



MORPHING CLIMATE DATA TO SIMULATE BUILDING ENERGY CONSUMPTION

Luke Troup and David Fannon
Northeastern University, Boston, MA

ABSTRACT

This research investigates projecting and ‘morphing’ weather files for building energy simulations in order to calculate lifetime energy consumption. Multiple weather-file modification tools and morphing methodologies have been developed over the last couple of decades to account for variable climate patterns. Two tools were used in this work to evaluate potential climate projections and explore differences in uncertainty and assumptions when applied to the same set of prototype buildings. The research uses Boston, Miami and San Francisco as diverse cities representing different climate challenges and to study regional effects on complete long-term energy use in future scenarios. The most recent climate projections from the IPCC and UKCP09 are compared with historic projections to understand how variances in algorithms alter building energy use over time. The comparison of energy simulations using ‘morphed’ weather files under different methodologies, current climate forecasts and adjusted emissions scenarios are visualized and discussed to demonstrate the impact of climate change on building energy consumption. Some results are to be expected, but Boston’s decreasing future energy use intensity (EUI) and variations in rates of change exhibit the importance of considering future climate projections in building energy simulations.

INTRODUCTION

Scientific research shows our global climate is changing and more recently anthropogenic influences on emissions are breaking historical records (IPCC 2014). These changes – along with our growing understanding of them – result in constantly evolving climate science. These changes directly affect building science and the development of our built environment. As the building industry turns increasingly towards sustainable and resilient approaches, accounting for dynamic climate variables and projections becomes progressively more difficult. Buildings designed today

must adapt to our rapidly changing environment, while mitigating further impacts. By aiming to reduce energy consumption, we can decrease emissions and design our new buildings for higher performance and longevity.

Building energy simulations require climate data files to calculate energy use based on local conditions. Weather and climate heavily drive the relationships between the envelope, passive systems, mechanical systems and the surrounding site. Data currently used for simulating building energy performance is based on historical records, which neither simulate future conditions based on projected trends, or account for variability in future climate scenarios.

Chaotic climate behavior combined with advances in analysis and predictions procedures makes integrating climate science and building science challenging. For the more immediate future, the uncertainty of climate non-stationarity is dominant (seen in orange in Figure 1); however, it stays relatively constant into the future. The influence of global circulation model, or global climate model (GCM), variations and emissions scenario possibilities become the controlling sources of uncertainty (blue and green, respectively, in Figure 1) as the projection distance increases (“Sources of Uncertainty in CMIP5 Projections | Climate Lab Book” 2016). This study evaluated impact that the uncertainty and variability among climate projections and data have on forecasting future weather data for building energy simulations in future scenarios. ‘Morphing’ methodologies were used to adjust current weather data for future scenarios and used in EnergyPlus to estimate total energy consumption. Three prototype buildings from Pacific Northwest National Laboratory (PNNL) (“Commercial Prototype Building Models | Building Energy Codes Program” 2016), the large office building, secondary school and hospital, were selected to study potential differences in building characteristics. The three buildings were simulated in Miami, San Francisco and Boston (climate regions 1A, 3C and 5A, respectively) to demonstrate the importance of

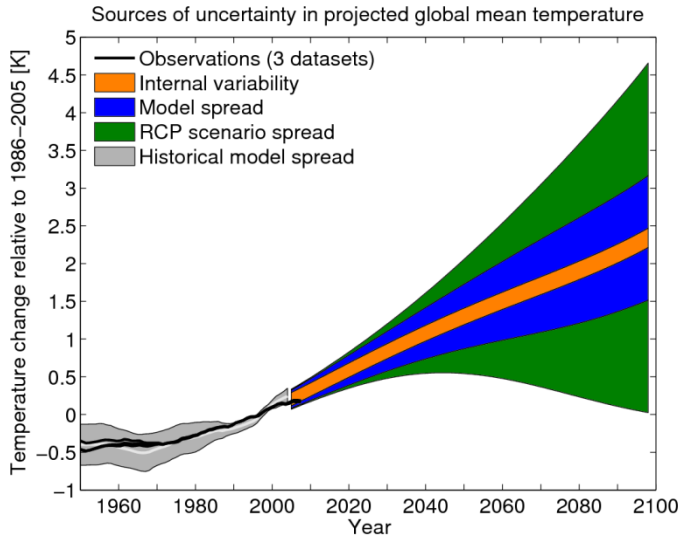


Figure 1: Uncertainty in future projections. ©IPCC

obtaining location specific data and to observe the ‘morphing’ effects over time.

BACKGROUND

Many variables need to be considered to incorporate climate projections into building science successfully. As climate research continues to advance, building energy modeling becomes more common practice (or even required) and general public concern for resilience increases, the more critical climate and building science integration becomes. Weather files and local climate data are the foundation of building performance simulation. Understanding options in emission scenarios, baselines and GCMs are vital to obtaining realistic results of ‘morphing’ weather data files for energy simulation.

Emission Scenarios

The Intergovernmental Panel on Climate Change (IPCC) released their Fifth Assessment Report (AR5) with a new ‘parallel phase’ planning approach to creating emissions scenarios, called the Representative Concentration Pathways (RCPs). This approach is the latest in a long series of attempts to incorporate uncertainty into climate models.

In the *First Assessment Report* (FAR), the SA90 emissions scenarios were developed to be simulated with global circulation models (GCMs) in order to compare the impacts of operating “Business-as-Usual” (Scenario A), shifting towards lower carbon fuels (Scenario B), moving towards renewables (Scenario C), or a 50% Carbon dioxide emissions reduction (Scenario D). The limitations of the SA90 scenarios lead to establishing six alternates (IS92a-f) in 1992 to cover a wider array of options and assumptions than their

predecessors. Six years later in 1998, the *Special Report on Emission Scenarios* (SRES) updated the initial four storylines (A1, A2, B1, B2), followed by a more comprehensive set of 40 SRES scenarios for the *Fourth Assessment Report* (AR4) published in 2000. The SRES scenarios have been widely utilized, but do not include the effects of any possible climate initiatives. The RCPs introduced in AR5, on the other hand, address this need, as they “were developed using Integrated Assessment Models (IAMs) that typically include economic, demographic, energy and simple climate components (IPCC 2014).” The timeline of emission scenario development is important because corresponding GCMs are influenced by their estimations and related to the time span of the ‘baseline’ weather data.

Baseline Years

The most current baseline weather data for 1020 US locations is the TMY3 (Typical Meteorological Year) data sets derived from the National Solar Radiation Data Base (NSRDB) 1961-1990 and 1991-2005 collections (“NSRDB: 1991- 2005 Update: TMY3” 2016). Available data sets will depend on specific regions (i.e., the UK has Typical Reference Years - TRY or Design Summer Years – DSY, Canada has Canadian Weather for Energy Calculations – CWEC, or the International Weather for Energy Calculation – IWEC) and are becoming increasingly accessible due to organizations providing a public domain. Personal weather stations are also more readily available (“Personal Weather Station Network | Weather Underground” 2016), which make it possible to obtain high resolution location weather data. Building energy simulators need to be aware of the baseline years in information sources because it will have a significant impact on simulations. TMYs are assembled by combining parts of historical data that usually span over 30 year intervals. The EnergyPlus weather files (.epw files) used with the prototype buildings in this research are based on the most recent collection interval from 1973-2005. That means the most ‘up-to-date’ baseline data has potential to be over 40 years old. The IPCC has released the AR4 and the AR5 since the end of that period, including the development of a new emissions scenario scheme. When baseline years in weather data do not overlap with global climate models (and in some cases, emissions scenarios), more uncertainty develops in the projections.

Global Climate Models

When the AR5 was released, approximately 40 climate models were listed, each simulated the four RCPs and additional different parameters to simulate for. The previously published AR4, seven years earlier, only has

20 models. The AR5 modeling increase was intended to fill in gaps in the AR4, cover a large range of uncertainty and reason any unnecessary assumptions. Along with the increase in the number of models, the process has become ‘parallel,’ opposed to ‘sequential,’ as it had been in the past. This allows the modeling groups to iteratively update and process models, scenarios and projections on shorter intervals, which keep data as current as possible.

MORPHING DEVELOPMENT

‘Morphing’ theory is a basic concept – obtain climate anomaly projections to calculate new weather data files for building energy simulations. In 2005, Belcher, Hacker and Powell published a methodology to ‘morph’ weather data to future time frames by modifying a historical 8760 (hourly) dataset based on future projections. The approach has been frequently used because it preserves real weather sequences and is specific to an observed location. The algorithms use three simple operations to modify present-day weather data; (1) a *shift* is applied when an absolute change to a variable is required, (2) a *stretch* or scaling factor when the change is projected in a percentage, and (3) a combination of both *shifting and scaling* may be used to adjust present-day data to reflect future projections (Belcher, Hacker, and Powell 2005). In the initial study, Belcher et al. used the weather data in the Chartered Institution of Building Services Engineers (CIBSE) Guide J (CIBSE Guide J 2001) for London, Manchester and Edinburgh and adjusted the recorded variables based on the 2002 UK Climate Impacts Programme (UKCIP02) (Hulme et al. 2002) projected climate variables. The UKCIP02 linked the four SRES emission scenarios with socio-economic scenarios developed by the Foresight Programme within the UK Office of Science and Technology (Hulme et al. 2002) to localize non-climate variables and quantify their impacts. Since one scenario is not more likely than another, and because regional climate simulations are computationally expensive, only two of the four emission scenarios were run (medium-high and medium-low) with the HadRM3 regional climate model (RCM) in two time slices; 1961-1990 for the baseline and 2071-2100 for future projections. The remaining scenarios and time periods were obtained by scaling the variables based on these findings (Belcher, Hacker, and Powell 2005). Creating weather data files under the ‘morphing’ methodology maintains weather sequences from the recorded data, but monthly projections from GCMs do not capture the details of diurnal patterns or allow for potential extreme anomalies (Jentsch, Bahaj, and James 2008).

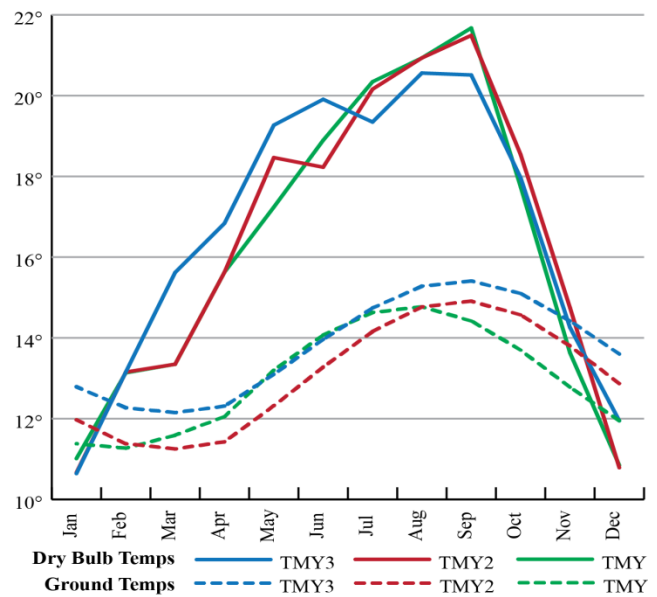


Figure 2: San Francisco baseline year temperature variation

Building off of the Belcher et al. approach, the Sustainable Energy Research Group (SERG) at University of Southampton developed a publically available Excel sheet for individual end users to generate future weather files (“Climate Change World Weather File Generator for World-Wide Weather Data – CCWorldWeatherGen | Sustainable Energy Research Group” 2015). The version for the UK (“CCWeatherGen: Climate Change Weather File Generator for the UK | Sustainable Energy Research Group” 2016) is based on RCM’s which provides a higher resolution specific to the 14 CIBSE weather sites and the four different emission scenario options in the UKCIP02. The version applicable to global locations, called CCWorldWeatherGen (“Climate Change World Weather File Generator for World-Wide Weather Data – CCWorldWeatherGen | Sustainable Energy Research Group” 2015), is based on the HadCM3 GCM under emissions scenario A2. Although the resolution of the HadCM3 model is not as high as the HadRM3, the generator calculates the average variable of three different models (all simulated using the same parameters) and the average of the four spatial grids closest to the actual coordinates of the location. More details of the weather generators can be found in Jentsch et al. (Jentsch, Bahaj, and James 2008).

The original Belcher et al. ‘morphing’ methodology was derived from the TRY and DSY weather data from the 1976-1995 collection and the baseline time slice in the UKCIP02 projections is 1961-1990 (Hulme et al. 2002, 2). This will cause a slight overestimation in the

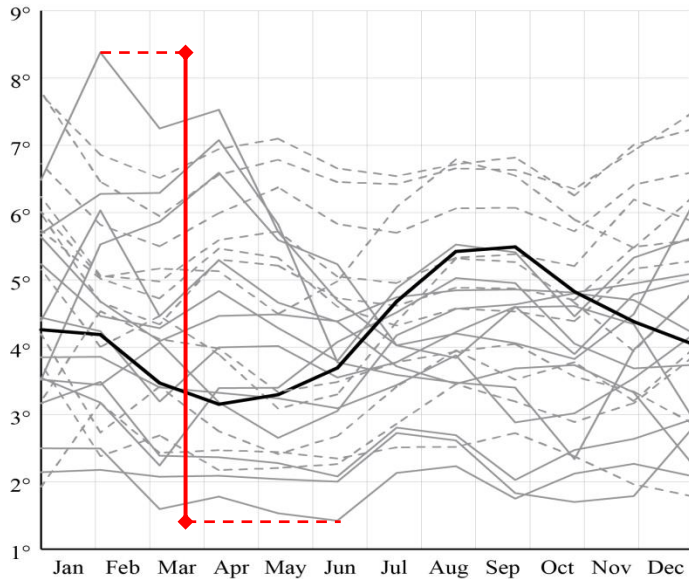


Figure 3: Comparison of a sample of global climate model (GCM) projections for Boston temperature anomalies.

‘morphing’ results. The overestimation will continue to grow as the distance between baseline time periods increase. Figure 2 shows the difference in TMY, TMY2 and TMY3 files for the dry bulb temperatures and ground temperatures in San Francisco. The HadCM3 model gives projections for all the required climate variables to directly ‘morph’ current weather data. This consideration makes selecting models more challenging for the building scientist because calculations do not stay consistent. The CCWorldWeatherGen requires nine climate variables to generate the EnergyPlus weather files (EPWs):

- daily mean temperature (TEMP)
- maximum temperature (TMAX)
- minimum temperature (TMIN)
- horizontal solar irradiation (DSWF)
- total cloud cover (TCLW)
- total precipitation rate (PREC)
- relative humidity (RHUM)
- mean sea level pressure (MSLP)
- wind speed (WIND)

Unfortunately, the limitation to specific models based on projected climate variables ignores the spread of projections. Figure 3 highlights the HadCM3 model (in black) and a sample of other GCMs for the temperature anomalies in Boston, MA. The red line indicates an eight degree Celsius range in just a sample of nine GCMs.

Arup and Argos Analytics, LLC have built upon the Belcher et al. methodology and created WeatherShift™

(“WeatherShift” 2016). Their approach blends 14 of the more recently simulated GCM’s, for two of the RCP emission scenarios (4.5 and 8.5), in to cumulative distribution functions (CDF). The 14 GCM’s are:

- | | |
|------------------|-------------------|
| 1. BCC-CSM1.1 | 2. BCC- CSM1.1(m) |
| 3. CanESM2 | 4. CSIRO- Mk3.6.0 |
| 5. GFDL-CM3 | 6. GFDL-ESM2G |
| 7. GFDL-ESM2M | 8. GISS-E2-H |
| 9. GISS-E2-R | 10. HadGEM2-ES |
| 11. IPSL-CM5A-LR | 12. IPSL-CM5A-MR |
| 13. IPSL-CM5B-LR | 14. NorESM1-M |

Creating CDFs allows a percentile distribution and “smooths out” the inter-modal uncertainty and stochastic climate behavior. The percentile distribution is for likelihood of frequency *not* confidence of projection. For example, suppose a 50th percentile projection from the CDF of temperature change is 5°. The 50th percentile describes 50% of the projections from the 14 GCMs are above 5° change and the other 50% is below a 5° projection.

The criteria for selecting the 14 models were the resolution scale, projection variables and the generation under the RCP 8.5 and 4.5 emission scenarios. (Note: in the initial release of the RCP scenarios, RCP 8.5 was the “high” emissions scenario, assuming an increase in greenhouse gas emissions (“Washington State of Knowledge Report” 2016). During the parallel phase processing and the development of WeatherShift™, RCP 8.5 has started to appear more the “business-as-usual” scenario (IBPSA Chicago, n.d.) as emissions continue to increase.) The 14 GCMs use the most current TMY3 (1976-2005) files for the baseline weather data and the CDF percentile distribution maintains meteorological consistency while also encompassing less likely events.

CDF curves are not a new theory, but are unique in the application of generating weather files. The same theory has been functional to the new UKCP09 probabilistic projections (Jenkins et al. 2009). This study has used WeatherShift™ and CCWorldWeatherGen as tools to evaluate the impacts of ‘morphing’ weather files in building energy simulations and is not intended to be an exhaustive demonstration of algorithms or methods. Many additional resources and tools exist, each serving their own specific purpose. The two approaches used here were selected based on ease of end user accessibility and wide industry recognition of appropriate methodologies.

METHODOLOGY

The PNNL prototype buildings, obtainable from the Department of Energy’s Building Energy Codes Program (DOE BECP) (“Commercial Prototype Building Models | Building Energy Codes Program” 2016), come with EnergyPlus (version 8.0) input data files (.idf) and a HTML output file with results from their simulations. The EPWs used for each climate region are also provided allowing a user to validate and duplicate the simulations if need be. The large office, secondary school and hospital prototype building used for this investigation are based on ANSI/ASHRAE/IES Standard 90.1.

The buildings were chosen to capture the different building characteristics (specific details can be found through the DOE BECP). In addition, the three building types are commonly used as places of refuge in the event of disasters; therefore, the resilience and future performance of these buildings is critical.

With the exception of the IDFs requiring location specific information from a preprocessing module in EnergyPlus, the simulations were run without making any adjustments to the prototype buildings.

Each building was simulated in Boston, San Francisco and Miami, using morphed weather files from the CCWorldWeatherGen tool and WeatherShift™. CCWorldWeatherGen projects in times slices of 2010-2039, 2040-2069 and 2070-2099, whereas WeatherShift™ uses 2026-2045, 2056-2075 and 2080-2099 because of the difference of when each tool was developed and the evolution of the GCM projection. For simplicity of understanding and display, this research uses 2020, 2050 and 2080 for the CCWorldWeatherGen files and 2030, 2060 and 2090 for the WeatherShift™ files to represent each time slice.

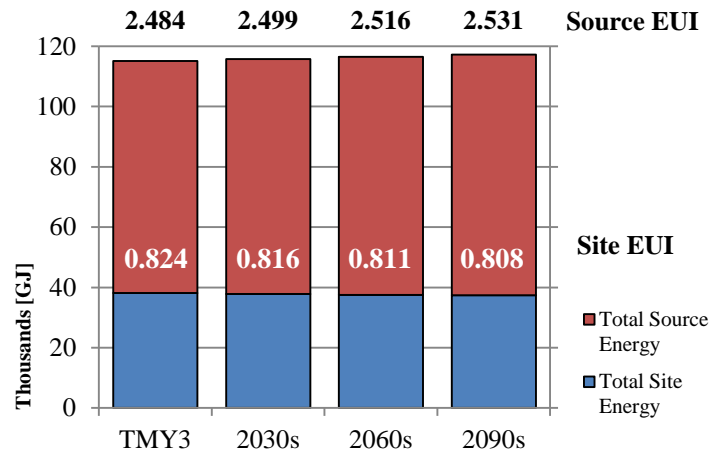


Figure 4: Source vs. Site EUI - Boston Office (RCP 8.5 50th percentile)

CCWorldWeatherGen is isolated to the HadCM3 GCM and A2 emissions scenario, but was used to morph TMY2 and TMY3 based EPW files to show the impact of baseline years within the tool. WeatherShift™ produces files from the CDFs for the 5th, 10th, 25th, 50th, 75th, 90th and 95th percentiles using both the RCP 4.5 and RCP8.5 emissions scenarios based on TMY3 EPWs. The combinations of these file options for each building and city pair resulted in six simulations with the CCWorldWeatherGen morphing method, thirty with the WeatherShift™ method and two ‘baseline’ year simulations (TMY2 and TMY3), for a total of 342 simulations.

The output file settings in EnergyPlus were kept constant - as set in the prototype IDF - to maintain consistency and standardized comparisons across all the simulations. The three primary output tables used for obtaining results were *Site and Source Energy*, *End Uses* and *End Uses By Subcategory* in the *Annual Building Utility Performance Summary* report.

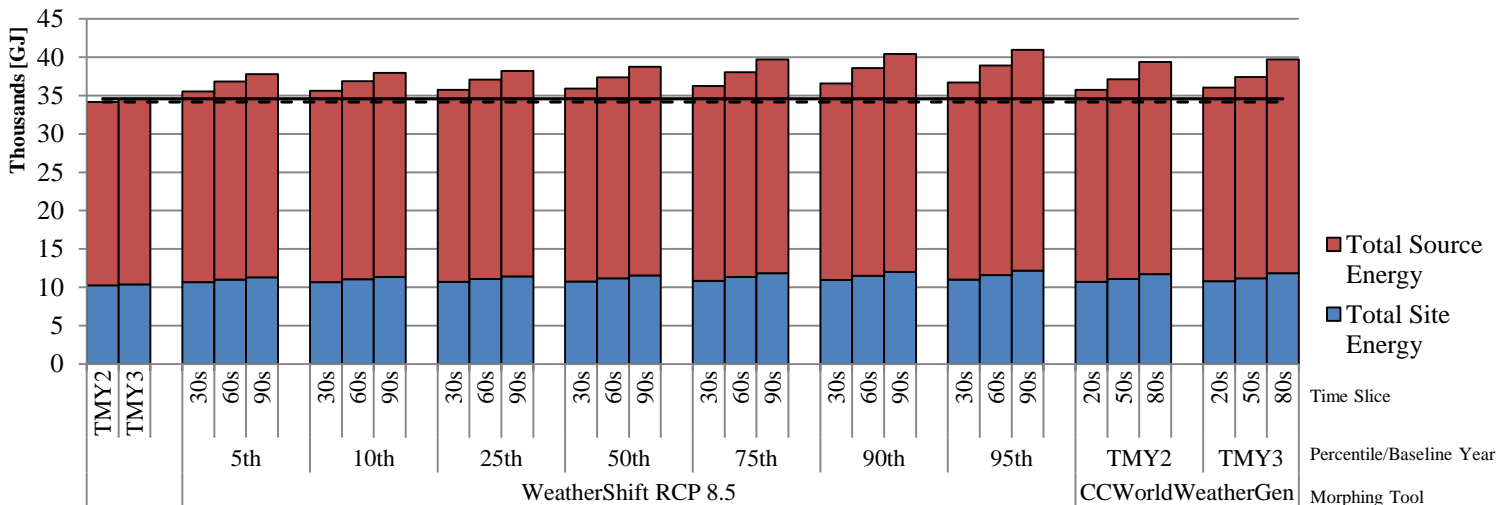


Figure 5: Source and Site Energy Consumption – Miami Secondary School.

TMY2 and TMY3 on the left are un-morphed simulations. The dotted (TMY2) and solid (TMY3) lines are for ease of visual comparison.

RESULTS

The generalized anticipation of building energy performance in future climate scenarios is to see an overall increase in total energy consumption with a decrease in heating demand and growth in cooling loads. When compared to the ‘baseline’ years, this anticipation for heating and cooling holds true for all simulations; however, some models show a decrease in total energy consumption. In Boston, the hospital and office has decreasing total site energy in all morphed simulations but the source energy still increases, with one exception of the WeatherShift™ RCP 4.5 5th percentile 2090 projection, where the source energy also decreases. Interestingly, this reduces the site EUI (Energy Use Intensity) while the source EUI increases. Figure 4 shows the decreasing site EUI in white and the increasing source EUI is at the top of the graph. Two models in San Francisco (the hospital and school) using the CCWorldWeatherGen morphing method, result in a lower site energy consumption, otherwise, all other simulations produce increasing site and source energy consumptions (Miami school results are shown in Figure 5 over the spread of morphed weather file).

When comparing differences to previous time slices, opposed to the ‘baseline’ years, more simulations do not meet the expectation of overall increasing site and source energy consumption. For example, heating energy in San Francisco, projected using the WeatherShift™ RCP 4.5 5th percentile morphed weather file, actually increases in the 2090s from the 2060s. With the same simulation parameters used for Boston, cooling energy decreases in the hospital and office buildings. The office prototype building is dominated by plug loads and lighting, consuming approximately 70% of the entire building’s energy use.

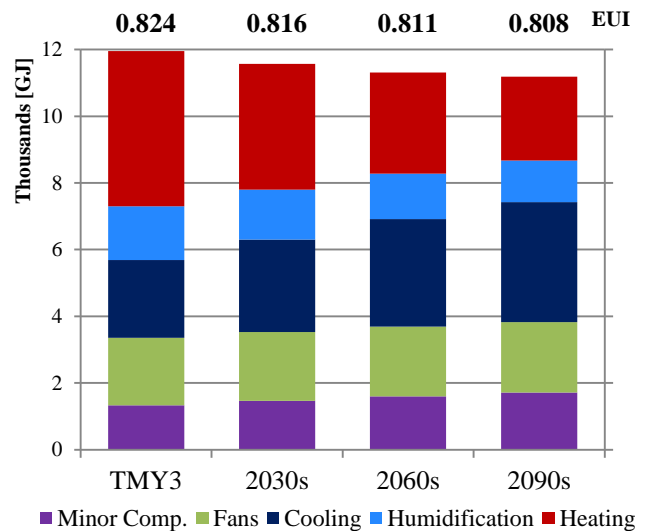


Figure 6: End Use Subcategory Breakdown – Boston Office (RCP 8.5 50th percentile)

Note: Plug loads and lighting have been excluded because they are constant in all future projection scenarios.

Not far behind lighting is heating followed by cooling. Pumps, heat rejection, heat recovery and the water heater all use negligible amounts of energy, relative to the other categories, therefore are summed for ease of display in Figure 6. The plug loads and lighting have also been excluded from the graph in Figure 6 because the energy consumption is constant over time and not contributing to any increase or decrease in energy usage. The bottom three categories in Figure 6, cooling, fans and the grouped negligible items (called ‘Minor Components’) are increasing in the future time slices, whereas the top two, heating and humidification are decreasing. The rate at which energy use is changing is what becomes the most impactful in this

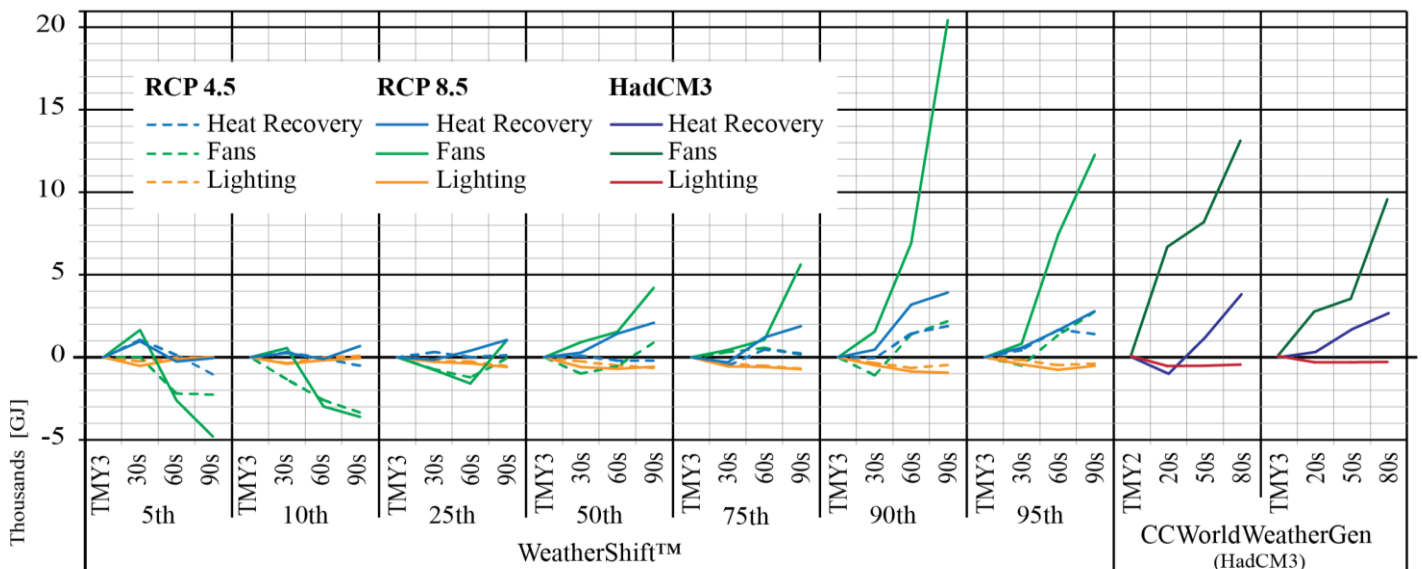


Figure 7: Time Slice Differences in Energy Consumption to Baseline by End Use Subcategory – Boston Hospital

The values indicate the amount of energy consumption morphed weather simulations deviate from the ‘baseline’ simulation. Where the lines cross the x-axis, the variations change from increasing to decreasing (or vice-versa).

example. Heating and humidification loads are decreasing at a much quicker rate than the other categories are increasing (approximately 18% and 8%, respectively).

Figure 7 displays the energy differences from the baseline year to each time slice for the hospital in Boston under the different morphed files. It has been isolated to heat recovery, fans and lighting in order to visualize the magnitude of variations. A negative value is how much a category has decreased from the baseline and a positive value, represents an increase. For example, fans (green, Figure 7), in the 5th percentile, increases in the first time slice but then decreases after. In the 90th percentile, fans increase in every time step. The magnitude of the values in Figure 7 indicate the size of the variation to the baseline – the further away from zero, the greater the change from the baseline. Where the results are the most surprising is where the values crosses the x-axis; this is where the values change from increasing to decreasing, or vice-versa. Figure 8 shows a form of a detail from Figure 7, the WeatherShift™ RCP 4.5 5th percentile is plotted versus the CCWorldWeatherGen (HadCM3) TMY3 file. The difference between fan energy, in the third time slice, is approximately 12,000 GJ, which is almost 40% of the total site energy consumed in the baseline building. In addition, heat recovery notably crosses the x-axis in the second time slice in Figure 8. For all three San Francisco buildings, in the 5th percentile under RCP 4.5,

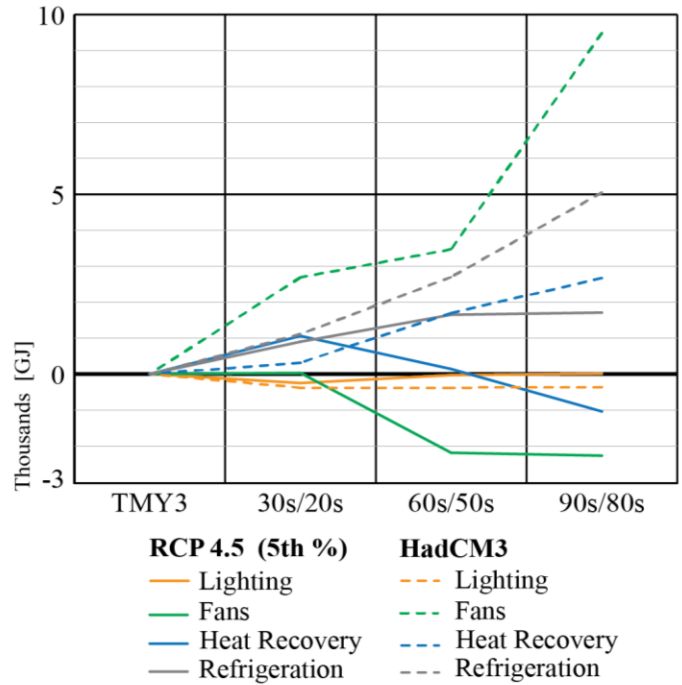


Figure 8: Subcategory Time Slice Differences – Boston Hospital RCP 4.5 5th Percentile vs HadCM3 Projections

heating loads decrease in the first two time slices and then increase in the 2090s. When using the HadCM3 coupled with TMY2 baseline, the San Francisco office shows an increase in the 2020s and decrease in the next two time slices. This makes it important to look at the

Table 1: Total Site and Source Energy Consumption for TMY3 ‘Baseline’, two WeatherShift™ (RCP 4.5 & 8.5 50th Percentile) and one CCWorldWeatherGen (TMY3 – HadCM3 A2) Morphed Weather File Simulations (Energy in Giga-Joules [GJ] and rounded to nearest 5)

	TMY3	WeatherShift™						CCWorldWeatherGen			
		RCP 4.5 50 th Percentile			RCP 8.5 50 th Percentile			HadCM3 A2			
		2030s	2060s	2090s	2030s	2060s	2090s	2020s	2050s	2080s	
Boston	Hospital										
	Site	32,225	32,050	31,965	31,940	32,055	31,870	31,880	32,140	32,100	31,940
	Source	82085	82,220	82,300	82,330	82,350	82,460	83,030	82,320	82,750	83,045
	Office										
	Site	38,190	37,785	37,620	37,655	37,805	37,545	37,420	38,005	37,915	37,555
	Source	115,075	115,550	115,835	116,095	115,755	116,540	117,260	115,540	116,330	117,010
	School										
	Site	8,790	8,845	8,895	8,930	8,865	9,015	9,195	8,810	8,930	9,105
	Source	26,615	27,170	27,500	27,650	27,280	28,100	28,905	26,955	27,610	28,565
San Francisco	Hospital										
	Site	27,790	27,885	27,960	28,040	27,910	28,305	28,750	27,850	28,105	28,535
	Source	70,480	71,165	71,645	72,030	71,320	73,135	75,070	71,140	72,450	74,520
	Office										
	Site	31,245	31,595	31,805	31,990	31,635	32,420	33,155	3,1630	32,295	33,235
	Source	102,065	103,365	104,150	104,765	103,535	106,230	108,720	103,490	105,780	108,985
	School										
	Site	8,015	8,040	8,050	8,095	8,035	8,195	8,330	8,050	8,180	8,360
	Source	23,255	23,765	24,045	24,265	23,840	24,800	25,555	23,790	24,595	25,625
Miami	Hospital										
	Site	31,840	32,130	32,320	32,360	32,170	32,550	32,895	32,065	32,390	32,870
	Source	88,240	89,730	90,620	90,860	89,935	91,770	93,395	89,715	91,355	93,760
	Office										
	Site	38,680	39,320	39,660	39,767	39,405	40,130	40,740	39,445	40,105	41,095
	Source	127,400	129,535	130,660	131,020	129,815	132,230	134,260	129,935	132,140	135,431
	School										
	Site	10,395	10,725	10,905	10,975	10,770	11,170	11,565	10,805	11,190	11,830
	Source	34,585	35,765	36,410	36,655	35,935	37,360	38,755	36,050	37,430	39,710

time steps and not just the end of the century. Also in the San Francisco office, the lighting demands fluctuate from increasing to decreasing (or vice versa) in almost every simulation set. Table 1 shows the total site and source energy for the TMY3 ‘baseline’ simulation, the 50th percentile WeatherShift™ morphed simulations (both RCP 4.5 and 8.5) and the TMY3 morphing using CCWorldWeatherGen (HadCM3 A2).

CONCLUSIONS

The results discussed here are several examples of unique findings in this investigation. This is not a complete representation of the analysis, and supplemental information is in the process of being generated (at the time of this writing) to provide more comprehensive and detailed information. This analysis serves as a strong testimony for the need to understand the elements behind future climate projections and weather file morphing. The impacts can be profound and any inaccuracies can become exaggerated. As with any simulation, there is not a universally correct answer, but future climate projections and the integration of climate and building science is a necessity for the development of our built environment and the future of energy simulation.

Luke Troup: l.troup@northeastern.edu

ACKNOWLEDGMENTS

This material is based on work supported by the National Science Foundation under Grant No. 1455450. The analysis and investigation would not be possible without the assistance of Arup and Argos Analytics, LLC.

REFERENCES

- Belcher, S. E., J. N. Hacker, and D. S. Powell. 2005. “Constructing Design Weather Data for Future Climates.” *Building Services Engineering Research and Technology* 26 (1): 49–61. doi:10.1191/0143624405bt1120a.
- “CCWeatherGen: Climate Change Weather File Generator for the UK | Sustainable Energy Research Group.” 2016. Accessed January 22. <http://www.energy.soton.ac.uk/ccweathergen/>.
- CIBSE Guide J. 2001. *Weather, Solar and Illuminance Data*. London: Chartered Institution of Building Services Engineers.
- “Climate Change World Weather File Generator for World-Wide Weather Data – CCWorldWeatherGen | Sustainable Energy Research Group.” 2015. Accessed November 30.

- <http://www.energy.soton.ac.uk/ccworldweathergen/>.
- “Commercial Prototype Building Models | Building Energy Codes Program.” 2016. Accessed April 23. https://www.energycodes.gov/development/commercial/prototype_models.
- Hulme, M, GJ Jenkins, X Lu, JR Turnpenny, TD Mitchell, RG Jones, J Lowe, et al. 2002. *Climate Change Scenarios for the United Kingdom: The UKCIP02 Scientific Report*. Norwich, UK: Tyndall Centre for Climate Change Research, School of Environmental Sciences, University of East Anglia.
- IBPSA Chicago. n.d. *Chicago Chapter of IBPSA-USA: Weather Data for Energy Modeling*. Chicago.
- IPCC. 2014. *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (Eds.)]*. Geneva, Switzerland: IPCC.
- Jenkins, G. J., J. M. Murphy, D. M. H. Sexton, J. A. Lowe, P. Jones, and C. G. Kilsby. 2009. “UK Climate Projections: Briefing Report.” Exeter, UK: Met Office Hadley Centre.
- Jentsch, Mark F., AbuBakr S. Bahaj, and Patrick A. B. James. 2008. “Climate Change Future Proofing of buildings—Generation and Assessment of Building Simulation Weather Files.” *Energy and Buildings* 40 (12): 2148–68. doi:10.1016/j.enbuild.2008.06.005.
- “NSRDB: 1991- 2005 Update: TMY3.” 2016. Accessed January 22. http://rredc.nrel.gov/solar/old_data/nsrdb/1991-2005/tmy3/.
- “Personal Weather Station Network | Weather Underground.” 2016. Accessed January 22. <http://www.wunderground.com/weatherstation/overview.asp>.
- “Sources of Uncertainty in CMIP5 Projections | Climate Lab Book.” 2016. Accessed January 21. <http://www.climate-lab-book.ac.uk/2013/sources-of-uncertainty/>.
- “Washington State of Knowledge Report.” 2016. *Climate Impacts Group*. Accessed January 23. <https://cig.uw.edu/resources/special-reports/wa-sok/>.
- “WeatherShift.” 2016. Accessed January 22. <http://www.weather-shift.com/>.