The COVID-19 Forecast Hub: using statistics and data science to support decision-making in a pandemic

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https://covid19forecasthub.org/

COVID-19 Forecast Hub

Team: Martha Zorn, Nutcha Wattanachit, Serena Wang, **Nicholas Reich**, Evan Ray, Jarad Niemi, Khoa Le, Abdul Hannan Kanji, Dasuni Jayawardena, Katie House, Estee Cramer, Matt Cornell, Andrea Brennen, Johannes Bracher

* underline denotes ensemble contributor

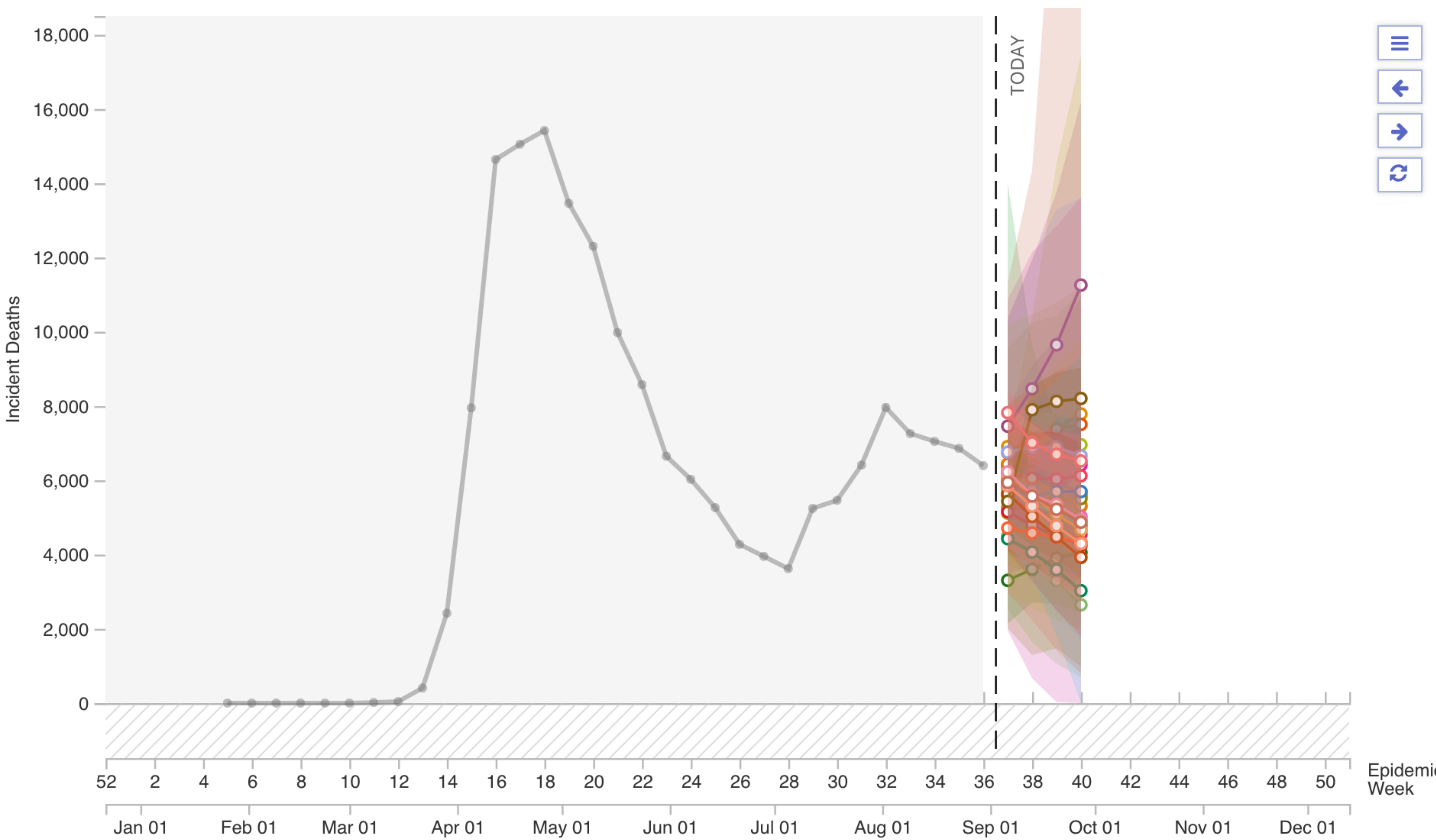
CDC Collaborators: Michael Johansson, Matthew Biggerstaff, Joseph Walker, Velma Lopez, Rachel Slayton

Ensemble "advisory committee": Jacob Bien, Logan Brooks, Sebastian Funk, Tilmann Gneiting, Anja Muhlemann, Aaron Rumack, Ryan Tibshirani

Modeling groups: Over 50 groups at various institutions have contributed forecasts to the hub

Demo Visualization

https://viz.covid19forecasthub.org/



Why Forecast?

To inform public health planning:

- Do we have enough hospital beds?
- Where will we need to send more resources (personal protective equipment)?
- Where should we select vaccine trial sites?

Our Contributions

Infrastructure for collecting forecasts

- Each week, teams submit csv files with forecasts to GitHub repository
- Files are automatically validated for formatting and reasonableness
  - For example, predicted cumulative deaths can’t be negative

Models

- Ensemble model — combines forecasts from all submitted models
- Baseline model — naive reference model

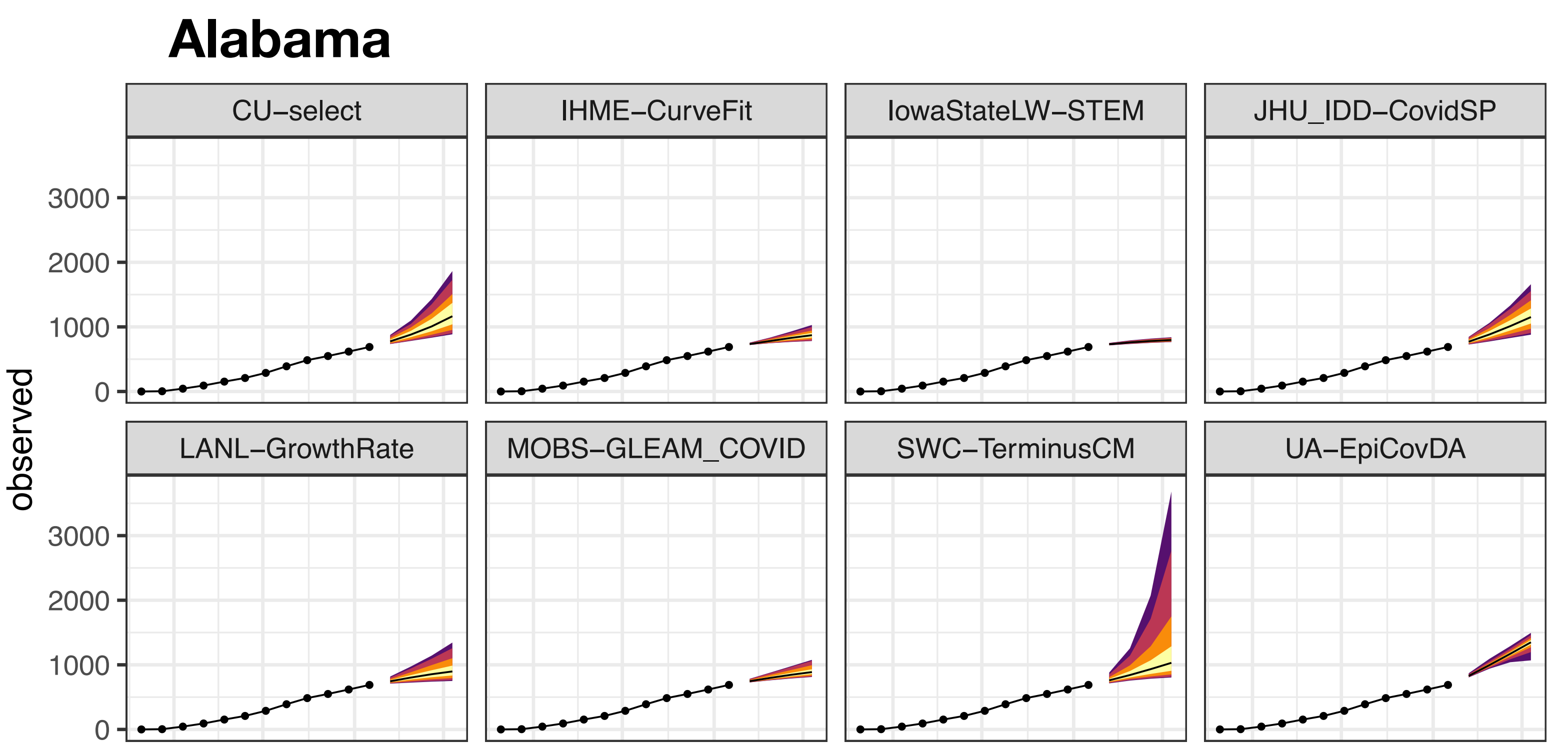
Visualization

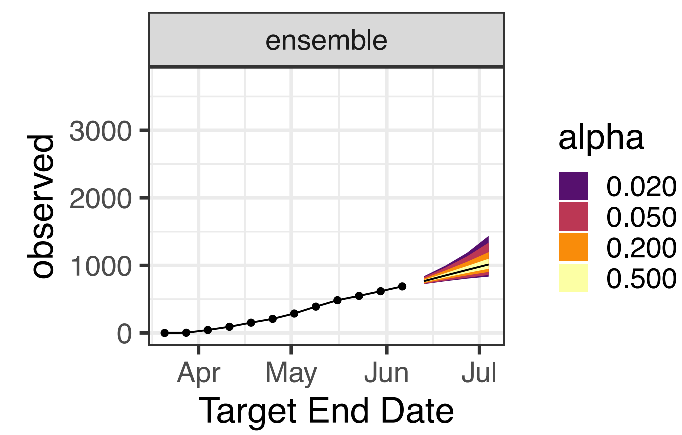
- Interactive visualizations shown earlier

Evaluation

- Are forecasts reliable?
- Are some models better than others?

Building the Ensemble: View 1





- For each combination of spatial unit s, time point t, and forecast horizon h, teams are required to submit K=23 quantiles of a predictive distribution:

$$\widehat{P}\,(Y \le q^m_{s,t,h,1}) = 0.01,\ \widehat{P}\,(Y \le q^m_{s,t,h,2}) = 0.025,\ \ldots,\ \widehat{P}\,(Y \le q^m_{s,t,h,12}) = 0.5,\ \ldots,\ \widehat{P}\,(Y \le q^m_{s,t,h,23}) = 0.99$$

The predictive median

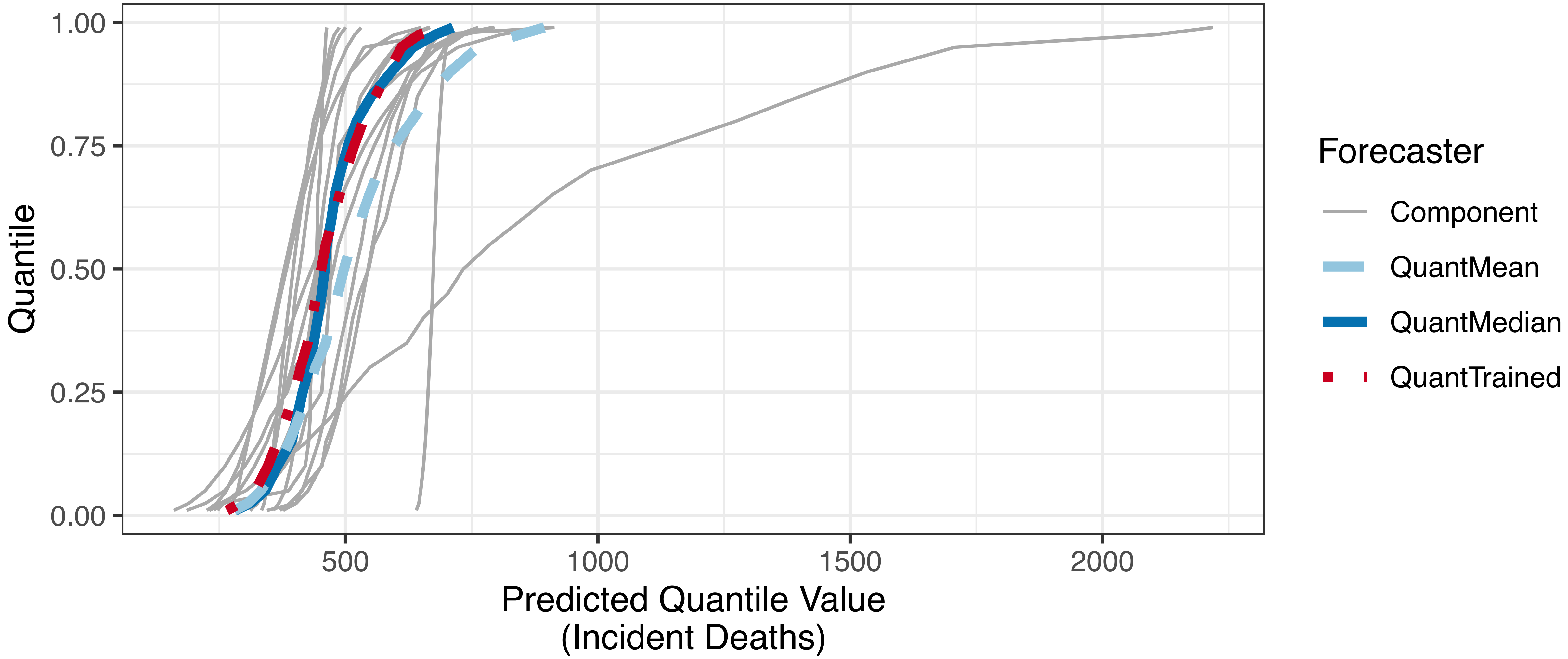
Limits of a 98% prediction interval

- The predictive quantiles for the ensemble are a combination of component predictions at each quantile level:

$$q_{s,t,h,k} = f(q^1_{s,t,h,k}, \ldots, q^M_{s,t,h,k}) \textbf{ for each } k = 1,\ldots,23$$

Building an Ensemble — View 2

- The pairs $\left(q^m_{s,t,h,k}, \widehat{P}(Y^m_{s,t,h} \leq q^m_{s,t,h,k})\right)$ fall along the predictive CDF for model m

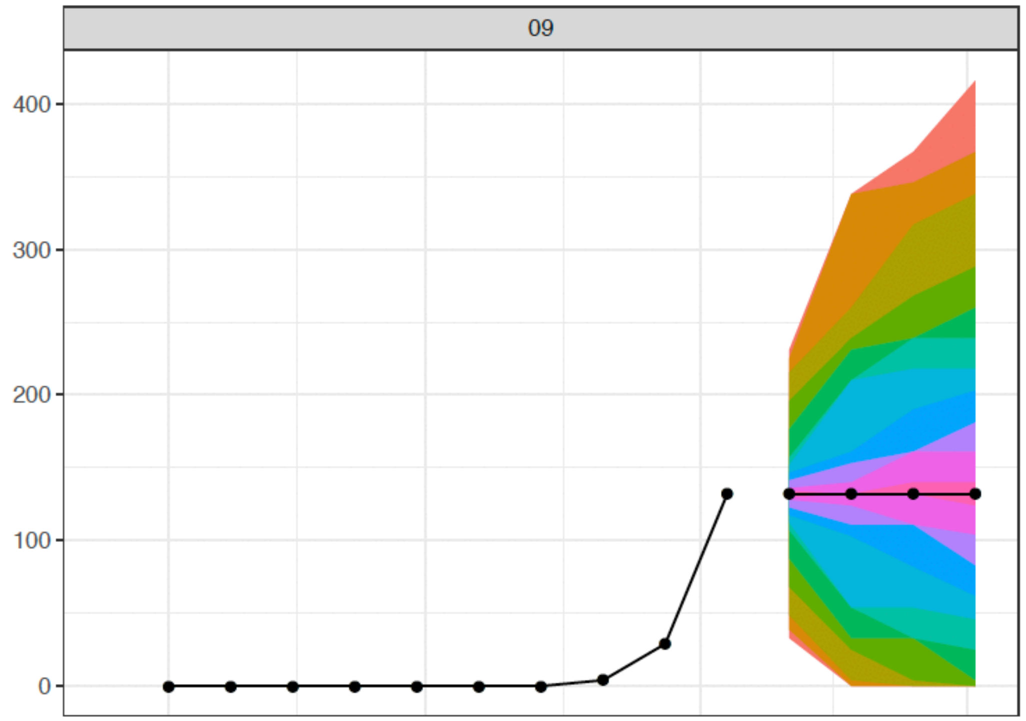


- Three options for the combination function f:
  - QuantMean: $q_{s,t,h,k} = \frac{1}{M}\sum_{m=1}^{M} q^m_{s,t,h,k}$ **Used through July 21, 2020**
  - QuantMedian: $q_{s,t,h,k} = \textbf{median}(q^1_{s,t,h,k}, \ldots, q^M_{s,t,h,k})$ **Used starting July 28, 2020**
  - QuantTrained: $q_{s,t,h,k} = \sum_{m=1}^{M} \beta^m_{t,h,k} \cdot q^m_{s,t,h,k}$ **Evaluated, not released each week**

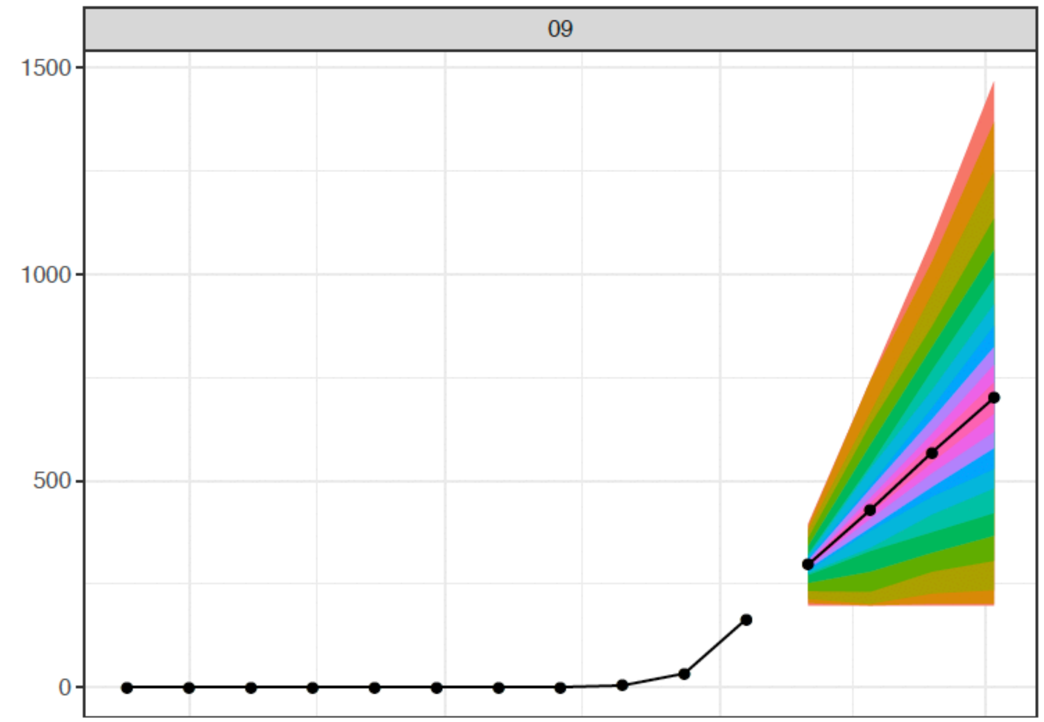
Baseline Model

- Acknowledgment: idea adapted from a suggestion by Ryan Tibshirani
- Goal: Median predicted incidence is most recent observed incidence
- Predictions of cumulative deaths derived from predictions of incident deaths

Incident Deaths



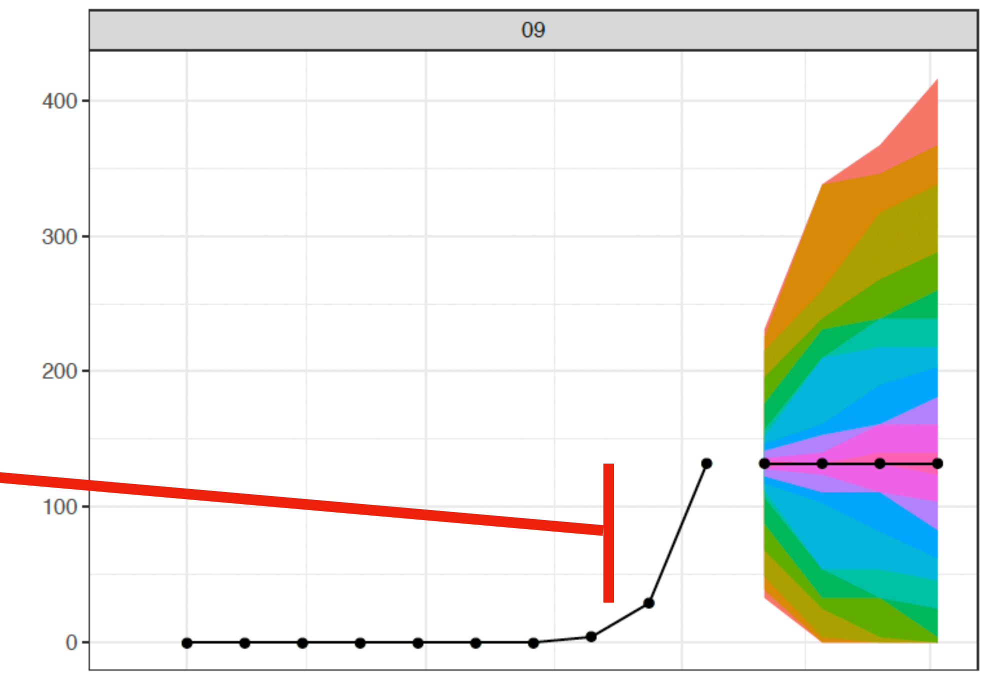
Cumulative Deaths



Baseline Model

- Procedure:
  - Compute first differences of historical incidence:

$$d_t = y_t - y_{t-1}$$



  - Collect first differences and their negatives
  - Sample first differences and add to last observed incidence
    (note: sampling not necessary for horizon 1, just use all observed differences)
  - Adjustments for “niceness”:
    - Force median = last observed incidence
    - Truncate at 0
  - Iterate for horizons > 1

Evaluation Part 1: Ensembles Compared (WIS)

- Weighted Interval Score (WIS) measures the distance of the predictive distribution from the observed response
  - Sum of mean absolute error and penalties for predictive intervals that miss
  - Smaller WIS is better

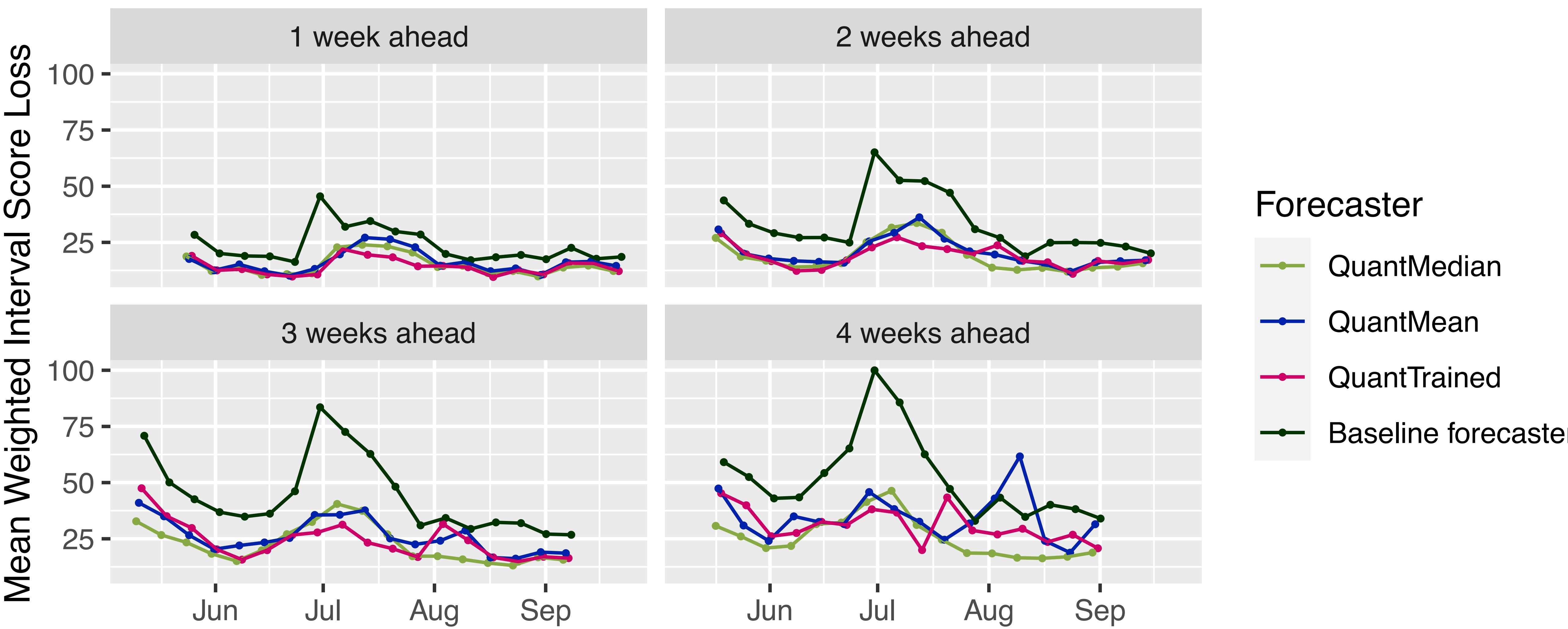
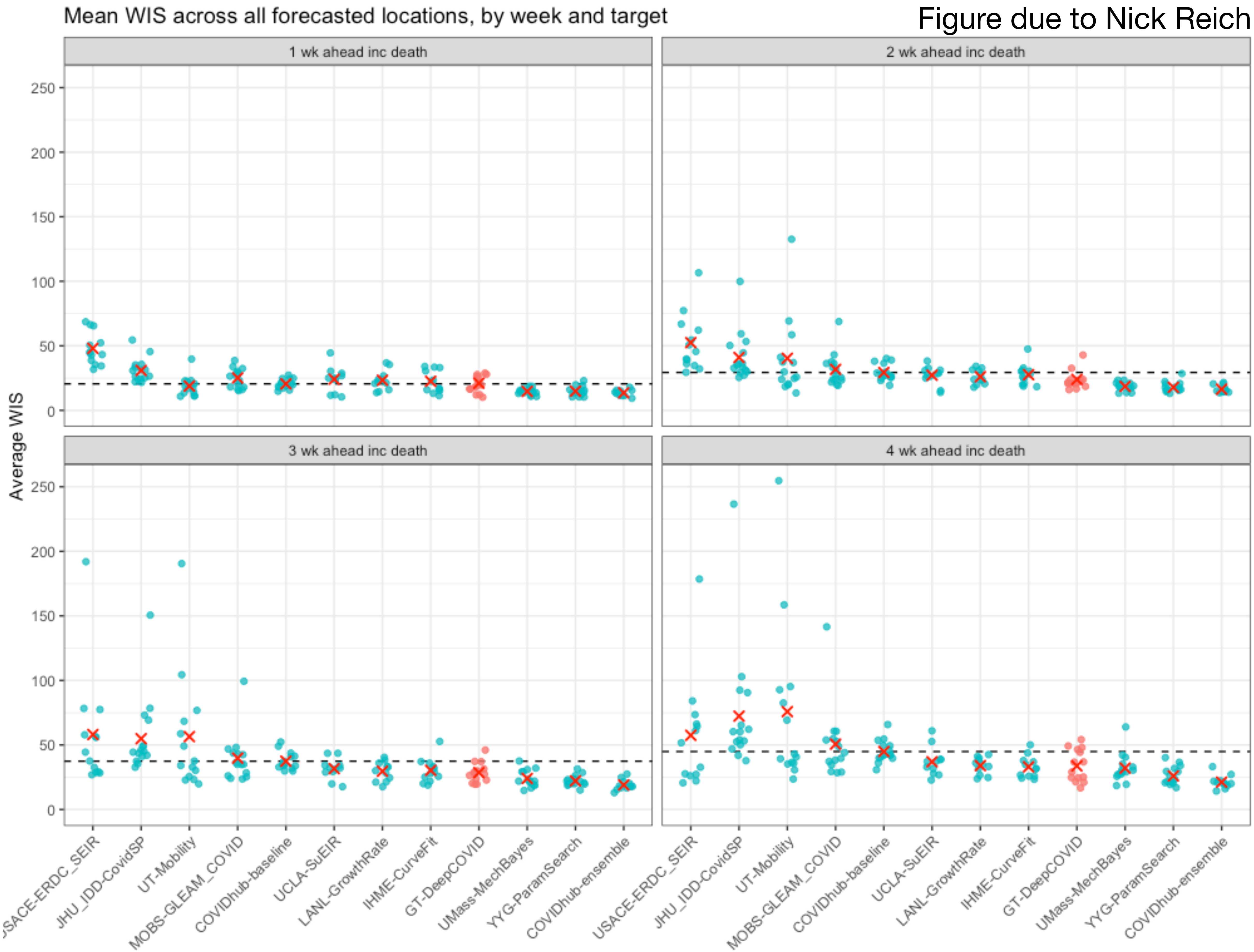


Figure due to Logan Brooks

- All three ensembles are better than the baseline
- QuantMedian and QuantTrained are comparable to or better than QuantMean
- No clear ordering of QuantMedian and QuantTrained

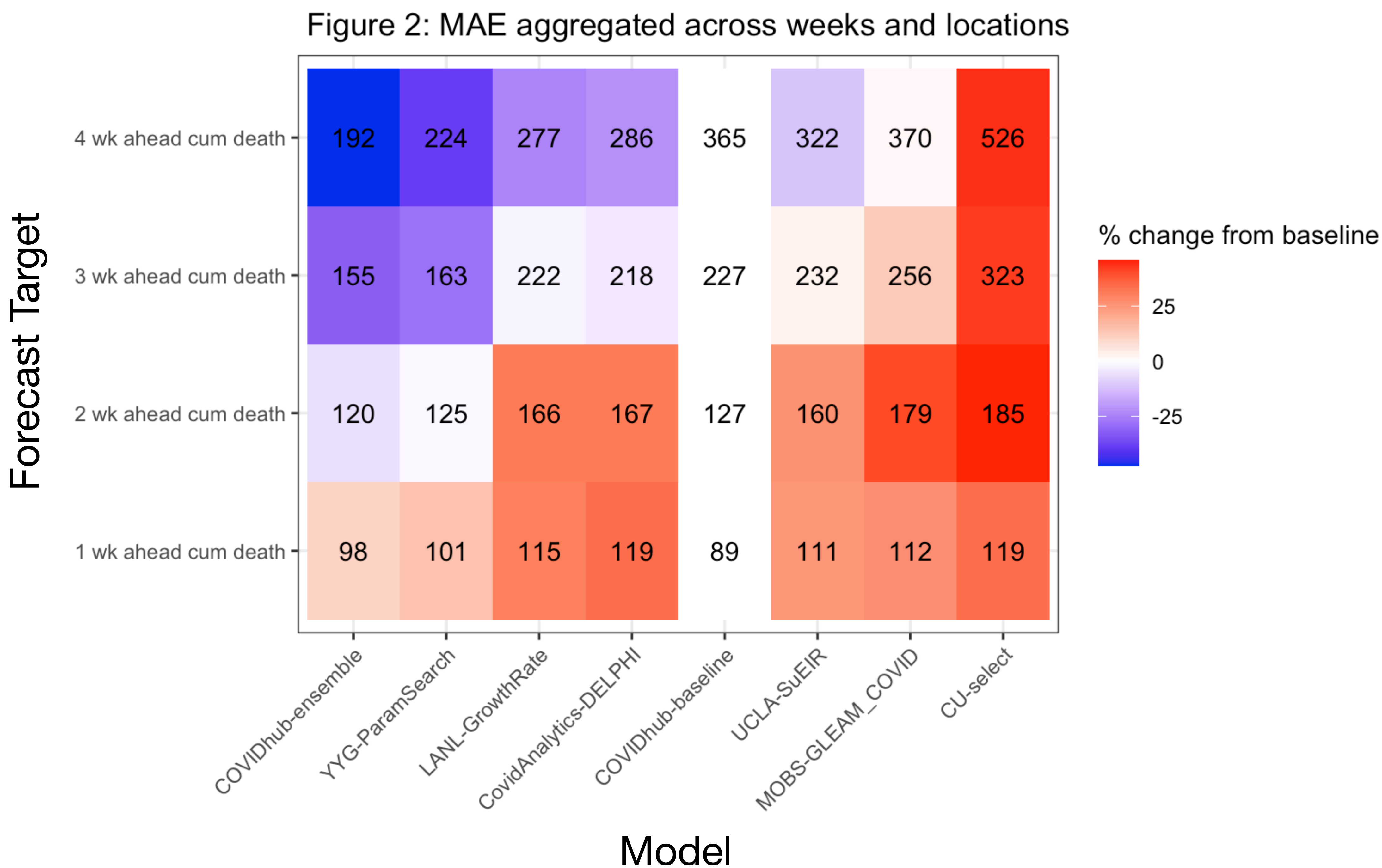
Evaluation Part 2(b): Ensemble vs Components (WIS)

Figure due to Nick Reich



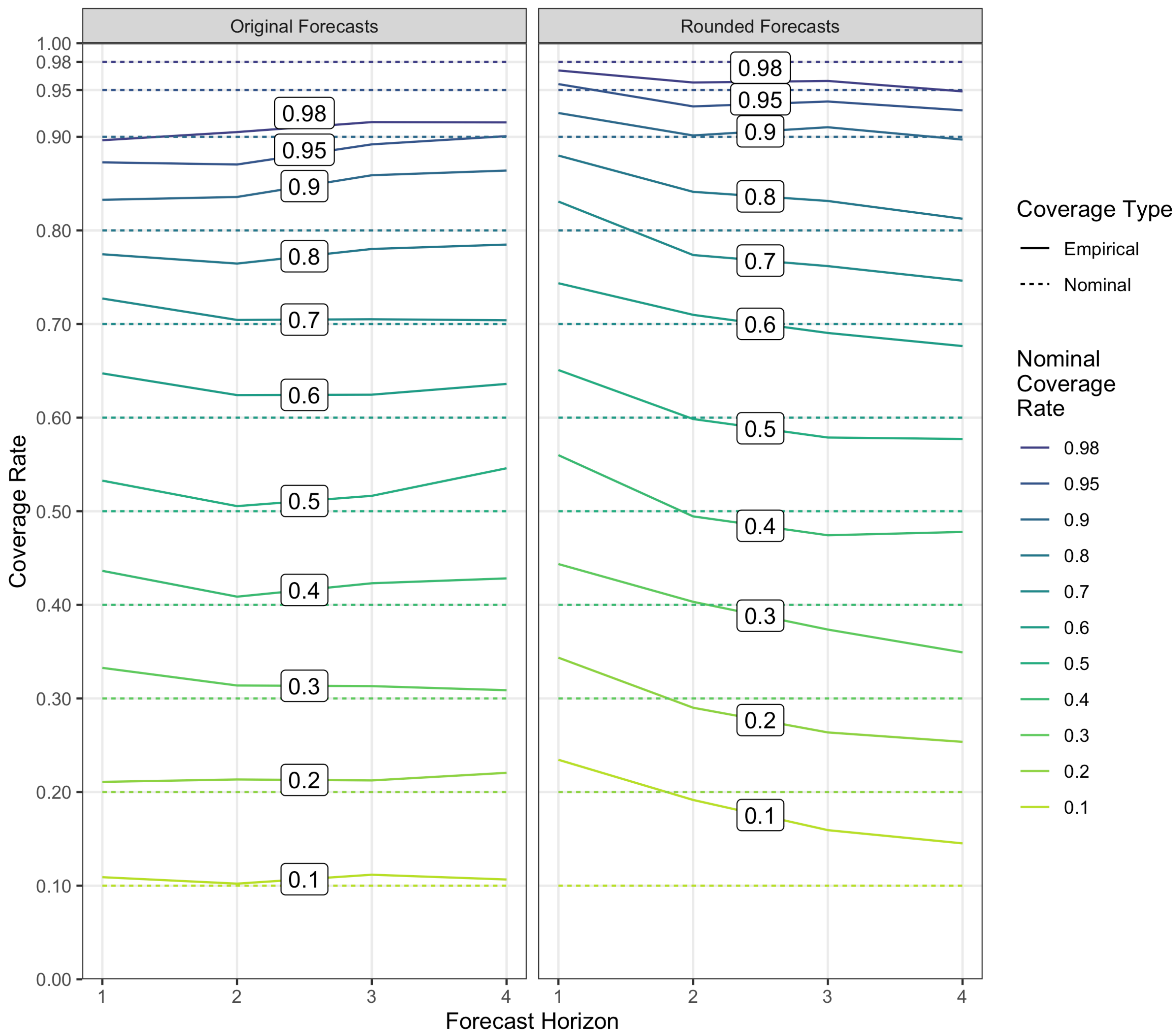
Evaluation Part 2(a): Ensemble vs Components (MAE)

- MAE: On average, how far was the median of the predictive distribution from the eventually-observed count?
- Looking here at results for a set of 8 models that have submitted forecasts for all states and the US since the week of May 2
- Credit to Estee Cramer for this figure



Evaluation: Probabilistic Calibration

- At each predictive interval level, what proportion of intervals contain the eventually-observed outcome?
- This figure shows calibration of the ensemble model only



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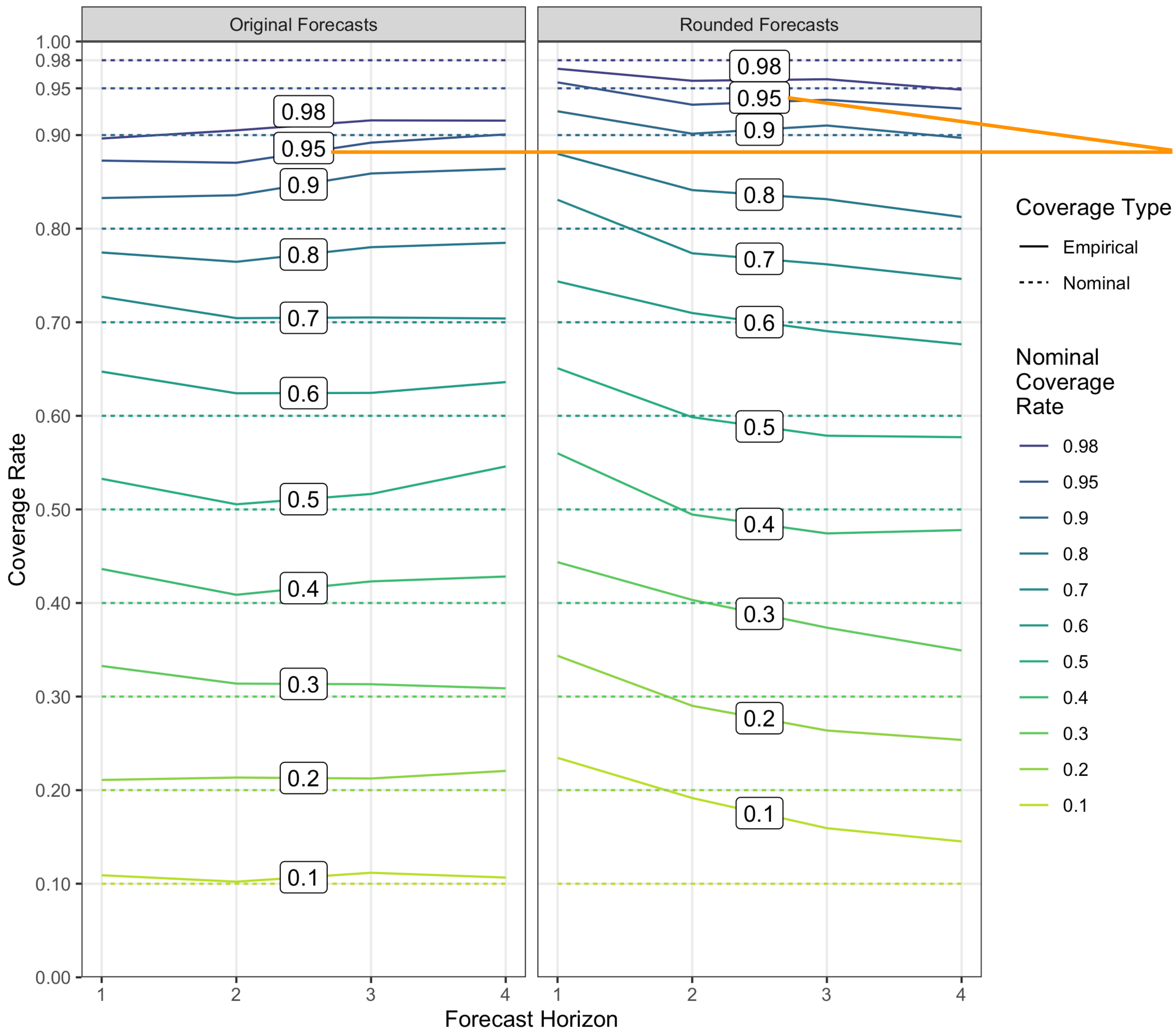
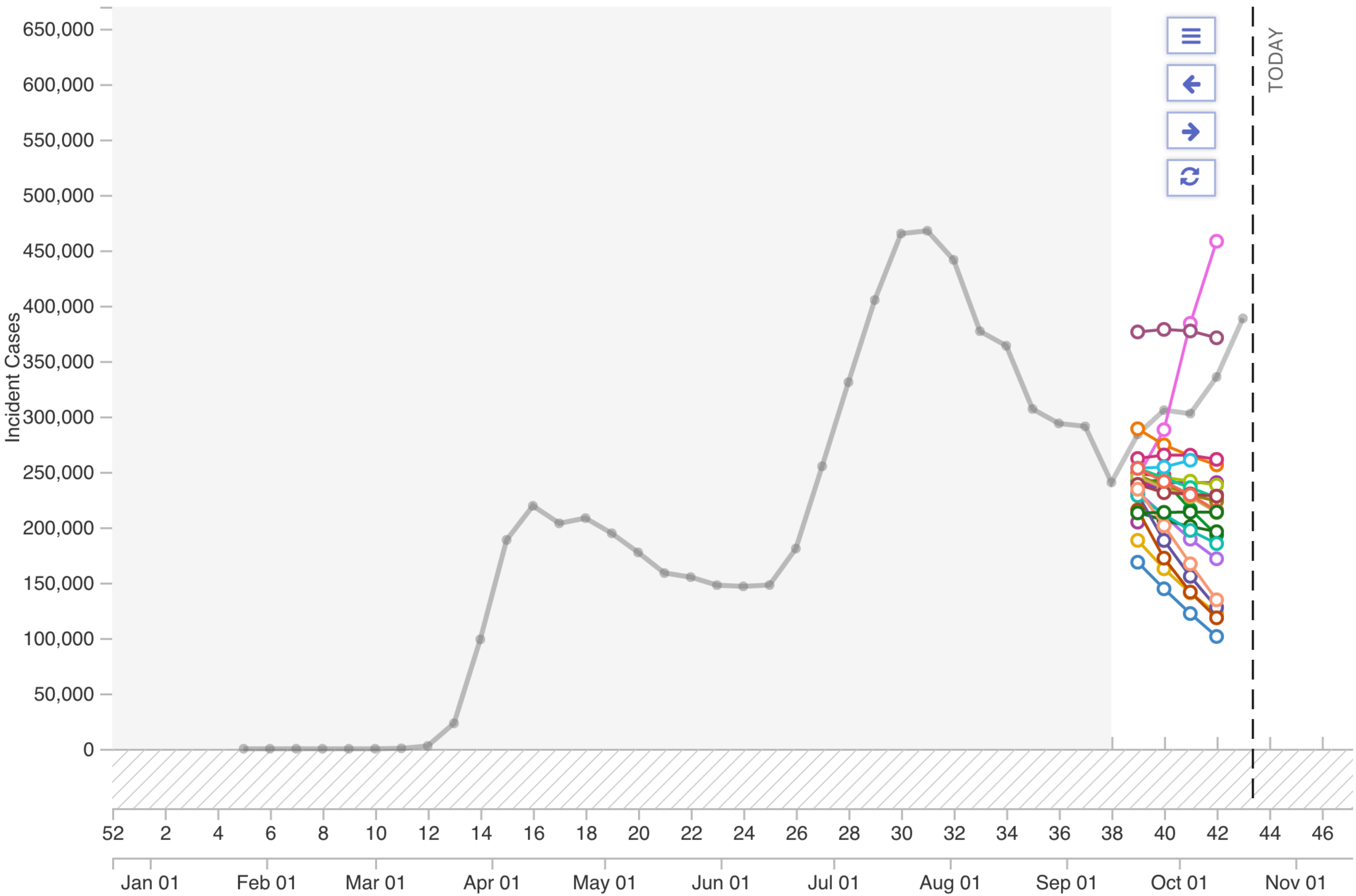


Of the 120 forecasts where rounding changed coverage status for 95% intervals, 99 were for weeks with no new deaths

A Current Challenge: Case Forecasts



Current Work/Future Directions

- Continue accepting and processing forecasts
  - Challenges:
    - Massive amount of data — how to store it?
    - Versioning forecasts

- Refining ensemble methods
  - Recent analyses indicate a weighted median may be helpful
  - Challenges:
    - Models change over time; relative skill may not be stable
    - Limited data, flexible ensemble approaches may be overfitting

- Forecasting model development
  - In flu forecasting, we saw that statistical time-series models were quite effective — we would like to develop these models for COVID-19
  - Challenges:
    - Time
    - Hierarchical structure, forecast horizon-specific model fits, merging mechanistic models with time series models

Thanks!

COVID-19 ForecastHub

Acknowledgments again to:

- Nick Reich
- The whole COVIDhub team
- CDC colleagues
- Contributing modeling teams
- Epidemiologists and medical workers everywhere

We’re hiring for a post-doctoral position, get in touch if interested!
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