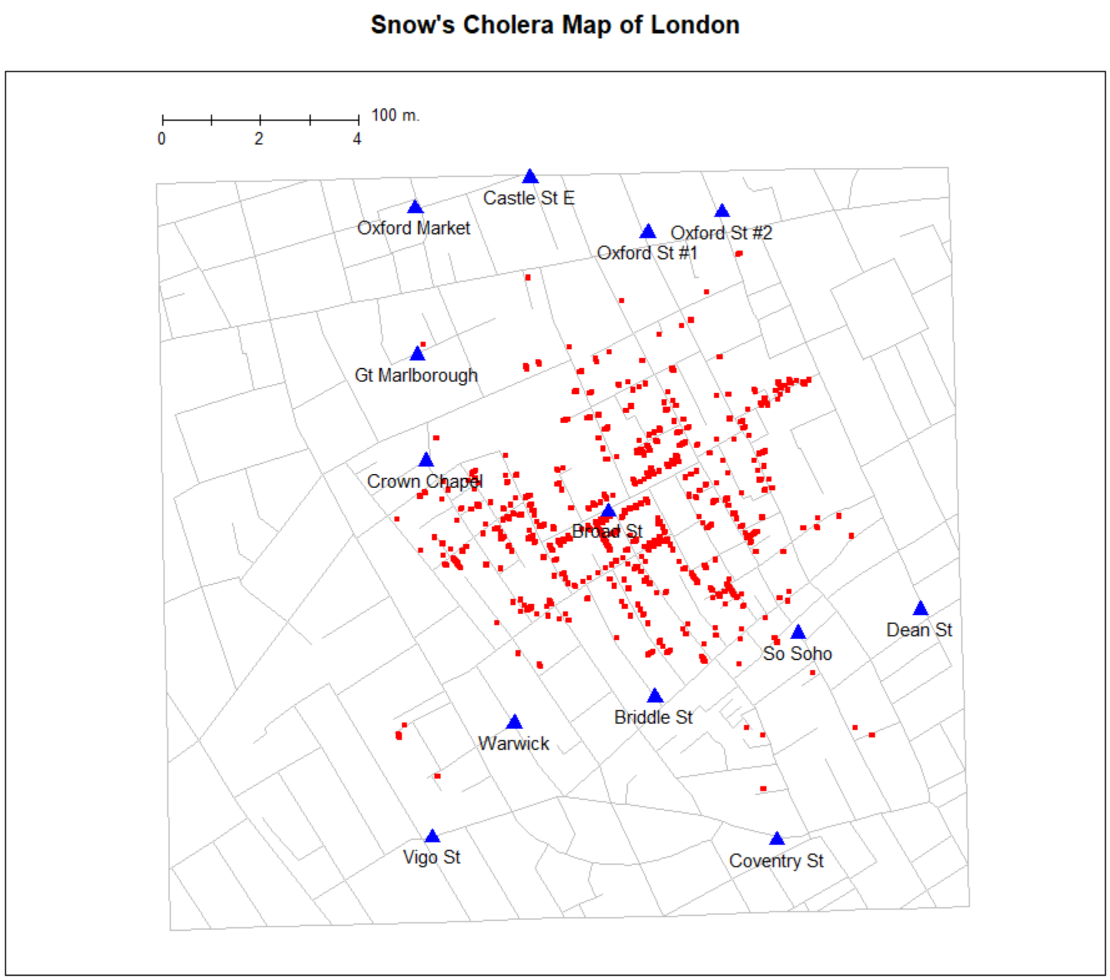
title: Beyond simple maps - Integrating space and time with Bayesian models author: - “Corey S. Sparks, Ph.D.” institute: - “Univerity of Texas at San Antonio - Department of Demography” - https://hcap.utsa.edu/demography date: “July 11, 2022” subtitle: Summer at Census Research Seminar output: beamer_presentation

Presentation Structure

- Spatial and temporal demography
- Data sources
- Modeling strategies
- Empirical analysis of Florida mortality rates
- Results & visualizations
- Wrap up

Beyond maps…



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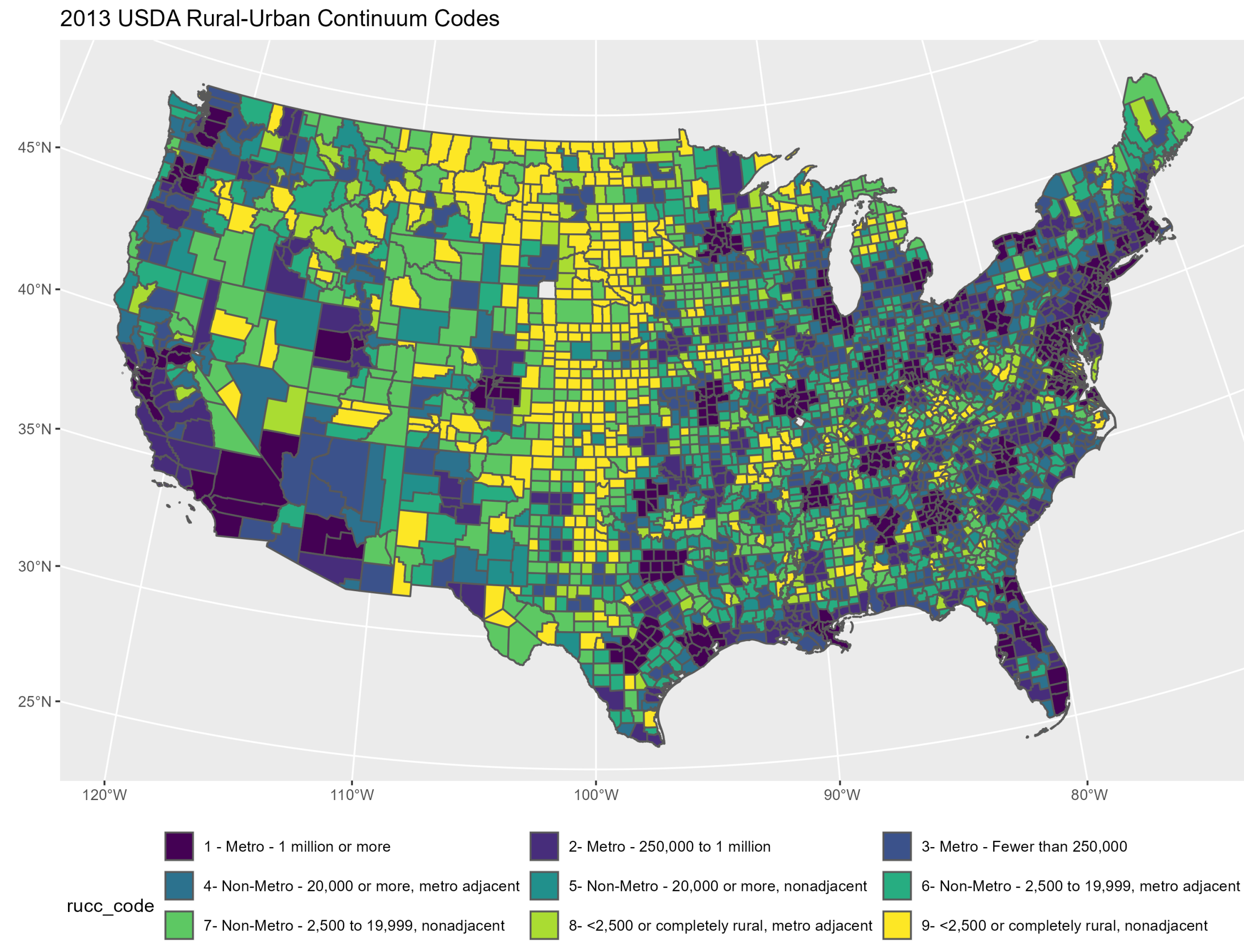

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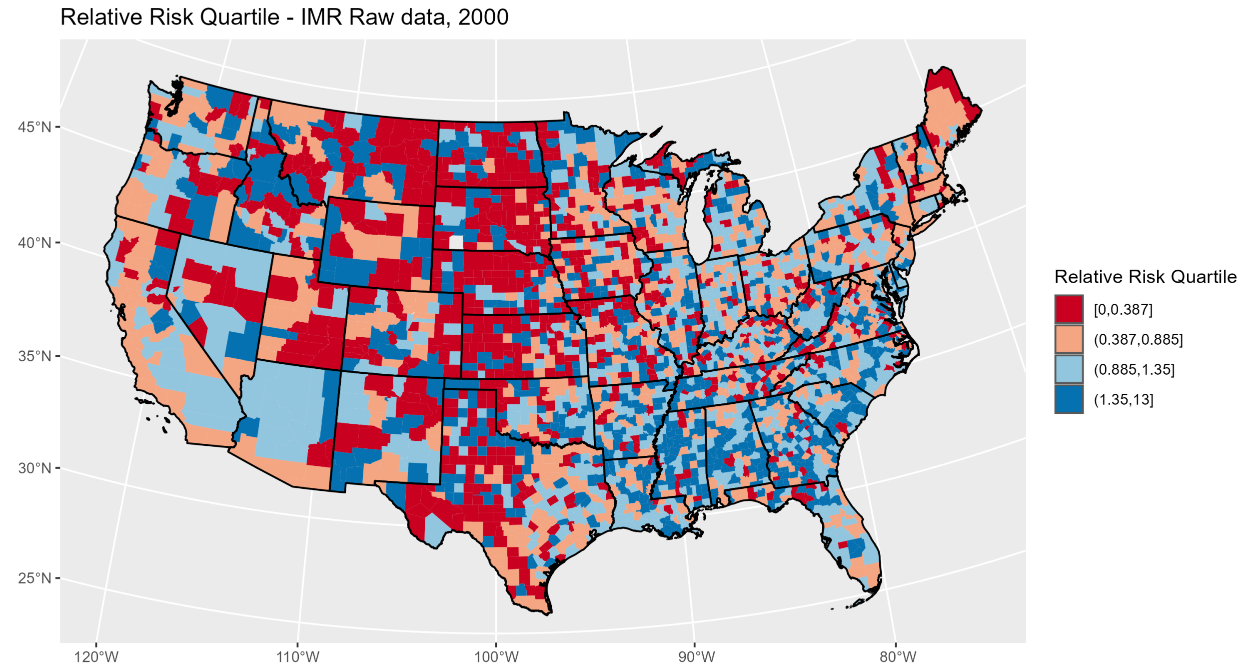

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Spatial Demography

- "Putting people into place" (Entwisle, 2007)
- Need to think about:
- Context
- Dynamics
- Processes

- Macro-demography (Voss, 2007) + Places as observations + Pre-1960's + Ecological inference
- Micro-demography + People as observations + Social theory + Individual choices

- Macro - demography (Voss, 2007) + Places as observations + Pre - 1960's + Ecological inference

- Multilevel - demography
  - People in places
  - Interaction between context and behavior

Space & Time

- Future directions in spatial demography report
  - Most participants listed time or temporal data as integral to the future of the field

- Time allows for dynamics of humans and environment + Snapshots/cross sections tell us nothing of this
- Data management + Combining and merging data

- Analysis/methods
  - Problems with space
  - Problems with time

- Advantages + Rich, dynamic contexts + Policy relevance of timely, prospective analysis

- Census/ACS

- DHS

- IPUMS

- International agencies

- Various administrative orgs.
  - State government
  - Private companies/Nonprofits

How to combine these things?

- Geocodes are essential
  - Limitation for many surveys

- **Caveats**
- Levels of geography
+ The evil tracts
- MAUP
- Changing boundaries

- You can basically get these data from the CDC Wonder website
- Suppresses counts where the number of deaths is less than 10
- Rates are labeled as "**unreliable**" when the rate

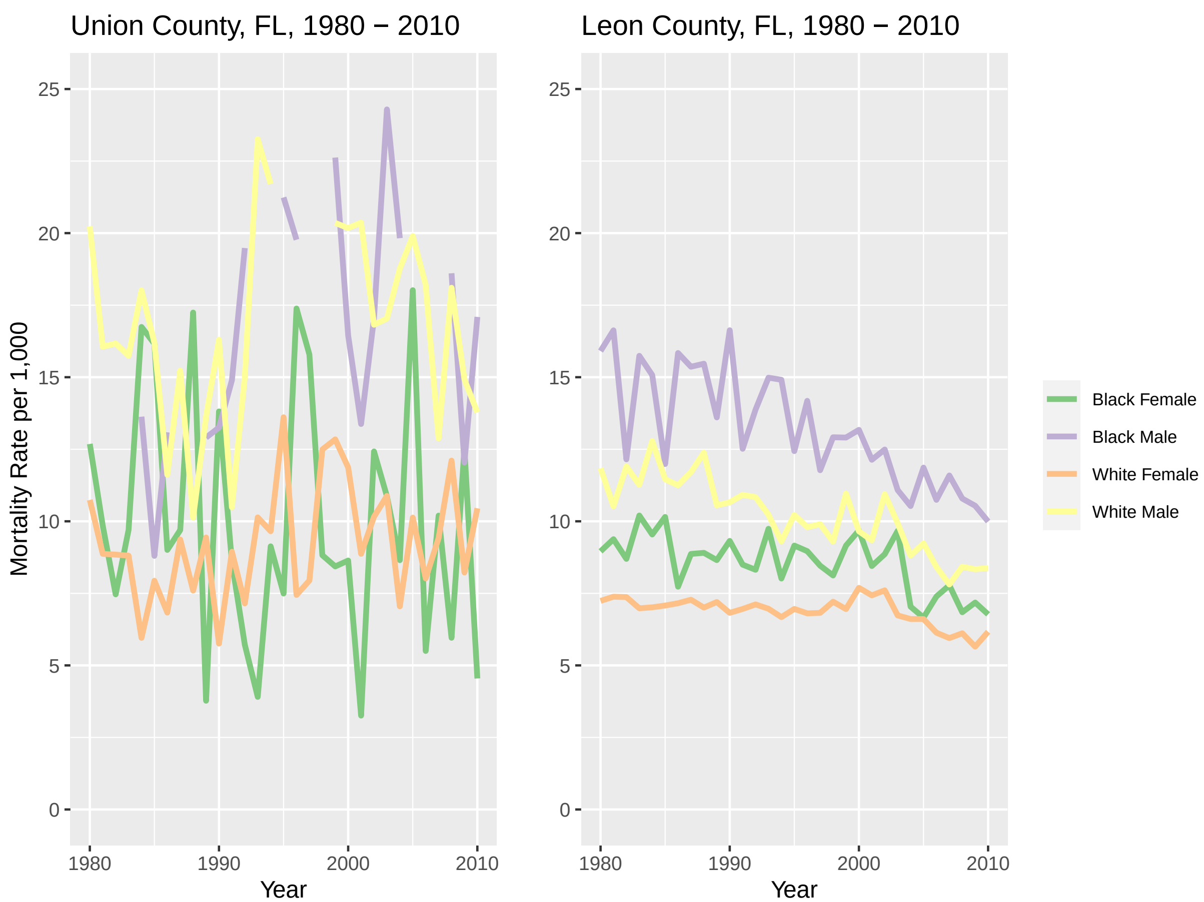
- **Caveats** - Levels of geography + The evil tracts - MAUP - Changing boundaries

- Restricted use data allows access to **ALL** data

Data example

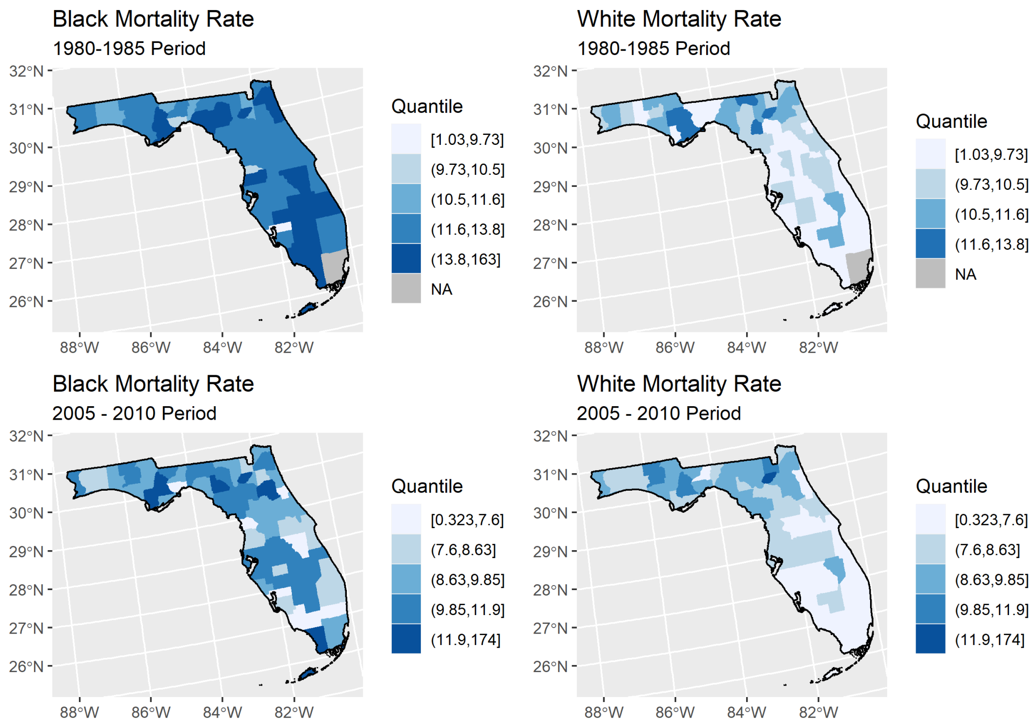
County	Year	Race-Sex	Rate
12073	1980	White Female	7.238632
12073	1980	Black Female	8.958174
12073	1980	White Male	11.840842
12073	1980	Black Male	15.907688
12073	1981	White Female	7.383039
12073	1981	Black Female	9.379846
12073	1981	White Male	10.518428
12073	1981	Black Male	16.626825
12073	1982	White Female	7.370335
12073	1982	Black Female	8.695655
12073	1982	White Male	11.902308
12073	1982	Black Male	12.149819

County specific temporal trends 1980 - 2010



Florida Example

- n = 67 counties ∗ 31 years ∗ 2 Races ∗ 2 Sexes = 8,308



Methods - Bayesian Hierarchical models

- Example case of Florida counties
- Examine county-specific time trends in Black/White mortality rates
- I specify a Bayesian Hierarchical model for the age-standardized mortality rate
- Controls for sex and county SES
- Spatial correlation in overall rate u_j
- Time varying Black/white disparity parameter ν_{t2}
- Spatially varying Black/White disparity parameter γ_j

$$
\begin{aligned}
\mathrm{y}_{ij} &\sim N(\mu, \tau_y) \\
\mu_{ij} &= \beta_0 + x'\beta + \gamma_j * Black + u_j + \nu_{t1} + \nu_{t2} * Black \\
\gamma_j &\sim \mathrm{CAR}(\bar{\gamma}_j, \tau_\gamma / n_j) \\
u_j &\sim \mathrm{CAR}(\bar{u}_j, \tau_u / n_j) \\
\nu_{t2} &\sim RW1(time) \\
\nu_{t1} &\sim N(0, \tau_t)
\end{aligned}
$$

Methods - Bayesian Hierearchical models

- This type of model is commonly used in epidemiology and public health
- Various types of data likelihoods may be used
- Need to get at:

*

$$p(\theta|y) \propto p(y|\theta)p(\theta)$$

- Traditionally, we would get $p(\theta|y)$ by:
  - either figuring out what the full conditionals for all our model parameters are (hard)

  - Use some form of MCMC to arrive at the posterior marginal distributions for our parameters (time consuming)

Methods - INLA approach

- Integrated Nested Laplace Approximation - Rue, Martino & Chopin (2009)
- One of several techniques that approximate the marginal and conditional posterior densities
  - Laplace, PQL, E-M, Variational Bayes
- Assumes all random effects in the model are latent, zero-mean Gaussian random field, x with some precision matrix
  - The precision matrix depends on a small set of hyperparameters
- Attempts to construct a joint Gaussian approximation for $p(x|\theta, y)$
  - where θ is a small subset of hyper-parameters

Methods - INLA approach

- Apply these approximations to arrive at:
- $\tilde{\pi}(x_i|y) = \int \tilde{\pi}(x_i|\theta, y)\tilde{\pi}(\theta|y)d\theta$
- $\tilde{\pi}(\theta_j|y) = \int \tilde{\pi}(\theta|y)d\theta_{-j}$
- where each $\tilde{\pi}(.|.)$ is an approximated conditional density of its parameters
- Approximations to $\pi(x_i|y)$ are computed by approximating both $\pi(\theta|y)$ and $\pi(x_i|\theta, y)$ using numerical integration to integrate out the nuisance parameters.
  - This is possible if the dimension of θ is small.
- Approximations to $\tilde{\pi}(\theta|y)$ are based on the Laplace appoximation of the marginal posterior density for $\pi(x, \theta|y)$
- Their approach relies on numerical integration of the posterior of the latent field, as opposed to a pure Gaussian approximation of it

INLA in R

`library(INLA)`

`std_rate~male+black+scale(lths)+`

`f(year2, model = "rw1",constr = T, scale.model = T)+` **nonparametric time trend**

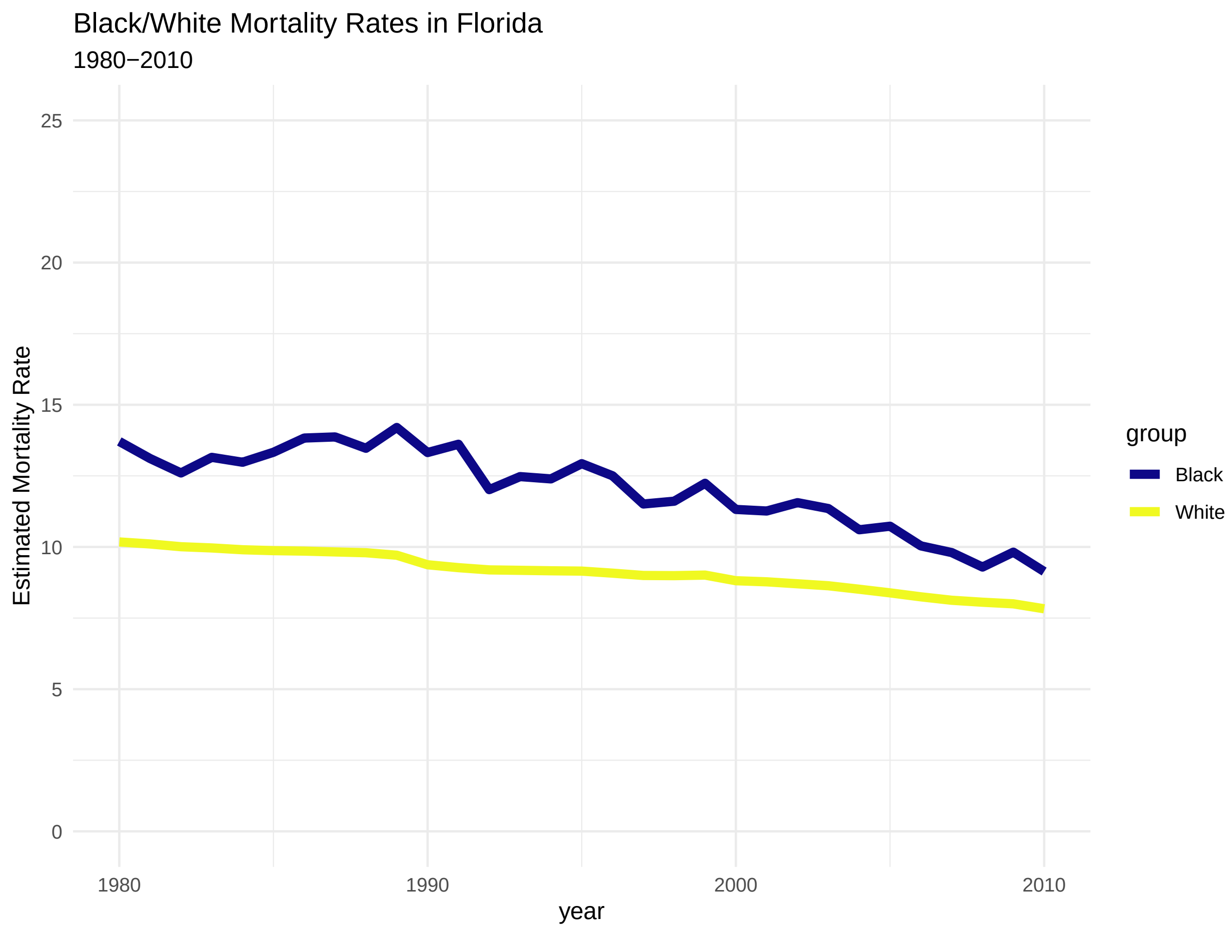
`f(struct, model="besag", graph="cl_graph", constr = T, scale.model = T)+` **spatial correlation**

`f(year3, bl2,  model="iid")+` **time - disparity**

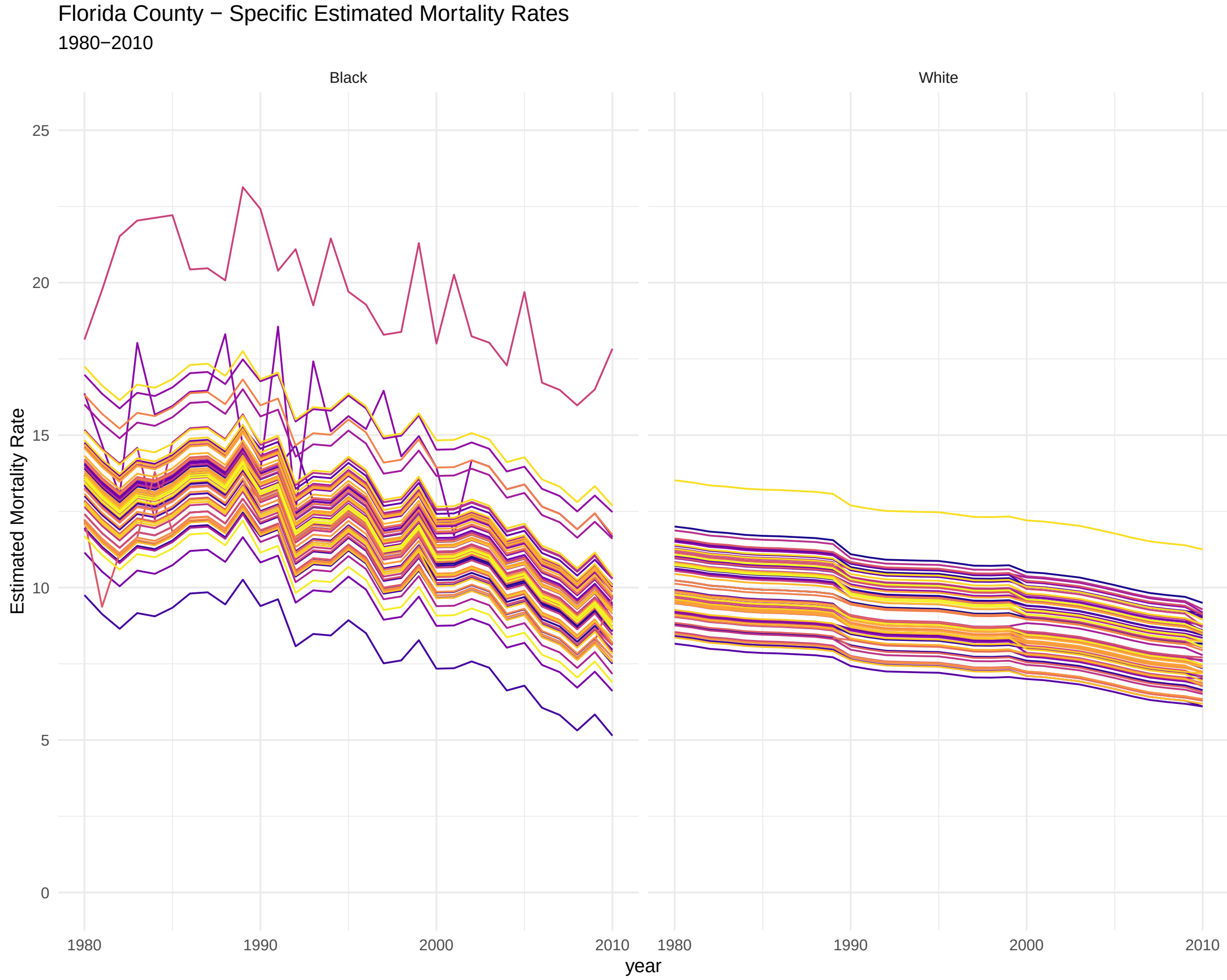
`f(struct2, bl2, model="besag", graph="cl_graph", constr = T, scale.model = T)` **spatial disparity**

Results

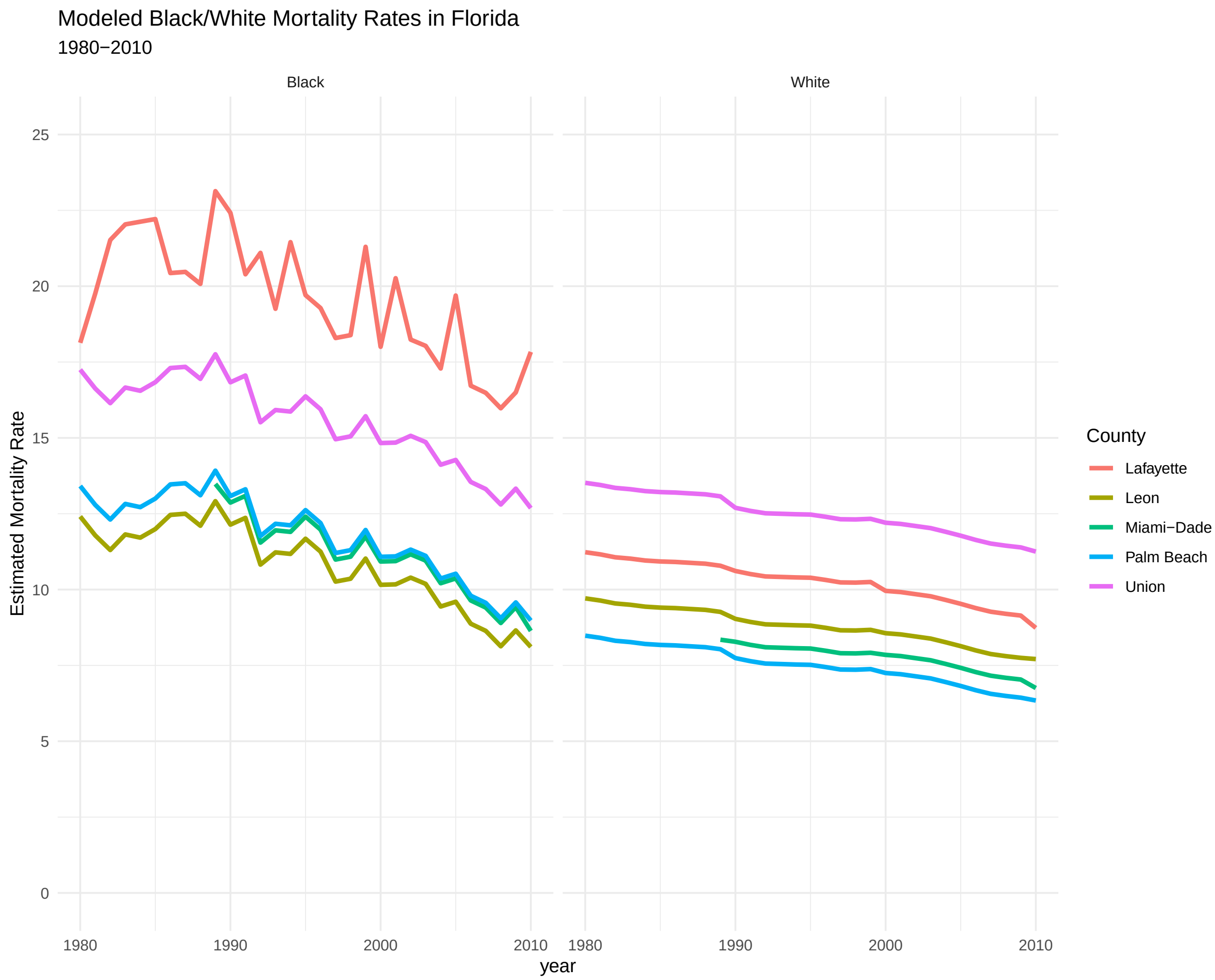
- Time trend in Black/white Mortality


Black/White Mortality Rates in Florida
1980−2010
Estimated Mortality Rate
25
20
15
10
5
0
1980
1990
2000
2010
year
group
Black
White

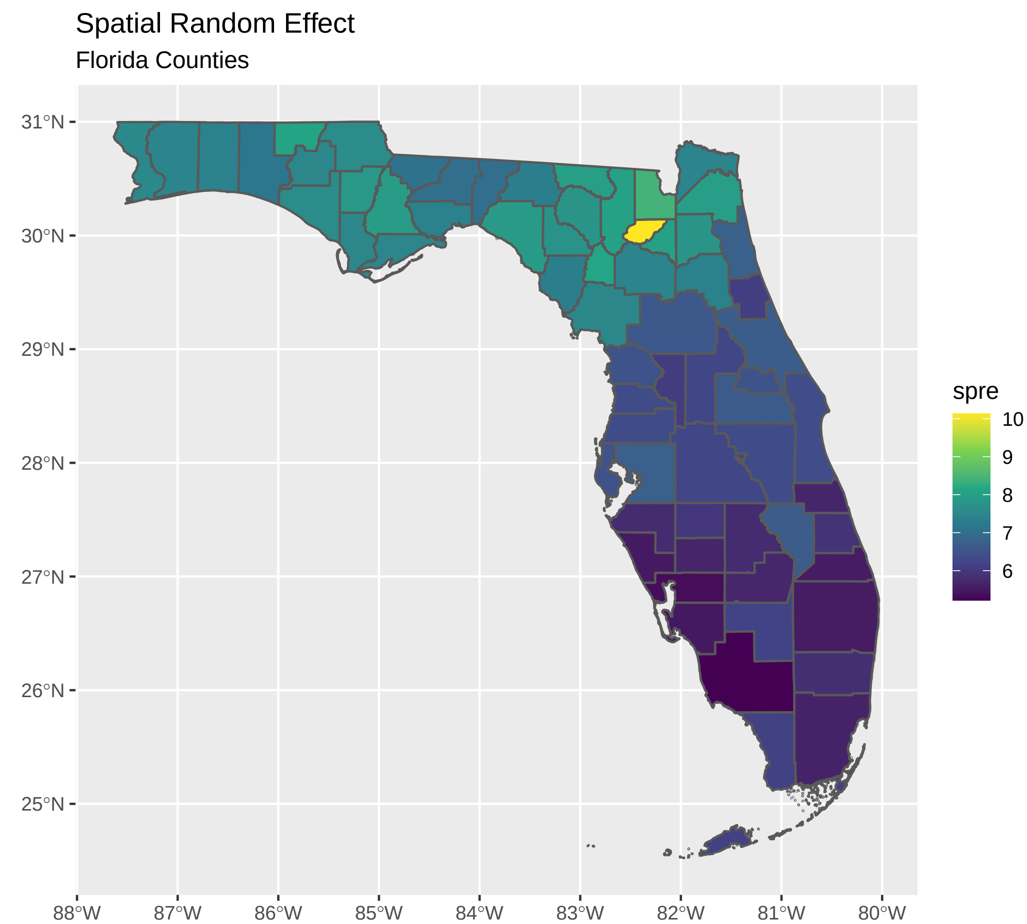
County time trends



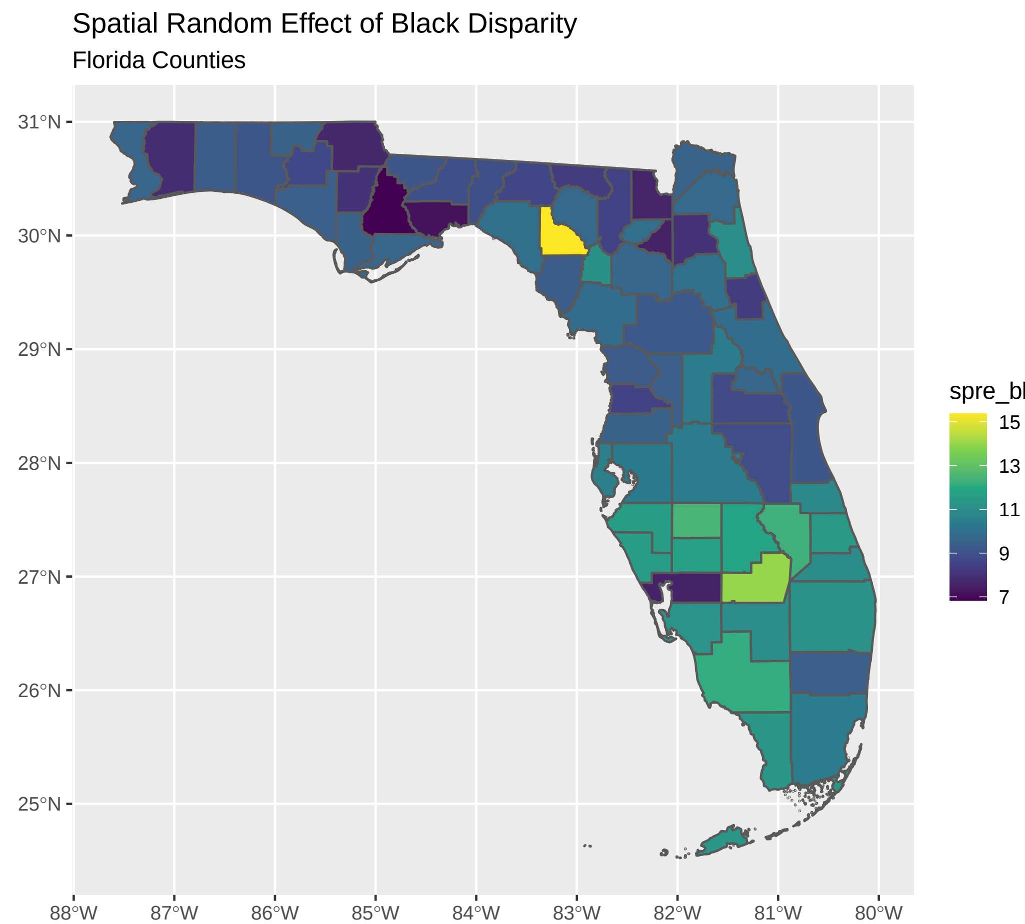
Highlighed trends



Spatial trend



Spatial disparity



Discussion

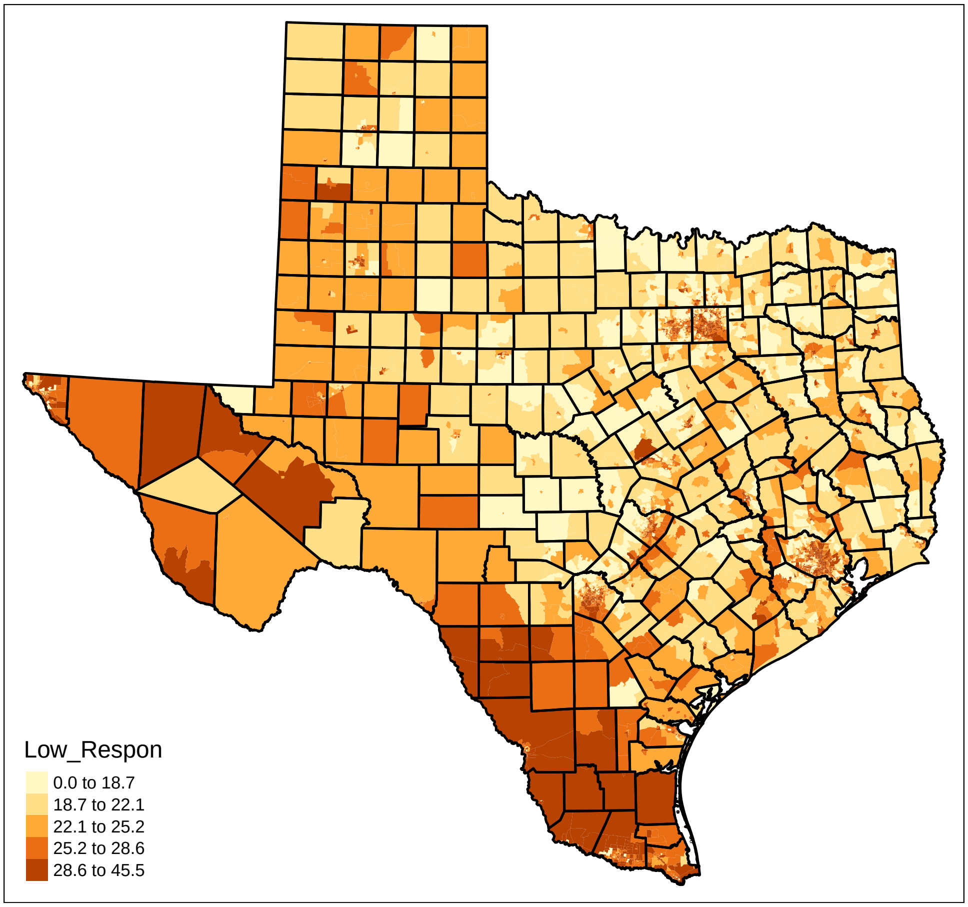
- We see that, while there is a persistence of the gap in black-white mortality:
  - The mortality gap appears to be fairly consistent over time
  - In some areas, the mortality difference are decreasing
  - Results point to higher disparities in several notable Florida rural areas
- Spatio-temporal modeling allows for the incorporation of dynamics that cross-sectional models cannot

Low Response Score Outcome

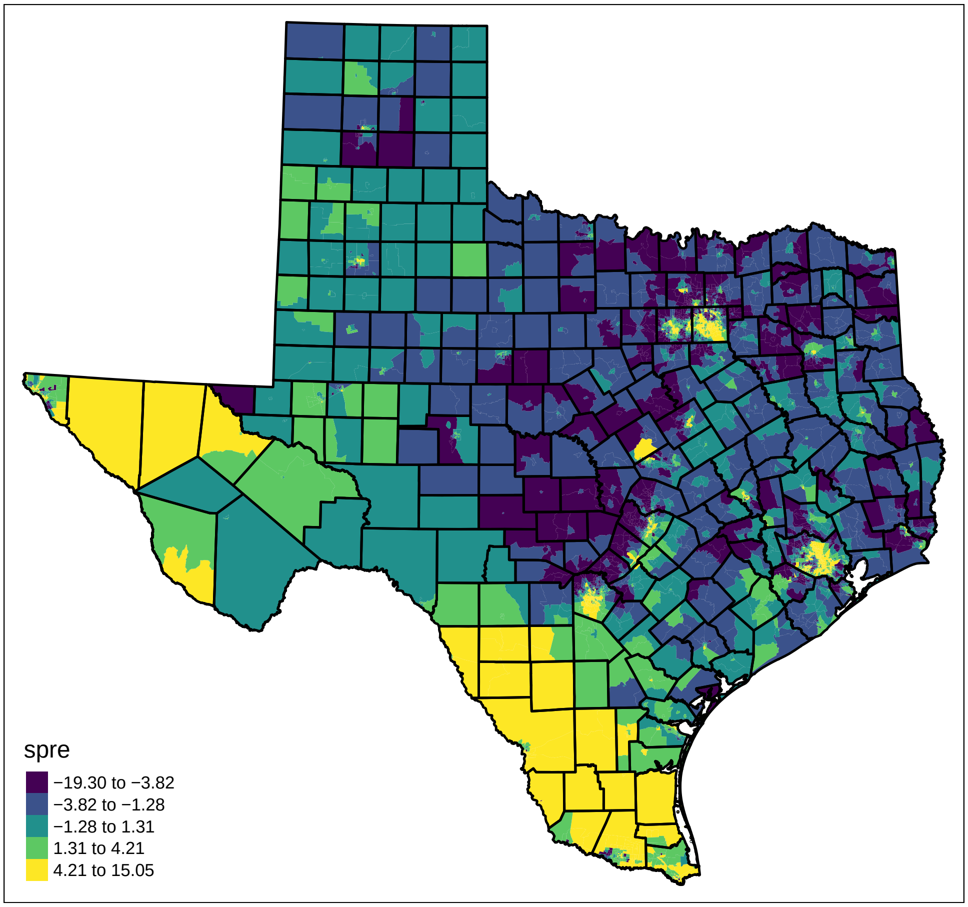
- INLA model for Low Response Score metric
- Considered both an unstructured and spatially structured random effect model
- Modeled LRS as Gaussian, considering how it is constructed
- Besag, York and Mollie specification for tract level heterogeneity

$$\begin{aligned}
\mathrm{y}_i &\sim \mathrm{Normal}\left(\mu_i, \tau_y\right) \\
\mu_i &= \beta_0 + u_i + v_i \\
u_i &\sim \mathrm{CAR}(\bar{u}_i, \tau_u / n_j) \\
u_i &\sim \mathrm{Normal}(\bar{0}, \tau_v / n_j)
\end{aligned}$$

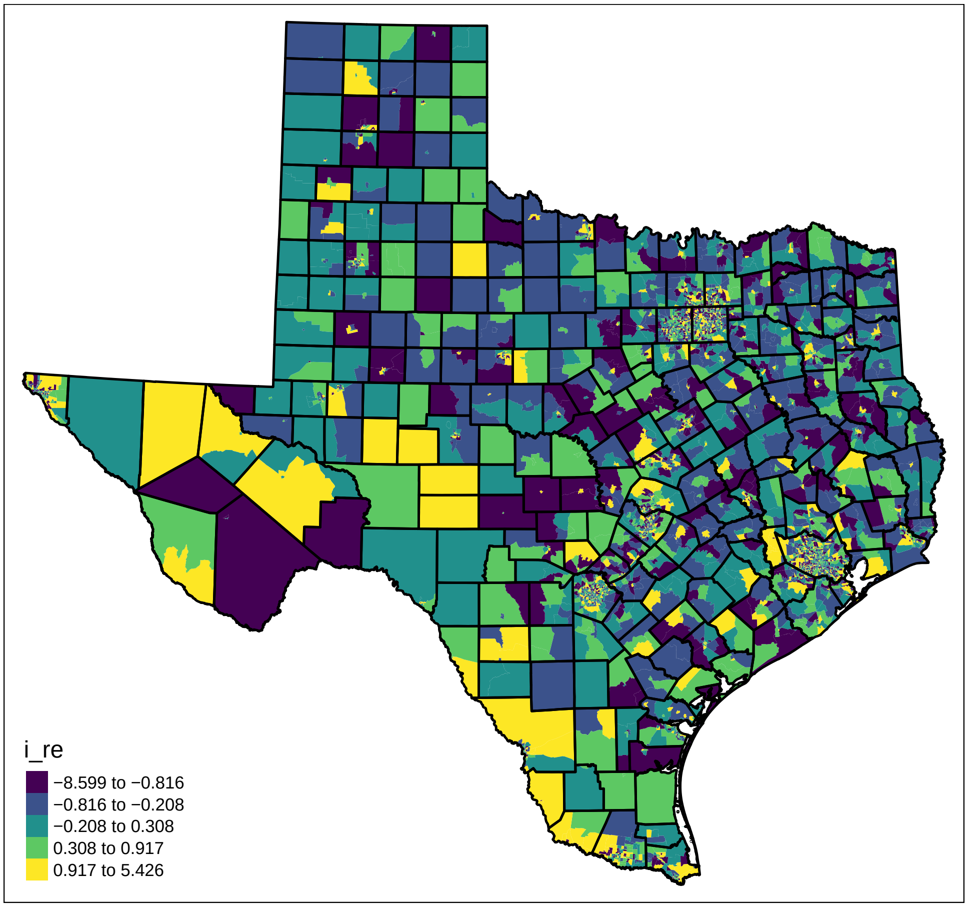
Low Response Score in Texas



Spatial correlation random effect



IID random effect



- Spatial model fits much better than non-spatial model using *WAIC*
- Suggests model should take into account spatial structure in LRS underlying data
- Larger suggestion is that spatial correlation needs to be included in the underlying construction of the LRS

More discussion

- INLA allows for rapid deployment of Bayesian statistical models with latent Gaussian random effects
  - Faster and *generally* as accurate as MCMC
  - Potentially an attractive solution for problems where large data/complex models may make MCMC less desirable

Thank you!

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UTSA Demography

Slides created via the R package **xaringan**

All talk materials available at my Github page

R-INLA examples available at my Rpubs page