

# Sunny with a Chance of Hurricane

## Decision Analytic Metrics for Forecast Evaluation

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April 2025

# Collaborators and Funding



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Brown University



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Stanford University

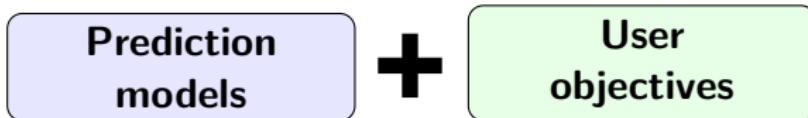
This work was supported in part by the Council of State and Territorial Epidemiologists (NU38OT000297) and the National Institute of Health through the National Institute of General Medical Sciences (1R35GM155224).

# Decision analysis

**Prediction  
models**

What might happen?

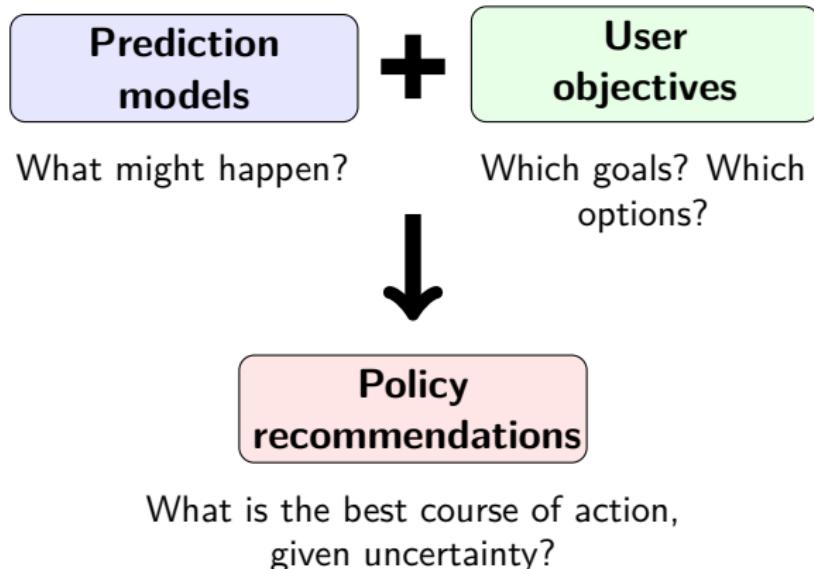
# Decision analysis



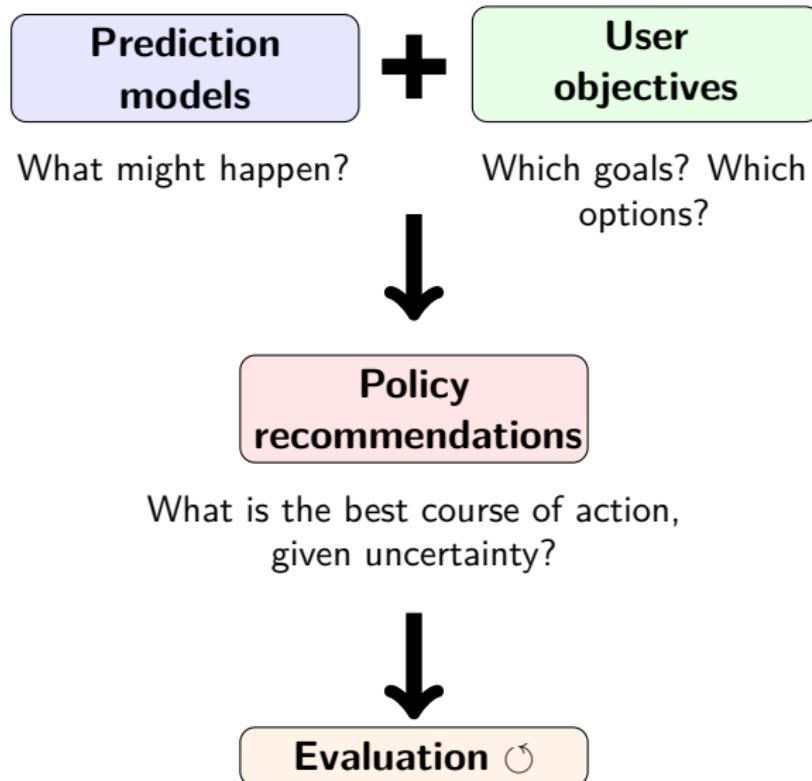
What might happen?

Which goals? Which options?

# Decision analysis



# Decision analysis



## Prior work

Throughout the life cycle of an outbreak, “triggers” for starting and stopping interventions should be:

1. Predictive of outcomes of policy interest

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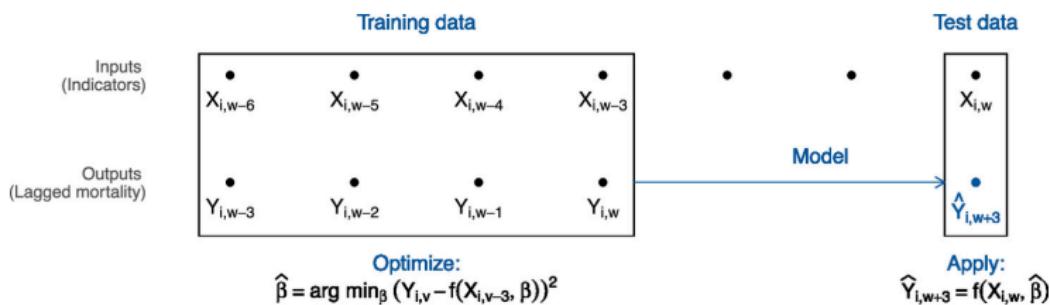
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Community Risk Metrics	Special Populations
<ul style="list-style-type: none"><li>1. <i>PNAS</i> 2023</li><li>2. <i>Annals of IM</i> 2022</li><li>3. <i>PNAS</i> 2021</li></ul>	<ul style="list-style-type: none"><li>1. Schools: <i>JAMA NO</i> 2022, <i>Annals</i> 2021, <i>JAMA Peds</i> 2022</li><li>2. Nursing homes: <i>JAMA HF</i> 2024</li><li>3. “High” respiratory disease season guidance for HC facilities (w/RIDOH, in progress)</li></ul>

# Disclosure

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But we thought it might be valuable to transport a decision-analytic framework to this context.

# Back to hurricanes...

## Categories of hurricane

	Category 1	Category 2	Category 3	Category 4	Category 5
Wind	74-95mph	96-110mph	111-130mph	131-155mph	<b>Over 155mph</b>
Storm surge	4-5ft	6-8ft	9-12ft	13-16ft	<b>Over 18ft</b>
<b>Minimal:</b> No real structural damage; some flooding	<b>Moderate:</b> Material damage to buildings; small craft break moorings	<b>Extensive:</b> Structural damage to small houses; inland flooding	<b>Extreme:</b> Major structural damage & heavy flooding; evacuation necessary	<b>Catastrophic:</b> Massive damage to buildings; small structures blown over or away	

Source: Saffir Simpson scale

# Back to hurricanes...

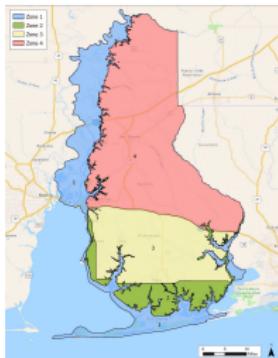
## Scenario 1:

**Category 1 - Zone 1:** All areas of Pleasure Island along with individuals living in manufactured homes, and those living in low lying flood prone areas countywide. (Pleasure Island consists of all areas south of the Intra-coastal Canal to include Fort Morgan, Gulf Shores, Orange Beach and Ono Island.)

**Category 2 - Zone 1 & 2:** All areas south of State Hwy 98 and the area on the Eastern Shore that is South of Interstate 10 and West of State Hwy 98. Additionally, all individuals living in proximity to the Fish, Styx, Blackwater and Perdido Rivers and all individuals living in manufactured homes, and those living in low lying flood prone areas countywide.

**Category 3 - Zones 1 through 3:** All areas south of State Hwy 98 and the area on the Eastern Shore west of State Hwy 98, and the area west of State Hwy 225 and west of Hwy 59 North of Stockton to the Baldwin/Monroe County line. Additionally, all individuals living in proximity to the Fish, Styx, Blackwater and Perdido Rivers and all individuals living in manufactured homes, and those living in low lying flood prone areas countywide.

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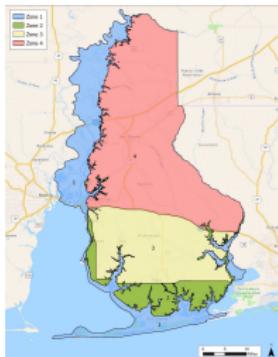
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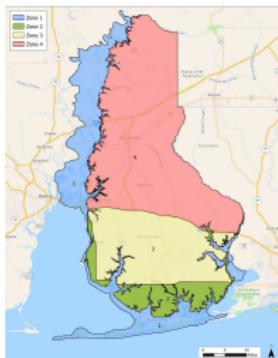
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- Similar guidance for government, first responders

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- There is a cost of staying put if a storm materializes.
- Ideally, we choose recommendations accounting for these.
  - Whether to cancel elective surgeries in a respiratory outbreak
  - Whether to start an mpox vaccination strategy

## Popular forecast evaluation metrics

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3. but...equally weights all points in time and can be difficult to substantively interpret

## Recent innovations

1. WIS of log-transformed estimates(Funk et. al., 2023)
2. Predicting shapes (Srivastava et. al., 2022, Srivastava et. al., 2023)
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...our questions were more basic.

## This work

*What information would make forecasts most interpretable and actionable to a decision-maker?*

1. Propose simple forecast evaluation metrics tied to binary “threshold” outcomes
2. Evaluate performance on COVID-19 case and hospitalization predictions
3. Propose how to operationalize forecast error and uncertainty in decision-making

Methods

Results

Discussion

# Metrics

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3. **Turning points:** Monotonic increase followed by decrease (or the converse)
  - Also considered a “fuzzy” version of this (e.g. predicting peak within 1-2 weeks)

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Maximize accuracy, weighting for preferences over different error types. We assume a decision-analytic framework.

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# Decision analysis

The expected cost of following a metric ( $M$ ) is:

$$C(M) = \underbrace{Pr(\hat{Y} = 1, Y = 0)S_0}_{\text{expected cost: false positives}} + \underbrace{Pr(\hat{Y} = 0, Y = 1)D}_{\text{expected cost: false negatives}} + \underbrace{Pr(\hat{Y} = 1, Y = 1)((1 - \alpha)D + S_1)}_{\text{expected cost: true positives}}$$

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We can rearrange this:

$$C(M) = Pr(\hat{Y} = 1, Y = 0)S_0 + \\ Pr(\hat{Y} = 0, Y = 1)(\alpha D - S_1) + \\ \underbrace{Pr(Y = 1)((1 - \alpha)D + S_1)}_{\text{constant across all metrics}}$$

# Decision analysis

We can rearrange this:

$$\begin{aligned}C(M) &\propto p_{FP}S_0 + p_{FN}(\alpha D - S_1) \\&\propto p_{FP} + p_{FN}w,\end{aligned}$$

where  $w$  is the ratio of the net benefit from taking action on a true positive ( $\alpha D - S_1$ ) to costs incurred by unnecessary action in the case of a false positive ( $S_0$ )

[Return](#)

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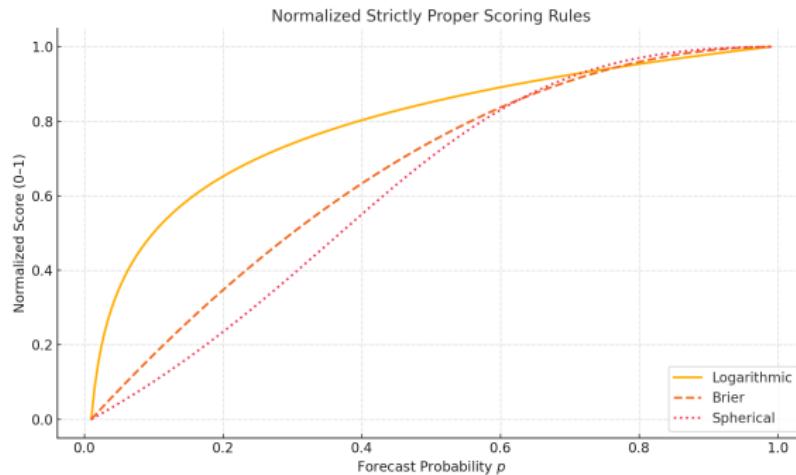
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## Quick note

Accuracy (and weighted accuracy) do not induce “strictly proper scoring rules.”

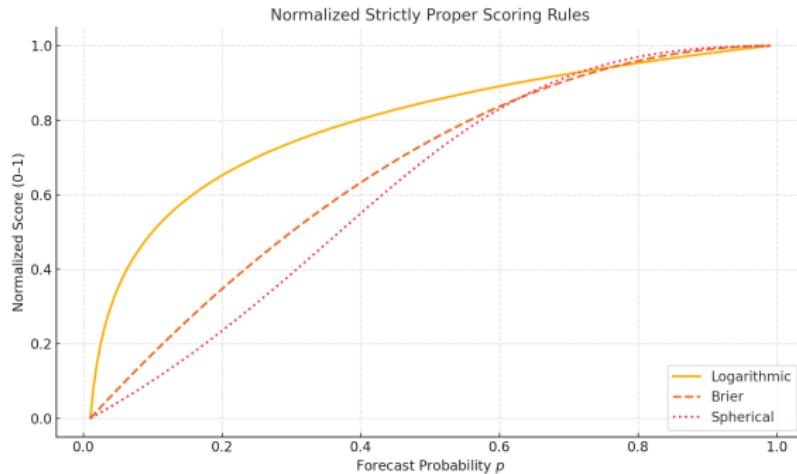
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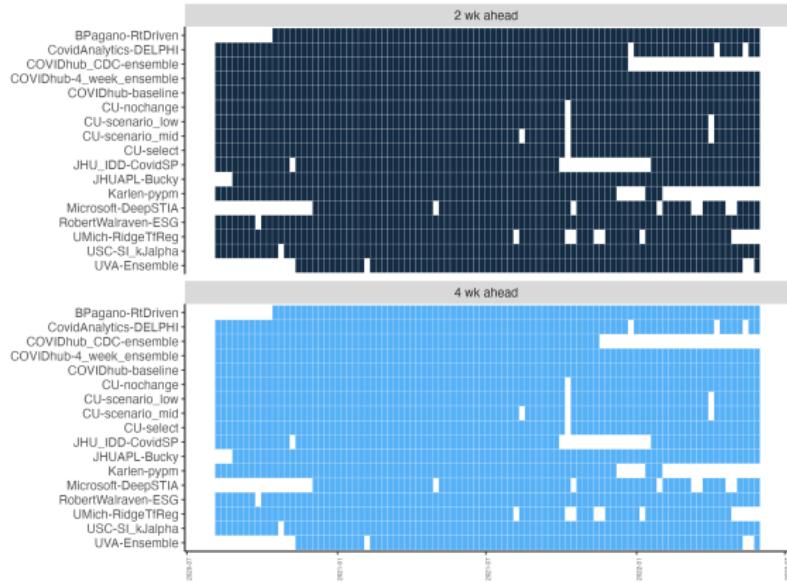
Considerations for both fitting and scoring, but we focus on the latter.

# Data

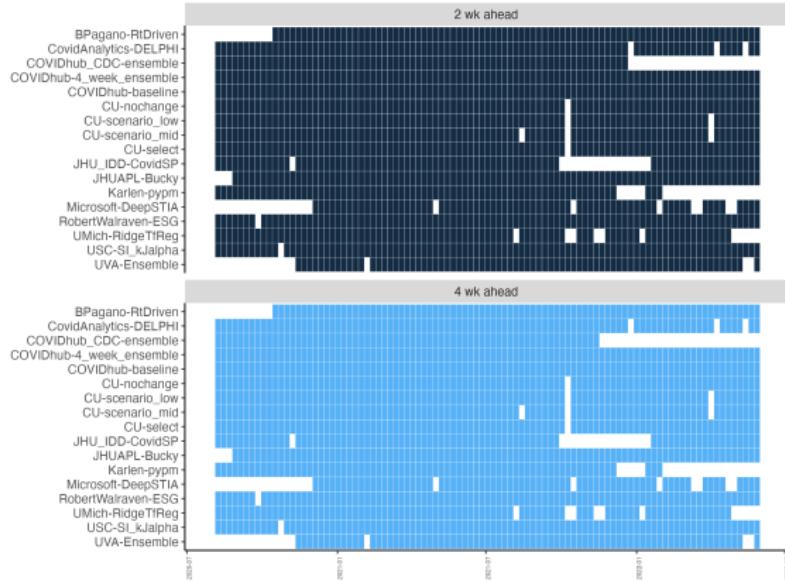
We analyzed COVID-19 Forecast Hub case and hospitalization projections from August 2020 through June 2022:

- National and state predictions
- Top 20 most frequently-reported models, ensemble models, baseline models (day-of prediction)
- quantile predictions → mean → binary outcomes (not sensitive to using median, preferred value)

# Imputation



# Imputation



When missing, impute average (sensitivity analyses: baseline, best, worst).

# Metrics

Using New York Times data as truth, we computed:

1. **Accuracy:** % correct
2. **Sensitivity/Specificity:** given true positive or negative status, how many correct?
3. **Positive predictive value/Negative predictive value:** given prediction class, how many correct?

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In more preliminary results, we:

1. Characterize decision rules
2. Explore alternative ensembles

## Extensions

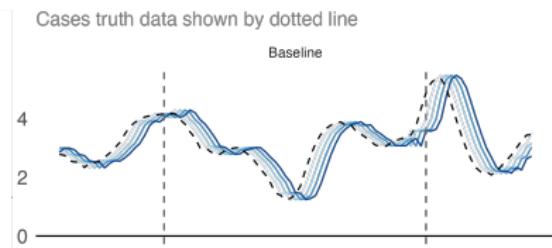
1. Limited decision points (in progress w/RIDOH)
2. Trade-offs between lead time and certainty

Methods

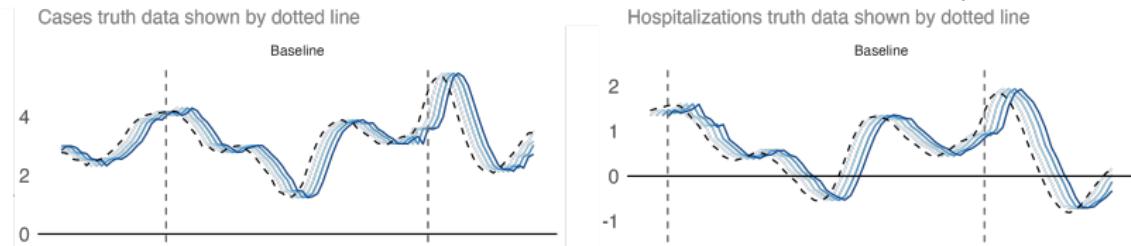
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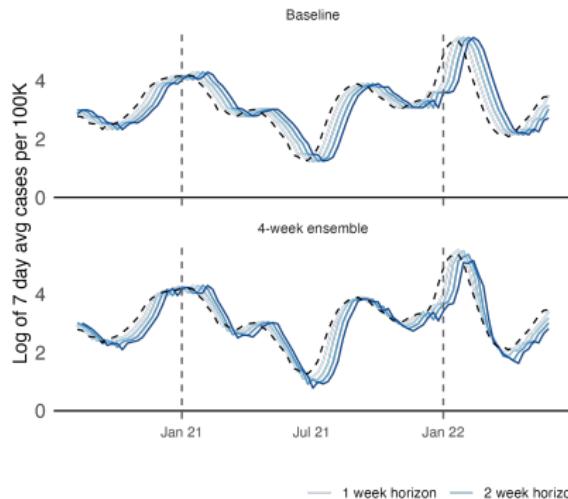


# Baseline comparison

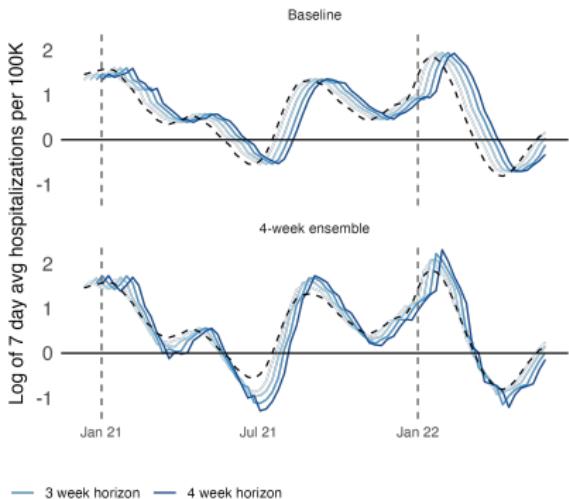


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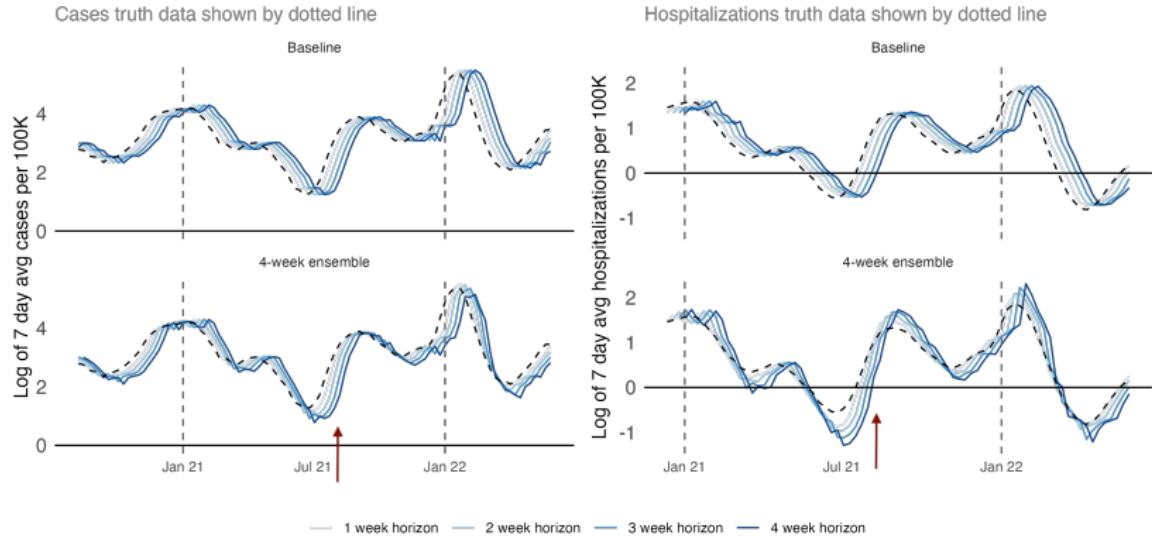
1- to 4-week horizon of State Level cases under scenario 1  
Cases truth data shown by dotted line



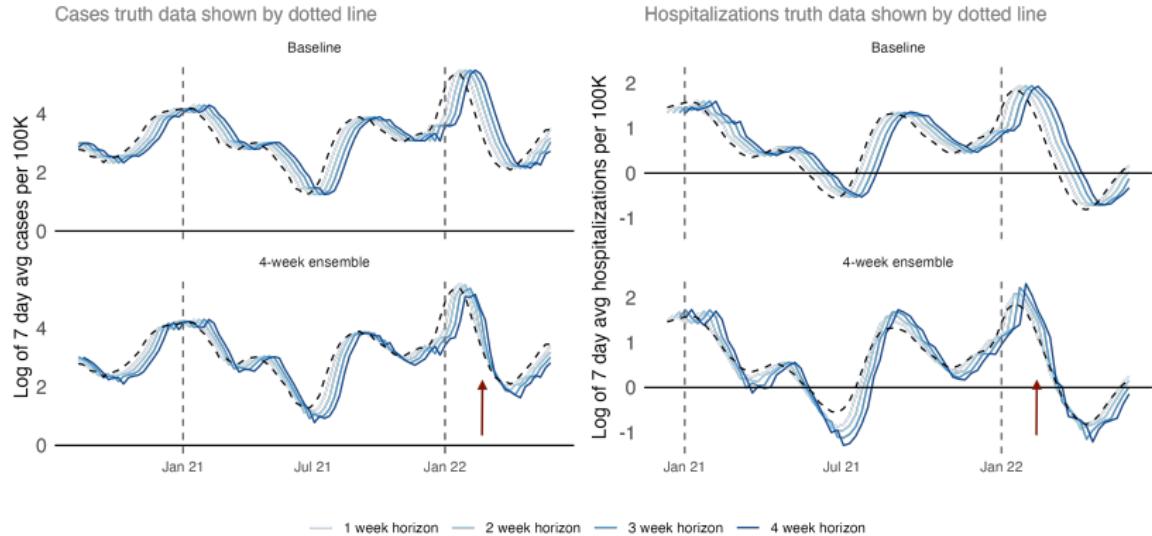
1- to 4-week horizon of State Level hospitalizations under scenario 1  
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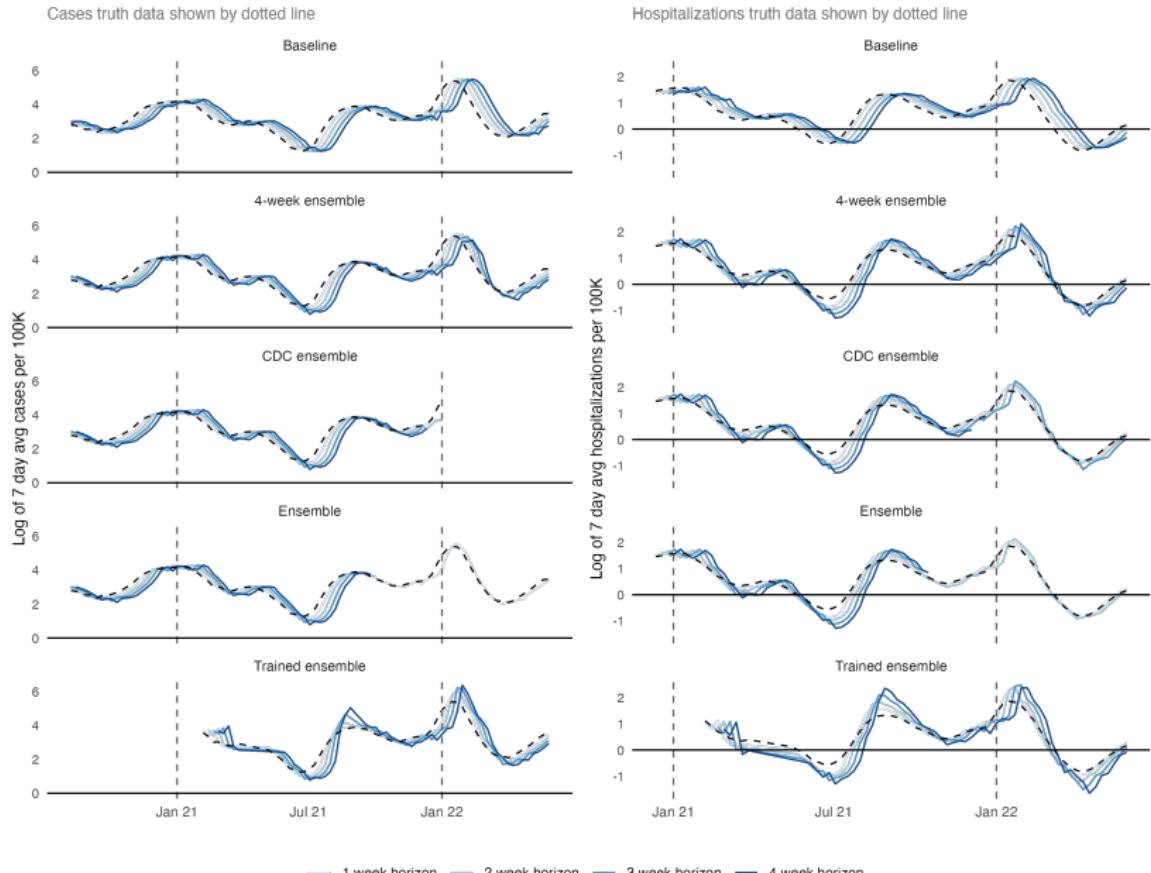
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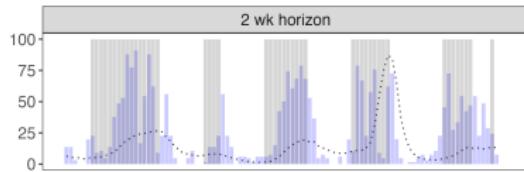
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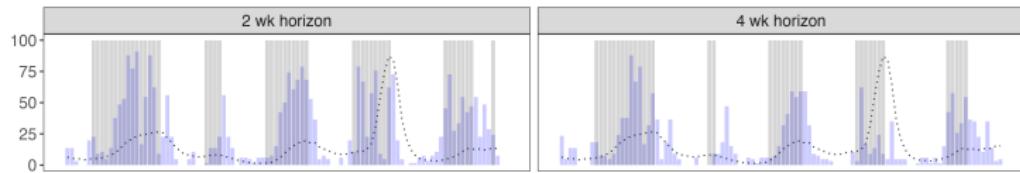


# Performance over time



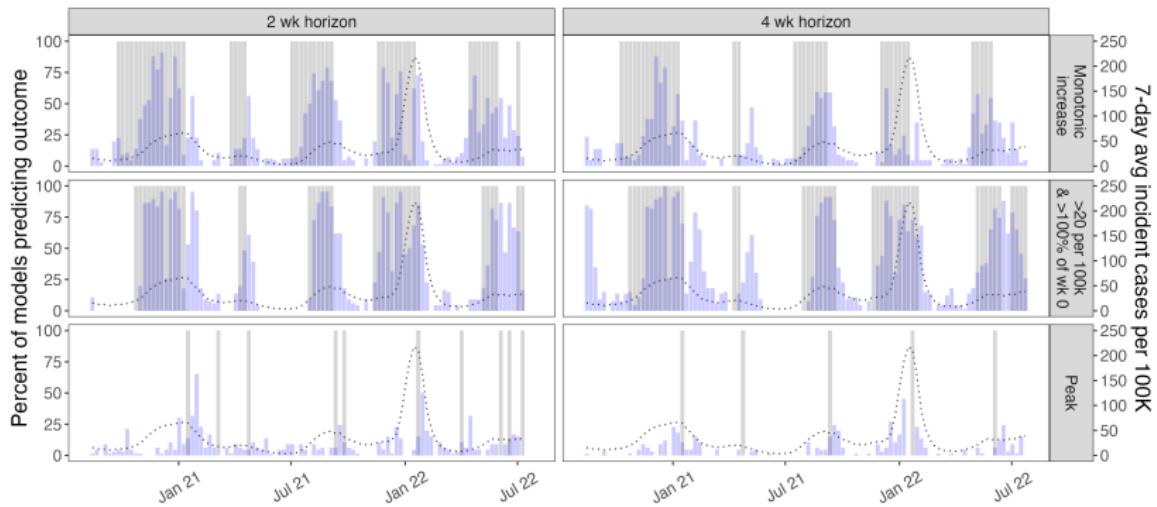
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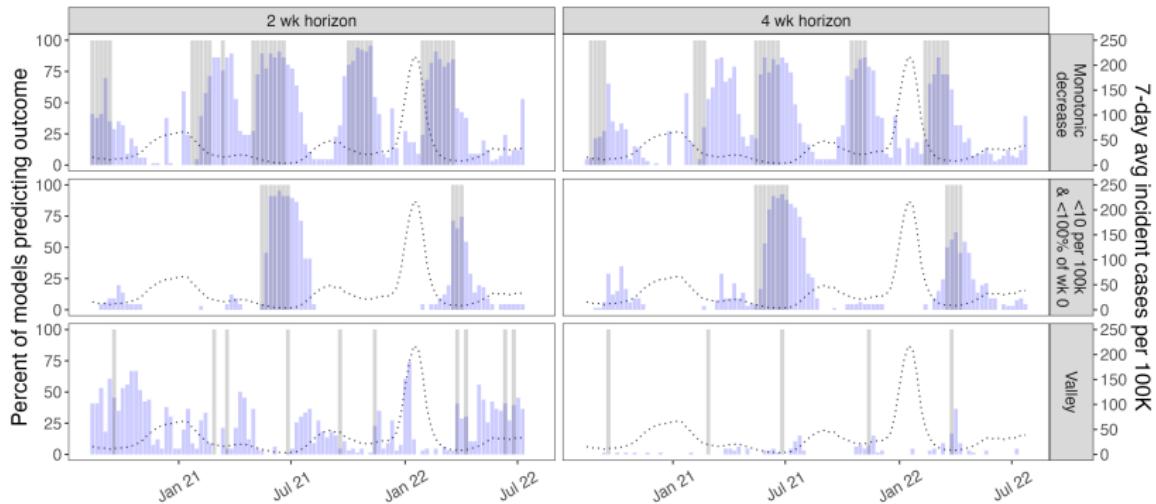


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Baseline	35	55	19	74	29	63
Top 20	35	69	33	88	60	71
4-week ensemble	35	76	42	95	83	75
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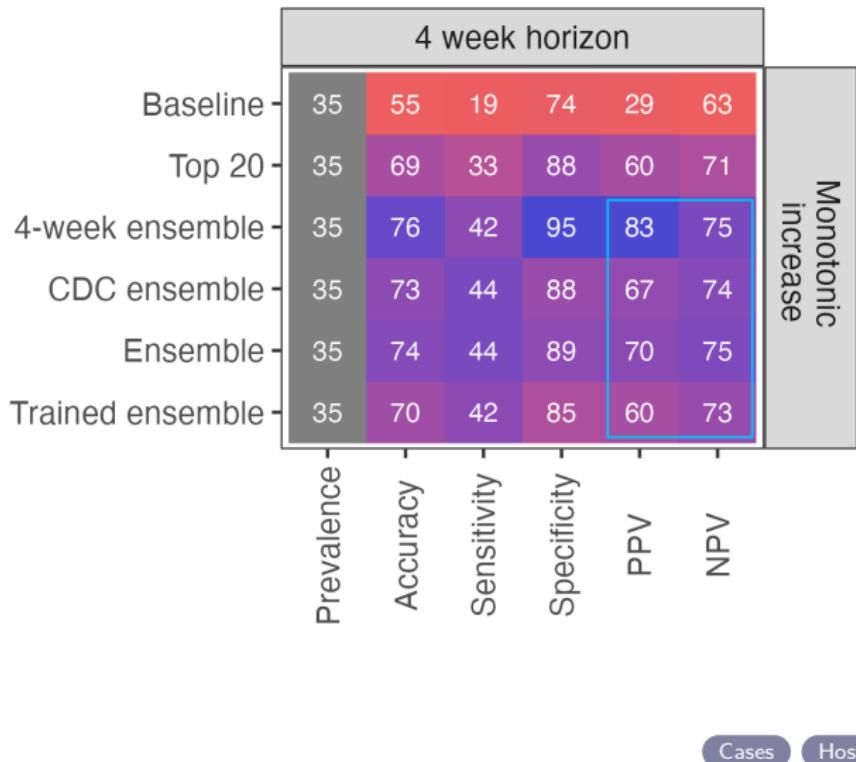
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# What to do with this?

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→ NPV and PPV are about 60-80%. Given a result (and the distribution of outcomes), about 1 in 3 chance it is correct.

# Decision rules

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For “increasing” metrics:

- *Act on “increase” signal if:* willing to accept one false alarm (false positive) for every 2-4 correct calls

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## For “decreasing” metrics:

- *Act on “decrease” signal if:* willing to accept 50-50% chance correct call

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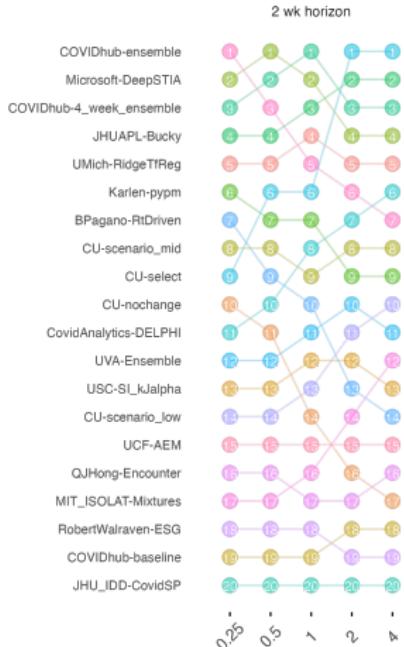
- *Act on “decrease” signal if:* willing to accept 50-50% chance correct call

## For both:

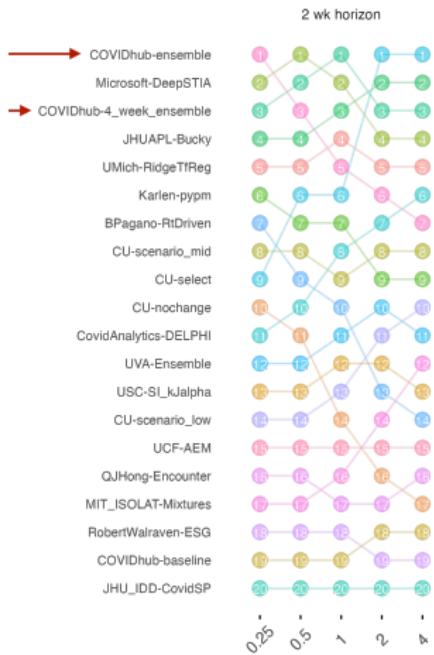
- *Stay put on “no change” signal:* 75-95% chance correct

There are caveats, but...**much appreciation for the work of state and local officials!**

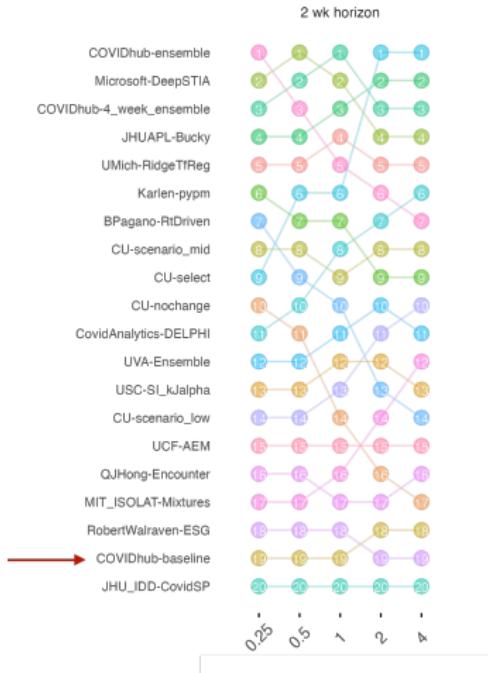
# Model rankings



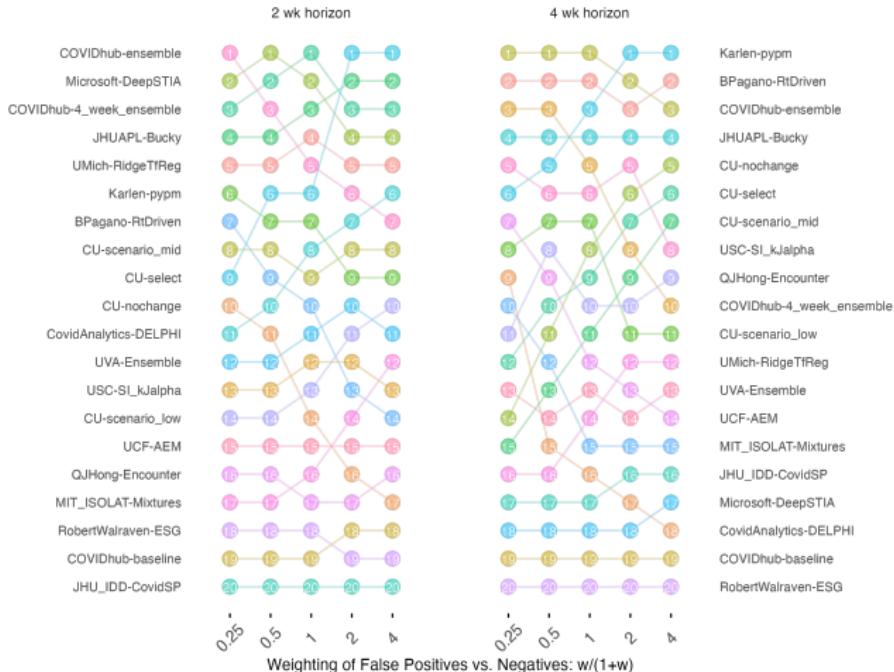
# Model ranking and aggregation



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# Extensions

## Alternative ensemble

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- Qualitatively similar results

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# Conclusions

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2. There are remains an unmet need to model changes in trajectory (and clearly communicate corresponding uncertainty).
3. For our metrics, ensemble models continue to perform best, but have considerable uncertainty.

# Limitations and next steps

## 1. Next steps

- Optimized ensemble
- More complex decision rules
- Fire alarms rather than forecasts
- Regression discontinuity for when actions change trajectory

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## 2. Limitations

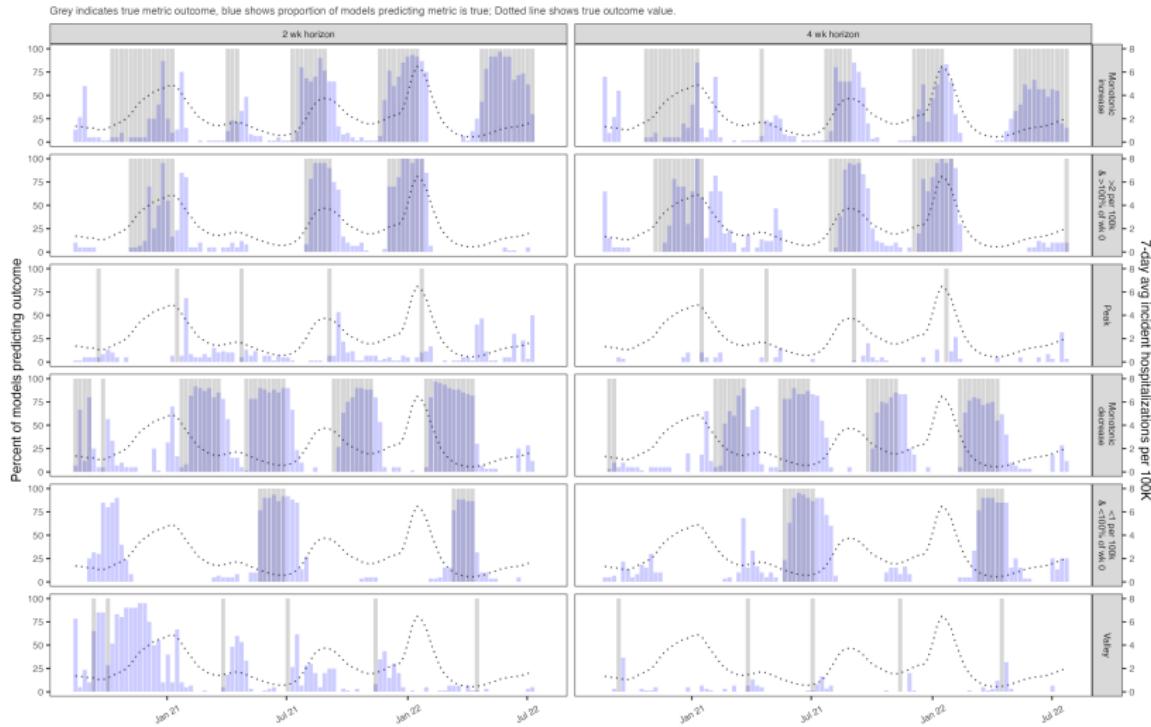
- Not a proper scoring rule – best way to fit models?
- Unusual data!

Thank you!

Questions?

Feel free to reach out: [alyssa\\_bilinski@brown.edu](mailto:alyssa_bilinski@brown.edu)

# Performance over time



Return

# Metrics

		2 week horizon						4 week horizon						Milestone
		Prevalence	Accuracy	NPV	Specificity	PPV	Sensitivity	Prevalence	Accuracy	NPV	Specificity	PPV	Sensitivity	
8 > 100% of Wk 0	Baseline	47	50	52	60	46	38	35	55	63	74	29	19	Milestone
	Top 20	47	64	62	83	70	43	35	69	71	88	60	33	
	4-week ensemble	47	69	65	89	79	47	35	76	75	95	83	42	
	CDC ensemble	47	73	69	91	83	53	35	73	74	88	67	44	
	Ensemble	47	70	66	91	81	47	35	74	75	89	70	44	
	Trained ensemble	47	66	65	79	69	51	35	70	73	85	60	42	
	Baseline	37	63	70	71	50	49	43	60	63	69	54	48	
< 20% of Wk 0	Top 20	37	75	79	83	68	63	43	68	70	78	65	56	Peak
	4-week ensemble	37	75	78	84	69	59	43	73	70	90	79	50	
	CDC ensemble	37	78	81	86	73	65	43	77	76	88	80	64	
	Ensemble	37	79	82	86	74	68	43	77	76	88	80	64	
	Trained ensemble	37	78	84	81	69	73	43	73	76	76	68	68	
	Baseline	10	73	89	80	5	10	5	93	96	97	25	20	
	Top 20	10	82	90	91	9	8	5	91	95	95	9	9	
Peak	4-week ensemble	10	82	89	91	0	0	5	94	96	98	33	20	Peak
	CDC ensemble	10	83	89	92	0	0	5	93	95	98	0	0	
	Ensemble	10	83	89	92	0	0	5	94	95	99	0	0	
	Trained ensemble	10	88	90	98	0	0	5	87	95	92	0	0	

Return

# Metrics

		2 week horizon						4 week horizon						Model class
		Prevalence	Accuracy	NPV	Specificity	PPV	Sensitivity	Prevalence	Accuracy	NPV	Specificity	PPV	Sensitivity	
8 > 100% of wks	Baseline	33	62	67	87	31	12	23	76	78	97	33	4	Model class
	Top 20	33	71	80	75	55	63	23	69	84	75	37	49	
	4-week ensemble	33	74	92	67	57	88	23	70	91	67	41	78	
	CDC ensemble	33	76	92	70	59	88	23	72	92	70	43	78	
	Ensemble	33	76	92	70	59	88	23	74	92	72	45	78	
	Trained ensemble	33	80	86	84	69	73	23	75	85	84	46	48	
8 < 100% of wks	Baseline	10	91	91	100	100	10	12	88	88	100	0	0	Model class
	Top 20	10	90	96	93	51	67	12	86	94	91	44	54	
	4-week ensemble	10	94	98	96	67	80	12	87	94	91	47	58	
	CDC ensemble	10	93	97	96	64	70	12	87	92	93	45	42	
	Ensemble	10	93	97	96	64	70	12	87	92	93	45	42	
	Trained ensemble	10	95	99	96	69	90	12	88	96	90	50	75	
All	Baseline	10	67	90	71	10	30	5	90	95	95	0	0	Model class
	Top 20	10	71	90	76	10	25	5	93	95	98	14	7	
	4-week ensemble	10	79	90	87	8	10	5	92	96	96	20	20	
	CDC ensemble	10	84	93	89	29	40	5	95	96	99	50	20	
	Ensemble	10	79	92	84	18	30	5	95	96	99	50	20	
	Trained ensemble	10	66	89	71	7	20	5	88	95	93	0	0	