Virginia Modeling, Analysis and Simulation Center
Old Dominion University
1030 University Blvd.
Suffolk, VA 23435
Phone: 757-638-7005; Fax: 757-686-6214
Email: vzamponi@odu.edu

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This paper, "Using Agent-Based Modeling to Understand and Assess Demographic (In)Equity of Extreme Heat Exposure In Norfolk, VA Due To Lack Of Tree Canopies", is a non-peer-reviewed preprint that has been submitted to the journal *Ecological Modeling* for possible publication.

Thank you,

Virginia Zamponi:	vzamponi@odu.edu	VMASC
Kevin O'Brien:	kobrien@odu.edu	VMASC
Erik Jensen:	ejjensen@odu.edu	CMSE
Brandon Feldhaus	bfeldhau@odu.edu	VMASC
Russell Moore	r1moore@odu.edu	VMASC
Christopher J. Lynch	cjlynch@odu.edu	VMASC
Ross Gore	rgore@odu.edu	VMASC

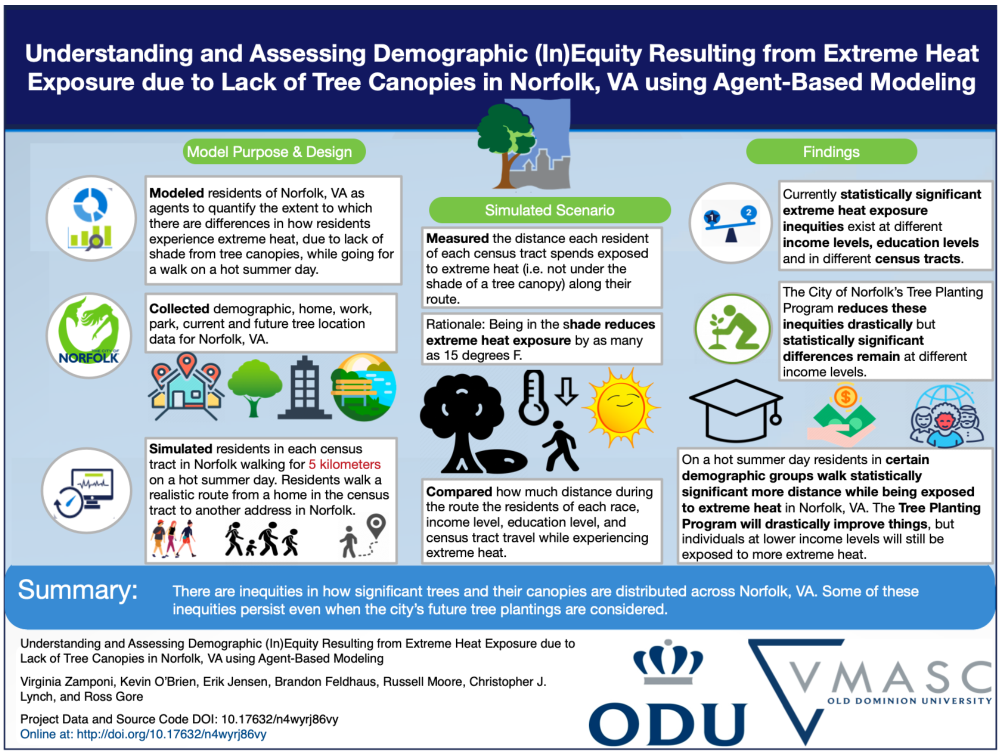
Old Dominion University
Virginia Modeling Analysis and Simulation Center (VMASC),
1030 University Blvd, Suffolk, Va 23435, USA

Old Dominion University
Computational Modeling and Simulation Engineering (CMSE),
5115 Hampton Blvd, Norfolk, Va 23539, USA

Graphical Abstract

Understanding and Assessing Demographic (In)Equity Resulting from Extreme Heat Exposure due to Lack of Tree Canopies in Norfolk, VA using Agent-Based Modeling

Virginia Zamponi, Kevin O'Brien, Erik Jensen, Brandon Feldhaus, Russell Moore, Christopher J. Lynch, Ross Gore



Highlights

Understanding and Assessing Demographic (In)Equity Resulting from Extreme Heat Exposure due to Lack of Tree Canopies in Norfolk, VA using Agent-Based Modeling

Virginia Zamponi, Kevin O'Brien, Erik Jensen, Brandon Feldhaus, Russell Moore, Christopher J. Lynch, Ross Gore

- Constructs a demographically representative 1 (agent): 1 (person) agent-based model to understand the extent to which within Norfolk, VA different demographics of residents are (in)equitably shaded from extreme heat conditions during a ≈ 5 kilometer walk on a clear summer day.

- Quantifies at a fine-grained demographic-level that tree canopies are inequitably distributed across Norfolk, VA. Results show that inequities exist across income levels, education levels, and at the census tract level within Norfolk.

- Evaluates how effective the City of Norfolk's Tree Planting Program will be in addressing these inequities once planted trees become mature. While the plan reduces every identified inequity, residents with lower income levels in the city still experience statistically significantly longer distances traveled while exposed to extreme heat.

Understanding and Assessing Demographic (In)Equity Resulting from Extreme Heat Exposure due to Lack of Tree Canopies in Norfolk, VA using Agent-Based Modeling

Virginia Zamponi[a], Kevin O'Brien[a], Erik Jensen[b], Brandon Feldhaus[a], Russell Moore[a], Christopher J. Lynch[a], Ross Gore[a]

[a] *Virginia Modeling, Analysis, and Simulation Center, Old Dominion University, 1030 University Blvd, Suffolk, 23435, Virginia, United States of America*
[b] *Computational Modeling and Simulation Engineering, Old Dominion University, 5115 Hampton Blvd, Norfolk, 23539, Virginia, United States of America*

Abstract

Prolonged exposure to extreme heat can result in illness and death. In urban areas of dense concentrations of pavement, buildings, and other surfaces that absorb and retain heat, extreme heat conditions can arise regularly and create harmful environmental exposures for residents daily during certain parts of the year. Tree canopies provide shade and help to cool the environment, making mature trees with large canopies a simple and effective way to reduce urban heat. We develop a demographically representative 1 (agent): 1 (person) agent-based model to understand the extent to which different demographics of residents in Norfolk, VA are equitably shaded from extreme heat conditions during a walk on a clear summer day. We use the model to assess the extent to which the city's Tree Planting Plan will be effective in remediating any existing inequities. Our results show that inequitable conditions exist for residents (1) at different education levels, (2) at different income levels and, (3) living in different census tracts. Norfolk's Tree Planting Program effectively reduces the distance residents of all demographics walk in extreme heat. However, residents of the city at lower income levels still experience statistically significantly more extreme heat exposure due to a lack of tree canopies in summer months than those at higher income levels.

Keywords: agent-based modeling, urban planning, public health, extreme heat exposure, tree canopy, health inequities

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1. Introduction

Urban areas have dense concentrations of pavement, buildings, and other surfaces that absorb and retain heat. These conditions, particularly during the summer months, can lead to daily occurrences of extreme heat conditions and result in daily harmful environmental exposure for residents [1, 2]. Prolonged exposure to extreme heat can result in illness and death [3, 4, 5]. In the 2010s, an estimated 12,000 (95% CI 7,400 – 16,500) annual premature heat-related deaths occurred across the United States [6]. In a study conducted from 2014 to 2018 of US Army soldiers on heat stroke and heat exhaustion, the costs of direct care resulting from heat conditions was 7.3 million dollars or an average of 559 dollars per encounter [7]. Extreme heat conditions are expected to continue increasing in frequency into the future [3]. At the same time, approximately 36 million trees are disappearing from United States' urban areas annually with a corresponding estimated annual loss of 96 million dollars USD in corresponding health benefits [8]. These factors serve to further compound and exacerbate contributors to health inequities for extreme heat exposure.

Trees and their resulting canopies provide shade which can help cool the environment, making mature trees with large canopies a simple and effective way to reduce urban heat [9, 10, 11, 12, 13]. Increased tree and vegetation cover have been found to reduce the negative health effects of extreme heat and to help reduce the risks of heat-related morbidity and mortality in outdoor spaces while improving actual and perceived levels of thermal comfort [14]. Tree planting strategies can mitigate the effects of pollution, pollen, heat index, and heat related ailments [15]. Studies on pollution removal strategies for ecosystem services showed an expected 4.3 to 6.2 million dollar per year gain in benefits from differing tree placement strategies in Baltimore, Maryland [15] and in mega-cities the estimated benefits of converting tree cover area to tree canopy is 1 billion per year [16].

We explore health inequities based on the prevalence of extreme heat exposure within demographic subgroups of the city's population compared with the other demographic subgroups [17, 18]. A systematic literature search and meta-analysis of forest cover and income found evidence of income-based inequity in urban forest cover [19]. A study of US urban areas also found that low-income areas were 15.2% less tree covered and 1.5 degrees Celsius hotter than high-income areas on average [20].

Our objective is to understand the extent to which the cooling provided by the shade of tree canopies is (in)equitably distributed across a variety of demographics in Norfolk, VA. To conduct our assessment we use an agent-based model of Norfolk which can produce a demographically representative 1 (agent): 1 (person) representation of the city. The model simulates each resident of Norfolk, VA walking $\approx$ five kilometer in extreme heat on a clear, summer day between their residence and another location in the city (i.e. another residence, business, recreation center, etc.). We quantify the amount of distance during the walk that individuals of each race, income level, education level, and census tract are exposed to extreme heat conditions due to a lack of tree canopy shade. Analysis of quantified results enable us to test for statistically significant inequities across the identified demographics. Our results show the extent to which: (1) the extreme heat is inequitable for certain demographics given the current significant trees in the city and (2) the extent to which those inequities will be reduced by the City of Norfolk's proposed Tree Planting Program.

Next, we provide necessary background material to understand the importance of identifying and addressing extreme heat exposure inequities and why taking a geographic and demographic specific approach is paramount. Then, we provide an overview of the representative agents within our model of Norfolk, VA, their walking paths, the locations of trees, and the dimensions of the trees' canopies. Finally, we present our results, summarize the findings, and discuss the limitations of our work.

2. Background and Related Work

2.1. Climate Change

Climate change is expected to increase heat exposure risk, as a non-linear function of temperature [21]. Heat exposure will increase significantly by 2030 and aggressive action is needed to mitigate future risk [22, 23]. As a result researchers have explored adding tree cover to urban area. Thom et al. worked to measure and validate the mitigating effects of the simulated trees on the real environment [24]. Similarly, Lachapelle et al. extended an existing computational model to demonstrate that shade-trees can reduce daytime temperature on sidewalks by almost 20°C [25]. Furthermore, Ziter, et al. found that urban temperatures experienced by residents decrease as a non-linear function of percent canopy cover [26]. Finally, Schwaab et al. analyzed satellite land-surface temperature (LST) and land-cover data for 293 European cities to show that urban areas with trees have LSTs on average 4-8°K lower than urban areas without trees [27].

2.2. Connection Between Wealth and Biodiversity Inequity

Researchers have identified a correlation between wealth inequality and tree canopy coverage and biodiversity inequity [28, 29, 30] and that the correlation between the two is growing stronger in more recent years [31]. In part this is due to the effects of *redlining*. The US Federal Home Loan Bank Board established the practice of redlining in the 1930s with the development of four real-estate investment classes, ranging in descending order of desirability from green to red. The practice of *redlining*, drawing the boundaries around the red class of properties, resulted in a set of policies that discriminated against people of color in mortgage lending. These policies, in part, created racially segregated and disparate neighborhoods [32] with significantly less tree cover and higher land surface temperatures in *redlined* zones than green zones [33].

2.3. Health Benefits of Biodiversity

Understanding health benefits of biodiversity is paramount as research has shown that temperature decreases caused by tree canopies can statistically significantly decrease the number of deaths and doctor visits in an urban area, especially for those age 65 or greater [12, 34]. Additional health and lifestyle improvements including high levels of physical exercise, mental well-being, and perceived safety have been linked at a fine-grained geographic level to extent of tree canopy coverage [35, 36, 37, 38]. Furthermore, Li et al. found that hospitals in redlined zones have more heat-related outpatient visits and high inpatient admission rates [39].

2.4. Agent-based Simulation of Tree Canopies

Despite all of this work there have not been many efforts to simulate the effects of tree canopies on individuals in an urban area. The study that most closely matches our effort was performed by Khan et al. In their work they use an urban micro-climate thermal modeling and a thermal comfort model, within an agent-based model, to determine how agents in a Chicago move throughout the city [40]. Our work furthers their effort by implementing ABM analysis at a more fine-grained geographic level with a focus on how different demographics are inequitably exposed to extreme heat.

3. Methods

3.1. Ethical Considerations

Our work uses publicly-available data related to addresses in Norfolk, VA, trees, and resident demographics. The data sets reflect aggregate variables measured at the demographic-levels of a city and do not contain any personally identifiable information. Therefore, they do not involve human subjects as defined by federal regulations and their use does not require ethics board review or approval [41]. Additionally, as presented in the next section, all of the data and code for our work is made publicly available to facilitate transparency and reproducibility of our study.

3.2. Publicly Available Data

3.2.1. Overview

Our approach to understanding and assessing demographic (in)equity of extreme heat exposure during a walk on a clear summer day in Norfolk, VA due to lack of tree canopies uses data from (1) the American Communities Survey (ACS) for census tract boundaries and demographic variables [42, 43]; (2) the Norfolk Master Gardeners for existing trees' types, canopies, and locations that they have classified as significant [44]; (3) the City of Norfolk's Tree Planting Program [45] for the locations and types of planned trees into the future; and (4) the City of Norfolk for the location of residences, businesses, and recreation centers within the city [46]. All the data sets, source code, and other supplementary materials are supplied in the appendices of this paper. A visual overview of our approach and these appendices is shown in Figure 1. The data is also available in our Mendeley Data repository online [47].

3.2.2. American Communities Survey (ACS)

Census tracts are small, contiguous, and relatively permanent statistical subdivisions of a county or an equivalent entity. The populations in census tracts vary from 1200 to 8000. Census tracts provide a stable geographic unit for statistical analysis in the US Census and ACS [43].

The ACS is an ongoing national survey that samples a subset of individuals within the same geographic areas in the US Census. Using the same questions, data were collected each month throughout the year. In contrast, the US Census provides a more comprehensive sample of individuals

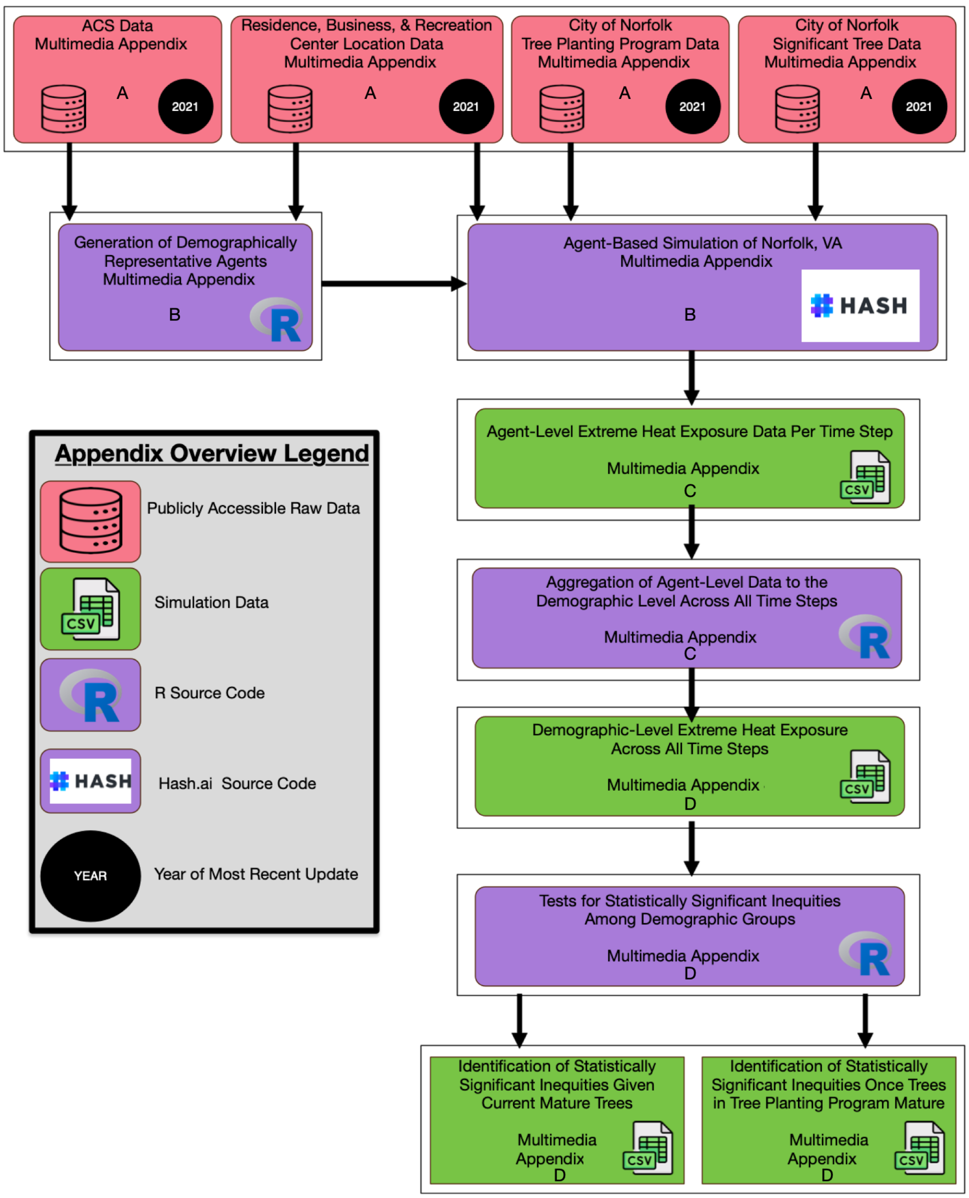

Figure 1: An overview of the datasets and other supplementary materials supplied in the appendices. ACS: American Communities Survey; CSV: Comma Separated Values.

in the United States, collecting data from more individuals during a particular period (March to August) but administered only once every 10 years. A metaphor helps elucidate the differences between the two surveys. The US Census serves as a high-resolution photograph of the US population once every 10 years, whereas the ACS serves as many low-resolution continually updated videos over the same period [43]. Appendix A.1 provides the data included within the ACS for this study.

3.2.3. Address Information Resource

The Address Information Resource is a compilation of active and pending addresses in the City of Norfolk. It provides a consolidated source to allow for quick and easy access to information about an address including details related to residences, businesses, recreation centers, school districts, municipal services, planning, public safety, civic leadership. The data is updated annually [46]. Appendix A.2 provides the address information data included in this study.

3.2.4. Current Significant Trees

The data collected about the significant trees in Norfolk, VA is gathered by volunteers with the Norfolk Master Gardener Association and provided to the city' Parks and Forestry Operations [48]. The diameter, height, canopy spread, general location and species of the tree is included for each tree in the data set. The data is updated every five years [44]. Appendix A.3 provides the current significant tree data included in this study.

3.2.5. Tree Planting Program

The City of Norfolk tracks each tree planted along city streets, within city parks, and on other city properties every year since 2018. For each entry in this data set the species, planting date, geographic location and estimated canopy is provided. City staff utilizes Microsoft excel to track tree planting information. The data is updated annually [45]. Appendix A.4 provides the tree planting program data included in this study.

3.3. Agent-based Model

We utilized the data described in the previous sections to construct a demographically representative agent-based model. Th model has the ability to provide one-to-one correspondence between residents and simulated agents, maintaining empirical connections to the real-world data, and also maintaining the spatial assumptions of the environment [49, 50]. This model is applied to understand the extent to which different demographics of residents are equitably shaded from extreme heat conditions during a *approx* five kilometer walk on a clear summer day in Norfolk, VA.

3.3.1. Iterative Proportional Fitting (IPF)

Our model leverages established demographic practices to generate representative agents at the census tract-level for the city of Norfolk, VA. We apply Iterative Proportional Fitting (IPF) [51, 52] to estimate joint probability distributions of demographics for each census tract, which we later sample when generating agents in our model [53, 54, 55, 56]. IPF is applied to the data from the from the 2021 ACS. For each census tract in Norfolk, VA, we assign the income level and education level of an individual by sampling from two derived distinct joint probability distributions using IPF. Our application of IPF that the values for every demographics group included in the analysis is positive (i.e. > 0). An overview of the application of IPF to estimate the joint distribution of two demographics within a census tract from the ACS is shown in Figure 2. It proceeds as follows. First, the levels associated with each of the two demographics form a two-dimensional matrix. In our example, the four groups associated with one demographic form the rows of the matrix and the three groups associated with another demographic for the columns.

Along the exterior of the matrix are marginal values (highlighted in red) for each demographic group. The initial marginal values for each demographic group are taken from the values provided in the ACS. Next, the initial interior values (highlighted in black) of the matrix are determined. These values are chosen such that the total sum of the interior rows equals the total sum of the interior columns. The IPF initialization matrix for two demographic attributes is shown in the left hand side of Figure 2. The exterior values are assigned from the sample data, and the total of all four interior rows is 96 (15+28+28+25) which is the same as the total of all three interior columns (26+40+30). [51, 52].

Next, we will show how iterations of IPF yield the joint probability estimate on the right hand side of Figure 2. Each iteration of IPF consists of a row adjustment and a column adjustment to the matrix. These adjustments fit the sum of the matrix values across columns and rows such that the values converge to the marginal distribution values from the data. During a row adjustment, each row of cells is proportionally adjusted to equal the marginal

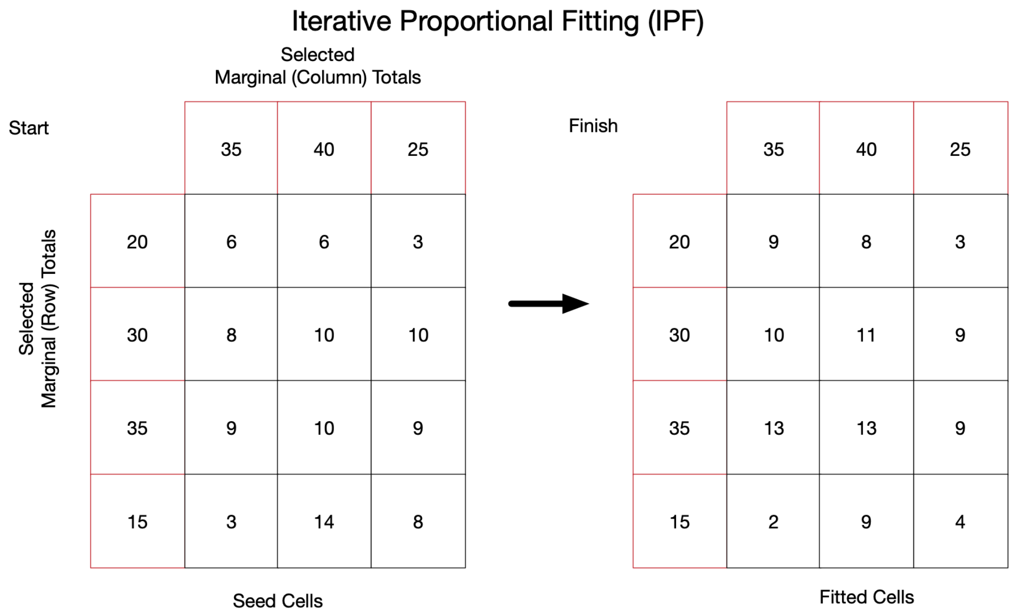

Figure 2: Start and finish state of an example of using Iterative Proportional Fitting to estimate a joint probability distribution.

row total. Specifically, each cell within a row is divided by the actual sum of the row of cells, then multiplied by the marginal row total. This process is shown on the left-hand side of Figure 3. During a column adjustment within an iteration each column of already row-adjusted cells is proportionally adjusted to equal the marginal column totals. Specifically, each cell within a column is divided by the actual sum of the column of cells, then multiplied by the marginal column total. This process is shown in the right hand side of Figure 3.

Iterations adjustments continue until the values in the matrix converge to the marginal totals. Once the process is complete any decimal values within a cell are rounded up or down and the joint probability distribution is specified as shown on the right hand side of Figure 2.

Iteration #1

Row Adjustment (Selected Marginal (Column) Totals across; Selected Marginal (Row) Totals down)

Selected Marginal (Row) Totals	29.62	39.61	30.76
20	8.00	8.00	4.00
30	8.57	10.71	10.71
35	11.25	12.50	11.25
15	1.80	8.40	4.80

→

Column Adjustment

Selected Marginal (Row) Totals	35	40	25
20.78	9.45	8.08	3.25
29.65	10.13	10.82	8.71
35.06	13.29	12.62	9.14
14.51	2.13	8.48	3.90

Iteration #2

Row Adjustment

Selected Marginal (Row) Totals	34.81	40.09	25.10
20	9.10	7.77	3.13
30	10.25	10.95	8.81
35	13.27	12.60	9.13
15	2.20	8.77	4.03

→

Column Adjustment

Selected Marginal (Row) Totals	35	40	25
20.02	9.15	7.76	3.12
30.00	10.30	10.92	8.77
35.01	13.34	12.57	9.09
14.98	2.21	8.75	4.02

Iteration #3

Row Adjustment

Selected Marginal (Row) Totals	34.99	40.00	25.00
20	9.14	7.75	3.11
30	10.30	10.92	8.78
35	13.34	12.57	9.09
15	2.21	8.76	4.02

→

Column Adjustment

Selected Marginal (Row) Totals	35	40	25
20.00	9.14	7.75	3.11
30.00	10.30	10.92	8.77
35.00	13.34	12.57	9.09
15.00	2.21	8.76	4.02

Figure 3: Iterations within an example of using Iterative Proportional Fitting to estimate a joint probability distribution.

3.3.2. Generating Representative Agents

We apply IPF to derive two joint probability distributions for each census tract. These are the joint probability distribution of: (1) race and education level, and (2) education level and income level. Once these two distributions are estimated we can sample them to generate representative agent residents for each census tract in Norfolk, VA using the process shown in Figure 5.

Figure 5 shows that the first step of agent is to sample a distribution of all residents in Norfolk, VA to identify the census tract of an agent. In the second step, the data from the ACS specific to the agent's census tract is sampled to determine the race of the agent. Next, the joint race/education level probability distribution for the census tract is sampled to determine the education level given the agent's race. Finally, the income level of the agent is determined by sampling the joint education level / income level probability distribution.

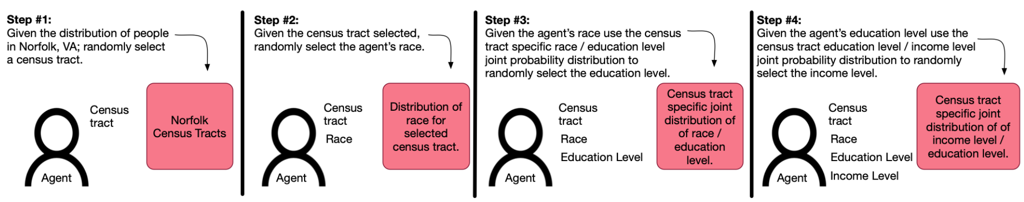

Figure 4: The step by step process of generating representative agents within our model.

Each generated agent is also assigned a home location and a destination location. The home location reflects the latitude and longitude of an address in the census tract that the agent resides. The home address is determined by sampling the addresses listed in Address Information Resource that are within the bounding box of the agent's census tract. The destination location is an address in the City of Norfolk. The destination location is determined by sampling the addresses listed in Address Information Resource.

Once a home and destination location are assigned a route of latitude and longitude points from the home to the destination and from the destination to the home is generated for the agent. The route reflects the shortest time estimated path between the two locations using road and walking paths within the City of Norfolk. The average length between consecutive points in a route is *approx* 250 meters [57].

3.3.3. Placement of Trees and Tree Canopies

Once all agent's have been generated trees and their canopies are placed on the simulation landscape. Each tree listed in the Significant Trees data set is placed on the simulation landscape with an of shade equal to its canopy spread. The shade region of a tree reflects the circumference distance around each tree that keeps agent's from being exposed to extreme heat.

The model can also be initialized with the trees included in the City's Tree Planting Program. In this scenario, all trees in the Tree Planting Program are added to the model landscape with an associated canopy spread based on the estimate supplied by the city.

3.3.4. Agent Decision Diagram

Recall, the goal of the simulation is to understand the extent to which different demographics of residents in Norfolk, VA are equitably shaded by trees from extreme heat conditions during the middle of a clear summer day while walking in the city. To this end, during the course of the simulation each agent walks between their home and their destination repeatedly for 200 time steps. Between each time step, each agent travels $\approx$ 250 meters resulting in a walk that is $\approx$ five kilometers long. We assume that agents take the shortest distance path between consecutive latitude and longitude points in their route. It should be noted that even though each agent has a destination, their walk is only complete when the 200 times steps have passed. In other words agent's can travel back and forth several times between their home and their destination during the run of the simulation. This design decision is made to ensure the length of agent's walks in the city are as equal as possible. The limitations imposed by this design decision, and others, are discussed in Section 4.4.

At each time step an agent follows the decision diagram specified in Figure 5. Figure 5 shows that at the beginning of a time step an agent calculates the amount of distance they traveled while they were exposed to extreme heat during the previous time step. An agent is exposed to extreme heat during their walk if their path does take them under the shade of a tree canopy. This implementation decision reflects the assumption that the agent's walk occurs in the middle of a hot, clear summer day. The shade of a tree can reduce the temperature 10-15 degrees Fahrenheit in this scenario which is a sufficient reduction to avoid extreme heat exposure. Recall, limitations imposed by our design decisions, including this one, are discussed in Section 4.4.

Next, Figure 5 shows the check the agent performs to determine if they are at their home location. If the agent is at home, then they set their walking route to be from their home to their destination. Next, the agent checks if they are at their destination. If if they are at their destination, then they set their route to be from their destination to their home. Finally, the agents moves to the next latitude, longitude location on their route. Once 200 time steps in the simulation have passed the model run is complete. Recall, 200 time steps is the time required for each agent to walk ≈ five kilometers.

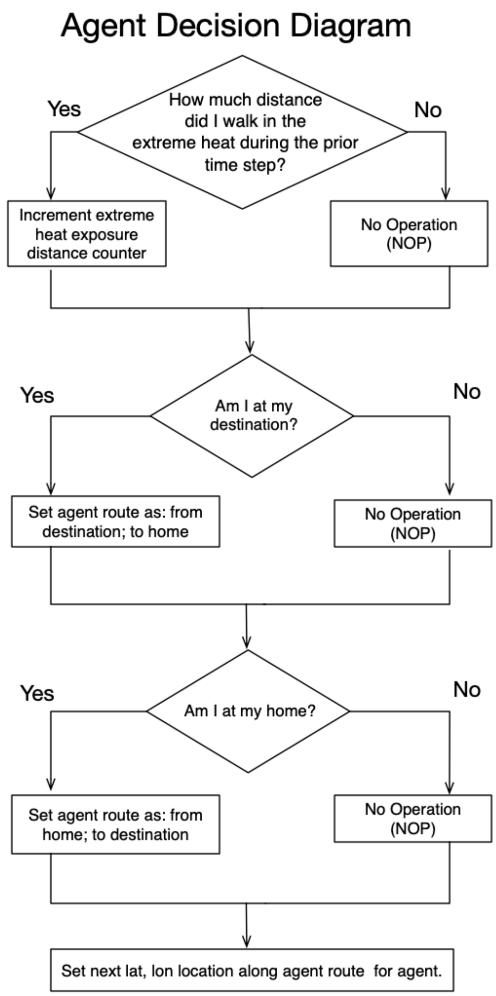

Figure 5: Decision diagram for agents, for each time step.

4. Evaluation

4.1. Research Question and Measures

Our research question is: *to what extent do trees and their canopies equitably reduce extreme heat exposure to residents of different demographic groups in Norfolk, VA*. The model output needed to address our research question is: *the distance agents travel during their walk while they are exposed extreme heat (i.e. not under the shade area of a tree)*. We compute this distance for the following resident demographics: (1) race, (2) education level, (3) income level, and (4) census tract of residence.

In the remainder of this section we explore the extent to which there are statistically significant differences, in terms of distance traveled while exposed to extreme heat, among different agent demographics. Then, we explore to what extent the Tree Planting Program currently in place by the City of Norfolk addresses any statistically significant differences. Recall, the Tree Planting Program reflects each tree planted along city streets, within city parks, and on other city properties for every year since 2018. While these trees are not yet mature, our goal is to explore the effects they will have on extreme heat exposure inequities among resident demographics, once they become mature trees. A statistically significant difference is determined by applying a two-sample, one-tailed t-test to determine if the demographic group with the highest mean extreme heat exposure (i.e. average for the maximally exposed group) is statistically significantly greater than the group with the lowest mean extreme heat exposure (i.e. average for the minimally exposed group) [58]. If the test shows a statistically significant difference between these two groups then we conclude there is an demographic inequity with respect to extreme heat exposure between the two groups.

4.2. Results

Figures 6-9 and tables 1-2 shows the results of our evaluation. Each figure elucidates the distribution of distances walked while being exposed to extreme heat for the minimally and maximally exposed group for each demographic. The left hand side of each figure, labelled **A**, shows the distribution of the two groups for each demographic given the current significant trees in Norfolk, VA. The right hand side of each figure, labelled **B**, shows the distribution of the two groups for each demographic once all trees in the city's Tree Planting Program have matured. The distribution for the minimally and maximally exposed groups for the race demographic is shown in Figure

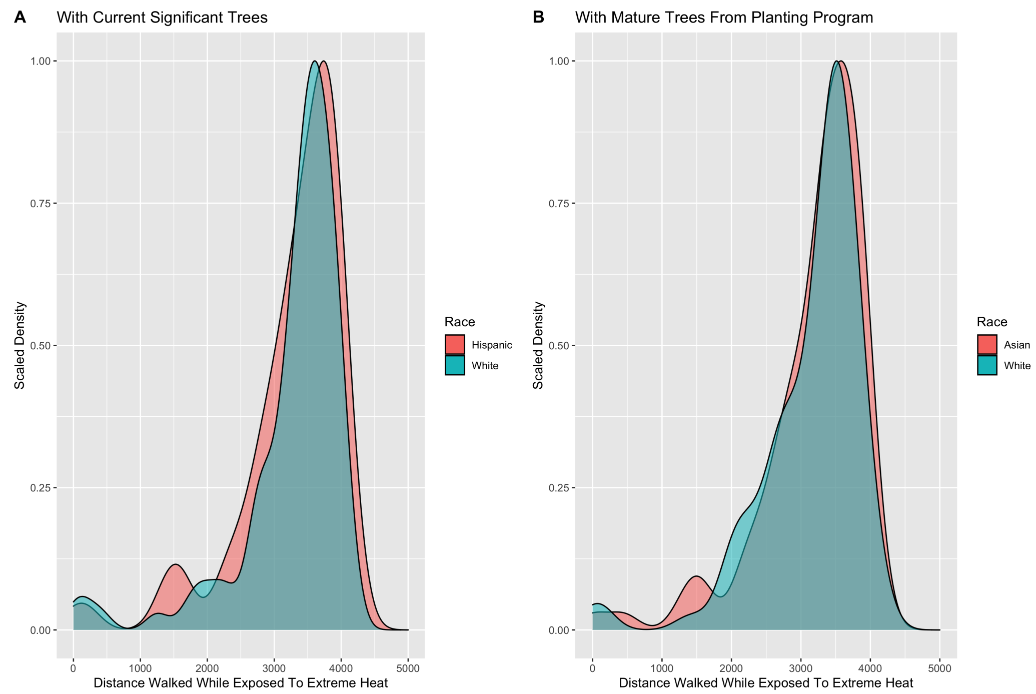

Figure 6: Distribution of distance traveled in meters for min (blue) and max (red) extreme heat exposure racial group with the current set of significant trees (A) and once all trees in the Tree Planting Program have matured (B).

6; education level is shown in Figure 7; income level is shown in Figure 8 and census tract is shown in Figure 9.

Table 1 shows the results of the evaluation given all current significant trees and Table 2 shows the results of the evaluation for the trees in the City of Norfolk's Tree Planting Program once they have matured.

4.3. Discussion of Principal Findings

The results in figures 6A-9A and Table 1 show that certain demographic groups walk statistically significant ($P < 0.05$) more distance while being exposed to extreme heat than others. This inequity is a result of those individuals encountering less shade from the current significant trees in the city. Specifically agents with less income ($35,000-$50,000), less education (9th-12th Grade) and living in census tract 42 in Norfolk, VA all walk more distance in extreme heat than agents with more income ($150K-$200K), more education (Bachelor's Degree) and those living in census tract 22 in Norfolk,

Demographic	Most Exposed Grp Norfolk, VA Grp Size	Least Exposed Grp Norfolk, VA Grp Size	T-Test P-Value
Race	Hispanic 16,144	White 113,159	0.427
Education Level	9th-12th Grade 30,786	Bachelor's Degree 28,117	0.012*
Income Level	$35,000-$50,000 32,964	$150K-$200K 9,942	0.014*
Census Tract of Residence	Census Tract 42 1,408	Census Tract 21 1,375	0.037*

Table 1: Largest inequities, in terms of distance traveled while being exposed to extreme heat, during model run given current significant trees in Norfolk, VA. '*' indicates that the inequity is statistically significant at $P < 0.05$.

Demographic	Most Exposed Grp Norfolk, VA Grp Size	Least Exposed Grp Norfolk, VA Grp Size	T-Test P-Value
Race	Asian 8,960	White 113,159	0.300
Education Level	9th-12th Grade 30,786	Bachelor's Degree 28,117	0.078
Income Level	$15,000-$35,000 53,525	$150K-$200K 9,941	0.049*
Census Tract of Residence	Census Tract 47 2,733	Census Tract 22 1,818	0.147

Table 2: Largest inequities, in terms of distance traveled while being exposed to extreme heat, during model run given current significant trees and maturation of trees in City of Norfolk's Tree Planting Program. '*' indicates that the inequity is statistically significant at $P < 0.05$.

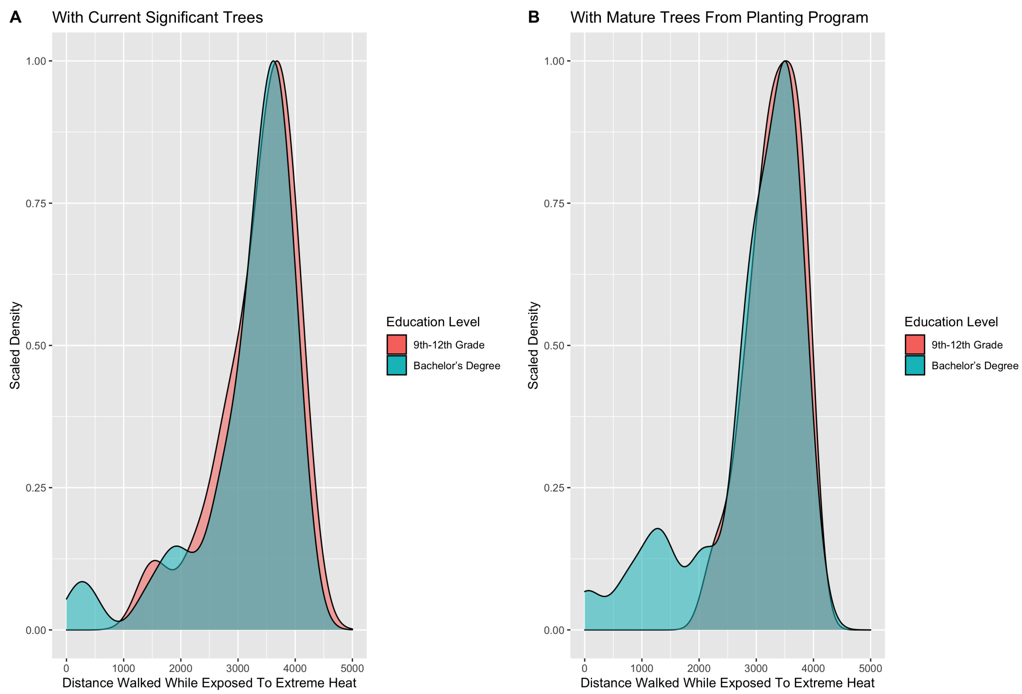

Figure 7: Distribution of distance traveled in meters for min (blue) and max (red) extreme heat exposure education level group with the current set of significant trees (A) and once all trees in the Tree Planting Program have matured (B).

VA. In each of these cases there are agents in the maximally exposed group that walk more than 95% of the distance they travel (4.5km out of 5.0km) without shade.

The results in Table 2 show that once the trees in the City of Norfolk's Tree Planting Program mature the added trees will effectively remediate: (1) the distance residents in all demographics walk in extreme heat and (2) most of the identified inequities highlighted in Table 1. Figures 6B-9B show that even in the maximally exposed groups there are rarely agents that walk more than 95% of the distance they travel (4.5km out of 5.0km) without shade. Furthermore, Table 2 shows that the only demographic group that remains exposed to statistically significantly (at $P < 0.05$) more extreme heat during their walk on a clear summer day are agents at different income levels. In the model run where all the trees in the City of Norfolk's Tree Planting Program have matured agents with less income (\$15,000-\$35,000) still walk longer in extreme heat than those with more income (\$150K-\$200K). However, even

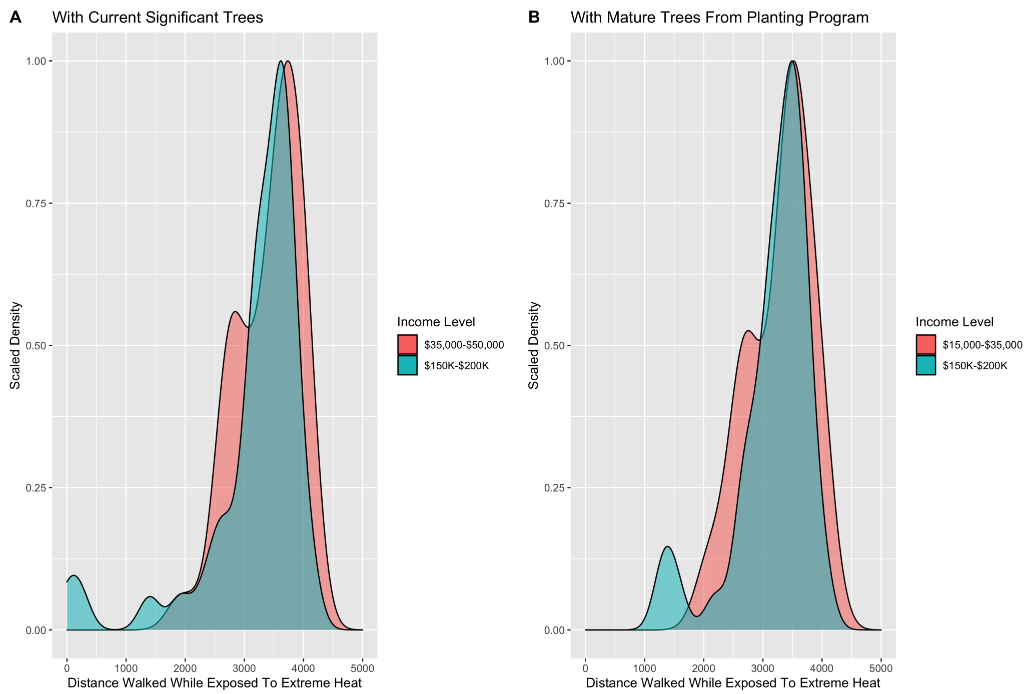

Figure 8: Distribution of distance traveled in meters for min (blue) and max (red) extreme heat exposure income level group with the current set of significant trees (A) and once all trees in the Tree Planting Program have matured (B).

in this case the Tree Planting Program reduces the evidence of a significant inequity by increasing the P-value for the income level demographic from 0.014 in Table 1 to 0.049 in Table 2.

4.4. Limitations

There are a number of methodological assumptions and limitations that limit the context in which our findings are valid.

4.4.1. Data Limitations

A number of limitations exist within the data sets we use in the model. Here we review each of these. We discuss the extent to which they limit the extent to which our results are actionable, and how we plan to address these limitations in future work.

First, The data in the Significant Trees data set only includes ≈ 500 trees. Furthermore, it is maintained by a volunteer group as opposed to a

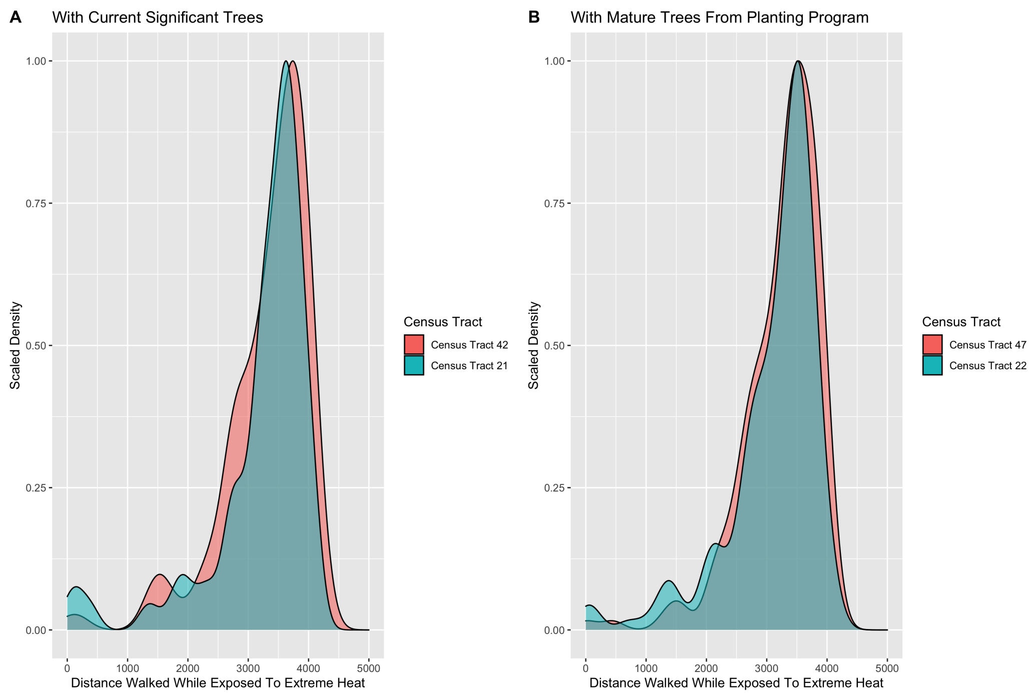

Figure 9: Distribution of distance traveled in meters for min (blue) and max (red) extreme heat exposure census tract with the current set of significant trees (A) and once all trees in the Tree Planting Program have matured (B).

professional organization. However, there is no other publicly data available that includes locations and attributes about the current trees in the city. We are working with the City of Norfolk address this limitation. However, even a more complete data set of mature trees provided by the city will not include trees planted on private property.

Another data limitation is that the addresses in the Address Information Resource are not categorized into zones such as: residential, commercial, industrial, agricultural, rural, municipal, rural, historic, and aesthetic. As a result, our home and destination address assignment for agents is very general. Once an agent is generated they are assigned a home address by sampling an address in the agent's census tract. This does not necessarily reflect a residential address within the city. Similarly, an agent's destination address was assigned by sampling a random address in the city. As a result, the destination of an agent for their walk may be not be a regularly visited location by city residents. In future work we would like to add in zone categorizations for our addresses to provide agents with more realistic residential and destination addresses.

Finally, the path of latitude and longitude points generated for each agent to walk is limited. Each path is based on the shortest time distance path between the two points using the arterial road network in Norfolk, VA. Since the data to assign routes is based on roadways and minimal travel time it does not account for the sidewalks, walking paths or other features that may make one route more attractive than another for a pedestrian. In future work we will identify pedestrian specific data to use in assigning the path of latitude and longitude points generated for each agent to walk between their home and destination.

4.4.2. Approach Limitations

Our approach to simulating extreme heat exposure on a clear, hot summer day comes with several limitations. It is important to note that while these assumptions limit the extent to which our model is a reflection of reality our results still provide high-level insight into which demographic inequities, with respect to extreme heat exposure, exist in the city of Norfolk. Furthermore, our model provides a well-grounded estimate of how effective the City of Norfolk's Tree Planting Program will be in addressing the identified inequities. The insight provided is still actionable to decision makers interested in our research question even though every agent action is not separately simulated in a fine-grained micro-simulation.

First, we assume that the temperature agents experience throughout their walk will always be extreme if they are not under the shade of a tree. This assumption is limiting because individuals can take other precautions (i.e., wide brimmed hat, cooling packs, taking a break indoors, dousing themselves with water, etc.) to avoid extreme heat exposure besides walking under tree canopies. Agents can learn and form behaviors to adapt to issues and challenges within environment spaces [59, 60]. While this certainly applies to settings involving extreme heat, our model specifically assumes that the agents maintain behaviors that match non-extreme heat conditions so that we can assess the benefits that tree canopies could provide based on normal routing.

Furthermore, temperature is dynamic throughout the day. Even though our model only simulates a $/approx$ 5km walk it is likely that the temperature will change during that period. Solar radiation and heat storage distribute spatially based on topography, humidity, land cover, and weather [61, 62];

however, these factors are not accounted for in our model. Additionally, we assume that agents walk back and forth between their home and destination for /*approx* 5km. This assumption equalizes travel distance between all agents but does not match the behavior of actual pedestrians.

We assume that the heat reduction benefits provided by the tree canopies are the same across significant trees; however, statistically significant differences have been observed between tree species with respect to cooling effects [63]. The cooling capacity of trees differs based on diversity for peri-urban forest, urban forest, and street trees [64]. Cooling benefits have also been shown to differ under canopies for trees that are east-west versus streets that are north-south with a higher average reduction from east-west streets [13]. While our model does capture the genus and species of each tree, it does not currently differentiate cooling effects per genus or species.

Finally, we assume that all current significant trees will still be present with the same canopy when all trees in the Tree Planting Program mature. This will not be the case as several of the mature trees will either have branches cut or die, particularly for trees adjacent to power lines which receive regular trimmings to ensure the safe and uninterrupted delivery of power. We maintain an assumption that every tree in the Tree Planting Program will mature with the estimated canopy. Unfortunately, some of the currently planted trees will either die or fail to fully mature.

4.4.3. Validity Threats

Threats to internal and external validity affected our study. Threats to internal validity arose when factors affected the dependent variables without evaluators' knowledge. It is possible that some flaws in the implementation of our model could have affected the evaluation results. However, our approach used established libraries to clean and wrangle the data, build the model, aggregate the results and conduct statistical analyses. Furthermore and the source code passed internal reviews [65, 66].

Threats to external validity occur when evaluation results cannot be generalized. Specifically, our results cannot be generalized to nearby areas or future time periods. Other cities in Virginia have residents with different demographics and distributions of tree canopies. Our results are specific to the City of Norfolk, using the identified data sets under the specified assumptions and limitations. However, it is very important to note that our approach, which yielded the model producing the presented results can be applied to other cities given that relevant data sets exist [65, 66].

5. Conclusion

In urban areas extreme heat conditions can arise regularly during summer months creating daily exposures for residents. Tree canopies provide shade as an effective way to reduce urban heat and avoid exposure to extreme heat. We use a demographically representative 1 (agent): 1 (person) agent-based model to understand the extent to which within Norfolk, VA different demographics of residents are equitably shaded extreme heat, by tree canopies, during a walk on a clear summer day. The model also assesses the extent to which the city's Tree Planting Plan will be effective in remediating any existing inequities. The results showed that currently there are inequitable for residents: (1) at different education levels, (2) at different income levels and (2) living in different census tracts. Our model shows that the Tree Planting Program reduces the distance residents walk in extreme heat and the identified inequities. However, residents of the city at lower income levels still experience statistically significantly more extreme heat exposure. In future work we will look to add additional details that removes several of the identified limitations in our work.

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7. Data Availability

The data and source code used in this paper are specified below as multimedia appendices and are supplied with the paper. They are also available on the web as a Mendeley Data repository online [47].

Appendix A Data sets used in the Model

This appendix contains data and metadata associated with the publicly available data sets used in our agent-based model.

A.1 American Communities Survey (ACS)

American Community Survey data used for modeling.

A.2 Address Information Resource in Norfolk, VA

Compilation of active and pending addresses in the Norfolk, VA.

A.3 Current Significant Trees in Norfolk, VA

The data collected about the current significant trees in Norfolk, VA.

A.4 Tree Planting Program in Norfolk, VA

The data collected about the Tree Planting Program in Norfolk, VA.

Appendix B Agent-based Model Source Code

This appendix contains the source code to generate demographically representative agents for Norfolk, VA and the source for the agent-based simulation of extreme heat exposure for the generated agents.

B.1 Source Code for Generating Representative Agents

This appendix contains the source code to generate demographically representative agents for Norfolk, VA using Iterative Proportional Fitting (IPF).

B.2 Source Code for Agent-Based Model of Extreme Heat Exposure in Norfolk, VA.

This appendix contains the source for the agent-based simulation of the distances residents traveled while enduring extreme heat exposure during a ≈ 5 km walk from their homes to another location in Norfolk, VA.

Appendix C Agent-based Model Results

This appendix contains the simulation output of the distances residents traveled while enduring extreme heat exposure during a ≈ 5 km walk from their homes to another location in Norfolk, VA.

Appendix D Statistical Analysis of Agent-based Model Results

This appendix contains the aggregated simulation output at the different demo-graphic levels and the statistical analysis of the results.

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