

Mapping and Geovisualization

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<http://spatial.uchicago.edu>

from mapping to geovisualization to ESDA

map design primer

statistical maps

mapping rates



From Mapping to Geovisualization to ESDA



- Definitions

a map is “a collection of spatially defined objects” (Monmonier)

beyond mapping

- map as analysis vs map as presentation

geovisualization

geospatial visual analytics

exploratory spatial data analysis (ESDA)



- Geovisualization

“the creation and use of visual representations to facilitate thinking, understanding and knowledge construction” (MacEachren)

exploration, synthesis, presentation, analysis



- Geospatial Visual Analytics

computer science perspective

visual analytics (Thomas and Cook 2005)

detect the expected and discover the unexpected (Kielman et al 2009) = facilitate analytical reasoning

bring in space = geospatial visual analytics



- Exploratory Spatial Data Analysis

“a collection of techniques to describe and visualize spatial distributions, identify atypical locations or spatial outliers, discover patterns of spatial association, clusters or hot spots and suggest spatial regimes or other forms of spatial heterogeneity” (Anselin 1999)



- Traditional Knowledge Discovery

deductive approach

hypothesis first, data later

inductive approach

data first, hypothesis later



- Alternative Knowledge Discovery

- abductive approach

pattern discovered along with hypothesis

interaction between data exploration and human perception

visual popout = aha moment



- Geovisual Analytics

leverages both geovisualization and visual analytics

interactive mapping

animation

linking and brushing





RESEARCH THEMES



GeoVisual Analytics

Knowledge Management & Geocollaboration

Spatial Cognition & Human Factors

Risk Assessment & Spatial Decision Support

Geographic Representation

GeoSemantics

SOFTWARE TOOLS



GeoViz Toolkit

Visual Inquiry Toolkit

GeoVISTA CrimeViz

HerbariaViz

United States Cancer Atlas

RELATED RESOURCES



Video: Flu Data Analysis with GeoViz Toolkit

GeoVisual Analytics



Tweet



Like 0

Representing, analyzing, modeling and extracting meaning from complex heterogeneous geospatial datasets requires new approaches that can scale up to current and future data complexity and data volume. Our work addresses a wide variety of issues, including:

- the development of 'complex' spatiotemporal systems with emergent properties,
- new techniques for data mining, knowledge discovery, visualization (for application to geospatial and spatiotemporal information about the past, present, and future),
- advanced and semantically aware spatial databases that can represent and integrate both the data and the various higher level knowledge constructs, such as categories and relationships that emerge from the data during knowledge construction and
- developing a geographical agent modeling environment for investigating human activities.

These activities, when integrated, support the entire geo-scientific process, from initial exploration of data, hypothesis generation, concept discovery, model formulation, analysis and validation, and, when fused together seamlessly in GeoVISTA Studio, will form a complete Problem Solving Environment (PSE) for teams of scientists to use, thus supporting our geocollaboration focus. By bringing these activities together in GeoVISTA Studio we avoid many of the integration problems that plague traditional computational analysis. To accomplish this goal, Center affiliates and their collaborators are working to integrate methods and tools that span many disciplines including machine learning, pattern recognition, agent and cellular modeling, data mining, multivariate information visualization and spatial statistics.

RELATED PROJECTS



VACCINE: Visual Analytics for Command, Control, and Interoperability Environments

GAIDD: Geovisual Analytics for Infectious Disease Dynamics

Vaccine Modeling Initiative

Geovisualization and Spatial Analysis of Cancer Data

STNexus: An Integrated Database and Visualization Environment for Space-Time Information Exploitation

[See all projects . .](#)

RELEVANT PAPERS



Robinson, A. (2009). Needs Assessment for the Design of Information Synthesis Visual Analytics Tools, IEEE International Conference on Information Visualization

Roth, R.E, MacEachren, A., McCabe, C. (2009). A workflow learning model to improve geovisual analytics utility. Proceedings of the

- How to Lie with Maps (Monmonier)

manipulate map design parameters

legends, colors, intervals, scale

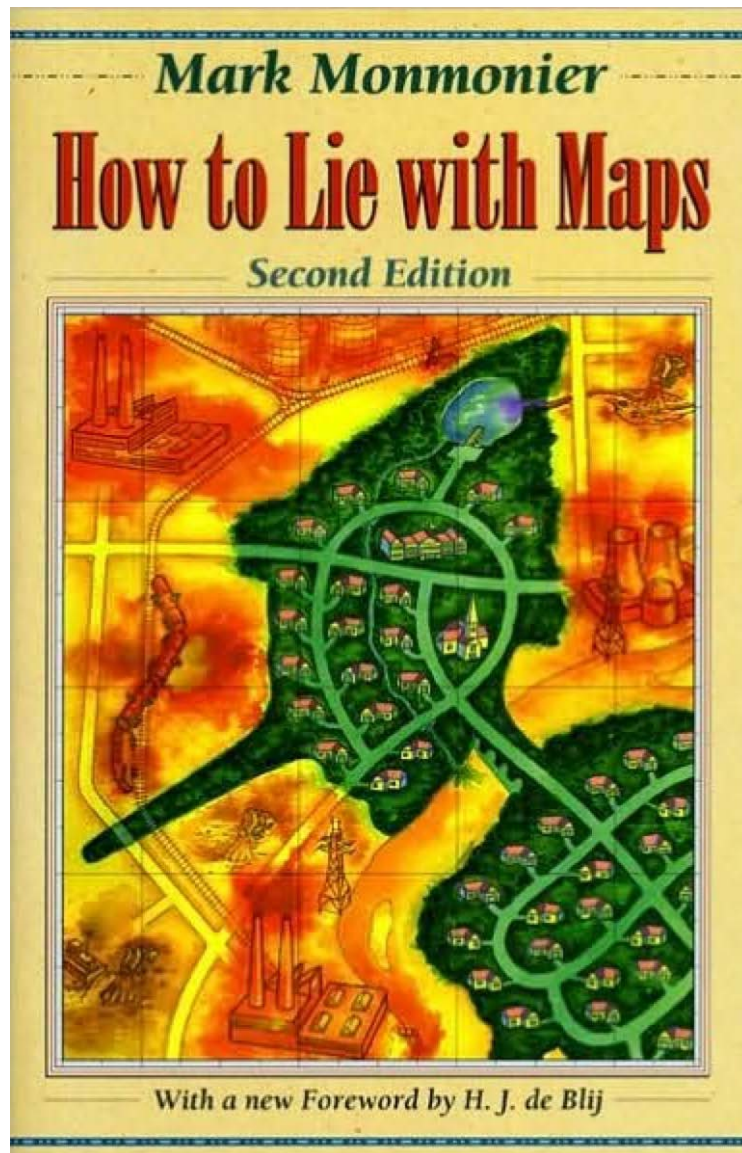
choice of projection

manipulate area through choice of projection
(political maps)

larger areas seem more important

human perception can be tricked

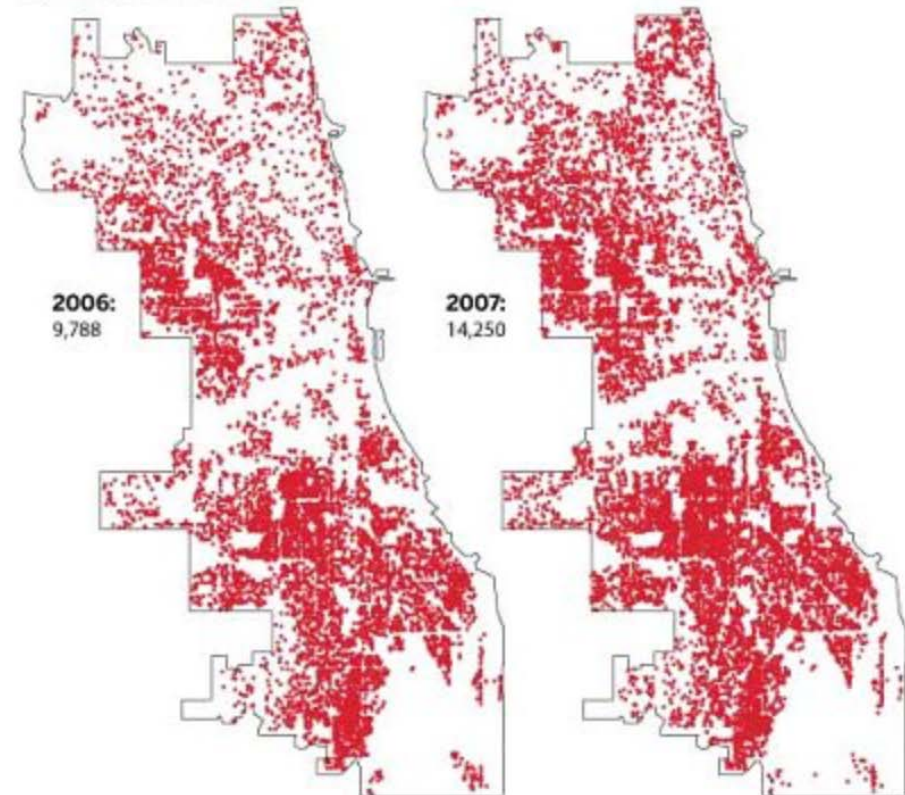




Where is it the worst?

More than 1 percent of all U.S. households were in some stage of foreclosure last year, nearly double the 2006 figure, and foreclosures soared to an all-time high in the final quarter of last year. Chicago has fared a bit better but has been stung by the real estate crisis nonetheless, with foreclosures growing by 45 percent in 2007.

CHICAGO FORECLOSURES



<http://xefer.com//2008/04/maps>

Map Design Primer



- Choropleth Map

choro from region, NOT chloro

visualizing a spatial distribution

values at locations

map counterpart of histogram

values for discrete spatial units



- Map Design Parameters

datum and coordinate system (geodesy)

scale

projection

shape, area, distance, direction

classification

color

legend



- Representing Value

- discrete

- selection of intervals

- all data points in same interval obtain the same color or shading

- continuous

- color ramp

- cross-hatch density

- symbol

- doesn't really work for large data sets



Classification



- Map Classification

choice of intervals

selection of cut points

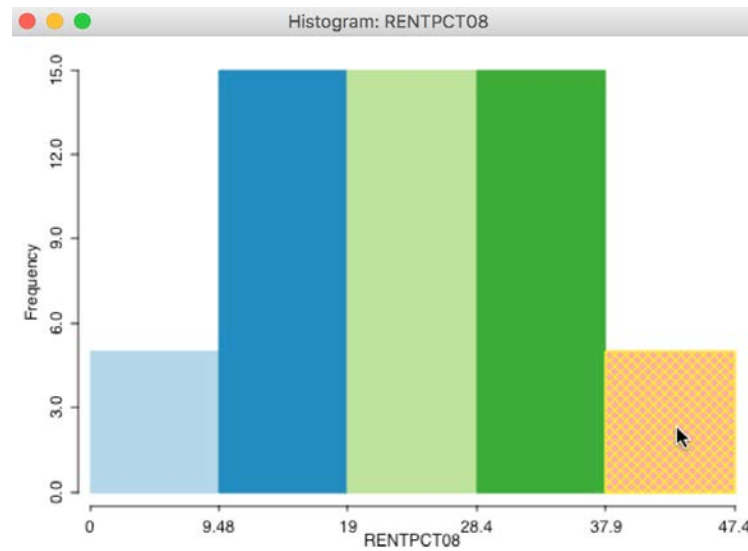
equal interval, natural breaks (Jencks), manual

- statistical criteria

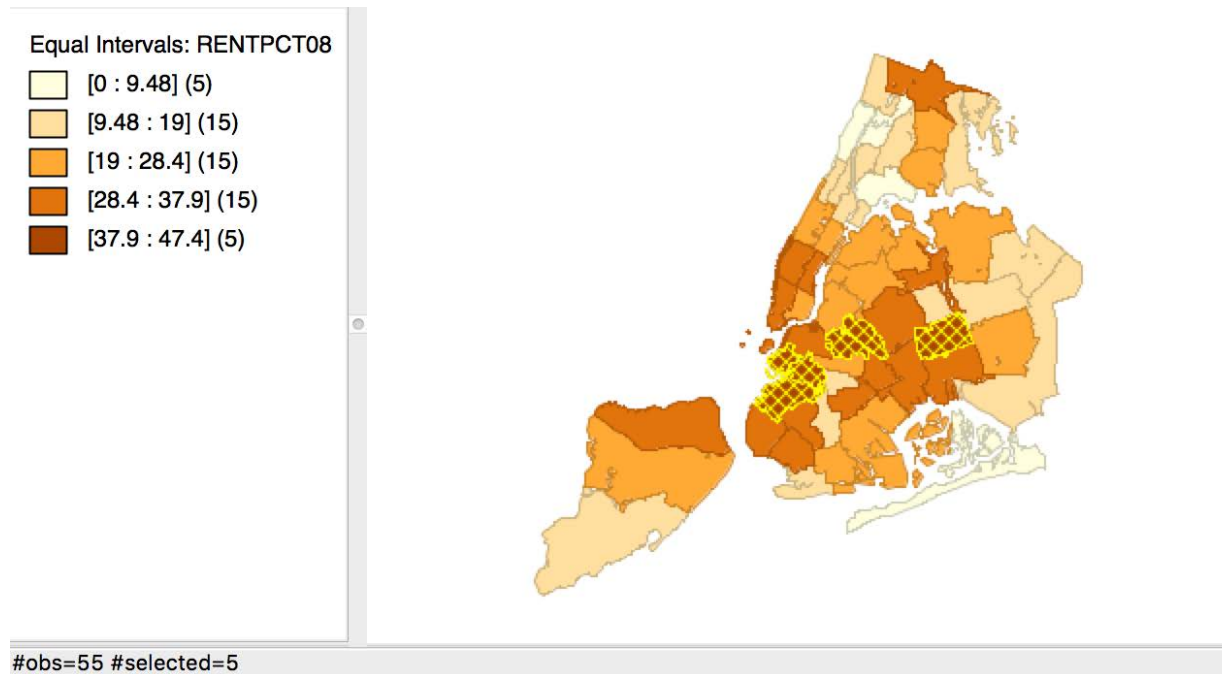
equal share (quantile), standard deviation

extreme values



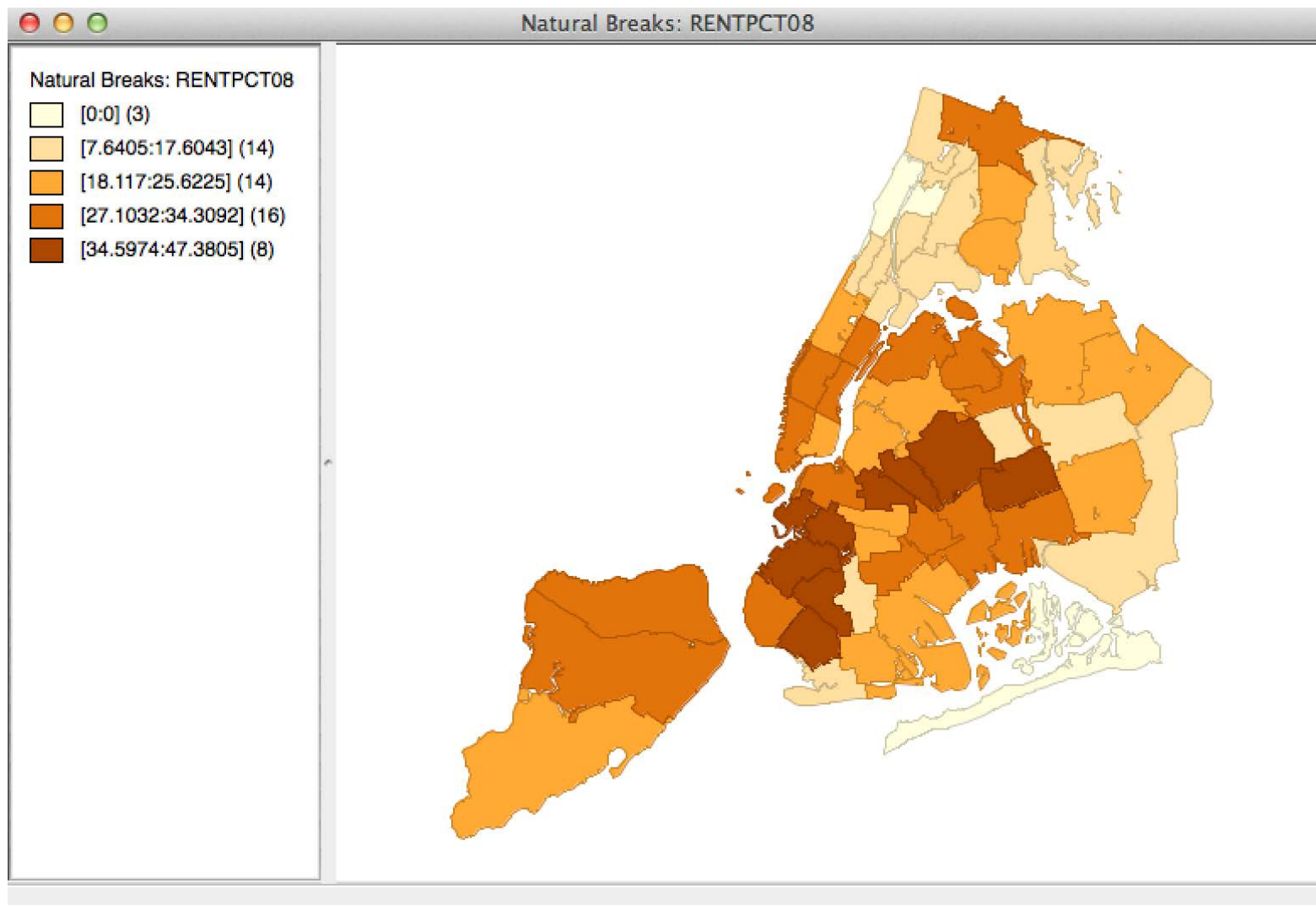


bin: 5, range: [37.9044, 47.3805], #obs: 5, %tot: 9.1%, #sel: 5, sd from mean: 1.32

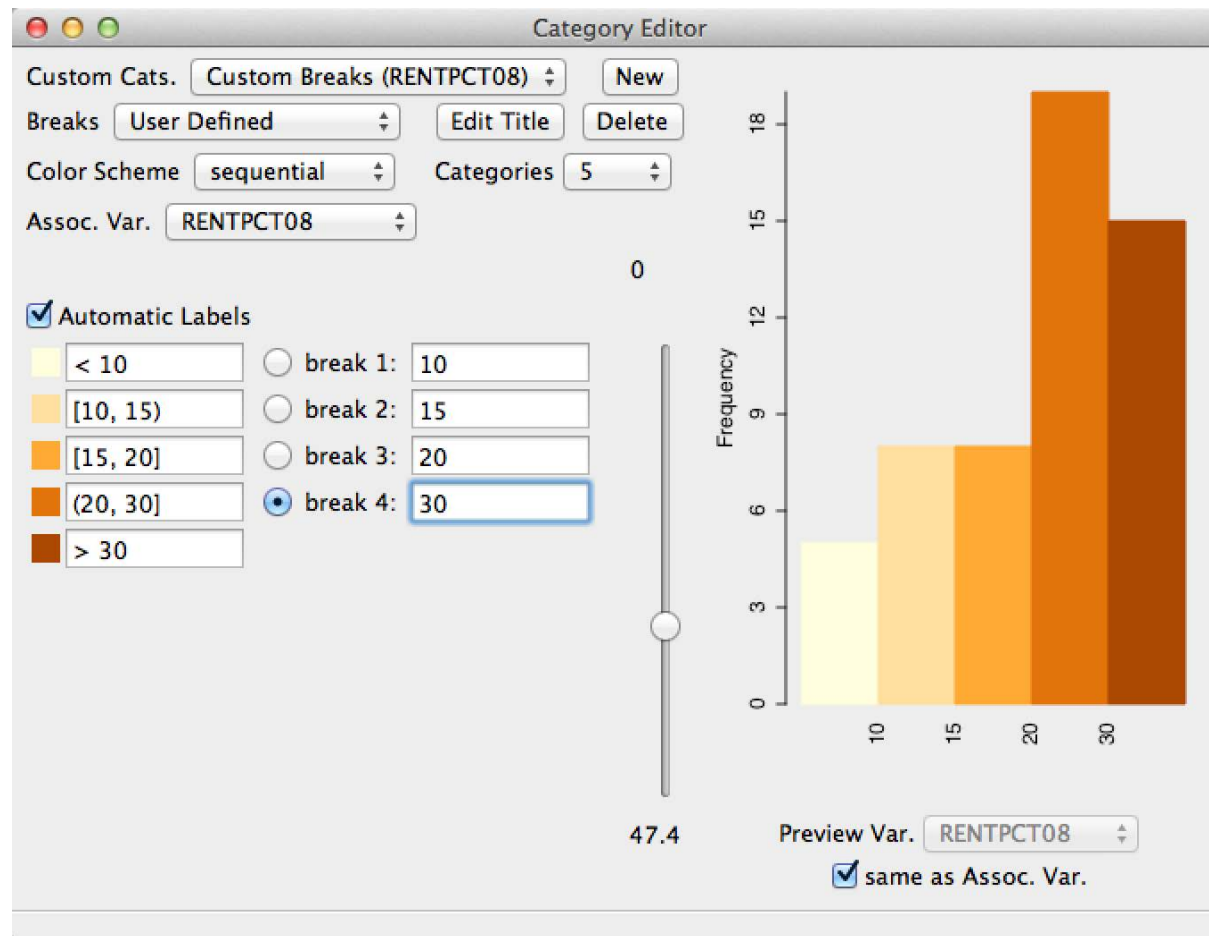


histogram and equal intervals choropleth map



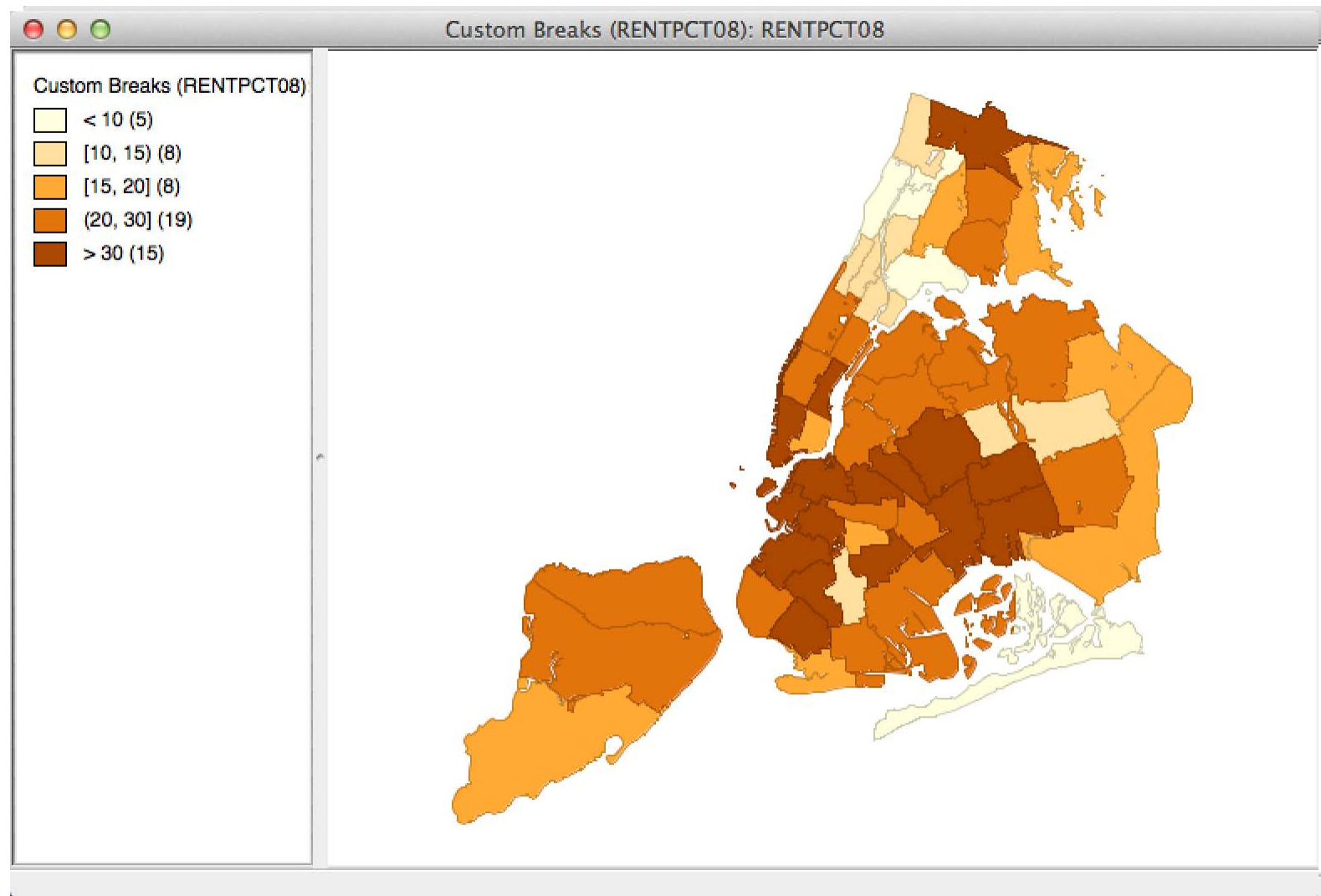


NYC Sub-boroughs - % rental Natural Breaks



GeoDa Custom Category Editor





NYC Sub-boroughs - % rental Custom Intervals

Colors



- Color Choice

perception of value

perception of pattern

- reds = hot, blues = cold

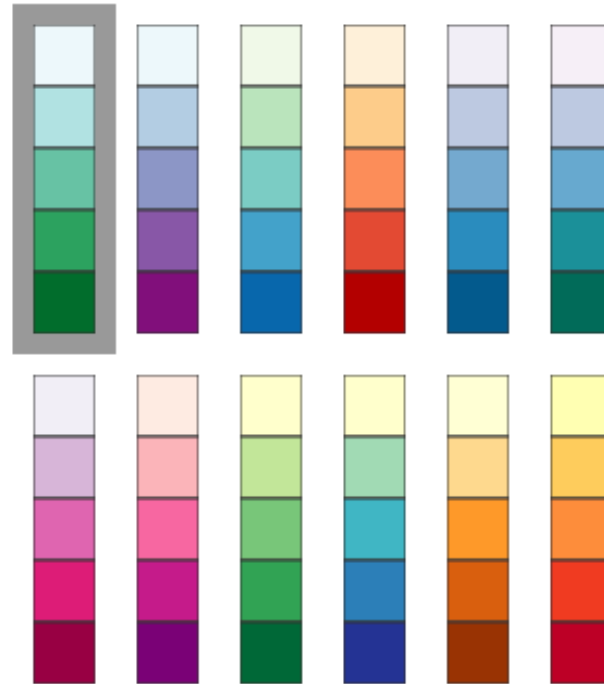
red = danger

colorbrewer2.org (Cynthia Brewer)



Pick a color scheme:

Multi-hue:



Single hue:



Color Brewer recommended color schemes



Legends



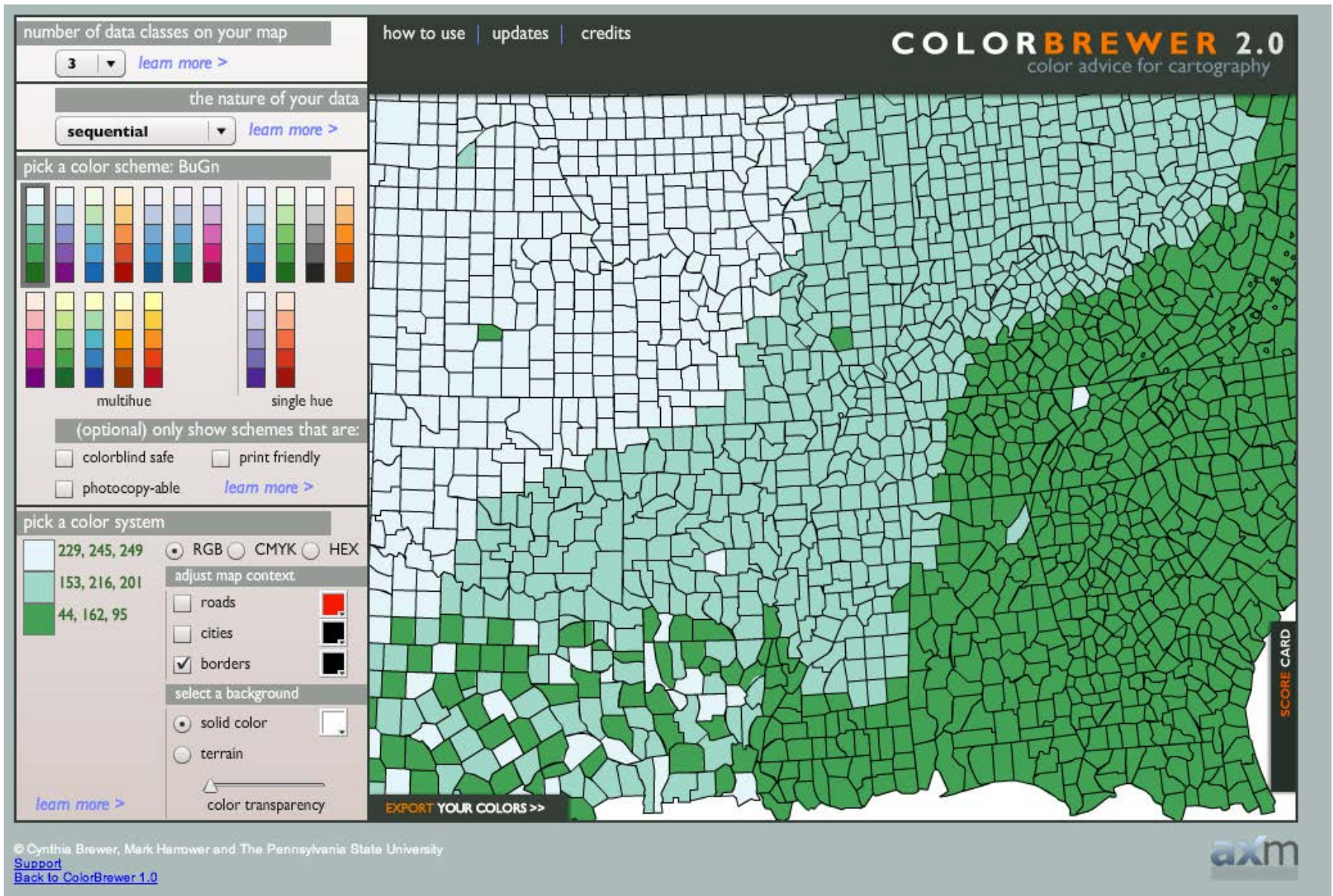
- Sequential Legend

ordered data

low to high

not appropriate for categorical data





ColorBrewer sequential legend



- Diverging Legend

equal emphasis on mid-range and extremes in either direction

stresses difference from central tendency, rather than ordering of data



number of data classes on your map
5 [learn more >](#)

the nature of your data
diverging [learn more >](#)

pick a color scheme: BrBG

(optional) only show schemes that are:
☐ colorblind safe ☐ print friendly
☐ photocopy-able [learn more >](#)

pick a color system
 166, 97, 26
 223, 194, 125
 245, 245, 245
 128, 205, 193
 1, 133, 113

adjust map context
☐ roads ☐ cities
☒ borders

select a background
☒ solid color ☐ terrain
 color transparency

EXPORT YOUR COLORS >>

how to use | updates | credits

COLORBREWER 2.0
color advice for cartography

SCORE CARD

[learn more >](#)

© Cynthia Brewer, Mark Harrower and The Pennsylvania State University
[Support](#)
[Back to ColorBrewer 1.0](#)

axm

ColorBrewer diverging legend



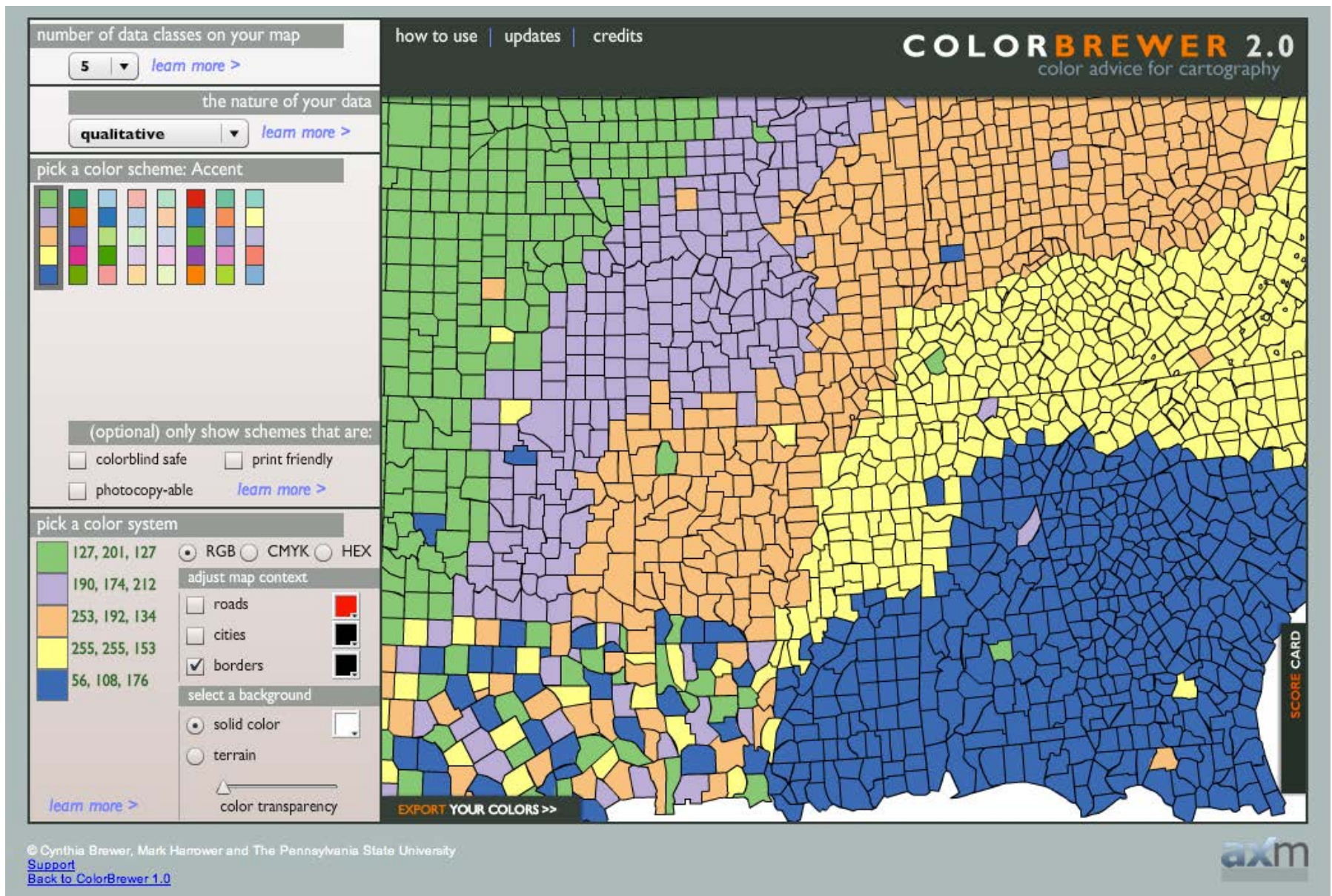
- Qualitative Legend

for categorical data

no ordering, no high or low

stress discrete categories, not values





ColorBrewer qualitative legend



Statistical Maps



- Quantile Map

data sorted from low to high

equal number of observations in each interval

examples

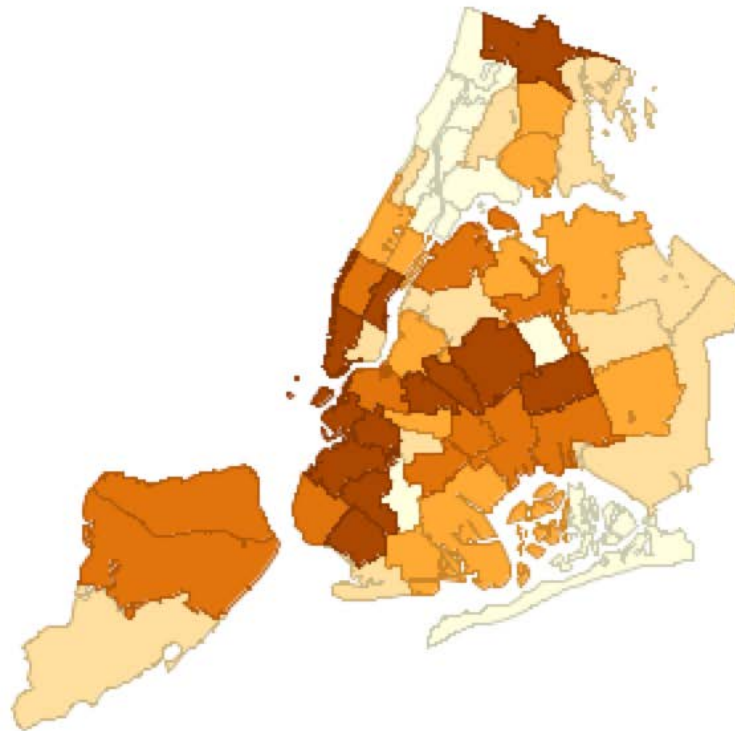
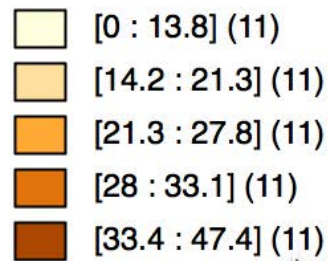
quartile map (4 categories)

quintile map (5 categories)

possible issues with ties



Quantile: RENTPCT08



quintile map (NYC % rental units)

- **Box Map**

identifying outliers

same principle as in box plot

fence = median + 1.5 IQR or + 3 IQR

IQR = inter quartile range, 25% to 75%

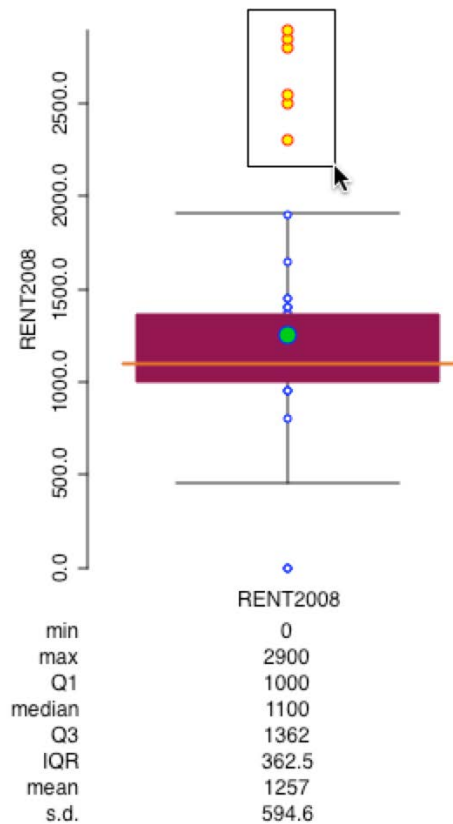
six intervals

same principle as quartile map

outliers identified as a separate category



Box Plot (Hinge=1.5): RENT2008

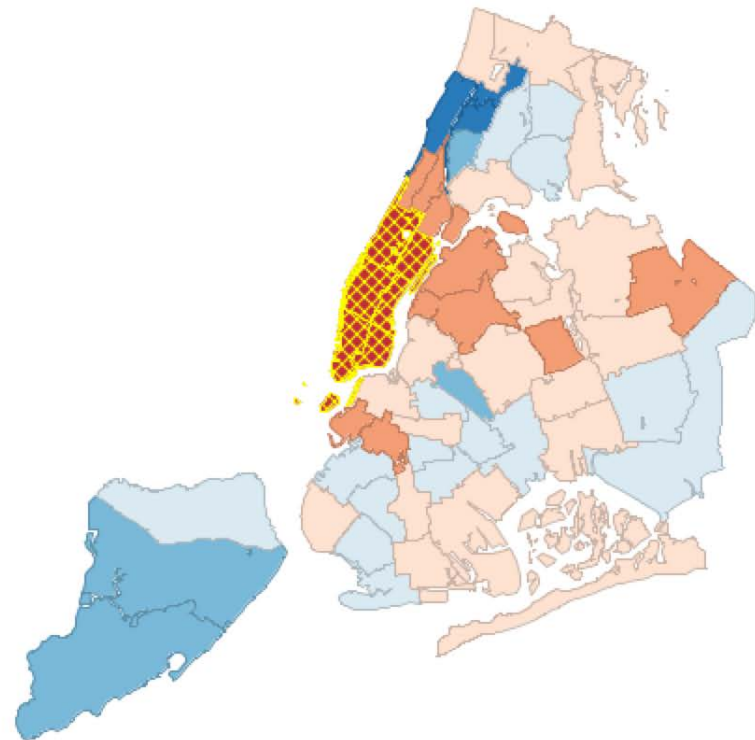


#selected=6

Hinge=1.5: RENT2008

- Lower outlier (3) [0.0e+00 : 1.36e+03]
- < 25% (4) [456 : 1e+03]
- 25% - 50% (15) [1e+03 : 1.36e+03]
- 50% - 75% (19) [1.36e+03 : 1.36e+03]
- > 75% (8) [1.36e+03 : 1.36e+03]
- Upper outlier (6) [1.36e+03 : 1.36e+03]

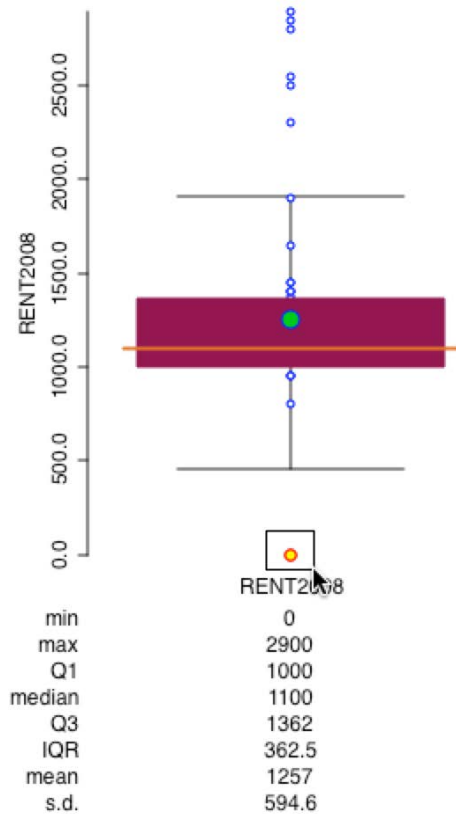
#obs=55 #selected=6



upper outliers in box plot and box map
(NYC median rent 2008)



Box Plot (Hinge=1.5): RENT2008

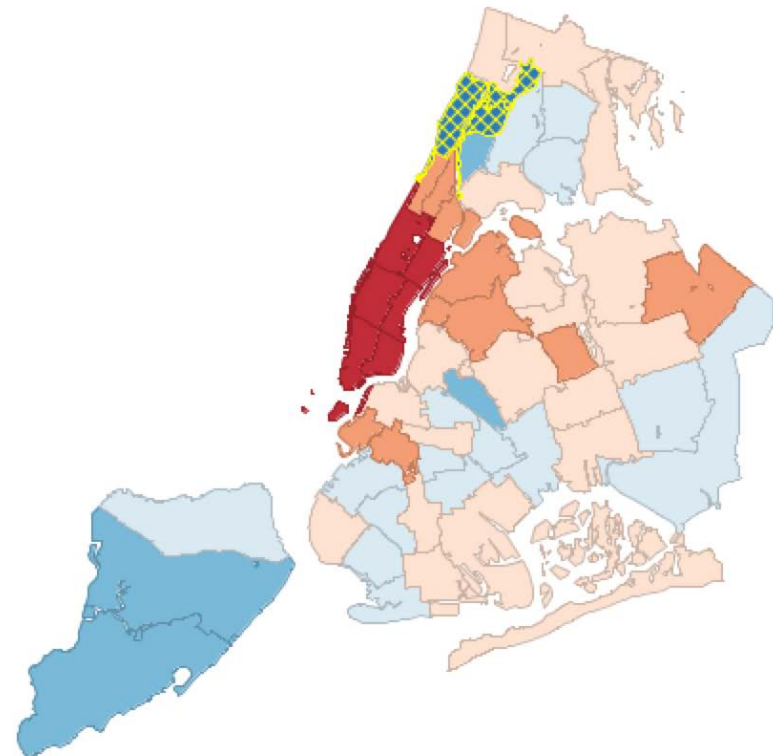


#selected=3

Hinge=1.5: RENT2008

- Lower outlier (3) [0
- < 25% (4) [456 : 1e
- 25% - 50% (15) [1e
- 50% - 75% (19) [1.1
- > 75% (8) [1.36e+0
- Upper outlier (6) [1.5

#obs=55 #selected=3



lower outliers in box plot and box map
(NYC median rent 2008)



- Standard Deviation Map

based on standardized data values

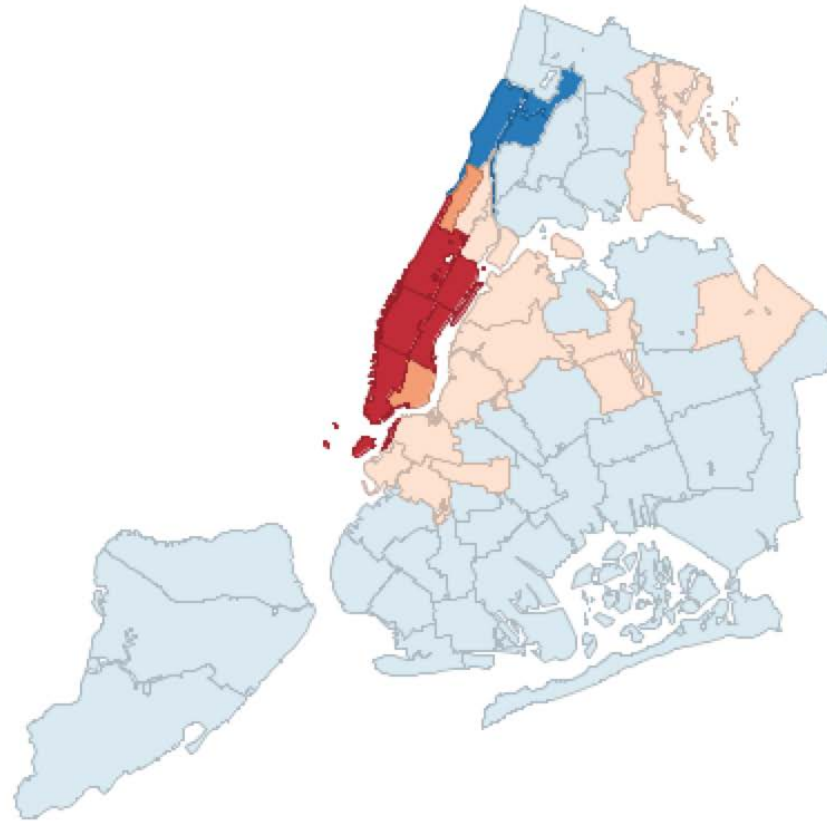
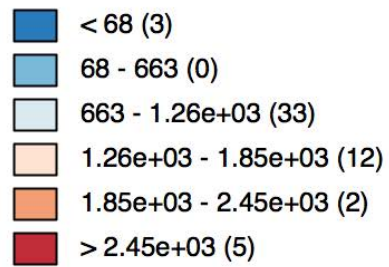
mean = 0, standard deviation = 1

intervals correspond to one standard deviation

outliers are more than 2 standard deviations from the mean



Standard Deviation: RENT2008



standard deviational map
(NYC median rent 2008)



- Cartogram

areal unit proportional to variable of interest

avoid misleading effect of area

use transformed shapes

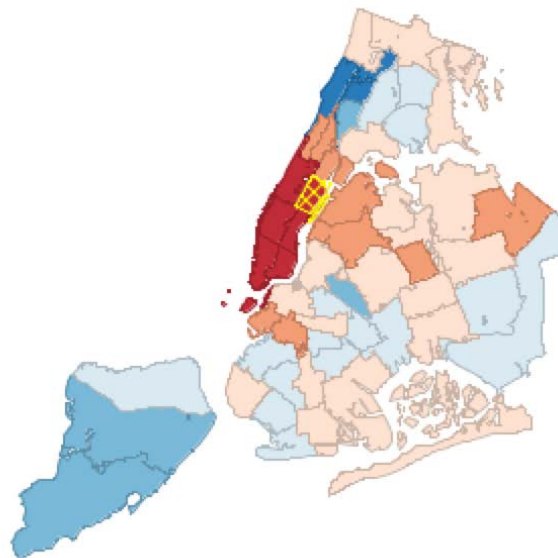
circular cartogram

contiguous cartogram



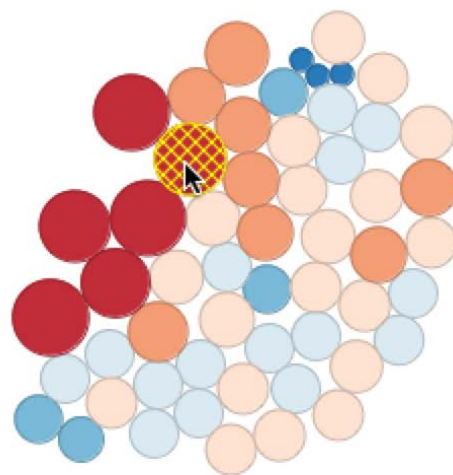
Hinge=1.5: RENT2008

- Lower outlier (3)
- < 25% (4) [456 : 1e
- 25% - 50% (15) [1e
- 50% - 75% (19) [1.
- > 75% (8) [1.36e+C
- Upper outlier (6) [1



Hinge=1.5: RENT2008

- Lower outlier (3) [0
- < 25% (4) [456 : 1e
- 25% - 50% (15) [1e
- 50% - 75% (19) [1.
- > 75% (8) [1.36e+C
- Upper outlier (6) [1



box map and circular cartogram

- Conditional Maps

cc maps, conditioned choropleth maps (Carr)

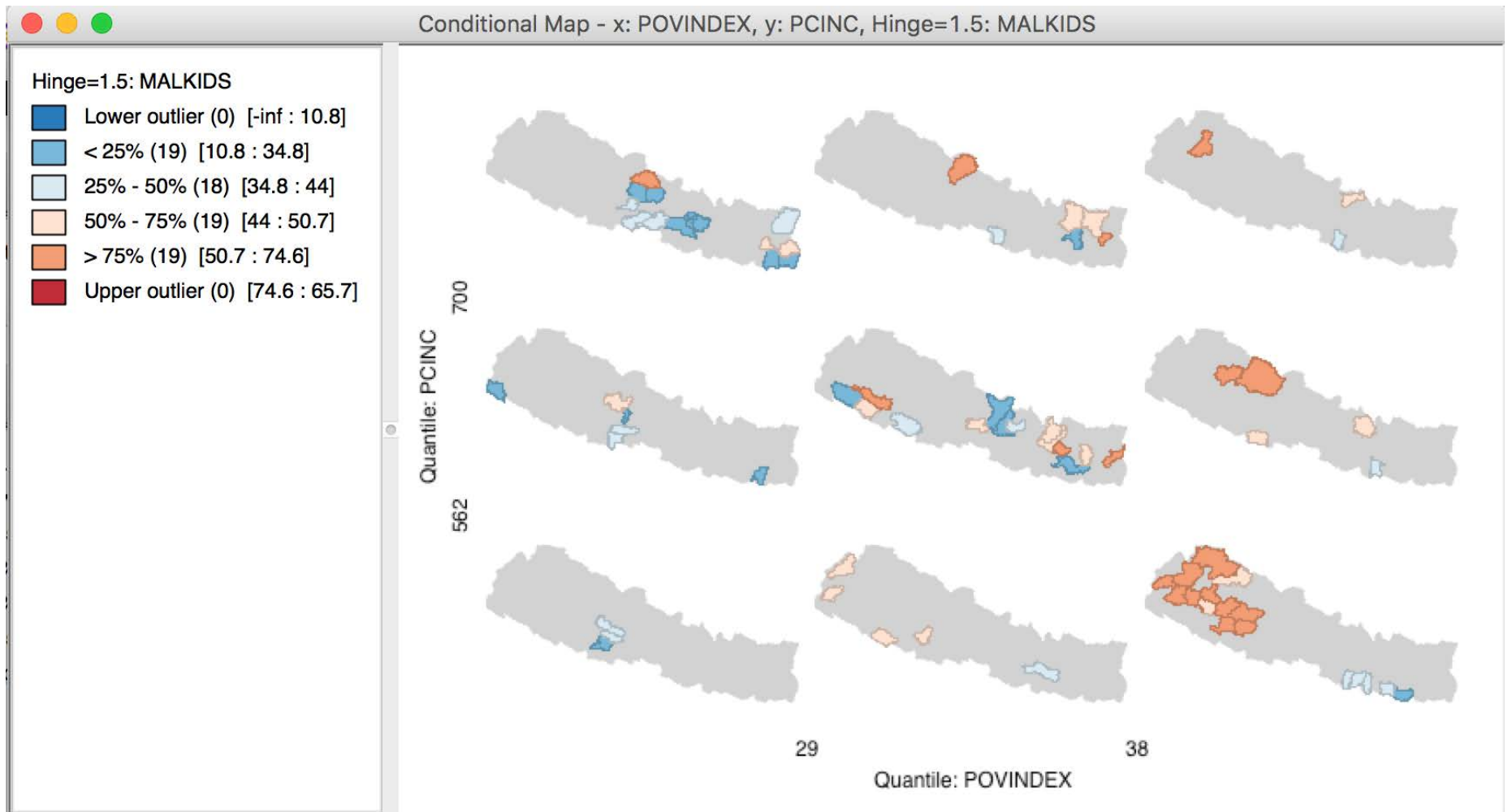
special case of trellis graphs

micromap matrix

conditioning variables on the axes

matrix of mini maps for the variable of interest
conditioned by the values on the axes





child malnutrition cc map conditioned on poverty index
and per capita income (Nepal districts)

- Map Animation

map movie

highlight observations in increasing or decreasing order

one at a time

cumulative

visual impression of patterning/clustering



Mapping Rates



Risk and Rates



- Concept of Risk

many meanings

risk = probability that an event may occur

actual risk is not observed

only events are observed



- Risk Estimate

raw rate or crude rate

number of events / population at risk

typically expressed in per 1,000 or some multiple

crude rate is maximum likelihood estimate



- Rate Maps

focus on spatial heterogeneity

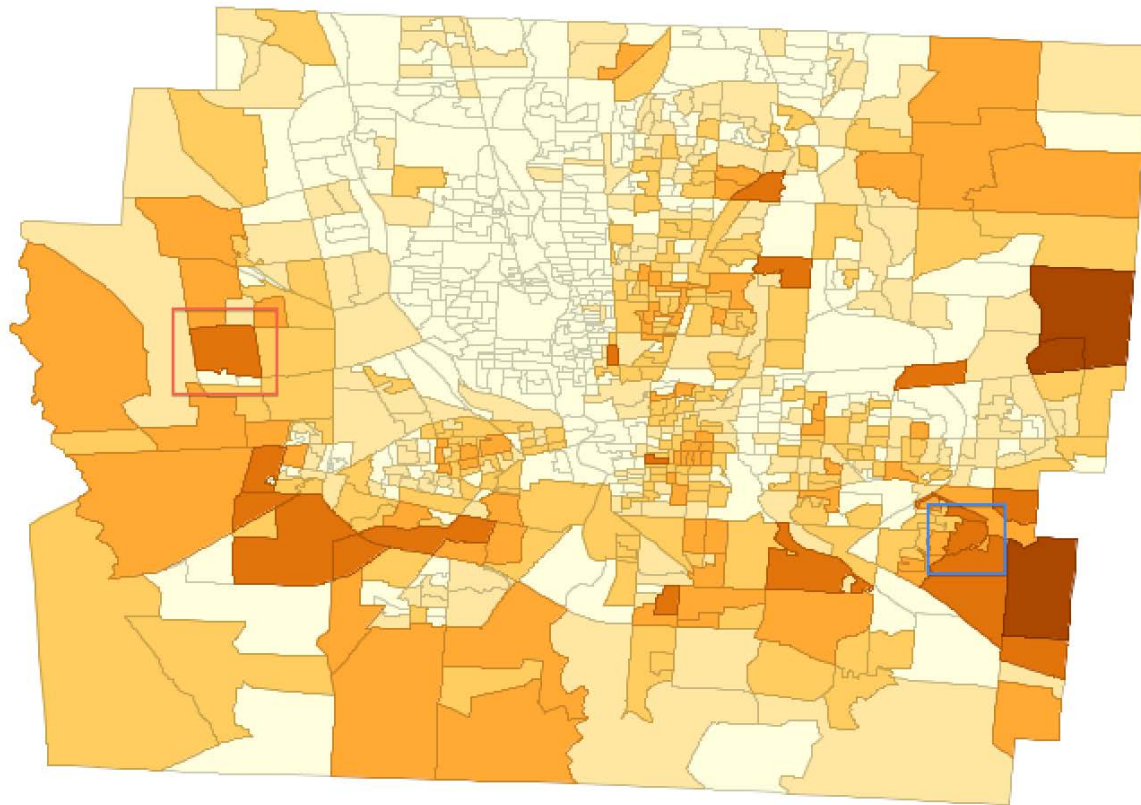
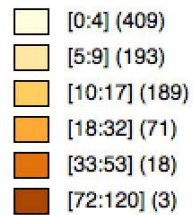
risk is not uniform across space

interest in identifying areas of elevated risk

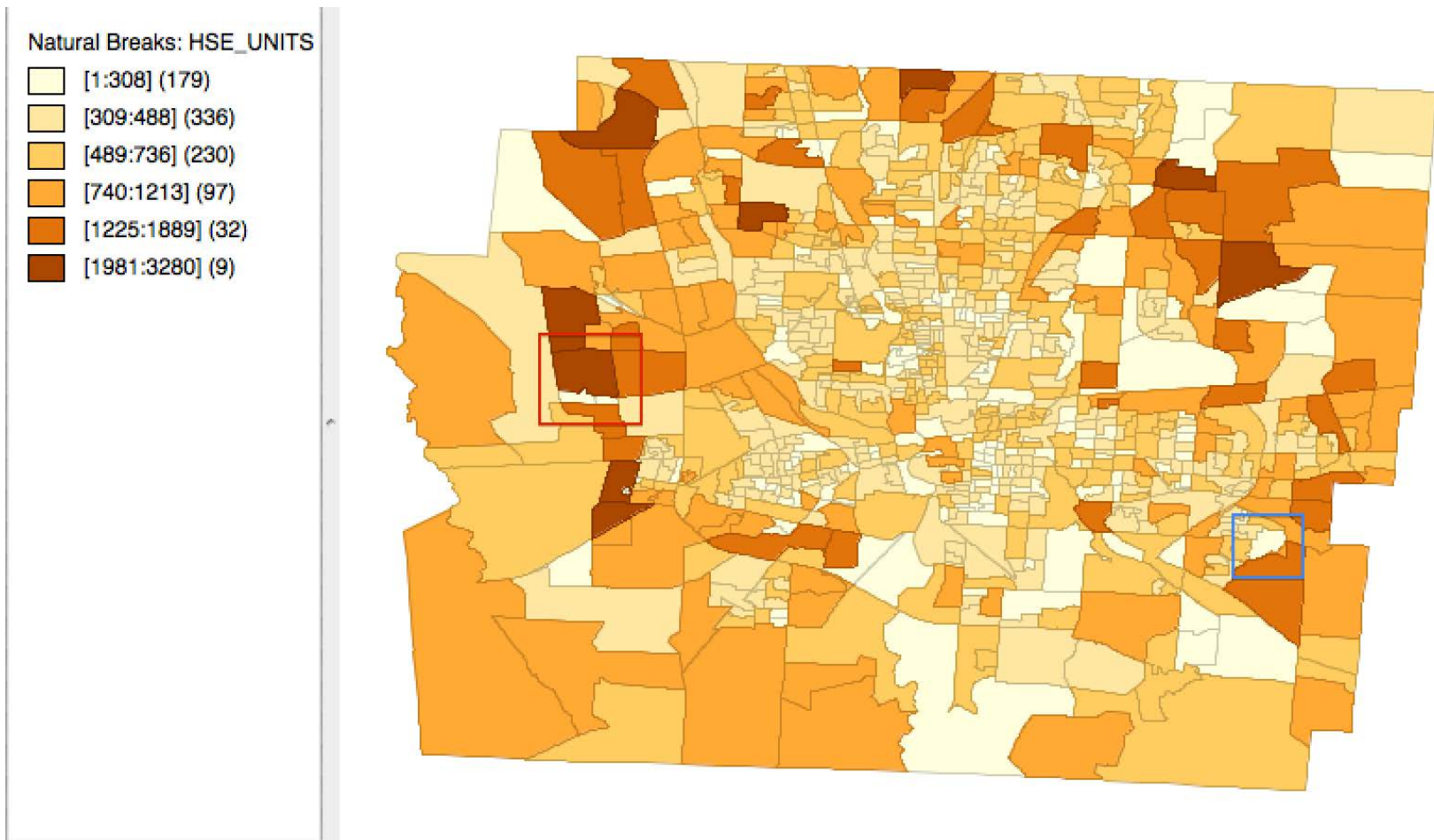
associate elevated risk with causal factors



Natural Breaks: FORECL

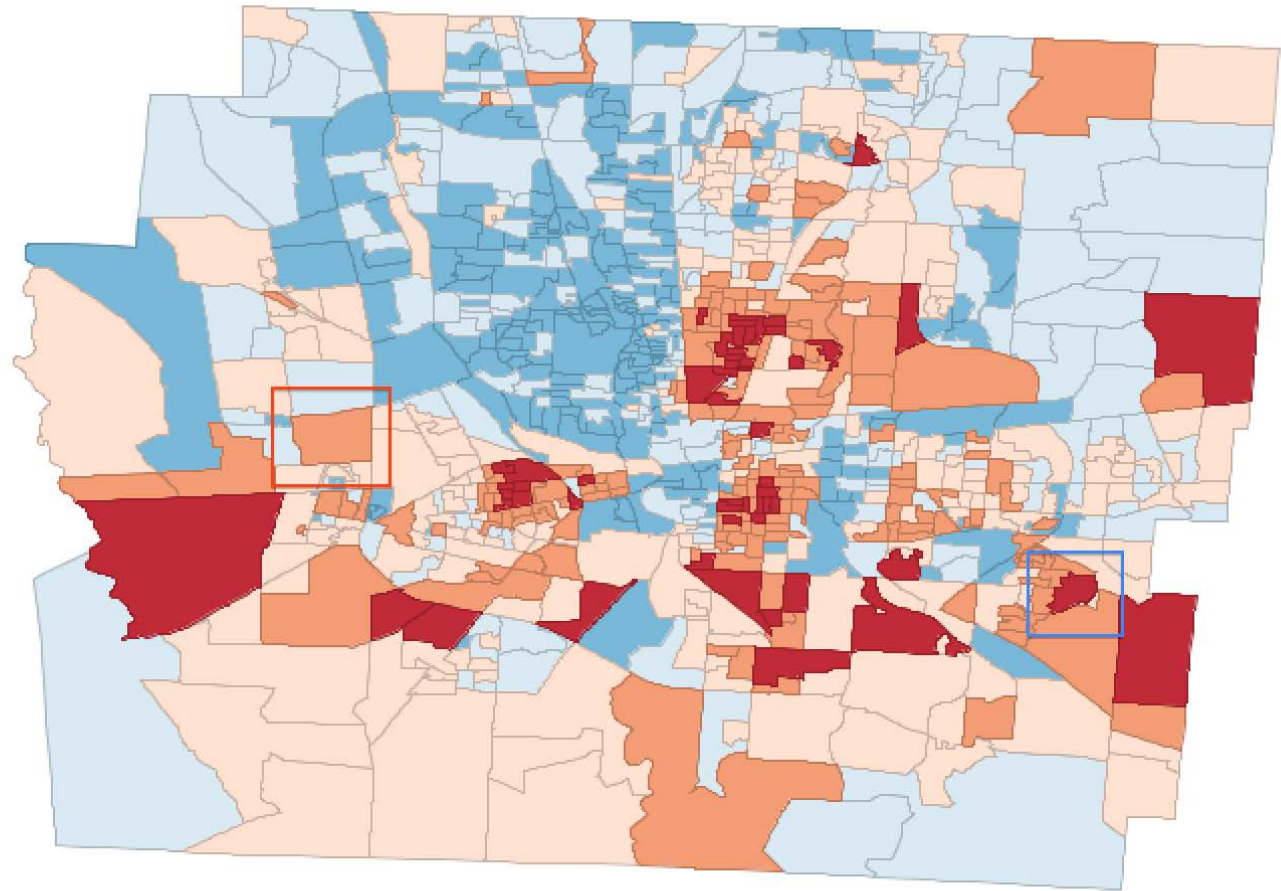
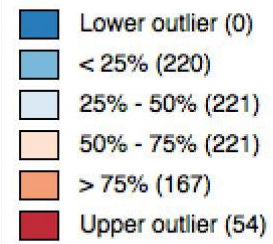


Foreclosure Count in Franklin county (OH), 2007



Housing Units in Franklin county (OH), 2007

Hinge=1.5: Raw Rate FO



Foreclosure Rate Outliers in Franklin county (OH), 2007

Excess Risk



- What is Excess Risk?

elevated risk = higher than some standard

what is the standard

rate computed for a reference group

e.g., foreclosure for the whole city



- Average Risk

not the average of the rates

total number of events / total population

e.g., all the foreclosed homes in the metro area
over all the homes in the metro area

weighted average of the rates, weighted by their
population share



- Average Risk Computation

O_i : observed number of events

P_i : “population at risk”

r_i : rate for i , $r_i = O_i / P_i$

average risk $r = (\sum_i O_i) / (\sum_i P_i)$



- Expected Events

$$E_i = r \times P_i$$

expected events = average rate times the
“population” in area i

e.g., if average risk of an event is 1 per 10,000,
then a county of 30,000 would have 3 expected
events



- Relative Risk

compare observed to expected

observed = number of events, O_i

expected = number of events if average were applied to population, E_i

relative risk

observed / expected, O_i / E_i



- Excess Risk Map

compare relative risk to unity

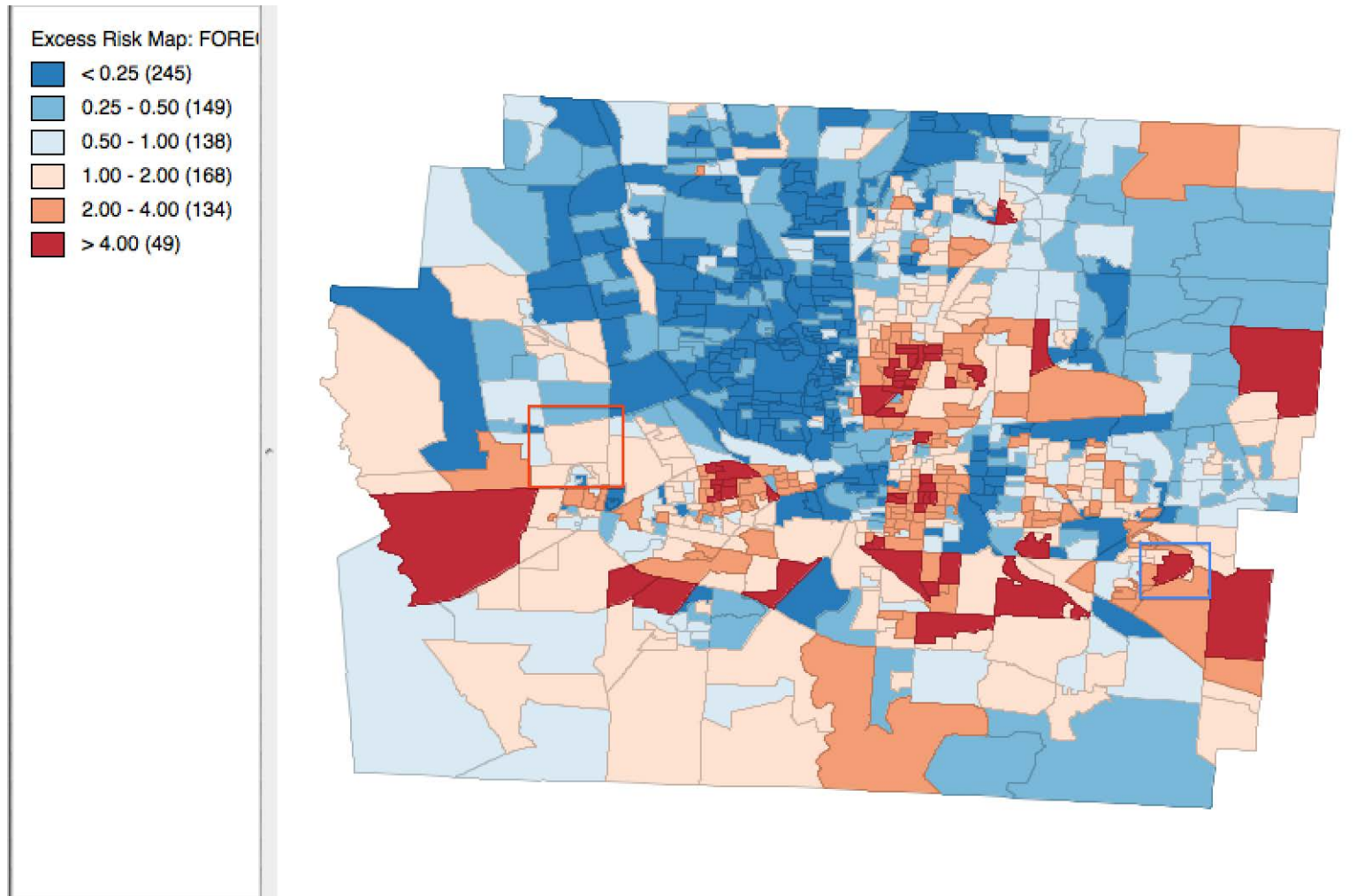
> 1: more events than on average

higher (excess) risk

< 1: fewer events than on average

choropleth map of excess risk





Franklin County 2007 foreclosures excess risk

Smoothing Rates



number of events as draws from a binomial distribution

$$\text{Prob}[O = x] = \binom{P}{x} \pi^x (1 - \pi)^{P-x}, \text{ for } x = 0, 1, \dots, P.$$

probability of x events given risk of π

$$\text{mean: } E [O] = \pi.P$$

$$\text{variance: } V [O] = \pi (1 - \pi).P$$



- Moments of the Rate Estimate

O is random variable, P is not

$$r = O / P \quad O \text{ events, } P \text{ population}$$

$$E[r] = E[O]/P = \pi P / P = \pi$$

$$\begin{aligned} \text{Var}[r] &= \text{Var}[O] / P^2 = \pi (1 - \pi) P / P^2 \\ &= \pi (1 - \pi) / P \end{aligned}$$



- Variance Instability

P in denominator

smaller areas have larger variance = less precision

Example

with true (unknown) $\pi = 0.1$

Pop 1 = 500 and Pop 2 = 100,000

SE1 = 0.013 and SE2 = 0.0009



- Why Smooth?

rate estimates have variable reliability

less precision for smaller areas

why trust (e.g., no events = zero risk?)

borrow strength

use additional information to improve estimate



- Shrinkage (James-Stein)

new estimate that improves overall precision
while sacrificing some bias

bias-variance tradeoff

shrink crude rate towards overall mean

overall mean contains useful information

shrink (smooth) rate as inverse function of variance



- Effect of Shrinkage

smoothing depends on variance

small population > large variance
> a lot of smoothing

large population > small variance
> little smoothing



- Empirical Bayes Smoothing

shrinkage estimate as a weighted average of the crude rate and a prior

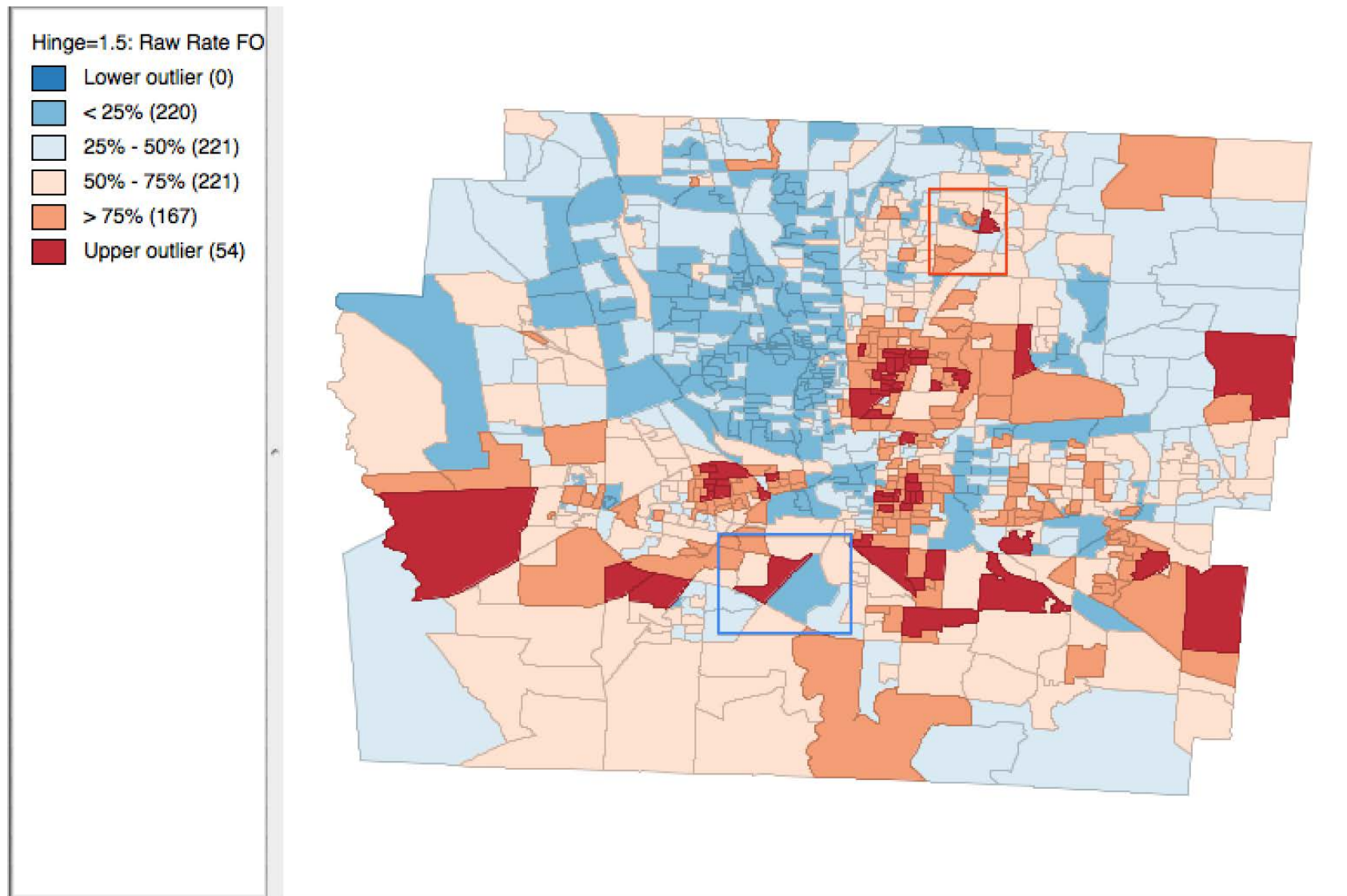
prior estimated from the data (reference rate)

hence “empirical” Bayes

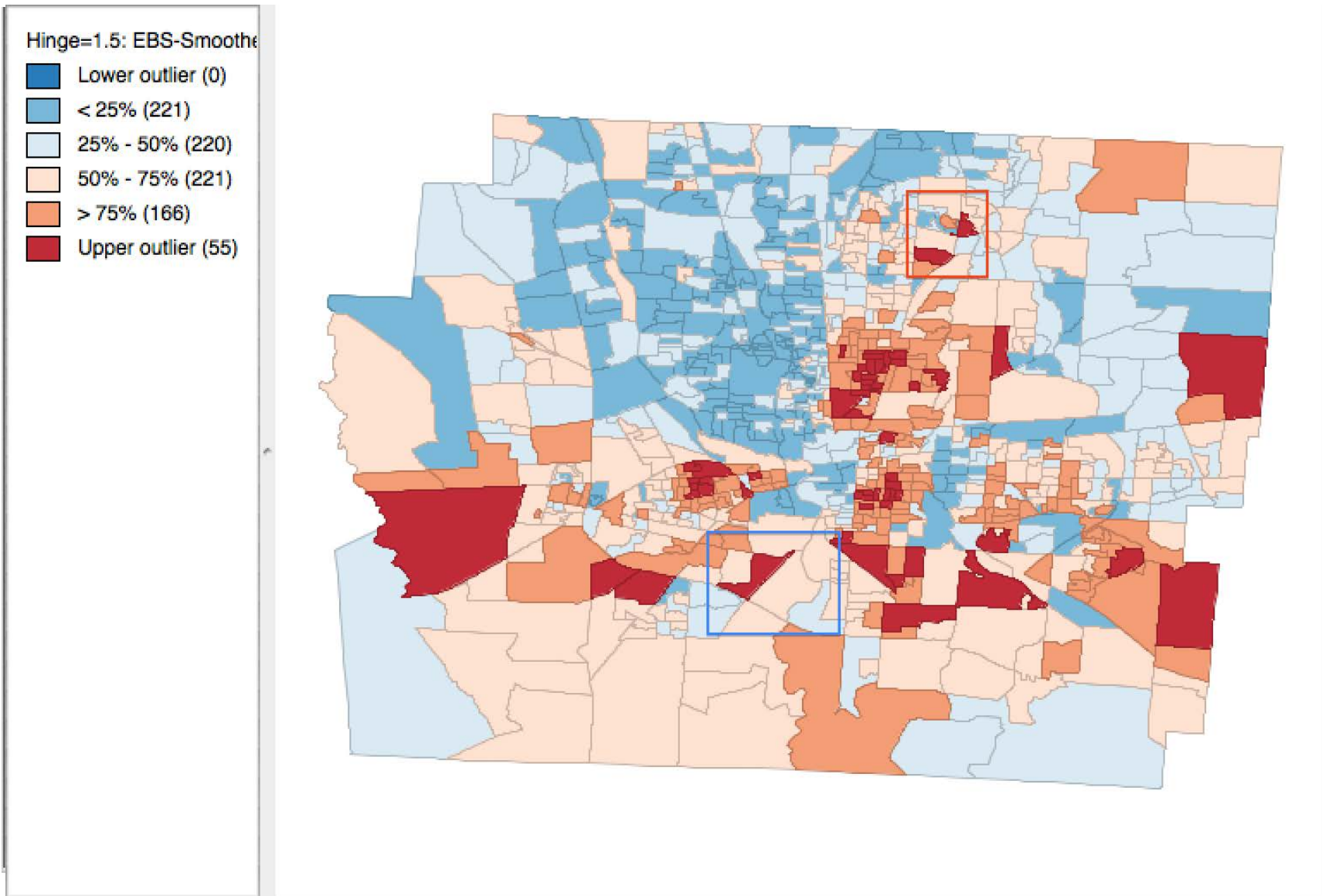
$\pi_i = w_i r_i + (1 - w_i) \theta$ with θ as reference rate

weights inversely proportional to variance





Foreclosure Raw Rate in Franklin county (OH), 2007



Foreclosure EB Rate in Franklin county (OH), 2007

- Effect of Empirical Bayes Smoothing

position changes in cumulative distribution

small outlier areas move towards the overall mean

large high/low value areas may become outliers

spurious outliers are removed



To Smooth or Not To Smooth



- Pros of Smoothing

better estimates in MSE sense

adjusts for variance instability

removes spurious outliers

better estimates of true extremes



- Cons of Smoothing

degree of arbitrariness

sensitive to smoothing method

oversmoothing hides interesting “outliers”



- Smoothing in Practice

some healthy debate

use of original data vs transformed data

many options

need for sensitivity analysis

