INTERNATIONAL BUILDING PERFORMANCE SIMULATION ASSOCIATION ENGLAND

Proceedings of BSO-VI 2022
Sixth Building Simulation and Optimisation Virtual Conference
13 - 14 December 2022
Hosted by University of Bath, UK

Optimisation of passive design implementations at an urban scale in an *Am* climate: simulation case study in Chattogram, Bangladesh

Nicholas Swedberg[1]
[1]Arup, Boston, USA

Abstract

This paper utilised Chattogram, Bangladesh, as a case study city in an *Am* climate zone, a typology found throughout the Global South, in order to test the ability of passive design measures to mitigate the formation of the urban heat island and the resultant impact on the urban inhabitants of Chattogram. Cities in hot-humid climates represent an understudied urban typology, and given the rapid population growth of Chattogram, careful consideration needs to be given to urban development in the city. This study utilised open-source tools and data to create a workflow for testing these passive measures. The study found that, while effective in reducing dry bulb temperatures in the case study city, the impacts of high humidity meant that some health and well-being risks were not neutralised to as great an extent.

Key Innovations

- Pairing open-source tools to create a low-cost workflow for UHI modelling and testing
- Examination of UHI formation under present and future climatic conditions

Practical Implications

The open-source tools in this study offer a cost-effective way to test UHI mitigation approaches. Regardless of the source, simulation practitioners should always test optimisation measures under both present and future climate scenarios.

Introduction

Chattogram, the second largest city in Bangladesh (Jafrin & Beza, 2018) located in the *Am* Köppen climate zone (Beck, et al., 2018), or a *tropical monsoon* climate (which corresponds with the ASHRAE *hot/very hot-humid* zone), represents a strong case study for the challenges that the urban heat island (UHI) places on cities in the Global South in this climate typology (Sharmin, et al., 2015). Already densely populated and growing rapidly (CDA, 2015), Chattogram is located in a climate zone that is under-represented in UHI research (Sharmin, et al., 2015) and poses unique challenges to human health (EPA, 2015). These risks are not just manifested in the present, but are set to increase in the future, as a changing climate poses many human health and well-being risks (de Wilde and Coley, 2012)

Given a system of factors affecting urban development in Chattogram, and the Global South more broadly, specifically those associated with the financial burden of implementing climate change adaptation strategies, this paper sought to address how passive urban-scale interventions in Chattogram, Bangladesh, could effectively mitigate the urban heat island effect and the resultant health risks posed to residents, and the effectiveness of these passive measures under both present and future climatic conditions. In order to address this research question, this study assessed the impact of different passive urban design interventions on a simulated neighbourhood in Chattogram, testing the resultant impact on the modelled UHI using both present weather data and morphed future climate data.

Background

Chattogram is the second largest city in Bangladesh, with a population of 4.1 million people, and a population density of over 24,000 people per square kilometre (Jafrin & Beza, 2018). Between the years 1991 and 2015, the city experienced a 4.58% average annual population growth rate (CDA, 2015). Population growth and development during this period has primarily been in the form of densification rather than via increased suburban sprawl (CDA, 2015). Additionally, the city is the country's largest port and commercial capital (Jafrin & Beza, 2018); the Chattogram Port Authority accounts for 85% of imports and 80% of exports for Bangladesh's seaborne trade (CDA, 2015). Located in the *Am* Köppen climate zone (Beck, et al., 2018), Chattogram experiences seasonal dichotomies. Critically, it experiences a combination of high temperatures and humidity; the combined effects of high temperatures and dew point temperatures can pose increased heat related health risks (EPA, 2016). Further, a changing climate will increase the severity of extreme conditions (Bastin, et al., 2019). Generally, cities will become hotter, notably during the winter and the summer (Bastin, et al., 2019). More significantly, wet seasons will become wetter and dry seasons will become drier (Bastin, et al., 2019). While Chattogram, and *Am/hot-humid* climates in general, will not experience the largest absolute change in annual or seasonal temperatures (Bastin, et al., 2019), even minor increases in temperature and humidity extremes can further elevate risk exposures for urban residents.

The urban heat island is a phenomenon wherein urban areas experience both elevated daytime and night-time temperatures as compared to outlying rural areas (EPA, 2022). This phenomenon is the result of the built environment, buildings, roads, etc. absorbing and re-emitting solar radiation more readily than the natural landscapes, forests, greenery, and water bodies found in the surrounding areas (EPA, 2022). While the UHI can form via a range of conditions and climate zones, critically, humid regions and cities that are both larger and more densely populated experience the greatest resultant UHI temperature differences (EPA, 2022). The principal drivers of the formation of the UHI result from common trends in urban development, which include the reduction of natural land cover, the prevalent use of materials within the built environment that generally absorb and re-emit more solar energy than they reflect, urban geometries, particularly dense mid- or high-rise zones that hinder the flow of air and cause the buildings to function as thermal masses, anthropogenic heat, or heat generated from human activities like vehicle use or the operation of A/C units, and finally, localised weather conditions, such as the amount of solar energy available in a given location as a result of latitude, cloud cover, etc. (EPA, 2022). Previous studies have demonstrated how the UHI affects the air temperature in urban environments, and also how the distinct properties within the urban environment contribute to these temperature impacts (Evola, et al., 2020).

As previously noted, the UHI can be more significant in *Am* climates, which is the context in which the city of Chattogram finds itself. Additionally, climate change will only increase the severity of seasonal extremes (Bastin, et al., 2019), which means that by mid-century, the impact of the UHI on urban residents may be more acute.

High levels of heat pose a number of human health risks, including fatigue, dehydration, heat stroke, heat cramps, heat exhaustion, and even death (EPA, 2016). Certain groups may be more at risk of heat-related risks, including the very young or the elderly (EPA, 2016). Extreme or even elevated levels of heat pose clear risks to human health, safety, and well-being, and in a city like Chattogram with high seasonal periods of heat and humidity, the risks are clear. Furthermore, extreme heat conditions need only have a short duration if their severity is sufficiently elevated in order to pose and cause the aforementioned health risks (Kesik, 2019). Therefore, even if annual mean increases in temperature and relative humidity (RH) levels are small, significant health risks can still be posed if extreme design day conditions are sufficiently elevated (EPA, 2016).

Chattogram was selected as a case study for this analysis as, in addition to being located in the *Am* climate zone, which features heat and humidity-related design challenges, it also provides a good example of related political and financial challenges posed to a Global South city. The city has no fundamental base plan (CDA, 2015), and as a result, most urban development has been unplanned (CDA, 2015). The residents of Chattogram exist across a broad socio-economic spectrum, but most prior developments have focused on the middle- and high-income groups, to the detriment of lower-income groups (CDA, 2015). This is of critical concern as few people in this latter group have the capacity to self-fund climate change adaptation measures (Sharmin, et al., 2015). Additionally, the requisite urban infrastructure is not always well-developed (CDA, 2015), and electricity access and availability for residents have been and will continue to remain a critical issue in terms of Chattogram's operation and development goals (CDA, 2015). As Sharmin, et al. (2015) notes, this level of energy inconsistency, even in the wealthiest areas of the city, means that active climate change adaptation measures to combat overheating risks, i.e.: air-conditioning (A/C), are not viable solutions; in sustained load-shedding scenarios, urban residents will be at risk (CDA, 2015).

The selection of Chattogram as a case study also sought to address a knowledge gap in that there have to date been a limited number of studies examining high-density megacities in *hot-humid* (i.e.: tropical) climates (Sharmin, et al., 2015). In such climates, passive architectural strategies are insufficient in ensuring comfortable thermal conditions, particularly in dense urban environments (Sharmin, et al., 2015). Unlike North American or European counterparts, urban morphologies in the Global South are often denser and more compact (Sharmin, et al., 2015), while any UHI mitigation strategies that call for reduced density in Global South cities are a major challenge, particularly in cities like Chattogram that are major centres of economic activity (Sharmin, et al., 2015). As a result, UHI mitigation strategies outside of the de-densification sphere must be explored (Sharmin, et al., 2015).

As noted in the most recent development plan for the city of Chattogram (CDA, 2015), cost is a key factor in driving development efforts. Consequently, this study sought to make use of largely free and open-source tools to run the analyses exploring UHI mitigation. With the exception of Rhino, which costs \$995 or ~1,02,000 Tk., all other specialist simulation tools used to complete this study are freely available (as of December 2022).

Methods

This study assessed the impact of a series of mitigation strategies upon the formation of the UHI within a one square kilometre area of the *Chittagong Port* area of the *Halishahar thana*. Using *Rhino 7.0* and the *Dragonfly* plug-in, an urban model of the analysed thana (district) was created. Then, future climate projections were used to generate morphed future weather files for the years 2050 and 2080; these files were generated using the *Climate Change World Weather File Generator* (Jentsch, et al., 2013). Subsequently, passive design parameters were defined, and performance metrics were established. The passive design parameters were then permutated and simulated against a baseline calibrated urban model with simulations using the various present and future weather files. Simulation outputs were then analysed to assess their impact on the formation of the UHI effect and the resultant human health and well-being risks via the use of the indicator metrics. Finally, these results were examined and used to highlight the effectiveness of differing UHI mitigation strategies. The below *Fig. 1* summarises the study design.

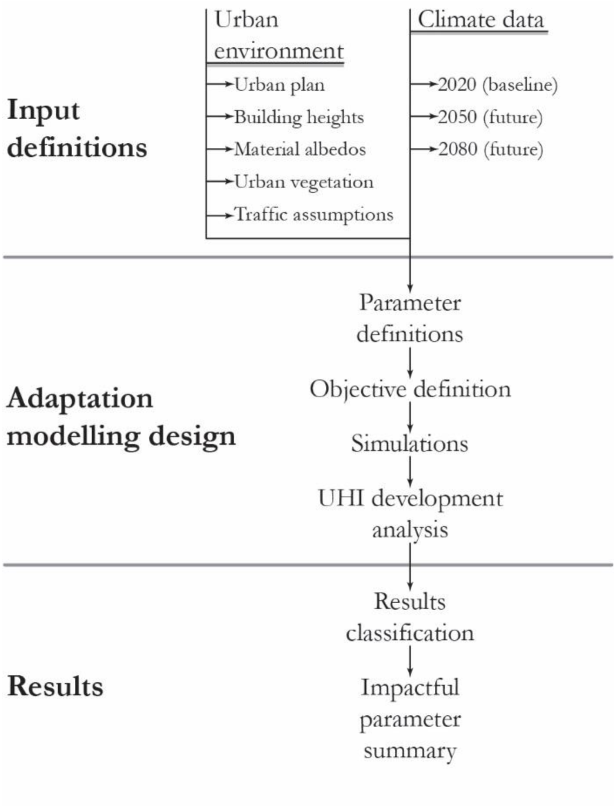

Figure 1: Study design

Urban Plan

Chattogram urban geometry was created in the 3D-modelling programme *Rhino 7*. The creation of this geometry was based on inputs from the *OpenStreetMap* repository (OpenStreetMap, 2022), the Chittagong Development Authority (CDA) ArcGIS map (ArcGIS, 2017), and the satellite and street-view imagery available via *Google Maps*. A one-kilometre square area in the Chittagong Port district, as defined per the CDA GIS (ArcGIS, 2017) was selected for modelling and analysis (see *Fig. 2* for indicated area). This selection was made primarily as the result of the availability of built environment and urban vegetation for the plot.

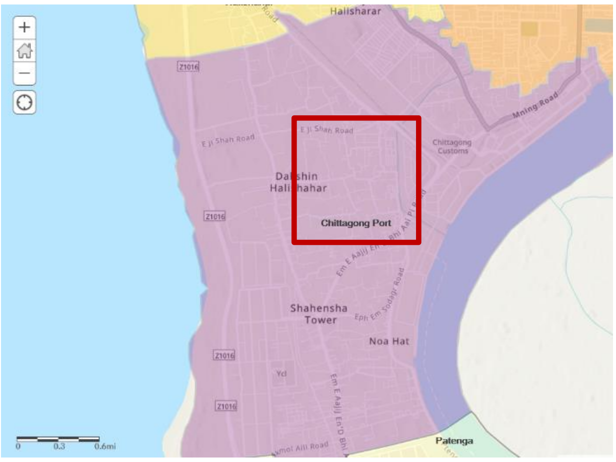

Figure 2: Indication of the general vicinity in the Chittagong Port area urban geometry modelled in the study (underlying image from ArcGIS, 2017).

The principal building, road, built infrastructure, vegetation, and waterways footprints and locations were based on data imported into *Rhino* from *OpenStreetMap* (2022). This data was cross-referenced against the CDA ArcGIS (2017) map. The imported urban layout data was then compared to the satellite imagery available on *Google Maps*. Several discrepancies were noted when modelling between the data available via *OpenStreetMap* and available on *Google Maps*. The dates on each were compared, and where large discrepancies were noted (i.e.: the omission of trees or a block of several buildings), in cases where the data on *Google Maps* was more recent than the data saved in *OpenStreetMap*, the underlying urban plan geometry (i.e.: the location of key features) was modified.

The urban geometry imported from *OpenStreetMap* consisted of a series of polylines. These were converted into planar surfaces in order to generate three-dimensional urban geometries consistent with the logic of the *Dragonfly* plug-in utilised.

Building Heights

After defining the urban plan, building heights were defined. Given the inconsistency in the availability of street-view visual data in Google Maps, as well as the age of some street-view visuals, the ability to reconstruct building heights was restricted. After review of street-view and satellite imagery, a mean building height of six (6) metres (two stories of three metres each) was assumed when no visual data could be acquired.

Based on a survey of open-source street imagery, buildings were universally assumed to have a window-to-wall ratio (WWR) of 0.2.

Material Albedos

With the exception of the albedo value of building roofs, the albedo values for the balance of the modelled urban environment were calculated automatically using the default assumptions inherent in the *Dragonfly* internal calculations. The roof albedo for all buildings in the analysis zone was set to 0.1 (Li, Harvey, & Kendall, 2012).

Urban Vegetation

Rather than model vegetated elements discretely, the vegetation data sourced from the *OpenStreetMap* data was used to calculate the percentage of treed area within the one-kilometre squared analysis zone. This calculated value was 6% (thus 6% of the total area within the test area was covered with trees).

Summary of Urban Geometry and Baseline Inputs

The resultant urban geometry is visualised in *Fig. 3*. The *Dragonfly* generated urban geometry includes the multi-story geometrical data for the analysed buildings and the principal building and neighbourhood characteristics.

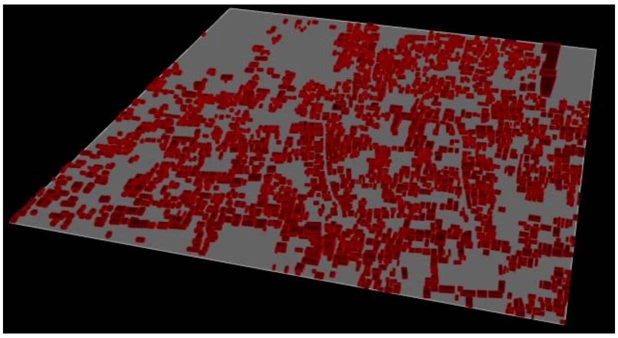

Figure 3: Urban morphology generated from OpenStreetMap *inputs using the* Dragonfly 'building from footprints' *component visualised in a* Rhino *environment*

Excepting the aforementioned albedo, WWR, and vegetation values, default calculated values using the native *Dragonfly* assumption algorithms were utilised. All baseline assumption inputs are summarised in *Table 1*.

Table 1: Input parameters for Chattogram urban area

Modeller inputs	
Building typology	Pre-1980
Bldg. occupancy profile	Apartment
Bldg. construction	Mass
Bldg. conditioning	Unconditioned
Typical no. of bldg. stories	2
Typical bldg. floor-to-floor height	3 m
Bldg. WWR	0.2
Bldg. roof albedo	0.1
Plot tree cover ratio	0.06
***Dragonfly* calculated values**	
Bldg. wall albedo	0.149
Road albedo	0.2
Glazing SHGC	0.25
Vegetation albedo	0.2
Traffic sensible heat flux	1.0 W/m^2
Default *Dragonfly* values	
Urban boundary layer: daytime	1,000 m
Urban boundary layer: night-time	80 m
Inversion height	150 m
Circulation coefficient	1.2
Exchange coefficient	1.0

UHI Assumption Benchmarking

The input values described in *Table 1* represent the assumed baseline conditions for the *Chittagong Port* area of the *Halishahar thana*. These inputs were then simulated with 2020 weather data from the Shah Amanat International Airport weather station using the *Urban Weather Generator* (UWG) component in the *Dragonfly* plug-in. The output of this UWG morphing procedure was compared to mean UHI intensity of the simulated model against values reported in the Yale University *Global Surface UHI Explorer* (Chakraborty & Lee, 2019). The data from the Chakraborty and Lee (2019) compiled database indicated a 0.0 to 1.5°C daytime mean annual UHI impact in the modelled area of Chattogram. The UWG simulated file returned a daytime mean annual UHI impact of 0.44. Given this output, the baseline assumptions were deemed suitable for optimisation analysis.

Climate Change Scenario Weather File Shifting

The *Climate Change World Weather File Generator* (Jentsch, et al., 2013) created by the University of Southampton was utilised as the principal tool for generating future weather files. The Excel-based tool is freely available and morphs .epw weather files for the future years 2050 and 2080 using a *'medium-high'* emissions scenario (Jentsch, et al., 2013).

The Shah Amanat International Airport weather file used in baseline simulations was not, however, compatible with the *Climate Change World Weather File Generator*. As a result, the baseline weather file was deconstructed and reconstructed using the related *Dragonfly* components for creating custom weather files. This approach rectified the compatibility issue and resulted in the *Climate Change World Weather File Generator* being able to morph the baseline weather files for the years 2050 and 2080.

UHI Mitigation Permutation Definition

This study sought to examine passive UHI mitigation strategies. The strategies identified for optimisation were the albedo of building roofs and the level of treed vegetation in the urban plan. The aforementioned 0.06 treed vegetation ratio and a roof albedo of 0.1 served as the baselines for the optimisation point of departure.

These two numeric values were considered linearly optimisable up to a maximum theoretical value of 1.0 (representing respectively a rooftop albedo value of 1.0 and a treed vegetation ratio of 1.0). In the case of the treed vegetation ratio, a value of 1.0 represents 100% of remaining available open land being used for tree planting. A value of 1.0 is therefore equivalent to 66% of the total area of the one-kilometre squared analysis area being used for trees; it does not represent a land use change from built area to vegetation.

Output Metrics

The principal output metrics to assess performance and facilitate comparison of the different permutations of passive strategies were dry bulb temperature in °C and heat index (HI) in correlated °C. The latter metric was selected in order to better account for the humidity impacts of the Chattogram climate. The formula for HI is identified in *equation 1*, where *T* is the dry bulb temperature in °C and *R* is the relative humidity. The variables c_1 through c_9 are constants.

$$HI = c_1 + c_2T + c_3R + c_4TR + c_5T^2 + c_6R^2 + c_7T^2R + c_8TR^2 + c_9T^2R^2 \quad (1)$$

The following HI adjustments are made given the following conditions. If exterior relative humidity is less than 13% and dry bulb temperature is between 26.7°C and 44.4°C, then the adjustment in *equation 2* is utilised. If relative humidity is greater than 85% and the dry bulb temperature is between 26.7°C and 30.6°C, then the adjustment in *equation 3* is applied. If the initial HI calculated in *equation 1* is less than 26.7°C, then the final HI is calculated using *equation 4*. The corresponding heat index stress values are summarised in *Table 2*. All equations are based on the National Weather Service (NWS) calculation methodology (NOAA/NWS, 2022).

$$\text{HI} \; - \left[\left(\frac{13-R}{4} \times \sqrt{\frac{17-|T-95|}{17}}\right) \times 1.8 + 32\right] \tag{2}$$

$$\text{HI} \; + \left[\left(\frac{R-85}{10} \times \frac{87-T}{5}\right) \times 1.8 + 32\right] \tag{3}$$

$$\text{HI} = \langle 0.5 \times \{T + 61 + [(T + 68) \times 1.2] + (R \times 0.094)\} \times 1.8 + 32 \rangle \tag{4}$$

Table 2: Heat Index (HI) correlated stress values

Heat Index (HI) in °C	Stress level
27 – 32	Caution: fatigue possible with prolonged exposure and activity
32 – 41	Extreme caution: heat cramps and exhaustion possible
41 – 54	Danger: heat stroke probable
> 54	Extreme danger: heat stroke imminent

Notes: values per EPA (2016).

Simulation Approach

The input permutations defined in the section *UHI Mitigation Permutation Definition* were simulated as iterations of the benchmarked baseline model using the UWG component in *Dragonfly* with the input values previously defined in *Table 1*.

Results

The simulation results found that the passive UHI mitigation strategies tested were able to have a limited positive impact on UHI formation. However, the mitigation strategies proved less effective under the future climate scenarios.

Table 3: Summary of passive UHI mitigation strategy effectiveness

	Baseline Scenario	Optimised Scenario
Mean annual dry bulb temperature	30.06°C (2020) 31.44°C (2050) 33.41°C (2080)	28.07 (2020) 29.56°C (2050) 31.52°C (2080)
HI annual hours 'extreme caution'	3,902 (2020) 4,125 (2050) 4,338 (2080)	1,697 (2020) 2,944 (2050) 3,088 (2080)
HI annual hours 'danger'	437 (2020) 1,401 (2050) 3,468 (2080)	1 (2020) 80 (2050) 804 (2080)
HI annual hours 'extreme danger'	0 (2020) 0 (2050) 30 (2080)	0 (2020) 0 (2050) 20 (2080)

The implementation of the maximum level of greenery and the highest albedo roofing resulted in a reduction in mean annual dry bulb temperature of about 2°C for all simulated test years (present, 2050, and 2080). Additionally, the implementation of these values reduced the number of annual hours when the HI resulted in the *extreme caution*, *danger*, and *extreme danger* stress levels, though the magnitude of severe HI hours increased under future climate conditions.

In addition to reviewing the impacts annually, the effect of the passive UHI adaptation measures were reviewed for the month of May, one of the hottest months in

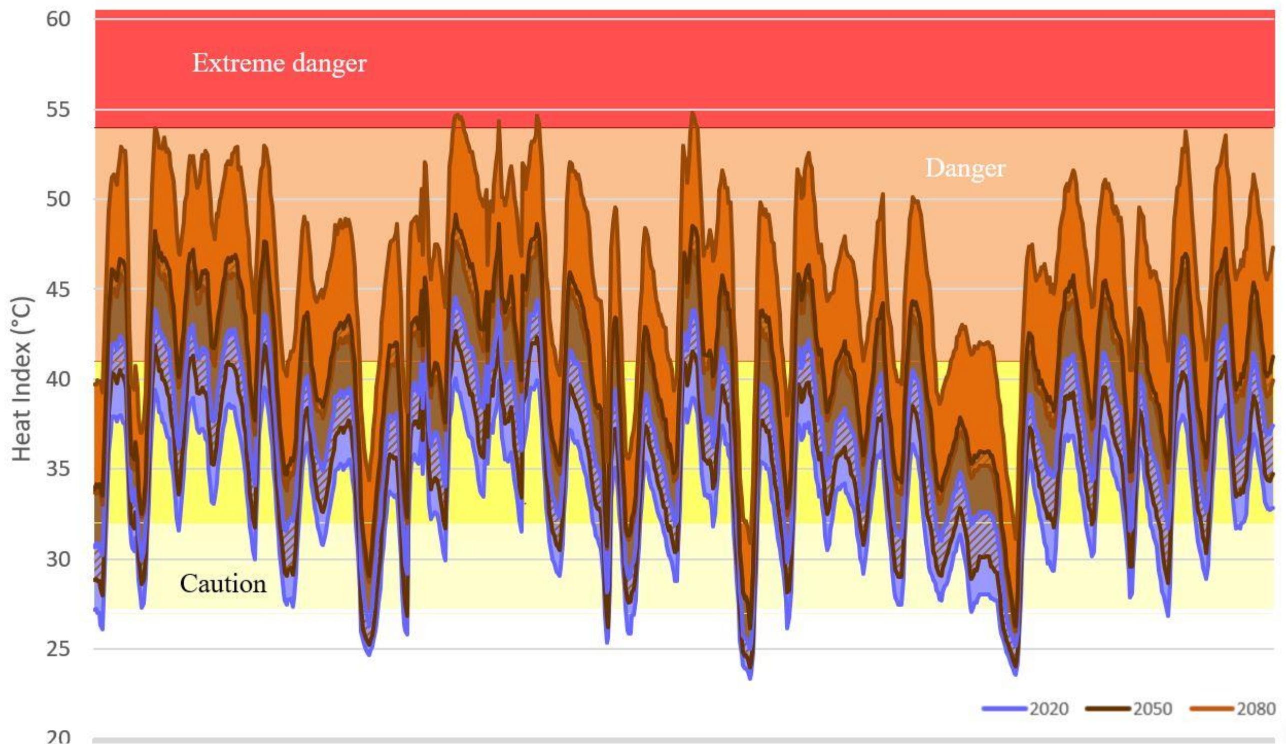

Figure 4: Visualised summary of Heat Index (HI) performance range of passive mitigation strategies on UHI formation across climate scenario years in the month of May.

Chattogram. The monthly impact performance ranges are visualised in *Fig. 4*. Annual results are summarised in *Table 3*, respectively.

Discussion

The result of this study permitted review of the impact of the implementation of passive UHI mitigation strategies on the formation of the UHI in the *Am* climate of Chattogram under present and future climate conditions.

Generally, the passive mitigation strategies had positive, albeit, limited effectiveness on the reduction of health and well-being risks posed to urban occupants in Chattogram. While improvements in roof albedo and increased vegetation did reduce dry bulb air temperatures and the number of hours of elevated heat stress (correlated to HI), the number of hours with correspondingly high levels of heat indexes remained elevated in all simulations. This could be a result of the high levels of humidity found in the Chattogram climate, which pose a unique challenge to for this climate typology (Sharmin, et al., 2015). However, it is important not to neglect the impact of humidity within the evaluation metrics, and the results of this study therefore, suggest that in the *Am* climate zone, passive UHI mitigation strategies as defined in the scope of this study can have positive impacts on reducing the magnitude of the UHI effect, but are not sufficiently holistic to mitigate heat-related risks for urban dwellers in *Am/hot-humid* climates.

Limitations

There were several assumptions made during the modelling phase. While these assumptions were benchmarked against measured real-world data to claim suitability for detailed simulation, some of the nuances of the local urban morphology could have impacted the simulated UHI mitigation results.

The use of the *Climate Change World Weather File Generator* offered the opportunity to make use of an open-source weather file morphing workflow. However, this tool only models one climate change scenario, and thus the range of uncertainty in climate change modelling could not be reflected in the results of this study given the presented results.

One of the major limitations of this study, and challenges with working with the particular case study of Chattogram, was the access to reliable urban data. *OpenStreetMap* was used to generate the principal urban geometry, but this data was at times incomplete and did not always align with data available from other open-source tools like Google Maps or satellite imagery. In the absence of municipally generated and/or vetted urban data, the reliability of the input data relied on implications on the part of the modeler. This reality was reflected in the outset of the study, as some of the *thanas* in Chattogram lacked sufficient open-source data to build an urban model for testing.

Conclusion

This paper presented the analysis of passive UHI mitigation strategies in the city of Chattogram under present and future climate scenarios. The study tested the effectiveness of mitigation approaches utilising the metrics of dry bulb temperature and heat index.

Future studies should consider the core workflow of this study and its ability to utilise free open-source tools as a way to quickly and cost-effectively test UHI mitigation strategies. Future study development would benefit from further benchmarking of baseline assumptions within the *Dragonfly* modelling approach and efforts to replicate study findings in other *Am* climate zone cities.

Nomenclature

heat index: an index that combines air temperature and relative humidity to equate human perceived temperature in a shaded area

thana: administrative unit of Chattogram, corresponding to a district served by a police station

urban heat island effect (UHI): a phenomenon wherein urban areas experience both elevated daytime and night-time temperatures as compared to outlying rural areas

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