Power TakeOff

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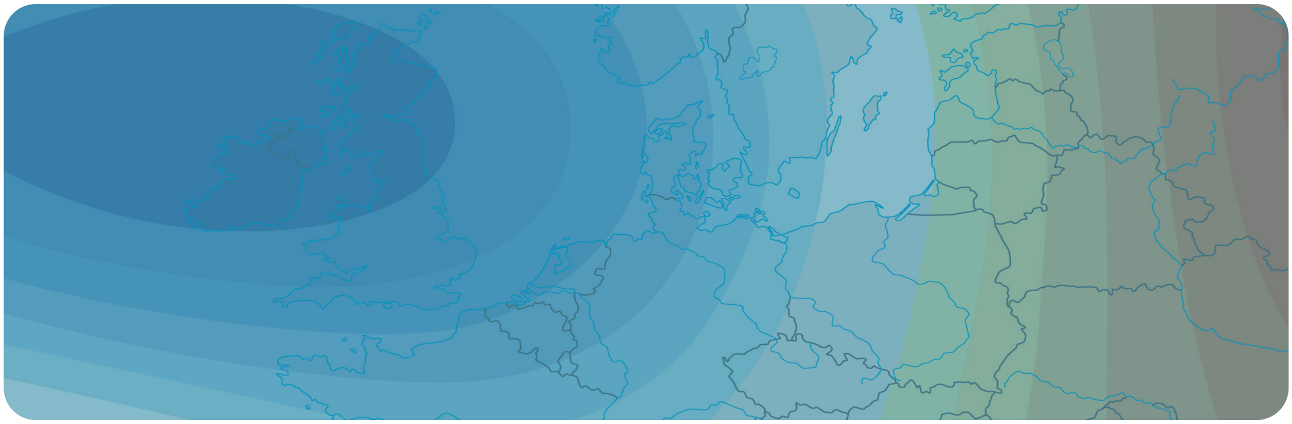
Revisiting Typical Weather Data

Anna Kelly &
Craig Sinnamon

Introduction



Energy efficiency program assumptions are dependent on the data used as inputs (Drury, 2016). We use weather data when predicting consumption for the lifetime of energy efficiency projects and make program assumptions that influence what measures are offered by a utility. For example, the number of heating degree days (HDD) or cooling degree days (CDD) that are in a utility territory influence whether the utility focuses on for reducing heating or cooling load in their offered portfolios. Furthermore, program staff use expected weather to predict how much energy a project might save, and to make judgements about what projects, and when, a customer might be interested in undertaking. The weather data that we use for predicting consumption has impacts throughout the entire lifecycle of energy efficiency programs: from initial assumptions to grid level capacity planning. However, the weather data needs to be accurate for it to fulfill its requirements. NYSERDA's Residential Retrofit Impact Evaluation Report noted that TMY3 "may no longer represent the current weather conditions in New York" and recommended that a vetted replacement be made available for future program years (York et al. 2020). However, there are no vetted replacements being used in these state Technical Resource Manuals (TRMs). Advances in methodology in the US are not adopted quickly enough to arrest climate change.

Energy efficiency programs rely on being able to use a typical meteorological year (TMY3) to normalize energy consumption for any given year. In these programs, energy savings are expected to last for a certain number of years after a project is implemented. In many TRMs, the TMY3 data is a central tenet of the required calculations to quantify energy consumption and demand. TMY3 data is the basis on which the data is normalized to differentiate the savings achieved in the first year from the savings expected in the future. In Illinois, where the data in this study is from, utilities use "Cumulative Annual Persisting Savings" to make long term estimates of how much energy is saved from a given program intervention for utility planning and regulatory compliance (Gold and Nowak 2019). Aside from the few programs that model savings, most programs have their savings deemed by previous analysis that use TMY3 data for their assumptions.

Importantly, when the use of TMY3 data is included in a state TRM, the continued use is required by all further stakeholders. For example, program engineers use it, and the private industry that serve these utilities also build processes/invest in tools around this. Program engineers identifying how much energy can be saved from any given improvement use weather data and assumptions about energy usage data to calculate how much heating and cooling is expected to estimate how many hours the equipment will be running at what capacity (Korn and John Walczyk 2016; Jenkins et al. 2010; Nursalam, 2013). These estimations are what are used to claim and report energy savings achieved. The assumptions used for resource programs have wide-reaching implications as the weather data becomes more outdated. In a review of TRMs and evaluation reports, it was discovered that TMY3 data is explicitly used in calculation assumptions in Indiana, Iowa, Hawaii, Texas, New Mexico, New Jersey, Maryland, Delaware, and Illinois. These are among the states with the most aggressive goals and are rated highly on ACEEE's state scorecard (ACEEE 2022). The industry will often say, "deeming is outdated, let's actually measure it" but even in measuring it, we're still assuming outdated weather data as an input, so regardless of the savings being deemed or measured, the outputs are not accurate because the weather data used for technical assumptions may not be appropriate.

The remaining introduction explains the uses of TMY3 with respect to normalizing whole building models to a typical year in IPMVP Option C whole building modeling, other choices for weather sources, the applicability of TMY3 data in the face of climate change, and the availability of TMY3 data. The scope section details the methods and data used throughout the study to assess both the temperatures in the created temperature datasets and the regression specification used to model the predicted energy consumption. The results section serves as a combined results and discussion section, where the data is further explored, sliced, diced, compared, and extrapolated. The conclusions section provides limitations of the study, and distinct conclusions from the results section.

IPMVP Option C and Normalized Energy Consumption

In the International Performance Measurement and Verification Protocol, each method for determining energy savings of a project is outlined. The method that this study focuses on is Option C, which uses metered energy data and measures the impact of all energy efficiency projects. Energy efficiency programs that use Option C typically have access to utility meter data or billing data and are implementing projects that are expected to save at least 5% of facility consumption (EVO 2022).

Energy Efficiency projects that are reported in terms of first-year savings usually need to be normalized for typical weather to be included in a portfolio. Normalized energy savings report the normal (fixed) conditions of a building in question, and both the baseline and reporting period are adjusted to the TMY conditions (EVO 2022). In the state of Illinois, where this study is focused, the Technical Resource Manual v10 normalizes several of the deemed measures using TMY3 data and requires the use of normalization for other programs using typical weather (IL SAG 2021).

TMYs contain one year of hourly data that best represents median weather conditions over a multiyear period. The data are considered "typical" because the entirety of the original solar radiation and meteorological data is condensed into one year's worth of the most usual conditions. Although a TMY can be thought of as a median, the methods used to calculate it consider many factors beyond a simple calculation of median values, including solar resource data and weather data such as wind speed and ambient temperature (Wilcox and Marion 1990). To calculate a TMY, a multiyear data set is analyzed and 12 months are chosen from that time frame that best represent the median conditions. For example, a TMY developed from a set of data for the years 1998–2005 might use data from 2000 for January 2003 for February, 1999 for March, and so on (NREL, Section 2.1, Page 11). The datasets are smoothed at the beginning and end of the months to allow for reasonable continuity. The most current version of the TMY3 data uses datasets from 1976-2005 from the National Solar Radiation Data Base Update. The dataset was constructed using 8760 hourly data for one year for 1020 locations across the USA (TMY locations). The data considered to be typical is based on the typical mean month from the available years, and then added to the dataset as the typical month for any given year. This data is used for a variety of purposes where accurate weather data is necessary.

TMY3 is used across the USA for practitioners using IPMVP Option C as their method to measure savings for energy efficiency projects. Nevertheless, there are limitations to the TMY3 dataset including data availability and relevance as the dataset becomes more outdated. This research explores the creation of typical temperature datasets comprising the most recent two and five years of temperature data. These datasets use only temperature data rather than all the inputs in TMY3, since the temperature data is all that program evaluators use when assessing models using IPMVP Option C.

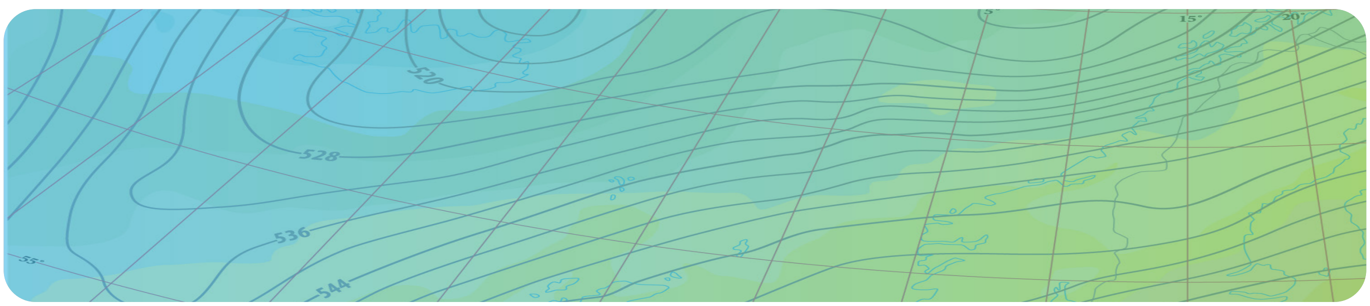
The study is designed to answer two research questions:

1. To what extent are predicted energy consumption values different using three- and five-year temperature datasets compared to TMY3 data?

2. How different are the temperatures in the TMY3 dataset compared to temperature datasets using two years and five years?

TMY3 data is now 17 years old, and the rate of climate change is accelerating every year. The background section explores the datasets that exist for weather normalization, the applicability of the dataset the face of accelerating climate change, and the geographic coverage and availability of TMY3 as it exists today.

Weather Choices



TMY3 is not the only dataset that is used for weather predictions across the world. In addition to the TMY data, there are Climate Normals, which are created by the National Climatic Data Center (NCDC). This data is a three-decade average of weather data that includes temperature, precipitation, snowfall, sea level pressure, wind, clouds, and more and estimate weather for a single weather data at a time (Durre et al. 2013; Arguez et al. 2012). The newest Climate Normals have been updated to reflect averages from 1991-2020. This data provides easy comparisons to the 30-year average and are designed to be easy to understand and reflect the impact of the changing climate on day-to-day experiences. Additionally, Climate Normals release supplementary 15-year datasets, with the most recent from 2006-2020 that captures more recent data only, which can be more useful to represent current and future weather conditions (Drury and Gattie-Garza 2016).

In addition to TMY and Climate Normals, US based weather data is available from TMYx, which is a repository of free climate data for building performance simulations, and California Climate Zone Data (CTZ) developed for the California Energy Commission and is updated through 2016.

Weather data has commercial, research, and other applications across the world. The datasets, in their most common forms, allow users to access hourly meteorological values that show typical conditions at a specific location over an extended period of time (Wilcox and Marion 1990). Researchers seeking to understand solar energy and daylight availability have used TMY data to predict future conditions of global irradiance that are used to improve solar model accuracy (Perez et al. 1990. Any time future energy performance needs to be assumed, and an annual estimate is required, some kind of typical data must be used. The model coefficients generated by the solar model is reapplied onto the TMY data to produce an estimate of "typical" consumption in any given year. In Option C modeling, only the temperature data is used to normalize models for a typical year. With so many critical applications, it is vital that TMY data be accurate to allow for the end uses to be representative of actual conditions. In 2017, CXassociates compared TMY3 data to 2016, 2015, and 2014 weather data. At the time of that publication, each of the preceding years had been the warmest year on record for their territory (Vermont). Only February was reasonably close (on average) to the TMY3 data. They recommended abandoning TMY3 data due to its inability to adapt to our rapidly changing climate and using instead a three-year average (2017).

There are other concerns as well for industries outside of energy efficiency. A 2015 white paper by Clean Power Research explored the accuracy of solar photovoltaic system performance when using TMY3 data. They noted that accuracy is dependent on the accuracy of TMY3 data, which is considered to be the gold standard for typical weather data. However, they found that it had limited usefulness for designing renewables projects. The data was insufficient for them to use for the sizing and financing for solar projects, and profitability because the TMY3 data was not precise enough for acceptable modeling, it increased risk for all stakeholders and jeopardized the profitability of the project. They suggested alternatives that included more recent data in their datasets on an ongoing basis.

Geographic Coverage

The 2015 Clean Power Research also focused on another availability issue of TMY3 - the number of TMY locations available in the dataset. They noted that NREL recommends not using TMY3 data for projects that are more than 25 km removed from the nearest TMY3 location, meaning that TMY3 data should not be used by more than 75% of US locations. The best data is only available at 6% of US sites. The paper concluded that choosing the right dataset for your TMY data is crucial. Not only can TMY3 be a challenge to incorporate into granular research, it can be difficult to find the data at all. Between the years of 2016-2020, the webpages where TMY3 was hosted were completely unavailable due to a lack of funding.

Scope

The sample consisted of a representative sample of 497 sites from 221 zip codes in northern Illinois, where TMY3 use is required to normalize savings from energy projects. The study considered electric data only; heating responses are electric heating, rather than gas heating. The year 2021 is used as the baseline year for savings prediction to capture post-COVID building behavior. The two-year and five-year typical temperature year datasets (2TTY and 5TTY) use temperature data from 2016-2021 and 2019-2021 as the basis of the typical years. The buildings in the study have annual kWh consumption ranging from 27 MWh to over 99 GWh. This study focuses on Option C whole building modeling.

Construction of the typical temperature years

The TTYs are constructed using hourly temperature data from the Weather Company for the number of years in the TTY (two or five). The Weather Company offers NOAA and other stations with algorithmic cleaning to ensure that there is no missing data. The TTY creation process begins with creating a typical month for each year to represent a normal month in a normal year. To create the typical month, the median temperature is calculated for every hour of the year. For each month, the Euclidean distance is calculated for each individual month. The distance is calculated between the vector of temperature values for that individual month and the vector of temperature values for that month of the median year.

For example, January 2019 is compared to population of Januarys and compared to the median year. The January that is closest to the median year is selected as the typical January. This process is repeated for each month resulting in the selection of one actual month for each month of the year that will make up the TTY. The typical year in this study is referred to as TTY (meteorological year): 2TTY is the TTY using the two most recent years of data, and 5TTY is the TTY using the five most recent years. The typical year is not the median of each hour but rather comprises the months that are closest to their associated median month. This is a representation of the process followed to create TMY3. Taking the median across all hours should eliminate outliers that may not be representative of conditions.

Typical Year Energy Consumption

Energy consumption data, for the site, are extracted with hourly temperature data and fit to an hourly consumption model. This model is then applied to TMY3, 2TTY, and 5TTY data to predict energy consumption.

Let

- i be an hour (YYYY/MM/DD hh),
- $temp(i)$ is the temperature in degrees Fahrenheit at hour i,
- $E(i)$ be the total electricity consumption for hour i,
- $HOW_j(i)$ be 1 if hour i is the j^{th} hour of the week and 0 otherwise (Monday at 00:00 is 0),
- $H(i)$ be the heating component comprised of four parameters (a piecewise-linear fit to the heating response),
  - $H(i) = h_1T_1(i) + h_2T_2(i) + h_3T_3(i) + h_4T_4(i)$
    - $T_1(i) = \min(\max(55 - temp(i), 0), 10)$
    - $T_2(i) = \min(\max(45 - temp(i), 0), 10)$
    - $T_3(i) = \min(\max(35 - temp(i), 0), 15)$
    - $T_4(i) = \max(20 - temp(i), 0)$
    - h_1, h_2, h_3, h_4 are coefficients to be fit

- $C(i)$ be the cooling component comprised of four parameters (a piecewise-linear fit to the cooling response)
  - $\mathrm{C}(i) = c_1T_1(i) + c_2T_2(i) + c_3T_3(i) + c_4T_4(i)$
    - $T_1(i) = \min(\max(temp(i) - 55{,}0), 10)$
    - $T_2(i) = \min(\max(temp(i) - 65{,}0), 10)$
    - $T_3(i) = \min(\max(temp(i) - 75{,}0), 15)$
    - $T_4(i) = \max(temp(i) - 90{,}0)$
    - c_1, c_2, c_3, c_4 are coefficients to be fit

Then the hourly electricity consumption is modeled as,

$$E(i) = \sum_{j=0}^{7\times 24-1} \beta_j HOW_j(i) + H(i) + C(i)$$

The regression model allows for the prediction of consumption for any collection of temperature and calendar data. The data is then normalized to the three temperature datasets to create predicted consumption values of what consumption would be during the temperatures represented in the 2TTY, 5TTY and TMY3 datasets. This study uses interval data from 1/1/2021 through 12/31/2021 for the regression, and the results are normalized onto the TTY data to compare the differences in predictions.

Results

Predicted Consumption

The coefficients from the fit model were used to predict consumption using both sets of TTY data and the TMY3 data. The cooling coefficients were applied to the TMY3, 2TTY and 5TTY datasets to create predicted normalized consumption contributions for each temperature range in the model. Cooling bins included 90° and hotter, 75°-90°, 65°-75°, and 55°-65°. Heating Bins included 20° and below, 20°-35°, 35°-45°, and 45°-55° degrees.

Table 1. Consumption Compared to TMY3

Temperature Bin	2 TTY Mean	5 TTY Mean
90° and hotter	72%*	66%*
75° to 90°	107%	112%*
65° to 75°	107%	113%
55° to 65°	102%	105%*
45° to 55°	106%	111%
35° to 45°	106%*	113%*
20° to 35°	64%*	89%
20° and below	28%*	22%*

Note: Values with an asterisk (*) following the value indicate a statistically significant difference from TMY3 data at p<0.05

The values in the table represent the predicted consumption using TTYs compared to the TMY3 predicted consumption. So, for the 90° and hotter bin, the 2TTY data is 72% as hot as the TMY3 consumption, and is statistically significantly different, and the 5TTY data is 66% of the TMY3 consumption for that bin (also significantly different.) The mid-temperature range consumption is hotter for both datasets. The 5TTY consumption is significantly different than the TMY3 data for five of the eight bins, and the 2TTY consumption is significantly different in four of the eight temperature bins. The coefficients times the total cooling degree hours in a range represents how often and how much the temperature was in or higher than that range. Together, the values in the bins give a tiered representation of the distribution of temperatures at that location in aggregate.

The consumption in the 90° and hotter temperature bin was significantly lower for both TTY datasets due to the overrepresentation of a 104° day in the TMY3 dataset. Except for the 20° and below bin, where the TTY consumption is 28% and 22% of the TMY3 consumption due to extremely cold temperatures in the TMY3 dataset, the values are as expected, with consumption being higher in using the TTY datasets. The results are inconsistent with respect to their actual difference or statistical significance from the TMY3 dataset. Consumption for some of the temperature bins were different from the TMY3 data, specifically in the mid temperature ranges. The 2TTY dataset did not show much difference from the TMY3 dataset, with only one midrange temperature being different from the TMY3 dataset, which indicates that two years of data may be insufficient. The 5TTY dataset had half of the mid-range temperatures come in with higher consumption for those ranges than the TMY3 dataset. The highest and lowest ranges were discarded due to the inclusion of severe weather events in the TMY3 dataset that could not be replicated with the TTY datasets. The TMY3 dataset, as mentioned above, had significant representation from a 104° day, which led to the 90° and hotter temperature bin showing extreme consumption due to air conditioning load. Additionally, this analysis only includes electric data, and thus may not be appropriate to model the extremely low temperatures below 20°F.

While there are significant variations across temperature ranges, overall, the differences in total consumptions are not statistically significant. Although there is some fluctuation in temperature contributions, there is not enough when considered at the whole building level, including the temperature independent contributions.

There are questions that the consumption similarities evoke. The consumption analysis is one part of the exploration between the sufficiency of the short TTY datasets. We also explored differences in the mean temperatures themselves between TMY3 and 2TTY and 5TTY, as well as the geographic coverage of the datasets with respect to the territory of interest.

Temperature Differences

The temperature ranges have a wider variance in the TTY datasets. The mean temperatures for the TTY datasets have a higher mean than the TMY3 dataset by 1.2°F, however, the 42% of the values in the TMY3 dataset include the impact of a 104°F day in 2005, leading to a general upward skew that is not represented in the TTY datasets. The minimum temperature in the TTY datasets was 7.8°F lower than TMY3. Figure 2. Average heating/cooling contributions to consumption for each temperature bin shows the means and medians across the 497 sites, demonstrating the differences in the overall available dataset. The high median (skewed due to the 104°F day) on the TMY3 values demonstrates that five years may not be sufficient to capture all temperature ranges.

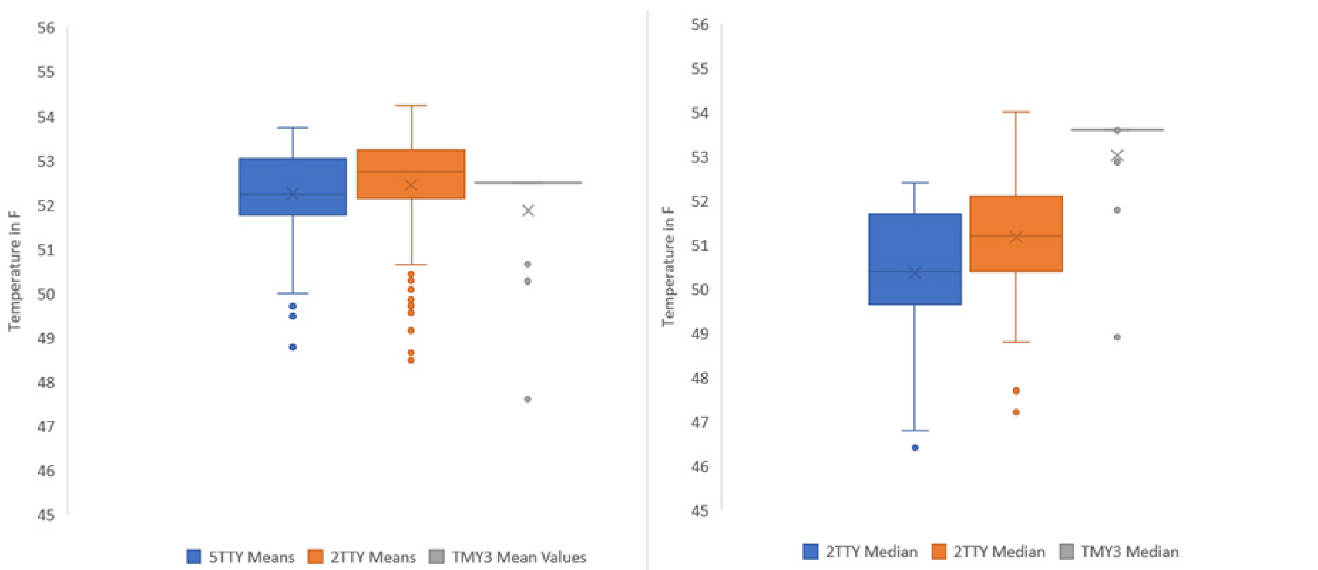


Figure 1. Mean and median values for typical temperature and meterological year datasets

The left side of the figure shows the temperature means from each dataset. The TMY3 dataset had the lowest overall mean at 51.8, despite the contribution of the 104°F day. The 2TTY had the highest mean of 52.4°F and the 5TTY had a mean of 52.2°F. T-tests were run comparing the mean temperatures in the TMY3 and each TTY dataset. Additionally, t-tests were run between each temperature bin in the datasets. All t-tests comparing TTY to TMY3 indicated statistically significant differences between each temperature at 99% confidence (see Table 2).

Table 2. Mean number of degree hours for each temperature bin, by dataset

Temperature Bin	2 TTY Mean Degree Hours	5 TTY Mean Degree Hours	TMY3
90° and hotter	90.3	90	126
75° to 90°	7,688	7,959	7,283
65° to 75°	20,158	21,463	19,154
55° to 65°	33,380	34,496	32,675
45° to 55°	43,063	43,642	41,050
35° to 45°	29,431	30,730	27,682
20° to 35°	12,731	14,960	19,830
20° and below	1,877	1,641	7,206

All the temperatures in each dataset are significantly ($p<0.05$) different from the TMY3 dataset. One difference between the datasets of interest is the higher number of degree hours represented from extreme temperatures in the TMY3 dataset compared to the TTY datasets. The TMY3 dataset has 126-degree hours in the 90° and hotter bin, while all the midrange temperatures are higher for the TTY datasets. Then, at the bottom of the temperature range at 20° and below, the TMY3 dataset has more degree days than either TTY dataset by a factor of four. The extreme temperatures have much more representation in TMY3. It also looks as though the shoulder seasons are getting longer and winter is shrinking, there are more 50–60-degree days instead of 30-degree days.

Note that the total consumptions are not significantly different, but that some temperature bins, and some heating/cooling consumption contributions are significantly different. Why is this? Looking at Figure 2 which shows the average heating/cooling contributions to consumption for each temperature bin, one can see that the increased contribution for cooling in the TTYs relative to the TMY is offset by the decrease in heating (specifically at the extreme cold temperatures).

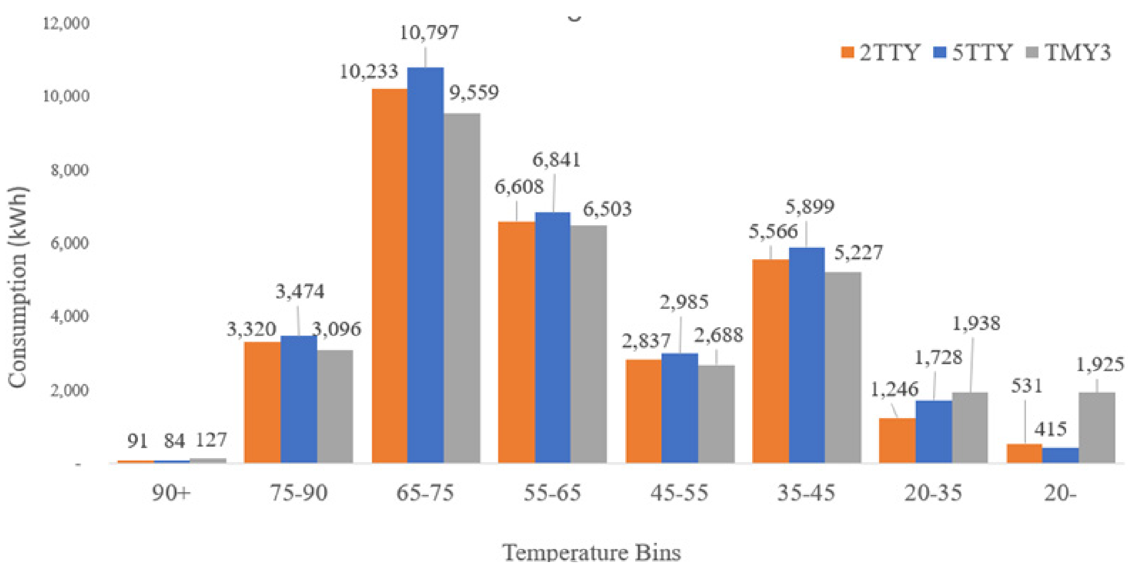


Figure 2. Average heating/cooling contributions to consumption for each temperature bin

This figure shows the contribution of each temperature bin to the overall consumption of all the buildings in the sample in aggregate. From left to right, the differences in consumption from the 2TTY, 5TTY, and TMY3 datasets are obvious. The TMY3 dataset over represents the extremely cold temperatures, which do not appear in the TTY datasets even though the mean minimums are lower in the TTY datasets by 7.8°F.

Geographical Coverage

TMY3 data is appropriate to use within 25km of the location of the weather station. In our sample frame, 66% of our sites are inappropriate to use with TMY3 data due to their distance from their weather station. It is important for IPMVP Option C models that they be able to normalize savings using typical weather as required by state TRMs. If TMY3 is inappropriate to use due to geographical coverage, it is necessary to normalize using another dataset, such as the TTY datasets. As shown in Figure 3 there are only ten weather locations available in northern Illinois for which TMY temperature data is available. The availabilities of the TTY datasets are superimposed on the TMY3 image in grey to illustrate the difference in coverage. The image on the right shows the TTY zip code coverage.

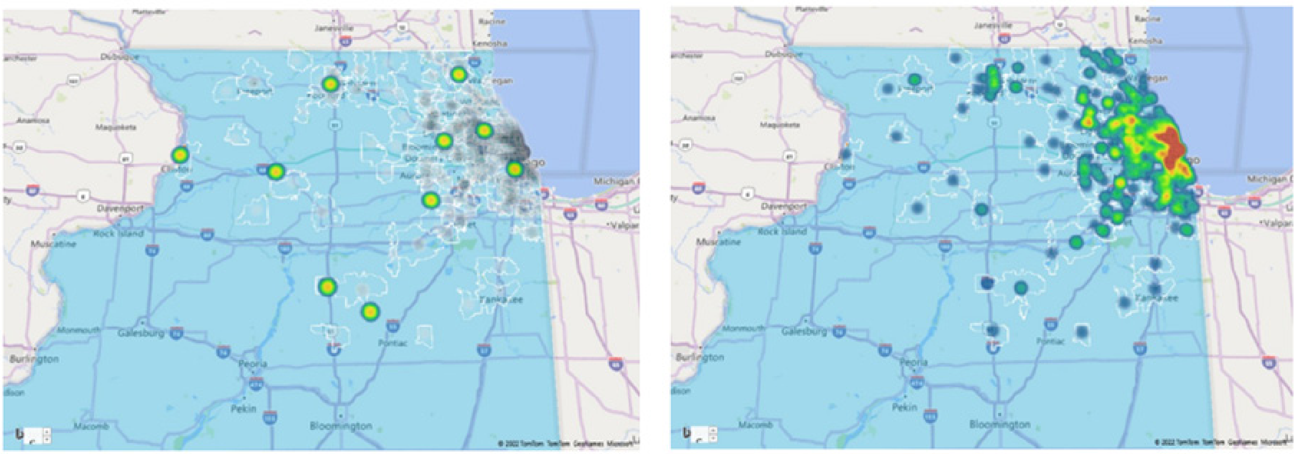


Figure 3. Mean temperature of available geographic regions in Illinois, TMY3 on left, TTY datasets on right

Using zip code data provides 221 individual points of temperature data in contrast to TMY3's ten locations on which to base consumption predictions, assess temperature and climate, and resolve missing data.

Limitations and Conclusions

There were two primary limitations to this study that further research could continue to explore:

1. Comparing to TMY3 only and not CWECS, CanadaData, TMYx or other international weather sources limits the generalizability to TMY3 compared to TTYs.

2. Our geographical area was limited to northern Illinois due to the requirement that TMY3 data be used in that territory for Option C models. This study should be repeated with real buildings in other climate zones. A more humid and hotter climate could represent the impact of an increase of summer, rather than just the decrease of winter.

With those limitations in mind, there are a few conclusions that can be drawn from the analysis. Predicted consumptions only varied for about half of the temperature ranges in the dataset. However, the TMY3 dataset includes so many outliers that it is difficult to compare the impact on buildings. This indicates that although the TMY3 dataset is not set up to represent extreme events, the data available is sufficient in TMY3 to create reasonable Option C models that are like using more recent temperature even with the mean temp increase of 2 degrees between the TMY3 dataset and the TTY datasets. The lack of representation of the 104°F day in the 2TTY and 5TTY datasets, as well as the minimum of the TMY3 dataset, which was a -12°F day, show that the 5TTY dataset may not be sufficient to capture all temperature ranges necessary to represent all conditions.

Additionally, the increase in acceptability for geographic coverage of TTY data using zip codes and weather stations rather than the availably TMY3 weather stations can lead to more appropriate representation. With only ten weather stations in the TMY3 dataset and 221 in the TTY datasets for northern Illinois, and with 66% of our data being outside the recommended 25km range, it is apparent that at the individual building level, it is more appropriate to use TTY data since that follows the NREL recommendation.

Most importantly, the extremely cold temperatures in the TMY3 are not represented in the data used fit the models. If that's the case, how can an energy model reasonably extrapolate to those extreme temperatures? Should they be in a typical year used for this purpose? Furthermore, there is a large non-heating/cooling contribution which means that it would take a substantial change to yield a change in consumption. Even though the total consumptions are not significantly different, it is not because there are not significant differences, it is just that they are canceling out to some extent.

If a building installed a heating only energy efficiency project, predicted savings using TMY3 are going to assume that the temperature drops to -13° every year, but the temperature does not decrease to that degree each year. The model would then be overrepresenting the amount of time that a building spends at that extremely low temperature, and the savings would be inflated. Furthermore, TMY3 is not representing the increase in medium high temperatures, so cooling measures will be undervalued. When constructing a whole building model that accounts for both heating and cooling, the values are cancelled out, leading to no discernable difference in consumption. However, not all projects are complete retrofits that upgrade or install both heating and cooling equipment. Should these extreme temperatures be used for projecting savings when they include these more extreme temperatures? What's typical about that?

In M&V 3.0, practitioners are going to want further disaggregated savings estimates: not just overall, but by time of use, by time of year, etc. The industry cannot count on heating and cooling cancellation. To properly project energy savings for grid capacity planning and climate change mitigation, the world needs more accuracy and more precision. If TMY3 is used to do normalized energy savings in Illinois, on aggregate, cooling will be underrepresented, and heating will be overrepresented. This matters for energy efficiency resource planning, meeting climate change goals, and for grid capacity planning.

References

ACEEE. 2022. “ACEEE State Scorecard Rank.” State and Local Policy Database. 2022. https://database.aceee.org/state-scorecard-rank.

Arguez, A,. S. Imke, A. Scott, S. Russell, M. Vose, F. Squires, Y. Xungang, R. Heim, and T. T. 2012. “Noaa’s 1981-2010 U.S. Climate Normals.” Bulletin of the American Meteorological Society 93 (11): 1687–97. https://doi.org/10.1175/BAMS-D-11-00197.1.

CXassociates. 2017. “Is Typical Meteorological Data Relevant for Energy Analysis? (Part 1).” 2017. https://buildingenergy.cx-associates.com/is-typical-meteorological-data-relevant-for-energy-analysis.

Drury, M,. M. Gattie-Garza. 2016. “Climate Change and Its Effect on Weather Data.”

Durre, I,. M. Squires, S. Russell. X. Vose, A. Arguez, S. Applequist. 2013a. “NOAA’s 1981-2010 U.S. Climate Normals: Monthly Precipitation, Snowfall, and Snow Depth.” Journal of Applied Meteorology and Climatology 52 (11): 2377–95. https://doi.org/10.1175/JAMC-D-13-051.1.

Elmore, A., J. Guggenberger. 2015. “International Journal of Smart Grid and Clean Energy Using TMY3 Data to Stochastically Predict the Performance of a PV/VRB Microgrid.” International Journal of Smart Grid and Clean Energy Using. https://doi.org/10.12720/sgce.4.4.336-345.

EVO. 2022. “Core Concepts 2022.”

Gold, R., and S. Nowak. 2019. “Energy Efficiency Over Time: Measuring and Valuing Lifetime Energy Savings in Policy and Planning.” https://www.aceee.org/research-report/u1902.

Jenkins, C., S. Dent, R.Faesy, S.Bower, C.Mcdonald. 2010. “State of Ohio Energy Efficiency Technical Reference Manual” IV: 1–33.

Korn, D., J. Walczyk. 2016. “Exactly What Is a Full Load Cooling Hour and Does Size Really Matter?”

Indiana Utility Regulatory Commission. 2016. Indiana TRM. Vol. 53. https://doi.org/10.1017/CBO9781107415324.004.

Perez, R., P. Ineichen, R. Seals, J. Michalsky, R. Stewart. 1990. “Modeling Daylight Availability and Irradiance Components from Direct and Global Irradiance.” Solar Energy 44 (5): 271–89. https://doi.org/DOI: 10.1016/0038-092X(90)90055-H.

Illinois Stakeholder Advisory Group (IL SAG). 2021. “2022 Illinois Statewide Technical Reference Manual for Energy Efficiency Volume 1: Overview and User Guide.”

Wilcox, S., and W. Marion. 1990. “User Manual for TMY3 Data Sets.” NREL National Renewable Energy Laboratory. Vol. 66.

Engel-Foweles, V., E. Funkhouser, J. Byrne, M. Stankovski, L. Wilson-Wright. 2020. “NYSERDA Residential Retrofit Impact Evaluation Report (PY2012-2016)