1 The Relative Circuity of Walkable and Drivable Urban Street Networks

2
3 October 15, 2017

4 Word Count: 7,498 (6,498 words + 1 table + 3 figures)

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15 CITATION INFORMATION:

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17 Boeing, G. 2018. "The Relative Circuity of Walkable and Drivable Urban Street Networks."
18 Transportation Research Board 97th Annual Meeting. January 7–11, Washington, DC.
19

ABSTRACT

Circuitry, the ratio of network distances to straight-line distances, is an important measure of urban street network structure and transportation efficiency. Circuitry results from a circulation network's configuration, planning, and underlying terrain. In turn, it impacts how humans use urban space for settlement and travel. Although past research has examined overall street network circuitry, researchers have not studied the relative circuitry of walkable versus drivable circulation networks. To address this gap, this study uses OpenStreetMap data to explore relative network circuitry. We download walkable and drivable networks for 40 US cities using the OSMnx software, which we then use to simulate two million routes and analyze circuitry to characterize network structure. We find that walking networks tend to allow for more direct trips than driving networks do in most cities: average driving circuitry exceeds average walking circuitry in all but four of the cities that exhibit statistically significant differences between network types. We discuss various reasons for this phenomenon, illustrated with case studies. Network circuitry also varies substantially between different types of places. These findings underscore the value of using network-based distances rather than straight-line distances when studying urban travel and access. They also suggest the importance of differentiating between walkable and drivable circulation networks when modeling and characterizing urban street networks: although different modes' networks overlap in any given city, their relative structure and performance vary in most cities.

Keywords: street network, circuitry, network analysis, GIS, OpenStreetMap, urban morphology

1 INTRODUCTION

2 Street networks organize and structure human spatial dynamics and flows in a city. They
3 underlie commutes, discretionary trips, and the location decisions of households and firms.
4 Accordingly, substantial research has been conducted in recent years to better characterize the
5 topological and geometric characteristics of urban street networks (1–3). Topological character
6 describes the configuration of the network and includes measures of connectivity, centrality, and
7 clustering. Geometric character describes the network’s distances, areas, and densities. Both
8 intermingle to define the network’s structure, efficiency, and performance.

9 Street network analysis has become an important bridge between network science and
10 urban planning (4–9). Recent studies have found that cities can be clustered and classified
11 according to their network’s structural characteristics (10–14). In other words, cities’ circulation
12 networks exhibit spatial signatures that can be quantified and operationalized to differentiate
13 types of places. One branch of this research literature augments urban morphology studies with
14 topological analyses of street networks (12, 13, 15–17). Another branch considers the
15 implications of network configuration and geometry on transportation and circulation (18–22).

16 Circuity, the ratio of network distances to straight-line distances, is an important measure
17 of network structure and transportation efficiency (23). Interest in circuity is not new. In 1929,
18 the modernist polemic Le Corbusier (24) wrote: “The circulation of traffic demands the straight
19 line; it is the proper thing for the heart of a city. The curve is ruinous, difficult and dangerous; it
20 is a paralyzing thing... The winding road is the Pack-Donkey’s Way, the straight road is man’s
21 way.” In particular, Corbusier argued that planners must eradicate walkable, self-organized
22 streets and paths from traditional cities to enable the development of deliberate, rational, straight-
23 line roads for cars. Similar plans were enacted throughout the twentieth century, including
24 Robert Moses’s “meat ax” carving up New York’s neighborhoods to make room for new
25 expressways (25–27). Over time, evolving street network pattern and design standards that
26 impact circuity have been bureaucratized by the ITE, the Federal Housing Administration, and
27 the Urban Land Institute (28–30).

28 Circuity results from a network’s planning, configuration, and underlying terrain. In turn,
29 it impacts how humans use urban space for settlement and travel. Levinson and El-Geneidy (31,
30 32) demonstrate that households tend to select residential locations that offer less circuitous work
31 commutes. Giacomini and Levinson (33) show that average US metropolitan circuities rose
32 between 1990 and 2000, as recent peripheral suburban development has featured more circuitous
33 street network designs. O’Sullivan and Morrall (34) find that walking trip circuity
34 (counterintuitively) increases in Calgary during winter months, as pedestrians avoid shortcuts
35 that have been rendered impassible by ice. Most circuity research has treated a city’s street
36 network as a single entity. However, multiple circulation networks – that may be disambiguated
37 by mode (e.g., walking, driving, biking) – overlap to constitute the city’s complete multimodal
38 circulation network.

39 Past research has measured the circuity of car (33, 35), bike (36, 37), and transit (23)
40 networks. However, the *relative* circuity of walkable networks versus drivable networks has been
41 underexplored. On one hand, car-only routes like freeways can provide straight paths to link
42 opposite sides of the city by cutting across grids and winding surface streets. On the other hand,
43 such routes may have circuitous elements such as cloverleaf interchanges and are engineered to
44 optimize trip time – a function of distance and speed – rather than distance itself (cf. 38).
45 Drivable networks may also include one-way streets, but pedestrians can traverse them

1 bidirectionally. Moreover, walking networks provide paths across parks, mid-block cut-throughs,
2 passageways between buildings, and other shortcuts that driving networks lack. The relative
3 circuitry of drivable versus walkable networks depends on the magnitude of the effect that each's
4 unique features have on enabling trips to approximate straight-line travel. This effect likely
5 varies by city, as a function of topography, planning history, and circulation network design (35,
6 39).

7 Although past research has examined overall street network circuitry in various cities (23,
8 31–37), researchers have not studied the relative circuitry of walking versus driving networks
9 across multiple cities. To address this gap, this study uses open-source software and open data to
10 explore relative network circuitry. We download OpenStreetMap data for walkable and drivable
11 circulation networks in 40 US cities using the OSMnx software, which we then use to simulate
12 two million routes and analyze each's circuitry. We find statistically significant differences
13 between driving circuitry and walking circuitry in most cities. In particular, driving circuitry
14 exceeds that of walking in all but four of the cities with statistically significant differences.
15 Moreover, circuitry varies in different kinds of places. These findings suggest the importance of
16 using network-based distances to study urban access as well as the importance of differentiating
17 between circulation network types. Although walkable and drivable networks overlap in every
18 city, their relative structure and performance differ in most cities.

19 The following section briefly introduces the science of networks and the data and tools
20 used to study street networks. Then we present the methods used to analyze relative circuitry and
21 the results of this analysis. Next, we discuss these results in the context of planning and design,
22 before concluding with a summary and future research agenda.

23 ANALYTICAL BACKGROUND

24 Street network analysis uses the tools of network science and graph theory (40–42). A network
25 (also called a *graph* in mathematics) is composed of a set of nodes which are connected to one
26 another by a set of edges (43). An undirected network's edges point mutually in both directions,
27 but a directed network's edges are one-way, from an origin node to a destination node.
28 Multigraphs allow multiple edges between a given pair of network nodes. A planar network can
29 be represented in two dimensions with edges only intersecting at nodes – otherwise, is nonplanar.
30 Street networks are nonplanar due to bridges and underpasses. Primal representations model
31 street segments as edges and intersections and dead-ends as nodes (11, 44). This study models
32 drivable street networks as primal, nonplanar, directed, weighted multigraphs, and walkable
33 networks as the same, only undirected (45). Street networks are spatial networks – their nodes
34 and edges are embedded in space and, in turn, have geometric characteristics, such as circuitry,
35 that rely on lengths and areas, alongside the standard topological traits of all networks (46).

36 Street network data traditionally come from various sources, including disparate
37 municipal and state repositories, expensive commercial data sets, and (in the US) the census
38 bureau's TIGER/Line roads shapefiles. Many studies rely on the latter because of its accessibility
39 and comprehensiveness. However, TIGER/Line suffers from substantial spatial inaccuracies,
40 broad classifiers that lump multiple path types together, and the misrepresentation of traffic-
41 diverting bollards as through-streets (47). The latter in particular biases routing results.
42 OpenStreetMap offers an alternative data source. It is an online collaborative mapping project
43 that covers the entire world (48, 49). As of 2017, OpenStreetMap contained over 4.4 billion
44 geospatial objects in its database, along with over 1.5 billion tags which describe these features.

1 The objects comprise streets, trails, building footprints, land parcels, rivers, power lines, points
2 of interest, and many other features.

3 These data are added to the OpenStreetMap database in typically one of two ways. The
4 first is through large-scale imports of publicly available data sources, such as census
5 TIGER/Line data or municipalities' shapefiles. The second is through the many individual
6 additions and edits performed on an ongoing basis by OpenStreetMap's users and contributors.
7 OpenStreetMap's data are largely high quality (50–55). In 2007, it imported the TIGER/Line
8 roads as a foundation, and since then, the user community has added innumerable additional
9 features, richer attribute data, and spatial corrections (56). Of particular relevance to the present
10 study, OpenStreetMap data go far beyond those available in TIGER/Line as they include
11 pedestrian paths, park trails, passages between buildings and through blocks, and finer-grained
12 codes classifying various path and street types.

13 Researchers typically acquire street network data from OpenStreetMap in one of three
14 ways. First, Overpass provides an API that allows users to query for geospatial features.
15 However, its query language is difficult to use. Second (and accordingly), a handful of
16 commercial services have sprung up as middle-men, downloading data extracts for certain areas
17 or bounding boxes and then providing them to users. However, these services are often
18 expensive, slow, and un-customizable. While they may work well for studying the street network
19 within a single bounding box, they are inconvenient for acquiring data in multiple study sites.
20 Further, they provide data as geometric shapefiles, which do not lend themselves immediately to
21 nonplanar, graph-theoretic network analysis.

22 A third method for acquiring OpenStreetMap network data is OSMnx. OSMnx is a free,
23 open-source Python package for downloading and analyzing street networks from
24 OpenStreetMap (57). It can query by bounding box, address plus network distance, polygon
25 (e.g., from a shapefile), or by place name (which resolves to a polygon representing the place's
26 borders) such as cities, boroughs, or counties. OSMnx can download drivable, walkable, or
27 bikeable networks, as well as other infrastructures such as power lines or subway systems.
28 Walkable and drivable paths are identified by OpenStreetMap metadata. Once the network has
29 been downloaded, OSMnx automatically assembles it into a nonplanar directed multigraph and
30 corrects its topology to retain nodes only at true intersections and dead-ends. This simplification
31 process faithfully retains the true geometry and length of each street segment. Finally, OSMnx
32 can analyze these street networks in various ways, including shortest-path calculations,
33 topological measures such as centrality and clustering, and geometric measures such as
34 intersection density and circuitry (16).

35 METHODS

36 This study uses OSMnx to calculate shortest path distances along walkable and drivable street
37 networks in various cities. It builds on the research designs of (31–33) by simulating thousands
38 of routes in each city and calculating circuitries as a function of network distance and straight-line
39 distance. Unlike many previous studies, we use nonplanar networks as a superior representation
40 of topology (57, 58) and we utilize the fine-grained classifier codes in OpenStreetMap data to
41 create separate (directed) driving and (undirected) walking networks that are more detailed than
42 those of most prior studies.

43 To study the difference in circuitry between walkable and drivable networks, we examine
44 40 US cities. We select cities across the breadth of the nation, including most of the largest cities

as well as several medium cities, small towns, and suburbs for contrast. For each city, we draw a convex hull around the municipal borders, then download the street network within this hull.

This technique offers two advantages. First, it allows us to focus on municipalities – the scale of urban planning jurisdiction and decision making – and their immediate vicinities without including the suburbs, exurbs, and urban fringe at the periphery of the broader metropolitan area. Second, it adjusts for substantial quirks in the shapes of municipal borders. Some cities' borders snake along a narrow linear feature to connect two disparate hemispheres. Others exhibit concavity and bend around large elbow curves. These quirks would cause inflated circuitry scores as trips are forced to route around city borders instead of taking shorter and more direct routes that briefly cross through a neighboring town. Convex hulls solve this problem while still constraining the analysis to a city and its immediate environs. They also help us mostly avoid large bodies of water around which some metropolitan areas wrap – such as the San Francisco Bay and the Puget Sound – and which significantly impact metropolitan-scale circuitry.

To acquire our street network data, we use OSMnx to download each city's walkable and drivable street networks – constrained to the convex hull – from OpenStreetMap. OSMnx uses OpenStreetMap's fine-grained tags to identify walkable and drivable streets and paths. In case of a disconnected network, we retain only the largest connected component. Then, for each city and network type, we simulate 50,000 random trips. This number of simulations was arrived at after a sensitivity analysis revealed that the means and *t*-statistics converge at stable values around this number.

FIGURE 1 Shortest path between two nodes, accounting for one-way streets, along a segment of Manhattan's drivable network (red) and the great-circle distance (blue)

For each simulation, we randomly select two nodes, calculate the shortest path between them using Dijkstra's algorithm (59), and then calculate the great-circle distance between these two nodes. The great-circle distance represents the shortest distance along the curved surface of the earth, and is thus more accurate than the Euclidean distance. These randomized origin-destination pairs do not necessarily reflect the spatial distribution and weighting of real-world

trips, as our goal is instead to characterize the structure of each network as a whole rather than just its most well-worn paths. We calculate each walking or driving trip's circuitry as:

$$\psi = \frac{\zeta_{\text{net}}}{\zeta_{\text{gc}}}$$

where, for each trip, ψ represents circuitry, ζ_{net} represents the shortest-path network distance between the origin and destination nodes, and ζ_{gc} represents the great-circle distance between these nodes. Thus, a trip's circuitry is the ratio of the shortest-path network distance to the great-circle distance between the origin and destination. Figure 1 illustrates the difference between a shortest-path route and a straight line between two nodes in Manhattan's driving network, accounting for one-way streets.

We hypothesize that the average circuitry of a city's walkable circulation network differs from that of its drivable circulation network. To test this hypothesis, for each city, we conduct a t -test to ascertain the statistical significance of the difference between the simulated walking trips' average circuitry and that of the simulated driving trips, to see if we may reject the null hypothesis H_0 :

$$H_0: \mu_w = \mu_d$$

$$H_1: \mu_w \neq \mu_d$$

where, for each city, μ_w is the mean circuitry of the trips along its walking network and μ_d is the mean circuitry of the trips along its driving network. We conduct two-sided t -tests because it is not known a priori if μ_w is expected to be greater than μ_d or vice-versa. For instance, if the effects of pedestrian pathways and cut-throughs exceed the effect of freeways on minimizing trip circuitry, we would expect μ_d to be greater than μ_w (that is, walking allows for more direct routes). Conversely, if the effect of freeways exceeds drawbacks of one-way streets and the effects of pedestrian pathways and cut-throughs on minimizing trip circuitry, we would expect μ_w to be greater than μ_d (that is, driving allows for more direct routes). Finally, for each city, we calculate an indicator ϕ to represent the ratio of average driving circuitry to average walking circuitry:

$$\phi = \frac{(\mu_d - 1)}{(\mu_w - 1)}$$

We subtract 1 from each term in the ϕ ratio because the minimum possible circuitry is 1 (cf. 33). The following section presents the results of these trip simulations and the resulting statistical analyses.

RESULTS

Table 1 presents the average circuitry of walking trips (μ_w) and driving trips (μ_d) in each city, with significance levels denoted by asterisks in the table. It also presents the mean distance of trips along the driving network (δ_d), the mean distance of trips along the walking network (δ_w), and the ϕ ratio expressed as a percentage. We find that the average circuitries of driving trips and walking trips differ by a statistically significant margin in 38 out of the 40 cities studied. Moreover, we find that the average driving circuitry exceeds that of walking in 34 out of the 38 cities that have a statistically significant difference.

Only four cities in the study have an average walking circuitry that exceeds that of driving by a statistically significant margin. All of the cities with either statistically insignificant results or negative ϕ values are located in sunbelt or midwestern states. However, some sunbelt and midwestern cities such as Phoenix and Chicago do have statistically significant differences with

positive φ values. The mean distance of trips along the driving network, δ_d , and the mean distance of trips along the walking network, δ_w , demonstrate how much distance can be saved, on an average trip, by taking the more direct mode of travel. For instance, in Manhattan, the average walking trip is 0.7 kilometers shorter than the average driving trip. However, the values of δ_w and δ_d are correlated with street network size, so cities with larger spatial extents demonstrate higher trip distances on average (cf. 60).

To adjust for this scaling effect, μ_d and μ_w represent circuitry as the mean of the simulated ψ values (each trip's ratio of shortest-path network distance to great-circle distance). Cities with orthogonal street grids or robust radial freeway systems tend to have the least circuitous average driving trips: in Philadelphia, Chicago, Detroit, Dallas, and Los Angeles the average driving trip is only 18% to 20% more circuitous than the straight-line distance from origin to destination. More-recently developed suburbs with curvilinear residential street networks have the most circuitous average driving trips: in Sugar Land and Redmond the average driving trip is over 52% more circuitous than the straight-line distance. Similar effects are seen in the walking networks. The average walking trip in Manhattan, Chicago, and Detroit is less than 18% more circuitous than the straight-line distance from origin to destination. However, the average walking trip in Sugar Land and Redmond are 40% more circuitous than the straight-line distance.

TABLE 1 Average Circuitry of Walking and Driving Trips

	μ_d	μ_w	δ_d (km)	δ_w (km)	φ	
Atlanta, GA	1.243	1.226	12.49	11.68	7.30%	***
Baltimore, MD	1.232	1.221	8.68	8.24	4.80%	***
Boston, MA	1.255	1.191	9.14	7.89	33.90%	***
Charlotte, NC	1.267	1.248	19.71	19.14	7.70%	***
Chicago, IL	1.194	1.178	18.79	18.40	8.80%	***
Cincinnati, OH	1.341	1.332	12.35	11.51	2.60%	***
Cleveland, OH	1.213	1.208	12.26	11.53	2.30%	***
Dallas, TX	1.177	1.180	24.23	24.33	-1.50%	***
Denver, CO	1.242	1.209	15.19	13.23	15.30%	***
Detroit, MI	1.190	1.178	13.03	12.36	6.30%	***
Fargo, ND	1.336	1.291	7.64	7.00	15.60%	***
Gary, IN	1.324	1.285	7.90	6.93	13.60%	***
Kansas City, MO	1.223	1.339	21.51	23.08	-34.20%	***
Las Vegas, NV	1.272	1.268	13.72	14.02	1.30%	**
Los Angeles, CA	1.198	1.196	28.47	27.93	0.60%	
Louisville, KY	1.274	1.254	18.85	17.47	7.70%	***
Manhattan, NY	1.209	1.142	7.57	6.87	47.60%	***
Miami, FL	1.259	1.246	7.83	7.93	5.50%	***
Minneapolis, MN	1.241	1.223	8.24	7.40	8.40%	***
Orlando, FL	1.306	1.300	13.60	13.79	2.00%	***
Philadelphia, PA	1.200	1.184	12.85	12.79	8.90%	***
Phoenix, AZ	1.256	1.224	25.53	24.41	14.00%	***
Pittsburgh, PA	1.345	1.328	9.58	9.18	5.30%	***
Portland, ME	1.389	1.347	6.09	6.15	12.20%	***

Portland, OR	1.289	1.264	12.05	11.97	9.50%	***
Redmond, WA	1.522	1.396	5.79	5.18	31.80%	***
Riverside, CA	1.312	1.289	10.78	11.30	7.90%	***
Salem, MA	1.505	1.487	4.83	4.66	3.80%	***
San Antonio, TX	1.218	1.199	22.43	21.77	9.90%	***
San Diego, CA	1.307	1.354	25.90	25.91	-13.30%	***
San Francisco, CA	1.308	1.210	11.46	6.96	46.20%	***
Scranton, PA	1.376	1.349	5.09	5.08	7.70%	***
Seattle, WA	1.289	1.251	12.29	11.08	15.10%	***
St Augustine, FL	1.373	1.331	4.39	3.88	12.90%	***
St Louis, MO	1.204	1.193	8.55	7.73	5.40%	***
Stamford, CT	1.340	1.340	6.93	6.63	0.10%	
Sugar Land, TX	1.523	1.405	7.92	7.15	29.20%	***
Tampa, FL	1.281	1.267	14.85	13.99	5.30%	***
Vicksburg, MS	1.363	1.379	6.74	6.16	-4.10%	***
Walnut Creek, CA	1.470	1.392	5.60	5.29	19.90%	***

NOTE: 1 km = 0.62 mi. μ_w = mean circuitry of the simulated trips along the walking network, μ_d = mean circuitry of the simulated trips along the driving network, δ_d = mean distance (in km) of trips along the driving network, δ_w = mean distance (in km) of trips along the walking network, ϕ represents how much μ_d exceeds μ_w , expressed as a percentage. Finally, * means the difference between μ_w and μ_d is significant at the .05 level, ** indicates statistical significance at the .01 level, and *** indicates significance at the .001 level.

The primary focus of this study is on the relationship between driving network circuitry and walking network circuitry (ϕ in Table 1). Manhattan and San Francisco exhibit the greatest values of ϕ . In each of these cities, the average driving trip is over 46% more circuitous than the average walking trip. In contrast, in San Diego and Kansas City, the average driving trip is 13% and 34% less circuitous, respectively, than the average walking trip.

DISCUSSION

Our statistical results suggest that in most cities, the average circuitry of the walking trips differs from that of the driving trips. In 38 of the 40 cities studied, this difference is statistically significant. Moreover, the average circuitry of driving trips exceeds that of walking trips in all but four of the cities with statistically significant results. There appears to be some geographical basis to this as well, as all of the cities with insignificant results or negative ϕ values belong to US sunbelt or midwestern states, possibly due to higher levels of sprawl and lower levels of walkability there. However, verification of this preliminary trend would require much larger sample sizes for clarity and reliability.

On average, driving trips tend to be more circuitous than walking trips in most cities. To interpret these network circuitry findings, we use Manhattan as an illustrative case. Its average driving trip is 48% more circuitous than its average walking trip. Figure 2 shows Manhattan's drivable street network on the left and its walkable street network on the right (note that its convex hull includes a sliver of the Bronx). We can immediately see that the walking network is much denser than the driving network. While the walking network contains 11,857 nodes and 1,331 kilometers of streets/paths, the driving network contains only 4,889 nodes and 1,064 kilometers of streets. Although it excludes expressways around the periphery of the island, the

walking network provides numerous mid-block passages, pedestrian walkways, and frequent juncture points that in aggregate allow for more direct routes. In particular, Central Park poses an obstacle to straight-line driving, but the park's dense mesh of walking paths provides many cross-cutting and diagonal routes for pedestrians whose origins and destinations lie on either side of it. Manhattan also has many one-way streets that pedestrians may traverse bidirectionally, improving walking efficiency. In this case, the findings suggest that the effects of pedestrian pathways, cut-throughs, and bidirectionality exceed the effect of car-only motorways on trip directness.

FIGURE 2 Manhattan's driving network (left) and walking network (right)

As a contrasting example – unlike Manhattan and most of the cities studied – San Diego's ϕ value is both negative and statistically significant. Its average driving trip is 13% less circuitous than its average walking trip. Figure 3 shows San Diego's drivable street network on the left and its walkable street network on the right. As in Manhattan, we can see that the walking network is denser than the driving network. While the walking network has 94,118 nodes and 14,293 kilometers of streets/paths, the driving network has only 51,544 nodes and 11,283 kilometers of streets.

There seem to be three primary reasons why San Diego has a negative ϕ value. First, its highway system runs at cross-cutting diagonals, providing direct routes across the city that local streets cannot match. Second, its hills and canyons create substantial open space, natural preserves, and in turn network thresholds. The walking network provides dendritic, circuitous access into these spaces without offering efficient links across them. Third, Coronado Island (technically a peninsula connected to the mainland by a trombolo) connects to downtown San Diego via the San Diego–Coronado Bridge for reasonably direct driving trips. However, this bridge is automobile-only, so walking trips between Coronado and the majority of the city must route along the peninsula and around the entire San Diego Bay (similarly, the Kansas City network has 7 driving bridges over the Missouri River but only 1 walkable bridge). In other words, due to topography and design, San Diego relies particularly heavily on its freeway system

1 for shortest-path connectivity. Accordingly, in this case, the findings suggest that the effect of
2 car-only motorways exceeds the effects of pedestrian paths and passageways on trip directness.
3 Nevertheless, we find that this effect is the exception rather than the rule across our study sites.

4
5 **FIGURE 3 San Diego's driving network (left) and walking network (right)**
6

7 Empirical studies in the urban economics, planning, and transportation literatures today
8 often rely on Euclidean or great-circle distances to model accessibility. Our findings add to the
9 growing body of evidence that such straight-line measures are both inaccurate and inconsistent.
10 Average network trip distances are at least 14% and sometimes over 50% longer than the
11 straight-line distance from origin to destination. The magnitude of this phenomenon varies
12 substantially between, for instance, Chicago and Sugar Land. This variation results from
13 different topographies, planning eras, transportation technologies, and design paradigms. Thus,
14 researchers and practitioners should use network-based distances and travel times to prevent
15 biased distance measures in different kinds of places.

16 Moreover, we find that trip circuitry along walkable versus drivable networks differs
17 significantly in most cities. A city's circulation network cannot be accurately modeled as a single
18 monolithic entity. Rather, it comprises an interwoven set of overlapping circulation networks

available to different modes of travel. Some one-way streets in the driving network may be accessible in both directions to pedestrians in the walking network. Similarly, pedestrian paths and mid-block passages may be unavailable to drivers, while expressways and certain bridges may be unavailable to pedestrians. Moreover, driving networks are more likely to be engineered to minimize travel time at high speeds rather than to minimize distance: distance itself is more important for modes with lower travel speeds. Measuring circuitry depends on carefully defining what the circulation network includes and which modes of travel are of interest to the study. Thus, urban street network structure and performance cannot be sufficiently assessed without specifying network types and travel modes.

CONCLUSION

This study examined the relative circuitry of walkable and drivable urban circulation networks by simulating trips along each using OpenStreetMap data and the OSMnx software. It found that, in most cities, driving networks tend to produce more circuitous trips than walking networks do. Specifically, average driving circuitry exceeds average walking circuitry in 38 out of the 40 cities that have statistically significant differences. Old, dense cities like Manhattan and San Francisco saw the greatest effects, with average driving trips over 46% more circuitous than average walking trips. Network analysis can help examine the spatial transferability of travel modes. Network circuitry also varies substantially between different types of places. These findings underscore the value of using network-based distances rather than straight-line distances when studying urban travel and access. They also suggest the importance of differentiating between walkable and drivable circulation networks: although these networks overlap, their relative structure and performance vary in most cities.

This study used simulated trip distances as an indicator of circuitry and network efficiency. Travel time is another important measure of efficiency. Future research can weight walking and driving trips by travel time to compare how simulated trip times vary by mode in different places as a function of network structure. Simulated trips could also be weighted by the likelihood of each being a real-world trip, based on travel survey data. This study randomized trips to examine overall network structure, but using actual trips would shed light on real-world travel behavior circuitry and reduce bias from random sampling when neighborhood trips may be more common. Travel surveys could also provide information about average trip distances by mode. Beyond simple measures of network existence, incorporating impedances based on grade, streetscape, traffic, and other data would provide a superior representation of routes. Finally, this study focused on US cities, but future work could use OSMnx and OpenStreetMap's worldwide data to compare networks in other countries to investigate the structure and performance of older European cities or rapidly growing African and Asian cities.

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