Learning from the uncertain: Modelling and forecasting of infectious disease outbreaks

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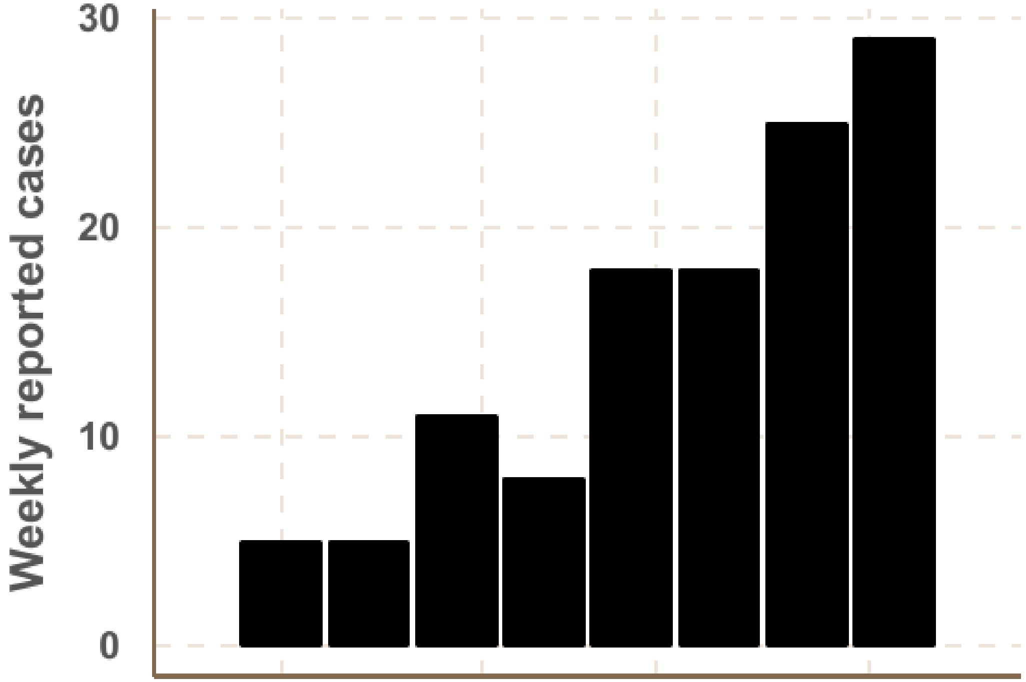
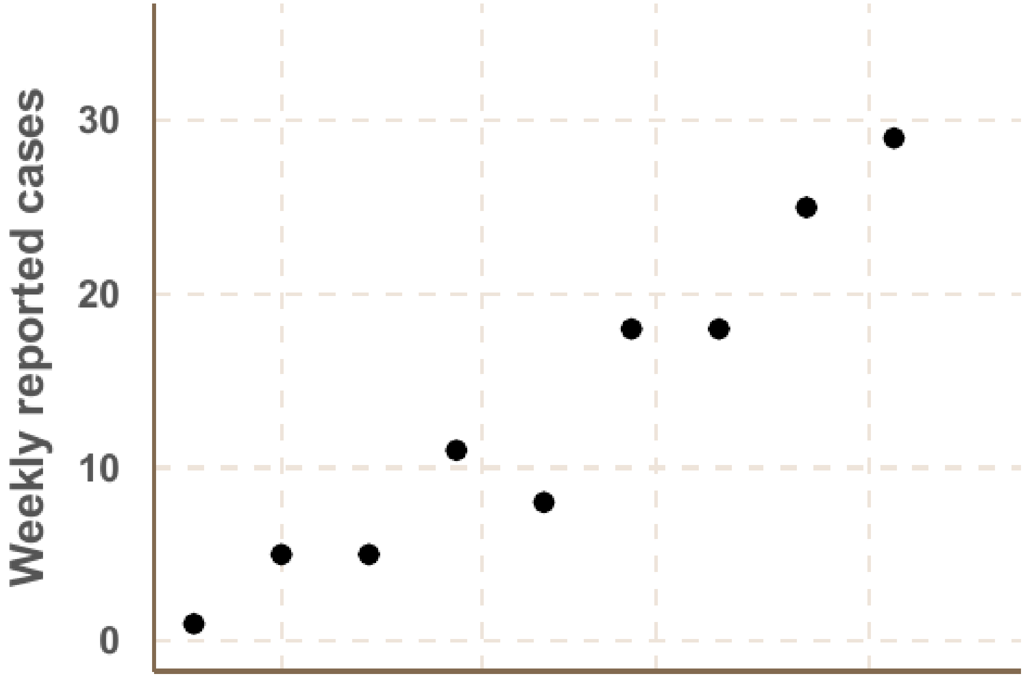
Probabilistic programming meeting, Uppsala

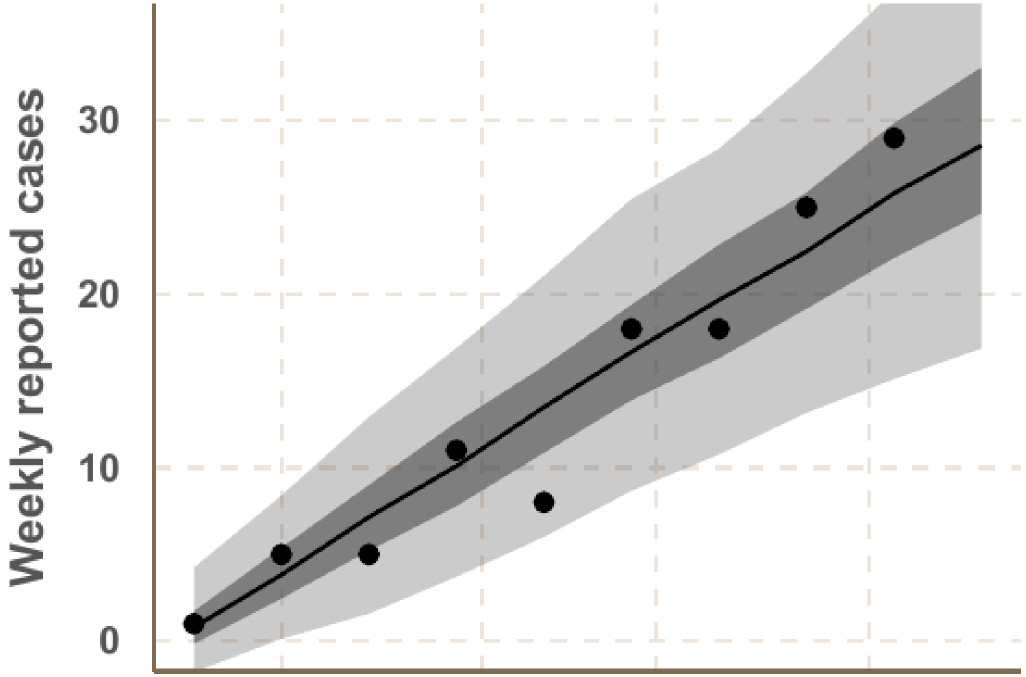
Public health emergencies driven by emerging infectious diseases are at the forefront of global awareness. From HIV in the 1980s to Zika virus's (ZIKV's) recent invasion of the Americas, models that mathematically capture disease processes have played a role in assessing the risk and framing the response to emerging pathogens. The most prominent, and perhaps most fraught, role of such models is to forecast the course of epidemics (*1*, *2*). Yet, expli

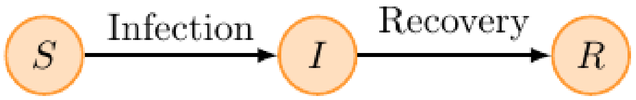
Forecasting the Ebola epidemic

Summer 2014

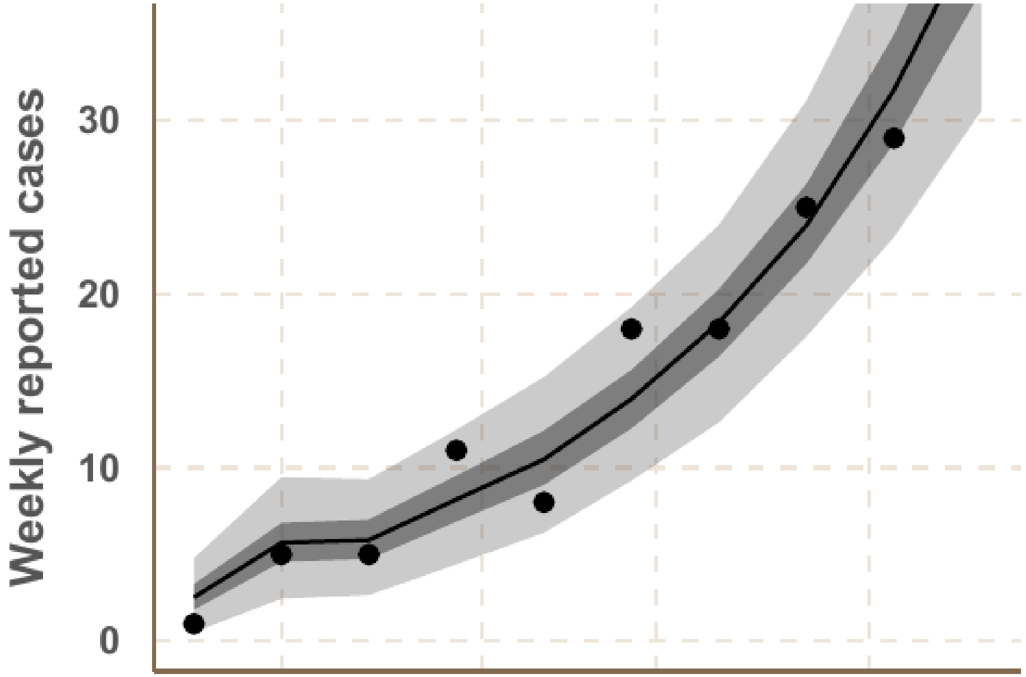

Weekly reported cases
30
20
10
0

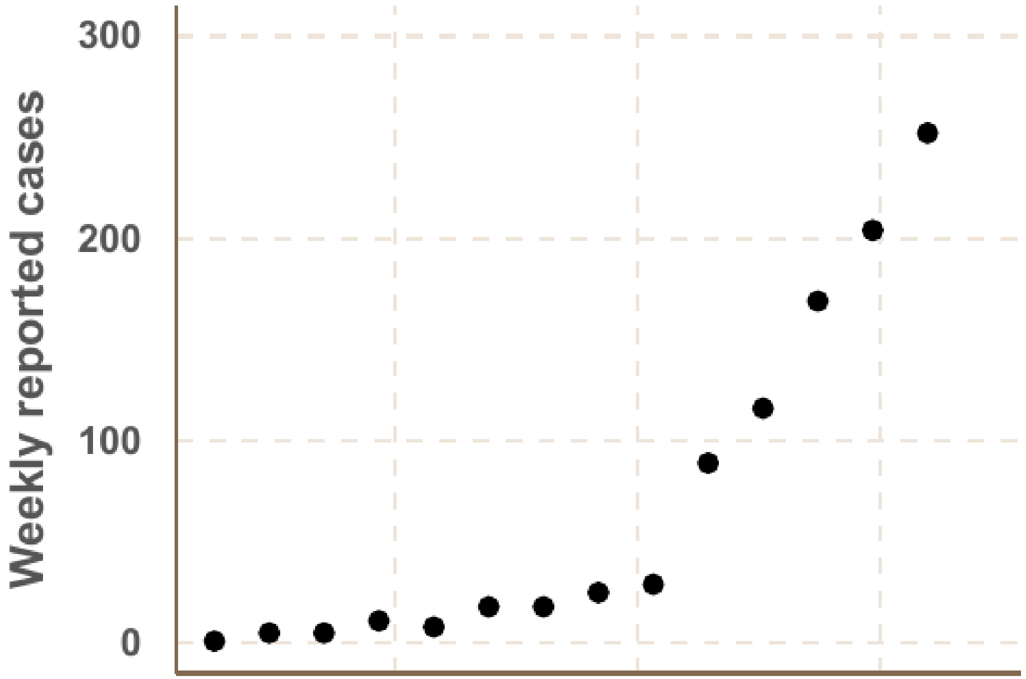

Weekly reported cases
30
20
10
0


Weekly reported cases
30
20
10
0

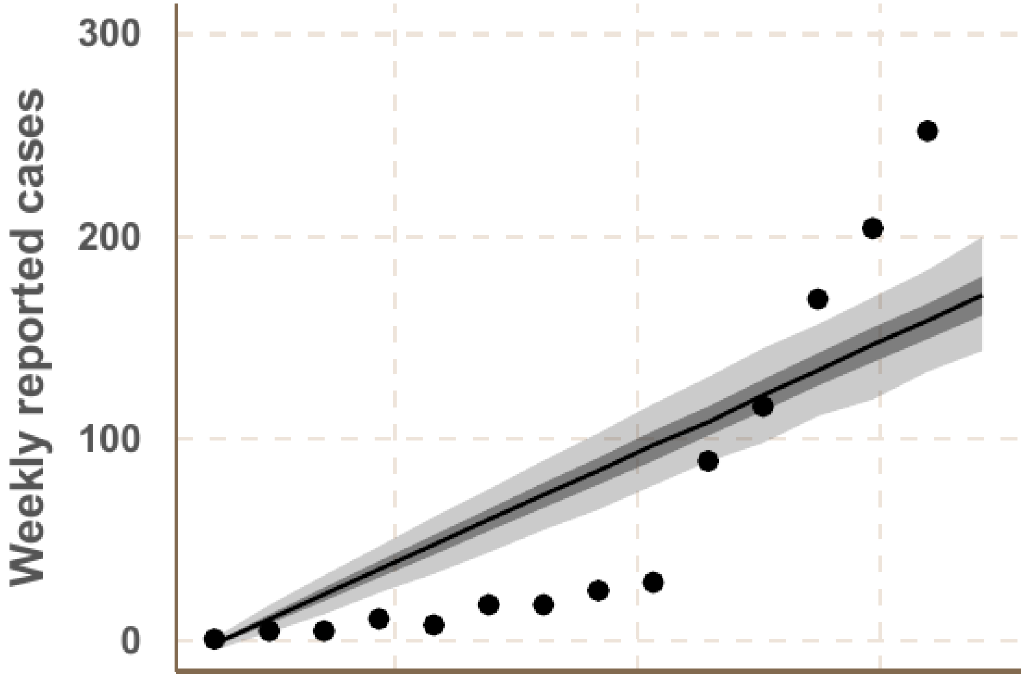


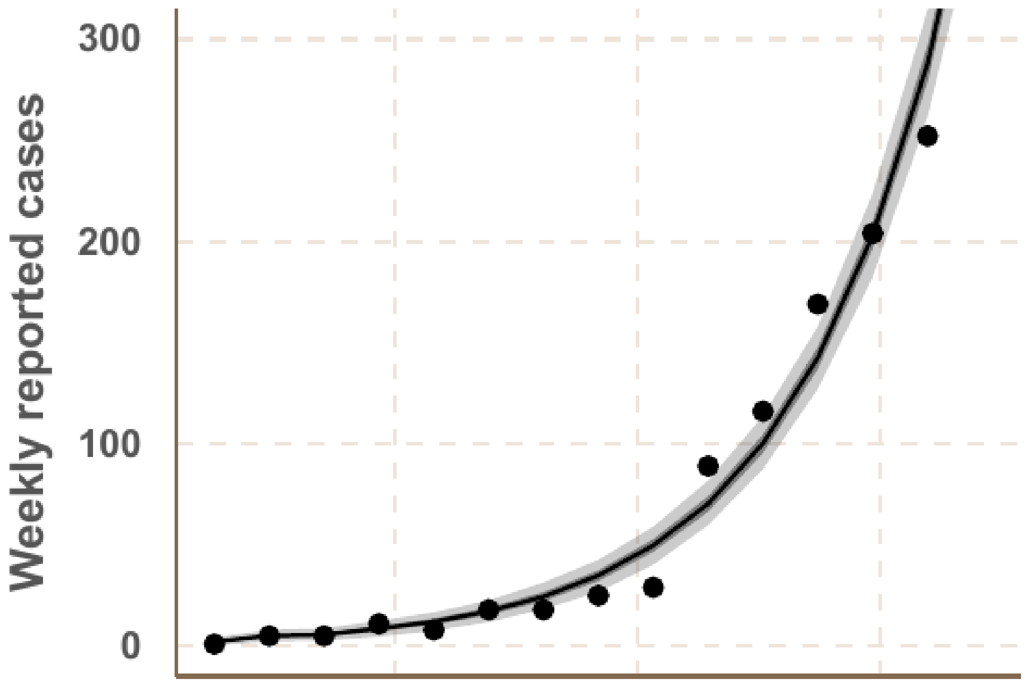
$$
\begin{aligned}
\dot{S} &= -\beta \frac{S}{N} I \\
\dot{I} &= +\beta \frac{S}{N} I - \gamma I \\
\dot{R} &= +\gamma I
\end{aligned}
$$

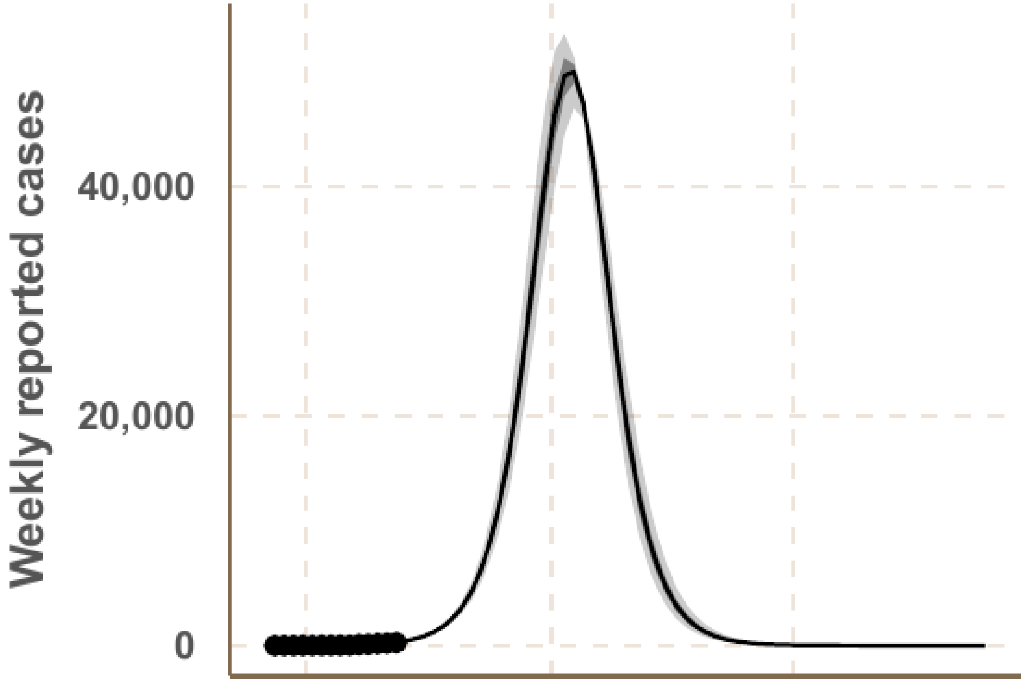

Weekly reported cases
30
20
10
0

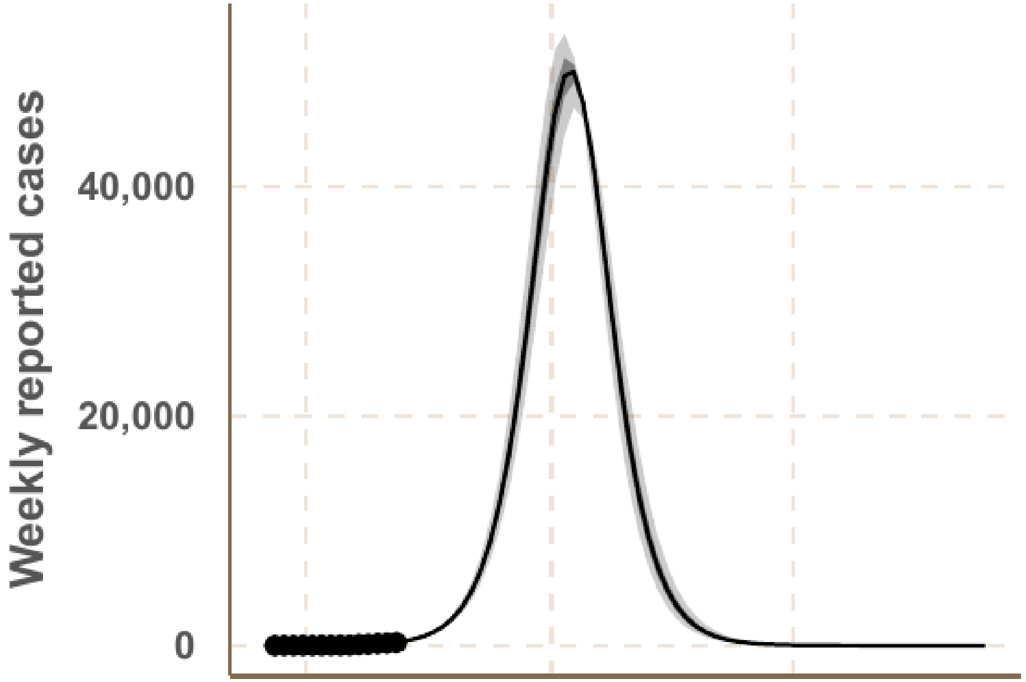


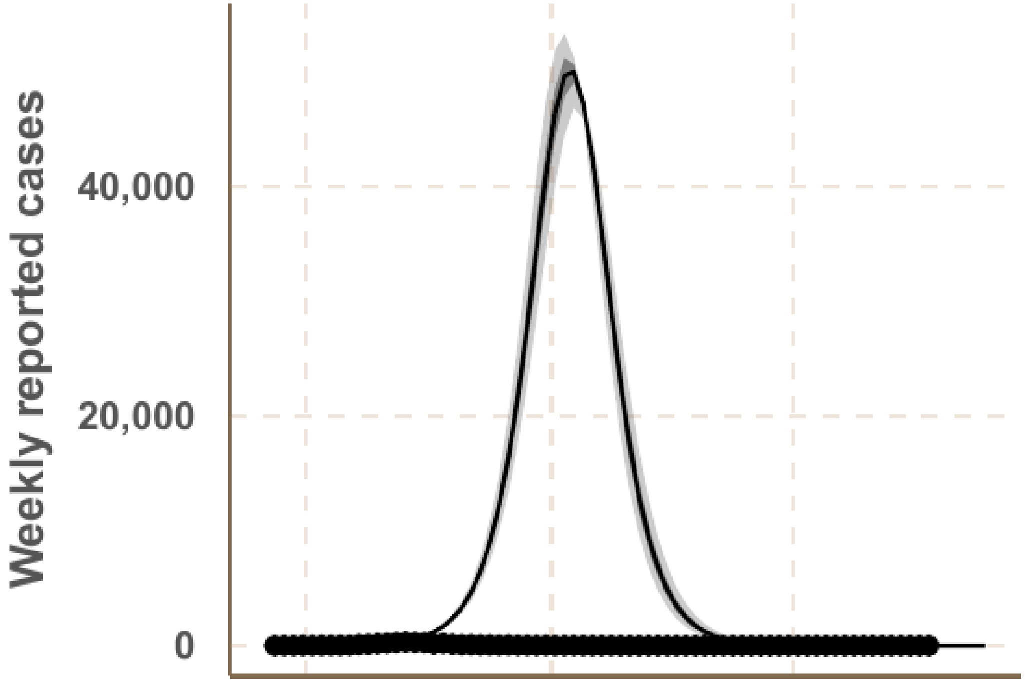
Weekly reported cases
300
200
100
0


Weekly reported cases
300
200
100
0

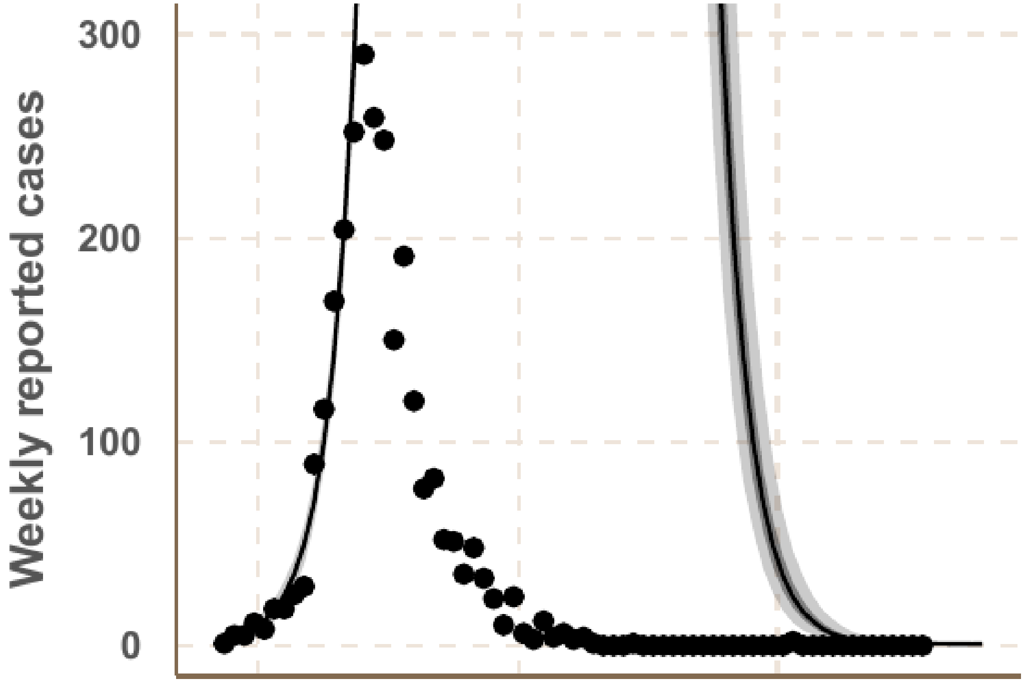

Weekly reported cases
300
200
100
0


Weekly reported cases
40,000
20,000
0


Weekly reported cases
40,000
20,000
0



Weekly reported cases
40,000
20,000
0



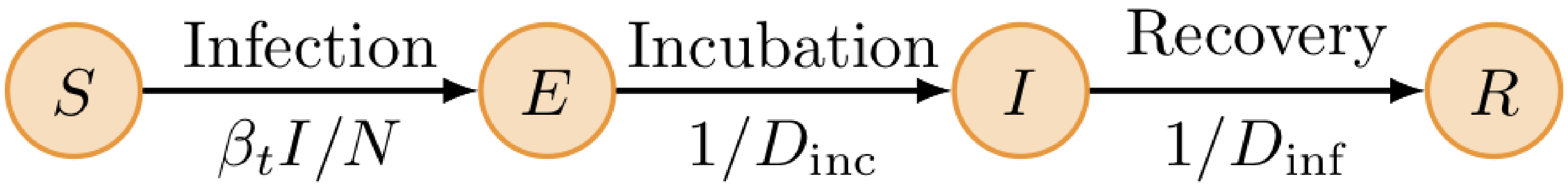
Weekly reported cases
300
200
100
0

A semi-mechanistic model for real-time forecasting

The unknown

- Community/hospital/funeral transmission
- Spatial dynamics
- Changes in behaviour
- Changes in reporting
- Interventions
- Seasonality
- etc

The known



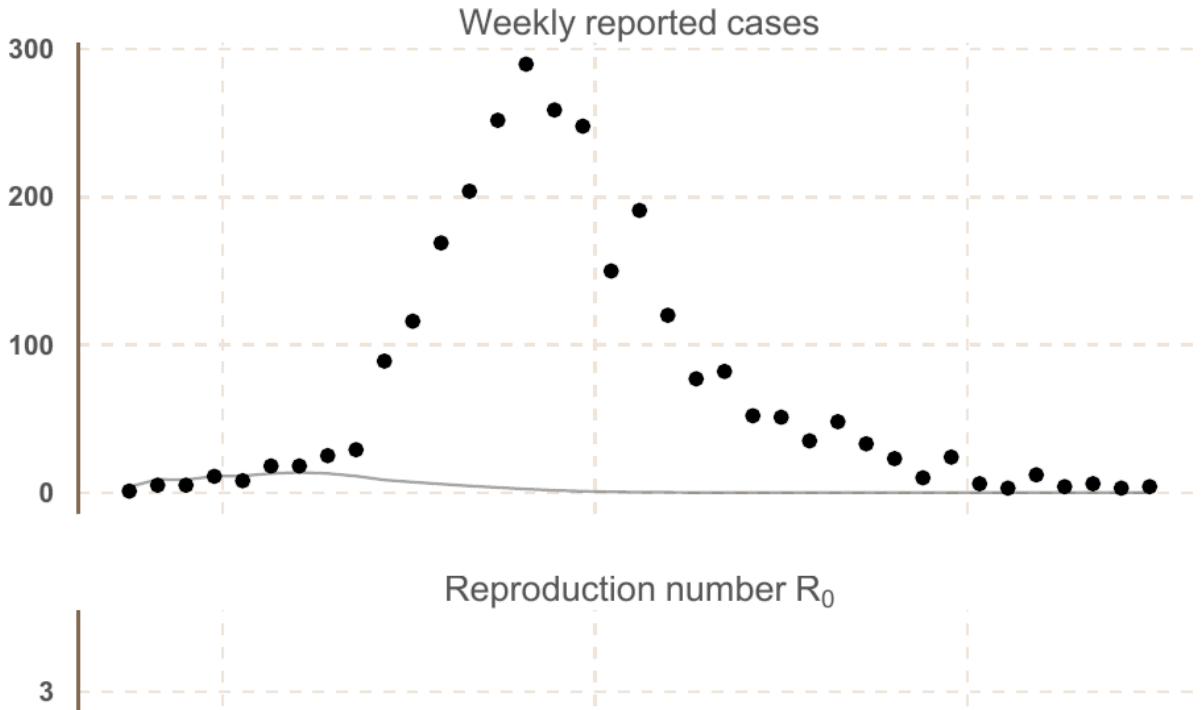
- Average incubation period (~9 days)
- Average infectious period (~11 days)
- Case-fatality rate (~70%)

WHO Ebola response team (2014)

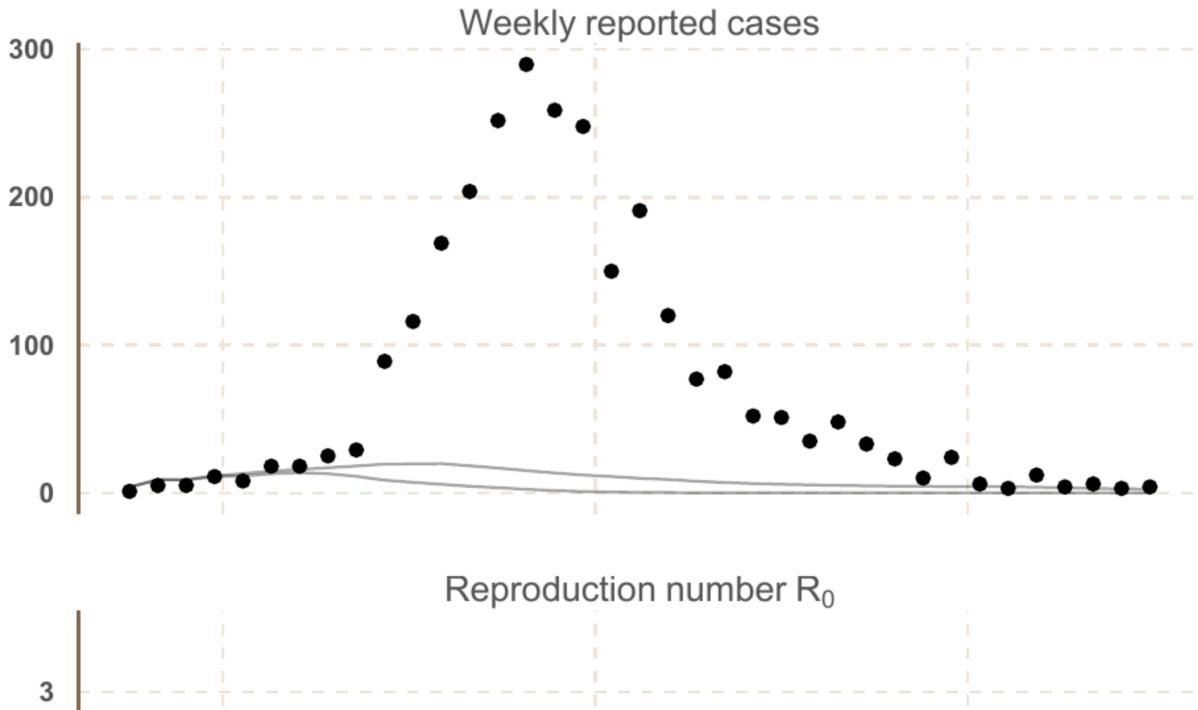
Time-varying transmission rate with smoothing prior

$$d \log \beta_t = \sigma dW_t$$

Dureau et al. (2013)



Weekly reported cases
300
200
100
0
Reproduction number R_0
3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Reproduction number R_0
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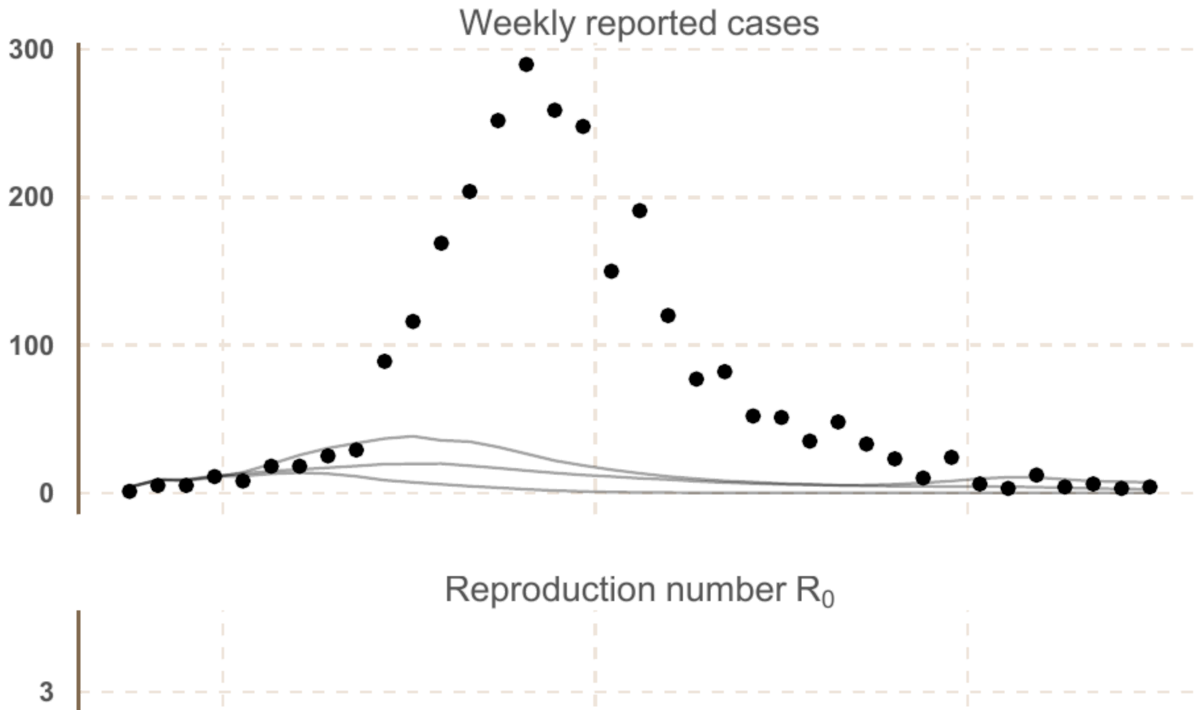
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Reproduction number R_0
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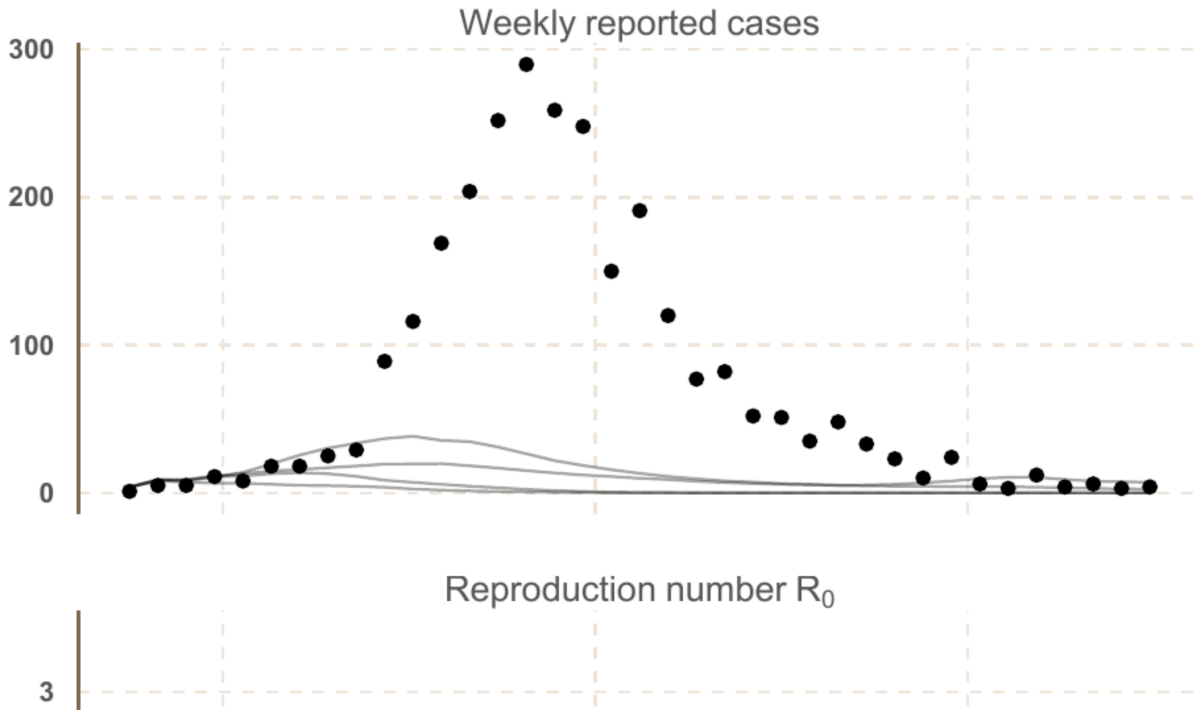

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Reproduction number R_0
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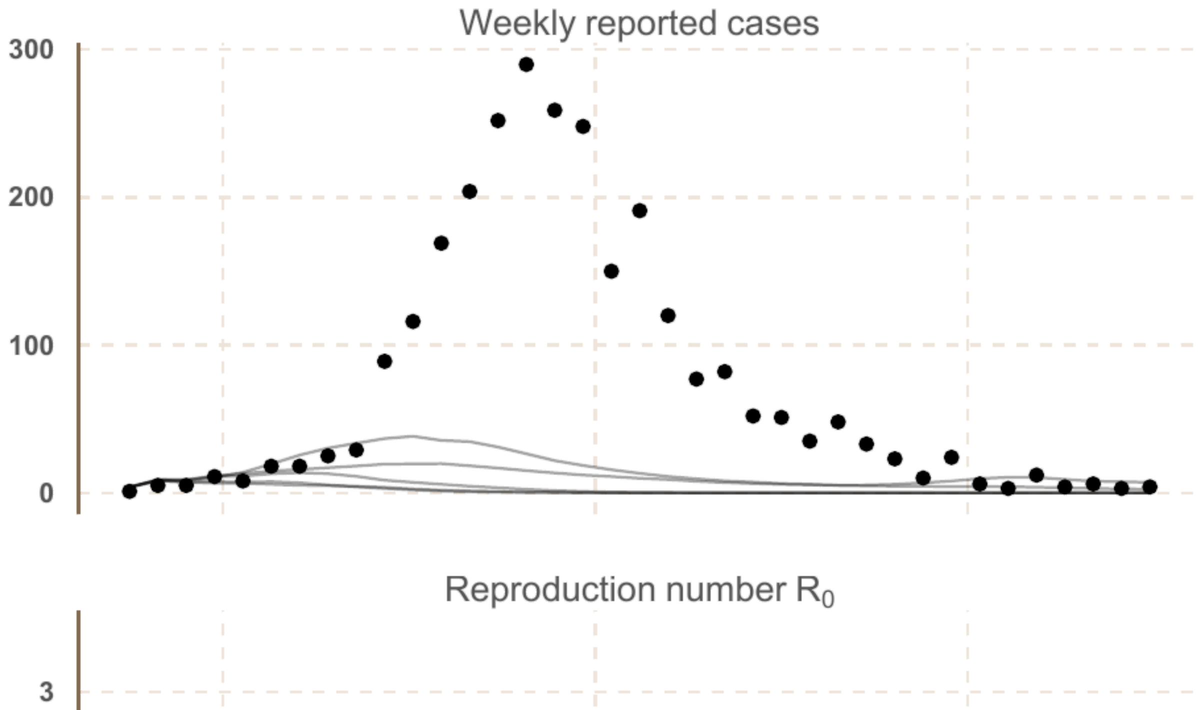
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Reproduction number R_0
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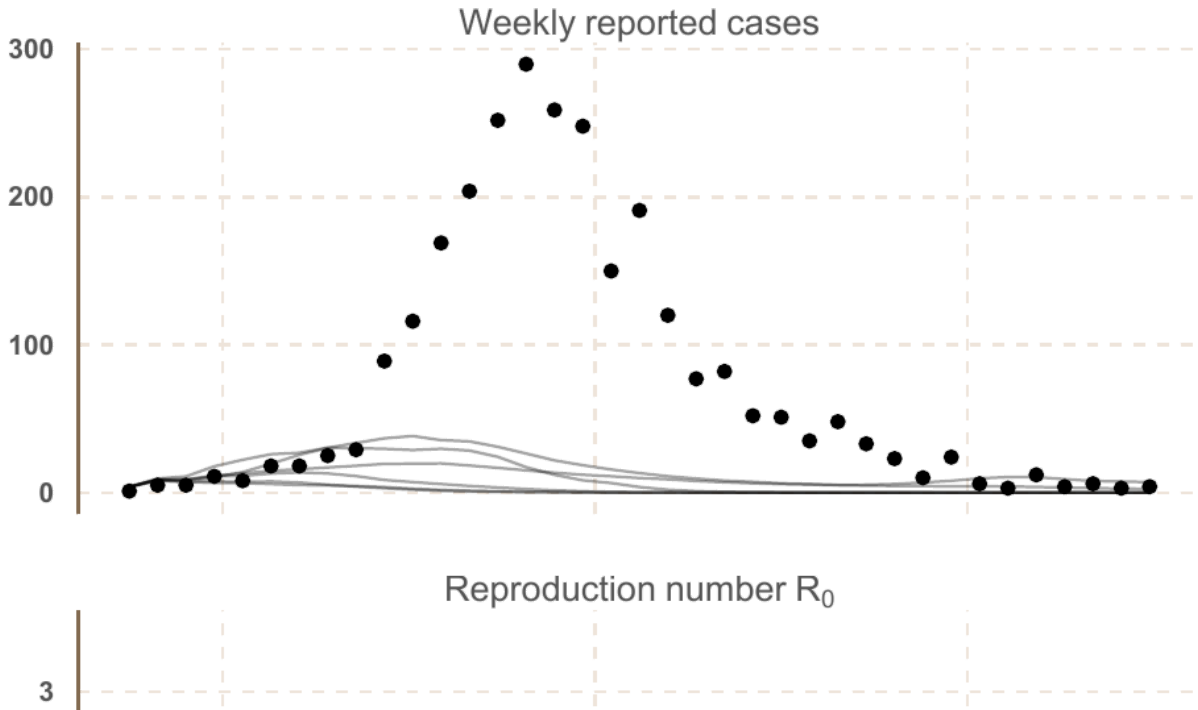

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Reproduction number R_0
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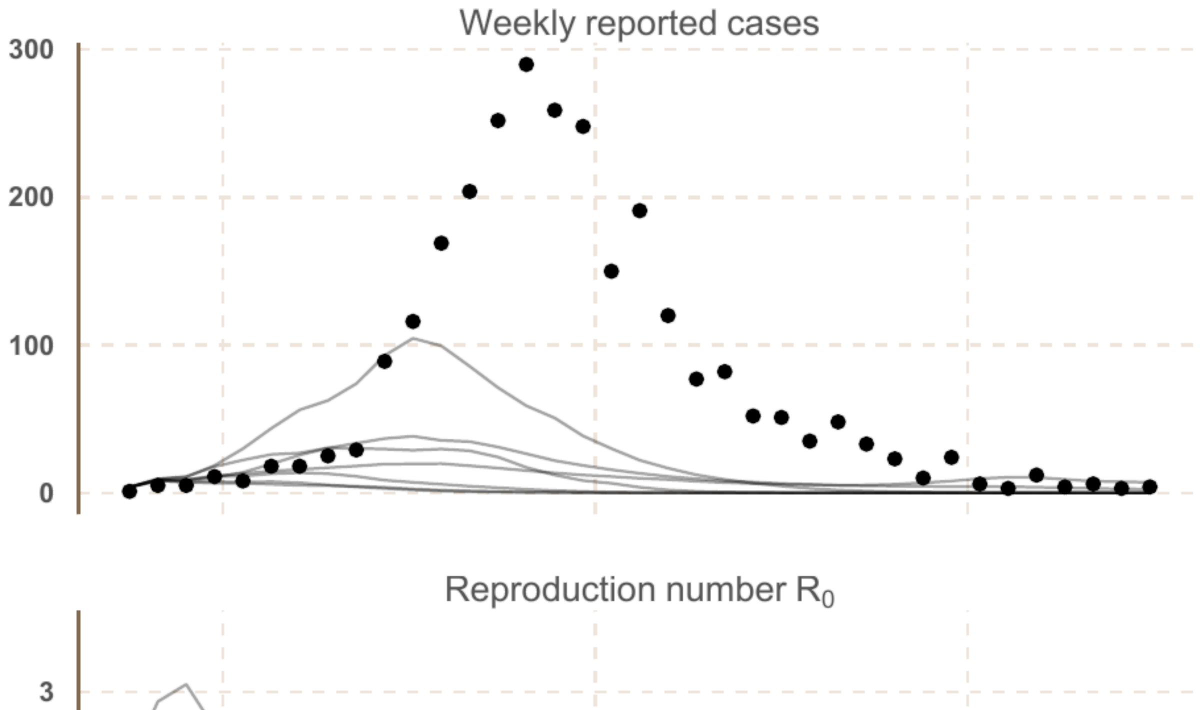
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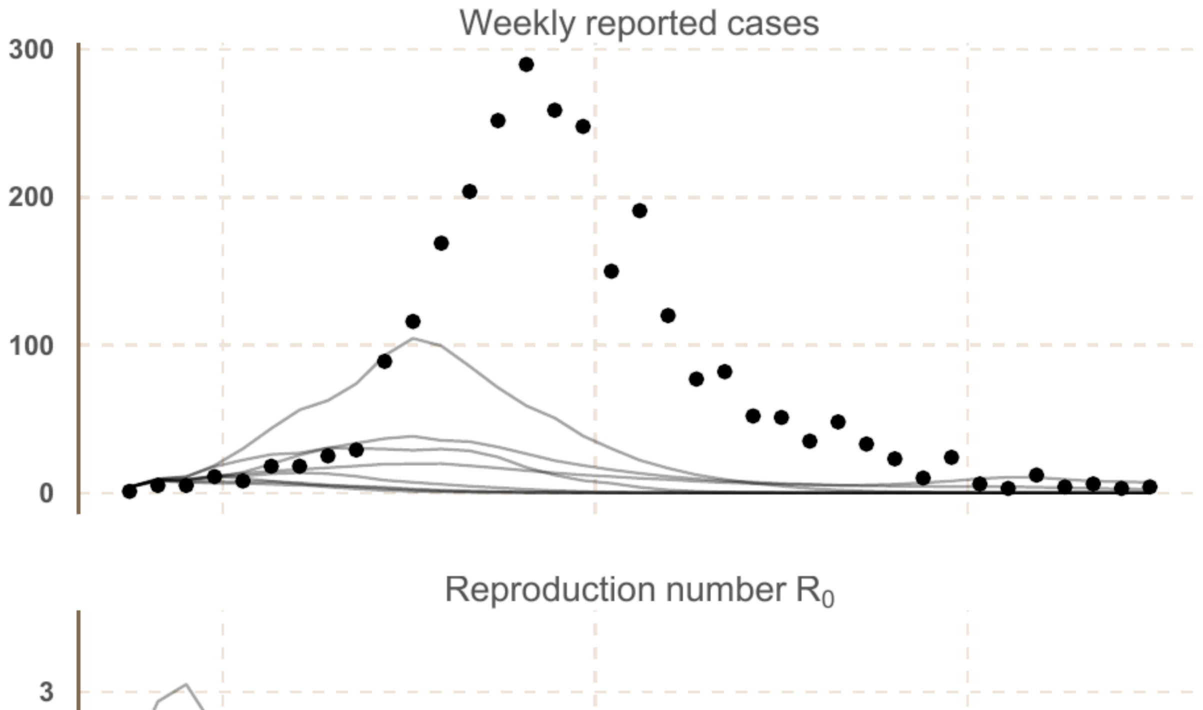
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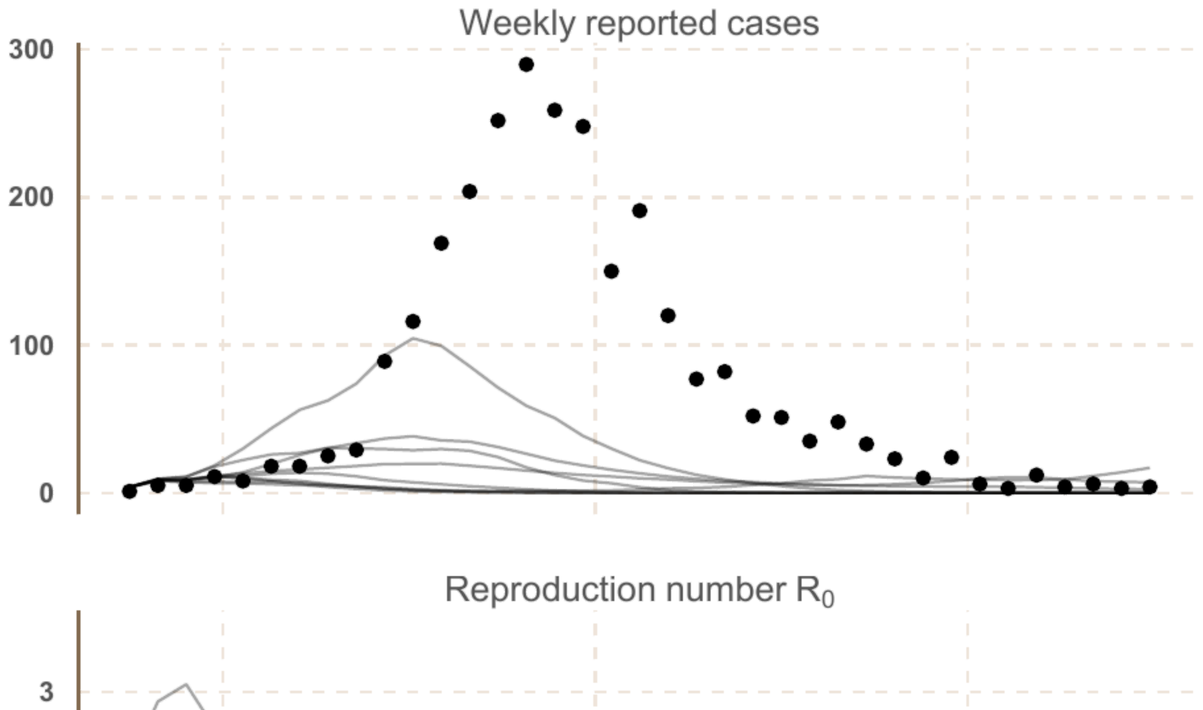
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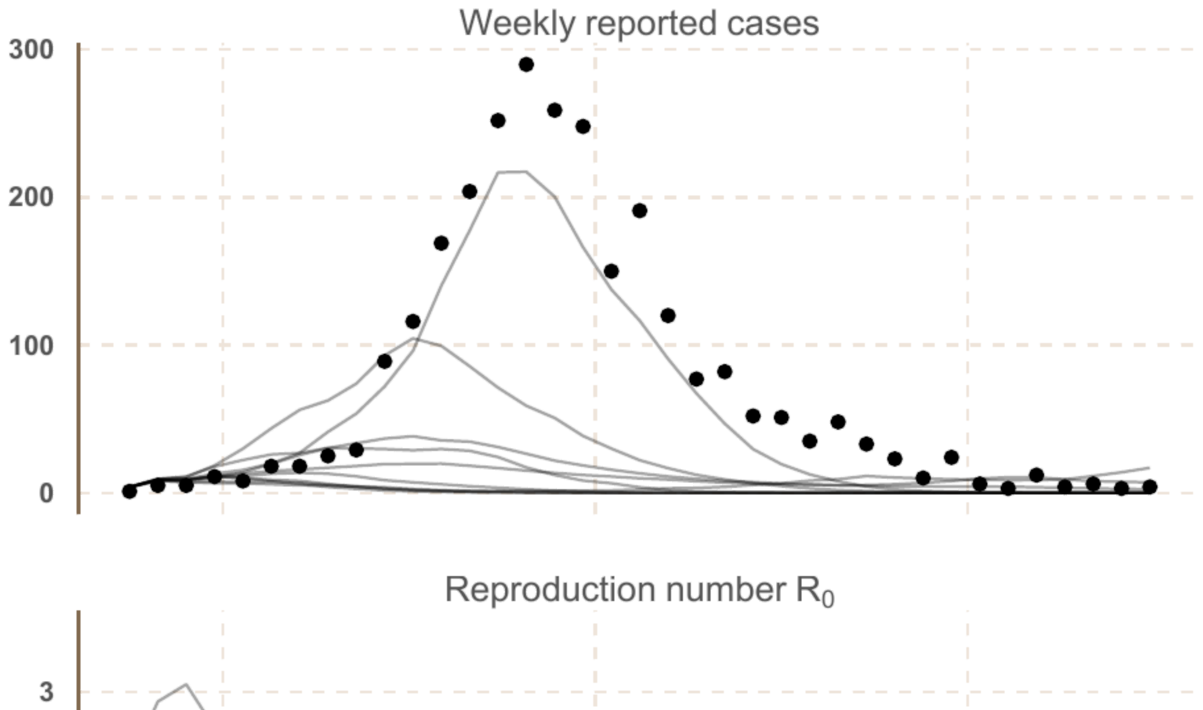
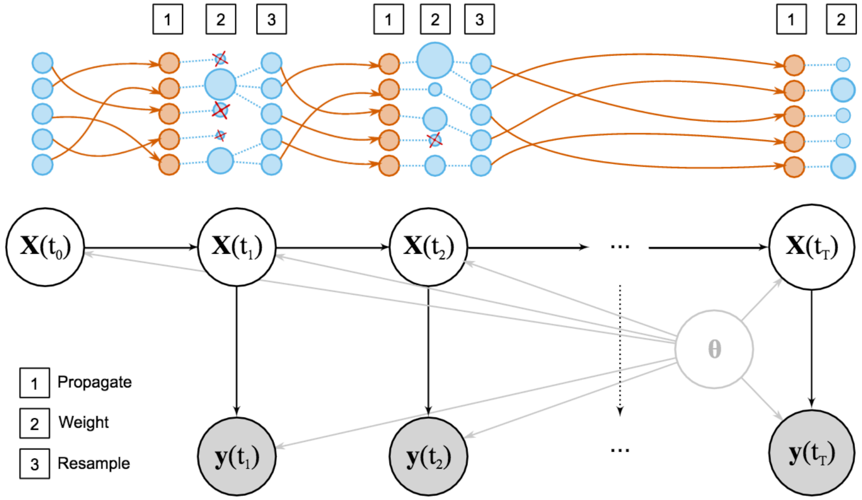
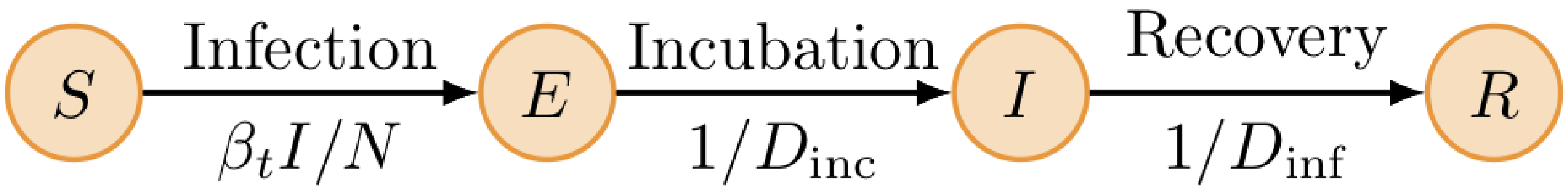

Weekly reported cases
300
200
100
0
Reproduction number R_0
3

Particle MCMC



Use particle Markov chain Metropolis-Hastings to
sample from $p(\theta|\text{Data})$ and $p(\beta_t|\text{Data})$



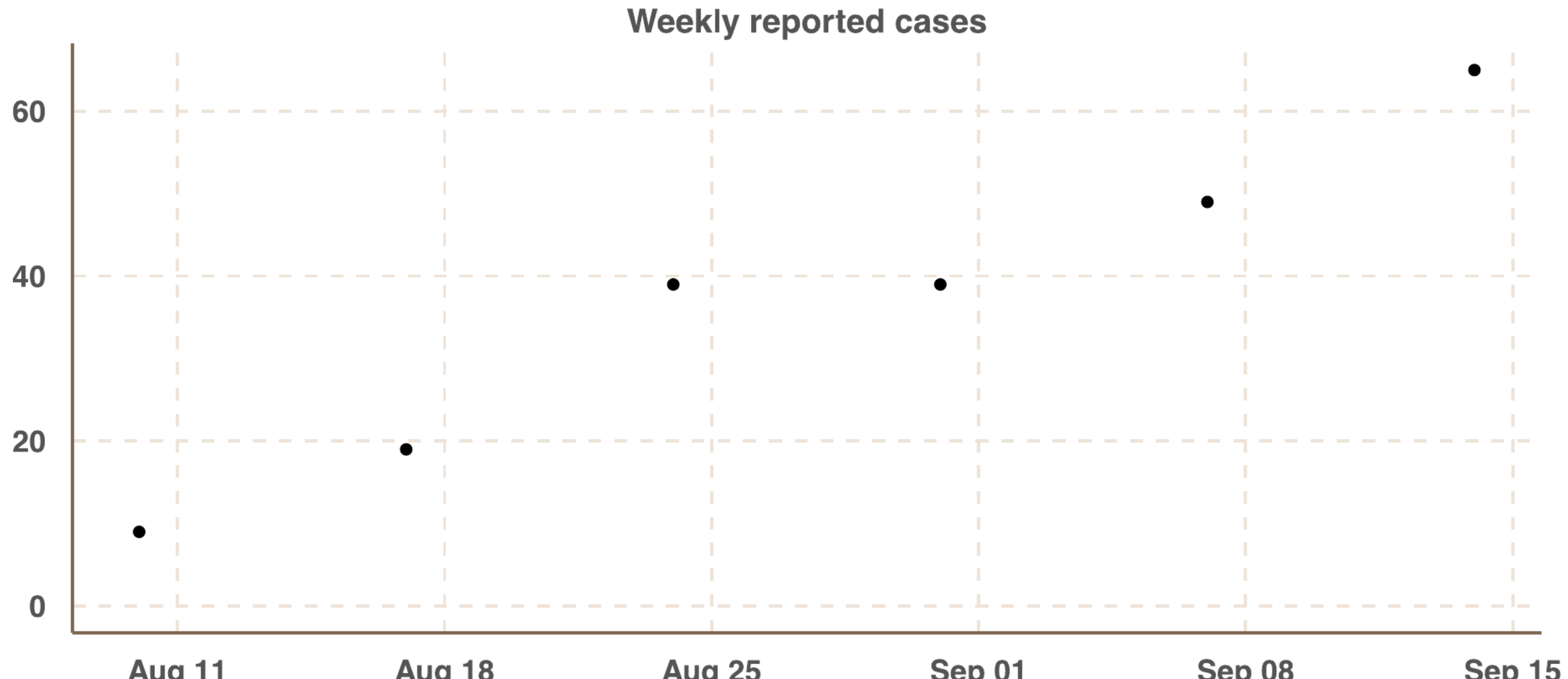
- $d \log \beta_t = \sigma dW_t$
- Negative binomial observations, overdispersion ϕ
- $\theta = \{\sigma, \phi, \beta_0, I_0\}$
  - Intensity of random walk
  - Overdispersion of reporting
  - Initial transmission rate
  - Initial number infective

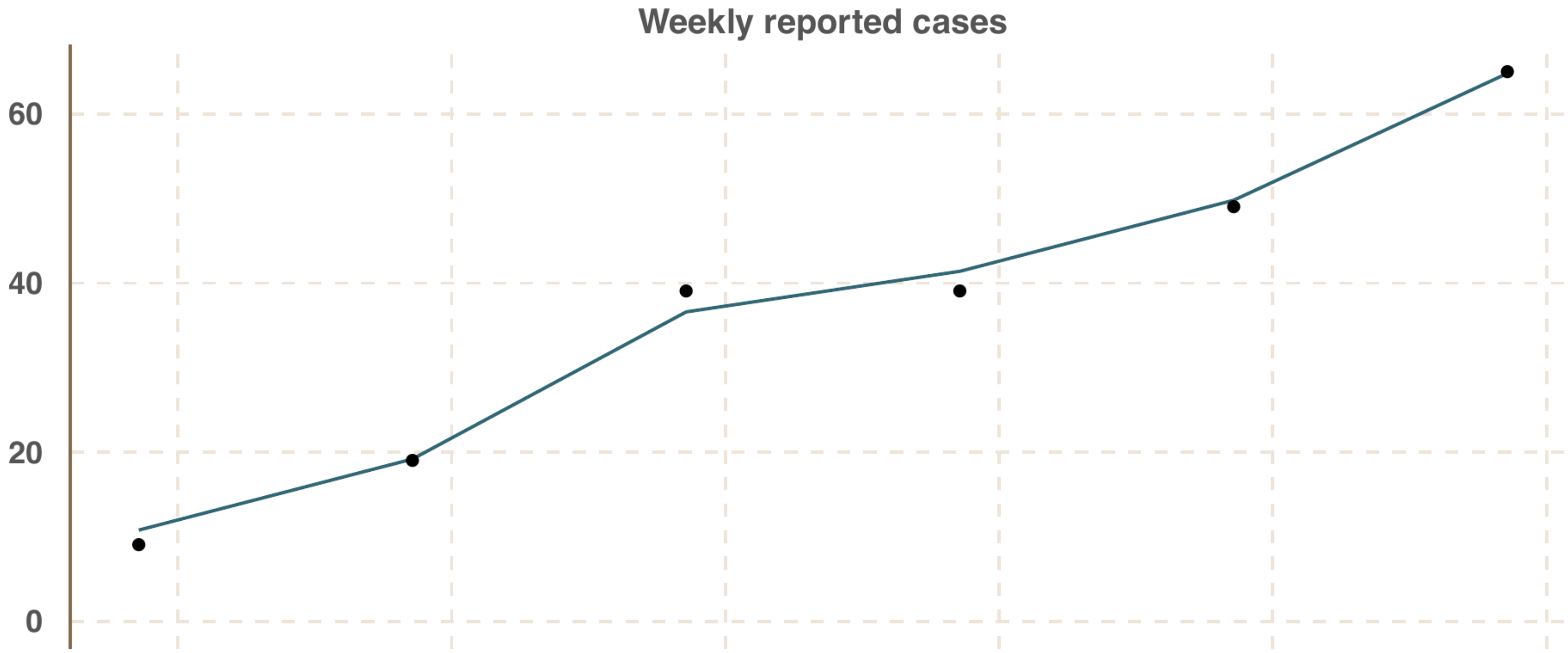
Camacho et al. (2015), Funk et al. (2016), Funk et al. (2017)

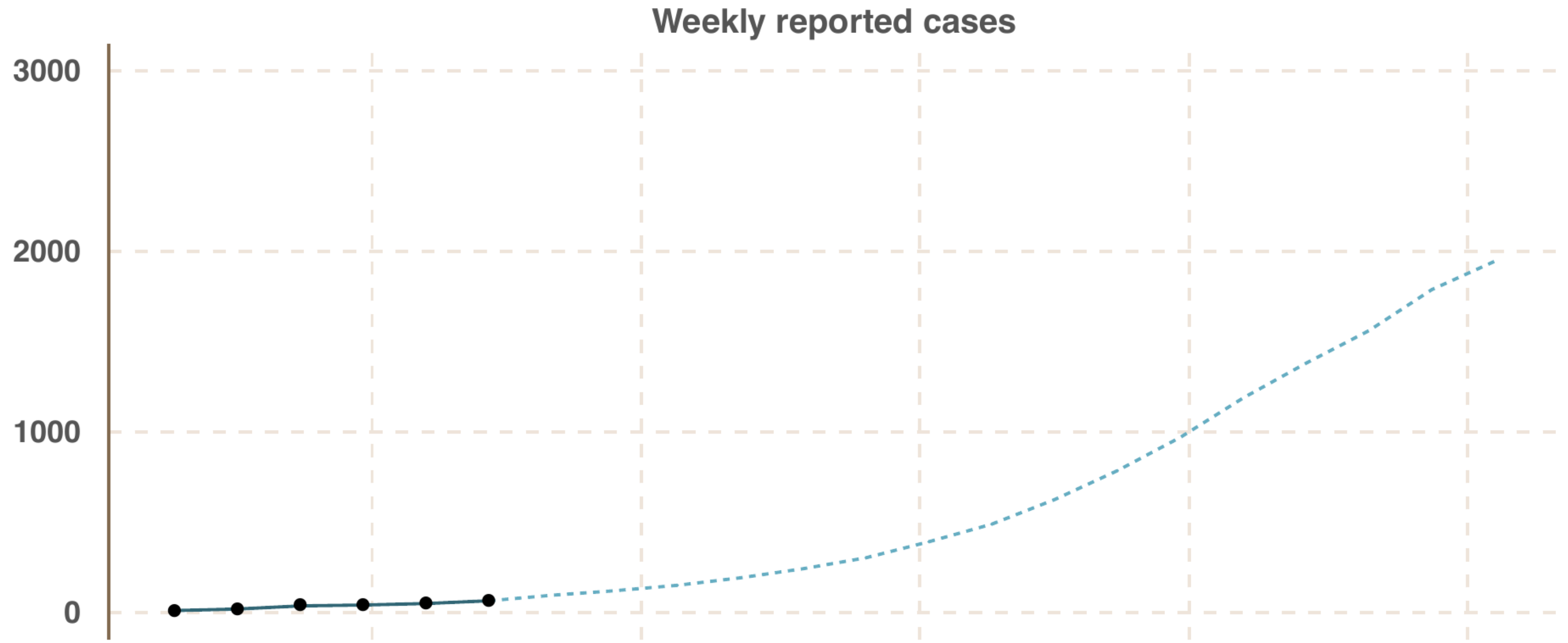
"We were losing ourselves in details [...] all we needed to know is, are the number of cases rising, falling or

levelling off?"

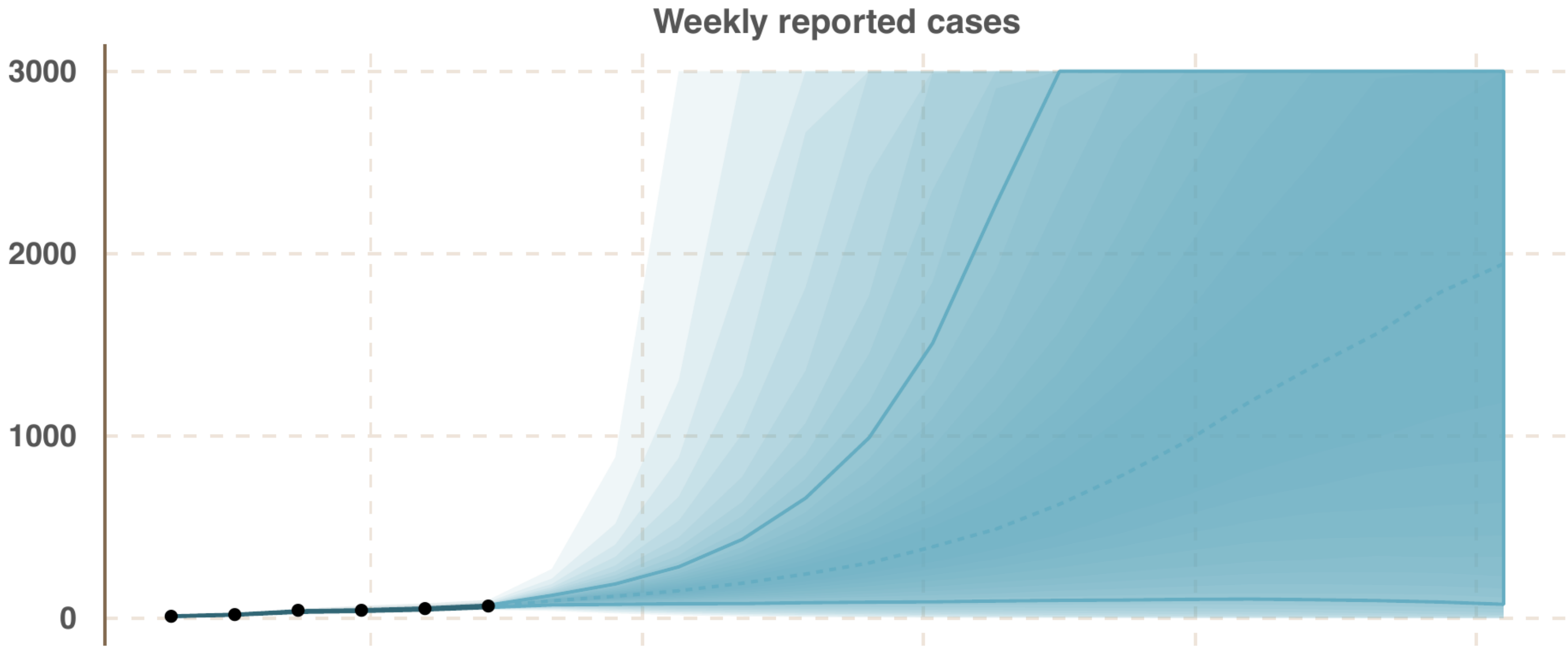
Hans Rosling


Weekly reported cases
60
40
20
0
Aug 11
Aug 18
Aug 25
Sep 01
Sep 08
Sep 15

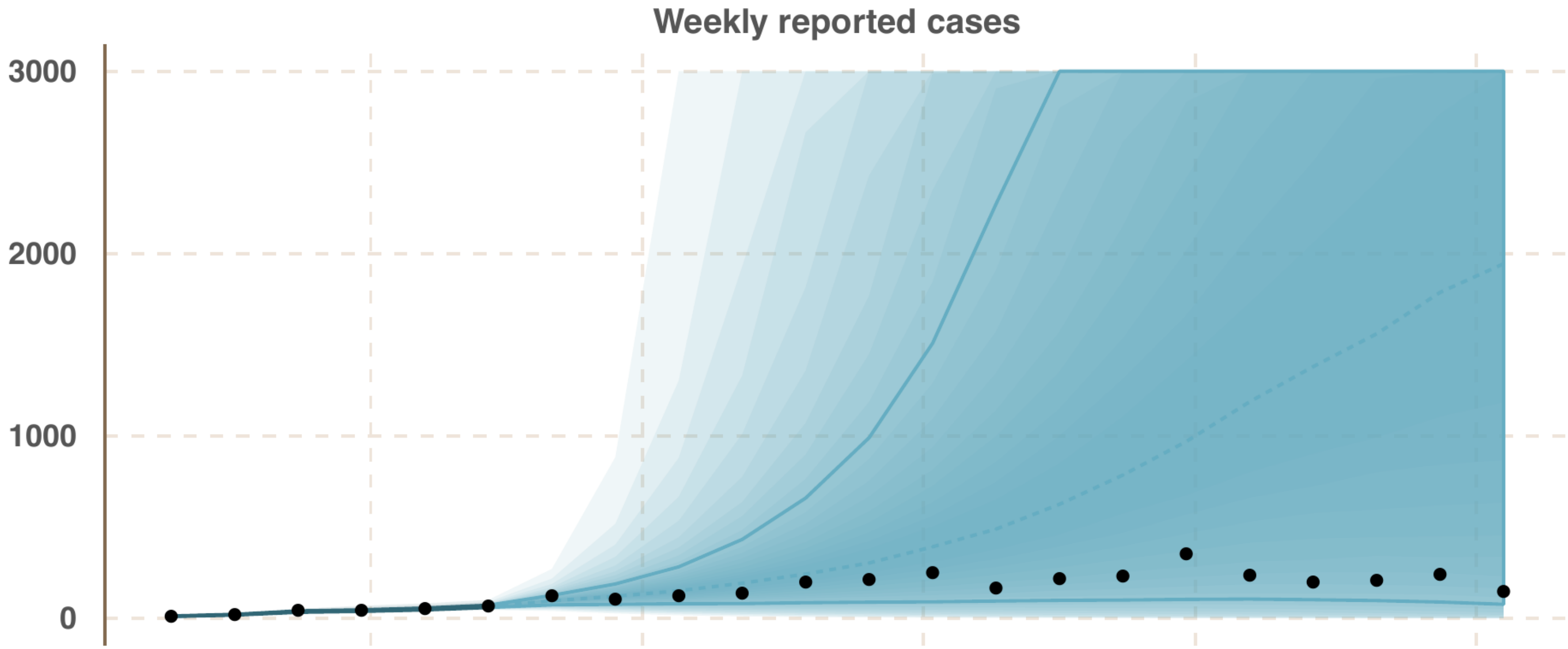

Weekly reported cases
60
40
20
0

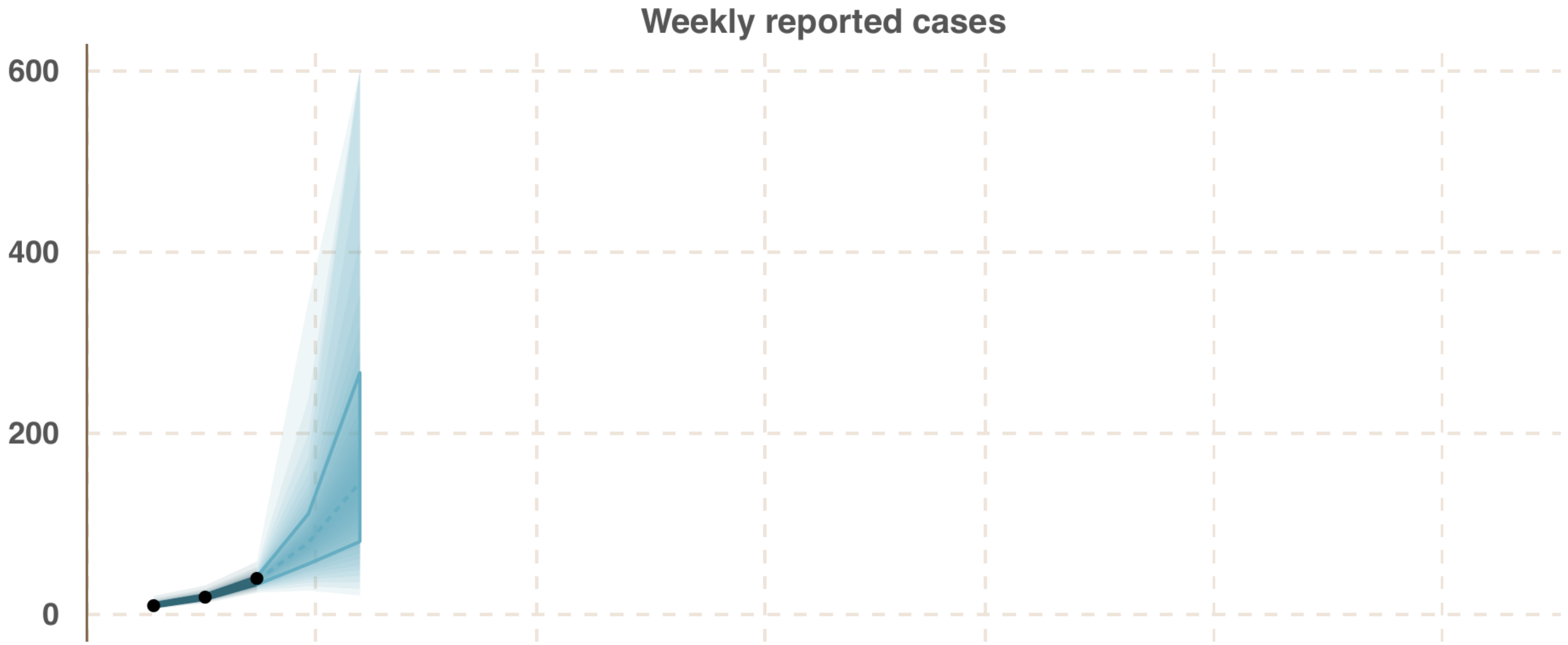


Weekly reported cases
3000
2000
1000
0

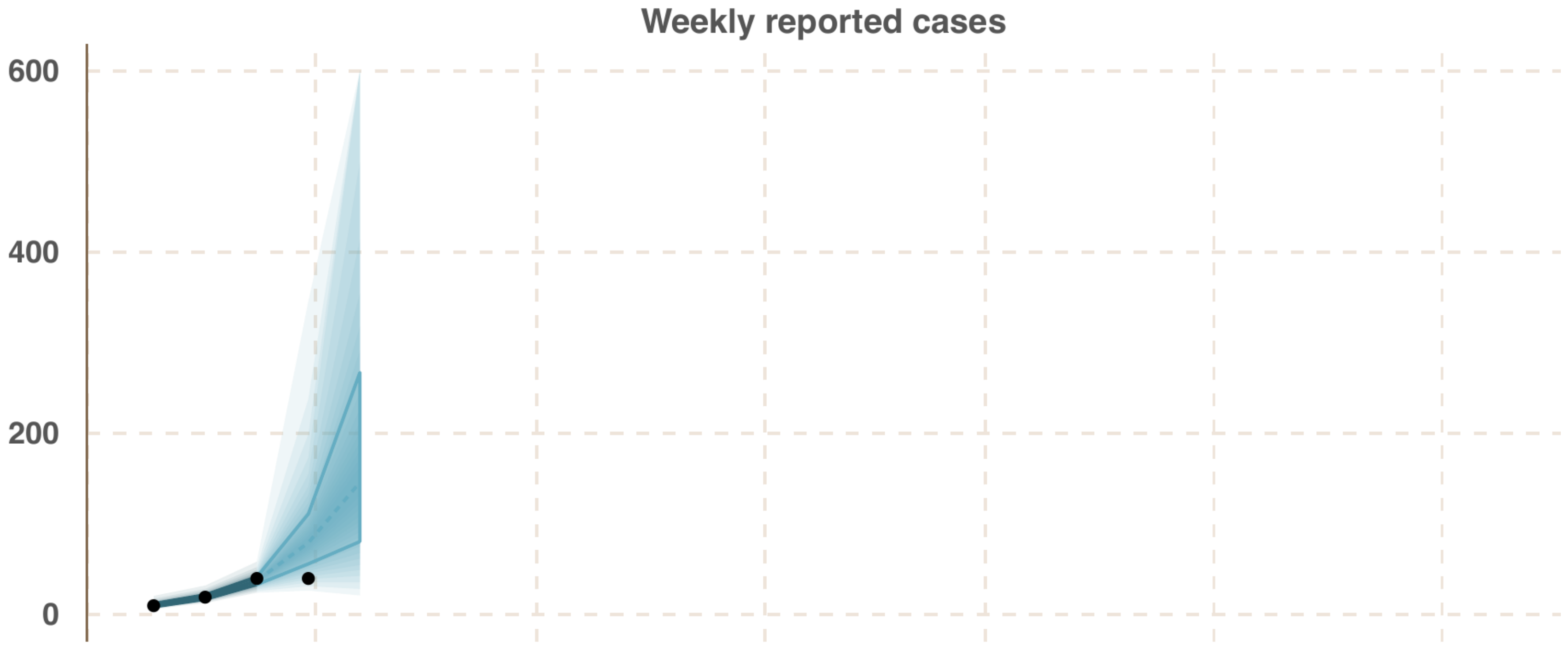


Weekly reported cases
3000
2000
1000
0


Weekly reported cases
3000
2000
1000
0



Weekly reported cases
600
400
200
0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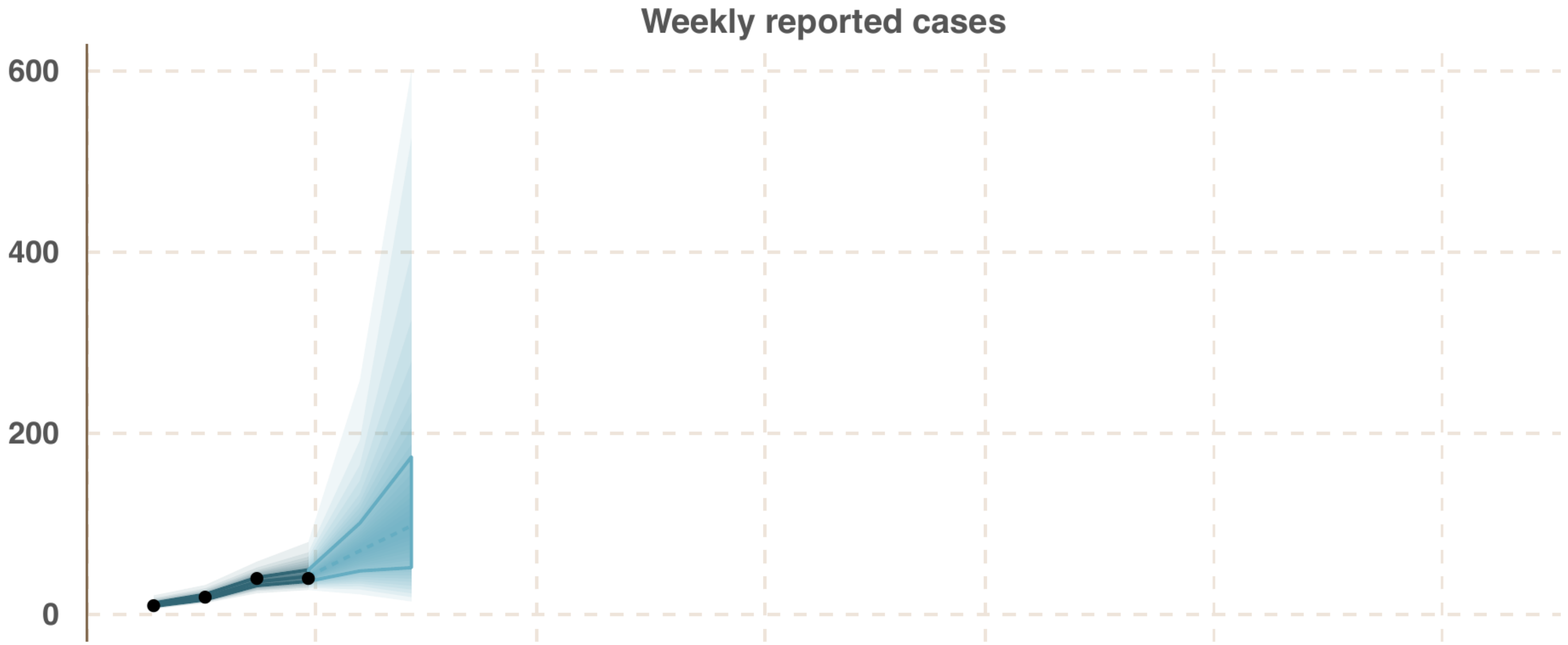
Weekly reported cases
600
400
200
0

Weekly reported cases
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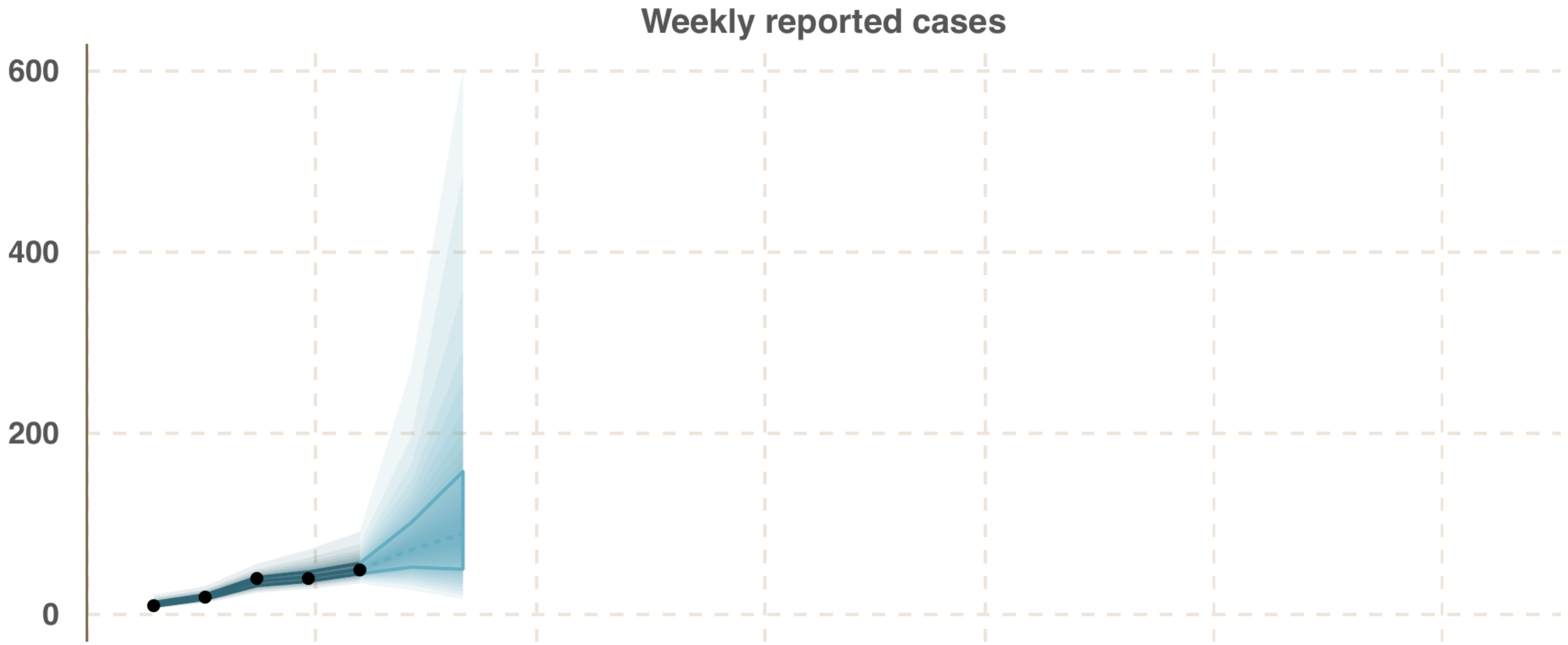
200
0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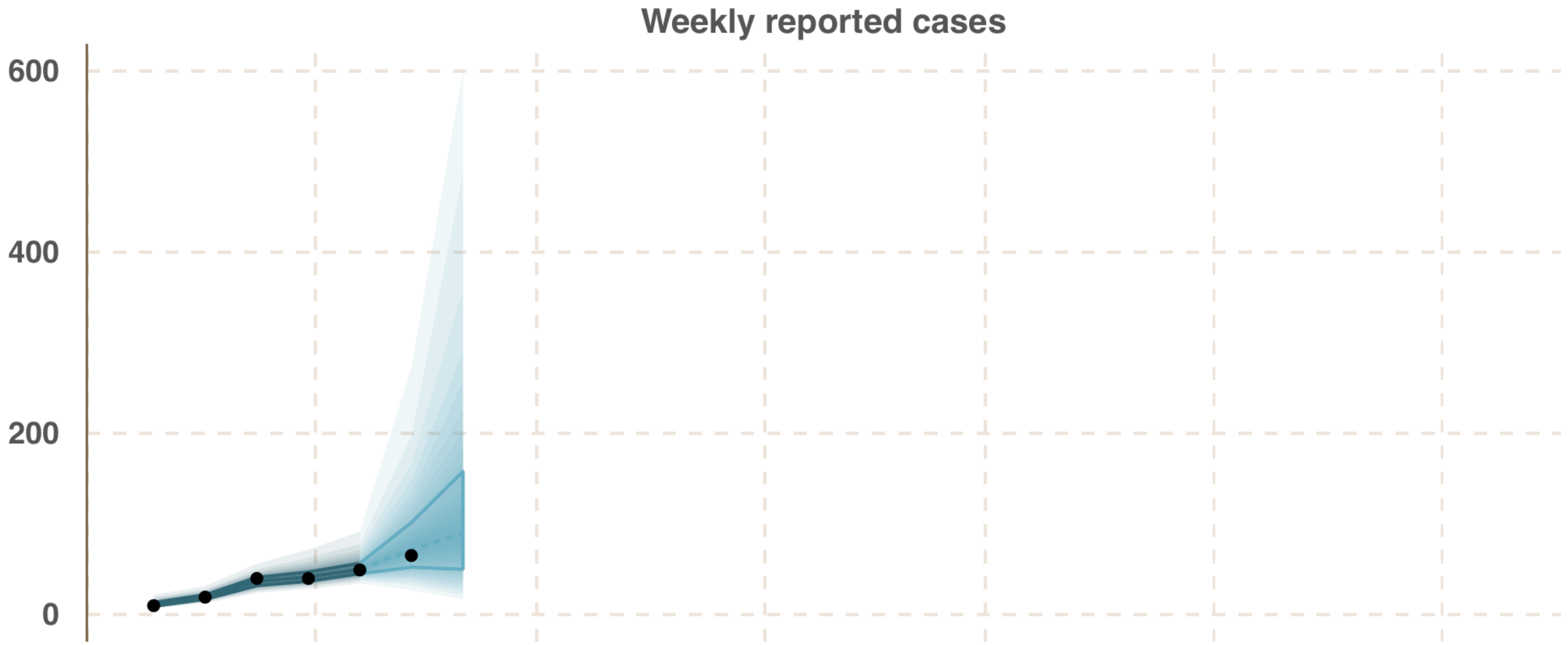

Weekly reported cases
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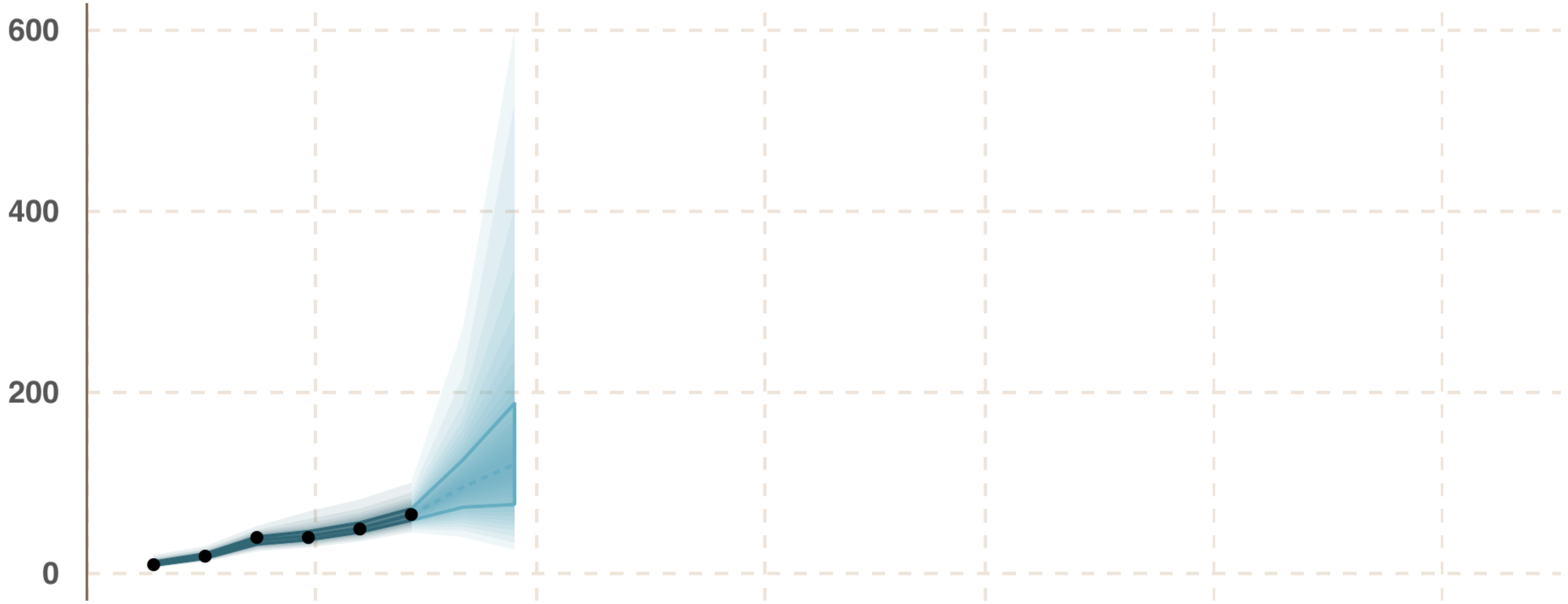
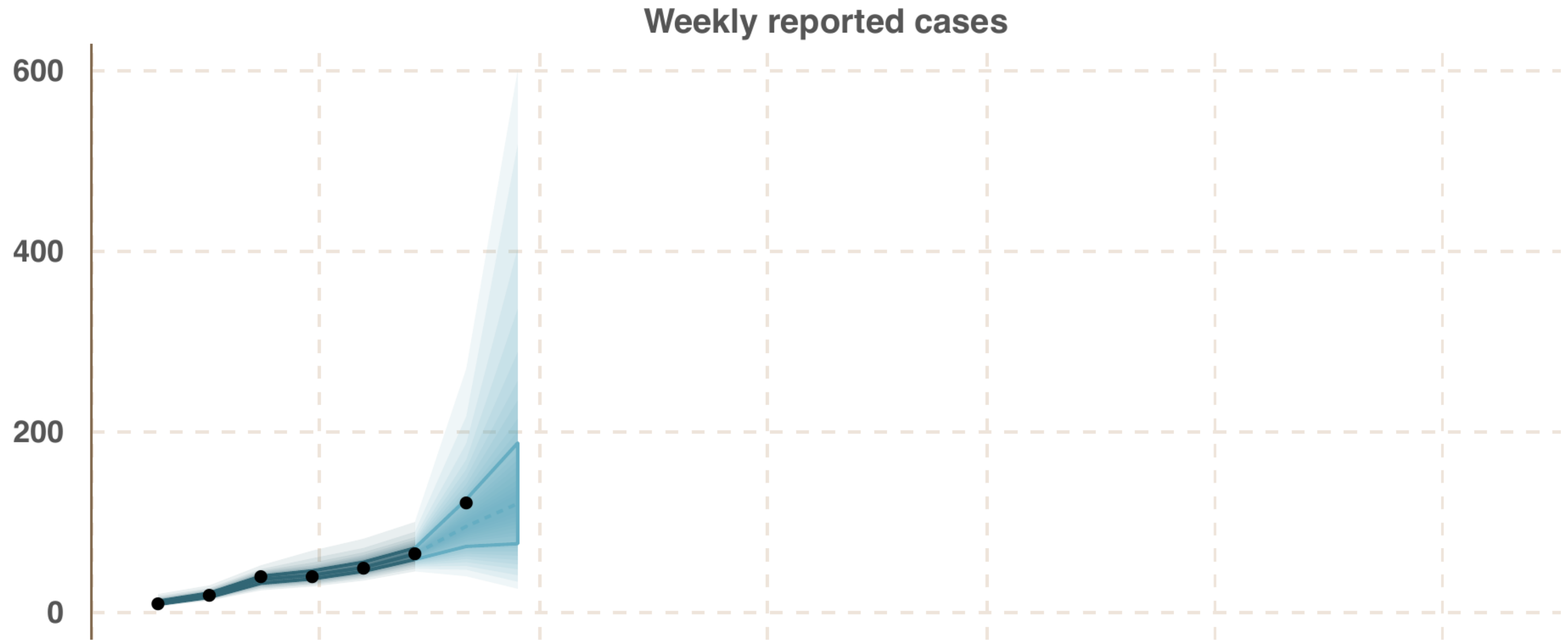
Weekly reported cases




Weekly reported cases
600
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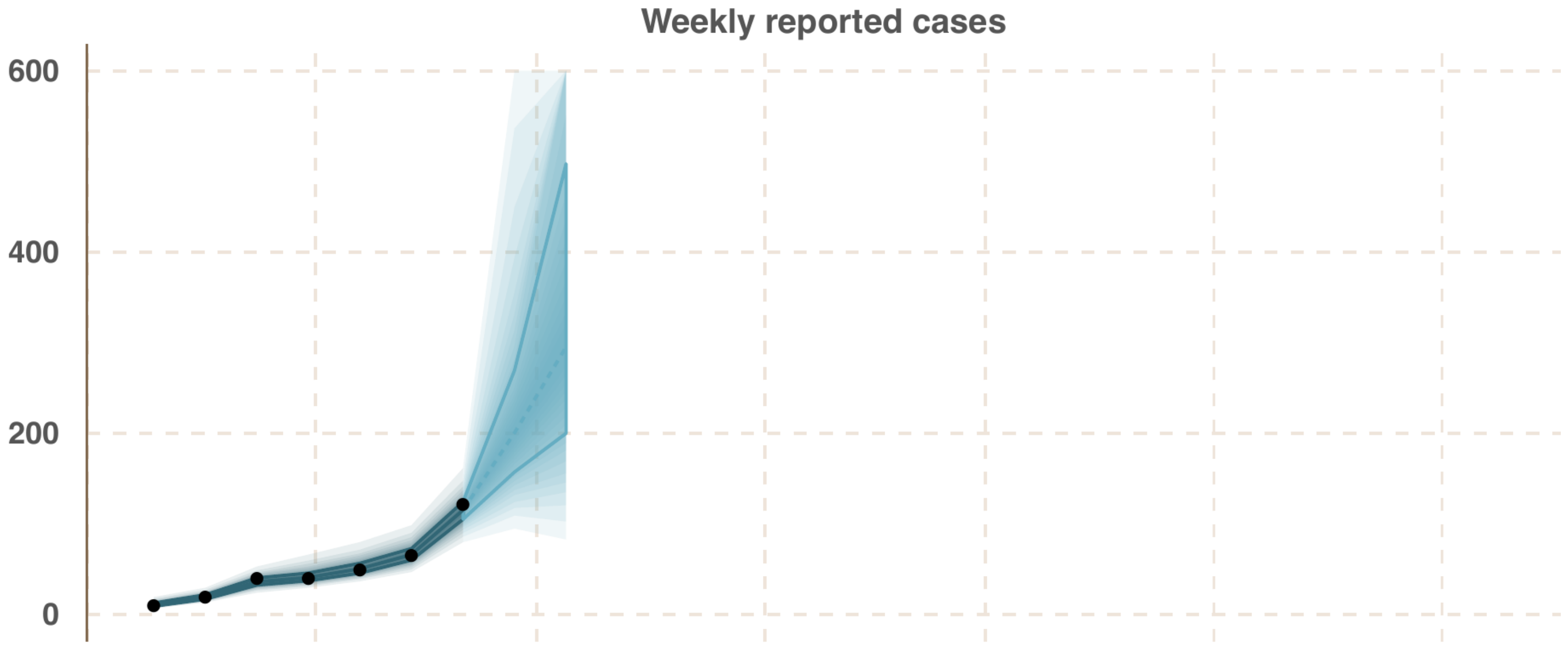
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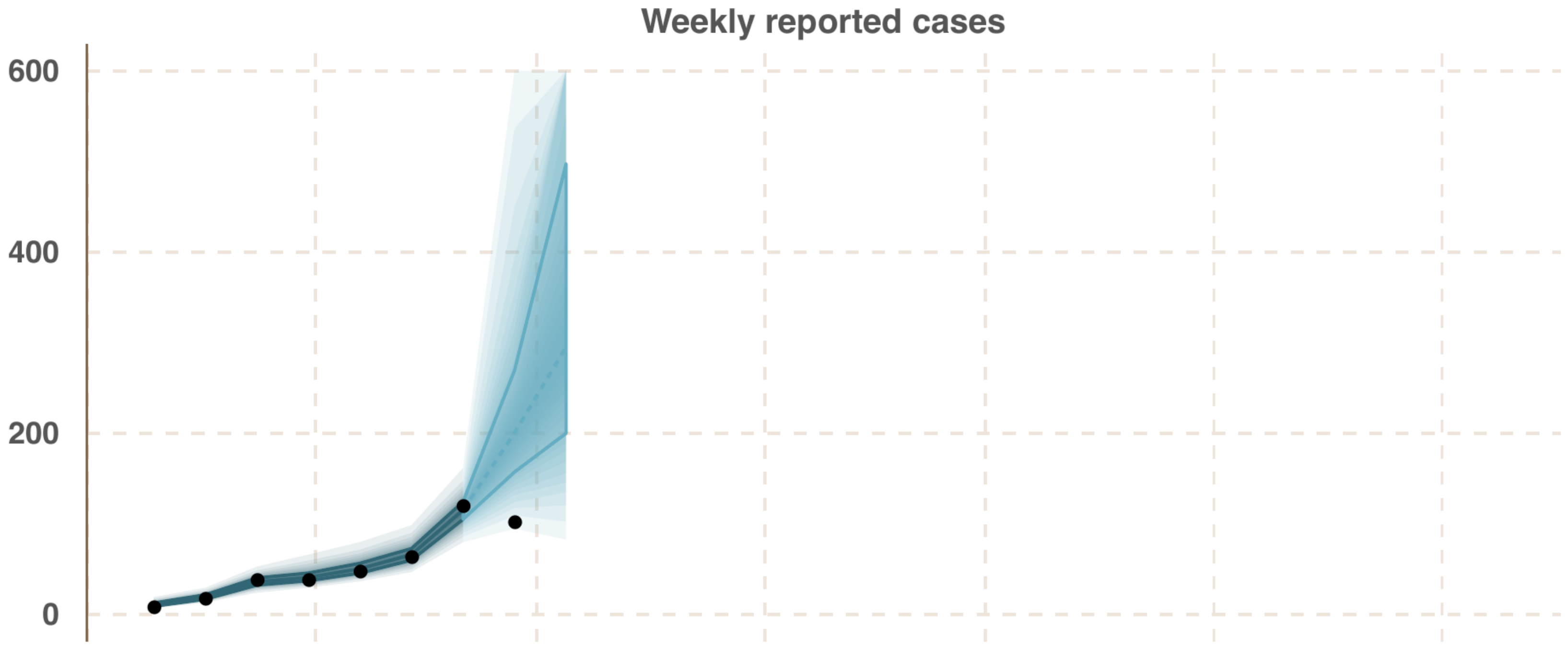

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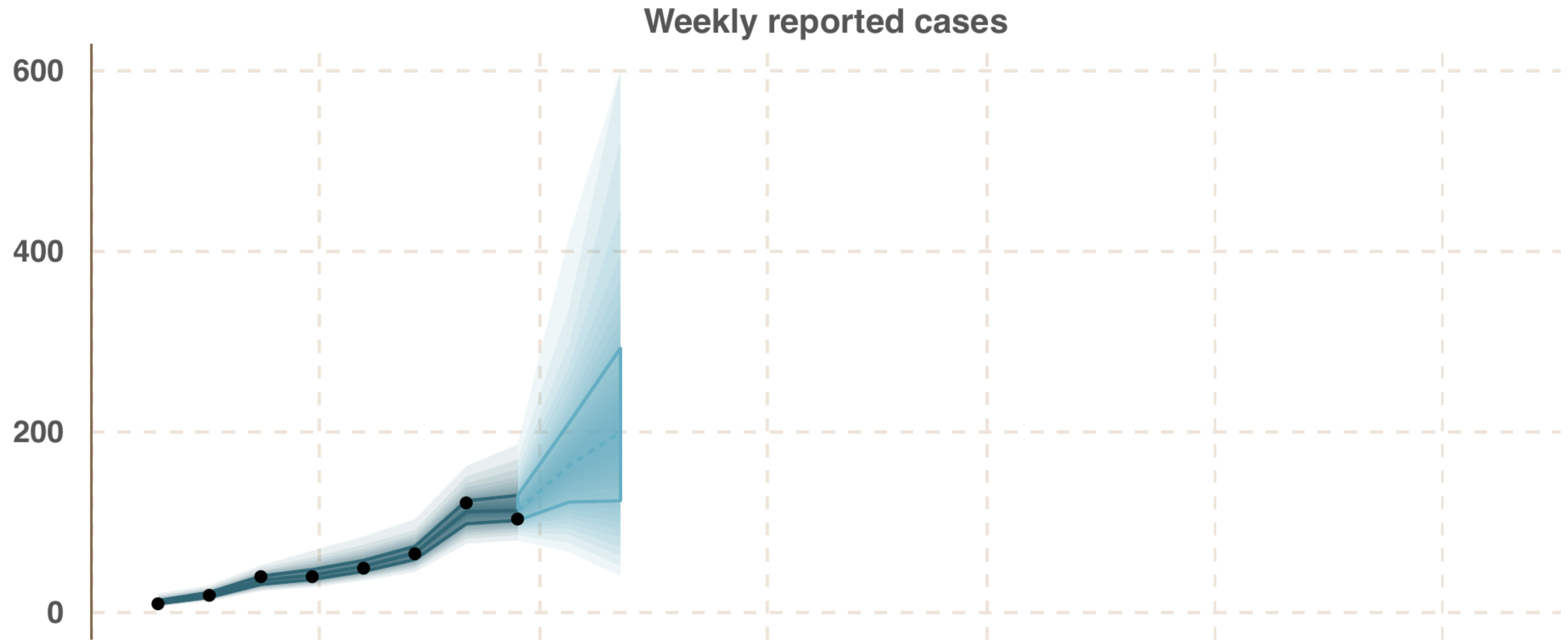
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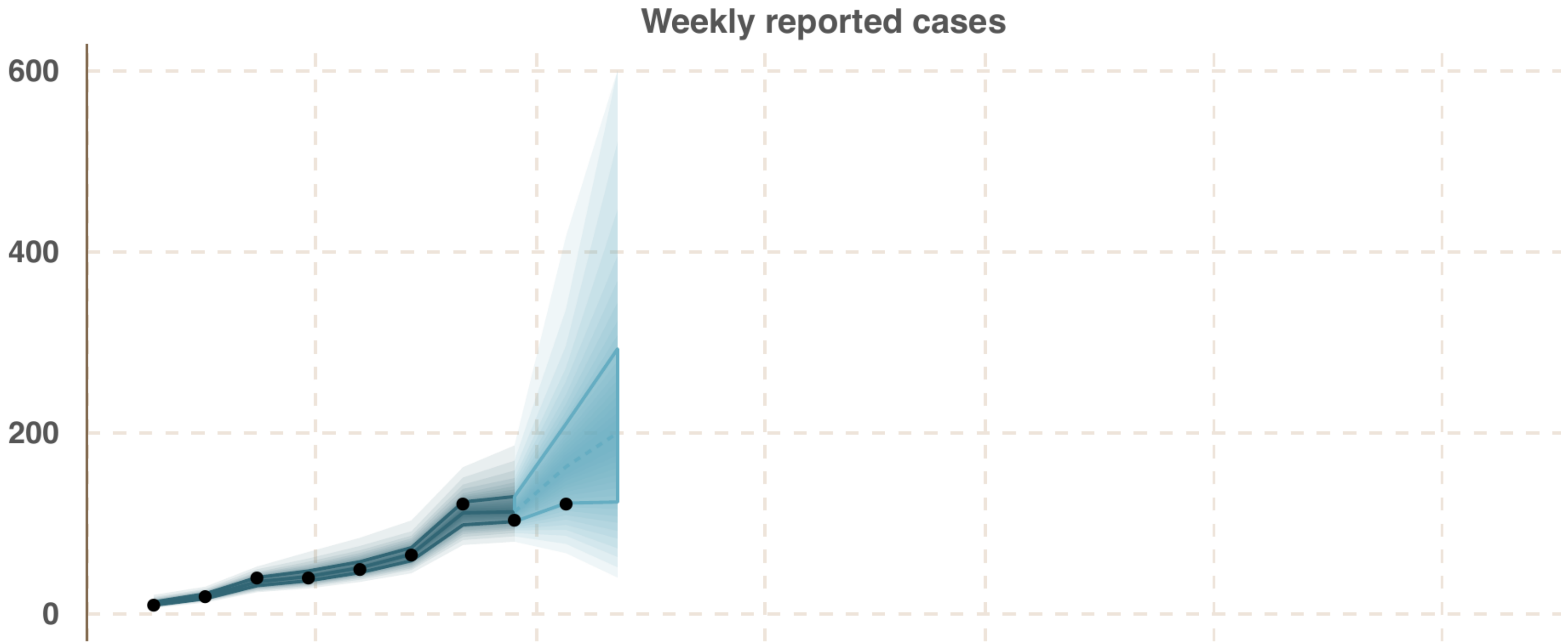

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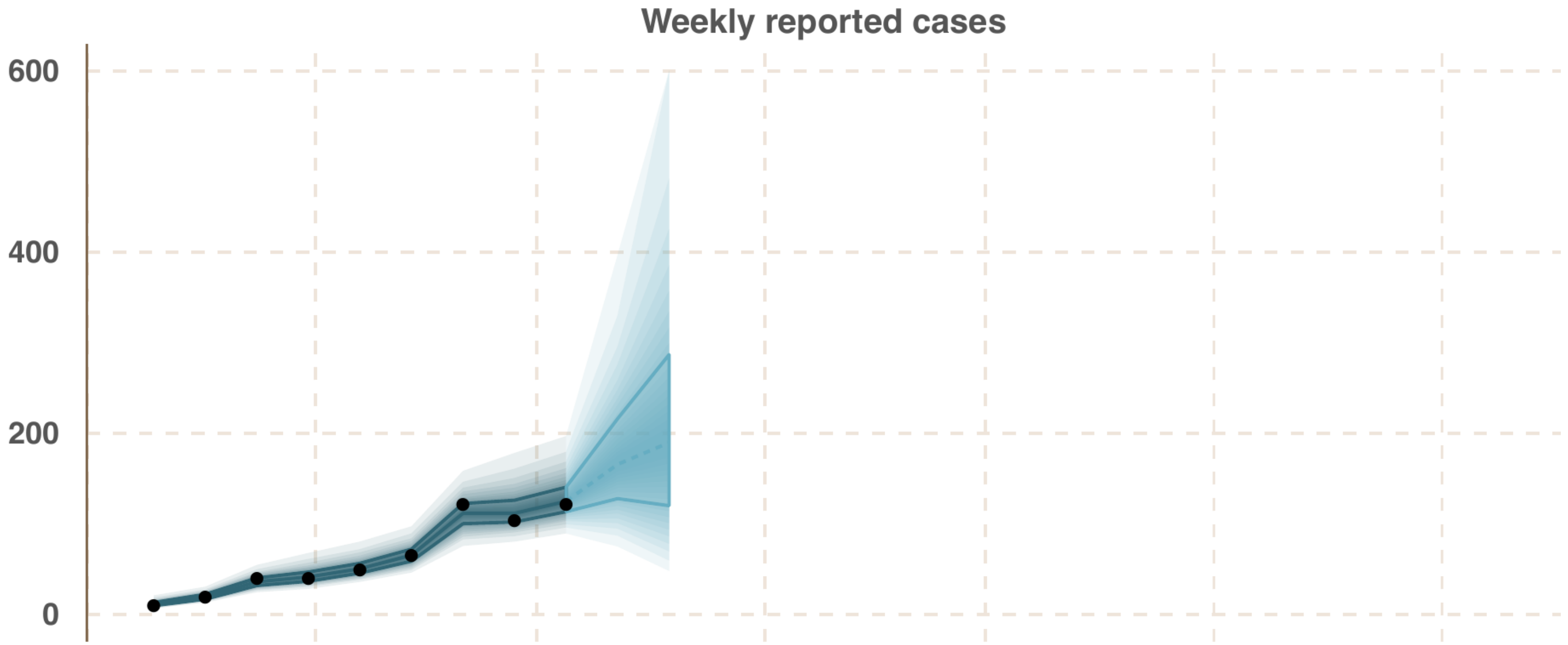
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600
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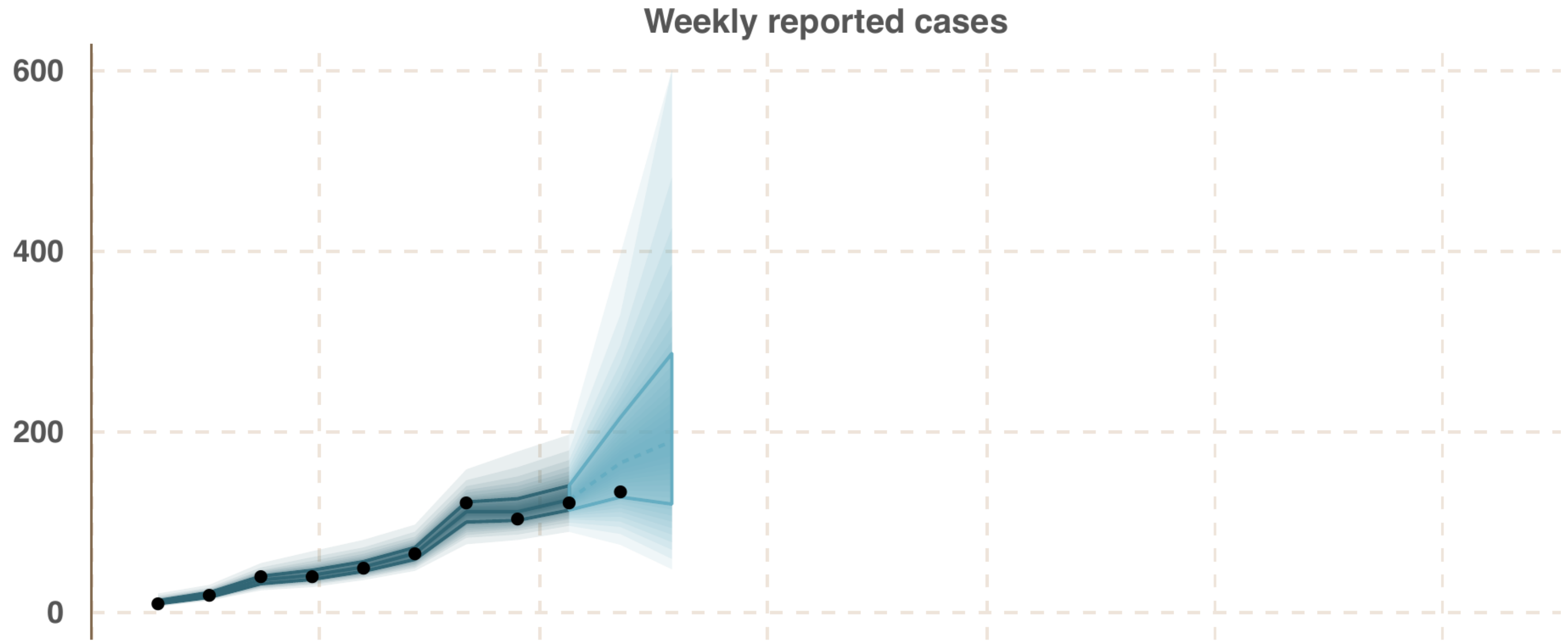
Weekly reported cases
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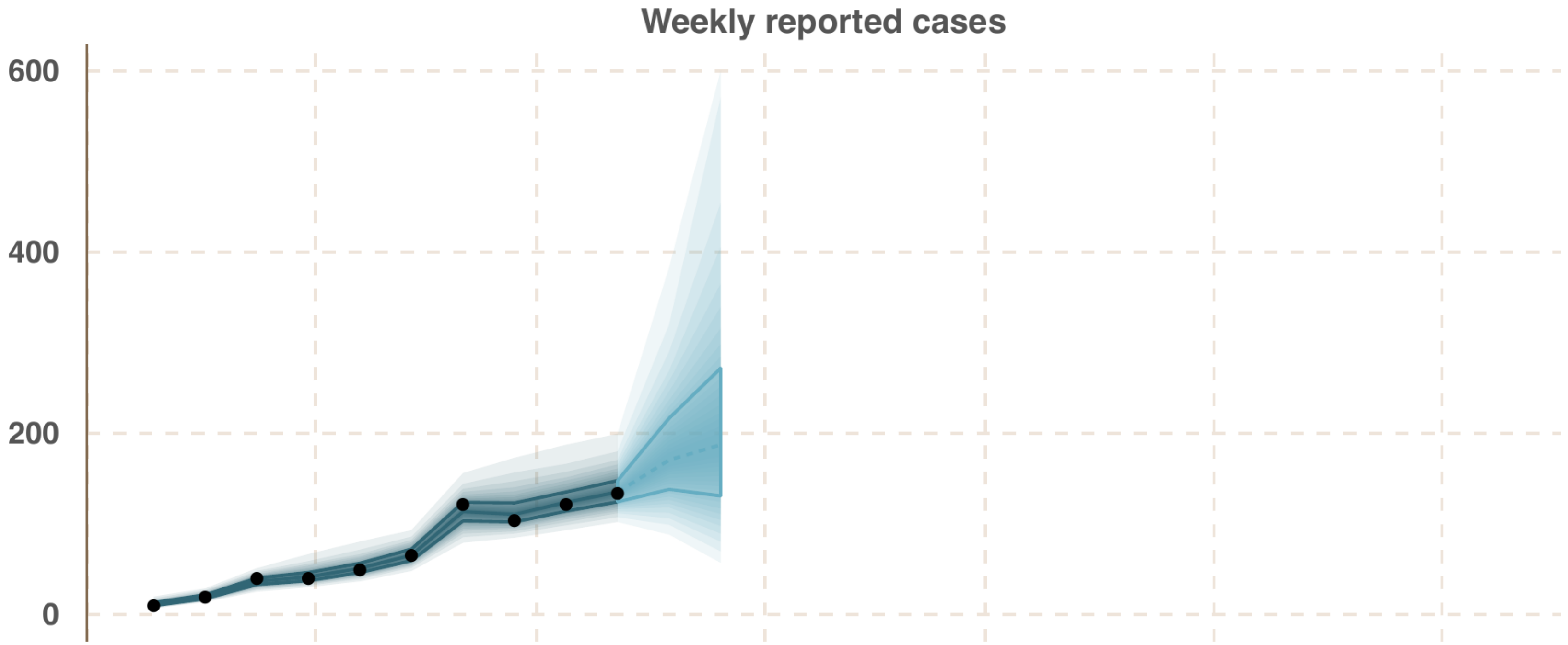
Weekly reported cases
600
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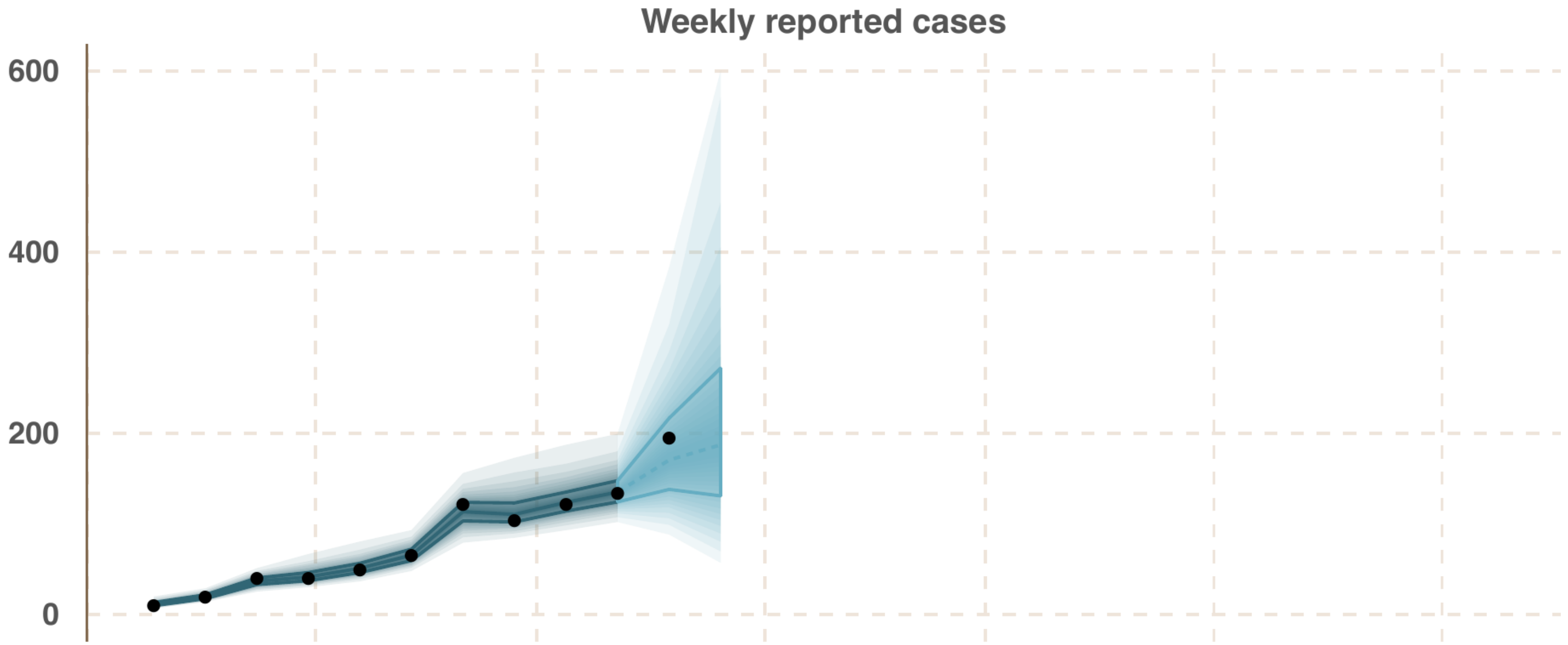
Weekly reported cases
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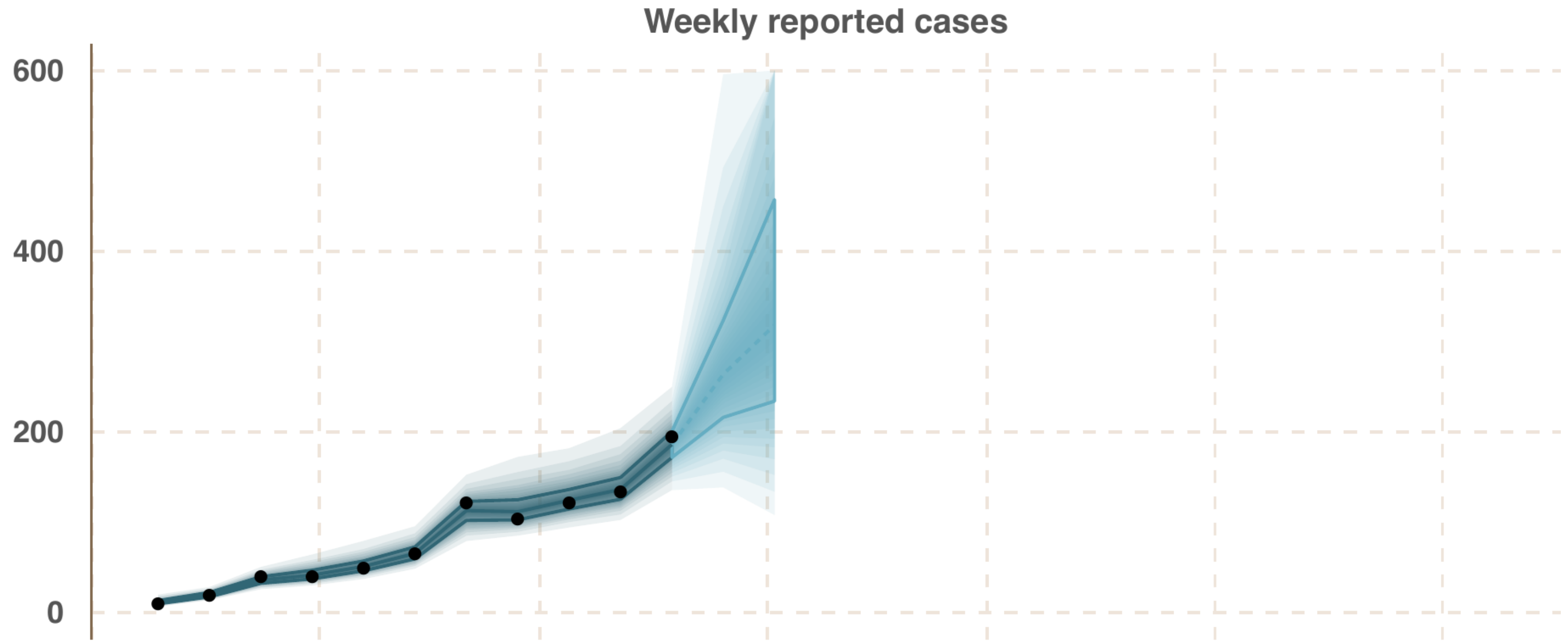
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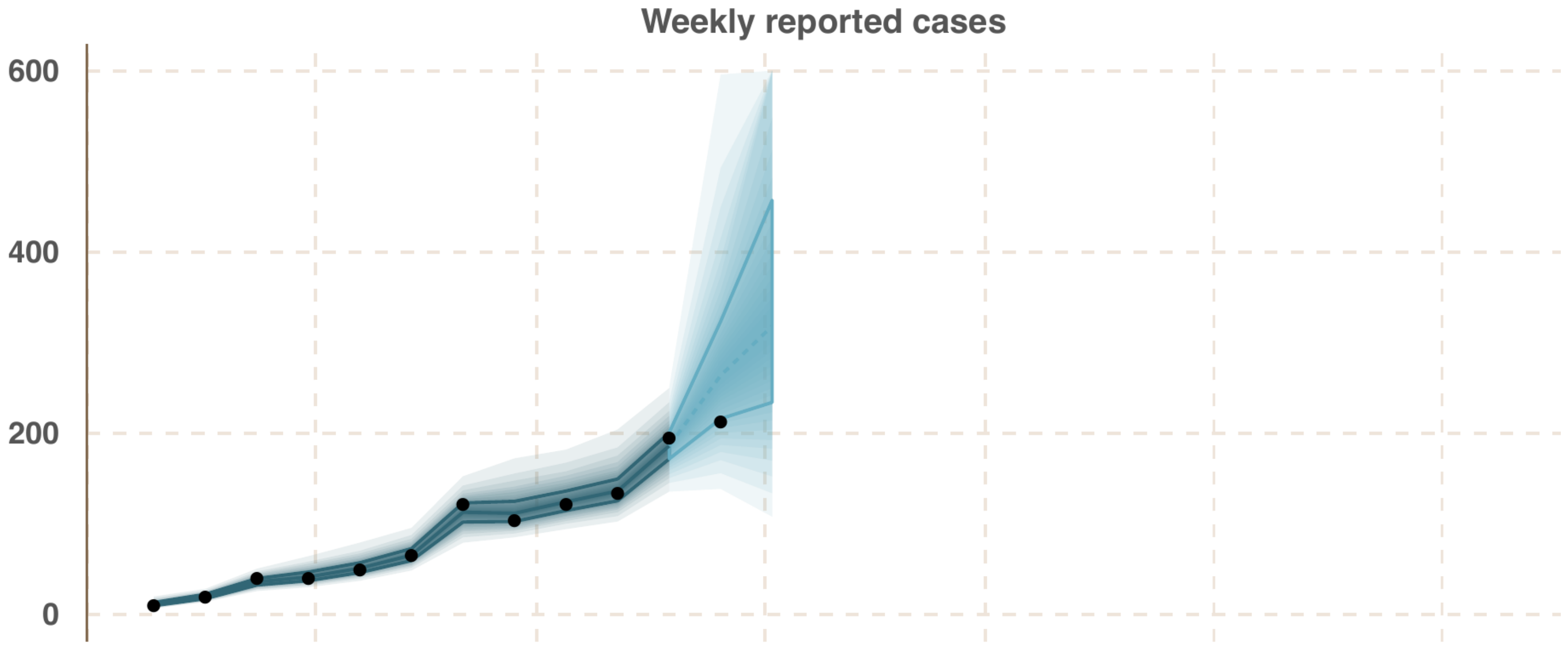
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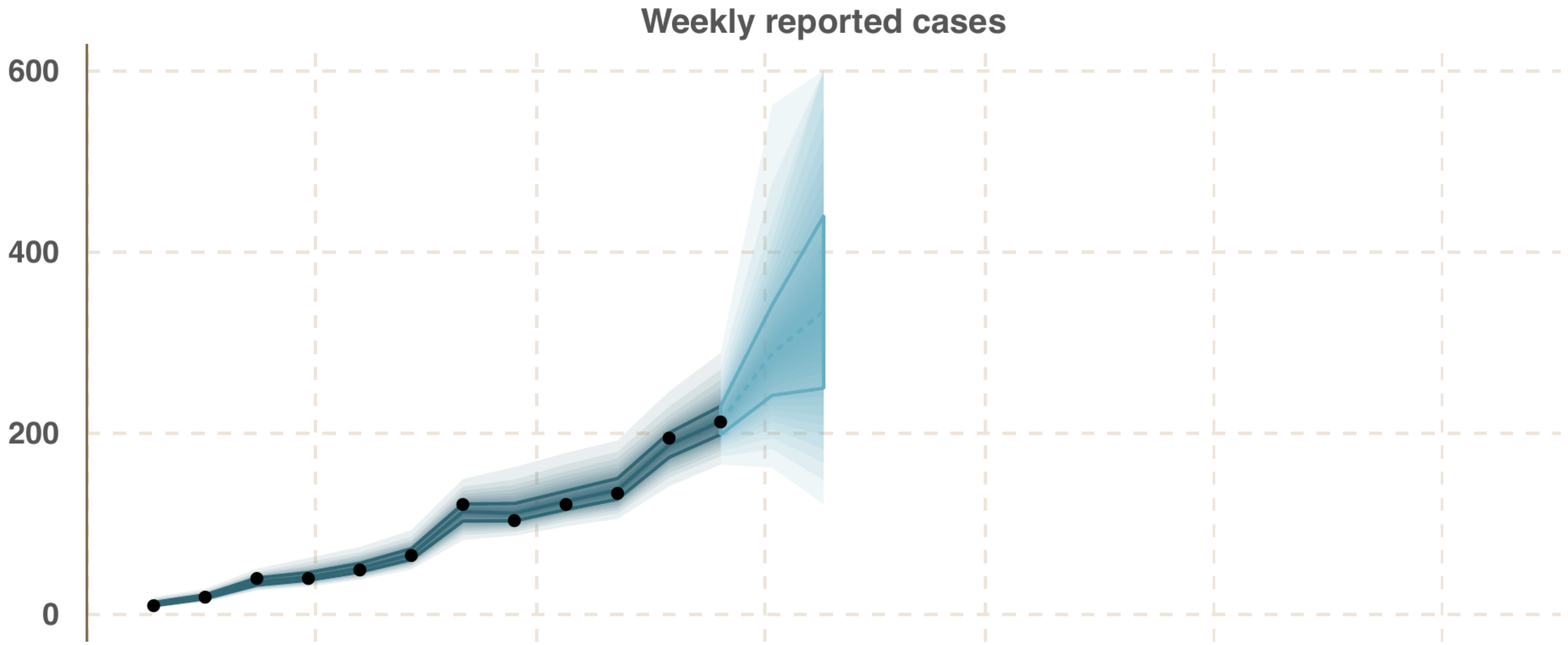
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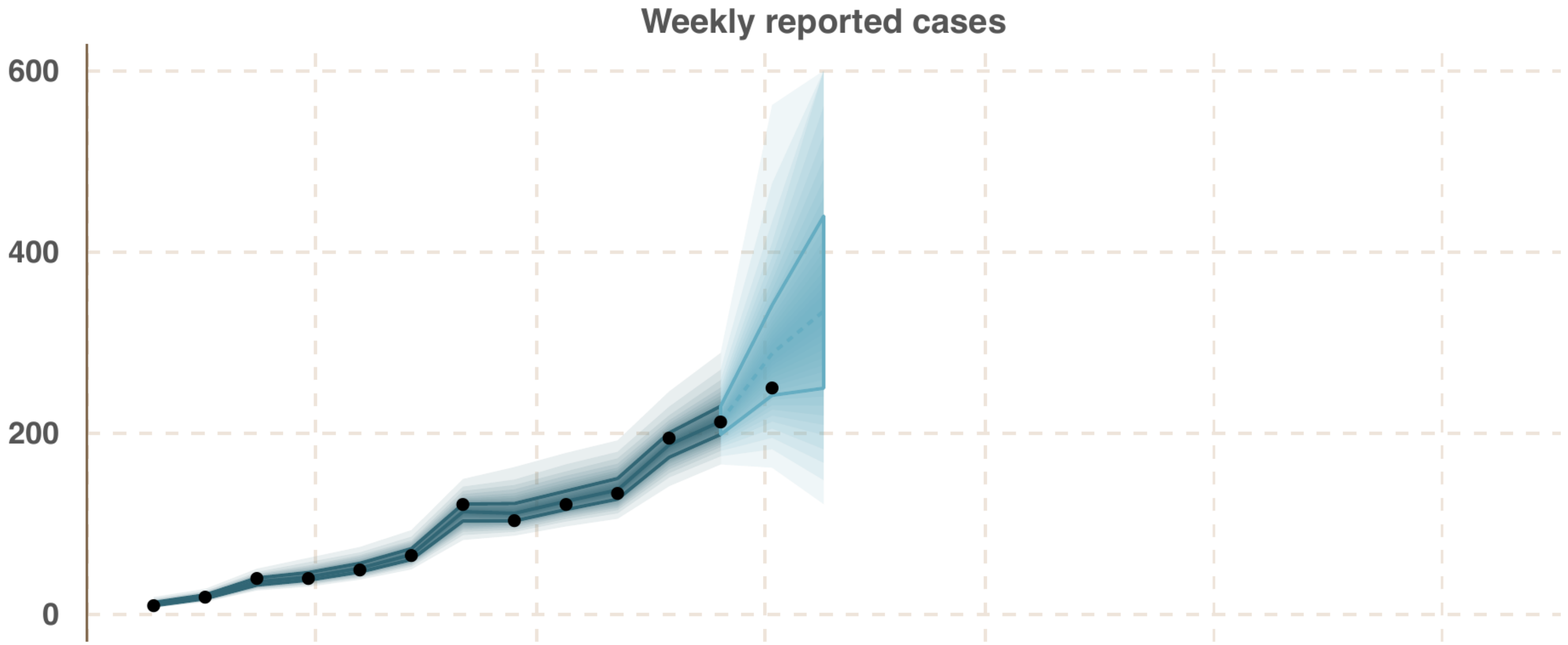

Weekly reported cases
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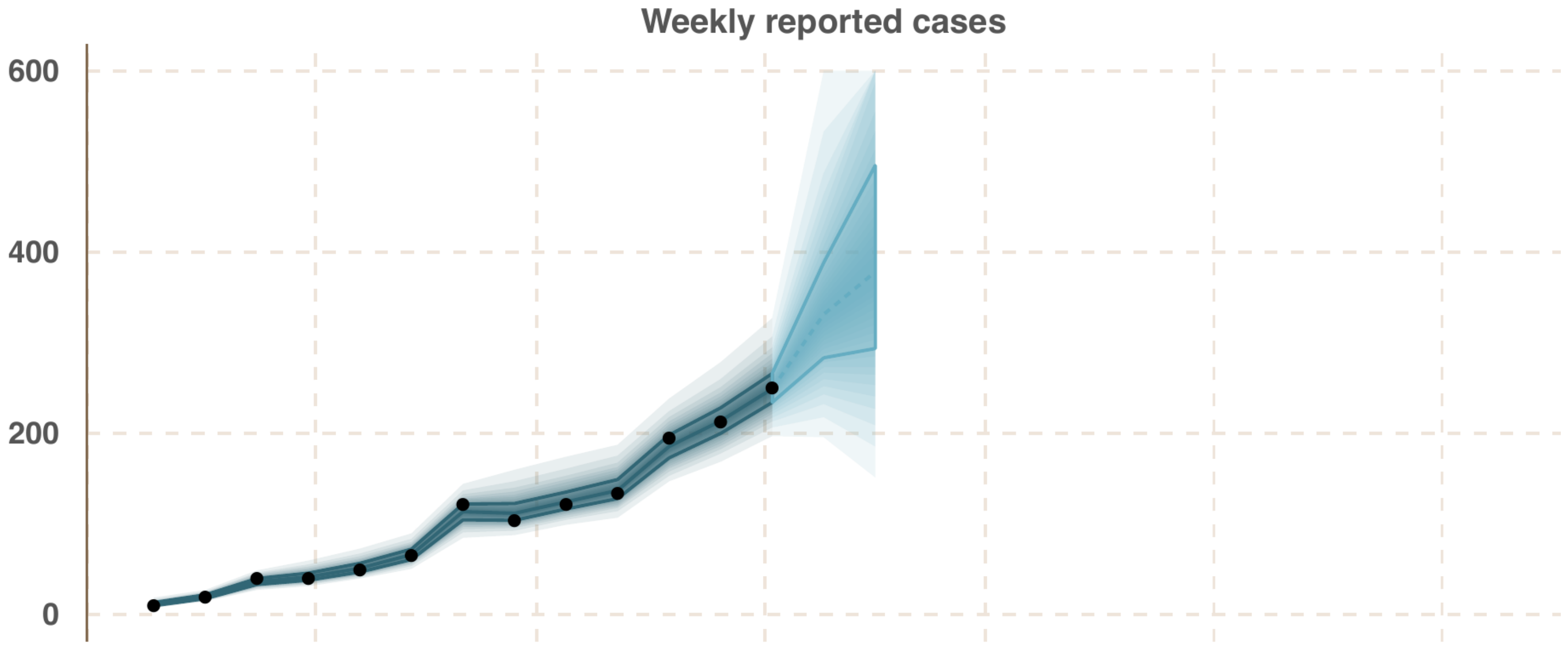

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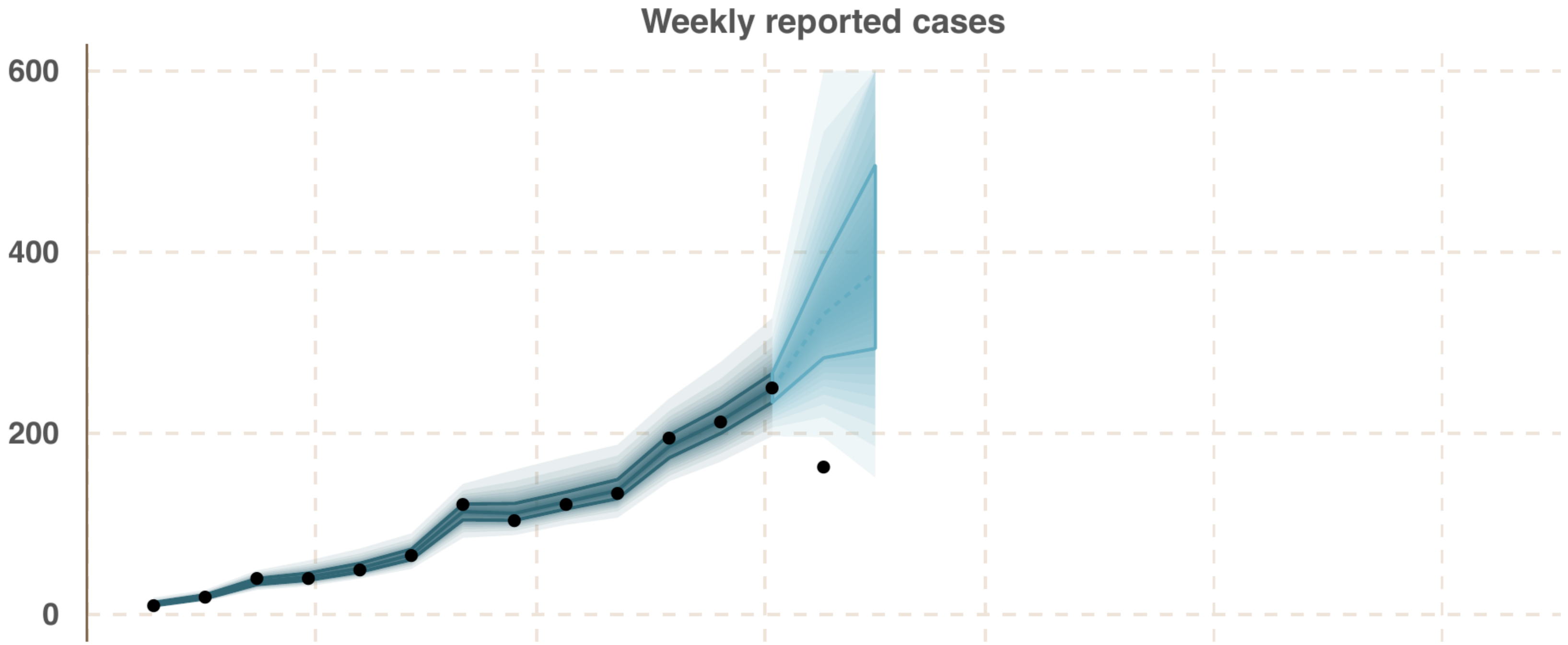
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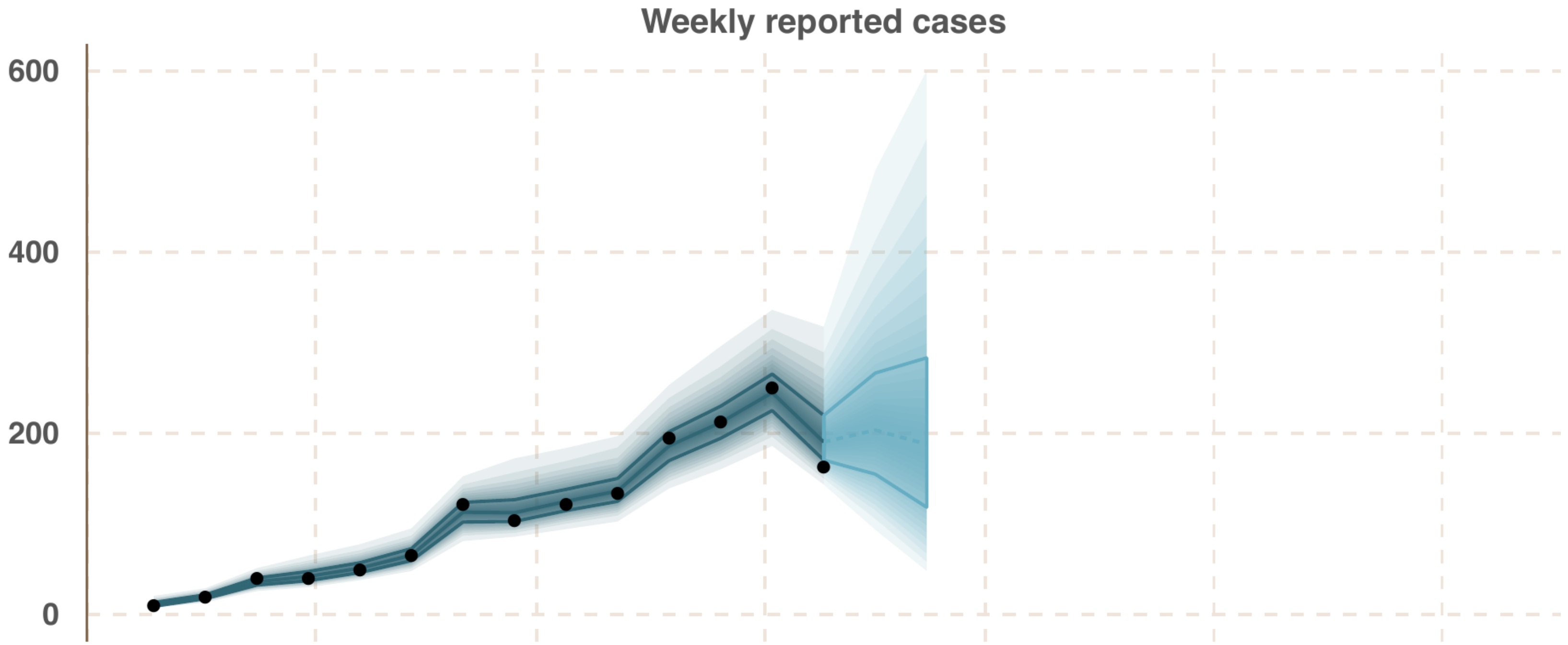
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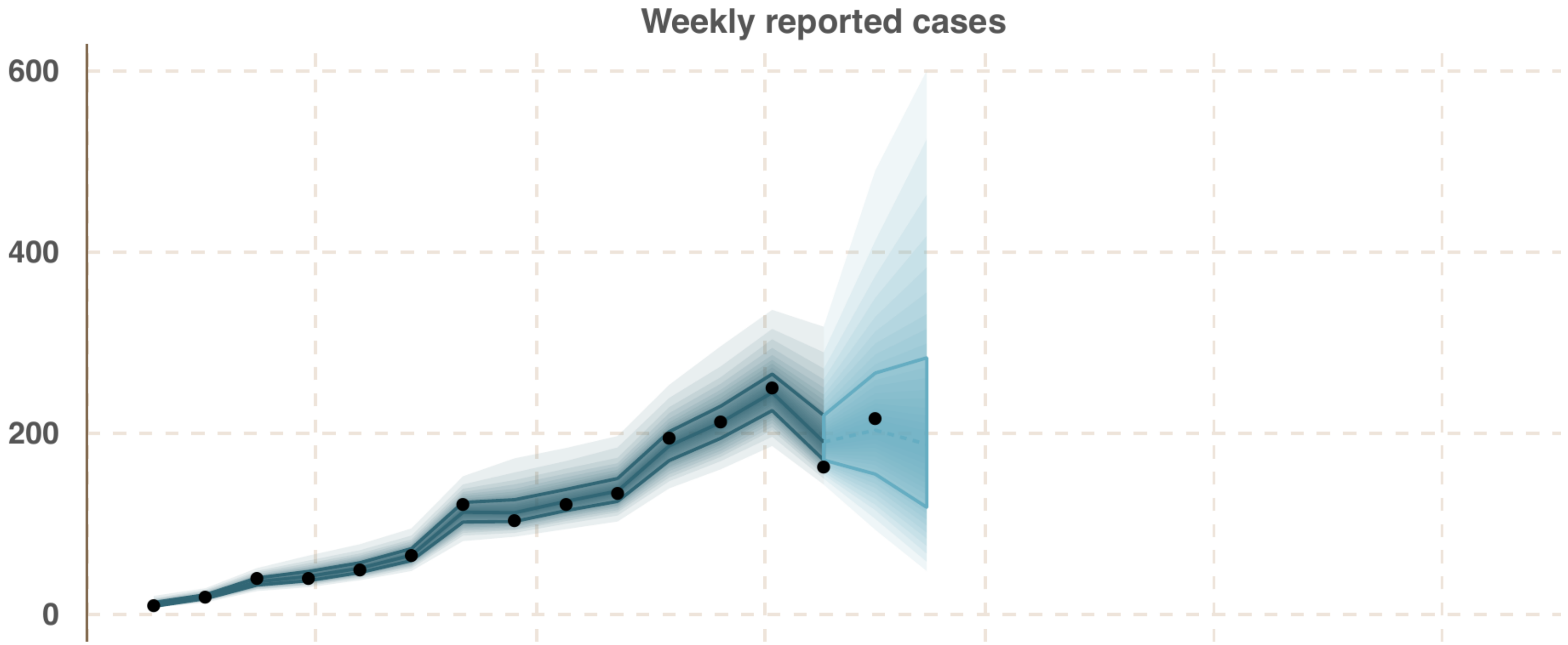

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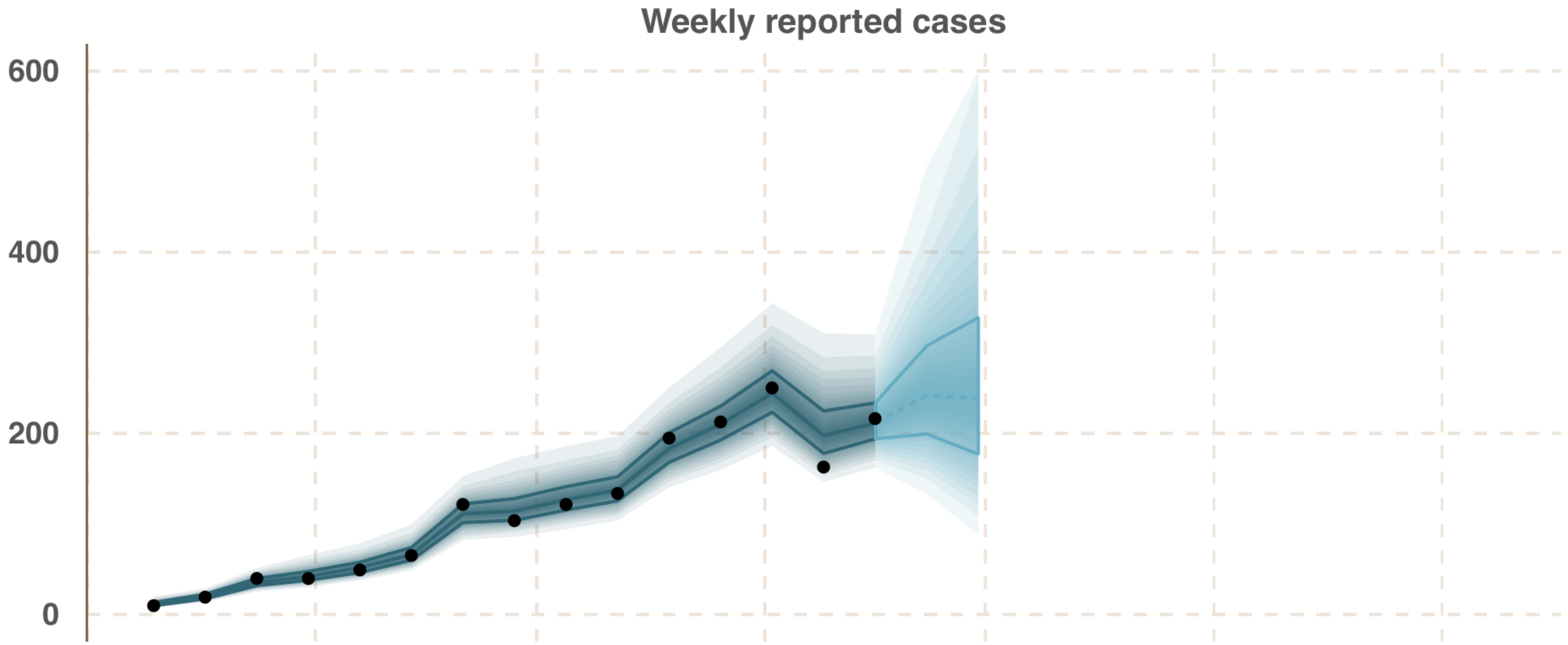

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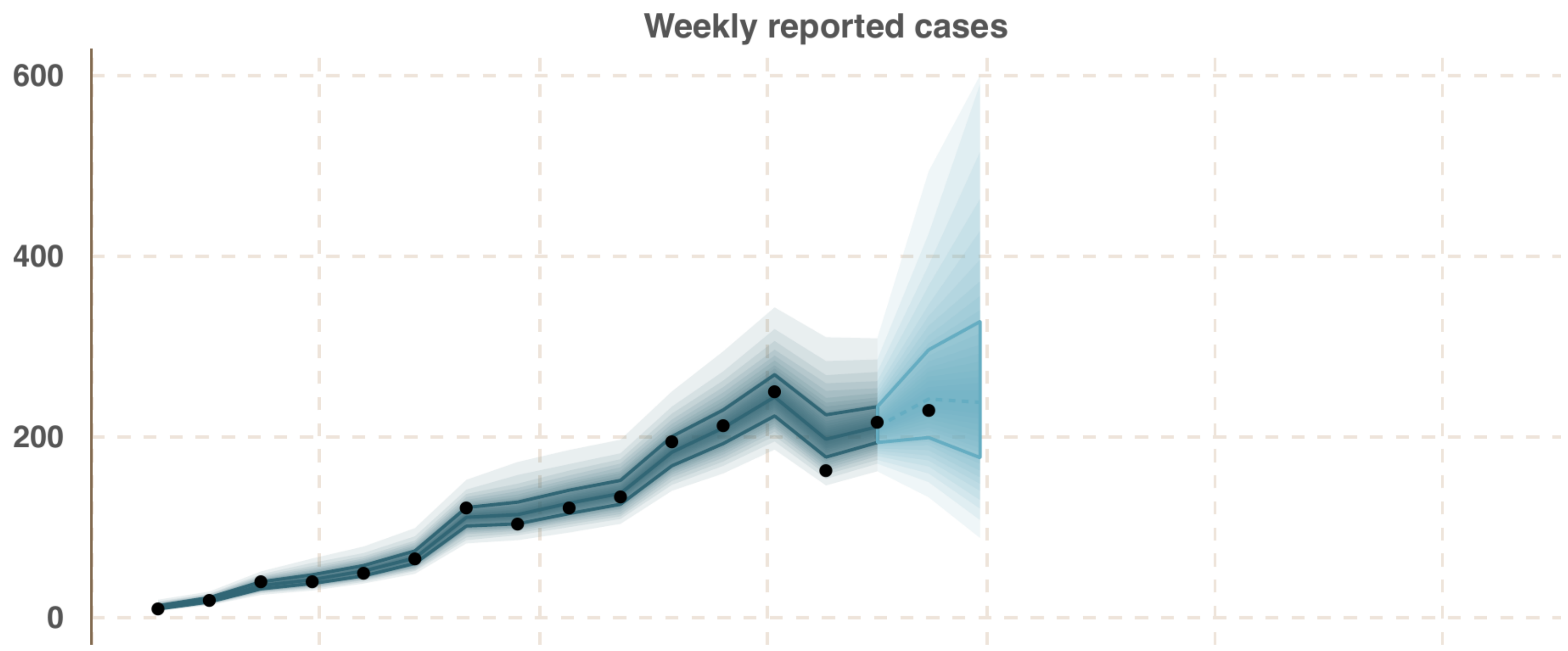
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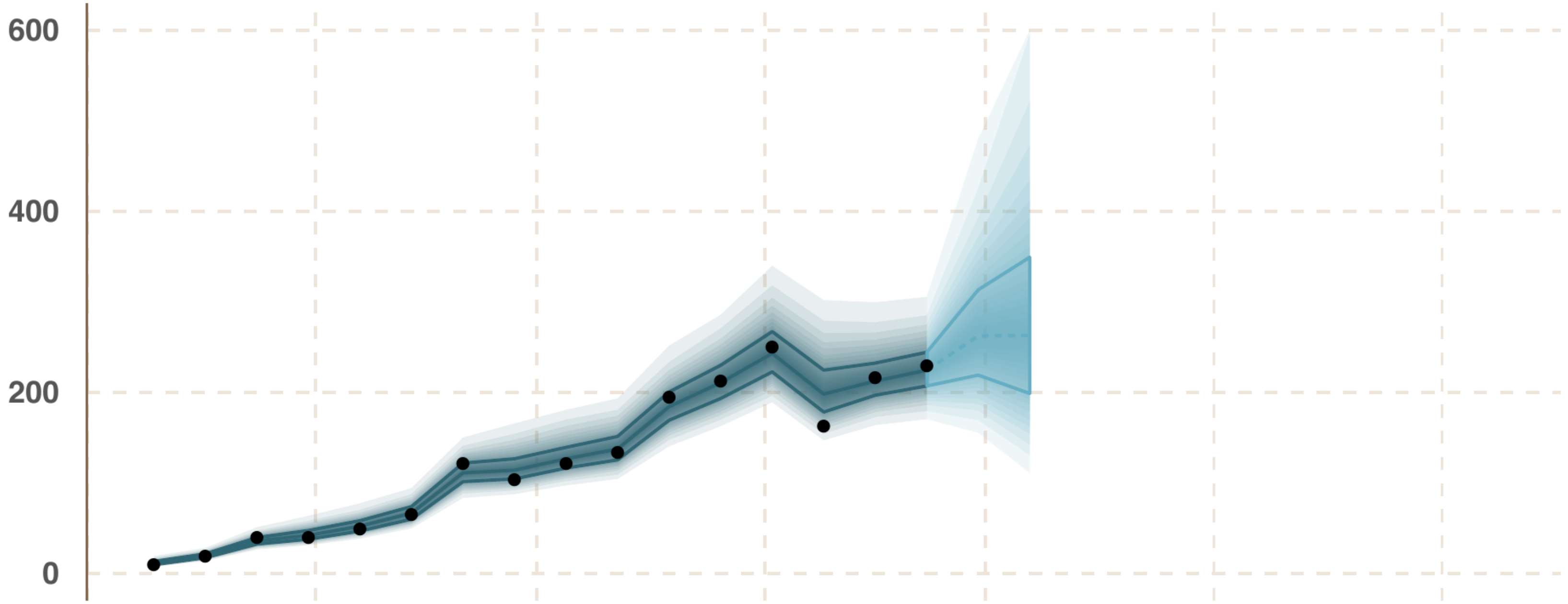

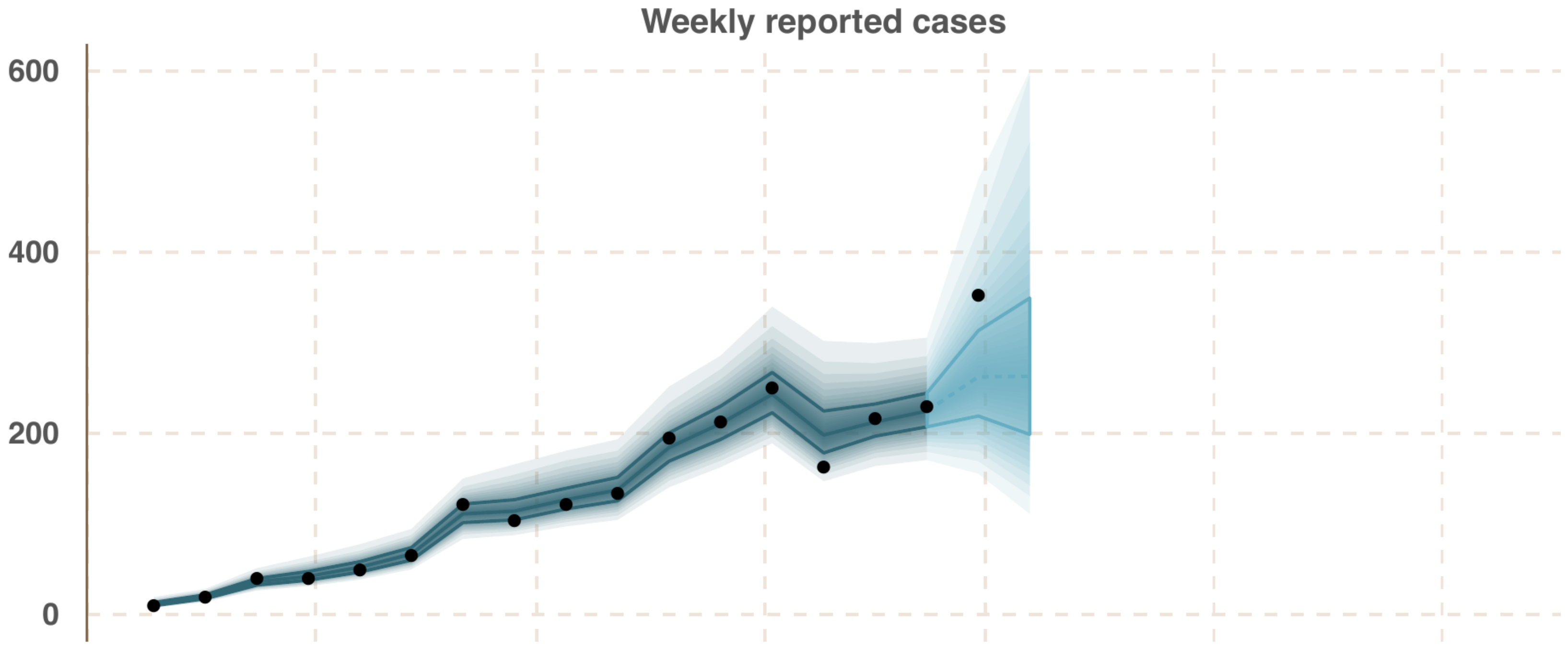
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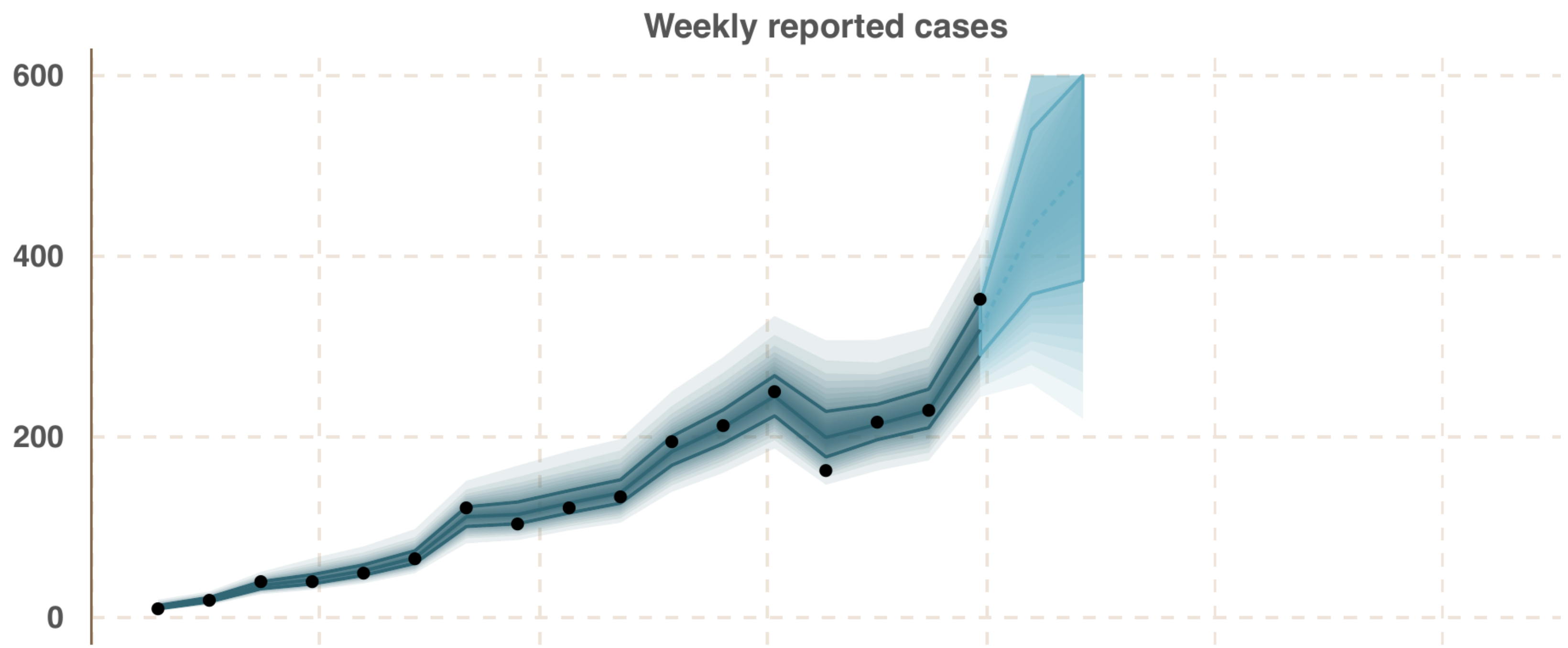

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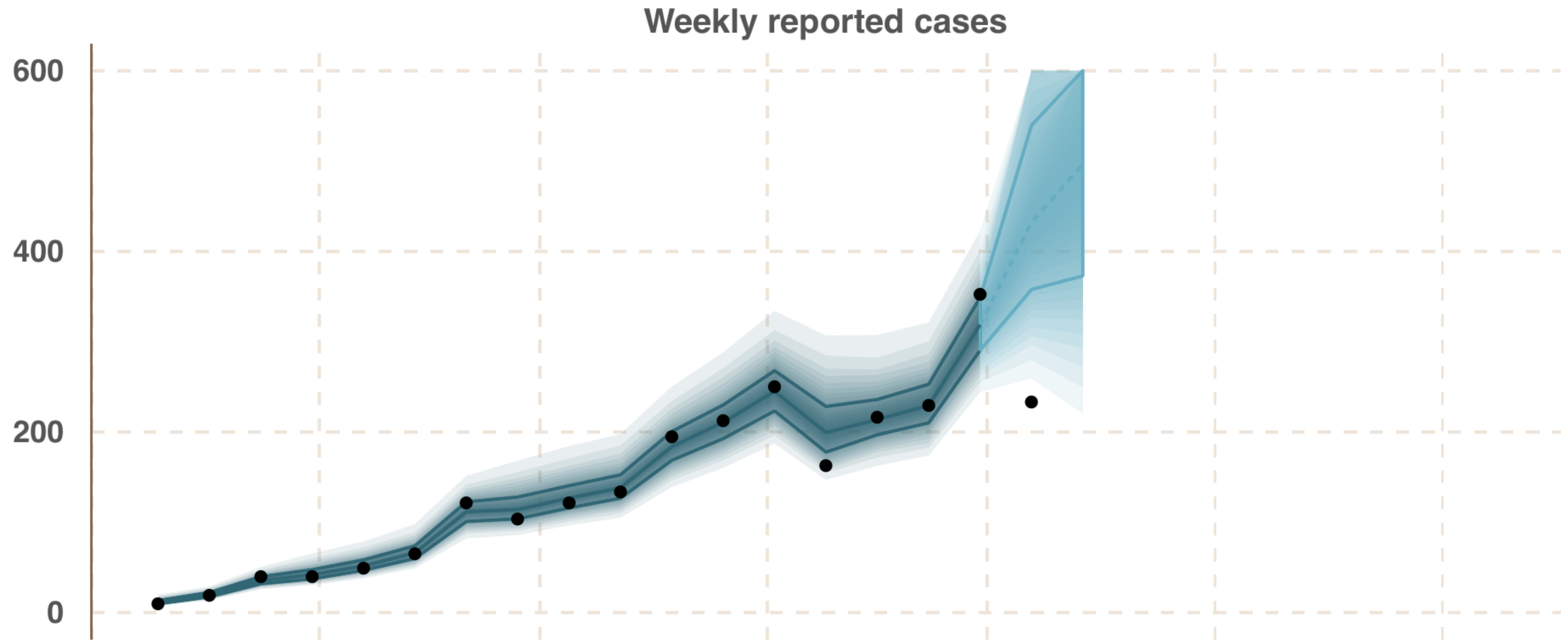
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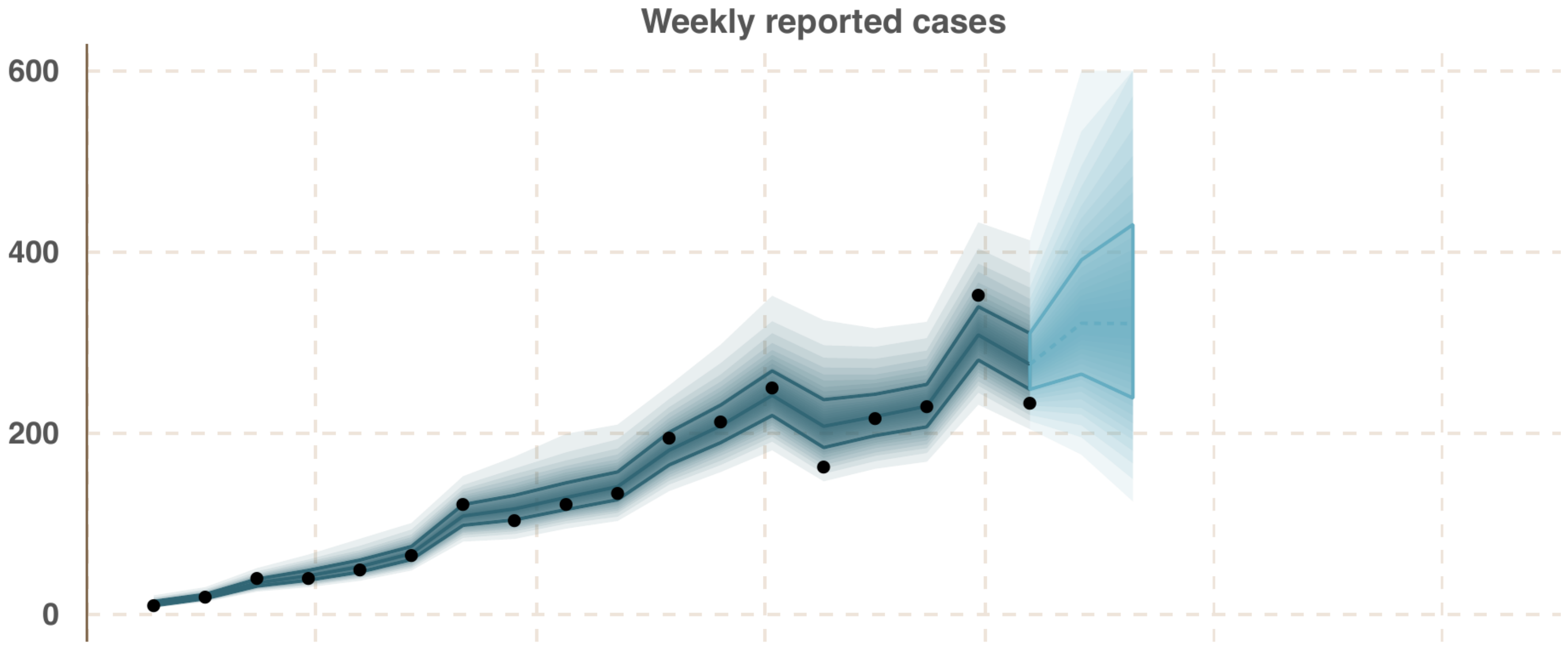
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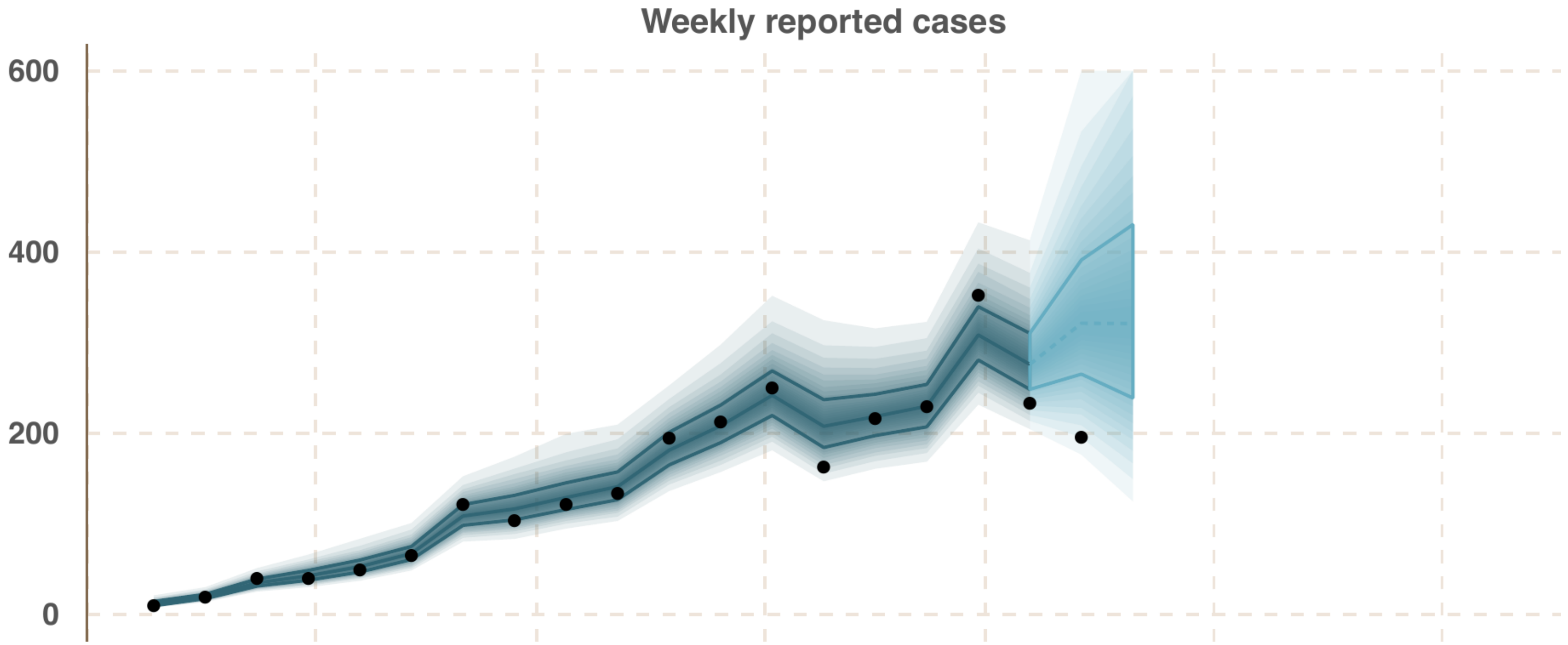
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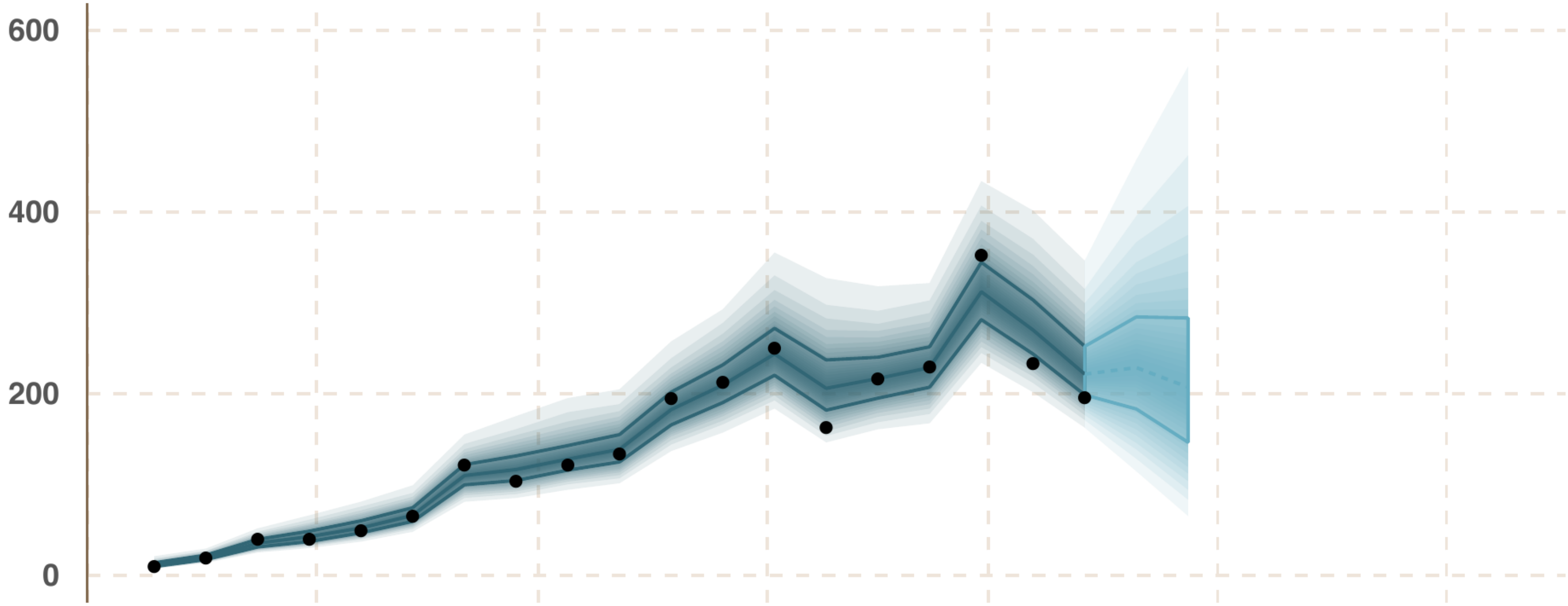
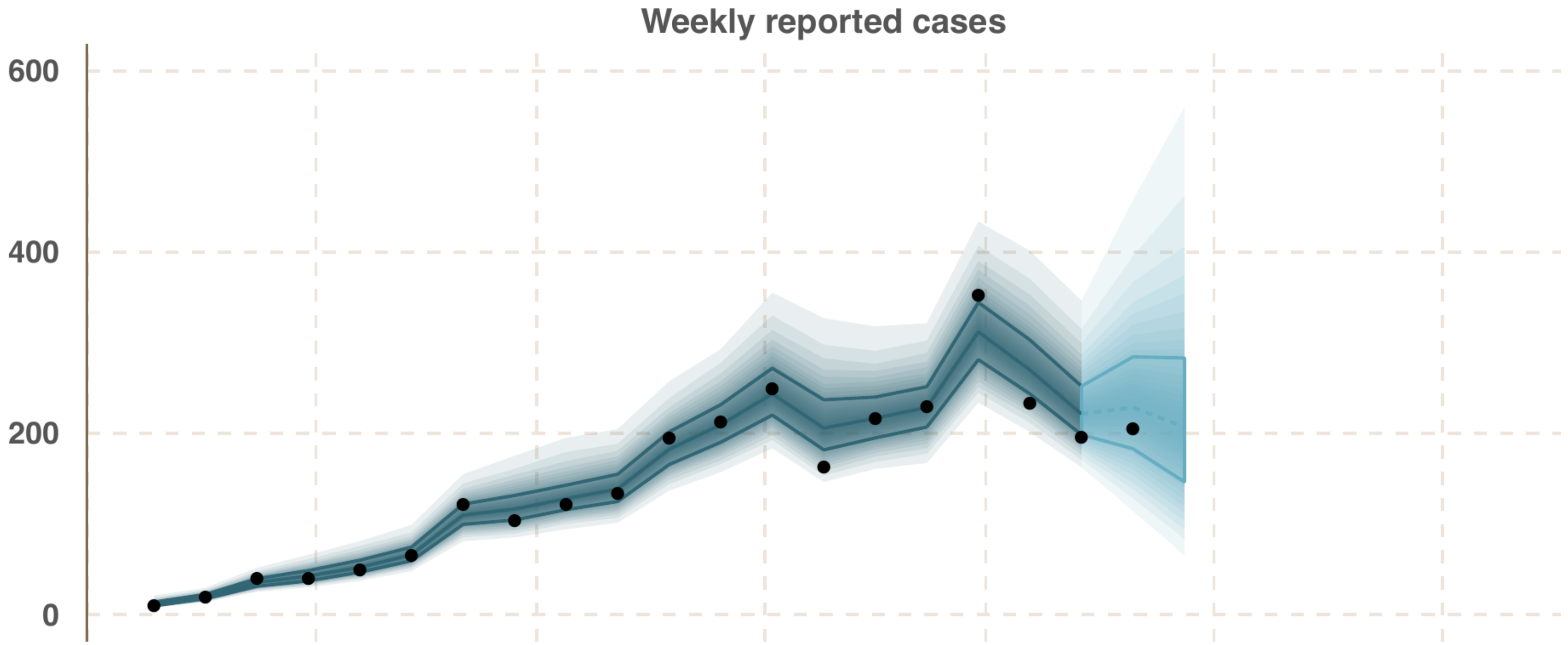
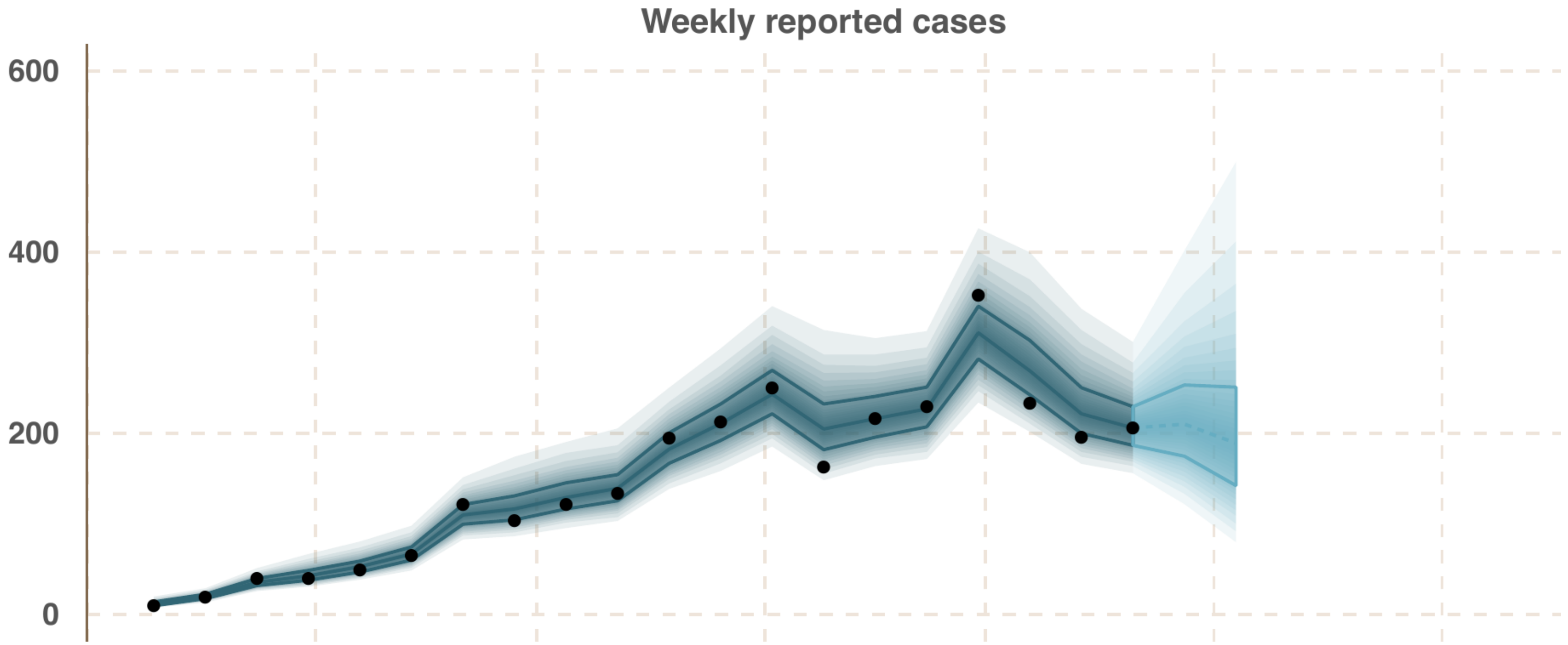
Weekly reported cases




Weekly reported cases
600
400
200
0


Weekly reported cases
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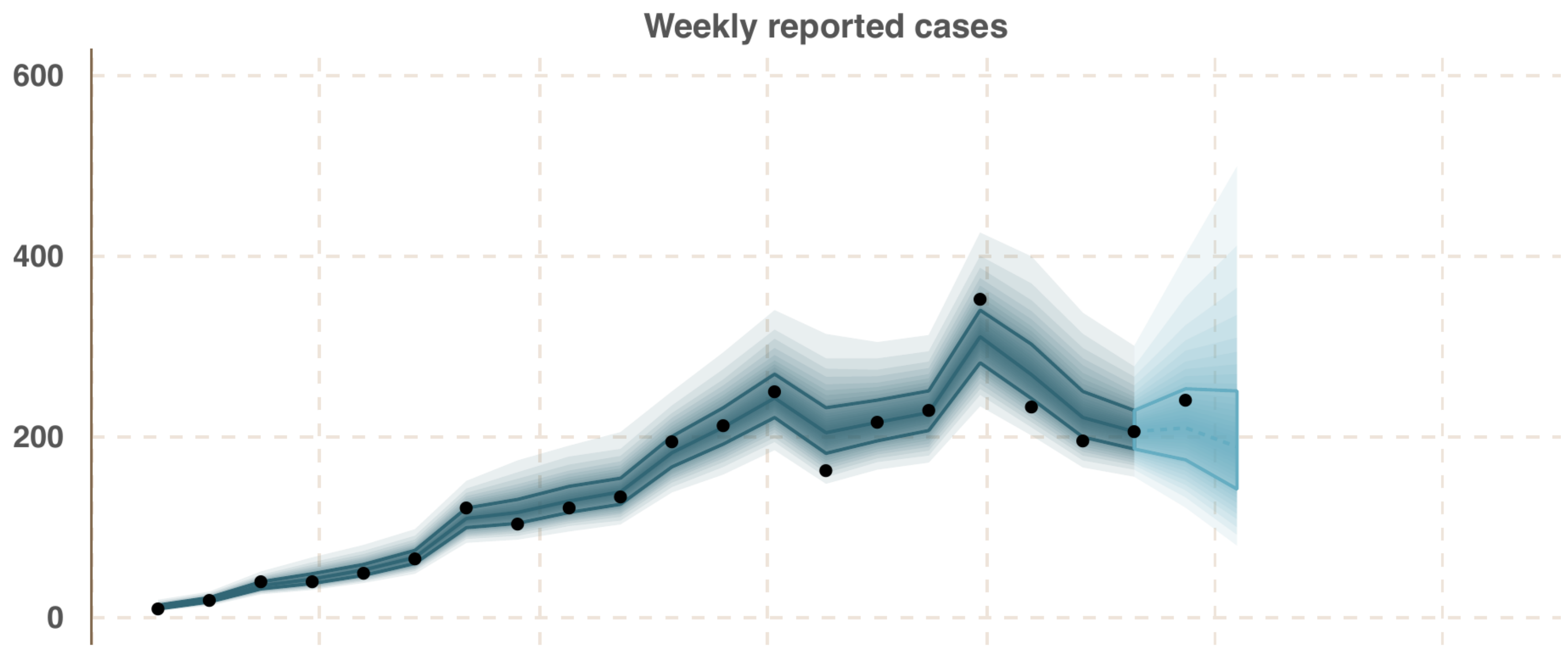
Weekly reported cases
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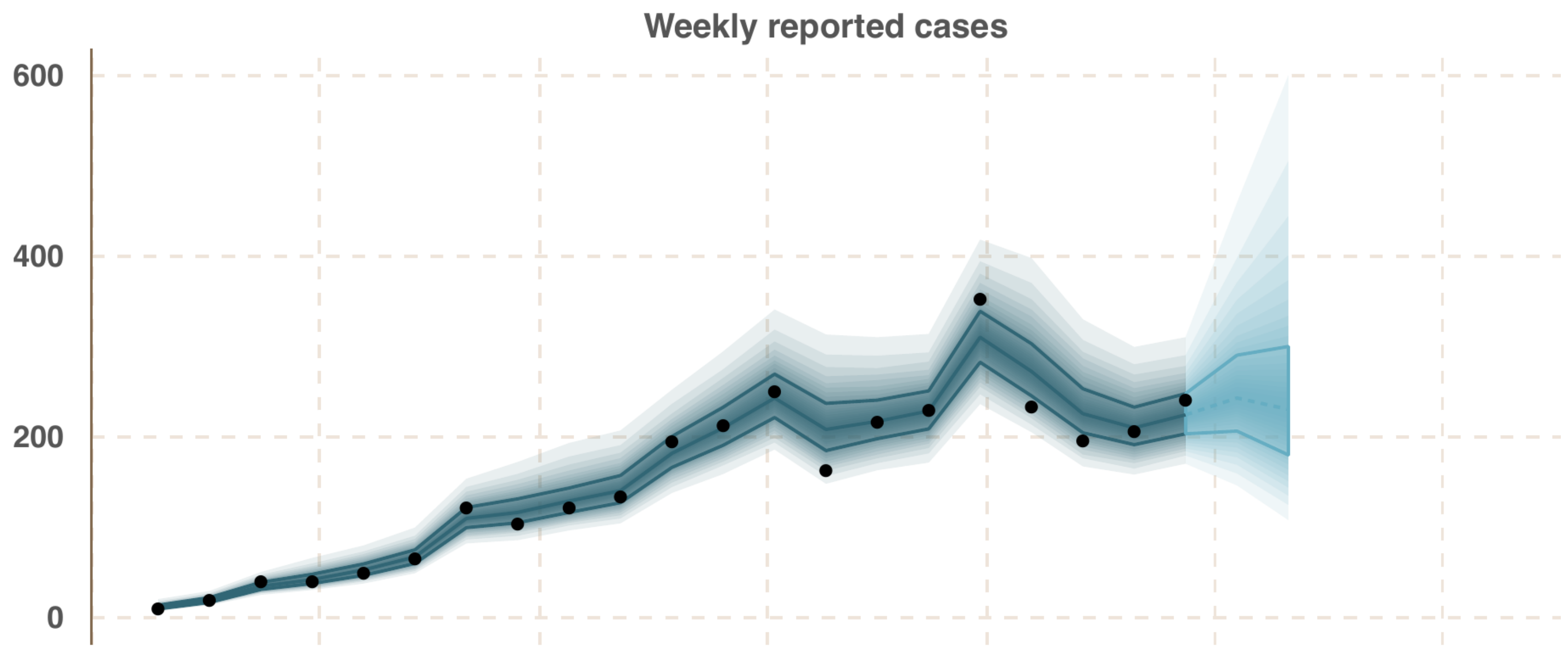
Weekly reported cases
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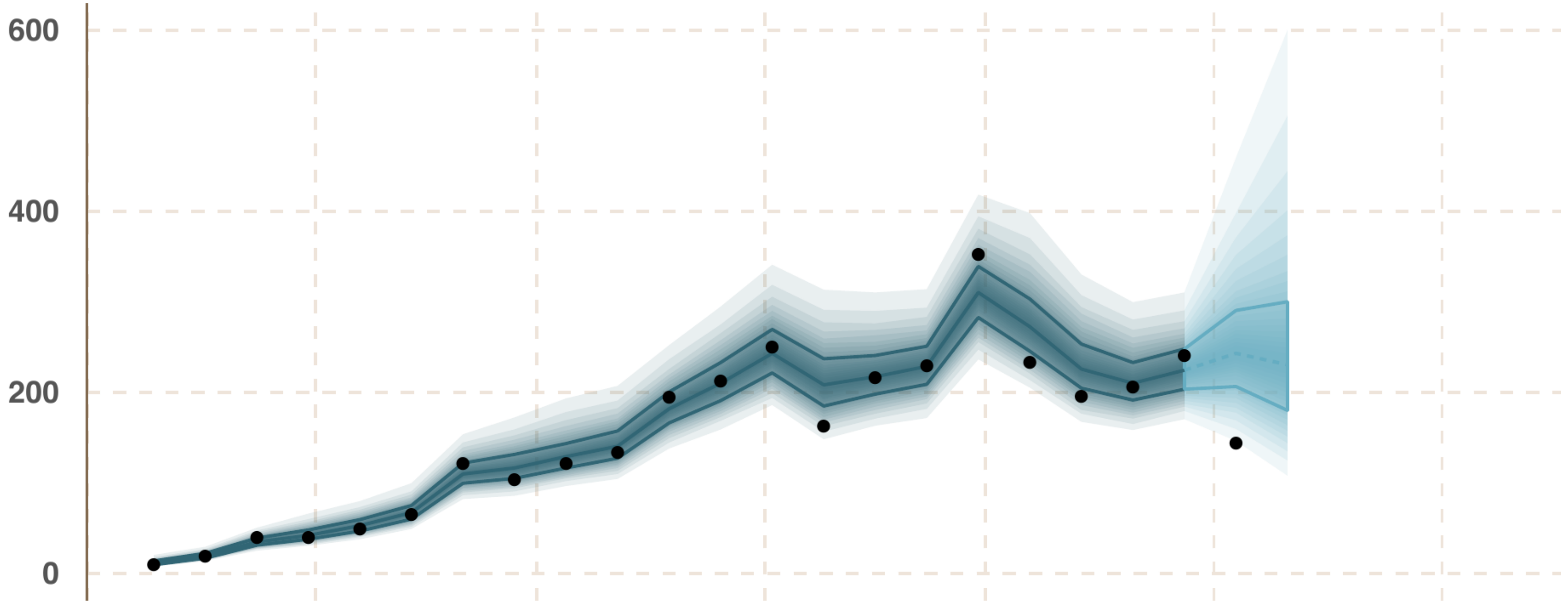
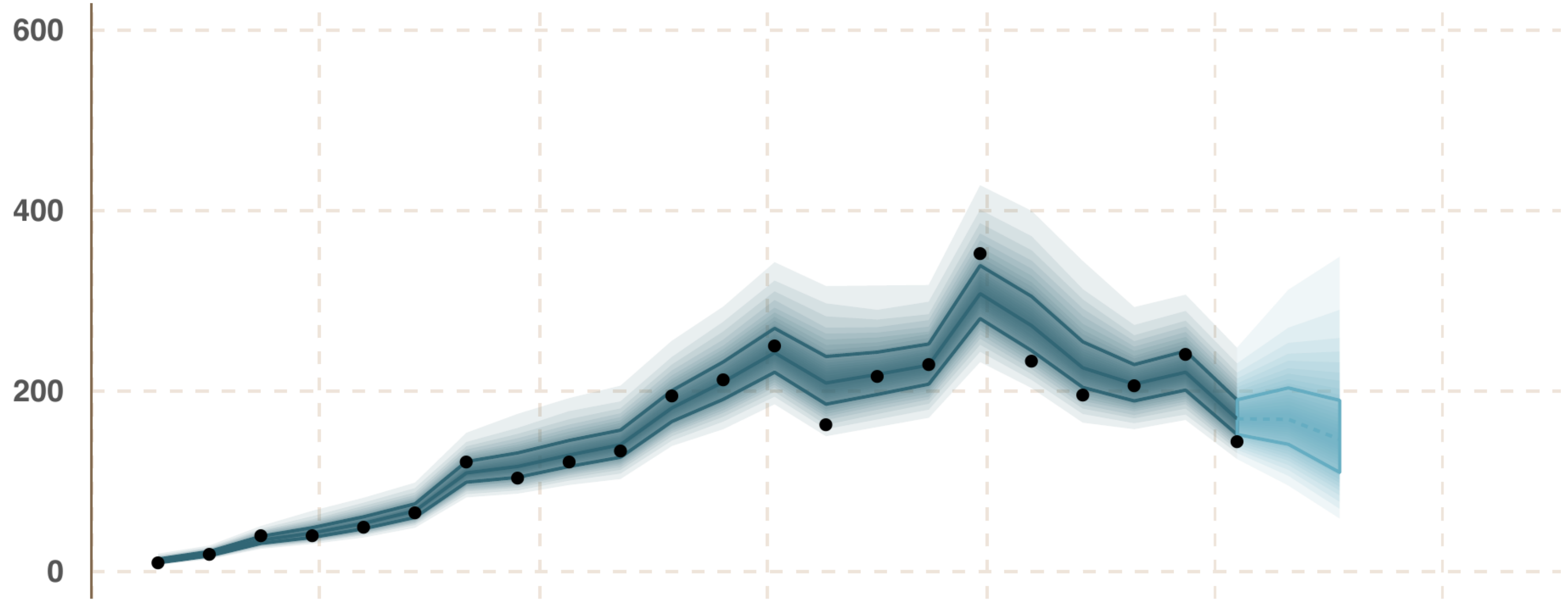
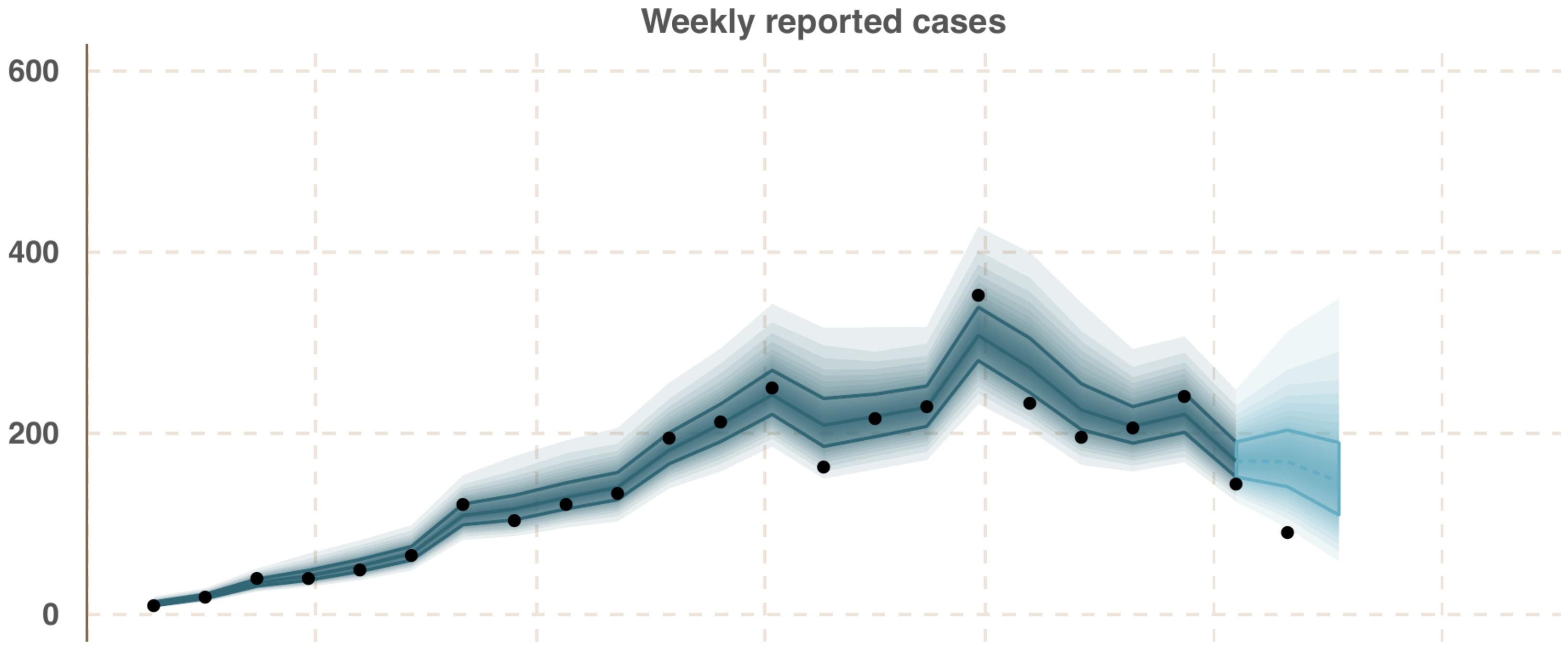
Weekly reported cases



Weekly reported cases

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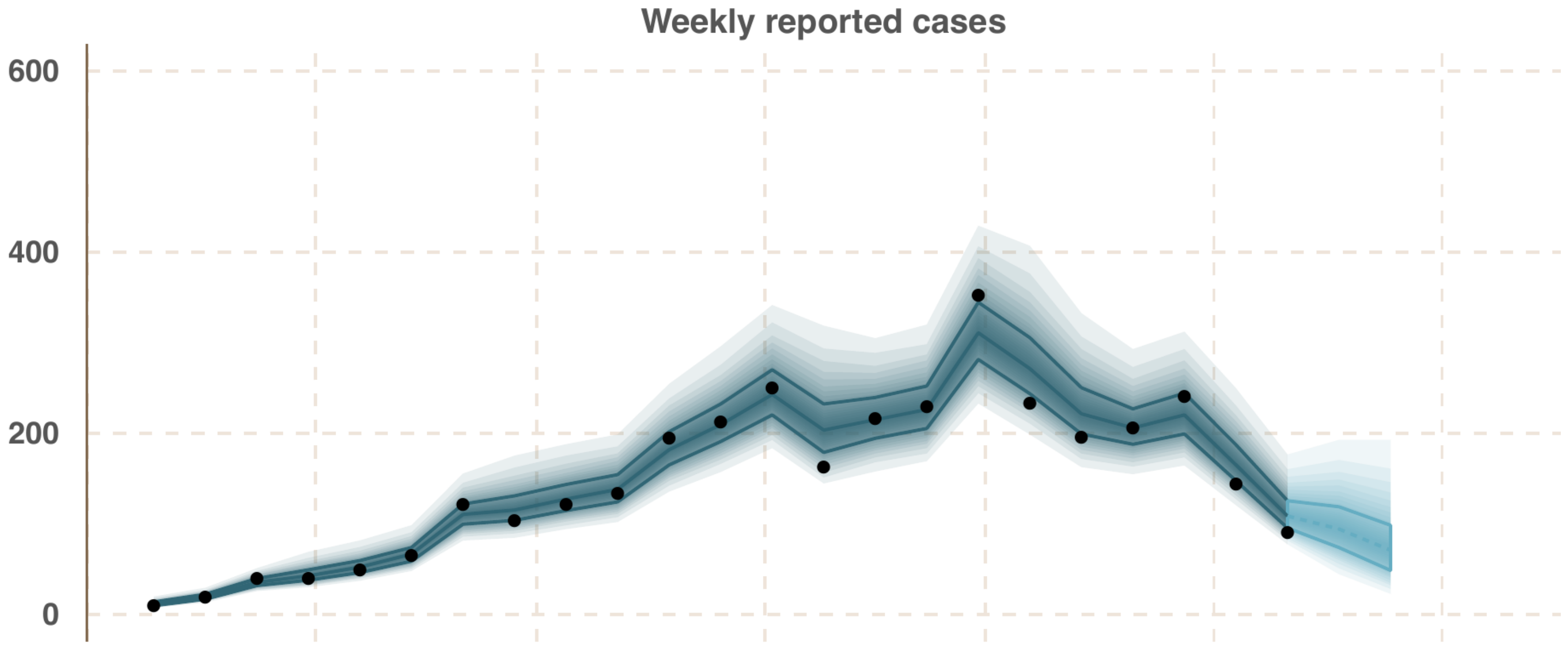
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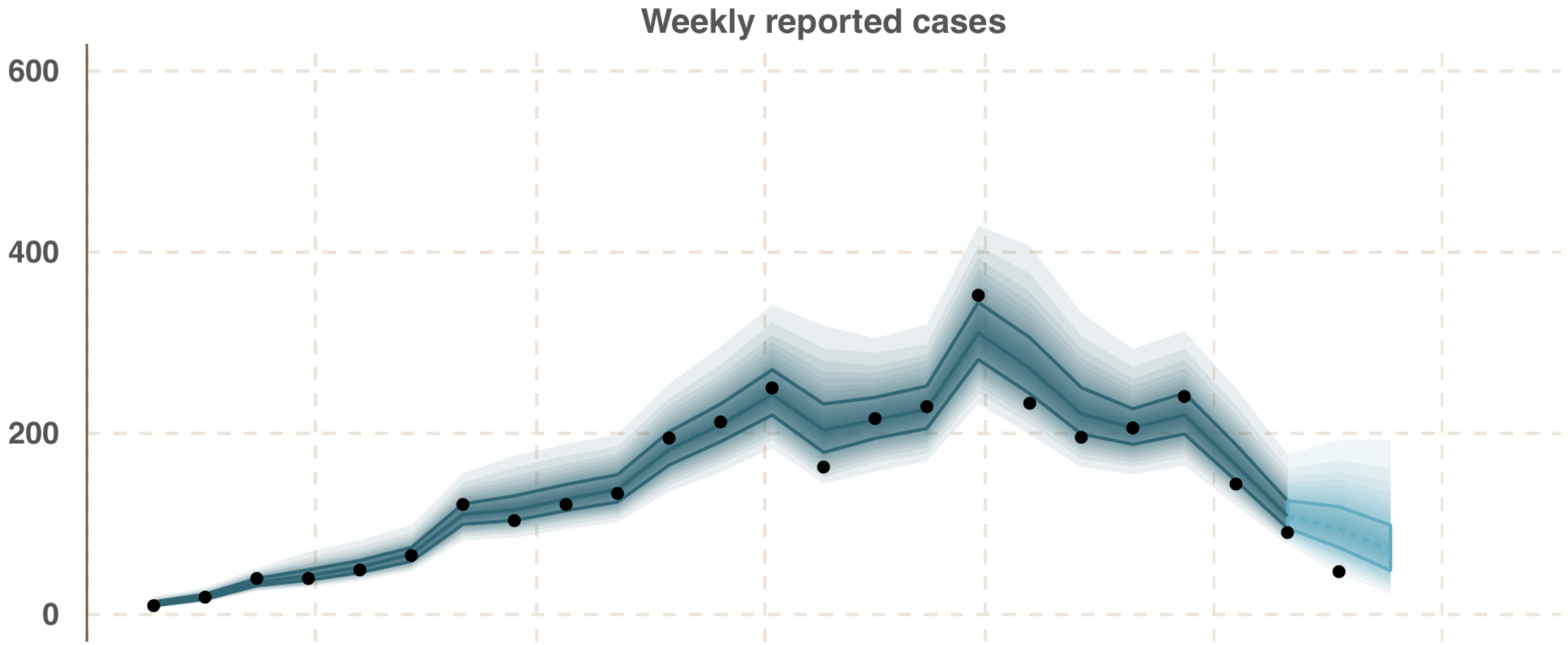
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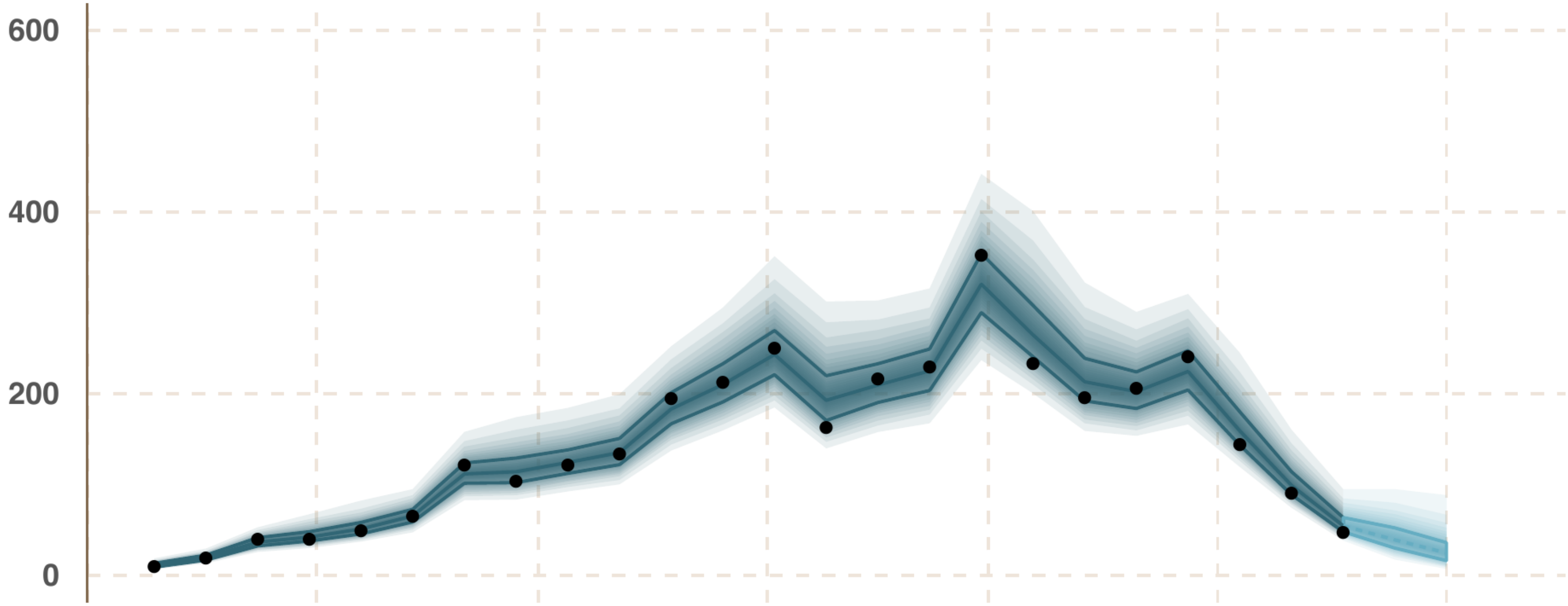
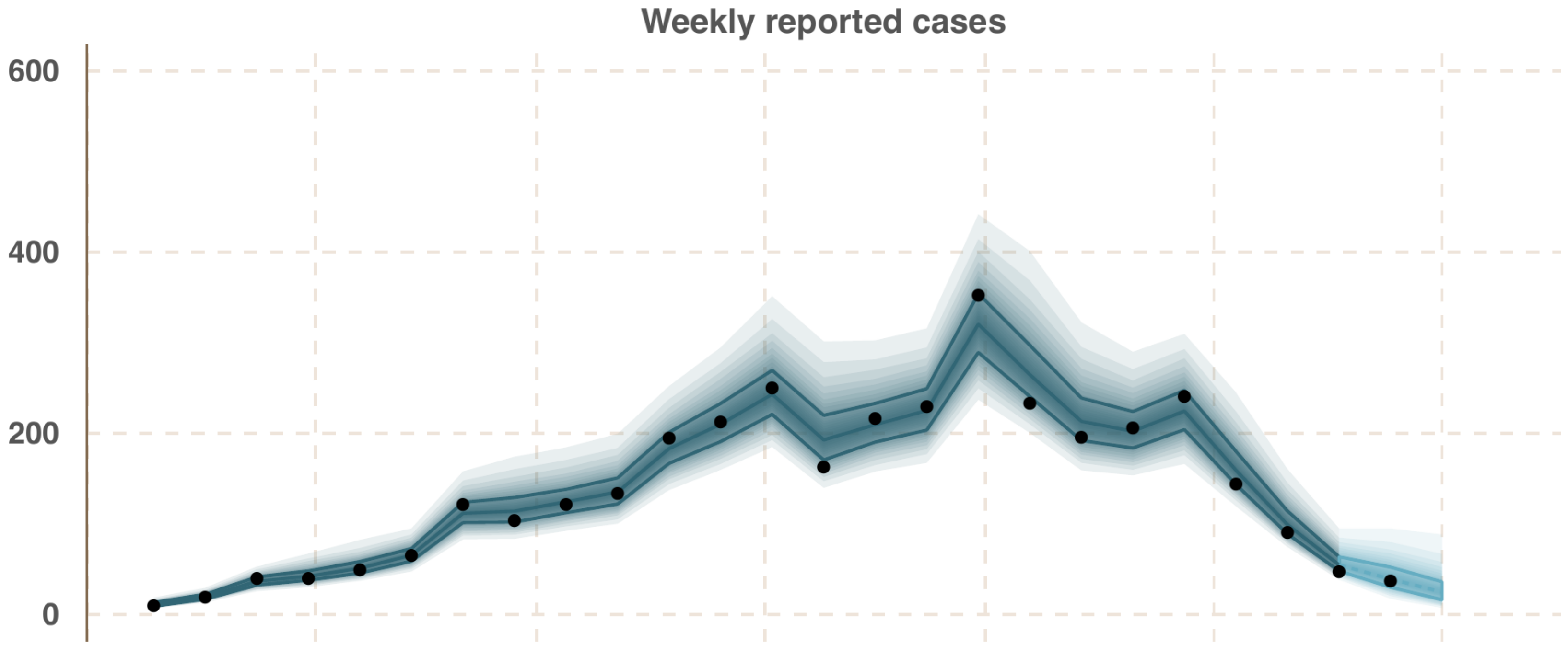
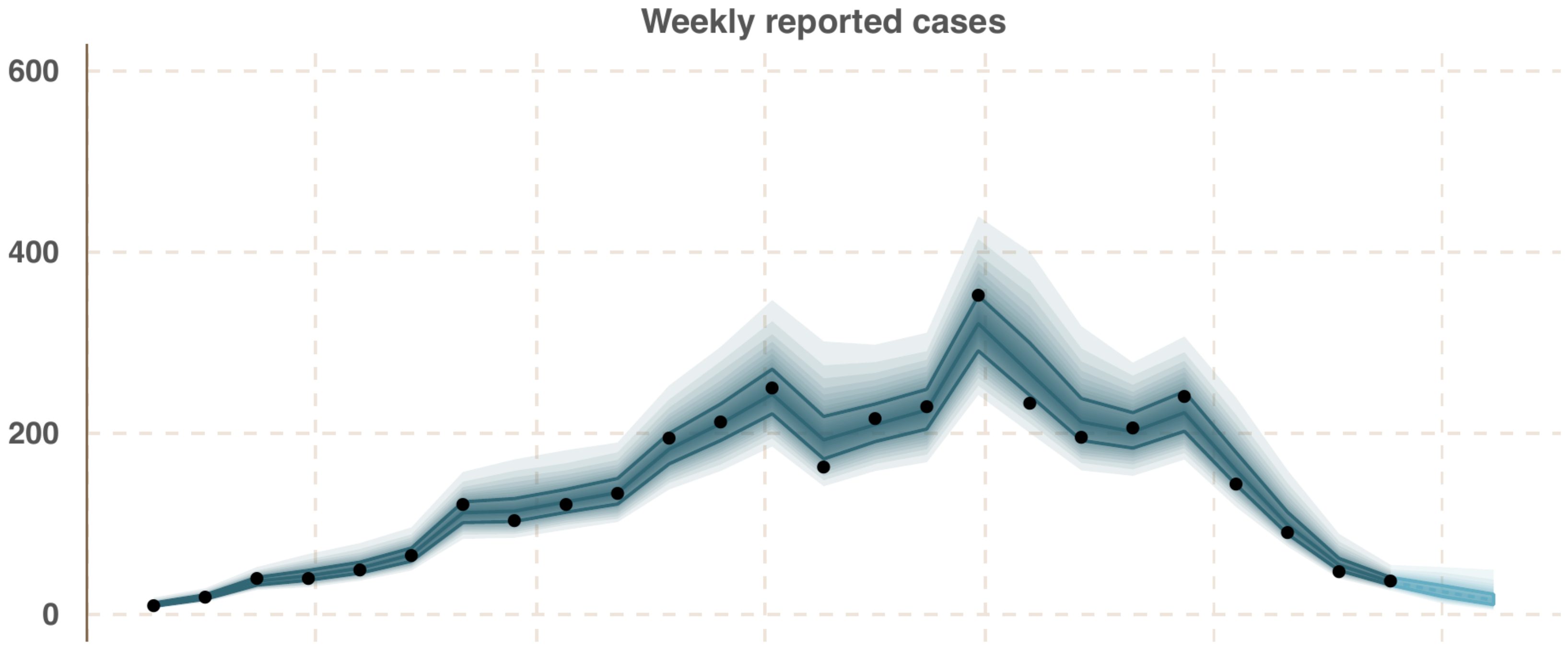
Weekly reported cases







Weekly reported cases
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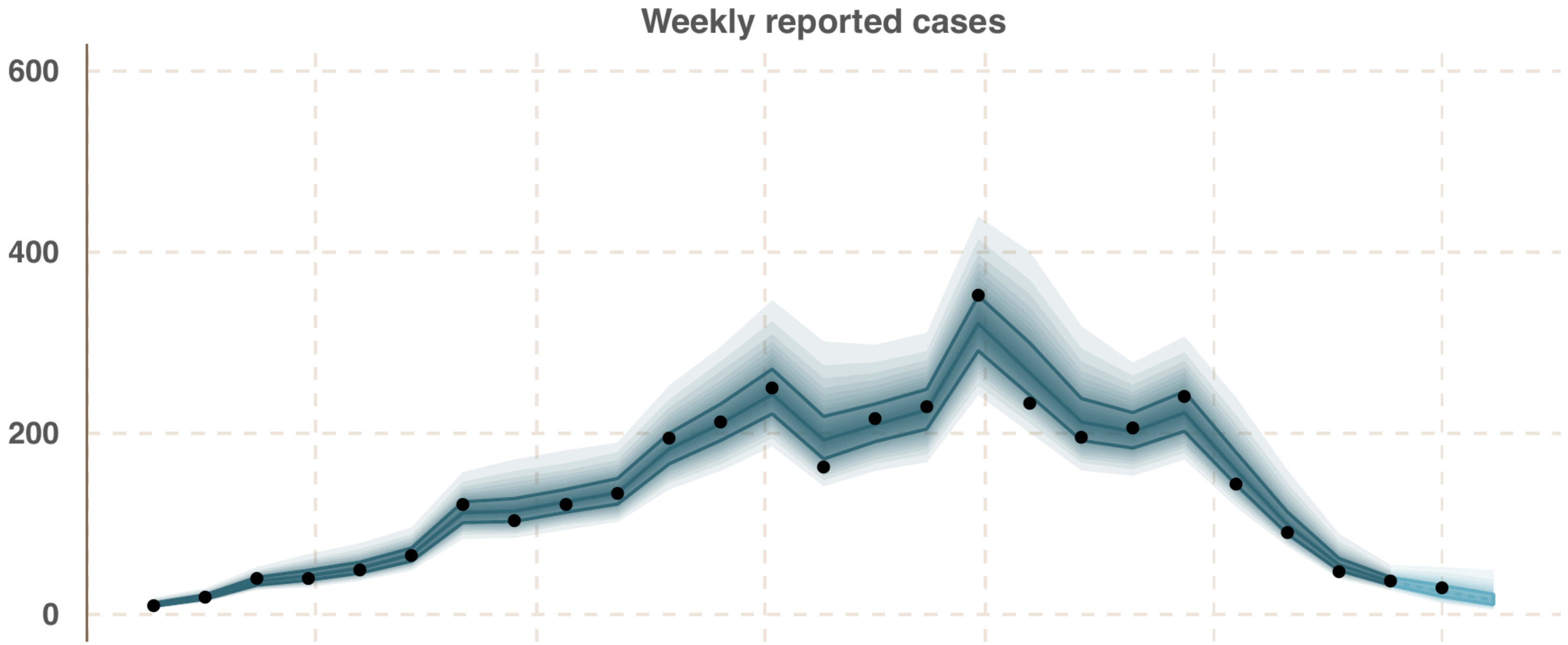

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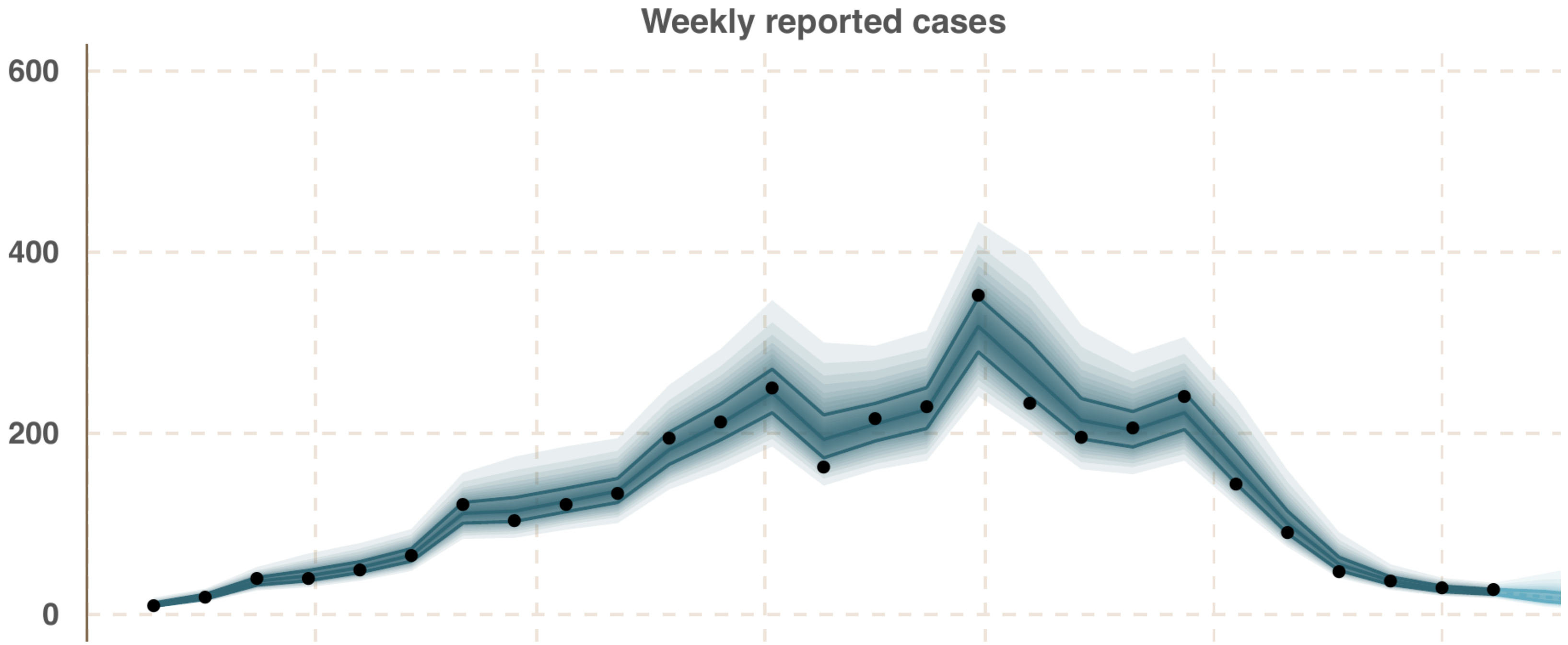
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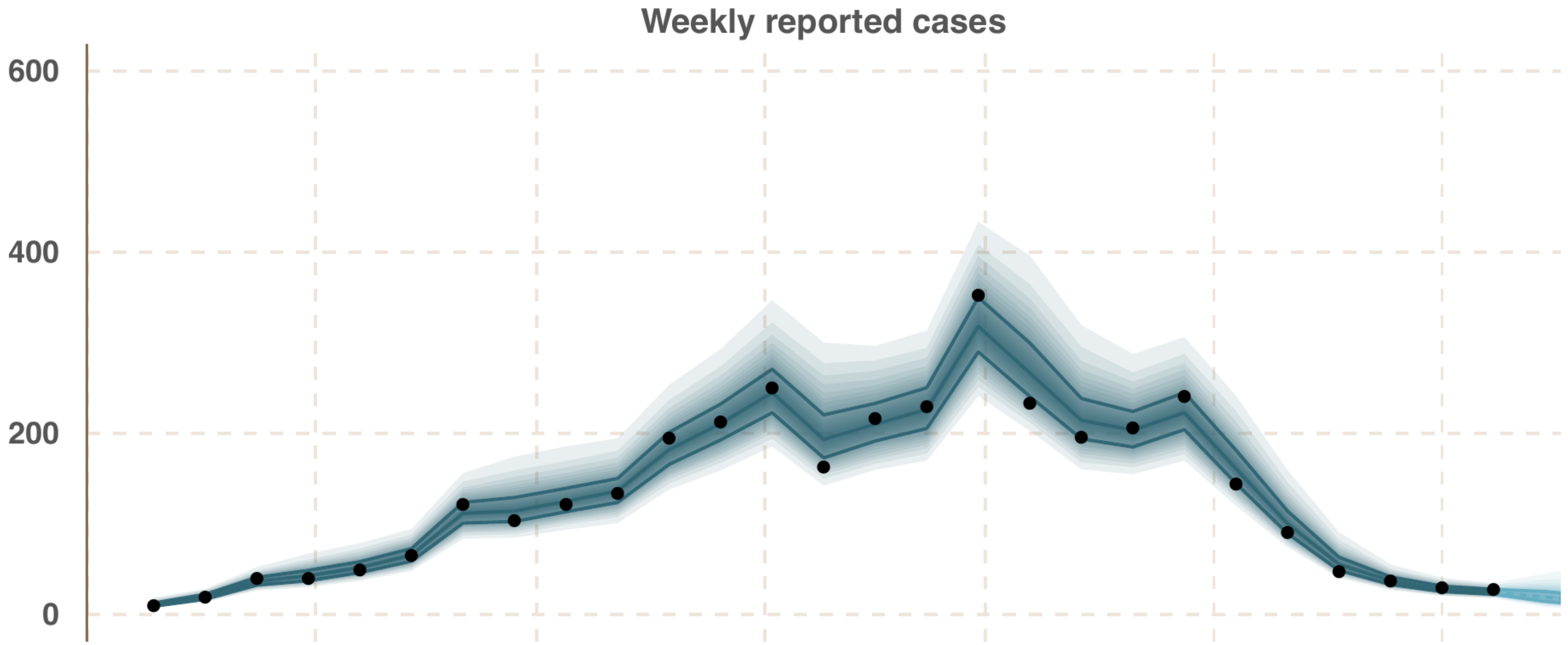
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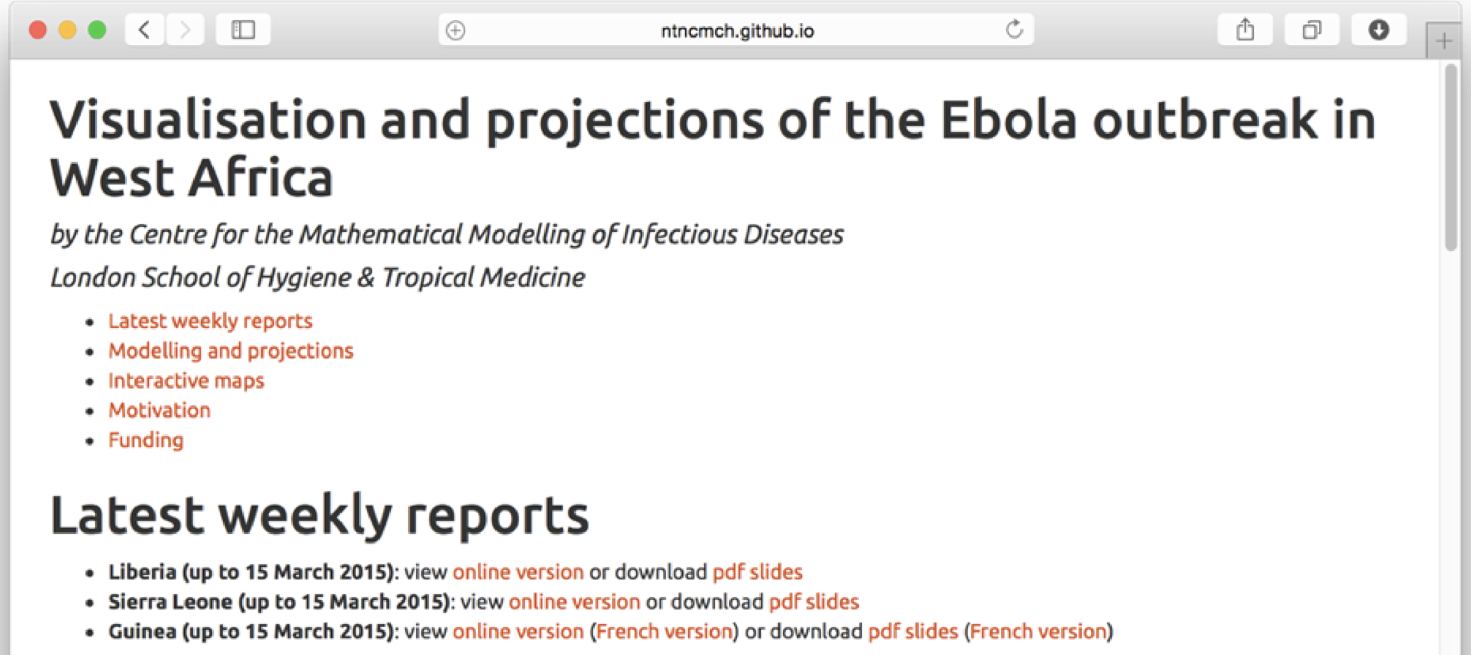

ntncmch.github.io

Visualisation and projections of the Ebola outbreak in West Africa

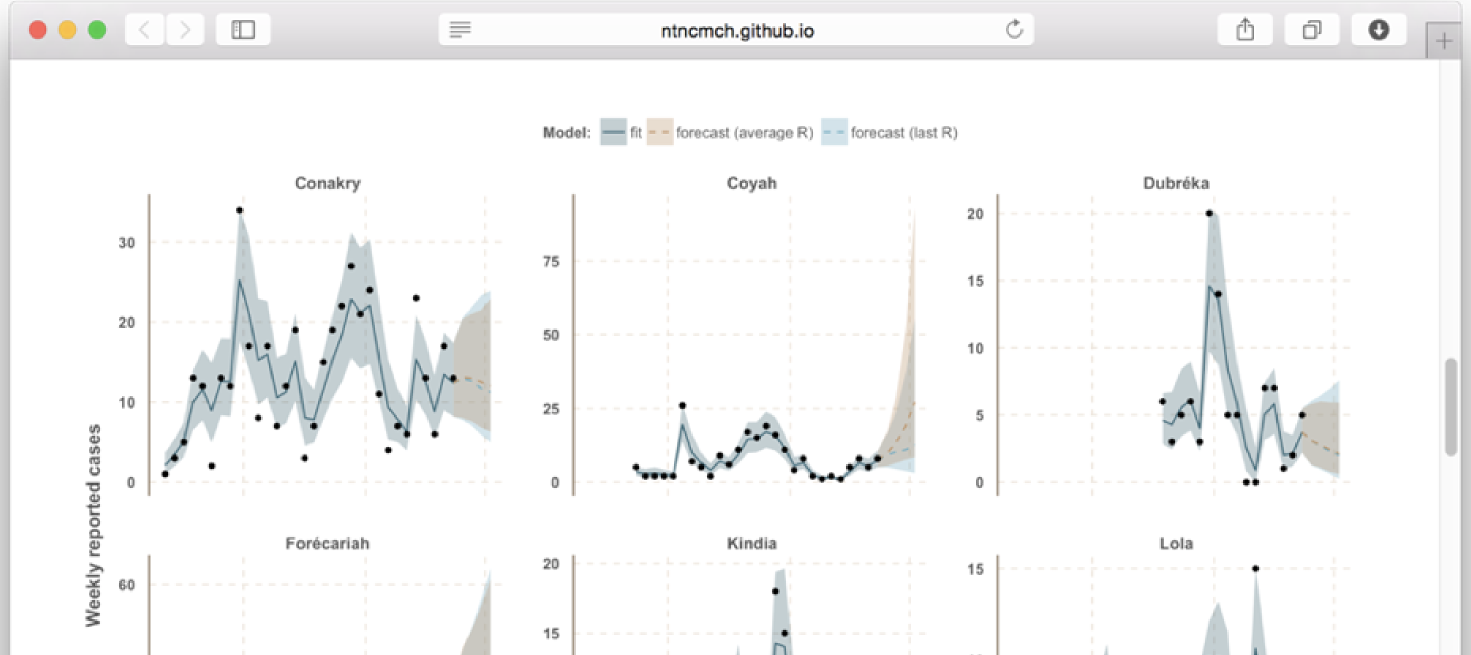
by the Centre for the Mathematical Modelling of Infectious Diseases

London School of Hygiene & Tropical Medicine

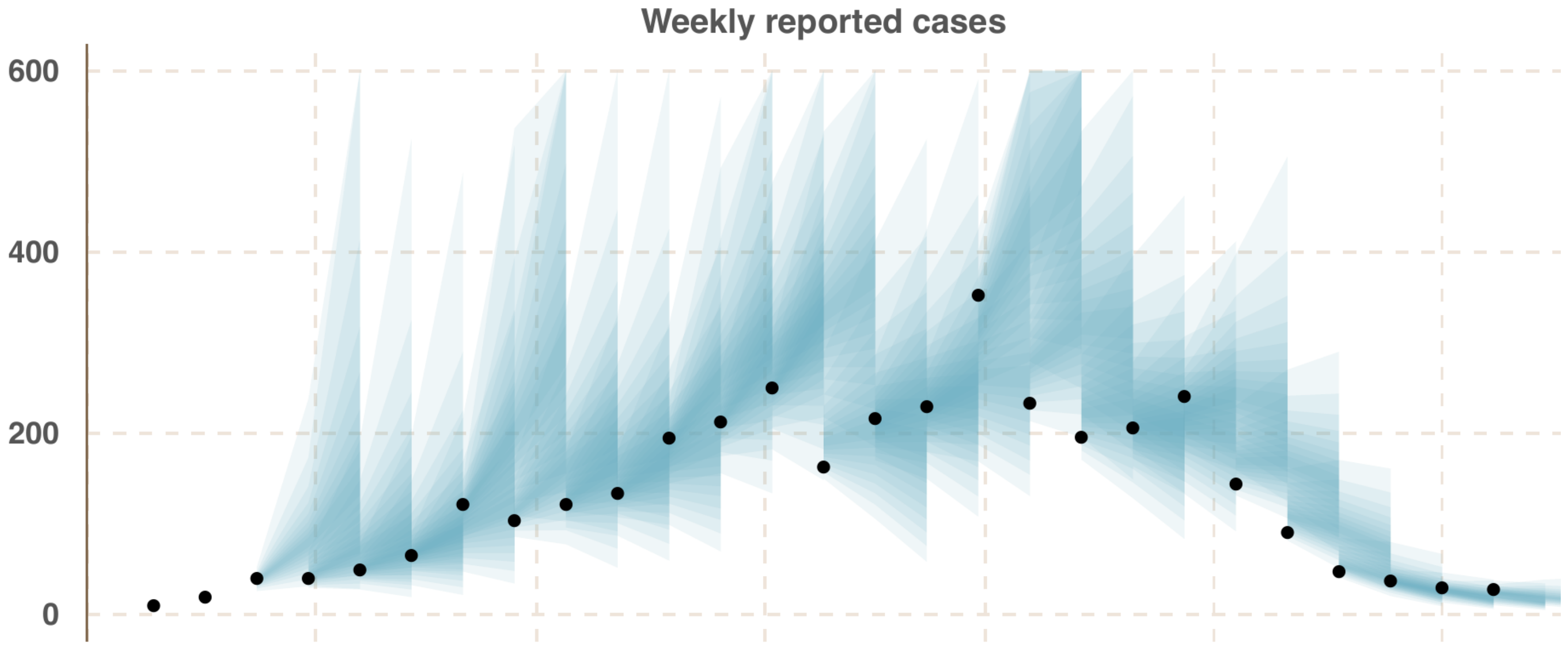
- Latest weekly reports
- Modelling and projections
- Interactive maps
- Motivation
- Funding

Latest weekly reports

- **Liberia (up to 15 March 2015)**: view online version or download pdf slides
- **Sierra Leone (up to 15 March 2015)**: view online version or download pdf slides
- **Guinea (up to 15 March 2015)**: view online version (French version) or download pdf slides (French version)



ntncmch.github.io
Model: fit forecast (average R) forecast (last R)
Conakry
Coyah
Dubréka
Forécariah
Kindia
Lola
Weekly reported cases


Weekly reported cases
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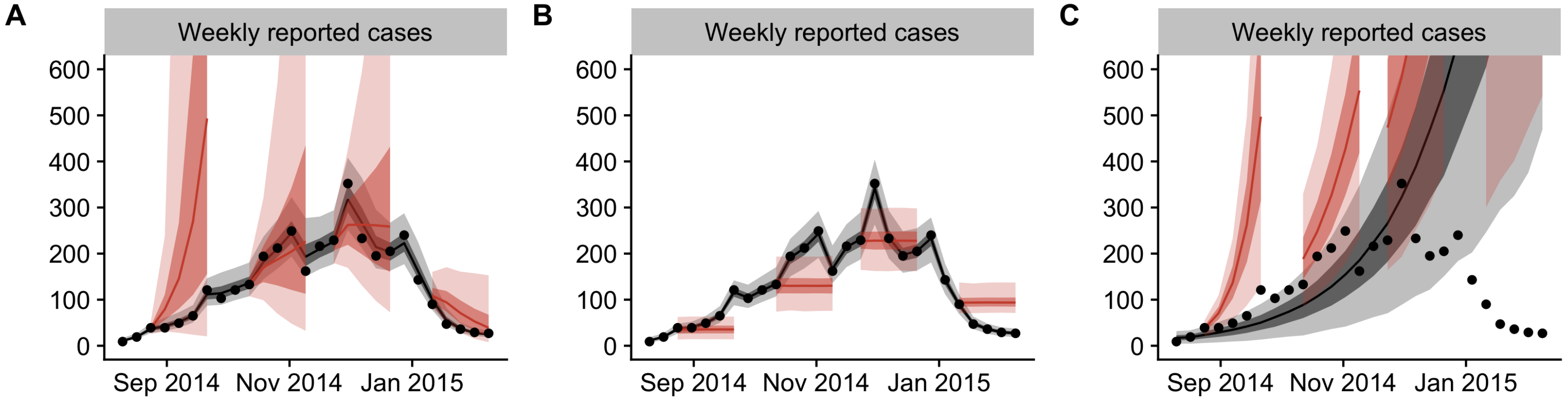
How good were the forecasts?

Comparison with null models



Calibration: Compatibility of forecasts and observations

Calibration: Compatibility of forecasts and observations

Divide $[0, 1]$ in m subintervals

$$C(F_t, x_t) = 1 - \frac{1}{2}\frac{m}{m-1}\sum_j \left|p_j - \frac{1}{m}\right|$$

p_j is the proportion of $u_t = F_t(x_t)$ that is in interval j

Sharpness: Concentration of predictive distribution

$$S_t(F_t) = 1 - \frac{\mathrm{MADM}(y)}{m(y)}$$

y is a variable distributed according to F_t

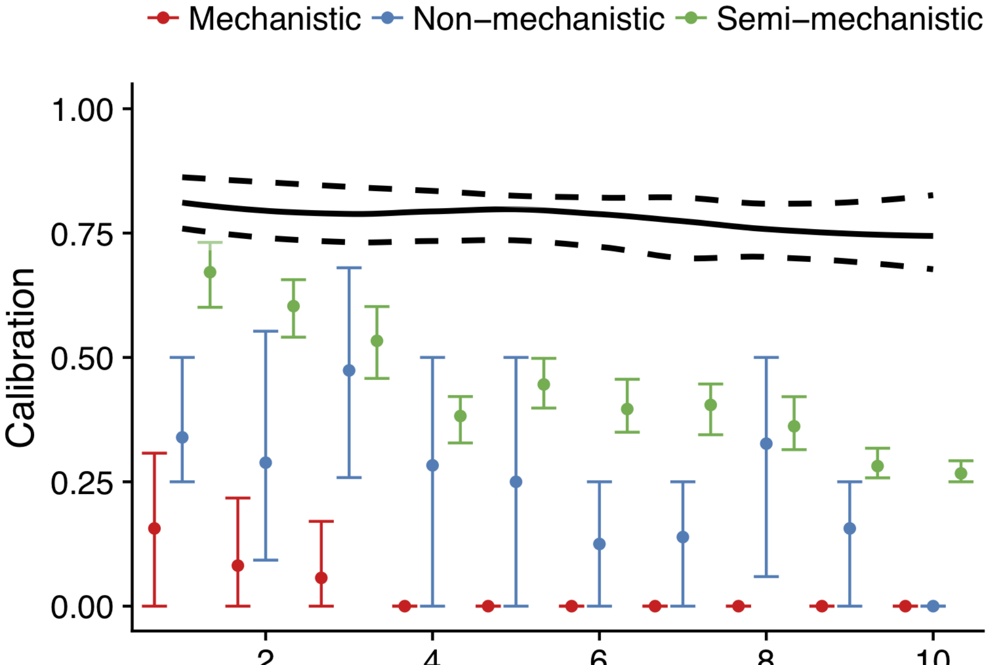
$\mathrm{MADM}(y)$: median absolute deviation about the median $m(y)$ of y

"Evaluate predictive performance on the basis of
maximising the sharpness of the predictive distribution

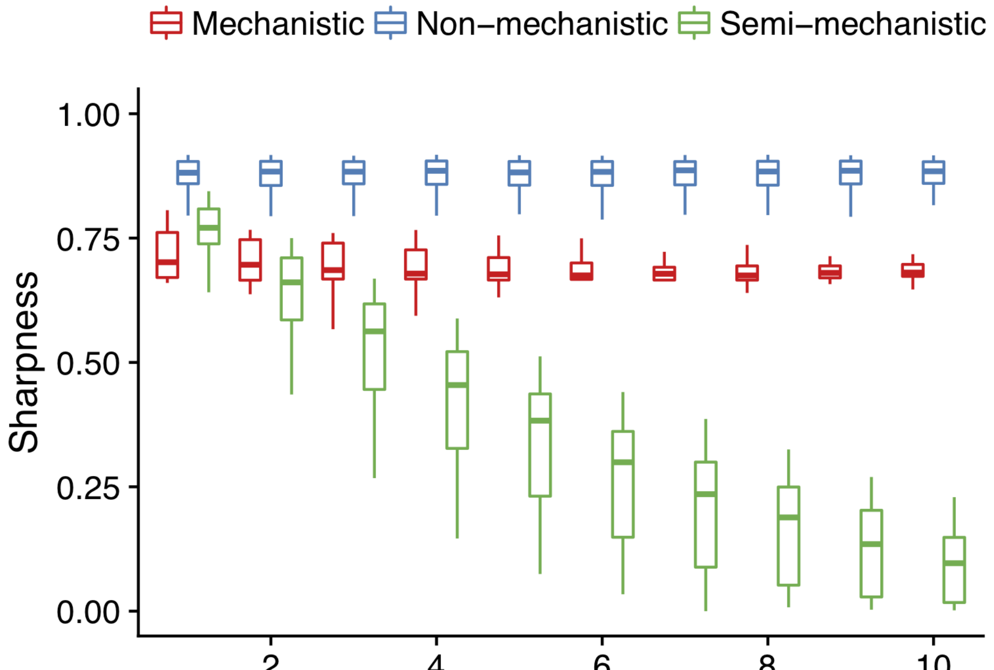
subject to calibration"

Gneiting et al., *J R Stat Soc B* (2007)

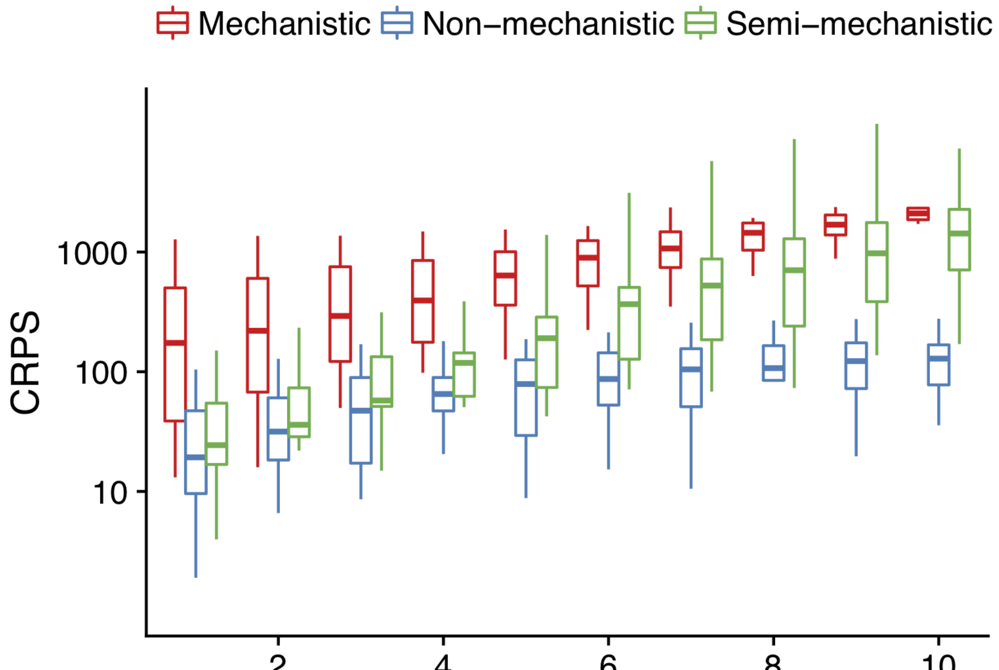
Calibration: Compatibility of forecasts and observations.



Sharpness: Concentration of predictive distribution



Continuous ranked probability score



Quality of forecasts vs quality of decisions

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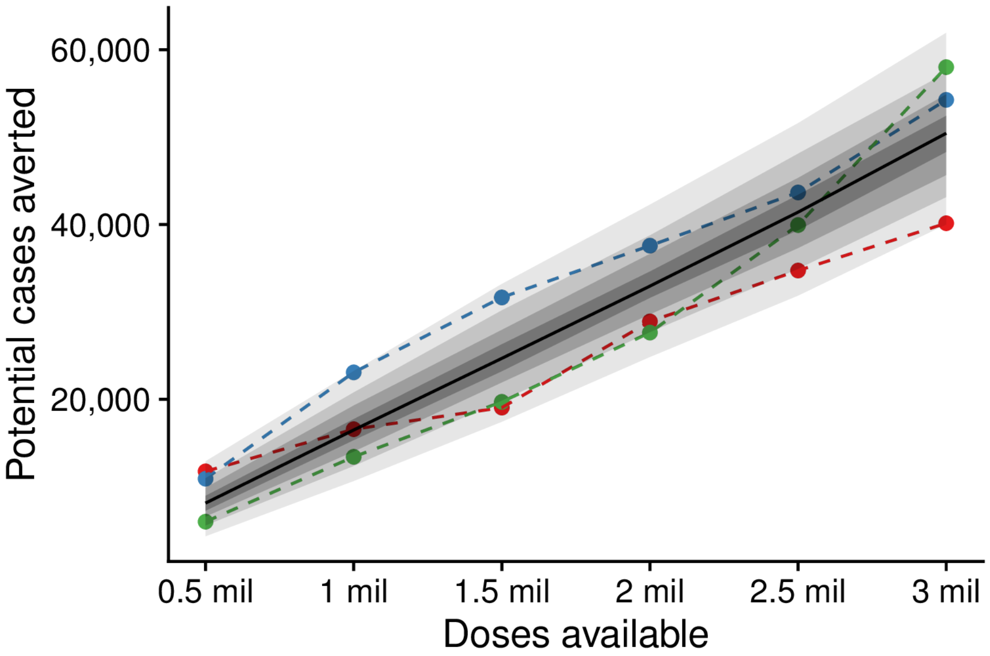
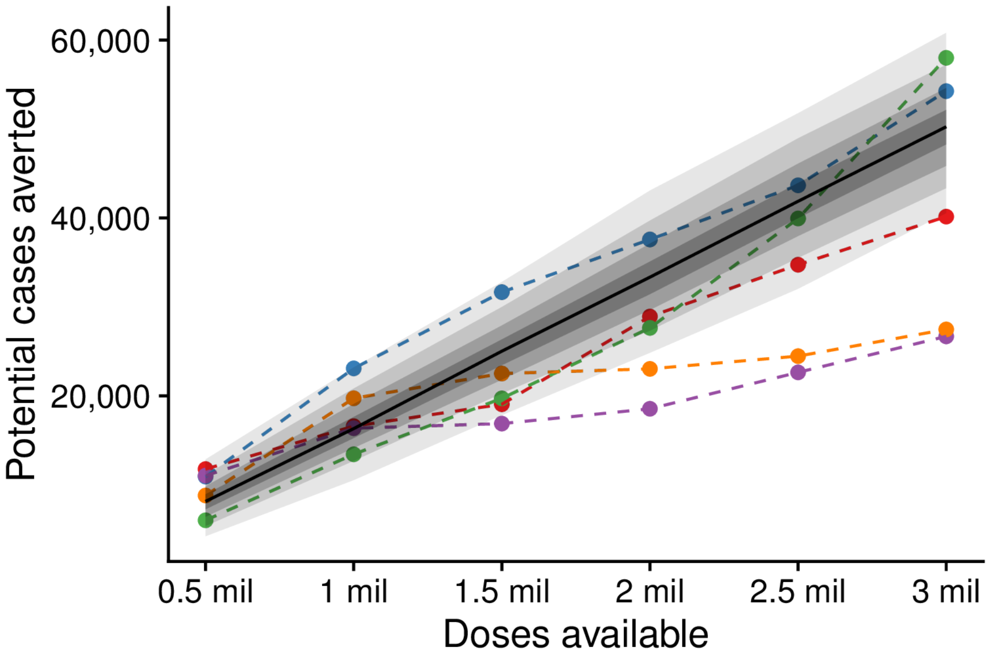
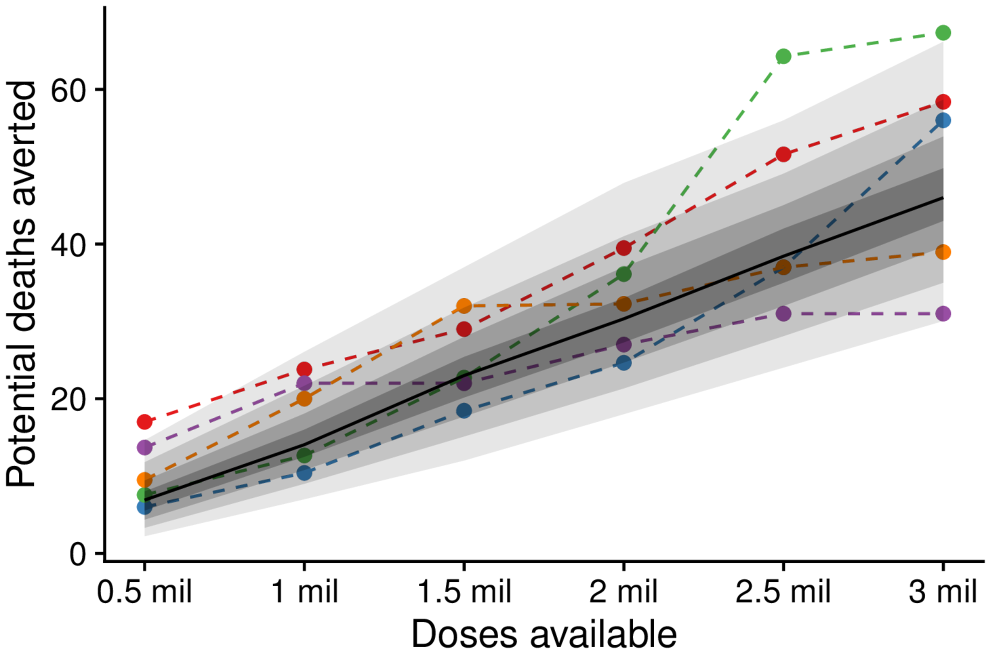


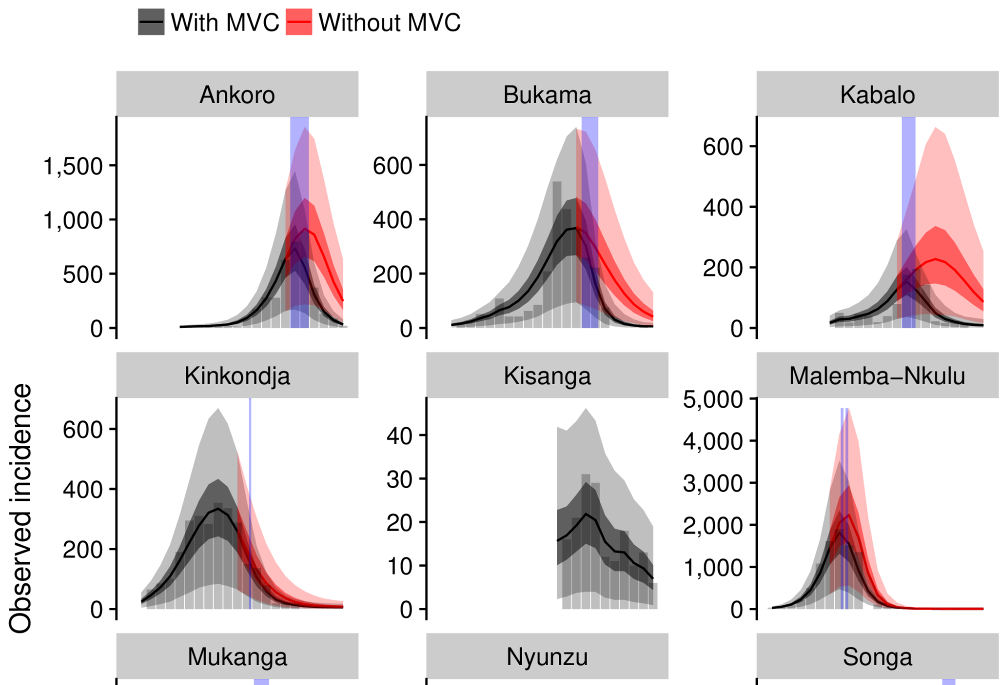
Quality of forecasts vs quality of decisions



Quality of forecasts vs quality of decisions

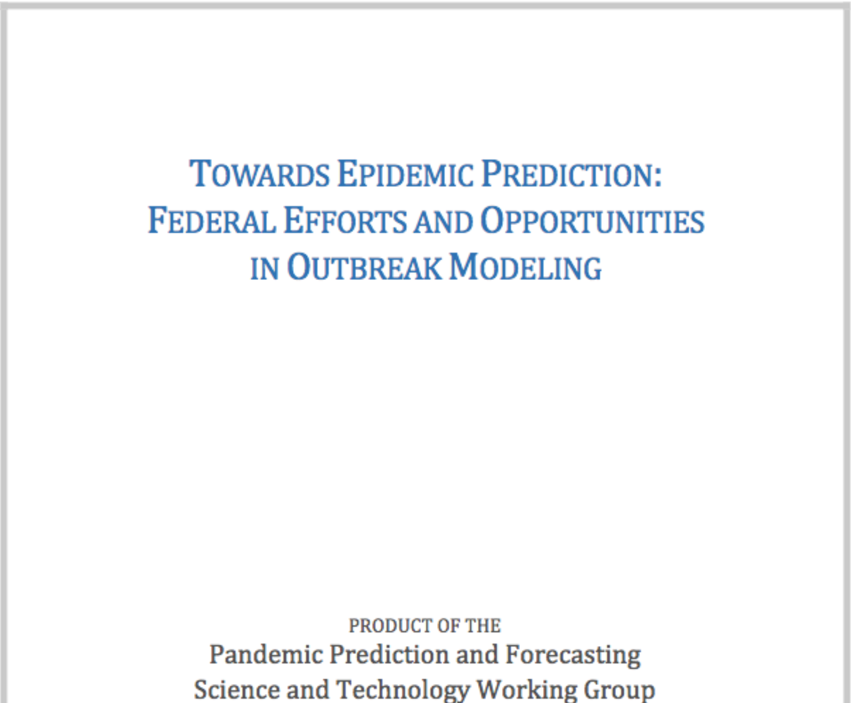


Evaluating quality of decisions



Outlook

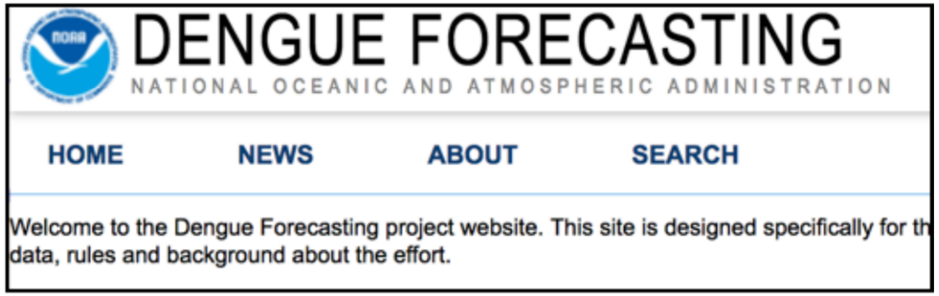
Forecasts are becoming part of outbreak response



TOWARDS EPIDEMIC PREDICTION:
FEDERAL EFFORTS AND OPPORTUNITIES
IN OUTBREAK MODELING

PRODUCT OF THE
Pandemic Prediction and Forecasting
Science and Technology Working Group

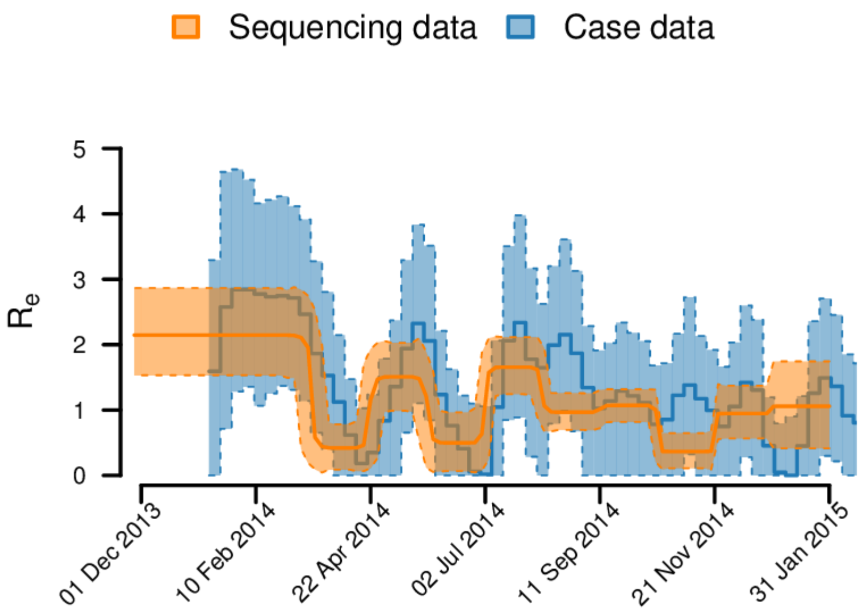
Forecasting challenges



Challenges in real-time modelling and forecasting

Need methods to
combine all available **data streams**
(individual/behavioural/spatial/genetic)

Challenges in real-time modelling and forecasting



Computationally efficient tools

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LibBi has been developed under a CSIRO

LibBi is used for state-space modelling and Bayesian inference on high-performance computer hardware, including multi-core CPUs, many-core GPUs (graphics processing units) and distributed-memory clusters.

The staple methods of LibBi are based on sequential Monte Carlo (SMC), also known as particle filtering. These methods include particle Markov chain Monte Carlo (PMCMC) and SMC^2. Other methods include the extended Kalman filter and some parameter optimisation routines.

LibBi consists of a C++ template library, as well as a parser and compiler, written in Perl, for its own modelling language.

News

- LibBi 1.3.0 released, new anytime features

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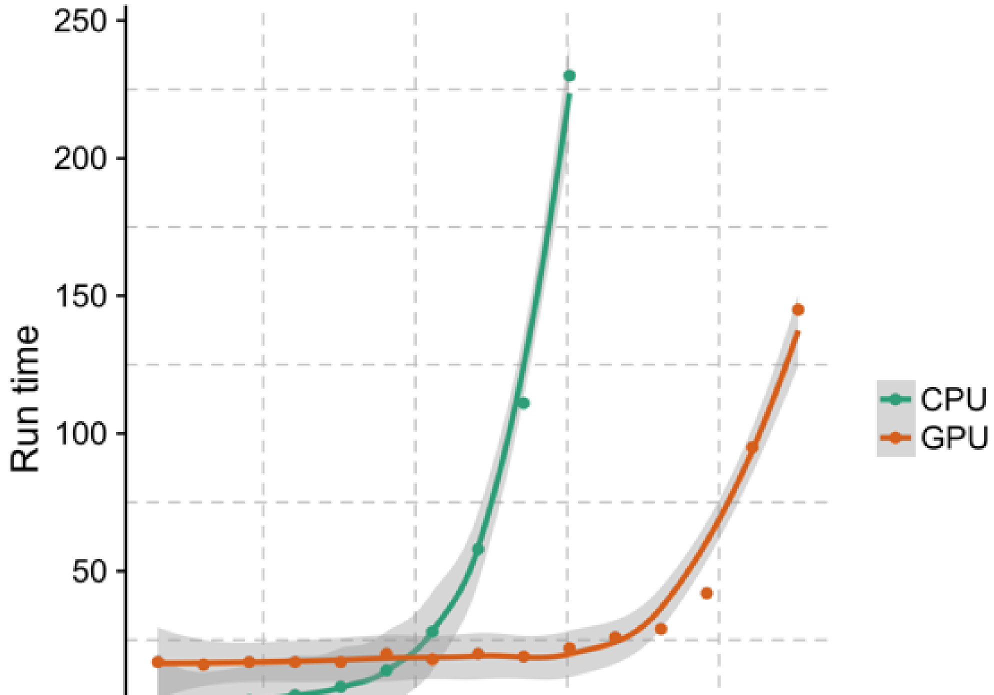

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James Hensman (Lancaster), Lawrence Murray (Uppsala)

Thank you!

http://sbfnk.github.io