Modeling perinatal and neonatal mortality in Colombia and the U.S.

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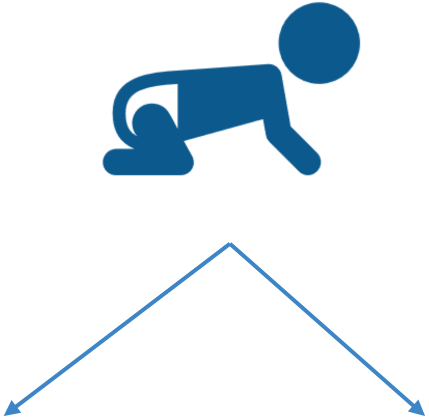
Motivation

Perinatal and Neonatal mortality

Perinatal:
Fetal period & early neonatal



Early neonatal:
Before 7 days of birth

Late neonatal:
7-28 days of birth

Motivation

Considerable differences in perinatal and neonatal mortality between developing and developed countries

Colombia: 32 states

$

U.S.: 50 states

$$$

Problem

This project will attempt to **model the probability of perinatal and late neonatal mortality in 2020** in different regions in **Colombia** and compare it with the **US**

Colombia: 32 states

$

U.S.: 50 states

$$$

Modeling idea

Deaths in the perinatal and neonatal period → **Treated as "successes"**

Births in the same year → **Treated as "trials"**

↓

Beta-binomial model:

The probability of success at each of n trials is not fixed, drawn from β distribution

Data

National Institute of Health (INS)

Epidemiological reports 2017-2020

No models found for this type of data

CDC wonder

Infant death records 2007-2020

Only predictive modeling for whole country

Models

Separate and hierarchical

Parameter of interest

$\theta \rightarrow$ Probability of perinatal and late neonatal death

Variables

y$\longrightarrow$ Number of deaths

n$\longrightarrow$ Number of births in the same period

Similarities

Likelihood

$$p(y_i|\theta_i) = \binom{n_i}{y_i} \theta_i^{y_i} (1 - \theta_i)^{y_i}$$

Both priors used death and birth means from the past data*

Priors and hyper-priors

Separate

$$\theta_i \sim Beta(\bar{a}_i, \bar{b}_i)$$

$\bar{a}_i$ → Mean of deaths in region i, from past data*

$\bar{b}_i$ → Mean of live births in region i, from past data*

Hierarchical

$$\theta i \sim \mathrm{Beta}(\alpha, \beta)$$

$$\alpha = \mu\eta, \beta = (1 - \mu)\eta$$

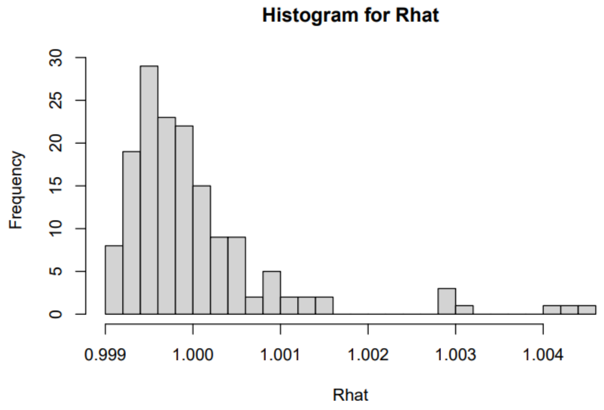
hyper-priors

$$\eta \sim \mathrm{exponential}(x)$$

$$\mu \sim Beta(\bar{\alpha}_i, \bar{\beta}_i)$$

Convergence

US Data



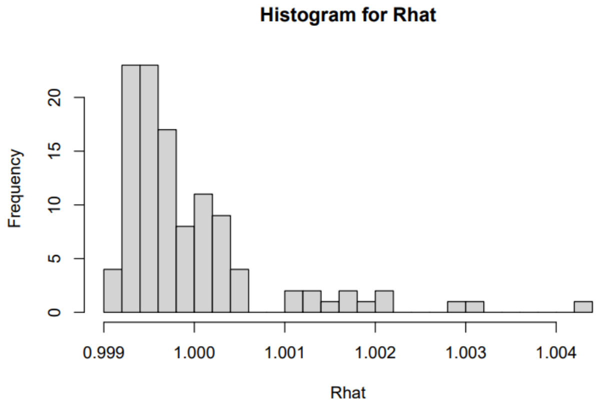

```
check_divergences(separate_modelUS)
```

```
## 0 of 4000 iterations ended with a divergence.
```

```
check_treedepth(separate_modelUS)
```

```
## 0 of 4000 iterations saturated the maximum tree depth of 10.
```

Colombia Data




```
check_divergences(separate_modelCol)
```

```
## 0 of 4000 iterations ended with a divergence.
```

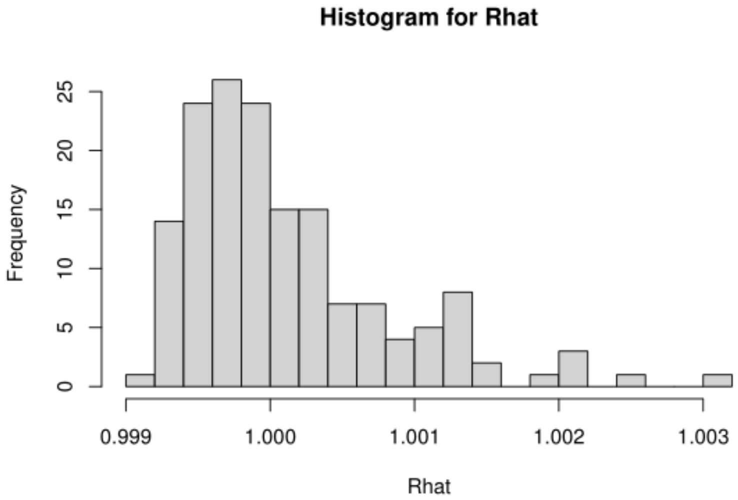
```
check_treedepth(separate_modelCol)
```

```
## 0 of 4000 iterations saturated the maximum tree depth of 10.
```

SEPARATE

Convergence

US Data



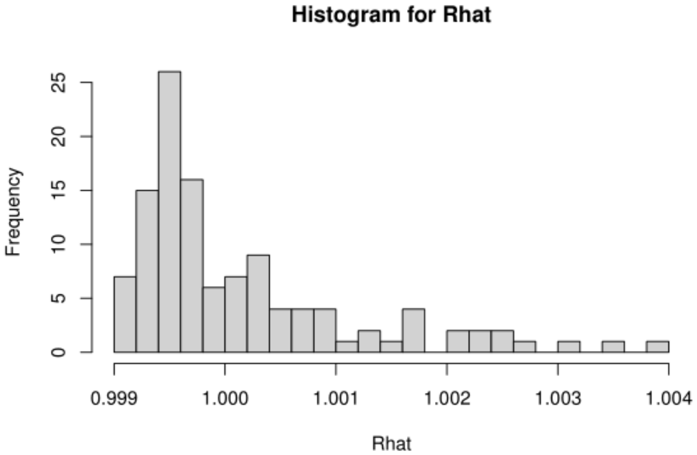

```
check_divergences(hierarchical_modelUS)
```

```
## 0 of 4000 iterations ended with a divergence.
```

```
check_treedepth(hierarchical_modelUS)
```

```
## 0 of 4000 iterations saturated the maximum tree depth of 10.
```

Colombia Data




```
check_divergences(hierarchical_modelCol)
```

```
## 0 of 4000 iterations ended with a divergence.
```

```
check_treedepth(hierarchical_modelCol)
```

```
## 0 of 4000 iterations saturated the maximum tree depth of 10.
```

HIERARCHICAL

Model improvements

Separate model

Hyper-priors

a[i] ~ normal(aMean[i], aStd[i])

b[i] ~ normal(bMean[i], bStd[i])

Prior

theta[j] ~ beta(a[j], b[j])

K-pareto analysis worse

Hierarchical model

$$\eta \sim \text{exponential}(x)$$

Instead of…

$$\eta \sim \text{gamma}(s,t)$$

Many s,t values were tried, k-pareto got worse

Model comparison

Separate model

US Data

```
##
## Computed from 4000 by 51 log-likelihood matrix
##
##           Estimate   SE
## elpd_loo    -233.2  9.6
## p_loo         31.4  4.7
## looic        466.4 19.2
## ------
## Monte Carlo SE of elpd_loo is NA.
##
## Pareto k diagnostic values:
##                          Count Pct.    Min. n_eff
## (-Inf, 0.5]   (good)     14    27.5%   703
##  (0.5, 0.7]   (ok)       25    49.0%   116
##    (0.7, 1]   (bad)      11    21.6%   31
##    (1, Inf)   (very bad)  1     2.0%   19
## See help('pareto-k-diagnostic') for details.
```

Colombia Data

```
##
## Computed from 4000 by 37 log-likelihood matrix
##
##           Estimate   SE
## elpd_loo    -164.6  6.7
## p_loo         21.4  3.8
## looic        329.1 13.4
## ------
## Monte Carlo SE of elpd_loo is NA.
##
## Pareto k diagnostic values:
##                          Count Pct.    Min. n_eff
## (-Inf, 0.5]   (good)      9    24.3%   366
##  (0.5, 0.7]   (ok)       22    59.5%   367
##    (0.7, 1]   (bad)       5    13.5%   48
##    (1, Inf)   (very bad)  1     2.7%   36
## See help('pareto-k-diagnostic') for details.
```

Hierarchical model

US Data

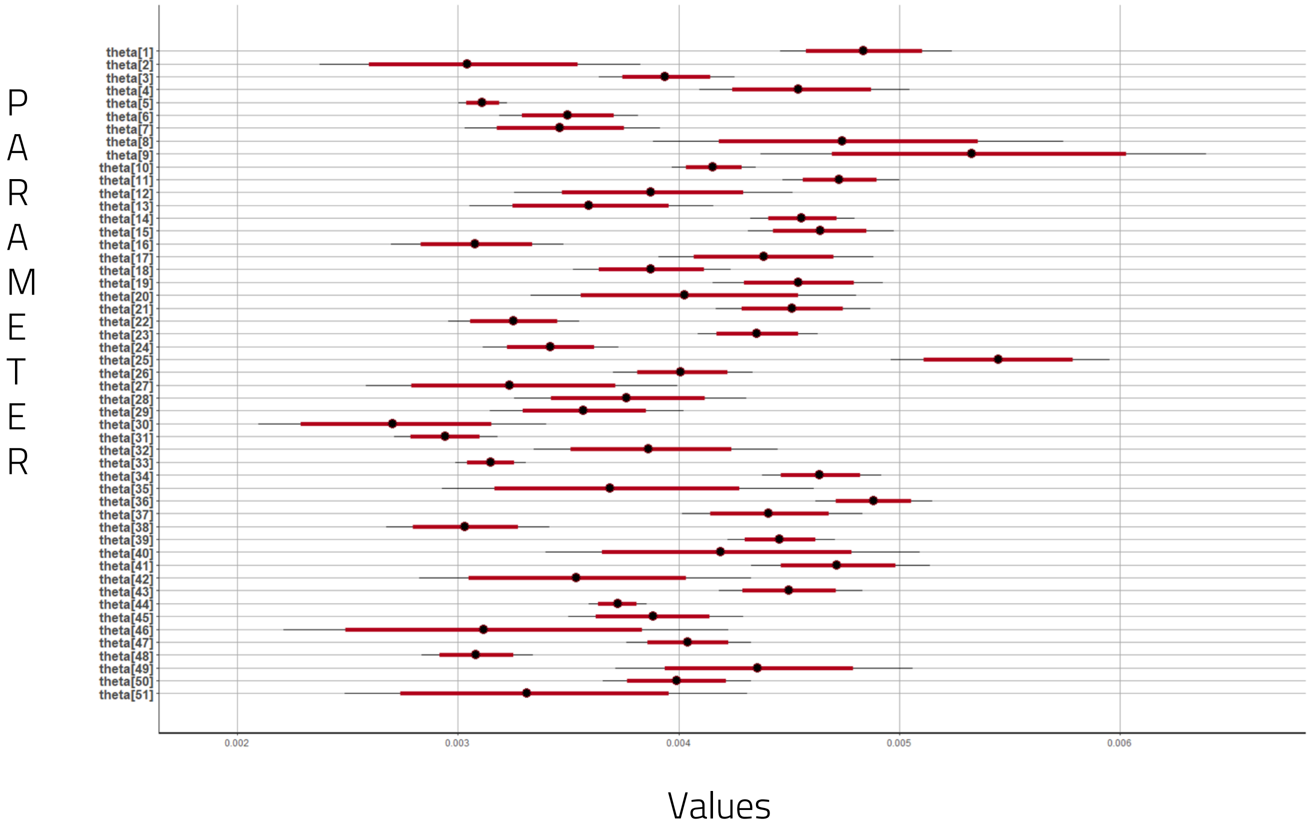
```
## Monte Carlo SE of elpd_loo is NA.
##
## Pareto k diagnostic values:
##                          Count Pct.    Min. n_eff
## (-Inf, 0.5]   (good)      3     5.9%   750
##  (0.5, 0.7]   (ok)       12    23.5%   230
##    (0.7, 1]   (bad)      30    58.8%   16
##    (1, Inf)   (very bad)  6    11.8%   15
## See help('pareto-k-diagnostic') for details.
```

Colombia Data

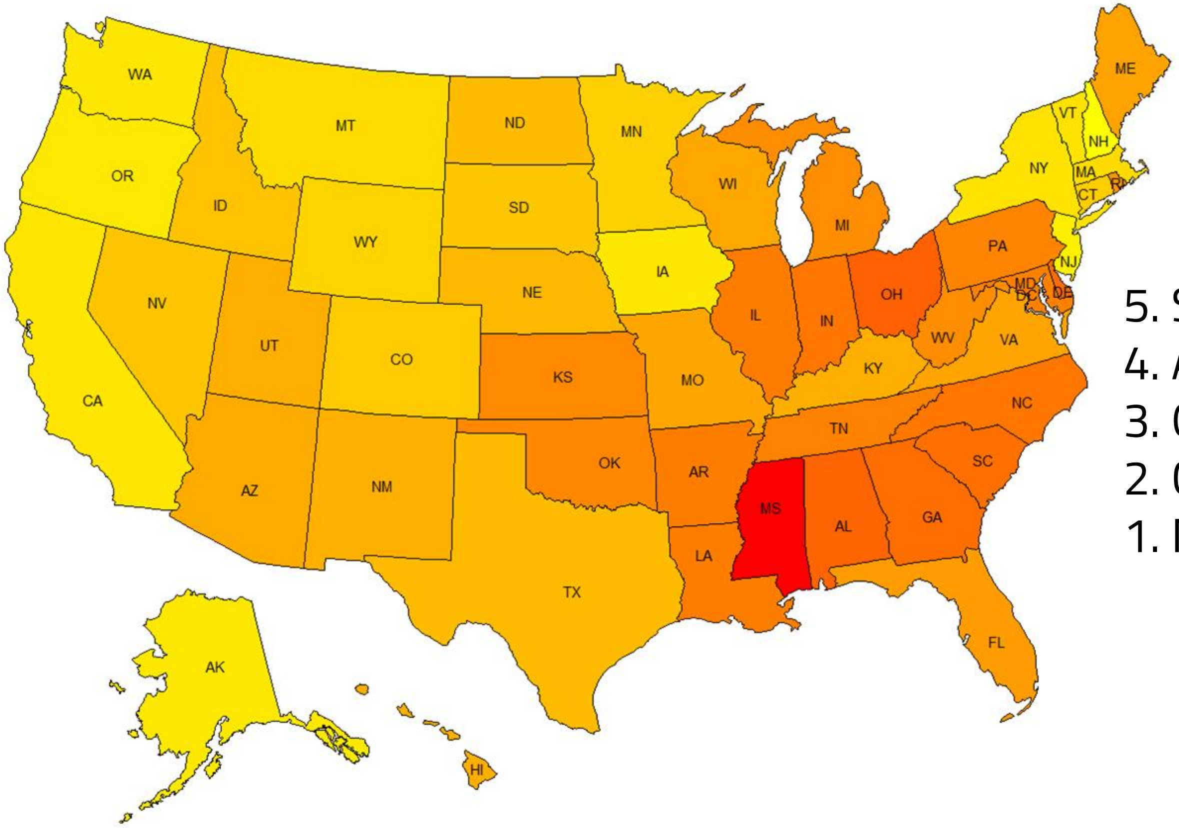
```
## Computed from 4000 by 37 log-likelihood matrix
##
##           Estimate   SE
## elpd_loo    -174.2  5.0
## p_loo         32.7  3.3
## looic        348.5 10.1
## ------
## Monte Carlo SE of elpd_loo is NA.
##
## Pareto k diagnostic values:
##                          Count Pct.    Min. n_eff
## (-Inf, 0.5]   (good)      0     0.0%   <NA>
##  (0.5, 0.7]   (ok)        6    16.2%   125
##    (0.7, 1]   (bad)      25    67.6%   21
##    (1, Inf)   (very bad)  6    16.2%   9
## See help('pareto-k-diagnostic') for details.
```

RESULTS

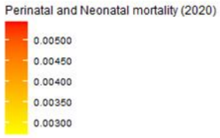
US DATA


P
A
R
A
M
E
T
E
R
theta[1]
theta[2]
theta[3]
theta[4]
theta[5]
theta[6]
theta[7]
theta[8]
theta[9]
theta[10]
theta[11]
theta[12]
theta[13]
theta[14]
theta[15]
theta[16]
theta[17]
theta[18]
theta[19]
theta[20]
theta[21]
theta[22]
theta[23]
theta[24]
theta[25]
theta[26]
theta[27]
theta[28]
theta[29]
theta[30]
theta[31]
theta[32]
theta[33]
theta[34]
theta[35]
theta[36]
theta[37]
theta[38]
theta[39]
theta[40]
theta[41]
theta[42]
theta[43]
theta[44]
theta[45]
theta[46]
theta[47]
theta[48]
theta[49]
theta[50]
theta[51]
0.002
0.003
0.004
0.005
0.006
Values

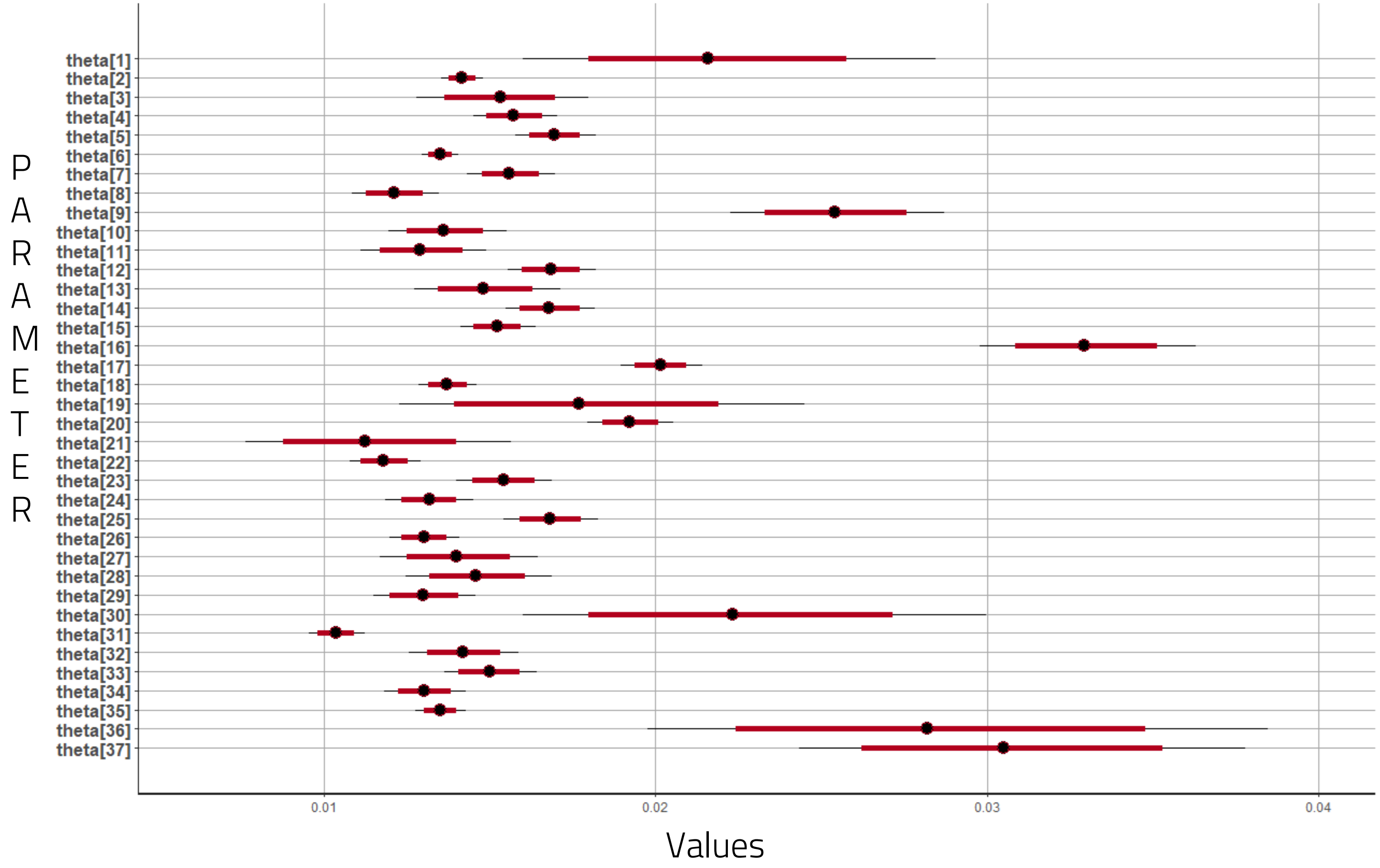
US

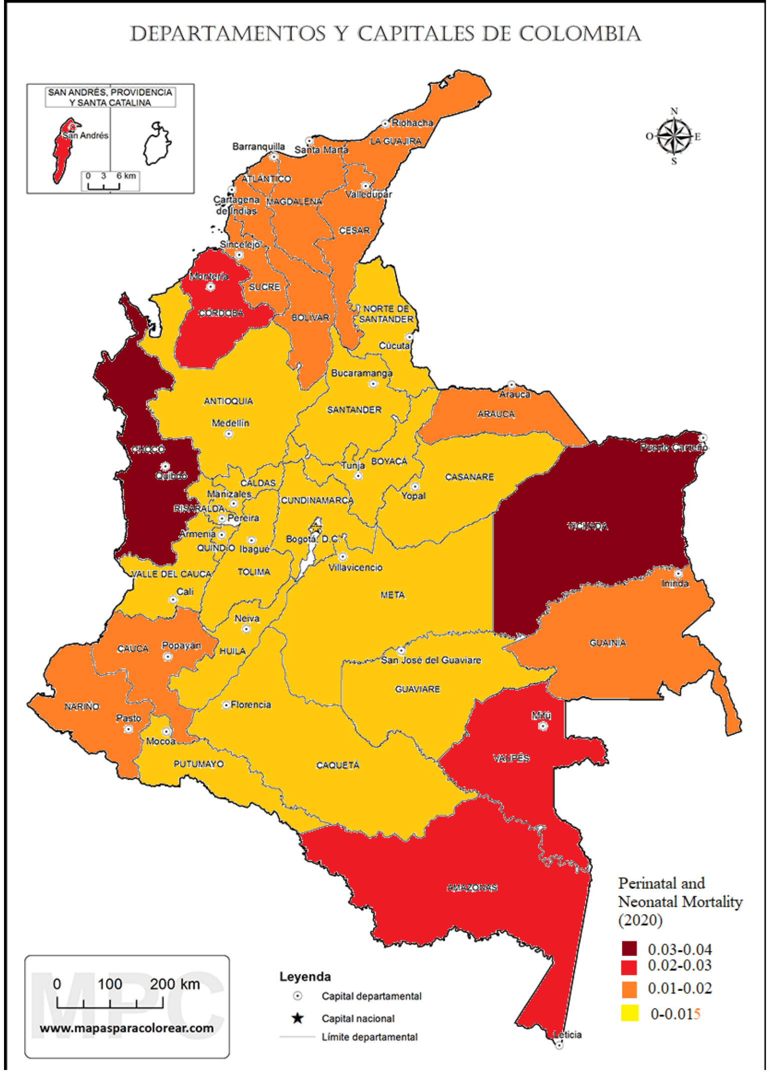


5. S. Carolina: 0.00472
4. Alabama: 0.00484
3. Ohio: 0.00488,
2. Columbia: 0.00534
1. Mississippi: 0.00545



COLOMBIA DATA





COLOMBIA

5. Cordoba: 0.0202
4. Buenaventura: 0.0284
3. Vaupes: 0.0284,
2. Vichada: 0.0306
1. Choco: 0.0330

Poorness vs Perinatal & Neonatal Mortality

Choco, Vichada and Vaupes are among the top 5 poorest states in Colombia [2]

South Carolina, Columbia, Mississippi and Alabama are between the top 10 poorest states in the US [3]

Discussion of Issues

Separate model

K-pareto analysis not optimal

Increase data size using not the mean but all past year data

Hierarchical model

K-pareto analysis not good

Try different hyper-priors and use all past data.

Interesting idea: Combine the model with a predictive one (using all data)→ Forecast probability of death in each state in the future years. → **Arima, ArimaX**

¿Any questions?

References

[1] “Neonatal Mortality.” UNICEF DATA, 20 July 2021, https://data.unicef.org/topic/child-survival/ neonatal-mortality/.

[2] Semana Magazine. “Pobreza En Colombia: Estos Son Los Departamentos Más Afectados.” Semana.com Últimas Noticias De Colombia y El Mundo, 21 Dec. 2020, https://www.semana.com/economia/articulo/pobreza-en-colombia-estos-son-los-departamentos-masafectados/202026/.

[3] November 10, 2021. “Top 10 Poorest States in the U.S.” Friends Committee On National Legislation, https://www.fcnl.org/updates/2021-11/top-10-poorest-states-us. Vehtari, Aki, and Markus Paasiniemi.

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“Bayesian Hierarchical Meta-Analysis of Asymptomatic Ebola Seroprevalence” (2019). CMC Senior Theses. 2228.https://scholarship.claremont.edu/cmc_theses/2228