An ENVI-met Simulation Data Pipeline for Evaluating Urban Tree Patterns Impact on Urban Micro-climate

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Abstract: This paper outlines the design of a data pipeline addressing the impact of urban tree patterns on urban heat islands (UHI) and describes a validation study using seven site(s) in Baltimore, MD, USA. Cities are experiencing an increasing rise in urban microclimate air temperatures due to the urban heat island effect (UHI) and climate change. Previous studies have identified tree canopy cover as a critical resource in reducing UHI. However, research has not disentangled the neighbourhood effects of tree patch size, shape, fragmentation, composition, or leaf area densities, hereafter referred to as urban tree patterns, have on mitigating UHI. The data pipeline outlined here allows researchers to aggregate multiple data sources into ENVI-met for microclimate simulations across various neighbourhoods and output the simulation results into an analytical python processing workflow for statistical analysis in r. Initial validation results show that potential air temperatures are within acceptable limits of field measurements. Correlations show relationships between five urban tree patterns, landscape class metrics: proportion of tree cover, patch density, largest patch index, edge density, landscape shape index, and effective mesh size. However, only two show binomial logistic regression significance: proportion of tree cover and effective mesh size.

Keywords: Urban heat island, micro-climate, ENVI-met, simulation, geospatial

1 Introduction

This paper outlines the design of a data pipeline addressing the impacts of tree planting patterns on urban heat islands (UHI) and describes a validation study using site(s) in Baltimore, MD, USA. UHIs are urban areas where the temperature is approximately one to four degrees Celsius higher than the surrounding areas due to the disruption of ecosystem services by the built environment (STEWART 2011). In urban areas, temperature is a function of several environmental properties: albedo, emissivity, thermal properties of materials, moisture, and the composition and structure of urban canopy (GOWARD 1981). As a result, urban areas have been exposed to extremely high temperatures, creating significant environmental injustices, quality of life, and ecological issues. In response to UHI, energy consumption increases as residents attempt to keep cool, creating a negative energy demand-climate change feedback loop, further exacerbating the urban climate. The increased need for cooling energy and built environment quality also disproportionately affects lower-income communities and communities of colour (DAHL et al. 2019, LIVESLEY et al. 2016). Ecological impacts include but are not limited to disrupted pollinator services due to premature soil warming and microclimatic phenological shifts, and thermal pollution of stormwater runoff (LIVESLEY et al. 2016). Climate change exacerbates UHI conditions due to record-breaking high temperatures, prolonged high heat index seasons, and extreme weather events. These events are not anomalies and are expected to get worse. Indeed, researchers project, using climate change modelling, that Baltimore will increase from approximately five to ten days per year with a heat index of 37.8° C (100° F) to 65 days by the end of the century (DAHL et al. 2019).

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Cities are adopting design and planning guidelines to address the growing UHI issue. Design and planning guidelines range from surface material and albedo changes (e. g., white roofing and increasing pavement reflectivity), shade structures, urban morphology, and increasing urban tree cover. The microclimate modelling literature is still growing, but it supports cities' increasing use of urban tree cover. There is consensus among ecologists, environmental engineers, landscape architects, and planners that vegetation plays a crucial role in reducing UHIs (HERIS et al. 2019). However, most research focuses solely on increasing urban tree cover and offers little guidance on species selection or other spacing and patch patterns of urban trees. Yet, emerging research is beginning to document various tree characteristics that influence the degree to which a tree can mitigate heat, such as tree type, leaf area density, size, and morphology (MORAKINYO et al. 2020). To our knowledge, the neighbourhood tree patterns such as patch size, patch shape, fragmentation, spacing, edge density effects on human comfort have not been explicitly explored.

Focusing on urban tree patterns and heat mitigating process relationships can offer empirical evidence to understand and compare different patterns and configurations of trees for optimal thermal comfort. At metropolitan scales, researchers have explored the use of ecological landscape metrics to explain the link between green spaces, urban vegetation patterns, and land surface temperatures (ASGARIAN et al. 2015, MADANIAN et al. 2018, WENG et al. 2007, ZHAO et al. 2020). However, these studies used coarse resolution data that could not explicitly disentangle trees from general vegetation, green space land use classifications, or the microscale materiality of the urban landscape. A scale of detail that Middel & Krayenhoff (2019) suggest is critical to explaining human heat exposure and comfort. Hence, there is a need for a more nuanced understanding of landscape patterns, urban heat, and thermal comfort to inform tree planting programs. Thus, despite this emerging literature, there are still two gaps that need addressing. First, little theory informs how urban tree planting patterns might mitigate UHI effects, specifically on a human scale. Second, methodologically, researchers have yet to link both land surface temperature and ambient temperatures to urban forest patterns beyond the quantification of shade through the proportion of tree cover (MIRZAEI & HAGHIGHAT 2010).

Currently, there are two simulation approaches used when studying the impacts of vegetation and more generally built environment elements on microclimate at the site (block) scale: (a) experimental designs that use field measurements and (2) computer simulations (MIRZAEI & HAGHIGHAT 2010). Computer simulations offer the capacity to backcast and project future scenario impacts; something field measurement experimental designs cannot feasibly produce. Two simulation model types consist of energy exchange and computational fluid dynamics. SOLWEIG (LINDBERG et al. 2019) and Ladybug Tools (LADYBUG TOOLS LLC 2021) use radiation-based energy exchanges to model UHI. However, they do not incorporate air movements (convection energy fluxes); as a result, they are limited to radiative heat computations. More complex models are based on computational fluid dynamics (CFD) such OpenFOAM (OPENCFD 2021), FLUENT (ANSYS INC 2021), and ENVI-met (ENVI-MET 2021). CFD-based models combine radiative heat and convection energy fluxes and offer a more holistic microclimate simulation approach. Among these, ENVI-met has been widely used in numerical computation of air temperature in the context of the urban built environment. Run ning such models requires considerable computation time and power but eventually generates spatially explicit outputs (LIU et al. 2021).

We chose ENVI-met software for this research because it can simulate climates in urban environments and assess the effects of atmosphere, vegetation, architecture, and materials (ENVI-MET 2021). ENVI-met is a prognostic model based on fluid dynamics and thermodynamics, which can analyse solar, air pollutant dispersion, building physics, and green and blue technologies (ENVI-MET 2021). While ENVI-met has a broader array of ecosystem service assessments and allows for more detailed surface material interaction computations at site scales than UMEP, it is proprietary software that is not seamlessly integrated into an iterative inventory, analysis, design, and impact assessment process. This paper seeks to address this gap by creating and critiquing a data pipeline integrating geospatial data, ENVI-met micro-climate simulations, landscape metrics, and statistical analyses.

2 Methods

2.1 Baltimore, Maryland

We chose Baltimore, Maryland, as the test city because of our prior working relationships. The city is also working to address growing urban heat island inequities in the face of worsening climate change conditions (ROUND, CONNER, ROWLEY & BANISKY 2019). We selected sample sites to represent a range of proportional tree cover and various neighbourhood morphological types (e. g., big-box retail, high- and low-income residential, mixed-use, and institutional land uses). We identified seven simulation sample sites.

2.2 Data Pipeline

The current data pipeline consists of three primary steps: pre-processing, processing, and post-processing. The following sub-section and Figure 1 outline the data pipeline in detail.

Pre-processing consisted of compiling tabular and spatial datasets. Tabular data needed for ENVI-met included soil moisture obtained from the United States Department of Agriculture (2020) and weather, specifically wind, temperature, and humidity from the National Oceanic and Atmospheric Administration (2021). Spatial datasets included trees, surface cover, and buildings. Tree variables necessary for simulation were location, height, and leaf area density (LAD). We compiled initial tree location and height variables from LIDAR data (WOOLPERT 2015) and Baltimore's 1-meter landcover (UNITED STATES ENVIRONMENTAL PROTECTION AGENCY 2017).

Additionally, each tree was assigned an Albero Code in the attribute table to ensure that ENVI-met correctly set the simulation's tree parameters. A LAD literature review and Google Street View (GOOGLE 2020) assisted in categorizing trees' appropriate Albero Codes in ENVI-met. Albero codes connect three-dimensional trees to a database entry containing a trees' morphological characteristics, specifically height, width, leaf area density, and shape.

We also used Baltimore's 1-meter landcover dataset to identify land surface areas: concrete, asphalt, grass, and bare soil. We created building footprint locations and heights from LIDAR and Baltimore's 1-meter land cover data. Due to COVID-19 institutional policies, we were not permitted to go into the field to verify our datasets. However, we triangulated and updated all the datasets, as necessary, using aerial imagery (ESRI 2020) and Google Street View. Data updates included missing buildings and tree locations, and heights. Finally, we ported the final tree, surface cover, and building shapefiles to ENVI-met's Spaces for simulation.

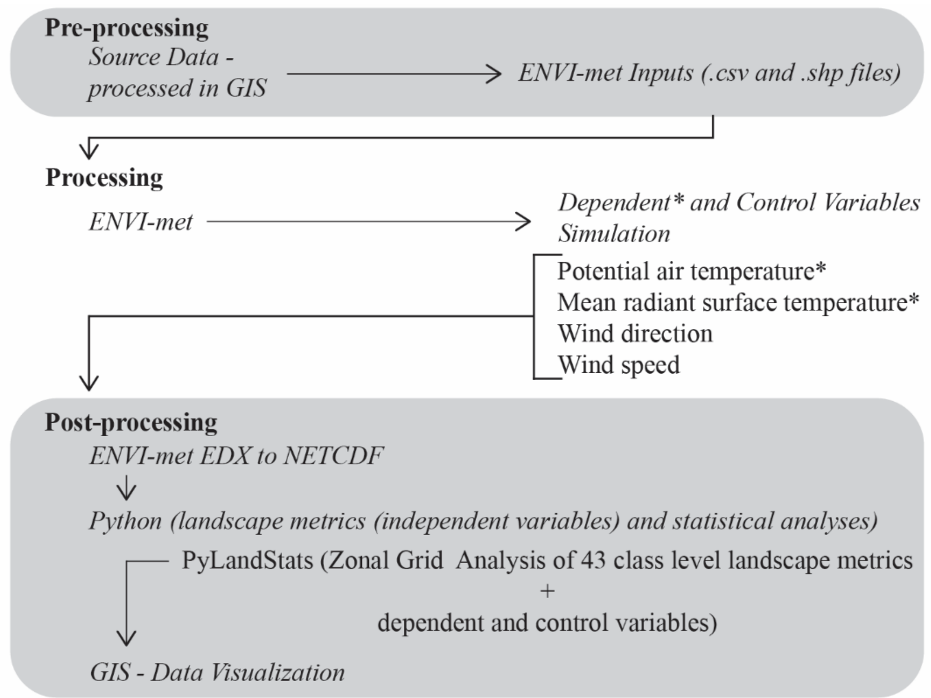

Fig. 1: Overview of the data pipeline processing steps and critical variables

At the start of this project, we used ENVI-met v.4.4.4 for data processing and simulations. However, during this project, ENVI-met v4.4.6 Summer21 was released and provided several advantages. First, the new version allowed the export of a more general-purpose and open file format for post-processing, specifically a Network Common Data Form (NetCDF). Second, increased processing speeds, cutting simulation times in half. Third, ENVI-met adjusted several of their temperature calculation algorithms and plant databases. Due to these advantages, we reran all simulations in version 4.4.6 Summer21. Each sample site's simulation area was 500 x 500 x 50 meters, with two cubic meters spatial resolution.

Simulations were run for July 20, 2020, with a start time of 22:00 on July 19 for a total simulation time of 24 hours. We set ENVI-met to simulate temperatures for every hour or 1-hour time step. We chose this date and time for two reasons. First, July 19th and 20th were among the warmest days in 2020. The air temperature was between 21 °C and 37 °C on July 19 and between 26 °C and 37.5 °C on July 20. Combined with relative humidity, the temperature felt between 29 °C and 42 °C. We chose these days as representatives of extremely high temperatures to see how vegetation can mitigate extreme heat. Second, we decided to use a simulation start time of 22:00 because nighttime has the lowest stored mean radiant temperatures, and the model requires several time steps to stabilize. Model stability ensures that daytime simulated temperatures are reliable and stable. Additional considerations were choosing a cloud-free day with no precipitation. However, the choice of day and time for simulations has critical implications for UHI.

Most importantly, as mentioned previously, UHI is a complex mixture of built environment characteristics (e. g., surface materials and vegetation) and dynamic processes (e. g., wind, humidity, transpiration). As such, our choice of day and the resultant model can not provide insights into the daytime and nighttime or diurnal nature of UHI. Our model results are calibrated for extreme heat days with low wind and stable simulated late afternoon temperatures. We used ENIV-met's advanced settings dialogue options with basic meteorological settings (Table 1). Default settings were used for *Project Features* and *Project Features Expert.* Computing options consisted of *Multi Core.*

Table 1: ENVI-met's basic meteorological settings

Wind uvm	
Wind speed measured in 10 m height (m/s)	2.28
Wind direction (deg.)	247
Roughness length at the measurement site	0.010
Temperature T	
Minimum temperature of the atmosphere	25.10 °C
Maximum temperature of the atmosphere	35.60 °C
Humidity q	
Minimum relative humidity in 2m (%)	42.60
Maximum relative humidity in 2m (%)	84.60

ENVI-met simulation files produce an EDX file format, which was not natively compatible with statistical analysis software at the time of simulations. Hence, ENVI-Met's EDX to NetCDF-converter is necessary to post-process and translate files into a format usable by geospatial and statistical software. The post-processing development environment used was Anaconda v3-2021.05 with Python v3.6.13. This version of Python is crucial, as it is compatible with the PyLandStats v2.3.0 library to compute landscape metrics. PyLandStats was used to calculate a zonal grid analysis for 43 class landscape metrics on the urban tree class using a 50-meter grid cell size. This grid size produced 81 zones per sample site for an n of 567.

2.3 Validation and Statistics

To validate ENVI-met's inputs and outputs, specifically tree leaf area density and median potential input, requires field measurements. However, due to institutional and governmental COVID-19 pandemic travel restrictions and research protocols, we could not validate leaf area density using hemispheric photography (PEPER & MCPHERSON 2003). Likewise, we could not validate temperatures using in-situ Hobo Pro v2 temperature and relative humidity sensors. As a result, we based leaf area densities of trees on the following: 1) a comprehensive literature review of documented, typical leaf area densities by genus and species; 2) ENVI-met model assumptions; and 3) Google Streetview tree assessments. Simulated median potential air temperatures were validated using historical weather station data from Weather Underground.

Binomial logistic regression (blogr) was conducted to explore the relationship between PyLandStats zonal grid class metrics (independent variables) (Table 2) and median potential air temperature (dependent variable). Blogr is applicable because the dependent variable was recoded into the following categories, as outlined in (CHEUNG & JIM 2019), moderate heat stress (29 to 35 °C) and strong heat stress (35 to 41 °C).

Table 2: PyLandStats class metrics

Category	Metric	Definition
Class	proportion	Proportional abundance of a particular class within the landscape
	nu_patches	Number of patches
	p_density	Density of class patches
	l_p_index	Proportion of total landscape comprised by the largest patch
	total_edge	Total edge length
	e_density	Edge length per area unit
	l_s_index	Measure of class aggregation. Provides a standardized measure of edginess
	e_m_size	Measure of aggregation based on the cumulative patch size distribution

3 Discussion

3.1 Data Pipeline

The primary contribution of this research is a data pipeline that integrates technologies currently used within landscape architectural design processes to increase the scale and rapid iteration of microclimatic simulations. ENVI-met fills the gap MIDDEL & KRAYENHOFF (2019) noted when urban microclimate studies over-rely on coarse resolution satellite, remotely sensed mean radiate temperature statistical analyses, but only if we can statistically analyze the simulation outputs. Hence the purpose of increasing the viability of integrating ENVI-met simulation outputs into a more comprehensive analysis framework is twofold. First, ENVI-met's simulations can represent human-scale impacts of microclimate discussed by MIDDEL & KRAYENHOFF (2019). Still, due to intensive hardware requirements and processing times, most use cases have limited simulations beyond the site scale. At the time of initiating this project (2019), ENVI-met's outputs were difficult to post-process into other statistical frameworks necessary to generalize and draw inferences about broader scale neighbourhood and metropolitan microclimate impacts of vegetations, materials, and morphology. As a result it is currently computationally expensive to iteratively simulate design impacts across multiple scenarios or large neighborhoods. Hence, the need for developing processes to statistically link built environment, vegetation, and other factors with UHI. Creating a process that creates links between urban tree patterns and UHI can facilitate a deeper understanding of urban vegetation design impact explorations earlier in the design process. To further expand beyond the limitations of chosing single day heat event simulations requires translating ENVI-met outputs into a framework that allows for many statistical and comparative analyses and graphic visualizations.

Despite the pipeline's advances in easing the transition between pre-processing, processing, post-processing, and statistical modelling; the process is still technically challenging, labour intensive, and computationally expensive for larger-scale simulations and cross-site comparisons. For context, pre-processing averaged 40 hours using the current pipeline, processing averaged 144 hours, and post-processing averaged 20 hours per sample site. Upon reflecting, we suggest two ways to improve the data pipeline. First, researchers should explore the use of imagery, lidar, and machine learning to collect individual tree locations and leaf area densities, as this is one of the most time-consuming portions of data collection and impacts simulation validity. Second, ENVI-met can now interface with Rhino and automatically output NetCDF, potentially streamlining the pre-processing and exporting processes. Finally, future research should compare the outputs of energy exchange and computational fluid dynamics heat simulations to determine an appropriate scale at which they are most valid for design impact assessment. Such research should balance accuracy and precision input and output requirements for more fluid design simulation iteration.

3.2 Validation and Statistics

The second outcome of this project validated the use of Weather Underground stations, in place of research in-situ measurements. Four Weather Underground stations were within proximity to the seven sample sites. We used GIS to identify the geographic nearest simulated temperature and present the results in Table 3. While in-situ temperature validation is preferred, Weather Underground weather stations demonstrate simulated temperatures are within a reasonable margin. Minimum, maximum, and mean temperature differences are as follows: 0.52, 2.64, and 1.85, respectively. These margins demonstrate that Weather Underground can be reliabily used for rapid assessments, when longer-term in-situ measurements are not possible; however, they are limitations that need to be considered.First, more than one station is needed. The use of single stations can potentially introduce instrument measurement errors. Second, collecting reliable air temperatures requires placing sensors in uniform conditions; however, it is currently impossible to validate Weather Underground users' placements.

Table 3: Potential air temperature validation

Weather Underground Station ID	Actual Temperature	Nearest Simulated Temperature	Difference
KMDBALTI122	38.06 °C	35.82 °C	2.24
KMDBALTI35	36.72 °C	36.20 °C	0.52
KMDBALTI61	37.22 °C	35.22 °C	2
KMDBALTI223	37.39 °C	34.75 °C	2.64

For example, one user could place their weather station in the shade above the grass, while another user could place their station in full sun over asphalt. Second, there are significant gaps in the station network, often in lower-income neighbourhoods, correlated with higher temperatures and less tree cover, potentially biasing cooler ambient temperatures.

Table 4 describes each sample site's summary temperature ranges. Notably, there were no significant differences in simulated temperatures between sites with the largest difference in median temperature of 0.6 °C. The combined sample site simulated minimum, maximum, and median temperatures of 34.5, 35.16, and 36.10. Table 5 outlines the remaining variable descriptive statistics. Simulated air temperature correlates with total_area, proportion, total_edge, e_density, and e_m_size (Figure 2), while all other variables exhibit no statistically significant correlations. However, several variables showed correlations with each other; as a result, we removed the following variables from the logistic regression model: total_area, nu_patches, and total_edge.

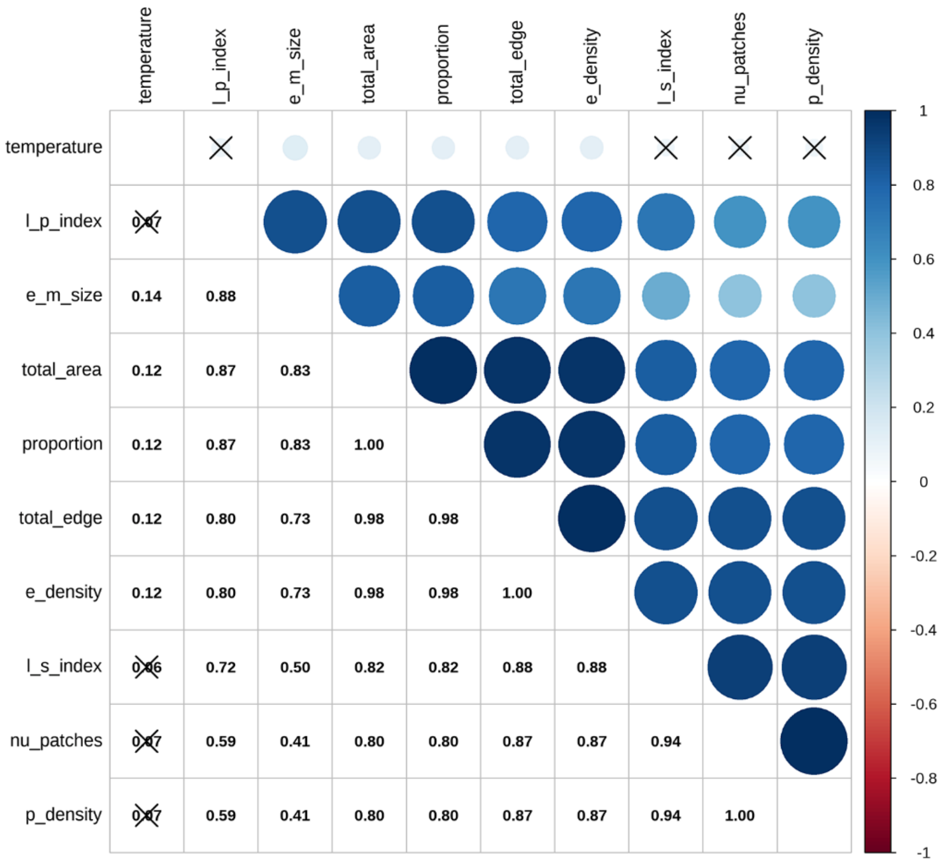

Fig. 2: Correlation plot, non-significant variables are noted with an X, while all other variables have a $p< 0.05$

Table 4: Summary of potential air temperature descriptive statistics per sample site

Sample Site	Min	Max	Median
1	34.9 °C	36.0 °C	35.4 °C
002a	34.9 °C	36.1 °C	35.3 °C
002b	34.9 °C	36.0 °C	35.4 °C
002c	34.5 °C	35.8 °C	35.0 °C
002d	34.7 °C	36.1 °C	35.1 °C
3	34.6 °C	36.0 °C	35.1 °C
4	34.5 °C	35.2 °C	34.8 °C

Table 5: Summary descriptive statistics of all variables across all sample sites

Variables	Min	Median	Max
Dependent variable			
temperature	34.50	35.16	36.10
Independent variables (urban tree patterns)			
total_area	0.00	0.00	0.05
proportion	0.00	0.32	21.92
nu_patches	0.00	1.00	14.00
p_density	0.00	400.00	5,600.00
l_p_index	0.00	0.16	10.56
total_edge	0.00	10.00	484.00
e_density	0.00	40.00	1,936.00
l_s_index	0.00	1.00	5.91
e_m_size	0.00	0.00	0.00

Table 6 reports the binomial logistic regression results. Zonal grids with each unit of increase in the proportion of tree cover decrease the log odds of being classified as strong heat stress by 1.14. This finding supports previous research suggesting that higher amounts of tree canopy reduce ambient air temperatures and can reduce extreme heat. Additionally, each unit of increase in the measure of aggregation based on the cumulative patch size distribution increases the log odds of strong heat stress by 11,430.

While the statistical results confirmed previous research, they did not produce additional insights into urban tree patterns or landscape metrics' effects on potential air temperature. Despite these results, we suggest further exploration is needed. First, additional sample sites are necessary to ensure a broader heterogeneity in landscape metrics. Second, we recommend exploring various zonal grid sizes when computing landscape metrics as aggregation scales can dramatically impact landscape metric outcomes. Future research should use a variety of zonal sizes to test variable sensitivity to these measures.

Table 6: Results of binary logistic regression modelling likelihood of class landscape metrics predicting strong heat stress (35 to 41 °C).

Independent Variable	Log odds
proportion	**-1.140000 (p< 0.001)**
p_density	0.00018
l_p_index	-0.51640
e_density	0.005339
l_s_index	0.3396
e_m_size	**11,430 (p<0.05)**

4 Conclusion

The data pipeline outlined here allows researchers to aggregate multiple data sources into ENVI-met for microclimate simulations across various neighbourhoods and output the simulation results into an analytical python processing workflow for statistical analysis. The process outlined also demonstrated that UHI researchers and designers can use Weather Underground to validate ENVI-met simulations. Additionally, this workflow expands the possibility of using ENVI-met simulations in a more expansive and statistically supported design framework. Future efforts will refine creating and inputting high-resolution land cover and three-dimensional vegetation and building datasets and integrate rule-based tree cover scenario modelling. Supporting rule-based tree cover scenario modelling will close the loop on an iterative inventory, analysis, design, and impact assessment process, better allowing designers to simulate future impacts of each design scenario in mitigating extreme urban microclimates. Statistically, this process confirms previous research efforts to assess the impact of tree cover on air temperature; however, further work is needed to provide more detailed urban tree patterns, which lead to specific landscape metric design recommendations.

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