

# Semi-parametric modeling of SARS-CoV-2 transmission in Orange County, California

## using **tests**, **cases**, **deaths**, and **seroprevalence** data

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### Motivation

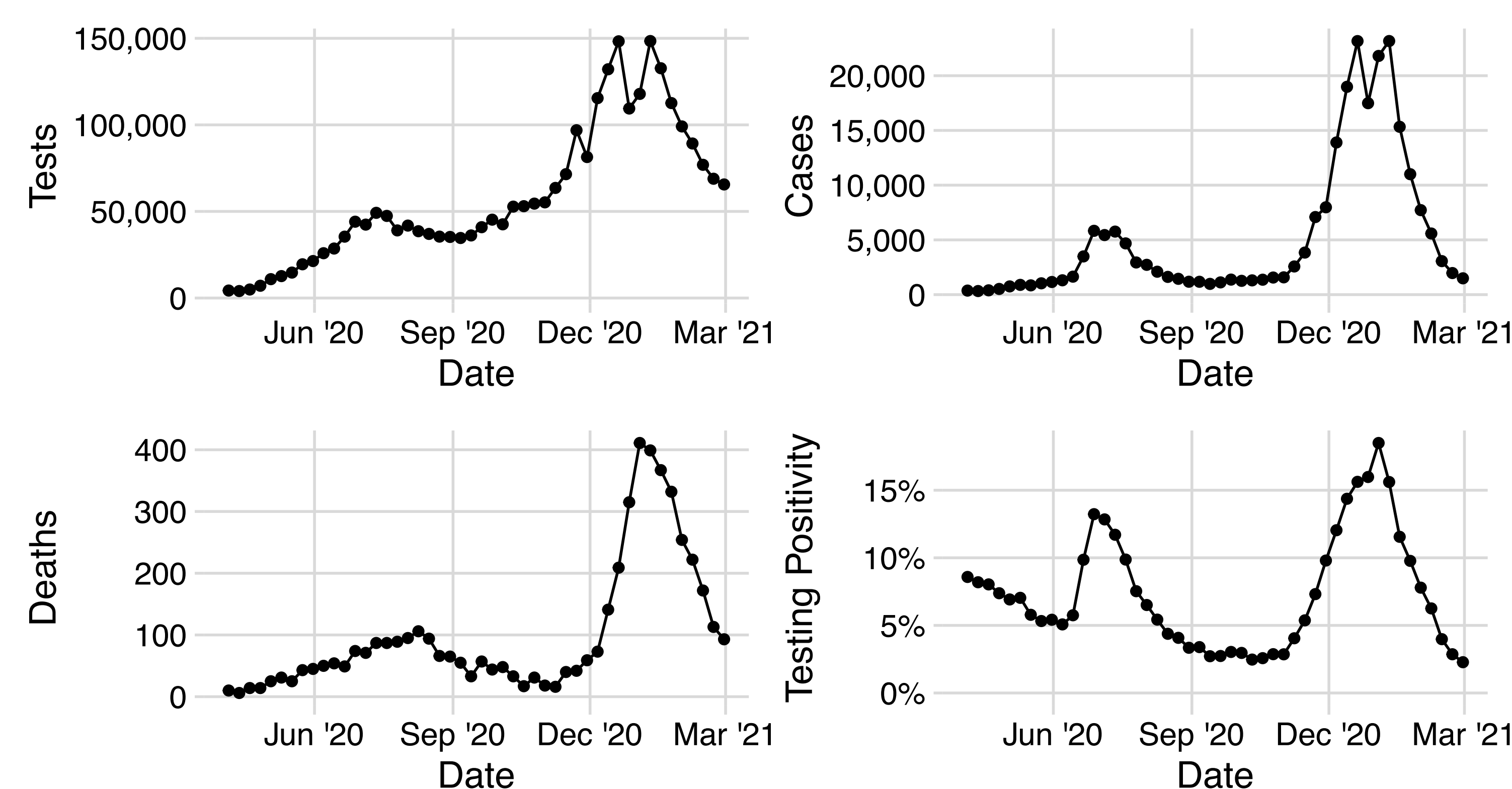
- Objectives:
  - Incorporate **multiple streams** of data into a COVID-19 model.
  - Account for **changes in testing** over time.
- Why?
  - Case data is the tip of the spear, earliest sign of increase in transmission.
  - Multiple data sources might lead to more robust inferences.

### Data

- Modeling period: Mar 30, 2020 - Feb 28, 2021 (No vaccination)
- Daily cases, tests, and deaths aggregated at weekly level
- Excluded repeat positive tests
- Countywide seroprevalence study from ~Aug 2020: 11.5% positivity among 3,000 tests
- Empirically estimated reporting delay for deaths due to COVID-19

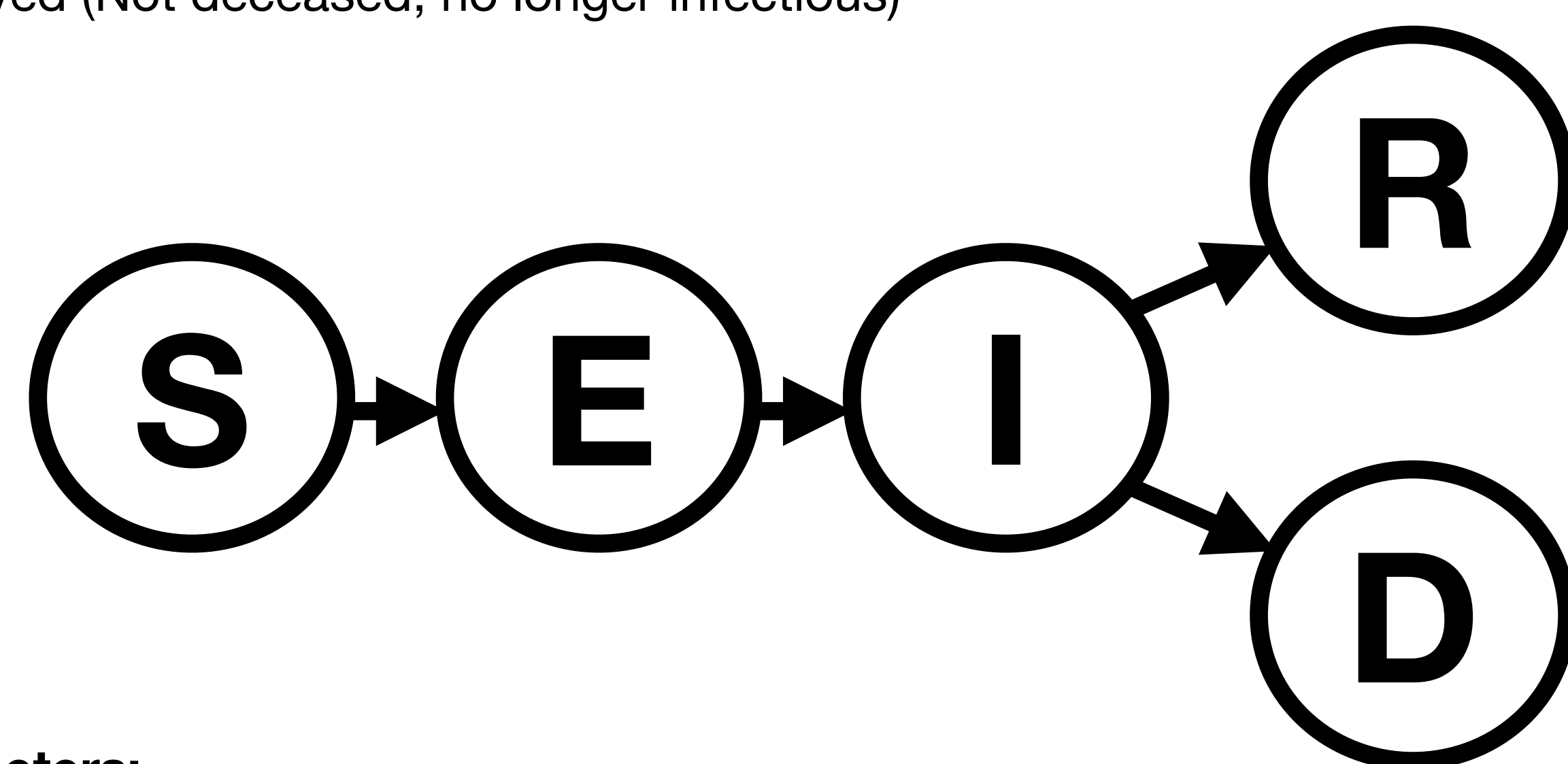
#### Orange County, CA data

Counts binned into weekly periods



### Transmission Model

- S: Susceptible
- E: Infected but not Infectious
- I: Infectious,
- D: Death due to COVID-19
- R: Removed (Not deceased, no longer infectious)



#### Key Parameters:

Constant: Mean Latent Period, Mean Infectious Period

Time Varying: Basic Reproduction Number ( $R_0$ ), Infection Fatality Ratio (IFR)

### Surveillance Model

$$\text{Obs. Deaths}_t \sim \text{Negative Binomial} \left( \mu_t^D = (\text{New Latent Deaths})_t \cdot (\text{Report Prob.})_t, \sigma_t^2 = \frac{\mu_t^D(1 + \mu_t^D)}{\text{Overdisp.}} \right)$$

$$\text{Obs. Cases}_t \sim \text{Beta-Binomial} \left( \text{Tests}_t, (\text{Overdisp.}) \cdot \mu_t^C, (\text{Overdisp.}) \cdot (1 - \mu_t^C) \right)$$

$$\text{logit}(\mu_t^C) = \alpha_t + \text{logit} \left( \frac{(\text{New Latent Infections})_t}{\text{Population Size}} \right)$$

$$\text{Seroprev. Cases}_t \sim \text{Binomial} \left( \text{Seroprev. Tests}_t, \frac{(\text{Cumulative Latent Recoveries})_t}{\text{Population Size} - (\text{Cumulative Latent Deaths})_t} \right)$$

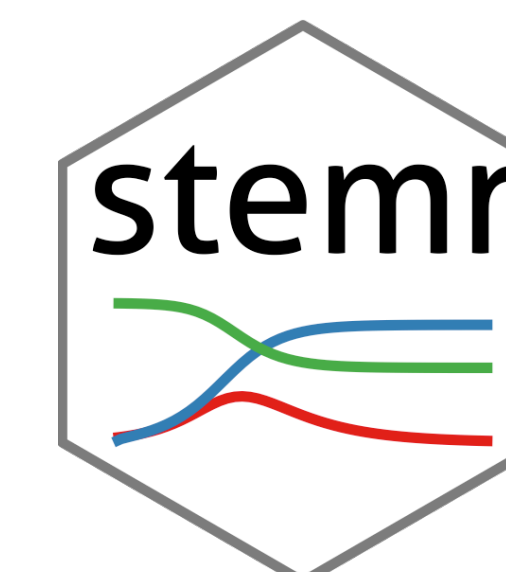
### Bayesian Model

- $\theta$ : vector of model parameters
- $Y$ : vector of observed cases
- $M$ : vector of observed deaths
- $Z$ : vector of observed seroprev. cases
- Likelihood:

$$\Pr(M, Y, Z | \theta) = \Pr(M | \theta) \Pr(Y | \theta) \Pr(Z | \theta) = \prod_{l=1}^L \Pr(M_l | \theta) \Pr(Y_l | \theta) \Pr(Z_l | \theta)$$

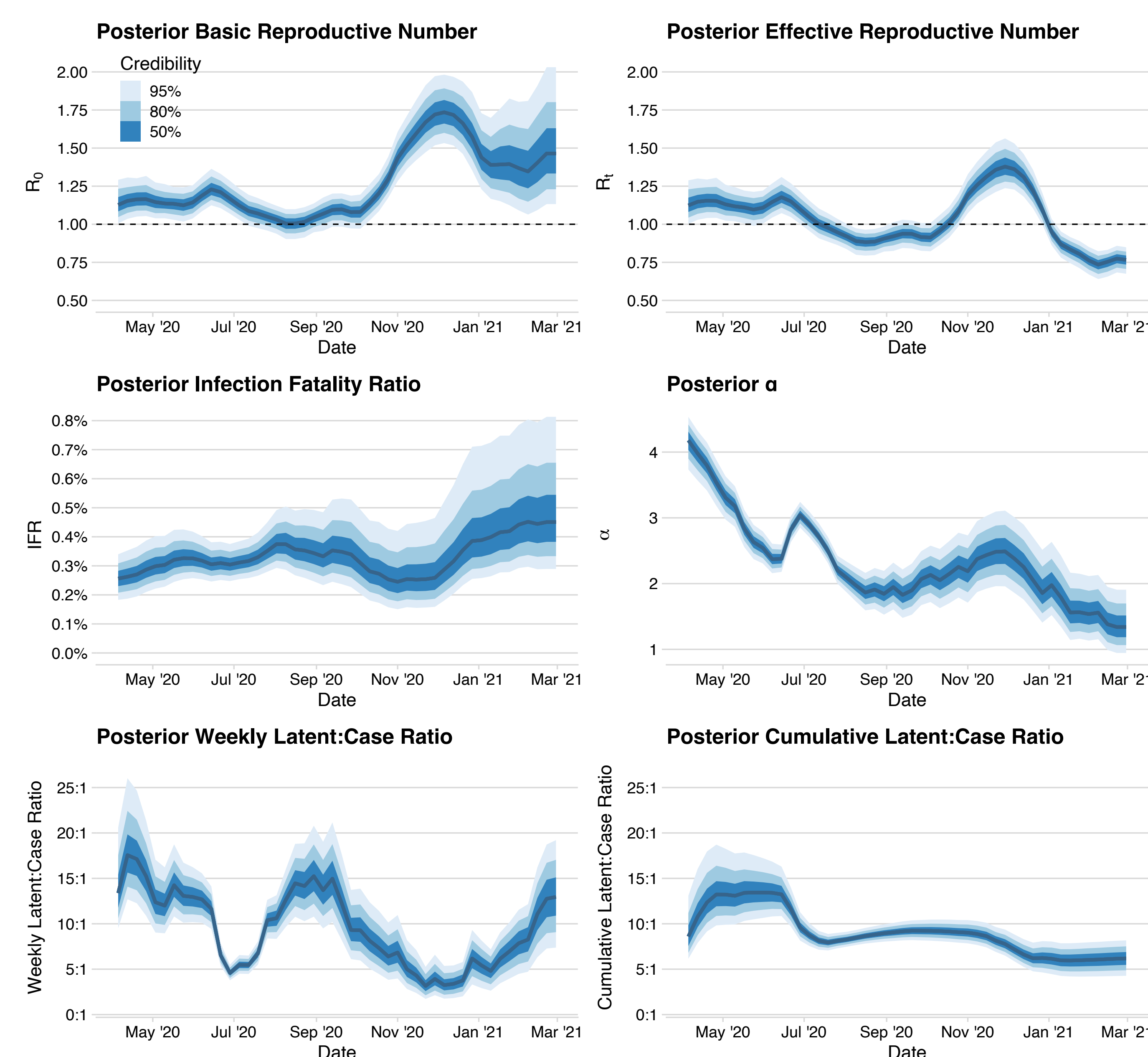
- Posterior:

$$\Pr(\theta | M, Y, Z) \propto \Pr(M, Y, Z | \theta) \Pr(\theta)$$

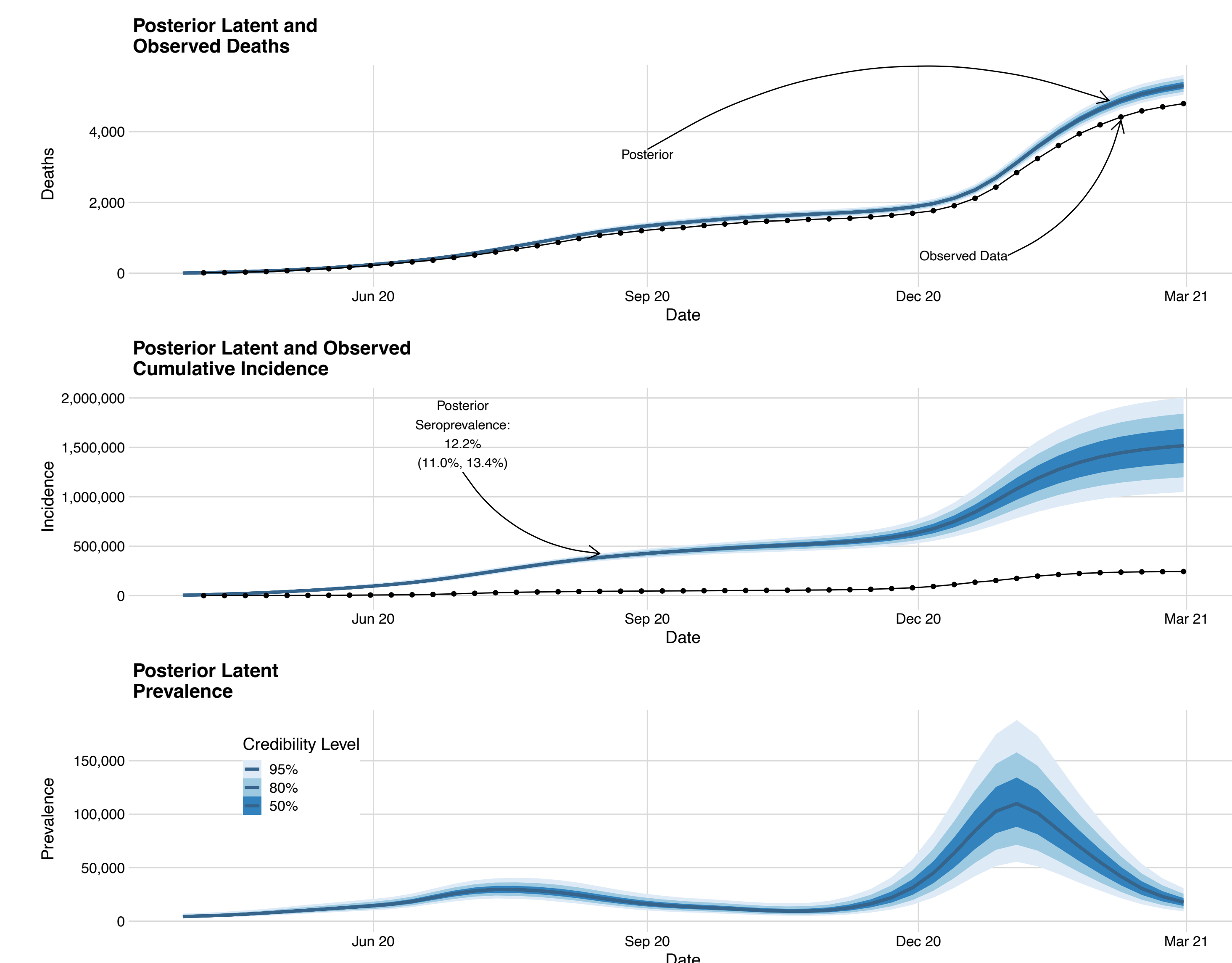


- Fit using stemr R package <https://fintzj.github.io/stemr/>

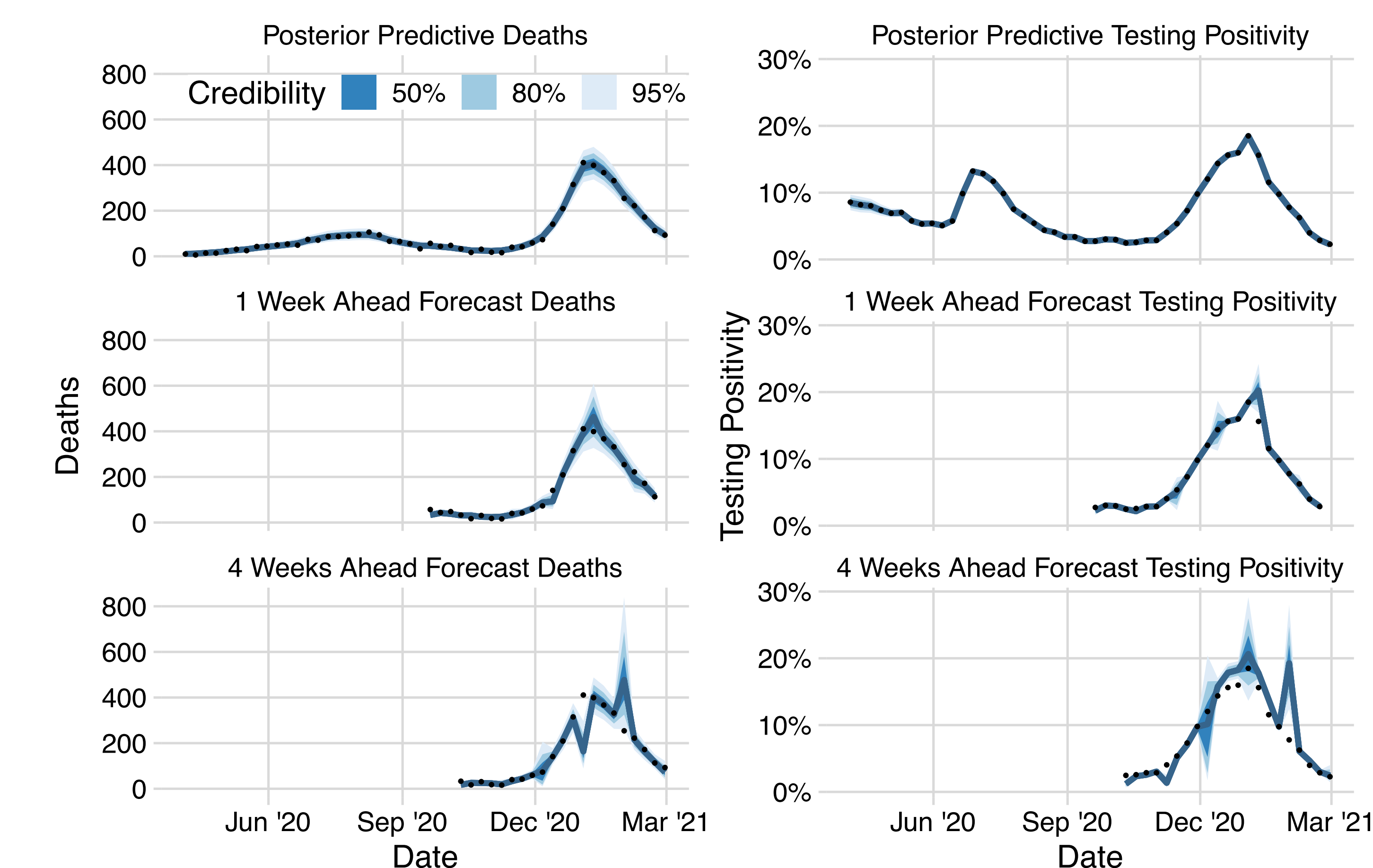
### Results



### Results



#### Posterior Predictive Distributions & Probabilistic Forecasts



- Sudden decrease in prevalence in January 2021 is attributable both to **high levels of accumulated immunity** and some **behavioral change**.
- Winter wave began in October 2021.
- 1/4-1/8 of cases are detected.
- By March 2021 1/3-2/3 of OC residents had been infected.
- Four weeks ahead forecasting is feasible when model parameters are stable.
- Preprint: <https://arxiv.org/abs/2009.02654>