Why Public Health Needs GIS?

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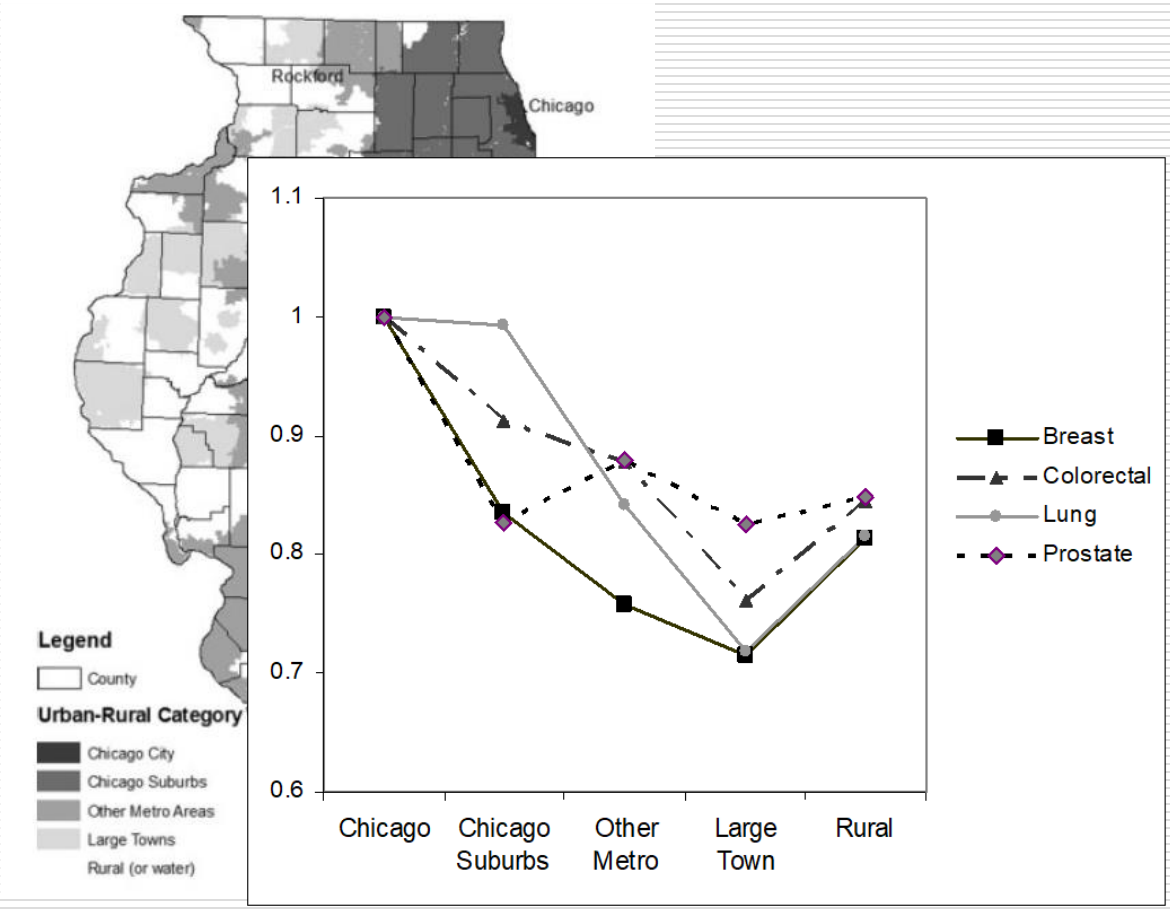
1. Geographic heterogeneity
2. S/D interaction across borders
3. Neighborhood effect
4. Small population problem
5. Delineating healthcare markets
6. Toward equality

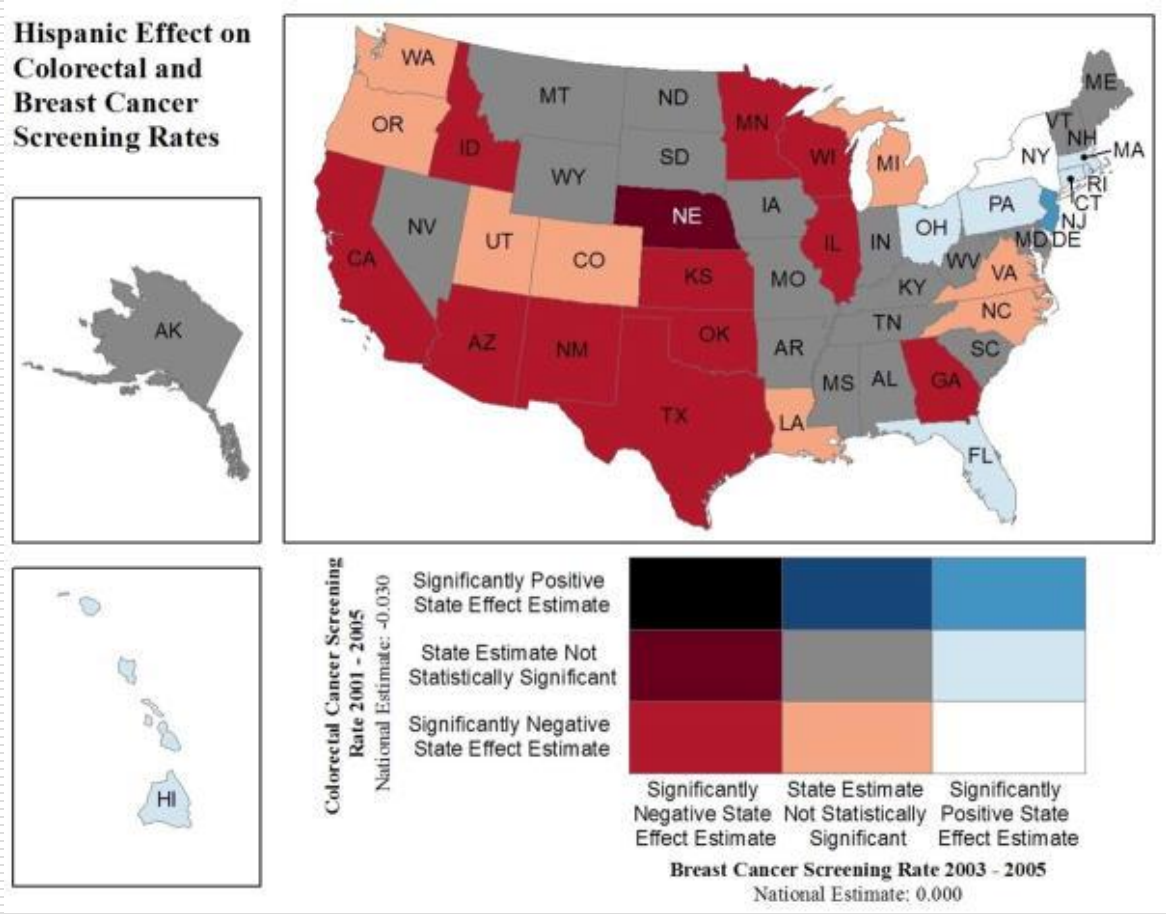
- recap

1. "One size does NOT fit all"

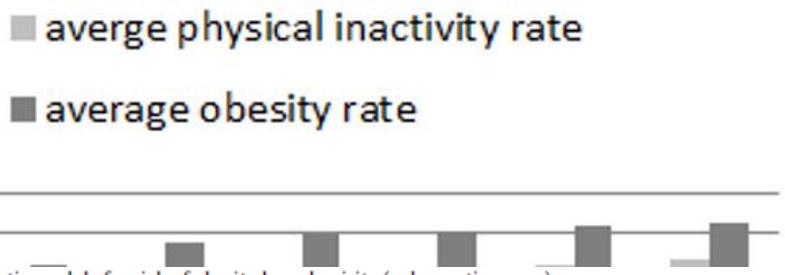
Late-stage cancer risks in IL 1998-2002



African American (Relative to Whites) Colorectal/Breast Cancer Screening 2001-05



Obesity rate in the U.S. 2012



Multilevel logistic models for risk of obesity by urbanicity (urban ratio range).

	Completely urban (0.99–1.00)[a]	Highly urban (0.90–0.99)	Mostly urban (0.50–0.89)	Marginally urban (0.01–0.49)	Completely rural (0–0.01)
Intercept	0.13670***	0.13880***	0.07865***	0.09523***	0.02024***
Individual-level variables					
Female	0.03315***	−0.00856*	−0.01254***	−0.00184	−0.01152
Age (18+)	0.01993***	0.01885***	0.01954***	0.01828***	0.01918***
Age squared	−0.00019***	−0.00019***	−0.00019***	−0.00019***	−0.00020***
Hispanic	−0.01487	−0.00784	−0.00334	0.00845	0.02436
Married	−0.02567***	−0.01184**	−0.00347	0.00734	0.00398
Education (1–6)	−0.04797***	−0.03150***	−0.02752***	−0.01900***	−0.01371***
Employed	0.00172	−0.00625	−0.01091**	−0.01879***	−0.01924
Income (1–8)	−0.01382***	−0.01797***	−0.01663***	−0.01761***	−0.01881***
Smoker	−0.01065	−0.03183***	−0.03556***	−0.04628***	−0.04918***
County-level variables					
Racial-ethnic heterogeneity	−0.14690*	−0.04767	0.00090	0.00828	0.00300
Poverty	0.00275*	0.00423***	0.00145**	0.00179***	0.00327***
Population-adjusted street connectivity	0.00002	−0.00039***	−0.00006	−0.00014	0.00021
No. observations	17,428	43,763	99,711	68,500	21,846
AIC	9038.2	7804.3	4118.4	1346.4	6136.2

*** Statistically significant at 0.001, ** statistically significant at 0.01, * statistically significant at 0.05.

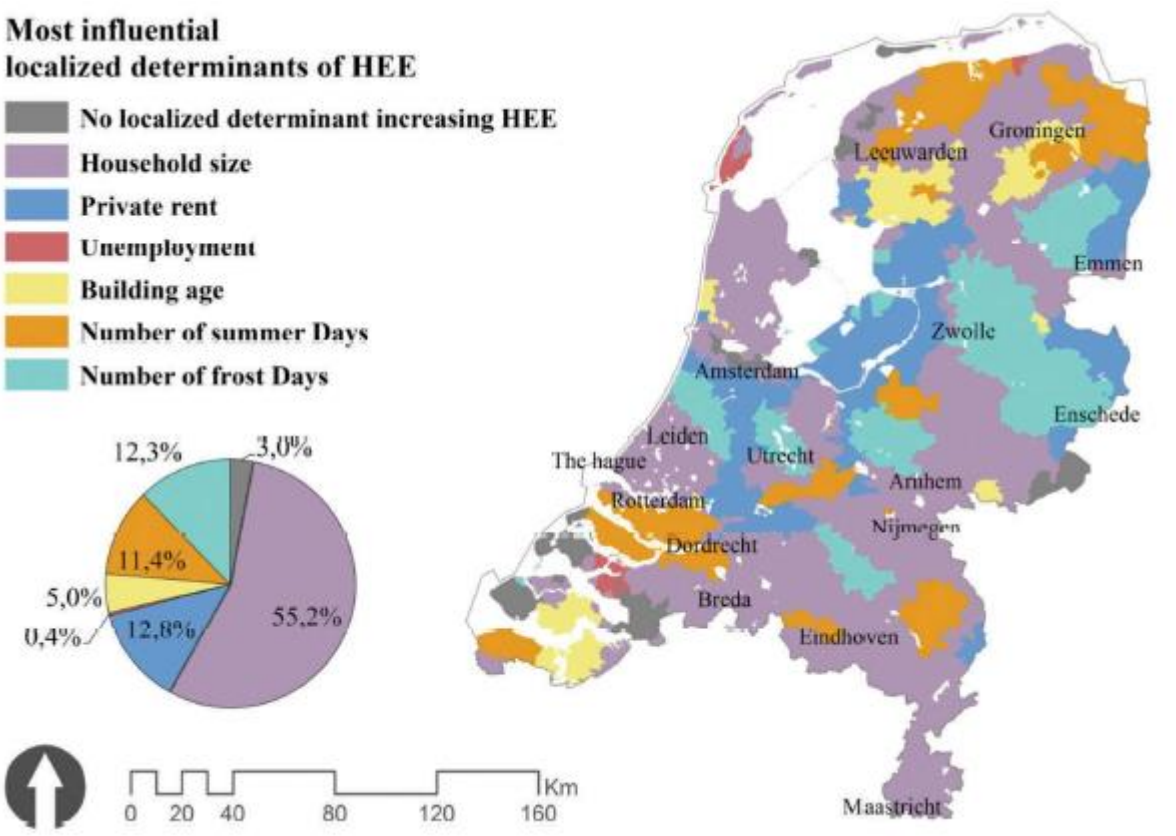
[a] Range of urban ratio in parenthesis.

Household energy expenditure in Netherland 2014

Table 3. Estimates of SGWR model.

Variable	Spati
Intercept	
Household size	
Private rent (%)	
Low income (%)	0.4
Unemployment (%)	
Pensioner (%)	0.1
Building age	
Number of summer days	
Number of frost days	
R^2	0.7
Adjusted R^2	0.7

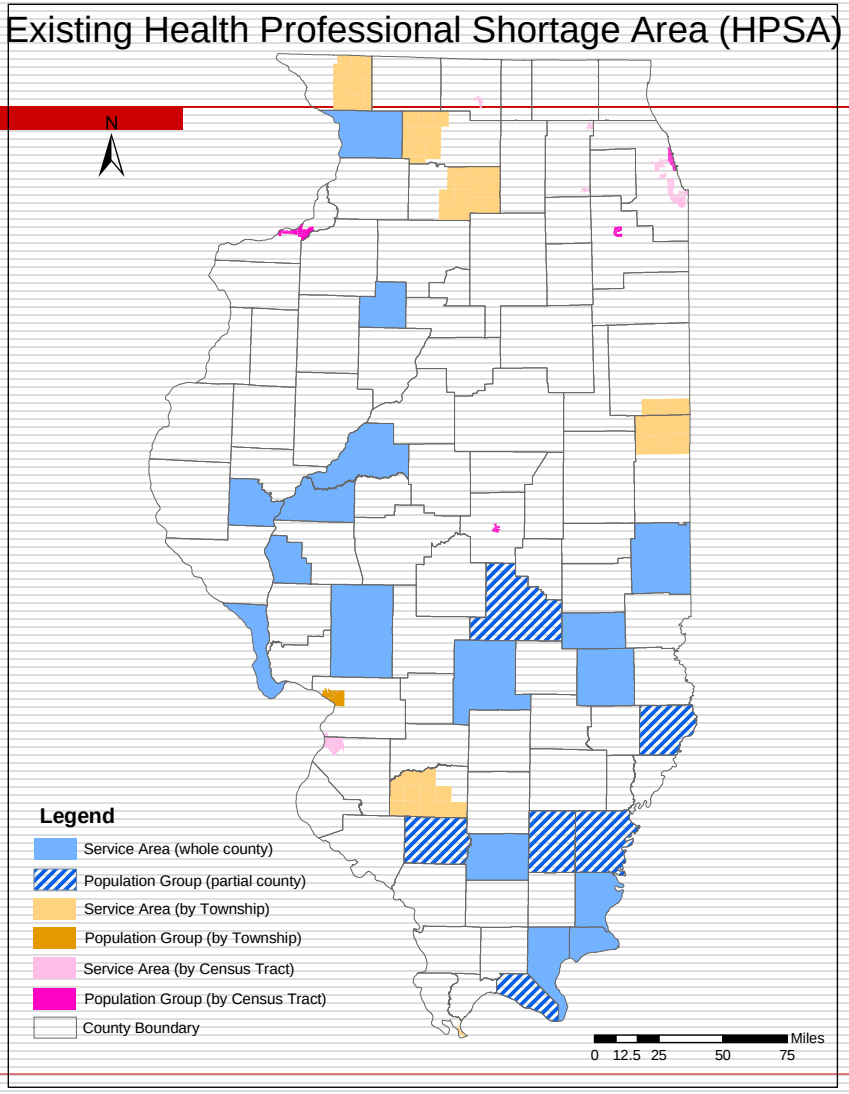
β: standardized regression coefficient.
**p value <0.01.



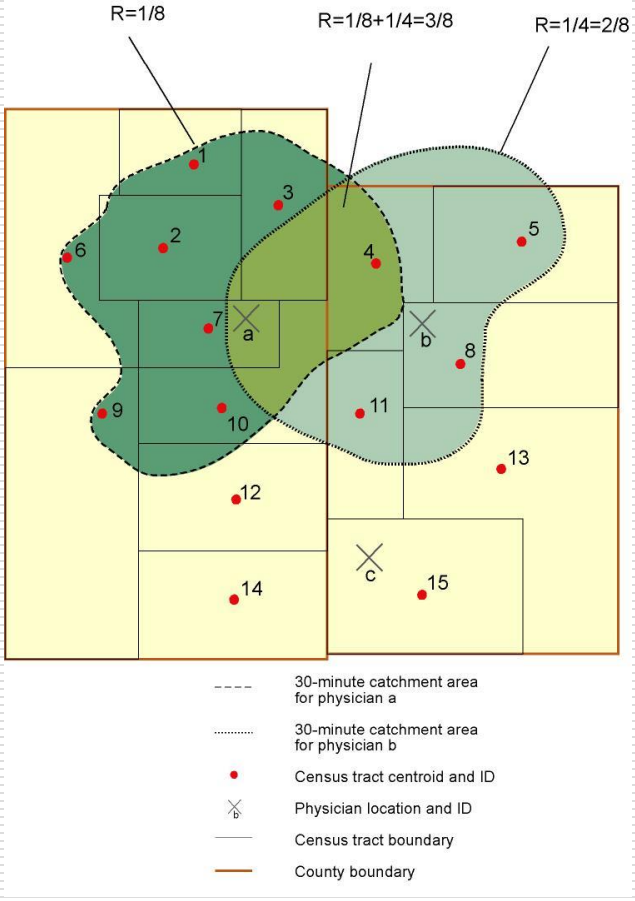
Reflection

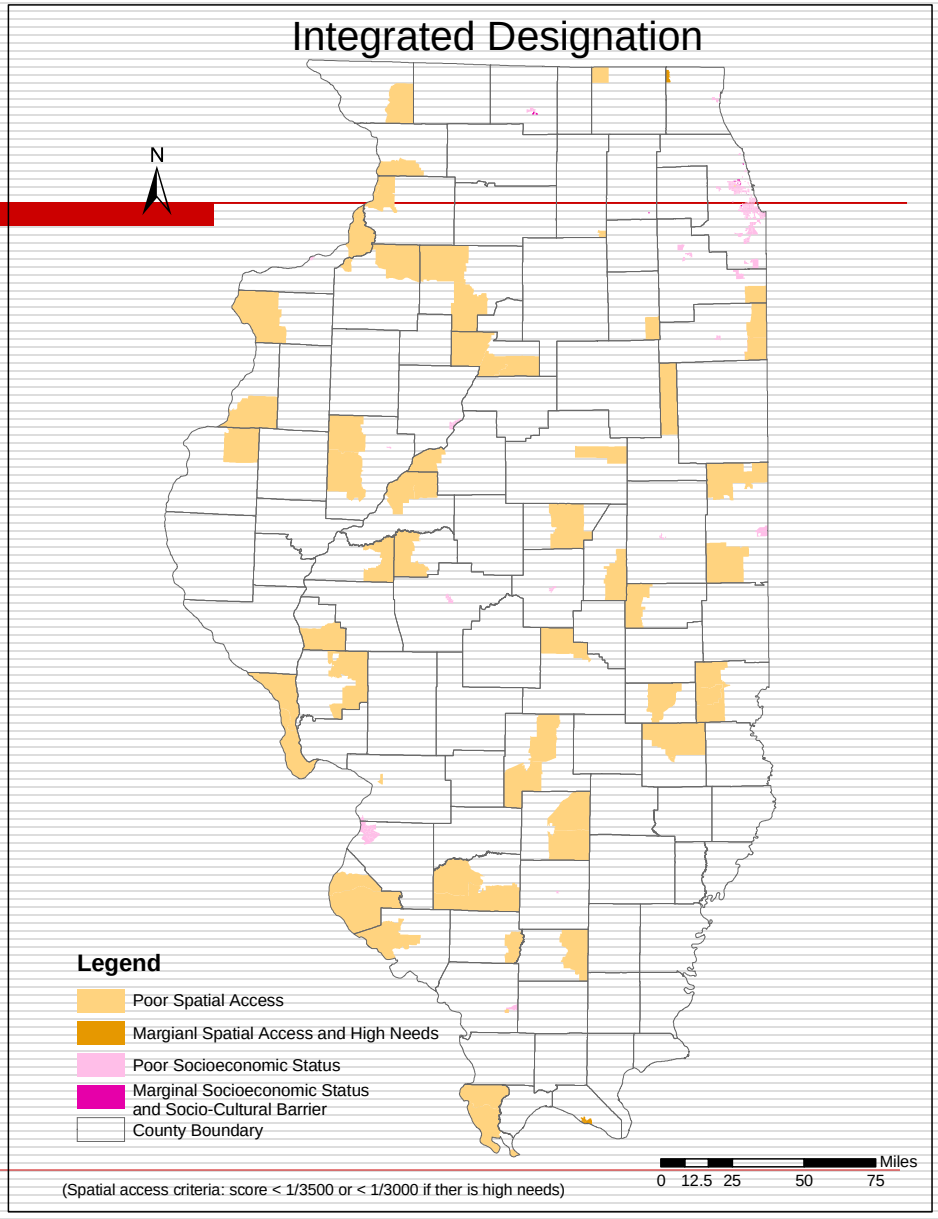
- Distinctive dynamics in various geographic settings
- GIS is best at delineating them
- SGWR sorts out global vs. local effects
- One-size-fits-all public policy approach is wasteful and ineffective

2. “No wall”


Existing Health Professional Shortage Area (HPSA)
N
Legend
Service Area (whole county)
Population Group (partial county)
Service Area (by Township)
Population Group (by Township)
Service Area (by Census Tract)
Population Group (by Census Tract)
County Boundary
Miles
0 12.5 25 50 75

2SFCA


R=1/8
R=1/8+1/4=3/8
R=1/4=2/8
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
a
b
c
30-minute catchment area for physician a
30-minute catchment area for physician b
Census tract centroid and ID
Physician location and ID
Census tract boundary
County boundary


Integrated Designation
N
Legend
Poor Spatial Access
Margianl Spatial Access and High Needs
Poor Socioeconomic Status
Marginal Socioeconomic Status and Socio-Cultural Barrier
County Boundary
Miles
0 12.5 25 50 75
(Spatial access criteria: score < 1/3500 or < 1/3000 if ther is high needs)

From 2SFCA to Inverted-2SFCA

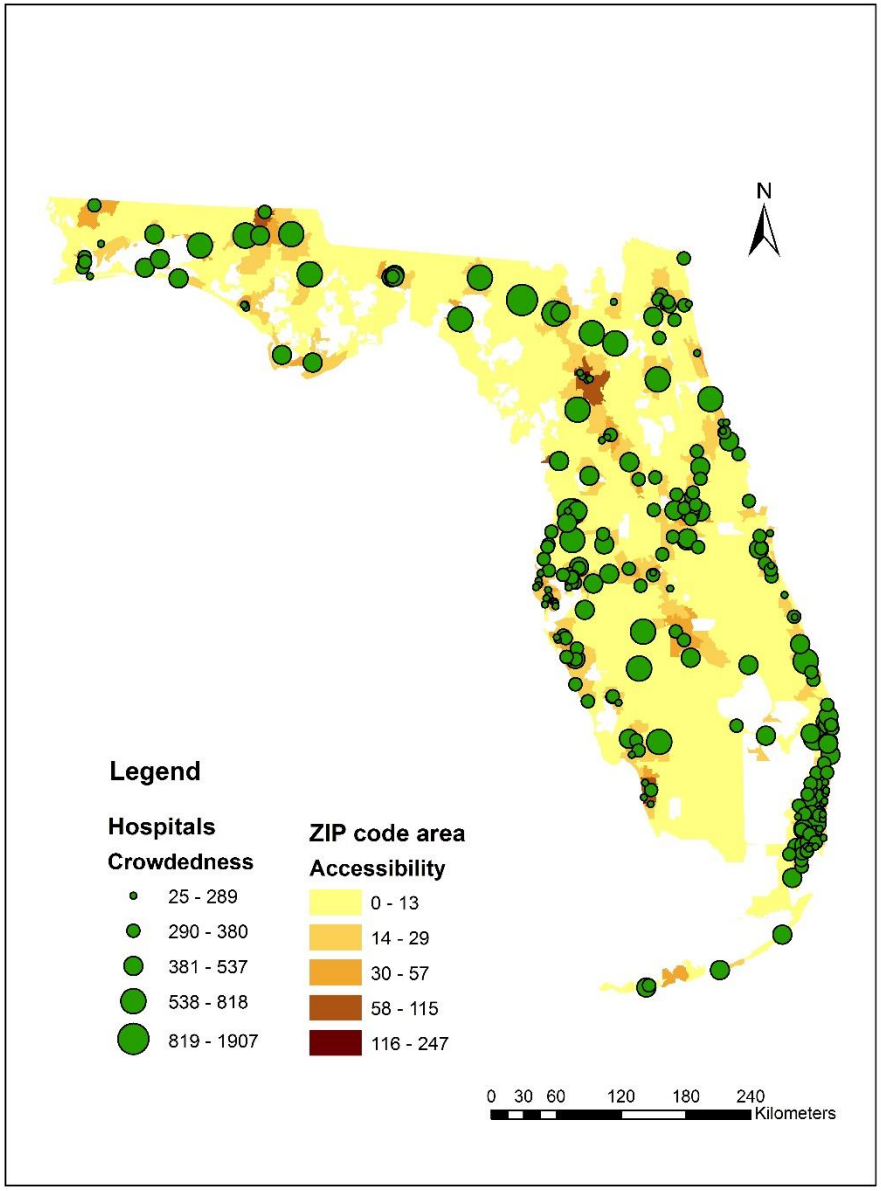
- Capture availability at each supply: $S/\Sigma P$
- Sum up accessible supplies around each demand: $\Sigma(S/\Sigma P)$

Resident accessibility

Facility crowdedness

- Capture competition intensity at each demand: $P/\Sigma S$
- Sum up reachable demands around each supply: $\Sigma(P/\Sigma S)$

Resident accessibility vs. Hospital crowdedness



Reflection

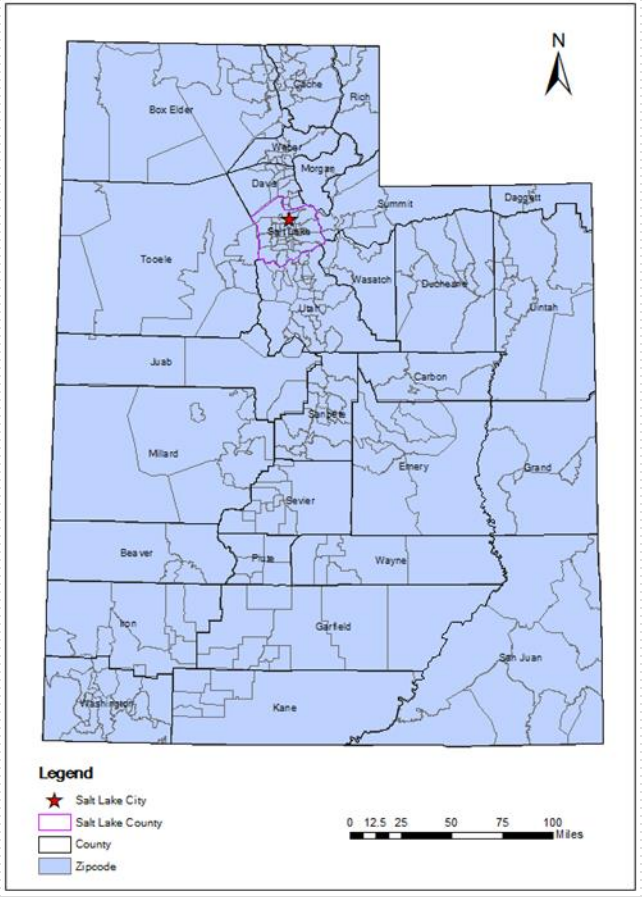
- Both proximity & availability matter in access to service
- Patients and service providers interact beyond unit borders
- GIS captures spatial behavior
- Geographic precision leads to policy precision and cost saving

3. "It depends on what the meaning of 'it (*neighborhood*)' is"

Table 1. Inferential errors due to the uncertain geographic context problem

True state of contextual effect	Observed state of contextual effect	
	Has effect	No effect
Has effect	Contextual units correct Correct inference	Contextual units incorrect False negatives (obscured contextual effect)
No effect	Contextual units incorrect False positives (spurious association)	Contextual units correct Correct inference

Obesity risk in Utah 2007-2011



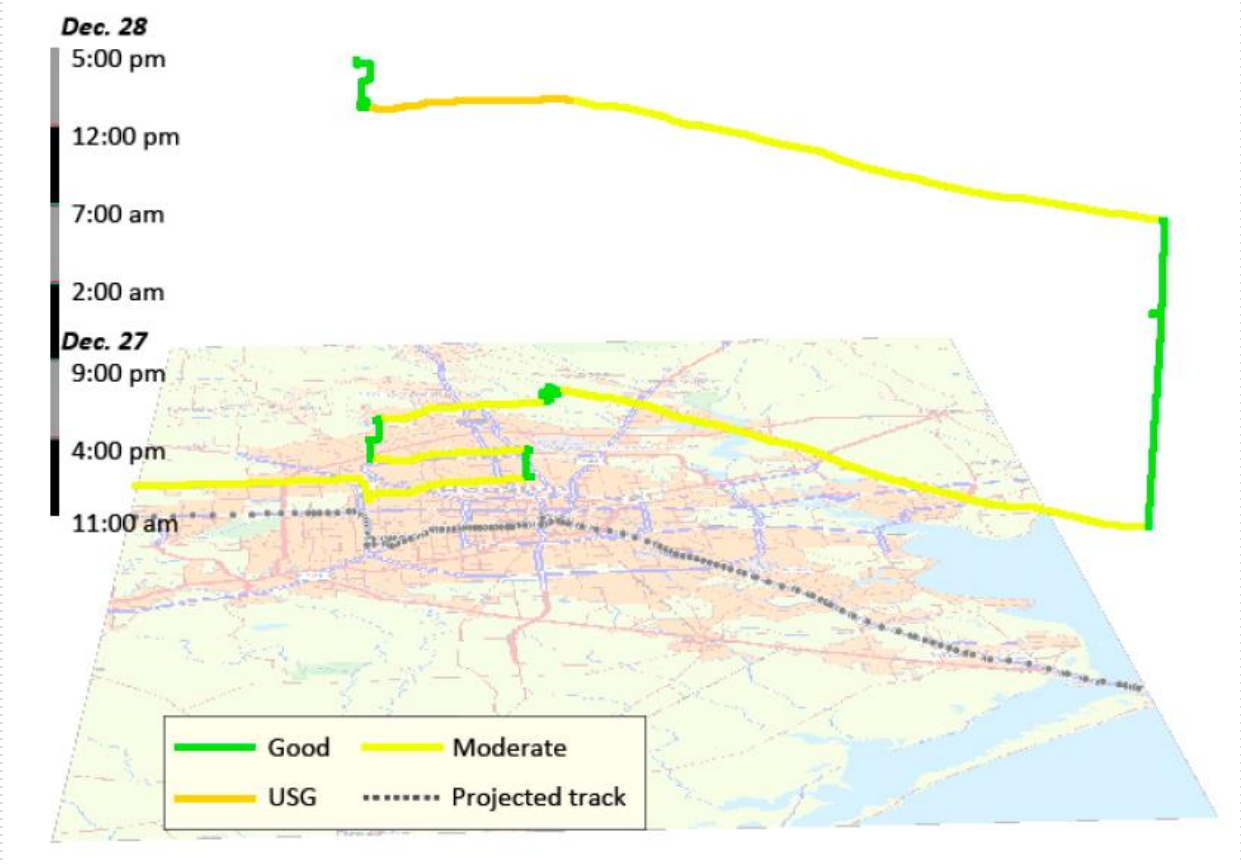
Adjusted odd ratios (95% Confidence interval) of the multilevel logistic models for odds of overweight or obesity (BMI $\geq$ 25).

	Model 1	Model 2	Model 3
Individual-level variables			
Age (18+)	1.135***	1.136***	1.136***
Age^2	0.999***	0.999***	0.999***
Female	0.475***	0.475***	0.475***
White	1.058	1.058	1.054
Married	1.039	1.039	1.040
College	0.823***	0.824***	0.820***
Self-employed	0.820***	0.821***	0.821***
Out of work for more than 1 year	0.964	0.964	0.962
Out of work for less than 1 year	0.967	0.970	0.969
Homemaker	0.734***	0.734***	0.734***
Student	0.861*	0.859	0.858
Retired	0.941	0.941	0.942
Smoker	0.945*	0.945*	1.768*
Zip code-level variables			
Poverty	2.104**	2.376*	1.768
Street connectivity	1.000	1.000	
Walk Score	1.000	1.000	
Distance to park	1.009	1.014*	1.012***
Fast food accessibility	0.999*	0.999	
Metro	1.003	0.975	
County-level variables			
Poverty		0.997	
Street connectivity		1.000	
Walk Score		1.005	
Distance to park		0.991	
Ratio of fast-food to full-service		1.128***	1.120***
Metro		0.926	
AIC	27,604.79	27,599.70	27,585.17

Sample size: 21,961 individuals living in 299 zip codes, 29 counties.
***$p \leq 0.001$, **$p \leq 0.01$, *$p \leq 0.05$ (two-tailed tests).

Dynamic exposure to green space & mental health

Personal Air Quality Index

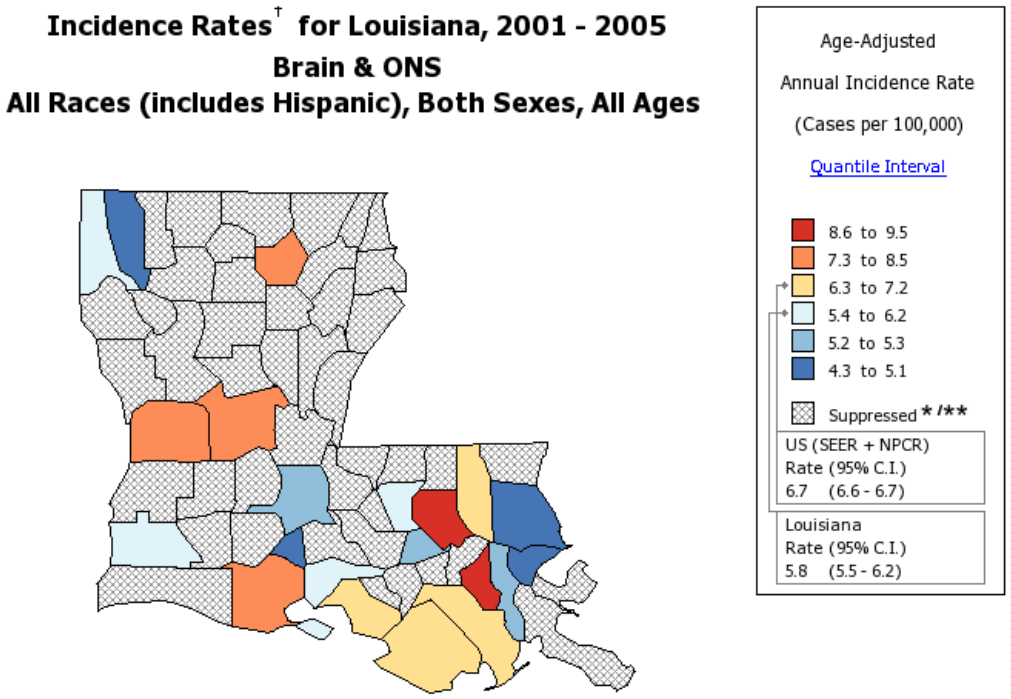


Reflection

- Policies at different levels of jurisdiction
- From neighborhood to “ego-hood”
- Activity space varies by activity purpose by demographic groups
- Dynamic exposure to environment
- GIS enables defining “individualized” neighborhoods

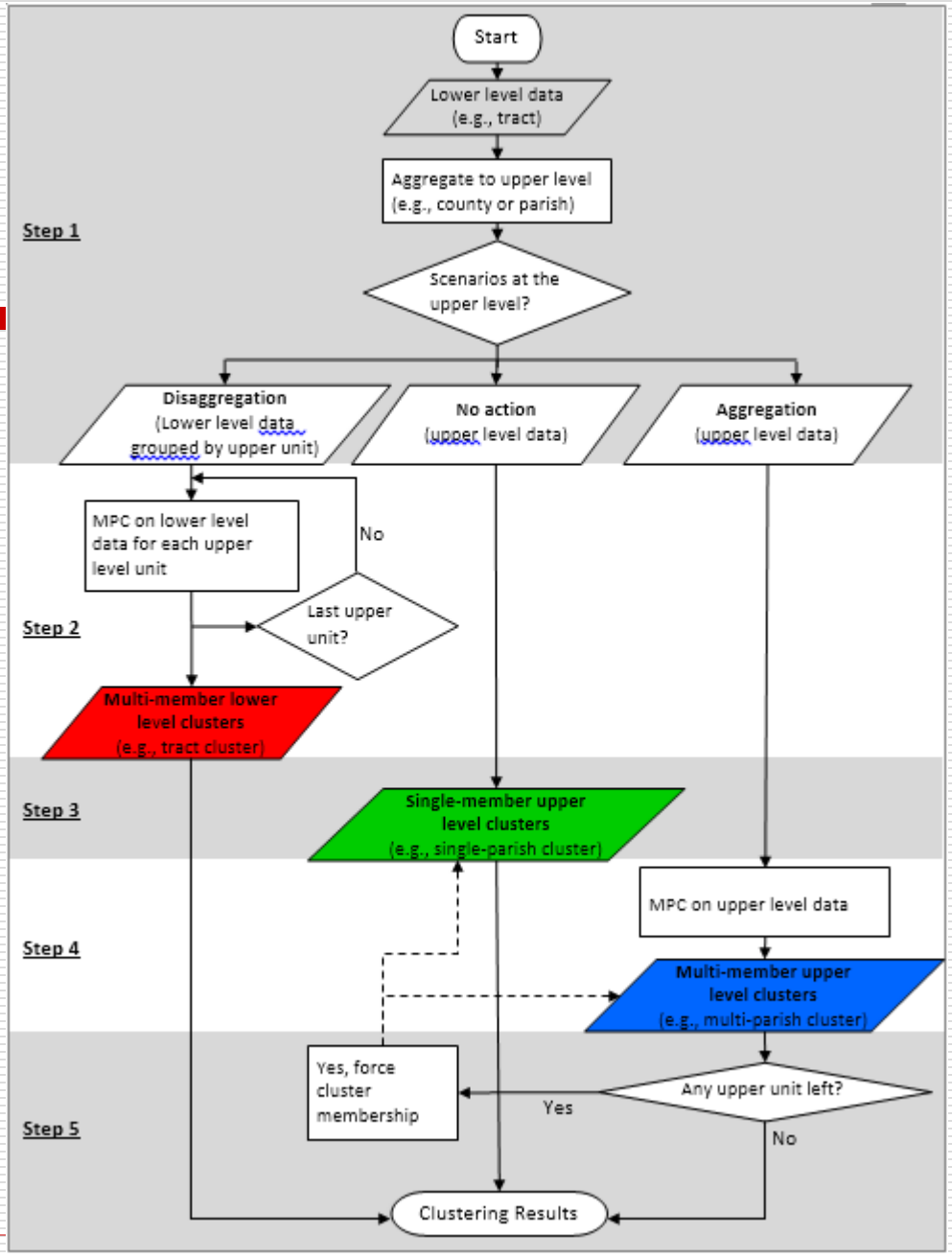
4. "Let the Data Speak for Themselves"?

- Small population problem
  - Unreliable
  - Sensitive to data errors
  - Statistical distribution
  - Data suppression
- Regionalization: constructing larger areas

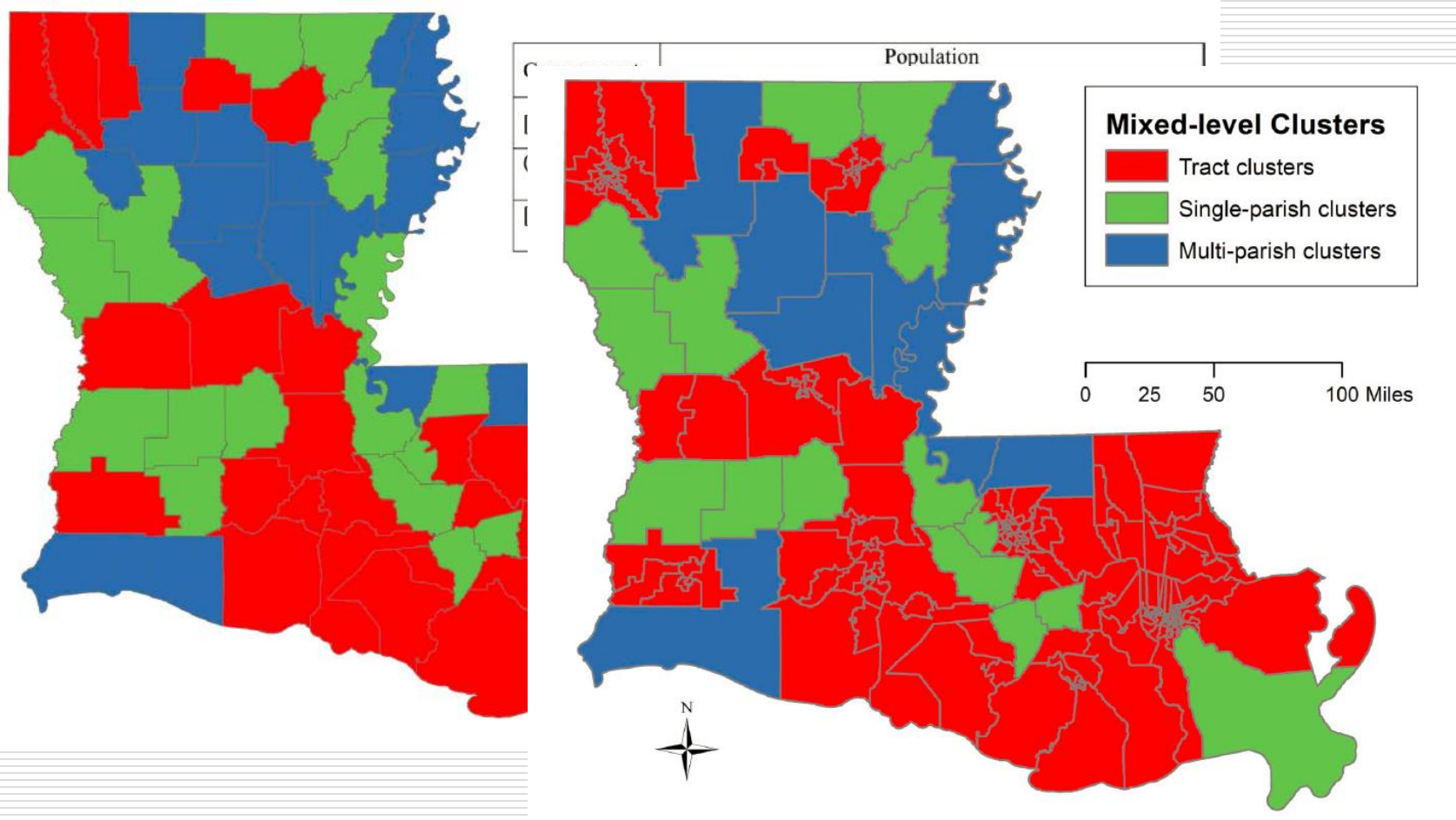


Mixed-Level Regionalization (MLR)

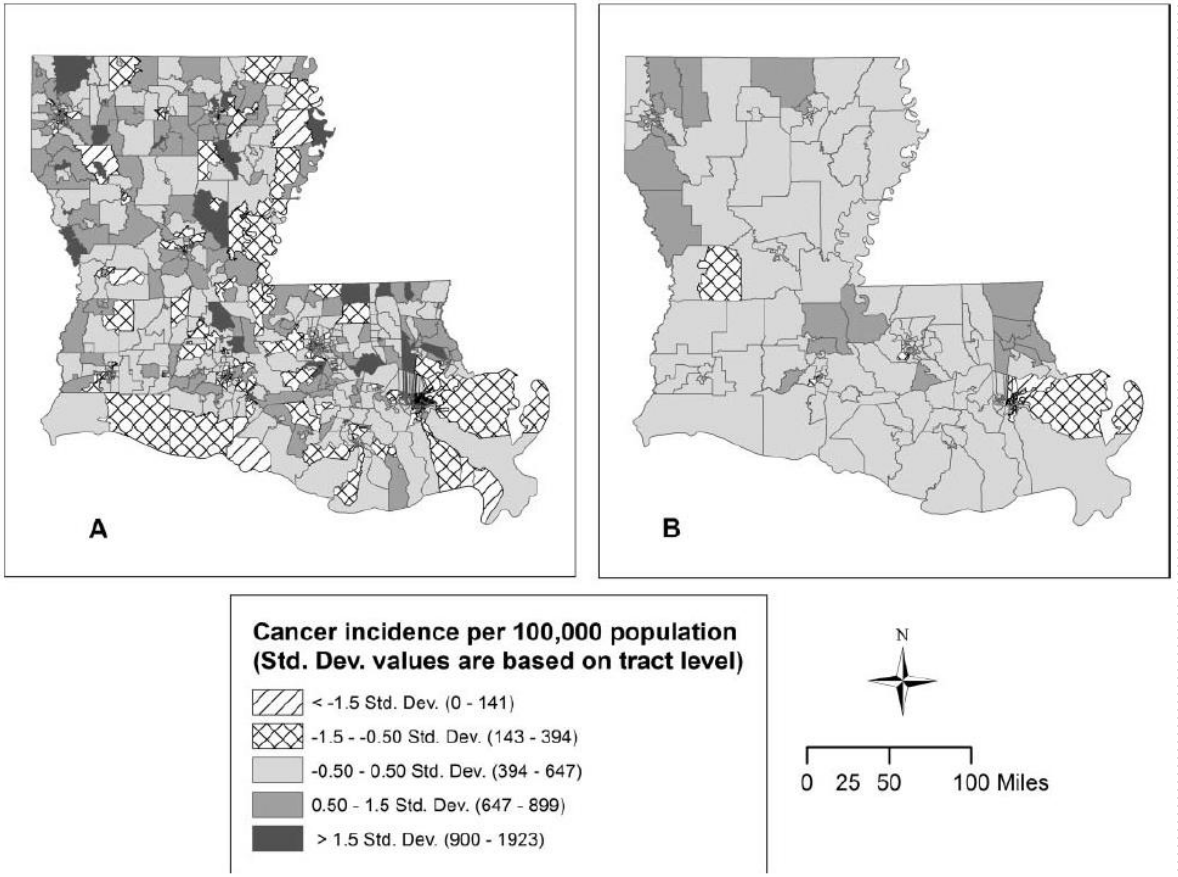
$$o_i = w_s o_{si} + w_a o_{ai}$$



Louisiana


Population
Mixed-level Clusters
Tract clusters
Single-parish clusters
Multi-parish clusters
0 25 50 100 Miles
N

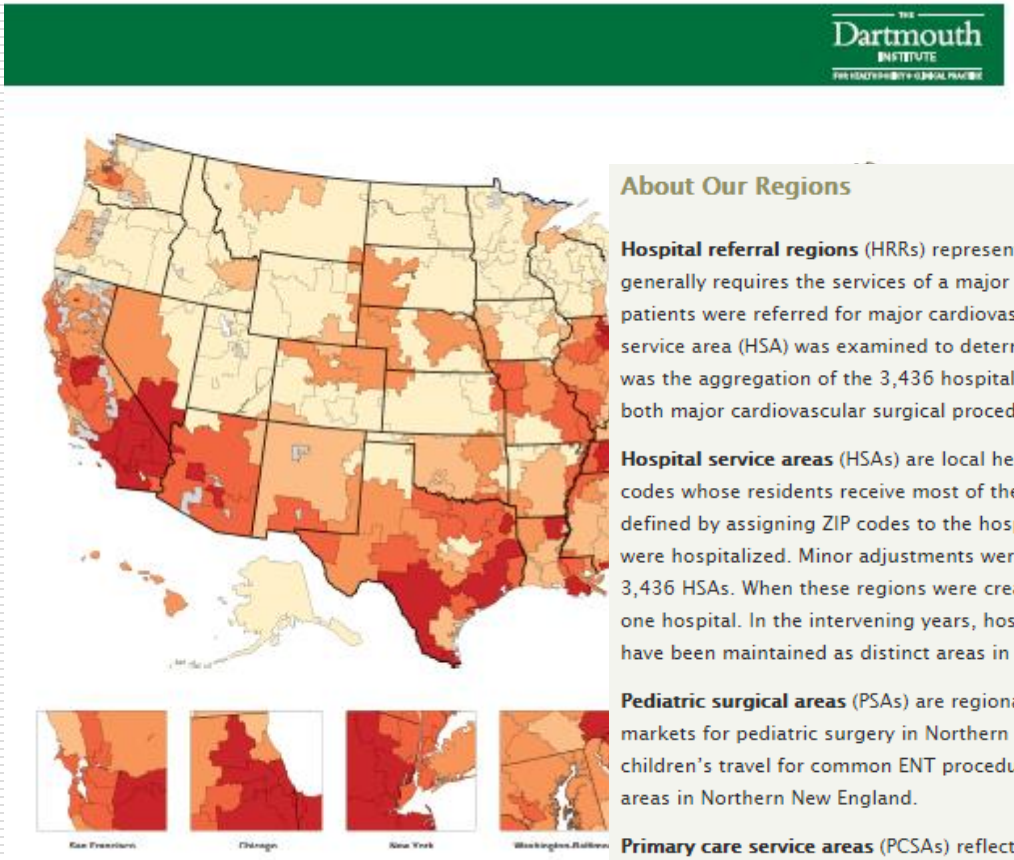
Cancer rates before & after MLR



Reflection

- More reliable rates in the new areas
- New rates conform to a normal distribution
- Larger areas to mask privacy
- Mitigating spatial autocorrelation
- GIS frees us from pre-defined arbitrary analysis unit(s)

5. "Act Locally"



About Our Regions

Hospital referral regions (HRRs) represent regional health care markets for tertiary medical care that generally requires the services of a major referral center. The regions were defined by determining where patients were referred for major cardiovascular surgical procedures and for neurosurgery. Each hospital service area (HSA) was examined to determine where most of its residents went for these services. The result was the aggregation of the 3,436 hospital service areas into 306 HRRs. Each HRR has at least one city where both major cardiovascular surgical procedures and neurosurgery are performed.

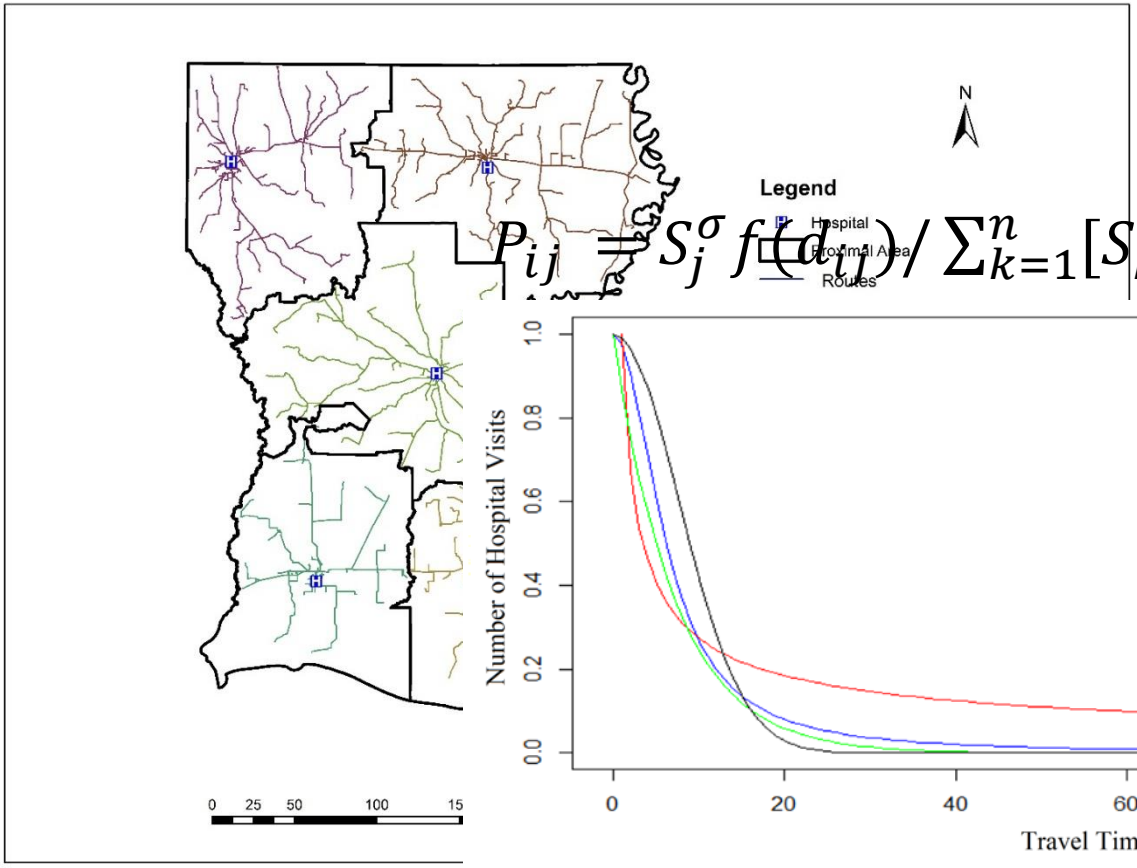
Hospital service areas (HSAs) are local health care markets for hospital care. An HSA is a collection of ZIP codes whose residents receive most of their hospitalizations from the hospitals in that area. HSAs were defined by assigning ZIP codes to the hospital area where the greatest proportion of their Medicare residents were hospitalized. Minor adjustments were made to ensure geographic contiguity. This process resulted in 3,436 HSAs. When these regions were created in the early 1990s, most hospital service areas contained only one hospital. In the intervening years, hospital closures have left some HSAs with no hospital; these HSAs have been maintained as distinct areas in order to preserve the continuity of the database.

Pediatric surgical areas (PSAs) are regional markets for pediatric surgery. In order to define geographic markets for pediatric surgery in Northern New England, we aggregated hospital service areas based on children's travel for common ENT procedures and appendectomies. This resulted in 30 pediatric surgical areas in Northern New England.

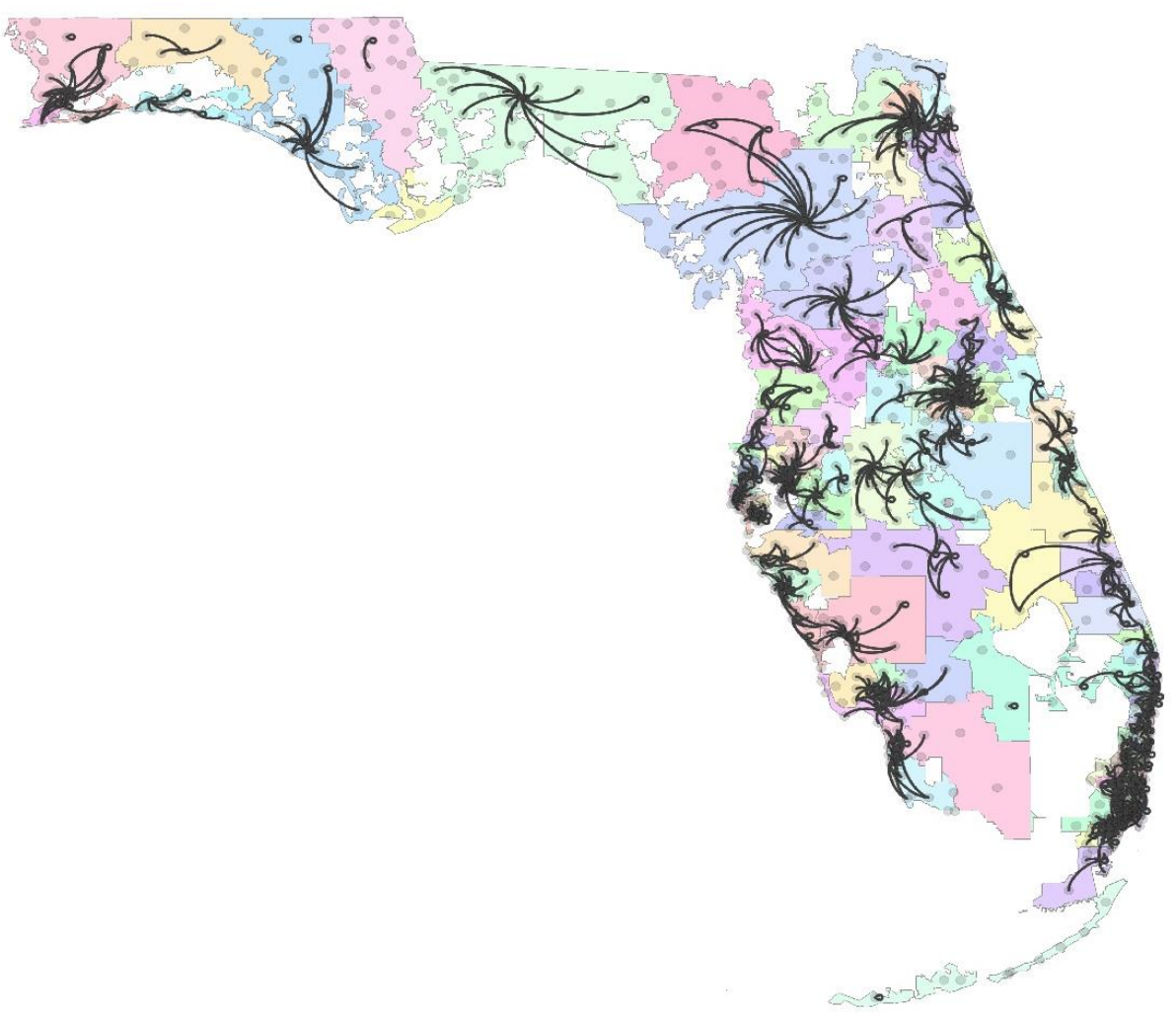
Primary care service areas (PCSAs) reflect Medicare patient travel to primary care providers. Version 3.1 (based on 2010 Census tracts) will be available soon from the Health Resources & Services Administration (HRSA).

Hospital Service Areas (HSAs) by the Huff Model

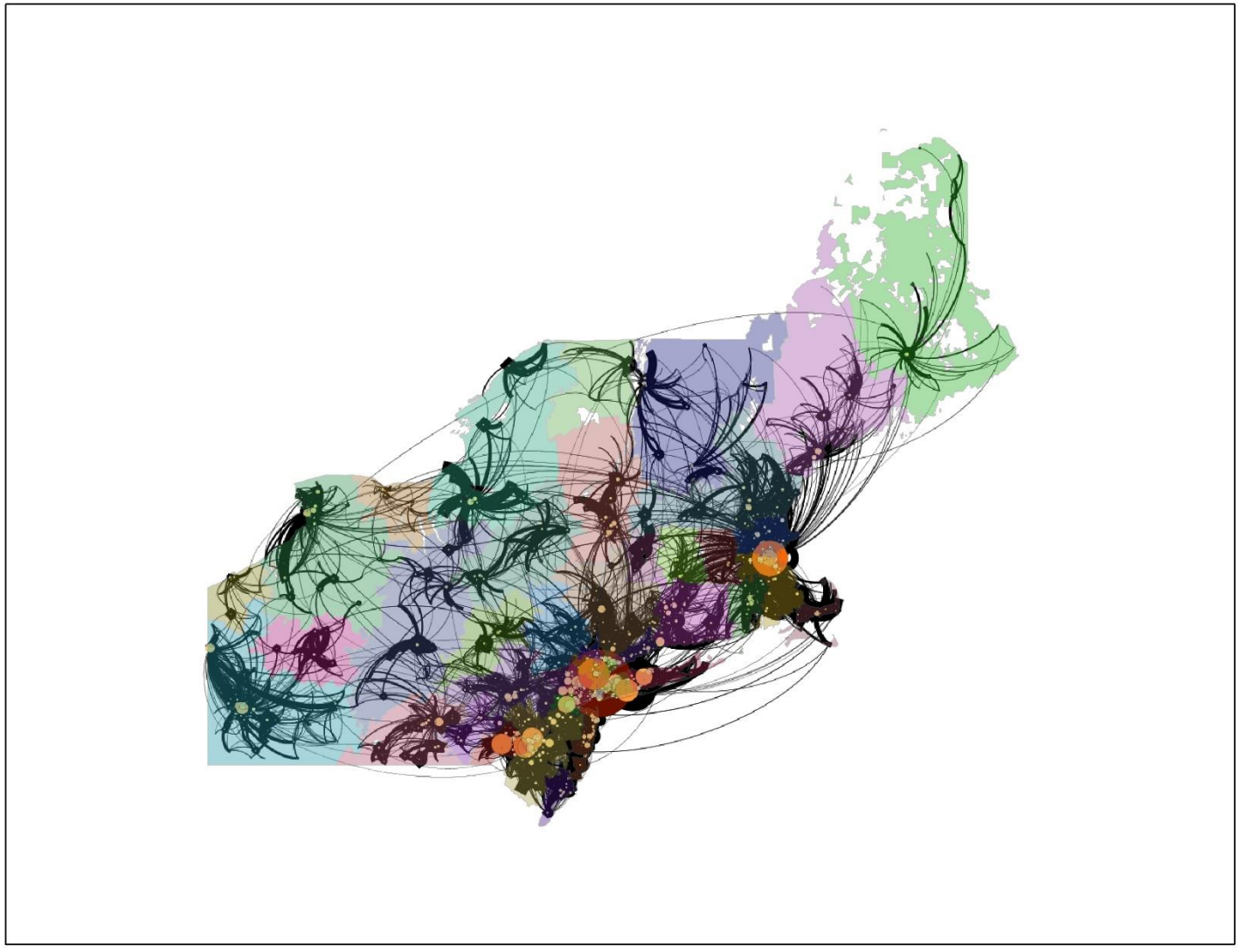
$$P_{ij} = S_j^{\sigma} f(d_{ij}) / \sum_{k=1}^{n} [S_k^{\sigma} f(d_{ik})]$$



HSAs in FL



CSAs in Northeast U.S.

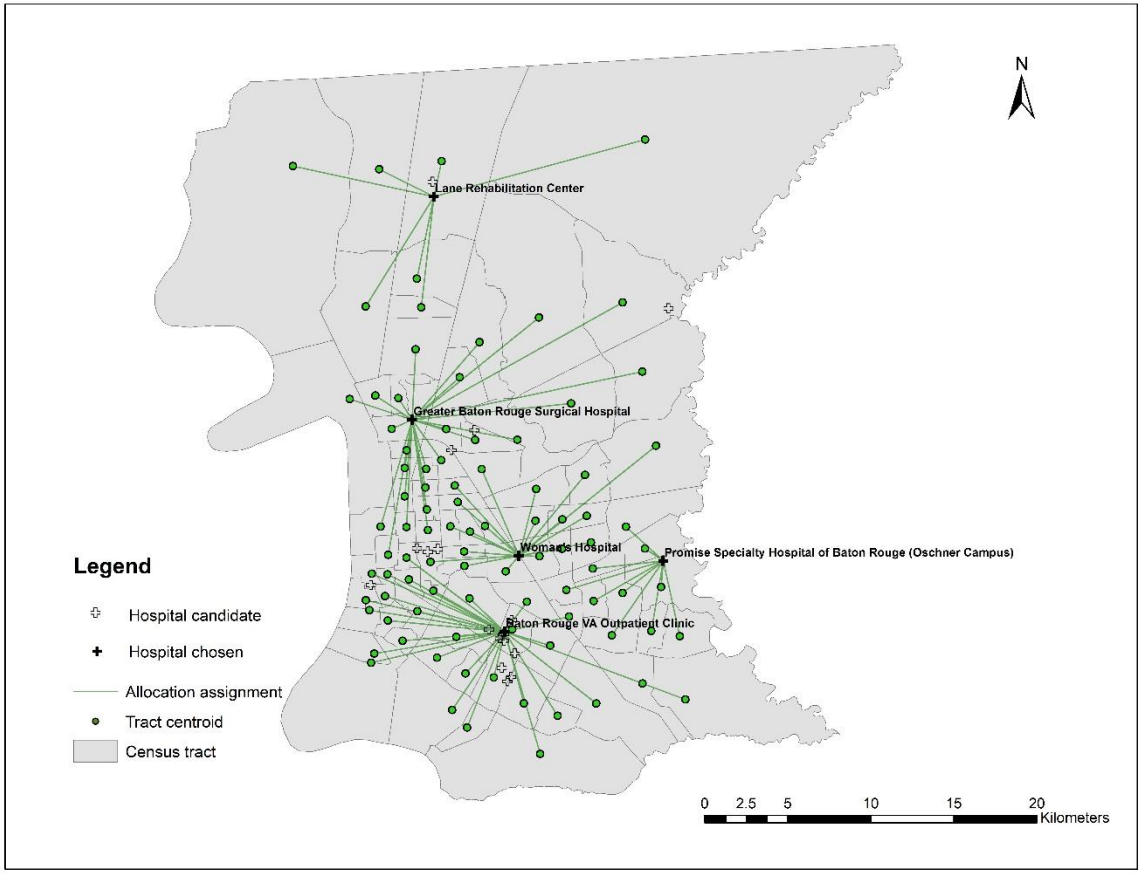


Reflection

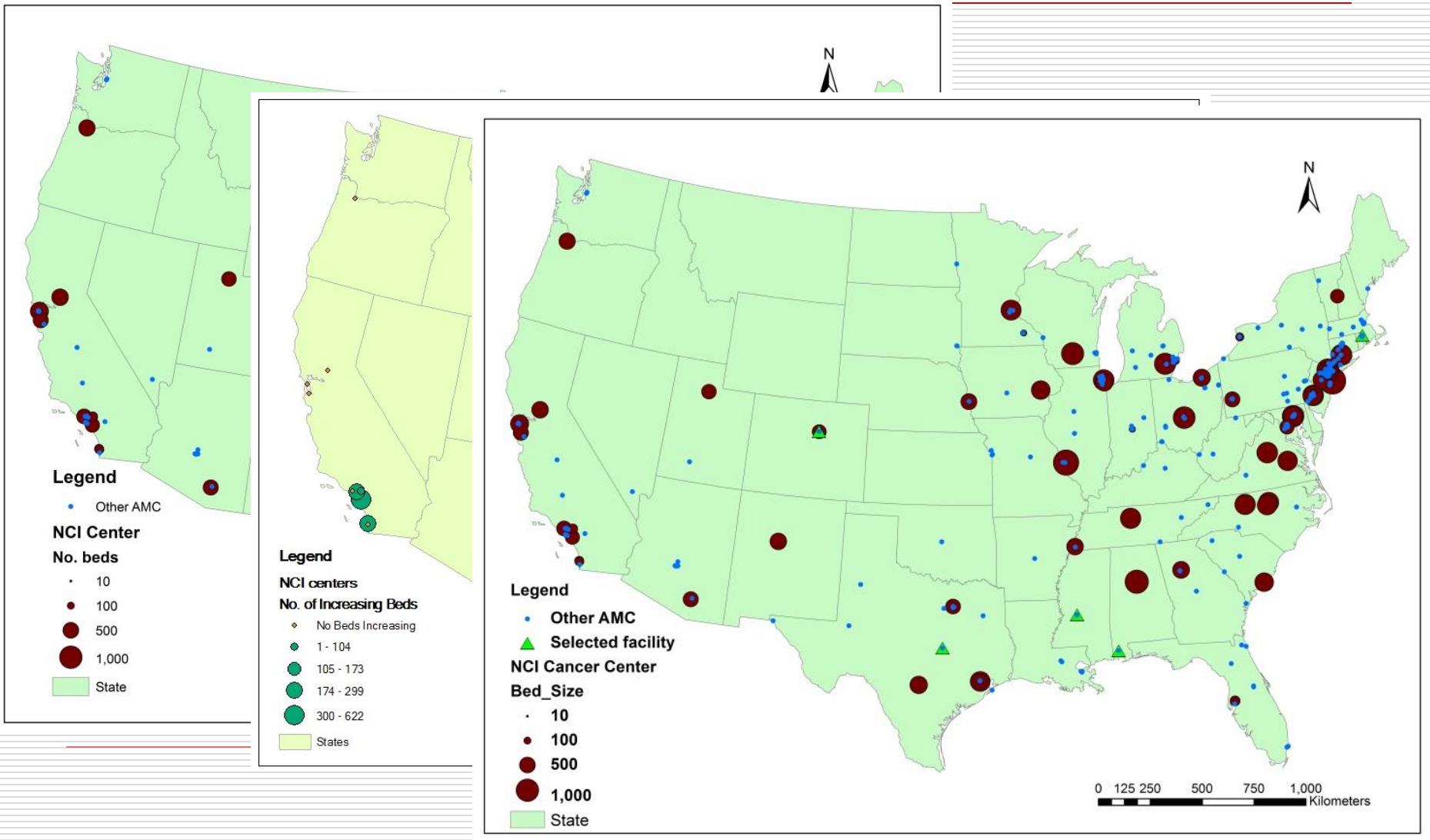
- HSA is a basic unit for healthcare assessment, management and planning
- WHO promotes healthcare localization
- Pursuit of *automated*, *data-driven*, *optimal* delineation of HSAs
- GIS defines HSAs that are maximally coherent

6. "Some are more equal than others"

***p*-median solution**



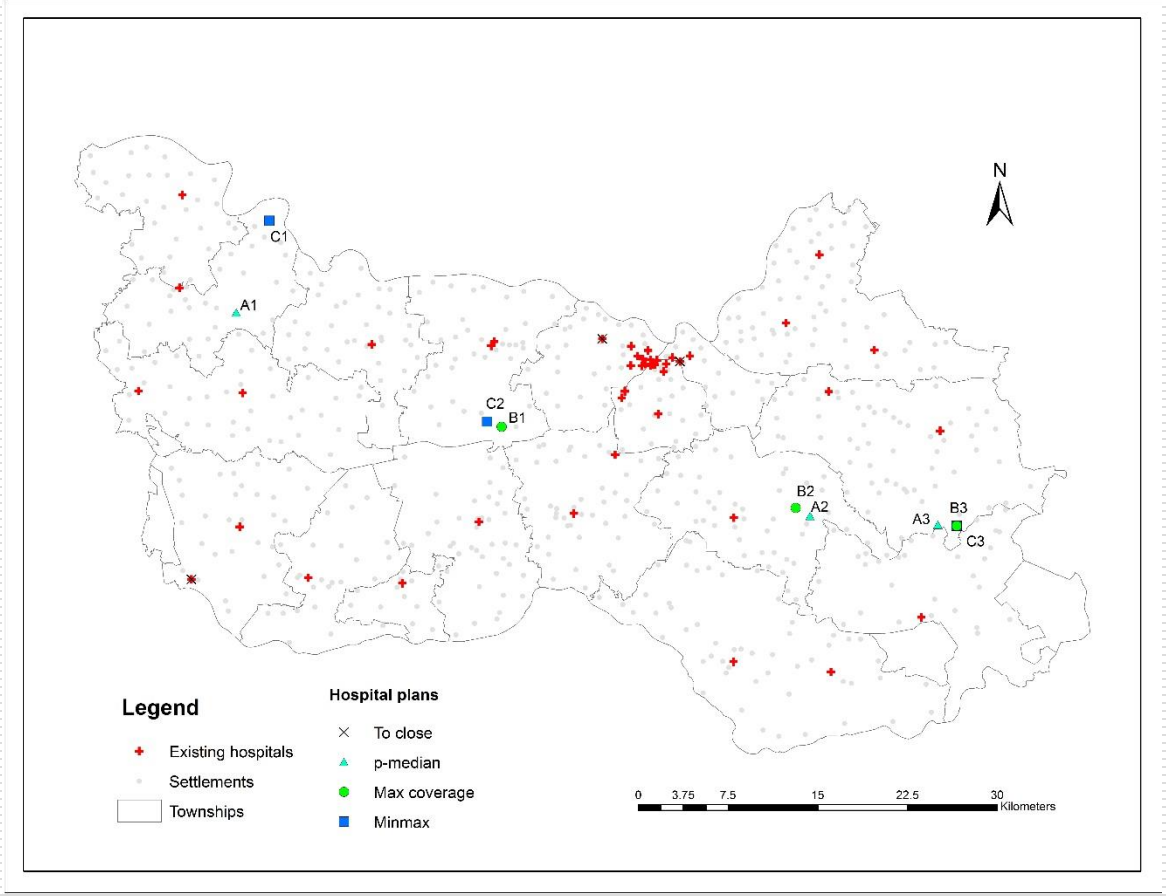
Planning NCI Cancer Centers



Integrated approach

- two-step optimization for spatial accessibility improvement (2SO4SAI)
- S1: site facilities for efficiency
- S2: adjust their capacities for equality

Xiantao, Hubei



Reflection

- Efficiency vs. equality
- Pursuit of equality in access not outcome
- How much equality vs. what equality
- Location adjustment favored over resource allocation
- GIS in *Spatially-integrated Social Sciences, Public Policy & Planning* (S^3P^3)

Recap

- Human behavior varies geographically, so should policy
- S-D interact beyond borders
- Neighborhood needs to capture activity space & policy domain
- Turn the small population "problem" to an advantage
- Localize health care market
- Toward equality

Take-home message

- Public policy negligent of geography costs $ and lives!
- Geography is the reality of complexity we live in. *Deal with it!*
- GIS is the *renaissance* of geography

Funding & References

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Thank You!

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