Future Typical Meteorological Year (fTMY) Weather Data and Climate Change Impacts to Maricopa County, Arizona

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ABSTRACT

Buildings contribute 38% of emissions worldwide. Reduced buildings-related emissions for use cases including building codes, policy impacts, utility planning, building design, sizing HVAC, and controlling building systems would benefit from relevant, standardized, future weather files. A method based on IPCC-defined climate change scenarios is described involving downscaling to regionally-accurate, hourly meteorological variables. Multi-decadal variability is then considered in generating future typical meteorological year (fTMY) weather files to showcase quantified, climate-induced energy shifts for buildings in Maricopa County, Arizona.

CCS CONCEPTS

• **Computing methodologies** → **Modeling and simulation**; • **Applied computing** → *Engineering*.

KEYWORDS

Buildings, Modeling, Climate, Energy

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1 INTRODUCTION

Buildings consume 35% percent of energy, 55% of electricity, and contribute 38% of total emissions world-wide [8]. A sustainable and adapted built environment may only be realizable by understanding climate-induced weather impacts - including synergies and tradeoffs among cost, energy, demand, emissions, and resilience improvements. Maricopa County, Arizona is selected as one of the fastest-growing US counties [16] to showcase building performance impacts based on future Typical Meteorological Year (fTMY) weather files covering all ASHRAE climate zones.

Models in this study were generated and simulated using Automatic Building Energy Modeling (AutoBEM) [11] software suite. AutoBEM has been used for city, county, utility, and nation-scale building energy modeling analyses considering electricity-saving technologies, peak-demand reduction techniques, climate projections, and other uses [10] [1] [3] [2]. AutoBEM utilizes OpenStudio [18] to generate building energy models and EnergyPlus [5] to simulate the models.

The simulated models of every building for this study leverages physical characteristics of each building provided in partnership with LightBox. LightBox has a long history collecting, unifying, and maintaining property data across the United States, including tax assessor records, parcel boundaries, and building footprint boundaries. This data feed from LightBox is important for scaling the building energy model because it would otherwise be a monumental data engineering effort to acquire the data and ensure a normalized schema and standardized fields. With over 300 property characteristics and the important geospatial boundaries pre-linked, the LightBox data truly enabled this scaled effort.

Future weather data for this analysis was gathered from Global Climate Models (GCMs). The Intergovernmental Panel on Climate Change (IPCC) created Representative Concentration Pathways (RCPs) to standardize the work of climate researchers and to explore how different levels of emissions would affect the global climate. These pathways were defined by the amount of radiative forcing (W/m^2) expected in a scenario through 2100. Four scenarios were created range from a low-emission scenario (2.6) to a high-emission scenario (8.5). Shared Socioeconomic Pathways (SSPs) build upon these RCP pathways to include socioeconomic variables to better understand how these factors will impact the global climate. These narratives provide baseline possibilities of different future socioeconomic pathways that allow researchers to understand what variables affect climate and how climate change mitigation can be achieved in these possible future scenarios. The RCPs combine with the SSPs to create a baseline future socioeconomic scenario based on the SSP with climate policies imposed by the RCPs to gather a future overall scenario [12]. These scenarios consisting of underlying economic and climate mitigation conditions are used in GCMs to produce predictions of future weather across the globe. This data can be extracted and used in many fields, including building energy modeling.

The building energy models created using AutoBEM are simulated with future weather data from IPCC scenarios to estimate how climate change will impact building energy use in Maricopa County.

2 METHODOLOGY

Models for nearly 1.5 million buildings in Maricopa County were simulated five times, with weather from different time periods, for

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a total of 7.35 million annual building simulations. For this analysis, we assume number of buildings and building efficiency/technologies remain the same in future years to clearly quantify energy use impacts of climate change, rather than accurately forecast the county's energy use in future years.

2.1 Future Typical Meteorological Year Weather

Future weather data was procured to be used in the building energy simulations. While the spatial and temporal resolution of current climate model data has improved over recent years, current resolutions may not be suitable for city-based analysis for all locations. For this reason, global climate model data was statistically downscaled for this analysis. The methodology for downscaling is described by Rastogi [13]. Future weather data from 2020 to 2100 was acquired for SSP 5 and RCP 8.5, representing an aggregated scenario as will be referred to in this document as SSP 5-8.5. SSP 5-8.5 represents a scenario in which fossil fuels drive economic development in the coming years, leading to increased emissions. This scenario illustrates an upper bound for climate change impacts. Six different climate models projecting this scenario that were used in this analysis are shown below:

Table 1: Reliable weather files are generated using six IPCC models were used to capture temporal and model variability.

ACCESS-CM2 [4]	BCC-CSM2-MR [24]	CNRM-ESM2-1 [15]
MPI-ESM1-2-HR [7]	MRI-ESM2-0 [6]	NorESM2-MM [14]

In building simulation, a Typical Meteorological Year (TMY) is used to represent the weather at a location over a period of time. Is contains a year of hourly weather data consisting of the most representative months over the time period of interest. These representative months are concatenated to represent a typical year of weather for a given location, eliminating months and years that are considered to be outliers. There is a public methodology for developing TMY weather data [23]. This same process may be applied to future weather data to develop Future Typical Meteorological Year (fTMY) weather data. The methodology retains the same advantages of reducing individual year variability; in this case, from the climate model output. In addition to selecting the most representative month over a time period for an individual climate model, one may also select the most representative month over several climate models. For this analysis, each month from each available climate model was considered with the most representative month from the total being selected. The resulting future weather data is considered typical of a future time period and eliminates both individual month, year, and model extreme variability. The time length of the fTMY was chosen to be 20 years to be able to illustrate changes in weather patterns over time while limiting the number of building simulations necessary. This resulted in the development of four fTMY files with the classic TMY for Phoenix also being considered.

Table 2: Typical meteorological weather files usually require 18 years of statistically-significant data for reliable baselines. Rather than highly-variable, individual-year weather projections, this study's fTMY files capture weather in 20-year increments.

TMY	fTMY 2020-2040	fTMY 2040-2060
	fTMY 2060-2080	fTMY 2080-2100

2.2 Building Data Aggregation

AutoBEM requires several building characteristics as an input to develop a building energy model. At a minimum, the building footprint, height, type, and age are needed. Other more specific building data such as number of floors, heating and cooling type, window-to-wall ratio, etc. may be used if available but are generally difficult to acquire for large numbers of buildings. Data for this analysis was provided by LightBox in the form of building and parcel data.

LightBox procures its data using a variety of methods. Most property attribution and parcel boundaries are obtained through county tax assessor departments. Building footprints are collected from authoritative local government sources in many cases, otherwise are created from either LiDAR, aerial, or satellite imagery using computer vision techniques. LightBox has developed methods to merge these datasets and maintain property records over time, making it easy to link data across systems.

This building and parcel data needed to be converted to a format that could be used as an input to AutoBEM. The building data was joined to the parcel data. This was done with a many-to-one match of buildings to parcels, potentially joining many buildings to each parcel. A unique building identifier (UBID) was assigned to each building [22]. The building footprints were direclty available and were converted into a format usale by AutoBEM. A mapping was developed between the parcel use code and Department of Energy (DOE) prototype buildings [17]. DOE prototype building energy models were developed to represent common buildings in the US and are used to estimate building characteristics such as occupancy, equipment, and many other building properties in AutoBEM. As DOE prototype buildings only currently cover 75% of the built environment, several parcel use codes did not have a direct match. For these buildings, the nearest reasonable DOE prototype was used. The height of the building was assigned or calculated based on several LightBox parameters: height, number of stories, and the ratio of building footprint area to total building area. If the building height was available, it was used directly. If the height was not available, the number of stories and floor-to-floor height of the was used to calculate the height. The floor-to-floor height of each building was estimated using typical values for each building type. If neither the height or the number of stories were available, the number of stories was calculated using the total area estimate for the building and the building footprint area. The height was similarly calculated using the typical floor-to-floor height of the building type and the calculated number of floors. The year built was available in the parcel data and was grouped into a building standard. These buildings standards based on the time a building was constructed impact the materials and other physical characteristics of the building.

3 RESULTS

The average annual dry bulb temperature for each of the weather files used is shown in Table 3. Under SSP 5-8.5, the dry bulb temperature is projected to increased subtly in the near future then drastically closer to 2100. Dry bulb temperature is the most important weather-based variable of building energy use as building conditioning typically dominates the building end-uses. In a location like Maricopa County that already uses lots of energy for building cooling, one would expect the further deviation of outdoor dry bulb temperature from indoor ambient setpoint to increase building energy use in this location.

Table 3: The average temperature is projected to increase in the future with the largest increase coming towards the end of the century under SSP 5-8.5.

Scenario	Average Dry Bulb Temperature (°F)
TMY	23.8
fTMY 2020-2040	24.1
fTMY 2040-2060	25.8
fTMY 2060-2080	26.6
fTMY 2080-2100	29.1

The building energy use from each building energy simulation and each future year range was aggregated. The total energy, electricity, and natural gas for the TMY weather simulation and the percent difference compared to the TMY simulation is shown in Table 4. Even though a range of years is shown in the Table, only one year (a typical year) is used for the analysis, making all of the values in the tables annual values.

While no measured data is directly available, a Maricopa County greenhouse gas inventory report from 2018 shared that the electricity usage was about 0.16 quads (calculated from greenhouse gas conversion) [9]. The simulation estimate of 0.20 quads from 2022 data used in this analysis is an overestimation of electricity use but the growth rate of the county could account for a significant part of the difference.

In Maricopa County, electricity dominates the building energy use as cooling is mostly used for building conditioning. One would expect that as global emissions and temperatures increase under SSP 5-8.5, the need for cooling will increase while the need for heating will decrease. As heating needs are low in Maricopa County, the cooling increase should dominate the change into future years, increasing the total energy usage. This is illustrated in 4 where the percent increase in total energy from current conditions (TMY) to 2080-2100 is close to 12%. The largest increase in energy usage is from 2060-2080 to 2080-2100. This shows that according to these climate models, the most drastic of the impact of climate change will be felt towards the end of the century. There is a decrease in total energy use from TMY to 2020-2040. This difference is small and can likely be attributed to the way the TMY weather data is measured vs how the climate model predicts.

These electricity and natural gas values may be used to estimate future costs and emissions. Energy costs were divided by sector and taken from the US Energy Information Administration tables for the state of Arizona [19]. Emissions rates were obtained from the US Environmental Protection Agency tables, also for the state of Arizona [20] [21]. The annual costs and emissions for each of the scenarios is shown in Table 5. By 2100, under SSP 5-8.5 the annual building costs are projected to increase by $ 1.2 billion while the annual emissions are projected to rise by 3 million tons of CO2 compared to the TMY baseline.

Table 4: The total energy use for all of the buildings in Maricopa County is shown for TMY weather. The percent difference of each of the scenarios is compared to TMY.

Scenario	Total Energy	Electricity	Natural Gas
TMY	0.24 Quads	0.20 Quads	0.04 Quads
fTMY 2020-2040	-1.0%	-1.0%	-1.1%
fTMY 2040-2060	3.4%	4.6%	-3.2%
fTMY 2060-2080	4.6%	6.9%	-8.1%
fTMY 2080-2100	11.6%	15.9%	-12.3%

Table 5: The total costs and emissions use for all of the buildings in Maricopa County is shown for TMY weather. The percent difference of each of the scenarios is compared to TMY.

Scenario	Total Costs	Total Emissions
TMY	$ 8.5 Billion	26 Million Tons CO2
fTMY 2020-2040	-1.0%	-1.0%
fTMY 2040-2060	4.0%	3.4%
fTMY 2060-2080	5.85%	4.6%
fTMY 2080-2100	14.0%	11.6%

One would expect the rising temperatures of SSP 5-8.5 to have a larger impact on the summer months in Maricopa County when more cooling is required. The total building energy use for Maricopa County for the month of July is shown for each of the scenarios in Table 6. These massive future increases in summer energy will require significant investment in electricity generation resources to be able to meet peak demand loads.

Table 6: The total energy use for all of the buildings in Maricopa County is shown for TMY weather for the month of July. The percent difference of each of the scenarios is compared to TMY.

Scenario	July Total Energy
TMY	0.02 Quads
fTMY 2020-2040	1.9%
fTMY 2040-2060	11.1%
fTMY 2060-2080	14.3%
fTMY 2080-2100	23.0%

4 CONCLUSION

Nearly 1.5 million buildings in Maricopa County were modeled using AutoBEM, a urban-scale building energy modeling software. The building characteristics required to develop the building energy models were supplied by LightBox in the form of parcel data. This data included footprints, physical building properties such as height and number of floors, parcel use type, and year built. This data was used as an input to AutoBEM to generate the buildings for Maricopa County. The building energy models were then simulated using TMY weather files representing current weather conditions as well as fTMY weather files representing future weather conditions to the year 2100. These files were developed using an ensemble of climate models and year combinations for SSP 5-8.5. SSP 5-8.5 is a climate scenario in which future economic development is driven by fossil fuels, leading to increased future emissions. The resulting simulation outputs were compared in terms of building electricity and natural gas use as well as cost and emissions to understand how the projected climate changes will impact use energy consumption behavior in the future.

The results showed that annual building energy use would rise in the future years under SSP 5-8.5, driven by the increase in dry bulb temperature in an already hot climate. The largest increase in building energy consumption comes near the end of the century, with energy increases more than double the increases of previous time periods. The summer month of July was also considered to estimate the impact the projected increase in energy use would have on the grid. The total energy in July is projected to increase by about 23% compared to TMY conditions. Meeting this increased summer demand will be a challenge and require investment in additional electricity generation capability.

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