CREATING FUTURE METEOROLOGICAL YEARS FOR USE IN BUILDING SIMULATIONS

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INTRODUCTION

The scientific consensus is that human-made emissions are the predominant cause of climate change [Edenhofer et al., 2014]. The warming trend has largely been ignored in the weather used for modeling in the building industry, which uses the typical meteorological year 3 (TMY3) (Wilcox and Marion, 2008) weather data. TMY3 is hourly weather taken from weather stations around the United States, representing a typical year over the measurement period; the third dataset was originally published with data through 2005. The Northwest Power and Conservation Council (NPCC) has recognized that TMY3 files are outdated and wishes to incorporate predictions of future climate conditions into building energy use simulations.

Here we describe plans to update simulation weather files to reflect those future climates. We consider what a typical year might look like in the 2030s, defined as the average climate from 2020 to 2049, which we refer to as the future meteorological year (FMY). This will result in weather files with differing input variables from TMY3 which will lead to different predictions of building energy use. The FMY will be adapted specifically for building simulation in Simplified Energy Enthalpy Model (SEEM) and for TMY stations specified by the NPCC: Boise, ID; Burley, MT; Soda Springs, ID; Havre, MT; Miles City, MT; Elko, NV; Corvallis, OR; Redmond, OR, and Seattle, WA. Data to create FMY will come from the Multivariate Adaptive Constructed Analogs Datasets (MACA).

GLOBAL CLIMATE MODEL DATA

Global Climate Model (GCM) data is provided by Multivariate Adaptive Constructed Analogs dataset (MACA) using the METDATA (Abatzoglou and Brown, 2011) observational dataset as training data. Specifically, climate forcings in the MACAv2-METDATA were drawn from a statistical downscaling of GCM data from the Coupled Model Intercomparison Project 5 (CMIP5, Taylor et al. 2010) utilizing a modification of the MACA (Abatzoglou and Brown, 2012).

The Intergovernmental Panel on Climate Change (IPCC) defines a few future scenarios of which two are accessible from MACA: the representative concentration pathways (RCP) RCP4.5 (intermediate) and RCP8.5 (high). The scenarios are representative of many possible pathways where radiative forcing is stabilized at 4.5 and 8.5 W m^{-2} after 2100. Data from MACA includes these scenarios from the IPCC's fifth assessment report (Edenhofer et al., 2014) with a temporal range from 1950 to 2100 in daily or monthly formats.

While the MACA datasets offer some of the most detailed predictions of future climates, resolved in both time and geography, they do not contain a comprehensive list of all the weather data that SEEM uses from the TMY3 files. Variables that the MACA datasets provide at the daily and monthly timescales are in Table 1. Therefore, the approach will be to modify as many TMY3 variables as possible to incorporate the future climate predictions. In reality, variables like dry bulb, solar radiation, and cloud cover are all correlated on an hourly level. Adjustments to one, without adjustments to another, will make them less correlated. However, in this project, we anticipated only nudging the values a bit. With only small changes, we will maintain reasonable correlations between variables over the course of a given day. Overall, we think that each variable we update will be an incremental improvement to the forecast.

To update the TMY3 we use MACA data from the GCM CanESM2 with scenario RCP8.5.

Table 1. MACA Variables

Variable	**Unit**
Maximum daily temperature	°C
Minimum daily temperature	°C
Maximum daily relative humidity	%
Minimum daily relative humidity	%
Average daily specific humidity	kg/kg
Average daily precipitation	mm
Average daily downward shortwave radiation	W m-2
Average daily wind speed near surface	m/s
Average daily northward component	m/s
Average daily eastward component	m/s

SIMPLIFIED ENERGY ENTHALPY MODEL

The FMY file is being converted for use within a residential housing simulation SEEM, although it could be used for any program that takes a TMY2 or TMY3 file format. SEEM uses the TMY2 file format to input various weather variables listed in Table 2.

Table 2. SEEM Variables

Dry Bulb Temperature	**Unit**
Relative Humidity	°F
Dew Point	%
Total Horizontal Solar	°C
Direct Normal Solar	Wh/m^2
Diffuse Horizontal Solar	Wh/m^2
Atmospheric Pressure	Wh/m^2
Windspeed	mbar
Wind Direction Azimuth	m/s
Opaque Cloud Cover Fraction	Tenths

We do not propose to change all the variables that SEEM uses from the MACA data. Instead, we target the variables that are the largest contributors to energy use in SEEM: temperature, solar, and humidity.

SEEM uses the solar variables for radiative heat transfer on the outside of houses; the direct component is distributed into cardinal directions with the sun angle based on the time of year, and latitude and longitude. The sky emittance and sky temperature are derived using the dew point, cloud cover, atmospheric pressure, and dry bulb temperature following the equations from Berdahl and Martin (1984). The humidity ratio of outdoor air (lbs H20/lbs air) is calculated from the dew point. Besides being used for heat loss, the dry bulb temperature is also used to find multiple lagged terms for calculating water temperatures used in the internal heat pump water heater simulation.

MACA does not include the dew point but does include the psychrometric variables: relative humidity and specific humidity, which can be used to find the dew point given the dry bulb. The relationship between these variables is also dependent on the atmospheric pressure which MACA does not provide. This forces the assumption that TMY3 pressure is maintained through morphing, which can result in uncorrelation from the baseline climate between the pressure and humidity variables.

METHODOLOGY

The basic idea of taking monthly or daily GCM output and transforming it into hourly weather files for building simulation is not new. There exist a multitude of methods to downscale GCM output to hourly data:

Dynamical downscaling (Xu et al., 2012, Kikumoto et al., 2014, Arima et al., 2016), where regional climate models are run over small spatial areas, gives better resolution in the GCM output. This is obviously computationally expensive and would require building a full climate model.

Stochastic weather generation (Paassen and Lou, 2002, Jones et al., 2009, Eames et al., 2010) where synthetic weather time series are generate using statistics derived from observed weather. This method requires large datasets to derive the statistics and might not always return physically possible results. Using principal component analysis authors (Lam et al., 2010a; 2010b; Wan et al., 2014) built upon the stochastic method. authors used observed weather to define correlations between variables and used regression models to predict trends from GCMs into the future period.

The most widely used method of downscaling is 'morphing', which was first developed in Belcher et al. (2005) and later used in a multitude of studies (Chan, 2011; Huang and Hwang, 2016; Jenstch et al., 2008; Jiang and O'Meara, 2018, Jiang et al., 2019; Jylhä et al., 2015; Sabunas and Kanapickas, 2017; Shen, 2017; Soga, 2018; Wang et al., 2010; Wang et al., 2016; Wang and Chen, 2014; Zhu et al., 2016) and future weather generation tools CCWorldWeatherGen (Jenstch et al., 2013) and WeatherShift (Dickinson and Brannon, 2016). The method uses the difference in monthly means of GCMs and a baseline climate to adjust present day design weather, here TMY3. Belcher et al. (2005) argues that this method is advantageous because the baseline climate is reliable as it can come from the present-day weather and second that the future weather time series is likely to be meteorologically consistent. The disadvantage to this method is that it maintains the same weather patterns as the original weather data, i.e. it has the same number of cloudy days. The omnipresent use of the morphing method, including in the Chartered Institution of Building Services Engineers (CIBSE) is likely due to the ease of application and lends credence to its acceptance.

The results of the morphing methodology depend on the GCM data and the baseline climate chosen. Here we do not directly correct for bias in the GCM to match the TMY3 station data. Instead, by using the using the GCM as the baseline climate morphing use changes in the GCM climate, instead of absolute values, avoiding bias between the stations and GCM. This is discussed in the following two sections.

Bias Correction

GCM historical data is not meant to exactly recreate the historical weather but instead just the statistical distribution of variables. However, GCM data often has a statistical bias when comparing the modeled historical weather to observational weather data. The most illustrated example of this is that the temperatures in the historical model are warmer than the observed data, and as such researchers often bias correct GCM temperature data to account for this (Abatzoglou and Brown, 2011; Li et al., 2010; Soga, 2018).

The MACA method downscales the weather variables for use in a process that bias corrects to observational data. The 4-km grid cells that the MACA data is distributed in can result in a large difference between the gridded data and the station data in complex terrain. When looking at a specific station, MACA recommends interpolation to that station or bias correcting to the station data. In this instance we can imagine correcting to the TMY3 data. This is not the perfect system as the TMY3 data represents a typical year, not the average climate (i.e. 30-year average), which would typically be used for a bias correction.

Baseline Climate

The TMY data is not meant to represent averages for a climate. It represents a typical year and is useful for modeling realistic conditions throughout the year. However, because it is a typical year using the averages from the TMY data would not represent a city's current climate and using as such would make an FMY shift the results towards extremes.

Since the TMY data does not represent the stations' average data, the GCM historical predictions would look biased if these datasets were compared to each other. However, the TMY itself is biased against the actual climate average. The typical practice in climatology is to define a climate with 30 years of weather data. The GCM baseline climate is meant to be representative of the observed baseline climate. The morphing transformations are calculated from 30 years of the GCM baseline and the GCM future climate. Changes to the hourly TMY3 data will then be based on the trends from the GCM between 1976 and 2005. This would be a logistically consistent method as one could find a 30-year mean to represent the baseline climate to compare the future climate to. Note that the WeatherShift application (Dickinson and Brannon, 2016) uses a similar method with the GCM as the baseline. Furthermore, this method does not bias the morphing results if we assume that the relative change between the baseline period and the future period of the GCM is representative of the actual change in climate.

Belcher Morphing

Belcher et al. (2005) dealt with a similar problem of adjusting monthly GCM data to hourly data for use in design weather data for building thermal simulations. The authors proposed a method called "morphing," where present-day weather variables are adjusted by comparing the monthly means between climate change scenarios and the baseline climate. Here we use the monthly MACA dataset, as the morphing methodology is based on changes in monthly means, and MACA warns that aggregating the daily downscaled data to monthly scales will not guarantee that statistical distributions will be preserved.

For each variable, x_0, subscript 0 for the historical climate, and for each month, m, the monthly mean is given by:

$$\tilde{x}_{0,m} = \frac{1}{N}\sum\nolimits_{N\ years} x_{0,m}$$

Where, N is the number of years averaged over, in this case we use a 30-year period for the historical period and future period. The morphing method uses the monthly means to transform hourly data by either, shifting, stretching, or shifting and stretching. The general formulas for these transformations taken from Belcher et al. (2005) are:

1) Shift present-day variables by the difference in monthly means to get the future variable:
$$x = x_0 + \Delta x_m ,$$
$$\Delta x_m = \tilde{x}_{f,m} - \tilde{x}_{0,m}$$
Where the subscript f stands for the future period. This method changes the mean of the variable but leave the variance unchanged and should be used when the GCM adjusts the mean of the variable. The new mean is then $\tilde{x} = \Delta x_m - \tilde{x}_0$.

2) Stretch the present-day variable by the fractional change of the monthly means:
$$x = \alpha_m * x_0 ,$$
$$\alpha_m = \tilde{x}_{f,m}/\tilde{x}_{0,m}$$
Which changes the monthly mean and variance of a variable, used when the variable is a percentage or the variable drops to zero frequently, i.e. solar radiation.

3) Combination Shift and Stretch:
$$x = x_0 + \Delta x_m + \alpha_m(x_0 - \tilde{x}_{0,m}) = \tilde{x}_{0,m} + \Delta x_m + (1 + \alpha_m)(x_0 - \tilde{x}_{0,m})$$

This will shift the mean and will stretch the variation, applicable to temperature changes where the daily mean, maximum, and minimum will all change.

Each morphed variable is shifted and/or stretched from an hourly time series given by the TMY data, but the changes in the monthly means are derived from the GCM. The transformations for each weather variable are explicitly given in the next sections making clear where the TMY and GCM data are used. A summary of which variables of the TMY variables and the corresponding MACA variable and how the TMY is morphed into FMY is available in Table 3.

Table 3. MACA and SEEM Variables

TMY (Hourly)	MACA (Daily / Monthly)	Method for FMY
Dry Bulb Temperature (dbt)	Max Temperature Min Temperature	Stretch and shift based on differences in the monthly mean of the max and min
Relative Humidity (rhs)	Max RHS Min RHS	Stretch based on differences in the monthly mean of the max and min
Dew Point (tdew)	Specific Humidity	Convert to specific humidity and stretch.
Total Horizontal Solar (Rg)	Average daily downward shortwave radiation at surface	Stretch by difference in monthly means
Direct Normal Solar (Rdir)		Stretch by difference in total solar monthly means
Diffuse Horizontal Solar (Rdif)		Stretch by difference in total solar monthly means

Dry Bulb Temperature (dbt)

MACA data sets give daily maximum temperatures, $TMAX$, and daily minimum temperatures $TMIN$. We will assume the average of these represents the daily mean temperature, $TMEAN$. An examination of the TMY3 data showed this to be an acceptable assumption. Belcher et al. (2005) suggests using a combination shift and stretch to the baseline hourly temperatures, where the shift is:

$$\Delta TMEAN_m = TMEAN_{GCM,f,m} - TMEAN_{GCM,0,m}$$

and the stretch is:

$$\alpha dbt_m = \frac{\Delta TMAX_m - \Delta TMIN_m}{\max(\widetilde{dbt}_{GCM,0,m}) - \min(\widetilde{dbt}_{GCM,0,m})}$$

And then the shift and stretch will be:

$$dbt_{FMY} = dbt_{TMY} + \Delta TMEAN_m + \alpha dbt_m(dbt_{TMY} - \widetilde{dbt}_{GCM,m})$$

Where the subscript TMY refers to the hourly TMY3 data and the subscript GCM refers to the monthly GCM data. To get the FMY dry bulb, the TMY dry bulb temperature is shifted by the difference in monthly means for the baseline and future climates, and scaled by differences in monthly maximum and minimum temperatures.

Relative Humidity (rhs)

Belcher et al. (2005) does not calculate the relative humidity as the GCM does not provide it. However, it is used in SEEM and the MACA dataset includes the daily maximum, $RMAX$, and minimum, $RMIN$, relative humidity. We will stretch the relative humidity by the factor:

$$\alpha rhs_m = \frac{\Delta RMAX_m - \Delta RMIN_m}{\max(\widetilde{rhs}_{GCM,0,m}) - \min(\widetilde{rhs}_{GCM,0,m})}$$

So, the future relative humidity will be:

$$rhs_{FMY} = \alpha rhs_m * rhs_{TMY}$$

Dew Point (tdew)

Along with the daily maximum and minimum for the relative humidity, MACA includes the daily average for the specific humidity. Belcher et al. (2005) uses the stretch method for the specific humidity to find the wet bulb temperature. Likewise, we propose a similar method to find the dew point from the specific humidity. An overview of this method would require:

1. Converting the hourly TMY3 dew point temperature to hourly specific humidity using TMY3 pressure and dry bulb temperature.
2. Using a stretch to calculate the future time series of specific humidity (huss):

$$huss_{FMY} = \alpha huss_m * huss_{TMY},$$

$$\alpha huss_m = \widetilde{huss}_{GCM,f,m} / \widetilde{huss}_{GCM,0,m}$$

3. Converting the future hourly time series of specific humidity to a future hourly time series of the dew point using the future dry bulb temperature but with the TMY3 pressure.

The python package MetPy is used for the psychometric conversions (May et al., 2020).

Solar Irradiance

Belcher et al. (2005) determines hourly values for solar irradiance on the horizontal and diffuse solar irradiation on the horizontal both integrated over one hour, the same method that is done in the TMY data. The method simply stretches the global solar radiation, using a stretch that will keep the values at zero unchanged, thus preventing the sun from shinning at night. This will not change the number of sunny days but will increase (or decrease) the total radiation depending on the change in the monthly means from the TMY to the GCM predicted. The scaling factor for the stretch is:

$$\alpha Rg_m = 1 + \frac{\Delta Rg_{GCM,f,m}}{\widetilde{Rg}_{\,GCM,0,m}}$$

For any month the change to the global horizontal radiation is:

$$Rg_{FMY} = \alpha Rg_m * Rg_{TMY}$$

The GCM that Belcher et al. (2005) uses only returns monthly averaged solar shortwave flux at the surface. To find the diffuse solar irradiation they use a stretch with the same scaler as above, αRg_m. Credence for the simple model comes from the fact that we can express the global solar radiation as a function of the direct normal radiation, $Rdir$, and the diffuse horizontal radiation, $Rdif$ (Cengal and Ghajar, 2011):

$$Rg = Rdir * \cos(z) + Rdif$$

Where z is the solar zenith angle of the sun.

Thus if $Rg = \alpha Rg_m * Rg_0 = \alpha Rg_m * Rdir_0 * \cos(z) + \alpha Rg_m * Rdif_0$, it follows that

$$Rdir_{FMY} = \alpha Rg_m * Rdir_{TMY},$$

and

$$Rdif_{FMY} = \alpha Rg_m * Rdif_{TMY}.$$

This simple model may be more beneficial than calculating the different parts of solar based on empirical methods as this will maintain the same correlation between the different solar variables. While the ratio between the total global radiation and the extraterrestrial radiation is well correlated with the ratio between the diffuse radiation and the total global radiation, the correlation is imperfect and subject to noise (see Figure 2 in Roderick, 1999). Using the Belcher method preserves the variance in the TMY3 data and maintains the observed correlation between the radiation variables instead of forcing the correlations onto an empirical line. This method used is also used in Jentsch et al. (2008), but is changed in CCWorldWeatherGen (Jenstch et al., 2013) to follow a form closer to the empirical calculation.

Variable Limitations

The morphing transformations have the potential to produce impossible results, for example increasing the relative humidity above 100%. Therefore, some of the variables are forced within their physical limits. The relative humidity is forced between 0 and 100%, and the dew point is forced to be less than or equal to the dry bulb temperature.

To match the TMY2 format, we impose the limits that are explicitly written in the TMY2 user's manual (Marion and Ubron, 1995) for all the adjusted variables. There are, however, no explicit limitations in the TMY3 format. For the dry bulb temperature, the range is -50°C to 50°C, a limit that our FMY data does not reach in the RCP 8.5 scenario. Nor does this method exceed the limits on solar radiation imposed by the TMY2 format. However, if this method is applied to much hotter climates than the Pacific Northwest, caution should be used. In already hot climates peak temperatures could be morphed above 50°C but could be incorrectly limited by the TMY2 format. Although this limitation is unlikely to occur in major US cities, the 50°C limit corresponds to record high temperatures in Death Valley during May and September.

RESULTS

The results from morphing the TMY weather files to FMY weather is presented as differences in monthly averages, such that positive numbers indicate a higher value in FMY for the dry bulb temperature (Figure 1), for the realtive humidity (Figure 2), for the dew point temperture (Figure 3), and for the total hoizontal solar irradiance (Figure 4).

The trends suggest that all modeled cities will, on average, be about 2.5°C warmer during the future period than the TMY, with dew point and dry bulb temperature increase similarly as they are related. Changes in the realitive humidty suggest that spring and fall months, on average, will be wetter and that summer months will be drier. Changes to the total horizontal solar irradiance predictably mirror that of the relative humidity, with irradiance increased during the summer months and decreased during the winter and spring months. Cities that are closer together also seem to follow a simlar pattern, a logical result from the GCM projecting regional scale climate patterns.

The morphing method cannot maintain correlated changes between the interacting weather variables because we nudge each variable independently of the others. However, while we do see small changes in the correlation coefficient between the morphed variables in the TMY and FMY, these changes are not statistically significant.

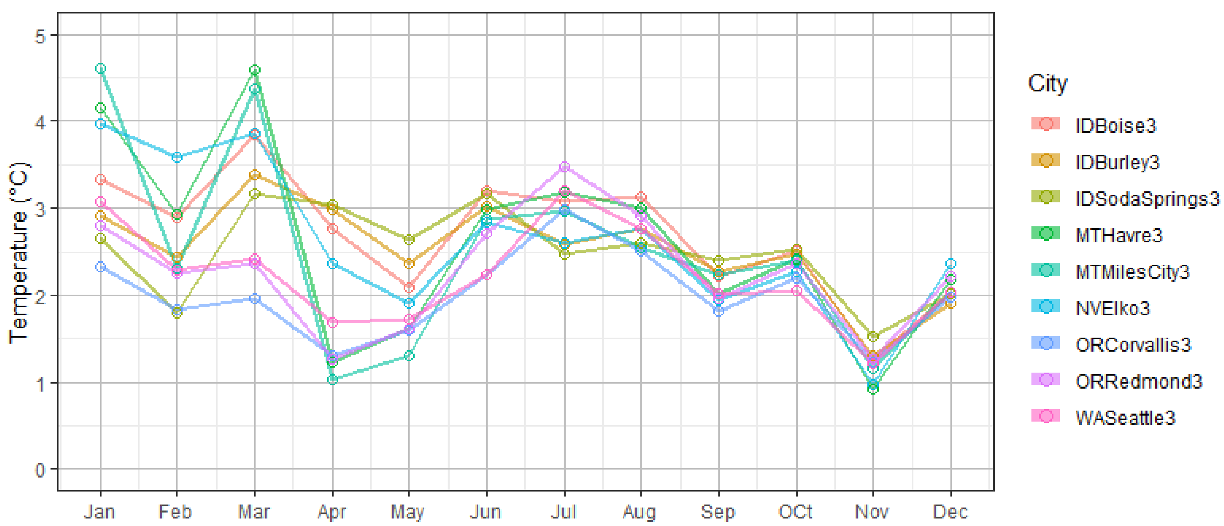

Figure 1. Temperature difference between monthly means of FMY and TMY for the studied cities.

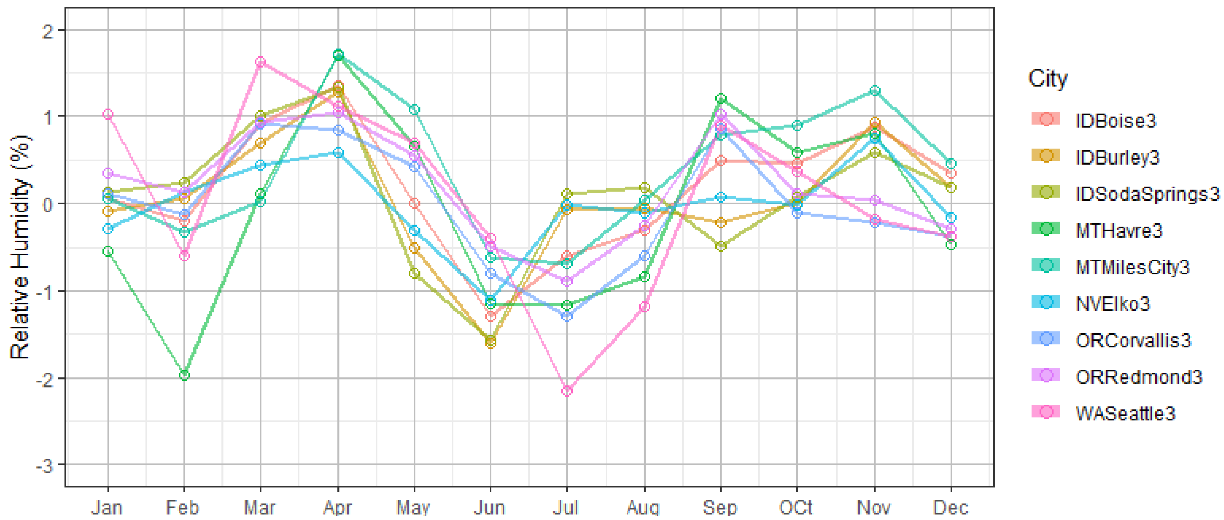

Figure 2. Relative humidity difference between monthly means of FMY and TMY for the studied cities.

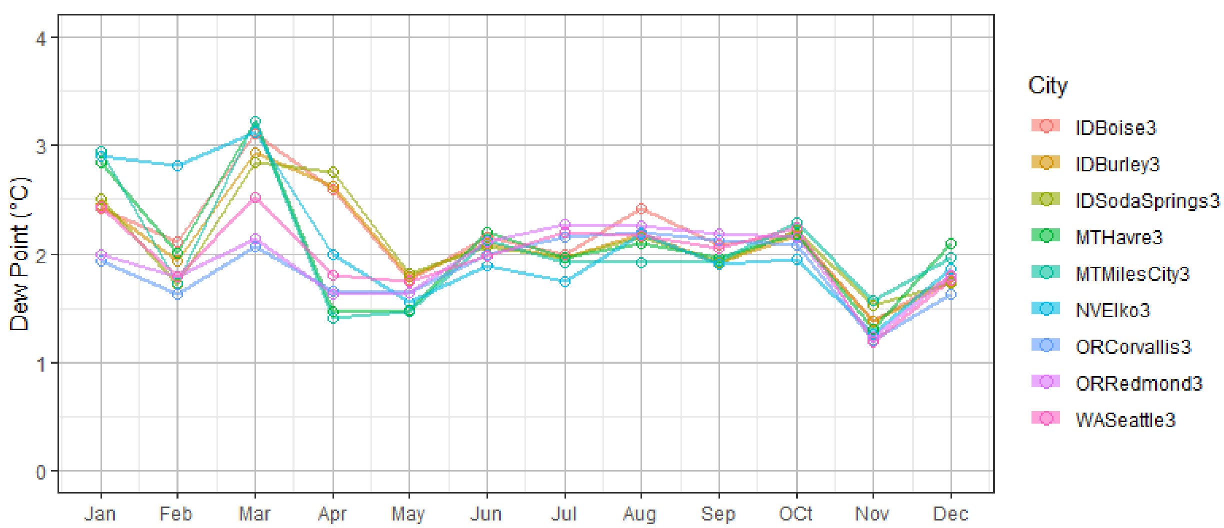

Figure 3. Dew point difference between monthly means of FMY and TMY for the studied cities.

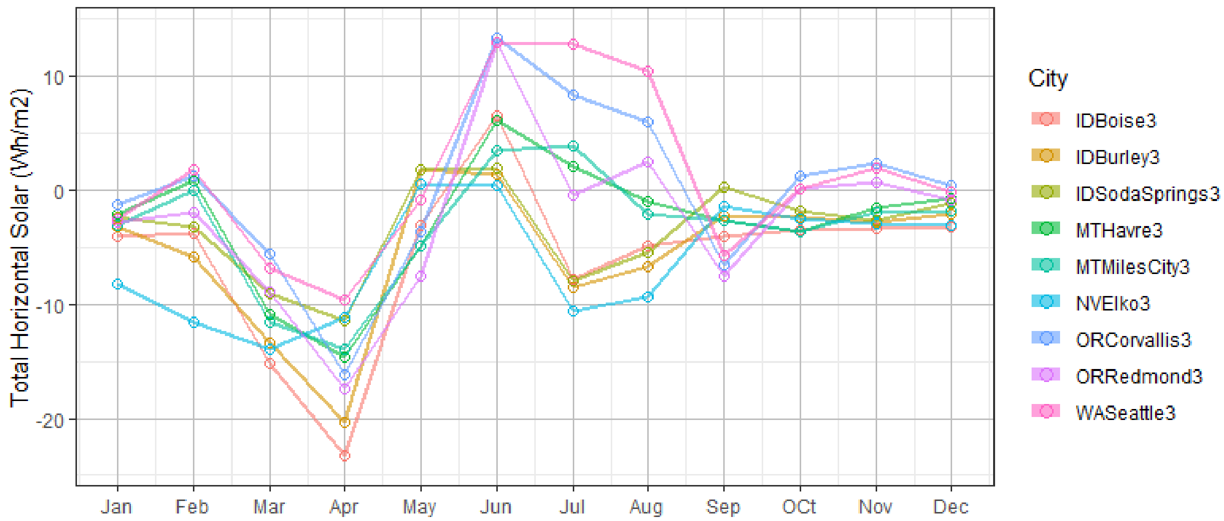

Figure 4. Total horizontal solar difference between monthly means of FMY and TMY for the studied cities.

Weather Extremes

Observing changes in monthly means obscures changes to extreme temperatures—like those during a heat wave. To understand changes in extreme weather patterns, we examine differences in the TMY and FMY *hourly* data. The quantitative measure and definition of heat waves is ambiguous and inconsistent, meaning a definition is usually contained within a research group and their analysis (Perkins and Alexander, 2012). Motivated to understand the increase in the number of hot days and continuous events, we follow the index hot day/events defined in Collins et al. (2000), which was focused on understanding the increasing trends of heat waves in Australia.

The "hot days index" is defined as the frequency of daily maximum temperatures ≥ 35°C (95°F) with units of days/year. The "hot day events index" is defined as frequency of three to five consecutive days ≥ 35°C (95°F) with units of events/year. We also use the frost days index to measure changes in the frequency of daily minimum temperatures ≤ 0°C, and the frost season length defined as the number of days between first and last frost day. We also define a new index within this scope, the frost day events index, to measure the frequency of three to five consecutive days ≤ 0°C, with units of events/year. The results of these indices are shown in Table 4 along with yearly mean temperatures in °F and heating degree days (HDD) and cooling degree days (CDD) referenced to 65°F.

Examples of results are shown in Table 4 comparing the TMY to the FMY. The trend is that there is an increase in mean temperatures, number of days with max temperatures above 95°F, and frequency of hot day events in all cities (besides Seattle). There is a decrease in number of days with minimum temperatures below 32°F, frequency of frost day events, and frost season length. Due to these changes the HDD decrease and the CDD increase across the board.

These results are consistent with the IPCC summary, which notes that the frequency of heat waves has likely already increased on other continents. This agrees with other research where a changing climate suggests that there will be increased hot and decreased cold temperature extremes and an increase in the frequency and severity of heat waves (Perkins and Alexander, 2013; Meehl and Tebaldi, 2004). The trend observed here in HDD and CDD is observed in other future weather forecasts focused on buildings (Belcher et al., 2005; Dickinson and Brannon, 2016; Jiang et al., 2019; Zhu et al., 2013)

Table 4. Yearly changes of indices in TMY to FMY for the CNRM-CM5 GCM.

CNRM-CM5 RCP8.5		Mean Temperature °F	Hot Days	Hot Days Freq.	Frost Days	Frost Days Freq.	Frost Season Length	HDD °F	CDD °F
Boise	TMY	52.2	17	3	104	26	166	5428	788
	FMY	57.0	38	10	59	14	134	4205	1333
Burley	TMY	49.5	8	1	140	38	226	6256	659
	FMY	54.1	35	6	86	19	214	5080	1146
Soda Springs	TMY	43.0	0	0	199	57	292	8470	229
	FMY	47.5	9	1	148	38	279	7167	569
Havre	TMY	44.1	9	1	169	44	248	8250	463
	FMY	48.8	32	7	135	34	230	6945	868
Miles City	TMY	46.1	9	2	146	41	223	7650	680
	FMY	50.6	31	4	119	34	204	6449	1118
Elko	TMY	47.0	5	0	185	52	239	7104	438
	FMY	51.7	30	5	137	32	235	5819	871
Corvallis	TMY	54.2	3	0	30	3	196	4293	438
	FMY	57.8	17	2	8	1	56	3401	861
Redmond	TMY	47.8	5	1	151	31	255	6615	236
	FMY	51.8	18	2	101	17	217	5450	561
Seattle	TMY	52.2	0	0	24	4	84	4673	160
	FMY	56.2	1	0	1	0	0	3523	474

DISCUSSION

Uncertainties

The morphing method is an excellent way to create hourly weather for future scenarios. There is confidence in it due to widespread acceptance and use within literature. Morphing results are not perfect, however, and careful attention should be paid to uncertainties and limitations in the method and GCM used. Uncertainties arise specifically from the limitations of the GCM and the validity of the morphing method.

The underlying GCM used is just one possible representation of the future, whose results will not necessarily agree with other GCMs. Figure 5 shows differences in the average yearly temperature between the FMY and TMY3, for each city diveded into the numerous models. The only thing all on which all GCMs agree is that the future is warmer, but the range in warming estimates for the 2030s is over 1°C for all the models. For the cities modeled here some GCMs are significantly warmer than others, and the only statement that can be made with certainty is that average yearly temperatures will be over 1°C greater during the 2030s than the baseline period (1976 – 2005). Programs such as Weather-Shift reduce the uncertainty in GCMs by looking at the mean of multiple GCMs; this is a practice that MACA recommends as well. Here analysis was performed on CanESM2, which is the warmest model, and as such the results likely correspond to the warmest likely prediction of future weather.

As the MACA method downscales GCMs to a 4-km grid, the likelihood of representing any given station within the grid cell is better than raw GCM output, often a 50-km grid. However, weather can vary greatly on a 4-km scale due to geophysical changes. For this reason, extra caution should be used in areas where stations are close to large geography or hydrological changes, such as the difference between a mountain top and a valley.

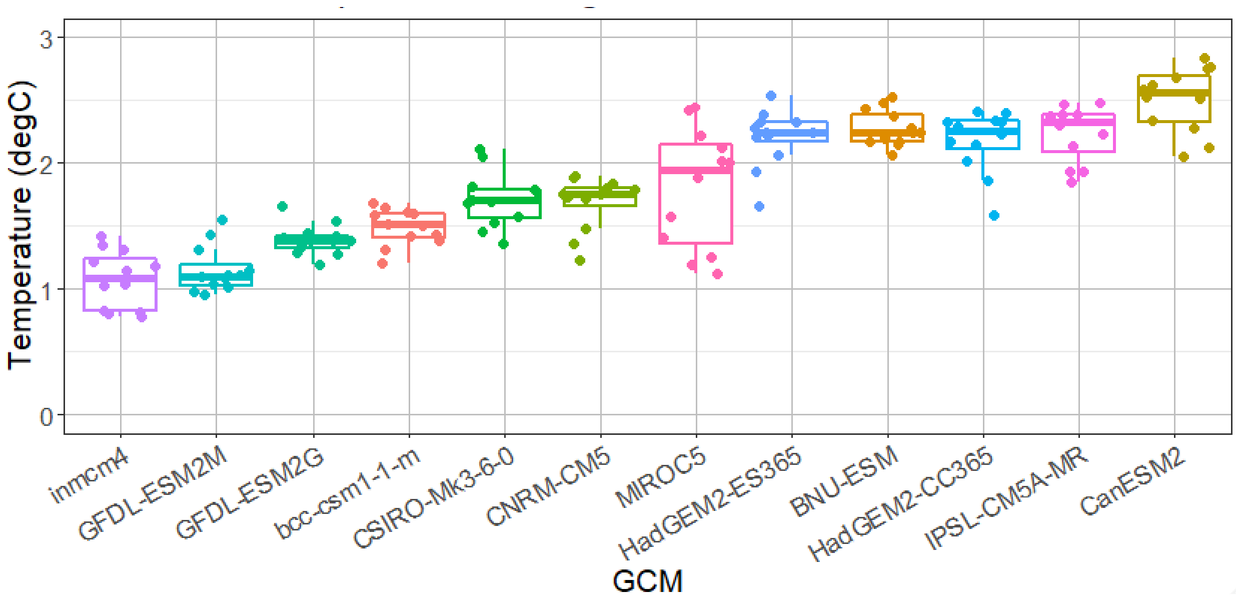

Figure 5. Yearly warming between FMY and TMY3 for different GCMs ordered by median temperature increase, each point represents a city.

Morphing Limits

The application of shifting and scaling variables can cause unrealistic weather values, for example scaling a relative humidity of 100% with an increase in the monthly means between TMY and FMY. Furthermore, the independent morphing of variables can lead to shifts or decorrelations in relationships between variables. Dear (2006) notes the interaction between dozens of weather variables and how these relationships are likely to break down with morphing. In short, morphing will nudge the cause-and-effect relationships between weather variables.

For example, the MACA data set does not provide changes to atmospheric pressure, which is a variable in TMY and used in SEEM. Here we use the TMY atmospheric pressure to find the FMY dew point, which leads to statistically significant changes in the correlation between the dew point and relative humidity that are larger than correlation changes between other variables.

Morphing depends on the historical TMY weather and uses those same weather patterns for the future, missing the possibility of change in future weather patterns and variability. Morphing can increase the number of heat waves or decrease the number of cold snaps as seen here, but it does not change the underlying weather pattern, it only shifts warm days above a standardized barrier. The method does not change the number of cloudy days or precipitation patterns either.

Here we have assumed the baseline climate is represented by the GCM historical prediction from 1976 to 2005. A potential source of error comes from the possible difference in reference time frames between this baseline and the TMY3 dataset. The TMY3 dataset uses 30 years from 1976-2005 for 239 sites across the US, and 15 years from 1991-2005 for approximately 950 sites. For sites with only 15 years of available data, the morphing method on average may overpredict climate change for the 2030s period. This is because the TMY3 data that is from 1991 to 2005 will see higher temperatures than the baseline period from 1976-2005. The number of pool years available for each of the studied cities is listed in Table 5 (Wilcox and Marion, 2008). The pool years for the 30-year period and the 15-year period are reduced to 24 and 12 candidate years for TMY selection respectively, due to volcanic eruptions effecting the local climate.

Table 5. Cities and TMY Years for Selection (Wilcox and Marion, 2008).

City	Pool Years	Time Period
Seattle (WA)	24	1976 to 2005
Corvallis (OR)	12	1991 to 2005
Boise (ID)	24	1976 to 2005
Redmond(OR)	24	1976 to 2005
Elko (NV)	24	1976 to 2005
Burley (ID)	12	1991 to 2005
Soda Springs (ID)	12	1991 to 2005
Havre (MT)	12	1991 to 2005
Miles City (MT)	22	1976 to 2005
Portland (OR)	24	1976 to 2005
Spokane (WA)	24	1976 to 2005
Kalispell (MT)	24	1976 to 2005

Limitations in GCMs may miss localized climate features such as lake effect snow (limited in this study) or the urban heat island effect. If the urban heat island is not captured in GCMs, and has increased, the FMY may underpredict the increasing temperatures. However, TMY3 is suspected to include an increase in temperatures—in part due to the urban heat island effect (ASHRAE, 2013). As many of the stations are at airports, this likely does not completely capture the effect that occurs in the dense urban areas where TMY3 data is used for simulation; however, the fact that it appears at all is a useful contribution to the TMY3 and thus FMY data. Herrera et al. (2017) argues that no established method of generating future weather is likely to incorporate the urban climate well, but that this should motivate an improved understanding of the physics that govern the urban heat island. These aspects of future hourly weather are still a developing research field for all methods, morphing and statistical.

CONCLUSIONS

The aim of creating FMY hourly weather data was not to create an exact representation of future weather but nudge the TMY hourly data so it better represents possible outcomes from climate change during future time periods. To create FMY weather we morphed TMY hourly data following established methodology (Belcher et al., 2005) using downscaled GCMs provide in the MACA dataset (Abatzoglou and Brown, 2012).

The morphing methodology works well for creating an FMY for building simulations where the predominate change is to temperature, which is the main driver in heating and cooling building energy use. The methodology fails to change the number of cloudy days (only magnitude of solar radiation), any cloud coverage parameters, wind magnitude and direction, or precipitation, making it less viable for simulating or estimating future green energy production. Estimations for future changes in solar irradiance often use statistical or machine learning methods (Voyant et al., 2017), and for wind power generation often use statistical or machine learning methods as well as numerical models (Chang, 2014). Despite the potential shortcomings, the ability to reasonably “nudge” the building simulation weather input values to represent a future climate provides a useful tool to begin to understand how energy use in buildings will change in coming years.

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