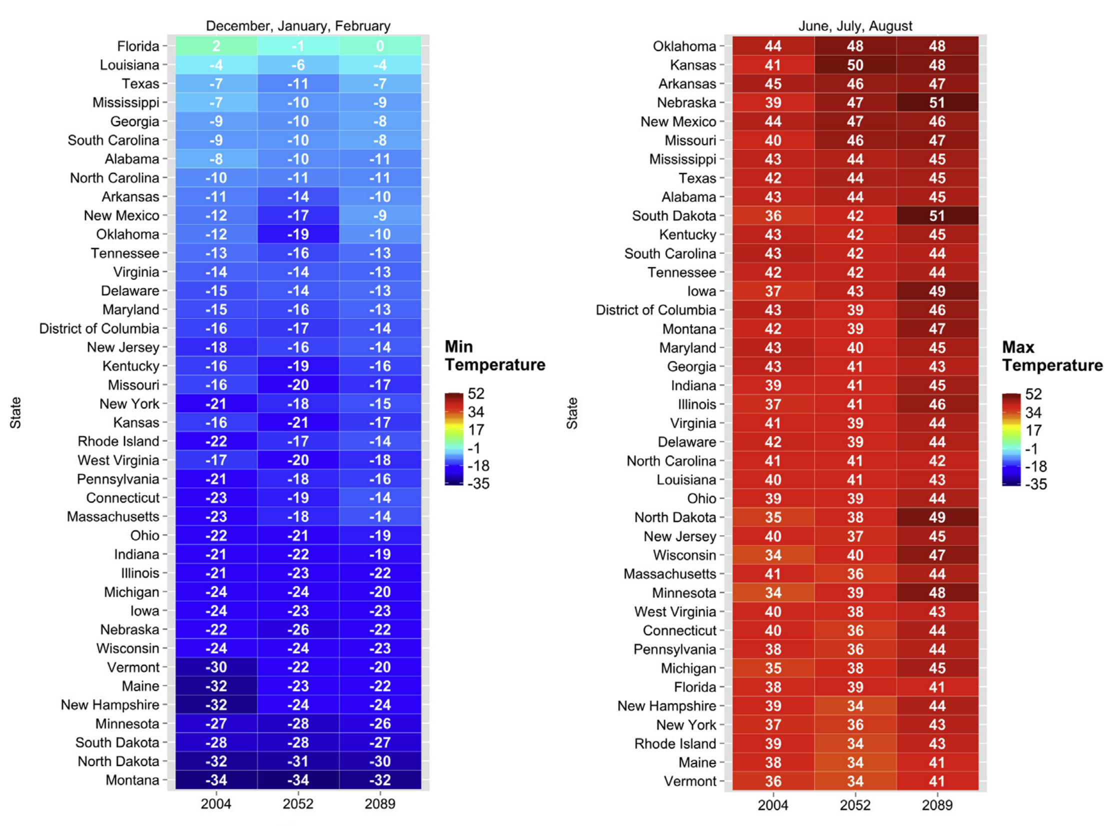

Fig. 7. Winter minimum and summer maximum temperatures (°C) by state for simulation years.

Table 5
Tenth and ninetieth percentile temperatures for simulation Years.

Temperature (°C)	2004		2052		2089	
	Winter 10th Percentile	Summer 90th Percentile	Winter 10th Percentile	Summer 90th Percentile	Winter 10th Percentile	Summer 90th Percentile
New England	-10.3	28.7	-7.8	29.1	-5.5	34.9
Middle Atlantic	-8.7	29.7	-5.9	30.6	-4.5	35.8
East North Central	-10.6	28.4	-8.9	32.2	-6.5	36.7
Central	-11.0	30.1	-11.6	35.0	-7.2	38.0
South Atlantic	1.0	33.7	0.8	34.3	2.8	36.9
East South Central	-2.5	35.0	-3.0	36.6	0.2	38.4
Central	0.1	35.9	-1.5	39.3	3.0	39.8

All comparisons are across years. Minimum is white, maximum is red, intermediate values are relative shades of pink.

Table 6
Electricity—total annual usage, cooling annual usage, and peak demand by census Division.

	2004			2052			2089		
	Total Annual Usage (PJ)	Cooling Annual Usage (PJ)	Peak Deman d (GW)	Total Annual Usage (PJ)	Cooling Annual Usage (PJ)	Peak Deman d (GW)	Total Annual Usage (PJ)	Cooling Annual Usage (PJ)	Peak Deman d (GW)
New England	348	36	39.5	336	37	29.1	392	99	51.0
Middle Atlantic	1054	140	95.2	1059	183	95.4	1251	392	145.7
East North Central	1228	143	125.6	1365	299	152.0	1529	484	198.2
West North Central	570	83	49.8	680	193	71.9	743	267	92.3
South Atlantic	1894	323	126.5	1980	433	117.0	2118	678	148.8
East South Central	632	82	47.2	694	130	44.9	687	167	54.8
West South Central	486	73	31.9	569	132	36.3	561	165	39.1

All comparisons are across years. Minimum is white, maximum is red, intermediate values are relative shades of pink.

very low base the percentage increase is very large). Note that these changes do not consider the addition of cooling to buildings that were not cooled in the 2005 baseline stock; this only includes the increased cooling demand for buildings that already have cooling.

Peak electricity demand changes were more variable, with mid-century changes ranging from a 26% decrease (New England) to a 44% increase (West North Central). By the end of the century, peak demand has increased in all census divisions by a range of 18%–85% with the selected states showing a range of 6%–136% which again demonstrates the increased specificity reveals greater levels of diversity.

Looking at changes across the EIC, the result of climate change as embodied in the IPCC A2 scenario from the CASCaDE dataset results in a 156% increase in cooling electricity consumption which causes a net 17% increase in total electricity consumption and a 42% increase in peak electricity demand. Thus, generating capacity will have to increase by roughly 42% to meet the higher demand, but this capacity will be only lightly utilized as the total consumption is increasing by only 17%. To make matters worse, there is a high amount of spatial variability across the region. For example, Minnesota shows an increased capacity requirement of about 136% to meet an increase in annual consumption of 23%, whereas Virginia only shows an increased capacity requirement of about 6% to meet an increase in annual consumption of 5%.

4.3.2. *EIC total energy consumption changes*

Looking at total energy consumption as shown in Table 8 presents a significantly different picture. Heating consumption

Table 7
Electricity—total annual usage, cooling annual usage, and peak demand for selected States.

	2004			2052			2089		
	Total Annual Usage (PJ)	Cooling Annual Usage (PJ)	Peak Deman d (GW)	Total Annual Usage (PJ)	Cooling Annual Usage (PJ)	Peak Deman d (GW)	Total Annual Usage (PJ)	Cooling Annual Usage (PJ)	Peak Deman d (GW)
Florida	620	144	28.5	671	184	30.9	753	279	37.3
Louisiana	187	32	9.3	213	54	10.0	217	75	11.5
Minnesota	135	4	9.9	144	16	12.9	166	40	23.3
Missouri	187	41	18.3	234	87	24.9	243	101	27.7
New York	484	59	39.3	484	78	39.9	565	167	64.0
Virginia	265	31	20.5	264	42	17.7	277	74	21.8

All comparisons are across years. Minimum is white, maximum is red, intermediate values are relative shades of pink.

dramatically decreases for both residential and commercial buildings resulting in a 5% decrease in building energy consumption by mid-century and an 11% decrease by the end of the century with no significant difference between the total percent changes in residential and commercial.

As expected (because the building stock and characteristics were held constant), for all quarters other than summer, over 97% of the change in facility energy consumption is due to changes in heating and cooling. The summer quarter has an additional increase in energy consumption due to greater ventilation energy requirements required to meet the increased cooling loads; this additional load change is missed in HDD/CDD and many other analyses. Hence, while the combined heating and cooling energy requirements (increased cooling and decreased heating) during the summer quarter increased by 38% in 2052 and 130% in 2089 relative to the 2004 base heating and cooling consumption, if the increased ventilation requirements are included, the rate of increase changes to 42% in 2052 and 143% in 2089. Similarly, using total facility consumption as the base shows increases of 9% and 30% for 2052 and 2089, respectively, when ignoring the change in ventilation consumption; these values increase to 10% and 33% when the increased ventilation energy requirements are included.

4.3.3. BEND building type specific results

If there is no significant difference in the total energy change between residential and commercial, why is it that we are suggesting that there is significant value in performing a large number of simulations with multiple building types, vintages, and sizes? Tables 6 and 7 have already hinted at the answer, showing that a high degree of spatial variability exists—but what is the source of this variability? Clearly some is weather; while there is a clear climate trend in all seasons shown in Fig. 4 there is still a fair amount of variability around that trend (i.e., weather). Additionally, when not taken in aggregate, the weather variations become more pronounced. However, there is another significant driver to the spatial variation in the change in energy consumption, and that is the difference in the mix and characteristics of the building stock; Table 9 begins to illuminate these differences. In Virginia for example, the change in energy consumption by the end of the century is highly dependent on building type, with values ranging from a decrease of 1.7% in offices to a decrease of 26.8% in warehouses. Single family houses show the least variation across states for the building types selected for Table 9 with a range from a 12.5% increase to a 15.8% decrease; while on the other end of the scale warehouse and storage shows a range from a 15.4% increase to a 31.4% decrease.

Exploring these results further, one can also see that there is significant variation across vintages within a particular building type and an individual state. For example, Table 10 shows that single family homes in Louisiana vary from a 0.5% decrease to a 5.9% increase while offices in Virginia vary from a 9.2% decrease to a 1.3% increase. Clearly different regional building cycles and patterns will result in different vintage distributions and different climate change impacts. Similar variations in climate impact are also seen across building size and other building characteristics that vary on a regional basis.

4.4. Discussion of BEND results

The BEND results are broadly consistent with findings from other studies where building energy models have been used [7]. used the EnergyPlus model for a small office building built to three different standards (no standard, current energy "standard" building equivalent to ASHRAE 90.1-2004, and a "low energy" version) to evaluate the impact of the climate change scenarios on annual commercial building energy use, although he did not report any data on peak demand. (Which this article does do for whole groups of buildings, highlighting the impact on peak cooling load). The most comparable scenario in his work is the A2 scenario fitted to the "standard" building for Washington, D.C., which can be roughly compared to BEND results for commercial buildings in Virginia for the newest and oldest vintage offices in Table 10. Crawley shows clear reductions in gas consumption for heating in his Figure 14 in the A2 case, but little difference in cooling. We echo his decline in heating energy, but show a largely offsetting increase in cooling energy. Thus, he shows about a four percent increase in annual energy consumption in the A2 case, while we show a smaller increase for the standard newer buildings. The BEND results show heating energy savings swamping cooling energy increases in older buildings while Crawley's Figure 15 "developing" no-standard building has substantial cooling increases. As exhibited in Fig. 4 above, year-to-year variability in weather can be significant. Crawley's Table 3 shows year-to-year variability in annual energy consumption for the standard building, even under current climate, can range from −6.3 percent to +2.5 percent.

Table 8
EIC region residential and commercial cooling, heating, and total energy Consumption.

Consumption (PJ)		2004			2052			2089		
		Cooling	Heating	Facility	Cooling	Heating	Facility	Cooling	Heating	Facility
Residential	DJF	3	5,504	8,457	3	5,343	8,294	6	4,388	7,312
	MAM	62	2,599	5,396	97	1,924	4,742	154	1,398	4,264
	JJA	475	0	2,616	703	0	2,869	1,235	0	3,457
	SON	87	1,934	4,361	235	1,332	3,906	291	927	3,551
	Total	626	10,037	20,829	1,038	8,599	19,811	1,685	6,712	18,585
Commercial	DJF	8	1,640	2,033	6	1,598	1,990	10	1,299	1,693
	MAM	46	814	1,251	61	629	1,080	94	456	940
	JJA	219	55	658	291	38	718	463	27	890
	SON	55	600	1,034	122	425	927	150	309	838
	Total	329	3,109	4,976	481	2,690	4,715	717	2,091	4,361
Total	DJF	11	7,144	10,490	10	6,941	10,285	15	5,687	9,005
	MAM	108	3,413	6,647	159	2,552	5,822	248	1,854	5,204
	JJA	694	56	3,274	993	38	3,587	1,698	27	4,347
	SON	142	2,533	5,395	357	1,757	4,833	441	1,236	4,389
	Total	955	13,146	25,806	1,518	11,289	24,527	2,402	8,804	22,946

All comparisons are across years. Minimum is white, maximum is red, intermediate values are relative shades of pink.

Table 9
Annual consumption and percentage change by state and building type.

Type	State	Annual Consumption (PJ) 2004	2052	2089	Percentage Change 2004 to 2052	2004 to 2089
Single Family Detached	Florida	466.9	496.7	525.0	6.4%	12.5%
	Louisiana	158.3	173.6	162.6	9.7%	2.7%
	Minnesota	536.4	504.4	485.0	-6.0%	-9.6%
	Missouri	450.0	455.7	403.9	1.3%	-10.2%
	New York	1290.4	1155.9	1086.6	-10.4%	-15.8%
	Virginia	433.9	416.5	395.8	-4.0%	-8.8%
Mercantile and Service	Florida	46.4	49.2	51.6	5.9%	11.2%
	Louisiana	14.1	15.5	14.6	9.8%	3.9%
	Minnesota	30.9	28.5	26.8	-7.9%	-13.3%
	Missouri	25.7	25.8	22.6	0.5%	-12.2%
	New York	82.3	73.4	67.5	-10.8%	-17.9%
	Virginia	31.8	30.4	28.2	-4.5%	-11.5%
Office	Florida	24.2	25.6	27.8	6.1%	15.2%
	Louisiana	6.7	7.5	7.5	11.8%	12.3%
	Minnesota	21.5	20.3	19.8	-5.6%	-7.9%
	Missouri	19.0	20.0	18.0	5.4%	-5.3%
	New York	71.1	64.4	61.5	-9.4%	-13.5%
	Virginia	12.4	12.4	12.2	0.0%	-1.7%
Warehouse and Storage	Florida	9.4	10.1	10.8	8.0%	15.4%
	Louisiana	3.2	3.6	3.2	12.8%	0.0%
	Minnesota	20.2	17.9	15.7	-11.4%	-22.3%
	Missouri	11.2	11.0	8.4	-1.5%	-24.8%
	New York	29.7	24.5	20.4	-17.5%	-31.4%
	Virginia	11.1	10.0	8.1	-9.9%	-26.8%

All comparisons are across years. Minimum is white, maximum is red, intermediate values are relative shades of pink.

Huang [17] used both single family houses and commercial office buildings to perform his analysis, which was done with the DOE-2 model, a predecessor to EnergyPlus. Huang analyzed Hadley model HadCM3 climate for four climate change scenarios (A1FI, A2M, B1, and B2M) at 16 U.S. locations with twelve commercial building prototypes, 16 multifamily prototypes, and six single-family prototypes. He estimated an increase in total energy consumption for the year 2080 of 9.9 percent in new single-family residential buildings in Lake Charles, LA. The BEND model estimated total energy use in Table 9 for single family detached homes in Louisiana for the year 2089 also rises, but by a slightly smaller value of 5.9 percent. Office buildings in Minnesota modeled with BEND showed a 7.9 percent reduction in energy consumption in 2089 by 7.9 percent; Huang's commercial buildings in Minneapolis showed slightly less reduction—3.7 percent to 4.1 percent, depending on vintage. BEND estimated cooling load for all

Table 10
Annual consumption and percentage change by state, building type, and vintage.

Type	State	Year	Annual Consumption (PJ) 2004	2052	2089	Percentage Change 2004 to 2052	2004 to 2089
Single Family Detached	Louisiana	1945	13.6	15.3	14.4	12.0%	5.9%
		1955	28.5	31.1	28.4	8.9%	-0.5%
		1965	19.4	21.1	19.4	8.7%	-0.2%
		1976	22.8	24.9	23.0	9.3%	1.0%
		1984	27.6	30.4	28.7	10.2%	3.9%
		1990	28.9	32.0	30.2	10.8%	4.5%
		2000	17.5	18.9	18.5	8.3%	5.9%
Office	Virginia	1945	0.8	0.8	0.8	-3.3%	-9.2%
		1955	0.5	0.5	0.5	-2.3%	-7.2%
		1965	2.7	2.7	2.6	-0.8%	-3.7%
		1976	0.7	0.7	0.6	-0.7%	-3.6%
		1984	4.2	4.2	4.2	1.2%	1.0%
		1990	3.0	3.0	3.0	0.3%	-0.4%
		2000	0.5	0.5	0.5	1.0%	1.3%

All comparisons are across years. Minimum is white, maximum is red, intermediate values are relative shades of pink.

buildings in Florida almost doubles from 2004 to 2089, while in Miami, Huang shows a 93 percent increase for single family housing and about a 60% increase for multi-family housing. Huang does not report commercial building cooling energy for Miami, but for the Southern Census region generally, he reports slightly greater than a doubling of cooling demand for all buildings by 2080, similar to the BEND result. Again the results are comparable in direction and magnitude. Differences between underlying assumptions such as the exact weather differences, vintages, and types of buildings, etc. make a straight comparison of annual energy difficult.

Results of this analysis compare well with other analyses at their finest level of specificity. This approach, however, provides an unprecedented level of specificity across multiple spectrums including:

- Spatial—Modeling geographic areas down to the one-eight degree grid with the ability to aggregate up to any larger geographic area
- Temporal—Annual, monthly, weekly, hourly, and sub-hourly modeling are possible
- Building Type—An array of building types possible; five residential and eleven commercial were used for this analysis.
- Building Vintage—Multiple vintage classes possible for each type of building; seven categories used here.
- Building Size—Limitless building size capability; six size bins were used.

This capability enables the ability to perform detailed hourly impact studies of building adaptation and mitigation strategies on energy use and electricity peak demand within the context of the entire grid and economy.

5. Future plans

There are three additional ways in which we are currently extending the BEND model. The first is designed to update the building stock and equipment in response to energy market conditions and socioeconomic change. To do this, BEND is being linked with the GCAM-USA [57] integrated assessment model within PRIMA so that market and regulatory factors that affect the efficiency of the building stock and energy-using equipment and cost of energy in GCAM-USA also affect the more disaggregated representation of the buildings in BEND. Thus, as the energy marketplace evolves in the 21st century, BEND will reflect these changes and produce a policy- and market-reflective detailed analysis of building energy demand that is also sensitive to climate and climate change. Second, we are working on linking the impact of heating and cooling hours, building diversity, and geographic diversity of hourly electricity demand produced by BEND with hourly industrial and transportation demand for electricity within the PRIMA framework. This overall MELD (Model of ELectricity Demand) will provide a basis for estimating consequences of electricity dispatch and impacts on reserve margin in the short run and for generation planning in the long run. The BEND model will contribute to PRIMA's feasibility analysis of the realism of energy supply scenarios produced at the aggregate level by GCAM-USA, by helping determine whether a) “required” generation is really required, and b) where new supplies are required, and where they could actually be sited. Third, the BEND model will also be calibrated for regions outside of the 14-state pilot region to contribute to energy–climate analyses in these regions as well.

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