Modelling COVID-19 from a physicist's perspective

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European COVID-19 Modelling Hub

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My background

- Professor in Particle Physics at the University of Victoria holding a joint appointment with the TRIUMF Laboratory (BC – Canada)
  - Build experiments and analyze data in large international collaborations
  - I teach data analysis to physicists

- Since April 2020, using a model based on a <u>physicists perspective</u>:
  - Incorporate the fundamental workings of the system.
  - Keep it as simple as possible. A model is never "perfect" (always wrong!)
  - Focus on its main purpose: interpret data to learn about the spread of COVID
  - The model (www.pypm.ca) has served that purpose well
  - Engaged in regular discussions with academics in epidemiology in BC

- Since July 2020, participating in the US CDC COVID-19 forecasting group
  - US case/hospitalization/death data are very useful to challenge models
  - Led to joining the German forecast-hub later in 2020 $\rightarrow$ European hub

Overview

- Introducing the pypm model

- Insights:
  - Piece-wise constant transmission rates:
    - describe case, hospitalization, death time series reasonably well
    - give models an ability to forecast the spread of COVID-19
  - Variants and Vaccination have large impact on the spread:
    - models that incorporate these have an improved ability to forecast

- Summary
 - comments on data access/collaboration/forecasts and public policy

pyPM.ca: python Population Modeller

- A general framework for building population models: pypmca
  - Based on finite time-difference equations
    - allows for arbitrary time delay distributions (not limited to exponential)
    - choose $\Delta t = 1$ day to match data sources

  - Model objects are built from "population" objects and "connection" objects
    - Separates model design from numerical implementation: simplifies model construction and modification
  - Model objects can <u>evolve expectation values</u> and <u>can produce simulated data</u>
    - Simulated data essential to evaluate parameter estimators and to report quantiles

- A technical graphical user interface for jupyter notebook: ipypm
  - interact with data and models, explore parameter space
  - model parameters are estimated by fitting to cumulative case data (no ML)

- Open source on pypi/github
  - See: www.pypm.ca
  - Single click startup

Basic pyPM.ca model

$$E[\Delta I_{t+1}] = \alpha \frac{E[S_t]}{E[N_t]} E[C_t]$$

α: transmission rate. Initially, the average number of people that a contagious person infects per day
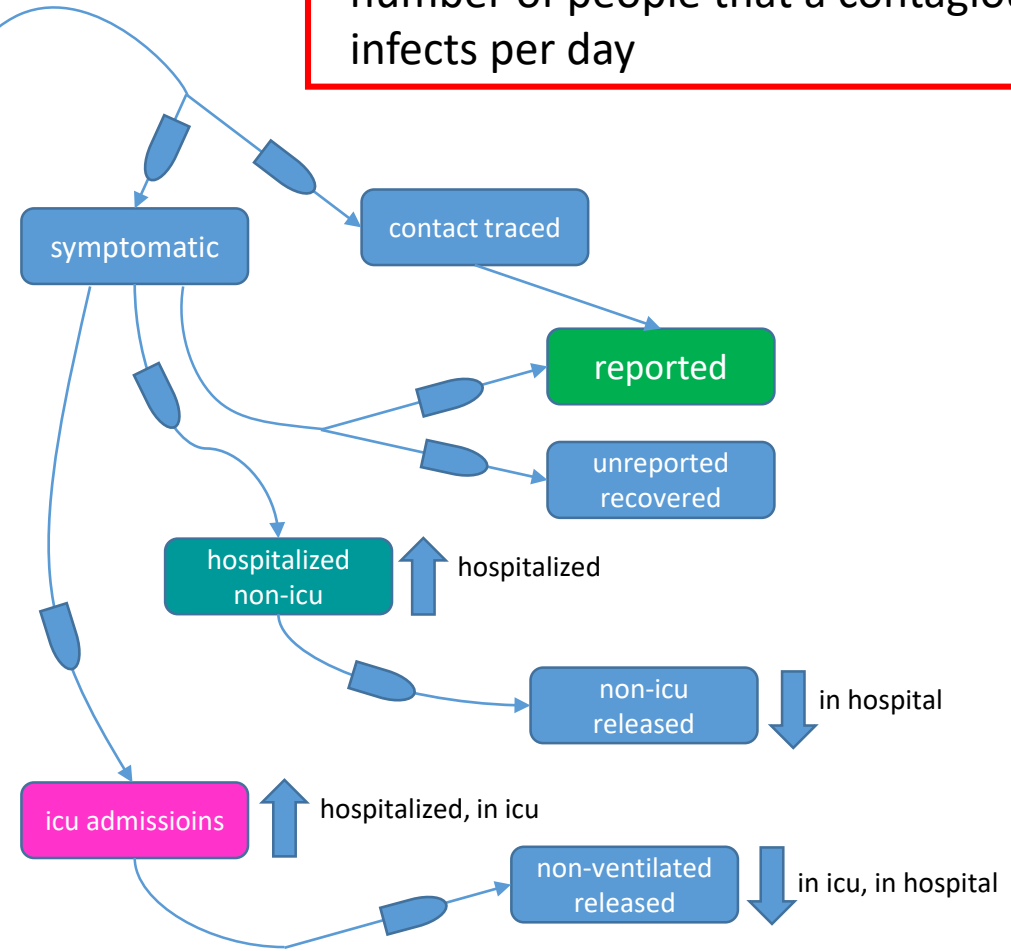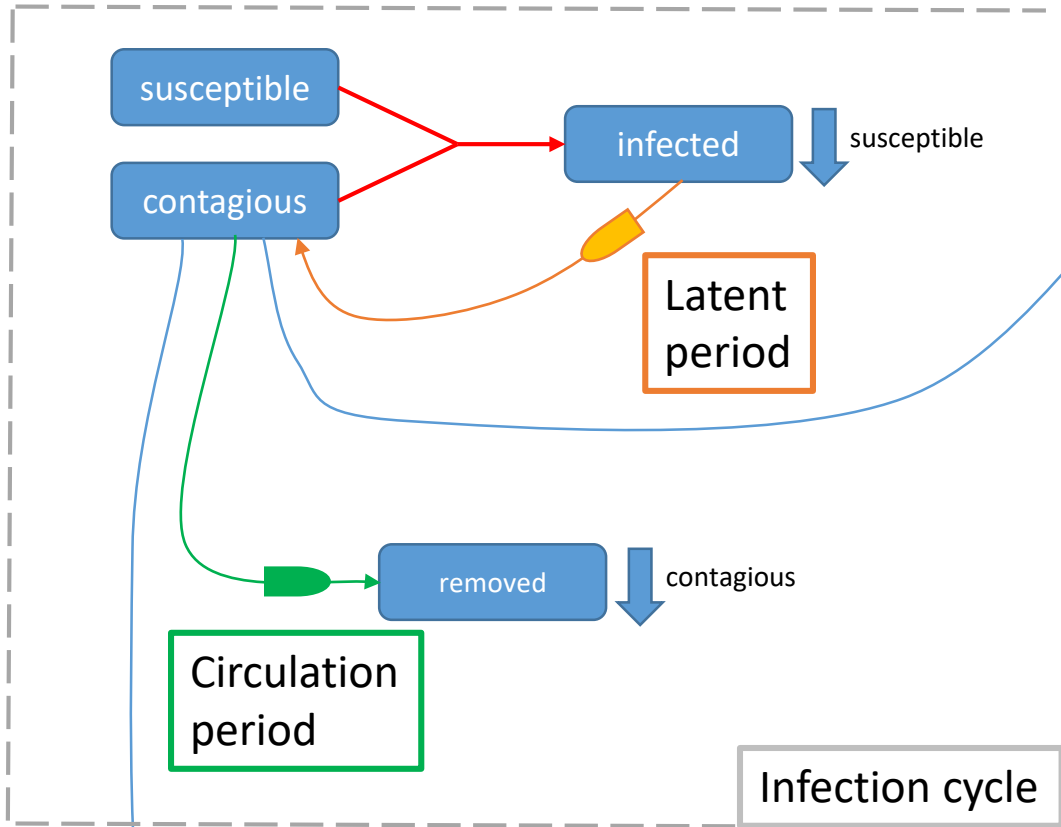
Epidemic growth

- The "steady state" solution to the infection cycle equations (with constant susceptible fraction) is exponential growth (or decline): characterized by δ:

$$E[C_{t+1}] = (1 + \delta)E[C_t]$$

  - C_t: size of the circulating contagious population on day t

- Imposing lockdown measures, reduces social contacts (reducing α), thereby reducing δ
  - Use case data to determine the transmission rate and when it changes

- Transmission rates alone do not determine the growth (δ)
  - In the pyPM model: also depends on the latent and circulation period delays
  - In my analyses I keep these delays fixed, so the estimated values for α are "effective transmission rates"

Example: BC-Canada case data (July 2020 – Feb 2021)
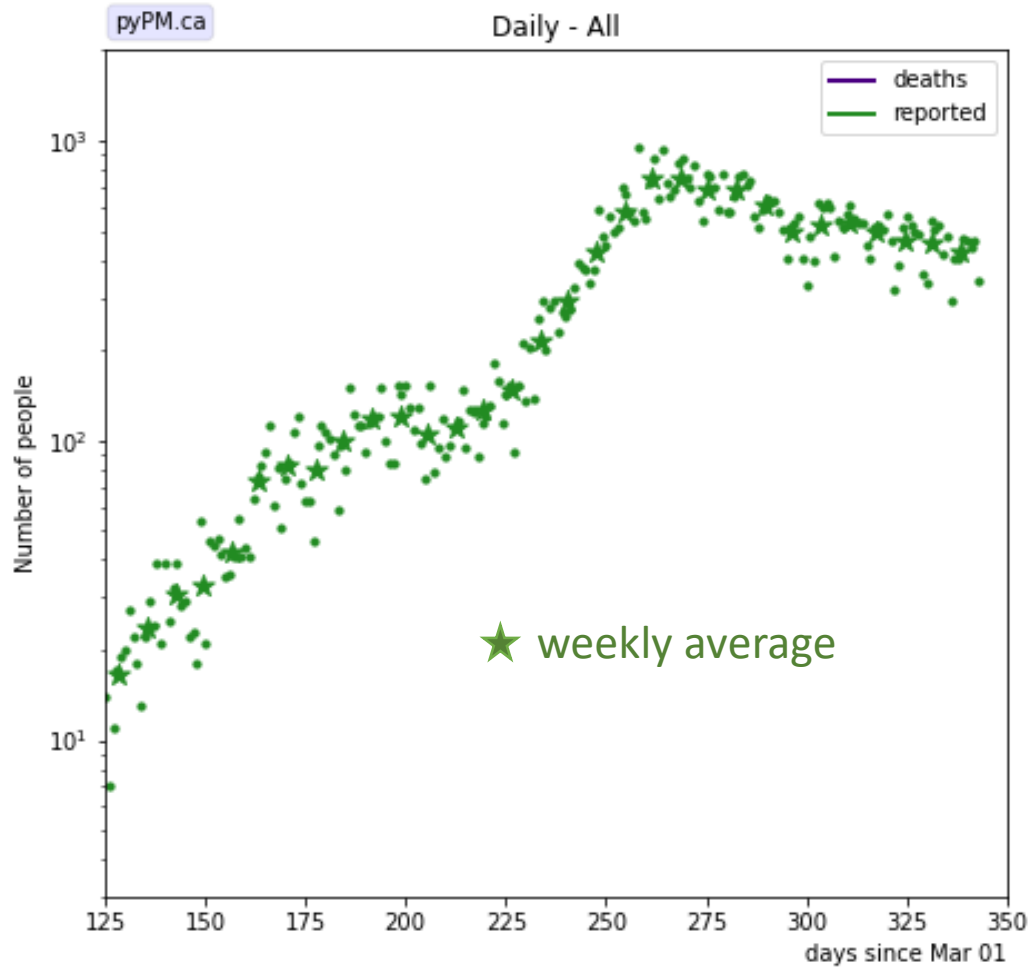
Jul 1, 2020   Feb 9, 2021
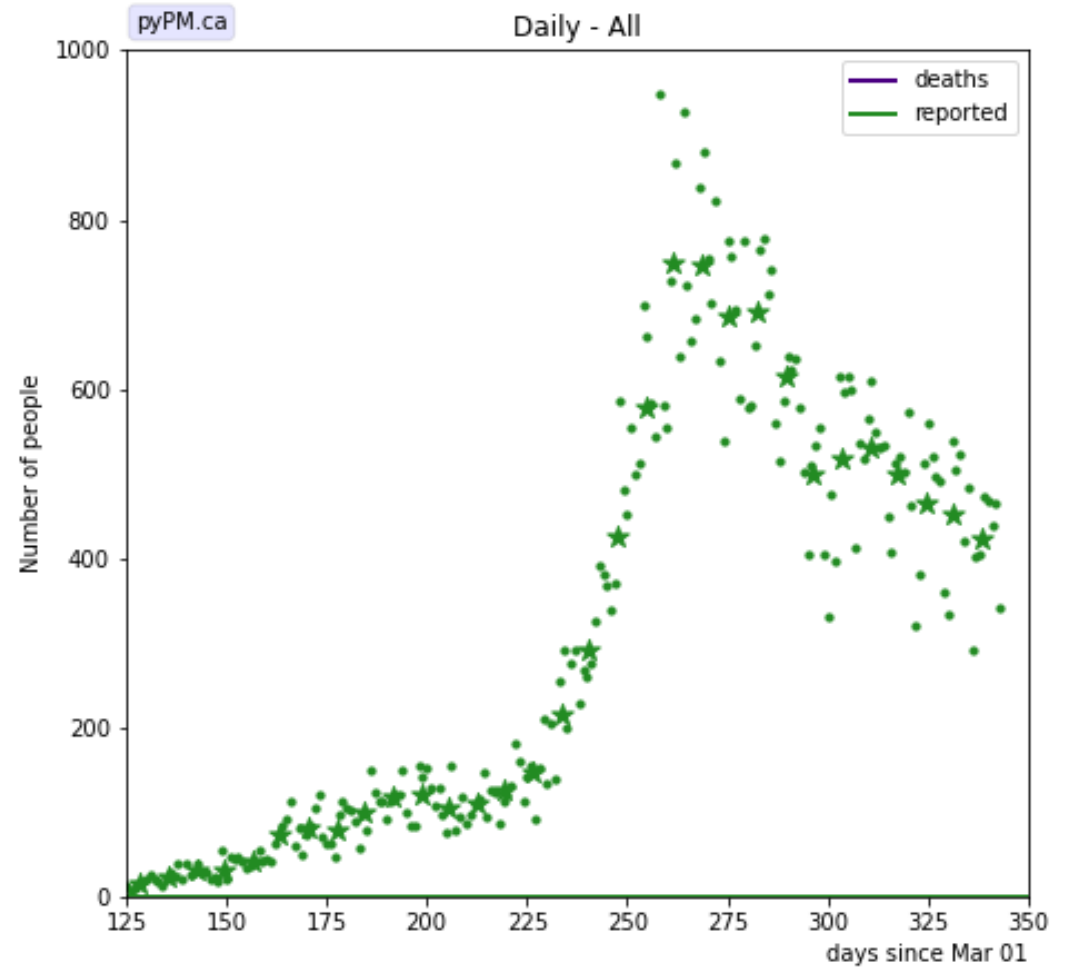
BC-Canada case data (with model)
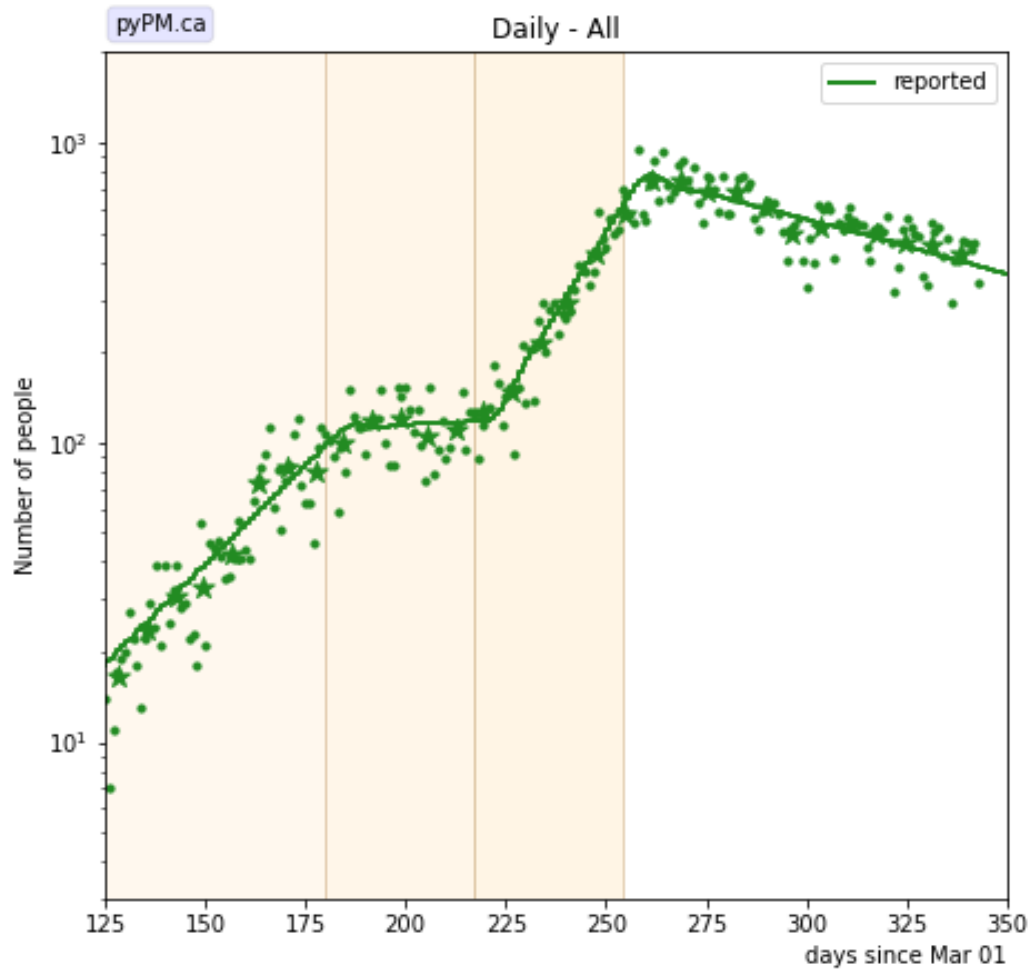
Jul 1   Aug 28   Oct 04   Nov 10   Feb 9
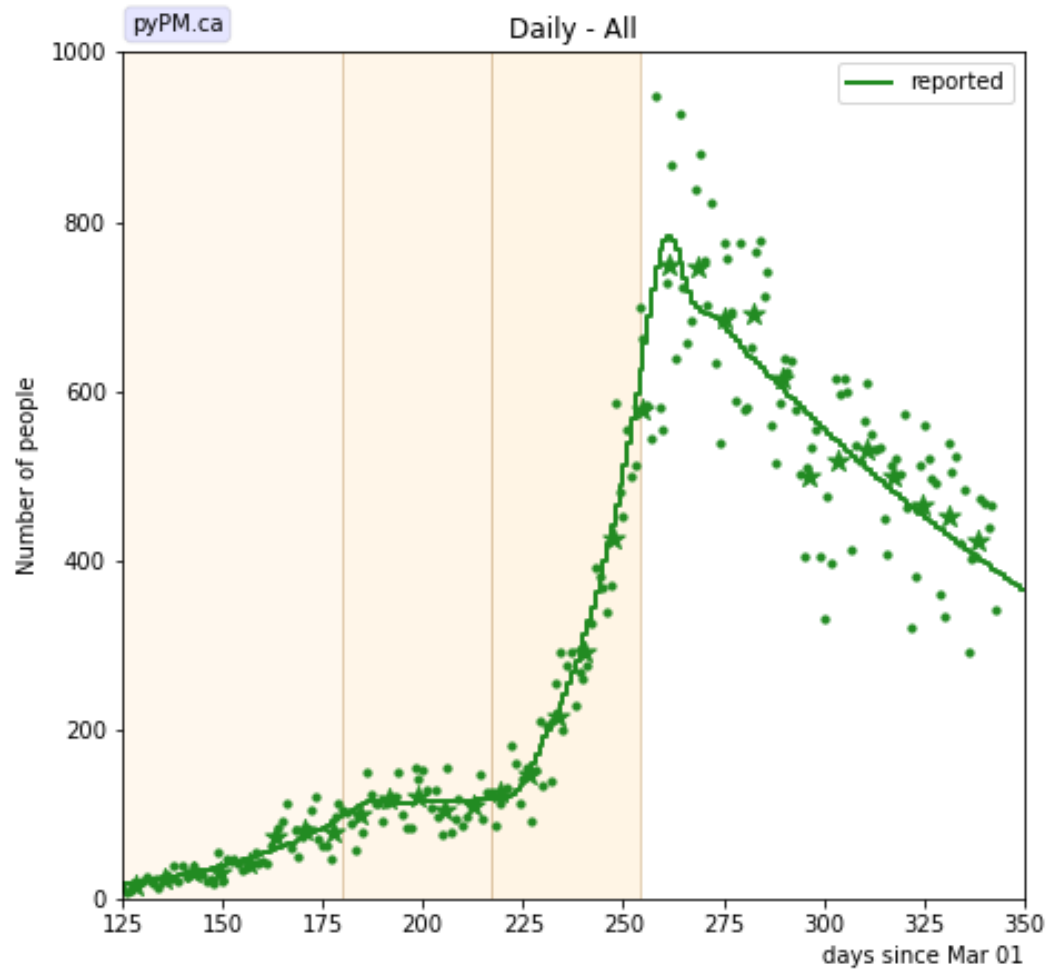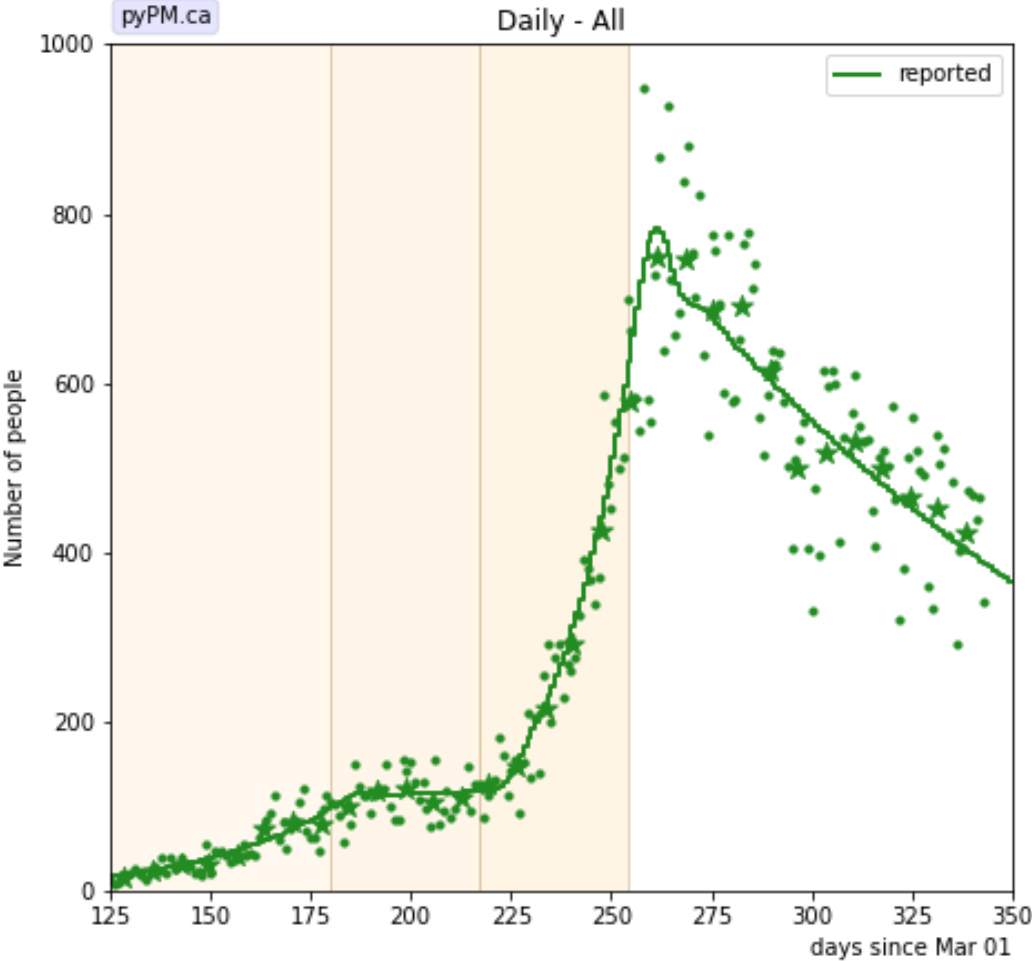
The spread of COVID-19 can be characterized by long periods of constant growth or decline.
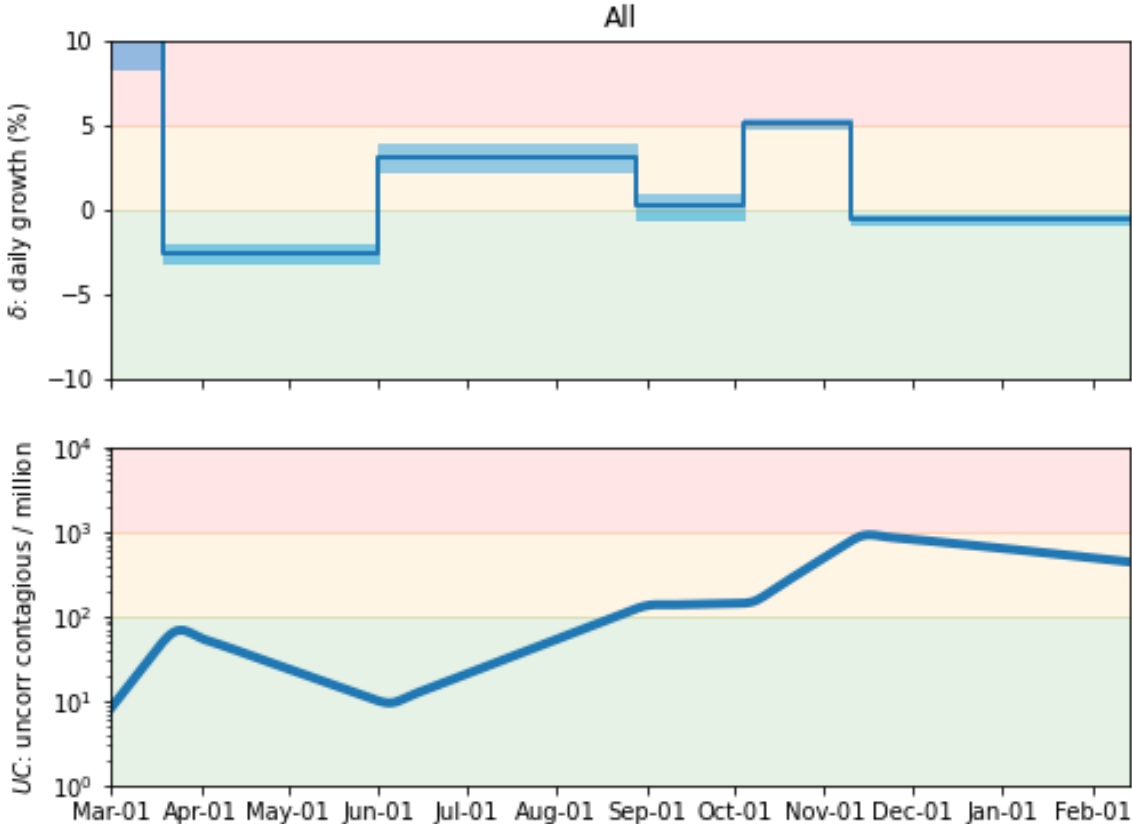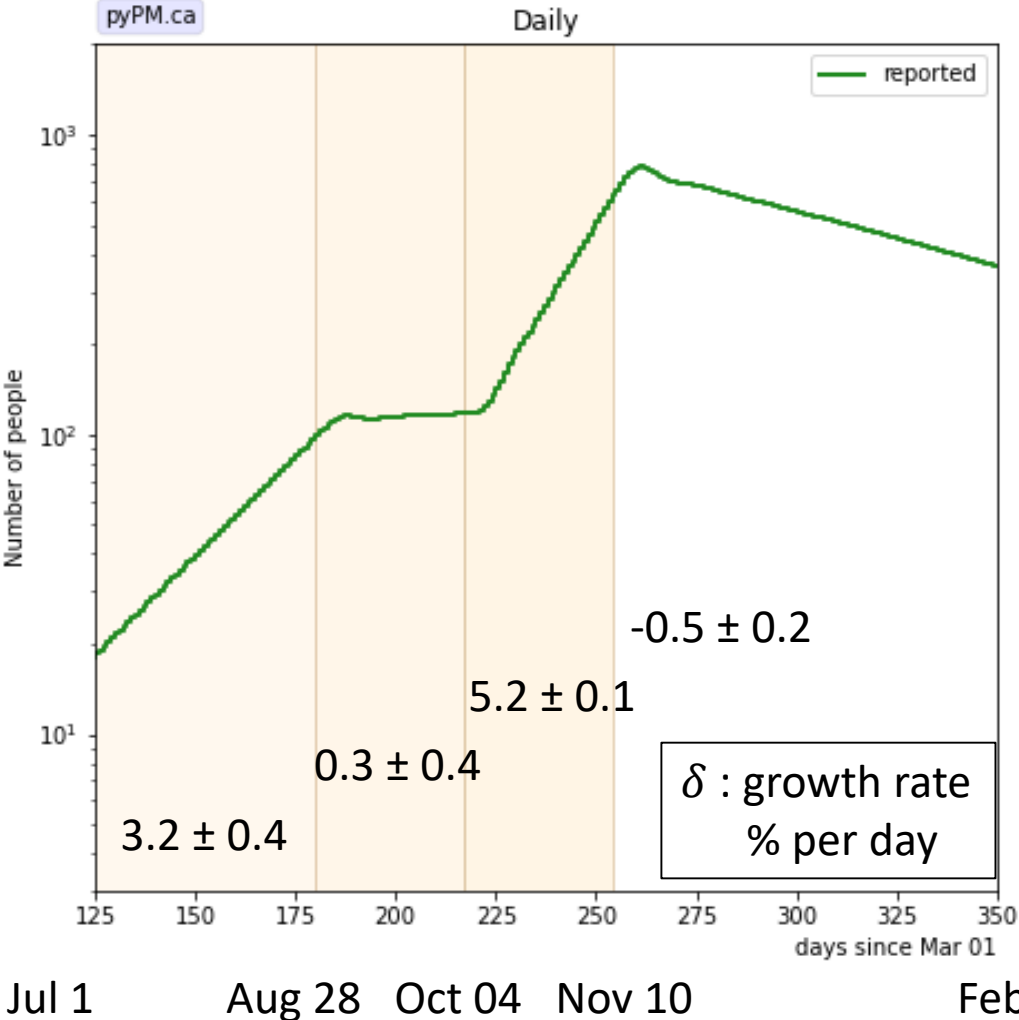
BC case data (with model)

-0.5 ± 0.2

5.2 ± 0.1

0.3 ± 0.4

3.2 ± 0.4

δ : growth rate
% per day

Jul 1   Aug 28   Oct 04   Nov 10   Feb 9

The spread of COVID-19 can be characterized by long periods of constant growth or decline.

BC model

BC case history characterized by just
a few "model independent" quantities.

Jul 1   Aug 28   Oct 04   Nov 10   Feb 9

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Dynamic Compartmental Modeling: Recent Trends

Provincially, our model-based estimate of R_t (average daily number of new infections generated per case) continues to hover near 1.

Whenever R_t is > 1, there is a risk that the number of new cases could grow rapidly.

Solid black line: median R_t based on data up to Feb 2, 2021; Grey band: 5%-95% credible interval; Purple bars: all reported cases. Due to a lag from symptom onset to reporting, the most recent cases are not shown.

Many epidemiologists do not use this approach

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# Dynamic Compartmental Modeling: Recent Trends

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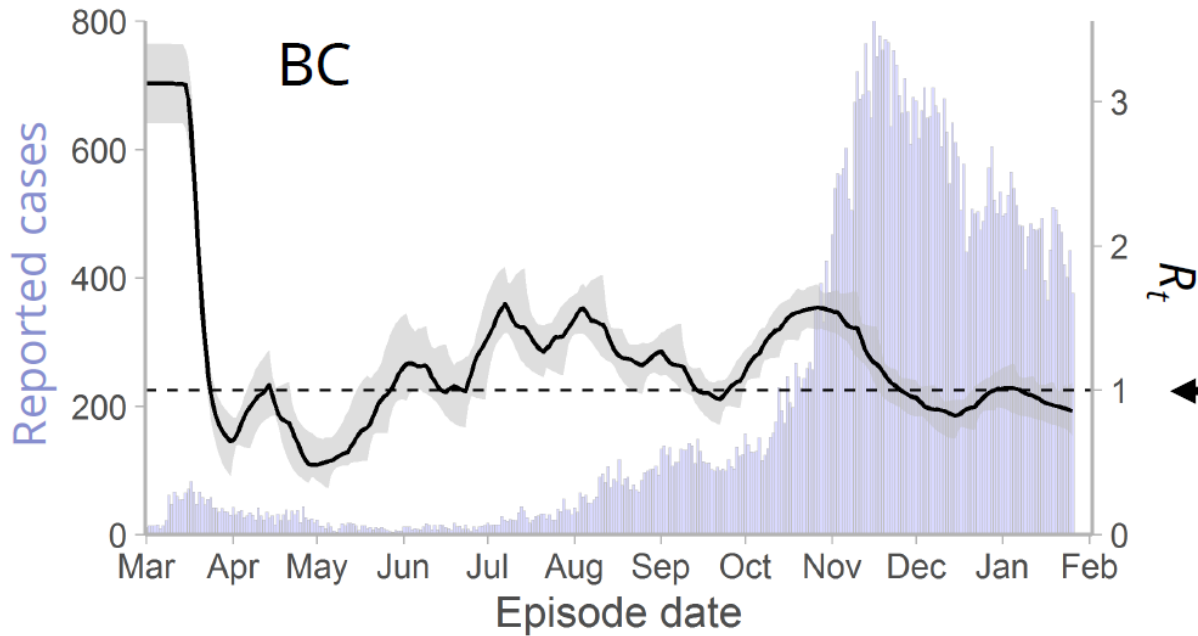
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COVID-19 IN BC

Many epidemiologists do not use this approach

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Modelling variation: BC model
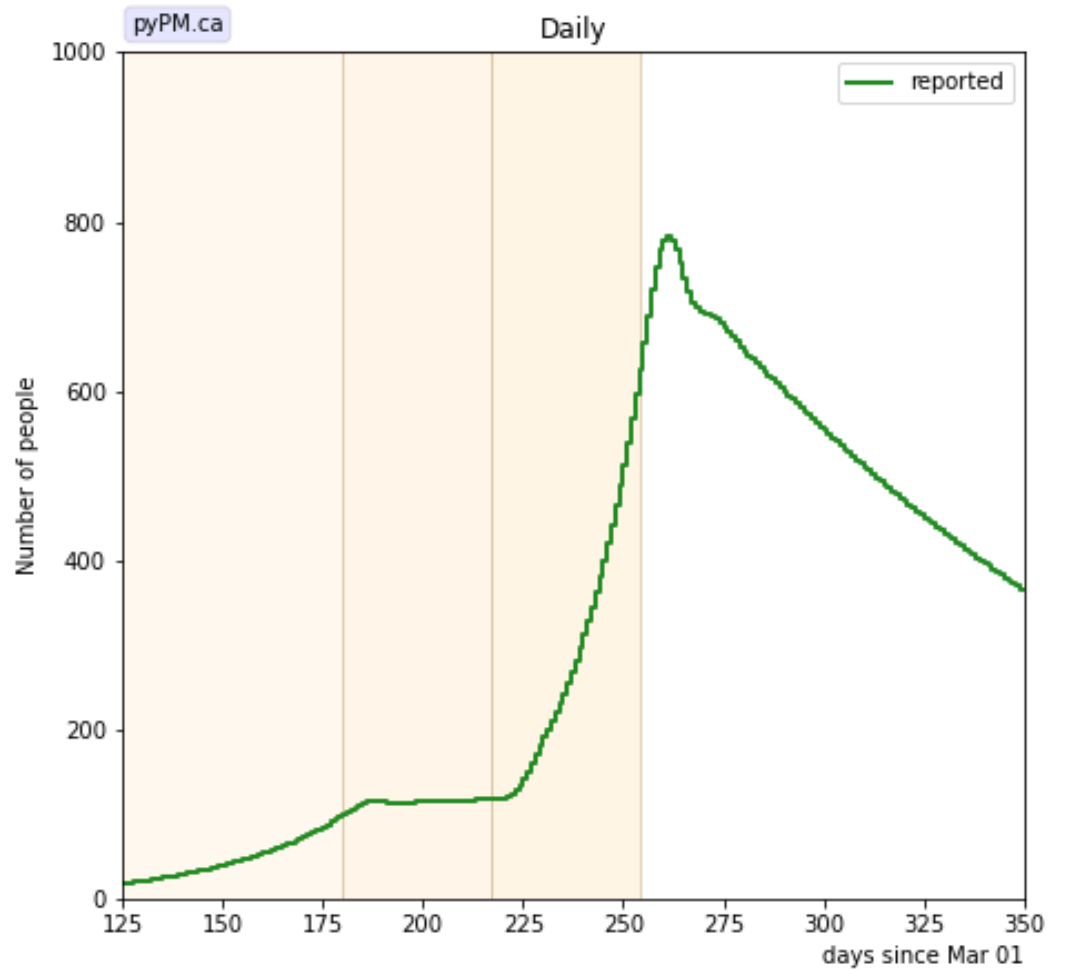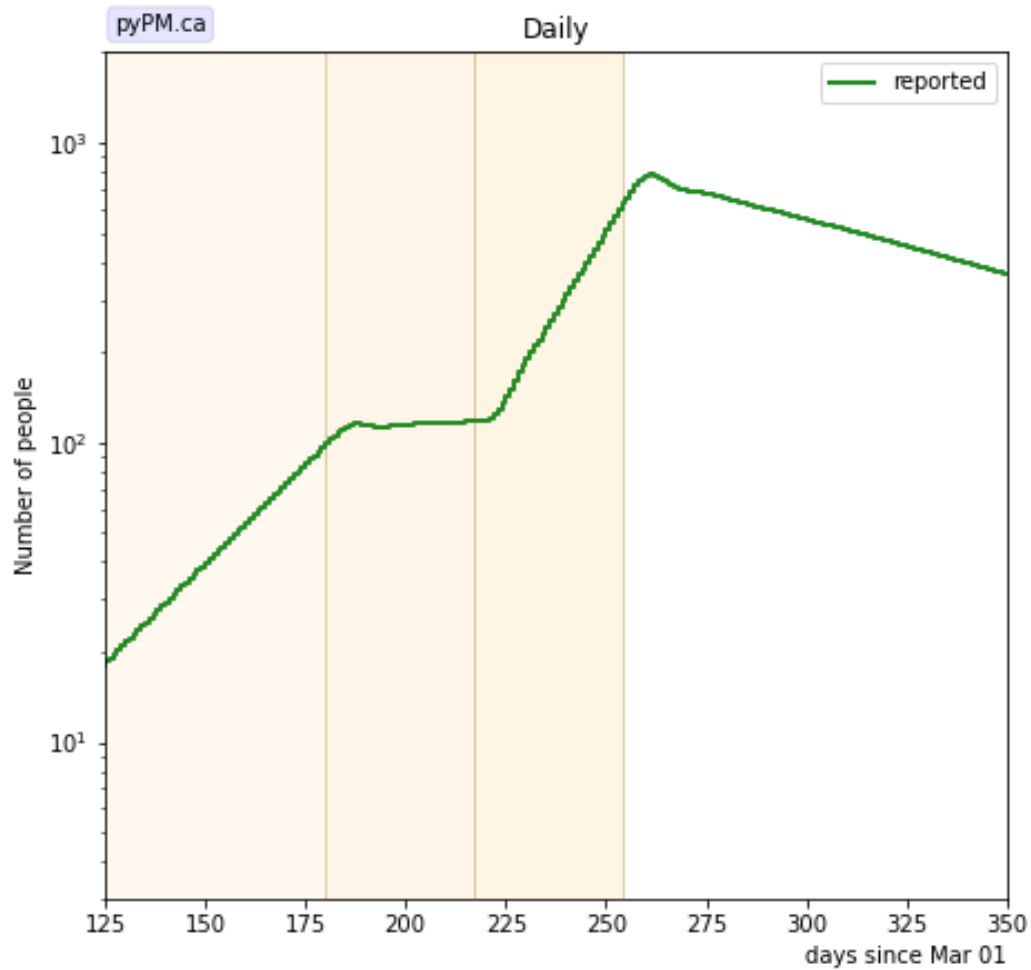
Modelling variation: BC model
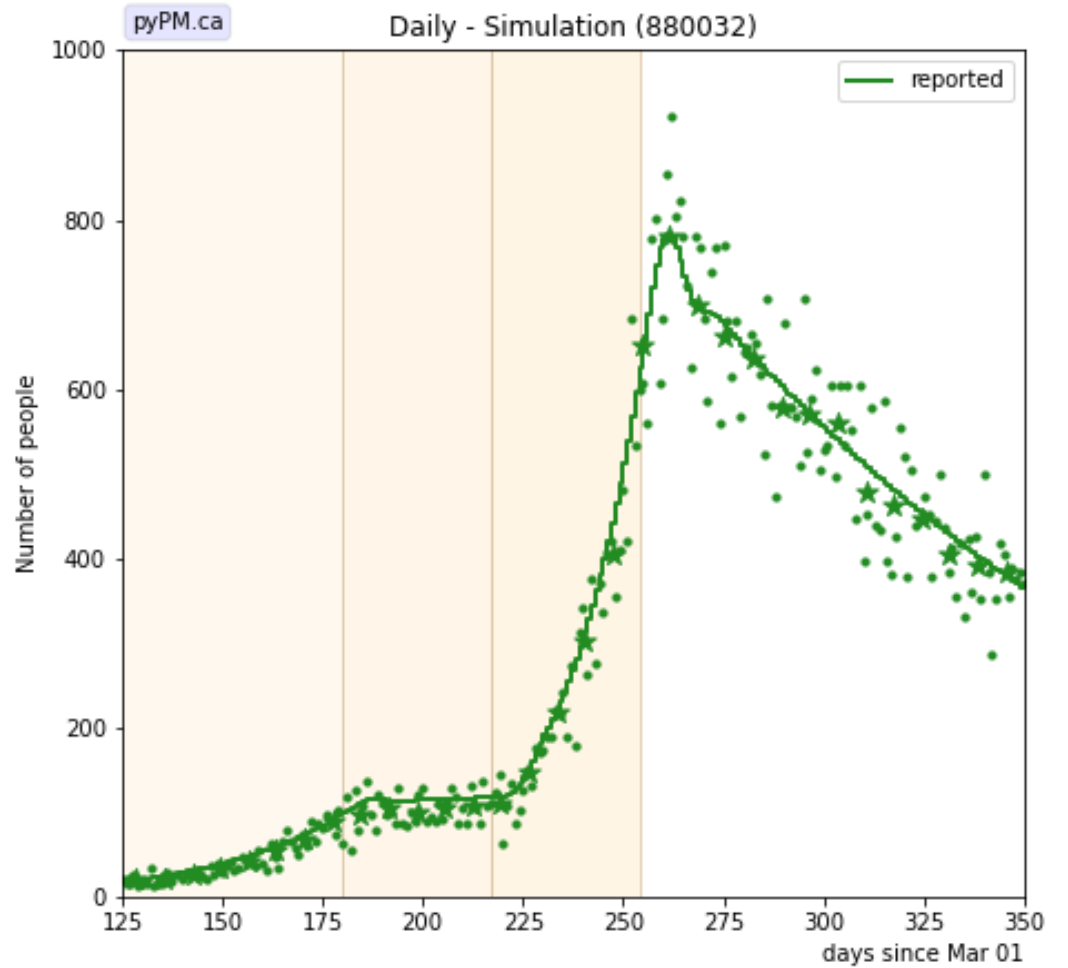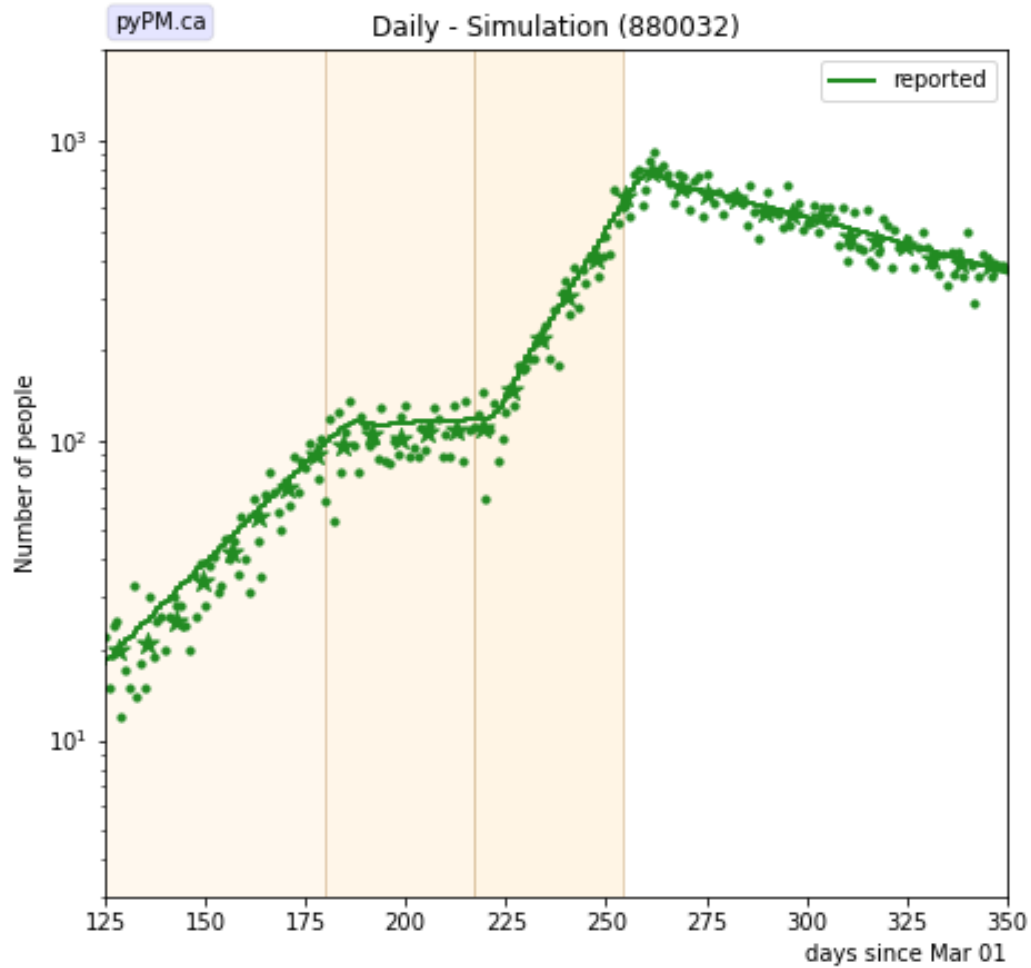
Modelling variation: BC model
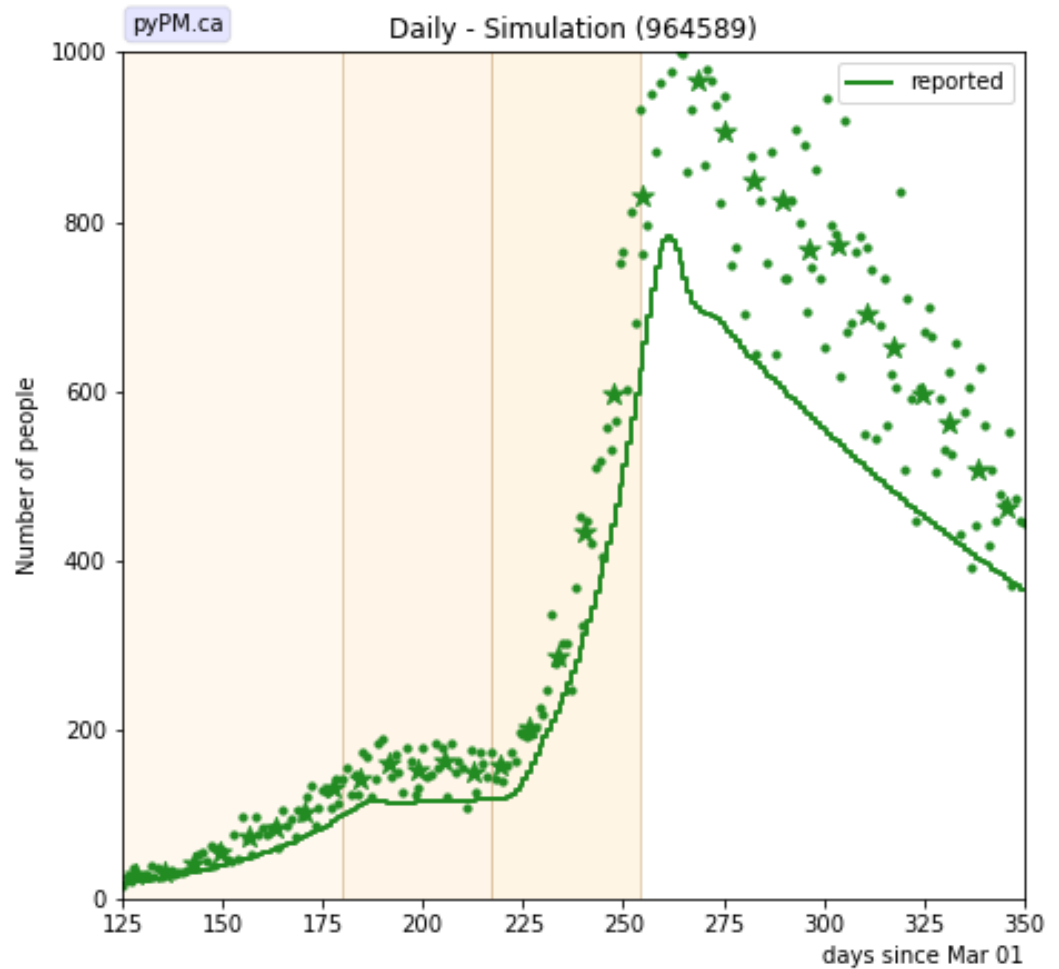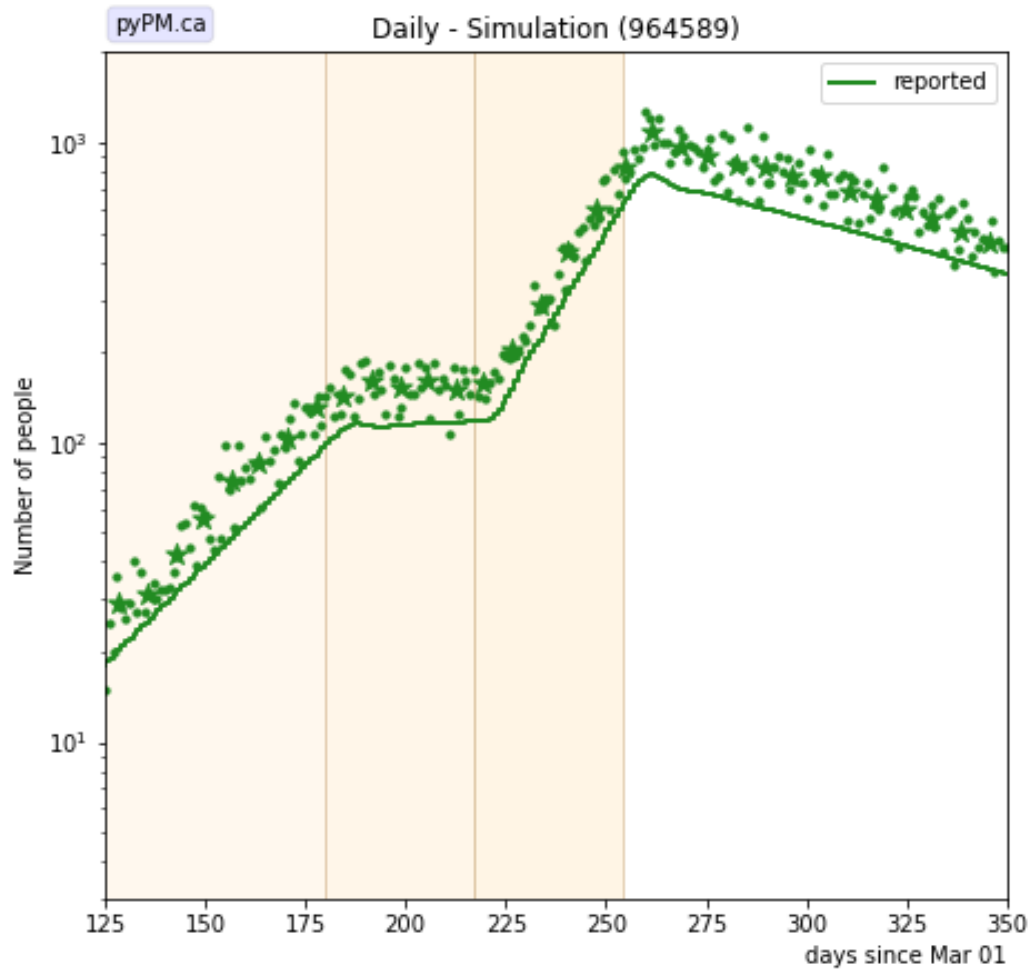
Modelling variation is essential to analyze data.

Example: Nevada (US)
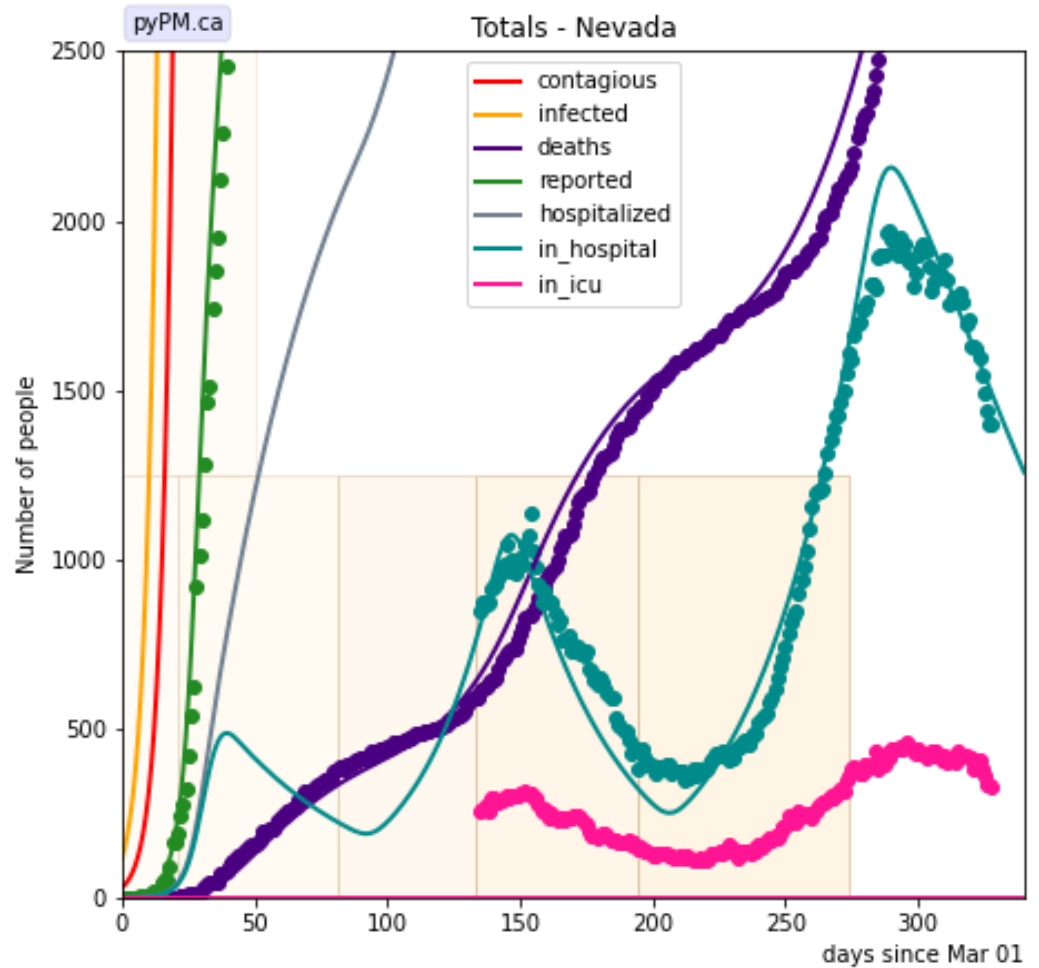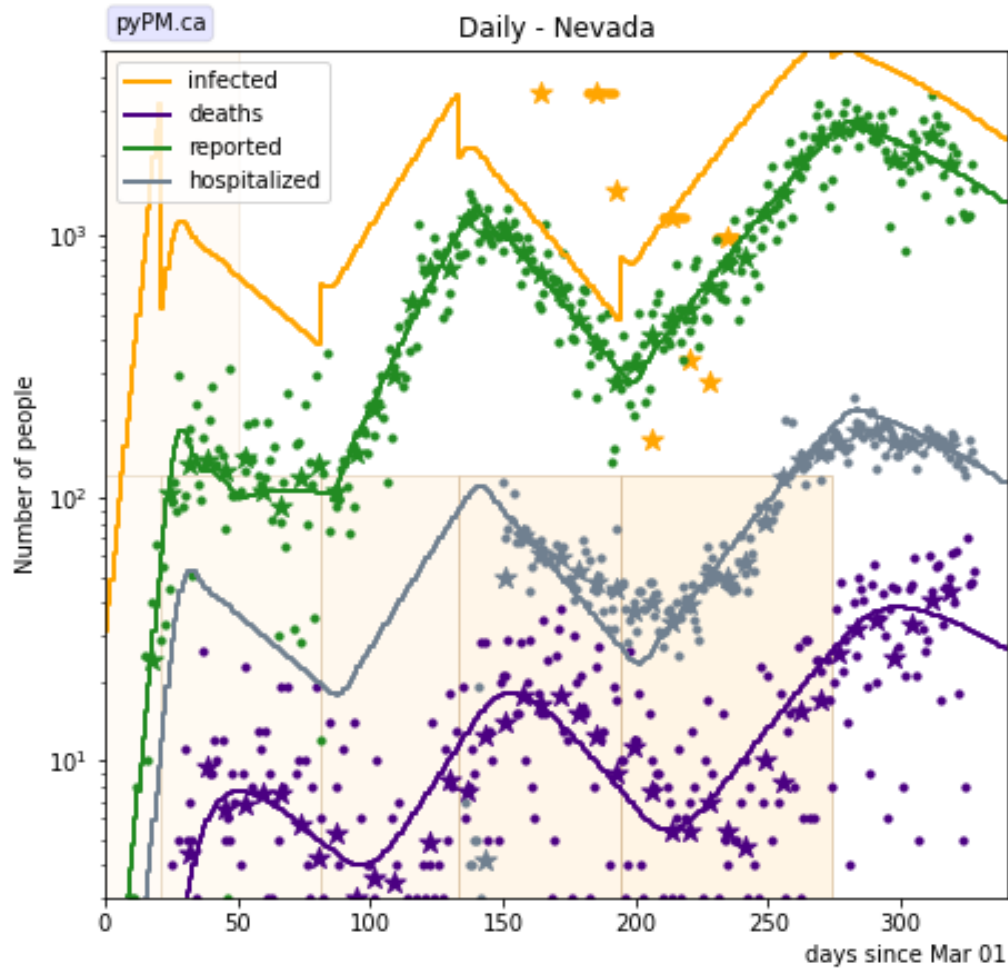
Periods of constant transmission are long

• Mean length almost 2 months (for US states)
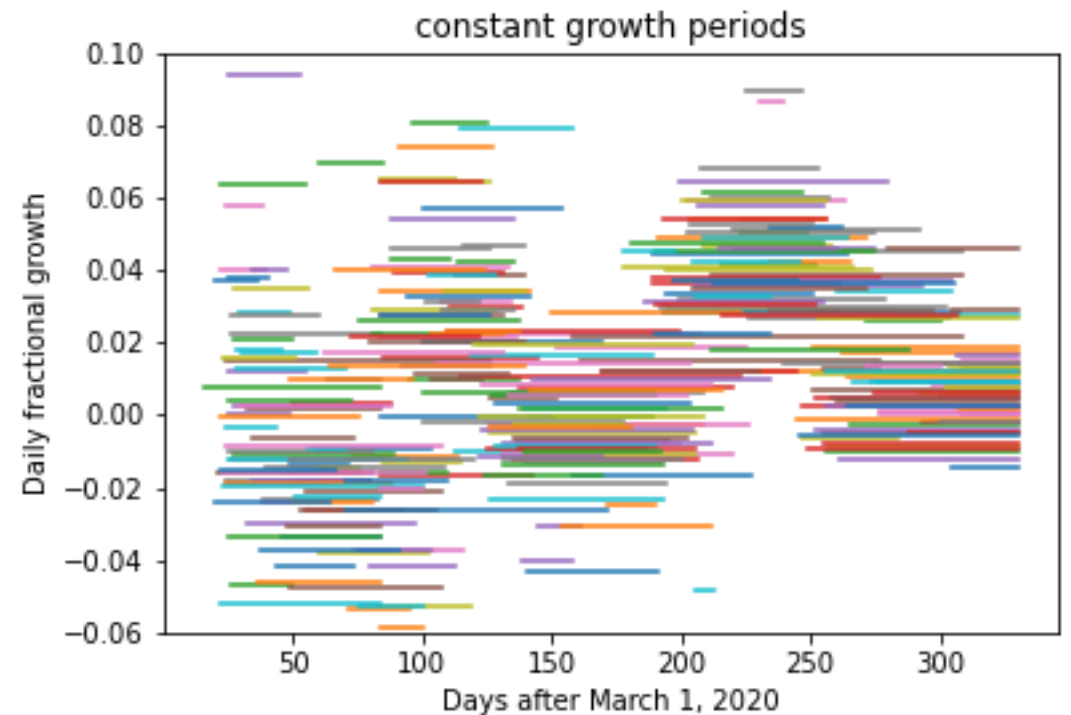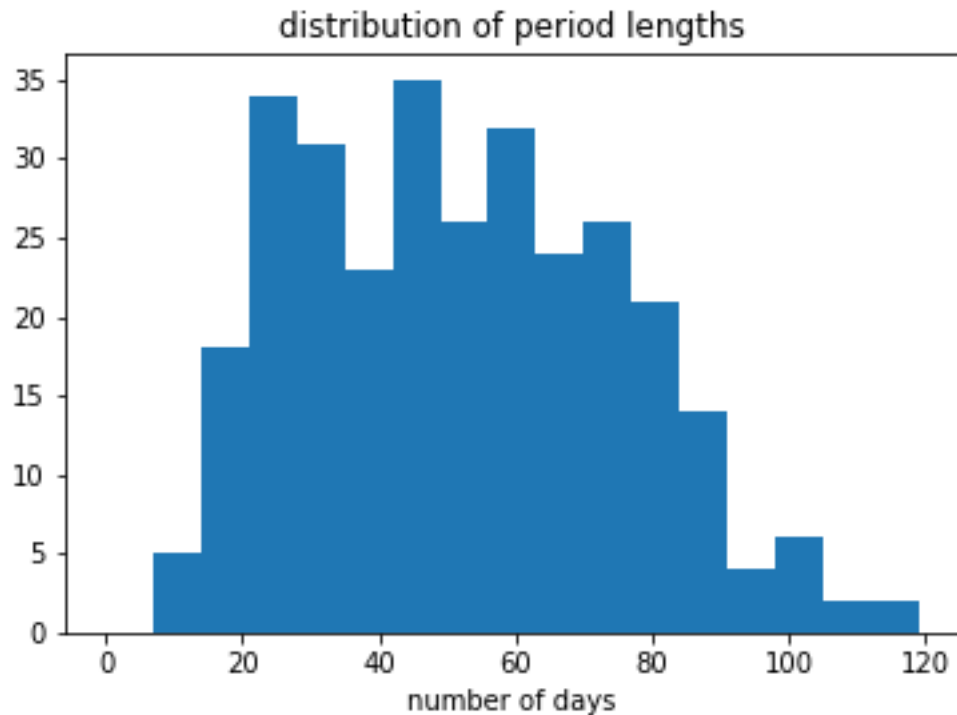
Forecasting the spread of COVID

- In 2020, models had some ability to forecast the future, thanks to long periods of constant transmission rate

- Changes to transmission rate (timing and amount) difficult to predict:
  - difficult to model effectiveness of NPI from first principles
  - difficult to model human behaviour

- Starting in 2021 – models could predict changes in the spread of COVID due to:
  - Variants – solution: add second (and third) infection cycle to model
    - properties of the variants known from genomic sampling
  - Immunity – solution: reduce susceptible fraction according to infections and vaccination
    - vaccination rate and effectiveness reasonably well known

The alpha variant

- Rapid case growth in the UK (shortly after relaxation measures)
- Their PCR test at the time targeted 3 genes to identify SARS-CoV-2
- Saw rapid growth in cases in which one of the genes was not present: S-gene
  - Referred to such cases as SGTF (S-gene target failure)
- A fortuitous indicator to identify the first "Variant of Concern": B.1.1.7 (alpha)

Figure 11. Weekly number and proportion of England Pillar 2 COVID-19 cases with SGTF among those tested with the TaqPath assay and with S gene detection results, by region of residence (1 September 2020 to 9 March 2021)
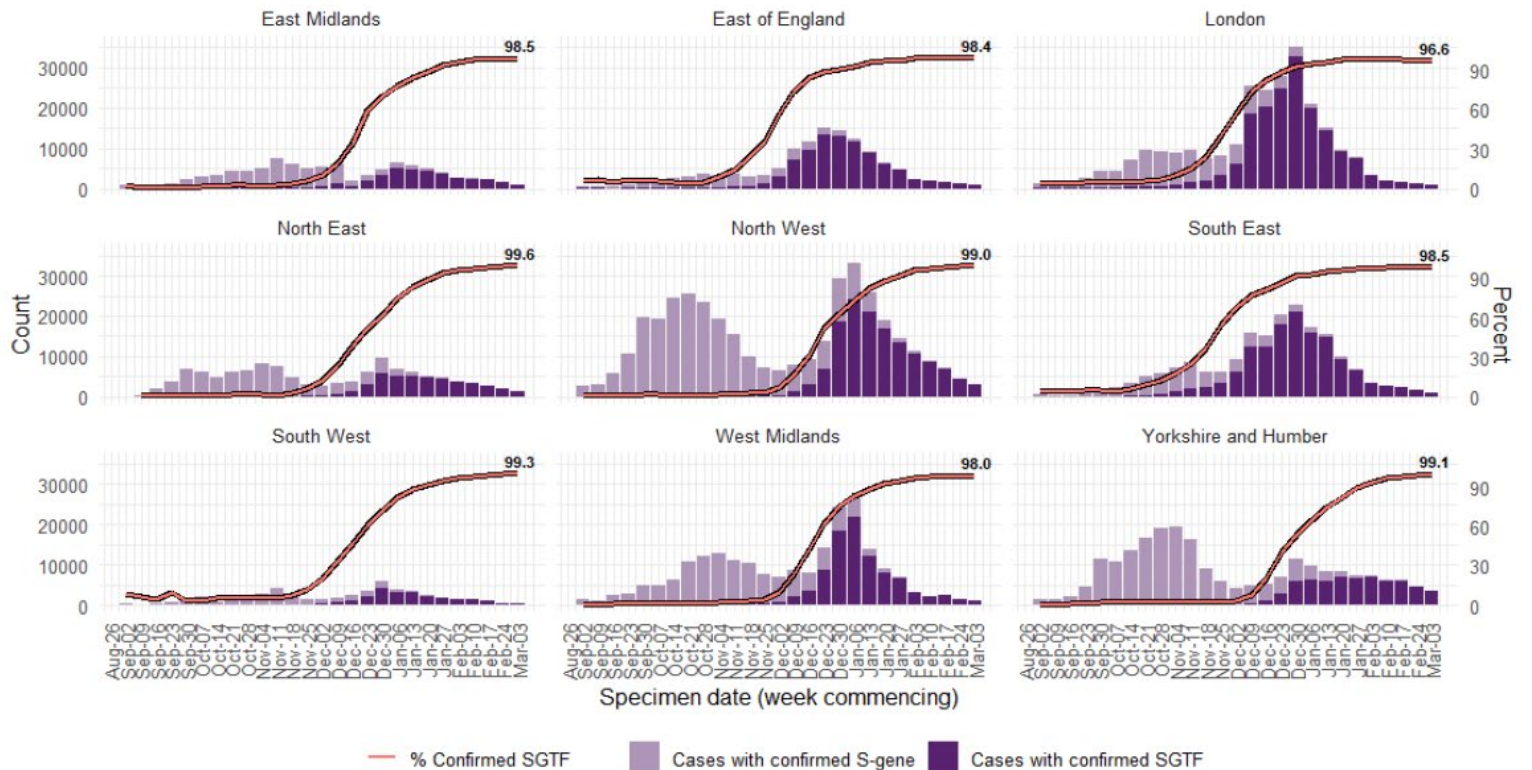
Modeling a rapidly spreading variant

- Consider steady-state exponential growth of two strains: their ratio

$$\frac{N_v(t)}{N_{nv}(t)} = \frac{N_{v0}e^{r_v t}}{N_{nv0}e^{r_{nv} t}} = ae^{[r_v - r_{nv}]t} = ae^{st} = e^{s(t - t_0)}$$

- In population modelling, s is called the "selection coefficient"
- The relation might be a good approximation in more dynamic situations, provided:

$$r_v(t) - r_{nv}(t) = s(t) \cong s$$

UK SGTF/non-SGTF ratio

- day = 0: date when ratio = 1 (crossover day)
- s1: selection coefficient prior to crossing
- s2: selection coefficient after crossing
- w: SGTF false identification for B.1.1.7

region	s1	s2	w
East Midlands	0.141 +/- 0.003	0.067 +/- 0.001	0.019 +/- 0.001
East of England	0.147 +/- 0.004	0.068 +/- 0.000	0.051 +/- 0.002
London	0.127 +/- 0.002	0.074 +/- 0.000	0.051 +/- 0.001
North East	0.112 +/- 0.002	0.070 +/- 0.001	0.013 +/- 0.001
North West	0.137 +/- 0.002	0.068 +/- 0.000	0.014 +/- 0.000
South East	0.108 +/- 0.002	0.058 +/- 0.000	0.055 +/- 0.003
South West	0.111 +/- 0.004	0.070 +/- 0.001	0.050 +/- 0.002
West Midlands	0.148 +/- 0.002	0.077 +/- 0.001	0.017 +/- 0.001
Yorkshire and Humber	0.140 +/- 0.002	0.064 +/- 0.001	0.020 +/- 0.000
England	0.122 +/- 0.000	0.054 +/- 0.000	0.024 +/- 0.000
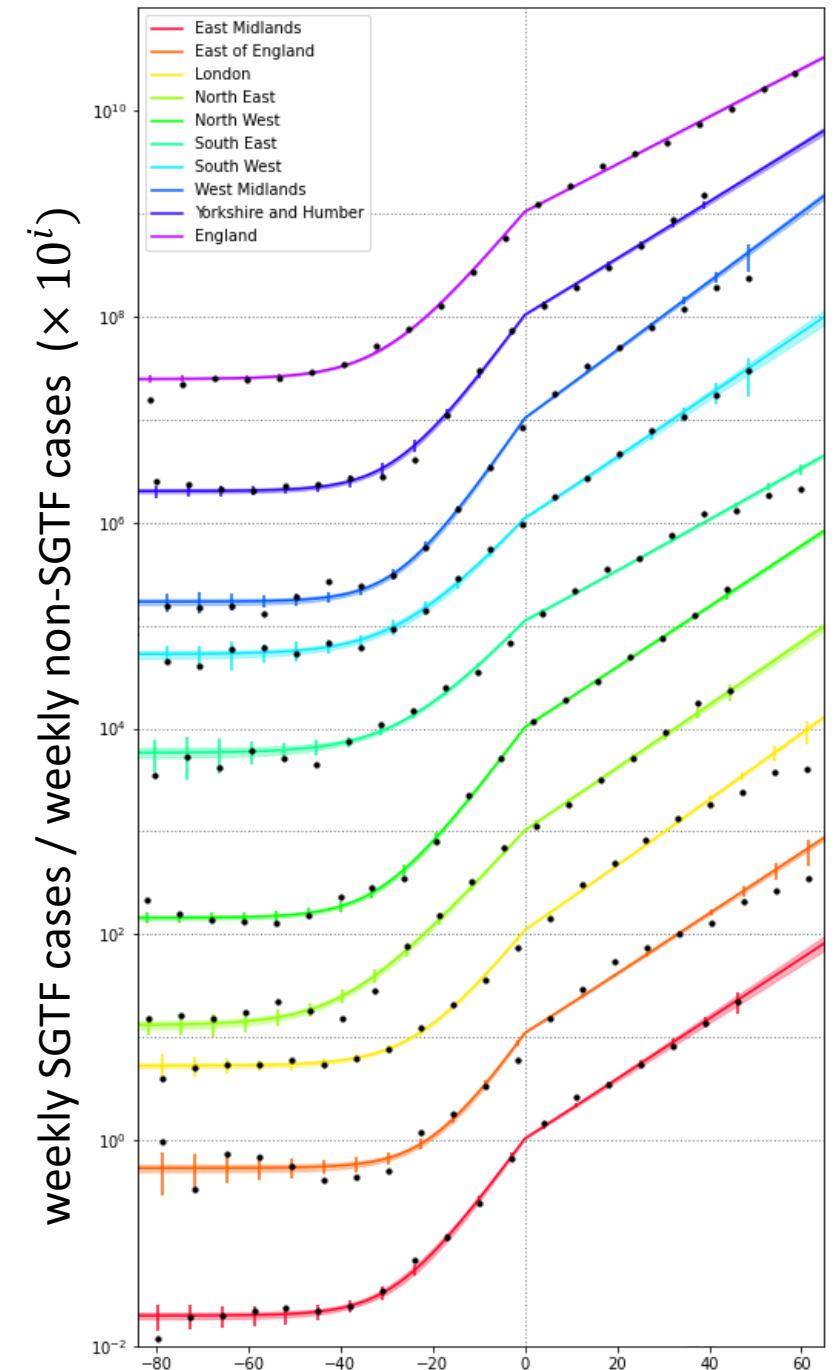
Alpha in USA (mid-March)

- Sufficient data available from 8 states
  - f_v: fraction of cases from variant on Mar 13
  - growth advantage remains, despite vaccination immunity

region	s	w	f_v (Mar 13)
California	0.070 ± 0.004	0.002 ± 0.012	0.381 ± 0.007
Florida	0.069 ± 0.001	0.008 ± 0.001	0.614 ± 0.007
Georgia	0.093 ± 0.002	0.004 ± 0.001	0.578 ± 0.011
Indiana	0.083 ± 0.010	0.000 ± 0.000	0.288 ± 0.044
Michigan	0.080 ± 0.010	0.000 ± 0.000	0.573 ± 0.045
North Carolina	0.092 ± 0.004	0.001 ± 0.003	0.313 ± 0.008
Pennsylvania	0.085 ± 0.002	0.003 ± 0.001	0.366 ± 0.004
Texas	0.087 ± 0.004	0.000 ± 0.000	0.572 ± 0.028

https://www.helix.com/pages/helix-covid-19-surveillance-dashboard
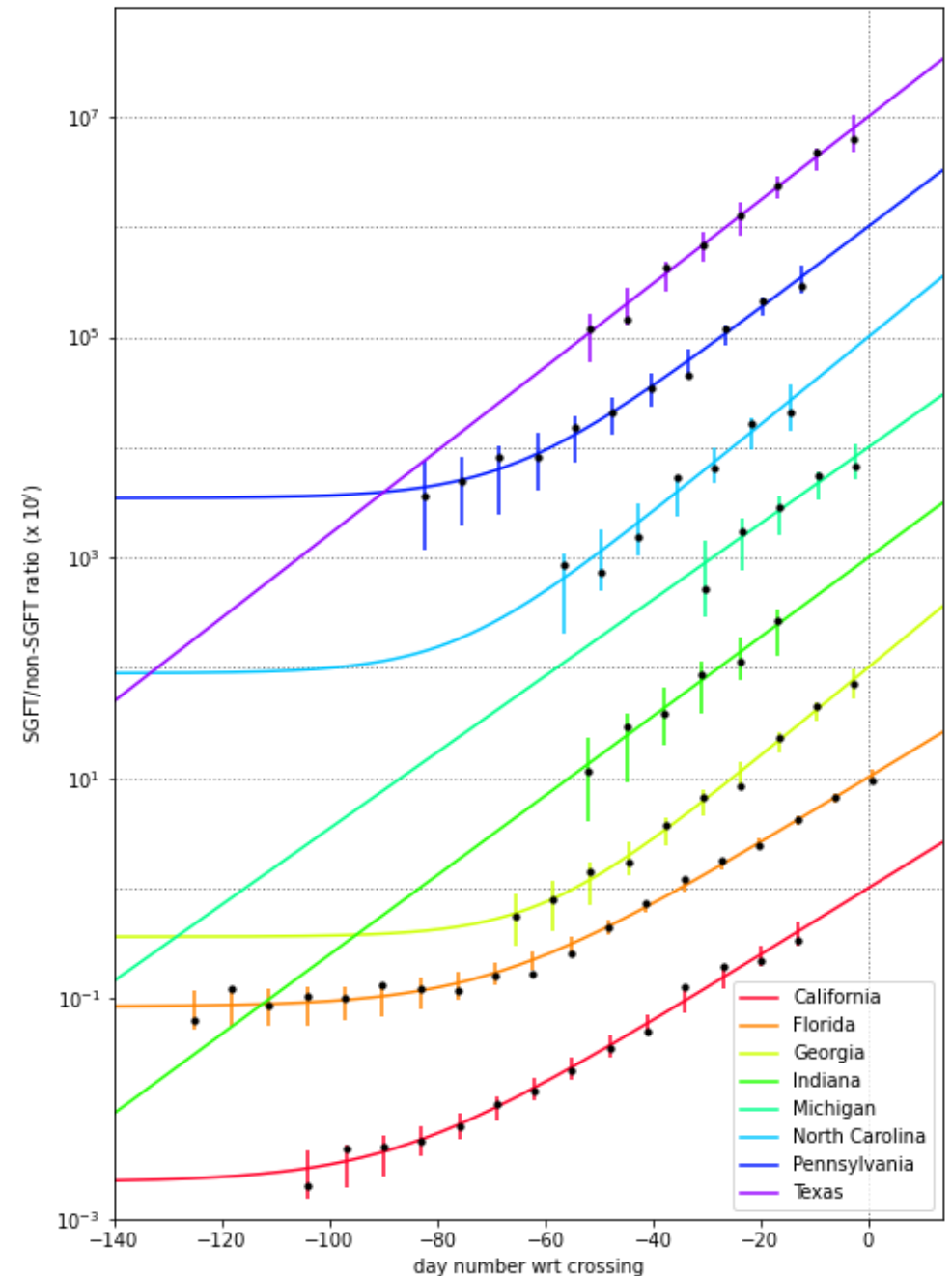
Florida

Data fit with B.1.1.7   Data fit without B.1.1.7: change in NPI
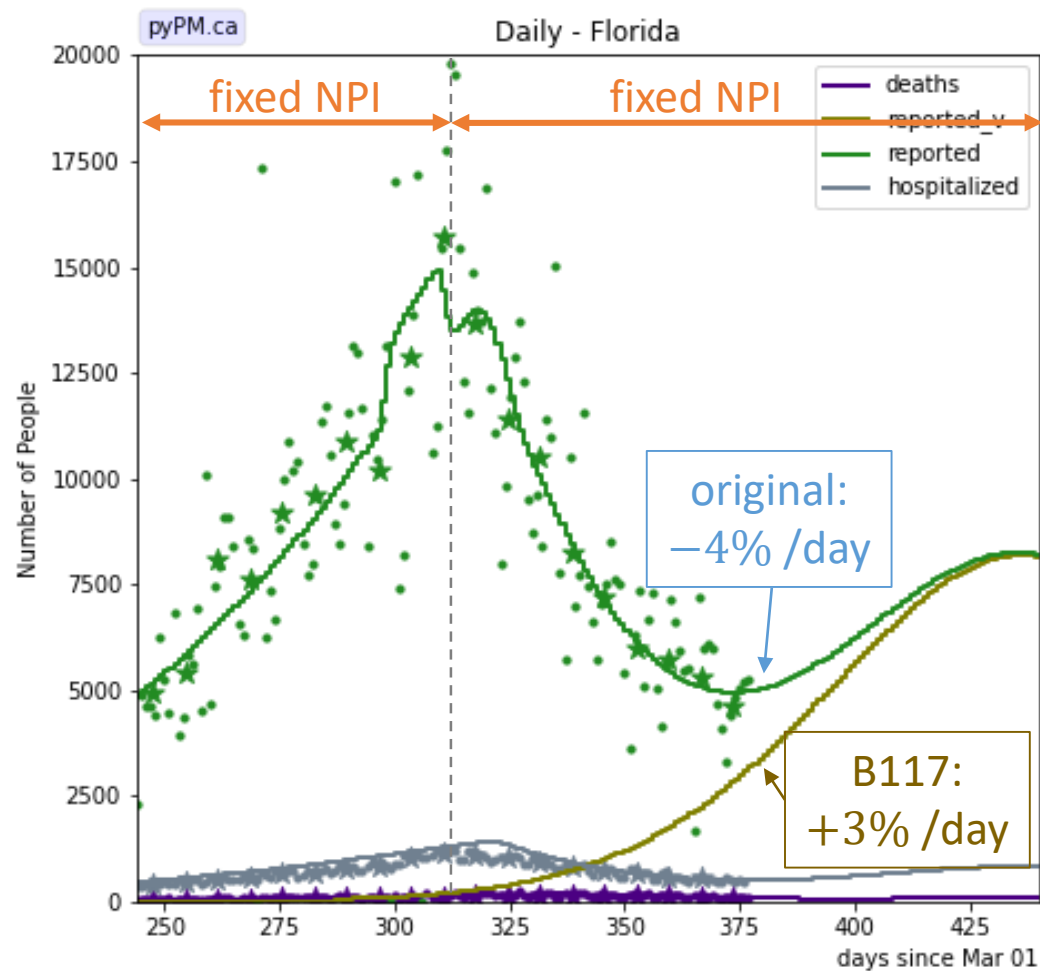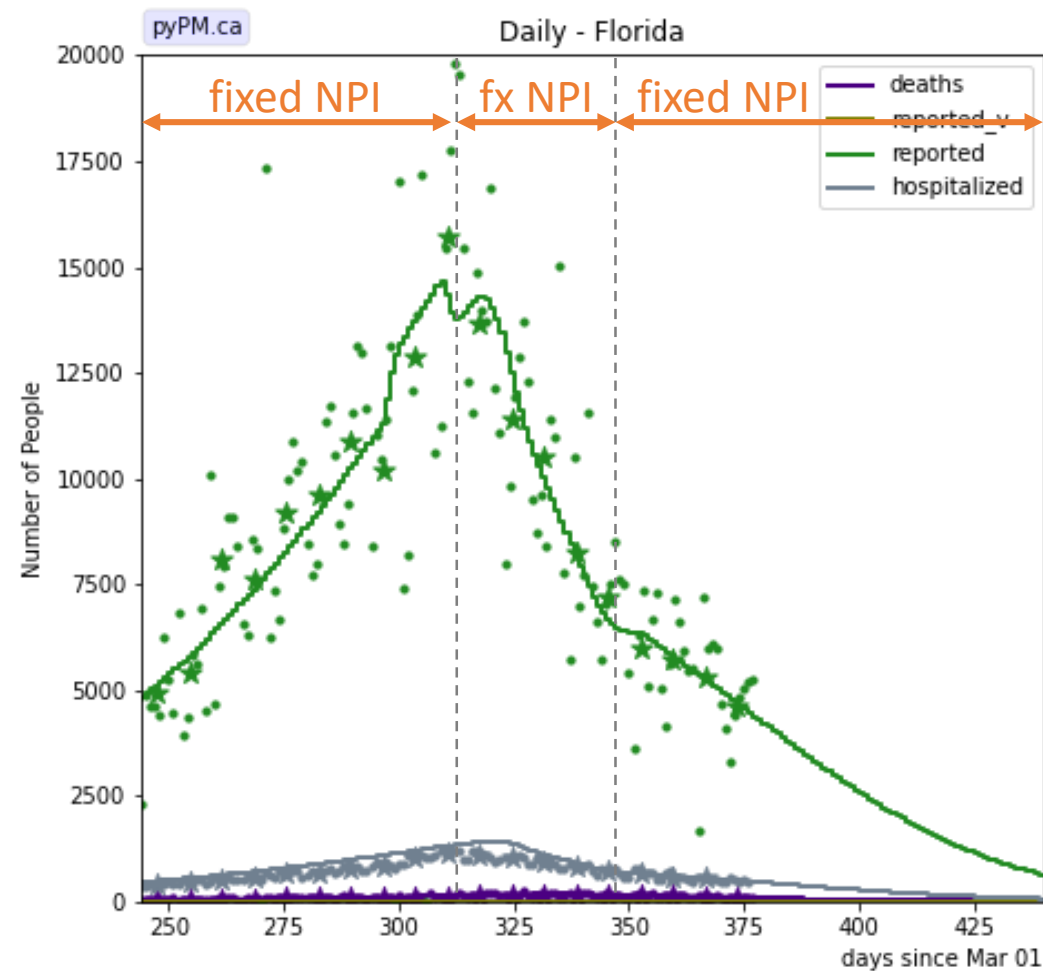
Michigan

Data fit with B.1.1.7

Data fit without B.1.1.7: only change in NPI

Left chart labels:
- fixed NPI
- fixed NPI
- fixed NPI
- original: 0% /day
- B117: +8% /day
- Sept 1

Right chart labels:
- fixed NPI
- fixed NPI
- fixed NPI
- Apparent growth: +4% /day
- Sept 1

Florida

Models had some ability to predict a change in the spread of COVID-19
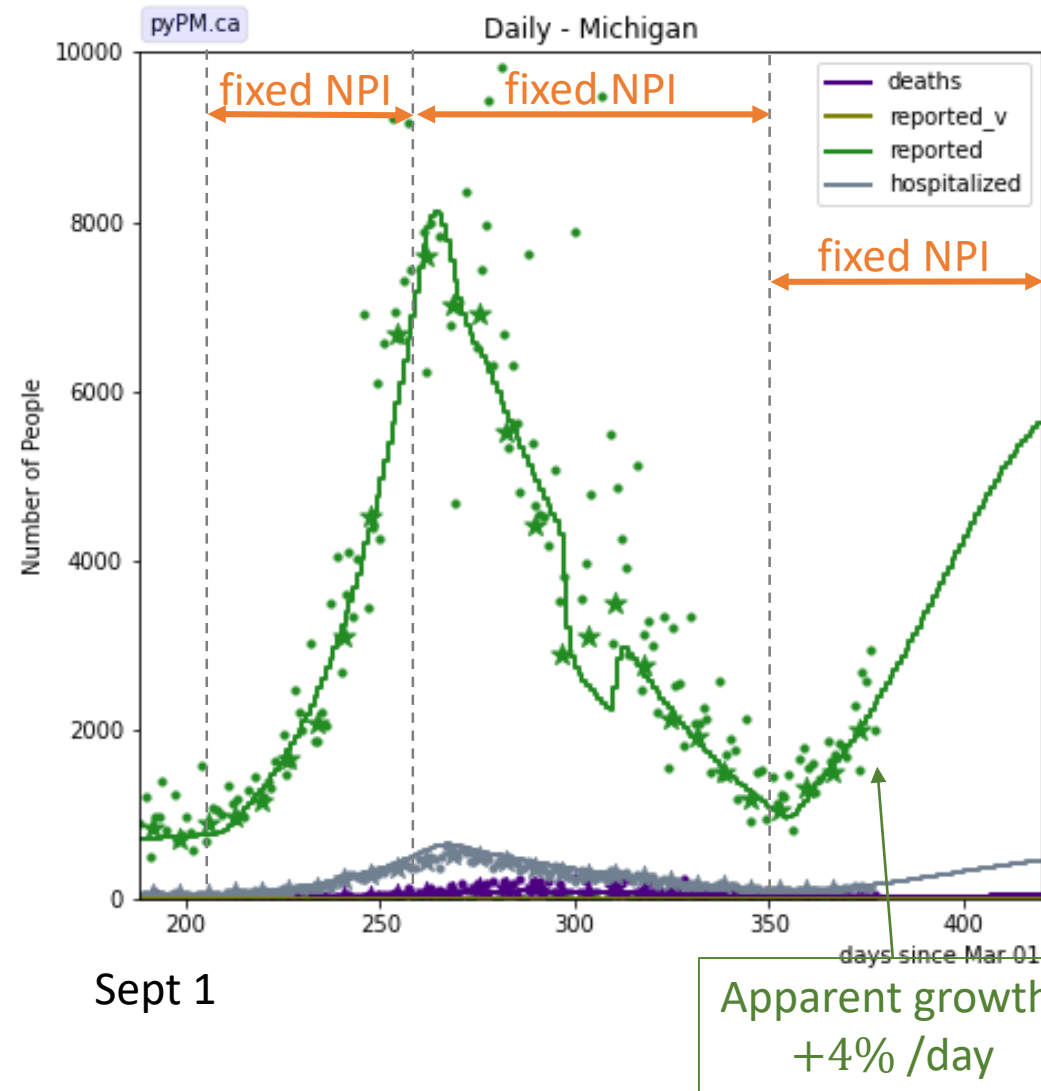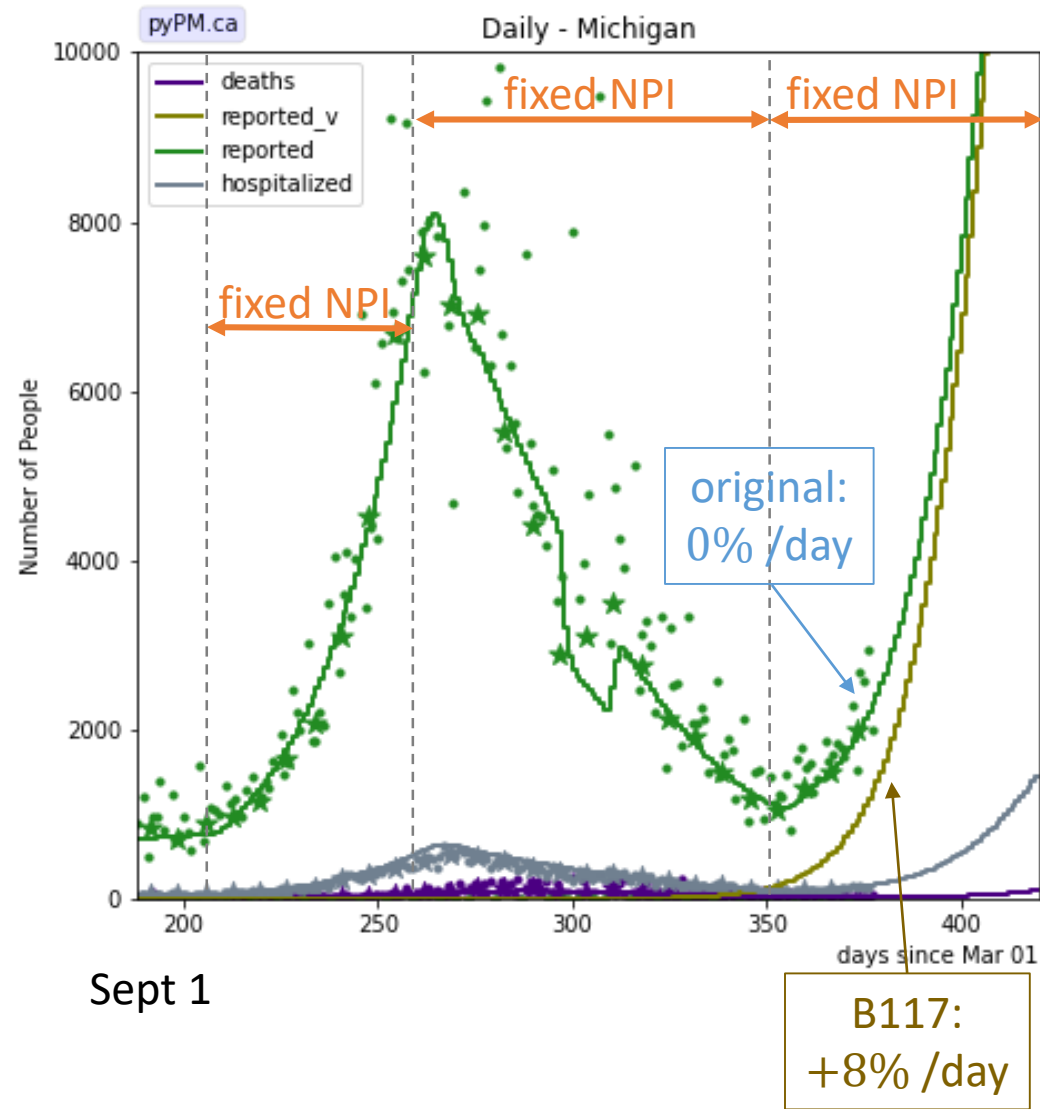
Michigan

curve: March 16 fit
red points: 4 weeks
data following
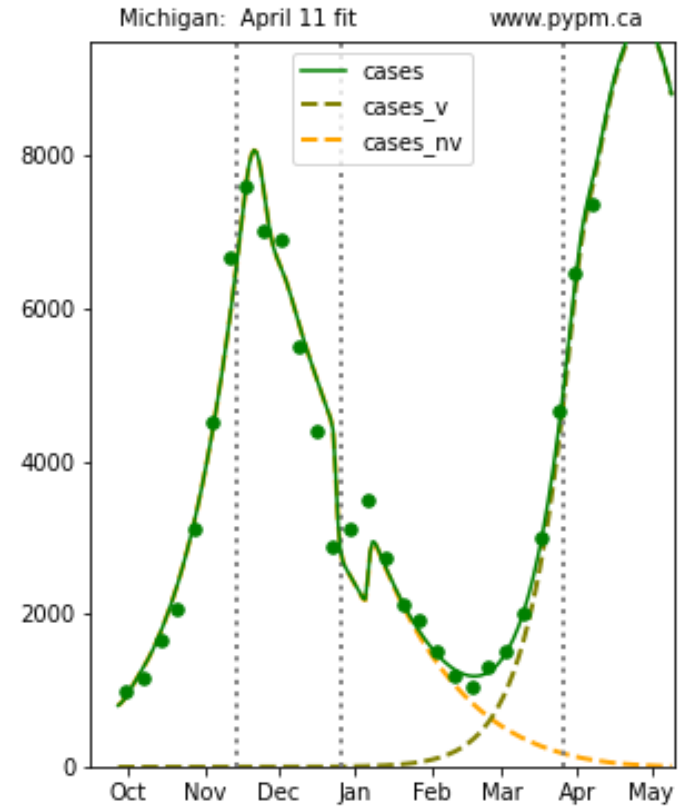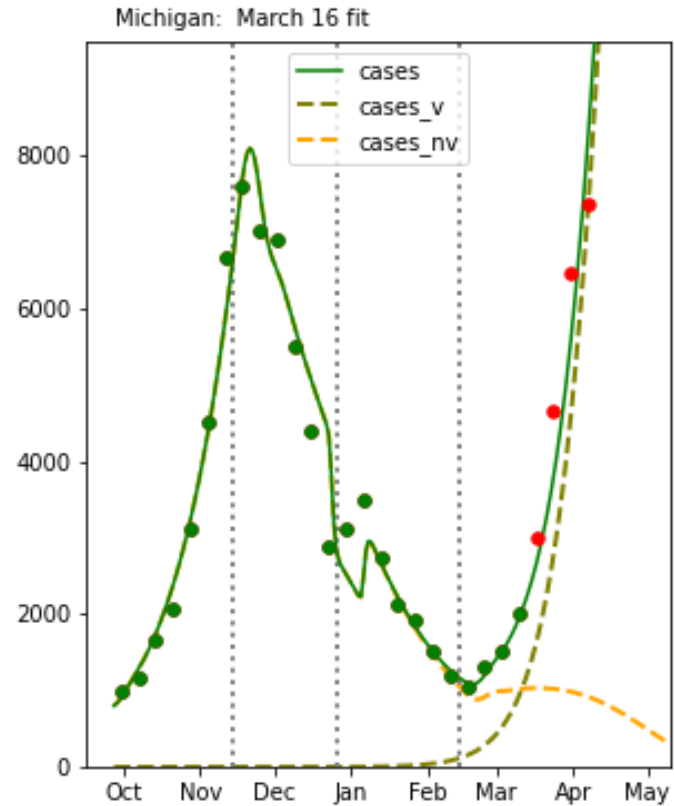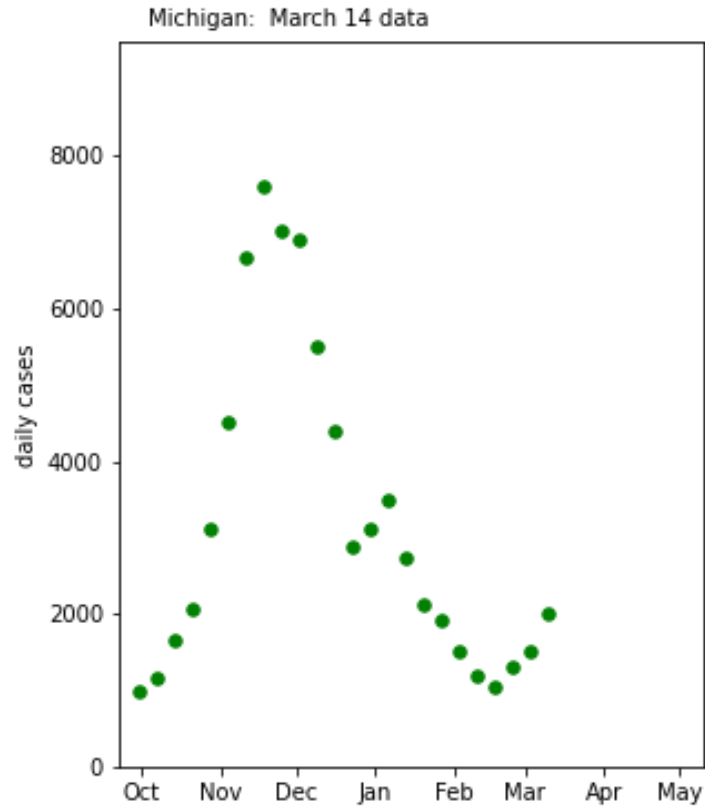
Immunity

- Natural immunity:
  - In early 2020 the fraction of infections that were reported not well known
  - In US – seroprevalence data was very useful to estimate that fraction

- Vaccination immunity:
  - Israel provided the earliest population-level data to benchmark vaccination immunity models

California
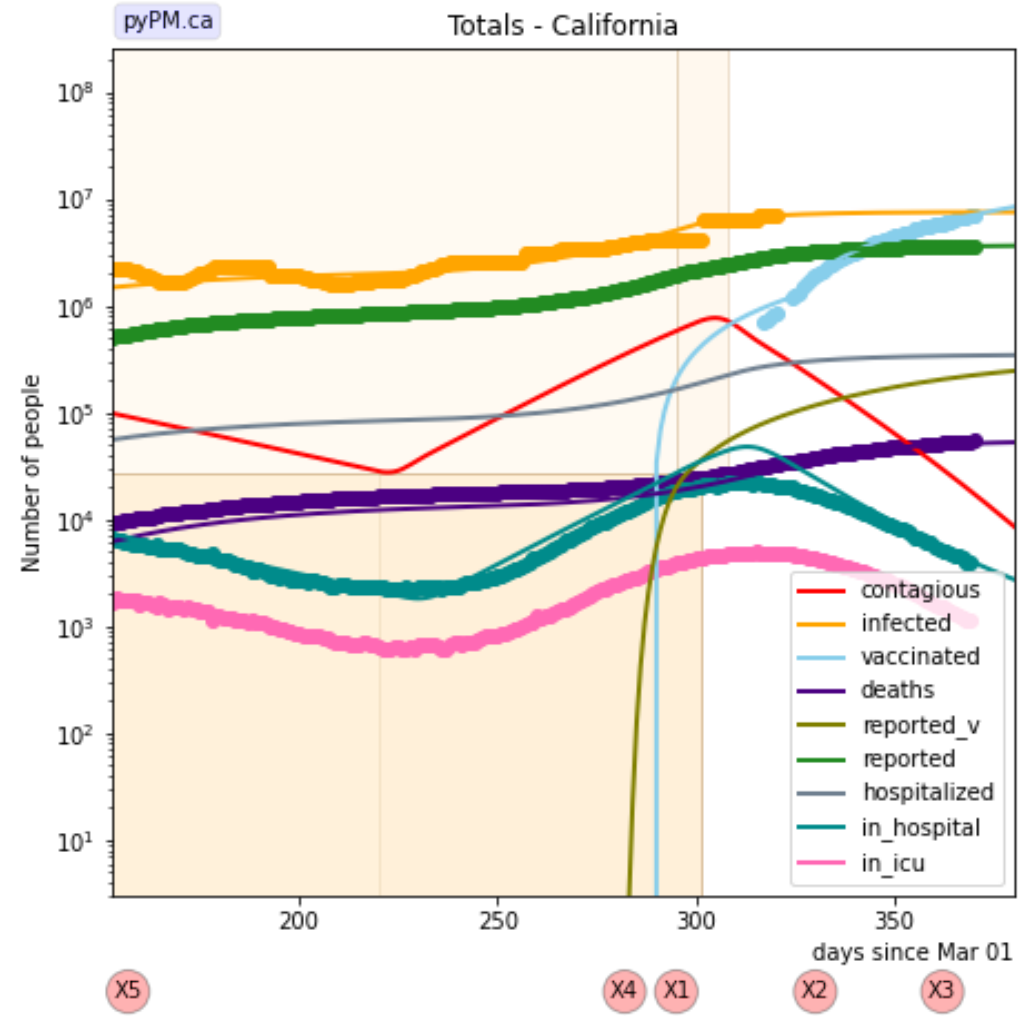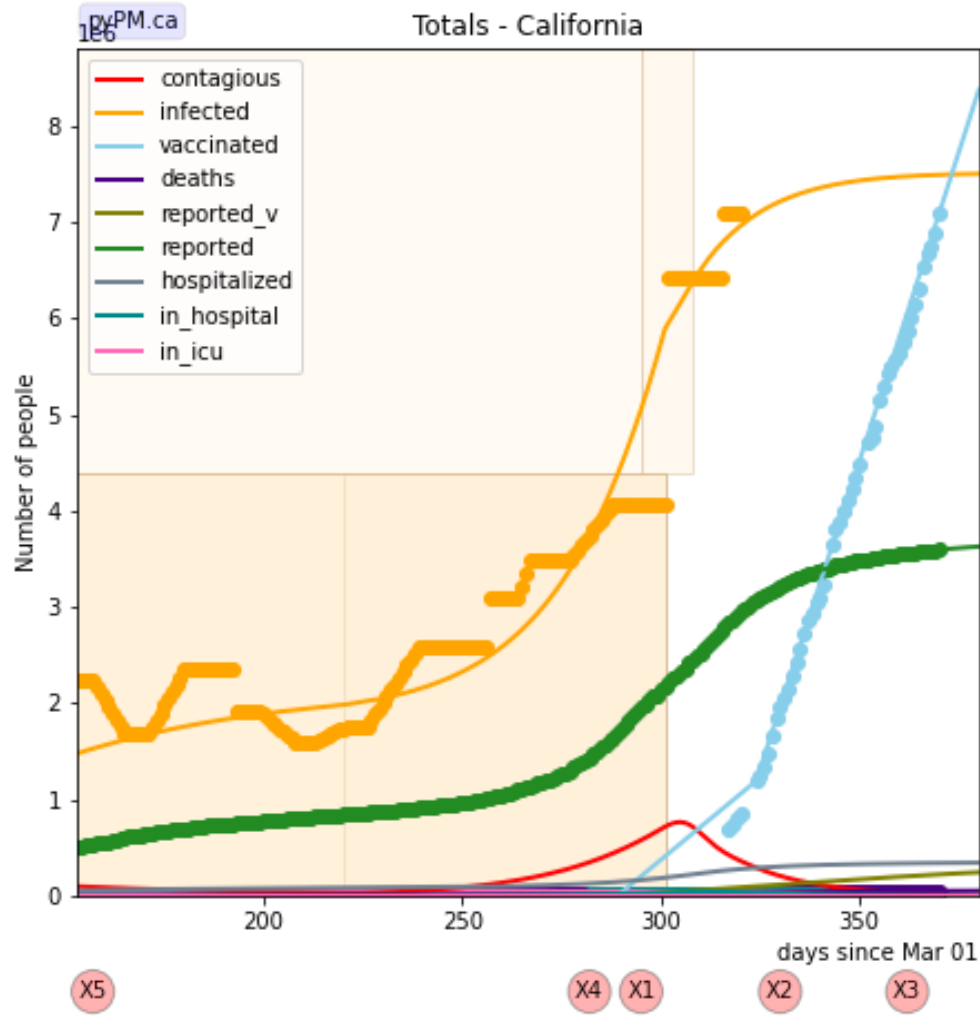
The Vaccination Model

60-69

Daily - 60s

constant NPI

Aug 1

Daily - 60s

Aug 1
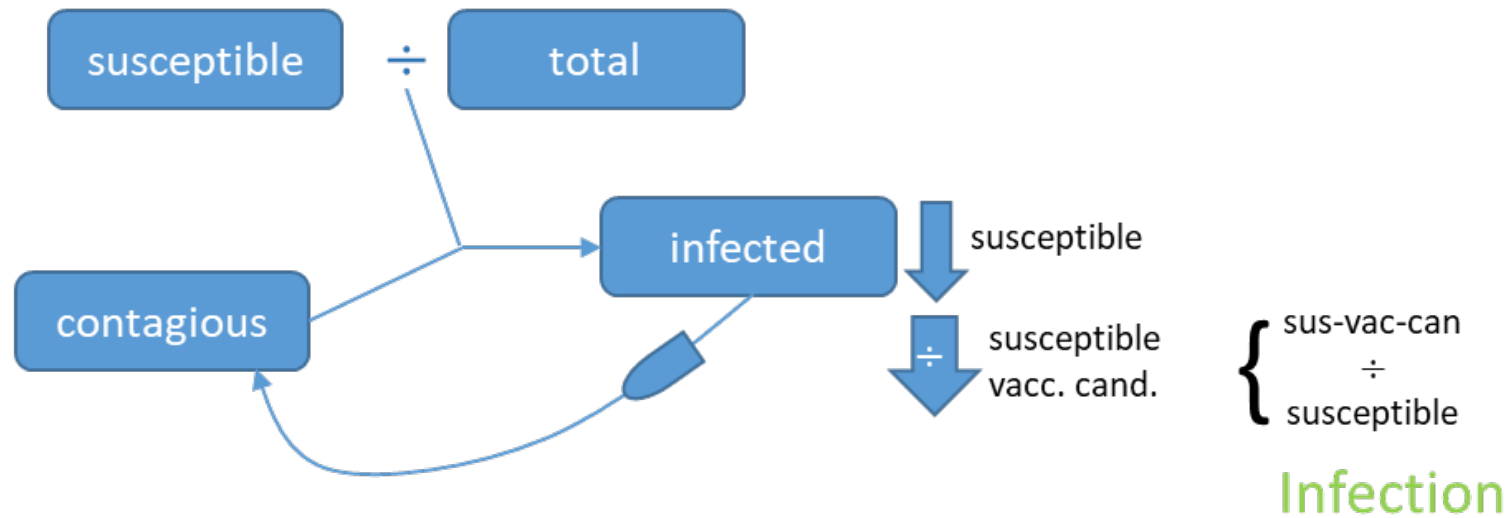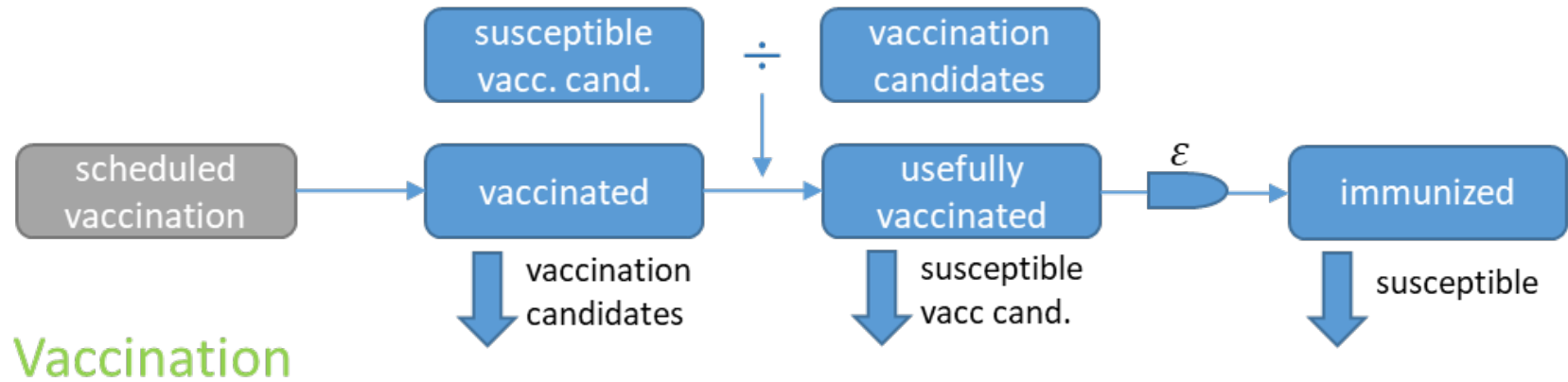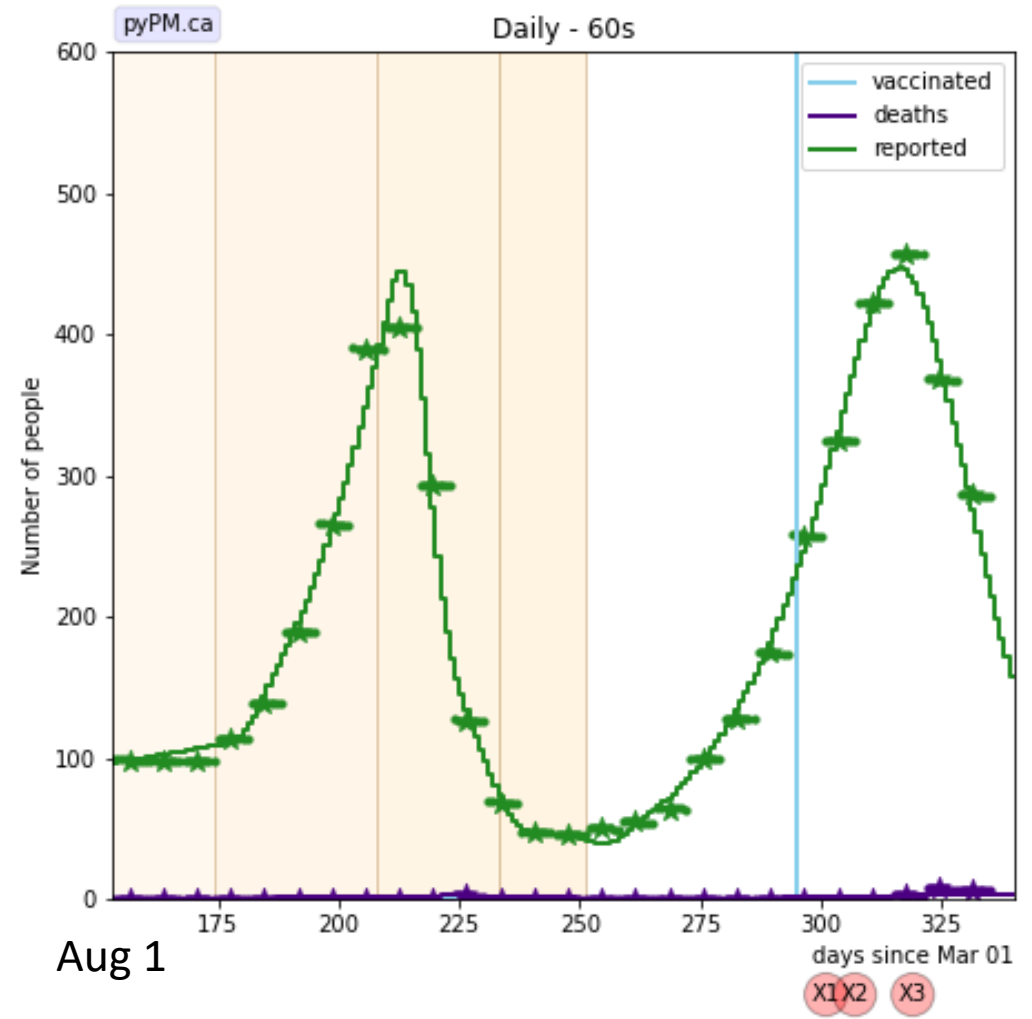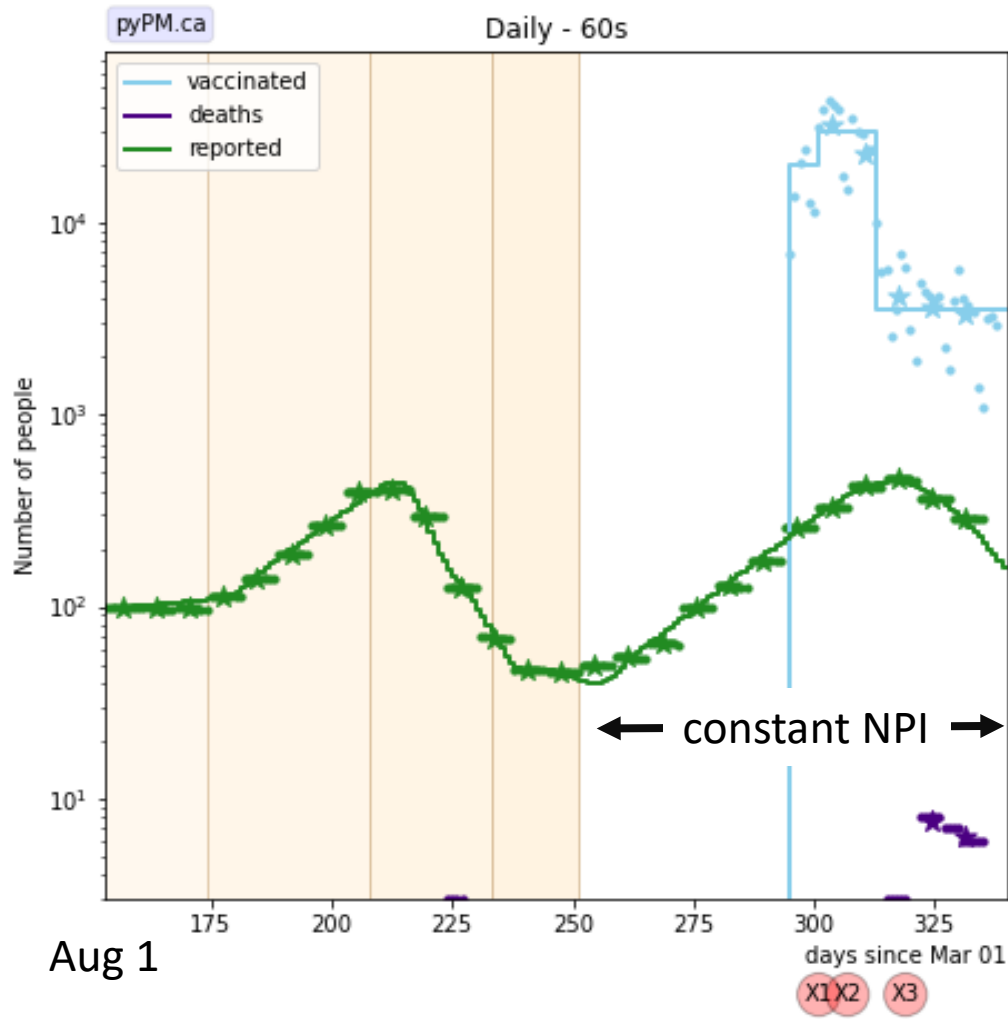
Declining growth rate with increasing immunity

- Currently in the US, the most important factor that determines growth rate is the susceptible fraction
  - wide immunity distribution
  - variation in transmission rates produces less variation in growth

- Transmission rates lower in Canada and Germany than in US
  - immunity distribution narrower
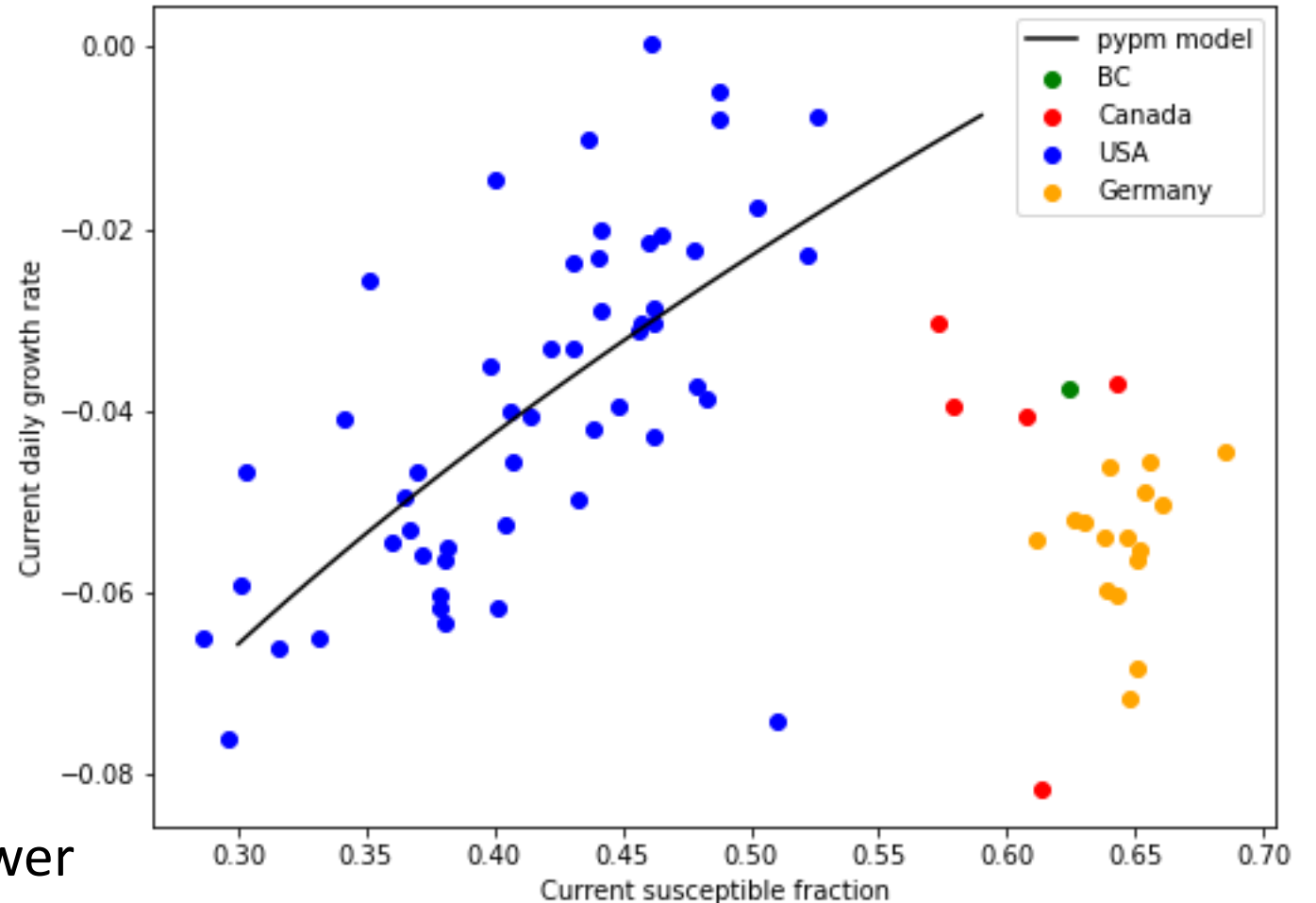
Declining growth rate with increasing immunity

- Animation: from Jan 15 – now
  - post Xmas decline, variant growth, variant turnaround, decline from immunity

Past 30 days
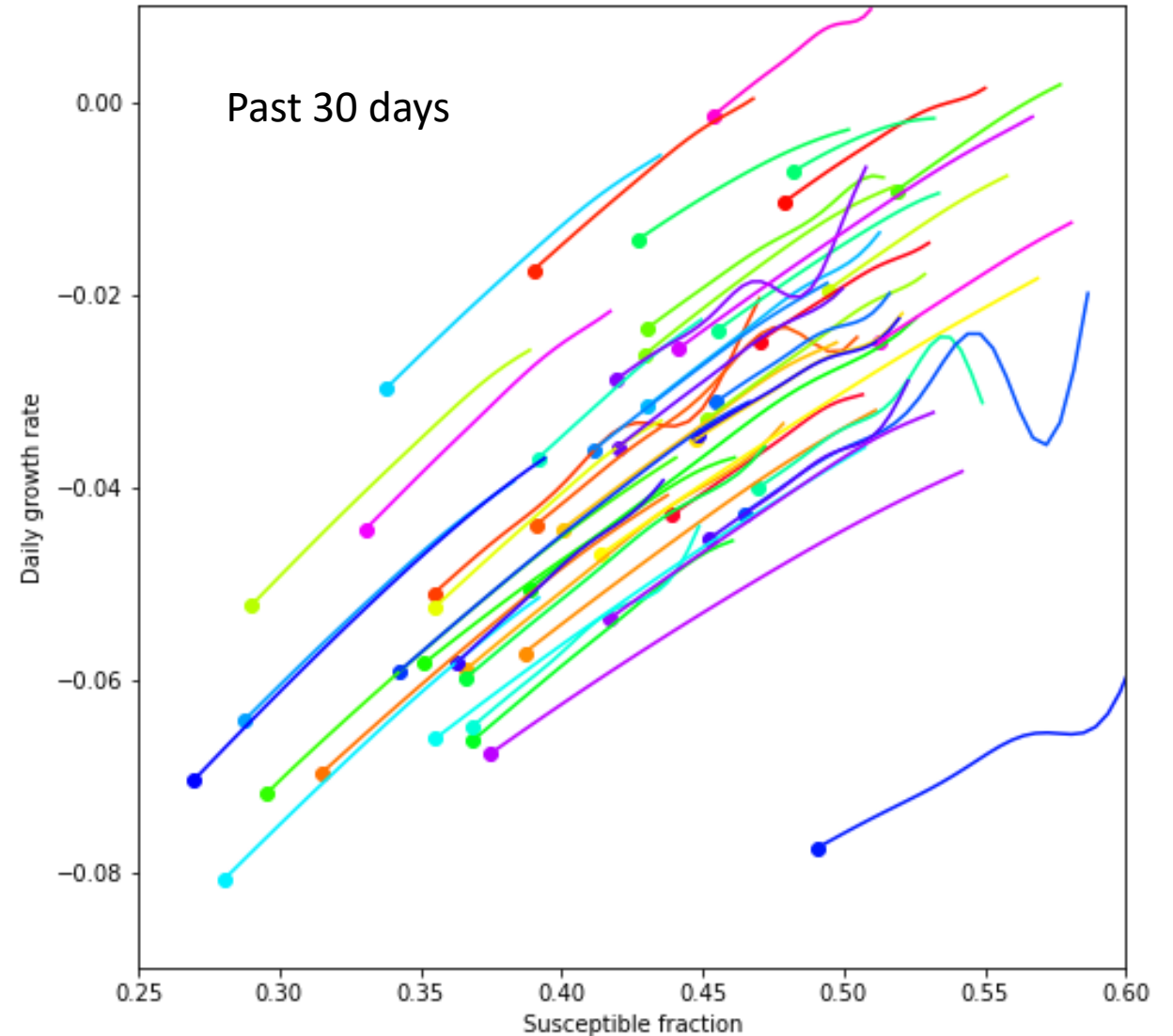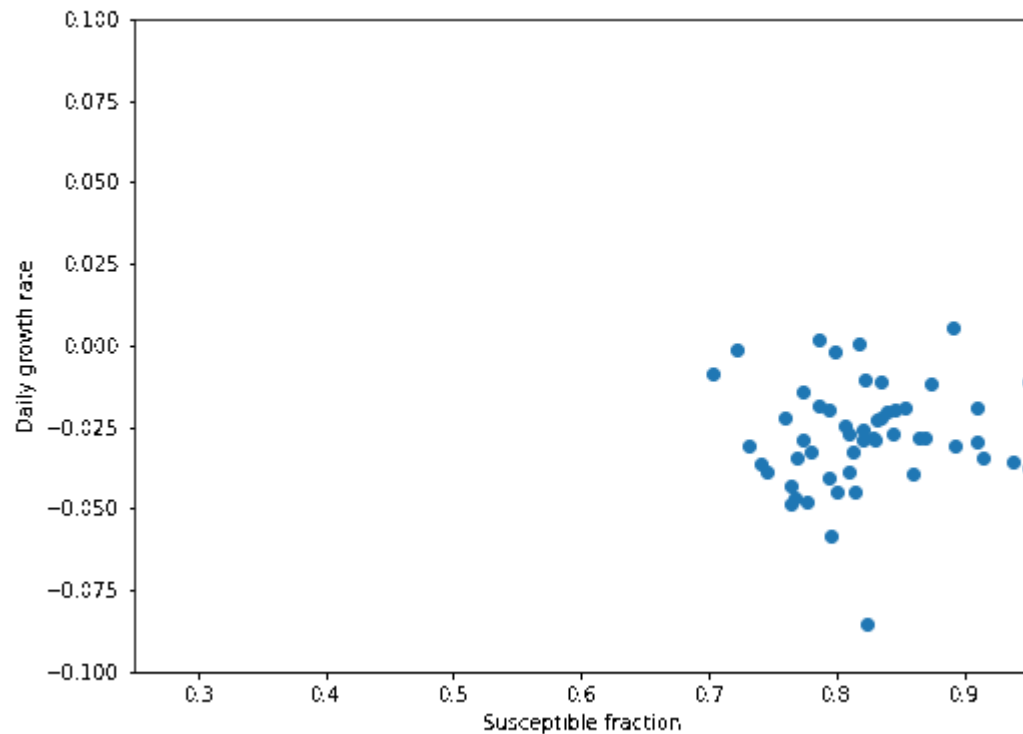
Delta in the USA
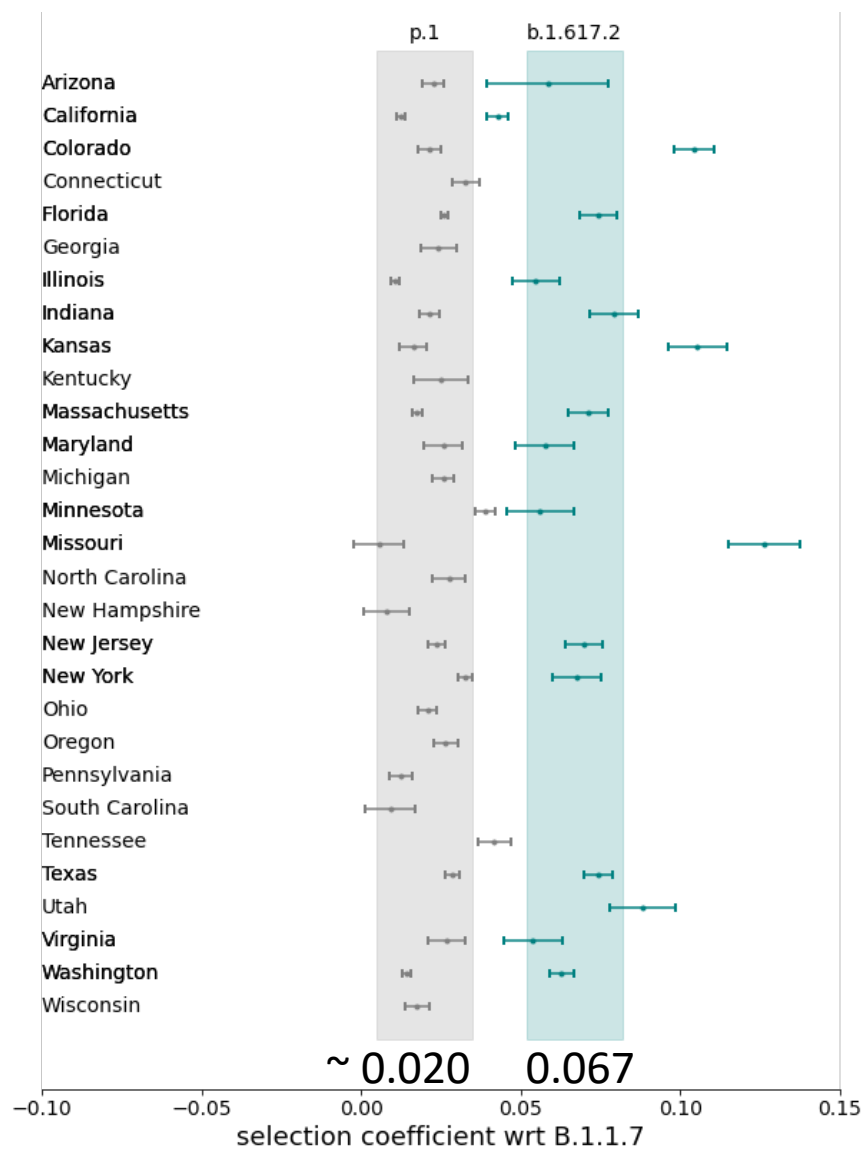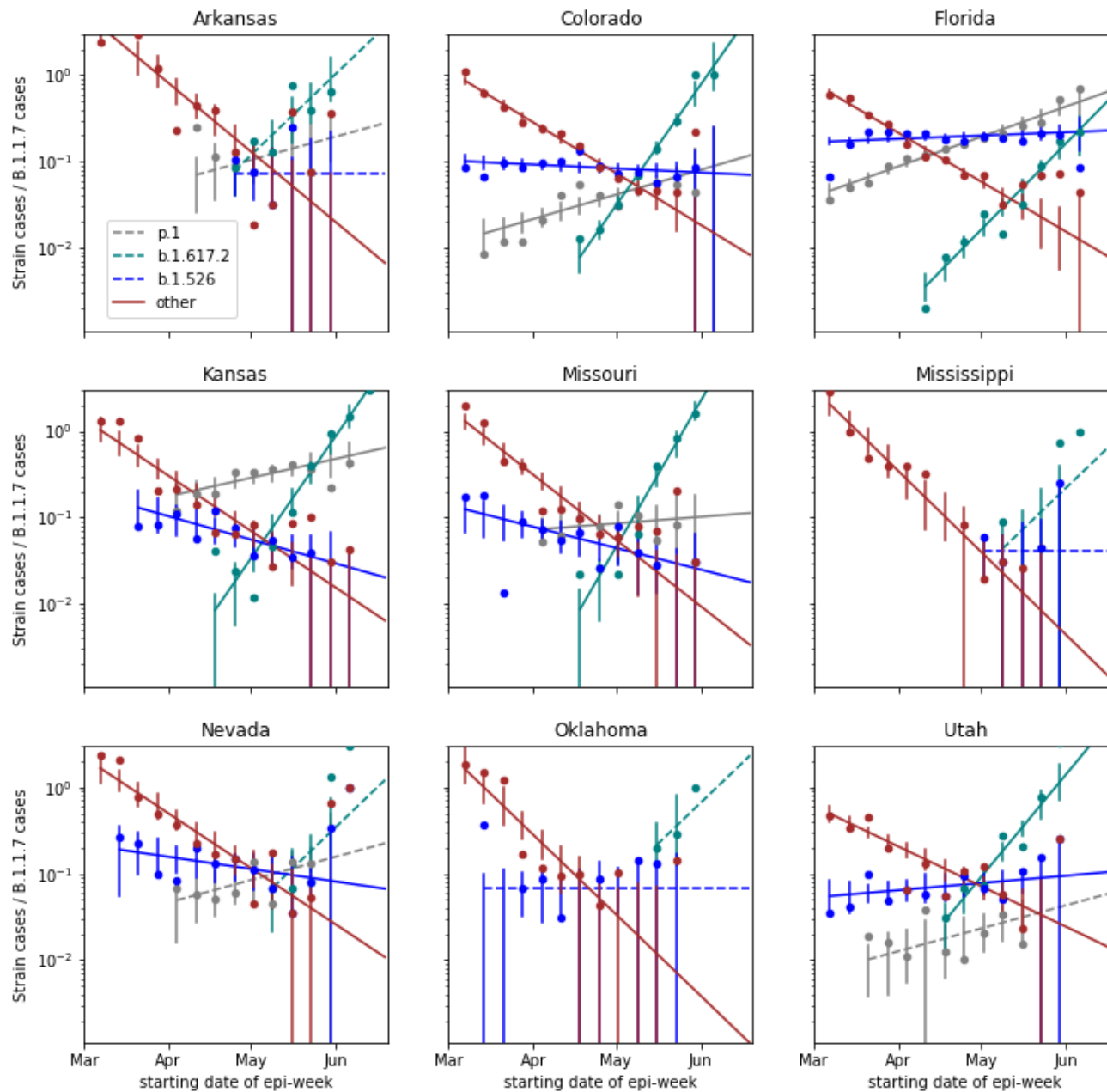
D. Karlen / UVic and TRIUMF   dashed: insufficient data to estimate s
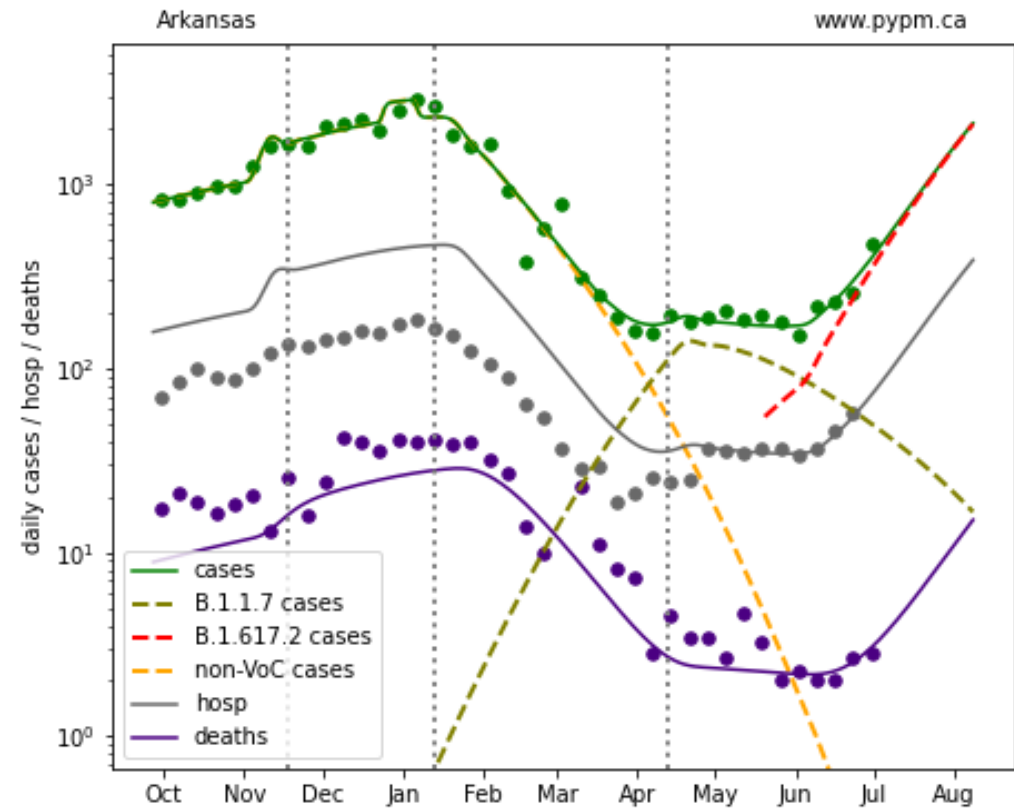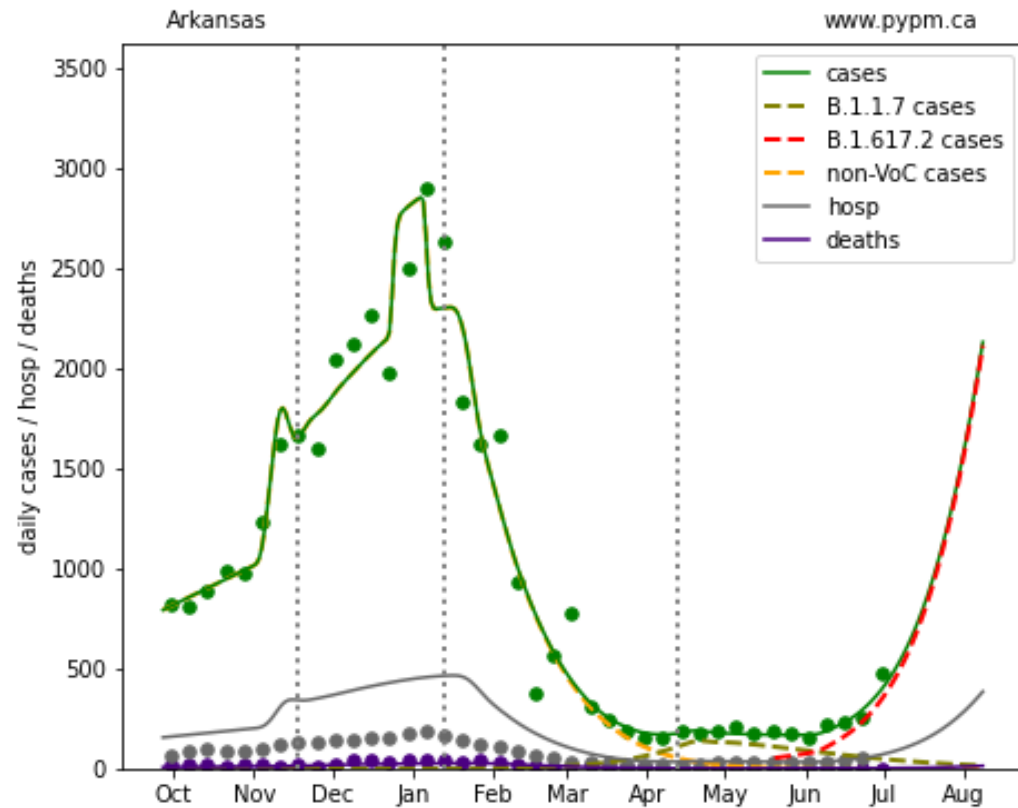
Missouri (June 20 fit)
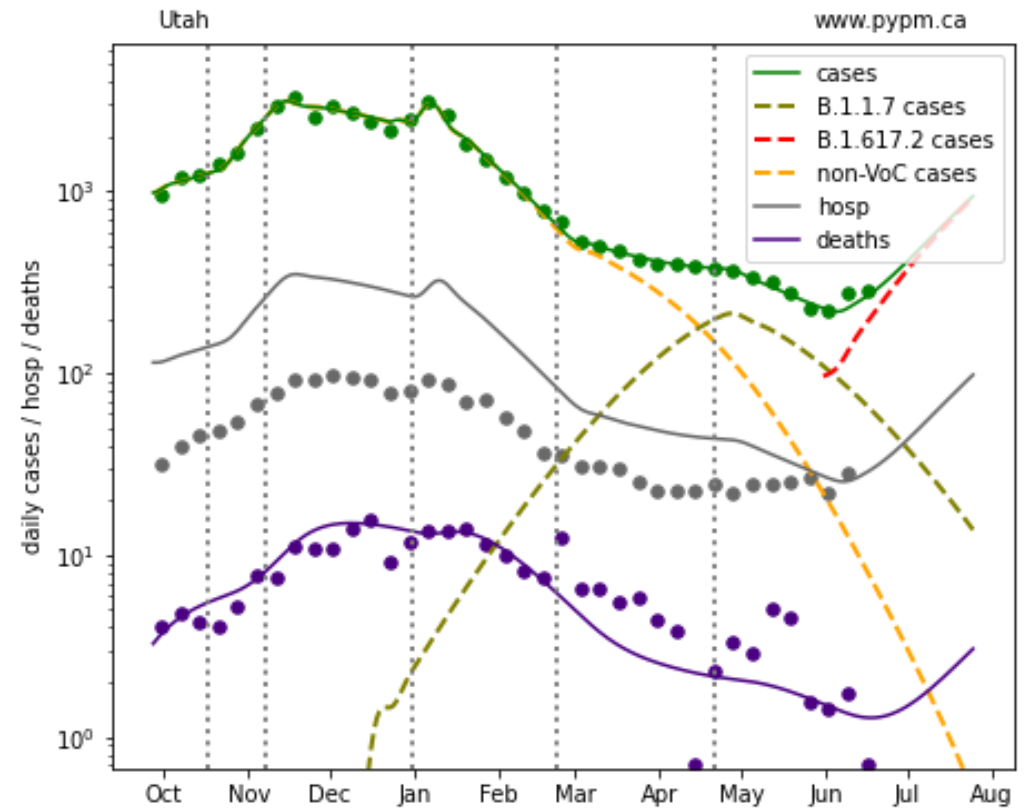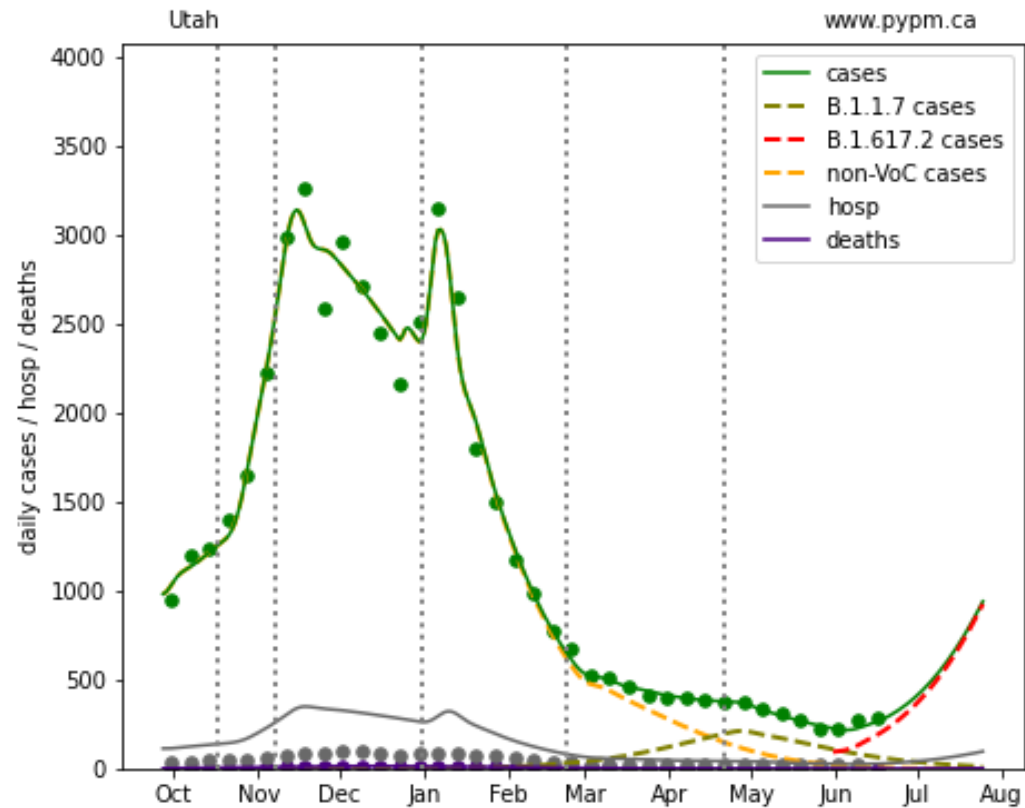
Fit assumes constant NPI since April 1
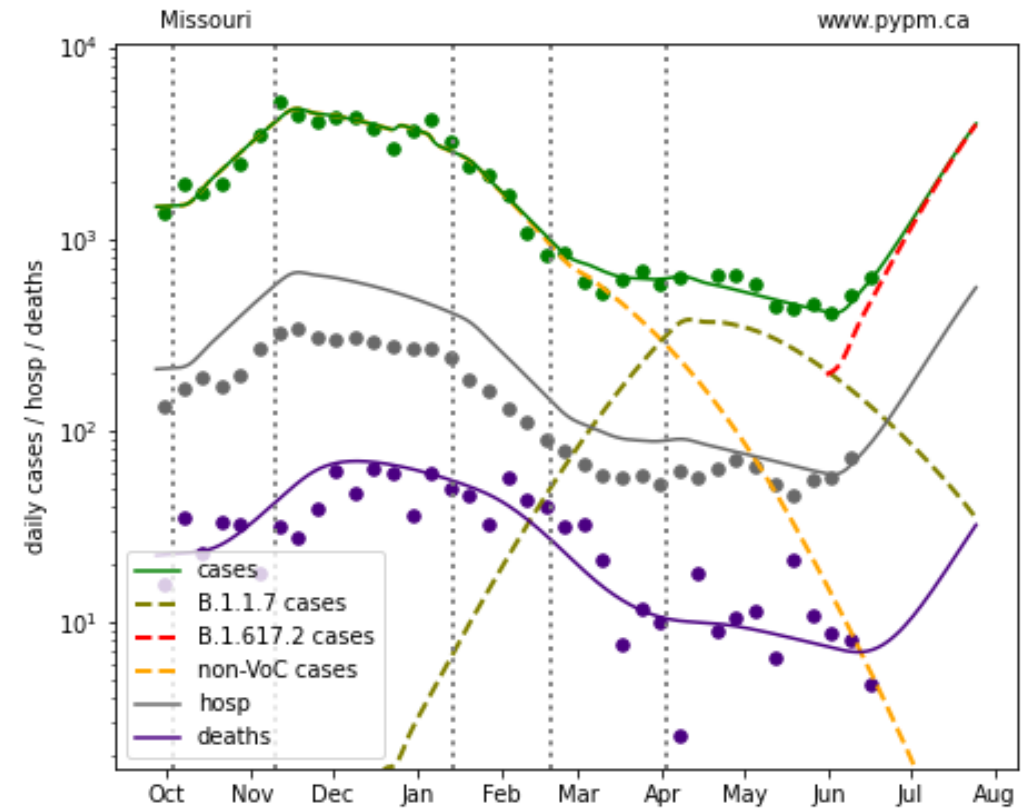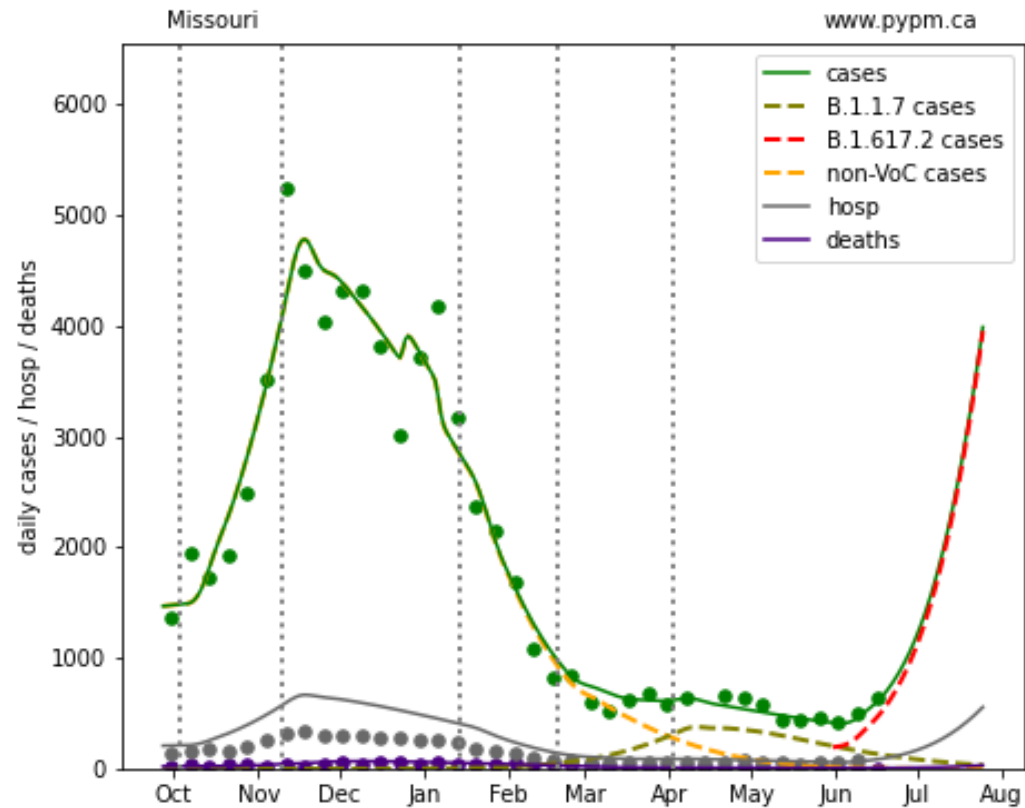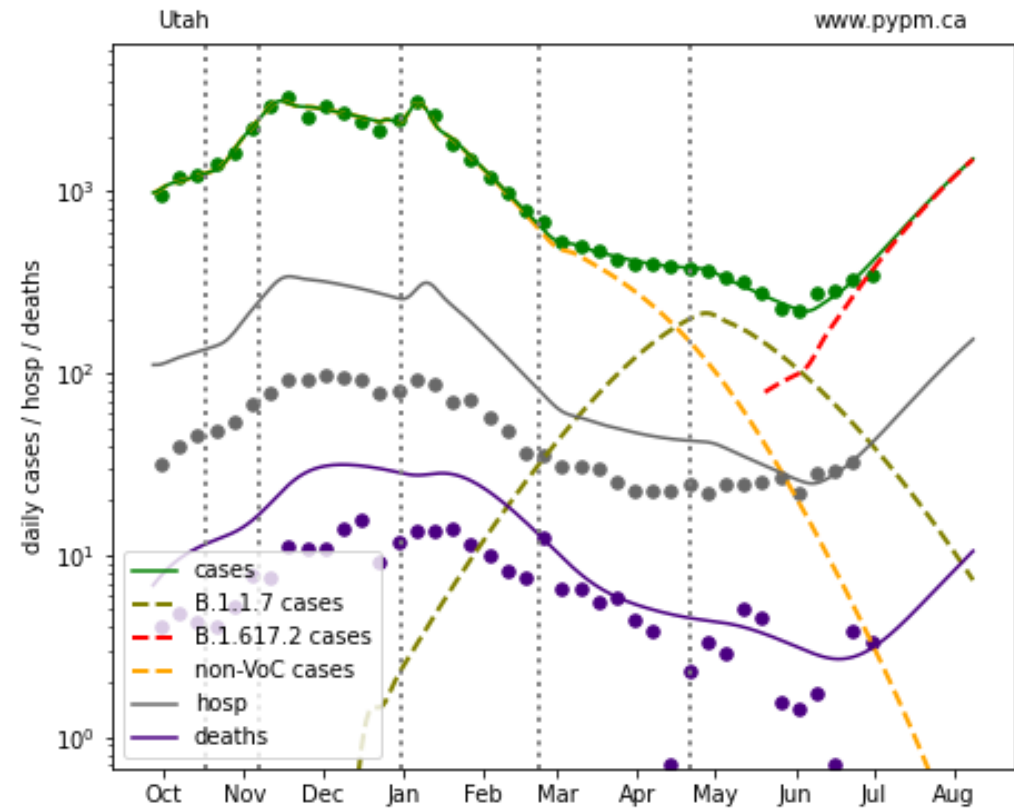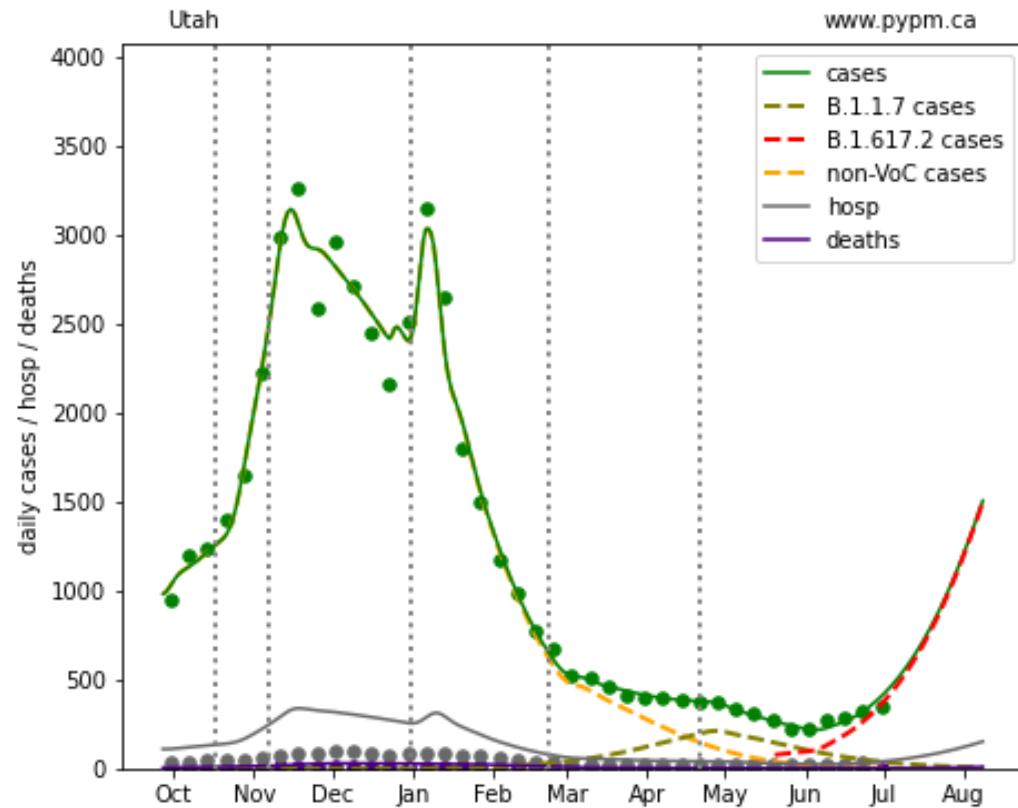
Missouri (July 4 fit)
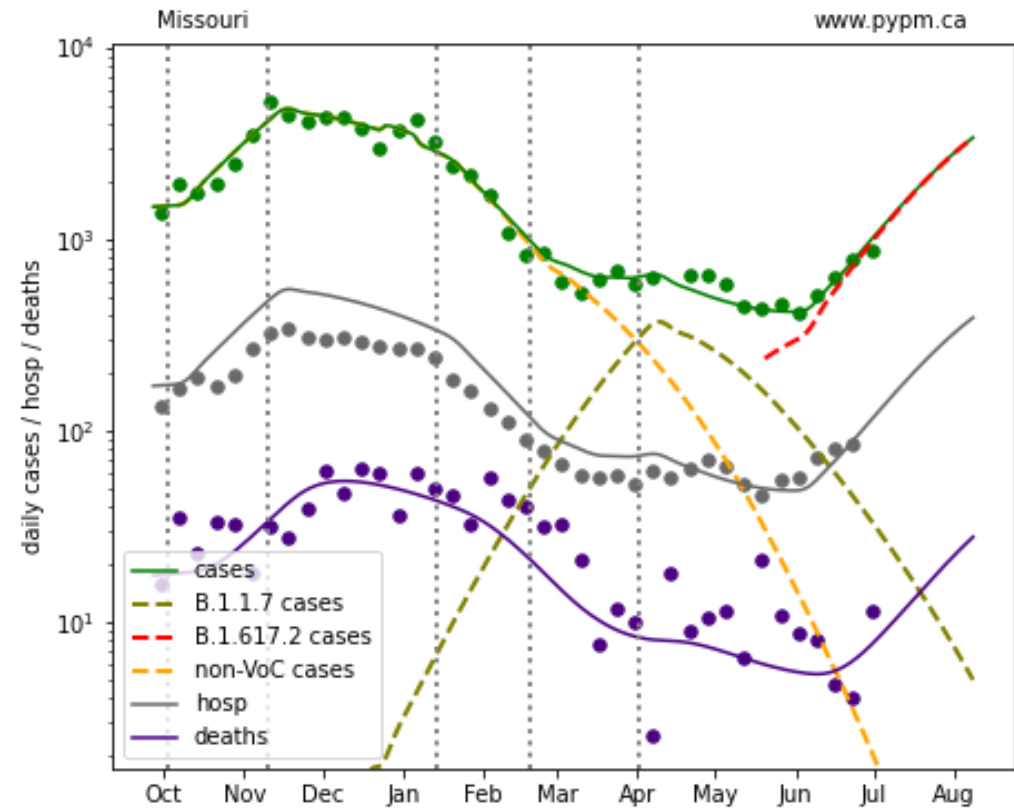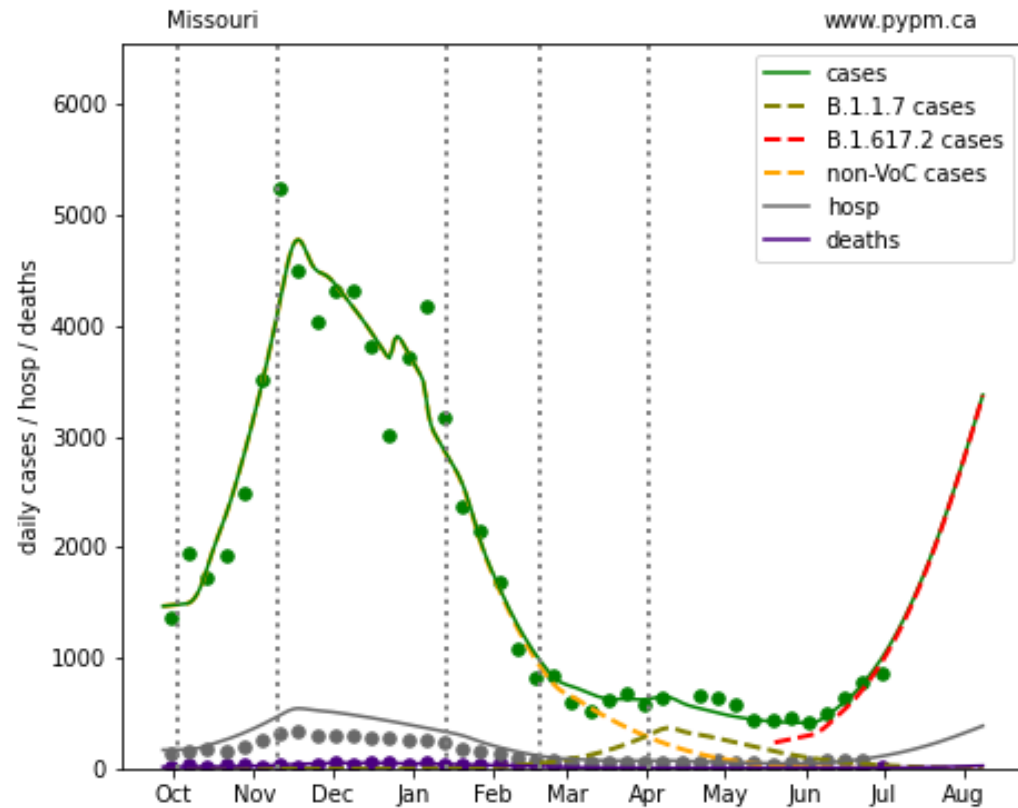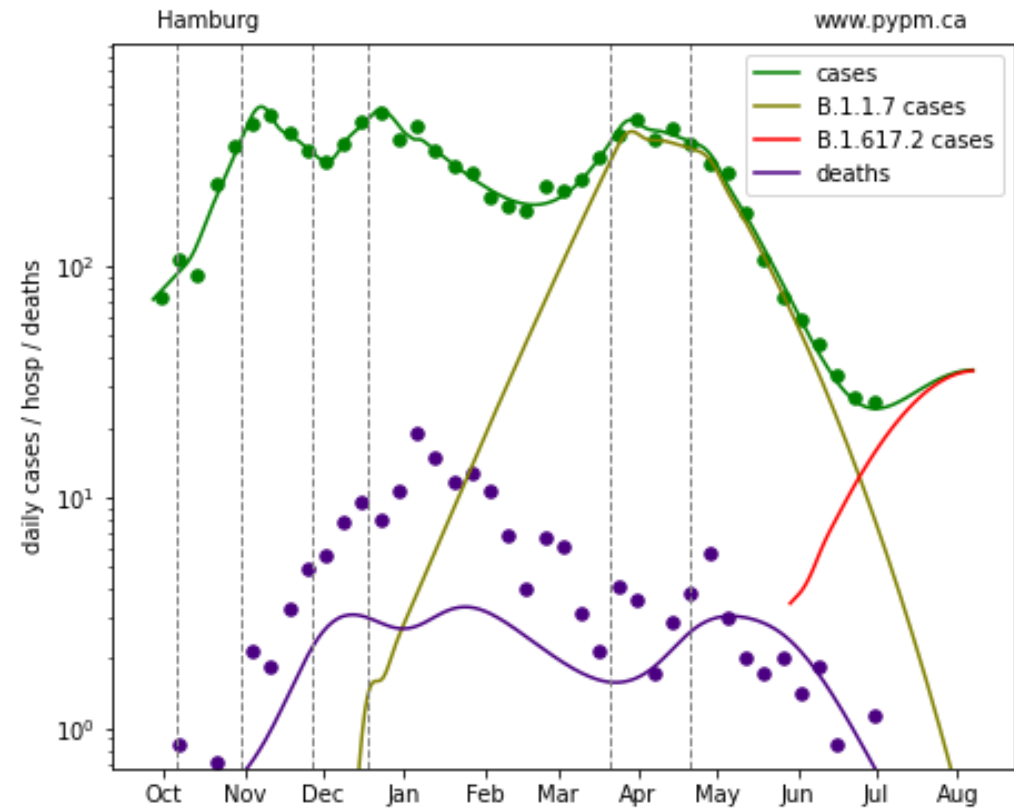
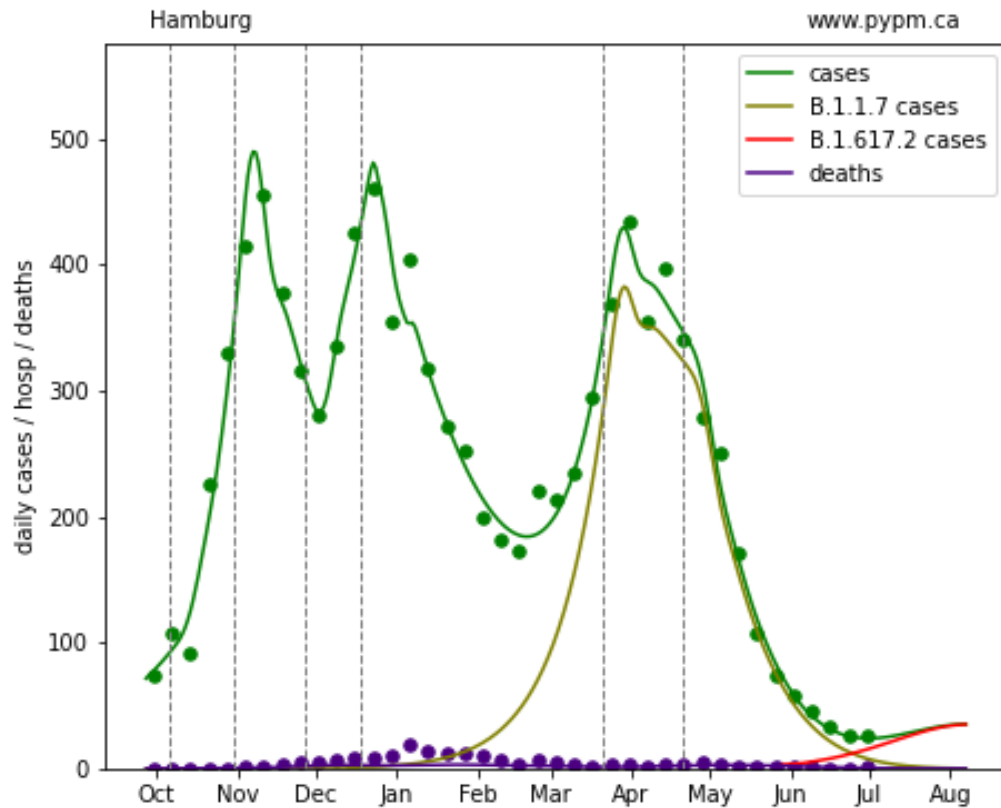# Arkansas (June 20 fit)
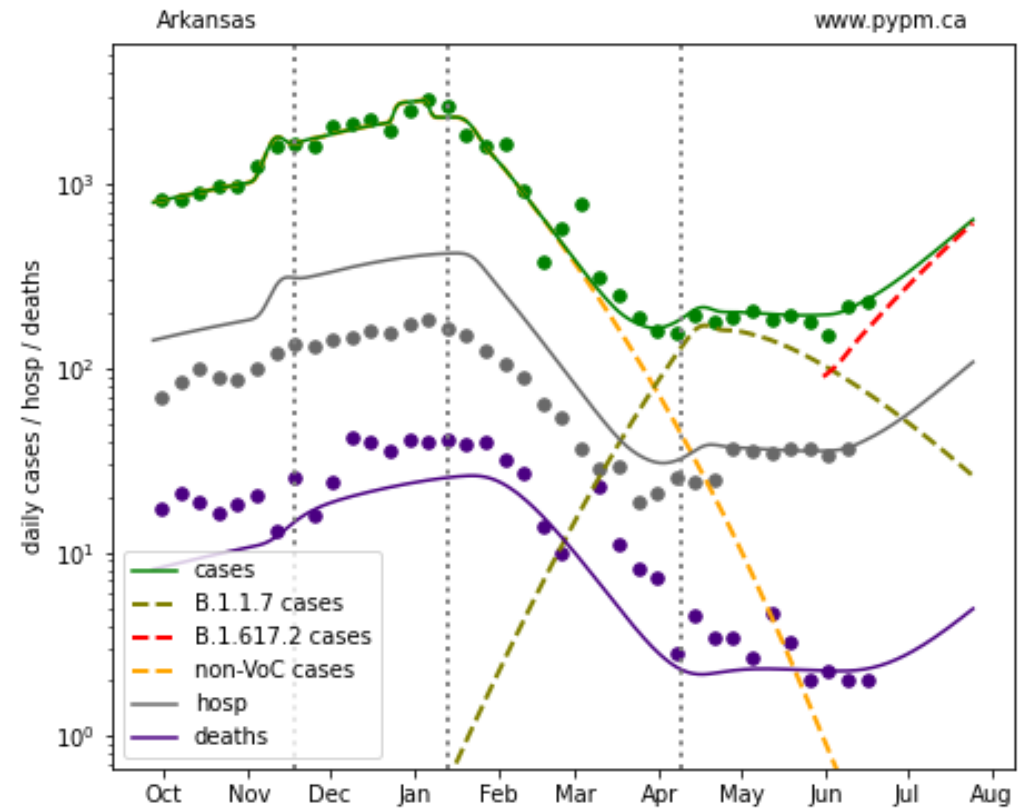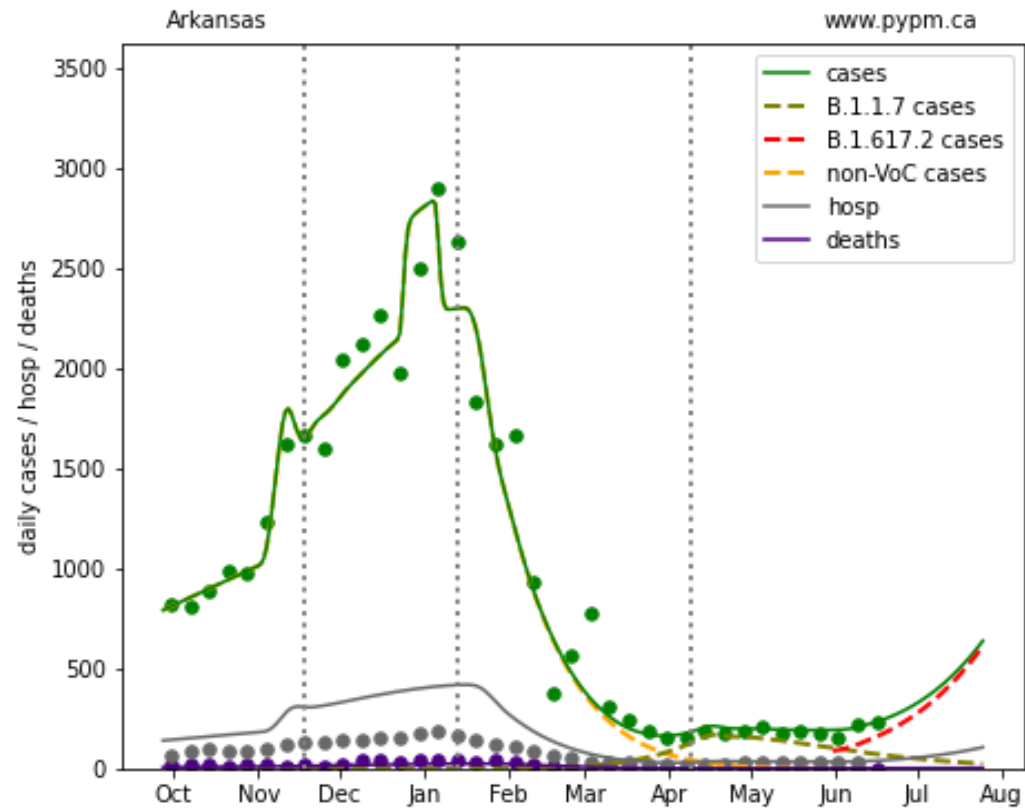
Arkansas (July 4 fit)
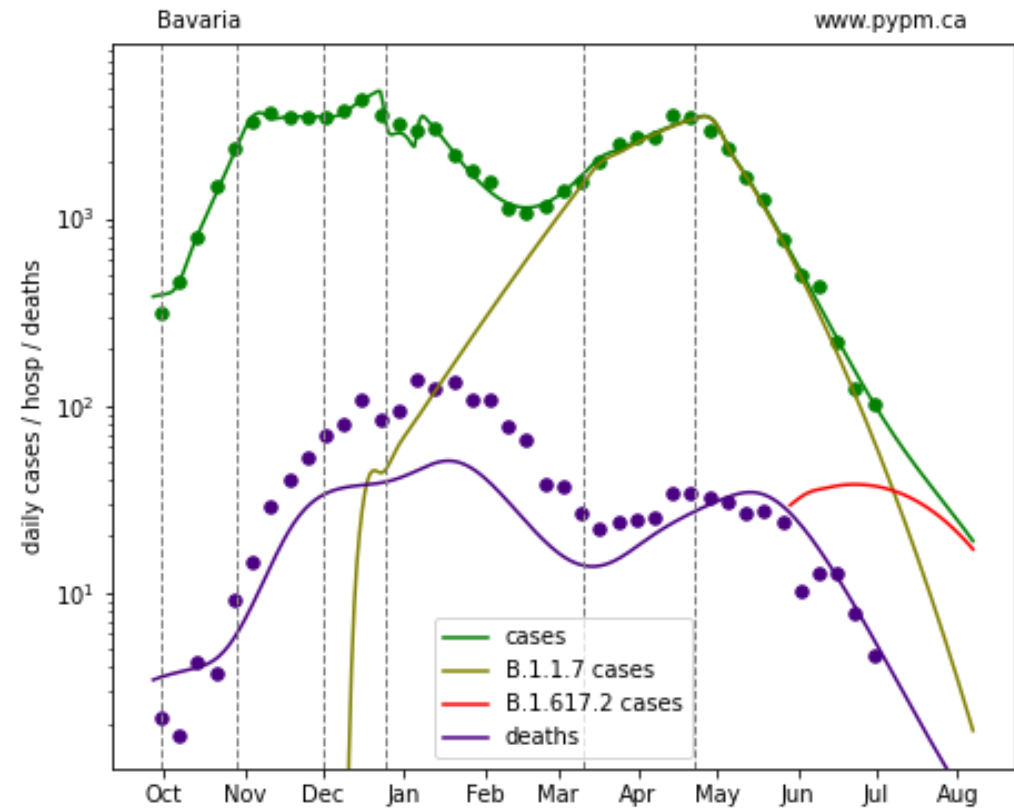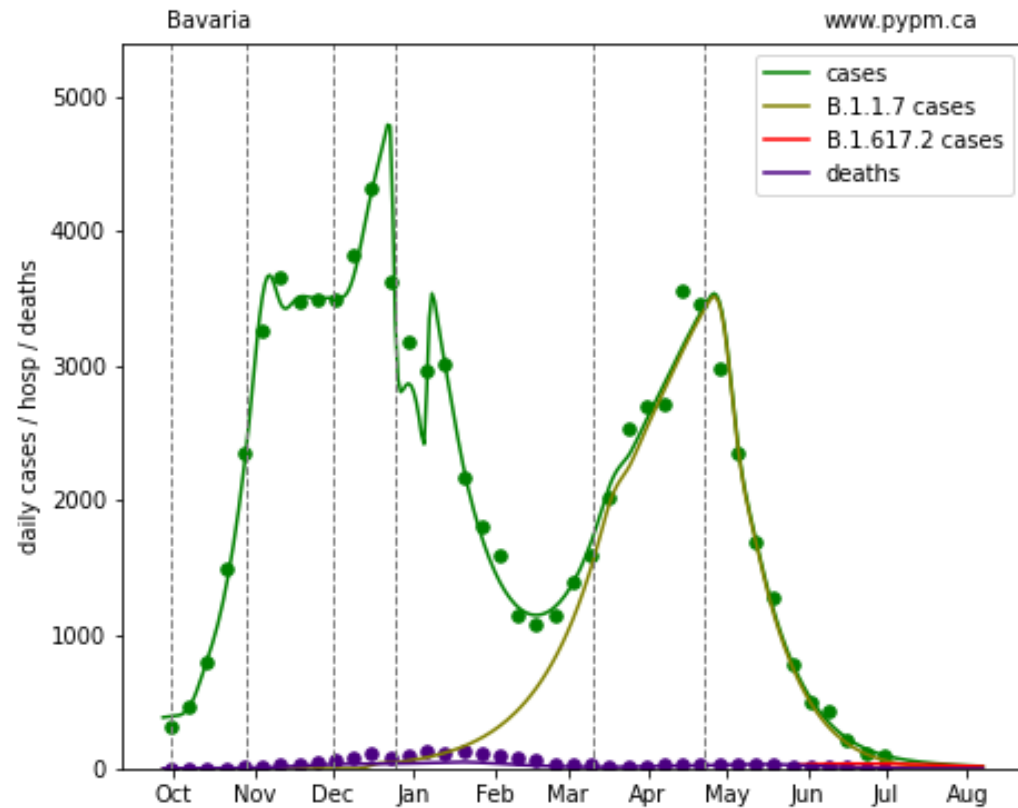
Utah (June 20 fit)

Utah (July 4 fit)

Hamburg (July 4 fit)

Bavaria (July 4 fit)

Summary

- It has been an interesting year being engaged in COVID modelling as an "outsider"

- Some general concerns/points for discussion
  - data access issues have stalled several analyses
    - in Canada, genomic data was slow to be released, often in an unusable form
  - there is limited amount of true collaboration across borders
    - working together on large problems by developing common frameworks/tools
  - public policy only weakly influenced by models
    - in Canada, the coming Alpha storm was not acted upon like a coming hurricane!

- For more information about this work, see: www.pypm.ca