COVID-19 Hospitalization Impact for Public Health Regions in Arkansas

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Contents

1 Motivation

1.1 Modeling COVID-19 outbreak in AR

The main aim of this project is to analyze the dynamics of outbreak of novel coronavirus using a hierarchical epidemiological model to forecast the spread of infection and its impact on hospitalization across the state and public health regions (PHR). This is a short report of our results so far.

Confirmed Covid-19 cases by State

https://usafacts.org/visualizations/coronavirus-covid-19-spread-map/
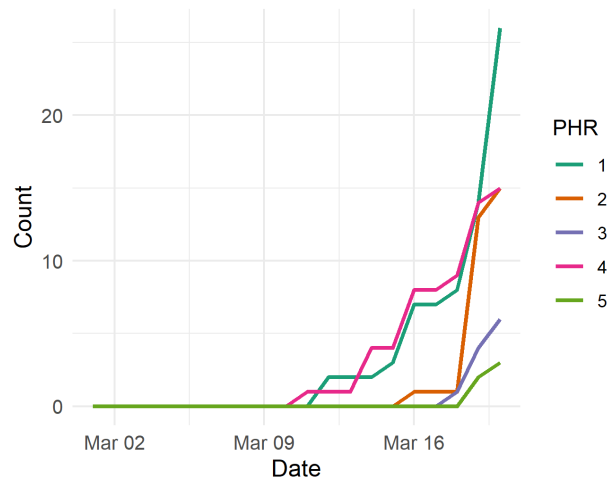
1.2 Spatial distribution of confirmed cases over county and PHR

Confirmed cases per county

Confirmed cases per PHR
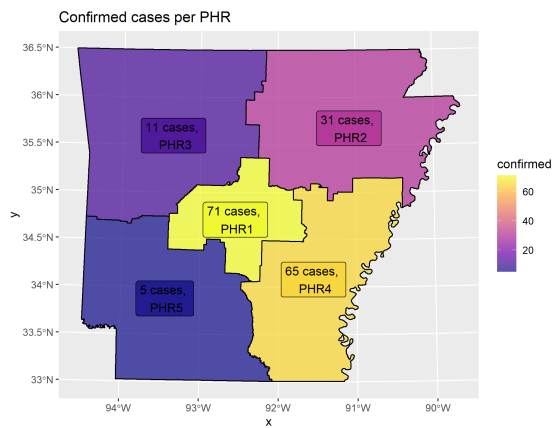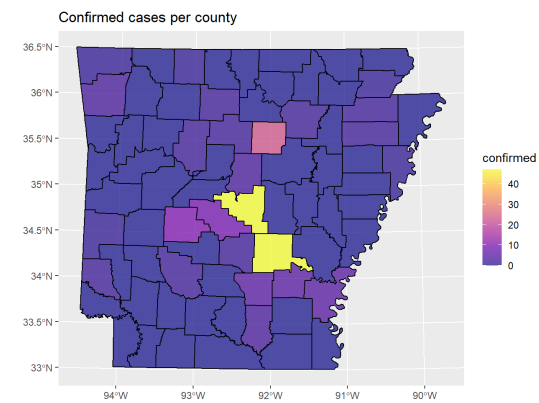
2 eSIR model

2.1 Description of eSIR

The standard SIR model [see 3] takes as input two time series of proportions of infected and removed cases, denoted by Y_t^I and Y_t^R at time t, respectively, where the removed part of the population is a sum of the recovered cases and deaths at time t. The standard SIR assumes a constant rate for both transmission and removal which does not reflect reality where these rates are affected by government imposed isolation measures. We apply an extension to the standard SIR model (eSIR, see [1,2]) by letting a time-varying probability that a susceptible person meets an infected person or vice versa. The dynamic model is represented below:

$$\frac{d\theta_t^S}{dt} = -\beta\pi(t)\theta_t^S\theta_t^I, \quad \frac{d\theta_t^I}{dt} = \beta\pi(t)\theta_t^S\theta_t^I - \gamma\theta_t^I, \quad \frac{d\theta_t^R}{dt} = \gamma\theta_t^I$$

Here θ_t^I and θ_t^R are the respective prevalence of infection and removal at time t, and expected proportions are equal to the prevalence of infection and the probability of removal at time t.

Here $\pi(t)$ is called a transmission modifier as it modifies the probability of a susceptible person meeting an infected person. In particular, Suppose at a time t, $q^S(t)$ is is the chance of an at-risk person being in-home isolation, and $q^R(t)$ is the chance of an infected person being in-hospital quarantine, then, we will have:

$$\pi(t) = (1 - q^s(t))(1 - q^R(t)) \in (0,1).$$

Note that the above extended SIR model assumes primarily that *both population-level chance of being susceptible and population-level chance of being infected remain the same, but the chance of a susceptible person meeting with an infected person is reduced by $\pi(t)$.*

For a real data analysis, $\pi(t)$, the transmission rate modifier needs to be specified according to isoloation measures taken in a given region. We can assume the following:

$$\pi(t) = \begin{cases} \pi_{01} & \text{Before March 12, no isolation} \\ \pi_{02} & \text{March 12-19, in-person class stops} \\ \pi_{03} & \text{March 19 onwards, mandatory work-from-home at UA} \end{cases}$$

Obviously, different values of π_{0i} leads to different dynamic behaviours; we chose $\pi_{02} = 0.9$ and $\pi_{03} = 0.8$ as that produces good three-steps ahead forecasts.

3 Results

3.1 PHR-level forecasts

State-level data from 01/22 to 03/25 pulled from USA facts and map them to the PHRs. The model forecasts the probability of infection and removal, over 200 days from the starting point (03/01). That is, the follow-up is from 03/01/20 to 09/16/20.

The forecasting plots of the prevalence of infected and removed compartments are given in Section 1.3 and in 2.1 (appendix). In each of these plots, the observed proprtions are denoted by the black dots left to the blue vertical line, which represents the last date of observations, or time t_0 (the current time up to which we have observed data). The two turning points are the green and purple vertical lines. The first turning point is where the daily increase of $P(I)$ starts decreasing, and the second turning point is where the $P(R)$ overtakes

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$P(I)$. The 95% credible interval of the predicted proportions of infected and removals are given by the salmon colored area. The relatively large area under these curves denote the large uncertainty in forecasting far ahead in time based on limited available data. The gray and red curves are the posterior mean and median curves for the prevalence of the infected θ_t^I in section 1.3, and prevalence of the removed θ_t^R in section 2.1.

3.2   P(Infection) plots for each PHR
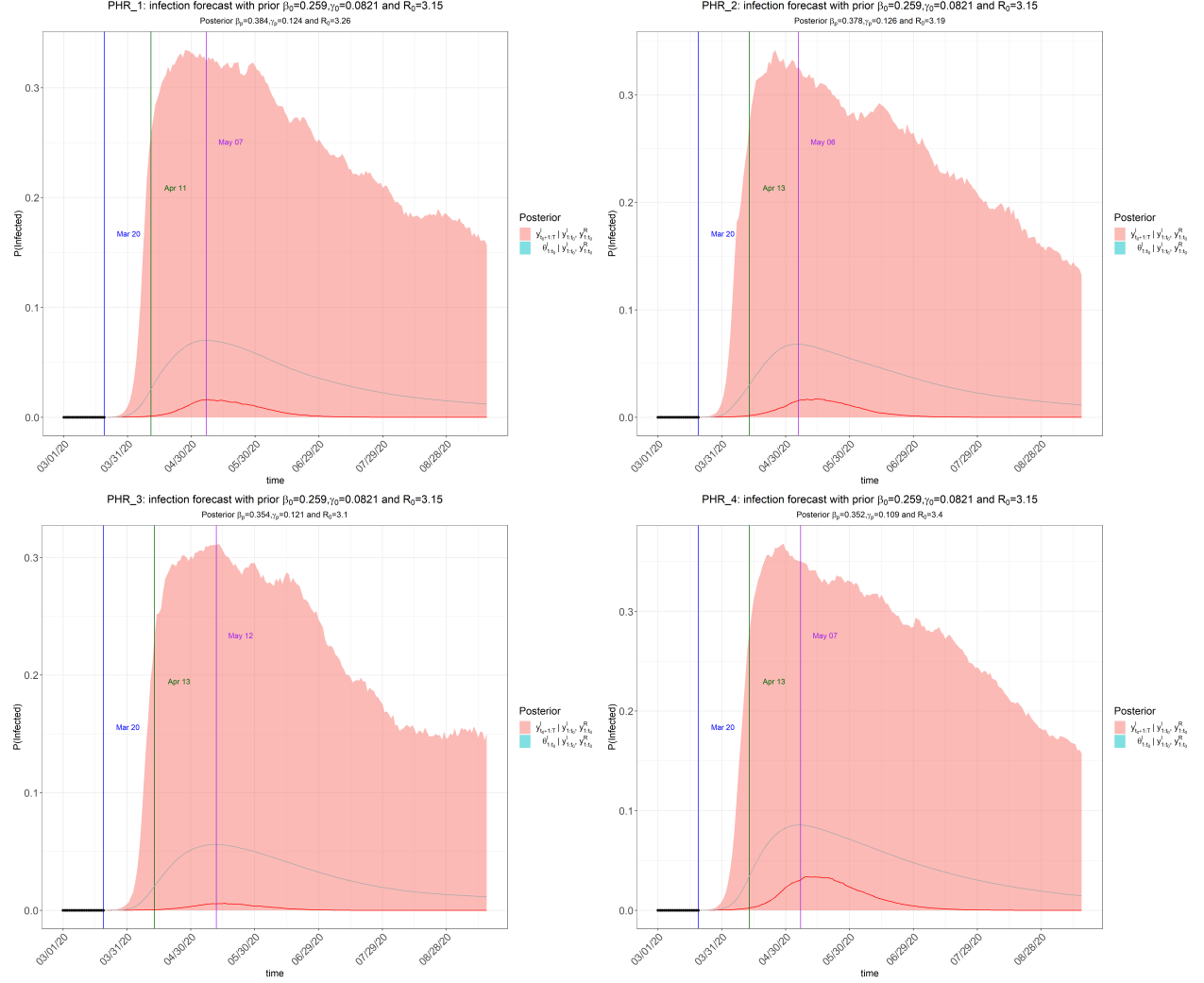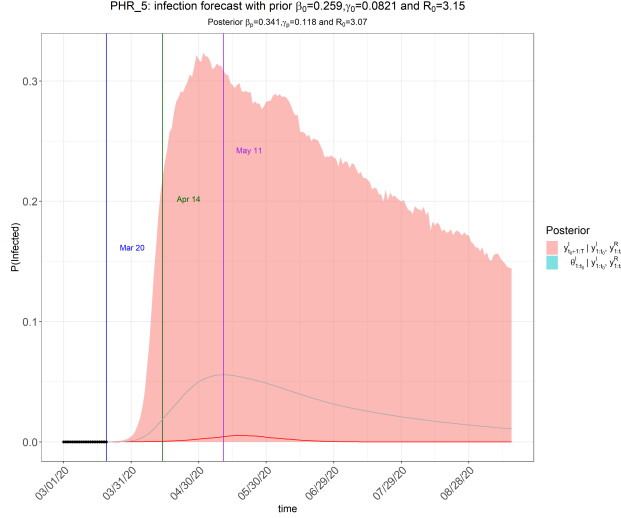
Next, we use a 14-day moving average of the probability of infection to account for the average length of stay for Covid-19 infected patients. Let us denote by $\bar{\theta}_t^I$ as the moving average of the prevalence of infected individuals $\hat{\theta}_t^I$, $t = 1, \ldots, 14$. The predicted value of number of affected individuals is going to be the number of susceptible times the prevalence of infected individuals, i.e.

$$\hat{N}^I = N \times \hat{\theta}_t^S \times \bar{\theta}_t^I.$$

The upper credible limit and the mean are very different on the figures above, representing the uncertainty involved in forecasting with limited data. We show the estimated number of infected individuals where $\hat{\theta}_t^I$ is taken to be the posterior mean and the upper credible limit of the posterior distribution of θ_t^I. The following table shows the maximum value of the expected number of infected and the date at which the maximum value is attained.

Table 1: Worst case and Mean case Predictions from the eSIR model by each PHR

| PHR	max total worstcase	max day worstcase	max total meancase	max day meancase
1	233468.2676	4/22/2020	52459.96028	4/27/2020
2	156669.8346	4/20/2020	37797.24111	4/24/2020
3	264771.4767	4/26/2020	56986.41571	4/30/2020
4	74340.20888	4/23/2020	18513.12375	4/29/2020
5	82295.79371	4/25/2020	16540.5404	4/30/2020

%

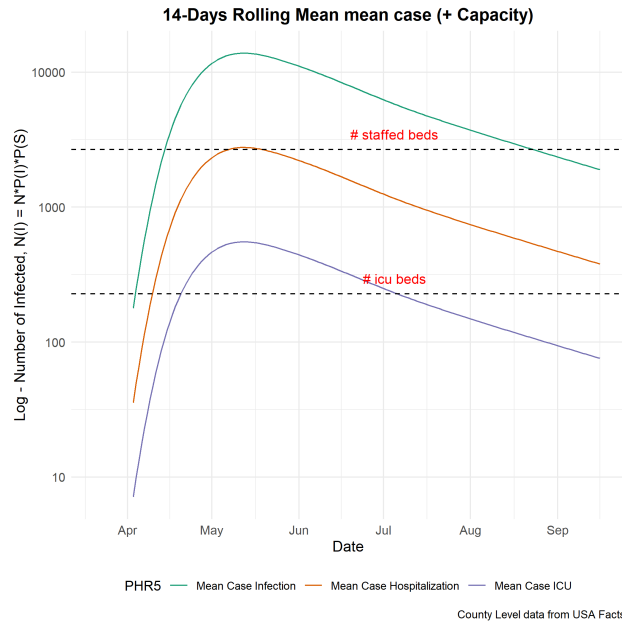## 3.3   Capacity crossover points for the mean case

The next set of plots show the prevalence of infection with projected hospitalizations and ICU admissions. Our assumption is 1/5 of infected will be hospitalized and 1/5 of those hospitalized will need ICU facilities, based on the current HGHI proportions.

%

Table 2: Dates when the projected hospitalization and ICU bed demands will cross the available hospital beds and ICU beds per PHR
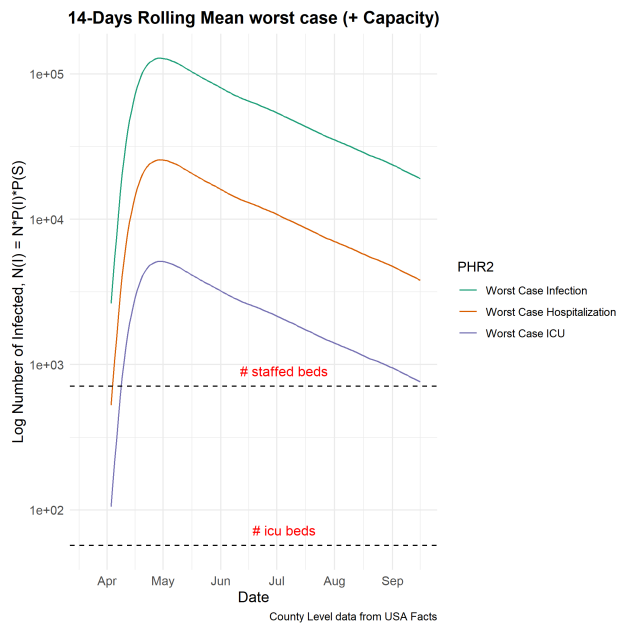
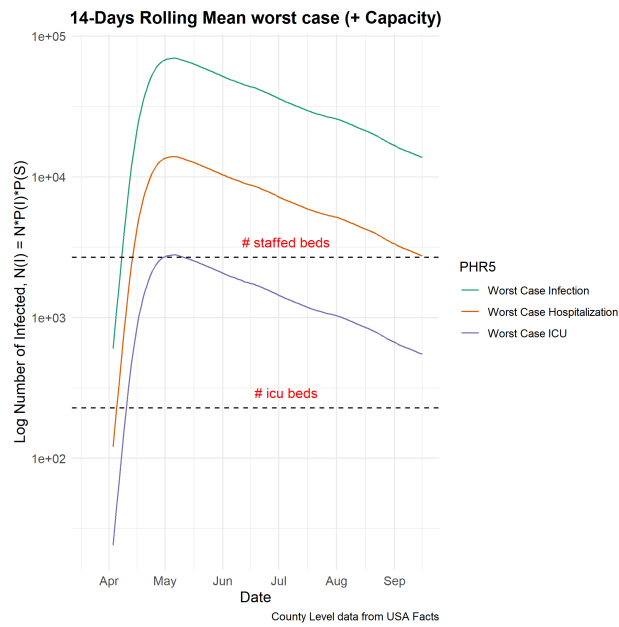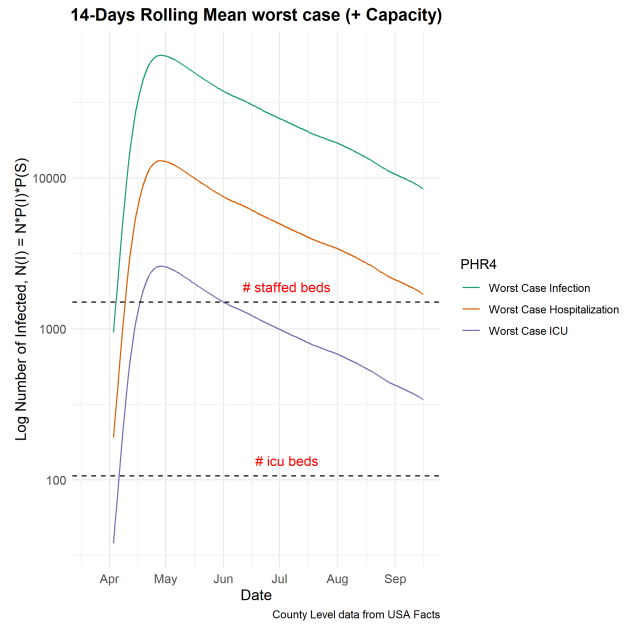| PHR	mean case hospital cross date	mean case icu cross date	worst case hospital cross date	worst case icu cross date
1	4/4/2020	4/3/2020	4/3/2020	4/3/2020
2	4/4/2020	4/3/2020	4/3/2020	4/3/2020
3	4/14/2020	4/7/2020	4/7/2020	4/3/2020
4	4/14/2020	4/8/2020	4/6/2020	4/4/2020
5	4/21/2020	4/13/2020	4/8/2020	4/6/2020
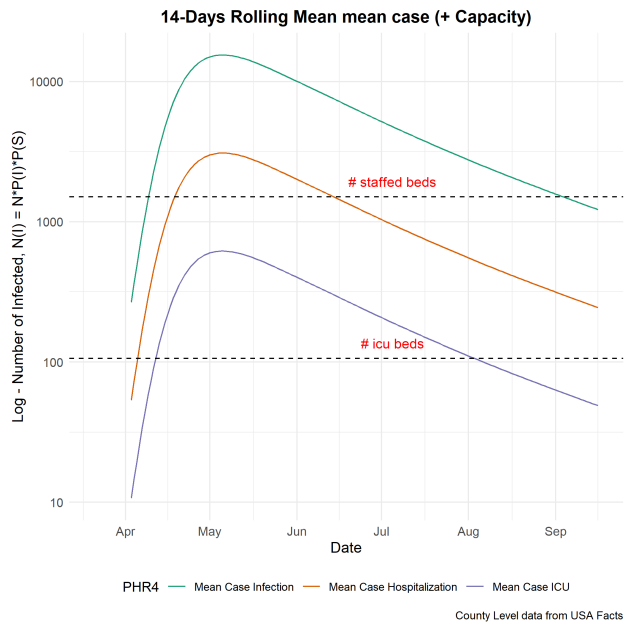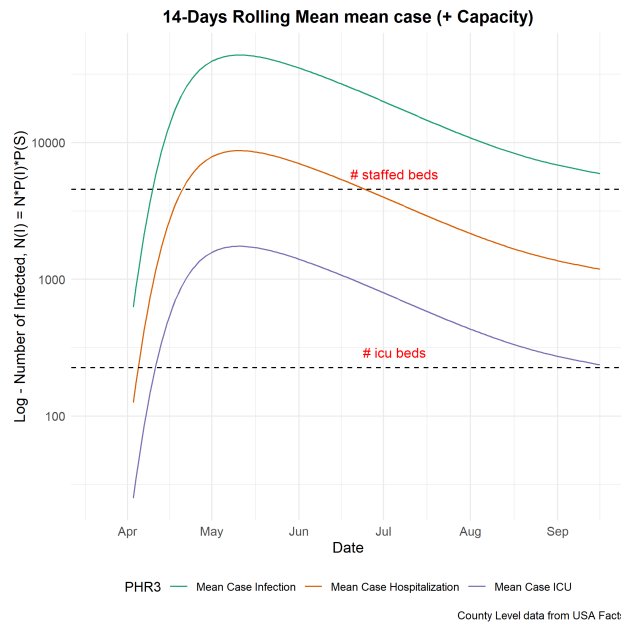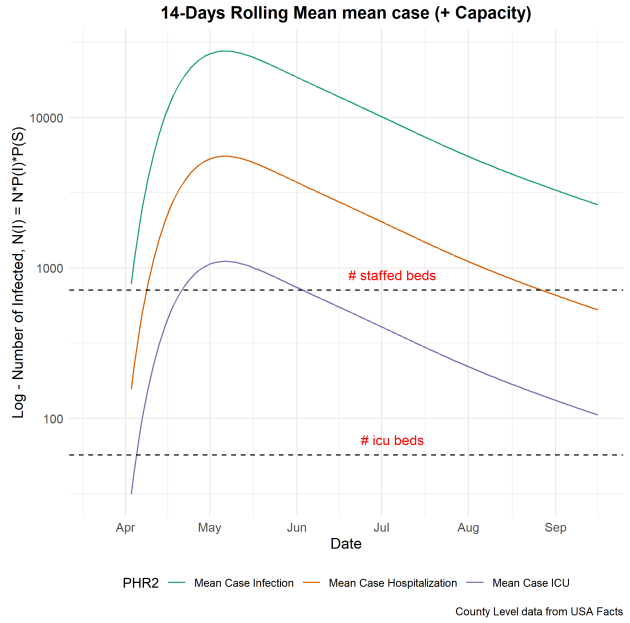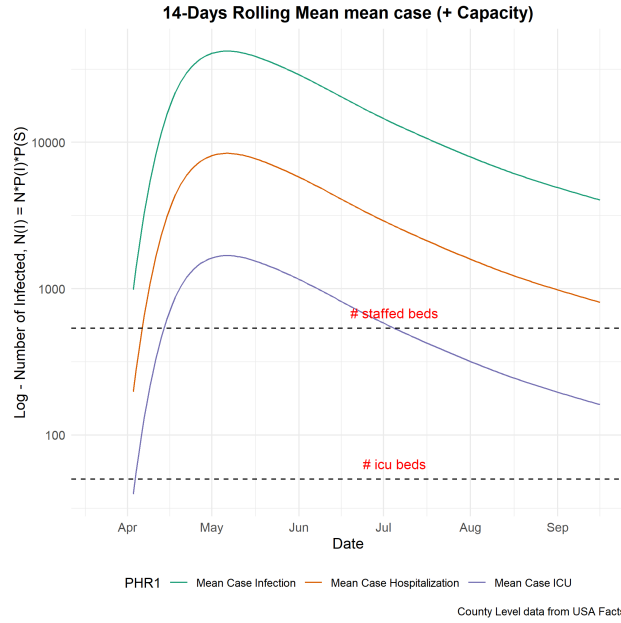
3.4 Capacity crossover points for the worst case

Same as before but worst case instead of mean.

14-Days Rolling Mean worst case (+ Capacity)

PHR3
— Worst Case Infection
— Worst Case Hospitalization
— Worst Case ICU

14-Days Rolling Mean worst case (+ Capacity)

PHR4
— Worst Case Infection
— Worst Case Hospitalization
— Worst Case ICU

14-Days Rolling Mean worst case (+ Capacity)

PHR5
— Worst Case Infection
— Worst Case Hospitalization
— Worst Case ICU
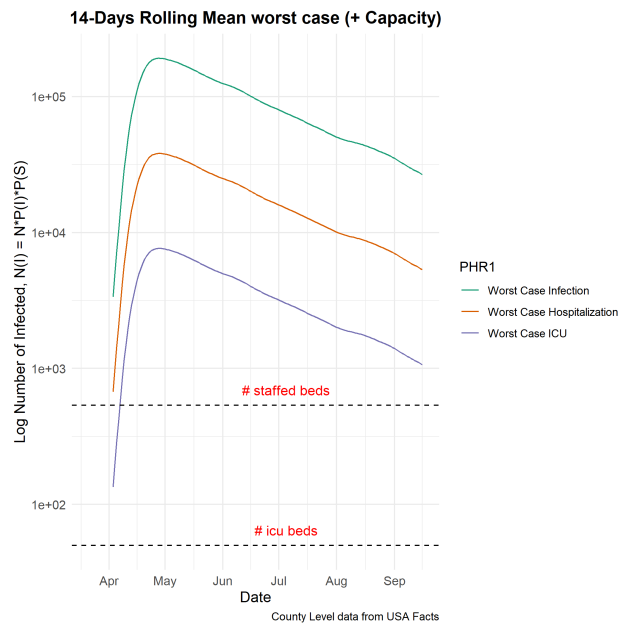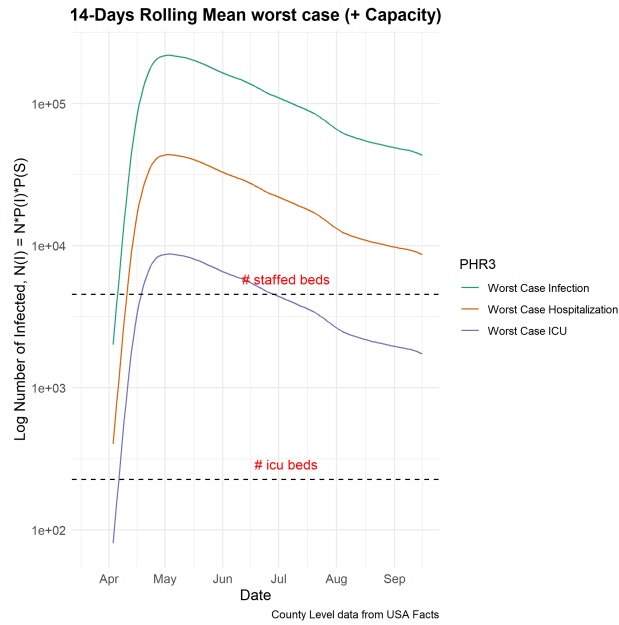
3.5 14-days rolling mean for mean case and worst case
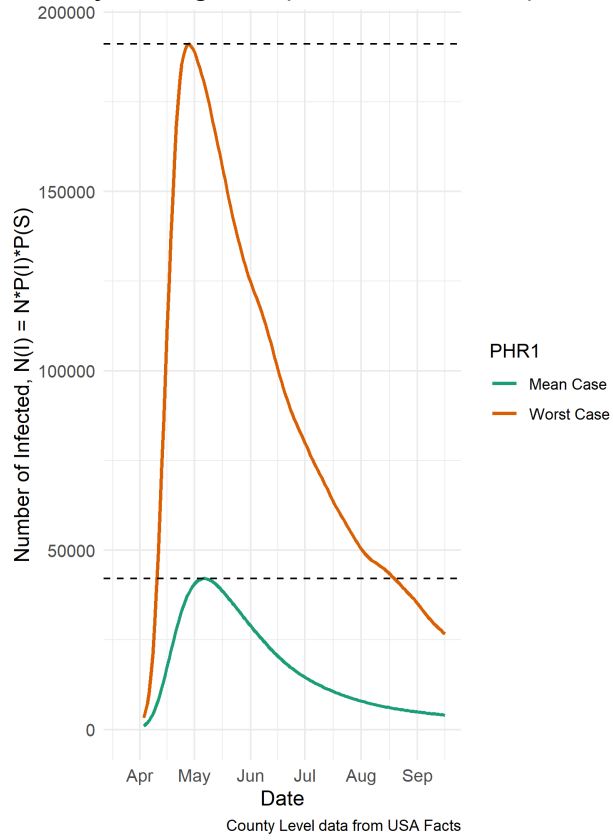
These plots show how the mean and the worst case differ.

14-Days Rolling Mean (Worst vs. Mean case)
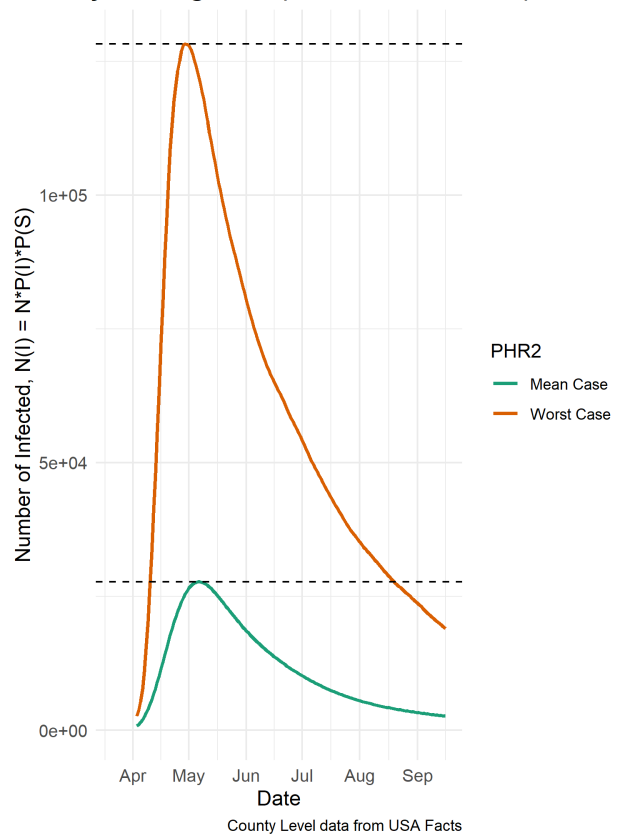
Number of Infected, N(I) = N*P(I)*P(S)

PHR1
— Mean Case
— Worst Case

Date

County Level data from USA Facts

14-Days Rolling Mean (Worst vs. Mean case)

Number of Infected, N(I) = N*P(I)*P(S)

PHR2
— Mean Case
— Worst Case

Date

County Level data from USA Facts

14-Days Rolling Mean (Worst vs. Mean case)

Number of Infected, N(I) = N*P(I)*P(S)

PHR3
- Mean Case
- Worst Case

Date

County Level data from USA Facts

14-Days Rolling Mean (Worst vs. Mean case)

Number of Infected, N(I) = N*P(I)*P(S)

PHR4
- Mean Case
- Worst Case

Date

County Level data from USA Facts

14-Days Rolling Mean (Worst vs. Mean case)

Number of Infected, N(I) = N*P(I)*P(S)

PHR5
— Mean Case
— Worst Case

Date

County Level data from USA Facts
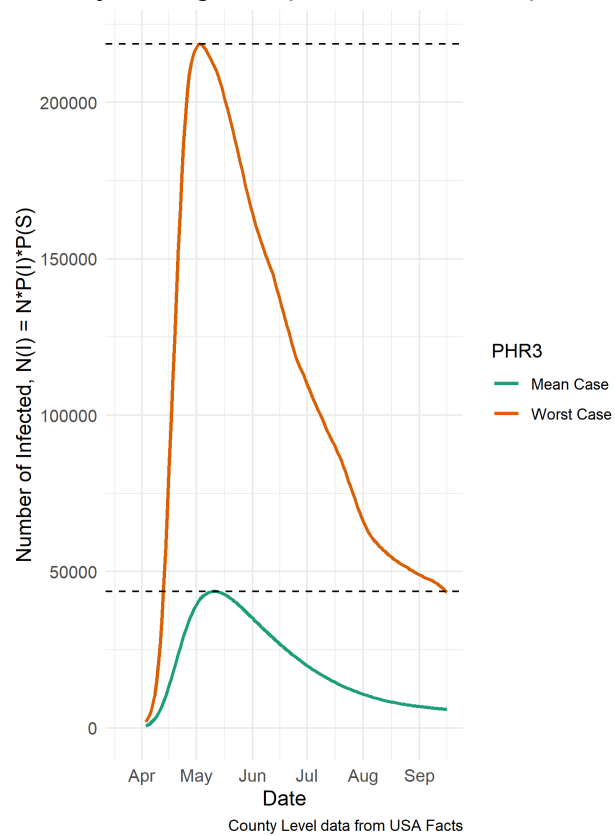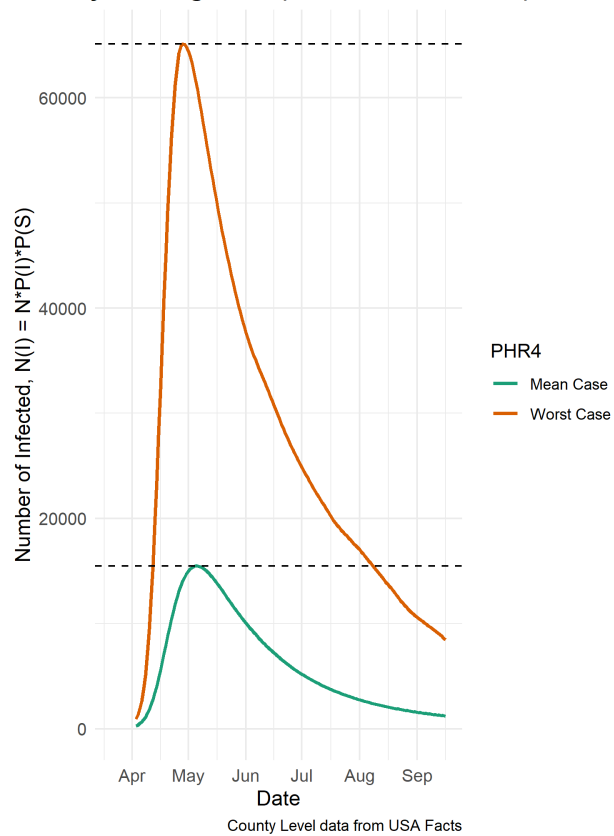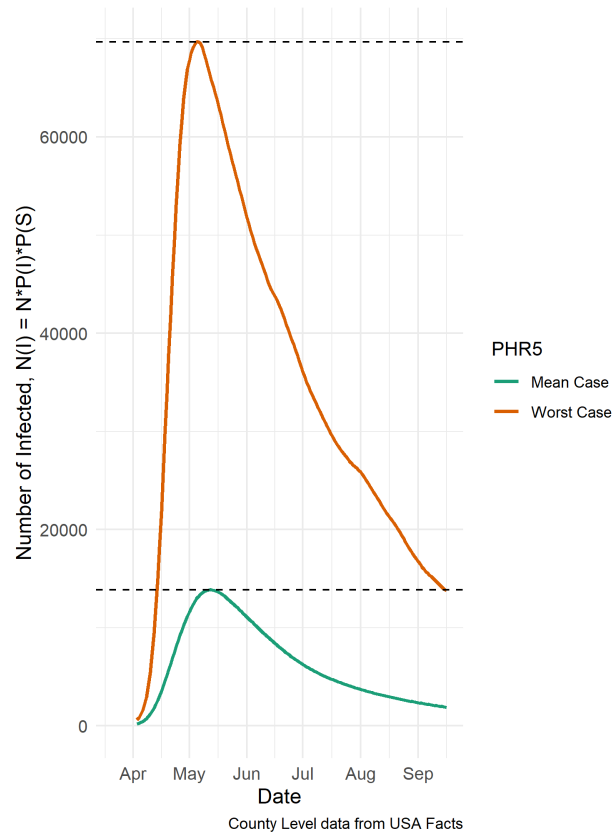
4 Appendix

4.1 P(removal) plots for each PHR

PHR_1: removed forecast with prior β_0=0.259,γ_0=0.0821 and R_0=3.15
posterior: β_p=0.384,γ_p=0.124 and R_0=3.26

PHR_2: removed forecast with prior β_0=0.259,γ_0=0.0821 and R_0=3.15
posterior: β_p=0.378,γ_p=0.126 and R_0=3.19

PHR_3: removed forecast with prior β_0=0.259,γ_0=0.0821 and R_0=3.15
posterior: β_p=0.354,γ_p=0.121 and R_0=3.1

PHR_4: removed forecast with prior β_0=0.259,γ_0=0.0821 and R_0=3.15
posterior: β_p=0.352,γ_p=0.109 and R_0=3.4

PHR_5: removed forecast with prior β_0=0.259,γ_0=0.0821 and R_0=3.15
posterior: β_p=0.341,γ_p=0.118 and R_0=3.07

4.2 Parameter choices

The output is dependent on the parameter choices, viz. death_in_R, beta0, gamma0 and R0. Here's what they mean and what we can do about them.

- `death_in_R`: the numeric value of average of cumulative deaths in the removed compartments. (I used 0 as right now we don't have info on this for AR, but can use values from other states and see what changes.)
- `beta0`: the hyperparameter β_0 of average transmission rate, the default is the one estimated from the SARS first-month outbreak (0.2586).
- `gamma0` : the hyperparameter γ_0 of average removed rate, the default is the one estimated from the SARS first-month outbreak (0.0821).
- R0: the hyperparameter of the mean reproduction number R_0. The default is thus the ratio of beta0/gamma0, which can be specified directly. (Our mean R_0 is 3.15). R_0 is highly important, and a different R0 would give different results.

5 References

1. Song, P. X., Wang, L., Zhou, Y., He, J., Zhu, B., Wang, F., ... & Eisenberg, M. (2020). An epidemiological forecast model and software assessing interventions on COVID-19 epidemic in China. medRxiv. https://www.medrxiv.org/content/medrxiv/early/2020/03/03/2020.02.29.20029421.full.pdf

2. Song Lab at UM. eSIR: Extended state-space SIR models, 2020. R package version 0.1.0.

3. Dave Osthus, Kyle S Hickmann, Petrutia C Caragea, Dave Higdon, and Sara Y Del Valle. Forecasting seasonal in uenza with a state-space sir model. The Annals of Applied Statistics, 11(1):202, 2017.

4. ICU and Ventilator rates: https://www.cdc.gov/coronavirus/2019-ncov/hcp/clinical-guidance-management-patients.html

5. Many models of Covid-19: https://sites.google.com/umich.edu/manymodelsclovid19/home

6. Link to the map: https://uark.maps.arcgis.com/apps/AttachmentViewer/index.html?appid=b0f181dd1084431d8cb91ba0053dfe47

7. HGHI study: Interactive map on NYTimes https://www.nytimes.com/interactive/2020/03/17/upshot/hospital-bed-shortages-coronavirus.html