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Multi-scenario Extreme Weather Simulator Application to Heat Waves

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Abstract

Heat waves are increasing in severity, duration, and frequency, making historical weather patterns insufficient for assessments of building resilience. This work introduces a stochastic weather generator called the multi-scenario extreme weather simulator (MEWS) that produces credible future temperature anomalies. First, MEWS calculates discrete Markov and truncated Gaussian distribution parameters from historical heat waves derived from National Oceanic and Atmospheric Administration (NOAA) daily summaries and climate norms data. Second, MEWS uses Intergovernmental Panel on Climate Change (IPCC) 2021 increased severity and frequency projections to capture the non-stationary effects of heat waves and adjust the historical parameters. The methodology is demonstrated by producing heat wave-adjusted input files for the EnergyPlus medium office proto-type model for climate zone 4B using five IPCC climate scenarios to 2060. The results show increases in energy and peak load with uncertainty intervals. Also, comfort metrics indicate that future heat waves for climate zone 4B are unlikely to require changes in design practices for office buildings out to 2060. This means that resilience efforts should focus on assuring buildings in climate zone 4B have fewer power outages rather than oversizing HVAC to assure performance during future heat waves.

Introduction

Analysis of paleoclimate data, meteorological measurements, and global circulation models reveal that the rate of climate change has increased dramatically in the last century compared to the last millenia (Huasfather 2018). Among other weather anomalies, climate change is increasing the frequency, intensity, and duration of heat waves (HW) (Keellings and Moradkhani 2020). Recent events with heat wave impacts in California in August 2020 and Cold Snaps (CS) in Texas in February 2021 demonstrate that extreme temperatures severely stress critical infrastructure and jointly affect mutually dependent systems such as the electric grid, gas pipelines, and buildings.

Understanding the impacts of climate change on the built environment - especially on critical infrastructure - requires new analysis tools that are able to produce localized stochastic weather patterns that are consistent with the general trends reported by Intergovernmental Panel for Climate Change (IPCC) climate projections. These tools should produce stochastic and highly temporally resolved weather patterns that are downscaled to the city level to be used by simulations of infrastructure systems performance such as the electric grid or Building Energy Models (BEM). This paper introduces and applies the Multi-scenario Extreme Weather Simulator (MEWS), which takes a data-driven approach to modify historical weather data to reflect periodic weather events that are consistent with global climate projections. MEWS operates in two stages. First, it reads several decades of historical hourly weather data to detect and characterize the frequency, timing, duration, and severity of both HW and CS. Second, it reads IPCC projections of increased frequency and intensity of climate scenarios to modify historical HW using a discrete Markov process to produce weather patterns consistent with these projections. This study does not shift CS statistics because of lack of scientific concensus on how CS will change in the future (Cohen et al. 2020). The study therefore assumes CS are unaltered. MEWS is implemented very efficiently to produce thousands of weather pattern instances that can be applied using MonteCarlo approaches to simulations of infrastructure systems.

Anaylsis of climate measurements and models shows a very high likelihood that anthroprogenic emissions are the primary cause of global warming (Masson-Delmotte et al. 2021a). Buildings therefore have an important role in mitigating carbon emissions because they are a significant contributor to demand for electricity, natural gas, and water. Hence, many efforts have been focused on increasing the energy efficiency of buildings to produce an energy transition to a carbon neutral world (Cabeza and Chafer 2020; De la Pena et al. 2022). Less attention has been given to the role of buildings in climate change adapation, especially their resilience performance under more extreme HW and CS. Assuring that buildings are equipped to handle HW and CS changes requires information decades in advance so that codes can be written to avoid significant failures. Much of the elderly building population already relies heavily on air-conditioning, refrigeration, and power sources for home medical devices to provide a safe indoor environment. The likelihood of these systems failing under the high stress of extreme temperature events is increased, with mortality being a possible outcome (Sun, Specian, and Hong 2020).

This study is a precursor to such complex resilience ananlysis that shows how MEWS can provide input to analyze future HW effects in Albuquerque New Mexico for office buildings during normal operations. MEWS is set up to ingest and produce weather files that can be employed on BEM. National Oceanic and Atmospheric Administration (NOAA) data is used to derive present weather conditions. Several IPCC scenarios with projections until 2060 are then evaluated through a stochastic study on a medium office building (i.e. 3-story, 4982 m^2 conditioned floor space) showing resulting statistical changes in 1) Total energy consumption per year, 2) Peak load change, and 3) Thermal comfort of occupants per the American Society of Heating, Refrigeration, and Air-conditioning Engineers (ASHRAE) standard 55 2004 (ASHRAE 2004). The BEM is constrained such that Heating, Ventilation, and Air-Conditioning (HVAC) system sizes are fixed to ASHRAE standard 90.1 2019 design conditions. The study therefore estimates the consequences of under-sizing equipment given unexpected increases in HW alongside average changes to the climate to 2060. This application of MEWS is generalizable to any location with appropriate historical weather data. To aid in these implementations, scripting to replicate results has been posted to the examples folder in the MEWS repository (Villa 2021a).

This paper commences with a brief literature review of stochastic weather generation and BEM climate change studies. It then provides the methods and procedure to quantify HW with a subsequent description of the BEM study. The results are then presented for the above metrics and ends with conclusions of the study.

Literature Review

This paper proposes a method and model to produce stochastic temporally-resolved weather patterns that are consistent with IPCC climate projections, and then demonstrates the application of this model to buildings using a BEM in a MonteCarlo approach. Hence, the literature review focuses on: 1) Existing models to produce synthetic weather data and (2 Impact of climate change induced heat waves on buildings.

Multiple studies in the literature have confirmed how current typical weather data are already failing in capturing the effects of a changing climate on buildings (Siu and Liao 2020; Yassaghi, Mostafavi, and Hoque 2019). Rohini et. al. (Rohini, Rajeevan, and Mukhopadhay 2019) observed the increase of HW frequency in India and Meehl and Tebaldi (Meehl and Tebaldi 2004) report that, under the current carbon emission scenarios, future HW are going to be more frequent and will last longer.

Calibrated regional climate models such as the Coordinated Climate Downscaling Experiments (CORDEX) (CORDEX 2021; Sylla et al. 2011; Meehl et al. 2018; Grossman-Clarke et al. 2014) have progressed enough to make global estimations of increases in severity and frequency of extreme weather events. Multiple recent studies have proposed statistical models to capture the increase in frequency and intensity of HW due to climate change (Cowan et al. 2014; Ragone, Wouters, and Bouchet 2018; Abadie, Chiabai, and Neumann 2019). Methods to stochastically produce synthetic weather data have been proposed to: 1) Project current weather data, accounting for climate change effects (Rastogi and Andersen 2016; Rastogi and Khan 2021; Semenov, Barrow, and Lars-Wg 2002), 2) Run sensitivity analysis on building models in the absence of complete historical weather data for a given location (Aguiar, Camelo, and Gonçalves 1999; Rastogi, Emtiyaz Khan, and Andersen 2021), 3) Simulate extreme weather conditions respecting the realistic weather patterns of the considered location (Adelard et al. 2012), and 4) model typical weather conditions (Rastogi and Andersen 2015). Farah et al. (Farah, Saman, and Boland 2018) proposed a method to stochastically produce robust weather data using only typical data, without needing historical weather data. However, none of these methods and models are intended to be used directly for building performance simulation, including the need to produce consistent weather inputs for BEM.

Studies concerning buildings and climate change have focused on: 1) How robust energy retrofits are affected by climate change (De Masi et al. 2021; Akkose, Akgul, and Dino 2021; Hosseini, Tardy, and Lee 2018) 2) Clear trends in increased energy demand using current weather data over typical meteorological data based on the last couple decades (Koci et al. 2019; Hosseini, Tardy, and Lee 2018; Bianchi and Smith 2019) 3) Energy Use Intensity (EUI), heating, and cooling demand changes in entire regions (Yang, Javanroodi, and Nik 2021; Fonseca, Nevat, and Peters 2020). A good review of resilience metrics to HW and power outages in the built environment is provided by (Attia et al. 2021). Studies of resilience measures to extreme heat or cold include loss of productivity due to power outages correlated to extreme heat conditions (Mathew et al. 2021), thermal comfort and survivability (Sun, Specian, and Hong 2020; Rahif, Amaripadath, and Attia 2021), and changes in peak load and energy consumption (Villa 2021b).

This study is one of the first to use IPCC's 2021 report information to investigate how HW statistics changes may affect future conditions for buildings. Also MEWS is the first method to produce direct inputs to EnergyPlus (DOE 2022) and DOE-2 (Hirsch and Associates 2022).

Method

Methods for HW will first be discussed followed by the BEM approach. For HW in MEWS, a minimal complexity process was sought that: 1) Characterizes the historical statistics and 2) Can extrapolate increasing frequency and severity as defined by IPCC. The resulting algorithm is too complex to elaborate in detail here. The details of the study can be found in the MEWS (v0.0.2) open source repository in the "albuquerque_heat_wave.py" file (Villa 2021a). As an overview, the basic steps of calculation in MEWS are provided here for convenience. Figure 1 shows the data sources (elipses) and order of steps (rectangles) that MEWS follows. Also, CS are included in this algorithm with minor changes to the procedure not shown here. A more detailed discussion of each point is provided in the following list:

1. **HW classification**: Though more complex methods are desirable (Bowles 2008), we only focus on temperature and climate norms threshold violations similar to (Li et al. 2021). A period of days is considered a HW if the daily maximum temperature from NOAA daily summaries data (NOAA 2021a) is above the 90% climate norm maximum daily temperature (NOAA 2021b) or the daily minimum temperature is above the 90% climate norm minimum daily temperature. This produces a set of HW, HW of varying lengths. For this study, the station ID and data lengths are shown in Table 1. The HW are divided into their respective months so that seasonal changes are captured as monthly statistics.

2. **Calculate probabilities**: HW can be used to calculate the probability of a HW, P_w, in any given hour as the ratio of total hours in the historic record divided by the number of HW found. The probability that a HW is sustained P_{sw} is estimated from a log-linear regression of probability of a HW being a specific duration, P_{sw}^D, where D is duration as an integer number of time steps. P_{sw} and P_w for HW are coupled to CS probabilities to form the 3x3 Markov transition matrix M.

3. **Calculate HW severity**: From HW, calculate the temperature difference between maximum HW temperature and average climate norm (ΔT). Also calculate the total energy difference (ΔE - in °C·hr) between the HW and the average climate norm for the duration of the HW.

4. **Regress HW severity vs. duration**: Use least squares to regress ΔT and ΔE normalized by their maximums (ΔT_{max}, ΔE_{max}) versus HW duration, D, normalized by the maximum duration D_{max}.

5. **Normalize by duration regressions**: Using the above regressions, normalize ΔT and ΔE by duration. This enables statistical sampling to be independent of duration based on the HW data.

6. **Transform**: Transforming to -1..1 provides comparable metrics for all statistics and makes it much easier to understand the nature of the data. A non-zero mean indicates skew in the data. The minimum value of the normalized data is mapped to -1 and the maximum value to 1.

7. **Calculate truncated Gaussian parameters** Truncated Gaussian distributions are chosen because they strictly limit the HW to those present in the data. Increased severity is therefore only attributable to IPCC increase factors rather than random sampling outliers. Eight parameters are calculated. The increased energy 1) mean $\mu_{\Delta E}$, 2) standard deviation $\sigma_{\Delta E}$, 3) upper bound $a_{\Delta E} = 1$, and 4) lower bound $b_{\Delta E} = -1$. The same parameters for increased temperature ($\mu_{\Delta T}$, $\sigma_{\Delta T}$, $a_{\Delta T} = 1$, $b_{\Delta T} = -1$). The bounds a, b will be shifted from -1 and 1 in the next step. At this point all calculations on the HW characteristics are finished. Figure 2 shows the monthly values calculated in this study for Albuquerque with a clear doubling in probability of HW in the summer thus justifying the monthly approach. MEWS uses the IPCC data in a stochastic framework to repeatedly apply the following steps.

8. **Calculate HW severity shift** The HW parameters for ΔT are shifted based on: 1) The current climate scenario's increase from 2020 baseline temperature (i.e. 1.0°C) where cubic polynomial coefficients fit to the scenarios curves in the IPCC tech summary

Figure SPM.8 (Masson-Delmotte et al. 2021b) are provided in Table 2. Overall climate temperature increase produced by these polynomial fits is only changed on a yearly basis in MEWS and is added to the historic weather in addition to the HW changes. 2) Finding the probabilities of 10 and 50 year events based on the historic truncated Gaussian distributions previously calculated and 3) Given that ΔT is increase by interpolated factors for increased temperature in Table 3, solve for $\Delta\mu_{\Delta T}$, $\Delta\sigma_{\Delta T}$, $\Delta a_{\Delta T}$, and $\Delta b_{\Delta T}$ that produce a new truncated Gaussian distribution with 10 and 50 year probabilities for the shifted frequency. It is then assumed that increase in temperature proportionately increases D and ΔE leading to $\Delta\mu_{\Delta E}$, $\Delta\sigma_{\Delta E}$, $\Delta a_{\Delta E}$, $\Delta b_{\Delta E}$ and the change in probability of sustaining a HW which leads to a change in the markov transition matrix ΔM. The probability of a HW occuring cannot perfectly satisfy the IPCC input because frequency is provided for 10 and 50 year events but only P_w is available to satisfy the factors. A weighted average solution is therefore chosen that mostly satisfies the 10 year event. The details of this complex step are fully available in the source code.

9. **Calculate future HW status** The shifted Markov process is then used to determine a new random set of HW. For this study 100 realizations of each year and each scenario were generated. This provides duration of each HW so that reverse normalization for each HW can be accomplished

10. **Calculate future HW severity** The shifted truncated Gaussian distributions are then sampled for each HW.

11. **Reverse transform and normalize** The sampled values of normalized, transformed temperature and energy are then reverse transformed to normalized values and then, based on the duration of each HW, reverse normalization is executed producing physical ΔE and ΔT.

12. **Add functional HW to Typical Meteorological Year (TMY3) weather input**: The HW form in MEWS uses two parameters A and B to fit a HW functional form to the sampled ΔE and ΔT.

$$\Delta T(t,D) = \begin{cases} A\sin\left(\frac{\pi t}{D_{odd}}\right) + B\left(1-\cos\left(\frac{2\pi t}{\Delta t_{min}}\right)\right) & t \leq D_{odd} \\ B\left(1-\cos\left(\frac{2\pi t}{\Delta t_{min}}\right)\right) & t > D_{odd} \end{cases} \quad (1)$$

Here $\Delta T(t,D)$ is the change from the original temperature signal due to the HW and Δt_{min} is the shortest permissible length of a HW which is one day in this study. The parameter D_{odd} is the closest odd multiple of Δt_{min} that is less than the HW duration D simulated by the Markov process.

$$D_{odd} = \Delta t_{min}\left[\lfloor\frac{D}{\Delta t_{min}}\rfloor - \delta\left(\lfloor\frac{D}{\Delta t_{min}}\rfloor \mod 2\right)\right] \quad (2)$$

Here $\mod$ is the modulus operator, $\lfloor\rfloor$ indicates the floor function or closest integer less than the input, and δ is the Dirac delta function. Using D_{odd} instead of D in equation 1 avoids erratic variations in the maximum temperature condition with respect to the HW duration which greatly simplifies mapping the maximum of $\Delta T(t,D)$ to ΔT. Integration of equation 1 from 0 to D produces the following total energy in $^{\circ}C \cdot hr$.

$$\Delta E = \frac{2AD_{odd}}{\pi} + BD - \frac{B\Delta t_{min}}{2\pi}\sin\left(\frac{2\pi D}{\Delta t_{min}}\right) \quad (3)$$

Though D_{odd} makes the energy relationship more complex, It makes the HW maximum temperature much more simple.

$$\Delta T = A + 2B \quad (4)$$

The relationships in equations 3 and 4 can be solved to provide values for A and B:

$$A = \frac{\Delta T - \frac{\pi}{2D_{odd}}\Delta E}{2 - \frac{\pi D}{2D_{odd}} + \frac{\Delta t_{min}}{4D_{odd}}\sin\left(\frac{2\pi D}{\Delta t_{min}}\right)} \quad (5)$$

$$B = \frac{\Delta T - A}{2} \quad (6)$$

Both the values of A and B must be greater than zero for HW (or less than zero for CSs) for the solution to be physically meaningful. If this is not the case, then only ΔT is enforced and only a single sinusoidal term is used. Ideally, all HW should be removed from the historic weather data being used but this was neglected for this study.

13. **Output weather file** Once the HW have been added to TMY3 data, EnergyPlus files are output for the BEM study.

BEM study

As a demonstration application of the MEWS HW algorithm, the EnergyPlus medium office prototype model (DOE 2021) configured to ASHRAE standard 90.1-2019 (ASHRAE 2019) in climate zone 4B (ASHRAE 2013) for Albuquerque was analyzed over the five IPCC climate scenarios in Table 2 and extrapolated to 9 future years {2025, 2030, ... , 2060}. The medium office prototype model was converted from EnergyPlus v9.0 to v9.6.0. It has HVAC systems that are fully sized assuring that HVAC system autosizing will not occur if heat loads change. The scenario is therefore a good test of whether future HW conditions are likely to abruptly overwhelm HVAC systems in Albuquerque. Each year and climate scenario in MEWS was sampled 100 times to provide a reasonable amount of statistical sampling of possible future weather outcomes. This totaled to 4500 EnergyPlus runs for the study. CS were also added to the weather data but no increase or decrease in CS were included into the future.

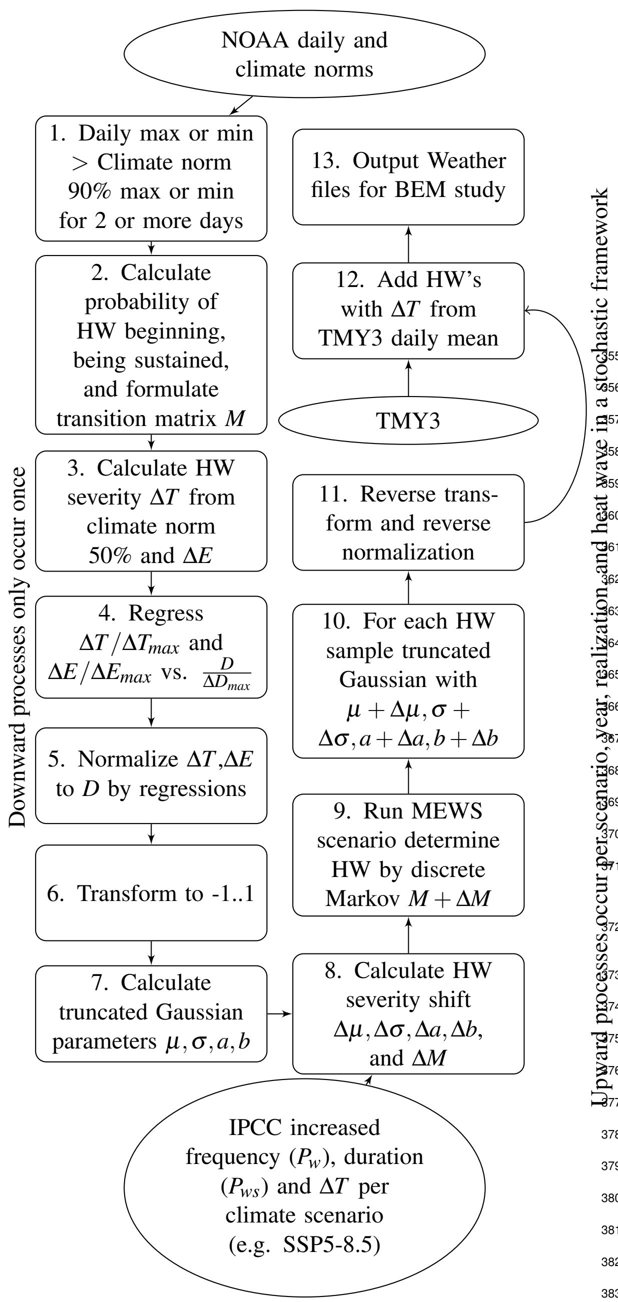

Figure 1: MEWS heat wave generation process. Cold snaps share the same process but for reversed signs and (Daily min temperature < Climate norms 10% temperature) for 2 or more days (step1)

Table 1: NOAA data characteristics

Input	Value
Station ID	USW00023050
Climate Norms	1991-2020
Daily Summaries	1931-2021

Table 2: IPCC scenario cubic polynomial fits from lowest carbon (top) to highest carbon (bottom) cases

	t^3	t^2	t	1	R^2
SSP1-1.9	0.367435	-1.26948	1.18047	0.271188	0.987573
SSP1-2.6	0.197661	-0.939153	1.31465	0.257824	0.99878
SSP2-4.5	-0.104421	0.00420024	1.19971	0.253296	0.999867
SSP3-7.0	-0.0789692	0.433801	1.16447	0.259598	0.999949
SSP5-8.5	-0.143983	0.678342	1.44848	0.267015	0.999994

Results

Results from MEWS are verified by identifying the heat waves created on the 100 instances produced for the BEM analysis. For this post-processing analysis which was different than the MEWS algorithm, heat waves are defined as two or more consecutive days in which the daily minimum temperature is above the 90th percentile of daily minimums from weather normals. This produced 877 HW detected in year 2020 over the 100 instances of scenario SSP5-8.5, which substantially increase to 2432 HW by 2060. The MEWS architecture changes to frequency and duration of HW are shown in Figure 3. The analysis shows roughly the expected increase of the number of HW compared to 2020. Table 3 combined to scenario SSP5-8.5 in 2060 produces an expected multiplying factor of 7.0 on frequency of 10-year heat wave events compared to the preindustrial 1850 to

Table 3: IPCC HW intensity and frequency multiplying factors

Event	Δ global temp. (°C)	5% CI ΔT (°C)	Avg ΔT (°C)	95% ΔT (°C)	5% CI Δ frequency	Avg Δf	95% CI Δf
HW 10 yr event	1.0	0.7	1.2	1.5	1.8	2.8	3.2
	1.5	1.3	1.9	2.3	2.8	4.1	4.7
	2.0	1.8	2.6	3.1	3.8	5.6	6
	4.0	4.3	5.1	5.8	8.3	9.4	9.6
HW 50 yr event	1.0	0.7	1.2	1.6	2.3	4.8	6.4
	1.5	1.3	2	2.4	4.3	8.6	10.7
	2.0	1.8	2.7	3.2	6.9	13.9	16.6
	4.0	4.4	5.3	6.0	27	39.2	41.4

global temperature change is the shift from 1850-1900 mean

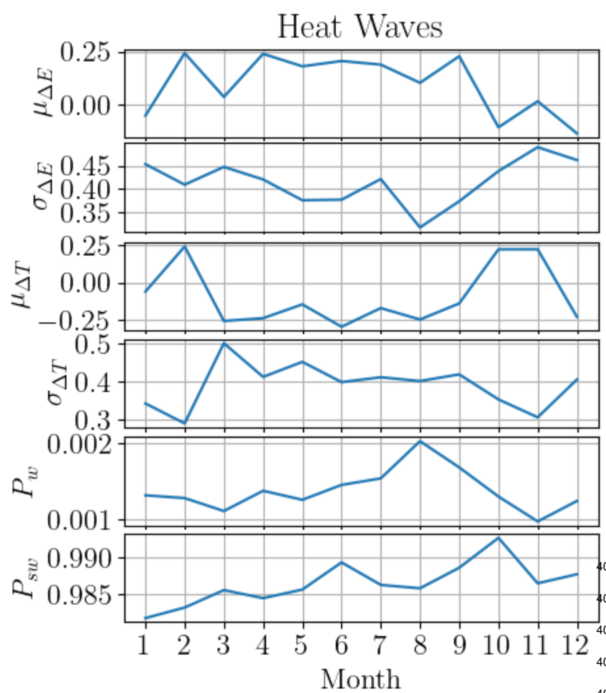

Figure 2: Monthly HW statistics for Albuquerque climate

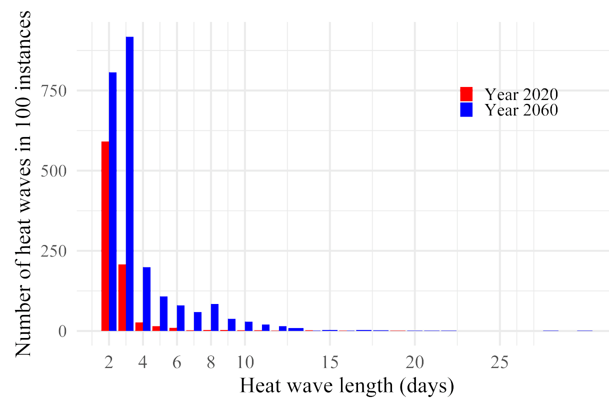

Figure 3: Shifting of heat wave frequency and duration in MEWS

1900 climate. The 2020 multiplying factor is 2.8 giving a multiplying factor of 2.5 between 2020 and 2060. The ratio of heat waves 2432/877 is 2.8 which is close enough given that only 100 realizations were sampled. In 2020, the longest HW produced lasts 19 days, whereas by 2060 the longest HW lasted 30 days. Finally, it is important to note that a large number of HW occur outside of the summer period. In both 2020 and 2060, over half of the HW occur outside the May-September period. Additional weather patterns for these months (precipitation, humidity, etc.) could impose challenging conditions for buildings even with relatively milder temperatures. These values demonstrate the ability of MEWS to produce future expected weather patterns combining the structure and timing of historical HW with IPCC-produced climate projections.

Two important outcomes were sought from the BEM study. The first was to evaluate how future HW conditions are likely to affect electricity use and peak loads. Figure 4 shows the EUI increase over time driven by global surface warming and increasing frequency, severity, and duration of HWs. Here the results for gradual climate change versus HW effects are blended. Another set of runs could show the relative effects but that is not analyzed here. Figure 4 contains the legend showing the color used for each scenario, which applies to all Figures similar to it. In general, wider error bars apply to lower carbon emissions scenarios. The error bars are for 2.5% and 97.5% quartiles enabling skew to be represented due to the truncated Gaussian HW severity distributions. Minimum and maximum values out of the 100

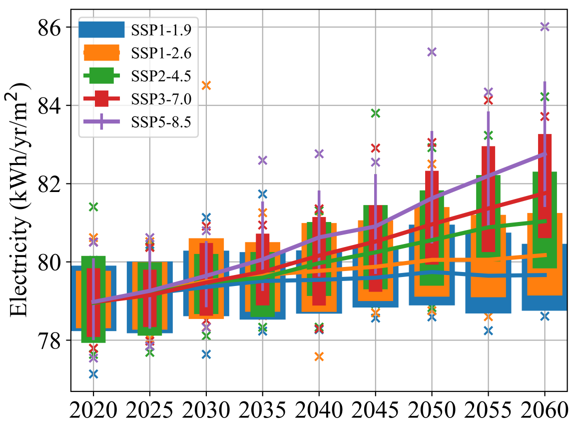

Figure 4: EUI increase total electricity

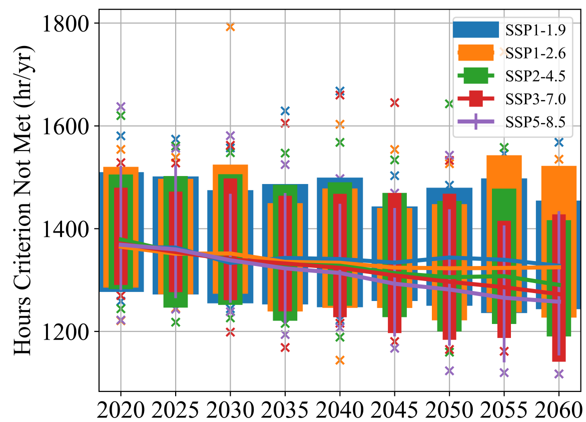

Figure 6: Hours not comfortable based on simple ASHRAE 55-2004 criterion as calculated by EnergyPlus V9.6.0

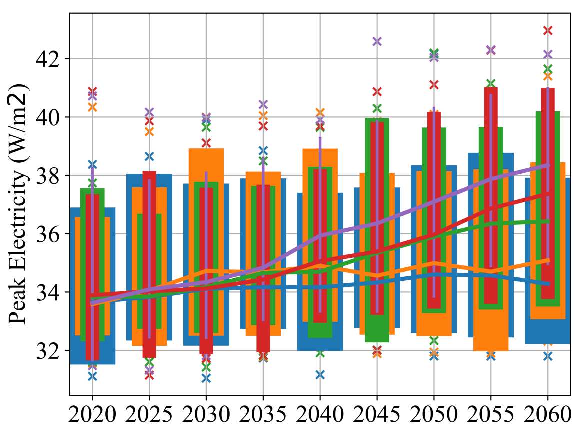

Figure 5: Peak load increase total electricity

runs for each scenario and year are represented by x's. EUI increases are significant but not alarming under all scenarios. The level of uncertainty in EUI also increases for the higher carbon emission scenarios. There is also very little effect observable until 2035. Peak loads are similarly significantly altered as seen in Figure 5 by 2060 with a slight increase over the years in uncertainty for the higher emissions scenarios. The variation of SSP1-2.6 indicates that more than 100 realizations is likely needed to characterize peak loads accurately since maximum heat wave events need to occur. The overall trend is fairly well captured though.

The second outcome of interest was whether static HVAC systems would lead to failures in thermal performance when HWs occur. Figures 6 and 7 estimate this outcome via discomfort calculations from ASHRAE standard 55-2004 and hours that the cooling setpoint was not met. Thermal discomfort actually drops because heating was generating more occupant discomfort hours. The cooling setpoint does show significant increases in setpoint not being met but not alarmingly above current values.

Discussion

The results show that the combined gradual shift in average temperature and HW's increases in frequency and severity in Albuquerque will have a modest affect on EUI. Though the change is not drastic in Albuquerque's climate, the same conclusion is not proven for other situations in other climates. Also the effects on overall energy use would be much more pronounced if the results were post-processed in the future to differentiate between periods when HWs are occuring. An important conclusion drawn from the decrease in thermal discomfort in Figure 6 is that global warming and HWs to 2060 should not require alteration of HVAC equipment designs in Albuquerque. This points to grid infrastructure resilience being of greater importance so that power outages will not cause complete failure of HVAC systems leading to extreme thermal discomfort or even thermal survivability issues during a severe HW.

The statistical approach presented here and applied briefly to a BEM example is important because dynamic downscaling methods (CORDEX 2021) would require prohibitively large numbers of calculations to adopt a

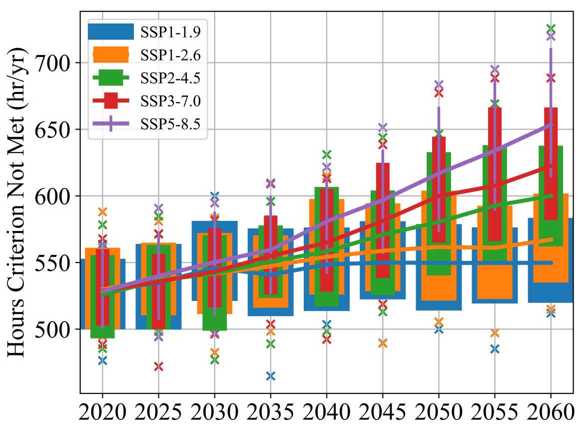

Figure 7: Hours cooling setpoint not met

truly stochastic methodology within a BEM and infrastructure analysis. Keeping a regional climate model in the loop for such analysis is not practical. Our approach therefore enables stochastic weather for BEM such that resilience can be fully assessed given an uncertain future. This is especially true if events such as power outages need to be evaluated alongside weather changes and the statistics of coincidence between power outages and extreme weather events. Under such simulation the significance of HW increases in frequency and duration may prove to be a larger problem than is percieved by the normal operations calculations shown here.

Conclusion

MEWS algorithms for HW and an example BEM study have been presented in this paper. The results show that HVAC design practice is unlikely to require changes in the coming decades for Albuquerque, New Mexico due to increasing severity and frequency of HW. They also show significant increases in EUI for the office building simulated. The methods presented herein are a template for applying BEM studies to stochastic weather in many climates. The entire results for this study can be replicated via the MEWS repository examples (Villa 2021a).

Continuation of this research requires demonstration that the statistical approaches used do not introduce significantly different statistical distributions than dynamic downscaling approaches using regional climate models. Specifically, resilience metric distributions for this study need to be vetted against a dynamic downscaling approach to assess whether there are systematic differences in conclusions. The authors postulate that our statistical approach will be shown to be ”good enough” given the stochastic nature of many other infrastructure resilience analyses where generalized changes are needed more than precision physics. Future research should include:

1. Extending the methods to allow a Monte-carlo type sampling of the relationship between duration, temperature, and energy instead of using expected values.

2. Historic weather needs to be cleaned from HW events through the MEWS algorithm.

3. Development of non-sinusoidal functions by machine learning that accurately capture heat up characteristics reflecting accurate peak temperature during day and night. These functions need to include humidity, barometric pressure, cloud cover, and precipitation effects. Research will use regional climate models to aid in finding reasonable functional alterations of these signals so that MEW's algorithms are sufficiently realistic physically.

4. Post processing for integrated results needs to differentiate between HW periods versus non-HW so that extreme weather conditions for occupants can be assessed rather than diluting the results with all times. New resilience metrics may be needed to properly assess such results.

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Disclaimer

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