

# Coastal Analysis June 24

## Summary

### Confounding Variables

1. Population Density. Reflects the role of social distance in airborne propagation. We should in all our comparisons keep this variable as fixed as we can while avoiding the comparison of small sets of data.
2. All Ages in Poverty (%). Reflects propensity to respect hygiene (notably mask adoption) and social distance rules (living circumstances and ability to stay-at-home).
3. Median Income. Similar to (2) while an independent variable (poverty rate may be high and median income high or low dependent on the wealth gap).
4. Percent adult obesity. Reflects propensity to generate respiratory droplets — and observed correlation with COVID infection/symptom severity.
5. Voter margin 2020 election. Reflects propensity to wear masks. Independent variable to (7).
6. Median age 2019. Reflects propensity to generate respiratory droplets — and observed correlation with COVID infection/symptom severity.
7. Voting party in the 2020 presidential election. See (5).
8. Air pollution (PM 2.5) (Dominici lab data). Reflects propensity to generate respiratory droplets — and observed correlation with COVID infection/symptom severity. Should use 2020 PM 2.5 data if available given the importance of the fire season in 2020.
9. Mean winter and summer humidity (Dominici lab data). Reflects propensity to generate respiratory droplets — and observed correlation with COVID infection/symptom severity.

### Analyses

- Atlantic coastal counties (bordering the ocean, ie 1st degree) versus Inland Counties (including all counties bordering non-ocean bodies of water).
- Atlantic urban coastal counties (bordering the ocean, ie 1st degree) versus Inland urban Counties (including all counties bordering non-ocean bodies of water).
- Atlantic rural coastal counties (bordering the ocean, ie 1st degree) versus Inland rural Counties (including all counties bordering non-ocean bodies of water).
- Pacific coastal counties (bordering the ocean, ie 1st degree) versus Inland Counties (including all counties bordering non-ocean bodies of water).
- Pacific urban coastal counties (bordering the ocean, ie 1st degree) versus Inland urban Counties (including all counties bordering non-ocean bodies of water).
- Pacific rural coastal counties (bordering the ocean, ie 1st degree) versus Inland rural Counties (including all counties bordering non-ocean bodies of water).

- Gulf coastal counties (bordering the ocean, ie 1st degree) versus Inland Counties (including all counties bordering non-ocean bodies of water).
- Gulf urban coastal counties (bordering the ocean, ie 1st degree) versus Inland urban Counties (including all counties bordering non-ocean bodies of water).
- Gulf rural coastal counties (bordering the ocean, ie 1st degree) versus Inland rural Counties (including all counties bordering non-ocean bodies of water).

```
library(readxl)
library(stringr)
library(gee)
library(sjPlot)
library(sjmisc)
```

```
## Learn more about sjmisc with 'browseVignettes("sjmisc")'.
```

```
library(sjlabelled)
```

## Analyses

Read in data and additional confounding variables from Dominici lab (air pollution 2020 from aqs, humidity from previous Dominici lab confounding set)

```
# Summary sheet from FEND data
coastal <- read_excel("FIPS-based datasets_05232021.xlsx", sheet = 13)
```

```
## New names:
## * ' ' -> ...12
## * ' ' -> ...22
## * ' ' -> ...25
## * ' ' -> ...39
```

```
# Contains 2020 AQS air pollution data
pm = read.csv("aqs-pm25-annual-aggregated.csv")
pm$fips = paste(str_pad(pm$state_code, 2, pad = "0"), str_pad(pm$fips3,
  3, pad = "0"), sep = "")
colnames(pm)[3] = "mean_pm25"
```

```
# Contains humidity data and other confounders used in 2020 study
load("confounding.Rda")
```

Create smaller datasets from previous datasets, dataclean, merge with PM25 and humidity data.

```
coastal.new = data.frame(coastal$`FIPS as Text`, coastal$state, coastal$cases,
  coastal$deaths, coastal$`Country REGION`, coastal$`Coastal Distance`,
  coastal$`Population 2019 Estimate`, coastal$`Population Density`, coastal$`All Ages in Poverty (%)`,
  coastal$`Median Income`, coastal$`percent adult obesity`, coastal$`diff/total`,
  coastal$`Political alignment 2020 election`, coastal$`median age 2019`)
colnames(coastal.new) = c("fips", "state", "cases", "deaths", "region",
  "coastal.distance", "population2019", "popdensity", "poverty", "median_income",
  "pct_obesity", "voter_margin_2020", "party", "median_age")

# Change NAs in coastal.distance to level 4, and save as factor with
```

```

# reference level 4.
coastal.new$coastal.distance[is.na(coastal.new$coastal.distance)] <- 4
coastal.new$coastal.distance = as.factor(coastal.new$coastal.distance)
coastal.new <- within(coastal.new, coastal.distance <- relevel(coastal.distance,
  ref = 4))

# Change NAs in coastal region to Inland, and save as factor with
# reference level Inland
coastal.new$region[is.na(coastal.new$region)] <- "Inland"
coastal.new$region[coastal.new$region == "0"] <- "Inland"
coastal.new$region[coastal.new$coastal.distance != 1] <- "Inland"
coastal.new$region = tolower(coastal.new$region)
coastal.new$region = factor(coastal.new$region, levels = c("inland", "atlantic",
  "gulf of mexico", "pacific"))
# coastal.new <- within(coastal.new, region <- relevel(region, ref =
# 'inland'))

## Create indicator for being a coast (degree 1)
coastal.new$indicatorcoast = ifelse(coastal.new$coastal.distance == "1",
  "Coastal", "NonCoastal")
coastal.new$indicatorcoast = as.factor(coastal.new$indicatorcoast)
coastal.new <- within(coastal.new, indicatorcoast <- relevel(indicatorcoast,
  ref = "NonCoastal"))

# Merge with humidity and mean_pm25
coastal.new = merge(coastal.new, cbind.data.frame(fips = confounding$fips,
  mean_summer_rm = confounding$mean_summer_rm, mean_winter_rm = confounding$mean_winter_rm),
  by = "fips")
coastal.new = merge(coastal.new, pm, by = "fips")

nrow(coastal.new)

```

```
## [1] 601
```

```
summary(coastal.new)
```

```
##      fips      state      cases      deaths
## Length:601    Length:601    Min.   :    53    Min.   :    0.0
## Class :character Class :character 1st Qu.:  4743    1st Qu.:   80.0
## Mode  :character Mode  :character Median : 14439    Median :  234.0
##                                     Mean  : 33038    Mean   :  573.6
##                                     3rd Qu.: 36119    3rd Qu.:  579.0
##                                     Max.   :1219237    Max.   :23101.0
##      region    coastal.distance population2019    popdensity
## inland      :481    4:390    Min.   :    928    Min.   :    0.5
## atlantic     : 45    1:120    1st Qu.:  54987    1st Qu.:   63.0
## gulf of mexico: 20    2: 57    Median : 161075    Median :  243.7
## pacific      : 25    3: 34    Mean   : 360181    Mean   :  654.0
## NA's        : 30           3rd Qu.: 413538    3rd Qu.:  618.4
##                                     Max.   :10039107    Max.   :17179.1
##      poverty    median_income    pct_obesity    voter_margin_2020
## Min.   :0.0270    Min.   : 30309    Min.   :13.60    Min.   : -0.86752
## 1st Qu.:0.0970    1st Qu.: 51603    1st Qu.:26.90    1st Qu.: -0.16533

```

```

## Median :0.1270    Median : 59253    Median :30.40    Median : 0.08237
## Mean   :0.1307    Mean   : 62841    Mean   :30.09    Mean   : 0.07122
## 3rd Qu.:0.1580    3rd Qu.: 69528    3rd Qu.:33.50    3rd Qu.: 0.32811
## Max.   :0.3660    Max.   :151806    Max.   :43.10    Max.   : 0.80967
##      party          median_age      indicatorcoast mean_summer_rm
## Length:601      Min.   :24.80    NonCoastal:481    Min.   :31.64
## Class :character 1st Qu.:35.80    Coastal   :120    1st Qu.:85.63
## Mode  :character Median :38.80                      Median :90.12
##                      Mean   :39.17                      Mean   :86.38
##                      3rd Qu.:42.10                      3rd Qu.:93.23
##                      Max.   :56.50                      Max.   :99.42
## mean_winter_rm    state_code      fips3      mean_pm25
## Min.   :58.16    Min.   : 1.00    Min.   : 1.00    Min.   : 1.322
## 1st Qu.:83.12    1st Qu.:17.00    1st Qu.: 27.00    1st Qu.: 6.357
## Median :87.28    Median :29.00    Median : 59.00    Median : 7.474
## Mean   :86.29    Mean   :29.64    Mean   : 83.31    Mean   : 7.727
## 3rd Qu.:90.47    3rd Qu.:42.00    3rd Qu.:111.00    3rd Qu.: 8.410
## Max.   :96.85    Max.   :56.00    Max.   :810.00    Max.   :24.562
##      min
## Length:601
## Class :character
## Mode  :character
##
##
##

```

## Analysis 1, 4, 7:

Atlantic coastal counties (bordering the ocean, ie 1st degree) versus Inland Counties (including all counties bordering non-ocean bodies of water). Pacific coastal counties (bordering the ocean, ie 1st degree) versus Inland Counties (including all counties bordering non-ocean bodies of water). Gulf coastal counties (bordering the ocean, ie 1st degree) versus Inland Counties (including all counties bordering non-ocean bodies of water).

```
model.byregion.cases = gee(cases ~ region + offset(log(population2019)) +
  scale(popdensity) + scale(poverty) + scale(log(median_income)) + scale(pct_obesity) +
  scale(voter_margin_2020) + scale(median_age) + factor(party) + mean_pm25 +
  mean_summer_rm + mean_winter_rm, family = poisson(link = "log"), data = coastal.new,
  id = as.factor(state))
```

```
## Beginning Cgee S-function, @(#) geeformula.q 4.13 98/01/27
```

```
## running glm to get initial regression estimate
```

##	(Intercept)	regionatlantic	regiongulf of mexico
##	-1.421545722	0.203473055	-0.113013140
##	regionpacific	scale(popdensity)	scale(poverty)
##	-0.050529779	0.001679485	-0.029614318
##	scale(log(median_income))	scale(pct_obesity)	scale(voter_margin_2020)
##	-0.116342218	-0.051311894	0.143955432
##	scale(median_age)	factor(party)Republican	mean_pm25
##	-0.110853751	-0.028071795	0.014058307
##	mean_summer_rm	mean_winter_rm	
##	0.004696333	-0.017088021	

```
summary(model.byregion.cases)$coefficients
```

##	Estimate	Naive S.E.	Naive z	Robust S.E.
## (Intercept)	-1.421545722	0.105854069	-13.4292970	0.285235406
## regionatlantic	0.203473055	0.029803252	6.8272097	0.065772691
## regiongulf of mexico	-0.113013140	0.042679842	-2.6479278	0.052700035
## regionpacific	-0.050529779	0.035029829	-1.4424786	0.094797833
## scale(popdensity)	0.001679485	0.008202978	0.2047408	0.010094173
## scale(poverty)	-0.029614318	0.026610503	-1.1128808	0.043889272
## scale(log(median_income))	-0.116342218	0.025103911	-4.6344259	0.050118619
## scale(pct_obesity)	-0.051311894	0.015213321	-3.3728266	0.043865231
## scale(voter_margin_2020)	0.143955432	0.021315682	6.7534988	0.041637322
## scale(median_age)	-0.110853751	0.015575312	-7.1172732	0.020979921
## factor(party)Republican	-0.028071795	0.032536518	-0.8627781	0.057350347
## mean_pm25	0.014058307	0.004598447	3.0571855	0.007711324
## mean_summer_rm	0.004696333	0.001126754	4.1680185	0.002670373
## mean_winter_rm	-0.017088021	0.001770602	-9.6509647	0.005774099
##	Robust z			
## (Intercept)	-4.9837632			
## regionatlantic	3.0935796			
## regiongulf of mexico	-2.1444605			
## regionpacific	-0.5330267			
## scale(popdensity)	0.1663816			

```
## scale(poverty) -0.6747507
## scale(log(median_income)) -2.3213372
## scale(pct_obesity) -1.1697623
## scale(voter_margin_2020) 3.4573653
## scale(median_age) -5.2838021
## factor(party)Republican -0.4894791
## mean_pm25 1.8230730
## mean_summer_rm 1.7586805
## mean_winter_rm -2.9594265
```

```
model.byregion.deaths = gee(deaths ~ region + offset(log(population2019)) +
  scale(popdensity) + scale(poverty) + scale(log(median_income)) + scale(pct_obesity) +
  scale(voter_margin_2020) + scale(median_age) + factor(party) + mean_pm25 +
  mean_summer_rm + mean_winter_rm, family = poisson(link = "log"), data = coastal.new,
  id = as.factor(state))
```

```
## Beginning Cgee S-function, @(#) geeformula.q 4.13 98/01/27
## running glm to get initial regression estimate
```

```
## (Intercept) regionatlantic regiongulf of mexico
## -4.592226641 0.199290912 -0.072272466
## regionpacific scale(popdensity) scale(poverty)
## -0.167801308 0.016844149 0.268192434
## scale(log(median_income)) scale(pct_obesity) scale(voter_margin_2020)
## 0.101659060 0.050308705 0.115115176
## scale(median_age) factor(party)Republican mean_pm25
## 0.197834845 -0.118582408 0.021638047
## mean_summer_rm mean_winter_rm
## 0.008991931 -0.031696350
```

```
summary(model.byregion.deaths)$coefficients
```

```
## Estimate Naive S.E. Naive z Robust S.E.
## (Intercept) -4.592226641 0.164792505 -27.866720 0.332187823
## regionatlantic 0.199290912 0.043822710 4.547663 0.070580315
## regiongulf of mexico -0.072272466 0.065100402 -1.110169 0.056099103
## regionpacific -0.167801308 0.056084684 -2.991927 0.097542478
## scale(popdensity) 0.016844149 0.011566114 1.456336 0.023598236
## scale(poverty) 0.268192434 0.040024291 6.700742 0.091924101
## scale(log(median_income)) 0.101659060 0.037956084 2.678334 0.090042315
## scale(pct_obesity) 0.050308705 0.023673224 2.125131 0.027867873
## scale(voter_margin_2020) 0.115115176 0.032551064 3.536449 0.048806675
## scale(median_age) 0.197834845 0.024521617 8.067773 0.034900100
## factor(party)Republican -0.118582408 0.051265974 -2.313082 0.060638301
## mean_pm25 0.021638047 0.007355935 2.941577 0.010860243
## mean_summer_rm 0.008991931 0.001829755 4.914282 0.004916046
## mean_winter_rm -0.031696350 0.002910036 -10.892084 0.008510842
## Robust z
## (Intercept) -13.8241872
## regionatlantic 2.8236047
## regiongulf of mexico -1.2882999
## regionpacific -1.7202896
```

```
## scale(popdensity)      0.7137885
## scale(poverty)         2.9175421
## scale(log(median_income)) 1.1290143
## scale(pct_obesity)     1.8052581
## scale(voter_margin_2020) 2.3585949
## scale(median_age)      5.6686040
## factor(party)Republican -1.9555694
## mean_pm25              1.9924092
## mean_summer_rm         1.8290982
## mean_winter_rm         -3.7242322
```



## Analysis 2, 5, 8

Atlantic urban coastal counties (bordering the ocean, ie 1st degree) versus Inland urban Counties (including all counties bordering non-ocean bodies of water). Pacific urban coastal counties (bordering the ocean, ie 1st degree) versus Inland urban Counties (including all counties bordering non-ocean bodies of water). Gulf urban coastal counties (bordering the ocean, ie 1st degree) versus Inland urban Counties (including all counties bordering non-ocean bodies of water).

```
coastal.urban = subset(coastal.new, coastal.new$popdensity >= 1500)

model.byregion.cases.urban = gee(cases ~ region + offset(log(population2019)) +
  scale(popdensity) + scale(poverty) + scale(log(median_income)) + scale(pct_obesity) +
  scale(voter_margin_2020) + scale(median_age) + factor(party) + mean_pm25 +
  mean_summer_rm + mean_winter_rm, family = poisson(link = "log"), data = coastal.urban,
  id = as.factor(state))
```

```
## Beginning Cgee S-function, @(#) geeformula.q 4.13 98/01/27
```

```
## running glm to get initial regression estimate
```

##	(Intercept)	regionatlantic	regiongulf of mexico
##	-0.0852311638	0.0836632777	-0.1313487202
##	regionpacific	scale(popdensity)	scale(poverty)
##	-0.1679560020	-0.0316965733	-0.0002881448
##	scale(log(median_income))	scale(pct_obesity)	scale(voter_margin_2020)
##	-0.0545560279	0.0296049522	0.1337628622
##	scale(median_age)	factor(party)Republican	mean_pm25
##	-0.0267402195	0.0927747140	0.0173391422
##	mean_summer_rm	mean_winter_rm	
##	-0.0061643103	-0.0236921411	

```
summary(model.byregion.cases.urban)$coefficients
```

##	Estimate	Naive S.E.	Naive z	Robust S.E.
## (Intercept)	-0.0852311638	0.581569044	-0.146553818	0.430463337
## regionatlantic	0.0836632777	0.068383148	1.223448760	0.081279960
## regiongulf of mexico	-0.1313487202	0.103117173	-1.273781239	0.079968785
## regionpacific	-0.1679560020	0.115645728	-1.452332086	0.116138929
## scale(popdensity)	-0.0316965733	0.031579245	-1.003715365	0.021901843
## scale(poverty)	-0.0002881448	0.078394969	-0.003675552	0.040913315
## scale(log(median_income))	-0.0545560279	0.080106625	-0.681042649	0.032018179
## scale(pct_obesity)	0.0296049522	0.045434431	0.651597297	0.030778974
## scale(voter_margin_2020)	0.1337628622	0.035423651	3.776089072	0.021071203
## scale(median_age)	-0.0267402195	0.029715816	-0.899864889	0.034416819
## factor(party)Republican	0.0927747140	0.114510806	0.810183048	0.118990753
## mean_pm25	0.0173391422	0.024685308	0.702407360	0.023092696
## mean_summer_rm	-0.0061643103	0.005459300	-1.129139319	0.002647607
## mean_winter_rm	-0.0236921411	0.005598259	-4.232054934	0.004876039
##	Robust z			
## (Intercept)	-0.197998660			
## regionatlantic	1.029322323			
## regiongulf of mexico	-1.642499891			

```
## regionpacific -1.446164552
## scale(popdensity) -1.447210338
## scale(poverty) -0.007042812
## scale(log(median_income)) -1.703907876
## scale(pct_obesity) 0.961856382
## scale(voter_margin_2020) 6.348136111
## scale(median_age) -0.776952088
## factor(party)Republican 0.779680030
## mean_pm25 0.750849622
## mean_summer_rm -2.328257517
## mean_winter_rm -4.858891285
```

```
model.byregion.deaths.urban = gee(deaths ~ region + offset(log(population2019)) +
  scale(popdensity) + scale(poverty) + scale(log(median_income)) + scale(pct_obesity) +
  scale(voter_margin_2020) + scale(median_age) + factor(party) + mean_pm25 +
  mean_summer_rm + mean_winter_rm, family = poisson(link = "log"), data = coastal.urban,
  id = as.factor(state))
```

```
## Beginning Cgee S-function, @(#) geeformula.q 4.13 98/01/27
## running glm to get initial regression estimate
```

##	(Intercept)	regionatlantic	regiongulf of mexico
##	-2.22609193	0.13219270	-0.02919697
##	regionpacific	scale(popdensity)	scale(poverty)
##	-0.41495483	0.01826963	0.16524613
##	scale(log(median_income))	scale(pct_obesity)	scale(voter_margin_2020)
##	0.09747730	0.08478289	0.11867685
##	scale(median_age)	factor(party)Republican	mean_pm25
##	0.22510216	-0.04184826	0.01181252
##	mean_summer_rm	mean_winter_rm	
##	-0.01436105	-0.03633786	

```
summary(model.byregion.deaths.urban)$coefficients
```

##	Estimate	Naive S.E.	Naive z	Robust S.E.
## (Intercept)	-2.22609193	1.08766139	-2.0466773	0.999480080
## regionatlantic	0.13219270	0.11890296	1.1117697	0.129991732
## regiongulf of mexico	-0.02919697	0.19437423	-0.1502101	0.158926873
## regionpacific	-0.41495483	0.21143311	-1.9625821	0.165174034
## scale(popdensity)	0.01826963	0.05461672	0.3345061	0.038399822
## scale(poverty)	0.16524613	0.14385491	1.1486999	0.090603545
## scale(log(median_income))	0.09747730	0.14704975	0.6628865	0.111561864
## scale(pct_obesity)	0.08478289	0.08390154	1.0105046	0.073142376
## scale(voter_margin_2020)	0.11867685	0.06766146	1.7539798	0.036164396
## scale(median_age)	0.22510216	0.05221094	4.3113986	0.047781305
## factor(party)Republican	-0.04184826	0.20259557	-0.2065606	0.202158533
## mean_pm25	0.01181252	0.04476009	0.2639075	0.052770255
## mean_summer_rm	-0.01436105	0.01067483	-1.3453186	0.008940204
## mean_winter_rm	-0.03633786	0.01090980	-3.3307547	0.008584142
##	Robust z			
## (Intercept)	-2.2272499			
## regionatlantic	1.0169316			

```

## regiongulf of mexico      -0.1837132
## regionpacific             -2.5122280
## scale(popdensity)         0.4757738
## scale(poverty)            1.8238373
## scale(log(median_income)) 0.8737511
## scale(pct_obesity)        1.1591487
## scale(voter_margin_2020)  3.2815935
## scale(median_age)         4.7110928
## factor(party)Republican   -0.2070071
## mean_pm25                  0.2238481
## mean_summer_rm             -1.6063449
## mean_winter_rm            -4.2331387

```

## Analysis 3, 6, 9

Atlantic rural coastal counties (bordering the ocean, ie 1st degree) versus Inland rural Counties (including all counties bordering non-ocean bodies of water). Pacific rural coastal counties (bordering the ocean, ie 1st degree) versus Inland rural Counties (including all counties bordering non-ocean bodies of water). Gulf rural coastal counties (bordering the ocean, ie 1st degree) versus Inland rural Counties (including all counties bordering non-ocean bodies of water).

```
coastal.rural = subset(coastal.new, coastal.new$popdensity < 1500)

model.byregion.cases.rural = gee(cases ~ region + offset(log(population2019)) +
  scale(popdensity) + scale(poverty) + scale(log(median_income)) + scale(pct_obesity) +
  scale(voter_margin_2020) + scale(median_age) + factor(party) + mean_pm25 +
  mean_summer_rm + mean_winter_rm, family = poisson(link = "log"), data = coastal.rural,
  id = as.factor(state))
```

```
## Beginning Cgee S-function, @(#) geeformula.q 4.13 98/01/27
```

```
## running glm to get initial regression estimate
```

##	(Intercept)	regionatlantic	regiongulf of mexico
##	-1.535567551	0.205367713	-0.023805275
##	regionpacific	scale(popdensity)	scale(poverty)
##	-0.188901171	0.044528820	0.021817099
##	scale(log(median_income))	scale(pct_obesity)	scale(voter_margin_2020)
##	-0.068162949	-0.033117866	0.172171546
##	scale(median_age)	factor(party)Republican	mean_pm25
##	-0.127498765	-0.040988963	-0.001230517
##	mean_summer_rm	mean_winter_rm	
##	-0.000178165	-0.009452678	

```
summary(model.byregion.cases.rural)$coefficients
```

##	Estimate	Naive S.E.	Naive z	Robust S.E.
## (Intercept)	-1.535567551	0.103649687	-14.8149752	0.234866830
## regionatlantic	0.205367713	0.034468166	5.9581852	0.066431463
## regiongulf of mexico	-0.023805275	0.050290191	-0.4733582	0.052643389
## regionpacific	-0.188901171	0.044202609	-4.2735299	0.126219416
## scale(popdensity)	0.044528820	0.010736339	4.1474864	0.022119752
## scale(poverty)	0.021817099	0.028516587	0.7650670	0.045663986
## scale(log(median_income))	-0.068162949	0.027336658	-2.4934631	0.031705372
## scale(pct_obesity)	-0.033117866	0.015183210	-2.1812163	0.041328024
## scale(voter_margin_2020)	0.172171546	0.024205498	7.1129107	0.032397071
## scale(median_age)	-0.127498765	0.015844305	-8.0469773	0.023224484
## factor(party)Republican	-0.040988963	0.036482710	-1.1235175	0.041726801
## mean_pm25	-0.001230517	0.004651052	-0.2645674	0.006920822
## mean_summer_rm	-0.000178165	0.001227545	-0.1451393	0.002847345
## mean_winter_rm	-0.009452678	0.001892123	-4.9958052	0.005060983
##	Robust z			
## (Intercept)	-6.53803498			
## regionatlantic	3.09142238			
## regiongulf of mexico	-0.45219875			

```
## regionpacific -1.49660946
## scale(popdensity) 2.01307955
## scale(poverty) 0.47777473
## scale(log(median_income)) -2.14988646
## scale(pct_obesity) -0.80134162
## scale(voter_margin_2020) 5.31441698
## scale(median_age) -5.48984277
## factor(party)Republican -0.98231741
## mean_pm25 -0.17779923
## mean_summer_rm -0.06257233
## mean_winter_rm -1.86775525
```

```
model.byregion.deaths.rural = gee(deaths ~ region + offset(log(population2019)) +
  scale(popdensity) + scale(poverty) + scale(log(median_income)) + scale(pct_obesity) +
  scale(voter_margin_2020) + scale(median_age) + factor(party) + mean_pm25 +
  mean_summer_rm + mean_winter_rm, family = poisson(link = "log"), data = coastal.rural,
  id = as.factor(state))
```

```
## Beginning Cgee S-function, @(#) geeformula.q 4.13 98/01/27
## running glm to get initial regression estimate
```

```
## (Intercept) regionatlantic regiongulf of mexico
## -4.851261740 0.181033127 0.039009199
## regionpacific scale(popdensity) scale(poverty)
## -0.336656816 0.034886901 0.329605666
## scale(log(median_income)) scale(pct_obesity) scale(voter_margin_2020)
## 0.130128355 0.076029702 0.161988007
## scale(median_age) factor(party)Republican mean_pm25
## 0.156555160 -0.162203724 -0.001117394
## mean_summer_rm mean_winter_rm
## 0.002665545 -0.019919905
```

```
summary(model.byregion.deaths.rural)$coefficients
```

```
## Estimate Naive S.E. Naive z Robust S.E.
## (Intercept) -4.851261740 0.155826355 -31.1324854 0.284057013
## regionatlantic 0.181033127 0.050018263 3.6193405 0.067124236
## regiongulf of mexico 0.039009199 0.071421913 0.5461797 0.099302043
## regionpacific -0.336656816 0.071800896 -4.6887551 0.091851734
## scale(popdensity) 0.034886901 0.016184735 2.1555435 0.024214515
## scale(poverty) 0.329605666 0.040714911 8.0954535 0.074408588
## scale(log(median_income)) 0.130128355 0.040155532 3.2406084 0.061160184
## scale(pct_obesity) 0.076029702 0.022656681 3.3557298 0.021398241
## scale(voter_margin_2020) 0.161988007 0.036243478 4.4694388 0.041578817
## scale(median_age) 0.156555160 0.023979775 6.5286335 0.043672944
## factor(party)Republican -0.162203724 0.055375308 -2.9291706 0.067562280
## mean_pm25 -0.001117394 0.007101572 -0.1573446 0.009673003
## mean_summer_rm 0.002665545 0.001921014 1.3875717 0.004315413
## mean_winter_rm -0.019919905 0.003021841 -6.5919762 0.006394443
## Robust z
## (Intercept) -17.0784790
## regionatlantic 2.6969860
```

```

## regiongulf of mexico      0.3928338
## regionpacific             -3.6652201
## scale(popdensity)         1.4407433
## scale(poverty)            4.4296724
## scale(log(median_income)) 2.1276645
## scale(pct_obesity)        3.5530819
## scale(voter_margin_2020)  3.8959263
## scale(median_age)         3.5847174
## factor(party)Republican   -2.4008030
## mean_pm25                 -0.1155168
## mean_summer_rm            0.6176802
## mean_winter_rm            -3.1151897

```

## Some splits

```
table(coastal.new$region)
```

```
##
##      inland      atlantic gulf of mexico      pacific
##      481         45         20         25
```

```
table(coastal.urban$region)
```

```
##
##      inland      atlantic gulf of mexico      pacific
##      37         14         3         5
```

```
table(coastal.rural$region)
```

```
##
##      inland      atlantic gulf of mexico      pacific
##      444         31         17         20
```

```
tab_model(model.byregion.cases, dv.labels = "Cases (All)", robust = T,
  digits = 3)
tab_model(model.byregion.deaths, dv.labels = "Deaths (All)", robust = T,
  digits = 3)
tab_model(model.byregion.cases.urban, dv.labels = "Cases (Urban)", robust = T,
  digits = 3)
tab_model(model.byregion.deaths.urban, dv.labels = "Deaths (Urban)", robust = T,
  digits = 3)
tab_model(model.byregion.cases.rural, dv.labels = "Cases (Rural)", robust = T,
  digits = 3)
tab_model(model.byregion.deaths.rural, dv.labels = "Deaths (Rural)", robust = T,
  digits = 3)
```

## Manually Calculate Confidence Intervals

```
for (i in c(2, 3, 4)) {
  print(exp(summary(model.byregion.cases)$coefficients[i, 1]))
  print(c(exp(summary(model.byregion.cases)$coefficients[i, 1] - 1.9599 *
    (summary(model.byregion.cases)$coefficients[i, 4])), exp(summary(model.byregion.cases)$coeffici
    1] + 1.9599 * (summary(model.byregion.cases)$coefficients[i, 4]))))
}
```

```
## [1] 1.225652
## [1] 1.077416 1.394284
## [1] 0.8931389
## [1] 0.8054937 0.9903208
## [1] 0.9507256
## [1] 0.7895248 1.1448395
```

```

for (i in c(2, 3, 4)) {
  print(exp(summary(model.byregion.deaths)$coefficients[i, 1]))
  print(c(exp(summary(model.byregion.deaths)$coefficients[i, 1] - 1.9599 *
    (summary(model.byregion.deaths)$coefficients[i, 4])), exp(summary(model.byregion.deaths)$coeffi
    1] + 1.9599 * (summary(model.byregion.deaths)$coefficients[i, 4]))))
}

```

```

## [1] 1.220537
## [1] 1.062857 1.401610
## [1] 0.9302774
## [1] 0.8334171 1.0383949
## [1] 0.8455218
## [1] 0.6983919 1.0236475

```

```

for (i in c(2, 3, 4)) {
  print(exp(summary(model.byregion.cases.rural)$coefficients[i, 1]))
  print(c(exp(summary(model.byregion.cases.rural)$coefficients[i, 1] -
    1.9599 * (summary(model.byregion.cases.rural)$coefficients[i, 4])),
    exp(summary(model.byregion.cases.rural)$coefficients[i, 1] + 1.9599 *
    (summary(model.byregion.cases.rural)$coefficients[i, 4]))))
}

```

```

## [1] 1.227977
## [1] 1.078066 1.398733
## [1] 0.9764758
## [1] 0.8807504 1.0826054
## [1] 0.8278683
## [1] 0.6464376 1.0602198

```

```

for (i in c(2, 3, 4)) {
  print(exp(summary(model.byregion.deaths.rural)$coefficients[i, 1]))
  print(c(exp(summary(model.byregion.deaths.rural)$coefficients[i, 1] -
    1.9599 * (summary(model.byregion.deaths.rural)$coefficients[i,
    4])), exp(summary(model.byregion.deaths.rural)$coefficients[i,
    1] + 1.9599 * (summary(model.byregion.deaths.rural)$coefficients[i,
    4]))))
}

```

```

## [1] 1.198455
## [1] 1.050721 1.366961
## [1] 1.03978
## [1] 0.8558905 1.2631786
## [1] 0.7141539
## [1] 0.5964994 0.8550147

```