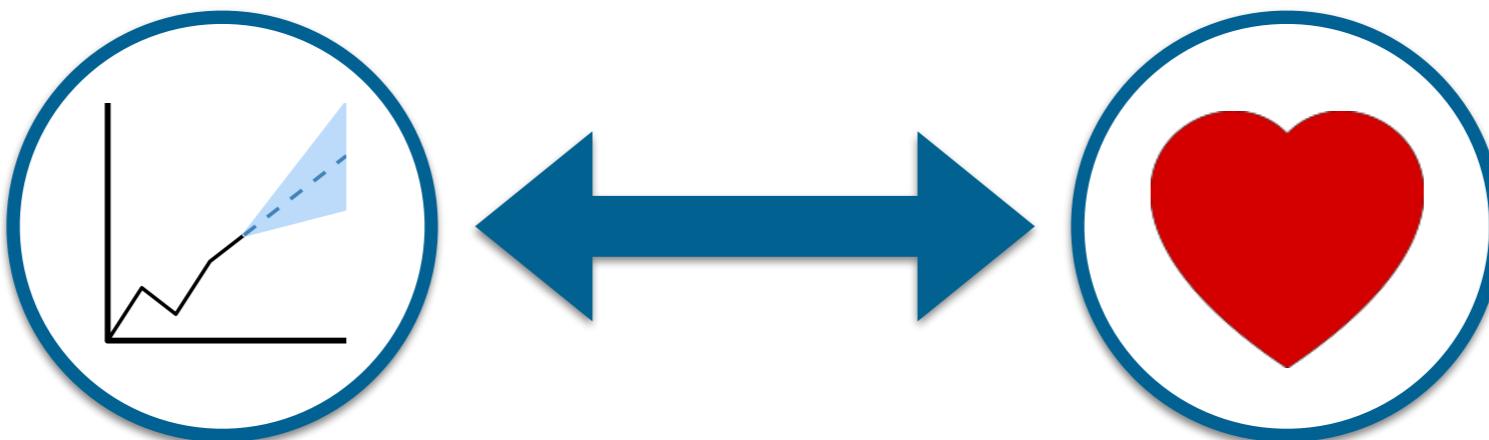


# Predictive Modeling to Support Public Health



Evan L. Ray

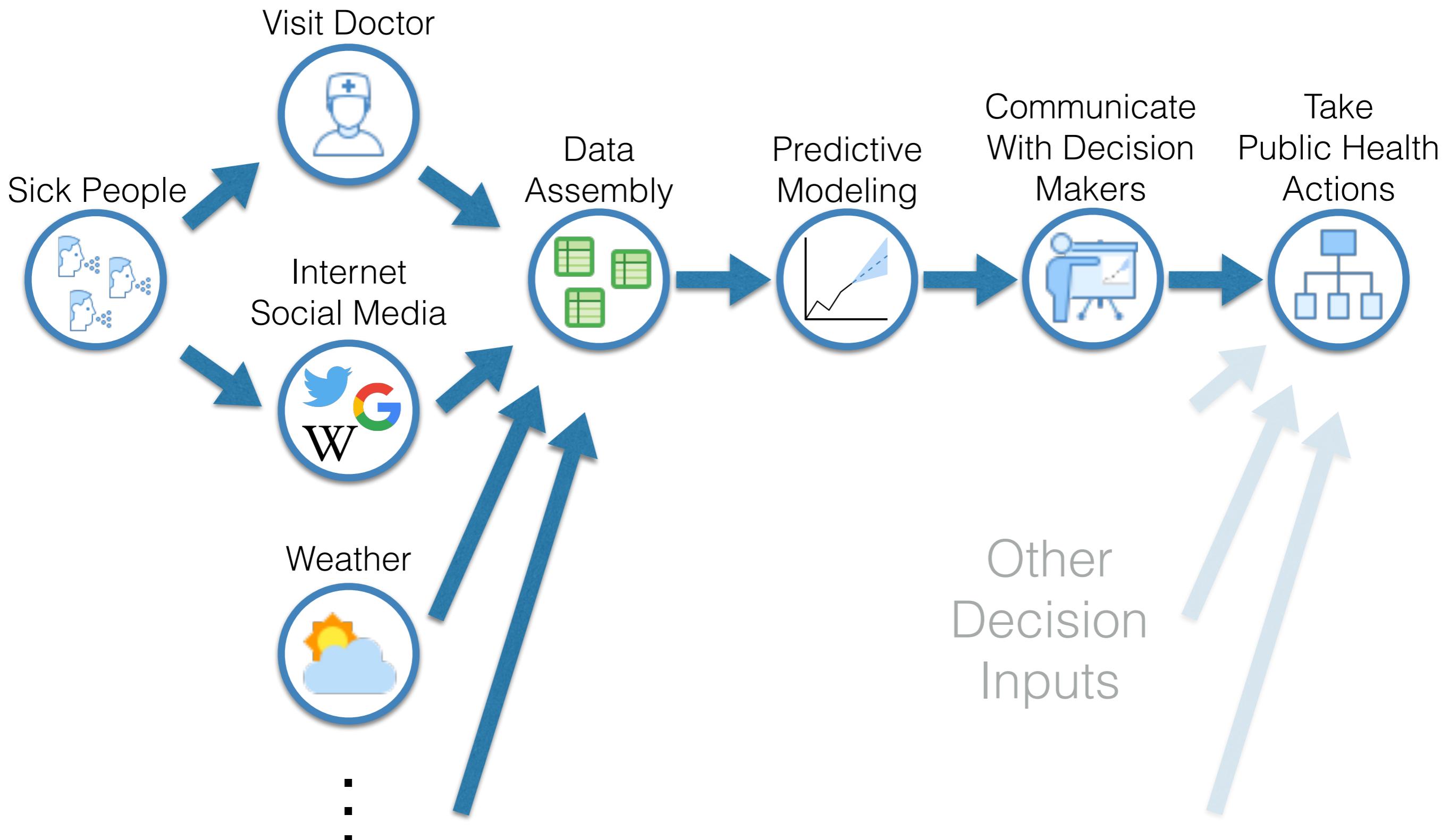
CSTE/CDC Forecasting and Modeling Workshop

16 November 2021

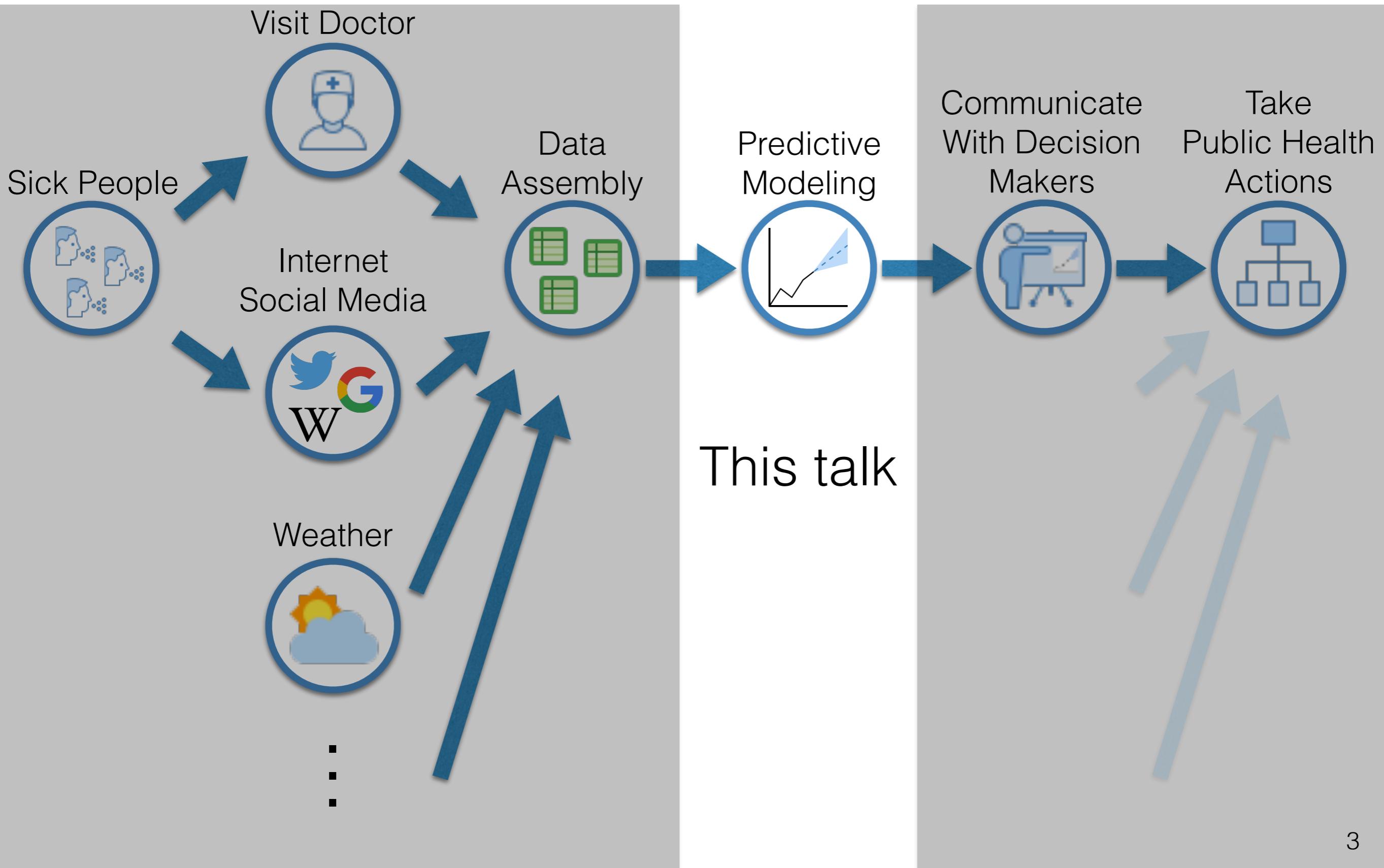


COVID-19  
**ForecastHub**

# Predictive Modeling for Public Health



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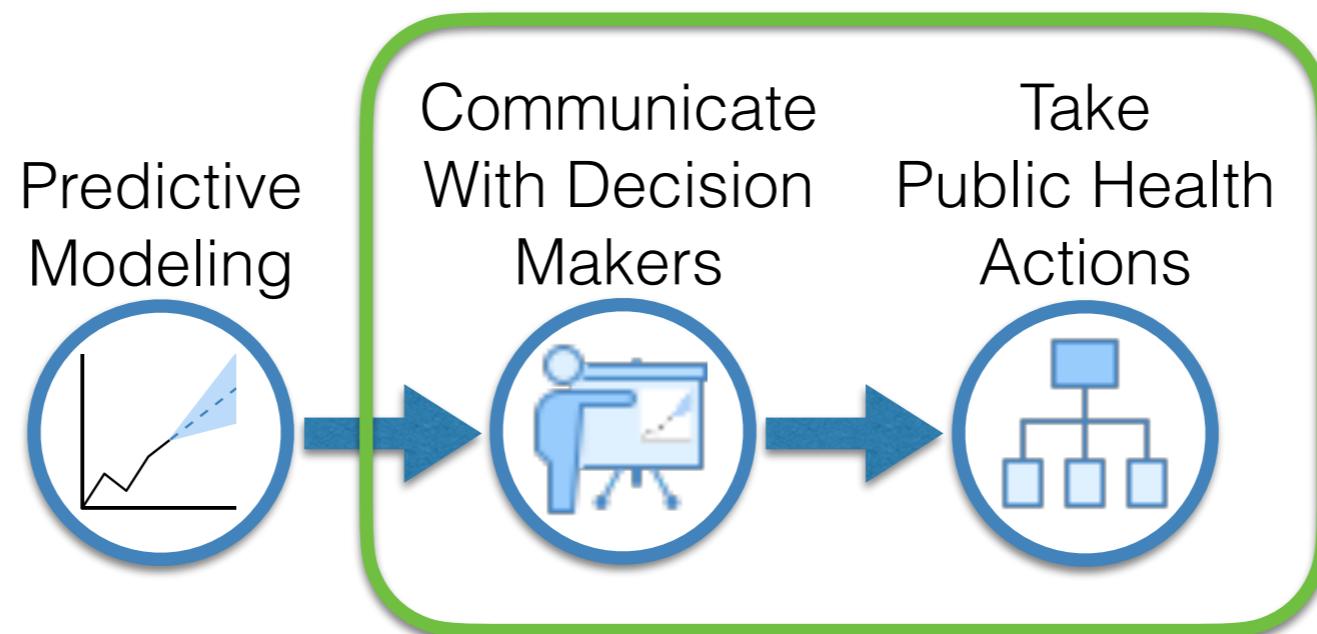


# Predictive Modeling for Public Health



Important note!!

# Predictive Modeling for Public Health



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**The goal is to support the decision making process**

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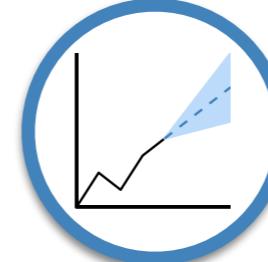
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## 2. Have a **record of accuracy** in past predictions

# Outline of This Talk

Predictive  
Modeling



- **Some common modeling tasks**
- Some common models and methods for these tasks
- Evaluating predictions

# Common Modeling Tasks

- **Nowcast:** what is the state of the system now (or in the past)?
- **Forecast:** what will the state of the system be in the future?
- **Scenario Projection:** what would the state of the system be in the future if certain specified conditions came about?

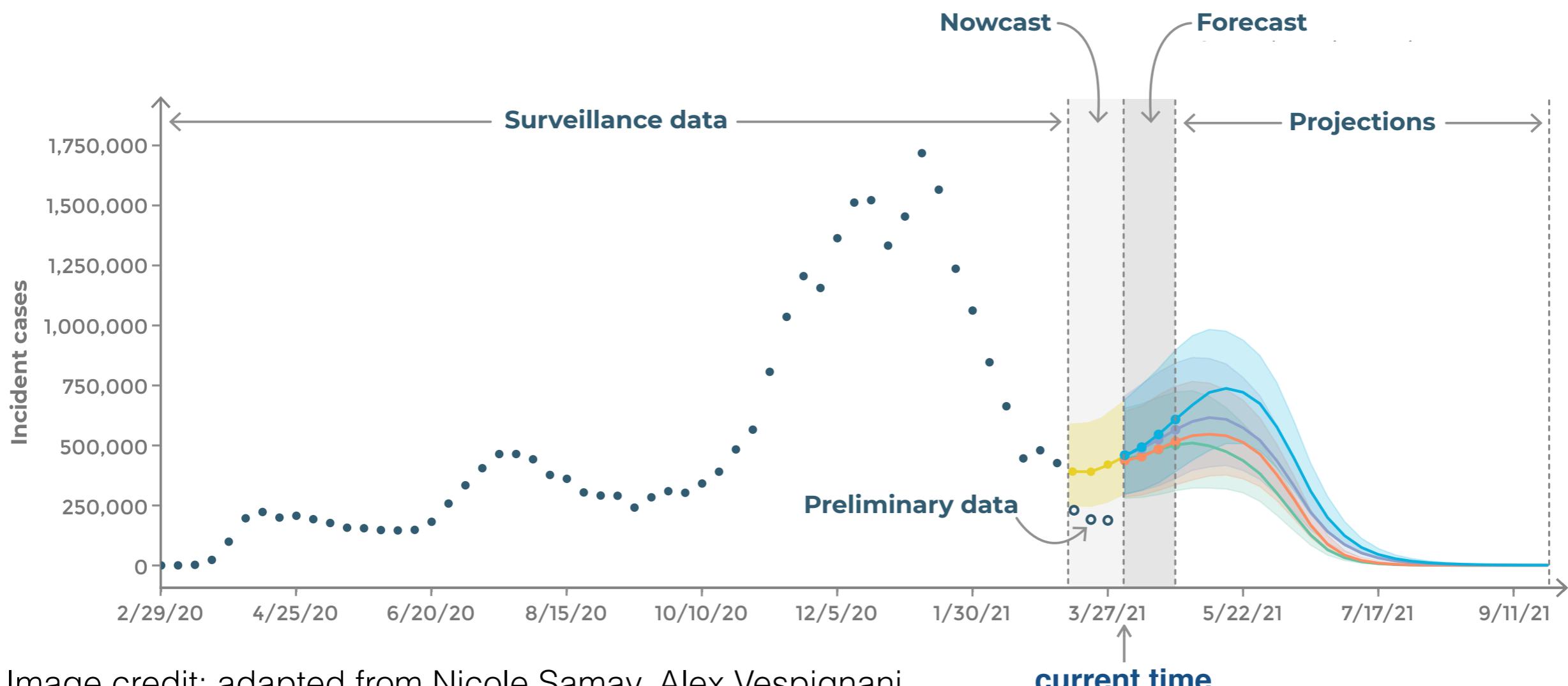
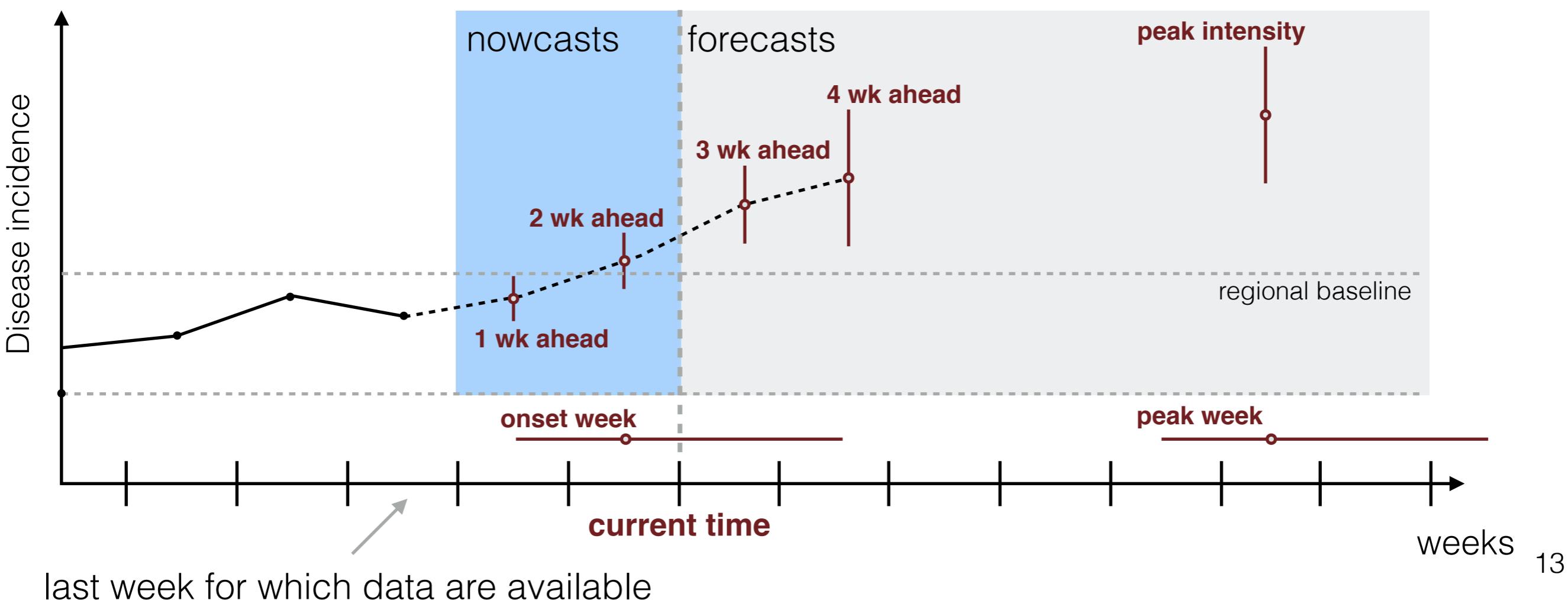


Image credit: adapted from Nicole Samay, Alex Vespignani,  
via the Scenario Modeling Hub, <https://covid19scenariomodelinghub.org/>

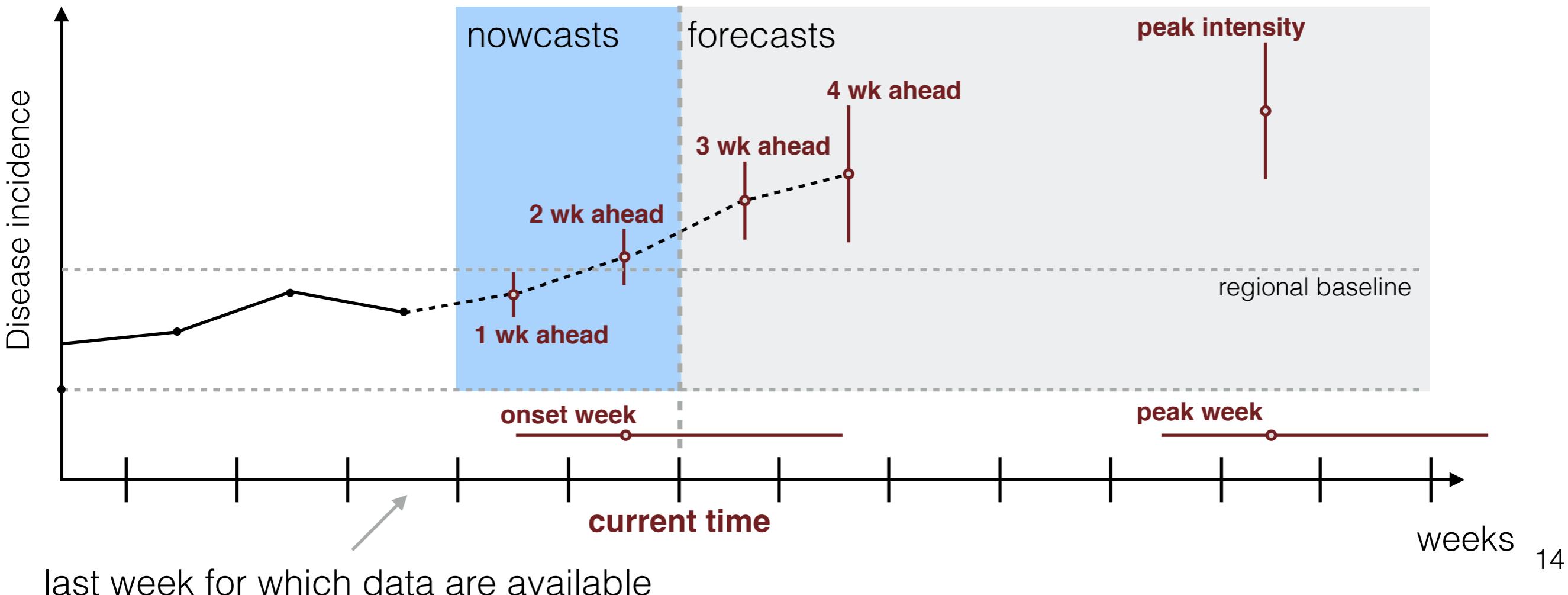
# Examples of Nowcast & Forecast Targets with Public Health Relevance

- Targets used in CDC annual influenza forecasting challenges
  - 4 short term weekly incidence targets (2 in recent past, 2 near future)
  - Timing of season onset
  - Timing of season peak
  - Peak incidence



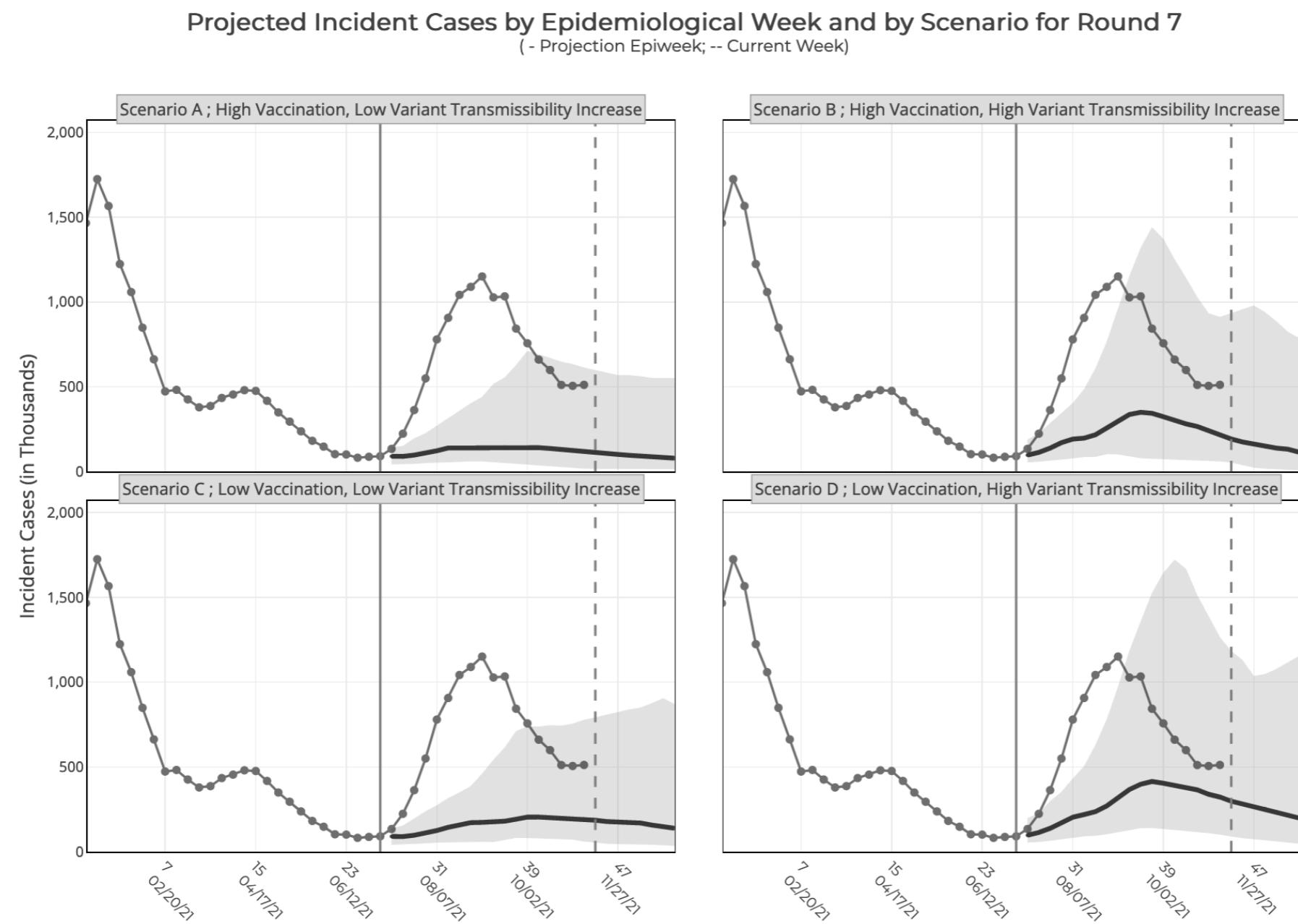
# [How] Could These Targets have Greater Public Health Relevance?

- Is a categorical assessment of season severity (e.g. as low, moderate, high, or very high) more relevant than numeric values of peak intensity?
- Maybe we care more about the largest incidence we'll observe over the next 4 weeks than the incidence in each of those weeks?
- Do we want to know whether there will be a change in growth rate or direction of trend over the next 4 weeks?



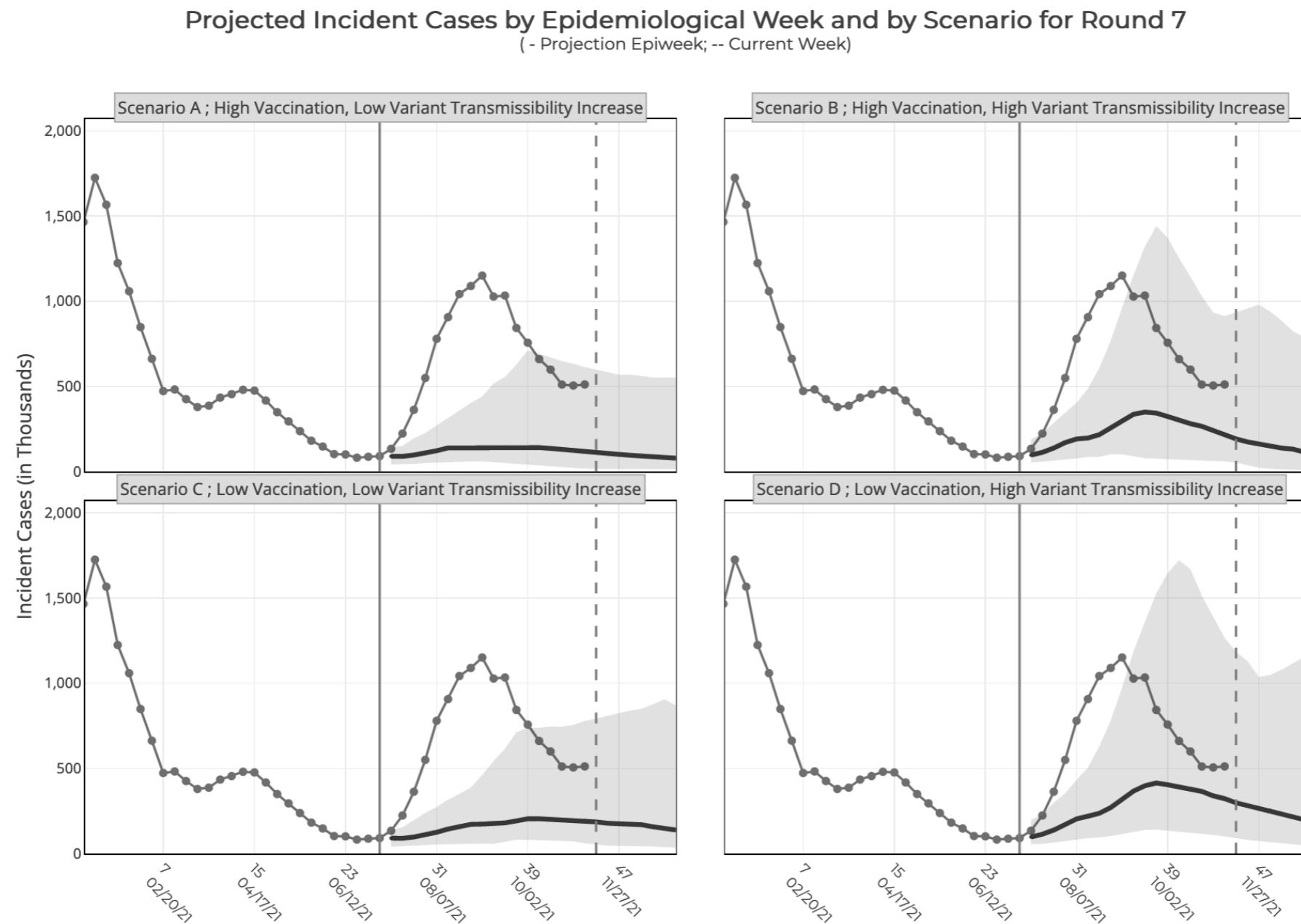
# Examples of Scenario Projection Targets with Public Health Relevance

- What would incident cases be over the next 6 months if there were low/high vaccination rates and a low/high variant transmissibility increase?



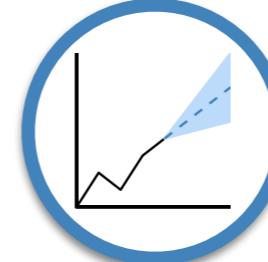
# [How] Could These Targets have Greater Public Health Relevance?

- Do we care more about projected cases under each scenario, or the expected *difference* or *ratio* of case levels between scenarios?



# Outline of This Talk

Predictive  
Modeling



- Some common modeling tasks
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# General Classes of Models

**Mechanistic:** Model *mechanisms* of disease transmission



- Individuals move between compartments at rates that depend on:
  - Current number of susceptible and infected individuals
  - Potentially, other factors (e.g., weather)

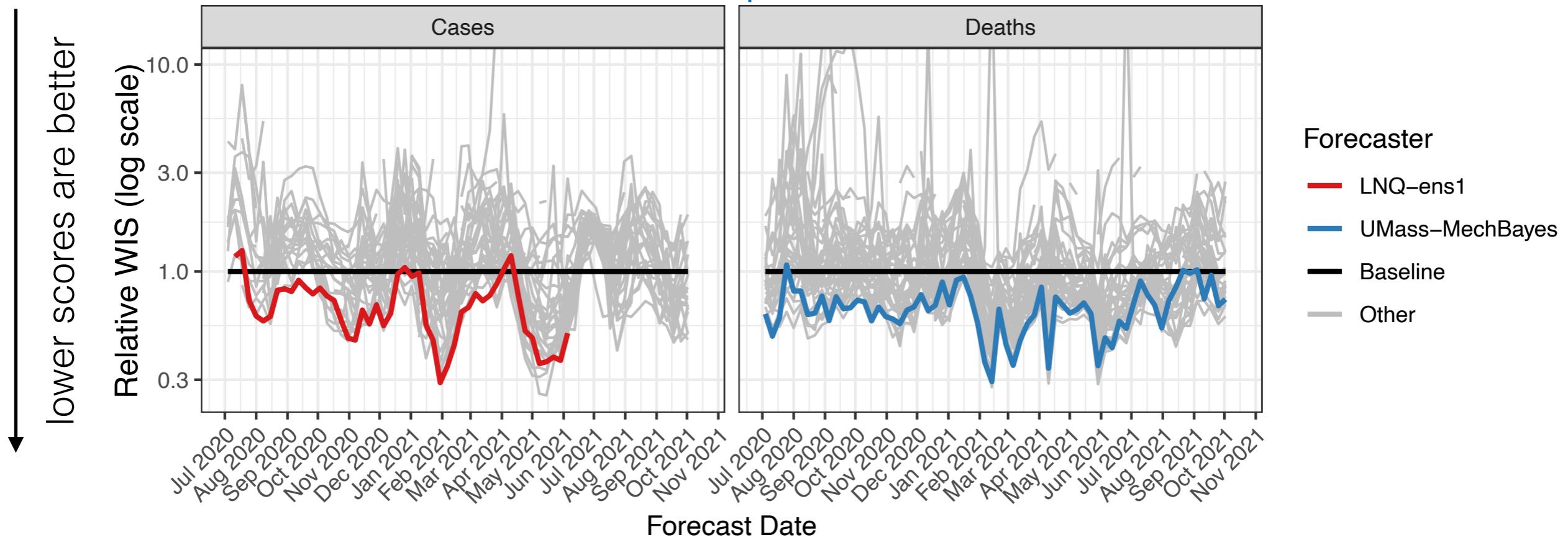
**Phenomenological:** Model the *association* between

- Predictive variables (past disease incidence, weather, Google search data, ...)
- Future disease incidence



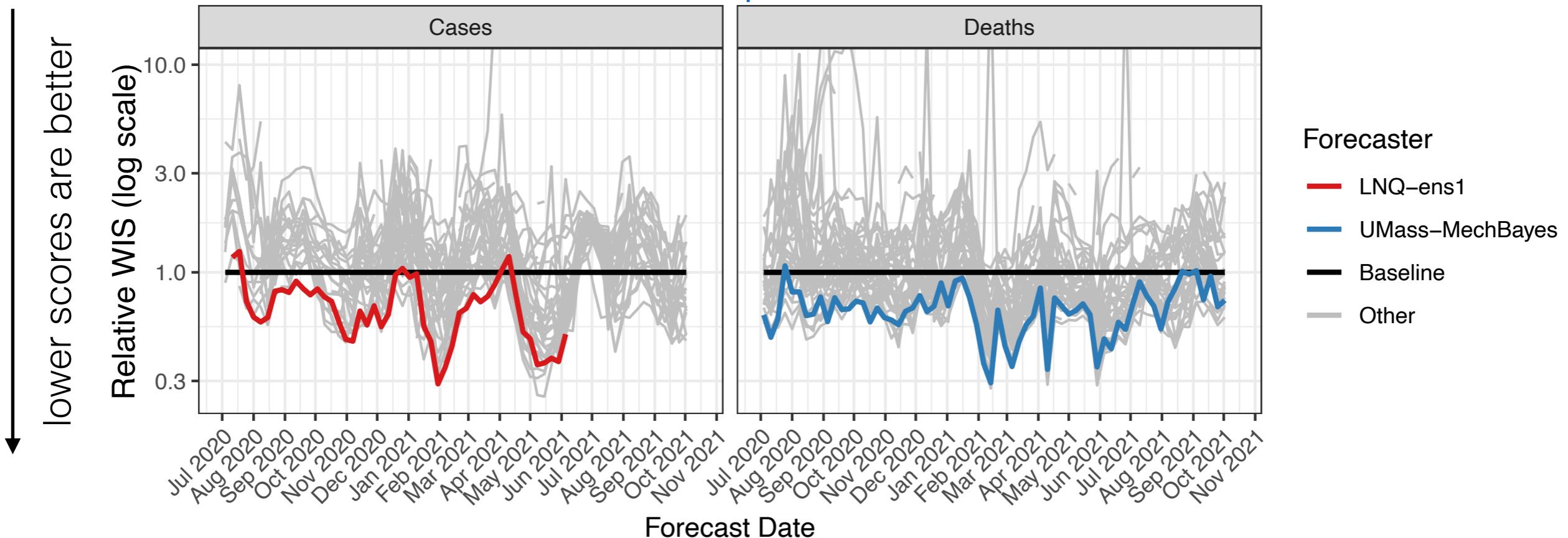
# When Should We Use Mechanistic or Phenomenological Models?

- For a generic forecasting task, neither is a priori better than the other
  - In the COVID-19 Forecast Hub, for a long time the best model was:
    - for cases, a **phenomenological machine learning** model
    - for deaths, a **mechanistic compartmental** model



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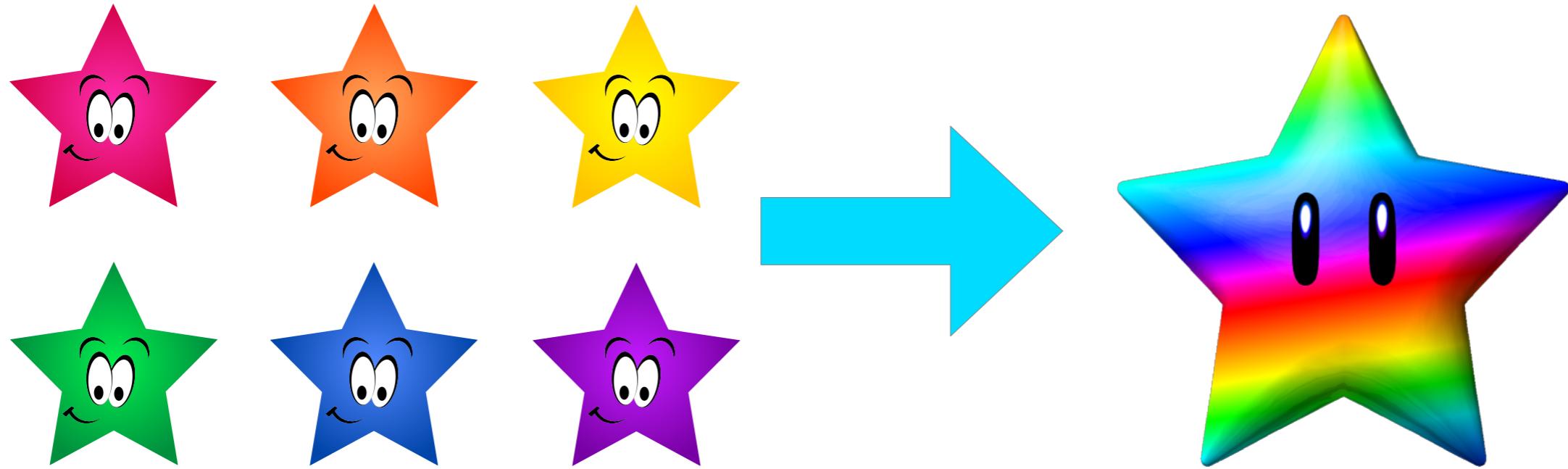
- For a scenario projection, mechanistic models have an advantage:
  - Can encode expert knowledge about the disease system that a phenomenological model may not be able to learn due to lack of relevant data.

# Models May Combine Mechanistic and Phenomenological Ideas

There are a few ways this has been done:

1. By temporal scale: Nowcasts or short term forecasts use phenomenological model, long term forecasts use mechanistic model
  - Examples:
    - Columbia University (Shaman Group) model for influenza forecasting
    - IHME for COVID-19
2. Mechanistic core, phenomenological model to capture biases of the core
  - Examples:
    - Los Alamos National Laboratory (Dave Osthus) model for influenza
    - DeepGLEAM model for COVID-19

# Ensembles Combine Models



Example:

- Ensemble prediction is average of predictions from component models

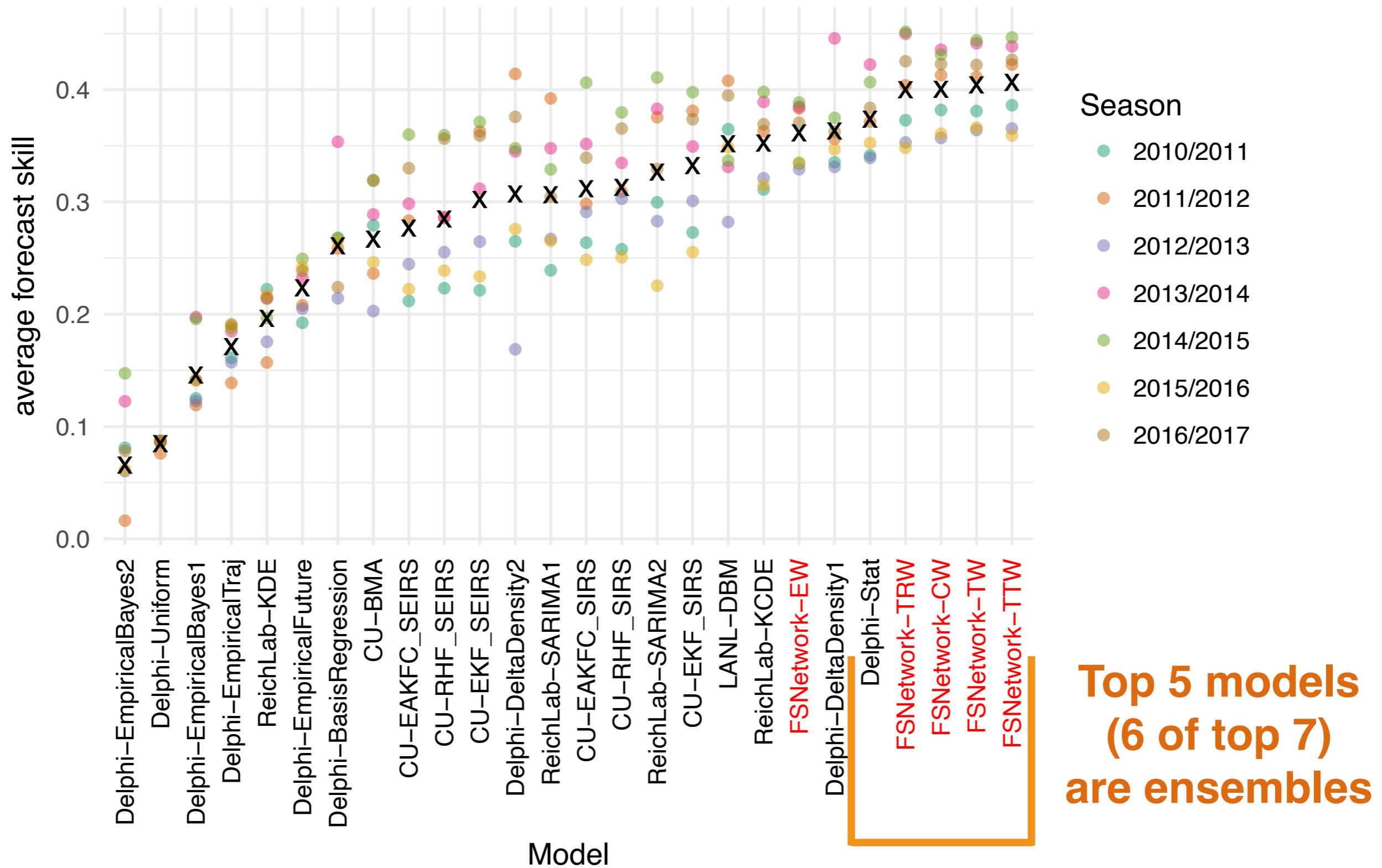
Theory (simplified):

- Ensembles are at least as good as the component models

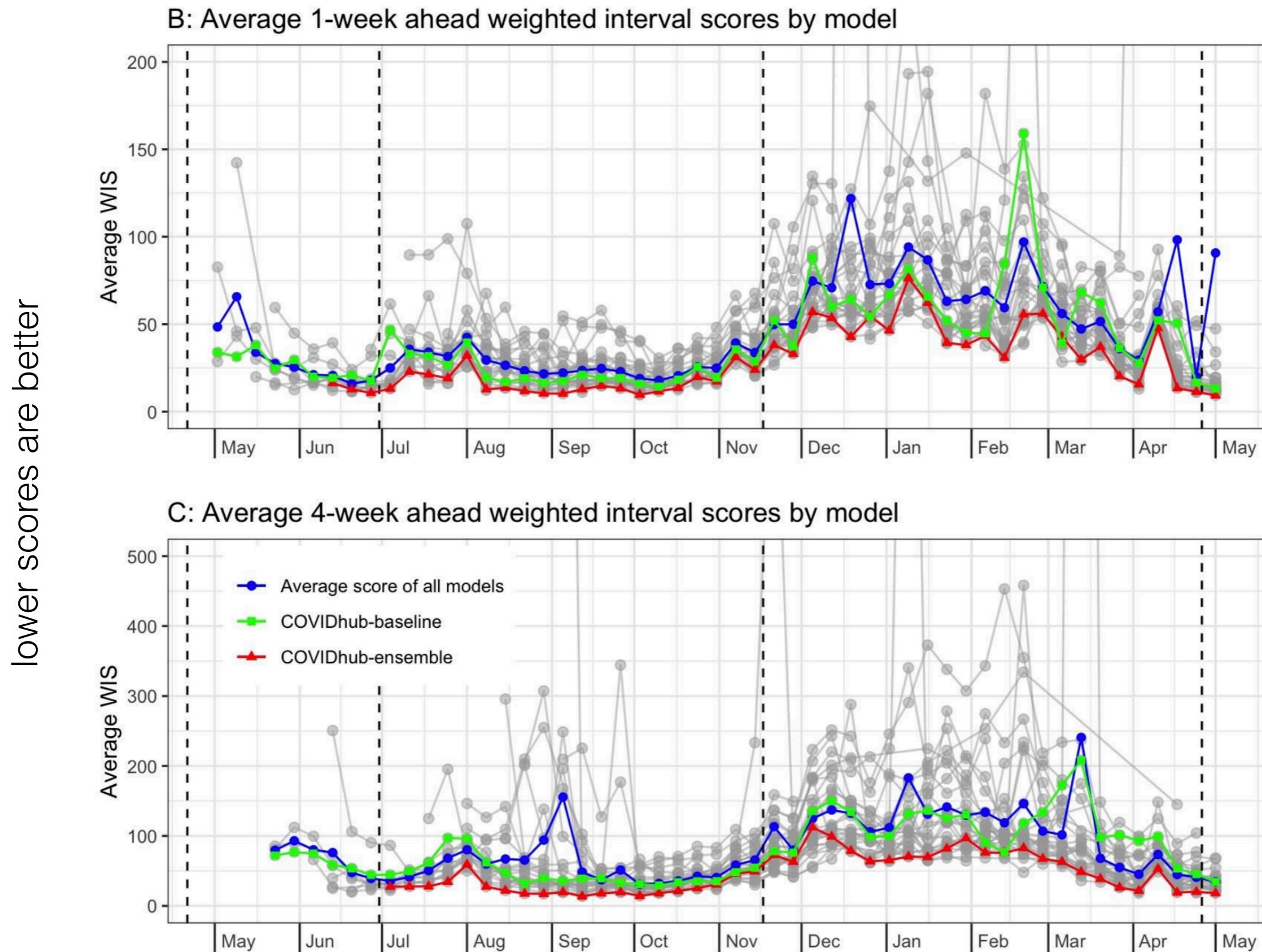
Practice:

- Performance depends on implementation details
- Ensembles are consistently at or near the top of the rankings

# Results from Influenza

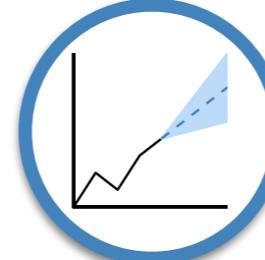


# Results from COVID-19



# Outline of This Talk

Predictive  
Modeling



- Some common modeling tasks
- Some common models and methods for these tasks
- **Evaluating predictions**

# Using Bad Predictions Can Have Bad Consequences

“Public health actions informed by forecasts that later prove to be inaccurate can have negative consequences, including the loss of credibility, wasted and misdirected resources, and, in the worst case, increases in morbidity or mortality.”

– Biggerstaff et al. BMC Infectious Diseases 2016.

"A bad prediction can be worse than no prediction at all"

– Dr. Carrie Reed, CDC Influenza Division

# A First Step Toward Avoiding Use of Bad Predictions

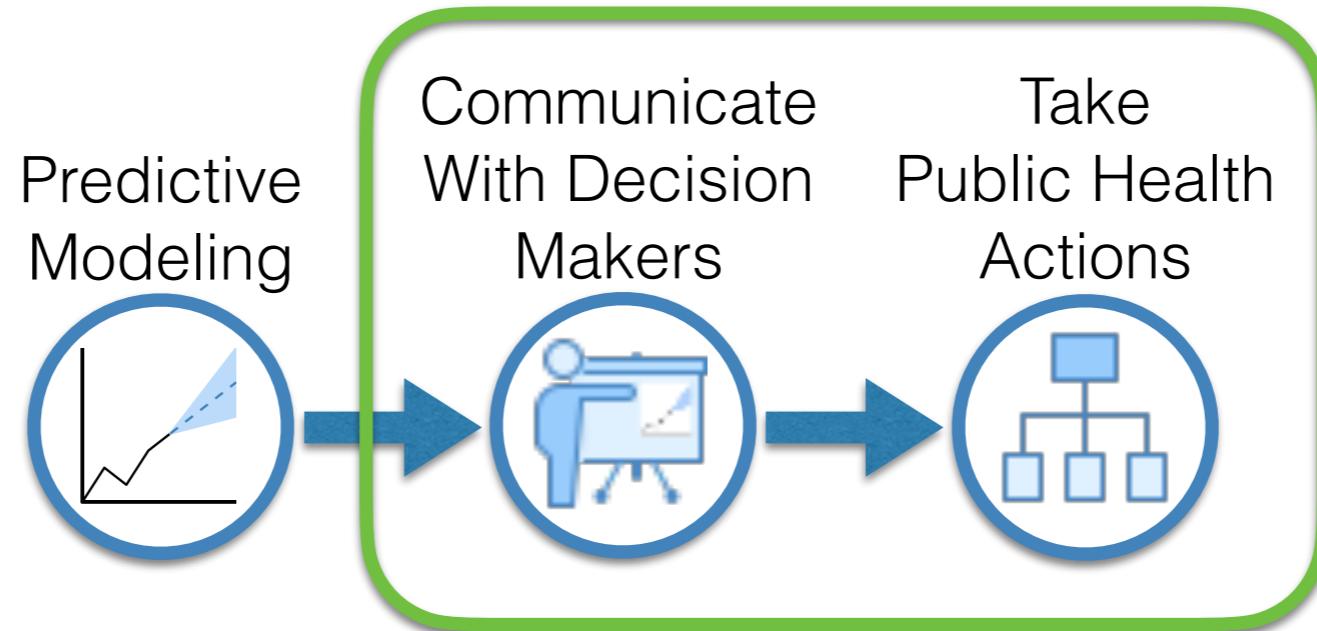
Only use predictions from models with a track record of reliable performance.

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Only use predictions from models with a track record of reliable performance.

(at minimum, use caution if limited track record)

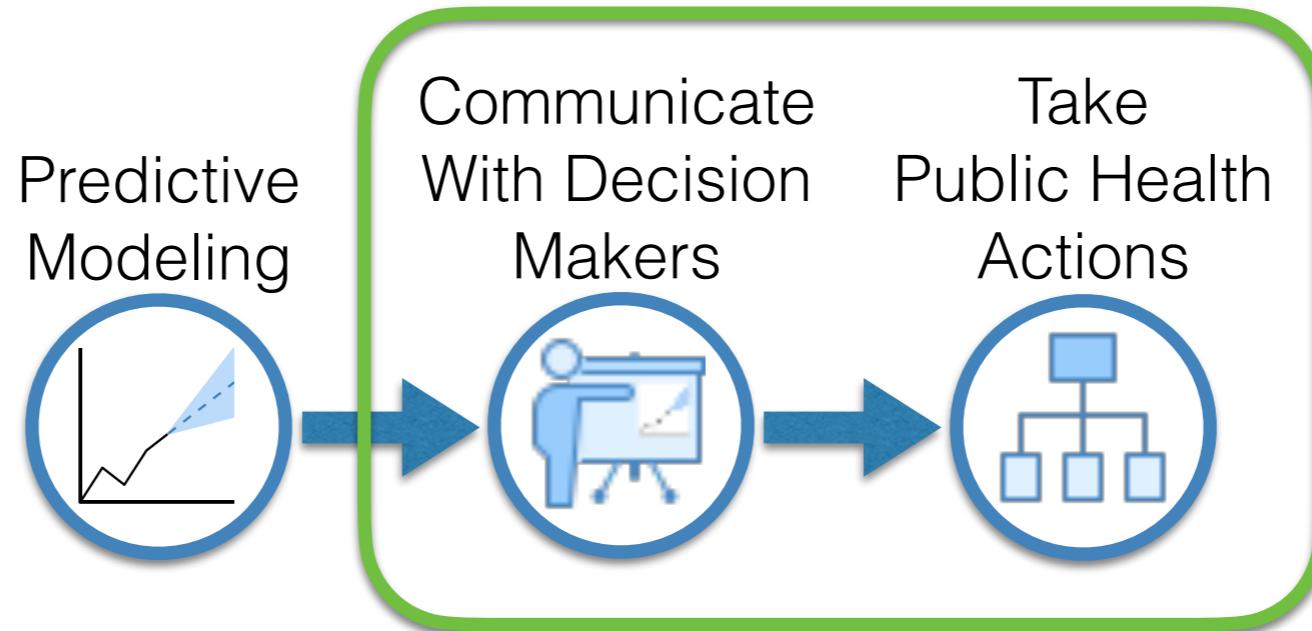
# Evaluating Nowcasts and Forecasts



**The goal is to support the decision making process**

- Ideally, we would evaluate the quality of forecasts in the specific context of the decision making process we have in mind.

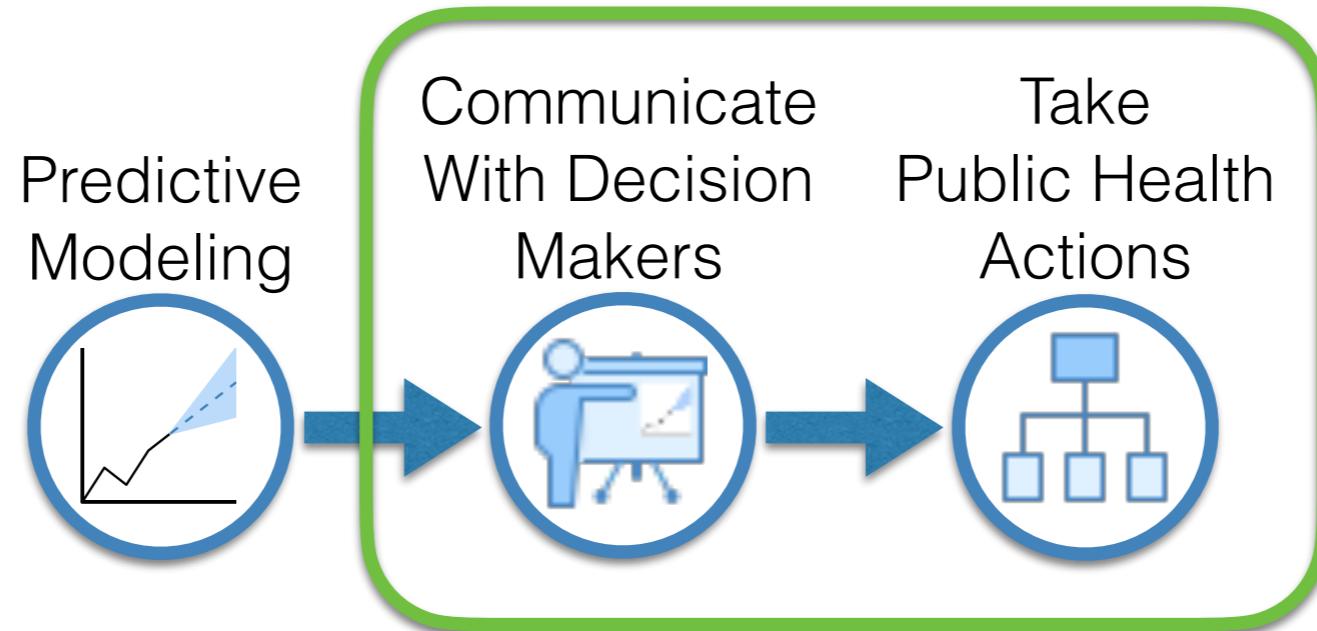
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  - Can we quantify the loss incurred if we use an incorrect forecast?
    - e.g., count of patients with unmet need
  - If so, prefer forecasts that minimize this loss
  - This is difficult: hard to characterize loss, different for every problem.

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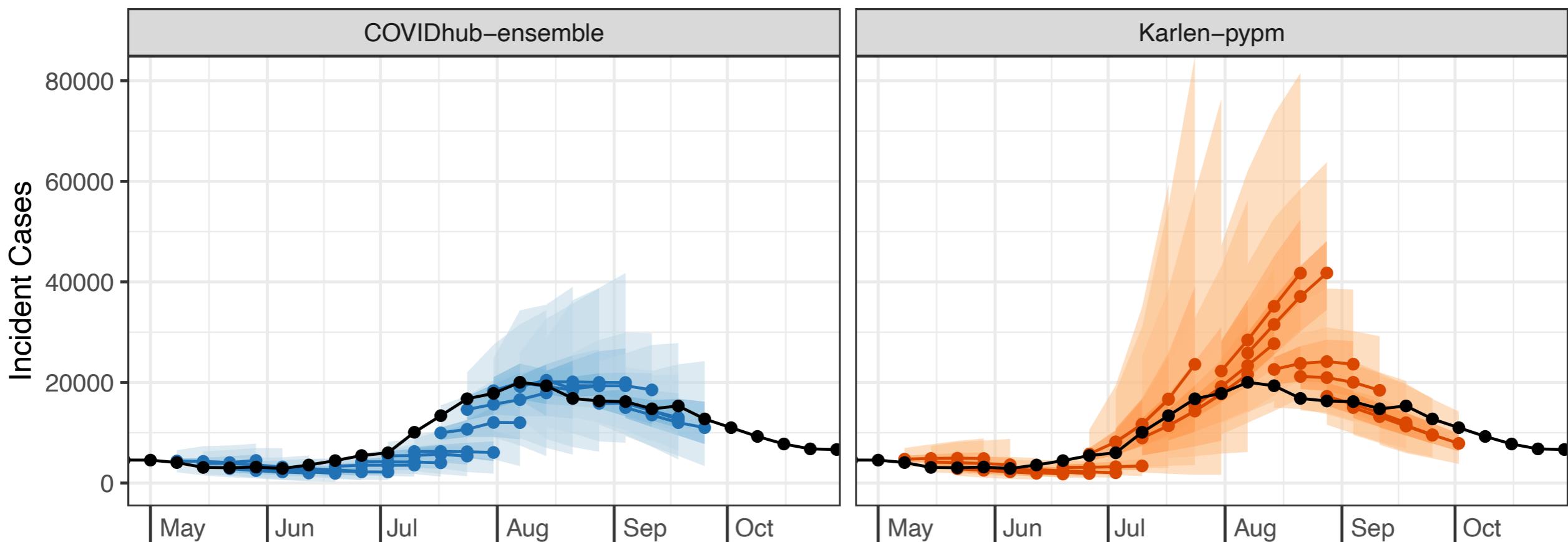


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  - This is difficult: hard to characterize loss, different for every problem.
- Backup plan: More generic comparisons of forecasts to observed data

# Overall Scores Can Obscure Details

- Forecasts of weekly COVID cases from COVIDhub-ensemble and Karlen-pypm in Missouri during the Delta wave:



- Karlen is better at identifying the rise of the Delta wave, misses badly near the peak.
- Karlen's overall WIS is worse, but there is a more nuanced story:
  - If you want to identify the start of a new wave, look to Karlen
  - The rest of the time, look at the ensemble

# Evaluating Nowcasts and Forecasts

- Look at lots of plots!

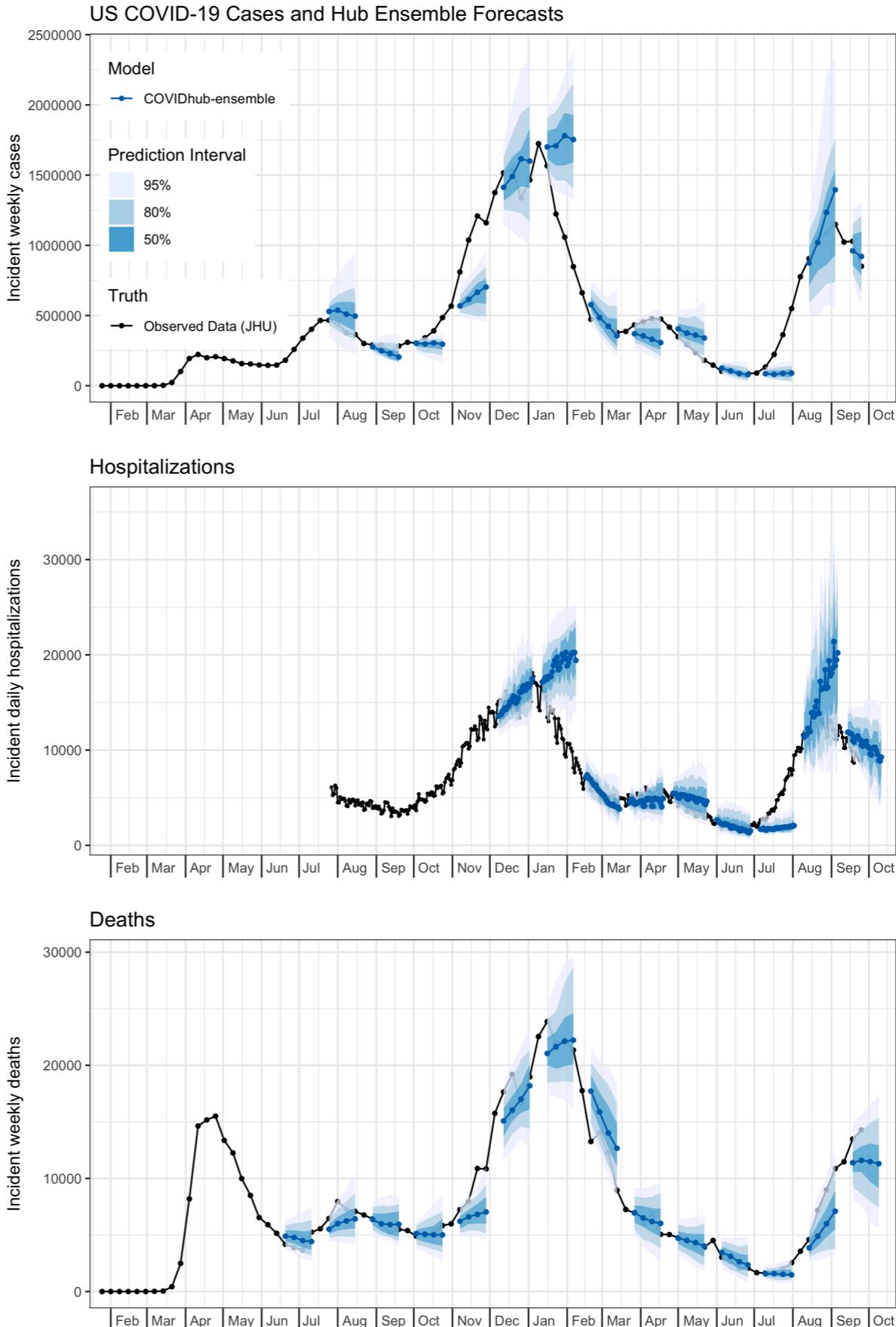
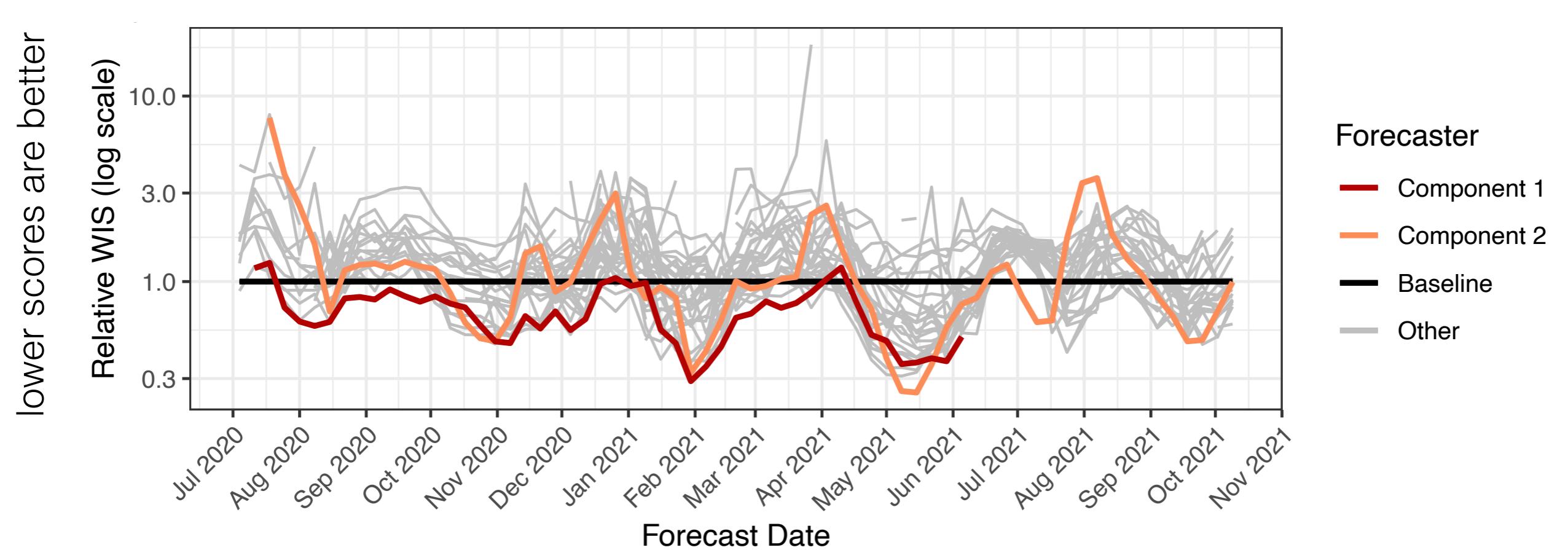


Image credit:

<https://forecasters.org/blog/2021/09/28/on-the-predictability-of-covid-19/>

# Evaluating Nowcasts and Forecasts

- Look at lots of plots!
- Use proper scores (log score, CRPS, WIS, ...) to compare models
  - Theory says you can't "cheat" proper scores
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  - Helpful to use a simple baseline model as a reference
- Examine calibration
  - Across many forecasts, a 95% prediction interval should contain the eventually observed outcome about 95% of the time

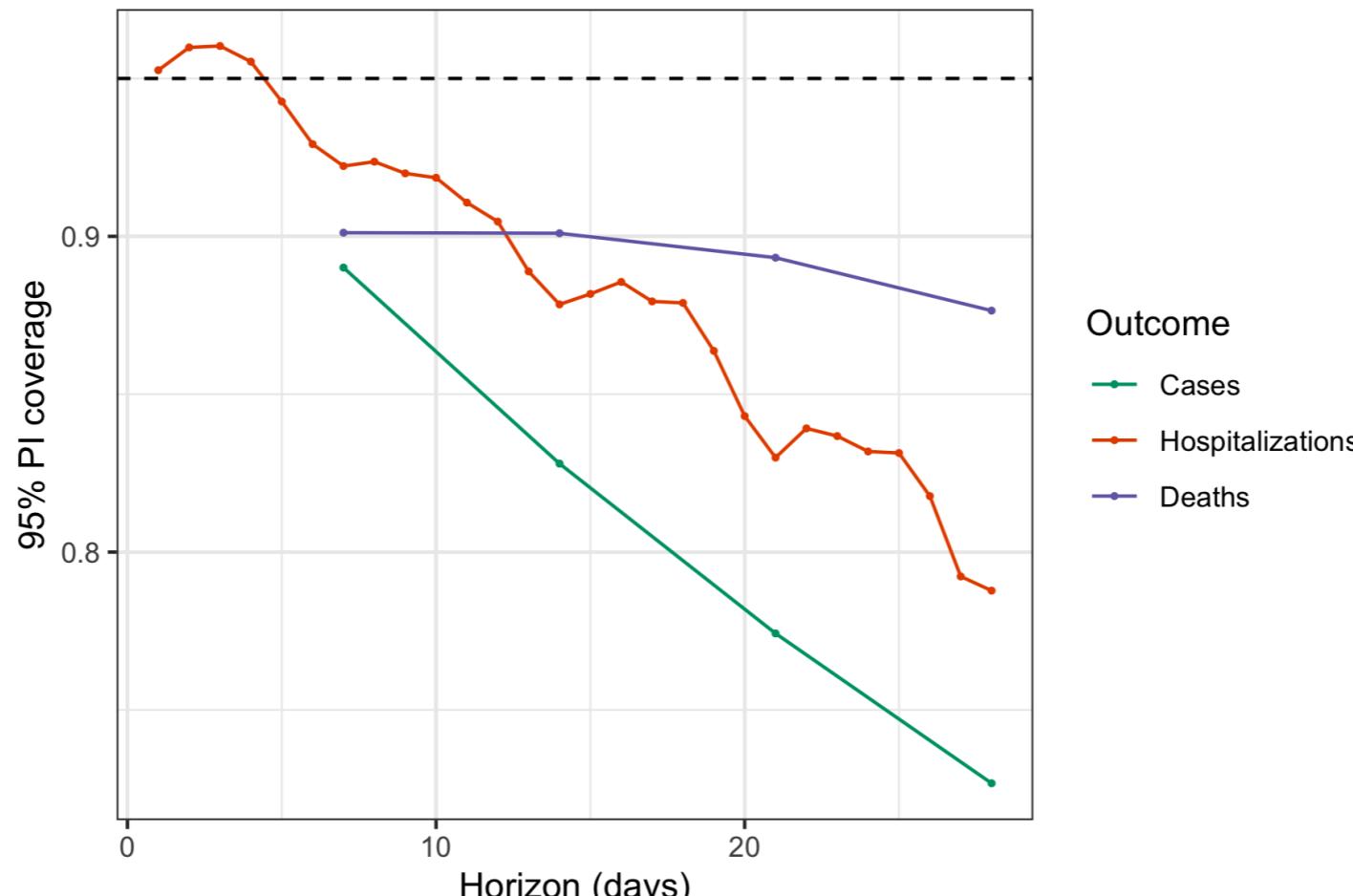


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# Evaluating Scenario Projections

- Evaluating scenario projections is difficult:
  - Care must be taken to specify the **objective of the projections**:
    - Is the goal conditional or counterfactual statements about what would happen in each scenario?
    - Is the goal to estimate causal effects of policy differences?
    - How should we handle potential confounding variables?
  - Care must be taken to specify how to **evaluate the projections**:
    - We can't directly compare to observed data
    - Causal parameters may not be identifiable from observed data
- But careful evaluations are still critical!
- A more rigorous conversation about evaluating projections should involve experts from the causal inference community

# Conclusions/Summary

- Predictive model outputs (nowcasts, forecasts, and scenario projections) may be helpful for a wide variety of public health decisions, **if**:
  - The predictions are relevant to the decision at hand
  - The predictions have a track record of good performance
- What methods to use?
  - Good forecasts can come from either mechanistic or phenomenological approaches
  - Across many applications, ensembles have shown good results
  - Preferences should be based on data about performance
- More work needs to be done to put evaluation of scenario projections on a solid footing.
- See similar discussion of forecasting in “Applying infectious disease forecasting to public health: a path forward using influenza forecasting examples” by Lutz et al. (2019) BMC Public Health

# Thanks!

I'd like to acknowledge helpful conversations and insights from  
Nick Reich, Ryan Tibshirani, Roni Rosenfeld, Aaron Gerdin,  
Meagan Burns, Rosa Ergas, Matthew Biggerstaff,  
and Mike Johansson