Results of the Friedman tests indicated that overall, distributions of neighborhood deprivation differed across the various neighborhood definitions in urbanized areas (Chi-square=897.75, P<0.001) and urban clusters (Chi-square=687.83, P<0.001), but not in rural areas (Chi-square=13.52, P=0.332). Pairwise comparisons of neighborhood definitions in urbanized areas and urban clusters (Table 6) demonstrate that there were significant differences in deprivation between most but not all neighborhood definitions. For example, in urbanized areas, census tract and Euclidean 1 mile/1.6 km buffers resulted in similar levels of exposure to neighborhood deprivation (P=1.000) whereas comparing census tract and Euclidean 5 mile/8 km buffers resulted in different levels of exposure to neighborhood deprivation (P<0.001). Similarly, in urban clusters, census tract and Euclidean 1 mile buffers resulted in similar levels of exposure to neighborhood deprivation (P=0.109) whereas comparing census tract and Euclidean 5 mile/8 km buffers resulted in different levels of exposure to neighborhood deprivation (P<0.001).

Discussion

While much research has sought to tease out the influence of neighborhood on various health and developmental outcomes, often researchers take an *off the shelf* approach to data using what datasets are available to them. This ad hoc (and often theoretically devoid) approach is problematic as it may lead to results that are both inconclusive, and that may confound findings as the measured exposure to neighborhood factors can change based on the zone

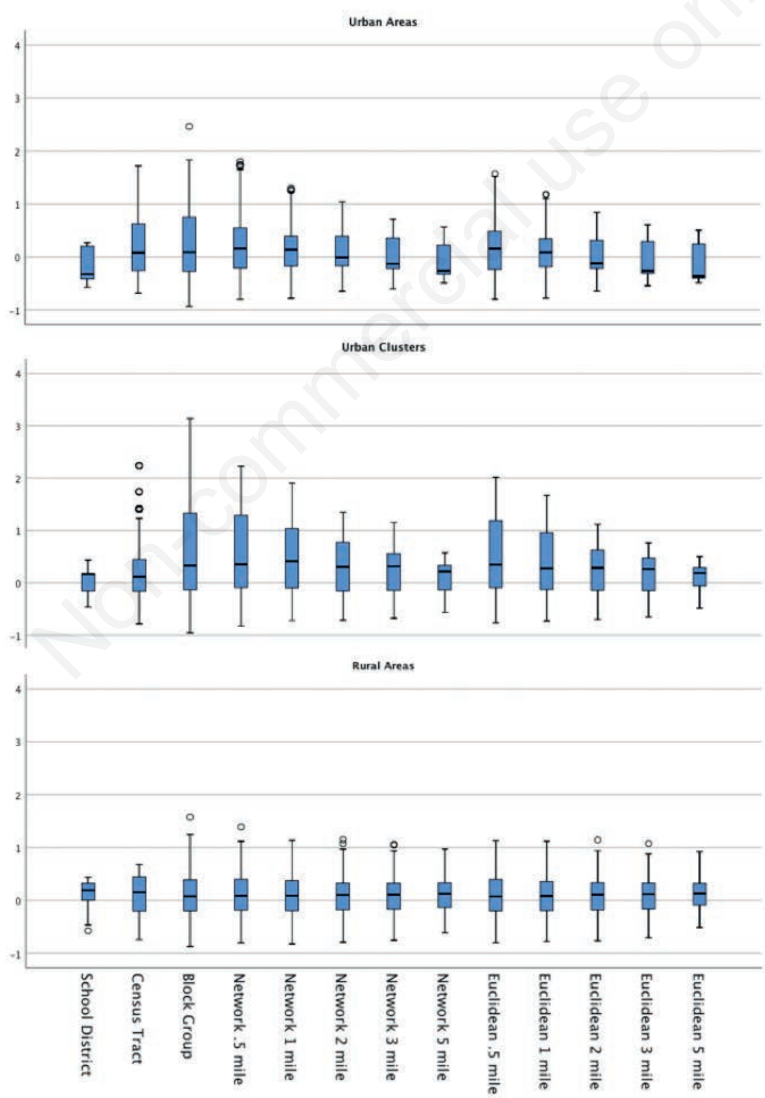

Figure 2. Boxplots depicting medians and distributions of neighborhood deprivation for each neighborhood definition in urbanized areas, urban clusters, and rural areas.

Table 2. Descriptive statistics for neighborhood deprivation.

	Urbanized areas			Urban clusters			Rural areas		
	Mean	SD	Range	Mean	SD	Range	Mean	SD	Range
School District	–0.16	0.30	[–0.57-0.27]	0.05	0.24	[–0.46-0.44]	0.12	0.28	[–0.57-0.44]
Census Tract	0.18	0.54	[–0.69-1.72]	0.34	0.71	[–0.78-2.23]	0.11	0.35	[–0.74-0.68]
Census Block Group	0.29	0.74	[–0.94-2.46]	0.59	0.94	[–0.96-3.13]	0.12	0.44	[–0.87-1.57]
Network 1/2 mile	0.23	0.57	[–0.81-1.8]	0.57	0.83	[–0.82-2.23]	0.12	0.41	[–0.8-1.39]
Network 1 mile	0.14	0.43	[–0.78-1.29]	0.48	0.69	[–0.72-1.9]	0.11	0.39	[–0.82-1.14]
Network 2 mile	0.07	0.37	[–0.65-1.04]	0.35	0.55	[–0.71-1.35]	0.09	0.36	[–0.79-1.15]
Network 3 mile	–0.01	0.33	[–0.6-0.71]	0.26	0.43	[–0.68-1.15]	0.09	0.34	[–0.75-1.06]
Network 5 mile	–0.10	0.30	[–0.49-0.57]	0.12	0.29	[–0.56-0.58]	0.10	0.32	[–0.61-0.97]
Euclidean 1/2 mile	0.20	0.52	[–0.8-1.57]	0.52	0.78	[–0.76-2.02]	0.11	0.40	[–0.8-1.13]
Euclidean 1 mile	0.11	0.41	[–0.78-1.18]	0.40	0.64	[–0.73-1.67]	0.10	0.38	[–0.77-1.12]
Euclidean 2 mile	0.00	0.35	[–0.64-0.84]	0.27	0.47	[–0.7-1.12]	0.09	0.35	[–0.76-1.14]
Euclidean 3 mile	–0.07	0.33	[–0.54-0.61]	0.18	0.36	[–0.65-0.77]	0.09	0.32	[–0.7-1.08]
Euclidean 5 mile	–0.13	0.33	[–0.49-0.5]	0.08	0.27	[–0.48-0.5]	0.09	0.30	[–0.51-0.92]

Note: Network and Euclidean buffer sizes are 0.5 mile/0.8 km, 1 mile/1.6 km, 2 mile/3.2 km, 3 mile/4.8 km, and 5 mile/8 km. SD, standard deviation.

Table 3. Correlations among exposure to neighborhood deprivation measured at various neighborhood definitions in urbanized areas.

	1	2	3	4	5	6	7	8	9	10	11	12
1. School District												
2. Census Tract	0.424**											
3. Census Block Group	0.394**	0.821**										
4. Network 1/2 mile	0.419**	0.844**	0.917**									
5. Network 1 mile	0.488**	0.825**	0.819**	0.931**								
6. Network 2 mile	0.504**	0.719**	0.717**	0.827**	0.932**							
7. Network 3 mile	0.641**	0.584**	0.614**	0.692**	0.778**	0.871**						
8. Network 5 mile	0.794**	0.456**	0.469**	0.519**	0.610**	0.665**	0.815**					
9. Euclidean 1/2 mile	0.433**	0.840**	0.883**	0.977**	0.958**	0.859**	0.722**	0.544**				
10. Euclidean 1 mile	0.487**	0.790**	0.780**	0.888**	0.976**	0.944**	0.824**	0.621**	0.933**			
11. Euclidean 2 mile	0.644**	0.622**	0.645**	0.737**	0.825**	0.906**	0.971**	0.797**	0.766**	0.867**		
12. Euclidean 3 mile	0.763**	0.543**	0.561**	0.616**	0.694**	0.755**	0.921**	0.910**	0.643**	0.736**	0.904**	
13. Euclidean 5 mile	0.853**	0.366**	0.387**	0.414**	0.487**	0.553**	0.730**	0.910**	0.428**	0.504**	0.715**	0.841**

**Correlation is significant at the 0.01 level (2-tailed). Note: Network and Euclidean buffer sizes are 0.5 mile/0.8 km, 1 mile/1.6 km, 2 mile/3.2 km, 3 mile/4.8 km, and 5 mile/8 km.

Table 4. Correlations among exposure to neighborhood deprivation measured at various neighborhood definitions in urban clusters.

	1	2	3	4	5	6	7	8	9	10	11	12
1. School District												
2. Census Tract	0.565**											
3. Census Block Group	0.386**	0.720**										
4. Network 1/2 mile	0.463**	0.776**	0.933**									
5. Network 1 mile	0.533**	0.848**	0.866**	0.949**								
6. Network 2 mile	0.579**	0.852**	0.776**	0.844**	0.945**							
7. Network 3 mile	0.562**	0.817**	0.723**	0.786**	0.897**	0.975**						
8. Network 5 mile	0.621**	0.693**	0.649**	0.696**	0.797**	0.892**	0.925**					
9. Euclidean 1/2 mile	0.508**	0.820**	0.917**	0.984**	0.974**	0.893**	0.837**	0.750**				
10. Euclidean 1 mile	0.569**	0.875**	0.844**	0.922**	0.986**	0.959**	0.911**	0.818**	0.963**			
11. Euclidean 2 mile	0.589**	0.837**	0.759**	0.823**	0.925**	0.984**	0.983**	0.923**	0.878**	0.946**		
12. Euclidean 3 mile	0.588**	0.773**	0.718**	0.777**	0.876**	0.949**	0.975**	0.971**	0.829**	0.894**	0.978**	
13. Euclidean 5 mile	0.717**	0.672**	0.598**	0.635**	0.730**	0.829**	0.851**	0.952**	0.690**	0.760**	0.860**	0.908**

**Correlation is significant at the 0.01 level (2-tailed). Note: Network and Euclidean buffer sizes are 0.5 mile/0.8 km, 1 mile/1.6 km, 2 mile/3.2 km, 3 mile/4.8 km, and 5 mile/8 km.

and size of the neighborhood definition. By examining if the measured exposure of neighborhood deprivation differed by the neighborhood definition used in the FLP this study addresses the aforementioned issues; the first within early childhood development to examine whether these differences occur across the urban to rural spectrum.

Overall, results demonstrated that in urbanized areas and urban clusters, neighborhood deprivation varied to a statistically significant degree based on the neighborhood definition used. These findings are largely consistent with the theory of the modifiable areal unit problem and past research which has shown that measurement of exposures is sensitive to the size and zone of the neighborhood definition in urban areas (Duncan *et al*., 2014). In measuring neighborhood deprivation specifically, this study builds on past work which found that the measurement of deprivation differs depending on the size of the administrative buffer chosen (Schuurman *et al*., 2007). Our post-hoc comparison results in urbanized areas are also consistent with past work which found no difference in deprivation exposure across census tracts and census block groups in Quito, Ecuador (Cabrera-Barona *et al*., 2016), although post-hoc comparisons did find differences in urban clusters. The current study extends this prior work by comparing both administrative and ego-centric neighborhood definitions of various size and demonstrating that different definitions lead to differences in measured exposure to neighborhood deprivation.

In rural areas, however, results suggested that measured exposure to neighborhood deprivation was not dependent on neighborhood definition. These results are consistent with visual inspection of the medians and distributions of neighborhood deprivation which appeared more stable across neighborhood definitions in rural areas. No prior studies have investigated this specific question in rural areas and few studies have compared neighborhood definitions for other types of exposures in rural areas. This finding is not entirely surprising in that administrative boundaries such as

Table 5. Correlations among exposure to neighborhood deprivation measured at various neighborhood definitions in rural areas.

	1	2	3	4	5	6	7	8	9	10	11	12
1. School District												
2. Census Tract	0.643**											
3. Census Block Group	0.435**	0.700**										
4. Network 1/2 mile	0.472**	0.741**	0.940**									
5. Network 1 mile	0.506**	0.769**	0.903**	0.983**								
6. Network 2 mile	0.552**	0.810**	0.864**	0.945**	0.976**							
7. Network 3 mile	0.583**	0.846**	0.830**	0.903**	0.935**	0.977**						
8. Network 5 mile	0.597**	0.867**	0.752**	0.820**	0.851**	0.901**	0.955**					
9. Euclidean 1/2 mile	0.491**	0.748**	0.939**	0.994**	0.985**	0.952**	0.913**	0.829**				
10. Euclidean 1 mile	0.533**	0.779**	0.899**	0.972**	0.989**	0.979**	0.949**	0.871**	0.982**			
11. Euclidean 2 mile	0.585**	0.841**	0.833**	0.908**	0.936**	0.971**	0.985**	0.944**	0.919**	0.960**		
12. Euclidean 3 mile	0.585**	0.869**	0.763**	0.838**	0.869**	0.917**	0.965**	0.980**	0.848**	0.892**	0.971**	
13. Euclidean 5 mile	0.593**	0.856**	0.662**	0.728**	0.754**	0.807**	0.873**	0.958**	0.735**	0.778**	0.873**	0.946**

**Correlation is significant at the 0.01 level (2-tailed). Note: Network and Euclidean buffer sizes are 0.5 mile/0.8 km, 1 mile/1.6 km, 2 mile/3.2 km, 3 mile/4.8 km, and 5 mile/8 km.

Table 6. Post-hoc pairwise comparisons from Friedman's tests in urbanized areas (bottom left) and urban clusters (top right).

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. School District	--	–1.79*~	–3.84*~	–4.32*~	–4.06*~	–2.88*~	–2.00*~	–0.37	–3.93*~	–2.75*~	–1.42*~	–0.5	0.05
2. Census Tract	–4.58*~	--	–2.05*~	–2.54*~	–2.27*~	–1.09*~	–0.22	1.42*~	–2.14*~	–0.96*	0.37	1.29*~	1.84*~
3. Census Block Group	–4.79*~	–0.21	--	–0.48	–0.22	0.96*	1.84*~	3.47*~	–0.09	1.09*~	2.42*~	3.34*~	3.90*~
4. Network 1/2 mile	–5.22*~	–0.64*	–0.43	--	0.27	1.44*~	2.32*~	3.96*~	0.4	1.57*~	2.90*~	3.82*~	4.38*~
5. Network 1 mile	–4.91*~	–0.33	–0.12	0.31	--	1.18*~	2.05*~	3.69*~	0.13	1.31*~	2.64*~	3.55*~	4.11*~
6. Network 2 mile	–4.16*~	0.42	0.63*	1.06*~	0.75*	--	0.87*	2.51*~	–1.05*~	0.13	1.46*~	2.38*~	2.93*~
7. Network 3 mile	–3.21*~	1.38*~	1.59*~	2.02*~	1.71*~	0.96*	--	1.64*~	–1.92*~	–0.75*	0.58	1.50*~	2.06*~
8. Network 5 mile	–1.51*~	3.07*~	3.28*~	3.71*~	3.40*~	2.65*~	1.69*~	--	–3.56*~	–2.38*~	–1.05*~	–0.14	0.42
9. Euclidean 1/2 mile	–4.78*~	–0.20	0.01	0.44	0.13	–0.62*	–1.58*~	–3.27*~	--	1.8*~	2.51*~	3.43*~	3.98*~
10. Euclidean 1 mile	–4.18*~	0.40	0.61*	1.04*~	0.73*	–0.02	–0.98*~	–2.67*~	0.60*	--	1.33*~	2.25*~	2.81*~
11. Euclidean 2 mile	–3.19*~	1.39*~	1.60*~	2.03*~	1.72*~	0.97*	0.01	–1.68*~	1.59*~	0.99*~	--	0.92*	1.47*~
12. Euclidean 3 mile	–1.95*~	2.63*~	2.84*~	3.27*~	2.96*~	2.21*~	1.26*~	–0.44	2.83*~	2.23*~	1.24*~	--	0.56
13. Euclidean 5 mile	–0.77*	3.81*~	4.02*~	4.45*~	4.14*~	3.39*~	2.43*~	–0.74*	4.01*~	3.41*~	2.42*~	1.18*~	--

*Unadjusted P<0.05; ~Bonferroni corrected P<0.05. Note: Network and Euclidean buffer sizes are 0.5 mile/0.8 km, 1 mile/1.6 km, 2 mile/3.2 km, 3 mile/4.8 km, and 5 mile/8 km.

block group area varies widely based on location of those block groups in urban areas, urban clusters, and rural areas with relatively larger boundaries in rural areas. For example, in our sample, the mean size of block groups within urban areas was 0.8 square miles/2.1 square km, those in urban clusters was 1.3 square miles/3.4 square km, and those in rural areas was 16.3 square miles/42.2 square km. Additionally, this means that a neighborhood buffer of a given size encompasses fewer block groups in rural areas than in urban areas. In our sample, 5 mile/8 km Euclidean buffers located in rural areas intersected with a mean of 17.8 unique block groups whereas those in urban clusters intersected with a mean of 30.8 unique block groups, and those in urbanized areas intersected with 57.9. Thus in rural areas, disperse exposures, such as neighborhood deprivation, which are aggregated across block groups, would be expected to change more slowly as geographic boundaries expand or change shape from Euclidean to network buffers. These findings highlight the need for researchers to carefully consider scale of the neighborhood unit, especially in rural areas.

Importantly, disperse exposures (such as neighborhood deprivation) are very different from point exposures (such as parks or grocery stores) as point exposures can be counted within a certain neighborhood geography. Point exposures are likely more sensitive to different neighborhood geography types and sizes. For example, most point exposures have to be reached by road networks and thus using Euclidean or administrative buffers to capture the number of exposures may lead to biased estimates. Thus non differences that were found for rural areas and in some post-hoc comparisons in urbanized areas and urban clusters may be specific to neighborhood deprivation or to similar disperse exposures. Point exposure may be more sensitive to neighborhood definition even in rural areas. Also, given research showing how far some rural residents have to travel to access amenities like grocery stores (Thatcher *et al*., 2017) and for health care (Yaemsiri *et al*., 2019), buffer sizes many need to be even larger to even have any exposure at all. This may also suggest why there is no significant difference in deprivation across neighborhood definitions in rural settings.

A close examination of urbanized areas, shows that median levels of deprivation appear to be lower when neighborhood buffers are larger and higher at smaller neighborhood geographies. This likely reflects that the high deprivation neighborhoods in which participants from this sample live are smaller and more densely populated geographies which border on more advantaged neighborhoods. This pattern of racial and economic segregation in urban areas may in part be a direct result of historic disinvestment in certain neighborhoods through policies of institutional racism, such as redlining (Kramer, 2018; Mitchell and Franco, 2018). In post-hoc comparisons of various neighborhood definitions, we also generally see that smaller (0.5 mile/0.8 km, 1 mile/1.6 km, and some 2 mile/3.2 km) neighborhood buffers largely show no differences in comparisons with each other. Similarly, these smaller buffers do not show differences from census tracts or block groups, which would also tend to be geographically smaller in these more densely populated urbanized areas.

In urban clusters, the post-hoc comparisons revealed a less clear pattern. Null differences were found both among some of the smaller neighborhood definitions as well as among most of the larger 3 and 5 neighborhood definitions. In comparing administrative buffers to person-centric buffers, for the most part, school districts did not differ from the larger 3 mile/4.8 km and 5 mile/8 km buffers and block groups were similar to the smaller 0.5 mile/0.8 km and 1 mile/1.6 km buffers. Census tracts, a commonly used neighborhood definition in developmental research, differed from all neighborhood definitions except for 1 mile/1.6 km and 2 mile/3.2 km Euclidean and 3 mile/4.8 km network buffers.

Implications and future directions

These findings have several implications for researchers seeking to understand the role of neighborhood exposures in children's health and development. In rural areas, our results suggest that neighborhood definition and scale largely may not impact measured exposure to neighborhood deprivation. Still, however, we urge researchers to choose a theoretically relevant neighborhood definition when aiming to answer questions related to child health and development and argue that an ego centric neighborhood definition will likely be more theoretically relevant for children's lived experiences than utilizing administrative boundaries. For example, ego centric buffers help to overcome issues related to spatial misclassification and edge effects that are present when researchers rely on administrative boundaries. Additionally, larger rural areas may be too homogenous with respect to NDI calculations and further investigation into how to best measure NDIs is warranted, approaches such as dasymetric mapping as well as utilizing remotely sensed ancillary data have been recommended (see *e.g*., Baud *et al*., 2010). In urban areas, it is clear that researchers' choice of neighborhood definition and scale will impact the quantification of children's exposure to neighborhood deprivation and thus will likely in turn have impacts on the extent to which neighborhood deprivation is found to impact children's health and development. A growing body of work has demonstrated that relatively small, ego centric buffers may be the most relevant for urban areas (for a review see: Duncan *et al*., 2018). We also note the policy implications of this research, including recognizing that the most theoretically appropriate neighborhood definition may not be a policy relevant unit.

Future work on child health and development thus would greatly benefit from a characterization of neighborhood context that is made on theoretical grounds rather than solely on data availability (Duncan *et al*., 2014). For researchers who are focused on precise measurement of developmental outcomes, this may be particularly difficult as measurement of neighborhood context may be a post-hoc addition to a study which is conducted with few resources and as privacy concerns may limit the ability to collect actual address data. The FLP data thus present a unique opportunity as the study contains rich longitudinal data on family processes and children's outcomes from birth through young adulthood including detailed geographical data. By providing descriptive information on neighborhood deprivation across multiple administrative and ego-centric neighborhood definitions, this study opens the door for more precise examination of the ways in which children's exposure to neighborhood deprivation predicts later outcomes across multiple domains of health and development. In seeking to answer these questions, future studies would greatly benefit from including multiple neighborhood definitions in order to understand what zones and sizes of neighborhood geography are most predictive of children's outcomes and to act as sensitivity checks on the role of the neighborhood geography which was chosen because of its theoretical relevance. Furthermore, in investigating the roles of different zones and sizes of neighborhood geography, future research is needed to examine how current and historical aspects of structural racism including investments and disinvestments in neighborhoods have shaped patterns of neighborhood deprivation across urban and rural areas.

Limitations

This study is geographically limited by its focus on areas of high rural poverty in North Carolina and Pennsylvania. Thus the results showing how neighborhood deprivation differs based on choice of neighborhood definition may be specific to these areas. Furthermore, given the wide variation in the landscape of rural settings, it may be that in other rural areas, like the Southwest, measured exposure to neighborhood deprivation is more sensitive to the neighborhood definition. However, the FLP counties do capture some of this rural variation given the relatively mountainous terrain in Pennsylvania impacting settlement patterns, which is not found in this part of North Carolina (Vernon-Feagans *et al*., 2013). Additionally, as discussed above, it is likely that the measurement of other neighborhood characteristics not examined in this study, could be differentially sensitive to the type and scale of neighborhood buffers examined here. This may be particularly true when counting point exposures in a neighborhood such as the number of grocery stores. Future work defining rural neighborhoods may consider even larger buffers perhaps based on the distance needed to travel to obtain goods and services. Furthermore, future work examining the prediction of neighborhood deprivation to indicators of child health and development may demonstrate differences in the neighborhood definitions that are most strongly related to different outcomes.

Conclusions

Measuring neighborhood deprivation in the neighborhoods in which children live is an important step in understanding how neighborhood socioeconomic context affects child health and development. To advance this goal, this study examined the ways in which measured exposure to neighborhood deprivation differs across various definitions of children's neighborhoods in the FLP. Overall, results suggest that measured exposure to neighborhood deprivation is more sensitive to differences in neighborhood definition in urban settings than in rural settings. In describing how measured exposure to neighborhood deprivation differs across neighborhood definitions, this study informs decision making about defining neighborhoods in non-urban areas and opens the door for others to use FLP data to more precisely examine the ways in which children's exposure to neighborhood deprivation predicts later health and development.

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