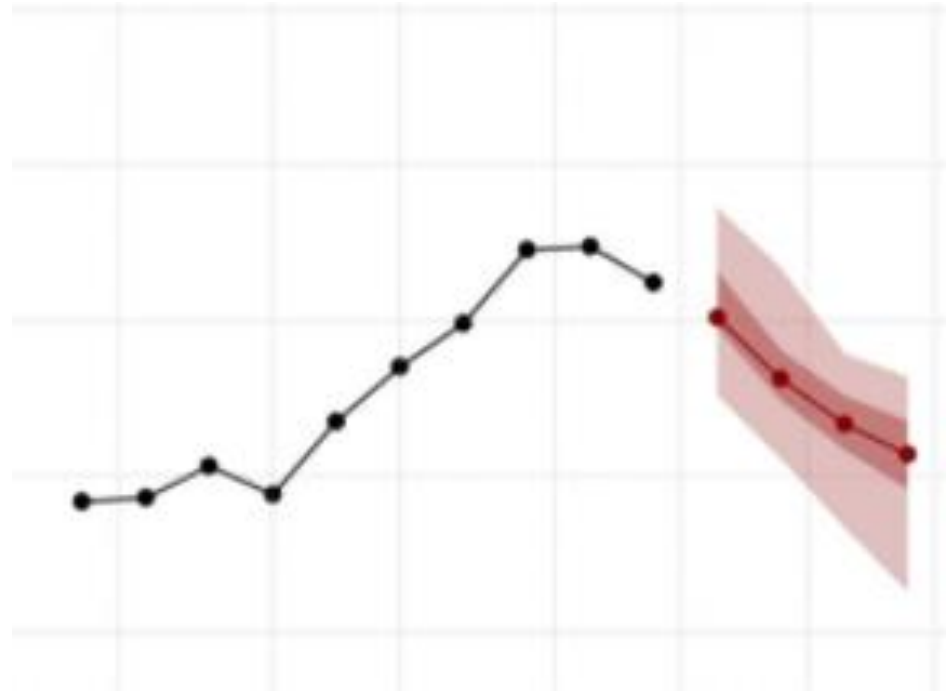


Connecting Forecasting Research to Decision-making Needs: Lessons Learned from CDC-organized Activities

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Why Forecast Epidemics and Pandemics?

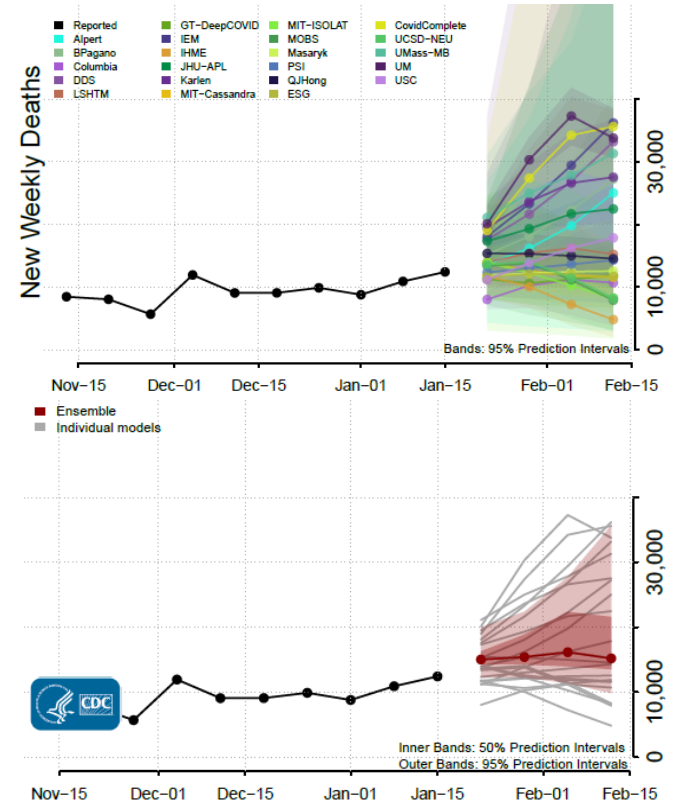
- Surveillance data provide insights into recent trends but do not show if and when changes may occur in the future
- A critical component of public health planning is anticipating changes in future trends to inform risk assessment, resource allocation, and healthcare preparedness
- Forecasts provide quantitative predictions of near-term most likely and plausible best- and worst-case futures

CDC Epidemic Prediction Initiative (established 2014)

- Objectives
 - Connect forecasting research to decision making needs
 - Evaluate forecast skill and facilitate forecasting research
 - Operationalize forecasting
- Forecasting projects
 - Influenza (2014–2020, 2022–2024)
 - Vector-borne: dengue (2015), Aedes mosquitoes (2019-2020), West Nile neuroinvasive disease (2020, 2022)
- Outcomes
 - Increased data availability and real-time forecasting
 - Forecast and evaluation standardization
 - Community building (e.g., CSTE, academia, industry)

COVID-19 Forecasting in the U.S.

- Built on the backbone of FluSight
- Began April 2020 and partnered with U Mass and CMU (CDC-funded Forecasting Centers of Excellence) to ensure forecasts solicited widely, stored openly, synthesized efficiently, communicated clearly, and evaluated honestly
- Cases (through 2021), hospitalizations, and deaths for nation, states/territories, and counties (cases only)
- 100+ academic, industry, and government teams participating
- Collected, disseminated, synthesized, and evaluated millions of real-time forecasts



Lessons Learned (or Reinforced) During COVID

1. Individual forecasts show high variability in skill but an ensemble forecast that combined these predictions was reliably one of the most accurate forecasts
2. Forecasts, including the ensemble, did not reliably predict changes in trends, especially for earlier outcomes (e.g., case reports)

Key Terms

- **Baseline forecast:** A forecast generated for comparison. The COVID baseline model forecasted a median incidence equal to the last week, with uncertainty based on observation noise
- **Weighted Interval Score (WIS):** Forecast skill metric that measures how consistent a collection of forecast prediction intervals is with an observed value. A lower value represents a better forecast
- **Coverage:** The percentage of times a prediction interval (such as 95%) correctly contains the observed value. It should be similar to the prediction interval
 - E.g., 95% of observations should fall within the 95% prediction interval

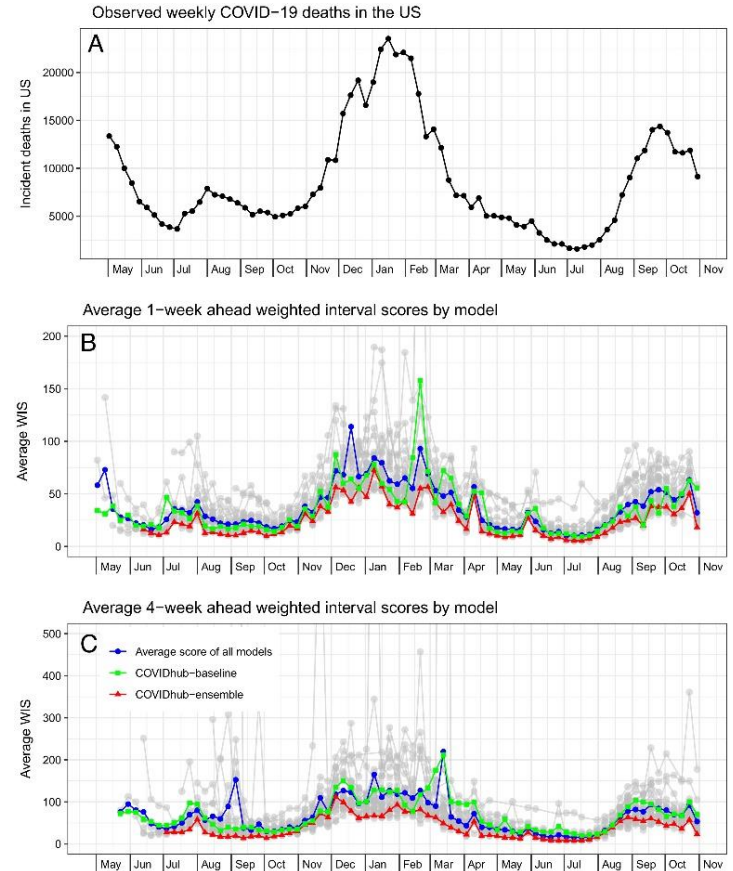
Lesson 1

Forecast skill varied but the ensemble was one of the most accurate forecasts



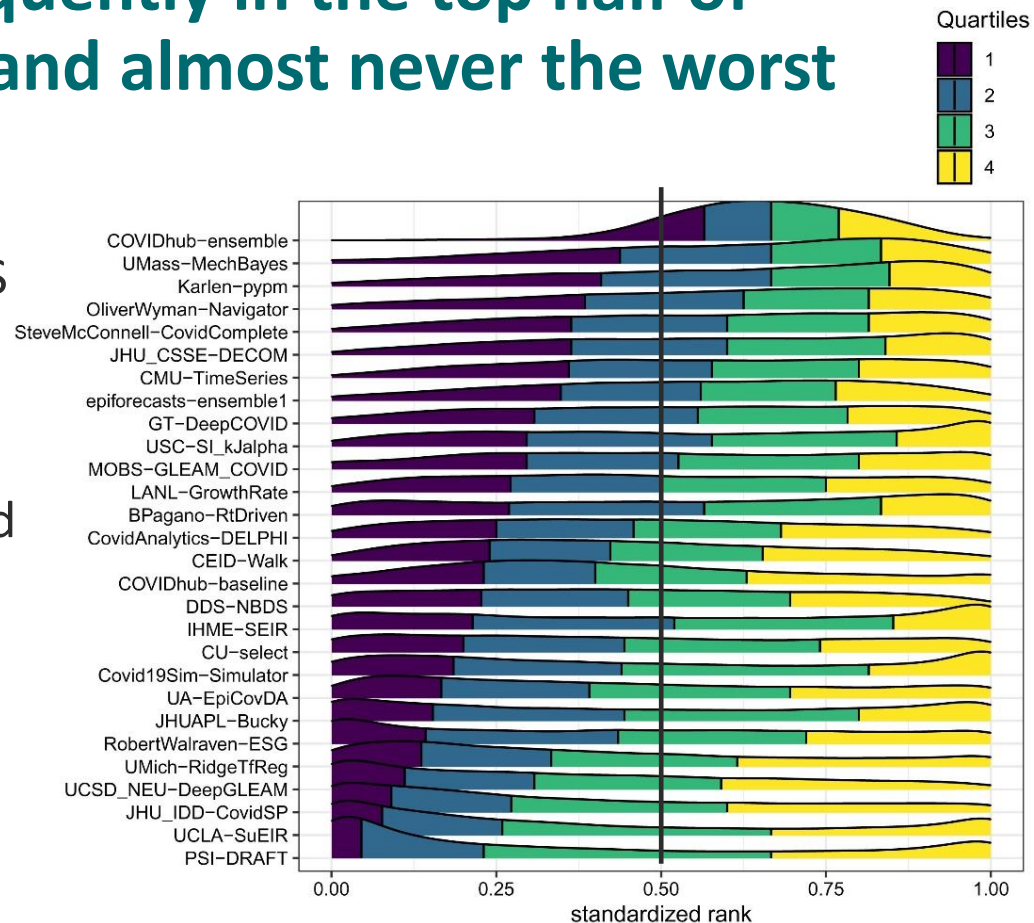
Performance between models varied but the ensemble was more accurate than most models

- The grey line is the WIS for individual models across all 50 states
- The blue line is the average for all models
- The green line is the baseline forecast
- The red line is the WIS for the ensemble model



The ensemble was frequently in the top half of forecast performance and almost never the worst

- This figure compares each model's distribution of its WIS rank
- A rank of 1 indicates that the model had the best WIS for a particular location, target, and week, and 0 indicates it had the worst
- Yellow is the top quarter and purple is the bottom quarter



Reasons for Model Variation

- Evaluated forecasts used different methods, data sources, and made varying assumptions about future transmission patterns
- Almost all models used case data as inputs to their forecast models, 10 models included data on COVID-19 hospitalizations, 10 models incorporated demographic data, and 9 models used mobility data
- 7 made explicit assumptions that social distancing and other behavioral patterns would change over the prediction period
- More evaluation needed to understand how behavioral, mobility, variant prevalence, or novel data streams forecasts

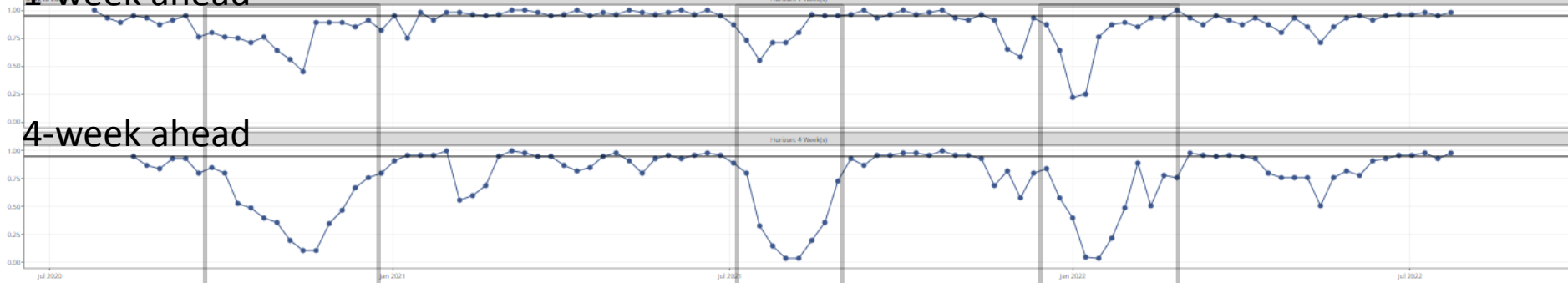
Lesson 2

Forecasts, including the ensemble, do not always predict changes in trends, especially for earlier outcomes

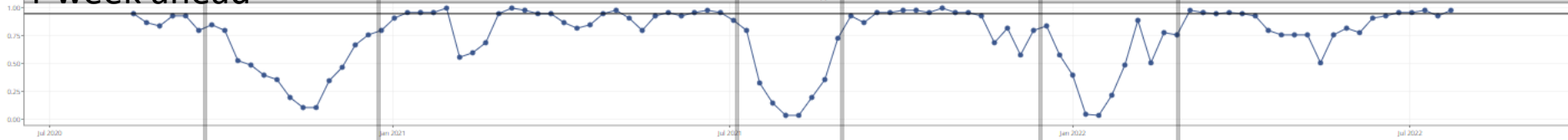


Case ensemble forecast coverage (95% prediction interval)

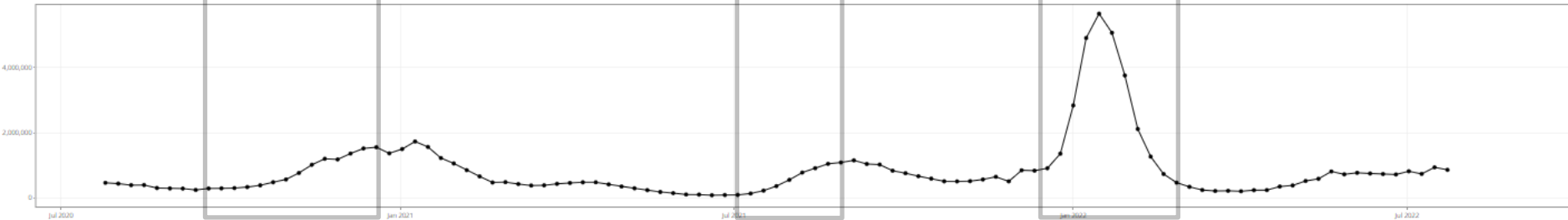
1-week ahead



4-week ahead



Observed new cases



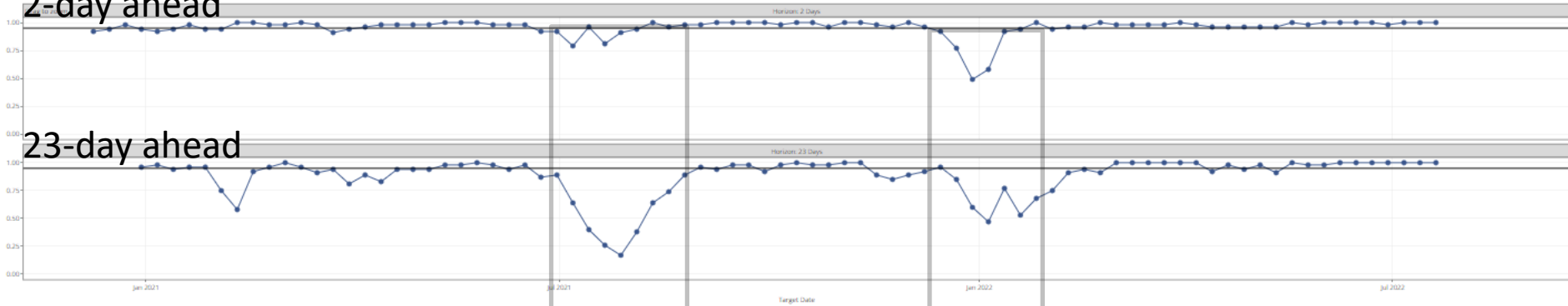
Winter 2020 wave

“Delta” wave

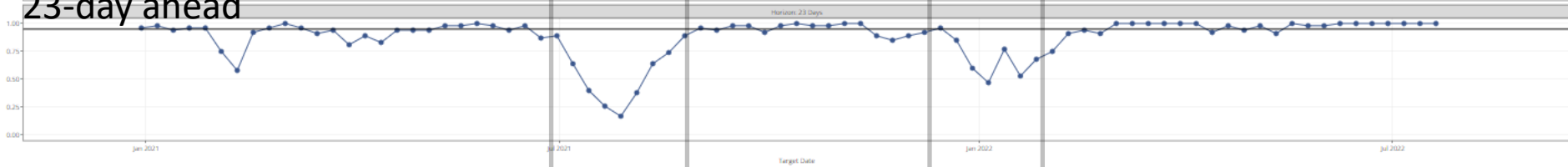
“Omicron” wave

Hospital ensemble forecast coverage (95% prediction interval)

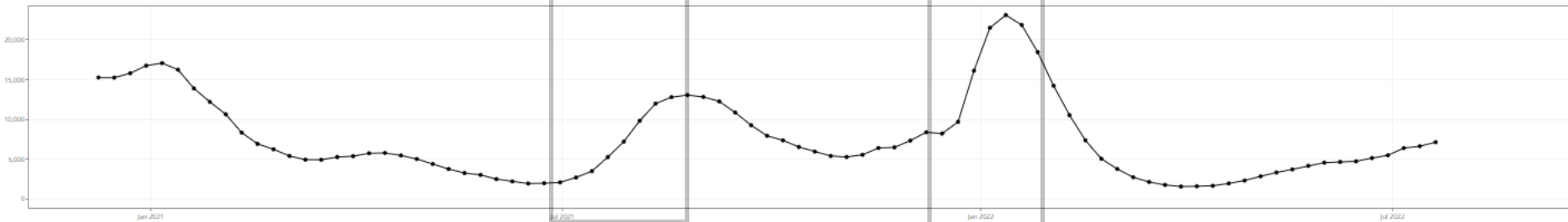
2-day ahead



23-day ahead



Observed new hospitalizations



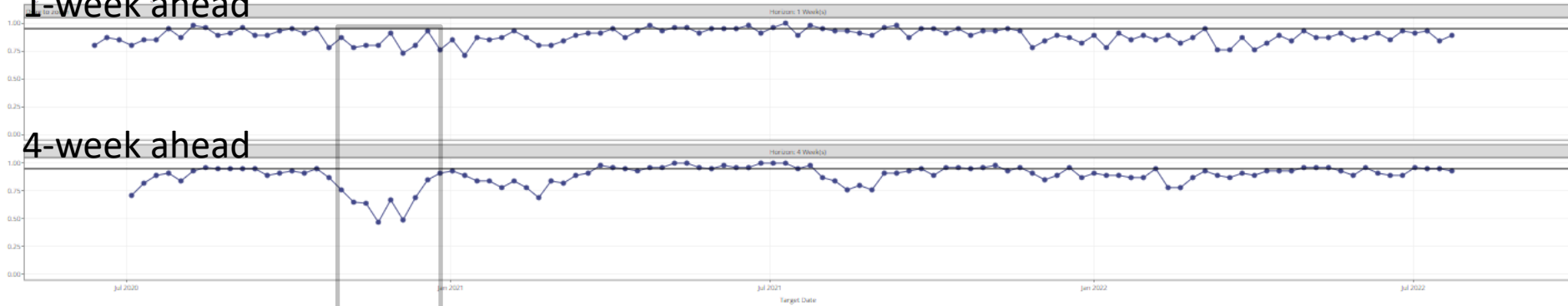
Winter 2020 wave

“Delta” wave

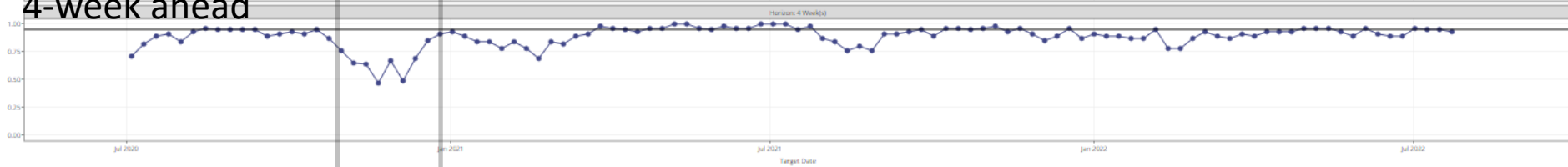
“Omicron” wave

New deaths ensemble forecast coverage (95% prediction interval)

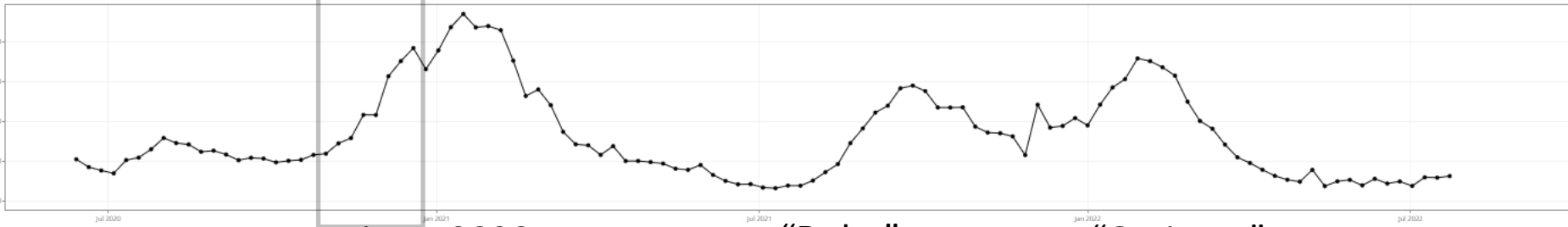
1-week ahead



4-week ahead



Observed new deaths

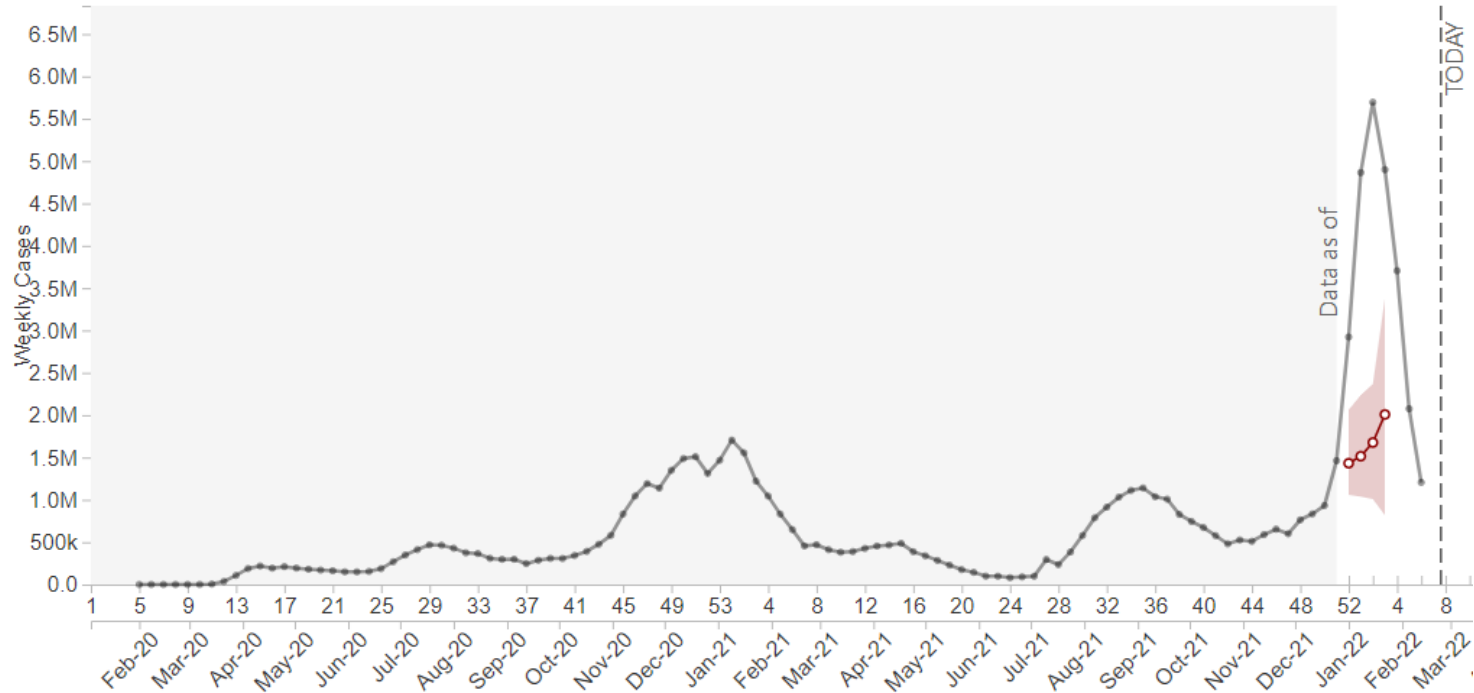


Winter 2020 wave

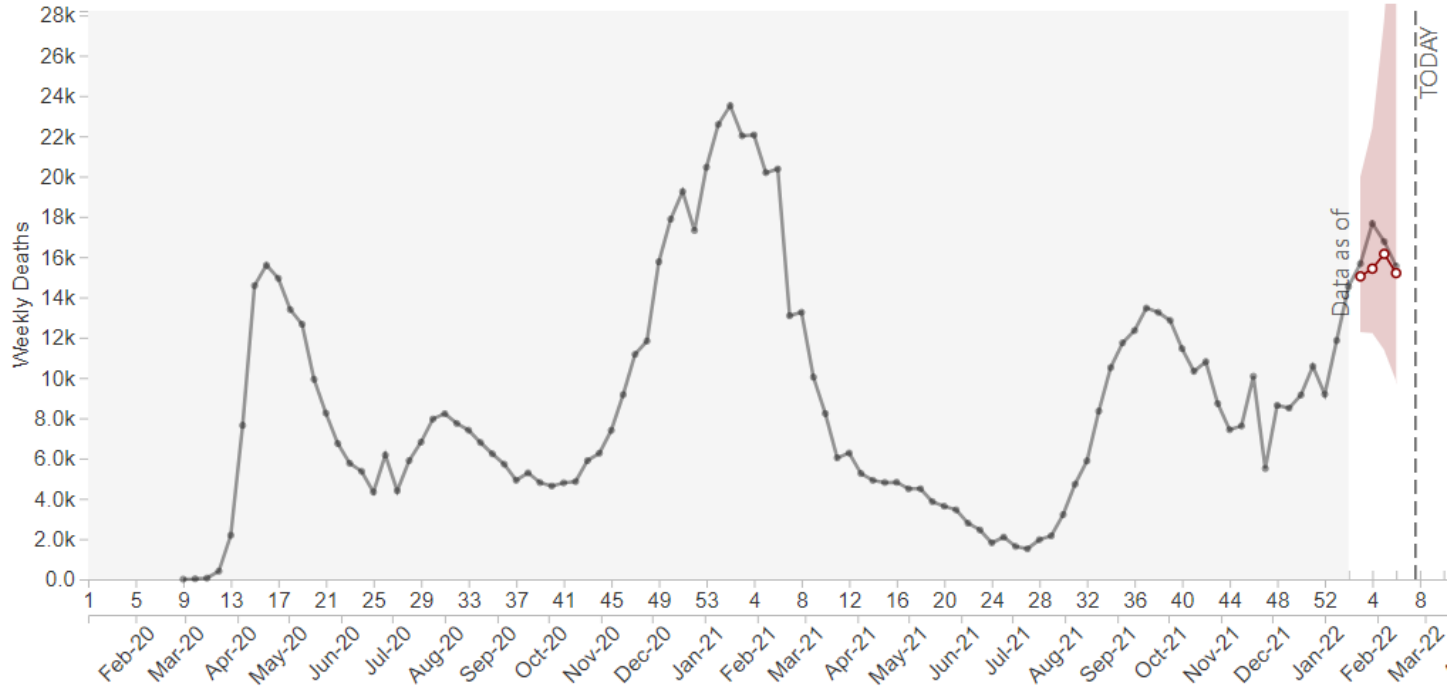
“Delta” wave

“Omicron” wave

Comparison of case forecasts & reported data



Comparison of death forecasts & reported data

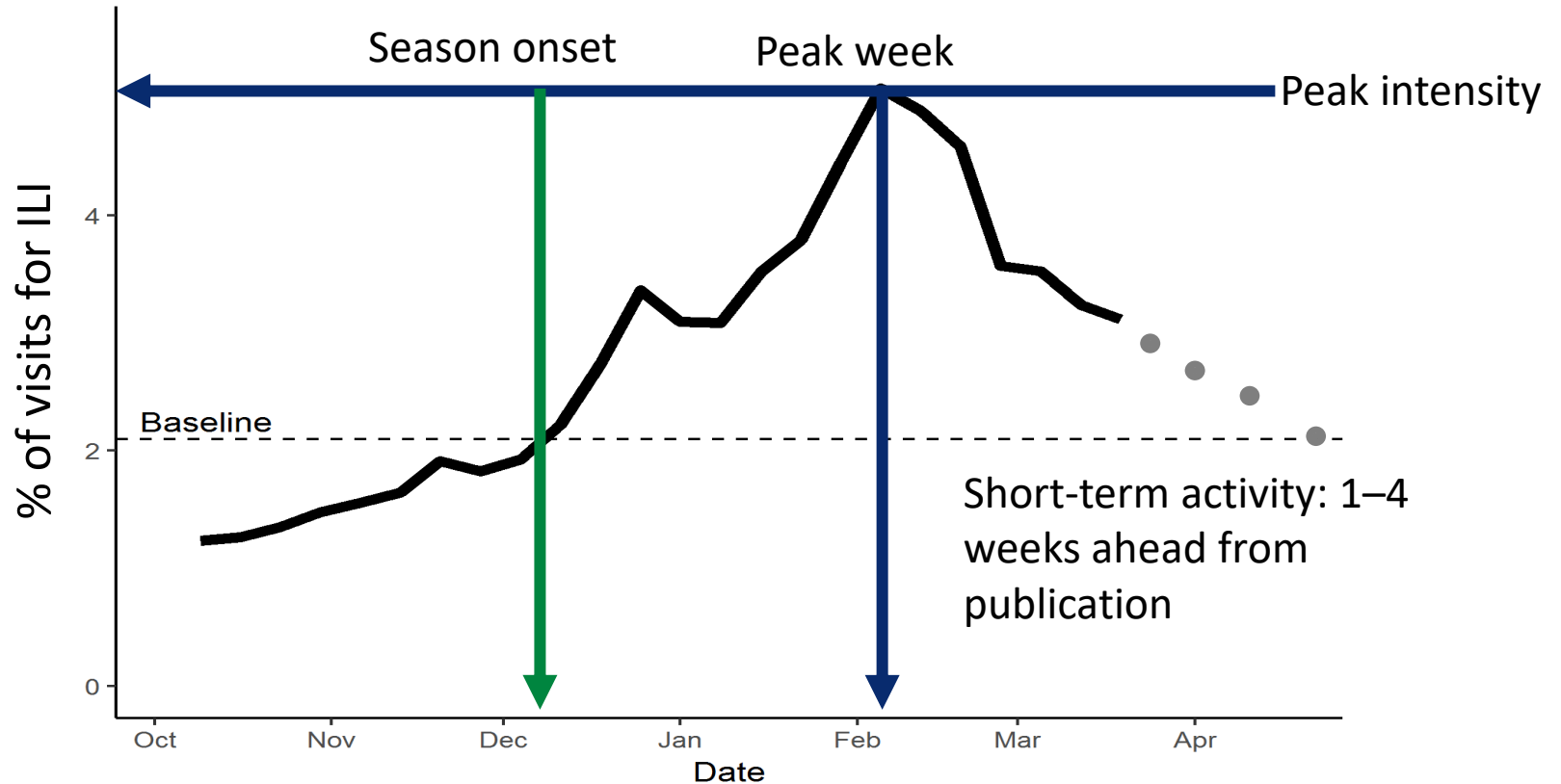


Future Plans

What are we doing for the 2022–23 season?



Previous influenza forecasting targets (data: ILINet)



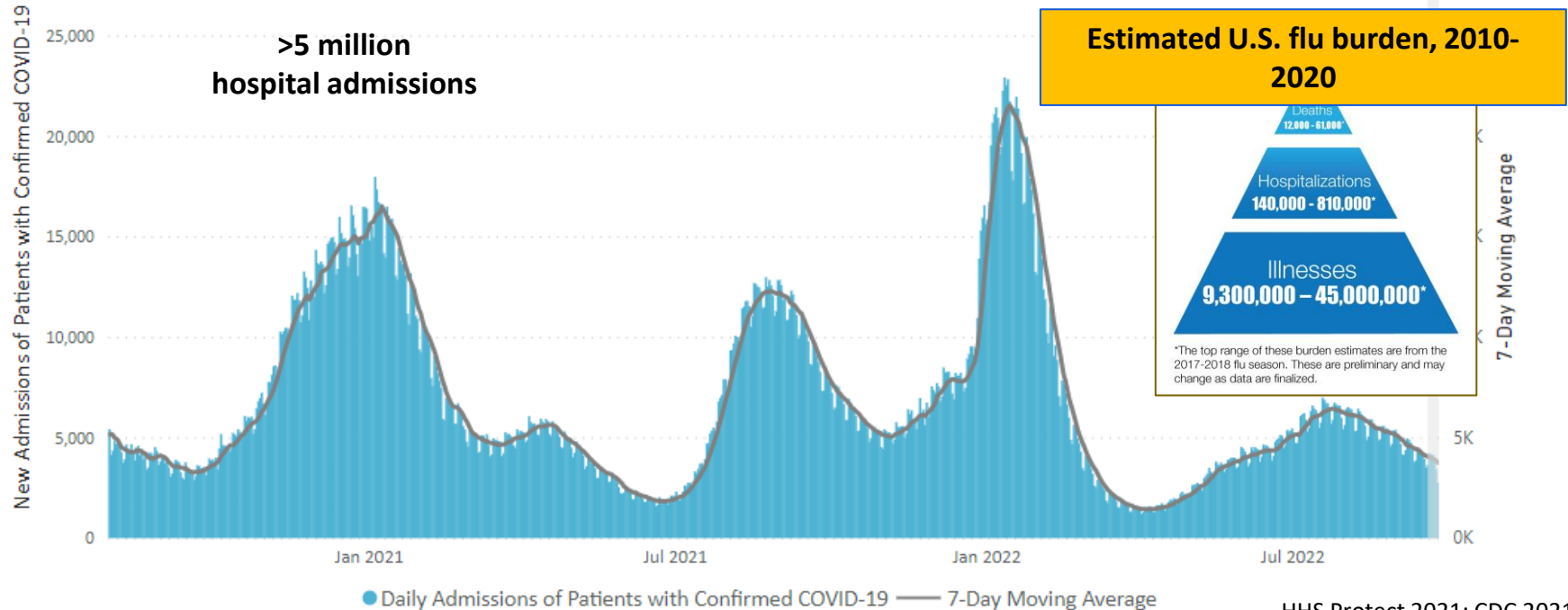
Locations: US, 10 regions, and states

ILI as a flu indicator likely impacted by the pandemic

- ILI not laboratory-confirmed influenza
 - Captures visits due to other respiratory pathogens, such as SARS-CoV-2, that present with similar symptoms
- Healthcare-seeking behaviors have changed dramatically during the COVID-19 pandemic
 - Many people either not accessing the healthcare system or doing it in alternative settings, which may or may not be captured as a part of ILINet

Need to Monitor Hospital Burden Caused by Both COVID-19 and Influenza

In the past year, high number of laboratory-confirmed COVID-19 hospital admissions
HHS Protect Unified Hospital data source, August 2020-September 2022



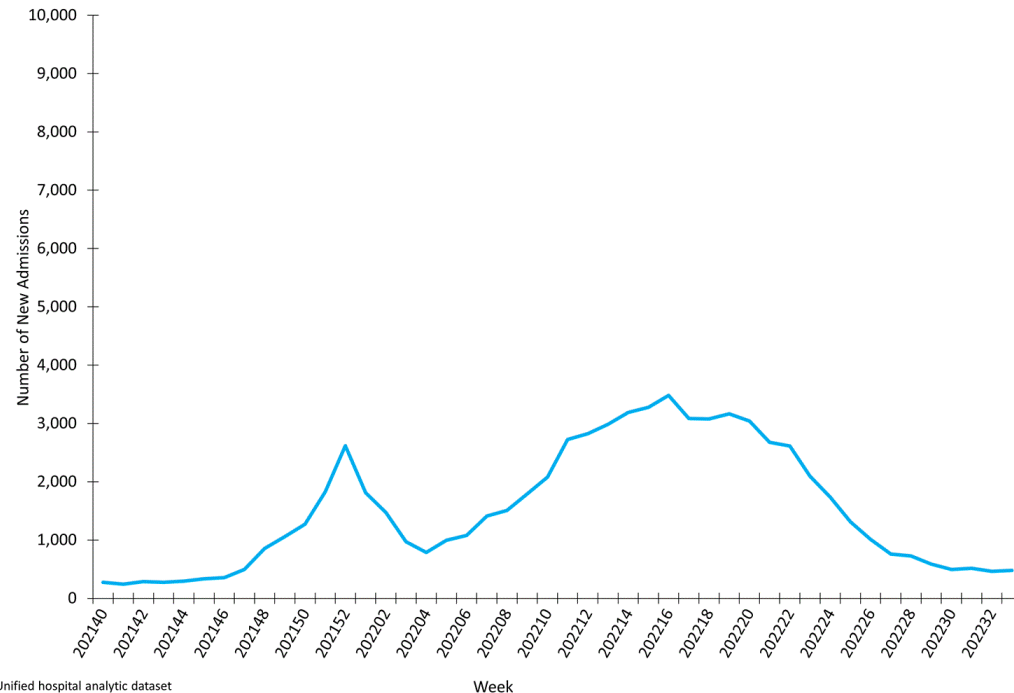
Plans for flu forecasting for the 2022–23 season

- Source: HHS Protect facility-level hospital data
- Main Target: Weekly number of confirmed influenza hospital admissions (same target as COVID hospitalization forecasts)
- Horizon: Up to 4 weeks
- Potential “Experimental” Targets: Increase/decrease or trajectory samples
- Geography: National and state
- Start date: mid-October 2022
- Communication: FluSight webpage
 - <https://www.cdc.gov/flu/weekly/flusight/index.html>



National New Flu Hospital Admissions, October 2021–August 2022

New Influenza Hospital Admissions Reported to HHS Protect, National Summary, October 3, 2021 – August 20, 2022

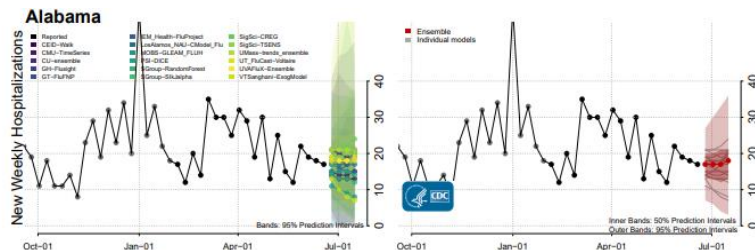


CDC Flu Forecast Communication

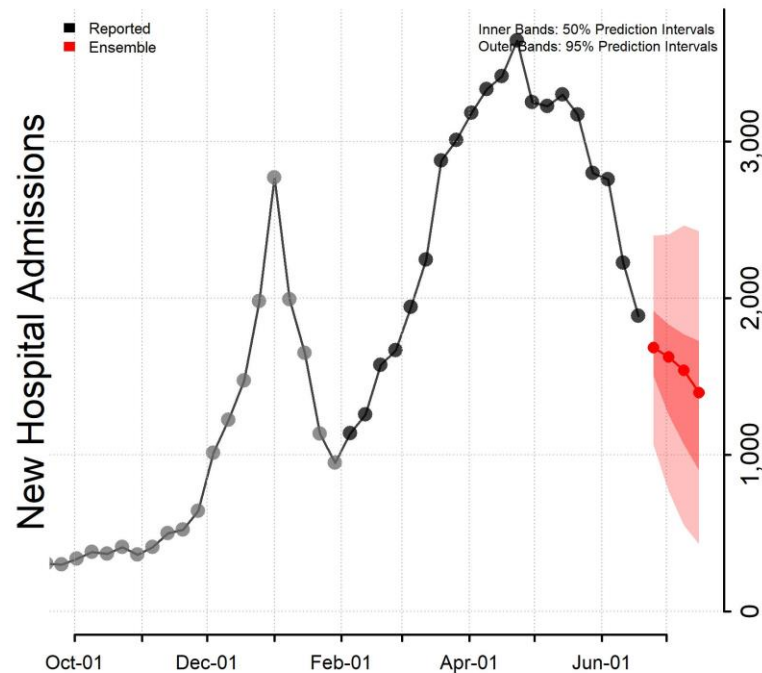
Reported and forecasted new influenza hospitalizations as of June 20, 2022.

Interpretation of National Forecasts of New Hospitalizations

- This week's ensemble predicts that the number of new weekly confirmed influenza hospital admissions will likely decrease nationally, with **400 to 2,400** new confirmed influenza hospital admissions likely reported in the week ending July 16, 2022.
- This week, 15 modeling groups contributed one or more forecasts that were eligible for inclusion in the new hospitalization ensemble forecasts for at least one jurisdiction. Contributing teams are listed below.
- Ensemble forecasts combine diverse independent team forecasts into one forecast. They have been among the most reliable forecasts in performance for previous influenza and COVID-19 forecasts, but even the ensemble forecasts may not reliably predict rapid changes in the trends.
- The figure shows the number of new confirmed influenza hospital admissions reported in the United States each week from September 26 through June 18 and forecasted new influenza hospital admissions per week over the next 4 weeks, through July 16. Effective February 2, 2022, hospitals are required to report laboratory-confirmed influenza hospitalizations to HHS Protect daily. Prior to this update, reporting influenza hospitalizations was optional (noted as grey in the above figure). See [COVID-19 Guidance for Hospital Reporting and FAQs](#) for additional details on this guidance.



National Forecast



<https://www.cdc.gov/flu/weekly/flusight/index.html>

Conclusions

- Forecasting lessons from COVID-19:
 - An ensemble is a robust option for public health
 - Forecast performance can degrade near inflection points
- Ensuring that future influenza forecasting efforts improve on and incorporate the lessons learned and best practices identified during COVID-19 activities will improve the utility of future a forecasts
- CDC continues to build on previous efforts to forecast COVID and flu into the future



Acknowledgements

- CDC colleagues; current and previous forecasting teams; data providers; state, tribal, territorial, and local public health officials

Evaluation of individual and ensemble probabilistic forecasts of COVID-19 mortality in the United States

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An open challenge to advance probabilistic forecasting for dengue epidemics

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Applying infectious disease forecasting to public health: a path forward using influenza forecasting examples

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