Using Google Street View to Audit Neighborhood Environments

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Background: Research indicates that neighborhood environment characteristics such as physical disorder influence health and health behavior. In-person audit of neighborhood environments is costly and time-consuming. Google Street View may allow auditing of neighborhood environments more easily and at lower cost, but little is known about the feasibility of such data collection.

Purpose: To assess the feasibility of using Google Street View to audit neighborhood environments.

Methods: This study compared neighborhood measurements coded in 2008 using Street View with neighborhood audit data collected in 2007. The sample included 37 block faces in high-walkability neighborhoods in New York City. Field audit and Street View data were collected for 143 items associated with seven neighborhood environment constructions: aesthetics, physical disorder, pedestrian safety, motorized traffic and parking, infrastructure for active travel, sidewalk amenities, and social and commercial activity. To measure concordance between field audit and Street View data, percentage agreement was used for categoric measures and Spearman rank-order correlations were used for continuous measures.

Results: The analyses, conducted in 2009, found high levels of concordance (≥80% agreement or ≥0.60 Spearman rank-order correlation) for 54.3% of the items. Measures of pedestrian safety, motorized traffic and parking, and infrastructure for active travel had relatively high levels of concordance, whereas measures of physical disorder had low levels. Features that are small or that typically exhibit temporal variability had lower levels of concordance.

Conclusions: This exploratory study indicates that Google Street View can be used to audit neighborhood environments.
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Introduction

The past decade has seen a rapid expansion of research on the health implications of neighborhood environment features such as aesthetics, physical disorder, social activities, and pedestrian safety. Studies have found associations between specific neighborhood characteristics and cardiovascular disease[1]; self-rated health[2]; walking and other forms of physical activity[3]; obesity[4–8]; lower-body functional limitations[9,10]; symptoms of depression, anxiety, and conduct disorders[11–13]; asthma[14,15]; and crime and violence.[1,16,17]

Neighborhood environment studies present practical challenges, especially in studies using large and geographically dispersed samples. Neighborhood features are commonly inventoried using survey respondent self-report, administrative data, or observer audits, and each of these strategies has benefits and limitations. Survey-based measures can be useful for assessing how residents perceive their neighborhoods; however, using respondent reports of neighborhood conditions can introduce bias because outcomes may be correlated with measurement error on the independent variable (i.e., the same-source bias problem).[18] One way to address same-source bias is to field a parallel survey, administered to an independent sample, to measure neighborhood conditions.[19,20] However, the additional sample increases survey costs substantially.

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Alternatively, some researchers use administrative data and GIS tools to characterize urban environments. Although spatially referenced administrative data are becoming more widely available and are clearly useful for neighborhood health studies,[21] such data are usually collected to meet local administrative priorities, such as needs assessment and evaluation of service quality. Although some cities are making administrative data publicly available, data are often inconsistently available or collected using different methodologies across jurisdictions. Even in areas with rich administrative geospatial data resources, the data often do not include many neighborhood features of interest to researchers.[22]

Because of these disadvantages, many researchers[17,23–26] have relied on neighborhood audits, also called systematic social observation. Neighborhood audits enable researchers to define theoretically relevant measures and allow assessment of reliability and validity. However, audits are time-consuming and expensive to conduct largely because of the costs of travel; as a result, they are typically limited to small, geographically circumscribed study areas.[27–29] Audits may also be perceived by local residents as intrusive and can involve safety problems for research staff.[30] Some studies[17,31,32] have conducted neighborhood "windshield surveys," in which researchers drive through a neighborhood to make observations, sometimes recording videotape for later coding. Windshield surveys may reduce concerns about the safety of research staff, but coding neighborhood characteristics from a moving vehicle provides less detail than coding on foot. Although videotape recording allows more detailed and careful coding, it also increases costs substantially.

Google Street View represents an alternative source of data on neighborhood environments. Street View, available from Google's online Maps application (maps.google.com) is a library of video footage captured by cars driven down the street. The images have been processed to provide panoramic, street-level views of city streets, in which the user can navigate forward or backward along the street, pan 360 degrees, rotate the camera vertically 290 degrees, and zoom in and out (see Figure 1). Google Street View was introduced in 2007 with coverage of a handful of cities but is being extended to new cities at a rapid pace. The image resolution varies depending on when the images were taken, with places photographed more recently being of higher resolution.

Using Google Street View, researchers can conduct "virtual" field audits of neighborhoods. The idea builds on older studies using videotaped images,[17] but leverages Google's industrial-scale collection of images and information technology infrastructure.[31] Street View audits can be implemented in multiple cities from one central location, eliminating travel costs as well as concerns about intrusiveness and research staff safety. Audit sessions conducted from a central computer lab also allow for better oversight and quality control because supervisors can be on-site to monitor the auditors and images of the auditor's screens (screen-shots) can be captured and archived for later quality-control review.

Little is known, however, about the feasibility of using Street View to audit neighborhood environments. To explore whether larger-scale deployment would be possible, data coded from Street View images were compared to data from a previous field audit of New York City streets.[33] The objectives of this research were to identify constructs that can be measured using Google Street View, identify barriers to its use, and to build an experience base with the Street View interface on which viewing protocols can be developed. The validity of Street View was compared by neighborhood environment construct (e.g., physical disorder, social activity, support for active travel) and by the size and temporal variability of neighborhood features.

Methods

This study compared neighborhood measures coded from Street View images with those based on field observation in a prior study of 38 high-walkability block segments in New York City; 19 blocks from poor (≥20% poverty) and 19 blocks from nonpoor (<20% poverty) census tracts matched on neighborhood walkability.[33] The use of high-walkability blocks was efficient for this exploratory study because such blocks tend to have a high density of the features typically included in neighborhood audits.

The field project collected detailed measures of aesthetics (including natural features and attractive architecture); physical disorder; pedestrian safety; motorized traffic and parking; infrastructure for active travel; sidewalk amenities; and social activity, with audit items adapted from previous audit tools. Field observers spent about 75 minutes evaluating each block face; in addition to the paper-and-pencil audit measures, observers took two 10-minute pedestrian counts, used a radar gun to gauge traffic speed, and used a rolling tape measure to measure sidewalk width.

One year after the field audits, a graduate research assistant not involved in the original project used Street View to examine the block segments included in the field audit, selecting the block face on the right side of the street from the initial intersection. One block segment was not available in Street View at the time of the study. To the extent possible, the research assistant implemented the field observation protocol in the remaining 37 block segments observed in the field study. The research assistant received instruction in the basics of the Google interface but no specific instructions, such as when

Figure 1. Screen captures of Google Street View panoramic images

to use the pan or magnify features, for implementing the field observation protocol via Street View tools. As this was our initial experience with Street View, one goal of this project was to develop experience on which such instructions could be based; the research assistant provided the research staff with feedback regarding the use of the interface. Thus the results provide a conservative measure of the validity of Street View measurement; specific instructions for using Street View to measure the audit items are likely to increase concordance between field and Street View measures.

The resulting data set included one field (in-person) measure and one Street View measure for 37 block faces and 143 items. For the 103 categoric items, the percentage agreement between the field and Street View measure was calculated. For the 40 count or percentage items, Spearman rank-order correlations between field audit and Street View data were calculated; correlations could not be computed for three items because there was no variation in field or Street View ratings. In addition, based on consensus ratings by the authors, neighborhood features that were "small" (smaller than a backpack) or temporally variable (likely to move or change within 1 week) were identified; these classifications were employed in order to examine whether item size and temporal variability were associated with the level of agreement between field and Street View measures.

Results

Field audit items that are intrinsically impossible to evaluate with static video images, including noises, odors, and traffic speeds, could not be evaluated with Street View. In addition, several items from the field audit—such as a 10-minute pedestrian count, and sidewalk width—could not be replicated as administered in the field and were also excluded. Because the field audits included measures not performed in the Street View sessions, the length of time required for each audit method cannot be directly compared. On a per-item basis, the time required for data gathering is similar using in-person or Street View–based observations; however, the Street View–based protocol does not require physical travel and saved approximately 33 hours per auditor in travel time.

Appendix: A (available online at www.ajpm-online.net) displays percentage agreement between field and Street View measures for the 103 categoric measures. Levels of agreement were high (≥80%) for 60.2% of the items and moderate (≥60% and <80%) for 22.3% of the items. Items with very low agreement included the presence of buildings with "pre-war" architecture (24%) and the presence of street corner curb cuts (3%). Appendix B (available online at www.ajpm-online.net) also reports Spearman correlations for 37 count or proportion items. Correlations were high (≥0.60) for

Table 1. Percentage agreement or Spearman rank-order correlation between field audit and Street View measures

Measures	*n*	Agreement or correlation[a] % high	% moderate	% low
Total	140	54.3	22.9	22.9
Neighborhood environment construct				
Aesthetics	23	34.8	30.4	34.8
Physical disorder	17	23.5	41.2	35.3
Pedestrian safety	29	72.4	17.2	10.3
Motorized traffic and parking	12	75.0	16.7	8.3
Infrastructure for active travel	11	90.9	0.0	9.1
Sidewalk amenities	20	40.0	25.0	35.0
Human presence and social interactions	28	57.1	21.4	21.4
Size				
Small	9	11.1	44.4	44.4
Other	131	57.3	21.4	21.4
Temporal stability				
Stable	91	58.2	24.2	17.6
Unstable	49	46.9	20.4	32.7

[a]A high agreement is ≥80%; a moderate agreement is 60%–79.9%; a low agreement is <60%. For the continuous measures, a high correlation is defined as ≥0.60; a moderate correlation is 0.40–0.59; a low correlation is <0.40.

37.8% of the items and moderate (≥0.40 and <0.60) for 24.3% of the items; 27 of the correlations were significant at the $p<0.05$ level. Notably poor correlations were obtained for counts of window boxes (−0.08); number of chairs on the sidewalk (−0.14); number of political or marketing sign-up tables (−0.03); and number of food vendors (−0.13).

Aggregating results for categoric and continuous measures, Table 1 summarizes concordance by neighborhood environment construct and by item size and temporal variability. For pedestrian safety, motorized traffic and parking, and infrastructure for active travel, most items had high concordance. Neighborhood aesthetics, physical disorder, and sidewalk amenities had the highest fraction of items with low concordance. As expected, items coded as "small" had lower levels of concordance: Only 11.1% of small items had high agreement or correlations, compared with 57.3% of other items. Temporally variable items, such as the presence of people, animals, or garbage and litter also had lower concordance, with 46.9% of the items exhibiting high agreement or correlations compared with 58.2% among the more-stable items. Differences in item size and temporal variability may help explain why agreement was higher for some neighborhood constructs than for others: Items related to pedestrian safety and motorized traffic and parking tended to be large and temporally stable, whereas many items related to physical disorder are small and transient.

The Street View camera has a different field of view than the observer walking along the sidewalk. Parked or moving vehicles can obscure portions of sidewalks and buildings. The satellite imagery in Google Maps and 3-D texture mapped data in Google Earth, both of which provide birds-eye views unobstructed by parked cars, was evaluated as a means to measure items when the Street View imagery is obstructed. However, the resolution of the Google Maps images was too coarse to be useful; the 3-D texture mapped data in Google Earth were not available in many areas and were useful only for large items.

Discussion

This exploratory study evaluated the feasibility, including barriers and limitations, of using Google Street View to audit neighborhood environments. Although Street View is generally limited to public spaces viewable from automobile-accessible streets, few barriers to the use of Street View were identified. Only one of the sampled 38 block faces was unavailable within Street View. Relatively few items from the field protocol—those measuring noise, odors, exact distances, and measures with a temporal dimension (traffic speed or volume, pedestrian crossing time)—were impossible to implement. Among the items that were measured using Street View, 54.3% exhibited high concordance between the field audit and Street View measures. Percentage agreement and Spearman rank-order correlations were higher for items that were larger or less temporally variable.

These results, though preliminary, are important because Street View offers a number of advantages for measuring neighborhood features shown to influence health. As discussed above, data collection via Street View is likely to be less costly and logistically simpler than in-person audits, facilitates supervision and quality control, and addresses some concerns about the intrusiveness of field audit studies as well as safety problems associated with fieldwork in high-crime neighborhoods. The Street View–based protocol does not require physical travel, which yields a large gain in productivity, and this gain in productivity is expected to be even larger for studies conducted over larger or geographically dispersed areas.

One limitation of Street View arises because of temporal variability in neighborhood features. Some neighborhood features are inherently unstable over short periods of time. These include the number, characteristics, and activities of pedestrians, as well as parked or moving vehicles and many markers of physical disorder such as trash. Levels and characteristics of these items may exhibit both random variability and regular diurnal, seasonal, or weather-related fluctuation. The field observations were taken during the summer in mid-morning or mid-afternoon and were not taken during inclement weather. By contrast, although Google does not release information about when Street View images are taken, many Street View images in New York City appeared to have been videotaped during the early morning hours, presumably to avoid heavy traffic. In a few instances, it was apparent from abrupt changes in lighting, shadows, and weather that the images from adjacent blocks were captured at different times of the day or on different days. Measurement error is likely to be higher for temporally variable items, and differences in the timing of field and Street View measurement may also lead to bias. For instance, collection of Street View video early in the morning is likely to result in lower observed levels of social and pedestrian activity, and may also—depending on the timing of garbage removal—affect measured levels of physical disorder.

An additional limitation is that property owners may request that Google remove or blur images that depict features of their property they object to having publicly displayed.[34] This policy may lead to undercounts of items related to physical and social disorder, and if the frequency of such requests varies by neighborhood sociodemographic characteristics, the selective removal of data may cause biases in research results. Lastly, Google faces criticism over privacy issues with their Maps and Street View products, which may lead to changes in the extent of coverage and in resolution of images in the future. In response, Google has implemented facial and license plate blurring and has removed shelters for victims of domestic violence from the imagery available in the U.S.[34,35]

The results suggest that differences between the perspectives of in-person auditors and the Street View camera have implications for the validity of measurement. Like most neighborhood audits, the field audit underlying this study was conducted by coders walking on the sidewalk, whereas Street View video images are taken from farther away and so views of the sidewalk may be blocked by parked vehicles. Small items, especially those located on the sidewalk surface or low to the ground, can be more difficult to discern via Street View. As Google produces images of higher resolution, the visibility of small items will improve. For elements designed to be seen from a driver's perspective, such as traffic lights, medians, and pedestrian crossing signs, we suspect that data collection via Street View will have higher validity than in-person audits from the sidewalk.

Strengths of this study include the use of a large number of items measuring a variety of neighborhood environment characteristics, as well as the inclusion of both poor and nonpoor urban neighborhoods. The focus on high-walkability block segments in New York City limits the generalizability of the study; although this sample was efficient in the sense that it included blocks with a high density of observable features, the study may not detect barriers and limitations specific to lower-density environments. Future research should consider feasibility, reliability, and validity of Street View measurement in other kinds of neighborhood environments.

Further Development and Validation of Street View–Based Methods

Although this study demonstrates the feasibility of using Street View for measuring some neighborhood characteristics, adapting Street View for use in systematic scientific analysis requires attention to several methodologic issues. The first is the development of Street View–specific protocols optimized to improve reliability and validity measures through the systematic use of the pan, rotate, and magnification functions to inspect blocks for specific audit items during multiple passes along the target block. For instance, further investigation of the discordance in street corner curb cuts showed that curb cuts were visible in Street View, but systematic use of the rotate and magnification functions from the middle of the street intersection portion of the panoramic images was required for visualization. Street View data collection protocols should also include the collection of quality metrics, including the occurrence of image quality issues related to lighting, shadows, and weather and obstructions such as traffic or parked vehicles.

Second is evaluation of the psychometric and ecometric properties and predictive power of neighborhood measures created from Street View. Subscales of existing commonly used scales should be assessed for validity and reliability because some items in these scales are impossible to measure or difficult to measure well. Physical disorder scales, for instance, often include measures of noise as well as small and/or transient items; Street View–based measures of physical disorder are likely to include only a subset of items included in previous field-based scales. In addition, the measurement properties including inter-rater reliability and validity of measures obtained using Street View protocols should be assessed. Because in-person studies expose the auditors to distractions, such as noise and interactions with pedestrians and commercial venues, inter-rater reliability could be higher for Street View versus in-person coding. However, there may be inter-rater differences in the extent to which the features and tools of the Google interface cause distraction, reducing inter-rater reliability. The impact of data-gathering mode on the psychometric properties of the audit scales needs to be assessed.

There is a growing interest among policymakers in understanding the ways in which neighborhood social or physical characteristics such as pedestrian infrastructure, traffic safety, bike-ability, urban design, urban forestry, or physical disorder affect health. Research to inform such policies requires efficient and valid methods to characterize neighborhoods. Although items that are small or temporally variable may not be appropriate for Street View measurement, it is demonstrated here that Google Street View can be an efficient tool for collecting data on many physical and urban design characteristics that are important for neighborhood health studies. The approach improves efficiency by removing the need for travel, and centralized data collection in a computer lab environment can improve quality control.

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Appendix

Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.amepre.2010.09.034.