

FINDING THE FAULT LINES:

ESTIMATING THE BOUNDARIES IN URBAN
SOCIAL-SPATIAL INEQUALITY



University of
BRISTOL

The
Alan Turing
Institute

LEVI JOHN WOLF

levi.john.wolf@bristol.ac.uk

 [@levijohnwolf](https://twitter.com/levijohnwolf)

ljwolf.org

UNDERSTANDING PLACE & SPACE

RETHINKING BOUNDARIES 3 WAYS

THINKING ABOUT URBAN BOUNDARIES

UNDERSTANDING PLACE & SPACE

an old tension in spatial science

RETHINKING BOUNDARIES 3 WAYS

THINKING ABOUT URBAN BOUNDARIES

Contested Boundaries: Explaining Where Ethnoracial Diversity Provokes Neighborhood Conflict¹

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.”

Contested Boundaries: Explaining Where Ethnoracial Diversity Provokes Neighborhood Conflict¹

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.”

Contested Boundaries: Explaining Where Ethnoracial Diversity Provokes Neighborhood Conflict¹

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.”

Contested Boundaries: Explaining Where Ethnoracial Diversity Provokes Neighborhood Conflict¹

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.”

Contested Boundaries: Explaining Where Ethnoracial Diversity Provokes Neighborhood Conflict¹

Joscha Legewie

Yale University

Merlin Schaeffer

University of Cologne

**Communities are neighborhoods,
territories that delimit a social group.**

**When territory is unclear, communities
come into conflict.**

CONCEPTUALIZING BOUNDARIES

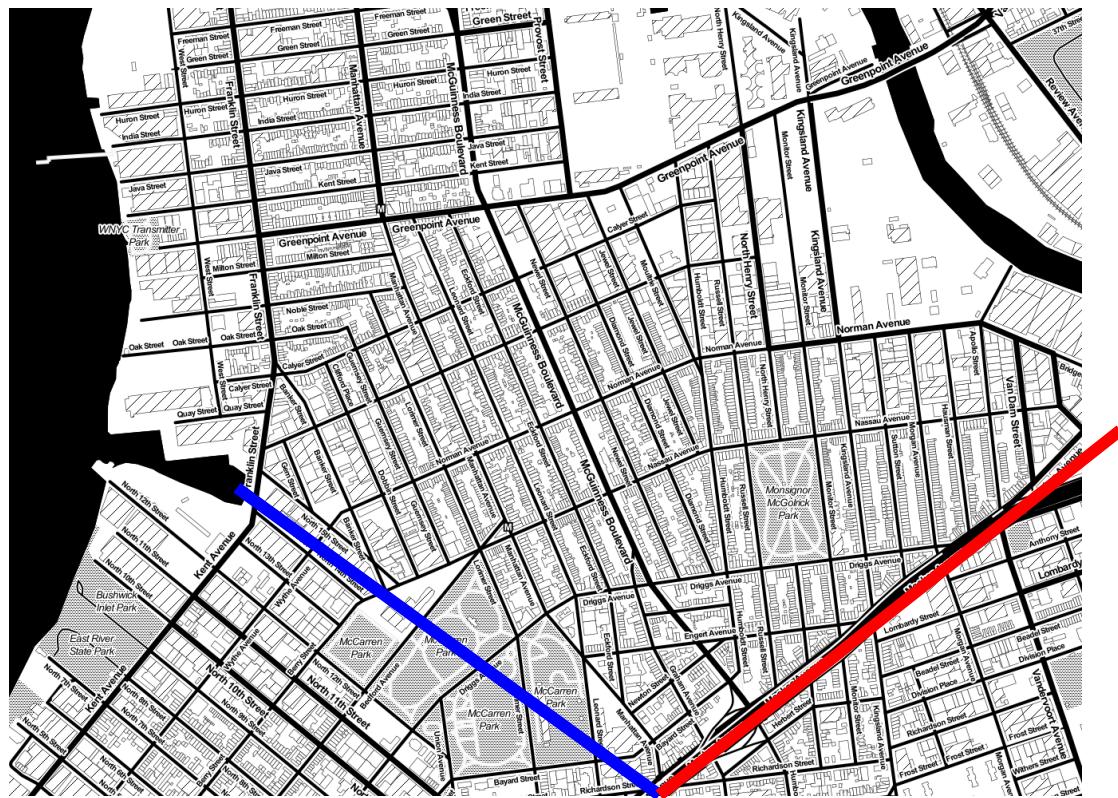
*“Williamsburg
becomes Greenpoint
at the Bushwick Inlet”*



CONCEPTUALIZING BOUNDARIES

*“Williamsburg
becomes Greenpoint
at the Bushwick Inlet”*

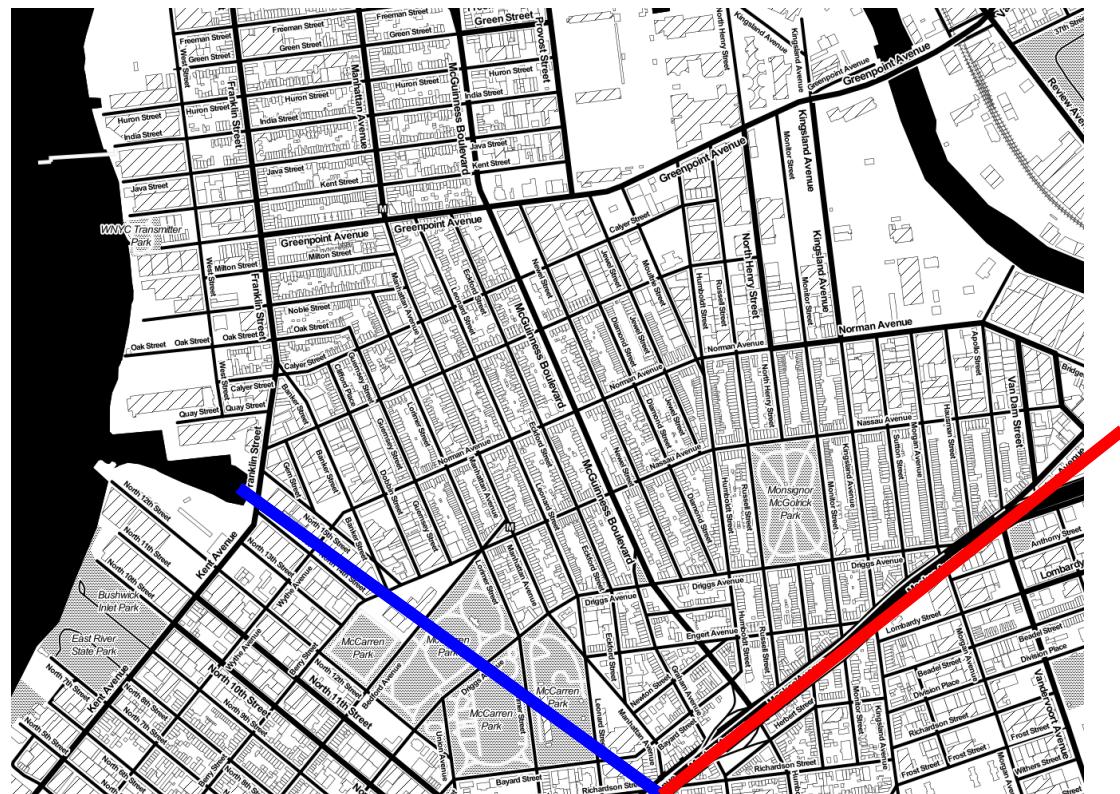
*“Greenpoint is
bordered on the
southeast by the BQE”*



CONCEPTUALIZING BOUNDARIES

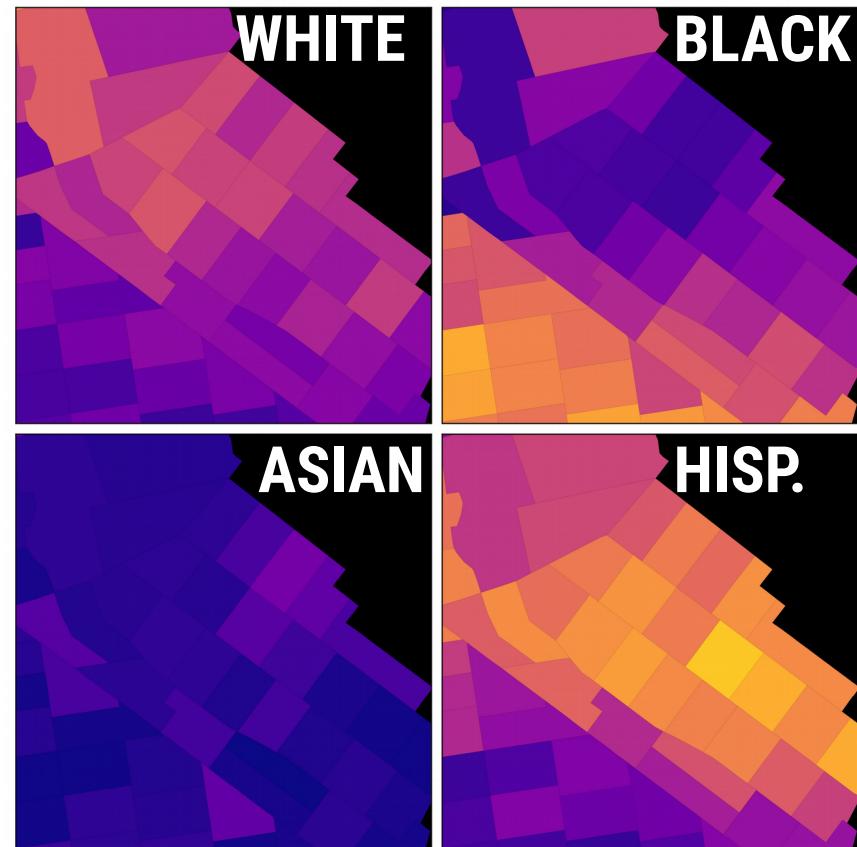
BOUNDARIES AS NATURALISTIC DIVISIONS OF URBAN LIFE

"Williamsburg becomes Greenpoint at the Bushwick Inlet"
"Greenpoint is bordered on the southeast by the BQE"



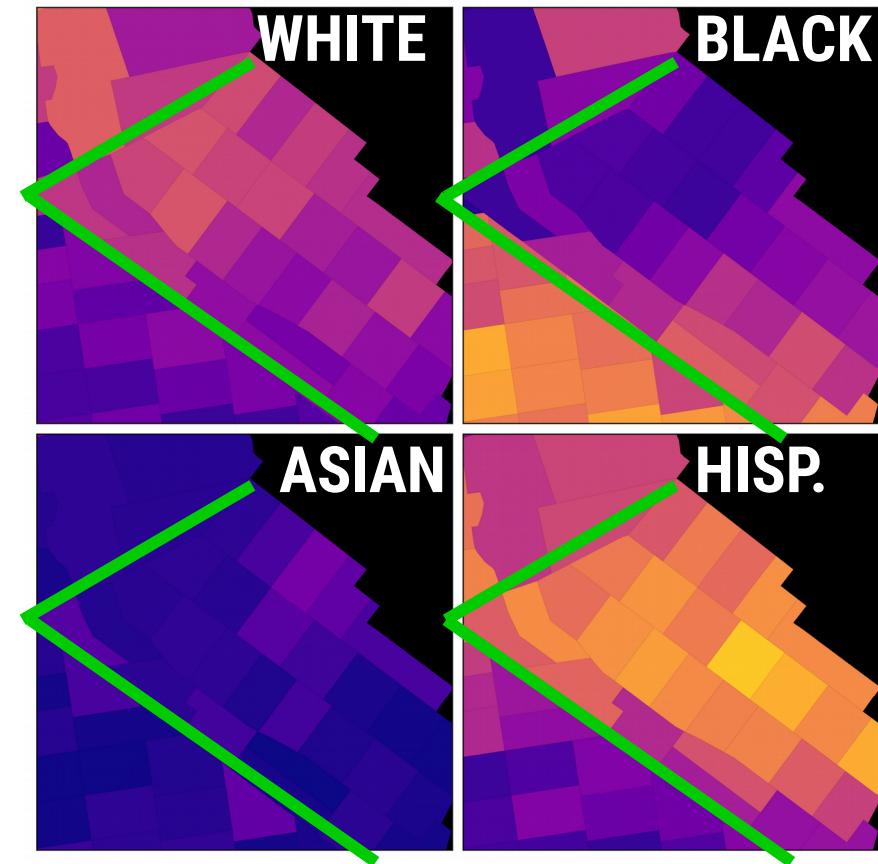
CONCEPTUALIZING BOUNDARIES

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



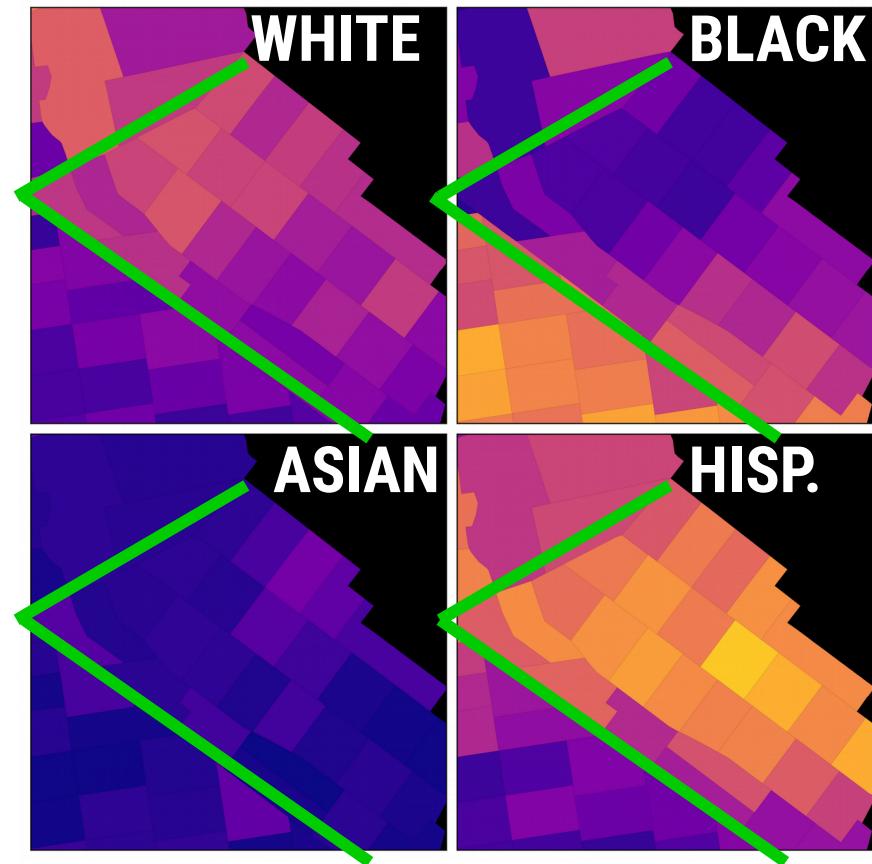
CONCEPTUALIZING BOUNDARIES

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



CONCEPTUALIZING BOUNDARIES

**BOUNDARIES AS
SOCIALLY
CONSTRUCTED
DIVISIONS
OF URBAN LIFE**



CONCEPTUALIZING BOUNDARIES

BOUNDARIES AS SOCIALLY CONSTRUCTED DIVISIONS OF URBAN LIFE

- “*Thoughts on the social neighborhood, Bushwick's population is, for a NYC neighborhood, relatively heterogeneous*”
- 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
 - KWAN (2018) Contingent social contexts
 - DEAN (2019) Social frontiers

CONCEPTUALIZING BOUNDARIES

BOUNDARIES AS SOCIALLY CONSTRUCTED DIVISIONS OF URBAN LIFE

- “*Thoughts on the social neighborhood, Bushwick's population is, for a NYC neighborhood, relatively heterogeneous*”
- 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
 - KWAN (2018) Contingent social contexts
 - DEAN (2019) Social frontiers

SPACE

PLACE

SPACE PLACE

Understanding the New Human Dynamics in Smart Spaces and Places: Toward a **Spatial** 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*

SPACE

The geographic system over which objects of study are related.

PLACE

Geographic entities that are constructed by distinctiveness.

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.

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.

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

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?

What are their properties?

What are their purpose?

Do they have effects on things we care about?

Article

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 Legewie¹

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.

Urban Analytics and
City Science

EPB: Urban Analytics and City Science
0(0) 1–19
Received 10 October 2019
Accepted 10 November 2019
Editorial handling: Nema Dean
DOI: 10.1177/239927319875732
<http://journals.sagepub.com>

California, 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 Legewie¹

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.

FRONTIERS IN RESIDENTIAL SEGREGATION: UNDERSTANDING NEIGHBOURHOOD BOUNDARIES AND THEIR IMPACTS

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

**Find boundaries between
“neighborhoods” using
large differences in a spatial
multilevel model’s predictions of crime.**

Wombling:

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

Inferring neighbourhood quality with
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

^b School of Geographical Sciences, University of Bristol, University Road, Clifton, Bristol BS8 1SS, UK

**Find boundaries between
“neighborhoods” using
large predicted differences in prices
in an adaptive spatial multilevel model**

Wombling:

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

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

Joscha Legewie¹

**Find boundaries between
“neighborhoods” using
large differences in a
multilevel model’s predictions of crime.**

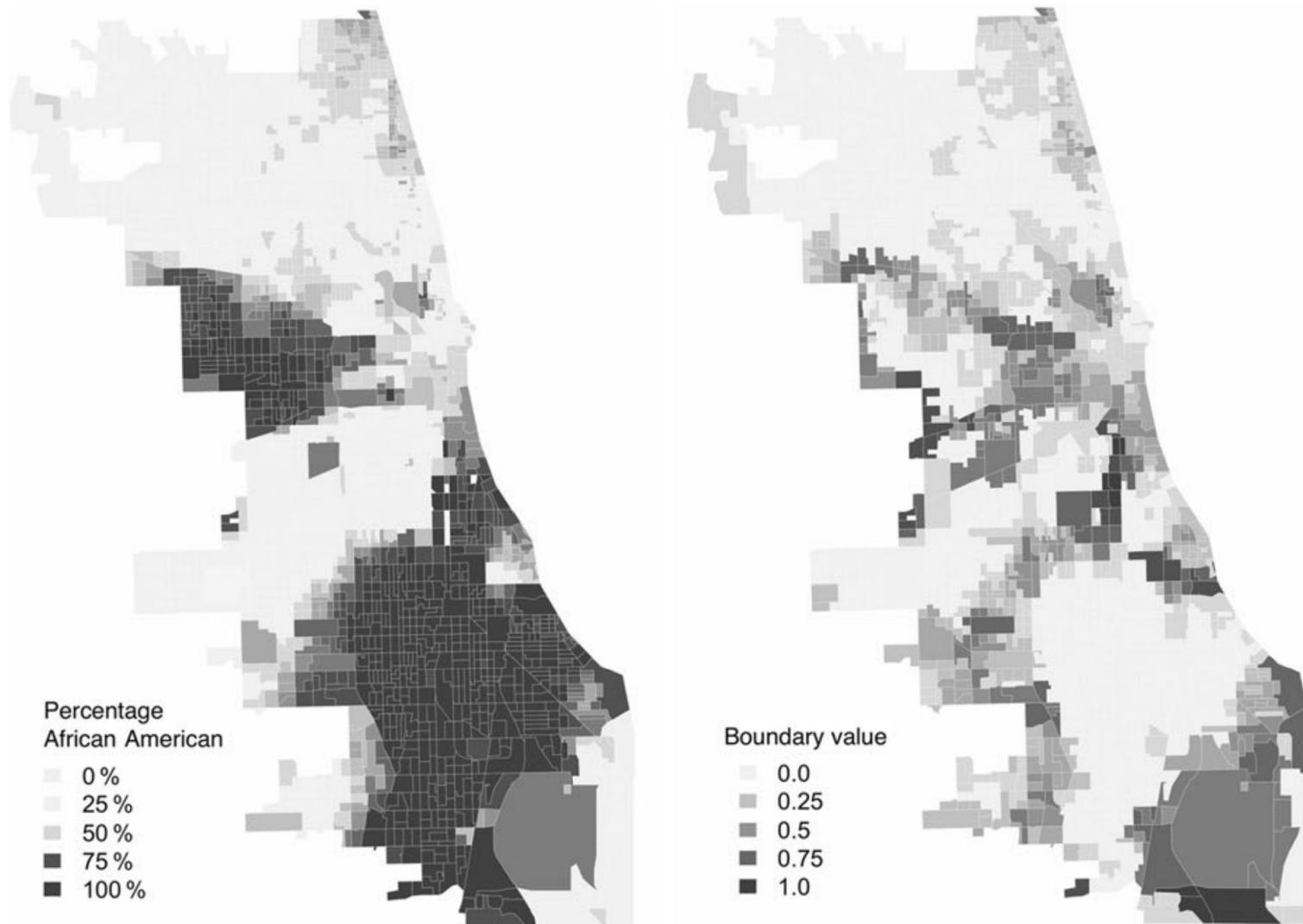


Fig. 1 Areal wombling for the proportion of African American residents

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.



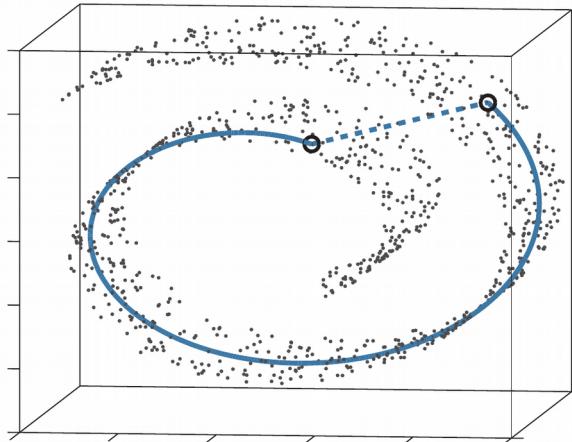
Fig. 1 Areal wombling for the proportion of African American residents

ROBUSTNESS FROM ENDOGENEITY

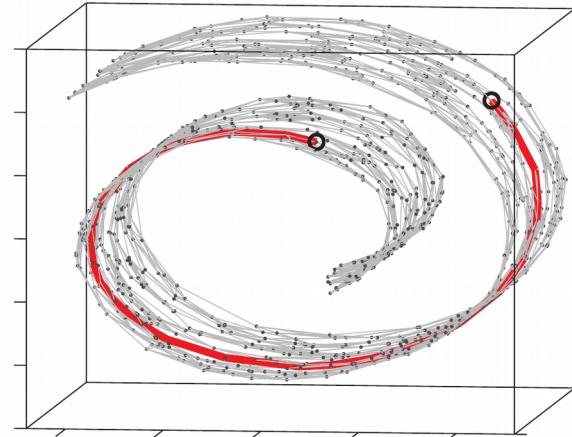
- Places are distinctive:
 - Geographically coherent
 - More similar than dissimilar
- Balancing nearness & similarity, we can see the “joint” social-spatial structure of the city.

ROBUSTNESS FROM ENDOGENEITY

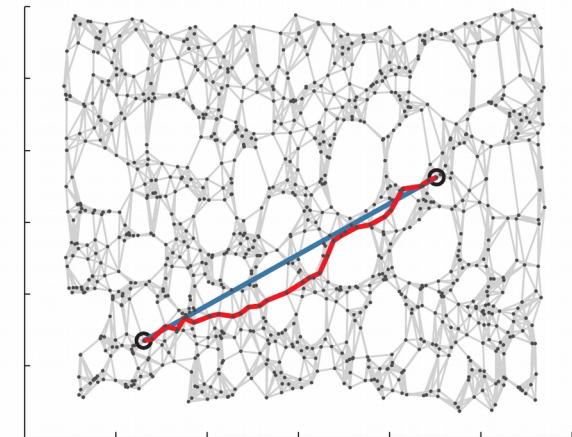
A



B



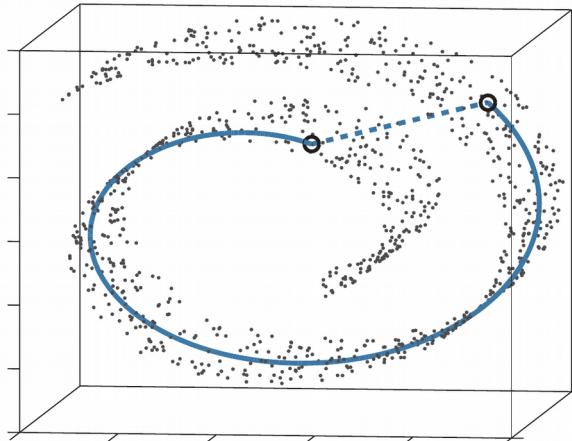
C



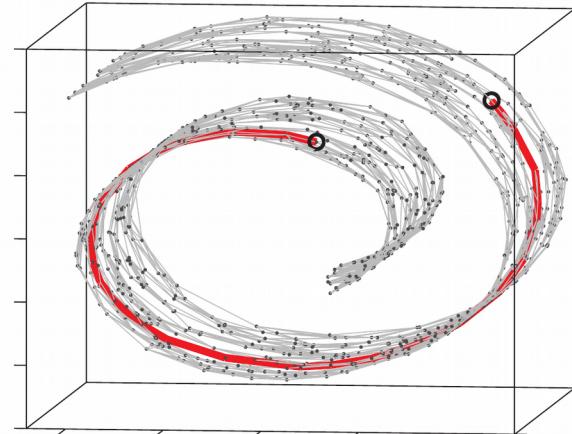
“Manifold Learning”

ROBUSTNESS FROM ENDOGENEITY

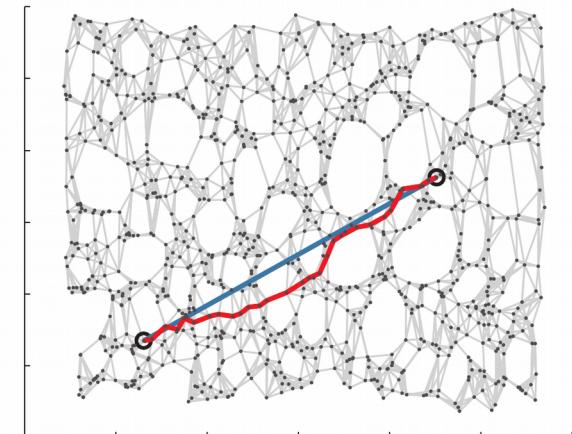
A



B



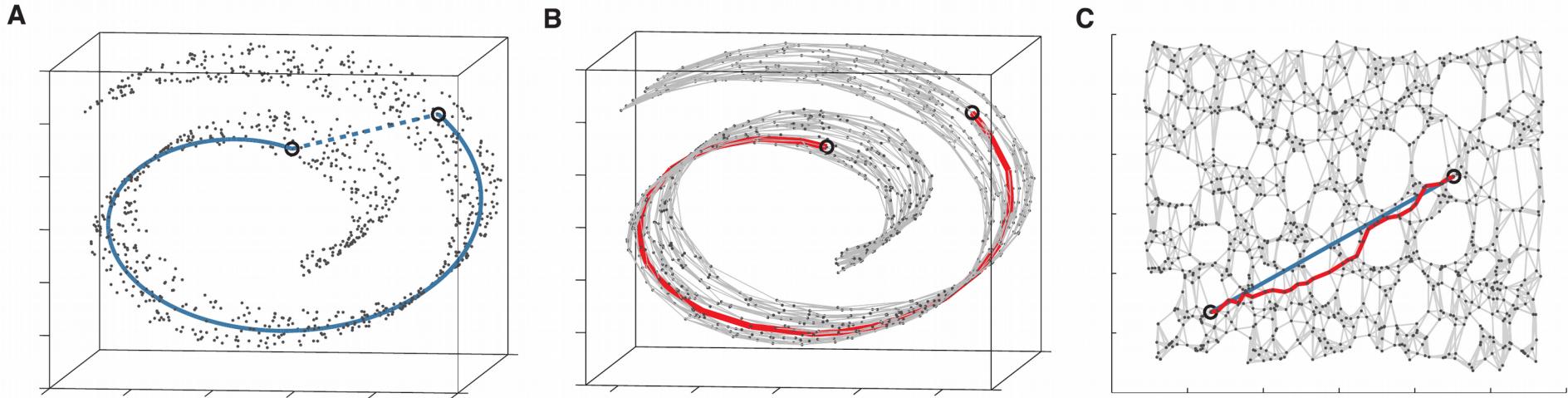
C



“Manifold Learning”

(non-linear PCA)

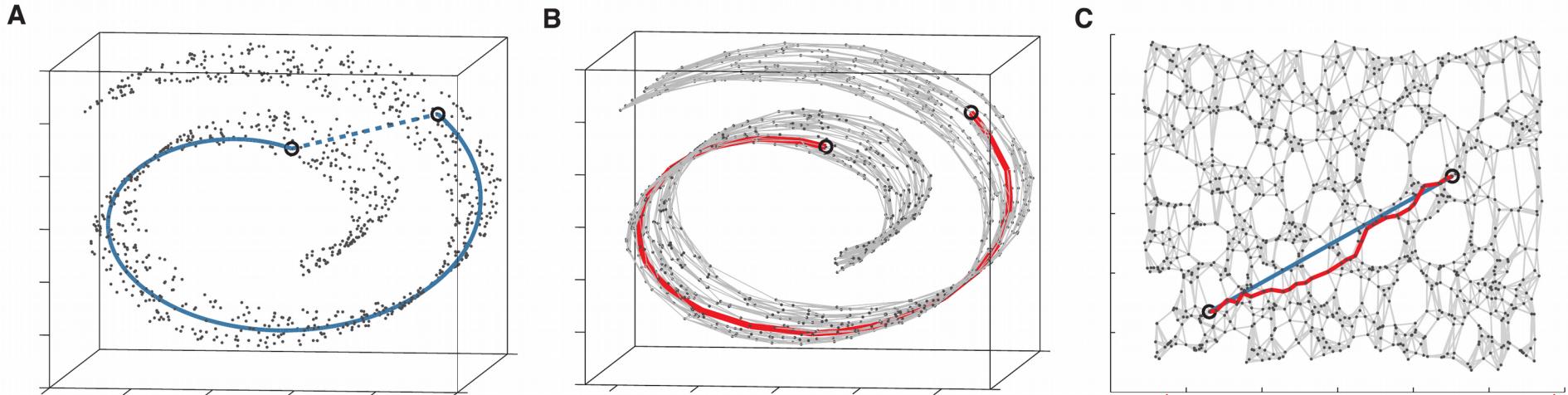
ROBUSTNESS FROM ENDOGENEITY



“Manifold Learning”

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

ROBUSTNESS FROM ENDOGENEITY



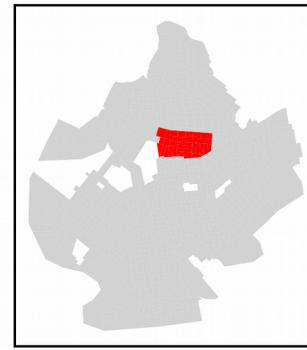
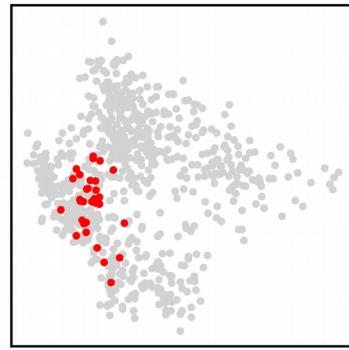
ISOMAP: (Tenenbaum, 2000)

Make “short hops” between
similar points.
Add up the length of short hops!

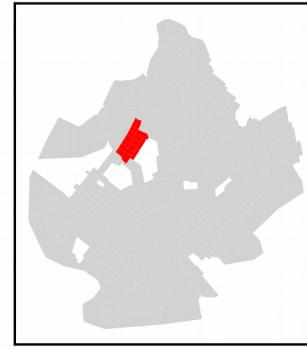
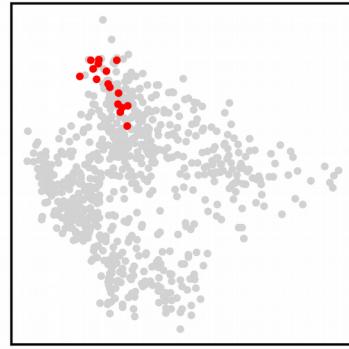
“Manifold Learning”

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

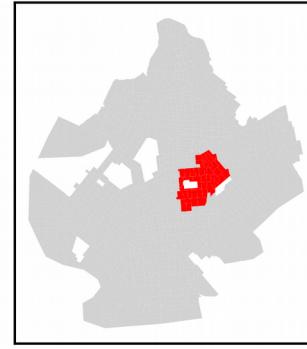
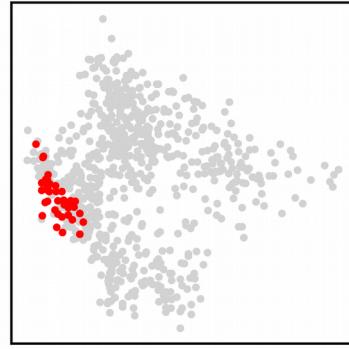
ASPATIAL



CROWN HEIGHTS



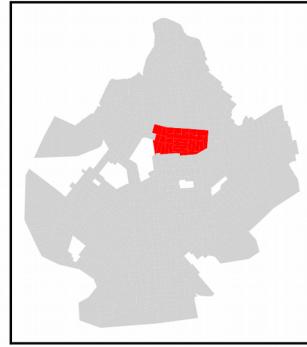
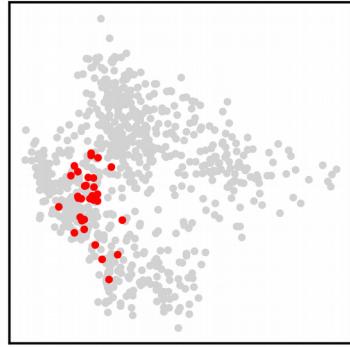
PARK SLOPE



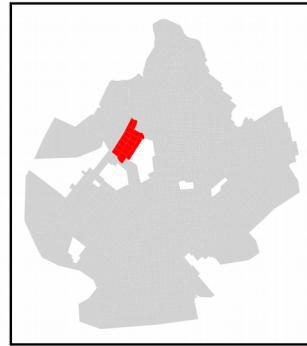
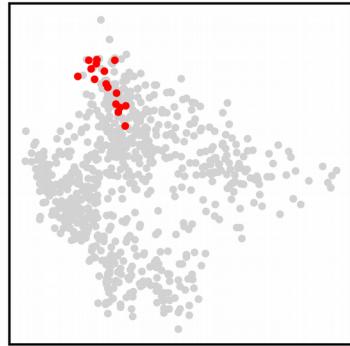
EAST FLATBUSH

ASPATIAL

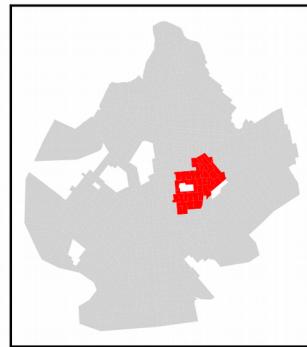
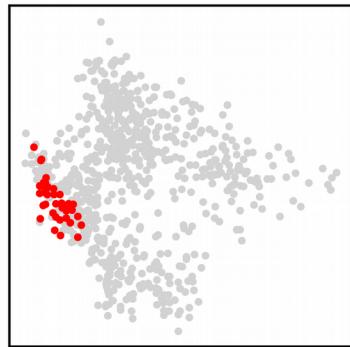
CROWN HEIGHTS



PARK SLOPE



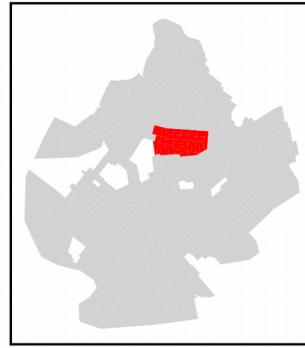
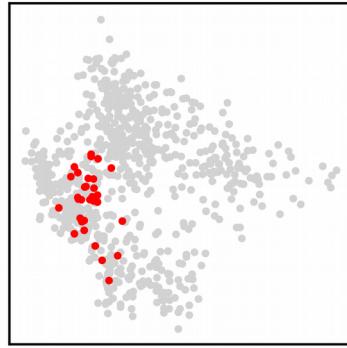
EAST FLATBUSH



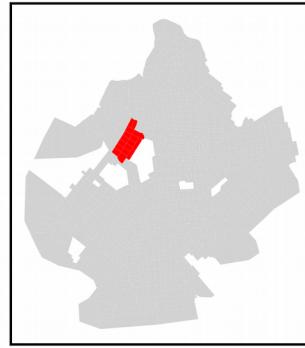
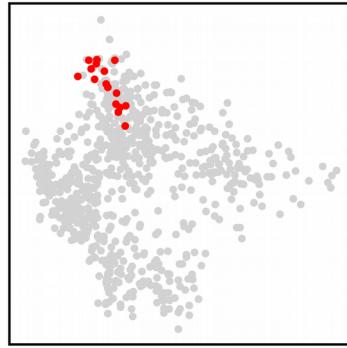
LITTLE
INFO IS
LOST
8 → 2

ASPATIAL

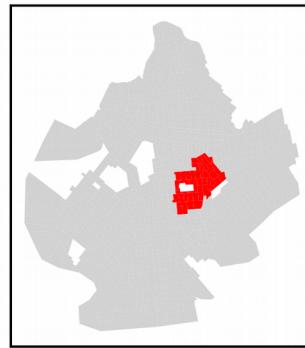
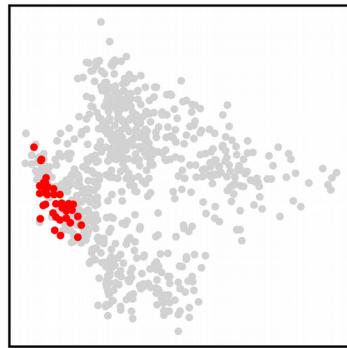
CROWN HEIGHTS



PARK SLOPE



EAST FLATBUSH



LITTLE
INFO IS
LOST

8 → 2

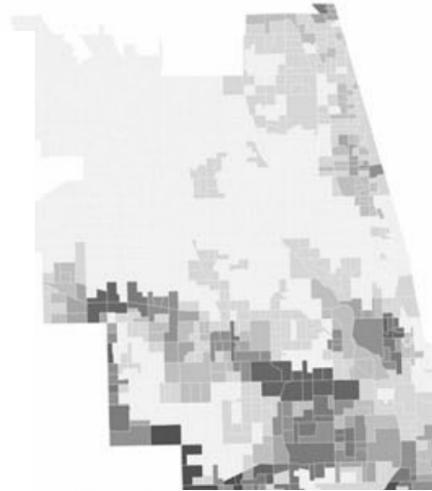
Any “outcome” will likely
provide the same boundary!

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 & pla

Article

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

B Urban Analytics and
City Science

EPB: Urban Analytics and City Science

0(0) 1–19

© The Author(s) 2019

Article reuse guidelines:

sagepub.com/journals-permissions

DOI: 10.1177/2399808319875752

journals.sagepub.com/home/epb



SILHOUETTE STATISTIC

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

SILHOUETTE STATISTIC

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

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

SILHOUETTE STATISTIC

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

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

Dissimilarity between member i & place c

SILHOUETTE STATISTIC

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

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

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

SILHOUETTE STATISTIC

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

$$\frac{\min \{ \bar{d}_k(i) \} - \bar{d}_c(i)}{\bar{d}_k(i)}$$

Positive when i is more like c than k

SILHOUETTE STATISTIC

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

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

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

SILHOUETTE STATISTIC

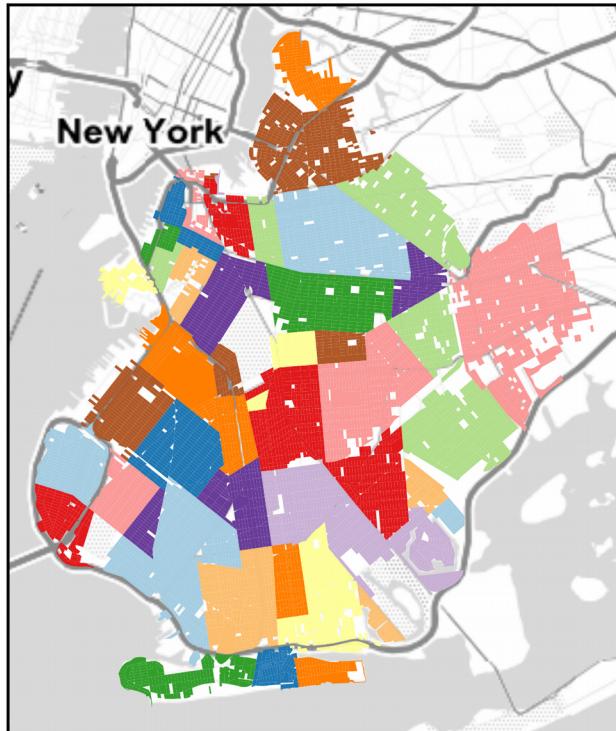
Say that observation i in graph G is assigned to place c and not another place, k .

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

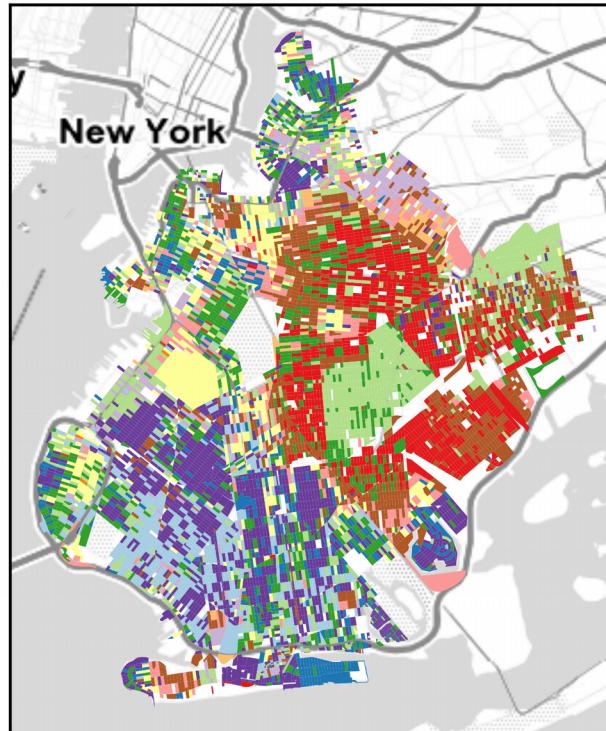
Gap between i 's current place and 2nd best alternative.

SILHOUETTE SCORES

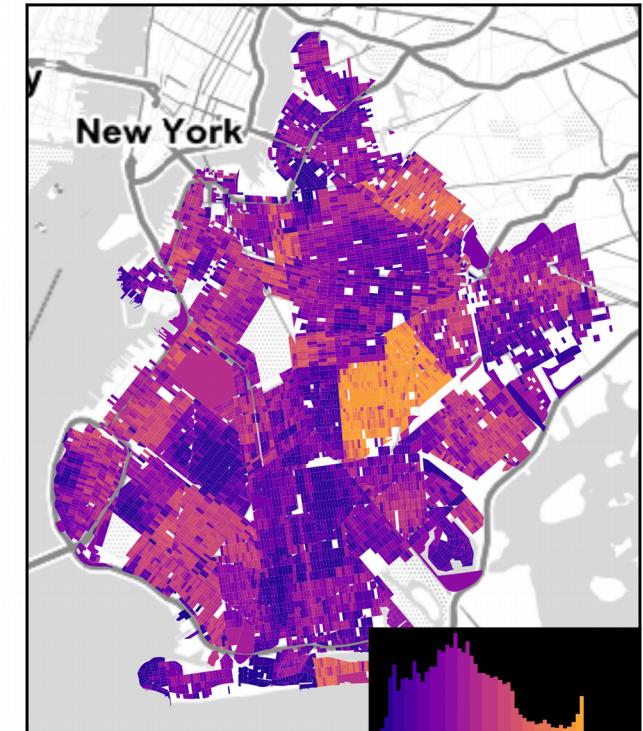
NEIGHBORHOODS



NEXT BEST FITS



SILHOUETTES

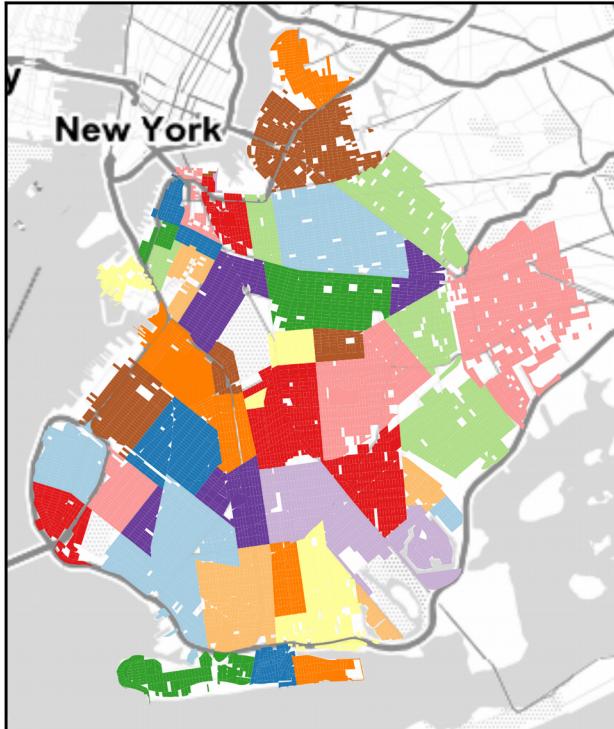


ROUSSEEUW (1987)

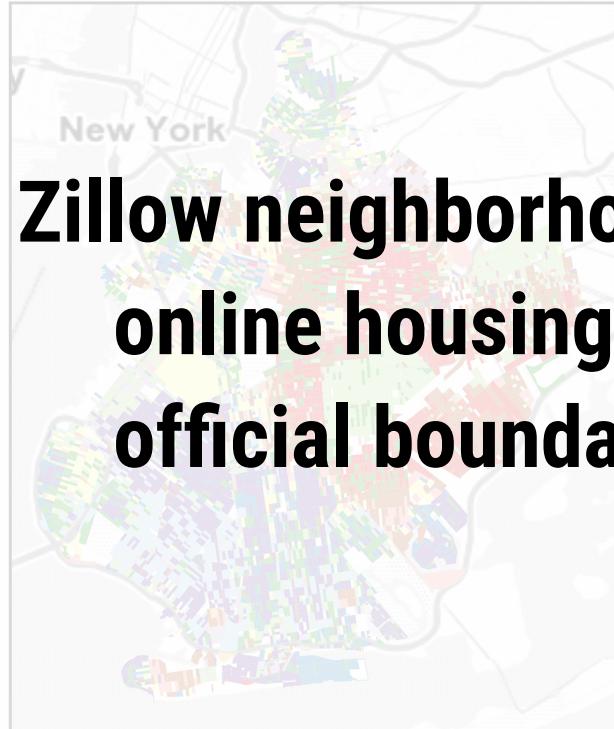
doi: 10/dd9c

SILHOUETTE SCORES

NEIGHBORHOODS

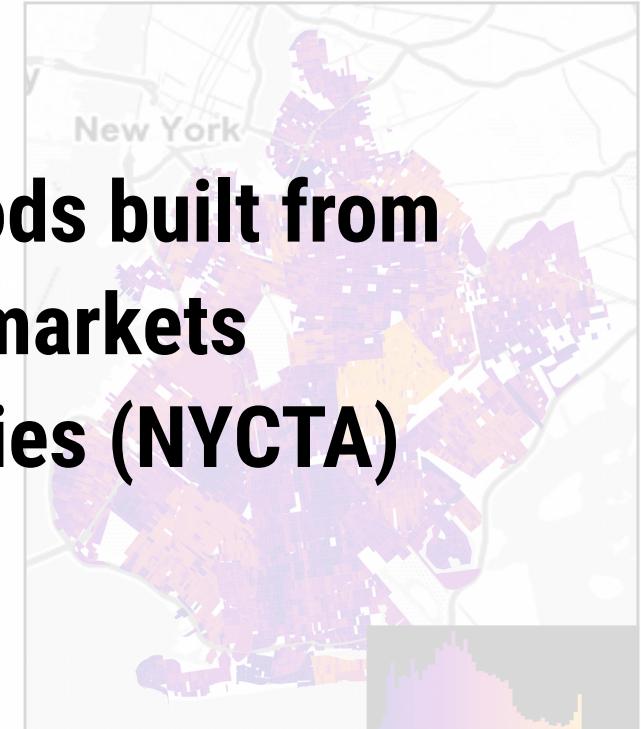


NEXT BEST FITS



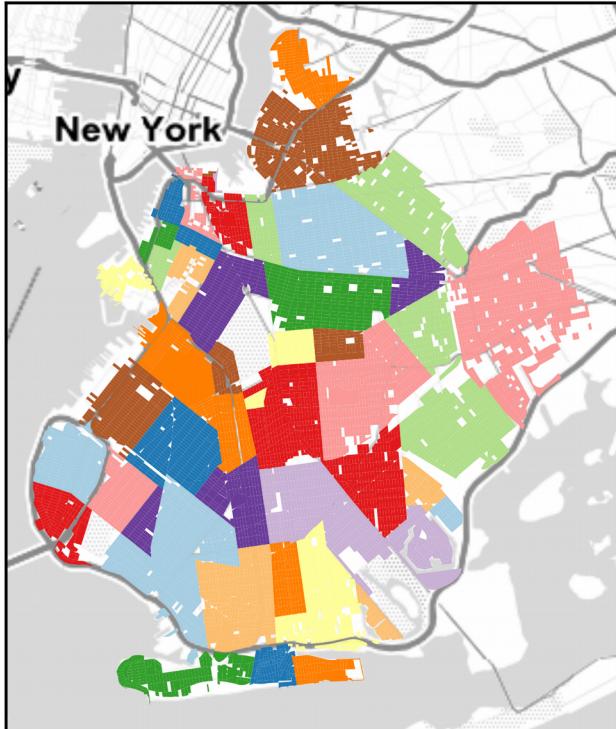
**Zillow neighborhoods built from
online housing markets
official boundaries (NYCTA)**

SILHOUETTES

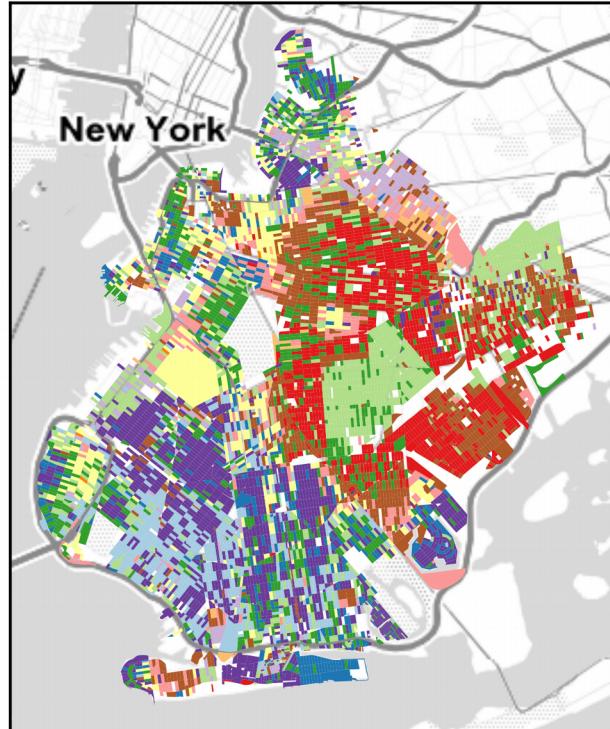


SILHOUETTE SCORES

NEIGHBORHOODS



NEXT BEST FITS

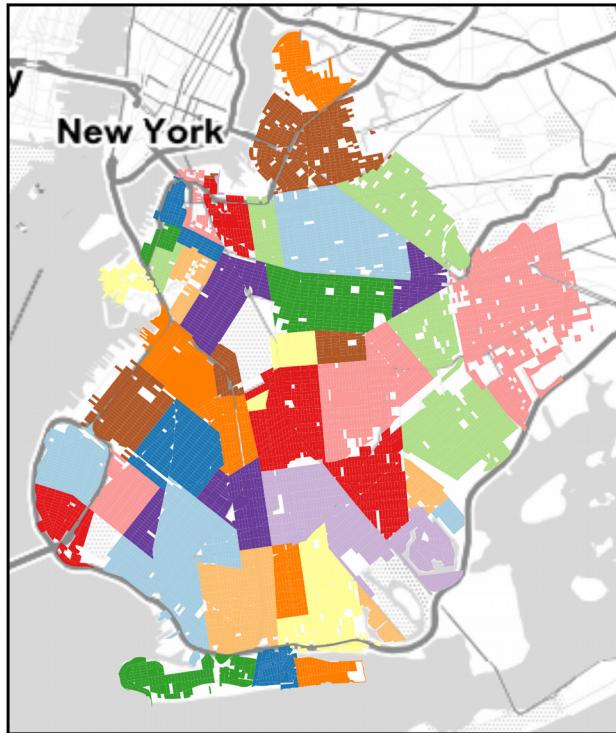


SILHOUETTES

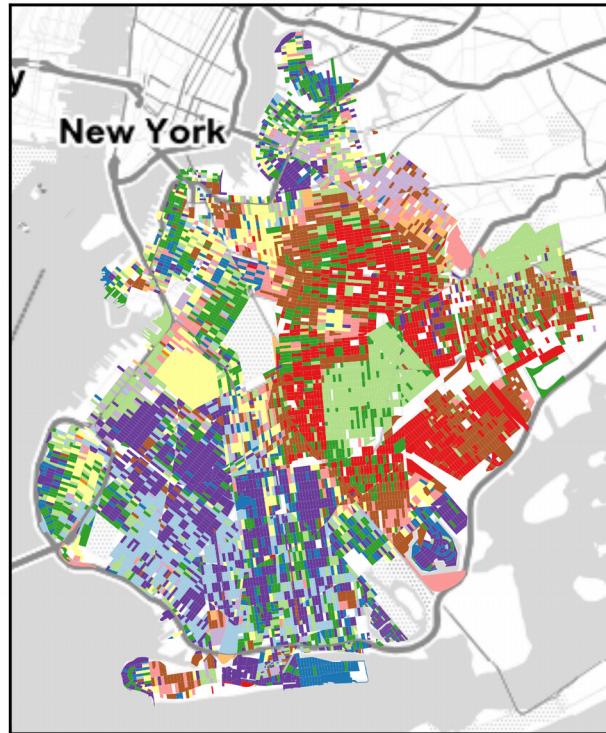
**Most similar
alternative
neighborhood for
each census
block**

SILHOUETTE SCORES

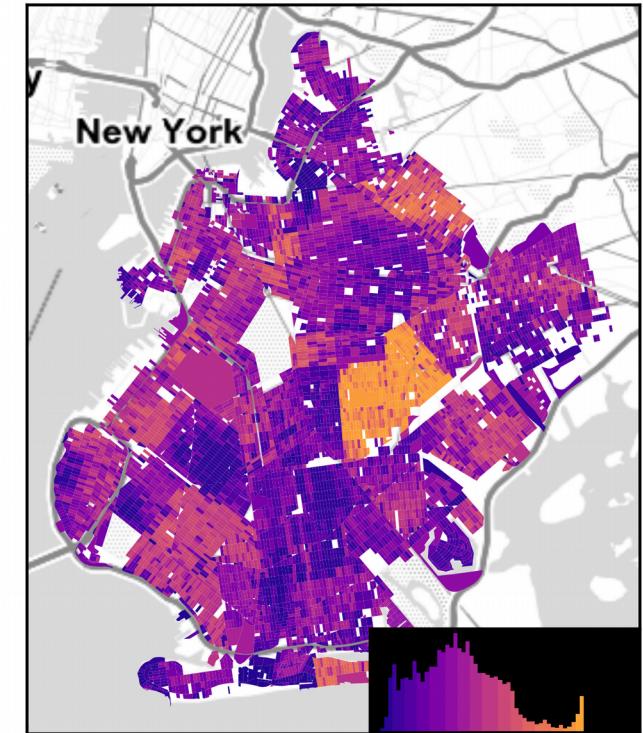
NEIGHBORHOODS



NEXT BEST FITS



SILHOUETTES



ROUSSEEUW (1987)

doi: 10/dd9c

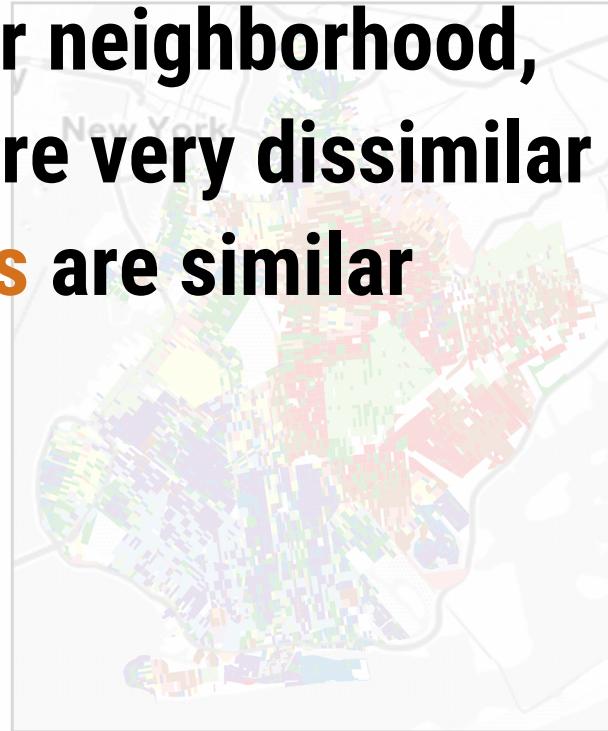
SILHOUETTE SCORES

NEIGHBORHOODS

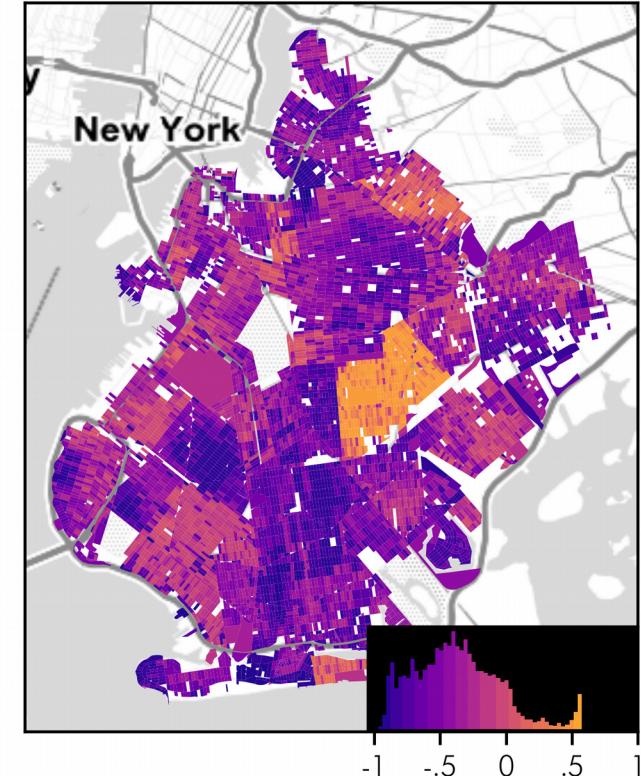
**With respect to their neighborhood,
blue observations are very dissimilar
orange observations are similar**



NEXT BEST FITS



SILHOUETTES



SILHOUETTE STATISTIC

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

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

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

BOUNDARY SILHOUETTE

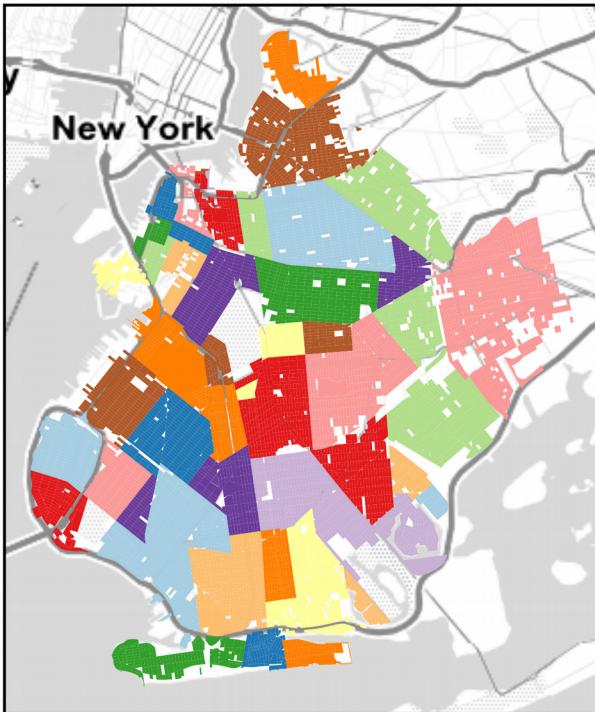
Say that observation i in graph G is assigned to place c and not another place, k , that is nearby i .

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

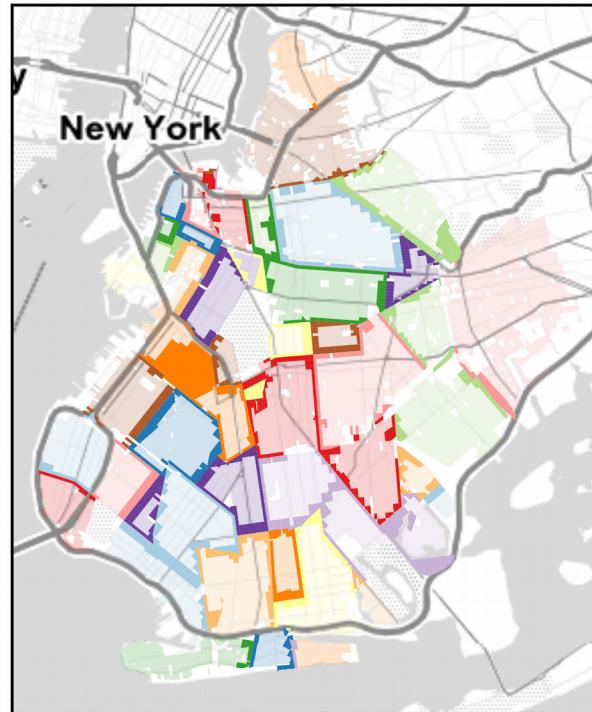
Gap between i 's current place and 2nd best local alternative.

BOUNDARY SILHOUETTE

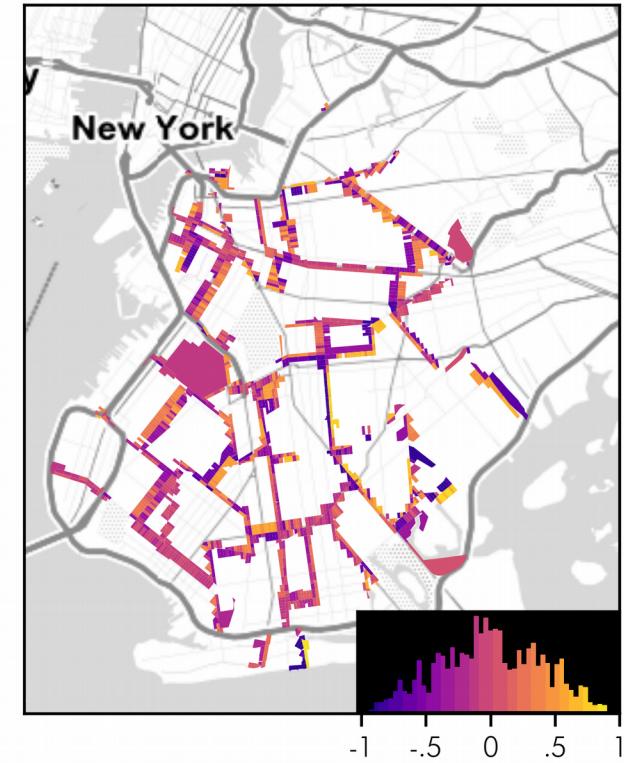
NEIGHBORHOODS



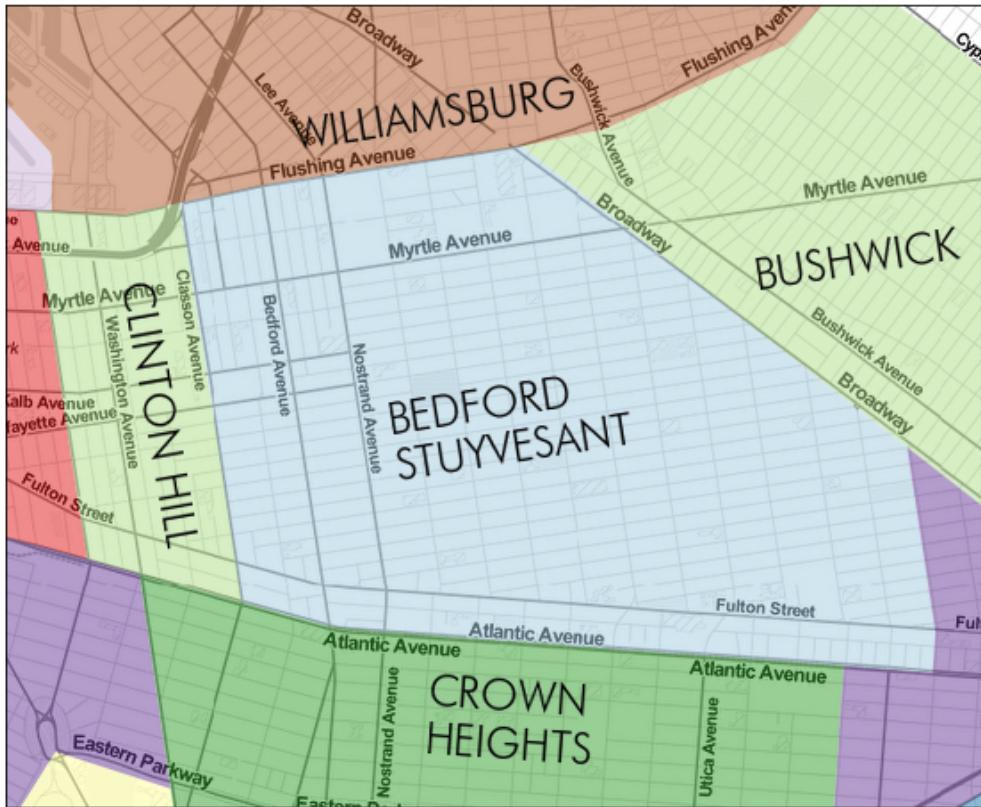
BOUNDARY BLOCKS



BOUNDARY SILHOUETTES



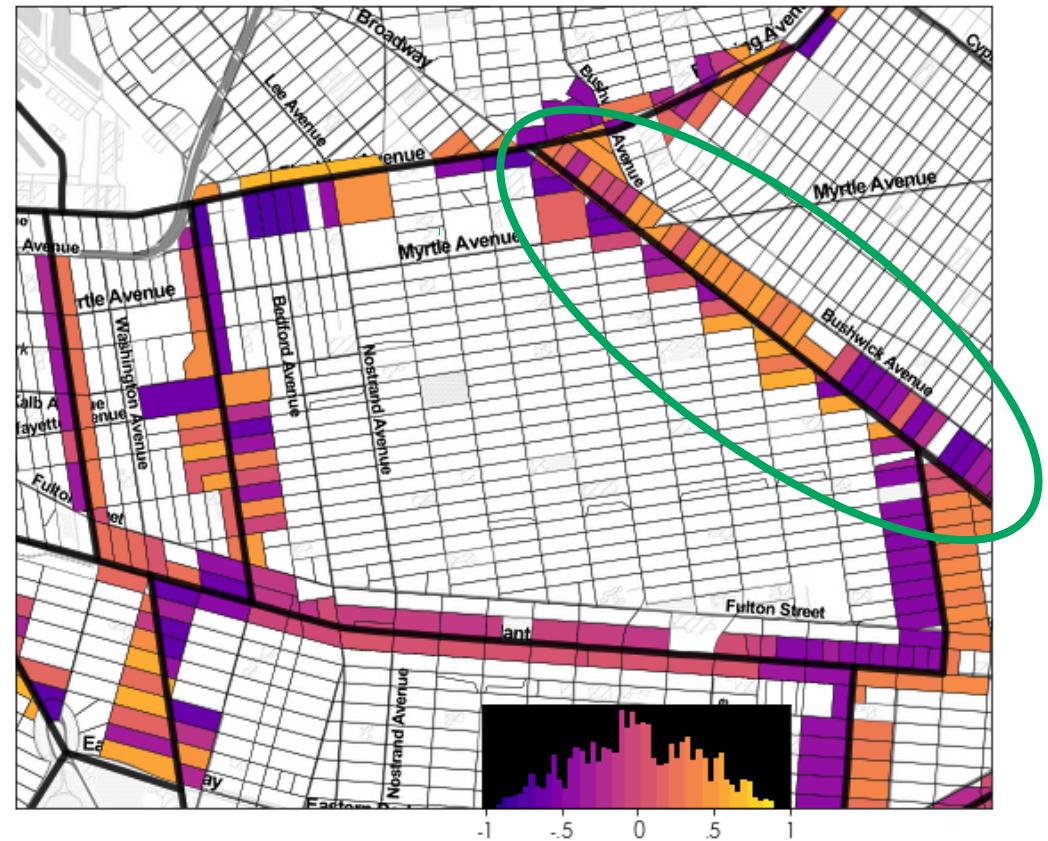
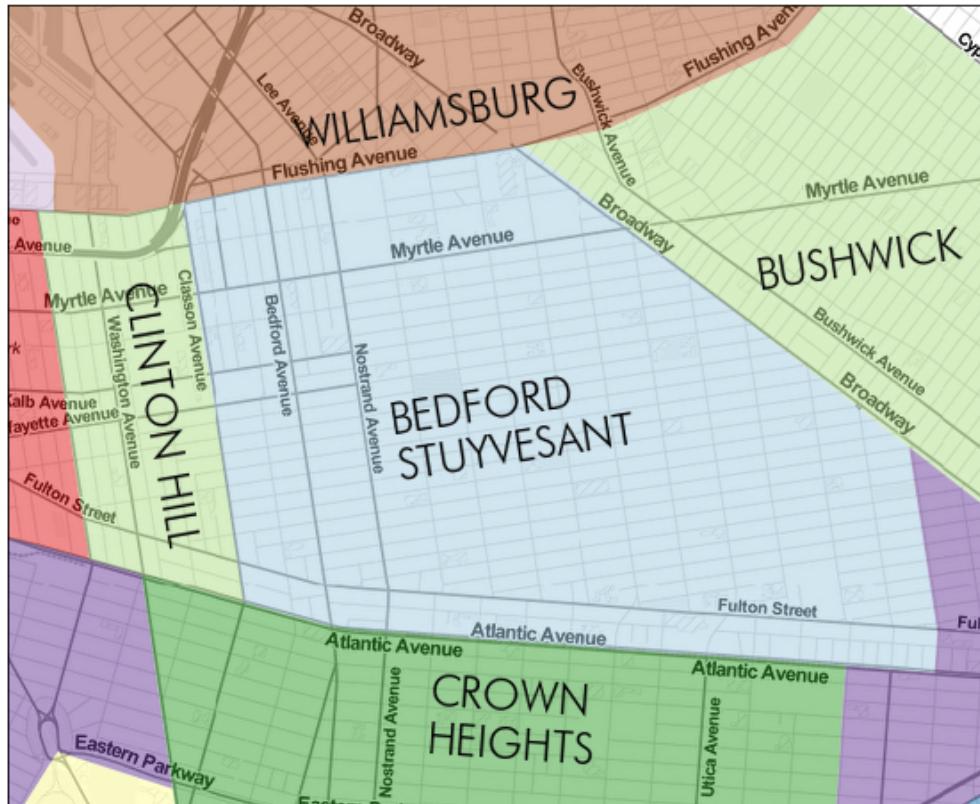
BOUNDARY SILHOUETTE



WOLF, KNAAP, & REY (2019)

doi: 10/dd9c

BOUNDARY SILHOUETTE



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.

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.

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

BOUNDARY SILHOUETTE

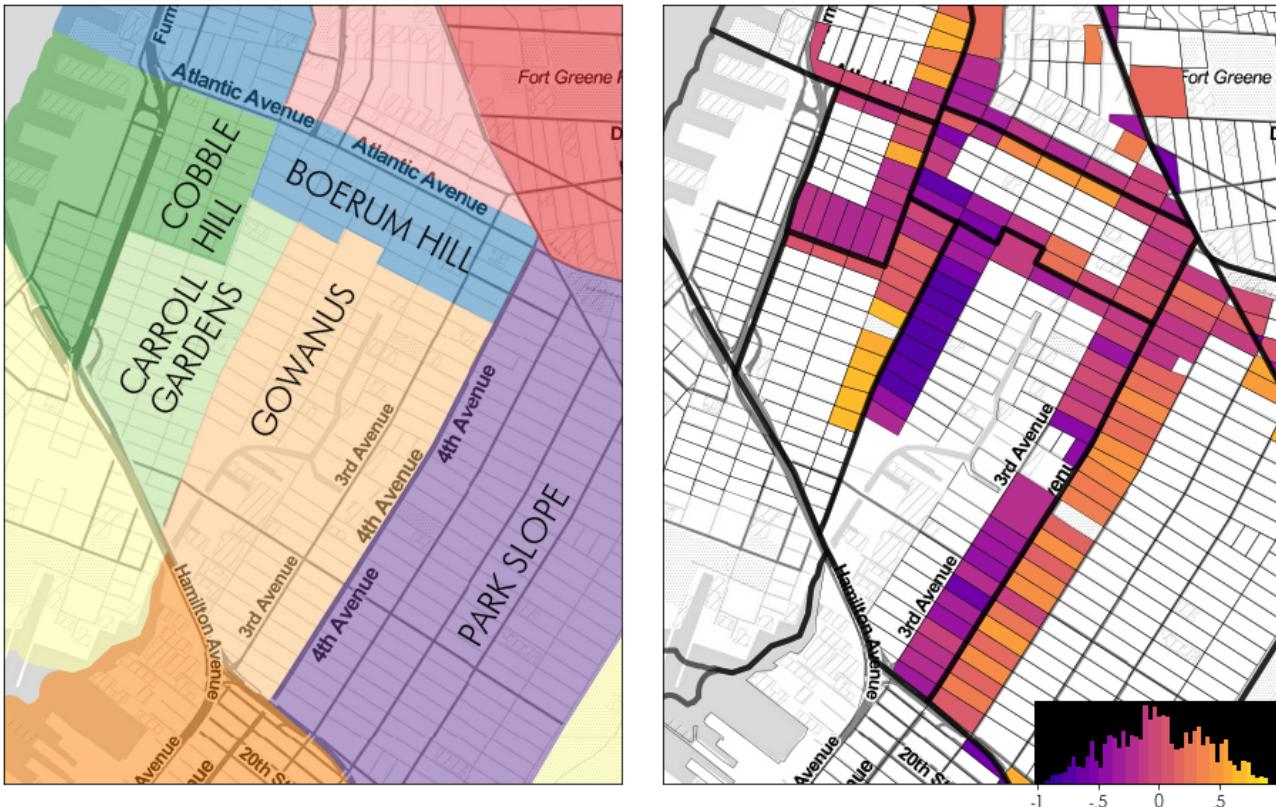
neighbor focal	Williamsburg	Bushwick	Bedford Stuyvesant	Clinton Hill	Crown Heights
Williamsburg	0	-0.096	0.693	0.516	-
Bushwick	0.288	0	0.482	-	-
Bedford Stuyvesant	-0.478	0.198	0.000	0.006	-0.059
Clinton Hill	-0.355	-	0.358	0	0.296
Crown Heights	-	-	0.077	-0.427	0

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

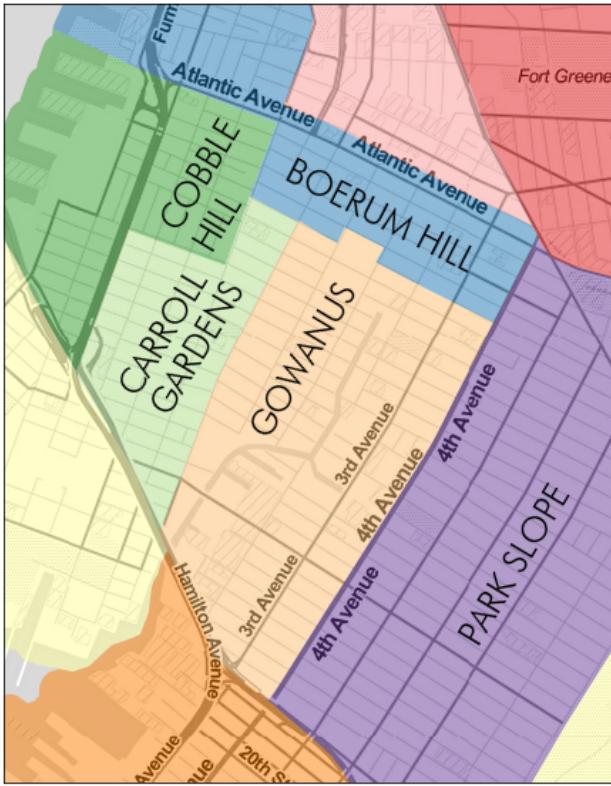
On the Bushwick side, blocks are more similar to blocks in Bushwick.

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

BOUNDARY SILHOUETTE



BOUNDARY SILHOUETTE



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

The boundary is asymmetric/unclear!

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**

NO SINGLE PLACE SCALE IS SUFFICIENT

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

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)

NO SINGLE PLACE SCALE IS SUFFICIENT

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

Urban society is embedded within this morphology

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

BATTY (2008)

NO SINGLE PLACE SCALE IS SUFFICIENT

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

Urban society is embedded within this morphology

Urban society also enforces or adjusts this morphology

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

BATTY (2008)

NO SINGLE PLACE SCALE IS SUFFICIENT

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)

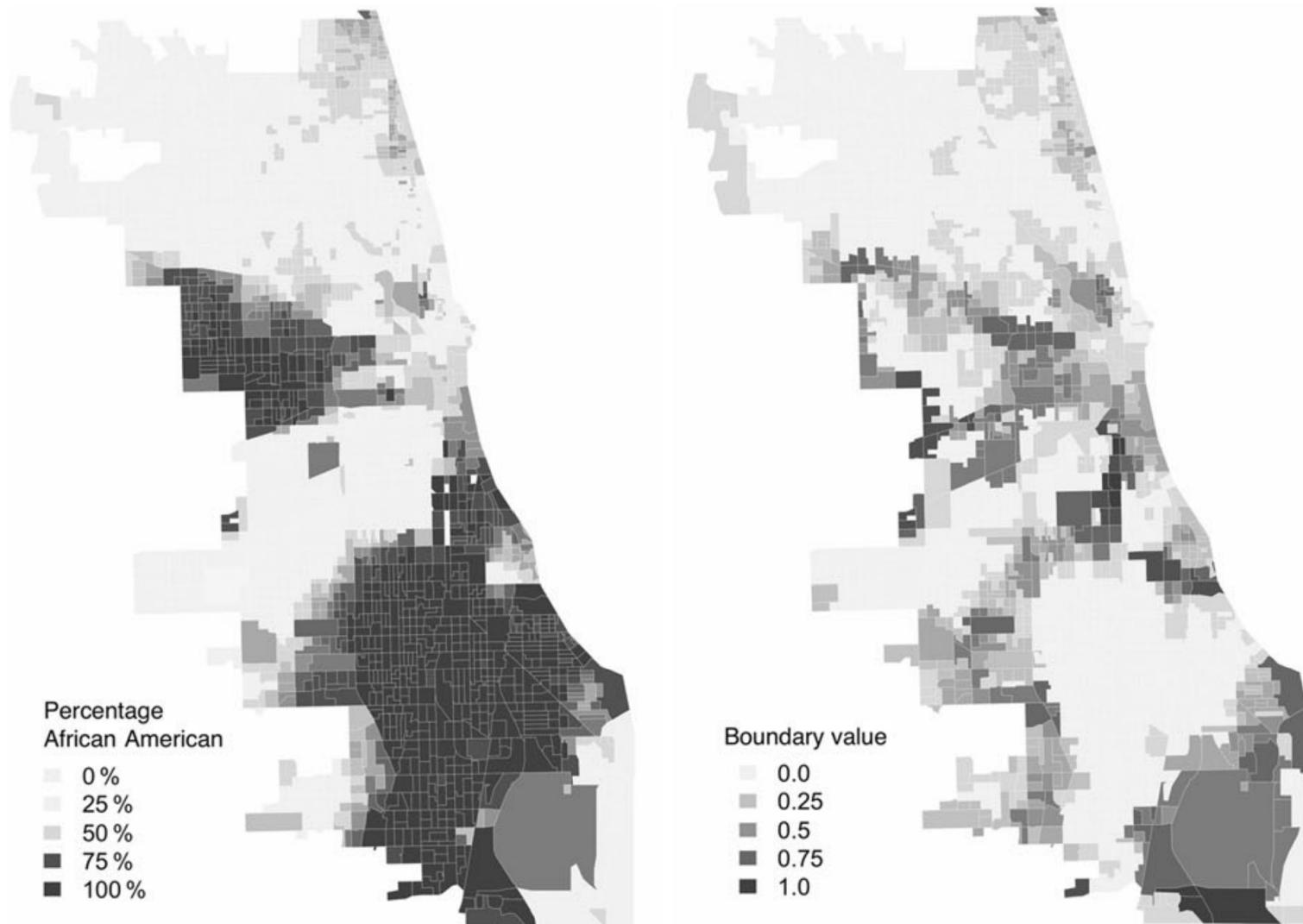


Fig. 1 Areal wombling for the proportion of African American residents

FOR YOUR INFORMATION (THEORY)

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

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

ENTROPY

FOR YOUR INFORMATION (THEORY)

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

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

**ENTROPY OF
CENSUS UNIT i**

ENTROPY

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

ENTROPY

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.

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

ENTROPY

FOR YOUR INFORMATION (THEORY)

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

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

FOR YOUR INFORMATION (THEORY)

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

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

**INFORMATION GAIN
ABOUT AREA i
FROM AREA j**

KULLBACK LEIBLER DIVERGENCE

FOR YOUR INFORMATION (THEORY)

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

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

**RATIO OF
POPULATION
PERCENTAGES**

KULLBACK LEIBLER DIVERGENCE

FOR YOUR INFORMATION (THEORY)

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

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

FOR YOUR INFORMATION (THEORY)

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

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

FOR YOUR INFORMATION (THEORY)

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

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

**AVERAGE OF POPULATIONS
IN AREA i AND j .**

JENSEN SHANNON DIVERGENCE

FOR YOUR INFORMATION (THEORY)

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

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

**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.

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

WEIGHTED JENSEN SHANNON DIVERGENCE

FOR YOUR INFORMATION (THEORY)

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

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

RAW POPULATION IN AREA j

WEIGHTED JENSEN SHANNON DIVERGENCE

FOR YOUR INFORMATION (THEORY)

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

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

**SET OF OTHER OBSERVATIONS
WITHIN DISTANCE δ**

WEIGHTED JENSEN SHANNON DIVERGENCE

FOR YOUR INFORMATION (THEORY)

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

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

**POPULATION-WEIGHTED AVERAGE D_{KL} FROM EACH
AREA TO THE AVERAGE OF J AREAS WITHIN δ**

WEIGHTED JENSEN SHANNON DIVERGENCE

FOR YOUR INFORMATION (THEORY)

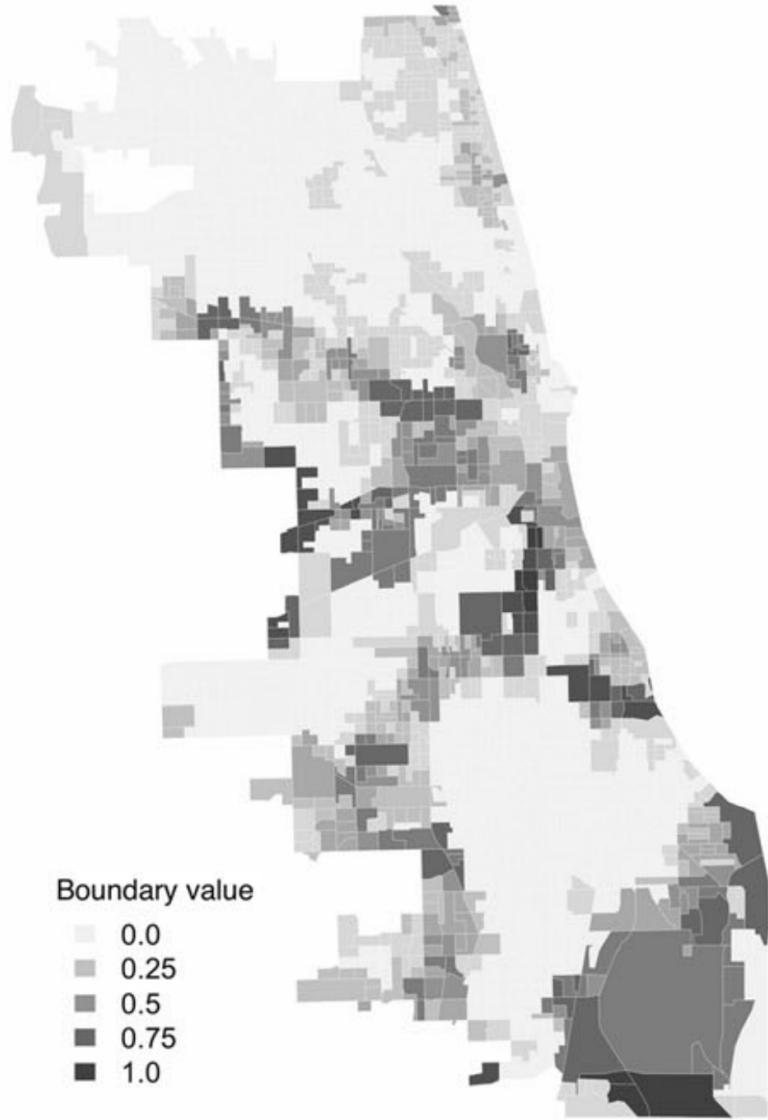
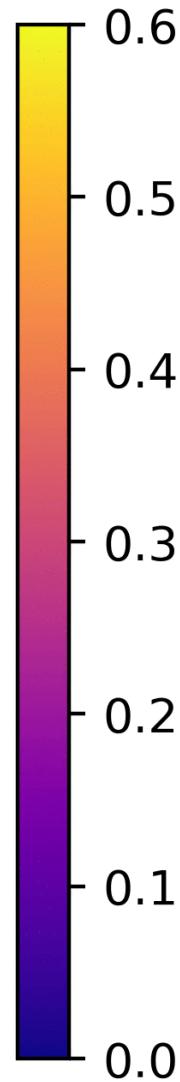
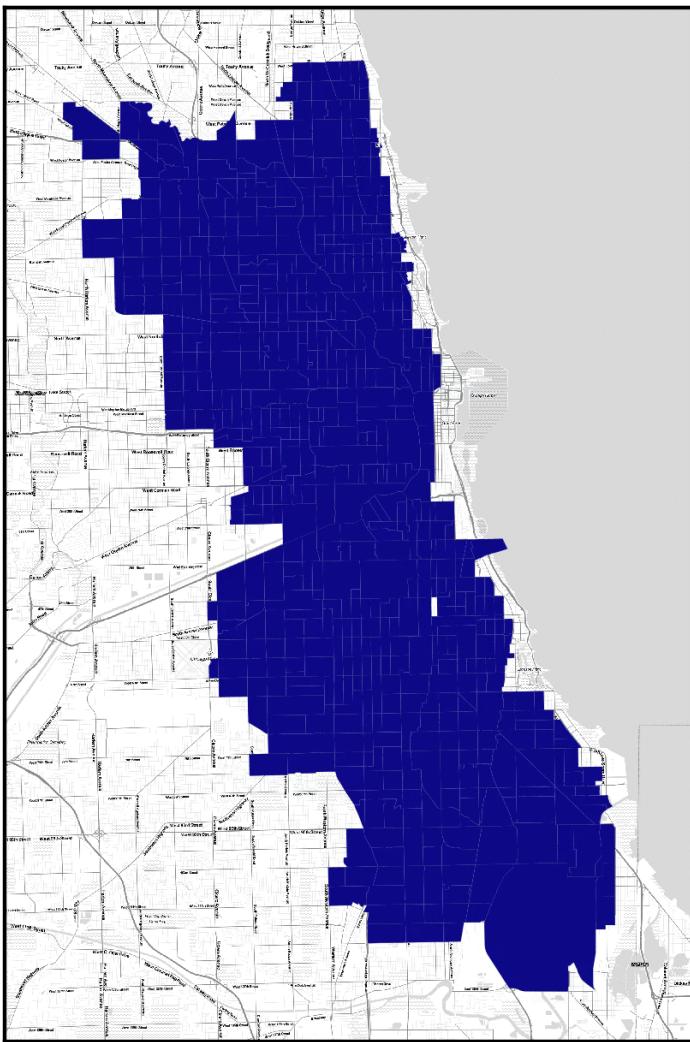
Let there be N blocks with m racial/ethnic classes.

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

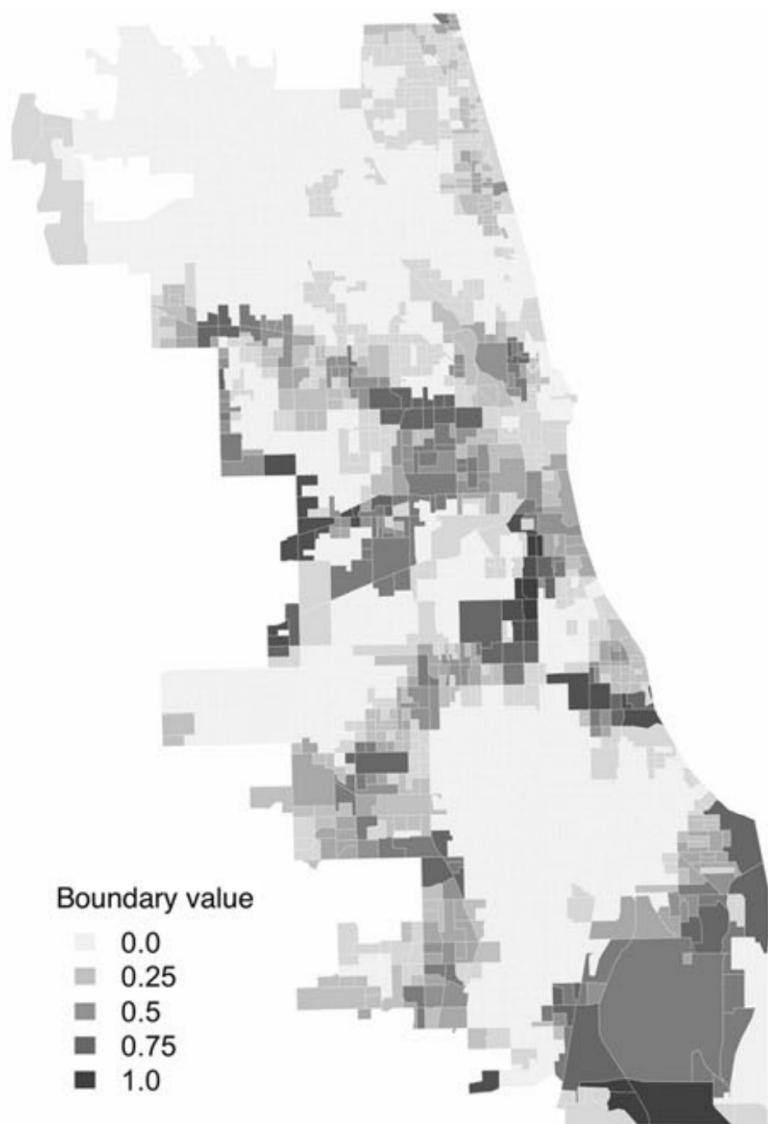
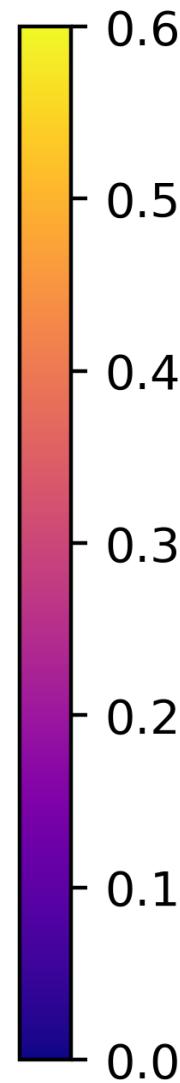
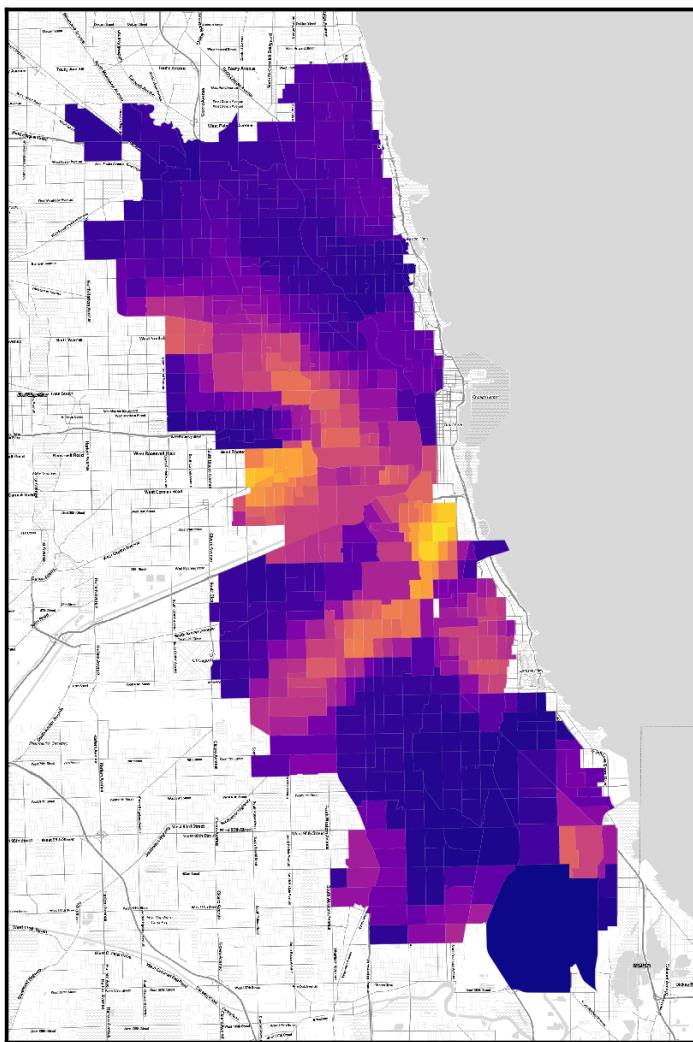
HOW DIFFERENT IS i FROM OTHERS WITHIN δ ?

WEIGHTED JENSEN SHANNON DIVERGENCE

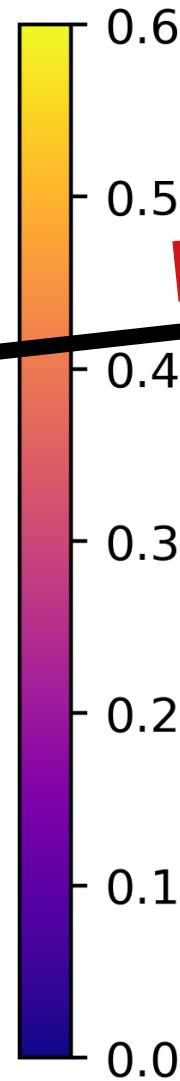
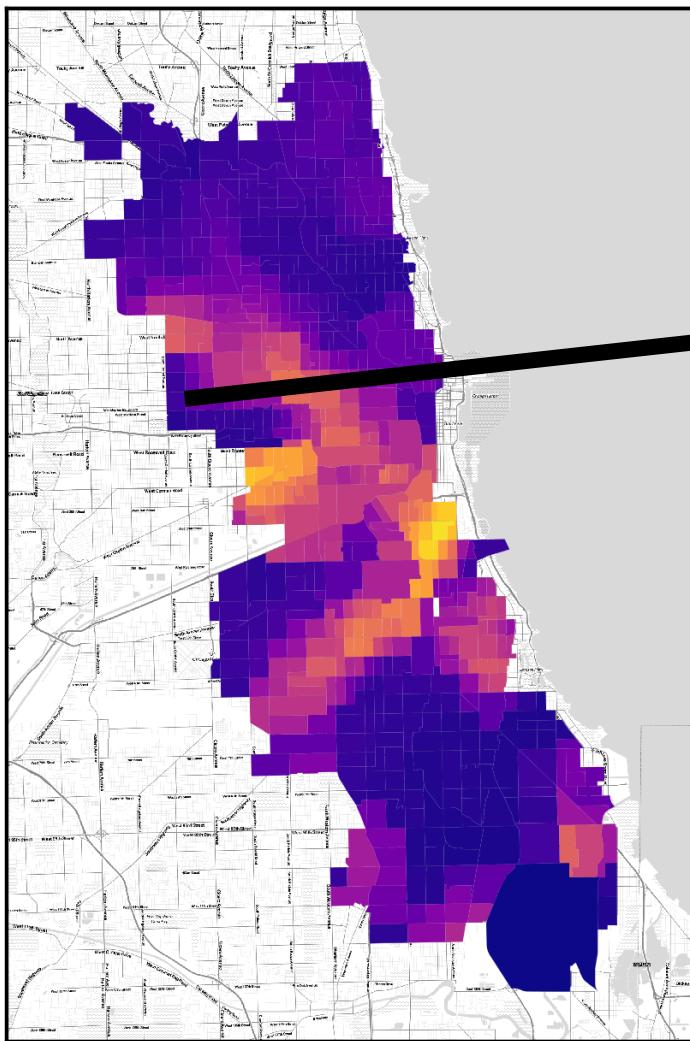
Jensen Shannon at 200.00 Ft



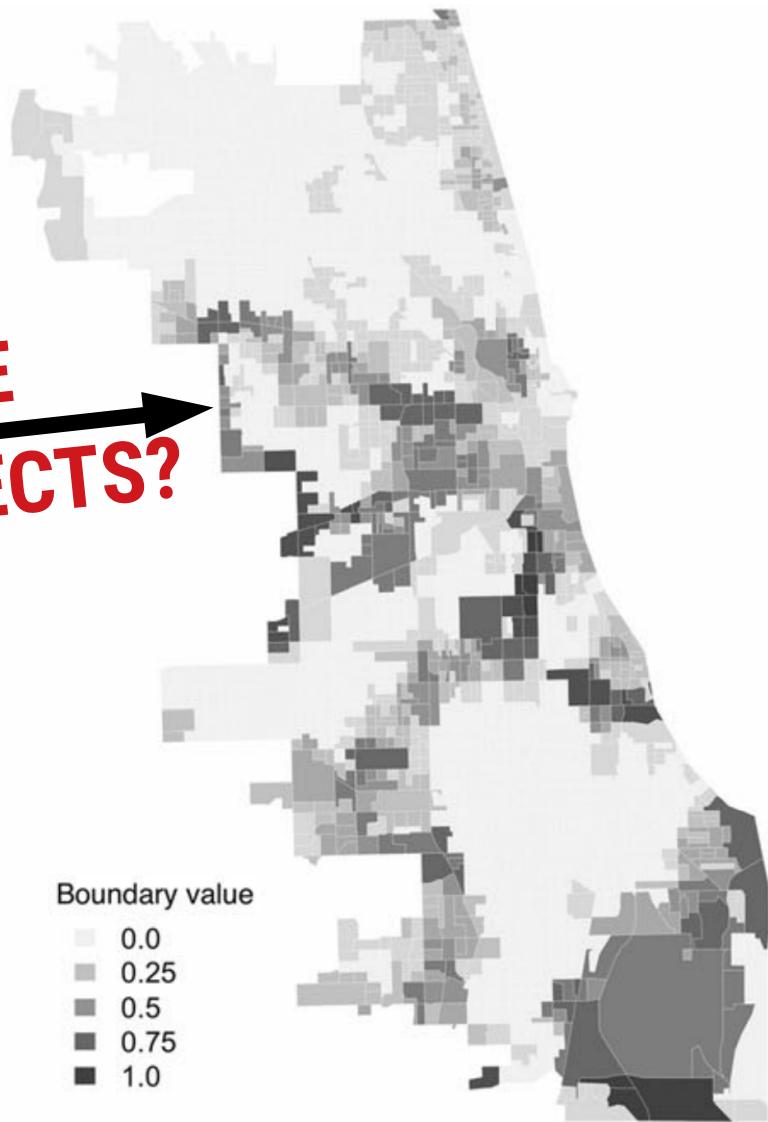
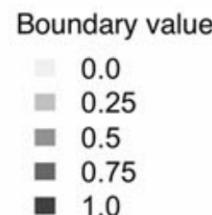
Jensen Shannon at 3772.41 Ft



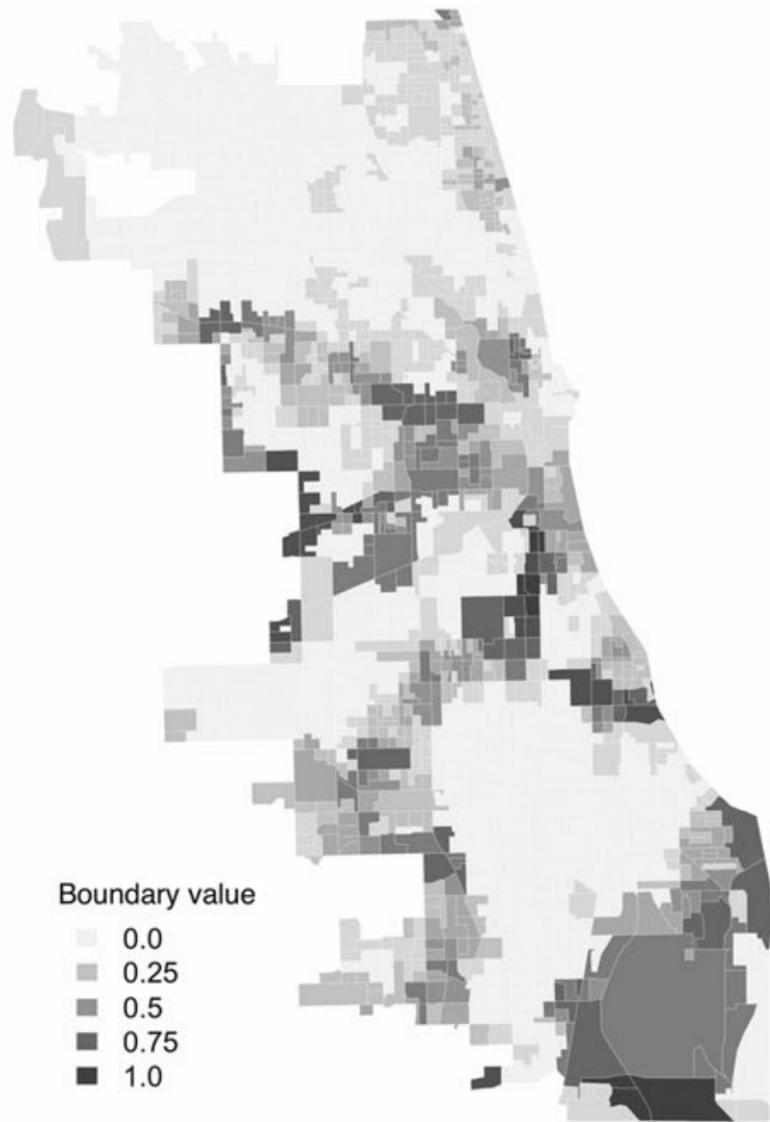
Jensen Shannon
at 3772.41 Ft



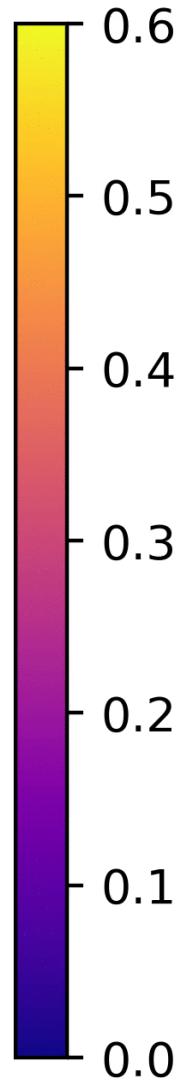
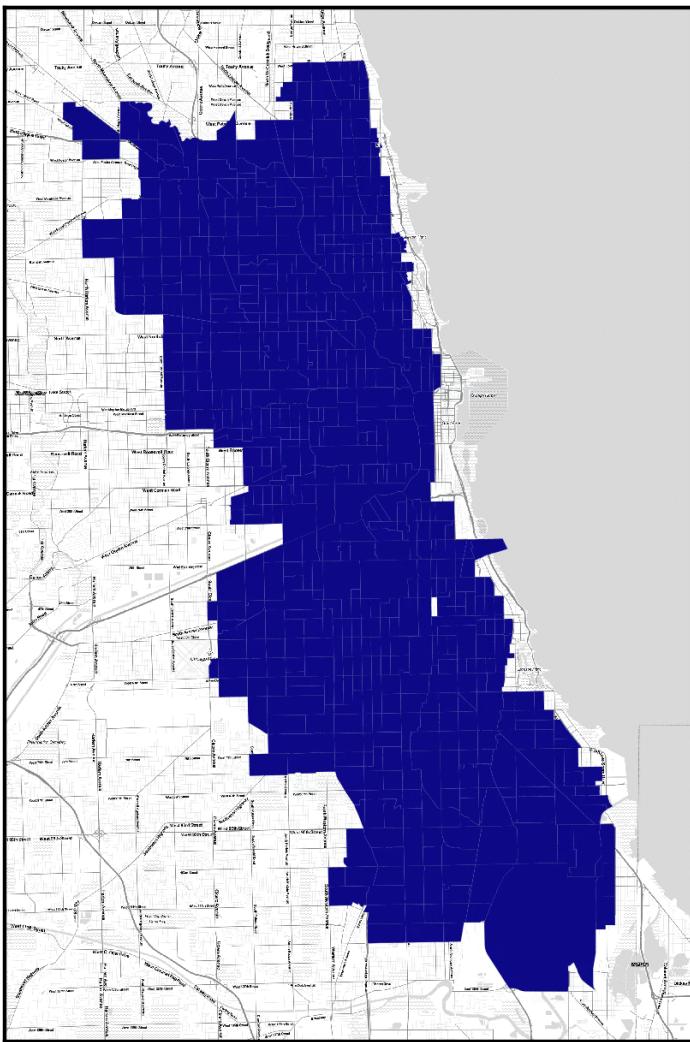
**EDGE
EFFECTS?**



Jensen Shannon
at 3772.41 Ft



Jensen Shannon
at 200.00 Ft



**ALWAYS
MULTI
SCALE**

RETHINKING BOUNDARIES:

Contingent on conflict outcome.

Conflict **over what, between whom?**

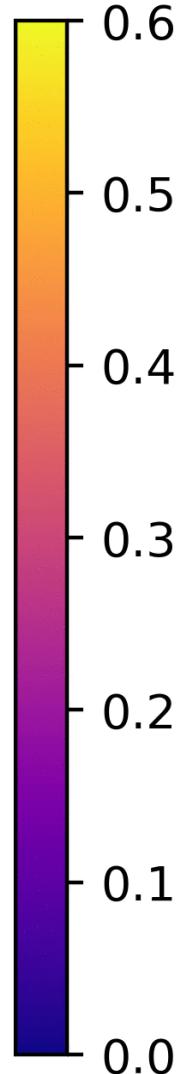
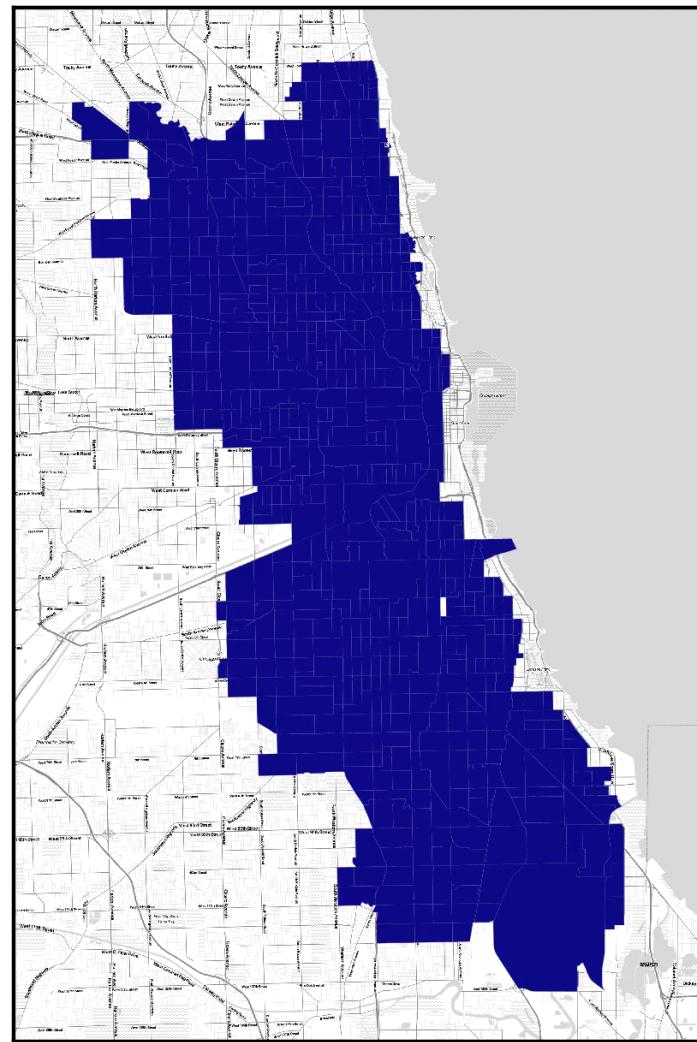
Robustness from place endogeneity!

Symmetric and reversible.

Sign matters, not magnitude.

Assume existence of place & place-scale.

Jensen Shannon
at 200.00 Ft



FINDING THE FAULT LINES:

ESTIMATING THE BOUNDARIES IN URBAN
SOCIAL-SPATIAL INEQUALITY



University of
BRISTOL

The
Alan Turing
Institute

LEVI JOHN WOLF

levi.john.wolf@bristol.ac.uk

 [@levijohnwolf](https://twitter.com/levijohnwolf)

ljwolf.org