land

MDPI

Article

Optimizing Sustainable Suburban Expansion with Autonomous Mobility through a Parametric Design Framework

Chenhao Zhu *, Jonah Susskind, Mario Giampieri, Hazel Backus O'Neil and Alan M. Berger *

P-REX Lab, Department of Urban Studies and Planning, Massachusetts Institute of Technology, Cambridge, MA 02139, USA
* Correspondence: chzhu@mit.edu (C.Z.); aberger@mit.edu (A.M.B.)

Abstract: Today, suburban areas are home to an ever-increasing majority of the global population. Models indicate that the next generation of US metropolitan growth will rapidly continue outside of urban cores, where car-based development patterns have served as the dominant paradigm for more than a century. With the emergence of autonomous mobility technologies and services, the suburbs of the future offer key opportunities to tackle pressing environmental challenges, such as significant GHG emissions from private vehicle trips, underutilized and fragmented landscape spaces, and a high proportion of impervious surfaces. To leverage this opportunity, our research team employed a novel scenario-based parametric modeling framework to generate and optimize suburban land use patterns and block configurations that leverage autonomous mobility to optimize environmental performance and accessibility metrics. The framework performed through our project, NOGAS (Next Optimized Generation of Autonomous Suburbs), consists of five key parametric modules and a heuristic design process covering various planning and design decision-making stages including scenario generation, analysis, optimization, and visualization. It is the first of its kind tailored for suburban settings with emerging mobility systems, which, more importantly, prioritizes landscape performance and accessibility over the traditional automobile-centric approach in suburban development. One of the most significant findings from this research is that substantial enhancements to a neighborhood's environmental performance and overall accessibility can be achieved by modifying existing suburban land use patterns and individual block configurations, without the necessity of increasing density. The results of the framework further suggest that a strategic atomized land use scheme, combined with an innovative clustered block typology, is favored for the anticipated widespread adoption of autonomous mobility systems and improved environmental performance. The innovative methods and findings introduced in this research illuminate an alternative approach to sustainable suburban development, offering valuable insights for city planners and developers to shape future suburban master plans, zoning regulations, and design guidelines.

Keywords: suburban expansion; sustainable development; environmental performance; autonomous mobility; parametric urban design

check for updates

Citation: Zhu, C.; Susskind, J.; Giampieri, M.; O'Neil, H.B.; Berger, A.M. Optimizing Sustainable Suburban Expansion with Autonomous Mobility through a Parametric Design Framework. *Land* **2023**, *12*, 1786. https://doi.org/10.3390/land12091786

Academic Editor: Richard Smardon

Received: 29 August 2023
Accepted: 9 September 2023
Published: 14 September 2023

1. Introduction

1.1. Environmental Opportunities in the Suburbs of Today and Tomorrow

Although often castigated as environmental disasters [1–6], suburban areas offer an abundance of opportunities for expanding ecosystem services, including habitat, biodiversity, hydrology, and carbon sequestration, at the metropolitan scale. For instance, urban ecologists have found that biodiversity, understood as the richness of species, is most pronounced in suburban settings [7]. Similar results have been found with various pollinators and birds [8,9]. Ecologist Robert Blair, who has studied avian biodiversity in urban, suburban, and rural settings, found that suburban sites have the highest levels of species richness when compared to both urban and rural sites [10].

Research also shows the environmental significance of residential landscape design choices and planting patterns in suburban areas. For instance, with current design and maintenance practices, suburban lawns account for a major portion of the urban watershed nitrogen budget [11]. However, redesigned suburban landscapes with mature trees, shrubs, undisturbed soil, and swaths of land with vegetative litter left in place are likely to sequester more atmospheric carbon [12,13]. One of the most important opportunities for increasing the environmental performance of suburban areas has to do with the size and quantity of leftover landscape surfaces in these areas. In suburban areas, the abundance of these landscapes, coming with potential redistribution opportunities for enhanced continuity, presents a distinct advantage for promoting crucial ecological functions and boosting landscape system services in ways that the urban core could never achieve [14].

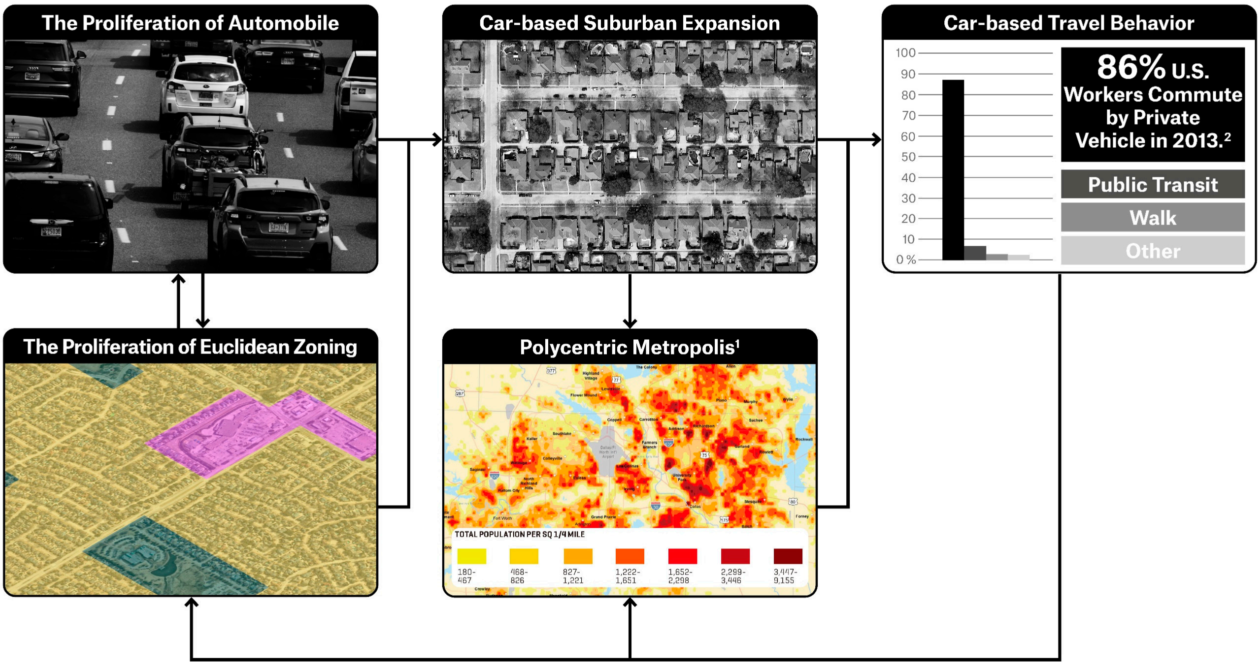
In the near future, the adoption of emergent transportation technology such as autonomous electric vehicles (AEVs), micro-mobility, and mobility as a service (MaaS) [15] presents a generational opportunity to reorganize suburban development patterns and roadways for massive new gains in environmental benefits. By redesigning infrastructure to prioritize connected autonomous vehicle fleets and ride-hailing services over privately owned vehicles, substantial reductions in street widths become feasible [16]. The space needed for parking lots can be reduced by an average of 62 percent, thanks to the significantly smaller parking footprint of self-parking cars [17], while dedicated curbside parking can be supplanted by more efficient pickup and drop-off zones [18]. With the adoption of MaaS, the demand for private cars can be significantly reduced as well [19], and thus garages and driveways can be eliminated or repurposed to support other programs, like home offices and gardens. In addition, through the reorganization of traditionally fragmented and underutilized landscape buffers, as well as the enormous potential to reduce impervious surfaces and paving, it becomes possible to create a more contiguous collection of higher-performing landscape spaces inside suburban neighborhoods. This can not only enhance ecological performance but also provide ample room for a diverse range of activities, maximizing the block's functionality and livability.

1.2. Historic Car-Based Suburban Expansion and Its Consequences

Historically, suburbs did not develop with these environmental performance objectives in mind. Using the US as a geographic example, car-based suburban expansion has been the dominant model of metropolitan growth for a century (Figure 1).

Cities first passed land use regulations beginning in the early 1900s, as new building forms, like skyscrapers, elicited responses from citizens about their impacts on light and street presence. The 1924 Standardized State Zoning Enabling Act (SZEA) expanded and further standardized this power, granting broad regulatory oversight of local land use to municipalities [20]. In 1926, the supreme court case Village of Euclid vs. Ambler Realty Co. codified the most common form of local land use control found in new suburban development [21]. Euclidean zoning, named after the case, allowed municipalities to divide communities into districts or zones that each allowed a single type of land use, such as single-family residential, multifamily residential, commercial, industrial, etc., and set parameters for block configurations, including minimum lot sizes, density limits, setbacks and massing requirements [22]. During this era, the rise of the automobile marked a paradigm shift in the way people traveled and perceived distance. From a planning standpoint, the car was the missing link between town and country and enabled dispersion of different uses from the city center. As an illustrative example, Checkoway describes how, by the 1920s, the widespread adoption of trucks enabled factories in the Philadelphia metro area to relocate to suburban locations [23]. This trend of jobs and residential relocations was further fueled by the growing prevalence of telecommuting [24,25].

The increasingly dynamic feedback loop between zoning policies and technologies progressively influenced people's travel behavior, subsequently bolstering governmental initiatives in favor of car-based suburban development. As the number of registered automobiles in the country ballooned almost exponentially—with approximately 1 million registered vehicles in 1913, 32 million in 1940, 108 million by 1970, 221 million by 2000, and 275 million by 2020 [26]—governments at all scales organized to lay down roads, highways, and bridges. The passage of the 1956 Federal-aid Highway Act, the largest public works project in American history, cast this proclivity toward an auto-oriented transportation network into concrete, as the federal government agreed to back 90 percent of the funding for municipalities to build new highways [27]. Gone were the days of the walking city; rather, car-based development, which has become the paradigm for suburban expansion, was designed with the driver in mind, with wide roads, garages, and carports becoming standard residential features, and parking saturating commercial and public places [28].



→ In the diagram, arrow means one thing facilitates another.

1. Dallas-Fort Worth Metropolitan Area Population Density 2018. Source: JLL

2. Source: U.S. Census Bureau, 2013 American Community Survey, Table S0801.

Figure 1. The typical process of car-based suburban expansion.

The proliferation of the automobile, coupled with favorable governmental policies, served as the foundation for car-based suburban expansion. As a result, the changing travel patterns between suburbs and urban cores have contributed to the solidification of car-based travel behavior among suburban residents. The concept of the encapsulated garden city characterized by distinct nodes has evolved into a paradigm of extensive polycentric urbanization, an occurrence initially examined by Jean Gottmann in his seminal 1961 work *Megalopolis: The Urbanized Northeastern Seaboard of the United States* [29]. Contemporary suburbanization exhibits a diminished tether to the urban core, with predominant growth regions consisting of multiple employment centers and commercial development [30]. Currently, intra-suburban trips (suburb-to-suburb commutes) outnumber metropolitan commutes to central business districts in the US by a factor of more than two [31]. In this new model, the prevailing transit infrastructure, traditionally designed to facilitate commuting between urban cores and suburban regions, fails to adequately cater to the mobility demands of contemporary suburban workers [32,33]. Simultaneously, as indicated by the criteria from previous studies, the economic viability of establishing a new high-frequency transit system between sparsely populated suburban areas is constrained by the dearth of potential users [34,35]. Consequently, in the American suburban landscape, the automobile reigns supreme and is anticipated to maintain its dominance. According to the latest National Household Travel Survey, more than 93 percent of US households own at least one car [36]. Conversely, per the 2019 census Journey-to-Work survey, a mere 5 percent of the U.S. working population utilized public transit for their daily commutes [37].

Reflecting on today's awareness of climate change, one major consequence of car-based development patterns is a larger carbon footprint due to an increased dependency on fossil fuels [38]. Each household in the United States makes an average of 5.1 vehicular trips per day, with the majority (65 percent) of these trips dedicated to shopping, running errands, and engaging in social or recreational activities [36]. According to the Environmental Protection Agency (EPA), transportation is the largest single source of greenhouse gases in the US, and nearly 60 percent of those emissions come from the country's millions of passenger cars, SUVs, and pickup trucks [39].

1.3. The Significance of Suburbs and Potential of Autonomous Mobility

These issues are particularly significant given the current rate of suburban growth. Today, 55 percent of the world's population lives in urban areas, which are largely defined by vast suburb fields outside small downtown cores. This number is expected to increase to as much as 68 percent by 2050 [40]. A steadily increasing urban population intensifies the reliance on surrounding areas to provide essential environmental resources and ecosystem services vital for sustaining adjacent high-density population hubs because most cities rely heavily on imported resources to sustain dense populations in the urban core [41]. Furthermore, the vast majority of people are moving to urban areas not to inhabit their centers but to suburbanize their peripheries [42]. Studies indicate that the next generation of metropolitan growth will rapidly continue outside of urban cores [43,44].

This trend holds when looking at development patterns in the United States. According to the American Housing Survey (2017) of nearly 76,000 households nationwide, about 52 percent of people in the United States describe their neighborhoods as suburban [45]. Moreover, 70 percent of US workers from metropolitan areas now live and work in the suburbs [46]. As population, production, and jobs continue to head toward the periphery, it is here that planners and designers can innovate new forms and environmental solutions to the growth challenge, particularly around carbon-based transportation.

Due to the increasing significance of the suburbs, planners and politicians have looked for ways to mitigate the negative externalities of car dependency in these areas. One common approach to this challenge is to increase the density of existing inner suburban neighborhoods by introducing housing around transit hubs to boost ridership and encourage residents to forgo car ownership [47,48]. However, numerous studies show that residential density in suburban settings does not have a direct impact on local transportation choices [49,50]. Furthermore, in the public sector, not only has increasing density within established communities been met with various resistance, such as the NIMBY movement [51], but baby boomers, who now make up 39% of home buyers [52], show a clear preference for single-family homes over other housing types, as reported by the NAHB [53].

Meanwhile, for the majority of the US population, commuting without an automobile is scarcely appealing, particularly in the wake of the COVID-19 crisis, as individuals seek safer and more private means of transportation [54]. Therefore, it is almost predictable that simply adding density or up-zoning may have a very limited impact on changing suburban travel patterns in the near future. Moreover, the "middle neighborhood" or up-zoning strategy itself is not harmless or an easy-to-achieve success. Without careful decision-making, the "middle neighborhood" development may neglect considerations of existing infrastructure, destroy the neighborhood's social fabric, and ultimately lead to gentrification [55–57].

In this context, the emergence of new mobility technologies and services, including AEVs, micro-mobility, and Mobility as a Service (MaaS), presents untapped possibilities for addressing car dependency while unlocking the potential environmental benefits inherent in suburban areas. According to a report from the transportation research board, "The world is on the cusp of three revolutions in transportation: vehicle electrification, automation, and sharing of vehicle trips. Separately or together, these revolutions will fundamentally change urban transportation around the world over the next few decades [58]". Hundreds of companies have begun rolling out various forms of driverless technology along with rapid advancements in micro-mobility offerings and shared mobility services. Cumulatively, these investments have surpassed USD 200 billion, as revealed in public disclosures [59].

Technological innovations including advanced sensors, artificial intelligence, and enhanced user interfaces have brought a slew of operational and environmental benefits, including higher energy efficiency [60], lower operational costs [61], less idle time [62], and so forth. Still, the second- and third-order effects of new mobility technologies, which are more likely to benefit the suburban areas, outside the reaches of established mass-transit systems where personal vehicular transport is the most ubiquitous, may be of even greater consequence. Arguably, based on the advanced features of autonomous mobility, its implementation could enhance the environmental performance of existing suburban areas.

However, technology itself is not the silver bullet. Drawing on a comprehensive body of research examining the potential impact of autonomous mobility systems on future urban development, it becomes evident that the realization of an ideal suburban development scenario through appropriate planning and design paradigms leads to more sustainable results. These results, in turn, hold promising prospects for addressing challenges related to greenhouse gas (GHG) emissions [63,64], land use efficiency [65], operational costs [66], pedestrian safety [67], and other pertinent environmental factors [68]. Adopting a technocentric approach can only result in solutions that fall short of achieving sustainable objectives due to a lack of comprehensive thinking. Furthermore, the introduction of autonomous vehicles, without appropriate policy measures in place, has the potential to increase both car ownership and miles traveled, rather than curbing them as intended [69].

1.4. Pre-Adapting Future Suburban Development through Urban Planning and Design

Based on all constraints, the main research gap filled by this research is that very few studies are suitable for influencing the design of autonomous mobility systems in suburban areas with a focus on environmental performance. This research is aimed at supporting urban planners and designers, who will have unprecedented opportunities for reinventing the suburbs of the future through new approaches to zoning, land use planning, and urban design that effectively anticipate the impacts of new autonomous mobility innovations.

The result of this research is NOGAS—a parametric design framework [70] developed in the P-REX Lab at MIT to help planners and designers effectively usher in an innovative suburban development paradigm that prioritizes environmental performance targets without compromising traditional engineering goals with neighborhood and block infrastructures. The NOGAS framework is specifically developed for greenfield development in suburban areas. Compared to the multifaceted challenges of retrofitting existing inner suburbs, greenfield developments typically follow similar procedures and goals. This consistency increases the reliability of applying the NOGAS framework in various contexts without extensive customization.

One important assumption of NOGAS is that autonomous mobility systems will become ubiquitous in future suburban areas. The autonomous mobility systems we refer to throughout this research are imagined as a collective bundle that not only encompasses new mobility technology and services, such as AEVs, (autonomous) micro-mobility, and (autonomous) MaaS systems, among others, but also incorporates a set of spatial elements that are either newly proposed or retrofitted through innovative planning, design, and policy solutions, which are essential to achieve an optimized operational environment for the future implementation of these new mobility technologies and services. We acknowledge that reaching ubiquity is a paradigm shift in transportation and lifestyle that will require significant structural change.

1.5. The Study Site—Northridge, McKinney, TX

To test the utility of our parametric design framework, we worked with the City of McKinney, Texas[1], to find sites for exploring scenarios to help inform planning and urban design decision-making over the next 20 years in tandem with emergent autonomous mobility systems at two distinct scales: the district scale and block scale. The city's 2040 vision plan (hereinafter, 2040 plan [71]) was used to establish baseline conditions from which the effectiveness of proposed outcomes could be measured. The design issues, assumptions, and objectives of each scale are outlined as follows:

- At the district scale, the parametric design framework was used to explore potential spatial relationships between different land uses within the context of a widespread autonomous mobility system. The predetermined objectives for these new land use configurations were to increase access to a more distributed array of commercial and recreational amenities.
- At the block scale, the parametric design framework was used to experiment with various block configurations. These configurations were developed to respond to opportunities related to the adoption of an autonomous mobility system, such as narrower vehicular rights-of-way or more distributed multi-modal mobility hubs. The predetermined objectives for these optimized block configurations were to achieve improved accessibility, reduce impervious surfaces, and achieve more contiguous inner-block landscape space.

McKinney has experienced rapid population growth during the past three decades. From 1990 to 2022, the city's total population grew from 21,283 to 206,654 [72]. In order to accommodate this growth McKinney created a 2040 vision plan in which unincorporated areas slated for annexation along the edges of McKinney provide a generalized framework for the future of suburban development broadly. According to the 2040 plan, more than 50 percent of the total undeveloped area is slated for single-family land uses, with the rest mostly allocated to low-lying riparian corridors and other hard-to-develop parklands (about 20 percent) along with a few small clusters earmarked for potential employment centers and commercial districts (less than 10 percent) [71].

Northridge district, which is designated as a residential area for one-third of the city's projected new population, is located in the northwest sector of McKinney. Zooming into the portion of the Northridge district, it is clear that the city's vision plan presupposes the addition of many more car-dependent neighborhoods (Figure 2). The district plan calls for mostly (80 percent) single-family residential land uses with lot sizes ranging from a half-acre to two acres. Neighborhood commercial development is planned, including small freestanding buildings located almost exclusively at major arterial intersections.

As shown in Figure 2 (the area within the red-bordered square), the selected study site is situated in the northeast corner of the Northridge district. This area encompasses four predominant land uses found in American suburbs: suburban living, estate residential, neighborhood commercial, and landscape space. By applying our framework to these prevalent land uses, we aim to demonstrate the potential adaptability of the NOGAS framework across various suburban contexts.

As planned, the selected site would largely repeat the typical car-based suburban expansion pattern, which we have already taken a critical position on, producing an inequitable and inadequate distribution of public open space with nearly 60 percent of the total expected population situated outside of a five-minute park walkshed. Furthermore, only 25 percent of households would have walkable access to commercial amenities, further reinforcing vehicle dependency, even for relatively short trips—once again putting a disproportionate burden on working-class households and residents with disabilities. Under this planning scenario, the absence of adequate access to amenities will be very likely to lead to a large number of vehicle trips and VMT. The findings also suggest that if new development followed the protocols and standards of existing suburban forms, a substantial portion of land within the study area would be designated for impervious surfaces, landscape buffers, or private yards with minimal provision of ecosystem services.

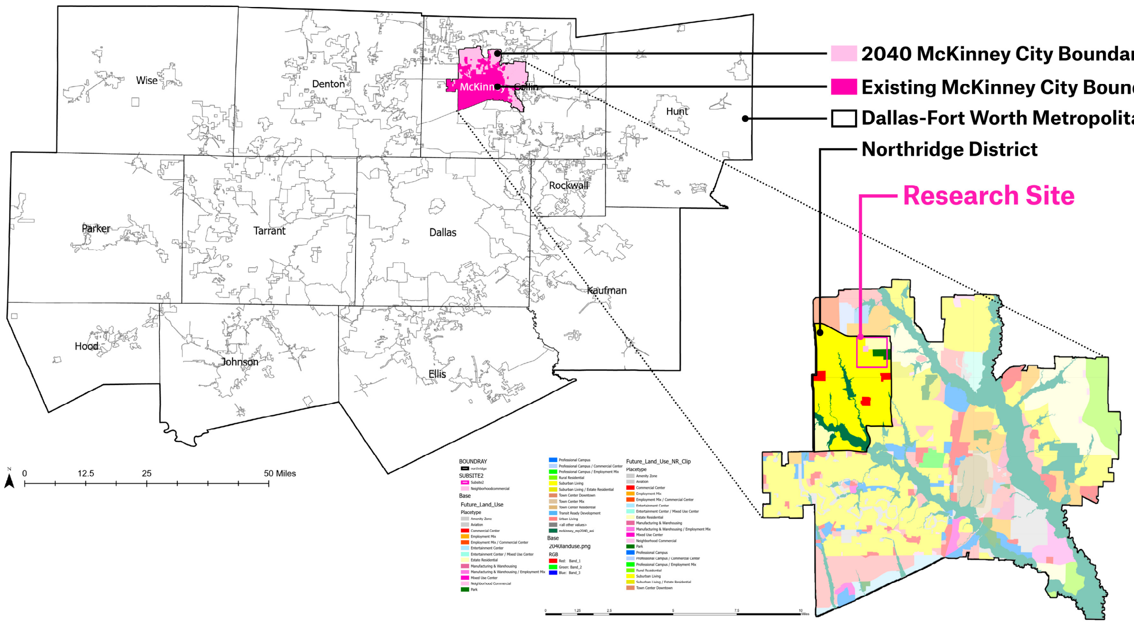


Figure 2. The geolocation of the study site.

The most significant finding from this research is that a collective bundle of autonomous mobility technologies combined with modifications to traditional suburban land use patterns and block configurations can have significant impacts on a community's environmental performance, capacity for integrating new forms of mobility, and overall accessibility, without the necessity of increasing density.

The subsequent section provides a comprehensive introduction to the proposed parametric design framework, elucidating its intricacies and functions. In the third section, a case study is presented to showcase the practical application of the proposed design framework within a real-world setting. In the end, design interpretations derived from the model outputs are discussed, followed by a conclusion.

2. Materials and Methods

2.1. A Heuristic Parametric Design Framework—NOGAS

Extensive research has shown that under ideal conditions, autonomous mobility systems have various positive impacts on development, while several studies have also highlighted that in the absence of appropriate regulations and designs, widespread implementation of autonomous mobility systems could have adverse effects [73,74]. Therefore, the implementation of new mobility technologies alone will not lead us toward a more sustainable future. To fully capitalize on the advantages of autonomous mobility, it is imperative that communities simultaneously adopt new approaches to development with specific objectives, such as prioritizing landscape performance and environmental services.

A crucial challenge encountered in the pursuit of a new suburban development paradigm lies in effectively reconciling divergent development objectives sought through such transformation, which further involves a large amount of design iterations. Employing conventional design methods to conduct numerous design iterations, even with assistance from computer-aided software, can be excessively time-consuming and resource-intensive [75]. However, design approaches that include generative and parametric features increase designers' ability to explore wider sets of potential solutions [76].

In this context, a significant body of research has been dedicated to exploring the potential role of computational algorithms in establishing more efficient and accurate design workflows. These research efforts encompass various design stages, including design generation, pre-/post-design analysis, and design optimization. Moreover, they cover a wide range of design topics, such as land use allocation [77], transportation planning [78], building structure optimization [79], and more [80,81].

An increasing number of studies have attempted to develop a parametric design framework with computational optimization techniques at various scales (Table 1). However, very few of them are suitable for influencing the design of autonomous mobility systems in suburban areas with a focus on environmental performance.

To fill this gap, a toolkit has been developed as a part of the NOGAS framework (Figure 3) to execute several key functions. Firstly, it can generate design scenarios by considering input parameters and predefined design logic. As the input parameters are altered, the generated scenarios will adapt accordingly. The performance of these scenarios can be assessed using predefined targets, which are formulated based on specific design objectives. The toolkit also has the ability to optimize input parameters in order to enhance performance. Lastly, the toolkit can be used to analyze key performance metrics across all generated scenarios and provides analytic graphs, which aids designers in comprehending the quantitative costs and benefits associated with each scenario with respect to various design objectives. In this research, the process of assessing and evaluating the costs and benefits of a given scenario, with the aim of ultimately selecting the optimized option, is referred to as trade-off analysis.

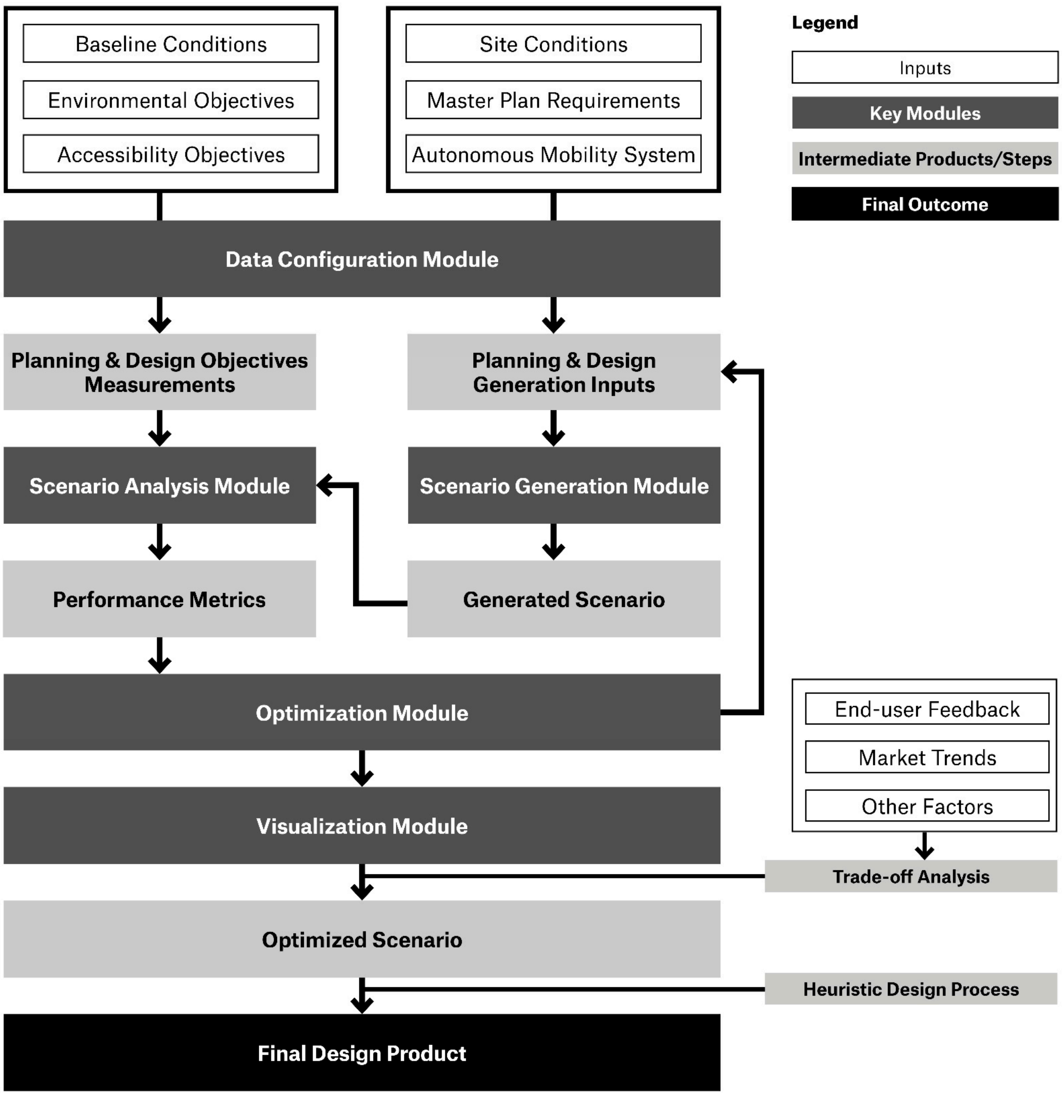


Figure 3. Roadmap of the NOGAS parametric design framework.

Table 1. A literature review on parametric design research with optimization techniques.

Land Use Allocation Optimization Reference	Planning and Design Context			Planning and Design Scales				Main Optimization Algorithm					Planning and Design Objectives			Operation Environment	
	Urban	Suburb	Rural	Regional	City	District	Block	Linear Optimization	Genetic Algorithm	Particle Swarm Optimization	Ant Colony Optimization	Simulated Annealing	Economic Performance	Environmental Performance	Mobility Access	GIS Platform and Coding	Rhinoceros/ Grasshopper Based Platform
Berawi et al. (2020) [82]	•						•	•							•		
Cao et al. (2012) [83]	•				•				•				•	•	•	•	
Caparros-Midwood et al. (2015) [84]	•				•							•		•	•	•	
Eikelboom et al. (2015) [85]			•	•					•					•		•	
Haque and Asami (2014) [86]						•			•				•			•	
Janssen et al. (2008) [87]			•			•			•					•		•	
Koenig et al. (2020) [88]	•					•									•		•
Li and Parrott (2016) [89]	•	•	•	•					•				•	•		•	
Liu et al. (2012) [90]	•	•	•	•							•		•			•	
Liu et al. (2013) [91]	•	•	•	•						•			•			•	
Liu et al. (2015) [92]	•	•	•	•					•				•	•		•	
Makki et al. (2019) [93]	•					•								•	•		•
Mi et al. (2015) [94]	•	•	•	•							•		•	•		•	
Mohammadi et al. (2016) [95]		•				•				•		•	•	•		•	
Porta et al. (2013) [75]	•	•	•	•					•					•		•	
Sante et al. (2016) [96]	•	•	•	•								•	•			•	
Sharmin et al. (2019) [97]	•					•			•				•			•	
Stewart and Janssen (2014) [98]			•	•					•					•		•	
Zhang et al. (2016) [99]	•	•	•	•						•			•	•		•	
This research		•				•	•		•					•	•		•

• This symbol indicates that the paper contains relevant topics.

Trade-off analysis is a central tenet of our research that is trying to address a multi-objective issue. In the context of land use planning and urban design, different objectives can be at odds with one another [100,101]. This means that as the performance factor of one design objective is increased, the performance factor of another design objective may be decreased due to their associative relationships. The theoretical trade-off point is represented by the equilibrium at which both performance objectives achieve their highest level possible given these associations. However, in reality, the trade-off point is also determined by many other factors, such as feedback from end users, particular governmental regulations, market trends, and more.

Another integral aspect of this modeling workflow is its adoption of a heuristic architecture. By heuristic, we mean the proposed parametric workflow is designated to provide quantitative and spatial information for early-stage planning and design decision-making. For this purpose, the outputs from the model, as suggested by previous research, are more suitable for starting the exploratory design process rather than offering a final design product [102]. The outputs serve as valuable references, insights, and sources of inspiration for planners and designers to develop a more comprehensive understanding of diverse future conditions. The ultimate design scheme can then emerge from an integrated consideration of the insights gleaned from the model, as well as other external factors.

2.2. Key Modules

To realize the proposed parametric design framework toward generating scenarios that are not only customized for autonomous mobility transformation in suburban contexts but also exhibit optimal sustainability performance, a series of models were developed utilizing Rhinoceros 3D (Rhino3D) and Grasshopper (GH)[2]. A cluster of models that serve a similar purpose constitutes a module. In total, the toolkit of the NOGAS framework contains five key modules. These five modules are presented in sequential order:

1. Data configuration module: This module provides users with the capability to set or input parameters in multiple formats. Some of these parameters are associated with the generation of design scenarios, such as block size, building height, and land use attributes. Other parameters are typically linked to specific design objectives and are utilized later on in the scenario analysis module. This module can accommodate various data formats, including but not limited to Rhino3D vector data, ESRI Shapefile data, and matrix data. Different data formats are then converted into appropriate formats for future usage.
2. Scenario generation module: With the input parameters from the data configuration module, this module is used to generate design scenarios based on predefined spatial objectives. As the parameters are modified, the generated results adapt accordingly.
3. Scenario analysis module: This module is specifically designed to measure the performance factors of each generated scenario based on predefined metrics and predetermined objectives, as described in Section 2.2.
4. Optimization module: This module is used to execute the design optimization processes. It serves as a crucial link between the scenario generation module and the scenario analysis module. By utilizing the performance metrics obtained from the scenario analysis module, this module dynamically adjusts the parameters that are input into the scenario generation module. This iterative process aims to refine and optimize the scenarios to achieve enhanced outcomes. It can accommodate various algorithms, including linear optimization [103], simulated annealing [104], particle swarm optimization [105], and others. After careful evaluation of different algorithms, Non-dominated Sorting Genetic Algorithm II (NSGA-II [106])[3] is applied for its efficient non-dominated sorting procedure [107], performance in optimizing problems with two or more objectives [108], and ability to generate a comprehensive set of Pareto-optimal solutions rather than a single optimum solution [109].
5. Visualization module: This module encompasses a collection of scripts that enable real-time visualization of output scenarios and performance metrics. By utilizing

this module, designers gain a clear understanding of the generated and optimized scenarios, facilitating improved design communication.

2.3. Optimization Factors

This design framework evaluates and optimizes the performance and design objectives at two distinct scales.

2.3.1. District Scale Optimization Factors

The district scale or neighborhood scale refers to a sub-division of urban, suburban, or rural locations in which people live [110]. In this research, a district is defined as a site between 500 and 1000 acres with a typical inner suburban population density of 1000 to 3000 people per square mile [111].

- Land Use Distribution

As illustrated in the introduction (Figure 1), land use planning, as an indispensable component of suburban form, has a profound impact on people's travel behavior and the perpetuation of car-based suburban expansion. The proliferation of autonomous mobility systems provides an unprecedented opportunity to rethink land use planning approaches that may facilitate mixed-use suburban development patterns with improved access, walkability, and environmental performance [112,113].

A land use matrix was developed to examine various land use distribution scenarios through a parametric cross-impact method. Cross-impact analysis, as a scenario-planning methodology, was first developed by Theodore Gordon and Olaf Helmer in 1966 to help determine how relationships between elements would impact outcomes and reduce uncertainty in the future [114,115]. Similarly, the proposed land use matrix can assist planners and designers in testing and evaluating various land use distribution scenarios. Furthermore, by integrating future needs into this land use matrix, we can enhance our understanding of potential outcomes based on specific assumptions.

The land use matrix is structured with the first row and column representing given land use types in a specific order. Within this matrix, each cell is assigned an incentive score (2, 1), indicating the degree to which two land uses should be pushed together, a penalty score (-1, -2), indicating the degree to which two land uses should be pulled apart, or a score of 0, representing no preference for their spatial relationships (Figure 4). By utilizing these incentive and penalty scores, new land use configurations can be generated under specific constraints, representing different assumptions for future conditions.

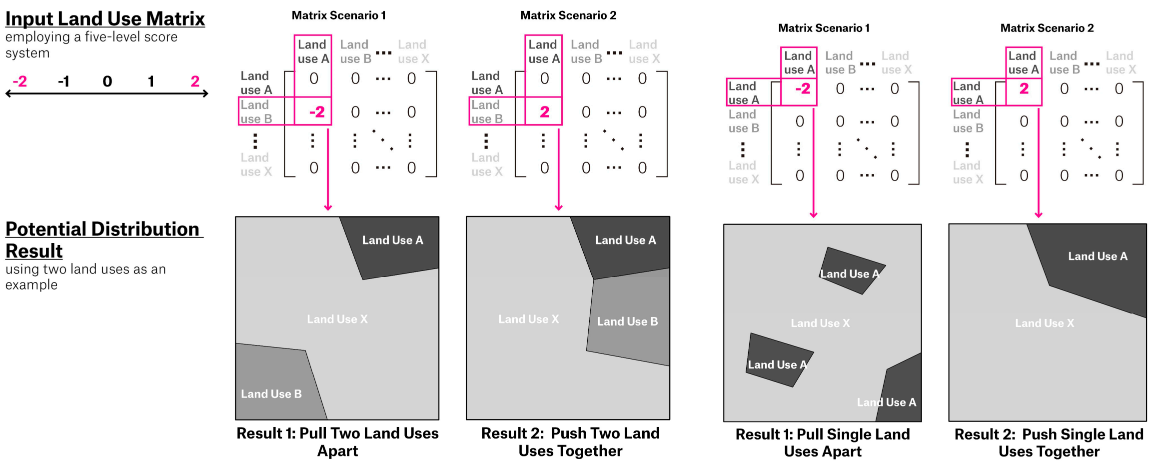


Figure 4. A set of diagrams that show how the land use distribution matrix and incentive scoring affects the potential land use distribution results.

The final score of a given land use cell is calculated by summing the scores between that cell and all adjacent land uses. Consequently, the performance factor of the entire site is determined by summing the scores of each individual land use cell (Figure 5). The quantitative formulation of the analysis process is shown as follows:

$$f_{\text{dist}} = \sum_{i=1}^{n} \sum_{j=1}^{r} disti, j \tag{1}$$

In the function, n is total land use cells in the study area, i represents any given land use cell, and r is the number of neighbor land use cells of cell i. In this research, r equals four, which means that in a grid system, any given land use cell has four neighbor cells. j is one of the neighbor cells of cell i. $disti,j$ is the score between land use types located in cell i and cell j. This value is derived through the Delphi method [116].

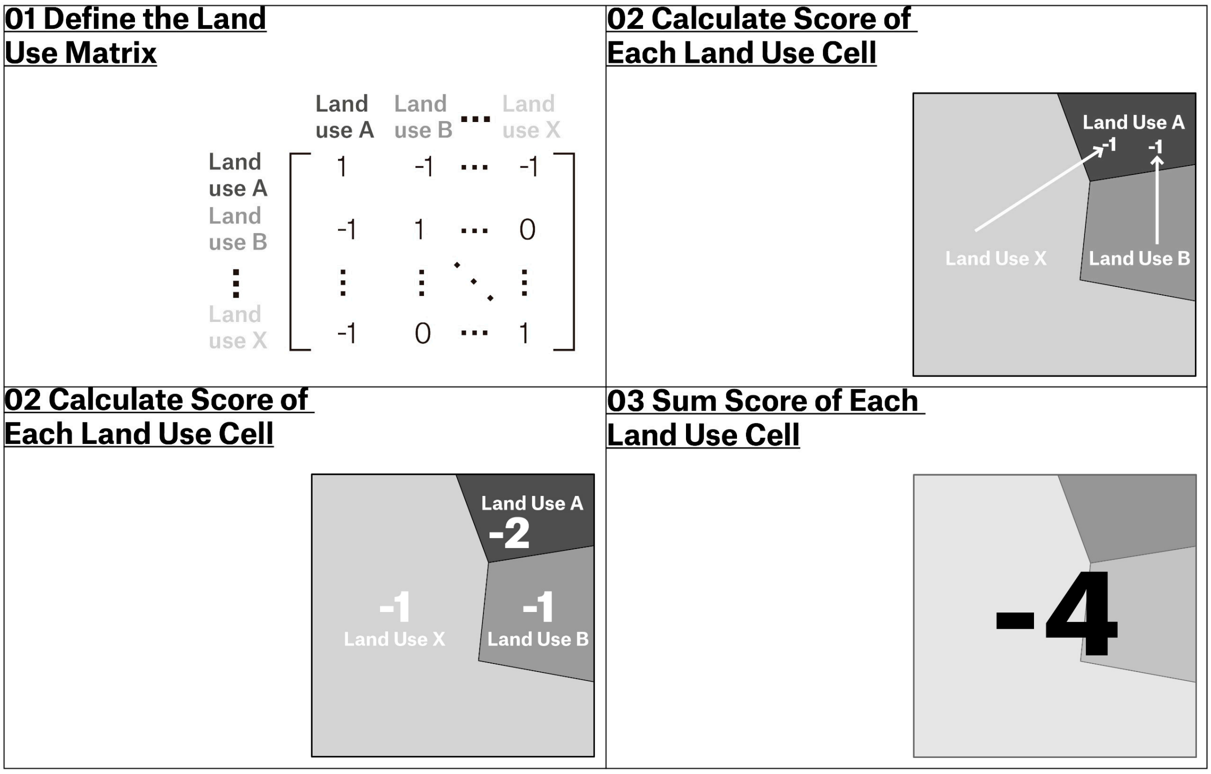


Figure 5. A set of diagrams that show how the final land use distribution score is calculated.

- Landscape Space Allocation

The possibility of new land use distribution models aimed at capturing the benefits of autonomous mobility systems may yield new approaches to landscape space allocation. When large contiguous and homogenous land use clusters are broken into smaller pieces, new configurations of public landscape space become possible. This presents a tremendous opportunity for improving the environmental performance of suburban areas, which can further bring benefits related to public health [117], heat mitigation [118], stormwater detention [119], the preservation of ecologically significant areas [120], and carbon sequestration [121]. Consequently, the allocation of landscape spaces, a crucial component of contemporary sustainable development [122], will assume even greater significance in the era of autonomous mobility. When evaluating the performance of public landscape space allocation, two key factors are closely interrelated.

Access (Distance from Residential Areas): Research emphasizes that the proximity of landscape spaces to residential areas significantly influences the frequency of their utilization. In other words, when residential areas have direct access to nearby landscape spaces, the utilization rate of those landscape spaces tends to be higher. This helps ensure a shorter distance between residential areas and landscape spaces, which is crucial for encouraging their utilization [123,124].

Contiguity: Contiguity plays a vital role in the ecological performance of landscape spaces. A well-connected landscape space usually has higher ecological production, more ecosystem resilience, and greater biodiversity [125]. The level of contiguity also determines the range of programs or activities that can be accommodated within it. Therefore, enhancing the contiguity of landscape spaces is essential for maximizing their ecological benefits and accommodating various activities.

As illustrated below, (Figure 6), a high contiguity of landscape space allocation (Figure 6, Scenario 1) contributes to the appearance of inequalities, which means that fewer residents have direct access to the landscape space [126]. However, another set of landscape space allocations (Figure 6, Scenario 2) with high access performance may have low contiguity and thus degraded environmental performance [127]. The optimized solution should consider both contiguity and accessibility of landscape spaces.

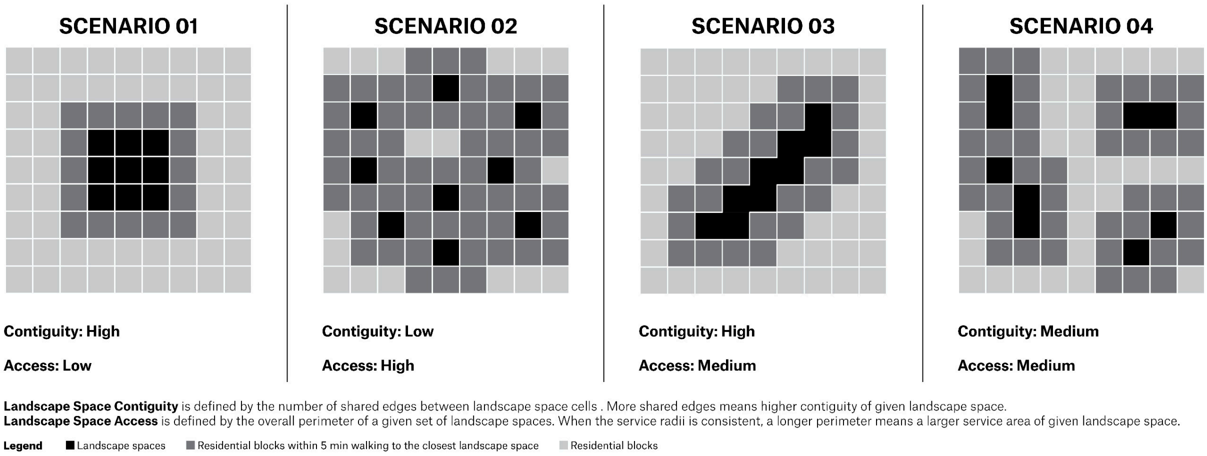


Figure 6. The diagrams show how access and contiguity can affect the potential results of landscape space allocation.

Hence, two measurements are formulated to measure landscape space accessibility and contiguity. Landscape space access is represented by the overall perimeter of a given set of landscape spaces [128]. The longer the total perimeter, the more residents will likely have direct access to it. Landscape space contiguity is defined by the number of shared edges between landscape space cells [129]. The higher counts of shared edges represent higher contiguity of landscape spaces. The quantitative formulations of two indices are shown below:

$$f_{access} = \sum_{i=1}^{n} P_i \tag{2}$$

In the function, n is the total number of landscape spaces, which is composed of adjacent landscape space land use cells. i is any given landscape space. P_i is the perimeter of the landscape patch i. Finally, by summing the perimeters of all landscape spaces, the landscape space access is measured.

$$f_{contiguity} = \sum_{i=1}^{n} \sum_{j=1}^{r} S_{ij} \tag{3}$$

In the function, n is the total number of landscape space land use cells, i is any given landscape space cell, and r is the set of neighbor cells of cell i. S_{ij} is a binary variable. When cell i and cell j are both landscape space cells and share an edge, S_{ij} equals 1; otherwise, S_{ij} equals 0.

2.3.2. Block Scale Optimization Factors

The block represents the smallest cohesive group of buildings enclosed by streets within a particular area.

- Impervious Surface Reduction and Landscape Space Contiguity

The widespread adoption of autonomous mobility systems presents a significant opportunity to address issues related to excessive impervious surfaces in suburban areas and to facilitate the creation of more contiguous landscape spaces. According to the US EPA, "Impervious surfaces are materials that do not allow the penetration of water, such as buildings, roads, and parking lots [130]". Much research has proven that impervious surfaces have various negative impacts on the environment such as a reduction in watershed protection [131], the conveyance of urban pollution [132], an increase in local temperatures [133], threats to biodiversity [134], and so forth. Hence, the investigation of impervious surfaces has emerged as a significant area of scientific interest concerning the management of Nonpoint Source Pollution (NSP) and as an indicator of the ecosystem quality of a given site [135].

As mentioned in the introduction, with the adoption of an autonomous mobility system, it becomes possible to reduce impervious surfaces and create a more contiguous collection of landscape spaces inside the block. This can not only enhance ecological performance but also provide ample room for a diverse range of activities, maximizing the block's functionality. Typical suburban areas are awash with impervious surfaces including driveways, sidewalks, parking lots, etc. The formula for calculating the ratio of impervious surface is shown below:

$$f_{impervious} = \frac{\sum_{i=1}^{n} A_i}{A} \tag{4}$$

In the function, n is the total number of driveways. i is any given driveway. A_i is the area of a single impervious surface i. A is the area of the whole block.

Given the different granularity and resolution, landscape space contiguity at the block scale is represented by the area of the largest single landscape space inside the given block.

$$f_{conti} = Max\ (A_L) \tag{5}$$

In the function, A_L is the area of each landscape space inside the block.

- Multi-modal Mobility Hub Access

As shown in many studies, in order to achieve a scenario in which an autonomous mobility system results in an overall reduction in vehicle miles traveled (VMT) and transportation-based GHG emissions, it is essential to roll out AEVs alongside a MaaS system, such as shared mobility or mobility on demand [63,136]. With this in mind, the design of passenger loading zones, as a fundamental infrastructure for MaaS, will become more important than ever [18]. In many cases, a key strategy will likely entail promoting a seamless mobility mode transfer by co-locating these spaces with other mobility infrastructures, like e-bike docking stations, to form a multi-modal mobility hub.

It may be challenging for planners to determine the ideal distribution of these hubs to ensure that optimal accessibility is achieved within the budgetary constraints of a project. The level of accessibility is typically a key factor in determining how many users will be willing to use these hubs and thus the overall mobility system. According to the research by TRB (2014), access (walking distance) will affect people's willingness to use a particular mobility mode, such as a bus. While at short distances (e.g., 0–50 m), most people are willing to walk to a bus stop, but less than 5 percent of people walk to destinations further than 600 m [137]. Similar empirical results have been found in other studies [138,139]. Furthermore, when access analysis is applied to analyze block configurations, trade-offs need to be negotiated between two measurements (Figure 7).

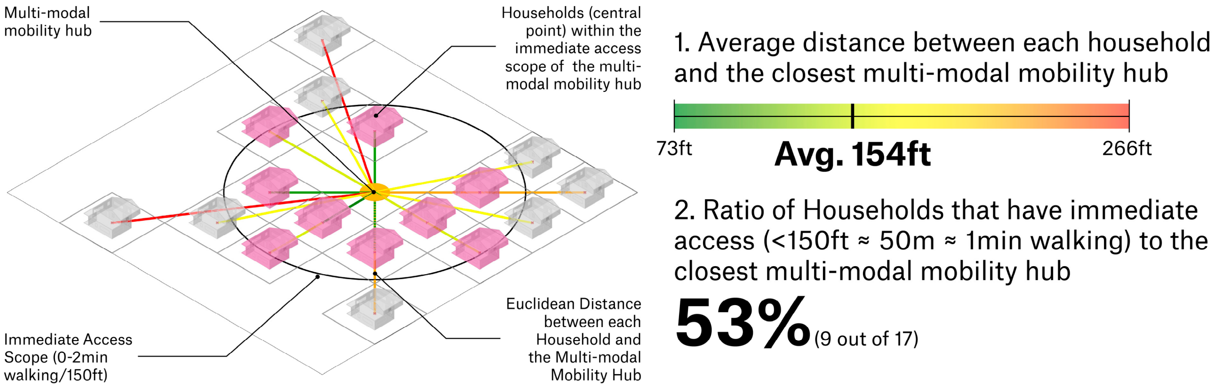


Figure 7. The diagram employs a block configuration to illustrate how the two metrics mentioned above are calculated.

One is the average distance between households and the closest multi-modal mobility hub. This formulation is shown below:

$$f_{avgdistance} = \frac{\sum_{i=1}^{n} D_i}{n} \quad (6)$$

In the formulation, n is the total number of households. i is any given household. D_i = Euclidean distance between the centroid of household i and multi-modal mobility hub.

Another is the ratio of households that have immediate access (<150 ft ≈ 50 m ≈ 1 min walking) to the closest multi-modal mobility hub. This formulation is shown below:

$$f_{householdaccess} = \frac{\sum_{i=1}^{n} X_i}{n} \quad (7)$$

In the formulation, n is the total number of households. i is any given household. X_i is a binary variable. When household i in inside the 1 min service buffer of the multi-modal mobility hub, the X_i = 1; otherwise, X_i = 0.

2.4. Baseline Analysis and Input Configurations

2.4.1. Baseline Analysis

A baseline analysis for two distinct scales was conducted to obtain inputs for the framework. The outcomes of this baseline analysis served two purposes. Firstly, these data were employed in the scenario generation module to establish essential parameters. Secondly, they were used as a basis for comparison against the outputs produced by the proposed framework. This comparative analysis aimed to evaluate the framework's effectiveness in improving scenario performance compared to the baseline conditions.

District scale: The research site has four land use types (Figure 8), which were identified in the plan as "Suburban Living", "Estate Residential", "Landscape Space", and "Neighborhood Commercial". Among them, suburban living (SL) takes the largest area (60 percent), followed by estate residential (ER), which takes 23 percent of total land. Landscape space (LS) and neighborhood commercial (NC) take 14 percent and 3 percent, respectively. Only 9 percent of the residential zones, including the SL and ER areas, are within a 5 min walk to the closest LS and NC areas.

Block scale: SL—the dominant block type within the research site—was selected as the survey object. Two of the most common SL block configurations—linear configurations and cul-de-sac configurations—are analyzed (Figure 9). The survey results revealed that these two configurations exhibit comparable landcover attributes. In both cases, approximately 25 percent of the total land area is allocated for vehicular use, indicating a significant portion dedicated to impervious surfaces. Additionally, nearly 50 percent of the land area consists of fragmented turf areas, which generally exhibit low environmental performance [140] and high maintenance costs [141].

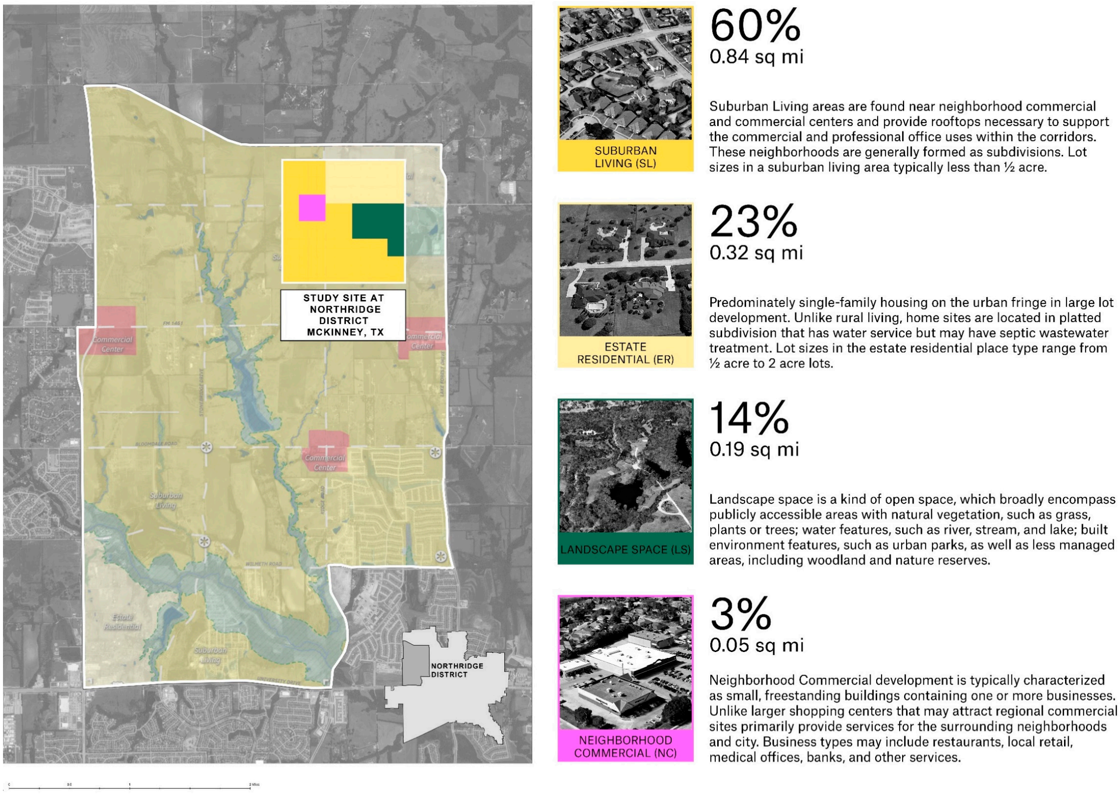


Figure 8. Existing land use allocation of the study site.

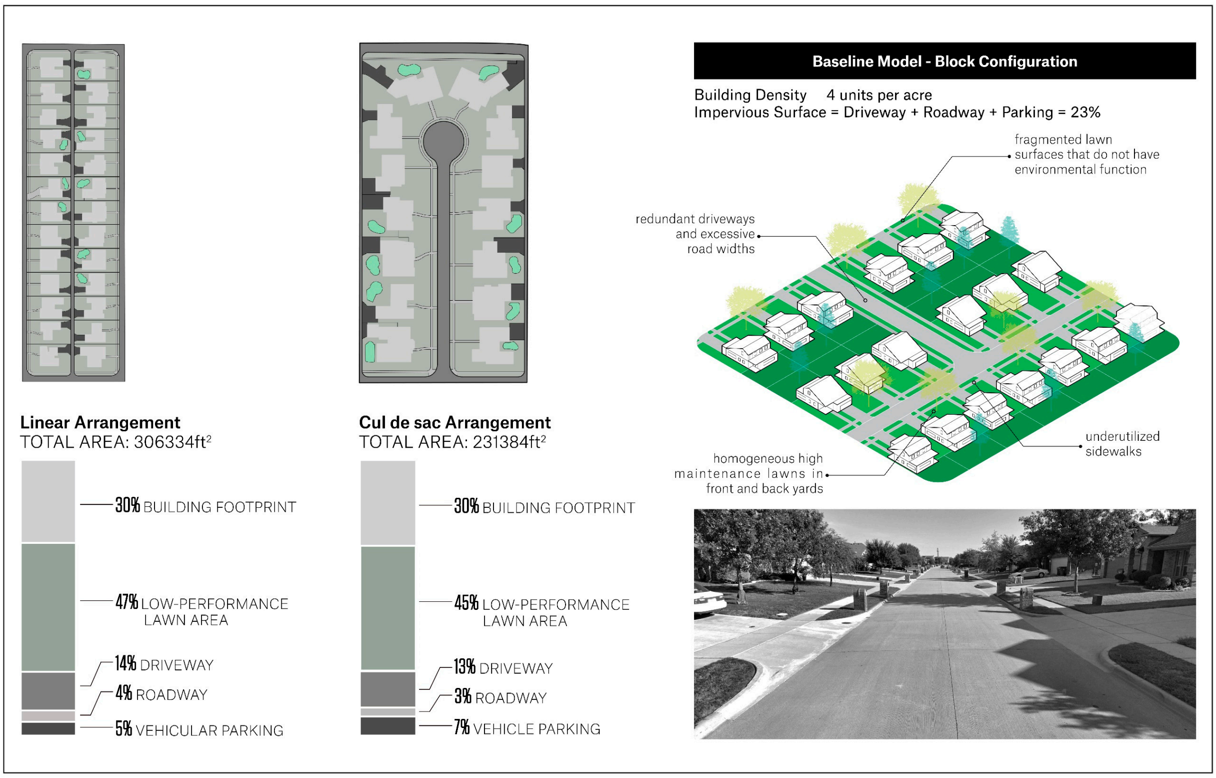


Figure 9. Block survey of suburban living block configurations in McKinney.

2.4.2. Input Configurations

For each scale, three different sets of parameters were input into corresponding modules. The first set of parameters, mainly including baseline data obtained from the baseline analysis, was input into the scenario generation module. The second set of parameters related to the optimization factors was input into the scenario analysis module. The last set of parameters was utilized for configuring the optimization process. All parameters are shown in Tables 2 and 3.

Table 2. Model inputs.

District Scale **Inputs -> Scenario Generation Module**	
1. Land use cell size	4.5 acres
2. Land use cell type	Suburban living; estate residential; Neighborhood commercial; landscape space
3. Land use cell count of each land use type	Suburban living: 114; estate residential: 45; Neighborhood commercial: 9; landscape space: 28
4. Site boundary	A spatial data input from Rhino3D
Inputs -> Scenario Analysis Module	
1. Land use matrix	See Figure 10 for detailed information
Block scale	
Inputs -> Scenario Generation Module	
1. Block size	4.5 acres
2. Building density	4 units per acre
3. Lot area	5400 ft^2
4. Building footprint (without garage)	1400 ft^2
5. Number of multi-modal mobility hub	1
Inputs -> Scenario Analysis Module	
1 min walking distance	150 ft

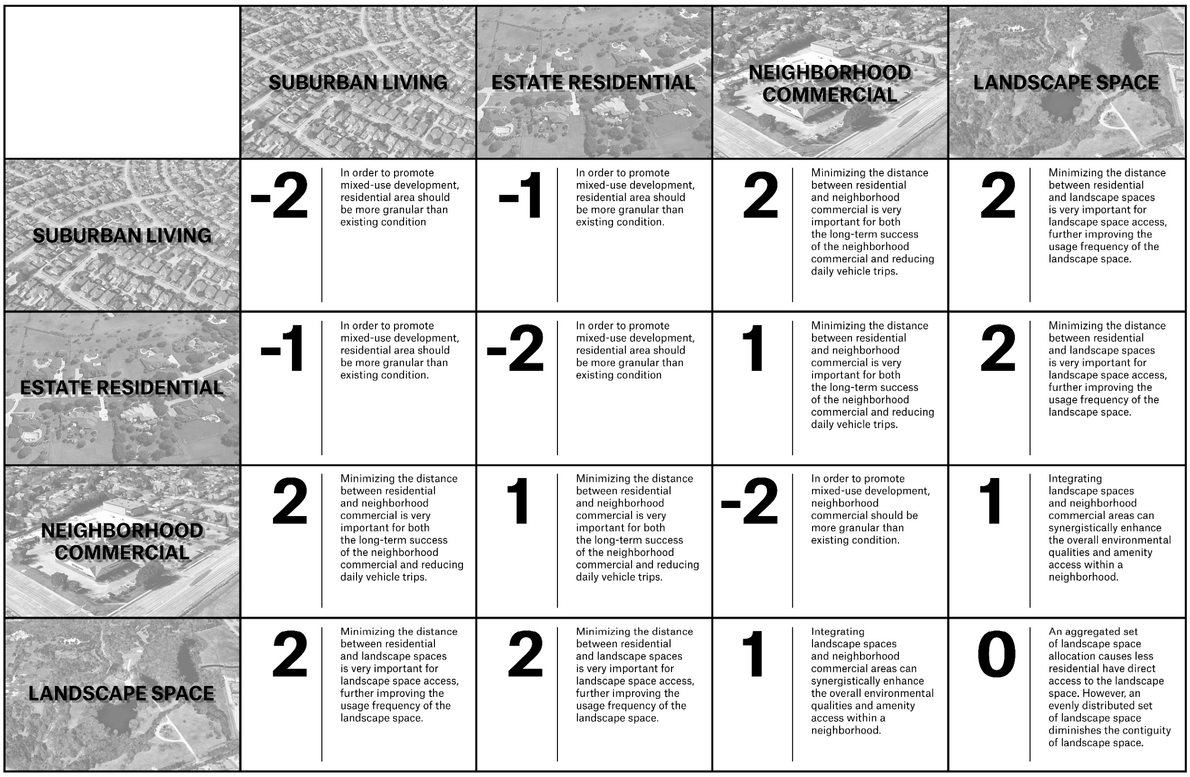


Figure 10. Applied land use distribution matrix with incentive and penalty scores.

Table 3. Optimization settings.

<table>
<tr><th>Optimization Size</th><th>District Scale | Block Scale</th><th>Algorithm Settings</th><th>District Scale | Block Scale</th></tr>
<tr><td>Generation size</td><td>50 | 50</td><td>Mutation rate</td><td>1/n | 1/n</td></tr>
<tr><td>Generation count</td><td>100 | 100</td><td>Crossover probability</td><td>0.9 | 0.9</td></tr>
<tr><td>Population size</td><td>5000 | 5000</td><td>Mutation distribution index</td><td>20 | 20</td></tr>
<tr><td>Number of variables</td><td>784 | 10,002</td><td>Crossover distribution index</td><td>20 | 20</td></tr>
<tr><td>Size of search space</td><td>1×10^{118} | 2.5×10^{7}</td><td>Simulation runtime</td><td>4 h 36 min | 18 min</td></tr>
</table>

It is noteworthy that at the district scale, a grid system has been adopted to adhere to the governmental master plan. As depicted in Figure 8, the local government utilizes a grid system to partition the land for future development. By incorporating a grid system that aligns with the established grid by the local government, our proposal can seamlessly integrate into the regional development framework. Moreover, the land use cell has been defined with a size of 4.5 acres (450 ft × 450 ft), which is equivalent to the dimensions of an average single block, which we considered as the minimum operational unit. The determination of this block size is based on the average block dimensions prevalent in the local context.

The land use matrix shown in Figure 10 is determined by researchers, developers, and planning officials from McKinney based on not only current development objectives but also future needs for mixed-use communities, improved environmental performance, enhanced accessibility, and autonomous mobility adaptations.

The modules were run on a PC with the following specifications: Intel(R) Core (TM) i7-8700 K CPU @ 3.70 GHz (3696 MHz) processor with 64.0 GB (2133 MHz) of RAM. The following settings have been applied to the optimization module (Table 3). For each scale, the generation size was set as 50, while the generation count was set as 100. The total number of generated scenarios is 5000. The value of crossover probability was set as 0.9.

3. Case Studies and Results

Based on the analysis of the standard deviation for each optimization factor across generations, the success of the model run is evident. As shown in Figure 11, compared to a larger variance of earlier generations (represented by red lines in the graph), later generations (represented by blue lines in the graph) typically display a convergence toward lower fitness values, indicating improved performance for each optimization factor. This suggests that an optimized value range emerges as the process progresses. More detailed analyses at two distinct scales are presented in the subsequent sections.

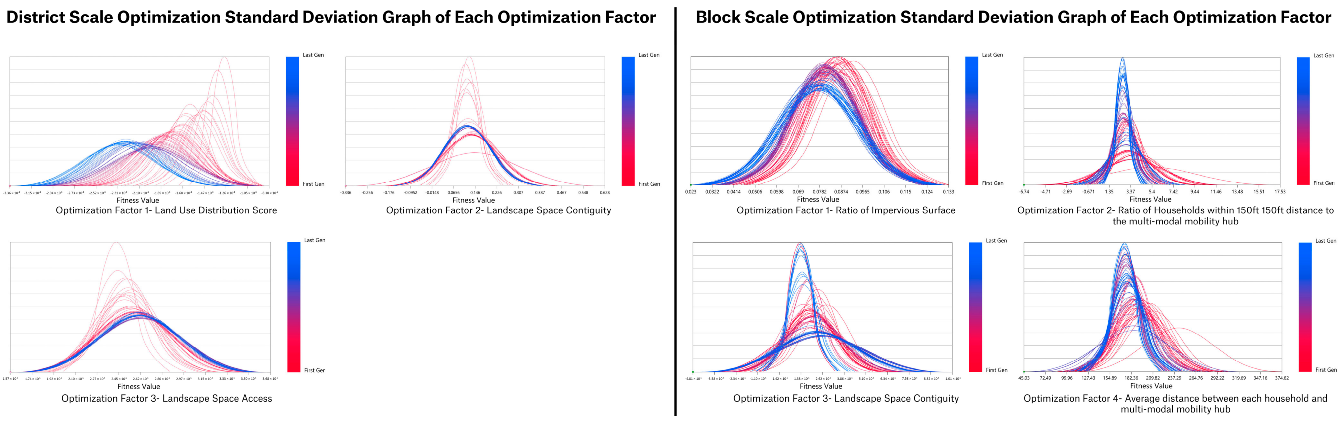


Figure 11. Standard deviation graph of each optimization factor.

3.1. District Scale Results

The performance of various district scale scenarios generated through this process is shown in various forms, including before/after land use plans, a parallel coordinate plot[4], and a radar chart (Figure 12). The plot indicates that no scenario has the best performance across all objectives, hence it is important to negotiate trade-offs between different objectives. Particular emphasis has been placed on prioritizing the land use distribution score and landscape space access when selecting the output. This choice is driven by the overarching goals of promoting a mixed-use land use pattern that aligns with the anticipated autonomous mobility system and ensuring convenient access to landscape spaces. Additionally, a minimum land use cell size has been established to maintain a certain level of contiguity for single landscape space land use. However, the selected scenario can vary based on different objectives derived from different stakeholders' viewpoints and site conditions.

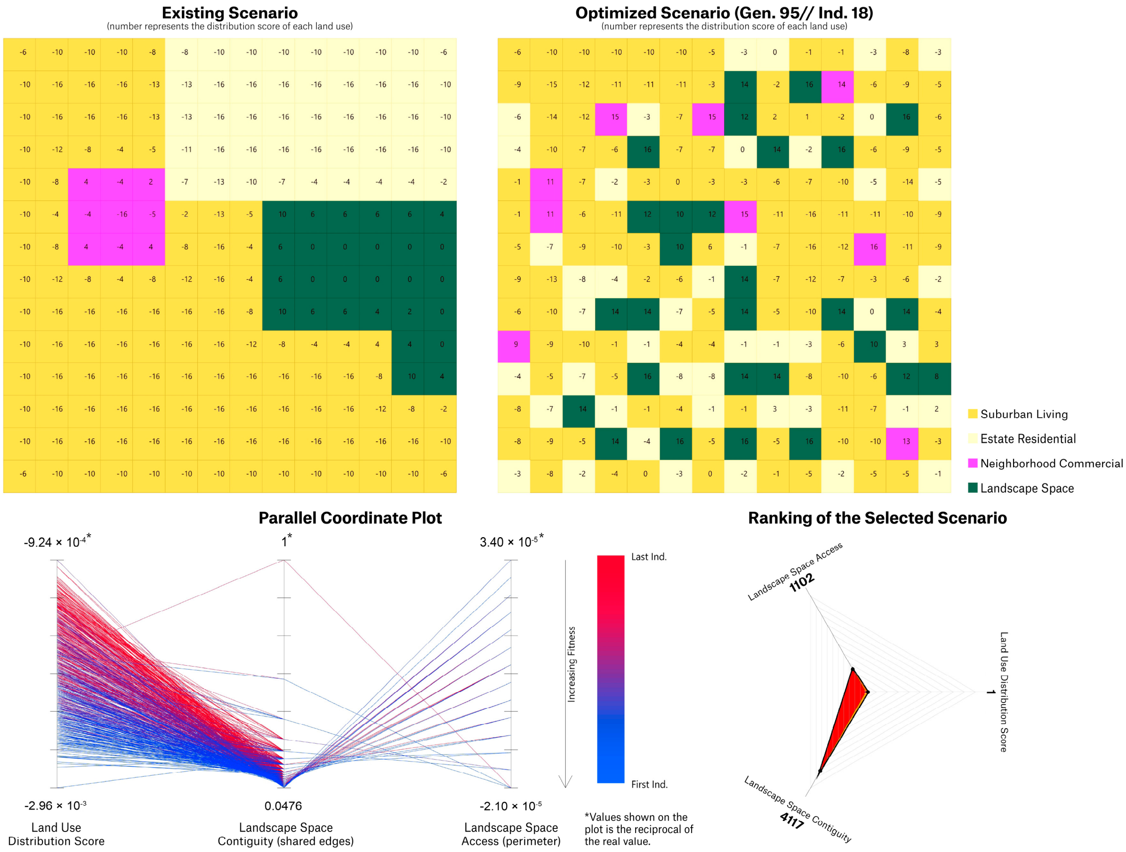


Figure 12. District scale outputs vs. the existing scenario.

The selected scenario has the highest performance in the land use distribution score, which means it aligns most closely with the predefined objectives. By comparing the baseline against the optimized land use plan (Table 4), it is clear that the landscape space allocation of the selected scenario has an improved balance between distribution and contiguity. Meanwhile, the NC land use areas are more equitably distributed across the site, which provides improved access overall. Moreover, the overall perimeters of the LS land use clusters have been increased by 300 percent, which means there is greater access for residents to public landscape spaces throughout the district. While this expansion has led to a decrease in the overall contiguity of landscape spaces, effective planning techniques, such as landscape corridors and innovative block configurations, can help mitigate this issue. Furthermore, the block configuration proposed in this research promotes a more contiguous landscape space connection through the residential block (as explained in the following sections). Overall, all four types of land use are more granular, providing various opportunities for mixed-use development through distribution.

Table 4. District scale output vs. existing scenario.

Optimization Factors		Existing Scenario	Optimized Scenario (Ranking out of 5000)	∆Variation
Land Use Distribution (f_{dist})		−1820	−388 (1)	+1432
Landscape Space Allocation	Access (f_{access})	10,618 ft	42,472 ft (1102)	+300%
	Contiguity ($f_{contiguity}$)	27	8 (4117)	−70%

3.2. Block Scale Results

The performance of various block scale scenarios generated from the design framework is shown in Figure 13. In the optimization process, the complex block configuration was simplified into line and point elements, as shown in the diagram. The plot shows that no scenario has been found to possess the best performance across all objectives, hence it is important to negotiate trade-offs between different objectives. When selecting the output scenario, balanced performances across all four metrics are considered optimal. One scenario with the highest performance in one metric may fall short in all other metrics, which will ultimately lead to an unfeasible scenario when applied to real-world conditions.

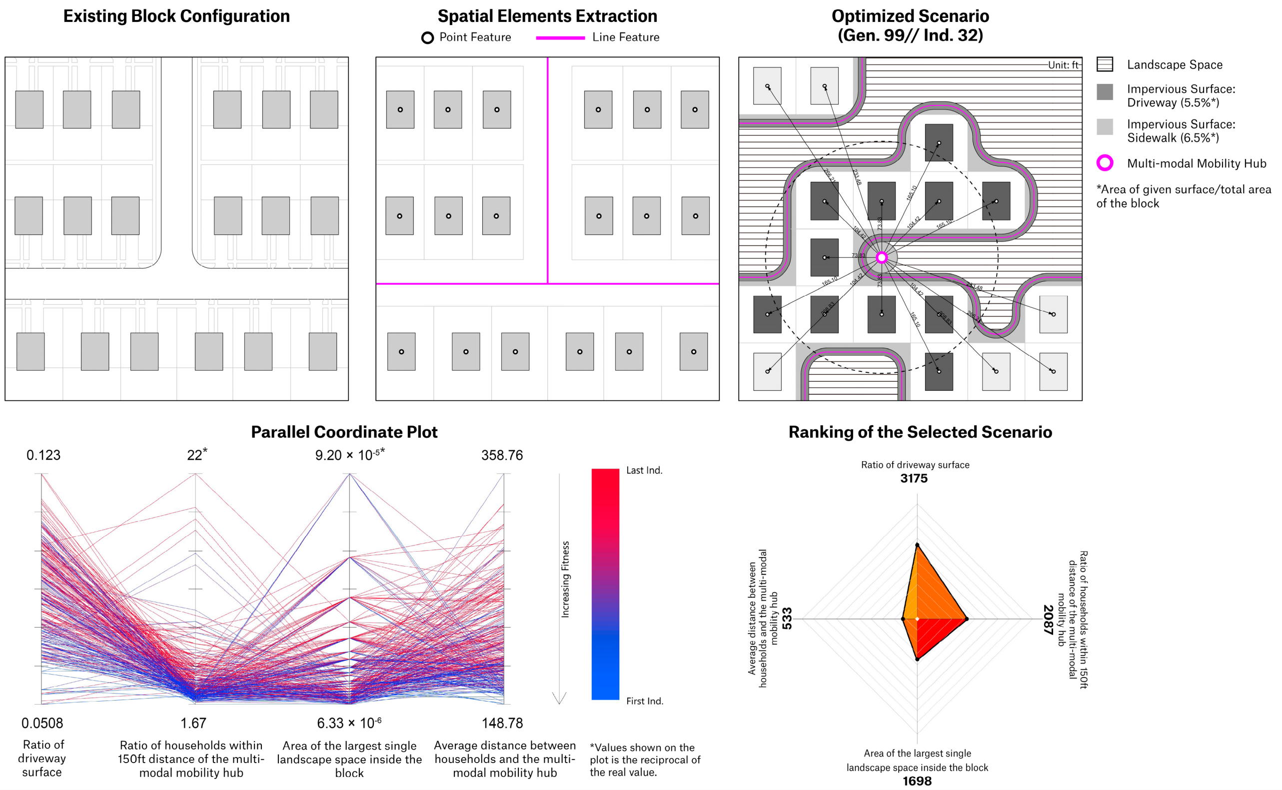


Figure 13. Block scale outputs vs. the baseline scenario.

The selected scenario has a balanced performance across all objectives (Table 5). As shown by the radar chart, the selected scenario has a relatively high capacity to help minimize the average distance between each household and multi-modal mobility hub and maximize the area of contiguous landscape space inside the block. It has a moderate capacity to help maximize households within a 150 ft distance to a multi-modal mobility hub and minimize the ratio of impervious surfaces. In the selected scenario, the ratio of impervious surfaces, mainly including driveways and roadways, is approximately 11 percent lower than the baseline scenario, which represents almost a 50 percent reduction. Moreover, through strategically clustering households, narrowing driveways, integrating landscape buffers, and reducing the household yard, a more contiguous communal landscape space is established within close proximity to all households. The largest single landscape space is 50 times larger than the largest landscape buffer that can be found in the baseline configuration, which can provide better recreational functions and environmental benefits. Meanwhile, a multi-modal mobility hub is strategically installed within a 1 min walking distance to 65 percent of all households.

Table 5. Block scale output vs. baseline conditions.

Optimization Factors		**Baseline Solution**	**Optimized Solution (Ranking out of 5000)**	**Δ Variation**
Ratio of impervious surface ($f_{impervious}$)		23%	12% (3173)	−11%
Landscape Space Contiguity	Area of the largest single landscape space inside the block (f_{conti})	1755	92,673 ft2 (1698)	+5180%
Multi-modal Mobility Hub Access	Average distance between each household and multi-modal mobility hub ($f_{avgdistance}$)	N/A	160 ft (533)	N/A
	Ratio of households within a 150 ft distance to the multi-modal mobility hub ($f_{householdaccess}$)	N/A	65% (2087)	N/A

4. Discussion: Design Interpretations from the Model Outputs

Inspired by the model outputs of the proposed design framework, several further design interpretations have been drawn at two distinct scales to achieve a more sustainable environment with higher accessibility and landscape performance in the era of autonomous mobility.

4.1. District Scale Design Interpretation

The output indicates that by breaking up large homogeneous land use clusters and distributing them more evenly, it becomes easier to accommodate mixed-use development patterns within the context of future autonomous mobility systems. This atomization of large land use clusters can also facilitate a more walkable and accessible living environment with reduced VMT [142,143]. As shown in the analytic diagram (Figure 14 and Table 6), in the selected scenario, 89 percent of residences are situated within a 5 min walking distance from the nearest landscaped area, 70 percent are within a 5 min walk of the closest neighborhood commerce, and in total, 46 percent of households are within a 5 min walk of both landscape space and neighborhood commercial land uses.

Table 6. District scale proximity analysis.

		Existing Scenario	**Optimized Scenario**	**ΔVariation**
Neighborhood Commercial	3 min walking *	10%	36%	+26%
	5 min walking **	25%	70%	+45%
Landscape Space	3 min walking *	12%	62%	+50%
	5 min walking **	27%	89%	+62%
Both	3 min walking *	0%	15%	+15%
	5 min walking **	4%	46%	+42%

* 3 min walking—one block away (450 ft), ** 5 min walking—two blocks away (900 ft).

Meanwhile, in the future, neighborhood commercial land uses can be utilized as strategic sites for shared mobility/mobility-on-demand dispatching centers, autonomous mobility idling, mobility maintenance, and more (Figure 15). Consequently, a reduced distance between neighborhood commercial areas and households results in shorter wait times for a mobility-on-demand/shared-mobility system. This, in turn, enhances the reliability and responsiveness of the system, which are crucial factors influencing its usage frequency [144]. Additionally, atomized land use patterns provide significant opportunities to configure a fine-grain urban fabric with pedestrian-scale circulation networks, which can further yield improved accessibility and higher mobility capacity [145,146].

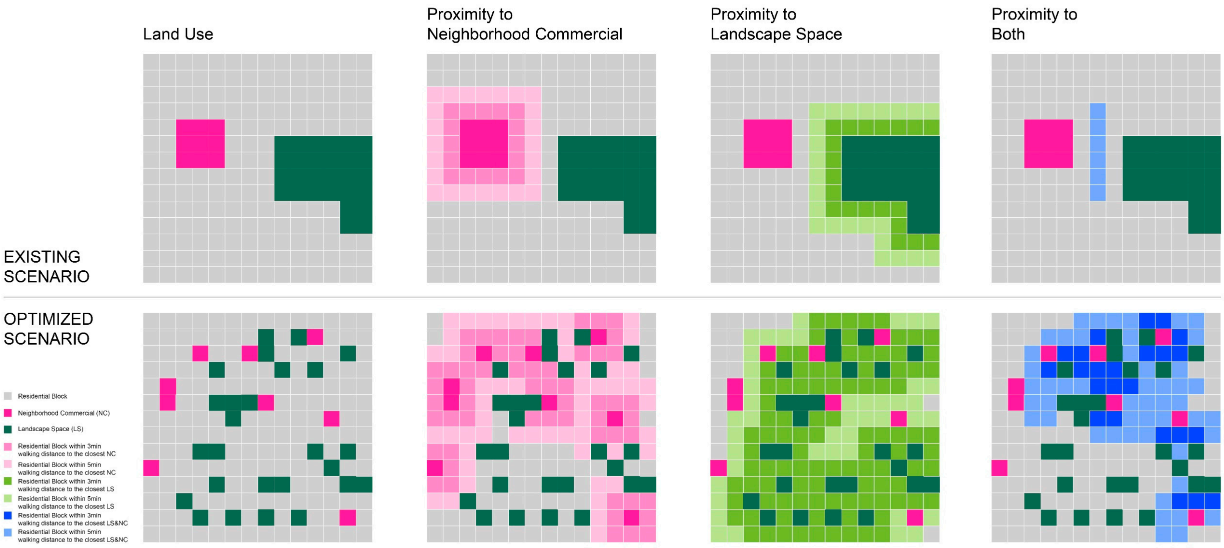


Figure 14. Proximity analysis of the district scale outputs.

Figure 15. Rendering of the future neighborhood commercial district.

It is worth noting that the output that reveals an optimized approach to distributing various land use types should also be developed based on their distinct characteristics. For example, the NC land use designation benefits from an equitable distribution throughout the site, ensuring access for all. On the other hand, the allocation of landscape spaces requires a delicate balance between access and contiguity. As a result, unlike neighborhood commercial land use, the distribution of landscape space land use tends to form small clusters, providing a balanced performance between ecology and accessibility.

4.2. Block Scale Design Interpretation

The model output shows that through strategically reducing private yard space and setbacks, combined with the extra spaces freed from driveways and household front parking, which is made possible by the autonomous mobility system, a large communal area, which is separated from vehicular traffic, can be gained. These larger open spaces can provide environmental advantages, public health benefits, and extra spaces for necessary infrastructure that is vital for future autonomous mobility systems, such as charging spaces. Meanwhile, a smaller private yard space aligns with current market trends. Research has shown that adults spent less than 15 min of time per week in their yards, while children averaged less than 40 min per week [147].

In the optimized scenario, with less demand for impervious surfaces, the block with the same number of houses can be designed with more permeable surfaces for vastly better environmental outcomes. These advantages might be accentuated in the context of multifamily zoning, where expansive parking spaces usually constructed within a block can be supplanted by on-site stormwater retention mechanisms and augmented recreational facilities. Replicating this re-envisioned block design across multiple blocks to establish a corridor and incorporating appropriate trees can markedly reduce summer temperatures and enhance the carbon sequestration capacity by over 300 percent (Figure 16).

Figure 16. A possible multi-block configuration inspired by the model outputs.

When it comes to the location of the multi-modal mobility hub, the outcome is somehow counterintuitive. Usually, in order to maximize the accessibility of the multi-modal mobility hub, the optimal location is the center of the block. However, there are two sets of trade-offs that need to be further considered. One is the accessibility of the multi-mobility hub versus the landscape space contiguity, another is the number of households with immediate access to the mobility hub versus the average distance between all households and the mobility hub. In the selected scenario, a relatively balanced outcome has been achieved. Approximately 67 percent of all households have immediate access to the hub, requiring less than a minute of walking. On average, the walking distance between all households and the hub is approximately 160 feet. As the crucial role of the proximity between households and mobility hubs in promoting higher usage of the given mobility service [148], this output achieves a balanced performance in both access and equality.

5. Conclusions

This research illustrates that with the proliferation of an autonomous mobility system, some environmental impacts of car-based infrastructures in suburban areas can be greatly reduced. The NOGAS framework provides a heuristic model for implementing new mobility systems in future suburban land use planning and block forms. Through it, city planners and other development decision-makers can easily envision future integrations of autonomous mobility systems with little cost, risk, or disruption.

The research results reveal that transitioning to autonomous mobility has vast potential for new types of land use distribution, landscape space allocation, and accessibility in suburbs without radically altering typical density ranges. Increased amounts of permeable surfaces, more equitable access to commercial and recreational amenities, and placement of multi-modal mobility hubs in the output scenarios further suggest a more walkable and livable suburb is achievable, ironically, by reducing the past century's development layouts dominated by car-based forms. Furthermore, as shown by the research, new types of mixed-use suburban neighborhoods can be created by leveraging new autonomous mobility technology, additional mobility path systems, and micro-mobility platforms. Based on the research findings, we offer several recommendations for future development and policy implementation in suburban areas.

1. When developing future suburbs, policymakers, developers, and planners must move away from the last century's car-centric models. Mobility in and around metro areas is much more diverse than the outdated transportation and policy model of planning solely for suburb to downtown core trunkline commuting patterns. People and jobs have spread out well beyond the historic cores of cities. Cities and towns should adopt a more dynamic transportation system for polycentric suburb-to-suburb linkages that prioritize accessibility and integrate a range of new mobility technologies and services.
2. Leveraging emerging mobility solutions and innovating zoning codes to allow for new mobility patterns will give policymakers, developers, and planners the opportunity to reimagine the current car-based mixed-use development paradigm, which forces an extraordinary number of extra household trips.
3. In shaping future suburbs integrated with new mobility systems, policymakers, developers, and planners should consider employing a landscape performance-oriented method of design optimization over the traditional pavement-come-first method, which can offer novel opportunities to devise more comprehensive and sustainable development strategies.
4. In formulating policies and plans for future suburbs, policymakers, developers, and planners ought to consider integrating a parametric design framework, like NOGAS. This not only enhances the process's efficiency and precision by accelerating iterations and delivering data-driven outcomes but also maximizes future prospects by offering a large testbed of innovative solutions in a relatively short period of iteration.

Admittedly, planning and design for future suburban development is a complex issue, encompassing various fields and specializations. This research delves into reinventing suburban development patterns to integrate autonomous mobility systems for better environmental outcomes. However, there are several other promising directions for future exploration. Firstly, while the current focus is on achieving improved environmental and access performance, it is essential to also consider universal access as an objective factor of the design framework. Given the increasing aging population and people with disabilities in the US [149,150], the distributed, hyper-flexible future offered by fully automated mobility systems could provide the most equitable remedy to this systemic mobility-access deficit, as substantiated by extensive research findings [151,152]. Secondly, the proposed design framework can be augmented with road network-based and efficiency-related metrics and algorithms, such as the traveling salesmen model [153] and the minimum cost paths model [154]. This integration would bolster the system's capacity to optimize the scenario's performance in mobility efficiency. Thirdly, in order to enhance the safety of the autonomous mobility system, new roadsides that can curb infrastructures are needed to support V2X (vehicle-to-everything) development [155] and provide a way for information exchange between pedestrian and autonomous mobility [156]. Hence, how to allocate these new infrastructures is an important aspect to be incorporated in reimagining future block configurations.

To conclude, the evolution of autonomous mobility systems will significantly influence future suburban development and further investigate how environmental benefits can be accrued and equitably distributed throughout increasingly suburban metropolitan regions. If policymakers and urban planners genuinely aim to curtail GHG emissions and achieve other environmental benefits in suburban areas, they ought to contemplate instituting contemporary land use regulations that align with physical planning and design innovations built around autonomous mobility technologies to greatly reduce the need for household trips to do everything outside the block or neighborhood. Incorporating ecological performance requirements into the retrofitting of middle suburban neighborhoods and new greenfield suburban developments could ameliorate overarching environmental impacts by removing vast amounts of paving and integrating ecological priorities such as corridors, continuous canopy habitats, and hydrological catchments, all of which can mitigate the impact of land consumption and climate change.

Author Contributions: Conceptualization, A.M.B., J.S., M.G. and C.Z.; methodology, A.M.B., J.S., M.G. and C.Z.; software, M.G. and C.Z.; validation, A.M.B. and J.S.; formal analysis, J.S. and C.Z.; investigation, A.M.B., J.S. and C.Z.; data curation, C.Z.; writing—original draft preparation, C.Z., A.M.B. and H.B.O.; writing—review and editing, J.S., H.B.O. and A.M.B.; visualization, C.Z.; supervision, A.M.B.; project administration, A.M.B.; funding acquisition, A.M.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Toyota Mobility Foundation.

Data Availability Statement: All data sets are associated with the paper.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Notes

1. The collaboration between P-REX lab, MIT and the City of McKinney, TX was funded by Toyota Mobility Foundation.
2. Rhino3D is a widely adopted professional 3D modeling platform developed by Robert McNeel & Associates, renowned in the planning and design industry. GH, serving as a plugin for Rhino3D, enables users to generate, analyze, and optimize design scenarios in a parametric manner. Additionally, GH provides a comprehensive coding environment, including Python and C++, allowing users to implement customized functions using programming languages. These capabilities grant Rhino3D and GH the necessary flexibility and usability to serve as the foundation for developing a new parametric design framework.
3. During optimization process, NSGA-II employs the crossover and mutation operation to generate new scenarios from old scenarios. These two operations mimic the process of natural evolution. The crossover operation is switching several parameters of two old scenarios to generate new scenarios. The mutation is randomly changing several parameters of an old scenario create new scenarios. Several open-source NSGA-II plugins are available on the market. The Wallacei evolutionary simulation engine was selected for this research.
4. The values shown in the plot are fitness values. Fitness value is an intermediate value used by algorithm to judge which scenario have better performance in terms of given objective. The smaller fitness value, the better performance of given scenario.

References

1. Ewing, R. Is Los Angeles-style sprawl desirable? *J. Am. Plan. Assoc.* **1997**, *63*, 107–126. [CrossRef]
2. Squires, G.D. Urban sprawl and the uneven development of metropolitan America. *Urban Spraw. Causes Conseq. Policy Responses* **2002**, 1–22.
3. Pařil, V.; Ondrůšková, B.; Krajíčková, A.; Petra, Z. The cost of suburbanization: Spending on environmental protection. *Eur. Plan. Stud.* **2022**, *30*, 2002–2021. [CrossRef]
4. Jones, C.; Kammen, D.M. Spatial distribution of US household carbon footprints reveals suburbanization undermines greenhouse gas benefits of urban population density. *Environ. Sci. Technol.* **2014**, *48*, 895–902. [CrossRef] [PubMed]

5. Brody, S. The characteristics, causes, and consequences of sprawling development patterns in the United States. *Nat. Educ. Knowl.* **2013**, *4*, 2.
6. Kahn, M.E. The environmental impact of suburbanization. *J. Policy Anal. Manag.* **2000**, *19*, 569–586. [CrossRef]
7. Kowarik, I. Novel urban ecosystems, biodiversity, and conservation. *Environ. Pollut.* **2011**, *159*, 1974–1983. [CrossRef] [PubMed]
8. Hinners, S.J.; Kearns, C.A.; Wessman, C.A. Roles of scale, matrix, and native habitat in supporting a diverse suburban pollinator assemblage. *Ecol. Appl.* **2012**, *22*, 1923–1935. [CrossRef]
9. Catterall, C.P.; Cousin, J.A.; Piper, S.; Johnson, G. Long-term dynamics of bird diversity in forest and suburb: Decay, turnover or homogenization? *Divers. Distrib.* **2010**, *16*, 559–570. [CrossRef]
10. Blair, R.B.; Launer, A.E. Butterfly diversity and human land use: Species assemblages along an urban grandient. *Biol. Conserv.* **1997**, *80*, 113–125. [CrossRef]
11. Law, N.; Band, L.; Grove, M. Nitrogen input from residential lawn care practices in suburban watersheds in Baltimore County, MD. *J. Environ. Plan. Manag.* **2004**, *47*, 737–755. [CrossRef]
12. Currie, W.S.; Kiger, S.; Nassauer, J.I.; Hutchins, M.; Marshall, L.L.; Brown, D.G.; Riolo, R.L.; Robinson, D.T.; Hart, S.K. Multi-scale heterogeneity in vegetation and soil carbon in exurban residential land of southeastern Michigan, USA. *Ecol. Appl.* **2016**, *26*, 1421–1436. [CrossRef] [PubMed]
13. Nassauer, J.I. Greening Sprawl—Lawn Culture and Carbon Storage in the Suburban Landscape. In *Infinite Suburbia*; Berger, A., Kotkin, J., Guzman, C., Eds.; Princeton Architectural Press: Hudson, NY, USA, 2017; pp. 506–517.
14. Hagan, S. Metabolic Suburbs, or the Virtue of Low Densities. In *Infinite Suburbia*; Berger, A., Kotkin, J., Guzman, C., Eds.; Princeton Architectural Press: Hudson, NY, USA, 2017; pp. 468–478.
15. Jittrapirom, P.; Caiati, V.; Feneri, A.M.; Ebrahimigharehbaghi, S.; Alonso-González, M.J.; Narayan, J. Mobility as a service: A critical review of definitions, assessments of schemes, and key challenges. *Urban Plan.* **2017**, *2*, 13–25. [CrossRef]
16. Ghanipoor, M.S.; Ahmadi, A.; Musial, W.; Katthe, A.; Melendez, B.; Jahangiri, A. Implications of a Narrow Automated Vehicle-Exclusive Lane on Interstate 15 Express Lanes. *J. Adv. Transp.* **2021**, *2021*, 6617205. [CrossRef]
17. Nourinejad, M.; Bahrami, S.; Roorda, M.J. Designing parking facilities for autonomous vehicles. *Transp. Res. Part B Methodol.* **2018**, *109*, 110–127. [CrossRef]
18. Marsden, G.; Docherty, I.; Dowling, R. Parking futures: Curbside management in the era of 'new mobility' services in British and Australian cities. *Land Use Policy* **2020**, *91*, 104012. [CrossRef]
19. Hensher, D.A.; Ho, C.Q.; Reck, D.J. Mobility as a service and private car use: Evidence from the Sydney MaaS trial. *Transp. Res. Part A Policy Pract.* **2021**, *145*, 17–33. [CrossRef]
20. American Planning Association. Standard State Zoning Enabling Act and Standard City Planning Enabling Act. Available online: https://www.planning.org/growingsmart/enablingacts.htm (accessed on 7 June 2023).
21. Village of Euclid v. Ambler Realty Co.; 272 U.S. 365, 1926. Available online: https://www.oyez.org/cases/1900-1940/272us365 (accessed on 7 June 2023).
22. Hall, E. Divide and sprawl, decline and fall: A comparative critique of Euclidean zoning. *Univ. Pittsburgh Law Rev.* **2006**, *68*, 915. [CrossRef]
23. Checkoway, B.N. *Suburbanization and Community: Growth and Planning in Postwar Lower Bucks County, Pennsylvania*; University of Pennsylvania: Philadelphia, PA, USA, 1977.
24. Nilles, J.M. Telecommuting and urban sprawl: Mitigator or inciter? *Transportation* **1991**, *18*, 411–432. [CrossRef]
25. Moeckel, R. Working from home: Modeling the impact of telework on transportation and land use. *Transp. Res. Procedia* **2017**, *26*, 207–214. [CrossRef]
26. U.S. Department of Transportation, Federal Highway Administration, State Motor-Vehicle Registrations. 1900–1995, 2000. 2020. Available online: https://www.fhwa.dot.gov/ohim/summary95/mv201.pdf (accessed on 7 June 2023).
27. 70 Stat. 374—Federal-Aid Highway Act of 1956. Available online: https://www.govinfo.gov/content/pkg/STATUTE-70/pdf/STATUTE-70-Pg374.pdf (accessed on 7 June 2023).
28. Jackson, K.T. *Crabgrass Frontier: The Suburbanization of the United States*; Oxford University Press: Oxford, UK, 1987.
29. Gottmann, J. *The Urbanized Northeastern Seaboard of the United States*; México, DF; The Twentieth Century Fund: New York, NY, USA, 1961.
30. Hall, P.G.; Pain, K. (Eds.) *The Polycentric Metropolis: Learning from Mega-City Regions in Europe*; Routledge: Oxfordshire, UK, 2006.
31. Laberteaux, K.; Brown, C.; Berger, A. Interburbia: Ground Truthing US Metropolitan Urbanization. In *Infinite Suburbia*; Berger, A., Kotkin, J., Guzman, B.C., Eds.; Princeton Architectural Press: New York, NY, USA, 2017; pp. 232–251.
32. English, J. Why Did America Give Up on Mass Transit. (Don't Blame Cars). Streetcar, Bus, and Metro Systems Have Been Ignoring One Lesson for 100 Years: Service Drives Demand. Bloomberg, Citylab. 2018. Available online: https://www.bloomberg.com/news/features/2018-08-31/why-is-american-mass-transit-so-bad-it-s-a-long-story (accessed on 7 June 2023).
33. Tomer, A.; Kane, J.; Vey, J. *Connecting People and Places: Exploring New Measures of Travel Behavior*; Brookings Institution: Washington, DC, USA, 2020.
34. Pushkarev, B.S.; Zupan, J.M. Where transit works: Urban densities for public transportation. *Urban Transp. Perspect. Prospect.* **1982**, 341–344.
35. Spieler, C. *Trains, Buses, People*; Island Press: Washington, DC, USA, 2021.

36. Federal Highway Administration. *National Household Travel Survey*; U.S. Department of Transportation: Washington, DC, USA, 2017.
37. Burrows, M.; Burd, C.; McKenzie, B. Commuting by Public Transportation in the United States: 2019. *Am. Community Surv. Rep.* **2021**, 802.
38. Wilson, J.; Spinney, J.; Millward, H.; Scott, D.; Hayden, A.; Tyedmers, P. Blame the exurbs, not the suburbs: Exploring the distribution of greenhouse gas emissions within a city region. *Energy Policy* **2013**, *62*, 1329–1335. [CrossRef]
39. U.S. Environmental Protection Agency. Fast Facts on Transportation Greenhouse Gas Emissions. 2021. Available online: https://www.epa.gov/greenvehicles/fast-facts-transportation-greenhouse-gas-emissions (accessed on 7 June 2023).
40. United Nations (UN) Population Division. *World Urbanization Prospects: The 2018 Revision*; United Nations (UN) Population Division: New York, NY, USA, 2018.
41. Rees, W.E. Ecological footprints and appropriated carrying capacity: What urban economics leaves out. *Environ. Urban.* **1992**, *4*, 121–130. [CrossRef]
42. Berger, A.; Kotkin, J. (Eds.) *Infinite Suburbia*; Chronicle Books: San Francisco, CA, USA, 2018.
43. Clapson, M.; Hutchison, R. *Suburbanization in Global Society*; Emerald: Bingley, UK, 2010.
44. Cox, W. All Major Metropolitan Area Growth Outside Urban Core: Latest Year. Newgeography.com. 2022. Available online: https://www.newgeography.com/content/007430-all-major-metropolitan-area-growth-outside-urban-core-latest-year (accessed on 7 June 2023).
45. U.S. Census Bureau, Department of Housing and Urban Development (HUD). *American Housing Survey (AHS)*; 2017. Available online: https://www.census.gov/programs-surveys/ahs.html (accessed on 7 June 2023).
46. Polzin, S.E.; Pisarski, A.E. *Commuting in America 2013: The National Report on Commuting Patterns and Trends*; American Association of State Highway and Transportation Officials: Washington, DC, USA, 2015.
47. Chandler, J. Proposal to Add Density near Transit Stations Quickly Rejected in California Senate. Curbed Los Angeles. 2018. Available online: https://la.curbed.com/2018/4/17/17249654/california-senate-bill-827-housing-transit-vote (accessed on 7 June 2023).
48. Symon, E. Senator Wiener Introduces 'SB 50 Lite' Housing Bill to End Single-Family Zoning in CA. California Globe. 2020. Available online: https://californiaglobe.com/articles/senator-wiener-introduces-sb-50-lite-housing-bill/ (accessed on 7 June 2023).
49. Ewing, R.; Hamidi, S.; Tian, G.; Proffitt, D.; Tonin, S.; Fregolent, L. Testing Newman and Kenworthy's theory of density and automobile dependence. *J. Plan. Educ. Res.* **2018**, *38*, 167–182. [CrossRef]
50. Transportation Research Board and National Research Council. *Driving and the Built Environment: The Effects of Compact Development on Motorized Travel, Energy Use, and CO_2 Emissions*; National Academies Press: Washington, DC, USA, 2009.
51. Hubbard, P. NIMBY. In *International Encyclopedia of Human Geography*; Kitchin, R., Thrift, N., Eds.; Elsevier: Amsterdam, The Netherlands, 2019; pp. 444–449.
52. National Association of Realtors. Home Buyers and Sellers Generational Trends. 2023. Available online: https://cdn.nar.realtor//sites/default/files/documents/2023-home-buyers-and-sellers-generational-trends-report-03-28-2023.pdf?_gl=1*c25d7v*_gcl_au*MTM4NDMzMDc5MC4xNjkyNzEzMDk1 (accessed on 22 August 2023).
53. Economics, National Association of Home Builders. *What Home Buyers Really Want*; Economics, National Association of Home Builders: Washington, DC, USA, 2019.
54. Shamshiripour, A.; Rahimi, E.; Shabanpour, R.; Mohammadian, A.K. How is COVID-19 reshaping activity-travel behavior? Evidence from a comprehensive survey in Chicago. *Transp. Res. Interdiscip. Perspect.* **2020**, *7*, 100216. [CrossRef] [PubMed]
55. Helms, A.C. Understanding gentrification: An empirical analysis of the determinants of urban housing renovation. *J. Urban Econ.* **2003**, *54*, 474–498. [CrossRef]
56. Davis, J. *The Double-Edged Sword of Upzoning*; Brookings Institution: Washington, DC, USA, 2021. Available online: https://www.brookings.edu/blog/how-we-rise/2021/07/15/the-double-edged-sword-of-upzoning/ (accessed on 7 June 2023).
57. Infranca, J. Differentiating Exclusionary Tendencies. *Fla. Law Rev.* **2020**, *72*, 1271.
58. Fulton, L.; Mason, J.; Meroux, D. Three revolutions in urban transportation: How to achieve the full potential of vehicle electrification, automation, and shared mobility in urban transportation systems around the world by 2050. In *Three Revolutions in Urban*; Fulton, L., Mason, J., Meroux, I.D., Eds.; UC Davis Institute for Transportation & Development Policy: Davis, CA, USA, 2017.
59. Holland-Letz, D.; Kässer, M.; Kloss, B.; Müller, T. Mobility's Future: An Investment Reality Check. McKinsey Insights. 2021. Available online: https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/mobilitys-future-an-investment-reality-check (accessed on 7 June 2023).
60. Nunno, R. Autonomous Vehicles: State of The Technology and Potential Role as A Climate Solution. Environmental and Energy Study Institute. 2021. Available online: https://www.eesi.org/files/IssueBrief_Autonomous_Vehicles_2021.pdf (accessed on 7 June 2023).
61. Stephens, T.S.; Gonder, J.; Chen, Y.; Lin, Z.; Liu, C.; Gohlke, D. *Estimated Bounds and Important Factors for Fuel Use and Consumer Costs of Connected and Automated Vehicles*; National Renewable Energy Lab. (NREL): Golden, CO, USA, 2016.
62. Hayes, B. Leave the driving to it. *Am. Sci.* **2011**, *99*, 362. [CrossRef]
63. Faisal, A.; Kamruzzaman, M.; Yigitcanlar, T.; Currie, G. Understanding autonomous vehicles: A systematic literature review on capability, impact planning and policy. *J. Transp. Land Use* **2019**, *12*, 45–72. [CrossRef]

64. Liu, F.; Zhao, F.; Liu, Z.; Hao, H. Can autonomous vehicle reduce greenhouse gas emissions? A country-level evaluation. *Energy Policy* **2019**, *132*, 462–473. [CrossRef]
65. Zhang, W.; Wang, K. Parking futures: Shared automated vehicles and parking demand reduction trajectories in Atlanta. *Land Use Policy* **2020**, *91*, 103963. [CrossRef]
66. Litman, T. *Autonomous Vehicle Implementation Predictions: Implications for Transport Planning*; Victoria Transport Policy Institute: Victoria, BC, Canada, 2020.
67. Sparrow, R.; Howard, M. When human beings are like drunk robots: Driverless vehicles, ethics, and the future of transport. *Transp. Res. Part C Emerg. Technol.* **2017**, *80*, 206–215. [CrossRef]
68. Fagnant, D.J.; Kockelman, K. Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. *Transp. Res. Part A Policy Pract.* **2015**, *77*, 167–181. [CrossRef]
69. Noy, K.; Givoni, M. Is 'smart mobility'sustainable? Examining the views and beliefs of transport's technological entrepreneurs. *Sustainability* **2018**, *10*, 422. [CrossRef]
70. Berger, A.; Susskind, J.; Giampieri, M.; Zhu, C. Next Optimized Generation of Autonomous Suburbs. Available online: https://nogas.mit.edu/ (accessed on 7 June 2023).
71. The City of McKinney. One McKinney 2040 Comprehensive Plan. 2018. Available online: https://www.mckinneytexas.org/292/2040-Comprehensive-Plan (accessed on 7 June 2023).
72. The City of McKinney. Population History—McKinney, Texas. Available online: https://www.mckinneytexas.org/DocumentCenter/View/27908/Population-History{-}{-}-by-Decade?bidId= (accessed on 7 June 2023).
73. Massar, M.; Reza, I.; Rahman, S.M.; Abdullah, S.M.; Jamal, A.; Al-Ismail, F.S. Impacts of autonomous vehicles on greenhouse gas emissions—Positive or negative? *Int. J. Environ. Res. Public Health* **2021**, *18*, 5567. [CrossRef] [PubMed]
74. Soteropoulos, A.; Berger, M.; Ciari, F. Impacts of automated vehicles on travel behaviour and land use: An international review of modelling studies. *Transp. Rev.* **2019**, *39*, 29–49. [CrossRef]
75. Porta, J.; Parapar, J.; Doallo, R.; Rivera, F.F.; Santé, I.; Crecente, R. High performance genetic algorithm for land use planning. *Comput. Environ. Urban Syst.* **2013**, *37*, 45–58. [CrossRef]
76. Lima, F.; Brown, N.; Duarte, J. Urban design optimization: Generative approaches towards urban fabrics with improved transit accessibility and walkability: Generative approaches towards urban fabrics with improved transit accessibility and walkability. In Proceedings of the 26th International Conference of the Association for Computer-Aided Architectural Design Research in Asia: Projections, CAADRIA 2021, Hong Kong, China, 29 March–1 April 2021; pp. 719–728.
77. Aerts, J.; Van Herwijnen, M.; Janssen, R.; Stewart, T. Evaluating spatial design techniques for solving land-use allocation problems. *J. Environ. Plan. Manag.* **2005**, *48*, 121–142. [CrossRef]
78. Axhausen, K.W.; Horni, A.; Nagel, K. *The Multi-Agent Transport Simulation MATSim*; Ubiquity Press: London, UK, 2016.
79. Monedero, J. Parametric design: A review and some experiences. *Autom. Constr.* **2000**, *9*, 369–377. [CrossRef]
80. Touloupaki, E.; Theodosiou, T. Performance simulation integrated in parametric 3D modeling as a method for early stage design optimization—A review. *Energies* **2017**, *10*, 637. [CrossRef]
81. Shi, Z.; Fonseca, J.A.; Schlueter, A. A review of simulation-based urban form generation and optimization for energy-driven urban design. *Build. Environ.* **2017**, *121*, 119–129. [CrossRef]
82. Berawi, M.A.; Saroji, G.; Iskandar, F.A.; Ibrahim, B.E.; Miraj, P.; Sari, M. Optimizing land use allocation of Transit-Oriented Development (TOD) to generate maximum ridership. *Sustainability* **2020**, *12*, 3798. [CrossRef]
83. Cao, K.; Huang, B.; Wang, S.; Lin, H. Sustainable land use optimization using Boundary-based Fast Genetic Algorithm. *Comput. Environ. Urban Syst.* **2012**, *36*, 257–269. [CrossRef]
84. Caparros-Midwood, D.; Barr, S.; Dawson, R. Optimised spatial planning to meet long term urban sustainability objectives. *Comput. Environ. Urban Syst.* **2015**, *54*, 154–164. [CrossRef]
85. Eikelboom, T.; Janssen, R.; Stewart, T.J. A spatial optimization algorithm for geodesign. *Landsc. Urban Plan.* **2015**, *144*, 10–21. [CrossRef]
86. Haque, A.; Asami, Y. Optimizing urban land-use allocation: Case study of Dhanmondi Residential Area, Dhaka, Bangladesh. *Environ. Plan. B Plan. Des.* **2011**, *38*, 388–410. [CrossRef]
87. Janssen, R.; Van, H.M.; Stewart, T.J.; Aerts, J.C. Multiobjective decision support for land-use planning. *Environ. Plan. B Plan. Des.* **2008**, *35*, 740–756. [CrossRef]
88. Koenig, R.; Miao, Y.; Aichinger, A.; Knecht, K.; Konieva, K. Integrating urban analysis, generative design, and evolutionary optimization for solving urban design problems. *Environ. Plan. B Urban Anal. City Sci.* **2020**, *47*, 997–1013. [CrossRef]
89. Li, X.; Parrott, L. An improved Genetic Algorithm for spatial optimization of multi-objective and multi-site land use allocation. *Comput. Environ. Urban Syst.* **2016**, *59*, 184–194. [CrossRef]
90. Liu, X.; Li, X.; Shi, X.; Huang, K.; Liu, Y. A multi-type ant colony optimization (MACO) method for optimal land use allocation in large areas. *Int. J. Geogr. Inf. Sci.* **2012**, *26*, 1325–1343. [CrossRef]
91. Liu, X.; Ou, J.; Li, X.; Ai, B. Combining system dynamics and hybrid particle swarm optimization for land use allocation. *Ecol. Model.* **2013**, *257*, 11–24. [CrossRef]
92. Liu, Y.; Tang, W.; He, J.; Liu, Y.; Ai, T.; Liu, D. A land-use spatial optimization model based on genetic optimization and game theory. *Comput. Environ. Urban Syst.* **2015**, *49*, 1–14. [CrossRef]

93. Makki, M.; Showkatbakhsh, M.; Tabony, A.; Weinstock, M. Evolutionary algorithms for generating urban morphology: Variations and multiple objectives. *Int. J. Archit. Comput.* **2019**, *17*, 5–35. [CrossRef]
94. Mi, N.; Hou, J.; Mi, W.; Song, N. Optimal spatial land-use allocation for limited development ecological zones based on the geographic information system and a genetic ant colony algorithm. *Int. J. Geogr. Inf. Sci.* **2015**, *29*, 2174–2193. [CrossRef]
95. Mohammadi, M.; Nastaran, M.; Sahebgharani, A. Development, application, and comparison of hybrid meta-heuristics for urban land-use allocation optimization: Tabu search, genetic, GRASP, and simulated annealing algorithms. *Comput. Environ. Urban Syst.* **2016**, *60*, 23–36. [CrossRef]
96. Santé-Riveira, I.; Boullón-Magán, M.; Crecente-Maseda, R.; Miranda-Barrós, D. Algorithm based on simulated annealing for land-use allocation. *Comput. Geosci.* **2008**, *34*, 259–268. [CrossRef]
97. Sharmin, N.; Haque, A.; Islam, M.M. Generating Alternative Land-use Allocation for Mixed Use Areas: Multi-Objective Optimization Approach. *Geogr. Anal.* **2019**, *51*, 448–474. [CrossRef]
98. Stewart, T.J.; Janssen, R.; Van Herwijnen, M. A genetic algorithm approach to multiobjective land use planning. *Comput. Oper. Res.* **2004**, *31*, 2293–2313. [CrossRef]
99. Zhang, H.; Zeng, Y.; Jin, X.; Shu, B.; Zhou, Y.; Yang, X. Simulating multi-objective land use optimization allocation using Multi-agent system—A case study in Changsha, China. *Ecol. Model.* **2016**, *320*, 334–347. [CrossRef]
100. Westerink, J.; Haase, D.; Bauer, A.; Ravetz, J.; Jarrige, F.; Aalbers, C.B. Dealing with sustainability trade-offs of the compact city in peri-urban planning across European city regions. *Eur. Plan. Stud.* **2013**, *21*, 473–497. [CrossRef]
101. Zhang, J.; Li, S.; Lin, N.; Lin, Y.; Yuan, S.; Zhang, L.; Zhu, J.; Wang, K.; Gan, M.; Zhu, C. Spatial identification and trade-off analysis of land use functions improve spatial zoning management in rapid urbanized areas, China. *Land Use Policy* **2022**, *116*, 106058. [CrossRef]
102. Bradner, E.; Iorio, F.; Davis, M. Parameters tell the design story: Ideation and abstraction in design optimization. In Proceedings of the Symposium on Simulation for Architecture & Urban Design, Tampa, FL, USA, 13–16 April 2014; Volume 26.
103. Bertsimas, D.; Tsitsiklis, J.N. *Introduction to Linear Optimization*; Athena Scientific: Belmont, MA, USA, 1997.
104. Van Laarhoven, P.J.M.; Aarts, E.H. *Simulated Annealing*; Springer: Dordrecht, The Netherlands, 1987.
105. Kennedy, J.; Eberhart, R. Particle swarm optimization. In Proceedings of the ICNN'95—International Conference on Neural Networks, Perth, Australia, 27 November–1 December 1995; Volume 4, pp. 1942–1948.
106. Deb, K.; Pratap, A.; Agarwal, S.; Meyarivan, T.A. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Trans. Evol. Comput.* **2002**, *6*, 182–197. [CrossRef]
107. Li, H.; Zhang, Q. Multi-objective optimization problems with complicated pareto sets MOEA/D and NSGA-II. *IEEE Trans. Evol. Comput.* **2009**, *13*, 284–286. [CrossRef]
108. Chow, C.K.; Yuen, S.Y. A multiobjective evolutionary algorithm that diversifies population by its density. *IEEE Trans. Evol. Comput.* **2011**, *16*, 149–172. [CrossRef]
109. Cao, K.; Batty, M.; Huang, B.; Liu, Y.; Yu, L.; Chen, J. Spatial multi-objective land use optimization: Extensions to the non-dominated sorting genetic algorithm-II. *Int. J. Geogr. Inf. Sci.* **2011**, *25*, 1949–1969. [CrossRef]
110. Sharifi, A. From Garden City to Eco-urbanism: The quest for sustainable neighborhood development. *Sustain. Cities Soc.* **2016**, *20*, 1–6. [CrossRef]
111. Federal Register "Part III, Department of Health and Human Services, Centers for Medicare & Medicaid Services, 42 CFR Parts 403 and 408 Medicare Program; Medicare Prescription Drug Discount Card; Interim Rule and Notice". 15 December 2003. Available online: https://www.cms.gov/Regulations-and-Guidance/Regulations-and-Policies/QuarterlyProviderUpdates/downloads/cms4063ifc.pdf (accessed on 28 June 2023).
112. Millard-Ball, A. The autonomous vehicle parking problem. *Transp. Policy* **2019**, *75*, 99–108. [CrossRef]
113. Duarte, F.; Ratti, C. The impact of autonomous vehicles on cities: A review. *J. Urban Technol.* **2018**, *25*, 3–18. [CrossRef]
114. Gordon, T.J. *Cross-Impact Method*; American Council for the United Nations University: Washington, DC, USA, 1994.
115. Amer, M.; Daim, T.U.; Jetter, A. A review of scenario planning. *Futures* **2013**, *46*, 23–40. [CrossRef]
116. Gordon, T.J. The delphi method. *Futures Res. Methodol.* **1994**, *2*, 1–30.
117. Lee, A.C.; Maheswaran, R. The health benefits of urban green spaces: A review of the evidence. *J. Public Health* **2011**, *33*, 212–222. [CrossRef] [PubMed]
118. Gunawardena, K.R.; Wells, M.J.; Kershaw, T. Utilising green and bluespace to mitigate urban heat island intensity. *Sci. Total Environ.* **2017**, *584*, 1040–1055. [CrossRef] [PubMed]
119. Prudencio, L.; Null, S.E. Stormwater management and ecosystem services: A review. *Environ. Res. Lett.* **2018**, *1*, 033002. [CrossRef]
120. Aronson, M.F.; Lepczyk, C.A.; Evans, K.L.; Goddard, M.A.; Lerman, S.B.; MacIvor, J.S.; Nilon, C.H.; Vargo, T. Biodiversity in the city: Key challenges for urban green space management. *Front. Ecol. Environ.* **2017**, *15*, 189–196. [CrossRef]
121. Niemelä, J.; Saarela, S.R.; Söderman, T.; Kopperoinen, L.; Yli-Pelkonen, V.; Väre, S.; Kotze, D.J. Using the ecosystem services approach for better planning and conservation of urban green spaces: A Finland case study. *Biodivers. Conserv.* **2010**, *19*, 3225–3243. [CrossRef]
122. Haq, S.M. Urban green spaces and an integrative approach to sustainable environment. *J. Environ. Prot.* **2011**, *2*, 601–608. [CrossRef]

123. Koohsari, M.J.; Mavoa, S.; Villanueva, K.; Sugiyama, T.; Badland, H.; Kaczynski, A.T.; Owen, N.; Giles-Corti, B. Public open space, physical activity, urban design and public health: Concepts, methods and research agenda. *Health Place* **2015**, *33*, 75–82. [CrossRef]
124. Madanipour, A. (Ed.) *Whose Public Space?: International Case Studies in Urban Design and Development*; Routledge: Oxfordshire, UK, 2013.
125. McCormack, G.R.; Rock, M.; Toohey, A.M.; Hignell, D. Characteristics of urban parks associated with park use and physical activity: A review of qualitative research. *Health Place* **2010**, *16*, 712–726. [CrossRef]
126. Pickett, S.T.; Cadenasso, M.; Grove, J.; Nilon, C.; Pouyat, R.; Zipperer, W.; Costanza, R. Urban ecological systems: Linking terrestrial ecological, physical, and socio-economic components of metropolitan areas. *Annu. Rev. Ecol. Syst.* **2001**, *32*, 127–157. [CrossRef]
127. Wu, X.; Murray, A.T.; Xiao, N. A multiobjective evolutionary algorithm for optimizing spatial contiguity in reserve network design. *Landsc. Ecol.* **2011**, *26*, 425–437. [CrossRef]
128. Wright, J.; Revelle, C.; Cohon, J. A multi-objective integer programming model for the land acquisition problem. *Reg. Sci. Urban Econ.* **1983**, *13*, 31–53. [CrossRef]
129. Nalle, D.J.; Athur, J.L.; Sessions, J. Designing compact and contiguous reserve networks with a hybrid heuristic algorithm. *For. Sci.* **2002**, *48*, 59–68.
130. U.S. Environmental Protection Agency. *EnviroAtlas Terms and Definitions*. Available online: https://enviroatlas.epa.gov/enviroatlas/glossary/glossary.html#impervious (accessed on 7 June 2023).
131. Arnold, C.L.; Gibbons, C.J. Impervious surface coverage. *J. Am. Plan. Assoc.* **1996**, *62*, 243–258. [CrossRef]
132. Klein, R.D. Urbanization and stream water quality impairment. *Water Resour. Bull.* **1979**, *15*, 948–963. [CrossRef]
133. Galli, J. *Thermal Impacts Associated with Urbanization and Stormwater Management Best Management Practices: Metropolitan Washington Council of Governments*; Maryland Department of the Environment: Washington, DC, USA, 1991; p. 188.
134. Schueler, T.R. The importance of imperviousness. *Watershed Prot. Tech.* **1994**, *1*, 100–111.
135. Tilley, J.S.; Slonecker, E.T. *Quantifying the Components of Impervious Surfaces*; Federal Highway Administration (US): Washington, DC, USA, 2007.
136. Agriesti, S.; Brevi, F.; Gandini, P.; Marchionni, G.; Parmar, R.; Ponti, M.; Studer, L. Impact of driverless vehicles on urban environment and future mobility. *Transp. Res. Procedia* **2020**, *49*, 44–59. [CrossRef]
137. Kittelson & Assoc, Inc.; Parsons Brinckerhoff, Inc.; KFH Group, Inc.; Texam A&M Transportation Institute, & Arup. *Transit Capacity and Quality of Service Manual*, 3rd ed.; Transit Cooperative Highway Research Program (TCRP) Report 165; Transportation Research Board: Washington, DC, USA, 2013.
138. Zacharias, J. Pedestrian Behavior and Perception in Urban Walking Environments. *J. Plan. Lit.* **2001**, *16*, 3–18. [CrossRef]
139. Handy, S.; Niemeier, A.D. Measuring Accessibility: An exploration of issues and alternatives. *Environ. Plan. A* **1997**, *29*, 1175–1194. [CrossRef]
140. Robbins, P.; Polderman, A.; Birkenholtz, T. Lawns and toxins: An ecology of the city. *Cities* **2001**, *18*, 369–380. [CrossRef]
141. Banks, J.; McConnell, R. National Emissions from Lawn and Garden Equipment. US Environmental Protection Agency (U.S. EPA). 2015. Available online: https://www.epa.gov/sites/default/files/2015-09/documents/banks.pdf (accessed on 7 June 2023).
142. Lee, O.; Guhathakurta, S. An analysis of the effects of suburban densification on vehicle use for shopping: Do existing residents respond to land-use changes in the same way as recent movers? *J. Transp. Geogr.* **2018**, *68*, 193–204. [CrossRef]
143. Saelens, B.E.; Handy, S.L. Built environment correlates of walking: A review. *Med. Sci. Sport. Exerc.* **2008**, *40*, S550–S566. [CrossRef] [PubMed]
144. Yang, H.; Liang, Y.; Yang, L. Equitable? Exploring ridesourcing waiting time and its determinants. *Transp. Res. Part D Transp. Environ.* **2021**, *93*, 102774. [CrossRef]
145. Zhang, L.; Menendez, M. Modeling and evaluating the impact of city block size on traffic performance. *J. Urban Plan. Dev.* **2020**, *146*, 04020021. [CrossRef]
146. Sevtsuk, A.; Kalvo, R.; Ekmekci, O. Pedestrian accessibility in grid layouts: The role of block, plot and street dimensions. *Urban Morphol.* **2016**, *20*, 89–106. [CrossRef]
147. Arnold, J.E.; Graesch, A.P.; Ochs, E.; Ragazzini, E. *Life at Home in the Twenty-First Century: 32 Families Open Their Doors*; ISD LLC: Bristol, CT, USA, 2012.
148. Kim, S.; Choo, S.; Choi, S.; Lee, H. What Factors Affect Commuters' Utility of Choosing Mobility as a Service? An Empirical Evidence from Seoul. *Sustainability* **2021**, *13*, 9324. [CrossRef]
149. U.S. Census Bureau. An Aging Nation: Projected Number of Children and Older Adults. 2018. Available online: https://www.census.gov/library/visualizations/2018/comm/historic-first.html (accessed on 7 June 2023).
150. Harvard University, Joint Center for Housing Studies. Projections and Implications for Housing a Growing Population: Older Adults 2015–2035. 2016. Available online: http://www.jchs.harvard.edu/housing-a-growing-population-older-adults (accessed on 7 June 2023).
151. Riggs, W.; Pande, A. *Gaps and Opportunities in Accessibility Policy for Autonomous Vehicles*; Project 2106; Mineta Transportation Institute: San Jose, CA, USA, 2021.
152. Bayless, S.H.; Davidson, S. *Driverless Cars and Accessibility: Designing the Future of Transportation for People with Disabilities*; The Intelligent Transportation Society of America (ITS America): Washington, DC, USA, 2019.

153. Graham, S.M.; Joshi, A.; Pizlo, Z. The traveling salesman problem: A hierarchical model. *Mem. Cogn.* **2000**, *28*, 1191–1204. [CrossRef] [PubMed]
154. Sweda, T.M.; Klabjan, D. Finding minimum-cost paths for electric vehicles. In Proceedings of the 2012 IEEE International Electric Vehicle Conference, Greenville, SC, USA, 4–8 March 2012; pp. 1–4.
155. Vijay, R.; Cherian, J.; Riah, R.; De, B.N.; Choudhury, A. Optimal placement of roadside infrastructure sensors towards safer autonomous vehicle deployments. In Proceedings of the 2021 IEEE International Intelligent Transportation Systems Conference (ITSC), Indianapolis, IN, USA, 19–22 September 2021; pp. 2589–2595.
156. Habibovic, A.; Lundgren, V.M.; Andersson, J.; Klingegård, M.; Lagström, T.; Sirkka, A.; Fagerlönn, J.; Edgren, C.; Fredriksson, R.; Krupenia, S.; et al. Communicating intent of automated vehicles to pedestrians. *Front. Psychol.* **2018**, *9*, 1336. [CrossRef]