FINDING THE FAULT LINES:

ESTIMATING THE BOUNDARIES IN URBAN SOCIAL-SPATIAL INEQUALITY

NSF-SES 1733705

University of BRISTOL

The Alan Turing Institute

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UNDERSTANDING PLACE & SPACE

RETHINKING BOUNDARIES 3 WAYS

UNDERSTANDING PLACE & SPACE

an old tension in spatial science

RETHINKING BOUNDARIES 3 WAYS

Contested Boundaries: Explaining Where Ethnoracial Diversity Provokes Neighborhood Conflict[1]

Joscha Legewie
Yale University

Merlin Schaeffer
University of Cologne

"We propose the *contested boundaries hypothesis* ... conflict arises at poorly-defined boundaries that separate ethnic and racial groups ... because [boundaries] threaten homogeneous community life and foster ambiguities about group rank."

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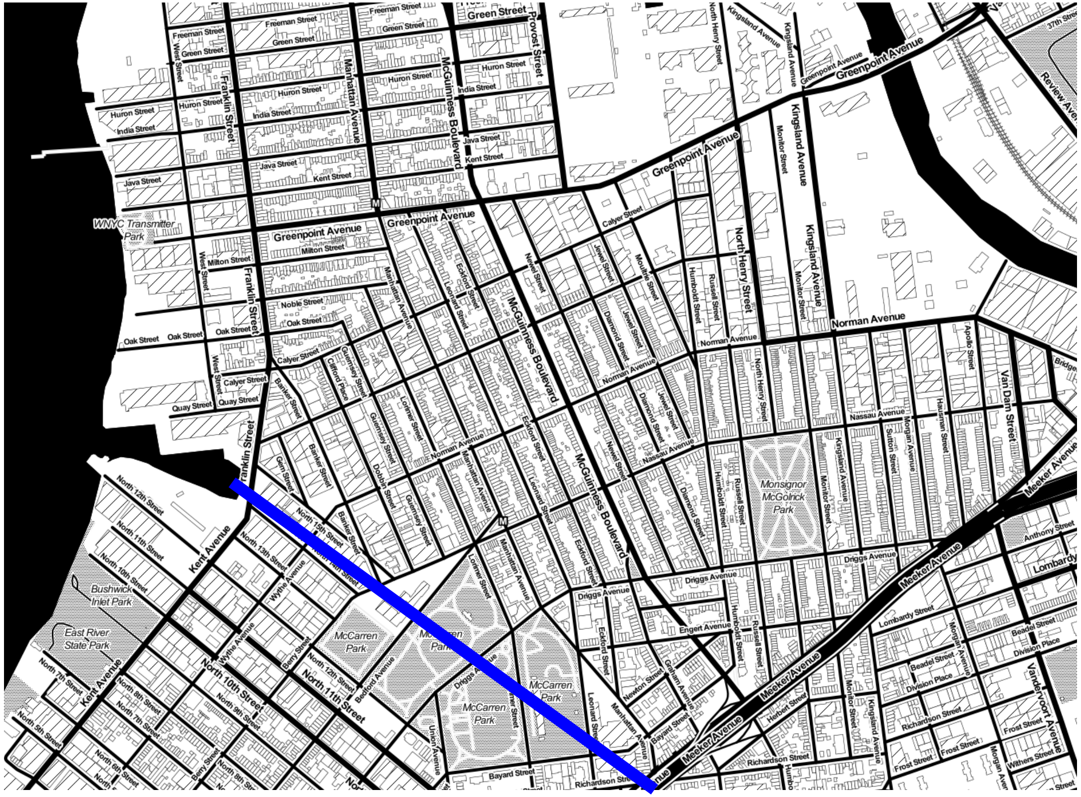
Communities are neighborhoods, territories that delimit a social group.

When territory is unclear, communities come into conflict.

CONCEPTUALIZING BOUNDARIES

“Williamsburg becomes Greenpoint at the Bushwick Inlet”



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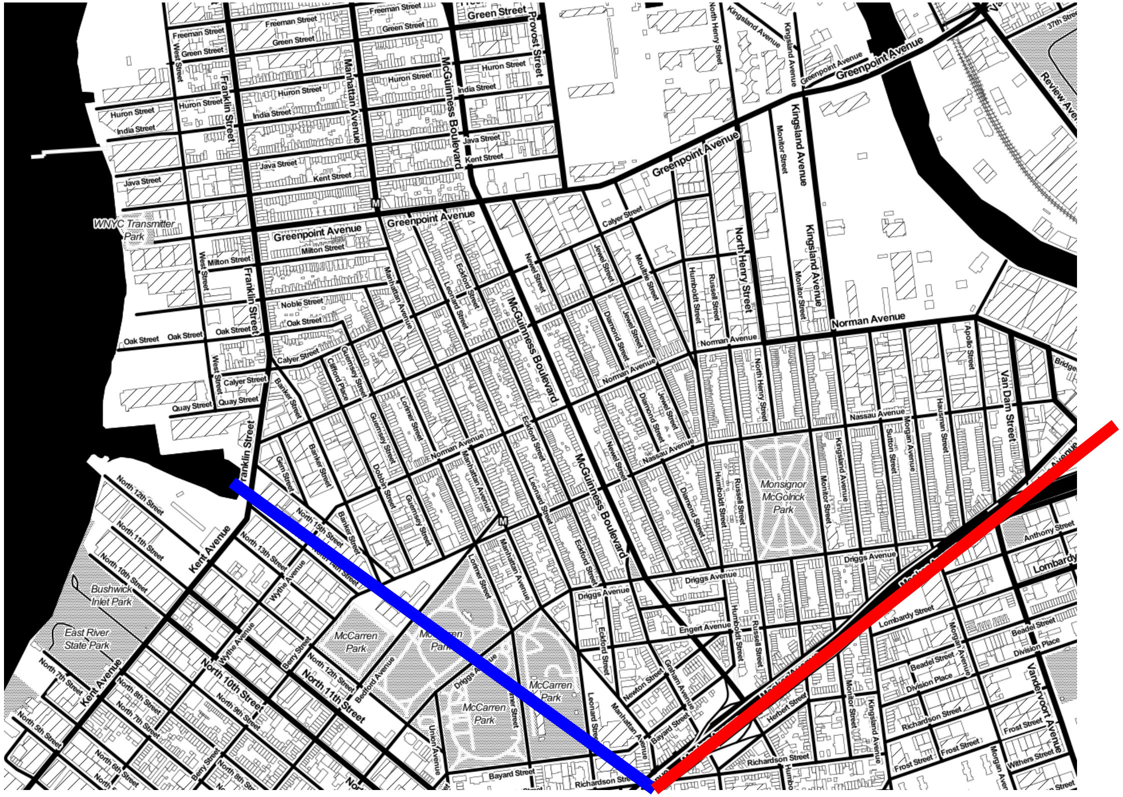
“Williamsburg becomes Greenpoint at the Bushwick Inlet”

“Greenpoint is bordered on the southeast by the BQE”



CONCEPTUALIZING BOUNDARIES

BOUNDARIES AS NATURALISTIC DIVISIONS OF URBAN LIFE

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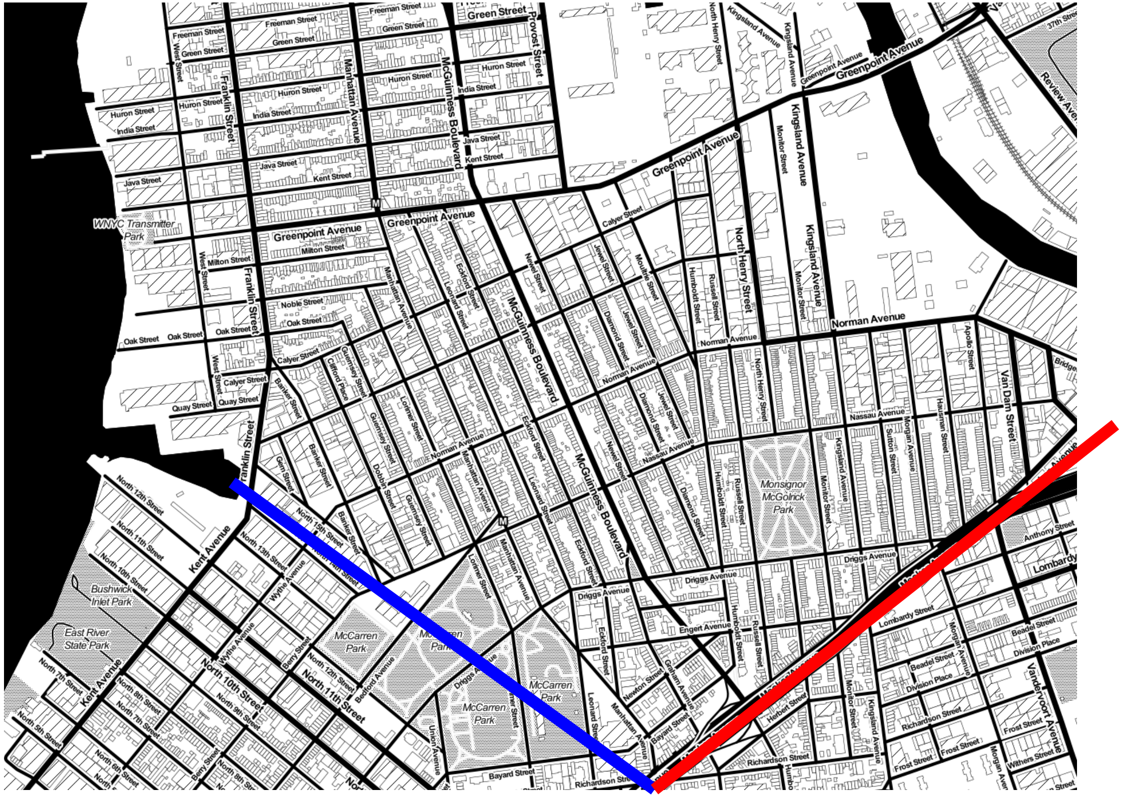
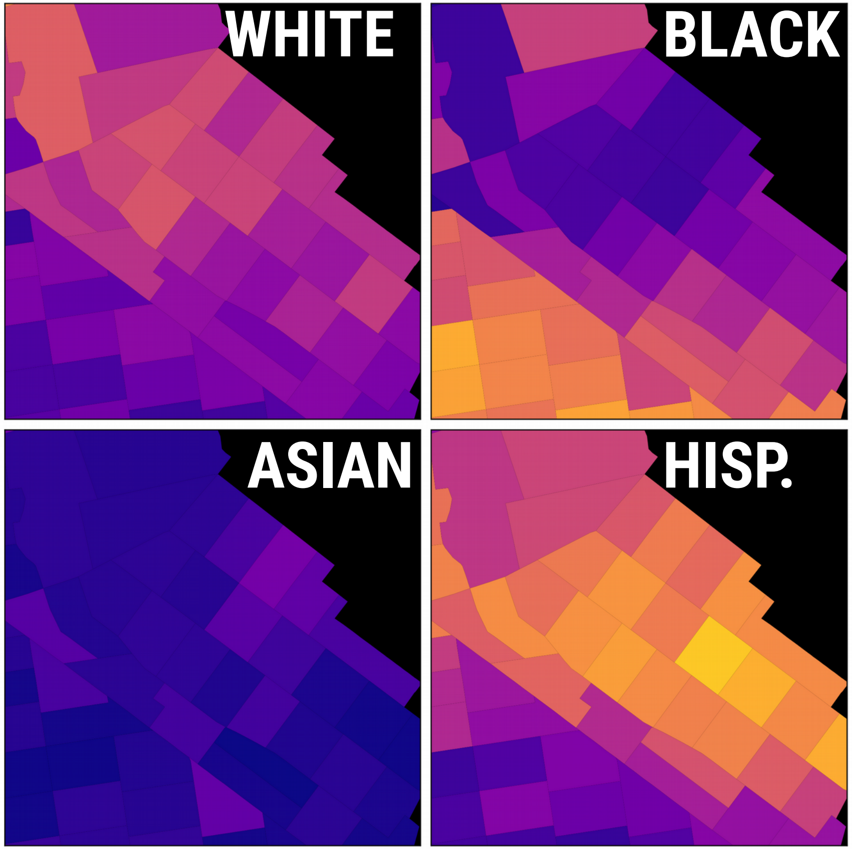


CONCEPTUALIZING BOUNDARIES

"Though an ethnic neighborhood, Bushwick's population is, for a NYC neighborhood, relatively heterogeneous"



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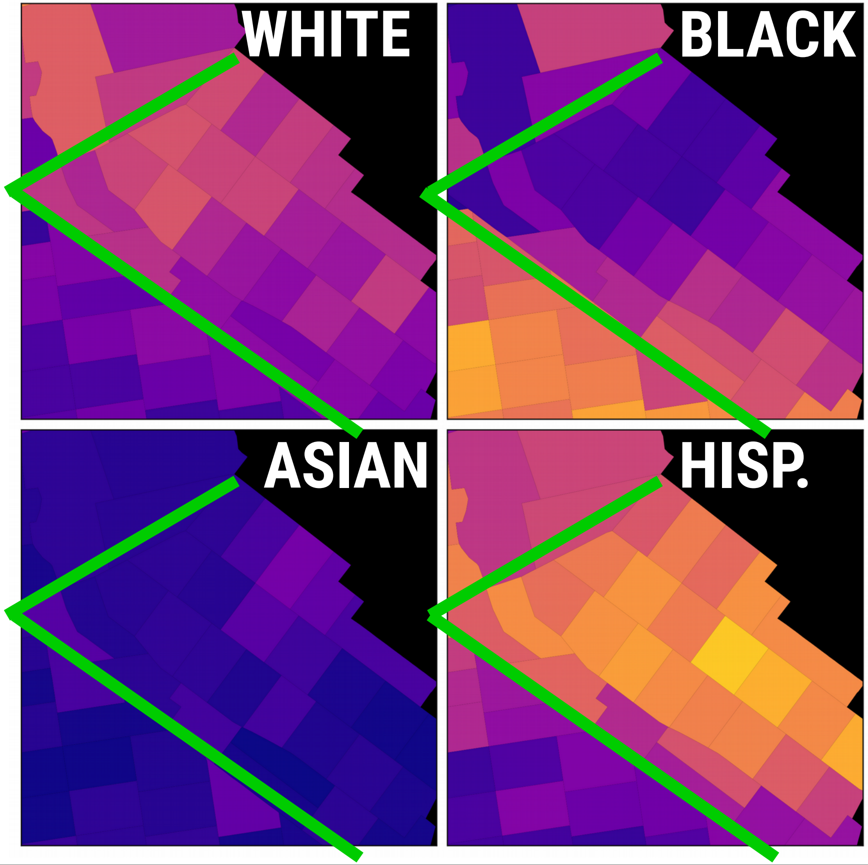

CONCEPTUALIZING BOUNDARIES

BOUNDARIES AS SOCIALLY CONSTRUCTED DIVISIONS OF URBAN LIFE

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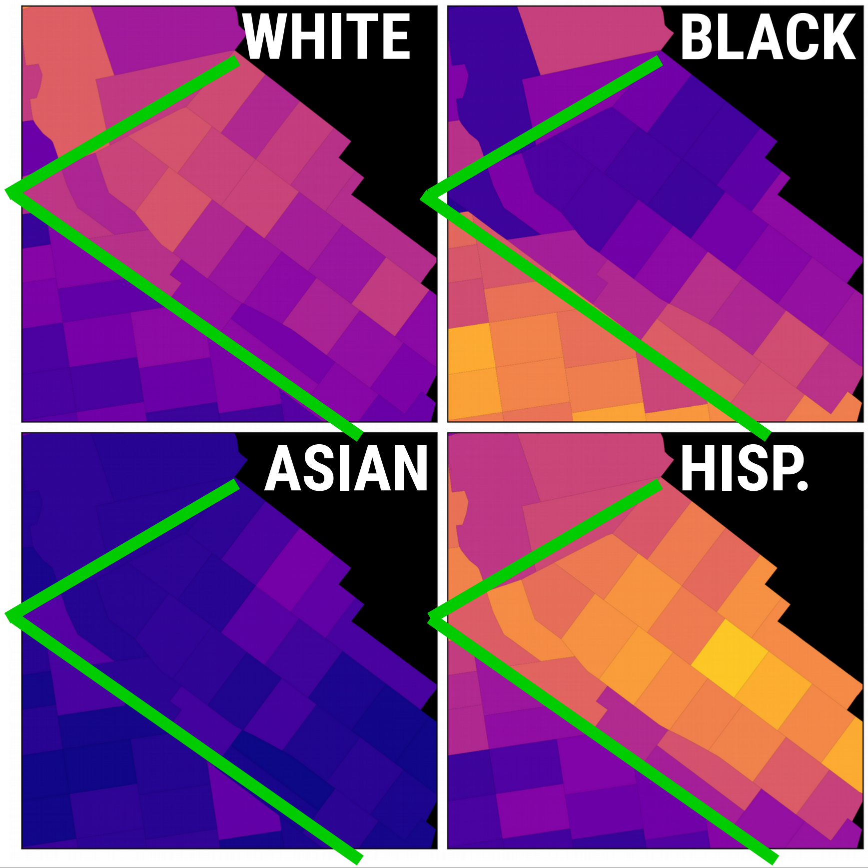

CONCEPTUALIZING BOUNDARIES

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SCHELLING (1971) Selective segregation

SUTTLES (1972) Defended communities

GRIGSBY (1987) Real income is everything

GRANNIS (1998) Transit network barriers

GALSTER (2001) House Attribute “bundles”

HEDMAN et al. (2011) Choice geographies

HIPP & BOESSEN (2013) Access areas

LEGEWIE & SCHAEFFER (2016) Friction

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SPACE

PLACE

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PLACE

Understanding the New Human Dynamics in Smart Spaces and Places: Toward a Splatial Framework

Shih-Lung Shaw[*] and Daniel Sui[†]

[*]Department of Geography, University of Tennessee
[†]Department of Geosciences, University of Arkansas

SPACE

PLACE

SPACE

The geographic system over which objects of study are related.

- ***Earth Surface***
- ***Road Systems***
- ***Social Networks***
- ***Economic Relations***

PLACE

Geographic entities that are constructed by distinctiveness.

- ***Regions***
- ***Neighborhoods***
- ***Home/Staying locales***
- ***Functional classifications***

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PLACE

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Geographic information science II:
less space, more places in smart cities

Stéphane Roche

Digital neighborhoods

Luc Anselin[a*] and Sarah Williams[b]

Towards the statistical analysis and visualization of places

René Westerholt et al.

SPACE

The geographic system over which objects of study are related.

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PLACE

Geographic entities that are constructed by distinctiveness.

How or why do they emerge?
What are their properties?
What are their purpose?
Do they have effects on things we care about?

SPACE

The geographic system over which objects of study are related.

How do things interact?
Over what spatial systems?
In what manner?
What impact do entities have on others nearby?

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Geographic entities that are constructed by distinctiveness.

How or why do they emerge?
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Do they have effects on things we care about?

Article

Urban Analytics and City Science

EPB: Urban Analytics and City Science
0(0) 1–19

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Geosilhouettes: Geographical measures of cluster fit

Levi J Wolf
School of Geographical Sciences, University of Bristol, UK

Elijah Knaap and Sergio Rey
Center for Geospatial Sciences, University of California Riverside, USA

FRONTIERS IN RESIDENTIAL SEGREGATION: UNDERSTANDING NEIGHBOURHOOD BOUNDARIES AND THEIR IMPACTS

NEMA DEAN*, GUANPENG DONG**, ANETA PIEKUT***
& GWILYM PRYCE ***

Living on the Edge: Neighborhood Boundaries and the Spatial Dynamics of Violent Crime

Joscha Legewie[1]

Inferring neighbourhood quality with property transaction records by using a locally adaptive spatial multi-level model

Guanpeng Dong[a,*], Levi Wolf[b], Alekos Alexiou[a], Dani Arribas-Bel[a]

[a] *Department of Geography and Planning, University of Liverpool, Room 713, Roxby Building, Chatham St, Liverpool L69 7ZT, UK*
[b] *School of Geographical Sciences, University of Bristol, University Road, Clifton, Bristol BS8 1SS, UK*

Wombling:

Using a known "outcome" variate, (price, crimes), examine anomalous but adjacent predictions in a multilevel GLM.

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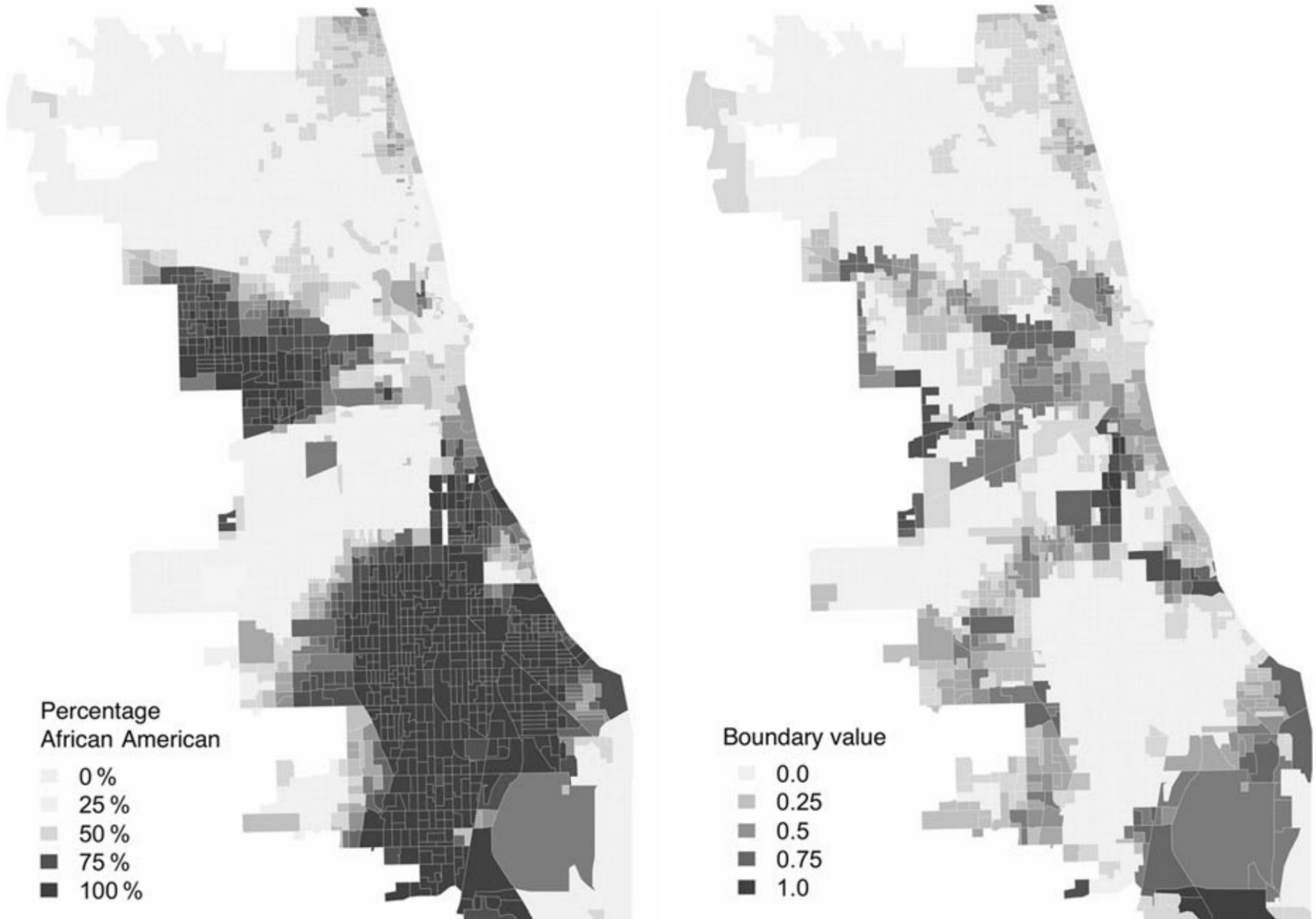


Fig. 1 Areal wombling for the proportion of African American residents

RETHINKING BOUNDARIES:

Contingent on conflict outcome.

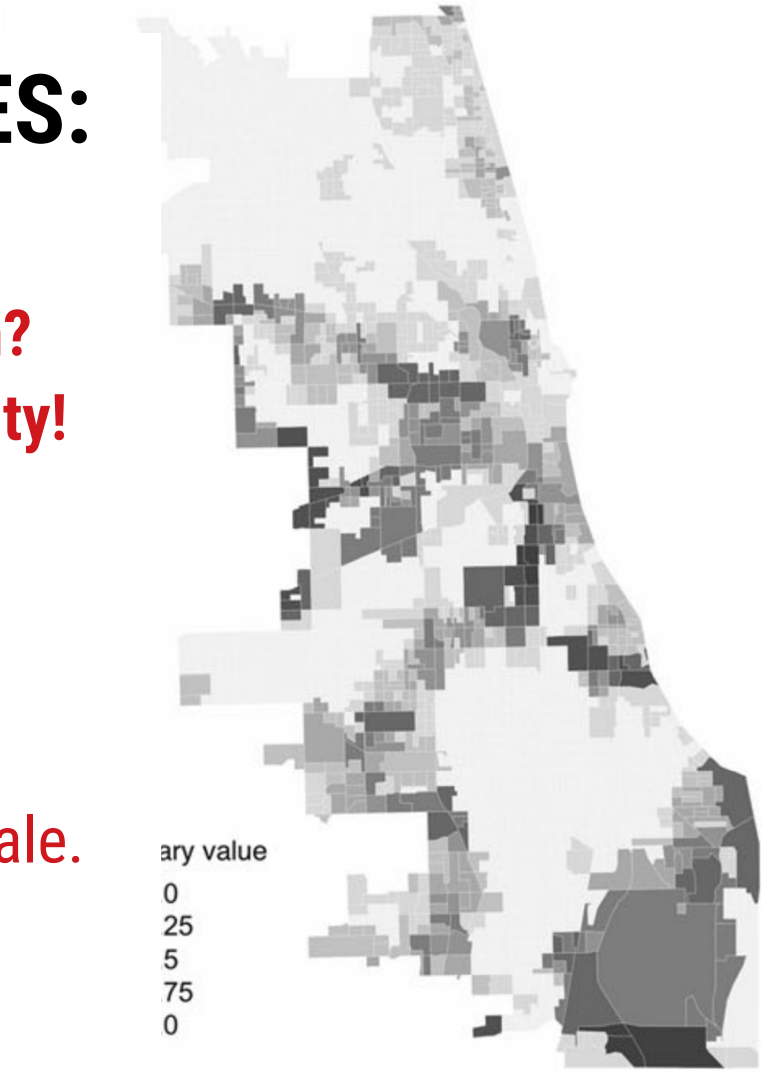
Conflict **over what, between whom?**

Robustness from place endogeneity!

Symmetric and reversible.

Only magnitude, no sign.

Assume existence of place & place-scale.



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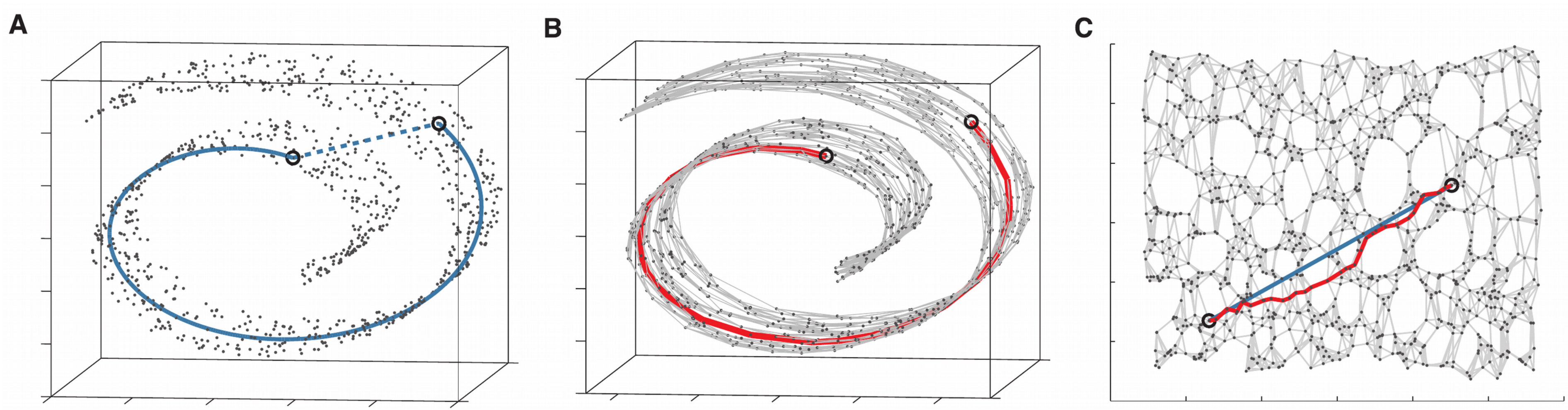
ROBUSTNESS FROM ENDOGENEITY

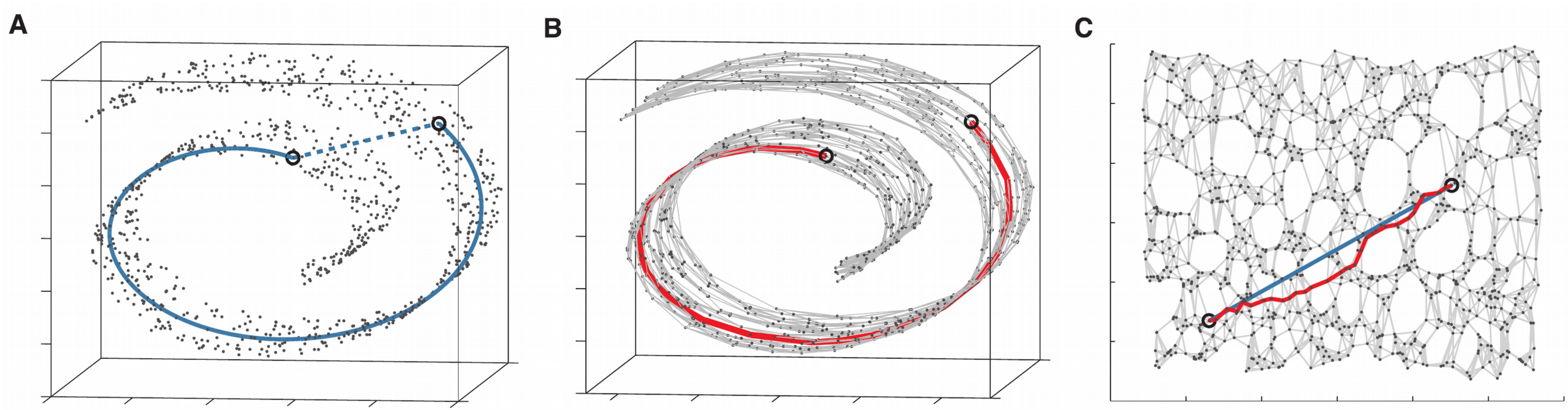
- Places are distinctive:
  - Geographically coherent
  - More similar than dissimilar
- Balancing nearness & similarity, we can see the “joint” social-spatial structure of the city.

ROBUSTNESS FROM ENDOGENEITY



“Manifold Learning”

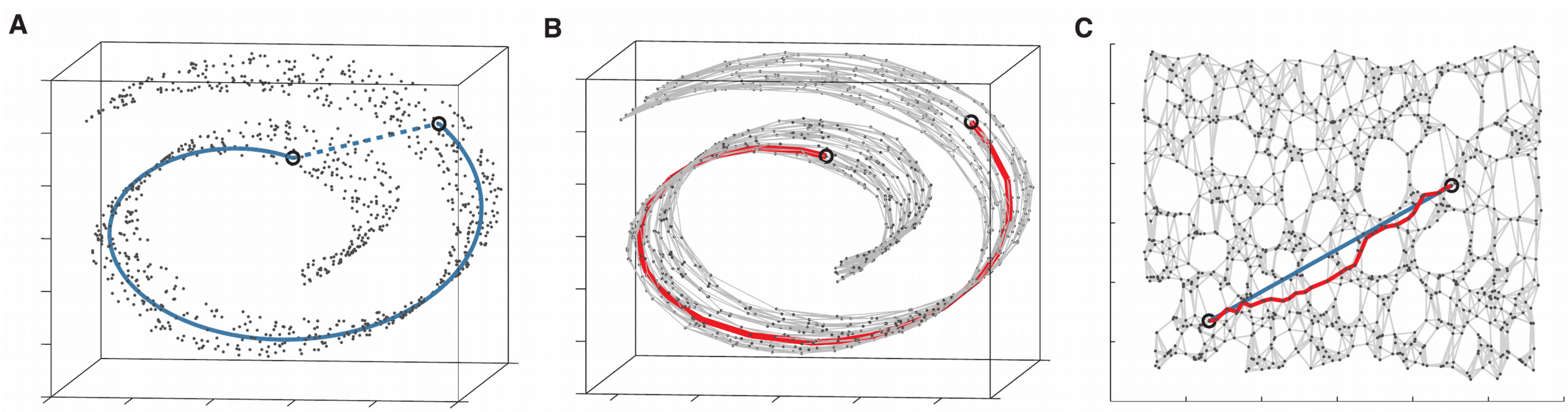
ROBUSTNESS FROM ENDOGENEITY



"Manifold Learning"

(non-linear PCA)

ROBUSTNESS FROM ENDOGENEITY

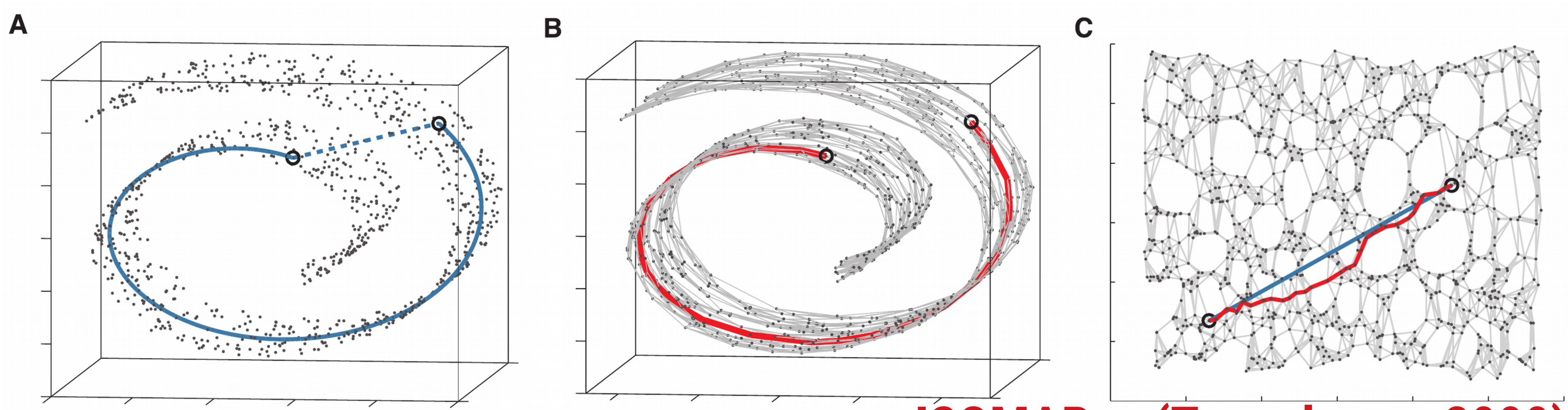


"Manifold Learning"

How can we understand boundaries in high-dimensional, highly-nonlinear data?

WOLF & KNAAP (2020) 10.31235/osf.io/75s8v

ROBUSTNESS FROM ENDOGENEITY



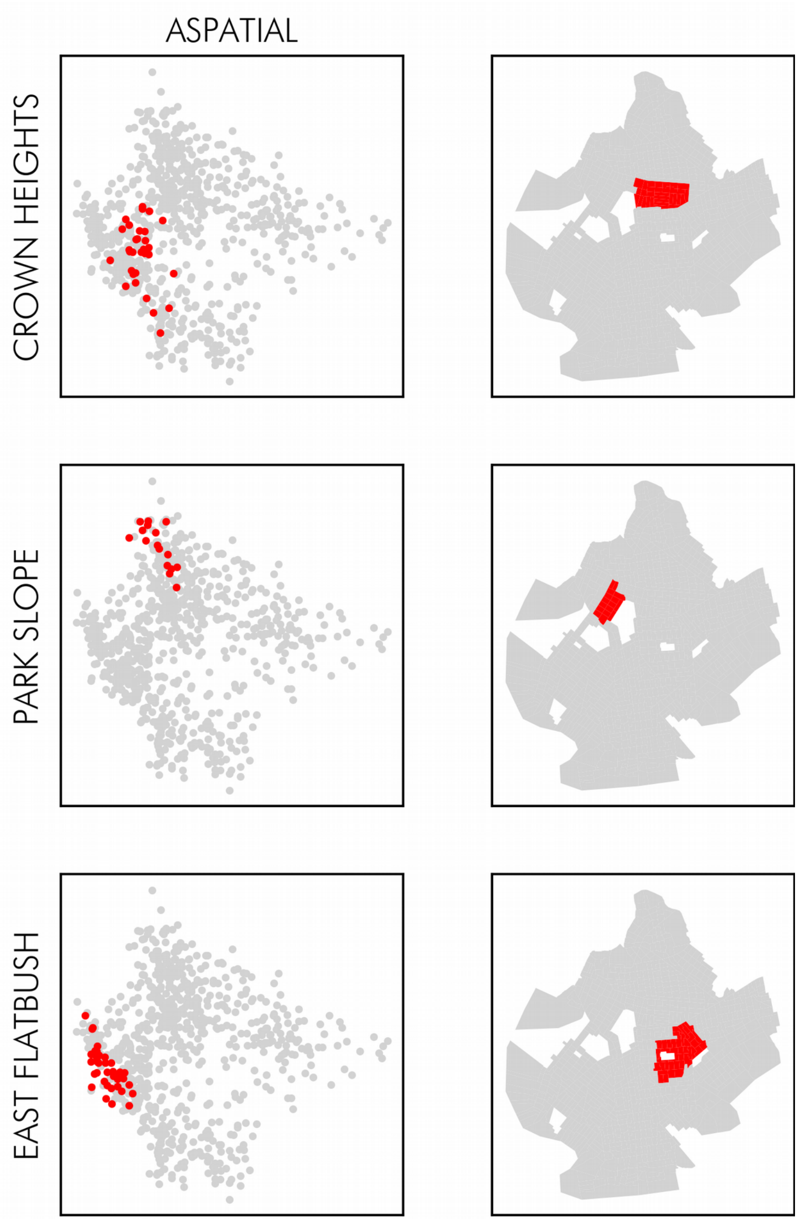
ISOMAP: (Tenenbaum, 2000)

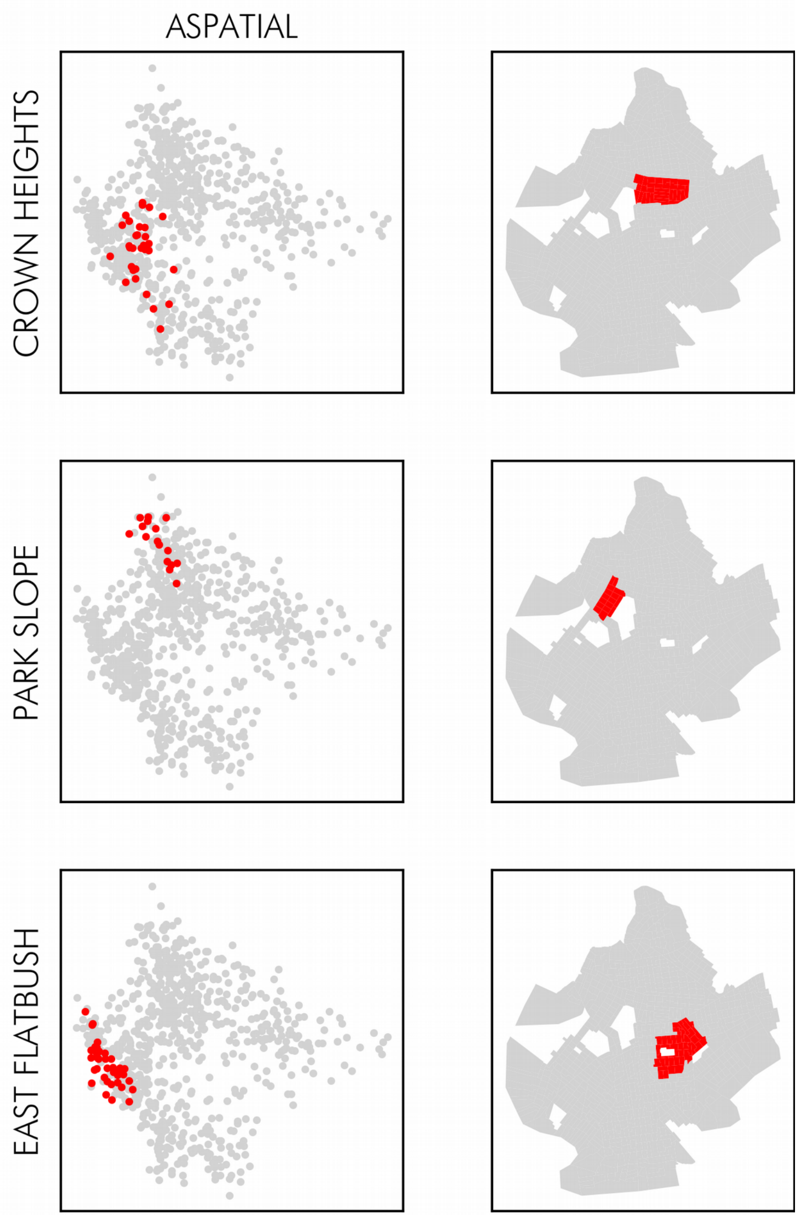
Make "short hops" between similar points.

Add up the length of short hops!

"Manifold Learning"

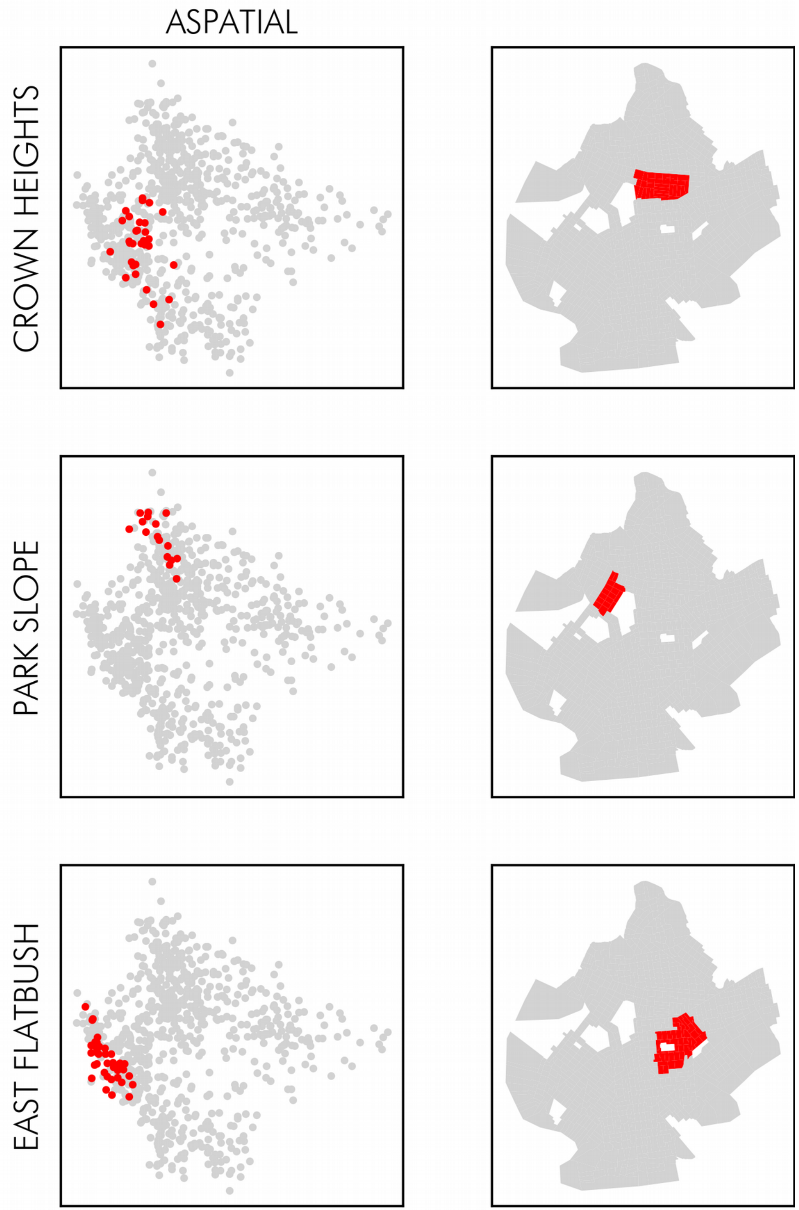
How can we understand boundaries in high-dimensional, highly-nonlinear data?


ASPATIAL
CROWN HEIGHTS
PARK SLOPE
EAST FLATBUSH



LITTLE INFO IS LOST

8 → 2



LITTLE INFO IS LOST

8 → 2

Any "outcome" will likely provide the same boundary!

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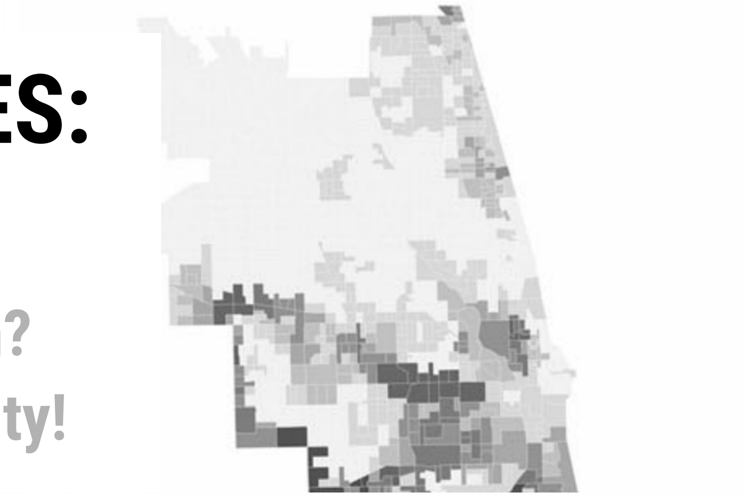

Symmetric and reversible.

Only magnitude, no sign.

Assume existence of place & pla

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Geosilhouettes: Geographical measures of cluster fit

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SILHOUETTE STATISTIC

Say that observation i in graph G is assigned to place c and not another place, k.

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$$s(i) = \frac{\min\left\{\bar{d}_k(i)\right\} - \bar{d}_c(i)}{\max\{\min\left\{\bar{d}_k(i)\right\}, \bar{d}_c(i)\}}$$

ROUSSEEUW (1987)

doi: 10/dd9c

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Dissimilarity between member i & place c

doi: 10/dd9c

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Dissimilarity between i & k that is most similar to i, but that doesn't contain i

ROUSSEEUW (1987)

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Positive when i is more like c than k

ROUSSEEUW (1987) doi: 10/dd9c

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Normalizing factor to ensure $|s(i)| \leq 1$

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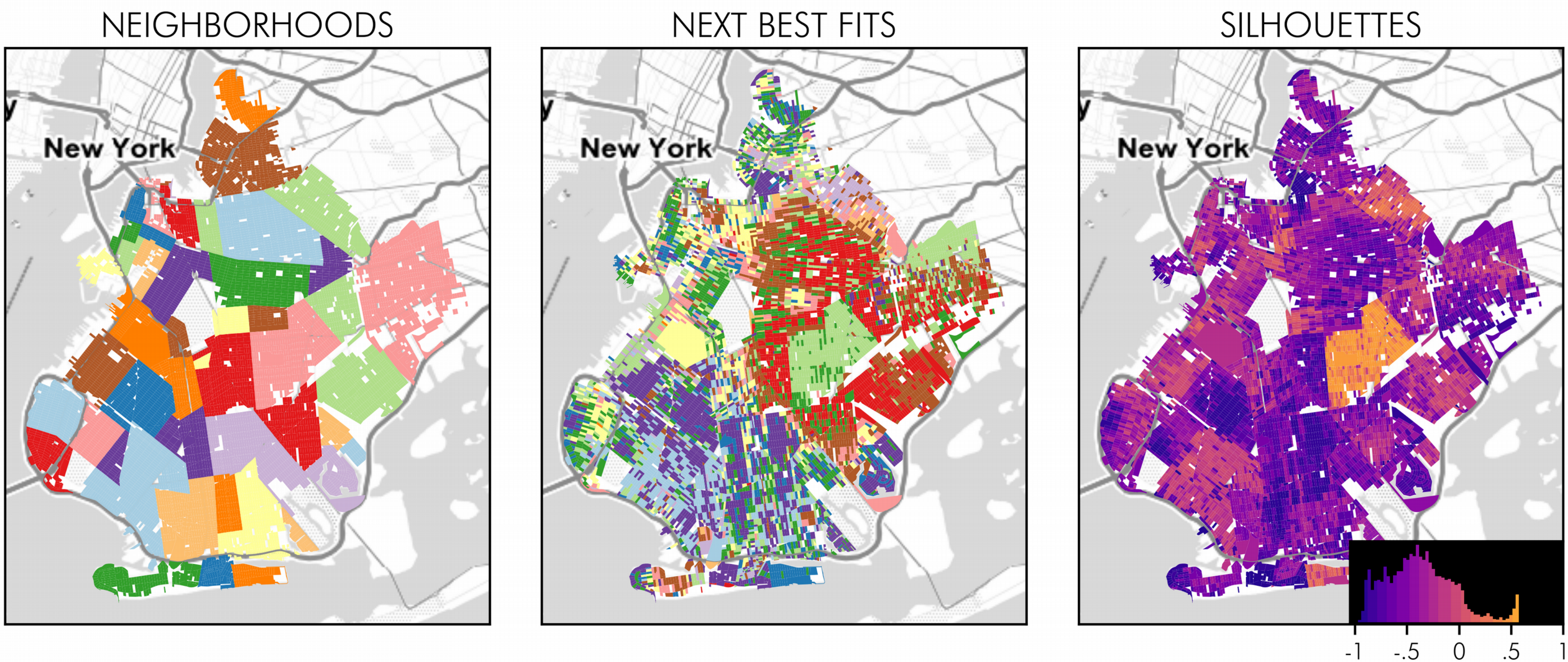
Gap between i's current place and 2nd best alternative.

ROUSSEEUW (1987) doi: 10/dd9c

SILHOUETTE SCORES



ROUSSEEUW (1987)

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SILHOUETTE SCORES

NEIGHBORHOODS NEXT BEST FITS SILHOUETTES

Zillow neighborhoods built from

online housing markets

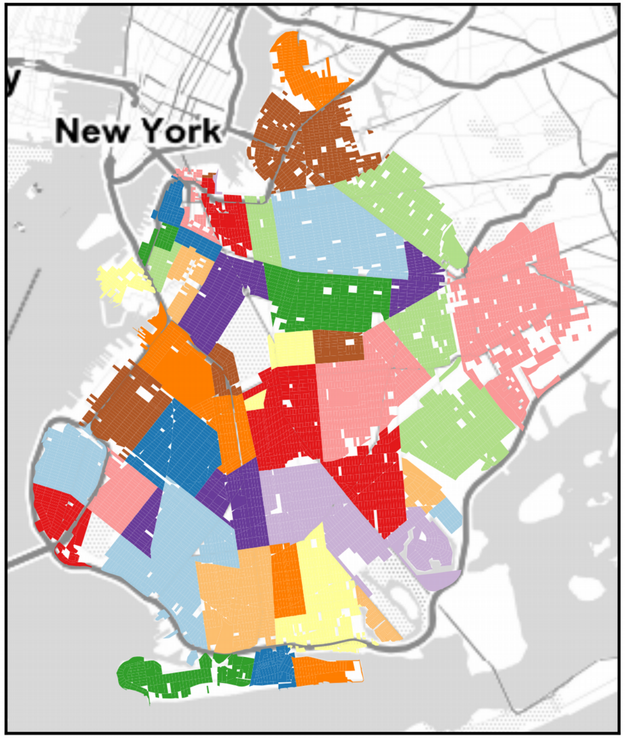
official boundaries (NYCTA)

ROUSSEEUW (1987)

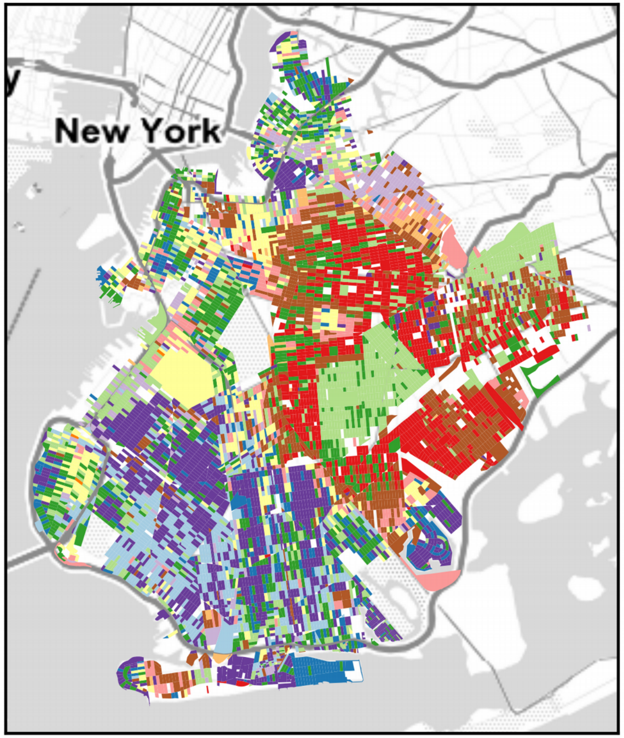
doi: 10/dd9c

SILHOUETTE SCORES

NEIGHBORHOODS



NEXT BEST FITS



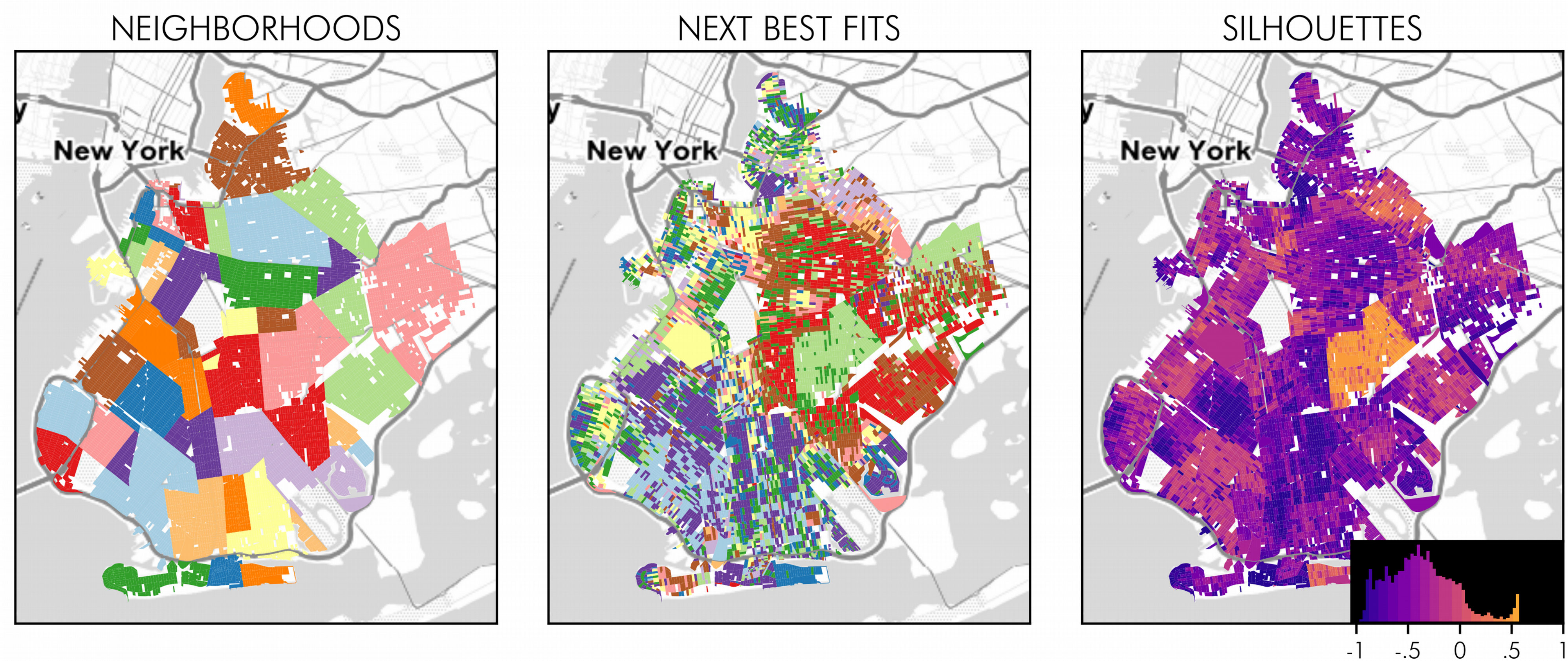
SILHOUETTES

Most similar alternative neighborhood for each census block

ROUSSEEUW (1987)

doi: 10/dd9c

SILHOUETTE SCORES



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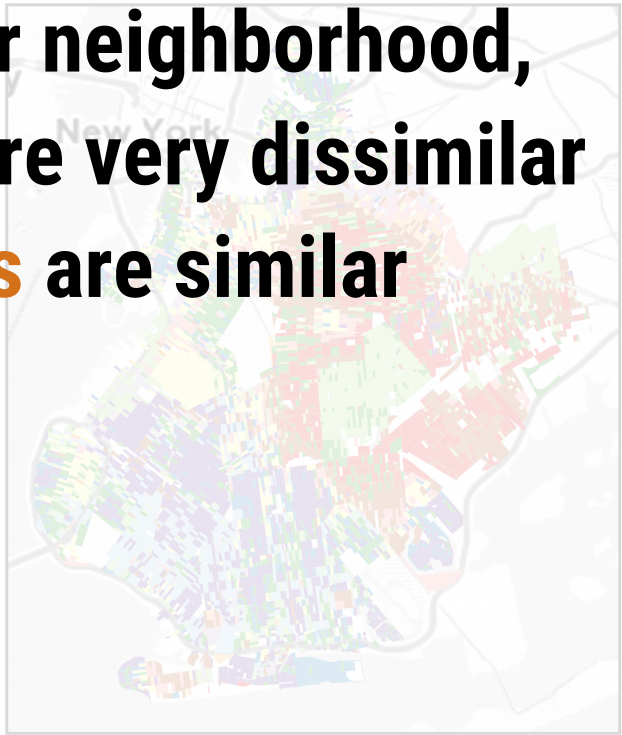
SILHOUETTE SCORES

With respect to their neighborhood,
blue observations are very dissimilar
orange observations are similar

NEIGHBORHOODS

NEXT BEST FITS



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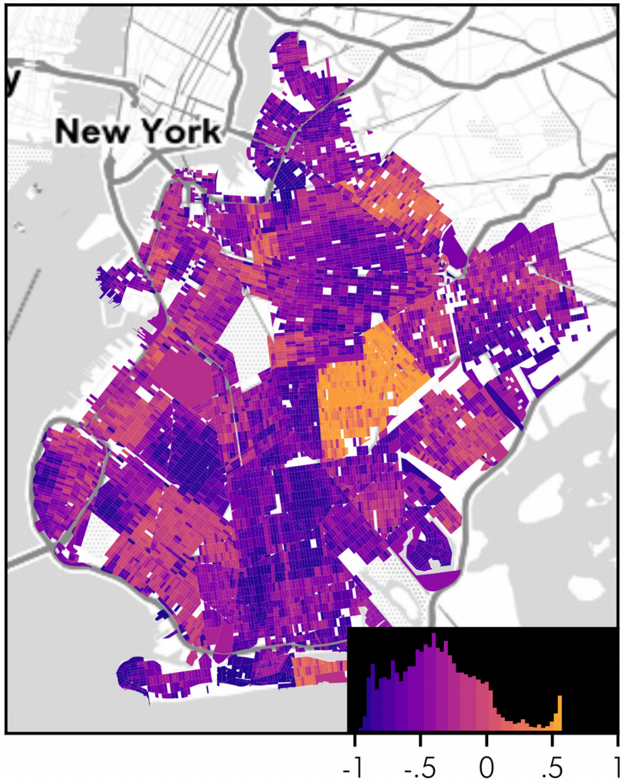

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Gap between *i*'s current place and 2nd best alternative.

ROUSSEEUW (1987) doi: 10/dd9c

BOUNDARY SILHOUETTE

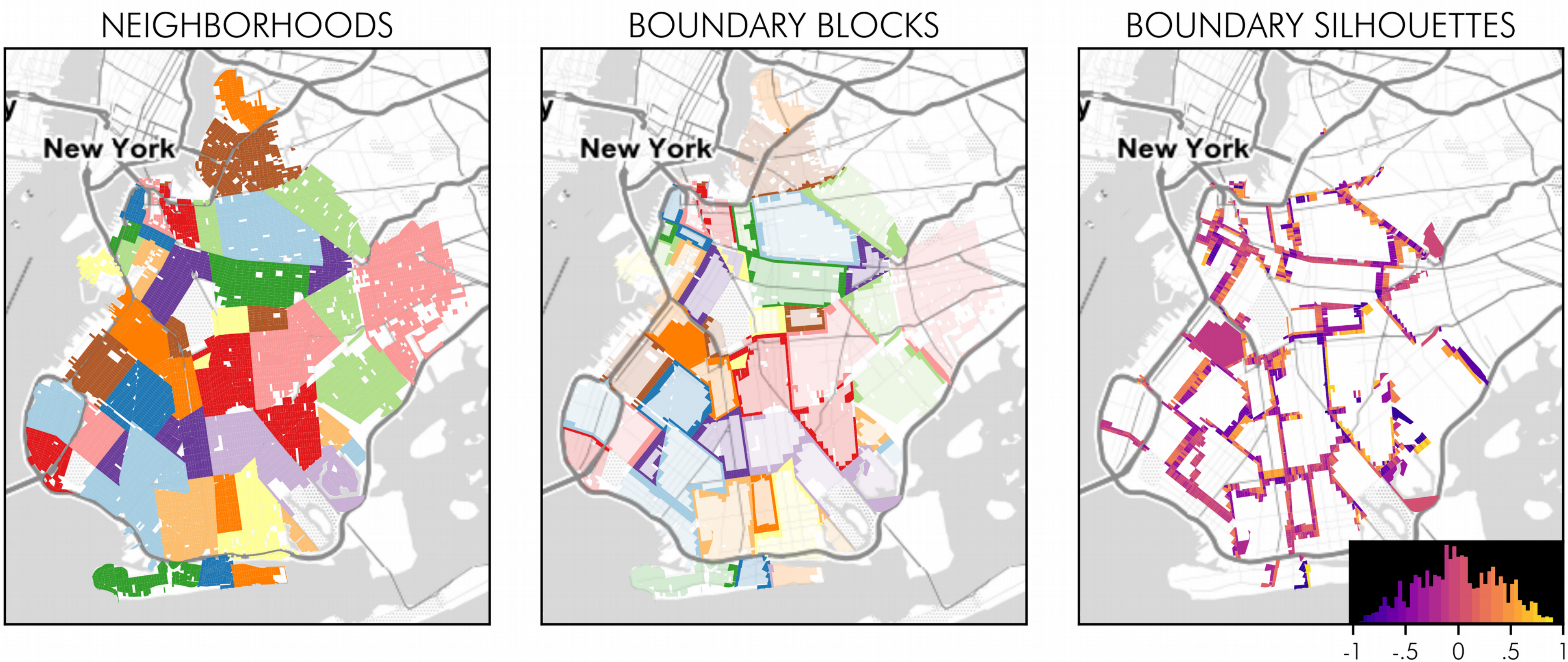
Say that observation i in graph G is assigned to place c and not another place, k, that is nearby i.

$$s(i) = \frac{\min\left\{\bar{d}_k(i)\right\} - \bar{d}_c(i)}{\max\{\min\left\{\bar{d}_k(i)\right\}, \bar{d}_c(i)\}}$$

Gap between i's current place and 2nd best **local** alternative.

doi: 10/dd9c

BOUNDARY SILHOUETTE



WOLF, KNAAP, & REY (2019)

doi: 10/dd9c

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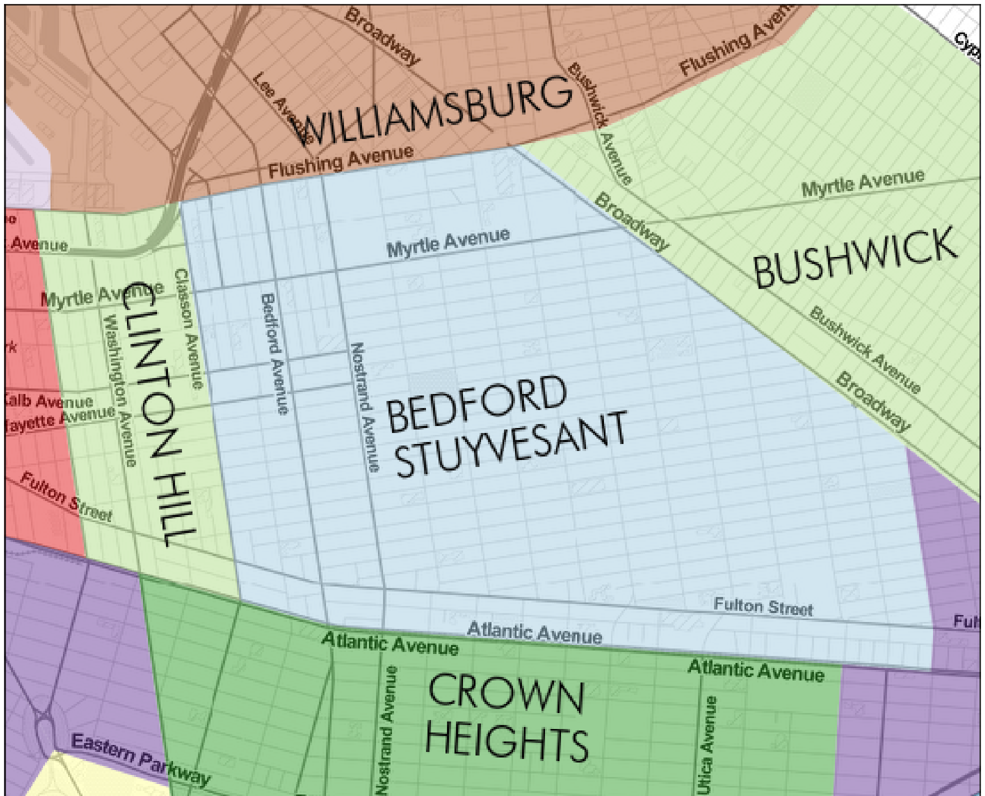

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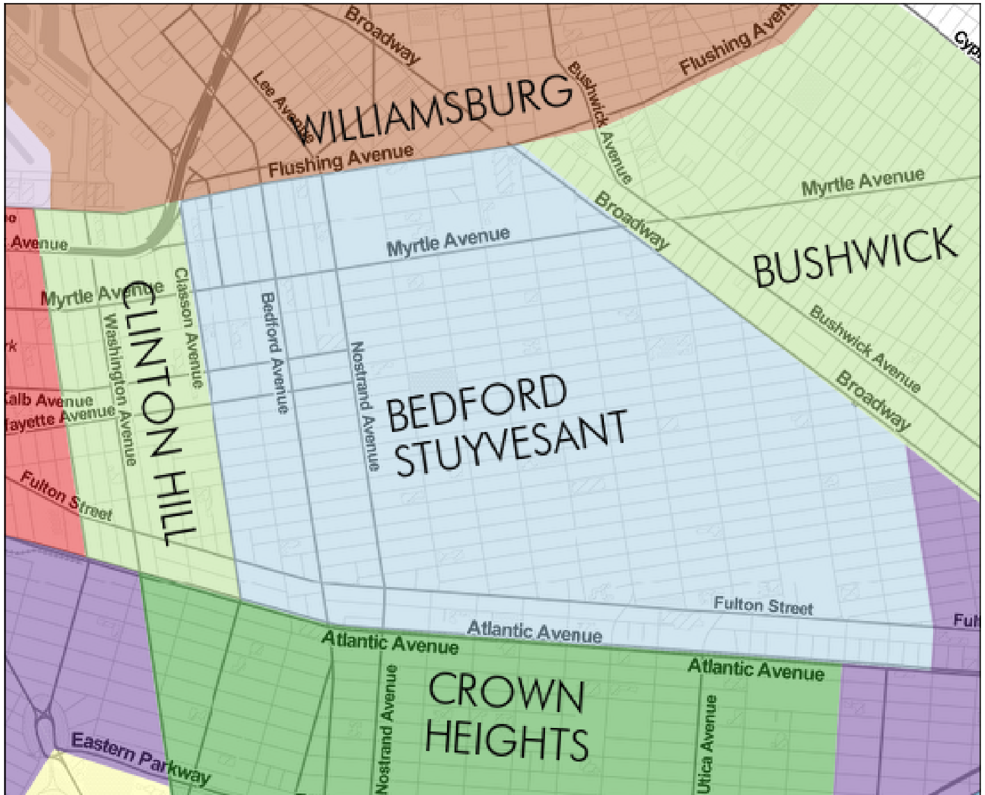

WOLF, KNAAP, & REY (2019)
doi: 10/dd9c

BOUNDARY SILHOUETTE

neighbor focal	Williamsburg	Bushwick	Bedford Stuyvesant	Clinton Hill	Crown Heights
Williamsburg	0	-0.096	0.693	0.516	-
Bushwick	0.288	0	0.482	-	-
Bedford Stuyvesant	-0.478	0.198	0.000	0.006	-0.059
Clinton Hill	-0.355	-	0.358	0	0.296
Crown Heights	-	-	0.077	-0.427	0

On the BedStuy side, blocks remain slightly more similar to blocks in BedStuy.

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On the Bushwick side, blocks are more similar to blocks in Bushwick.

Boundary is “sharp” or “crisp,” should not lead to conflict under CBH

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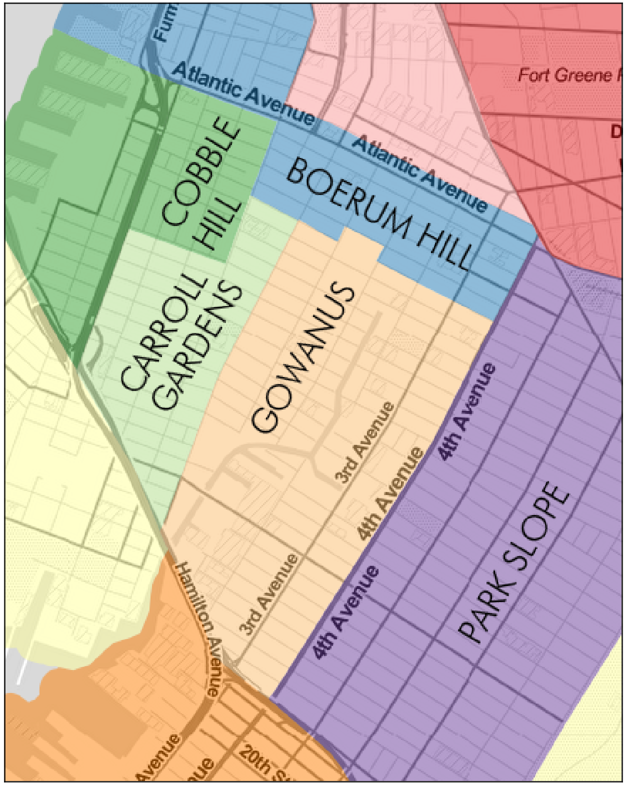

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BOUNDARY SILHOUETTE

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BOUNDARY SILHOUETTE

neighbor focal	Boerum Hill	Cobble Hill	Carroll Gardens	Gowanus	Park Slope
Boerum Hill	0.000	-0.32	-0.358	0.274	0.122
Cobble Hill	0.627	0	-0.156	0.639	-
Carroll Gardens	0.339	0.152	0	0.710	-
Gowanus	-0.071	-0.359	-0.647	0.000	-0.168
Park Slope	0.050	-	-	0.390	0

On the Gowanus side, blocks are much more similar to those in Carroll Gardens.

BOUNDARY SILHOUETTE

neighbor focal	Boerum Hill	Cobble Hill	Carroll Gardens	Gowanus	Park Slope
Boerum Hill	0.000	-0.32	-0.358	0.274	0.122
Cobble Hill	0.627	0	-0.156	0.639	-
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WOLF, KNAAP, & REY (2019) doi: 10/dd9c

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The boundary is asymmetric/unclear!

WOLF, KNAAP, & REY (2019) doi: 10/dd9c

RETHINKING BOUNDARIES:

Contingent on conflict outcome.

Conflict **over what, between whom?**

Robustness from place endogeneity!

Symmetric and reversible.

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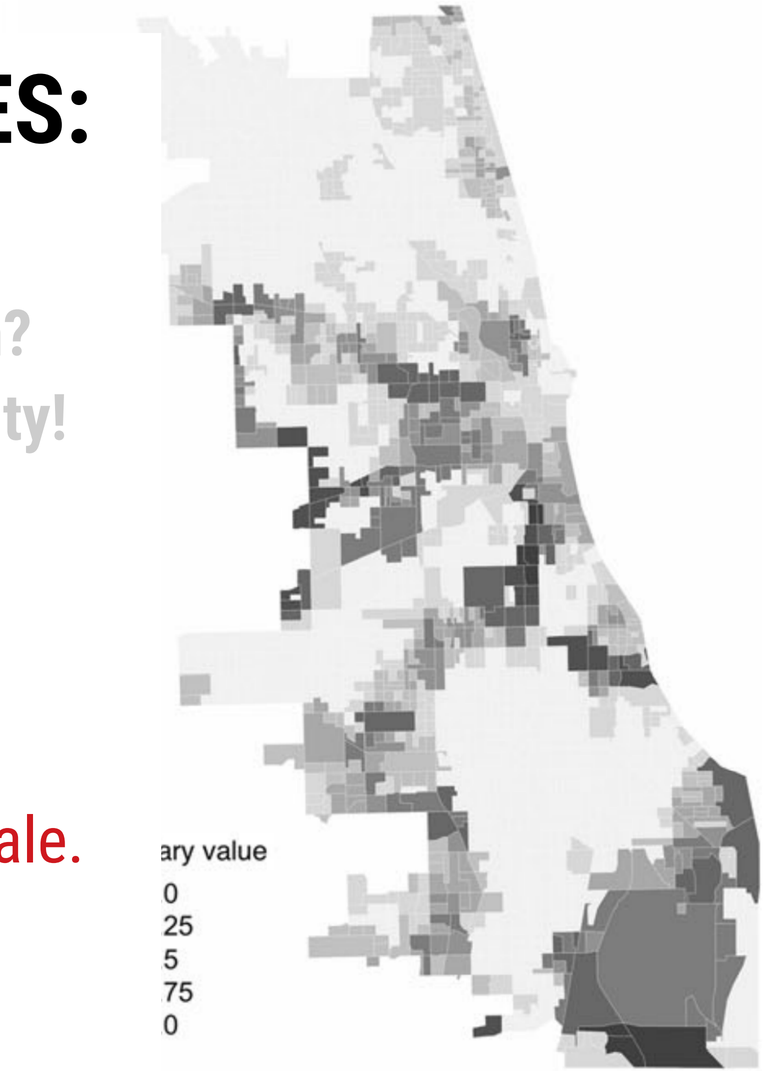

Fig. 1 Areal wombling for the proportion of African American residents

NO SINGLE PLACE SCALE IS SUFFICIENT

Urban morphology is **FRACTAL, MULTI-SCALE**

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City morphology is reflected in a hierarchy of different sub-centers or clusters across many scales … [that] reflect the resources needed to service them and the spatial range over which their demand is sustainable.

Cities are thus classic examples of fractals, in that their form reflects a statistical self-similarity or hierarchy of clusters.

BATTY (2008)

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Urban society is embedded within this morphology

(Urban society also enforces or adjusts this morphology)

∴ Social boundaries are **FRACTAL, MULTI-SCALE**

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BATTY (2008)

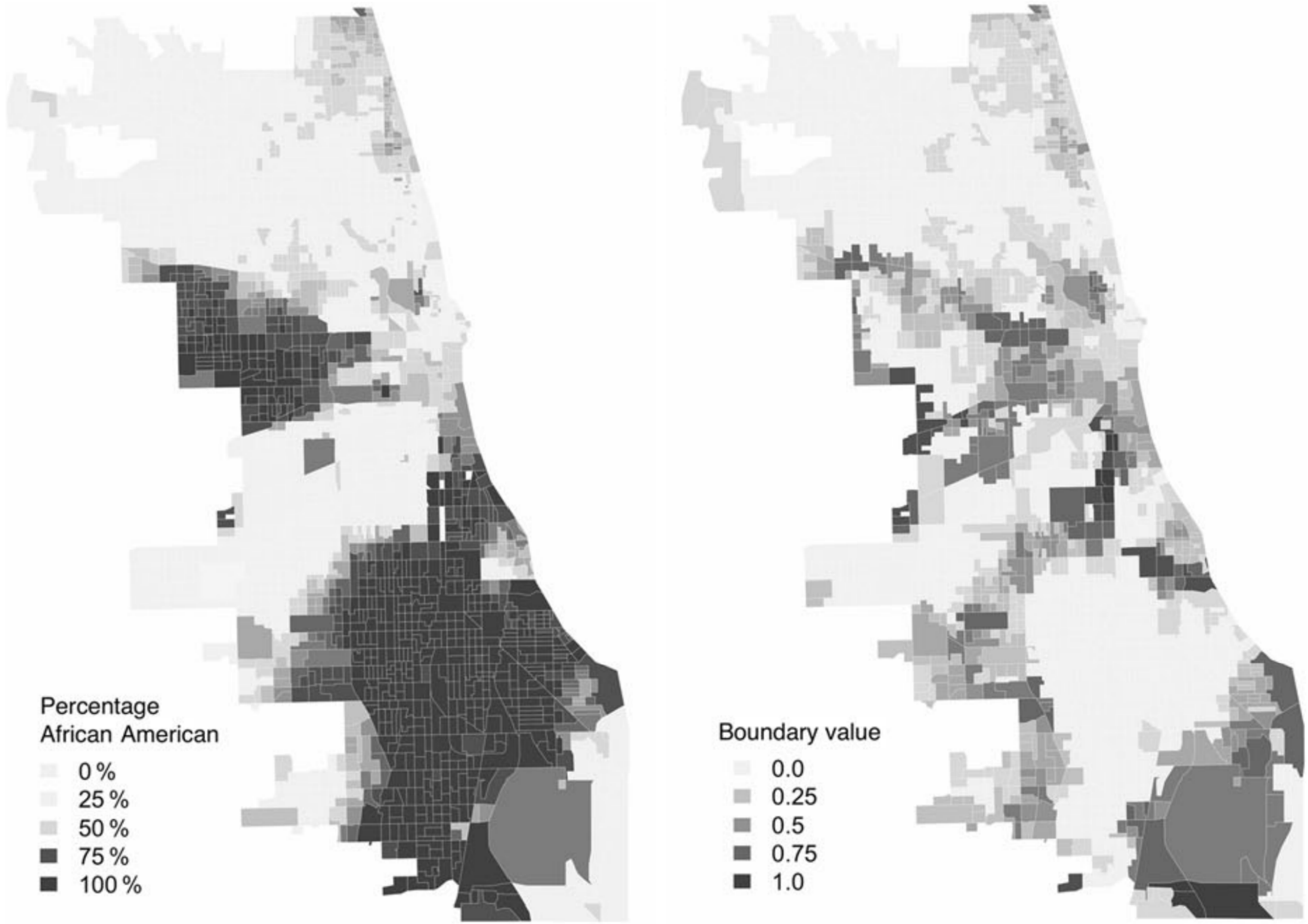

Fig. 1 Areal wombling for the proportion of African American residents

FOR YOUR INFORMATION (THEORY)

Let there be N blocks with m racial/ethnic classes.

$$H(p_i) = -\sum_{r}^{m} p_{ir} \ln(p_{ir})$$

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ENTROPY OF CENSUS UNIT i

FOR YOUR INFORMATION (THEORY)

Let there be N blocks with m racial/ethnic classes.

$$H(p_i) = -\sum_{r}^{m} p_{ir} \ln(p_{ir})$$

PERCENT OF POPULATION IN i THAT IS GROUP r

FOR YOUR INFORMATION (THEORY)

Let there be N blocks with m racial/ethnic classes.

$$H(p_i) = -\sum_{r}^{m} p_{ir} \ln(p_{ir})$$

SUMMED OVER ALL GROUPS m

FOR YOUR INFORMATION (THEORY)

Let there be N areas with m racial/ethnic classes.

$$H(p_i) = -\sum_{r}^{m} p_{ir} \ln(p_{ir})$$

FOR YOUR INFORMATION (THEORY)

Let there be N blocks with m racial/ethnic classes.

$$D_{KL}(p_i||p_j) = -\sum_{r}^{m} p_{ir} \ln\left(\frac{p_{jr}}{p_{ir}}\right)$$

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INFORMATION GAIN
ABOUT AREA i
FROM AREA j

FOR YOUR INFORMATION (THEORY)

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RATIO OF POPULATION PERCENTAGES

KULLBACK LEIBLER DIVERGENCE

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KULLBACK LEIBLER DIVERGENCE

FOR YOUR INFORMATION (THEORY)

Let there be N blocks with m racial/ethnic classes.

$$D_{JS}(p_i||p_j) = \frac{1}{2}\left[D_{KL}(p_i||\bar{p}) + D_{KL}(p_j||\bar{p})\right]$$

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AVERAGE OF POPULATIONS IN AREA i AND j.

FOR YOUR INFORMATION (THEORY)

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$$D_{JS}(p_i||p_j) = \frac{1}{2}\left[D_{KL}(p_i||\bar{p}) + D_{KL}(p_j||\bar{p})\right]$$

AVERAGE D_{KL} FROM EACH AREA

TO THE AVERAGE OF AREAS

JENSEN SHANNON DIVERGENCE

FOR YOUR INFORMATION (THEORY)

Let there be N blocks with m racial/ethnic classes.

$$D_{WJS}(p_i||\eta_i(\delta)) = \frac{\sum_j n_j * D_{JS}(p_j||\bar{p}_J)}{\sum_j n_j}$$

WEIGHTED JENSEN SHANNON DIVERGENCE

FOR YOUR INFORMATION (THEORY)

Let there be N blocks with m racial/ethnic classes.

$$D_{WJS}(p_i || \eta_i(\delta)) = \frac{\sum_j n_j * D_{JS}(p_j || \bar{p}_J)}{\sum_j n_j}$$

RAW POPULATION IN AREA j

FOR YOUR INFORMATION (THEORY)

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$$D_{WJS}(p_i || \eta_i(\delta)) = \frac{\sum_j n_j * D_{JS}(p_j || \bar{p}_J)}{\sum_j n_j}$$

"EGOHOOD" OF i:

SET OF OTHER OBSERVATIONS

WITHIN DISTANCE δ OF i

FOR YOUR INFORMATION (THEORY)

Let there be N blocks with m racial/ethnic classes.

$$D_{WJS}(p_i||\eta_i(\delta)) = \frac{\sum_j n_j * D_{JS}(p_j||\bar{p}_J)}{\sum_j n_j}$$

POPULATION-WEIGHTED AVERAGE D_{KL} FROM EACH BLOCK TO AVERAGE OF THE EGOHOOD

WEIGHTED JENSEN SHANNON DIVERGENCE

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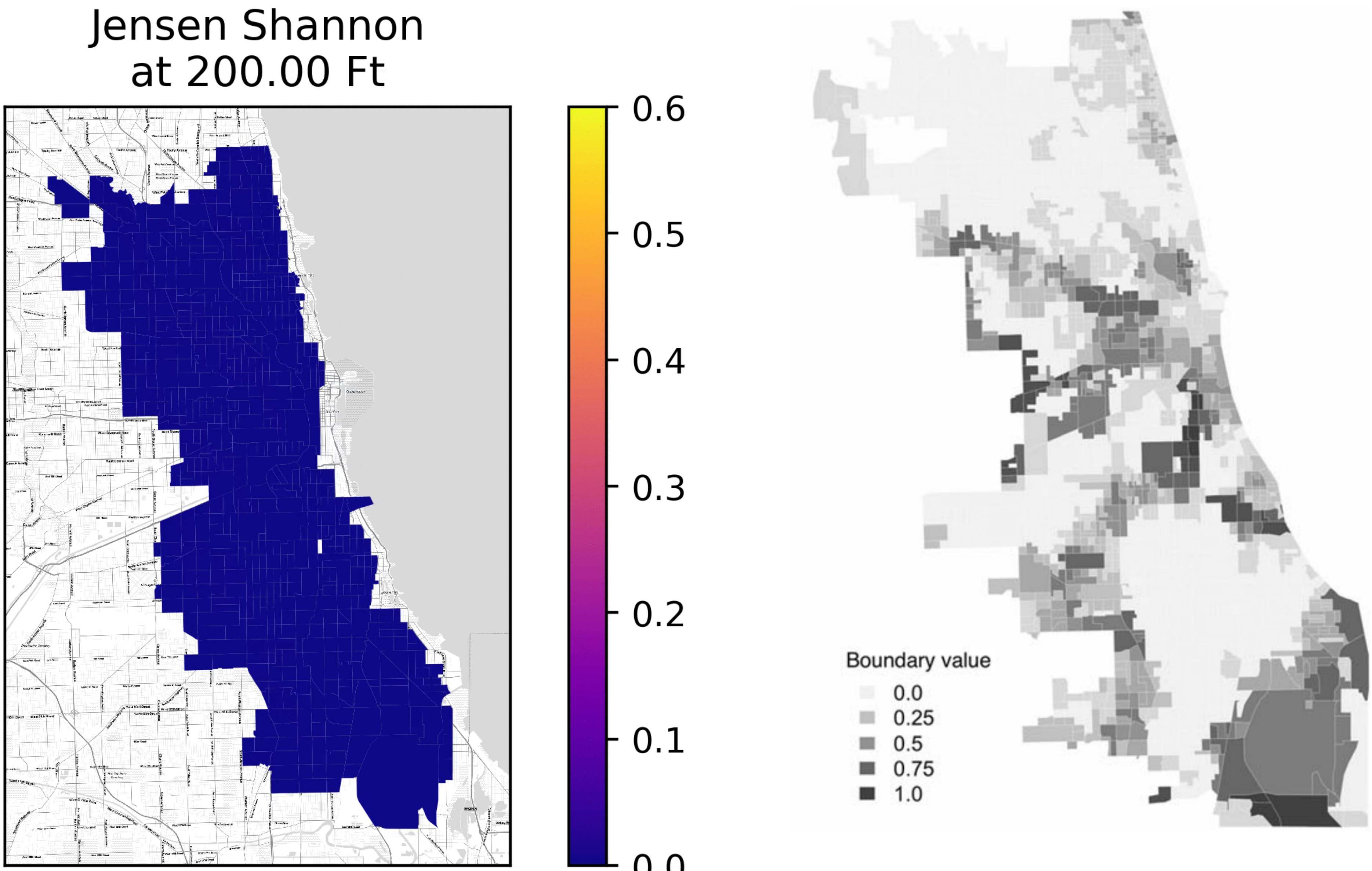
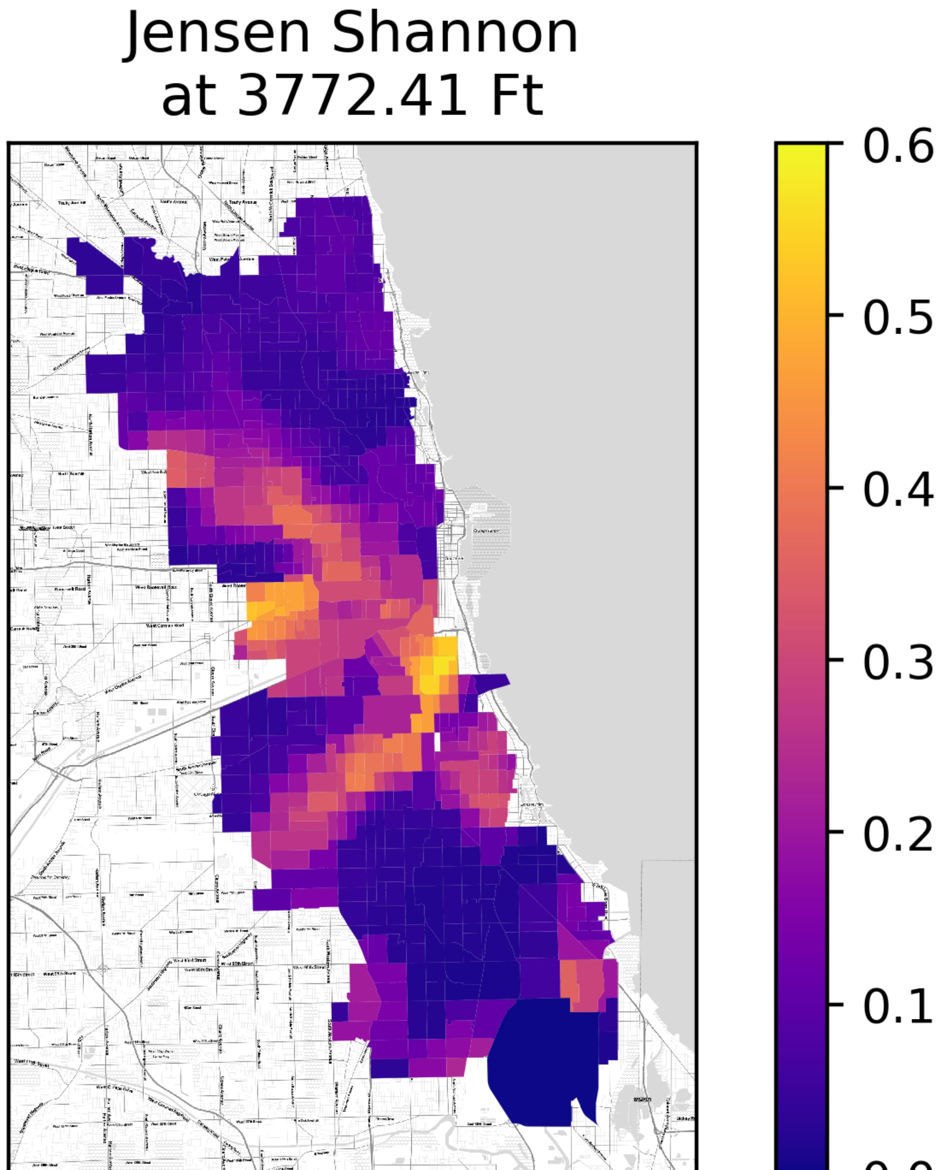
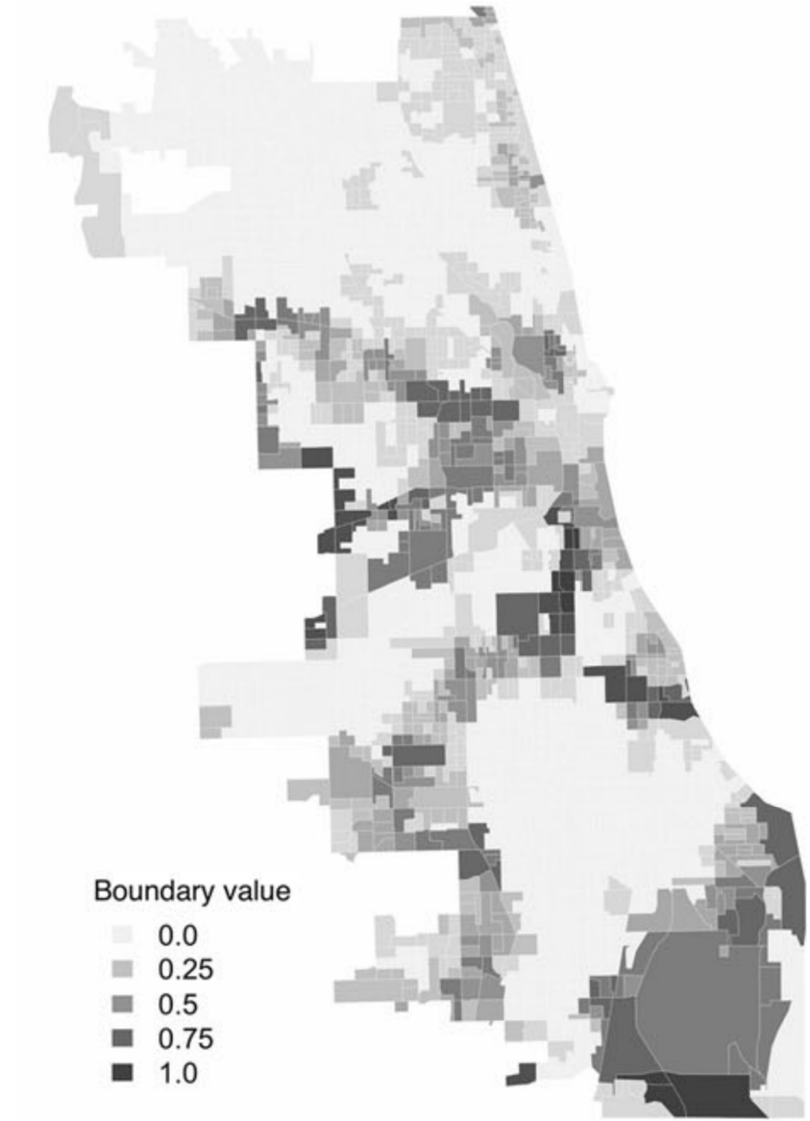
HOW DIFFERENT IS i FROM OTHERS IN EGOHOOD?

WEIGHTED JENSEN SHANNON DIVERGENCE


Jensen Shannon
at 200.00 Ft
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Boundary value
0.0
0.25
0.5
0.75
1.0


Jensen Shannon
at 3772.41 Ft
0.6
0.5
0.4
0.3
0.2
0.1
0.0


Boundary value
0.0
0.25
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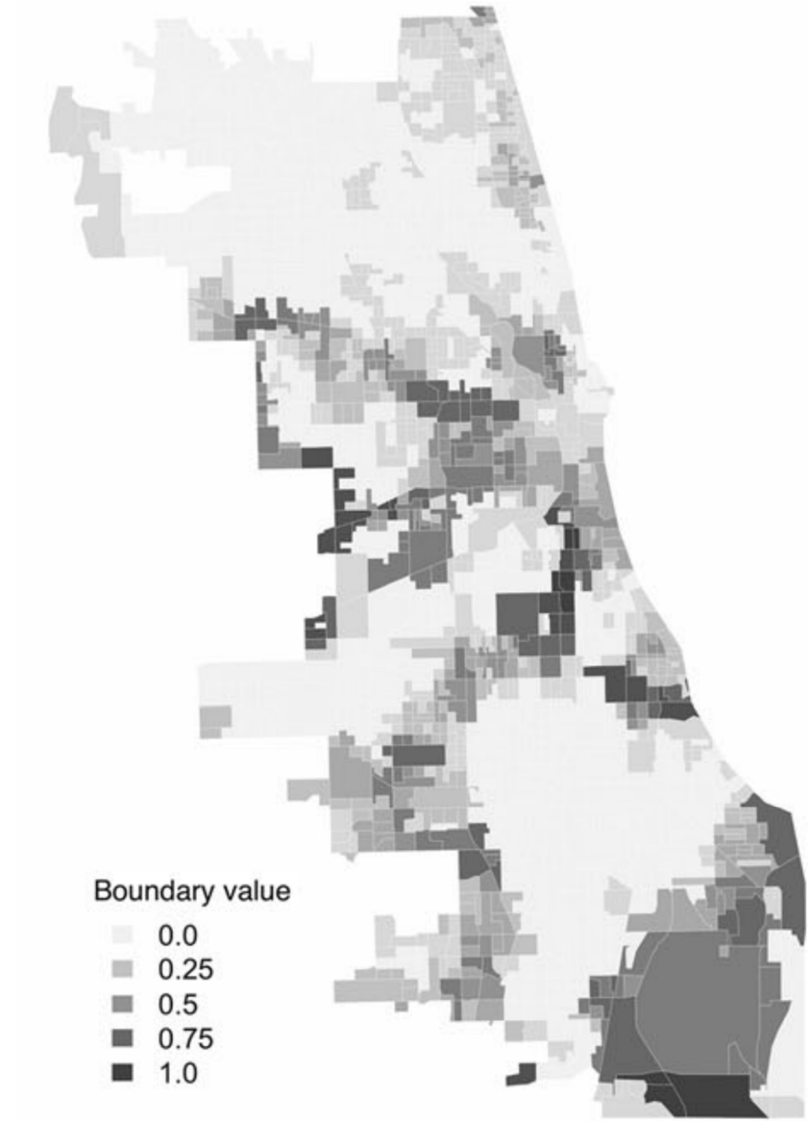
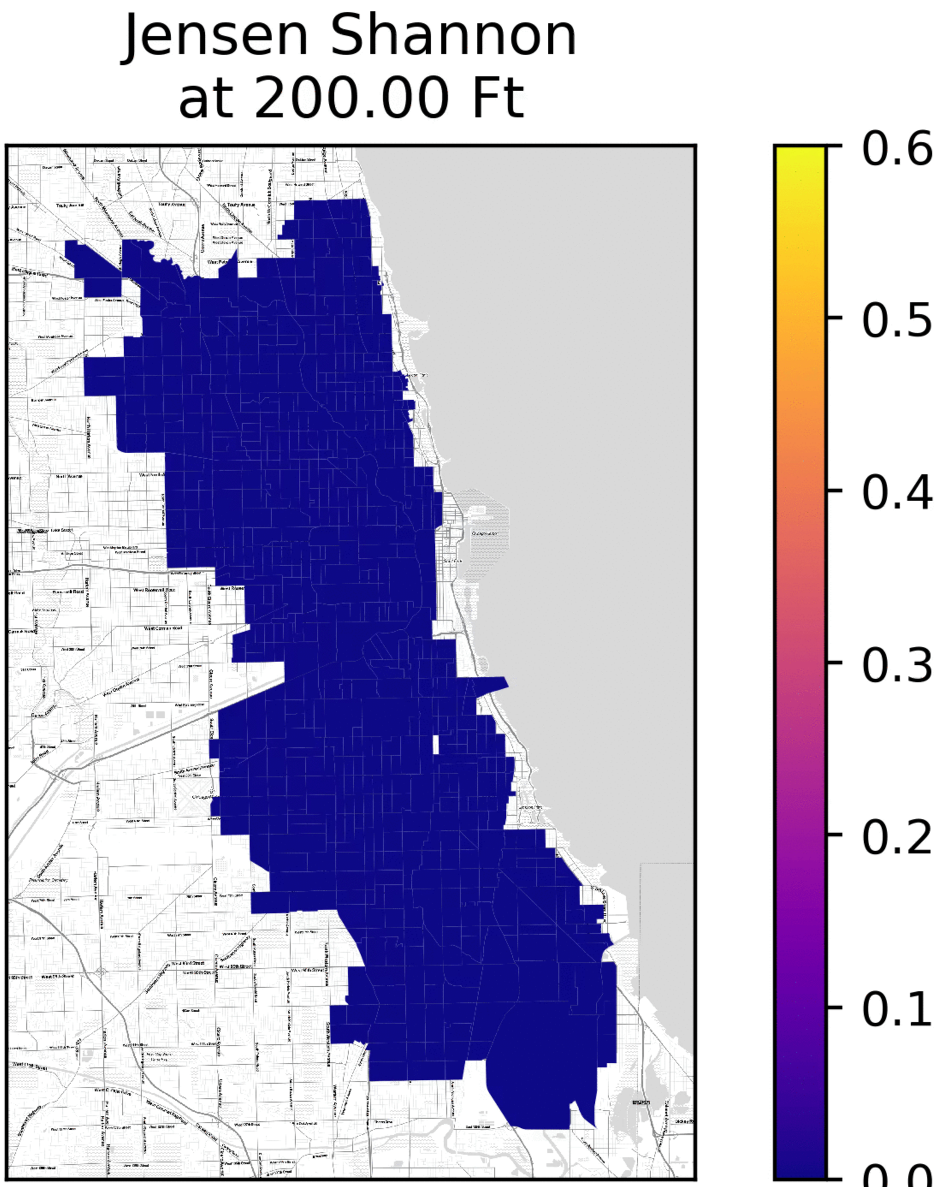
ONLY ONE SCALE





ALWAYS MULTI SCALE

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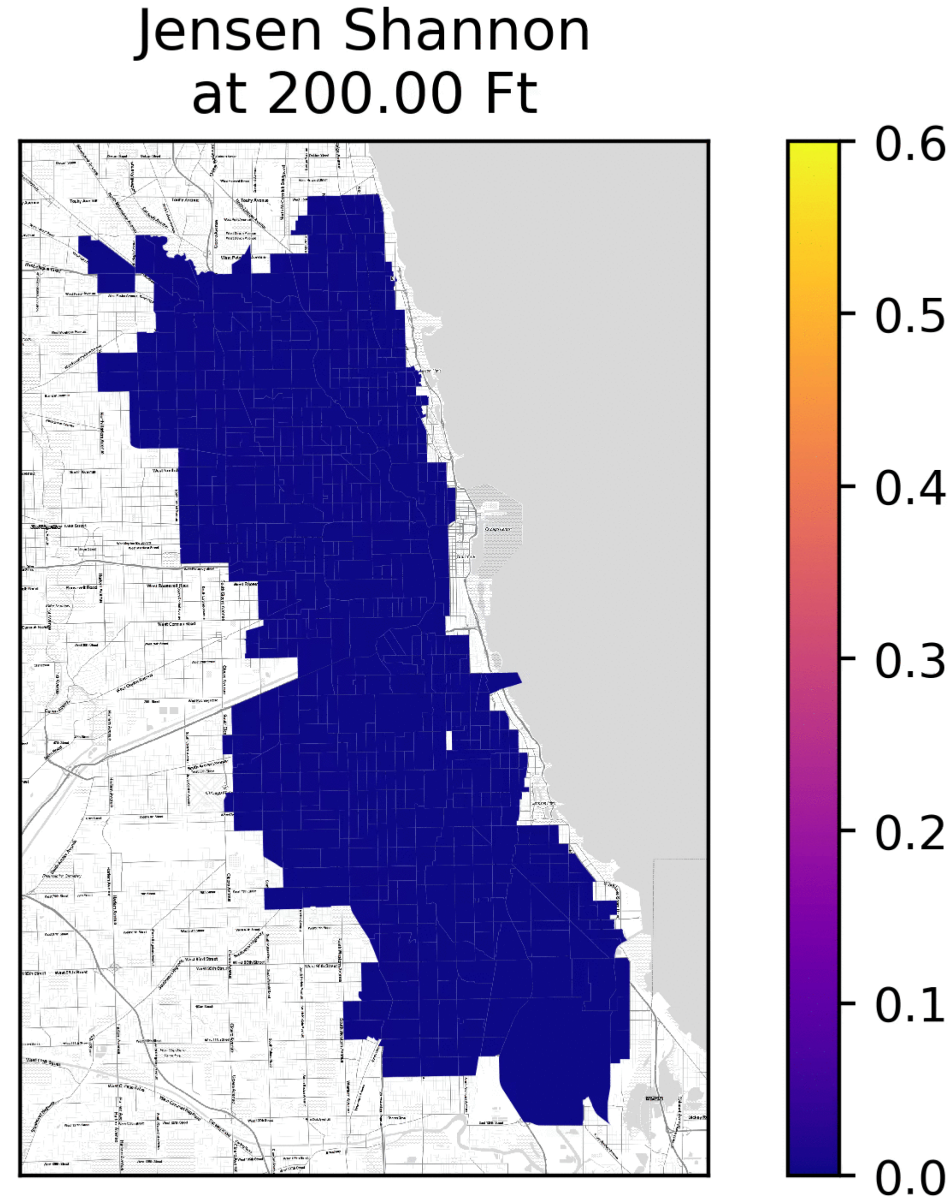

FINDING THE FAULT LINES:

ESTIMATING THE BOUNDARIES IN URBAN SOCIAL-SPATIAL INEQUALITY

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The Alan Turing Institute

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