URBANO: A computational tool-kit for integrated urban design incorporating active transportation, pollution, and outdoor comfort models to facilitate the design of healthy and sustainable urban habitats

Center for Transportation, Environment, and Community Health
Final Report

by
Timur Dogan, Samitha Samaranayake
December 31, 2019

DISCLAIMER

TECHNICAL REPORT STANDARD TITLE PAGE

1. Report No.	2.Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle URBANO: A computational tool-kit for integrated urban design incorporating active transportation, pollution, and outdoor comfort models to facilitate the design of healthy and sustainable urban habitats		5. Report Date December 31, 2019 6. Performing Organization Code
7. Author(s) Timur Dogan (https://orcid.org/0000-0003-0749-8465) Samitha Samaranayake(https://orcid.org/0000-0002-5459-3898)		8. Performing Organization Report No.
9. Performing Organization Name and Address Department of Architecture, Cornell University, 129 Sibley Dome, Cornell University, Ithaca, NY 14853		10. Work Unit No. 11. Contract or Grant No. 69A3551747119
12. Sponsoring Agency Name and Address U.S. Department of Transportation 1200 New Jersey Avenue, SE Washington, DC 20590		13. Type of Report and Period Covered Final Report 10/01/2018– 12/31/2019 14. Sponsoring Agency Code US-DOT
15. Supplementary Notes		

16. Abstract

Rapid urbanization and new global construction estimated to be 250x NYC by 2050 is increasing traffic congestion, pollution, and related health threats. Thus, it is imperative that we develop new modeling capabilities that allow urban designers to quantify the performance of mobility solutions, sustainability, public health impacts, pedestrian thermal comfort and pollution exposure during the earliest stages of a design process. Embedded in a generative, performance-driven design process, such a tool can significantly facilitate the design of healthy and sustainable urban habitats that promote active mobility.

17. Key Words	18. Distribution Statement
Walkability, active mobility, urban design, computational design, modeling, software	Public Access: Conference Proceedings and Journal Paper. Free software downloadable from urbano.io

19. Security Classif (of this report)	20. Security Classif. (of this page)	21. No of Pages	22. Price
Unclassified	Unclassified		

Form DOT F 1700.7 (8-69)

URBANO: A computational tool-kit for integrated urban design incorporating active transportation, pollution, and outdoor comfort models to facilitate the design of healthy and sustainable urban habitats

Abstract

Modern planning paradigms promote the design of walkable neighborhoods. To allow urban designers to understand the consequences of design choices regarding the street network as well as the allocation of density, program, and amenities, it is imperative to develop new modeling capabilities to facilitate the design of healthy and sustainable urban habitats that promote active mobility. The paper introduces a new, easy-to-use, urban design tool called Urbano that can import and translate urban data into actionable urban design feedback using active mobility simulations. The tool evaluates accessibility and utilization of amenities, streets, and public spaces and introduces two new urban design metrics called Streetscore and Amenityscore, and an expanded version of the well-known Walkscore. The tool and metrics are tested in a series of case studies.

Keywords

Urban Design, Mobility Simulation, Network Analysis, Walkability, Urban Data

Context

Traffic congestion in cities corresponds to an economic cost of roughly $121 billion per year (Schrank, Eisele, and Lomax 2012), and studies attribute 3.3 million and rising premature deaths globally to traffic-related pollution (Apte et al. 2015). This is a worrisome circumstance, especially in the context of rapid population growth and urbanization that require a densification of existing cities and the building of new urban habitats equivalent to 250 times New York City in the next thirty years (UNEP 2015). However, this can also be seen as a unique opportunity to improve the built environment through integrated and well-informed urban design processes.

Current planning paradigms promote high density, walkable neighborhoods for several reasons. The risk for chronic diseases may be reduced if the neighborhoods are walkable (Frank et al. 2006) (Lee and Buchner 2008). Further, walkable neighborhoods support local businesses, promote tourism, attracted investors, higher employment, and property values (Claris and Scopelliti 2016). Finally, it has been shown that walkable cities foster an increase in social capital and political participation (Leyden 2003). The portion of greenhouse gas emissions caused by the transportation sector has increased more than any other sector since 1990 (United States Environmental Protection Agency. 2012). Promoting walking and biking instead of driving is widely recognized as a strategy to mitigate traffic-related emissions (Ogilvie et al. 2011) (Lindsay, Macmillan, and Woodward 2011). Further, walkable neighborhoods support local businesses, promote tourism, attract investors, higher employment, and property values (Claris and Scopelliti 2016). Finally, walkable cities foster an increase in social capital and political participation (Leyden 2003).

Mobility Simulation

Understanding the implications of urban design choices on the mobility of urban dwellers while incorporating this understanding into very early stages of urban design processes provides a unique opportunity to facilitate the design of walkable cities. One of the major hindering factors in this process is the lack of tools that can quantify urban design trade-offs and assist with the design process (Besserud and Hussey 2011).

While many mobility simulators exist, mobility aware urban design remains challenging. State-of-the-art travel demand modeling software like TransCAD (Caliper 2008) have detailed and sophisticated travel demand models that focus on the precision of transportation modeling and forecasting processes. These tools are intended to be used by transportation professionals and traffic engineers. Further, their standalone character separates the design and analysis processes. This lack of interactivity between the two processes is not feasible for a co-design process where immediate feedback for design choices is critical.

Other tools are integrated into computer-aided design (CAD) software and calculate simplified urban mobility metrics that are more suitable. The Urban Network Analysis (UNA) toolbox (Sevtsuk and Mekonnen 2012) for ArcGIS (ESRI 2017) and Rhinoceros (McNeel 2016b), allows designers to analyze urban street networks using Geographic Information Systems (GIS) data. However, UNA only computes spatial metrics like network centrality, reach, and closeness. While the above metrics are fast to compute and rely on widely available street network data, they do neither incorporate key urban design parameters such as program allocation, amenities, and attractions nor do they consider the population density distribution in the model.

In order to evaluate the walkability of cities, efforts have been made to rank them based on a shortest-distance analysis between different points of interest. These walkability ratings, commonly referred to as Walkscore (Brewster et al. 2009), are computed on a scale of 1-100 and include factors such as accessibility to services and amenities like grocery stores, doctors, parks, schools, hospitals, and public transportation. The Urban Modelling Interface (Reinhart et al. 2013) can compute the Walkscore metric. The main challenge with this tool is to provide the required inputs, such as street networks, buildings, and the locations of amenities that have to be entered manually by the user.

While contextual urban data is readily available for most cities, the absence of workflows to quickly gather and utilize the data in urban design tools is one of the major bottlenecks that urban modelers currently face. Furthermore, a simple metric like the Walkscore does not provide adequate information to help improve the design process. Firstly, services and amenities to which it may be essential to have walking access differ by demographic groups. Thus, designers should be able to evaluate walkability with demographic-specific metrics. Secondly, a designer might add many services and amenities to improve the Walkscore of a proposal. However, these may not be financially viable without adequate demand. This showcases that the design process should aim to strike a balance between the availability of services and the demand to sustain these services, and new metrics that can evaluate this balance are needed.

Methodology

This paper introduces a modeling framework, named Urbano, to facilitate the design of walkable and sustainable neighborhoods through mobility-aware urban design. It aims to facilitate site analysis and can provide valuable early design feedback for urban designers, planners, and developers concerning street layout as well as program and density allocation. The framework utilizes and translates urban data from different sources in order to compute a series of new location-aware, travel-related urban design metrics. The generated simulation results may then be used to make urban design proposals more conducive to active mobility.

This research facilitates the generation of measurable, actionable and differentiated design feedback and offers the following contributions: (1) Automated model setup from GIS and other urban data sources, (2) The ability to create detailed models of the population and amenity demand profiles that describe the needs and preferences of different demographic groups, (3) The introduction of an Amenityscore that describes the demand for services at a specific amenity, (4) The introduction of a Street Utilization metric that indicates the pedestrian density on particular street segments, (5) A mobility toolkit inside a visual scripting environment that includes the ability to customize workflows and to define custom performance metrics.

Software Workflow

Urbano allows designers to build mobility models, run network and amenity analyses within the Rhinoceros CAD platform and the visual scripting environment Grasshopper (McNeel 2016a). The tool follows a four-step workflow: (1) It imports contextual data such as existing streets, buildings, and points of interest. (2) The contextual model can then be edited, and design interventions can be inserted using regular CAD workflows or scripted inputs. (3) This information is then used to generate a mobility simulation model automatically. (4) Analysis and design metrics are then run that can be visualized numerically or spatially.

Importing and Editing Metadata

After the location and a boundary for the study area is selected, Urbano can import streets and buildings, along with their metadata, from sources such as shapefiles that can be obtained from municipal GIS such as New York City's OpenData (City of New York 2017) or OpenStreetMap (OSM) (OpenStreetMap 2018). For points of interest (POIs), Urbano can directly download map data from OSM or extract location information using the Google Places API (Google 2018). By automating the process of parsing the map data from different sources, users can build up-to-date contextual models. It is essential to mention that the quality of the input data can have a significant effect on the computed results, and it varies by source. For example, in most cases, OpenStreetMap has significantly fewer POI entries compared with Google data.

Consequently, a model that uses data where only a few POIs have been recorded, will yield lower Walkscore results. Further, a potential bias that may be contained in the data is difficult to detect without reference data. Hence, it is crucial to use consistent input data quality when modelers intend to compare simulation results.

Streets, buildings, and amenities are represented by geometric primitives such as curves or points. Metadata such as names, types, and addresses are attached to the geometric data using serializable dictionaries that can be modified and customized alongside the geometric objects parametrically within Grasshopper or through the CAD user interface in Rhino. To run the Amenityscore and Walkscore analyses, metadata on building-level population density and the amenity capacity is necessary. If this information is not available, the tool can estimate population size and amenity-capacities according to Equation 1 and 2 using total building floor area, area usage breakdown, and generalized occupant densities (ASHRAE 2013) (SIA 2006). In NYC, for example, users can leverage lot-level zoning data from the City of New York's Parcel Land Use and Tax Ownership (PLUTO) to obtain all required inputs.

$$P = S * UF * (1 - Lp) \,/\, Pd$$

P = Building-level Population

S (Building Area) = Building Footprint Area * Building Floors

UF (Area Usage Breakdown Fraction (residential / non-residential))

Lp (Circulation and Secondary Use Area Proportion) = 0.2 (default)

Pd (People Density in m^2/People) = $\begin{cases} \text{(default) } 40, & \text{if residential} \\ \text{(default) } 14, & \text{if non} - \text{residential} \end{cases}$

Equation 1. Building-level Population Synthesis

$$\forall\, i \in \{\, 1,2,\ldots, N_A \,\} \qquad AA_i = (CA_{lot} - OA_{lot})/N_A \qquad C_i = AA_i/\, P$$

N_A = Number of Amenities in the Lot

AA = Amenity Area

CA_{lot} = Commercial Area of the Lot

OA_{lot} = Office Area of the Lot

C = Amenity Capacity

Pd (People Density in m^2/People) = (refer to ASHRAE or SIA reference)

Equation 2. Amenity Capacity Synthesis

Since the lot-level area usage breakdown is usually hard to acquire, a dataset with generic amenity capacities is provided in Urbano as a guide for users (Table 1). The distribution of the derived areas of each activity is plotted as Figure 1. The Interquartile Range is used to filter outliers that yield huge areas for certain amenities. This can occur where other existing POIs are not correctly recorded in the GIS dataset. The mean of the data within the IQR is then defined as the activity-specific generic capacity. The area of each amenity in the borough of Manhattan is derived using Equation 2 with the inputs from PLUTO.

Table 1. Generic Amenity Capacities

Study Type	Area Lower Boundary (sqm)	Area Upper Boundary (sqm)	Generic Area (sqm)	Area Per Person (sqm/p)	Capacity (person)
convenience_store	29	121	62	2	31
department_store	34	440	148	2	74
restaurant	29	112	61	2	31
clothes_store	13	103	43	1	43
pharmacy	27	134	65	1	65
café	24	115	60	2	30
bank	22	171	72	5	14
books_store	14	103	44	1	44
bar	33	131	72	2	36
cinema	25	389	144	1	144

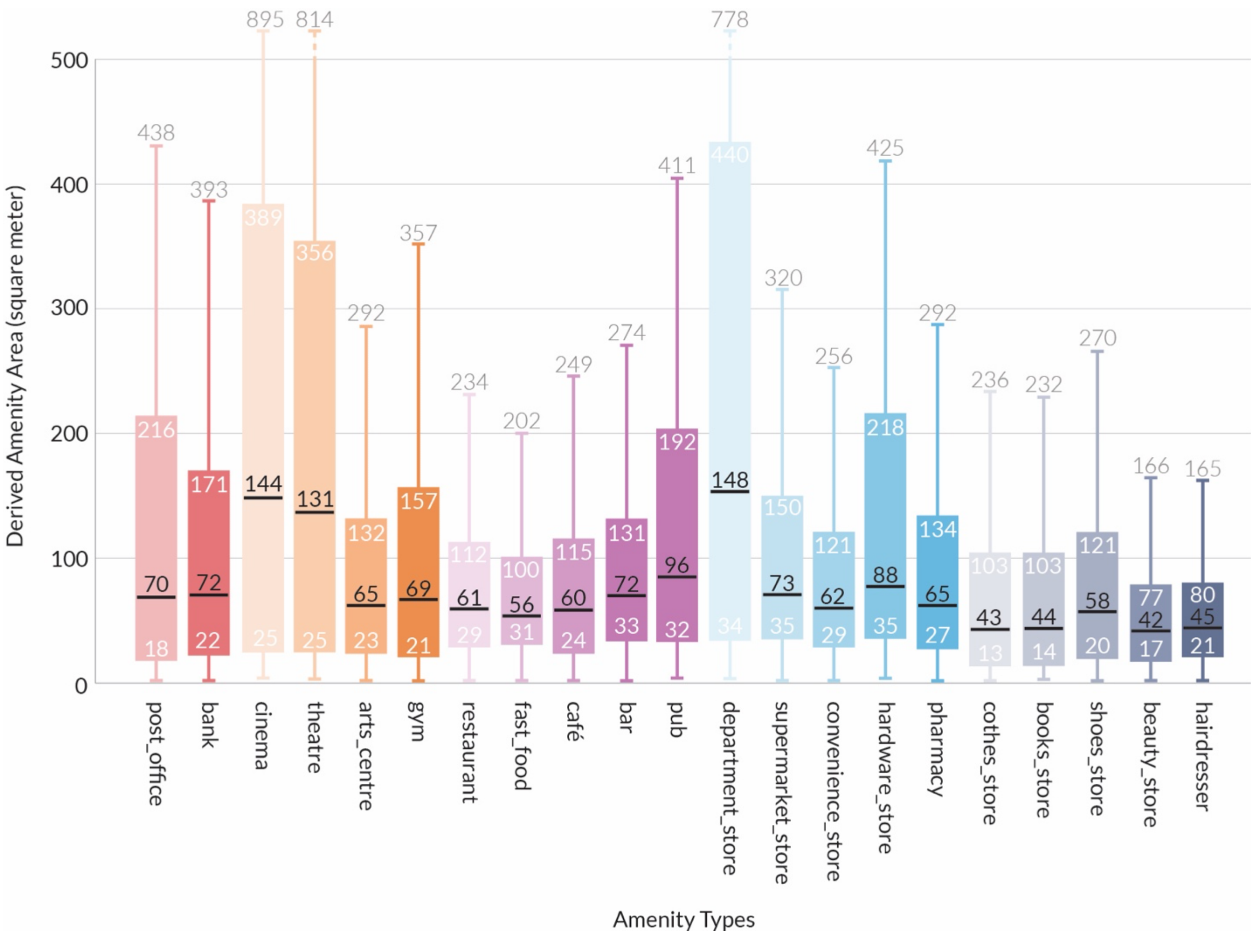


Figure 1. Shows the interquartile range (IQR), minimum, maximum, and the IQR-median of floor area footprints (square meter) observed for different amenity types in Manhattan.

Urbano Model

The model consists of streets, buildings, and POIs/amenities. Figure 2 provides an overview of the flow of information. The tool merges several input streams containing buildings, streets, amenities, and their metadata. To construct the mobility network, the software post-processes and cleans up the street networks and then connects the buildings to their closest street. After checking for intersections in streets and splitting the street curves into segments, a topological graph is built using street segments as edges and the intersections (and endpoints) as vertices. This graph is later used for pathfinding. As part of this processing, the shortest distance path matrix is computed for all the vertices of the graph.

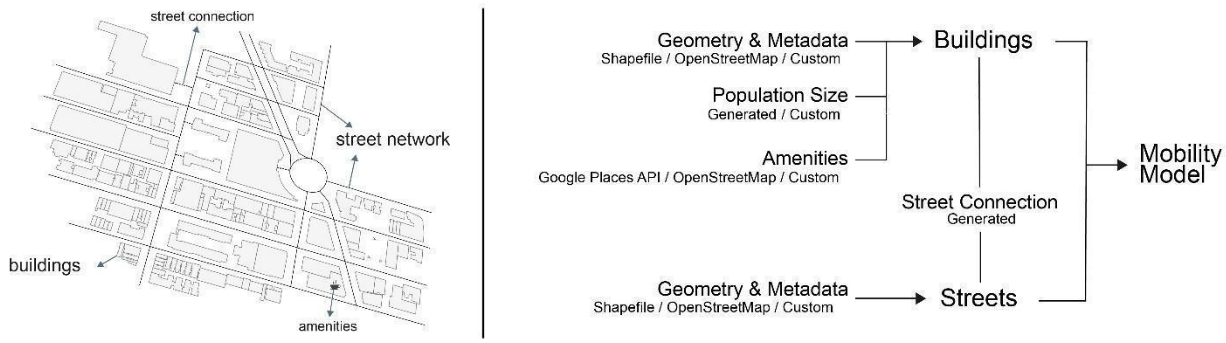


Figure 2. Keymap of Columbus Circle and diagram of contributing data used for building an Urbano model

Amenity Demand Profiles

The active mobility simulation is based on the concept of activity trips, defined by the shortest path between a trip origin in a building and the destination's amenity. The activity trips are generated via a data-driven metric of amenity demand profiles (ADP). ADPs describe the spatiotemporal distribution of human activities according to the activeness in urban amenities. The ADP drives Urbano's trip-sending algorithm. In theory, the more detailed an ADP can describe human behavior in cities, the more accurate the urban mobility pattern and amenity utilization predictions would be. However, defining ADPs at a high level of detail is notoriously difficult, and the required data is often not available to support a design process. Hence, the tool utilizes a simple ADP that lists desired activities over time. This data can be created by the user to test scenarios for an assumed demographic, or it can be derived from urban data sources if available.

Deriving location-specific ADPs:

In this study, location-specific ADP's are derived using Google Places "Popular Times" data shown in Table 2. This data represents a normalized utilization of an amenity for a given time. To use this information in Urbano, a post-processing workflow (Yang, Samaranayake, and Dogan 2019) is implemented that requires two additional inputs: The amenity capacities (C_{type}) given in Table 1 and the total population in the analysis area (P_{area}). Equation 3 summarizes this process and yields ADP data as shown in Table 3. The equation computes the percentage of the total population in the study area that engages in a particular activity (x_t). The resulting ADP data can be represented by a 24-hour timeline (Figure 3). The y-axis of the graph represents the overall amount of activities in the studied region. Activities peak during the day and the lowest point in the early morning. Each layer in the graph represents the demand pattern of a particular amenity. Some amenities peak earlier or later due to their services offered. For example, banks and post offices tend to stop service early in the afternoon, while bars and pubs become dominant activities during the night.

These amenity demand profiles can change significantly between locations and times of the week. To illustrate this phenomenon, the ADPs for two different urban areas (Lower Manhattan, NYC, and Central Paris, France) are shown for both weekdays and weekends (Figures 3). The number of data points included in the ADP generation is summarized in Table 4, and the areas that were analyzed are drawn in Figure 4. The total population assumed for the two study areas was 0.6 million for Manhattan (NYC Open Data 2019) and 2.2 million for Paris (Data.Gouv.Fr 2019).

$$\bar{\alpha}_t = \frac{1}{m}\sum_{i=1}^{m}\alpha_i \quad x_t = \left(n \cdot C_{type} \cdot \bar{\alpha}_t\right)/P_{area}$$

n = Total number of amenities of the same type in the ADP analysis area (Table 4)

m = Number of amenity samples from (n) that are used to successfully query Google Places "Popular Times" data

α_i= Activeness from Google Places Popular Times normalized to a 0-100% range. Specific time steps or weekday/weekend averages can be used. (A data sample for one amenity is shown in Table 2)

$\bar{\alpha}_t$= Average activeness of all sampled amenities in percent.

x_t = Percent of the total population engaging in an activity. The output is shown in Table 3.

C_{type} = Amenity capacity of an amenity type given in the number of persons (Table 1).

P_{area} = Total population in the study area

Equation 3. Function to compute ADP data for each amenity-type and time-step.

Table 2. A sample sheet of the comprehensive information collected for one amenity from Google Places API. An array of 24-hour activeness in percent (%) is calculated independently for weekdays and weekends, expressing its temporal utility pattern.

Amenity type: café		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Name: Orens Coffee	Mon	0	0	0	0	0	0	0	29	90	87	48	58	80	93	90	70	45	25	0	0	0	0	0	0
Phone: +1 212-717-3907	Tue	0	0	0	0	0	0	0	45	87	90	70	67	77	80	74	61	41	25	0	0	0	0	0	0
	Wed	0	0	0	0	0	0	0	51	77	74	58	61	80	100	96	77	48	22	0	0	0	0	0	0
	Thu	0	0	0	0	0	0	0	22	58	90	87	61	54	67	83	80	58	32	0	0	0	0	0	0
Address: 985 Lexington Ave, New York	Fri	0	0	0	0	0	0	0	51	77	67	61	67	74	74	64	54	38	25	0	0	0	0	0	0
	Weekday Average ($\bar{\alpha}_i$)	0	0	0	0	0	0	0	39.6	77.8	81.6	64.8	62.8	73	82.8	81.4	68.4	46	25.8	0	0	0	0	0	0
Coordinate: 40.769769, -73.962482																									
	Sat	0	0	0	0	0	0	0	22	38	51	61	58	58	67	87	93	80	48	0	0	0	0	0	0
	Sun	0	0	0	0	0	0	0	0	51	61	51	61	67	61	61	67	61	0	0	0	0	0	0	0
Rating: 4.2 **Rating Number:** 60	Weekend Average ($\bar{\alpha}_i$)	0	0	0	0	0	0	0	11	44.5	56	56	59.5	62.5	64	74	80	70.5	24	0	0	0	0	0	0

Table 3. Amenity Demand Profile data in percent for a weekday in NYC.

Study Type	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
convenience_store	0.3	0.2	0.2	0.2	0.2	0.3	0.4	0.6	0.8	0.8	0.8	0.9	1	1	1.1	1	0.8	0.7	0.7	0.6	0.6	0.6	0.5	0.4
department_store	0	0	0	0	0	0	0	0	0.2	0.4	0.7	1	1.3	1.5	1.5	1.5	1.6	1.7	1.6	1.2	0.8	0.3	0	0
restaurant	1	0	0	0	0	0	0	1	2.1	3.1	4.1	7.2	12.4	14.4	12.4	9.3	8.3	11.3	15.5	17.5	16.5	12.4	7.2	3.1
clothes_store	0	0	0	0	0	0	0	0	0	1.1	3.3	5.5	6.6	7.7	7.7	7.7	8.8	9.9	8.8	5.5	2.2	0	0	0
pharmacy	1.1	0.5	0.5	0.3	0.3	0.3	0.8	1.6	3	4.1	4.9	5.7	6.3	6.8	7.1	7.3	7.6	7.6	7.1	6	4.9	4.1	3	1.9
cafe	0	0	0	0	0	0.3	1.4	3.9	5.5	5.5	5.3	5	5.3	5.5	5.5	5.3	4.7	4.2	3.6	2.8	1.7	0.8	0.6	0
bank	0	0	0	0	0	0	0	0	0.4	1	1.2	1.4	1.5	1.7	1.7	1.7	1.5	1	0.2	0.2	0.2	0.2	0	0
books_store	0	0	0	0	0	0	0	0	0	0.2	0.2	0.5	0.7	0.8	0.9	0.8	0.9	1	1.1	0.9	0.2	0.1	0	0
bar	3.1	2	1.5	0.5	0	0	0	0	0	0	0	1	2	2	2.6	2.6	4.1	6.1	8.7	10.2	10.2	9.7	8.7	7.2
cinema	0	0	0	0	0	0	0	0	0	0	0	0.3	0.6	0.9	1.2	1.5	1.9	2.6	3.7	4.7	5	4.3	3	1.7

Table 4. The total number of amenities in the ADP analysis area. Data source: OSM.

Activity	Convenience	Department	Restaurant	Clothes	Pharmacy	Cafe	Bank	Books	Bar	Cinema
NYC	303	44	2363	512	223	876	347	56	467	30
Paris	911	31	6934	1943	1098	1831	1026	433	1459	81

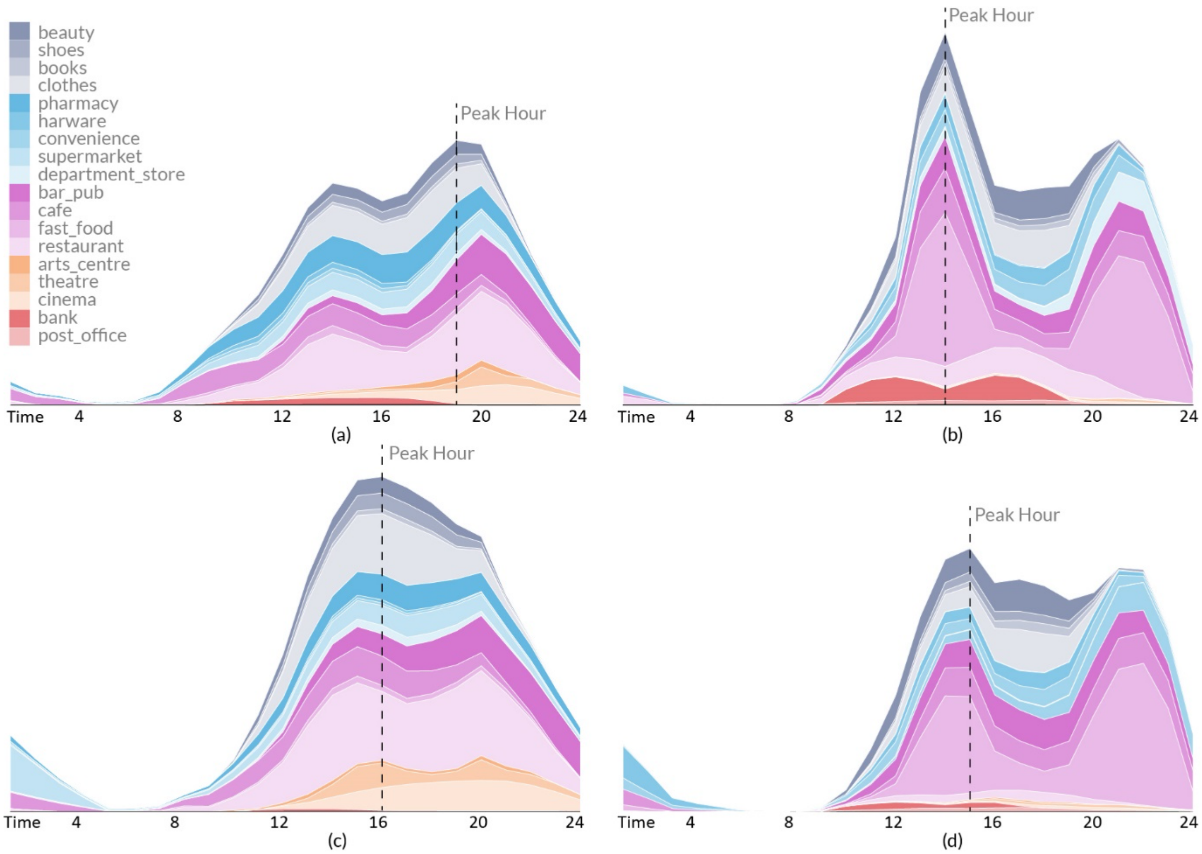


Figure 3. The timeline graph for ADPs reveals spatiotemporal differences. (a) Weekday pattern in Lower Manhattan; (b) Weekday pattern in Central Paris; (c) Weekend pattern in Lower Manhattan; (d) Weekend pattern in Central Paris

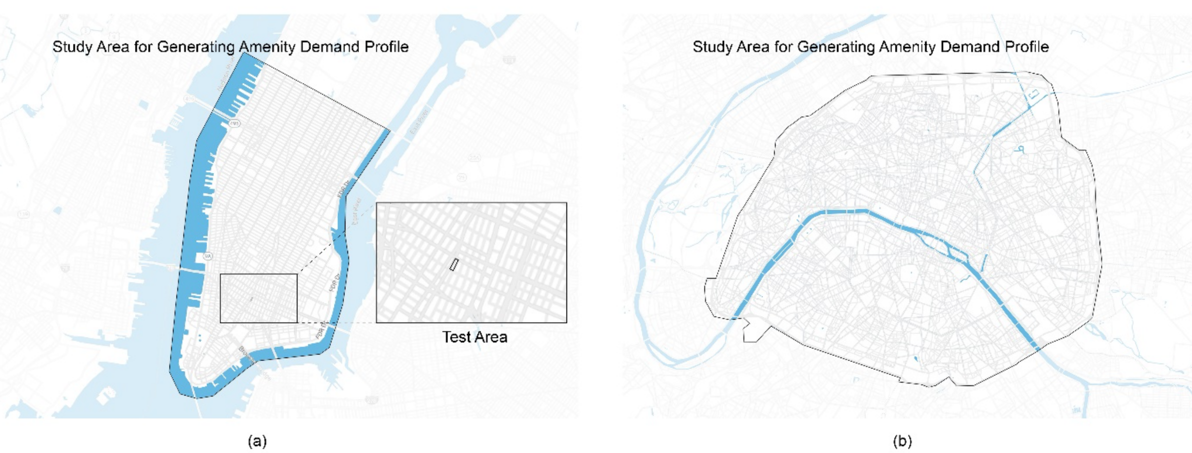


Figure 4. Study areas for generating ADPs. (a) Manhattan NYC; (b) Central Paris

Simulate and Analyze

The active mobility simulation utilizes the Urbano Model consisting of streets, amenities and buildings, and one or multiple ADPs as input. The simulation iterates through each building (trip origin) in the analysis area and then executes a trip-sending algorithm. The trip-sending algorithm calculates the total population in the origin-building and divides it into activities defined in the ADP-data. It then searches for corresponding amenities within walking distance using the shortest paths. This procedure is repeated for if multiple timesteps such as Morning, Noon, Evening, or 24-hour patterns are simulated.

In the trip-sending process, the user can select between different trip-sending modes. For example, in the "Single-Nearest-Destination" mode, the entire population at the origin is sent to one corresponding nearest amenity, which generates the least trips and saves computing time but is less realistic with respect to the population's destination selection behavior. The "Multiple-Destinations-By-Capacities" mode sends people to all reachable amenities in the proportion of the destinations' capacities. The "Distance-Decay" mode models the population's decreasing willingness to go to an amenity that is farther away. Figure 5 visualizes the discrete steps in the trip-sending logic as well as the different trip-sending modes.

The simulation logic outputs a list of trips. Each trip carries information about the origin, destination, route, activity, time, and population. In order to make use of this data in the design process, a set of three new mobility metrics are introduced: Street Utilization, an advanced Walkscore, and Amenityscore.

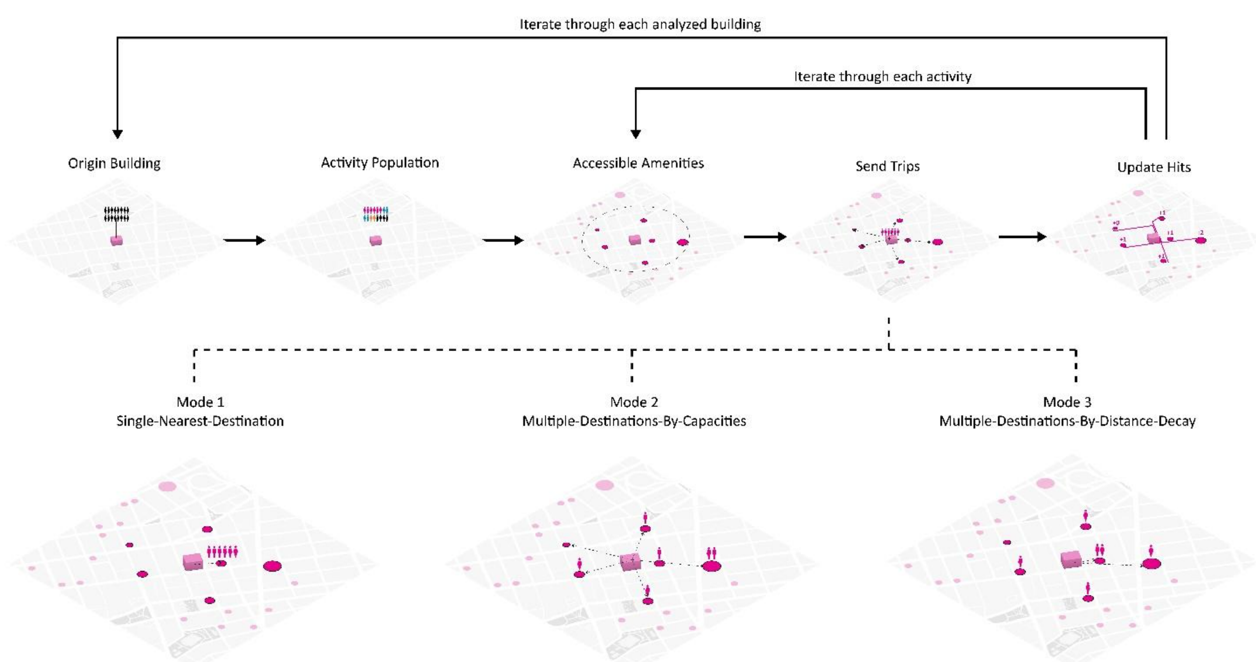


Figure 5. Diagram of the trip-sending process in an Urbano simulation

1) Streetscore

The tool measures street utilization using a simple counter called Streetscore, which evaluates how many people use a certain street segment. This may be used as an indicator of how vibrant a street is within the network in general or at a given time of interest.

2) Walkscore and a new advanced version

Walkscore is a popular walkability metric that gives a point score in the range of 0 to 100 based on the proximity to amenities such as grocery stores, restaurants, shops, banks, and coffee shops. The building-level Walkscore can be computed based on all trips that originate from a building using a decay function (Equation 4) and the weights given in Table 5.

$$Decay(x) = -17.15x^5 + 89.45x^4 - 126.37x^3 + 4.639x^2 + 7.58x + 99.5$$

Equation 4. Decay function for the Walkscore implementation. According to (Brewster et al. 2009)

Table 5. Amenity weights of Walkscore. According to (Brewster et al. 2009)

Amenity	Weights
Grocery	3
Restaurants	.75, .45, .25, .25, .225, .225, .225, .225, .2, .2
Shopping	.5, .45, .4, .35, .3
Coffee	1.25, .75
Banks	1
Parks	1
Schools	1
Books	1
Entertainment	1

While the parameters in Table 5 are defined by the Walkscore metric, Urbano advances the Walkscore and can apply customized weighting to compute a personalized Walkscore (Dogan, Samaranayake, and Saraf 2018) or can adapt the amenity demand to local and demographic preferences (such as shown in Figure 3). Further, this flexibility enables, for example, time-based walkability analysis to evaluate walkability for the morning, lunch, evening, and late-night activities using schedules such as shown in Table 3.

3) Amenityscore

Amenityscore is introduced as a counter-balancing metric to the Walkscore metrics. In an urban design process, it is easy to increase the Walkscore by adding more amenities to the neighborhood. However, adding amenities can be costly and can present an economic risk, especially when it is unclear whether there is sufficient user demand to sustain them. Amenityscore (A) aims to measure the difference between the supply and the demand for a particular amenity type in the area as specified in Equation 5. It employs a simple counter (H) that tallies up the total number of people that are sent to a specific amenity on all trips. Amenity Capacity (C) represents the maximum occupancy. A desirable Amenityscore is close to 0, which indicates a balance of supply and demand. A higher Amenityscore is a sign for a demand that exceeds the supply, while a negative score is an indicator for underutilization of a specific amenity.

$$A = H/C - 1$$

H : People Counter (Amenity Hits)

C : Amenity Capacity

Equation 5. Amenityscore

Case Study

A series of tests are conducted to evaluate the new metrics in the urban design process. Interventions in the street layout are studied, and the impact on overall connectivity and utilization of streets in the model is evaluated. Further, the study iterates through architectural development scenarios with different programs and density allocations to study the impact on walkability and amenity utilization.

The hypothetical site (Figure 6) has residential neighborhoods to the South, a high-density commercial downtown district to the North, institutions to the West, and an industrial area to the East. A highway and a railway adjacent to the East and the North form obstacles in the connectivity of the site. However, the site also offers urban design potential as it could connect the railway station with the downtown, institutional, and residential areas. The design objective is to develop a mixed-use district that can take advantage of the existing conditions and alleviate some of the described connectivity issues.

Figure 6. Site and study area for the case study.

Case Study Setup

The case study imports contextual data from OpenStreetMap. Networks are automatically generated from the imported street segments, residential and non-residential buildings are identified, as shown in Figure 7, and amenities found in the OpenStreetMap data follow the general assumptions presented in Table 1. The trips are generated using the "Multiple-Destination-By-Capacity" trip-sending mode, and the amenity demand profile (ADP) uses the 2pm slice of the NYC Weekday ADP presented in Table 3.

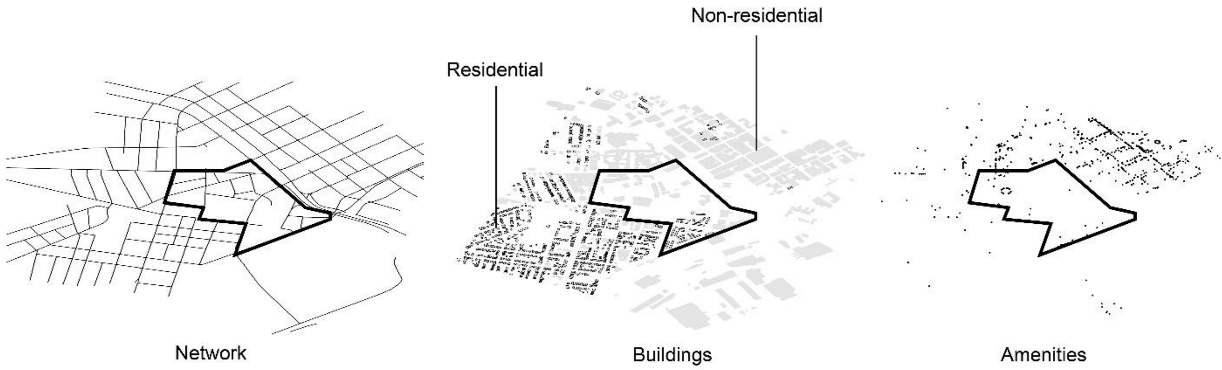


Figure 7. Case study setup

Streetscore

The initial model and the unmodified street network is used for site analysis to identify opportunities and limitations within the existing urban fabric (Figure 8(a)). The Streetscore counts trips through each segment of the network. The most used street segment counts 429 trips or hits, and the overall sum of trips in the network reaches 3080 trips. The analysis reveals that there are several well-utilized streets linking the residential neighborhood with downtown, the station, and the institutions that run through or along the edges of the site. However, the center and the eastern corner are not frequented as much. In response to these findings, two new network design scenarios (Figure 8) are tested: Scenario (b) aims to straighten the links from the residential area to downtown and the station. Results show that the hit count for the central link increases and could thus serve as a major boulevard in the proposed design. Scenario (c) attempts to create multiple routing options within the site to better distribute pedestrians. Results show a lower standard deviation of the Streetscores within the site. This means pedestrian flows are more equally distributed. In this case study, Scenario (c) is chosen because it also has the highest cumulative study area Streetscores. This means that there are new shortest links created in this area that are attracting people to take this route as well as more amenities come into the walking distance for some buildings, resulting in more people walking.

Streetscore is not only influenced by changes in the street network but also incorporates other changes in the Urbano model. The addition of new residential buildings, for example, increases the area's respective number of pedestrians. Further, additional amenities can activate street segments and increase the overall trip count. Besides these parameters, users can override the street length or street resistance to allow biased route selection. This can be useful when considering factors such as street crossings or narrow sidewalks, steps, and elevation changes that pose accessibility challenges.

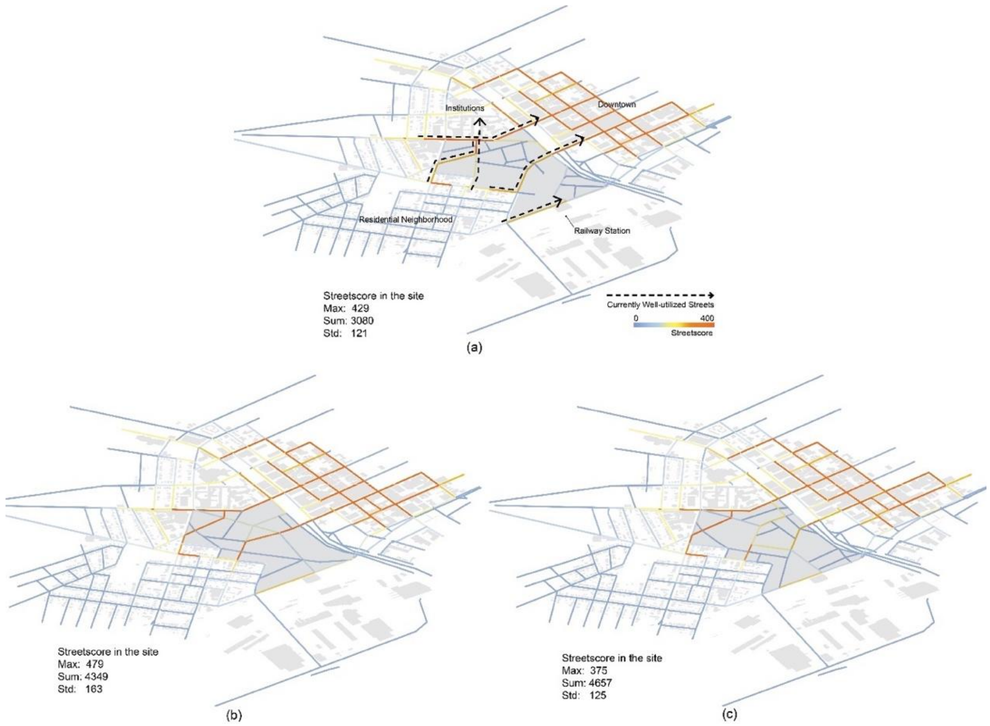


Figure 8. Streetscore analysis (a) for the current site; (b)(c) Two network design scenarios

Amenityscore and Walkscore

The initial Amenityscore analysis is used to identify potential mismatches in the supply and demand for amenities. A cumulative Amenityscore for the entire analysis area by amenity type is shown in Figure 9. It shows clearly that the study area does not have enough walkable banks, restaurants, cafes, and clothes stores. Figure 10 provides further visualization of the spatial distribution of the amenities showing that most of them are concentrated in the downtown area. These findings can help to identify development goals for zoning and program allocation in new developments. The mixed-use development planned on the site thus poses an opportunity to supplement the area with missing amenities while bringing some of those amenities into the walking range of the residential area. This notion is supported by a Walkscore rating for all buildings shown in Figure 11 that shows satisfactory scores in the downtown area but significantly lower scores in the residential and industrial areas. Based on these findings, three design modifications are tested iteratively: (1) Increasing the count and capacity of different amenity types, (2) changing population density, and (3) making small alterations to the street network.

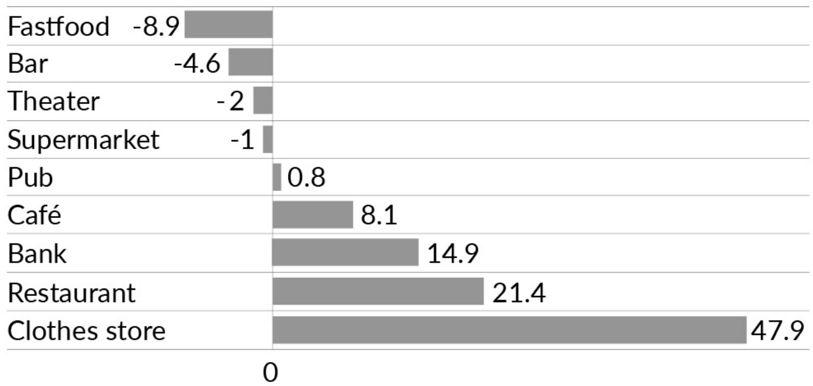


Figure 9. Cumulative Amenityscores for the analysis area by amenity type.

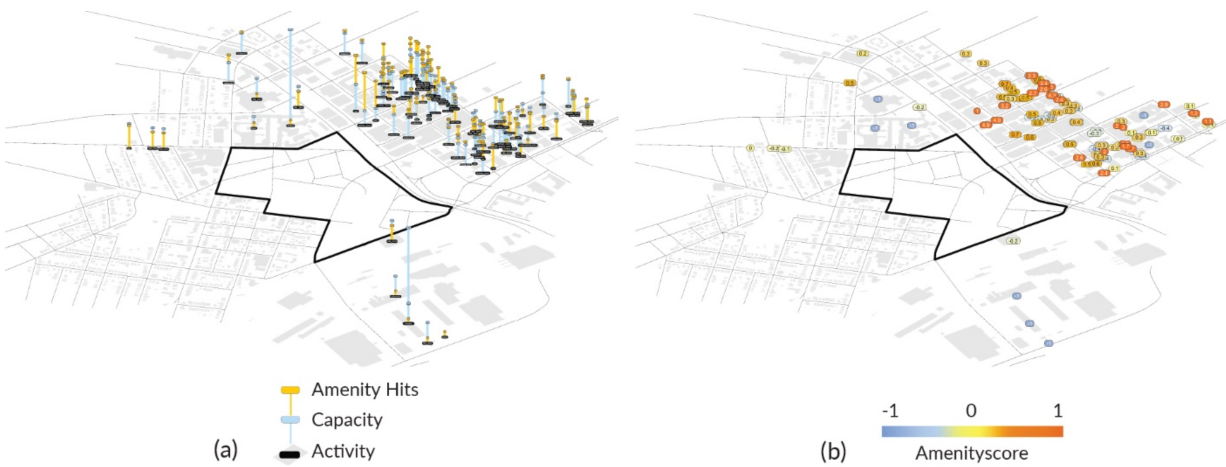


Figure 10. Amenity utilization analysis showing (a) amenity hits and capacities of all amenities in the study area and (b) Amenityscores in the study area.

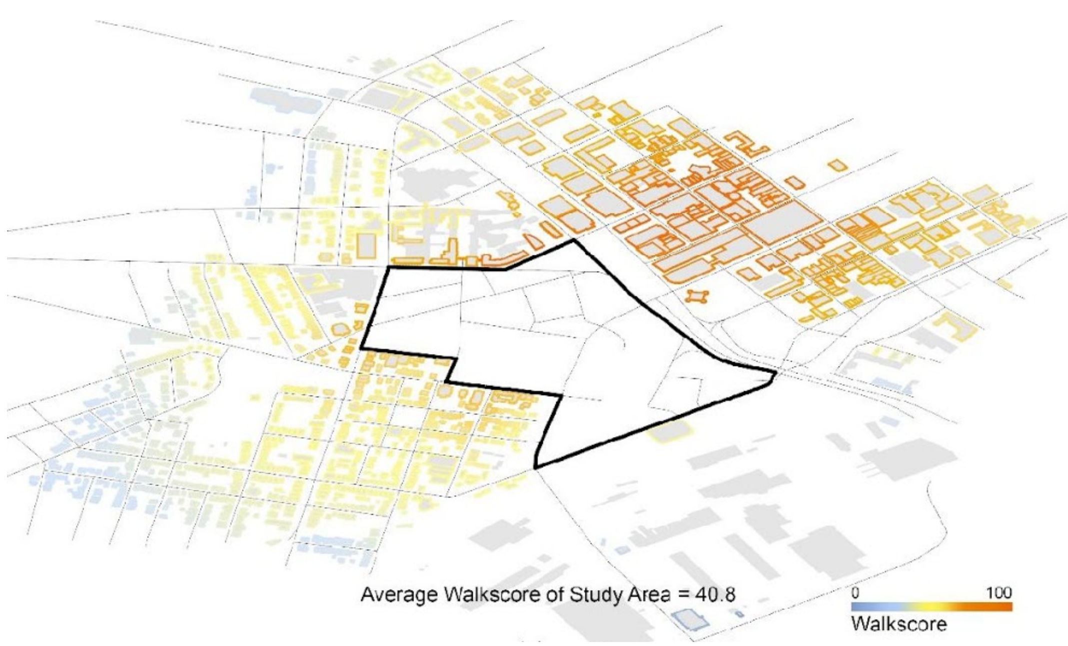


Figure 11. Walkscore rating of all buildings in the study area.

The new design scenarios for the site are shown in Figure 12. Scenario (a) consists of a theater, several apartments, and several office buildings with some amenities on the ground floors, including three restaurants, three clothes stores, and one bar. In this design, restaurants, and clothes stores receive higher Amenityscores while the theatre receives a negative score. The Walkscore rises sharply once amenities are added in Scenario (a) (from 40.8 to 57.9), and it keeps rising in (b) due to an increased supply of clothes stores, an amenity type that is in high demand in the study area as shown in Figure 9. However, adding too much capacity of one amenity type quickly turns the Amenityscore negative (from 7.7 to -1.6). This is an indicator that there will be insufficient demand for the newly added stores and their number should either be scaled back, or more population should be brought to the site. Scenario (c) adds more offices and apartments that raise the total population number and thus increases demand for all amenities from 7.7 to 9.1 score.

This shows that both metrics in tandem can help urban designers to test whether supply and demand for the urban program and amenities are in balance and further allows designers to capitalize on allowable zoning capacities and adjacencies to neighboring urban assets.

Other changes to the mobility system, such as modifications of the street network, also impact the Amenity- and Walkscore. While the extraction of some shortcuts in Scenario (d) reduces most of the Amenityscores, one restaurant's hits increase from 91 to 106 instead. This can be explained by the fact that restaurants further away in the downtown area, are becoming harder to reach by the other neighborhoods. The overall Walkscore decreases (from 57.9 to 55.0) as some amenities become less accessible.

Figure 12. Metrics are responding to different design scenarios.

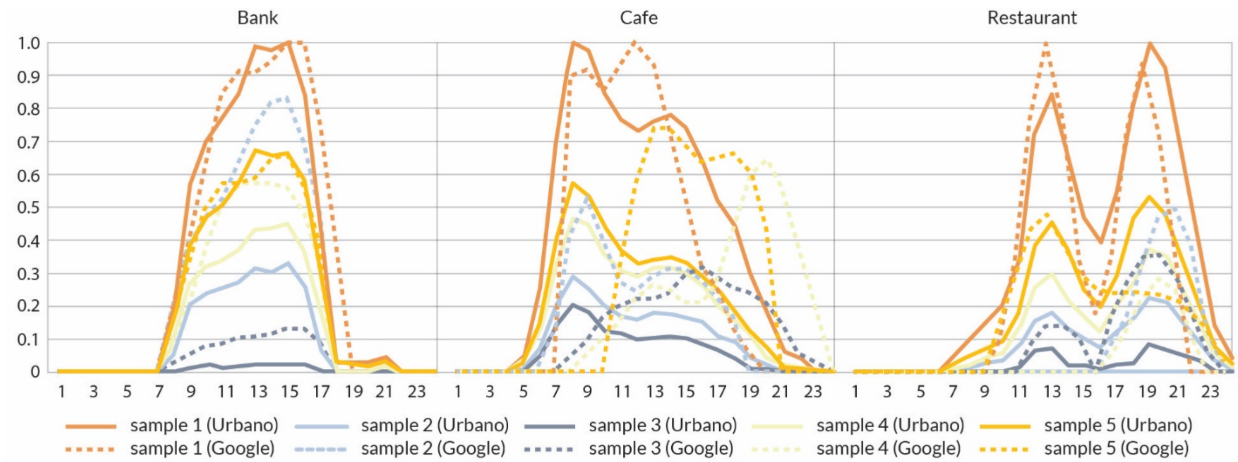
Discussion

It has been demonstrated that readily available geospatial data-sets from OpenStreetMaps, municipal GIS databases as well as service APIs such as GooglePlaces can be translated into new actionable design feedback that can assist urban designers with site analysis, questions about program allocation, density allocation and the resulting consequences on walkability and mobility in general using the two new urban design metrics called Streetscore and Amenityscore, and an expanded version of the well-known Walkscore.

Limitations

Applications for network analysis and data-driven urban design are on the rise with the increasing availability of urban data. However, limitations in data availability, accessibility, and quality remain. For example, the level of detail and quality of data largely differ between countries and cities. While OpenStreetMap provides robust street network data globally, information on buildings and amenities is only provided in major metropolitan areas, and there is often only a fraction of amenities and businesses when compared to Google Places. This raises questions regarding data accessibility, as Google's information is proprietary and can become costly to use. Further, user-generated data that mostly relies on mobile phone location data is problematic due to inconsistent coverage and bias. Popular Times data is not available for all walking destinations such as schools and other civic infrastructure. Hence, modelers should be aware of this bias and always check whether the ADPs used in a simulation are capturing all relevant parameters for a study. An ADP for schools can be derived from typical class schedules and then added to the model. Further, ongoing efforts to improve urban data quality and accessibility will most likely remedy these issues, and the workflows and metrics proposed in this paper will be able to benefit from these improvements.

A further limitation of the presented research is that it is difficult to fully validate the simulation results as there is no openly available reference data with which to compare the modeling results. To provide a basic check of the results, the Urbano workflow was tested in an area in Manhattan using the ADP data shown in Figure 3. Assuming that Urbano's population estimates and amenity capacities are sufficiently accurate, one can compare individual Google PopularTimes profiles (normalized and scaled to amenity capacity) with those predicted by Urbano's trip-sending mode called "Multiple-Destinations-By-Capacities." Figure 13 compares Google's data of five randomly selected banks, cafes, restaurants to Urbano's prediction of the amenities customer count. The profile shapes are similar in general. However, exceptions exist. Figure 13 also shows that cafe visits are harder to predict than visits to other amenity types, likely due to greater diversity within this amenity type (brunch cafes, cafes that also offer dinner, etc.). Considering more details, such as opening hours and popularity, could be leveraged to improve consistency further



.

Figure 13. Comparison of Google Popular Times and amenity use predicted by Urbano.

Future

This paper presents a series of "simple" scores, and a critical reader may conclude any series of score-based evaluations under-represent the range of dynamism inherent to urban life. Whether dwellers will choose to walk within a neighborhood is not only dependent on travel distances to amenities, but also on other factors such as outdoor thermal comfort, exposure to pollution, and personal safety. Further, a pedestrian might not always walk the shortest route but instead might select a path according to other parameters such as shade, sun, number of other people as well as the attractiveness of amenities. While methodologies to quantify street quality exist (Ewing and Handy 2009) that could potentially be used to drive route selection, further research needs to be undertaken to implement them in an urban modeling tool such as Urbano. In addition, further research is required to relate these scores to higher-level metrics on sustainability, public health, economics, and quality of life to understand the broader impacts of good urban design.

Conclusion

Urbano is a new, user-friendly modeling framework that facilitates the assessment of neighborhoods through automated, mobility-aware urban design. The paper shows how geospatial data-sets from OpenStreetMaps, municipal GIS databases as well as service APIs such as GooglePlaces can be translated into new actionable design feedback regarding questions about program allocation, density allocation and the resulting consequences on walkability. The framework models access and utilization of amenities, streets, and public spaces based on an algorithm that estimates active-mobility trips in a given study area. A series of case studies demonstrate the capability and applicability of the new modeling framework, including the trip-sending logic and three novel metrics in urban design framed as StreetScore, AmenityScore, and WalkScore. Urbano provides urban designers, and other stakeholders of the built environment, the ability to quantify and understand the impacts of design choices of new site designs on active mobility, and access to urban amenities.

REFERENCES

Apte, Joshua S., Julian D. Marshall, Aaron J. Cohen, and Michael Brauer. 2015. "Addressing Global Mortality from Ambient PM2.5." *Environmental Science & Technology* 49 (13): 8057–66. https://doi.org/10.1021/acs.est.5b01236.

ASHRAE. 2013. *ASHRAE Handbook—Fundamentals (SI)*. ASHRAE Atlanta.

Besserud, Keith, and Thomas Hussey. 2011. "Urban Design, Urban Simulation, and the Need for Computational Tools." *IBM Journal of Research and Development* 55 (1 & 2): 13–29.

Brewster, Mark, David Hurtado, Sara Olson, and Jessica Yen. 2009. "Walkscore.Com: A New Methodology to Explore Associations between Neighborhood Resources, Race, and Health." In . https://apha. confex. com/recording/apha/137am/pdf/free/4db77adf5df9fff0d3caf5cafe28f496/paper205082_1. pdf.

Caliper, C. 2008. "Travel Demand Modeling with TransCAD." *Caliper Corporation, Boston, MA*.

City of New York, NYC Open. 2017. "NYC Open Data." NYC Open Data: Open Data for All New Yorkers. 2017. https://opendata.cityofnewyork.us/.

Claris, S, and D Scopelliti. 2016. "Cities Alive: Towards a Walking World." *ARUP Publications*. https://www.arup.com/-/media/arup/files/publications/c/cities-alive_towards-a-walking-world_lowres.pdf.

Data.Gouv.Fr. 2019. "Plateforme Ouverte Des Données Publiques Françaises." 2019. https://www.data.gouv.fr/fr/territories/commune/75056@latest/Paris/.

Dogan, Timur, Samitha Samaranayake, and Nikhil Saraf. 2018. "Urbano: A New Tool to Promote Mobility-Aware Urban Design, Active Transportation Modeling and Access Analysis for Amenities and Public Transport." In *Proceedings of SimAUD 2018*. Delft, Netherlands.

ESRI. 2017. *ArcGIS Pro*.

Ewing, Reid, and Susan Handy. 2009. "Measuring the Unmeasurable: Urban Design Qualities Related to Walkability." *Journal of Urban Design* 14 (1): 65–84.

Frank, Lawrence D, James F Sallis, Terry L Conway, James E Chapman, Brian E Saelens, and William Bachman. 2006. "Many Pathways from Land Use to Health: Associations between Neighborhood Walkability and Active Transportation, Body Mass Index, and Air Quality." *Journal of the American Planning Association* 72 (1): 75–87.

Google. 2018. "Google Places API." Google Places API. 2018. https://developers.google.com/places/.

Lee, I-Min, and David M Buchner. 2008. "The Importance of Walking to Public Health." *Medicine and Science in Sports and Exercise* 40 (7 Suppl): S512–8.

Leyden, Kevin M. 2003. "Social Capital and the Built Environment: The Importance of Walkable Neighborhoods." *American Journal of Public Health* 93 (9): 1546–1551.

Lindsay, Graeme, Alexandra Macmillan, and Alistair Woodward. 2011. "Moving Urban Trips from Cars to Bicycles: Impact on Health and Emissions." *Australian and New Zealand Journal of Public Health* 35 (1): 54–60.

McNeel, Robert. 2016a. *Grasshopper*. http://www.grasshopper3d.com/.

———. 2016b. *Rhinoceros* (version 5). https://www.rhino3d.com/.

NYC Open Data. 2019. “New York City Population By Community Districts.” 2019. https://data.cityofnewyork.us/City-Government/New-York-City-Population-By-Community-Districts/xi7c-iiu2.

Ogilvie, David, Fiona Bull, Jane Powell, Ashley R Cooper, Christian Brand, Nanette Mutrie, John Preston, Harry Rutter, and iConnect Consortium. 2011. “An Applied Ecological Framework for Evaluating Infrastructure to Promote Walking and Cycling: The IConnect Study.” *American Journal of Public Health* 101 (3): 473–481.

OpenStreetMap. 2018. “OpenStreetMap.” OpenStreetMap. 2018. https://www.openstreetmap.org.

Reinhart, Christoph, Timur Dogan, J Alstan Jakubiec, Tarek Rakha, and Andrew Sang. 2013. “Umi-an Urban Simulation Environment for Building Energy Use, Daylighting and Walkability.” In *13th Conference of International Building Performance Simulation Association, Chambery, France*.

Schrank, David, Bill Eisele, and Tim Lomax. 2012. “TTI’s 2012 Urban Mobility Report.” *Texas A&M Transportation Institute. The Texas A&M University System*, 4.

Sevtsuk, Andres, and Michael Mekonnen. 2012. “Urban Network Analysis: A New Toolbox for Measuring City Form in ArcGIS.” In *Proceedings of the 2012 Symposium on Simulation for Architecture and Urban Design*, 18. Society for Computer Simulation International.

SIA. 2006. “2024: Standard-Nutzungsbedingungen Für Die Energie-Und Gebäudetechnik.” *Zürich: Swiss Society of Engineers and Architects*.

UNEP. 2015. “Sustainable Buildings and Climate Initiative.” http://www.unep.org/sbci/AboutSBCI/Background.asp.

United States Environmental Protection Agency. 2012. “Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2010. Report EPA 430-R-12-001.” United States Environmental Protection Agency. https://www.epa.gov/sites/production/files/2015-12/documents/us-ghg-inventory-2012-main-text.pdf.

Yang, Yang, Samitha Samaranayake, and Timur Dogan. 2019. “Using Open Data to Derive Local Amenity Demand Patterns for Walkability Simulations and Amenity Utilization Analysis.” In *Proceedings of ECAADe 37 / SIGraDi 23*. Porto, Portugal.