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Park Equity Modeling: A Case Study of Asheville, North Carolina

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PARK EQUITY MODELING: A CASE STUDY OF ASHEVILLE, NORTH CAROLINA

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ABSTRACT

Parks and greenspaces are publicly available entities that serve the vital purpose of promoting multiple aspects of human welfare. Unfortunately, the existence of park disparities is commonplace within the park setting. Specifically, marginalized individuals encounter limited park access, insufficient amenity provision, and poor maintenance. To remedy these disparities, we propose a process in which we select candidate park facilities and utilize facility location models to determine the optimal primary parks from both existing and candidate sites.

We note that platforms currently exist to identify the geographical areas where residents lack sufficient access to parks. However, these platforms do not yet integrate the variety of demographic, infrastructural, dimensional, monetary, and environmental factors to guide decisions of future park locations. Further, these tools do not have the ability to recommend multiple park sites by considering how simultaneous park selection affects overall access. To support park and government agencies in their aims to improve the distribution and quality of greenspaces, we present a case study of park selection optimization modeling in Asheville, North Carolina. We propose mixed-integer programs that maximize park access across different dimensions of equity. The developed facility location models serve as intuitive preliminary tools to support proactive park and greenspace planning initiatives.

Our research process includes developing an understanding of current park and greenspace inequities. We determine the key indicators of park goodness in order to formulate and analyze facility location models that promote park and greenspace equity. We begin this study with an introduction to park and greenspace benefits and disparities and discuss current park distribution and equity initiatives within Asheville, North Carolina. We explore literature concerning park requirements and facility location modeling. We represent the components of park goodness and equity in the formulation of two facility location models and include the data collection, analysis, and visualization of Asheville to depict model elements. Finally, we present and discuss the results of multiple analyses to recommend new park locations in Asheville and to determine the effectiveness of our models as a tool to guide strategic park location decisions based upon user-defined criteria and goals. This study serves as an initial step in the further development and incorporation of mathematical modeling to achieve social goals within the recreational setting.

DEDICATION

I would like to dedicate this thesis manuscript to both my immediate and extended family. I love you all! To my parents, Jay and Shoaleh, and siblings, Adib, Isabella, and Solomon: Thank you for all of the laughs and advice over the years. These individuals have been my stronghold and dearest companions, and I admire each of them for their compassion and dedication to their calling. Their example and encouragement has inspired me to utilize my skills and passion to serve humanity in whatever capacity possible. To my grandparents: Thank you for your continual prayers and hopes for my success in academics and beyond. Your interest in my projects and offering of new perspectives from which to view problems has provided me with open-mindedness and perseverance. To the many uncles, aunts, cousins, and more: Thank you all for your continual support.

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CHAPTER ONE

INTRODUCTION

Parks and greenspaces are essential components of a community that serve to foster both human and environmental health. Further, the underlying purpose of a park is to provide inclusion and community engagement. Yet, several park disparities currently exist that are barriers to proper access and quality of greenspaces. We note that, commonly, individuals of marginalized racial-ethnic classifications encounter the most park disparities.

In our case study of Asheville, North Carolina, we seek to create facility location models that remedy the aforementioned disparities by selecting candidate park sites that create an equitable distribution of primary park facilities, i.e., the parks designated as primarily visited by residents. In our models, we integrate the multi-dimensional elements that contribute to overall park goodness and equity and simultaneously select multiple primary parks from candidate sites. The utilization of facility location models in the selection of parks introduces a new perspective in equity modeling that differs from traditional park equity tools.

This introductory chapter seeks to provide background information concerning the specific benefits and disparities of parks and greenspaces. We discuss the access of parks and greenspaces within Asheville, North Carolina and note the currently existing city initiatives that strive to promote equity within the park setting.

Parks and Greenspaces: Benefits and Disparities

To facilitate an understanding of the importance of and necessity for a model that promotes the equitable access of parks, we note the multiple benefits associated with greenspaces. We also emphasize the causes of park disparities to provide background concerning the social pressures and constructs that create inequities.

Park Benefits

Parks and greenspaces are natural resources that contribute directly to human welfare [1]. A positive correlation exists between exposure to greenspaces and an increased physical health [1], [2] [3]. The publically open spaces and amenities that parks provide facilitate physical activity within a recreational setting throughout a community. Notably, outdoor spaces such as parks and trails facilitate the greatest amount of physical activity [2]. This increased physical activity directly relates to decreased physical ailments such as heart disease, cancer, and obesity [3]. Additionally, access to parks and greenspaces benefits mental health [1], [4], [5]. The leisurely atmosphere of parks allows individuals a respite from the stressful commotion of daily mental pressures, and a connection with the natural environment promotes a sense of self and belonging.

An indirect benefit to human welfare results from the positive impact of parks and greenspaces upon the surrounding natural environment. Parks decrease air and noise pollution, assist with water runoff, and regulate temperature [1]. The result is an improved quality of human life with minimized natural disasters, such as flooding, and decreased environmental extremes.

Park Disparities

According to the principle of environmental justice, there should exist an equitable distribution of and access to the natural resources and aforementioned benefits of parks and greenspaces [6]. However, historical discrimination continues to prevent park access for marginalized groups. Individuals classified by non-white racial ethnicity, low-income economic status, age dependency, and physical or mental disability are frequently undermined [1], [7]. Commonly, these groups have a limited access to parks, which are plagued with poor or nonexistent maintenance, crime, few facilities, and overcrowding [1]. Further, visiting a park often requires that these undermined individuals traverse great distances [1].

One main cause of park disparities originates from human discrimination. Specifically, we note that prejudices with regard to racial-ethnic demographic classification are especially significant indicators of inequity. Deficits in park access and quality occur most frequently within racially marginalized and impoverished communities [1]. The negative attitudes of distrust toward these individuals prompts inequities of park quality and maintenance [8]. These feelings of distrust couple with other sentiments created by “neighborhood stigma” to result in the augmentation of racial separation and fear between groups of differing racial classification [8].

The process of gentrification further alienates racially marginalized individuals from areas of park development. Gentrification, defined as the “influx of wealthy residents to historically disenfranchised neighborhoods due to new greenspaces”, is a social process by which marginalized individuals must vacate their homes [6]. The increase in property value that results from the beautification of the community forces escalated renting prices that are too expensive for marginalized groups to afford. Therefore, gentrification consistently forces marginalized groups to abide within underdeveloped and poorly maintained areas, many of which do not incorporate space for parks and greenspaces.

Overview of Parks and Recreation in Asheville, NC

Within this section, we provide background information concerning the current allocation of parks and greenspaces within Asheville. Further, we discuss the strategic plans of the City of Asheville that seek to provide increased equity within the park and recreational setting.

Parks and Access Overview

Asheville, North Carolina is an artsy and outgoing community located near the Appalachian mountains. The city has a reputation for being outdoorsy and is home to many local parks and a handful of national greenspaces. To quantify the degree to which Asheville's current parks satisfy the concept of distributional justice, we cite statistics from the Trust for Public Land (TPL), an organization that created a park scoring system for major United States cities upon the basis of park quantity, quality, spatial capacity, and access [9]. As a goal, the TPL asserts that all residents should reside within a 10-minute walking distance to "publicly-owned local, state, [or] national parks, trails, [or] open space" [9]. The overall percentage of Asheville residents within a 10-minute walking distance to a park is 44% [10]. This percentage is less than the 55% median for a dataset of 14,000 cities and towns recorded in the TPL database [10]. Figure 1.1 categorizes the overall demographic percentage of racial-ethnic classifications within a 10-minute walk to an Asheville park as re-created from the TPL [10]. We note that the highest percentage of residents within an acceptable distance to parks, 56%, are black residents while the lowest percentage of residents, 34%, are Hispanics [10]. Therefore, there exists a range of 22% between racial-ethnic demographics.

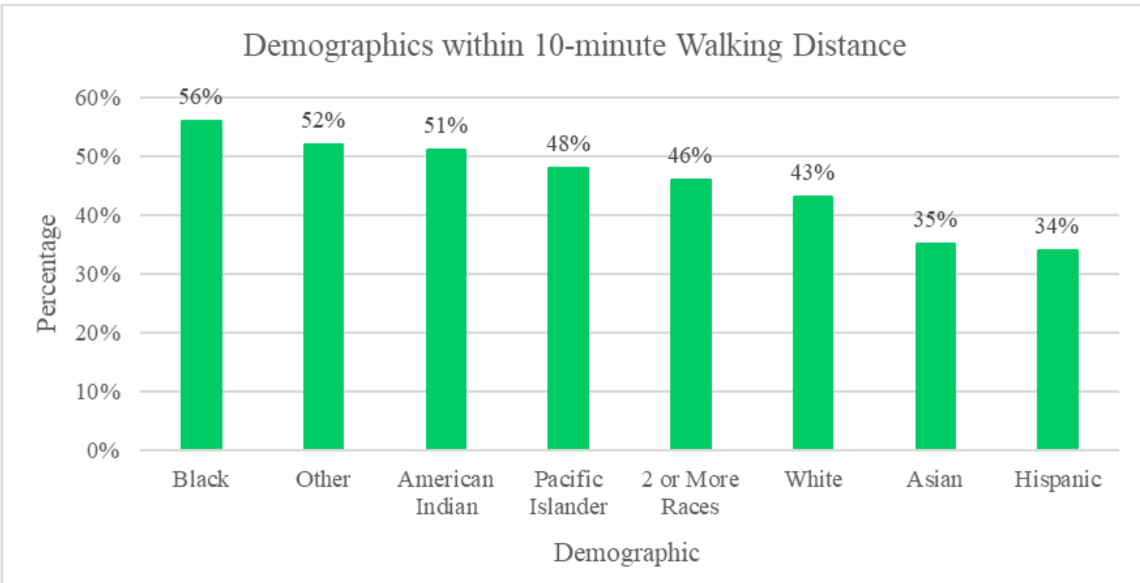

Figure 1.1: Within a 10-minute Walk: Asheville's Current Park Access by Race-Ethnicity

An additional indicator of park access is the percentage of overall city land dedicated to recreational uses [9]. Only 3% of Asheville's 44.93 square-mile land area includes parks and greenspaces while the median percentage for other surveyed cities is 19% [10], [11].

The TPL provides a visual component of analysis, a geography-based tool that illustrates distribution of current parks and park service areas and highlights park priority area based upon income, race, health, local heat, and local pollution [9], [10]. Listed are the top five priority areas for ideal future greenspace sites based upon the need to locate parks within a 10-minute walk of all residents; the map portrays these sites with a yellow-green point feature class [10]. The top five priority areas for ideal future greenspace sites based upon the need to locate parks within a 10-minute walk of all residents and upon the need to mitigate heat are represented with a blue point feature class [10].

Figure 1.2 visualizes the TPL's map of Asheville's city limits with the aforementioned elements [10]. We observe that a park service area coverage exists for the central region of Asheville and for several areas within the eastern region. However, park coverage is non-existent for a majority of the northern, western, and southern portions of the city limits. Notably, the suggested priority sites for future park development do not significantly increase park access for these underserved areas.

There are several limitations in the TPL scoring method. The first limitation is that the TPL model does not account for monetary spending restrictions in the selection of new candidate park sites. Realistically, budget constraints limit the amount of park land that an organization may purchase. Further, the TPL model does not recommend specific park land for purchase. Rather, the model determines the general area that possesses the greatest park priority. Finally, the TPL model does not include the simultaneous selection of multiple new parks. Therefore, the model has the inability to analyze how the selection of one new park site may affect the practicality of selecting another candidate park site.

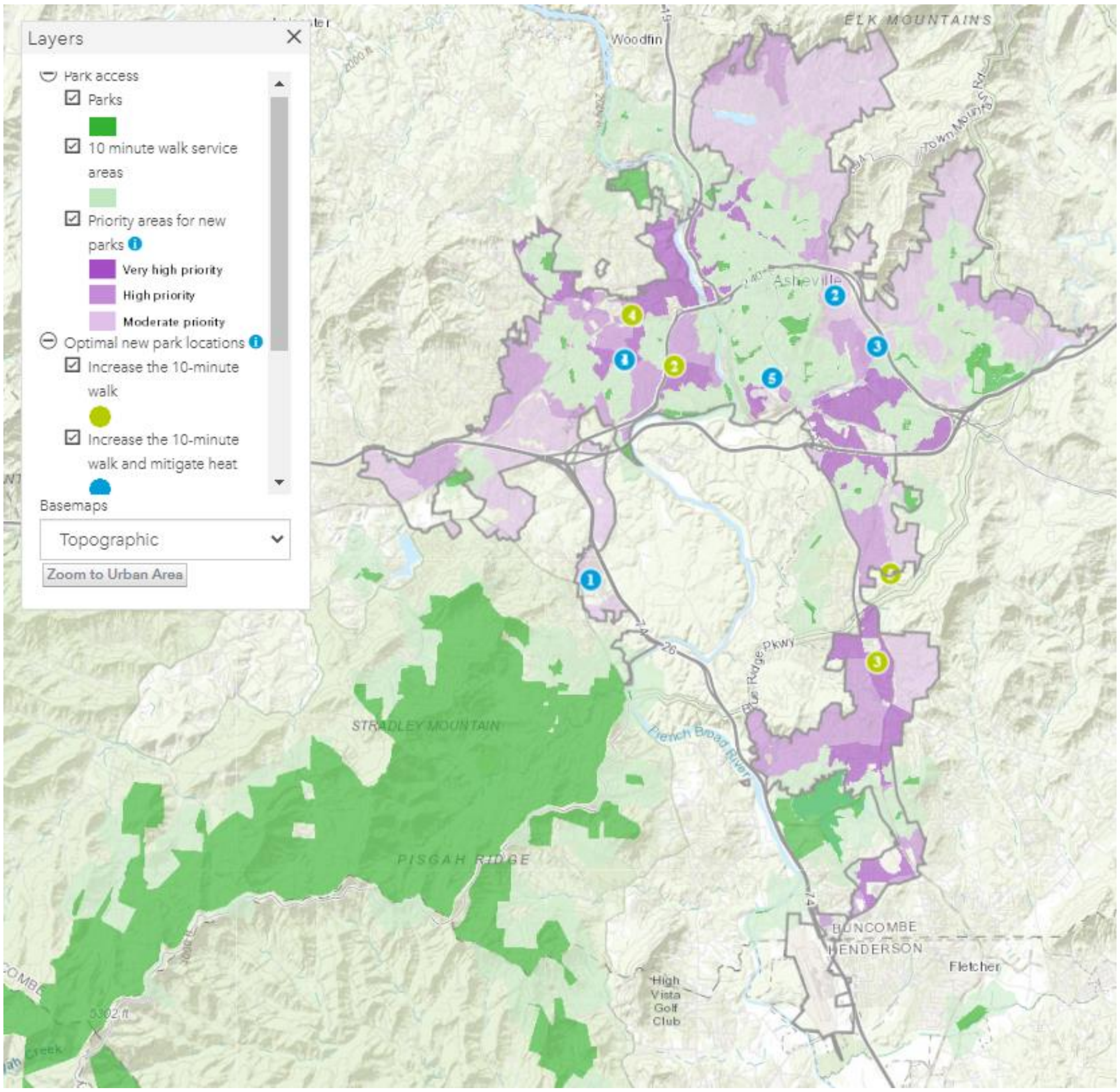

Figure 1.2: Asheville Parks and TPL Priority Areas

The statistics and figures within this section serve as an initial current-state benchmark of park access and quality in Asheville. We note that sub-ideal park access exists throughout Asheville City Limits (ACL) and that, therefore, there exists much value in the creation of strategic park location planning that would increase park availability and expand the amount of city land dedicated to recreational purposes. Further, we note that the development of facility location models that incorporates improvements to the current TPL model limitations would offer new location insights that would greatly benefit both demographic and locational equity.

Asheville's Equity Plan

The Asheville Parks and Recreation Department (ARPD) defines equity as existent when a cultural environment "values and operates with fairness [toward an individual] despite one's race, ethnicity, gender, physical or intellectual ability" [12]. We select Asheville, NC as the subject of our case study specifically because initiatives toward park and greenspace equity already exist in city organizational endeavors. One such initiative is the ARPD's proposed "Racial Equity Action Plan" (2017-2020), which seeks to combat the injustices encountered by individuals defined by marginalized racial-ethnic characteristics [12]. Objectives of the proposed plan include increasing environmental justice in terms of racial equity, support for community needs, and celebration of diversity [12]. The city accomplishes these goals through representation within the organization, the examination and prevention of the main sources of park inequities, and developments in policy [12].

Generally, the ARPD focuses upon the inclusion of "historically underserved communities" by pursuing a proper allocation of monetary and human resources to the benefit of groups facing racial, gender, and disability marginalization [12]. The ARPD employs a Rehabilitation Community Investment Program (CIP) to provide funding to minimize inequities within these and other categories [12]. To identify target sites for CIP improvements, the ARPD utilizes a point-based method of neighborhood and park characteristics such that areas with the greatest need for improvement have the largest score value [12]. Table 1.1 is a translation of the ARPD point-based criteria [12].

Table 1.1: ARPD Point-Based Criteria for Measuring Park Inequities

Focus	Category	Attribute	Score
Neighborhood-Focused	Racially Concentrated Areas of Poverty	Racially concentrated area of poverty	5
		Area of concentrated poverty	3
		Neither	0
	Neighborhood Population Density [per square mile]	Over the average	3
		900 - 1968(average)	2
		0 - 899	1
	Youth Population of Neighborhood [below 18 yrs.]	> 24%	2
		16% - 24%	1
		< 16%	0
	Neighborhood Crime [crimes against persons/1000 people]	> 10	2
		4.1 – 9.99	1
		< 4	0
Park-Focused	Park Asset Condition	Needs rehabbing or replacement	5
		Function and reliable	3
		New or like new	0
	Age of Park Assets [Lifespan duration]	Expired before 2016	3
		Expires between 2017 and 2023	1
		Still in lifespan in 2023	0
	Proportion of Value [capital invested since 2009 vs. total cost to replace all park assets]	0%	3
		0.1% - 9.9%	2
		10.0% - 24.9%	1
		> 25%	0

We provide reasoning for the selection of the listed neighborhood-focused measures for CIP projects. There is an increased need for improvement projects within areas of poverty since impoverished residents likely lack access to transportation, which prevents them from accessing distanced parks [12]. The ARPD includes neighborhood population density as a documented criteria because areas with increased population density likely experience park overcrowding due to insufficient park land area [12]. Greater emphasis is placed upon locating parks in areas with youthful populations to foster in children a positive mentality toward physical activity [12]. Parks located in areas with greater crime require CIP projects to provide improvements that increase safety [12]. Park-focused criteria ensure that CIP projects occur for parks that are worn and old as well as for parks in areas that are normally unmaintained [12].

This point-based method of determining areas of Asheville that most require funds to facilitate increased park access and quality is effective. However, we note that compiling and analyzing this information requires a significant amount of resources, which many smaller cities and towns do not possess. Further, the overall process is both time-consuming and difficult to replicate for other geographical locations. Therefore, an impactful development to equity modeling includes the creation of an informative tool that utilizes input data that is both simple to collect and to analyze for any city or town.

Modeling and Data Analysis Overview

The purpose of our facility location models is to provide an insightful tool for decision makers that incorporates the key indicators of park equity into the selection of primary parks. Current literature concerns equity in facility location models with the purpose of increasing access to healthcare facilities [13], [14], increasing the efficiency of ambulance dispatch [15], and increasing equitable allocation of disaster relief resources

[16]. Our purpose of facilitating equity in the distribution of parks and greenspaces provides a new context in which we may use operations research to benefit humanitarian efforts.

Within our models, we incorporate several key indicators of park equity into a singular objective function. The preferable model is one with the ability to optimally solve numerous, multi-faceted decisions within a reasonable amount of time. We note that this ability is an important requirement in the analysis and representation of large cities. Our deviation-based model satisfies these requirements in considering park selection to represent a large number of resident locations and candidate park sites. Further, our model not only possesses a reasonable solve time but also allows for the maximization of equity while not adversely impacting the goodness of park decisions. In other words, we balance an equity-goodness tradeoff.

Notably of interest within the scope of this study is the need to collect and analyze geospatial data concerning the current state of Asheville's demographic composition and park distribution and features. We collect this data from several publically available local, regional, and national databases. We synthesize and visually display data with multiple maps by utilizing a geographic mapping software that visualizes tabular data as connected to the spatial dimension of feature classes such as polygons, lines, and points. The need to extrapolate and summarize data in terms of defined resident locations and parks requires that we utilize several geoprocessing tools and data analyses to translate raw data into usable model parameter inputs. Further, the representation of primary park designations and selected candidate park facilities becomes more comprehensible within the visual format of maps.

Creating a holistic park equity model requires the active participation of members that compose a multidisciplinary team. Understanding the implications and requirements of parks and greenspaces requires the input of experienced social scientists, such as individuals working within the realm of study of Parks, Recreation, and Tourism Management (PRTM). The collaboration between the fields of industrial engineering (IE) and PRTM provides a holistic perspective of the integral concerns that cause park disparities and of the practicality of representing these elements mathematically. Throughout the data collection and model development process, the team achieves a shared understanding of important model requirements, of existing park benchmarks, and of available data sources. Further, this collaboration ensures that we include within the models only the most important and impactful elements of park equity while disregarding the less significant components that would unnecessarily complicate the formulation.

Not only is collaboration within a multidisciplinary team important in the model formulation process but it is also necessary in the model implementation phase. Our park equity models seek to select ideal park locations such that we maximize equitable access and quality for all individuals. Therefore, our models target marginalized residents and underserved areas to promote equity. However, we note that gentrification commonly results when beautification and improvement initiatives occur in marginalized areas. Therefore, our model selections may inadvertently lead to the augmentation of gentrification and a decreased access for marginalized individuals in the event that park decisions are made without the enactment of proper policy measures. Thus, the existence of equitable park access and quality is dependent upon the participation of housing officials in collaboration with park planners.

Finally, another component in the context of study is the likely inability for any developed model to obtain a fully feasible solution in actual park location decisions. In the selection of optimal candidate park sites, realities of political and social factors may prevent decision makers from adopting parks at model-optimal locations. Specifically, our park equity models may output candidate locations that require further evaluation concerning metrics and policy concerns that are not easily incorporated into our models a priori. Therefore, the model solutions, themselves, are not absolute solutions. Yet, our models do serve as a vital initial park decision-making tool that guides equitable location decisions to facilitate increased access for residents.

Current Study Overview

This study discusses the formulation and analysis of mathematical models designed to serve as a guide in park urban planning endeavors. The models presented uniquely identify and relate factors of equity that specifically contribute to park and greenspace goodness. We note that, though there are quantitative tools and mapping techniques that assist with the analysis and visualization of equity elements and resulting disparities, there does not exist a method that facilitates the integration of a variety of environmental, health, demographic, monetary, and dimensional factors in the determination of candidate park sites and primary park designations. Therefore, this study contributes to the field of parks and recreation, social sciences, and industrial engineering applications. Specifically, the formulation of equity in terms of parks and greenspaces provides a new perspective and context to the traditional scope of humanitarian facility location models.

We propose that the new insights and modeling notation techniques gained from the completion of this study be modified and incorporated in the creation of additional equity models that serve to solve access initiatives concerning the location of social services and other humanitarian facilities. For example, our model framework may serve as an initial reference for the maximization of equity in the location of food banks, homeless shelters, and other social service providers.

The remaining chapters within this document serve to provide greater detail concerning the background of our models, the creation of our models, and the results of our models. Chapter two provides a literature review concerning park measures, facility location models, equity, and outdoor-focused models. Chapter three presents the formulation for our developed deviation-based and score-based models. Chapter four is a presentation of our data collection process and data analyses. We list data sources and discuss how we utilize geoprocessing tools to translate original data into model parameters values. Chapter five provides results from a number of model analyses that seek to address questions regarding the effectiveness of our models in increasing park and greenspace equity. We conclude with chapter six, which provides a discussion of analysis results, a list of our study's limitations, and a compilation of suggestions for future work.

CHAPTER TWO

LITERATURE REVIEW

In this section, we provide a literature review that seeks to provide background knowledge of measures of park goodness, general facility location models, applications of equity within facility location models, and considerations for outdoor-focused models.

Measures of Park Goodness

There are several measures and considerations when determining the effectiveness of parks to provide an appropriate social and recreational space for the community. The first of these considerations is qualitative in nature. The worth of parks is a function of human likes and opinions about the facility [17]. Therefore, a successful park is a space that the community deems preferable and that generates mental and physical human welfare [17]. A survey reveals that individuals are more likely to visit parks with amenities that are well-maintained and “interesting” [18]. Further, the visual appeal and safety of greenspaces is another indicator of an individual’s willingness to visit a park [17], [18].

Several park goodness measures are quantitative in nature. The number of park amenities offered at each park has a direct relationship to the amount of physical activity of the park visitor [19]. Further, elements such as park accessibility, physical placement, and capacity are common measures in park analysis [17], [20], [21]. Specifically concerning the spatial distribution of greenspaces, there must be a balance between having a shortage and an excess of parks [21]. While a shortage of parks leads to inequities, an excess of parks decreases novelty, which leads to a decrease in the desire of individuals to visit any park [21].

Literature also exists concerning a point-based method to communicate the degree of park access within a determined region. Park access may be scored as dependent upon distance from residents to parks as well as upon park quantity, spatial capacity, and quality [22]. Though individual point-based scoring initiatives exist, there is a desire and need for a common park score indexing criteria to be employed among multiple recreational organizations and government agencies [22]. Additionally, this method is reactive in nature [22]. There is limited research on point-based techniques that proactively recommend new sites for parks and greenspaces.

Facility Location Models

We mention the different general formulations of facility location models and their application in real-world scenarios. In discrete location models, binary decision variables represent facility location decisions [23]. The maximum coverage model seeks to satisfy demand nodes given a specific objective and constraints [23]. Van den Berg, Kommer, and Zuzáková create a facility location model to effectively locate ambulances by allowing a fractional coverage of demand sites [24]. The main objective is to maximize the expected coverage of demand subject to allocation and capacity constraints [24]. O'Brien et al. explore the application of a maximum coverage facility location model to promote resilience during a global pandemic [25]. The formulation considers values of capacity and demand in the determination of optimal locations at which to place sanitization stations throughout campus buildings at a large public university [25].

The p-center problem concerns the minimization of the maximum distance between demand nodes and facility locations sites while requiring that a predefined number of facilities are selected and that demand is fully satisfied [23]. Lin and Lin explore using the p-center model formulation to allocate refueling stations while decreasing distance deviations [26]. Utilized is a network-based structure that requires flow balance constraints [26].

The p-median problem assigns one facility to each demand node while selecting a predefined number of facilities [23]. Jia et al. seek to utilize the p-median model structure to visualize the location of optimal healthcare facilities dependent upon capacity and spatial compactness [27]. The objective is to minimize demand weighted distance while requiring that all demand points are assigned to a facility [27]. Daskin and Tucker include the p-median model in an exploration of the tradeoff in satisfying demand-weighted distance average values and ranges within the context of facility location formulations [28]. The authors present a multi-objective model, noting the range formulation as a basis by which modelers may represent equity [28].

Other contexts of facility location models in practice include disaster relief supply allocation. Balcik and Beamon optimize both the location of disaster relief facilities and the allocation of resources at those facilities [29]. The proposed objective function maximizes the amount of demand that distribution centers are able to fulfill and constrains the total amount of available funding and facility volume capacity [29]. Shehadeh and Tucker consider uncertainty in the determination of the distribution and allocation of disaster relief resources with a two-stage stochastic program [30]. Their model seeks to minimize both fixed and stochastic costs, such as shortage and holding costs as well as transportation costs [30].

Some facility literature focuses upon the incorporation of stochasticity within models. The inclusion of stochasticity is commonplace within the topic of resiliency. Considerations for facility location models include accounting for stocastic disturbances in networks that may lead to the unusability of one or more existent facilities [31]. An appropriate analysis would be to examine the ability of a system to function provided that a number of facilities become inaccessible [31].

An additional incorporation of stochasticity in facility location models is in the consideration of human behavior. A multinomial logit problem assists in modeling human behavior given that the probability distribution of an indidivual's visit to a particular location is known [32]. A practical model objective function is the maximization of utility [32]. Haase and Müller introduce a facility location problem that uses a multinomial logit structure to trade off workload and participation in modeling client involvement at a preventive healthcare facility [33]. The authors equate workload to the number of service staff needed to achieve a given service level [33].

Equity in Facility Location Models

Existing literature discusses methods of incorporating equity into objective functions. One such method is the inclusion of distance in the objective function of the facility location model [34]. The need for simplicity in the selection of equity measures is achieved with a minimizing function of distance – the center, the range, the mean absolute deviation, the variance, and the maximum deviation [34]. Marsh and Schilling define assessing equity as "a comparison of the impact or effect of an action on two or more individuals or groups" [35]. The incorporation of a weight parameter that allows mathematical models to represent the emphasis of importance placed upon classifications as social need, desire, value, population, and demand assists in modeling the impact of equitable practices [35]. Further model considerations define equity as a component of spatial, demographic, or temporal dimensions [35].

Several researchers explore methods of practical equity implementation by modeling distance. Drezner and Drezner seek to develop an equity-based facility location model by utilizing the Big Triangle Small Triangle branch and bound method [36]. The considered objective functions seek to minimize the variance and the range in origin-destination distances [36]. Ohsawa, Ozaki, and Plastria discuss the development of a facility location model that maximizes equity by either minimizing or maximizing the sum of square distances from residents to facilities, dependent upon whether the facility in question is attractive or repulsive [37]. A recent study highlights the utilization of stochastic modeling in the equitable location of healthcare facilities by minimizing weighted distance [38].

Other research utilizes demand satisfaction as a component of equity. Gutjahr and Nolz present a literature review that explores methods and existing knowledge concerning the equity of resource distribution [39]. The authors define coverage as the number of actual resources supplied to a group over the number of resources needed for the group's wellbeing [39]. We may define these groups by geographic location and/or by demographic characteristics [39].

Some literature considers equity as a function of distance and demand. A recent study discusses a facility location model that considers healthcare facility capacity and demand while noting the travel time from demand nodes to the facilities [13]. The authors consider equity in selecting a facility location as a function of accessibility deviations [13]. Chea et al. propose an anti-coverage model to study the location of trauma center facilities with respect to historic vehicle accidents [40]. The authors define an anti-coverage model that maximizes the amount of benefit that facilities create while constraining a lower-bound accessibility requirement from demand nodes to facilities [40].

Another study considers elements of both distance and demand satisfaction in the proposition of an optimization model that seeks to maximize equity in the location of residential care facilities within an aging community [41]. One essential optimization model input includes spatial distance, though the authors recommend that future studies consider aspatial access in maximizing access to facilities [41]. Other model inputs include facility capacity, resident demand, and the physical distance between supply and demand nodes to represent equity [41]. You notes that equity in facility location should consider both the access to the facility and the demands that residents of specific demographic characteristics have of the facility [14]. The proposed formulations consider satisfying the daily demand of residents while taking into account road networks and potential blockages [14]. The structure of a weighted multi-objective model is effective in representing differing goals and allows for the development of Pareto solutions for analysis [42]. Zhang et al. utilize a multi-objective model to represent the desire to maximize equity, access, and coverage of healthcare facilities and to minimize monetary costs [42]. The authors consider the marginal benefit of adding a facility to a particular region by considering that region's current accessibility to a healthcare provider [42].

Other research defines fairness in terms of costs. Facility location models may consider customer satisfaction in site selection [43]. A recent study considers the minimization of customer spending to access a facility and defines fairness as the notion that customers receive a sufficient result from accessing the facility compared to the cost of access [43].

Researchers explore multiple methods for modeling vulnerability and marginalization in order to measure equity. A recent study explores minimizing accessibility inequities by minimizing a “p-envy function", which represents the difference in accessibility between individual demand nodes [13]. Alem et al. indicate the marginalization within distinct geographic locations throughout Brazil with the creation of a Social Vulnerability Index, which considers elements such as resident gender and economic status [16]. The authors incorporate the developed Social Vulnerability Index into their optimization model to foster equitable allocation of disaster relief resources to regions with greater marginalization [16]. Another method to incorporate equity concerns the creation of an index of priority for differing demand types [15]. Enayati et al. utilize this method in the utilization of a multi-criteria optimization model that maximizes the equity and efficiency of ambulance dispatch processes [15]. In this context, priority equates to the severity of the given presented health risk [15].

Outdoor-Focused Models

Within this section, we discuss two types of outdoor-focused models. One model concerns promoting conservation. Noteworthy are the similarities between the requirements of parks and conservation sites. Inherently, the purpose of conservation sites is the preservation of unique and valuable species of vegetation and animal [21]. Parks serve to increase biodiversity and should support environmental conservation initiatives [21], [44]. The creation and preservation of urban parks, specifically, results in the greatest conservation gains [44].

There exists an ample supply of literature to express the formulation of conservation models. One such study introduces a multiple-knapsack structure to maximize the overall benefit of conservation program outcomes given capacity and budget constraints [45]. The article mentions that the integration of multiple programs may result in the greatest amount of environmental improvement [45].

Land compactness and the connectivity of land and vegetation are vital to conservation initiatives [46], [47]. Billionnet considers a mathematical model that preserves reserve compactness and shape by adding a constraint to restrict the maximum value of the perimeter divided by the area [46]. Another study introduces a model that reflects the need for land connectivity in a two-step optimization process that seeks to determine optimal conservation sites and then determine routes of connectivity between those choosen reserves [47]. It is possible to achieve connectivity by a least-distance calculation technique [46].

Another form of outdoor-focused model concerns invasive species management. A connection between park equity models and invasive species management models is the underlying purpose of promoting and bettering human welfare. An invasive species is a creature “non-native to the ecosystem under consideration and… [is a cause of] economic or environmental harm or harm to human health” [48]. Invasive species attack the rich biodiversity inherent in parks and recreational facilities [49].

A proposed solution to the invasive species management problem is the creation of a model that considers spatial and temporal components in allocating resources to initiatives that mitigate the appearance of and spread of pests [48], [49]. Additional model considerations include the representation of budget constraints and the minimization of destruction caused by invasive species [48]. Such a model incorporates the stochasticity of unknown invasive species growth and distribution and a temporal element of effective program mitigation initiation [48], [49].

CHAPTER THREE

FORMULATION MODELING

Our developed equity models seek to mathematically address several dimensions of park and greenspace equity in an framework. Considered dimensions that directly impact equity are park distance, capacity, heat, and tree cover. We measure and define the overall equity generated by these individual elements by means of weighting and normalization. We present two differing models that quantify equity by means of deviations from ideal park goodness measures. Our deviation-based model maximizes equity by minimizing the deviations that directly result from the model-optimal location decisions. Our score-based model maximizes equity by maximizing park score. In this model, we assign scores for individual deviations such that a minimal deviation results in a high score, and a large deviation results in a decreased score. Our models follow the structure of a facility location model that improves the park access and quality experienced by residents. We utilize demographic population counts and demographic strategic target weights to place emphasis upon an equitable allocation of parks.

This chapter provides the structure for our two developed facility location models. We first address the included elements of park equity within our models. Then, we introduce the formulation notation of our deviation-based and score-based park equity models and address assumptions. We conclude with a discussion of additional demographic sets to be added in future work.

Indicators of Park Equity

The purpose of our park equity model is to address the disparities within the park setting. Therefore, the prerequisites to formulating park equity models are to understand the causes of park disparities and to identify the main indicators of park goodness. We collaborate with PRTM professionals. In our deliberations, we determine the four key park equity elements to be (1) the distance from residents to parks, (2) the capacity of parks, (3) the heat of parks, and (4) the tree cover of parks.

The concept of environmental justice concerns multiple dimensions. While we consider only a portion of the elements that contribute to overall environmental justice, we argue that the four listed goodness factors are among the most impactful in park location decisions. Distance from residents to parks is a direct measure of park *access* because this dimension considers the realities of transportation networks and travel practicality. Park capacity is a measure of park *quality*, since overcrowding results in a decreased ability for the members of the community to utilize park amenities. Park heat and tree cover also contribute to the *quality* of parks. A moderate park heat provides a more pleasurable condition with regard to the comfortability of temperature within an outdoor setting. The tree cover within parks provides an aesthetic component which augments the desirability of greenspaces. Further, there is a direct relationship between increased tree cover and decreased heat.

There is great importance in determining the park goodness experienced by individuals of differing demographics to note any differences between these resident classifications. Therefore, we include within our models the number of individuals within each resident location represented by each demographic classification. Within the scope of this thesis, we simplify the formulation and succeeding analyses by including only demographics of race-ethnicity.

The Deviation-Based Model

Our first presented model is a deviation-based model, which maximizes equity by minimizing the deviations of distance, capacity, heat, and tree cover that directly result from the model-optimal location decisions. Within the objective function, we represent the importance of the contribution of each deviation classification by weighing its normalized numerical value. We present a demographic element in the objective function by noting demographic population counts of residents per location as well as by including a strategic target weight per demographic, which defines a level of importance in selecting parks with an increased goodness for a specific demographic. In our objective function, we propose the minimization of the maximum demographic deviation. With constraints, we ensure that all residents have a primary park and that we do not exceed the given budget in the purchasing of candidate site land.

We begin by introducing the sets included within our model that serve to represent geospatial and demographic factors. Further, we present parameters, which are known values concerning the representation of incorporated factors of equity, and decision variables, which include binary, integer, and continuous variables. We then present the objective function of our deviation-based main model as well as constraints.

After introducing the main model, we consider additional objective functions to incorporate. Further, we discuss the linearization of non-linear model components.

Deviation-Based Model: Defining Sets, Parameters, and Decision Variables

In Table 3.1, we define the sets and parameters to formulate the deviation-based park equity model.

Table 3.1: Main Model Sets and Parameters

Sets	
K	Set of All Parks $K = K^{existing} \cup K^{candidate}$
$K^{existing}$	Set of Existing Parks
$K^{candidate}$	Set of Candidate Parks
L	Set of Resident Locations
R	Set of Races/Ethnicities $R = \{\text{White, Black, Indigenous, Asian, Pacific Islander, Other}\}$
Parameters	
e_k	$:= \begin{cases} 1 & \text{if park already exists at park } k \in K \\ 0 & \text{otherwise} \end{cases}$
d_{kl}^{act}	actual distance from resident location $l \in L$ to park $k \in K$
m	desired max distance from any resident to its primary park
a_k^{act}	actual capacity of park $k \in K$
b	budget for park purchasing
f_k	fee to purchase the land for park $k \in K$
c_k^+	amount of heat above the desireable range for park $k \in K$
c_k^-	amount of heat below the desireable range for park $k \in K$
v_k^+	amount of tree cover above the desireable range for park $k \in K$
v_k^-	amount of tree cover below the desireable range for park $k \in K$
t_{lr}	count of individuals in location $l \in L$ of demographic $r \in R$
q_r	importance weight of resident demographic $r \in R$
w^{dist+}	penalty weight of excess distance
w^{cap+}	penalty weight of park overcrowding
w^{heat+}	penalty weight of excess park heat
w^{heat-}	penalty weight of deficit park heat
w^{tree+}	penalty weight of excess park tree cover
w^{tree-}	penalty weight of deficit park tree cover
n^{dist}	normalization of distance
n^{cap}	normalization of capacity
n^{heat}	normalization of heat
n^{tree}	normalization of tree cover

In Table 3.2, we define the decision variables to formulate the deviation-based park equity model.

Table 3.2: Main Model Decision Variables

Decision Variables	
Main	
y_k	$:= \begin{cases} 1 & \text{if park } k \in K \text{ is open} \\ 0 & \text{otherwise} \end{cases}$
x_{kl}	$:= \begin{cases} 1 & \text{if residents in location } l \in L \text{ primarily visit park } k \in K \\ 0 & \text{otherwise} \end{cases}$
Deviation Calculation	
α_r^{act}	total weighted deviation of each demographic classification $r \in R$
α^{max}	maximum total weighted demographic deviation
Slack	
d_l^+	distance to primary park beyond desired for location $l \in L$
a_k^+	amount of overcrowding in park $k \in K$
u_l^{dist}	$:= \begin{cases} 1 & \text{if distance to primary park is within desired for location } l \in L \\ 0 & \text{otherwise} \end{cases}$
u_k^{cap}	$:= \begin{cases} 1 & \text{if the capcity of park } k \in K \text{ meets or exceeds its needed capacity} \\ 0 & \text{otherwise} \end{cases}$

Deviation-Based Model: Main Formulation

The model's main formulation includes an objective function and constraints. The formulation of the deviation-based park equity model is as follows:

$$\text{minimize } \alpha^{max} \tag{1}$$

Subject to:

$$\alpha_r^{act} = \sum_{l \in L} \sum_{k \in K} \left(q_r t_{lr} \left[n^{dist} w^{dist+} d_l^+ + \begin{pmatrix} n^{cap} w^{cap+} a_k^+ \\ + n^{heat} w^{heat+} c_k^+ \\ + n^{heat} w^{heat-} c_k^- \\ + n^{tree} w^{tree+} v_k^+ \\ + n^{tree} w^{tree-} v_k^- \end{pmatrix} x_{kl} \right] \right) \quad \forall r \in R \tag{2}$$

$$\alpha^{max} \geq \alpha_r^{act} \quad \forall r \in R \tag{3}$$

$$\sum_{k\in K} x_{kl} = 1 \quad \forall l \in L \tag{4}$$

$$x_{kl} \leq y_k \quad \forall k \in K, l \in L \tag{5}$$

$$e_k \leq y_k \quad \forall k \in K \tag{6}$$

$$\sum_{k\in K} f_k y_k \leq b \tag{7}$$

$$\sum_{k\in K} d_{kl}^{act} x_{kl} - d_l^+ \leq m \qquad \forall l \in L \tag{8}$$

$$d_l^+ - \left(1 - u_l^{dist}\right)\left(\sum_{k\in K} d_{kl}^{act} x_{kl} - m\right) \leq 0 \qquad \forall l \in L \tag{9}$$

$$\sum_{l\in L}\sum_{r\in R} t_{lr} x_{kl} - a_k^+ \leq a_k \quad \forall k \in K \tag{10}$$

$$a_k^+ - \left(1 - u_k^{cap}\right)\left(\sum_{l\in L}\sum_{r\in R} t_{lr} x_{kl} - a_k^{act}\right) \leq 0 \qquad \forall k \in K \tag{11}$$

$$y_k \in \{0,1\} \quad \forall k \in K \tag{12}$$

$$x_{kl} \in \{0,1\} \quad \forall k \in K, l \in L \tag{13}$$

$$\alpha^{max} \geq 0 \tag{14}$$

$$\alpha_r^{act} \geq 0 \quad \forall r \in R \tag{15}$$

$$d_l^+ \geq 0 \quad \forall l \in L \tag{16}$$

$$a_k^+ \geq 0 \quad \forall k \in K \tag{17}$$

$$u_l^{dist} \in \{0,1\} \quad \forall l \in L \tag{18}$$

$$u_k^{cap} \in \{0,1\} \quad \forall k \in K \tag{19}$$

The objective function (1) minimizes the maximum weighted demographic deviation, the largest total deviation experienced by a single demographic classification. Constraint (2) defines the total weighted demographic deviation for each demographic classification. The amount of total deviations is a function of the normalized and weighted values of distance, park capacity, park heat, and park tree cover. A linearization of this constraint is provided with constraints (30) and (33)-(36). Constraint (3) determines the maximum weighted demographic deviation of all demographic classification deviations.

Constraint (4) ensures that all locations have exactly one primary park. Constraint (5) states that residents may only visit open parks. Constraint (6) requires that a park be open if that park exists. Constraint (7) requires that the monetary cost to purchase land must be within the allocated budget.

Constraint (8) requires that residents belonging to a demographic classification are within the desirable distance of their primary park. Constraint (9) places a maximum limit upon the distance slack variable to prevent artificial slack. A linearization of this constraint is provided with constraints (37)-(41). If the actual distance from residents to their primary parks is greater than desired, then the value of the distance slack variable is less than or equal to the actual distance minus the desired distance. If the actual distance from residents to their primary parks is less than or equal to the desired distance, then the combination of constraints (9) and (16) requires the distance slack variable to equal zero.

Constraint (10) requires that the park capacity accommodate the number of visiting residents. Constraint (11) places a maximum limit upon the capacity slack variable to prevent artificial slack. A linearization of this constraint is provided with constraints (42)-(46). If the number of residents that visit a park is greater than the actual park capacity, then the value of the capacity slack variable is less than or equal to the number of visiting residents minus the actual park capacity. If the number of visiting residents to a park is less than the actual park capacity, then the combination of constraints (11) and (17) requires the capacity slack variable to equal zero. Constraints (12)-(13) and (18)-(19) are integrality constraints. Constraints (14)-(17) are domain constraints.

Deviation-Based Model: Objective Function Variations

We introduce three additional variations of objective function that we may incorporate into the model to represent a different perspective of equity. These objective functions use the additional decision variables provided in Table 3.3.

Table 3.3: Additional Decision Variables for Objective Function Variations

Decision Variables	
Additional Deviation Calculation	
λ_l^{act}	total weighted deviation experienced by each location $l \in L$
λ^{max}	maximum total weighted deviation of all locations
φ_{lr}^{act}	total weighted deviation of each demographic $r \in R$ in each location $l \in L$
φ^{max}	maximum total weighted deviation of all demographic and location pairs

Using the newly defined decision variables within this subsection, we add the following objectives and constraints:

Objective Functions

$$\min \sum_{r \in R} \alpha_r^{act} \tag{20}$$

$$\min\ \lambda^{max} \tag{21}$$

$$\min\ \varphi^{max} \tag{22}$$

Constraints

Subject to:

$$\lambda_l^{act} = \sum_{r \in R} \sum_{k \in K} \left(q_r t_{lr} \left[n^{dist} w^{dist+} d_l^+ + \begin{pmatrix} n^{cap} w^{cap+} a_k^+ \\ + n^{heat} w^{heat+} c_k^+ \\ + n^{heat} w^{heat-} c_k^- \\ + n^{tree} w^{tree+} v_k^+ \\ + n^{tree} w^{tree-} v_k^- \end{pmatrix} x_{kl} \right] \right) \quad \forall l \in L \tag{23}$$

$$\varphi_{lr}^{act} = \sum_{k \in K} \left(q_r t_{lr} \left[n^{dist} w^{dist+} d_l^+ + \begin{pmatrix} n^{cap} w^{cap+} a_k^+ \\ + n^{heat} w^{heat+} c_k^+ \\ + n^{heat} w^{heat-} c_k^- \\ + n^{tree} w^{tree+} v_k^+ \\ + n^{tree} w^{tree-} v_k^- \end{pmatrix} x_{kl} \right] \right) \forall l \in L, r \in R \tag{24}$$

$$\lambda^{max} \geq \lambda_l^{act} \quad \forall l \in L \tag{25}$$

$$\varphi^{max} \geq \varphi_{lr}^{act} \quad \forall l \in L, r \in R \tag{26}$$

$$\lambda_l^{act} \geq 0 \quad \forall l \in L \tag{27}$$

$$\varphi_{lr}^{act} \geq 0 \quad \forall l \in L, r \in R \tag{28}$$

$$\alpha^{min}, \lambda^{max}, \lambda^{min}, \varphi^{max}, \varphi^{min} \geq 0 \tag{29}$$

Objective function (20) minimizes overall weighted deviations by adding weighted demographic deviations across all demographic classifications. Objective function (21) minimizes the maximum total weighted location deviation. Objective function (22) minimizes the maximum total weighted deviation experienced by individuals of demographic-location pairs.

Constraint (23) defines the weighted park deviation encountered by residents belonging to each resident location. The amount of total deviations is a function of the normalized and weighted values of distance, park capacity, park heat, and park tree cover. A linearization of this constraint is provided with constraints (31) and (33)-(36). Constraint (24) defines the weighted park deviation encountered by residents belonging to each demographic-location pair. The amount of total deviations is a function of the normalized and weighted values of distance, park capacity, park heat, and park tree cover. A linearization of this constraint is provided with constraints (32)-(36). Constraints (25) and (26) determine the maximum park weighted deviations for each resident location and for each demographic-location pair respectively. Constraints (27)-(29) are domain constraints.

To utilize objective function (20) as the benchmark for equity creation, the analyst would substitute objective function (20) for objective function (1). Analyzing equity with objective function (21) would require the switching of constraints (2), (3), (14), and (15) with constraints (23), (25), (27), and (29). Analyzing equity with objective function (22) would require the switching of constraints (2), (3), (14), and (15) with constraints (24), (26), (28), and (29).

Deviation-Based Model: Constraint Linearization

We use non-linear functions within constraints (2), (9), (11), (23), and (24) since we multiply two decision variables. We use the parameters and decision variables within Table 3.4 in the linearization of these constraints.

Table 3.4: Parameters and Decision Variables for Linearization

Parameters	
Maximum Values for Linearization	
$\mu^{maxdist}$	big M (max) value for actual distance from resident locations to parks
μ^{maxcap}	big M (max) value for actual capacity of parks
μ^{cap+}	big M (max) value for overcrowding of parks
Decision Variables	
Linearization	
$\pi_l^{actdist}$	linearization variable for limiting distance slack for location $l \in L$
π_k^{actcap}	linearization variable for limiting capacity slack for park $k \in K$
π_{kl}^{cap+}	linearization variable for the overcrowding of park $k \in K$ experienced by location $l \in L$

We linearize constraints (2), (9), (11), (23), and (24) with the following additional constraints, which use the inputs defined within this subsection as well as in the main deviation-based formulation:

Linearization of Park Goodness Deviations (Constraints 2, 23, and 24):

$$\alpha_r^{act} = \sum_{l \in L} \sum_{k \in K} \Big(q_r t_{lr} \big[n^{dist} w^{dist+} d_l^+ + n^{cap} w^{cap+} \pi_{kl}^{cap+} + n^{heat} x_{kl} \, (w^{heat+} c_k^+ + w^{heat-} c_k^-) + n^{tree} x_{kl} \, (w^{tree+} v_k^+ + w^{tree-} v_k^-) \big] \Big) \quad \forall r \in R \tag{30}$$

$$\lambda_l^{act} = \sum_{r\in R}\sum_{k\in K}\Big(q_r t_{lr}\big[n^{dist}w^{dist+}d_l^{+} + n^{cap}w^{cap+}\pi_{kl}^{cap+} + n^{heat}x_{kl}\,(w^{heat+}c_k^{+} + w^{heat-}c_k^{-}) + n^{tree}x_{kl}\,(w^{tree+}v_k^{+} + w^{tree-}v_k^{-})\big]\Big) \quad \forall l \in L \tag{31}$$

$$\varphi_{lr}^{act} = \sum_{k\in K}\Big(q_r t_{lr}\big[n^{dist}w^{dist+}d_l^{+} + n^{cap}w^{cap+}\pi_{kl}^{cap+} + n^{heat}x_{kl}\,(w^{heat+}c_k^{+} + w^{heat-}c_k^{-}) + n^{tree}x_{kl}\,(w^{tree+}v_k^{+} + w^{tree-}v_k^{-})\big]\Big) \quad \forall l \in L, r \in R \tag{32}$$

$$\pi_{kl}^{cap+} \le \mu^{cap+}x_{kl} \quad \forall k \in K, l \in L \tag{33}$$

$$\pi_{kl}^{cap+} \le a_k^{+} \quad \forall k \in K, l \in L \tag{34}$$

$$\pi_{kl}^{cap+} \ge a_k^{+} - (1 - x_{kl})\,\mu^{cap+} \quad \forall k \in K, l \in L \tag{35}$$

$$\pi_{kl}^{cap+} \ge 0 \quad \forall k \in K, l \in L \tag{36}$$

Linearization of Distance Slack Calculation (Constraint 9):

$$d_l^{+} - \sum_{k\in K} d_{kl}^{act}x_{kl} + m + \pi_l^{actdist} - u_l^{dist}m \le 0 \quad \forall l \in L \tag{37}$$

$$\pi_l^{actdist} \le \mu^{maxdist}u_l^{dist} \quad \forall\, l \in L \tag{38}$$

$$\pi_l^{actdist} \le \sum_{k\in K} d_{kl}^{act}x_{kl} \quad \forall l \in L \tag{39}$$

$$\pi_l^{actdist} \ge \sum_{k\in K} d_{kl}^{act}x_{kl} - \left(1 - u_l^{dist}\right)\mu^{maxdist} \quad \forall l \in L \tag{40}$$

$$\pi_l^{actdist} \ge 0 \quad \forall l \in L \tag{41}$$

Linearization of Capacity Slack Calculation (Constraint 11):

$$a_k^{+} - \sum_{l \in L} \sum_{r \in R} t_{lr} x_{kl} + a_k^{act} + \pi_k^{actcap} - u_k^{cap} a_k^{act} \leq 0 \quad \forall k \in K \tag{42}$$

$$\pi_k^{actcap} \leq \mu^{maxcap} u_k^{cap} \quad \forall\, k \in K \tag{43}$$

$$\pi_k^{actcap} \leq \sum_{l \in L} \sum_{r \in R} t_{lr} x_{kl} \quad \forall\, k \in K \tag{44}$$

$$\pi_k^{actcap} \geq \sum_{l \in L} \sum_{r \in R} t_{lr} x_{kl} - \left(1 - u_k^{cap}\right) \mu^{maxcap} \quad \forall\, k \in K \tag{45}$$

$$\pi_k^{actcap} \geq 0 \quad \forall\, k \in K \tag{46}$$

The Score-Based Model

Our second presented model is a score-based model that maximizes equity by maximizing goodness scores. The goodness score is dependent upon the deviations of distance, capacity, heat, and tree cover that directly result from the model-optimal location decisions. We develop a criterion in which a deviation within a certain range of values is given a specific score. We note that a negligible deviation value receives a higher score versus a large deviation value, which receives a low score.

Within the objective function, we represent the importance of the contribution of each element of park goodness (distance, capacity, heat, and tree cover) in the overall equity calculation by weighing its normalized score value. We present a demographic element in the objective function by noting demographic population counts of residents per location as well as the strategic target weight per demographic, which defines a level of importance in selecting parks with increased goodness for a specific demographic. In our objective function, we propose the maximization of the minimum demographic score. With constraints, we ensure that all residents have a primary park and that we do not exceed the given budget in the purchasing of candidate site land.

We begin by introducing an additional sets, parameters, and decision variables that are included within the score-based model but not within the deviation-based model. We then present the objective function of our score-based main model as well as introduce constraints that differ from the deviation-based model. We then consider additional objective functions to incorporate and discuss the linearization of new non-linear model components.

Score-Based Model: Defining Sets, Parameters, and Decision Variables

Table 3.5: Additional Sets, Parameters, and Decision Variables for the Score-Based Main Model

Sets	
δ	Set of score placeholders $\delta = \{0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10\}$
Parameters	
θ_i^{updist}	upper threshold value for distance score index $i \in \delta$
$\theta_i^{lowdist}$	lower threshold value for distance score index $i \in \delta$
θ_i^{upcap}	upper threshold value for space score index $i \in \delta$
θ_i^{lowcap}	lower threshold value for space score index $i \in \delta$
σ_i	score for score index $i \in \delta$ $\sigma_i \coloneqq [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]$
ρ_k^{heat+}	score for heat excess for park $k \in K$
ρ_k^{heat-}	score for heat deficit for park $k \in K$
ρ_k^{tree+}	score for tree cover excess for park $k \in K$
ρ_k^{tree-}	score for tree cover deficit for park $k \in K$
Decision Variables	
Score Index Identification	
ω_{li}^{dist+}	$\coloneqq \begin{cases} 1 & \text{if index } i \in \delta \text{ indicates primary park distance from location } l \in L \\ 0 & \text{otherwise} \end{cases}$
ω_{ki}^{cap+}	$\coloneqq \begin{cases} 1 & \text{if index } i \in \delta \text{ represents overcrowding for park } k \in K \\ 0 & \text{otherwise} \end{cases}$

Our score-based model utilizes all previous sets, parameters, and decision variables from the deviation-based model in addition to those listed in Table 3.5.

Score-Based: Model Main Formulation

We use all inputs within this section as well as all inputs of the deviation-based model to formulate our score-based model. We use the same main formulation for the deviation-based model as in the score-based model with the following modifications:

1. The objective function seeks to maximize the minimum demographic score verses to minimize the maximum demographic deviation. Therefore, we propose objective function (47) to replace objective function (1).
2. Rather than use the original constraint (2) to calculate total weighted demographic deviations, we instead use constraint (48), which calculates the total weighted score for each demographic classification as a function of the normalized and weighted score values of distance, park capacity, park heat, and park tree cover.
3. Rather than use the original constraint (3) to determine the maximum of all weighted demographic deviations, we instead use constraint (49), which determines the minimum of all weighted demographic scores.
4. We add constraints (50)-(57).

maximize α^{min} (47)

Subject to:

$$\alpha_r^{act} = \sum_{i\in\delta}\sum_{l\in L}\sum_{k\in K}\left(q_r t_{lr}\left[\sigma_i w^{dist+}\omega_{li}^{dist+} + \sigma_i x_{kl} w^{cap+}\omega_{ki}^{cap+} + x_{kl}\begin{pmatrix} w^{heat+}\rho_k^{heat+} \\ + w^{heat-}\rho_k^{heat-} \\ + w^{tree+}\rho_k^{tree+} \\ + w^{tree-}\rho_k^{tree-} \end{pmatrix}\right]\right) \quad \forall r \in R \tag{48}$$

$$\alpha^{min} \le \alpha_r^{act} \quad \forall r \in R \tag{49}$$

$$\sum_{i\in\delta}\omega_{li}^{dist+} = 1 \qquad \forall l \in L \tag{50}$$

$$\sum_{i\in\delta}\omega_{ki}^{cap+} = 1 \quad \forall k \in K \tag{51}$$

$$d_l^+ \le \sum_{i\in\delta}\theta_i^{updist}\,\omega_{li}^{dist+} \quad \forall l \in L \tag{52}$$

$$d_l^+ \ge \sum_{i\in\delta}\theta_i^{lowdist}\,\omega_{li}^{dist+} \quad \forall l \in L \tag{53}$$

$$a_k^+ \le \sum_{i\in\delta}\theta_i^{upcap}\,\omega_{ki}^{cap+} \quad \forall k \in K \tag{54}$$

$$a_k^+ \ge \sum_{i\in\delta}\theta_i^{lowcap}\,\omega_{ki}^{cap+} \quad \forall k \in K \tag{55}$$

$$\omega_{li}^{dist+} \in \{0,1\} \quad \forall l \in L, i \in \delta \tag{56}$$

$$\omega_{ki}^{cap+} \in \{0,1\} \quad \forall k \in K, i \in \delta \tag{57}$$

Constraint (50) ensures that only one distance score identifier variable is selected across all possible score indices for each location. Constraint (51) ensures that only one capacity score identifier variable is selected across all possible score indices for each park. Constraints (52) and (53) determine the value of the distance score binary identifier variable for each location using distance slack and distance score threshold values. Constraints (54) and (55) determine the value of the capacity score binary identifier variable for each park using capacity slack and capacity score threshold values. Constraints (56) and (57) are integrality constraints.

Score-Based Model: Objective Function Variations

Additional objective function variations to the score-based model formulation utilize the same decision variables and objective functions as defined in the "Deviation-Based Model: Objective Function Variations" subsection. We also utilize the same constraints as defined within that subsection with the following exceptions:

1. We substitute constraint (23) for constraint (58).
2. We substitute constraint (24) for constraint (59).

$$\lambda_l^{act} = \sum_{i\in\delta}\sum_{r\in R}\sum_{k\in K}\left(q_r t_{lr}\left[\sigma_i w^{dist+}\omega_{li}^{dist+} + \sigma_i x_{kl} w^{cap+}\omega_{ki}^{cap+} + x_{kl}\begin{pmatrix} w^{heat+}\rho_k^{heat+} \\ + w^{heat-}\rho_k^{heat-} \\ + w^{tree+}\rho_k^{tree+} \\ + w^{tree-}\rho_k^{tree-} \end{pmatrix}\right]\right) \quad \forall l \in L \tag{58}$$

$$\varphi_{lr}^{act} = \sum_{l\in L}\sum_{r\in R}\sum_{k\in K}\left(q_r t_{lr}\left[\sigma_i w^{dist+}\omega_{li}^{dist+} + \sigma_i x_{kl} w^{cap+}\omega_{ki}^{cap+} + x_{kl}\begin{pmatrix} w^{heat+}\rho_k^{heat+} \\ + w^{heat-}\rho_k^{heat-} \\ + w^{tree+}\rho_k^{tree+} \\ + w^{tree-}\rho_k^{tree-} \end{pmatrix} \right]\right) \quad \forall l \in L, r \in R \tag{59}$$

Constraint (58) defines the weighted park score for residents within each location as a function of the normalized and weighted values of distance, park capacity, park heat, and park tree cover. Constraint (59) defines the weighted park score experienced by residents belonging to each demographic-location pair as a function of the normalized and weighted values of distance, park capacity, park heat, and park tree cover.

Score-Based Model: Constraint Linearization

We use non-linear functions within constraints (48), (58), and (59) since we multiply two decision variables. We use the decision variable listed in Table 3.6 in the linearization of these constraints.

Table 3.6: Additional Decision Variables for Additional Linearizations in the Score-Based Model

Decision Variables	
Score Linearization	
γ_{kli}^{cap+}	linearization variable of overcrowding score for index $i \in \delta$ for park $k \in K$ as experienced by location $l \in L$

We linearize constraints (48), (58), and (59) with the following additional constraints, which use the inputs defined within this subsection as well as in the main deviation-based and main score-based formulations:

$$\alpha_r^{act} = \sum_{i\in\delta}\sum_{l\in L}\sum_{k\in K}\Big(q_r t_{lr}\big[\sigma_i w^{dist+}\omega_{li}^{dist+} + \sigma_i w^{capacity+}\gamma_{kli}^{cap+} + w^{heat+}\rho_k^{heat+}x_{kl} + w^{heat-}\rho_k^{heat-}x_{kl} + w^{tree+}\rho_k^{tree+}x_{kl} + w^{tree-}\rho_k^{tree-}x_{kl}\big]\Big) \quad \forall r \in R \tag{60}$$

$$\lambda_l^{act} = \sum_{i\in\delta}\sum_{r\in R}\sum_{k\in K}\Big(q_r t_{lr}\big[\sigma_i w^{dist+}\omega_{li}^{dist+} + \sigma_i w^{capacity+}\gamma_{kli}^{cap+} + w^{heat+}\rho_k^{heat+}x_{kl} + w^{heat-}\rho_k^{heat-}x_{kl} + w^{tree+}\rho_k^{tree+}x_{kl} + w^{tree-}\rho_k^{tree-}x_{kl}\big]\Big) \quad \forall l \in L \tag{61}$$

$$\varphi_{lr}^{act} = \sum_{i\in\delta}\sum_{k\in K}\Big(q_r t_{lr}\big[\sigma_i w^{dist+}\omega_{li}^{dist+} + \sigma_i w^{capacity+}\gamma_{kli}^{cap+} + w^{heat+}\rho_k^{heat+}x_{kl} + w^{heat-}\rho_k^{heat-}x_{kl} + w^{tree+}\rho_k^{tree+}x_{kl} + w^{tree-}\rho_k^{tree-}x_{kl}\big]\Big) \quad \forall l \in L, r \in R \tag{62}$$

$$\gamma_{kli}^{cap+} \le x_{kl} \quad \forall k \in K, l \in L, i \in \delta \tag{63}$$

$$\gamma_{kli}^{cap+} \le \omega_{ki}^{cap+} \quad \forall k \in K, l \in L, i \in \delta \tag{64}$$

$$\gamma_{kli}^{cap+} \ge x_{kl} + \omega_{ki}^{cap+} - 1 \quad \forall k \in K, l \in L, i \in \delta \tag{65}$$

Constraints (60) and (63)-(65) are the linearization of constraint (48). Constraints (61) and (63)-(65) are the linearization of constraint (58). Constraints (62)-(65) are the linearization of constraint (59). Constraints (63)-(65) are the limitations utilized in the linearization of the product of two binary variables.

Deviation-Based and Score-Based Model Assumptions

We discuss model assumptions for both the deviation-based and score-based park equity models. We define a primary park as the existing or candidate park to which a resident location is assigned as defined by the value of the decision variable x_{kl}. We assume that a resident location will always choose to visit their primary park, despite how distant or overcrowded that park may be.

Additional Demographic Sets

We consider the demographic classifications of race in our models. Table 3.7 provides additional demographic sets that may be incorporated into the models in future work. In future analyses, we may utilize additional demographic data to locate parks near youthful populations and poor populations since these groups to not drive or do not have access to private vehicles. We may utilize disability data to ensure that parks near populations of disabled persons have accessible amenities and paths. We note that the numerical data exists for each listed set and set element (see Appendix A).

Table 3.7: Additional Demographic Sets

$R = R^{Race} \cup R^{Gender} \cup R^{Age} \cup R^{Economic} \cup R^{Disability}$

R^{Gender} := gender classification of residents
$R^{Gender} = \{\text{Male}, \text{Female}\}$

R^{Age} := age classification of residents
$R^{Age} = \{$0to4, 5to9, 10to14, 15to17, 18to19,20,21,22to24, 25to29, 30to34, 35to39, 40to44, 45to49, 50to54, 55to59, 60to61, 62to64, 65to66, 67to69, 70to74, 75to79, 80to84, 85&older$\}$

$R^{Economic}$:= economic classification of residents
$R^{Economic} = R^{Income} \cup R^{Poverty} \cup R^{Assistance}$
$R^{Income} = \{$less\$10k, \$10kto\$15k, \$15kto\$20k, \$20kto\$25k, \$25kto\$30k, \$30kto\$35k, \$35kto\$40k, \$40kto\$45k, \$45kto\$50k, \$50kto\$60k, \$60kto\$75k, \$75kto\$100k, \$100kto\$125k, \$125kto\$150k, \$150kto\$200k, \$200plus$\}$
$R^{Poverty} = \{\text{Below Poverty Level}, \text{Above Poverty Level}\}$
$R^{Assistance} = \{\text{Public Assistance}, \text{No Public Assistance}\}$

$R^{Disability}$:= disability classification of residents
$R^{Disability} = \{\text{Yes Disability}, \text{No Disability}\}$

CHAPTER FOUR

DATA COLLECTION AND ANALYSIS

This chapter discusses our data collection and analysis process. We begin by providing a compilation of the data sources used. We then discuss the geoprocessing analyses completed to transfer original data into usable model parameters. We begin with the classification of demographic data in terms of resident locations. We note the amenities and purpose of existing parks to ensure that the facilities included within the study meet our requirements of the definition of a park. We then discuss the process of candidate park creation and the determination of land costs. We also include calculations of the distance between residents and parks as well as the capacity, heat, and tree cover of parks. We conclude with a determination of the normalization values for deviation types that we use within model analyses.

Collection of Geospatial Data

We conduct an extensive data collection process in order to obtain relevant geospatial data concerning the current state of the City of Asheville. Our data collection procedure includes databases originating from city, state, and federal sources such as the City of Asheville, Buncombe County, the North Carolina Department of Transportation (NCDOT), the Multi-Resolution Land Characteristics (MRLC) Consortium, the Trust for Public Land (TPL), the Federal Emergency Management Agency (FEMA), and the

United States Census Bureau (USCB). Throughout the data collection process, contact with the data source provider affirmed the accuracy of recorded information. Table 4.1 lists the data collected with the inclusion of a description, the geospatial data type, the year of file creation or update, and the data source.

Table 4.1: Geospatial Data Sources

Data	Data Description	GIS Type	Year Updated	Source	Citation
Race	Number of individuals of racial categorization -- 2020 block groups	table	2020	US Census	[50]
Gender	Number of individuals of gender categorization -- 2019 block groups	table	2019	US Census (American Community Survey)	[51]
Age	Number of individuals of age categorization -- 2019 block groups	table	2019	US Census (American Community Survey)	[51]
Poverty	Number of households below poverty in the past 12 months -- 2019 block groups	table	2019	US Census (American Community Survey)	[52]
Income	Number of households within certain income ranges in the past 12 months -- 2019 block groups	table	2019	US Census (American Community Survey)	[53]
Public Assistance	Number of households receiving public assistance in the past 12 months -- 2019 block groups	table	2019	US Census (American Community Survey)	[54]
Disability	Number of individuals with a disability -- 2019 Census tracts	table	2019	US Census (American Community Survey)	[55]
Pedestrian and bike routes	Spatial distribution of bicycle paths network	line	2021	NCDOT	[56]
Streets	Spatial distribution of all Asheville streets network	line	2020	Buncombe County Open Data	[57]
Existing Parks	Spatial distribution of existing parks	polygon	2021	The City of Asheville Open Data	[58]
Floodways	Spatial distribution of flood zones	polygon	2021	FEMA	[59]
Water Features	Spatial distribution of water -- lakes, ponds, streams	shapefile	2020	US Census	[60]
Heat Severity	Index (1-5) of the severity of heat above the city average	raster	2021	Living Atlas Trust for Public Land (GIS Support)	[61]
Tree cover	Percentage (0-100) of tree cover in a cell	raster	2016	MRLC	[62]
City Limit	n/a (spatial)	polygon	2017	The City of Asheville Open Data	[63]
Building zoning codes	n/a (spatial)	polygon	2020	The City of Asheville Open Data	[64]
Census Tracts	n/a (spatial)	polygon	2020	US Census Tiger Shapefile	[65]
Census Block Groups	n/a (spatial)	polygon	2019 & 2020	US Census Tiger Shapefile	[66], [67]
Buncombe Parcels	n/a (spatial)	polygon	2020	Buncombe County Open Data	[68]

Data Analysis: Racial-Ethnic Demographics (t_{lr})

In order that the collected data be usable in the context of our models, we complete a series of data analyses to translate the original geospatial data into applicable formulation parameters. The first of our data analyses regards the extrapolation of racial-ethnic demographic data. Specifically, this section describes the process to calculate data for the parameter t_{lr}, the number of people of race $r \in R$ who live in resident location $l \in L$.

A main focus of our objective concerns the equitable distribution of parks with regard to racial-ethnic compositions within Asheville, NC. The most detailed available data concerning race-ethnicity originates from the US Census of 2020 [50]. Provided within the data table of race information is the number of individual persons residing within each 2020 block group (BG20) geographical area. The US Census Bureau defines six races/ethnicities: (1) White, (2) Black or African American, (3) American Indian and Alaska Native, (4) Asian, (5) Native Hawaiian and Other Pacific Islander, and (6) Some Other Race. We label these as *race classifications.* For each BG20, the data table includes the number of individuals who identify as belonging to solely one *race classification*. We label these individuals as having *single race associations.* The table also includes the number of individuals who identify as any combination of two, three, four, or five of the six *race classifications.* Some persons classify themselves as belonging to all six *race classification* groups. We label these individuals with non-single race associations as having *multiple race associations.* We calculate the total number of individuals that identify as belonging to each *race classification* as the addition of the number of individuals with *single race associations* and *multiple race associations* that include that *race classification.* The outcome of this grouping method is that individuals with *multiple race associations* are included in calculations multiple times. Therefore, the sum of calculated *race classification* totals across each BG20 is greater than the actual count residing within that BG20.

Between the years of 2019 and 2020, the US Census redistricted block groups such that the shapefile areas encompassed by 2019 block groups (BG19) [66] and BG20 [67] are not congruent. The most updated data regarding the demographic categorizations of gender, age, income, poverty, and public assistance are from the US Census Bureau's 2019 American Community Survey (ACS19). All data from the ACS19 is grouped by BG19 rather than BG20. To optimize park equity by considering gender, age, or economic status simultaneously with race, the data for each demographic must reflect population totals for the same set of locations. Therefore, we note the practicality of converting the racial data from BG20 to BG19.

Utilizing the "Overlay Layers" and "Tabulate Intersection" tools provided within the ArcGIS Pro software, we convert race data from BG20 to BG19 by representing category counts as dependent upon land area [69]. Figure 4.1 (left) shows the difference in BG20 and BG19 areas. Notably, the majority of BG20 remains the same as BG19. Figure 4.2 (right) illustrates how the "Overlay Layers" function separates Asheville into smaller land areas with unique BG19-BG20 designations. Assuming that the population distribution is homogenous across Asheville, we divide BG20 race counts into overlay polygon race counts. Under the same assumption, we add the overlay polygon race counts appropriately to compose BG19 race counts. Appendix C provides a more detailed procedure of block group racial data conversion.

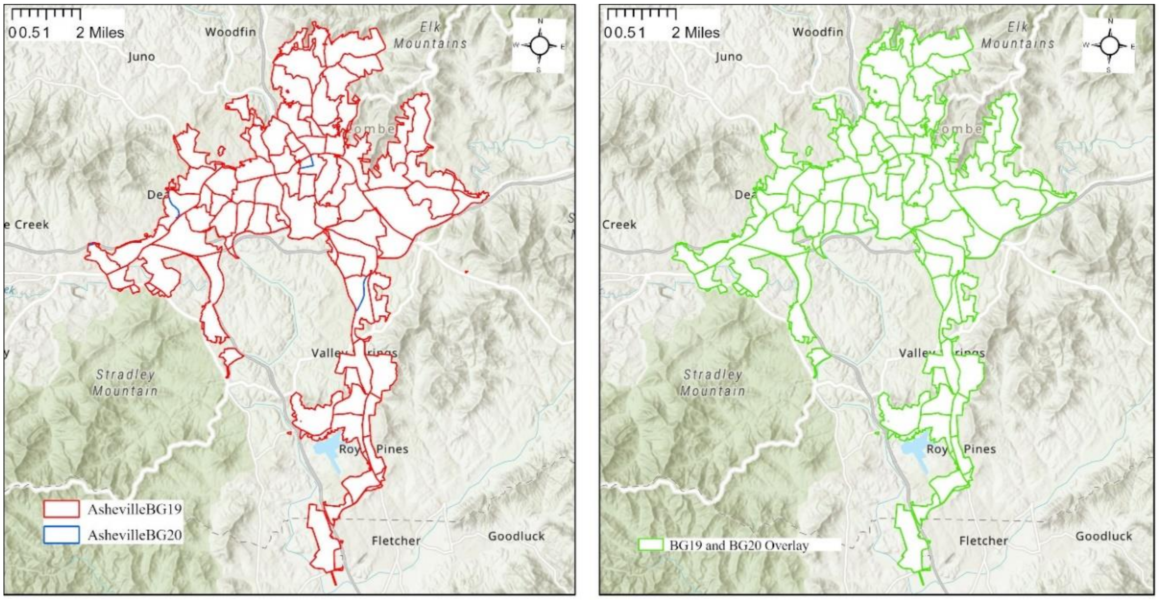

Figure 4.1: Asheville Block Groups (left) and Overlays (right)

We focus upon including resident data that best represents the individuals who will utilize Asheville's parks and greenspaces. As seen in Figure 4.2 (left), some BG19 have only a small portion of their area within Asheville City Limits (ACL). A desire to visit Asheville parks is less likely for individuals residing in these BG19, where a majority of the land area is distant from ACL. To fairly represent residents who likely visit Asheville parks, we structure the calculation of racial-ethnic population counts such that we include only the individuals who reside within the ACL of each BG19. Figure 4.2 (right) provides an illustration of BG19 as clipped to ACL. The original number of BG19 within City Limits equals 88.

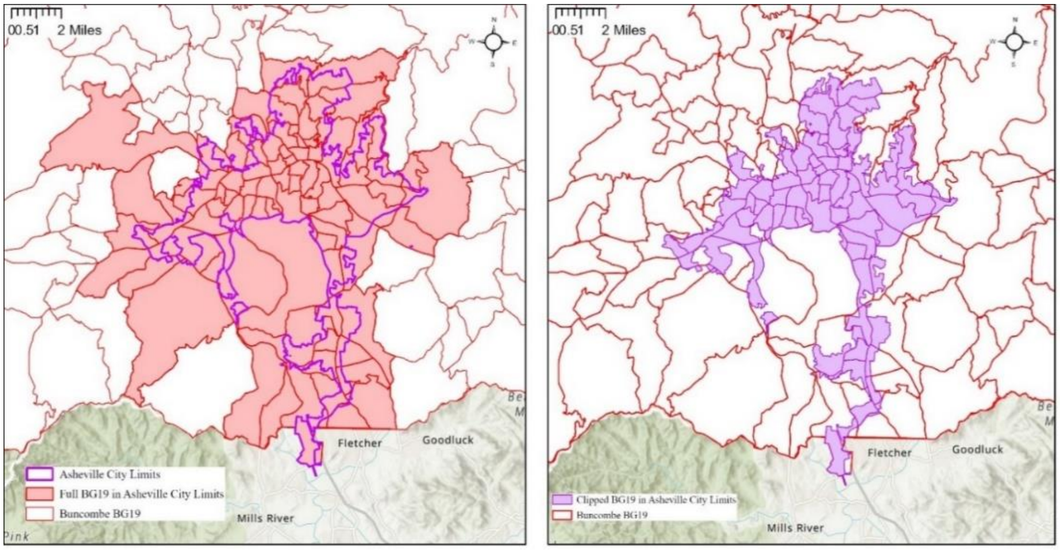

Figure 4.2: Defining the BG19 Study Area

To calculate the population counts for *race classifications* within the ACL of each BG19, we utilize the ArcGIS software "Tabulate Intersection" geoprocessing tool, which calculates the percentage of BG19 land area that is within ACL [63], [69]. We assume homogeneity in population density across BG19 as we calculate new population counts. The population count of each *race classification* within the ACL of each BG19 equals the product of the original BG19 *race classification* total and the intersection percentage of the ACL and BG19. For simplicity, we round new individual count totals to the nearest whole number. Figure 4.3 provides a visualization of the variation in population count for BG19 within ACL.

To further ensure that we present meaningful data, we eliminate from the study BG19 that are not impactful in park decisions. From the newly-calculated BG19 population totals within ACL, we determine a population cutoff of significance. Figure 4.4 indicates that an initial cutoff of BG19 population count occurs between the totals of

22 and 48. Therefore, we consider that a block group with an ACL population of less than 25 individuals is irrelevant to the study. Using this process, we create an updated study area that deletes 11 block groups, finalizing a study area with 77 total BG19.

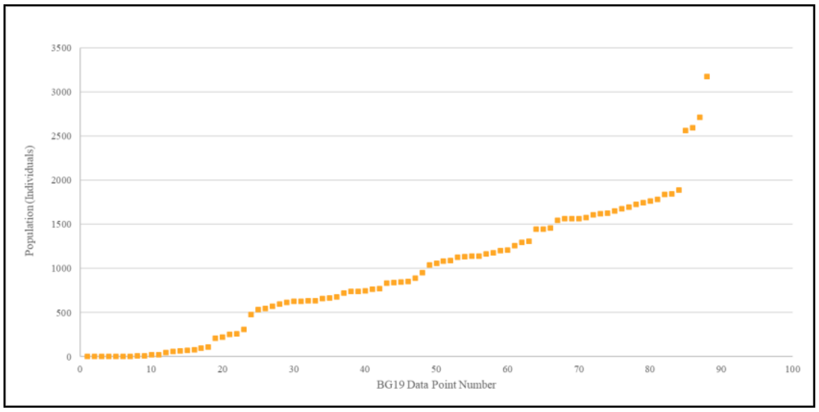

Figure 4.3: Total Population Counts BG19

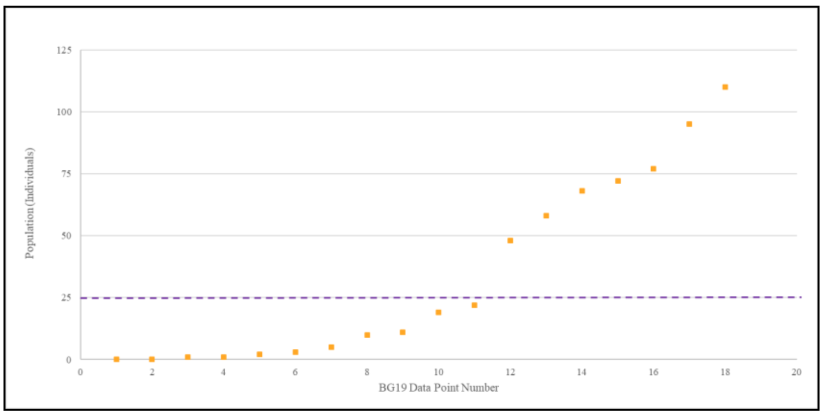

Figure 4.4: Cutoff of Total Population Counts BG19

Appendix Table A.1 provides population totals for each of the 77 BG19 resident locations within this study. Mentioned in the table are the total number of individuals belonging to each of the six *race classifications* per BG19. Figure 4.5 and Appendix Figure A.1 to Appendix Figure A.6 provide map illustrations of the data in Appendix Table A.1 by indicating the demographic population quantity within each block group and the distribution of racial-ethnic composition throughout the City of Asheville.

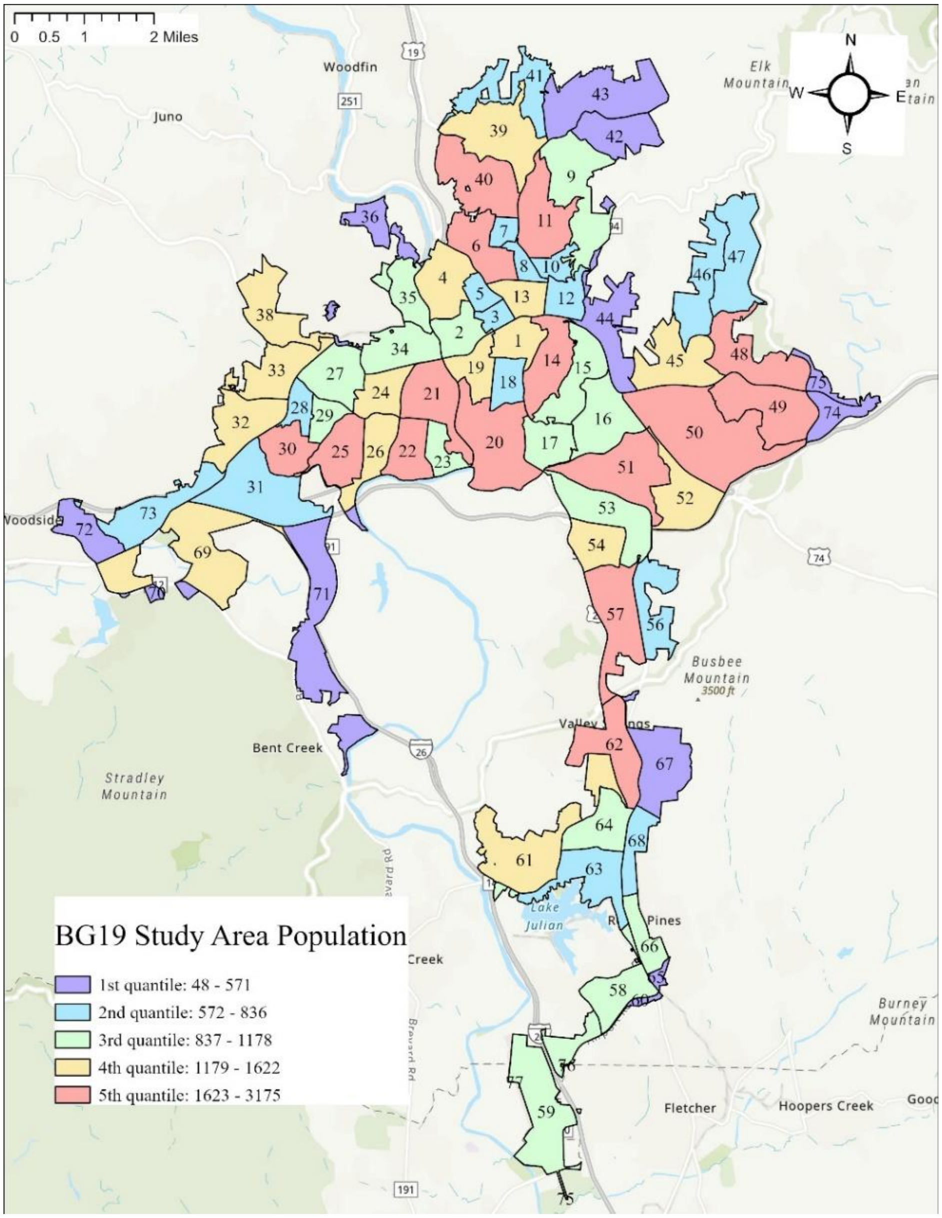

Figure 4.5: Asheville BG19 by Population Count

Label	GEOID	Label	GEOID	Label	GEOID	Label	GEOID
1	370210001001	21	370210010001	41	370210016003	61	370210022042
2	370210002001	22	370210010002	42	370210017001	62	370210022043
3	370210002002	23	370210010003	43	370210017002	63	370210022044
4	370210003001	24	370210011001	44	370210018011	64	370210022051
5	370210003002	25	370210011002	45	370210018012	65	370210022053
6	370210004001	26	370210011003	46	370210018021	66	370210022061
7	370210004002	27	370210012001	47	370210018022	67	370210022062
8	370210004003	28	370210012002	48	370210018023	68	370210023021
9	370210005001	29	370210012003	49	370210019001	69	370210023022
10	370210005002	30	370210012004	50	370210019002	70	370210023024
11	370210005003	31	370210012005	51	370210020001	71	370210025052
12	370210006001	32	370210013001	52	370210020002	72	370210025061
13	370210006002	33	370210013002	53	370210020003	73	370210030011
14	370210007001	34	370210014001	54	370210020004	74	370210030014
15	370210008001	35	370210014002	55	370210021021	75	370899306001
16	370210008002	36	370210014003	56	370210021022	76	370899306002
17	370210008003	37	370210014004	57	370210022031	77	370899307011
18	370210009001	38	370210014005	58	370210022032		
19	370210009002	39	370210016001	59	370210022033		
20	370210009003	40	370210016002	60	370210022041		

Because the scope of our current study currently only considers the demographic of race-ethnicity, we do not include other demographic here. Numerical and visual communication of factors of gender, age, economic status, and disability are within Appendix A.

Data Analysis: Existing Park Selection (K^{existing})

This section describes the process to determine the existing park elements within the set of all parks, *K*. The Trust for Public Land defines parks as "publicly-owned local, state, and national parks, trails, and open space" [9]. The definition excludes "parks in gated communities", "private golf courses", and "private cemeteries" [9]. Specifically, we define a park as an open and free facility that can host a variety of activities. We analyze the 64 existing parks listed within the City of Asheville's open database [58] to determine whether they satisfy our requirements to be considered within the study.

Using Asheville Parksmap [70], we construct Appendix Table B.1, an informational matrix that lists the amenities offered at each park. For parks not included within Asheville Parksmap, we utilize a Google map search to explore park images to gain knowledge of present amenities. We determine that 12 of the 64 existing parks do not satisfy the desired criteria to be an open and multifaceted park. Table 4.2 provides the names of the removed parks and the reason for removal.

Table 4.2: Existing Parks Removed from Study

Park	Reason for Removal
Aston Park and Tennis Courts	Payment required for entry
Asheville Municipal Golf Course	Single purpose
Grace’s Garden	Limited infrastructure and space
Griffing Boulevard Rose Garden	Limited infrastructure and space
Harvest House Recreation Center	Single purpose
McCormick Field	Professional teams only
Memorial Stadium	Professional teams only
North Asheville Community Center	Single purpose
Riverside Cemetery	Limited infrastructure and space
Senior Opportunity Center	Single purpose
Skate Park	Single purpose
WNC Nature Center	Payment required for entry

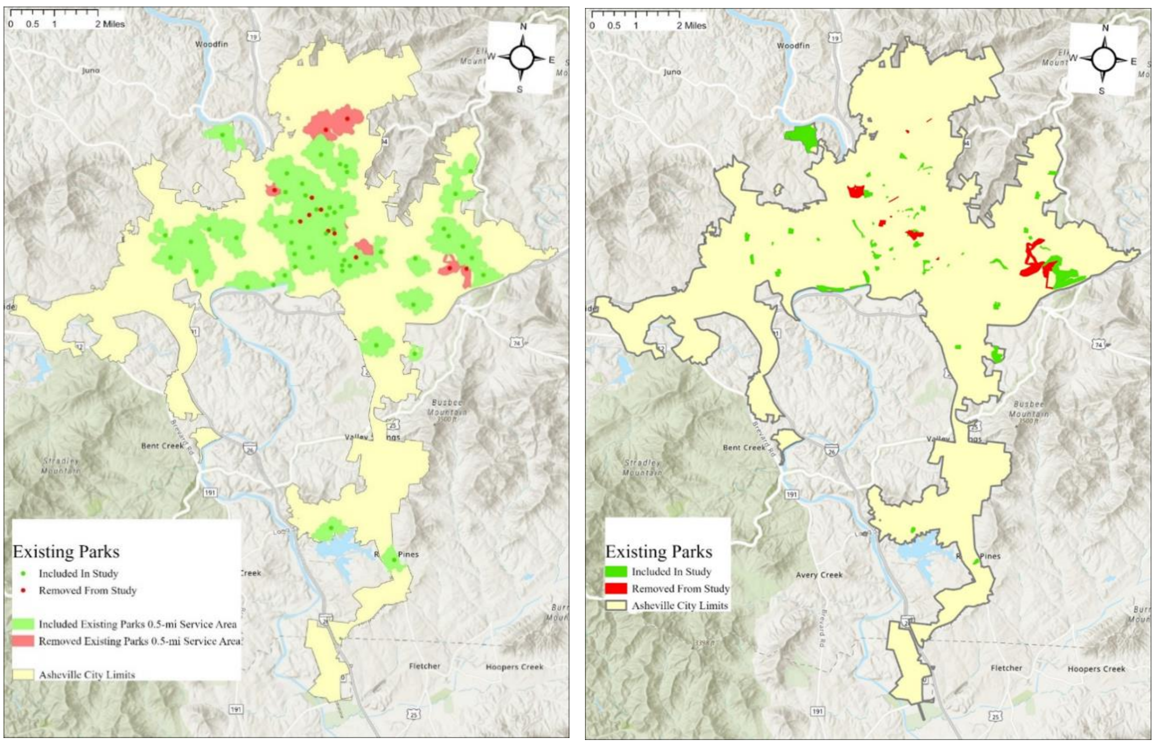

Figure 4.6: Existing Included and Removed Parks

We calculate a 0.5-mile walking distance service area to parks by using a combined network of pedestrian and bicycle paths. We present Figure 4.6 (left), a map that depicts the service area for the 52 included parks (in green). Red polygons represent the regions of Asheville within the service area of one or more of the 12 excluded existing parks. These areas are uncovered by considered parks. Figure 4.6 (right) provides the shapefiles of included (green) and excluded (red) park polygons. The map illustrates the size and shape of park land.

Data Analysis: Candidate Park Selection ($K^{candidate}$)

This section describes the process to determine the candidate park elements within the set of all parks, *K*. We utilize the shapefile of the Buncombe County parcels [68] to select candidate parks sites from defined parcels within ACL. We seek to select candidate park sites that possess the desirable characteristics of parks, such as compactness, space capacity, and environmental structure. To select candidate parks that provide the most benefit to the Asheville community, we present the following procedure to transform parcels into candidate park sites:

1. We eliminate all parcels in ACL that are within building zones that prohibit the construction of parks are greenspaces. We accomplish this task by clipping the polygon feature class of Buncombe County parcels to the polygon feature class of Asheville urban development zones. As shown in Table 4.3 [71], the only zone that does not allow park and greenspace development is the airport zone.
2. We complete a query that eliminates all land parcels with existing edifices. No demolition must occur to clear space for park amenities when we select land that includes no existing buildings.
3. We remove all parcels within a protected land area.

4. We delete all parcels that compose currently existing parks (both included in the study and excluded).
5. We remove all remaining parcels located within a 0.5-mile walking distance service area from the existing parks included within our study. This step ensures that we select candidate parks in currently underserved areas.
6. We remove all remaining parcels that have an area of less than one acre in order to ensure that our candidate parks have sufficient capacity.
7. We visually inspect all remaining parcels to delete inadequate candidate park sites.
    a. We delete parcels that are not compact in shape such that the land would be unsuitable for a park layout.
    b. We ensure that parcels are of an appropriately compact shape.
    c. We use a visual imagery basemap to verify that selected candidate park parcels not exist as roadways or parking lots. We verify that all selected parcels do not house an existing structure. This step ensures that we note any inaccuracies within the Buncombe County Parcels dataset. Figure 4.7 provides two images of parcels with these restricted characteristics.
    d. We note, but do not delete, candidate parks that partially contain water features or that are within flood zones. We specifically note these features since the type of park amenities that are feasible within a flood zone may be more limited.

Table 4.3: Asheville Zones for Recreational Use

Recreational Uses	RS2	RS4	RS8	RM6	RM8	RM16	NB	OFF I	OFF II	OB	CBI	CBII	NCD	HB	RB	CI	CBD	LI	IND	RES	INST	RIV	UR	UV	UP	ARPT	CBD EXP	COM EXP	RES EXP
Arboretums	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P		P	P	P
Community Centers	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P				P	P	P	P	P		P	P	P
Golf Courses	P	P	P	P	P	P				P				P	P	P				P	P	P						P	P
Parks, Passive and greenways	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P		P	P	P
Recreational uses, governmental such as, but not limited to, parks for active use	P	P	P	P	P	P		P	P	P	P	P	P	P	P	P	P			P	P	P	P	P	P		P	P	P
Recreational uses, restricted to membership, non-profit	S	S	S	S	S	S			P	P	P	P		P	P	P	P			P	P	P	S				P	P	
Recreational uses accessory to residential uses	P	P	P	P	P	P				P	P	P	P	P	P	P	P			P	P	P	P	P	P		P		


Figure 4.7: Candidate Park Parcel Elimination

Our parcel selection process creates 138 candidate parks from an initial total of 39480 parcels. Figure 4.8 maps these candidate parks. Here, we note the difference between parks in flood zones and parks outside of flood zones. Figure 4.9 provides the distribution of the finalized list of existing and candidate parks included within the study.

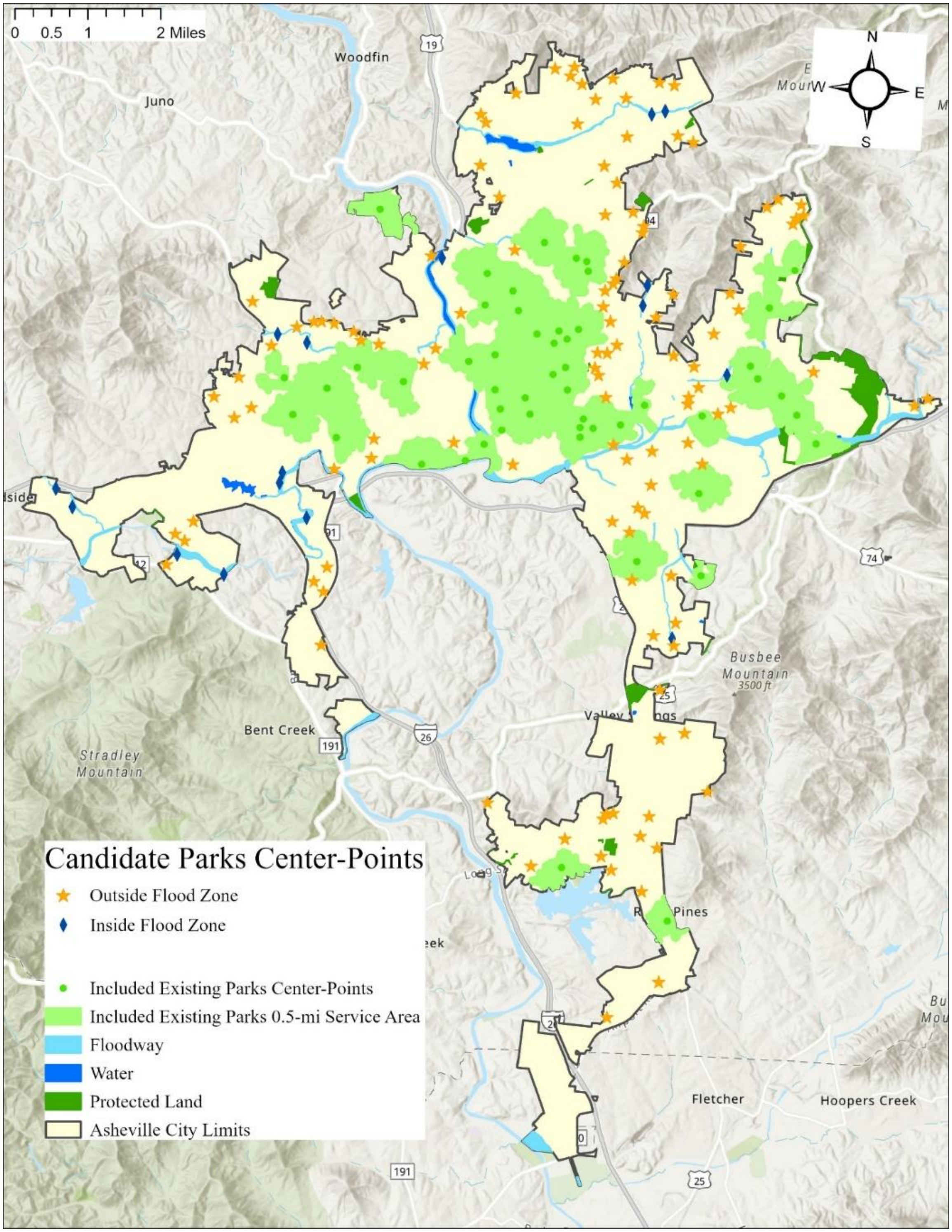

Figure 4.8: Selecting Candidate Parks

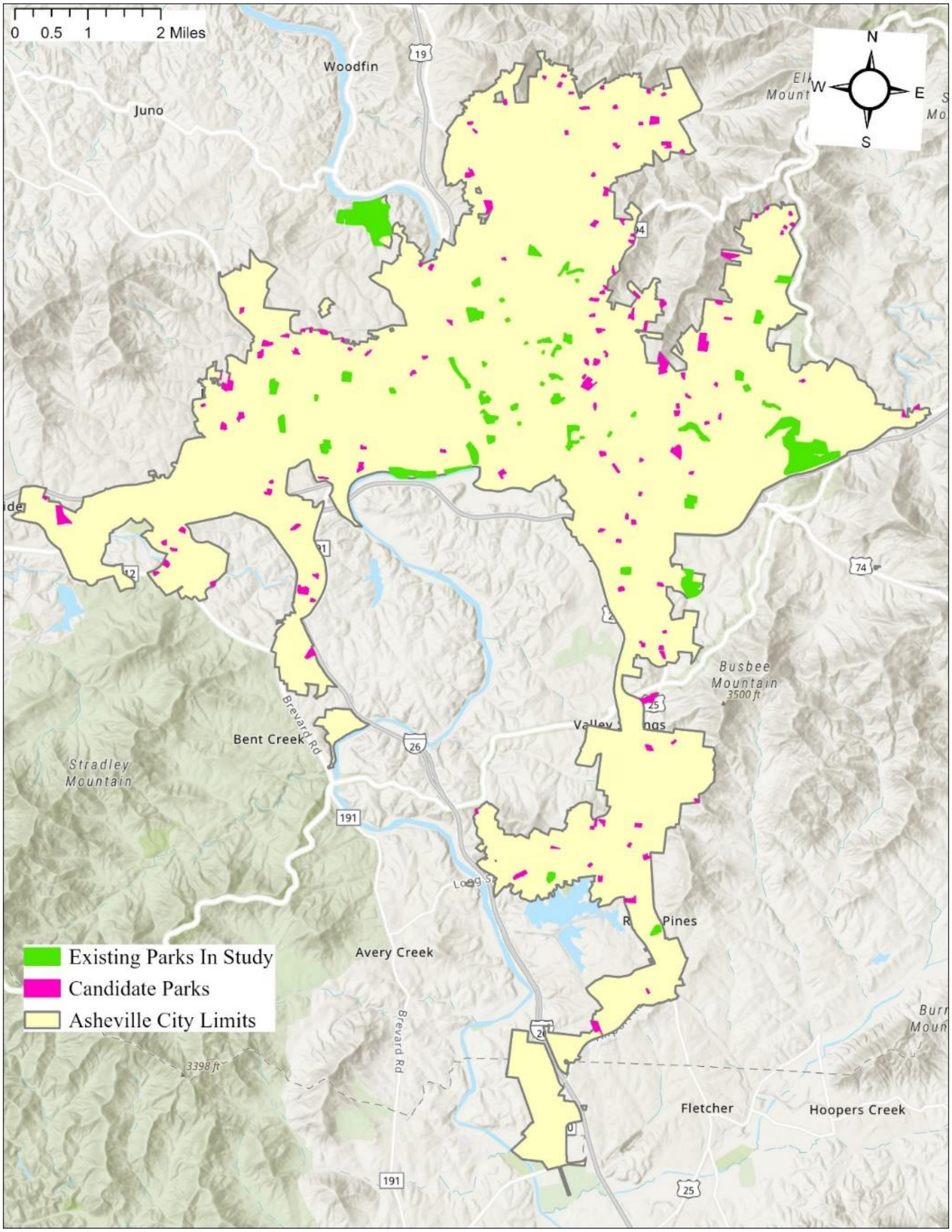

Figure 4.9: Distribution of Existing and Candidate Parks

Data Analysis: Park Cost (f_k)

This section describes the process to calculate data for the parameter f_k, the cost of land to purchase park $k \in K$. To determine the cost to purchase candidate park land, we utilize the "Land Value" column within the Buncombe County parcels attribute table [68]. If a candidate park has a non-zero land value, then we record this cost as the purchase price. We note that any parcels already owned by the City of Asheville have no cost. If the land value is not listed within the attribute table, then we determine the parcel purchase fee as the approximate unit price of land acreage multiplied by the number of acres in size of the potential candidate park.

To determine the unit price of land acreage within regions of Asheville, we divide the city into distinct zones by grouping sets of potential candidate parks geographically. Figure 4.10 shows the 13 zones that we consider, and Figure 4.11 illustrates the distribution of candidate parks within each cost zone. We note whether each candidate park has a listed or originally null land value. Appendix Table B.2 lists the average unit cost per acre for each of the price zones. Appendix Table B.3 provides the price for each candidate park as well as whether the park cost is exact or estimated.

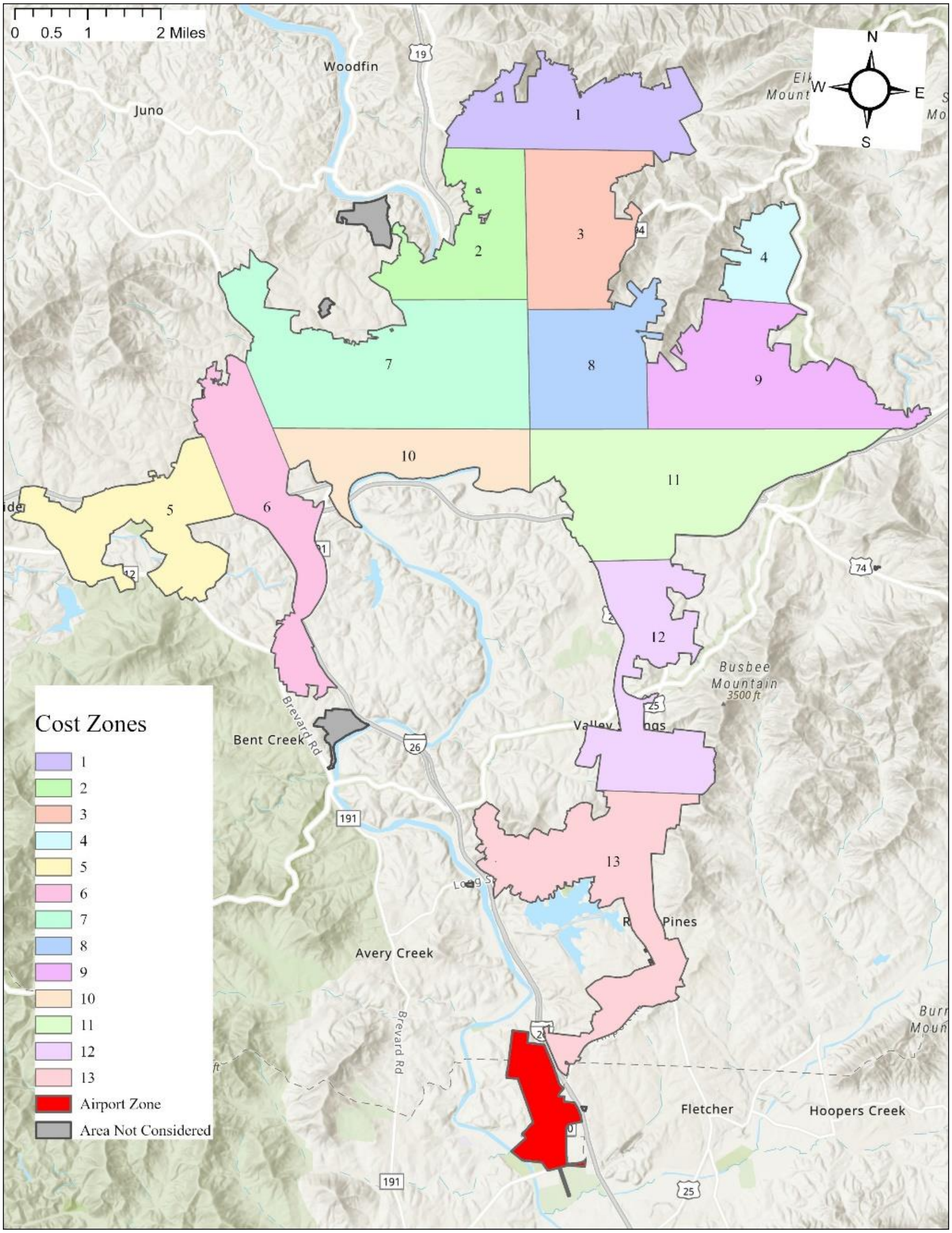

Figure 4.10: Defined Asheville Cost Zones

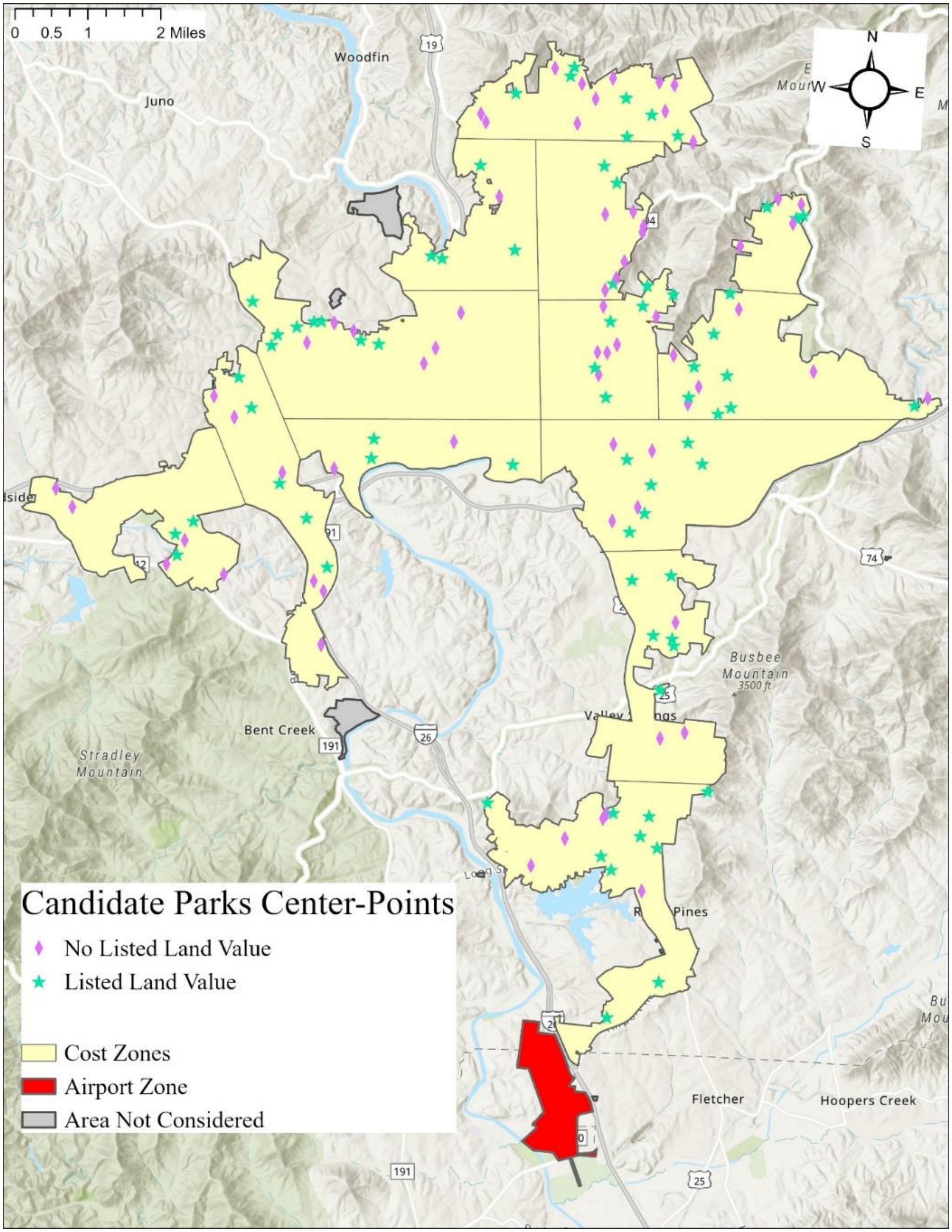

Figure 4.11 Candidate Park Distribution in Price Zones

Data Analysis: Capacity Calculation (a_k)

This section describes the process to calculate data for the parameter a_k, the number of individuals that park $k \in K$ can accommodate. We calculate park capacity as the number of residents that a park may serve considering the park's size. We use the "Calculate Geometry" feature within ArcGIS Pro to determine the size, in units of acres, of each existing and candidate park [69]. There should be at least one acre of park land for every 100 residents that visit a park [72]. Therefore, we determine the capacity of each park as the rounded down product of the number of park acres multiplied by 100. Appendix Table B.5 provides the capacity of each existing and candidate park.

Data Analysis: Environmental Factors ($c_k^+, c_k^-, v_k^+, v_k^-$)

This section describes the process to calculate, exogenously, the excess and deficit park heat (c_k^+ and c_k^-) and the excess and deficit park tree cover (v_k^+ and v_k^-). Our collected data for heat index [61] and tree cover [62] are both raster datasets, information composed in the form of cell images. The heat index of each cell is a number (1-5) that describes the amount of heat above the city average within a location. An index of 1 equates to a heat slightly above the city average while an index of 5 represents a heat greatly larger than the city average. Regions of Asheville with no data experience a heat less than or equal to the city average. The collected tree cover data is a number (0-100) that represents the percentage of tree cover existent within each raster cell. Figure 4.12 and Figure 4.13 show the heat index and tree cover rasters, respectively, for Asheville.

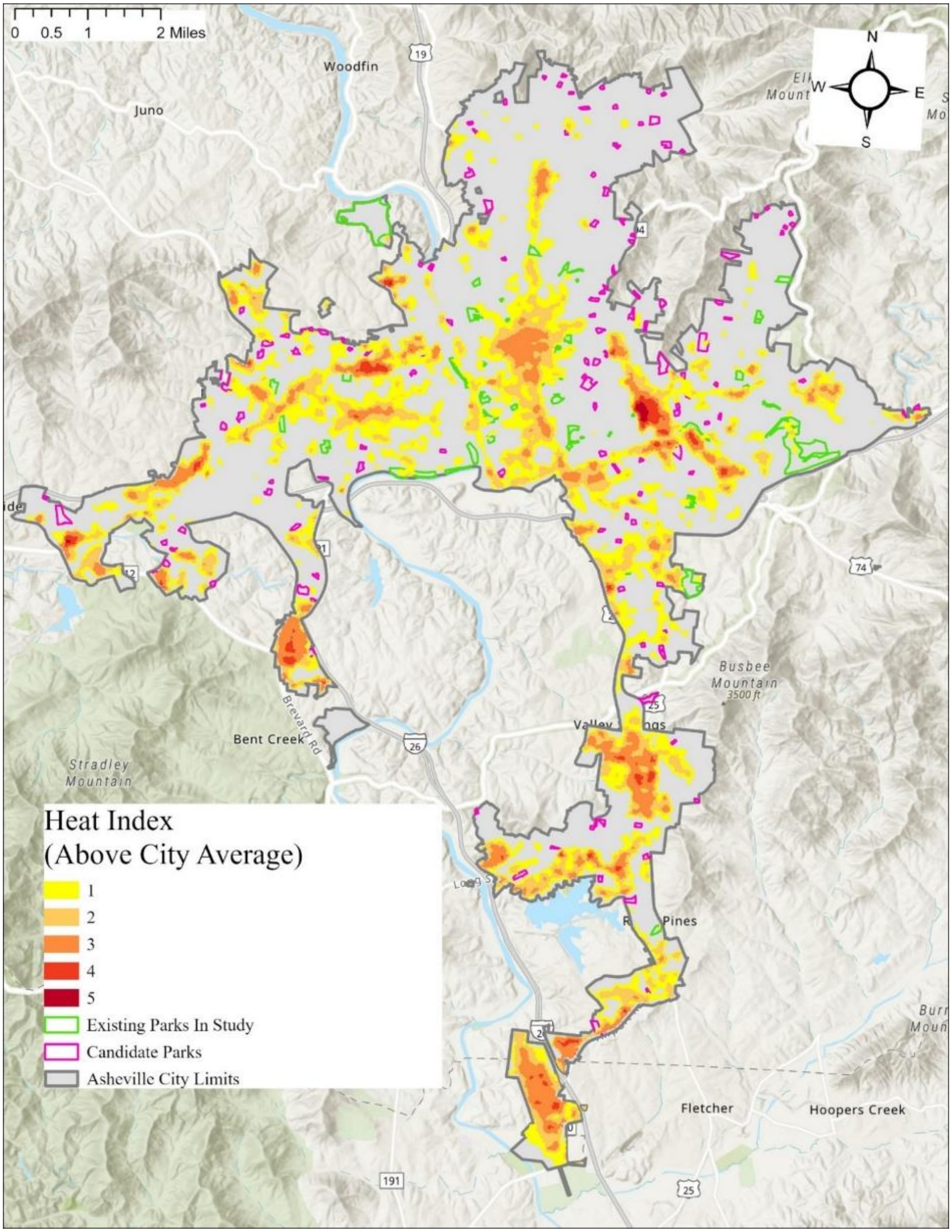

Figure 4.12: Heat in Parks

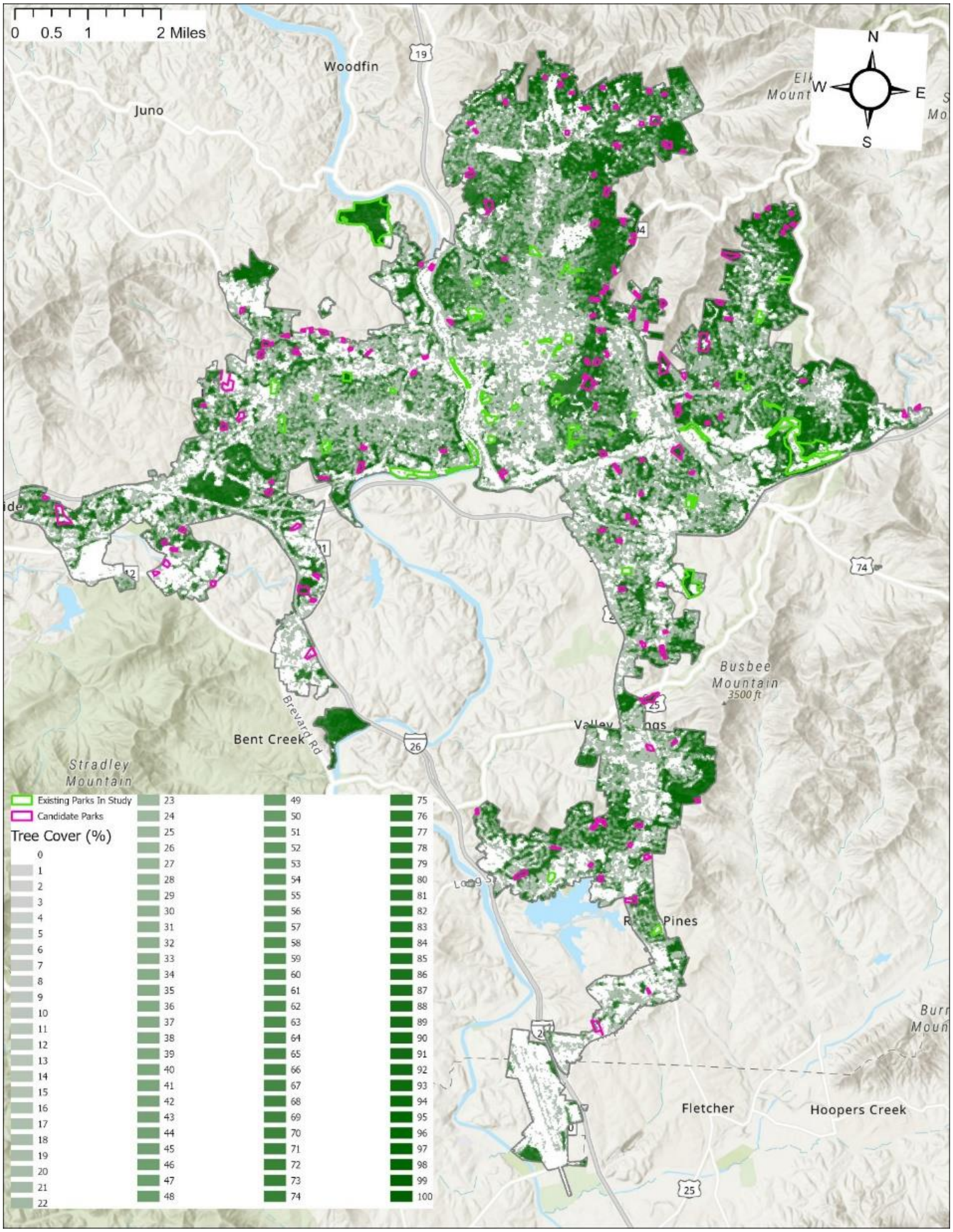

Figure 4.13: Tree Cover in Parks

Both raster datasets have original cell sizes of approximately 30m x 30m. To determine the park heat index and park tree cover for both existing parks and candidate parks, we resample both datasets to have a cell size of 5m x 5m. We use the "Summarize Categorical Raster" tool within ArcGIS Pro to summarize the number of resampled cells within each park polygon [69]. Because the summarize tool records only the cells completely within the park polygon, having a smaller cell size for each raster dataset increases the accuracy of documented heat and tree cover within each park polygon.

The output from the summarize tool is a table that lists the number of cells equal to each index or percentage value within each park polygon. We utilize this information to determine a heat index average and a tree cover average for each park. Appendix Table B.6 provides the average heat and tree cover of each considered existing and candidate park. We calculate the deviations for excess and deficit heat and tree cover for each park by determining how the ideal range in heat and tree cover differs from the park average heat and tree cover. We score these environmental components for each park by assigning a score value to deviation ranges of heat and tree cover.

Data Analysis: Distance Calculation (d_{kl})

This section describes the process to calculate data for the parameter d_{kl}, the distance from resident location $l \in L$ to park $k \in K$. One of the paramount elements in our equity models concerns the minimization of the distance from residents to parks. Therefore, vital to our data collection process is the determination of an accurate origin-to-destination distance from each park resident to each park (both existing and candidate). To calculate this distance, we utilize the "Origin-Destination Cost Analysis" feature provided within ArcGIS Pro's Network Analysis Toolbox [69].

Inputs of origins and destinations must be of a point feature class type; however, BG19 and parks are polygon feature classes. Therefore, we complete a geospatial analysis to represent these polygons as points. Using the "Calculate Geometry" feature within ArcGIS Pro, we determine the x-coordinate and y-coordinate of BG19 central-points and of existing and candidate park central-points [69]. We map the central-point coordinates to create a new point feature class to represent the origins (BG19) and destinations (parks). Figure 4.14 provides the map illustration of BG19 and park central points.

The ArcGIS Pro "Origin-Destination Cost Analysis" feature has the ability to calculate walking distance and driving distance along a network of paths [69]. The walking distance description states that the calculation "follows paths and roads that allow pedestrian traffic and finds solutions that optimize travel distance" [69]. The driving distance description states that the calculation "models the movement of cars… and finds solutions that optimize travel distance… [while following driving] rules that are specific to cars" [69].

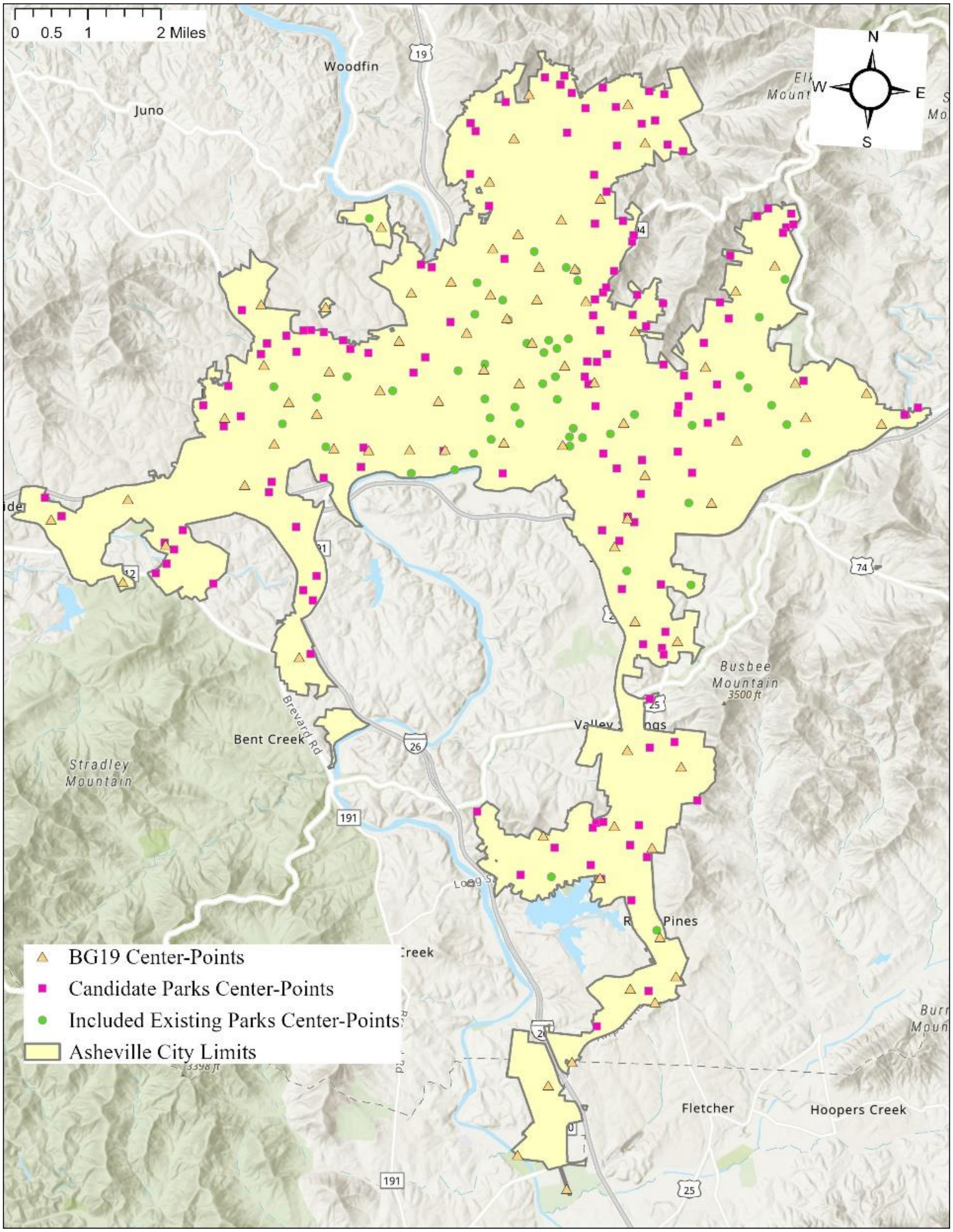

Figure 4.14: Origin and Destination Points for Distance Calculation

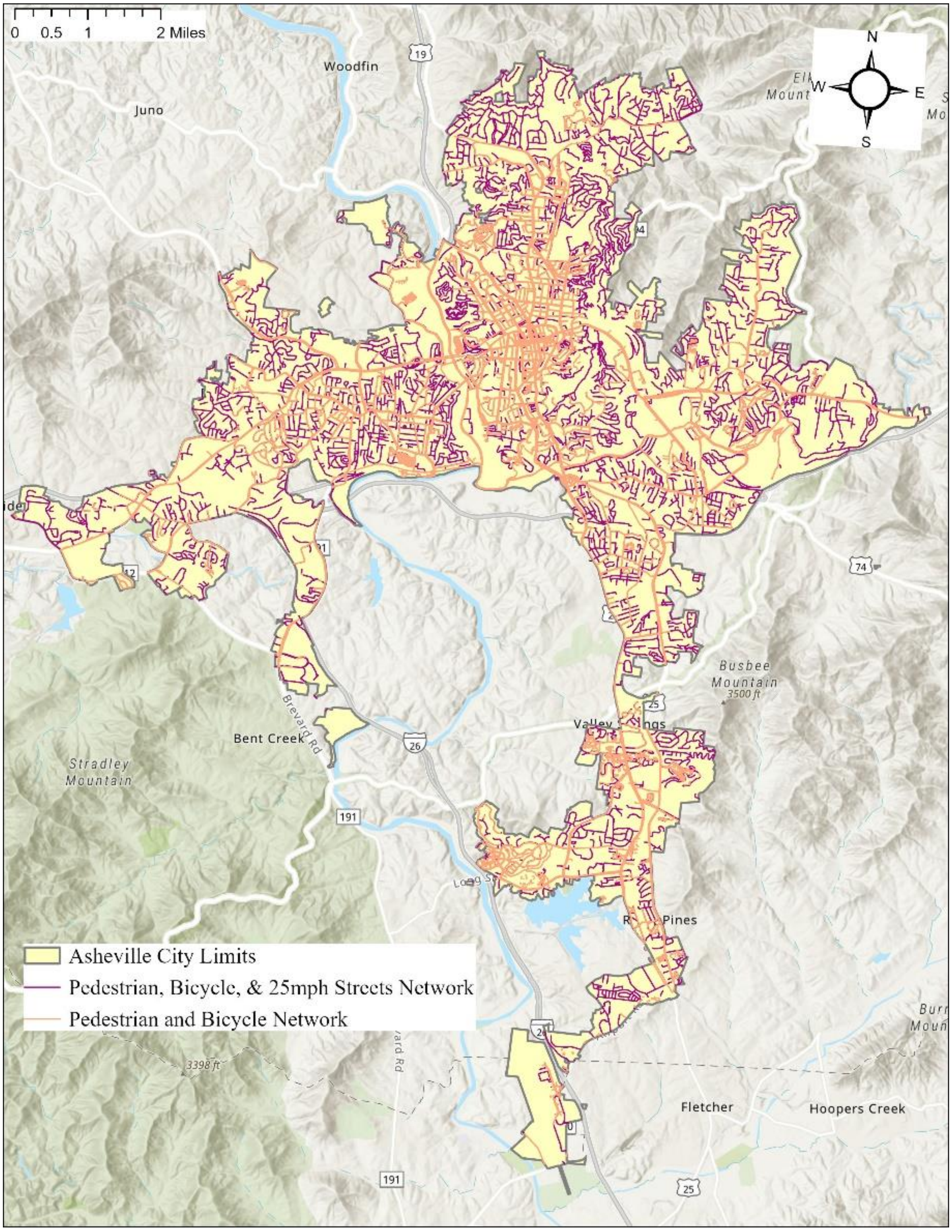

Figure 4.15: Asheville Networks

In our data collection process, we determine two distance matrices. The first distance matrix contains the walking distance from BG19 central points to park central points along the network of combined pedestrian and bicycle paths obtained from the NCDOT [56]. The second distance matrix contains the minimum of walking and driving distances from BG19 central points to park central points along a network containing a combination of pedestrian pathways, bicycle pathways, and streets with a driving speed limit of 25 miles per hour or less. We obtain the street shapefile from the Buncombe County Open Database [57]. Figure 4.15 is a map illustrating the combined networks used to calculate the distance matrices. Appendix Table B.4 provides the distance matrix from residents to parks as calculated along the network including pedestrian and bicycle paths.

Determination of Normalization Values

Our models utilize deviations of distance, capacity, heat, and tree cover to represent park goodness. These measures have different units. Therefore, to effectively incorporate the aforementioned elements into the objective function, we normalize deviation classifications by projecting them onto the same numerical scale. We determine the range of values that exist for each deviation type to determine the appropriate normalization multiplier for that deviation classification. Table 4.4 provides the Asheville-specific data used in the calculation of normalization multipliers. We list the deviation classification and units. We include the minimum and maximum values of distance, capacity, heat, and tree cover observed from data analyses. From these minimum and maximum numbers, we determine a representative range of possible distance, capacity, heat, and tree cover values.

We define a practical same-scale numerical range and determine the normalization multiplier needed to convert each deviation classification representative range to the same-scale range. Because all representative ranges and the same-scale range have a minimum value of zero, we may calculate the normalization multiplier of each deviation classification as the maximum same-scale range value divided by the maximum representative range value of that deviation classification.

Table 4.4: Determining Deviation Normalizations

Deviation Classification	Measure [units]	Min Value in Dataset	Max Value in Dataset	Represent Range	Same-Scale Range	Normalization Multiplier
Distance	Distance from residents to parks [miles]	0.046	19.145	(0, 20)	(0, 100)	5
Capacity	Individuals that a park accommodates [count]	16	15004	(0, 15000)		1/150
Heat	Heat within a park [unitless index]	0	2.85	(0, 5)		20
Tree Cover	Tree cover within a park [%]	0	98.10	(0, 100)		1

CHAPTER FIVE

MODEL ANALYSES AND RESULTS

This chapter discusses the solution methods that we utilize to complete model analyses with the purpose of studying the multiple components of park equity. Concerning model inputs, we discuss the numerical values of parameter constants for weights and scoring thresholds. We provide a list of questions concerning park equity that we seek to answer within our analysis section. Included analyses concern equity measures dependent upon budget, demographic strategic target, and desired distance from residents to parks. We seek to consolidate model results in an informative manner and to provide insight about practical and equitable park decisions by graphical and geospatial visual techniques.

Solution Methods

To program our park equity facility location models and run analyses, we use AMPL as the programming language and Gurobi as the optimization solver [73], [74]. Our procedure of running the models consists in importing sets and parameters from Microsoft Excel into AMPL, solving the equity models with the given inputs, and exporting decision variables and other results to a new Excel file. Appendix D includes the overall model .run file, the model formulation .mod file, and .run files for data importing and exporting for our deviation-based model.

Constant Parameters for Analyses

We note that our models allow for flexibility of user input in the determination of parameter values of deviation classification weights and of acceptable heat and tree cover ranges. For consistency, we hold these parameters constant throughout all model analyses. Table 5.1 provides the selected values of these parameters. We place the greatest amount of importance upon distance as a park goodness measure versus capacity, heat, and tree cover. Thus, the distance weight scalar is greater in numerical value than any other deviation type weight. We place a greater priority upon capacity goodness than upon the goodness created by environmental factors.

Concerning environmental parameters, there is a greater penalty for having an excess of heat than for obtaining a deficit of heat. Likewise, the weight of excess tree cover is greater than the weight of deficit tree cover, though the difference between these weights is less significant than that of the heat deviation weights. We determine our acceptable heat range such that we target areas that experience relatively high amounts of heat. Therefore, we may focus upon providing heat mitigation for these areas. We determine our acceptable tree cover range such that we target areas that have a moderate amount of vegetation. This enables us to select park sites that may support the development of multiple amenities while maintaining the provision of shade.

We present within the analyses both models of minimizing park goodness deviations and maximizing park goodness scores. In running our score-based model, we utilize the scoring thresholds for deviations of distance, capacity, heat, and tree cover listed in Table 5.2. We select scoring upper threshold values such that a maximum score results when no deviation is present and a minimum score results when the maximum possible deviation exists. We structure the range of deviations assigned to score values as being small for high scores and increasing as the score value decreases. Figure 5.1 illustrates the relationship between distance deviation and score as an example.

Table 5.1: Constant Analysis Parameters – Weights and Environmental Ranges

Parameter	Numerical Value
Distance	
Distance Weight	0.90
Capacity	
Capacity Weight	0.25
Heat	
Heat Excess Weight	0.20
Heat Deficit Weight	0.05
Max Acceptable Heat	4
Min Acceptable Heat	1
Tree Cover	
Tree Cover Excess Weight	0.25
Tree Cover Deficit Weight	0.20
Max Acceptable Tree Cover	70
Min Acceptable Tree Cover	20

Table 5.2: Constant Analysis Parameters – Deviation Scoring

Score	Distance Upper Threshold	Distance Lower Threshold	Capacity Upper Threshold	Capacity Lower Threshold	Heat Upper Threshold	Tree Cover Upper Threshold
0	20.00	15.75001	4000	2926	5.000	100.0
1	15.75	12.60001	2925	2341	3.375	72.0
2	12.60	9.80001	2340	1821	2.700	57.6
3	9.80	7.35001	1820	1366	2.100	44.8
4	7.35	5.25001	1365	976	1.575	33.6
5	5.25	3.50001	975	651	1.125	24.0
6	3.50	2.10001	650	391	0.750	16.0
7	2.10	1.05001	390	196	0.450	9.6
8	1.05	0.35001	195	66	0.225	4.8
9	0.35	0.00001	65	1	0.075	1.6
10	0.00	0.00000	0	0	0.000	0.0

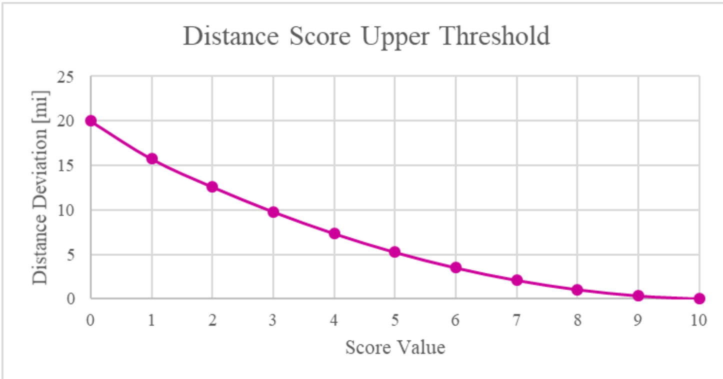

Figure 5.1: Relationship for Scoring Deviations

Introduction of Model Analyses

We run multiple iterations of code with varying input values to address specific questions with regard to the nature of our models and the extent to which they may provide park location insights for governmental and recreational decision makers. Here, we pose these specific questions:

1. How does the budget amount affect park goodness deviation measures and primary park locations?
2. What is the impact of overall park spending versus iterative park spending upon park goodness deviation measures and selected candidate park locations?
3. How does budget spending impact the selection of primary parks?
4. How does the score-based model compare to the deviation-based model?
5. What is the impact of a strategic demographic target upon equitable primary park assignment and location decisions and upon equitable spending?
6. How does the desired distance from residents to parks affect the selection of primary parks?

Analysis Question 1: Park Goodness and Park Selection vs. Budget

Government and recreational organizations may experience a limited amount of monetary availability with regard to allocation of resources in the purchasing of new park land. Therefore, a needed analysis determines how the budget impacts park goodness. We complete analyses of minimizing park goodness deviations versus budget and consider park goodness measures resulting from the utilization of two different objective functions. The first objective function concerns overall park goodness, and the second concerns the park goodness of a specific demographic. The former objective serves as a park goodness baseline while the latter objective is an incorporation of equity.

To complete the park goodness versus budget analyses, we generate data from a series of four deviation-based model types. *Min All Dev Cap* is the model type concerning the minimization of all park goodness deviations while *Min Max Dev Cap* is the model type concerning the minimization of the maximum demographic deviation. We also consider the impact of budget upon park goodness when parks are considered as uncapacitated entities. Therefore, we remove capacity from the objective function in our calculation of the minimization of all park goodness deviations and in the minimization of the maximum demographic deviation. We label these model types as *Min All Dev Uncap* and *Min Max Dev Uncap*, respectively.

In our analysis of park goodness versus budget, we maintain a constant ideal distance of 0.5 miles from residents to parks and a constant demographic weight of one for all demographic classifications. We consider a budget range of $0 to $6,000,000 and analyze results at each increment of $250,000.

Weighted Overall Deviations vs. Budget

In analyzing how budget affects park goodness, we determine how the overall weighted park goodness deviation changes as a function of budget. Figure 5.2 provides a visualization of the variation in overall deviation value as budget increases from $0 to $3,000,000 for *Min All Dev Cap*, *Min Max Dev Cap*, *Min All Dev Uncap*, and *Min Max Dev Uncap*. We note that the deviations resulting from a budget of $3,000,000 to $6,000,000 change insignificantly compared to other budget-dependent deviation values. Appendix Figure E.1 provides the entire deviation versus budget ($0 to $6,000,000) graphic, and Appendix Table E.1 lists the numerical results of this analysis.

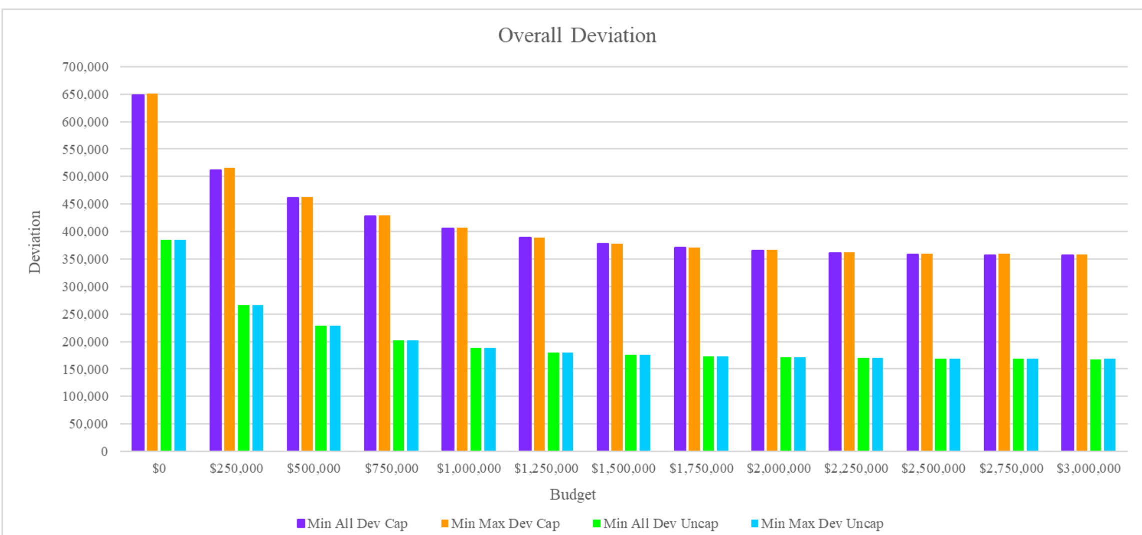

Figure 5.2: Overall Park Goodness Deviations vs. Budget

Figure 5.2 reflects that there exists a negligible difference between overall deviation value for *Min All Dev Cap* versus *Min Max Dev Cap* and for *Min All Dev*

Uncap versus *Min Max Dev Uncap* when each demographic has the same strategic target weight.

Figure 5.2 also reveals that there is a decreasing significance in the impact that budget affects upon the increase in park goodness as the amount of monetary resources allocated to park purchasing increases. For example, an increase in budget from $0 to $250,000 presents a larger decrease in overall park goodness deviations versus the decrease resulting in a budget increase from $250,000 to $500,000.

To visualize the incremental cost-effectiveness in increasing park goodness, we create Figure 5.3 and Figure 5.4. Figure 5.3 provides slope as a representation of the cost effectiveness in minimizing overall park goodness deviations for *Min All Dev Cap* versus *Min All Dev Uncap.* Figure 5.4 mirrors the content of Figure 5.3 with results from *Min Max Dev Cap* versus *Min Max Dev Uncap*.

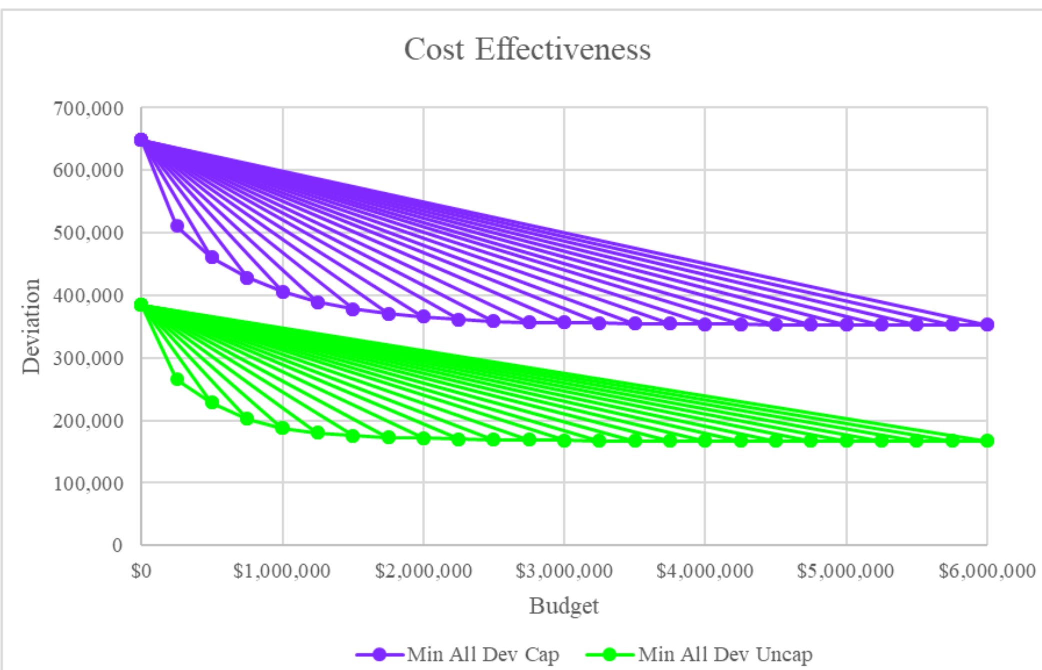

Figure 5.3: Cost Effectiveness in Decreasing Overall Deviations – Min All Dev Cap and Min All Dev Uncap

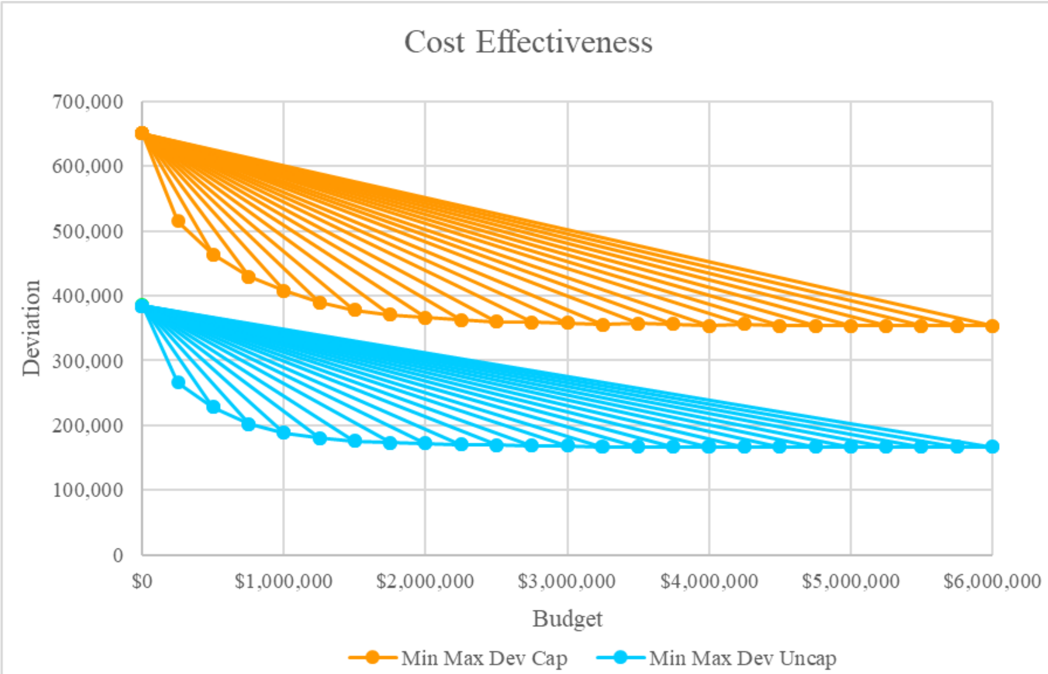

Figure 5.4: Cost Effectiveness in Decreasing Overall Deviations – Min Max Dev Cap and Min Max Dev Uncap

In Figures 5.3 and 5.4, the slope of cost effectiveness becomes less steep as budget increases, indicating that the impact upon overall deviations decreases as budget increases. These figures also visualize that there exists an upper limit to park goodness unaffected by the amount of monetary resources available. This trend proves true for both the capacitated and uncapacitated model types. Notably, the overall deviation value for the uncapacitated model types converges more quickly than that of the capacitated model types. While the uncapacitated model types converge at a budget of $3,500,000, the capacitated model types converge at a budget of $4,750,000.

To provide another visualization of cost effectiveness with regard to overall deviations, we present Figure 5.5, a chart depicting the decrease in overall deviation value between increases in budget. The figure follows the budget amount labeling system defined in Table 5.3.

Table 5.3: Budget Labels

Label	Budget	Label	Budget	Label	Budget	Label	Budget	Label	Budget
1	$0	6	$1,250,000	11	$2,500,000	16	$3,750,000	21	$5,000,000
2	$250,000	7	$1,500,000	12	$2,750,000	17	$4,000,000	22	$5,250,000
3	$500,000	8	$1,750,000	13	$3,000,000	18	$4,250,000	23	$5,500,000
4	$750,000	9	$2,000,000	14	$3,250,000	19	$4,500,000	24	$5,750,000
5	$1,000,000	10	$2,250,000	15	$3,500,000	20	$4,750,000	25	$6,000,000

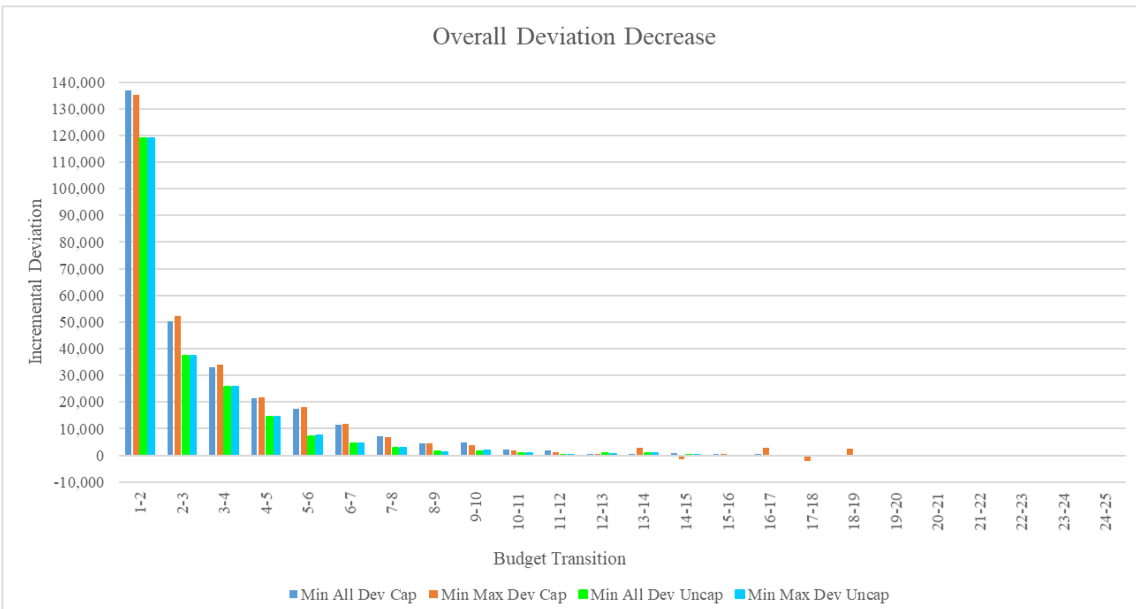

Figure 5.5: Overall Deviation Decrease by Budget Transition

Figure 5.5 presents that, as a general overview, the amount of overall deviation decrease lessens as greater amounts of budget exist. We note that the change in overall deviation between budget iterations is not always a decrease. Specifically, results from *Min Max Dev Cap* indicate that, in two individual instances, the overall deviation increases. In these two instances, the value of *overall* park goodness deviations increases in order that the objective of minimizing the maximum *demographic* deviation may result.

To visualize how deviations of distance, capacity, heat, and tree cover compose overall deviations for *Min All Dev Cap*, *Min Max Dev Cap*, *Min All Dev Uncap*, and *Min Max Dev Uncap*, we create Figures 5.6, 5.7, 5.8, and 5.9, respectively. In Figure 5.7, we show the budget range from $0 to $6,000,000 to further evaluate the cause of increase in overall deviation for *Min Max Dev Cap* instances. Appendix Figures E.3, E.5, and E.6 are continuations of Figures 5.6, 5.8, and 5.9 with results for a budget of $0 to $6,000,000.

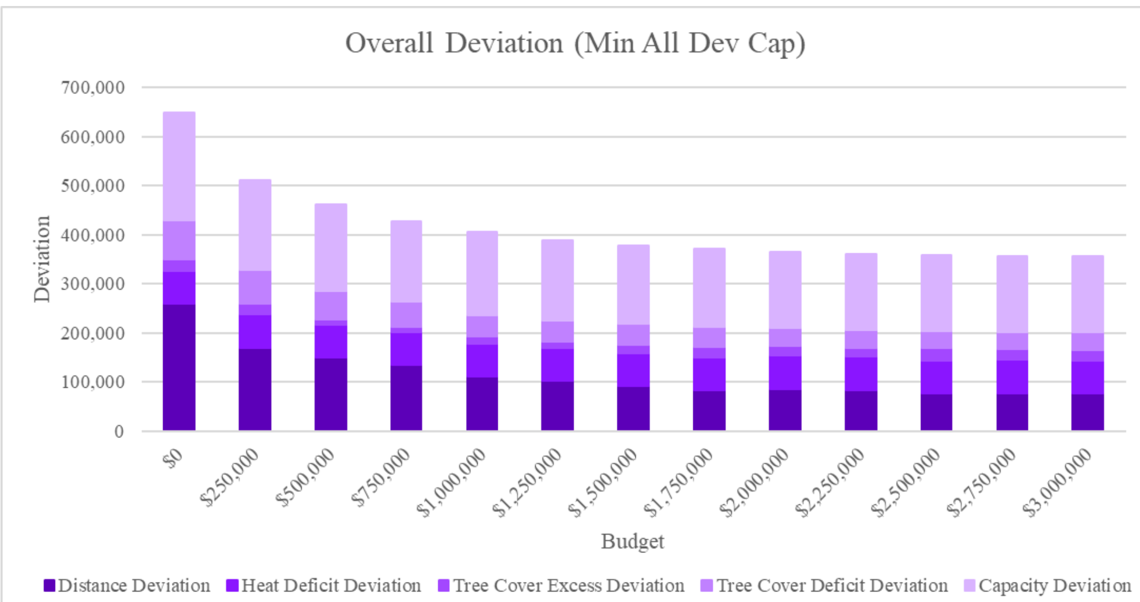

Figure 5.6: Overall Deviation by Classification – Min All Dev Cap

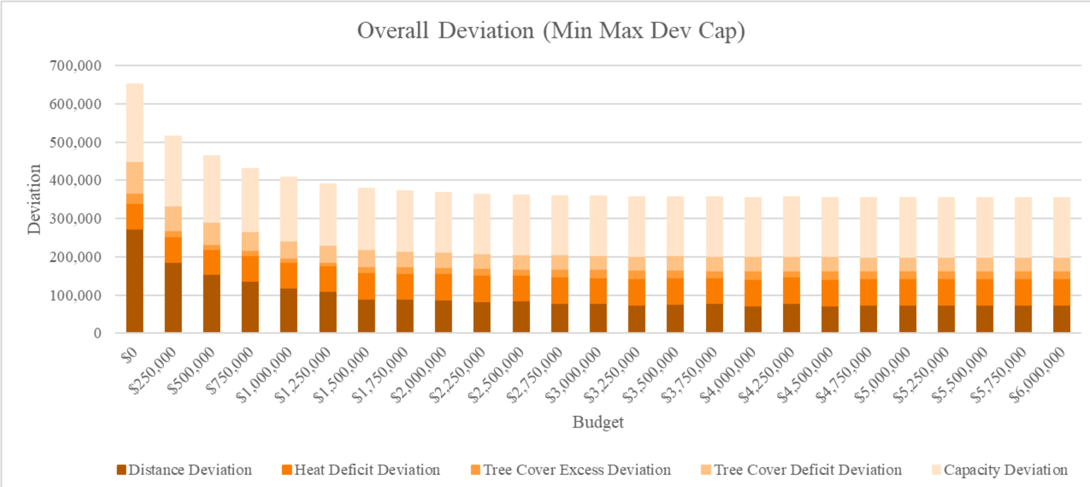

Figure 5.7: Overall Deviation by Classification – Min Max Dev Cap

Figure 5.7 illustrates that the overall deviation increase for *Min Max Dev Cap* from a budget transition of $3,250,000 to $3,500,000 and of $4,000,000 to $4,250,000 results from an increased distance deviation. We determine that this distance deviation increase results from the need to balance the excess distance from residents to parks and park overcrowding. Specifically, to minimize overcrowding, residents may have a primary park located farther than ideal.

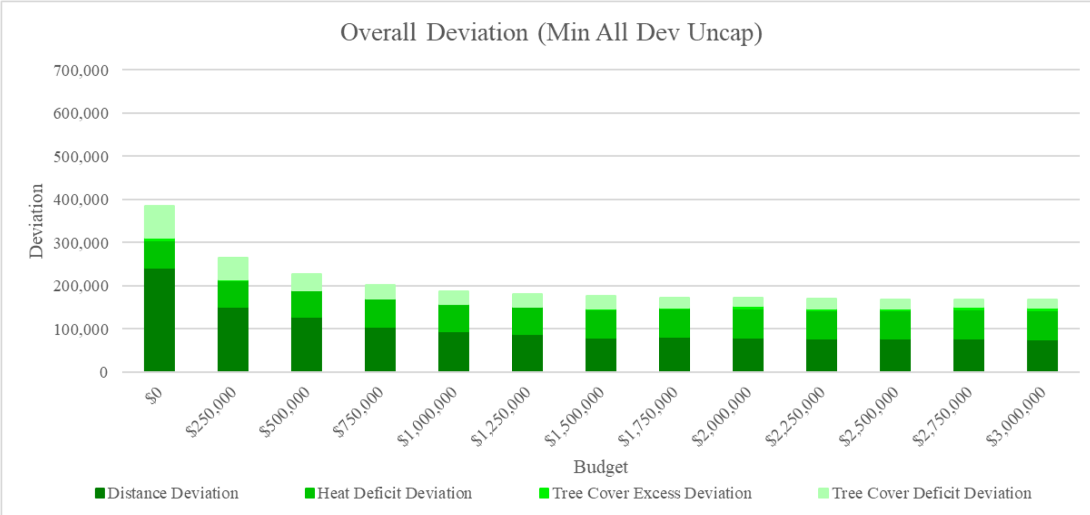

Figure 5.8: Overall Deviation by Classification – Min All Dev Uncap

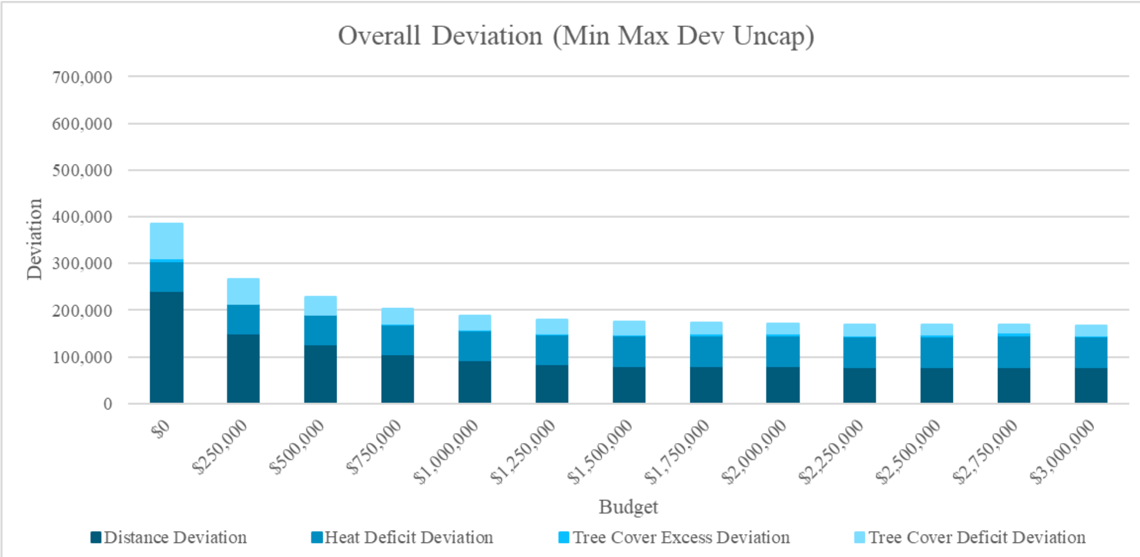

Figure 5.9: Overall Deviation by Classification – Min Max Dev Uncap

The actual deviation classification values portrayed in Figures 5.6, 5.7, 5.8, and 5.9 are consistent with the expected proportions of deviation type in contribution to the overall park goodness deviation. Specifically, as the budget increases, the greatest deviation decreases are of distance, even if at the expense of other equity criteria. This is intuitive since we place greater emphasis on equity created by distance than upon capacity, heat, and tree cover. Also evident is that the increase in budget allows for the selection new of candidate park sites that more closely match desired environmental conditions than existing parks. Therefore, overall deviations of heat and tree cover are less when a non-zero budget exists versus when there is no budget allowance.

Weighted Demographic Deviations vs. Budget

In addition to analyzing the overall park goodness deviation, we consider the value of the maximum demographic deviation as dependent upon budget value and objective function selection. Appendix Table E.2 provides the values of the maximum demographic park goodness deviation for *Min All Dev Cap*, *Min Max Dev Cap*, *Min All Dev Uncap*, and *Min Max Dev Uncap*. Figure 5.10 provides a visualization of the variation in maximum demographic deviation value as budget increases from $0 to $3,000,000. We note that the deviations resulting from a budget of $3,000,000 to $6,000,000 change insignificantly compared to other budget-dependent deviation values. Appendix Figure E.2 provides the entire deviation versus budget graphic.

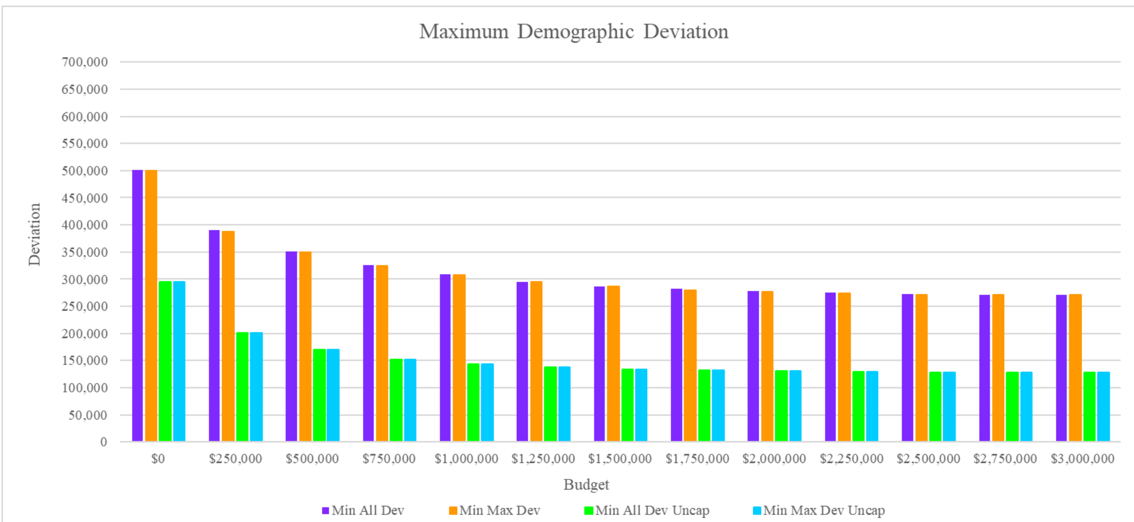

Figure 5.10: Maximum Demographic Park Goodness Deviation vs. Budget

We note that the results for the maximum demographic deviation display similar trends as the results for the overall deviation. Figure 5.10 reflects that there exists a negligible difference between maximum demographic deviation value for *Min All Dev Cap* versus *Min Max Dev Cap* and for *Min All Dev Uncap* versus *Min Max Dev Uncap* when each demographic has the same strategic target weight.

Figure 5.10 also reveals that there is a decreasing significance in the impact that budget affects upon the decrease of the maximum demographic deviation as the amount of monetary resources allocated to park purchasing increases. To visualize the incremental cost-effectiveness in increasing park goodness, we create Figure 5.11 and Figure 5.12. Figure 5.11 provides slope as a representation of the cost effectiveness in minimizing the maximum demographic park goodness deviation for *Min All Dev Cap* versus *Min All Dev Uncap.* Figure 5.12 mirrors the content of Figure 5.11 with results from *Min Max Dev Cap* versus *Min Max Dev Uncap*. These charts present maximum demographic deviation values resulting from a budget of $0 to $6,000,000.

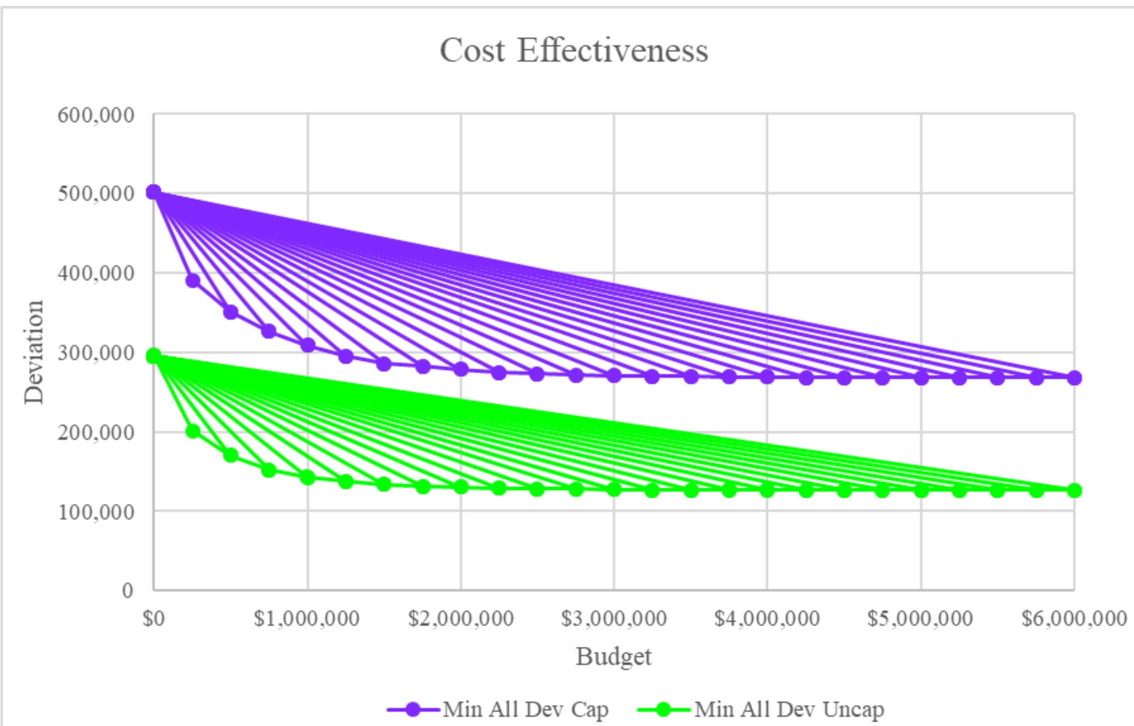

Figure 5.11: Cost Effectiveness in Decreasing Maximum Demographic Deviations – Min All Dev Cap and Min All Dev Uncap

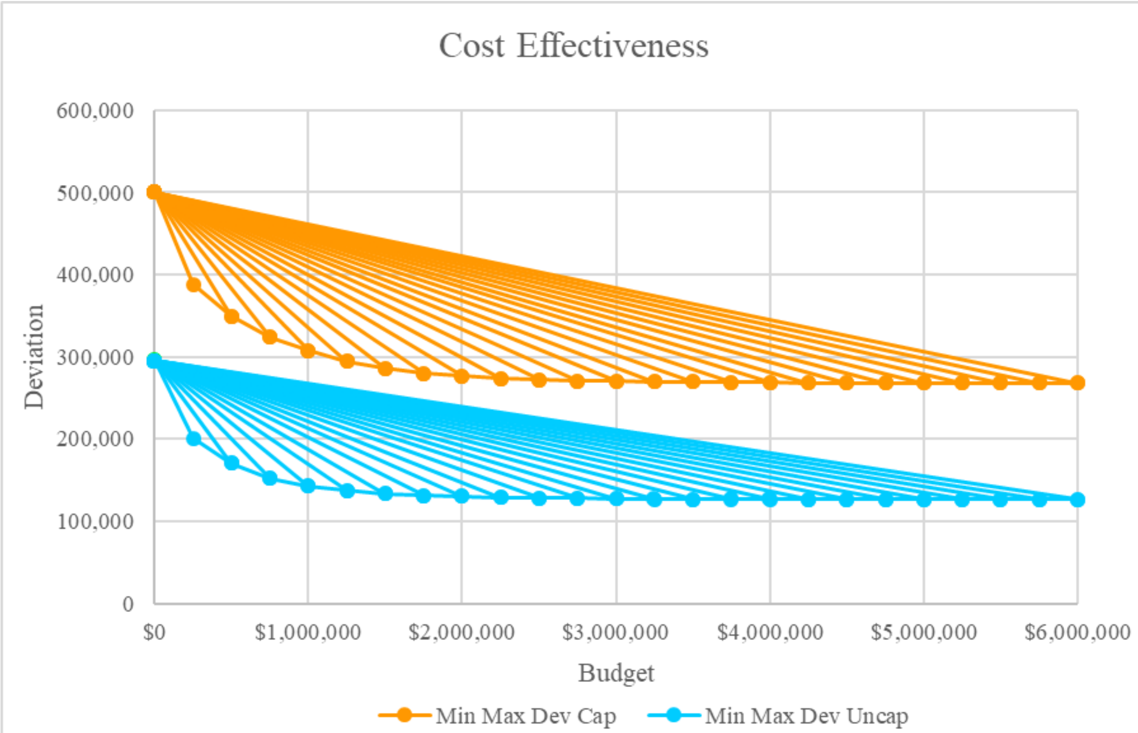

Figure 5.12: Cost Effectiveness in Decreasing Maximum Demographic Deviations – Min Max Dev Cap and Min Max Dev Uncap

In Figures 5.11 and 5.12, the slope of cost effectiveness becomes less steep as the budget increases, indicating that the impact upon maximum demographic deviations decreases as budget increases. These figures also visualize that there exists a lower limit to the value of maximum demographic deviation unaffected by the amount of monetary resources available. This trend proves true for both the capacitated and uncapacitated model types. Notably, the maximum demographic deviation value for the uncapacitated model types converges more quickly than that of the capacitated model types. While the uncapacitated model types converge at a budget of $3,500,000, the capacitated model types converges at a budget of $4,750,000.

To provide another visualization of cost effectiveness with regard to maximum demographic deviations, we present Figure 5.13, a chart depicting the decrease in maximum demographic deviation value between increases in budget. The figure follows the budget amount labeling system defined in Table 5.3.

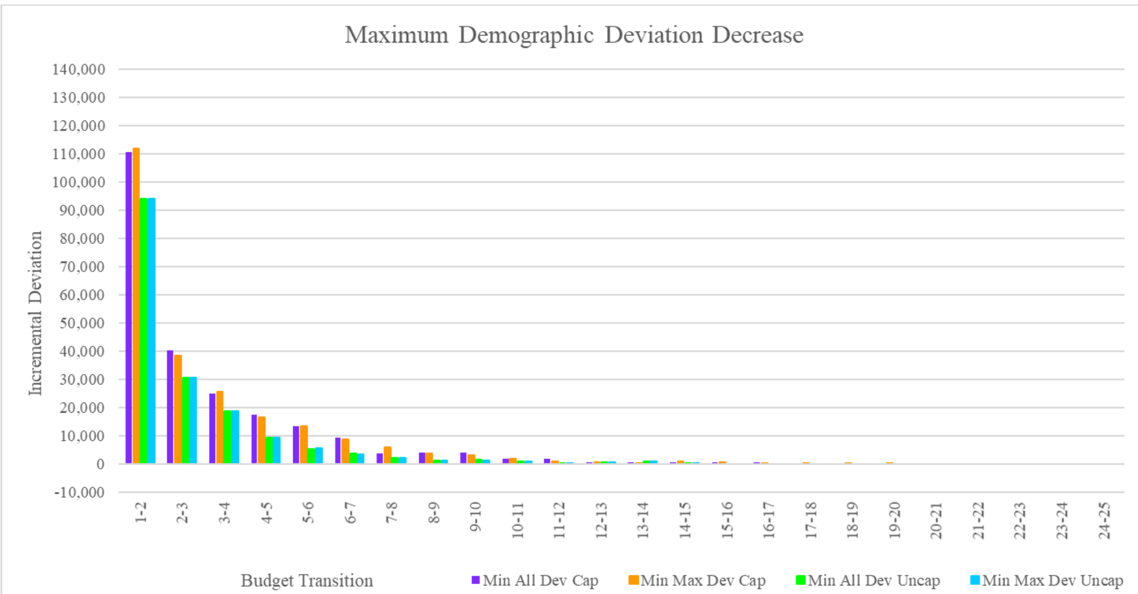

Figure 5.13: Maximum Demographic Deviation Decrease by Budget Transition

Figure 5.13 presents that the amount of maximum demographic deviation decrease lessens as greater amounts of budget exist. To visualize how deviations of distance, capacity, heat, and tree cover compose maximum demographic deviations for *Min All Dev Cap*, *Min Max Dev Cap*, *Min All Dev Uncap*, and *Min Max Dev Uncap,* we create Figures 5.14, 5.15, 5.16, and 5.17, respectively. We show the budget range from $0 to $3,000,000 and provide Appendix Figures E.7, E.8, E.9, and E.10 to show the range from $0 to $6,000,000.

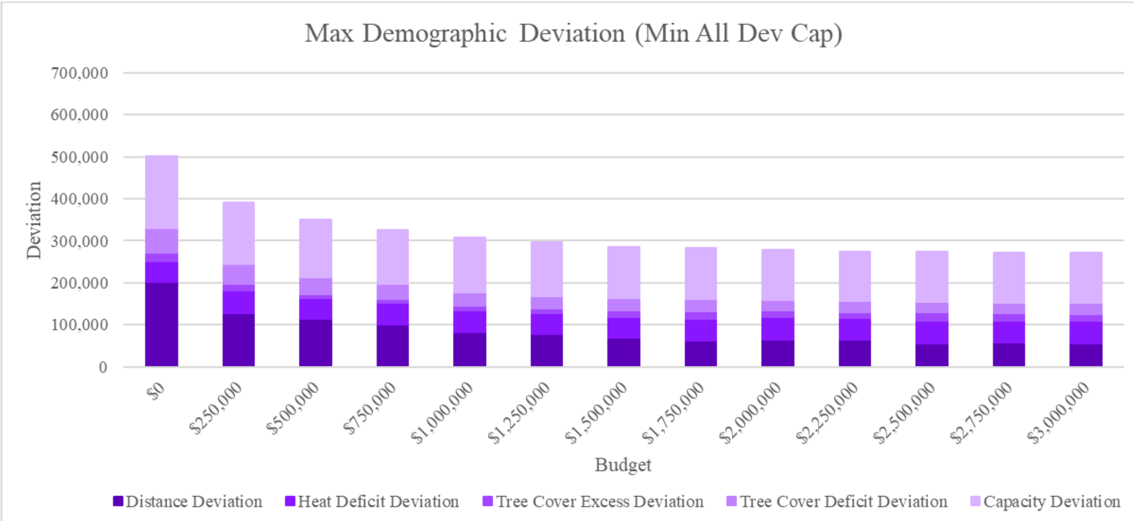

Figure 5.14: Maximum Demographic Deviation by Classification – Min All Dev Cap

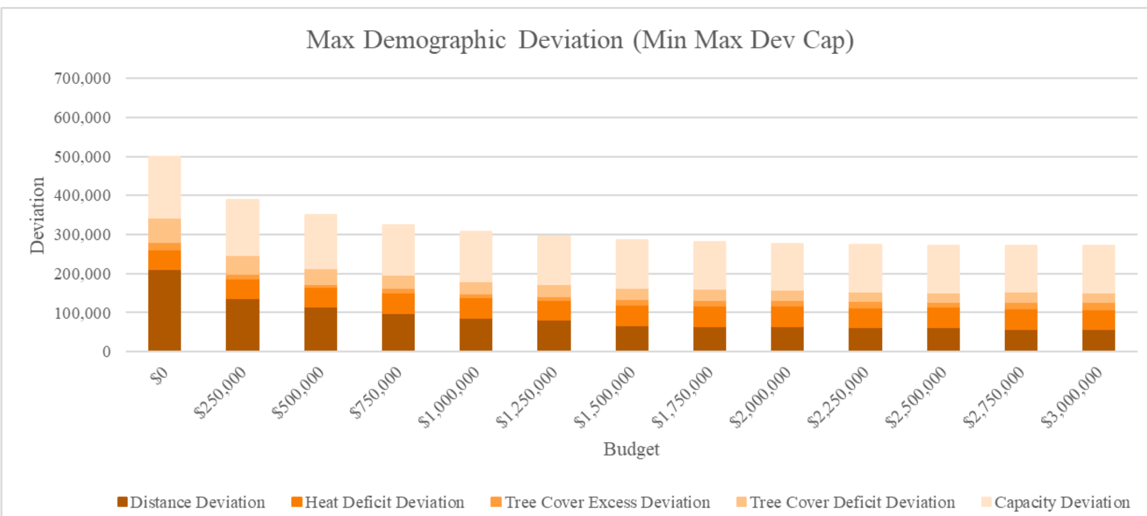

Figure 5.15: Maximum Demographic Deviation by Classification – Min Max Dev Cap

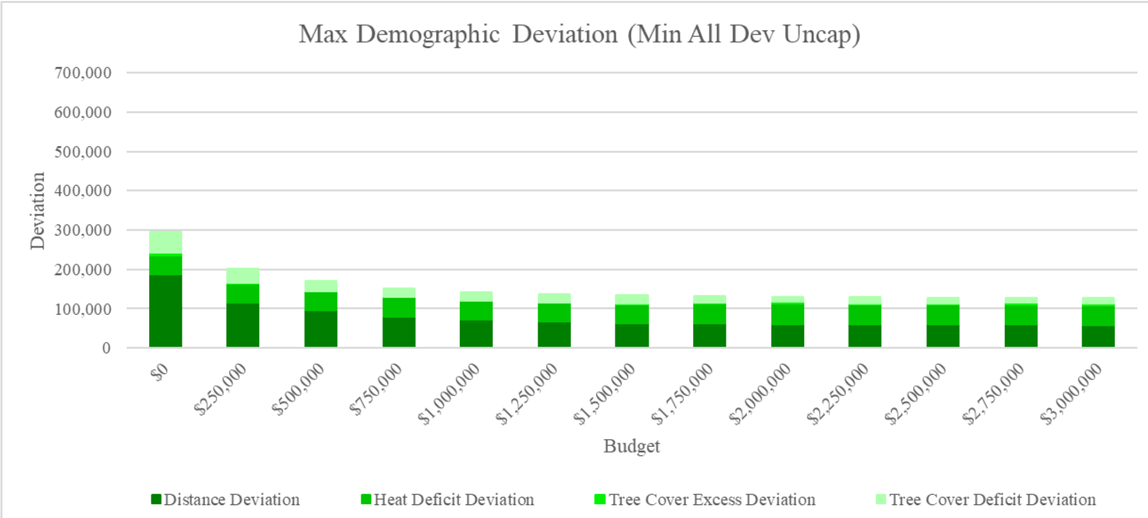

Figure 5.16: Maximum Demographic Deviation by Classification – Min All Dev Uncap

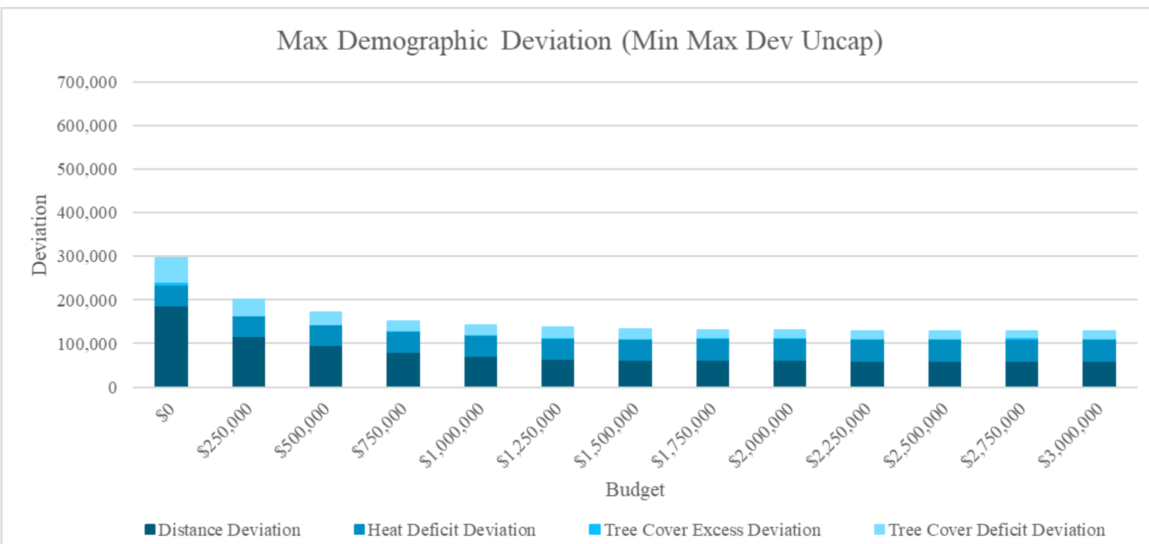

Figure 5.17: Maximum Demographic Deviation by Classification – Min Max Dev Uncap

The actual deviation classification values portrayed in Figures 5.14, 5.15, 5.16, and 5.17 are consistent with the expected proportions of deviation type in contribution to the maximum demographic park goodness deviation. Specifically, as the budget increases, the greatest deviation decreases are of distance, even if at the expense of other equity criteria. This is intuitive since we place greater emphasis on equity created by distance than upon capacity, heat, and tree cover. Also evident is that the increase in budget allows for the selection new of candidate park sites that more closely match desired environmental elements than existing parks. Therefore, maximum demographic deviations of heat and tree cover are less when a non-zero budget exists versus when there is no budget allowance.

Distance and Capacity Deviations vs. Budget

We continue to focus upon components of the objective function. We determine and analyze the unweighted deviation values of distance and capacity to understand how budget directly affects the accessibility and quality of parks for Asheville residents. The model records the distance deviation experienced by each resident location. From this data, we calculate both the maximum distance deviation and the average distance deviation, shown by Figure 5.18 and Figure 5.19, respectively. We present these distance deviation values as dependent upon budget for *Min All Dev Cap*, *Min Max Dev Cap, Min All Dev Uncap*, and *Min Max Dev Uncap.*

Figure 5.18 indicates that the relationship between maximum distance deviation and budget is not strictly monotonic for *Min All Dev Cap* and *Min Max Dev Cap*. Because capacity is also a component that contributes to equity, a significant decrease in overcrowding may couple with an increase in distance deviation to equal an overall increase in park goodness. In contrast, results from the uncapacitated model types present a monotonic decrease in maximum distance deviation as budget increases.

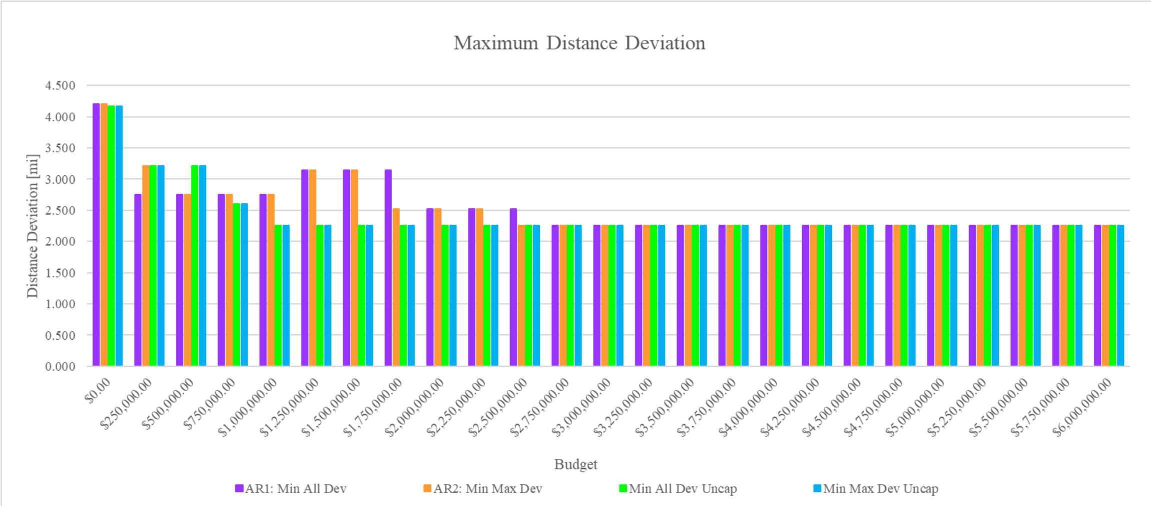

Figure 5.18: Maximum Distance Deviation vs. Budget

Notably, the maximum distance deviation value has a lower-bound limit that is equivalent for all model types beginning at a budget of $2,750,000. The maximum distance deviation resulting from the uncapacitated model types converges at a lower budget than the maximum distance deviation from the capacitated model types. The maximum distance deviation converges for *Min Max Dev Cap* at a lower budget than the maximum distance deviation from *Min All Dev Cap*.

Average distance deviation values are significantly less than the maximum distance deviation values, indicating that several resident locations are within a desirable distance of their primary park. Figure 5.19 indicates that model instances of *Min All Dev Cap* and *Min Max Dev Cap* yield average distance values that are not strictly monotonic as budget increases. This outcome is due to the tradeoff between improvements in distance and capacity. However, overall, there is a decreasing trend between average distance deviation and budget.

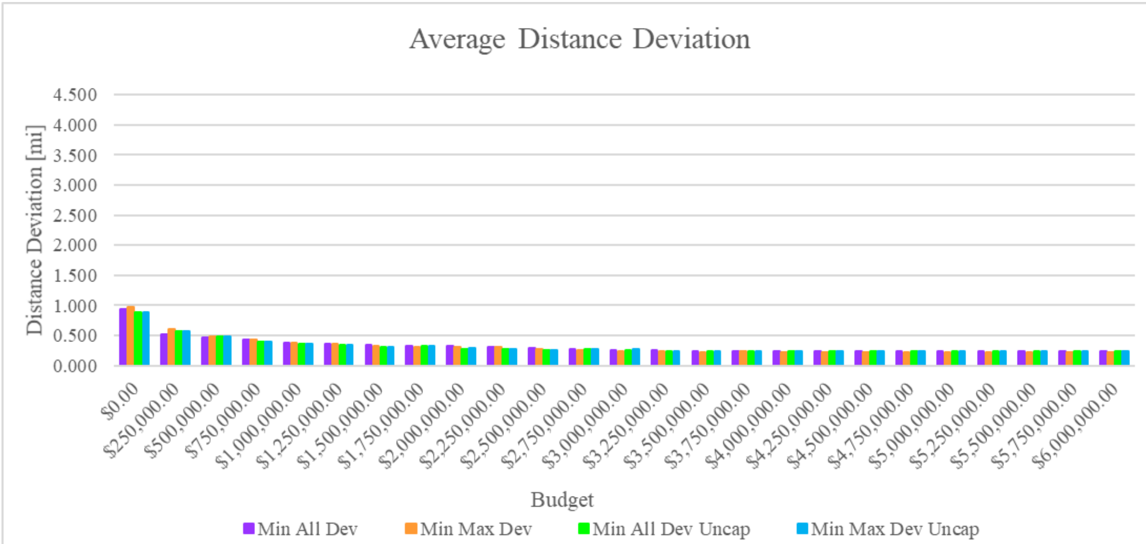

Figure 5.19: Average Distance Deviation vs. Budget

Figure 5.19 indicates that the average distance deviation value has a lower-bound limit, which is a unique value for both of the capacitated model types. Notably, the average distance deviation value at convergence is greater for *Min All Dev Cap* versus *Min Max Dev Cap*. Further, we note that the uncapacitated model types result in an average distance deviation converging value that is between the converging distance deviations of *Min All Dev Cap* and *Min Max Dev Cap*. Interestingly, a lesser average distance deviation convergence value results from *Min All Dev Cap*, a capacitated model type that inherently incorporates a distance-capacity tradeoff in maximizing park equity goodness, versus the uncapacitated model types, which primarily focus upon distance as an equity measure.

We record the capacity deviation experienced by each resident location for the capacitated model types. For the uncapacitated model types, we determine the value of overcrowding that would result if parks were treated as capacitated entities. From this data, we calculate both the maximum capacity deviation (overcrowding) and the average capacity deviation (overcrowding) as shown in Figure 5.20 and Figure 5.21, respectively. We present these distance deviation values as dependent upon budget for *Min All Dev Cap*, *Min Max Dev Cap*, *Min All Dev Uncap*, and *Min Max Dev Uncap.*

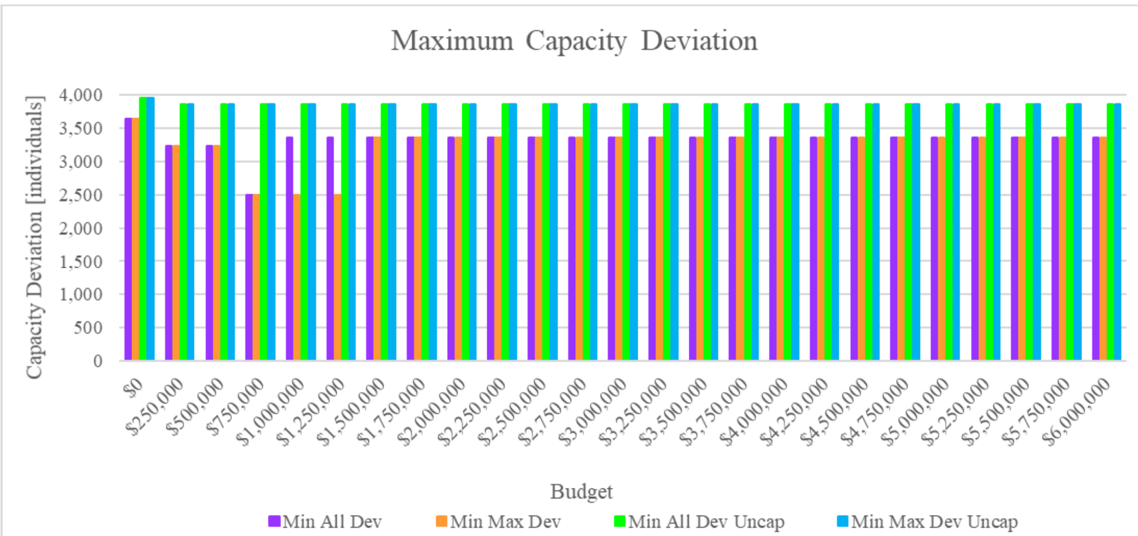

Figure 5.20: Maximum Capacity Deviation vs. Budget

Figure 5.20 indicates that the relationship between the maximum amount of park overcrowding and budget is not monotonic for the capacitated model types. Interestingly, the converging value of maximum capacity deviation for these types is greater than the lowest achieved maximum capacity deviation instance. This is due to the increased importance in minimizing distance, heat, and tree cover deviations versus capacity deviations. Another insight is that the amount of maximum park overcrowding for both uncapacitated model types converges to the same numerical amount, a value equal to only 502 individuals greater than the converging maximum park overcrowding deviation value for the capacitated model types.

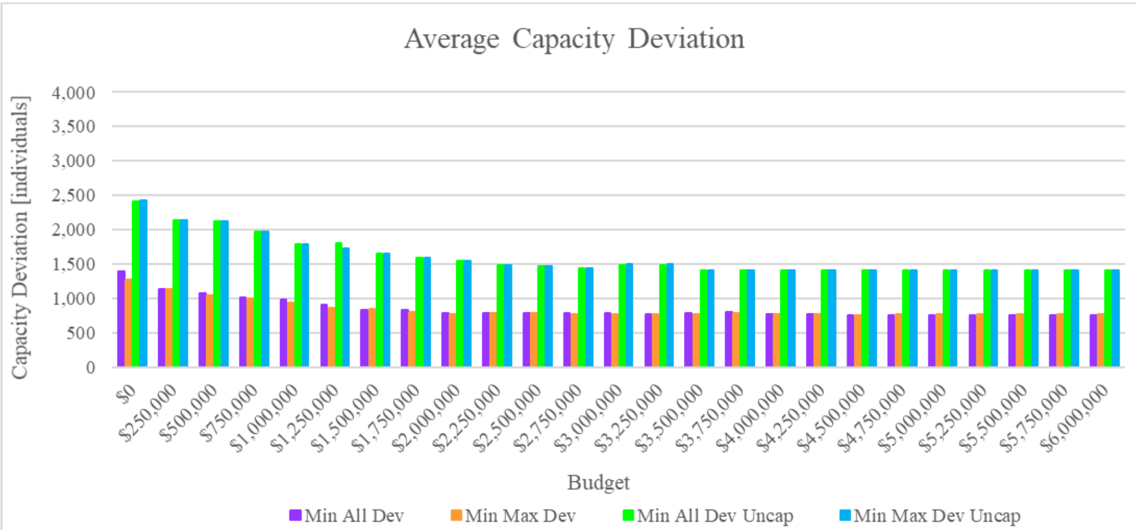

Figure 5.21: Average Capacity Deviation vs. Budget

Figure 5.21 indicates that the relationship between the average amount of park overcrowding and budget is not monotonic for the capacitated or uncapacitated model types. Interestingly, the converging value of average capacity deviation for *Min Max Dev Cap* is only 3 individuals greater than the average capacity deviation converging value for *Min All Dev Cap.* Further, we note that the converging amount of average park overcrowding for the uncapacitated model types is approximately 650 individuals greater than the amount resulting from the capacitated model types.

Primary Park Selection vs. Budget

We consider how the selection of primary park locations changes as the budget increases. We provide Figure 5.22 as a representation of a baseline that visualizes the current distribution of primary parks by including only existing park facilities. The figure reveals that the distribution of current primary parks is mainly focused within the central and eastern regions of Asheville. The northern, southern, and western portions of the city experience a deficit of primary parks.

To analyze the impact of budget upon the location of primary parks, we map existing and candidate primary park sites as defined by the decision variable solutions of model type *Min Max Dev Cap*. We display model-optimal primary parks as dependent upon budget values of $750,000, $1,750,000, and $2,750,000 in Figure 5.23. The map illustration symbolizes park site feature classes by increasingly darker hues and larger symbols as the budget value increases.

Figure 5.23 visualizes that several sites continue to have the designation of primary park as the park budget increases. Specifically, 33 existing park sites and 13 candidate park sites remain as primary parks throughout the three budget iterations. We distinguish that, as the budget increases from $0 (the baseline) to $750,000, the majority of new candidate park sites are distributed in the extremities of the northern, southern, and western regions of Asheville. This confirms that the model first seeks to locate parks in areas with the greatest park service deficit. As budget increases, the distribution of primary park candidate sites widens to serve areas within Asheville's underserved extremities and underserved areas located within a closer proximity to existing parks.

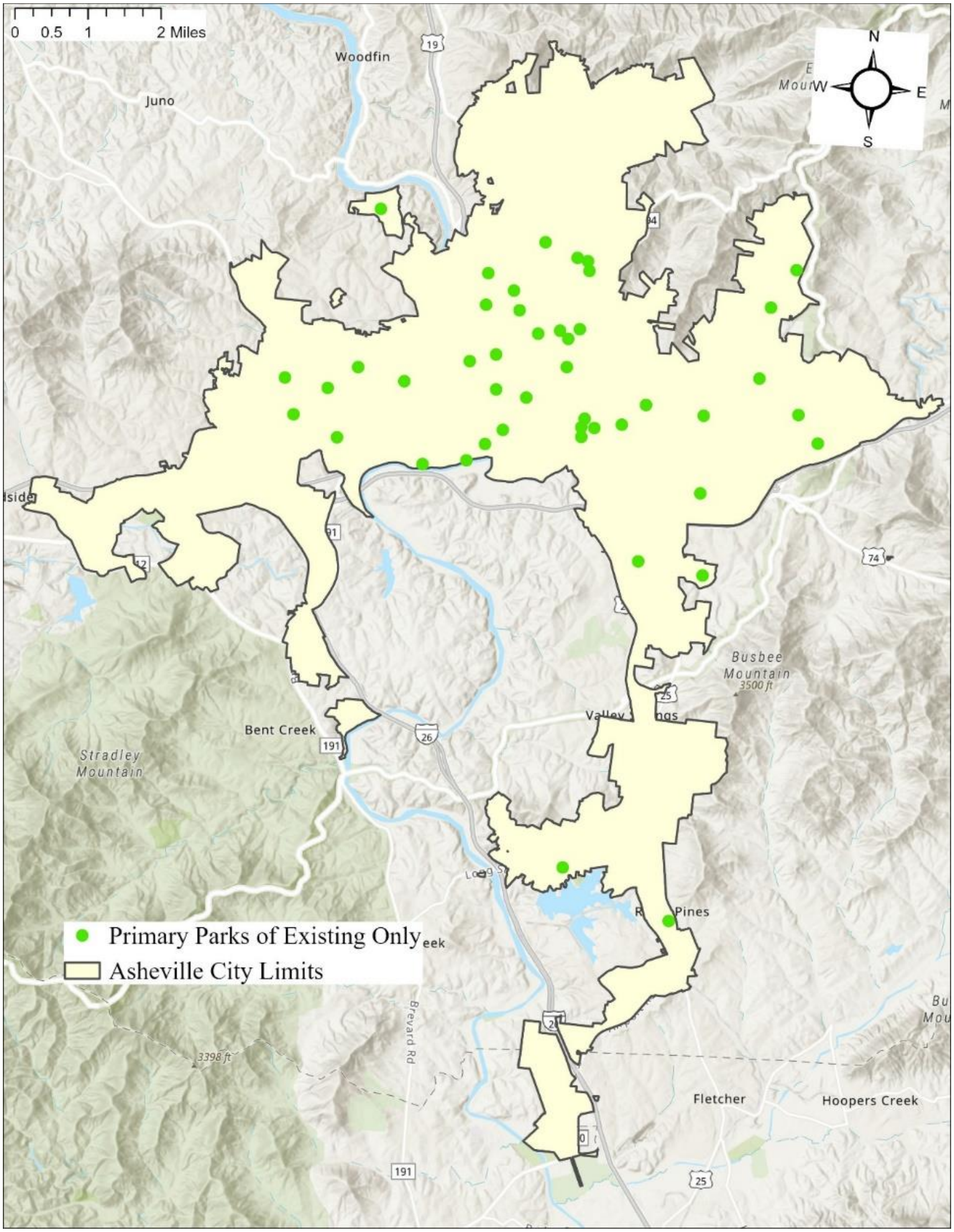

Figure 5.22: Asheville Current-State Primary Park Selection

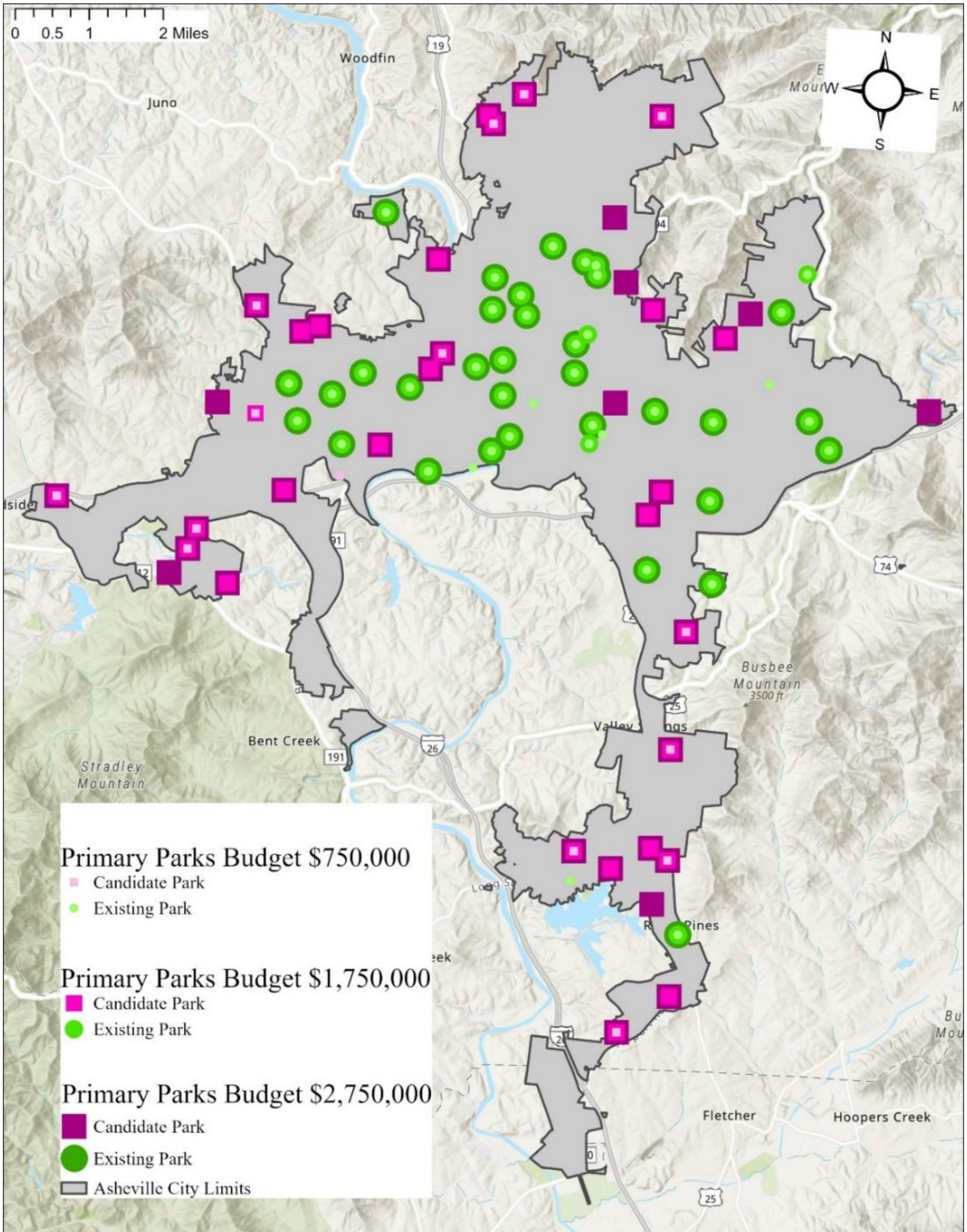

Figure 5.23: Primary Park Selection vs. Budget

Analysis Question 2: Overall Spending vs. Iterative Spending

Government and recreational organizations may employ one of two different timelines within their park planning agenda. Several cities use a one-time park purchasing method in which they spend all budget money simultaneously. We label this technique as *overall spending*. Other cities apply a long-term park purchasing plan in which a portion of overall budget money is spent during each year of the plan period. We label this technique as *iterative spending.* An insightful analysis determines how the application of overall spending versus iterative spending impacts park goodness deviation measures as well as park selection. To provide these insights, we complete two analyses using the model type *Min Max Dev Cap*. In these analyses, we maintain a constant demographic priority weight of one for all demographics and a desired distance from residents to parks of 0.5 miles.

In our first analysis scenario, the City of Asheville (COA) has a 10-year budget of $1,000,000. The COA may elect to spend the entirety of these funds in a one-time park purchasing decision, or the COA may use $100,000 per year to purchase park land. In our second analysis scenario, the COA has a 10-year budget of $2,500,000. The COA may elect to spend the entirety of these funds in a one-time park purchasing decision, or the COA may use $250,000 per year to purchase park land.

Park Goodness Deviation Measures vs. Spending Method

In our analysis of park goodness measures, we determine the weighted deviations of distance, capacity, heat, and tree cover, the overall total weighted deviation, and the weighted maximum demographic deviation as dependent upon a method of overall spending versus iterative spending. Figure 5.24 provides these outcomes for the total budget of $1,000,000, and Figure 5.25 provides these outcomes for the total budget of $2,500,000.

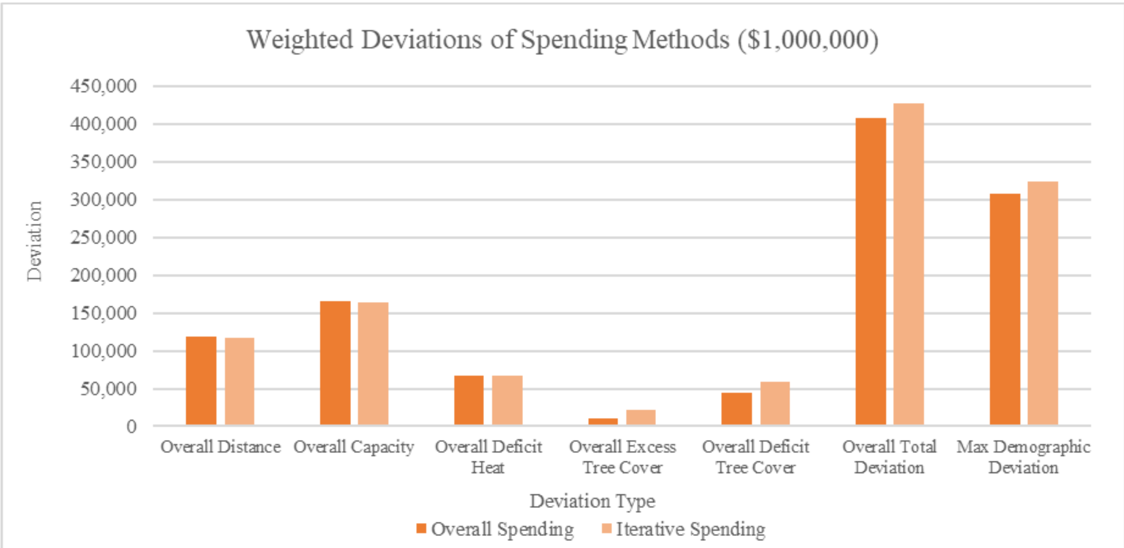

Figure 5.24: Weighted Deviations vs. Spending Method ($1,000,000)

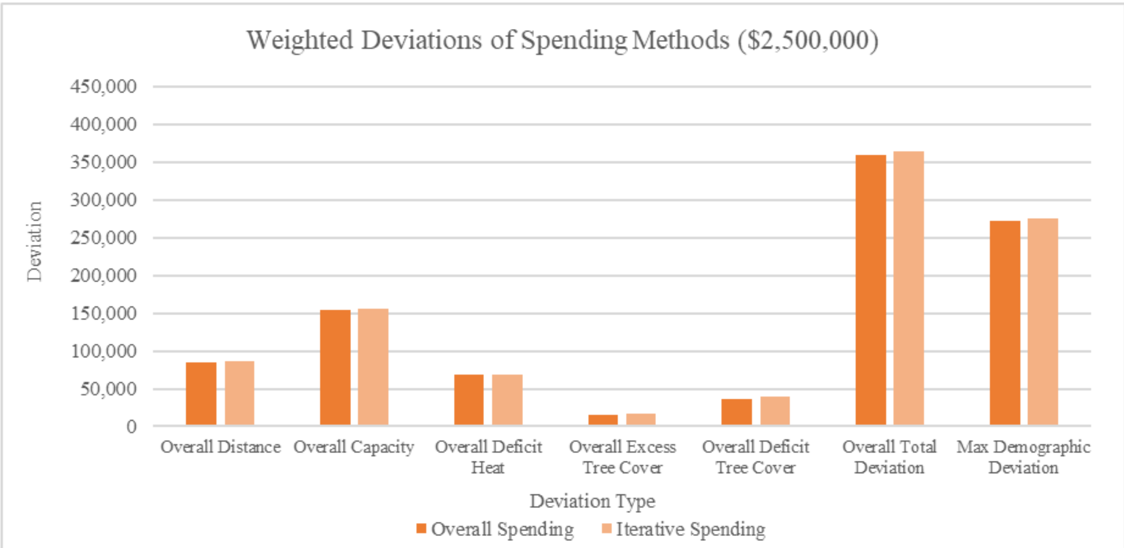

Figure 5.25: Weighted Deviations vs. Spending Method ($2,500,000)

Figure 5.24 reveals that, when the budget for park purchasing is \$1,000,000, an overall spending method results in a greater amount of weighted distance and capacity deviations versus the iterative spending method. However, the former spending method provides a lesser amount of weighted heat and tree cover deviations as well as a lower overall total weighted deviation and weighted maximum demographic deviation versus the latter spending method. Therefore, the additional goodness created by the environmental factors in the overall spending method outweighs the additional goodness generated by the distance and capacity factors in the iterative spending method.

Figure 5.25 reveals that, when the budget for park purchasing is \$2,500,000, an overall spending method results in a greater amount of weighted heat deviations versus the iterative spending method. However, the former spending method provides a lesser amount of weighted distance, capacity, and tree cover deviations as well as a lower overall total weighted deviation and weighted maximum demographic deviation versus the latter spending method. Though the weighted distance and capacity deviations significantly improve for the overall spending method as the budget increases from \$1,000,000 to \$2,500,000, the benefit of selecting the overall spending method rather than the incremental spending method decreases, as indicated when comparing the values of overall total weighted deviation and weighted maximum demographic deviation between iterations.

Further, we calculate the unweighted, resident-experienced deviations of distance and capacity for both scenarios. From a dataset of individual resident location deviations, we calculate the maximum and average deviation values for both distance and capacity.

Figure 5.26 provides these results for a total budget of $1,000,000, and Figure 2.27 provides these results for a total budget of $2,500,000.

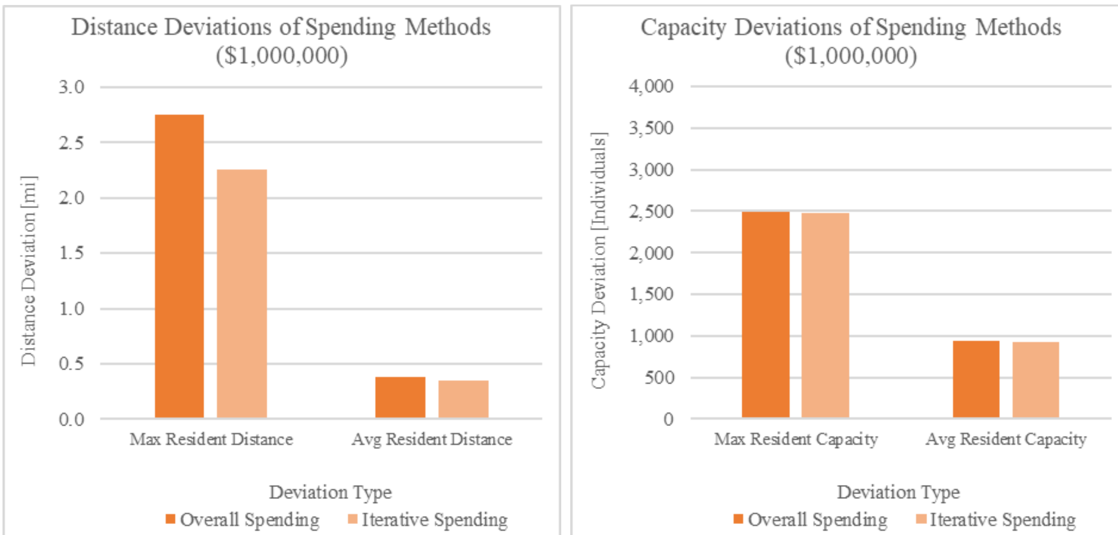

Figure 5.26: Distance and Capacity Deviations vs. Spending Method ($1,000,000)

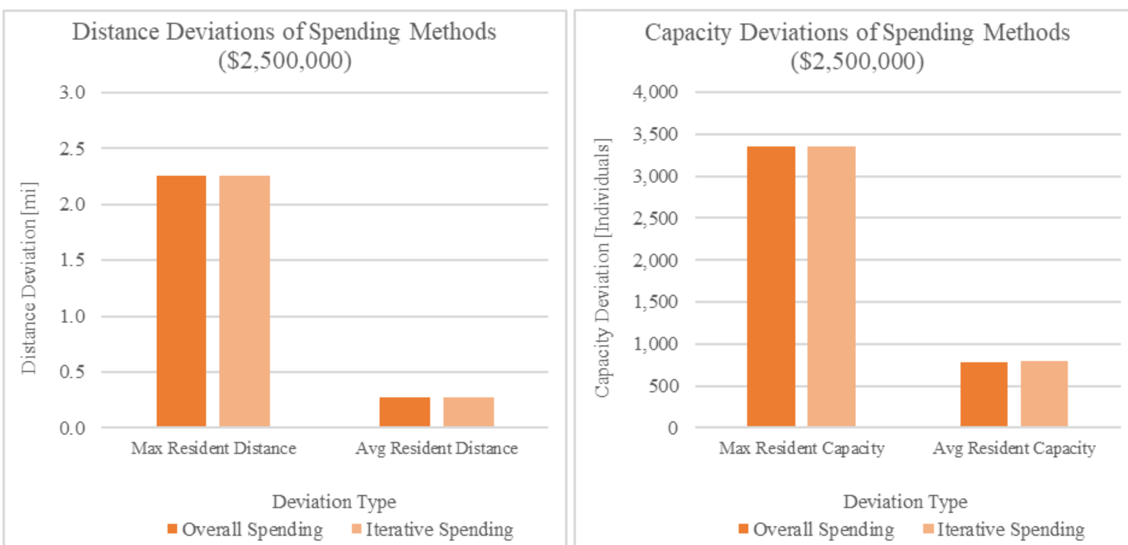

Figure 5.27: Distance and Capacity Deviations vs. Spending Method ($2,500,000)

Figure 5.26 illustrates that the deviations of minimum and average distance and capacity are less for the iterative spending method versus the overall spending method when the budget is $1,000,000. The difference between average distance, maximum capacity, and average capacity deviations between spending methods is negligible. However, significantly, the maximum distance deviation for the iterative spending method is approximately 0.5 miles less than that of the overall spending method. Figure 5.27 visualizes that the deviation for maximum distance and maximum capacity equals the same numerical value between spending methods when the budget equals $2,500,000. There exist negligible differences between spending methods for average deviation values of distance and capacity. Therefore, when the budget equals $2,500,000, there is no significant preference in spending method when considering solely resident-experienced distance and capacity deviations.

Selected Candidate Parks vs. Spending Method

We consider how the selection of candidate park sites varies dependent upon the spending method. Figures 5.28 and 5.29 consider the iterative spending method in which the 10-year budget totals $1,000,000. In Figure 5.28, we depict the candidate parks selected for each annual purchasing period in order to view how the distribution of candidate parks develops over time. The color key provided within the map legend defines the symbology used to represent the iterative candidate park purchases. Figure 5.29 illustrates the 10-year candidate park selection differences resulting from the overall spending method versus the iterative spending method. We provide existing parks as well as candidate parks within both figures to provide context concerning underserved areas.

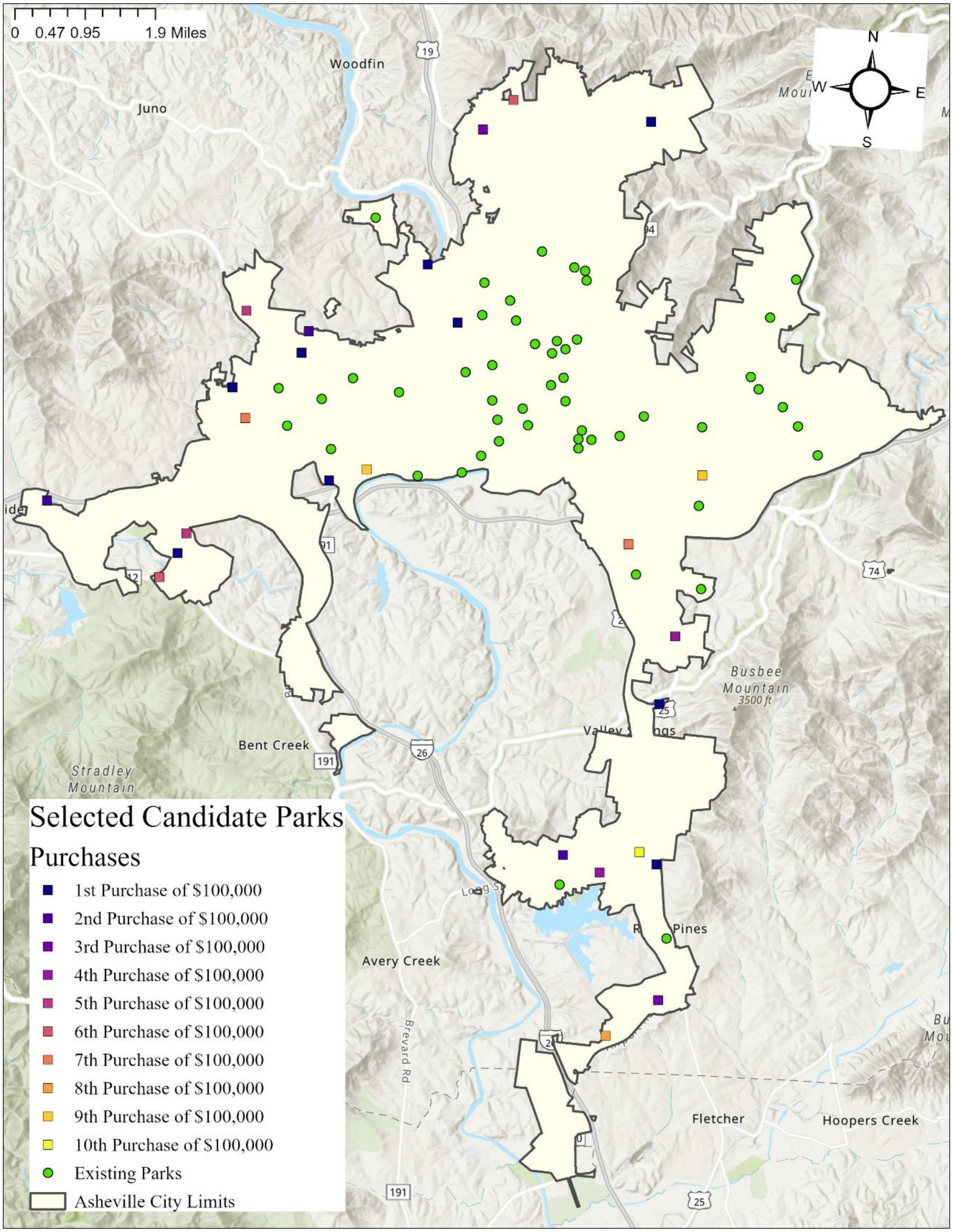

Figure 5.28: Iterative Park Purchasing over Time ($1,000,000)

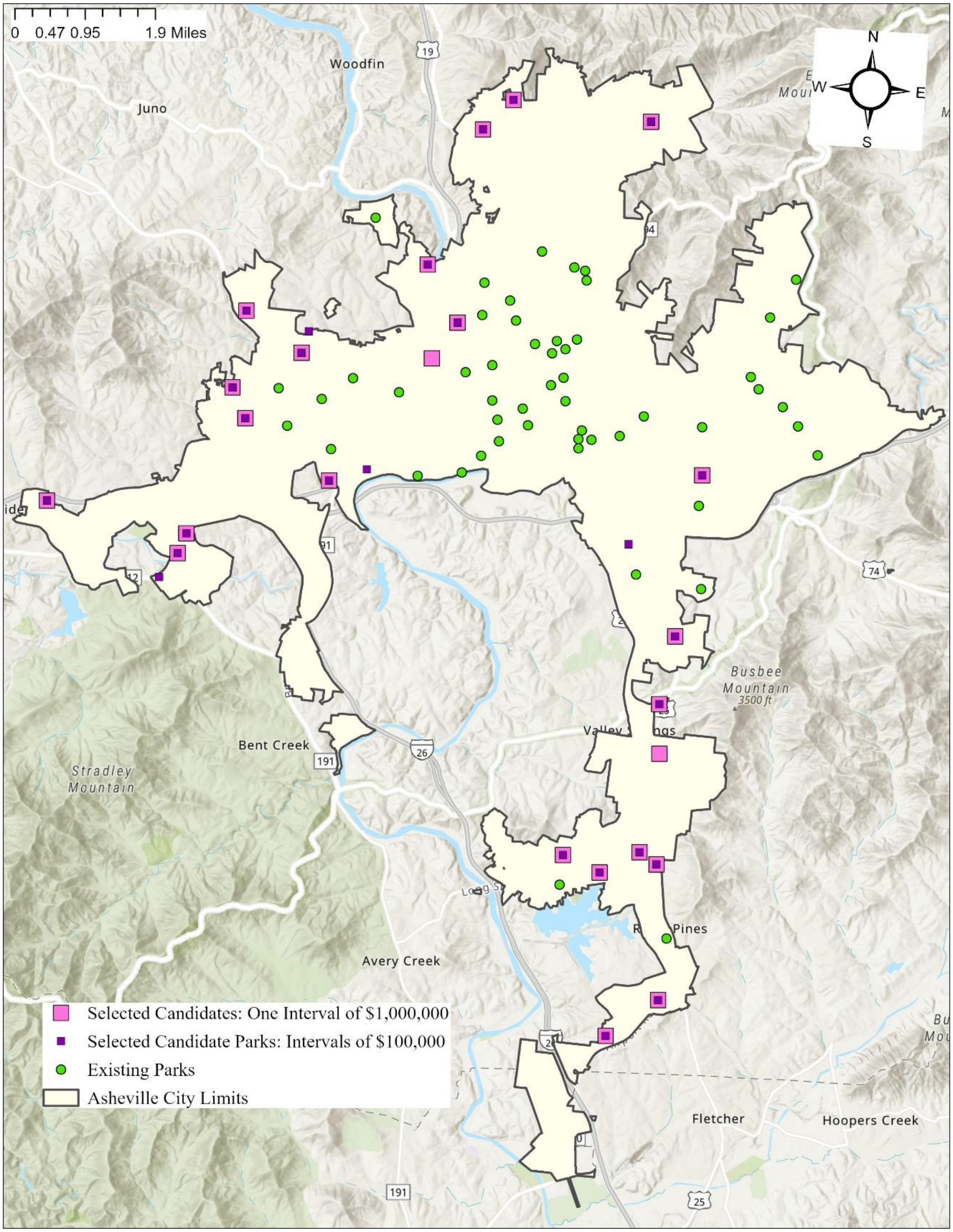

Figure 5.29: Overall Park Purchasing vs. Iterative Park Purchasing ($1,000,000)

As depicted in Figure 5.28, iterative spending purchases seek to locate candidate parks in underserved areas of Asheville that are located a great distance from existing parks. These areas are along the periphery of Asheville City Limits. Throughout the first four years of iterative spending, the model locates candidate parks such that there exists a fairly even distribution of greenspaces throughout the northern, western, and southern periphery of Asheville. In the fifth year of spending, the model revisits these regions to select additional candidate parks that further facilitate park service. Within the final three years of iterative spending, the model selects candidate parks that are physically nearer to the central and eastern regions of Asheville, the hub of initial existing parks. Figure 5.29 illustrates that there exist a total of 24 selected candidate parks resulting from the overall spending method while 26 parks result from the iterative spending method. A total of 22 parks remain the same between spending methods such that there exist two unique parks from the overall spending method and four unique parks from the iterative spending method.

Figures 5.30 and 5.31 consider the iterative spending method in which the 10-year budget totals $2,500,000. In Figure 5.30, we depict the candidate parks selected for each annual purchasing period in order to view how the distribution of candidate parks develops over time. The color key provided within the map legend defines the symbology used to represent the iterative candidate park purchases. Figure 5.31 illustrates the 10-year candidate park selection differences resulting from the overall spending method versus the iterative spending method. We provide existing parks as well as candidate parks within both figures to provide context concerning underserved areas.

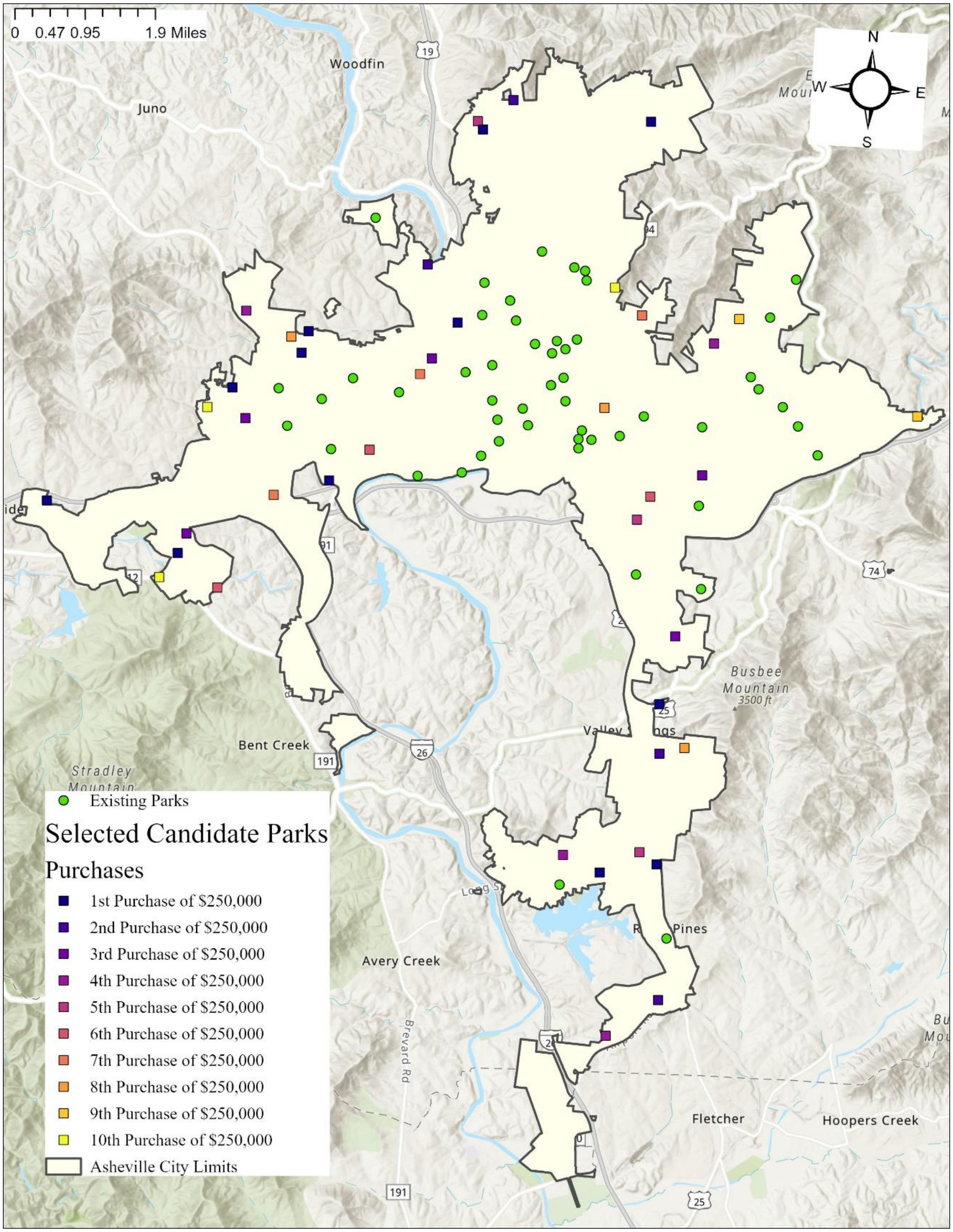

Figure 5.30: Iterative Park Purchasing over Time ($2,500,000)

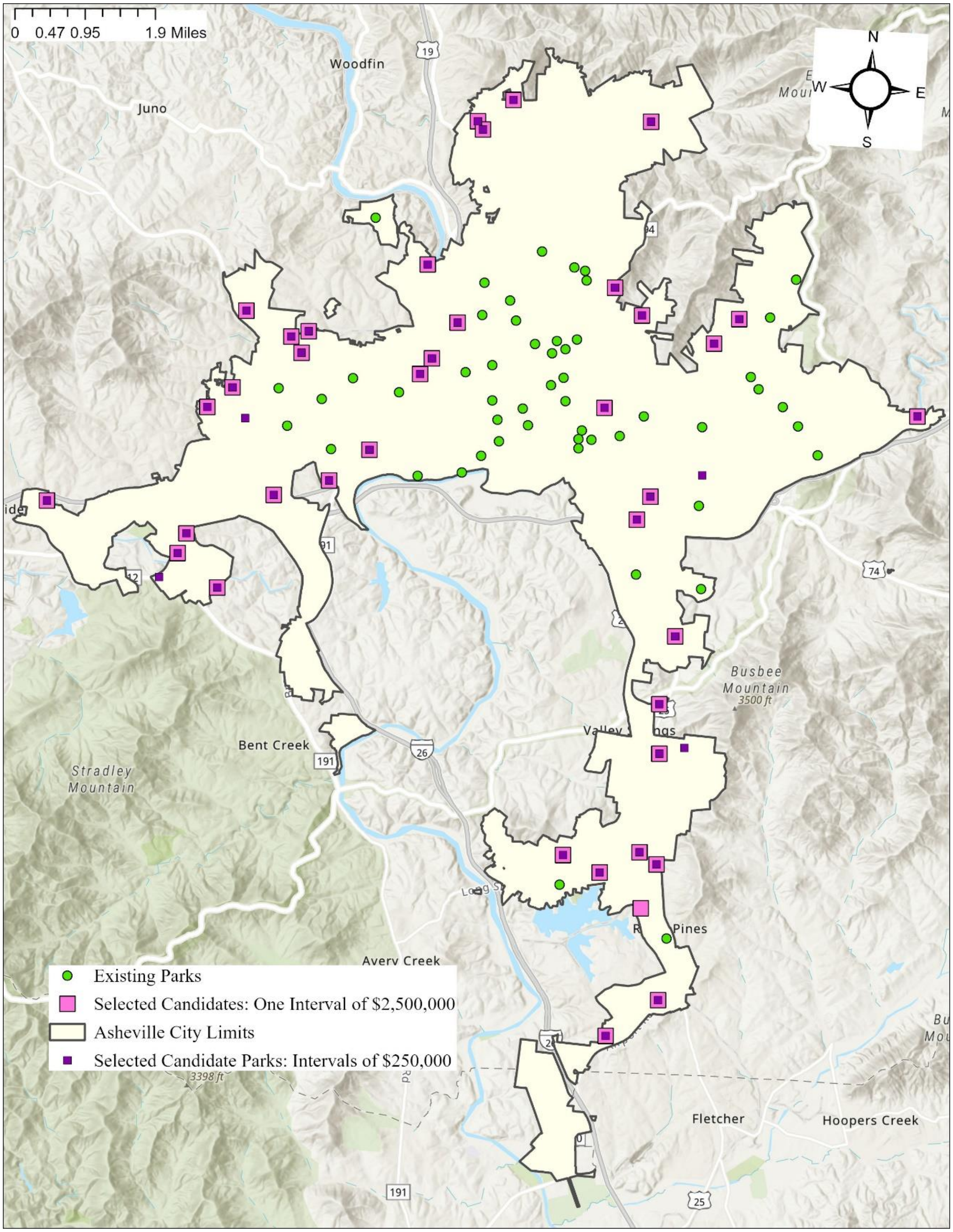

Figure 5.31: Overall Park Purchasing vs. Iterative Park Purchasing ($2,500,000)

As depicted in Figure 5.30, iterative spending purchases seek to locate candidate parks in underserved areas of Asheville that are located a great distance from existing parks. These areas are along the periphery of Asheville City Limits. Throughout the first three years of iterative spending, the model locates candidate parks such that there exists a fairly even distribution of greenspaces throughout the northern, western, and southern periphery of Asheville. In the fourth year of spending, the model revisits these regions to select additional candidate parks that further facilitate park service. Within the final five years of iterative spending, the model selects candidate parks that are physically nearer to the central and eastern regions of Asheville, the hub of initial existing parks. The trend of iterative candidate park location selection for a budget of $1,000,000 and for budget of $2,500,000 is similar. Yet, because an increased amount of budget equates a greater capacity to purchase candidate parks, the second scenario presents a more densely distributed candidate park selection than the first scenario.

Figure 5.31 illustrates that there exists a total of 39 selected candidate parks resulting from the overall spending method while 42 parks result from the iterative spending method. A total of 38 parks remain the same between spending methods such that there exists one unique park from the overall spending method and three unique parks from the iterative spending method. A comparison of Figures 5.29 and 5.31 indicates that unique candidate parks differ between budget scenarios. Further, we note that the number of uniquely selected candidate parks for overall spending versus iterative spending decreases as the amount of monetary availability increases.

Analysis Question 3: Deviation-Based Model vs. Score-Based Model

To complete our analysis of the score-based park equity model, we consider the maximization of the minimum demographic score when parks are treated as uncapacitated entities. We label this model type as *Max Min Score Uncap*. To analyze the effectiveness of using the deviation-based model versus the score-based model, we compare distance deviations experienced by resident locations for the model types of *Min Max Dev Uncap* and *Max Dev Score Uncap* as budget increases from $0 to $3,000,000. For each budget instance, we calculate the maximum distance deviation and average distance deviation across all resident locations. Figures 5.32 and 5.33 provide visuals of maximum and average distance deviations, respectively.

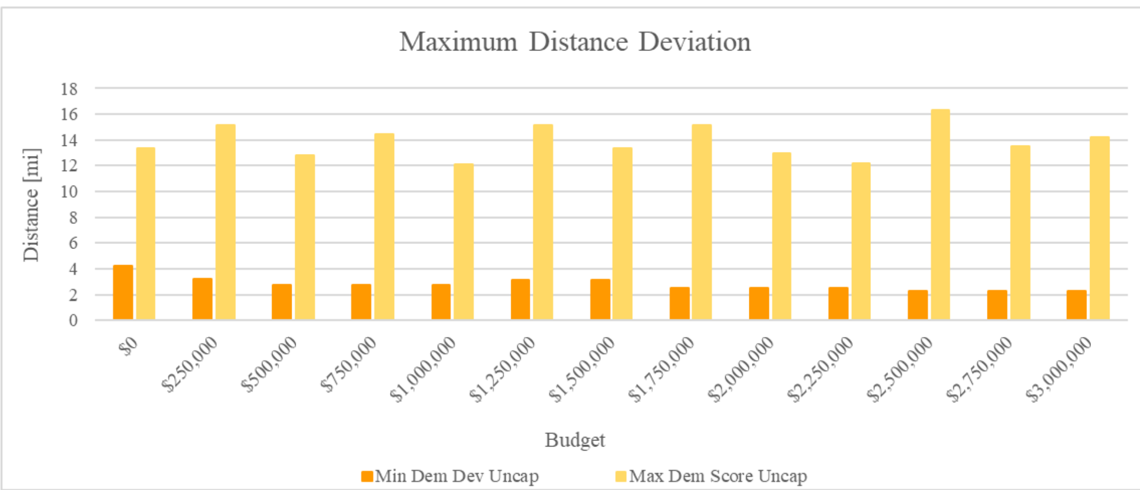

Figure 5.32: Maximum Distance Deviation – Deviation-Based Model vs. Score-Based Model

Figure 5.32 reveals that the maximum distance deviation resulting from the score-based model is significantly greater than the maximum distance deviation value of the deviation-based model. Further, there exists no correlation between the increases and decreases in maximum distance deviation value between instances for both model types. Notably, the variability in maximum distance deviation value between iterations is more drastic for the score-based model versus the deviation-based model.

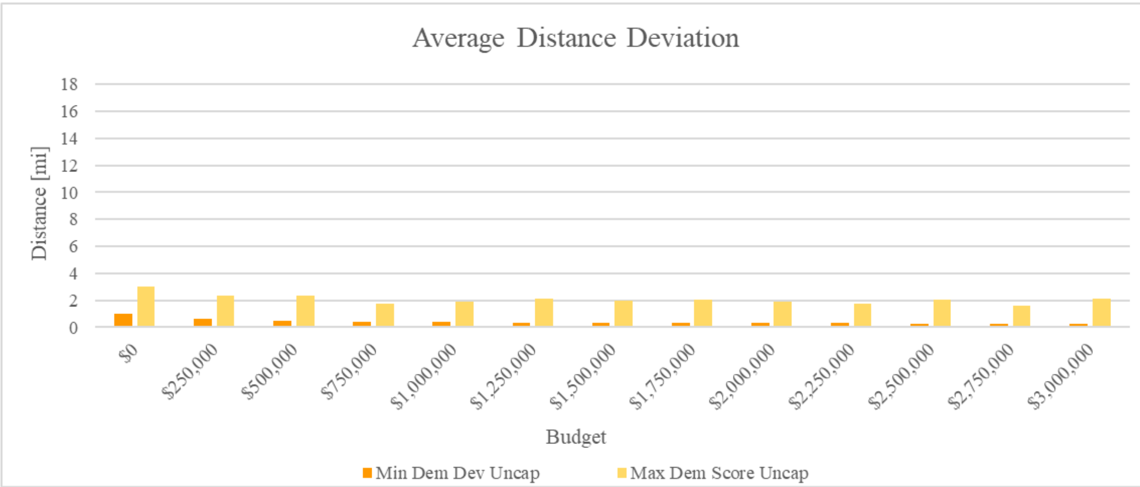

Figure 5.33: Average Distance Deviation – Deviation-Based Model vs. Score-Based Model

Figure 5.33 reveals that the average distance deviation resulting from the score-based model is significantly greater than the average distance deviation value of the deviation-based model. Concerning *Max Dem Score Uncap,* we note that the average distance deviation is less volatile than the maximum distance deviation.

Analysis Question 4: Primary Parks vs. Demographic Strategic Target

Government and recreational organizations may desire to place a greater priority upon locating park facilities for individuals of particular demographics to emphasize an increased experience of park goodness. Our models utilizes a demographic weight parameter that allows the user to translate a strategic demographic target into park location decisions. We analyze the effectiveness of our deviation-based model in selecting candidate park sites and assigning primary parks as we place different levels of emphasis upon creating park equity for specific demographics. We also determine how an increase in strategic target weight affects park spending for demographics. All analyses within this section use results from the model type *Min Max Dem Cap* with inputs of a 0.5-mile desired distance and a budget of $500,000.

Primary Park Assignments and Locations vs. Strategic Target for Black Residents

First, we analyze the strategic target weight for black residents by testing weights from 0 to 50 in increments of 5. To ensure that we focus upon only black residents, we maintain a constant demographic weight of one for white, indigenous, Asian, Pacific Islander, and other residents. A transition in strategic target weight for black residents from 5 to 10 yields a differentiation in value of the binary primary park assignment variable. All other strategic target weight transitions proved insignificant. Therefore, we declare that a strategic target weight for black residents of 5 provides a *low strategic emphasis for black residents* (BL) while a weight of 10 equals a *high strategic emphasis for black residents* (BH) in selecting parks that contribute to equitable park distribution.

Figure 5.34 and Figure 5.35 show primary park assignments for each resident location when there exists BL and BH, respectively. In these maps, we represent resident locations as the center points of BG19. We symbolize these center points as triangles of varying color to represent the number of residents within each location that consider themselves as belonging to the black racial-ethnic classification. We determine five quantiles from the dataset of black resident demographic counts across the 77 block groups within this study. Blue triangles represent BG19 with a black resident population count within the 1st quantile. These block groups have the least number of black residents. Red triangles represent BG19 with a black resident population count within the 5th quantile. These block groups have the greatest number of black residents.

Figure 5.34 visualizes that, given BL, model recommendations place candidate parks in the northern portion of Asheville such that locations with fewer black residents within that region have a greater access to parks. Figure 5.35 illustrates that, given BH, the model removes candidate sites from the northern portion of Asheville such that residents within that region must traverse greater distances to visit their primary parks. There is a reallocation of resources between BL and BH that places primary candidate parks near residents of black racial classification as strategic emphasis for these residents increases.

To better visualize primary park designations and locations, we introduce Figures 5.36 and 5.37. Figure 5.36 includes the routes between residents and their determined primary parks for model instances of BL and BH. These routes are of brown and purple line feature classes, respectively. Only included are the routes and primary parks that differ between iterations of low and high emphasis. Figure 5.37 visualizes the distribution of existing and candidate primary parks as dependent upon BL and BH. We represent the primary parks of BL with smaller symbols of lighter hue and primary parks of BH with larger symbols of darker hue. We continue to symbolize block groups by graduated colors to represent the number of black residents within each defined location.

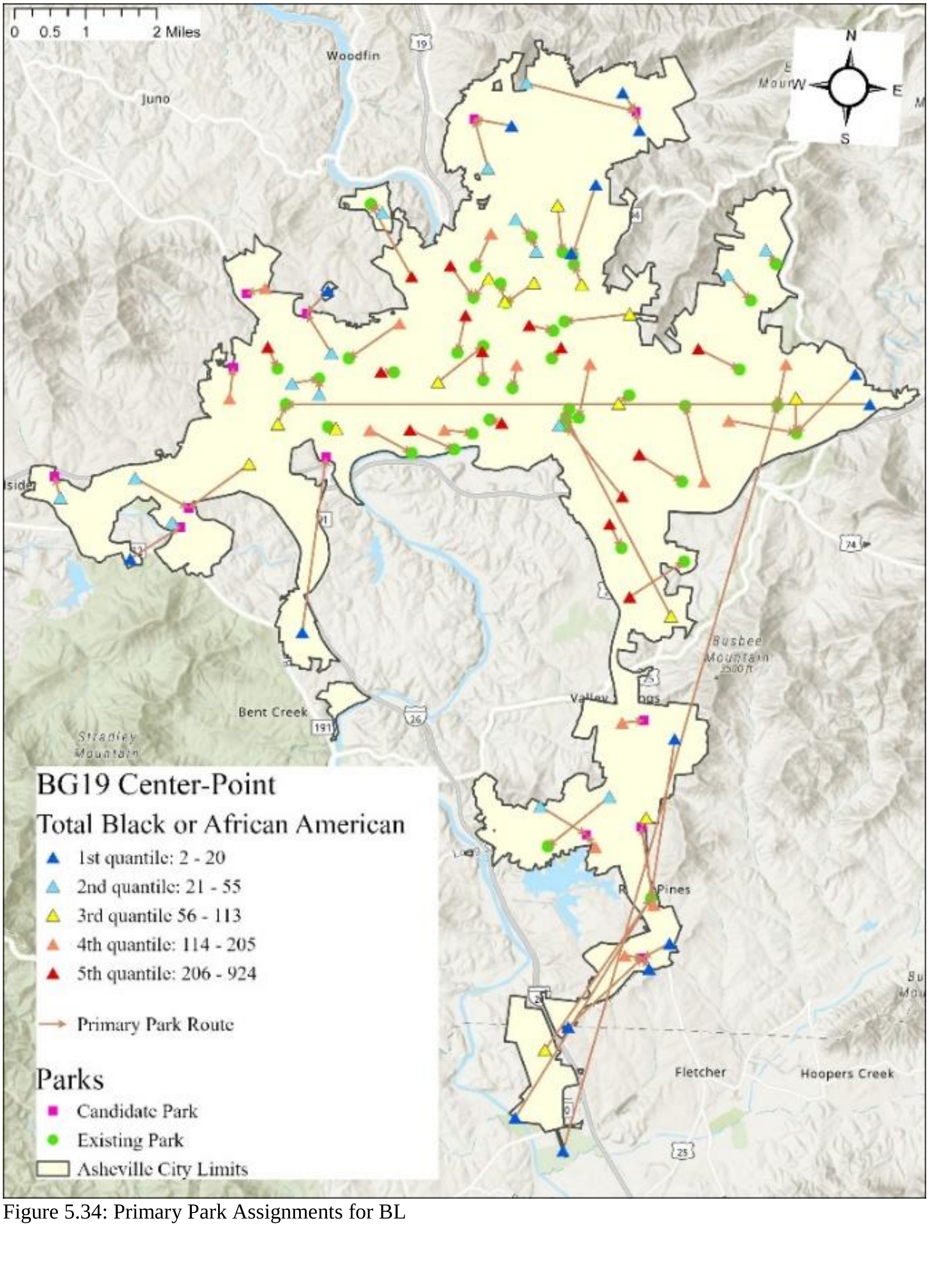

Figure 5.34: Primary Park Assignments for BL

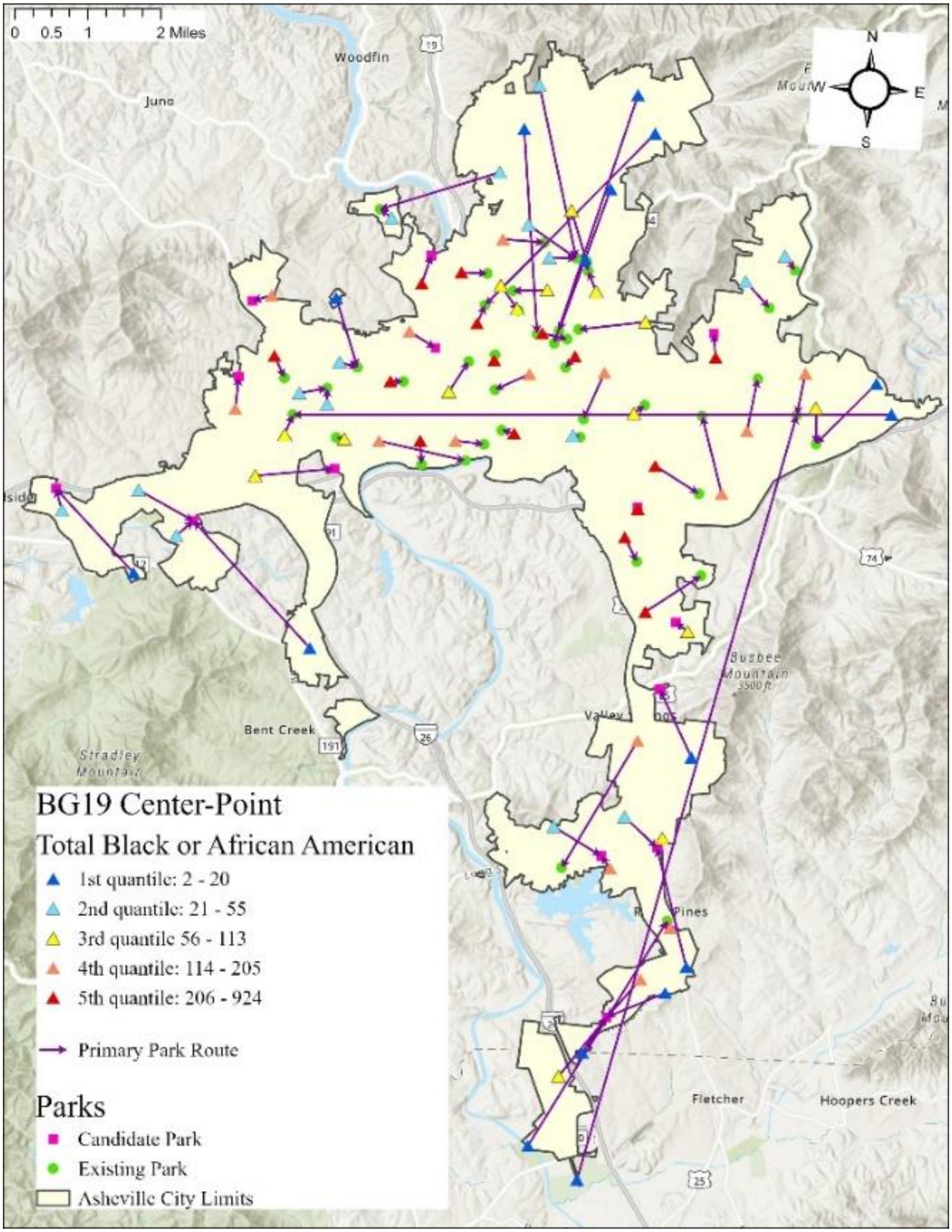

Figure 5.35: Primary Park Assignments for BH

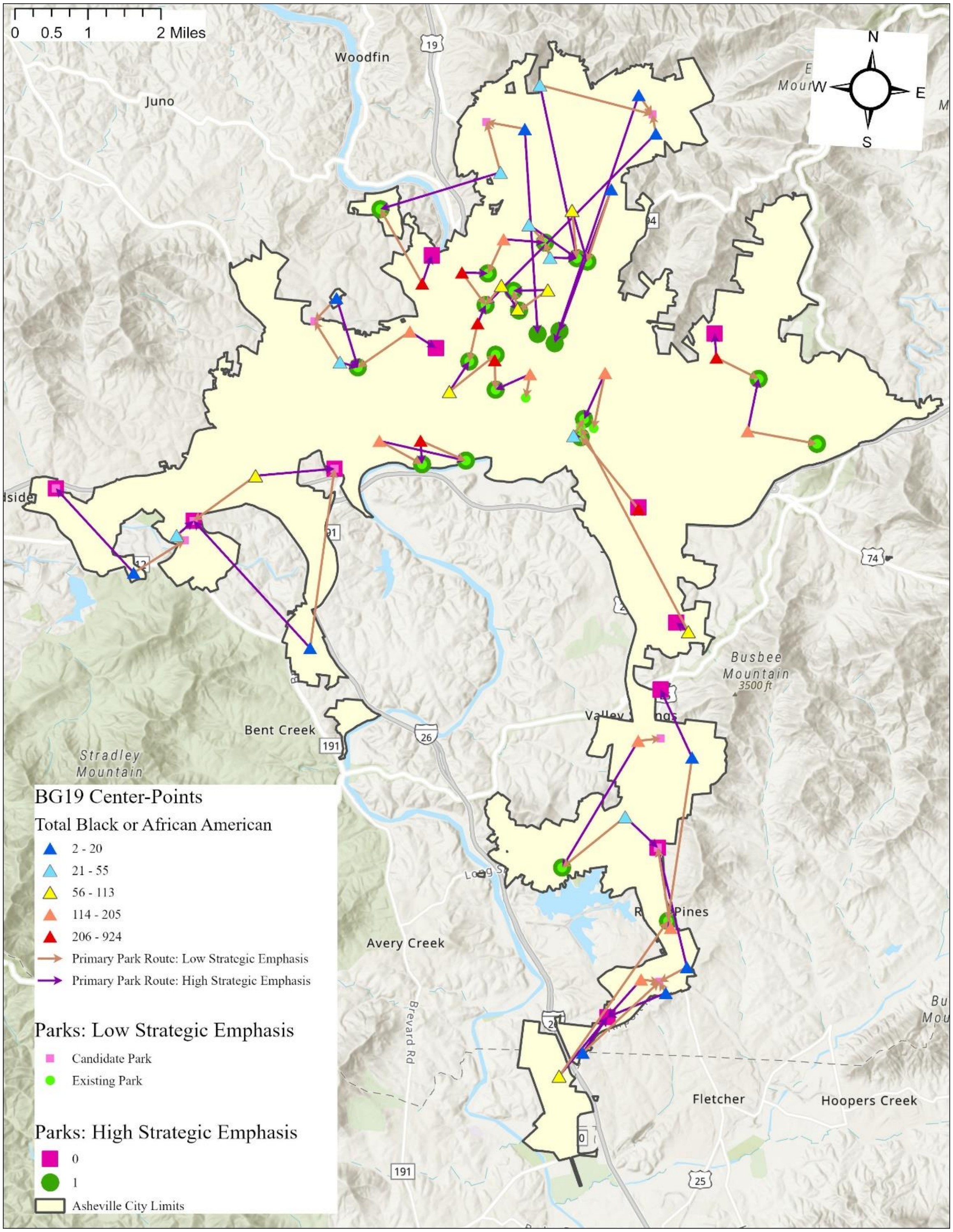

Figure 5.36: Primary Park Assignments for BL vs. BH

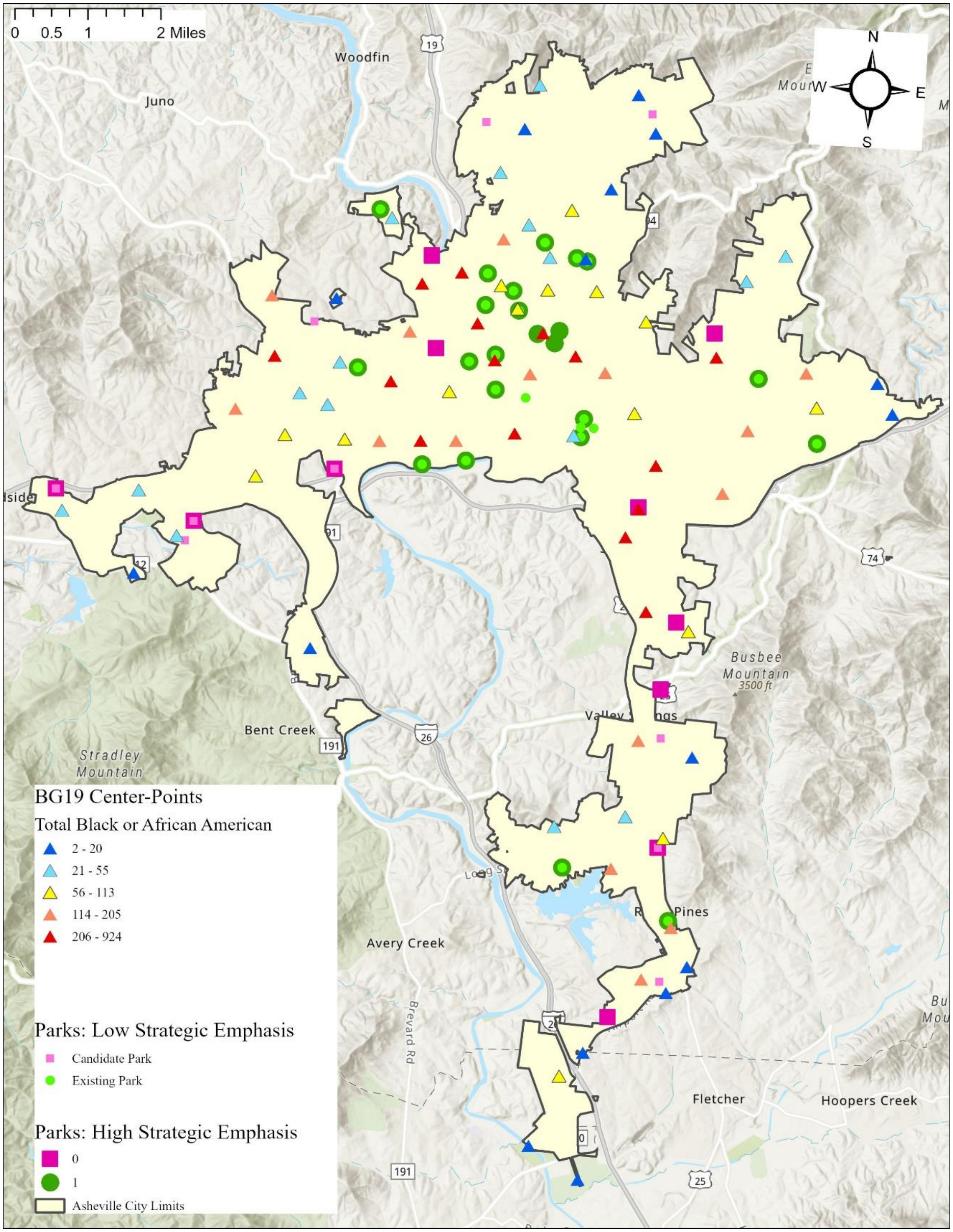

Figure 5.37: Primary Park Locations for BL and BH

Figure 5.36 shows that there exist many instances in which the distance from locations with a large number of black residents to their primary parks decreases as strategic target emphasis transitions from low to high. Further, there are many residents from locations with a smaller number of black individuals that encounter greater distances to their primary parks between iterations of BL and BH as the allocation of recourses focuses upon benefiting the black community. In Figure 5.37, 24 park sites remain primary parks between BL and BH. Notably, as strategic emphasis for black residents increases, an increased number of primary parks exist in the central and southern portions of Asheville that are home to the greatest number of black residents.

Primary Park Assignments and Locations vs. Strategic Target for Indigenous Residents

To further confirm that the strategic demographic target weight influences primary park decisions to systematically present equity, we analyze the strategic target weight for Native American (indigenous) residents by testing weights from 0 to 50 in increments of 5. To ensure that we focus upon only indigenous residents, we maintain a constant demographic weight of one for all other residents. A transition in strategic target weight for indigenous residents from 30 to 35 and from 35 to 40 yield a differentiation in value of the binary primary park assignment variable. All other strategic target weight transitions proved insignificant. Therefore, we declare that a strategic target weight for indigenous residents of 30 provides a *low strategic emphasis for indigenous residents* (IL). A weight of 35 equates a *medium strategic emphasis for indigenous residents* (IM), and a weight of 40 represents a *high strategic emphasis for indigenous residents* (IH).

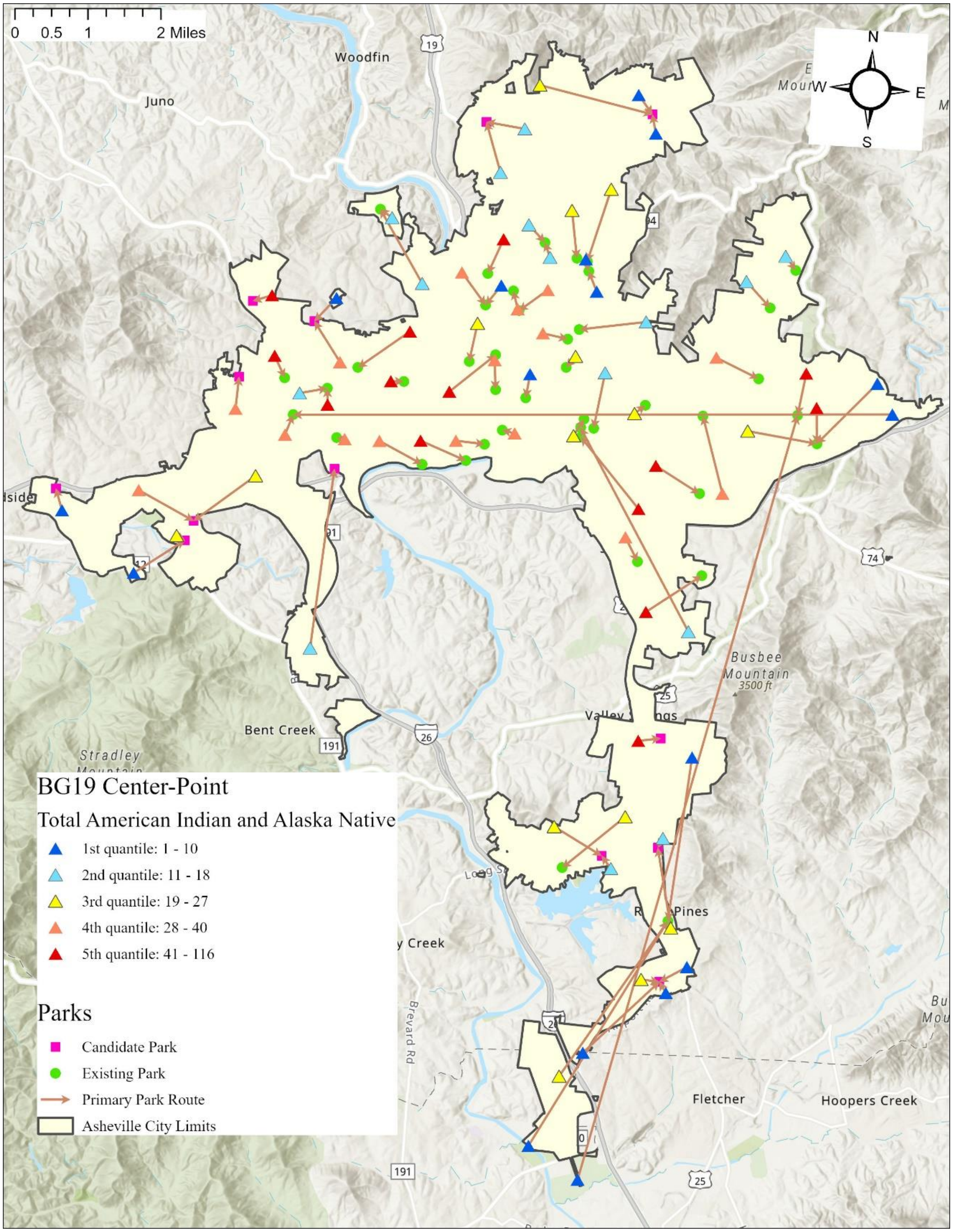

Figure 5.38: Primary Park Assignments for IL

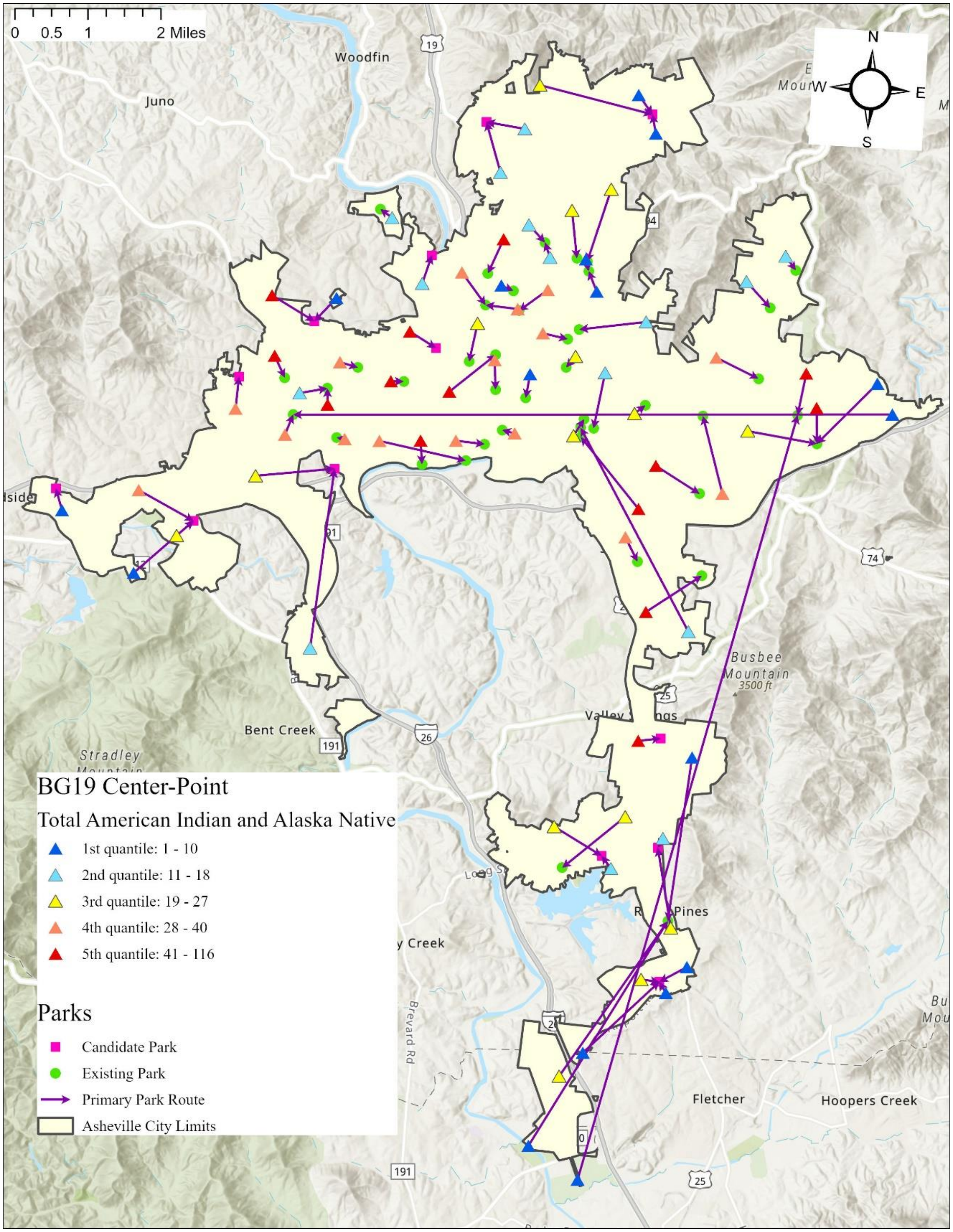

Figure 5.39: Primary Park Assignments for IM

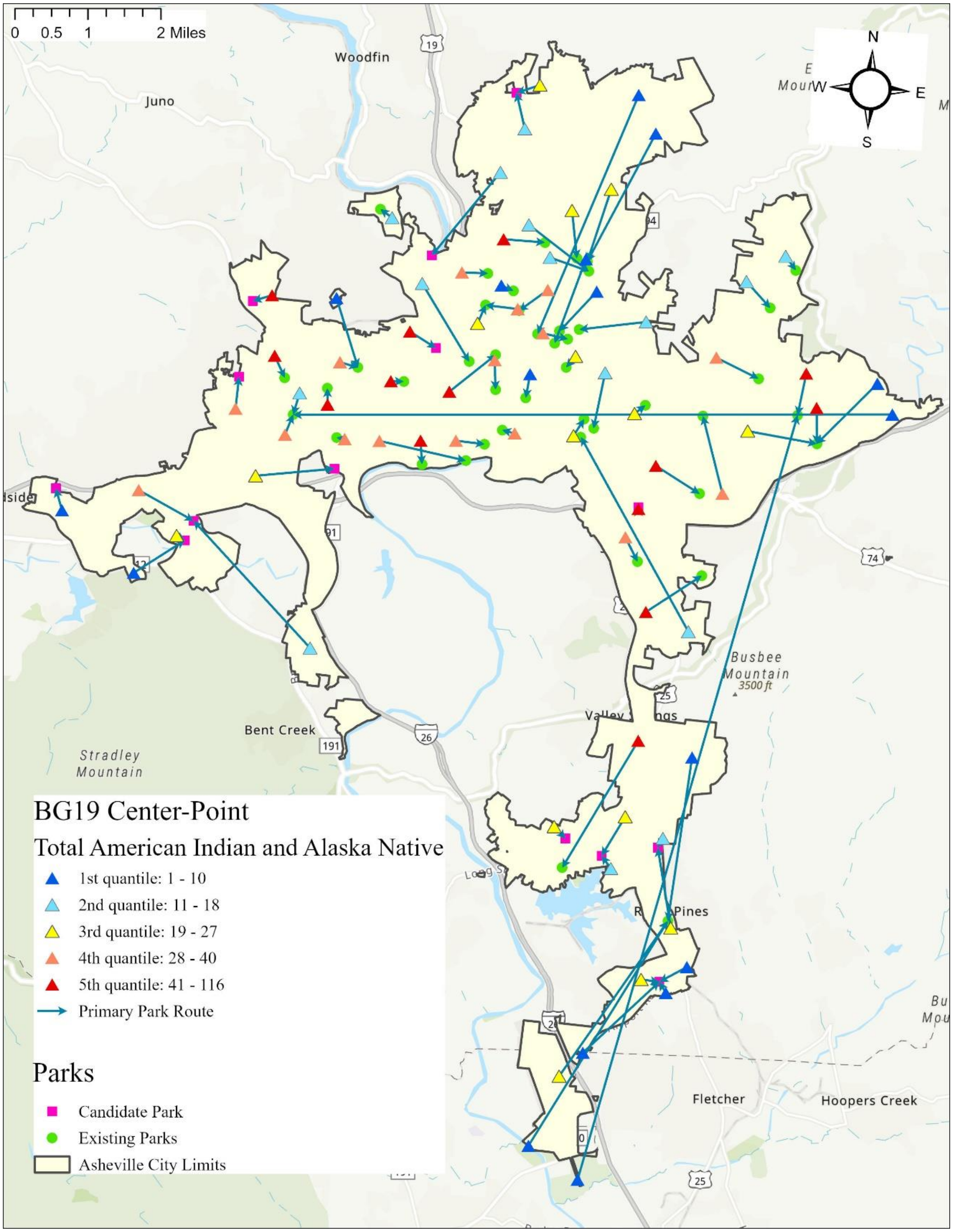

Figure 5.40: Primary Park Assignments for IH

Figures 5.38, 5.39, and 5.40 show primary park assignments for each resident location when there is IL, IM, and IH, respectively. In these maps, we represent resident locations as the center points of BG19. We symbolize these center points as triangles of varying color to represent the number of residents within each location that consider themselves as belonging to the indigenous racial-ethnic classification. We determine five quantiles from the dataset of indigenous resident demographic counts across the 77 BG19 within this study. Blue triangles represent BG19 with an indigenous resident population count within the 1st quantile. These block groups have the least number of indigenous residents. Red triangles represent BG19 with an indigenous resident population count within the 5th quantile. These block groups have the greatest number of indigenous residents.

We note that the number of indigenous residents in Asheville is significantly less than the number of black residents. Therefore, there is a smaller range in population count for a majority of the quantiles. The greatest indicator of equity is to view how primary park assignment differs for locations within the 5th quantile of indigenous population composition. At a glance, Figure 5.39 appears unchanged from Figure 5.38. Yet, we note that primary park designations within the western regions of Asheville vary between IL and IM. Figure 5.40 illustrates that, given IH, the model removes candidate sites from the northern portion of Asheville such that residents within that region must traverse greater distances to visit their primary parks. There is a reallocation of resources between IM and IH that places primary candidate parks near indigenous residents as strategic emphasis for these residents increases.

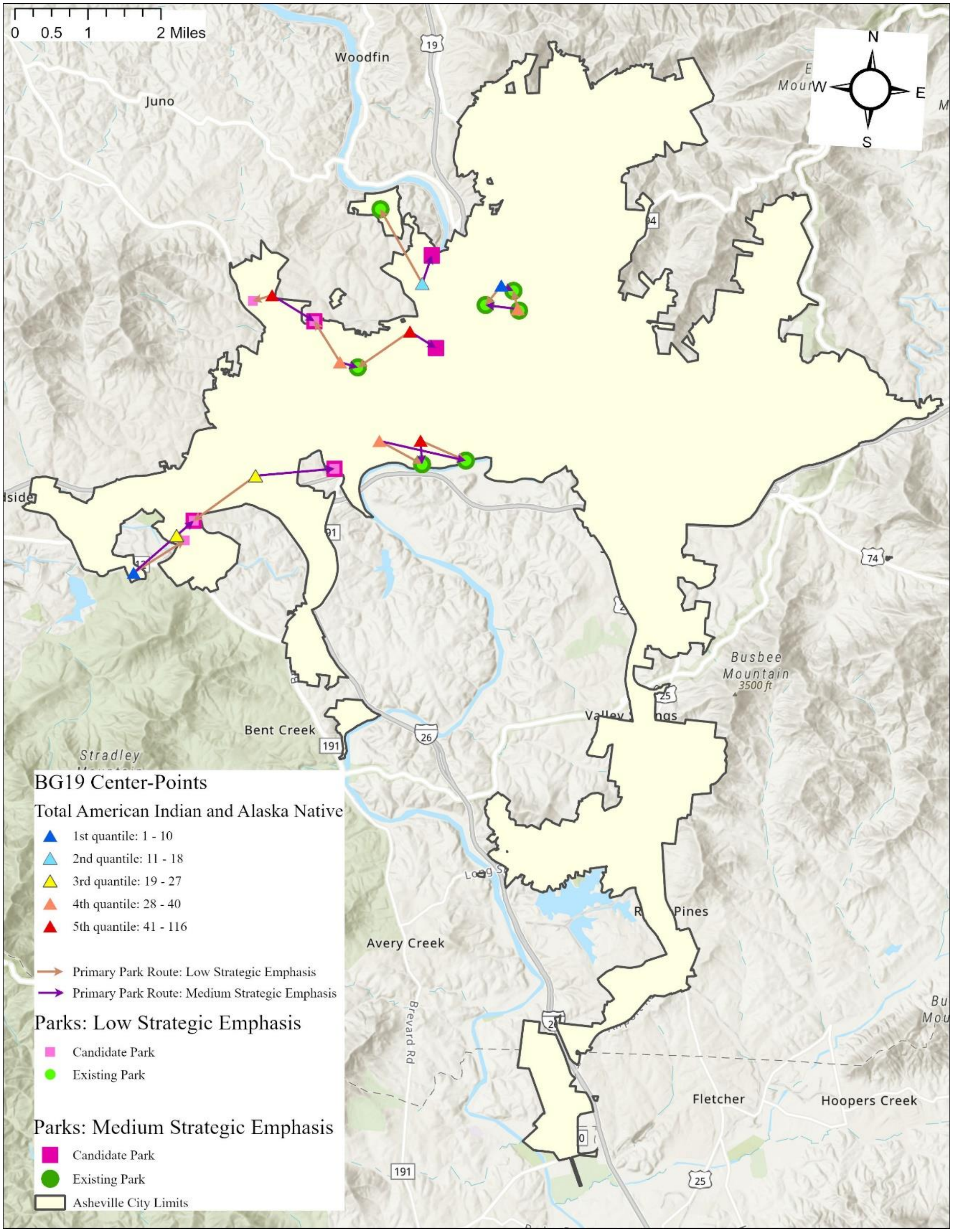

Figure 5.41: Primary Park Assignments for IL vs. IM

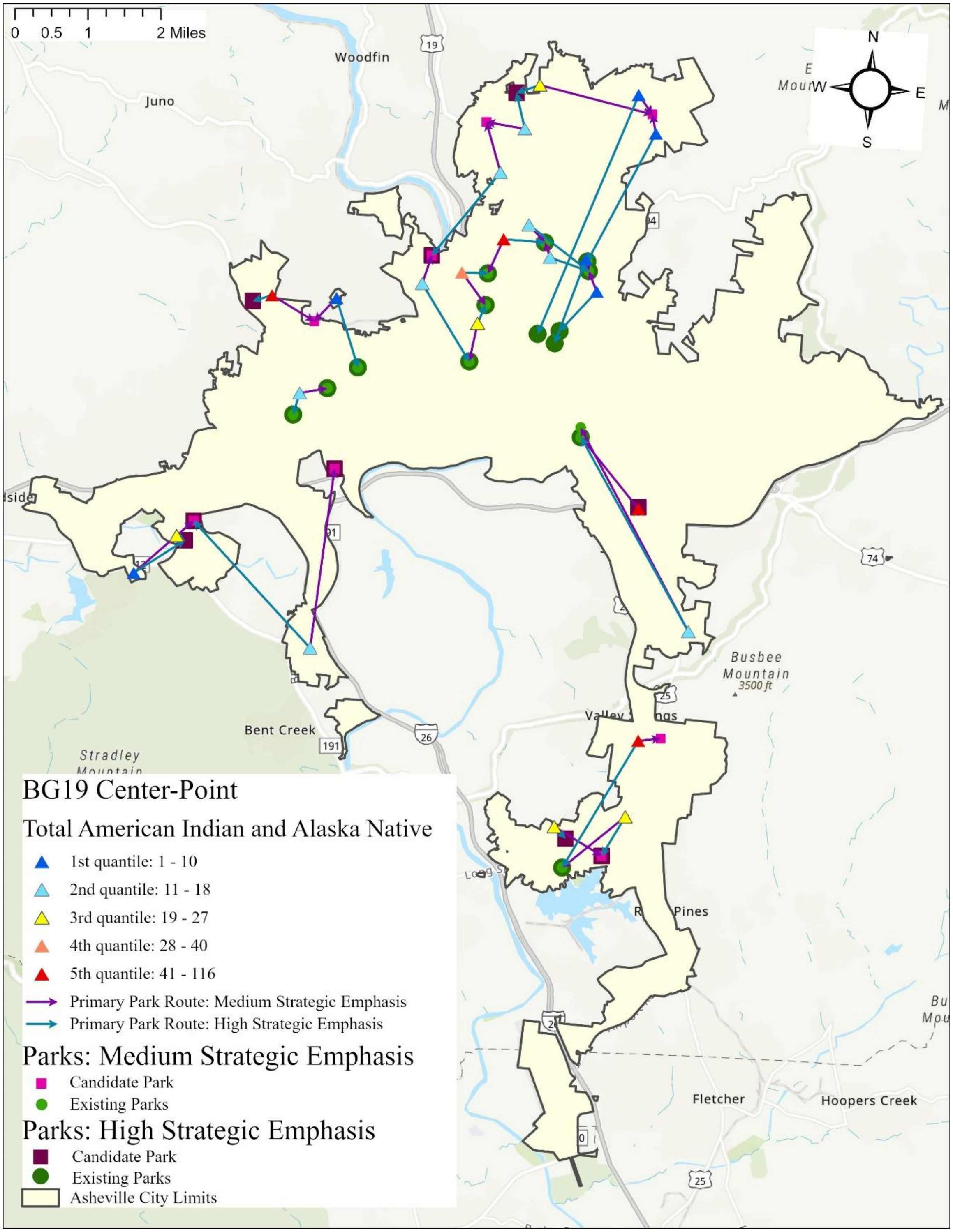

Figure 5.42: Primary Park Assignments for IM vs. IH

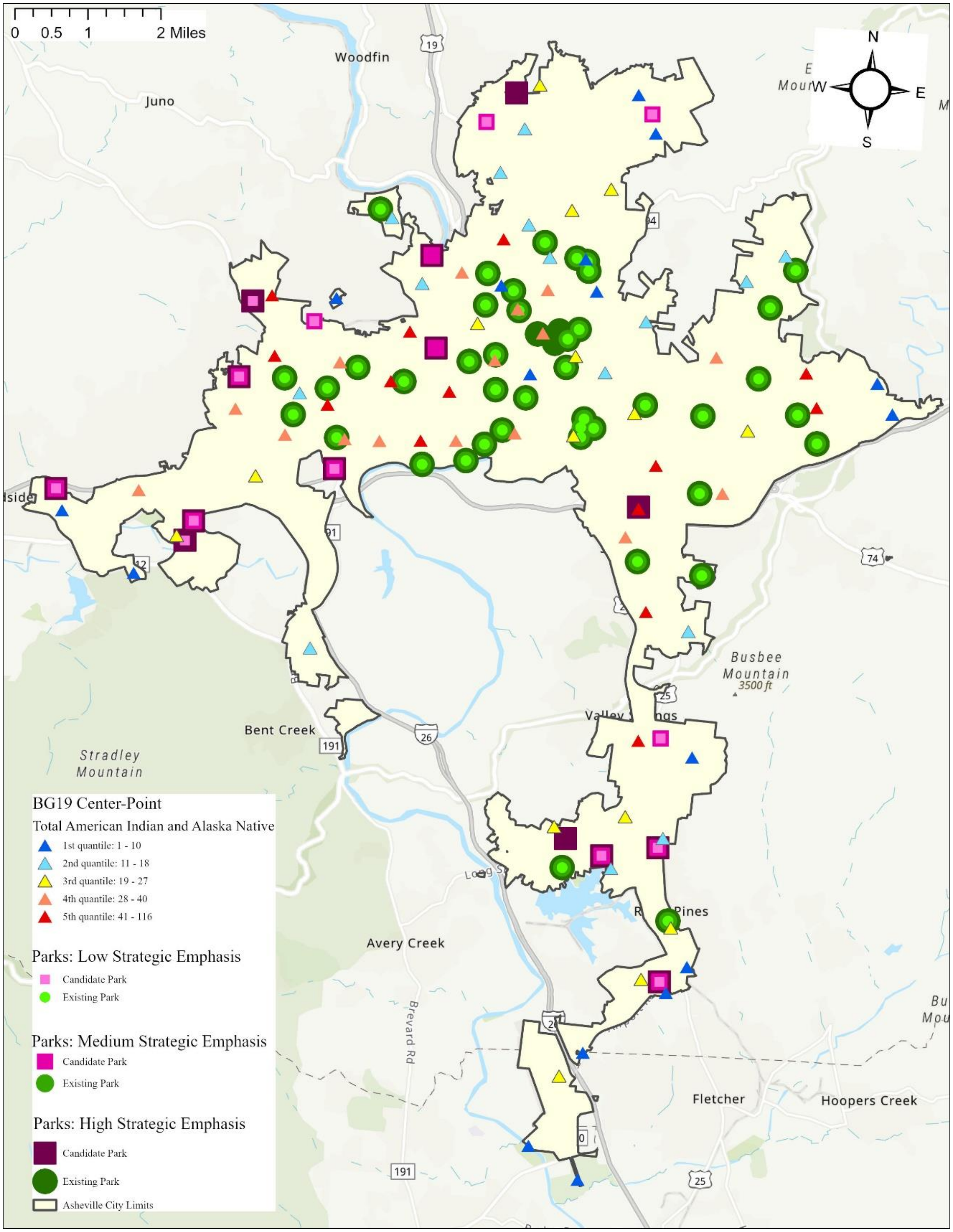

Figure 5.43: Primary Park Locations for IL, IM, and IH

To better visualize primary park designations and locations, we introduce Figures 5.41, 5.42, and 5.43. Figure 5.41 includes the differing routes between residents and their determined primary parks for model instances of IL and IM, represented by brown and purple line feature classes, respectively. Figure 5.42 includes the differing routes between residents and their determined primary parks for model instances of IM and IH, represented by purple and teal line feature classes, respectively. Figure 5.43 visualizes the distribution of existing and candidate primary parks as dependent upon IL, IM, and IH. We represent primary parks as increasing in size and darkening in hue as strategic emphasis increases. We place both primary parks and resident demographic compositions to show a clear interpretation of the change in park location near resident locations of differing demographic composition.

Figure 5.41 shows that primary park assignments differ in the northwestern and southwestern regions of Asheville between iterations of IL and IM. In IM, two new primary candidate parks are selected. We note that two of the three block groups within the 5th quantile of indigenous population experience a decreased distance to their primary park between iterations of IL and IM. Further, while some resident locations with fewer numbers of indigenous individuals experience a decreased distance to their primary park, the majority have an increased distance as resources are reallocated to support areas with the greatest number of indigenous residents.

There are a greater number of primary park changes resulting from a transition of IM to IH than from a transition of IL to IM. Of the four block groups within the 5th quantile of indigenous population count that experience a change in primary park assignment between instances of IM and IH, three resident locations experience a decrease in distance to their primary park while the fourth resident location experiences a negligible increase in distance. Figure 5.42 also reveals that several residents within locations with the least indigenous population count (1st quantile) face decreased park access between instances. Specifically, residents within the northern region of Asheville have an increased distance between IM and IH as the monetary resources to purchase primary candidate parks are reallocated to best serve the indigenous population.

Figure 5.43 reveals that the model instance IL results in a distribution of primary parks that seeks to locate candidate facilities along the extremities of the northern, southern, and eastern regions of Asheville. As the strategic emphasis of locating parks to maximize park goodness for the indigenous populations increases, primary parks develop near resident locations within the 3rd, 4th, and 5th quantiles of indigenous population count.

Primary Park Assignments and Locations vs. Strategic Target for Black and Indigenous Residents

We now analyze the impact of strategic target weight in simultaneously emphasizing the importance of both black and indigenous residents. In this analysis, we use as a baseline the primary park assignments resulting when all demographic weights equal a value of one. We designate this baseline as a having *low strategic emphasis for black and indigenous racial-ethnic classifications* (BLIL). To determine demographic weights to represent high strategic emphasis for black and indigenous groups, we run model instances in which the strategic target for blacks equals 10 while weights for racial-ethnic classifications of white, Asian, Pacific Islander, and other equal 1. We test target weights for the indigenous classification equal to 30, 35, 40, 45, and 50 to discover that the only impact in primary park assignment results in using the latter two numerical values. We designate that a target weight for black residents of 10 and a target weight for indigenous residents of 45 results in *high strategic emphasis for black residents and medium strategic emphasis for indigenous residents* (BHIM). We elect to analyze primary parks when the target weight for the black demographic equals 10 and the target weight for the indigenous population equals 50, a combination which we label as having *high strategic emphasis for black and indigenous residents* (BHIH).

Figure 5.44 and Figure 5.45 show primary park assignments for each resident location when there is BLIL and BHIH, respectively. In these maps, we represent resident locations as the center points of block groups. We symbolize these center points as triangles of varying color to represent the number of residents within each location that consider themselves as belonging to a racial-ethnic classification. Small triangles represent the number of black residents within a resident location while larger triangles symbolize the number of indigenous residents. We determine five quantiles from the dataset of resident demographic counts across the 77 BG19 within this study. Blue triangles represent BG19 with a demographic resident population count within the 1st quantile, which defines lower population counts. Red triangles represent BG19 with a demographic resident population count within the 5th quantile, which defines higher population counts.

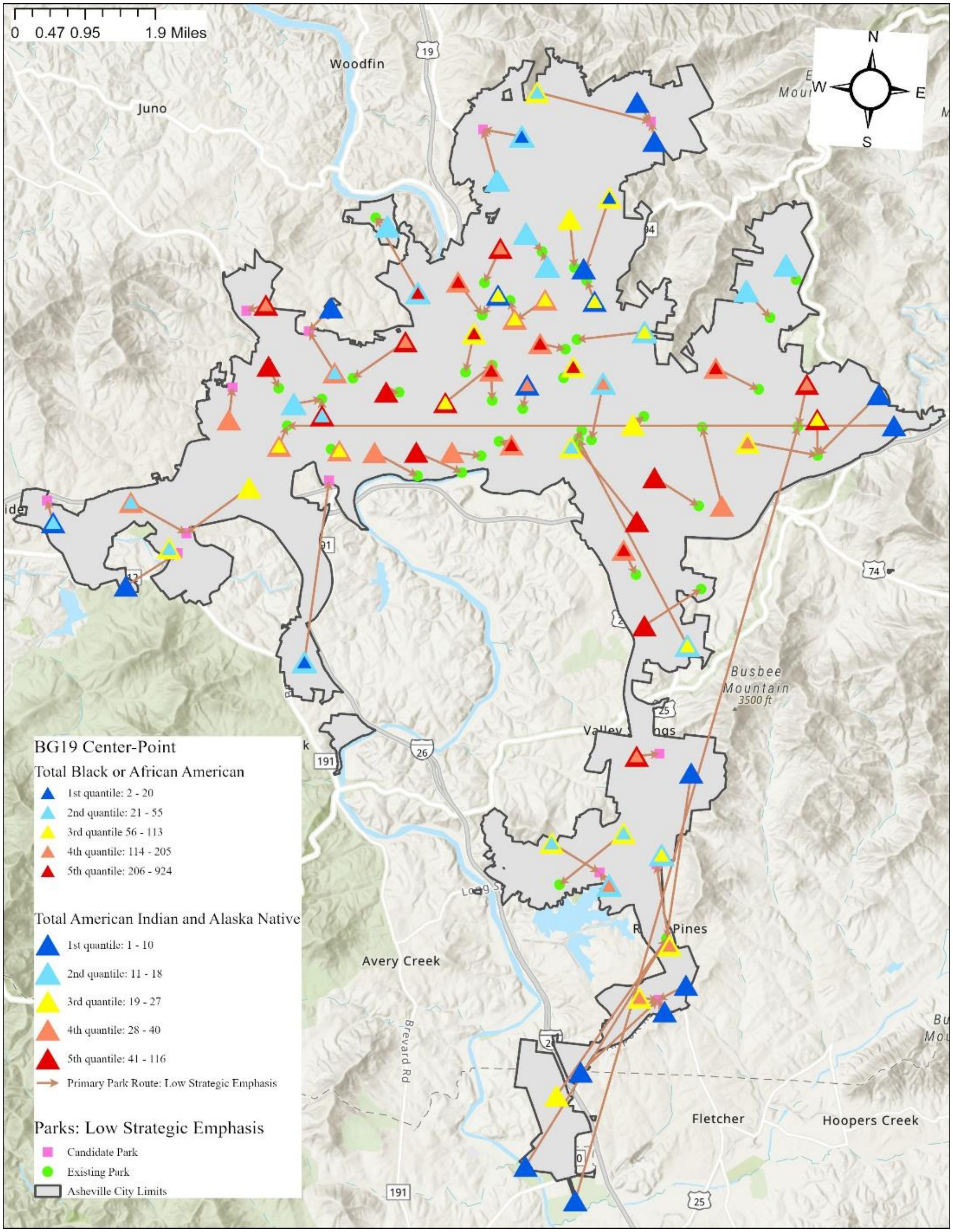

Figure 5.44: Primary Park Assignments for BLIL

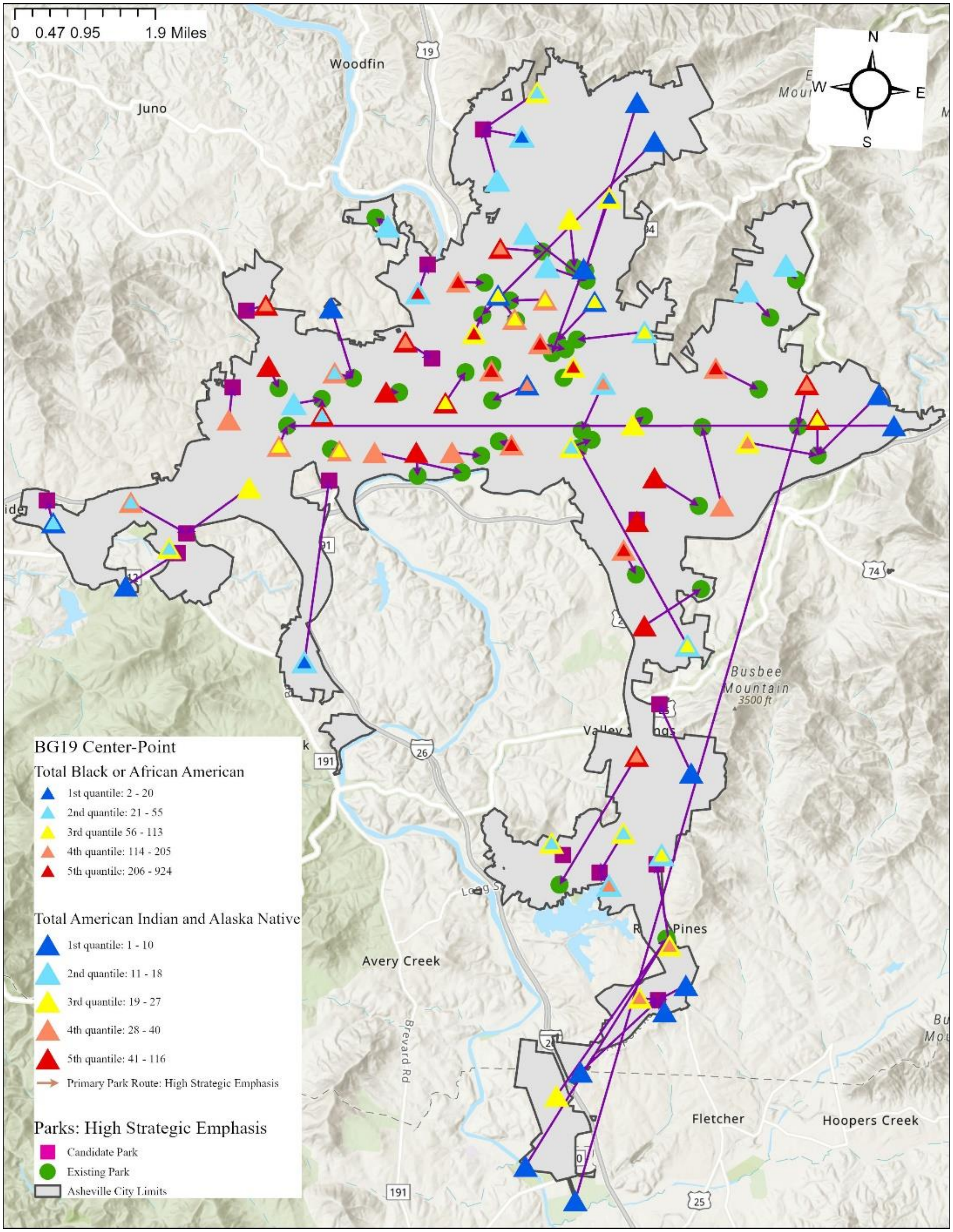

Figure 5.45: Primary Park Assignments for BHIH

A notable difference between Figure 5.44 and Figure 5.45 that demonstrates the model's effectiveness in maximizing demographic equity given specific strategic target values is in the assignment of primary parks to resident locations in the northernmost region of Asheville. In Figure 5.46, we provide a visual of BLIL versus BHIH that specifies primary park assignment changes for block groups labeled a, b, and c. As the model instance transitions from BLIL to BHIH, resident locations b and c, which have a low number of both black and indigenous residents, experience an increased distance to their primary park. In contrast, resident location a, which has a moderate number of black and indigenous residents, experiences a decreased park distance between instances.

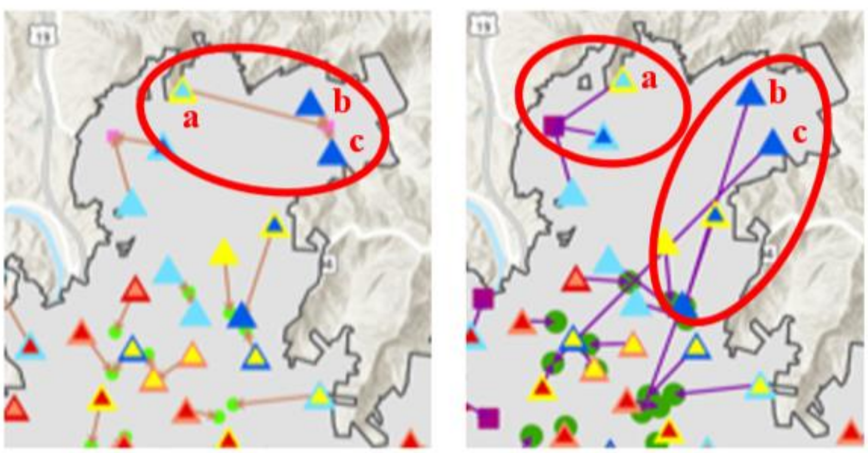

Figure 5.46: Northern Asheville Primary Park Assignments for BLIL (left) and BHIH (right)

To better visualize primary park assignments and locations, we introduce Figures 5.47 and 5.48. Figure 5.47 includes the routes between residents and their determined primary parks for model instances of BLIL versus BHIH. These routes are of brown and purple line feature classes, respectively. Only included are the routes and primary parks that differ between iterations of BLIL and BHIH.

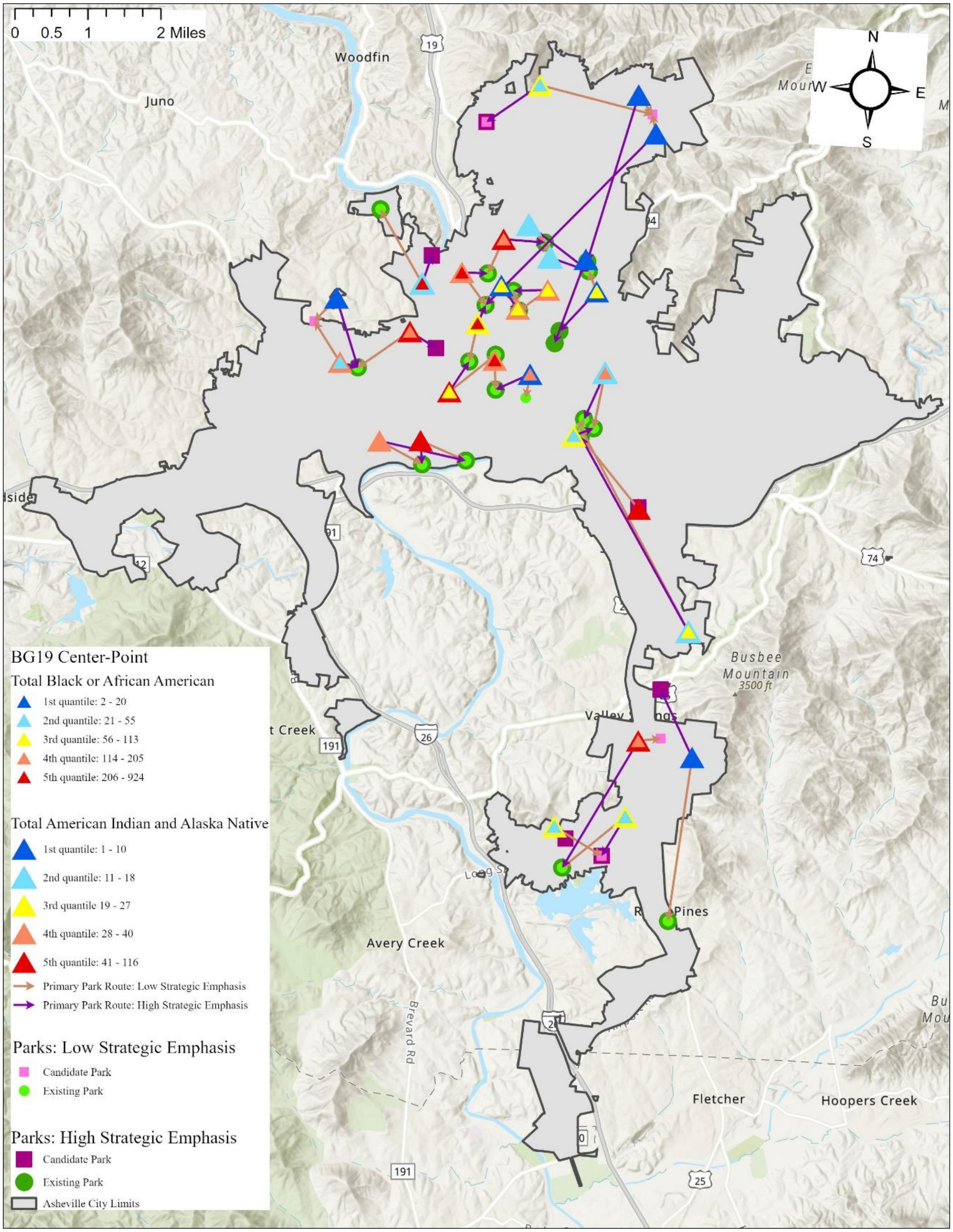

Figure 5.47: Primary Park Assignments for BLIL vs. BHIH

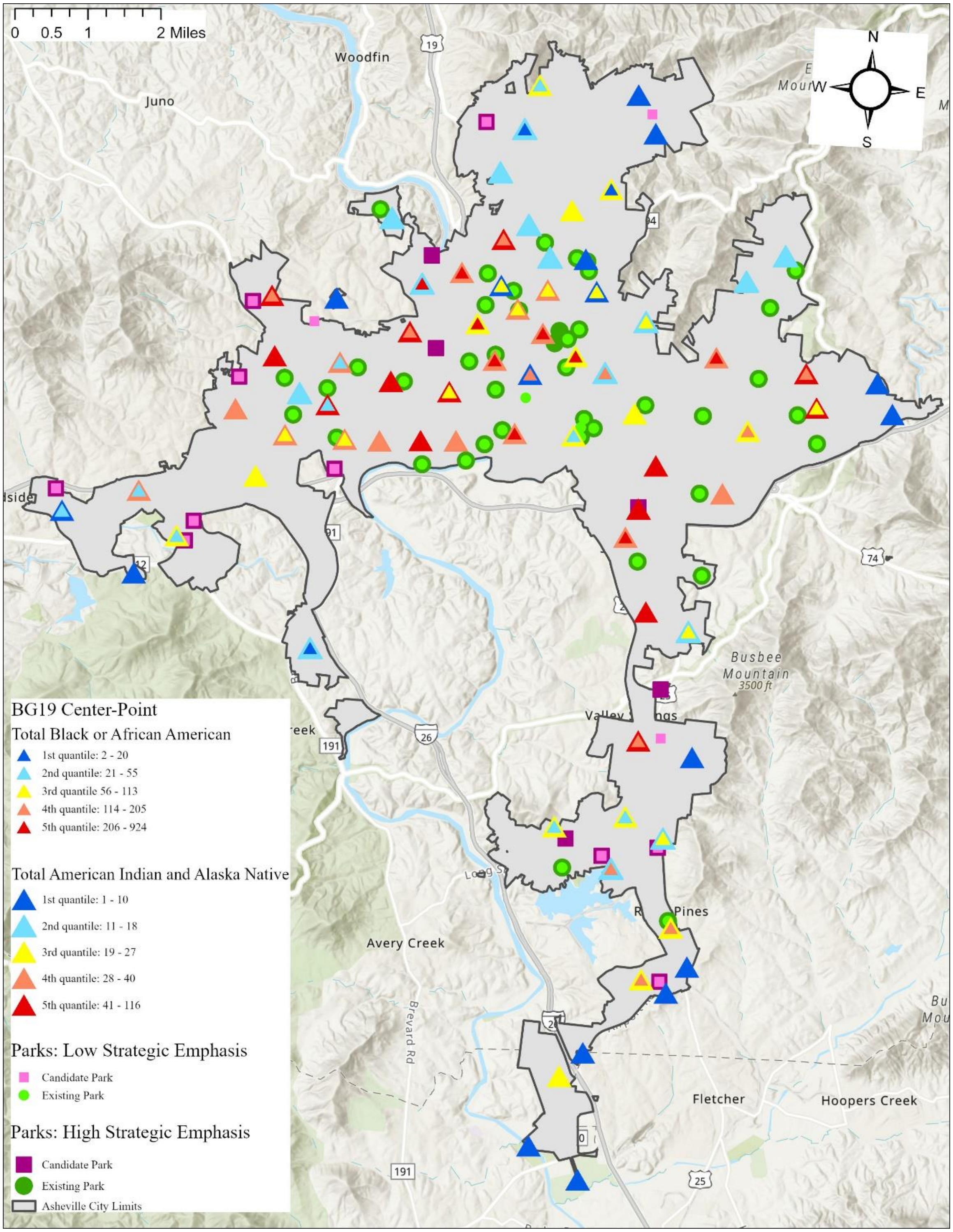

Figure 5.48: Primary Park Locations for BLIL and BHIH

Figure 5.48 visualizes the distribution of existing and candidate primary parks as dependent upon BLIL and BHIH. We represent the primary parks of BLIL with smaller symbols of lighter hue and primary parks of BHIH with larger symbols of darker hue. We continue to symbolize block groups with graduated colors to represent the number of black and indigenous residents within each defined location. Placement of both primary parks and resident demographic compositions allows a clear interpretation of the change in park location near resident locations of differing demographic composition.

Figure 5.47 indicates that the transition from BLIL to BHIH results in an increased distance to primary parks for locations with a low number of both black and indigenous residents. There exist several instances in which resident locations that contain either a high number of black or indigenous residents experience an decreased distance to their primary parks as the strategic target for both black and indigenous residents increases. Figure 5.48 indicates that, as strategic emphasis for black and indigenous residents increases, an increased number of primary parks exist in portions of Asheville that are home to the greatest number of black and indigenous residents.

Park Spending vs. Demographic Strategic Target

We study how park spending for individuals of a specific demographic varies as the strategic emphasis toward that demographic increases. We calculate the composition of each demographic classification within each resident location as a percentage. We also determine the fee of each location's primary park. We multiply the demographic composition percentage per location by the primary park fee per location to designate an amount of money spent per demographic per location for each location. We determine the amount of money spent per demographic as the sum across all locations of the amount of money spent per demographic per location. We calculate the amount of monetary spending per demographic (defined as β_r^{total}) with the following equation using parameters and decision variables defined within the modeling chapter:

$$\beta_r^{total} = \sum_{l \in L} \left(\frac{t_{lr}}{\sum_{r \in R} t_{lr}} \left(\sum_{k \in K} f_k x_{kl} \right) \right) \forall r \in R$$

To visualize the amount of monetary spending allocated to demographic classifications dependent upon demographic park goodness prioritization, we include data from model instances of BL versus BH, IL versus IM versus IH, and BLIL versus BHIM versus BHIH, depicted in Figures 5.49, 5.50, and 5.51, respectively.

Figure 5.49: Park Spending for BL vs. BH

Figure 5.50: Park Spending for IL vs. IM vs. IH

Figure 5.51: Park Spending for BLIL vs. BHIM vs. BHIH

Figure 5.49 visualizes that the amount of park spending for black residents increases as the strategic emphasis toward black residents increases (model instance BL to model instance BH). Figure 5.50 confirms that a similar trend exists between park spending for indigenous residents and the strategic emphasis toward indigenous residents. As model instances transition from IL to IM to IH, primary park spending for indigenous residents increases. We note that the amount of increase for indigenous residents is less than the amount of increase for black residents.

Figure 5.51 indicates that park spending for both black and indigenous residents does not result in a strictly increasing pattern, as in the other analyses. An initial spending increase for both black and indigenous residents occurs between iterations of BLIL and BHIM. However, a spending decrease for both residents results as the model instance transitions from BHIM to BHIH. This decrease occurs because BHIH primary parks consist of a greater number of existing parks versus model instance BHIM. Therefore, though park spending may provide some perspective as to the amount of equitable emphasis toward a demographic group, it is not a definite or significant measure of equity within the parameters of the current model.

Analysis Question 5: Primary Parks vs. Ideal Park Distance

A significant component of our models concerns the desired distance from residents to parks. Several recreational organizations set specific access goals of which distance is a key element. Therefore, we analyze the degree of variability in the determination of primary parks dependent upon a user-determined maximum desired distance. We maintain a constant demographic weight of one for all demographic classifications and a budget of $500,000. We analyze the desired distance impact by testing distances of 0.5 miles, 1 mile, and 1.5 miles. Figure 5.52 visualizes an increase in desired distance by symbolizing primary parks with increasingly larger and darker icons.

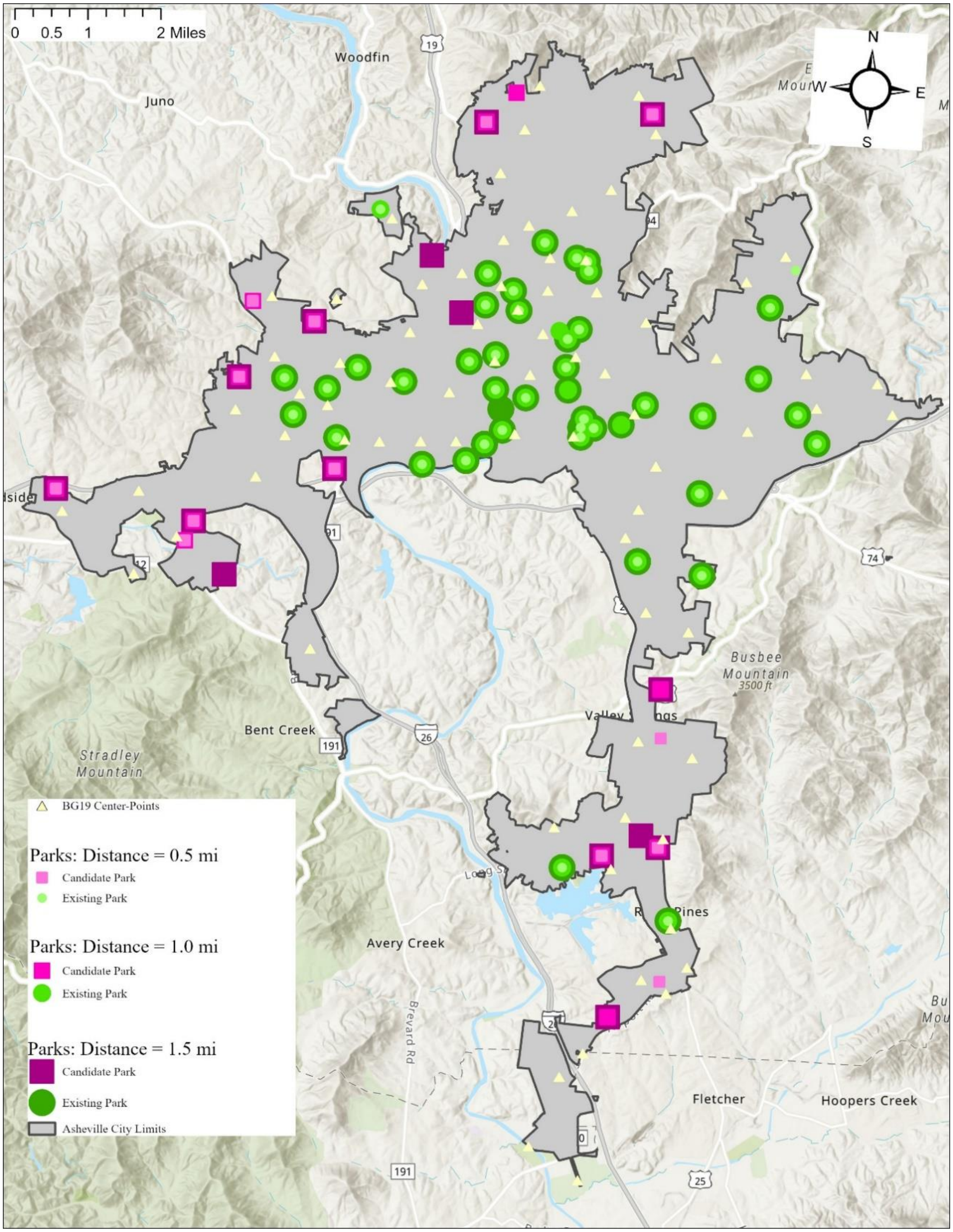

Figure 5.52: Primary Park Locations – Distance 0.5 mi vs. 1.0 mi

Figure 5.52 indicates that a majority of the primary parks remain consistent throughout all model instances. We note, however, that the primary parks added as a result of increased allowable distance from residents to parks tend to exist near the periphery of Asheville City Limits.

CHAPTER SIX

DISCUSSION AND CONCLUSION

This chapter serves to present a discussion of the results of our analyses in order to elaborate upon the implications of our models. We begin with a review of the contribution of our models in serving the humanitarian needs of society. We then discuss the insights gained in order to answer the five aforementioned analyses questions. We consider how our models may be applied to other cities and present the limitations of our study and proposals for future work. We conclude with a final summary of our presented study.

Review of Model Contribution

We note that current park planning initiatives are reactive in nature and do not yet integrate a variety of demographic, infrastructural, dimensional, monetary, and environmental factors that prevalently affect the effectiveness of park-planning decisions. Therefore, we structure our mathematical models as proactive park planning tools that reflect the realism of the diverse considerations in park equity decision-making. Our mathematical formulations are of the form of facility location models that serve as guides in recreational and government planning endeavors. A characteristic of our facility location deviation-based model is the ability to solve park planning decisions within a timely manner. The amount of model solving time is significantly less than the amount of time required to manually analyze cities. We note that our deviation-based model not only requires less solving time than traditional methods but it also requires less time and effort by human resources to collect input data.

Discussion of Analysis Questions

Within this section, we answer the five posed analysis questions that seek to analyze the nature of our models and to determine the extent to which they may provide park planning insights. We first discuss the question related to park goodness as dependent upon budget. We then review the outcomes of the deviation-based model versus the score-based model. We reflect upon how demographic strategic target impacts park planning. Lastly, we discuss how desired distance from residents to parks affects park selection.

Interpreting Results: Park Goodness and Park Selection vs. Budget

We note that our deviation-based model effectively represents individual deviations of distance, capacity, heat, and tree cover into an overall park goodness deviation. Results from both the capacitated and uncapacitated model types confirm that utilizing a weighted method in the objective function to represent the priority given to each park goodness measure is an effective technique in the minimization of park goodness deviations. Specifically, our model places a greater importance upon minimizing deviation classifications that are weighted more heavily in the objective function. Figures 5.6 to 5.9 support this statement since the greatest deviation decrease that occurs as the budget increases is that of distance, the highest weighted park goodness measure in our analyses. This outcome validates the notion that our model allows the park planner to select a priority of achieving one goodness measure over another in the determination of optimal primary park sites. This capability is especially desirable given that different cities may have differing goals with respect to which park requirements have precedence.

In our study of how budget directly affects total park goodness deviations, we determine that an overall trend exists in which increased amounts of available budget equate to a decrease of park goodness deviations. We note, however, that there exists a minimum deviation level such that the purchasing of additional park land does not improve the outcome of park goodness, as demonstrated in Figures 5.3 and 5.4. Therefore, city planners must be vigilant in ensuring that the monetary funds for park purchasing are spent only in a manner that is impactful for the creation of park goodness and equity. We emphasize that spending money excessively on park land is wasteful if the purchase does not significantly increase greenspace access or quality.

Another insight is that the amount of improvement in park goodness deviations between budget iterations decreases as the value of the available budget increases, as shown in Figures 5.3 and 5.4. In other words, the cost effectiveness in increasing park goodness diminishes as the budget value augments. Therefore, as monetary effectiveness becomes negligible, park planners must consider whether accumulating large amounts of expenditures is worth the potentially small enhancement of park goodness. In this situation, it would be desirable to determine how increases in the weighted goodness directly benefit residents.

We discuss in our analyses how the model solution directly impacts residents by observing the unweighted distance and capacity deviations that residents encounter. Figures 5.18 and 5.20 visualize that the values of maximum distance deviations and maximum capacity deviations experienced by residents fluctuate for lower budget values of the capacitated model types. There exists a tradeoff between distance and capacity such that a decrease in distance deviation may be coupled with an increase in overcrowding. Likewise, a decrease in overcrowding may be coupled with an increase in distance deviation. However, after a certain budget amount is reached, both distance deviations and capacity deviations converge to unique values. Because fluctuations in distance and capacity exist, there is a need for city planners to not only plan decisions based upon overall weighted park goodness deviations but to also consider outcomes of individual resident deviations. The most knowledgeable decisions result from a simultaneous consideration of overall weighted deviations and resident-experienced deviations to determine the solution that most positively impacts all aspects of equitable park distribution.

Other results of interest to discuss with regard to distance and capacity include comparisons of the capacitated and uncapacitated model types. The converging maximum distance deviation value is equivalent for both the capacitated and uncapacitated model types (see Figure 5.18). Therefore, one may argue that there is no added benefit in using any particular deviation-based model type when seeking to minimize the maximum distance deviation with a budget greater than the amount needed for convergence. Interestingly, *Min Max Dev Cap* converges at a lower average distance deviation value than both of the uncapacitated models, which converge at a lower average distance deviation value than *Min All Dev Cap* (see Figure 5.19). Though further research is needed to determine whether these results remain consistent given other model inputs, we argue that *Min Max Dev Cap* appears to present the most desirable results with respect to distance goodness measures when large amounts of economic resources are available to reach convergence.

In our consideration of capacity across deviation-based model types, we note (from Figure 5.20) that the convergence value of maximum overcrowding for *Min Max Dev Cap* and *Min All Dev Cap* is equivalent. With regard to average capacity deviation, the convergence value is greater for *Min Max Dev Cap* versus *Min All Dev Cap* by a negligible amount (see Figure 5.21). Therefore, though further research is needed to determine whether these results remain consistent given other model inputs, we argue that both of the capacitated model types are equally advantageous with respect to providing capacity goodness measures when large amounts of economic resources are available to reach convergence.

As a finalizing statement with regard to analyzing unweighted deviations of distance and capacity, we note that the selection of an appropriate model type becomes easier with a budget large enough to experience deviation convergence. However, when determining the ideal amount of money to spend on park purchasing given that available funds are less than the amount needed for deviation convergence, planners must analyze the values of distance deviations and capacity deviations resulting from each budget instance to determine which model type formulation to use. This analysis is especially important since, between budget instances, tradeoffs occur between distance and capacity and the ideal results fluctuate between model types.

In our study of how budget affects primary park locations, we note that several primary parks remain the same across budget instances (see Figure 5.23). Our model does not incorporate a temporal element into park planning decisions to describe situations in which an agency has a given amount of money to spend now and will obtain more funds in the future. However, we argue that an agency may analyze a map depicting the selected primary parks given differing available budget amounts to identify and place the greatest emphasis upon the creation and/or betterment of park sites that remain labeled as primary parks throughout all iterations.

Interpreting Results: Overall Spending vs. Iterative Spending

We analyze how park goodness and candidate park selection differs between purchasing methods by modeling one-time spending initiatives versus iterative spending plans. We note that utilization of the overall spending method results in a more desirable park goodness condition than the usage of the iterative spending method when fewer monetary resources are available. Specifically, we note that the weighted total deviation and weighted maximum demographic deviation are lower as a result of the overall spending method (see Figure 5.24). However, as the budget amount increases, goodness disparities between spending methods lessen such that a decreased priority exists in the application of one spending method over another (see Figure 5.25). Further, we affirm that differences in resident-experienced deviations of distance and capacity become more negligible between the two spending methods as the budget increases (see Figure 5.26 versus Figure 5.27).

From these reflections, we certify that park goodness is not necessarily equivalent for overall spending and iterative spending structures at a given budget value. Therefore, we suggest that decision-makers evaluate park plans for any given budget amount to understand the impact that each spending technique may affect upon equitable park location selection. Some park institutions have the resources to attain the entirety of budget funds to complete a one-time purchase of candidate parks. In this situation, the evaluation and selection of the optimal park spending method is practical. However, certain parks and recreation departments may have an overall budget for a given duration yet be unable to obtain all finances immediately so as to spend all funds simultaneously. In this instance, though the most optimal option be unattainable, an analysis of feasible spending patterns throughout the duration of the park plan will assist planners in selecting the most beneficial, realistic spending program.

We note that the selection of candidate park sites becomes more similar between spending methods as the budget increases. Therefore, we determine that the selection of candidate park sites is not necessarily equivalent for methods of overall spending versus iterative spending when the resulting deviations of both techniques are unequal. Thus, concerning the distribution of candidate park sites, we reaffirm the importance of analyzing park goodness to select the most impactful, feasible method of park spending dependent upon the available budget amount at any given time during the plan's duration.

Concerning candidate park visualization, we note that the realization of a map that depicts the optimal selection of parks iteratively over the duration of an improvement plan allows the planner to clearly determine the candidate park sites that have the greatest priority. Specifically, candidate parks of precedence are those that are selected within the initial years (or purchasing intervals) of the plan. This insight is helpful in determining which selected candidate parks warrant the greatest focus.

Interpreting Results: Deviation-Based Model vs. Score-Based Model

We discuss the implications for the utilization of a deviation-based model versus a score-based model. We note that the optimal solution of the score-based model provides outcomes for maximum and average distance deviations that are significantly greater than the maximum and average distance deviations resulting from the solution of the deviation-based model (see Figures 5.32 and 5.33). These results indicate that we face a tradeoff between efficiency and interpretability when deciding which model formulation to promote.

Because the deviation-based model translates actual deviations of distance, capacity, heat, and tree cover directly into the objective function minimization, the deviation-based formulation provides a more efficient and ideal solution in promoting park equity versus the score-based model, which inputs into the objective function a numerical score based upon a range of possible deviation values. The score-based model formulation translates large deviations into low scores, a mathematical structure that is practical in theory. However, when running model analyses, a low score does not provide a value that successfully conveys the degree of negative impact that a non-ideal decision would affect. Specifically, low scores do not have a significant differentiation from high scores to prevent the model from proposing insufficient solutions.

Though the deviation-based model provides the greatest park equity effectiveness, we note that the score-based model provides an objective function solution value that is more easily understood by park planners. In general, the provision of a single weighted deviation value does not provide an intuitive understanding of park goodness. However, the utilization of a scoring method allows us to determine score ranges for which overall equity may be considered as very poor, poor, average, good, and excellent. In other words, we may associate a park score to a level of equity provision, a more understandable measure for users.

In terms of solving time, the deviation-based model type *Min All Dev Cap* determines optimal solutions in approximately 5-10 minutes, and *Min Max Dev Cap* runs within about five minutes. In contrast, the score-based model type *Max Dem Score Uncap* requires approximately 10-15 minutes to run. We were unable to analyze the capacitated model types of the score-based model within this thesis because solve times proved excessively long. Specifically, we note that the uncapacitated model types of the score-based model failed to complete solving after seven hours of run time.

As aforementioned, there are tradeoffs between solution ideality, solution interpretability, and model run time when concerning deviation-based and score-based park equity models. Preferably, further research and modeling considerations will combine the benefits of both models into a single park equity model.

Interpreting Results: Primary Parks vs. Demographic Strategic Target

We note that our deviation-based model effectively represents how individuals of specific demographic classifications experience park goodness. Our analyses reflect that the incorporation of a demographic strategic target weight allows the model to emphasize a prioritization of park goodness for specific demographics. Specifically, our model places a greater emphasis upon minimizing the deviations of demographics that have a greater weight within the objective function.

When all demographic classifications possess the same strategic target weight, the equity model places primary parks such that no demographic or resident location is greatly disadvantaged in terms of park access. Because we weigh the objective function by demographic population counts per location and because individuals of the white racial-ethnic demographic compose the majority of Asheville, holding the demographic strategic target weight constant for all demographics results in the placement of primary parks that primarily serve white populations. Therefore, the distribution of several primary candidate parks are within the suburbs of Asheville, the home to a majority of white individuals. However, we also note that a distribution of candidate facilities along this periphery of Asheville City Limits is necessary, despite the demographic composition, since existing parks are located almost completely within the central portion of Asheville.

In three analyses, we determine the change in primary park assignments and locations as dependent upon increasing the priority of a park goodness experience for black residents, indigenous residents, and both black and indigenous residents. In each of these studies, as the strategic emphasis of park goodness priority increases, we see a visible reallocation of resources to the selection of primary parks in regions where a greater number of residents of the prioritized demographic reside (see Figures 5.36, 5.41, 5.42, and 5.47). Specifically, prioritized demographic regions mostly experience a decreased park distance. Meanwhile, many residents within the regions of Asheville mostly populated by white individuals experience an increased distance to their primary parks. However, we note that the increased distance does not adversely affect park access for these individuals.

A necessary discussion concerns the determination of the numerical value of the demographic strategic target weight such that it has an impact upon the assignment of primary parks. To determine impactful weight values, we evaluate several instances of demographic weights and discover a possible mathematical manipulation to determine the weight numerical value. As mentioned within the results section, a strategic demographic weight from 5 to 10 creates a difference in primary park assignments when prioritizing solely black residents. The total population of white residents within the City of Asheville divided by the total population of black residents within the City of Asheville equals a value between 5 and 10. A strategic demographic weight from 35 to 40 created a difference in primary park assignments when prioritizing solely indigenous residents. The total population of white residents within the City of Asheville divided by the total population of indigenous residents within the City of Asheville equals a value between 35 and 40. We have not yet confirmed whether this relationship between demographic proportions and needed demographic weights is consistent. However, it provides an initial insight to further investigate in future work.

Currently, we have two suggestions for park planners with regard to using the demographic strategic target weight. Firstly, we propose that planners evaluate several instances of demographic weights to determine their impact on primary park assignments and selections. Secondly, we recommend that the planner analyze the specific deviation results of distance, capacity, heat, and tree cover resulting from model solutions to ensure that the use of a demographic strategic weight does not inadvertently prompt the model to select primary parks that are inequitable to non-prioritized demographic groups.

Within our analyses, we reactively calculate the amount of funds in actual park spending allocated to each demographic as a result of the demographic strategic target weight. Our findings indicate that there is commonly a relationship between increased priority toward a demographic and increased park spending for that demographic. However, this relationship is not explicitly true. Park spending is not required in the selection of existing parks, and candidate parks require monetary purchase. Therefore, as an example, an increase in the number of existing parks designated as primary parks for a prioritized demographic results in a decreased needed monetary allocation toward that demographic.

Interpreting Results: Primary Parks vs. Desired Distance

We study how the numerical input of desired distance from residents to parks affects the location of primary parks. We note that a majority of the designated primary parks remain as primary parks throughout all iterations. However, there are a few instances when an increase in allowable distance results in the location of primary parks closer to the periphery of Asheville City Limits, which are mostly underserved by greenspace facilities. We propose one notable comment for park planners with regard to the impact of desired distance upon primary park selection. Though the primary park assignments remain relatively unchanged throughout Asheville, we cannot state that this same result will occur in other cities and towns, where the distribution of existing and candidate parks and resident locations is unique.

Application of Park Planning for Other Cities

One major benefit of our park equity models is that they may be easily adopted as planning tools by any community since they allow for versatility of user input. Our models require parameter inputs such as distance, capacity, heat, tree cover, park fees, budget, and demographic counts. Such data is easily accessible in online local, regional, and national databases. Further, recreational facilities may receive data collection and analysis assistance from local and county GIS departments. Other input data, such as acceptable ranges of heat and tree cover and weights, are specific to user-defined requirements. Park planners may incorporate the unique sets and parameters of their city into the consistent park equity model structure. The mathematical models complete all calculations, and decision-makers can represent solution results visually using GIS software.

Limitations of the Study

There are limitations with regard to both our data and our models. Concerning the data, we are currently unable to acquire information defining the population density *within* block groups. Therefore, we assume homogeneity of population distribution within these resident locations. The lack of population density information directly impacts the accuracy of the representation of demographics, especially in the conversion of racial-ethnic data from BG20 to BG19. Further, in the calculation of distance from residents to parks, we must assume the origin as the block group geometric center-point rather than the center of population density, which is a more accurate representation of population distribution.

Another limitation of our study is the insufficient level of granularity provided by utilizing block groups coupled with the model assumption that residents will always choose to visit their designated primary park. Because our models dictate that all residents within each block group visit one same primary park, we not only limit the flexibility of human choice in visiting parks but also assume that residents residing in separate, geospatially distanced portions of the same block group would visit the same park when, in reality, it may be ideal for each set of individuals to visit different parks. This negative impact of the assumption of primary park visitation would be lessened in the event that we possessed spatial and demographic data for smaller geographic regions than block groups since, overall, there would be increased ease in satisfying distance and park capacity requirements.

We have not yet incorporated the concept of resident demand for parks into our models as a component of park planning decisions. One essential consideration in determining the location of primary parks is to place emphasis upon meeting desired park demand. The inclusion of demand and park use within our models would constitute an additional equity measure that would ensure that we locate parks such that individuals who will most frequently visit the parks have sufficient park access. Further, this consideration of demand within the models would determine park decisions such that we eliminate any excessive expenditure of resources in the creation and maintenance of parks that residents will visit infrequently.

We do not yet consider in our models a focus upon increasing equity dependent upon the provision of park amenities, specifically. We have yet to include any analysis concerning the current amenity quality of existing parks. A needed addition to our models is an objective that includes amenity quality as a component of equity by including factors such as amenity quantity, type, and maintenance. The ideal outcome of this inclusion would be a determination of the existing parks that require amenity renovations or additions as well as a determination of the needed amenity quality to be provided in selected candidate park sites. The purchasing for these amenity improvements would be limited within the overall the budget constraint such that there may be a tradeoff between the selection of new candidate parks (access) and the improvement of park amenities (quality).

Future Work

We place within future work the multiple improvements and additions to our models that would provide increased realism for and assistance to parks and recreation decision makers. We note that an important next step is to validate the current models with stakeholders in order to receive feedback to ensure that the models are usable and reflective of park planning requirements. In the following paragraphs, we provide personal suggestions for model improvements.

A considered future improvement to our models would be to restructure the determination of primary parks within the formulation notation. One suggestion is to redefine the assignment decision variable such that a percentage of each block group may visit a park. This would allow individuals within differing regions of each block group to visit multiple separate parks. Another consideration is to formulate the models such that they incorporate human behavior and choice in primary park visitation. An impactful modification would be to assume that individuals of each block group would prefer to visit multiple parks. Therefore, the models could determine primary, secondary, and even tertiary parks for each resident location.

Another aspect of future work is a reconsideration of how finances contribute to park decisions. We note that there is potential in the creation of a temporal element to our models that specifically considers the availability of park land purchasing over time. Further, of interest is an equity model that not only considers monetary expenditures as a hard budget constraint but also incorporates the amount of money expended for land purchasing and quality improvements per demographic or per regional location as an essential component of equity, itself.

Concerning element additions, an essential next step is the integration into the models of other collected demographic data of gender, age, economic status, and disability. We note that, once these elements are incorporated, we may further modify the models such that we not only determine the optimal locations of parks but also determine the most practical type of park that should exist dependent upon demographic and environmental factors. Though several existing parks already have defined amenities and purpose, several Asheville parks compose only open space upon which specific amenities may be added. Therefore, a model could determine amenity types to include in parks for these no-amenity existing parks and candidate parks. Suggestions for formulating this model include (1) labeling as a parameter the types of amenities currently present at each existing park such that parks with close geographic proximity to one another may exhibit different amenities and (2) formulating a point-based criteria dependent upon demographics, environmental characteristics, and resident feedback and demand that determines ideal park type for facilities. Some examples of park amenity preferences include locating playgrounds near areas with a large number of young children, adding soccer fields in areas with a large number of Hispanics, and constructing walking trails, rather than basketball courts, in heavily wooded areas.

Finally, future endeavors are to include additional social and spatial elements within park decisions. Firstly, new models may incorporate public safety from a collection of crime data. We may seek to provide park in improvements in locations that encounter the greatest number and severity of crimes. Secondly, we suggest modifications to the distance calculation concerning topographic realities and demographic classifications. We can consider the strenuousness of the walk between resident locations and parks by including an additional penalty distance to represent the greater effort required in uphill journeys. Currently, the experience of distance is represented homogenously. We can calculate experienced distance for each demographic classification as the actual distance value multiplied by a weight per demographic. One reason to utilize a demographic distance weight would be to represent a limited mobility encountered by older and/or disabled residents, who face a greater difficulty in accessing parks. Thirdly, we could also incorporate connectivity by locating parks such that there exist accessible pathways between greenspaces.

Conclusion

Our study focuses upon the development of new integer programming models that serve as a guide to improve equity within the recreational setting. We provide for urban planners park and greenspace facility location tools that integrate the demographic, geospatial, monetary, and environmental factors prevalent in the decision-making process. Our models incorporate key indicators of park access and quality to quantify the amount of park goodness experienced by residents of differing demographic classifications. Using Asheville, North Carolina as a case study, we complete extensive data collection and analyses to translate current-state park realities into usable model inputs. We complete model analyses to answer key policy questions of budget use, strategic targeting, and metrics of access. The developed insights and modeling techniques from our study may be further applicable to questions of equitable distribution beyond the recreational setting, including other humanitarian services such as food banks and homeless shelters. We provide the initial framework for the incorporation of equity in access and quality to best serve the needs to people.

APPENDICES

Appendix A

Additional Demographic Data and Visualization

Racial-Ethnic Demographic Data

Table A.1 provides individual count totals of race-ethnicity for each of the 77 BG19 resident location within ACL included in this study [50].

Table A.1: Racial-Ethnic Demographic Counts by BG19

GEOID2019	Total	Total White	Total Black or African American	Total American Indian and Alaska Native	Total Asian	Total Native Hawaiian and Other Pacific Islander	Total Some Other Race
370210001001	1563	1286	260	35	23	5	33
370210002001	1165	589	525	19	8	35	72
370210002002	737	628	79	32	27	9	42
370210003001	1456	1139	308	33	25	2	41
370210003002	678	598	70	10	11	0	22
370210004001	2596	2224	179	53	92	10	174
370210004002	662	590	49	13	24	0	24
370210004003	632	578	55	14	11	0	17
370210005001	1135	1101	12	22	16	1	33
370210005002	629	601	16	2	17	0	17
370210005003	1783	1674	78	26	35	11	67
370210006001	768	675	72	5	19	1	53
370210006002	1204	1060	95	37	37	2	58
370210007001	1648	1241	362	22	34	0	89
370210008001	1129	895	190	18	24	11	65
370210008002	1141	1010	104	25	21	3	52
370210008003	1088	1002	46	22	21	1	68
370210009001	616	400	185	3	17	0	39
370210009002	1256	918	325	32	14	3	36
370210009003	1677	721	924	29	19	26	59
370210010001	1840	1707	106	50	47	3	96
370210010002	1728	1389	304	51	45	15	100
370210010003	1039	835	182	31	27	9	59
370210011001	1607	1319	232	50	45	3	96
370210011002	1885	1781	83	40	37	1	88
370210011003	1622	1437	119	37	33	3	133
370210012001	1060	990	36	39	17	1	64
370210012002	767	716	33	17	28	0	38
370210012003	890	834	44	42	24	3	50
370210012004	1765	1634	72	40	28	1	126
370210012005	737	532	92	21	46	2	113
370210013001	1443	1215	133	37	32	5	151
370210013002	1566	1149	257	44	25	31	188
370210014001	1141	672	116	44	21	4	410
370210014002	845	440	236	16	15	13	205
370210014003	308	269	23	11	3	0	24
370210014004	68	49	4	2	1	0	19
370210014005	1578	1325	161	47	39	7	149

GEOID2019	Total	Total White	Total Black or African American	Total American Indian and Alaska Native	Total Asian	Total Native Hawaiian and Other Pacific Islander	Total Some Other Race
370210016001	1307	1250	18	14	34	2	50
370210016002	1846	1781	41	16	29	3	92
370210016003	593	542	22	20	13	1	41
370210017001	251	245	2	2	3	0	7
370210017002	479	464	11	3	8	1	20
370210018011	532	468	57	16	8	1	17
370210018012	1447	1075	340	29	48	4	68
370210018021	630	597	23	12	15	1	17
370210018022	746	707	27	15	18	1	21
370210018023	1743	1546	136	46	42	1	100
370210019001	1625	1484	70	47	26	7	109
370210019002	1697	1466	136	24	57	7	125
370210020001	3175	2448	689	71	43	3	219
370210020002	1545	1351	166	35	25	1	109
370210020003	838	542	248	42	31	2	87
370210020004	1564	965	555	29	24	9	93
370210021021	633	537	72	18	13	1	51
370210021022	2560	1564	446	116	101	4	647
370210022031	952	501	183	21	17	2	383
370210022032	851	659	113	27	20	3	111
370210022033	77	56	14	2	2	0	12
370210022041	1292	1166	51	26	69	4	69
370210022042	2710	2367	205	45	94	4	154
370210022043	836	609	116	14	47	2	128
370210022044	1178	1108	50	26	38	1	49
370210022051	72	65	5	1	2	0	4
370210022053	1085	921	114	21	23	14	73
370210022061	571	529	20	8	17	2	22
370210022062	658	567	70	13	21	4	38
370210023021	1208	1092	53	19	29	0	101
370210023022	110	104	2	2	3	0	5
370210023024	262	220	17	11	6	1	32
370210025052	548	491	28	10	8	1	52
370210025061	719	639	53	34	12	3	56
370210030011	95	84	10	2	2	0	4
370210030014	223	201	11	5	4	1	26
370899306001	48	43	3	1	2	0	4
370899306002	208	175	17	4	9	0	19
370899307011	58	54	2	1	1	0	3

Appendix Figure A.1 to Appendix Figure A.6 provide map illustrations of the data in Table A.1 by indicating the demographic population within each block group and the distribution of racial composition throughout the City of Asheville.

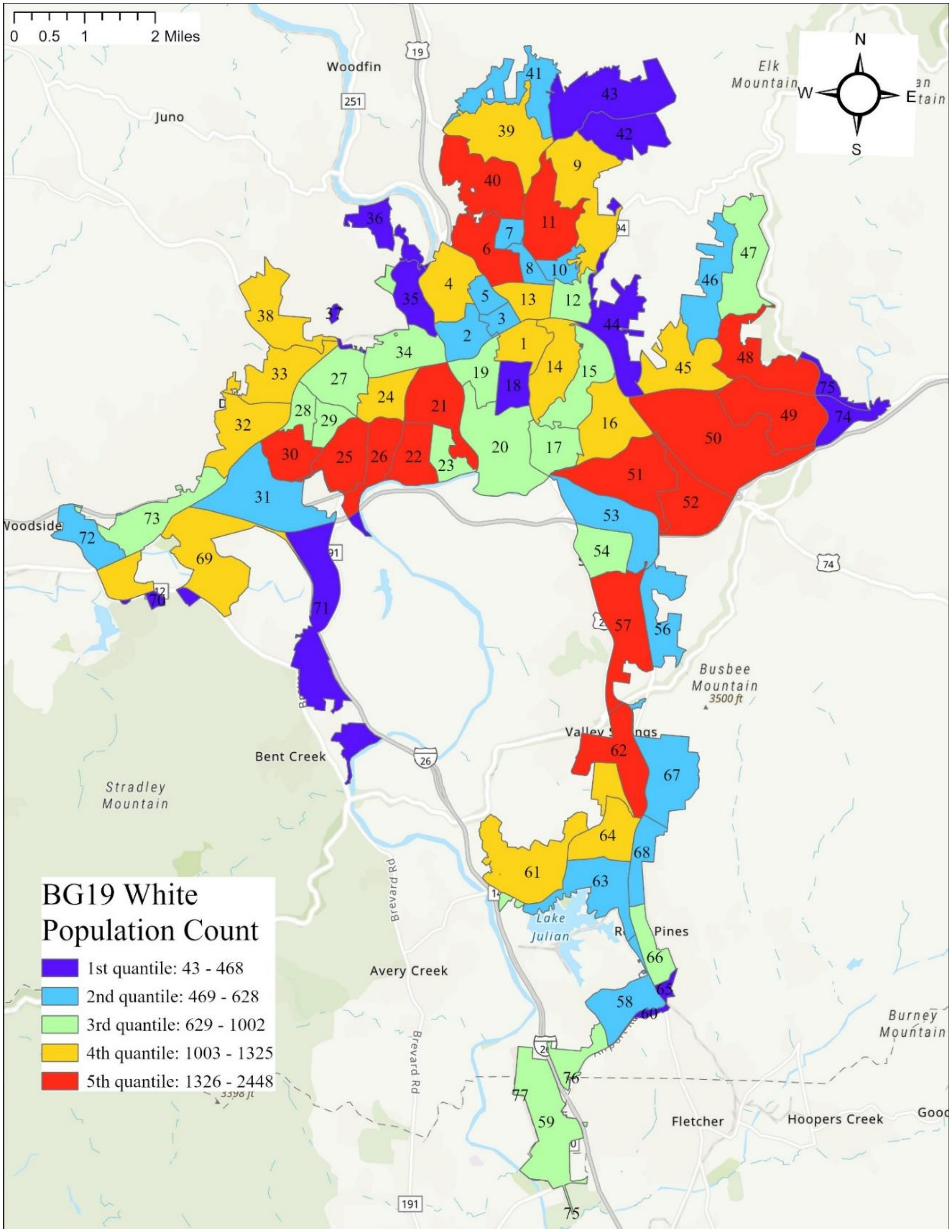

Figure A.1: White Population Counts by BG19

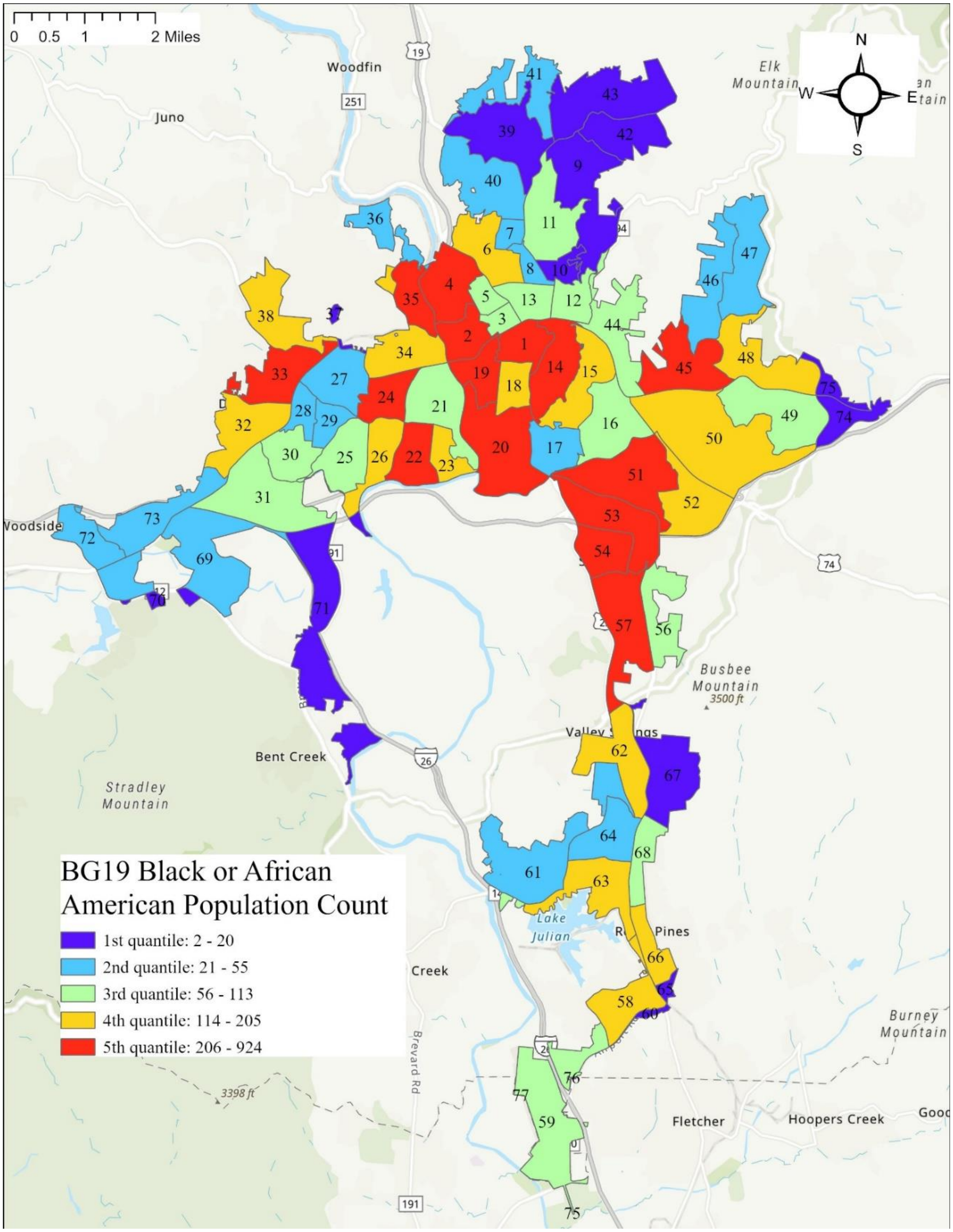

Figure A.2: Black or African American Population Counts by BG19

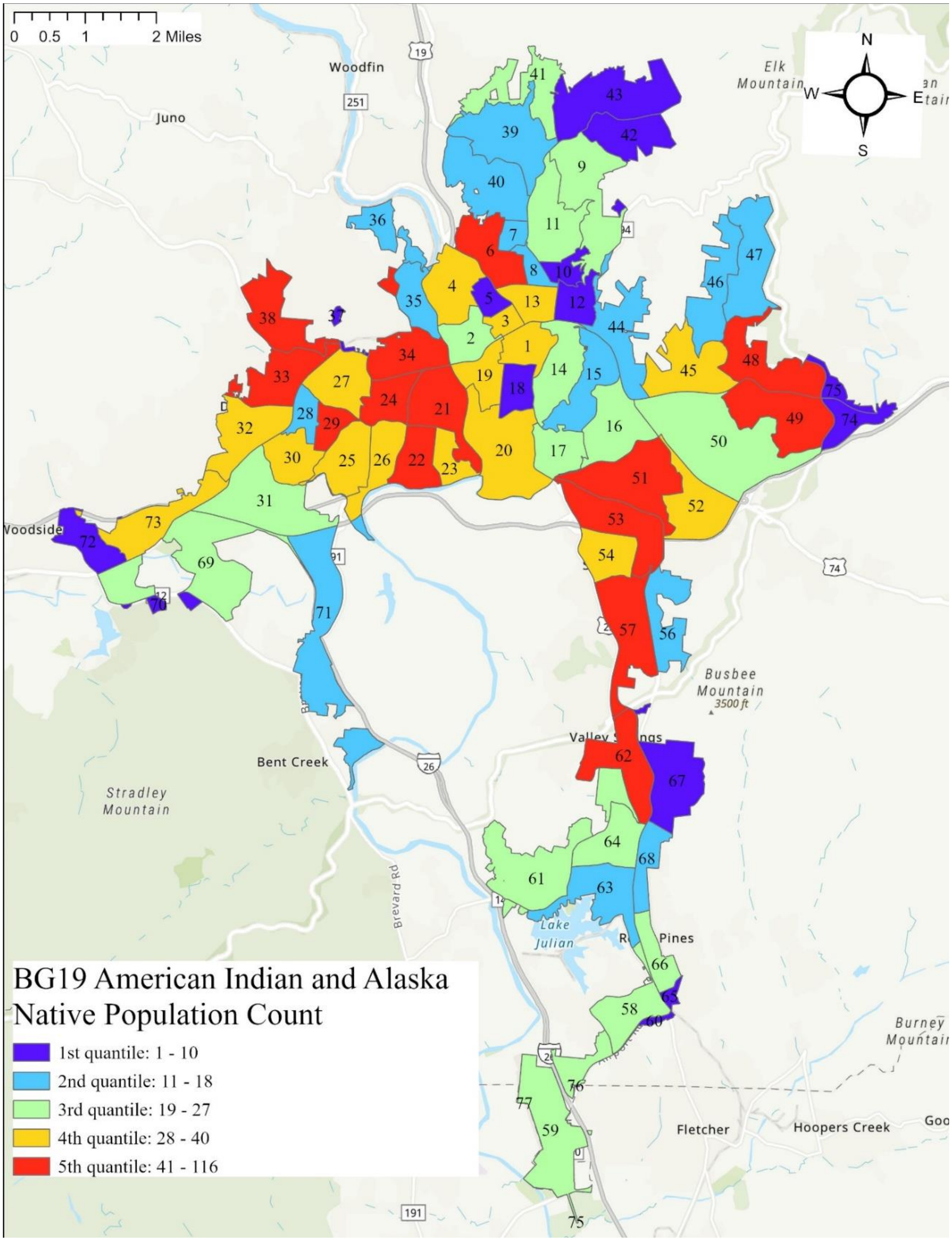

Figure A.3: American Indian and Alaska Native Population Counts by BG19

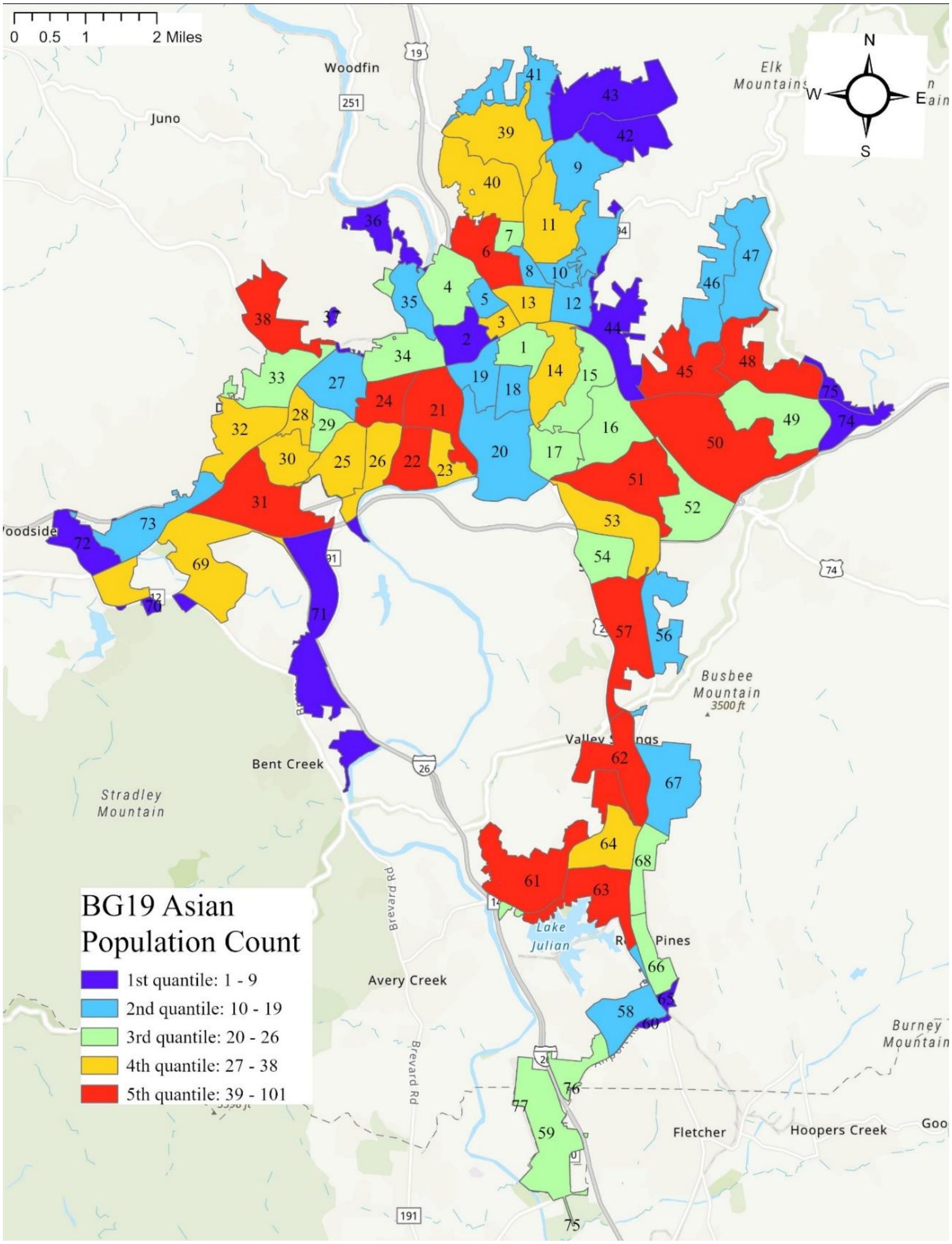

Figure A.4: Asian Population Counts by BG19

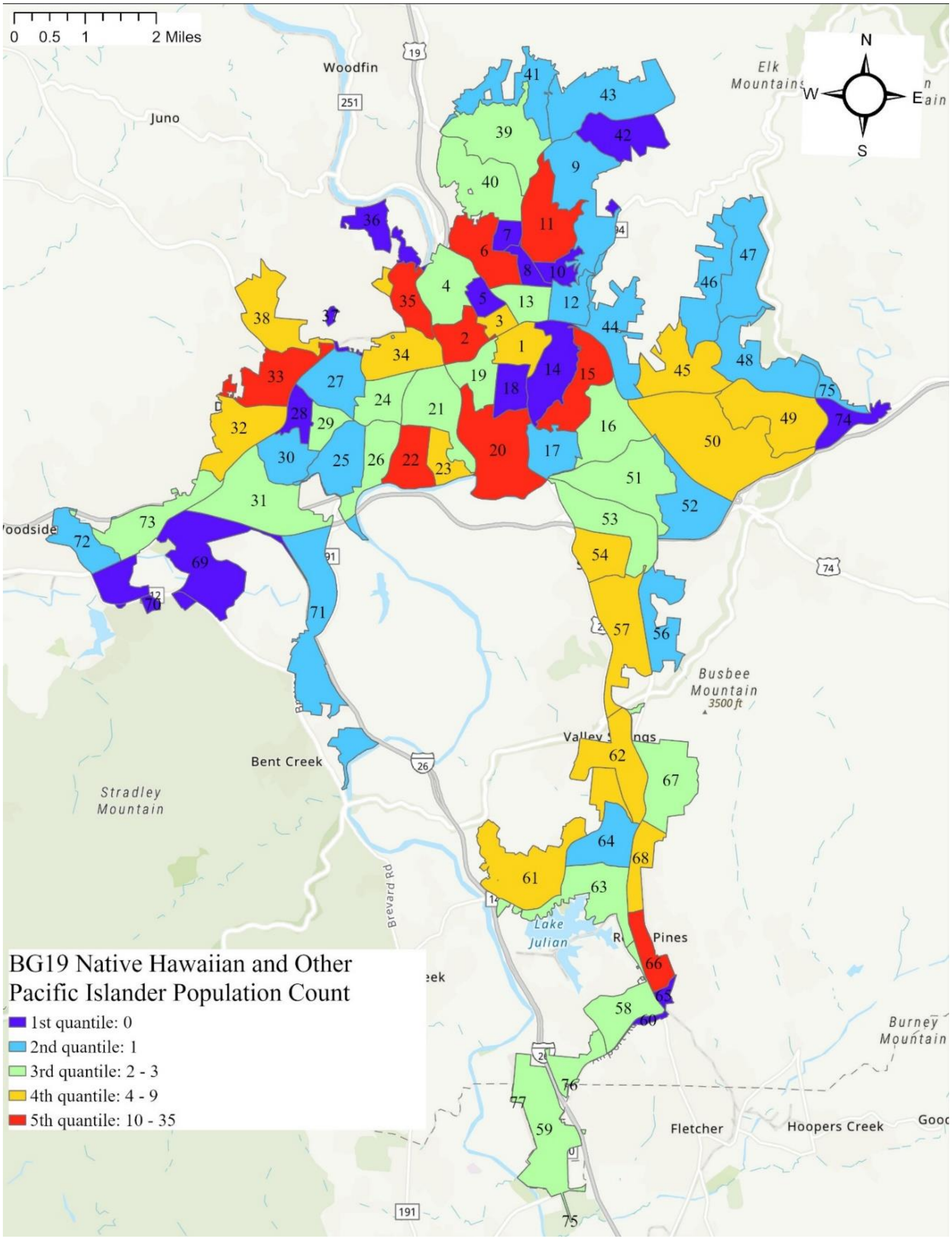

Figure A.5: Native Hawaiian and Other Pacific Islander Population Counts by BG19

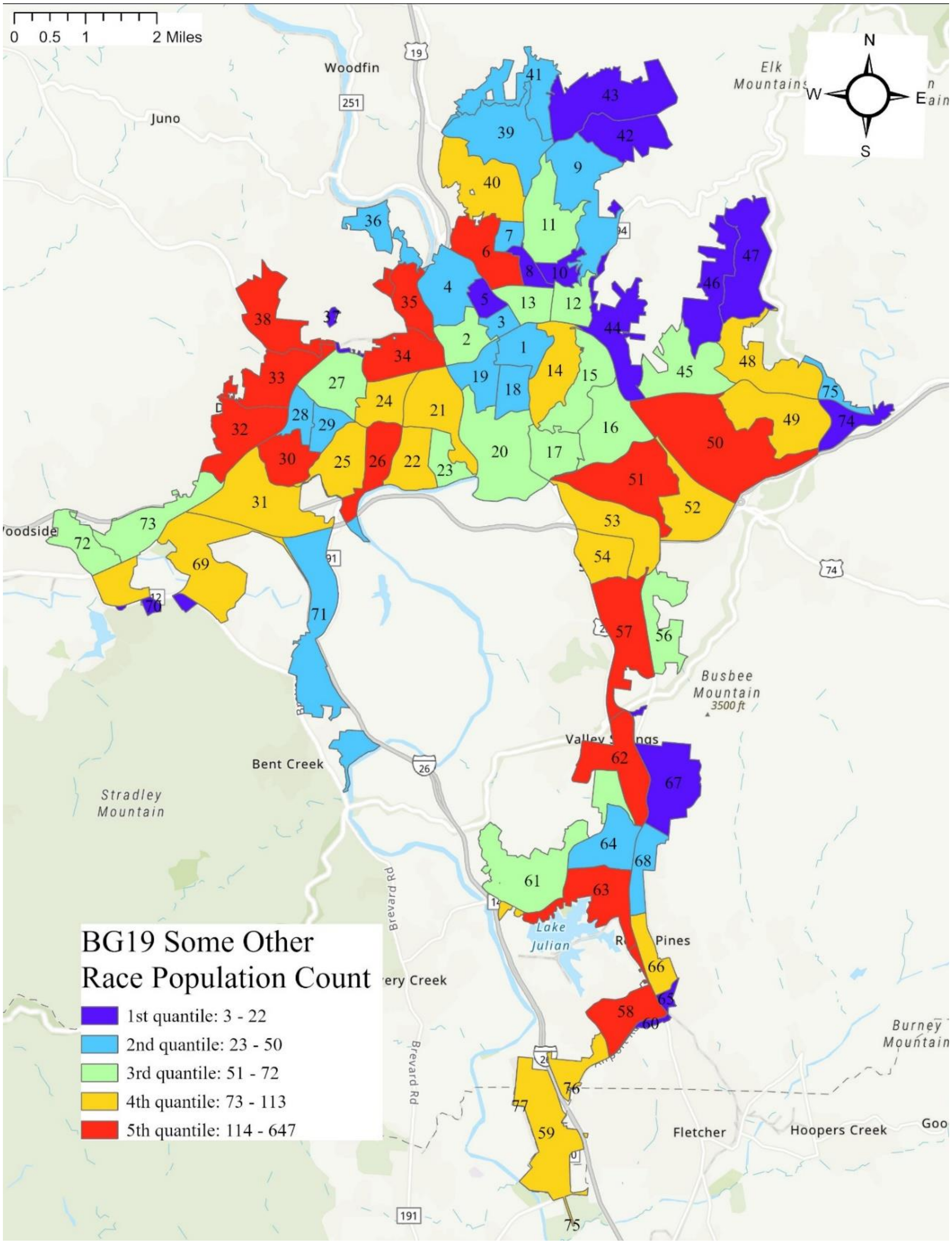

Figure A.6: Some Other Race Population Counts by BG19

Gender Demographic Data

Within this subsection, we provide gender data for the 77 block groups within this study. Table A.2 provides numerical gender data [51], Figure A.7 and Figure A.8 are illustrations of the counts of males and females in each block group, respectively.

Table A.2: Gender Demographic Counts by BG19

GEOID	Total Male	Total Female
370210001001	914	531
370210002001	385	302
370210002002	331	384
370210003001	523	964
370210003002	433	427
370210004001	967	1205
370210004002	239	412
370210004003	301	318
370210005001	433	616
370210005002	237	345
370210005003	833	930
370210006001	325	366
370210006002	544	636
370210007001	883	722
370210008001	451	417
370210008002	683	807
370210008003	538	558
370210009001	264	221
370210009002	472	337
370210009003	704	995
370210010001	940	1093
370210010002	1025	879
370210010003	361	501
370210011001	733	837
370210011002	994	968
370210011003	881	1144
370210012001	642	455
370210012002	369	195
370210012003	238	393
370210012004	733	734
370210012005	627	311
370210013001	612	605
370210013002	943	861
370210014001	505	504
370210014002	600	654
370210014003	107	118
370210014004	35	35
370210014005	572	692

GEOID	Total Male	Total Female
370210016001	677	722
370210016002	976	900
370210016003	226	205
370210017001	101	124
370210017002	228	240
370210018011	312	277
370210018012	507	719
370210018021	270	382
370210018022	384	405
370210018023	872	1083
370210019001	1020	1134
370210019002	653	801
370210020001	1274	1373
370210020002	671	714
370210020003	198	300
370210020004	809	1099
370210021021	254	365
370210021022	1367	1318
370210022031	193	181
370210022032	272	383
370210022033	34	32
370210022041	487	572
370210022042	1989	1945
370210022043	90	228
370210022044	326	637
370210022051	39	38
370210022053	445	631
370210022061	253	313
370210022062	229	373
370210023021	649	612
370210023022	46	57
370210023024	93	183
370210025052	280	259
370210025061	453	374
370210030011	32	45
370210030014	96	146
370899306001	18	25
370899306002	97	122

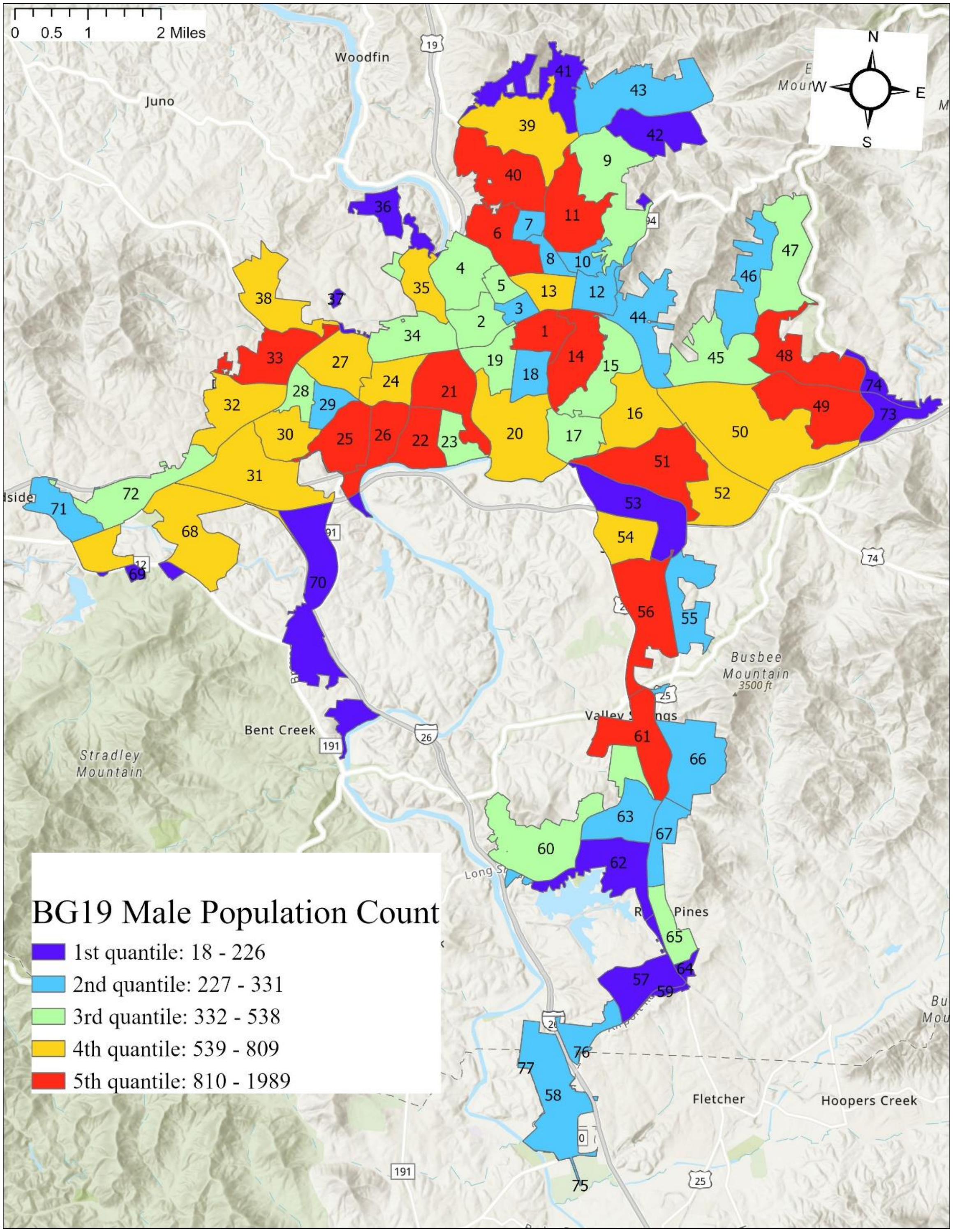

Figure A.7: Male Population Counts by BG19

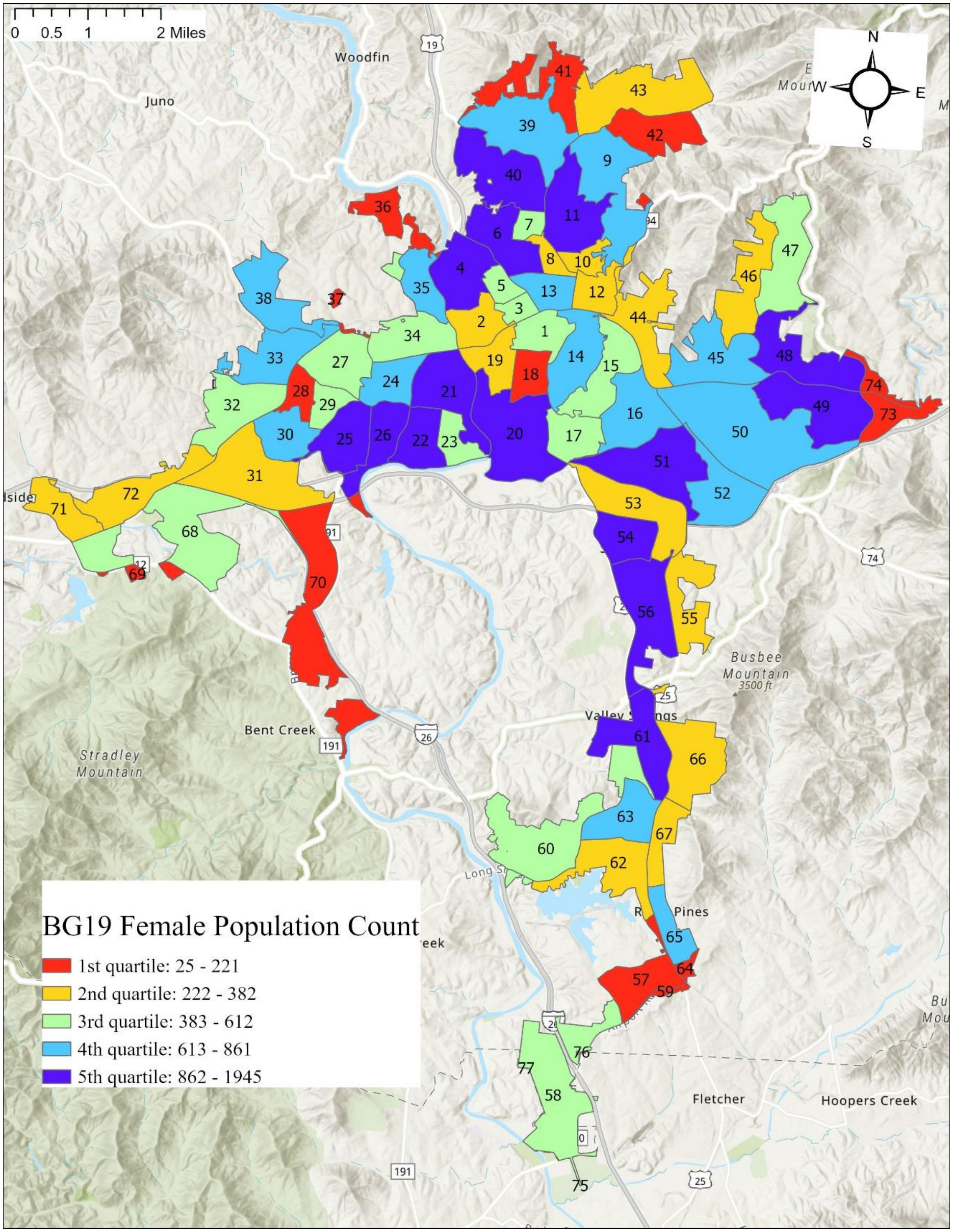

Figure A.8: Female Population Counts by BG19

Age Demographic Data

Within this subsection, we provide age data for the 77 block groups considered within this study [51]. Table A.3 provides numerical age data. We create four age classifications to simplify mapping: childhood = 0-17 years, youth = 18-29 years, middle-age adult = 30-59 years, older adult = 60-85+ years. Using the data in Table A.3, we calculate totals for each age classification to create Figure A.9 to Figure A.12.

Table A.3: Age Demographic Counts by BG19

GEOID	Age [years]																					
	0-4	5-9	10-14	15-17	18-19	20	21	22-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-61	62-64	65-66	67-69	70-74	75-79	80-84	85
370210001001	0	10	3	14	27	0	0	62	110	181	139	102	99	84	75	41	45	91	80	155	38	57	22
370210002001	25	94	69	0	0	0	0	6	72	89	87	11	43	29	68	20	19	42	9	4	0	0	0
370210002002	28	30	45	16	19	0	0	51	76	47	51	58	59	46	78	0	41	5	40	10	15	0	0
370210003001	51	83	75	29	60	45	0	93	233	79	93	73	33	52	57	31	53	55	35	84	15	18	12
370210003002	39	80	47	28	10	0	0	19	123	69	143	28	25	57	17	34	59	27	25	19	4	0	7
370210004001	71	56	30	19	619	143	0	242	154	153	87	75	81	48	9	0	46	8	32	45	59	33	59
370210004002	10	16	28	14	21	57	0	19	54	80	39	55	13	0	7	0	10	0	77	28	0	0	0
370210004003	0	10	0	0	22	34	0	0	67	17	59	32	28	107	64	51	35	31	42	10	0	10	0
370210005001	37	53	29	75	33	0	0	38	29	36	59	68	29	97	60	30	81	28	32	105	32	52	53
370210005002	48	18	17	6	0	0	0	32	7	68	14	44	36	42	85	0	54	8	37	42	15	9	0
370210005003	76	134	91	114	22	10	0	165	58	69	96	86	104	214	65	20	51	43	127	138	39	25	16
370210006001	24	38	67	0	0	0	0	26	24	52	121	62	39	30	44	20	16	28	15	0	33	13	13
370210006002	52	38	19	0	0	11	0	27	177	190	128	122	90	40	74	9	36	0	46	39	25	10	0
370210007001	96	61	79	47	0	14	0	125	311	178	111	68	55	99	119	28	25	47	32	48	27	8	12
370210008001	0	104	23	57	11	0	0	43	32	76	75	54	76	69	96	9	7	19	50	15	14	4	34
370210008002	34	30	0	67	18	18	0	22	96	95	173	113	102	178	158	11	125	25	49	29	42	17	30
370210008003	44	35	69	62	2	17	0	45	58	48	93	93	189	49	54	32	46	22	56	31	30	0	0
370210009001	16	21	9	1	0	0	0	25	73	82	35	25	74	1	14	17	0	17	36	26	13	0	0
370210009002	50	0	0	0	0	3	0	0	115	36	78	58	24	63	110	34	116	28	25	24	0	18	27
370210009003	218	164	72	35	7	14	0	82	113	197	116	74	32	90	159	15	34	8	48	33	33	42	116
370210010001	124	100	92	24	0	0	0	141	407	245	162	237	130	93	68	0	56	17	8	56	8	43	8
370210010002	150	111	185	100	18	0	0	18	154	416	141	136	23	204	72	57	34	16	28	0	31	0	14
370210010003	81	36	35	0	31	0	0	12	58	79	88	117	32	35	83	32	72	16	13	44	0	0	0
370210011001	34	49	36	84	20	0	0	18	88	287	161	184	95	143	87	0	17	47	116	53	9	9	33
370210011002	134	40	195	93	48	0	0	60	164	269	198	175	298	103	51	17	23	10	14	35	21	5	0
370210011003	83	92	132	153	0	0	0	34	110	361	277	154	178	125	72	15	13	0	21	75	23	39	68
370210012001	213	120	1	5	0	0	0	0	0	104	304	22	67	21	47	26	53	62	10	22	0	0	20
370210012002	40	82	0	0	0	0	0	11	38	16	143	46	24	48	50	17	0	0	0	31	18	0	0
370210012003	52	0	0	0	0	0	0	18	43	137	124	35	57	0	22	59	0	0	0	28	23	33	0
370210012004	24	162	41	29	91	0	0	48	93	147	137	64	148	65	156	46	77	0	28	57	0	12	16
370210012005	0	48	137	17	62	0	0	3	180	10	11	91	42	291	5	0	11	11	0	0	0	16	0
370210013001	65	53	67	16	0	17	0	49	107	135	112	155	22	103	53	16	58	1	47	71	48	0	9
370210013002	96	156	134	36	0	6	0	78	273	98	97	98	151	106	113	0	7	90	48	44	50	55	37
370210014001	68	77	94	0	10	0	0	0	41	126	172	61	37	18	37	67	57	8	30	15	35	17	0
370210014002	99	0	16	141	20	0	0	95	282	163	45	0	16	184	73	0	44	0	0	0	64	0	12
370210014003	0	0	0	0	0	0	0	3	27	9	8	24	27	3	7	13	1	17	14	30	9	16	17
370210014004	3	2	0	2	2	3	0	6	5	12	3	4	3	1	4	1	1	5	6	1	2	2	0
370210014005	88	51	40	26	31	6	0	97	157	150	41	89	126	69	37	38	25	22	36	64	13	7	47
370210016001	97	81	27	121	0	0	0	50	19	129	36	84	98	96	140	35	18	116	127	112	15	0	0

Table A.3 (cont.): Age Demographic Counts by BG19 Location

GEOID	Age [years]																					
	0-4	5-9	10-14	15-17	18-19	20	21	22-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-61	62-64	65-66	67-69	70-74	75-79	80-84	85
370210016002	65	59	105	36	200	5	0	88	89	79	93	140	153	90	48	0	179	70	88	88	75	66	53
370210016003	3	35	2	7	2	0	0	0	4	7	18	8	21	36	26	31	11	19	26	61	17	54	40
370210017001	7	0	8	17	14	6	0	0	2	15	6	2	15	17	27	16	15	8	22	18	4	2	5
370210017002	10	23	22	12	13	0	0	17	33	15	23	34	19	10	20	27	22	18	27	49	34	10	28
370210018011	31	11	12	12	0	0	0	21	17	29	32	39	22	42	52	2	26	40	35	54	54	16	39
370210018012	55	52	60	10	0	0	0	73	125	120	101	28	62	63	102	43	56	35	53	78	20	29	68
370210018021	43	61	19	1	15	0	0	0	10	41	62	0	14	48	72	36	24	18	56	35	42	31	25
370210018022	18	52	102	12	17	0	0	22	37	29	37	65	72	43	46	51	14	32	24	83	10	22	0
370210018023	111	49	73	67	23	9	0	129	225	107	158	94	150	76	39	113	108	53	64	78	68	11	135
370210019001	125	82	230	57	18	0	0	75	64	196	203	164	123	65	100	64	118	54	79	124	74	57	59
370210019002	48	66	59	18	0	0	0	148	133	76	72	85	48	29	110	38	89	25	69	125	85	56	68
370210020001	125	63	117	63	10	0	0	48	670	169	235	97	222	272	80	34	58	77	57	72	107	55	16
370210020002	20	20	58	45	18	23	0	17	313	22	171	165	96	48	92	18	16	30	31	110	41	16	0
370210020003	0	71	33	12	0	0	0	41	4	16	52	39	50	3	0	4	8	23	32	24	19	24	43
370210020004	128	165	72	90	0	21	0	68	174	104	66	293	53	0	68	33	72	83	112	226	45	35	0
370210021021	67	6	35	25	4	5	0	43	35	96	50	60	45	27	18	2	10	8	12	26	8	7	3
370210021022	235	362	92	116	63	106	0	80	105	349	411	88	83	29	73	83	60	32	34	171	8	73	30
370210022031	0	0	0	0	0	9	0	1	26	26	1	66	77	55	32	5	0	15	24	6	0	0	31
370210022032	20	19	57	28	3	9	0	9	103	24	59	26	75	22	38	19	7	17	28	29	55	10	0
370210022033	7	10	2	3	1	2	0	0	3	1	8	8	2	5	5	0	2	2	0	1	1	3	2
370210022041	80	57	85	26	39	0	0	22	25	64	45	31	123	121	96	13	77	7	57	34	33	6	20
370210022042	17	130	141	79	29	100	0	309	385	488	127	556	188	33	94	0	180	45	44	68	162	270	359
370210022043	0	0	0	0	0	0	0	0	0	0	30	27	0	77	43	36	19	0	32	19	18	0	16
370210022044	0	56	92	32	0	0	0	10	44	40	0	83	156	116	93	52	24	0	36	0	0	48	81
370210022051	1	3	8	4	3	2	0	2	3	2	5	5	4	7	8	2	4	4	3	2	3	0	0
370210022053	70	145	98	0	0	0	0	8	148	182	59	59	32	18	0	59	38	0	14	29	18	17	79
370210022061	14	26	33	20	3	0	0	4	3	9	17	34	44	38	22	6	31	29	14	38	50	25	101
370210022062	66	14	0	10	15	0	0	62	67	33	39	10	46	24	18	10	43	11	15	50	21	0	20
370210023021	109	106	81	47	19	0	0	81	9	124	90	101	111	75	45	0	61	19	31	61	61	18	12
370210023022	5	6	12	2	0	0	0	0	2	1	12	7	4	2	7	6	5	3	12	8	2	2	5
370210023024	0	0	10	0	7	21	0	12	65	3	14	23	28	23	26	0	4	12	0	20	5	0	4
370210025052	47	11	30	15	0	8	0	17	88	37	19	17	23	34	38	17	19	7	33	25	24	21	8
370210025061	44	101	45	54	53	7	0	30	45	55	65	74	69	70	21	4	4	4	17	34	11	4	9
370210030011	1	1	7	3	1	0	0	2	11	4	8	5	4	5	4	2	3	5	3	1	2	3	3
370210030014	9	5	15	3	2	0	0	7	4	17	4	0	18	18	23	2	27	0	6	25	39	6	9
370899306001	3	2	5	1	0	0	0	2	1	3	4	3	3	2	3	1	1	0	2	1	1	1	1
370899306002	5	8	21	3	14	15	0	1	6	2	12	24	30	11	16	4	7	3	8	12	7	5	6
370899307011	7	2	3	4	0	1	0	1	4	7	4	4	6	3	4	1	1	1	3	2	1	1	0

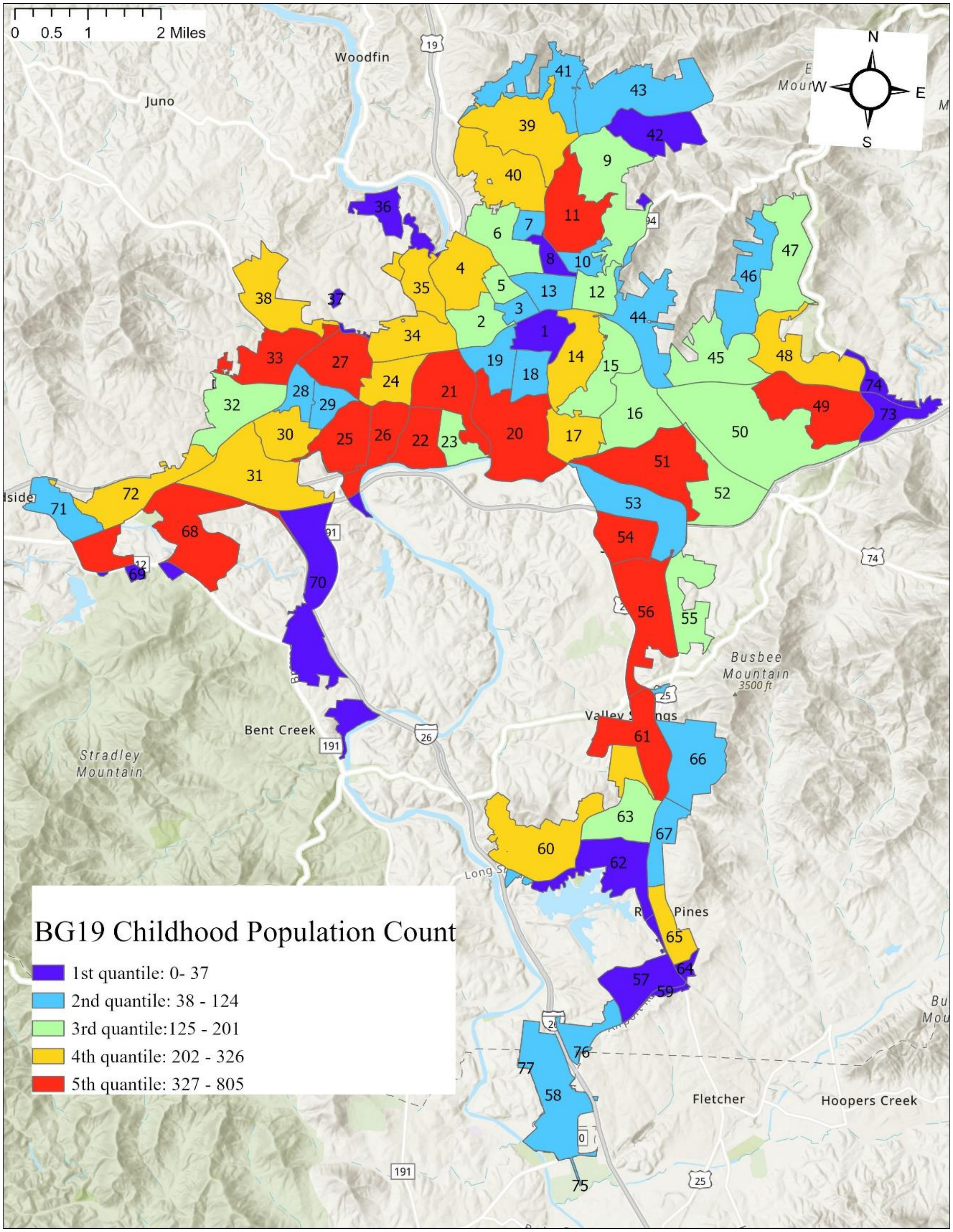

Figure A.9: Childhood Population Counts by BG19

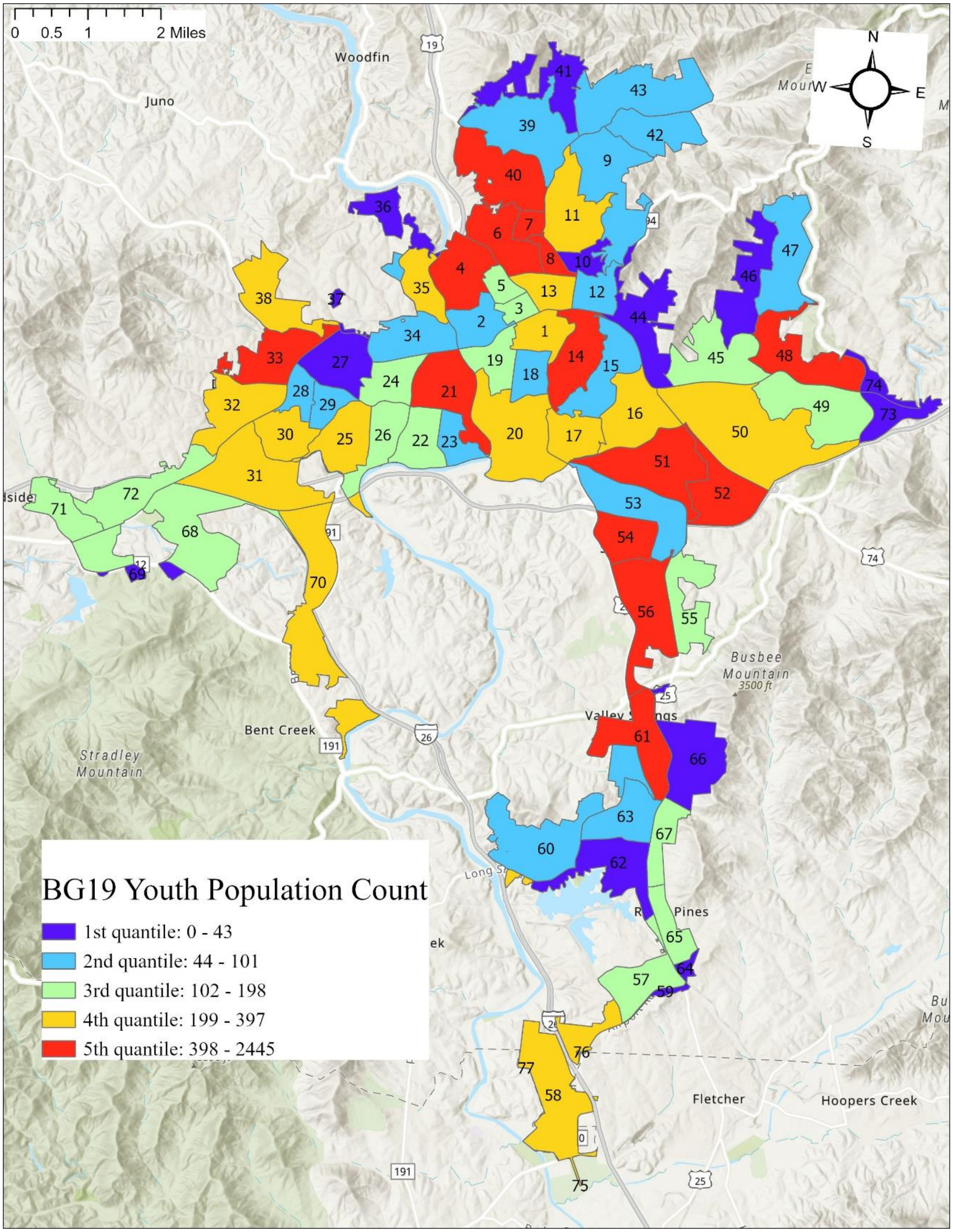

Figure A.10: Youth Population Counts by BG19

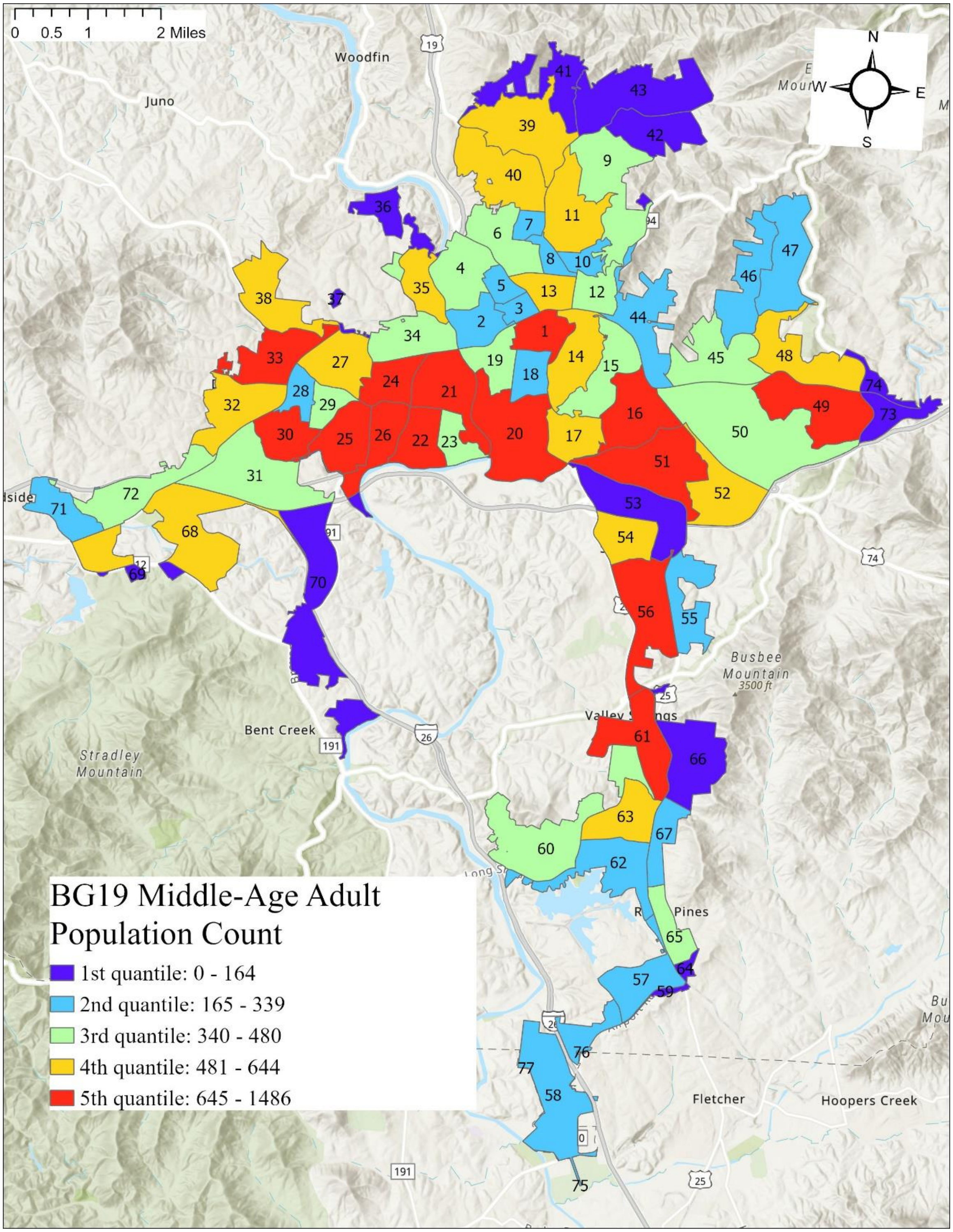

Figure A.11: Middle-Age Adult Population Counts by BG19

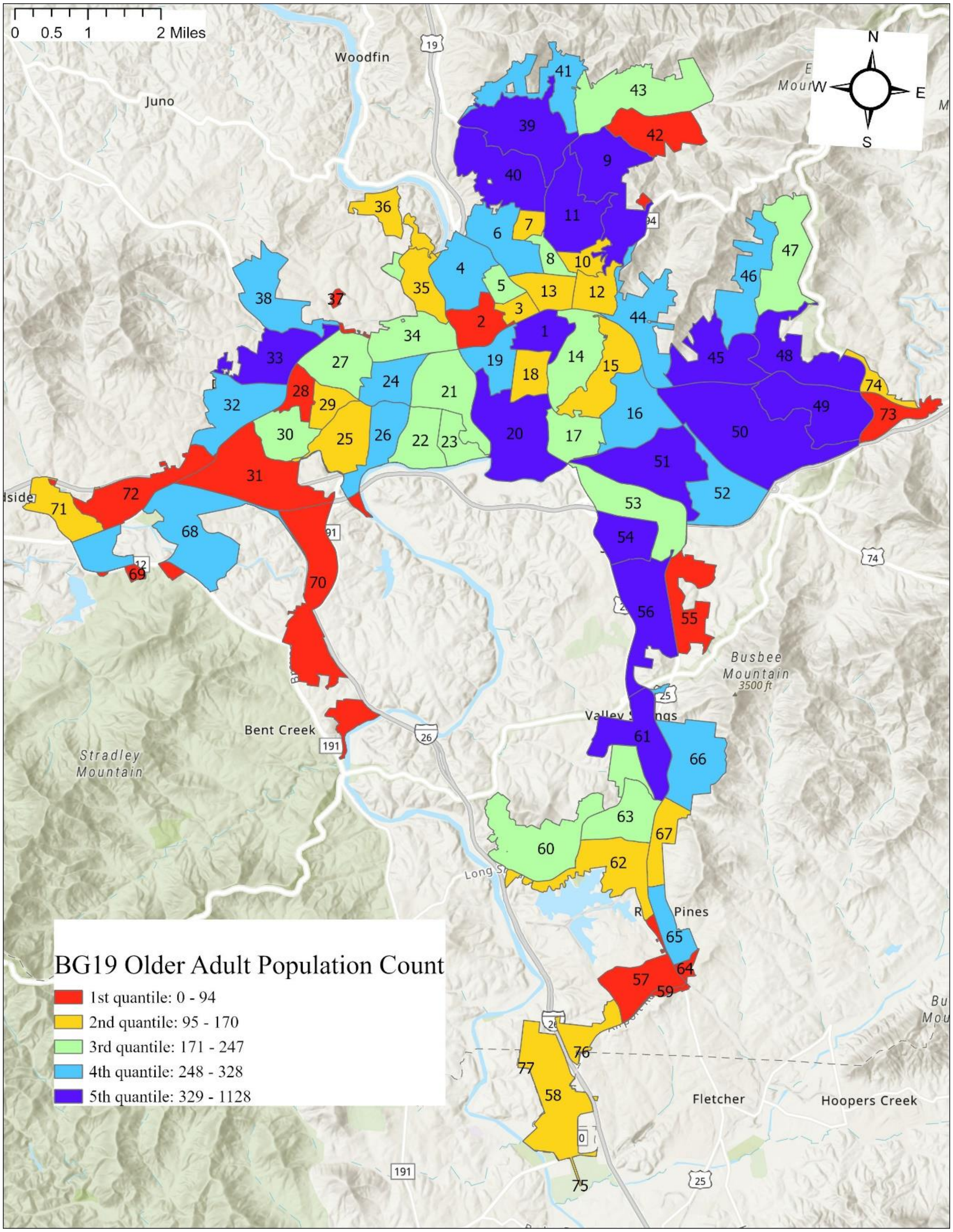

Figure A.12: Older Adult Population Counts by BG19

Economic Status Demographic Data

Within this section, we explore three different measures of economic status. We provide numerical data and map visualization of annual income, poverty status, and public assistance status. Each of these measures is in terms of counts of households rather than counts of individuals.

Income Data

Table A.4 lists the household count for differing income ranges for BG19 [53]. We create six income classifications to simplify mapping: $0k-$25k, $25k-$50k, $50k-$75k, $75k-$100k, $100k-$125k, and $125k and greater. Using the data in Table A.4, we calculate totals for each classification to create Figure A.13 to Figure A.18.

Table A.4: Income Range Household Counts by BG19

GEOID	< $10k	$10k-$15k	$15k-20k	$20k-$25k	$25k-$30k	$30k-$35k	$35k-$40k	$40k-$45k	$45k-$50k	$50k-$60k	$60k-$75k	$75k-$100k	$100k-$125k	$125k-$150k	$150k-$200k	$200k +
370210001001	144	143	88	29	43	42	21	44	16	46	37	39	19	12	23	12
370210002001	45	40	29	28	21	7	7	0	0	33	39	35	6	9	5	5
370210002002	32	5	28	20	14	31	7	5	5	34	23	32	22	21	8	53
370210003001	42	115	9	51	45	44	33	33	0	18	24	72	41	21	10	36
370210003002	0	6	29	35	26	6	5	5	10	31	44	62	25	2	30	49
370210004001	13	0	9	61	23	40	61	9	36	59	75	64	64	7	18	22
370210004002	27	46	82	23	8	0	49	0	0	33	0	32	8	0	7	0
370210004003	29	11	55	9	10	49	47	16	14	66	0	37	16	18	0	9
370210005001	8	8	8	0	17	16	8	21	30	41	35	43	37	13	41	138
370210005002	15	7	0	0	0	71	9	58	0	21	46	7	18	17	18	65
370210005003	19	36	0	33	28	41	33	19	57	56	58	53	25	75	78	147
370210006001	16	13	64	43	29	41	0	0	18	58	24	8	16	0	5	34
370210006002	19	9	63	66	45	52	33	54	54	37	25	38	71	11	18	20
370210007001	16	11	88	61	53	69	30	40	29	28	71	121	15	48	66	14
370210008001	36	39	0	28	28	70	29	36	0	7	19	28	18	6	40	8
370210008002	0	5	24	56	44	0	0	25	25	45	23	73	225	53	34	20
370210008003	0	20	8	61	44	18	23	44	41	33	7	81	47	6	68	24
370210009001	35	0	48	7	0	11	6	0	10	34	17	0	30	7	0	17
370210009002	212	61	16	24	14	0	18	0	0	9	41	18	6	6	10	4
370210009003	104	97	90	72	62	36	18	55	4	26	36	35	19	0	0	0
370210010001	70	59	9	29	20	89	30	27	11	50	104	98	114	34	22	12
370210010002	115	38	20	55	35	41	18	13	6	25	36	130	81	26	22	37
370210010003	24	22	0	27	0	8	34	30	37	0	36	51	30	23	36	9
370210011001	58	25	37	31	0	57	0	47	0	38	154	76	16	32	77	62
370210011002	26	73	13	8	77	34	45	6	22	72	125	109	101	102	28	0
370210011003	46	19	32	0	37	39	15	0	72	164	102	114	0	36	50	64
370210012001	30	0	12	21	0	8	13	0	50	97	44	29	19	13	27	79
370210012002	0	0	24	47	0	0	17	52	29	0	42	15	0	47	0	22
370210012003	0	0	13	24	46	25	0	22	5	0	40	76	0	23	11	0
370210012004	18	0	0	0	0	14	52	77	64	115	91	58	79	47	55	0
370210012005	12	0	15	59	0	66	10	44	0	11	45	16	0	0	25	0
370210013001	23	78	23	55	60	23	33	32	26	51	39	84	34	12	0	4
370210013002	58	78	112	99	13	48	8	11	0	63	43	44	56	29	13	15
370210014001	0	47	10	9	0	61	56	21	27	77	18	37	26	9	0	38
370210014002	0	98	113	36	0	149	82	0	0	0	15	0	44	0	0	0
370210014003	3	7	9	4	3	4	15	0	7	0	4	11	7	13	3	0
370210014004	1	4	9	1	2	6	0	0	0	0	5	1	1	0	1	0
370210014005	9	25	17	18	22	65	85	7	0	35	34	101	17	0	24	22
370210016001	0	14	0	0	62	0	81	0	0	12	116	44	64	23	84	85
370210016002	58	11	38	30	25	14	11	14	17	79	42	99	75	78	113	54
370210016003	25	11	8	4	4	14	4	5	5	19	15	0	7	24	39	34
370210017001	11	0	2	4	9	6	6	8	6	8	9	1	9	5	13	10
370210017002	5	7	8	3	11	0	11	11	7	5	11	19	43	3	26	28
370210018011	36	37	28	12	45	10	19	22	17	21	38	33	22	7	5	12
370210018012	38	67	54	132	23	29	12	67	20	50	53	51	41	10	23	41
370210018021	15	10	3	15	8	0	5	32	27	7	25	41	30	17	36	24
370210018022	20	0	14	0	0	0	29	0	0	30	49	37	12	11	43	55
370210018023	0	29	71	82	86	77	32	14	21	134	62	84	102	19	39	62
370210019001	26	80	132	93	47	78	63	39	0	76	135	79	74	62	20	0
370210019002	24	57	24	29	24	77	16	60	81	118	150	74	57	8	0	7
370210020001	89	191	159	172	31	68	104	33	0	116	135	86	57	13	35	12
370210020002	0	75	17	33	29	75	15	113	49	47	115	104	52	22	0	0
370210020003	12	16	17	0	12	0	18	36	0	13	11	15	0	0	0	0
370210020004	0	75	28	52	46	97	19	70	33	28	91	127	32	0	36	0
370210021011	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	4
370210021021	0	32	3	17	47	7	19	22	8	12	30	28	3	3	8	21
370210021022	16	57	211	94	54	32	39	14	69	58	104	71	76	35	31	0
370210022031	4	26	44	52	55	0	6	25	0	11	0	12	0	8	6	0
370210022032	6	21	29	6	0	4	26	20	38	28	34	53	23	0	9	14
370210022033	0	2	0	0	6	3	1	1	1	0	2	4	3	1	0	1
370210022041	0	7	5	9	15	22	7	15	8	39	69	27	24	25	83	95
370210022042	21	19	0	41	107	322	80	59	257	195	439	271	34	78	52	54
370210022043	0	19	49	19	18	0	0	0	0	11	16	58	19	0	0	0
370210022044	0	98	0	50	24	0	39	104	22	37	60	0	28	27	54	0
370210022051	0	1	2	1	0	1	1	0	1	1	3	5	2	3	3	2
370210022053	0	0	0	15	12	13	54	58	13	28	73	38	37	0	0	0
370210022061	0	7	3	4	25	2	21	14	27	11	21	27	35	25	33	23
370210022062	5	9	18	22	11	22	22	13	3	59	16	30	15	20	5	6
370210023021	0	58	0	13	34	18	39	10	37	64	70	74	45	23	24	7
370210023022	0	1	1	0	2	1	1	1	2	1	0	5	7	4	6	8
370210023024	3	0	10	9	12	11	12	2	6	34	2	7	16	0	0	0
370210025052	2	2	6	9	3	5	6	6	7	37	17	55	18	14	16	2
370210025061	21	9	18	9	34	21	26	31	6	25	44	36	0	0	0	0
370210030011	2	0	3	1	0	1	1	5	3	2	2	7	4	1	2	0
370210030014	5	16	10	2	8	15	2	6	2	21	20	6	9	0	2	0
370899306001	1	0	0	1	0	1	1	0	2	1	3	3	2	1	0	1
370899306002	1	0	5	0	4	3	5	24	0	9	3	21	20	0	2	0
370899307011	1	0	3	0	3	0	0	0	1	1	2	5	2	2	1	1

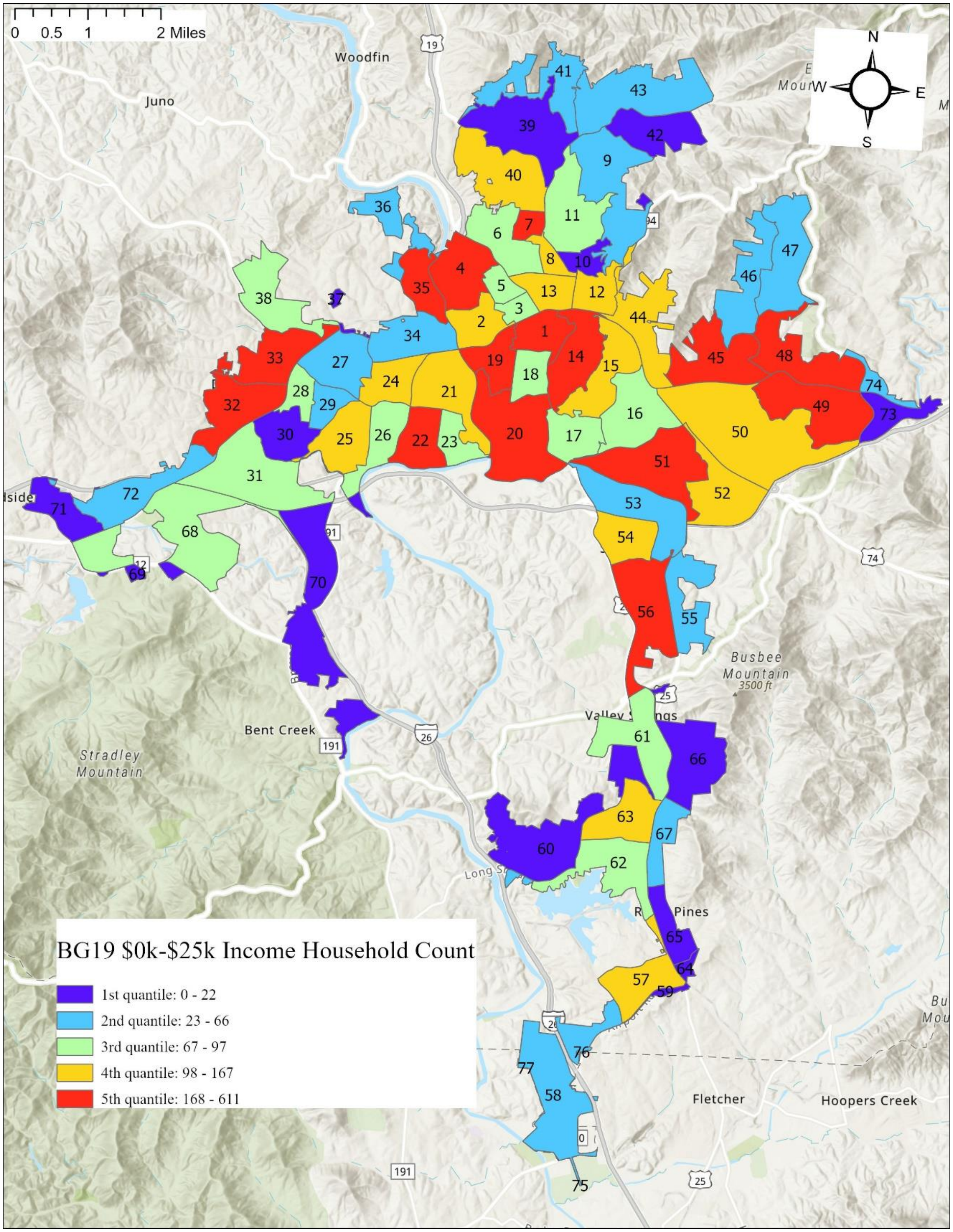

Figure A.13: Income Range $0 to $25,000 Household Counts by BG19

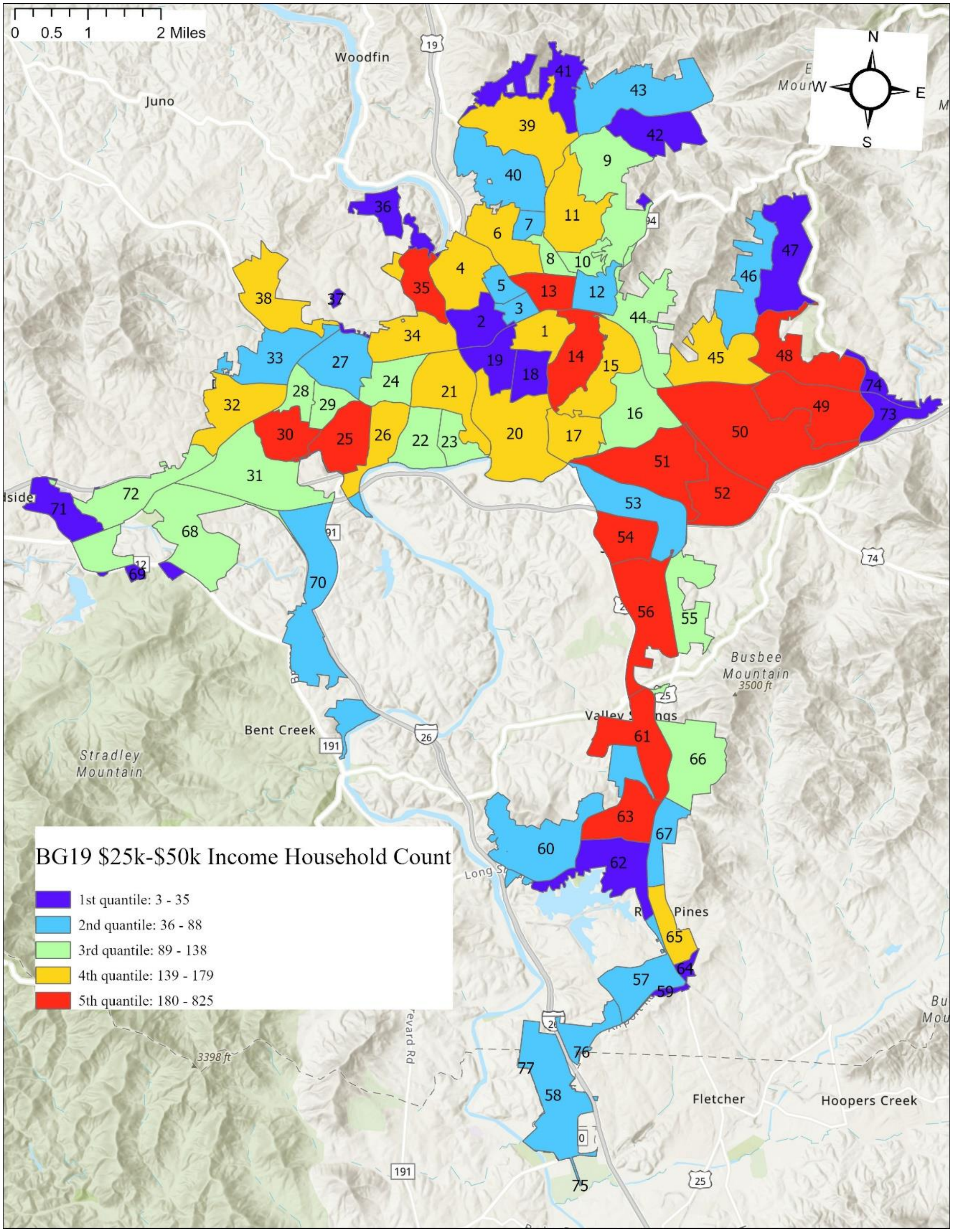

Figure A.14: Income Range $25,000 to $50,000 Household Counts by BG19

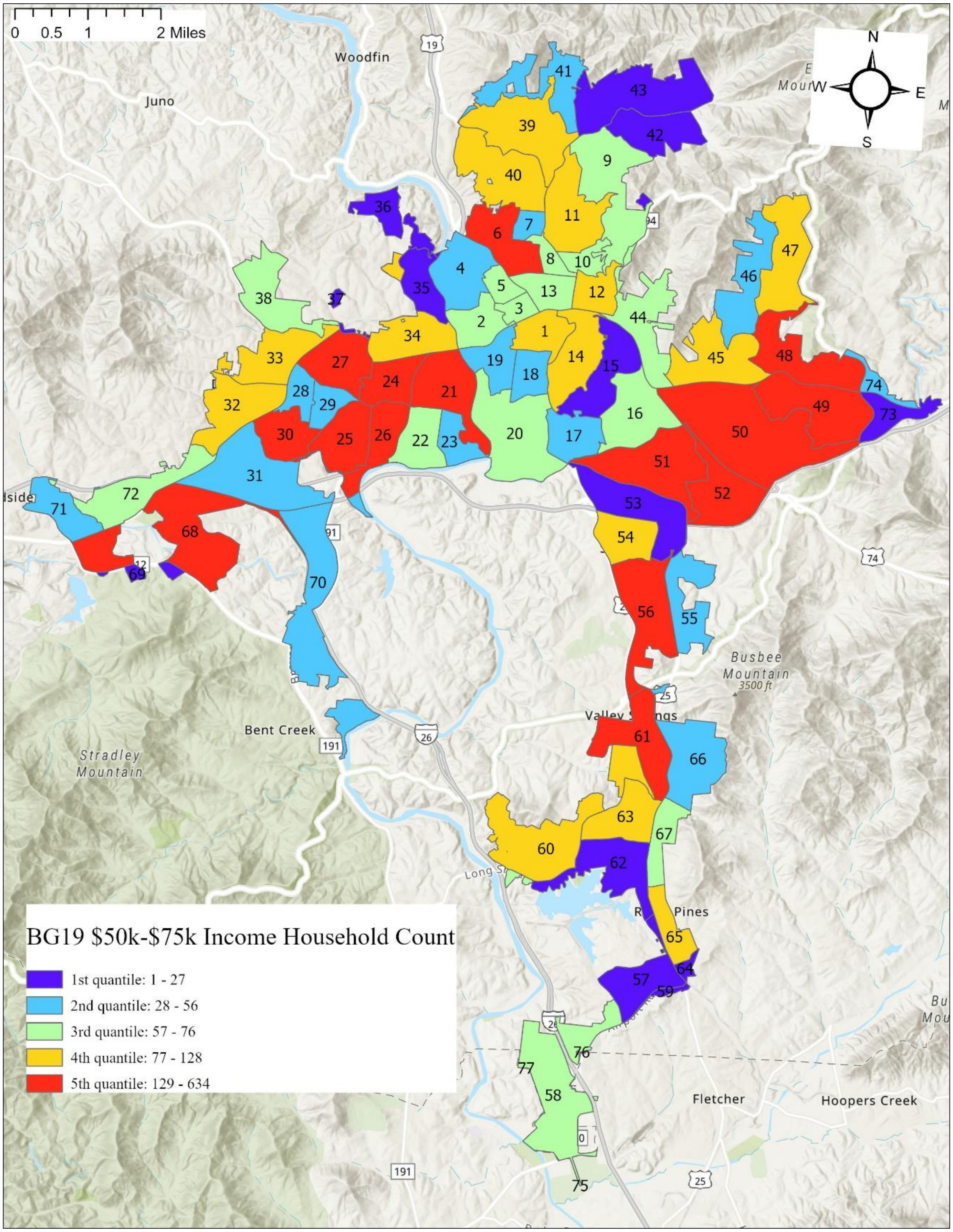

Figure A.15: Income Range $50,000 to $75,000 Household Counts by BG19

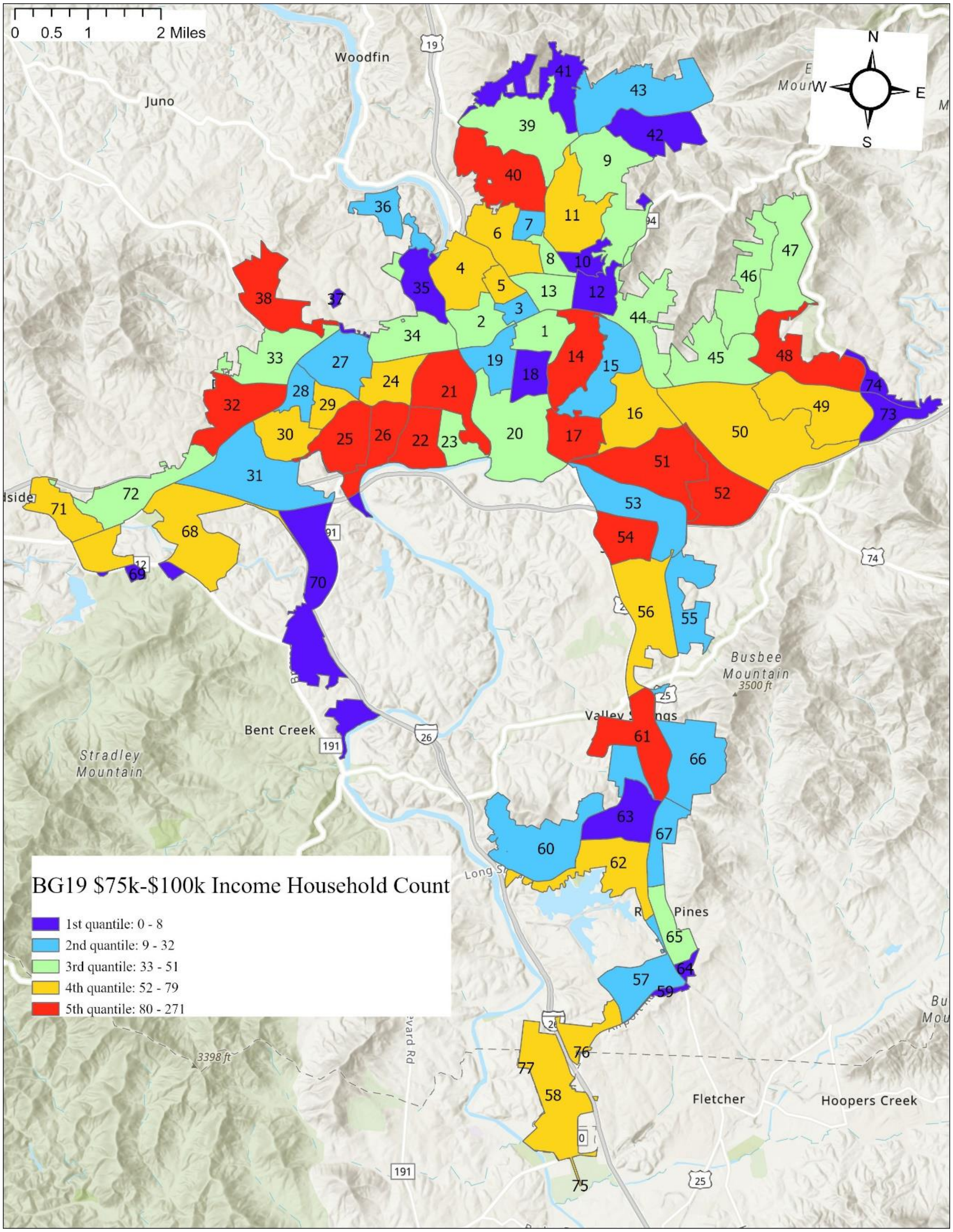

Figure A.16: Income Range $75,000 to $100,000 Household Counts by BG19

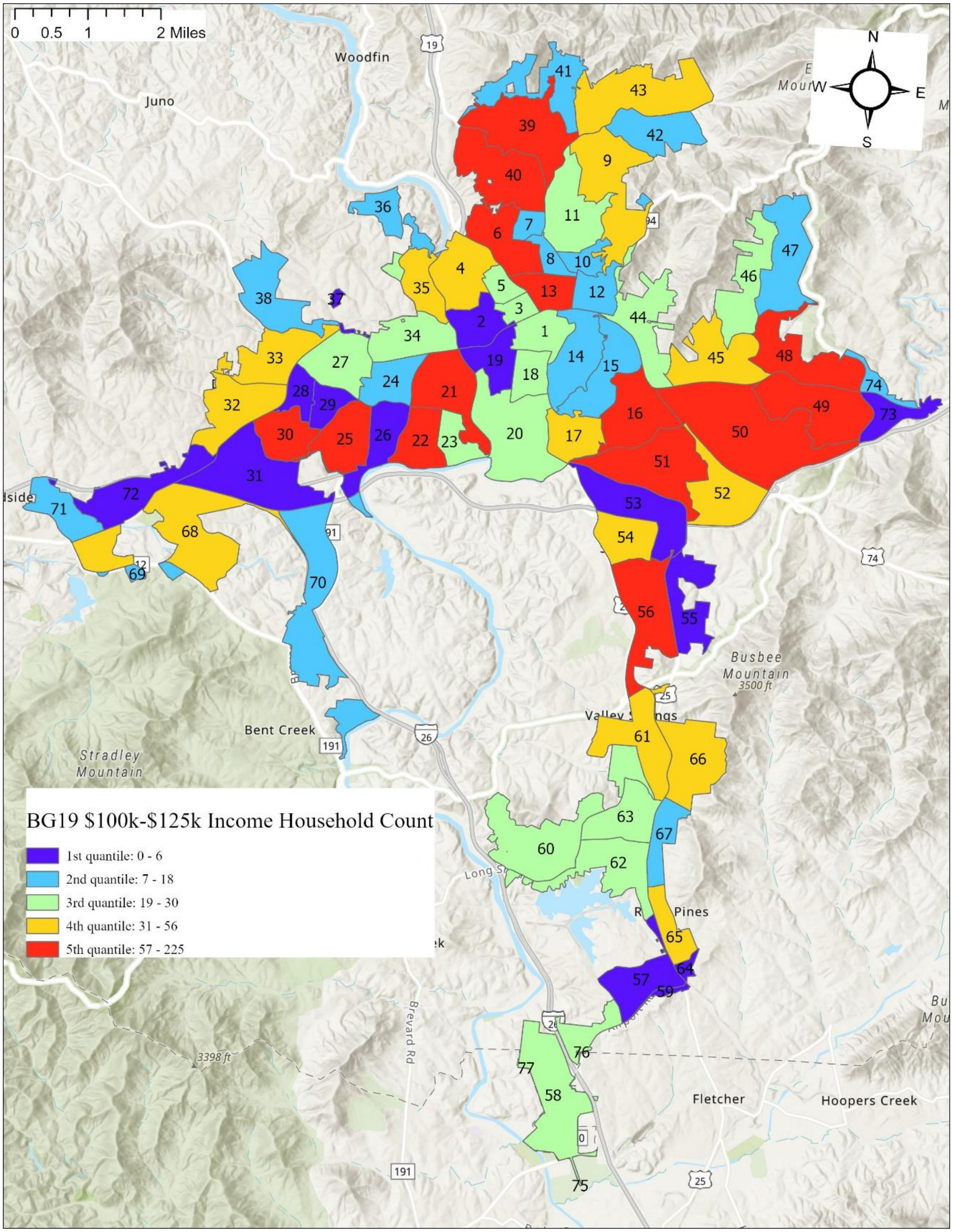

Figure A.17: Income Range $100,000 to $125,000 Household Counts by BG19

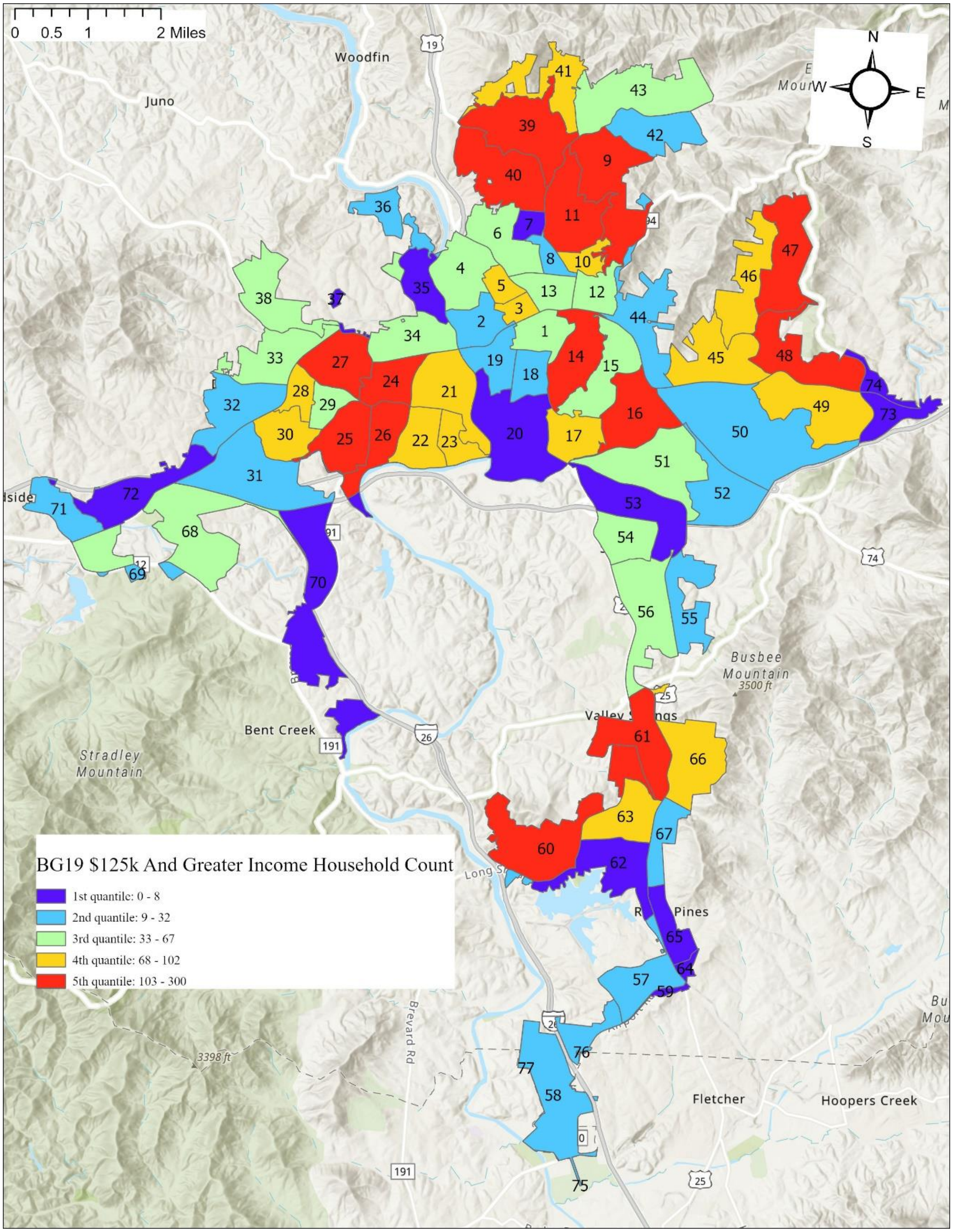

Figure A.18: Income Range $125,000+ Household Counts by BG19

Poverty Status Data

Table A.5 provides the number of households of each BG19 that are within and outside the poverty limit [52]. Figure A.19 shows the distribution of poverty throughout Asheville.

Table A.5: Poverty Household Counts by BG19

GEOID	Poverty	No Poverty
370210001001	10	112
370210002001	50	105
370210002002	0	130
370210003001	65	161
370210003002	13	196
370210004001	12	190
370210004002	0	140
370210004003	0	117
370210005001	0	264
370210005002	0	129
370210005003	10	395
370210006001	46	92
370210006002	17	177
370210007001	38	200
370210008001	0	196
370210008002	0	374
370210008003	10	221
370210009001	0	61
370210009002	7	78
370210009003	138	174
370210010001	41	299
370210010002	94	341
370210010003	9	181
370210011001	49	286
370210011002	40	459
370210011003	0	432
370210012001	0	300
370210012002	0	123
370210012003	0	138
370210012004	0	353
370210012005	10	181
370210013001	29	323
370210013002	136	329
370210014001	0	225
370210014002	16	217
370210014003	3	46
370210014004	1	11
370210014005	0	270
370210016001	0	405

GEOID	Poverty	No Poverty
370210016002	0	460
370210016003	9	103
370210017001	8	56
370210017002	5	128
370210018011	0	106
370210018012	14	227
370210018021	0	204
370210018022	14	214
370210018023	7	380
370210019001	54	435
370210019002	43	232
370210020001	19	541
370210020002	27	177
370210020003	0	60
370210020004	31	269
370210021011	0	7
370210021021	13	122
370210021022	158	322
370210022031	34	40
370210022032	0	161
370210022033	2	12
370210022041	0	304
370210022042	34	718
370210022043	0	82
370210022044	0	142
370210022051	1	19
370210022053	0	201
370210022061	0	163
370210022062	9	122
370210023021	12	316
370210023022	1	25
370210023024	0	61
370210025052	3	158
370210025061	39	123
370210030011	1	15
370210030014	9	52
370899306001	1	10
370899306002	0	59
370899307011	2	17

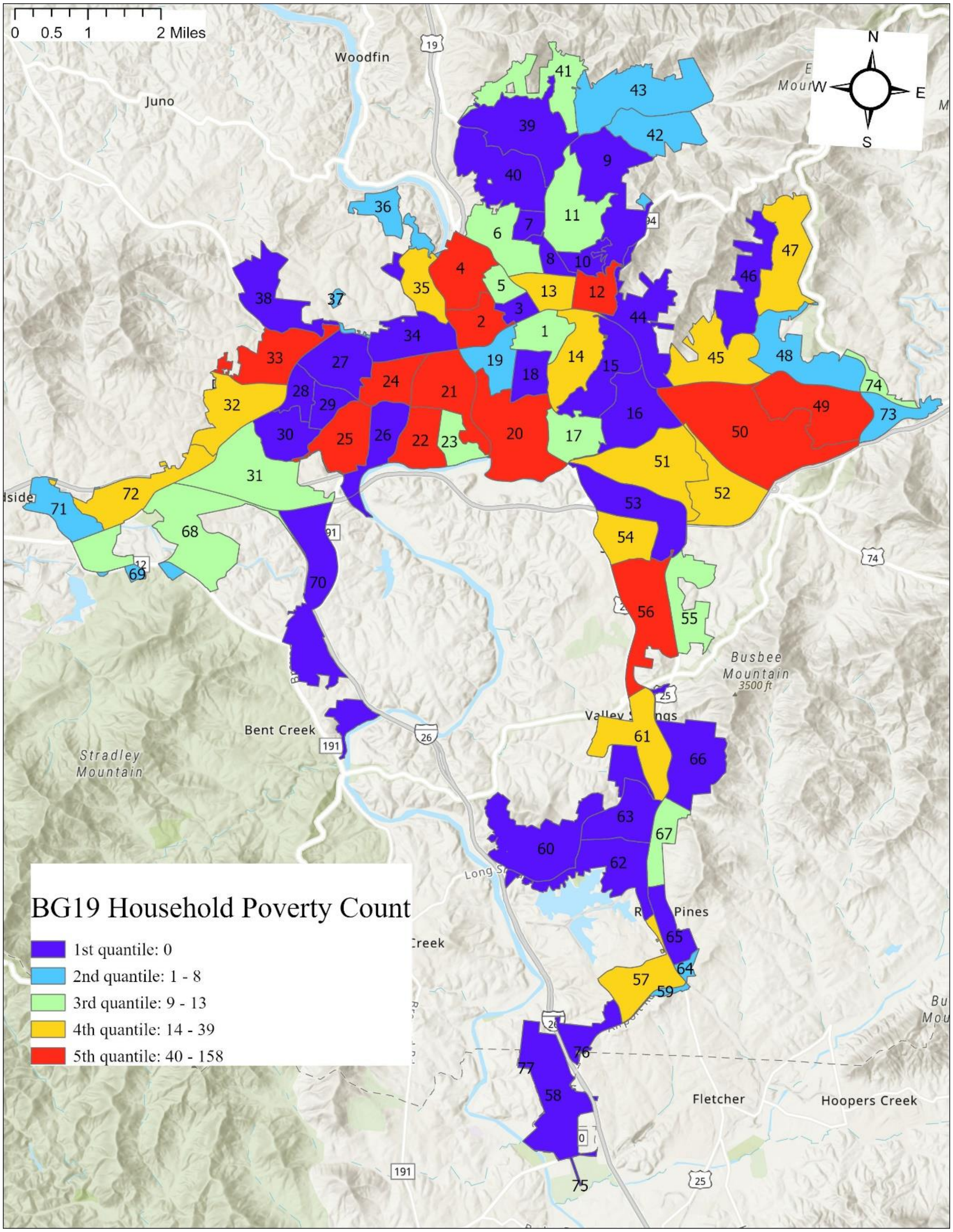

Figure A.19: Household Poverty Counts by BG19

Public Assistance Status Data

Table A.6 provides the number of households of each BG19 that are (and are not) receiving public assistance, such as food stamps [54]. Figure A.20 shows the distribution of poverty throughout Asheville.

Table A.6: Public Assistance Household Counts by BG19

GEOID	Assistance	No Assist
370210001001	178	580
370210002001	62	247
370210002002	34	306
370210003001	90	503
370210003002	0	365
370210004001	64	499
370210004002	0	315
370210004003	52	334
370210005001	8	456
370210005002	30	322
370210005003	6	752
370210006001	25	344
370210006002	26	589
370210007001	93	667
370210008001	52	340
370210008002	0	652
370210008003	34	491
370210009001	35	187
370210009002	131	308
370210009003	283	370
370210010001	107	671
370210010002	197	500
370210010003	36	328
370210011001	118	592
370210011002	16	825
370210011003	29	760
370210012001	13	429
370210012002	7	288
370210012003	0	285
370210012004	63	607
370210012005	37	267
370210013001	56	520
370210013002	204	487
370210014001	35	402
370210014002	133	404
370210014003	0	93
370210014004	4	28
370210014005	54	427
370210016001	49	535

GEOID	Assistance	No Assist
370210016002	50	708
370210016003	8	210
370210017001	4	101
370210017002	13	183
370210018011	47	318
370210018012	29	678
370210018021	8	287
370210018022	0	299
370210018023	28	886
370210019001	70	934
370210019002	35	768
370210020001	351	950
370210020002	85	661
370210020003	19	131
370210020004	133	601
370210021011	0	9
370210021021	46	213
370210021022	235	725
370210022031	11	239
370210022032	38	274
370210022033	3	20
370210022041	8	443
370210022042	13	2017
370210022043	56	153
370210022044	0	543
370210022051	2	25
370210022053	23	317
370210022061	11	267
370210022062	14	261
370210023021	40	476
370210023022	1	39
370210023024	16	109
370210025052	7	197
370210025061	32	247
370210030011	3	29
370210030014	9	114
370899306001	0	17
370899306002	3	95
370899307011	4	19

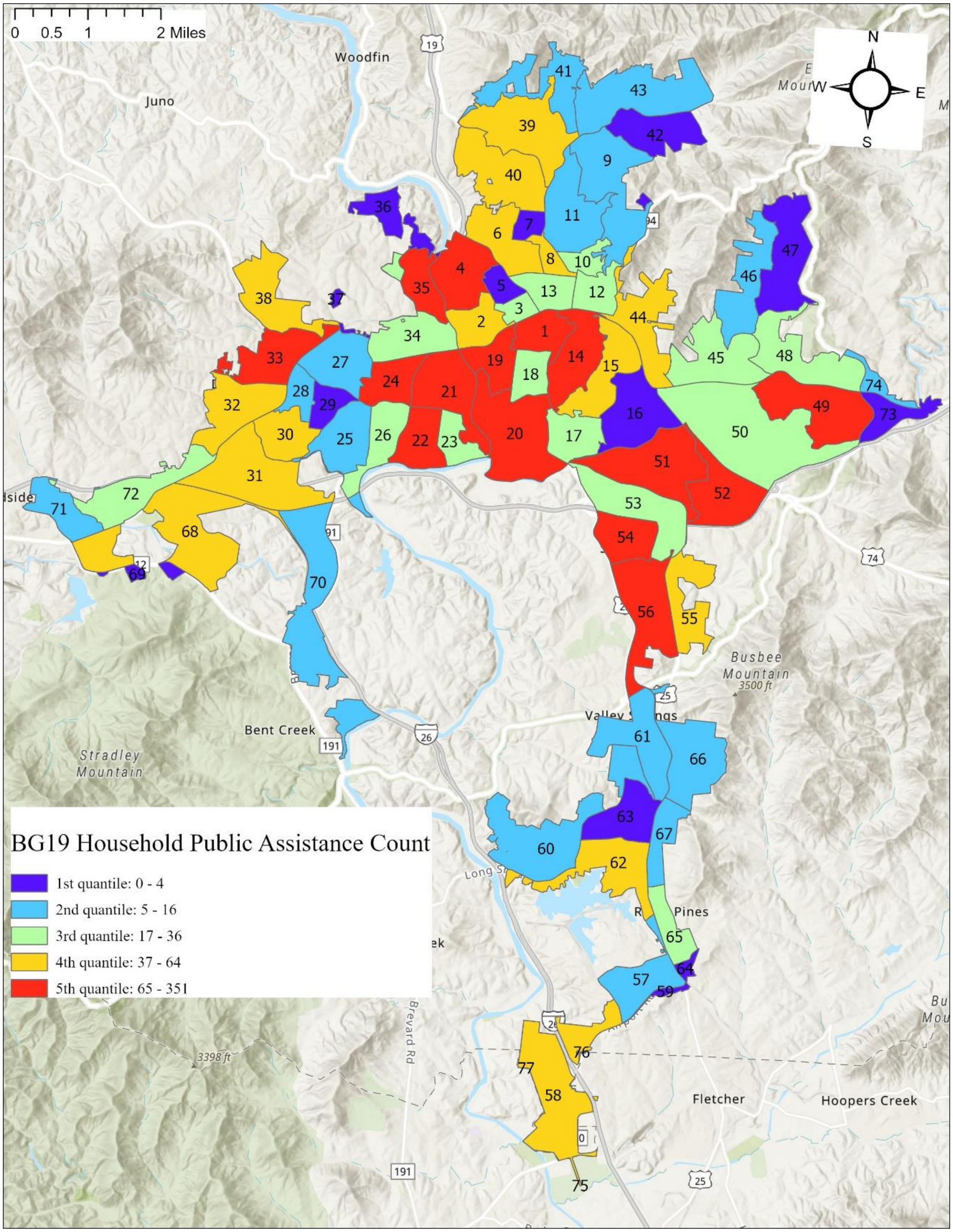

Figure A.20: Household Public Assistance Counts by BG19

Disability Demographic Data

Table A.7 provides the number of noninstitutionalized individuals with (and without) a disability for each BG19 [55]. Figure A.21 shows the disability distribution throughout Asheville.

Table A.7: Disability Population Counts by BG19

GEOID	Disability	No Disable
370210001001	262	680
370210002001	119	889
370210002002	47	347
370210003001	191	1623
370210003002	54	457
370210004001	225	2025
370210004002	54	490
370210004003	58	523
370210005001	111	1620
370210005002	20	287
370210005003	80	1170
370210006001	53	873
370210006002	54	891
370210007001	163	1442
370210008001	114	1091
370210008002	132	1262
370210008003	77	735
370210009001	92	358
370210009002	119	467
370210009003	353	1382
370210010001	242	2158
370210010002	151	1348
370210010003	91	810
370210011001	208	1344
370210011002	289	1863
370210011003	232	1495
370210012001	165	834
370210012002	63	320
370210012003	66	332
370210012004	126	637
370210012005	317	1604
370210013001	261	1285
370210013002	241	1182
370210014001	124	813
370210014002	74	489
370210014003	69	456
370210014004	10	64
370210014005	131	863
370210016001	99	775
370210016002	90	706
370210016003	68	535
370210017001	17	217
370210017002	33	406
370210018011	136	627
370210018012	149	689
370210018021	104	838
370210018022	122	991
370210018023	120	970
370210019001	165	971
370210019002	335	1974
370210020001	257	1920
370210020002	174	1301
370210020003	200	1495
370210020004	114	852
370210021011	2	20
370210021021	110	843
370210021022	179	1374
370210022031	66	317
370210022032	164	784
370210022033	6	27
370210022041	196	1574
370210022042	115	921
370210022043	112	898
370210022044	85	684
370210022051	9	92
370210022053	47	483
370210022061	114	637
370210022062	47	262
370210023021	61	463
370210023022	4	33
370210023024	60	450
370210025052	62	319
370210025061	114	444
370210030011	15	91
370210030014	7	44
370899306001	4	32
370899306002	25	224
370899307011	6	41

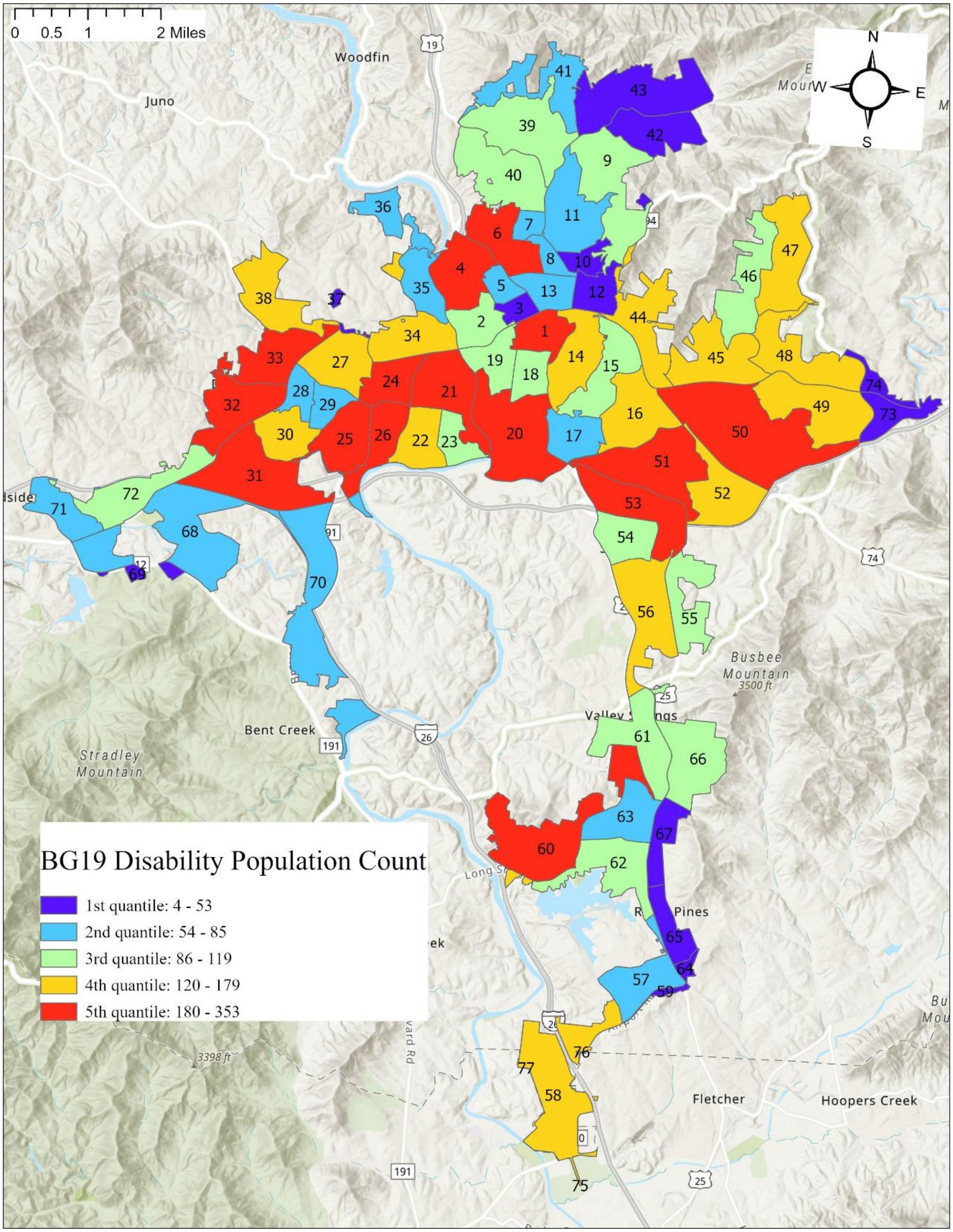

Figure A.21: Disability Population Counts by BG19

Appendix B

Additional Park Data and Visualization

Existing Park Amenities

Table B.1 is a table translation from Asheville Parksmap [70] that provides the amenities offered at each listed park. Within the matrix, 1 indicates that the amenity exists at that park while 0 reflects that the amenity is absent. When no information is provided about a park, the value is listed as not applicable.

Table B.1: Amenities of Listed Existing Parks in Asheville

Name	Athletic Field	Baseball Field	Basketball Court	Benches	Dog Park	Loop Walk	Multi-Use Trail/	Open Play Area	Picnic Tables	Playground	Pool	Recreation Center	Tennis Court	Volleyball Court
Albemarle Park	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Amboy Riverfront Park	0	0	0	1	0	0	1	1	0	0	0	0	0	0
Ann Patton Joyce Park	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Asheville Municipal Golf Course	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Aston Park and Tennis Center	0	0	1	1	0	0	1	1	1	1	0	0	1	0
Azalea Park	1	0	0	1	1	0	0	0	1	1	0	0	0	0
Burton Street Center	0	0	1	1	0	0	0	1	1	1	0	1	0	0
Carrier Park	0	0	1	1	0	1	1	1	1	1	0	0	0	1
Charlie Bullman Park	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Choctaw Street Park	0	0	0	1	0	0	0	1	0	0	0	0	0	0
Dr. Wesley Grand Sr. Southside Center	0	0	0	0	0	0	0	1	0	0	0	1	0	0
E.W. Grove Park	0	0	0	1	0	1	0	1	0	0	0	0	0	0
East Asheville Center	0	0	1	1	0	0	0	1	1	1	0	0	0	0
Falconhurst Park	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Forest Park	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
French Broad River Park	0	0	0	1	1	1	1	1	1	1	0	0	0	0
Grace's Garden	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a

Name	Athletic Field	Baseball Field	Basketball Court	Benches	Dog Park	Loop Walk	Multi-Use Trail/ Greenway	Open Play Area	Picnic Tables	Playground	Pool	Recreation Center	Tennis Court	Volleyball Court
Griffing Boulevard Rose Garden	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Harvest House Recreation Center	0	0	0	0	0	0	0	0	1	0	0	1	0	0
Haw Creek Park	0	0	0	1	0	1	0	0	1	0	0	0	0	0
Herb Watts Park	0	0	0	1	0	0	0	0	1	1	0	0	0	0
Hummingbird Park	0	0	0	1	0	0	0	1	0	0	0	0	0	0
Irby Brinson Complex	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Jake Rusher Park	0	0	0	1	0	1	0	1	1	1	0	0	0	0
Jean Webb Park	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Kenilworth Park	1	0	1	1	0	0	0	0	1	1	0	0	1	0
Leah Chiles Park	0	0	1	1	0	0	0	1	1	1	0	0	0	0
Lynwood Crump Shiloh Complex	0	1	1	1	0	1	0	0	1	1	0	1	0	0
Magnolia Park	0	0	1	1	0	1	0	1	1	1	0	0	0	0
Malvern Hills Pool and Park	0	0	0	1	0	0	1	1	1	1	1	0	1	0
Martin Luther King Jr. Park	0	1	0	1	0	0	0	0	1	1	0	0	0	0
Masters Park	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
McCormick Field	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Meadow Park	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Memorial Stadium	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Montford Park	0	0	1	1	0	0	0	1	0	0	0	0	1	0
Mountainside Park	0	0	0	0	0	0	0	1	1	1	0	0	0	0
Murphy-Oakley Park	0	1	1	1	0	0	0	0	1	1	0	1	1	0
Murray Hill Park	0	0	0	1	0	1	0	1	1	0	0	0	0	0
North Asheville Community Center	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Oakhurst Park	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Owens-Bell Park	0	0	0	1	0	1	0	0	0	0	0	0	0	0
Pack Square Park	0	0	0	1	0	0	1	1	0	0	0	0	0	0
Pritchard Park	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Ray L. Kisiah Park	0	1	0	1	0	0	0	0	1	0	0	0	0	0
Recreation Park and Pool	0	0	1	1	0	0	0	1	1	1	1	0	0	0
Richmond Hill Park	0	0	0	1	0	0	1	0	0	0	0	0	0	0
Riverbend Park	0	0	0	1	0	0	1	1	1	0	0	0	0	0
Riverside Cemetery	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Roger Farmer Memorial Park	0	1	1	1	0	0	0	0	1	0	0	0	0	0
Senior Opportunity Center	0	0	0	0	0	0	0	0	0	0	0	1	0	0

Name	Athletic Field	Baseball Field	Basketball Court	Benches	Dog Park	Loop Walk	Multi-Use Trail/ Greenway	Open Play Area	Picnic Tables	Playground	Pool	Recreation Center	Tennis Court	Volleyball Court
Seven Springs Park	0	0	0	1	0	0	1	0	1	0	0	0	0	0
Skate Park	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Stephens-Lee Recreation Center	0	0	1	1	0	0	1	0	1	1	0	1	0	0
Sunset Park	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Tempie Avery Montford Complex	0	0	1	1	0	0	0	0	1	1	0	0	0	0
Triangle Park	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Walton Street Park and Pool	0	1	1	1	0	0	0	0	1	1	1	0	0	0
Weaver Park	0	1	1	1	0	1	0	1	1	1	0	0	0	0
West Asheville Community Center	0	0	1	1	0	0	0	0	0	1	0	0	0	0
West Asheville Park	0	1	0	1	0	0	0	1	1	1	0	0	0	0
White Fawn Park	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
White Pine Park	0	0	0	0	0	0	0	1	1	0	0	0	0	0
WNC Nature Center	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a

Candidate Park Costs

Table B.2 lists the average unit cost per acre for each price zone.

Table B.2: Price Zone Land Unit Cost

Zone	Cost ($/acre)
1	65331.46
2	35678.18
3	60684.43
4	51136.45
5	16855.14
6	111782.59
7	39966.77
8	61116.47
9	64116.54
10	22896.38
11	40837.51
12	35524.54
13	47442.32

Table B.3 provides the price for each candidate park as well as whether the park cost is exact or estimated.

Table B.3: Candidate Park Cost

Park	Cost	Exact?
Candidate1	$21,926.12	Y
Candidate2	$60,010.04	Y
Candidate3	$67,865.84	Y
Candidate4	$153,157.60	Y
Candidate5	$265,800.00	N
Candidate6	$75,200.00	N
Candidate7	$143,300.00	N
Candidate8	$190,439.40	Y
Candidate9	$175,908.33	Y
Candidate10	$26,500.00	N
Candidate11	$198,100.00	N
Candidate12	$54,000.00	N
Candidate13	$304,624.69	Y
Candidate14	$43,800.00	N
Candidate15	$35,000.00	N
Candidate16	$82,900.00	N
Candidate17	$81,905.72	Y
Candidate18	$136,100.00	N
Candidate19	$66,300.00	N
Candidate20	$85,277.14	Y
Candidate21	$77,100.00	N
Candidate22	$126,600.00	N
Candidate23	$67,213.44	Y
Candidate24	$78,002.49	Y
Candidate25	$140,528.52	Y
Candidate26	$37,900.00	N
Candidate27	$489,497.24	Y
Candidate28	$704,233.94	Y
Candidate29	$97,190.23	Y
Candidate30	$88,352.63	Y
Candidate31	$57,900.00	N
Candidate32	$66,527.28	Y
Candidate33	$0.00	N
Candidate34	$0.00	N
Candidate35	$236,021.70	Y
Candidate36	$235,300.00	N
Candidate37	$66,800.00	N
Candidate38	$60,000.00	N
Candidate39	$42,100.00	N
Candidate40	$66,715.66	Y
Candidate41	$46,475.51	Y
Candidate42	$100,468.23	Y
Candidate43	$171,600.00	N
Candidate44	$245,700.00	N
Candidate45	$267,859.93	Y
Candidate46	$116,376.94	Y
Candidate47	$111,937.44	Y
Candidate48	$71,915.00	Y
Candidate49	$46,502.82	Y
Candidate50	$0.00	Y
Candidate51	$65,100.00	N
Candidate52	$455,827.93	Y
Candidate53	$32,900.00	N
Candidate54	$194,000.00	N
Candidate55	$103,447.85	Y
Candidate56	$179,574.93	Y
Candidate57	$63,236.11	Y
Candidate58	$87,600.00	N
Candidate59	$66,816.10	Y
Candidate60	$33,932.91	Y
Candidate61	$105,000.00	N
Candidate62	$55,800.00	N
Candidate63	$51,600.00	N
Candidate64	$64,500.00	N
Candidate65	$50,400.00	N
Candidate66	$111,294.19	Y
Candidate67	$86,900.00	N
Candidate68	$1,021,528.39	Y
Candidate69	$962,700.00	N
Candidate70	$55,527.84	Y
Candidate71	$61,400.00	N
Candidate72	$4,300.00	N
Candidate73	$49,900.00	N
Candidate74	$403,642.20	Y
Candidate75	$33,900.00	N
Candidate76	$124,900.00	N
Candidate77	$42,000.00	N
Candidate78	$100,000.00	N
Candidate79	$98,361.34	Y
Candidate80	$77,118.32	Y
Candidate81	$77,400.00	N
Candidate82	$80,215.24	Y
Candidate83	$43,363.58	Y
Candidate84	$247,400.00	N
Candidate85	$89,275.51	Y
Candidate86	$94,600.00	N

Park	Cost	Exact?
Candidate87	$43,300.00	N
Candidate88	$109,780.92	Y
Candidate89	$52,800.00	N
Candidate90	$135,604.45	Y
Candidate91	$0.00	Y
Candidate92	$91,725.30	Y
Candidate93	$123,442.41	Y
Candidate94	$40,600.00	N
Candidate95	$82,400.00	N
Candidate96	$68,704.63	Y
Candidate97	$102,400.00	N
Candidate98	$63,400.00	N
Candidate99	$745,317.99	Y
Candidate100	$70,900.00	N
Candidate101	$41,307.01	Y
Candidate102	$73,600.00	N
Candidate103	$31,274.15	Y
Candidate104	$54,517.91	Y
Candidate105	$52,900.00	N
Candidate106	$295,191.44	Y
Candidate107	$211,000.00	N
Candidate108	$25,000.00	N
Candidate109	$35,696.77	Y
Candidate110	$152,800.00	N
Candidate111	$87,755.88	Y
Candidate112	$160,220.96	Y

Park	Cost	Exact?
Candidate113	$45,700.00	N
Candidate114	$190,200.00	N
Candidate115	$32,300.00	N
Candidate116	$70,000.00	N
Candidate117	$74,000.00	N
Candidate118	$20,000.00	N
Candidate119	$50,900.00	N
Candidate120	$38,888.36	Y
Candidate121	$0.00	Y
Candidate122	$54,486.25	Y
Candidate123	$135,271.81	Y
Candidate124	$206,679.19	Y
Candidate125	$62,419.43	Y
Candidate126	$298,398.87	Y
Candidate127	$90,700.00	N
Candidate128	$105,700.00	N
Candidate129	$19,200.00	N
Candidate130	$71,015.09	Y
Candidate131	$1,002,672.06	Y
Candidate132	$133,300.00	N
Candidate133	$133,030.66	Y
Candidate134	$87,400.00	N
Candidate135	$74,100.00	N
Candidate136	$149,500.00	N
Candidate137	$90,800.00	N
Candidate138	$53,200.00	N

Resident to Park Distances

Table B.4 provides the distance matrix from residents to parks as calculated along the network including pedestrian and bicycle paths.

Table B.4: Distance Matrix using Pedestrian and Bicycle Paths

Park\Location	BG370210001001	BG370210002001	BG370210002002	BG370210003001	BG370210003002	BG370210004001	BG370210004002	BG370210004003	BG370210005001	BG370210005002	BG370210005003	BG370210006001	BG370210006002	BG370210007001	BG370210008001	BG370210008002	BG370210008003	BG370210009001	BG370210009002	BG370210009003	BG370210010001
Albemarle Park	1.412	2.051	1.462	1.966	1.399	1.374	1.243	0.687	1.717	0.392	1.180	0.725	0.801	1.674	2.383	3.202	2.831	2.118	2.245	3.019	3.162
Amboy Riverfront Park	2.848	2.946	3.059	3.881	3.459	4.287	4.677	4.070	5.618	4.294	4.982	4.066	3.571	3.466	3.529	4.746	2.195	2.686	1.989	2.123	1.403
Ann Patton Joyce Park	4.150	5.188	4.617	5.593	4.906	5.566	5.340	4.700	5.865	4.540	5.328	4.137	4.327	4.011	3.015	2.712	3.850	4.684	4.984	4.716	5.901
Azalea Park	5.149	6.187	5.616	6.592	5.905	6.565	6.339	5.699	6.864	5.539	6.327	5.136	5.326	5.010	4.014	3.711	4.592	5.619	5.983	5.458	6.900
Burton Street Center	2.447	2.387	2.299	3.121	2.699	3.519	3.891	3.284	4.946	3.621	4.197	3.573	2.853	3.239	4.209	5.079	3.700	2.585	1.857	2.791	1.060
Carrier Park	2.920	2.988	3.131	3.953	3.531	4.359	4.749	4.142	5.690	4.366	5.054	4.138	3.643	3.562	4.106	5.323	2.772	2.904	2.061	2.701	1.321
Charlie Bullman Park	4.400	5.437	4.866	5.842	5.155	5.816	5.589	4.949	6.114	4.789	5.577	4.386	4.576	4.260	3.264	2.961	4.373	4.934	5.233	5.239	6.150
Choctaw Street Park	1.156	1.992	1.575	2.397	1.975	2.795	2.971	2.364	3.785	2.460	3.248	2.212	1.865	1.260	2.156	3.423	1.024	0.477	1.170	0.724	1.747
Dr. Wesley Grant Sr. Southside Center	1.487	1.936	1.636	2.458	2.036	2.856	3.232	2.625	4.100	2.775	3.537	2.573	2.194	1.575	2.514	3.781	1.381	0.771	0.770	0.486	1.396
E.W. Grove Park	1.459	2.098	1.509	2.013	1.446	1.169	1.038	0.632	1.406	0.240	0.975	0.981	0.848	1.721	2.430	3.249	2.878	2.165	2.292	3.066	3.209
East Asheville Center	3.564	4.601	4.030	5.006	4.320	4.980	4.754	4.113	5.278	3.954	4.741	3.550	3.740	3.424	2.428	2.125	3.434	4.098	4.397	4.300	5.314
Falconhurst Park	2.871	2.811	2.723	3.544	3.123	3.942	4.315	3.708	5.370	4.045	4.620	3.996	3.277	3.663	4.633	5.503	4.384	3.009	2.542	3.476	1.744
Forest Park	1.938	3.066	2.492	3.471	2.840	3.585	3.737	3.130	4.522	3.197	3.985	2.949	2.631	1.821	1.188	2.455	0.386	1.505	2.348	1.494	3.046
French Broad River Park	2.704	2.779	2.915	3.737	3.315	4.143	4.533	3.926	5.474	4.149	4.838	3.921	3.427	3.321	3.385	4.602	2.051	2.540	1.843	1.979	1.399
Haw Creek Park	3.751	4.789	4.218	5.194	4.507	5.167	4.941	4.301	5.466	4.141	4.929	3.738	3.928	3.612	2.616	2.313	3.622	4.285	4.585	4.488	5.502
Herb Watts Park	1.367	2.224	1.807	2.629	2.207	3.014	3.182	2.575	3.996	2.671	3.459	2.423	2.076	1.471	2.063	3.330	0.930	0.688	1.253	0.517	1.829
Hummingbird Park	0.526	0.703	0.065	1.099	0.465	1.352	1.708	1.101	2.801	1.476	2.013	1.437	0.602	1.374	2.255	3.166	2.140	1.122	1.044	1.950	1.961
Irby Brinson Complex	8.806	9.902	9.360	10.306	9.708	10.453	10.605	9.998	11.390	10.065	10.853	9.817	9.499	8.865	8.680	9.605	7.346	8.336	9.161	8.057	9.452
Jake Rusher Park	9.230	10.325	9.784	10.730	10.131	10.877	11.029	10.422	11.813	10.489	11.277	10.241	9.923	9.289	9.049	9.529	7.659	8.649	9.514	8.480	9.876
Jean Webb Park	1.324	1.062	1.535	2.077	1.789	2.600	3.119	2.546	4.094	2.770	3.458	2.542	2.047	1.966	2.976	4.063	2.288	1.308	0.702	1.379	0.976
Kenilworth Park	1.743	2.870	2.297	3.275	2.644	3.390	3.542	2.935	4.326	3.002	3.790	2.754	2.436	1.625	1.186	2.453	0.329	1.310	2.153	1.448	2.851
Leah Chiles Park	2.208	3.335	2.762	3.740	3.109	3.855	4.006	3.400	4.791	3.467	4.254	3.042	2.900	1.905	1.273	2.540	0.811	1.775	2.618	1.913	3.316
Lynwood Crump Shiloh Complex	3.889	4.984	4.443	5.389	4.790	5.536	5.687	5.081	6.472	5.148	5.936	4.900	4.581	3.948	3.746	4.502	2.412	3.402	4.244	3.139	4.661
Magnolia Park	0.785	0.941	0.373	0.908	0.200	1.043	1.537	0.980	2.701	1.434	1.880	1.415	0.580	1.634	2.515	3.425	2.400	1.395	1.421	2.327	2.339
Malvern Hills Pool and Park	4.148	4.087	3.999	4.821	4.399	5.219	5.592	4.985	6.646	5.322	5.897	5.273	4.554	4.861	5.871	6.779	5.170	4.203	3.360	4.294	2.520
Martin Luther King Jr. Park	0.608	1.736	1.101	2.120	1.449	2.085	1.954	1.314	2.479	1.154	1.942	0.871	0.940	0.600	1.308	2.309	1.864	1.151	1.423	2.052	2.340
Masters Park	5.257	6.295	5.724	6.700	6.013	6.673	6.447	5.807	6.972	5.647	6.435	5.244	5.434	5.118	4.122	3.818	5.231	5.791	6.090	6.097	7.008
Meadow Park	1.906	3.034	2.460	3.438	2.808	3.553	3.705	3.098	4.490	3.165	3.953	2.917	2.599	1.903	1.402	2.669	0.254	1.473	2.316	1.363	3.014
Montford Park	1.332	1.063	0.770	0.410	0.393	0.679	1.195	1.140	2.733	1.635	1.921	1.935	1.101	2.180	3.061	3.962	2.946	1.771	1.693	2.599	2.610
Mountainside Park	0.853	1.995	1.422	2.400	1.769	2.481	2.590	1.983	3.171	1.847	2.635	1.551	1.484	0.529	1.702	2.829	1.518	0.806	1.327	1.706	2.245
Murphy-Oakley Center Complex	3.921	5.047	4.475	5.452	4.822	5.509	5.378	4.738	5.903	4.578	5.366	4.047	4.364	3.921	2.925	2.622	2.461	3.482	4.307	3.202	4.737
Murray Hill Park	1.304	1.933	1.516	2.338	1.916	2.737	3.113	2.506	4.000	2.675	3.418	2.427	2.028	1.475	2.649	3.775	1.589	0.671	0.858	0.902	1.434
Oakhurst Park	0.686	1.814	1.240	2.219	1.588	2.333	2.485	1.878	3.213	1.889	2.677	1.641	1.379	0.689	1.862	2.989	1.142	0.563	1.145	1.426	2.063
Owens-Bell Park	0.789	1.417	1.000	1.822	1.400	2.228	2.618	2.011	3.559	2.234	2.923	2.006	1.512	1.431	2.441	3.527	1.992	0.773	0.070	1.345	0.988
Pack Square Park	0.231	1.396	0.823	1.801	1.170	1.850	1.955	1.291	2.557	1.233	2.021	1.042	0.831	0.760	1.516	2.525	1.737	0.963	1.090	1.926	2.007
Pritchard Park	0.069	1.127	0.570	1.532	0.917	1.750	1.929	1.322	2.865	1.540	2.234	1.312	0.823	0.917	1.798	2.833	1.683	0.663	0.790	1.696	1.708
Ray L. Kisiah Park	5.129	6.255	5.683	6.660	6.031	6.776	6.713	6.073	7.238	5.913	6.701	5.536	5.700	5.188	4.395	3.905	3.463	4.484	5.349	4.410	5.946
Recreation Park and Pool	4.613	5.714	5.080	6.098	5.428	6.061	5.931	5.291	6.455	5.131	5.919	4.599	4.916	4.474	3.478	3.174	4.056	5.083	5.446	4.922	6.364
Richmond Hill Park	3.603	2.694	3.205	2.721	3.029	2.615	3.138	3.427	4.676	3.978	3.863	4.319	3.484	4.395	5.365	6.234	5.118	3.740	3.283	4.237	3.457
Riverbend Park	3.157	4.268	3.636	4.673	3.983	4.690	4.461	3.821	4.986	3.661	4.449	3.436	3.448	3.244	2.006	1.702	2.347	3.685	4.015	3.512	4.938
Roger Farmer Memorial Park	3.755	3.695	3.607	4.429	4.007	4.827	5.199	4.593	6.254	4.929	5.505	4.881	4.161	4.547	5.517	6.387	5.301	3.893	3.435	4.393	2.625
Seven Springs Park	1.904	3.031	2.458	3.436	2.805	3.551	3.702	3.095	4.487	3.162	3.950	2.915	2.596	1.963	1.455	2.722	0.252	1.471	2.314	1.353	3.012
Stephens-Lee Recreation Center	0.391	1.557	0.983	1.962	1.331	2.011	2.081	1.440	2.605	1.281	2.068	1.033	1.002	0.562	1.460	2.554	1.630	0.917	1.199	1.818	2.117
Sunset Park	1.458	2.097	1.508	2.012	1.446	1.350	1.219	0.734	1.478	0.279	1.156	0.981	0.848	1.720	2.429	3.248	2.877	2.164	2.291	3.065	3.209
Tempie Avery Montford Complex	1.038	0.578	0.511	0.770	0.482	1.293	1.812	1.435	3.156	1.870	2.335	1.831	0.996	1.886	2.767	3.738	2.652	1.438	1.360	2.266	2.126
Triangle Park	0.282	1.447	0.874	1.852	1.221	1.910	2.019	1.412	2.796	1.471	2.204	1.243	0.913	0.588	1.599	2.725	1.512	0.800	1.005	1.701	1.922
Walton Street Park and Pool	1.784	2.239	1.995	2.817	2.395	3.215	3.613	3.006	4.443	3.118	3.906	2.870	2.507	1.918	2.545	3.812	1.199	1.115	1.073	0.204	1.649
Weaver Park	1.586	2.050	1.483	1.728	1.307	0.662	0.462	0.391	1.566	0.791	0.754	1.358	0.887	2.120	2.828	3.622	3.176	2.287	2.376	3.282	3.293
West Asheville Community Center	3.367	3.306	3.218	4.040	3.618	4.438	4.810	4.204	5.865	4.540	5.116	4.492	3.773	4.158	5.128	5.998	4.534	3.504	2.692	3.626	1.895
West Asheville Park	3.581	3.453	3.639	4.460	4.039	4.858	5.231	4.624	6.286	4.961	5.536	4.798	4.193	4.223	5.233	6.319	4.516	3.565	2.722	3.656	1.924
White Fawn Park	1.556	2.722	2.148	3.126	2.496	3.184	3.293	2.687	3.875	2.550	3.338	2.165	2.188	0.948	1.551	2.818	0.903	1.246	2.067	1.384	2.832
White Pine Park	2.581	3.682	3.048	4.066	3.395	4.029	3.898	3.258	4.423	3.098	3.886	2.567	2.884	2.441	1.445	0.184	2.598	3.115	3.414	3.573	4.331
Candidate1	8.207	8.147	8.059	8.881	8.459	9.279	9.651	9.044	10.706	9.381	9.957	9.333	8.613	8.999	9.969	10.839	9.172	8.345	7.723	8.657	6.926
Candidate2	1.532	1.471	1.384	2.205	1.784	2.603	2.976	2.369	4.031	2.706	3.281	2.657	1.938	2.324	3.294	4.164	2.889	1.670	1.212	2.377	1.410
Candidate3	4.211	4.675	4.108	4.317	3.932	3.243	2.885	3.166	2.900	3.603	2.568	4.168	3.511	4.904	5.613	6.432	5.801	4.912	5.001	5.907	5.918
Candidate4	2.050	3.151	2.517	3.535	2.865	3.498	3.368	2.727	3.892	2.568	3.355	2.036	2.353	2.153	1.416	1.997	2.720	2.756	2.883	3.657	3.801
Candidate5	9.022	10.100	9.575	10.522	9.923	10.669	10.820	10.213	11.605	10.280	11.068	10.032	9.714	9.081	8.895	9.821	7.561	8.551	9.140	8.272	8.965
Candidate6	3.231	3.104	3.169	3.991	3.569	4.389	4.761	4.154	5.816	4.491	5.067	4.443	3.723	3.873	4.883	5.949	4.215	3.215	2.373	3.306	1.575
Candidate7	3.384	4.114	3.524	3.957	3.462	2.883	2.553	2.609	1.044	2.012	1.671	2.336	2.864	3.488	4.121	4.892	4.804	4.091	4.218	4.992	5.135
Candidate8	3.493	4.531	3.960	4.936	4.249	4.909	4.683	4.043	5.208	3.883	4.671	3.479	3.670	3.354	2.358	2.054	2.978	4.005	4.326	3.844	5.244
Candidate9	1.301	2.185	1.572	2.372	1.665	2.090	1.959	1.347	1.920	1.155	1.943	0.253	0.983	1.404	2.037	2.808	2.720	2.007	2.134	2.908	3.051
Candidate10	6.634	6.506	6.672	7.494	7.072	7.892	8.264	7.657	9.319	7.994	8.570	7.852	7.226	7.276	8.286	9.373	7.617	6.618	5.775	6.709	4.978
Candidate11	1.000	2.101	1.467	2.485	1.815	2.449	2.318	1.678	2.843	1.518	2.306	0.987	1.303	1.103	1.167	1.764	2.420	1.707	1.833	2.608	2.751
Candidate12	3.509	4.611	3.976	4.995	4.324	4.958	4.827	4.187	5.352	4.027	4.815	3.496	3.813	3.370	2.374	2.071	2.715	3.743	4.343	3.484	5.019

Park\Location	BG370210001001	BG370210002001	BG370210002002	BG370210003001	BG370210003002	BG370210004001	BG370210004002	BG370210004003	BG370210005001	BG370210005002	BG370210005003	BG370210006001	BG370210006002	BG370210007001	BG370210008001	BG370210008002	BG370210008003	BG370210009001	BG370210009002	BG370210009003	BG370210010001
Candidate13	7.324	7.263	7.176	7.997	7.576	8.395	8.768	8.161	9.823	8.498	9.073	8.449	7.730	8.116	9.086	9.956	8.682	7.462	6.840	7.774	6.042
Candidate14	3.469	3.341	3.507	4.329	3.907	4.727	5.099	4.492	6.154	4.829	5.404	4.687	4.061	4.111	5.121	6.208	4.338	3.453	2.610	3.544	1.812
Candidate15	3.812	3.752	3.664	4.485	4.064	4.883	5.256	4.649	6.311	4.986	5.561	4.937	4.218	4.604	5.574	6.444	5.461	3.950	3.492	4.727	3.070
Candidate16	4.915	4.840	4.779	5.600	5.179	5.998	6.371	5.764	7.426	6.101	6.676	6.052	5.333	5.445	6.292	7.559	4.958	4.791	3.925	4.890	3.085
Candidate17	4.465	5.503	4.932	5.908	5.221	5.882	5.655	5.015	6.180	4.855	5.643	4.452	4.642	4.326	3.330	3.027	4.308	4.999	5.299	5.173	6.216
Candidate18	3.697	4.734	4.164	5.139	4.453	5.113	4.887	4.247	5.411	4.087	4.875	3.683	3.873	3.558	2.561	2.258	3.044	4.071	4.530	3.910	5.448
Candidate19	6.518	6.391	6.556	7.378	6.956	7.776	8.149	7.542	9.204	7.879	8.454	7.736	7.111	7.160	8.171	9.257	7.502	6.503	5.660	6.594	4.862
Candidate20	1.424	2.589	2.016	2.994	2.363	3.043	2.957	2.317	3.482	2.157	2.945	1.674	1.943	1.193	0.526	1.634	1.831	1.867	2.206	2.767	3.123
Candidate21	3.274	4.401	3.828	4.805	4.176	4.921	5.073	4.466	5.858	4.533	5.321	4.285	3.967	3.333	3.148	4.023	1.814	2.835	3.661	2.556	4.091
Candidate22	3.328	4.455	3.882	4.860	4.230	4.975	5.127	4.520	5.912	4.587	5.375	4.339	4.021	3.387	3.202	2.938	1.868	2.889	3.715	2.610	4.145
Candidate23	6.152	7.190	6.619	7.595	6.908	7.568	7.342	6.702	7.867	6.542	7.330	6.139	6.329	6.013	5.017	4.713	6.126	6.686	6.985	6.992	7.903
Candidate24	5.160	5.624	5.057	5.266	4.881	4.192	3.834	4.115	3.610	4.375	3.279	4.426	4.460	5.577	6.210	6.981	6.750	5.860	5.950	6.856	6.867
Candidate25	3.029	2.968	2.880	3.702	3.280	3.977	4.473	3.866	5.527	4.203	4.778	4.154	3.435	3.820	4.791	5.660	4.678	3.166	2.709	3.944	2.551
Candidate26	2.315	1.406	1.917	1.332	1.641	1.227	1.749	2.039	3.287	2.590	2.474	2.930	2.095	3.107	4.077	4.946	3.830	2.452	1.995	2.949	2.289
Candidate27	4.481	4.946	4.378	4.587	4.203	3.513	3.156	3.437	2.932	3.697	2.600	3.747	3.782	4.899	5.531	6.303	6.072	5.182	5.271	6.177	6.189
Candidate28	1.684	2.849	2.275	3.254	2.623	3.303	3.217	2.577	3.742	2.417	3.205	1.934	2.203	0.945	1.489	2.616	1.287	1.631	2.345	1.768	3.171
Candidate29	3.982	3.911	3.655	2.969	3.278	2.864	2.656	2.937	2.736	3.374	2.404	3.939	3.282	4.675	5.384	6.203	5.572	4.624	4.507	5.452	4.794
Candidate30	2.906	3.962	3.373	4.367	3.680	4.340	4.114	3.474	4.639	3.314	4.102	2.892	3.101	2.767	1.771	1.467	2.924	3.440	3.739	3.898	4.657
Candidate31	1.584	2.468	1.855	2.655	1.948	2.373	2.242	1.630	1.716	1.438	2.226	0.536	1.266	1.687	2.320	3.091	3.003	2.290	2.417	3.191	3.334
Candidate32	3.723	4.084	3.620	3.142	3.444	2.755	2.397	2.679	2.478	3.115	2.145	3.681	3.024	4.417	5.125	5.945	5.313	4.424	4.513	5.419	4.967
Candidate33	4.543	4.483	4.395	5.216	4.795	5.615	5.987	5.380	7.042	5.717	6.292	5.668	4.949	5.335	6.305	7.175	6.037	4.681	4.195	5.129	3.398
Candidate34	6.160	7.255	6.713	7.660	7.061	7.806	7.958	7.351	8.743	7.418	8.206	7.170	6.852	6.219	6.033	6.062	4.699	5.689	6.515	5.410	6.805
Candidate35	1.282	2.447	1.874	2.852	2.221	2.901	2.815	2.175	3.340	2.015	2.803	1.532	1.801	1.051	0.770	1.897	2.075	1.725	2.064	2.625	2.981
Candidate36	4.289	4.754	4.186	4.395	4.010	3.321	2.964	3.245	2.739	3.505	2.408	4.118	3.590	4.857	5.566	6.385	5.879	4.990	5.079	5.985	5.997
Candidate37	4.362	4.302	4.214	5.036	4.614	5.434	5.806	5.199	6.861	5.536	6.112	5.488	4.768	5.154	6.124	6.994	6.012	4.500	4.042	5.183	3.452
Candidate38	3.409	4.447	3.876	4.851	4.165	4.825	4.599	3.959	5.124	3.799	4.587	3.395	3.586	3.270	2.274	1.970	2.894	3.921	4.242	3.760	5.160
Candidate39	4.109	4.574	4.006	4.215	3.830	3.141	2.784	3.065	2.559	3.325	2.228	3.938	3.410	4.677	5.386	6.205	5.699	4.810	4.899	5.805	5.817
Candidate40	3.231	4.326	3.785	4.731	4.133	4.878	5.030	4.423	5.815	4.490	5.278	4.242	3.924	3.290	3.105	4.221	1.771	2.761	3.586	2.482	4.003
Candidate41	2.703	2.643	2.555	3.377	2.955	3.652	4.147	3.540	5.202	3.877	4.452	3.828	3.109	3.495	4.465	5.335	4.352	2.841	2.383	3.618	2.226
Candidate42	2.396	3.281	2.668	3.467	2.761	3.185	3.055	2.442	1.640	1.956	2.351	1.348	2.079	2.500	3.133	3.904	3.816	3.103	3.230	4.004	4.147
Candidate43	3.604	4.667	4.071	5.072	4.386	5.046	4.820	4.179	5.344	4.020	4.807	3.590	3.806	3.465	2.468	2.165	2.819	3.846	4.437	3.685	5.274
Candidate44	3.165	3.009	2.754	2.068	2.376	1.962	2.449	2.774	3.233	3.325	2.836	3.665	2.831	3.950	4.822	5.692	4.772	3.723	3.606	4.550	3.893
Candidate45	8.540	9.635	9.094	10.040	9.442	10.187	10.339	9.732	11.124	9.799	10.587	9.551	9.233	8.599	8.414	9.228	7.080	8.070	8.895	7.790	9.186
Candidate46	6.025	7.063	6.492	7.468	6.781	7.441	7.215	6.575	7.740	6.415	7.203	6.012	6.202	5.886	4.890	4.586	5.867	6.559	6.858	6.733	7.776
Candidate47	4.952	4.892	4.804	5.626	5.204	6.024	6.396	5.789	7.451	6.126	6.701	6.077	5.358	5.744	6.714	7.584	6.419	5.090	4.577	5.511	3.779
Candidate48	4.106	4.571	4.003	4.212	3.827	3.138	2.780	3.062	2.556	3.322	2.225	3.935	3.407	4.674	5.383	6.202	5.696	4.807	4.896	5.802	5.814
Candidate49	3.448	4.574	4.002	4.979	4.350	5.095	5.247	4.640	6.032	4.707	5.495	4.459	4.141	3.507	3.322	3.057	1.988	3.009	3.834	2.729	4.265
Candidate50	2.277	1.854	1.747	1.710	1.517	2.303	2.820	2.470	4.191	2.949	3.370	3.004	2.170	3.126	4.006	4.976	3.891	2.678	2.599	3.505	3.497
Candidate51	3.993	4.458	3.890	3.694	3.714	3.025	2.668	2.949	2.748	3.385	2.415	3.951	3.294	4.687	5.395	6.215	5.583	4.694	4.783	5.689	5.518
Candidate52	4.924	4.864	4.776	5.598	5.176	5.996	6.368	5.761	7.423	6.098	6.674	6.050	5.330	5.716	6.686	7.556	6.282	5.062	4.440	5.374	3.643
Candidate53	5.107	6.202	5.661	6.607	6.009	6.754	6.906	6.299	7.691	6.366	7.154	6.118	5.800	5.166	4.981	5.774	3.647	4.637	5.462	4.357	5.753
Candidate54	4.686	5.812	5.240	6.217	5.587	6.333	6.485	5.878	7.269	5.945	6.733	5.697	5.379	4.745	4.560	4.518	3.226	4.247	5.072	3.967	5.503
Candidate55	5.165	5.629	5.062	5.271	4.886	4.197	3.839	4.120	3.615	4.380	3.284	4.431	4.465	5.582	6.215	6.986	6.755	5.866	5.955	6.861	6.872
Candidate56	5.828	5.740	5.680	6.502	6.080	6.900	7.272	6.665	8.327	7.002	7.578	6.953	6.234	6.446	7.294	8.460	5.960	5.792	4.826	5.791	3.986
Candidate57	3.160	4.286	3.714	4.691	4.061	4.807	4.958	4.352	5.743	4.419	5.206	4.171	3.852	3.219	3.034	3.909	1.699	2.721	3.546	2.441	3.976
Candidate58	2.581	3.682	3.047	4.066	3.395	4.029	3.898	3.258	4.278	3.098	3.886	2.567	2.884	2.683	1.946	2.528	3.251	3.287	3.414	4.188	4.331
Candidate59	5.457	5.922	5.354	5.563	5.179	4.489	4.132	4.413	3.908	4.673	3.576	4.723	4.758	5.875	6.507	7.279	7.047	6.158	6.247	7.153	7.165
Candidate60	6.803	6.676	6.841	7.663	7.241	8.061	8.434	7.827	9.488	8.164	8.739	8.021	7.396	7.445	8.455	9.542	7.787	6.787	5.945	6.878	5.147
Candidate61	7.355	8.450	7.909	8.855	8.256	9.002	9.153	8.546	9.938	8.613	9.401	8.366	8.047	7.414	7.228	8.127	5.894	6.884	7.710	6.605	8.000
Candidate62	4.550	5.377	4.809	5.018	4.634	3.944	3.587	3.868	2.923	3.891	3.031	3.502	4.213	4.653	5.286	6.057	5.969	5.256	5.383	6.157	6.300
Candidate63	6.296	7.334	6.763	7.739	7.052	7.712	7.486	6.846	8.011	6.686	7.474	6.283	6.473	6.157	5.161	4.857	6.270	6.830	7.129	7.135	8.047
Candidate64	2.381	3.342	2.925	3.747	3.283	4.028	4.180	3.573	4.965	3.640	4.428	3.392	3.074	2.440	2.776	3.993	1.442	1.790	2.225	1.098	2.389
Candidate65	4.836	5.873	5.302	6.278	5.591	6.252	6.025	5.385	6.550	5.225	6.013	4.822	5.012	4.696	3.700	3.397	4.809	5.369	5.669	5.675	6.586
Candidate66	2.951	3.835	3.223	4.022	3.315	3.740	3.554	2.997	1.860	2.510	2.571	1.903	2.633	3.054	3.687	4.458	4.370	3.657	3.784	4.558	4.701
Candidate67	3.336	4.373	3.802	4.778	4.092	4.752	4.526	3.885	5.050	3.725	4.513	3.322	3.512	3.196	2.200	1.897	3.309	3.870	4.169	4.175	5.086
Candidate68	2.612	3.714	3.079	4.097	3.427	4.061	3.930	3.290	4.455	3.130	3.918	2.599	2.915	2.715	1.978	2.560	3.283	3.319	3.445	4.220	4.363
Candidate69	5.651	5.563	5.503	6.325	5.903	6.723	7.095	6.488	8.150	6.825	7.401	6.776	6.057	6.269	7.117	8.283	5.783	5.615	4.649	5.614	3.809
Candidate70	8.250	9.346	8.804	9.750	9.152	9.897	10.049	9.442	10.834	9.509	10.297	9.261	8.943	8.310	8.124	9.050	6.790	7.780	8.605	7.501	8.896
Candidate71	8.508	9.603	9.062	10.008	9.409	10.155	10.306	9.700	11.091	9.767	10.555	9.519	9.201	8.567	8.382	9.280	7.048	8.037	8.863	7.758	9.153
Candidate72	8.125	9.220	8.679	9.625	9.027	9.772	9.924	9.317	10.709	9.384	10.172	9.136	8.818	8.184	7.999	8.425	6.665	7.655	8.480	7.375	8.771
Candidate73	4.358	4.298	4.210	5.032	4.610	5.430	5.802	5.196	6.857	5.532	6.108	5.484	4.764	5.150	6.120	6.990	6.008	4.496	4.038	5.273	3.616
Candidate74	5.563	6.600	6.030	7.005	6.319	6.979	6.753	6.113	7.277	5.953	6.741	5.549	5.739	5.424	4.427	4.124	5.536	6.097	6.396	6.402	7.314
Candidate75	6.722	7.760	7.189	8.165	7.478	8.138	7.912	7.272	8.437	7.112	7.900	6.709	6.899	6.583	5.587	5.283	6.696	7.256	7.555	7.562	8.473
Candidate76	6.193	7.231	6.660	7.636	6.949	7.609	7.383	6.743	7.908	6.583	7.371	6.180	6.370	6.054	5.058	4.754	6.167	6.727	7.026	7.032	7.944

Park\Location	BG370210001001	BG370210002001	BG370210002002	BG370210003001	BG370210003002	BG370210004001	BG370210004002	BG370210004003	BG370210005001	BG370210005002	BG370210005003	BG370210006001	BG370210006002	BG370210007001	BG370210008001	BG370210008002	BG370210008003	BG370210009001	BG370210009002	BG370210009003	BG370210010001
Candidate77	3.394	4.520	3.948	4.925	4.296	5.041	5.193	4.586	5.978	4.653	5.441	4.405	4.087	3.453	3.268	4.143	1.934	2.955	3.780	2.676	4.211
Candidate78	8.547	9.642	9.101	10.047	9.449	10.194	10.346	9.739	11.131	9.806	10.594	9.558	9.240	8.606	8.421	9.319	7.087	8.077	8.902	7.797	9.193
Candidate79	4.594	5.632	5.061	6.037	5.350	6.010	5.784	5.144	6.309	4.984	5.772	4.581	4.771	4.455	3.459	3.156	4.568	5.128	5.428	5.434	6.345
Candidate80	1.746	1.484	1.958	2.499	2.212	3.031	3.542	2.968	4.517	3.192	3.881	2.964	2.469	2.388	3.398	4.485	2.949	1.730	1.137	2.058	0.890
Candidate81	2.970	4.096	3.523	4.501	3.871	4.617	4.768	4.161	5.553	4.228	5.016	3.980	3.662	3.029	2.843	2.847	1.509	2.530	3.356	2.251	3.786
Candidate82	7.513	8.608	8.067	9.013	8.415	9.160	9.312	8.705	10.096	8.772	9.560	8.524	8.206	7.572	7.387	8.312	6.053	7.043	7.868	6.763	8.159
Candidate83	6.971	8.066	7.525	8.471	7.872	8.618	8.769	8.163	9.554	8.230	9.017	7.982	7.663	7.030	6.845	6.873	5.510	6.500	7.326	6.221	7.616
Candidate84	2.279	3.381	2.746	3.765	3.094	3.728	3.597	2.957	3.812	2.797	3.585	2.266	2.582	2.382	1.645	2.227	2.950	2.986	3.113	3.887	4.030
Candidate85	4.471	4.936	4.368	4.577	4.192	3.503	3.145	3.427	2.921	3.687	2.590	4.300	3.772	5.039	5.748	6.567	6.061	5.172	5.261	6.167	6.179
Candidate86	3.715	3.655	3.567	4.389	3.967	4.787	5.159	4.553	6.214	4.889	5.465	4.841	4.121	4.507	5.477	6.347	5.365	3.853	3.395	4.630	2.973
Candidate87	4.298	4.763	4.195	4.404	4.020	3.330	2.973	3.254	2.749	3.514	2.417	3.796	3.599	4.867	5.575	6.351	5.889	4.999	5.088	5.994	6.006
Candidate88	1.893	2.778	2.165	2.964	2.258	2.682	2.551	1.939	1.328	1.453	2.039	0.845	1.575	1.997	2.629	3.400	3.312	2.599	2.726	3.500	3.644
Candidate89	5.059	4.998	4.910	5.732	5.310	6.130	6.503	5.896	7.557	6.233	6.808	6.184	5.465	5.850	6.821	7.690	6.417	5.196	4.575	5.508	3.777
Candidate90	4.596	4.468	4.634	5.456	5.034	5.854	6.226	5.619	7.281	5.956	6.532	5.814	5.188	5.238	6.248	7.335	5.568	4.580	3.737	4.671	2.940
Candidate91	4.245	4.185	4.097	4.919	4.497	5.317	5.689	5.082	6.744	5.419	5.995	5.371	4.651	5.037	6.007	6.877	5.895	4.383	3.925	5.031	3.299
Candidate92	0.998	1.969	1.331	2.230	1.523	1.977	1.847	1.234	2.222	1.043	1.831	0.245	0.870	1.102	1.734	2.506	2.418	1.705	1.831	2.606	2.749
Candidate93	2.446	3.574	3.000	3.978	3.348	4.093	4.245	3.638	5.029	3.705	4.493	3.457	3.139	2.469	1.837	2.353	0.986	2.013	2.856	1.851	3.441
Candidate94	6.073	5.945	6.111	6.932	6.511	7.331	7.703	7.096	8.758	7.433	8.008	7.291	6.665	6.715	7.725	8.811	7.056	6.057	5.214	6.148	4.416
Candidate95	7.723	8.818	8.277	9.223	8.625	9.370	9.522	8.915	10.307	8.982	9.770	8.734	8.416	7.782	7.597	8.495	6.263	7.253	8.078	6.973	8.369
Candidate96	2.537	3.422	2.809	3.608	2.902	3.326	3.196	2.583	1.781	2.097	2.492	1.489	2.220	2.641	3.273	4.045	3.957	3.244	3.371	4.145	4.288
Candidate97	1.607	2.772	2.198	3.177	2.546	3.226	3.140	2.500	3.665	2.340	3.128	1.857	2.126	0.998	1.413	2.539	1.340	1.683	2.389	1.821	3.224
Candidate98	1.380	1.594	1.100	1.166	0.823	1.012	1.243	0.686	2.407	1.348	1.586	1.728	0.886	2.164	3.036	3.907	2.986	2.081	2.141	3.047	3.059
Candidate99	7.148	7.037	7.011	7.833	7.411	8.231	8.604	7.997	9.659	8.334	8.909	8.285	7.566	7.677	8.525	9.791	7.191	7.023	6.158	7.122	5.318
Candidate100	4.721	4.594	4.759	5.581	5.159	5.979	6.351	5.745	7.406	6.082	6.657	5.939	5.314	5.363	6.373	7.460	5.693	4.705	3.862	4.796	3.065
Candidate101	7.615	7.487	7.827	8.503	8.215	9.034	9.444	8.837	10.386	9.061	9.750	8.833	8.338	8.257	9.267	10.354	8.429	7.599	6.756	7.690	5.959
Candidate102	8.876	9.971	9.430	10.376	9.778	10.523	10.675	10.068	11.460	10.135	10.923	9.887	9.569	8.935	8.750	9.176	7.416	8.406	9.231	8.126	9.522
Candidate103	6.916	6.788	6.954	7.775	7.354	8.173	8.546	7.939	9.601	8.276	8.851	8.133	7.508	7.558	8.568	9.654	7.899	6.900	6.057	6.991	5.259
Candidate104	6.382	7.419	6.849	7.824	7.138	7.798	7.572	6.932	8.096	6.772	7.560	6.368	6.558	6.243	5.246	4.943	6.355	6.916	7.215	7.221	8.133
Candidate105	4.002	5.097	4.556	5.502	4.904	5.649	5.801	5.194	6.586	5.261	6.049	5.013	4.695	4.061	3.876	4.992	2.542	3.532	4.357	3.252	4.774
Candidate106	8.946	10.042	9.500	10.446	9.848	10.593	10.745	10.138	11.530	10.205	10.993	9.957	9.639	9.005	8.820	9.745	7.486	8.476	9.301	8.197	9.592
Candidate107	4.091	4.556	3.988	4.197	3.812	3.123	2.765	3.047	2.541	3.306	2.210	3.919	3.392	4.659	5.368	6.187	5.681	4.792	4.881	5.787	5.798
Candidate108	10.122	11.218	10.676	11.622	11.024	11.769	11.921	11.314	12.706	11.381	12.169	11.133	10.815	10.181	9.996	10.519	8.662	9.652	10.477	9.373	10.768
Candidate109	5.139	6.234	5.692	6.639	6.040	6.785	6.937	6.330	7.722	6.397	7.185	6.149	5.831	5.198	5.012	4.991	3.678	4.668	5.494	4.389	5.784
Candidate110	3.458	3.953	3.371	3.594	3.210	2.520	2.190	2.247	1.262	2.183	1.309	2.699	2.734	3.834	4.483	5.254	4.991	4.159	4.248	5.154	5.165
Candidate111	3.302	3.766	3.199	3.408	3.023	2.334	1.976	2.257	1.752	2.517	1.421	3.130	2.602	3.870	4.579	5.398	4.892	4.003	4.092	4.998	5.009
Candidate112	4.031	4.496	3.928	4.137	3.753	3.063	2.706	2.987	2.482	3.247	2.150	3.860	3.332	4.600	5.308	6.128	5.622	4.732	4.821	5.727	5.739
Candidate113	3.200	3.139	3.051	3.873	3.451	4.148	4.644	4.037	5.698	4.374	4.949	4.325	3.606	3.991	4.962	5.831	4.849	3.337	2.880	4.115	2.699
Candidate114	2.365	2.305	2.217	3.038	2.617	3.436	3.809	3.202	4.864	3.539	4.114	3.490	2.771	3.157	4.127	4.997	4.014	2.503	2.045	3.240	1.971
Candidate115	7.355	8.450	7.909	8.855	8.256	9.002	9.153	8.547	9.938	8.614	9.402	8.366	8.048	7.414	7.229	8.154	5.895	6.884	7.710	6.605	8.000
Candidate116	5.226	6.321	5.779	6.725	6.127	6.872	7.024	6.417	7.809	6.484	7.272	6.236	5.918	5.285	5.099	5.197	3.765	4.755	5.581	4.476	5.871
Candidate117	3.982	4.446	3.879	4.088	3.703	3.014	2.656	2.937	2.432	3.197	2.101	3.810	3.282	4.550	5.259	6.078	5.572	4.683	4.772	5.678	5.689
Candidate118	2.463	1.555	2.065	1.582	1.890	1.476	1.998	2.288	3.536	2.839	2.724	3.179	2.345	3.255	4.225	5.095	3.979	2.601	2.143	3.098	2.438
Candidate119	3.198	3.137	3.049	3.871	3.449	4.146	4.641	4.035	5.696	4.371	4.947	4.323	3.604	3.989	4.959	5.829	4.847	3.335	2.877	4.112	2.557
Candidate120	2.661	2.813	2.873	3.694	3.273	4.100	4.490	3.884	5.432	4.107	4.796	3.879	3.384	3.303	3.937	5.154	2.602	2.645	1.803	2.531	1.208
Candidate121	4.082	3.983	3.945	4.767	4.345	5.165	5.538	4.931	6.592	5.268	5.843	5.219	4.500	4.611	5.459	6.725	4.125	3.957	3.092	4.056	2.252
Candidate122	6.501	7.539	6.968	7.944	7.257	7.917	7.691	7.051	8.216	6.891	7.679	6.488	6.678	6.362	5.366	5.062	6.475	7.035	7.334	7.341	8.252
Candidate123	6.431	7.527	6.985	7.931	7.333	8.078	8.230	7.623	9.015	7.690	8.478	7.442	7.124	6.490	6.305	7.230	4.971	5.961	6.786	5.682	7.077
Candidate124	2.304	2.943	2.354	2.858	2.292	1.910	1.679	1.373	0.512	0.859	0.696	1.827	1.694	2.567	3.275	4.095	3.723	3.010	3.137	3.911	4.055
Candidate125	7.845	8.940	8.399	9.345	8.747	9.492	9.644	9.037	10.429	9.104	9.892	8.856	8.538	7.904	7.719	8.644	6.385	7.375	8.200	7.095	8.491
Candidate126	2.656	2.731	2.340	2.105	1.963	1.065	0.859	1.612	2.052	2.048	1.554	2.614	1.957	3.350	4.058	4.878	4.246	3.357	3.344	4.250	4.261
Candidate127	3.237	4.275	3.704	4.679	3.993	4.653	4.427	3.787	4.952	3.627	4.415	3.223	3.413	3.098	2.102	1.798	3.210	3.771	4.070	4.076	4.988
Candidate128	2.128	3.255	2.682	3.660	3.029	3.765	3.714	3.074	4.238	2.914	3.702	2.431	2.699	1.389	0.661	1.928	0.858	1.695	2.538	1.833	3.236
Candidate129	3.569	3.509	3.421	4.242	3.821	4.640	5.013	4.406	6.068	4.743	5.318	4.694	3.975	4.361	5.331	6.201	5.218	3.707	3.249	4.484	2.827
Candidate130	1.564	2.449	1.836	2.635	1.929	2.353	2.223	1.610	1.656	1.419	2.207	0.516	1.247	1.668	2.301	3.072	2.984	2.271	2.398	3.172	3.315
Candidate131	5.946	5.858	5.798	6.620	6.198	7.018	7.390	6.783	8.445	7.120	7.695	7.071	6.352	6.564	7.412	8.578	6.078	5.910	4.944	5.909	4.104
Candidate132	5.344	6.439	5.898	6.844	6.246	6.991	7.143	6.536	7.928	6.603	7.391	6.355	6.037	5.403	5.218	5.315	3.884	4.874	5.699	4.594	5.990
Candidate133	1.091	2.256	1.682	2.661	2.030	2.710	2.624	1.984	3.149	1.824	2.612	1.417	1.610	0.539	1.170	2.297	1.605	1.436	1.873	2.086	2.790
Candidate134	11.128	12.223	11.682	12.628	12.030	12.775	12.927	12.320	13.712	12.387	13.175	12.139	11.821	11.187	11.002	11.537	9.668	10.658	11.483	10.378	11.774
Candidate135	3.117	4.218	3.584	4.602	3.932	4.566	4.435	3.795	4.960	3.635	4.423	3.104	3.420	2.978	1.982	1.678	2.202	3.229	3.950	3.068	4.657
Candidate136	5.750	6.792	6.217	7.197	6.510	7.171	6.944	6.304	7.469	6.144	6.932	5.736	5.931	5.610	4.614	4.311	5.592	6.284	6.583	6.458	7.500
Candidate137	2.569	3.671	3.036	4.055	3.384	4.018	3.887	3.247	4.266	3.087	3.875	2.556	2.872	2.672	1.935	2.517	3.240	3.276	3.403	4.177	4.320
Candidate138	3.948	4.986	4.415	5.391	4.704	5.364	5.138	4.498	5.663	4.338	5.126	3.934	4.125	3.809	2.813	2.509	3.922	4.482	4.781	4.787	5.699

Park\Location	BG370210010002	BG370210010003	BG370210011001	BG370210011002	BG370210011003	BG370210012001	BG370210012002	BG370210012003	BG370210012004	BG370210012005	BG370210013001	BG370210013002	BG370210014001	BG370210014002	BG370210014003	BG370210014004	BG370210014005	BG370210016001	BG370210016002	BG370210016003	BG370210017001	BG370210017002
Albemarle Park	4.059	3.739	3.601	4.919	4.590	4.009	4.740	4.805	5.479	6.286	6.216	5.430	3.904	4.204	3.845	4.943	5.594	2.787	2.888	3.468	3.743	3.924
Amboy Riverfront Park	0.782	0.816	1.894	2.202	1.934	2.621	2.957	2.570	3.291	3.495	4.301	3.662	2.771	3.512	4.651	3.573	4.206	6.220	5.772	6.901	7.353	7.534
Ann Patton Joyce Park	5.985	5.513	6.454	7.743	7.137	6.863	7.594	7.659	8.332	9.015	9.070	8.284	6.758	6.949	7.637	7.793	8.448	7.011	7.113	7.692	7.452	8.199
Azalea Park	6.727	6.255	7.453	8.283	7.879	7.862	8.593	8.515	9.331	9.576	10.069	9.283	7.757	7.948	8.636	8.792	9.447	8.010	8.112	8.691	8.451	9.198
Burton Street Center	1.035	1.530	0.334	1.557	1.187	1.095	1.825	1.586	2.474	2.828	3.302	2.515	0.990	2.440	3.401	2.028	2.671	5.435	5.213	6.116	6.567	6.748
Carrier Park	0.427	0.998	1.536	1.706	1.579	2.263	2.602	2.215	2.796	3.000	3.904	3.307	2.452	3.404	4.569	3.218	3.848	6.292	5.814	6.973	7.425	7.606
Charlie Bullman Park	6.508	6.036	6.703	8.003	7.578	7.112	7.843	7.908	8.582	9.274	9.319	8.533	7.007	7.198	7.886	8.043	8.697	7.261	7.362	7.942	7.701	8.449
Choctaw Street Park	2.643	2.323	2.844	3.599	3.175	3.320	4.015	3.628	4.517	4.870	5.355	4.720	3.121	3.031	4.038	3.876	4.905	4.514	4.615	5.195	5.527	5.828
Dr. Wesley Grant Sr. Southside Center	2.242	1.922	2.417	3.206	2.782	2.825	3.654	3.266	4.155	4.509	5.004	4.359	2.720	2.660	3.644	3.505	4.818	4.775	4.762	5.456	5.889	6.089
E.W. Grove Park	4.105	3.785	3.736	5.054	4.637	4.145	4.875	4.941	5.614	6.333	6.352	5.565	4.040	4.042	3.682	5.078	5.729	2.582	2.683	3.263	3.538	3.719
East Asheville Center	5.569	5.097	5.868	7.167	6.721	6.276	7.007	7.072	7.746	8.438	8.483	7.697	6.171	6.362	7.050	7.207	7.861	6.425	6.526	7.106	6.865	7.613
Falconhurst Park	1.531	2.215	0.790	1.514	1.297	0.314	1.044	1.110	1.783	2.700	2.521	1.734	1.242	1.954	2.915	1.365	1.898	5.678	5.051	6.539	6.991	7.172
Forest Park	3.067	2.596	4.143	4.623	4.219	4.698	5.242	4.855	5.712	5.917	6.583	5.947	4.491	4.313	5.310	5.158	6.283	5.280	5.381	5.961	6.264	6.594
French Broad River Park	1.121	0.607	2.187	2.540	2.272	2.970	3.296	2.909	3.630	3.834	4.704	4.001	3.020	3.500	4.487	3.912	4.610	6.076	5.605	6.757	7.209	7.390
Haw Creek Park	5.757	5.285	6.055	7.355	6.908	6.464	7.195	7.260	7.933	8.626	8.671	7.885	6.359	6.550	7.238	7.394	8.049	6.612	6.714	7.293	7.053	7.800
Herb Watts Park	2.726	2.406	2.927	3.682	3.258	3.552	4.098	3.711	4.600	4.953	5.438	4.803	3.204	3.114	4.121	3.959	5.137	4.725	4.826	5.406	5.738	6.039
Hummingbird Park	2.858	2.538	2.537	3.814	3.389	2.946	3.676	3.742	4.415	5.085	5.153	4.367	2.841	3.009	3.176	3.854	4.530	3.251	3.353	3.932	4.384	4.565
Irby Brinson Complex	9.132	8.660	9.652	9.519	9.991	10.254	10.192	9.805	9.775	9.832	10.866	10.897	10.591	11.022	12.029	11.326	11.716	12.148	12.250	12.829	13.133	13.462
Jake Rusher Park	9.555	9.083	10.664	10.848	10.707	11.391	11.730	11.343	11.077	11.135	12.688	12.435	11.731	11.446	12.453	12.290	12.976	12.572	12.673	13.253	13.556	13.885
Jean Webb Park	1.935	1.699	1.543	2.696	2.272	1.952	2.682	2.725	3.421	3.967	4.159	3.372	1.847	1.757	2.764	2.601	3.536	4.516	3.888	5.377	5.829	6.010
Kenilworth Park	3.101	2.630	3.948	4.657	4.253	4.503	5.119	4.732	5.621	5.951	6.460	5.824	4.295	4.118	5.115	4.963	6.088	5.085	5.186	5.766	6.069	6.398
Leah Chiles Park	3.492	3.021	4.413	5.048	4.644	4.968	5.584	5.197	6.086	6.342	6.924	6.289	4.760	4.583	5.580	5.428	6.553	5.550	5.651	6.231	6.358	6.863
Lynwood Crump Shiloh Complex	4.340	3.869	5.449	6.099	5.492	6.176	6.515	6.128	6.506	6.564	7.856	7.220	6.485	6.105	7.112	6.949	7.761	7.231	7.332	7.912	8.215	8.544
Magnolia Park	3.235	2.915	2.796	4.115	3.767	3.205	3.936	4.001	4.675	5.463	5.412	4.626	3.100	3.364	3.075	4.138	4.790	3.080	3.181	3.761	4.213	4.394
Malvern Hills Pool and Park	2.307	2.990	1.866	1.647	1.926	1.152	0.422	0.697	0.555	1.346	1.394	1.210	2.519	3.318	4.279	2.351	2.413	7.043	6.415	7.816	8.268	8.448
Martin Luther King Jr. Park	3.237	2.917	3.060	4.193	3.769	3.469	4.200	4.222	4.938	5.464	5.676	4.890	3.364	3.388	4.121	4.233	5.054	3.498	3.599	4.179	4.187	4.686
Masters Park	7.366	6.894	7.561	8.860	8.436	7.970	8.701	8.766	9.439	10.132	10.177	9.391	7.865	8.056	8.744	8.900	9.555	8.118	8.220	8.799	8.559	9.306
Meadow Park	2.936	2.464	4.045	4.491	4.088	4.666	5.111	4.724	5.581	5.785	6.451	5.816	4.458	4.281	5.278	5.126	6.251	5.248	5.349	5.929	6.232	6.562
Montford Park	3.507	3.187	3.000	4.319	3.997	3.409	4.140	4.205	4.879	5.693	5.616	4.830	3.304	2.991	2.631	4.118	4.994	3.099	2.787	3.780	4.232	4.413
Mountainside Park	3.141	2.821	2.996	4.097	3.673	3.405	4.136	4.126	4.875	5.368	5.612	4.826	3.300	3.292	4.179	4.137	4.990	4.133	4.235	4.814	4.866	5.378
Murphy-Oakley Center Complex	4.417	3.945	5.526	6.151	5.569	6.253	6.592	6.205	7.094	7.447	7.933	7.297	6.564	6.168	7.175	7.012	7.838	6.922	7.023	7.603	7.362	8.110
Murray Hill Park	2.330	2.010	2.506	3.286	2.862	2.914	3.702	3.315	4.204	4.557	5.043	4.408	2.809	2.718	3.725	3.563	4.847	4.656	4.757	5.337	5.742	5.969
Oakhurst Park	2.959	2.639	2.815	3.915	3.491	3.223	3.954	3.944	4.693	5.186	5.431	4.644	3.118	3.111	3.997	3.955	4.808	4.028	4.129	4.709	4.956	5.342
Owens-Bell Park	1.884	1.564	2.007	2.840	2.416	2.416	3.146	2.869	3.758	4.111	4.597	3.836	2.311	2.194	3.189	3.039	4.000	4.161	4.262	4.842	5.294	5.475
Pack Square Park	2.904	2.584	2.615	3.860	3.436	3.024	3.755	3.820	4.494	5.131	5.231	4.445	2.919	3.055	3.798	3.900	4.609	3.498	3.600	4.179	4.357	4.790
Pritchard Park	2.604	2.284	2.220	3.538	3.136	2.628	3.359	3.424	4.098	4.831	4.835	4.049	2.523	2.755	3.402	3.562	4.213	3.472	3.573	4.153	4.605	4.786
Ray L. Kisiah Park	5.625	5.154	6.734	7.153	6.777	7.461	7.800	7.413	8.302	7.830	9.141	8.505	7.567	7.376	8.383	8.221	9.046	8.410	8.512	9.091	8.851	9.599
Recreation Park and Pool	6.191	5.719	7.118	7.948	7.342	7.527	8.258	7.978	8.867	9.221	9.706	8.948	7.422	7.411	8.100	8.256	9.112	7.474	7.575	8.155	7.915	8.662
Richmond Hill Park	4.258	4.232	3.445	4.242	4.024	3.227	3.952	4.022	4.691	5.427	5.429	4.483	3.082	1.931	0.094	3.058	4.335	4.335	3.707	5.220	6.160	6.341
Riverbend Park	4.618	4.146	5.445	6.037	5.769	5.854	6.584	6.405	7.294	7.648	8.061	7.275	5.749	6.000	6.627	6.787	7.438	6.215	6.316	6.896	6.975	7.529
Roger Farmer Memorial Park	2.411	3.095	1.971	2.016	2.030	1.004	0.334	1.013	1.012	1.982	1.402	0.463	2.127	3.154	4.123	2.203	1.666	6.743	6.266	7.424	7.875	8.056
Seven Springs Park	2.926	2.454	4.035	4.489	4.078	4.664	5.101	4.714	5.579	5.783	6.441	5.806	4.456	4.279	5.276	5.124	6.249	5.246	5.347	5.927	6.230	6.559
Stephens-Lee Recreation Center	3.013	2.693	2.688	3.969	3.545	3.097	3.828	3.893	4.567	5.241	5.304	4.518	2.992	3.165	3.871	4.009	4.682	3.624	3.725	4.305	4.348	4.812
Sunset Park	4.105	3.785	3.647	4.965	4.637	4.055	4.786	4.852	5.525	6.332	6.263	5.476	3.951	4.223	3.863	4.989	5.640	2.762	2.864	3.443	3.718	3.899
Tempie Avery Montford Complex	3.082	2.849	2.421	3.739	3.417	2.829	3.560	3.625	4.299	5.113	5.036	4.250	2.724	2.906	2.945	3.751	4.414	3.535	3.345	4.216	4.668	4.849
Triangle Park	2.818	2.498	2.558	3.775	3.350	2.967	3.697	3.763	4.436	5.046	5.174	4.388	2.862	2.970	3.741	3.814	4.552	3.563	3.664	4.244	4.558	4.876
Walton Street Park and Pool	2.545	2.225	2.720	3.501	3.077	3.128	3.918	3.530	4.419	4.773	5.258	4.623	3.023	2.934	3.940	3.778	5.072	5.156	5.065	5.837	6.186	6.470
Weaver Park	4.190	3.870	3.884	5.146	4.721	4.293	5.024	5.089	5.763	6.417	6.500	5.714	4.188	3.538	3.178	4.665	5.878	2.005	2.106	2.686	3.138	3.319
West Asheville Community Center	1.681	2.365	1.240	1.240	1.300	0.558	0.566	0.238	1.110	1.867	1.949	1.271	1.738	2.729	3.690	1.762	2.090	6.354	5.826	7.035	7.486	7.667
West Asheville Park	1.711	2.394	1.270	0.083	1.330	1.397	1.604	0.980	1.847	2.171	2.780	2.309	2.231	3.074	4.035	2.601	3.128	6.774	6.170	7.455	7.907	8.088
White Fawn Park	3.597	3.125	3.929	4.684	4.260	4.439	5.100	4.713	5.602	5.956	6.441	5.806	4.231	4.032	5.029	4.876	6.024	4.837	4.938	5.518	5.480	6.082
White Pine Park	5.228	4.818	4.885	6.184	5.760	5.293	6.024	6.089	6.763	7.455	7.500	6.714	5.188	5.379	6.067	6.224	6.878	5.442	5.543	6.123	5.883	6.630
Candidate1	6.679	7.265	6.271	6.065	6.331	5.404	4.673	5.061	4.615	4.102	4.198	5.429	6.579	7.570	8.531	6.603	6.665	11.195	10.667	11.876	12.327	12.508
Candidate2	2.099	2.172	1.407	2.725	2.415	1.816	2.546	2.612	3.285	3.980	4.023	3.237	0.755	2.210	3.180	2.749	3.392	4.519	4.298	5.200	5.652	5.833
Candidate3	6.815	6.495	6.455	7.771	7.346	6.864	7.595	7.660	8.333	9.042	9.071	8.264	6.759	5.713	5.353	6.840	8.117	1.233	2.551	0.543	2.596	2.777
Candidate4	4.697	4.377	4.354	5.653	5.229	4.763	5.493	5.559	6.232	6.924	6.970	6.183	4.658	4.848	5.536	5.693	6.347	4.911	5.012	5.592	5.352	6.099
Candidate5	8.644	8.173	9.753	9.769	9.796	10.480	10.511	10.106	10.024	10.081	11.221	11.254	10.982	10.795	11.802	11.435	12.065	12.364	12.465	13.045	13.348	13.677
Candidate6	1.336	2.045	0.921	1.095	0.640	1.473	1.680	1.292	2.181	2.532	3.020	2.385	1.846	2.874	3.835	2.462	3.092	6.305	5.930	6.986	7.437	7.618
Candidate7	6.031	5.711	5.663	6.981	6.563	6.072	6.803	6.868	7.541	8.259	8.279	7.493	5.967	5.767	5.407	6.894	7.657	2.706	2.940	2.933	1.632	2.424
Candidate8	5.113	4.641	5.797	6.791	6.265	6.206	6.936	6.901	7.675	8.085	8.413	7.627	6.101	6.291	6.979	7.136	7.790	6.354	6.455	7.035	6.795	7.542
Candidate9	3.948	3.628	3.605	4.904	4.479	4.014	4.745	4.810	5.484	6.175	6.221	5.435	3.909	4.099	4.318	4.944	5.599	3.502	3.603	4.183	3.258	4.050
Candidate10	4.764	5.448	4.323	4.043	4.383	4.140	3.443	3.364	2.704	1.734	3.290	4.198	5.099	6.106	7.067	5.344	5.434	9.808	9.202	10.489	10.940	11.121
Candidate11	3.647	3.327	3.304	4.603	4.179	3.713	4.443	4.509	5.182	5.875	5.920	5.134	3.608	3.799	4.486	4.643	5.298	3.861	3.962	4.542	4.302	5.049
Candidate12	4.699	4.227	5.807	6.406	5.850	6.222	6.874	6.486	7.375	7.699	8.214	7.579	6.117	6.308	6.996	7.153	7.807	6.370	6.472	7.051	6.811	7.559

Park\Location	BG370210010002	BG370210010003	BG370210011001	BG370210011002	BG370210011003	BG370210012001	BG370210012002	BG370210012003	BG370210012004	BG370210012005	BG370210013001	BG370210013002	BG370210014001	BG370210014002	BG370210014003	BG370210014004	BG370210014005	BG370210016001	BG370210016002	BG370210016003	BG370210017001	BG370210017002
Candidate13	5.795	6.381	5.388	5.181	5.448	4.521	3.790	4.177	3.731	3.218	3.315	4.545	5.695	6.686	7.648	5.720	5.781	10.311	9.783	10.992	11.444	11.625
Candidate14	1.416	2.283	1.273	1.643	0.264	1.852	2.059	1.671	2.560	2.914	3.399	2.764	2.205	3.233	4.195	2.821	3.451	6.642	6.168	7.323	7.775	7.956
Candidate15	2.857	3.540	2.056	2.525	2.577	1.272	1.310	1.586	1.965	2.935	2.124	0.661	2.102	2.906	3.867	1.528	0.881	6.631	6.003	7.480	7.932	8.113
Candidate16	2.464	3.050	2.657	1.823	2.400	2.937	2.565	2.161	2.078	2.136	3.276	3.377	3.564	4.566	5.527	4.140	4.395	7.914	7.662	8.595	9.047	9.228
Candidate17	6.442	5.971	6.769	8.069	7.594	7.178	7.909	7.974	8.648	9.340	9.385	8.599	7.073	7.264	7.952	8.109	8.763	7.326	7.428	8.007	7.767	8.515
Candidate18	5.179	4.707	6.001	6.937	6.330	6.409	7.140	6.966	7.855	8.209	8.617	7.830	6.304	6.495	7.183	7.340	7.994	6.558	6.659	7.239	6.999	7.746
Candidate19	4.649	5.332	4.208	3.928	4.268	3.970	3.239	3.248	2.588	1.619	2.764	3.994	4.984	5.990	6.951	5.169	5.230	9.692	9.087	10.373	10.825	11.006
Candidate20	4.020	3.700	3.826	4.976	4.551	4.235	4.966	5.005	5.705	6.247	6.442	5.656	4.130	4.171	5.004	5.016	5.820	4.501	4.602	5.182	4.990	5.689
Candidate21	3.771	3.299	4.880	5.505	4.922	5.607	5.946	5.558	6.447	6.798	7.286	6.651	5.918	5.521	6.528	6.366	7.192	6.616	6.718	7.297	7.601	7.930
Candidate22	3.825	3.353	4.934	5.559	4.976	5.661	6.000	5.613	6.501	6.852	7.340	6.705	5.972	5.575	6.582	6.420	7.246	6.670	6.772	7.351	7.655	7.984
Candidate23	8.261	7.789	8.456	9.755	9.331	8.865	9.595	9.661	10.334	11.027	11.072	10.286	8.760	8.951	9.638	9.795	10.450	9.013	9.114	9.694	9.454	10.201
Candidate24	7.763	7.443	7.404	8.720	8.295	7.813	8.544	8.609	9.282	9.991	10.020	9.234	7.708	7.049	6.690	8.176	9.398	3.234	3.857	3.271	1.146	1.416
Candidate25	2.338	3.021	1.524	2.286	2.104	0.850	1.476	1.546	2.215	3.156	2.953	1.461	1.162	1.966	2.927	0.588	1.504	5.691	5.063	6.575	7.149	7.329
Candidate26	3.249	3.013	2.846	3.965	3.585	2.950	3.675	3.745	4.414	5.150	5.151	4.206	2.805	1.654	1.294	2.781	4.058	2.946	2.318	3.831	4.772	4.953
Candidate27	7.085	6.765	6.726	8.041	7.617	7.135	7.865	7.931	8.604	9.313	9.342	8.555	7.030	6.371	6.011	7.498	8.719	2.555	3.178	2.592	0.468	0.738
Candidate28	3.937	3.465	4.126	5.024	4.599	4.534	5.265	5.053	5.941	6.295	6.741	5.955	4.429	4.310	5.264	5.155	6.119	4.760	4.862	5.441	5.249	5.949
Candidate29	5.753	5.517	5.446	6.470	6.090	5.455	6.180	6.250	6.919	7.655	7.656	6.711	5.662	4.159	3.799	5.286	6.563	1.035	1.145	1.608	3.188	3.369
Candidate30	5.247	4.775	5.228	6.509	6.085	5.637	6.367	6.433	7.106	7.780	7.844	7.058	5.532	5.704	6.393	6.549	7.222	5.767	5.868	6.448	6.208	6.955
Candidate31	4.231	3.911	3.888	5.187	4.762	4.297	5.028	5.093	5.767	6.458	6.504	5.718	4.192	4.382	4.601	5.227	5.882	3.785	3.886	4.466	3.054	3.847
Candidate32	5.926	5.690	5.619	6.643	6.263	5.628	6.353	6.423	7.092	7.828	7.829	6.884	5.835	4.332	3.972	5.459	6.736	0.777	1.170	1.661	2.930	3.110
Candidate33	3.184	3.868	2.743	2.749	2.803	1.740	1.122	1.695	1.480	2.449	1.056	1.141	2.914	3.906	4.867	2.939	2.401	7.530	7.002	8.211	8.663	8.844
Candidate34	6.485	6.013	7.594	8.244	7.637	8.321	8.660	8.273	8.793	8.851	10.000	9.365	8.772	8.375	9.382	9.220	9.906	9.502	9.603	10.183	10.486	10.815
Candidate35	3.878	3.558	3.684	4.834	4.409	4.093	4.824	4.863	5.563	6.105	6.300	5.514	3.988	4.029	4.862	4.874	5.678	4.359	4.460	5.040	4.848	5.547
Candidate36	6.893	6.573	6.534	7.849	7.425	6.942	7.673	7.738	8.412	9.120	9.149	8.363	6.837	6.061	5.701	7.188	8.465	1.581	2.899	0.891	2.248	2.429
Candidate37	3.238	3.922	2.606	2.806	2.857	1.779	1.207	1.835	1.620	2.590	1.779	0.501	2.652	3.456	4.418	2.078	1.432	7.181	6.553	8.031	8.482	8.663
Candidate38	5.029	4.557	5.713	6.707	6.181	6.122	6.852	6.817	7.591	8.001	8.329	7.542	6.017	6.207	6.895	7.052	7.706	6.270	6.371	6.951	6.711	7.458
Candidate39	6.713	6.393	6.354	7.669	7.245	6.762	7.493	7.558	8.232	8.940	8.970	8.183	6.657	5.999	5.639	7.126	8.347	1.800	2.806	1.111	2.068	2.249
Candidate40	3.683	3.211	4.792	5.442	4.834	5.519	5.858	5.471	5.865	5.923	7.198	6.563	5.844	5.447	6.454	6.292	7.104	6.573	6.674	7.254	7.557	7.887
Candidate41	2.012	2.696	1.198	1.996	1.778	0.858	1.484	1.554	2.223	3.164	2.961	1.787	0.836	1.641	2.602	0.779	1.830	5.365	4.737	6.250	6.823	7.004
Candidate42	5.043	4.723	4.701	6.000	5.575	5.110	5.841	5.906	6.579	7.271	7.317	6.531	5.005	5.195	5.414	6.040	6.695	3.798	4.006	4.418	2.370	3.163
Candidate43	4.954	4.482	5.934	6.713	6.106	6.342	7.073	6.742	7.630	7.984	8.469	7.763	6.237	6.402	7.091	7.247	7.927	6.465	6.566	7.146	6.906	7.653
Candidate44	4.852	4.616	4.544	5.568	5.188	4.553	5.278	5.348	6.017	6.753	6.755	5.809	4.761	3.257	2.898	4.384	5.662	1.992	1.364	2.877	4.100	4.281
Candidate45	8.865	8.394	9.974	10.070	10.017	10.701	11.040	10.653	10.299	10.357	11.910	11.745	11.152	10.756	11.763	11.600	12.286	11.882	11.983	12.563	12.866	13.195
Candidate46	8.002	7.530	8.329	9.628	9.154	8.738	9.468	9.534	10.207	10.900	10.945	10.159	8.633	8.824	9.511	9.668	10.323	8.886	8.987	9.567	9.327	10.074
Candidate47	3.566	4.249	3.125	2.969	3.185	2.149	1.454	1.914	1.699	2.529	0.452	1.570	3.323	4.315	5.276	3.348	2.831	7.939	7.411	8.620	9.072	9.253
Candidate48	6.710	6.390	6.350	7.666	7.242	6.759	7.490	7.555	8.229	8.937	8.966	8.180	6.654	5.996	5.636	7.123	8.344	2.180	2.803	1.514	2.065	2.246
Candidate49	3.944	3.473	5.053	5.678	5.096	5.780	6.119	5.732	6.621	6.972	7.460	6.824	6.091	5.695	6.702	6.540	7.365	6.790	6.891	7.471	7.774	8.103
Candidate50	4.413	4.093	3.792	5.110	4.788	4.200	4.931	4.996	5.670	6.484	6.407	5.621	4.095	4.277	4.135	5.122	5.785	4.570	4.291	5.251	5.703	5.884
Candidate51	6.477	6.242	6.238	7.194	6.814	6.179	6.904	6.974	7.643	8.379	8.380	7.435	6.541	4.883	4.523	6.010	7.247	0.914	1.869	0.762	2.838	3.019
Candidate52	3.429	4.113	2.988	2.832	3.048	2.121	1.390	1.778	1.332	2.081	0.086	1.649	3.296	4.287	5.248	3.320	2.909	7.912	7.384	8.593	9.044	9.225
Candidate53	5.432	4.961	6.541	7.191	6.584	7.269	7.608	7.220	7.741	7.799	8.948	8.313	7.719	7.323	8.330	8.168	8.853	8.449	8.550	9.130	9.433	9.763
Candidate54	5.182	4.710	6.291	6.938	6.334	7.018	7.357	6.970	7.654	7.711	8.698	8.062	7.351	6.933	7.940	7.778	8.603	8.028	8.129	8.709	9.012	9.341
Candidate55	7.768	7.448	7.409	8.725	8.300	7.818	8.549	8.614	9.287	9.996	10.025	9.239	7.713	7.054	6.695	8.182	9.403	3.239	3.862	3.276	1.151	1.421
Candidate56	3.366	3.951	3.557	2.723	3.300	3.837	3.465	3.061	2.978	3.036	4.176	4.277	4.466	5.466	6.427	5.040	5.295	8.816	8.562	9.496	9.948	10.129
Candidate57	3.656	3.184	4.765	5.390	4.808	5.492	5.831	5.444	6.333	6.684	7.171	6.536	5.803	5.407	6.414	6.251	7.077	6.502	6.603	7.183	7.486	7.815
Candidate58	5.228	4.908	4.885	6.184	5.759	5.293	6.024	6.089	6.763	7.455	7.500	6.714	5.188	5.379	6.067	6.224	6.878	5.442	5.543	6.123	5.616	6.408
Candidate59	8.061	7.741	7.702	9.017	8.593	8.110	8.841	8.906	9.580	10.288	10.318	9.531	8.006	7.347	6.987	8.474	9.695	3.531	4.154	3.568	1.444	1.713
Candidate60	4.934	5.617	4.493	4.213	4.553	4.309	3.612	3.533	2.873	1.903	3.459	4.367	5.268	6.275	7.236	5.513	5.603	9.977	9.372	10.658	11.110	11.290
Candidate61	7.680	7.208	8.789	9.439	8.832	9.516	9.855	9.468	9.988	10.046	11.195	10.560	9.967	9.571	10.577	10.415	11.101	10.697	10.798	11.378	11.681	12.010
Candidate62	7.197	6.877	7.157	8.153	7.729	7.565	8.296	8.182	9.035	9.424	9.773	8.986	7.461	6.802	6.442	7.929	9.150	2.986	3.609	3.023	0.376	1.168
Candidate63	8.405	7.933	8.600	9.899	9.475	9.009	9.739	9.805	10.478	11.170	11.216	10.430	8.904	9.094	9.782	9.939	10.594	9.157	9.258	9.838	9.598	10.345
Candidate64	2.069	1.597	3.178	3.624	3.220	3.905	4.244	3.857	4.714	4.918	5.584	4.949	4.229	4.085	5.092	4.860	5.490	5.723	5.824	6.404	6.707	7.036
Candidate65	6.944	6.472	7.139	8.439	8.014	7.548	8.279	8.344	9.018	9.710	9.755	8.969	7.443	7.634	8.322	8.479	9.133	7.697	7.798	8.378	8.137	8.885
Candidate66	5.598	5.278	5.256	6.554	6.129	5.664	6.395	6.460	7.134	7.825	7.871	7.085	5.559	5.749	5.968	6.594	7.249	4.018	4.226	4.638	3.032	3.825
Candidate67	5.444	4.972	5.640	6.939	6.514	6.048	6.779	6.844	7.518	8.210	8.255	7.469	5.943	6.134	6.822	6.979	7.633	6.197	6.298	6.878	6.637	7.385
Candidate68	5.259	4.939	4.916	6.215	5.791	5.325	6.055	6.121	6.794	7.487	7.532	6.746	5.220	5.411	6.099	6.255	6.910	5.473	5.574	6.154	5.914	6.661
Candidate69	3.189	3.774	3.380	2.546	3.123	3.660	3.288	2.884	2.801	2.859	3.999	4.100	4.289	5.289	6.250	4.863	5.118	8.639	8.385	9.319	9.771	9.952
Candidate70	8.576	8.104	9.685	9.143	9.727	10.412	10.486	10.017	9.999	10.056	10.983	11.263	10.858	10.466	11.473	11.311	11.997	11.592	11.694	12.273	12.577	12.906
Candidate71	8.833	8.361	9.942	9.354	9.931	10.669	10.768	10.005	9.583	9.640	11.194	11.473	11.069	10.724	11.731	11.568	12.254	11.850	11.951	12.531	12.834	13.163
Candidate72	8.450	7.979	9.559	10.209	9.602	10.287	10.626	10.238	10.582	10.640	11.966	11.331	10.737	10.341	11.348	11.186	11.871	11.467	11.568	12.148	12.451	12.781
Candidate73	3.403	4.086	2.602	3.248	3.169	1.819	2.033	2.309	2.669	3.638	2.685	1.385	2.648	3.452	4.414	2.063	0.649	7.172	6.549	7.945	8.478	8.659
Candidate74	7.671	7.199	7.867	9.166	8.742	8.275	9.006	9.071	9.745	10.437	10.483	9.696	8.170	8.361	9.049	9.206	9.860	8.424	8.525	9.105	8.865	9.612
Candidate75	8.831	8.359	9.026	10.325	9.901	9.435	10.166	10.231	10.904	11.597	11.642	10.856	9.330	9.521	10.209	10.365	11.020	9.583	9.685	10.264	10.024	10.771
Candidate76	8.302	7.830	8.497	9.796	9.372	8.906	9.636	9.702	10.375	11.067	11.113	10.327	8.801	8.991	9.679	9.836	10.491	9.054	9.155	9.735	9.495	10.242

Park\Location	BG370210010002	BG370210010003	BG370210011001	BG370210011002	BG370210011003	BG370210012001	BG370210012002	BG370210012003	BG370210012004	BG370210012005	BG370210013001	BG370210013002	BG370210014001	BG370210014002	BG370210014003	BG370210014004	BG370210014005	BG370210016001	BG370210016002	BG370210016003	BG370210017001	BG370210017002
Candidate77	3.891	3.419	4.999	5.624	5.042	5.727	6.066	5.678	6.094	6.152	7.406	6.771	6.038	5.641	6.648	6.486	7.311	6.736	6.837	7.417	7.720	8.050
Candidate78	8.872	8.401	9.981	9.999	10.024	10.708	11.047	10.650	10.228	10.285	11.839	11.752	11.210	10.763	11.770	11.608	12.293	11.889	11.990	12.570	12.873	13.202
Candidate79	6.703	6.231	6.898	8.198	7.773	7.307	8.038	8.103	8.776	9.469	9.514	8.728	7.202	7.393	8.081	8.237	8.892	7.455	7.557	8.136	7.896	8.644
Candidate80	1.281	1.620	1.286	2.041	1.617	2.131	2.457	2.070	2.958	3.312	3.802	3.162	2.118	1.901	3.066	2.746	3.716	4.938	4.311	5.800	6.251	6.432
Candidate81	3.466	2.994	4.575	5.200	4.618	5.302	5.641	5.254	6.143	6.494	6.981	6.346	5.613	5.217	6.224	6.061	6.887	6.312	6.413	6.993	7.296	7.625
Candidate82	7.838	7.366	8.947	9.597	8.990	9.674	10.013	9.626	10.147	10.204	11.354	10.718	10.125	9.729	10.736	10.573	11.259	10.855	10.956	11.536	11.839	12.168
Candidate83	7.296	6.824	8.405	9.055	8.448	9.132	9.471	9.084	9.890	9.947	10.811	10.176	9.634	9.187	10.194	10.031	10.717	10.313	10.414	10.994	11.297	11.626
Candidate84	4.926	4.606	4.583	5.882	5.458	4.992	5.723	5.788	6.461	7.154	7.199	6.413	4.887	5.078	5.766	5.922	6.577	5.140	5.242	5.821	5.150	5.943
Candidate85	7.075	6.755	6.715	8.031	7.607	7.124	7.855	7.920	8.594	9.302	9.331	8.545	7.019	6.361	6.001	7.488	8.709	2.545	3.168	2.582	1.661	1.842
Candidate86	2.760	3.443	1.959	2.612	2.526	1.176	1.453	1.729	2.132	3.102	2.315	0.805	2.005	2.809	3.771	1.431	0.844	6.534	5.906	7.384	7.835	8.016
Candidate87	6.902	6.582	6.543	7.858	7.434	6.952	7.682	7.748	8.421	9.130	9.159	8.373	6.847	6.188	5.828	7.315	8.536	2.372	2.995	2.409	0.285	0.555
Candidate88	4.540	4.220	4.198	5.496	5.072	4.607	5.337	5.403	6.076	6.767	6.814	6.027	4.502	4.691	4.911	5.536	6.191	3.486	3.694	4.106	2.666	3.458
Candidate89	3.564	4.247	3.123	2.966	3.183	2.255	1.525	1.912	1.466	2.215	0.384	1.912	3.430	4.421	5.383	3.454	3.173	8.046	7.518	8.727	9.179	9.359
Candidate90	2.726	3.410	2.285	2.005	2.345	2.102	1.405	1.326	0.666	0.304	1.863	2.160	3.061	4.068	5.029	3.306	3.396	7.770	7.164	8.451	8.902	9.083
Candidate91	3.086	3.769	2.489	2.653	2.705	1.627	1.438	1.714	2.117	3.086	2.300	0.789	2.535	3.339	4.301	1.961	1.315	7.064	6.436	7.914	8.365	8.546
Candidate92	3.645	3.325	3.303	4.601	4.177	3.712	4.442	4.508	5.181	5.873	5.919	5.133	3.607	3.797	4.176	4.641	5.297	3.390	3.491	4.071	3.560	4.353
Candidate93	3.121	2.649	4.229	4.676	4.272	4.957	5.296	4.908	5.766	5.970	6.636	6.001	4.998	4.817	5.818	5.662	6.541	5.788	5.889	6.469	6.772	7.101
Candidate94	4.203	4.887	3.762	3.482	3.822	3.579	2.881	2.803	2.142	1.173	2.845	3.636	4.538	5.544	6.506	4.782	4.872	9.246	8.641	9.927	10.379	10.560
Candidate95	8.049	7.577	9.157	9.807	9.200	9.885	10.224	9.836	10.357	10.415	11.564	10.929	10.335	9.939	10.946	10.784	11.469	11.065	11.166	11.746	12.049	12.379
Candidate96	5.184	4.864	4.842	6.140	5.716	5.251	5.982	6.047	6.720	7.412	7.458	6.672	5.146	5.336	5.555	6.180	6.836	3.939	4.147	4.559	2.021	2.814
Candidate97	3.989	3.517	4.009	5.076	4.652	4.418	5.149	5.105	5.887	6.348	6.625	5.839	4.313	4.354	5.187	5.199	6.003	4.684	4.785	5.365	5.173	5.872
Candidate98	3.955	3.635	3.668	4.911	4.487	4.077	4.807	4.873	5.546	6.182	6.284	5.498	3.972	3.405	3.045	4.532	5.661	2.786	2.887	3.467	3.919	4.100
Candidate99	4.697	5.283	4.854	4.020	4.597	5.134	4.762	4.358	4.275	4.333	5.473	5.574	5.797	6.763	7.724	6.337	6.592	10.147	9.860	10.828	11.280	11.461
Candidate100	2.851	3.535	2.411	2.130	2.471	2.227	1.530	1.451	0.791	0.274	1.988	2.285	3.186	4.193	5.154	3.431	3.521	7.895	7.290	8.576	9.027	9.208
Candidate101	5.743	6.429	5.305	4.471	5.047	5.334	4.637	4.558	3.898	2.928	4.484	5.392	6.294	7.213	8.175	6.538	6.628	10.938	10.310	11.669	12.120	12.301
Candidate102	9.201	8.730	10.310	10.960	10.353	11.037	11.376	10.989	11.510	11.567	12.717	12.081	11.488	11.092	12.099	11.937	12.622	12.218	12.319	12.899	13.202	13.532
Candidate103	5.046	5.729	4.605	4.325	4.665	4.421	3.724	3.645	2.985	2.016	3.571	4.479	5.381	6.387	7.349	5.625	5.715	10.089	9.484	10.770	11.222	11.403
Candidate104	8.490	8.019	8.686	9.985	9.561	9.094	9.825	9.890	10.564	11.256	11.302	10.515	8.989	9.180	9.868	10.025	10.679	9.243	9.344	9.924	9.684	10.431
Candidate105	4.454	3.982	5.562	6.213	5.605	6.290	6.629	6.241	6.737	6.795	7.969	7.334	6.716	6.218	7.225	7.063	7.875	7.344	7.445	8.025	8.328	8.658
Candidate106	9.167	8.800	9.480	9.045	9.621	10.028	9.787	9.382	9.300	9.357	10.497	10.599	10.419	11.162	12.169	11.120	11.490	12.288	12.390	12.969	13.273	13.602
Candidate107	6.695	6.375	6.335	7.651	7.227	6.744	7.475	7.540	8.214	8.922	8.951	8.165	6.639	5.981	5.621	7.108	8.329	2.165	2.788	2.202	0.959	1.140
Candidate108	10.448	9.976	11.557	11.654	11.599	12.284	12.623	12.235	11.882	11.940	13.493	13.328	12.735	12.338	13.345	13.183	13.869	13.464	13.566	14.145	14.449	14.778
Candidate109	5.464	4.992	6.573	7.223	6.616	7.300	7.639	7.252	7.772	7.830	8.979	8.344	7.751	7.354	8.361	8.199	8.885	8.481	8.582	9.162	9.465	9.794
Candidate110	6.062	5.742	5.733	7.018	6.594	6.142	6.872	6.938	7.611	8.289	8.349	7.563	6.037	5.404	5.045	6.532	7.727	2.344	2.578	2.785	1.814	2.606
Candidate111	5.906	5.586	5.546	6.862	6.437	5.955	6.686	6.751	7.424	8.133	8.162	7.376	5.850	5.192	4.832	6.319	7.540	1.376	1.999	1.254	1.539	1.720
Candidate112	6.635	6.315	6.276	7.591	7.167	6.685	7.415	7.481	8.154	8.863	8.892	8.105	6.580	5.921	5.561	7.048	8.269	2.105	2.728	2.142	1.221	1.402
Candidate113	2.485	3.169	1.684	2.337	2.251	0.901	1.528	1.598	2.266	3.207	2.900	1.389	1.333	2.137	3.098	0.759	1.432	5.862	5.234	6.746	7.320	7.500
Candidate114	1.946	2.441	0.860	1.978	1.761	0.963	1.689	1.759	2.427	3.164	3.165	2.261	0.498	1.665	2.626	1.253	2.304	5.352	4.762	6.033	6.485	6.666
Candidate115	7.680	7.208	8.789	9.439	8.832	9.516	9.855	9.468	9.989	10.046	11.196	10.560	9.967	9.571	10.578	10.415	11.101	10.697	10.798	11.378	11.681	12.010
Candidate116	5.551	5.079	6.660	7.310	6.703	7.387	7.726	7.339	7.859	7.917	9.066	8.431	7.838	7.441	8.448	8.286	8.972	8.568	8.669	9.248	9.552	9.881
Candidate117	6.586	6.266	6.226	7.542	7.117	6.635	7.366	7.431	8.104	8.813	8.842	8.056	6.530	5.872	5.512	6.999	8.220	2.056	2.679	2.093	1.344	1.525
Candidate118	3.397	3.161	2.918	3.716	3.498	2.701	3.426	3.496	4.165	4.901	4.902	3.957	2.556	1.405	1.045	2.532	3.809	3.195	2.568	4.080	5.021	5.202
Candidate119	2.344	3.028	1.543	2.196	2.110	0.760	1.386	1.456	2.125	3.066	2.863	1.816	1.829	2.135	3.096	0.940	1.859	5.860	5.232	6.744	7.317	7.498
Candidate120	0.650	0.416	1.759	2.233	1.801	2.486	2.825	2.437	3.322	3.526	4.165	3.530	2.639	3.282	4.447	3.441	4.070	6.034	5.640	6.715	7.166	7.347
Candidate121	1.631	2.217	1.749	0.915	1.492	1.937	1.389	0.985	1.181	1.448	2.523	2.262	2.630	3.658	4.626	3.140	3.220	7.081	6.806	7.762	8.214	8.394
Candidate122	8.610	8.138	8.805	10.104	9.680	9.214	9.945	10.010	10.683	11.376	11.421	10.635	9.109	9.300	9.988	10.144	10.799	9.362	9.463	10.043	9.803	10.550
Candidate123	6.757	6.285	7.866	8.516	7.908	8.593	8.932	8.544	9.095	9.153	10.272	9.637	9.073	8.647	9.654	9.492	10.178	9.773	9.875	10.454	10.758	11.087
Candidate124	4.951	4.631	4.493	5.811	5.483	4.902	5.632	5.698	6.371	7.178	7.109	6.323	4.797	4.783	4.423	5.835	6.486	2.226	2.434	2.846	2.917	3.235
Candidate125	8.170	7.699	9.279	9.821	9.322	10.006	10.345	9.958	10.050	10.107	11.661	11.050	10.457	10.061	11.068	10.905	11.591	11.187	11.288	11.868	12.171	12.500
Candidate126	5.157	4.837	4.900	6.084	5.669	5.069	5.794	5.864	6.533	7.269	7.271	6.325	5.204	3.773	3.413	4.900	6.177	2.391	2.492	3.072	3.523	3.704
Candidate127	5.345	4.874	5.541	6.840	6.416	5.949	6.680	6.745	7.419	8.111	8.157	7.370	5.845	6.035	6.723	6.880	7.534	6.098	6.199	6.779	6.539	7.286
Candidate128	3.631	3.159	4.333	5.088	4.664	4.888	5.504	5.117	6.006	6.359	6.845	6.209	4.680	4.503	5.500	5.348	6.473	5.257	5.358	5.938	5.746	6.445
Candidate129	2.613	3.297	1.813	2.466	2.379	1.029	1.656	1.726	2.395	3.336	2.689	1.179	1.859	2.663	3.624	1.285	1.222	6.388	5.760	7.237	7.689	7.870
Candidate130	4.211	3.891	3.869	5.168	4.743	4.278	5.009	5.074	5.747	6.439	6.485	5.699	4.173	4.363	4.582	5.207	5.863	3.766	3.867	4.435	2.994	3.787
Candidate131	3.483	4.069	3.675	2.841	3.418	3.954	3.583	3.179	3.096	3.154	4.293	4.395	4.583	5.584	6.545	5.158	5.413	8.933	8.680	9.614	10.066	10.247
Candidate132	5.669	5.198	6.778	7.428	6.821	7.506	7.845	7.457	7.978	8.036	9.185	8.550	7.956	7.560	8.567	8.405	9.090	8.686	8.787	9.367	9.670	10.000
Candidate133	3.686	3.366	3.704	4.643	4.218	4.113	4.843	4.672	5.560	5.914	6.320	5.533	4.008	3.838	4.671	4.683	5.697	4.168	4.269	4.849	4.733	5.356
Candidate134	11.453	10.982	12.562	11.958	12.535	13.289	13.365	12.610	12.187	12.245	14.076	14.077	13.673	13.344	14.351	14.189	14.874	14.470	14.571	15.151	15.454	15.784
Candidate135	4.337	3.865	5.421	6.013	5.488	5.830	6.512	6.125	7.013	7.307	7.852	7.217	5.725	5.916	6.603	6.760	7.415	5.978	6.079	6.659	6.419	7.166
Candidate136	7.727	7.255	8.058	9.353	8.878	8.467	9.198	9.263	9.937	10.624	10.674	9.888	8.362	8.548	9.237	9.393	10.052	8.611	8.712	9.292	9.052	9.799
Candidate137	5.216	4.896	4.873	6.172	5.748	5.282	6.013	6.078	6.751	7.444	7.489	6.703	5.177	5.368	6.056	6.212	6.867	5.430	5.532	6.111	5.604	6.397
Candidate138	6.056	5.585	6.252	7.551	7.127	6.661	7.391	7.457	8.130	8.822	8.868	8.082	6.556	6.746	7.434	7.591	8.245	6.809	6.910	7.490	7.250	7.997

Park\Location	BG370210018011	BG370210018012	BG370210018021	BG370210018022	BG370210018023	BG370210019001	BG370210019002	BG370210020001	BG370210020002	BG370210020003	BG370210020004	BG370210021021	BG370210021022	BG370210022031	BG370210022032	BG370210022033	BG370210022041	BG370210022042	BG370210022043	BG370210022044	BG370210022051	BG370210022053
Albemarle Park	2.304	3.582	4.960	5.551	4.519	4.951	4.376	4.473	4.536	4.511	4.619	4.353	6.574	5.800	11.472	13.527	11.470	9.645	7.460	9.569	8.699	11.017
Amboy Riverfront Park	4.551	4.779	6.158	6.748	5.585	5.617	4.561	3.063	3.931	3.101	3.210	2.898	4.993	4.219	9.891	11.947	9.890	8.064	5.880	7.988	7.118	9.437
Ann Patton Joyce Park	3.040	1.480	2.189	2.687	0.626	0.617	0.977	2.840	2.066	4.184	4.297	4.494	4.784	4.629	10.294	12.294	10.157	8.801	6.617	8.698	7.856	9.674
Azalea Park	4.039	2.400	3.109	3.607	1.333	0.821	1.498	3.248	2.473	4.592	4.704	4.902	5.191	5.037	10.702	12.701	10.565	9.209	7.025	9.106	8.263	10.082
Burton Street Center	4.181	5.713	7.091	7.681	6.649	7.082	6.239	4.741	5.609	4.779	4.888	4.577	6.672	5.897	11.569	12.714	11.568	9.742	7.558	9.666	8.796	11.115
Carrier Park	4.760	5.357	6.735	7.325	6.162	6.195	5.138	3.640	4.508	3.678	3.787	3.476	5.571	4.796	10.468	11.984	10.467	8.641	6.457	8.565	7.695	10.014
Charlie Bullman Park	3.289	1.135	0.681	1.068	1.803	2.257	2.040	3.938	3.400	5.115	5.224	5.179	6.118	5.964	11.629	13.629	11.492	10.136	7.952	10.033	9.190	11.009
Choctaw Street Park	2.835	4.057	5.435	6.025	4.993	5.042	3.985	2.659	3.527	2.697	2.806	2.310	4.729	3.955	9.627	11.682	9.626	7.800	5.616	7.724	6.854	9.172
Dr. Wesley Grant Sr. Southside Center	3.150	4.414	5.793	6.383	5.345	5.378	4.322	2.878	3.745	2.915	3.024	2.709	4.948	4.173	9.845	11.901	9.844	8.018	5.834	7.943	7.073	9.391
E.W. Grove Park	2.351	3.717	5.096	5.686	4.654	5.086	4.423	4.520	4.583	4.558	4.666	4.400	6.621	5.847	11.519	13.574	11.517	9.692	7.507	9.616	8.746	11.064
East Asheville Center	2.454	0.953	1.662	2.160	0.845	1.293	0.847	2.999	2.338	4.176	4.285	4.260	5.056	4.902	10.567	12.567	10.430	9.074	6.890	8.971	8.128	9.947
Falconhurst Park	4.605	6.136	7.515	8.105	7.073	7.505	6.686	5.321	6.189	5.359	5.468	5.156	7.251	6.477	12.149	13.197	12.148	10.322	8.138	10.246	9.376	11.694
Forest Park	2.210	3.089	4.468	5.058	4.026	4.084	3.027	1.979	2.812	2.017	2.126	1.661	4.080	3.306	8.978	11.034	8.977	7.151	4.967	7.075	6.205	8.524
French Broad River Park	4.406	4.635	6.014	6.604	5.440	5.473	4.417	2.919	3.787	2.957	3.065	2.754	4.849	4.075	9.747	11.802	9.745	7.920	5.735	7.844	6.974	9.292
Haw Creek Park	2.641	0.838	1.546	2.045	0.972	1.427	1.035	3.187	2.526	4.364	4.473	4.447	5.244	5.090	10.755	12.754	10.618	9.262	7.078	9.159	8.316	10.135
Herb Watts Park	3.046	3.963	5.342	5.932	4.894	4.927	3.871	2.427	3.294	2.464	2.573	2.232	4.497	3.722	9.394	11.450	9.393	7.567	5.383	7.492	6.622	8.940
Hummingbird Park	2.268	3.660	5.038	5.629	4.597	5.029	4.339	3.782	4.499	3.820	3.929	3.659	5.883	5.109	10.781	12.837	10.780	8.954	6.770	8.878	8.008	10.326
Irby Brinson Complex	9.702	9.475	10.854	11.444	9.476	9.167	8.575	7.621	7.409	6.438	5.759	6.185	4.998	4.633	3.260	4.760	3.258	1.165	2.621	0.789	1.596	3.036
Jake Rusher Park	10.017	9.399	10.778	11.368	9.400	9.091	8.499	7.752	7.333	6.751	6.164	6.456	4.772	4.946	1.410	3.495	1.409	2.706	2.983	1.505	2.041	0.952
Jean Webb Park	3.164	4.696	6.075	6.665	5.633	6.065	5.228	3.784	4.652	3.822	3.931	3.584	5.854	5.080	10.752	12.807	10.750	8.925	6.740	8.849	7.979	10.297
Kenilworth Park	2.208	3.087	4.465	5.055	4.023	4.282	3.226	2.013	2.881	2.051	2.160	1.695	4.114	3.340	9.012	11.068	9.011	7.185	5.001	7.109	6.239	8.558
Leah Chiles Park	2.295	3.174	4.552	5.142	4.110	4.297	3.241	2.404	3.026	2.442	2.551	2.086	4.505	3.731	9.403	11.459	9.402	7.576	5.392	7.500	6.630	8.949
Lynwood Crump Shiloh Complex	4.784	4.371	5.750	6.340	4.372	4.063	3.471	2.461	2.305	1.278	0.475	1.210	2.055	1.047	7.038	9.094	7.037	5.211	3.027	5.136	4.266	6.584
Magnolia Park	2.527	3.858	5.236	5.827	4.795	5.227	4.599	4.041	4.759	4.079	4.188	3.921	6.143	5.368	11.040	13.096	11.039	9.213	7.029	9.138	8.268	10.586
Malvern Hills Pool and Park	5.881	7.413	8.791	9.382	8.350	8.593	7.536	6.139	7.007	6.177	6.285	5.876	8.069	7.295	12.617	12.437	12.616	9.916	8.956	10.136	10.194	12.393
Martin Luther King Jr. Park	1.411	2.942	4.321	4.911	3.879	4.311	3.492	3.506	3.642	3.543	3.652	3.386	5.607	4.833	10.505	12.560	10.503	8.678	6.493	8.602	7.732	10.050
Masters Park	4.147	1.993	1.164	0.685	2.661	3.115	2.898	4.796	4.258	5.973	6.082	6.037	6.976	6.822	12.487	14.486	12.350	10.994	8.809	10.891	10.048	11.867
Meadow Park	2.423	3.302	4.681	5.271	4.191	4.224	3.167	1.847	2.715	1.885	1.994	1.529	3.949	3.174	8.847	10.902	8.845	7.020	4.835	6.944	6.074	8.392
Montford Park	3.064	4.383	5.762	6.352	5.320	5.752	5.136	4.588	5.296	4.626	4.734	4.468	6.689	5.915	11.587	13.642	11.585	9.760	7.575	9.684	8.814	11.132
Mountainside Park	2.173	3.463	4.841	5.431	4.399	4.832	4.003	3.160	4.028	3.198	3.307	2.842	5.261	4.487	10.159	12.215	10.158	8.332	6.148	8.256	7.386	9.705
Murphy-Oakley Center Complex	3.110	2.521	3.899	4.490	2.521	2.213	1.621	0.866	0.455	2.395	2.508	2.521	2.994	2.840	8.505	10.505	8.368	7.012	4.828	6.909	6.066	7.885
Murray Hill Park	3.050	4.409	5.787	6.378	5.345	5.607	4.551	3.225	4.092	3.262	3.371	2.877	5.295	4.520	10.192	12.248	10.191	8.365	6.181	8.290	7.420	9.738
Oakhurst Park	2.264	3.623	5.001	5.591	4.559	4.992	4.104	2.784	3.652	2.822	2.930	2.466	4.885	4.111	9.783	11.838	9.781	7.956	5.772	7.880	7.010	9.328
Owens-Bell Park	2.629	4.161	5.539	6.130	5.098	5.530	4.701	3.627	4.495	3.665	3.774	3.300	5.697	4.923	10.595	12.651	10.594	8.768	6.584	8.692	7.822	10.141
Pack Square Park	1.627	3.159	4.538	5.128	4.096	4.528	3.709	3.379	3.859	3.417	3.526	3.259	5.481	4.706	10.378	12.434	10.377	8.551	6.367	8.475	7.605	9.924
Pritchard Park	1.935	3.467	4.845	5.435	4.403	4.836	4.007	3.325	4.167	3.363	3.471	3.155	5.426	4.652	10.324	12.379	10.322	8.497	6.312	8.421	7.551	9.869
Ray L. Kisiah Park	4.413	3.702	5.081	5.671	3.687	3.362	2.770	2.262	1.496	2.721	2.334	2.601	1.635	2.431	7.321	9.320	7.184	5.866	3.682	5.725	4.921	6.701
Recreation Park and Pool	3.662	1.864	2.573	3.071	0.796	0.360	0.962	2.711	1.937	4.056	4.168	4.564	4.655	4.501	10.166	12.165	10.029	8.672	6.488	8.570	7.727	9.546
Richmond Hill Park	5.336	6.797	8.175	8.766	7.734	8.166	7.418	6.642	7.510	6.680	6.788	6.491	8.712	7.938	13.610	15.665	13.608	11.783	9.598	11.707	10.837	13.155
Riverbend Park	2.190	1.052	2.431	3.021	1.989	1.863	0.806	1.911	1.305	3.089	3.439	2.974	4.023	3.869	9.534	11.534	9.397	8.041	5.857	7.938	7.095	8.914
Roger Farmer Memorial Park	5.489	7.021	8.399	8.989	7.957	8.390	7.570	6.238	7.106	6.276	6.385	6.074	8.169	7.394	13.066	13.240	13.065	10.855	9.055	11.075	10.293	12.612
Seven Springs Park	2.477	3.302	4.680	5.270	4.107	4.140	3.083	1.838	2.705	1.876	1.984	1.527	3.939	3.165	8.837	10.892	8.835	7.010	4.825	6.934	6.064	8.382
Stephens-Lee Recreation Center	1.655	3.187	4.566	5.156	4.124	4.556	3.727	3.272	3.887	3.310	3.418	3.152	5.373	4.599	10.271	12.326	10.270	8.444	6.260	8.368	7.498	9.816
Sunset Park	2.350	3.628	5.007	5.597	4.565	4.997	4.422	4.519	4.582	4.557	4.666	4.399	6.620	5.846	11.518	13.574	11.517	9.691	7.507	9.615	8.745	11.064
Tempie Avery Montford Complex	2.840	4.206	5.584	6.175	5.143	5.575	4.912	4.293	5.072	4.331	4.439	4.142	6.363	5.589	11.261	13.316	11.259	9.434	7.249	9.358	8.488	10.806
Triangle Park	1.866	3.359	4.737	5.328	4.295	4.728	3.899	3.154	4.022	3.192	3.301	2.836	5.255	4.481	10.153	12.209	10.152	8.326	6.142	8.250	7.380	9.699
Walton Street Park and Pool	3.493	4.293	5.671	6.262	5.098	5.131	4.075	2.631	3.499	2.669	2.777	2.480	4.701	3.927	9.599	11.654	9.597	7.772	5.587	7.696	6.826	9.144
Weaver Park	2.724	4.000	5.379	5.969	4.937	5.369	4.806	4.818	4.956	4.856	4.964	4.698	6.919	6.145	11.817	13.872	11.815	9.990	7.805	9.914	9.044	11.362
West Asheville Community Center	5.100	6.632	8.010	8.601	7.568	8.001	6.969	5.471	6.339	5.509	5.618	5.306	7.402	6.627	12.299	12.646	12.298	10.125	8.288	10.345	9.526	11.845
West Asheville Park	5.421	6.953	8.331	8.922	7.890	7.939	6.883	5.501	6.369	5.539	5.647	5.223	7.431	6.657	11.963	11.783	11.962	9.263	8.317	9.483	9.556	11.739
White Fawn Park	2.507	3.497	4.875	5.465	4.433	4.865	3.865	2.545	3.412	2.582	2.691	2.226	4.646	3.872	9.544	11.644	9.542	7.728	5.532	7.641	6.771	9.089
White Pine Park	1.630	1.776	3.154	3.744	2.712	3.144	2.316	2.719	2.476	3.897	4.006	3.833	5.063	4.909	10.574	12.574	10.437	9.081	6.897	8.978	8.135	9.954
Candidate1	9.941	11.473	12.851	13.441	12.409	12.595	11.539	10.084	11.087	9.971	9.677	11.661	10.886	13.285	13.001	13.406	10.671	12.226	10.937	11.644	13.183	12.532
Candidate2	3.265	4.797	6.176	6.766	5.734	6.166	5.347	4.894	5.497	4.932	5.041	6.964	6.190	11.862	13.786	11.861	10.046	7.851	9.959	9.089	11.408	10.807
Candidate3	5.534	7.023	8.402	8.992	7.960	8.392	7.606	7.443	7.766	7.481	7.589	9.544	8.770	14.442	16.497	14.440	12.615	10.430	12.539	11.669	13.987	13.367
Candidate4	0.184	2.369	3.748	4.338	3.306	3.738	3.171	3.575	3.331	4.411	4.520	5.919	5.700	11.372	13.428	11.293	9.545	7.361	9.469	8.599	10.809	10.190
Candidate5	9.917	9.690	11.069	11.659	9.691	9.382	8.790	7.836	7.624	6.653	5.975	5.213	4.849	4.928	5.117	4.927	1.558	3.588	2.458	2.624	4.704	4.053
Candidate6	5.051	6.583	7.961	8.551	7.519	7.680	6.624	5.126	5.993	5.163	5.272	7.056	6.281	11.954	11.876	11.952	9.356	7.942	9.576	9.181	11.499	10.879
Candidate7	3.994	5.526	6.904	7.494	6.462	6.894	6.066	6.446	6.225	6.483	6.592	8.547	7.773	13.445	15.500	13.443	11.618	9.433	11.542	10.672	12.990	12.370
Candidate8	2.383	1.046	2.424	3.015	1.983	2.415	1.465	2.543	2.005	3.720	3.829	4.723	4.569	10.234	12.234	10.097	8.741	6.557	8.638	7.795	9.614	8.994
Candidate9	1.910	3.442	4.820	5.410	4.378	4.810	3.982	4.362	4.142	4.400	4.508	6.463	5.689	11.361	13.416	11.359	9.534	7.349	9.458	8.588	10.906	10.286
Candidate10	8.475	10.006	11.385	11.975	10.943	11.109	10.052	8.554	9.422	8.592	8.701	9.717	8.942	11.011	10.727	11.132	8.397	9.952	8.663	9.370	10.909	10.258
Candidate11	0.866	2.398	3.776	4.367	3.334	3.767	2.938	3.341	3.098	4.099	4.208	5.686	5.388	11.060	13.116	11.059	9.233	7.049	9.158	8.288	10.576	9.956
Candidate12	2.559	2.053	3.431	4.022	2.696	2.388	1.796	1.148	0.653	2.641	2.754	3.241	3.086	8.751	10.751	8.614	7.258	5.074	7.155	6.313	8.131	7.512

Park\Location	BG370210018011	BG370210018012	BG370210018021	BG370210018022	BG370210018023	BG370210019001	BG370210019002	BG370210020001	BG370210020002	BG370210020003	BG370210020004	BG370210021021	BG370210021022	BG370210022031	BG370210022032	BG370210022033	BG370210022041	BG370210022042	BG370210022043	BG370210022044	BG370210022051	BG370210022053
Candidate13	9.057	10.589	11.968	12.558	11.526	11.712	10.655	9.200	10.203	9.088	8.794	10.777	10.003	13.349	13.066	13.471	10.735	11.499	11.002	11.709	13.248	12.597
Candidate14	5.309	6.841	8.220	8.810	7.728	7.761	6.704	5.206	6.074	5.244	5.353	7.136	6.362	12.034	12.566	12.033	10.046	8.023	10.131	9.261	11.580	10.960
Candidate15	5.546	7.077	8.456	9.046	8.014	8.446	7.627	6.646	7.514	6.684	6.793	8.577	7.802	13.474	13.922	13.473	11.402	9.463	11.572	10.702	13.020	12.400
Candidate16	6.661	7.543	8.921	9.511	8.705	8.381	7.324	5.711	6.872	5.598	5.304	7.288	6.514	10.789	10.609	10.788	8.088	7.714	8.308	8.952	10.565	9.913
Candidate17	3.355	1.694	2.403	2.901	0.701	1.229	1.703	3.453	2.678	4.797	4.910	5.397	5.242	10.907	12.907	10.770	9.414	7.230	9.311	8.468	10.287	9.667
Candidate18	2.587	1.234	2.401	2.964	1.547	1.837	1.281	2.608	1.948	3.786	3.895	4.666	4.512	10.177	12.176	10.040	8.684	6.499	8.581	7.738	9.557	8.937
Candidate19	8.359	9.891	11.269	11.860	10.828	10.993	9.937	8.439	9.306	8.476	8.243	9.601	8.827	12.051	11.768	12.173	9.437	9.899	9.703	10.411	11.950	11.299
Candidate20	1.087	2.267	3.646	4.236	3.204	3.636	2.808	3.211	2.967	3.522	3.630	5.555	4.811	10.483	12.538	10.481	8.656	6.472	8.580	7.710	10.028	9.408
Candidate21	4.170	4.057	5.435	6.025	4.074	3.766	3.174	1.831	2.007	1.072	1.173	2.532	1.658	7.657	9.712	7.655	5.830	3.645	5.754	4.884	7.202	6.582
Candidate22	3.426	2.971	4.349	4.940	3.136	2.827	2.235	0.274	1.069	1.923	2.032	3.432	3.278	8.943	10.942	8.806	7.315	5.131	7.239	6.369	8.323	7.703
Candidate23	5.042	2.888	2.059	1.241	3.555	4.010	3.793	5.690	5.153	6.868	6.977	7.871	7.717	13.382	15.381	13.245	11.888	9.704	11.785	10.943	12.762	12.142
Candidate24	6.083	7.615	8.993	9.583	8.551	8.984	8.155	8.392	8.315	8.430	8.538	10.493	9.719	15.391	17.446	15.389	13.564	11.379	13.488	12.618	14.936	14.316
Candidate25	4.762	6.294	7.672	8.263	7.231	7.663	6.844	6.128	6.994	6.166	6.274	8.058	7.284	12.956	13.603	12.954	11.082	8.944	11.053	10.183	12.501	11.881
Candidate26	4.048	5.408	6.787	7.377	6.345	6.777	6.130	5.354	6.222	5.392	5.500	7.424	6.650	12.322	14.377	12.320	10.495	8.310	10.419	9.549	11.867	11.247
Candidate27	5.405	6.936	8.315	8.905	7.873	8.305	7.477	7.713	7.636	7.751	7.860	9.815	9.040	14.712	16.768	14.711	12.885	10.701	12.810	11.940	14.258	13.638
Candidate28	2.079	3.250	4.628	5.218	4.186	4.619	3.790	2.929	3.797	2.967	3.076	5.030	4.256	9.928	11.984	9.927	8.101	5.917	8.025	7.155	9.474	8.854
Candidate29	5.305	6.794	8.173	8.763	7.731	8.163	7.377	7.214	7.537	7.252	7.360	9.315	8.541	14.213	16.268	14.211	12.386	10.201	12.310	11.440	13.758	13.138
Candidate30	1.814	0.691	2.070	2.660	1.628	2.060	1.505	2.677	2.139	3.854	3.963	4.857	4.703	10.368	12.367	10.231	8.875	6.690	8.772	7.929	9.748	9.128
Candidate31	2.193	3.725	5.103	5.693	4.661	5.093	4.265	4.645	4.425	4.683	4.791	6.746	5.972	11.644	13.699	11.642	9.817	7.632	9.741	8.871	11.189	10.569
Candidate32	5.047	6.535	7.914	8.504	7.472	7.904	7.119	6.955	7.278	6.993	7.102	9.056	8.282	13.954	16.010	13.953	12.127	9.943	12.051	11.181	13.500	12.880
Candidate33	6.277	7.808	9.187	9.777	8.745	9.177	8.358	6.974	7.842	7.012	7.121	8.904	8.130	13.802	13.834	13.801	11.504	9.791	11.770	11.029	13.348	12.728
Candidate34	6.550	5.932	7.310	7.900	5.932	5.624	5.032	4.285	3.865	3.791	3.112	1.416	1.987	4.838	6.837	4.701	3.826	2.386	3.242	2.928	4.218	3.598
Candidate35	1.360	2.531	3.909	4.499	3.467	3.899	3.071	3.474	3.230	3.766	3.874	5.818	5.055	10.727	12.782	10.725	8.900	6.715	8.824	7.954	10.272	9.652
Candidate36	5.487	7.019	8.397	8.988	7.956	8.388	7.559	7.521	7.719	7.559	7.668	9.622	8.848	14.520	16.576	14.519	12.693	10.509	12.617	11.747	14.066	13.446
Candidate37	6.096	7.628	9.006	9.596	8.564	8.997	8.177	7.028	7.896	7.066	7.175	8.959	8.184	13.856	13.975	13.855	11.645	9.845	11.902	11.083	13.402	12.782
Candidate38	2.299	0.962	2.340	2.931	1.898	2.331	1.381	2.459	1.921	3.636	3.745	4.639	4.485	10.150	12.149	10.013	8.657	6.473	8.554	7.711	9.530	8.910
Candidate39	5.307	6.839	8.218	8.808	7.776	8.208	7.379	7.341	7.539	7.379	7.488	9.443	8.668	14.340	16.396	14.339	12.513	10.329	12.437	11.567	13.886	13.266
Candidate40	4.127	4.254	5.633	6.223	4.849	4.541	3.949	2.031	2.783	0.849	0.425	2.554	1.780	7.452	9.508	7.451	5.625	3.441	5.549	4.679	6.998	6.378
Candidate41	4.437	5.968	7.347	7.937	6.905	7.337	6.518	5.802	6.668	5.840	5.949	7.732	6.958	12.630	13.277	12.629	10.757	8.619	10.727	9.857	12.176	11.556
Candidate42	3.006	4.538	5.916	6.506	5.474	5.906	5.078	5.458	5.237	5.495	5.604	7.559	6.785	12.457	14.512	12.455	10.630	8.445	10.554	9.684	12.002	11.382
Candidate43	2.520	1.166	2.334	2.924	1.534	1.825	1.183	2.384	1.723	3.561	3.670	4.441	4.287	9.952	11.952	9.815	8.459	6.275	8.356	7.513	9.332	8.712
Candidate44	4.794	6.144	7.522	8.113	7.080	7.513	6.866	6.414	7.026	6.452	6.560	8.515	7.741	13.413	15.468	13.412	11.586	9.402	11.510	10.640	12.958	12.338
Candidate45	9.436	9.097	10.476	11.066	9.098	8.789	8.197	7.355	7.031	6.172	5.493	4.582	4.367	1.753	3.808	1.751	1.818	2.354	0.718	1.263	1.529	0.877
Candidate46	4.915	3.253	3.962	4.461	1.899	2.512	2.985	4.661	3.887	5.847	5.791	6.045	5.891	11.556	13.826	11.418	10.476	7.787	9.892	9.380	10.935	10.335
Candidate47	6.686	8.217	9.596	10.186	9.154	9.586	8.767	7.356	8.224	7.394	7.502	9.286	8.512	13.787	13.607	13.786	11.087	10.172	11.306	11.411	13.563	12.911
Candidate48	5.304	6.836	8.214	8.805	7.773	8.205	7.376	7.338	7.536	7.376	7.485	9.439	8.665	14.337	16.393	14.336	12.510	10.326	12.434	11.564	13.882	13.263
Candidate49	3.545	3.091	4.469	5.059	3.328	3.020	2.427	0.154	1.261	2.043	2.152	3.624	3.470	9.135	11.134	8.998	7.435	5.250	7.359	6.489	8.515	7.895
Candidate50	4.078	5.445	6.824	7.414	6.382	6.814	6.150	5.532	6.309	5.570	5.679	7.602	6.828	12.500	14.555	12.498	10.673	8.488	10.597	9.727	12.045	11.425
Candidate51	5.317	6.806	8.184	8.774	7.742	8.174	7.389	7.225	7.548	7.263	7.372	9.326	8.552	14.224	16.280	14.223	12.397	10.213	12.321	11.451	13.770	13.150
Candidate52	6.658	8.190	9.568	10.158	9.126	9.559	8.717	7.219	8.087	7.257	7.366	9.149	8.375	13.645	13.465	13.643	10.944	10.036	11.164	11.274	13.421	12.768
Candidate53	6.003	5.644	7.022	7.613	5.645	5.336	4.744	3.922	3.578	2.739	2.060	1.129	0.934	6.196	8.247	6.111	4.369	2.185	4.294	3.423	5.628	5.008
Candidate54	5.006	4.387	5.766	6.356	4.388	4.079	3.487	2.740	2.321	2.399	1.584	1.048	1.691	6.582	8.582	6.445	5.127	2.942	4.986	4.181	5.962	5.342
Candidate55	6.088	7.620	8.998	9.588	8.556	8.989	8.160	8.397	8.320	8.435	8.543	10.498	9.724	15.396	17.451	15.394	13.569	11.384	13.493	12.623	14.941	14.321
Candidate56	7.562	8.444	9.822	10.413	9.590	9.282	8.226	6.929	7.773	6.957	6.278	7.235	6.460	9.784	9.604	9.783	7.084	7.533	7.304	8.111	9.560	8.908
Candidate57	4.055	3.942	5.320	5.911	4.144	3.836	3.244	1.717	2.078	0.672	0.996	2.839	2.356	8.106	10.162	8.105	6.279	4.095	6.204	5.334	7.652	7.032
Candidate58	0.972	2.900	4.278	4.869	3.837	4.269	3.702	4.105	3.861	4.941	5.050	6.449	6.231	11.903	13.958	11.823	10.076	7.891	10.000	9.130	11.340	10.720
Candidate59	6.381	7.912	9.291	9.881	8.849	9.281	8.452	8.689	8.612	8.727	8.836	10.791	10.016	15.688	17.744	15.687	13.861	11.677	13.785	12.915	15.234	14.614
Candidate60	8.644	10.176	11.554	12.145	11.112	11.278	10.222	8.723	9.591	8.761	8.870	9.841	9.067	10.841	10.558	10.963	8.227	9.783	8.494	9.201	10.740	10.089
Candidate61	8.250	7.996	9.375	9.965	7.997	7.688	7.096	6.169	5.930	4.987	4.308	3.480	3.182	3.045	5.100	3.043	1.726	1.169	1.142	0.883	2.796	2.169
Candidate62	5.159	6.691	8.069	8.659	7.627	8.060	7.231	7.611	7.391	7.649	7.757	9.712	8.938	14.610	16.665	14.608	12.783	10.598	12.707	11.837	14.155	13.535
Candidate63	5.186	3.032	2.203	1.385	3.699	4.154	3.937	5.834	5.297	7.012	7.120	8.015	7.861	13.526	15.525	13.389	12.032	9.848	11.929	11.087	12.906	12.286
Candidate64	3.798	4.027	5.405	5.995	4.832	4.865	3.808	2.488	3.356	2.526	2.635	4.568	3.794	9.466	11.521	9.464	7.639	5.454	7.563	6.693	9.011	8.391
Candidate65	3.725	1.518	0.393	1.333	2.331	2.786	2.568	4.374	3.836	5.551	5.660	6.554	6.400	12.065	14.064	11.928	10.572	8.388	10.469	9.626	11.445	10.825
Candidate66	3.560	5.092	6.470	7.060	6.028	6.461	5.632	6.012	5.792	6.050	6.158	8.113	7.339	13.011	15.066	13.009	11.184	8.999	11.108	10.238	12.556	11.936
Candidate67	2.226	0.493	1.951	2.595	1.825	2.257	1.702	2.874	2.336	4.051	4.160	5.054	4.900	10.565	12.565	10.428	9.072	6.888	8.969	8.126	9.945	9.325
Candidate68	0.746	2.932	4.310	4.900	3.868	4.300	3.733	4.137	3.893	4.973	5.082	6.481	6.262	11.934	13.990	11.855	10.107	7.923	10.031	9.161	11.372	10.752
Candidate69	7.385	8.267	9.645	10.236	9.413	9.105	8.049	6.752	7.596	6.780	6.101	7.058	6.283	9.607	9.427	9.606	6.907	7.356	7.127	7.934	9.383	8.731
Candidate70	9.146	8.919	10.298	10.888	8.920	8.611	8.019	7.065	6.853	5.882	5.203	4.442	4.077	3.352	5.125	3.351	0.218	2.065	0.882	1.048	3.128	2.477
Candidate71	9.403	9.149	10.528	11.118	9.150	8.841	8.249	7.322	7.083	6.140	5.461	4.634	4.335	2.766	4.821	2.764	0.905	2.322	0.295	1.018	2.542	1.890
Candidate72	8.913	8.294	9.673	10.263	8.295	7.986	7.394	6.647	6.228	5.757	5.078	3.779	3.952	2.456	4.455	2.319	2.104	1.940	1.004	1.506	1.836	1.216
Candidate73	6.092	7.624	9.002	9.593	8.560	8.993	8.173	7.193	8.061	7.231	7.339	9.123	8.349	14.021	14.646	14.019	12.125	10.009	12.118	11.248	13.566	12.946
Candidate74	4.453	2.298	1.470	0.651	2.966	3.421	3.204	5.101	4.563	6.278	6.387	7.281	7.127	12.792	14.792	12.655	11.299	9.115	11.196	10.353	12.172	11.552
Candidate75	5.612	3.458	2.629	1.811	4.126	4.580	4.363	6.261	5.723	7.438	7.547	8.441	8.287	13.952	15.951	13.815	12.459	10.274	12.356	11.513	13.332	12.712
Candidate76	5.083	2.929	2.100	1.282	3.596	4.051	3.834	5.731	5.194	6.909	7.017	7.912	7.758	13.423	15.422	13.286	11.929	9.745	11.826	10.984	12.803	12.183

Park\Location	BG370210018011	BG370210018012	BG370210018021	BG370210018022	BG370210018023	BG370210019001	BG370210019002	BG370210020001	BG370210020002	BG370210020003	BG370210020004	BG370210021021	BG370210021022	BG370210022031	BG370210022032	BG370210022033	BG370210022041	BG370210022042	BG370210022043	BG370210022044	BG370210022051	BG370210022053
Candidate77	4.290	4.176	5.555	6.145	4.676	4.368	3.776	1.951	2.610	0.769	0.046	2.360	1.485	7.291	9.347	7.290	5.464	3.280	5.389	4.519	6.837	6.217
Candidate78	9.443	9.188	10.567	11.157	9.189	8.880	8.288	7.362	7.122	6.179	5.500	4.673	4.374	2.364	4.420	2.363	1.746	2.361	0.647	1.270	2.140	1.489
Candidate79	3.484	1.277	0.962	1.605	2.090	2.544	2.327	4.133	3.595	5.310	5.419	6.313	6.159	11.824	13.823	11.687	10.331	8.146	10.228	9.385	11.204	10.584
Candidate80	3.587	5.119	6.497	7.087	6.055	6.487	5.659	4.463	5.331	4.501	4.609	6.533	5.759	11.431	12.944	11.429	9.604	7.419	9.528	8.658	10.976	10.356
Candidate81	3.335	2.880	4.259	4.849	3.585	3.276	2.662	0.650	1.518	1.565	1.673	3.648	3.111	8.783	10.839	8.782	6.956	4.772	6.880	6.010	8.329	7.709
Candidate82	8.409	8.182	9.560	10.150	8.182	7.874	7.282	6.328	6.115	5.145	4.466	3.704	3.340	3.466	5.522	3.465	1.078	1.327	1.349	0.450	3.217	2.591
Candidate83	7.361	6.743	8.121	8.711	6.743	6.435	5.843	5.096	4.677	4.603	3.924	2.227	2.798	4.416	6.415	4.279	3.404	1.964	2.820	2.506	3.796	3.176
Candidate84	0.671	2.599	3.977	4.567	3.535	3.967	3.400	3.804	3.560	4.640	4.749	6.148	5.929	11.601	13.657	11.522	9.774	7.590	9.699	8.829	11.039	10.419
Candidate85	5.669	7.201	8.579	9.170	8.138	8.570	7.741	7.703	7.901	7.741	7.850	9.804	9.030	14.702	16.758	14.701	12.875	10.691	12.799	11.929	14.248	13.628
Candidate86	5.449	6.981	8.359	8.949	7.917	8.350	7.530	6.550	7.418	6.588	6.696	8.480	7.706	13.378	14.009	13.376	11.489	9.366	11.475	10.605	12.923	12.303
Candidate87	5.453	6.985	8.363	8.954	7.921	8.354	7.525	7.530	7.685	7.568	7.677	9.632	8.857	14.529	16.585	14.528	12.702	10.518	12.627	11.757	14.075	13.455
Candidate88	2.502	4.034	5.412	6.003	4.971	5.403	4.574	4.954	4.734	4.992	5.101	7.055	6.281	11.953	14.009	11.952	10.126	7.942	10.050	9.180	11.499	10.879
Candidate89	6.792	8.324	9.702	10.293	9.261	9.693	8.852	7.353	8.221	7.391	7.500	9.284	8.509	13.779	13.599	13.778	11.078	10.170	11.298	11.409	13.555	12.903
Candidate90	6.437	7.968	9.347	9.937	8.905	8.990	7.934	6.393	7.384	6.281	5.987	7.970	7.196	11.982	11.802	11.981	9.281	8.813	9.501	10.051	11.758	11.105
Candidate91	5.979	7.511	8.889	9.479	8.447	8.879	8.060	6.876	7.744	6.914	7.022	8.806	8.032	13.704	14.050	13.702	11.530	9.692	11.750	10.931	13.249	12.629
Candidate92	1.608	3.139	4.518	5.108	4.076	4.508	3.679	4.059	3.839	4.097	4.206	6.161	5.386	11.058	13.114	11.057	9.231	7.047	9.156	8.286	10.604	9.984
Candidate93	2.841	2.386	3.764	4.355	3.191	3.224	2.168	1.568	1.952	1.969	2.078	4.032	3.258	8.930	10.986	8.929	7.103	4.919	7.027	6.157	8.476	7.856
Candidate94	7.913	9.445	10.824	11.414	10.382	10.547	9.491	7.993	8.861	8.031	8.139	9.155	8.381	11.572	11.288	11.693	8.958	9.454	9.224	9.931	11.471	10.819
Candidate95	8.619	8.365	9.743	10.333	8.365	8.057	7.465	6.538	6.299	5.355	4.676	3.849	3.550	2.706	4.761	2.705	1.251	1.538	0.803	0.459	2.457	1.830
Candidate96	3.147	4.678	6.057	6.647	5.615	6.047	5.219	5.598	5.378	5.636	5.745	7.700	6.925	12.597	14.653	12.596	10.770	8.586	10.695	9.825	12.143	11.523
Candidate97	2.002	3.173	4.551	5.142	4.109	4.542	3.713	2.982	3.849	3.019	3.128	5.083	4.309	9.981	12.036	9.979	8.154	5.969	8.078	7.208	9.526	8.906
Candidate98	3.009	4.323	5.701	6.292	5.259	5.692	5.081	4.628	5.240	4.666	4.775	6.730	5.955	11.627	13.683	11.626	9.800	7.616	9.724	8.854	11.173	10.553
Candidate99	8.893	9.775	11.154	11.744	10.887	10.613	9.557	7.944	9.094	7.831	7.537	8.532	7.758	9.162	8.878	9.283	6.548	8.107	6.814	7.521	9.061	8.409
Candidate100	6.562	8.094	9.472	10.062	9.030	9.116	8.059	6.519	7.509	6.406	6.112	8.096	7.321	12.107	11.927	12.106	9.406	8.938	9.626	10.177	11.883	11.231
Candidate101	9.456	10.988	12.366	12.956	11.815	11.780	10.791	9.154	10.022	9.069	8.503	9.460	8.686	10.460	10.176	10.581	7.846	9.402	8.112	8.819	10.359	9.707
Candidate102	9.664	9.045	10.424	11.014	9.046	8.737	8.145	7.398	6.979	6.508	5.829	4.529	4.703	4.447	6.364	4.227	3.771	2.690	3.188	2.928	3.744	3.544
Candidate103	8.756	10.288	11.666	12.257	11.225	11.390	10.334	8.836	9.703	8.874	8.982	9.998	9.224	11.547	11.263	11.668	8.933	10.296	9.199	9.906	11.446	10.794
Candidate104	5.272	3.117	2.289	1.470	3.785	4.240	4.023	5.920	5.382	7.097	7.206	8.100	7.946	13.611	15.611	13.474	12.118	9.934	12.015	11.172	12.991	12.371
Candidate105	4.898	5.025	6.404	6.994	5.067	4.759	4.167	2.817	3.001	1.634	0.955	1.680	0.905	6.577	8.633	6.576	4.750	2.566	4.674	3.804	6.123	5.503
Candidate106	9.842	9.615	10.994	11.584	9.616	9.307	8.715	7.761	7.549	6.578	5.899	5.138	4.773	3.674	4.534	3.673	0.831	2.761	1.194	1.747	3.450	2.799
Candidate107	5.289	6.821	8.199	8.790	7.757	8.190	7.361	7.323	7.521	7.361	7.469	9.424	8.650	14.322	16.377	14.321	12.495	10.311	12.419	11.549	13.867	13.248
Candidate108	11.007	10.389	11.767	12.358	10.389	10.081	9.489	8.742	8.323	7.754	7.075	5.873	5.949	0.322	2.238	0.225	3.400	3.937	2.300	2.845	0.469	1.230
Candidate109	5.479	4.860	6.239	6.829	4.861	4.552	3.960	3.213	2.794	2.770	2.057	0.256	0.966	5.855	7.855	5.718	4.401	2.216	4.259	3.455	5.235	4.615
Candidate110	4.356	5.888	7.267	7.857	6.825	7.257	6.428	6.632	6.588	6.670	6.779	8.734	7.960	13.632	15.687	13.630	11.805	9.620	11.729	10.859	13.177	12.557
Candidate111	4.500	6.032	7.410	8.000	6.968	7.401	6.572	6.534	6.732	6.572	6.680	8.635	7.861	13.533	15.588	13.531	11.706	9.521	11.630	10.760	13.078	12.458
Candidate112	5.230	6.761	8.140	8.730	7.698	8.130	7.302	7.263	7.461	7.301	7.410	9.365	8.590	14.262	16.318	14.261	12.435	10.251	12.360	11.490	13.808	13.188
Candidate113	4.933	6.465	7.843	8.434	7.402	7.834	7.015	6.275	7.143	6.313	6.422	8.205	7.431	13.103	13.735	13.102	11.214	9.092	11.200	10.330	12.649	12.029
Candidate114	4.099	5.630	7.009	7.599	6.567	6.999	6.180	5.652	6.330	5.690	5.799	7.582	6.808	12.480	13.260	12.479	10.653	8.469	10.577	9.707	12.026	11.406
Candidate115	8.250	8.024	9.402	9.992	8.024	7.716	7.123	6.169	5.957	4.987	4.308	3.546	3.182	3.308	5.363	3.307	1.111	1.169	1.381	0.292	3.059	2.432
Candidate116	5.685	5.066	6.445	7.035	5.067	4.758	4.166	3.419	3.000	2.857	2.178	0.552	1.053	5.630	7.629	5.493	4.488	2.303	4.034	3.542	5.010	4.390
Candidate117	5.180	6.712	8.090	8.680	7.648	8.081	7.252	7.214	7.412	7.252	7.360	9.315	8.541	14.213	16.268	14.211	12.386	10.201	12.310	11.440	13.758	13.138
Candidate118	4.197	5.658	7.036	7.626	6.594	7.026	6.278	5.502	6.370	5.540	5.649	7.573	6.798	12.470	14.526	12.469	10.643	8.459	10.567	9.697	12.016	11.396
Candidate119	4.931	6.463	7.841	8.432	7.399	7.832	7.012	6.134	7.002	6.172	6.281	8.064	7.290	12.962	13.772	12.961	11.135	8.951	11.059	10.189	12.508	11.888
Candidate120	4.502	5.187	6.566	7.156	5.992	6.025	4.969	3.471	4.338	3.509	3.617	5.401	4.627	10.299	12.354	10.297	8.472	6.287	8.396	7.526	9.844	9.224
Candidate121	5.827	6.709	8.088	8.678	7.871	7.547	6.491	5.171	6.039	5.209	5.318	7.293	6.554	11.572	11.392	11.571	8.871	8.207	9.091	9.446	11.348	10.695
Candidate122	5.391	3.237	2.408	1.590	3.905	4.359	4.142	6.039	5.502	7.217	7.326	8.220	8.066	13.731	15.730	13.594	12.238	10.053	12.135	11.292	13.111	12.491
Candidate123	7.327	7.100	8.479	9.069	7.101	6.792	6.200	5.246	5.034	4.063	3.384	2.623	2.258	4.444	6.499	4.442	2.617	0.388	2.541	1.671	3.989	3.369
Candidate124	3.197	4.474	5.853	6.443	5.411	5.843	5.268	5.365	5.428	5.403	5.512	7.466	6.692	12.364	14.420	12.363	10.537	8.353	10.461	9.591	11.910	11.290
Candidate125	8.741	8.514	9.892	10.482	8.514	8.206	7.614	6.660	6.447	5.477	4.798	4.036	3.672	3.177	5.233	3.176	0.929	1.659	1.197	0.548	2.928	2.302
Candidate126	3.980	5.257	6.636	7.226	6.194	6.626	6.051	5.888	6.211	5.926	6.034	7.989	7.215	12.887	14.942	12.886	11.060	8.876	10.984	10.114	12.432	11.813
Candidate127	2.127	0.490	1.657	2.248	1.325	1.757	1.202	2.775	2.223	3.953	4.061	4.941	4.787	10.452	12.451	10.315	8.959	6.774	8.856	8.013	9.832	9.212
Candidate128	1.683	2.562	3.940	4.531	3.499	3.931	3.102	2.542	3.262	2.580	2.689	4.644	3.869	9.542	11.597	9.540	7.714	5.530	7.639	6.769	9.087	8.467
Candidate129	5.303	6.834	8.213	8.803	7.771	8.203	7.384	6.403	7.271	6.441	6.550	8.334	7.559	13.231	13.863	13.230	11.342	9.220	11.329	10.459	12.777	12.157
Candidate130	2.174	3.705	5.084	5.674	4.642	5.074	4.246	4.625	4.405	4.663	4.772	6.727	5.952	11.625	13.680	11.623	9.798	7.613	9.722	8.852	11.170	10.550
Candidate131	7.680	8.562	9.940	10.531	9.707	9.400	8.344	7.047	7.891	7.075	6.396	7.353	6.578	9.902	9.722	9.901	7.202	7.651	7.421	8.228	9.678	9.026
Candidate132	5.803	5.185	6.563	7.154	5.185	4.877	4.285	3.538	3.119	2.976	2.297	0.670	1.171	5.511	7.511	5.374	4.499	2.422	3.915	3.601	4.891	4.271
Candidate133	1.760	2.931	4.309	4.899	3.867	4.299	3.471	3.246	3.630	3.284	3.393	5.348	4.574	10.246	12.301	10.244	8.419	6.234	8.343	7.473	9.791	9.171
Candidate134	12.024	11.407	12.785	13.375	11.407	11.099	10.507	9.760	9.341	8.760	8.081	6.891	6.955	1.040	1.359	1.066	4.406	4.942	3.306	3.851	1.486	2.248
Candidate135	2.166	1.661	3.039	3.629	2.466	2.499	1.442	1.767	1.334	2.944	3.053	3.922	3.767	9.432	11.432	9.295	7.939	5.755	7.836	6.993	8.812	8.192
Candidate136	4.644	2.978	3.687	4.185	1.623	2.236	2.710	4.460	3.685	5.804	5.813	6.066	5.912	11.528	13.848	11.440	10.209	7.516	9.625	9.196	10.957	10.356
Candidate137	0.961	2.889	4.267	4.857	3.825	4.258	3.690	4.094	3.850	4.930	5.039	6.438	6.219	11.891	13.947	11.812	10.064	7.880	9.989	9.119	11.329	10.709
Candidate138	2.838	0.833	2.292	2.935	2.396	2.851	2.314	3.486	2.949	4.664	4.772	5.667	5.513	11.178	13.177	11.041	9.684	7.500	9.581	8.739	10.557	9.938

Park\Location	BG370210022061	BG370210022062	BG370210023021	BG370210023022	BG370210023024	BG370210025052	BG370210025061	BG370210030011	BG370210030014	BG370899306001	BG370899306002	BG370899307011
Albemarle Park	10.397	8.529	9.047	7.777	8.874	8.153	9.070	7.431	5.766	5.614	14.702	12.788
Amboy Riverfront Park	8.817	6.949	7.467	5.303	6.400	4.708	6.350	4.718	6.832	7.025	13.122	11.207
Ann Patton Joyce Park	9.055	6.789	7.705	10.506	11.603	10.249	11.891	10.259	1.744	1.592	13.469	11.554
Azalea Park	9.462	7.197	8.112	11.248	12.345	10.789	12.431	10.799	1.356	2.299	13.877	11.962
Burton Street Center	10.495	8.627	9.145	4.319	5.416	4.925	6.155	4.517	7.896	7.744	13.669	12.149
Carrier Park	9.394	7.526	8.044	4.948	6.046	4.213	5.855	4.222	7.409	7.607	12.938	11.418
Charlie Bullman Park	10.389	8.124	9.039	10.765	11.862	10.693	12.173	10.534	3.050	2.898	14.804	12.889
Choctaw Street Park	8.553	6.685	7.203	6.361	7.458	6.786	8.209	6.570	6.240	6.316	12.858	10.943
Dr. Wesley Grant Sr. Southside Center	8.771	6.903	7.421	5.999	7.097	6.386	7.858	6.219	6.592	6.713	13.076	11.162
E.W. Grove Park	10.444	8.576	9.094	7.824	8.921	8.289	9.205	7.567	5.901	5.749	14.749	12.835
East Asheville Center	9.327	7.062	7.977	9.929	11.026	9.833	11.337	9.698	2.092	1.940	13.742	11.827
Falconhurst Park	11.075	9.207	9.725	4.190	5.288	4.923	5.374	3.736	8.320	8.168	14.151	12.631
Forest Park	7.904	6.036	6.554	7.588	8.686	7.129	8.771	7.139	5.273	5.121	12.209	10.294
French Broad River Park	8.672	6.805	7.322	5.642	6.739	5.047	6.689	5.057	6.687	6.858	12.977	11.063
Haw Creek Park	9.515	7.250	8.165	10.116	11.214	10.021	11.525	9.886	2.219	2.068	13.930	12.015
Herb Watts Park	8.320	6.452	6.970	6.444	7.541	6.869	8.292	6.653	6.141	6.223	12.625	10.710
Hummingbird Park	9.707	7.839	8.357	6.576	7.673	7.090	8.006	6.368	5.844	5.692	14.012	12.097
Irby Brinson Complex	2.384	3.284	1.927	8.341	8.616	6.212	10.028	9.467	10.594	10.396	5.714	4.194
Jake Rusher Park	0.099	2.752	1.251	10.411	10.687	8.282	12.099	11.193	10.517	10.336	4.653	2.738
Jean Webb Park	9.677	7.810	8.328	5.458	6.555	5.862	7.012	5.374	6.880	6.807	13.983	12.068
Kenilworth Park	7.938	6.070	6.588	7.465	8.563	7.163	8.805	7.173	5.270	5.468	12.243	10.328
Leah Chiles Park	8.329	6.461	6.979	7.930	9.027	7.554	9.196	7.564	5.357	5.205	12.634	10.719
Lynwood Crump Shiloh Complex	5.964	4.061	4.614	8.354	9.451	7.436	9.162	7.530	5.490	5.688	10.269	8.354
Magnolia Park	9.966	8.098	8.616	6.953	8.051	7.349	8.266	6.627	6.042	5.890	14.271	12.356
Malvern Hills Pool and Park	11.741	10.025	10.543	2.837	3.934	4.311	4.248	2.609	9.597	9.445	13.391	11.871
Martin Luther King Jr. Park	9.430	7.562	8.080	6.955	8.052	7.561	8.530	6.891	5.126	4.974	13.735	11.821
Masters Park	11.247	8.982	9.897	11.622	12.720	11.550	13.031	11.392	3.908	3.756	15.661	13.747
Meadow Park	7.772	5.904	6.422	7.457	8.554	6.998	8.640	7.008	5.438	5.498	12.077	10.163
Montford Park	10.512	8.645	9.162	7.183	8.281	7.553	8.470	6.831	6.567	6.415	14.817	12.903
Mountainside Park	9.085	7.217	7.735	6.859	7.956	7.284	8.466	6.827	5.646	5.737	13.390	11.475
Murphy-Oakley Center Complex	7.265	5.000	5.915	8.938	10.035	8.657	10.299	8.667	3.639	3.487	11.680	9.765
Murray Hill Park	9.118	7.250	7.768	6.048	7.146	6.475	7.896	6.258	6.592	6.614	13.423	11.508
Oakhurst Park	8.708	6.841	7.359	6.677	7.775	7.102	8.284	6.646	5.806	5.859	13.014	11.099
Owens-Bell Park	9.521	7.653	8.171	5.602	6.699	6.027	7.450	5.812	6.345	6.217	13.826	11.911
Pack Square Park	9.304	7.436	7.954	6.622	7.719	7.143	8.085	6.446	5.343	5.191	13.609	11.694
Pritchard Park	9.249	7.381	7.899	6.322	7.419	6.747	7.689	6.050	5.650	5.643	13.554	11.640
Ray L. Kisiah Park	6.081	3.816	4.731	10.146	11.140	8.702	10.998	8.796	4.789	4.637	10.496	8.581
Recreation Park and Pool	8.926	6.661	7.576	10.711	11.809	10.454	12.096	10.464	1.914	1.964	13.340	11.426
Richmond Hill Park	12.535	10.667	11.185	6.918	8.015	7.651	8.282	6.644	8.981	8.829	16.840	14.926
Riverbend Park	8.294	6.029	6.944	9.138	10.236	9.128	10.185	8.553	3.236	3.084	12.709	10.794
Roger Farmer Memorial Park	11.992	10.124	10.642	3.473	4.570	4.944	4.604	2.965	9.204	9.053	14.330	12.810
Seven Springs Park	7.762	5.894	6.412	7.447	8.544	6.995	8.637	7.005	5.354	5.414	12.067	10.153
Stephens-Lee Recreation Center	9.197	7.329	7.847	6.731	7.829	7.157	8.158	6.519	5.371	5.219	13.502	11.587
Sunset Park	10.444	8.576	9.094	7.823	8.920	8.200	9.116	7.478	5.812	5.660	14.749	12.834
Tempie Avery Montford Complex	10.186	8.318	8.836	6.604	7.701	6.973	7.890	6.251	6.390	6.238	14.491	12.577
Triangle Park	9.079	7.211	7.729	6.536	7.634	6.962	8.028	6.389	5.542	5.431	13.384	11.469
Walton Street Park and Pool	8.524	6.656	7.174	6.263	7.361	6.689	8.111	6.473	6.345	6.543	12.829	10.915
Weaver Park	10.742	8.875	9.393	7.908	9.005	8.437	9.354	7.715	6.184	6.032	15.048	13.133
West Asheville Community Center	11.225	9.357	9.875	3.358	4.456	4.428	4.802	3.164	8.815	8.664	13.600	12.080
West Asheville Park	11.087	9.387	9.904	3.661	4.759	3.980	5.633	3.995	9.137	9.084	12.738	11.218
White Fawn Park	8.489	6.646	7.119	7.446	8.544	7.670	9.294	7.656	5.680	5.878	12.819	10.905
White Pine Park	9.334	7.069	7.984	8.946	10.043	9.402	10.354	8.715	3.959	3.807	13.749	11.834
Candidate1	13.432	12.075	2.853	2.056	4.809	0.358	2.337	13.656	13.505	14.187	12.666	14.827
Candidate2	9.022	9.438	5.470	6.568	6.015	6.877	5.238	6.981	6.829	14.741	13.220	15.529
Candidate3	11.500	12.017	10.533	11.630	11.008	11.925	10.286	9.207	9.055	17.672	15.758	17.899
Candidate4	7.924	8.840	8.415	9.512	8.881	9.823	8.185	4.553	4.401	14.603	12.688	14.829
Candidate5	4.437	3.596	8.686	8.961	6.556	10.373	9.811	10.809	11.007	6.071	4.551	6.860
Candidate6	9.011	9.529	4.023	5.120	4.004	5.750	4.118	8.766	8.614	12.831	11.311	13.620
Candidate7	10.502	11.020	9.750	10.847	10.216	11.133	9.494	7.709	7.603	16.675	14.761	16.902
Candidate8	6.729	7.644	9.634	10.731	9.298	10.940	9.308	3.230	3.078	13.409	11.494	13.635
Candidate9	8.418	8.936	7.666	8.763	8.133	9.075	7.436	5.625	5.473	14.591	12.677	14.818
Candidate10	11.158	9.801	0.243	0.854	2.535	2.266	1.369	12.190	12.117	11.913	10.392	12.553
Candidate11	7.691	8.607	7.365	8.463	7.832	8.774	7.135	4.581	4.430	14.291	12.376	14.517
Candidate12	5.246	6.162	9.219	10.317	8.912	10.554	8.922	3.814	3.686	11.926	10.011	12.152

Park\Location	BG370210022061	BG370210022062	BG370210023021	BG370210023022	BG370210023024	BG370210025052	BG370210025061	BG370210030011	BG370210030014	BG370899306001	BG370899306002	BG370899307011
Candidate13	12.864	12.140	2.397	2.121	4.874	1.521	1.412	12.773	12.621	14.251	12.731	14.892
Candidate14	9.092	9.610	4.404	5.502	4.694	6.253	4.614	8.975	8.952	13.521	12.001	14.310
Candidate15	10.532	11.050	4.426	5.523	5.683	5.557	3.918	9.261	9.109	14.877	13.357	15.666
Candidate16	9.258	9.301	3.394	4.450	2.762	4.964	3.332	9.807	9.655	11.709	10.043	12.498
Candidate17	7.402	8.317	10.831	11.928	10.850	12.239	10.600	1.948	1.797	14.082	12.167	14.308
Candidate18	6.672	7.587	9.699	10.797	9.443	11.085	9.453	2.794	2.642	13.351	11.437	13.578
Candidate19	11.443	10.842	0.797	1.895	3.576	2.654	0.843	12.074	12.002	12.953	11.433	13.594
Candidate20	7.541	8.059	7.738	8.835	8.344	9.296	7.657	4.451	4.299	13.714	11.799	13.940
Candidate21	4.538	5.232	8.291	9.389	7.852	9.578	7.946	5.192	5.390	10.887	8.973	11.114
Candidate22	5.438	6.353	8.346	9.443	8.065	9.707	8.075	4.254	4.102	12.117	10.203	12.344
Candidate23	9.877	10.792	12.517	13.615	12.445	13.925	12.287	4.802	4.651	16.556	14.642	16.783
Candidate24	12.448	12.966	11.482	12.579	11.957	12.874	11.235	9.798	9.237	18.621	16.707	18.848
Candidate25	10.013	10.531	4.647	5.744	5.716	5.806	4.168	8.478	8.326	14.557	13.037	15.346
Candidate26	9.379	9.897	6.641	7.738	7.374	8.005	6.366	7.592	7.440	15.552	13.638	15.779
Candidate27	11.770	12.288	10.803	11.901	11.279	12.195	10.557	9.120	8.761	17.943	16.028	18.170
Candidate28	6.986	7.504	7.786	8.883	8.055	9.595	7.956	5.433	5.631	13.159	11.244	13.385
Candidate29	11.271	11.788	9.145	10.243	9.878	10.510	8.871	8.978	8.826	17.443	15.529	17.670
Candidate30	6.863	7.778	9.271	10.369	9.453	10.698	9.059	2.875	2.744	13.543	11.628	13.769
Candidate31	8.702	9.219	7.949	9.046	8.416	9.358	7.719	5.908	5.756	14.874	12.960	15.101
Candidate32	11.012	11.530	9.318	10.416	10.051	10.683	9.044	8.719	8.567	17.185	15.270	17.411
Candidate33	10.860	11.378	3.706	4.804	5.538	4.515	2.876	9.992	9.840	15.118	13.598	15.660
Candidate34	1.333	2.248	10.238	11.294	9.129	11.449	9.817	7.050	7.248	8.012	6.098	8.239
Candidate35	7.784	8.302	7.596	8.693	8.202	9.154	7.515	4.714	4.562	13.957	12.043	14.184
Candidate36	11.578	12.096	10.611	11.708	11.086	12.003	10.364	9.203	9.133	17.751	15.836	17.977
Candidate37	10.914	11.432	4.081	5.178	5.679	5.211	3.573	9.811	9.660	15.157	13.637	15.801
Candidate38	6.645	7.560	9.550	10.647	9.214	10.856	9.224	3.145	2.994	13.325	11.410	13.551
Candidate39	11.398	11.916	10.431	11.529	10.906	11.823	10.185	9.023	8.953	17.571	15.656	17.797
Candidate40	4.510	5.028	7.713	8.810	6.795	8.521	6.889	5.967	5.932	10.683	8.768	10.909
Candidate41	9.688	10.206	4.655	5.752	5.404	5.814	4.176	8.152	8.000	14.232	12.712	15.021
Candidate42	9.514	10.032	8.762	9.859	9.229	10.171	8.532	6.721	6.569	15.687	13.773	15.914
Candidate43	6.447	7.362	9.475	10.572	9.268	10.910	9.278	2.781	2.630	13.127	11.212	13.353
Candidate44	10.471	10.989	8.244	9.341	8.977	9.608	7.970	8.327	8.176	16.644	14.729	16.870
Candidate45	2.561	1.060	9.624	9.900	7.495	11.311	10.415	10.033	9.757	4.983	3.069	5.210
Candidate46	8.050	8.966	12.390	13.488	12.276	13.799	12.160	0.803	1.782	14.781	12.866	15.570
Candidate47	11.242	11.760	3.103	4.200	5.667	3.911	2.273	10.401	10.249	14.562	13.042	15.351
Candidate48	11.395	11.913	10.428	11.525	10.903	11.820	10.181	9.019	8.950	17.568	15.653	17.794
Candidate49	5.630	6.545	8.465	9.563	8.184	9.826	8.194	4.446	4.294	12.310	10.395	12.536
Candidate50	9.558	10.076	7.975	9.072	8.344	9.261	7.622	7.629	7.477	15.731	13.816	15.957
Candidate51	11.282	11.800	9.870	10.967	10.602	11.234	9.595	8.989	8.837	17.455	15.540	17.681
Candidate52	11.105	11.623	2.960	4.058	5.219	3.769	2.130	10.373	10.221	14.419	12.899	15.208
Candidate53	2.743	3.658	9.185	10.242	8.076	10.397	8.765	6.762	6.961	9.422	7.508	9.649
Candidate54	3.077	3.993	9.501	10.599	8.486	10.310	8.678	5.506	5.704	9.757	7.842	9.983
Candidate55	12.454	12.971	11.487	12.584	11.962	12.879	11.240	9.803	9.242	18.626	16.712	18.853
Candidate56	9.077	8.448	3.690	4.118	1.762	5.530	4.147	10.708	10.557	10.559	9.039	11.884
Candidate57	4.845	5.682	8.177	9.274	7.676	9.402	7.770	5.262	5.460	11.337	9.422	11.563
Candidate58	8.455	9.370	8.946	10.043	9.412	10.354	8.715	5.084	4.932	15.133	13.219	15.360
Candidate59	12.746	13.264	11.779	12.877	12.255	13.171	11.533	10.096	9.107	18.919	17.004	19.145
Candidate60	10.989	9.632	0.413	0.688	2.366	2.100	1.538	12.359	12.287	11.743	10.223	12.384
Candidate61	1.460	1.145	10.048	10.324	7.919	11.736	10.830	8.847	8.572	6.275	4.361	6.502
Candidate62	11.668	12.186	10.915	12.012	11.521	12.626	10.988	8.874	9.072	17.841	15.926	18.067
Candidate63	10.021	10.936	12.661	13.759	12.589	14.069	12.431	4.946	4.795	16.700	14.786	16.927
Candidate64	6.523	7.041	6.590	7.687	6.131	7.773	6.140	6.079	6.139	12.696	10.782	12.923
Candidate65	8.560	9.475	11.201	12.298	11.129	12.609	10.970	3.578	3.426	15.240	13.325	15.466
Candidate66	10.069	10.586	9.316	10.413	9.783	10.725	9.086	7.275	7.124	16.241	14.327	16.468
Candidate67	7.060	7.975	9.701	10.798	9.629	11.109	9.470	3.072	2.920	13.740	11.825	13.966
Candidate68	8.487	9.402	8.977	10.075	9.444	10.386	8.747	5.115	4.963	15.165	13.250	15.391
Candidate69	8.900	8.271	3.513	3.941	1.585	5.353	3.970	10.531	10.380	10.382	8.862	11.707
Candidate70	2.861	2.020	8.565	8.841	6.436	10.253	9.488	9.743	9.467	6.079	4.559	6.809
Candidate71	2.613	1.426	8.917	9.193	6.788	10.604	9.698	10.001	9.725	5.996	4.082	6.223
Candidate72	1.758	0.257	9.910	10.186	7.781	11.598	10.698	9.413	9.342	5.630	3.716	5.857
Candidate73	11.079	11.597	5.129	6.227	6.407	6.144	4.505	9.807	9.656	15.600	14.080	16.389
Candidate74	9.287	10.202	11.928	13.025	11.856	13.336	11.698	4.213	4.061	15.967	14.052	16.193
Candidate75	10.447	11.362	13.087	14.185	13.015	14.496	12.857	5.373	5.221	17.126	15.212	17.353
Candidate76	9.918	10.833	12.558	13.656	12.486	13.966	12.328	4.843	4.692	16.597	14.683	16.824

Park\Location	BG370210022061	BG370210022062	BG370210023021	BG370210023022	BG370210023024	BG370210025052	BG370210025061	BG370210030011	BG370210030014	BG370899306001	BG370899306002	BG370899307011
Candidate77	4.349	4.867	7.941	9.039	7.024	8.750	7.118	5.794	5.852	10.522	8.608	10.749
Candidate78	2.652	1.154	9.553	9.828	7.424	11.240	10.344	10.155	9.879	5.595	3.680	5.821
Candidate79	8.319	9.234	10.959	12.057	10.888	12.368	10.729	3.337	3.185	14.998	13.084	15.225
Candidate80	8.489	9.006	4.803	5.900	5.172	6.814	5.182	7.302	7.500	13.898	12.378	14.687
Candidate81	5.654	6.359	7.987	9.084	7.706	9.348	7.716	4.703	4.551	12.014	10.099	12.240
Candidate82	2.174	2.091	9.425	9.701	7.296	11.112	10.318	9.006	8.730	6.697	4.782	6.923
Candidate83	0.911	1.826	11.049	12.001	9.597	12.546	10.914	7.861	8.059	7.590	5.676	7.817
Candidate84	8.154	9.069	8.644	9.742	9.111	10.053	8.414	4.782	4.630	14.832	12.917	15.058
Candidate85	11.760	12.278	10.793	11.890	11.268	12.185	10.546	9.385	9.315	17.933	16.018	18.159
Candidate86	10.436	10.954	4.592	5.690	5.827	5.723	4.085	9.164	9.013	14.964	13.444	15.753
Candidate87	11.587	12.105	10.620	11.718	11.096	12.012	10.374	9.168	8.944	17.760	15.846	17.987
Candidate88	9.011	9.529	8.258	9.356	8.725	9.667	8.029	6.218	6.066	15.184	13.269	15.410
Candidate89	11.239	11.757	3.094	4.192	5.353	3.903	2.264	10.508	10.356	14.553	13.033	15.342
Candidate90	10.057	10.400	1.795	2.892	3.861	4.062	2.251	10.152	10.079	12.756	11.236	13.545
Candidate91	10.762	11.280	4.577	5.674	5.812	5.708	4.069	9.694	9.542	15.005	13.485	15.794
Candidate92	8.116	8.634	7.363	8.461	7.831	8.773	7.134	5.323	5.171	14.289	12.374	14.515
Candidate93	5.988	6.506	7.641	8.739	7.182	8.824	7.192	4.438	4.499	12.161	10.246	12.387
Candidate94	10.998	10.362	0.318	1.415	3.097	2.736	0.925	11.629	11.556	12.474	10.954	13.114
Candidate95	1.829	1.330	9.597	9.873	7.468	11.285	10.479	9.216	8.940	5.937	4.022	6.163
Candidate96	9.655	10.173	8.902	10.000	9.370	10.312	8.673	6.862	6.710	15.828	13.914	16.055
Candidate97	7.038	7.556	7.838	8.936	8.132	9.479	7.840	5.356	5.205	13.211	11.297	13.438
Candidate98	8.685	9.203	7.673	8.770	8.196	9.137	7.499	6.506	6.355	14.858	12.943	15.084
Candidate99	9.309	7.952	2.893	3.169	0.196	4.580	4.019	12.040	11.888	10.068	8.548	10.704
Candidate100	10.182	10.525	1.764	2.862	3.987	4.032	2.221	10.277	10.205	12.881	11.361	13.670
Candidate101	10.607	9.250	1.438	1.713	1.985	3.125	2.564	13.062	13.126	11.362	9.842	12.002
Candidate102	2.509	2.194	12.094	12.369	9.965	13.781	12.534	10.164	10.093	7.539	5.624	7.765
Candidate103	11.694	10.337	0.525	1.390	3.071	2.802	1.651	12.472	12.399	12.449	10.929	13.089
Candidate104	10.106	11.021	12.747	13.844	12.675	14.155	12.517	5.032	4.880	16.786	14.871	17.012
Candidate105	3.635	4.153	8.244	9.300	7.135	9.393	7.761	6.185	6.383	9.808	7.893	10.034
Candidate106	3.560	2.339	7.866	8.142	5.737	9.553	8.992	10.733	10.801	5.488	3.968	6.277
Candidate107	11.380	11.898	10.413	11.510	10.888	11.805	10.166	9.004	8.935	17.553	15.638	17.779
Candidate108	3.853	2.351	11.207	11.482	9.077	12.894	11.998	11.507	11.339	3.413	1.499	3.640
Candidate109	2.350	3.265	9.217	10.273	8.108	10.428	8.796	5.979	6.177	9.030	7.115	9.256
Candidate110	10.689	11.207	9.780	10.877	10.286	11.203	9.564	8.072	7.966	16.862	14.948	17.089
Candidate111	10.591	11.108	9.624	10.721	10.099	11.016	9.377	8.215	8.146	16.763	14.849	16.990
Candidate112	11.320	11.838	10.353	11.451	10.829	11.745	10.107	8.945	8.876	17.493	15.578	17.719
Candidate113	10.161	10.679	4.698	5.796	5.768	5.858	4.219	8.649	8.497	14.689	13.169	15.478
Candidate114	9.538	10.056	4.654	5.752	5.387	6.019	4.380	7.814	7.662	14.214	12.694	15.003
Candidate115	2.016	1.933	9.458	9.733	7.328	11.145	10.350	8.848	8.572	6.539	4.624	6.765
Candidate116	2.125	3.040	9.304	10.360	8.195	10.515	8.883	6.185	6.383	8.805	6.890	9.031
Candidate117	11.271	11.788	10.304	11.401	10.779	11.696	10.057	8.895	8.826	17.443	15.529	17.670
Candidate118	9.528	10.046	6.391	7.489	7.124	7.756	6.117	7.841	7.689	15.701	13.786	15.927
Candidate119	10.020	10.538	4.557	5.654	5.626	5.716	4.078	8.646	8.495	14.726	13.206	15.515
Candidate120	7.357	7.874	5.170	6.268	4.739	6.381	4.749	7.239	7.437	13.464	11.615	13.756
Candidate121	9.298	9.794	2.939	4.036	3.256	5.206	3.395	8.974	8.822	12.346	10.826	13.135
Candidate122	10.226	11.141	12.866	13.964	12.794	14.275	12.636	5.151	5.000	16.905	14.991	17.132
Candidate123	1.976	2.019	9.922	10.636	8.231	11.751	10.119	7.954	7.678	7.674	5.760	7.901
Candidate124	9.422	9.940	8.669	9.767	9.046	9.962	8.324	6.658	6.506	15.595	13.680	15.821
Candidate125	2.405	1.802	9.276	9.552	7.147	10.964	10.166	9.338	9.062	6.408	4.493	6.634
Candidate126	9.945	10.463	8.760	9.857	9.453	10.124	8.486	7.441	7.289	16.118	14.203	16.344
Candidate127	6.947	7.862	9.602	10.699	9.530	11.010	9.372	2.572	2.420	13.626	11.712	13.853
Candidate128	6.599	7.117	7.850	8.947	7.693	9.335	7.703	4.746	4.594	12.772	10.858	12.999
Candidate129	10.289	10.807	4.826	5.924	5.896	5.986	4.347	9.018	8.866	14.817	13.297	15.606
Candidate130	8.682	9.200	7.929	9.027	8.397	9.339	7.700	5.889	5.737	14.855	12.941	15.082
Candidate131	9.195	8.566	3.808	4.236	1.880	5.648	4.265	10.826	10.674	10.677	9.157	12.002
Candidate132	2.006	2.921	9.422	10.479	8.313	10.634	9.002	6.303	6.501	8.686	6.771	8.912
Candidate133	7.303	7.821	7.405	8.502	8.011	9.173	7.535	5.114	5.312	13.476	11.562	13.703
Candidate134	4.871	3.369	11.445	11.720	9.315	13.132	12.570	12.525	12.357	2.534	0.619	2.760
Candidate135	5.927	6.843	8.858	9.955	8.520	10.162	8.529	3.713	3.692	12.607	10.692	12.833
Candidate136	8.072	8.987	12.115	13.212	12.006	13.528	11.889	0.528	1.511	14.803	12.887	15.315
Candidate137	8.444	9.359	8.934	10.032	9.401	10.343	8.704	5.072	4.920	15.122	13.207	15.348
Candidate138	7.673	8.588	10.313	11.411	10.241	11.721	10.083	3.643	3.491	14.352	12.438	14.579

Park Capacity

Table B.5 provides the capacity of each considered existing and candidate park. Capacity is in units of number of individuals that the park can accommodate.

Table B.5: Park Capacity

Park	Capacity
Albemarle Park	42
Amboy Riverfront Park	520
Ann Patton Joyce Park	327
Azalea Park	13589
Burton Street Center	206
Carrier Park	3124
Charlie Bullman Park	718
Choctaw Street Park	267
Dr. Wesley Grant Sr. Southside Center	945
E.W. Grove Park	313
East Asheville Center	272
Falconhurst Park	797
Forest Park	41
French Broad River Park	1356
Haw Creek Park	624
Herb Watts Park	43
Hummingbird Park	78
Irby Brinson Complex	573
Jake Rusher Park	582
Jean Webb Park	768
Kenilworth Park	570
Leah Chiles Park	71
Lynwood Crump Shiloh Complex	606
Magnolia Park	85
Malvern Hills Pool and Park	856
Martin Luther King Jr. Park	515
Masters Park	826
Meadow Park	109
Montford Park	426
Mountainside Park	319
Murphy-Oakley Center Complex	1002
Murray Hill Park	689
Oakhurst Park	55
Owens-Bell Park	85
Pack Square Park	257
Pritchard Park	37
Ray L. Kisiah Park	3443
Recreation Park and Pool	2167
Richmond Hill Park	15004

Park	Capacity
Riverbend Park	1279
Roger Farmer Memorial Park	957
Seven Springs Park	401
Stephens-Lee Recreation Center	259
Sunset Park	210
Tempie Avery Montford Complex	1560
Triangle Park	16
Walton Street Park and Pool	440
Weaver Park	713
West Asheville Community Center	108
West Asheville Park	890
White Fawn Park	733
White Pine Park	95
Candidate1	130
Candidate2	150
Candidate3	103
Candidate4	250
Candidate5	135
Candidate6	172
Candidate7	402
Candidate8	297
Candidate9	289
Candidate10	376
Candidate11	296
Candidate12	123
Candidate13	1807
Candidate14	477
Candidate15	518
Candidate16	346
Candidate17	127
Candidate18	131
Candidate19	221
Candidate20	139
Candidate21	215
Candidate22	121
Candidate23	131
Candidate24	119
Candidate25	351
Candidate26	195

Park	Capacity
Candidate27	749
Candidate28	1152
Candidate29	148
Candidate30	137
Candidate31	164
Candidate32	101
Candidate33	952
Candidate34	978
Candidate35	386
Candidate36	127
Candidate37	403
Candidate38	152
Candidate39	183
Candidate40	163
Candidate41	116
Candidate42	165
Candidate43	125
Candidate44	557
Candidate45	564
Candidate46	181
Candidate47	100
Candidate48	110
Candidate49	113
Candidate50	176
Candidate51	172
Candidate52	407
Candidate53	196
Candidate54	223
Candidate55	158
Candidate56	160
Candidate57	154
Candidate58	400
Candidate59	102
Candidate60	201
Candidate61	288
Candidate62	508
Candidate63	116
Candidate64	402
Candidate65	285
Candidate66	183
Candidate67	209
Candidate68	1593
Candidate69	193
Candidate70	117
Candidate71	138
Candidate72	301
Candidate73	202
Candidate74	789
Candidate75	111

Park	Capacity
Candidate76	159
Candidate77	164
Candidate78	242
Candidate79	153
Candidate80	192
Candidate81	267
Candidate82	169
Candidate83	122
Candidate84	233
Candidate85	136
Candidate86	212
Candidate87	128
Candidate88	180
Candidate89	455
Candidate90	121
Candidate91	275
Candidate92	150
Candidate93	302
Candidate94	299
Candidate95	137
Candidate96	113
Candidate97	117
Candidate98	100
Candidate99	666
Candidate100	339
Candidate101	245
Candidate102	152
Candidate103	185
Candidate104	106
Candidate105	263
Candidate106	622
Candidate107	159
Candidate108	106
Candidate109	100
Candidate110	137
Candidate111	134
Candidate112	245
Candidate113	133
Candidate114	150
Candidate115	272
Candidate116	200
Candidate117	211
Candidate118	124
Candidate119	106
Candidate120	169
Candidate121	147
Candidate122	106
Candidate123	380
Candidate124	340

Park	Capacity
Candidate125	131
Candidate126	836
Candidate127	111
Candidate128	172
Candidate129	100
Candidate130	117
Candidate131	896

Park	Capacity
Candidate132	262
Candidate133	217
Candidate134	785
Candidate135	1089
Candidate136	166
Candidate137	377
Candidate138	1726

Park Environmental Factors

Table B.6 provides the average heat and tree cover of each considered existing and candidate park

Table B.6: Average Park Heat and Tree Cover

Park	Heat	Tree Cover
Albemarle Park	0.00	59.00
Amboy Riverfront Park	0.00	25.39
Ann Patton Joyce Park	0.00	79.79
Azalea Park	0.11	37.69
Burton Street Center	1.00	12.67
Carrier Park	0.38	7.83
Charlie Bullman Park	0.00	11.18
Choctaw Street Park	0.00	16.82
Dr. Wesley Grant Sr. Southside Center	0.30	7.82
E.W. Grove Park	0.89	25.02
East Asheville Center	0.00	22.83
Falconhurst Park	0.30	81.31
Forest Park	0.00	38.12
French Broad River Park	0.00	25.36
Haw Creek Park	0.00	81.84
Herb Watts Park	1.00	0.00
Hummingbird Park	0.00	43.92
Irby Brinson Complex	1.60	0.20
Jake Rusher Park	0.07	8.22
Jean Webb Park	0.09	10.15
Kenilworth Park	0.00	41.55
Leah Chiles Park	0.00	49.95
Lynwood Crump Shiloh Complex	1.18	5.39
Magnolia Park	0.10	12.86
Malvern Hills Pool and Park	0.03	29.68

Park	Heat	Tree Cover
Martin Luther King Jr. Park	0.08	13.68
Masters Park	0.00	88.74
Meadow Park	0.00	74.13
Montford Park	0.00	25.69
Mountainside Park	1.03	10.36
Murphy-Oakley Center Complex	0.33	12.80
Murray Hill Park	0.00	27.05
Oakhurst Park	0.52	11.09
Owens-Bell Park	0.10	22.96
Pack Square Park	2.13	4.44
Pritchard Park	2.85	0.00
Ray L. Kisiah Park	0.00	57.31
Recreation Park and Pool	0.22	27.26
Richmond Hill Park	0.00	82.14
Riverbend Park	0.36	38.61
Roger Farmer Memorial Park	0.19	9.23
Seven Springs Park	0.00	57.50
Stephens-Lee Recreation Center	0.36	40.18
Sunset Park	0.01	60.95
Tempie Avery Montford Complex	0.09	24.46
Triangle Park	2.07	0.00
Walton Street Park and Pool	0.12	14.87
Weaver Park	0.00	16.40
West Asheville Community Center	1.50	11.85
West Asheville Park	0.00	31.52

Park	Heat	Tree Cover
White Fawn Park	0.00	56.66
White Pine Park	0.47	22.12
Candidate1	0.00	5.26
Candidate2	0.96	46.94
Candidate3	0.00	85.91
Candidate4	0.00	92.09
Candidate5	0.00	38.03
Candidate6	0.00	84.01
Candidate7	0.00	91.31
Candidate8	0.00	90.65
Candidate9	0.00	87.76
Candidate10	0.00	3.51
Candidate11	0.00	89.58
Candidate12	0.00	67.85
Candidate13	0.00	38.25
Candidate14	0.00	90.71
Candidate15	0.01	82.93
Candidate16	0.00	30.62
Candidate17	0.00	92.23
Candidate18	0.00	87.53
Candidate19	0.00	85.34
Candidate20	0.00	78.04
Candidate21	0.00	83.55
Candidate22	0.00	71.00
Candidate23	0.00	95.42
Candidate24	0.00	86.31
Candidate25	0.00	66.66
Candidate26	0.00	20.20
Candidate27	0.00	58.82
Candidate28	0.00	85.63
Candidate29	0.00	42.27
Candidate30	0.85	74.78
Candidate31	0.00	90.61
Candidate32	0.07	24.88
Candidate33	0.24	2.10
Candidate34	0.00	86.19
Candidate35	0.00	87.11
Candidate36	0.00	94.58
Candidate37	0.00	79.40
Candidate38	0.00	84.94
Candidate39	0.00	91.04
Candidate40	0.00	85.82
Candidate41	0.00	9.51
Candidate42	0.00	87.26
Candidate43	0.00	94.25
Candidate44	0.00	76.68
Candidate45	0.00	46.07
Candidate46	0.00	86.99
Candidate47	0.00	70.41
Candidate48	0.00	70.79
Candidate49	0.00	88.53
Candidate50	0.00	73.57
Candidate51	0.00	74.36
Candidate52	0.00	82.93
Candidate53	0.19	18.68

Park	Heat	Tree Cover
Candidate54	0.00	46.52
Candidate55	0.00	83.40
Candidate56	0.13	77.91
Candidate57	0.00	67.46
Candidate58	0.00	70.86
Candidate59	0.00	87.87
Candidate60	1.37	0.00
Candidate61	0.00	80.27
Candidate62	0.00	92.30
Candidate63	0.00	96.49
Candidate64	0.06	64.68
Candidate65	0.00	98.10
Candidate66	0.00	94.80
Candidate67	0.11	18.13
Candidate68	0.00	74.05
Candidate69	0.00	49.51
Candidate70	0.01	70.41
Candidate71	1.18	68.40
Candidate72	0.01	57.37
Candidate73	0.00	52.05
Candidate74	0.00	95.50
Candidate75	0.00	70.18
Candidate76	0.00	95.85
Candidate77	0.00	77.30
Candidate78	0.00	78.08
Candidate79	0.00	57.65
Candidate80	0.00	43.05
Candidate81	0.00	84.10
Candidate82	0.00	27.44
Candidate83	0.00	77.17
Candidate84	0.00	17.44
Candidate85	0.00	85.58
Candidate86	0.00	37.96
Candidate87	0.00	20.11
Candidate88	0.00	77.72
Candidate89	0.00	14.27
Candidate90	0.00	78.59
Candidate91	0.00	84.30
Candidate92	0.00	88.87
Candidate93	0.00	83.67
Candidate94	0.00	66.92
Candidate95	0.99	48.82
Candidate96	0.00	92.81
Candidate97	0.00	83.14
Candidate98	0.00	78.77
Candidate99	0.55	14.77
Candidate100	0.00	78.05
Candidate101	0.00	49.86
Candidate102	0.00	88.17
Candidate103	0.09	34.02
Candidate104	0.00	94.11
Candidate105	0.00	89.35
Candidate106	0.01	85.67
Candidate107	0.00	69.09
Candidate108	0.25	0.15

Park	Heat	Tree Cover
Candidate109	0.32	42.60
Candidate110	0.00	87.90
Candidate111	0.13	7.00
Candidate112	0.00	70.59
Candidate113	0.17	62.08
Candidate114	0.20	55.68
Candidate115	0.00	88.84
Candidate116	0.00	73.81
Candidate117	0.00	91.73
Candidate118	0.00	58.03
Candidate119	0.00	77.86
Candidate120	0.00	85.62
Candidate121	0.00	78.73
Candidate122	0.00	96.45
Candidate123	1.60	21.12

Park	Heat	Tree Cover
Candidate124	0.00	88.70
Candidate125	0.00	89.90
Candidate126	0.00	84.71
Candidate127	0.00	72.00
Candidate128	0.00	61.58
Candidate129	0.20	39.62
Candidate130	0.00	76.15
Candidate131	0.00	86.36
Candidate132	0.00	82.11
Candidate133	0.00	89.16
Candidate134	0.33	35.36
Candidate135	0.25	76.07
Candidate136	0.33	32.34
Candidate137	0.00	89.97
Candidate138	0.15	59.86

Appendix C

ArcGIS Pro Geoprocessing Procedures

Within this appendix, we provide procedural information regarding our utilization of the geoprocessing features provided with ArcGIS to extrapolate spatial data for our modeling purposes.

Converting Race from BG19 to BG20

1. Complete an overlay of BG20 and BG19 in order to create polygons with unique classifications of BG19-BG20.

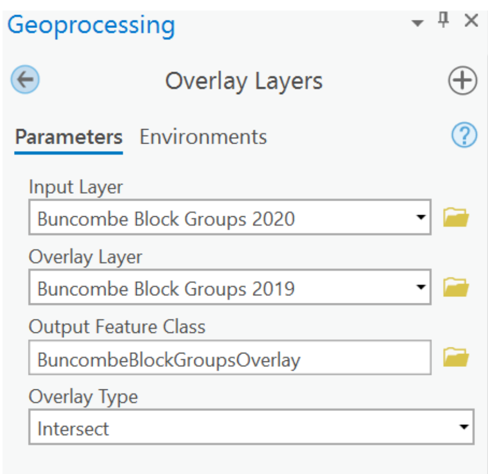

Figure C.1: ArcGIS Interface – Overlay Layers

2. Tabulate the intersection of BG20 and the newly created overlay. The result of this step is a table including percentage of each BG20 within each overlay polygon. We will label this table as *Intersection Table 1*.

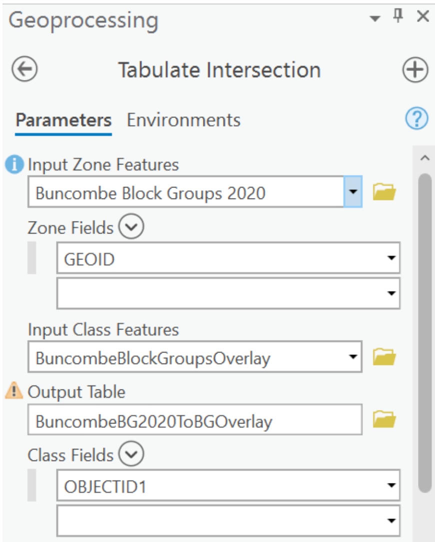

Figure C.2: ArcGIS Interface – Tabulate Intersection of BG20 and Overlay

3. Tabulate the intersection of the overlay polygon and BG19. The result of this step is a table including percentage of each overlay polygon within each BG19. We will label this table as *Intersection Table 2*.

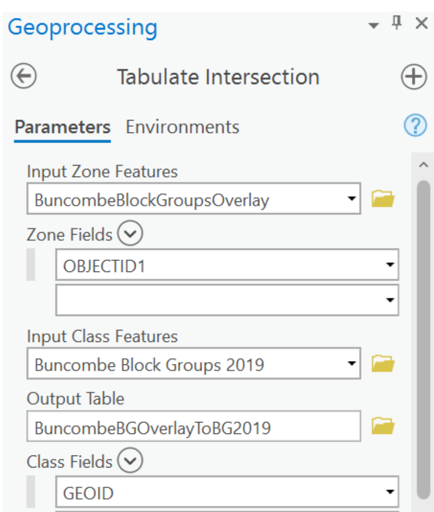

Figure C.3: ArcGIS Interface – Tabulate Intersection of Overlay and BG19

4. Export both *Intersection Table 1* and *Intersection Table 2* to Excel.

5. Complete the following concerning *Intersection Table 1:*

    a. When the only one BG20 composes an overlay polygon, ensure that the percentage of BG20 within that overlay polygon is listed as 100%.

    b. When multiple BG20 compose an overlay polygon, verify listed percentage accuracy by referring to the Asheville map.

6. Ensure that all listed percentage values within *Intersection Table 2* equal 100% since entire overlay polygons combine or stand alone to create BG19 polygons.
7. Export the attribute table of Asheville BG20 race counts to Excel.
8. Import *Intersection Tables 1 and 2* into the Excel document with BG20 race counts.
9. Use VBA to convert race totals from BG20 to overlay polygons by multiplying original BG20 race totals by the intersection percentages of *Intersection Table 1.*

```
For i = 1 To 251
    tractMatch = ThisWorkbook.Worksheets("PT1").Range("A1").Offset(i)
    percentArea = ThisWorkbook.Worksheets("PT1").Range("D1").Offset(i)
    numTotal = 0
    numWhite = 0
    numBlack = 0
    numNA = 0
    numAsian = 0
    numPI = 0
    numOther = 0

    For j = 1 To 202

        tractSearch = ThisWorkbook.Worksheets("RaceOrig").Range("A1").Offset(j)
        If tractMatch = tractSearch Then
            addTotal = ThisWorkbook.Worksheets("RaceOrig").Range("A1").Offset(j, 1)
            addWhite = ThisWorkbook.Worksheets("RaceOrig").Range("A1").Offset(j, 2)
            addBlack = ThisWorkbook.Worksheets("RaceOrig").Range("A1").Offset(j, 3)
            addNA = ThisWorkbook.Worksheets("RaceOrig").Range("A1").Offset(j, 4)
            addAsian = ThisWorkbook.Worksheets("RaceOrig").Range("A1").Offset(j, 5)
            addPI = ThisWorkbook.Worksheets("RaceOrig").Range("A1").Offset(j, 6)
            addOther = ThisWorkbook.Worksheets("RaceOrig").Range("A1").Offset(j, 7)

            numTotal = numTotal + percentArea / 100 * addTotal
            numWhite = numWhite + percentArea / 100 * addWhite
            numBlack = numBlack + percentArea / 100 * addBlack
            numNA = numNA + percentArea / 100 * addNA
            numAsian = numAsian + percentArea / 100 * addAsian
            numPI = numPI + percentArea / 100 * addPI
            numOther = numOther + percentArea / 100 * addOther
        End If
    Next j

    ThisWorkbook.Worksheets("PT1").Range("A1").Offset(i, 5) = numTotal
    ThisWorkbook.Worksheets("PT1").Range("A1").Offset(i, 6) = numWhite
    ThisWorkbook.Worksheets("PT1").Range("A1").Offset(i, 7) = numBlack
    ThisWorkbook.Worksheets("PT1").Range("A1").Offset(i, 8) = numNA
    ThisWorkbook.Worksheets("PT1").Range("A1").Offset(i, 9) = numAsian
    ThisWorkbook.Worksheets("PT1").Range("A1").Offset(i, 10) = numPI
    ThisWorkbook.Worksheets("PT1").Range("A1").Offset(i, 11) = numOther
Next i
```

Figure C.4: VBA Code – Convert Race Counts from BG20 to Overlay Polygons

10. Convert race totals from overlay polygons to BG19 by adding overlay polygon race totals as defined by *Intersection Table 2*. We use a VBA to complete this calculation and round decimal value totals to the nearest whole number.

```
For i = 1 To 183
    BGMatch = ThisWorkbook.Worksheets("PT2").Range("F1").Offset(i)

    numTotal = 0
    numWhite = 0
    numBlack = 0
    numNA = 0
    numAsian = 0
    numPI = 0
    numOther = 0

    For j = 1 To 251
        BGSearch = ThisWorkbook.Worksheets("PT2").Range("B1").Offset(j)

        If BGMatch = BGSearch Then
        OverlayMatch = ThisWorkbook.Worksheets("PT2").Range("B1").Offset(j, -1)
            For k = 1 To 251
                OverlaySearch = ThisWorkbook.Worksheets("PT1").Range("B1").Offset(k)
                If OverlayMatch = OverlaySearch Then

                    addTotal = ThisWorkbook.Worksheets("PT1").Range("F1").Offset(k)
                    addWhite = ThisWorkbook.Worksheets("PT1").Range("F1").Offset(k, 1)
                    addBlack = ThisWorkbook.Worksheets("PT1").Range("F1").Offset(k, 2)
                    addNA = ThisWorkbook.Worksheets("PT1").Range("F1").Offset(k, 3)
                    addAsian = ThisWorkbook.Worksheets("PT1").Range("F1").Offset(k, 4)
                    addPI = ThisWorkbook.Worksheets("PT1").Range("F1").Offset(k, 5)
                    addOther = ThisWorkbook.Worksheets("PT1").Range("F1").Offset(k, 6)

                    numTotal = numTotal + addTotal
                    numWhite = numWhite + addWhite
                    numBlack = numBlack + addBlack
                    numNA = numNA + addNA
                    numAsian = numAsian + addAsian
                    numPI = numPI + addPI
                    numOther = numOther + addOther
                End If
            Next k
        End If
    Next j
    ThisWorkbook.Worksheets("PT2").Range("D1").Offset(i, 3) = numTotal
    ThisWorkbook.Worksheets("PT2").Range("D1").Offset(i, 4) = numWhite
```
Figure C.5: VBA Code – Convert Race Counts from Overlay Polygons to BG19

11. Export BG19 race data table to a .csv file.

12. Upload the BG19 race data table to ArcGIS, and join it to the BG19 shapefile for visual display.

Converting Disability Data from Tract19 to BG19

The data provided by the US Census for disability is in terms of tracts for 2019 (tract19), rather than block groups. We note that tract19 are larger than BG19. We use the following procedure to convert disability data from tract19 to BG19:

1. Complete an overlay with tract19 disability data and BG19 polygons to create unique polygons defined by distinct tract19-BG19 designations.

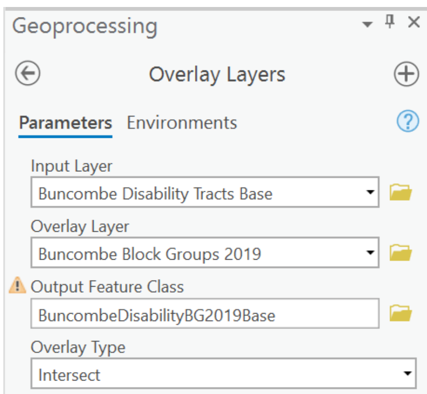

Figure C.6: ArcGIS Interface – Disability Data from Tract19 to BG19

2. Export the overlay disability table to Excel.
3. Tabulate the intersection of the disability overlay polygons and BG19. The result of this step is a table including the percentage of each tract19 within each BG19. Export this intersection table, *Intersection Table 3*, to Excel.

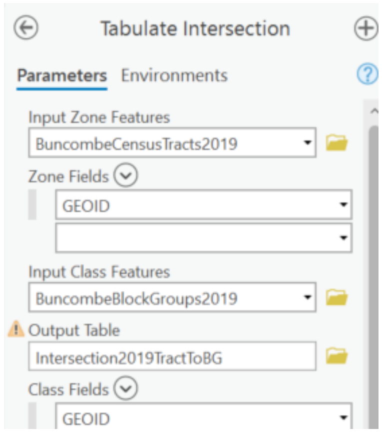

Figure C.7: ArcGIS Interface – Tabulate Intersection of Tract19 in BG19

4. Use Excel functions to calculate the disability count in BG19 by rounding the multiplication of the percentage listed in *Intersection Table* 3 by the original tract disability total.

5. Save the newly created BG19 disability table to a new .csv file.

Calculating Demographic Totals for BG19 within ACL

The following is the procedure utilized to find the total demographic counts for portions of BG19 within Asheville City Limits (ACL).:

1. Tabulate intersection to find the percentages of BG19 within ACL. We label this table as *Intersection Table 4.*

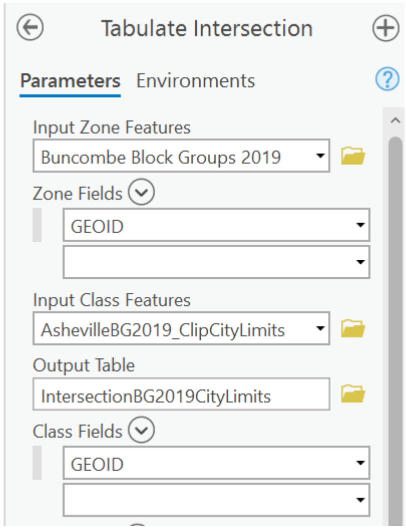

Figure C.8: ArcGIS Interface – Tabulate Intersection of BG19 in ACL

2. Export *Intersection Table 4* to Excel.
3. Import given BG19 demographic data into the macro-enabled Excel document.
4. Multiply the percentage of each BG19 with ACL by the originally listed demographic count values to calculate the new BG19 counts.
5. Delete all BG19 not partially within ACL.

```
Sub CityLimitsRaceCalc()

Dim i As Integer, j As Integer
Dim percentage As Double
Dim idMatch As String, idSearch As String
Dim origTotal As Integer, origWhite As Integer, origBlack As Integer, origNA As Integer
Dim origAsian As Integer, origPI As Integer, origOther As Integer
Dim newTotal As Double, newWhite As Double, newBlack As Double, newNA As Double
Dim newAsian As Double, newPI As Double, newOther As Double

For i = 1 To 183
    idMatch = ThisWorkbook.Worksheets("Race").Range("A1").Offset(i)
    origTotal = ThisWorkbook.Worksheets("Race").Range("B1").Offset(i)
    origWhite = ThisWorkbook.Worksheets("Race").Range("C1").Offset(i)
    origBlack = ThisWorkbook.Worksheets("Race").Range("D1").Offset(i)
    origNA = ThisWorkbook.Worksheets("Race").Range("E1").Offset(i)
    origAsian = ThisWorkbook.Worksheets("Race").Range("F1").Offset(i)
    origPI = ThisWorkbook.Worksheets("Race").Range("G1").Offset(i)
    origOther = ThisWorkbook.Worksheets("Race").Range("H1").Offset(i)

    percentage = 0

    For j = 1 To 88
        idSearch = ThisWorkbook.Worksheets("Percentages").Range("A1").Offset(j)

        If idMatch = idSearch Then
            percentage = ThisWorkbook.Worksheets("Percentages").Range("B1").Offset(j)
        End If
    Next j

    newTotal = Round(percentage / 100 * origTotal, 0)
    newWhite = Round(percentage / 100 * origWhite, 0)
    newBlack = Round(percentage / 100 * origBlack, 0)
    newNA = Round(percentage / 100 * origNA, 0)
    newAsian = Round(percentage / 100 * origAsian, 0)
    newPI = Round(percentage / 100 * origPI, 0)
    ThisWorkbook.Worksheets("Race").Range("I1").Offset(i) = newTotal
    ThisWorkbook.Worksheets("Race").Range("J1").Offset(i) = newWhite
    ThisWorkbook.Worksheets("Race").Range("K1").Offset(i) = newBlack
    ThisWorkbook.Worksheets("Race").Range("L1").Offset(i) = newNA
    ThisWorkbook.Worksheets("Race").Range("M1").Offset(i) = newAsian
    ThisWorkbook.Worksheets("Race").Range("N1").Offset(i) = newPI
    ThisWorkbook.Worksheets("Race").Range("O1").Offset(i) = newOther

    If percentage = 0 Or newTotal = 0 Then
        ThisWorkbook.Worksheets("Race").Range("P1").Offset(i) = 0
        ThisWorkbook.Worksheets("Race").Range("Q1").Offset(i) = 0
        ThisWorkbook.Worksheets("Race").Range("R1").Offset(i) = 0
        ThisWorkbook.Worksheets("Race").Range("S1").Offset(i) = 0
        ThisWorkbook.Worksheets("Race").Range("T1").Offset(i) = 0
        ThisWorkbook.Worksheets("Race").Range("U1").Offset(i) = 0
    ElseIf percentage <> 0 Then
        ThisWorkbook.Worksheets("Race").Range("P1").Offset(i) = newWhite / newTotal
        ThisWorkbook.Worksheets("Race").Range("Q1").Offset(i) = newBlack / newTotal
        ThisWorkbook.Worksheets("Race").Range("R1").Offset(i) = newNA / newTotal
        ThisWorkbook.Worksheets("Race").Range("S1").Offset(i) = newAsian / newTotal
        ThisWorkbook.Worksheets("Race").Range("T1").Offset(i) = newPI / newTotal
        ThisWorkbook.Worksheets("Race").Range("U1").Offset(i) = newOther / newTotal

    End If
Next i

End Sub
```

Figure C.9: VBA Code – Demographic BG19 in ACL

```
Sub ConsolidateGEOIDs()

Dim i As Integer, j As Integer
Dim idMatch As String, idSearch As String
Dim matches As Boolean
Dim numDeletes As Integer

numDeletes = 0

For i = 1 To 183
    idMatch = ThisWorkbook.Worksheets("RaceAsheville").Range("A1").Offset(i - numDeletes)

    matches = False

    For j = 1 To 88
        idSearch = ThisWorkbook.Worksheets("Percentages").Range("A1").Offset(j)

        If idMatch = idSearch Then
            matches = True
        End If
    Next j

    If matches = False Then
        Rows(i + 1 - numDeletes).EntireRow.Delete
        numDeletes = numDeletes + 1
    End If

Next i

End Sub
```

Figure C.10: VBA Code – Delete BG19 outside ACL

Calculating Distance Matrices

1. Find the origin as the central point of BG19
    a. Clip BG19 to ACL.
    b. Create x and y coordinate columns to the BG19 polygon attribute table and use “Calculate Geometry” functions to find x and y central-point coordinates.
    c. Use the “XY Table to Point” tool to make a point feature class of the center point coordinates.

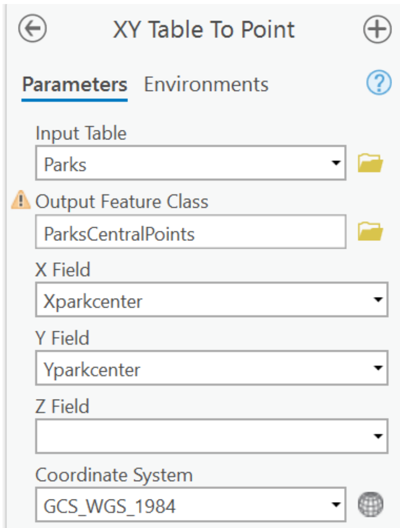

Figure C.11: ArcGIS Interface – XY Table to Point

2. Find the destination as the central point of parks.
    a. Create x and y coordinate columns to the park polygon attribute table and use "Calculate Geometry" functions to find x and y central-point coordinates.
    b. Use the "XY Table to Point" tool to make a point feature class of the center point coordinates.
3. Find the distance between origin and destination points.
    a. Complete an "Origin-Destination Cost Analysis" as a network analysis using merged Pedestrian and Bicycle Paths.
    b. Import origin and destination points.
    c. Set to calculate walking distance in miles.

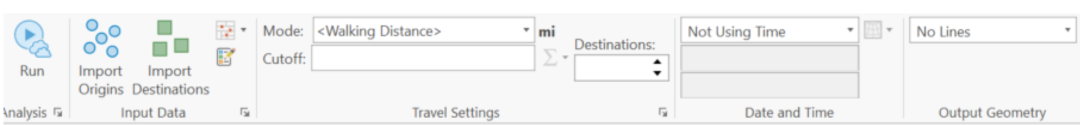

Figure C.12: ArcGIS Interface – OD Cost Analysis

d. Run the “Origin-Destination Cost Analysis” tool.

e. Export the resulting Origin-Destination distances to Excel.

f. Use VBA to populate a matrix of distances from a three-columned list of origin, destination, and distance.

```
Sub PopulateDistMatrix()

Dim i As Integer, j As Integer, k As Integer
Dim BGMatch As String, BGSearch As String
Dim ParkMatch As String, ParkSearch As String

For k = 1 To 4992
    ParkSearch = ThisWorkbook.Worksheets("ODdistance").Range("B1").Offset(k)
    BGSearch = ThisWorkbook.Worksheets("ODdistance").Range("A1").Offset(k)

    For i = 1 To 64
        ParkMatch = ThisWorkbook.Worksheets("Matrix").Range("A1").Offset(i)

        For j = 1 To 78
            BGMatch = ThisWorkbook.Worksheets("Matrix").Range("A1").Offset(0, j)

            If ParkMatch = ParkSearch And BGMatch = BGSearch Then
                ThisWorkbook.Worksheets("Matrix").Range("A1").Offset(i, j) = ThisWorkbook.Worksheets("ODdistance").Range("C1").Offset(k)
            End If
        Next j
    Next i
Next k

End Sub
```

Figure C.13: VBA Code – Distance List to Matrix

Creating A Network of Pedestrian and Bicycle Paths with Roads of at Most 25 mph

1. Import streets from the Buncombe feature class file.
2. Delete all line feature classes that have street type of HWY, I240, I26, and I40.
3. Delete all streets with a speed limit of greater than 25mph.
4. Merge the updated road network with the pedestrian and bicycle paths.

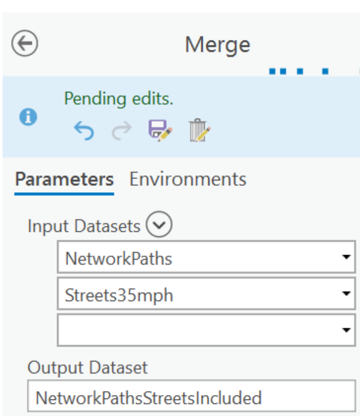

Figure C.14: ArcGIS Interface – Merge Network Paths

Calculating Average Park Tree Cover

1. Resample the raster data set such that the cell size is 5m x 5m rather than 30m x 30m. This recalibration will add increased accuracy to the future raster summary.

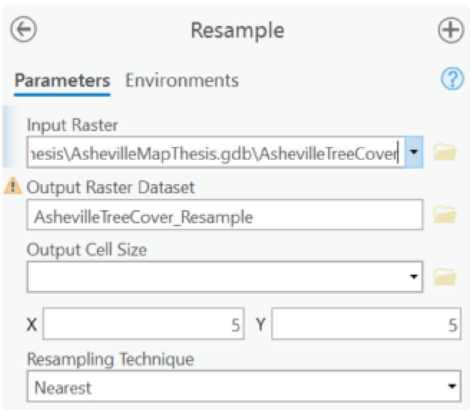

Figure C.15: ArcGIS Interface – Resample Tree Cover Raster

2. Summarize all tree cover raster cells within each park polygon. This step outputs the number of cells within each park that correspond to each unique tree cover classification (a percentage between 0 and 100).

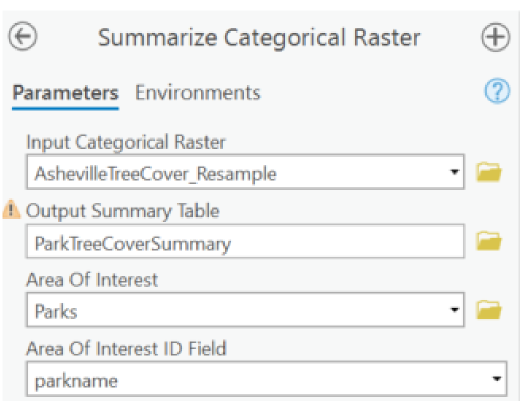

Figure C.16: ArcGIS Interface – Summarize Categorical Raster for Tree Cover

3. Export tree cover raster summary table to Excel.
4. Use a sum product to find the weighted sum of tree cover within each park. The weighted sum equals the number of raster cells of each tree cover classification multiplied by the value of that tree cover classification. These values are within the summary table.
5. Find the total number of tree cover raster cells in each park from the summary table.
6. Find the average tree cover for each park by dividing the sum-product total by the cell count of the park.

Calculating Average Park Heat

Finding the average park heat index is the same procedure as the one for tree cover with the following change to Step 5:

5. Calculate the total number of raster cells within each park as the maximum of the number of tree cover cells in that park and the number of cells for that park listed in the heat raster summary.

Appendix D

AMPL Code

Within this appendix, we provide images of the park equity deviation-based model as coded within AMPL. We include the run file, data input file, model file, and data export file.

```
# RESET
reset;
display "Begin Code Process";

# CALL .MOD FILE
model PEM3Formulation.mod;
display "Model Load Complete";

# UPLOAD DATA (from Excel)
commands PEM3ImportFile.run;
display "Data Load Complete";

# DEFINE SOLVER
option solver gurobi_ampl;

# SOLVE
#option gurobi_options 'mipgap = 0.75 outlev = 1';
option gurobi_options 'outlev = 1';
solve;

# Output Solving Completion
display AssignNum;
display "Solving Complete";

# EXPORT DATA (to Excel)
commands PEM3ExportFile.run;

# Output Export Completion
display "Full Export Complete";
```

Figure D.1: AMPL Run File of Deviation-Based Model

```
# File Name
param DataFileInput symbolic := "ParkEquityInputData.xlsb";

# PREPARING TABLES

# Sets

# Import the parks set
table tabSetParks IN "tableproxy" "odbc" (DataFileInput) "SetParks":
K <- [SetOfParks]; # table of set of parks

# Import the locations set
table tabSetLocations IN "tableproxy" "odbc" (DataFileInput) "SetLocations":
L <- [SetOfLocations]; # table of set of resident locations

# Import the demographics set
table tabSetDemographic IN "tableproxy" "odbc" (DataFileInput) "SetDemographic":
R <- [SetOfDemographics]; # table of set of demographic categories


# Parameters

# Import distance parameters
table tabDistanceParams "tableproxy" "odbc" (DataFileInput) "DistParams": [],
DistDevBigM, # the largest value that a distance deviation would have
DistNorm, # normalization of distance
DistWeight, # the weight of importance of not having distance deviations
ActDistBigM; # the largest value that actual distance from location to primary park would have

# Import capacity parameters
table tabCapacityParams "tableproxy" "odbc" (DataFileInput) "CapParams": [],
CapDevBigM, # the largest value that a capacity deviation would have
CapNorm, # normalization of capacity
CapWeight, # the weight of importance of not having capacity deviations
ActCapBigM; # the largest value that actual capacity of a primary park would have

# Import heat parameters
table tabHeatParams "tableproxy" "odbc" (DataFileInput) "HeatParams": [],
HeatDevBigM, # the largest value that a heat deviation would have
HeatNorm, # normalization of heat
HeatPlusWeight, # the weight of importance of not having excess heat deviations
HeatMinusWeight, # the weight of importance of not having deficit heat deviations
MaxHeat, # maximum acceptable heat index value
MinHeat; # minimum acceptable heat index value
```
Figure D.2: AMPL Import Data File – Sets and Parameters

```
# Import tree cover parameters
table tabTreeParams "tableproxy" "odbc" (DataFileInput) "TreeParams": [],
TreeDevBigM, # the largest value that a tree cover deviation would have
TreeNorm, # normalization of tree cover
TreePlusWeight, # the weight of importance of not having excess tree cover deviations
TreeMinusWeight, # the weight of importance of not having deficit tree cover deviations
MaxTree, # maximum acceptable tree cover percentage value
MinTree; # minimum acceptable tree cover percentage value

# Import budget parameter
table tabBudget IN "tableproxy" "odbc" (DataFileInput) "BudgetParam": [],
Budget; # budget

# Import parameter of desired distance from a location to a park
table tabIdealDist IN "tableproxy" "odbc" (DataFileInput) "IdealDist": [],
IdealDist; # ideal distance

# Import count of residents of a demographic in a location
# table of counts LR for demographic classifications
table tabCountLRdem IN "tableproxy" "odbc" (DataFileInput) "CountLRdem":
[l ~ L], {r in R} <LRcount[l,r] ~ (r)>;

# table distances to park from resident location using pedestrian and bicycle path
# Import distance from location to park using pedestrian and bike paths network
table tabPedBikeDist IN "tableproxy" "odbc" (DataFileInput) "PedBikeDistKL": s
[k ~ K], {l in L} <Distance[k,l] ~ (l)>;

#                                    OR
# Import distance from location to park using pedestrian and bike and streets of <= 25mph network
#table tabPedBike25mphDist IN "tableproxy" "odbc" (DataFileInput) "PedBike25mphDistKL":
#[k ~ K], {l in L} <Distance[k,l] ~ (l)>;

# Import weight of importance of residents of a certain demographic being near a park
table tabDemParams IN "tableproxy" "odbc" (DataFileInput) "DemParams": [R], # table of demographic parameters
DemWeight; # maximum distance allowable between the resident location and the park for specific demographic-specific

# Import park parameters
table tabParkParams IN "tableproxy" "odbc" (DataFileInput) "ParkParams": [K], # table of park-specific parameters
ParkFee, # park fee
ParkExists, # 0/1 park already exists or not
ParkCap, # park capacity in terms of number of people
HeatPlus, # exogenous heat deviation param
HeatMinus, # exogenous tree cover deviation param
TreePlus, # exogenous heat deviation param
TreeMinus; # exogenous tree cover deviation param
```

Figure D.3: AMPL Import Data File – More Parameters

```
# Upload Data

read table tabSetParks;
read table tabSetLocations;
read table tabSetDemographic;

read table tabDistanceParams;
read table tabCapacityParams;
read table tabHeatParams;
read table tabTreeParams;
read table tabBudget;
read table tabIdealDist;

read table tabCountLRdem;

read table tabPedBikeDist;
#           OR
#read table tabPedBike25mphDist;

read table tabDemParams;
read table tabParkParams;
```

Figure D.4: AMPL Import Data File – Read from Excel to AMPL

```
# SETS

set K; # set of all parks (existing and candidate) --> k
set L; # set of all resident locations (Census block groups 2019) --> l
set R; # set of all demographics (currently race)
    # later could include gender, age, proverty, economic, SNAP, and disability)

# -----------------------------------------------------------------------------------------------

# PARAMETERS

# Normalization Parameters (n in formulation)
param DistNorm; # normalization for distance deviation
param CapNorm;  # normalization for capacity deviation
param HeatNorm; # normalization for heat deviation
param TreeNorm; # normalization for tree cover deviation

# Weight Parameters (w in formulation)
param DistWeight; # importance weight of added distance
param CapWeight; # importance weight of overcrowdiing
param HeatPlusWeight; # importance weight of heat beyond the desired range
param HeatMinusWeight; # importance weight of heat below the desired range
param TreePlusWeight; # importance weight of tree cover beyond the desired range
param TreeMinusWeight; # importance weight of tree cover below the desired range

# Big M Values (mu in the formulation)
param DistDevBigM; # big M for distance deviation
param CapDevBigM; # big M for capacity deviation
param HeatDevBigM; # big M for heat deviation
param TreeDevBigM; # big M for tree cover deviation
param ActDistBigM; # big M for actual distance
param ActCapBigM; # big M for actial capacity

# Heat and Tree Cover Ranges (for export only)
param MaxHeat; # maximum desired heat
param MinHeat; # minimum desired heat
param MaxTree; # maximum desired tree cover
param MinTree; # minimum desired tree cover
```

Figure D.5: AMPL Model File – Sets and Parameters

```
# Demographic Importance Parameter (q in formulation)
param DemWeight {r in R}; # importance weight for demographic group r in R

# General Resident Parameters
param LRcount {l in L, r in R}; # count of residents in location l in L with demographic characteristic r in R (t in formulation)

# Distance Parameters
param Distance {k in K, l in L}; # distance from park k in K to resident location l in L (d in formulation)
param IdealDist; # max distance desired from resident characteristic r in R to its primary park (m in formulation)

# Existing Park Parameters
param ParkExists {k in K}; # 0/1 park does not/does exist at park site k in K (e in formulation)

# Park Capacity Parameters
param ParkCap {k in K}; # amount of capacity in park k in K (a in formulation)

# Park Monetary Parameters
param Budget; # budget for park purchasing (b in formulation)
param ParkFee {k in K}; # fee to purchase park k in K (f in formulation)

# Park Environment Parameters
param HeatPlus {k in K}; # amount of heat in park k in K above the allowable range (c_heat+ in formulation)
param HeatMinus {k in K}; # amount of heat in park k in K below the allowable range (c_heat- in formulation)
param TreePlus {k in K}; # amount of tree cover in park k in K above the allowable range (c_tree+ in formulation)
param TreeMinus {k in K}; # amount of tree cover in park k in K below the allowable range (c_tree- in formulation)
```

Figure D.6: AMPL Model File – More Parameters

```
# DECISION VARIABLES

# Main Decision Variables
var y {k in K} binary >= 0; # 0/1 park not/located at park site k in K
var x {k in K, l in L} binary >= 0; # 0/1 residents in location l in L not/assigned to park k in K

# Slack Variables
var DistPlus {l in L} >= 0; # distance to primary park beyond desired limit for location l in L (d+ in formulation)
var CapPlus {k in K} >= 0; # amount of overcrowding in park k in K for location l in L (a+ informulation)

# Binary Variable for Needing Slack Parameters
var NoDistSlack {l in L} binary >= 0; # 1 if do not need slack variable for distance (u in formulation)
var NoCapSlack {k in K} binary >= 0; # 1 if do not need slack variable for capacity (u in formulation)

# Linearization DVs (pi in formulation)
var LinActDist {l in L} >= 0; # DV defines the linearization of actual distance of location l in L to its primary park
var LinActCap {k in K} >= 0; # DV defines the linearization of actual capacity within park k in K
var LinCapPlusKL {k in K, l in L} >= 0; # DV defines the linearization of capacity of location l in L at park k in K

# DV defines the total cost of park purchasing
var TotalParkFee >= 0;
```
Figure D.7: AMPL Model File – Decision Variables

```
# * * * * * * * * * * * * * * WEIGHTED MAX AND MIN DEVIATION DVS * * * * * * * * * * * * *

# Deviation Decision Variables
var MaxTotalDevR >= 0; # maximum total deviation of all demographic groupings
var MinTotalDevR >= 0; # minimum total deviation of all demographic groupings

var MaxTotalDevL >= 0; # maximum total deviation of all location groupings
var MinTotalDevL >= 0; # minimum total deviation of all location groupings

var MaxTotalDevLR >= 0; # maximum total deviation of all location-demographic groupings
var MinTotalDevLR >= 0; # minimum total deviation of all location-demographic groupings

# Set Deviation Value Variables
var DistDeviation >= 0;
var CapDeviation >= 0;
var HeatPDeviation >= 0;
var HeatMDeviation >= 0;
var TreePDeviation >= 0;
var TreeMDeviation >= 0;
var AllDeviations >= 0;

# Calculate R deviations --> deviations in terms of demographics
var DistDeviationR {r in R} >= 0;
var CapDeviationR {r in R} >= 0;
var HeatPDeviationR {r in R} >= 0;
var HeatMDeviationR {r in R} >= 0;
var TreePDeviationR {r in R} >= 0;
var TreeMDeviationR {r in R} >= 0;
var AllDeviationsR {r in R} >= 0;

# Calculate L deviations --> deviations in terms of locations
var DistDeviationL {l in L} >= 0;
var CapDeviationL {l in L} >= 0;
var HeatPDeviationL {l in L} >= 0;
var HeatMDeviationL {l in L} >= 0;
var TreePDeviationL {l in L} >= 0;
var TreeMDeviationL {l in L} >= 0;
var AllDeviationsL {l in L} >= 0;

# Calculate LR deviations --> deviations in terms of location-demographic pair
var DistDeviationLR {l in L, r in R} >= 0;
var CapDeviationLR {l in L, r in R} >= 0;
var HeatPDeviationLR {l in L, r in R} >= 0;
var HeatMDeviationLR {l in L, r in R} >= 0;
var TreePDeviationLR {l in L, r in R} >= 0;
var TreeMDeviationLR {l in L, r in R} >= 0;
var AllDeviationsLR {l in L, r in R} >= 0;

# * * * * * * * * * * * * * * * * * * * * STATUS DVs * * * * * * * * * * * * * * * *

# Check how many assignments exist (should be equal to the number of locations L)
var AssignNum >= 0;
```
Figure D.8: AMPL Model File – Intermediate Decision Variables

```
# OBJECTIVE FUNCTION

minimize OF: MaxTotalDevR;
#minimize OF: AllDeviations;

# -----------------------------------------------------------------------------------------------

# CONSTRAINTS

# * * * * * * * * * * * * * * * * SOME MAIN CONSTRAINTS * * * * * * * * * * * * * * * *

# Allocation and Coverage Constraints
s.t. AssignOnePark {l in L}: sum {k in K} x[k,l] = 1; # ensure that all resident location have exactly one primary park
s.t. VisitOpenPark {k in K, l in L}: x[k,l] <= y[k]; # patrons may only visit selected parks
s.t. PickExistPark {k in K}: ParkExists[k] <= y[k]; # if a park exists, then must select it

# Distance Constraints
# patrons within the maximum desired distance from their primary park
s.t. DesiredDistance {l in L}: (sum {k in K} Distance[k,l] * x[k,l]) - DistPlus[l] <= IdealDist;
# sets the minimum allowable distance slack variable value
s.t. MinDistSlack {l in L}: DistPlus[l] - (sum {k in K} Distance[k,l] * x[k,l]) + IdealDist + LinActDist[l] - (NoDistSlack[l] * IdealDist) <= 0;
s.t. SetLinActDist1 {l in L}: LinActDist[l] <= ActDistBigM * NoDistSlack[l]; # linearization constraint
s.t. SetLinActDist2 {l in L}: LinActDist[l] <= (sum {k in K} Distance[k,l] * x[k,l]); # linearization constraint
s.t. SetLinActDist3 {l in L}: LinActDist[l] >= (sum {k in K} Distance[k,l] * x[k,l]) - (ActDistBigM * (1 - NoDistSlack[l])); # linearization constraint
s.t. SetLinActDist4 {l in L}: LinActDist[l] >= 0; # linearization constraint

# Land Purchasing Constraints
s.t. BudgetLimit: sum {k in K} ParkFee[k] * y[k] <= Budget; # the monetary cost to purchase land must be within the allocated budget

# Land Capacity Constraints
# the park size must be able to accommodate the patrons
s.t. DesiredCapacity {k in K}: (sum {l in L, r in R} LRcount[l,r] * x[k,l]) - CapPlus[k] <= ParkCap[k];
# sets the minimum allowable distance slack variable value
s.t. MinCapSlack {k in K}: CapPlus[k] - (sum {l in L, r in R} LRcount[l,r] * x[k,l]) + ParkCap[k] + LinActCap[k] - (ParkCap[k] * NoCapSlack[k]) <= 0;
s.t. SetLinActCap1 {k in K}: LinActCap[k] <= ActCapBigM * NoCapSlack[k]; # linearization constraint
s.t. SetLinActCap2 {k in K}: LinActCap[k] <= (sum {l in L, r in R} LRcount[l,r] * x[k,l]); # linearization constraint
s.t. SetLinActCap3 {k in K}: LinActCap[k] >= (sum {l in L, r in R} LRcount[l,r] * x[k,l]) - (ActCapBigM * (1 - NoCapSlack[k])); # linearization constraint
s.t. SetLinActCap4 {k in K}: LinActCap[k] >= 0;

# Linearization of Capacity --> Overcrowding of Parks to Locations
s.t. SetLinCapPlusKL1 {k in K, l in L}: LinCapPlusKL[k,l] <= CapDevBigM * x[k,l];
s.t. SetLinCapPlusKL2 {k in K, l in L}: LinCapPlusKL[k,l] <= CapPlus[k];
s.t. SetLinCapPlusKL3 {k in K, l in L}: LinCapPlusKL[k,l] >= CapPlus[k] - (CapDevBigM * (1 - x[k,l]));
s.t. SetLinCapPlusKL4 {k in K, l in L}: LinCapPlusKL[k,l] >= 0;
```

Figure D.9: AMPL Model File – Objective Function and Constraints

```
# * * * * * * * * * * * * WEIGHTED AND NORMALIZED DEVIATION BY POPULATION * * * * * * * * * * *

# Intermediate Step - Set Deviation Value Variables
s.t. SetDistDeviation: DistDeviation = DistNorm * DistWeight * sum {l in L, r in R} DemWeight[r] * LRcount[l,r] * DistPlus[l];
s.t. SetCapDeviation: CapDeviation = CapNorm * CapWeight * sum {k in K, l in L, r in R} DemWeight[r] * LRcount[l,r] * LinCapPlusKL[k,l];
s.t. SetHeatPDeviation: HeatPDeviation = HeatNorm * HeatPlusWeight * sum {k in K, l in L, r in R} DemWeight[r] * LRcount[l,r] * HeatPlus[k] * x[k,l];
s.t. SetHeatMDeviation: HeatMDeviation = HeatNorm * HeatMinusWeight * sum {k in K, l in L, r in R} DemWeight[r] * LRcount[l,r] * HeatMinus[k] * x[k,l];
s.t. SetTreePDeviation: TreePDeviation = TreeNorm * TreePlusWeight * sum {k in K, l in L, r in R} DemWeight[r] * LRcount[l,r] * TreePlus[k] * x[k,l];
s.t. SetTreeMDeviation: TreeMDeviation = TreeNorm * TreeMinusWeight * sum {k in K, l in L, r in R} DemWeight[r] * LRcount[l,r] * TreeMinus[k] * x[k,l];
s.t. SetTotalDeviation: AllDeviations = DistDeviation + CapDeviation + HeatPDeviation + HeatMDeviation + TreePDeviation + TreeMDeviation;

# Intermediate Step - Calculate R deviations
s.t. SetDistDeviationR {r in R}: DistDeviationR[r] = DistNorm * DistWeight * sum {l in L} DemWeight[r] * LRcount[l,r] * DistPlus[l];
s.t. SetCapDeviationR {r in R}: CapDeviationR[r] = CapNorm * CapWeight * sum {k in K, l in L} DemWeight[r] * LRcount[l,r] * LinCapPlusKL[k,l];
s.t. SetHeatPDeviationR {r in R}: HeatPDeviationR[r] = HeatNorm * HeatPlusWeight * sum {k in K, l in L} DemWeight[r] * LRcount[l,r] * HeatPlus[k] * x[k,l];
s.t. SetHeatMDeviationR {r in R}: HeatMDeviationR[r] = HeatNorm * HeatMinusWeight * sum {k in K, l in L} DemWeight[r] * LRcount[l,r] * HeatMinus[k] * x[k,l];
s.t. SetTreePDeviationR {r in R}: TreePDeviationR[r] = TreeNorm * TreePlusWeight * sum {k in K, l in L} DemWeight[r] * LRcount[l,r] * TreePlus[k] * x[k,l];
s.t. SetTreeMDeviationR {r in R}: TreeMDeviationR[r] = TreeNorm * TreeMinusWeight * sum {k in K, l in L} DemWeight[r] * LRcount[l,r] * TreeMinus[k] * x[k,l];
s.t. SetTotalDeviationR {r in R}: AllDeviationsR[r] = DistDeviationR[r] + CapDeviationR[r] + HeatPDeviationR[r] + HeatMDeviationR[r] + TreePDeviationR[r] + TreeMDeviationR[r];

# Intermediate Step - Calculate L deviations
s.t. SetDistDeviationL {l in L}: DistDeviationL[l] = DistNorm * DistWeight * sum {r in R} DemWeight[r] * LRcount[l,r] * DistPlus[l];
s.t. SetCapDeviationL {l in L}: CapDeviationL[l] = CapNorm * CapWeight * sum {k in K, r in R} DemWeight[r] * LRcount[l,r] * LinCapPlusKL[k,l];
s.t. SetHeatPDeviationL {l in L}: HeatPDeviationL[l] = HeatNorm * HeatPlusWeight * sum {k in K, r in R} DemWeight[r] * LRcount[l,r] * HeatPlus[k] * x[k,l];
s.t. SetHeatMDeviationL {l in L}: HeatMDeviationL[l] = HeatNorm * HeatMinusWeight * sum {k in K, r in R} DemWeight[r] * LRcount[l,r] * HeatMinus[k] * x[k,l];
s.t. SetTreePDeviationL {l in L}: TreePDeviationL[l] = TreeNorm * TreePlusWeight * sum {k in K, r in R} DemWeight[r] * LRcount[l,r] * TreePlus[k] * x[k,l];
s.t. SetTreeMDeviationL {l in L}: TreeMDeviationL[l] = TreeNorm * TreeMinusWeight * sum {k in K, r in R} DemWeight[r] * LRcount[l,r] * TreeMinus[k] * x[k,l];
s.t. SetTotalDeviationL {l in L}: AllDeviationsL[l] = DistDeviationL[l] + CapDeviationL[l] + HeatPDeviationL[l] + HeatMDeviationL[l] + TreePDeviationL[l] + TreeMDeviationL[l];

# Intermediate Step - Calculate LR deviations
s.t. SetDistDeviationLR {l in L, r in R}: DistDeviationLR[l,r] = DistNorm * DistWeight * DemWeight[r] * LRcount[l,r] * DistPlus[l];
s.t. SetCapDeviationLR {l in L, r in R}: CapDeviationLR[l,r] = CapNorm * CapWeight * sum {k in K} DemWeight[r] * LRcount[l,r] * LinCapPlusKL[k,l];
s.t. SetHeatPDeviationLR {l in L, r in R}: HeatPDeviationLR[l,r] = HeatNorm * HeatPlusWeight * sum {k in K} DemWeight[r] * LRcount[l,r] * HeatPlus[k] * x[k,l];
s.t. SetHeatMDeviationLR {l in L, r in R}: HeatMDeviationLR[l,r] = HeatNorm * HeatMinusWeight * sum {k in K} DemWeight[r] * LRcount[l,r] * HeatMinus[k] * x[k,l];
s.t. SetTreePDeviationLR {l in L, r in R}: TreePDeviationLR[l,r] = TreeNorm * TreePlusWeight * sum {k in K} DemWeight[r] * LRcount[l,r] * TreePlus[k] * x[k,l];
s.t. SetTreeMDeviationLR {l in L, r in R}: TreeMDeviationLR[l,r] = TreeNorm * TreeMinusWeight * sum {k in K} DemWeight[r] * LRcount[l,r] * TreeMinus[k] * x[k,l];
s.t. SetTotalDeviationLR {l in L, r in R}: AllDeviationsLR[l,r] = DistDeviationLR[l,r] + CapDeviationLR[l,r] + HeatPDeviationLR[l,r] + HeatMDeviationLR[l,r] + TreePDeviationLR[l,r] + TreeMDeviationLR[l,r];

# Select Min and Max Deviations
s.t. SetMaxTotalDevR {r in R}: MaxTotalDevR >= AllDeviationsR[r]; # find the maximum deviation of all demographic deviations
s.t. SetMinTotalDevR {r in R}: MinTotalDevR <= AllDeviationsR[r]; # find the minimum deviation of all demographic deviations
s.t. SetMaxTotalDevL {l in L}: MaxTotalDevL >= AllDeviationsL[l]; # find the maximum deviation of all location deviations
s.t. SetMinTotalDevL {l in L}: MinTotalDevL <= AllDeviationsL[l]; # find the minimum deviation of all location deviations
s.t. SetMaxTotalDevLR {l in L, r in R}: MaxTotalDevLR >= AllDeviationsLR[l,r]; # find the maximum deviation of all demographic/location deviations
s.t. SetMinTotalDevLR {l in L, r in R}: MinTotalDevLR <= AllDeviationsLR[l,r]; # find the minimum deviation of all demographic/location deviations

# * * * * * * * * * * * * * * * * SET STATUS DVs * * * * * * * * * * * * * * * *

# Set Cost Variable
s.t. SetTotalParkFee: TotalParkFee = sum {k in K} ParkFee[k] * y[k];

# NOT IN FORMULATION - Check how many assignments exist (should be equal to the number of locations L)
s.t. SetAssignNum: AssignNum = sum {k in K, l in L} x[k,l];
```

Figure D.10: AMPL Model File – More Constraints

```
# File Name
param DataFileExport symbolic := "ParkEquityResultsM3.xlsx";

# PREPARING TABLES

# Main Decision Variables

# Export decision variable y[k] --> 0/1 select a park or not
table ParkSelection OUT "tableproxy" "odbc" (DataFileExport):
K -> [Park], y;

# Export decision variable x[k,l] --> 0/1 park k is primary park of location l
# table distances to park from resident location using pedestrian and bicycle paths
table PrimaryPark OUT "tableproxy" "odbc" (DataFileExport):
{k in K} -> [ParkLocation], {l in L} <x[k,l] ~ (l)>;

# Slack Variables

# Export distance deviation to a primary park for each location
table DistanceSlack OUT "tableproxy" "odbc" (DataFileExport):
L -> [Location], DistPlus;

# Export capacity deviation of a primary park k
table CapacitySlack OUT "tableproxy" "odbc" (DataFileExport):
K -> [Park], CapPlus;

# Export Capacity Variable --> Linearized amount of capacity deviation in a park k for a location l
# table distances to park from resident location using pedestrian and bicycle paths
{k in K} -> [ParkLocation], {l in L} <LinCapPlusKL[k,l] ~ (l)>;
table LinearizedCapTable OUT "tableproxy" "odbc" (DataFileExport):
```

Figure D.11: AMPL Export File – Prepare Decision Variables Tables (part 1)

```
# Intermediate Variables

# * * * * * * * * * * * * * * WEIGHTED DEVIATION DVS * * * * * * * * * * * * * * * *

# Export demographic deviations of distance, capacity, heat, and tree cover
table DemographicDeviations OUT "tableproxy" "odbc" (DataFileExport):
R -> [Demographic], DistDeviationR, CapDeviationR, HeatPDeviationR, HeatMDeviationR,
TreePDeviationR, TreeMDeviationR, AllDeviationsR;

# Export location deviations of distance, capacity, heat, and tree cover
table LocationDeviations OUT "tableproxy" "odbc" (DataFileExport):
L -> [Location], DistDeviationL, CapDeviationL, HeatPDeviationL, HeatMDeviationL,
TreePDeviationL, TreeMDeviationL, AllDeviationsL;

# Export distance deviation of location-demographic pairs
# table distances to park from resident location using pedestrian and bicycle paths
table LRDistDev OUT "tableproxy" "odbc" (DataFileExport):
{l in L} -> [Distance], {r in R} <DistDeviationLR[l,r] ~ (r)>;

# Export capacity deviation of location-demographic pairs
# table distances to park from resident location using pedestrian and bicycle paths
table LRCapDev OUT "tableproxy" "odbc" (DataFileExport):
{l in L} -> [Capacity], {r in R} <CapDeviationLR[l,r] ~ (r)>;
```

Figure D.12: AMPL Export File – Prepare Decision Variables Tables (part 2)

```
# Export heat excess deviation of location-demographic pairs
# table distances to park from resident location using pedestrian and bicycle paths
table LRHeatPDev OUT "tableproxy" "odbc" (DataFileExport):
{l in L} -> [HeatP], {r in R} <HeatPDeviationLR[l,r] ~ (r)>;

# Export heat deficit deviation of location-demographic pairs
# table distances to park from resident location using pedestrian and bicycle paths
table LRHeatMDev OUT "tableproxy" "odbc" (DataFileExport):
{l in L} -> [HeatM], {r in R} <HeatMDeviationLR[l,r] ~ (r)>;

# Export tree cover excess deviation of location-demographic pairs
# table distances to park from resident location using pedestrian and bicycle paths
table LRTreePDev OUT "tableproxy" "odbc" (DataFileExport):
{l in L} -> [TreeP], {r in R} <TreePDeviationLR[l,r] ~ (r)>;

# Export tree cover deficit deviation of location-demographic pairs
# table distances to park from resident location using pedestrian and bicycle paths
table LRTreeMDev OUT "tableproxy" "odbc" (DataFileExport):
{l in L} -> [TreeM], {r in R} <TreeMDeviationLR[l,r] ~ (r)>;

# Export sum of all deviations for locataion-demographic pairs
# table distances to park from resident location using pedestrian and bicycle paths
table LRAllDev OUT "tableproxy" "odbc" (DataFileExport):
{l in L} -> [AllDev], {r in R} <AllDeviationsLR[l,r] ~ (r)>;

# Export the overall raw deviations for distance, capacity, heat, and tree cover
table OverallDeviations OUT "tableproxy" "odbc" (DataFileExport):
[], DistDeviation, CapDeviation, HeatPDeviation, HeatMDeviation,
TreePDeviation, TreeMDeviation, AllDeviations;

# Other Results

# Export total cost to purchase new park site land
table ParkCost OUT "tableproxy" "odbc" (DataFileExport):
[], TotalParkFee;
```

Figure D.13: AMPL Export File – Prepare Decision Variables Tables (part 3)

```
# Inputs

# Export the deviation type weight of importance
table DevTypeWeightInputs OUT "tableproxy" "odbc" (DataFileExport):
[], DistWeight, CapWeight, HeatPlusWeight, HeatMinusWeight, TreePlusWeight, TreeMinusWeight;

# Export the heat acceptable range
table HeatRangeInput OUT "tableproxy" "odbc" (DataFileExport):
[], MaxHeat, MinHeat;

# Export the tree cover acceptable range
table TreeRangeInput OUT "tableproxy" "odbc" (DataFileExport):
[], MaxTree, MinTree;

# Export the monetary budget
table BudgetInput OUT "tableproxy" "odbc" (DataFileExport):
[], Budget;

# Export the desired maximum distance from primary parks to locations
table IdealDistInput OUT "tableproxy" "odbc" (DataFileExport):
[], IdealDist;

# Export demographic type weight of importance
table DemTypeWeightInput OUT "tableproxy" "odbc" (DataFileExport):
R -> [Demographic], DemWeight;

# Export the BigM value for capacity
table CapBigMInput OUT "tableproxy" "odbc" (DataFileExport):
[], CapDevBigM;

# Export the BigM value for capacity
table MaxCapValue OUT "tableproxy" "odbc" (DataFileExport):
[], ActCapBigM;

# Export the BigM value for distance
table MaxDistValue OUT "tableproxy" "odbc" (DataFileExport):
[], ActDistBigM;
```

Figure D.14: AMPL Export File – Prepare Input Parameters Tables

```
# WRITE TABLES
write table ParkSelection;
write table PrimaryPark;
write table DistanceSlack;
write table CapacitySlack;
write table LinearizedCapTable;
write table OverallDeviations;
write table DemographicDeviations;
write table LocationDeviations;
write table LRDistDev;
write table LRCapDev;
write table LRHeatPDev;
write table LRHeatMDev;
write table LRTreePDev;
write table LRTreeMDev;
write table LRAllDev;
write table ParkCost;
write table DevTypeWeightInputs;
write table HeatRangeInput;
write table TreeRangeInput;
write table BudgetInput;
write table DemTypeWeightInput;
write table CapBigMInput;
write table MaxCapValue;
write table MaxDistValue;
```
Figure D.15: AMPL Export File – Write Tables from AMPL to Excel

Appendix E

Additional Model Analysis Data and Visualization

This appendix provides result data tables and additional result visualizations for completed analyses.

Park Goodness vs. Budget

Minimizing Park Goodness Deviations vs. Budget

Table E.1 provides the table of overall park goodness deviations resulting from *Min All Dev Cap*, *Min Max Dev Cap*, *Min All Dev Uncap*, and *Min Max Dev Uncap*.

Table E.1: Overall Park Goodness Deviations (Tabulated Results)

Budget	Min All Dev Cap	Min Max Dev Cap	Min All Dev Uncap	Min Max Dev Uncap
$0	647808	650570	384452	384452
$250,000	510969	515476	265586	265586
$500,000	460758	463203	228103	228103
$750,000	427820	429318	202235	202235
$1,000,000	406251	407452	187653	187899
$1,250,000	388816	389476	180392	180435
$1,500,000	377513	377520	175849	175849
$1,750,000	370341	370662	172881	172881
$2,000,000	365718	366042	171493	171561
$2,250,000	361059	362053	169858	169858
$2,500,000	358894	360059	168926	168926
$2,750,000	356900	359017	168634	168634
$3,000,000	356282	358399	167922	167957
$3,250,000	355632	355639	166990	166994
$3,500,000	354931	357048	166831	166831
$3,750,000	354427	356544	166831	166831
$4,000,000	353838	353845	166831	166831
$4,250,000	353602	355995	166831	166831
$4,500,000	353344	353351	166831	166831
$4,750,000	353107	353114	166831	166831
$5,000,000	353107	353114	166831	166831
$5,250,000	353107	353114	166831	166831
$5,500,000	353107	353114	166831	166831
$5,750,000	353107	353114	166831	166831
$6,000,000	353107	353114	166831	166831

Figure E.1 is a graph that provides the overall park goodness deviations resulting from *Min All Dev Cap*, *Min Max Dev Cap*, *Min All Dev Uncap*, and *Min Max Dev Uncap* for the entire budget range of $0 to $6,000,000 (as listed in Table E.1).

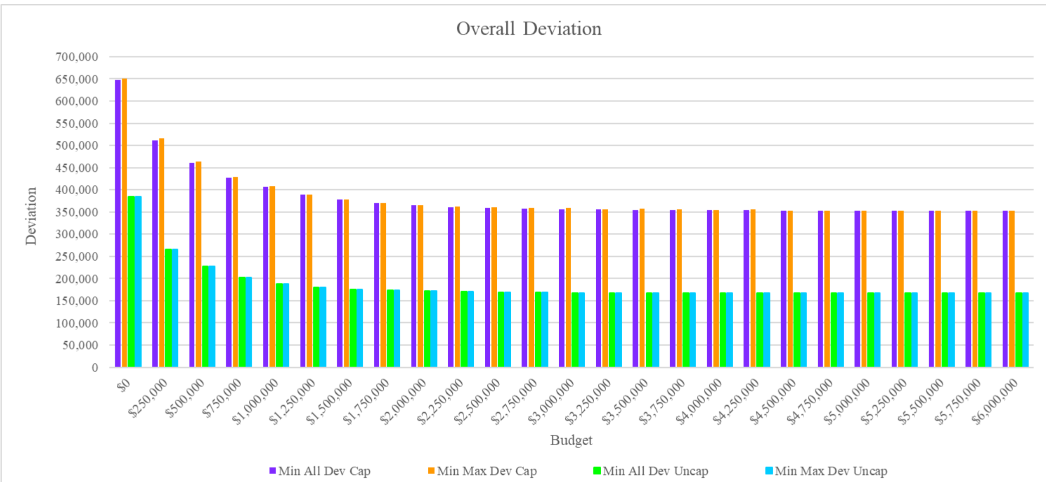

Figure E.1: Total Goodness Deviations vs. Budget ($0 to $6,000,000)

Figure E.2 is a graph that provides the maximum demographic park goodness deviation resulting from *Min All Dev Cap*, *Min Max Dev Cap*, *Min All Dev Uncap*, and *Min Max Dev Uncap* for the entire budget range of $0 to $6,000,000 (as in Table E.2).

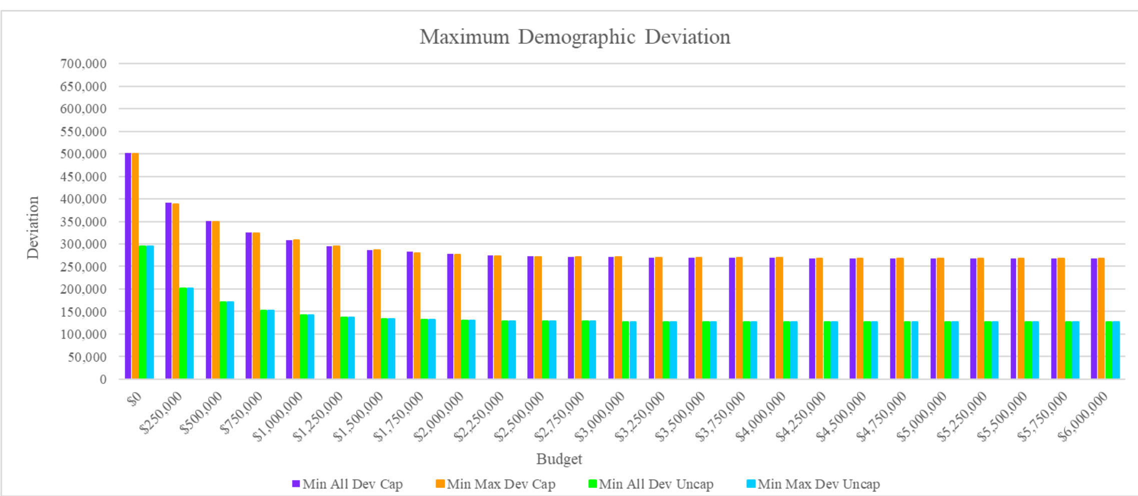

Figure E.2: Maximum Demographic Goodness Deviations vs. Budget ($0 to $6,000,000)

Table E.2 provides the table of maximum demographic park goodness deviation resulting from *Min All Dev Cap*, *Min Max Dev Cap*, *Min All Dev Uncap*, and *Min Max Dev Uncap*.

Table E.2: Maximum Demographic Park Goodness Deviations (Tabulated Results)

Budget	Min All Dev Cap	Min Max Dev Cap	Min All Dev Uncap	Min Max Dev Uncap
$0	501672	500152	295232	295232
$250,000	390888	388155	201155	201155
$500,000	350803	349687	170584	170584
$750,000	325991	324167	152057	152057
$1,000,000	308659	307844	142715	142699
$1,250,000	295350	294673	137423	137112
$1,500,000	285985	285955	133683	133683
$1,750,000	282334	280144	131477	131477
$2,000,000	278514	276459	130414	130365
$2,250,000	274692	273405	129085	129085
$2,500,000	272869	271719	128293	128293
$2,750,000	271182	270831	128092	128092
$3,000,000	270702	270351	127632	127569
$3,250,000	270095	270066	126840	126844
$3,500,000	269693	269341	126707	126707
$3,750,000	269238	268886	126707	126707
$4,000,000	268720	268691	126707	126707
$4,250,000	268516	268419	126707	126707
$4,500,000	268259	268230	126707	126707
$4,750,000	268055	268026	126707	126707
$5,000,000	268055	268026	126707	126707
$5,250,000	268055	268026	126707	126707
$5,500,000	268055	268026	126707	126707
$5,750,000	268055	268026	126707	126707
$6,000,000	268055	268026	126707	126707

Tables E.3, E.4, E.5, and E.6 provide max and average overall, distance, and capacity deviations for *Min All Dev Cap*, *Min Max Dev Cap*, *Min All Dev Uncap*, and *Min Max Dev Uncap*, respectively, as budget increases from $0 to $6,000,000.

Figures E.3, E.4, E.5, and E.6 visualize the overall deviations of the deviation types of distance, capacity, heat, and tree cover for *Min All Dev Cap*, *Min Max Dev Cap*, *Min All Dev Uncap*, and *Min Max Dev Uncap*, respectively, as budget increases from $0 to $6,000,000 (as in Tables E.7 to E.10).

Table E.3: Min All Dev Cap Results Compilation

Analysis	Budget	Spending	Total Dev	Max Dem Dev	Min Dem Dev	Max Distance Dev	Min Distance Dev	Avg. Distance Dev	Max Capacity Dev	Min Capacity Dev	Avg. Capacity Dev
A01.01	$0	$0	647808	501672	1969	4.201	0.000	0.947	3645	0	1394
A01.02	$250,000	$247,855	510969	390888	1597	2.756	0.000	0.517	3229	0	1134
A01.03	$500,000	$497,535	460758	350803	1591	2.756	0.000	0.466	3229	0	1069
A01.04	$750,000	$749,634	427820	325991	1401	2.756	0.000	0.435	2489	0	1009
A01.05	$1,000,000	$999,634	406251	308659	1472	2.756	0.000	0.384	3352	0	985
A01.06	$1,250,000	$1,241,977	388816	295350	1437	3.143	0.000	0.369	3352	0	901
A01.07	$1,500,000	$1,485,267	377513	285985	1417	3.143	0.000	0.343	3352	0	837
A01.08	$1,750,000	$1,742,986	370341	282334	1243	3.143	0.000	0.335	3352	0	832
A01.09	$2,000,000	$1,990,687	365718	278514	1245	2.517	0.000	0.333	3352	0	789
A01.10	$2,250,000	$2,249,116	361059	274692	1203	2.517	0.000	0.313	3352	0	779
A01.11	$2,500,000	$2,488,910	358894	272869	1203	2.517	0.000	0.289	3352	0	781
A01.12	$2,750,000	$2,736,772	356900	271182	1202	2.260	0.000	0.265	3352	0	788
A01.13	$3,000,000	$2,996,272	356282	270702	1201	2.260	0.000	0.255	3352	0	790
A01.14	$3,250,000	$3,240,670	355632	270095	1201	2.260	0.000	0.250	3352	0	767
A01.15	$3,500,000	$3,486,483	354931	269693	1196	2.260	0.000	0.239	3352	0	788
A01.16	$3,750,000	$3,741,111	354427	269238	1195	2.260	0.000	0.247	3352	0	796
A01.17	$4,000,000	$3,979,481	353838	268720	1195	2.260	0.000	0.231	3352	0	766
A01.18	$4,250,000	$4,146,510	353602	268516	1195	2.260	0.000	0.235	3352	0	772
A01.19	$4,500,000	$4,478,379	353344	268259	1195	2.260	0.000	0.231	3352	0	754
A01.20	$4,750,000	$4,555,507	353107	268055	1194	2.260	0.000	0.235	3352	0	760
A01.21	$5,000,000	$4,726,522	353107	268055	1194	2.260	0.000	0.235	3352	0	760
A01.22	$5,250,000	$5,092,332	353107	268055	1194	2.260	0.000	0.235	3352	0	760
A01.23	$5,500,000	$5,490,171	353107	268055	1194	2.260	0.000	0.235	3352	0	760
A01.24	$5,750,000	$5,235,067	353107	268055	1194	2.260	0.000	0.235	3352	0	760
A01.25	$6,000,000	$5,260,508	353107	268055	1194	2.260	0.000	0.235	3352	0	760

Table E.4: Min Max Dev Cap Results Compilation

Analysis	Budget	Spending	Total Dev	Max Dem Dev	Min Dem Dev	Max Distance Dev	Min Distance Dev	Avg. Distance Dev	Max Capacity Dev	Min Capacity Dev	Avg. Capacity Dev
A01.01	$0	$0	647808	501672	1969	4.201	0.000	0.947	3645	0	1394
A01.02	$250,000	$247,855	510969	390888	1597	2.756	0.000	0.517	3229	0	1134
A01.03	$500,000	$497,535	460758	350803	1591	2.756	0.000	0.466	3229	0	1069
A01.04	$750,000	$749,634	427820	325991	1401	2.756	0.000	0.435	2489	0	1009
A01.05	$1,000,000	$999,634	406251	308659	1472	2.756	0.000	0.384	3352	0	985
A01.06	$1,250,000	$1,241,977	388816	295350	1437	3.143	0.000	0.369	3352	0	901
A01.07	$1,500,000	$1,485,267	377513	285985	1417	3.143	0.000	0.343	3352	0	837
A01.08	$1,750,000	$1,742,986	370341	282334	1243	3.143	0.000	0.335	3352	0	832
A01.09	$2,000,000	$1,990,687	365718	278514	1245	2.517	0.000	0.333	3352	0	789
A01.10	$2,250,000	$2,249,116	361059	274692	1203	2.517	0.000	0.313	3352	0	779
A01.11	$2,500,000	$2,488,910	358894	272869	1203	2.517	0.000	0.289	3352	0	781
A01.12	$2,750,000	$2,736,772	356900	271182	1202	2.260	0.000	0.265	3352	0	788
A01.13	$3,000,000	$2,996,272	356282	270702	1201	2.260	0.000	0.255	3352	0	790
A01.14	$3,250,000	$3,240,670	355632	270095	1201	2.260	0.000	0.250	3352	0	767
A01.15	$3,500,000	$3,486,483	354931	269693	1196	2.260	0.000	0.239	3352	0	788
A01.16	$3,750,000	$3,741,111	354427	269238	1195	2.260	0.000	0.247	3352	0	796
A01.17	$4,000,000	$3,979,481	353838	268720	1195	2.260	0.000	0.231	3352	0	766
A01.18	$4,250,000	$4,146,510	353602	268516	1195	2.260	0.000	0.235	3352	0	772
A01.19	$4,500,000	$4,478,379	353344	268259	1195	2.260	0.000	0.231	3352	0	754
A01.20	$4,750,000	$4,555,507	353107	268055	1194	2.260	0.000	0.235	3352	0	760
A01.21	$5,000,000	$4,726,522	353107	268055	1194	2.260	0.000	0.235	3352	0	760
A01.22	$5,250,000	$5,092,332	353107	268055	1194	2.260	0.000	0.235	3352	0	760
A01.23	$5,500,000	$5,490,171	353107	268055	1194	2.260	0.000	0.235	3352	0	760
A01.24	$5,750,000	$5,235,067	353107	268055	1194	2.260	0.000	0.235	3352	0	760
A01.25	$6,000,000	$5,260,508	353107	268055	1194	2.260	0.000	0.235	3352	0	760

Table E.5: Min All Dev Uncap Results Compilation

Analysis	Budget	Spending	Total Dev	Max Dem Dev	Min Dem Dev	Max Distance Dev	Min Distance Dev	Avg. Distance Dev	Max Capacity Dev	Min Capacity Dev	Avg. Capacity Dev
A01.01	$0	$0	384452	295232	1164	4.170	0.000	0.878	3956	0	2407
A01.02	$250,000	$249,650	265586	201155	908	3.216	0.000	0.571	3868	0	2130
A01.03	$500,000	$498,122	228103	170584	805	3.216	0.000	0.486	3868	0	2128
A01.04	$750,000	$745,722	202235	152057	768	2.597	0.000	0.404	3868	0	1966
A01.05	$1,000,000	$992,675	187653	142715	733	2.260	0.000	0.365	3868	0	1789
A01.06	$1,250,000	$1,244,413	180392	137423	695	2.260	0.000	0.352	3868	0	1799
A01.07	$1,500,000	$1,498,340	175849	133683	687	2.260	0.000	0.313	3854	0	1657
A01.08	$1,750,000	$1,749,259	172881	131477	665	2.260	0.000	0.318	3854	0	1589
A01.09	$2,000,000	$1,986,459	171493	130414	664	2.260	0.000	0.282	3854	0	1543
A01.10	$2,250,000	$2,246,252	169858	129085	644	2.260	0.000	0.269	3854	0	1484
A01.11	$2,500,000	$2,495,480	168926	128293	642	2.260	0.000	0.265	3854	0	1476
A01.12	$2,750,000	$2,738,432	168634	128092	641	2.260	0.000	0.266	3854	0	1437
A01.13	$3,000,000	$2,992,263	167922	127632	637	2.260	0.000	0.249	3854	0	1489
A01.14	$3,250,000	$3,241,491	166990	126840	635	2.260	0.000	0.246	3854	0	1479
A01.15	$3,500,000	$3,498,717	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.16	$3,750,000	$3,634,321	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.17	$4,000,000	$3,634,321	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.18	$4,250,000	$4,003,704	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.19	$4,500,000	$4,493,201	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.20	$4,750,000	$4,705,816	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.21	$5,000,000	$4,805,816	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.22	$5,250,000	$4,805,816	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.23	$5,500,000	$4,805,816	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.24	$5,750,000	$4,805,816	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.25	$6,000,000	$4,805,816	166831	126707	635	2.260	0.000	0.234	3854	0	1409

Table E.6: Min Max Dev Uncap Results Compilation

Analysis	Budget	Spending	Total Dev	Max Dem Dev	Min Dem Dev	Max Distance Dev	Min Distance Dev	Avg. Distance Dev	Max Capacity Dev	Min Capacity Dev	Avg. Capacity Dev
A01.01	$0	$0	384452	295232	1164	4.170	0.000	0.878	3956	0	2431
A01.02	$250,000	$249,650	265586	201155	908	3.216	0.000	0.571	3868	0	2130
A01.03	$500,000	$498,122	228103	170584	805	3.216	0.000	0.486	3868	0	2123
A01.04	$750,000	$745,722	202235	152057	768	2.597	0.000	0.404	3868	0	1966
A01.05	$1,000,000	$986,803	187899	142699	733	2.260	0.000	0.363	3868	0	1788
A01.06	$1,250,000	$1,244,503	180435	137112	697	2.260	0.000	0.339	3854	0	1733
A01.07	$1,500,000	$1,498,340	175849	133683	687	2.260	0.000	0.313	3854	0	1650
A01.08	$1,750,000	$1,749,259	172881	131477	665	2.260	0.000	0.318	3854	0	1589
A01.09	$2,000,000	$1,997,120	171561	130365	665	2.260	0.000	0.295	3854	0	1547
A01.10	$2,250,000	$2,246,252	169858	129085	644	2.260	0.000	0.269	3854	0	1482
A01.11	$2,500,000	$2,495,480	168926	128293	642	2.260	0.000	0.265	3854	0	1476
A01.12	$2,750,000	$2,738,432	168634	128092	641	2.260	0.000	0.266	3854	0	1437
A01.13	$3,000,000	$2,988,191	167957	127569	637	2.260	0.000	0.269	3854	0	1505
A01.14	$3,250,000	$3,241,491	166994	126844	635	2.260	0.000	0.246	3854	0	1502
A01.15	$3,500,000	$3,467,443	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.16	$3,750,000	$3,513,143	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.17	$4,000,000	$3,513,143	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.18	$4,250,000	$3,513,143	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.19	$4,500,000	$3,513,143	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.20	$4,750,000	$3,513,143	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.21	$5,000,000	$3,513,143	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.22	$5,250,000	$3,513,143	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.23	$5,500,000	$3,513,143	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.24	$5,750,000	$3,513,143	166831	126707	635	2.260	0.000	0.234	3854	0	1409
A01.25	$6,000,000	$3,513,143	166831	126707	635	2.260	0.000	0.234	3854	0	1409

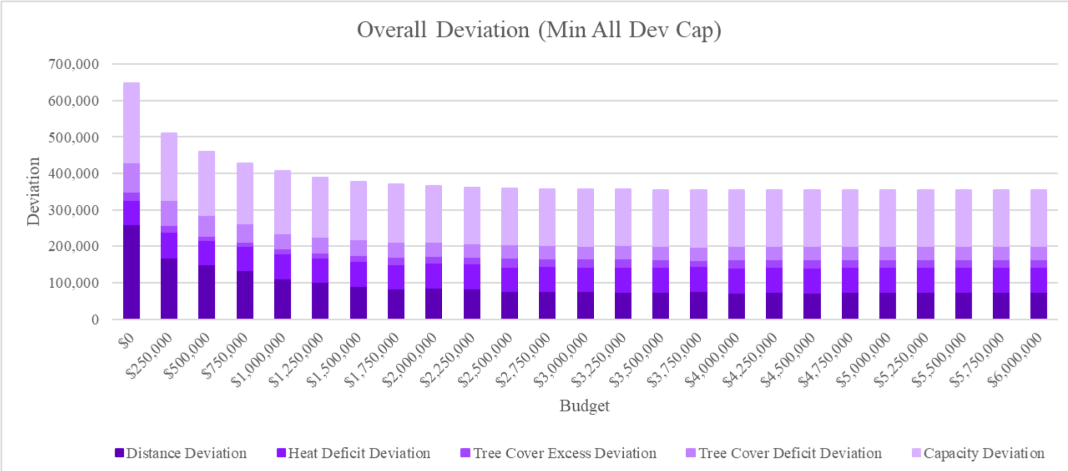

Figure E.3: Min All Dev Cap Overall Deviation Classifications vs. Budget ($0 to $6,000,000)

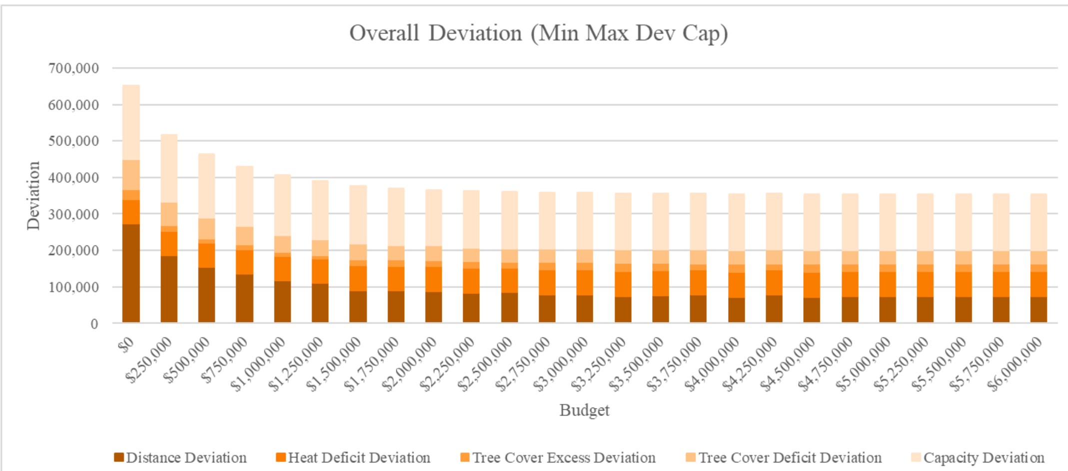

Figure E.4: Min Max Dev Cap Overall Deviation Classifications vs. Budget ($0 to $6,000,000)

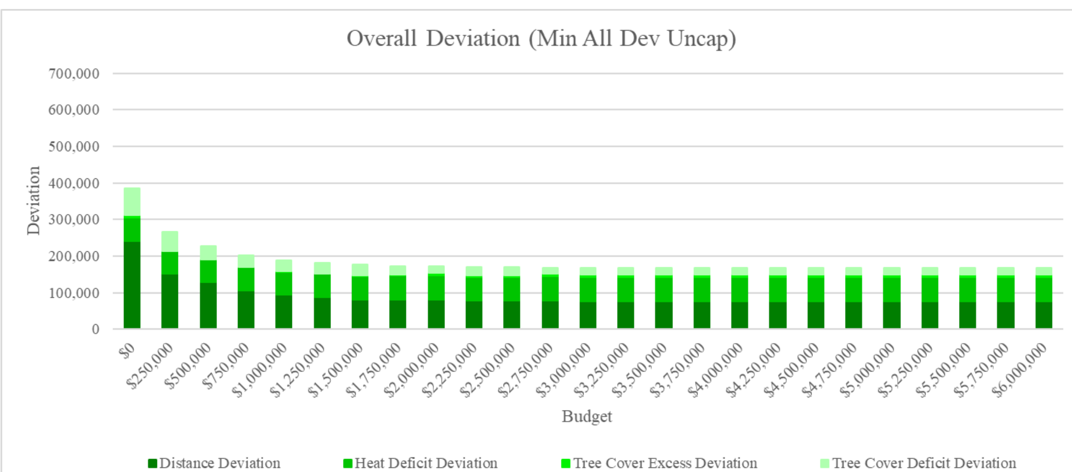

Figure E.5: Min All Dev Uncap Overall Deviation Classifications vs. Budget ($0 to $6,000,000)

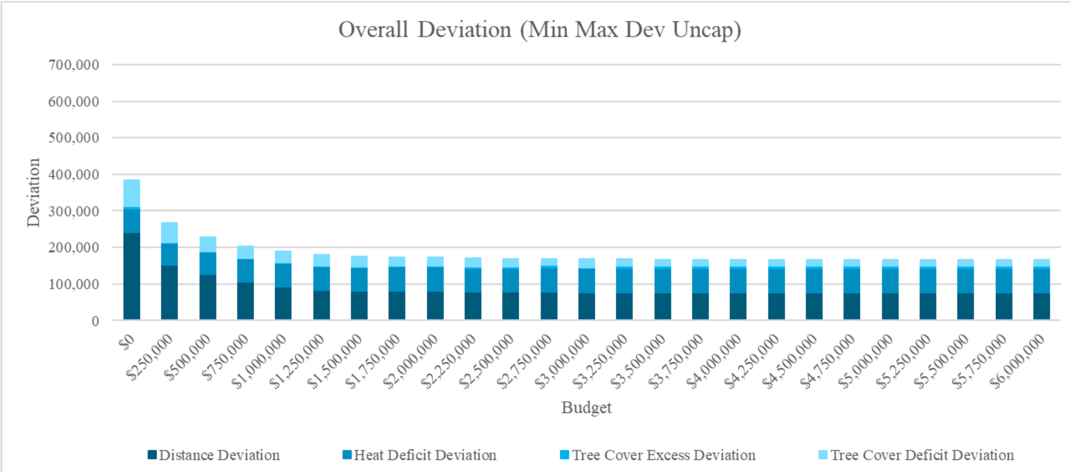

Figure E.6: Min Max Dev Uncap Overall Deviation Classifications vs. Budget ($0 to $6,000,000)

Tables E.7, E.8, E.9, and E.10 provide the overall deviation value of each deviation type (distance, capacity, heat, and tree cover) for *Min All Dev Cap*, *Min Max Dev Cap*, *Min All Dev Uncap*, and *Min Max Dev Uncap*, respectively, as budget increases from $0 to $6,000,000.

Tables E.11, E.12, E.13, and E.14 visualize the maximum demographic deviations of the deviation types of distance, capacity, heat, and tree cover for *Min All Dev Cap*, *Min Max Dev Cap*, *Min All Dev Uncap*, and *Min Max Dev Uncap*, respectively, as budget increases from $0 to $6,000,000.

Table E.7: Min All Dev Cap Overall Deviation Classification (Tabular Results)

Analysis	Budget	Distance Deviation	Capacity Deviation	Excess Heat Deviation	Deficit Heat Deviation	Excess Tree Deviation	Deficit Tree Deviation
A01.01	$0	259524	218316	0	66179	24493	79295
A01.02	$250,000	169571	183468	0	68946	20464	68520
A01.03	$500,000	150877	175728	0	64985	11254	57913
A01.04	$750,000	134664	164325	0	66732	11111	50988
A01.05	$1,000,000	111816	170152	0	67184	13716	43383
A01.06	$1,250,000	102844	163873	0	66623	12879	42596
A01.07	$1,500,000	91397	158992	0	67087	17441	42596
A01.08	$1,750,000	83805	157514	0	67265	20727	41030
A01.09	$2,000,000	86494	154620	0	68237	18794	37573
A01.10	$2,250,000	84368	154110	0	68160	17723	36698
A01.11	$2,500,000	76230	154255	0	68221	24532	35656
A01.12	$2,750,000	77286	154916	0	68206	20836	35655
A01.13	$3,000,000	76340	155074	0	68209	20715	35945
A01.14	$3,250,000	75206	152978	0	68213	23290	35945
A01.15	$3,500,000	75191	154896	0	68052	20836	35956
A01.16	$3,750,000	76406	155906	0	68399	17471	36246
A01.17	$4,000,000	73289	152958	0	68056	23290	36246
A01.18	$4,250,000	75094	153811	0	68405	20046	36246
A01.19	$4,500,000	73289	152464	0	68056	23290	36246
A01.20	$4,750,000	75094	153316	0	68405	20046	36246
A01.21	$5,000,000	75094	153316	0	68405	20046	36246
A01.22	$5,250,000	75094	153316	0	68405	20046	36246
A01.23	$5,500,000	75094	153316	0	68405	20046	36246
A01.24	$5,750,000	75094	153316	0	68405	20046	36246
A01.25	$6,000,000	75094	153316	0	68405	20046	36246

Table E.8: Min Max Dev Cap Overall Deviation Classification (Tabular Results)

Analysis	Budget	Distance Deviation	Capacity Deviation	Excess Heat Deviation	Deficit Heat Deviation	Excess Tree Deviation	Deficit Tree Deviation
A01.01	$0	273989	201531	0	65562	26961	82527
A01.02	$250,000	186382	181494	0	65712	16270	65618
A01.03	$500,000	154271	172723	0	66211	12429	57568
A01.04	$750,000	136059	163807	0	67322	13918	48212
A01.05	$1,000,000	118376	166096	0	66742	11111	45127
A01.06	$1,250,000	110297	158514	0	66546	8992	45127
A01.07	$1,500,000	91055	159028	0	67094	17441	42901
A01.08	$1,750,000	89540	155599	0	68135	17563	39824
A01.09	$2,000,000	87790	152513	0	68140	17775	39824
A01.10	$2,250,000	83605	154266	0	68210	18992	36981
A01.11	$2,500,000	84661	154927	0	68195	15296	36980
A01.12	$2,750,000	79544	153596	0	68082	20836	36958
A01.13	$3,000,000	78597	153754	0	68085	20715	37248
A01.14	$3,250,000	74864	153015	0	68219	23290	36251
A01.15	$3,500,000	77449	153576	0	67928	20836	37258
A01.16	$3,750,000	78663	154587	0	68275	17471	37548
A01.17	$4,000,000	72947	152995	0	68063	23290	36551
A01.18	$4,250,000	78572	154092	0	68393	17471	37467
A01.19	$4,500,000	72947	152500	0	68063	23290	36551
A01.20	$4,750,000	74752	153353	0	68412	20046	36551
A01.21	$5,000,000	74752	153353	0	68412	20046	36551
A01.22	$5,250,000	74752	153353	0	68412	20046	36551
A01.23	$5,500,000	74752	153353	0	68412	20046	36551
A01.24	$5,750,000	74752	153353	0	68412	20046	36551
A01.25	$6,000,000	74752	153353	0	68412	20046	36551

Table E.9: Min All Dev Uncap Overall Deviation Classification (Tabular Results)

Analysis	Budget	Distance Deviation	Capacity Deviation	Excess Heat Deviation	Deficit Heat Deviation	Excess Tree Deviation	Deficit Tree Deviation
A01.01	$0	240886	0	0	63630	7340	72595
A01.02	$250,000	150958	0	0	61630	1002	51996
A01.03	$500,000	127780	0	0	62063	0	38260
A01.04	$750,000	105728	0	0	63602	868	32037
A01.05	$1,000,000	93948	0	0	62856	868	29981
A01.06	$1,250,000	87918	0	0	62681	1028	28764
A01.07	$1,500,000	80792	0	0	64427	1988	28642
A01.08	$1,750,000	81182	0	0	65527	3610	22563
A01.09	$2,000,000	79999	0	0	67158	6666	17669
A01.10	$2,250,000	77843	0	0	65379	3610	23027
A01.11	$2,500,000	77951	0	0	65502	3489	21985
A01.12	$2,750,000	77631	0	0	67208	6545	17250
A01.13	$3,000,000	75925	0	0	66897	6666	18434
A01.14	$3,250,000	76033	0	0	67020	6545	17392
A01.15	$3,500,000	75372	0	0	67058	6545	17856
A01.16	$3,750,000	75372	0	0	67058	6545	17856
A01.17	$4,000,000	75372	0	0	67058	6545	17856
A01.18	$4,250,000	75372	0	0	67058	6545	17856
A01.19	$4,500,000	75372	0	0	67058	6545	17856
A01.20	$4,750,000	75372	0	0	67058	6545	17856
A01.21	$5,000,000	75372	0	0	67058	6545	17856
A01.22	$5,250,000	75372	0	0	67058	6545	17856
A01.23	$5,500,000	75372	0	0	67058	6545	17856
A01.24	$5,750,000	75372	0	0	67058	6545	17856
A01.25	$6,000,000	75372	0	0	67058	6545	17856

Table E.10: Min Max Dev Uncap Overall Deviation Classification (Tabular Results)

Analysis	Budget	Distance Deviation	Capacity Deviation	Excess Heat Deviation	Deficit Heat Deviation	Excess Tree Deviation	Deficit Tree Deviation
A01.01	$0	240886	0	0	63630	7340	72595
A01.02	$250,000	150958	0	0	61630	1002	51996
A01.03	$500,000	127780	0	0	62063	0	38260
A01.04	$750,000	105728	0	0	63602	868	32037
A01.05	$1,000,000	92674	0	0	64235	1010	29981
A01.06	$1,250,000	84057	0	0	64106	1707	30566
A01.07	$1,500,000	80792	0	0	64427	1988	28642
A01.08	$1,750,000	81182	0	0	65527	3610	22563
A01.09	$2,000,000	81065	0	0	65496	3610	21390
A01.10	$2,250,000	77843	0	0	65379	3610	23027
A01.11	$2,500,000	77951	0	0	65502	3489	21985
A01.12	$2,750,000	77631	0	0	67208	6545	17250
A01.13	$3,000,000	77321	0	0	65336	3610	21690
A01.14	$3,250,000	76033	0	0	67024	6545	17392
A01.15	$3,500,000	75372	0	0	67058	6545	17856
A01.16	$3,750,000	75372	0	0	67058	6545	17856
A01.17	$4,000,000	75372	0	0	67058	6545	17856
A01.18	$4,250,000	75372	0	0	67058	6545	17856
A01.19	$4,500,000	75372	0	0	67058	6545	17856
A01.20	$4,750,000	75372	0	0	67058	6545	17856
A01.21	$5,000,000	75372	0	0	67058	6545	17856
A01.22	$5,250,000	75372	0	0	67058	6545	17856
A01.23	$5,500,000	75372	0	0	67058	6545	17856
A01.24	$5,750,000	75372	0	0	67058	6545	17856
A01.25	$6,000,000	75372	0	0	67058	6545	17856

Table E.11: Min All Dev Cap Maximum Demographic Deviation Classification (Tabular Results)

Analysis	Budget	Distance Deviation	Capacity Deviation	Excess Heat Deviation	Deficit Heat Deviation	Excess Tree Deviation	Deficit Tree Deviation
A01.01	$0	201673	170902	0	50711	18987	59398
A01.02	$250,000	127991	145288	0	52732	15475	49403
A01.03	$500,000	113357	137544	0	49776	9263	40863
A01.04	$750,000	100149	127652	0	51155	9621	37414
A01.05	$1,000,000	83049	131256	0	51525	11221	31608
A01.06	$1,250,000	77059	127263	0	51068	10878	29082
A01.07	$1,500,000	67869	123236	0	51444	14354	29082
A01.08	$1,750,000	63219	121824	0	51602	17001	28688
A01.09	$2,000,000	65193	119109	0	52385	15526	26301
A01.10	$2,250,000	63352	118661	0	52307	14578	25794
A01.11	$2,500,000	56081	118725	0	52358	20763	24941
A01.12	$2,750,000	57112	119318	0	52346	17452	24954
A01.13	$3,000,000	56361	119449	0	52347	17352	25193
A01.14	$3,250,000	55406	117624	0	52351	19522	25193
A01.15	$3,500,000	55526	119303	0	52227	17452	25184
A01.16	$3,750,000	56566	120169	0	52527	14552	25424
A01.17	$4,000,000	53936	117608	0	52231	19522	25424
A01.18	$4,250,000	55494	118344	0	52532	16722	25424
A01.19	$4,500,000	53936	117147	0	52231	19522	25424
A01.20	$4,750,000	55494	117883	0	52532	16722	25424
A01.21	$5,000,000	55494	117883	0	52532	16722	25424
A01.22	$5,250,000	55494	117883	0	52532	16722	25424
A01.23	$5,500,000	55494	117883	0	52532	16722	25424
A01.24	$5,750,000	55494	117883	0	52532	16722	25424
A01.25	$6,000,000	55494	117883	0	52532	16722	25424

Table E.12: Min Max Dev Cap Maximum Demographic Deviation Classification (Tabular Results)

Analysis	Budget	Distance Deviation	Capacity Deviation	Excess Heat Deviation	Deficit Heat Deviation	Excess Tree Deviation	Deficit Tree Deviation
A01.01	$0	210297	157522	0	50118	21222	60993
A01.02	$250,000	136784	141686	0	50259	12601	46825
A01.03	$500,000	114482	135366	0	50460	8398	40980
A01.04	$750,000	99654	126645	0	51564	10956	35347
A01.05	$1,000,000	87244	128756	0	51187	9621	31036
A01.06	$1,250,000	82028	122771	0	51061	7777	31036
A01.07	$1,500,000	67581	123231	0	51449	14354	29340
A01.08	$1,750,000	66140	119813	0	52309	14454	27428
A01.09	$2,000,000	64754	117371	0	52314	14593	27428
A01.10	$2,250,000	61545	118691	0	52370	15616	25184
A01.11	$2,500,000	62575	119284	0	52358	12305	25197
A01.12	$2,750,000	57797	118128	0	52257	17452	25197
A01.13	$3,000,000	57046	118258	0	52258	17352	25436
A01.14	$3,250,000	55117	117619	0	52356	19522	25451
A01.15	$3,500,000	56211	118113	0	52138	17452	25427
A01.16	$3,750,000	57251	118979	0	52438	14552	25667
A01.17	$4,000,000	53647	117604	0	52236	19522	25682
A01.18	$4,250,000	57213	118518	0	52543	14552	25594
A01.19	$4,500,000	53647	117143	0	52236	19522	25682
A01.20	$4,750,000	55206	117879	0	52538	16722	25682
A01.21	$5,000,000	55206	117879	0	52538	16722	25682
A01.22	$5,250,000	55206	117879	0	52538	16722	25682
A01.23	$5,500,000	55206	117879	0	52538	16722	25682
A01.24	$5,750,000	55206	117879	0	52538	16722	25682
A01.25	$6,000,000	55206	117879	0	52538	16722	25682

Table E.13: Min All Dev Uncap Maximum Demographic Deviation Classification (Tabular Results)

Analysis	Budget	Distance Deviation	Capacity Deviation	Excess Heat Deviation	Deficit Heat Deviation	Excess Tree Deviation	Deficit Tree Deviation
A01.01	$0	186689	0	0	48659	5977	53907
A01.02	$250,000	116210	0	0	47528	816	36601
A01.03	$500,000	96898	0	0	47836	0	25850
A01.04	$750,000	80112	0	0	48735	612	22598
A01.05	$1,000,000	72089	0	0	47878	612	22136
A01.06	$1,250,000	67783	0	0	47757	736	21147
A01.07	$1,500,000	61859	0	0	49211	1546	21067
A01.08	$1,750,000	62153	0	0	50061	2617	16646
A01.09	$2,000,000	61218	0	0	50992	4377	13826
A01.10	$2,250,000	59474	0	0	49933	2617	17062
A01.11	$2,500,000	59645	0	0	50042	2516	16090
A01.12	$2,750,000	59352	0	0	51034	4277	13429
A01.13	$3,000,000	58005	0	0	50778	4377	14473
A01.14	$3,250,000	58175	0	0	50887	4277	13501
A01.15	$3,500,000	57594	0	0	50920	4277	13917
A01.16	$3,750,000	57594	0	0	50920	4277	13917
A01.17	$4,000,000	57594	0	0	50920	4277	13917
A01.18	$4,250,000	57594	0	0	50920	4277	13917
A01.19	$4,500,000	57594	0	0	50920	4277	13917
A01.20	$4,750,000	57594	0	0	50920	4277	13917
A01.21	$5,000,000	57594	0	0	50920	4277	13917
A01.22	$5,250,000	57594	0	0	50920	4277	13917
A01.23	$5,500,000	57594	0	0	50920	4277	13917
A01.24	$5,750,000	57594	0	0	50920	4277	13917
A01.25	$6,000,000	57594	0	0	50920	4277	13917

Table E.14: Min Max Dev Uncap Maximum Demographic Deviation Classification (Tabular Results)

Analysis	Budget	Distance Deviation	Capacity Deviation	Excess Heat Deviation	Deficit Heat Deviation	Excess Tree Deviation	Deficit Tree Deviation
A01.01	$0	186689	0	0	48659	5977	53907
A01.02	$250,000	116210	0	0	47528	816	36601
A01.03	$500,000	96898	0	0	47836	0	25850
A01.04	$750,000	80112	0	0	48735	612	22598
A01.05	$1,000,000	70795	0	0	49037	731	22136
A01.06	$1,250,000	64296	0	0	48956	1322	22538
A01.07	$1,500,000	61859	0	0	49211	1546	21067
A01.08	$1,750,000	62153	0	0	50061	2617	16646
A01.09	$2,000,000	62120	0	0	50036	2617	15592
A01.10	$2,250,000	59474	0	0	49933	2617	17062
A01.11	$2,500,000	59645	0	0	50042	2516	16090
A01.12	$2,750,000	59352	0	0	51034	4277	13429
A01.13	$3,000,000	59214	0	0	49915	2617	15823
A01.14	$3,250,000	58175	0	0	50891	4277	13501
A01.15	$3,500,000	57594	0	0	50920	4277	13917
A01.16	$3,750,000	57594	0	0	50920	4277	13917
A01.17	$4,000,000	57594	0	0	50920	4277	13917
A01.18	$4,250,000	57594	0	0	50920	4277	13917
A01.19	$4,500,000	57594	0	0	50920	4277	13917
A01.20	$4,750,000	57594	0	0	50920	4277	13917
A01.21	$5,000,000	57594	0	0	50920	4277	13917
A01.22	$5,250,000	57594	0	0	50920	4277	13917
A01.23	$5,500,000	57594	0	0	50920	4277	13917
A01.24	$5,750,000	57594	0	0	50920	4277	13917
A01.25	$6,000,000	57594	0	0	50920	4277	13917

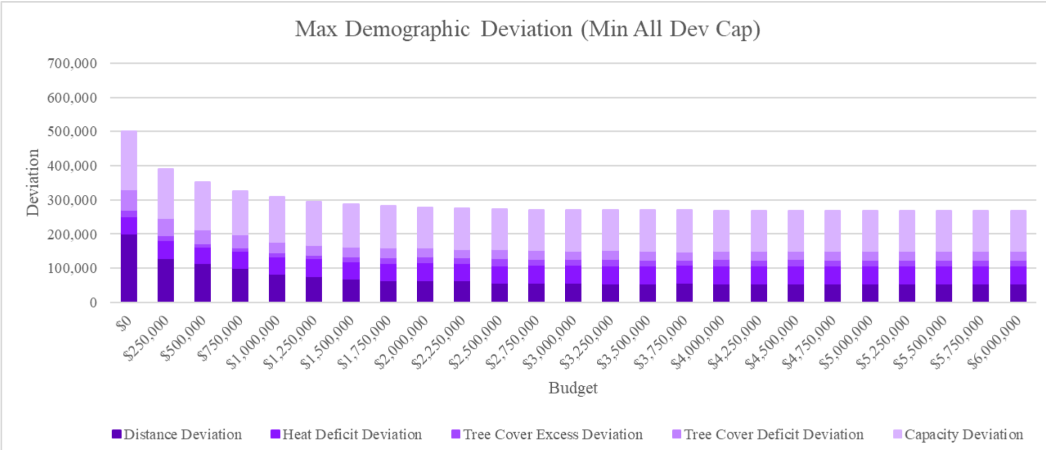

Figure E.7: Min All Dev Cap Maximum Demographic Deviation Classifications vs. Budget ($0 to $6,000,000)

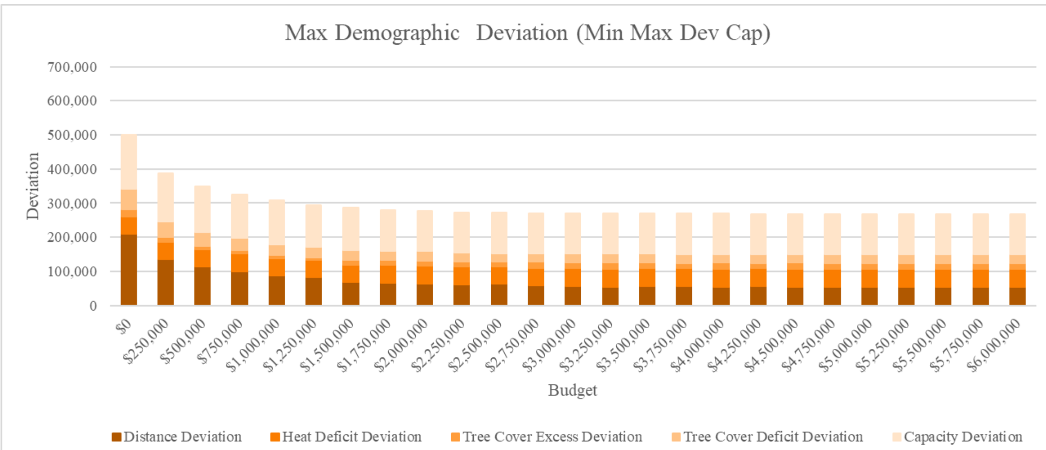

Figure E.8: Min Max Dev Cap Maximum Demographic Deviation Classifications vs. Budget ($0 to $6,000,000)

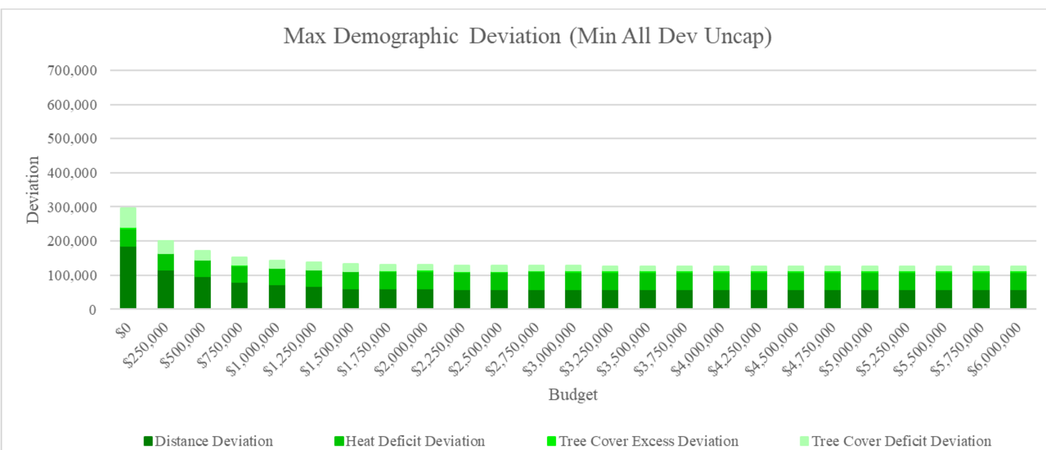

Figure E.9: Min All Dev Uncap Maximum Demographic Deviation Classifications vs. Budget ($0 to $6,000,000)

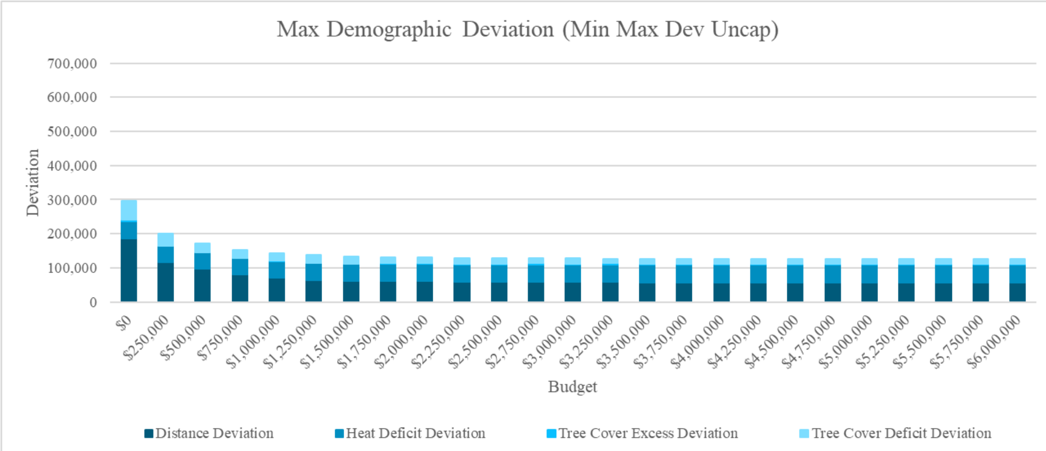

Figure E.10: Min Max Dev Uncap Maximum Demographic Deviation Classifications vs. Budget ($0 to $6,000,000)

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