Response to Invited Commentary

Mooney et al. Respond to "Observing Neighborhood Physical Disorder"

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We appreciate Dr. Jackelyn Hwang's comments (1) on our paper in which we compared a virtual audit of Detroit, Michigan, using data from Google Street View (Google, Inc., Mountain View, California) with an in-person audit of the same city (2). Broadly, we concur with her observations regarding the benefits and limitations of virtual audits and share her excitement regarding how the technique might be leveraged in the future. We elaborate here on key points raised by Dr. Hwang, emphasizing decision points relevant to future research using virtual audits.

First, we concur that ordinary kriging, the interpolation technique that we and others have used for spatially sampled neighborhood data (3–6), does not account for block-by-block differences in neighborhood physical disorder that can arise in rapidly changing neighborhoods (7). More broadly, many built environment characteristics of researcher interest, including sidewalk accessibility (8), transit access (9–11), many aspects of urban form (12), and pedestrian safety (13) display microscale spatial patterns (i.e., block-by-block differences) that make spatial interpolation imprecise at that level of aggregation. However, these microscale patterns do not preclude the use of a virtual audit, only interpolation. That is, a virtual audit of every block in a neighborhood would capture the granular variation in these features as well as would an in-person audit of every block. Thus, researchers considering neighborhood audits should allow the expected microscale variation of the characteristics being audited to inform the sample design.

Second, we also concur that "big data" (14), such as 3-1-1 (nonemergency) and 9-1-1 (emergency) call records, could supplement virtual audits by measuring aspects of social disorder indicators that virtual audits cannot (15); however, these data may introduce biases because some demographic groups are more engaged with 3-1-1 and 9-1-1 systems than are others (16). Indeed, we expect that researchers will develop models that integrate indicators of disorder from multiple sources in future research; administrative and audit data used together in a single spatial model may provide better measurement accuracy than any one source alone. Such models, potentially leveraging universal kriging, will benefit from further work comparing the reliability and validity of available assessment techniques for similar domains of inquiry (17).

Finally, we caution researchers considering virtual audits or using other online geospatial tools that using subject's home addresses to select block faces to audit may violate the privacy of those study subjects (18). Web browsers and virtual audit systems such as the Forty Area Study Street View (19) and the Computer Assisted Neighborhood Visual Assessment System (20) send location information to Google to identify the street segment to audit, thus passing identifying information to a third party. Spatial interpolation, as used in the present study, and spatial imputation minimize the risks of identity disclosure (2, 18).

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REFERENCES

1. Hwang J. Invited commentary: observing neighborhood physical disorder in an age of technological innovation. *Am J Epidemiol*. 2017;186(3):274–277.
2. Mooney SJ, Bader MDM, Lovasi GS, et al. Street audits to measure neighborhood physical disorder: virtual or in-person? *Am J Epidemiol*. 2017;186(3):265–273.
3. Keyes KM, McLaughlin KA, Koenen KC, et al. Child maltreatment increases sensitivity to adverse social contexts: neighborhood physical disorder and incident binge drinking in Detroit. *Drug Alcohol Depend*. 2012;122(1-2):77–85.
4. Bader MDM, Ailshire JA. Creating measures of theoretically relevant neighborhood attributes at multiple spatial scales. *Sociol Methodol*. 2014;44(1):322–368.
5. Mooney SJ, Bader MD, Lovasi GS, et al. Validity of an ecometric neighborhood physical disorder measure constructed by virtual street audit. *Am J Epidemiol*. 2014; 180(6):626–635.
6. Auchincloss AH, Diez Roux AV, Brown DG, et al. Filling the gaps: spatial interpolation of residential survey data in the estimation of neighborhood characteristics. *Epidemiology*. 2007;18(4):469–478.
7. Hwang J, Sampson RJ. Divergent pathways of gentrification: racial inequality and the social order of renewal in Chicago neighborhoods. *Am Sociol Rev*. 2014;79(4):726–751.
8. Hara K, Le V, Froehlich J. Combining crowdsourcing and google street view to identify street-level accessibility problems. Presented at Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Paris, France, April 27–May 2, 2013.
9. Appleyard B. Sustainable and healthy travel choices and the built environment: analyses of green and active access to rail transit stations along individual corridors. *Transp Res Rec*. 2012;2303:38–45.
10. Hara K, Azenkot S, Campbell M, et al. Improving public transit accessibility for blind riders by crowdsourcing bus stop landmark locations with Google Street View: an extended analysis. *ACM Trans Accessible Comput*. 2015;6(2):Article 5.
11. Kelly CM, Wilson JS, Baker EA, et al. Using Google Street View to audit the built environment: inter-rater reliability results. *Ann Behav Med*. 2013;45(suppl 1):S108–S112.
12. Neckerman KM, Lovasi GS, Davies S, et al. Disparities in urban neighborhood conditions: evidence from GIS measures and field observation in New York City. *J Public Health Policy*. 2009;30(suppl 1):S264–S285.
13. Mooney SJ, DiMaggio CJ, Lovasi GS, et al. Use of Google Street View to assess environmental contributions to pedestrian injury. *Am J Public Health*. 2016;106(3):462–469.
14. Mooney SJ, Westreich DJ, El-Sayed AM. Commentary: epidemiology in the era of big data. *Epidemiology*. 2015;26(3): 390–394.
15. O'Brien DT, Sampson RJ. Public and private spheres of neighborhood disorder: assessing pathways to violence using large-scale digital records. *J Res Crime Delinq*. 2015;52(4): 486–510.
16. O'Brien DT. Custodians and custodianship in urban neighborhoods: a methodology using reports of public issues received by a city's 311 hotline. *Environ Behav*. 2013;47(3): 304–327.
17. Pliakas T, Hawkesworth S, Silverwood RJ, et al. Optimising measurement of health-related characteristics of the built environment: comparing data collected by foot-based street audits, virtual street audits and routine secondary data sources. *Health Place*. 2016;43:75–84.
18. Bader MD, Mooney SJ, Rundle AG. Protecting personally identifiable information when using online geographic tools for public health research. *Am J Public Health*. 2016;106(2):206–208.
19. Griew P, Hillsdon M, Foster C, et al. Developing and testing a street audit tool using Google Street View to measure environmental supportiveness for physical activity. *Int J Behav Nutr Phys Act*. 2013;10:103.
20. Bader MD, Mooney SJ, Lee YJ, et al. Development and deployment of the Computer Assisted Neighborhood Visual Assessment System (CANVAS) to measure health-related neighborhood conditions. *Health Place*. 2015;31:163–172.