Network Systems Science & Advanced Computing

Biocomplexity Institute & Initiative

University of Virginia

Foresight and Analysis of Infectious Disease Threats to Virginia's Public Health

February 2nd, 2023

(data current to January 25th – February 1st)

Biocomplexity Institute Technical report: TR BI-2023-8

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About Us

- Biocomplexity Institute at the University of Virginia
  - Using big data and simulations to understand massively interactive systems and solve societal problems
- Over 20 years of crafting and analyzing infectious disease models
  - Pandemic response for Influenza, Ebola, Zika, and others

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Overview

- **Goal**: Understand impact of current and emerging Infectious Disease threats to the Commonwealth of Virginia using modeling and analytics

- **Approach:**
  - Provide analyses and summaries of current infectious disease threats
  - Survey existing forecasts and trends in these threats
  - Analyze and summarize the current situation and trends of these threats in the broader context of the US and world.
  - Provide broader overview of other emerging threats

Key Takeaways

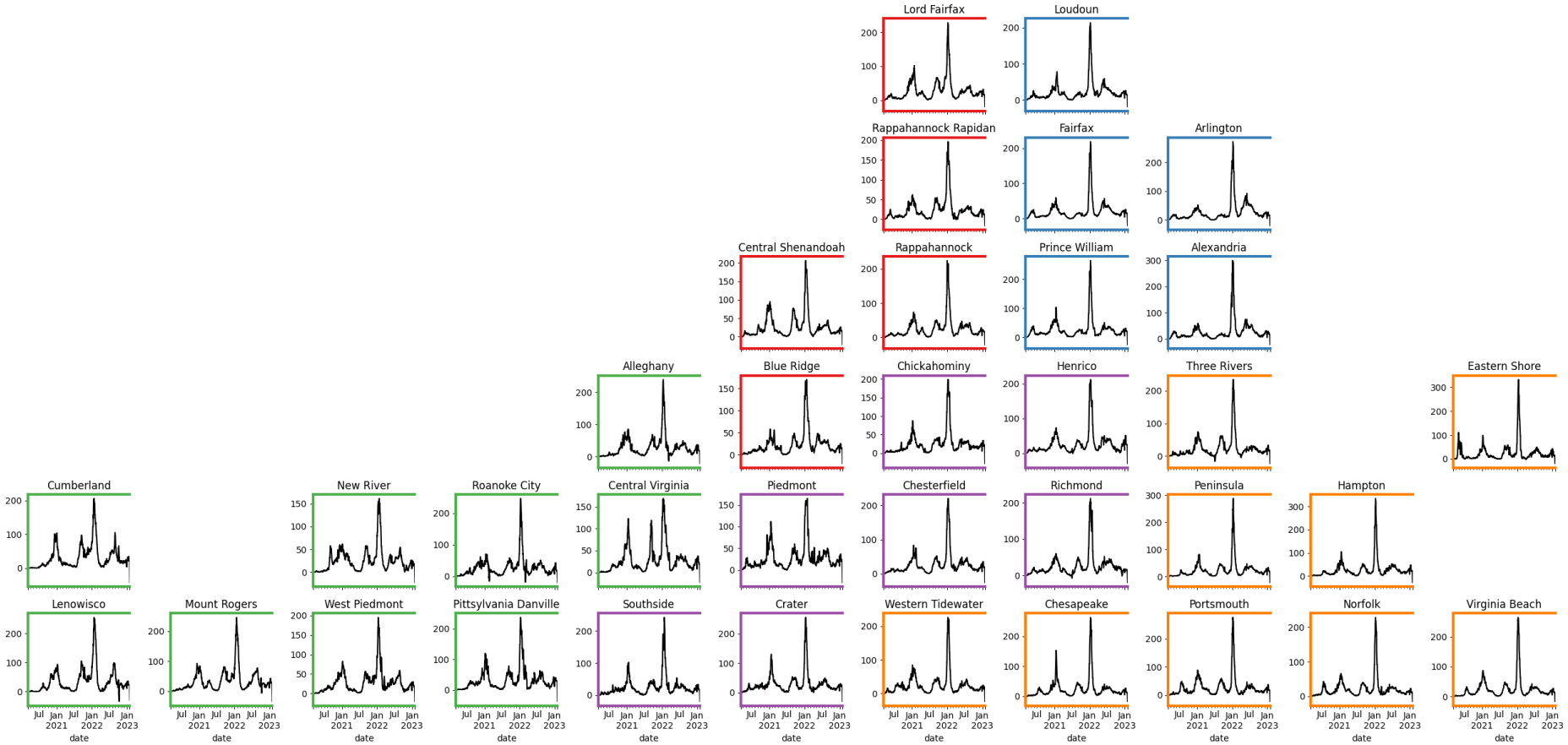
Projecting future cases precisely is impossible and unnecessary.
Even without perfect projections, we can confidently draw conclusions:

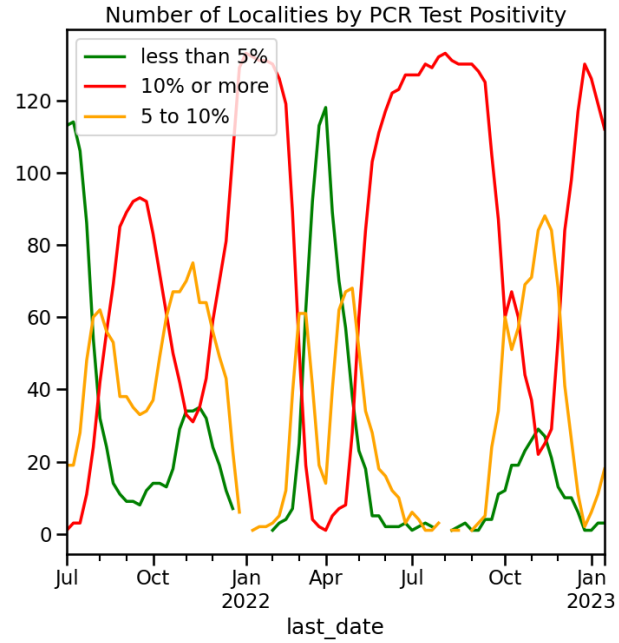
- Case rates and hospitalizations from COVID-19 remain on the decline with limited activity in isolated areas
- Case rates and hospitalizations from Influenza are almost back to early season lows

- Model Updates
  - Projection model from Dec 9th remains roughly on track with current trajectory, however, the recent decline is occurring earlier than anticipated by the model
  - COVID-19 forecast models anticipate a plateauing of COVID-19 hospital admissions in near term, though historically Feb and March have had limited activity
  - Influenza forecast models call for low levels of Influenza hospital admissions to persist

COVID-19 Surveillance

Case Rates (per 100k) and Test Positivity





County level RT-PCR test positivity

Green: <5.0% (or <20 tests in past 14 days)

Orange: 5.0%-10.0% (or <500 tests and <2000 tests/100k and >10% positivity over 14 days)

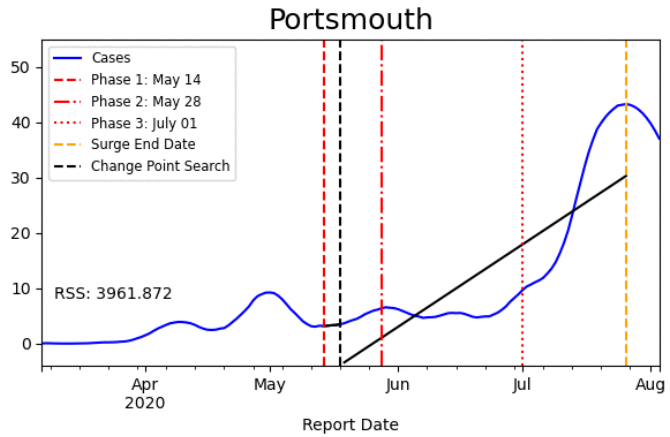
Red: >10.0% (and not "Green" or "Yellow")

District Trajectories

Goal: Define epochs of a Health District's COVID-19 incidence to characterize the current trajectory

Method: Find recent peak and use hockey stick fit to find inflection point afterwards, then use this period's slope to define the trajectory

Hockey stick fit

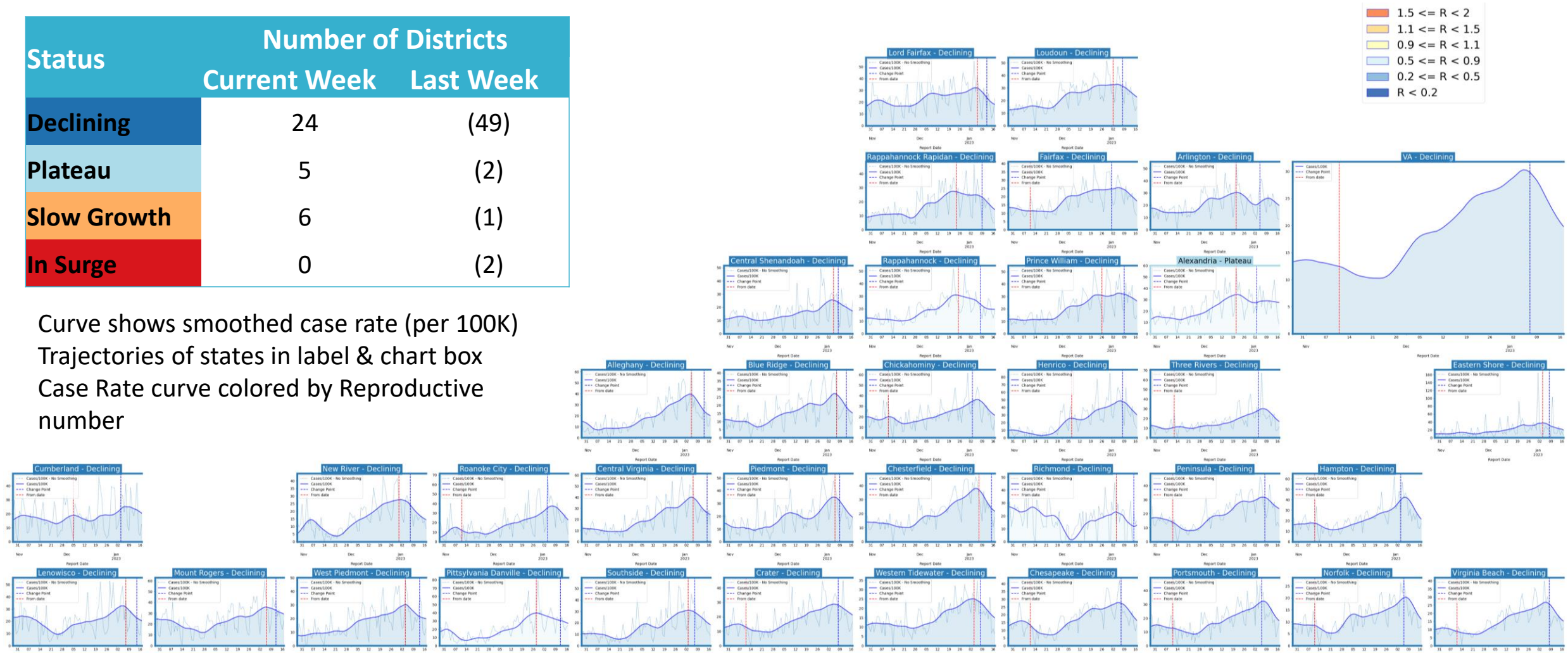


Trajectory	Description	Weekly Case Rate Slope (per 100k)	Weekly Hosp Rate Slope (per 100k)
Declining	Sustained decreases following a recent peak	slope < -0.88/day	slope < -0.07/day
Plateau	Steady level with minimal trend up or down	-0.88/day < slope < 0.42/day	-0.07/day < slope < 0.07/day
Slow Growth	Sustained growth not rapid enough to be considered a Surge	0.42/day < slope < 2.45/day	0.07/day < slope < 0.21/day
In Surge	Currently experiencing sustained rapid and significant growth	2.45/day < slope	0.21/day < slope

District Case Trajectories – last 10 weeks

Status	Number of Districts	
	Current Week	Last Week
Declining	24	(49)
Plateau	5	(2)
Slow Growth	6	(1)
In Surge	0	(2)

Curve shows smoothed case rate (per 100K)
Trajectories of states in label & chart box
Case Rate curve colored by Reproductive number



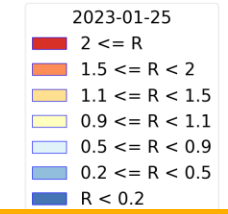
District Hospital Trajectories – last 10 weeks

Status	Number of Districts	
	Current Week	Last Week
Declining	29	(22)
Plateau	1	(2)
Slow Growth	5	(8)
In Surge	0	(3)

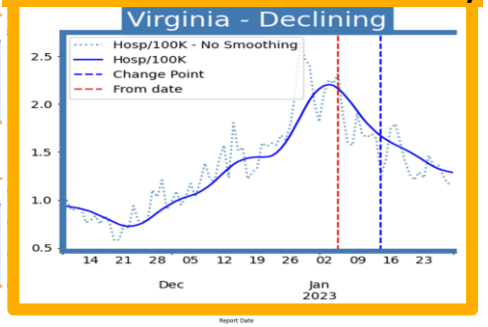
Curve shows smoothed hospitalization rate (per 100K) by district
Hosp rate curve colored by R_e number

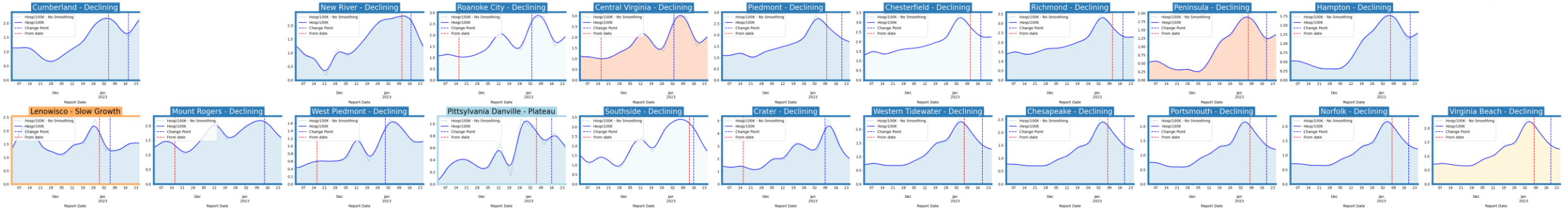
Hospitalization by county is delayed, these data are current as of

January 25th

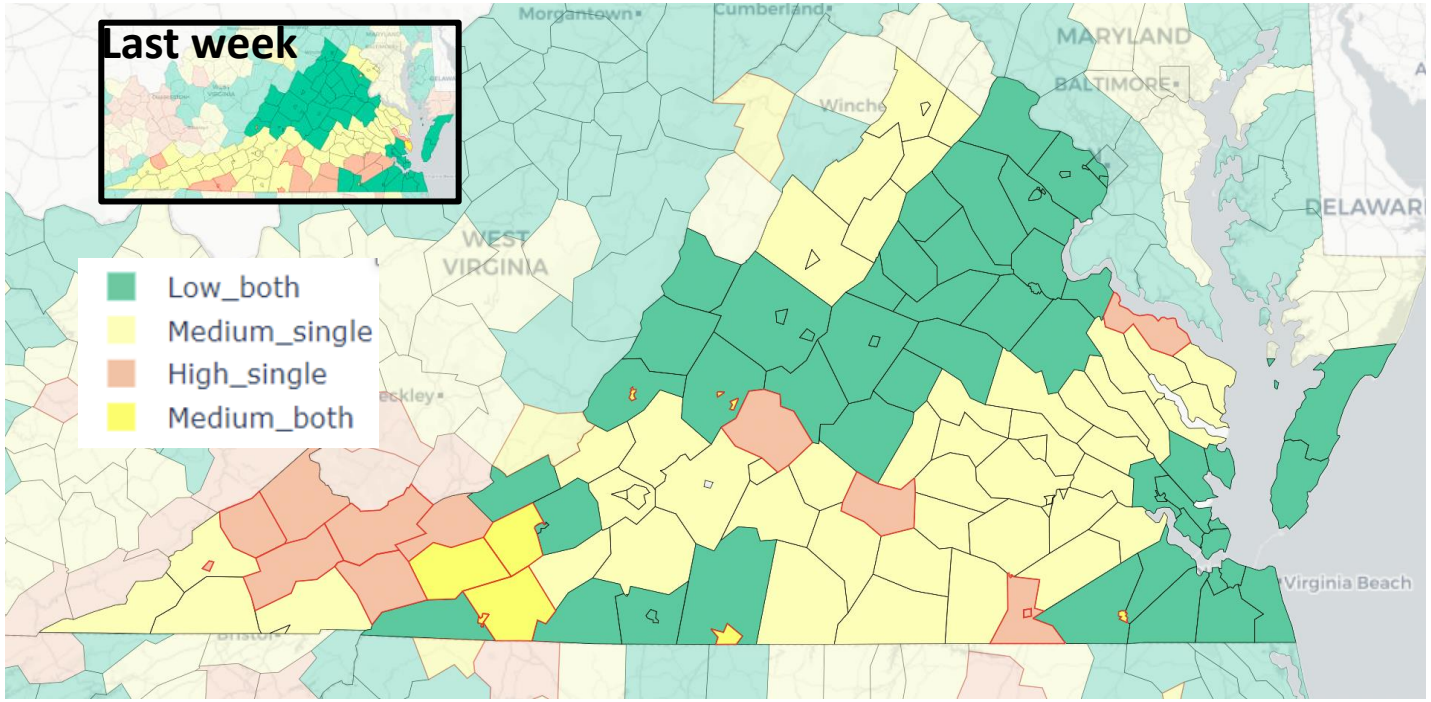


State level without delay





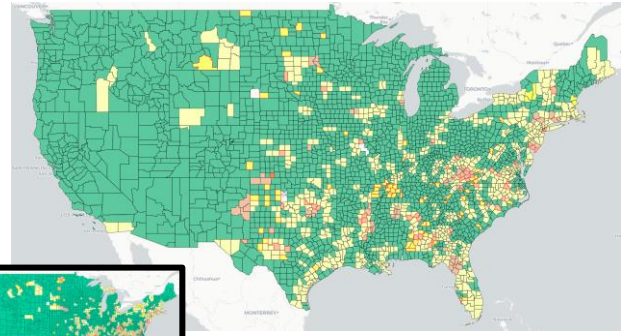
CDC's COVID-19 Community Levels



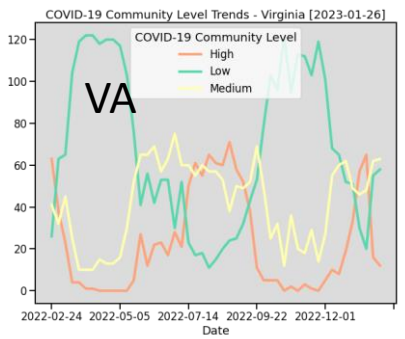
Red outline indicates county had 200 or more cases per 100k in last week

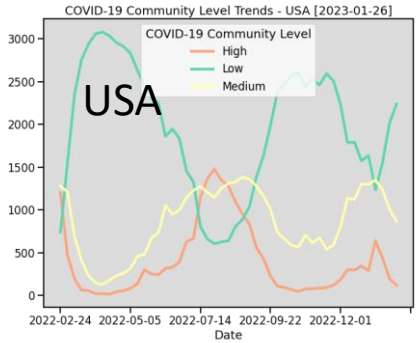
Pale color indicates either beds or occupancy set the level for this county

Dark color indicates both beds and occupancy set the level for this county



Last week





COVID-19 Community Levels – Use the Highest Level that Applies to Your Community

New COVID-19 Cases Per 100,000 people in the past 7 days	Indicators	Low	Medium	High
Fewer than 200	New COVID-19 admissions per 100,000 population (7-day total)	<10.0	10.0-19.9	≥20.0
	Percent of staffed inpatient beds occupied by COVID-19 patients (7-day average)	<10.0%	10.0-14.9%	≥15.0%
200 or more	New COVID-19 admissions per 100,000 population (7-day total)	NA	<10.0	≥10.0
	Percent of staffed inpatient beds occupied by COVID-19 patients (7-day average)	NA	<10.0%	≥10.0%

The COVID-19 community level is determined by the higher of the new admissions and inpatient beds metrics, based on the current level of new cases per 100,000 population in the past 7 days

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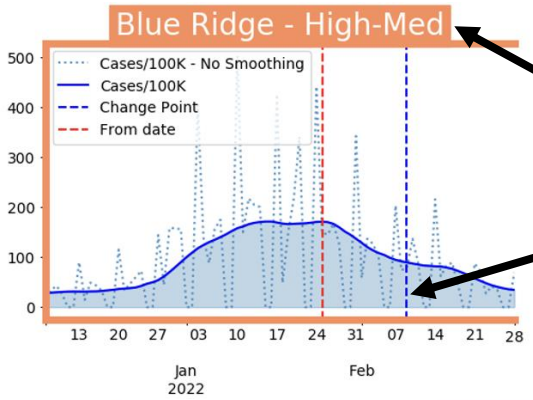
Data from: CDC Data Tracker Portal

District Trajectories with Community Levels

Community Level (Title Color)
- High
- High-Med
- Med-High
- Medium
- Med-Low
- Low-Med
- Low

Curve shows smoothed case rate (per 100K)
CDC's new Community Level aggregated to district level in label & chart box color
Case Rate curve colored by Trajectory

Trajectory (Curve Shading)
- In Surge
- Slow Growth
- Plateau
- Declining



District's Aggregate Community Level
Aggregate level a simple mean of all levels for counties in district

Case rate Trajectory

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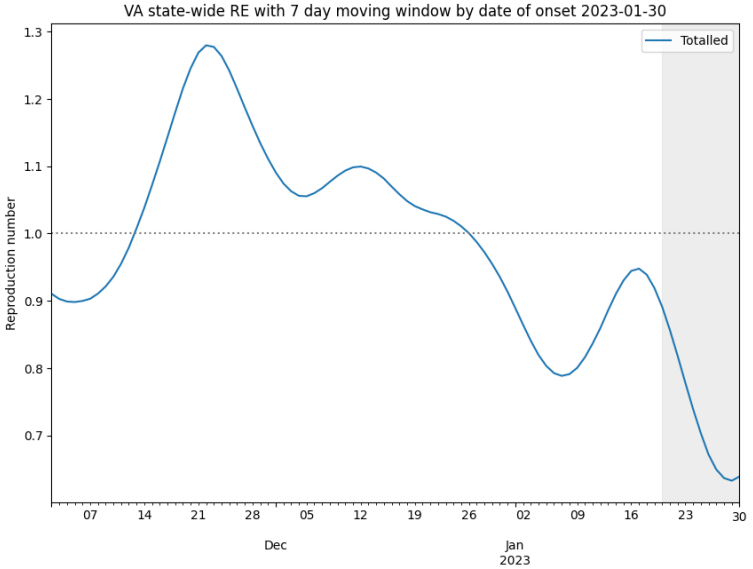
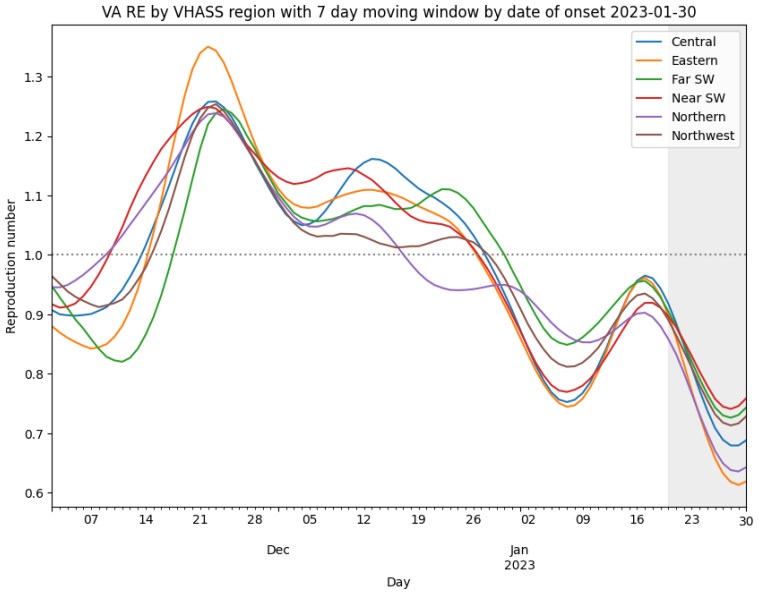
COVID-19 Growth Metrics

Estimating Daily Reproductive Number –
Date of Onset

Jan 21st Estimates

Region	Date of Onset R_e	Date Onset Diff Last Week
State-wide	0.856	-0.064
Central	0.885	-0.043
Eastern	0.860	-0.080
Far SW	0.880	-0.090
Near SW	0.879	-0.018
Northern	0.833	-0.095
Northwest	0.865	-0.101





Methodology

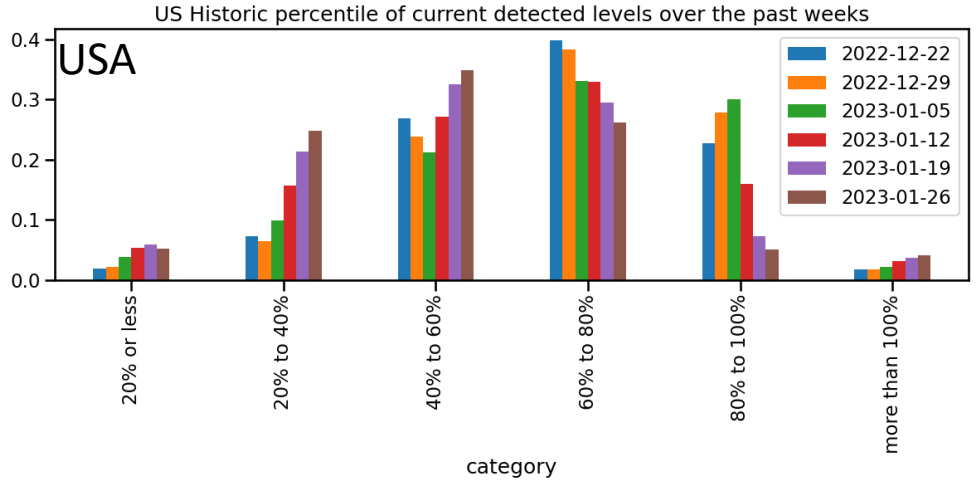
- Wallinga-Teunis method (EpiEstim[1]) for cases by **confirmation date**
- Serial interval: updated to discrete distribution from observations (mean=4.3, Flaxman et al, Nature 2020)
- Using Confirmation date since due to increasingly unstable estimates from onset date due to backfill

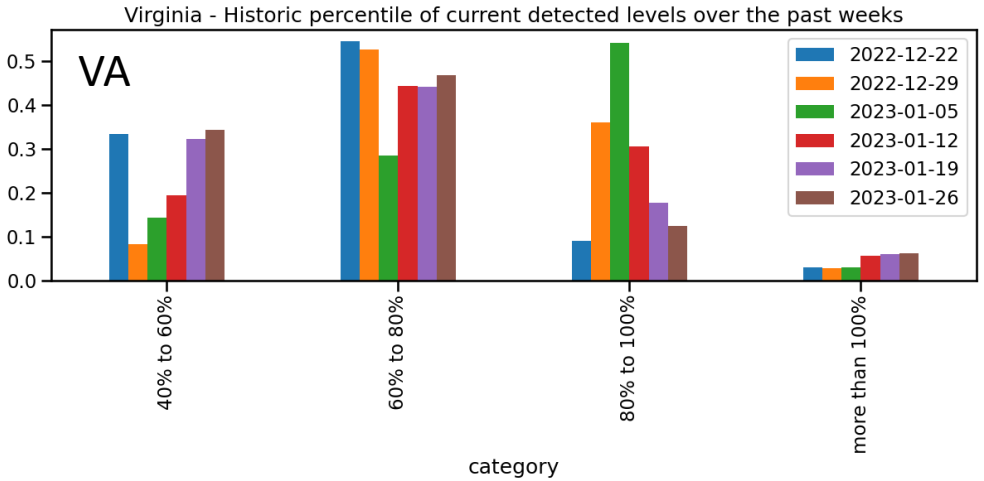
1. Anne Cori, Neil M. Ferguson, Christophe Fraser, Simon Cauchemez. A New Framework and Software to Estimate Time-Varying Reproduction Numbers During Epidemics. American Journal of Epidemiology, Volume 178, Issue 9, 1 November 2013, Pages 1505–1512, https://doi.org/10.1093/aje/kwt133

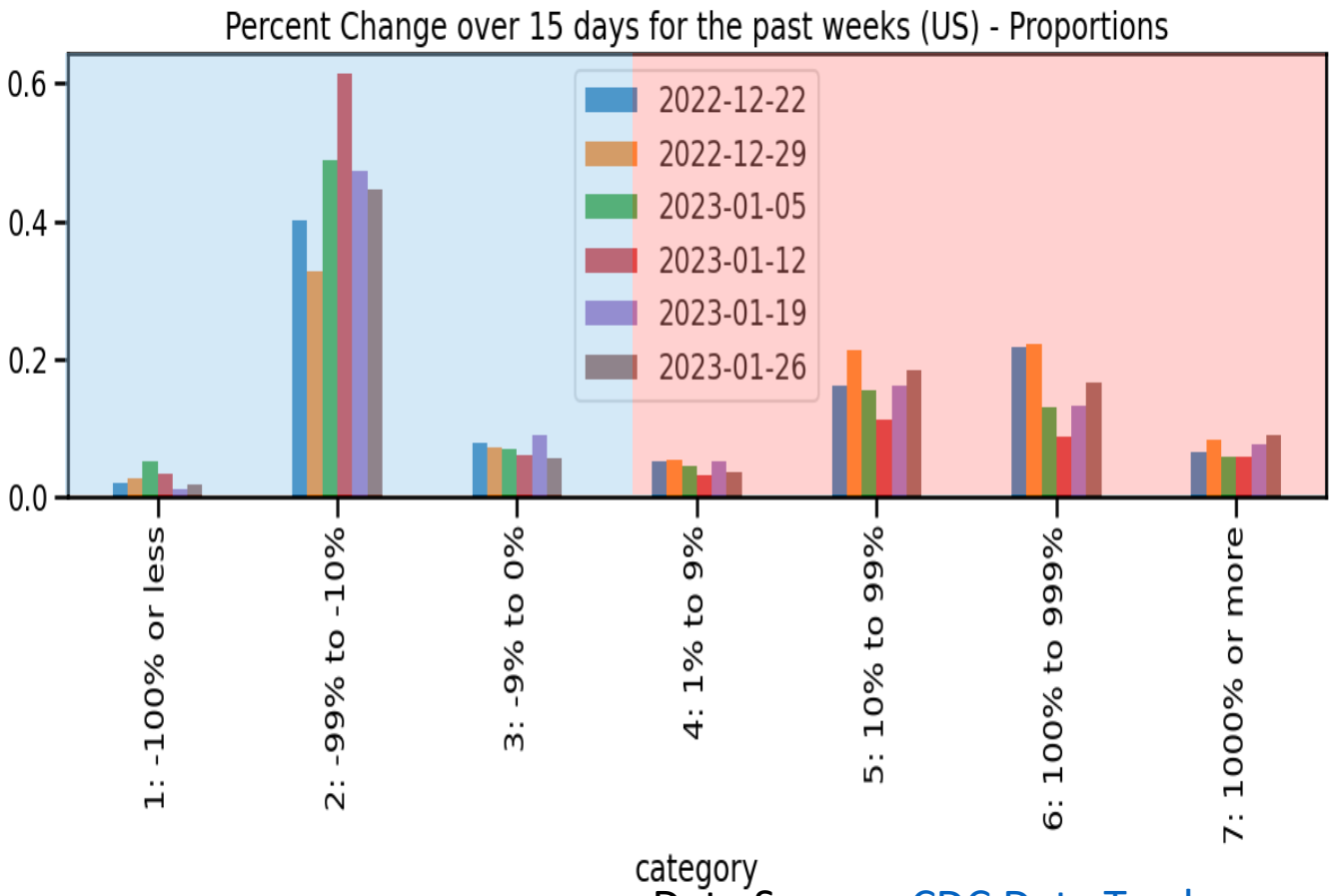
Wastewater Monitoring

Wastewater provides a coarse early warning of COVID-19 levels in communities

- Overall in the US, there is an increase in sites with increased levels of virus compared to 15 days ago
- Growth seen in the category where current virus levels are at or exceeding max of previous historical levels





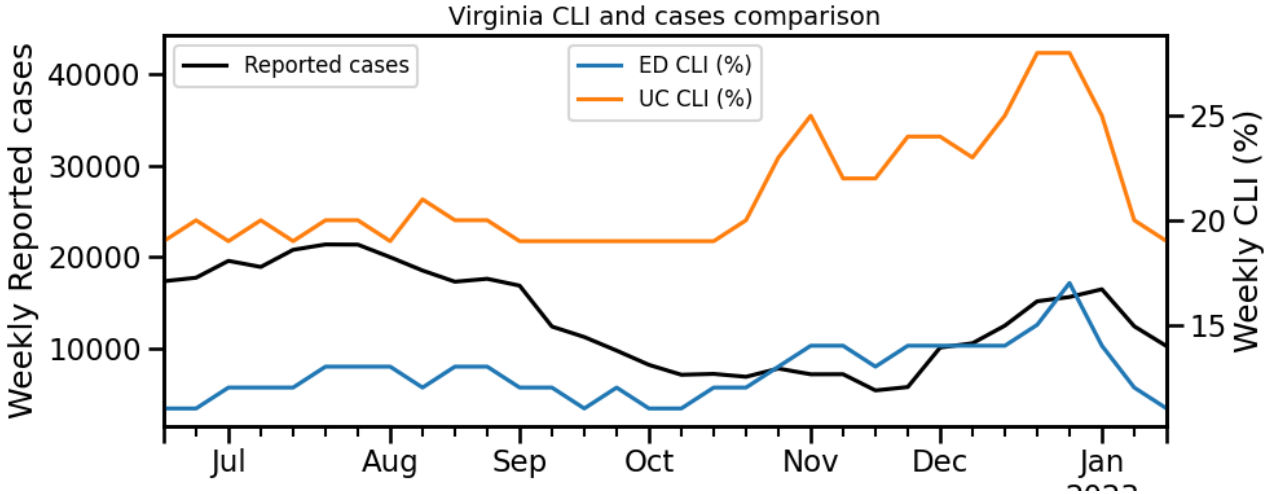


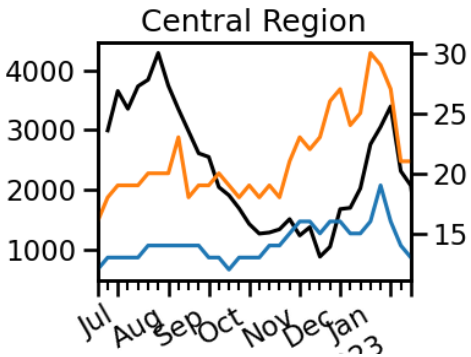
Data Source: [CDC Data Tracker]

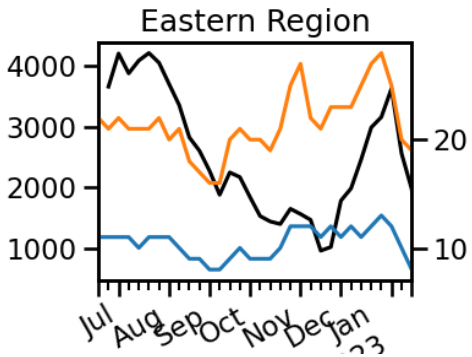
COVID-like Illness Activity

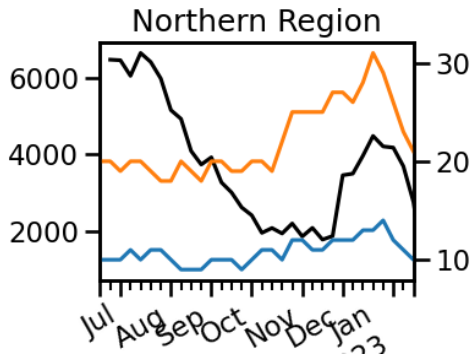
COVID-like Illness (CLI) gives a measure of COVID transmission in the community

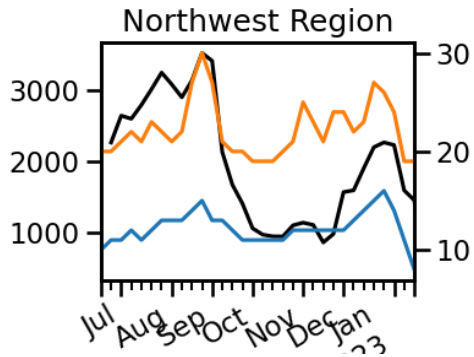
- Emergency Dept (ED) based CLI is more correlated with case reporting
- Urgent Care (UC) is a leading indicator but may be influenced by testing for other URIs
- **After recent surges, levels are now at lowest levels in past 7 months**

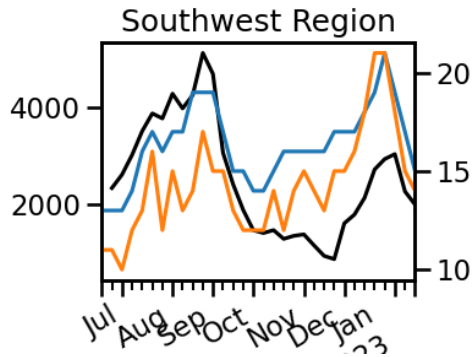








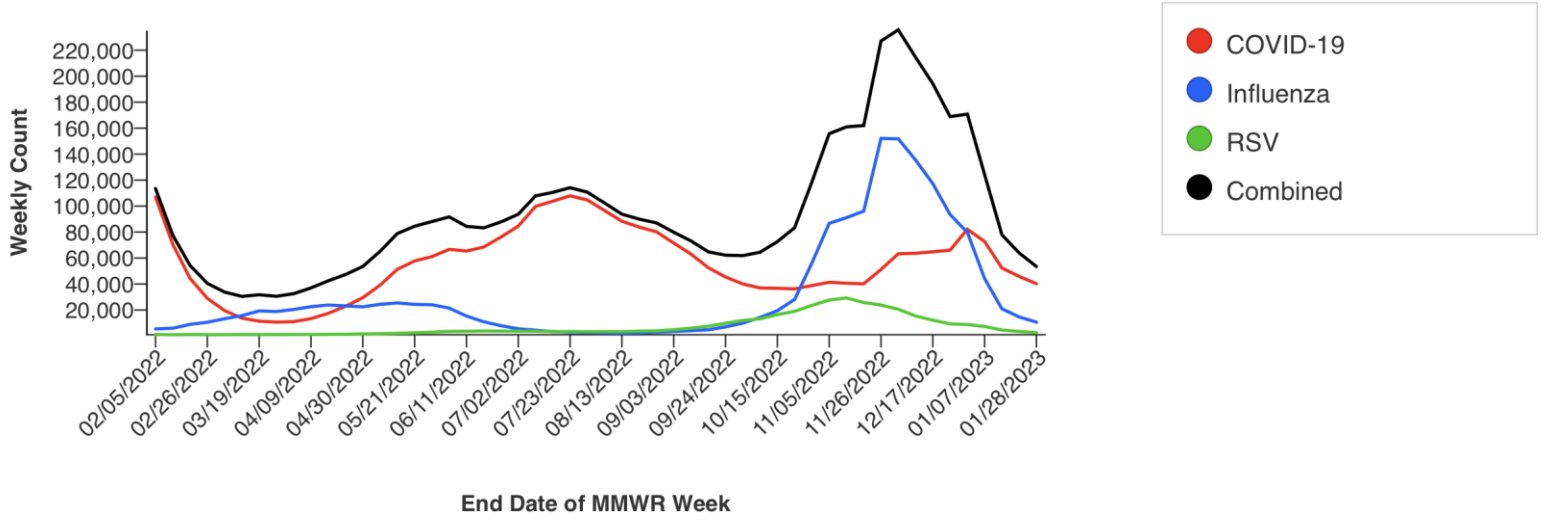


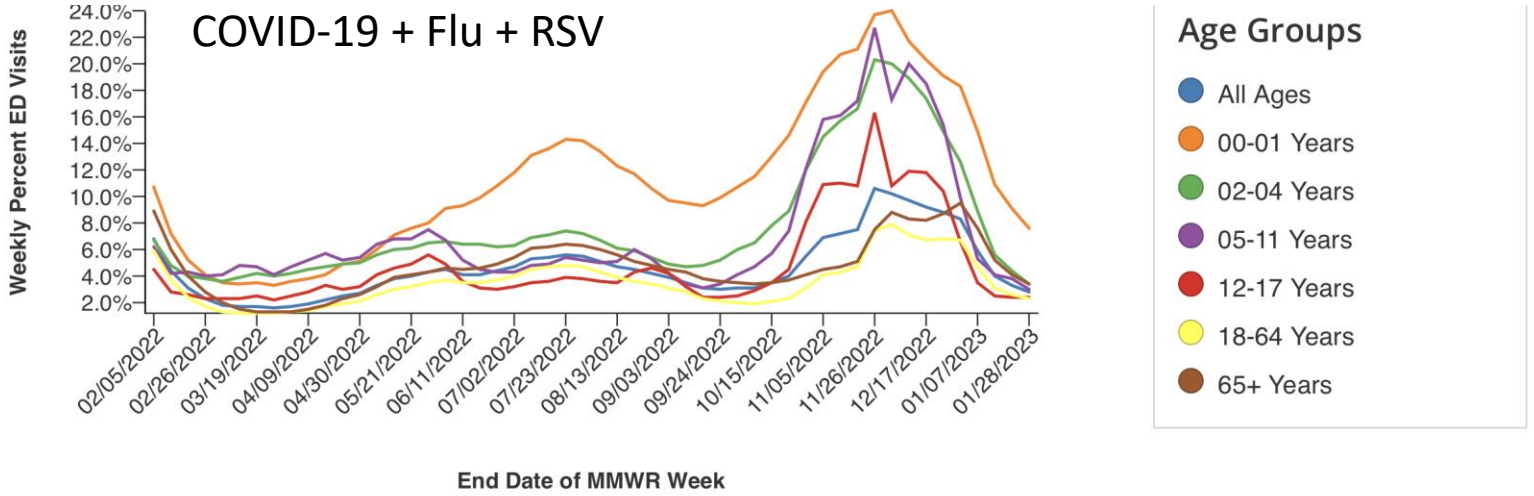


Emergency Department Visits

COVID-19 Diagnoses across the Country via the National Syndromic Surveillance Program (NSSP)

- Current declines seen in ED visits across all 3 diseaseas and across ages





Data Source:
CDC Surveillance

COVID-19 Spatial Epidemiology

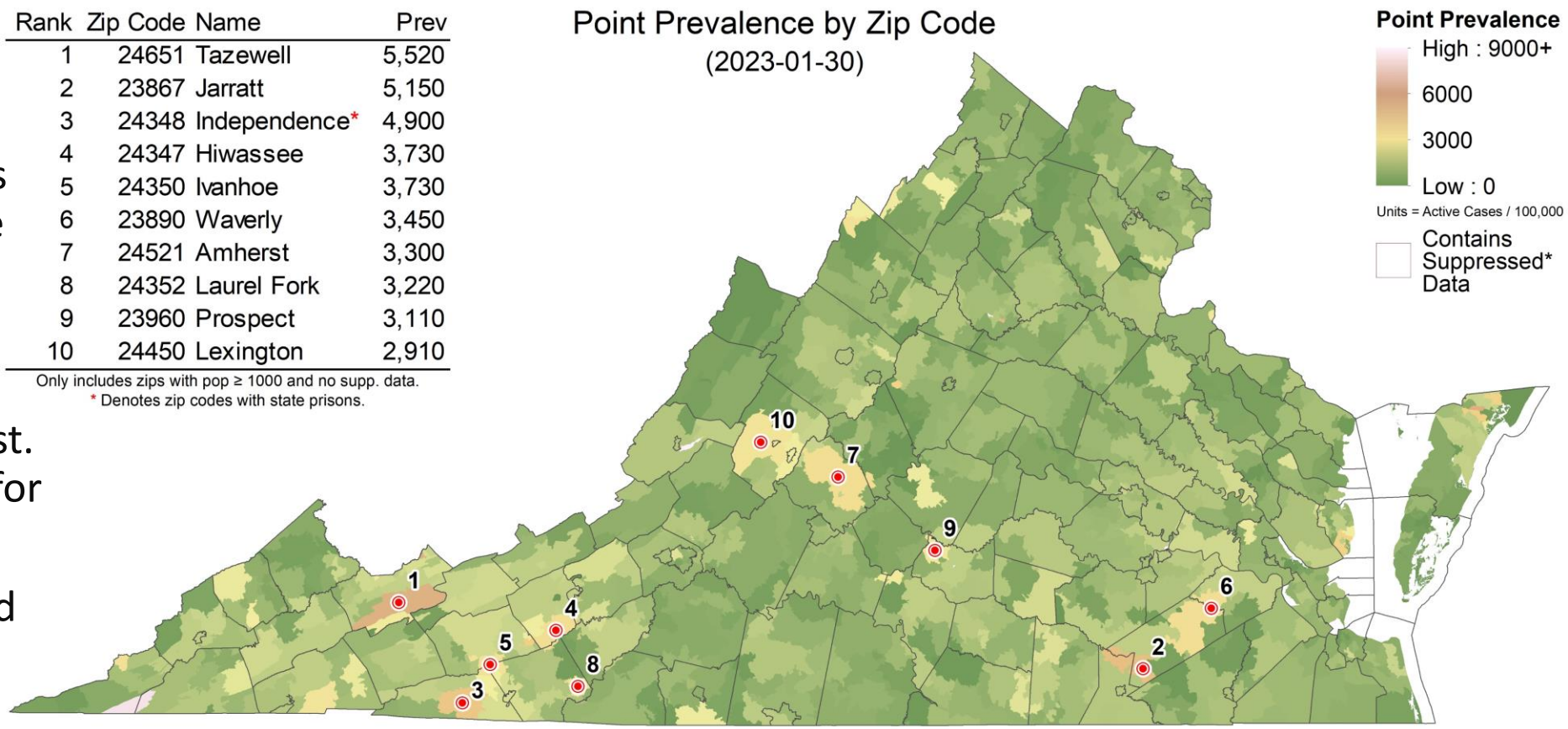
Zip code level weekly Case Rate (per 100K)

Case Rates in the last week by zip code

- Statewide prevalence peaked in the first week of January and has since declined by 40%.
- Current prevalence rates are comparable to those of early December.
- Independence, VA is the only zip code containing a prison on the top 10 list. It has been in the top 3 for over a fortnight.
- Some counts are low and suppressed to protect anonymity. They are shown with a red outline.

Rank	Zip Code	Name	Prev
1	24651	Tazewell	5,520
2	23867	Jarratt	5,150
3	24348	Independence*	4,900
4	24347	Hiwassee	3,730
5	24350	Ivanhoe	3,730
6	23890	Waverly	3,450
7	24521	Amherst	3,300
8	24352	Laurel Fork	3,220
9	23960	Prospect	3,110
10	24450	Lexington	2,910

Only includes zips with pop ≥ 1000 and no supp. data.
* Denotes zip codes with state prisons.



Based on Spatial Empirical Bayes smoothed point prevalence, with an 8:1 ascertainment ratio, for week ending 2023-01-30.

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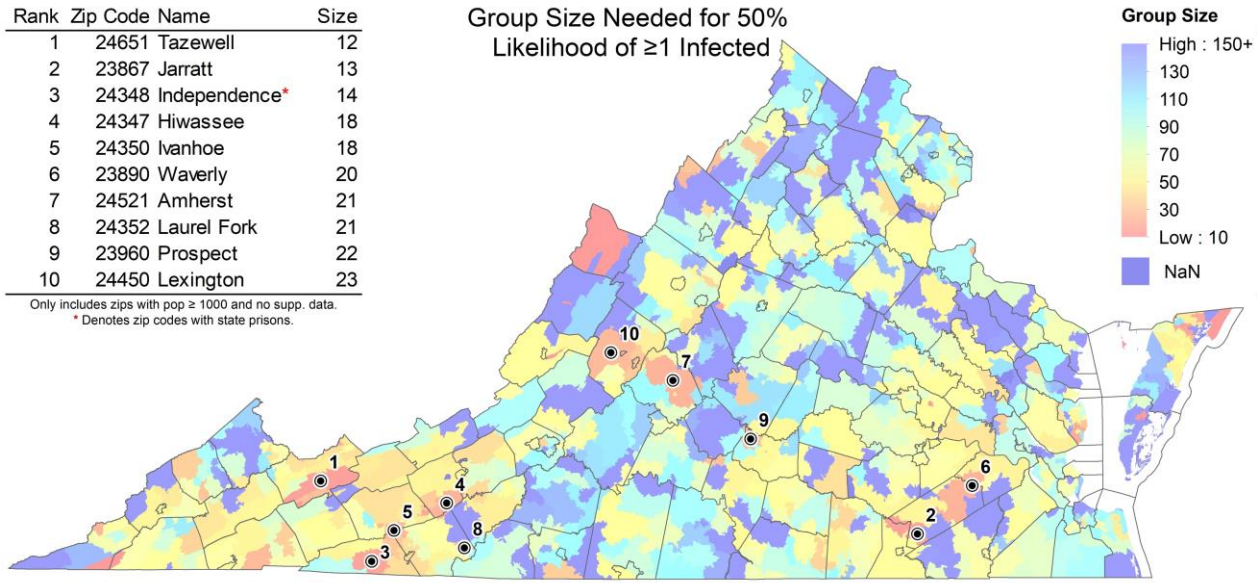
Risk of Exposure by Group Size and HCW prevalence

Case Prevalence in the last week by zip code used to calculate risk of encountering someone infected in a gathering of randomly selected people

- **Group Size**: Assumes **8 undetected infections** per confirmed case (ascertainment rate from recent seroprevalence survey) and shows minimum size of a group with a 50% chance an individual is infected by zip code (e.g., in a group of 12 in Tazewell, there is a 50% chance someone will be infected).
- **HCW ratio**: Case rate among health care workers (HCW) in the last week using patient facing health care workers as the numerator / population's case prevalence. Alleghany and Covington represent 10 HCWs.

Rank	Zip Code	Name	Size
1	24651	Tazewell	12
2	23867	Jarratt	13
3	24348	Independence*	14
4	24347	Hiwassee	18
5	24350	Ivanhoe	18
6	23890	Waverly	20
7	24521	Amherst	21
8	24352	Laurel Fork	21
9	23960	Prospect	22
10	24450	Lexington	23

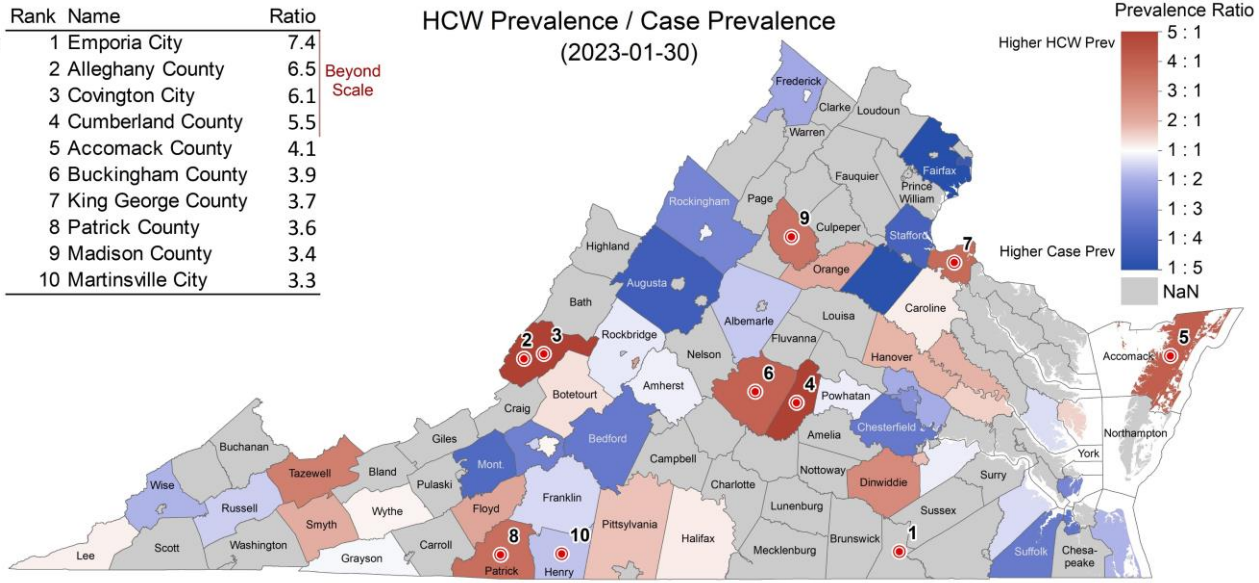
Only includes zips with pop ≥ 1000 and no supp. data.
* Denotes zip codes with state prisons.



Based on Spatial Empirical Bayes smoothed point prevalence, with an 8:1 ascertainment ratio, for week ending 2023-01-30.

Rank	Name	Ratio
1	Emporia City	7.4
2	Alleghany County	6.5
3	Covington City	6.1
4	Cumberland County	5.5
5	Accomack County	4.1
6	Buckingham County	3.9
7	King George County	3.7
8	Patrick County	3.6
9	Madison County	3.4
10	Martinsville City	3.3

Beyond Scale



Note: This assumes that the ascertainment rate of healthcare workers is double that of the public.

Current Hot-Spots

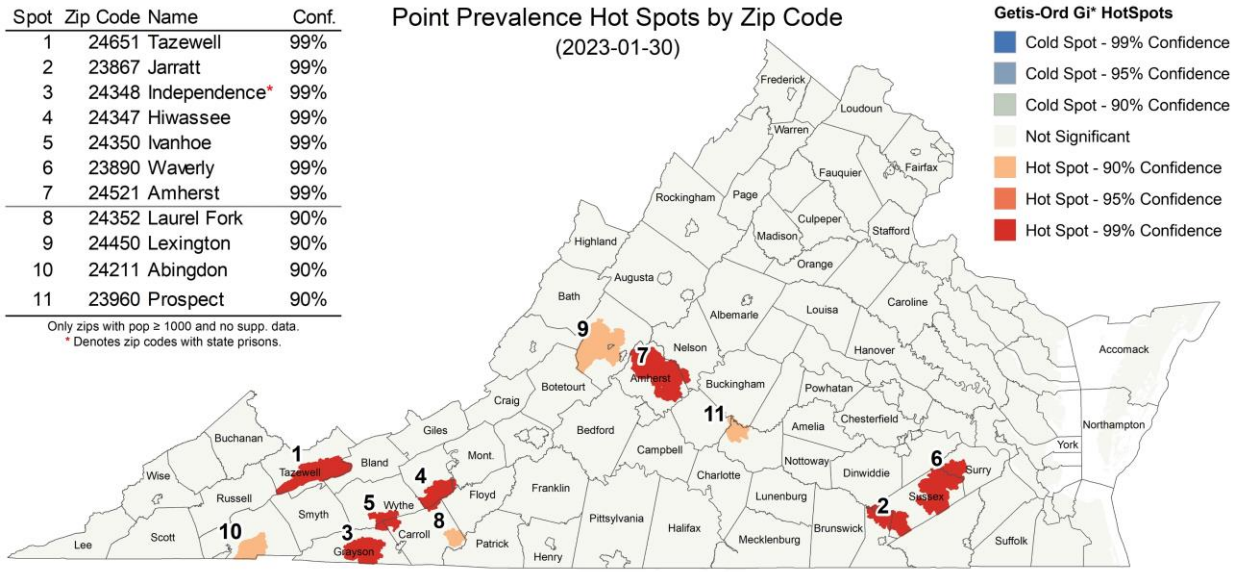
Case rates that are significantly different from neighboring areas or model projections

- **Spatial**: Getis-Ord Gi* based hot spots compare clusters of zip codes with weekly case prevalence higher than nearby zip codes to identify larger areas with statistically significant deviations
- **Temporal**: The weekly case rate (per 100K) projected last month compared to those observed by county, which highlights temporal fluctuations that differ from the model's projections.
- Hotspots are concentrated in the Far SW, north of Lynchburg, and south of Richmond. The VariantX forecast from mid-December was fairly accurate, but overpredicted case rates in LHDs west of Lynchburg.

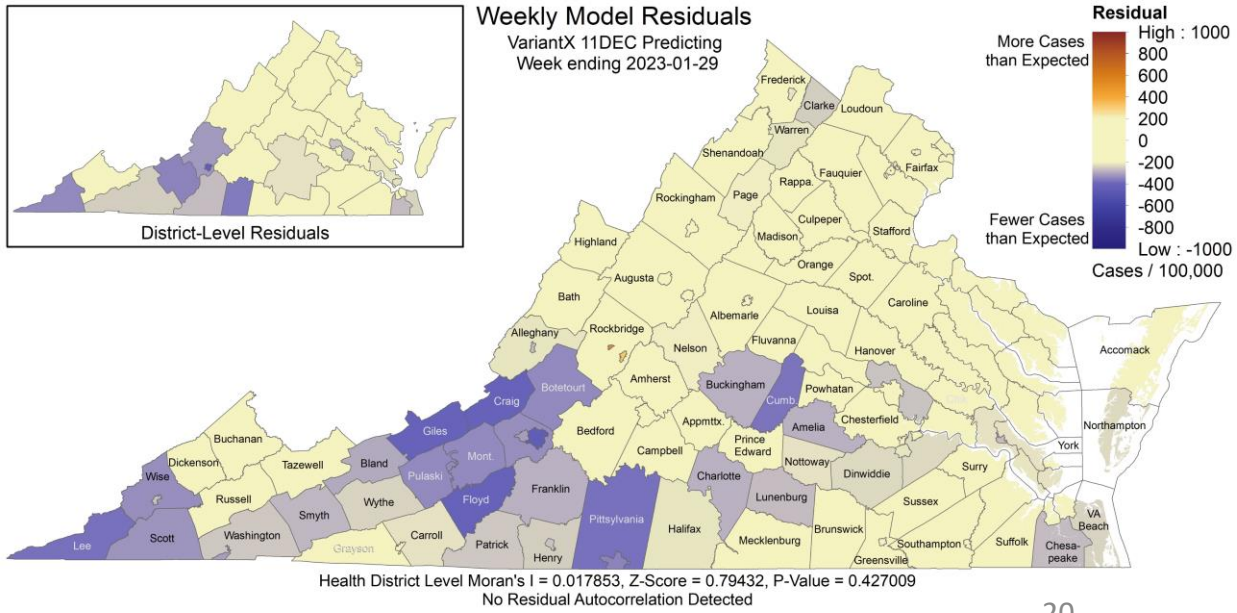
Spatial Hotspots

Spot	Zip Code	Name	Conf.
1	24651	Tazewell	99%
2	23867	Jarratt	99%
3	24348	Independence*	99%
4	24347	Hiwassee	99%
5	24350	Ivanhoe	99%
6	23890	Waverly	99%
7	24521	Amherst	99%
8	24352	Laurel Fork	90%
9	24450	Lexington	90%
10	24211	Abingdon	90%
11	23960	Prospect	90%

Only zips with pop ≥ 1000 and no supp. data.
* Denotes zip codes with state prisons.



Clustered Temporal Hotspots

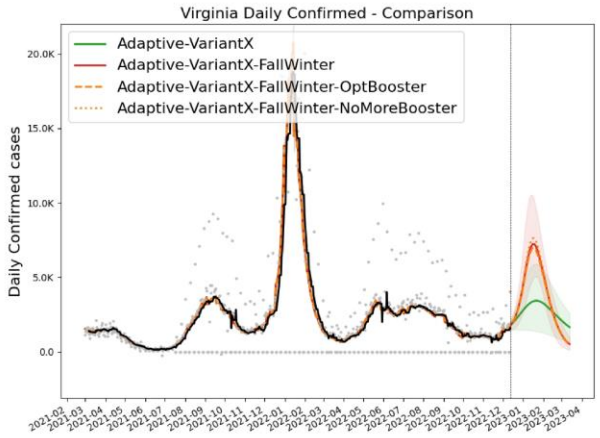


Scenario Trajectory Tracking

Which scenario from a month ago did projection for each county track closest?

Six Weeks Ago

Four Weeks Ago



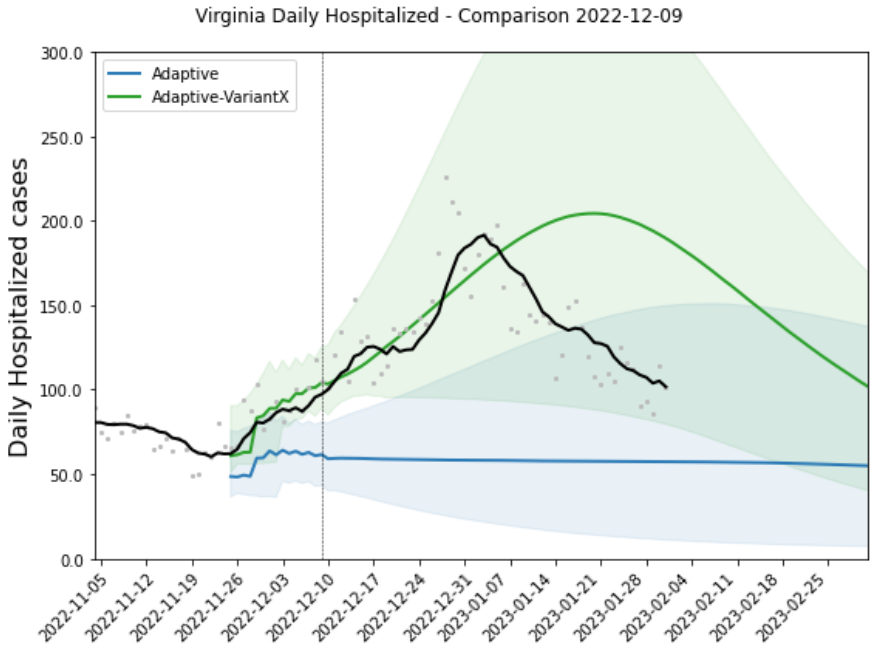
- One-month projections separate the scenarios more clearly and reveals larger overall patterns.
- Among models run in mid-December, the Adaptive scenario was closest to ground truth for most counties in the Commonwealth. The FallWinter scenario was best in far Southwest, and areas south of Richmond.

Last Projection Model

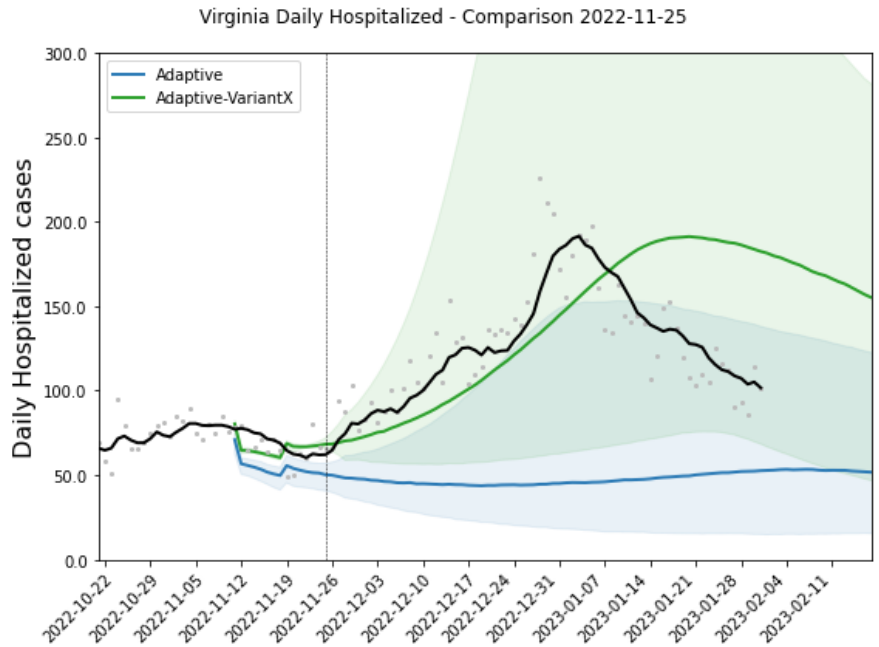
Previous projections comparison - Hospitalizations

- Previous projections have tracked observed hospitalizations reasonably well under the VariantX scenario, though the peak has occurred earlier than anticipated
- VariantX scenario assumed a high immune escape variant would continue to grow and was roughly aligned, though a little earlier than XBB.1.5
- Seasonal forcing may be less important this season due to behavioral changes early in the season

Previous round early December



Projection from late November



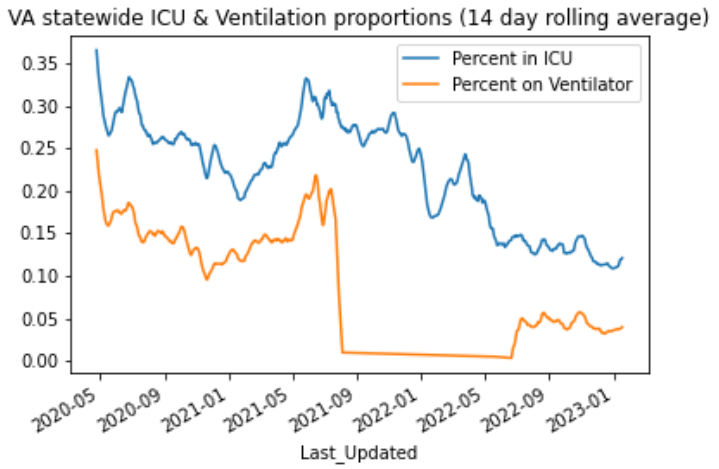
COVID-19 Severity Metrics

Hospitalizations and Severe Outcomes

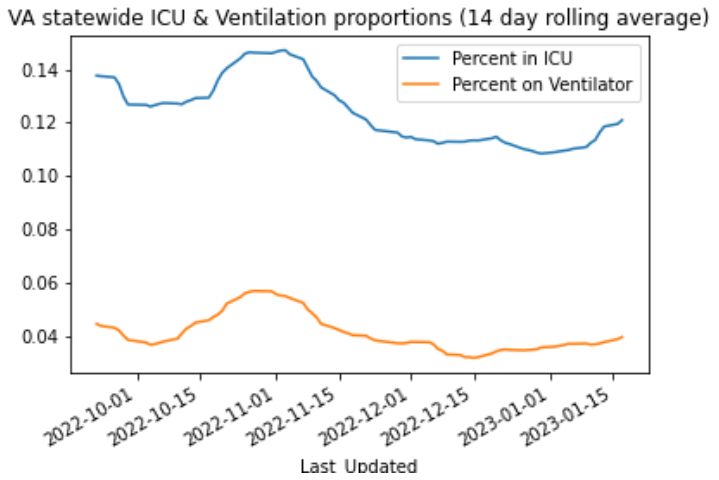
Proportion of most severe outcomes decreasing among those who are hospitalized

- ICU has declined from ~20% of hospitalized to 10-15% since initial Omicron wave
- Recent trend tipping up, though current levels near historic lows
- Regional variation tracks state-level

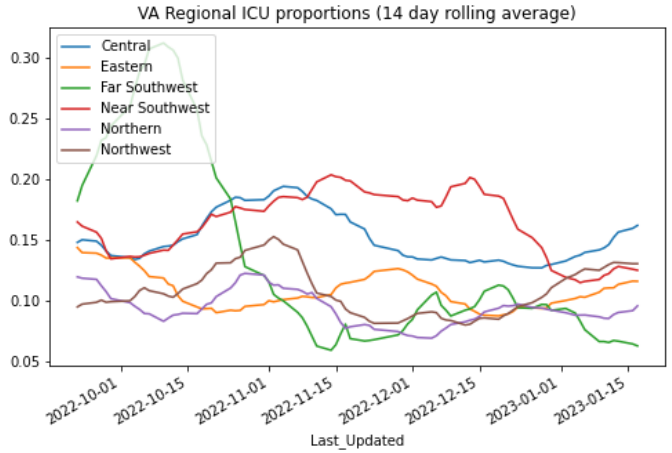
Virginia-wide – full pandemic



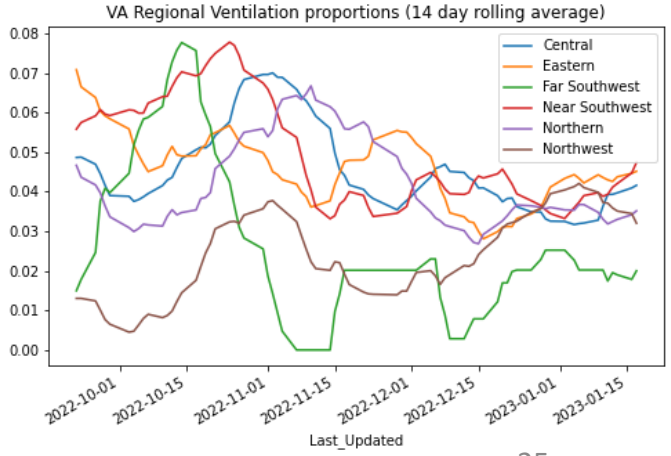
Virginia-wide – recent



Virginia Regional ICU percent



Virginia Regional Ventilation %



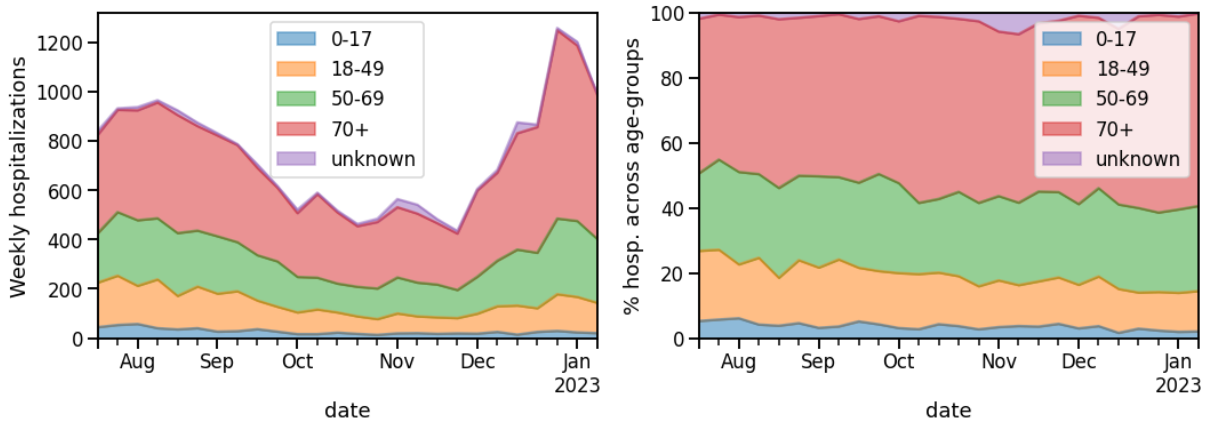
Hospitalizations in VA by Age

Age distribution in hospitals relatively stable

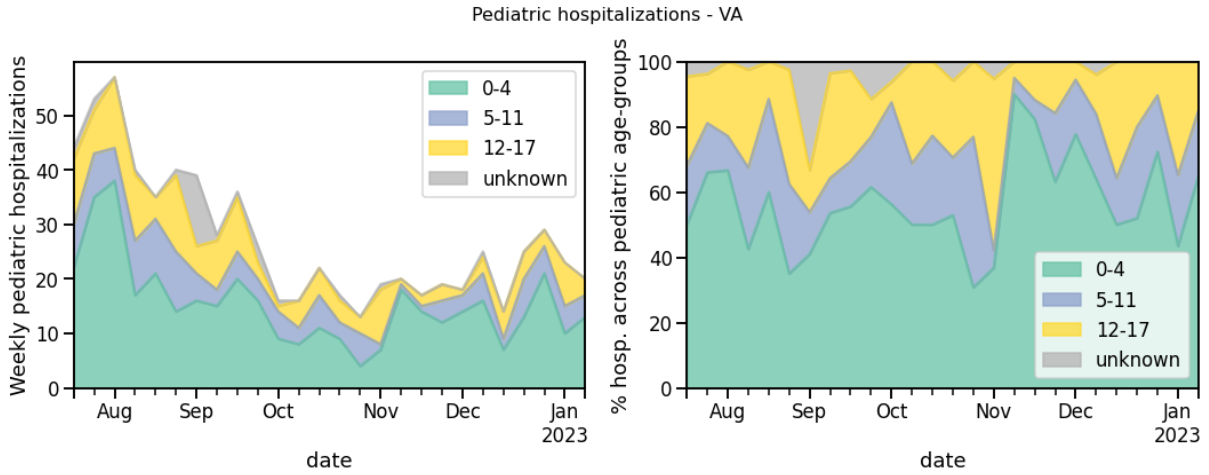
- Uptick in hospitalizations mostly fueled by 70+ age group
- Pediatric hospitalizations have been steady despite the surge in activity in other age-groups

Note: These data are lagged and based on HHS hospital reporting

Virginia Hospitalizations by Age (all ages)



Pediatric Hospitalizations by Age (0-17yo)



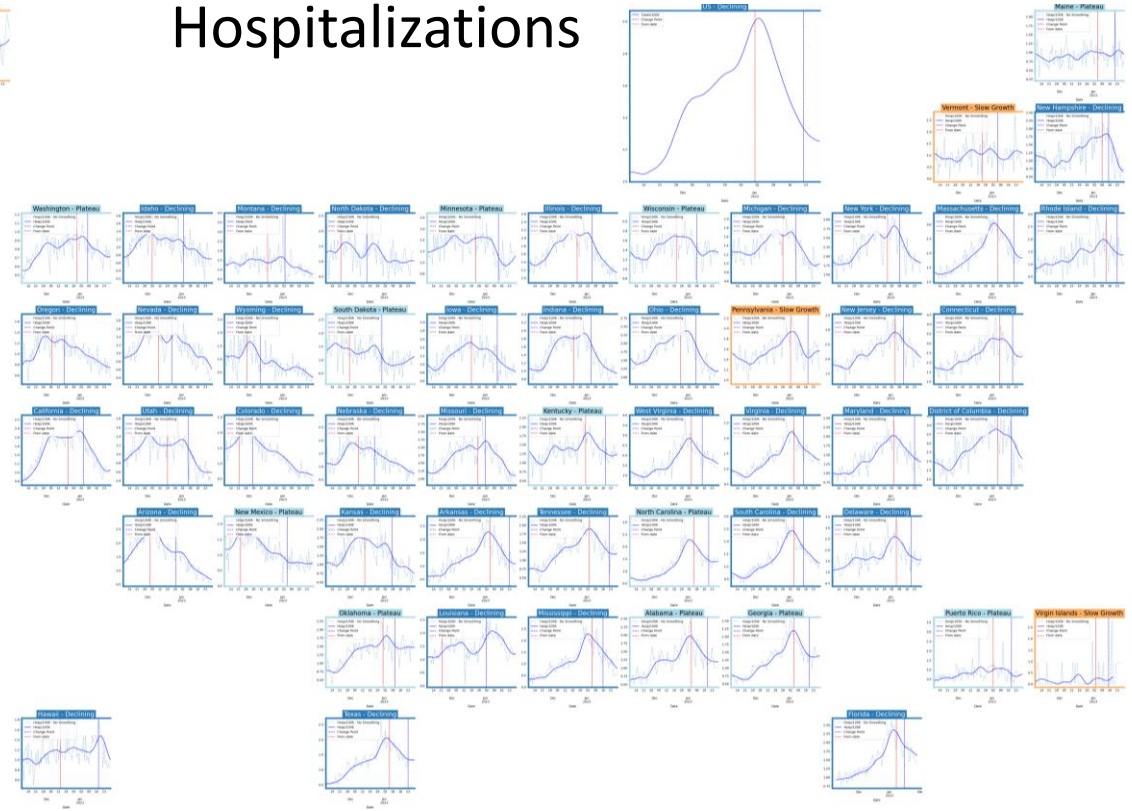
Data Source: Delphi and HHS

COVID-19 Broader Context

United States Cases & Hospitalizations

Cases

Hospitalizations

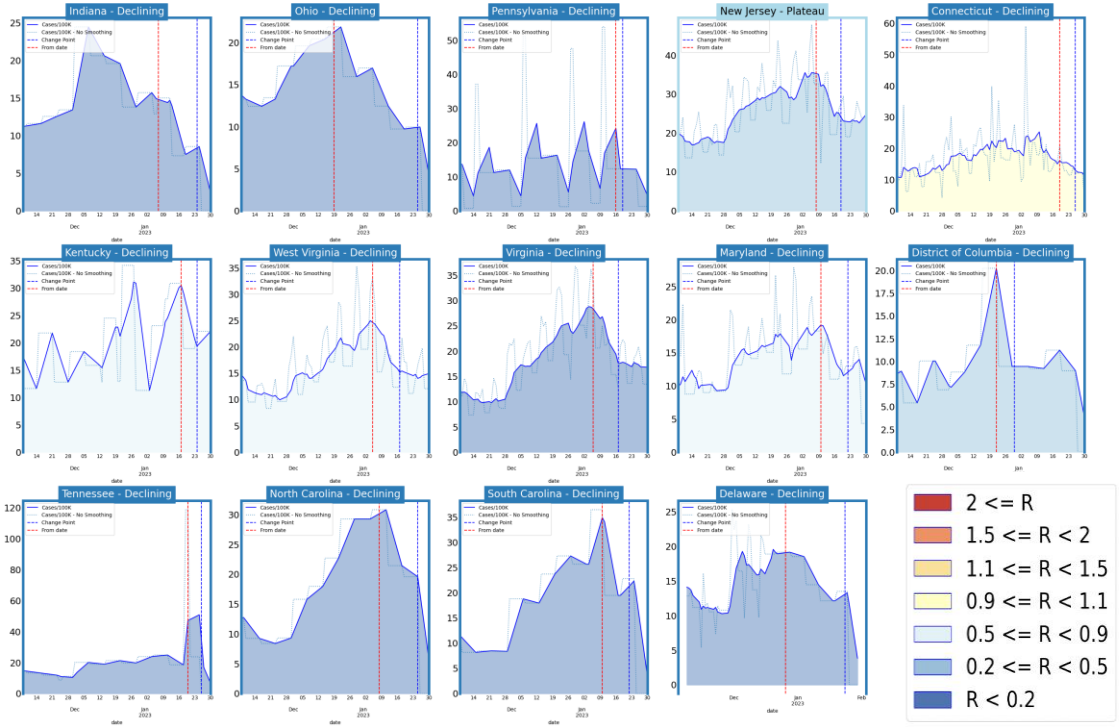


Status	Number of States	
	Current Week	Last Week
Declining	50	(49)
Plateau	4	(2)
Slow Growth	0	(1)
In Surge	0	(2)

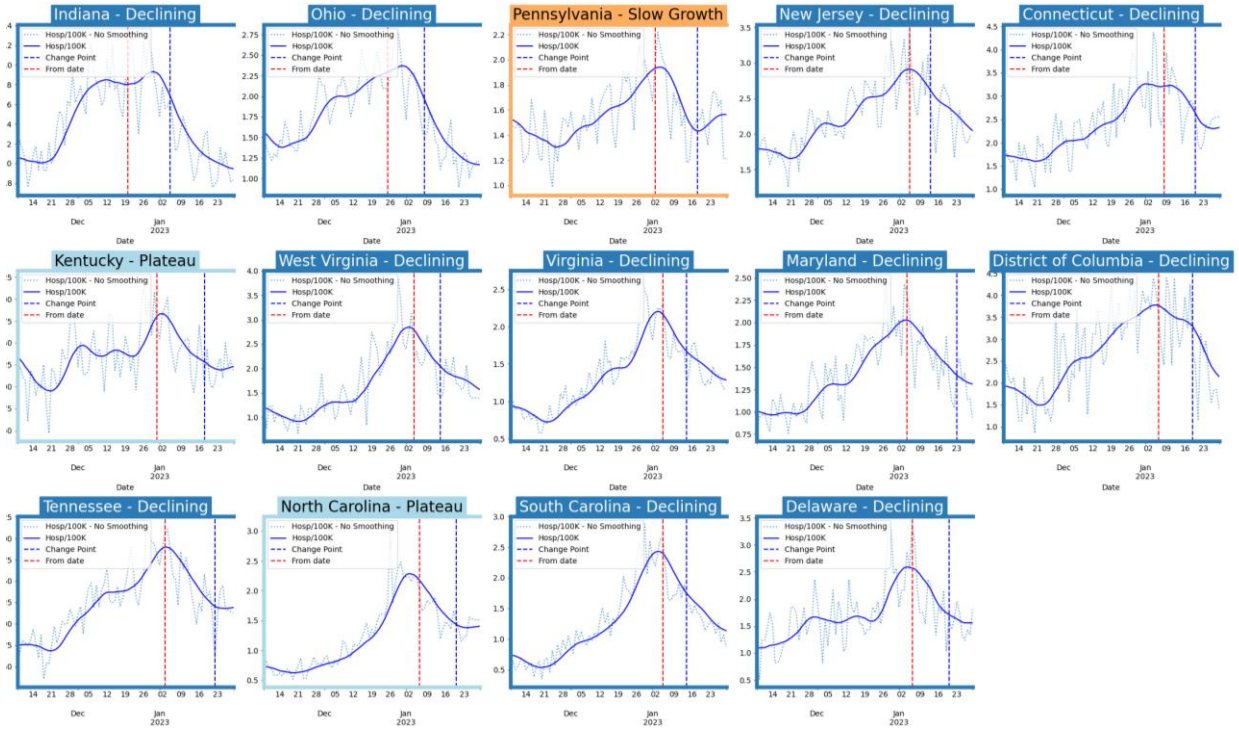
Status	Number of States	
	Current Week	Last Week
Declining	37	(42)
Plateau	12	(7)
Slow Growth	4	(3)
In Surge	0	(1)

Virginia and Her Neighbors

Cases

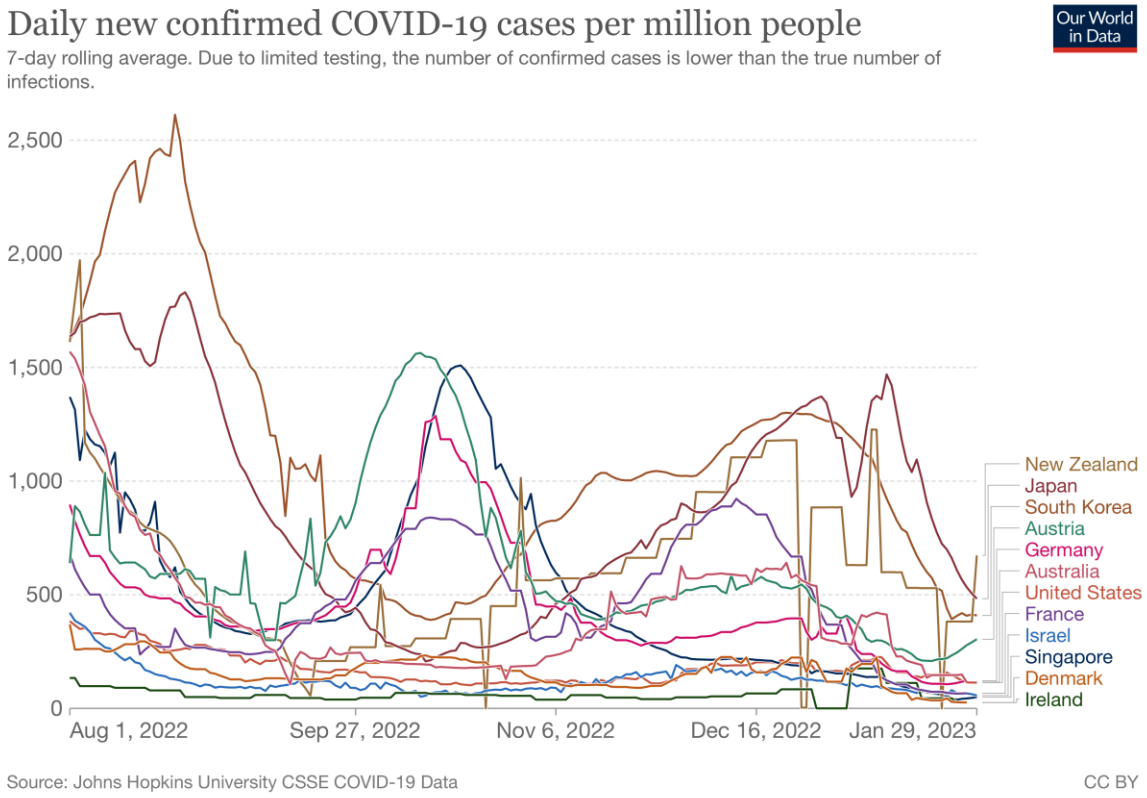


Hospitalizations

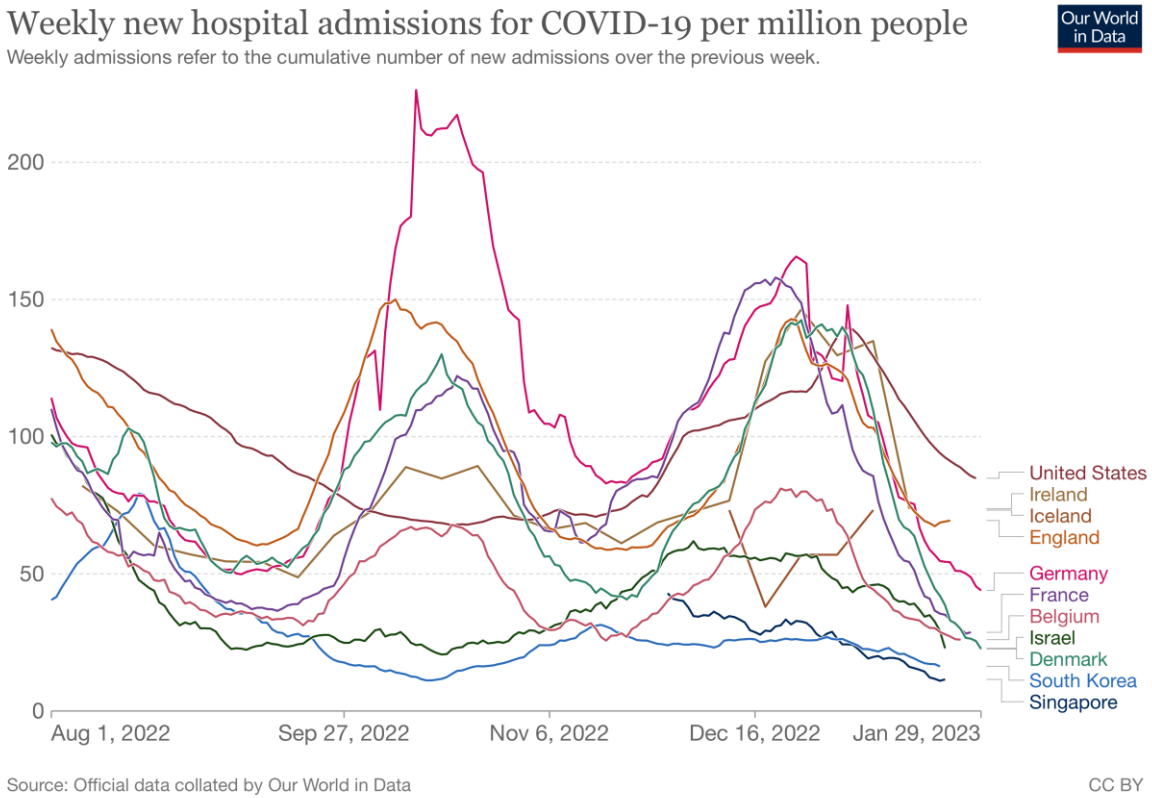


Around the World – Various trajectories

Confirmed cases



Hospitalizations



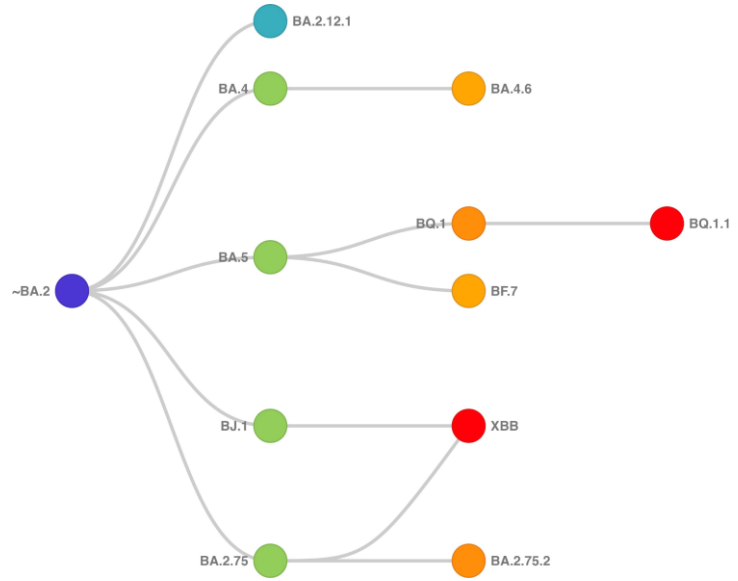
Our World in Data [Our World in Data]

COVID-19 Genomic Update

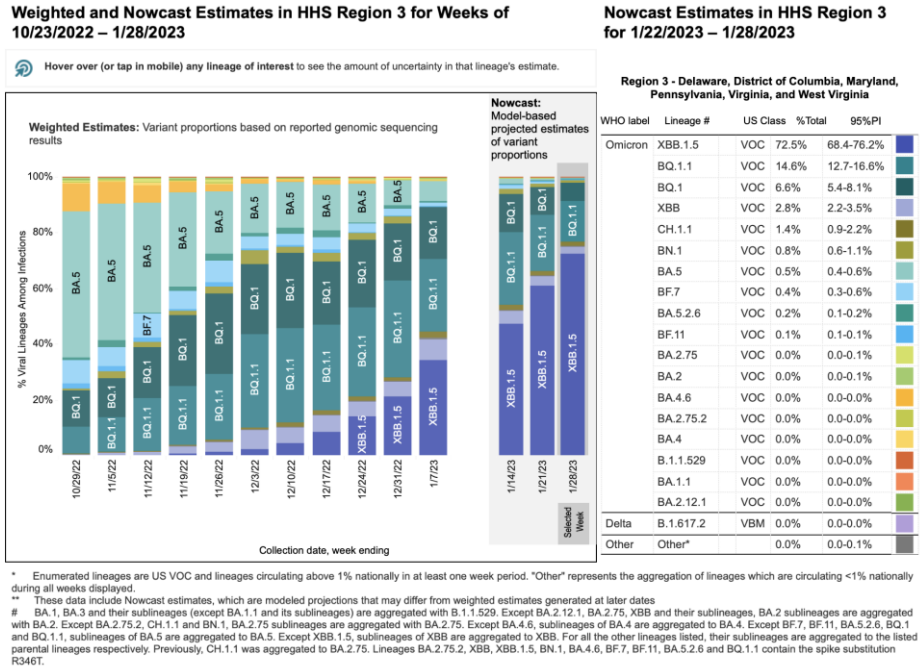
SARS-CoV2 Variants of Concern

Emerging variants have potential to continue to alter the future trajectories of pandemic and have implications for future control

- **Variants have been observed to:** increase transmissibility, increase severity (more hospitalizations and/or deaths), and limit immunity provided by prior infection and vaccinations



https://clades.nextstrain.org



* Enumerated lineages are US VOC and lineages circulating above 1% nationally in at least one week period. "Other" represents the aggregation of lineages which are circulating <1% nationally during all weeks displayed.
** These data include Nowcast estimates, which are modeled projections that may differ from weighted estimates generated at later dates
\# BA.1, BA.3 and their sublineages (except BA.1.1 and its sublineages) are aggregated with B.1.1.529. Except BA.2.12.1, BA.2.75, XBB and their sublineages, BA.2 sublineages are aggregated with BA.2. Except BA.2.75.2, CH.1.1 and BN.1, BA.2.75 sublineages are aggregated with BA.2.75. Except BA.4.6, sublineages of BA.4 are aggregated to BA.4. Except BF.7, BF.11, BA.5.2.6, BQ.1 and BQ.1.1, sublineages of BA.5 are aggregated to BA.5. Except XBB.1.5, sublineages of XBB are aggregated to XBB. For all the other lineages listed, their sublineages are aggregated to the listed parental lineages respectively. Previously, CH.1.1 was aggregated to BA.2.75. Lineages BA.2.75.2, XBB, XBB.1.5, BN.1, BA.4.6, BF.7, BF.11, BA.5.2.6 and BQ.1.1 contain the spike substitution R346T.

Omicron Updates*

- XBB.1.5 has grown rapidly now accounting for 73%
- BQ.1 and BQ.1.1 have lost ground to XBB to dominate at 6% and 14% respectively
- XBB not in XBB.1.5 has fallen from 6% to 3%
- BA.2.75.* family variants (includes BN.1) have fallen from 5% to 2%

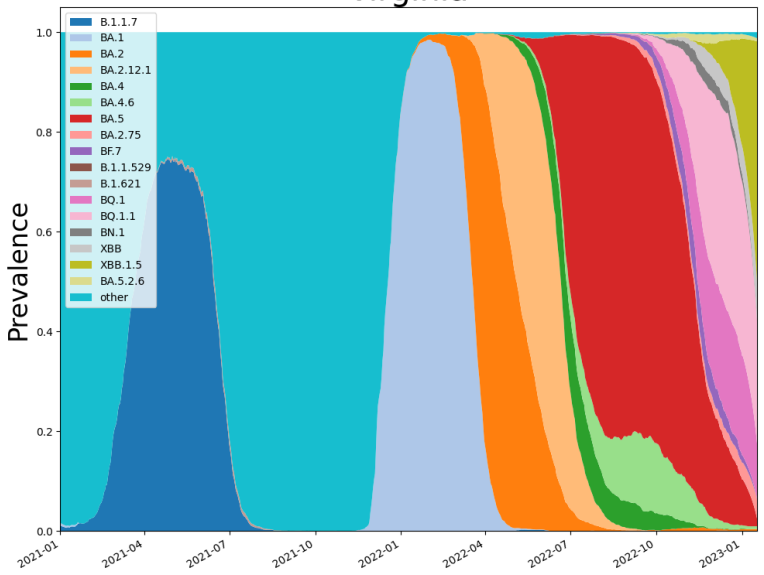
*percentages are CDC NowCast Estimates

SARS-CoV2 Omicron Sub-Variants

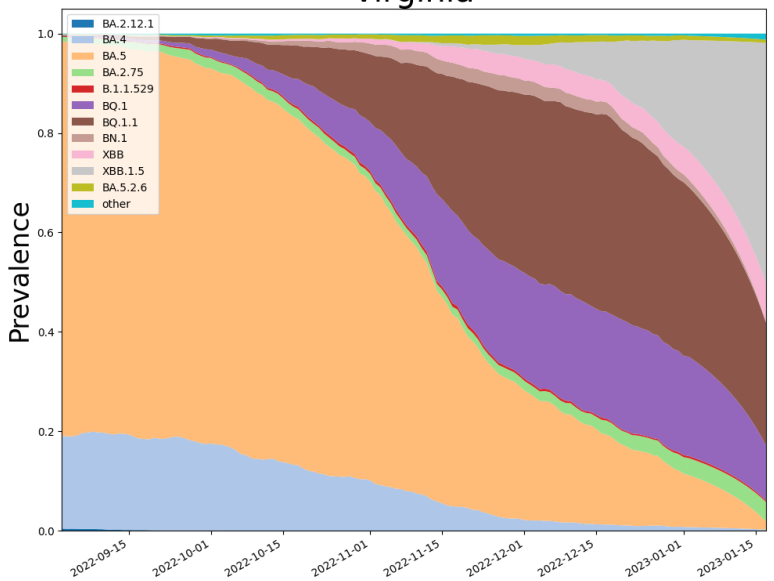
covSPECTRUM
Enabled by data from GISAID

As detected in whole Genomes in public repositories

Virginia

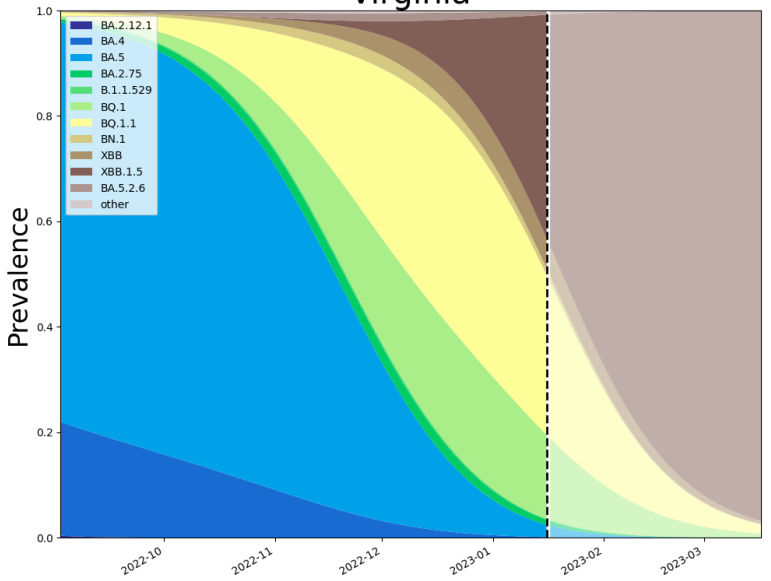


Virginia

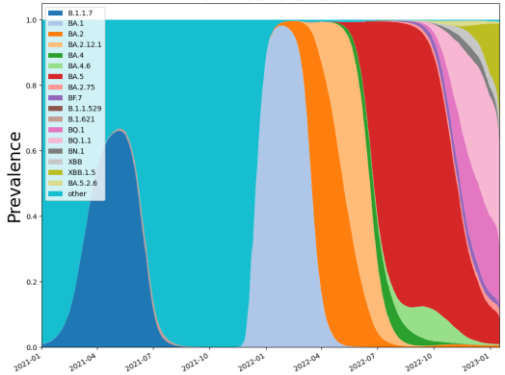


VoC Polynomial Fit Projections

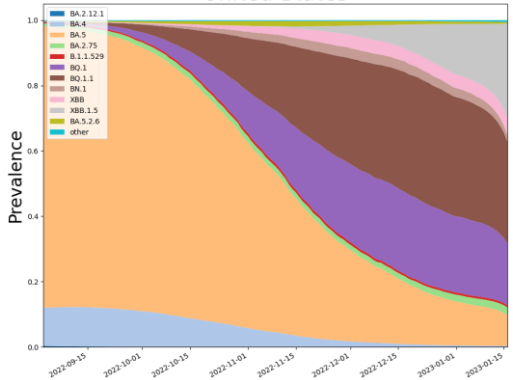
Virginia



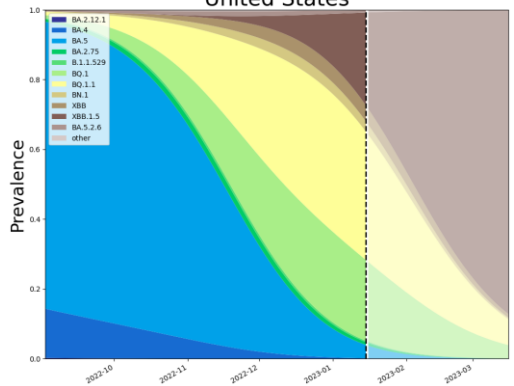
United States



United States



United States



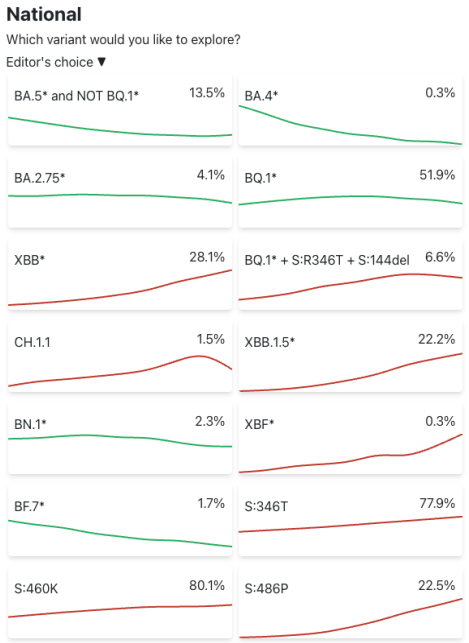
Note: Data lags force projections to start in past. Everything from dotted line forward is a projection.

SARS-CoV2 Omicron Sub-Variants

[COV-spectrum](#)

"Editor's choice"

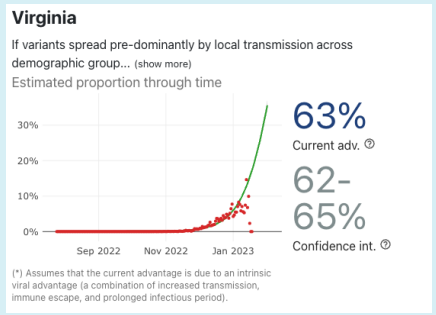
Variants to watch

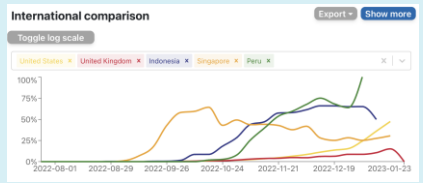


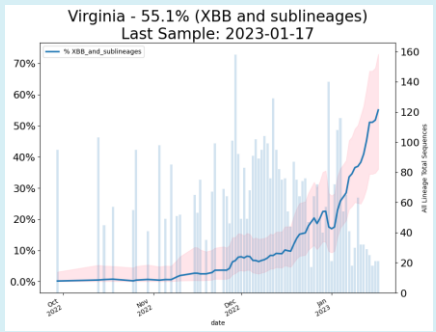
covSPECTRUM

Enabled by data from GISAID

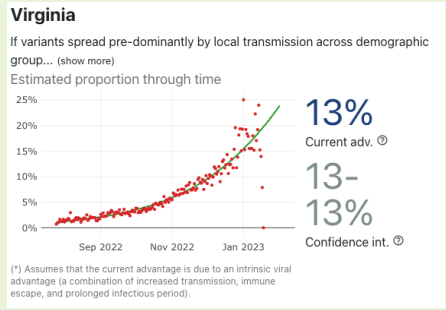
XB.1.5

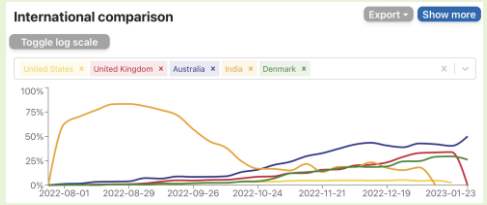


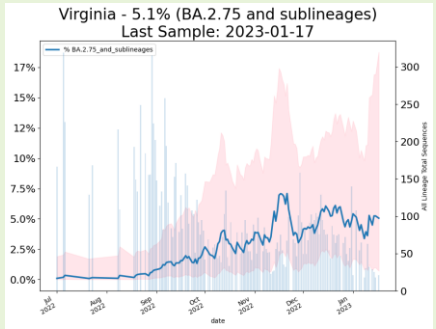




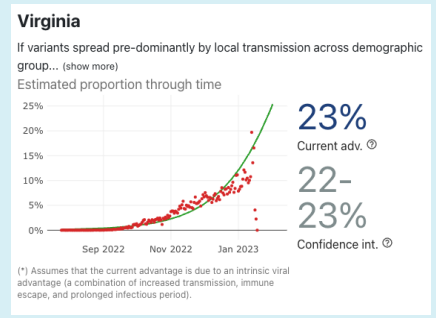
BA.2.75.*

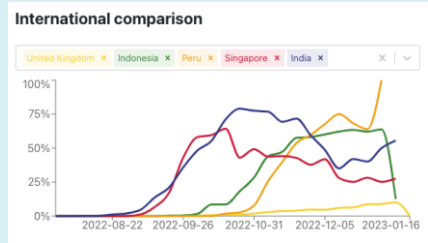


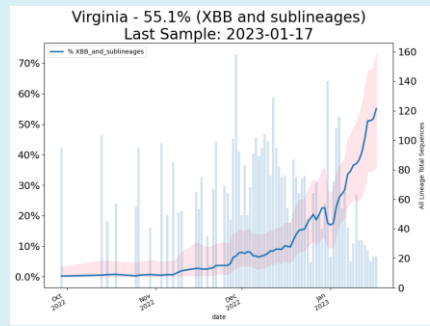




XBB*



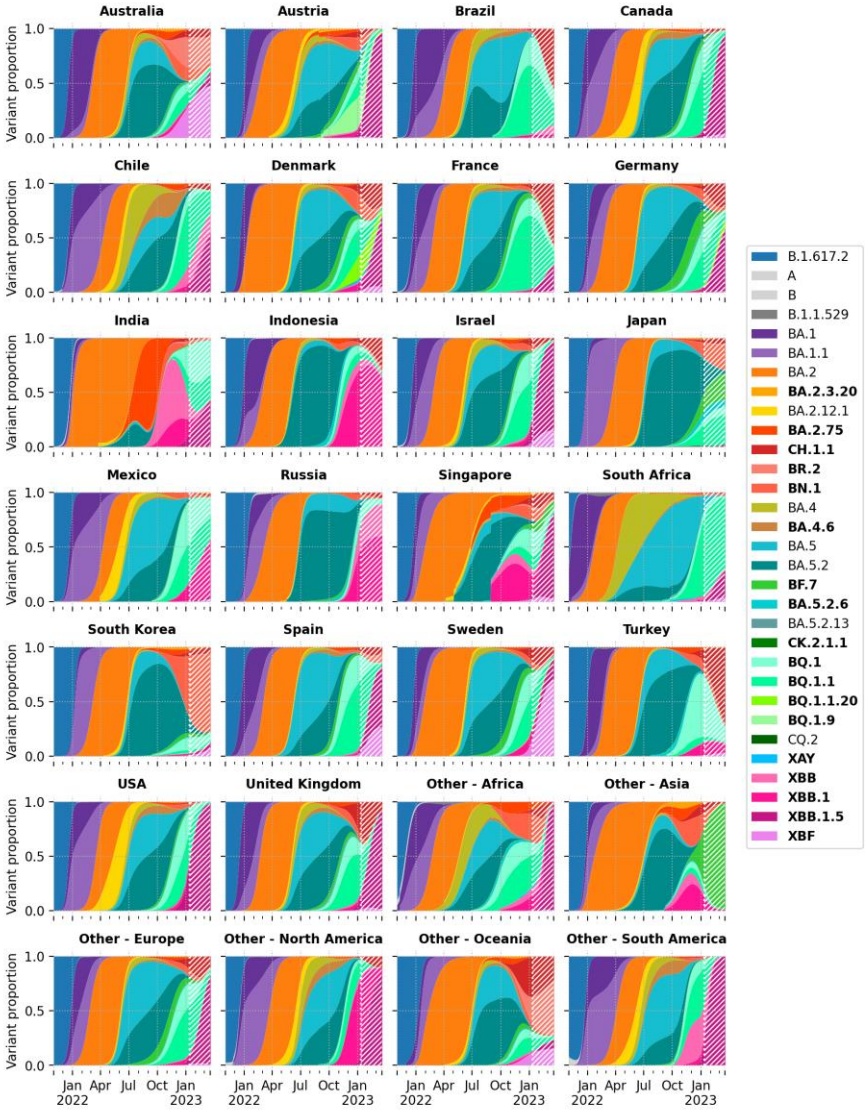


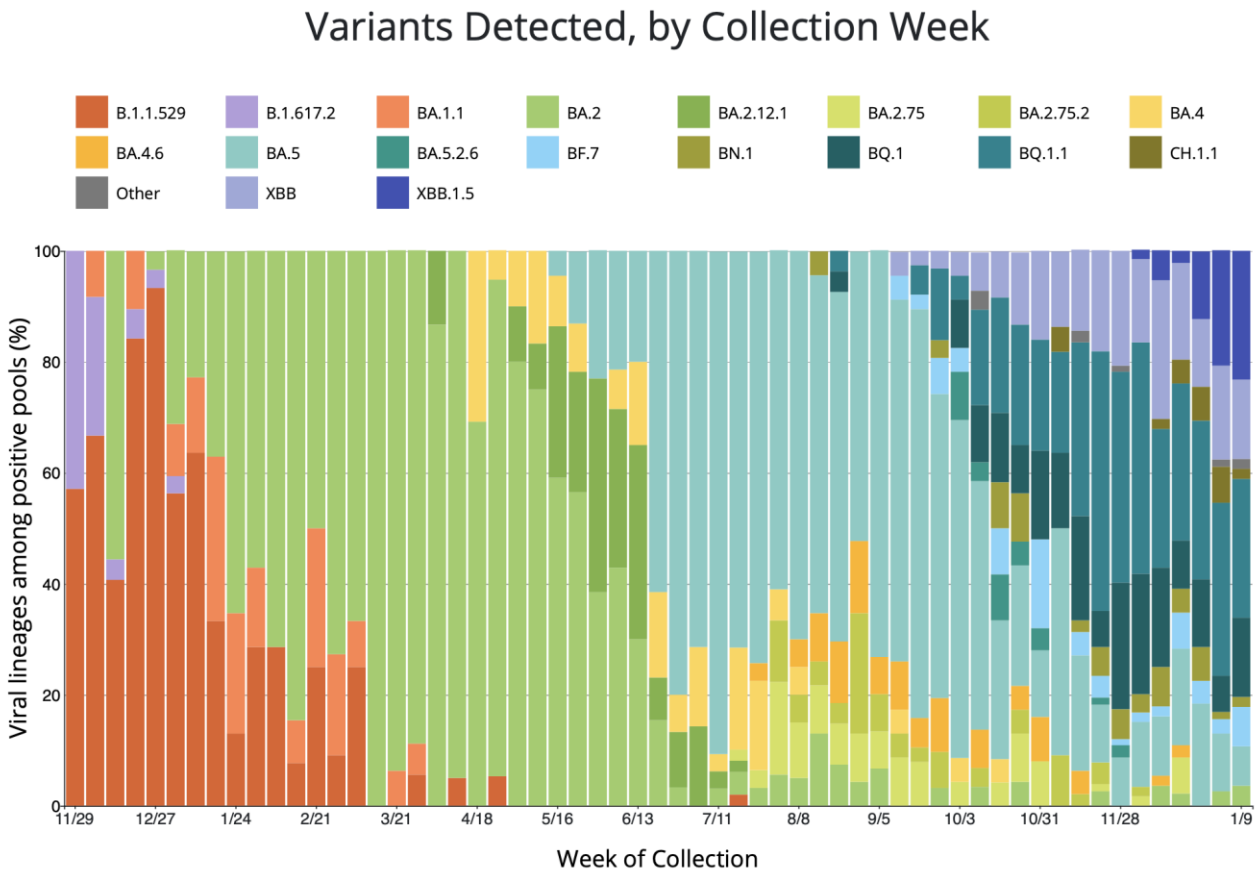


UNIVERSITY of VIRGINIA

BIOCOMPLEXITY INSTITUTE

Global SARS-CoV2 Variant Status





https://covid.cdc.gov/covid-data-tracker/#traveler-genomic-surveillance
https://github.com/gerstung-lab/SARS-CoV-2-International

Pandemic Pubs (Feb 1st, 2023)

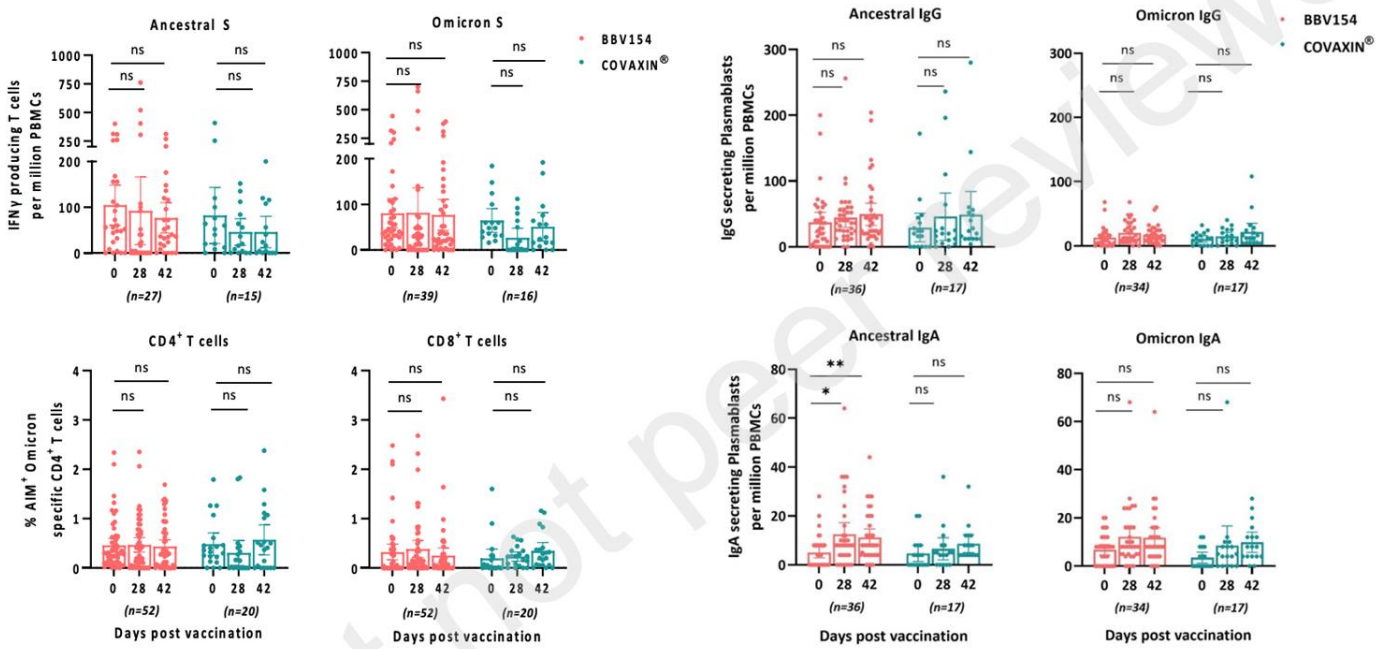
1. Two intranasal doses of BBV154 were well tolerated with no safety concerns while eliciting superior humoral and mucosal immune responses compared with two intramuscular Covaxin injections.

Table 3: SARS-CoV-2 S1 protein specific IgG and IgA binding antibody responses (ELISA) and mucosal salivary (secretory) sIgA (ELISA) at Days 0, 42 and 90, after two doses of intranasal BBV154 or intramuscular Covaxin.

		n	GMT	(95% CI)	GMT ratio (BBV154:Covaxin) Ratio	(95% CI)
Anti-S1 IgG (serum)						
Day 0	**BBV154**	481	**3675**	(3191–4232)	**1·2**	(0·9–1·6)
	Covaxin®	159	**3090**	(2435–3922)		
Day 42	**BBV154**	481	**7175**	(6490–7932)	**1·3**	(1·0–1·5)
	Covaxin®	159	**5689**	(4952–6537)		
Day 90	**BBV154**	481	**8851**	(8100–9672)	**1·1**	(0·95–1·33)
	Covaxin®	158	**7866**	(6824–9066)		
Anti-S1 IgA (serum)						
Day 0	**BBV154**	481	**1978**	(1754–2230)	**1·2**	(0·9–1·5)
	Covaxin®	159	**1701**	(1382–2093)		
Day 42	**BBV154**	481	**3069**	(2794–3371)	**0.9**	(0·74–1·01)
	Covaxin®	159	**3537**	(3102–40356)		
Day 90	**BBV154**	479	**3670**	(3400-3962)	**1·3**	(1·1-1·6)
	Covaxin®	158	**2843**	(2409-3354)		
Anti-S1 secretory IgA (saliva)						
Day 0	**BBV154**	58	**10·7**	(8·4–13·5)	**1·3**	(0·9–2·1)
	Covaxin®	22	**8·0**	(5·4–11·8)		
Day 42	**BBV154**	58	**12·3**	(8·7–17·4)	**1·9**	(1·1–3·0)
	Covaxin®	22	**6·6**	(4·6–9·5)		
Day 90	**BBV154**	58	**9·9**	(7·5–13·2)	**0.8**	(0·4, 1·4)
	Covaxin®	22	**13·2**	(7·6–23·3)		

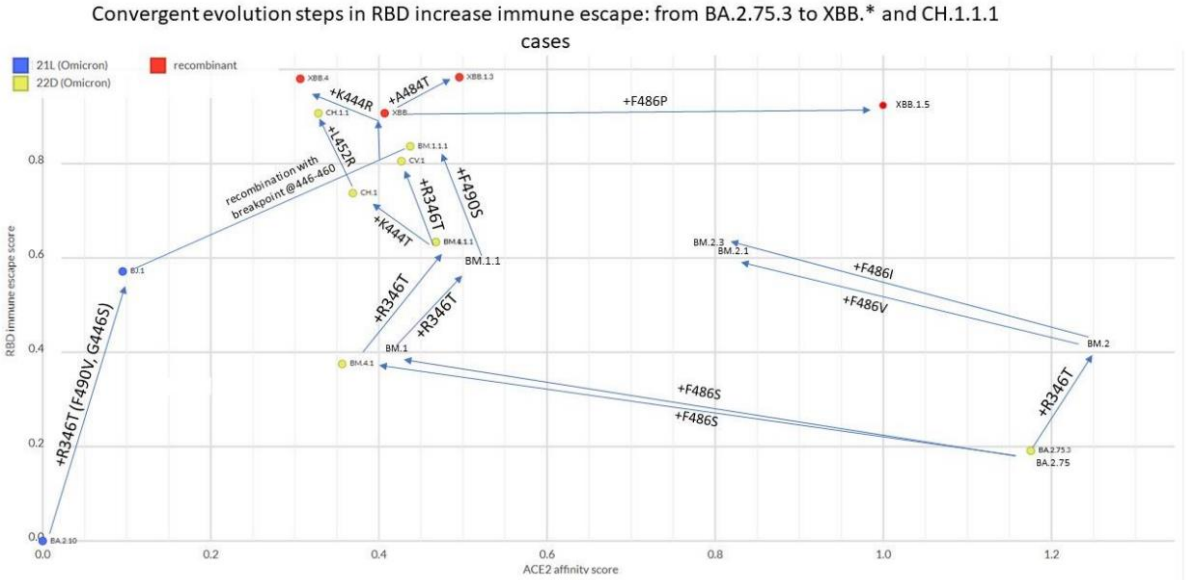
In this open-label, multicentre, phase 3 clinical trial, healthy Indian adults were randomised to receive either two doses of BBV154 (n = 3,000) or Covaxin® (n = 160) 28 days apart. Primary immunogenicity outcome was geometric mean neutralisation antibody titres (PRNT50) against SARS-CoV-2 viruses; key secondary outcomes were safety and solicited adverse events, secretory-IgA and serum-IgA responses and cell-mediated immune responses.
On Day 42, 14 days after the second dose, serum GMTs against ancestral (Wuhan) SARS-CoV-2 were superior in BBV154 and Covaxin groups. BBV154 also elicited a higher serum neutralising GMTagainst Omicron BA.5 than Covaxin. Similarly, at day 42 GMTs of secretory IgA were superior to Covaxin. BBV154 induced higher serum IgA titres and significantly higher levels of antibody-secreting plasmablasts on Day 42. Both vaccines induced equivalent T cell memory responses.

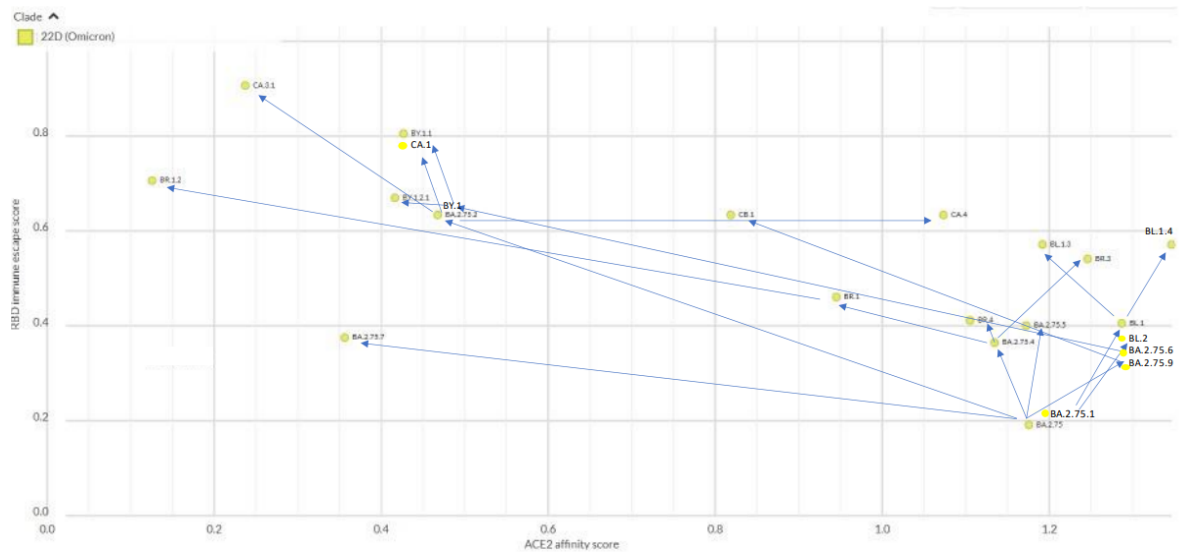
Figure 2: T cell responses (panel A) and B cell responses (panel B)



Pandemic Pubs (Jan 25th, 2023)

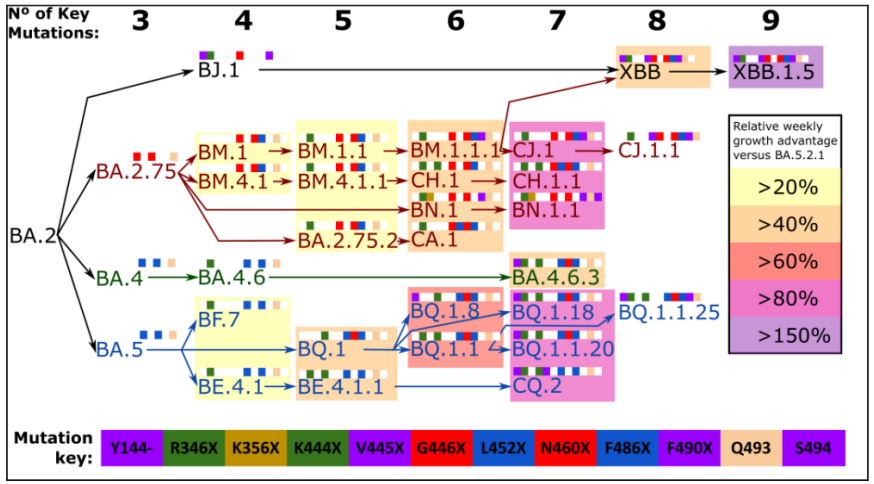
1. Convergent evolution demonstrated in mutations that select for transmissibility and immune escape

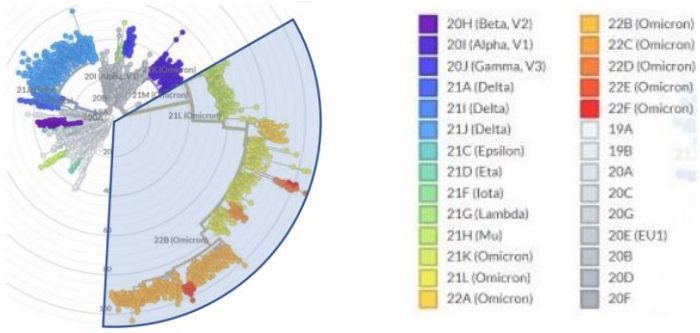




Convergent evolution has led to the observation of different lineages acquiring recuring mutations at specific locations, namely R346, K444, N450, N460, F486, F490, Q493, and S494. Mutations at these residues have become increasingly prevalent during Summer and Autumn 2022. Authors speculate this is due to selective pressure from previous infection and vaccination. Mutational profiles have lead to failure of numerous pharmaceutical interventions.

https://www.mdpi.com/1422-0067/24/3/2264





Pandemic Pubs (Jan 11th, 2023)

1. Bivalent boosters are highly effective in in preventing hospitalization (81% reduction) and death (86% reduction) in adults over 65 yo.

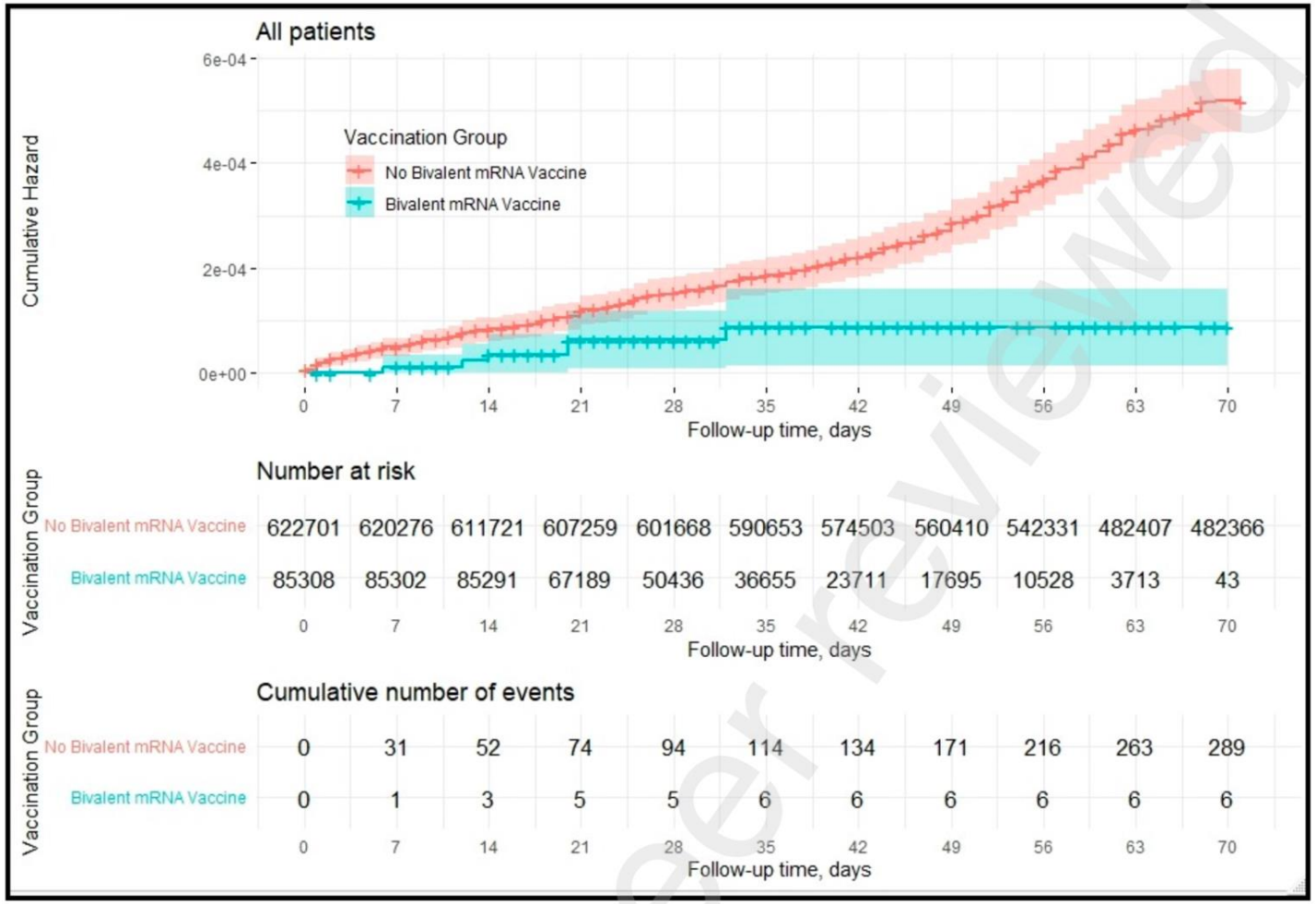


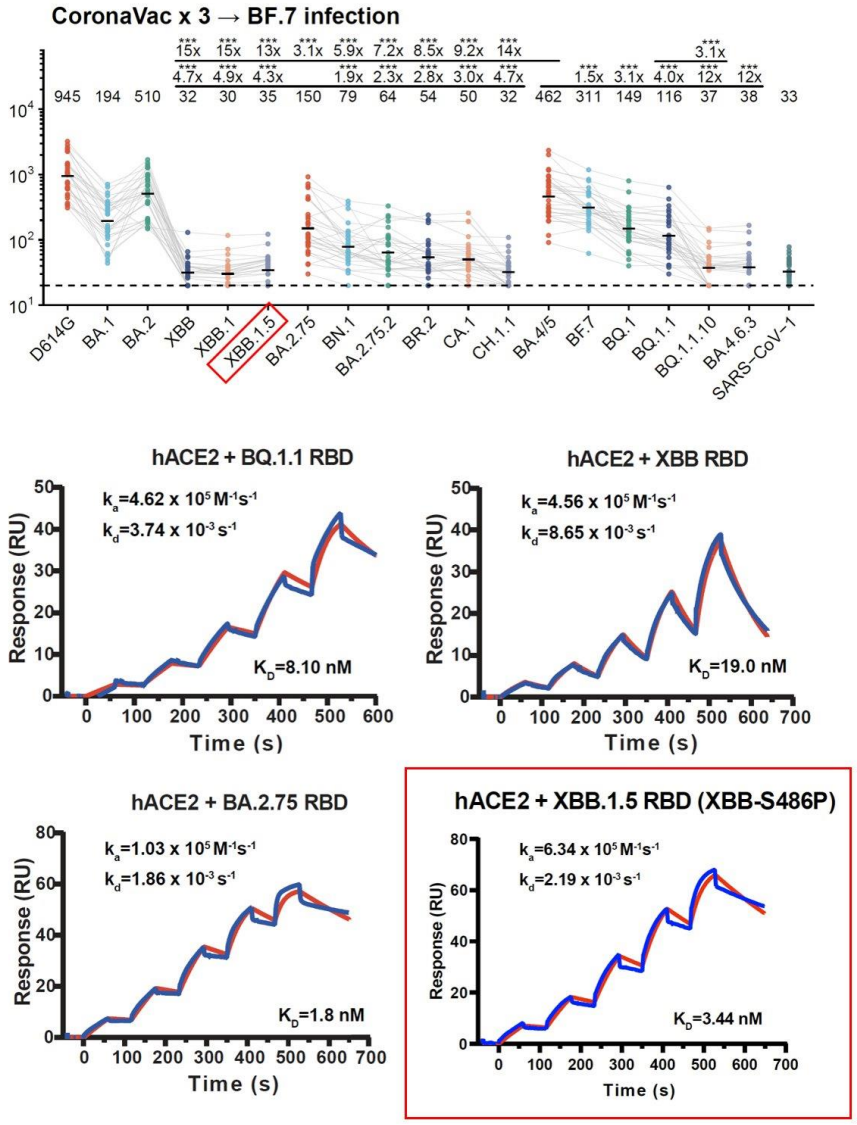
Figure 1: Cumulative hazard for Covid-19 hospitalization

Preprint in Lancet, included over 620K participants in Israel, while it was limited to 70 days of follow-up, was able to capture nearly 300 events in this largely well protected population. This study captured more of a population effect, whereas, previous publications (in MMWR in late Dec) were based on purely hospitalized patients and thus were limited to evaluating degrees of severity.

https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4314067

Pandemic Pubs (Jan 11th, 2023)

2. XBB.1.5 has enhanced ACE binding efficiency which makes it likely to be more transmissible on top of being more immune evasive than BQ.1.1 and other BA.5 descended variants.



Using VSV psuedovirus neutralization assays along with surface plasmon resonance (SPR) assays to measure actual binding affinity to ACE2. They demonstrate that XBB.1.5 has stronger and more rapid binding to hACE2 in convalescent sera of individuals with 3 doses of CoronaVac with subsequent BA.1, BA.5, or BF.7 breakthrough infections. So despite vaccination and boosting of natural infection this affinity remained very strong for XBB.1.5

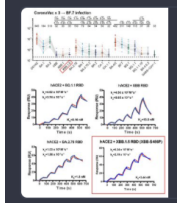
BioRxiv

https://www.biorxiv.org/content/10.1101/2023.01.03.522427v1

Bloom Lab
@jbloom_lab@mstdn.science

The difference between XBB.1.5 and its immediate parent XBB.1 is that it has traded the more costly F486S mutation for F486P. Therefore, XBB.1.5 isn't expected to have more antibody escape than XBB.1 (which already had mutated F486), but it should have greater ACE2 affinity.

And as @yunlong_cao nicely describes, this is exactly what is directly measured: twitter.com/yunlong_cao/status...

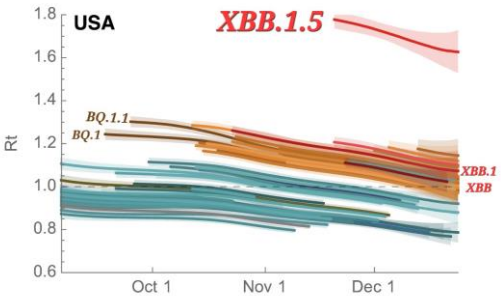


Yunlong Richard Cao on Twitter
"The superior growth advantage of XBB.1.5 has been...
Twitter

Jan 02, 2023, 15:15 · Web · 6 · 10

https://mstdn.science/@jbloom_lab/109621446854109094

XBB.1.5 is more transmissible than other variants like BQ.1.1 that until recently dominated in US.



https://twitter.com/JPWeiland/status/1607835958388432896

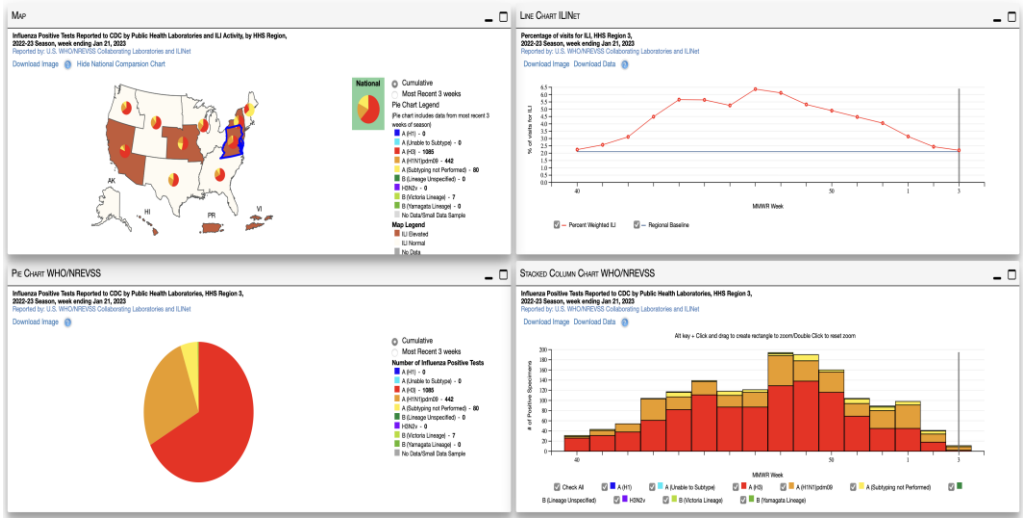
Influenza Update

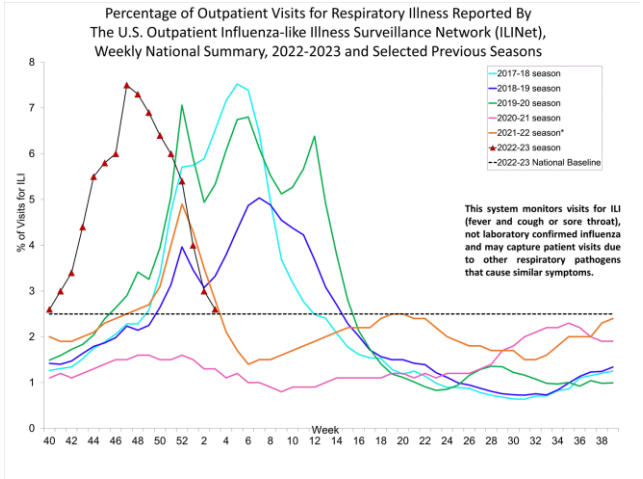
Current Influenza Situation – ILI Activity

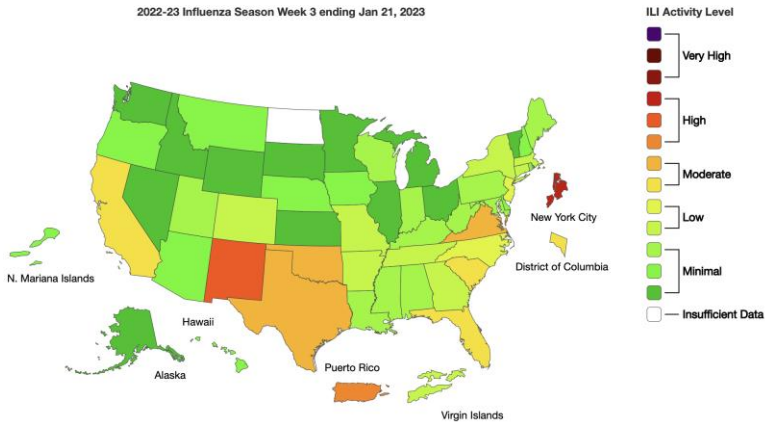
Influenza Activity is Higher than Usual

- Virginia has shifted to ”Moderate” level as most states have receded to Low and Minimal levels in the past couple weeks.
- In VA ILI Activity has declined to 3-4% which is the same as in early October at the beginning of the season
- National ILI activity has also consistently declined since a peak in late November, now almost below the seasonal threshold
- Over half of the HHS regions are now below the seasonal threshold for ILI activity

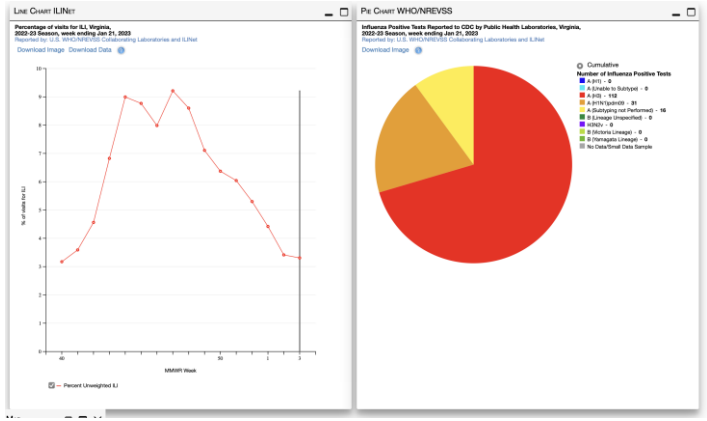
Region 3







Virginia



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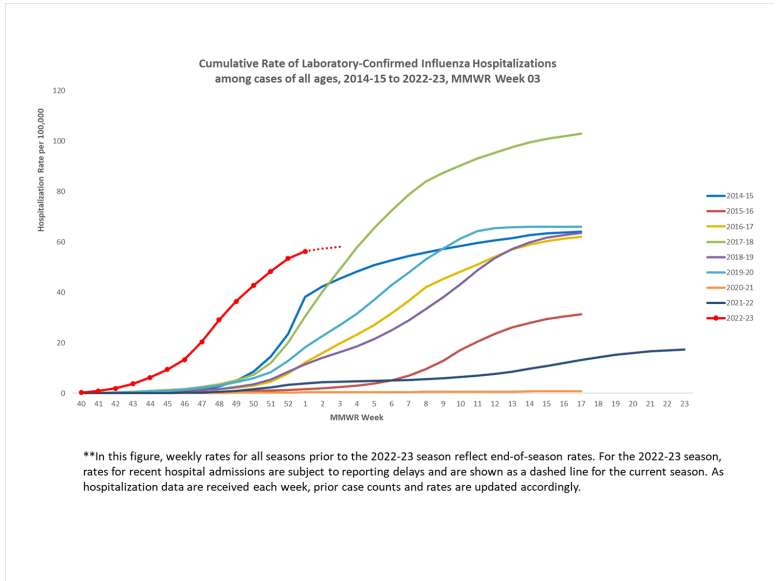
FLUVIEW
A Weekly Influenza Surveillance Report Prepared by the Influenza Division

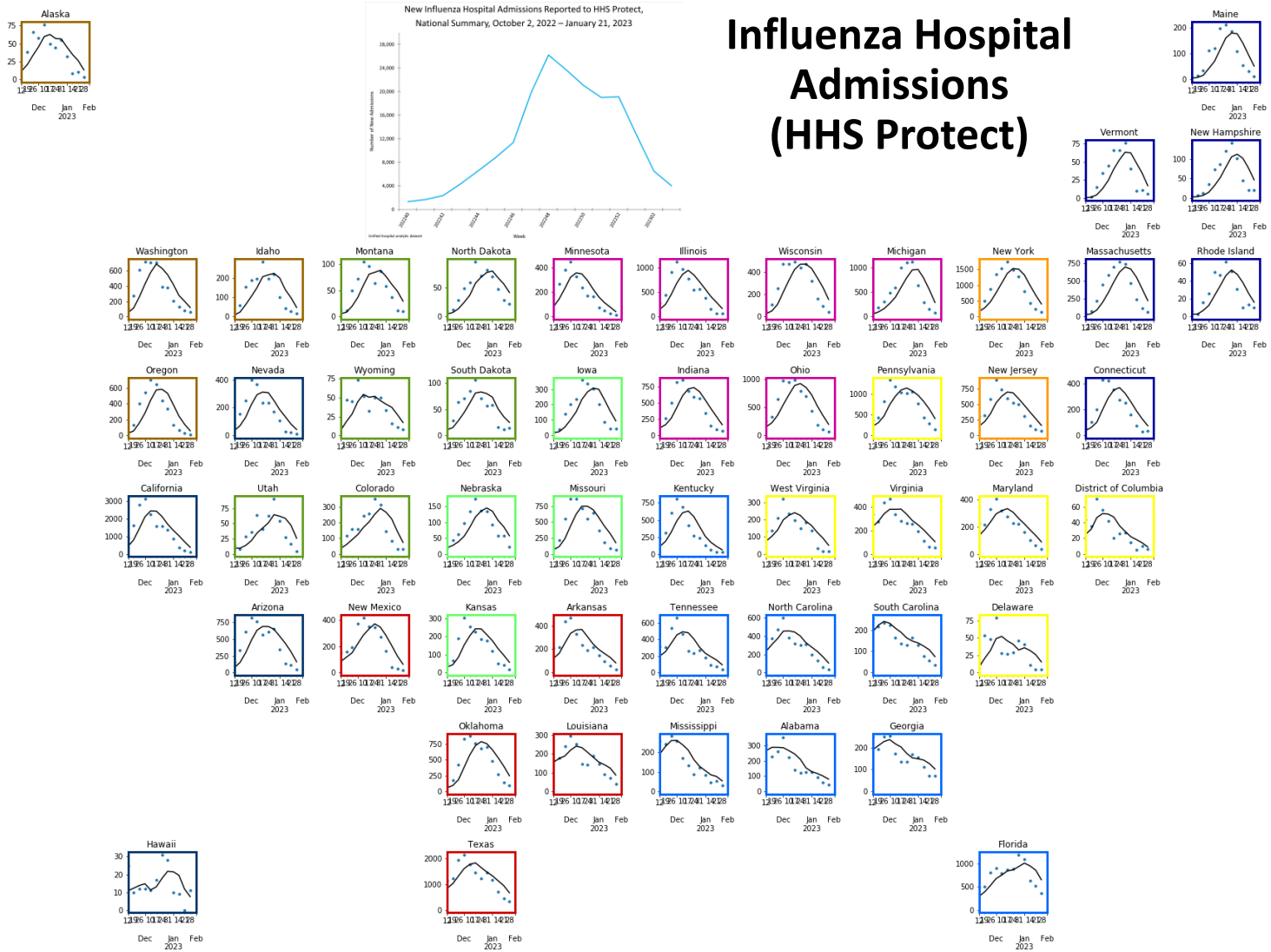
Current Influenza Situation - Hospitalizations

Influenza A hospitalizations continue decline

- National level of influenza hospitalizations have dropped to nearly pre-season levels
- Nearly all states have returned to levels below early December before the initial rise to to the peak



**In this figure, weekly rates for all seasons prior to the 2022-23 season reflect end-of-season rates. For the 2022-23 season, rates for recent hospital admissions are subject to reporting delays and are shown as a dashed line for the current season. As hospitalization data are received each week, prior case counts and rates are updated accordingly.



Influenza Hospital Admissions (HHS Protect)

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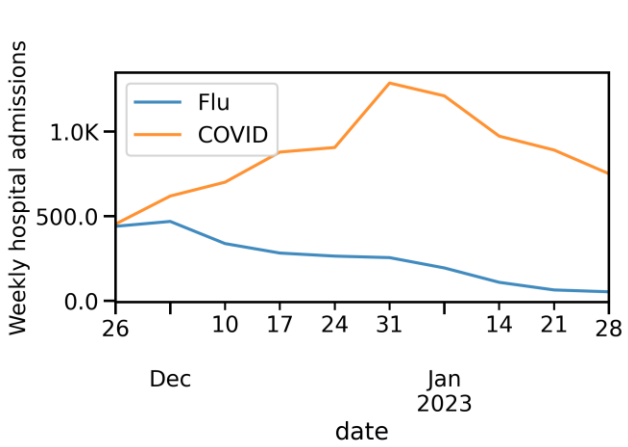
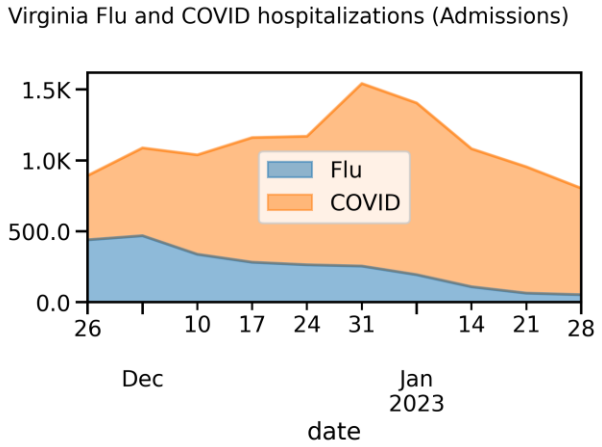
FLUVIEW
A Weekly Influenza Surveillance Report Prepared by the Influenza Division

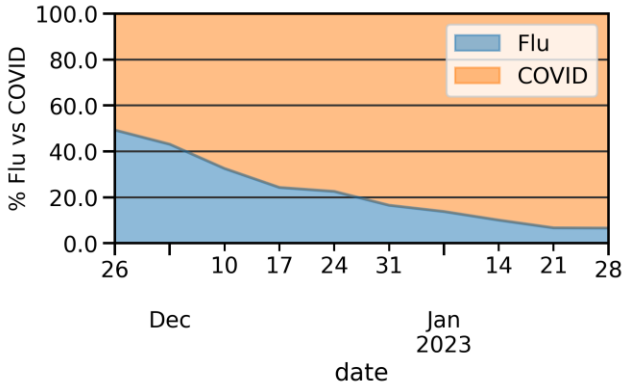
Current Combined Hospitalizations (COVID-19 & Influenza)

COVID-19 and Influenza Weekly Hospitalizations (HHS Protect)

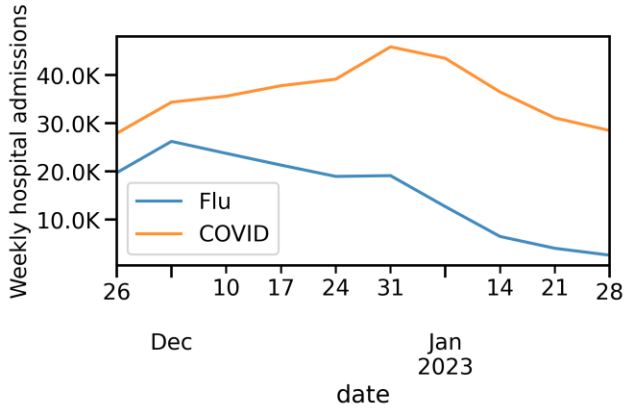
Virginia

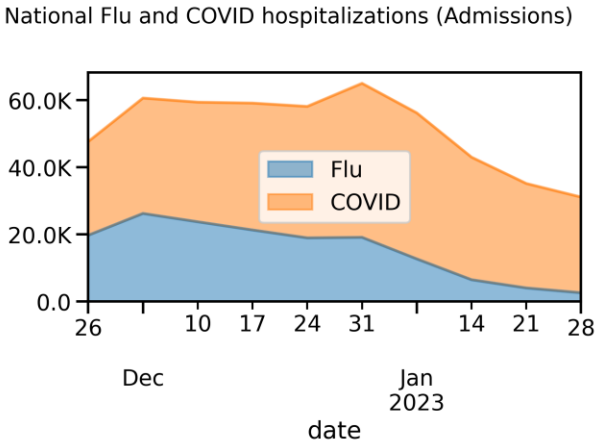


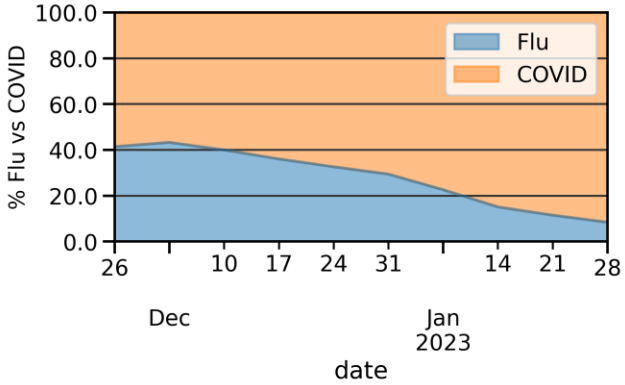




USA







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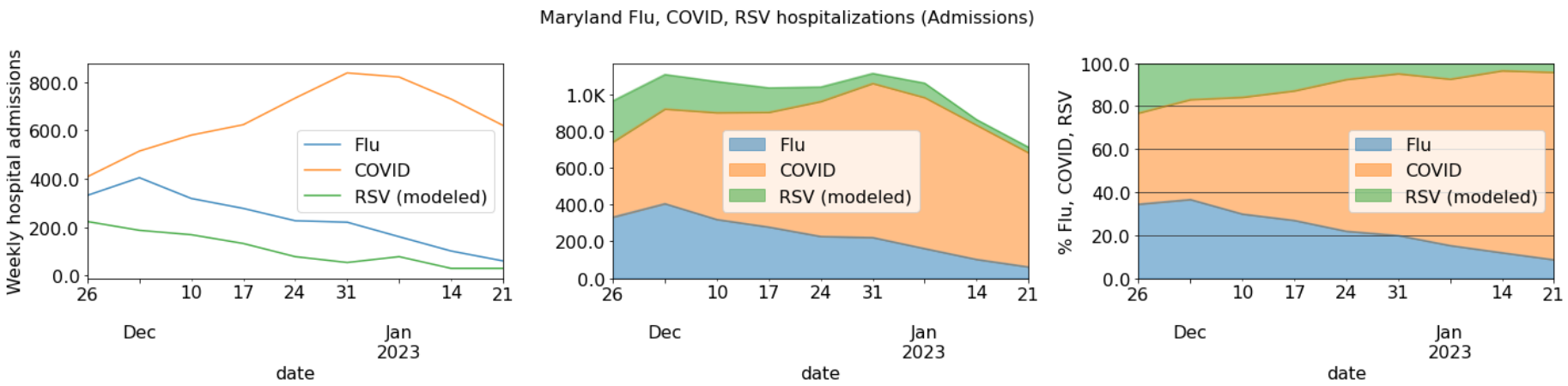
Current Combined Hospitalizations (COVID-19, Flu & RSV)

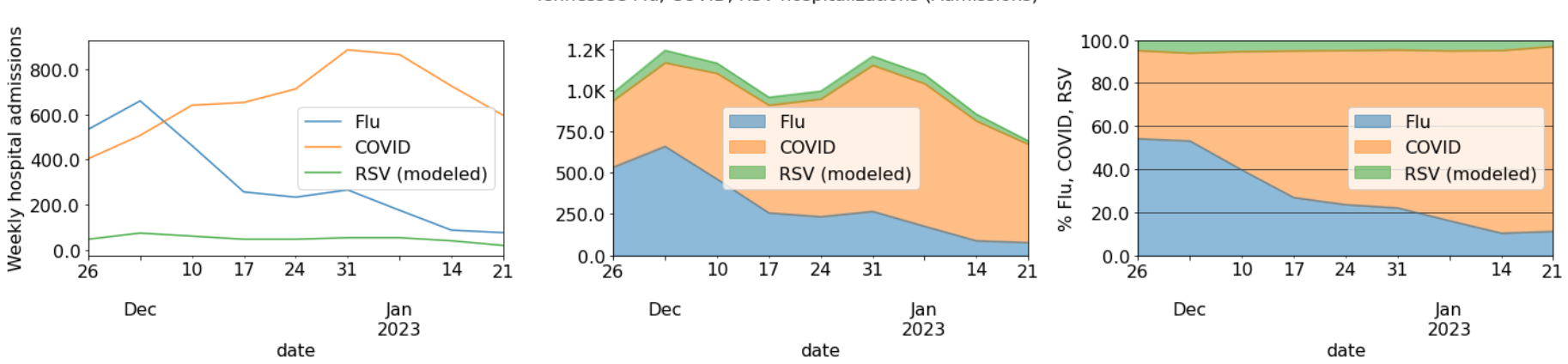
COVID-19, Influenza, and RSV Weekly Hospitalizations

RSV Hospitalizations captured by RSV-Net which has lagged reporting and does not cover Virginia, thus her closest neighbors are shown for comparison

Maryland



Tennessee



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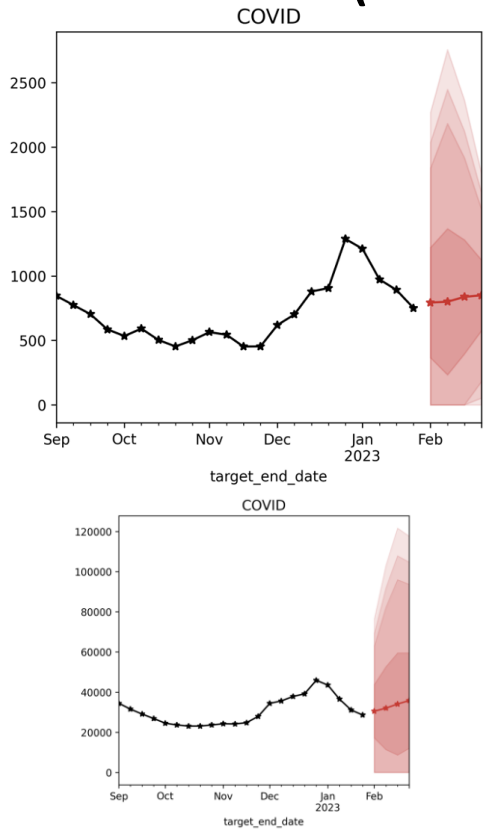
National Modeling Hub Updates

Current COVID-19 Hospitalization Forecast

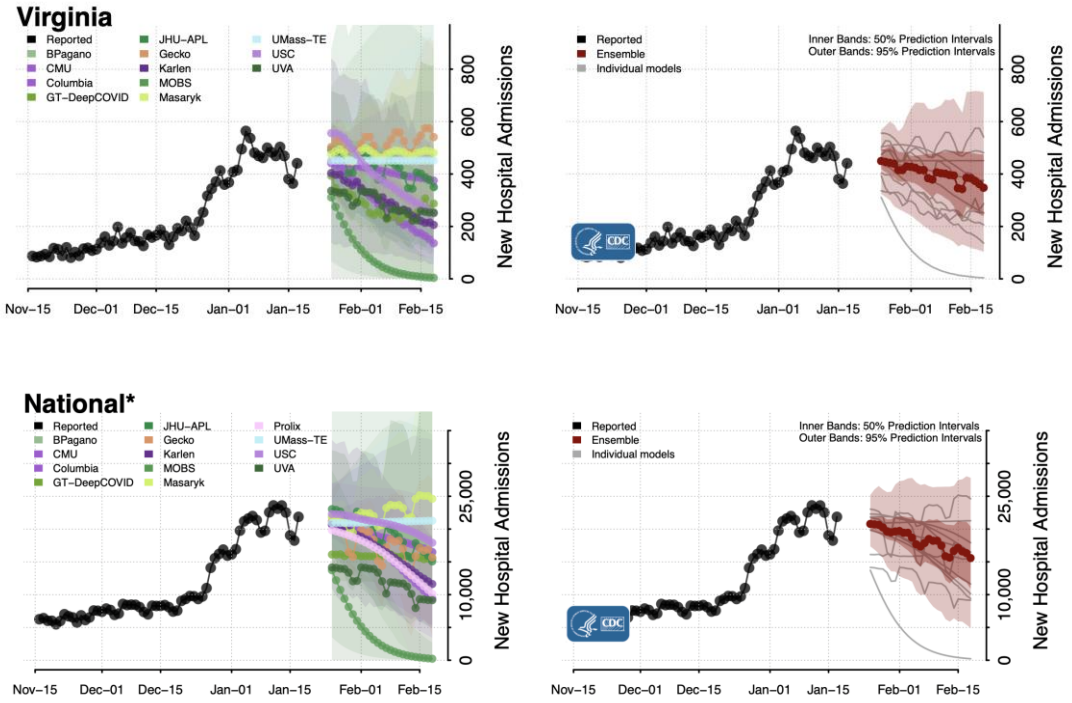
Statistical models for submitting to CDC FluSight forecasting challenge

- Uses a variety of statistical and ML approaches to forecast weekly hospital admissions for the next 4 weeks for all states in the US

Hospital Admissions for COVID-19 and Forecast for next 4 weeks (UVA ensemble)



Hospital Admissions for COVID-19 and Forecast for next 4 weeks (CDC COVID Ensemble)

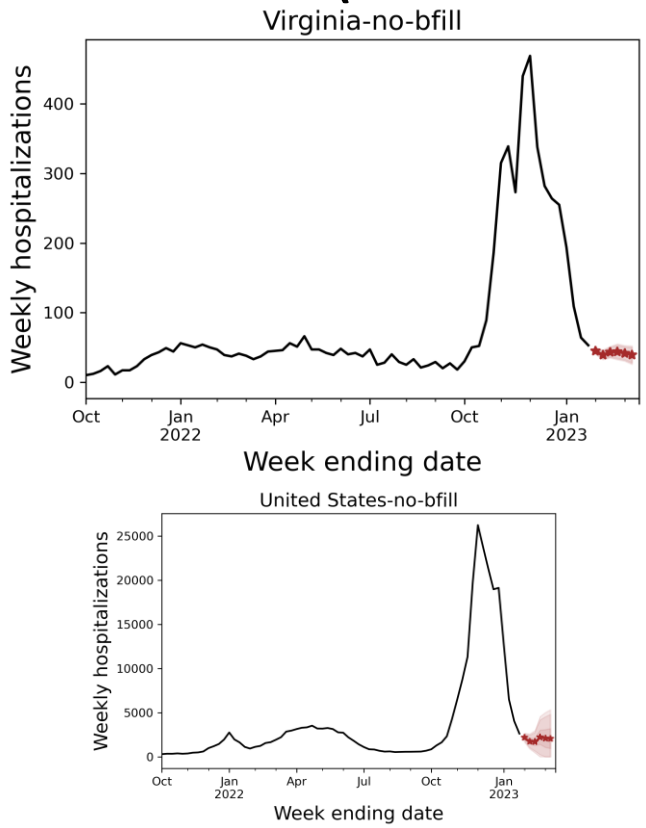


Current Influenza Hospitalization Forecast

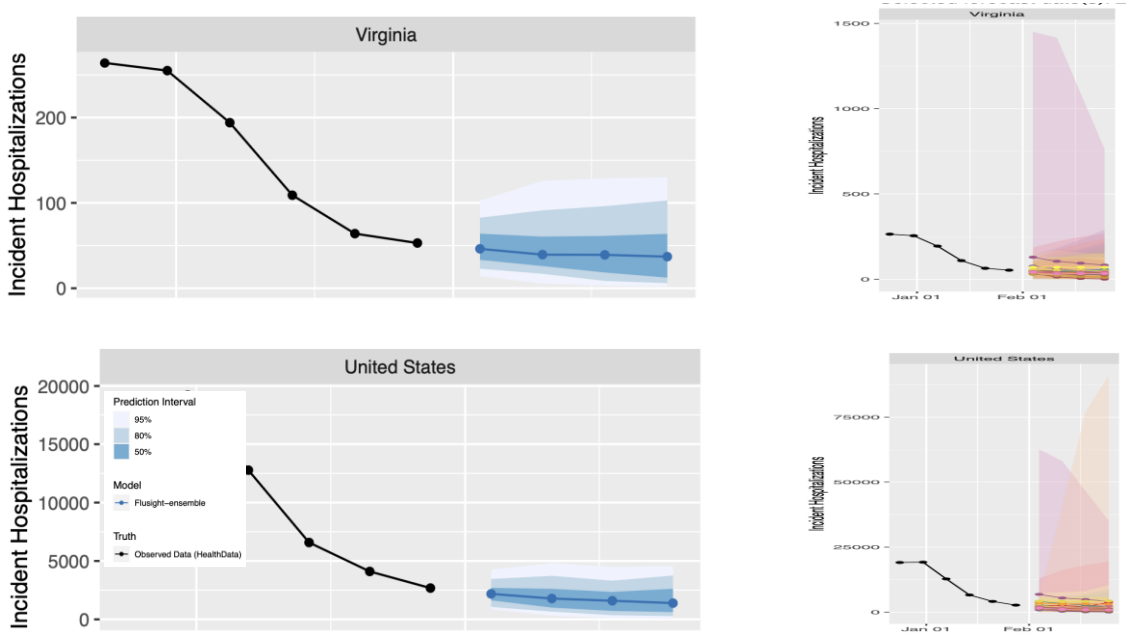
Statistical models for submitting to CDC FluSight forecasting challenge

- Similar to COVID-19 case forecasts, uses a variety of statistical and ML approaches to forecast weekly hospital admissions for the next 4 weeks for all states in the US

Hospital Admissions for Influenza and Forecast for next 4 weeks (UVA ensemble)



Hospital Admissions for Influenza and Forecast for next 4 weeks (CDC FluSight Ensemble)



Combined ILI and COVID-19 Hospitalizations

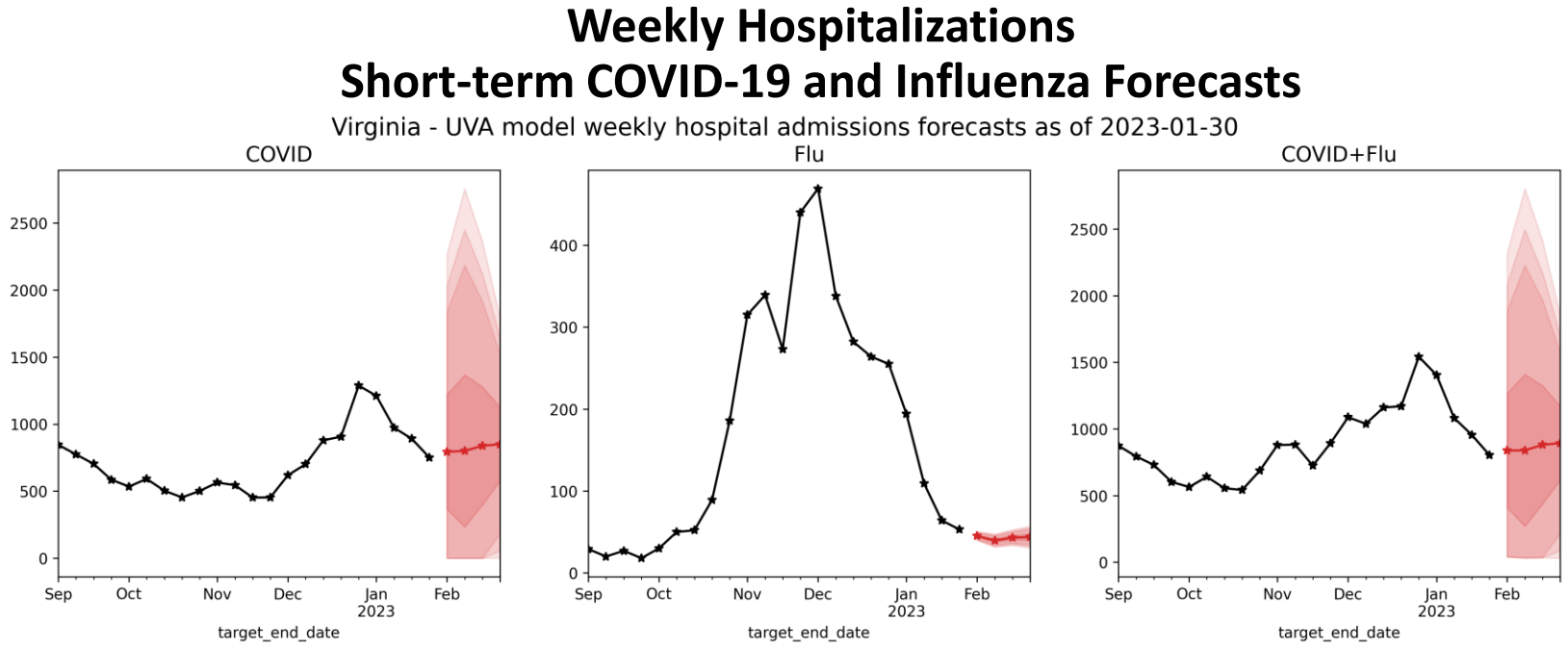
Ensemble methodology that combines the Adaptive with machine learning and statistical models such as:

- Autoregressive (AR, ARIMA) , Neural networks (LSTM), Kalman filtering (EnKF), G-model (phase), Holt-Winters

Weekly forecasts of hospitalizations done at state level.

Models chosen because of their track record in disease forecasting and to increase diversity and robustness.

Both are regularly submitted to CDC Forecast Hubs



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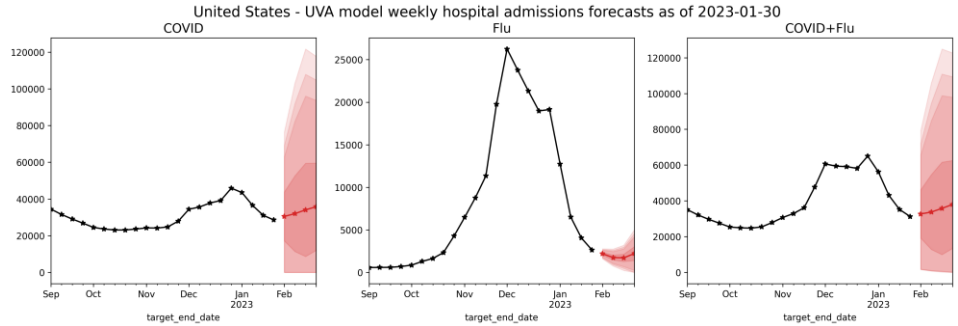
Combined ILI and COVID-19 Hospitalizations

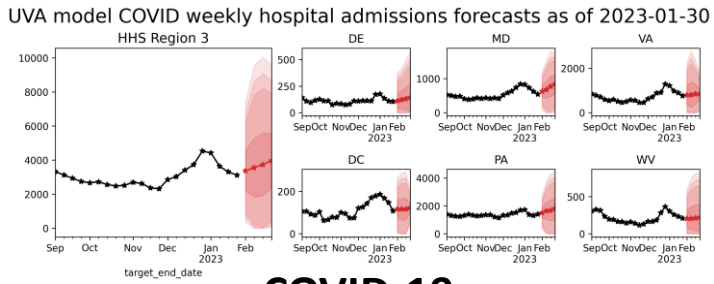
National

Short-term COVID-19 and Influenza Forecasts

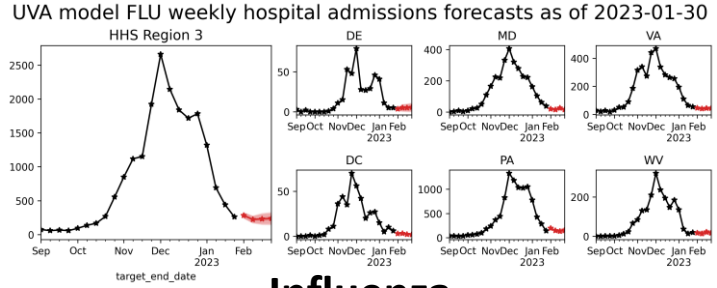


HHS Region 3

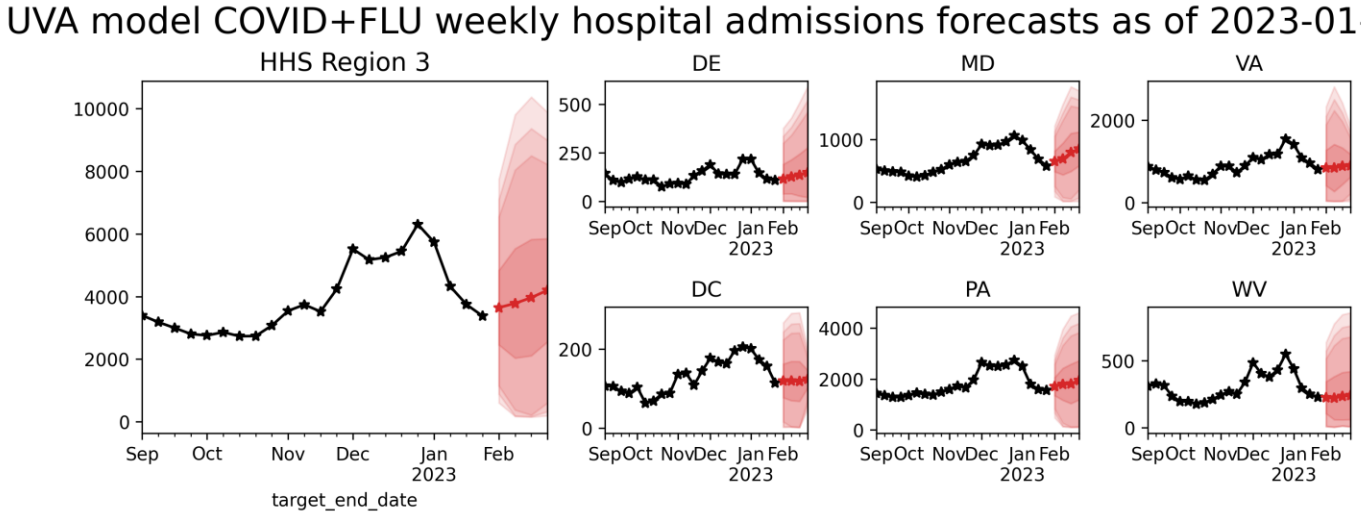
Short-term COVID-19 and Influenza Forecasts



COVID-19



Influenza



COVID-19 and Influenza

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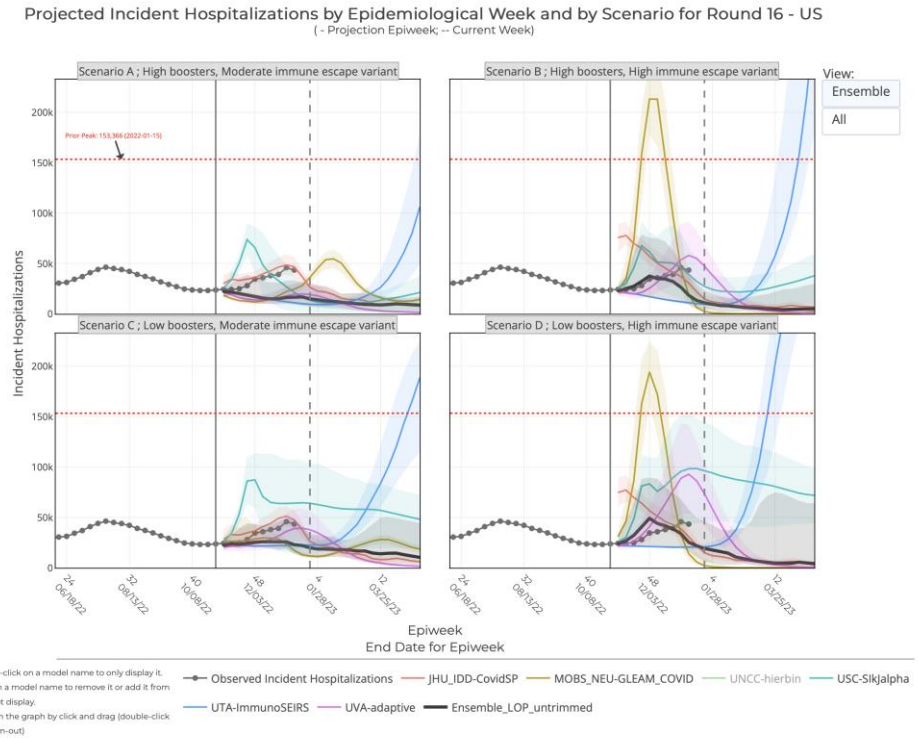
Scenario Modeling Hub – COVID-19 (Round 16)

Collaboration of multiple academic teams to provide national and state-by-state level projections for 4 aligned scenarios

- Round 16 results published
- Moderate escape scenarios tracking best

	"Level 5" Variants	"Level 6/7" Variants
Accelerating uptake levels of reformulated boosters	"Level 5" Variants Scenario A - Variants have a 25% immune escape from BA.5.2 - Seeding based on combined observed prevalence of Level 5 variants at the start of the projection period - No change in severity given symptomatic infection **Accelerating uptake levels of reformulated boosters, with coverage plateauing at 90% of flu vaccination levels by February 1st, 2023** - Teams are free to use available data and information from current and previous rollouts as tehy see fit to define rates - Teams should assume increasing uptake through October and November as necessary to reach the projected February 1st, 2022 plateau	"Level 6/7" Variants Scenario B - Variants have a 50% immune escape from BA.5.2 - Seeding based on combined observed prevalence of Level 6 and 7 variants at the start of the projection period - No change in severity given symptomatic infection **Accelerating uptake levels of reformulated boosters, with coverage plateauing at 90% of flu vaccination levels by February 1st, 2023** - Teams are free to use available data and information from current and previous rollouts as tehy see fit to define rates - Teams should assume increasing uptake through October and November as necessary to reach the projected February 1st, 2022 plateau
Current uptake levels of reformulated boosters	"Level 5" Variants Scenario C - Variants have a 25% immune escape from BA.5.2 - Seeding based on combined observed prevalence of Level 5 variants at the start of the projection period - No change in severity given symptomatic infection **Current uptake levels of reformulated boosters, with coverage plateauing at booster 1 levels by the end of the simulation** - Teams are free to use available data and information from current and previous rollouts as tehy see fit to define rates - Based on current rates, plateau date is flexible as long as it occurs before the end of the simulation (Teams can adjust rates up if needed to achieve adequate coverage by target date)	"Level 6/7" Variants Scenario D - Variants have a 50% immune escape from BA.5.2 - Seeding based on combined observed prevalence of Level 6 and 7 variants at the start of the projection period - No change in severity given symptomatic infection **Current uptake levels of reformulated boosters, with coverage plateauing at booster 1 levels by the end of the simulation** - Teams are free to use available data and information from current and previous rollouts as tehy see fit to define rates - Based on current rates, plateau date is flexible as long as it occurs before the end of the simulation (Teams can adjust rates up if needed to achieve adequate coverage by target date)

https://covid19scenariomodelinghub.org/viz.html



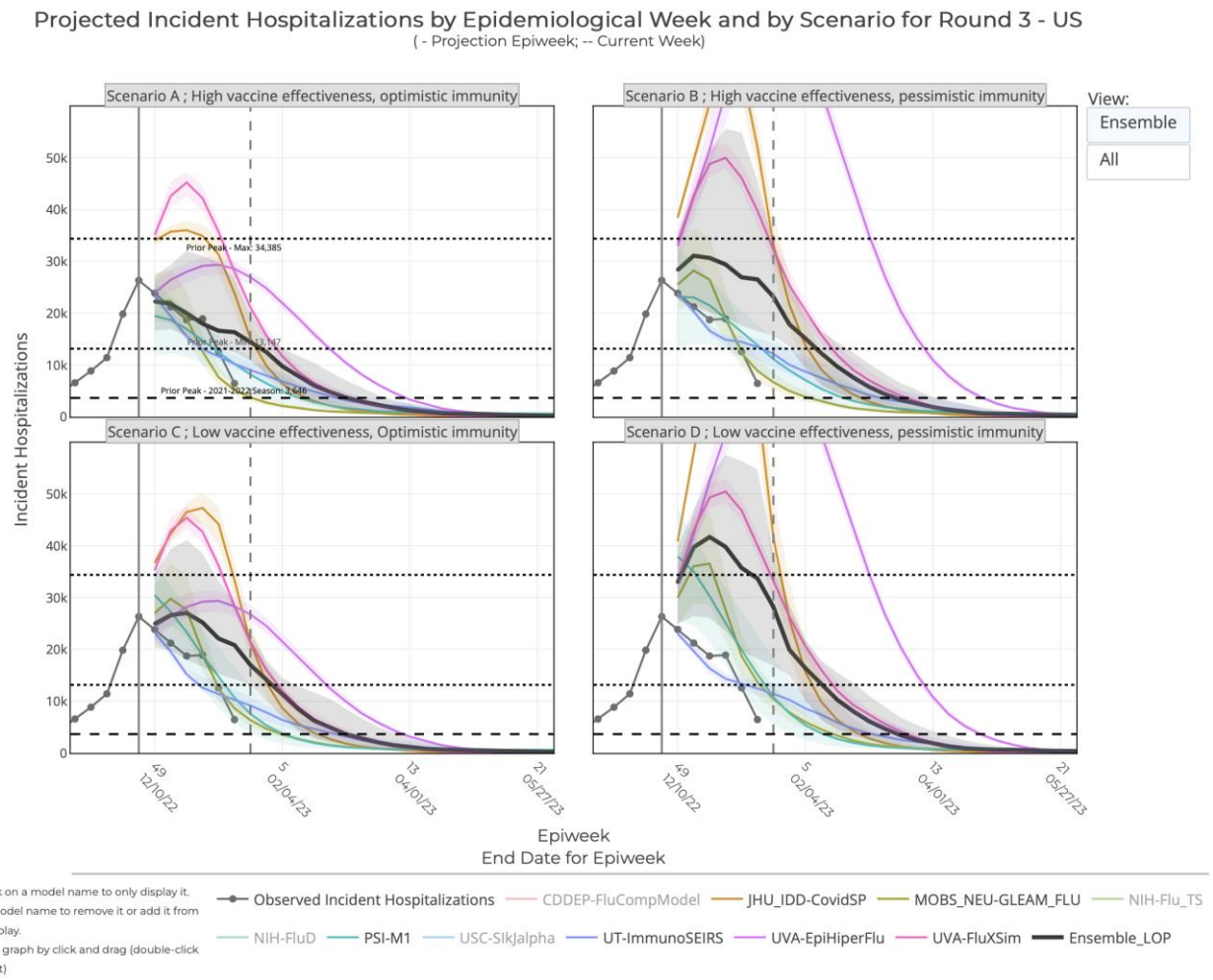
Scenario Modeling Hub – Influenza (Round 3)

Collaboration of multiple academic teams to provide national and state-by-state level projections for 4 aligned scenarios

- All rounds so far have explored the combination of a prior immunity axis and a vaccine effectiveness axis
- Round 2 and 3 are identical in design (Round 3 cutoff December 3rd)

	Optimistic flu prior immunity	Pessimistic flu prior immunity
High Vaccine Effectiveness	Scenario A Optimistic flu prior immunity - No impact of missed flu seasons due to the COVID-19 pandemic on prior immunity.* - Same amount of prior immunity as in a typical, pre-COVID19 pandemic prior season. High Vaccine Effectiveness - VE = 50% against medically attended influenza illnesses and hospitalizations (comparable to 2015-16 season).	Scenario B Pessimistic flu prior immunity - Substantial impact of missed flu seasons due to the COVID-19 pandemic on prior immunity.* - 50% lower immunity than a typical, pre-COVID19 pandemic season. High Vaccine Effectiveness - VE = 50% against medically attended influenza illnesses and hospitalizations (comparable to 2015-16 season).
Low Vaccine Effectiveness	Scenario C Optimistic flu prior immunity - No impact of missed flu seasons due to the COVID-19 pandemic on prior immunity.* - Same amount of prior immunity as in a typical, pre-COVID19 pandemic prior season. Low Vaccine Effectiveness - VE = 30% against medically attended influenza illnesses and hospitalizations (comparable to 2018-19 season).	Scenario D Pessimistic flu prior immunity - Substantial impact of missed flu seasons due to the COVID-19 pandemic on prior immunity.* - 50% lower immunity than a typical, pre-COVID19 pandemic season. Low Vaccination Protection - VE = 30% against medically attended influenza illnesses and hospitalizations (comparable to 2018-19 season).

https://fluscenariomodelinghub.org/viz.html



Scenario Modeling Hub – Influenza
(UVA Update to Round 3)

Collaboration of multiple academic teams to provide national and state-by-state level projections for 4 aligned scenarios

- Update with more data (until Jan 7th)
- No scenarios seem to fully explain season's trajectory

	Optimistic flu prior immunity	Pessimistic flu prior immunity
High Vaccine Effectiveness	Scenario A Optimistic flu prior immunity - No impact of missed flu seasons due to the COVID-19 pandemic on prior immunity.* - Same amount of prior immunity as in a typical, pre-COVID19 pandemic prior season. High Vaccine Effectiveness - VE = 50% against medically attended influenza illnesses and hospitalizations (comparable to 2015-16 season).	Scenario B Pessimistic flu prior immunity - Substantial impact of missed flu seasons due to the COVID-19 pandemic on prior immunity.* - 50% lower immunity than a typical, pre-COVID19 pandemic season. High Vaccine Effectiveness - VE = 50% against medically attended influenza illnesses and hospitalizations (comparable to 2015-16 season).
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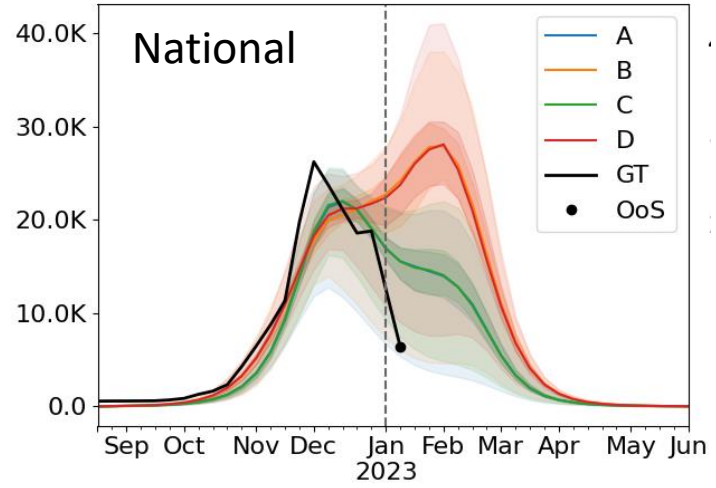

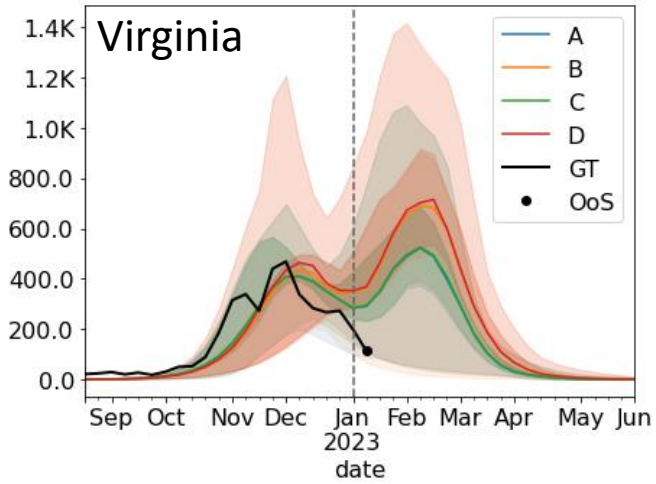

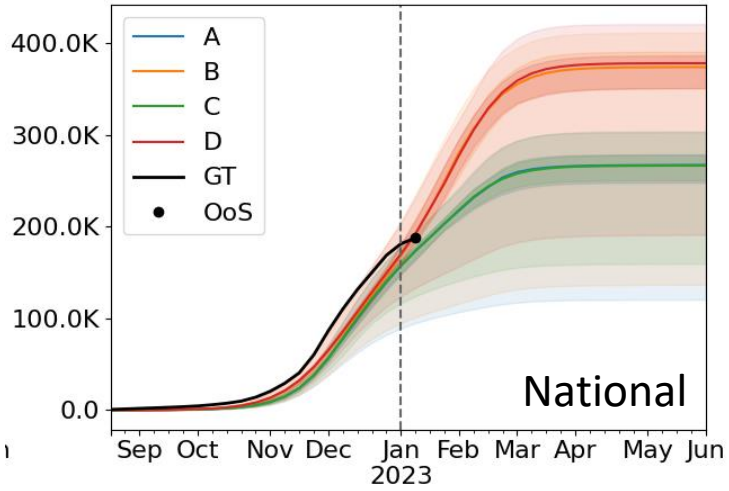

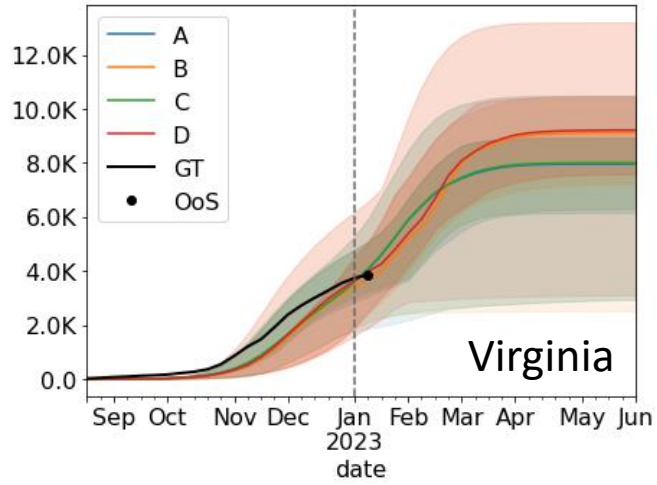

Key Takeaways

Projecting future cases precisely is impossible and unnecessary.
Even without perfect projections, we can confidently draw conclusions:

- Case rates and hospitalizations from COVID-19 remain on the decline with limited activity in isolated areas
- Case rates and hospitalizations from Influenza are almost back to early season lows

- Model Updates
  - Projection model from Dec 9th remains roughly on track with current trajectory, however, the recent decline is occurring earlier than anticipated by the model
  - COVID-19 forecast models anticipate a plateauing of COVID-19 hospital admissions in near term, though historically Feb and March have had limited activity
  - Influenza forecast models call for low levels of Influenza hospital admissions to persist

Questions?

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