Local Context and Older Adults' Movement Patterns in Chicago

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What is the relationship between local context and individual movement patterns?

Motivation

- Neighbourhood effects research (e.g., Sampson 2012)
  - Where you live shapes social, health outcomes
- But individuals don’t just exist *in*, they select *into* a given context
  - To understand neighbourhood effects, we must improve our understanding of mobility patterns

Hypotheses

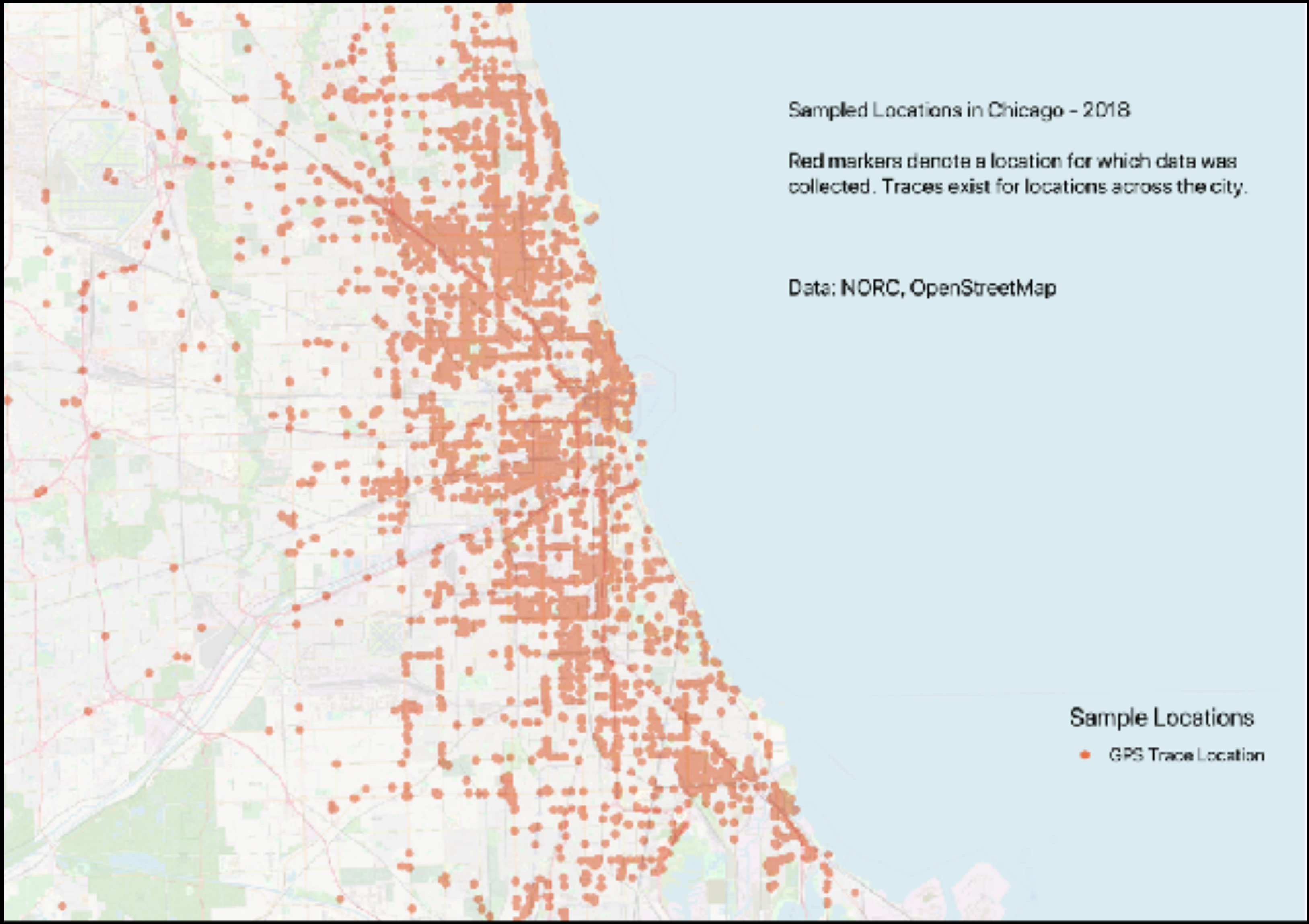
- (1) Measures of activity space derived from observed movement patterns (i.e., Autocorrelated Kernel Density Estimation) will provide a different picture of individual exposure to local context than administrative boundaries.
- (2) Individuals' daily movement patterns are associated with (i) the immediate spatio-temporal context in which movement takes place, and (ii) individuals' membership in social groups (e.g., race, gender).

Contributions

- How best to model activity space
- Explores links between mobility and neighbourhood effects
- Connect neighbourhood effects/EMA-based literature with movement modelling methods from ecology

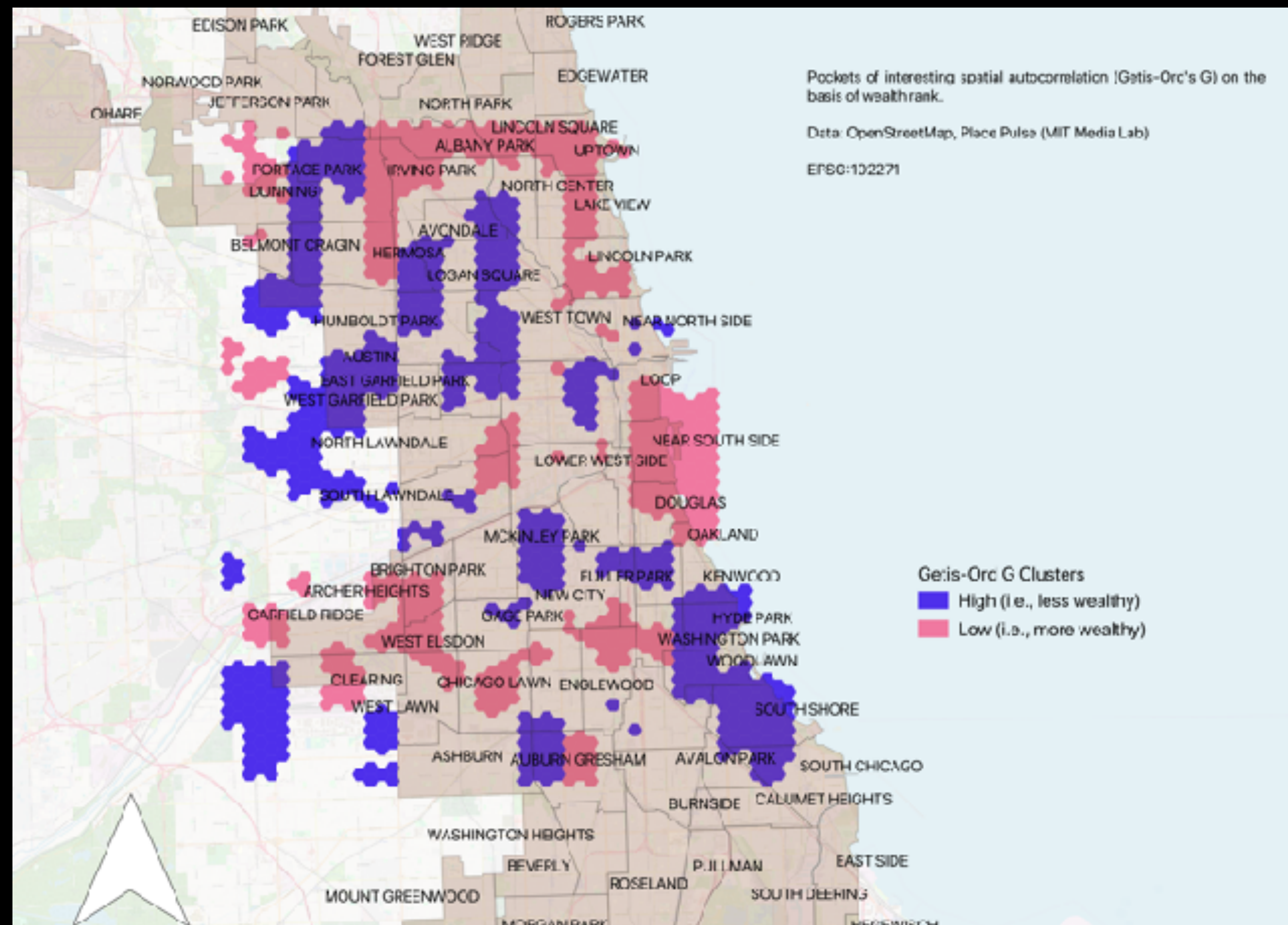
EMA/GPS Traces

- GPS tracks collected for a sample of seniors in Chicago from NORC (PI K. Cagney)
  - 449 individuals, 1 week period in spring 2018



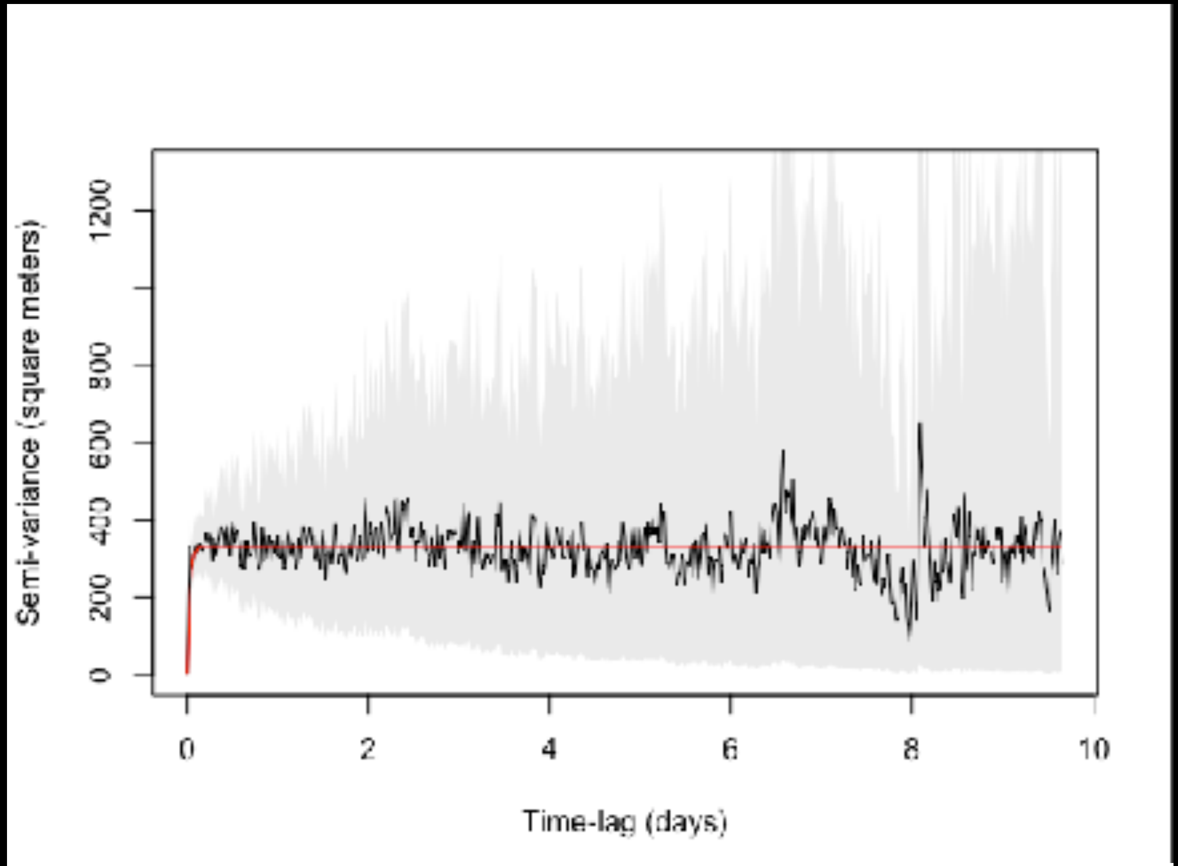
Place Pulse

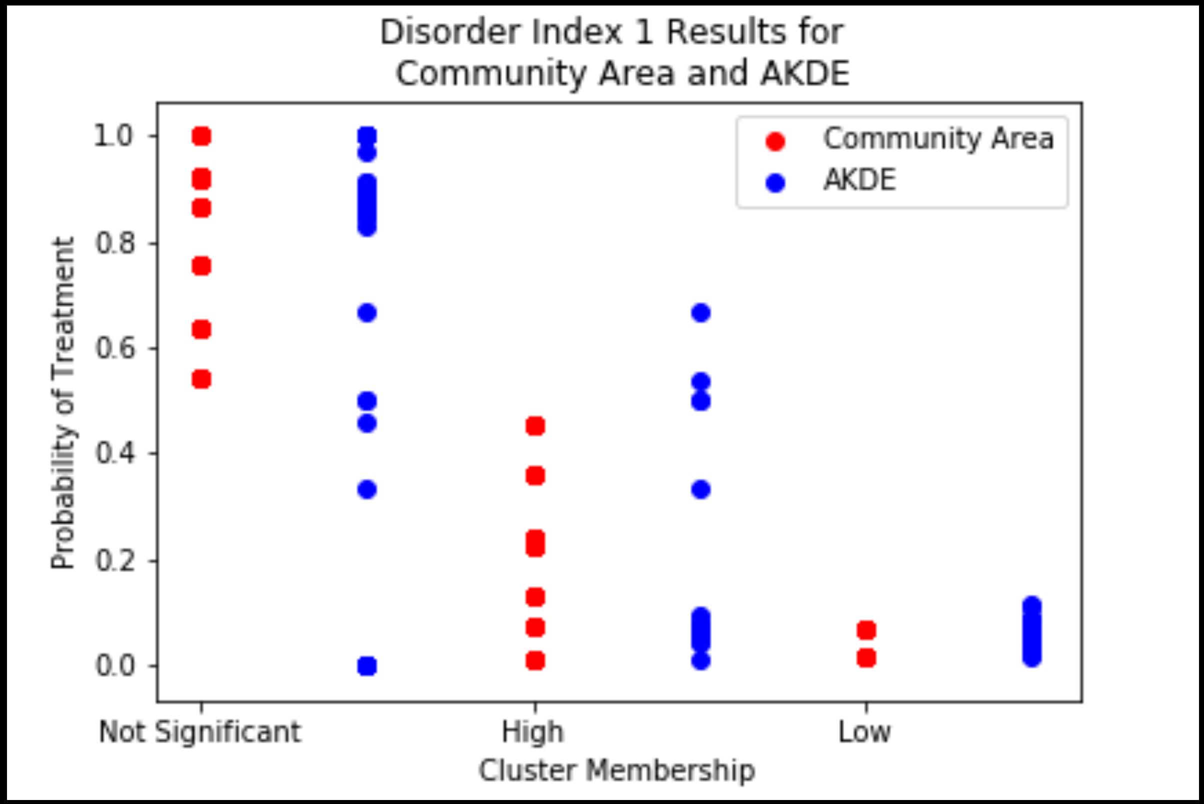
- Place Pulse ratings of Google StreetView scenes
  - Rankings along 6 dimensions (e.g., safety, depressing)
  - IDW interpolation, Multidimensional Scaling to reduce to 2 gridded indices, clustered with Getis-Ord Statistic

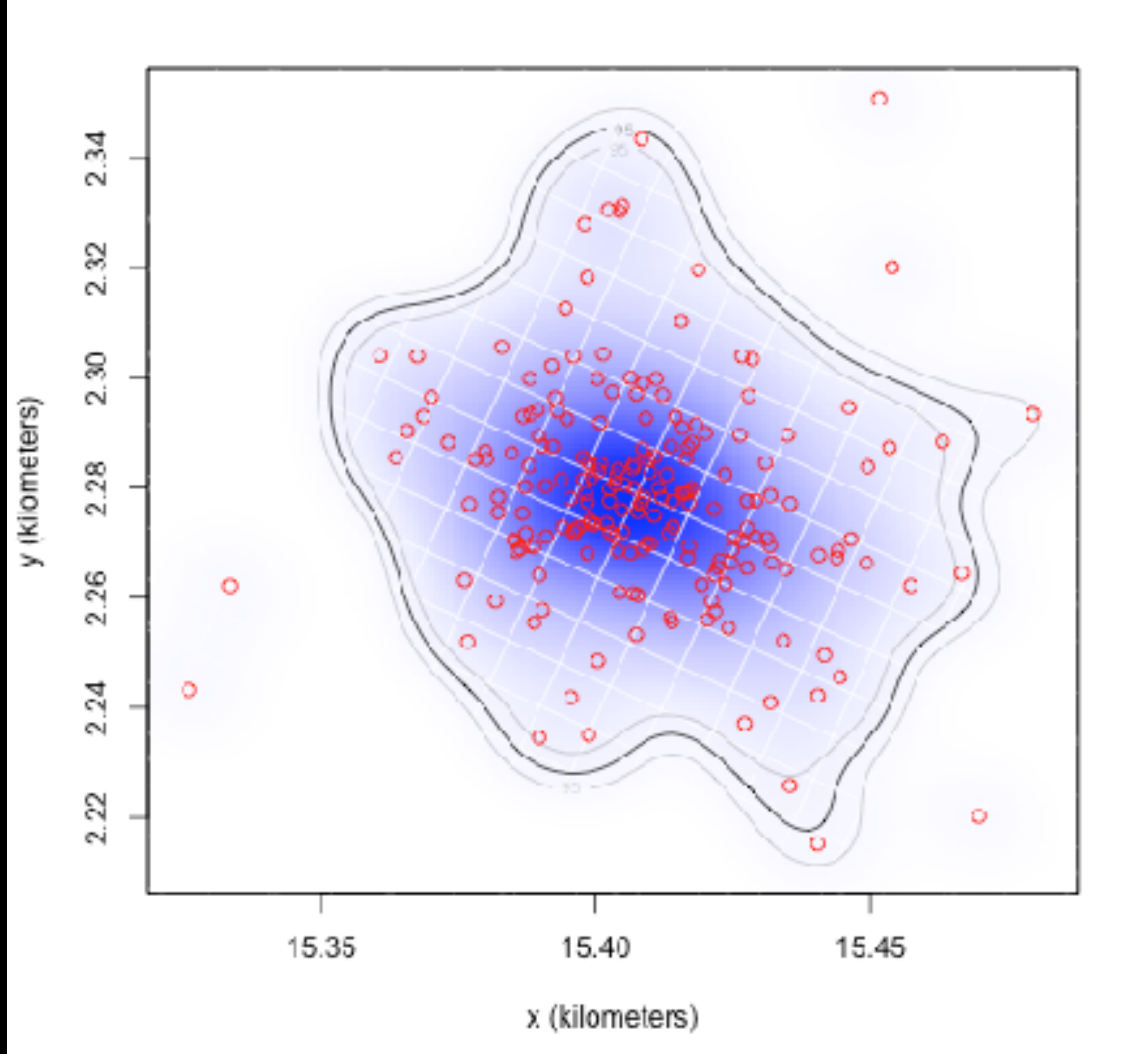


H1: Supported

- Autocorrelated Kernel Density Estimation (Fleming et al. 2015)
    - Fit a set of GPS tracks to a random walk model
    - Generate a hypothesized home range from the fitted model







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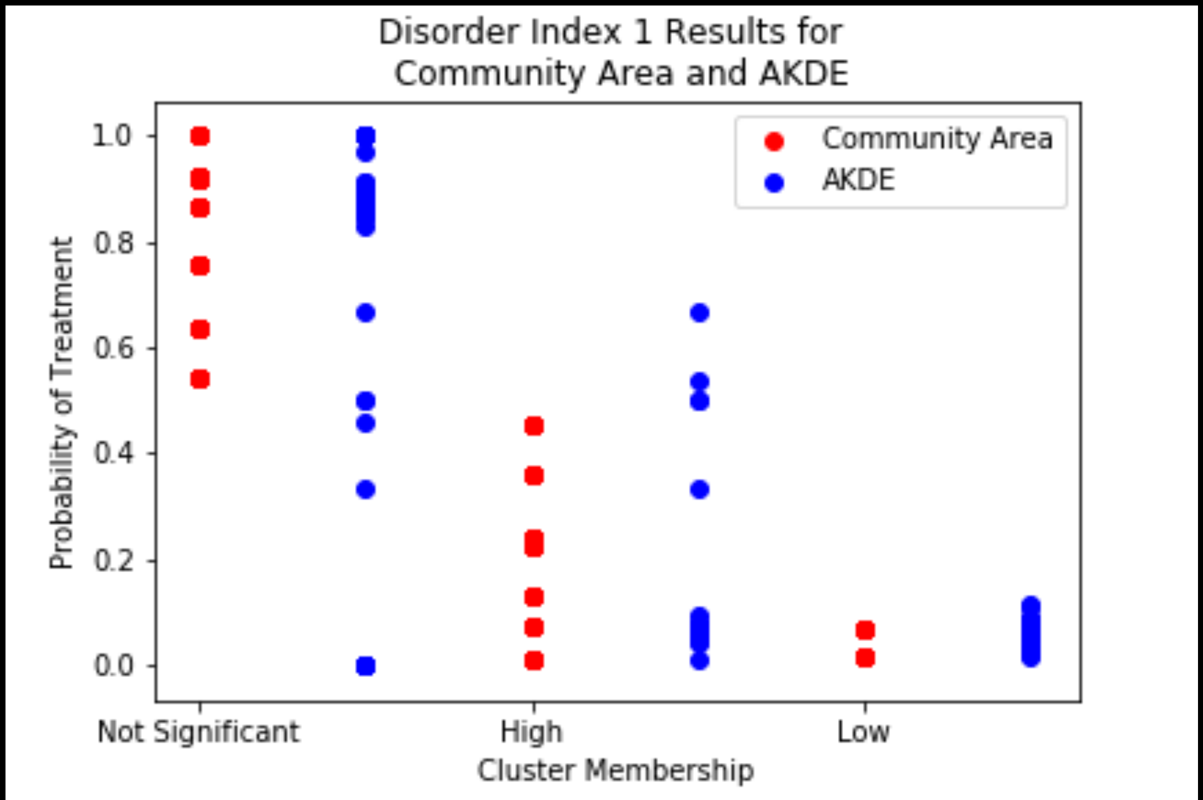

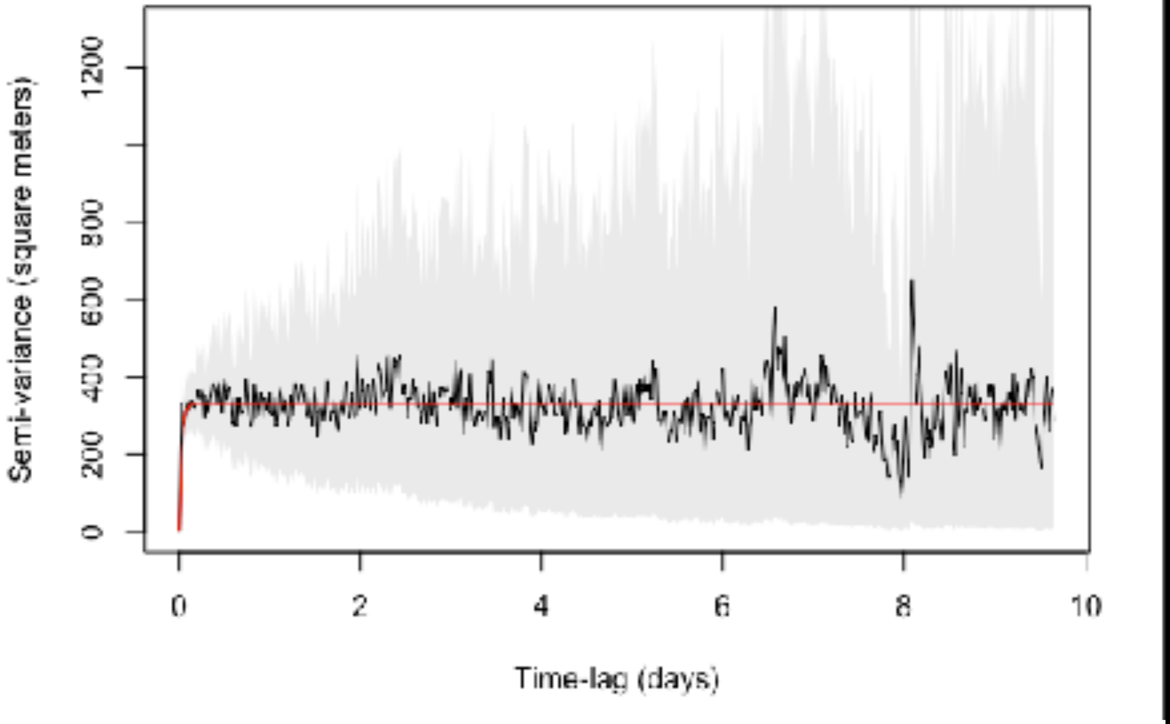

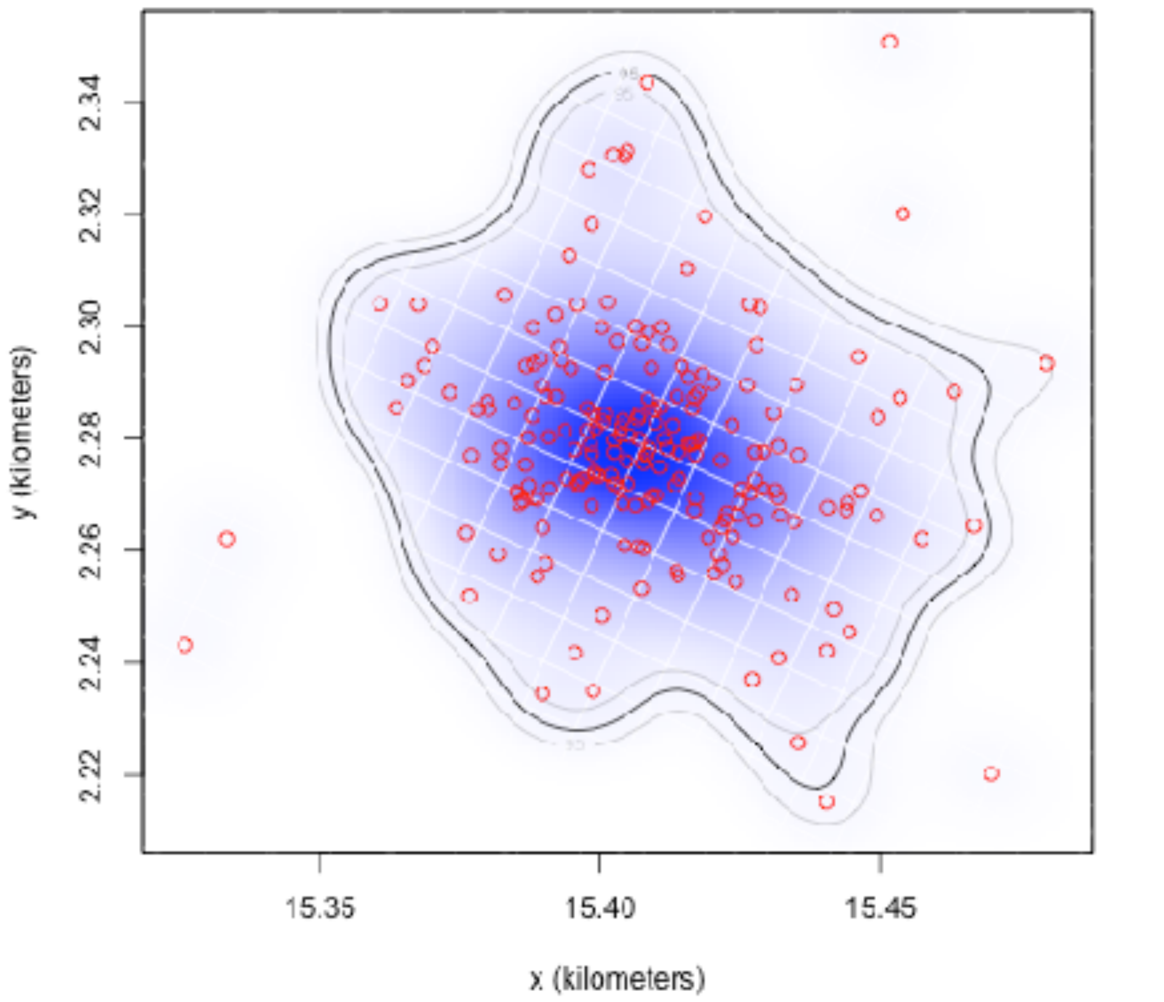

H2: No Clear Finding (Yet)

- Hidden Markov Models to identify movement types (Whoriskey et al. 2017)
- Movement is an unobserved process, split into two types of movement (sedentary vs active)
  - Using turning angles, speed, bearing, contextual factors can specify probability of transitioning between types of movement

$$P(m_t | m_{t-1}) = f(x_1, x_2, \ldots, x_k)$$

- When a study participant is in what mode should be driven by membership in groups and context (time of day, etc.) according to H2
  - No clear findings thus far

Limitations, Next Steps

- HMM Methods are numerically unstable
    - Increase number of simulations, tweak parameters
- AKDE and HMM use random walk models built for ecological applications
- Data quality and extent issues with Place Pulse
    - Incorporate MapsCorps data on types of opportunities available in Chicago (e.g., restaurants, churches)