Urban Heat Islands in Future Climate Scenarios

Violeta Lialios-Bouwman[1], J. Alstan Jakubiec[1]

[1]University of Toronto, Ontario, Canada

Abstract

We demonstrate a case study of Urban Heat Island (UHI) indicators in Toronto, ON, Canada under five climate change scenarios until 2080. We simulated 48,600 UHI predictions by varying nine urban design parameters: building height, site coverage ratio (SCR), façade-to-site ratio (FSR), green coverage ratio (GCR), tree canopy ratio (TCR), building type, albedo, green roof coverage, and material thermal properties (of the window, roof, and walls). Results show that under future climates, UHI intensity decreases slightly, while our indicator of heat stress (hours above 30 C°) rises significantly. Vegetation, SCR, FSR, and building height are found to have the strongest effect on mediating UHI under climate change, indicating the importance of increasing greenspace and reducing building surface area and density in urban design.

Key Innovations

- A novel method for modelling representative urban neighborhoods and microclimates using typical weather data modified to include impacts of climate change and Urban Heat Island (UHI).
- Reveals how urban microclimates may change under future climate scenarios in a large northern city and what urban design parameters have the most capacity to reduce associated UHI.

Practical Implications

This study implements a model calculation method using open-source tools and datasets. The analysis evaluates which types of urban design settings have beneficial impacts on urban microclimates under forecasted climate change and UHI scenarios. This process can be applied to other cities and climates without technical or intellectual property limitations. The code used in this research is published as a re-useable repository for other researchers: https://github.com/C38C/UHI_in_Future_Climates

Introduction

Despite current efforts, Earth's changing climate continues to follow the worst-case scenarios laid out by the Intergovernmental Panel on Climate Change (IPCC), indicating a hot future is extremely likely (IPCC, 2014). Decisions must be made in local and regional planning departments regarding the construction and renovation of buildings and public spaces that reduce dangerous heat, especially in cities where heat is intensified due to the Urban Heat Island (UHI) effect. Developing location-specific, data-based heat mitigation strategies and tools can provide realistic urban design recommendations that will be vital for maintaining human comfort, safety, and access to outdoor space in the future.

This paper presents an accessible and cost-effective method for assessing urban microclimates under future climate change scenarios and UHI. We briefly review the state of the art in climate and UHI morphing prediction methods, then describe a methodology to assess UHI under future climates in Toronto, Ontario, Canada based on typical urban neighborhood types and an extensive range of common UHI-mitigating urban and high-performance building design parameters.

Urban Heat Island (UHI)

UHI is a result of complex interactions between urban microclimates, created by variations in nearby surface and mass properties, anthropogenic heat gains, wind, views to the sky, and thermal inertia (Oke, 1967). UHI increases human heat stress, puts high demand on building operational energy, changes urban rainfall patterns, and increases the intensity of air pollution, flood risk, and urban runoff (Heaviside, 2017; Shepherd, 2003; Sarrat, 2006; Adamowski et al., 2013). Due to its considerable impact on the natural and built environment, UHI should be examined alongside climate change when running current and future urban energy simulations and comfort analysis.

Morphing Weather Data: Climate Change and UHI

'Morphing' refers to combining recorded weather data with projected future climate data, producing new weather files for use in building and urban performance simulations. Morphing can be applied using Global Circulation Models (GCMs) or based on urban physics models to adjust an open site for UHI effects. Morphed weather files provide valuable information on how the built environment will perform under future climates and UHI scenarios, although their usage in planning departments is limited due to financial, computational, and accessibility barriers.

Methodology

We evaluated nine urban design parameters in terms of their impact on UHI: building height, site coverage ratio (SCR), façade-to-site ratio (FSR), green coverage ratio (GCR), tree canopy ratio (TCR), building type, albedo, green roof coverage, and material thermal properties (including window, roof, and walls).

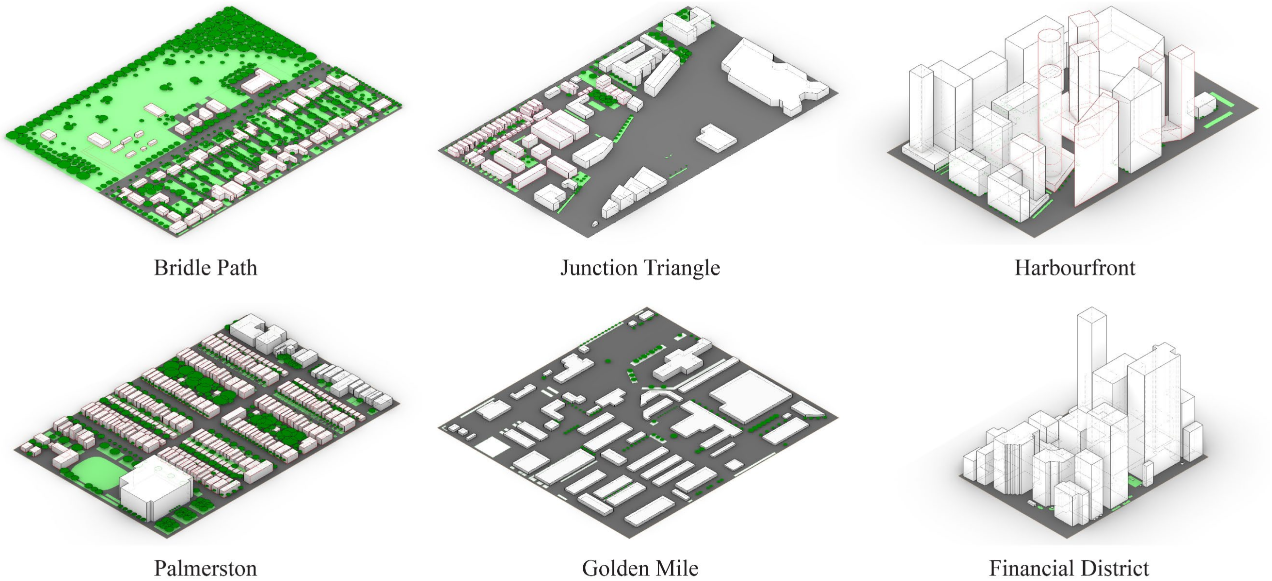

Figure 1. Visualization of six representative urban neighborhoods used to extract urban design parameter ranges for the UWG. Red lines indicate residential buildings.

Table 1. Key neighborhood statistics needed to run the UWG based on the neighborhoods in Figure 1.

Neighborhood	Building Height (m)	Site Coverage Ratio (SCR)	Façade-to-Site Ratio (FCR)	Tree Coverage Ratio (TCR)	Grass Coverage Ratio (GCR)	BT: Large Office Pre-1980s	BT: Large Office New Const.	BT: Midrise Apartment New Const.
Palmerston	11	0.34	0.87	0.2	0.15	0.37	0.13	0.5
Bridle Path	7	0.11	0.14	0.28	0.6	0	0	1
Golden Mile	5	0.3	0.16	0.02	0.07	0	1	0
Junction Triangle	11	0.26	0.41	0.04	0.1	0	0.74	0.26
Financial District	95	0.51	3.81	0.08	0.01	0	1	0
Harbourfront	67	0.48	2.55	0.01	0.03	0	0.64	0.36

In total, we simulated 48,600 UHI scenarios under two historical climates and three future climates. Each predicted UHI scenario was assessed for typical UHI metrics: maximum annual UHI, mean daily UHI, maximum daytime temperature, maximum nighttime temperature, hours above 30 °C (indicator of heat stress), and hours below 5 °C (indicator of cold stress). Mean daily UHI is defined as the mean of the maximum UHI range for each day in the simulated year, $\frac{\sum max\ daily\ UHI}{365}$.

Determining Urban Design Parameter Ranges

We assessed six representative neighborhoods based on a geographic information system (GIS) massing file of the City of Toronto that contained detailed building footprints and heights (City of Toronto, 2020). The model neighborhoods we created were used to determine the range of key urban design parameters required as inputs for the Urban Weather Generator (UWG), the main mechanism for simulating UHI in our study (Bueno, 2013). Tree locations and ground cover were determined on the basis of Google Maps satellite imagery.

We selected neighborhoods that covered a wide range of urban planning and design scenarios, including high-density/low-vegetation neighborhoods commonly found in downtown cores, and low-density/high-vegetation neighborhoods found in more suburban areas. The UWG independently simulated each typology, yielding data about how each urban design setting impacted our UHI metrics. Figure 1 visualizes the six neighborhood models and Table 1 describes the parameters derived from each model required as inputs for UWG.

Simulating Future Climate

Several methods exist for morphing weather time series data to include the impacts of climate change but either sit behind paywalls or require resources and expertise that are not often found in local planning departments (Troup et al., 2016; Belcher et al., 2005; Crawley, 2007; Eames et al., 2011; Rastogi et al., 2015; Zhu et al., 2015). In 2012, the free, Excel-based CCWorld-WeatherGen (CCWWG) tool was developed by combining common Energy Plus Weather (EPW) files with the HadCM3 global circulation model outputs that are freely available via the IPCC (Jentsch et al., 2013; IPCC, 2014).

Compared to other methods, CCWWG facilitates a low-cost, easy process for generating future weather time series data for any location in the world, based on the IPCC's A2 climate change scenario. We collected TMYx weather data in the form of EPW files for the years 1950-2018 and 2004-2018 from climate.onebuilding.org, a free repository of climate data for use in building performance simulations.

We included the TMYx 1950-2018 climate data as a reference point comparable in range to the official Canadian climate data (CWEC), since it covers a similar period from 1953-1995. However, we used the TMYx 2014-2018 data to run our future climate simulations because it was more up to date and used a more consistent data capture methodology between historic and recent climate data files.

The TMYx data were recorded at Toronto Pearson Airport, roughly 25 km from the urban core. We generated new, climate change-influenced weather data at this nearly open site using the CCWWG. The resulting EPW weather files represented the predicted typical years of 2020, 2050, and 2080 for Toronto, which we refer to as CCWWG 2020, CCWWG 2050, and CCWWG 2080 hereafter.

Simulating Urban Heat Island (UHI)

Modelling the urban heat island is difficult due to inherent issues with downscaling complex physical interactions, as well as a general lack of assessment tools for building and urban planners to understand how UHI impacts their designs (Salvati et al., 2017; Saitoh et al., 1996). Nonetheless, many attempts have been made to apply urban physical processes to weather data measured at rural stations (Crawley, 2007; Saitoh et al., 1996; Mirzaei, 2015; Jusuf et al., 2009).

UWG is a MATLAB-based modelling application for UHI which uses rural EnergyPlus weather files to 'morph' new urban weather files (Bueno, 2013)[1]. It calculates annual air temperature and humidity differences between rural weather data and nearby urban areas by accounting for the UHI effect using a physics-based simulation model. UWG is an accessible alternative to other urban climate simulations such as the CAT model or the EnergyPlus mesoscale atmospheric simulation model, which are computationally expensive (Oxizidis et al., 2008; Errel, 2013).

UWG requires inputs for a wide variety of urban and building parameters such as building height, building plan density, vertical surface area to horizontal plot area ratio, HVAC waste heat, non-building anthropogenic heat, urban vegetation, and surface characteristics such as albedo, road thickness, conductivity, thermal capacity, and many more. (Bueno, 2013).

The input parameters which are parametrically varied in our simulations are listed within Table 2. They were determined based on observable changes between neighborhoods in Toronto that we analyzed in Figure 1 as well as typically varying parameters of buildings and urban materials. A full list of the urban and building type settings used for our UWG calculations can be found in Appendices A and B. Certain values were left at common defaults as they are not commonly changeable design parameters, such as road thickness or anthropogenic heat.

Proximate large-scale topographic features have been found to impact UWG calculations, including large bodies of water and elevation changes (Street, 2013). We attempted to address this by accounting for the average height of building obstructions around Toronto Pearson Airport where the rural data were collected, as this was used by UWG to set roughness (0.3) and displacement length (1.5) that approximate a suburban context. The morphing process also accounts for a 41 percent vegetation coverage surrounding the weather station. The effect of Lake Ontario (12 km from the base weather station) should be further investigated, as it cannot currently be accounted for by the UWG.

We used the UWG to simulate all combinations of the parameters listed in Table 2, ignoring the sets where the FSR divided by SCR were greater than 14 as this unrealistic scenario of very tall, narrow buildings crashed the UWG. We combined greenness into one parameter after assessing the neighborhoods in Figure 1 and finding that the relationship of GCR/1.7 explained about 74 percent of the variance in tree coverage, or TCR. Note that GCR is defined as the percentage of non-built area that is covered by urban greenery, so it is possible for SCR and GCR to sum to a value greater than one. Although material thermal properties can vary independently, we tied the window U-value, roof R-value and wall R-value parameters together, indicating improved building envelope quality. A total of 48,600 combinations were simulated in this manner (9,720 per climate file).

Table 2. Parametrically varying inputs for UWG.

Parameter	Values Calculated
Urban Type Settings	
Building height (m)	5, 35, 65, 95
SCR	0.15, 0.35, 0.55
FSR	0.2, 1.4, 2.5, 3.7
GCR (percent of non-building urban area which has vegetation coverage)	0.0, 0.3, 0.6
Building Type Settings	
Building type	85/15 Office/Residential, 15/85 Office/Residential, 50/50 Office/Residential
Albedo	0.2, 0.5, 0.8
Green Roof Coverage	0.0, 0.3, 0.6
Material Thermal Properties	
Window U-value (W/m^2-K)	2.2, 1.5, 1.1
Roof R-value (m^2-K/W)	5.5, 8.2, 11.0
Wall R-value (m^2-K/W)	3.6, 5.4, 7.2

1 Note: A Python version of UWG has been developed by Saeran Vasanthakumar; however, it is less accurate when considering the effects of urban greenery, so the MATLAB version has been used in this study.

Table 3. Mean UHI metrics across all simulated urban and building variants for each base climate file.

Climate file	Max UHI (°C)	Mean Daily UHI (°C)	Max Day Temp (°C)	Max Night Temp (°C)	Hours >30 °C	Hours <5 °C
TMYx 1950-2018	8.6	2.1	33.9	31.2	69	3,455
TMYx 2004-2018	6.2	1.8	34.0	32.2	81	3,047
CCWWG 2020	6.1	1.9	35.8	34.0	206	2,714
CCWWG 2050	6.1	1.9	37.9	36.1	432	2,381
CCWWG 2080	6.1	1.9	41.9	40.0	922	1,764

Table 4. Thermal metrics for rural climate files.

Climate file	Solar Irrad (kWh/m^2)	Mean Temp (°C)	Max Day Temp (°C)	Max Night Temp (°C)	Hours >30 °C	Hours <5 °C
TMYx 1950-2018	1,280.1	10.9	34.1	30.7	68	3,617
TMYx 2004-2018	1,420.2	11.7	34	32	72	3,141
CCWWG 2020	1,441.9	13.1	36.4	33.6	201	2,886
CCWWG 2050	1,453.8	14.6	38.1	35.7	395	2,577
CCWWG 2080	1,473.8	17.0	42.2	39.6	866	1,922

Results

Table 3 displays the mean UHI metrics for each climate file based on the 9,720 simulations UWG calculated using that file. Column three refers to the mean of all simulated mean daily UHIs, hereafter referred to as 'average mean daily UHI'. Table 4 presents thermal metrics for the rural climate files, without a UHI morphing applied.

Overall, as predicted future climates warm, the mean maximum annual UHI and average mean daily UHI values decrease in magnitude. The sharp change in UHI intensity seen between TMYx 1950-2018 and TMYx 2014-2018 can be explained by the intense increase in solar irradiation. In contrast, the mean maximum daytime and mean maximum nighttime temperatures increase significantly. Mean hours above 30 °C and mean hours below 5 °C underwent the greatest change with future climate warming compared to all other metrics.

Boxplots of the distribution of UHI metrics for each climate file are portrayed on the following page in Figure 2. The distribution of the 9,720 simulations for each climate file can inform us to which extent design has an impact on the urban microclimate. For example, even though hours of heat stress (hours above 30 °C) increases overall with climate change (from a median of 67 hours using TMYx 1950-2017 to 915 hours using CCWWG 2080), the range of possible outcomes due to urban design factors also increases, indicating the importance of urban design in future climates.

Similarly, TMYx 1950-2018 simulation results have a heat stress range of 41 hours while the CCWWG 2080 has a range of 180 hours, which is visualized in Figure 2. This emphasizes the importance of UHI-driven urban analysis to improve the comfort of the outdoors during hot summers in Toronto and elsewhere. Cold stress outcomes do not change as significantly compared to heat stress (TMYx 1950-2018 range of 381 hours; CCWWG 2080 range of 303 hours).

Although the range of maximum annual UHI and mean daily UHI outcomes shrink slightly under warmer climates, the impact of design on heat stress increases. We used Pearson correlation analysis to assess the impacts of the different urban and building design variables on UHI for each of the five climate scenarios, which are illustrated in Figure 3. Values farther from 0 indicate stronger positive or negative correlations with the design variables. However, most results where the correlation was not near 0 were still significant (p-values <0.00001), as the inputs and outputs were directly related by UWG.

Under the Toronto climate, factors found to increase the maximum annual UHI and mean daily UHI levels were SCR, FSR, and building height which each had notably positive Pearson correlations. Over time, the influence of SCR, FSR, and building height on the maximum annual UHI and mean daily UHI decreased, significantly in the case of maximum annual UHI.

The influence of urban greenery—GCR and TCR—is important for reducing UHI under future climate files. The negative correlation of GCR and TCR on mean daily UHI, for example, more than doubles from TMYx 1950-2018 (r = -.2029) to CCWWG 2080 (r = -.4432). TCR and GCR also have very strong negative correlations with maximum annual UHI, maximum daytime temperatures, maximum nighttime temperatures, and hours above 30 °C. Hours below 5 °C is negatively correlated with SCR (nearly -0.8) across all climate files, with building height having the second strongest negative correlation. Hours above 30 °C has a strong negative correlation with both TCR and GCR equally, as well as with FSR which decreased in correlation at a faster rate over time compared to other urban and building type parameters.

Discussion

UHI Metrics

Our proxy for heat stress (hours above 30 °C) rose dramatically—from a mean of 72 to 866 hours, with the rural data experiencing a similar increase. Rural thermal metrics in Table 4 follow the mean results of our urban scenarios closely and experience hotter maximum daytime and colder maximum nighttime urban temperatures, characteristic of UHI.

The range of maximum annual UHI and mean daily UHI outcomes in Figure 2 clearly indicate that urban design has a strong localized impact on climate and can exacerbate the impacts of climate change. For example, the worst-case urban scenario exhibits 1,023 hours of temperatures above 30 °C, far greater than those observed in rural conditions (Table 4).

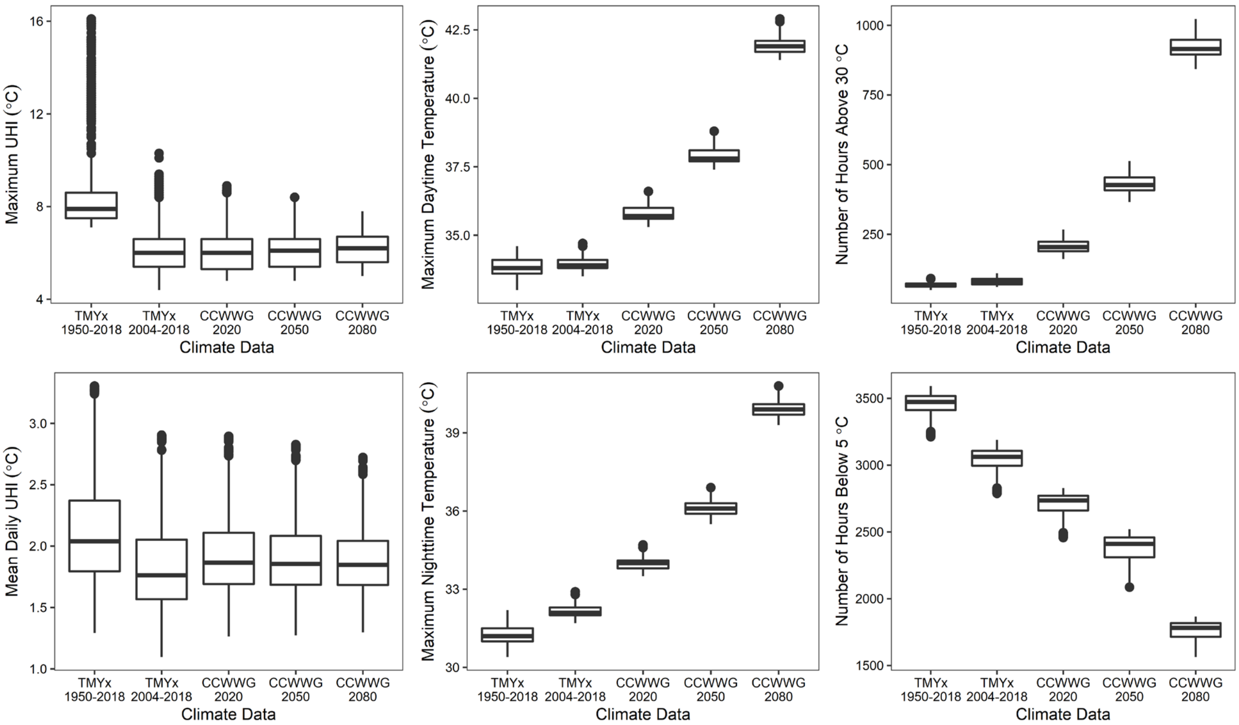

Figure 2. Boxplots of the relationship between UHI metrics calculated for historic and future climate datasets.

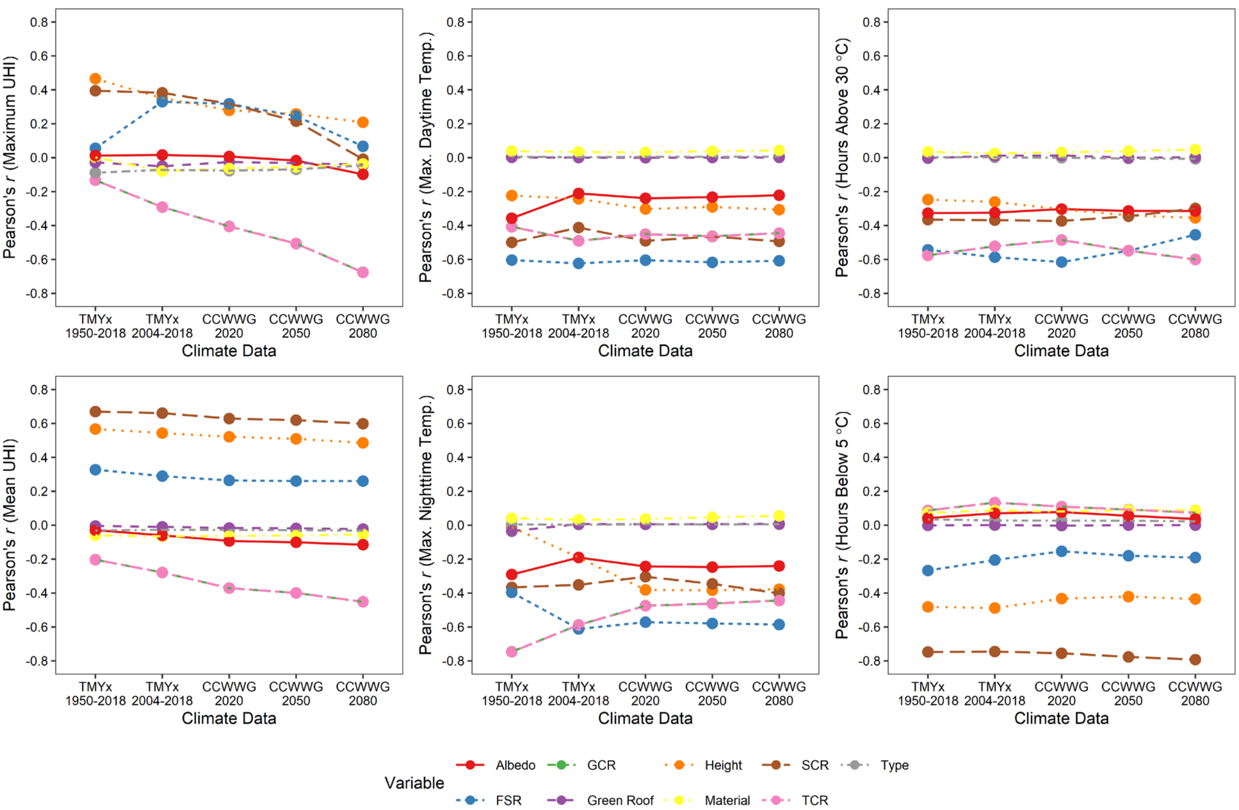

Figure 3. Plots of the Pearson correlations between UHI metrics and the urban and building type variables using historic and future climate datasets.

In contrast, the range of possible values for maximum annual UHI declines rapidly under future climate data (from 9 °C in TMYx 1950-2018 to 2.8 °C in CCWWG 2080), indicating that either our urban design parameters have less impact on maximum annual UHI under climate change or that increased rural ambient temperatures decrease the maximum annual UHI possible.

While the median maximum annual UHI per-climate file increases under future climates (Figure 2), the means slightly decrease (Table 3), hinting of a rural-urban ambient temperature saturation effect. Mean daily UHI sees a wide range of possible temperature values across all historical and future climate files despite average mean daily UHI increasing by only 0.1 percent. This indicates that combinations of our selected urban design parameters can have a strong effect on mediating mean daily UHI.

Urban Design Parameters

Across all five climate scenarios in our study, both TCR and GCR (together representative of urban vegetation) have a strong negative correlation with mean daily UHI. This correlation becomes stronger under future climate scenarios, indicating that urban greenery will become more important in the future for reducing heat stress and building energy loads associated with climate change and the UHI effect in northern cities.

Building type, material thermal properties, and green roof coverage have minimal effect on UHI. Whereas green roofs could be explained by the lack of complexity in how UWG deals with green roofs (see the *limitations* section), building type and material thermal properties may not be as important when designing for cities experiencing UHI; however, these aspects influence energy consumption.

Albedo has a moderate, negative effect on limiting mean daily UHI and reducing maximum annual UHI, a correlation that grows stronger further into the future (neglecting the TMYx 1950-2018 data which has very low solar irradiation—see Table 4).[2] We see a stronger negative effect from albedo on maximum daytime temperatures, maximum nighttime temperatures, and hours above 30 °C, indicating that high albedo is a productive heat stress mitigation strategy for urban areas. Other research has shown that albedo has the strongest negative effect on UHI in highly dense, built up urban areas, while evapotranspiration likely drives UHI in more peripheral urban areas (Trlica, 2016). Thus, albedo is especially important in the downtown core.

SCR, FSR, and building height are all found to have a strong positive effect on mean and maximum annual UHI. These results confirm that urban density is a major contributor of rising urban temperatures (Li et al., 2020). Comparing the historical TMYx 1950-2018 data with the current TMYx 2004-2018 climate, we see a large jump in FSR's negative effect on maximum nighttime temperatures, likely corresponding to an increase in shortwave solar radiation in the climate data (Table 4).

FSR also exerts a strong negative effect on maximum daytime temperature and hours above 30 °C, indicating FSR's role in mediating UHI. A causal factor could be wind. FSR has a strong negative effect on wind speed ratio (Tsichritzis, 2019), and FSR is used by UWG to determine urban wind velocity. Reducing high-rise, cramped urban neighbourhood layouts to promote more wind flow in cities should thus be a goal for current and future planning departments. Integrating plants into building façades (green walls) has also been found to be an effective method for improving building performance and mitigating UHI (Lassandro, 2017).

Limitations

CCWWG's usage of older IPCC report data is limiting and replicating this study with current projections would provide more up-to-date data. We believe that such data would likely still support the findings from this study.

Our simulation outcomes expose a significant limitation of the UWG software—green roofs showed negligible impact on UHI as the consideration of green roof performance embedded in the UWG does not account for transpiration, only changes in rooftop albedo.

The six neighborhoods used to define the ranges of urban design input parameters were selected to illustrate the types of urban neighborhoods found within Toronto. This process could have been more rigorous, to ensure a broader spectrum of input parameters used by UWG.

Our use of the worst-case scenario for the generation of climate change-influenced weather data means that the climate change results and subsequent UHI predictions presented in this paper are dire. Despite a record that we are indeed on track for the worst-case scenario, it would be interesting to see what other IPCC scenarios look like, especially if carbon sequestration technology is able to rapidly improve emissions alongside other mitigation techniques.

Conclusion

The impacts of climate change and urbanization are manifold with heat as a major symptom in cities across the world. Urban planners and architects can mitigate dangerous heat through thoughtful building and neighborhood design. The purpose of this study was to evaluate the impact urban design variables have on urban microclimates under projected climate change and UHI scenarios. We used open-source tools and datasets so that the method can be applied to other regions without intellectual or technical property limitations. We encourage local planning departments to engage with our study to better inform urban design and future architecture.

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2 The CCWWG predicts solar irradiation to increase by 3.7 percent by 2080 compared to the 2004-2018 TMYx data (see Table 4).

Appendix A. Urban type settings used in UWG automation.

Urban Type Settings	**Value**
Building height (m)	5, 35, 65, 95
SCR	0.15, 0.35, 0.55
FSR	0.2, 1.4, 2.5, 3.7
GCR	0.0, 0.3, 0.6
TCR	GCR / 1.7
Fraction of HVAC waste heat released to street canyon	0.5
Characteristic length	1,000
Road albedo	0.1
Road thickness (m)	0.5
Road conductivity (W/m-K)	1
Road heat capacity (J/m^3-K)	1,600,000
Anthropogenic sensible heat (W/m^2)	20
Anthropogenic latent heat (W/m^2)	2
Month leaves emerge (start of evapotranspiration)	4
Month leaves drop (end of evapotranspiration)	10
Vegetation albedo	0.25
Latent heat absorption from grass	0.4
Latent heat absorption from trees	0.6
Amount of rural coverage of vegetation	0.9

Appendix B. Building type settings used in UWG automation.

Building Type Settings	**Value**
Building type	85/15 Office / Residential, 15/85 Office / Residential, 50/50 Office / Residential
Albedo	0.2, 0.5, 0.8
Green roof coverage	0.0, 0.3, 0.6
WWR	0.4
SHGC	0.45
HVAC	Fully air-conditioned
Cooling COP	3.2
Heating COP	0.8
Material thermal properties	
Window U-value (W/m^2-K)	2.2, 1.5, 1.1
Roof R-value (m^2-K/W)	5.5, 8.2, 11.0
Wall R-value (m^2-K/W)	3.6, 5.4, 7.2

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