# 2015 National Conference on Health Statistics

## Spatiotemporal Variation in Selected Health Outcomes from the National Vital Statistics System


Lauren M. Rossen, PhD, MS

Office of Analysis and Epidemiology
National Center for Health Statistics

# Acknowledgements:

**Co-authors:**
Diba Khan
Brady Hamilton
Margy Warner

**Colleagues in the Division of Vital Statistics, Office of Research Methodology, and the Research Data Center**

# Small Area Estimation Methods for Spatiotemporal Smoothing

Applications:

1. Drug Poisoning Death Rates in the U.S., 2002-2013
    - Two-stage hierarchical generalized linear models

2. Teen Birth Rates in the U.S., 2003-2012
    - Hierarchical Bayesian space-time interaction models

# First Example of Smoothing

## Drug Poisoning Mortality, 2002-2013

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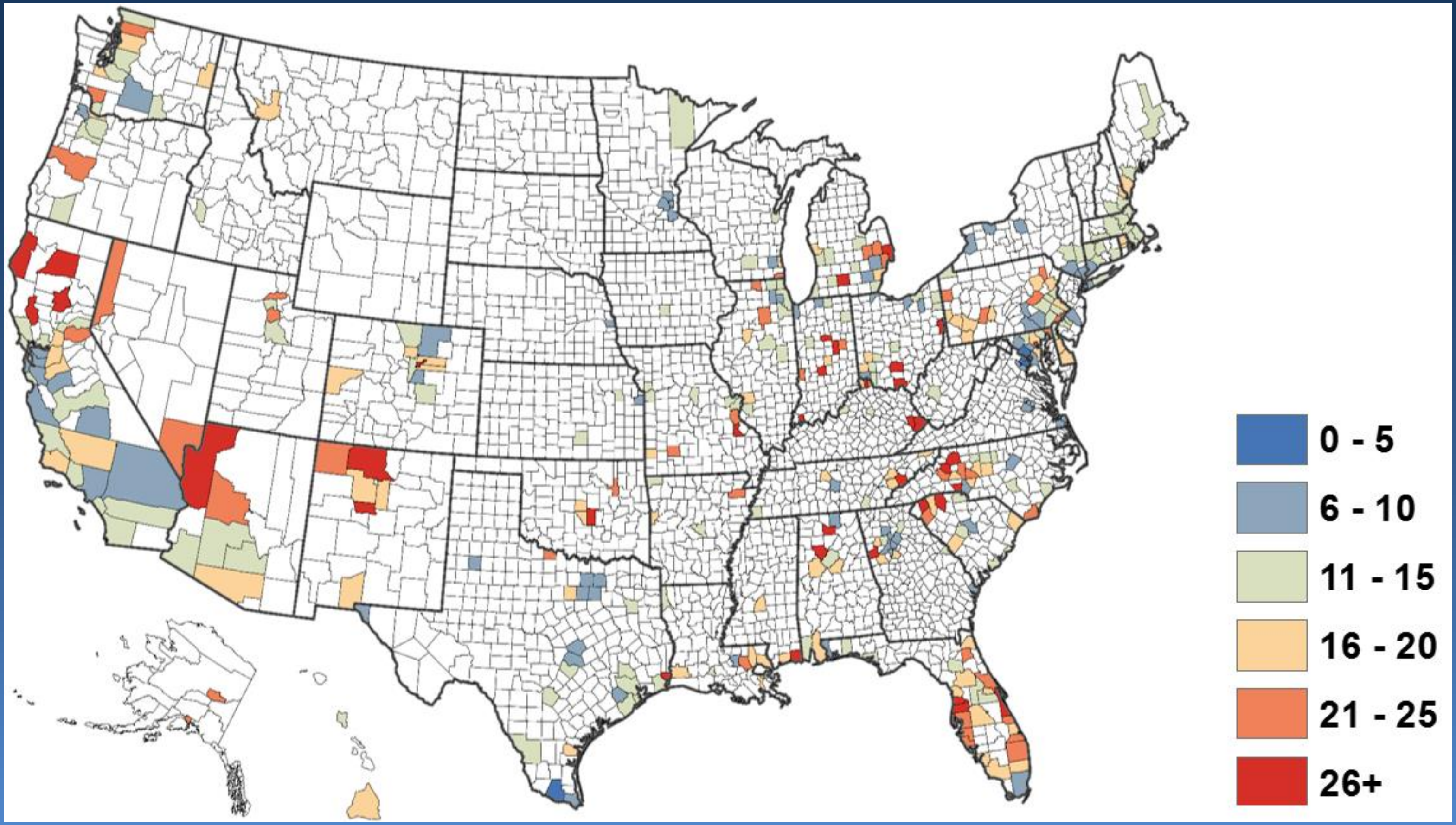
## BACKGROUND

- Death rates associated with drug poisoning have doubled since 2000, to ~ 14 per 100,000 in 2013
  - More deaths due to drug poisoning than motor vehicle crashes
  - Drug overdoses are a major public health concern
- Death rates highest in West Virginia (32), Kentucky (24), New Mexico (23), Rhode Island (22) and Utah (22)
- Interest in county-level variation:
  - Where are death rates due to drug poisoning highest or lowest?
  - Where have we seen larger or smaller increases over time?

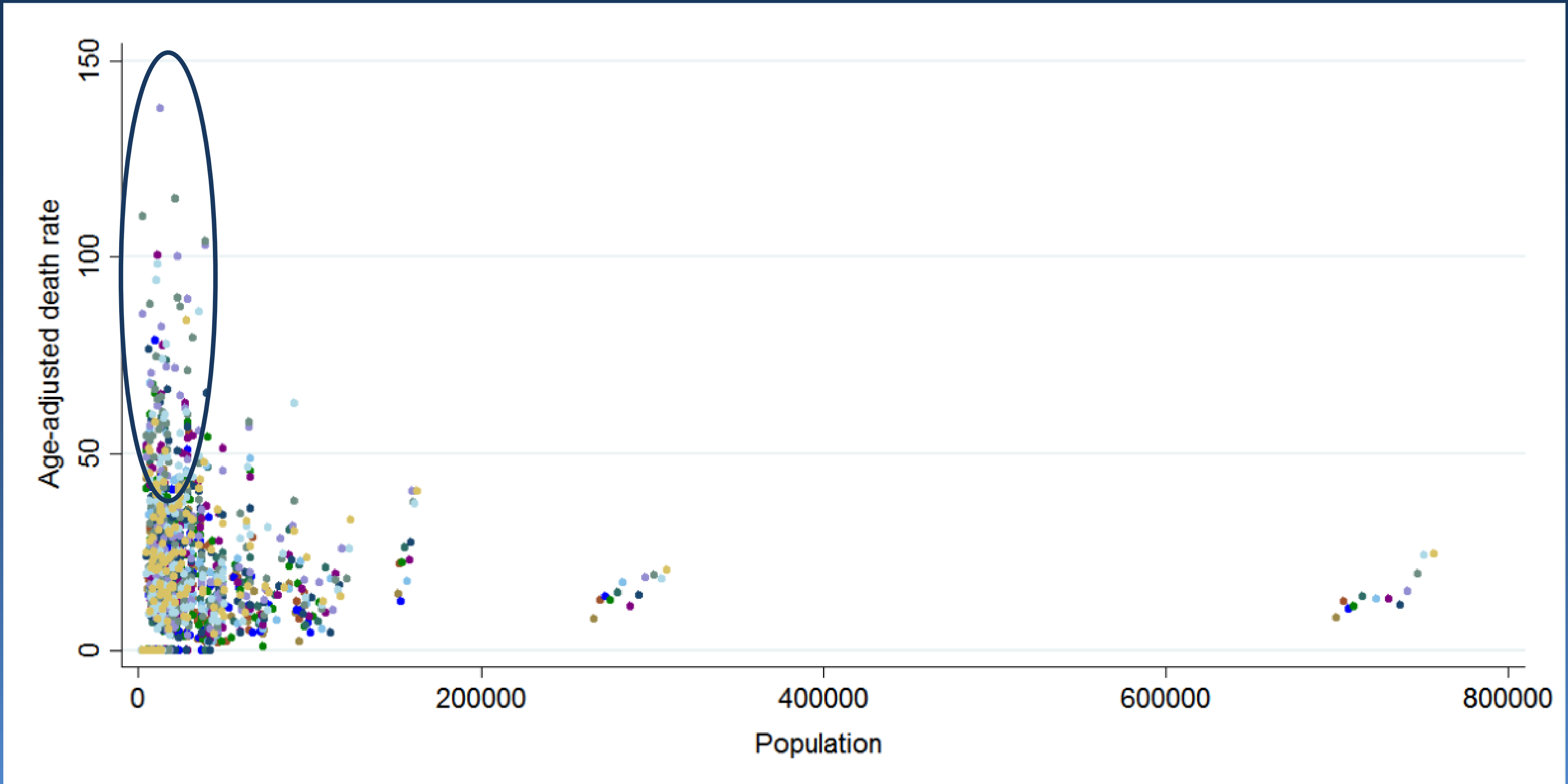
# RATIONALE FOR SMOOTHING: Drug Poisoning

- Death rates with data suppressed for counties with < 20 deaths in 2009
  - 87% of counties suppressed!
  - Rare outcomes ➔ cannot look at sub-state variation using direct estimates



# RATIONALE FOR SMOOTHING (continued)

- Rates are unstable for counties with small populations
  - Could combine years, but would mask temporal trends



# AN EXAMPLE OF UNSTABLE RATES…

- Solid sand-colored line is a large city, other 4 counties are small
  - Death rates fluctuate from 0 to 200 per 100,000 from year-to-year

# DATA AND ANALYSES

- $y_{it}$ = Age-adjusted death rate (AADR) from drug poisoning for county *i* at time *t*
  - from National Vital Statistics Multiple Cause of Death Files, 2002-2013
- $y_{it} \sim$ highly zero-inflated, right-skewed distribution
  - Use two-stage models
    - Stage 1: model probability of observing a death
    - Stage 2: model death rate, given death was recorded

# TWO STAGE MODELS

Stage 1: $\text{logit}(y_{it}=0) = \alpha^{(1)} + A_i^{(1)} + B_t^{(1)} + X_i'\gamma^{(1)}$

Stage 2: $\log(y_{it}|y_{it}>0) = \alpha^{(2)} + A_i^{(2)} + B_t^{(2)} + X_i'\gamma^{(2)}$

$\alpha$ = intercept

$A_i$ = county-level random effect

$B_t$ = fixed effects for year

$X_i'\gamma$= vector of covariates and corresponding parameters, $\gamma$

- urban/rural classification, socio-demographic and economic characteristics at the county-level

# SMOOTHED ESTIMATES

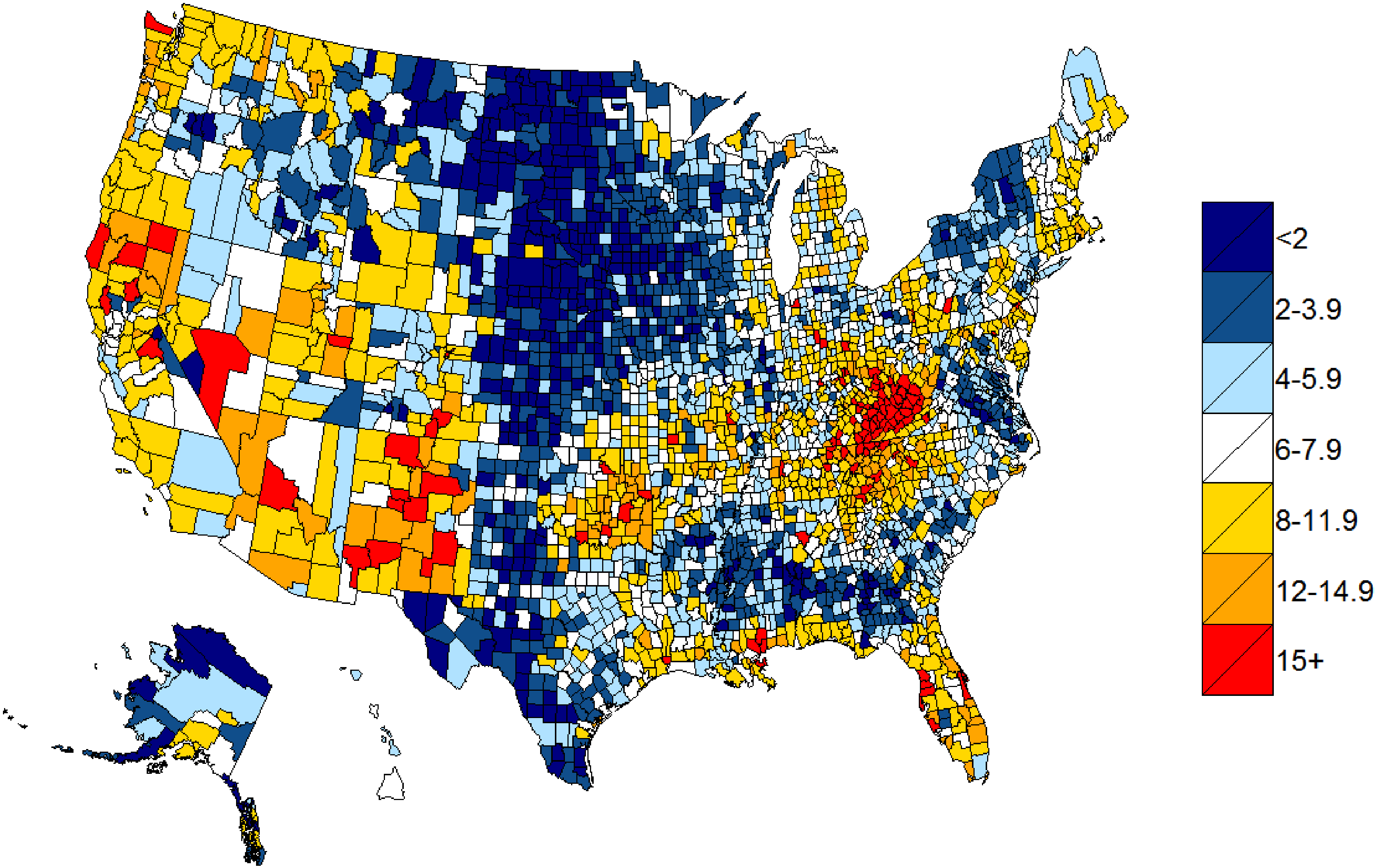
- Models run in Stata using GLAAMM (generalized linear latent and mixed models)

- Empirical Bayes predictions

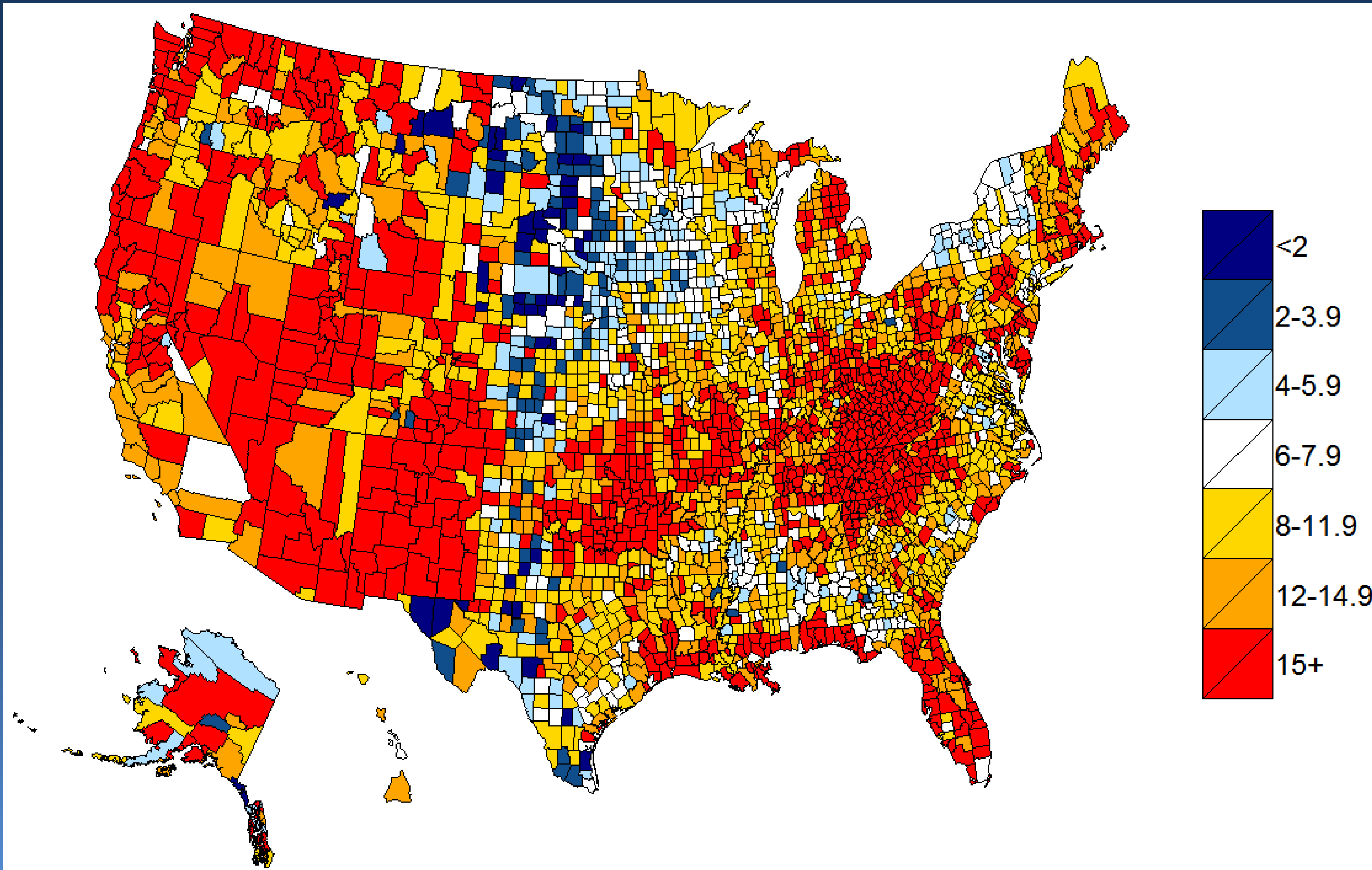
$$E(AADR) = [1\text{-}Pr(y_{it}=0)]*e^{\hat{y}_{it}}$$

- AADRs were mapped to examine spatiotemporal patterns
  - Hot and cold spots
    - Clusters of counties with high/low AADRs

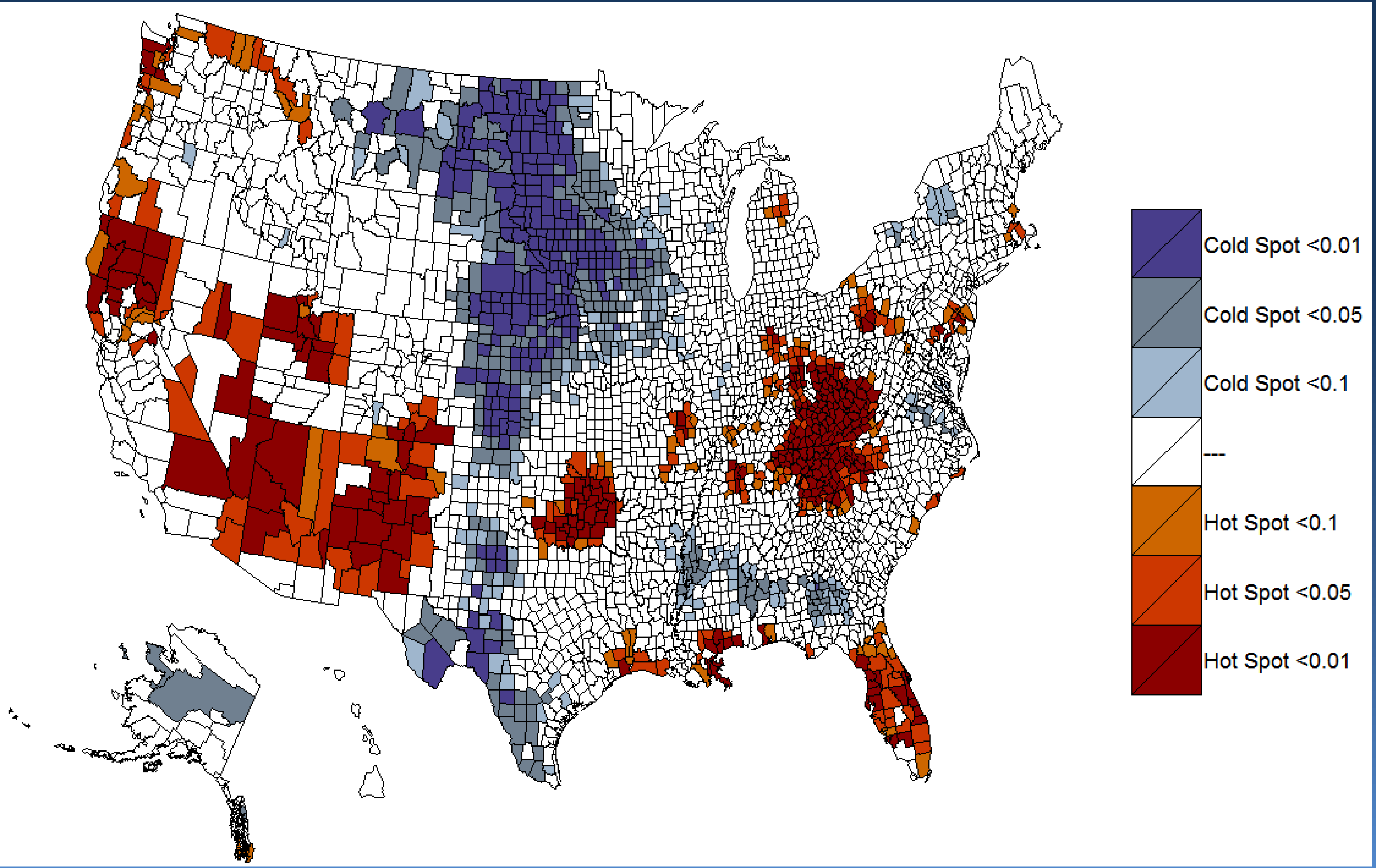
# RESULTS: Age-adjusted death rates (per 100,000) due to drug poisoning - 2002



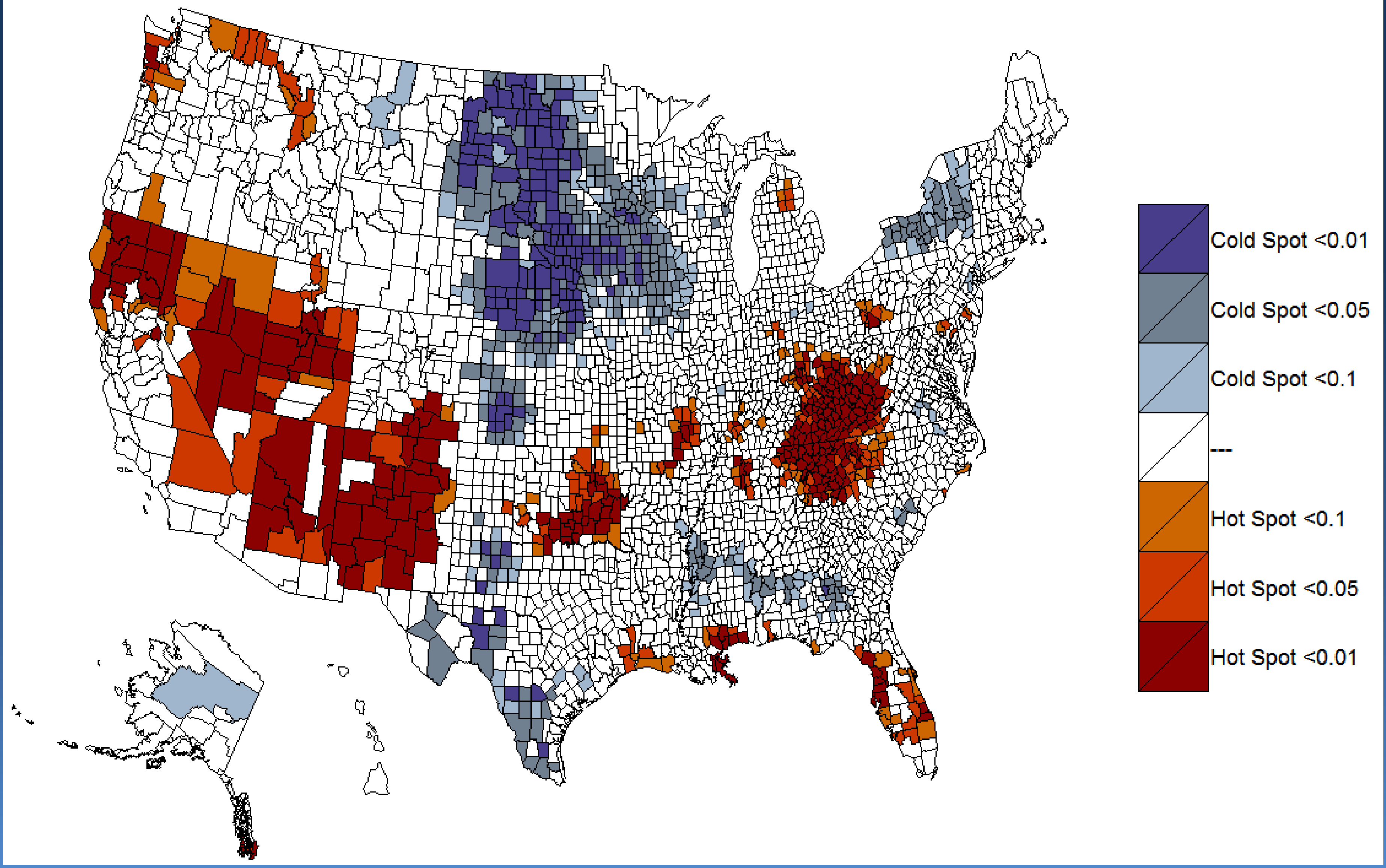
# RESULTS: Age-adjusted death rates (per 100,000) due to drug poisoning - 2013



# RESULTS: Hot and Cold Spots - 2002



# RESULTS: Hot and Cold Spots - 2013



# CONCLUSIONS

- Looking at spatiotemporal patterns can inform efforts to address drug poisoning mortality in the U.S.
  - Can help point to what might be driving drug poisoning mortality higher or lower in specific regions

- Patterns emerge that would have been missed using state estimates
  - Hot or cold spots that cross state boundaries
    - Appalachia, South West, Gulf coast
  - Significant sub-state variation
    - Mississippi, Montana, Virginia contain both hot and cold spots

# Second Example of Smoothing

## Teen Birth Rates in the U.S., 2003-2012

# Teen Birth Rates in the U.S., 2003-2012

## BACKGROUND

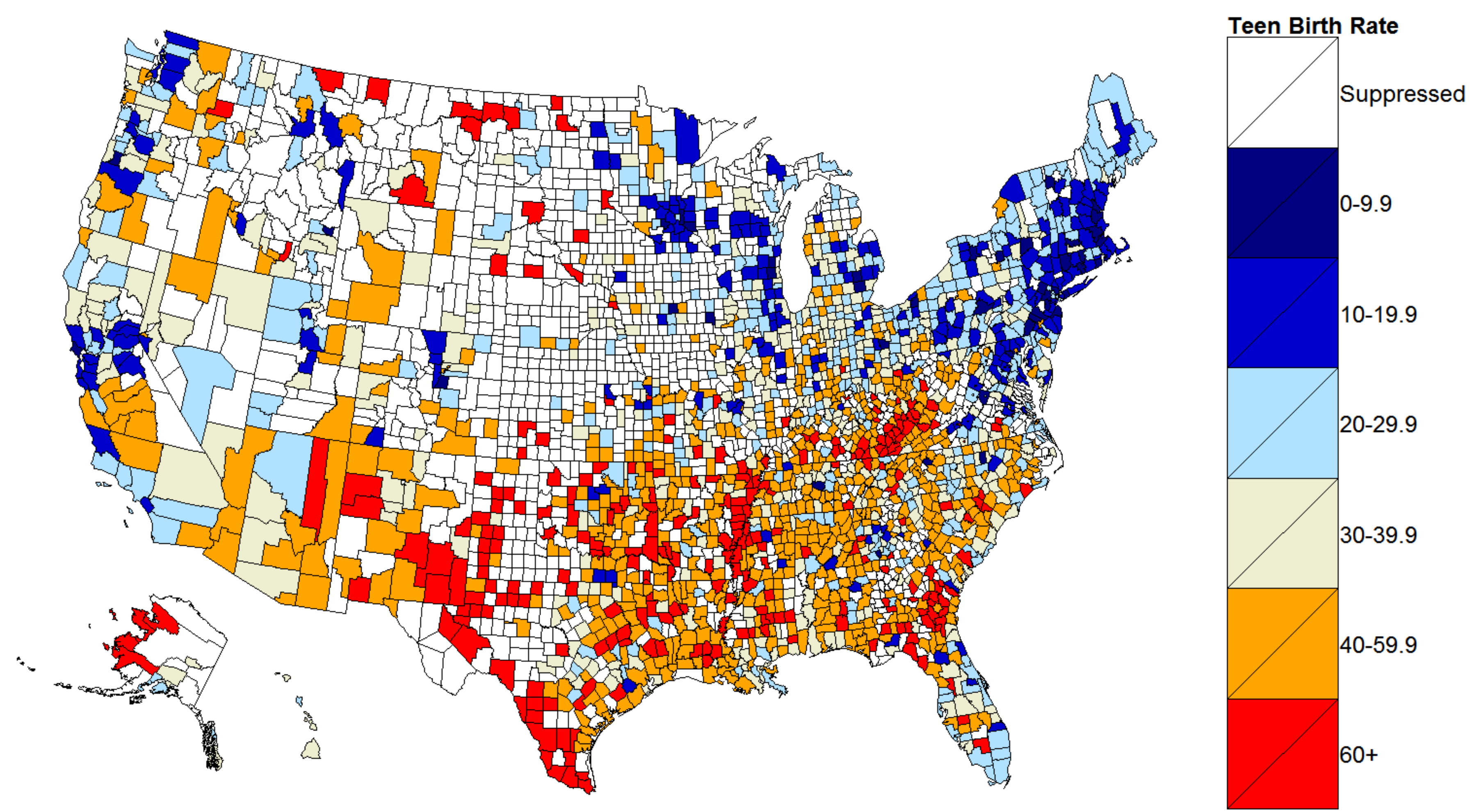
- In 2014, there were 24.2 births for every 1,000 adolescent females (15-19 years)

- Reducing teen pregnancy rates is a CDC Winnable Battle
  - Large-scale impact on health
  - Established preventive measures

- Teen birth rates vary by state, as do trends over time
  - Spatiotemporal variation at the sub-state level has not yet been explored

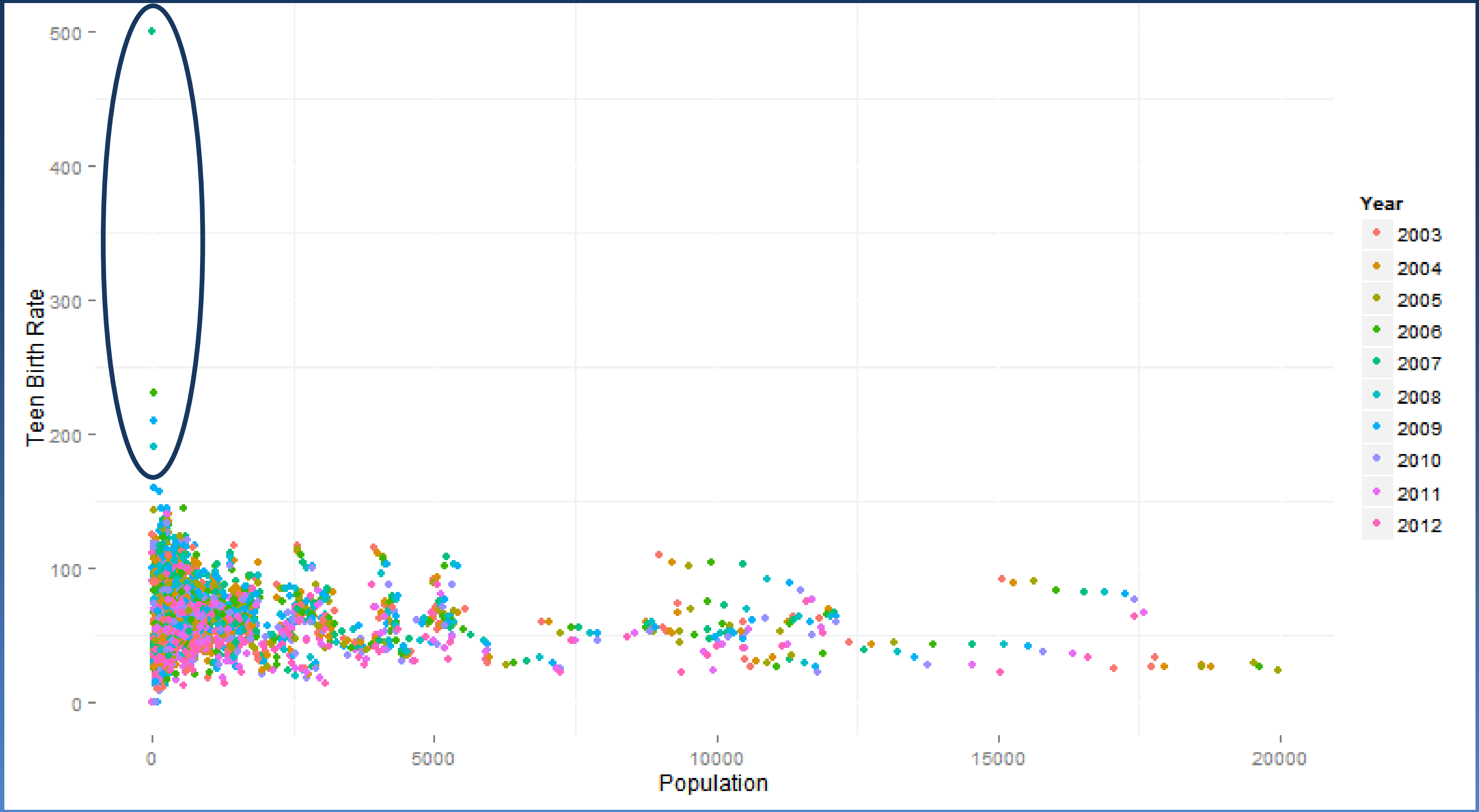
# RATIONALE FOR SMOOTHING: Teen Birth Rates

- Observed county-level teen birth rates in 2012
  - Suppressing counties with < 20 births
    - 'Missing' information for ~36% counties with small populations



# RATIONALE FOR SMOOTHING (continued)

- Rates are unstable for counties with small populations
  - Teen birth rates range from 0 to **<u>500</u>** per 1,000
  - Could combine years, but that may mask temporal trends



# DATA AND ANALYSES

$y_{it}$ = counts of births to women 15-19 years of age in county *i* at time *t*

- from National Vital Statistics Birth Data Files from 2003-2012

$n_{it}$ = counts of women between 15-19 years in county *i* at time *t*

- from bridged-race post-censal population estimates

$y_{it} \sim \text{Binomial}(n_{it}, p_{it})$, where
$p_{it}$ = the probabilities of teen birth for county *i* at time *t*

$X_i'$ = set of covariates related to urban/rural designation, socio-demographic and economic characteristics

- from Area Resource File, NCHS urban/rural classification scheme

# HIERARCHICAL BAYESIAN MODELS

General space-time structure for modeling $p_{it}$:

$$\text{logit}(p_{it}) = \alpha + A_i + B_t + C_{it} + X_i'\gamma$$

$\alpha$ = intercept

$A_i$ = spatial effect

$B_t$ = temporal effect

$C_{it}$ = space-time interaction

$X_i'\gamma$ = vector of covariates and corresponding parameters, $\gamma$

Models run in WinBUGS

# MAPPING SMOOTHED ESTIMATES

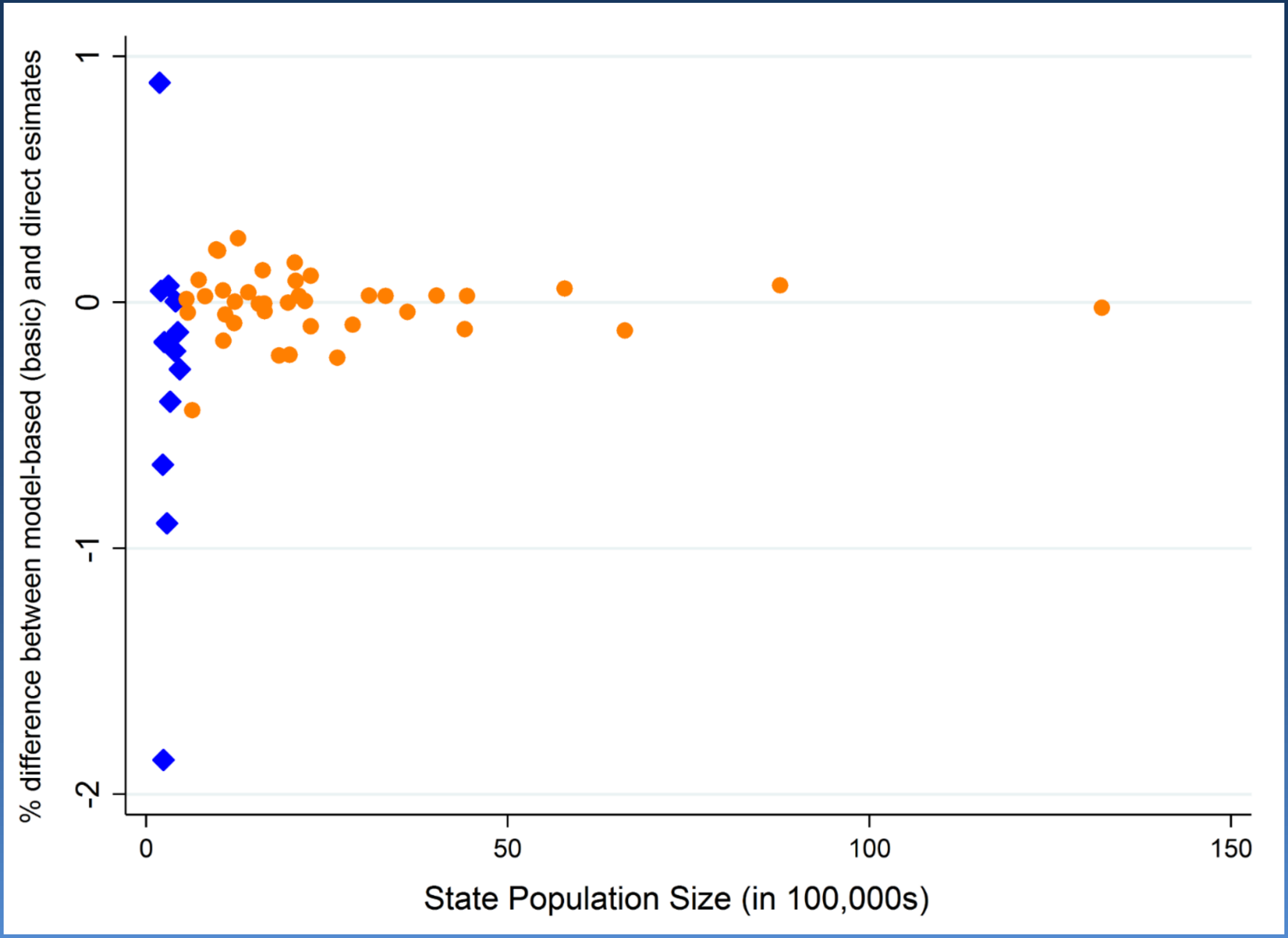
- Posterior teen birth rates ($1000*\hat{p}_{it}$) mapped to examine spatiotemporal patterns:
  - Exceedance probabilities
    - Probability that counties exceed a specified threshold, *c*
      - We chose *c* = 36 to reflect the mean county-level TBR in 2012
  - Hot and cold spots
    - Clusters of counties with high or low rates

# RESULTS

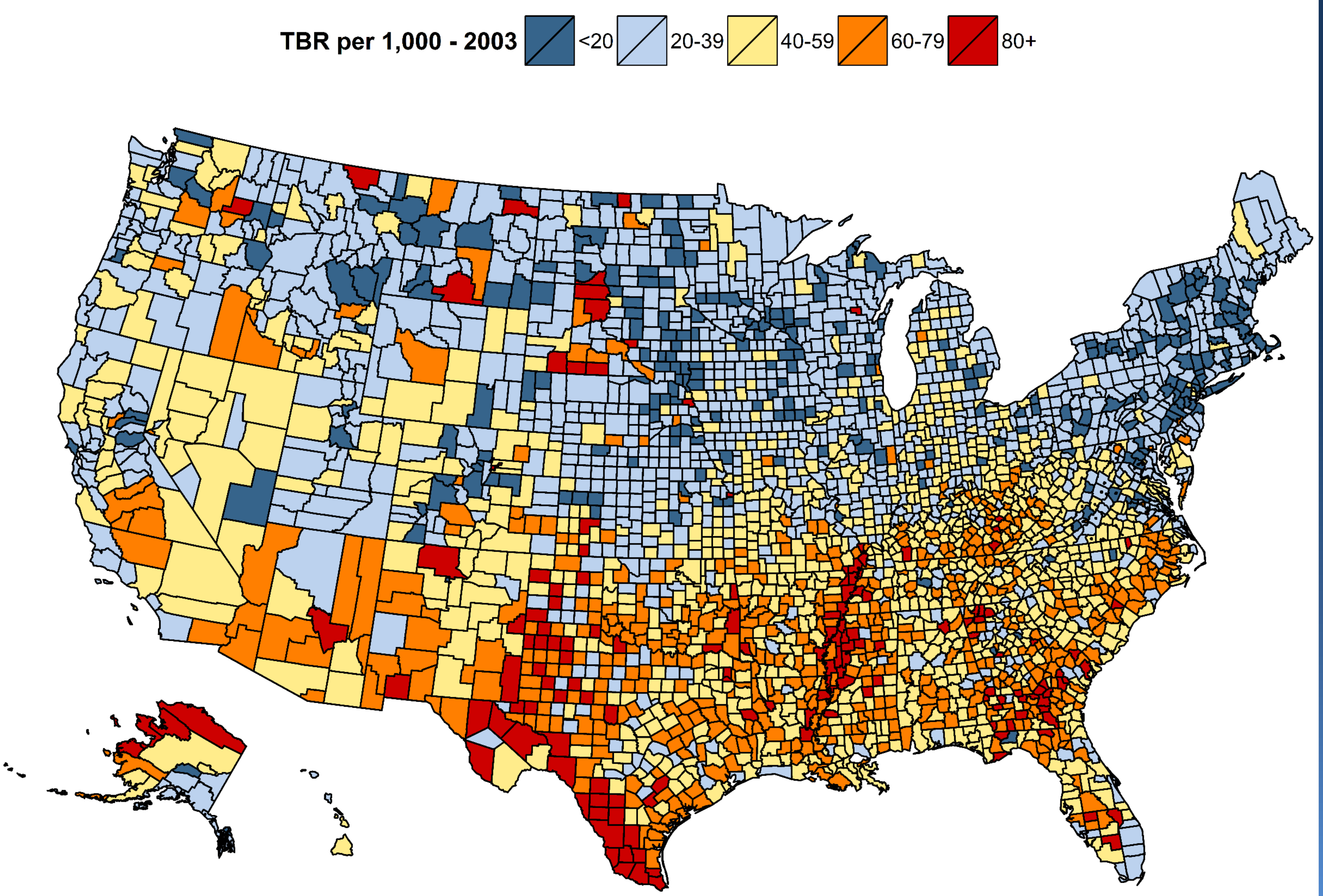
- From 2003-2012, teen birth rates:
  - declined for ~80% of counties
  - no change for ~19% of counties
  - increased for < 1% of counties

- Comparisons to direct estimates at the state level were within 2%
  - Differences between model-based and direct estimates were larger for sparsely populated states

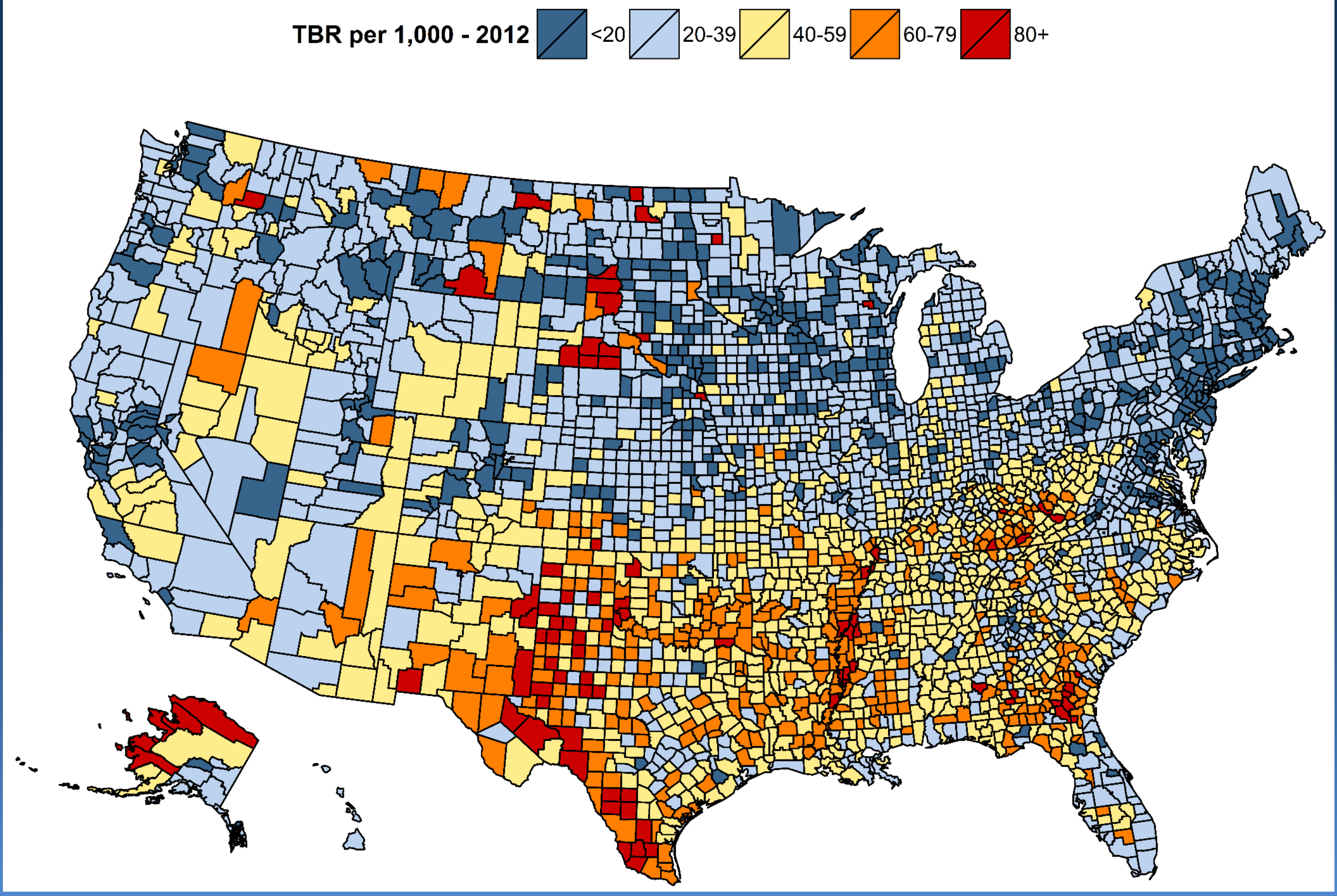
# MODEL DIAGNOSTICS (Teen Birth Rates): Comparison to state estimates



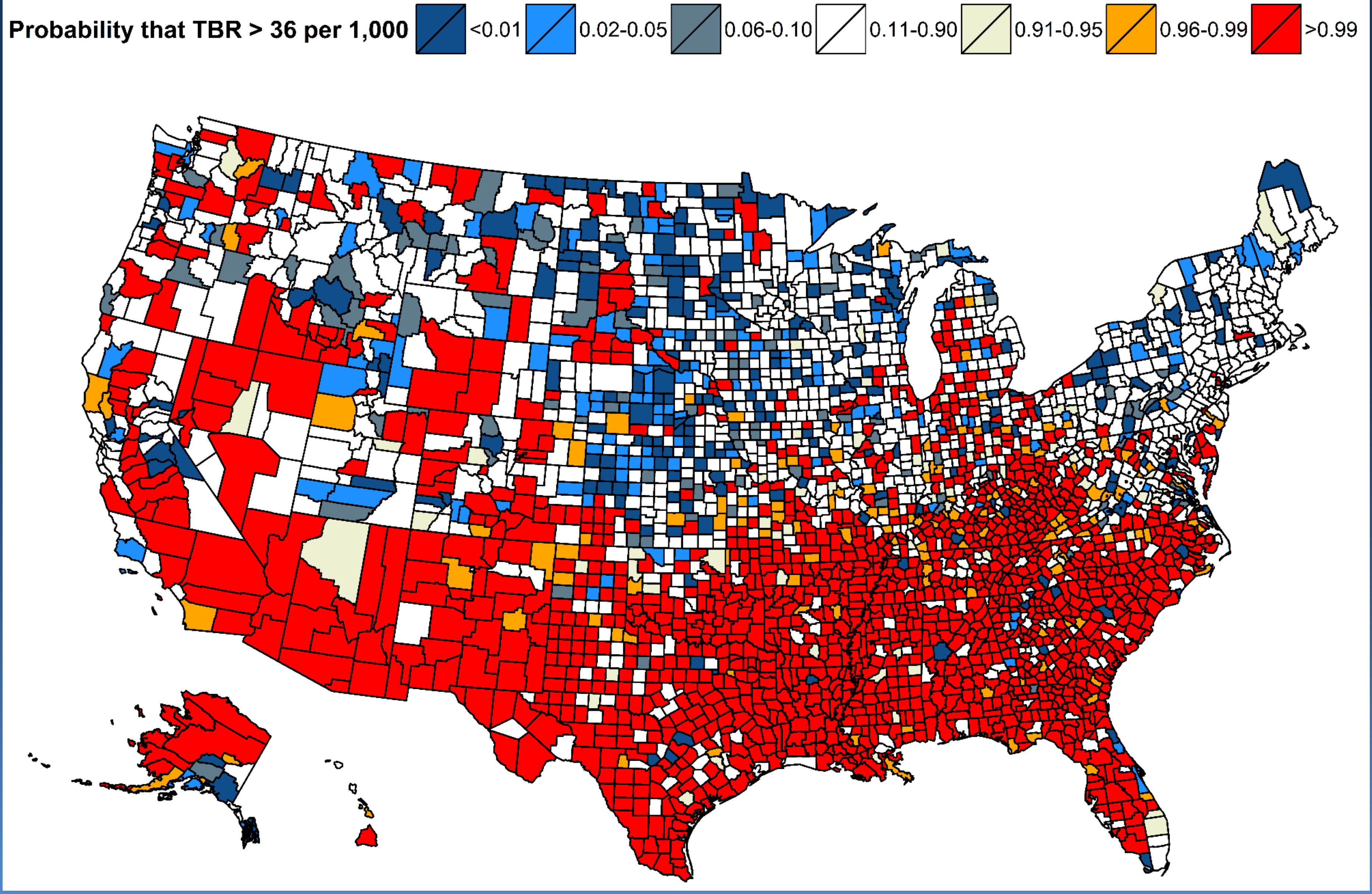
# Estimated teen birth rates (per 1,000) - 2003



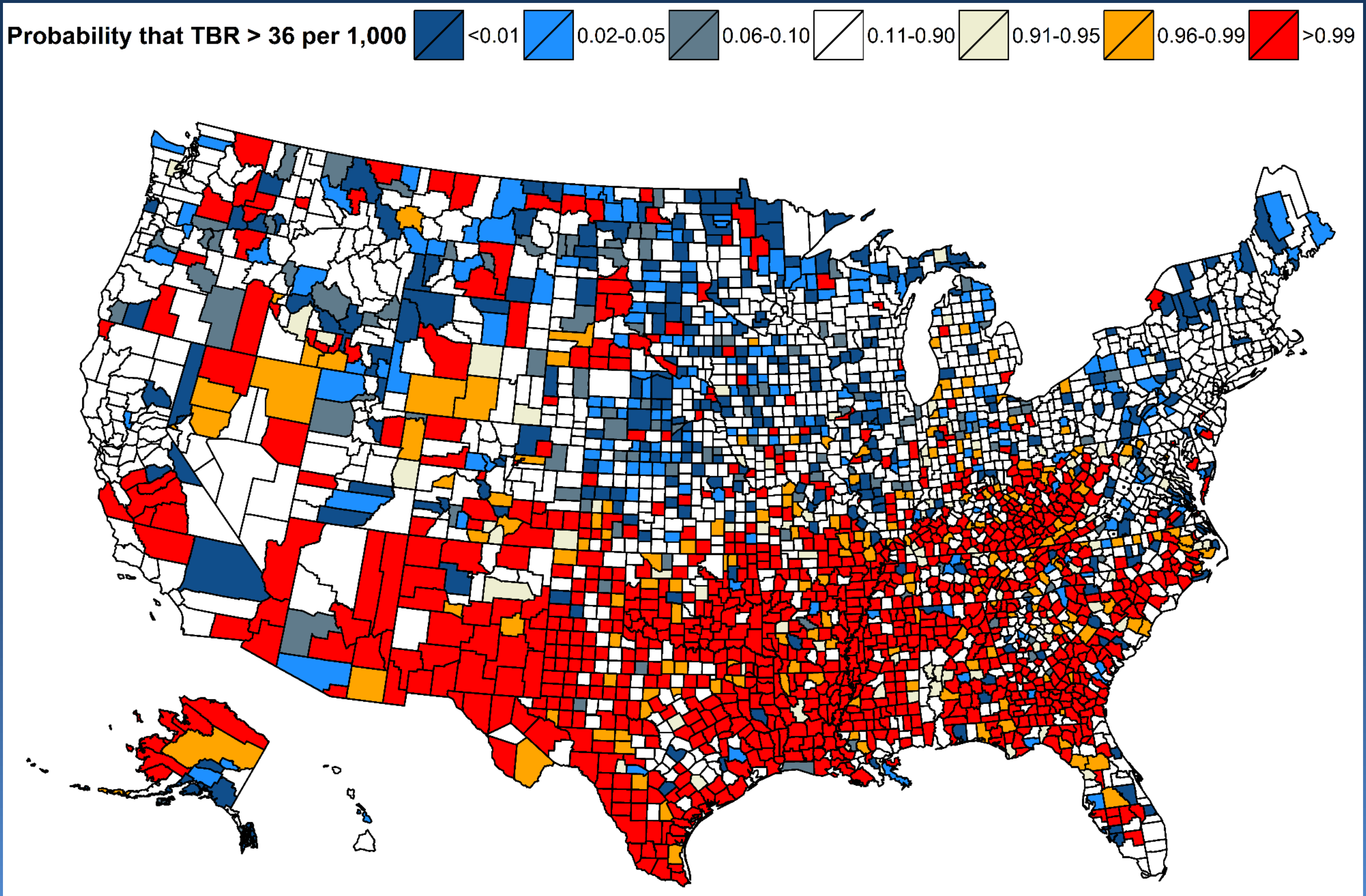
# Estimated teen birth rates (per 1,000) - 2012



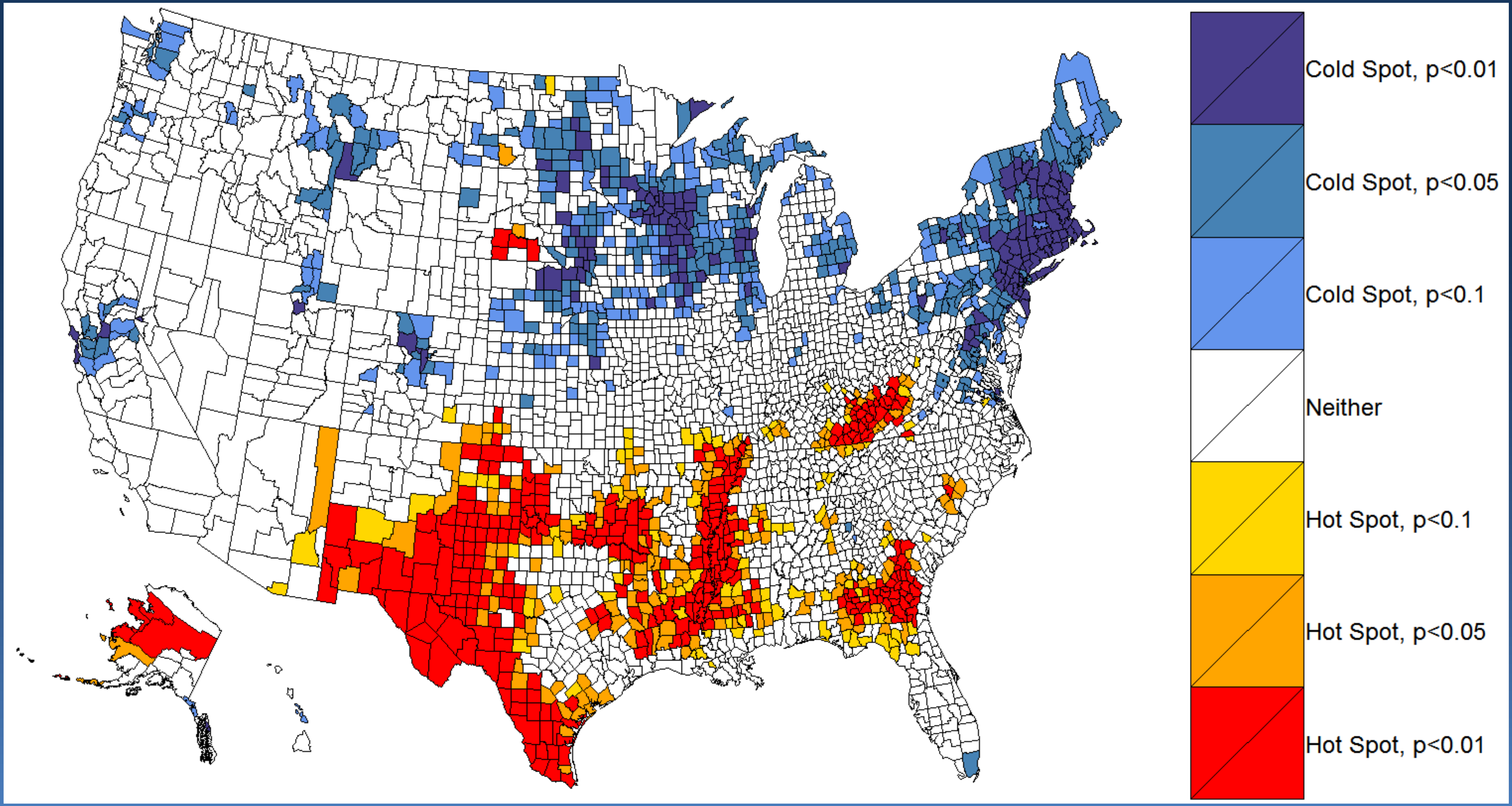
# Exceedance Probabilities - 2003



# Exceedance Probabilities - 2012



# Hot and Cold Spots - 2012



# CONCLUSIONS

- Findings highlight counties where teen birth rates are relatively higher or lower
  - How trends over time vary geographically
- Patterns emerge that we would have missed using state estimates
  - For example, the hot spot along the Mississippi River crosses state boundaries
- Examination of spatiotemporal patterns may inform efforts to further reduce birth rates to adolescents in the U.S.
  - Can look at where teen birth rates are higher than a given ‘target’

# SOME CONSIDERATIONS

- Strengths:
  - Can see 'full picture' of what is happening across the U.S.
  - Pick up on important patterns that might be masked by state estimates or other groupings (urban/rural)
- Limitations:
  - Might smooth away important effects
    - Either in space or in time
  - With birth/death data, difficult to check models
    - We already have 100% of the data!

# QUESTIONS?

Email: LRossen@cdc.gov

- For more on teen births, sit tight for the next session – "Teen and Young Adult Health Disparities: More Than Just Sex and Pregnancy"
- For more on drug poisoning, head to Salon D for "From Health to Harm: The Burden of Drug Poisoning in the United States"

# Helpful References


- NCHS Fact Sheet: Data on Drug Poisoning Deaths. June 2015. http://www.cdc.gov/nchs/data/factsheets/factsheet_drug_poisoning.pdf
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