Neighborhood Poverty Estimates Using Spatial Interpolation

Doug Geverdt, National Center for Education Statistics
P. Mae Cooper, U.S. Census Bureau
Javier Gomez, U.S. Census Bureau

NCES SIDE Project

- Initiated in 2015 by NCES with Census EDGE Branch
- Spatially interpolated demographic estimates (SIDE)
- Applies model-based spatial interpolation methods to ACS responses to create an income prediction surface
- Primary objectives:
  - Develop additional poverty indicator for students and schools (+ Free/Reduced-price lunch counts)
  - Provide better neighborhood poverty indicator to support educational research

Design Challenges

- Need a flexible neighborhood definition that can be anchored at specific locations (not tract boundaries)
- Need neighborhood estimates with reasonable reliability (ideally the size of a block group with the CV of a tract)
- Need geographic precision without risking disclosure
- Need regular updates that are operationally feasible within existing production environment

Design Strategy

- Define neighborhoods based on neighbors (not boundaries)
- Use kriging to model a continuous prediction surface of the income-to-poverty ratio (IPR) for the U.S.
  - Based on ACS responses from households with school-age children
  - Not constrained by Census geography
- Create raster approximation of prediction surface for NCES
  - Produce IPR estimates at specific geocoded locations
  - Supports scalable assignment solution for student address geocodes

Kriging

- Geostatistical interpolator that uses information from measured locations to predict values at unmeasured location
- Two stage modeling:
  - Models semivariogram to quantify spatial structure in data (how differences in paired responses vary by distance)
  - Applies model weights from stage #1 to nearest neighbors (25) to predict value at unsampled location
- Stationarity:
  - Kriging models assume a consistent distance-difference relationship across study area (often not the case for larger regions)
  - Empirical Bayesian kriging (EBK) manages non-stationarity by creating and blending a large collection of local models

Figure 1.
Model IPR to quantify spatial structure in the data
(functions provide a continuous prediction surface)

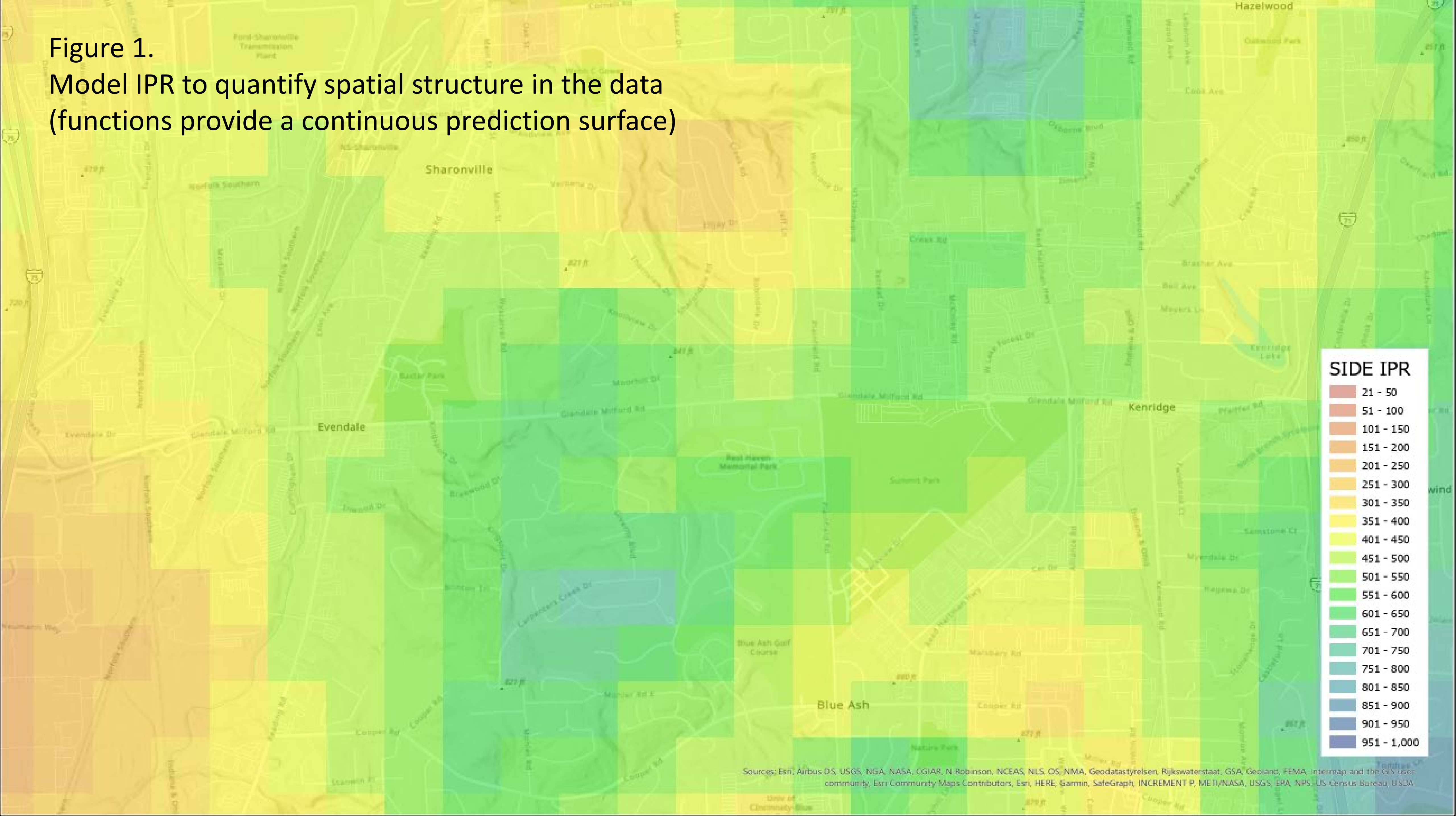


Figure 2.
Select unmeasured location for prediction

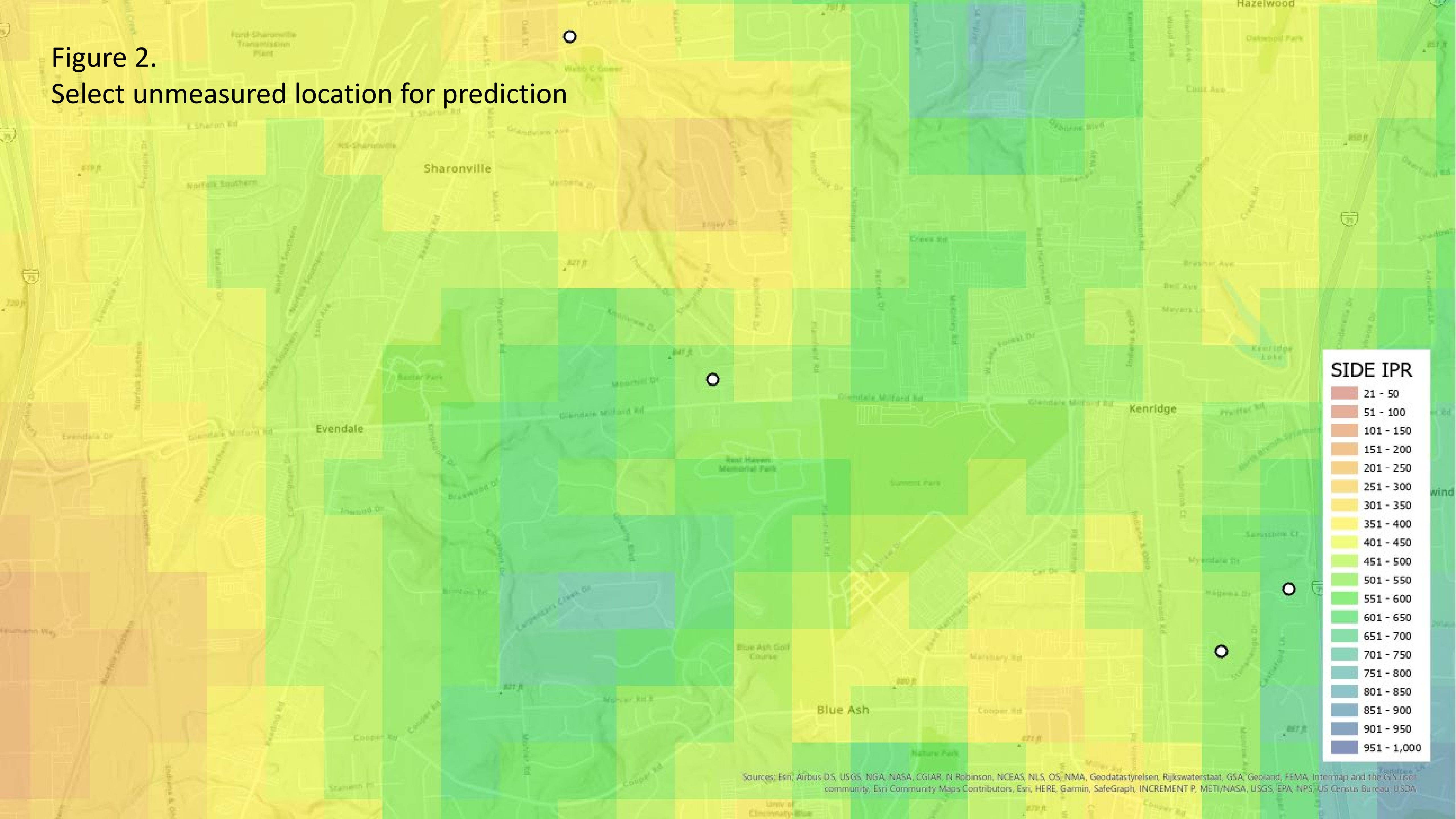


Figure 3.
Identify and weight nearest neighbors to create prediction at unmeasured location

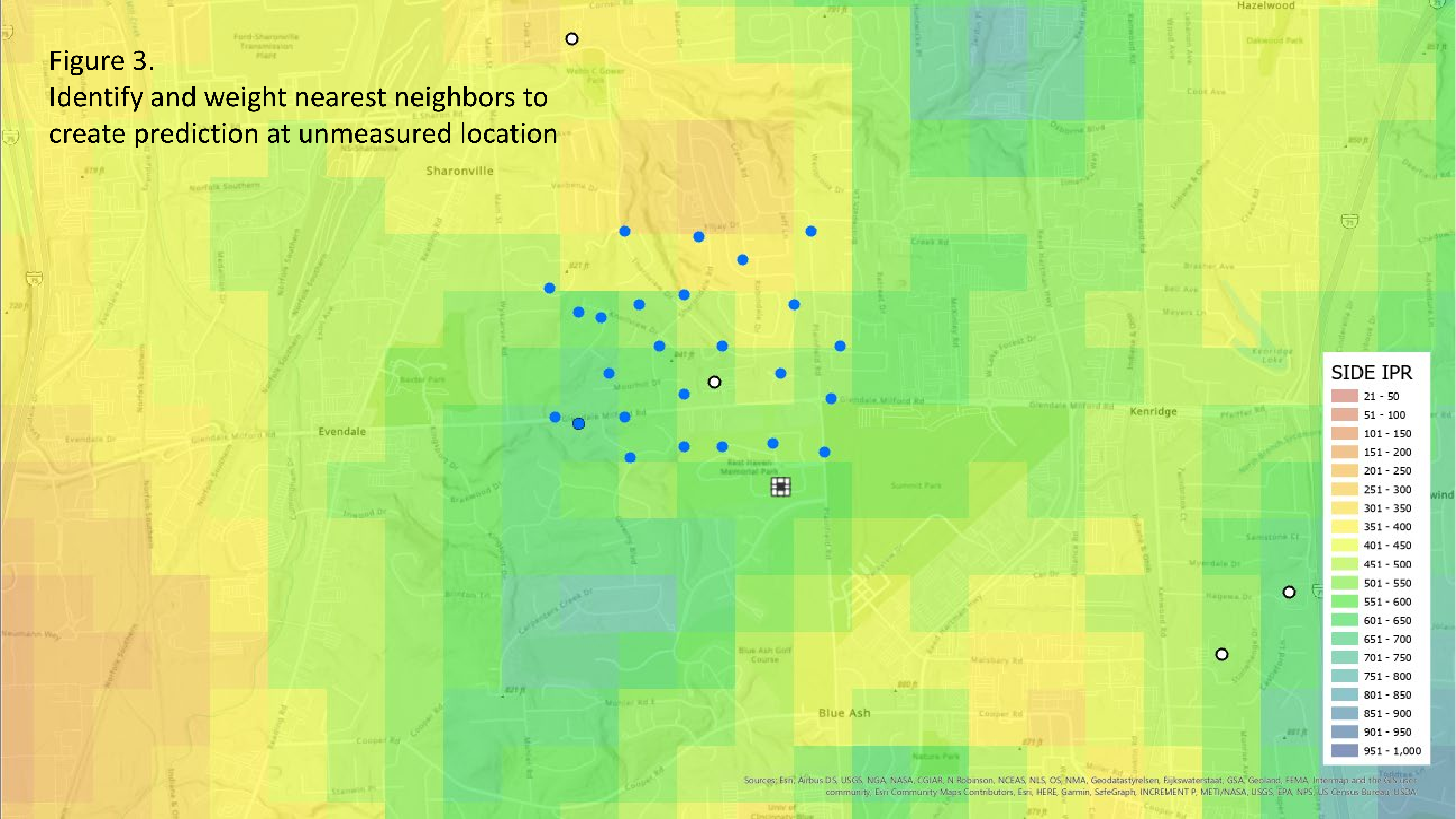
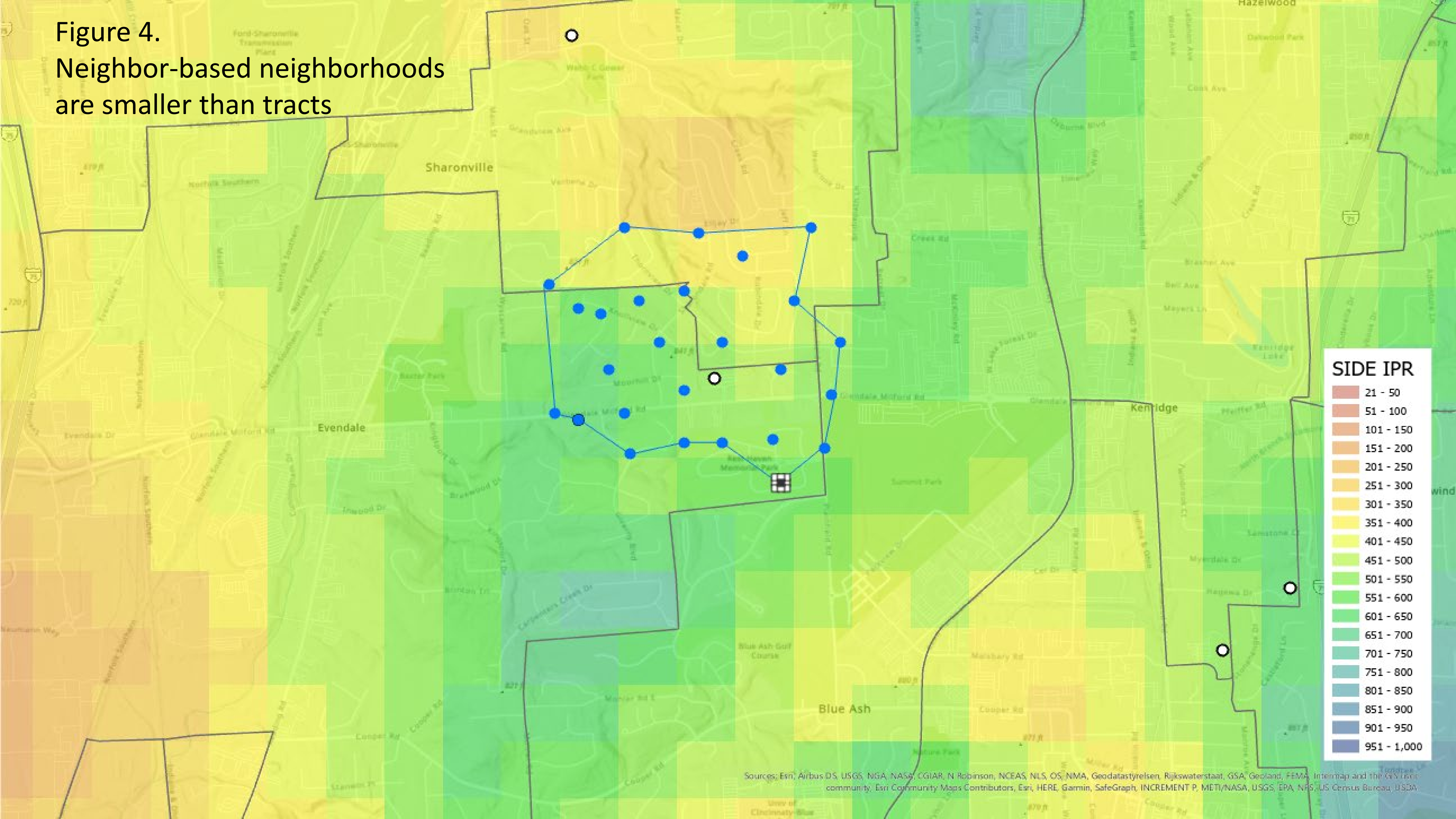


Figure 4.
Neighbor-based neighborhoods are smaller than tracts

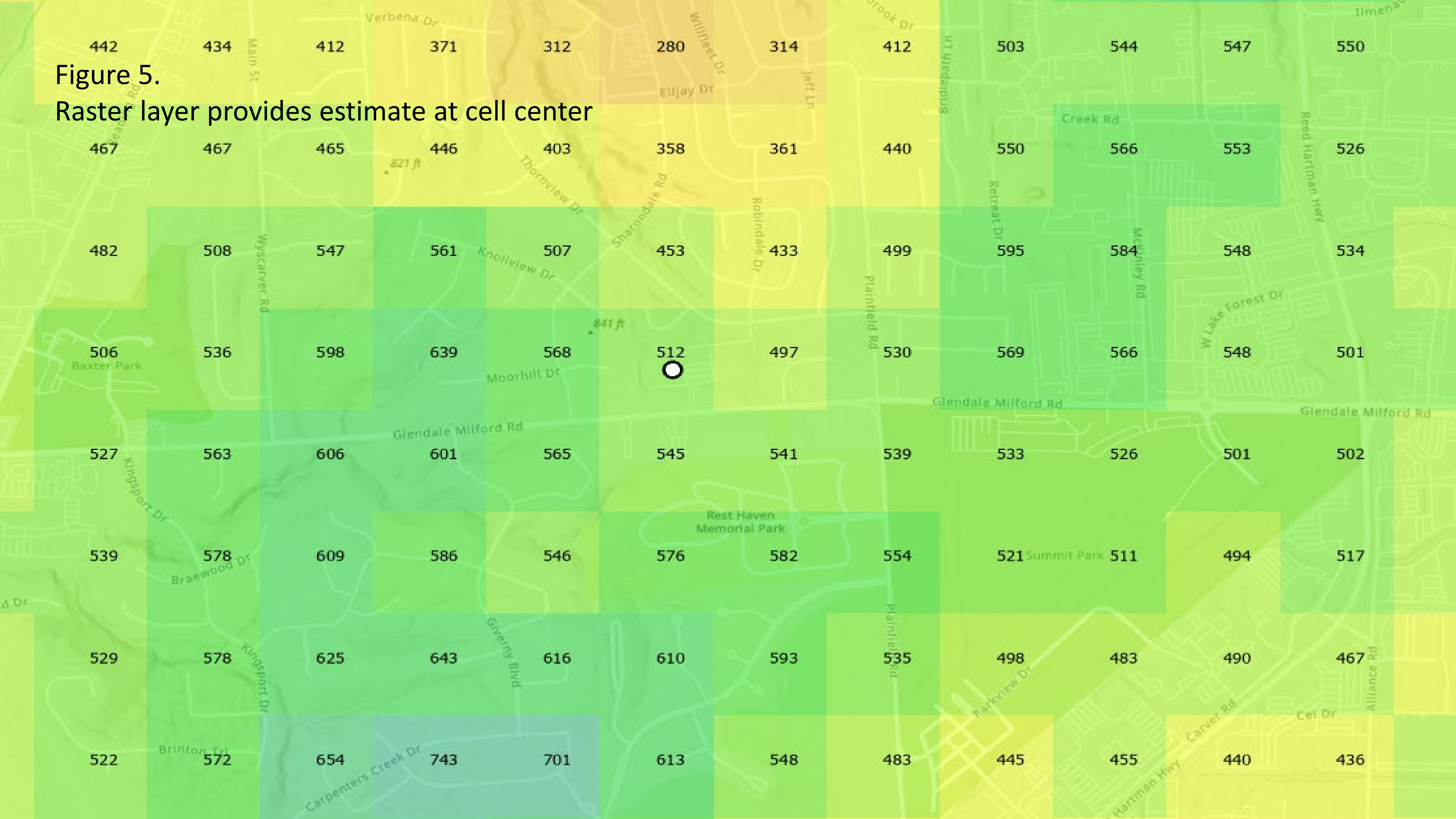


SIDE Neighborhood Extent

Neighborhood Geography	Mean Size (SQM)	Median Size (SQM)
Block Group	30	1
Tract	83	4
ZCTA	91	33
SIDE	12	0.71

**Based on 2015 TIGER Shapefiles and 95,000+ school locations from 2014-2015 Common Core of Data (CCD)*

Figure 5.
Raster layer provides estimate at cell center



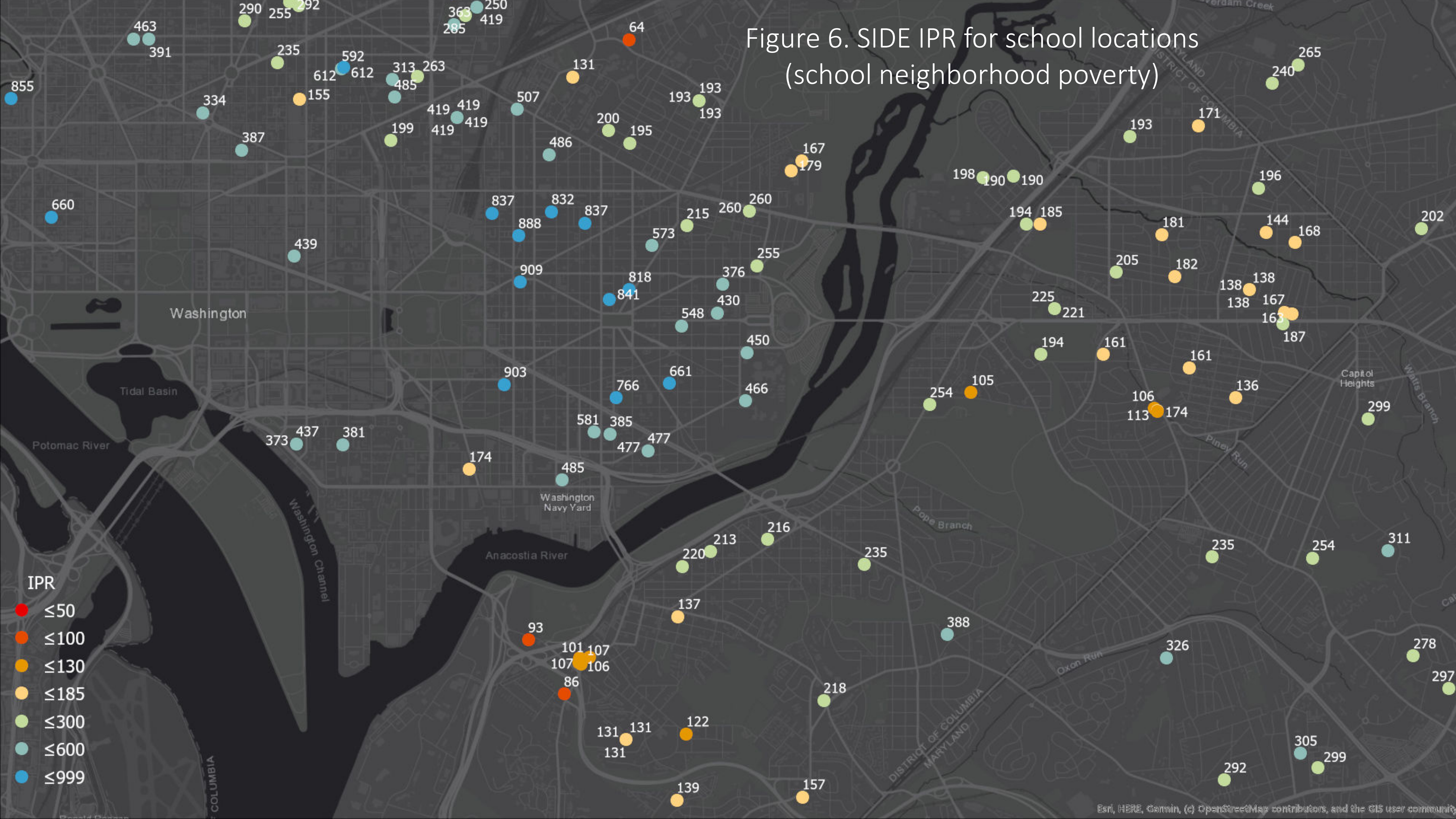


Figure 6. SIDE IPR for school locations (school neighborhood poverty)

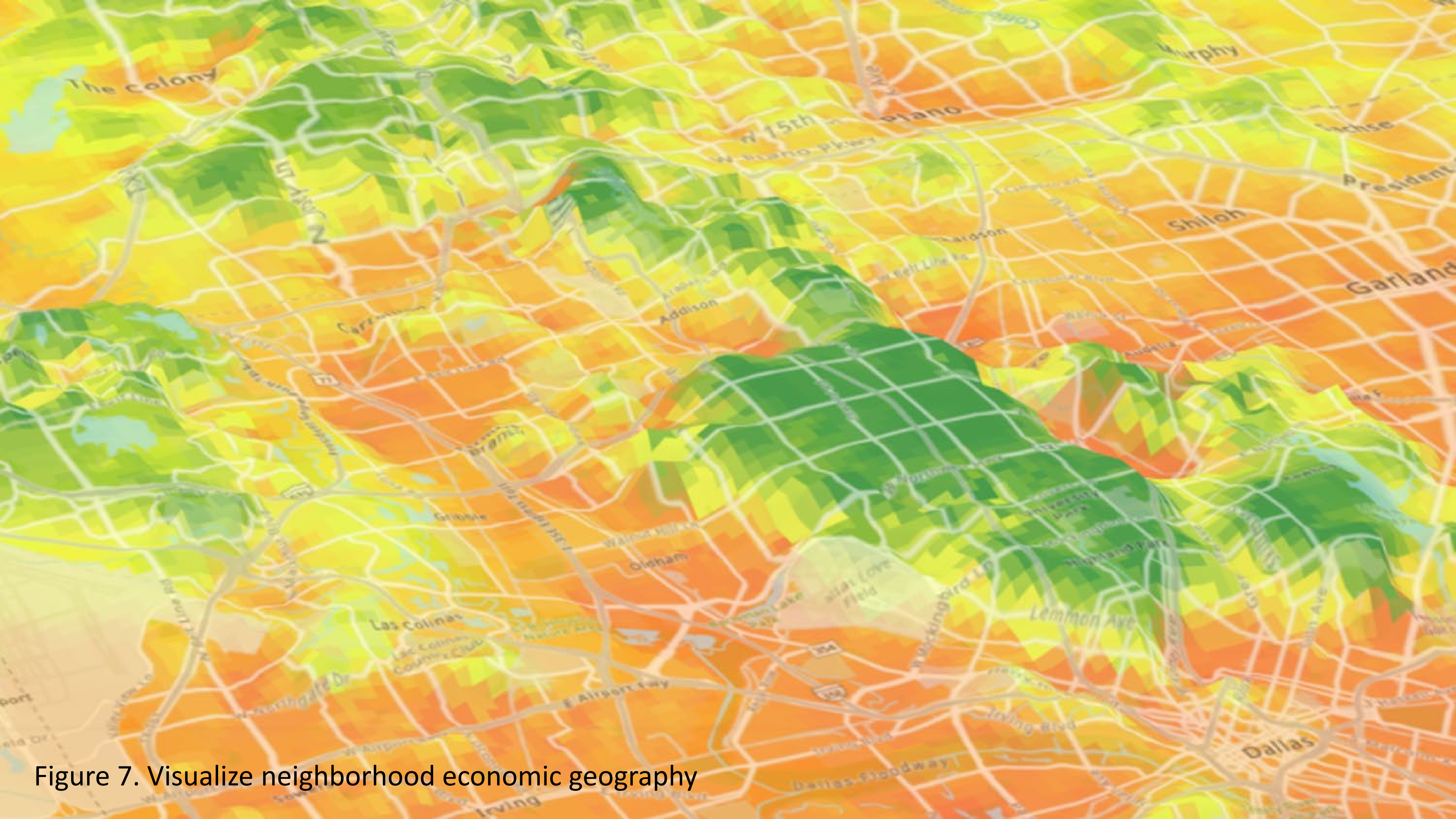


Figure 7. Visualize neighborhood economic geography

Benefits, Limitations, and Next Steps

- Spatially precise income indicator optimized for any location
- Safe to develop and apply
- Significant potential as a school poverty indicator

- Does not provide estimates for populations or jurisdictions
- Ignores potentially meaningful boundaries
- Lack of intuition about IPR (What does 317 mean?)

- Compare with Free/Reduced-price meal data
- Increase processing efficiency
- Improve model (e.g., integrate tax data)

Questions?

Doug Geverdt douglas.geverdt@ed.gov

National Center for Education Statistics

Education Demographic, Geographic, and Economic Statistics (EDGE) Program

NCES school neighborhood poverty estimates

https://nces.ed.gov/programs/edge/Economic/NeighborhoodPoverty