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Future Meteorological Year weather data from IPCC Scenarios

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ABSTRACT

Climate change and anthropogenically-forced shift of weather in the future has the potential to impact energy use and resilience of the built environment and electric grids. This study analyzes this impact for 2030, 2045, and 2100 using Representative Concentration Pathways (RCP) scenarios defined in Intergovernmental Panel on Climate Change (IPCC) Assessment Report 6. The large, gridded simulation of meteorological variables for RCPs 2.6, 4.5, 6.0, and 8.5 are selected and downscaled to create an hourly weather file appropriate for building energy model simulation. This weather is then simulated on high performance computing resources to quantify the urban-scale impact of climate change on anticipated electrical load characteristics in a test area of Chattanooga, TN.

INTRODUCTION

Advances in high-performance computing have allowed for modeling at larger geographical scales and with more accuracy. Two fields that have largely benefited from these advances are climate modeling and urban-scale energy modeling. With building energy using more than 40% of all energy use in the United States (Administration 2018), understanding the relationship between the changing climate and the energy used by buildings is critical.

The IPCC created the RCP scenarios to assess future risks and to consider how decisions may affect possible futures. These climate scenarios were created to unify the many climate researchers across the globe with the same starting point. The RCPs contain this set of starting values with varying emissions up until the year 2100 for each pathway. Four RCPs were developed with the naming of the pathways coming from the level of radiative forcing (Wm-2) at the year 2100. Radiative forcing measures the influence a factor has in altering the balance of incoming and outgoing energy in Earths atmosphere. The different pathways represent projections varying from a decline in radiative forcing to a steady rise (Wayne 2013).

This study uses data from the Coupled Model Intercomparison Project 5 (CMIP5) where each RCP scenario is projected using an ensemble of climate models. Climate models have different initialization parameters and utilizing ensemble models allow for the quantification of variability in the simulations. While CMIP5 climate models may share a common lineage, and therefore common biases, the ensemble technique provides a more thorough solution than using any individual model (Flato and Rummukainen 2013). Variability and uncertainty are beyond the scope of this study. Therefore, only one ensemble (r1i1p1) was used for this analysis, but the methods presented in this paper could be extended to multiple ensembles in order to further quantify the effect of variability on building energy use.

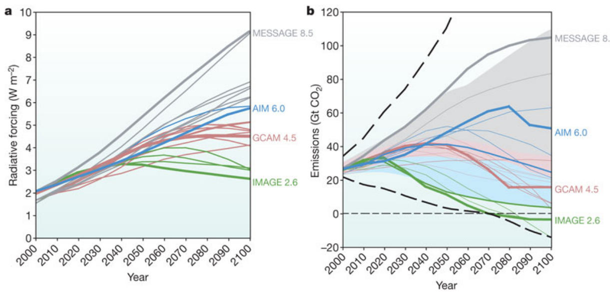

Figure 1: The Intergovernmental Panel on Climate Change (IPCC) defines Representative Concentration Pathways (RCP) scenarios that range from 1.5°C to 4.9°C by 2100. This could have significant impacts on building simulation, cities, and utilities. (Silverman 2012)

Error-informed urban scale building energy modeling has been done for the city of Chattanooga, TN. Partnering with the Electric Power Board (EPB) of Chattanooga has allowed for empirical validation of models created by comparing the simulation results to 15-minute electricity data from smart meters in more than 178,000 buildings. These models are created in several steps. The structure of each building is obtained by combining 2D footprints from deep learning computer vision segmentation algorithms with LiDAR datasets. Once the structure of the building is established, systematically assigning building type and vintage (based on the Department of Energy's Prototype Buildings (DOE 2019)) allows for a more representative model of what equipment would be in the building and results in a more accurate model. This process is combined and applied under the term Automatic Building detection and Energy Model creation (AutoBEM) (New et al. 2018).

There are a number of prevalent concerns regarding the

IPCC scenarios and how possible climate trajectories may impact many of the systems on which humans are reliant. Many researchers in the ASHRAE and IBPSA communities are interested in Future Meteorological Year (FMY) weather files so that future impacts of weather shift can be accounted for in building energy models. ASHRAE's Standing Standard Project Committee 169 (SSPC169) defines "Climatic Data for Building Design Standards" and plans to release climate-informed shifts to weather and sizing data for heating, ventilation, and air conditioning (HVAC) systems in the next release of the handbook. At a larger scale, generation utilities have to plan to handle higher cooling loads and electrical distributors need to plan infrastructure deployment (feeders, substations, transformers) to accommodate weather-induced shift of building energy loads within their service territory.

With EnergyPlus being used to simulate building energy models for buildings within the utility, different weather files can readily be used in the simulation. For this analysis, a representative building of each building type was selected and simulated for a baseline year (2015) as well as each of the RCPs for the given future years of 2030, 2045, and 2100. These results were then scaled up to represent climate change impacts to the entire utility.

Methodology

Weather can significantly impact non-base HVAC loads within a building. The weather files for meteorological years acquired from different providers can impact energy use ±7% and monthly heating/cooling loads by ±40% in different building types (Bhandari and New 2012). However, simply describing it as weather and interchanging a single file masks the complexity of the underlying meteorological variables. While dependent upon primary HVAC system and other variables, changes in dry bulb and/or wet bulb (for a hydronic system) tend to dominate the impacts of HVAC energy use. Figure 2 quantifies this impact using DOE's Medium Office Reference Building (Deru et al. 2011).

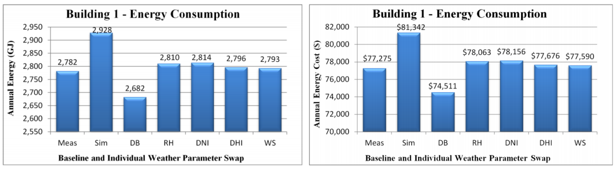

Figure 2: Dry bulb temperature, on average, tends to dominate changes in building energy use as shown here for DOE's Medium Office reference model. The next most important meteorological variables tend to be relative humidity, direct normal incident radiation, direct horizontal incident radiation, and wind speed.

By assuming the IPCC scenarios as the basis for our analysis, the climate model output data (Table 1) had to be morphed into a format that EnergyPlus could use to simulate buildings. This study used (actual) meteorological year weather data from the Chattanooga airport from calendar year 2015 as well as the typical meterological year (TMY) as the baseline weather file. This file was then morphed based on the IPCC scenarios. IPCC data was used for all meteorological variables with the exception of wind speed, which was left unchanged from the original TMY data.

Table 1: Description of IPCC climate model characteristics used in this study to determine weather impacts to a utility.

Project	CMIP5
Model	MRI-CGCM3
Modeler	Meteorological Research Institute
Experiment	2.6, 4.5, 6, 8.5
Time Frequency	3hr
Modeling Realm	atmos
Ensemble	r1i1p1
Version	20120119

Table 2: Name and units of meteorological variables found in IPCC data.

Variable Long Name	Variable Short Name	Unit
Near-Surface Air Temperature	tas	K
Surface Downwelling Shortwave Radiation	rsds	W m-2
Surface Diffuse Downwelling Shortwave Radiation	rsdsdiff	W m-2
Surface Air Pressure	ps	Pa
Near-Surface Specific Humidity	huss	1

The most impactful meteorological variables (Figure 2) were identified for each of the RCPs and future years. The data for each scenario was downloaded in netcdf format and the data was morphed into a format that was required by EnergyPlus. Some of the things that had to be done included selecting the area of the Earth that was being used for analysis (Chattanooga), unit conversions, as well as down-scaling from 3-hour data to hourly data. This downscaling was done linearly, with awareness that this simple method is unlikely to accurately represent the variability of some meteorological variables (e.g. solar radiation). The necessary variables were then entered into an EnergyPlus Weather (EPW) editing software "Elements" to create twelve weather files.

The next step was to create the building models. Each of DOEs reference buildings(Deru et al. 2011) for the area (i.e. 97 building type and vintage combinations) was simulated with 2015 weather. The simulated electrical profile of 15-minute Energy Use Intensity for a year was then compared to actual 15-minute EUI data from

Table 3: Breakdown of building vintages by conditioned area and percent of buildings identified in EPB's service area (New and Campbell 2019).

BuildingType	Area	Percent of Buildings in EPB Area
HighriseApartment	1767	5.46%
Hospital	756	0.79%
Residential (IECC)	3459	68.29%
LargeHotel	1197	0.49%
LargeOffice	1353	5.47%
MediumOffice	3091	0.00%
MidriseApartment	1930	1.92%
Outpatient	975	0.10%
QuickServiceRestaurant	2354	0.31%
RetailStandalone	1436	0.00%
RetailStripmall	4163	0.03%
SecondarySchool	4521	0.00%
SmallOffice	1476	0.01%
Warehouse	9950	17.14%

each of the 178,368 buildings to assign a building type that most closely matched each buildings electrical use profile(Garrison, New, and Adams 2019). The fourteen building types that best represent the largest percentage of buildings in EPBs service territory are shown in Table 3.To reduce computational burden, one building of each type was chosen to represent a portion of the service areas buildings with the table providing the multiplier for utility-scale impacts. A representative sample of each building type in the EPB service area was chosen based on the median area. The physical makeup of these buildings was determined by combing 2D footprints from deep learning computer vision segmentation algorithms with LiDAR to obtain height. This structure was associated with an electrical meter by finding the smallest distance between the GPS coordinates of each electrical meter with the buildings centroid. Importantly, since the utility partner provides only electricity (i.e. not natural gas), all building types were assumed to have both electric heating and electric cooling for their HVAC systems. This has the effect of defining an optimistic value for maximum technical adoption potential of energy and demand savings on the utility's electrical distribution network.

The models were simulated with a baseline meteorological year file (2015) as well as with the 12 RCP, future year combinations. Baseline results were compared (not calibrated) to the real electricity data for quality assurance and building type assignment (Garrison, New, and Adams 2019). The referenced paper shows a non-calibrated, crude approach to urban-scale energy modeling compared against 15-minute CV(RMSE) and NMBE (not traditional monthly or hourly values) yields variation by building type from 87–531,000% and 3.7–478,000%, respectively. The authors anticipate that future urban/multi-scale empirical validation studies will show significant variability in the distribution of model accuracy across each building, but that the aggregation to portfolios of buildings will show significantly less error with enhanced community attention to bias (i.e. central limit theorem, law of large numbers). This study leverages those mathematical principles by using a representative building of each type for aggregate electrical energy use impacts (e.g. multiplying by the number of those buildings in the utility's service area) that show more certain future weather and meteorological impacts on area-wide building electrical consumption.

Results

Weather files

An initial investigation into the weather files themselves allows for an intuitive understanding underlying the building simulation results. The averages for the most significant weather variables are shown in the Appendix (Table 4). The first observation that is apparent is the difference between average dry bulb temperature between 2015, TMY, and the climate scenarios. The baseline files temperature and pressure is significantly higher than the RCP scenarios. This difference is likely explained by how coarse the grid points are for this batch of climate models. Rather than choosing an exact location, the grid point with the location that was closest to the coordinates of Chattanooga was selected. For this reason, total energy values are shown as the different RCPs and years may still be effectively compared. It also seems that 2015 was a significantly warmer year than the TMY for Chattanooga.

Comparing only the scenarios across the years in (figure 3), the temperature values make sense and the trend is apparent. For the scenario with the greatest mitigation (RCP 2.6), the dry bulb temperature remains relatively constant while the dew point decreases slightly on average by 2100. For the highest radiative forcing scenario (RCP 8.5), the average temperatures increase significantly. There is a greater standard deviation as years go farther into the future for most cases other than for the RCP 8.5 scenario in which the 2030 year has the greatest standard deviation. This case is interesting as the temperatures are also significantly lower than the other 2030 scenarios which is unexpected given the increase in radiative forcing.

Energy Use

The simulated energy use results are shown for the EPB area in (Figure 4) in GWh. The Tables containing all results for energy use for both individual buildings as well as scaled to the EPB area can be found in the Appendix (Tables 5, 6). While TMY (typical) and 2015 (actual) data are provided for completeness, discontinuities between these and future years (IPCC) should be disregarded; only

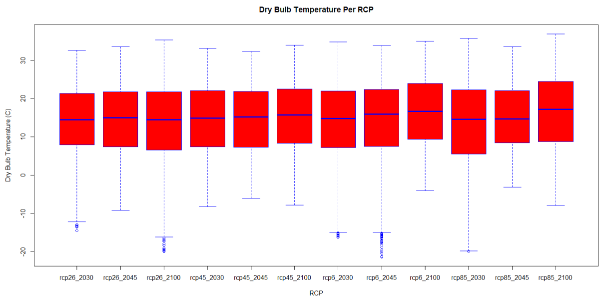

Figure 3: Box and whisker plot of dry bulb temperature (most impactful variable) across RCPs and years.

2030, 2045, and 2100 are from the same location and model source for direct comparison. It is important to note that only static multipliers are used on existing building simulations with different weather files; the current study does not consider sprawl of the built environment or land use changes during those time periods.

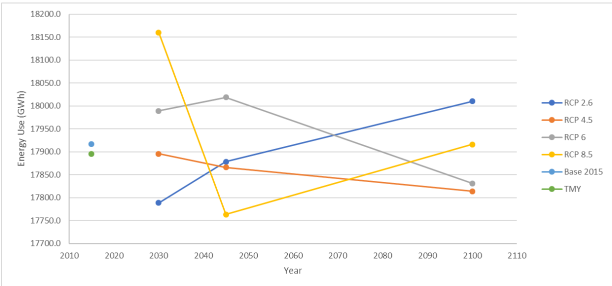

Figure 4: Simulated energy use (GWh) for the EPB service area across all RCP scenarios and years with baseline years included.

The trend seems somewhat clear other than RCP 8.5, 2045. The highest mitigation scenario (RCP 2.5) increase in energy from 2030 to 2100 while the other three scenarios decrease in total energy with a change proportional to their scale of emission escalation.

Taking a closer look at cooling and heating energy for the building type that dominates the EPB service area (IECC - Residential) makes the trend more clear. The heating energy and cooling energy for a representative residential buildings are shown in (Figures 5, 6).

It is apparent that the heating energy makes a greater percent of total energy use than cooling energy for the residential buildings which explains the increase in energy use for RCP 2.6 with the dry bulb temperature decreasing. This also explains the decrease in total EPB service area energy for the other three scenarios without nearly as much emission meditation. In addition to the scale of heating to cooling energy; the change in heating energy

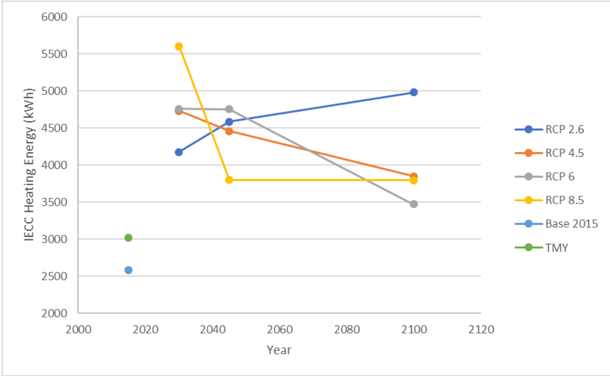

Figure 5: Heating Energy use (kWh) for a representative EPB IECC building across all RCP scenarios and years with baseline years included.

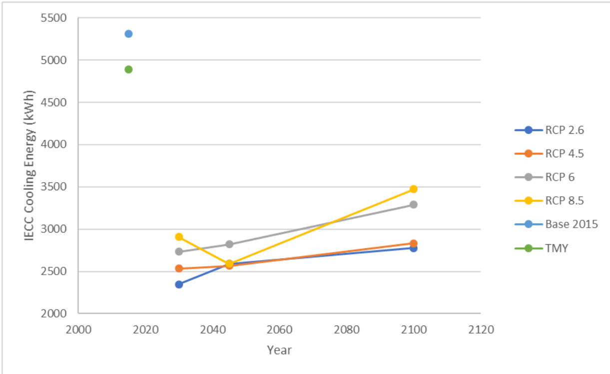

Figure 6: Cooling Energy use (kWh) for a representative EPB IECC building across all RCP scenarios and years with baseline years included.

is greater than the change in cooling energy across the scenarios. For RCP 8.5, from 2030 to 2100, the heating energy decreases by about 1,800 kWh while the cooling energy only increases by about 550 kWh.

These total energy use results are significant. This states that with increasing temperatures for RCP scenarios, total energy use will actually decrease in Chattanooga. It should be noted that this could be impacted by the assupmtion that all buildings in the EPB area use electricity for heating while in reality, this would not be exactly the case.

Demand

Utilities are very sensitive to pricing and peak generation hours for each calendar month. This can often constitute 25% of a non-residential energy bill and is the worst-case scenario that utilities have to build or purchase power for to supply without blackouts or brownouts. As such, many utilities and organizations are interested in how to best adapt their infrastructure to be resilient against challenges

from climate change.
The demand results are shown in the Appendix (Table 7). The high and low mitigation scenarios (2.6, 8.5) for years 2030 and 2100 are shown in (Figure 7).

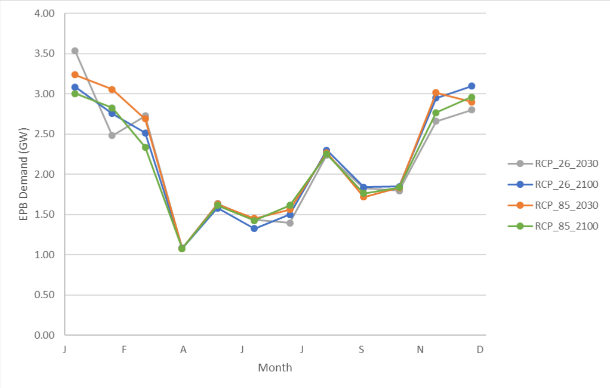

Figure 7: Cooling Energy use (kWh) for a representative EPB IECC building across all RCP scenarios and years with baseline years included.

The demand results show some interesting trends. For example, for RCP 2.6, the demand results for the winter are mixed over time with demand decreasing significantly during January from 2030 to 2100 but increasing in February and December. One would expect the demand to increase from 2030 to 2100 in the winter in the high mitigation scenario as temperatures decreased. It could be that the peak demand hour could have changed as climate model forecasts move farther into the future. Also for RCP 2.6, summer cooling demand is lower for the peak hours of June and July. For the high emission, low mitigation scenario; heating demand decreases significantly in January and February (as expected), but slightly increases during December which could be a similar situation as the low mitigation scenario for the Winter months in which the peak how may adjust based on the different climate scenario.
It is interesting to note that the transitional months of the Spring and Fall remain relatively constant across the extreme years and RCPs with more minor changes in the Summer months than the Winter months as well. This observation makes sense with the total energy use as the change in cooling energy over different RCPs and years was smaller than the change in heating over the same scenarios.

CONCLUSION

This paper has described methods for translating IPCC RCP scenario data for 2030, 2045, and 2100 into EnergyPlus weather files. DOE prototype building energy models were simulated with these weather scenarios to assess climate change impacts to building energy use for an electrical utility using a baseline of calendar year 2015. Some of the limitations of these particular climate models were shown by how coarse the granularity is wihtin the climate grid. Nevertheless, the buildings could be simulated and compared down the RCP pathways for useful information. Dry-bulb temperature is the most influential variable in affecting simulated building results and it was shown to decrease over time for RCP 2.6 while it increased over time for RCPs 4.5, 6, and 8.5. This led directly to an increase in total energy from 2030 to 2100 for RCP 2.6 and a decrease in total energy from 2030 to 2100 for RCPs 4.5, 6, and 8.5. This was shown to be caused by the larger proportion of total energy used by heating electricity vs cooling electricity as well as the larger decrease in decrease in heating energy vs decrease in cooling energy for the EPB area.
The monthly demand profile mostly followed these same patterns as the total energy use. Demand decreases for low mitigation scenarios and increases for high mitigation scenarios in the winter. There are some exceptions likely due to and adjusted demand peak hour as forecasts go farther into the future. Spring, Summer , and Fall months were mostly unchanged comparatively across RCPs and into the future as cooling energy was impacted less by the climate scenarios.

Future Work

There are several opportunities to further extend this work or build upon the techniques employed. The authors intend to simulate all 178,000 buildings rather than selecting a representative sample and scaling up to show variability distributions rather than portfolio-level performance. Several shortcomings with the current study could be addressed including: assumption of all-electric HVAC, no urban sprawn, no land use changes, linear interpolation of 3-hour meteorological variables, and more direct comparison between current and future weather.
Newer, higher fidelity climate models could be utilized. The models used in this study were created in 2012 and thus are outdated but had to be used as they were the last complete simulations of all the RCPs for these years. Higher temporal resolution would allow avoidance of interpolation for hourly values currently required for building simulation, and higher geographical resolution (or downscaling) could allow more direct comparison to existing weather stations or even building-specific weather data.
Empirical validation (with error/bias distributions), sensitivity analysis and uncertainty quantification could lead to new best practices, metrics, guidelines, or standards for urban/multi-scale building energy modeling. Stakeholder-specific metrics regarding traditional energy use, more difficult time-sensitive demand management, and ill-defined resilience could allow urban/multi-scale modeling

to impact application areas such as assessing financial risk of portfolio-level investments for building upgrades that could significantly impact existing markets and informed adaptions to the built environment.

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NOMENCLATURE

1. AutoBEM – Automatic Building detection and Energy Model creation
2. EPB – Electric Power Board of Chattanooga, Tennessee
3. EPW – EnergyPlus Weather file
4. FMY – Future Meteorological Year
5. IPCC – Intergovernmental Panel on Climate Change
6. RCP – Representative Concentration Pathways scenarios
7. SSPC – Standing Standard Project Committee
8. TMY - Typical Meterological Year

Appendix

Table 4: Average values of meteorological variables found in EPW files used for simulations.

RCP	dry_bulb (C)	dew_point (C)	relative_humidity	pressure (Pa)	direct_normal (Wh/m2)
2015	16.94	10.69	69.89	99457.72	186.61
TMY	15.77	9.93	71.23	99338.68	168.23
rcp26_2030	14.16	9.21	73.73	97559.08	191.26
rcp26_2045	14.48	9.36	72.82	97670.31	200.56
rcp26_2100	14.12	8.85	72.45	97543.24	203.67
rcp45_2030	14.44	9.52	73.97	97641.68	189.23
rcp45_2045	14.52	9.20	72.01	97622.84	199.38
rcp45_2100	15.35	10.42	73.91	97453.98	198.65
rcp6_2030	14.21	8.92	71.98	97624.47	197.84
rcp6_2045	14.48	8.92	70.78	97679.60	201.19
rcp6_2100	16.33	11.74	75.76	97465.89	193.80
rcp85_2030	13.68	7.47	68.25	97527.67	214.44
rcp85_2045	14.98	10.23	74.73	97415.45	191.92
rcp85_2100	16.47	11.71	74.97	97427.03	189.86

Table 5: Simulation energy outputs for individually simulated buildings across RCP scenarios and years (MWh)

BuildingType	Base_2015	TMY	RCP_26_2030	RCP_26_2045	RCP_26_2100	RCP_45_2030	RCP_45_2045	RCP_45_2100	RCP_6_2030	RCP_6_2045	RCP_6_2100	RCP_85_2030	RCP_85_2045	RCP_85_2100
RetailStandalone	74.7	74.7	72.8	73.5	74.1	73.5	73.3	73.4	74.0	74.2	74.1	74.9	72.9	74.7
Hospital	1101.8	1101.9	1105.3	1105.2	1106.0	1105.5	1105.3	1104.5	1106.1	1105.9	1104.4	1106.6	1104.7	1104.4
LargeOffice	761.0	760.9	763.3	763.8	764.8	763.9	763.8	763.4	764.8	765.2	763.8	765.8	763.1	764.2
QuickServiceRestaurant	227.7	228.4	216.9	220.3	223.7	221.2	220.1	219.7	223.1	223.9	223.8	227.8	217.0	227.5
IECC	43.2	43.3	41.8	42.5	43.1	42.5	42.3	42.0	42.7	42.8	42.1	43.8	41.7	42.6
LargeHotel	649.1	648.9	647.7	648.3	649.5	648.5	648.3	648.0	649.4	649.8	648.3	650.6	647.6	649.2
MediumOffice	114.7	114.7	117.2	117.3	118.6	117.6	117.3	116.8	118.7	118.6	117.1	119.7	116.7	117.5
Outpatient	164.3	165.7	170.4	170.8	171.0	170.4	170.0	169.6	169.0	167.7	169.5	168.7	170.8	169.3
SmallOffice	29.0	28.8	27.4	27.6	27.8	27.6	27.4	27.5	27.8	27.9	27.8	28.1	27.3	28.0
RetailStripmall	86.1	80.7	86.3	86.9	87.5	87.3	87.0	86.7	87.8	87.9	87.9	88.5	86.4	88.7
Warehouse	53.0	52.1	54.2	53.9	54.8	54.1	54.0	54.2	55.6	56.0	53.9	55.8	53.9	54.1
MidriseApartment	79.8	81.2	78.6	79.9	81.4	80.0	79.6	78.8	80.7	80.5	79.6	83.1	78.1	80.9
HighriseApartment	109.6	109.6	108.9	109.5	110.6	109.7	109.5	109.0	110.3	110.6	109.0	111.6	108.8	109.8
SecondarySchool	411.8	415.1	410.7	414.0	422.2	413.9	413.7	413.9	422.0	422.6	418.0	430.4	409.9	420.7
RCP Average	279.0	279.0	278.7	279.5	281.1	279.7	279.4	279.1	280.9	281.0	279.9	282.5	278.5	280.8
RCP Total	3905.9	3905.8	3901.4	3913.6	3935.2	3915.9	3911.8	3907.4	3932.0	3933.6	3919.1	3955.5	3898.8	3931.6
RCP Median	112.2	112.2	113.0	113.4	114.6	113.7	113.4	112.9	114.5	114.6	113.1	115.7	112.7	113.6

Table 6: Simulation energy outputs for simulated buildings scaled to EPB area across RCP scenarios and years (GWh)

BuildingType	Base_2015_EPB	TMY_EPB	RCP_26_2030_EPB	RCP_26_2045_EPB	RCP_26_2100_EPB	RCP_45_2030_EPB	RCP_45_2045_EPB	RCP_45_2100_EPB	RCP_6_2030_EPB	RCP_6_2045_EPB	RCP_6_2100_EPB	RCP_85_2030_EPB	RCP_85_2045_EPB	RCP_85_2100_EPB
RetailStandalone	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
Hospital	1544.7	1544.9	1549.6	1549.5	1550.6	1549.8	1549.6	1548.5	1550.7	1550.5	1548.3	1551.4	1548.8	1548.4
LargeOffice	7422.0	7420.6	7444.9	7449.3	7459.3	7450.2	7449.5	7445.2	7459.5	7462.9	7449.0	7469.1	7442.5	7453.0
QuickServiceRestaurant	125.4	125.8	119.5	121.4	123.3	121.9	121.3	121.1	123.0	123.4	123.3	125.5	119.6	125.3
IECC	5263.4	5264.1	5087.4	5167.5	5241.6	5176.6	5153.4	5110.4	5202.2	5214.0	5126.4	5332.5	5076.8	5188.4
LargeHotel	569.2	569.1	568.0	568.6	569.6	568.8	568.6	568.3	569.5	569.9	568.5	570.6	567.9	569.3
MediumOffice	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	1.0	0.9	0.9
Outpatient	28.4	28.7	29.5	29.5	29.6	29.5	29.4	29.3	29.2	29.0	29.3	29.2	29.6	29.3
SmallOffice	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
RetailStripmall	3.9	3.6	3.9	3.9	3.9	3.9	3.9	3.9	4.0	4.0	4.0	4.0	3.9	4.0
Warehouse	1617.3	1591.2	1654.8	1647.0	1674.9	1651.7	1650.4	1654.5	1698.8	1710.5	1646.7	1704.6	1646.2	1650.9
MidriseApartment	273.5	278.3	269.6	273.9	279.1	274.3	272.9	270.1	276.7	275.9	272.7	285.0	267.7	277.2
HighriseApartment	1066.1	1066.4	1058.9	1065.2	1075.7	1066.5	1064.6	1060.0	1073.0	1076.0	1060.5	1085.9	1058.0	1067.8
SecondarySchool	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.9	0.8	0.8
RCP Average EPB	1279.7	1278.2	1270.6	1277.0	1286.4	1278.3	1276.1	1272.4	1284.9	1287.0	1273.7	1297.2	1268.8	1279.7
RCP Total EPB	17916.5	17895.2	17788.6	17878.3	18010.2	17895.8	17866.1	17813.8	17989.2	18018.5	17831.3	18160.3	17763.4	17916.2
RCP Median EPB	199.5	202.1	194.6	197.7	201.2	198.1	197.1	195.6	199.8	199.6	198.0	205.2	193.6	201.3

Table 7: Simulation demand outputs for simulated buildings scaled to EPB area across RCP scenarios and years (GW)

RCP	Jaunary	February	Jaunary	April	May	June	July	August	September	October	November	December	**Average Demand EPB**	**Total Demand EPB**
Base_2015	3.57	2.98	2.94	1.33	1.82	1.61	1.77	2.55	2.02	2.07	3.01	2.80	2.37	28.45
TMY	3.23	2.53	2.36	1.29	1.78	1.62	1.52	2.42	1.74	1.93	2.71	2.85	2.16	25.97
RCP_26_2030	3.53	2.48	2.72	1.08	1.64	1.44	1.39	2.24	1.83	1.79	2.66	2.80	2.13	25.61
RCP_26_2045	3.24	2.45	2.41	1.09	1.58	1.43	1.50	2.29	1.81	1.78	2.94	3.06	2.13	25.59
RCP_26_2100	3.08	2.75	2.52	1.08	1.58	1.33	1.50	2.30	1.84	1.85	2.95	3.10	2.16	25.87
RCP_45_2030	3.48	2.44	2.34	1.09	1.58	1.38	1.46	2.19	1.74	1.83	2.72	3.02	2.10	25.24
RCP_45_2045	3.14	2.82	2.76	1.08	1.56	1.39	1.44	2.20	1.66	1.83	2.67	2.91	2.12	25.47
RCP_45_2100	3.28	2.81	2.74	1.09	1.62	1.50	1.44	2.39	1.85	1.78	2.96	3.03	2.21	26.47
RCP_6_2030	3.00	2.90	2.34	1.09	1.62	1.49	1.52	2.39	1.78	1.80	3.00	3.23	2.18	26.16
RCP_6_2045	3.27	2.80	2.47	1.09	1.60	1.46	1.44	2.31	1.84	1.87	3.05	3.09	2.19	26.28
RCP_6_2100	2.91	2.73	2.34	1.08	1.66	1.47	1.45	2.42	1.97	1.93	2.81	3.04	2.15	25.80
RCP_85_2030	3.24	3.05	2.69	1.08	1.63	1.45	1.56	2.27	1.72	1.83	3.01	2.90	2.20	26.44
RCP_85_2045	3.27	2.60	2.50	1.08	1.60	1.44	1.45	2.34	1.83	1.77	2.72	2.99	2.13	25.59
RCP_85_2100	3.00	2.83	2.34	1.08	1.61	1.42	1.62	2.25	1.76	1.84	2.77	2.96	2.12	25.48