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
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"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.

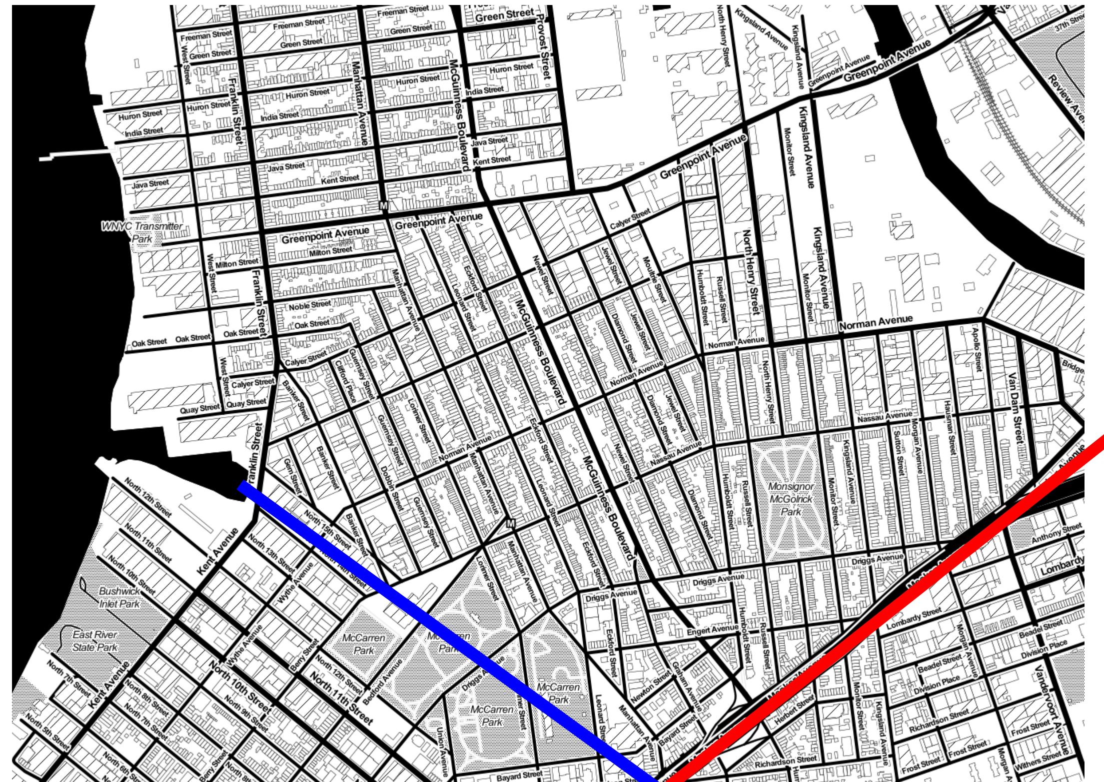
CONCEPTUALIZING BOUNDARIES

“Williamsburg becomes Greenpoint at the Bushwick Inlet”

CONCEPTUALIZING BOUNDARIES

"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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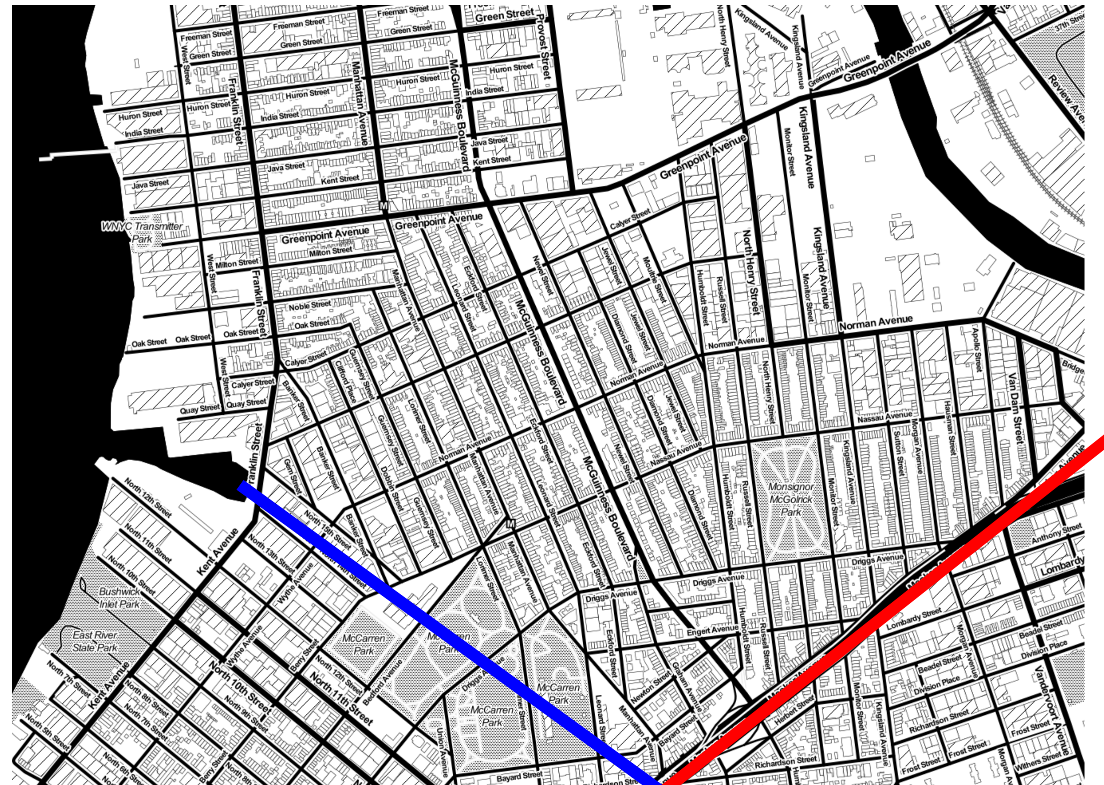
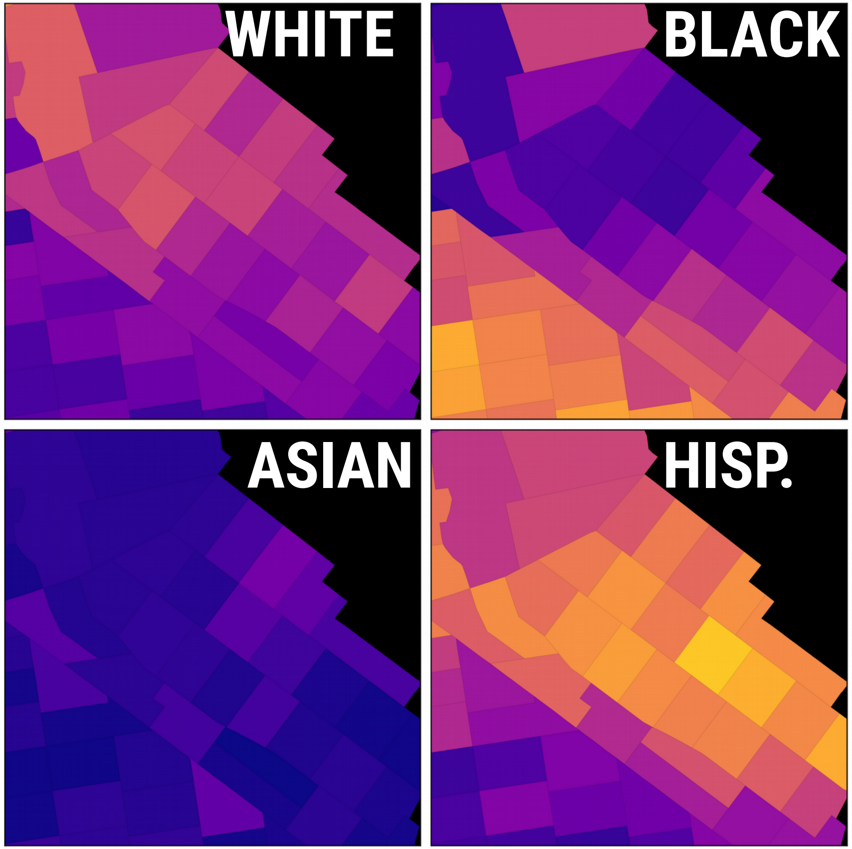


CONCEPTUALIZING BOUNDARIES

“Though an ethnic neighborhood, Bushwick’s population is, for a NYC neighborhood, relatively heterogeneous”



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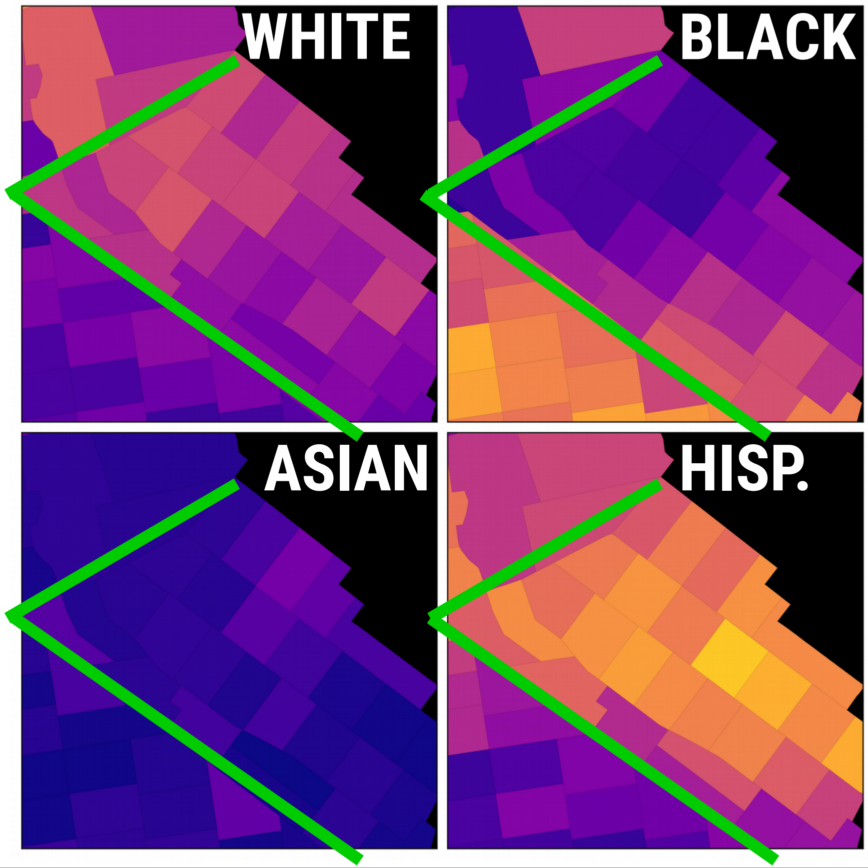

CONCEPTUALIZING BOUNDARIES

BOUNDARIES AS SOCIALLY CONSTRUCTED DIVISIONS OF URBAN LIFE

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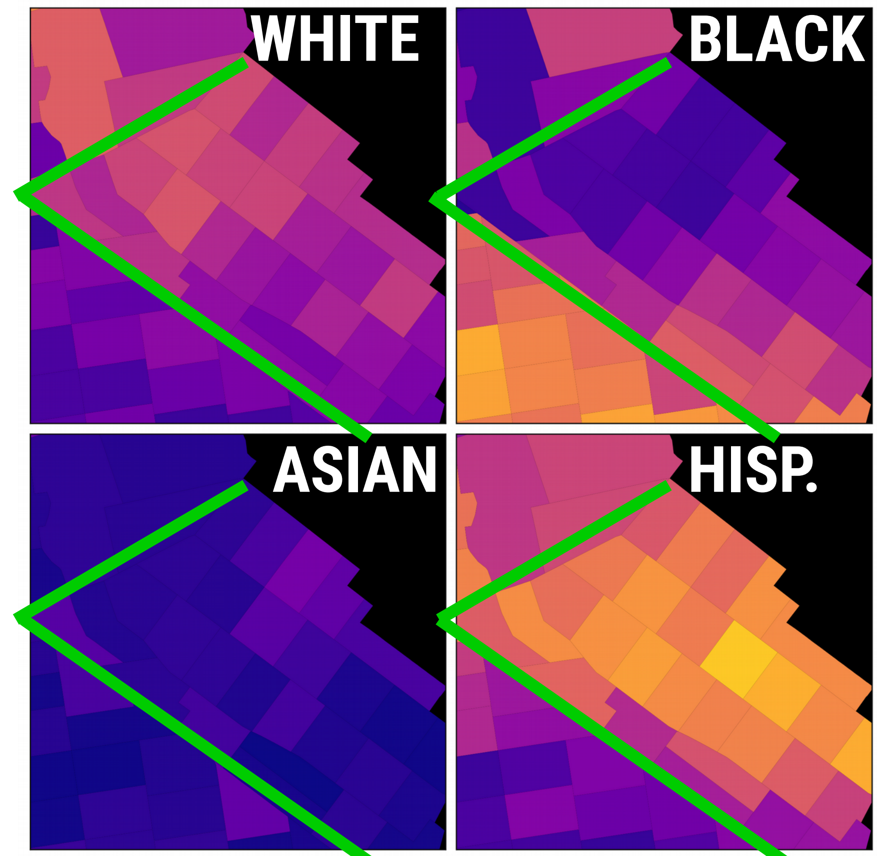

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SUTTLES (1972) Defended communities
GRIGSBY (1987) Real income is everything
GRANNIS (1998) Transit network barriers
GALSTER (2001) House Attribute “bundles”
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SPACE

PLACE

SPACE 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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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?

PLACE

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?

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Geosilhouettes: Geographical measures of cluster fit

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FRONTIERS IN RESIDENTIAL SEGREGATION: UNDERSTANDING NEIGHBOURHOOD BOUNDARIES AND THEIR IMPACTS

NEMA DEAN*, GUANPENG DONG**, ANETA PIEKUT***
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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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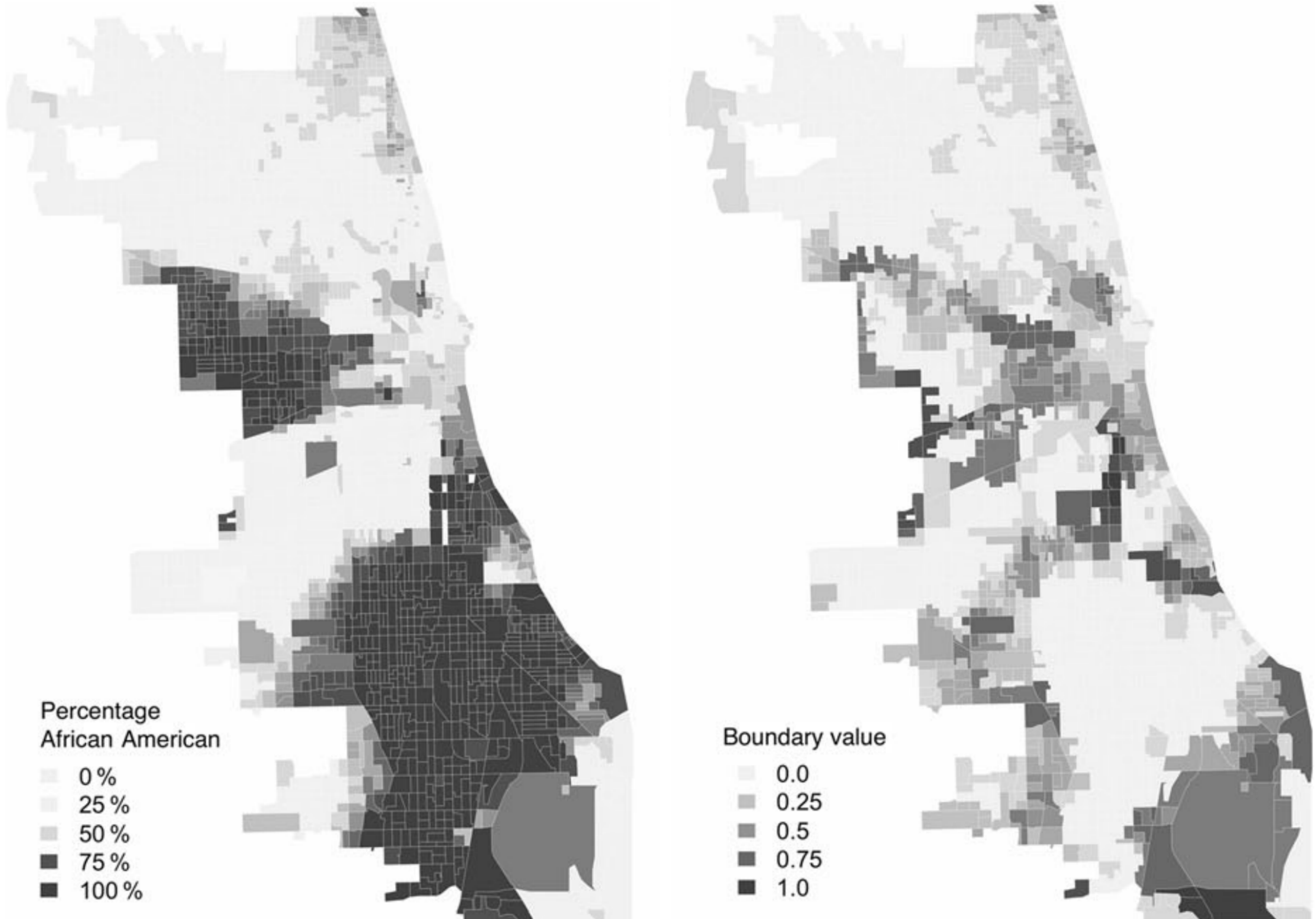


Fig. 1 Areal wombling for the proportion of African American residents

RETHINKING BOUNDARIES:

Contingent on conflict outcome.

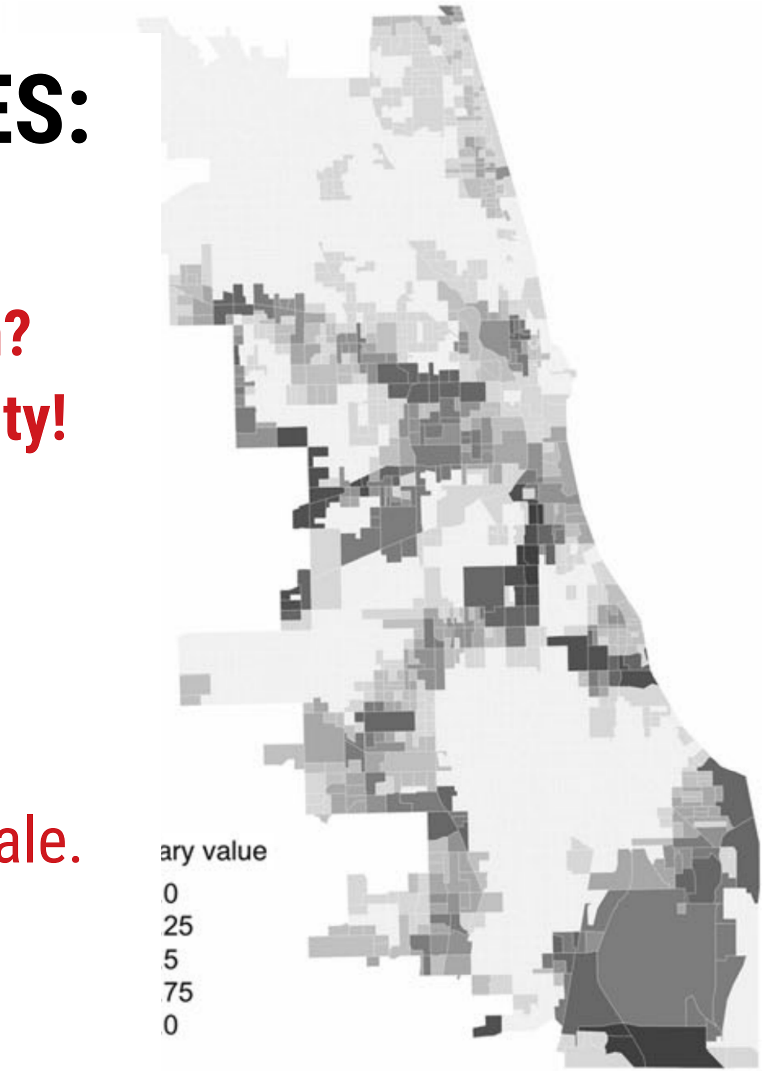
Conflict **over what, between whom?**

Robustness from place endogeneity!

Symmetric and reversible.

Only magnitude, no sign.

Assume existence of place & place-scale.



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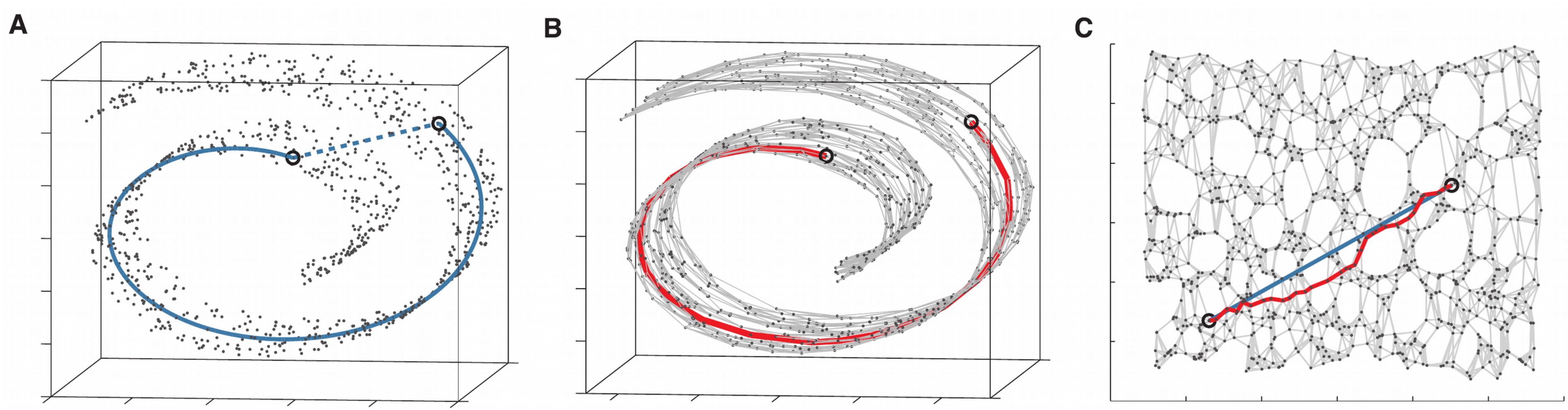
ROBUSTNESS FROM ENDOGENEITY

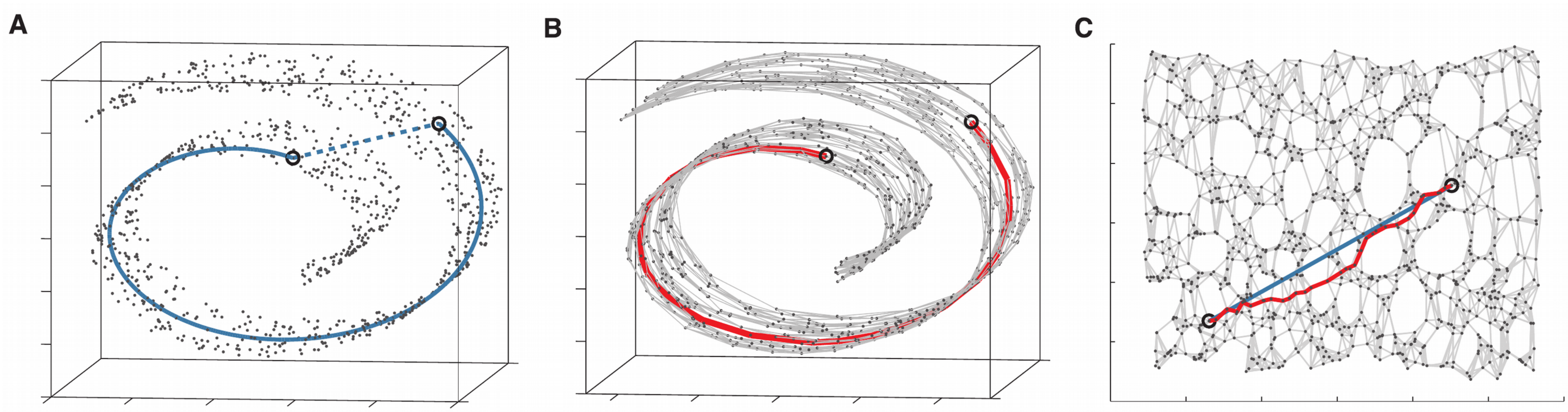
- Places are distinctive:
    - Geographically coherent
    - More similar than dissimilar
- Balancing nearness & similarity, we can see the “joint” social-spatial structure of the city.

ROBUSTNESS FROM ENDOGENEITY



“Manifold Learning”

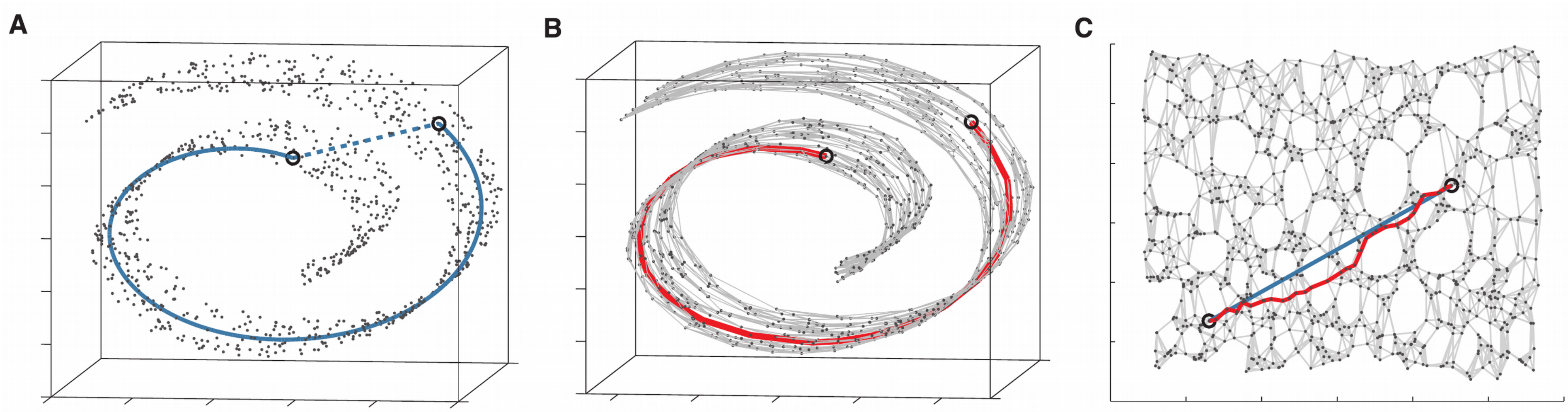
ROBUSTNESS FROM ENDOGENEITY



“Manifold Learning”

(non-linear PCA)

ROBUSTNESS FROM ENDOGENEITY



"Manifold Learning"

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

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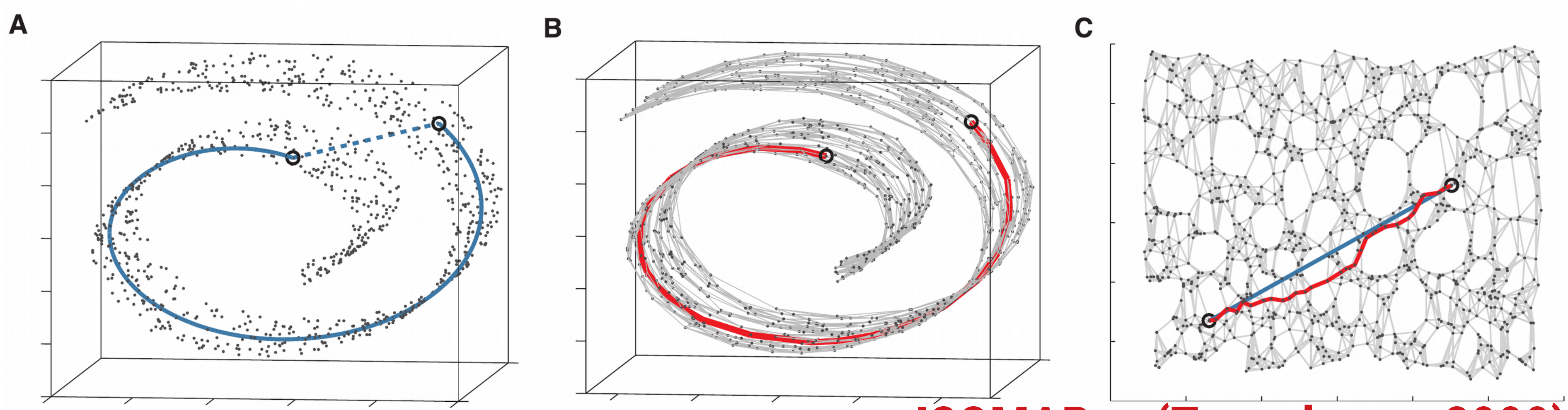


“Manifold Learning”

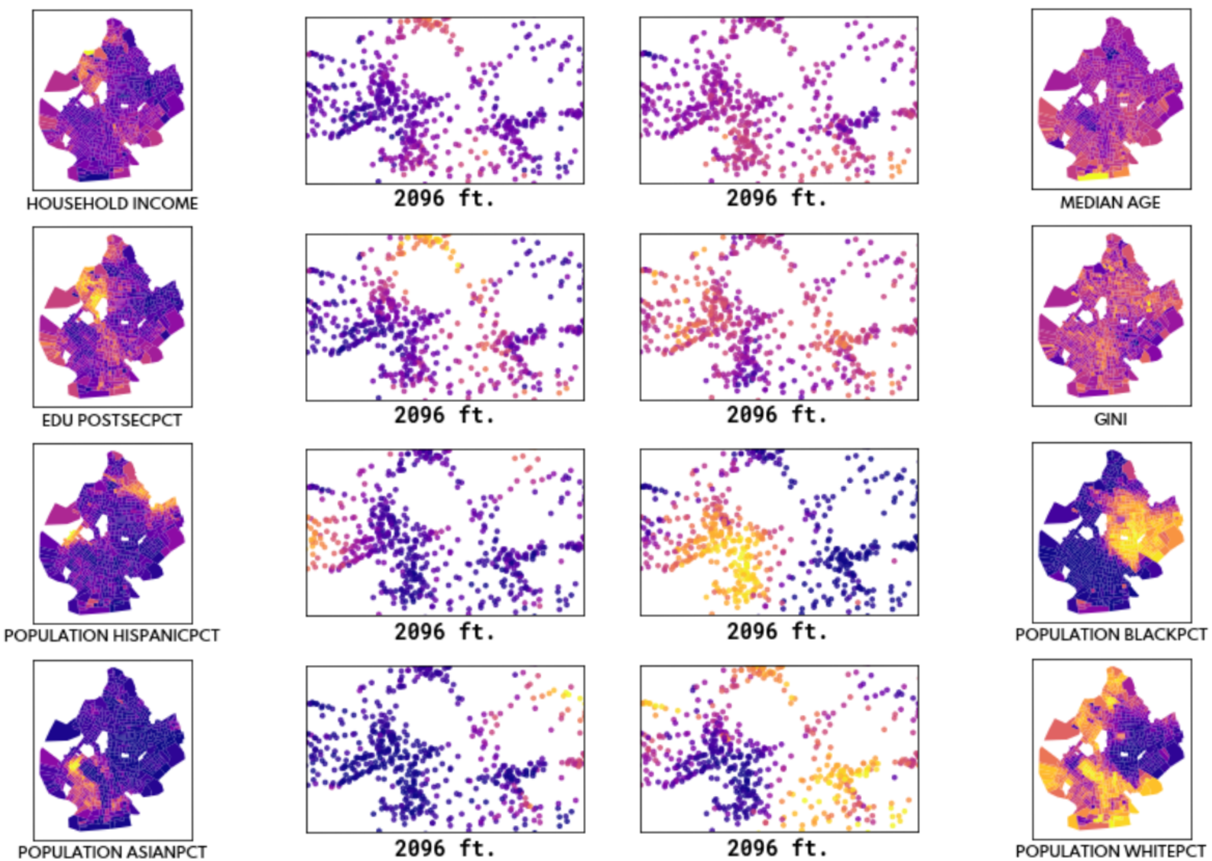
How can we understand boundaries in high-dimensional, highly-nonlinear data?

ISOMAP: (Tenenbaum, 2000)

Make “short hops” between similar points.

Add up the length of short hops!

ROBUSTNESS FROM ENDOGENEITY



AT ONE END

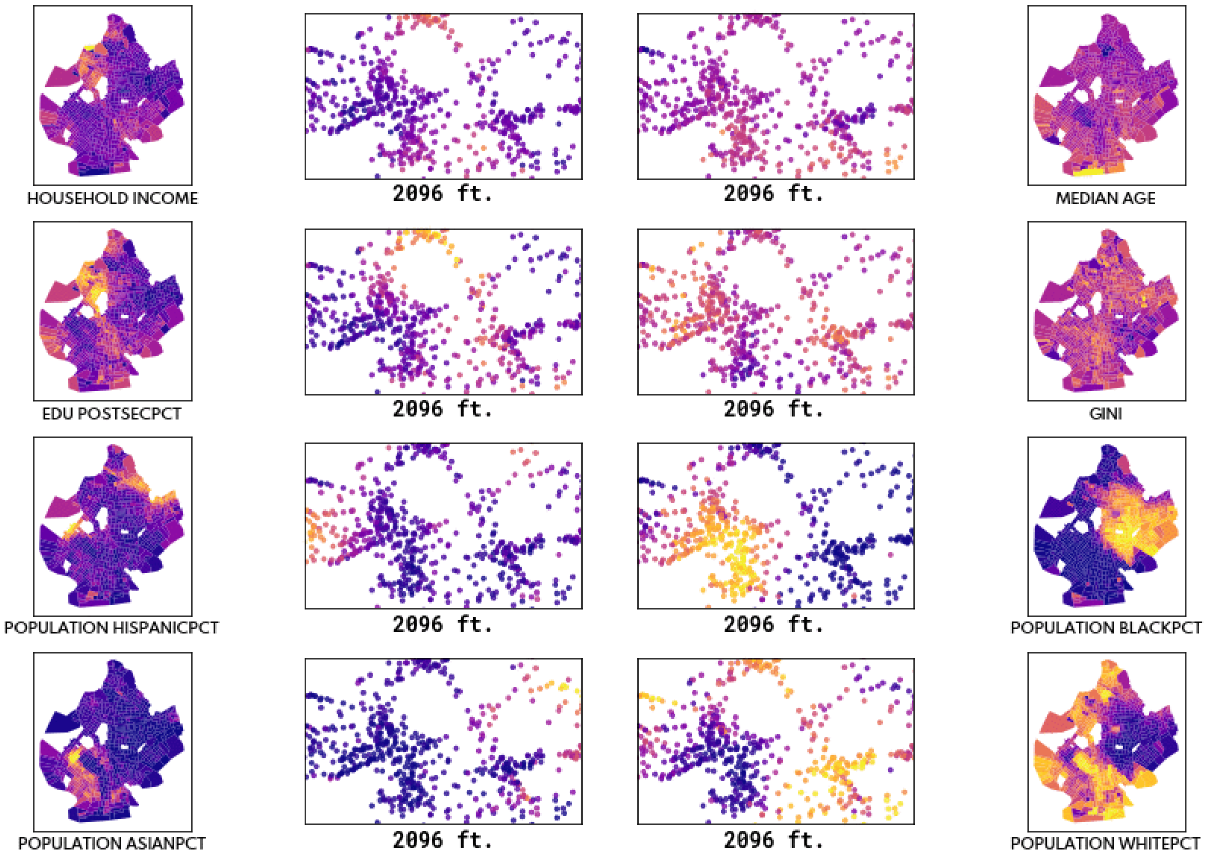
Basically Brooklyn,
if you squint

(turn 90° & stretch it)

WOLF & KNAAP (2020)

10.31235/osf.io/75s8v

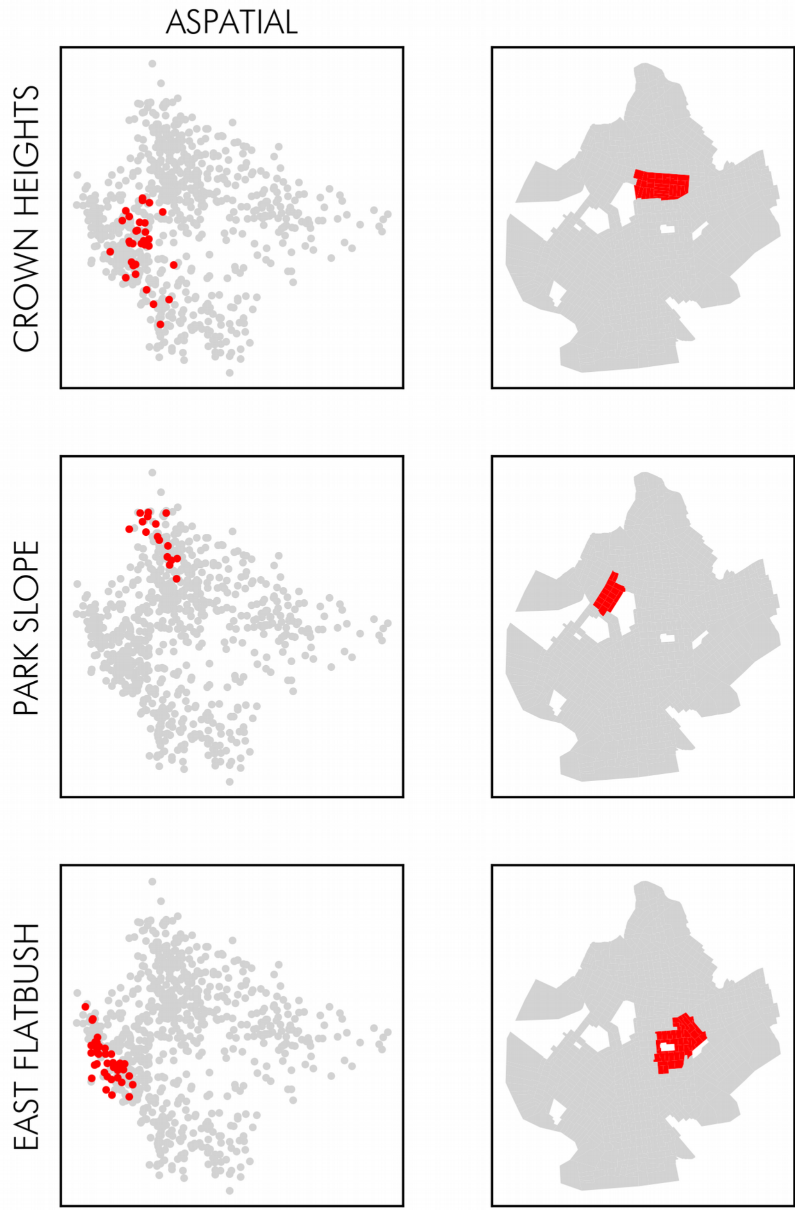
ROBUSTNESS FROM ENDOGENEITY



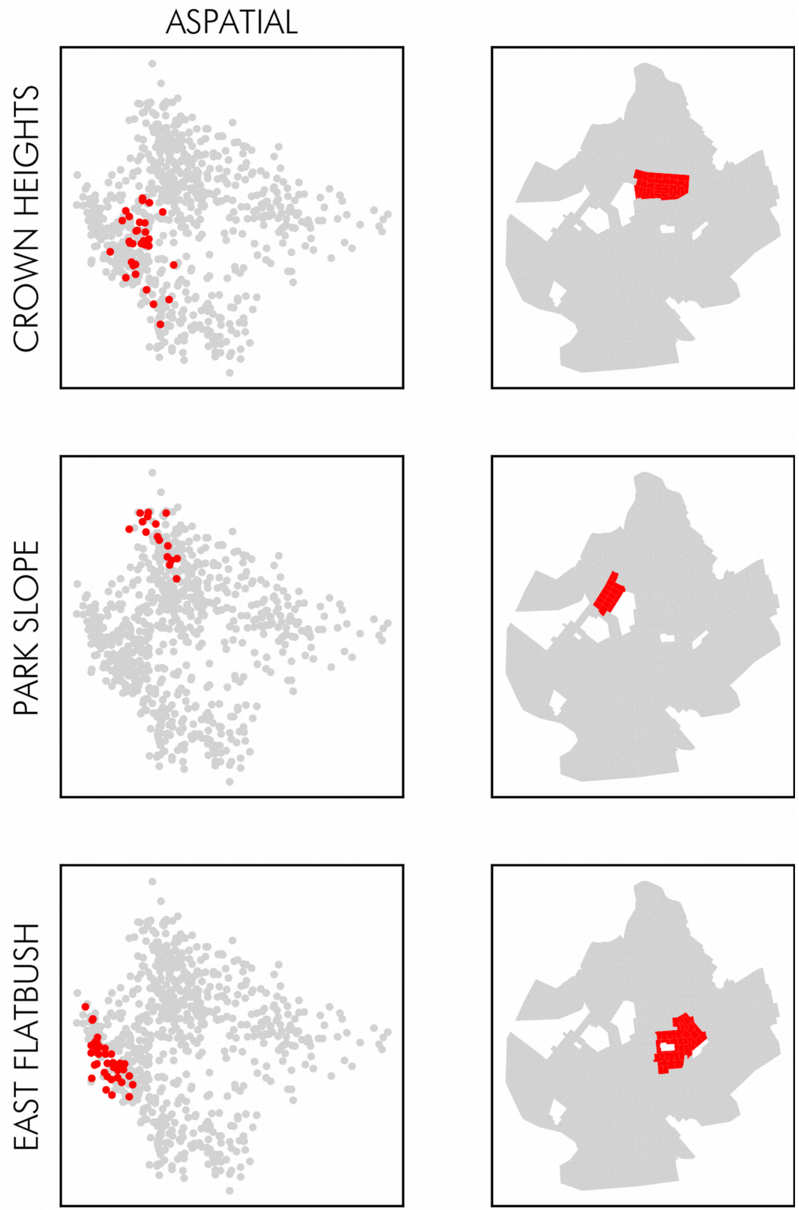
As the manifold learner increasingly ignores space,

The “map projection” warps & moves blocks that are similar near one another.

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

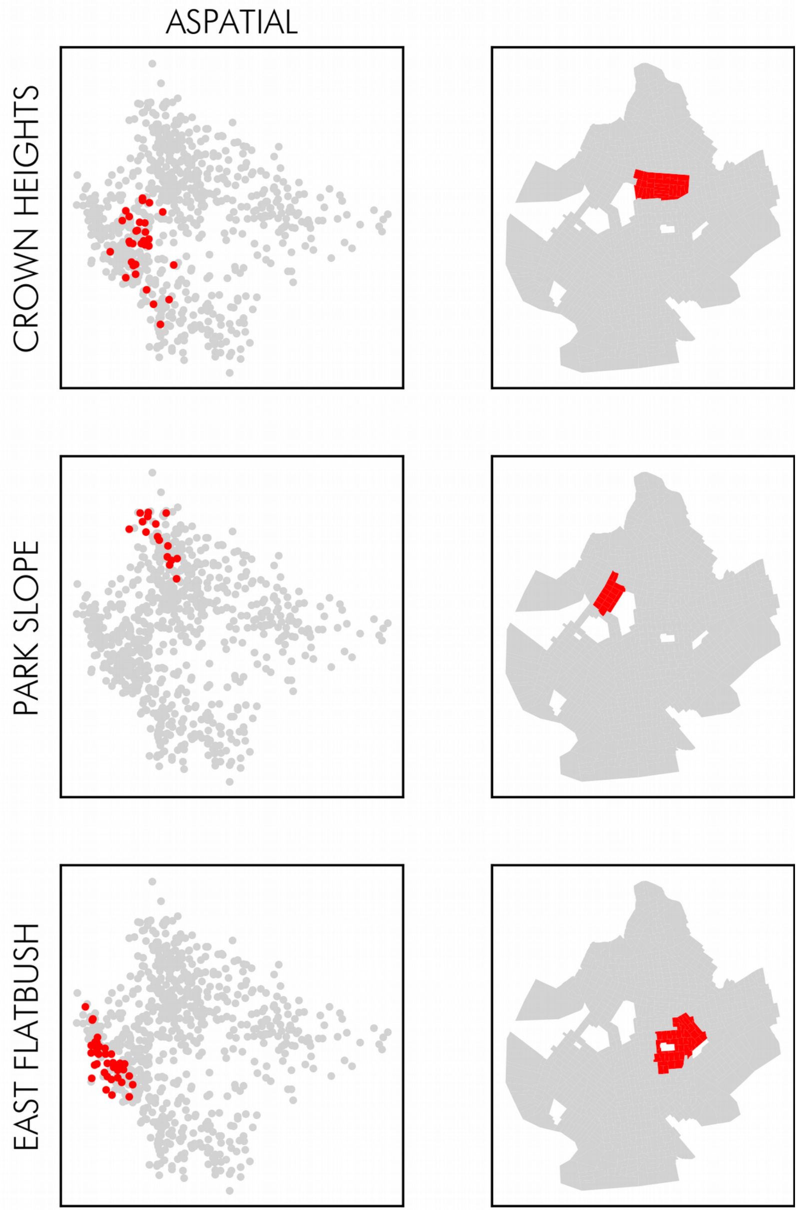


When ignoring spatial relationships,



When ignoring spatial relationships,

LITTLE INFO IS LOST

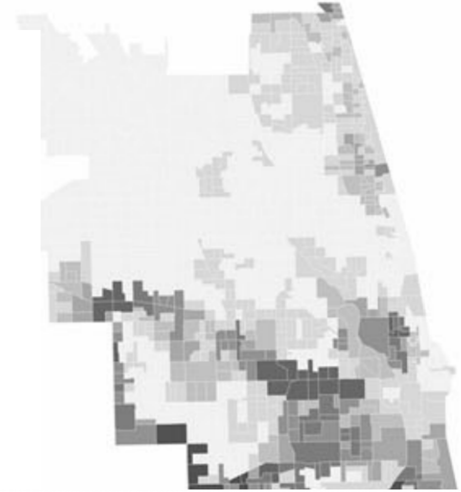


When ignoring spatial relationships,

LITTLE INFO IS LOST

Any "outcome" will likely provide the same boundary!

RETHINKING BOUNDARIES:



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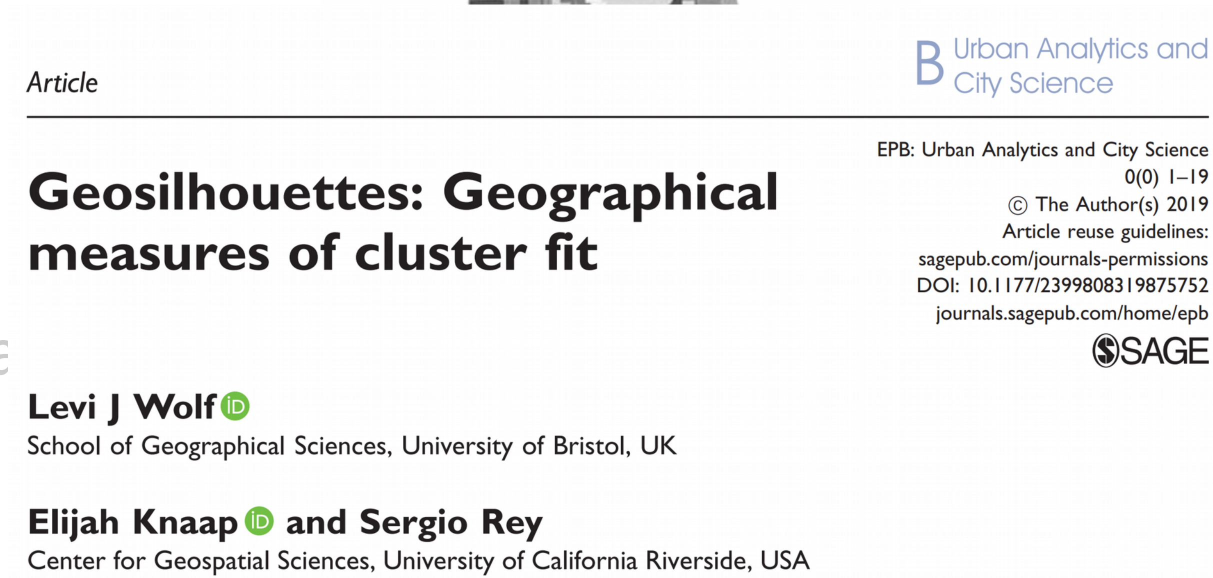

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Geosilhouettes: Geographical measures of cluster fit

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doi: 10/dd9c

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Dissimilarity between member i & place c

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

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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)

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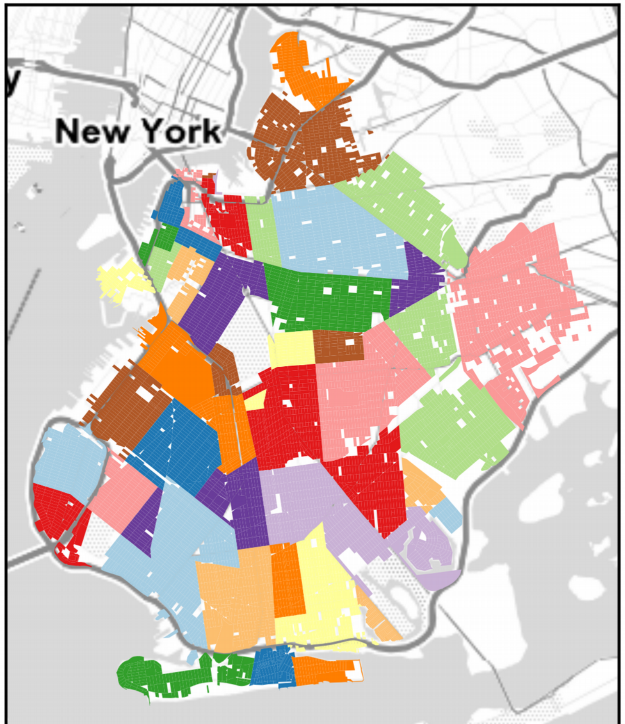
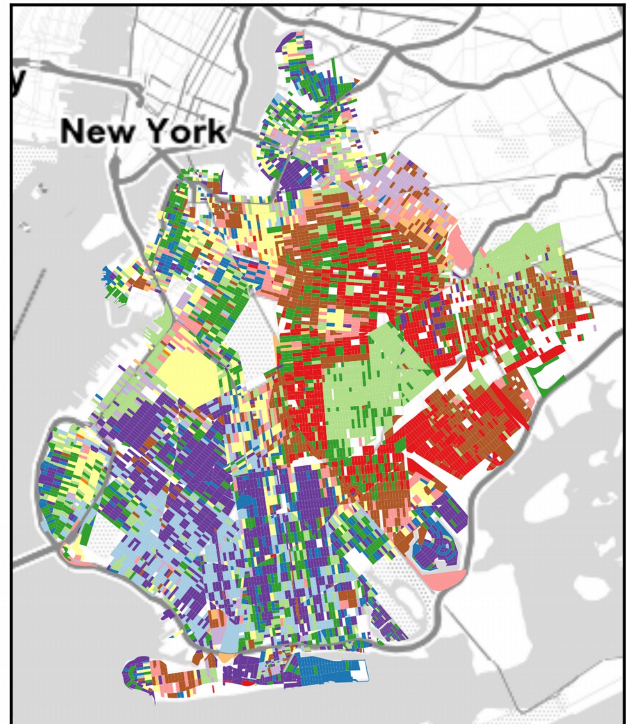
SILHOUETTE SCORES

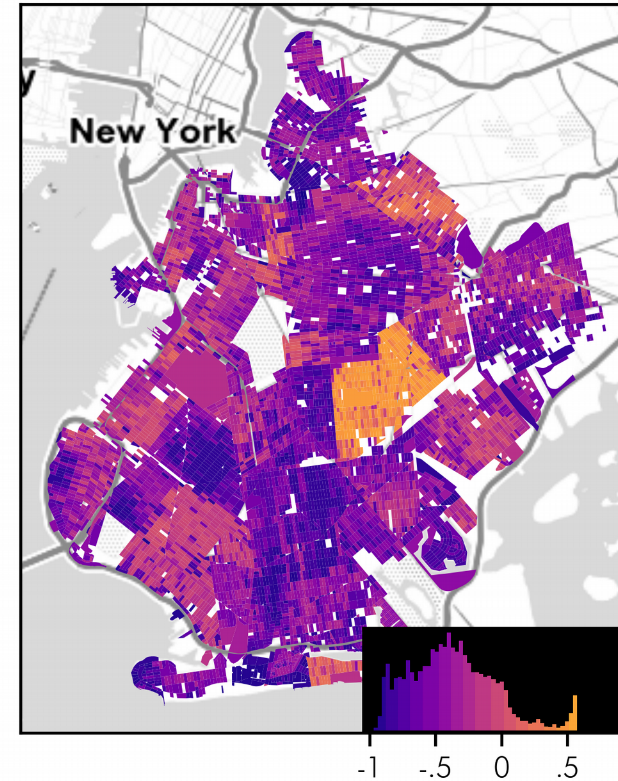
NEIGHBORHOODS



NEXT BEST FITS



SILHOUETTES



ROUSSEEUW (1987)

doi: 10/dd9c

SILHOUETTE SCORES

Zillow neighborhoods built from

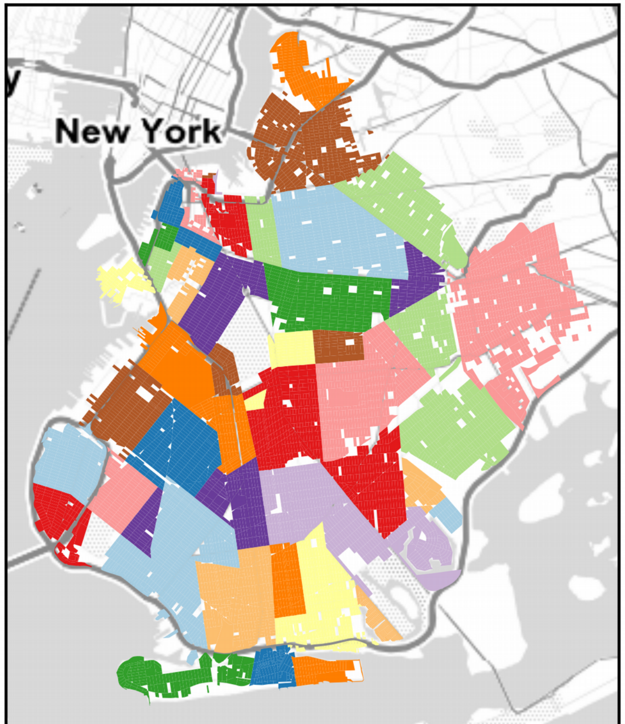
online housing markets

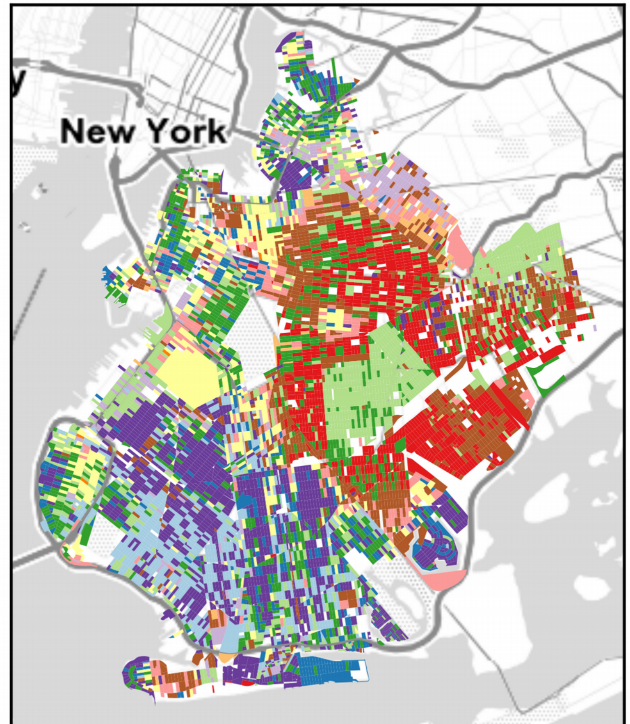
official boundaries (NYCTA)

ROUSSEEUW (1987)

doi: 10/dd9c

SILHOUETTE SCORES





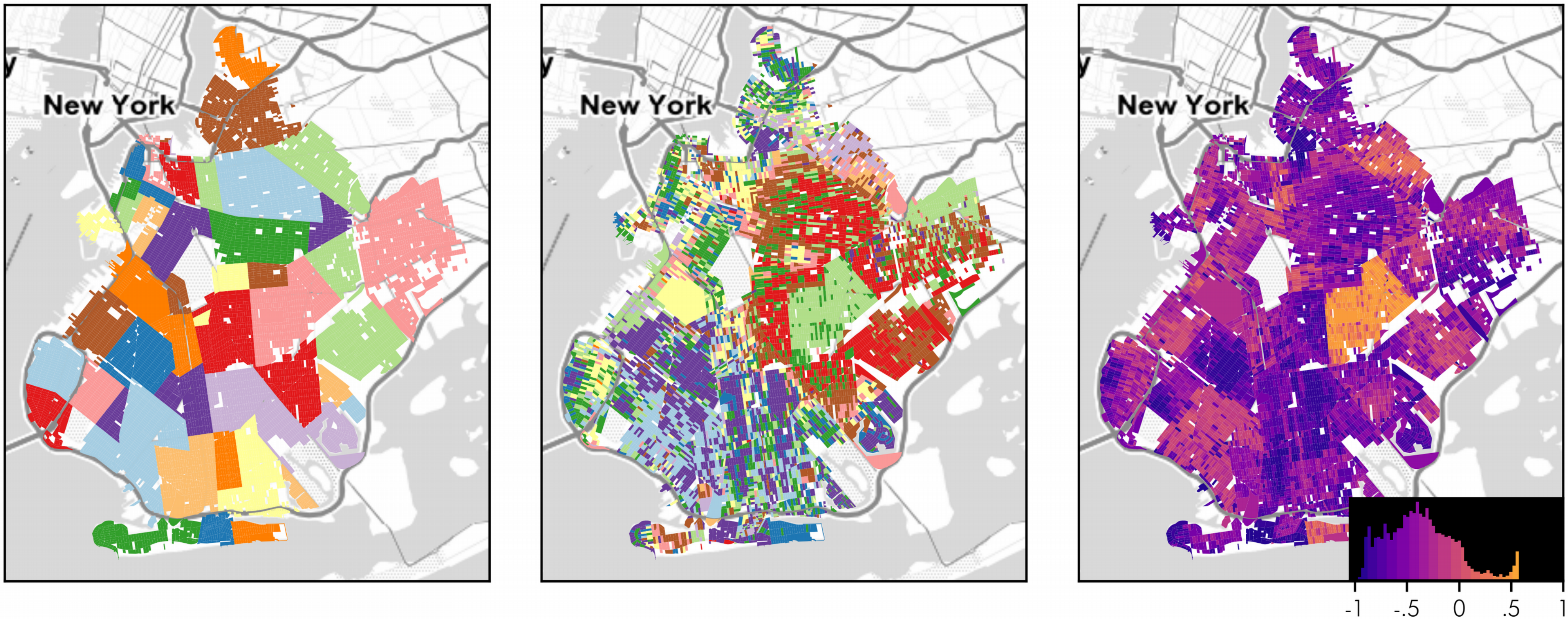
Most similar alternative neighborhood for each census block

ROUSSEEUW (1987)

doi: 10/dd9c

SILHOUETTE SCORES

NEIGHBORHOODS NEXT BEST FITS SILHOUETTES



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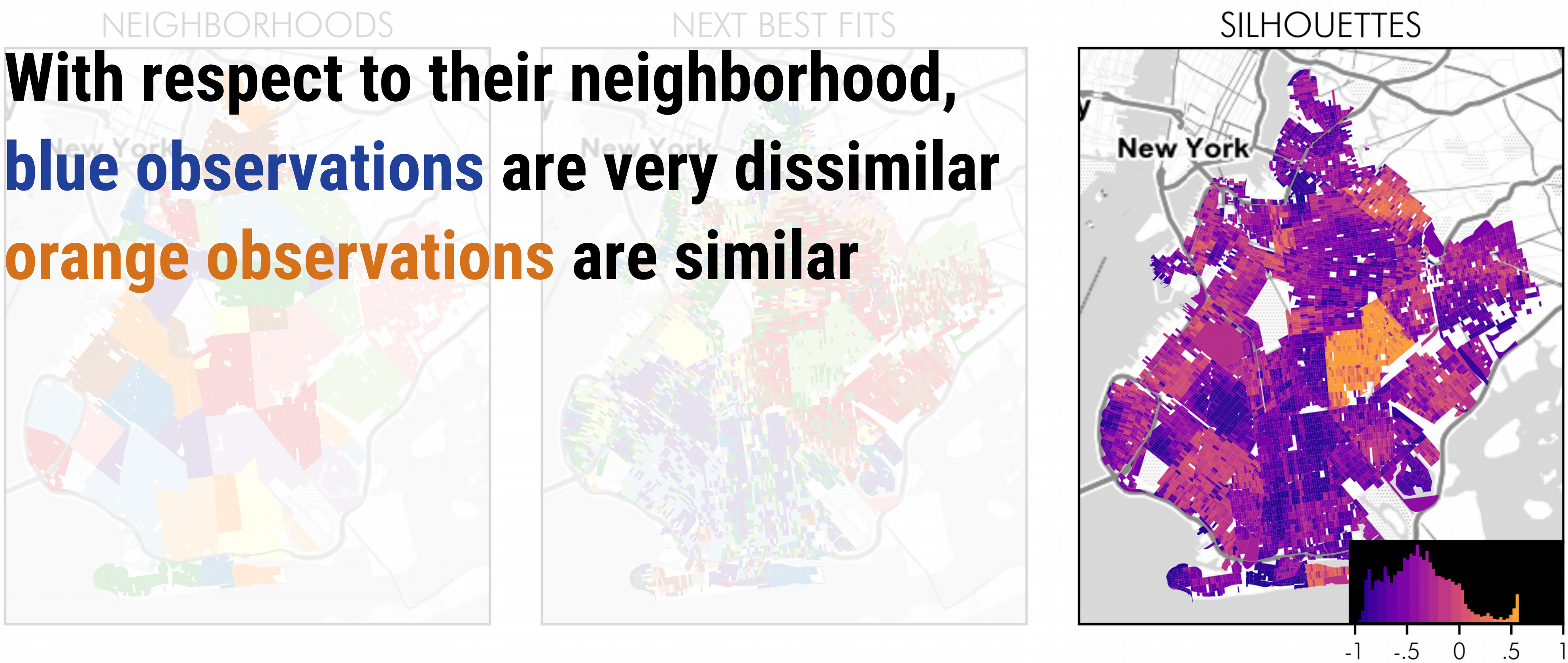
SILHOUETTE SCORES

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



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

ROUSSEEUW (1987) doi: 10/dd9c

BOUNDARY SILHOUETTE

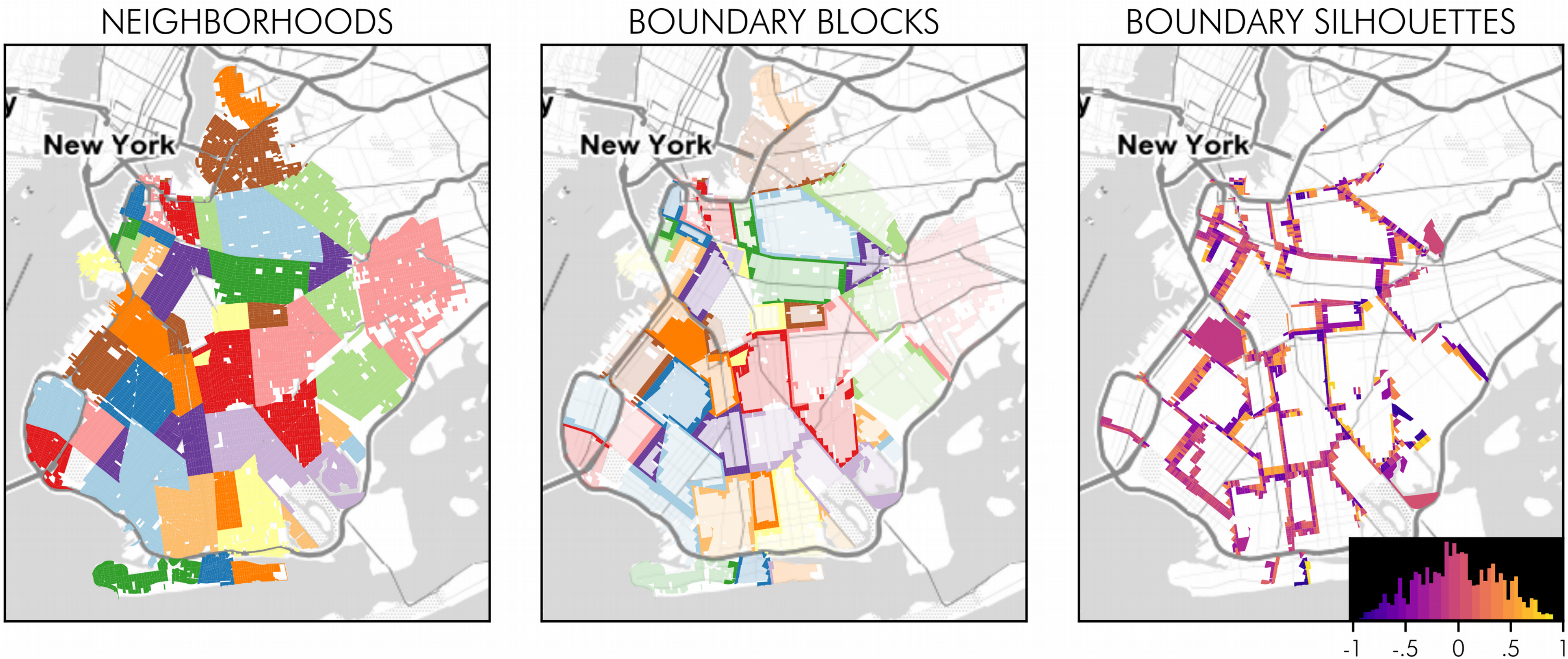
Say that observation i in graph G is assigned to place c and not another place, k, that is nearby i.

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

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

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

BOUNDARY SILHOUETTE



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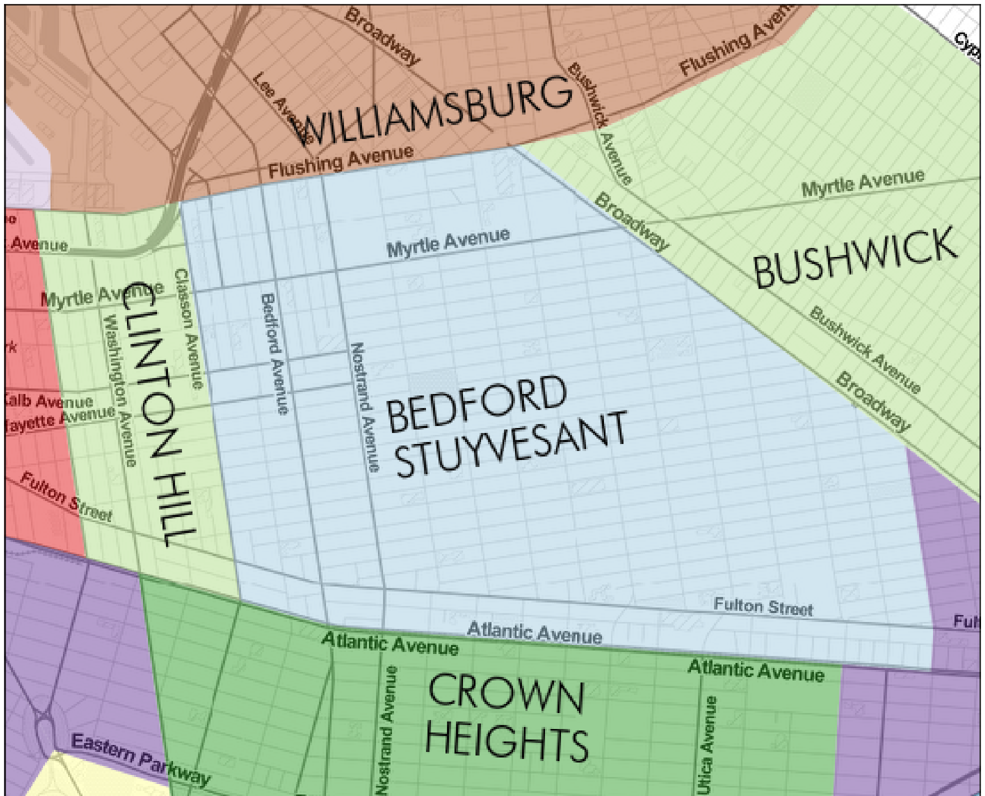

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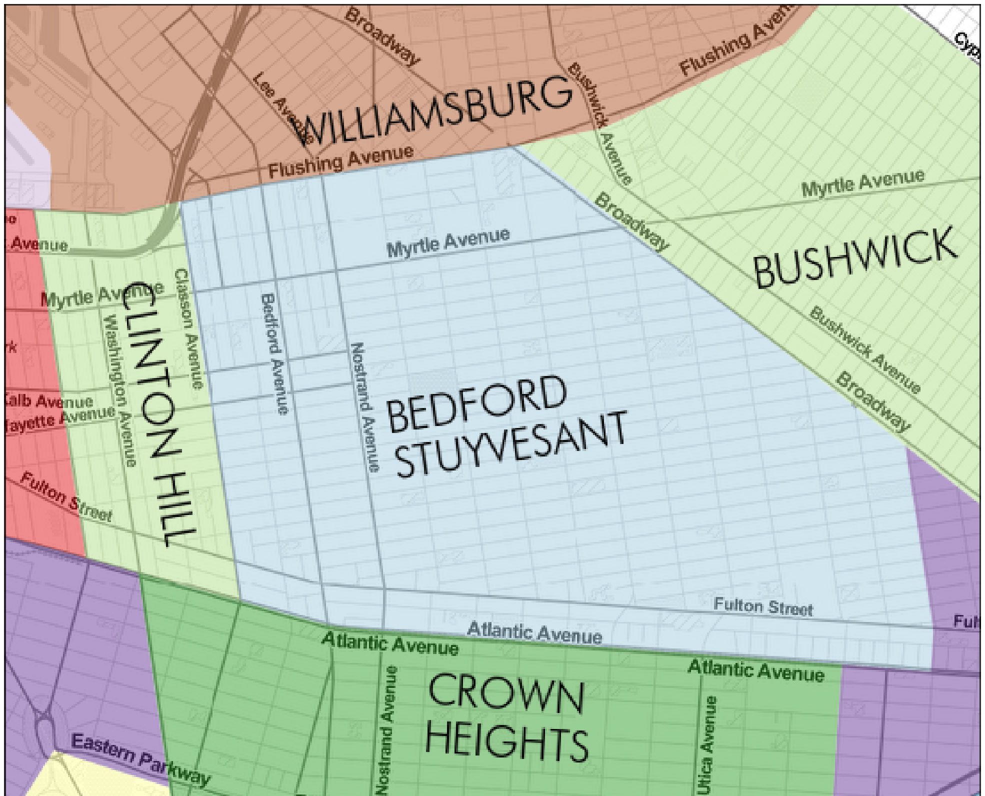

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BOUNDARY SILHOUETTE

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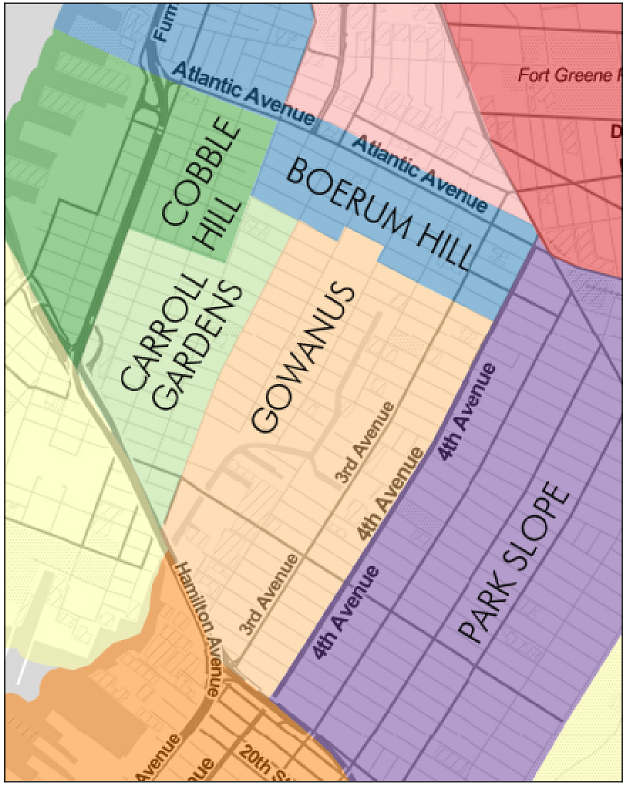
On the BedStuy side, blocks remain slightly more similar to blocks in BedStuy.

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

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

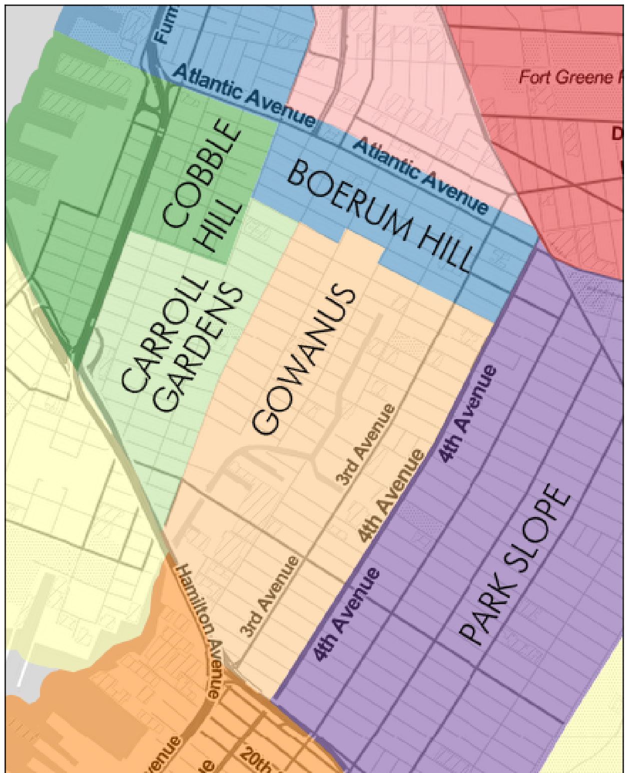
BOUNDARY SILHOUETTE



WOLF, KNAAP, & REY (2019)

doi: 10/dd9c

BOUNDARY SILHOUETTE



WOLF, KNAAP, & REY (2019)

doi: 10/dd9c

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.

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

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

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.

Sign matters, not magnitude.

Assume existence of place & place-scale.

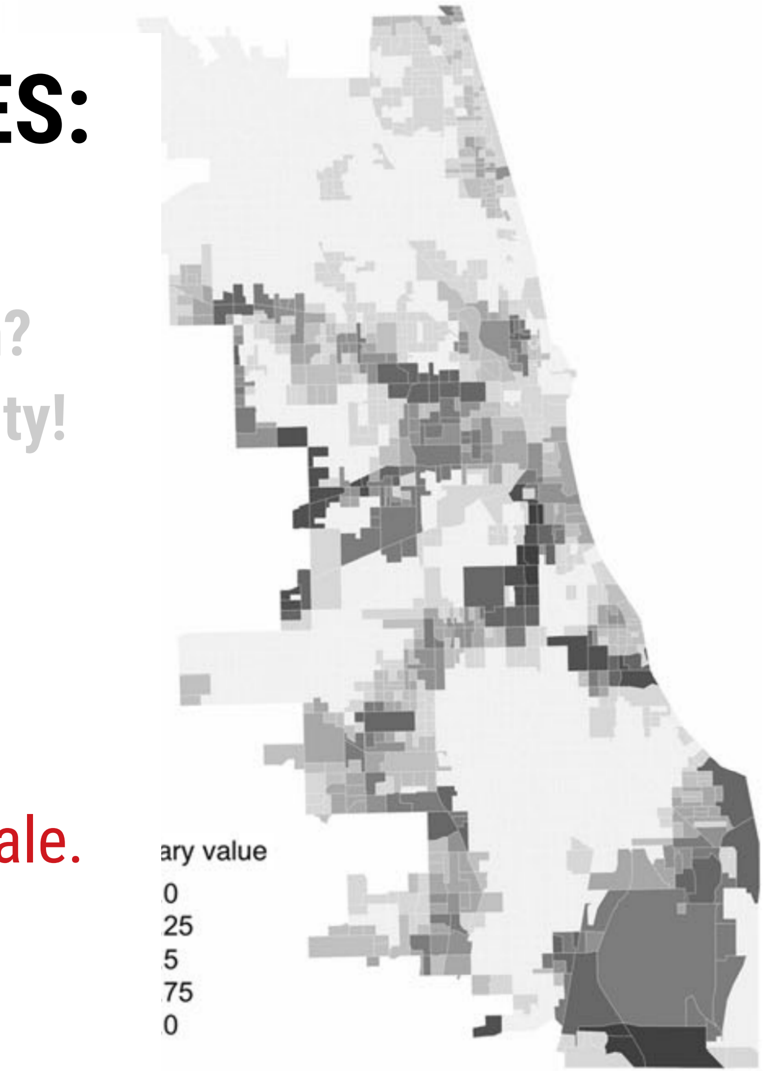

Fig. 1 Areal wombling for the proportion of African American residents

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

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BATTY (2008)

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BATTY (2008)

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

Urban society is embedded within this morphology

(Urban society also enforces or adjusts this morphology)

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

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

BATTY (2008)

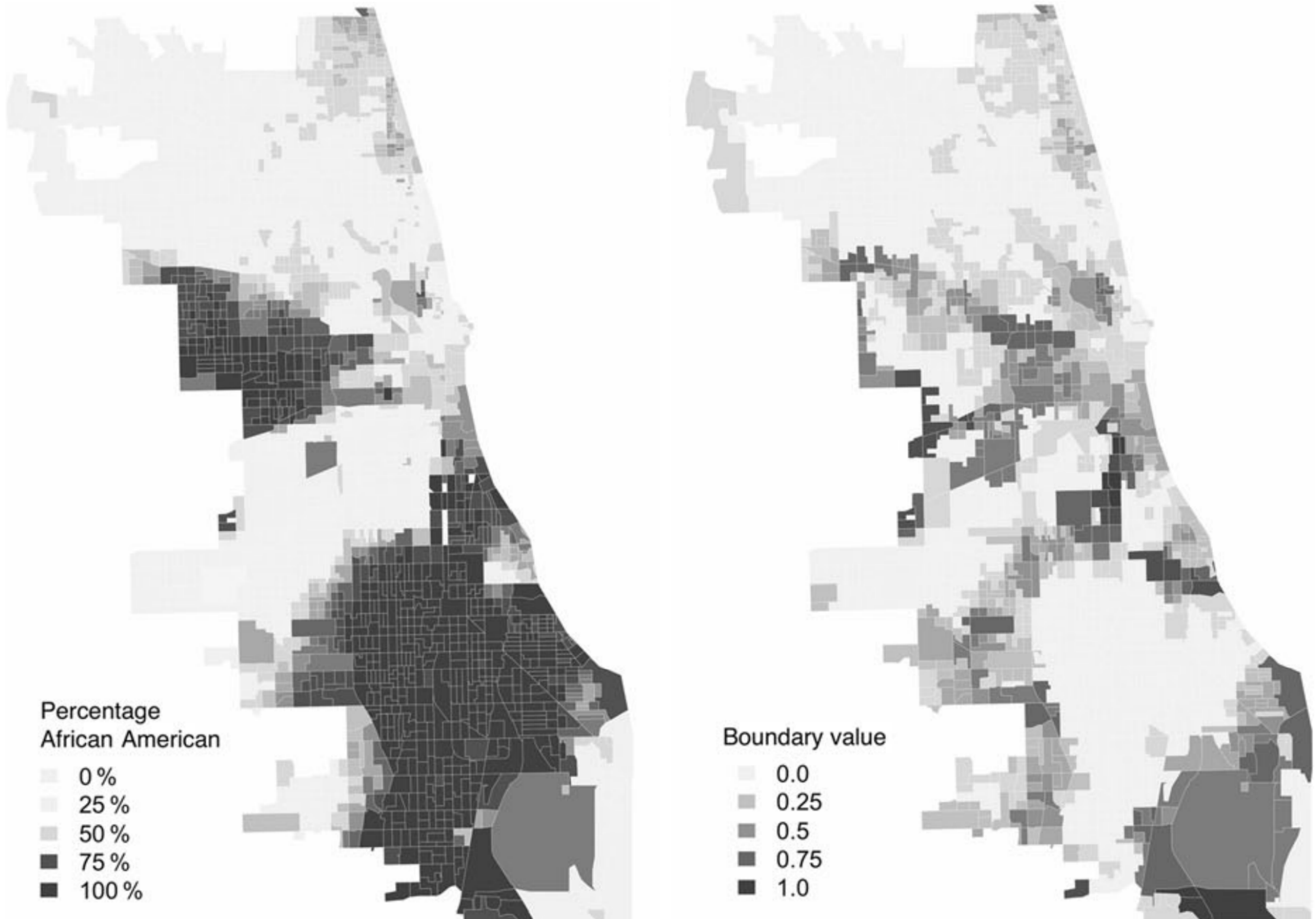

Fig. 1 Areal wombling for the proportion of African American residents

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

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

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.

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

FOR YOUR INFORMATION (THEORY)

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

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INFORMATION GAIN
ABOUT AREA i
FROM AREA j

FOR YOUR INFORMATION (THEORY)

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

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

RATIO OF POPULATION PERCENTAGES

FOR YOUR INFORMATION (THEORY)

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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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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)

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

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

"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

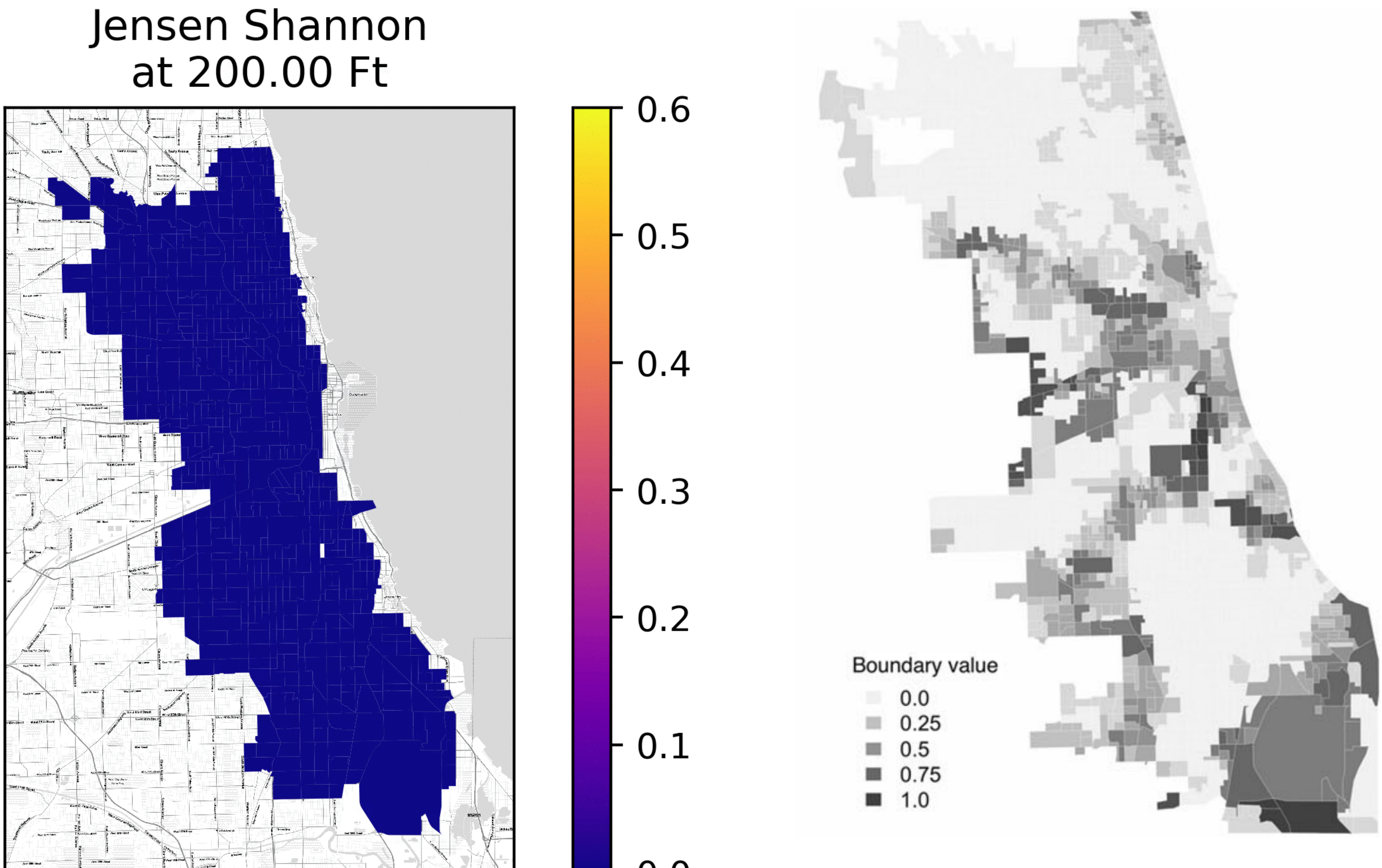
FOR YOUR INFORMATION (THEORY)

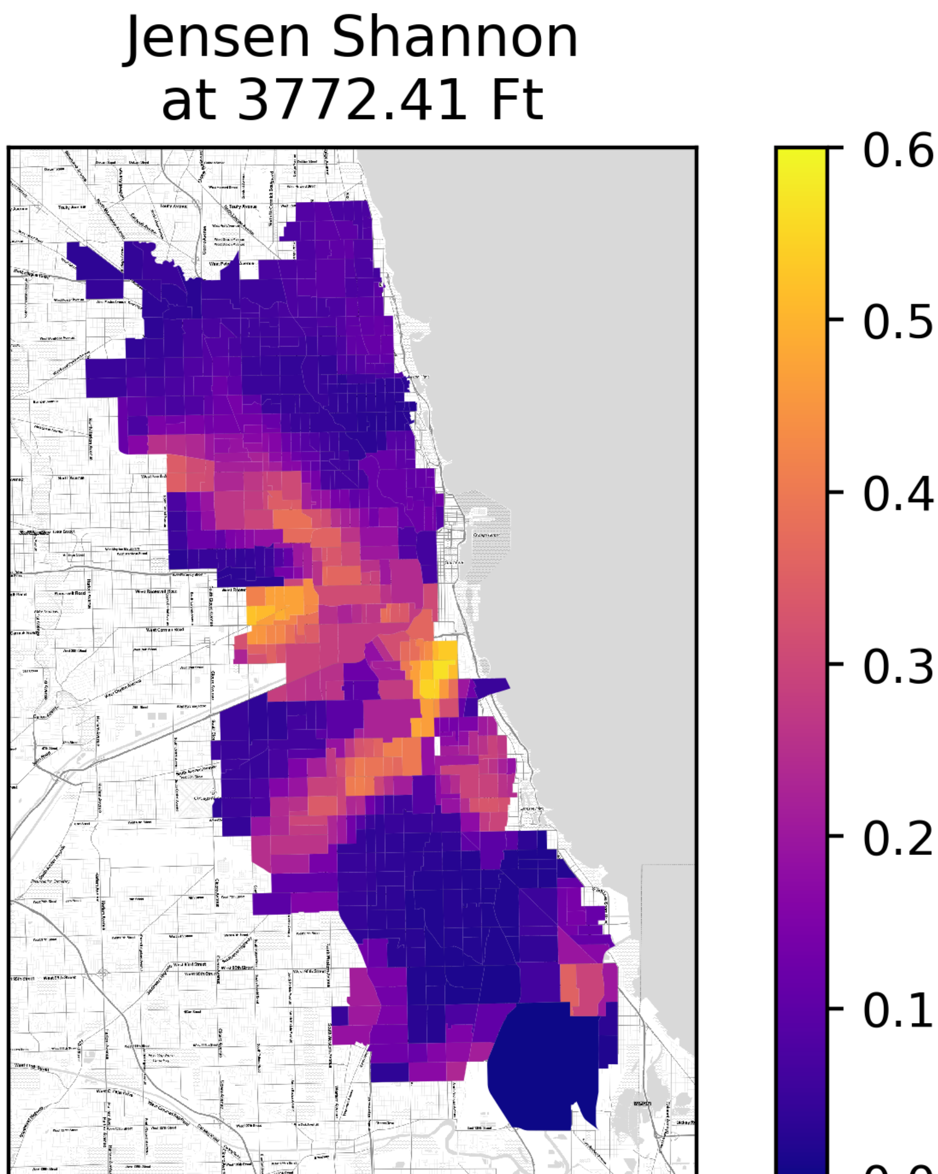
Let there be N blocks with m racial/ethnic classes.

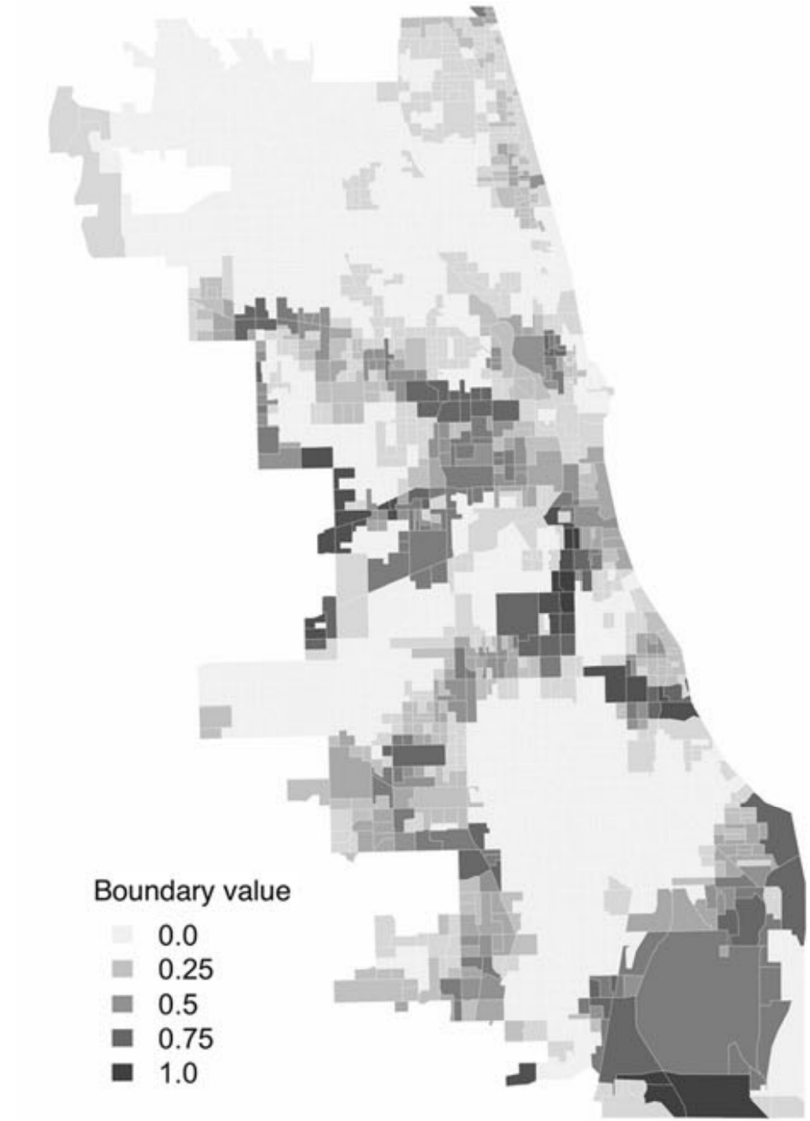
$$D_{WJS}(p_i||\eta_i(\delta)) = \frac{\sum_j n_j * D_{JS}(p_j||\bar{p}_J)}{\sum_j n_j}$$

HOW DIFFERENT IS i FROM OTHERS IN EGOHOOD?

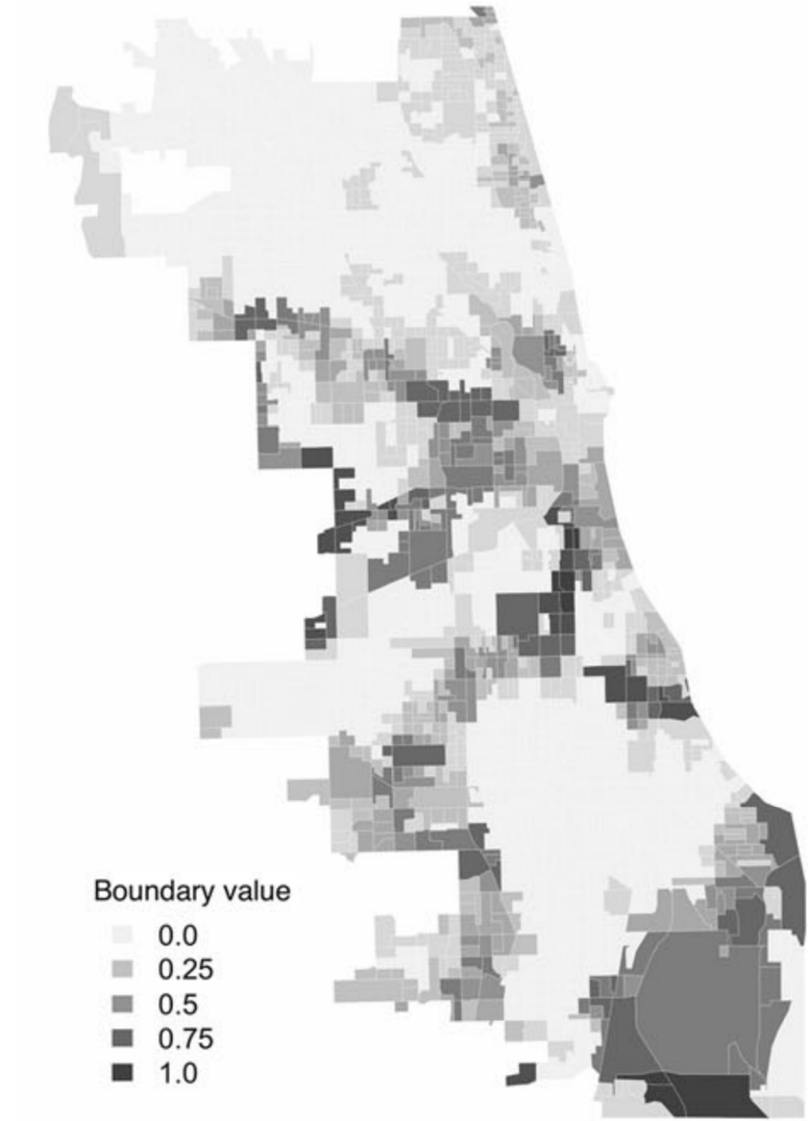
WEIGHTED JENSEN SHANNON DIVERGENCE


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

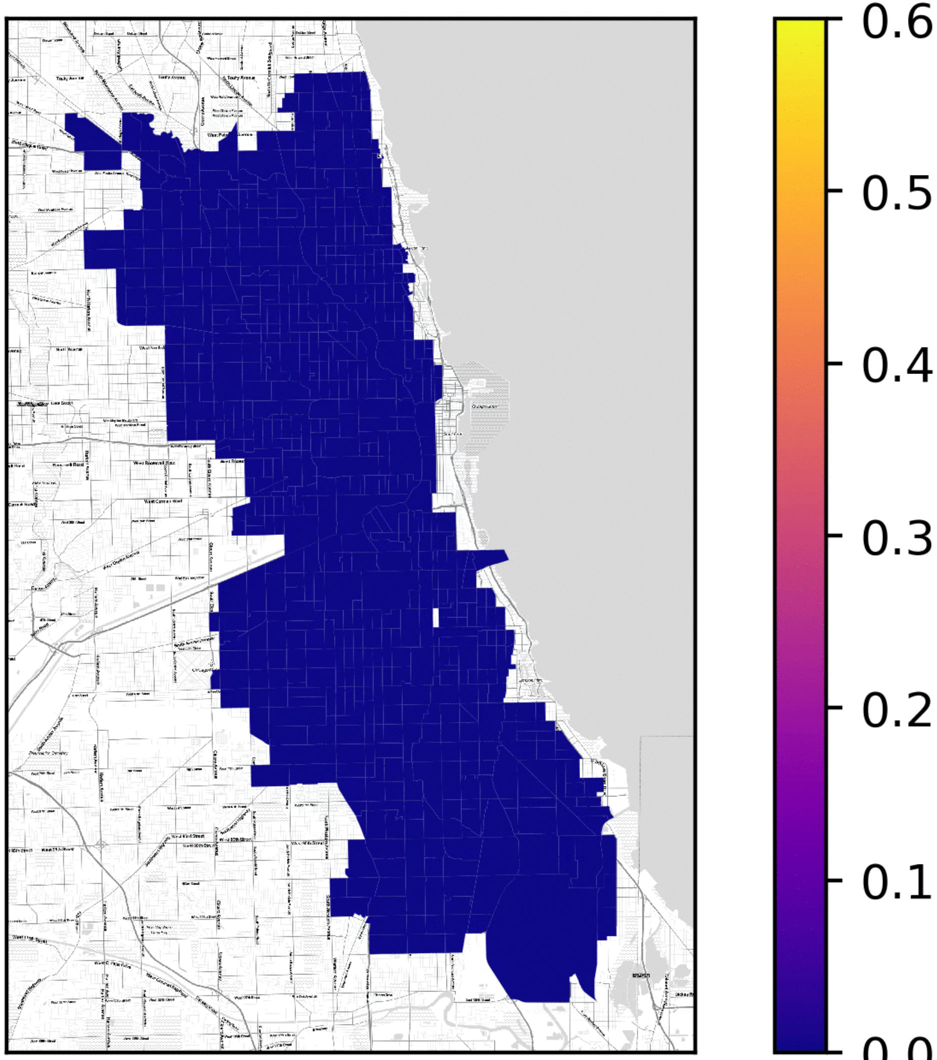

Jensen Shannon
at 3772.41 Ft
0.6
0.5
0.4
0.3
0.2
0.1
0.0


Boundary value
0.0
0.25
0.5
0.75
1.0

ONLY ONE SCALE



Jensen Shannon
at 200.00 Ft



ALWAYS MULTI SCALE

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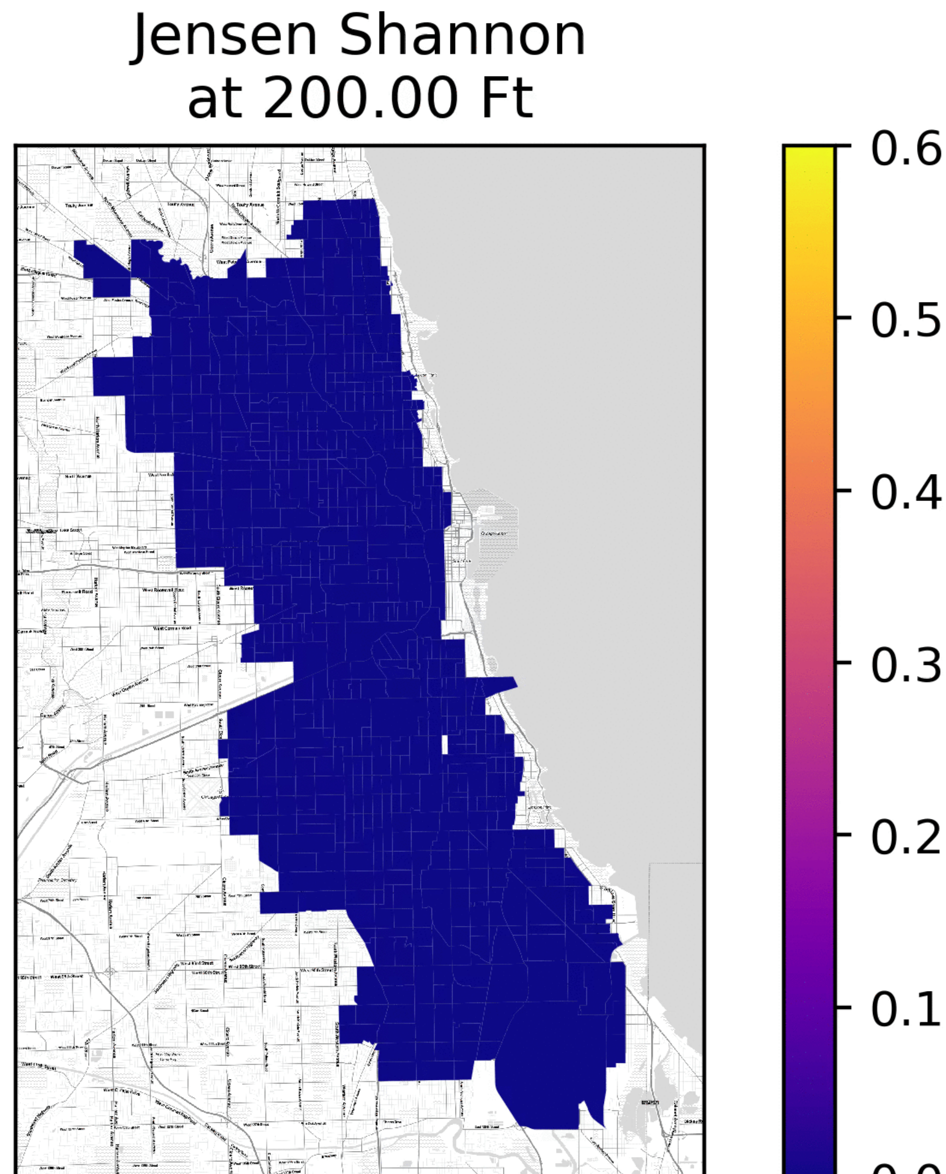

FINDING THE FAULT LINES:

NSF-SES 1733705

ESTIMATING THE BOUNDARIES IN URBAN SOCIAL-SPATIAL INEQUALITY

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The Alan Turing Institute

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