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Urban Microclimate and Its Impact on Building Performance: A Case Study of San Francisco

Abstract: Urban microclimate exerts an increasing influence on urban buildings, energy, and sustainability. This study uses 10-year measured hourly weather data at 27 sites in San Francisco, California, to (1) analyze and visualize the urban microclimate patterns and urban heat island effect; (2) simulate annual energy use and peak electricity demand of typical large office buildings and large hotels to investigate the influence of urban microclimate on building performance; (3) simulate indoor air temperature of a single-family house without air-conditioning during the record three-day heatwave of 2017, to quantify the divergence of climate resilience due to urban microclimate effect. Results show significant microclimate effects in San Francisco with up to 11°C outdoor air temperature difference between the coastal and downtown areas on September 1, 2017, during the record three-day heatwave. The simulated energy results of the prototype large office and large hotel buildings using the 2017 weather data show over 100% difference in annual heating energy use and 65% difference in annual cooling energy use across different stations; as well as up to 30% difference in peak cooling electricity demand. The impacts on annual site or source energy use are minimal (less than 5%) as cooling and heating in a mild climate are a relatively small portion of overall building energy use in San Francisco. Results also show the microclimate effects influence indoor air temperature of unconditioned homes by up to 5°C. Newer buildings and homes are much less affected by microclimate effects due to more stringent performance requirements of the building envelope and energy systems. These findings inform that San Francisco microclimate variations should be considered in urban energy planning, building energy codes and standards, as well as heat resilience policymaking.

Keywords: Urban microclimate; CityBES; building energy use; building performance; building simulation; climate resilience

1. Introduction

A microclimate can be defined as any area where the climate differs from its surrounding area [1]. Urban microclimate refers to the local climate effects in cities and urban areas, which observe a higher heterogeneity than their surrounding rural areas [2]. The features of an urban microclimate include variations in outdoor air temperature, surface temperature, humidity, wind speed, and wind direction [3]. Several human-induced factors can cause urban microclimates. Building and construction materials can affect the albedo, thermal conductivity, and different heat capacity of urban surfaces, and therefore impact the amount of reflected energy [4]. In the meantime, less evapotranspiration from plants, fewer water surfaces, and less irrigation in typical urban areas can lead to lower latent heat exchange with the outdoor environment. Urban morphology, including building densities and heights, can affect the wind patterns [5], shading patterns [6], and create the thermal trappings between dense buildings (e.g., the urban canyon effect) [7]. Moreover, anthropogenic heat (from vehicles, buildings, industry, and human metabolism, etc.) dispersed into the urban environment is one of the most important causes of the urban heat island (UHI) effect [8]. Researchers have studied the spatiotemporal variations of the UHI due to the changes in land-use/land-cover, urban sprawling, and population shifts [9], and

found the spatial distribution and seasonal patterns of urban thermal patterns can be diverse across the studied urban area [10].

Local weather conditions determine the heat and mass flow between buildings and their environment through (1) conductive and convective heat flux at the urban surfaces, (2) solar and long-wave radiation exchange, and (3) sensible and latent heat transfer through ventilation and infiltration [11]. Hence, urban climate and microclimate can strongly influence building energy use, demand, and building thermal resilience. Toparlar et al. performed building energy simulations based on different microclimate conditions with a set of prototype buildings in July 2013 in Antwerp, Belgium [2]. The results demonstrated that average air temperatures at the urban sites away from the park was 0.9 °C higher than the area close to the park, and the residential buildings near the park had 13.9% less cooling demand than those away from the same park. Bourikas also demonstrated that microclimate plays an essential role in building heating and cooling loads [12]. The study used the actual measurements of air temperature and relative humidity at 26 sites within a 250-meter radius in Hangzhou, China, and the results showed that up to 20% differences were observed in the heating and cooling loads computed with/without microclimate considerations. In recent years, building resilience to urban microclimate variations has also become a significant topic. Chokhachian et al. presented methods to evaluate urban resilience at a micro-scale. The study used mobile micro-meteorological sensors to measure wind speed, air temperature, humidity, globe temperature, and solar radiation, and calculated the universal thermal comfort Index (UTCI) score to assess outdoor comfort under heat events [13]. Katal et al. also applied the urban microclimate simulation tool, City Fast Fluid Dynamics (CityFFD), to model a snowstorm event with more than 1500 buildings in Montreal, Canada, investigating their resilience against the three-day power outage due to the storm [14].

Various approaches have been employed in the past decades to quantify the urban microclimate, including field data measurement and collection, remote sensing and GIS-based assessment, and computational simulation and modeling [15]. Historically, most urban microclimate studies were conducted by collecting measurement data from different parts of an urban area [16]–[20]. For example, Pioppi et al. carried out a cluster analysis with data-driven identification of urban microclimate peculiarities to its morphology, and the measurements in the dense district show a non-negligible dependency on the urban land cover both in winter and in summer [21]. Measurements in urban areas can face some challenges, such as the problem of data quality issues, spatial representativeness, and the lack of sufficient weather parameters [22]. However, in recent studies, some of these challenges can be overcome with the applications of emerging technologies, such as low-cost sensor networks distributed vastly in urban areas [23]. Urban microclimate can also be investigated with modeling and simulation approaches [24]–[30]. Computational Fluid Dynamics (CFD) is also frequently used to assess and predict urban microclimate in a finer spatial resolution [14], [31]. For example, Javanroodi and Nik use CFD simulation generated weather data based on mesoscale meteorological models to study the overall energy performance of buildings. Considering the fluctuations of air pressure, relative humidity, and heat flux, the average and peak outside surface temperature showed over 67% and 7% higher magnitude, respectively, compared to typical weather. Simulation methods allow investigating urban microclimate effects under a variety of urban morphology and design scenarios, and can generate more targeted weather parameters with higher fidelity [32].

San Francisco is a coastal city in Northern California, USA. It has a mild climate (climate zone 3C) and an area of 121.4 km². Even though the city is not large geographically, its local weather can vary significantly across the city. During the record

three-day heatwave event in September 2017, there were six heat-related deaths in the San Francisco Bay Area, and a large difference in outdoor air temperature of up to 11 °C was observed between the coastal and downtown area of San Francisco. Such microclimate variations have substantial implications on building energy demand and outdoor thermal environment. In this study, we analyzed 10-year hourly weather data measured at 27 weather stations across San Francisco, and visualized the results using microclimate maps with the CityBES tool to reveal the spatial patterns and temporal trends (Section 2). We also use building energy modeling to quantify the urban microclimate impact on building energy demand and thermal resilience using local weather data at 14 sites (Section 3). Here, the impact refers to the same building in different locations of San Francisco having different energy uses and peak demands due to local microclimate conditions. Section 4 describes implications of the results, limitations of this study and potential future research. Conclusions are drawn in Section 5.

2. San Francisco Microclimate

We developed a web-based map interface to visualize the spatial variation and temporal trends of a city's local climate, and use San Francisco as a case study to demonstrate the features. It is part of the CityBES, a free-to-use open data and computing platform for city buildings, energy, and sustainability [33]. CityBES, an urban building energy modeling tool [34], [35], simulates the energy performance of a city's building stock [36], from a small group of buildings in an urban district to all buildings in a city. CityBES builds upon the Commercial Building Energy Saver Toolkit [37], which provides retrofit analysis of individual commercial and residential buildings using a comprehensive library of more than 100 energy technologies and control strategies. CityBES also provides a quick assessment of district energy systems using EnergyPlus simulations. CityBES uses CityGML and GeoJSON as the data schema to represent the urban building stock [38]. It provides 3D visualization of the building shapes and an array of performance metrics for whole-building energy use and end uses, peak electricity demand, utility costs, GHG emissions, energy savings, and retrofit economics.

2.1. Data Source and Data Cleaning

San Francisco weather data— hourly weather data of 2008 to 2017 were acquired from White Box Technologies [39]. The data set consists of 149 weather files in EnergyPlus epw format, each with a one-year duration, containing 22 weather variables. The format and detailed variable descriptions follow the EnergyPlus weather data definition [40]. Among the files we received, seven of them have non-matching weather station IDs in the weather file, and in the file name. This makes it difficult to locate the associated stations for those files. Mis-placing weather station data will impair the accuracy of the spatial interpolation. Thus we removed them from the data set. The second cleaning step involves dropping measurements with invalid data ranges. In this step, we removed three records with negative relative humidity values. After cleaning, we selected four variables to visualize in the interface: dry bulb temperature (°F), relative humidity (%), global horizontal radiation (Wh/m²), and wind speed (m/s). There are 27 weather stations in the cleaned data set. Figure 1 shows the location and start and end year of each weather station. Table 1 lists the summary statistics of the four variables across the 10-year period at 27 stations. Overall, San Francisco has a mild climate with limited seasonal differences in average ambient air temperature and relative humidity. On the other hand, the distributions of many weather variables are heavily tailed with many extremely high or low records,

140 especially the wind speed in winter months and the dry bulb temperature in summer
141 months.

142 **Figure 1.** Weather Stations in San Francisco

143 **Table 1.** Summary Statistics of San Francisco Hourly Weather Data at 27 sites.

Variables		Mi n	Media n	Mea n	Max	Skewnes s	Kurtos is
Overall		26.					
	DryBulb (F)	1	55.8	56.4	107.6	0.8	4.9
	GloHorzRad (Wh/m2)	0.0	12.0	200.	1142.	1.3	3.4
	RelHum (percent)	0.0	84.0	78.4	100.0	-1.1	3.4
	WindSpd (m/s)	0.0	0.5	1.2	19.6	2.1	9.4
February		32.					
	DryBulb (F)	4	52.7	53.2	80.2	0.5	3.3
	GloHorzRad (Wh/m2)	0.0	0.0	142.	870.0	1.3	3.3
	RelHum (percent)	7.0	82.0	77.5	100.0	-0.9	3.2
	WindSpd (m/s)	0.0	0.3	1.0	19.1	2.7	13.6
August		34.					
	DryBulb (F)	9	59.0	60.0	100.0	1.3	6.1
	GloHorzRad (Wh/m2)	0.0	70.0	241.	1055.	1.0	2.6
	RelHum (percent)	0.0	90.0	84.8	100.0	-1.6	5.3
		*					

WindSpd (m/s)	0.0	1.2	1.7	17.0	1.2	4.1
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*The very low relative humidity can be due to data quality issues of those data points.

San Francisco geographical boundary—The shapefile of the geographical boundary of San Francisco is retrieved from DataSF [41].

In addition to the four direct measurements, the interface also displays four derived weather metrics: heating degree-day (HDD), cooling degree-day (CDD), heat index (HI), and urban heat island index (UHII). HDD and CDD could inform urban planners and policymakers about the potential heating and cooling loads at various locations and at different times of the year. Heat index and UHII could assist policy analysis of adaptation strategies to short-term heatwaves and long-term climate change. The calculations of the derived metrics are described as follows.

2.1.1 HDD and CDD

Degree-days are often used for a rough estimation of the heating or cooling load. Degree-days for a certain period P (e.g., a month or a year) are computed as the accumulated difference between the mean daily temperature and some base temperature (Equation 1 and 2). Here we use 65°F as the base temperature for heating degree day and 50°F for cooling degree day, consistent with the practice of ASHRAE handbooks [42].

$$HDD_P = \sum_{i \in P} \max(0, 65 - T_{i, \text{mean}}) \quad (1)$$

$$CDD_P = \sum_{i \in P} \max(0, T_{i, \text{mean}} - 50) \quad (2)$$

$T_{i, \text{mean}}$ is the average of the daily max and the daily min temperature of day i in the period P .

2.1.2 Heat Index (HI)

This metric reflects the hotness considering both temperature and relative humidity. Adding humidity to the picture is essential, as the ambient moisture could affect the evaporative cooling of the human body, which then influences how a certain temperature feels like to the body. High HI could lead to various adverse health consequences, including heat exhaustion or heat stroke [43]. The calculation follows the NOAA method [44]. First, a simplified formula following Steadman's result is applied. This formula only has first-order temperature and relative humidity terms. For high HI cases (higher than 80), the Rothfus formula with higher-order temperature and RH terms is used. This formula also considers further adjustments for low RH and hot and humid cases.

2.1.3 Urban Heat Island Index (UHII)

Taha and Freed developed a UHII metric [45] as is shown in Equation 3, where the UHII is calculated for each census tract as the accumulated hourly temperature difference between the urban and the non-urban areas within the census tract. $T_{c, h, \text{urban}}$ is the temperature for urban areas in census tract c at timestamp h . $T_{c, h, \text{non-urban}}$ is the temperature for non-urban areas in census tract c at timestamp h . h ranges in the summer of 2013 and 2006.

$$UHII = \sum_{h \in D} UHII_{c, h} = \sum_{h \in D} (T_{c, h, \text{urban}} - T_{c, h, \text{non-urban}}) \quad (3)$$

One issue of this definition is that the inner term $UHII_{c,h}$ is un-defined for geographical units with urban-only or non-urban-only land uses. We changed the non-urban reference temperature from specific to each geographical unit $T_{c,h,\text{non-urban}}$ to the average across the region $T_{h,\text{non-urban}} = \text{mean}_c(T_{c,h,\text{non-urban}})$. This could make $UHII_{c,h}$ definable for the urban-only geographical units. We also added an indicator $I[\text{withUrban}(c)]$ that checks whether a geographical unit contains some portion of urban land use. This could cover the geographical units with only non-urban land uses.

$$UHII_{c,h} = I[\text{withUrban}(c)] (T_{c,h,\text{urban}} - \min(T_{c,h,\text{urban}}, T_{h,\text{non-urban}})) \quad (4)$$

Comparing with Taha and Freed UHII, the metric used in this study produces the same aggregated results for $UHII = \sum_{h \in D} UHI I_{c,h}$ when every geographical unit (for example, census tract) in the analysis has some portion of urban area and non-urban area. It also defines $UHII_{c,h}$ for geographical units with homogeneous urban or non-urban land uses. This allows the metric to be applied to a finer geographical resolution, which is more likely to have single land use within each geographical unit. We applied the modified UHII metric to 30m x 30m gridded cells, and each cell c represents a 30m x 30m square region in San Francisco.

We used the land use data to classify whether a cell on the map is urban or non-urban. The land use data of San Francisco is a subset of the 2011 National Land Cover Database (NLCD) raster file [46], retrieved with the R package, FedData [47]. We label the “developed” land use type (category 21 to 24 in NLCD) as an urban area, and the rest as a non-urban area (Figure 2(a)).

Figure 2. (a) Land use pattern from NLCD; (b) urban heat island index for April 2008

2.2. Interface Design

The map interface (Figure 3) displays the space-time patterns of various weather metrics in the study region, with a 2D map view, a time slider, and an animation view navigating through different snapshots of the map view, and some data summary charts.

Users can toggle the display of various weather metrics using the variable selector (component 9). The spatial heterogeneity of each weather metric is presented as a heat map overlaid on top of the regional map. The heat map of each weather variable is generated for each time stamp with an inverse distance weighted spatial interpolation of measurements at

211 each weather station. The value of a weather variable at each location and each time stamp
212 is computed as a weighted average of values of all available weather stations at that time
213 stamp. The weight of each weather station is the reciprocal of the squared distance between
214 the target location and the weather station. This spatial interpolation is computed with the R
215 package, gstat [48]. Exact measurements at each weather station are shown as white labels
216 on the map. Users can navigate through different time stamps with a time slider at the
217 bottom of the interface.

(a)

(b)

218 **Figure 3. (a) Components of the Interface; (b) a screenshot of the interface**

The temporal trend is shown as time-series plots (components 2 and 4). The plot below the map window shows the spatial-temporal aggregation (the solid line) and the spatial extremes (the min and max of the color-coded values displayed on the map, shown with two dashed lines) of the temporal aggregation, and the plot at the bottom left corner is a zoomed-in view of the time series plot at the current time stamp. A histogram to the left of the map (component 5) shows the distribution of the spatial-temporal aggregation for the displayed period, with the value of the current time step marked as a vertical dashed line. The animation button (component 12) allows an automatic slide show of the visualization at a speed set by the user, to display the changes of the selected microclimate variable over time.

Weather variables are anticipated to have strong seasonality at various temporal scales, thus we provided several temporal resolutions and temporal aggregation options (component 8). For example, when the “year” resolution and the “mean” aggregation method are chosen, weather station data are aggregated to annual averages. Then a heat map is generated for each year with spatial interpolation of the annual average weather station data. The scale of the heat map can be switched between “global” and “local” by the toggle at the bottom left corner of the map, where the global scale uses the statistics of all the historical data aggregated by the selected time resolution and aggregation method, and the local scale uses the statistics of the current time stamp.

Apart from San Francisco, we also acquired historical weather data of Sydney, Australia from the University of Sydney to visualize. Several other cities are under development as well. Users can select the region of interest through the dropdown list at the upper left corner (component 11).

2.3. Implementation

R is used for data cleaning, processing, image and data file (CSV or JSON) generation. The heat maps are png images generated using the R raster package [49], gstat package [48], and sf package [50]. The interface is written in HTML and JavaScript. We use Leaflet [51] to create the map view and load the heat map image onto the regional map. The time-series plots are created with dygraphs [52]. The histogram is produced with Plotly [53]. The animation feature is implemented with JavaScript.

2.4. Example use cases

The visualization tool reveals some interesting patterns in the weather data. We present three use cases as examples:

1. With the daily or hourly view, users could identify certain historical weather events. For instance, in the 2017 daily dry-bulb temperature display (Figure 4), we could observe the timing (September 1) and the magnitude (101.4°F) of the heatwave from the time-series plot, and the current-value label (component 6). The distribution plot further demonstrated that the temperature at the current time stamp is at the right end of the distribution.

Figure 4. Identification and illustration of the historical heatwave on September 1, 2017 in San Francisco.

2. With the monthly views, users could spot the seasonality of certain variables. For example, we could observe strong seasonal patterns in temperature, solar radiation, and wind speed, while relative humidity is relatively stable – not seasonal. Figure 5 shows the average monthly ambient air temperature from 2008 to 2012, with a seasonal pattern shown in the bottom time-series plot.

Figure 5. The monthly view shows the seasonal pattern of average monthly ambient air temperature.

3. Using the time-series plot (component 2), users could identify the overall level of spatial heterogeneity of a variable (the distance between the two dashed lines in the bottom-right sub-figure showing the mean, min, and max of the displayed variable, relative humidity in this case, in Figure 6). With the map view, the user could locate the spatial extreme positions. For example, in the daily mean relative humidity view,

we notice substantial spatial variations where the maximum (90.7%) is over twice the minimum (43.7%). The map view (Figure 6) shows the highest values are close to the coastal area, and the lowest values appear in inland regions.

Figure 6. Spatial heterogeneity of ambient air relative humidity

3. Microclimate impact on building performance

3.1. Impact on building energy performance

A simulation study was performed to evaluate the impact of microclimate on building energy use. The San Francisco weather data in 2017 at selected 14 stations were applied to four DOE prototype building models [54], covering two building types (the large office and the large hotel, as shown in Figure 7) and two vintages (2004 and 2013). The selected 14 stations, based on data quality, are R48, R49, R73, R79, R100, R107, R128, R161, R169, R327, R348, R435, R887, R957, whose locations can be found in Figure 1. Table 2 lists the geometry and HVAC characteristics of the two prototype buildings. Table 3 lists the envelope properties of the two vintages, based on ASHRAE standards requirements.

EnergyPlus is used as the building performance simulation tool in this study to calculate the annual energy use and peak demand of the four building models using the weather files at the 14 weather stations. EnergyPlus is an open-source program that models heating, ventilation, cooling, lighting, water use, renewable energy generation, and other building energy flows [55] and is the flagship building simulation engine supported by the United States Department of Energy (USDOE).

Figure 7. 3D geometry of the prototype building models: (a) Large Office; (b) Large Hotel

Table 2. Basic characteristics of the prototype large office and large hotel models

	Large Office	Large Hotel
Number of floors above ground	12	6
Number of basement floors	1	1
Total floor area [m ²]	46,320	11,350
Window-to-wall ratio (%)	40	30.2
Heating type	Gas-fired boilers	Gas-fired boilers
Cooling type	Two water-cooled centrifugal chillers for most spaces. Water-source DX cooling coil with fluid cooler for data center in the basement and IT closets in other floors;	Air-cooled chillers
Distribution and terminal units	VAV with hot-water reheat coils except non-datacenter portion of the basement and IT closets that are served by CAV units.	Public spaces: VAV with hot water reheat coils; Guest rooms: dedicated outside air system + four-pipe fan-coil units.

Table 3. Envelope properties of vintage 2004 and 2013

	2004 [56]	2013 [57]
Wall U-factor [W/m ² -K]	0.857	0.701
Roof U-factor [W/m ² -K]	0.357	0.220
Window U-factor [W/m ² -K]	6.93	3.12
Window Solar heat gain coefficient (SHGC)	0.34	0.25

Figures 8-11 illustrate the box-whisker plots, which indicate the distribution of several energy performance indices on the four prototype models, including the annual site and

source energy, annual cooling energy use (electricity), annual heating energy use (natural gas), peak electricity & natural gas use. Key findings are summarized as follows:

(1) The impact of microclimate on the energy use of the HVAC systems is significant. Using different microclimate data can lead to as much as over 100% difference in annual heating energy use and 65% difference in annual cooling energy use.

(2) The impact of microclimate on the total annual site or source energy is much smaller. This is because (1) microclimate only affects HVAC energy use, which accounts for 20~25% of the total energy use in the large office, and 40~50% in the large hotel; in this case, the relative impact on the total energy use is reduced. (2) the impacts on heating demand and cooling demand compensate each other. For example, when the cooling demand is increased under warmer weather, the heating demand is decreased, so the overall impact is reduced.

(3) The impact of microclimate on building peak cooling and heating demand is significant, as much as a 30% difference in peak cooling electricity demand and over 100% difference in peak natural gas demand. This is critical from the supply-side perspective, as it will directly affect the required utility generation capacity. The impact on the building peak demand is a bit less than the peak HVAC demand because of other end uses (e.g., lighting and plug loads).

(4) The impact of microclimate on energy performance varies with building types and vintages. Cooling and heating loads mainly consist of (1) heat gains through the envelope, mechanical ventilation, and infiltration, which microclimate has an impact on, and (2) heat gains from other sources, such as occupant, lighting and plug loads, which do not change with climate. The variation of the absolute values of energy performance is purely affected by the former heat gains. On the other hand, the percentage difference is affected by the proportion of former heat gains in the total load and the baseline level. All the above factors vary with building types and vintages, resulting in different levels of microclimate impact on building energy performance.

In summary, microclimate data are recommended for use in estimating the total building energy consumption, especially considering the needs of a more accurate estimation of the cooling and heating energy use, and more importantly, the peak demand, from the perspective of the utility supply side.

Figure 8. Box-whisker plot of energy performance index for the large hotel of the 2004 vintage.

Figure 9. Box-whisker plot of energy performance index for the large hotel of the 2013 vintage.

Figure 10. Box-whisker plot of energy performance index for the large office of the 2004 vintage.

LargeOffice_2013

Figure 11. Box-whisker plot of energy performance index for the large office of the 2013 vintage.

3.2. Impact on indoor air temperature of unconditioned residential buildings

In San Francisco, it is very common that residential buildings are not equipped with air conditioning systems due to the mild climate. Microclimate affects the indoor environment of such unconditioned buildings, especially under extreme weather conditions. A simulation study was conducted to investigate the impact of microclimate on indoor air temperature of unconditioned residential buildings during heat waves.

The 2017 3-day heatwave was selected for this study, during which San Francisco smashed all-time record high temperature and hit 106 degrees in the downtown area on September 1, 2017 [58]. We adopt the one-story single-family prototype building as the baseline model, which is from the Alternative Calculation Method Approval Manual for California building energy efficiency standards Title 24 [59]. As shown in Figure 12, The building has pitched roofs, an unconditioned attic under the roof, and an unconditioned ground-level garage attached to the living zone. All the living area is modeled as a single conditioned thermal zone. Two vintages, pre1978 and 2013, are simulated to represent old and new constructions. The envelope properties and internal loads are derived from Title 24 minimum efficiency requirements [59], [60].

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Figure 12. 3D geometry of the one-story single-family prototype building defined in the Title 24 ACM.

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Figures 13 and 14 illustrate the hourly variations of outdoor air temperature and indoor air temperature at all 14 weather stations during the three-day heatwave period. While the outdoor air temperature differs as much as 11°C among different locations during peak hours, the indoor air temperature differ by a maximum of 5°C. Recently built houses have better envelope performance and lower internal heat gains due to more stringent code requirements. As a result, the peak indoor air temperature and the difference of indoor air temperature across the local 14 stations get reduced.

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Standard effective temperature (SET) is a temperature metric that factors in relative humidity, mean radiant temperature, air velocity, and anticipated activity rate and clothing level of the occupants. SET is adopted to evaluate passive survivability by the U.S. Green Building Council’s Leadership in Energy and Environmental Design (LEED) green building program. The “Livable Temperatures” are defined as SET between 12.2°C and 30°C. The SET-hours is an accumulated metric to measure thermal safety based on the indoor SET. It weights each hour when the indoor SET exceeds a certain threshold by the number of degrees Celsius by which it surpasses that threshold. In this study, we adopt the upper SET limit of “Livable Temperatures”, i.e., 30°C, as the threshold for calculating SET-hours. Figures 15 and 16 illustrate the hourly variations of indoor SET and the variation of accumulated SET-hours at all 14 weather stations. Among different microclimates, the SET could differ by as much as 3°C, and the highest SET-hours could be twice the lowest SET-hours for the home built before 1978. Similar to the trend of indoor air temperature, the SET-hours, peak SET, and the hourly variation range of SET all get shrunk as the building performance gets better.

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Figure 13. Hourly distribution of outdoor air temperature (September 2017) at all 14 weather stations.

Figure 14. Hourly distribution of indoor air temperature in single-family homes at all 14 weather stations: (a) Pre 1978; (b) 2013

Figure 15. Hourly distribution of indoor standard effective temperature in single-family homes at all 14 weather stations: (a) Pre 1978; (b) 2013

Figure 16. Distribution of indoor SET degree hours over 30°C for all 14 weather stations: (a) Pre 1978; (b) 2013

4. Discussion

4.1 Implications

Findings from the study can inform building energy and climate resilience policy, including:

- For cities with significant urban heat island effect (e.g., the mild climate of the coastal city of San Francisco), the local climate characteristics should be considered in building energy codes and standards, as well as thermal resilience planning. For example, the peak cooling and heating load calculations and annual energy estimation should use local weather data in the building performance simulations so that HVAC systems can be correctly sized to have adequate capacity to handle the energy demand.
- During heatwave, especially for vulnerable populations living in unconditioned homes, it is recommended they stay in the cooler coastal areas of the city to mitigate the heat.
- Weatherization and retrofitting existing residential buildings especially those very old or leaky homes with limited envelope insulation can significantly reduce the risk of heat or cold hazard for occupants. The technological measures can include making the homes airtight, adding insulation to walls and roofs (floors if applicable), applying cool coatings to roofs, and enabling natural ventilation with operable windows.

4.2 Limitations

This study has limitations. With a total of more than 10 million data points for the 27 weather stations' 10-year hourly meteorological parameter values, it is unavoidable that some data are missing or not valid. Our study only did high-level checking of data quality and removed the periods with missing data. As an improvement for the future, the time-series data can be analyzed to detect outliers and fill in the data gaps using various data imputation techniques [61].

4.3 Future work

Future work can expand the coverage of urban microclimate analysis and modeling for other cities and climates (e.g., data of Sydney was added in 2020) to reveal any different patterns or trends. Future efforts can also develop APIs for other tools or applications to interact with CityBES's urban microclimate mapping feature. For winter storms and extreme cold snaps, e.g., the 2021 winter storm in the State of Texas, USA, it would benefit from a microclimate mapping for such events to inform resilience planning and response.

5. Conclusions

San Francisco microclimate variations (up to 11°C difference in outdoor air temperature between the coastal and downtown areas during the 2017 Labor Day heatwave) are significant and strongly influence annual cooling and heating energy use, peak cooling electricity demand, as well as heat resilience of residential buildings without air-conditioning. Such microclimate effects should be considered in urban energy planning, building energy codes and standards, and heat resilience policymaking. Local weather data considering urban microclimate effects should be used in building energy modeling to estimate building energy use and peak demand.

Current building energy codes and standards such as ASHRAE Standards 90.1/90.2/189.1 or International Energy Conservation Code usually designate a city with a single climate zone and associated energy efficiency requirements. A single representative

TMY weather data file (with data collected usually at a nearby airport station) is usually used for building performance modeling. With cities like San Francisco that have strong microclimate effects, it is recommended to consider multiple sub-climate zones and different energy efficiency requirements if necessary. Newer buildings are much less influenced by the variations of microclimate due to more stringent performance requirements of building envelope and energy systems.

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