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Understanding and assessing demographic (in)equity resulting from extreme heat and direct sunlight 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, VA, United States of America

[b] Computational Modeling and Simulation Engineering, Old Dominion University, 5115 Hampton Blvd, Norfolk, 23539, VA, United States of America

A R T I C L E I N F O

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A B S T R A C T

Prolonged exposure to extreme heat and direct sunlight can result in illness and death. In urban areas of dense concentrations of pavement, buildings, and other surfaces that absorb and retain heat, harmful environmental exposures to extreme heat and direct sunlight for residents can occur on a daily basis 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 and avoid direct sunlight. We develop a demographically representative agent-based model to understand the extent to which different demographics of residents in Norfolk, VA are (in)equitably shaded from direct sunlight and extreme heat conditions during a walk on a clear summer day. In the model each agent represents a different resident of Norfolk, VA. 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 at (1) different education levels, (2) 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 and are exposed to direct sunlight. However, residents of the city at lower income levels still experience statistically significantly more extreme heat and direct sunlight exposure due to a lack of tree canopies in summer months than those at higher income levels.

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 prolonged exposure to direct sunlight and extreme heat for residents (Hsu et al., 2021; Coffel et al., 2018). Exposure to extreme heat and direct sunlight can result in sunburns, cancer, illness and ultimately death (Tuholske et al., 2021; Vaidyanathan et al., 2020; Wondmagegn et al., 2019). In the 2010s, an estimated 12,000 (95% CI 7,400–16,500) annual premature heat stress related deaths occurred across the United States (Shindell et al., 2020). 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 (Forrest et al., 2020). Extreme heat conditions are expected to continue increasing in frequency into the future (Tuholske et al., 2021). 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 in corresponding health benefits (Nowak and Greenfield, 2018). These factors serve to further compound and exacerbate contributors to health inequities for exposure to direct sunlight and extreme heat.

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 (Ziter et al., 2019; Tamaskani Esfehankalateh et al., 2021; Aram et al., 2019; Sinha et al., 2021; Sanusi et al., 2016). Increased tree and vegetation cover have been found to reduce the negative health effects of exposure to direct sunlight and extreme heat, and to help reduce the risks of heat stress related morbidity and mortality in outdoor spaces, while improving actual and perceived levels of thermal comfort (Wolf et al., 2020). Tree planting strategies can mitigate the effects of pollution, pollen, heat index, and heat related ailments (Bodnaruk et al., 2017). In addition, studies have shown that: (1) increased residential proximity to any type of green space is associated with significantly decreased risks of

* Corresponding author.
E-mail address: vzamponi@odu.edu (V. Zamponi).

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mortality from all causes of death (Crouse et al., 2017; Kardan et al., 2015), and (2) the removal of green spaces, and in particular trees and their canopies, can have cascading negative consequence for the health and fitness of those residing nearby (Widyastuti et al., 2022).

Studies on pollution removal strategies for ecosystem services showed an expected 4.3 to 6.2 million dollars gain per year in benefits from differing tree placement strategies in Baltimore, Maryland (Bodnaruk et al., 2017), whereas in mega-cities the estimated benefits of converting tree cover area to tree canopy is 1 billion dollars per year (Endreny et al., 2017). Furthermore, researchers have found that the positive health effects of urban greenness can mitigate the negative effects of fine particulate matter air pollution (Crouse et al., 2019).

We explore health inequities based on the prevalence of exposure to direct sunlight and extreme heat within demographic subgroups of the city's population compared with the other demographic subgroups (Braveman, 2014; Kawachi et al., 2002). A systematic literature search and meta-analysis of forest cover and income found evidence of income-based inequity in urban forest cover (Gerrish and Watkins, 2018). A study of US urban areas also found that low-income areas were on average 15.2% less tree covered and 1.5 degrees Celsius (2.7 Fahrenheit) hotter than high-income areas (McDonald et al., 2021). Similarly, another study showed that communities in Greater Bahr el Ghazal and the Equatorias in South Sudan, where less trees were planted, were more likely to experience issues related to food scarcity (Bunch et al., 2020).

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 representation of the city. In the model each agent represents a resident of Norfolk, VA. The model simulates each resident of Norfolk, VA walking *approx* five kilometers 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 direct sunlight and extreme heat 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/direct sunlight exposure 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/direct sunlight 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 (Andrews et al., 2018). Heat exposure will increase significantly by 2030 and aggressive action is needed to mitigate future risk (Sun et al., 2019; Wilhelmi and Hayden, 2010). 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 (Thom et al., 2016). Similarly, Lachapelle et al. extended an existing computational model to demonstrate that shade-trees can reduce daytime temperature on sidewalks by almost 20 °C (36 °F) (Lachapelle et al., 2022). Furthermore, Ziter, et al. found that urban temperatures experienced by residents decrease as a non-linear function of percent canopy cover (Ziter et al., 2019). 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 °C (7–14 °F) lower than urban areas without trees (Schwaab et al., 2021).

2.2. Connection between wealth and biodiversity inequity

Researchers have identified a correlation between wealth, tree canopy coverage, and biodiversity inequity (Pedlowski et al., 2002; Harlan et al., 2013; Gabbe et al., 2022), and that the correlation between the two is growing stronger in more recent years (Jenerette et al., 2011). This is in part 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 (Nier III, 1998) with significantly less tree cover, and higher land surface temperatures, in *redlined* zones than green zones (Nowak et al., 2022).

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 (Sinha et al., 2021; McDonald et al., 2020). 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 (Lafortezza et al., 2009; Mouratidis, 2019; Collins et al., 2020; Gore et al., 2022). Furthermore, Li et al. found that hospitals in *redlined* zones have more heat-related outpatient visits and high inpatient admission rates (Li et al., 2022).

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 Chicago move throughout the city (Khan, 2021). 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 datasets 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 (Kearl, 2012). 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.

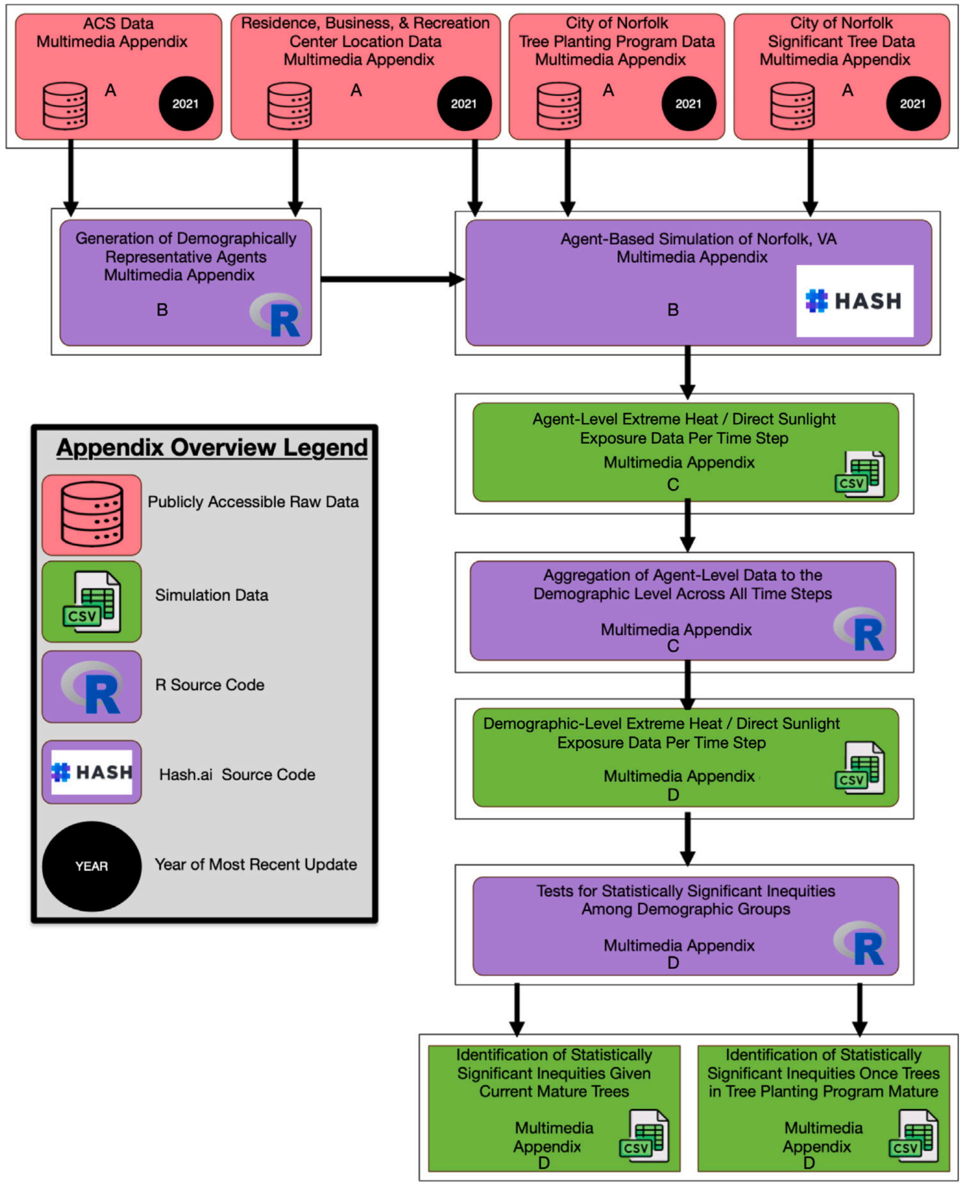

Fig. 1. An overview of the datasets and other supplementary materials supplied in the appendices. ACS: American Communities Survey; CSV: Comma Separated Values.

3.2. Publicly available data

3.2.1. Overview

Our approach to understanding and assessing demographic (in)equity of extreme heat/direct sunlight 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 (National Research Council et al., 2007; Berkley, 2017); (2) the Norfolk Master Gardeners for existing trees' types, canopies, and locations that they have classified as significant (Norfolk Open Data, 2023b); (3) the City of Norfolk's Tree Planting Program (Norfolk Open Data, 2023c) 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 (Norfolk Open Data, 2023a). All the datasets, 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 Fig. 1. The data is also available in our Mendeley Data repository online (Zamponi et al., 2023b).

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 (Berkley, 2017).

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 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 (Berkley, 2017). Appendix A.1 provides the data included within the ACS for this study.

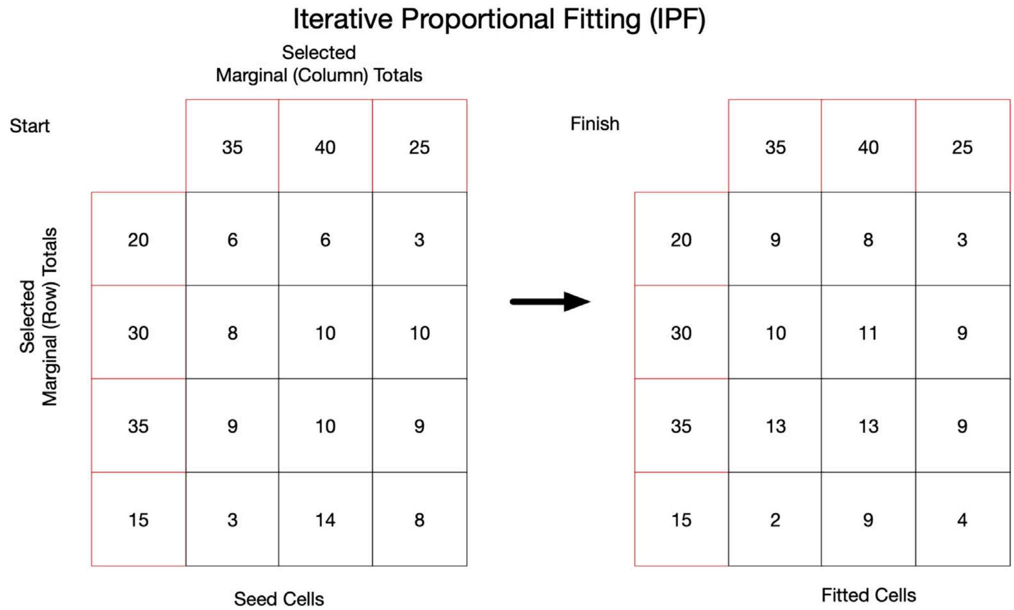

Fig. 2. Start and finish state of an example of using Iterative Proportional Fitting to estimate a joint probability distribution.

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 (Norfolk Open Data, 2023a). 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 (Norfolk Master Gardeners, 2023). The diameter, height, canopy spread, general location and species of the tree is included for each tree in the dataset. The data is updated every five years (Norfolk Open Data, 2023b). Appendix A.3 provides the current significant tree data included in this study.

3.2.5. Tree Planting Program

The City of Norfolk has tracked each tree planted along city streets, within city parks, and on other city properties every year since 2018. For each entry in this dataset 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 (Norfolk Open Data, 2023c). 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. The model is an extension of our previous work (Zamponi et al., 2023a). It 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 (Gilbert and Terna, 2000; Kavak et al., 2018). This model is applied to understand the extent to which different demographics of residents are (in)equitably shaded from extreme heat/direct sunlight conditions during a *approx* five kilometer walk on a clear summer day in Norfolk, VA. The Overview, Design concepts, and Details (ODD) protocol for this model is provided in Appendix E.

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) (Fienberg and Meyer, 1981; Wong, 1992) to estimate joint probability distributions of demographics for each census tract, which we later sample when generating agents in our model (Kolenikov, 2014; Norman, 1999; Simpson and Tranmer, 2005; Choupani and Mamdoohi, 2016). IPF is applied to the data 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 Fig. 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 Fig. 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) (Fienberg and Meyer, 1981; Wong, 1992).

Next, we will show how iterations of IPF yield the joint probability estimate on the right hand side of Fig. 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 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 Fig. 3. During a column adjustment within an iteration each column of already row-adjusted cells is proportionally adjusted to equal

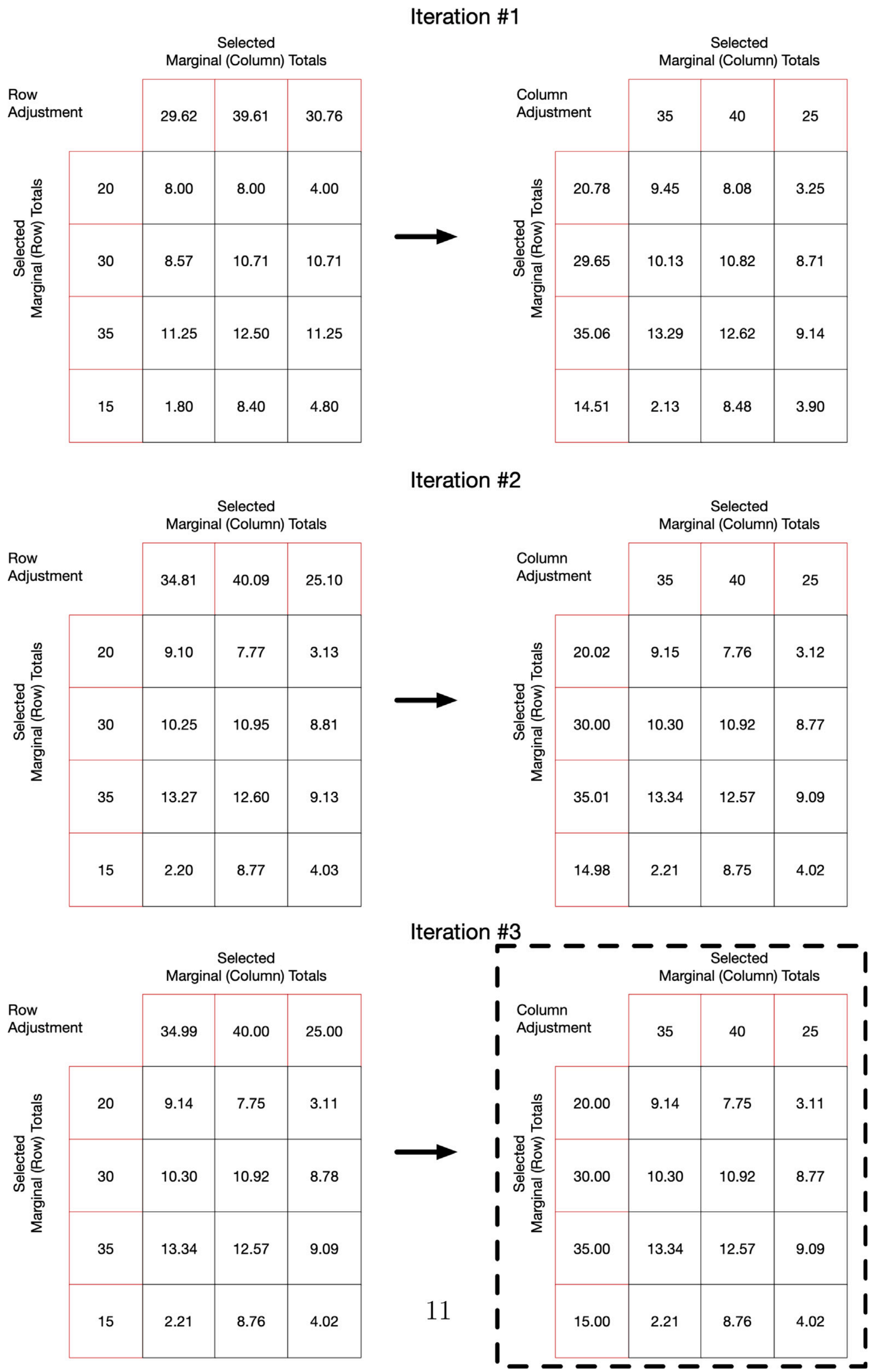

Fig. 3. Iterations within an example of using Iterative Proportional Fitting to estimate a joint probability distribution.

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 Fig. 3.

Iteration 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 Fig. 2.

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

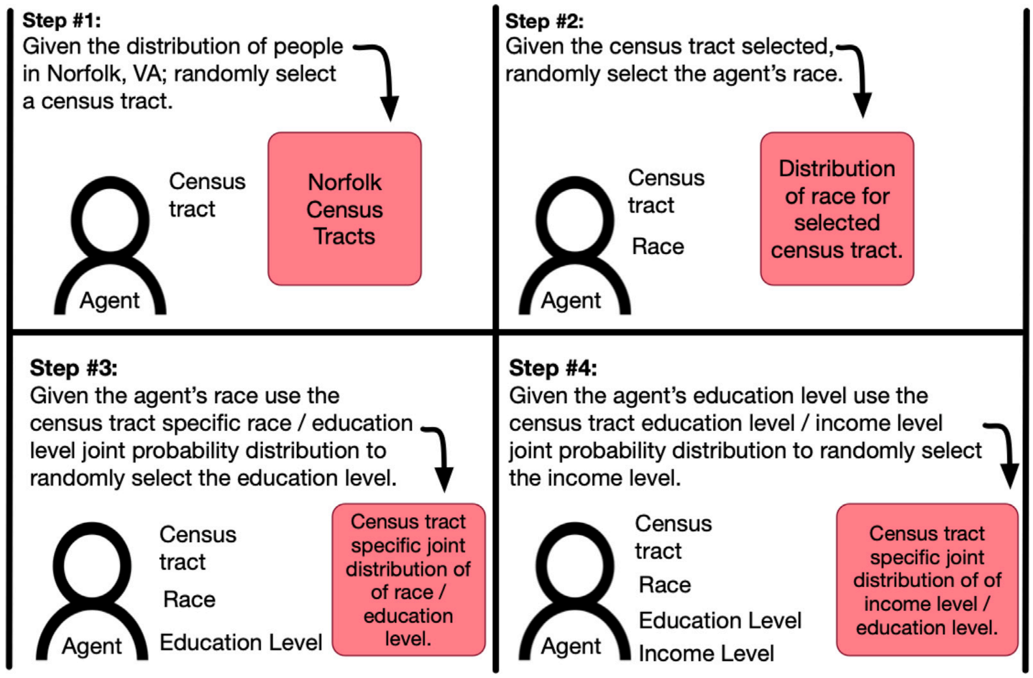

Fig. 4. The step by step process of generating representative agents within our model.

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 Fig. 4.

Fig. 4 shows that the first step in the agent-generation process is to sample a distribution of all residents in Norfolk, VA to identify the census tracts that are assigned to the agents. 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.

Each generated agent is also assigned a home, 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 locations are addresses in the City of Norfolk. These are determined by sampling the addresses listed in Address Information Resource.

Once each location is assigned, a route of latitude and longitude points from the home to their destination location, and back, are 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 m (Hash.ai, 2020).

3.3.3. Placement of trees and tree canopies

Once all agents have been generated, the trees and their canopies are placed on the simulation landscape. Each tree listed in the Significant Trees dataset is placed on the simulation landscape with a radius of shade equal to its canopy spread. The shade region of a tree reflects the circumference distance around each tree that keeps the agents from being exposed to extreme heat/direct sunlight.

The model can also be initialized with the trees included in the City's Tree Planting Program. In this scenario, all trees from the Tree Planting Program dataset, which also includes the current significant trees, 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 (in)equitably shaded by trees from extreme heat/direct sunlight 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 m 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 time steps have passed. In other words, agents can travel back and forth several times between their assigned locations during the run of the simulation. This design decision is made to ensure the length of the agent's walk in the city are as equal as possible. The limitations imposed by this design decision, and others, are discussed in Section 4.5.

At each timestep an agent follows the decision diagram specified in Fig. 5. Fig. 5 shows that at the beginning of each timestep an agent calculates the amount of distance they traveled while they were exposed to extreme heat/direct sunlight during the previous timestep. An agent is exposed to extreme heat/direct sunlight during their walk if their path does not 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 (5–8 °C) in this scenario which is a sufficient reduction to avoid extreme heat/direct sunlight exposure. Limitations imposed by our design decisions, including this one, are discussed in Section 4.5.

Next, Fig. 5 shows the check the agent performs to determine if they are at their destination. If the agent is at their destination, then they set their walking route to be from their destination to their home. Next, the agent checks if they are at their home. If they are, they set their route to be from their home to their destination. Finally, the agent 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 *approx* five kilometers.

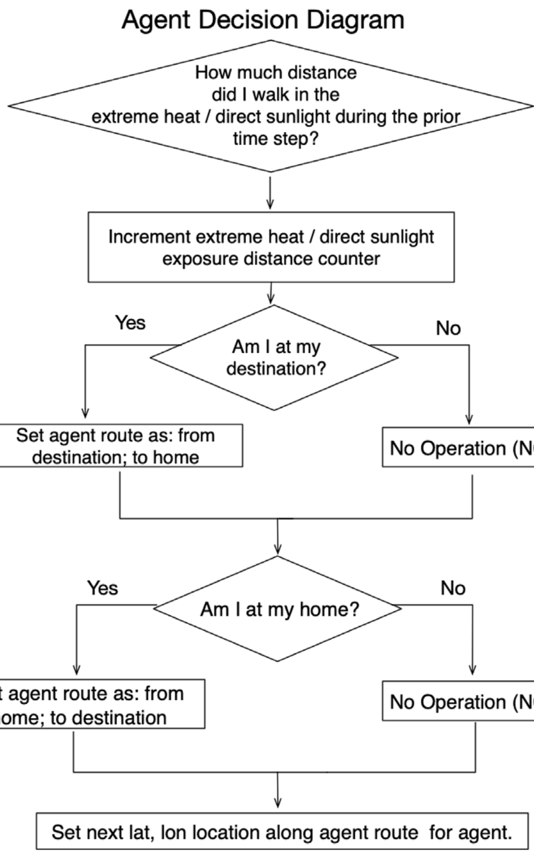

Fig. 5. Decision diagram for agents, for each time step.

4. Evaluation

4.1. Research question and measures

Our research question is: *to what extent do trees and their canopies equitably reduce extreme heat/direct sunlight 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/direct sunlight (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/direct sunlight 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/direct sunlight 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/direct sunlight exposure (i.e. average for the maximally exposed group) is statistically significantly greater than the group with the lowest mean extreme heat/direct sunlight exposure (i.e. average for the minimally exposed group) (Posten, 1984). 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/direct sunlight exposure between the two groups.

Table 1
Largest inequities, in terms of distance traveled while being exposed to extreme heat/direct sunlight, during model run given current significant trees in Norfolk, VA.

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 9942	0.014*
Census tract of residence	Census Tract 42 1408	Census Tract 21 1375	0.037*

*Indicates that the inequity is statistically significant at $P < 0.05$.

Table 2
Largest inequities, in terms of distance traveled while being exposed to extreme heat/direct sunlight, during model run given current significant trees and maturation of trees in City of Norfolk's Tree Planting Program.

Demographic	Most exposed Grp Norfolk, VA Grp size	Least exposed Grp Norfolk, VA Grp size	T-Test P-Value
Race	Asian 8960	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 9941	0.049*
Census tract of residence	Census Tract 47 2733	Census Tract 22 1818	0.147

*Indicates that the inequity is statistically significant at $P < 0.05$.

4.2. Results

Figs. 6–9 and Tables 1–2 show the results of our evaluation. Each figure elucidates the distribution of distances walked while being exposed to extreme heat/direct sunlight for the minimally and maximally exposed group for each demographic. The left hand side of each figure, labeled **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, labeled **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 Fig. 6; education level is shown in Fig. 7; income level is shown in Fig. 8 and census tract is shown in Fig. 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 Figs. 6A–9A and Table 1 show that certain demographic groups walk statistically significantly ($P < 0.05$) more distance while being exposed to extreme heat/direct sunlight 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/direct sunlight than agents with more income ($150K–$200K), more education (Bachelor's Degree), and those living in census tract 22 in Norfolk, VA. In each of these cases there are agents in the maximally exposed group that walk more than 95% of the distance they travel (4.5 km out of 5.0 km) 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

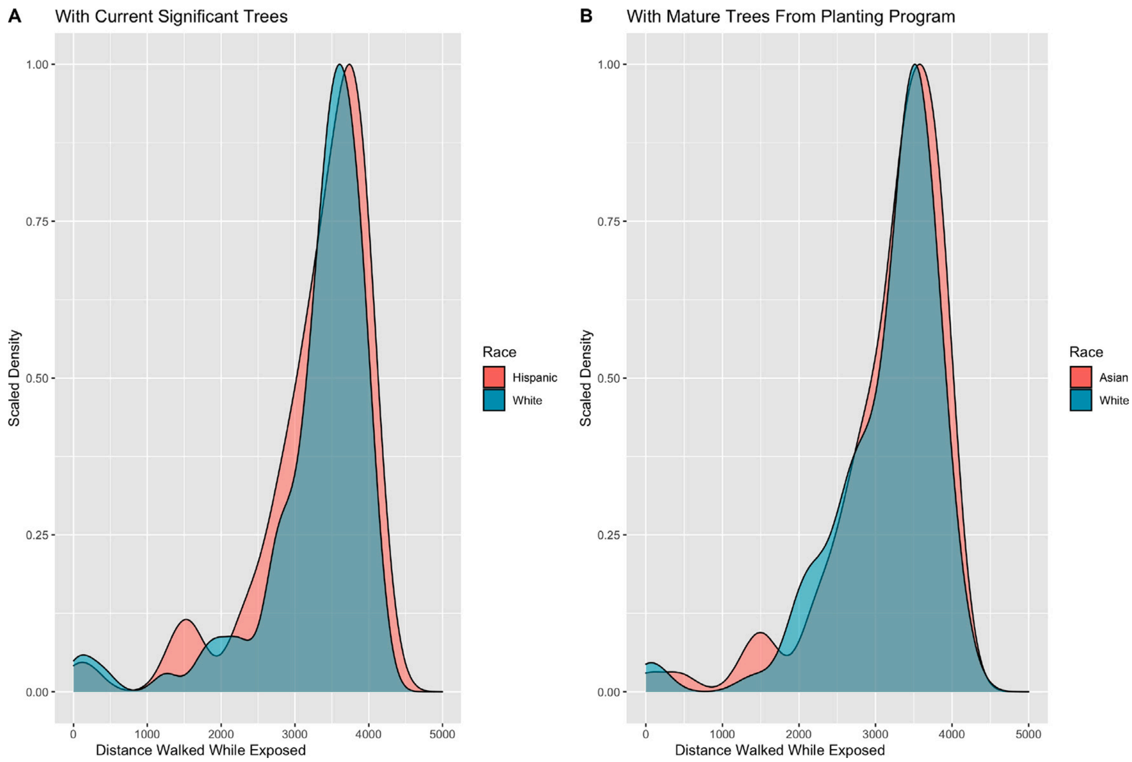

Fig. 6. Distribution of distance traveled in meters for min (blue) and max (red) extreme heat/direct sunlight exposure racial group with the current set of significant trees (A) and once all trees in the Tree Planting Program have matured (B).

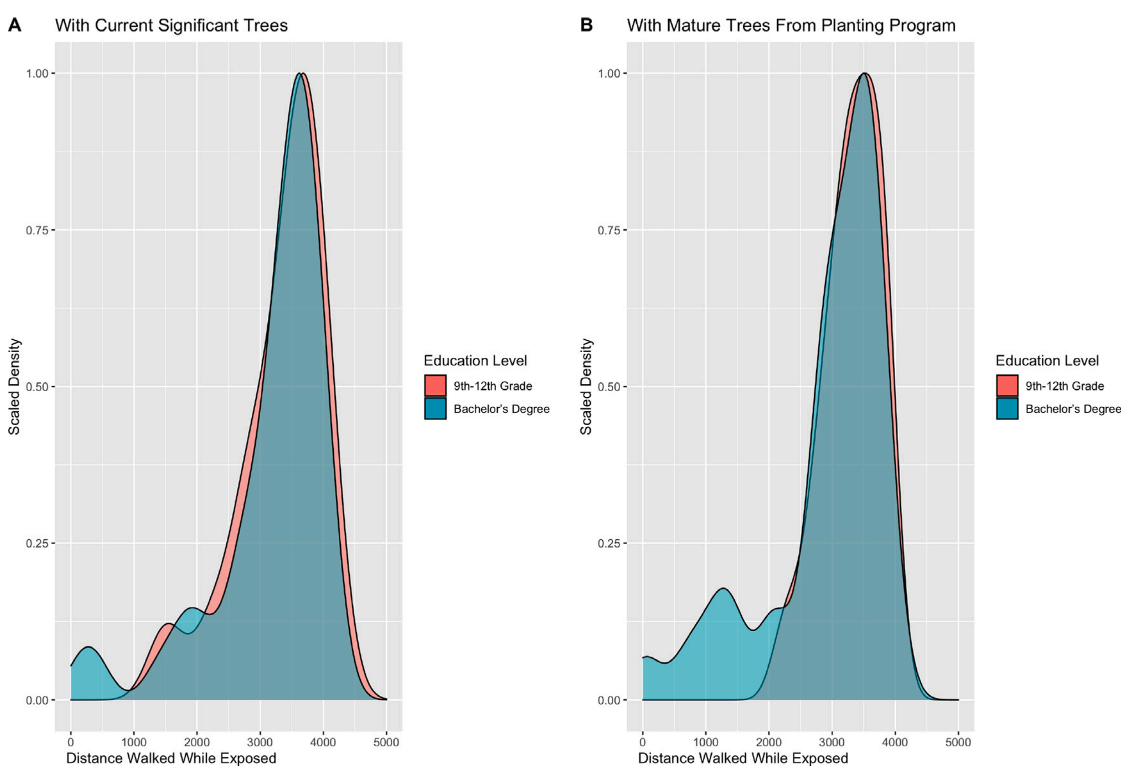

Fig. 7. Distribution of distance traveled in meters for min (blue) and max (red) extreme heat/direct sunlight exposure education level group with the current set of significant trees (A) and once all trees in the Tree Planting Program have matured (B).

remediate: (1) the distance residents in all demographics walk in extreme heat/direct sunlight and (2) most of the identified inequities highlighted in Table 1. Figs. 6B–9B show that even in the maximally exposed groups there are rarely agents that walk more than 95% of the distance they travel (4.5 km out of 5.0 km) without shade. Furthermore, Table 2 shows that the only demographic groups that remain exposed to statistically significantly (at $P < 0.05$) more extreme heat/direct sunlight during their walk on a clear summer day are agents at different

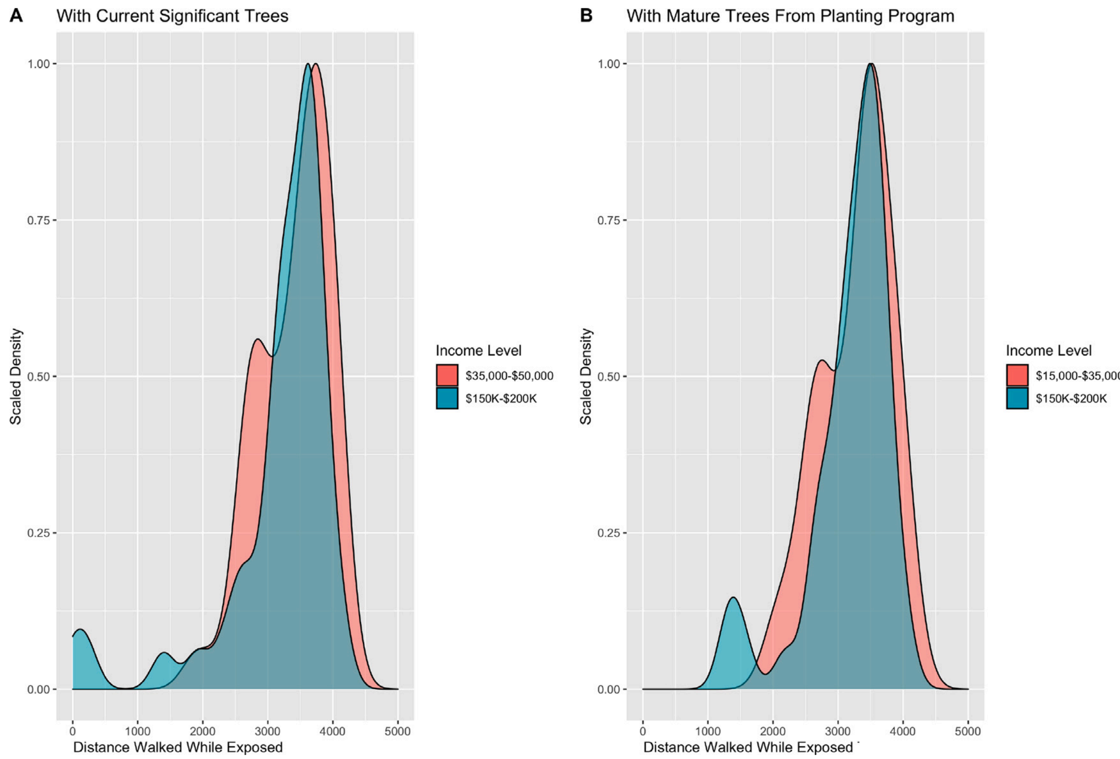

Fig. 8. Distribution of distance traveled in meters for min (blue) and max (red) extreme heat/direct sunlight exposure income level group with the current set of significant trees (A) and once all trees in the Tree Planting Program have matured (B).

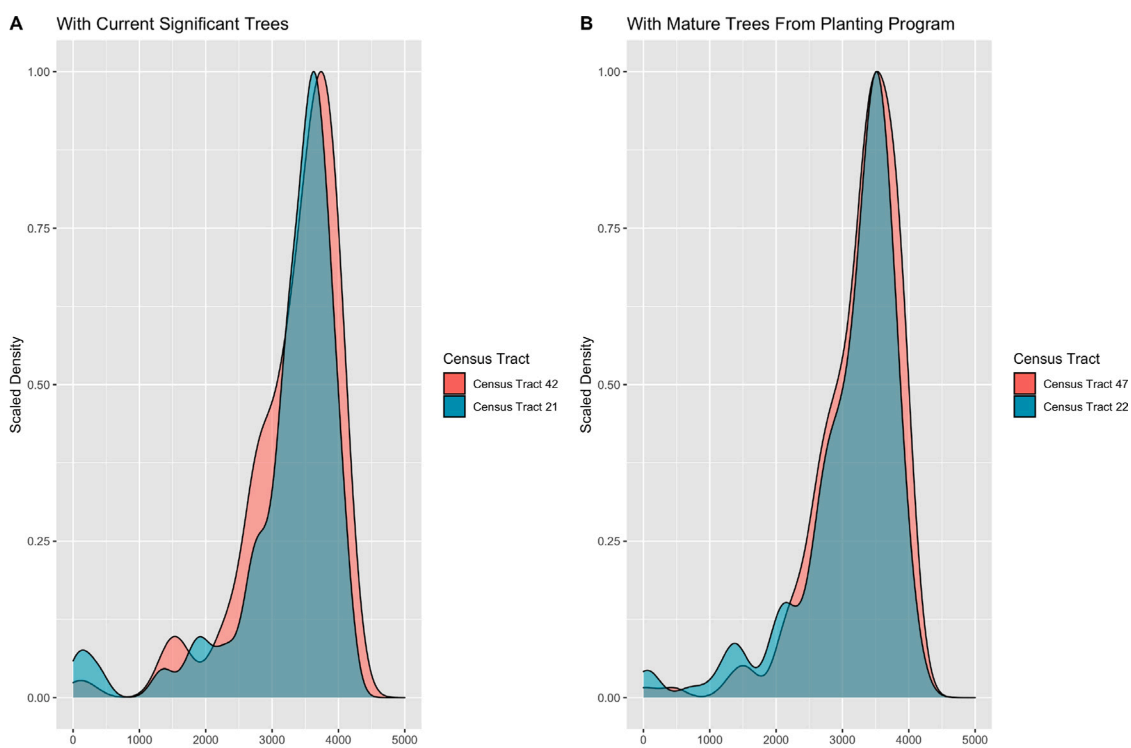

Fig. 9. Distribution of distance traveled in meters for min (blue) and max (red) extreme heat/direct sunlight exposure census tract with the current set of significant trees (A) and once all trees in the Tree Planting Program have matured (B).

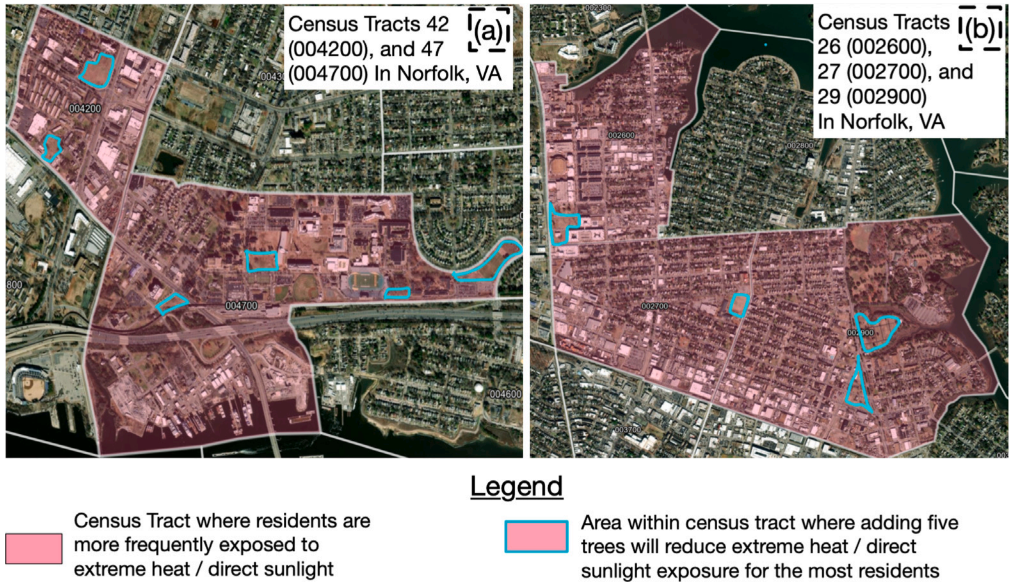

Fig. 10. The locations of areas where adding five equally spaced trees in those census tracts where residents experience the most extreme heat/direct sunlight exposures along *approx* 5 km in Norfolk, VA due to a lack of tree canopies, even when considering the City of Norfolk's Tree Planting Program. Census tracts 42 (004200) and 47 (004700) are shown in (A). Census tracts 26 (002600), 27 (002700) and 29 (002900) are shown in (B).

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/direct sunlight than those with more income ($150K–$200K). However, even 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. Specific recommendations

Our work can also support specific recommendations to decision-makers about priority locations in the city where new trees should be planted to address extreme heat/direct sunlight exposure. Fig. 10 provides an example. To generate Fig. 10 we identified the five census tracts where residents experience the most extreme heat/direct sunlight exposures due to a lack of tree canopies during their *approx* 5 km walk, even after those tree planted in the City of Norfolk's Tree Planting Program have matured. These census tracts (26, 27, 29, 42, and 47) are outlined and colored in red in Fig. 10. Next, we identified ten areas in those census tracts where planting five additional tree in the area would reduce the extreme heat/direct sunlight exposure the most along the walking routes of residents of the census tracts. These areas are outline in light blue. To produce these recommendations we used the results of our simulation and assumed that the new five trees to be planted would be equally spaced within the identified area and the future tree canopy sizes of the new trees would be the mean canopy size of the trees listed in the Tree Planting Program. In addition, we required at least one area to be identified for each of the census tracts. The results of this analysis are location specific recommendations for the next 50 trees to be planted in Norfolk, VA.

4.5. Limitations

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

4.5.1. Data limitations

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

First, the data in the Significant Trees dataset only includes *approx* 500 trees. Furthermore, it is maintained by a volunteer group as opposed to a professional organization. However, there is no other publicly available data that includes locations and attributes about the current trees in the city. We are currently working with the City of Norfolk to address this limitation. Nevertheless, even a more complete dataset of mature trees provided by the city will not include trees planted on private property. Assessing the quality of the utilized data was not conducted as we had no direct access to an independent dataset to utilize for conducting data evaluation (Augusiak et al., 2014).

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 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.

4.5.2. Approach limitations

Our approach to simulating extreme heat/direct sunlight 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/direct

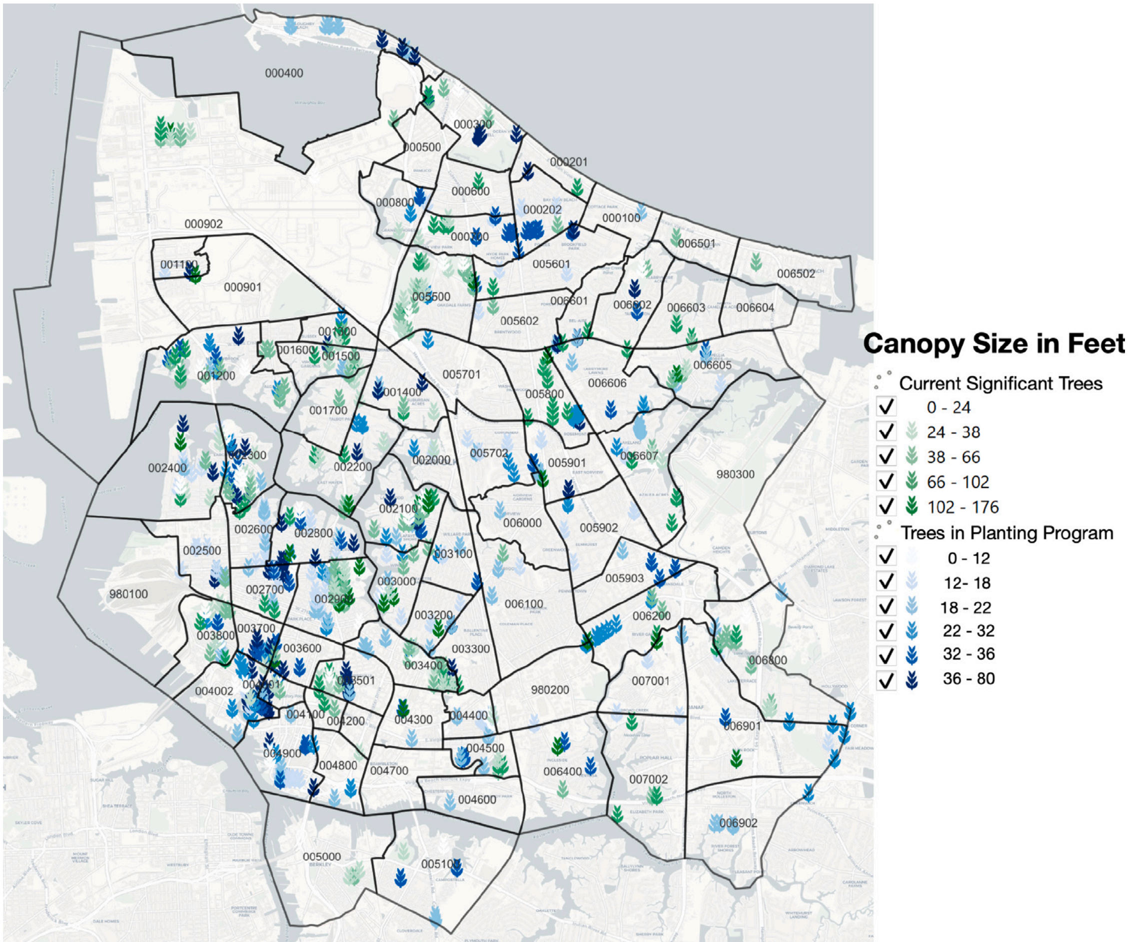

Fig. 11. The locations and canopy size in feet of current significant trees in and future trees from the Tree Planting Program in Norfolk, VA.

sunlight 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/direct sunlight exposure besides walking under tree canopies. Agents can learn and form behaviors to adapt to issues and challenges within environment spaces (An et al., 2021; Manson et al., 2020). While this certainly applies to settings involving extreme heat and direct sunlight, our model specifically assumes that the agents maintain behaviors that match non-extreme heat/non-direct sunlight 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* 5 km 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 (Lookingbill and Urban, 2003; Yang et al., 2013); 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* 5 km. 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 (Sanusi et al., 2017). The cooling capacity of trees differs based on diversity for peri-urban forest, urban forest, and street trees (Marando et al., 2019). 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 (Sanusi et al., 2016). 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.

4.5.3. *Confounding factors*

There are a number of confounding factors not considered in our analysis. The census tracts in Norfolk have different geographic characteristics. Trees need fertile soil to be planted and space to grow. In some census tracts there is less suitable space available to plant trees, our analysis does not consider these factors, nor does it consider greenfield development to create these spaces. However, we do consider the City of Norfolk's Tree Planting Program in our analysis. Specifically, our findings include considerations for extreme heat/direct sunlight exposure in the city due to lack of tree canopies with respect to the placement and mature canopies of trees that the program recently planted. The placement and canopy size of these trees once matured is shown in Fig. 11.

As a result of these considerations our analysis does consider the future tree canopy state of several new neighborhoods that are more affordable and tend to attract younger couples but currently lack mature trees. In future work we expect to drill down on additional confounding factors in more which may affect the distribution of race/ethnicity, income, and education within the city with respect to extreme heat/direct sunlight exposure from a lack of tree canopies.

4.5.4. 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, the source code passed internal reviews (Spencer, 1978; Yu and Ohlund, 2010).

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 datasets 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 datasets exist (Spencer, 1978; Yu and Ohlund, 2010).

5. Conclusion

In urban areas conditions can arise regularly during summer months creating daily exposures to extreme heat and direct sunlight for residents. Tree canopies provide shade as an effective way to reduce urban heat and avoid exposure to extreme heat and direct sunlight. We use a demographically representative agent-based model to understand the extent to which, within Norfolk, VA, different demographics of residents are (in)equitably shielded from extreme heat and direct sunlight by tree canopies during a walk on a clear summer day. The model also assesses the extent to which the city's Tree Planting Program will be effective in remediating any existing inequities. The results showed that, currently, there are inequities for residents at (1) different education levels, (2) different income levels, and (3) living in different census tracts. Our model shows that the Tree Planting Program reduces the distance residents walk in extreme heat/direct sunlight and the identified demographic inequities. However, residents of the city at lower income levels still experience statistically significantly more extreme heat/direct sunlight exposure. In future work we will look to add additional details that removes several of the identified limitations.

CRediT authorship contribution statement

Virginia Zamponi: Model development, Conducted analysis, Helped write the paper. **Kevin O'Brien:** Model development, Helped write the paper. **Erik Jensen:** Conducted analysis, Helped write the paper. **Brandon Feldhaus:** Helped write the paper. **Russell Moore:** Helped write the paper. **Christopher J. Lynch:** Model development, Analytics, Helped write the paper. **Ross Gore:** Model development, Conducted analysis, Helped write the paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Our data is publicly accessible on the following Mendeley Data webpage: https://data.mendeley.com/datasets/n4wyrj86vy.

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Appendix A. Datasets used in the model

This appendix contains data and metadata associated with the publicly available datasets 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 on the current significant trees in Norfolk, VA.

A.4. Tree Planting Program in Norfolk, VA

The data collected on 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/direct sunlight 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/direct sunlight exposure in Norfolk, VA

This appendix contains the source code for the agent-based simulation of the distances residents traveled while enduring extreme heat/direct sunlight exposure during a *approx* 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/direct sunlight exposure during a *approx* 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 demographic levels and the statistical analysis of the results.

Appendix E. Model overview design concepts, and details protocol

The Overview, Design concepts, and Details (ODD) protocol for the model.

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