Wind, Sun, Surface Temperature, and Heat Island: Critical Variables for High-Resolution Outdoor Thermal Comfort

Christopher Mackey[1], Theodore Galanos[2], Leslie Norford[3], Mostapha Sadeghipour Roudsari[4]
[1] Payette Architects, United States of America
[2] NEAPOLI Sdn Bhd, Malaysia
[3] Massachusetts Institute of Technology, United States of America
[4] University of Pennsylvania, United States of America

Abstract

As interest in comfortable outdoor spaces grows, the demand to simulate, map, and understand these microclimates has also grown. However, such mapping rarely occurs in practice, as it requires the modelling of several complex factors: wind, sun, surface temperature, and urban heat island. At present, it is clear that a workflow to map outdoor comfort cannot include all of these factors without requiring months to compute. Accordingly, this study attempts to simulate the most accurate map of outdoor thermal comfort currently possible for a 3-block urban setting in Singapore. Next, the contributing factors are systematically removed to deduce the minimum needed to create a sufficiently accurate map. Findings indicate that, on average, the comfort conditions reported on meteorological weather networks are ~2.4ºC different from a given microclimate within the urban test site. The diversity of direct sun and sky heat exchange can account for a little over a third of this discrepancy. Wind patterns similarly account for a significant fraction of this difference but results suggest that a small number wind simulations are needed to appropriately account for such patterns. Surface temperatures and heat island effect each account for a smaller ~0.5ºC difference. Strategies for generating faster microclimate maps are discussed and recommendations for meteorological reporting methods are proposed.

Introduction

As interest in outdoor thermal comfort continues to rise and the demand for passively comfortable urban microclimates increases with global city growth, the desire to simulate and map these microclimates has also increased. While the building simulation field possesses several tools and methods for evaluating indoor comfort to high spatial and temporal resolutions (Webb, 2013; Hoyt et al., 2014; Mackey, 2015), there is a relative dearth of comprehensive methods for evaluating outdoor comfort to the same degree of accuracy. Much of this can be explained by the difficulty in modelling the many variables of outdoor comfort, which are typically kept stable indoors. Notably, outdoor environments have much higher wind speeds with complex flow patterns, which often must be modelled with Computational Fluid Dynamics (CFD). Such environments also require more detailed radiative transfer calculations since urban areas have many more surface conditions. Finally, outdoor conditions introduce macro-scale climate variables such as urban heat island (UHI), which is the condition where an urban area is a few degrees warmer than the surrounding rural area. Such urban heat effects are typically ignored in the modelling of indoor environments but can make a significant difference when the area of interest is exposed to outdoor air (Bueno et al., 2013).

At present, if a practitioner wishes to create a detailed and accurate map of outdoor comfort, one must typically simulate all of these factors together using one large interlinked model. Examples of such a models include those produced by the validated microclimate-modelling engine ENVI-met (Elnabawi et al., 2015) and the software CitySim (Walter and Kämpf, 2015).

While large models such as these can produce accurate results, they often take a minimum of several days to simulate a small fraction of the year and can require over a month to compute a year's-worth of results for some cases. In their current state, these models are not suitable to inform an iterative design process, which frequently requires several quick simulations of different options to be helpful. Similarly, these models cannot easily be scaled to understand the discrepancies between the weather data that is collected at airports and the diverse microclimates of a city. As a result, they are not ideal for closing the gap between comfort conditions reported by meteorological networks and the conditions that people experience within their neighbourhoods.

In response to these dilemmas, this paper proposes an alternate "hybrid" approach of separating the factors that contribute to outdoor thermal comfort and simulating each individually with an engine that is validated to model this factor. Starting first from the largest scale, the outputs of each model are used to help inform the smaller scale models until the scale of the human is reached. While this approach is not any less time consuming that the alternative described above, it affords an opportunity to test the relative importance of each factor and understand the implications of substituting this factor with a more quickly calculated default. As such, this study aims to establish faster methods for mapping urban microclimates that are informed by the implications of such simplifications.

Methods

Site Selection and Time Period

The city of Singapore was chosen as a location where outdoor thermal comfort is a year-round concern and new

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construction affords many opportunities to help shape microclimates more effectively. The particular three-block portion of the city that was modelled for this study possesses a diversity of urban conditions that are outlined in Figure 1. This diversity of conditions helps identify the types of microclimates that will be prone to error in the simplification of a given climatic factor: open plaza, shaded plaza with canopy, shaded plaza with trees, narrow alley, semi-enclosed entry.

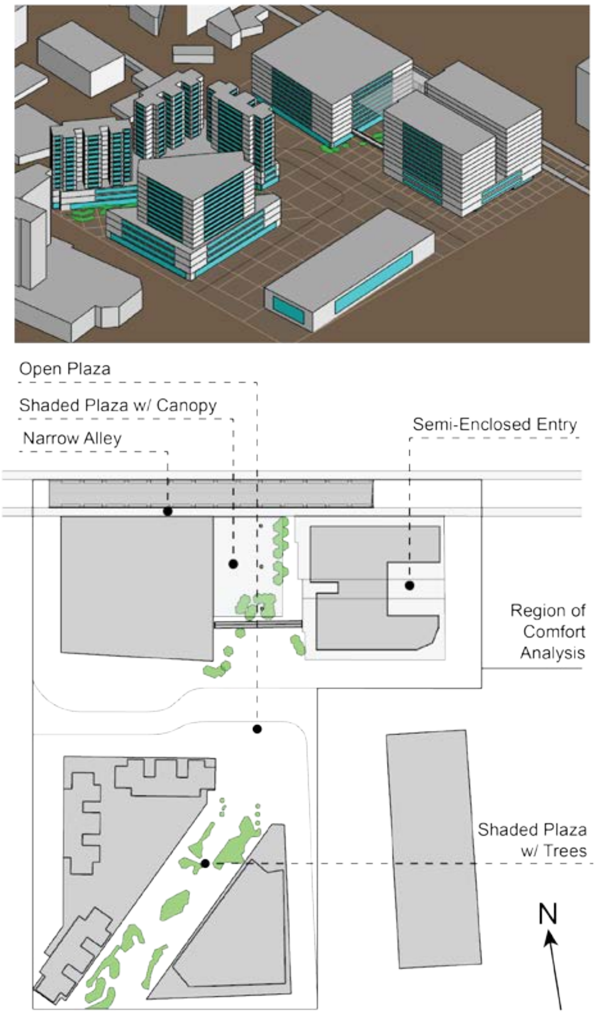

Figure 1: Diagram of the Selected Site in Singapore with Individual Microclimates Labelled.

The geometric model that served as a base for all simulations was developed using the commercial NURBS 3D modeller Rhinoceros 5. The four blocks within the area of interest were modelled explicitly, with high geometrical detail. The buildings further away from the area of interest were modelled as simple volumes, which represent an approximation of the building massing. The urban landscape was modelled to include buildings up to a distance of 500 m away from the area of interest for the purposes of CFD and UHI modelling.

In addition to the selection of the urban site, short time periods were selected from the Singapore Typical Meteorological Year (TMY) in order to decrease the run time as multiple comfort factors were tested. Specifically, the comfort results were generated for the following three weeks, which are taken from the header file of the climate file: Typical Week (7/30-8/5), Cold Week (12/10-12/16), Hot week (6/4-6/10).

Urban Heat Island

UHI was integrated into this study by morphing the Singapore Airport TMY weather data using the validated Urban Weather Generator (UWG) (Bueno et al., 2013). The UWG approximates the thermal conditions of a city using several key geometric and material variables of the urban landscape, including average building height, site coverage ratio, facade-to-site ratio, and road/roof/wall/window constructions. These parameters are fed into a generic model of an urban canyon, for which an energy balance calculation is run. Ultimately, the UWG outputs a morphed TMY file in which the air temperature has been adjusted to reflect the urban conditions. Generic road/roof/wall/window constructions were selected based on building codes and standard construction practices. Figure 2 illustrates the difference between the original airport data and the morphed data that accounts for the conditions of the site.

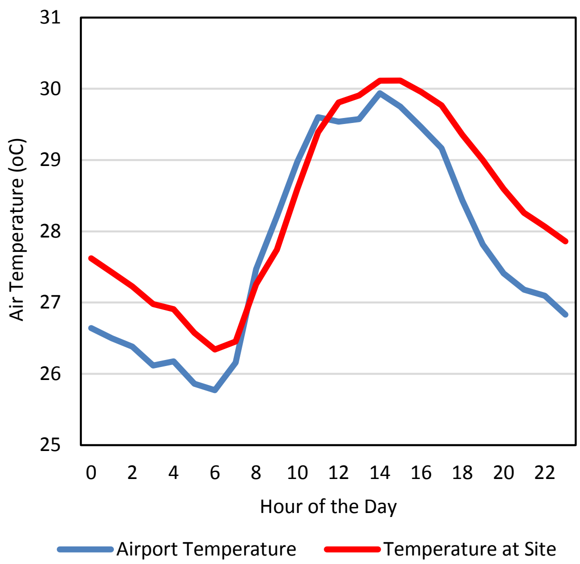

Figure 2: Comparison of the Singapore Typical Week at the Airport (a) and at the Urban Site (b).

Wind Speed

In order to account for the diversity of airflow patterns that exist throughout the urban site, a total of 36 CFD simulations were run, providing a high resolution of wind direction patterns that matches the resolution of wind direction measurements in the TMY data.

A number of best practices for CFD simulation in the urban environment were followed in order to ensure a minimum level of accuracy and quality of the results. (Franke et al., 2007). A predominately hexahedral mesh was used with additional refinement achieved through a multiple grading scheme, creating higher cell density near the area of interest. A refinement region was introduced at the first 5 meters from the ground at the area of interest. Finally, a highly refined mesh was introduced near the ground of the domain, allowing for four layers within the first 2m.

The top boundary was positioned approximately 2×H_{max} away from the ground at height of 300 meters and a lateral extension of approximately 3×H_{max} was used. A small extension of the domain was selected for the approach region (3×H_{max}) and, for the wake region, a large extension of the domain (15 x H_{max}) was used in order to allow for flow re-development.

For each of the 36 cases, the simulated wind speed was derived from statistical analysis of the Singapore TMY data, where the simulated speed represented the average velocity from that direction. The inbound vertical wind profile was assumed to be given by a Logarithmic Law, assuming a roughness length (z_0) of 1 meter for a typical urban area. The wind profile was determined using the following equation:

$$U(z) = U_{met}\left[\frac{\ln\left({}^{z}/_{z_0}\right)}{\ln\left({}^{z_{ref}}/_{z_0}\right)}\right] \qquad (1)$$

where $U(z)$ is the speed at height z, U_{met} is the meteorological wind speed, and z_{ref} is the meteorological reference height. The cases were simulated using the validated OpenFOAM engine (Robertson, 2015). To ensure that the changes in solution variables from one iteration to the next are negligible, 4 orders of magnitude of residual control was achieved. For each of the 36 CFD simulations, wind velocity plots were extracted at the height of an adult human's center of gravity (1.1m above ground). These velocities were used to produce Wind

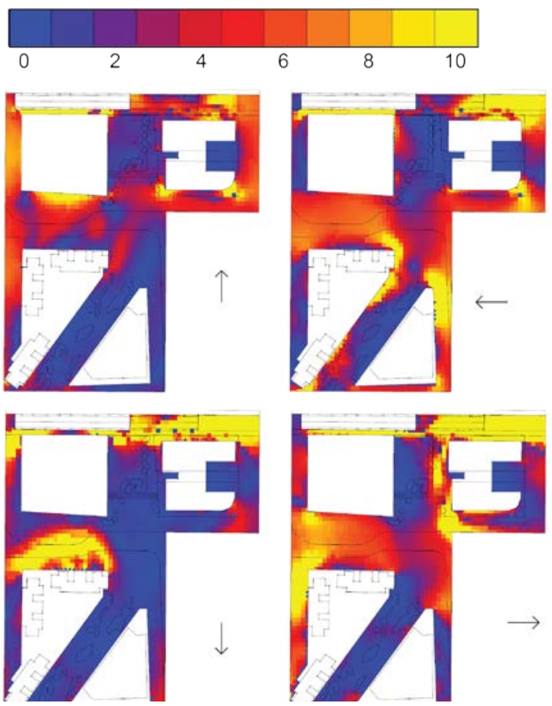

Figure 3: Wind Factors in the Singapore Site for Winds Blowing in Different Directions.

Factors (WF) by dividing the simulated wind velocities at 1.1m height with the meteorological wind speed found in the Singapore weather file. These WF were used in combination with the TMY data to derive hourly wind velocities within the area of interest. Figure 3 displays a visual of these wind factors over the site.

Surface Temperature

Surfaces temperatures of buildings, windows, and the ground were modelled using the EnergyPlus simulation engine. Specifically, a solar distribution setting of FullExteriorWithReflections was used to ensure that a correct portion of solar energy was calculated for each urban surface on a 15-minute time step. The surfaces within the three-block area-of-interest were geometrically modelled to be no larger than a 5m×5m square, ensuring a minimum resolution of surface temperature variation. Smaller surface dimensions were used in areas of temperature transition and each floor of each building was modelled with its own set of separate surfaces. Figure 4 illustrates the average temperature of these urban surfaces over the annual EnergyPlus simulation.

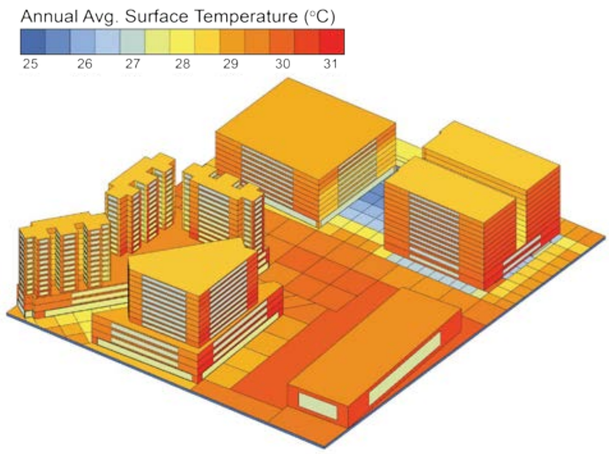

Figure 4: Annual Average Surface Temperature Output from EnergyPlus.

Sky Heat Transfer

In order to compute a mean radiant temperature (MRT) for the outdoor comfort model, a base longwave MRT was computed using the surface temperatures of the previous step and following formula (Thorsson, 2007):

$$MRT = \left[\sum_{i=1}^{N} F_i T_i^4\right]^{1/4} \qquad (2)$$

where F is the fraction of the spherical view occupied by a given indoor surface, T is the temperature of the surface. View factors (F) to each of the EnergyPlus surfaces were calculated using the ray-tracing capabilities of the Rhino 3D modelling engine. The long-wave temperature of the sky was estimated using the horizontal infrared radiation contained within the TMY data along with the following formula (Blazejczyk, 1992):

$$T_{sky} = \frac{L_a}{\left(\varepsilon_{person}\sigma\right)^{1/4}} \qquad (3)$$

where L_a is the downwelling long wave radiation from the sky in W/m^2, ε_{person} is the emissivity of the human (assumed to be 0.95), and σ is the Stefan-Boltzmann constant (5.667×10^{-8}). To account for shortwave solar radiation that falls on people, the SolarCal model was used to produce an effective radiant field (ERF) and corresponding MRT delta that was added to the base longwave MRT (Arens et al., 2015). Published in the ASHARAE-55 standard for thermal comfort (2016), the SolarCal model offers advantages over other models to estimate shortwave radiation falling on people. Notably, it allows for inputs of seated vs. standing among other variables. The formula to calculate the ERF with SolarCal is as follows:

$$ERF_{solar} = (0.5\, f_{eff}\, f_{svv}\, (I_{diff} + I_{TH}\, R_{floor}) + A_p\, f_{bes}\, I_{dir} / A_D)\ \ (\alpha_{SW}/\alpha_{LW})$$

where f_{eff} is the fractional of the body that can radiate heat (0.725 for a standing person), f_{svv} is the sky view factor (computed here thorugh ray-tracing) and f_{bes} is a 1/0 value indicating whether direct sun is on the person (computed by tracing the sun vector). I_{diff} is the diffuse sky radiation, I_{TH} is the global horizontal radiation, and I_{dir} is the direct radiation (all taken from TMY data). A_p and A_D are geometry coefficients of the human body, which are computed based on sun altitude and azimuth. Finally, R_{floor} is the reflectivity of the ground (assumed to be 0.25) and the α values refer to the absorptivity and reflectivity of the persons clothing. This ERF is converted into a MRT delta using the following equation:

$$ERF = f_{eff}\, h_r\, (MRT - T_{LW}) \qquad (5)$$

Where h_r is the radiation heat transfer coefficient (W/m^2 K) and T_{LW} is the base longwave MRT temperature (ºC)

Outdoor Comfort Model

Over the past decades, there have been several dozen proposed outdoor thermal comfort metrics, many of which were built to account for such individual climatic factors as humidity, wind speed, or direct sun. As such, the selection of the most relevant and comprehensive outdoor comfort metric for this study is critical. Universal Thermal Climate Index (UTCI) was chosen as it has become a standard for the "feels like" temperature used by meteorologists across the globe (Jendritzky et al., 2007). Furthermore, the UTCI's inputs are fairly straightforward, requiring only four variables to be calculated: air temperature, radiant temperature, humidity, and wind speed. The model accounts for clothing using correlations derived from observations of human adaptive behaviour in the outdoors. All other personal factors such as age, height, and weight are averaged over the population.

Perhaps the only area in which UTCI falls short of the needs of this study is that it was originally designed to accept the wind speed at meteorological height (10 meters). As such, it is not immediately usable for the CFD-informed studies of this paper and, for this reason, some researchers prefer to use Physiological Equivalent Temperature (PET) for cases such as this (Rodrigues et al., 2009). However, PET is not averaged over the human population and includes no adaptive clothing model. Accordingly, a decision was made to "back-convert" wind speeds derived from the CFD studies to the wind speed at the meteorological height for the UTCI model. Thankfully, the relation between the UTCI's theoretical wind speed at meteorological height and the wind speed at the height of the occupant is simple, involving only a multiplication by 1.5 (Jendritzky et al., 2007).

Combining the Model Components

As mentioned previously, the full set of methods proposed here is a "hybrid" approach where each parameter of the urban comfort map is modelled with a dedicated engine. As such, the inter-relation of the results of each engine to one another is critical for ensuring an accurate final output. Figure 5 illustrates this inter-relation and shows how data is moved from the starting EPW weather data and urban parameters to the final urban UTCI map. Where possible, the outputs of one simulation engine are set as the inputs for another. For example, the epw that has been warped to account for urban heat island is used in the EnergyPlus simulation for surface temperature. A notable departure from this is that the CFD studies have been run without buoyant forces and without being informed by the surface temperatures of the EnergyPlus simulation. Primarily, this was done because different hours of the year have different patterns in urban surface temperature (driven by solar position and varying amounts of cloud cover over time). The fact that the 36 CFD simulations are abstracted to produce wind speeds for 8760 hours of the year means that, while including surface temperatures in these simulations might make some hours more accurate, it might also make others less accurate if the surface temperature pattern does not match that of a given hour. Accordingly, it was decided that only simulating wind-driven flows in the CFD and not buoyant flows was the safest means of accounting for wind.

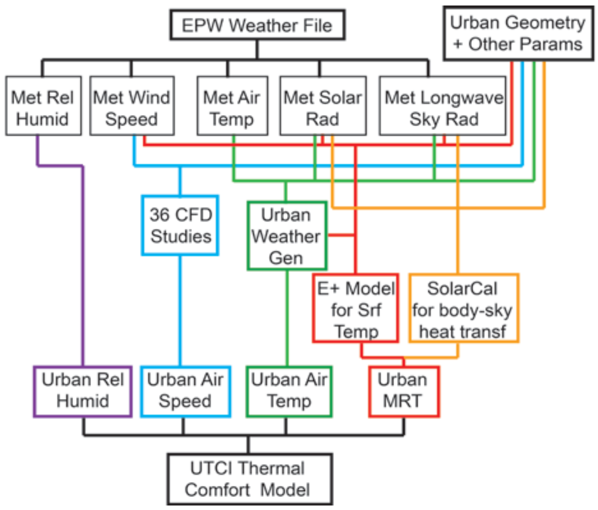

Figure 5: Flowchart showing how different inputs and engine outputs are related to one another.

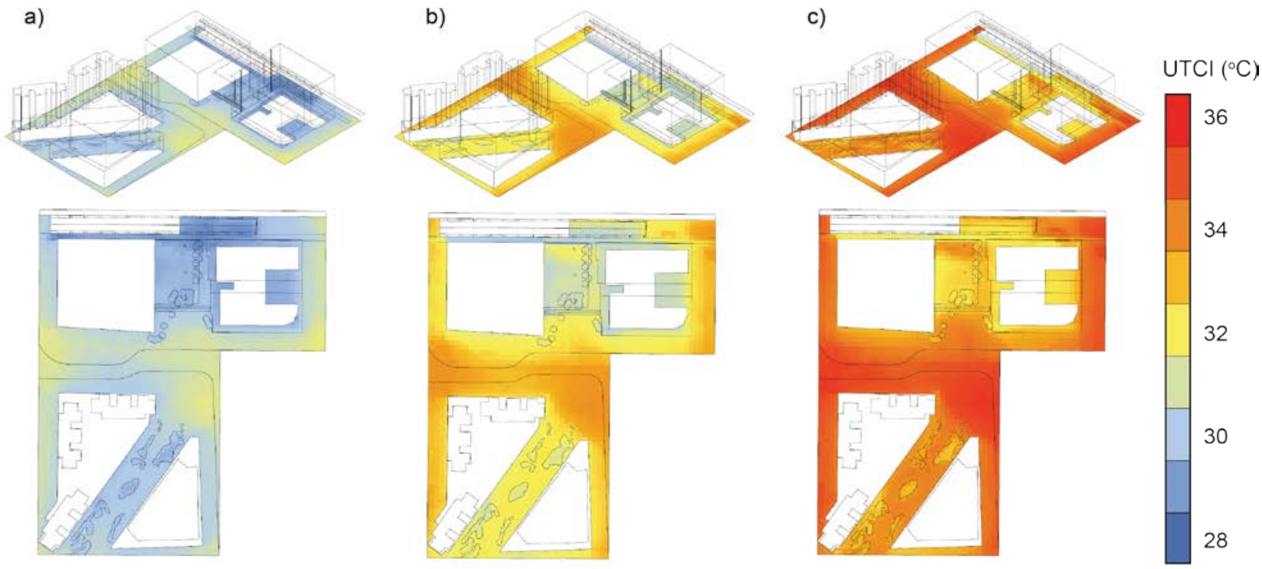

Figure 6: Maps of Average UTCI over the Singapore Cold Week (a), Typical Week (b), and Hot Week (c).

Results

The Most Accurate Microclimate Map

After all factors of the most accurate case were plugged into the UTCI model, several high resolution maps of UTCI were generated on an hourly basis for the three previously-mentioned weeks of the TMY file. Figure 6 displays the average UTCI for each of the weeks. These maps include air temperature that accounts for the local UHI, utilize 36 CFD cases to establish hourly wind speeds, contain surface temperatures modelled with EnergyPlus, and incorporate sky heat exchange modelled with an altered SolarCal method. As such, these maps of urban microclimate are among the most complete outdoor microclimate maps produced to date at this resolution.

Error Mapping

With a most accurate case of UTCI mapping established, it is now possible to substitute factors in this UTCI map with default assumptions and evaluate the error of associated with such substitutions. Figure 7 illustrates this with maps of the UTCI difference between the most accurate case and cases that used smaller and smaller numbers of CFD simulations to account for wind patterns. As the maps illustrate, the error of simplifying the wind patterns is greatest in the areas where wind patterns change, such as the corners of buildings, the windward sides of buildings, and the entrances to narrow passages. The maps also illustrate that, as the number of CFD simulations is dialled down from 36 to 2, there is relatively small error in those areas that are fully exposed (such as open plazas) and those area that are semi-enclosed (such as the entry to the building in the upper right corner of the site). Furthermore, the overall error from decreasing the number of CFD scenarios is relatively small. However, there is a fairly substantial jump in error that occurs when all CFD simulations are substituted with an assumption that the log wind profile governs everywhere over the site. As the map of average UTCI for this case indicates, this large jump in error is largely the result of overestimation of the wind speed in most locations over the site. This overestimation of air speed causes a fairly even distribution of error over the site, although it is slightly greater in semi-enclosed areas.

Figure 8 is organized similarly to Figure 7 but tests the error associated with other factors of urban microclimate. The first case removes the UHI model from the analysis and replaces it with the unaltered data from the Singapore airport. Unsurprisingly, this substitution of UHI results in a very even distribution of error over the site. The magnitude of this error (~0.5C) is notable, particularly in comparison to the other factors. The second case substitutes the detailed EnergyPlus model of urban surface temperatures with an assumption that all surfaces are always at the temperature of the air. Interestingly, this error does not appear to be greatest in the regions closest to the most surfaces, such as narrow passages and streets. Rather, the error is greatest in those areas that are most exposed to the sun, such as the centres of large plazas. This can be explained by the fact that the temperature difference between the air and urban surfaces tends to be greatest in areas that are heavily exposed to the sun. The overall magnitude of this error is fairly comparable to that induced by a lack of UHI, which is roughly 0.5ºC. Finally, the largest error of all cases in Figures 7+8 is that which occurs from the removal of a sky heat exchange model. This includes the replacement of the altered SolarCal model with an assumption that the sky is effectively the same as the air temperature. This substitution results in very large quantities of error in the most sky-exposed locations, which is on the order of magnitude of 2.4ºC. The error over the whole site is similarly large and in excess of 1.1ºC. However, the maps also illustrate that, in semi-enclosed locations, this assumption regarding the sky temperature does not result in very large quantities of error.

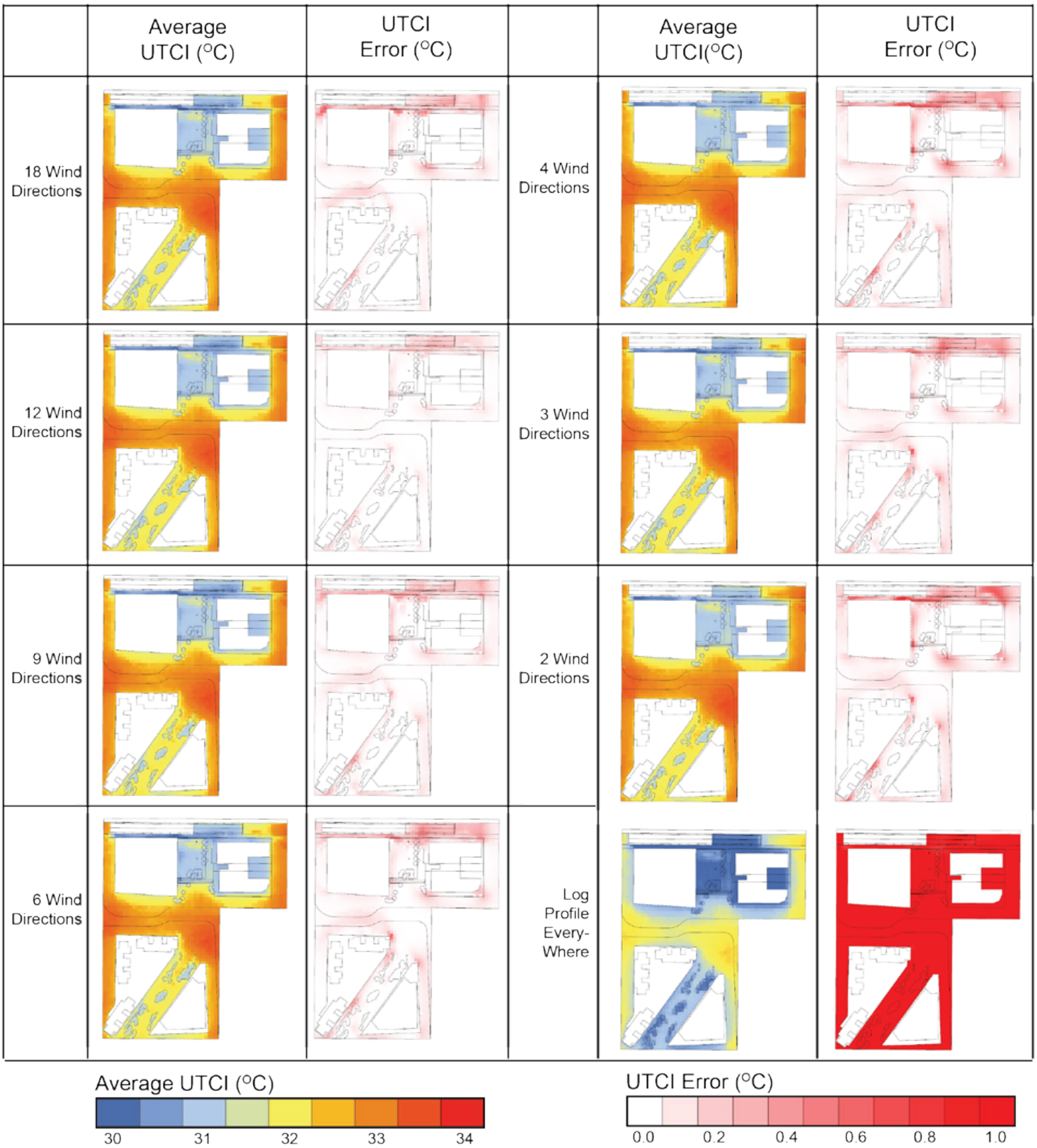

Figure 7: Maps of Average UTCI and UTCI Error for Different Numbers of CFD Simulations.

Total Error

In addition to visualizing the error spatially over the site, it is also helpful to observe the overall quantities of error that are incurred by the simplification of a given parameter. Figure 9 illustrates this with a bar chart that plots both the average error over the whole site as well as the error of the most error-prone region. In addition to the cases presented in Figures 7+8, Figure 9 includes an assessment of the error between the single UTCI value that is typically published on weather reporting networks (Metrologic UTCI) and the values simulated over the site. The error between this single value and the detailed microclimates of the city is substantial, on the order of magnitude of 2.4°C overall and 3.4°C in some of the worst-case scenarios. To help assess a means of improving this number, several variations of this single number are also compared with the values simulated over the site. Specifically, these are 1) the Metrologic UTCI where the MRT is assumed to be the same as the air temperature (no sun) and the wind is assumed to be zero, 2) the UTCI computed using a weather file that has been passed through the UWG to account for UHI, and 3) this UHI-altered UTCI with the wind and MRT removed. Interestingly, all three of these variations succeed in reducing the overall error of this value, although they do not always reduce the error in the most error-prone regions.

Discussion

Recommendations for Microclimate Map Creation

From observation of Figure 9, it is clear that the single-most important parameter to emphasize in the creation of urban microclimate maps is a sky heat exchange model. The absence of such a model results in 1.1ºC error over the site in this study and causes a substantial 2.4ºC error in worse case scenarios. Without accounting for the presence/absence of direct sun during the day and the heat loss to the cooler sky at night, there seems to be little point to generating high-resolution descriptions of outdoor thermal comfort.

The second-most important parameter for the generation of urban microclimate maps is the urban wind pattern. From Figure 9, it is clear that the simple substitution of CFD results with an assumption that the meteorological wind profile governs everywhere is not sufficient. This will result in overall errors that are comparable to the removal of the sky heat exchange model (1.1ºC). However, it is worth noting that, unlike the absence of a sky heat exchange model, the error in the worse-case scenario of this wind assumption is 1.2ºC, which is much smaller than that of the sky model. Perhaps the most surprising of all findings in this study is that the use of only two CFD studies from opposite directions (one directly north and one directly south in this case) greatly reduces the overall error associated with this simplification of wind. In other words, two CFD studies can be enough to establish the regions of the site that typically experience more or less wind, which in turn greatly drops the overall error. Notably, while this reduces the overall error, it does not substantially reduce the discrepancy in the most error-prone regions, such as the corners of buildings and the windward sides of

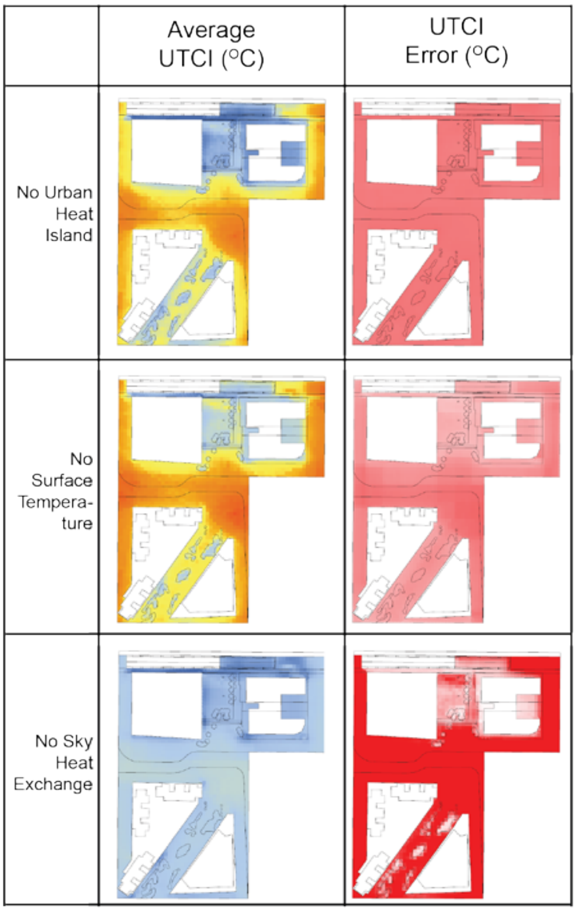

Figure 8: UTCI Error for Simplified Surface Temperatures, UHI Effect, and No Sky Heat Exchange.

obstructions. Increasing the number of CFD studies to nine reduces this "worst-case-scenario" error to a third of its original value, which is more safely in the limits of acceptability. Curiously, this study found that increasing

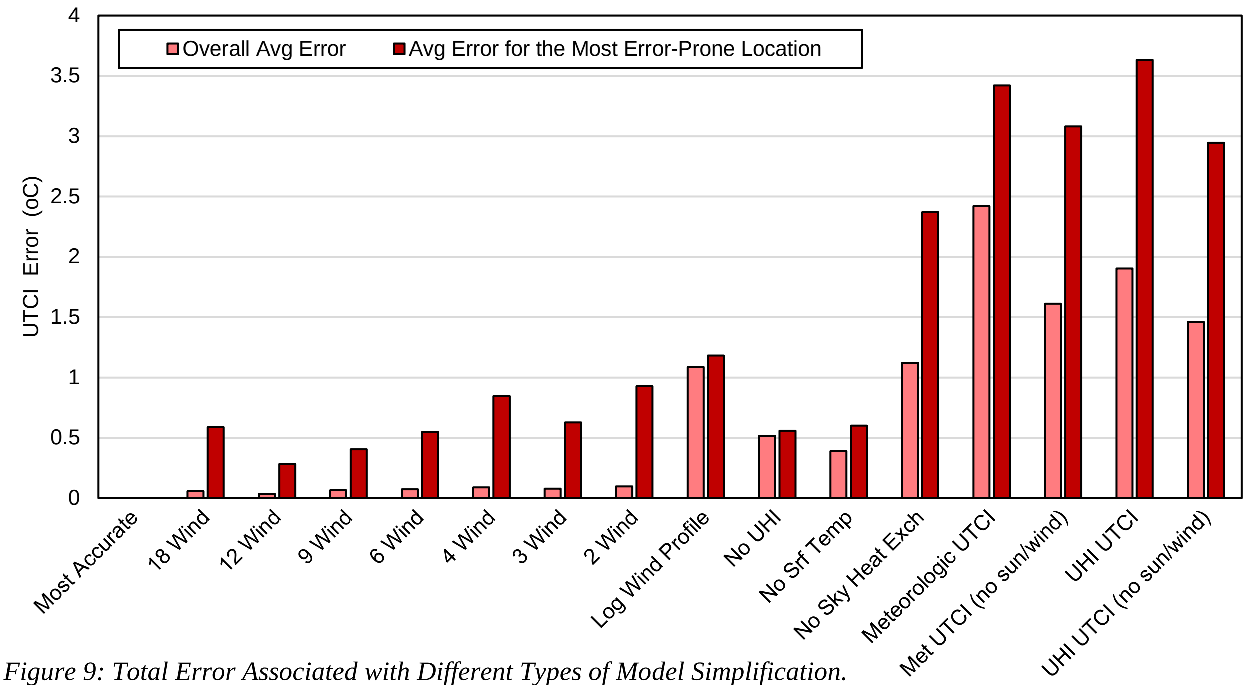

Figure 9: Total Error Associated with Different Types of Model Simplification.

the number of wind directions beyond nine did not consistently create further drops in error but this is likely a result of the peculiarities of the site and the TMY weather conditions of this study. Accordingly, depending on whether a study is intended to depict the general urban microclimate over a large area or is meant to describe specific microclimates on an hourly basis, this paper recommends using either 2 CFD simulations or 9 simulations respectively.

Both the UHI model and the surface temperature model of this study had the smallest effect on the error, each producing a difference of 0.5ºC when substituted with default values. It therefore follows that these two may be suitable candidates for removal from a workflow to generate fast outdoor thermal comfort maps, assuming a given a margin of error. However, it is worth noting that the warping of the TMY weather data to account for the UHI of the site was the fastest modelling process out of the four factors in this study. Taking just a few minutes to set up and 15 minutes to run, the workflow for warping TMY files with the UWG should be considered if only for the accuracy it lends per unit of time invested.

Recommendations for Meteorologists

As noted previously, the error between the single UTCI value given by meteorologists and the diverse conditions of the city can be substantial, on the order of 2.4ºC. Of the three tested alternatives, all proved to be better indicators of the average conditions in the urban site of this study. As such, it is recommended that meteorologists either exclude or minimize the effects of sky heat exchange and wind from the UTCI values reported to the public of a city. The apparent explanation for this is that the buildings, trees and other features of a city decrease the exposure to sun and wind from rural levels. As such, citizens who inhabit urban sites will often experience lower amounts of sky and wind exposure in comparison to the weather stations at airports, which are typically used for such weather reporting.

Additionally, passing recorded weather data through an UHI-modelling engine such as the UWG can increase the accuracy of these values by a noticeable margin. As previously noted, the calculation time of this engine is small and it is therefore recommended that meteorologist make use of such a simple UHI engine when it is relevant.

Limitations and Future Work

While the method for simulating microclimates presented in this study is one of the most comprehensive to date, it is important to note a few critical limitations. Most notable is the fact that it relies on separately validated engines as opposed to one integrated engine. While this separation has enabled the sensitivity analysis of this study, it holds the potential to increase error as data is passed from one engine to the other. Similarly, it means that interactions between these various climate factors may be under-represented. While this study attempted to minimize this shortcoming by setting the outputs of one engine to be the inputs of other engines, this was not always possible. The greatest example of this is that the surface temperatures from the EnergyPlus simulation were not used to inform the 36 CFD simulations. As previously stated, this was done because different hours of the year have different surface temperature patterns and would interfere with the abstraction of 36 CFD results to the full year. However, it is also worth noting that previous studies, which have compared the relative effect of buoyancy and wind-driven flows in the urban environment show that buoyancy does not come to dominate as a driver of airflow until meteorological wind speeds are less than 2 m/s (Magnusson et al., 2014). Given that such low wind speeds do not substantially influence the UTCI comfort model, one might infer that the inclusion of surface temperature in the CFD studies would not greatly alter the results of this study. At the least, one could argue that it would not change the results by any more than the removal of the other variables that this study tested (i.e. the reduction in the number of CFD wind directions, the removal of surface temperature, or the removal of urban heat island).

Needless to say, future research should still include a validation of this method against fully-integrated engines as well as empirically measured climate conditions of the urban environment.

Another limitation of this study is that it has only been run for a single urban site in a tropical climate. While attempts were made broaden its relevance by selecting a site with a number of different urban conditions, there are still a multitude of urban typologies that are under-represented including courtyards and row-house typologies. Future research should test the relevance of this study's findings in colder and/or drier climates. Until such time, caution should be taken in using the conclusions here for other climates and/or different urban typologies.

Conclusion

By analysing a detailed model of an urban site, this study has derived a hierarchy of critical variables for modelling thermal comfort in outdoor spaces. Such variables can now be arranged from most to least significant: sky heat exchange, wind patterns, and UHI/surface temperature. This hierarchy not only highlights the key phenomena that must be addressed for the design of thermally comfortable outdoor environments but also distils a core set of methods for constructing a faster, more accurate, and high-resolution outdoor comfort simulation. Ultimately, such faster simulations can inform both the reports that meteorologists give to the public of a city as well as the design of future outdoor microclimates.

Acknowledgements

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