Response to Reviewers for EPB-2019-0343

Modeling the impacts of park access on health outcomes: a utility-based accessibility approach.

We would like to thank both reviewers for their thoughtful and helpful comments. We are delighted that they found our submission a "well-written paper that makes a useful contribution to the accessibility literature regarding quantifying accessibility" as well as "a nice added-value to the extensive literature on the subject."

We feel we have addressed each comment raised by the reviewers. Responses are noted in blue. Specific text added to the paper is noted in red and is reproduced in blue in the draft manuscript where feasible. In formulating our response to the reviewers, we grouped comments by theme and whether they were major or minor comments.

Major Comments

One note should be made at the beginning. In an effort to address the comments surrounding the methodology raised by reviewer 2, we restructured and clarified our data assembly and computation code including the code used to compute the logsums. As a result of intermediate rounding and unit conversions revised in this restructuring, the specific model estimates changed modestly from the initial submission. The overall magnitude of the findings and the conclusions of the analysis are unaffected. The entire project code is available at https://github.com/gregmacfarlane/parks_access.

Contribution within the Scope of EP:B

Reviewer 1: The introduction should be written in a way which justify a publication in EPB rather than in a more specialized journal (ex: Public Health, LUP, etc.). Could you please elaborate on the relation between city size, morphology, dynamics and access to green? How could your study provide new insights for city planners? Etc.

We appreciate the reviewer's suggestion to frame the paper in the context of urban planning more than in public health. We began this project from more of a public health perspective, noting the large number of prior studies that have employed simplistic and arbitrary definitions of access, and the concomitant disagreement between findings. Our study contributes an application of the accessibility methods developed prominently in the *Environment and Planning* journals (e.g. deJong et al., 2007; Handy and Niemeier, 2007; Coutts 2008; Logan et al., 2019), and that is why we submitted it here. Further, we hoped to receive a review of our work from scholars with an ability to comment on our application of spatial econometrics, which would have been less likely in a journal with a specific public health purview. In an effort to more clearly articulate our contribution within the scope of EPB, we have added this sentence to the introduction:

It is similarly necessary for urban planners to identify which neighborhoods have access to quality green space, and which neighborhoods need intervention in the form of new or rehabilitated green space, or improved transportation access to existing quality green space.

We have also added a modest reference to the question of park access in light of the COVID-19 pandemic to the future research section:

The COVID-19 pandemic and its associated social distancing behavior in many regions of the world has also drawn attention to problems of park access, use, and equity.

Situation in the Literature

Reviewer 1: The literature review suggests that the originality of the paper relies on the study of accessibility levels to urban parks on the health of local residents at the intra-metropolitan level. The section only quotes four papers out of the many ones published on the topic, each of them working making inter city comparisons and therefore working at a meso level. This is not acceptable for an academic article. I would suggest to the authors to take the time to position their work properly within the literature before publication.

We appreciate the reviewer alerting us to several more of the many studies that precede ours in attempting to establish a relationship between urban green space and public health. We have made several adjustments to the literature review to clarify for the reader the position of this work in the parks accessibility literature. Most notably, we have integrated the discussion of the macro/meso-level studies into the access calculation presentation. We hope that this will more properly position what we feel to be our contribution to the literature, which is the application of a little-used accessibility score. The first two paragraphs of this section contain new and repurposed text:

The question of how green space in the urban environment affects the physical, emotional, and mental well-being of urban residents is not new to the academic literature. Comprehensive reviews and analysis of this literature up to 2007 can be had from Tzoulas et al. (2007), and for the subsequent decade from Kabish et al. (2015). In spite of the depth of this research arena – or perhaps because of it – quantitative approaches for assessing both health outcomes and access to green space vary widely. It is therefore not surprising that in a meta-analysis of 20 recent peer reviewed journal articles exploring the relationship between access to parks and objectively measured physical activity, Bancroft (2015) found that five studies reported a significant positive association, six studies produced mixed results, and nine studies found no association at all.

Loosely defined, the *accessibility* of an arbitrary place describes the ease with which people can accomplish activities there. Accessibility is an abstract concept with tempting quantifiability (Handy and Niemeier, 1997), but objective quantification may not be strictly necessary. For example, Takano et al. (2002) showed improved survival rates among senior citizens in Japan who self-reported having access to qualitatively good walking spaces. Though encouraging, this result could simply reveal self-selection: Those seniors who felt the walking space was good were those who chose to enjoy it. Urban planners seeking to evaluate which residents have good access to quality green space may desire objectively comparable measures.

We have also introduced citations to two studies by de Vries and one by Carlson illustrating applications of an isochrone-based measure,

DeVries et al. (2003) showed the amount of greenspace within a 3-kilometer radius was positively associated with a suite of self-reported health outcomes. Similarly, DeVries et al. (2013) showed that streetscape greenery within 500 meters of a residence was associated with perceived general health. Conversely, Carlson et al. (2012) found no relationship between the health of senior citizens and the number of parks within 500 meters.

The Hillsdon reference develops a gravity-based accessibility term, and we have added the following to the discussion on gravity models:

Hillsdon, et al. (2006) found no relationship between a gravity-based accessibility term and self-reported physical activity among middle-aged individuals in Norwich, England.

Some other minor rewording in this section helps to integrate the new changes.

Network versus Euclidean Distance Calculations

Reviewer 2: Measure of distance. I'm concerned by the use of tract centroid and Euclidean distance. I see that you've mentioned this in the limitations, but the difference between tract centroid vs parcel distance to a park can be around a 1000 meters (Logan et al. 2019) and this is using network (not Euclidean) distance. As a result, I have little confidence in the findings regarding the relationship between park access and health. However, I defer to the editor as to whether the paper's novelty is solely the utility-based access measure, or if it's the findings related to parks and health. I still think that this discussion is a contribution I'd like to see published.

We appreciate the reviewer's concern as to the importance of the distance measure in computing our utility-based accessibility statistic. In an effort to investigate the influence of this, we used the OSMNX package for Python to retrieve a routable walk mode network from OpenStreetMap for the five boroughs of New York City, and attempted to calculate the network-based distance along this network using the networkx package between the population-weighted tract centroid and the nearest point of each park in the city.

The network calculator we chose for this additional analysis works node-to-node. At the tract centroid end, it was simple enough to find the nearest node to each centroid. For the parks, we needed to find the *set* of nodes surrounding the park boundary. To do this, we sampled points along a linestring comprising the boundaries of the park polygon object, and found the nearest node to *those* points. The sampling density was approximately one point for every 500 feet; some small parks therefore have only one point, and larger parks have several dozen. This introduces some level of imprecision, as the network may or may not have a node precisely at that point, and there may be a point on the park boundary that was nearer a different node. A map of these sampled points is shown in Figure 1 below.

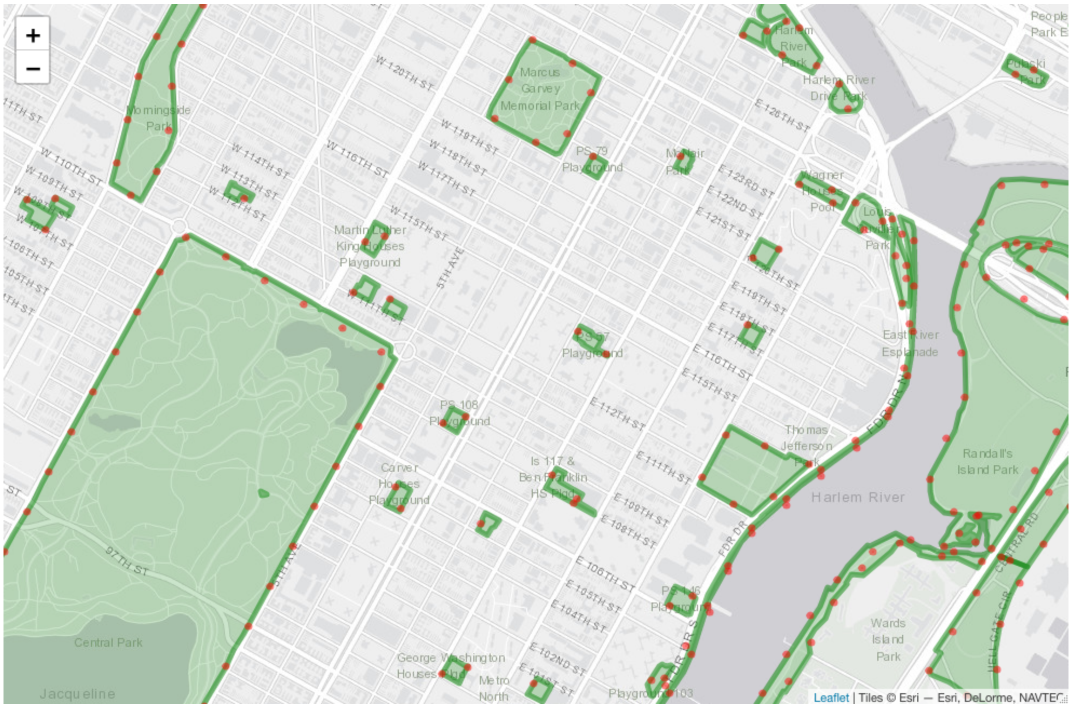

Figure 1. Sampled points along park boundaries in Upper Manhattan.

With approximately 13,000 park points and 2,100 tract centroids, we need to compute 29.3 million shortest paths. Even on a 39 core parallel process (which is the computational power available for this response), this calculation was estimated to take several weeks. As a result, we simplify the problem by first identifying the "closest" point of the park by Euclidean distance and then computing the network path to that point. This introduces some distortion where if the closest Euclidean point is across a river or interstate, the method calculates the network distance to *that* point instead of the first point in the park the person would encounter following the network. This may end up *overstating* the true experienced distance, whereas Euclidean distances traditionally *understate* it.

After calculating these paths, we wished to evaluate the relative “accuracy” of the network and Euclidean calculations. Figure 2 shows the distance between tract centroids and parks calculated by Euclidean and Network distance, facetted by park borough ("B"rooklyn, "M"anhattan, "Q"ueens, "R" for Staten Island, and Bron"X") across the top. Cemeteries get their own category "C". The tract borough is listed by FIPS code going down the rows, with Staten Island as 085. The 1/1 line through each facet indicates what would be a perfect relationship between Euclidean and network distance. Though there is some variability in some zones, in every case the network distance is longer than the Euclidean distance, EXCEPT for parks and tracts on Staten Island.

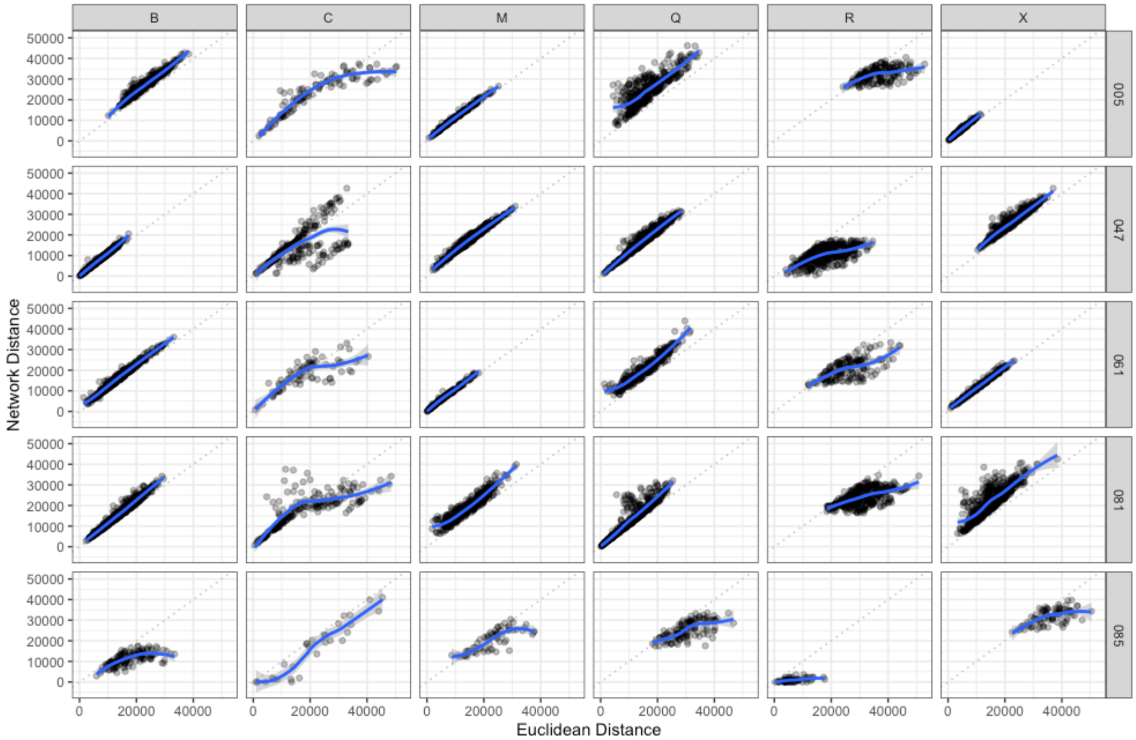

Figure 2. Comparison of Euclidean and Network distance by park and tract boroughs.

It is clear that something is incorrect with the OpenStreetMap network in Staten Island. Almost every exchange between a park or a tract involving Staten Island appears to have a ***shorter*** network distance than a Euclidean distance, which violates elementary geometry. The shortest path calculator we created would have returned infinite values for cases where there was no path (and did for some exchanges), but the networkx / OpenStreetMap combination we employed returned a valid network path length. To illustrate this further, Figure 3 shows the network-calculated distance to Central Park. Our network did not include the I-78 / Bayonne Bridge providing a route through New Jersey to Manhattan, so the tracts in Staten Island closest to Central Park *should* be on the eastern tip of the island near to the Verrazano Narrows Bridge, but this is not the case. Given the difficulties in calculating plausible network distances for tracts on Staten Island, we replace these distances *only* with the Euclidean distance and move forward to model estimation.

Table 1 shows the results of the SDEM physical activity models using Euclidean and network-based distance calculations, with the stipulation that interchanges involving Staten Island continue to use the Euclidean distances. The differences between the models are practically immaterial. For what it is worth, the Euclidean distance accessibility appears to have a slightly higher model likelihood (though not significantly so), while the network distance accessibility has a somewhat narrower confidence interval on the accessibility parameter of interest. The implementation of network distances does not therefore appear to affect the findings of the study. Were we able to compute rational network distances for all exchanges, we would happily convert the entire analysis over to the network distance. But given that we needed to make a simplifying assumption to overcome apparent network limitations for Staten Island, we prefer to keep the entire analysis on the same footing.

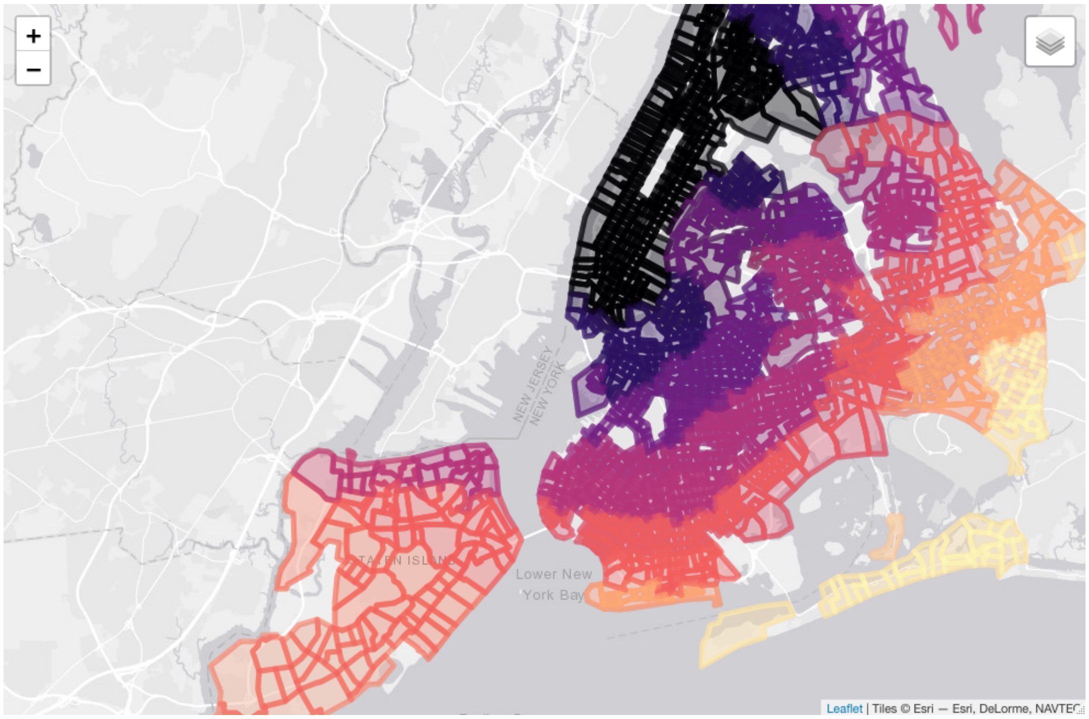

Figure 3. Network-calculated distance to Central Park

It is worth considering why the network and Euclidean distance result in such similar findings, when for any given interchange the network distance may be considerably longer. We have two hypotheses. First, we recall that there may be some error in the network distance resulting from the selection of the nearest point on the park boundary, though this would serve to make the network distances even more different than the Euclidean distance. The second hypothesis is that the decision to standardize the accessibility scores ends up sorting the tracts into the same basic order and variance, regardless of the distance calculation method used. Were we to calculate the effect of accessibility on the original un-normalized utility logsum, we may well have ended up with more divergent findings. But because the utility logsum is unitless and only can be compared against other logsums derived from the same utility coefficients (see Equation 3 in the manuscript), we feel this would be inappropriate. As an additional note, the models presented in Table 1 differ from the models in the manuscript modestly as a result of a difference in projection system. The manuscript measures Euclidean distances in NAD83(NSRS2007) / New York Long Island (ftUS), and the analysis presented here used UTM zone 18N (meters), both converted into miles. We use the original NAD83 projection in the models in the resubmitted manuscript.

We have revised the relevant paragraph in the Limitations section to reflect that the analysis presented in this response occurred but feel including the bulk of this content in the manuscript would be distracting from the overall purpose of the paper. At the invitation of the reviewers and editor we could include it as a technical appendix. The relevant paragraph in the manuscript now includes the following:

We examined replacing the Euclidean distance with a network-based distance; the choice of distance metric appeared inconsequential to our larger findings in this case while substantially increasing the computation load required. Additionally, we could not verify the accuracy of the underlying network data at the scale of this analysis. We therefore retain the Euclidean distance for simplicity.

Table 1. Model Comparison using Network and Euclidean Accessibility

	Access Euclidean	Access Network	Amenities Euclidean	Amenities Network
(Intercept)	-24.8266 **	-24.6491 **	-24.8920 **	-24.7534 **
	(8.6317)	(8.6228)	(8.6457)	(8.6366)
log(density)	0.1766 *	0.1716 *	0.1757 *	0.1715 *
	(0.0710)	(0.0709)	(0.0710)	(0.0710)
log(income)	5.9976 ***	5.9801 ***	5.9964 ***	5.9795 ***
	(0.2163)	(0.2160)	(0.2164)	(0.2161)
fulltime	0.1275 ***	0.1280 ***	0.1275 ***	0.1280 ***
	(0.0094)	(0.0094)	(0.0094)	(0.0094)
college	0.0076	0.0072	0.0073	0.0070
	(0.0119)	(0.0119)	(0.0119)	(0.0119)
single	-0.0362 ***	-0.0362 ***	-0.0360 ***	-0.0361 ***
	(0.0084)	(0.0084)	(0.0084)	(0.0084)
youth	-0.1311 ***	-0.1312 ***	-0.1310 ***	-0.1311 ***
	(0.0135)	(0.0135)	(0.0135)	(0.0135)
young_adults	0.0293 **	0.0288 **	0.0294 **	0.0289 **
	(0.0103)	(0.0103)	(0.0103)	(0.0103)
seniors	0.0403 **	0.0413 **	0.0408 **	0.0417 **
	(0.0140)	(0.0139)	(0.0140)	(0.0139)
black	-0.0499 ***	-0.0499 ***	-0.0498 ***	-0.0498 ***
	(0.0045)	(0.0045)	(0.0045)	(0.0045)
asian	-0.0767 ***	-0.0767 ***	-0.0768 ***	-0.0768 ***
	(0.0054)	(0.0054)	(0.0054)	(0.0054)
hispanic	-0.1025 ***	-0.1025 ***	-0.1025 ***	-0.1025 ***
	(0.0047)	(0.0046)	(0.0047)	(0.0047)
other	0.0035	0.0025	0.0037	0.0027
	(0.0452)	(0.0452)	(0.0452)	(0.0452)
access	0.1610 *	0.1453 *	0.1472 *	0.1352 *
	(0.0700)	(0.0621)	(0.0722)	(0.0649)
lambda	0.6906 ***	0.6898 ***	0.6917 ***	0.6909 ***
	(0.0200)	(0.0200)	(0.0199)	(0.0199)
Num. obs.	2099	2099	2099	2099
Parameters	28	28	28	28

**** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; Standard errors in parentheses; lagged dependent variables suppressed for concision*

Spatial Aggregation

Reviewer 2: I would suggest that even the Euclidean distance from block/parcel with a population-based mean would be suitable – that is, if the network distance is unpalatable. If not, change the title and conclusion to reflect the paper's purpose ("a utility-based accessibility approach").

Calculating the distance between block group centroids and parks instead of tracts is straightforward enough, but the other elements of our model are not available at a spatial resolution lower than tracts. This includes both the CDC 500 Cities data that provides our dependent variables as well as the sociodemographic information from the American Community Survey. Nevertheless, we did attempt to perform this analysis by repeating tract-level data within all of the block groups of the tract. This analysis was not entirely successful for reasons that will be explained here.

Consider the spatial lag of X (SLX) model for one region with one predictor variable:

$$y_i = \alpha + \beta x_i + \gamma W\boldsymbol{x} + \varepsilon$$

where the lagged component $W\boldsymbol{x}$ is the average value of x_j in the geographic regions bordering region i. Because we were unable to obtain separate measures of x in each block group, the values of x were simply repeated throughout the tract. That is, $x = W\boldsymbol{x}$ for a large number of observations. This introduced severe collinearity into the model matrix, and we were consequently unable to estimate any models with lagged independent variables.

We did, however, attempt to estimate the SEM model without any lagged variables at the block group and tract level. These models are presented in Table 2. While some of the variables have the same sign, scale, and interpretation across models, some --- specifically college and young adults --- do not. It is impossible to tell whether this is a result of the block group-level accessibility, or a manifestation of the ecological inference fallacy, or something else. It should be noted that in this SEM specification, the accessibility term of the tract model is not significant though it appears of the same sign and magnitude as in the SDEM model shown in the manuscript. We would argue the appropriate econometric model for this problem is the SDEM based on the discussion in the manuscript. There is no guarantee that an SDEM at the block group level (could it be estimated) would show a negligible effect akin to the BG model coefficient shown here. We have added the following sentence to the limitations section of the manuscript:

The socioeconomic and public health data used in this study are only available at the tract level; projecting the tract-level data to the block group level and computing more spatially precise accessibility logsums proved infeasible as the spatial lags of the independent variables introduced substantial collinearity in the model equations.

Table 2. SEM Estimated at the Tract and Block Group

	Tracts	BG
(Intercept)	5.6200 *	9.0269 ***
	(2.7406)	(1.5723)
log(density)	0.1740 *	0.0505
	(0.0691)	(0.0402)
log(income)	5.8583 ***	5.6940 ***
	(0.2095)	(0.1207)
fulltime	0.1420 ***	0.1369 ***
	(0.0083)	(0.0047)
college	0.0116	0.0283 ***
	(0.0111)	(0.0062)
single	-0.0331 ***	-0.0305 ***
	(0.0074)	(0.0042)
youth	-0.1309 ***	-0.1250 ***
	(0.0124)	(0.0070)
young_adults	0.0223 *	0.0156 **
	(0.0097)	(0.0054)
seniors	0.0431 ***	0.0389 ***
	(0.0125)	(0.0071)
black	-0.0517 ***	-0.0562 ***
	(0.0042)	(0.0026)
asian	-0.0773 ***	-0.0767 ***
	(0.0053)	(0.0031)
hispanic	-0.1026 ***	-0.1073 ***
	(0.0046)	(0.0027)
other	-0.0297	-0.0336
	(0.0390)	(0.0224)
euc_access	0.1334	0.0014
	(0.0711)	(0.0394)
lambda	0.7890 ***	0.9052 ***
	(0.0157)	(0.0058)
Num. obs.	2102	6402
Parameters	16	16
Log Likelihood	-4498.0118	-11966.8091

Twitter Analysis

Reviewer 1: The use of Twitter data is poorly justified and discussed. Why chosen a 0.1 estimate of the effect of tweets on the accessibility of parks? Could you please provide some sensibility measures? Again, there is no critical review of the literature. I would particularly recommend to discuss your findings in relation with Roberts HV. Using Twitter data in urban green space research: A case study and critical evaluation. Applied Geography. 2017; 81:13–20 or to drop this indicator if you are not making any conclusions out of it and have no clue of how to integrate it properly in your study.

We agree with the reviewer that our inclusion of geolocated Twitter activity at the parks in the accessibility utility calculations was not well-considered, particularly given our need to assert a utility parameter for which we had no reference. We have removed this analysis from the manuscript, though we have added a suggestion for related future research and a reference to the Roberts work in the Limitations section,

The set of amenities we included in the utility calculation – and the contribution of each amenity to the overall utility – was dictated by the availability of data on the park amenities in New York City and our ability to find comparable prior studies with transferrable utility parameters. We can envision a study where mobile device data revealing the home locations of park users would be paired with more detailed park amenities and use data (e.g. geolocated Twitter data *a la* Roberts, 2017).

Minor Comments

Reviewer 1: I would consider a diverging palette as the map depicts census tracts below or above the average accessibility level to parks.

We agree with this suggestion and have updated the graphic accordingly.

Reviewer 2: Data: please provide details of the park distance data. Is it tract centroids to all parks? Using Euclidean, walking network, driving network etc.? what is the park distance data and how did you calculate it? (I see you discuss this in the limitations, but this should be in the data section)

We clarified that the distance is explicitly Euclidean in the Accessibility sub-section, according to the discussion above.

Reviewer 2: Please bold the beta (as per your following sentence).

We have reviewed the mathematics and bolded all symbols that refer to vectors.

Reviewer 2: Eqn 4 (and subsequent): I understand the formula for linear regression is \beta X rather than X \beta.

In our notation we follow the that of LeSage and Pace (2009), who employ matrix notation to substantially simplify the spatial autoregressive equations. In this notation, X is a matrix of $n \times p$ where n is the number of observations and p is the number of parameters. The vector of estimates $\boldsymbol{\beta}$ is a vector of length p. As matrix multiplication requires conforming dimensions, it is common to represent $X\boldsymbol{\beta}$ as an $n \times p * p \times 1$ operation resulting in an $n \times 1$ vector. We feel that a clarifying comment on the notation is best positioned after Equation 8:

where X is a matrix of dimension $n \times p$ where n is the number of observations and p is the number of predictor variables, and $\boldsymbol{\beta}$ is a $p \times 1$ vector of estimated parameters. The accessibility vector $\boldsymbol{A}$ influences physical activity or obesity rates by the single estimated parameter β_a, and a vector $\boldsymbol{\varepsilon}$ represents the model residual as a random variable.

Table 2. Please align right and have a separate column for CI to allow for comparison between the mean values.

We have reconstructed Table 2 to show the confidence intervals in their own columns. We hope this makes comparing the mean values and confidence intervals more convenient. More simple tables elsewhere in the paper show the confidence intervals and parameter estimates on separate rows.

Table 3. I find it hard to read so maybe faint row lines would be useful. Or switch columns Twitter and Amenities.

We agree that some of the other model estimation tables could have been clearer. We have elected to improve these tables by referring to each accessibility score as "Accessibility," with the specific accessibility equation distinguished by model names in the header row. We hope that this, combined with removing the Twitter analysis, resolves the issues the reviewer experienced.