

Article

Evaluation of Impact of Change in Climatic Conditions on Net-Zero Energy Designs for Residential Buildings

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Abstract

This study examines the impact of updated weather datasets on the selection of energy-efficient measures (EEMs) and photovoltaic (PV) sizing to reach net-zero energy (NZE) performance for residential buildings in four USA cities with different climates: Minneapolis, MN, Chicago, IL, San Francisco, CA, and Phoenix, AZ. The analysis results show that annual heating and cooling degree days from various climatic datasets can differ from those estimated using 2025 data by 0.5–23.3%. These differences in climatic datasets can result in substantial deviations in predicting annual energy needs for residential buildings. For buildings in heating-dominated climates, such as Minneapolis, MN, significant reductions in annual energy demands of up to 8.2% are incurred when using the most recent climate dataset, while increases of up to 5.0% are found for the cooling-dominated climate of Phoenix, AZ. Moreover, variations in climatic datasets affect design specifications and economic indicators of residential buildings. Life-cycle costs of baseline designs are lowered by 3.6% for buildings in Minneapolis, MN, but are increased by 2.3% for buildings in Phoenix, AZ. Similarly, capacities for rooftop PV systems required for net-zero energy designs decrease by 9.5% for buildings in Minneapolis and increase by 11.7% for buildings in Phoenix, AZ.

Keywords: net-zero buildings; weather files; energy; energy efficiency; photovoltaic (PV) sizing; life-cycle cost analysis

1. Introduction

Energy efficiency, sustainability, and achieving net-zero energy specifications have become central design and operation goals for buildings. To optimize the selection of building systems, modeling and simulation analyses have become crucial approaches especially to design energy efficient buildings. These optimized design methods are required due to the complex and dynamic interactions between various building systems and external climatic conditions [1]. Since most of the detailed whole-building modeling and simulation tools require at least hourly variations of the climatic conditions, the provision of suitable weather data becomes critical [2]. Traditionally, historical weather data are used to design building energy systems. This approach may not be suitable to predict the energy performance of buildings over future periods dominated by climate change [3].

Historically, building energy simulation tools have relied on a Typical Meteorological Year (TMY). A TMY file represents a typical year of weather data created by selecting representative months from historical records each month where the most “typical” year is



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identified based on criteria that minimize the deviations from long-term monthly averages of different key metrics such as the heating and cooling degree days and solar irradiances [4]. As climate variability intensifies, the dependence on older datasets is being increasingly questioned, driving a transition toward updated weather datasets and future weather datasets [5]. These datasets provide more current representations of climate conditions as the static nature of TMY data fail to incorporate changes in the accelerating impact of climate change on the energy performance of buildings, the required HVAC system capacities, and the building integration levels for renewable energy systems [6–8]. A review of both conventional and emerging TMY-generation methodologies suitable for whole-building energy analysis identifies persistent challenges related to representativeness, non-stationarity, and climate variability that limit the reliability of current used weather datasets to perform long-term performance assessments [9]. Parallel efforts have focused on improving urban-scale weather data generation methods to better capture local microclimatic conditions, thereby enhancing the fidelity of building energy consumption estimates at city and district levels [10]. Large-scale housing energy modeling investigations similarly demonstrate that uncertainties in input assumptions and environmental conditions propagate into substantial variability in predicted energy consumption, reinforcing the necessity of robust uncertainty treatment when results from simulations based on historical weather data are used for policy development or large building stock assessments [11].

Several studies have highlighted the limitations of older weather datasets on simulation accuracy. Crawley [12] compared the use of three weather datasets including TMY2, WYEC2, and SAMSON on annual energy use predicted by the whole-building energy simulation program, DOE-2.1E. The analysis reveals that the energy use variations ranging between -2.3% and 5.4% across eight USA cities. Moreover, Crawley et al. [13] argued that TMY weather datasets may not accurately capture extreme climate variability, proposing the use of eXtreme Meteorological Year (XMY) datasets, which incorporate months with extreme weather conditions, which could be used to supplement the TMY weather data sets to enhance the robustness of the predicted results from the simulations.

Studies have also compared the use of TMY datasets with actual measured data. A study by Bhandari et al. (2012) evaluated the accuracy of the TMY3 weather data by comparing measured on site data with predictions using EnergyPlus and PVWatts. The comparative analysis has showed up to 7% differences in annual energy consumptions and 40% in monthly heating and cooling loads [14]. Cui et al. [15] have investigated the effectiveness of using the traditional TMY data instead of newer multiple-year weather datasets for Chinese cities to carry out building-energy-simulation-based analyses to predict energy consumption and peak loads. They used DeST and EnergyPlus whole-building simulation engines to compare the energy performance predictions using traditional and multi-year simulations. The simulation analysis has indicated that using TMY data often failed to capture the extreme weather variations [15]. Similarly, Lupato et al. [16] observed that the analysis using newer weather datasets indicated an increasing cooling loads and a reduction in heating demands for buildings in Italy due to global warming. Moradi et al. [17] have compared simulation-based predictions using TMY and Actual Weather Year (AWY) data for residential buildings in cold and Mediterranean climates, showing significant inaccuracies in TMY datasets, especially during extreme weather conditions. Recently, Mardaljevic et al. [18] questioned the reliability of Typical Meteorological Year (TMY) files, as these datasets were found to be highly variable and misaligned with observed conditions. Instead, they recommended the use of satellite-derived Actual Meteorological Year (AMY) data as a superior alternative for building design and daylight assessment [18].

Similarly, Parker, et al. further demonstrated the benefits of using updated weather datasets by highlighting the impact of transitioning from older TMY3 weather data to the more recent TMY2021 data on residential building energy simulations across 64 North American locations. Their findings revealed a shift in energy loads, with heating and cooling demands decreasing by around 11% each. The solar PV output was also more improved and accurate because of the more recent irradiance data [19].

Comparative studies further show that substituting one weather dataset for another, without modifying any building design parameters, can shift predicted heating and cooling demands and alter the apparent effectiveness of design measures, implying that changes in dataset vintage alone can modify design conclusions [20]. In addition to heating and cooling, updated weather data have significant effects on the sizing and performance of photovoltaic systems to achieve net-zero energy. Some analyses reveal that TMY data struggle to accurately capture the variability of solar irradiance while others suggest that it was credible in predicting general trends. Yimprayoon et al. evaluated four weather datasets, including TMY2 and TMY3, in the PV performance simulations. Their findings revealed that TMY datasets were insufficient in capturing the variability and uncertainty of solar power generation. The results showed that availability outputs deviated significantly, ranging from -28% to 17% , when compared to other recent datasets like NSRDB and SolarAnywhere [21]. Similarly, Rudniak [22] examined differences between locally measured irradiance and updated TMY data from the European PV Geographical Information System databases, finding that newer datasets closely reflected actual summer conditions highlighting the importance of using more updated datasets for better accuracy. Similarly, Kneifel et al. [23] analyzed the energy performance of a net-zero energy residential building in Gaithersburg, MD, using 34 years of historical weather data compared to TMY3 datasets. Their findings revealed that annual electricity use ranged between 11,300 and 12,983 kWh, whereas TMY3 data estimated 11,783 kWh. This disparity highlights TMY3's dependence on older climate data, which failed to capture the full extent of modern climatic variability. As a result, energy consumption patterns aligned more closely with past weather rather than evolving trends. These results underscore the limitations of outdated datasets and the critical importance of adopting updated weather files, such as TMYx, to account for evolving climate patterns and improve the accuracy of building energy performance predictions in net-zero energy scenarios.

Within the net-zero research domain, recent studies emphasize the importance of integrated, system-level evaluation frameworks that assess coordinated packages of envelope upgrades, mechanical systems, renewable energy, and operational controls rather than isolated technologies. Such holistic simulation approaches capture interactions among sub-systems and reduce the risk of misleading conclusions from component-level analyses [24].

The literature further integrates energy simulation with economic decision-making frameworks, demonstrating that tool selection and modeling workflows significantly influence early-stage net-zero design outcomes [25]. Accordingly, life-cycle cost (LCC)-based simulation frameworks are widely used to identify economically optimal bundles of efficiency measures, while multi-objective optimization methods enable simultaneous evaluation of energy performance, occupant comfort, and cost trade-offs [26,27]. Recent economic studies extend this paradigm by incorporating long-term uncertainty, showing that external risks, replacement cycles, and energy price trajectories can materially affect cost-effectiveness and alter the ranking of competing design strategies [28].

Although there have been several studies on the influences of weather data on building energy simulations, most are focused on traditional metrics such as annual energy consumption and peak load predictions. However, very few studies have discussed the impact of updated weather files on specific strategies required for achieving net-zero energy

in construction and the impacts on PV sizing to achieve net-zero energy buildings. To address this need, the study aims to compare the traditional TMY/TMY2/TMY3 files against updated TMYx files in understanding how more recent weather data influences net-zero analysis for a typical USA residential building across various climate zones to ensure more accurate strategies in achieving net-zero energy goals.

2. Materials and Methods

This study evaluates the impacts of using updated TMY weather datasets on life-cycle costs (LCCs), annual energy performance, and photovoltaic (PV) system capacities required to achieve net-zero energy (NZE) designs for residential buildings. The methodology is designed to quantify the economic and energy impacts of weather datasets selection on energy and cost benefits of various design options for residential buildings across multiple USA climate zones.

Figure 1 outlines the methodology approach used in this study. Initially, a series of building energy analyses is conducted using progressively updated Typical Meteorological Year (TMY) datasets to assess annual heating and cooling thermal loads and energy end-uses, energy efficiency measures (EEMs) selection, total source energy consumption, and corresponding life-cycle costs for baseline, cost-optimal, and NZE designs for residential buildings.

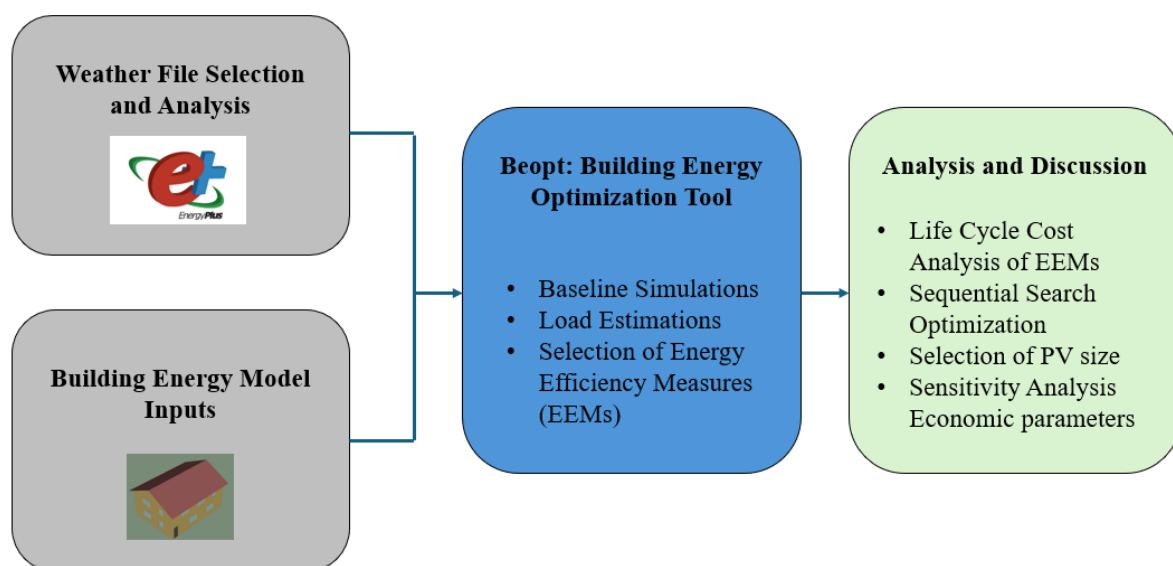


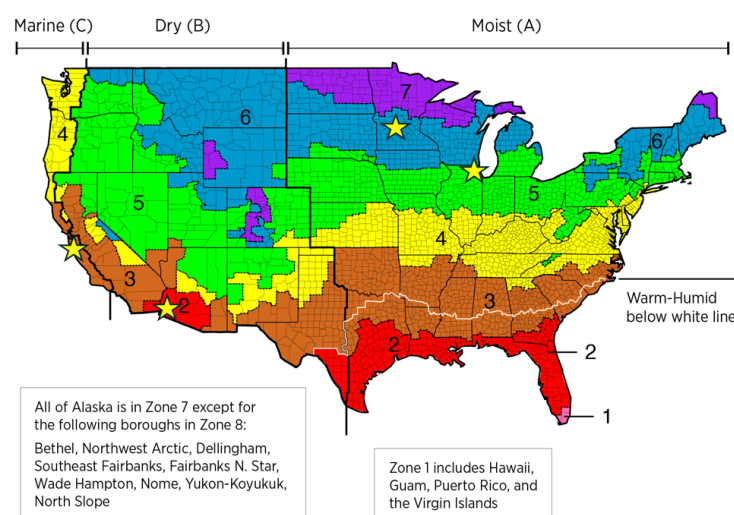
Figure 1. Methodology considered in the study.

The analysis methodology, outlined in Figure 1, is used to isolate and quantify the impact of well-established changes in the climatic conditions on net-zero energy designs of USA residential buildings. By applying the same baseline building specifications, energy efficiency measure packages, and optimizing environment to different climatic datasets, it is ensured that any observed changes in the energy performance metrics (annual energy consumption and PV capacities) and economic benefit indicators (capital costs, annual energy cost reductions, and life-cycle costs) are attributed to the differences specific to the characteristics of the climate, as captured by the considered weather files.

Four USA cities are selected, as shown in Table 1, to capture a spectrum of heating dominated, cooling dominated, and mixed marine climate zones. The locations of the selected cities are marked with a star (★) in Figure 2.

Table 1. Summary of selected climates [29].

City, State	Climate Zone	Climate Type	Weather Station	Heating Degree Days (18 °C)	Cooling Degree Days (18 °C)
Minneapolis, MN	6A	Cold, Humid	Minneapolis Saint Paul Airport	3651	748
Chicago, IL	5A	Cool, Humid	Chicago Midway Airport	2732	715
San Francisco, CA	3C	Mixed, Marine	San Francisco Airport	1381	197
Phoenix, AZ	2B	Hot, Dry	Phoenix Sky Harbor Airport	575	3127

**Figure 2.** IECC/ASHRAE USA climate zone map with selected USA cities highlighted by stars (★) [30].

Specifically, the heating and cooling degree days during year 2025 for all four cities are listed in Table 1 [31]. The weather stations used to estimate HDD and CDD values as well as to develop TMY climatic datasets are listed in Table 1.

For each city, four generations of historical Typical Meteorological Year datasets, TMY, TMY2, TMY3, and the most recent TMYx are considered. The time frame considered for these weather files is outlined in Table 2.

Table 2. Years used to generate various TMY weather datasets.

Types of TMY Files	Time Frame
TMY [32]	1948–1980
TMY2 [33]	1961–1990
TMY3 [4]	1991–2005
TMYx [32]	2009–2023

Initially, the selected weather files are analyzed to compare the heating and cooling degree days and global solar irradiance across the four climate zones to assess the variability of these parameters under changing climatic conditions. Next, the baseline building designs are modeled using BEOpt [34] based on IECC 2021 specifications [35] and PNNL prototype energy models as illustrated in Figure 3 [36] for each representative climate, as summarized in Table 3. The heating and cooling energy demands are analyzed for the baseline design cases. Sequential search optimization is carried out to select optimum packages of EEMs to reduce annual energy source use while minimizing LCCs. For the LCC analysis, a discount rate of 3% and a lifetime of 30 years are considered. All the costs and lifespan for EEMs are accounted for using BEOpt databases. Finally, net-zero energy (NZE) building

designs are determined using appropriately sized rooftop PV systems. The life-cycle costs of incorporating the PV system are evaluated considering various alternative scenarios with and without surplus PV generation sold to the grid.



Figure 3. BEopt energy model for the residential building geometry.

Table 3. Building model baseline specifications for residential building for different climate zones based on IECC 2021 specifications.

Categories	Subcategories	Minneapolis, MN	Chicago, IL	Phoenix, AZ	San Francisco, CA
Building	Orientation	North	North	North	North
Walls	Wood Stud	RSI-3.70 Fiberglass Batt	RSI-3.70 Fiberglass Batt	RSI-3.70 Fiberglass Batt	RSI-3.70 Fiberglass Batt
	Wall Sheathing	OSB	OSB	OSB	OSB
	Exterior Finish	Stucco, Medium/Dark	Stucco, Medium/Dark	Stucco, Medium/Dark	Stucco, Medium/Dark
Ceilings/Roof	Unfinished Attic	Ceiling RSI-10.57 Fiberglass, Vented	Ceiling RSI-10.57 Fiberglass, Vented	Ceiling RSI-8.63 Fiberglass, Vented	Ceiling RSI-8.63 Fiberglass, Vented
	Roof Material	Asphalt Shingles, Medium	Asphalt Shingles, Medium	Asphalt Shingles, Medium	Asphalt Shingles, Medium
Foundation/Floors	Slab	Whole Slab RSI 1.76 XPS	Whole Slab RSI 1.76 XPS	Uninsulated	Whole RSI 1.76 XPS
	Carpet	80% Carpet	80% Carpet	80% Carpet	80% Carpet
Thermal Mass	Exterior Wall Mass	0.013 m Drywall	0.013 m Drywall	0.013 m Drywall	0.013 m Drywall
	Partition Wall Mass	0.013 m Drywall	0.013 m Drywall	0.013 m Drywall	0.013 m Drywall
	Ceiling Mass	0.013 m Drywall	0.013 m Drywall	0.013 m Drywall	0.013 m Drywall
Fenestrations	Window Areas	F15 B15 L15 R15	F15 B15 L15 R15	F15 B15 L15 R15	F15 B15 L15 R15
	Windows	U-0.3 SHGC-0.4	U-0.3 SHGC-0.4	U-0.3 SHGC-0.4	U-0.3 SHGC-0.4
	Interior Shading	70%	70%	70%	70%
	Door Area	1.86 m ²	1.86 m ²	1.86 m ²	1.86 m ²
	Eaves	0.61 m	0.61 m	0.61 m	0.61 m
	Overhangs	0.015 m	0.015 m	0.015 m	0.015 m

Table 3. Cont.

Categories	Subcategories	Minneapolis, MN	Chicago, IL	Phoenix, AZ	San Francisco, CA
Airflow	Air Leakage	ACH50 = 3	ACH50 = 3	ACH50 = 5	ACH50 = 3
	Mechanical Ventilation	ERV, 70%	ERV, 70%	ERV, 70%	ERV, 70%
	Natural Ventilation	Cooling Months Only, 3 days/week	Cooling Months Only, 3 days/week	Cooling Months Only, 3 days/week	Cooling Months Only, 3 days/week
Space Conditioning	Air Source Heat Pump	SEER = 14.3 HSPF = 8.2	SEER = 14.3 HSPF = 8.2	SEER = 14.3 HSPF = 8.2	SEER = 14.3 HSPF = 8.2
	Ducts	7.5% Leakage, RSI-1.41	7.5% Leakage, RSI-1.41	7.5% Leakage, RSI-1.41	7.5% Leakage, RSI-0.41
Conditioning schedule	Heating/Cooling Seasons	Year-Round	Year-Round	Year-Round	Year-Round
	Cooling Set Point	23.9 °C	23.9 °C	23.9 °C	23.9 °C
	Heating Set Point	22.2 °C	22.2 °C	22.2 °C	22.2 °C
Water Heating	Water Heater	Electric, Tankless, UEF = 0.99	Electric, Tankless, UEF = 0.99	Electric, Tankless, UEF = 0.99	Electric, Tankless, UEF = 0.99
	Distribution	Insulated, Copper	Insulated, Copper	Insulated, Copper	Insulated, Copper
Lighting	Lighting	80% LED	80% LED	80% LED	80% LED

Note: ACH50 = Air Change per Hour at 50 Pa; ERV = Energy Recovery Ventilator; OSB = Oriented Strand Board; RSI = R-value in SI units; XPS = Extruded Polystyrene; SHGC = Solar Heat Gain Coefficient; UEF = Uniform Energy Factor; SEER = Seasonal Energy Efficiency Ratio; HSPF = Heating Seasonal Performance Factor, LED = Light-Emitting Diode.

3. Discussion of Analysis Results

3.1. Impact of Weather DataSet

Figure 4 illustrates the variations in the annual heating and cooling degree days estimated from four TMY weather datasets and those obtained for year 2025 across the four USA selected cities [31]. It can be clearly noted that more recent TMY weather datasets exhibit increased cooling degree days and decreased heating degree days. This trend reflects the increase in global ambient air temperatures over the past few decades. Table 4 shows the deviations in annual cooling and heating degree days obtained from year 2025 and those estimated from the TMY weather datasets. Annual heating degree days (HDD) calculated from the conventional TMY dataset are significantly lower than those from 2025 by 40.2% for San Francisco, CA, 89.2% for Phoenix, AZ, 9.3% for Chicago, IL, and 13.8% for Minneapolis, MN. Annual HDD values estimated from TMY2 and TMY3 are closer than those from 2025 but remain substantially lower depending on climate. In contrast, the use of TMYx datasets consistently yields the lowest HDD deviations relative to those from 2025 across all locations, limited to 0.5% for San Francisco, CA, 36.5% for Phoenix, AZ, 2.3% for Chicago, IL, and 2.4% for Minneapolis, MN, indicating closer agreement with observed heating demand. Annual cooling degree days (CDD) computed from TMY and TMY2 datasets exhibit large deviations from those obtained from 2025 for cooling-dominated climates. However, annual CDD values estimated from TMY3 and TMYx datasets are close to these determined from 2025 for all the four USA cities. For instance, annual CDD values from TMYx deviate from those obtained from 2025 by 7.3% for Phoenix, AZ, 17.7% for Chicago, IL, and 10.5% for Minneapolis, MN. For San Francisco, annual CDD values are inherently low, leading to high percentage deviations between all weather datasets. The TMY climatic datasets are compared with the HDD and CDD values for 2023–2025 for Minneapolis, MN, as shown in Figure 5. The TMYx climatic dataset is consistently the closest to the values estimated for the period of 2023–2025.

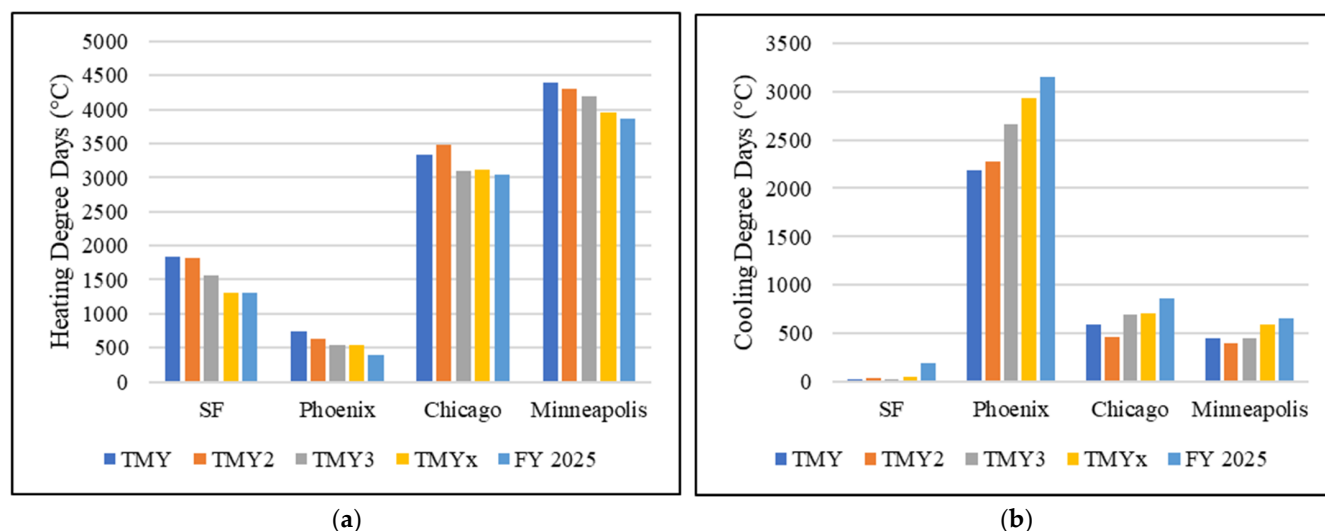


Figure 4. Total annual (a) heating and (b) cooling degree days for different TMY weather datasets and year 2024 for four selected cities.

Table 4. Differences between actual 2025 and TMY dataset based annual heating and cooling degree days.

Percentage Deviations from Annual Heating Degree Days Specific to FY 2025				
Data Set	San Francisco, CA	Phoenix, AZ	Chicago, IL	Minneapolis, MN
TMY	40.2	89.2	9.3	13.8
TMY2	39.2	58.8	13.9	11.4
TMY3	18.8	38.0	1.8	8.9
TMYx	0.5	36.5	2.3	2.4
Percentage Deviations from Annual Cooling Degree Days Specific to FY 2025				
Data Set	San Francisco, CA	Phoenix, AZ	Chicago, IL	Minneapolis, MN
TMY	89.3	30.7	30.9	30.7
TMY2	83.8	27.8	45.7	39.5
TMY3	88.3	15.7	19.1	30.7
TMYx	74.6	7.3	17.7	10.5

Figure 6 illustrates the monthly HDD and CDD variations for Minneapolis, MN, characterized by its cold climate. The TMYx weather dataset exhibits a noticeable reduction in maximal monthly HDD values compared to TMY, TMY2, and TMY3 datasets. This indicates a moderation in extreme heating demands over the years captured by the most recent datasets. In contrast, TMY2 results in the lowest monthly CDD values and TMYx produces the highest CDD values. Additionally, the monthly CDD-distribution-obtained TMYx dataset is more spread out across the year, suggesting a prolonged cooling season and increased cooling demand, while the older weather datasets exhibit narrower peaks in CDD concentrated within fewer months.

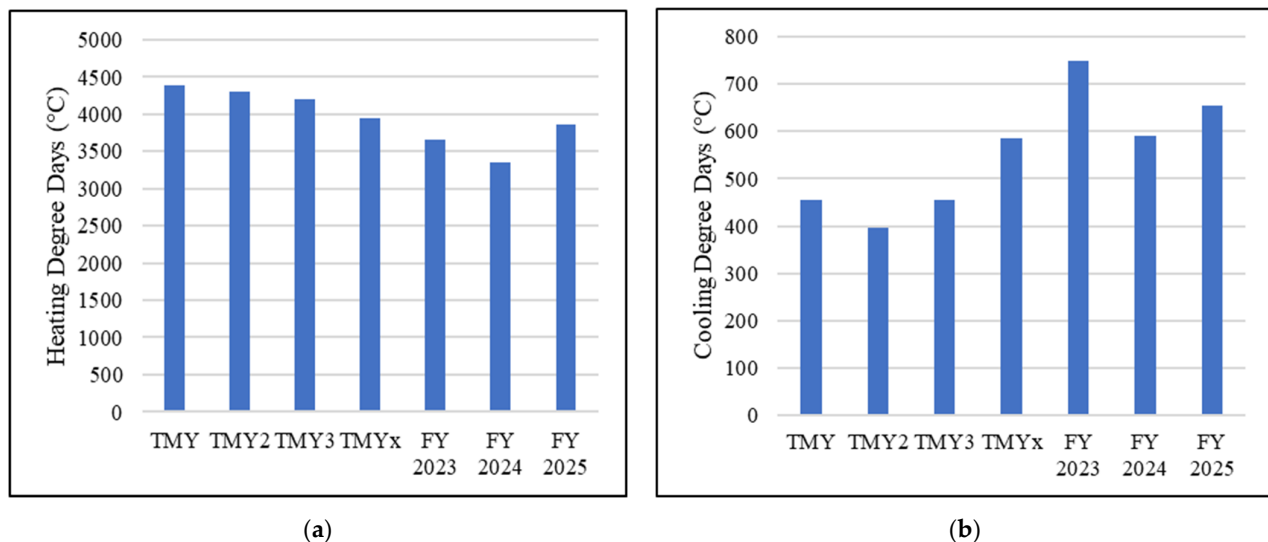


Figure 5. Total annual (a) heating and (b) cooling degree days for different TMY climate datasets and years 2023–2025 for Minneapolis, MN.

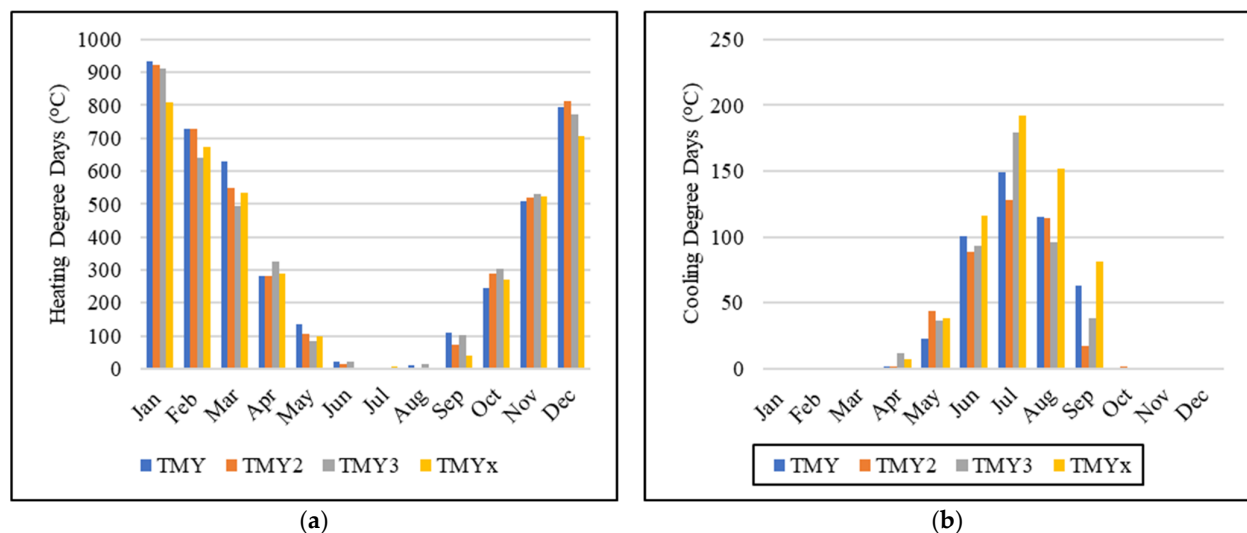


Figure 6. Monthly variations of (a) heating and (b) cooling degree days for Minneapolis, MN, for different TMY weather datasets.

3.2. Baseline Building Designs

This section presents the impact of weather dataset on source energy consumption predicted for baseline designs for prototypical residential buildings in four USA cities considered in this study. The specifications for the baseline designs are listed in Table 3 for all four cities. The analysis results, summarized in Figure 7, indicate that the impacts of weather datasets are most significant for extreme climates including Minneapolis, MN, and Phoenix, AZ. Indeed, Figure 7a shows that the annual energy consumption for baseline design of the prototypical residential building in Minneapolis, MN has decreased substantially as more recent weather datasets are used, primarily due to the reduction in heating requirements. In contrast, the annual energy use for the baseline design in Phoenix, AZ increases as more updated TMY datasets are used as illustrated in Figure 7c. An interesting anomaly is observed in Figure 7b,d, where heating energy end use obtained using TMY2 is higher than that predicted using TMY for Chicago, IL and San Francisco, CA. This anomaly can be attributed to the recorded drop in average USA temperatures (by approximately 0.56–0.83 °C) during the 1960–1980 period, which is effectively captured by the TMY2

weather dataset [37]. In summary, the energy consumption trend shown in Figure 7 is consistent with the variations of both HDD and CDD estimated for different TMY weather files as shown in Figure 4.

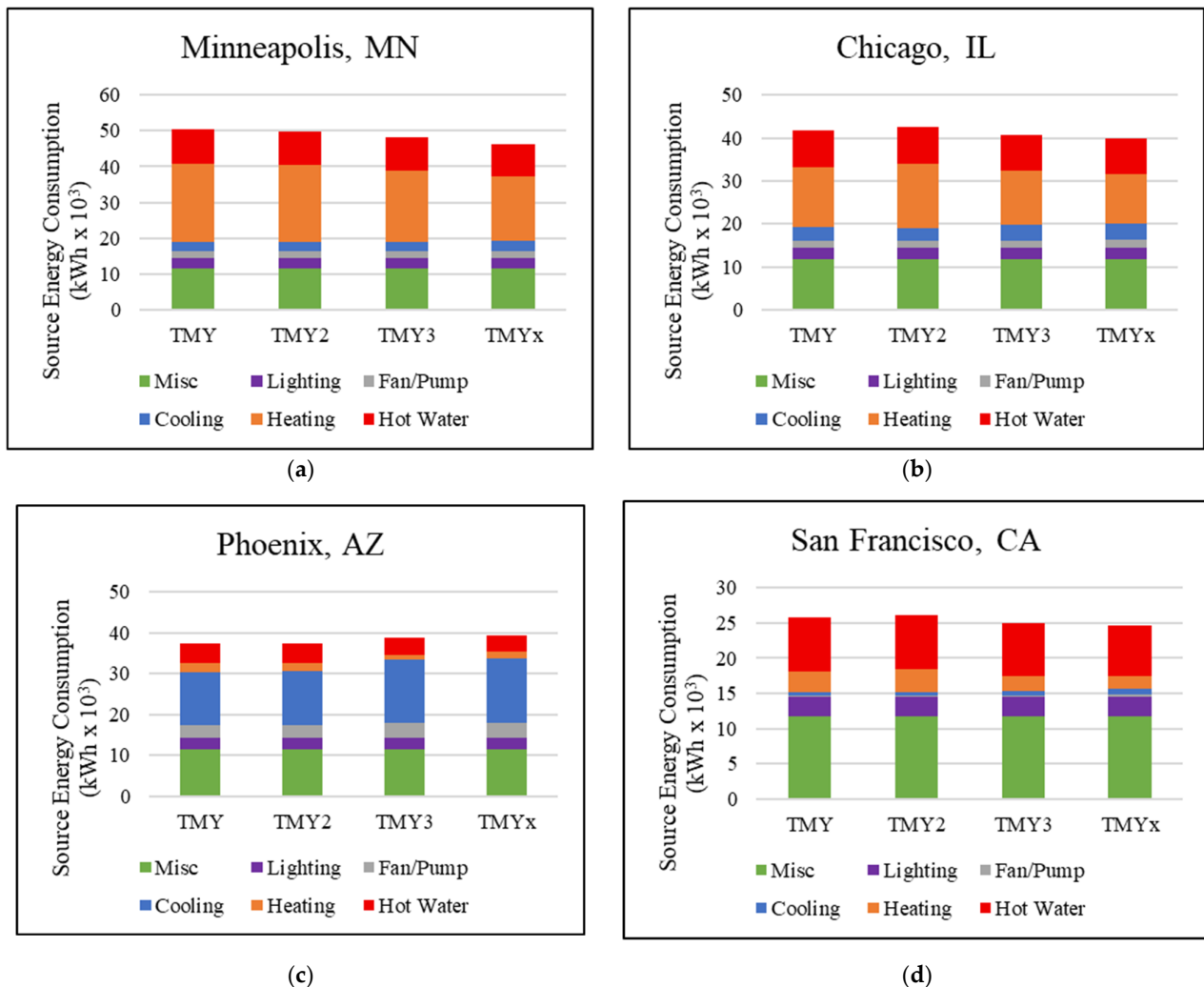


Figure 7. Annual source energy consumption for (a) Minneapolis, MN, (b) Chicago, IL, (c) Phoenix, AZ, (d) San Francisco, CA.

3.3. Selection of Energy Efficiency Measures

In this section, sets of energy efficiency measures (EEMs) are identified to reduce the annual energy needs required for the baseline designs of the residential building for the four cities considered in this study. Figures 8 and 9 show the components for the heating and cooling thermal loads determined for Minneapolis, MN and Phoenix, AZ using the TMYx dataset. The analysis reveals that most of the heating and cooling thermal loads for the baseline building are envelopes dominated. Specifically, envelopes are responsible for 75.39% of heating thermal loads for Minneapolis, MN, and 63.4% of cooling thermal loads in Phoenix, AZ. To lower both heating and cooling thermal loads of the baseline designs, several energy efficiency measures are considered to primary improve energy performance of building envelopes. Specifically, wall insulation and sheathing insulation level, ceiling insulation, slab insulation, air leakage reduction, and window upgrade are identified for further analysis in addition to improvements in energy performance in heating, ventilating, and air conditioning (HVAC) systems, domestic hot water (DHW), and supply ducts. For each EEM, three to four different options were provided, where the sequential search

optimization selected the optimum option based on the source energy savings as well as the life-cycle cost (LCC) of the EEMs.

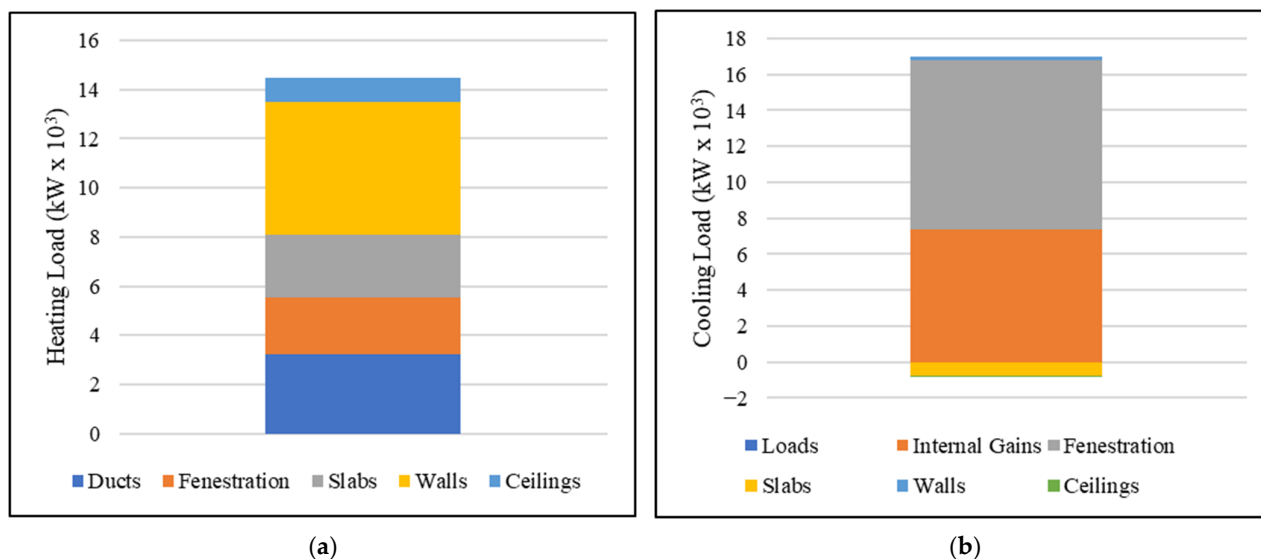


Figure 8. Components of (a) heating and (b) cooling thermal loads for baseline building design in Minneapolis, MN.

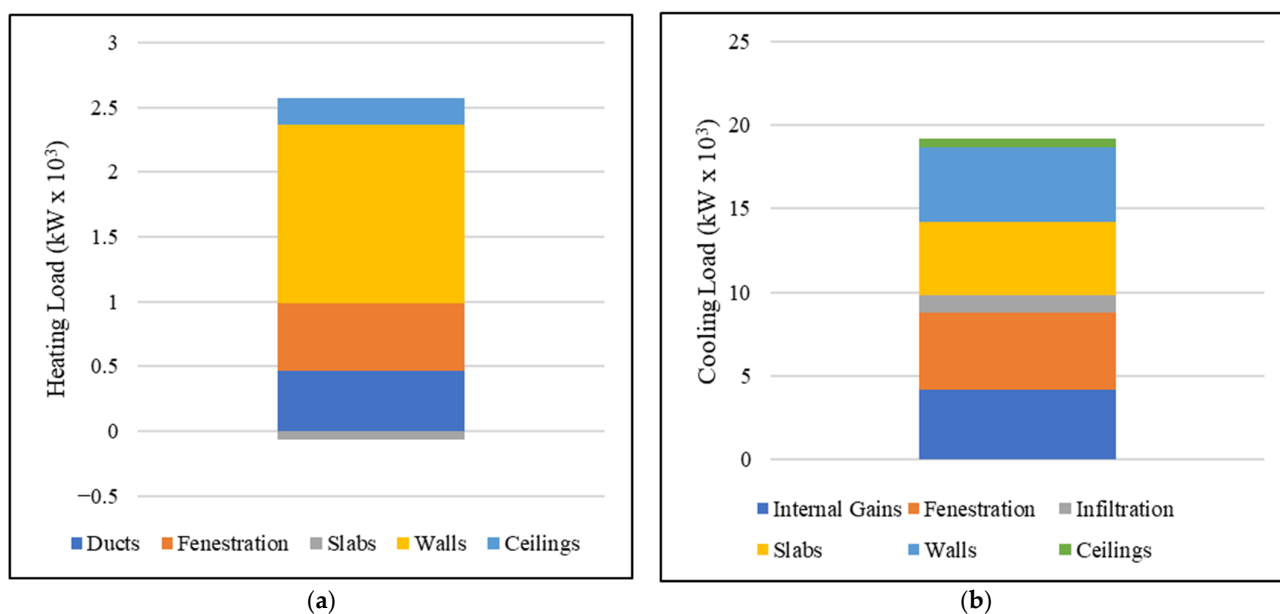


Figure 9. (a) Heating and (b) cooling energy distribution for Phoenix.

3.4. Cost-Optimal Building Designs

The selection of best combination of EEMs to minimize annual source energy use as well as the life-cycle costs (LCCs) of the residential buildings using different weather datasets is discussed in this section. Sequential search optimization, implemented as part of the BEOpt tool, is applied to determine the optimal set of EEMs [38]. The electricity price, used in the analysis, is based on the USA average utility rate, and includes a fixed monthly charge of USD 12/month and a marginal electricity cost of USD 0.1242/kWh [39]. Tables 5–9 represent the optimization analysis results including the list of EEMs obtained for different weather datasets specific to residential buildings in Minneapolis, MN, Chicago, IL, San Francisco, CA, and Phoenix, AZ, respectively.

3.4.1. Optimal Building Design for Minneapolis, MN

For residential buildings in Minneapolis, as shown in Table 5, the selection of optimal set of EEMs varies slightly with the TMY weather dataset used. Wall sheathing ranges from RSI 0.88 XPS for TMY2 (USD 2463) to RSI 2.64 XPS for TMY, TMY3, and TMYx (USD 3714) while the slab insulation adjusts between RSI 1.76 XPS (USD 1081) and RSI 3.52 XPS (USD 1850). However, other design specifications, i.e., windows, air leakage reduction, and heat pump performance ratings remain consistent throughout the weather datasets.

Table 5. Optimal EEMs for residential buildings in Minneapolis, MN using different TMY weather datasets.

TMY			TMY2		TMY3		TMYx	
Entity	Selected EEM	Cost of EEM	Selected EEM	Cost of EEM	Selected EEM	Cost of EEM	Selected EEM	Cost of EEM
Wall Sheathing	OSB, RSI 2.64 XPS	USD 3714	OSB, RSI 0.88 XPS	USD 2463	OSB, RSI 2.64 XPS	USD 3714	OSB, RSI 2.64 XPS	USD 3714
Slab	Whole slab RSI 3.52 XPS	USD 1850	Whole slab RSI 1.76 XPS	USD 1081	Whole slab RSI 1.76 XPS	USD 1081	Whole slab RSI 5.28 XPS	USD 1850
Windows	IECC Standard	USD 7231	IECC Standard	USD 7231	IECC Standard	USD 7231	IECC Standard	USD 7231
Air Leakage	0.5 ACH 50	USD 1118	0.5 ACH 50	USD 1118	0.5 ACH 50	USD 1118	0.5 ACH 50	USD 1118
Heat pump	SEER2 14.3 8.2 HSPF2	USD 17,005	SEER2 14.3 8.2 HSPF2	USD 17,504	SEER2 14.3 8.2 HSPF2	USD 17,165	SEER2 14.3 8.2 HSPF2	USD 17,005
Duct	0.20 L/s·m ⁻² RSI 1.41	USD 3300	0.20 L/s·m ⁻² RSI 1.41	USD 3300	0.20 L/s·m ⁻² RSI 1.41	USD 3300	0.20 L/s·m ⁻² RSI 1.41	USD 3300
Water Heater	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162

3.4.2. Optimal Building Design for Chicago, IL

For residential buildings in Chicago, IL, cost optimal designs for various TMY weather datasets are summarized in Table 6. Optimization analysis using the TMY2 dataset identifies triple-glazed low-gain windows (USD 15,135) and RSI 5.28 XPS slab insulation to maximize thermal performance of the residential building during the heating season. In contrast, other weather datasets (TMY, TMY3, TMYx) opt for double pane windows (USD 11,389) and lower slab insulation levels.

Table 6. Optimal EEMs for residential buildings in Chicago, IL using different TMY weather datasets.

TMY			TMY2		TMY3		TMYx	
Entity	Selected EEM	Cost of EEM	Selected EEM	Cost of EEM	Selected EEM	Cost of EEM	Selected EEM	Cost of EEM
Wall Sheathing	OSB, RSI 2.64 XPS	USD 3830	OSB, RSI 2.64 XPS	USD 3830	OSB, RSI 2.64 XPS	USD 3830	OSB, RSI 2.64 XPS	USD 3830
Slab	Whole slab RSI 3.52 XPS	USD 1850	Whole slab RSI 5.28 XPS	USD 2619	Whole slab RSI 1.76 XPS	USD 1081	Whole slab RSI 3.52 XPS	USD 1850
Windows	Low-E, Double, Insulated, Air, M-Gain	USD 11,389	Low-E, Triple, Insulated, Air, L-Gain	USD 15,135	Low-E, Double, Insulated, Air, L-Gain	USD 11,774	Low-E, Double, Insulated, Air, M-Gain	USD 11,389
Air Leakage	0.5 ACH 50	USD 1118	0.5 ACH 50	USD 1118	0.5 ACH 50	USD 1118	0.5 ACH 50	USD 1118

Table 6. *Cont.*

TMY			TMY2		TMY3		TMYx	
Entity	Selected EEM	Cost of EEM	Selected EEM	Cost of EEM	Selected EEM	Cost of EEM	Selected EEM	Cost of EEM
Heat pump	SEER2 20.9 8.9 HSPF2	USD 10,680	SEER2 20.9 8.9 HSPF2	USD 10,756	SEER2 20.9 8.9 HSPF2	USD 10,752	SEER2 20.9 8.9 HSPF2	USD 10,680
Duct	0.20 L/s·m ⁻² RSI 1.41	USD 3300	0.20 L/s·m ⁻² RSI 1.41	USD 3300	0.20 L/s·m ⁻² RSI 1.41	USD 3300	0.20 L/s·m ⁻² RSI 1.41	USD 3300
Water Heater	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162

3.4.3. Optimal Building Design for San Francisco, CA

When the residential building is in San Francisco, CA, as outlined in Table 7, the optimized design leads to more stable selection of EEMs between TMY weather datasets. Only wall sheathing varies notably, from RSI 0.88 XPS (\$2463) for TMY to uninsulated OSB (\$1699) for TMY3 and TMYx. The reduced wall insulation for TMY3 and TMYx suggests that milder future weather conditions may allow for cost savings without compromising the overall energy performance of the residential building.

Table 7. Optimal EEMs for residential buildings in San Francisco, CA, using different TMY weather datasets.

TMY			TMY2		TMY3		TMYx	
Entity	Selected EEM	Cost of EEM	Selected EEM	Cost of EEM	Selected EEM	Cost of EEM	Selected EEM	Cost of EEM
Wall Sheathing	OSB, RSI 0.88 XPS	USD 2463	OSB, RSI 1.76 XPS	USD 3095	OSB	USD 1699	OSB	USD 1699
Ceiling	Ceiling RSI 8.63 Fiberglass	USD 1449	Ceiling RSI 8.63 Fiberglass	USD 1449	Ceiling RSI 8.63 Fiberglass	USD 1449	Ceiling RSI 8.63 Fiberglass	USD 1449
Slab	Whole slab RSI 1.76 XPS	USD 1081	Whole slab RSI 1.76 XPS	USD 1081	Whole slab RSI 1.76 XPS	USD 1081	Whole slab RSI 1.76 XPS	USD 1081
Windows	IECC Standard	USD 7231	IECC Standard	USD 7231	IECC Standard	USD 7231	IECC Standard	USD 7231
Air Leakage	3 ACH 50	USD 599	3 ACH 50	USD 599	3 ACH 50	USD 599	3 ACH 50	USD 599
Heat pump	SEER2 14.3 8.2 HSPF2	USD 6392	SEER2 14.3 8.2 HSPF2	USD 6356	SEER2 14.3 8.2 HSPF2	USD 6455	SEER2 14.3 8.2 HSPF2	USD 6455
Duct	0.20 L/s·m ⁻² RSI 1.41	USD 3300	0.20 L/s·m ⁻² RSI 1.41	USD 3300	0.20 L/s·m ⁻² RSI 1.41	USD 3300	0.20 L/s·m ⁻² RSI 1.41	USD 3300
Water Heater	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162

3.4.4. Optimal Building Design for Phoenix, AZ

The list of EEMs selected by the optimization analysis is provided in Table 8 when the residential building is in Phoenix, AZ for four TMY weather datasets. Most EEMs aim at reducing cooling thermal loads for a building exposed to hot and dry climatic conditions. Since Phoenix, AZ remains a consistently cooling-dominated climate regardless of the weather dataset used, the optimal EEMs do not vary significantly as noted in Table 8.

Table 8. Optimal EEMs for residential buildings in Phoenix, AZ using different TMY weather datasets.

Entity	TMY		TMY2		TMY3		TMYx	
	Selected EEM	Cost of EEM	Selected EEM	Cost of EEM	Selected EEM	Cost of EEM	Selected EEM	Cost of EEM
Wood Stud	RSI 3.70 Fiberglass Batt	USD 3685	RSI 3.70 Fiberglass Batt	USD 3685	RSI 3.70 Fiberglass Batt	USD 3685	RSI 3.70 Fiberglass Batt	USD 3685
Ceiling	Ceiling RSI 8.63 Fiberglass	USD 1449	Ceiling RSI 8.63 Fiberglass	USD 1449	Ceiling RSI 8.63 Fiberglass	USD 1449	Ceiling RSI 8.63 Fiberglass	USD 1449
Slab	Whole slab RSI 1.76 XPS	USD 1081	Whole slab RSI 1.76 XPS	USD 1081	Whole slab RSI 1.76 XPS	USD 1081	Whole slab RSI 1.76 XPS	USD 1081
Windows	IECC Standard	USD 7457	IECC Standard	USD 7457	IECC Standard	USD 7457	IECC Standard	USD 7457
Air Leakage	5 ACH 50	USD 452	5 ACH 50	USD 452	5 ACH 50	USD 452	5 ACH 50	USD 452
Heat pump	SEER2 20.9 8.9 HSPF2	USD 8807	SEER2 20.9 8.9 HSPF2	USD 8806	SEER2 20.9 8.9 HSPF2	USD 8807	SEER2 20.9 8.9 HSPF2	USD 8807
Duct	0.20 L/s·m ⁻² RSI 1.41	USD 3271	0.20 L/s·m ⁻² RSI 1.41	USD 3271	0.20 L/s·m ⁻² RSI 1.41	USD 3271	0.20 L/s·m ⁻² RSI 1.41	USD 3271
Water Heater	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162

3.5. Comparative Analysis of Cost Optimal Building Designs

The energy and cost performance for the cost optimal building designs depend on the TMY weather datasets used for the modeling and optimization analyses as summarized in Tables 9 and 10. Specifically, Table 10 compares the annual source energy consumption (SEC) while Table 11 lists the life-cycle cost (LCC) for both baseline and cost optimal buildings designs between various TMY weather datasets for four USA cities.

Table 9. Comparative of annual source energy consumption for baseline and cost optimal building designs for various TMY weather datasets and USA cities.

Building Design	TMY		TMY2		TMY3		TMYx	
	SEC (kWh/yr)	Savings (%)	SEC (kWh/yr)	Savings (%)	SEC (kWh/yr)	Savings (%)	SEC (kWh/yr)	Savings (%)
Minneapolis, MN								
Baseline	52,016.93	-	51,460.09	-	51,460.09	-	47,732.10	-
Cost Optimal	36,683.36	29.46	36,214.45	29.61	35,247.32	28.95	34,255.88	28.23
Chicago, IL								
Baseline	43,168.21	-	44,076.53	-	42,428.54	-	41,284.56	-
Cost Optimal	30,417.67	29.53	29,239.39	33.64	30,212.52	28.79	29,063.37	29.59
San Francisco, CA								
Baseline	27,223.10	-	27,604.09	-	26,343	-	26,108.53	-
Cost Optimal	21,654.87	20.45	21,801.41	21.21	21,215.27	19.44	20,922.20	19.86
Phoenix, AZ								
Baseline	38,597.32	-	38,568.02	-	40,092.91	-	40,590.20	-
Cost Optimal	28,134.72	27.10	28,310.56	26.59	29,594.07	26.169	30,417.67	25.05

Table 10. Comparative of life-cycle costs for baseline and cost optimal building designs for various TMY weather datasets and USA cities.

Building Design	TMY		TMY2		TMY3		TMYx	
	LCC (USD)	Savings (%)	LCC (USD)	Savings (%)	LCC (USD)	Savings (%)	LCC (USD)	Savings (%)
Minneapolis, MN								
Baseline	111,259	-	110,730	-	108,997	-	107,250	-
Cost Optimal	91,020	18.18	90,578	18.20	89,676	17.60	88,730	17.02
Chicago, IL								
Baseline	92,377	-	93,505	-	91,686	-	90,624	-
Cost Optimal	83,301	9.82	85,398	8.67	83,044	9.42	82,038	9.47
San Francisco, CA								
Baseline	70,114	-	70,478	-	69,295	-	69,058	-
Cost Optimal	66,237	5.53	66,678	5.39	65,464	5.52	65,194	5.59
Phoenix, AZ								
Baseline	85,425	-	85,655	-	86,930	-	87,370	-
Cost Optimal	74,328	13	74,525	13	75,700	12.91	76,560	12.31

Table 11. Required PV sizes and onsite generated electricity for achieving NZE designs for residential buildings using various TMY weather datasets for four USA cities.

	TMY	TMY2	TMY3	TMYx
Minneapolis, MN				
Required PV size (kW)	10.5	9.8	10	9.5
Chicago, IL				
Required PV size (kW)	8.8	8.6	8.1	7.6
San Francisco, CA				
Required PV size (kW)	8.0	8.0	7.8	7.5
Phoenix, AZ				
Required PV size (kW)	6.0	6.3	6.6	6.7

When the residential building is in Minneapolis, MN, the source energy consumption for the baseline design decreases from 52,016.93 kWh/yr for TMY to 47,732.10 kWh/yr for TMYx, reflecting reduced heating thermal loads as more recent weather dataset is used. As a result, the LCC for baseline building designs is lowered from USD 111,259 to USD 107,250. Significant source energy savings are achieved when cost optimal building designs are considered instead of baseline designs, especially for TMY due to higher heating thermal loads.

For residential buildings in Chicago, IL, the source energy consumption of the baseline design varies, peaking at 44,076.53 kWh/yr for TMY2 and decreasing to 41,284.56 kWh/yr for TMYx, driven by changes in heating and cooling thermal loads between weather datasets. Moreover, cost optimal designs achieve the highest annual energy savings of 33.64% for TMY2, reflecting higher heating thermal loads, while other weather datasets show savings between 28.79% and 29.59%. The LCC values for the baseline building designs range from \$93,505 for TMY2 to USD 90,624 for TMYx. Meanwhile, the cost optimal building designs lower these LCC values by 9.82% for TMY and by only for other weather datasets.

For the milder climate of San Francisco, CA, the energy and cost performance for both baseline and cost-optimal designs exhibit minimal variations among the weather datasets. Specifically, the source energy consumption of the baseline building design ranges from 27,223.10 kWh/yr for TMY to 26,108.53 kWh/yr for TMYx. Moreover, the LCC values for the baseline design vary slightly between the weather datasets, decreasing slightly from USD 70,114 for TMY to USD 69,058 for TMYx. For the cost optimal building designs, the source energy savings and LCC values remain consistent between different weather datasets.

In Phoenix, AZ, the impacts of the weather dataset are significant on both energy and cost performance for the baseline and cost-optimal designs due to increasing cooling demands. The source energy consumption of the baseline design increases slightly from 38,597.32 kWh/yr for TMY to 40,590.20 kWh/yr for TMYx. For the cost optimal building designs, the reductions in annual source energy consumption relative to the baseline designs are consistent between the weather datasets, ranging from 25.05% for TMYx to 27.10% for TMY. However, the LCC for the baseline design increases from USD 85,425 for TMY to USD 87,370 for TMYx, reflecting higher cooling operational costs.

3.6. Net-Zero Energy Building Designs

The net-zero energy building designs are based on the combined of cost optimal designs and the addition of rooftop PV systems. The capacities of the PV systems are determined using TMY weather datasets in BEOpt. Specifically, the capacity for each PV rooftop system is estimated so that the onsite generated electricity meets the energy demand for the cost optimal building design. The amounts of electricity required to generate onsite to meet the annual energy needs for the residential buildings are estimated to be consistent with the whole-building energy simulation 15-min timestep. The impacts of weather dataset on the design of the PV system and onsite generated electricity are listed in Table 11. For Minneapolis, MN, the required PV size decreases from 10.5 kW for TMY to 9.5 kW for TMYx, which aligns with the trend of decreasing heating energy use. In contrast, NZE designs for residential buildings in Chicago, IL require PV capacities of 8.8 kW from TMY and 7.6 kW for TMYx. For San Francisco, the rooftop PV size required for NZE designs varies slightly between 8 kW for TMY3 to 7.5 kW for TMYx reflecting the milder increase in cooling needs. Meanwhile, NZE building designs for Phoenix, AZ exhibit a gradual increase in the required PV size from 6.0 kW for TMY to 6.7 kW for TMYx.

3.7. Sensitivity Analysis of Building Designs

To evaluate the impacts of economic parameters on the NZE building design specifications, a sensitivity analysis is conducted to account for variations in lifetime period, discount rate, PV system cost, and net metering option using the TMYx weather dataset for Minneapolis, MN. The initial optimization analysis assumes a 30-year analysis period, a discount rate of 3%, and an installed PV system cost of USD 2.60/W [34] without any net metering incentives. Figure 8 illustrates the differences in LCC values and source energy use reductions for three building designs including baseline (refer to Table 3), cost optimal (refer to Table 5) and NZE (refer to PV size in Table 11). Figure 10 illustrates the sequential search process, where the optimization analysis begins by using a wide range of candidate design points, progressively narrowing them down to those leading to cost-optimal energy efficiency measures (EEMs), and then selecting the appropriate PV system size to achieve net-zero energy performance [39].

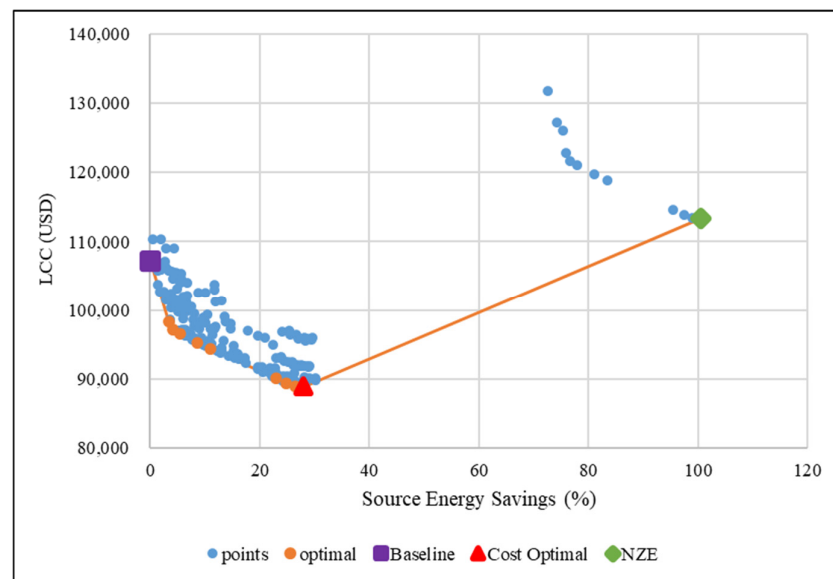


Figure 10. LCC values and source energy savings for three building designs in Minneapolis, MN using the TMYx weather dataset.

3.7.1. Impact of Lifetime

The lifetime is used in estimating life-cycle cost and thus in the optimization analysis results used to identify the specifications for both the cost optimal and NZE building designs. When the lifetime is adjusted to be 15 years and 50 years [34], the LCC values and the source energy savings for the three building designs change as noted in Figure 11. Indeed, the life-cycle cost increases with the increasing lifetime with the added operational costs over a longer period affecting the optimization results. For a 15-year lifetime, all three building designs exhibit lower LCC values. However, the LCC values specific to cost optimal designs are relatively lower than those the baseline designs when the lifetime is shorter because avoided electricity costs only partially offset the capital investments to deploy the energy efficiency measures. For a 15-year analysis period, the optimal cost design achieves higher savings of 30.69%, while the PV capacity required to reach net-zero is reduced to 9.1 kW, compared to 9.5 kW for the 30- and 50-year analysis periods as indicated in Table 12.

Table 12. List of EEMs for cost optimal building designs for various lifetime periods.

Entity	15 Years		30 Years		50 Years	
	Selected EEM	Cost of EEM	Selected EEM	Cost of EEM	Selected EEM	Cost of EEM
Wall Sheathing	OSB, RSI 2.64 XPS	USD 2463	OSB, RSI 2.64 XPS	\$3714	OSB, RSI 2.64 XPS	USD 3714
Slab	Whole slab RSI 3.52 XPS	USD 1081	Whole slab RSI 5.28 XPS	\$1850	Whole slab RSI 5.28 XPS	USD 1850
Windows	IECC Standard	USD 7231	IECC Standard	\$7231	IECC Standard	USD 7231
Air Leakage	0.5 ACH 50	USD 1118	0.5 ACH 50	\$1118	0.5 ACH 50	USD 1118
Heat pump	SEER 20.9, 8.9 HSPF2	USD 17,504	SEER2 14.3 8.2 HSPF2	\$17,005	SEER2 14.3 8.2 HSPF2	USD 17,005
Duct	0.20 L/s·m ⁻² RSI 1.41	USD 3271	0.20 L/s·m ⁻² RSI 1.41	\$3271	0.20 L/s·m ⁻² RSI 1.41	USD 3271
Water Heater	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162

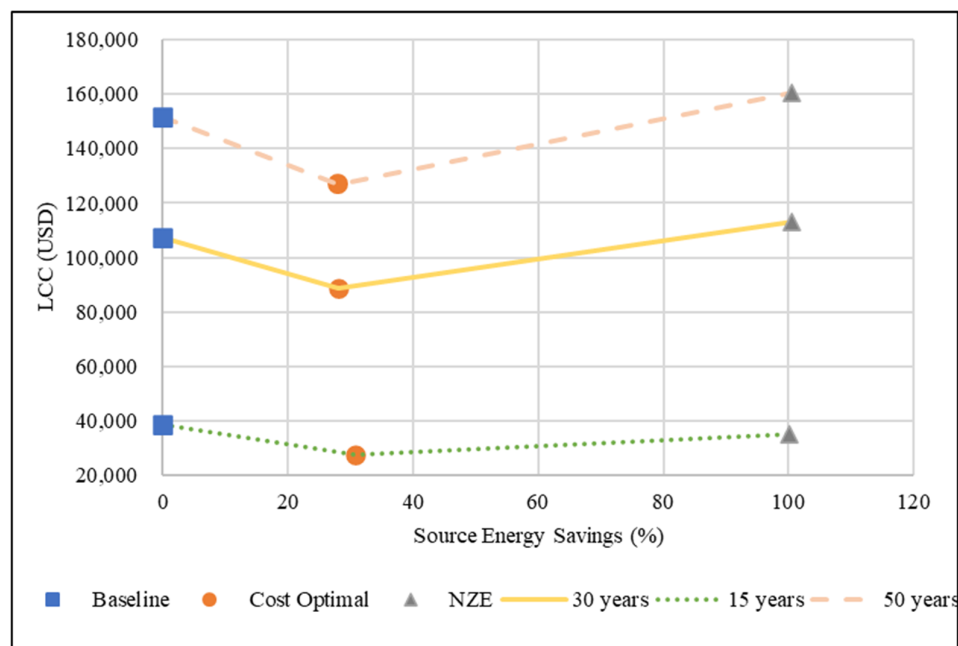


Figure 11. Impact of lifetime on LCC values and source energy savings for three building designs in Minneapolis, MN using the TMYx weather dataset.

3.7.2. Impact of Discount Rate

The discount rate accounts for the time value of money by converting future costs and savings into present-value terms [40]. As the discount rate increases from 1.5% to 4.5%, the life-cycle cost (LCC) of all cases decreases due to stronger discounting of future energy expenditures. As seen in Figure 12, the LCC values for all three building designs decrease with the increasing discount rate. However, the LCC values for NZE designs remain more costly than those of the baseline designs for all discount rates, as high initial capital costs dominate while long-term energy savings are increasingly discounted at higher rates. For 4.5% discount rate, the energy savings reduces to 27.54% with the EEMs of the optimal cost designs provided in Table 13, while the PV size remains the same (9.5 kW) for all the cases considered.

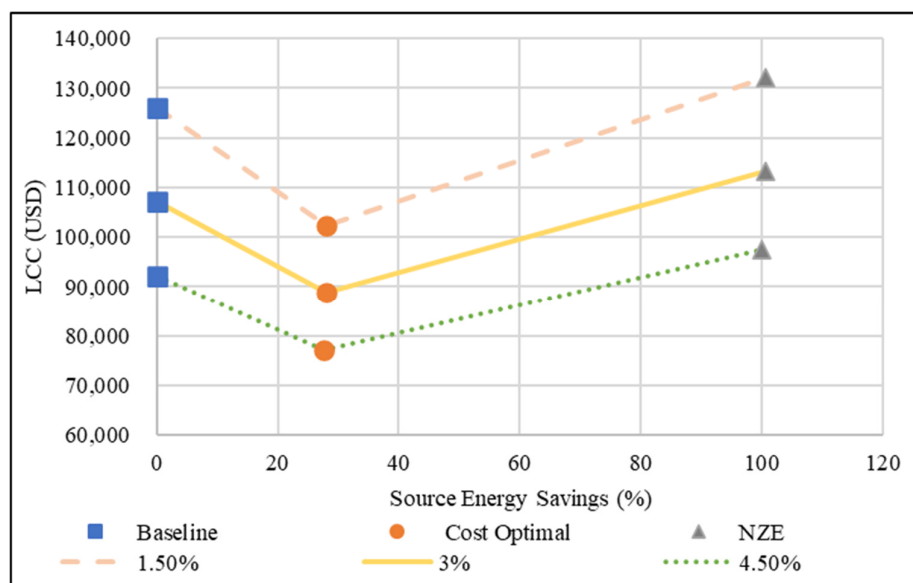


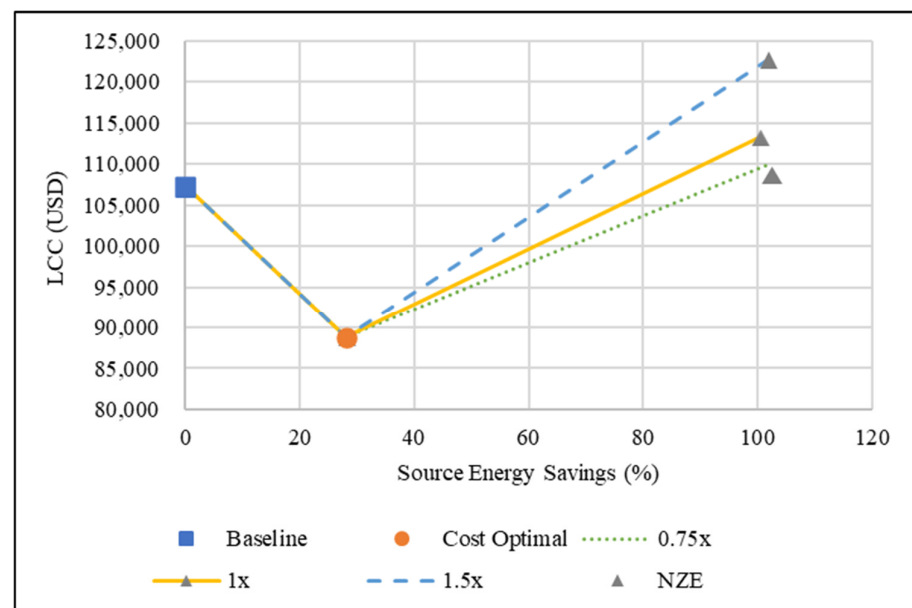
Figure 12. Impact of discount rate on LCC values and source energy savings for three building designs in Minneapolis, MN using the TMYx weather dataset.

Table 13. List of EEMs for cost optimal building designs for various discount rates.

Entity	1.5%		3.0%		4.5%	
	Selected EEM	Cost of EEM	Selected EEM	Cost of EEM	Selected EEM	Cost of EEM
Wall Sheathing	OSB, RSI 2.64 XPS	USD 2463	OSB, RSI 2.64 XPS	USD 3714	OSB, RSI 2.64 XPS	USD 3714
Slab	Whole slab RSI 7.04 XPS	USD 1081	Whole slab RSI 5.28 XPS	USD 1850	Whole slab RSI 3.52 XPS	USD 1850
Windows	IECC Standard	USD 7231	IECC Standard	USD 7231	IECC Standard	USD 7231
Air Leakage	0.5 ACH 50	USD 1118	0.5 ACH 50	USD 1118	0.5 ACH 50	USD 1118
Heat pump	SEER 20.9, 8.9 HSPF2	USD 17,504	SEER2 14.3 8.2 HSPF2	USD 17,005	SEER2 14.3 8.2 HSPF2	USD 17,005
Duct	0.20 L/s·m ⁻² RSI 1.41	USD 3271	0.20 L/s·m ⁻² RSI 1.41	USD 3271	0.20 L/s·m ⁻² RSI 1.41	USD 3271
Water Heater	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162	Electric, heat pump, UEF = 3.5, 50 gal	USD 3162

3.7.3. Impact of PV System Costs

The life-cycle costs are strongly influenced by variations in capital costs including those of the PV systems. Figure 13 illustrates the impacts of the PV system cost using multipliers of 0.75, 1.0, 1.5 relative to the BEOpt default values. As expected, reduced PV costs lower the LCC values for the NZE building designs. As noted in figure, the LCC values for the baseline and cost optimal designs remain unaffected by the variations in PV costs. When the PV system costs are reduced by 25% (i.e., a multiplier of 0.75), the LCC of the NZE design approaches that of the baseline design and thus becomes cost beneficial.

**Figure 13.** Impact of PV system costs on LCC values and source energy savings for three building designs in Minneapolis, MN using the TMYx weather dataset.

3.7.4. Impact of PV Net Metering

In this section, net metering option is considered to assess the life-cycles of costs of NZE designs. In the case of net metering, any excess electricity generated by the PV system is compensated when sold to the grid. Specifically, the analysis summarized in Figure 14 assumes that excess of PV electricity sold to the grid is compensated at an avoided-cost rate of USD 0.03/kWh, representing a conservative net-metering scenario. Figure 14 shows the

impact of PV compensation on the life-cycle cost. With the feasibility of PV compensation through net metering, the LCC of the NZE building design decreases significantly compared to the scenario with no compensation for any excess PV electricity. This reduction improves the cost benefits of the NZE design relative to both the baseline and cost optimal designs as noted in Figure 14.

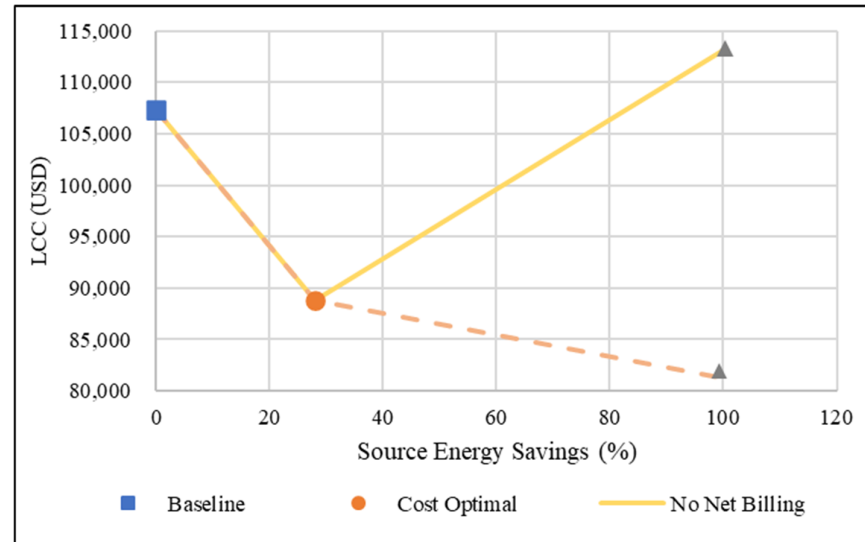


Figure 14. Impact of net metering on LCC values and source energy savings for three building designs in Minneapolis, MN using the TMYx weather dataset.

4. Conclusions

This study evaluated the impacts of the updated Typical Meteorological Year (TMY) weather datasets on Net-Zero Energy (NZE) residential buildings across multiple USA climate zones. The results demonstrate that the selection of weather dataset plays a critical role in designing building energy systems as well as in shaping predicted building energy performance, life-cycle cost outcomes, and photovoltaic (PV) system sizing.

A comparative analysis of TMY climatic datasets against year 2025 conditions shows that older datasets can substantially misrepresent current climate behavior. Annual heating degree days (HDD) from the original TMY dataset deviate from those of year 2025 values by 40.2% for San Francisco, CA, 89.9% for Phoenix, AZ, 9.3% for Chicago, IL, and 13.8% for Minneapolis, MN. However, these deviations using more recent TMYx weather datasets are reduced to 0.5%, 36.5%, 2.3%, and 2.4%, respectively. Similarly, annual cooling degree day (CDD) deviations remain large for older datasets, reaching 30.7% for Phoenix, AZ using TMY. This deviation is reduced to 7.3% when using the TMYx dataset for Phoenix, AZ.

These climatic differences translate into substantial changes in predictions of annual energy performance when using whole-building energy simulation analysis. For baseline design case of residential buildings, annual source energy consumption decreases from 52,016.93 kWh/yr (TMY) to 47,732.10 kWh/yr (TMYx) for Minneapolis, MN, representing −8.2% deviation, reflecting reduced heating demands using more recent climate datasets. In contrast, annual source energy consumption increases from 38,597.32 kWh/yr (TMY) to 40,590.20 kWh/yr (TMYx) for the baseline design case of residential buildings in Phoenix, AZ, representing a relative change of +5.2%, due to increased cooling requirements. These changes also affect economic benefits of various building designs, with the life-cycle costs of baseline design cases shifting from USD 111,259 to USD 107,250 for Minneapolis, MN and from USD 85,425 to USD 87,370 for Phoenix, MN when using TMY instead of TMYx climatic datasets for energy analysis.

Moreover, the capacities for the rooftop PV systems required to reach NZE performance for residential buildings are found to change significantly depending on the weather dataset used. Indeed, the rooftop PV size decreases from 10.5 kW for TMY to 9.5 kW for TMY_x when the building is in Minneapolis and from 8.8 kW to 7.6 kW for a building in Chicago, IL, demonstrating that the use of outdated climatic datasets can lead to inadequate selection of rooftop PV systems required to achieve NZE designs for residential buildings.

A sensitivity analysis for Minneapolis, MN using the TMY_x climatic dataset shows that NZE feasibility is also strongly affected by economic analysis assumptions. Reducing the lifetime period from 30 to 15 years increases cost-optimal savings to 30.69% and reduces the rooftop PV capacity from 9.5 to 9.1 kW to achieve NZE design. In addition, lowering the costs for deploying rooftop PV systems by 25% can reduce the life-cycle costs to achieve NZE design to be close to those obtained for the baseline case design.

Overall, the findings highlight that reliance on outdated weather datasets can lead to misrepresentation of both energy and economic performance for various building designs including those set to achieve net-zero energy performance. The use of updated weather datasets is therefore essential to ensure proper design of building energy systems and accurate prediction of their actual performance.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

EEMs	Energy Efficiency Measures
PV	Photovoltaic
TMY	Typical Meteorological Year
TMY2	Typical Meteorological Year 2
TMY3	Typical Meteorological Year 3
TMY _x	Extended Typical Meteorological Year
HDD	Heating Degree Days
CDD	Cooling Degree Days
LCC	Life-Cycle Cost
IECC	International Energy Conservation Code
SEER	Seasonal Energy Efficiency Ratio
HSPF	Heating Seasonal Performance Factor
ACH	Air Changes per Hour
HVAC	Heating, Ventilation, and Air Conditioning
UEF	Uniform Energy Factor
FY	Fiscal Year
XMY	Extreme Meteorological Year
SEC	Source Energy Consumption

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