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A Fresh Look at Weather Impact on Peak Electricity Demand and Energy Use of Buildings Using 30-Year Actual Weather Data

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Abstract

Buildings consume more than one third of the world's total primary energy. Weather plays a unique and significant role as it directly affects the thermal loads and thus energy performance of buildings. The traditional simulated energy performance using Typical Meteorological Year (TMY) weather data represents the building performance for a typical year, but not necessarily the average or typical long-term performance as buildings with different energy systems and designs respond differently to weather changes. Furthermore, the single-year TMY simulations do not provide a range of results that capture yearly variations due to changing weather, which is important for building energy management, and for performing risk assessments of energy efficiency investments. This paper employs large-scale building simulation (a total of 3162 runs) to study the weather impact on peak electricity demand and energy use with the 30-year (1980 to 2009) Actual Meteorological Year (AMY) weather data for three types of office buildings at two design efficiency levels, across all 17 ASHRAE climate zones. The simulated results using the AMY data are compared to those from the TMY3 data to determine and analyze the differences. Besides further demonstration, as done by other studies, that actual weather has a significant impact on both the peak electricity demand and energy use of buildings, the main findings from the current study include: 1) annual weather variation has a greater impact on the peak electricity demand than it does on energy use in buildings; 2) the simulated energy use using the TMY3 weather data is not necessarily representative of the average energy use over a long period, and the TMY3 results can be significantly higher or lower than those from the AMY data; 3) the weather impact is greater for buildings in colder climates than warmer climates; 4) the weather impact on the medium-sized office building was the greatest, followed by the large office and then the small office; and 5) simulated energy savings and peak demand reduction by energy conservation measures using the TMY3 weather data can be significantly underestimated or overestimated. It is crucial to run multi-decade simulations with AMY weather data to fully assess the impact of weather on the long-term performance of buildings, and to evaluate the energy savings potential of energy conservation measures for new and existing buildings from a life cycle perspective.

Keywords: Actual meteorological year; Building simulation; Energy use; Peak electricity demand; Typical meteorological year; Weather data

1. Introduction

Buildings consume more than one third of the world's total primary energy. The IEA Annex 53 [1] identified and studied six influencing factors on building energy performance, including climate, building envelope, building equipment, operation and maintenance, occupant behavior, and indoor environmental conditions. Among these influencing factors, climate plays a unique and significant role. Weather contributes directly and significantly to the variations of thermal loads and energy use of HVAC (heating, ventilation, and air conditioning) systems, lighting (for buildings with daylighting controls), and energy production from solar-based renewable systems. In residential and commercial buildings in the US, heating and cooling accounts for more than 40% of end-use energy demand. It is important to understand and estimate the impact of weather on the long-term performance of buildings in order to support policy making, and to allow building operators and owners to respond better to climate changes in terms of building energy supply and demand. Additionally, considering the impact of yearly variations in weather can improve the evaluation of investment risks of energy conservation measures (ECMs) for new and existing buildings by taking into account their life-cycle energy and cost savings.

The accuracy of building energy simulations and economic assessments of renewable energy systems depend on the availability of reliable weather data. There are two primary sources of weather data that are used to generate weather data files used in building simulation: measured weather data using physical sensors and observations, and simulated data using mathematical weather models. Various methods to generate annual hourly weather data have been developed in the past. Such weather data include the typical metrological year (TMY), the test reference year (TRY), the weather year for energy calculation (WYEC), the design reference year (DRY), as well as the synthetically modeled meteorological year (SMY). However, the lack of long-term weather records usually limits the generation of typical annual weather data files in any format [2].

A TMY weather file contains hourly values of solar radiation and meteorological elements for a 1-year period. The 12 typical meteorological months (TMMs) are selected from various calendar months in a multi-year weather database. The criteria for TMM selection is based on the statistical analysis and evaluation of four weather parameters: the ambient dry-bulb temperature, the dew-point temperature, the wind speed and the global solar radiation. Algorithms are used to smooth discontinuities from the data to avoid drastic changes between two adjacent months selected from different years. The first generation of TMY weather data for the U.S. is derived from the 1952-1975 SOLMET/ERSATZ database, while the second generation of data (TMY2) is derived from the 1961-1990 National Solar Radiation Database (NSRDB) covering 239 U.S. locations. The latest, third generation data (TMY3) is derived from the 1976-1990 and 1991-2005 National Solar Radiation Data Base (NSRDB). TMY3 covers 1,020 U.S. locations. TMY, TMY2 and TMY3 data sets cannot be used interchangeably because of differences in the data structure such as time (solar versus local), formats, elements, and units. The intended use of TMY weather data is for computer-based building performance simulations of solar energy conversion systems and building systems to facilitate performance comparisons of different system types, configurations, and locations in the U.S. and its territories. Because they represent typical rather than extreme conditions, they are not suited for designing systems to meet the worst-case conditions occurring at a location [3]. For the calculations of peak cooling and heating loads of buildings, and sizing HVAC equipment, design day weather data are used. Design-day weather data tend to represent more extreme weather conditions in order to guarantee that HVAC systems can meet peak loads for most of the time during their life cycle. Various methods are used to create design-day weather data [4].

As TMY data may not be available for some cities or sites, SMY weather data provide a practical and useful alternative. SMY weather data can be generated from monthly average or total values of weather parameters using stochastic models and auto-regressive moving average processes to represent the seasonal and daily weather variations [5]. Such stochastic weather models can be used to generate AMY weather data for use in deterministic building simulations, or together with a stochastic internal loads model, can be integrated with a building thermal model to obtain directly the probability distribution of building performance to investigate the uncertainty caused by the random meteorological processes and internal heat gains [6].

A new online weather data service with immediate access to precision, localized weather history, current conditions and forecasts are presented by Keller and Khuen [7]. Localized weather data is created by integrating all available ground station observations with high-resolution datasets from NOAA (National Oceanic and Atmospheric Administration). Both historical and forecast time series data are available for direct user access and application/system access through Web Data Services and API interfaces.

Selecting appropriate weather data to be used in building performance simulation is important. The use of inappropriate weather data can result in large discrepancies between the predicted and measured performance of buildings. In the late 1970s, Freeman [8] evaluated how well TMY represents actual long-term weather data based on simulations of an active residential space solar heating and cooling system for six U.S. climates, Albuquerque, Fort Worth, Madison, Miami, New York, and Washington DC. High variability of the weather and solar heating system performance year to year was noted. Crawley et al [9] compared the influence of the various weather data sets on simulated annual energy use and cost. Using different weather data sets can cause significant variations in annual energy consumption and cost from simulation results. The results show that the TMY and the WYEC data sets represent the closest typical weather patterns. Simulated results using the TMY weather data provides the average/typical energy use for buildings, but the peak electricity demand predictions and uncertainty analyses based on TMY are often not reliable because a single year cannot capture the full variability of the long-term climate change [10]. In view of the long-term climate change, the time period assigned for TMY selection should include the most recent meteorological data and should be reasonably long to reflect well the weather variations [11]. Most of the available TMY weather data are from weather stations located at airports. It is possible to create a new TMY file localized to a building location by integrating the weather station observations with gridded reanalysis data. However, there are limited complete weather data collected by weather stations over 15 to 30 years, so TMY data is only available for only 1,020 locations. Furthermore, some of the TMY weather data files were created up to 20 years ago. They are less representative of the typical present day climate and do not describe extreme weather conditions. Compared with the TMY weather data, the AMY is created from actual hourly data for a particular calendar year. AMY weather data is particularly useful for modeling years with extremes in weather and verifying the energy performance of buildings. However, as with the TMY weather data, the AMY weather data needs to be chosen as close to the building location as possible.

The potential impacts of various types of weather forecast models, weather data, and building prototypes have been studied from a number of perspectives. A prototypical small office building was modeled operating at three energy efficiency levels, using typical and extreme meteorological weather data for 25 locations, to study various predicted climate change and heat island scenarios [12]. The largest change to the annual energy use due to climate change was seen in the temperate, mid-latitude climates, where there was a swapping of energy use from heating to cooling. The heating energy was reduced by more than 25% and cooling energy was increased by up to 15%. The TMY weather data provides more localized and comprehensive climate indicators to further support the HVAC system design in buildings [3, 13]. The space cooling plays a major role in determining the magnitude and timing of peak electricity demand. The archived General Circulation Model (GCM) projections were statistically downscaled to the site scale, which were then used for input to building cooling and heating simulations to study the California specific impact of global warming on building energy consumption [14]. The IPCC's different carbon emission scenarios predict that climate change will lead to a 25% to 50% increase in space cooling electricity use over the next 100 years. Under the worst case carbon emission scenario the total energy consumption will increase between 8% and 20%. The energy performance of an office building in Hong Kong, using multi-year weather data sets was simulated to investigate the diversity in simulation predictions [15]. The results concluded that the choice of weather data sets was not crucial for the comparative energy studies during the initial design stage. However, it becomes important to select a particular standard weather year data set when absolute energy consumption data are required. Similar studies on office buildings were conducted in five major climate zones in China by using multi-year weather databases as well as TMY data [16-18]. The results showed a decreasing trend for heating loads and an increasing trend for cooling loads due to predicted climate change. The monthly loads and energy use profiles calculated using the TMY and long-term means profiles fell well within the maximum and minimum ranges of the 30-year individual predictions. It was concluded that building performance predictions using TMY weather data can be used in comparative energy efficiency studies.

In recent years, various types of weather data have been used in building simulation to evaluate energy performance and demand response. Accurate estimation of building performance relies on the appropriate selection of accurate weather data. The quality of weather data and their impact on building cooling and heating loads and energy consumption were studied by comparing three weather datasets for a specific location for the calendar year 2010 [19]. The three sources of data included site measured data and AMY weather data provided by two vendors. Key weather variables from the three datasets were compared statistically, and building loads and energy use were simulated using EnergyPlus version 6.0. The study concluded that the maximum difference in individual hourly weather variables can be as high as 90%, annual building energy consumption can vary by ±7%, while monthly building loads can vary by ±40% when using different weather datasets.

Using TMY weather data to calculate the energy use in buildings aims to represent the average or typical values. However, different types of buildings with different energy service systems and operation strategies have different responses to weather. Furthermore, a single set of energy use results from TMY simulations does not provide the range of variations due to the change of weather from year to year. The typical life of a building is more than 50 years; therefore the assessment of long-term building performance becomes very important. TMYs are often recommended to be used in building simulations to evaluate and compare performance of design alternatives under the assumption that energy savings from a design alternative would not vary noticeably with yearly weather variations. This assumption is not necessarily true. Although previous studies have demonstrated actual weather has a significant impact on peak electric demand and energy use in buildings, there are limited studies that focus on investigating the sensitivity of energy savings and peak demand reduction of energy conservation measures to the yearly variation of weather, using multi-decade AMY weather data across a complete coverage of climate zones for typical commercial buildings. This study aims to address that gap in the literature.

This study does not touch the topics of previous studies on impacts of long-term climate change or local heat island effects on building performance; instead it focuses on providing insights to the following important questions:

1) How significant is the weather impact on both the peak electricity demand and building energy use?
2) Does the simulated building energy use using the TMY3 weather data represent the average or typical energy use over a 30-year period?
3) Building simulation results from which climates are greater affected by using different weather data sets?
4) What types of office buildings are subject to the greatest impact of weather?
5) What are the risks from using the TMY3 weather data in building simulations to evaluate the energy savings and electricity demand reduction of energy efficiency technologies?

Through better understanding of which building technologies and system designs are more sensitive to yearly weather variation, building designers, owners, operators, and policy makers can make more informed decisions on energy efficiency implementations to reduce peak electricity demand and building energy use.

2. Methodology

2.1. Overview

To study the impact of weather on building performance, the most typical commercial buildings located in typical climate zones are the natural starting point. The U.S. 2003 Commercial Building Energy Consumption Survey (CBECS) [20] indicates that office buildings are the most common building type, comprising the largest floor area, and consuming the most energy in the commercial building sector. Therefore, the prototypical office buildings with three different sizes at two design efficiency levels for 17 climates are chosen from the PNNL's prototype buildings. Three building sizes represent large, medium, and small office buildings based on the statistics of the 2003 CBECS. The 17 climates represent all of the ASHRAE climate zones. The two design efficiency levels correspond to the ASHRAE Standard 90.1-2004 and 2010. ASHRAE standard 90.1 is an energy standard providing prescriptive and mandatory requirements for energy efficiency levels of major building systems including building envelopes (opaque construction and fenestration), lighting systems, service water heating, and HVAC systems. The 90.1-2004 standard was published in 2004 and represented the minimum performance of recently built new constructions that comply with the standard. While 90.1-2010 [21] represents more efficient designs, with about 30% energy savings over 90.1-2004 [22].

The TMY3 weather data and 30 years of AMY weather data (1980 to 2009) are used in the building performance simulations. The simulations were run using EnergyPlus 7.1. There was a total of 3162 simulation runs: 3 office building types, 2 design efficiency levels, 17 climates, and

31 weather files. The HVAC equipment is autosized by EnergyPlus to meet peak cooling and heating loads based on the 2009 ASHRAE design day weather data. The structure of the simulation runs is illustrated in Fig. 1. Performance metrics, including building total source energy (including all end uses), HVAC source energy (including end uses of cooling, heating, and ventilation), and peak electricity demand, of each simulation run were extracted from the EnergyPlus output reports. The performance metrics of each AMY run were then compared with those of the corresponding TMY3 run to calculate the percentage changes, equal to 100 x (AMY_Results – TMY3_Results) / TMY3_Results, as indicators of deviations from the TMY3 results. The ranges of these percentage changes are graphed as key results for analysis and discussions. To filter out the extreme weather years, the variation ranges excluding those of the top three and the bottom three weather years were overlapped on the same graphs. The variation ranges of the percentage changes of building total source energy, HVAC source energy and peak electricity demand give a clear picture on how the AMY results differ from the TMY3 results. The smaller the range of difference, the closer of TMY3 results to AMY results.

To investigate the weather impact on energy savings and demand reduction of building technologies, two office models under two design efficiency levels (ASHRAE standard 90.1-2004 and 90.1-2010) were simulated using the TMY3 and 30-year AMY weather files. The energy savings and demand reductions of the 90.1-2010 models over the corresponding 90.1-2004 models were determined using the same TMY3 or AMY weather files.

Furthermore, values of key weather parameters, such as annual average ambient air temperature, global horizontal solar radiation, and heating and cooling degree days, were extracted from the EnergyPlus weather statistics (stat) files and used to identify potential variation patterns and trends.

In this study, source energy (also referred to as primary energy) is used because it considers the energy loss during energy generation, transmission, and distribution. EnergyPlus calculates the source energy by multiplying the calculated site energy with corresponding source factors, which depend on types of energy sources and building location.

2.2. Weather data

In general, two kinds of weather data packaged in weather files are used in building performance simulation. One is the TMY weather data and the other is the AMY weather data. The TMY weather data is usually used for annual energy simulations during the building design process, either to evaluate the energy and cost effectiveness of design alternatives, to demonstrate code compliance, or to calculate credit points towards building rating systems or utility incentive programs. The AMY weather data, containing measured data for a particular year, is usually used in simulations post occupancy to verify and diagnose the actual building energy performance. The AMY weather data can be obtained from several sources, including Weather Bank, National Climatic Data Center (NCDC), Weather Source, Weather Analytics, and Meteonorm. Weather Bank maintains hourly and daily historical data records from every National Weather Service reporting station in the United States, as well as other locations around the world. The weather data are archived on a real-time basis and updates are made hourly. NCDC is the world’s largest active archive of weather data. The Integrated Surface Database (ISD) consists of global hourly and synoptic observations compiled from numerous sources. Currently there are over 11,000 stations active and updated daily in the database [23]. Weather

Source provides historical and real-time digital weather information for tens of thousands of locations across the US and around the world. Weather Analytics [7] provides site-specific TMY and AMY weather files based on the last 30 years of hourly data. The files combine hourly weather station observations and the new NOAA reanalysis data sets. Meteonorm is a weather data generation tool. It integrates a climate database, a spatial interpolation tool and a stochastic weather generator. The typical years with hourly or one-minute time resolution can be calculated for any site [24].

In this study, the weather data for 17 climate zones, including the 30-year AMY weather files covering 1980 to 2009 from Weather Analytics and the TMY3 weather data, were used in the simulations to investigate the weather impact on building performance. Table 1 lists the climate type, criteria, and representative cities for the 17 climates – major U.S. cities except Riyadh in Saudi Arabia and Vancouver in Canada.

2.3. Prototype buildings

To calculate the impact of ASHRAE Standard 90.1, researchers at Pacific Northwest National Laboratory (PNNL) created a suite of 16 prototype buildings [25] covering 80% of the commercial building floor area in the United States for new construction. These prototype buildings were derived from the U.S. Department of Energy (USDOE) [26] but with substantial modifications based on extensive inputs from ASHRAE 90.1 Standing Standards Project Committee members and other building industry experts. The prototype models include the 16 building types in 17 climate locations for three editions of ASHRAE Standard 90.1 (90.1-2004, 90.1-2007 and 90.1-2010). Table 2 summarizes the building types. The EnergyPlus models of these buildings are available; including EnergyPlus model input files (.idf) and output files (.html). The description of the building, HVAC systems, internal loads, operating schedules, and other key model inputs are summarized in scorecard spreadsheet files that are also available from the web site. The detailed methodology and modeling strategy used to develop these prototype models as well as the energy and cost saving analysis is presented in [22].

From these prototype buildings, the three types of office buildings with different sizes, small, medium and large, were chosen for this study. Office buildings represent the most typical commercial buildings in the United States in terms of buildings numbers and total floor area [20]. The large-size office building is served by a central built-up variable air volume (VAV) system with a central plant. The medium office has packaged VAV systems, and the small office has packaged single zone systems. The key features of these office buildings are summarized in Table 3. The EnergyPlus models for the three office buildings in 17 climates based on ASHRAE Standard 90.1-2004 and 90.1-2010 were downloaded and converted for use with EnergyPlus version 7.1. The 90.1-2010 models represent high energy-efficiency designs, with better insulation and windows, more efficient lighting and HVAC systems, exceeding the performance of the 90.1-2004 models by approximately a 30% reduction in site energy use.

2.4. Simulation engine

EnergyPlus [27] version 7.1, released in June 2012, was used to perform the building simulations. EnergyPlus is developed by USDOE as a new generation building energy modeling program that builds upon the most popular features and capabilities of BLAST [28] and DOE-2 [29]. EnergyPlus has innovative simulation capabilities including sub-hourly time steps, an integrated solver for system models with a zone heat balance model, and user definable and configurable HVAC systems and components. It calculates space temperature, occupant thermal comfort, cooling and heating loads, HVAC equipment sizes, energy consumption, utility cost, air emissions, water usage, renewable energy, etc. EnergyPlus is a stand-alone simulation program without a 'user friendly' graphical interface. It reads input and writes output as text files. Since the first release in April 2001, EnergyPlus has been evolving with new and enhanced modeling features and improved usability. EnergyPlus has been validated through three types of tests, including analytical tests, comparative tests and empirical tests.

The EnergyPlus weather file, an epw file, contains 29 weather variables at one-hour intervals (but can be sub-hourly), among which nine important variables were used in the simulations. These key variables can be sorted into four groups: 1) outdoor air conditions: dry-bulb temperature, dew-point temperature, relative humidity, and atmospheric pressure; 2) solar radiation: direct normal solar radiation and diffuse horizontal solar radiation; 3) sky radiation: horizontal infrared radiation; and 4) wind conditions: wind direction and wind speed. Another important weather variable contained in the epw weather file and used by EnergyPlus is the monthly ground temperature at various soil depth levels. EnergyPlus is usually run with a time step of 10 or 15 minutes, and the hourly weather variables are interpolated to the half-hour intervals.

3. Results and discussion

3.1. Variations of weather data

Variations of weather data and climate zone classification for each of the 17 cities based on the annual HDD18 (Heating Degree Days with base temperature of 18°C) and CDD10 (Cooling Degree Days with base temperature of 10°C) of the AMY data from 1980 to 2009 are illustrated in Fig. 2. The climate zones displayed in Fig. 2 correspond to the criteria listed in Table 1. It can be seen that most cities do not belong to only one climate zone. For the 30-year period, the climates of some cities vary across two zones and some even across three or more zones. For example, Fairbanks exhibits climatic conditions indicative of the very cold Climate Zone 7 and the subarctic Climate Zone 8, while Helena shows conditions typical of five climate zones: the cool-humid 5A, the cool-dry 5B, the cool-marine 5C, the cold-humid 6A, and the cold-dry 6B. The spread of climate zones for a city based on 30-year AMY weather data is a good indicator of weather change year-over-year, which cannot be represented by a single-year TMY3 weather data file. Therefore, running simulations using multi-decade AMY weather data is necessary to evaluate fully the effect of weather on the energy performance of buildings.

The variation in annual average global horizontal solar radiation for the 17 cities from 1980 to 2009 is listed in Table 4. In general, the highest and lowest levels of annual average global horizontal solar radiation occur in the hotter and colder climates respectively. For example, Riyadh has the highest value of 6588 Wh/m^2 in 2001, while Fairbanks has the lowest value of 2473 Wh/m^2 in 1995. Table 4 also shows the maximum variations, defined as the maximum of the annual difference between the highest and the lowest values of all cities across the 30-year period. Among the 17 cities, Chicago has the largest variation of 652 Wh/m^2, while Boise has the smallest variation of 360 Wh/m^2. The values listed in the fifth and sixth columns represent the average global horizontal solar radiation over the 30 years for the AMY data and TMY3 data respectively. The values listed in the last two columns are the absolute and relative differences between the TMY3 values and the average values. The largest difference between TMY3 and the average AMY is 809 Wh/m^2 which occurs in Miami, a hot climate. However, compared with the cities in hotter and colder climates, cities in mixed climates tend to have greater differences. There is a noted trend that the AMY data have higher global horizontal solar radiation than the TMY3 data, which can lead to the AMYs overestimating the cooling energy use and underestimating the heating energy use when compared to the TMY3s. Further discussion is provided in Section 3.7.

Table 5 shows the variations in annual average dry-bulb temperature of the 17 cities from 1980 to 2009. The variations are more significant for cold climates. For example Fairbanks, Helena and Duluth all have variations greater than 3.7°C. In general, the differences between the TMY3 values and the average AMY are small, except the TMY3 values have a higher average temperature by 0.6°C for Fairbanks and a lower temperature by 0.8°C for Vancouver.

In summary, the variation in weather data year-over-year is significant, especially for cold climates. Such variations should not be ignored and cannot be represented by single-year weather data - either a historical year or a synthetic year such as TMY.

3.2 Weather impact on HVAC source energy use for individual cities

HVAC energy use is directly affected by weather, because the cooling and heating loads of buildings are dependent upon weather conditions such as outdoor air temperature and humidity, wind speed, and solar radiation. The percentage variation of HVAC source energy use intensity (EUI, kWh/m^2) for the three types of office buildings with two design efficiency levels in the 17 cities are shown in Fig. 3. The simulation results from using the TMY3 weather data are used as the baseline and are represented as 0% in these figures. The red bars represent the variation of the percentage changes across the 30-year period (1980 to 2009). The green bars show the same results but excluding the top three largest and the bottom three smallest values to filter out the extreme AMY cases. The left side bars with negative values indicate TMY3 results are over-estimating the AMY results while the right side bars with positive values indicate TMY3 results are under-estimating the AMY results. The cities on the vertical axis of the figures from the top to the bottom are arranged by climate zone from the very hot and humid climate zone 1A to the subarctic climate zone 8.

In general, the AMY results show large differences when compared to results using the TMY3 weather data. The TMY3 results can over-estimate AMY results as much as 18% and under-predict as much as 37%. Three-dimensional comparisons are made to analyze the relative weather impact by climate zone, building type, and building design efficiency. First, it can be seen that most large changes occur in colder climates, regardless of the building type (large-, medium-, or small-size office) or building design efficiency level (low, 90.1-2004, or high, 90.1-2010). Usually the largest under-estimates occur in Boise, followed by Helena and then San Francisco, while the largest over-estimates occur in Fairbanks, followed by Chicago and then Duluth. Secondly, the larger changes occur for the medium-size office building, followed by the large-size and then the small-size building. The medium office building has a larger perimeter area than the large office, and has air-side economizers, while the small office does not. Thirdly, the larger changes occur for the large and medium offices with the high-efficiency design level (90.1-2010) than the low- efficiency design level (90.1-2004). The opposite is true for the small office - the low-efficiency design level shows larger changes. Fourthly, the differences between the red and the green bars for each case are compared. The largest differences occur in Boise regardless of building type and building efficiency design level, followed by Helena, Fairbanks, and Miami. In general, the differences in the hotter and colder climates are larger than those in the mixed climates. Finally, comparing the HVAC source EUI between the average of the 30-year AMYs and the TMY3 for the large office at both efficiency design levels in Table 6 and Table 7, it can be seen that the TMY3 results are usually lower than the AMY results, occurring in 13 out of the 17 cities, and by as much as 9 to 9.2% in Riyadh, 5.6 to 8.7% in Boise, and 5.2 to 7.7% in San Francisco. Similar trends can be observed for the medium and small offices.

As an example, detailed variations of the HVAC source EUI of the large office in Chicago with low and high building efficiency levels from 1980 to 2009 are illustrated in Fig. 4. The TMY3 results, the average of the AMY results, as well as the average results plus and minus one and two standard deviations are plotted on the same figures. The TMY3 results are fairly close to those of the average AMY results, within the range of +2.6% and one standard deviation. Except for 1992, all AMY results fall within one standard deviation. The variation, in percentage changes, between the maximum and minimum AMY results is large, 22.6% for the 90.1-2004 office and 28% for the 90.1-2010 office.

In summary, the weather impacts on the HVAC source energy use are significant, especially for the medium-size office building and for all office buildings in cold climates. The impacts are the least for the small-size office among the three office types. The medium-size office buildings have air-side economizers, as required by ASHRAE standard 90.1 in appropriate climates, and more window area than the small offices, but have less window area and more perimeter zone area than the large offices. This makes the medium offices more sensitive to weather variation than the other two.

Weather impacts on buildings are about the same across the two efficiency design levels. Meanwhile, large differences between the simulated results using TMY3 weather data and the AMY weather data are observed across the 30-year period. The TMY3 results are lower than the AMYs mainly due to the AMYs having higher solar irradiance. Further discussion is provided in Section 3.7.

3.3 Weather impact on the building total source energy use for individual cities

Similar results as shown in Fig. 3 are shown in Fig. 5, but for the building total source energy use intensity (EUI, kWh/m^2). The variation of the building total source EUI are about one-third of those of the HVAC source EUI, because weather changes only affect the HVAC source energy use. The percentage changes of the building total source energy, although much smaller, represent a significant amount of the absolute differences in the building total source energy use.

Similar but slightly different patterns are observed for the building total source EUI. In general, the AMY results show noticeable differences from those from the TMY3. The TMY3 results over-estimate the AMY results by as much as 7.8% and under-estimate by as much as 9.7%. First, it can be seen that most large changes occur in colder climates, regardless of the building type or building efficiency design level. Usually the largest under-estimates occur in four climates: Riyadh, Boise, Helena and Fairbanks, while the largest over-estimates occur in four climates: Miami, Chicago, Duluth and Fairbanks. Secondly, the larger changes occur for the medium-size office, followed by the large-size and then the small-size. Thirdly, the slightly larger changes occur for the large and medium offices with the high efficiency design level than the low efficiency design level. The opposite is true for the small office - the low efficiency design level shows larger changes. Fourthly, the differences between the red and the green bars for each case are compared. The largest differences occur in five climates: Miami, Chicago, Boise, Helena, and Fairbanks. This implies that these climates tend to have more severe weather impacts. Finally, comparing the building total source energy use between the TMY3 weather data and the average of the 30-year AMY weather data, for the large office at both efficiency design levels in Table 8 and Table 9, it can be seen that the TMY3 results are usually lower than the AMY results, occurring in 13 out of the 17 cities; but except for Riyadh, the under-estimates are less than 2% for all other climates.

3.4 Weather impact on the HVAC and building total source energy use aggregated for the U.S. office building stock

To analyze the variation in the HVAC and building total source energy for all office buildings in the U.S., the source energy use are aggregated across the 15 U.S. cities using weighting factors based on the volume of new construction in each of the 15 cities [22]. The percentage changes at the national level are then calculated and shown in Fig. 6.

From Fig. 6, the simulated HVAC source energy use using the TMY3 data can over-estimate and under-estimate the AMY results by 4.8% and 6.1% respectively for the large office, by 4.7% and 7.6% for the medium office, and by 2.5% and 4.8% for the small office. The corresponding percentage changes for the building total source energy use are 1.4% and 1.7%, 1.7% and 2.7%, and 0.8% and 1.7%. In general, the weather impacts are about the same for buildings with the two efficiency design levels, with slightly larger impacts for the low-efficiency buildings. The largest impacts are for the medium-size office followed by the large and then the small office.

Compared with the variations shown in Fig. 3 and Fig. 5, the variations in Fig. 6 are much smaller. This implies the weather impacts across different climates are not uniform and tend to cancel out each other. For example, during a particular year, the TMY3 results may over-estimate the AMY results for some climates but under-estimate for others, so the overall TMY3 results at the national level are not so different from the AMY results. However, this should not overshadow the large discrepancies between the TMY3 results and the AMY results for individual climates, because energy efficiency technologies are evaluated and applied locally, and energy policy is made by local jurisdictions.

3.5 Weather impact on the peak electricity demand of buildings

The variations of the percentage changes of the building peak electricity demand are displayed in Fig. 7. The peak demands of the medium office using the TMY3 weather data can under-estimate that from the AMY data by up to 32.4%, and over-estimate by up to 21%. Unlike the variation in the HVAC source energy use mentioned above, there is no clear correlation between the change in peak demand and the climate/city. Except for the medium office, the mixed climates show larger percentage differences. The variations for the medium office, as shown in Figs. 7(c) and (d), are much larger than those for the large and small offices.

Additionally, the percentage changes for the small office are mostly within ±6% except for a few cases as shown in Figs. 7(e) and (f). For a particular city, if only one green bar can be seen, it is because the red bar is almost the same as the green bar but overlapped by the red bar, and thus cannot be seen. This implies that for the small office building in this city, the peak demand is not so sensitive to extreme weather conditions (the top three and bottom three years). On the other hand, if only one red bar can be seen, it is because the green bar is too small to be seen. This implies that the peak demand is sensitive to extreme weather conditions. When the top three and the bottom three years are eliminated, peak demands from the remaining 24-year AMY data and the TMY3 data are very close or equal, thus the differences cannot be seen.

As an example, detailed variations of the simulated peak demand of the large office in Chicago with low and high efficiency levels from 1980 to 2009 are illustrated in Fig. 8. The TMY3 results, the average of the AMY results, as well as the average results plus and minus one and two standard deviations are plotted on the same figures. The TMY3 result is higher than the average AMY result by 1.1% (within one standard deviation) for the 90.1-2004 office, but lower by 6% (outside two standard deviations) for the 90.1-2010 office. For the 90.1-2004 office, the variation of peak demand is relatively small except for 1991, 2004, and 2008 which has lower peak demand by as much as 7.7% compared to the average value. For the 90.1-2010 office, the variation of peak demand from individual AMY results is more significant, up to 13.4% between the minimum and maximum values.

In summary, the weather impact on the peak electricity demand is significant, even greater than the impact on building energy use. The simulated peak demands from TMY3 can significantly under- or over- estimate those from the AMY. It is necessary to run simulations using multi-decade of AMY weather data to assess accurately demand response strategies.

3.6 Weather impact on peak electricity demand reduction and energy savings of energy conservation measures

The peak demand reduction (in %) and the HVAC and building total source energy savings (in %) are calculated by comparing the peak demand and source energy use of the building with the high energy efficiency level, to those of the same building with the low energy efficiency level, using the TMY3 and the 30-year AMY weather data for the three building types across the 17 climates. The results are shown in Fig. 9, where the green bars represent the variation in the demand reduction and source energy savings, using the 30-year AMY weather data. The red marks represent the corresponding results using the TMY3 weather data. A few key points can be seen from the results in Fig. 9:

- Weather impact on peak demand reduction and HVAC source energy savings are large. There are no consistent patterns across the building type or climate.
- Generally the weather impact on the peak demand reduction is much greater than on the HVAC source energy savings.
- For HVAC source energy savings, larger weather impacts occur for the mixed to cold climates, from San Francisco to Fairbanks. The savings based on TMY3 weather files are usually within the ranges of savings based on the AMY weather files, except for over-estimates in San Francisco, Albuquerque, Boise, Vancouver, and Helena, where the red marks are usually at the very right end or outside of the green bars.
- The peak demand reduction can vary significantly year-over-year for most climates. The differences in demand reduction can be as high as 15% for Chicago and Fairbanks across the 30-year period for the large office, as shown in Fig. 9(a).
- Generally the peak demand reductions based on the TMY3 data are within the ranges of reductions based on the AMY data, but a few cases show the TMY3 results (the red marks) are at the high or low end of, or even outside the AMY results (the green bars). Furthermore, some climates even demonstrate opposing weather impacts. For example, in

Phoenix, the TMY3 demand reduction is greater than that from the AMY data for the large office, but less for the small office. El Paso shows the totally opposite situation as Phoenix.

- To assess accurately the peak demand reduction and energy savings of ECMs, it is necessary and important to run simulations using multi-decade AMY weather data in comparative studies of energy conservation measures. Results from TMY3 data can sometimes significantly over- or under-estimate the actual energy and cost savings.

It should be noted that the calculated peak demand reduction and source energy savings come from a combination of energy efficiency improvements from ASHRAE standard 90.1-2004 to 90.1-2010. Whether similar trends apply to an individual energy efficiency improvement, such as better wall or roof insulation, better windows, high efficiency lighting systems, or high efficiency HVAC systems, is an open question worth further studies.

3.7 Discrepancies of weather data from different sources and different time periods

Radhi [30] studied the impact of weather data from two different periods, 1961-1990 and 1961-2005, on the simulated electricity use of a low-rise and a high-rise commercial building in Bahrain. Significant variations in simulated energy use from the two different weather periods were found and weather data covering more recent periods were recommended to be used for better prediction of actual energy use in buildings. Bhandari et al [19] studied the quality of weather data from two different sources by comparing them to actual measured weather data, and the associated impact on building cooling and heating loads and energy consumption for a single year at a specific U.S. location.

The AMY weather data from Weather Analytics and the TMY3 from NREL were used in the current study, although they are from different sources and cover slightly different time periods. The AMYs cover 1980 to 2009, about four years ahead of the TMY3s which cover 1976 to 2005. Two constraints determined the choice of the AMYs and TMY3s: 1) both data sources are reliable and available to the public [3, 7]; 2) Weather Analytics does not provide TMY3 (based on same selection criteria as the NREL TMY3) weather files created from their 30-year AMYs, and the AMYs used to create NREL TMY3 weather files, although available to the public at http://rredc.nrel.gov/solar/old_data/nsrdb/1991-2010/NCDCStationData/, are not in EnergyPlus weather data epw format and thus need data mapping and conversion.

The temperature data from both sources tend to be more consistent than the solar radiation data, as seen from Table 4 which shows that the TMY3s have lower global horizontal solar radiation than the average of the AMYs across all the 17 climates. Although both sources used similar algorithms, either the original or the enhanced Perez model [31-33] to calculate solar radiation, Weather Analytics data sets lack high quality aerosol data which can lead to a high bias of modeled solar radiation under certain cloudy / high humidity conditions. This explains that, in Table 4, Miami (a humid climate) and San Francisco (with frequent morning fog) have the greatest deviations in solar radiation between the average AMYs and the TMY3. Another source of discrepancies in the solar data is the NREL TMY3s do not include data for certain calendar years due to eruptions of the volcanoes El Chichón and Mount Pinatubo (1982–1984 and 1992–1994, respectively) that decreased solar radiation in the U.S. [3]. This explains that, in Table 4, 8 out of the 15 U.S. cities have the lowest solar radiation in those years across the 30-year period.

To quantify what portion of the overestimate of HVAC source energy by the AMYs in tables

6 and 7 is attributable to the high bias of solar radiation, there is a need to study the correlation between the key weather variables and the simulated building performance. Apadula et al [34] studied the effect of the meteorological variability on the national monthly electricity demand in Italy. A multiple linear regression model based on calendar and four weather variables, including air temperature, wind speed, relative humidity and cloud cover, is developed to study the relationships between meteorological variables and electricity demand as well as to predict the monthly electricity demand up to 1 month ahead. The model demonstrated an accuracy of better than 1% over the data covering the period 1994–2009. Lam et al [35] used principal component analysis to study prevailing weather conditions in subtropical Hong Kong. Regression models were developed to correlate the simulated monthly building cooling loads and total energy use, for a generic office building, with a developed climatic index Z, which is a function of the dry-bulb temperature, wet-bulb temperature and global solar radiation. The regression models showed an accuracy of 1% for annual and 4% for monthly simulated energy use over the period 1979–2008.

In the current study, a regression model is derived to calculate the HVAC source energy EUI based on the annual cooling degree days (CDD10), annual heating degree days (HDD18), and the annual average daily global horizontal solar radiation (GHSR):

$$\text{HVAC Source Energy EUI} = c_0 + c_1 \times \text{CDD10} + c_2 \times \text{HDD18} + c_3 \times \text{GHSR}$$

Where, c_0 to c_3 are regression coefficients.

Table 10 lists the regression results for the large office buildings compliant with ASHRAE Standard 90.1-2004, when the above regression was applied to the 30-year AMYs in the four climates, Miami, San Francisco, Boise, and Fairbanks. The results show that there are more significant discrepancies in solar radiation between the average AMYs and the TMY3s (Table 4). The linear regressions are reasonable with R-squared between 0.84 and 0.95. The variations of CDD10, HDD18, and GHSR in the AMYs directly contribute to the variations of the simulated HVAC source energy. AMYs with higher CDD10 and HDD18 will lead to higher HVAC source energy use. Except for the cooling dominated climate of Miami, the other three climates show that higher solar radiation leads to lower HVAC source energy use. The impact of solar radiation on building performance depends on climate – lower or higher solar radiation does not necessarily always dominate.

The regression coefficient c_3 represents the sensitivity of the HVAC Source Energy EUI to the annual average daily global horizontal solar radiation, assuming the indirect impact of solar radiation on ambient air temperature is considered separately in the sensitivity of CDD10 and HDD18. Based on the regression models, the lower solar radiation of the TMY3s in Miami (by 14.4%), San Francisco (11.6%), Boise (10.1%), and Fairbanks (9.7%) would contribute to the underestimate (for Miami) or overestimate (for the other three climates) of HVAC Source Energy EUI of the TMY3s by 3.6%, 16.6%, 14.8%, and 0.9% respectively. The percentages for San Francisco and Boise are much higher mainly due to their much lower HVAC source energy EUI compared to those of Miami and Fairbanks. In conclusion, the discrepancy in solar radiation between different weather data sources can have a significant impact on differences in the simulated HVAC source energy. High quality solar radiation data is key to improving the accuracy of simulated building performance.

It should be noted that the regression model is used to appropriately estimate the effect of the high bias solar data, it is not recommended to replace whole building dynamic simulation for calculating the HVAC source energy.

4. Conclusions

Nowadays with the availability of long-term AMY weather data and sufficient computational power of personal computers, it is feasible and necessary to run simulations with AMY weather data covering multiple decades to fully assess the impact of weather on the long-term performance of buildings, and to evaluate the energy savings potential of energy conservation measures for new and existing buildings from a life cycle perspective. Main findings from this study are: 1) annual weather variation has a greater impact on the peak electricity demand than on the energy use in buildings; 2) simulated building energy use using the TMY3 weather data is not necessarily representative of the average energy use using the AMY data, across the 30-year period. The TMY3 results can be significantly higher or lower than those from the AMY data; 3) the weather impact is greater for buildings in cold climates; 4) the weather has the greatest impact on the medium-size office building, followed by the large office and then the small office; and 5) simulated energy savings and peak demand reduction by energy conservation measures using the TMY3 weather data can be significantly lower or higher when compared to the results using the AMY data. These findings can support energy policy making, energy code development, building technologies evaluation, and utility incentive programs planning.

Future work will continue to investigate the weather impact for other building types, and aggregate the impact across the entire U.S. building stock. If more AMY weather data, for example 50 to 100 years, is available, methods will be developed to define and select various TMY weather data representing different conditions. For example, cool vs. warm years, dry vs. wet years, cloudy vs. sunny years, for various applications including HVAC design, demand response for smart grids, and solar renewable energy systems.

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Table 1 Climate zone classification based on ASHRAE Standard 90.1-2010.

Climate zone	Climate type	Criteria	Representative city
1A	Very Hot – Humid	5000 < CDD10℃	Miami, USA
1B	Very Hot – Dry	5000 < CDD10℃	Riyadh, Saudi Arabia
2A	Hot – Humid	3500 < CDD10℃ ≤ 5000	Houston, USA
2B	Hot – Dry	3500 < CDD10℃ ≤ 5000	Phoenix, USA
3A	Warm – Humid	2500 < CDD10℃ ≤ 3500	Memphis, USA
3B	Warm – Dry	2500 < CDD10℃ ≤ 3500	EI Paso, USA
3C	Warm – Marine	CDD10℃ ≤ 2500 and HDD18℃ ≤ 2000	San Francisco, USA
4A	Mixed – Humid	CDD10℃ ≤ 2500 and 2000 < HDD18℃ ≤ 3000	Baltimore, USA
4B	Mixed – Dry	CDD10℃ ≤ 2500 and 2000 < HDD18℃ ≤ 3000	Albuquerque, USA
4C	Mixed – Marine	2000 < HDD18℃ ≤ 3000	Salem, USA
5A	Cool – Humid	3000 < HDD18℃ ≤ 4000	Chicago, USA
5B	Cool – Dry	3000 < HDD18℃ ≤ 4000	Boise, USA
5C	Cool – Marine	3000 < HDD18℃ ≤ 4000	Vancouver, Canada
6A	Cold – Humid	4000 < HDD18℃ ≤ 5000	Burlington, USA
6B	Cold – Dry	4000 < HDD18℃ ≤ 5000	Helena, USA
7	Very Cold	5000 < HDD18℃ ≤ 7000	Duluth, USA
8	Subarctic	7000 < HDD18℃	Fairbanks, USA

Table 2 Commercial reference buildings.

Building type	Subtype
Offices	Small office; Medium office; Large office
Retails	Stand-alone retail; Strip mall
Schools	Primary school; Secondary school
Hospitals	Outpatient healthcare; Hospital
Hotels	Small hotel; Large hotel
Restaurants	Quick service restaurant; Full service restaurant
Apartments	Mid-rise apartment; High-rise apartment
Others	Warehouse (non-refrigerated)

Table 3 Summary of key features of the three types of office buildings.

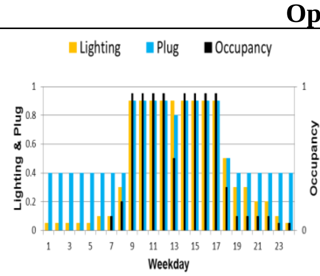
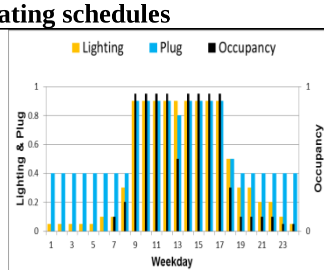
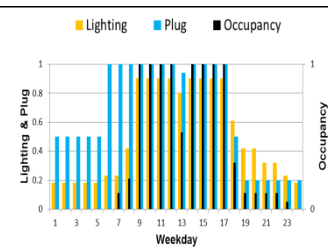
	Large-size office	Medium-size office	Small-size office
Total Floor Area (m^2)	46320	4980	510
Number of stories	12	3	1
% Perimeter Zone Area	30%	40%	70%
Envelope			
Window-wall-ratio (WWR)	40%	33%	24.4% for South and 19.8% for the other three orientations
Walls, roofs, floors: U-factor	ASHRAE 90.1 Requirements, Nonresidential; Walls, Above-Grade, Steel-Framed; Roofs, Insulation entirely above deck		
Windows: U-factor and SHGC	ASHRAE 90.1 Requirements Nonresidential	ASHRAE 90.1 Requirements Nonresidential; Vertical Glazing, 31.1-40%, U fixed	ASHRAE 90.1 Requirements Nonresidential; Vertical Glazing, 20-30%, U fixed
HVAC systems			
System type	Central built-up VAV systems	Packaged VAV systems	Packaged single zone systems
Heating source	Gas boiler	Gas furnace	Air-source heat pump with gas furnace as back up
Cooling source	Water-cooled centrifugal chillers	Air-cooled direct expansion	Air-source heat pump
Air distribution and terminal units	VAV terminal box with hot-water reheat coil, minimum damper position set at 30%	VAV terminal box with hot-water reheat coil, minimum damper position set at 30%	No terminal unit
Thermostat setpoint	24°C Cooling / 21°C Heating	24°C Cooling / 21°C Heating	24°C Cooling / 21°C Heating
Air-side economizer	Applicable based on 90.1	Applicable based on 90.1	None
Internal loads			
Average lighting power density (W/m^2)	90.1-2004: 10.76 90.1-2010: 8.99	90.1-2004: 10.76 90.1-2010: 8.87	90.1-2004: 10.76 90.1-2010: 9.15
Average plug-load power density (W/m^2)	7.8	8.07	6.78
Average occupant density (m^2/person)	18.6	18.6	16.6
Operating schedules			
Lighting, plug-loads, and occupants			
Misc.			
Exterior Lighting Peak Power (W)	90.1-2004: 62787 90.1-2010: 43305	90.1-2004: 14385 90.1-2010: 7476	90.1-2004: 1634 90.1-2010: 896

Table 4 Statistics of the annual average global horizontal solar radiation of the 17 cities from year 1980 to 2009.

City	Annual average global horizontal solar radiation (Wh/m^2), year			Average AMYs	TMY3	Variation (Highest – Lowest)	Variation (TMY3 – Average)	Variation % (TMY3 – Average)/ Average
	Highest	Medium	Lowest					
Miami	5825, 1986	5614, 1991	5444, 1992	5612	4803	380	-809	-14.4
Riyadh	6588, 2001	6329, 1983	5977, 1982	6318	6114	611	-204	-3.2
Houston	5099, 1999	4765, 1992	4474, 1982	4750	4459	624	-291	-6.1
Phoenix	6069, 2002	5868, 1980	5531, 1983	5832	5738	538	-94	-1.6
Memphis	4799, 1999	4560, 1996	4230, 1991	4564	4493	570	-71	-1.6
EI Paso	6072, 2003	5749, 1997	5519, 1986	5758	5657	554	-101	-1.8
San Francisco	5520, 1988	5352, 1981	4952, 1998	5322	4703	568	-619	-11.6
Baltimore	4435, 2006	4240, 1987	3918, 2003	4223	4078	517	-145	-3.4
Albuquerque	6054, 2003	5906, 2009	5635, 1983	5881	5426	419	-455	-7.7
Salem	4110, 1987	3865, 1995	3692, 1998	3881	3701	418	-180	-4.6
Chicago	4484, 1988	4099, 2008	3832, 1993	4100	3854	652	-246	-6.0
Boise	5106, 2002	4927, 1990	4746, 1982	4926	4429	360	-497	-10.1
Vancouver	3946, 1985	3682, 1998	3361, 2007	3674	3369	585	-305	-8.3
Burlington	3863, 1995	3715, 2002	3465, 2000	3699	3675	398	-24	-0.6
Helena	4598, 2001	4367, 1981	4082, 1998	4377	3997	517	-380	-8.7
Duluth	4069, 1988	3746, 1999	3525, 1993	3744	3678	544	-66	-1.8
Fairbanks	3018, 1987	2860, 1998	2473, 1995	2868	2591	545	-277	-9.7

Table 5 Statistics of the annual average dry-bulb temperature of the 17 cities from year 1980 to 2009.

City	Annual average dry-bulb temperature (℃), year			Average AMYs	TMY3	Variation (Highest – Lowest)	Variation (TMY3 – Average)
	Highest	Medium	Lowest				
Miami	25.3, 1998	24.8, 2003	23.8, 1984	24.7	24.5	1.5	-0.2
Riyadh	27.8, 1999	26.7, 1981	25.0, 1992	26.6	26.2	2.8	-0.4
Houston	21.4, 2006	20.6, 2003	19.0, 1983	20.5	20.4	2.4	-0.1
Phoenix	24.8, 1989	23.9, 2000	22.5, 1998	23.9	23.8	2.3	-0.1
Memphis	18.5, 2007	17.1, 2002	16.2, 1997	17.2	17	2.3	-0.2
EI Paso	19.8, 1994	18.5, 2008	16.7, 1987	18.3	18	3.1	-0.3
San Francisco	14.7, 1997	13.8, 2009	12.8, 1982	13.8	13.8	1.9	0
Baltimore	14.4, 1990	13.2, 2005	12.2, 2003	13.2	13.2	2.2	0
Albuquerque	15.0, 2003	14.1, 2008	13.0, 1984	14.0	13.7	2.0	-0.3
Salem	12.9, 1992	11.6, 2002	10.0, 1985	11.6	11.7	2.9	0.1
Chicago	12.1, 1998	10.1, 2000	8.7, 1985	10.0	10	3.4	0
Boise	12.7, 2003	11.3, 2005	8.1, 1985	11.1	11.2	4.6	0.1
Vancouver	11.6, 2004	10.5, 2002	9.1, 1985	10.5	9.7	2.5	-0.8
Burlington	9.2, 1998	7.8, 2007	7.0, 1980	7.9	7.9	2.2	0
Helena	9.1, 2007	7.4, 2005	4.8, 1996	7.1	7.2	4.3	0.1
Duluth	6.3, 1998	4.3, 2000	2.6, 1996	4.3	4	3.7	-0.3
Fairbanks	0.3, 1981	-1.8, 2001	-4.4, 1999	-2.0	-1.4	4.7	0.6

Table 6 Statistics of the HVAC source EUI of the Large Office, 90.1-2004 during the 30-year period

City	HVAC source EUI (kWh/m^2), year			Average AMYs	TMY3	Variation (Highest – Lowest)	Variation (TMY3 – Average)	Variation % (TMY3 – Average)/ Average
	Highest	Medium	Lowest					
Miami	250.8,1998	229.3,1999	206.1,1984	228.9	227.6	44.7	-1.4	-0.6
Riyadh	217.4,1998	197.9,1980	181.7,1992	200.1	182.1	35.7	-18.1	-9
Houston	206.7,1980	193.6,1986	178.3,1984	193.8	189.2	28.4	-4.7	-2.4
Phoenix	205.2,1984	196.5,2008	185.3,2004	195.9	189.8	19.9	-6.1	-3.1
Memphis	165.3,1985	151.4,1996	140.5,1992	152.6	148.8	24.9	-3.8	-2.5
EI Paso	108.2,1981	103.1,1982	96.5,2004	102.5	97.8	11.7	-4.7	-4.6
San Francisco	74.9,1997	65.9,1998	60.9,1999	66.9	63.5	13.9	-3.4	-5.2
Baltimore	144.9,1994	134.9,2004	125.1,1984	133.6	136.5	19.9	2.8	2.1
Albuquerque	102,2007	96.8,1981	91.5,1986	96.8	93.1	10.5	-3.7	-3.8
Salem	83.1,1990	74.7,1988	71.4,1981	75.1	75.1	11.7	-0.1	-0.1
Chicago	138.2,1983	128,1986	112.7,1992	127.6	130.9	25.5	3.3	2.6
Boise	111.3,1985	92.8,1982	83.7,1995	93.2	87.9	27.6	-5.2	-5.6
Vancouver	74.9,1990	67.1,1989	61.1,1983	66.8	67.5	13.8	0.6	0.9
Burlington	133.3,1989	118.9,2004	108.2,2006	120.1	118.4	25.1	-1.6	-1.4
Helena	116.6,1985	99.5,1986	88.7,1999	100.1	95.5	27.9	-4.6	-4.6
Duluth	146.2,1989	128.6,2005	117.9,1992	130.7	133.1	28.2	2.5	1.9
Fairbanks	180.1,1999	163.6,1997	135.8,1981	161.3	157.7	44.2	-3.6	-2.2

Table 7 Statistics of the HVAC source EUI of the Large Office, 90.1-2010 during the 30-year period

City	HVAC source EUI (kWh/m^2), year			Average AMYs	TMY3	Variation (Highest – Lowest)	Variation (TMY3 – Average)	Variation % (TMY3 – Average)/ Average
	Highest	Medium	Lowest					
Miami	167.2,1998	151.9,1991	136.2,1984	151.2	151.4	31.1	0.2	0.2
Riyadh	164.1,1998	151.2,1980	137.4,1992	152	138	26.7	-14	-9.2
Houston	122.2,1998	114.2,2003	106.1,1984	114.4	111.3	16.1	-3.1	-2.7
Phoenix	129,1981	122.9,2009	116.3,1982	122.9	119.6	12.7	-3.3	-2.7
Memphis	99.5,1985	92,1991	85.1,1992	92.5	90	14.4	-2.5	-2.7
EI Paso	79.2,1981	75.8,1990	71.3,2004	75.5	71.7	7.9	-3.8	-5
San Francisco	45.5,1997	38.2,2008	35.3,1999	39	36	11.2	-2.9	-7.7
Baltimore	84.1,1994	76,1985	69.7,1984	76.1	77.3	14.3	1.2	1.6
Albuquerque	74.9,2007	71.1,1981	66.9,1986	71.6	66.9	7.9	-4.6	-6.4
Salem	53.7,1990	48.4,2002	45.3,1980	48.7	48	8.3	-0.7	-1.5
Chicago	88.7,1985	80.8,1986	69.2,1992	80.9	83	19.5	2.1	2.6
Boise	75.4,1985	62.4,1991	55.3,1981	62.5	57.1	20.1	-5.4	-8.7
Vancouver	47.8,1998	42.1,2008	38.2,2001	42.3	39.9	9.6	-2.4	-5.7
Burlington	85.5,1989	74.9,1983	66.9,2006	75.7	74.5	18.6	-1.3	-1.7
Helena	78.5,1985	63.7,1980	55.8,1999	64.8	60.1	22.7	-4.4	-7.1
Duluth	93.9,1989	79.6,2005	70.6,1992	81.7	83.6	23.3	1.8	2.2
Fairbanks	134.2,1999	116.3,1988	91.8,1981	115.9	111.7	42.4	-4.2	-3.7

Table 8 Statistics of the total building total source EUI of the Large Office, 90.1-2004 during the 30-year period

City	Total building source EUI (kWh/m^2), year			Average AMYs	TMY3	Variation (Highest – Lowest)	Variation (TMY3 – Average)	Variation % (TMY3 – Average)/ Average
	Highest	Medium	Lowest					
Miami	533,1998	511.5,1999	488.3,1984	511.2	509.9	44.7	-1.4	-0.3
Riyadh	499.5,1998	479.9,1980	463.8,1992	482.2	464.1	35.7	-18.1	-3.7
Houston	489.3,1980	476.2,1986	460.9,1984	476.4	471.7	28.4	-4.7	-1
Phoenix	487.6,1984	478.9,2008	467.7,2004	478.3	472.1	19.9	-6.1	-1.3
Memphis	448.2,1985	434.3,1996	423.3,1992	435.5	431.7	24.9	-3.8	-0.9
EI Paso	391,1981	385.9,1982	379.3,2004	385.3	380.6	11.7	-4.7	-1.2
San Francisco	358.1,1997	349.2,1998	344.2,1999	350.2	346.7	13.9	-3.4	-1
Baltimore	428.2,1994	418.1,1981	408.3,1984	416.9	419.7	19.9	2.8	0.7
Albuquerque	385.2,2007	380,1981	374.7,1986	379.9	376.3	10.5	-3.7	-1
Salem	366.5,1990	358.2,1988	354.8,1981	358.5	358.4	11.7	-0.1	0
Chicago	421.6,1983	411.5,1986	396.2,1992	411.1	414.3	25.5	3.3	0.8
Boise	394.7,1985	376.3,1982	367.1,1995	376.6	371.4	27.6	-5.2	-1.4
Vancouver	358.4,1990	350.5,1989	344.6,1983	350.3	350.9	13.8	0.6	0.2
Burlington	417,1989	402.6,2004	391.9,2006	403.7	402.1	25.1	-1.6	-0.4
Helena	400.4,1985	383.2,1986	372.5,1999	383.8	379.2	27.9	-4.6	-1.2
Duluth	430.2,1989	412.7,2005	402,1992	414.7	417.1	28.2	2.5	0.6
Fairbanks	464.3,1999	447.9,1997	420.2,1981	445.7	442.1	44.2	-3.6	-0.8

Table 9 Statistics of the total building source EUI of the Large Office, 90.1-2010 during the 30-year period

City	Total building source EUI (kWh/m^2), year			Average AMYs	TMY3	Variation (Highest – Lowest)	Variation (TMY3 – Average)	Variation % (TMY3 – Average)/ Average
	Highest	Medium	Lowest					
Miami	401.1,1998	385.8,1991	369.9,1984	385	384.9	31.1	-0.1	0
Riyadh	397.9,1998	385,1980	371.2,1992	385.8	371.6	26.6	-14.2	-3.7
Houston	357.6,1998	349.6,2003	341.2,1984	349.5	345.8	16.4	-3.7	-1.1
Phoenix	363.3,1981	357.3,2009	350.6,1982	357.2	354	12.7	-3.2	-0.9
Memphis	333.9,1985	326.4,1983	319.4,1992	326.9	323.9	14.6	-3.1	-0.9
EI Paso	312.7,1981	309.3,2005	304.7,2004	308.9	305.2	8	-3.7	-1.2
San Francisco	279.5,1997	272.6,1995	268.5,1999	273.2	270.1	11	-3.1	-1.1
Baltimore	318.3,1994	310.1,1985	303.8,1984	310.2	310.9	14.5	0.7	0.2
Albuquerque	308.1,2007	304.2,1981	300.1,1986	304.7	300.3	7.9	-4.3	-1.4
Salem	288.6,1990	293.2,1988	280,1980	283.5	282.2	8.5	-1.3	-0.5
Chicago	323.1,1985	315.2,1986	303.5,1992	315.3	317.1	19.6	1.8	0.6
Boise	309.1,1985	296.2,1991	289.2,1981	296.3	291.1	19.9	-5.3	-1.8
Vancouver	282.9,1998	277.3,1995	273.4,2001	277.4	275.3	9.5	-2.1	-0.8
Burlington	320.3,1989	309.8,1983	302,2006	310.6	308.9	18.3	-1.6	-0.5
Helena	312.7,1985	298.1,1980	290.1,1999	299	294.5	22.6	-4.5	-1.5
Duluth	328.8,1989	314.8,2005	305.7,1992	316.9	318.3	23.1	1.5	0.5
Fairbanks	371.6,1999	353.8,1988	329.4,1981	353.5	349.3	42.2	-4.2	-1.2

Table 10 Regression of HVAC source energy for the 90.1-2004 Large Office during the 30-year period

City	c_0	c_1	c_2	c_3	R^2
Miami	-69.19	0.05367	0.02736	0.0101	0.84
San Francisco	6.57	0.03674	0.01388	-0.01795	0.95
Boise	13.15	0.02675	0.01932	-0.02778	0.86
Fairbanks	-40.46	0.05493	0.02366	-0.00532	0.92

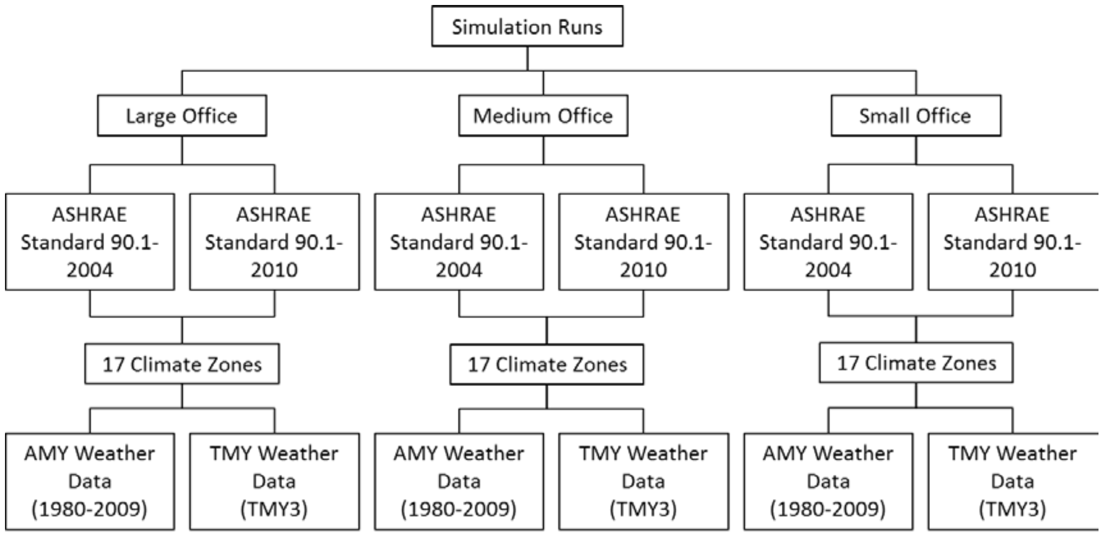


Fig. 1. The structure of simulation runs.

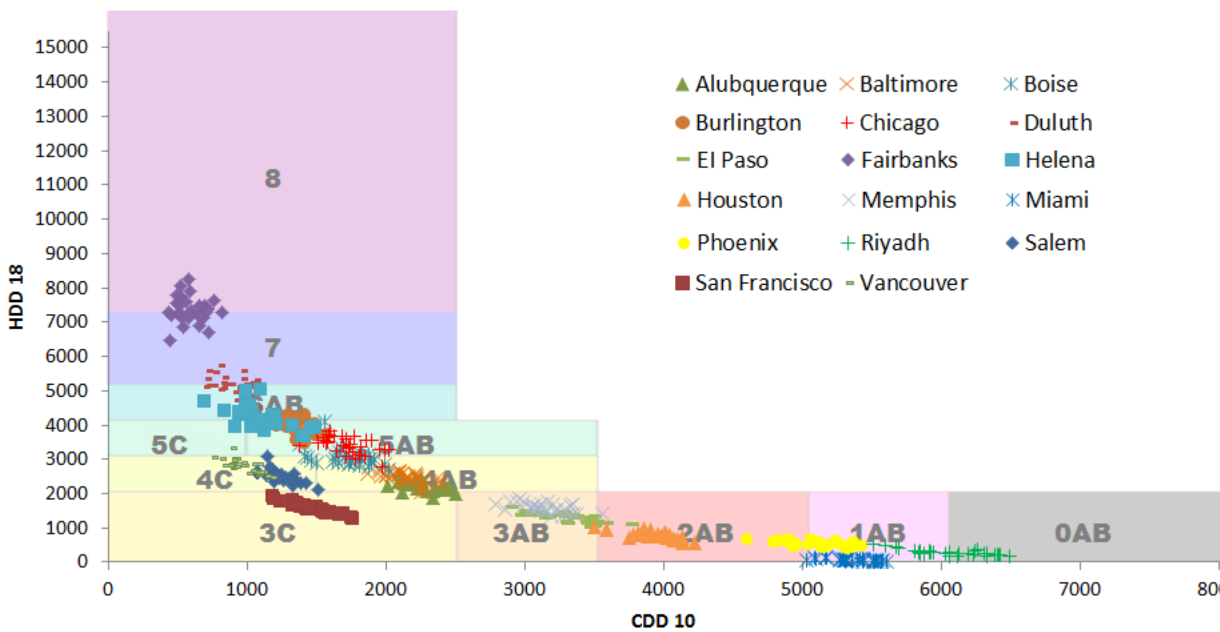


Fig. 2. Variations of climate zone based on annual HDD and CDD for 17 cities using AMY weather data from year 1980 to 2009.

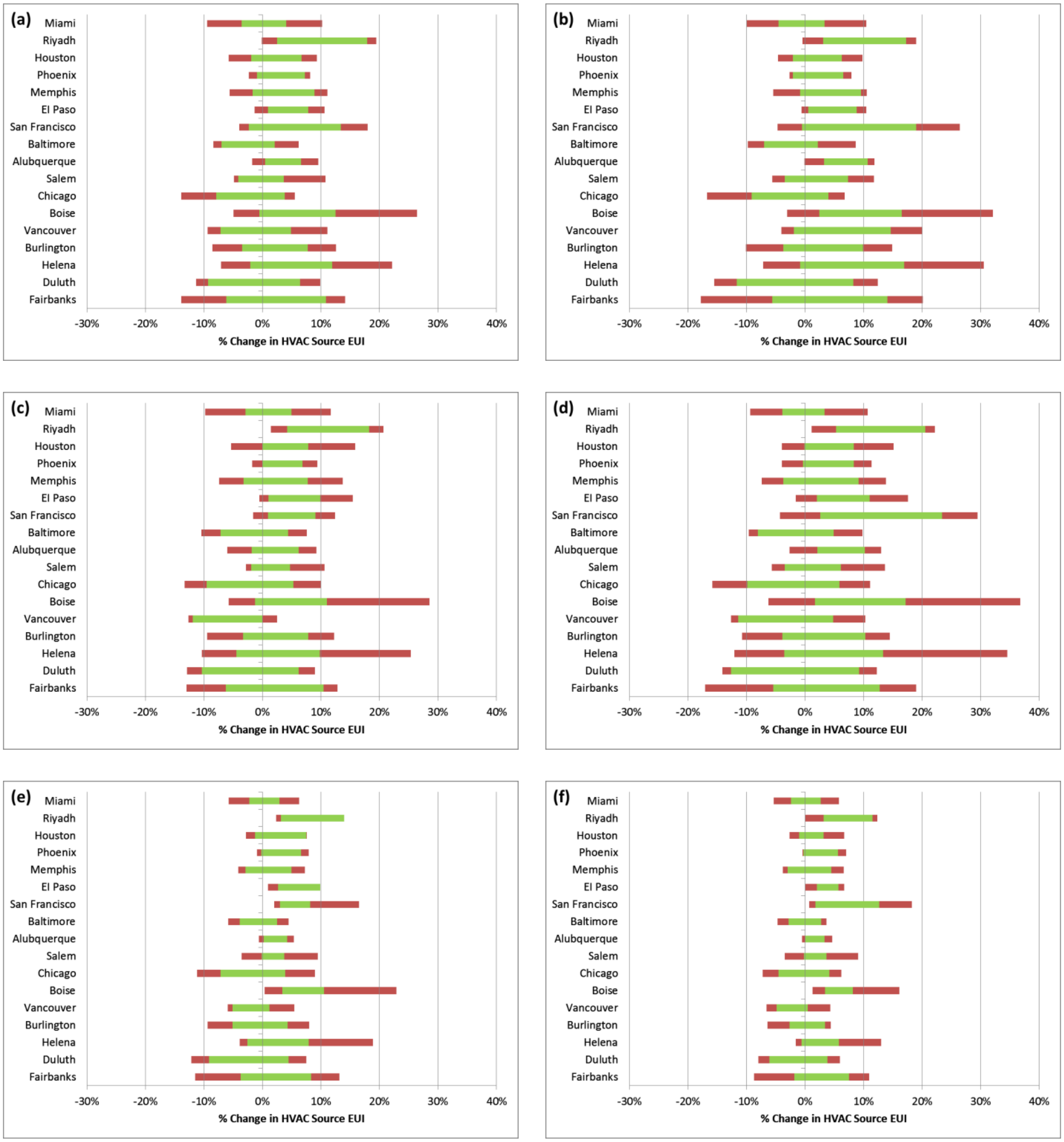


Fig. 3. Variations of percentage changes of HVAC source EUI between AMY and TMY3. (a) large office, 90.1-2004 models; (b) large office, 90.1-2010 models; (c) medium office, 90.1-2004 models; (d) medium office, 90.1-2010 models; (e) small office, 90.1-2004 models; (f) small office, 90.1-2010 models. The red bars represent the variations across the 30-year while the green bars excluding the six percentage changes from the top three and the bottom three extreme weather years.

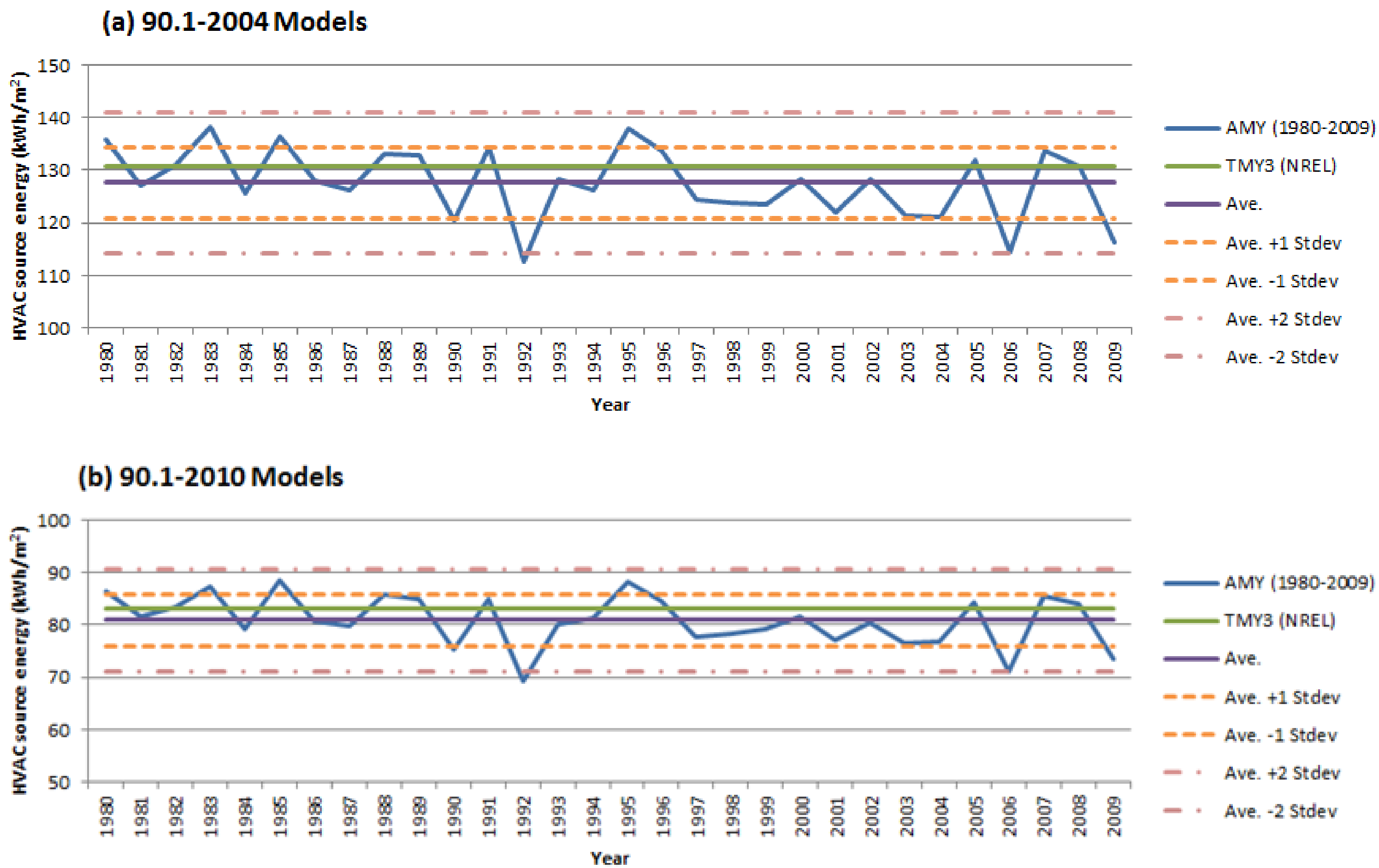


Fig. 4. Variations of HVAC source energy of the large office buildings in Chicago from year 1980 to 2009.

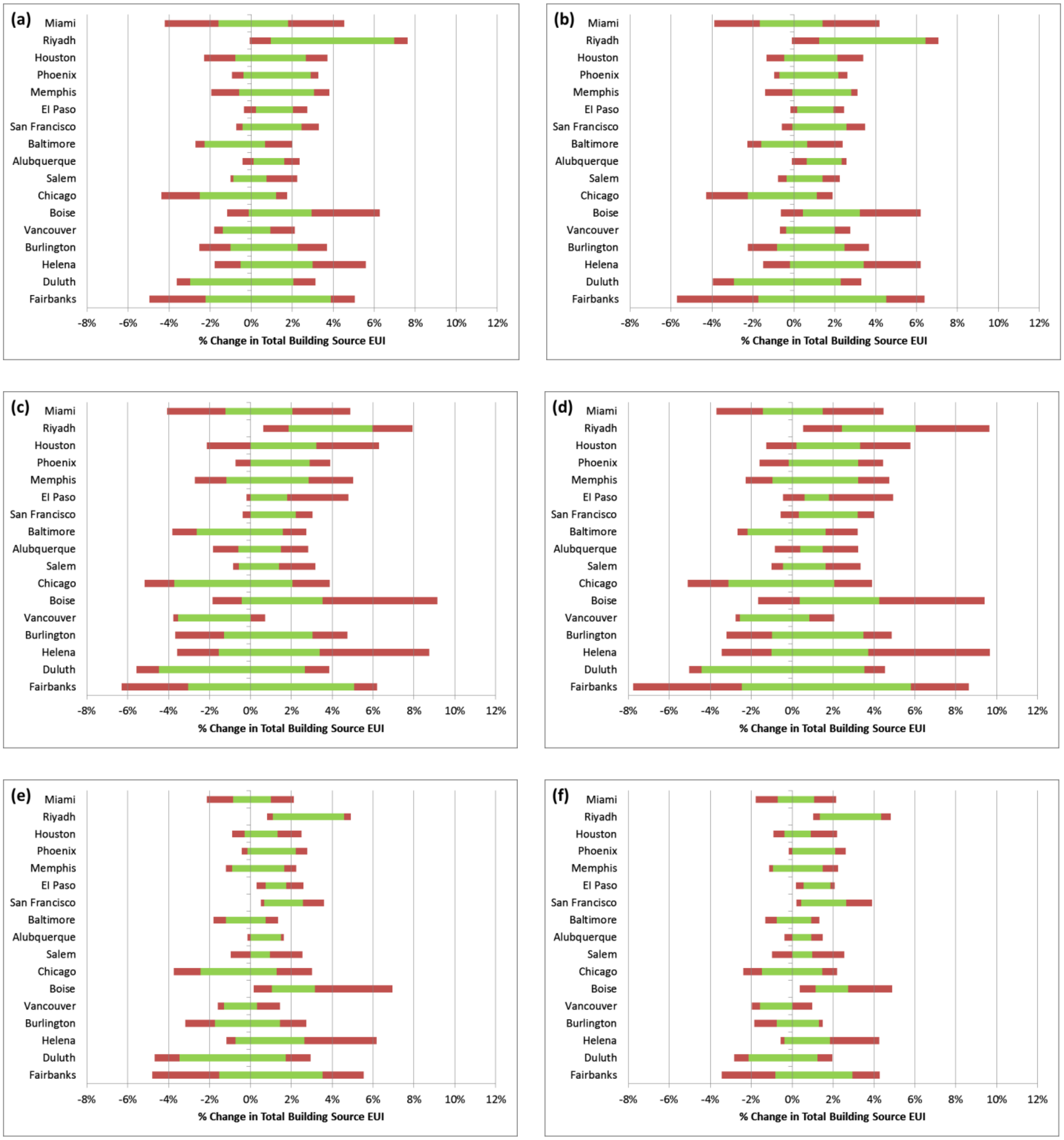


Fig. 5. Variations of percentage changes of total building source EUI. (a) large office, 90.1-2004 models; (b) large office, 90.1-2010 models; (c) medium office, 90.1-2004 models; (d) medium office, 90.1-2010 models; (e) small office, 90.1-2004 models; (f) small office, 90.1-2010 models. The red bars represent the variations across the 30-year while the green bars excluding the six percentage changes from the top three and the bottom three extreme weather years.

Fig. 6. Variations of percentage changes of HVAC and total source EUIs of the three types of office buildings with low (90.1-2004 standard) and high (90.1-2010 standard) energy efficiency levels. (a) changes in HVAC source EUI; (b) changes in total source EUI.

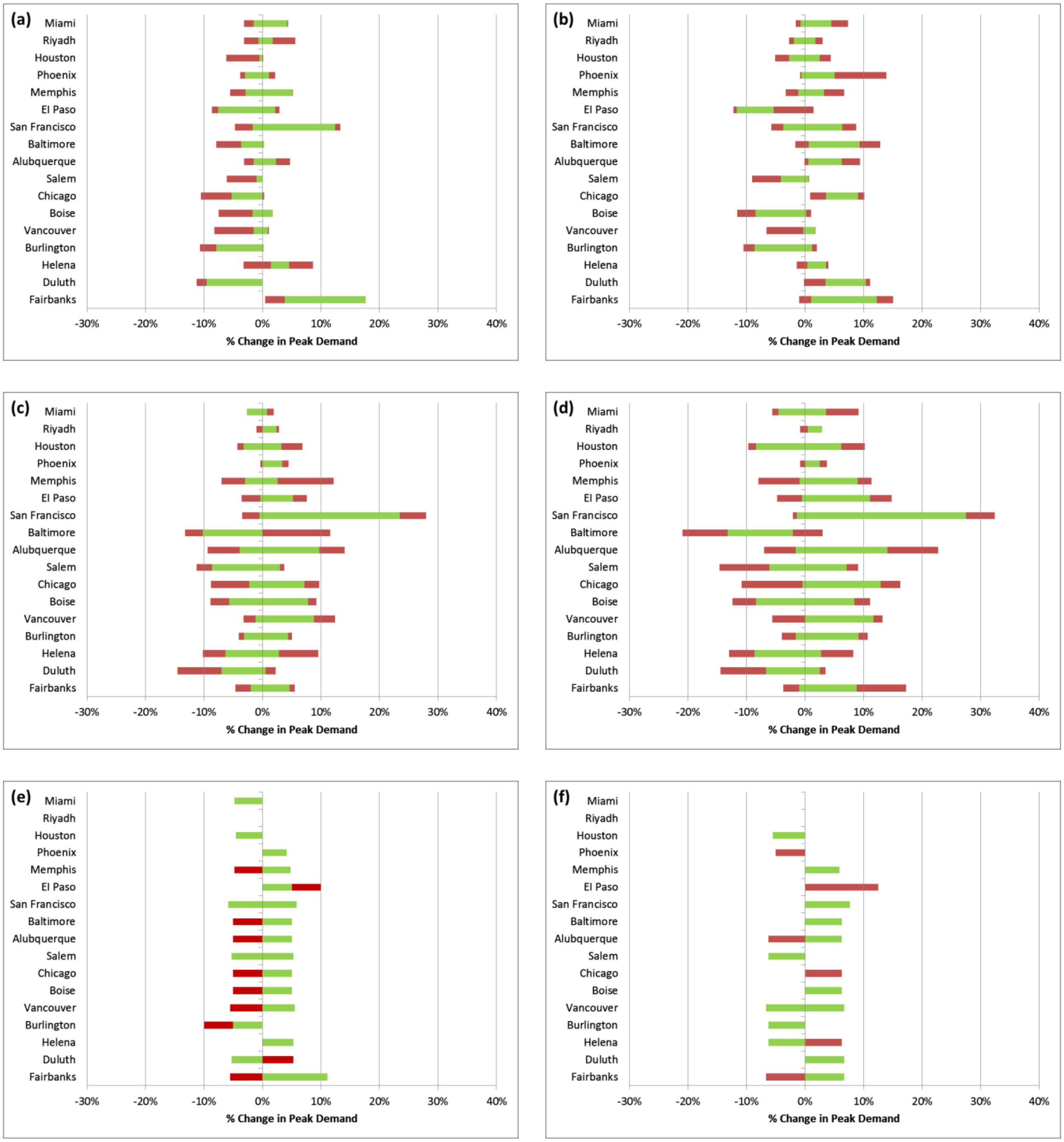


Fig. 7. Variations of percentage changes of peak electricity demand. (a) large office, 90.1-2004 models; (b) large office, 90.1-2010 models; (c) medium office, 90.1-2004 models; (d) medium office, 90.1-2010 models; (e) small office, 90.1-2004 models; (f) small office, 90.1-2010 models. The red bars represent the variations across the 30-year while the green bars excluding the six percentage changes from the top three and the bottom three extreme weather years.

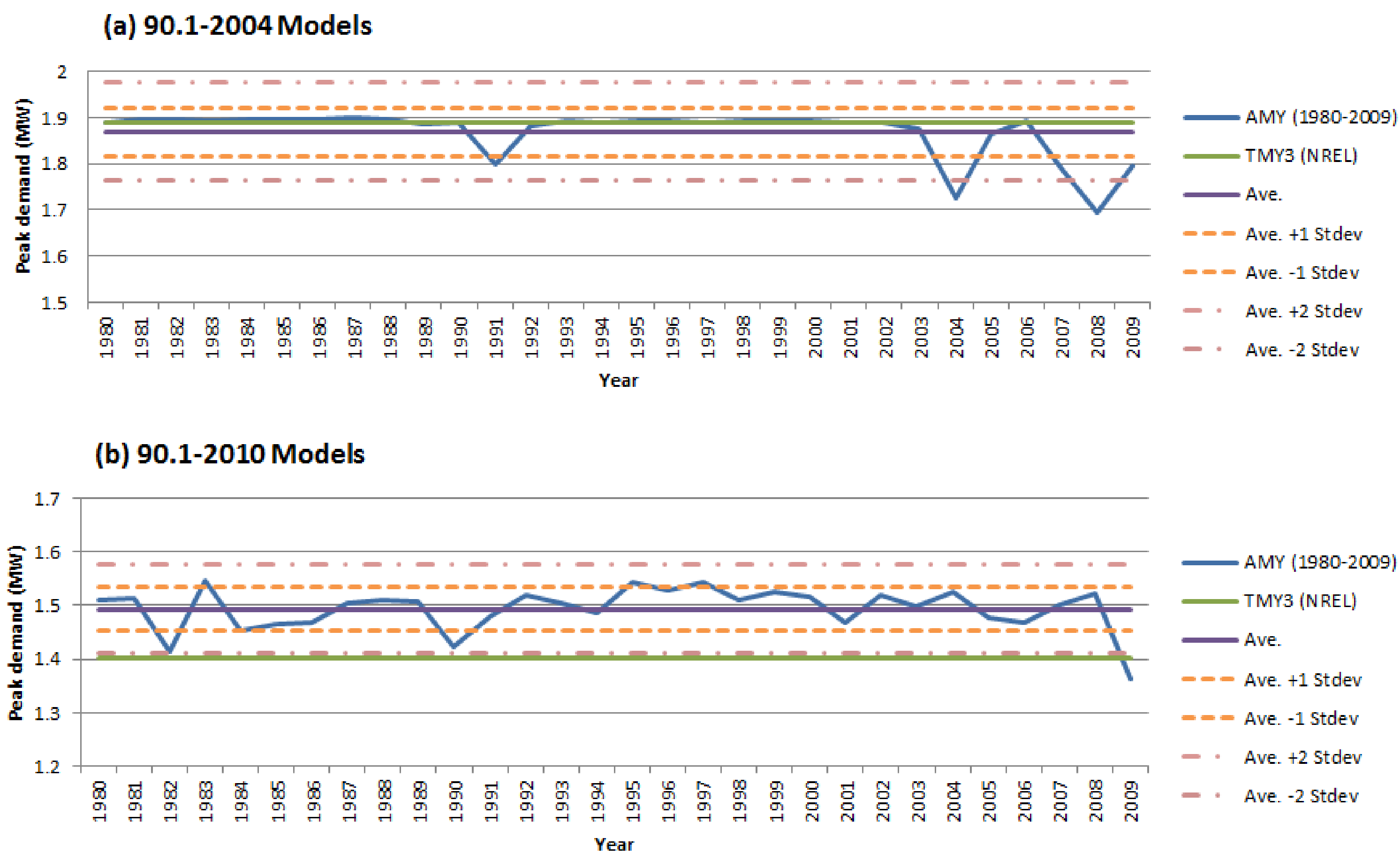


Fig. 8. Variations of peak electricity demand of the large office buildings in Chicago from year 1980 to 2009.

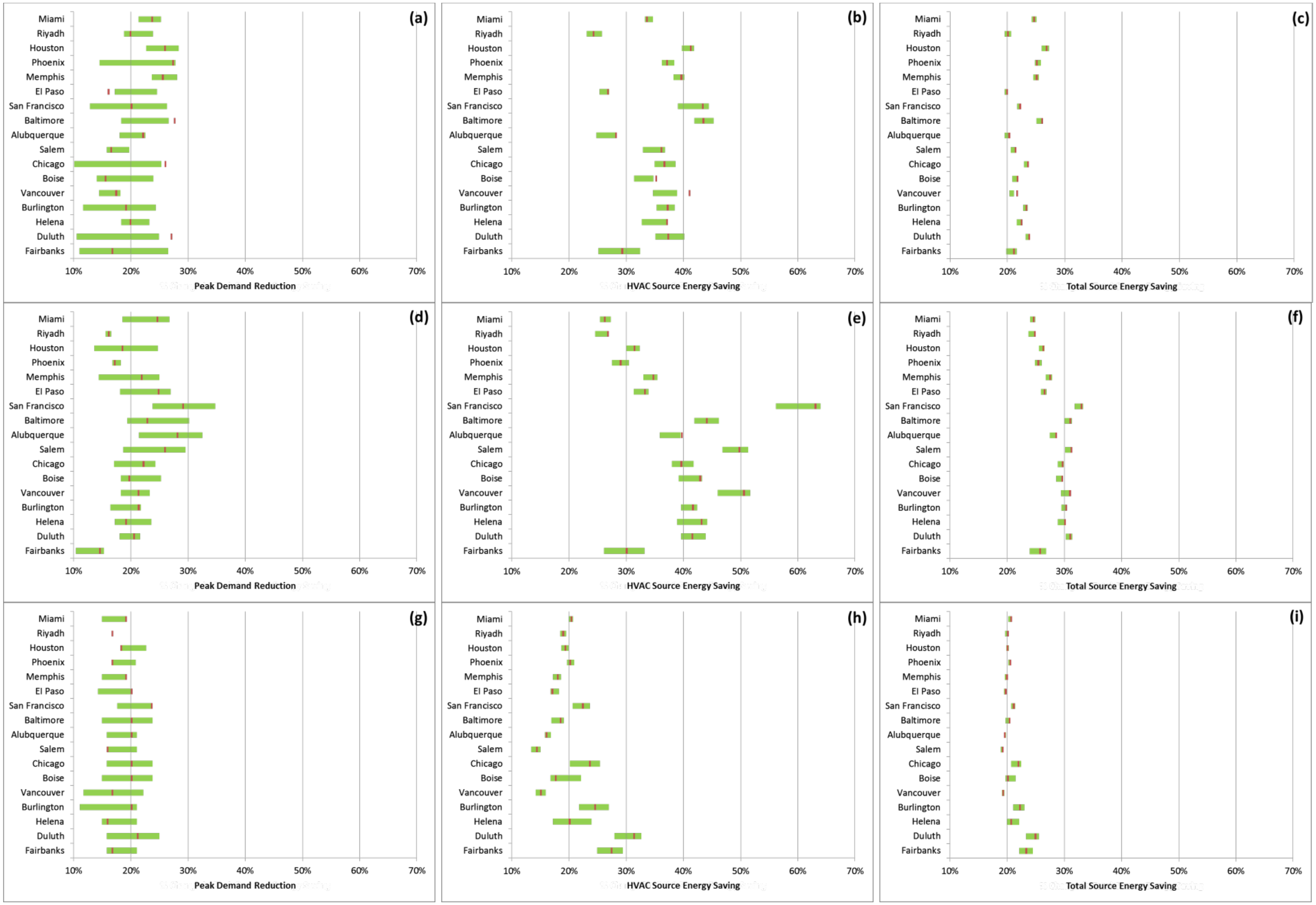


Fig. 9. Variations of percentage reduction of peak electricity demand, and percentage savings of HVAC source energy and total source energy of the 90.1-2010 models over the 90.1-2004 models. (a)-(c) large office; (d)-(f) medium office; (g)-(i) small office.