1 **The variation of climate change impact on building energy consumption**
2 **to building type and spatiotemporal scale**

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Abstract

Building energy consumption is vulnerable to climate change due to the direct relationship between outside temperature and space cooling/heating. This work quantifies how the relationship between climate change and building energy consumption varies across a range of building types at different spatiotemporal scales based on estimates in 925 U.S. locations. Large increases in building energy consumption are found in the summer (e.g., 39% increase in August for the *secondary school* building), especially during the daytime (e.g., >100% increase for the *warehouse* building, 5-6 pm), while decreases are found in the winter. At the spatial scale of climate-zones, annual energy consumption changes range from -17% to +21%, while at the local scale, changes range from -20% to +24%. Buildings in the warm-humid (Southeast) climate zones show larger changes than those in other regions. The variation of impact within climate zones can be larger than the variation between climate zones, suggesting a potential bias when estimating climate-zone scale changes with a small number of representative locations. The large variations found in the relationship between climate change and building energy consumption highlight the importance of assessing climate change impacts at local scales, and the need for adaptation/mitigation strategies tailored to different building types.

Key words

Climate change impacts; building energy consumption; energy impacts; sustainable energy; spatiotemporal impacts; energy policy

Highlights

The climate change impact on energy demand is sensitive to building type examined
The *secondary school* building shows increases of > 39% energy consumption in August
The *warehouse* shows increases of >100% energy consumption at some summer hours
At climate zone scale, changes in annual energy consumption range from -17% to +21%
Changes in building energy consumption show strong variation within climate zones

1. Introduction

Energy consumption in commercial and residential buildings accounted for 41% of U.S. primary energy consumption in 2010, of which 37% was used for space heating and

cooling. Within the commercial sector, space heating and cooling together account for 31% of building primary energy consumption, while in residential buildings, the share is 43% [1]. Building energy consumption, especially space cooling and heating, is directly influenced by climate change.

Different methods have been utilized to study the impact of climate change on residential and/or commercial building energy consumption [2–4]. These methods can be generally classified into three categories: observation-based regression/prediction, global/regional energy modeling, and individual building energy simulation.

The observation-based regression/prediction approach takes advantage of the historical relationship between energy consumption and climate variables to predict future energy consumption under a changing climate. Because this method is based on historical data, it is self-calibrated when fitted to a model. The output resolution from this approach is usually determined by the resolution of the historical data, and the accuracy of the estimation depends on the quality of the selected regression model (usually evaluated with statistical criteria, such as R^2). This approach has been used to estimate the impacts of climate change on annual/monthly energy consumption [5–8] and peak energy demand [8–11] in some U.S. states. For example, Huang *et al.* used this method to estimate the building energy demand changes and financial implications of climate change at the state/month scale in the contiguous U.S. [12].

The global/regional energy modeling approach simulates energy consumption in a numerical model composed of multiple variables such as energy demand and supply, economy, technology, population, policy, and climate. The impact of climate change on building energy consumption is assessed through simulated climate change scenarios. Besides climate change, this approach can be also used to study the impact of other key variables such as population change, land use change, carbon taxes, and emissions mitigation policy. However, the complexity and flexibility of this method comes at the expense of output resolution. Hence, this method has been employed to estimate the impacts of climate change on building energy consumption at annual timescales and at global, national, and state spatial scales, at the finest [13–18].

The individual building energy simulation approach can be used to simulate high-frequency output (e.g., hourly) for specific building types. However, it usually requires detailed building characteristics and hourly weather data to drive the simulation. Such detailed information (e.g. building characteristics, occupants, operation schedules) is limited. As a result, this approach has been used for a few building types in particular locations only [19–22]. Although Huang [23] and Wang *et al.* [24] used this approach to evaluate the impact of climate change for the whole U.S., the results are based on building energy simulations in less than 20 cities.

Similar methods have been employed to estimate the impact of climate change on building energy consumption in other countries [25–32] or globally [33–35]. Although the impact of climate change on energy consumption across different building types has been explored down to the monthly temporal scale and for spatial scales down to climate zones (covering several to hundreds of counties) [23,24], the importance of sub-monthly timescales and variation within climate zones has rarely been studied. Given the spatial and temporal heterogeneity of climate change, building energy consumption impact can vary substantially within climate zones at sub-monthly timescales.

In this study we quantitatively explore the impact of climate change on building energy consumption using the individual building energy simulation approach. Our focus is on the variation of impact across different building types at multiple time scales (e.g., annual, monthly, and hourly) and spatial scales (e.g., national, climate zone, and location). We quantify these impacts at over 900 U.S. locations across the 16 U.S. climate zones. We also explore the variation of the impact across 15 commercial building types (each with three different age classes, representing different building technology) and 2 residential building types. High spatiotemporal-resolution combined with building energy consumption simulation at over 900 locations allows us to detect the temporal and spatial patterns of the impacts. Consideration of different building age classes, approximates the sensitivity of climate change impact to variation in building technology. Compared to past research that estimated the impact of climate change on regional building energy consumption using a few locations, the analysis performed here is based on a large number of simulations, offering regional estimates that are more statistically representative.

The remainder of this paper is divided into three parts: methodology, results and discussion, and conclusions. The methodology section includes a description of the building energy simulation model, the weather data and building prototypes used to drive the energy consumption simulations, calibration of results, and the metrics used for comparing results. The variation of building energy consumption impacts to building types/technology at different spatial and temporal scales are explored in the results and discussion section. The main findings, caveats, and the potential for future work are discussed in the conclusions section.

2. Methodology

2.1. Building energy simulation model

EnergyPlus, a well-known building energy simulation tool developed by the U.S. Department of Energy (DOE), is used to simulate building energy consumption. EnergyPlus has been extensively tested and validated for the ANSI/ASHRAE standards and is widely used by engineers and scientists to model building energy consumption

[36]. EnergyPlus requires hourly weather data (e.g., temperature, humidity, and solar radiation) and hundreds of building characteristics (e.g., heating, ventilating, and air conditioning system, building materials, and occupancy) associated with specific building prototypes to drive the energy simulations. It produces hourly energy consumption by end use and fuel type for a given building prototype.

2.2. Weather data

The current hourly weather data used in EnergyPlus is retrieved from the third (and the latest) Typical Meteorological Year (TMY3) collection [37]. Each TMY3 file includes hourly weather data in one year duration for a specific location, which is developed based on 1991-2005 weather data or 1976-2005 weather data, if the latter exists. The meteorological data is available for 925 locations in the contiguous U.S., most of which reflect the 1991-2005 weather data. Future monthly weather is derived from the World Climate Research Programme's (WCRP) Coupled Model Intercomparison Project phase 3 (CMIP3) [38]. The monthly temperature change between a future time period and the present for each TMY3 location is represented as the average temperature change of its four closest CMIP3 neighbor grid cells. The average temperature change at each location is calculated for two future periods (2040s and 2090s, relative to 1991-2005), each under three IPCC emission scenarios (A2, A1B, and B1 representing high, medium and low emissions respectively [39]) with an ensemble of 15 climate model outputs. These average monthly temperature differences are then added to the current hourly TMY3 temperature data, as a constant, to generate the future hourly weather conditions in each month and location, similar to the approach followed in other studies [19,20,23]. The hourly temperature data generated with this method may not capture the sub-monthly temperature changes, but it ensures that the sub-monthly temperature pattern is consistent with the other climate variables (e.g., humidity and solar radiation) [20].

The projected temperature change for the decades of the 2040s and 2090s are spatially heterogeneous with the temperature change magnitude dependent upon emissions scenario (Figure 1). Generally, inland locations see larger temperature increases than coastal areas, and high latitude regions show greater differences than low latitude regions. In the 2040s, the temperature increase is less than (or around) 2 °C in all emission scenarios for most locations. In the 2090s, the temperature change shows larger variation across the emission scenarios, with more than a 4 °C increase in most U.S. locations under the A2 scenario and about a 2.5 °C increase under the B1 scenario. The temperature change is always smallest under the B1 scenario, and it is largest under the A1B and A2 scenarios in the 2040s and 2090s, respectively. These spatial patterns are consistent with previous research [40].

2.3 Building prototypes

To specify commercial building characteristics, we used the building prototypes developed by the U.S. DOE. The DOE based these building prototypes on the 2003 Commercial Buildings Energy Consumption Survey (CBECS) data, an effort by the U.S. Energy Information Administration (EIA) to collect building characteristics, occupant schedules, energy consumption and energy expenditures for various commercial building types covering different U.S. regions [41]. The U.S. DOE developed 16 commercial building prototypes for the EnergyPlus model (Table 1), reflecting three different age classes (pre-1980, post-1980, and new-2004), located in 15 reference cities. For each of the 16 building prototypes, there are multiple age classes and/or building characteristics, but they share the same floor area and number of floors. These 16 building types account for 70% of the existing commercial floor area in the U.S., while the 15 reference locations represent all U.S. climate zones (Figure 2).

The climate zones are based on the number of heating/cooling degree days (HDD/CDD), average temperature, and precipitation [42]. Each climate zone is represented as a combination of a thermal zone (number) and a hydrological zone (letter). The thermal zone numbers range from 1 to 7 representing large CDD to small CDD (or small HDD to large HDD). The letters “A”, “B”, and “C” represent moist, dry, and marine hydrological zones, respectively.

The three building age classes are used as a proxy for building technology as they represent progressively newer, more efficient standards. The pre-1980 building prototype represents building technology up to 1979, the post-1980 building prototype represents building technology from 1980 to 2003, and the new-2004 building prototype represents building technology following the ANSI/ASHRAE/IESNA Standard 90.1-2004 guidelines [43]. Buildings with newer technology have more energy-efficient equipment and better insulation to mitigate the impact of non-optimal outside temperature. For example, the wall R-value (resistance to heat flow) in the new-2004 building class is about twice that of the pre-1980 building class. Furthermore, the energy intensity of interior lighting in the new-2004 building class is approximately 50% smaller and new buildings are usually equipped with more energy-efficient HVAC system [43]. All of the DOE commercial building prototypes are used for energy simulation except the “midrise-apartment” prototype, for which the calibration data is not available (see section 2.4 for calibration details). Two of the reference cities, Los Angeles and Las Vegas, are located in the same climate region - 3B. Los Angeles is used to represent the 3B region within California (3B-CA) and Las Vegas is used to represent the 3B region outside of California (“3B-non-CA”). For each TMY3 location, the commercial building prototypes developed for the reference city within the same climate region, are used to simulate energy consumptions.

The DOE also developed prototypes for residential buildings in 2009 based on the building codes specified in the International Energy Conservation Code (IECC) [44].

These codes establish the requirements for new building design and construction. Besides these IECC building requirements, the DOE also relies upon other resources such as Residential Energy Consumption Survey (RECS) [45] to develop the building characteristics for residential building prototypes. These prototypes contain no age class divisions (in contrast to commercial buildings), instead reflecting new building stock only. There are two residential prototypes: single-family (SF) detached houses and multi-family (MF) low-rise apartment buildings (Table 1). Each of these prototypes was modified to represent three types of heating systems (electric resistance, gas furnace, and heat pump), resulting in 6 residential sub-prototypes for each representative city. Unlike the commercial building prototypes, which were developed for 15 representative cities, the residential building prototypes were developed for 119 representative locations. For each of the 925 TMY3 locations, the residential building prototypes associated with the closest representative city within the same state and climate zone are used.

2.4 Calibration to survey data

“Site energy” and “source energy” are usually used to describe end-use energy consumed in a building and the raw energy required to meet the on-site demand, respectively. Because source energy accounts for the energy loss during production and delivery, it reflects the total energy consumption more comprehensively and it is more comparable across different fuel types. In this study, we chose source energy as the comparison target, and converted the site energy consumption generated by EnergyPlus to source energy consumption using source-to-site ratios [46].

To correct for potential bias in the EnergyPlus simulated energy consumption intensity (energy consumption divided by building areas), we calibrate the model output to the CBECS and RECS survey results. For commercial buildings, we apply this calibration for each building type and age class at the spatial scale of the census division. This is done by generating a population-weighted mean energy consumption intensity within a census division using the consumption values at all TMY3 locations within a division. The population used for each TMY3 location is the population in census tracts [47] closest (shortest distance from tract center to TMY3 location) to the TMY3 point. To achieve the CBECS surveyed intensity, the total energy consumption in a division/domain is divided by the total building area. The ratio between the surveyed and simulated value is used to adjust (e.g., the simulated value is multiplied by this ratio to achieve an adjusted value) the simulated energy consumption intensity at each TMY3 location in both current and future periods.

For the residential buildings, the same procedure is followed, but the calibration value is specific to building type and heating system and at the RECS survey domain spatial scale (typically covering one or more states).

The annual energy consumption in each location is further distributed to each month or hour according to the time-structure output from EnergyPlus. Because new-2004 commercial buildings are not available in the 2003 CBECS data, the EnergyPlus output for new-2004 commercial buildings are not calibrated and they are not used for most analysis except in section 3.7 where the impact of building technology changes are discussed (see section 3.7 for details).

The annual energy consumption intensity from the EnergyPlus model is close to the RECS/CBECS survey data for most building types except the *full service restaurant* and *outpatient* building types (Figure 3). The energy consumption intensity in residential buildings is generally less than commercial buildings, with the smallest RECS/CBECS energy consumption intensity appearing in the *single-family house* building type (86 kBtu/sq-ft) and the largest RECS/CBECS energy consumption intensity occurring in the *quick service restaurant* building type (1103 kBtu/sq-ft). In contrast, the *warehouse building type* exhibits the smallest EnergyPlus energy consumption intensity (88 kBtu/sq-ft), while the *quick service restaurant* building type exhibits the largest (1286 kBtu/sq-ft).

The discrepancies between the EnergyPlus model output and the RECS/CBECS survey data may be caused by several factors. First, simulated output will always differ from actual data, because the model cannot account for all the factors that determine building energy consumption and energy thermodynamics. Second, the building prototypes were developed based on the most commonly used technologies/building characteristics in the survey data, which may not correctly represent the energy consumption patterns and fuel mixes of the real building stock. Finally, the definition/measurement of floor area may differ between the survey data and the EnergyPlus model, resulting in energy consumption intensity differences. The calibrated current (1991-2005) energy consumption intensity from EnergyPlus, in the end, is required to match the intensity value derived from the survey data exactly at the scale of census division/domain.

2.5 Comparison metrics

Relative difference (RD) and intensity difference (ID) are used to quantify the impact of climate change on building energy consumption. RD (%) represents the relative change in energy consumption, defined as the energy consumption difference between the future and current period, divided by the energy consumption in the current period:

$$RD = (E_{ft} - E_{cr})/E_{cr} \quad (1)$$

where E is the energy consumption in the current (cr) and future (ft) periods.

ID (KBTU/sq-ft) represents the change in energy consumption intensity, calculated as the calibrated current energy consumption intensity, multiplied by the RD:

$$ID = RD \times EI'_{cr} \quad (2)$$

where EI' is the calibrated current energy consumption intensity (KBTU/sq-ft).

To capture aggregated results, the RD and ID values are summed for each combination of commercial building type and age class, and each combination of residential building type and heating system, weighted by their current energy consumptions. RD and ID values for two of the three age classes (pre-1980 and post-1980) are aggregated (weighted by their calibrated current energy consumption) to get the RD and ID for each commercial building type. Similarly, the RD and ID values for the three heating systems (electric resistance, gas furnace, and heat pump) are aggregated to get the RD and ID values for each residential building type. RD and ID values for all commercial/residential building types are further aggregated to calculate the RD and ID values for the integral of all commercial/residential buildings. Since the current energy consumption is used as the denominator in equation (1), the RD tends to be big for the building types with small current energy consumption (e.g., warehouse). However, the ID avoids this problem, because it includes a multiplier which accounts for the energy consumption intensity in the current period. The combination of RD and ID, reflecting both the relative and absolute changes, comprehensively depict the impact of climate change.

In section 3.3, the median and quantile values (25%-75%, and 0%-100%) of the 925 ID values are compared between the three building technologies (pre-1980, post-1980, and new-2004) to study the sensitivity of climate change impact to building technology improvement such as building thermal efficiency and HVAC efficiency. Because the new-2004 buildings cannot be calibrated with the 2003 CBECS data, the energy consumptions for the three building technologies are not calibrated in section 3.3. Since section 3.3 is not aimed at studying the impacts of climate change in future periods relative to 1991-2005, but the impact of building technology changes, the calibration of energy consumption in the current period is less important.

2.6. Cluster analysis

Local Indicators of Spatial Association (LISA) is used to identify spatial clustering of climate change impact. LISA depends on the statistics of the Local Moran's I, which is calculated as follows [48]:

$$I_i = (x_i - \bar{x}) \sum_{j=1}^n w_{ij} (x_j - \bar{x}) \quad (3)$$

where, x is the observation value, I is the local Moran's I value for observation i , n is the total number of observations, w_{ij} is the weighting matrix defining the weight of observation j on observation i .

For each observation i , equal weights (uniform weighting) are given to all of its neighbors, and 0 for non-neighbors. Neighbors are defined as the observations that are within a distance of 175 km to the observation i . The distance limit is set as 175 km, because it is the smallest distance that guarantees each weather location has at least one neighbor. With the given distance limit (175 km), each observation has about 12 neighbors on average. A larger distance limit increases the number of neighbors and assumes low climate change impact spatial heterogeneity. Given the observed spatial variation of climate change (Figure 1) and RD/ID values, it is not appropriate to use a large distance limit. A 175 km threshold assures that the TMY3 locations have an adequate number of neighbors for a spatial clustering calculation, and better reflect the spatial heterogeneity of climate change. We also test the sensitivity of the spatial clustering to the distance threshold (e.g., 175 km vs. 500 km) and the spatial weighting matrix (e.g., uniform weighting vs. inverse distance weighting).

A LISA map usually contains five categories: high-high (high values surrounded by high values), low-low (low values surrounded by low values), high-low (high values surrounded by low values), low-high (low values surrounded by high values), and insignificant (the p-value of local Moran's I is not statistically significant). The observation value, the local Moran's I , and the significance of local Moran's I (p-value ≤ 0.05 is deemed significant) are used to decide which category a given observation belongs to with the following rules [48]:

- high-high: $x_i > \bar{x}$, $I_i > 0$, and p-value ≤ 0.05
- low-low: $x_i < \bar{x}$, $I_i > 0$, and p-value ≤ 0.05
- high-low: $x_i > \bar{x}$, $I_i < 0$, and p-value ≤ 0.05
- low-high: $x_i < \bar{x}$, $I_i < 0$, and p-value ≤ 0.05
- insignificant: p-value > 0.05

Because no results belong to the high-low or low-high category in this research, these two categories are not displayed on the LISA map.

3. Results and discussion

The impact of climate change on building energy consumption varies across building types, and the strength of variation depends on the spatial scale, temporal scale, and building technology. The impacts are estimated and compared across building types at three time scales (annual, monthly, and hourly), three spatial scales (national, climate zone, and location), and for three building technologies (pre-1980, post-1980, and new-2004).

3.1. Climate change impact: variation across building type & temporal scale

3.1.1 Annual time scale

The national annual energy consumption ID and RD values driven by the difference between future and present climate, vary by building type, emissions scenario, and future time period (Table 2). The differences for “all” buildings (the weighted sum of the individual building types – see section 2.5) show very small increases in the 2040s under all three emission scenarios. Because residential buildings consume more energy than commercial buildings, the ID and RD values for the *all* buildings category are dominated by the differences in the residential buildings, which are comparatively small.

There exists little building energy consumption change in future decades for the two residential building types, particularly in the decade of the 2040s where the changes are close to zero. By contrast, the building energy consumption differences in the commercial buildings are larger and vary to a greater extent across the different commercial building types. The large commercial building increases usually appear in the buildings with high space cooling demands (e.g., *hotel* and *restaurant*), while the decreases appear in the buildings with low space cooling demands (e.g., *warehouse*). For example, in the decade of the 2040s, the RD values for commercial buildings range from -4.6% (*warehouse*) to 2.8% (*quick service restaurant*) under the A1B scenario. By the end of this century, the RD variation increases, ranging from -8.7% (*warehouse*) to 7.8% (*large hotel*) under the A2 scenario.

3.1.2 Monthly time scale

The impact of climate change on building energy consumption analyzed at the annual scale masks larger changes estimated at smaller timescales (Figure 4). Although the annual ID/RD values are positive for all except the warehouse building type, the monthly differences show both positive and negative values for each building type, with the largest positive difference in July/August and the largest negative difference in January. The monthly ID values for the two residential building types are similar, with values ranging from -1.4 kBtu/sq-ft in January to +1.7 kBtu/sq-ft in August for both building types. In percentage terms, the *single-family house* building type show larger variation (ranging from -14% in January to 23% in August) than the *multi-family apartment* building type (ranging from -11% in January to 17% in August), due to the smaller energy consumption intensity in the *single-family house* building type under the current period.

Compared to the relatively small monthly ID/RD values for the residential buildings, commercial buildings usually show larger monthly ID/RD values with greater variation among the different building types. The positive ID values in August range from 0.7 kBtu/sq-ft (*outpatient building*) to 11.4 kBtu/sq-ft (*quick service restaurant*). The negative ID values in January range from -0.3 kBtu/sq-ft (*large hotel*) to -6.5 kBtu/sq-ft (*quick service restaurant*). These are accompanied by a large variation in RD values with a maximum percent increase in August of 39% (*secondary school*) and a maximum

percent decrease in January of -22% (*warehouse*). The large ID values usually appear in building types with high energy intensity (e.g., *restaurant*), while the large RD values appear in the building types with low energy intensity (e.g., *warehouse*).

3.1.3 Hourly time scale

Since the largest increase in energy consumption usually appears in the July/August timeframe, a more detailed examination of the hourly ID/RD values and their variation across building types in this time period is worthwhile. Figure 5 shows the average hourly ID/RD values during July and August in the 2090s under the A2 emissions scenario. In contrast to the monthly change patterns described in section 3.1.2 where the building consumption differences matched the seasonal cycle (increased energy demand in warmer months and decreased energy demand in colder months), the hourly changes are more diverse and show larger variations across building types. Unlike the monthly case where the two residential building types had very similar monthly ID/RD values, the hourly ID/RD values for the *single-family house* building type shows greater variation within the 24 hour cycle than the *multi-family apartment* building type, with both the largest hourly ID (2.6 Btu/sq-ft) and RD (37.7%) values appearing in the *single-family house* building type. This is probably because *single-family houses* typically have a larger surface to volume ratio, thus the inside temperature and space heating/cooling demand is more influenced by fluctuations in the outside temperature via faster thermal heat transmission [49]. The two maximum ID values appear around 10-11 am and 7-8 pm for residential buildings, probably due to the high internal heat gain (heat emitted from any source/equipment inside the building, for example, lighting, cooking, and human metabolism) during these two periods, when the buildings are occupied and/or most appliances (e.g., clothes washer, clothes dryer, bathroom, and lighting) are used to a greater extent [44]. The increased temperature caused by climate change, on top of the two periods with high internal heat gain, requires more space cooling and leads to larger ID values compared to other hours. By contrast, the maximum RD values usually appear at midnight. This is probably because the energy consumption is low during late night hours driven by low appliance use and space cooling demands [44]. This, in turn, results in a small denominator within the RD calculation and a high RD value. The different diurnal patterns of ID and RD demonstrate the importance of including both ID and RD in analysis of climate change impacts on building energy consumption.

The commercial buildings show greater hourly ID and RD variation both within and across the commercial building types. ID values range from 0 to 20 Btu/sq-ft and RD values range from 0% (midnight, for multiple building types) to 110% (5-6 pm, in the *warehouse*). The maximum ID appears in the *quick service restaurant* building type for which the energy consumption intensity is the largest, while the maximum RD value occurs in the *warehouse* building type for which the energy consumption intensity is the smallest (Figure 3). The maximum ID values for commercial buildings usually appear

around midday due to the high occupancy and equipment use, and the subsequent high space cooling demands during business hours [43]. There are some building-specific maxima appearing in other hours. For example, the maximum ID values for the *full service restaurant* and the *quick service restaurant* building types appear around 9 am, 2 pm, and 8 pm consistent with maximum customer patronage in these two building types. The maximum ID value for large hotels appears around 10 pm likely due to the high activity of hotel guests, lighting, and equipment use [43]. In contrast to the changes during the daytime, the nighttime ID/RD values are usually small.

3.2 Climate change impact: variation across building type & spatial scale

3.2.1 Climate zone scale

The impact of climate change on building energy consumption also displays a strong spatial variation at the spatial scale of climate zones. Figure 6 shows the climate-zone-scale annual RD values for each of the residential/commercial building types in the 2090s under the A2 emission scenario. Although the annual/national RD values for both the *multi-family apartment* and *single-family house* building types are very small (< 2% in most cases), the RD values across the climate zones show large variation, ranging from -5.8% to 11.3% in the *multi-family apartment* building type and -6.2% to 14.7% in the *single-family house* building type.

For commercial buildings, the majority of RD values across all climate zones show net increases in energy consumption with the *secondary school* building type showing a maximum energy demand increase of 20.9% (climate zone 1A). The *warehouses* building type is an exception with negative RD values as large as -16.6% (climate zone 7A). Within each building type, the warmer climate zones usually show a net increase in energy consumption due to space cooling demand increases, while colder climate zones display a net decrease driven by declines in space heating demand. For example, the RD values in the *warehouse* building type range from a net decrease of -16.6% in climate zone 7A to a net increase of 12.4% in climate zone 1A. Within each climate zone, the RD values also display strong variation across building types. For example, the RD values in climate zone 4A range from -8.4% in the *warehouse* building type to 8.1% in the *secondary school* building type. Relatively small variations of climate-zone-level RD values exist in the *hospital* (ranging from -1.1% to 2.7%) and *outpatient* building types (ranging from -2% to 2.4%) compared to other commercial building types. This could be due to the stricter ventilation requirements for healthcare (*outpatient* and *hospital*) building types [43]. The strict ventilation requirements weaken the impact of outside temperature change on the indoor environment, and result in small RD values over the whole U.S..

3.2.2. Local scale

Even larger annual RD variations are found at the local scale (Figure 7), with the largest increase in energy consumption (+24%) appearing in the *secondary school* building type (in Aroostook, Texas, climate zone 2A) and the largest decrease (-20%) appearing in the *warehouse* building type (in Aransas, Maine, climate zone 7A). Within each climate zone and building type, there still exists a large variation in local-scale RD values, especially in the climate zones covering large areas. For example, the local-scale RD values in the *secondary school* building type range from -11.8% to 5.8% (17.6 percentage point span) in climate zone 6A, covering 8 climate-zone-scale RD values for this building type. The strength of such variation also depends on building type. For example, in the same climate zone (6A), the local-scale RD values in the *warehouse* building type only range from -19% to -11% (8 percentage point span), covering only 5 climate-zone-scale RD values. The variation of RD values within climate zones indicates that these within climate zone differences can be larger than the differences between climate zones, and hence systematic bias could result from representing the changes in a climate zone from a single reference location.

3.2.3. Spatial clustering

Despite the RD variation across spatial scales and building types, the spatial clustering displays consistent patterns. Based on uniform weighting of the spatial neighbors within a 175 km distance threshold, the LISA maps show that high RD values cluster in climate zones 1, 2, and 3, low RD values cluster in climate zones 6 and 7, with insignificant RD values in climate zones 4 and 5 (Figure 8). Although coastal locations typically show small temperature increases compared to inland locations (Figure 1), they often display large changes in energy consumption. The use of a larger distance threshold (500 km, with uniform weighting) for the weighting matrix results in larger areas of high and low cluster values, and a lessened area for insignificant values (Figure A1). The choice of inverse distance weighting, however, results in little change to the LISA maps (Figure A2).

The high-high result is found mostly in climate zones 1A and 2A. This may be due to three reasons. Firstly, the current outdoor temperatures are typically higher than the cooling thermostat set-point temperature (less or equal to 75 °F for different building types) in climate zone 1A and 2A, especially during summer [50]. Thus any temperature increase in the future will require additional space cooling. By contrast, the current outdoor temperature in the North is usually lower than the set-point temperature, even in summer. Hence, the future temperature increase may require little, or no, additional space cooling. Secondly, the humidity is usually high in coastal areas, and it requires additional energy to dehumidify the air in order to maintain a comfortable indoor environment [51]. Finally, the buildings in warmer climate zones usually have smaller wall and ceiling insulation R-values compared to the colder climate zones [43,44]. This implies that

warmer climate zones have buildings that are more vulnerable to the increased outside temperature and will require more space cooling.

3.2.4 Drivers of spatial variation

In order to explore the drivers of the spatial variation in energy consumption changes, we use the results for the *quick service restaurant* building type (the building type with the largest energy intensity) and examine the RD values in comparison to projected surface temperature change within and across climate zones (Figure 9). When examining the RD at the climate zone-scale (Figure 9a), values decrease along the climate zones from 1 to 7, indicating that the spatial variation of altered energy consumption is primarily caused by the current HDD/CDD gradient variation across the climate zones. For example, the positive RD values appear in the high-CDD zones due to the dominance of increased cooling demands, while the negative RD values occur in the high-HDD zones due to the dominance of reduced heating demands. Within each climate zone, the RD values for hydrological zone C (marine) are usually less than zone A and B due to moderated climate change along coastal areas. The RD values for hydrological zone B (dry) are typically less than zone A (wet) because less energy is required to dehumidify the air in drier climates.

In contrast to the variation across climate zones, the variation of RD values within climate zones is related to projected temperature change. RD values are positively correlated with temperature changes within most climate zones except 2A and 2B, and the correlation coefficients are greater than 0.5 in about half of the climate zones (Figure 9b). The slopes of the linear regression show that energy consumption within most climate zones will increase more than 1% per °C increase in temperature. This indicates that temperature change is the major driver of RD variation within each climate zone, and large temperature changes usually lead to large RD values. Were the temperature to further increase after the 2090s, the locations seeing net decreases in energy consumption will likely switch to net increases. This is because there is a limit to space heating declines, which can't drop below zero. There is no limit for space cooling increases, however. When the temperature further increases, the dominance of space heating reductions in cold climates will weaken, and the space cooling increase will eventually outweigh the space heating decrease.

Although the analysis in this section is based on the *quick service restaurant* building type, it represents the general pattern seen for all building types (Figure A3 and A4 in Appendix).

3.3 Variation across building technology

Building technology plays an important role in determining building energy efficiency and consumption. Advanced technologies (e.g., efficient HVAC, well-insulated walls)

can mitigate the impact of climate change on the indoor environment. To quantify the potential effectiveness of new building technology in mitigating the impact of climate change, we show the median and quantiles (25%-75%, and 0%-100%) of the 925 ID values for the three different age classes of building in Figure 9. Effective building technology that can reduce the impacts of climate change on building energy consumption will be represented by a small median ID value and/or narrow quantiles.

The median space cooling demand increases in the pre-1980 buildings are similar to the post-1980 building values. However, the new-2004 buildings consistently exhibit the smallest median increase (Figure 10a). The median space heating demand decreases are usually greatest in the pre-1980 buildings, followed by the post-1980 buildings. The new-2004 buildings generally have the smallest median space heating demand decrease (Figure 10b). Besides the smaller space cooling/heating median changes, the new-2004 buildings also display narrower 25%-75% and 0%-100% quantiles for both space cooling and space heating. The median IDs for total energy consumption show less of a range among the different building technology due to the cancellation between increased cooling demands and decreased heating demands (Figure 10c). However, the new-2004 buildings still show the narrowest quantile values (25%-75% and 0%-100%) for most building types. These results confirm the expectation that the buildings equipped with newer technology are more efficient in maintaining a comfortable indoor environment and less sensitive to outdoor temperature changes due to the stronger insulation.

4. Conclusions

This paper estimates the impact of climate change on building energy consumption for 2 residential and 15 commercial building types at 925 U.S. locations. This research is aimed at isolating the sensitivity of building energy consumption to climate change, and highlights the variation due to building type, spatial scales, and temporal scales. Information at small spatial/temporal scales is potentially more relevant for informing the implementation of climate change adaptation/mitigation policies.

We find a small national annual energy consumption increase for residential building types, but a large increase (up to 8%) for commercial building types by the decade of the 2090s. Larger variations are found across different building types, when the impacts are examined at the monthly/hourly temporal scales. At the monthly scale, national energy consumption increases up to 39% in August for the *secondary school* building type. By contrast, national energy consumption decreases up to 22% in January for the *warehouse* building type. At the hourly scale during summer, the variation is even larger, ranging from a 0% change at midnight for multiple building types to a 110% increase at 5-6 pm for the *warehouse* building type.

Large variations are also found within and between building types, when impact is examined at sub-national spatial scales. At the climate zone scale, the RD value increases up to 21% in the *secondary school* building type (climate zone 1A), while it decreases up to 17% in the *warehouse* building type (climate zone 7A). Larger variations are found across building types at the local scale, ranging from -20% to 24%. There also exists large variations within climate zones in individual building types (e.g., the RD values range from -12% to 6% in the climate zone 6A for the *secondary school* building type), suggesting a potential bias when representing the impacts of climate change in each climate zone with a single reference location. The clustering analysis suggests that large energy consumption changes are mainly clustered in areas with warm-humid (Southeast) climates. The variation of current CDD/HDD in different climate zones is the major driver of the spatial variation in energy consumption changes between climate zones, while the variation of local-scale temperature change is strongly related to the variation of local-scale energy consumption change within each climate zone. Energy consumption for different commercial building technologies indicates that the new-2004 building types are less sensitive to climate change, compared to the pre-1980 and post-1980 building types.

It is worthwhile to note that the residential building prototypes were developed following the IECC guidance, not based on the historical building characteristics. As a result, the impacts of climate change on residential buildings should be interpreted as the impact on future residential buildings constructed according to the IECC rules, instead of reflecting impacts on current residential building stock. The building stock used here represents the current spatial distribution and mix of building types. In future analysis, it may be useful to update these building stock attributes with projected land use datasets such as the Integrated Climate and Land-Use Scenario (ICLUS) [52].

The results presented here suggest a number of fruitful next steps. The impacts of climate change on building energy consumption were explored in this study using the CMIP3 long-term monthly temperature changes. Recently, the CMIP3 results have been updated to CMIP5 which used new emission scenarios, more models, and model improvements [53]. Analysis using the CMIP5 output may offer improved insight into the impact of climate change on building energy consumption.

Some research has suggested that climate change will result in more intense and frequent heat waves, of longer duration [54]. Because it requires a large amount of energy to satisfy the increased cooling demand during heat waves and the electricity grid is vulnerable to extreme events, it is important to study the impacts of extreme events on energy consumption, energy supply, and energy security. Such large and sudden changes in energy consumption might be captured in the building energy simulation approach adopted here, or estimated based on the historical relationship between energy consumption and climate.

Recent research [55–57] has also indicated that some urban areas will experience additional temperature increases due to urban expansion and the associated urban heat island effect. Furthermore, studies have found a positive specific humidity trend in the United States suggesting additional energy consumption due to the needs for dehumidification [58]. Finally, there has been some research suggesting future changes in solar radiation [59,60]. A change in solar radiation can alter building solar heat gain and therefore, cooling/heating demand. The combination of increasing extreme events, increasing urban heat island effects, increasing humidity, and changes in radiation, could exacerbate the energy consumption implications found here and are worthy of greater study.

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630

631 **Figure A1.** Local Indicators of Spatial Association (LISA) map of annual building energy
632 consumption RD values (%) between the 2090s and the 1991-2005 time period under the A2
633 emission scenario. Results are based on uniform weighting for neighbors with a 500 km distance
634 threshold.

Figure A2. Local Indicators of Spatial Association (LISA) map of annual building energy consumption RD values (%) between the 2090s and the 1991-2005 time period under the A2 emission scenario. Results are based on inverse distance weighting for neighbors with a 175 km distance threshold.

Figure A3. Annual building energy consumption relative difference (%) for climate zones between the 2090s and the 1991-2005 time period under the A2 emission scenario for residential and commercial building types. The bar color represents the average temperature change of all locations within each climate zone.

Figure A4. Relationship between the location-level relative difference (%) of annual building energy consumption and temperature change for all commercial and residential building types. The relative difference reflects changes between the 2090s and the 1991-2005 time period under the A2 emission scenario.

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821

822 **Figure Captions**

823 **Figure 1.** Population (for 2010) and temperature difference (°C) between future time periods
824 (2040s and 2090s) and the current time period (1991-2005) under three IPCC emission scenarios
825 at 925 TMY3 locations in the U.S.. Symbol color represents temperature change, symbol size
826 represents population.

Figure 2. Energy Information Administration (EIA) climate zones and reference cities for the commercial building prototypes [42].

Figure 3. Comparison between the CBECS/RECS surveyed building energy intensity and the EnergyPlus simulation results. Results reflect the 1991-2005 time period for both commercial and residential buildings.

Figure 4. U.S. average monthly (a) residential and (b) commercial building energy consumption ID and RD values between the 2090s and the 1991-2005 time period under the A2 emission scenario.

Figure 5. U.S. average hourly residential and commercial building energy consumption ID/RD values in July and August between the 2090s and the 1991-2005 time period under the A2 emission scenario.

Figure 6. Annual residential and commercial building energy consumption relative differences (%) for climate zones (thermal and hydrological zones) between the 2090s and the 1991-2005 time period under the A2 emission scenario.

Figure 7. Local-scale annual building energy consumption relative difference (%) between the 2090s and the 1991-2005 time period under the A2 emission scenario for all residential and commercial building types. Each quantile plot displays the intensity differences at 925 TMY3 locations, with the middle bar representing the median value, the box representing the 25% – 75% quantiles, and the whiskers representing the 0% and 100% quantiles.

Figure 8. Local Indicators of Spatial Association (LISA) map of annual building energy consumption RD values (%) between the 2090s and the 1991-2005 time period under the A2 emission scenario. Results are based on uniform weighting for neighbors within a 175 km distance threshold.

Figure 9. *Quick service restaurant* energy consumption RD (%) variation between the 2090s and the 1991-2005 time period under the A2 emission scenario. **(a)** RD across climate zones (sorted from high CDD to low CDD); **(b)** RD versus temperature change within each climate zone (each point represents a TMY3 location). The first parenthetical value represents the correlation coefficient between the RD and the temperature change. The second value represents the slope of the linear regression line (percentage change in energy per °C rise in temperature). The shaded area represents the 95% confidence interval of the regression line.

Figure 10. Space cooling **(a)**, space heating **(b)**, and total **(c)** energy consumption intensity differences (kBtu/sq-ft) for commercial buildings between the 2090s and the 1991-2005 time period under the A2 scenario. Each quantile plot displays the intensity differences in 925 TMY3 locations, with the middle bar representing the median value, the box representing 25% – 75% quantiles, and the whiskers representing the 0% and 100% quantiles. The red, green, and blue numbers are the median values (kBtu/sq-ft) for new-2004, post-1980, and pre-1980 buildings respectively.

Tables and Figures

Table 1. U.S. average building floor area and average number of floors for residential and commercial building prototypes [43,44].

Building Type	Floor Area (ft ²)	Number of Floors
Residential		
Single-family House	2,400	2
Multi-family Apartment	21,600	3
Commercial		
Large Office	498,588	12
Medium Office	53,628	3
Small Office	5,500	1
Warehouse	52,045	1
Stand-alone Retail	24,962	1
Strip Mall	22,500	1
Primary School	73,960	1
Secondary School	210,887	2
Supermarket	45,000	1
Quick Service Restaurant	2,500	1
Full Service Restaurant	5,500	1
Hospital	241,351	5
Outpatient Health Care	40,946	3
Small Hotel	43,200	4
Large Hotel	122,120	6
Midrise Apartment	33,740	4

Table 2. U.S. average annual building energy consumption intensity difference (kBtu/sq-ft) and relative difference (% , value in parentheses) between two future time periods and the present (1991-2005).

Building Type	2040s			2090s		
	A1B	A2	B1	A1B	A2	B1
Residential						
Multi-family Apartment	0.2(0.2)	0(0)	0.1(0.1)	0.8(0.9)	1.9(2.1)	0.1(0.1)
Single-family House	0.3(0.2)	0(0)	0.2(0.1)	1(0.8)	2.1(1.8)	0.2(0.2)
Commercial						
Full Service Restaurant	0.2(0.2)	0(0)	0.1(0.1)	0.8(0.9)	1.8(2.1)	0.1(0.1)
Hospital	1.7(0.7)	1.1(0.5)	1.1(0.5)	4.3(1.9)	7.2(3.2)	1.9(0.9)
Large Hotel	5.6(1.2)	4.3(0.9)	3.4(0.7)	12.1(2.6)	17.6(3.7)	6.4(1.3)
Large Office	2(0.4)	1.6(0.3)	1.3(0.3)	4.5(1)	6.9(1.5)	2.4(0.5)
Medium Office	7.3(2.8)	6.1(2.4)	4.7(1.8)	14.8(5.8)	19.9(7.8)	8.9(3.5)
Out Patient	3.8(1.7)	3(1.3)	2.5(1.1)	8.6(3.7)	12.8(5.5)	4.7(2)
Primary School	3.1(1.3)	2.2(1)	2(0.9)	7.1(3.1)	11(4.7)	3.7(1.6)
Quick Service Restaurant	0.1(0)	0(0)	0.1(0.1)	0.4(0.2)	1(0.4)	0.1(0.1)
Secondary School	2.8(1.9)	2.2(1.5)	1.8(1.2)	6.2(4.2)	9.2(6.3)	3.4(2.3)
Small Hotel	6.1(0.6)	4.2(0.4)	3.6(0.3)	14.7(1.3)	23.7(2.1)	6.6(0.6)
Small Office	3.4(2.1)	2.5(1.5)	2.2(1.4)	7.9(4.8)	12(7.3)	4.1(2.5)
Stand-alone Retail	3.3(1.9)	2.7(1.6)	2.2(1.3)	7.2(4.2)	10.6(6.2)	4.1(2.4)
Strip Mall	2.6(1.1)	1.8(0.8)	1.6(0.7)	6.2(2.7)	9.7(4.2)	3(1.3)
Super Market	1.8(1)	1.3(0.7)	1.1(0.6)	4.3(2.4)	7(3.8)	2(1.1)
Warehouse	3.1(1)	2.2(0.7)	1.8(0.6)	7.3(2.5)	11.5(3.9)	3.4(1.2)
All buildings	6.2(1)	4.6(0.7)	4(0.6)	13.7(2.2)	20.5(3.3)	7.3(1.2)
	-4.8(-4.6)	-4.4(-4.3)	-3.1(-3)	-8.4(-8.1)	-9(-8.7)	-6.1(-5.9)
	0.5(0.4)	0.2(0.2)	0.3(0.3)	1.5(1.3)	3(2.5)	0.5(0.4)

Figure 1.

Figure 2.

Figure 3

881

882

883 **Figure 4**

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886 **Figure 5**

Figure 6

Figure 7

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892 **Figure 8**

Figure 9

Figure 10