

Network Systems
Science & Advanced
Computing
Biocomplexity Institute
& Initiative
University of Virginia

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

July 13th, 2023

(data current to July 3rd – July 12th)

Biocomplexity Institute Technical report: TR BI-2023-160



BIOCOMPLEXITY INSTITUTE

biocomplexity.virginia.edu

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 broad 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 are in an undulating plateau, currently in an upswing
- Hospitalization rates remain in plateau, with very slight growth
- Most indicators still point to continued plateaus, though some indicate slow growth
- Scenerio Modeling Hub, round 17 results published, impact of fall booster is high

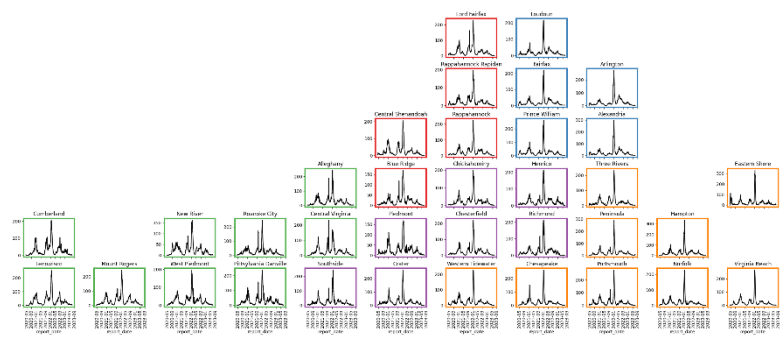
VDH – UVA Updates

- SPHINX project update – PePITA tool piloted at CSTE conference in Salt Lake City
- Projected Trajectories from previous rounds remain on target, no new projections made this round

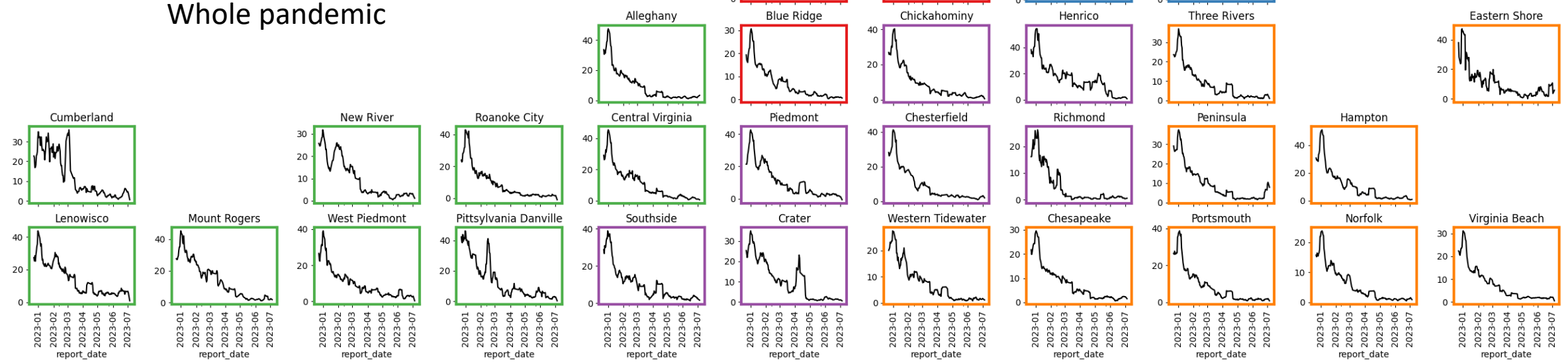
COVID-19 Surveillance



Case Rates (per 100k)



Whole pandemic

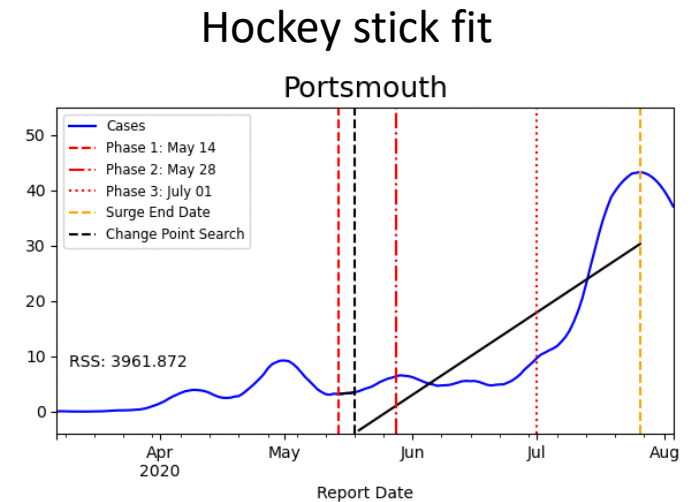


Since December 2021

District Trajectories

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

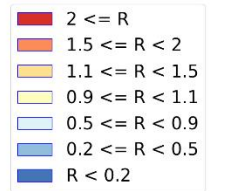
Method: Find recent peak and use hockey stick fit to find inflection point afterwards, then use this period's slope to define the trajectory



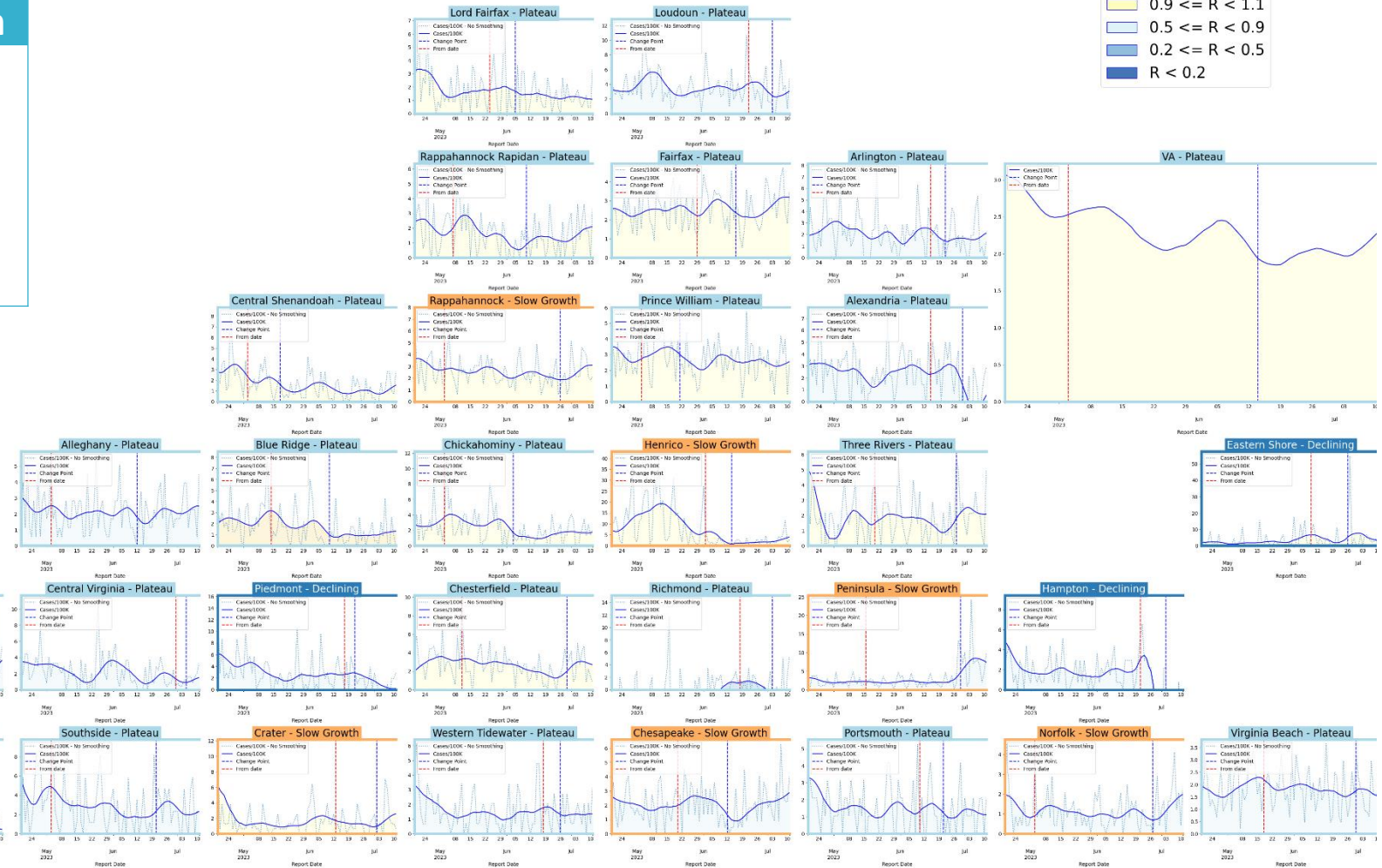
Trajectory	Description	Weekly Case Rate Slope (per 100k)	Weekly Hosp Rate Slope (per 100k)
Declining	Sustained decreases following a recent peak	slope < -0.88/day	slope < -0.07/day
Plateau	Steady level with minimal trend up or down	-0.88/day < slope < 0.42/day	-0.07/day < slope < 0.07/day
Slow Growth	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

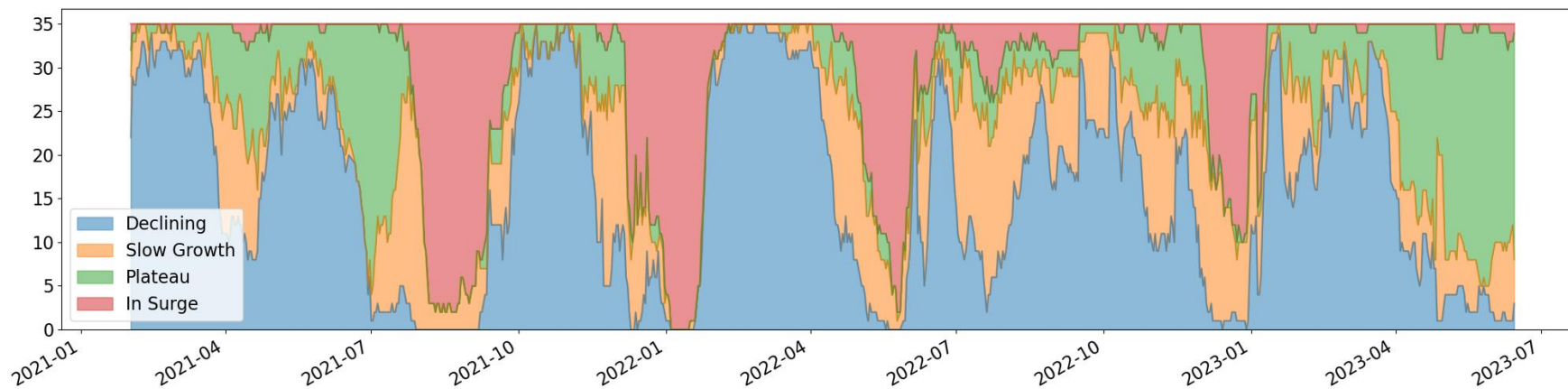
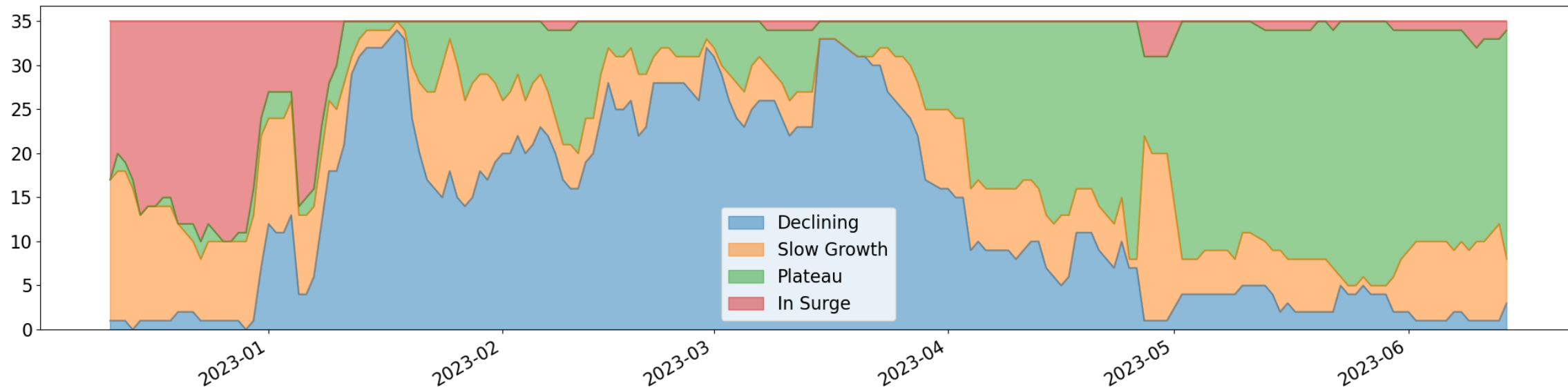
Status	Number of Districts	
	Current Week	Last Month
Declining	3	(2)
Plateau	25	(25)
Slow Growth	7	(7)
In Surge	0	(1)



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



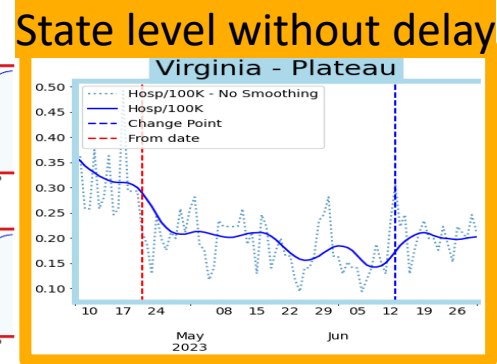
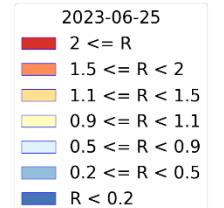
District Case Trajectories – Recent 6 months



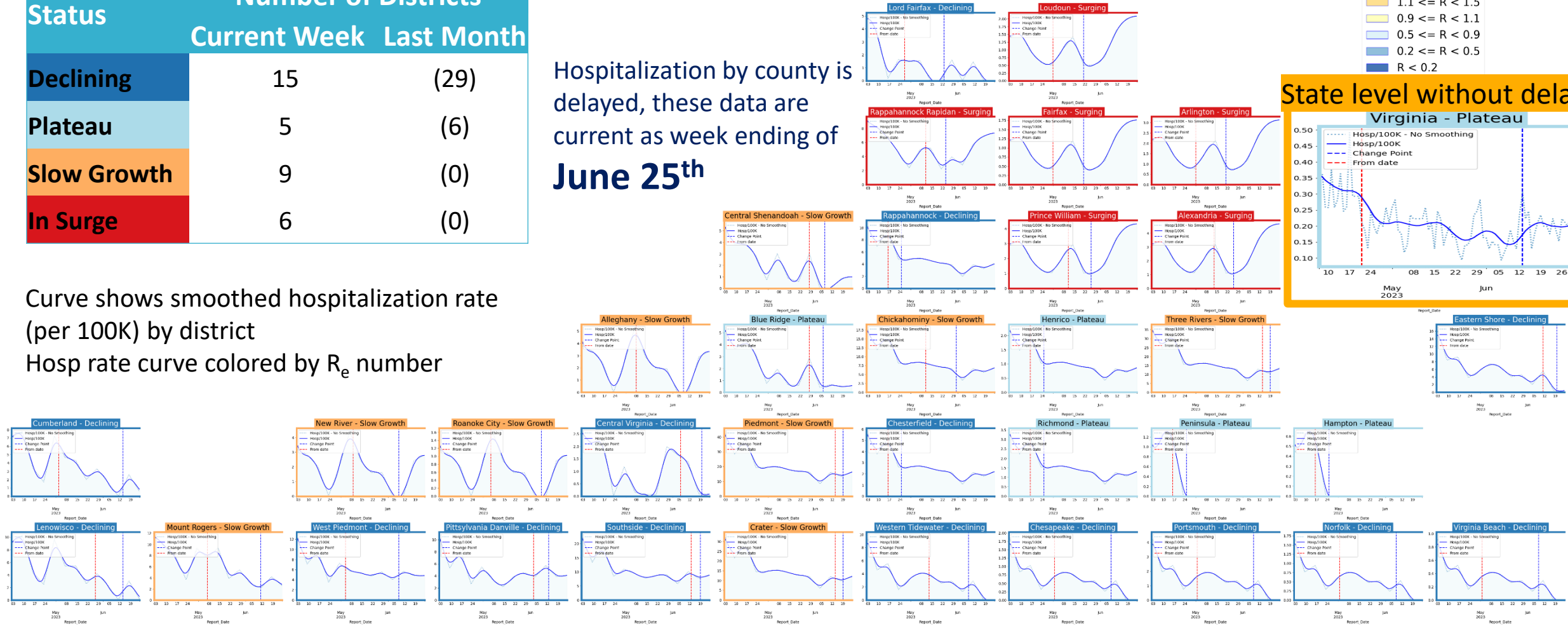
District Hospital Trajectories – last 10 weeks

Status	Number of Districts	
	Current Week	Last Month
Declining	15	(29)
Plateau	5	(6)
Slow Growth	9	(0)
In Surge	6	(0)

Hospitalization by county is delayed, these data are current as week ending of **June 25th**



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



COVID-19 Growth Metrics

Estimating Daily Reproductive Number – VDH report dates

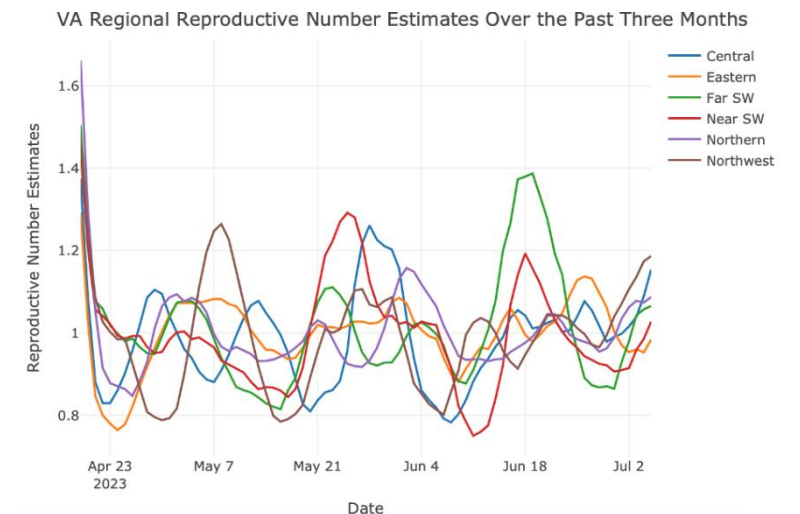
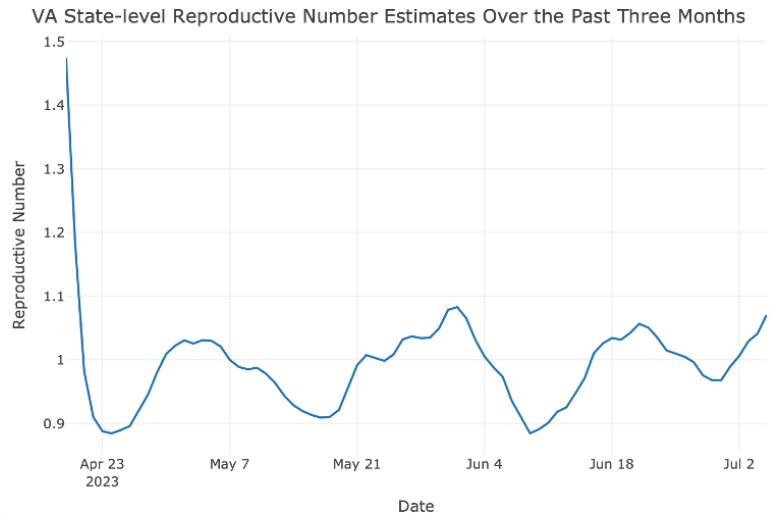
July 11th Estimates

Region	Date Confirmed R_e	Date Confirmed Diff Last Week
State-wide cases	1.071	0.103
State-wide hosps	0.987	-0.005
Central	1.154	0.175
Eastern	0.984	-0.078
Far SW	1.065	0.195
Near SW	1.028	0.106
Northern	1.087	0.125
Northwest	1.187	0.192

Methodology

- Wallinga-Teunis method (EpiEstim¹) 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>



Estimating Daily Reproductive Number – VDH report dates – EpiNow2 estimation

July 11th Estimates

Region	Reproductive number estimate	Confidence interval	Trend forecast
State-wide cases	1.10	0.70 - 1.8	Likely increasing
State-wide hosp	1.00	0.78 - 1.4	Stable
Central	1.10	0.85 - 1.5	Likely increasing
Eastern	1.10	0.79 - 1.4	Likely increasing
Far SW	1.00	0.76 - 1.3	Stable
Near SW	1.00	0.78 - 1.3	Stable
Northern	1.00	0.76 - 1.4	Stable
Northwest	1.10	0.82 - 1.5	Likely increasing

Initial results based on past 3 months of data with updated EpiNow2 method

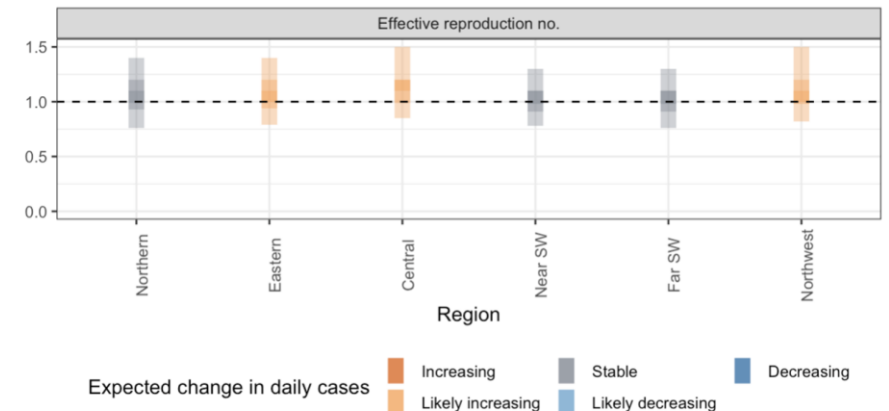
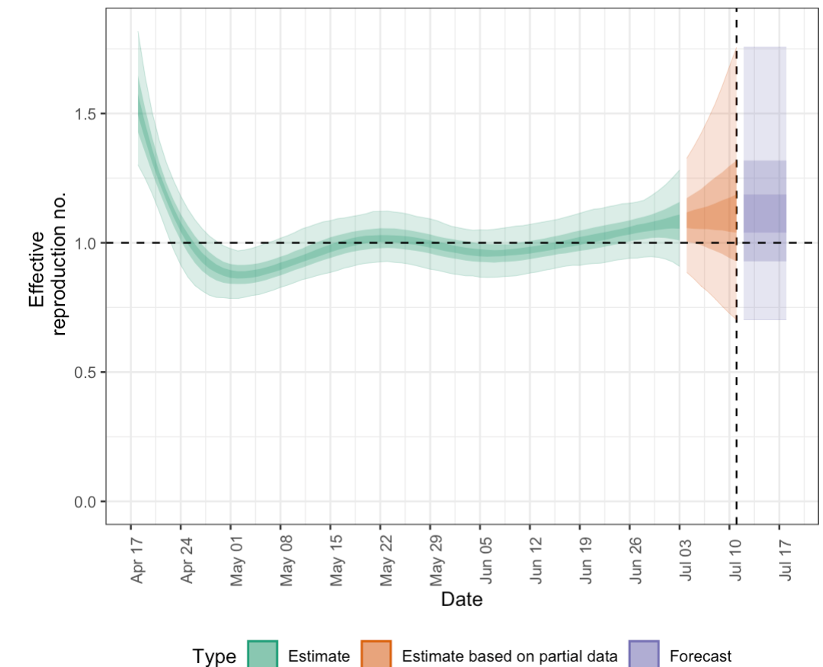
Methodology

- [EpiNow2](#) which is based on similar approach as EpiEstim (currently used on previous slide)
- Serial interval updates with COVID-19 disease model in EpiNow2
- Continue to use confirmation date but report date biases are better accounted for

Sam Abbott, Joel Hellewell, Katharine Sherratt, Katelyn Gostic, Joe Hickson, Hamada S. Badr, Michael DeWitt, Robin Thompson, EpiForecasts, Sebastian Funk (2020). EpiNow2: Estimate Real-Time Case Counts and Time-Varying Epidemiological Parameters. doi:10.5281/zenodo.3957489.

EpiNow2 home: <https://epiforecasts.io/EpiNow2/>

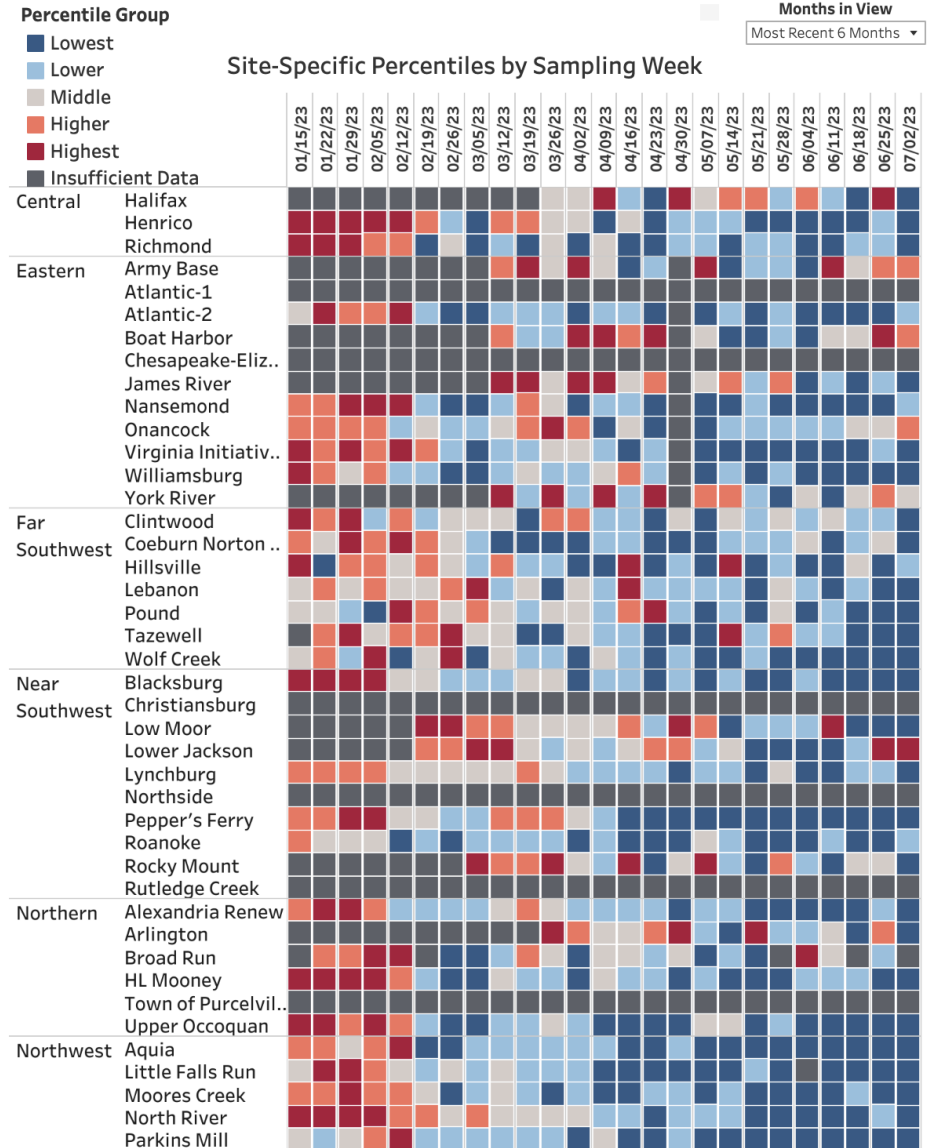
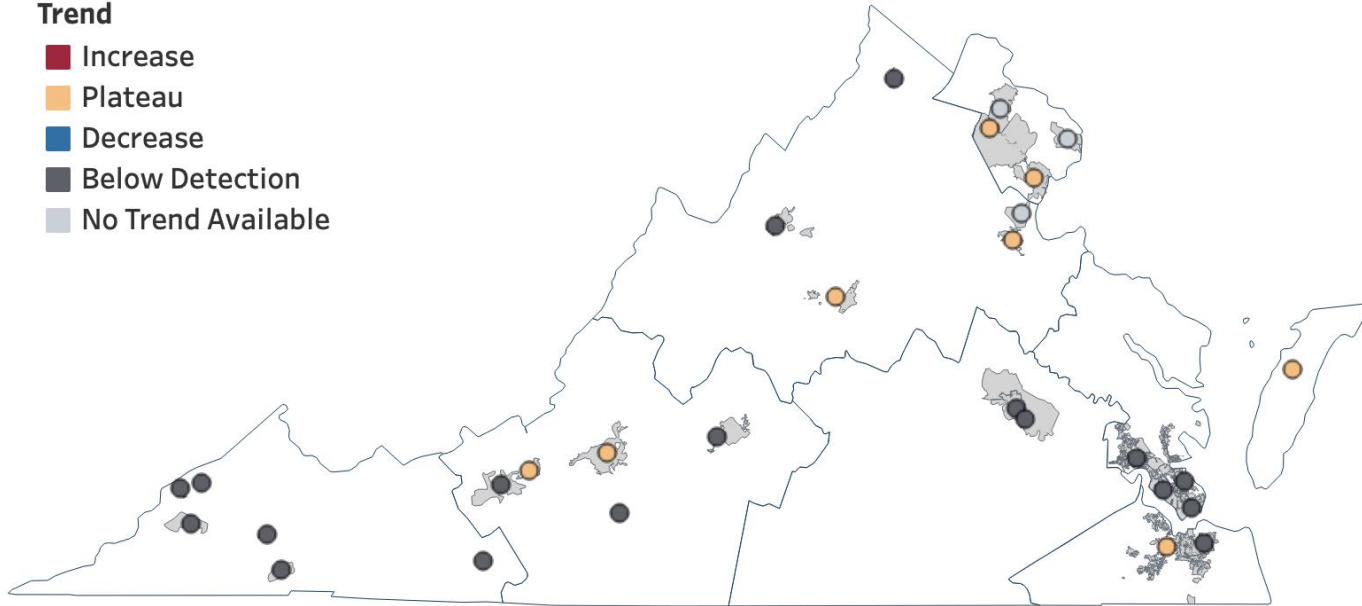
Re from VDH Cases (last 3 months)



VA Wastewater Data Update

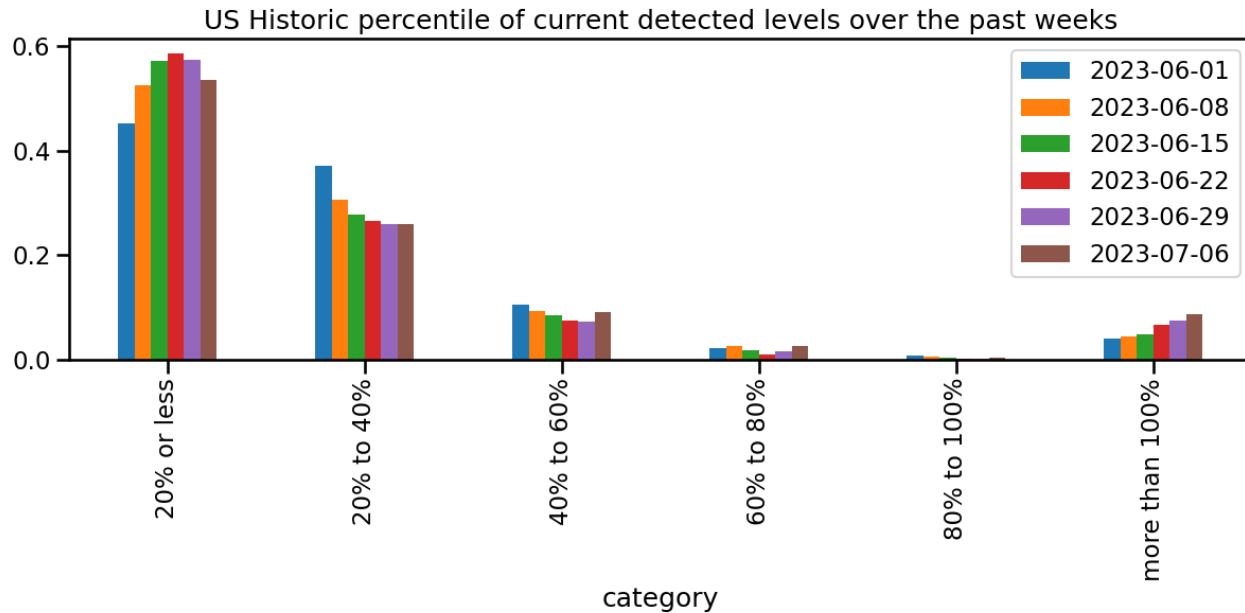
Start of Sample Collection Week

- Trend**
- Increase
 - Plateau
 - Decrease
 - Below Detection
 - No Trend Available

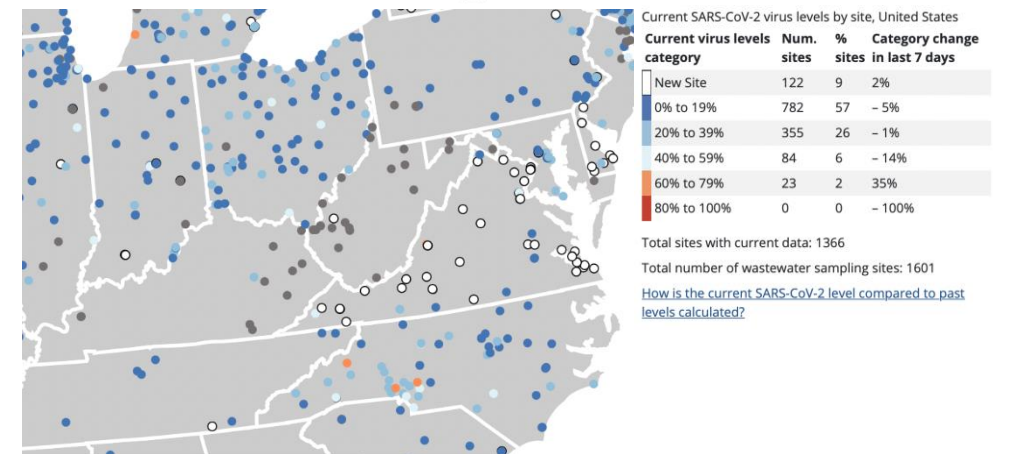
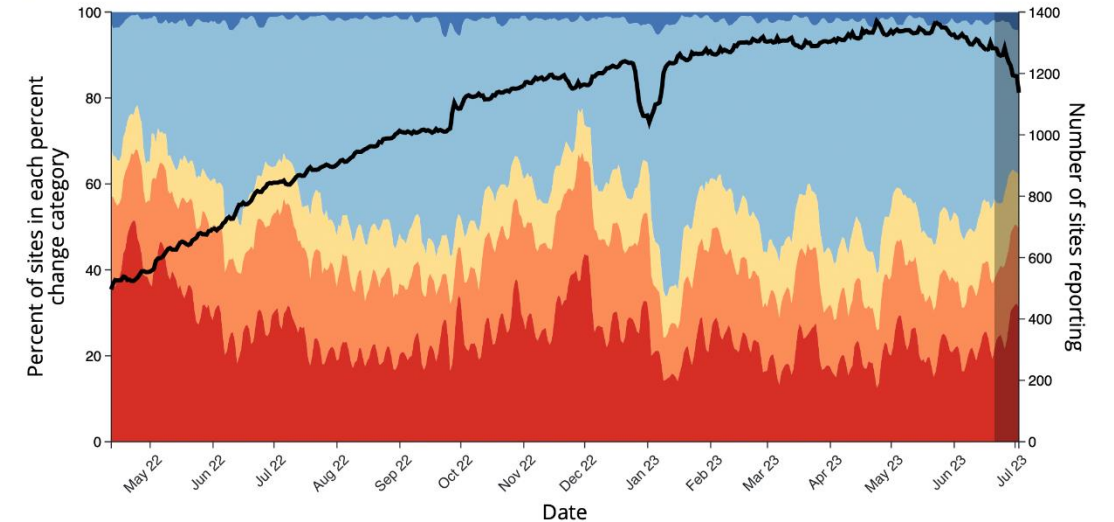


US Wastewater Monitoring

Wastewater provides a coarse estimate of COVID-19 levels in communities and can be a good indicator of activity levels



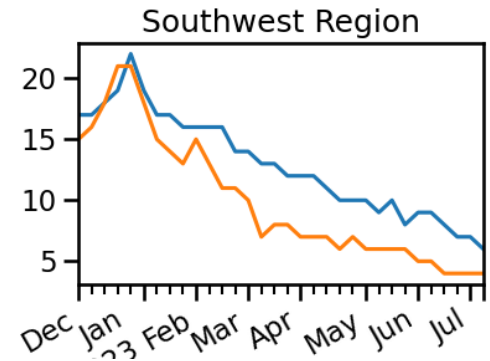
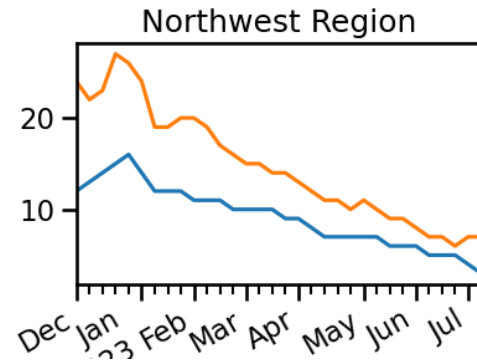
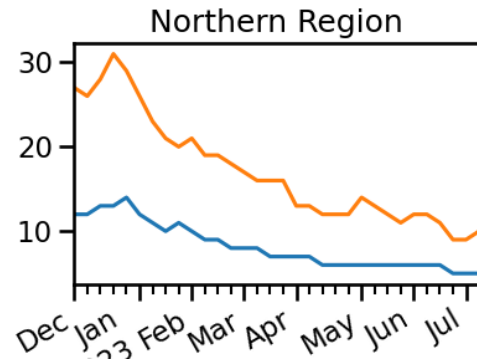
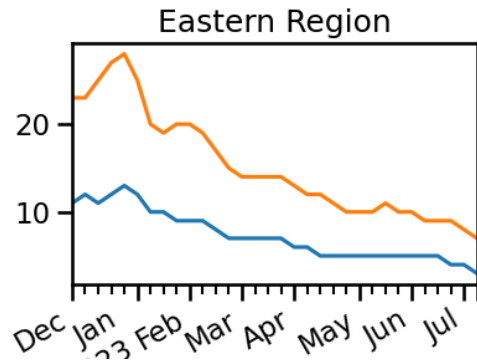
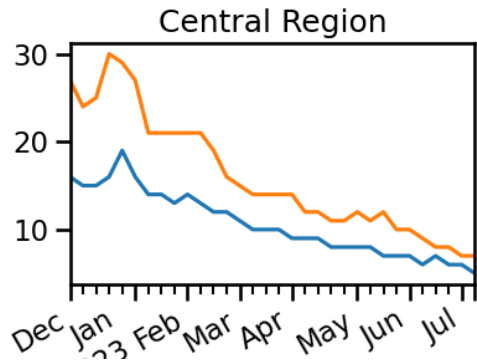
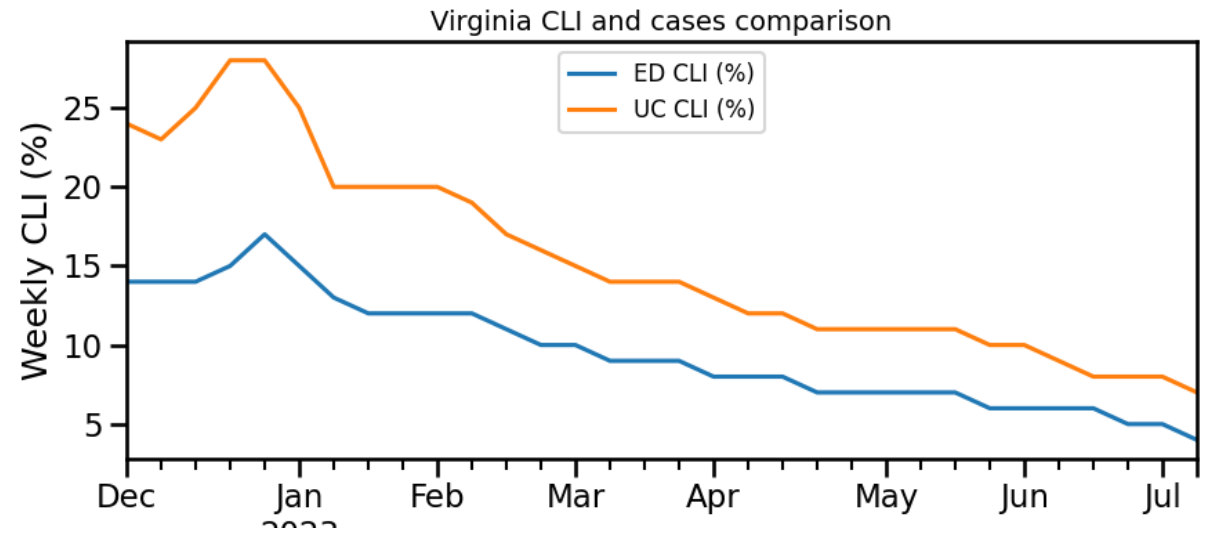
Percent of sites in each percent change category over time, United States*



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
- **Levels continue to decline into lowest levels in past 8 months**



COVID-19 Severity Metrics

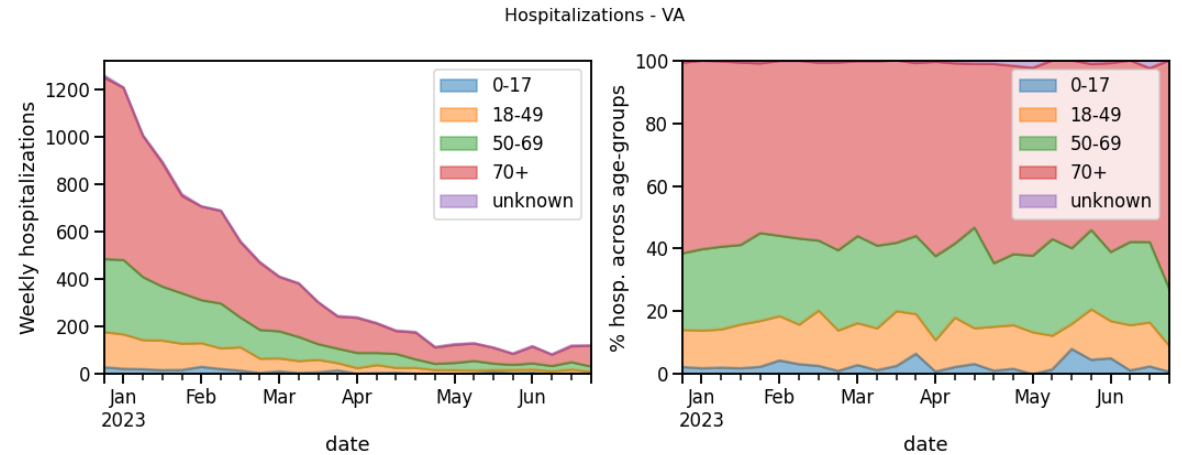
Hospitalizations in VA by Age

Age distribution in hospitals relatively stable

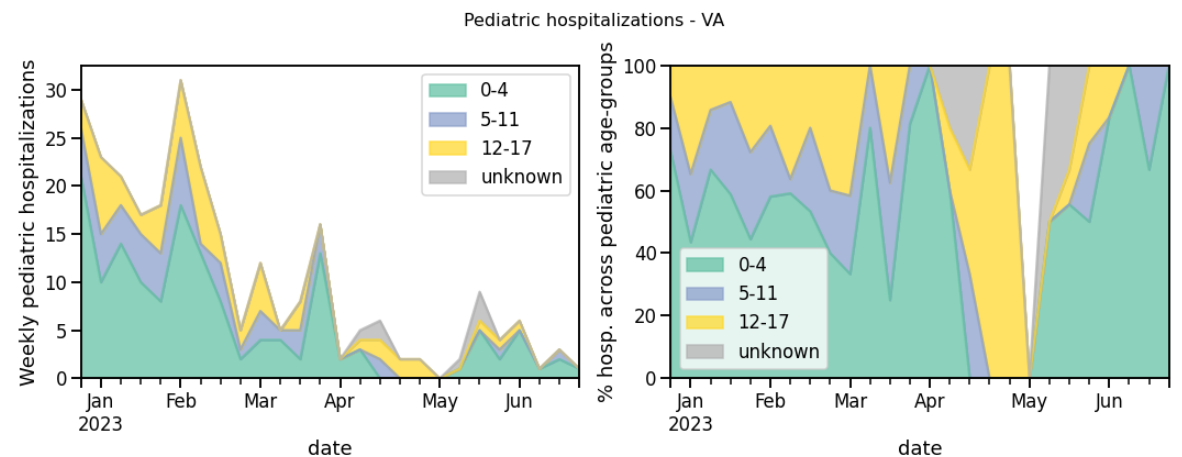
- Uptick in hospitalizations mostly fueled by 70+ age group
- Pediatric hospitalizations level off after uptick last week

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

Virginia Hospitalizations by Age (all ages)



Pediatric Hospitalizations by Age (0-17yo)



COVID-19 Spatial Epidemiology

ZIP Code level case rate per 100K over last four weeks

New cases per 100k in the last four weeks by ZIP code

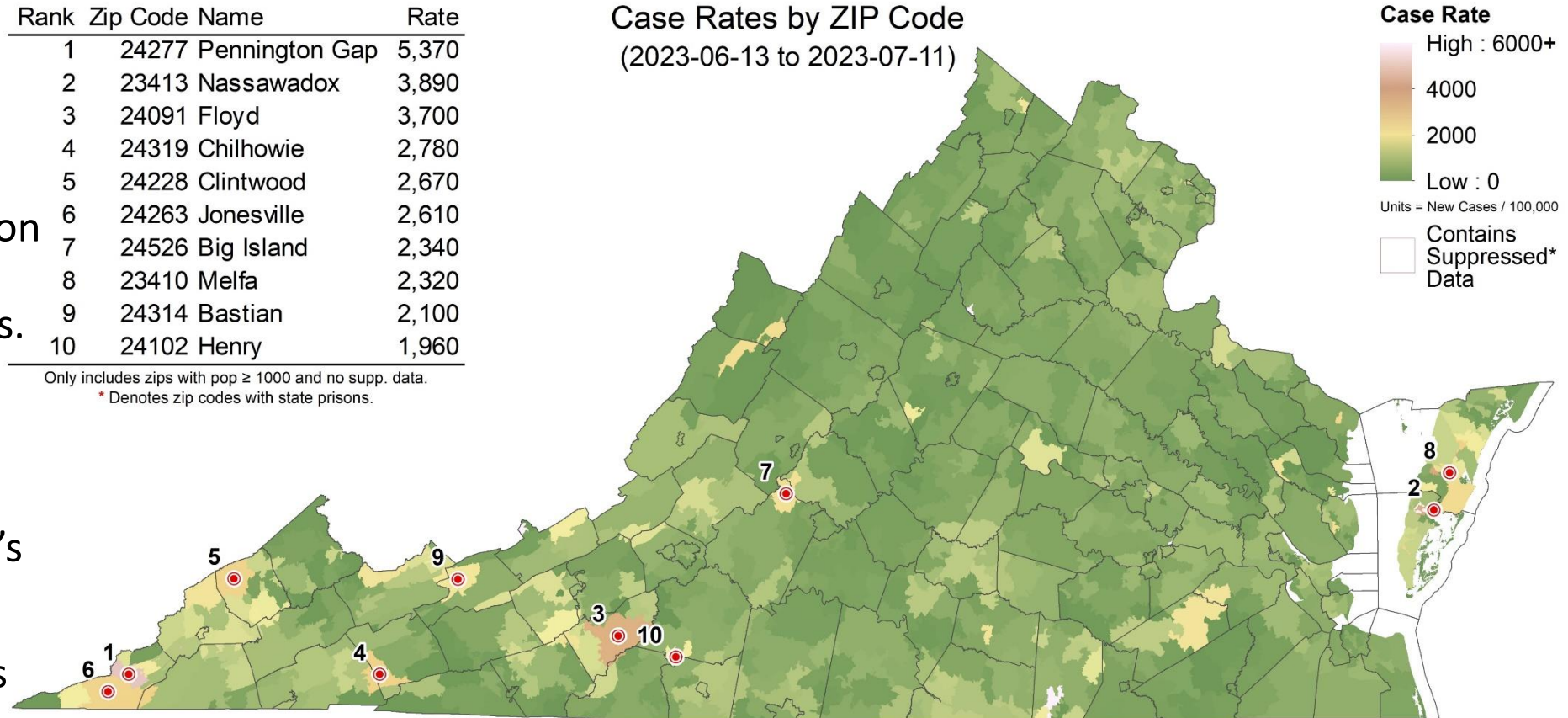
- Statewide COVID19 case rates continue to remain at near historic lows.
- Divide rates by four to calculate average weekly incidence. Even Pennington Gap averaged fewer than 1,350 / 100k weekly cases.
- Nassawadox is yet again reporting an unusually high case rate. It was in the #1 spot in last month's report.
- No ZIP codes with prisons are reported in this month's top 10.

Rank	Zip Code	Name	Rate
1	24277	Pennington Gap	5,370
2	23413	Nassawadox	3,890
3	24091	Floyd	3,700
4	24319	Chilhowie	2,780
5	24228	Clintwood	2,670
6	24263	Jonesville	2,610
7	24526	Big Island	2,340
8	23410	Melfa	2,320
9	24314	Bastian	2,100
10	24102	Henry	1,960

Only includes zips with pop ≥ 1000 and no supp. data.

* Denotes zip codes with state prisons.

Case Rates by ZIP Code
(2023-06-13 to 2023-07-11)



Based on Spatial Empirical Bayes smoothed case rates, with an 8:1 ascertainment ratio, for four weeks ending 2023-07-11.

Risk of Exposure by Group Size and HCW prevalence

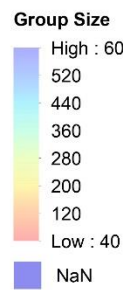
Case prevalence in the last **four weeks** by zip code used to calculate risk of encountering someone infected in a gathering of randomly selected people

- **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 50 in Pennington Gap, there is a 50% chance someone will be infected).
- **HCW ratio:** Case rate among health care workers (HCW) in the last four weeks using patient facing health care workers as the numerator / population's case prevalence. High HCW ratios are found in Southwest.

Rank	Zip Code	Name	Size
1	24277	Pennington Gap	50
2	23413	Nassawadox	70
3	24091	Floyd	74
4	24319	Chilhowie	98
5	24228	Clintwood	102
6	24263	Jonesville	105
7	24526	Big Island	117
8	23410	Melfa	118
9	24314	Bastian	130
10	24102	Henry	140

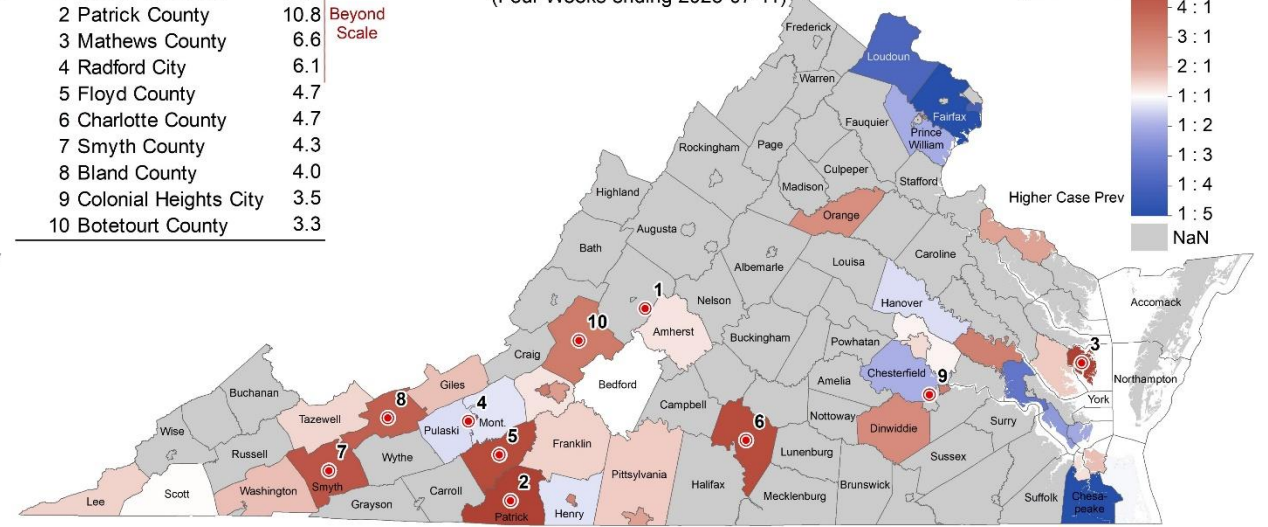
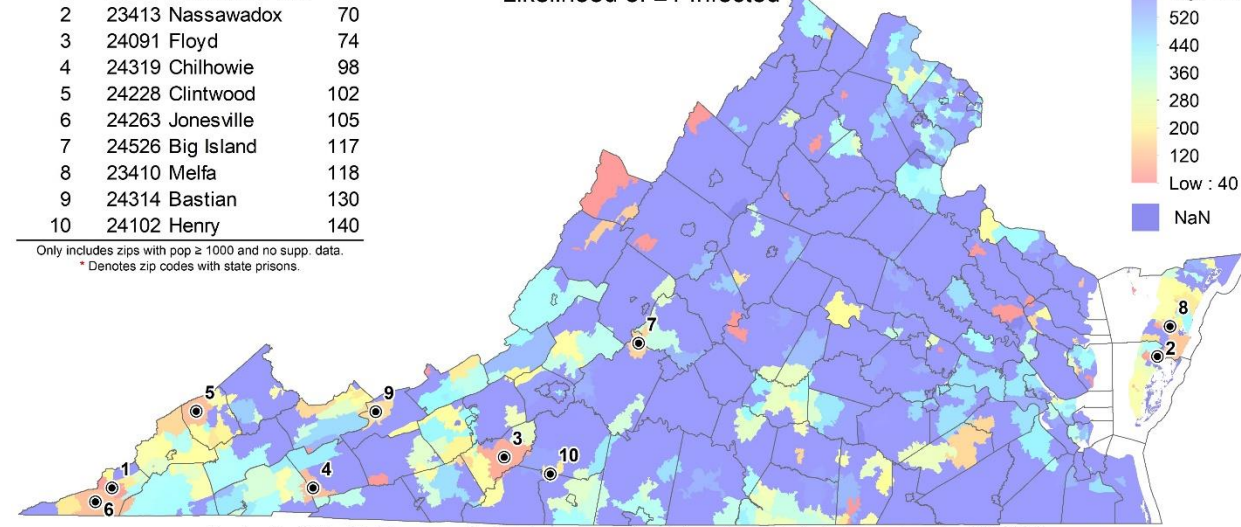
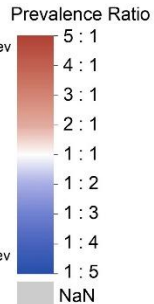
Only includes zips with pop ≥ 1000 and no supp. data.
 * Denotes zip codes with state prisons.

Group Size Needed for 50% Likelihood of ≥1 Infected



Rank	Name	Ratio
1	Buena Vista City	12.7
2	Patrick County	10.8
3	Mathews County	6.6
4	Radford City	6.1
5	Floyd County	4.7
6	Charlotte County	4.7
7	Smyth County	4.3
8	Bland County	4.0
9	Colonial Heights City	3.5
10	Botetourt County	3.3

HCW Prevalence / Case Prevalence (Four Weeks ending 2023-07-11)



Based on Spatial Empirical Bayes smoothed point prevalence, with an 8:1 ascertainment ratio, for four weeks ending 2023-07-11.

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

Current Hot-Spots

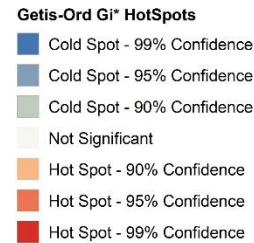
Case rates that are significantly different from neighboring areas or model projections

- **Spatial:** Getis-Ord Gi* based hot spots compare clusters of zip codes with **four-week** case prevalence higher than nearby zip codes to identify larger areas with statistically significant deviations
- **Temporal:** The **cumulative** case rate (per 100K) projected in March compared to those observed by county, which highlights temporal fluctuations that differ from the model's projections.
- Spatial hotspots were found in the Southwest and Eastern Shore. Model overpredictions seen in Southside, New River and Crater. Lenowisco saw more cases than expected. Overall error was ~4.1% since March.

Spatial Hotspots

Spot	Zip Code	Name	Conf.
1	24277	Pennington Gap	99%
2	24091	Floyd	99%
3	23413	Nassawadox	99%
4	24319	Chilhowie	99%
5	24228	Clintwood	99%
6	24263	Jonesville	99%
7	23410	Melfa	95%
8	24526	Big Island	95%
9	24279	Pound	90%

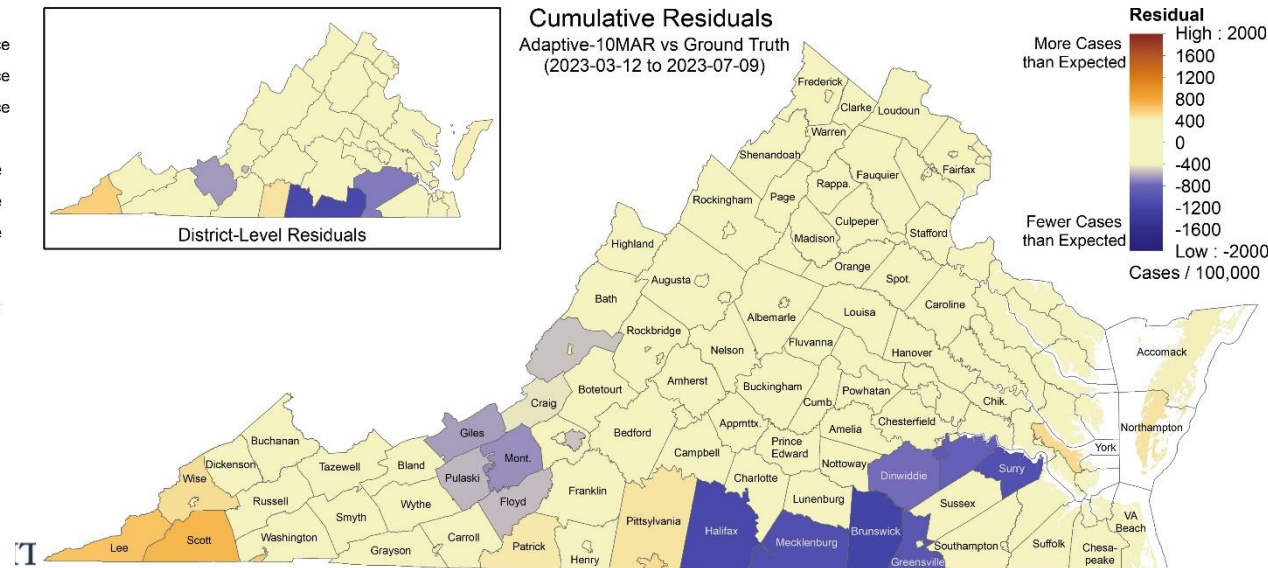
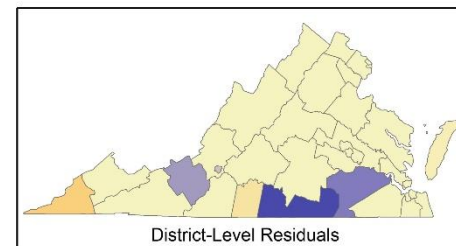
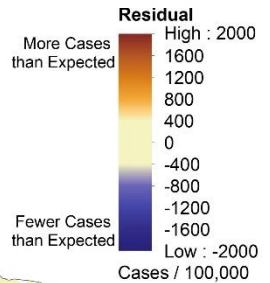
Point Prevalence Hot Spots by Zip Code
(2023-06-13 to 2023-07-11)



Based on Global Empirical Bayes smoothed point prevalence for the four weeks ending 2023-07-11.

Clustered Temporal Hotspots

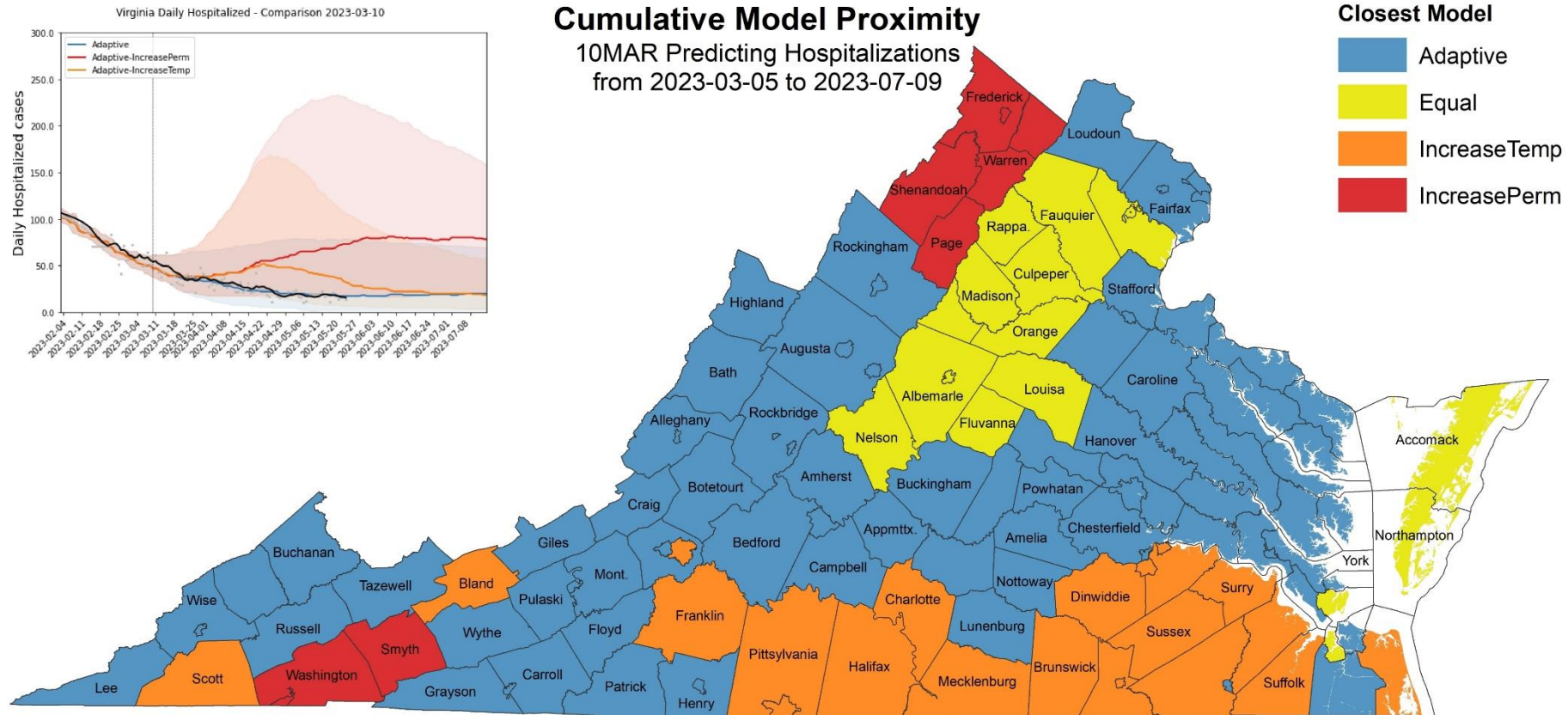
Cumulative Residuals
Adaptive-10MAR vs Ground Truth
(2023-03-12 to 2023-07-09)



Health District Level Moran's I = -0.000227, Z-Score = 0.507557, P-Value = 0.611764
No Residual Autocorrelation Detected

Hospitalization Scenario Trajectory Tracking

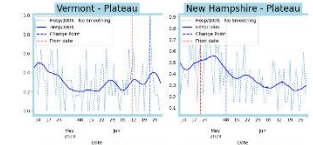
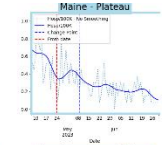
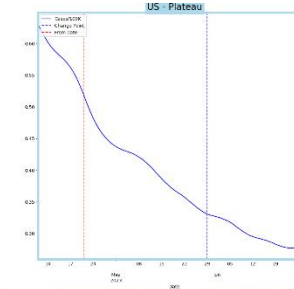
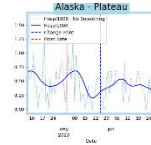
Which scenario from **three** months ago did each county track closest?



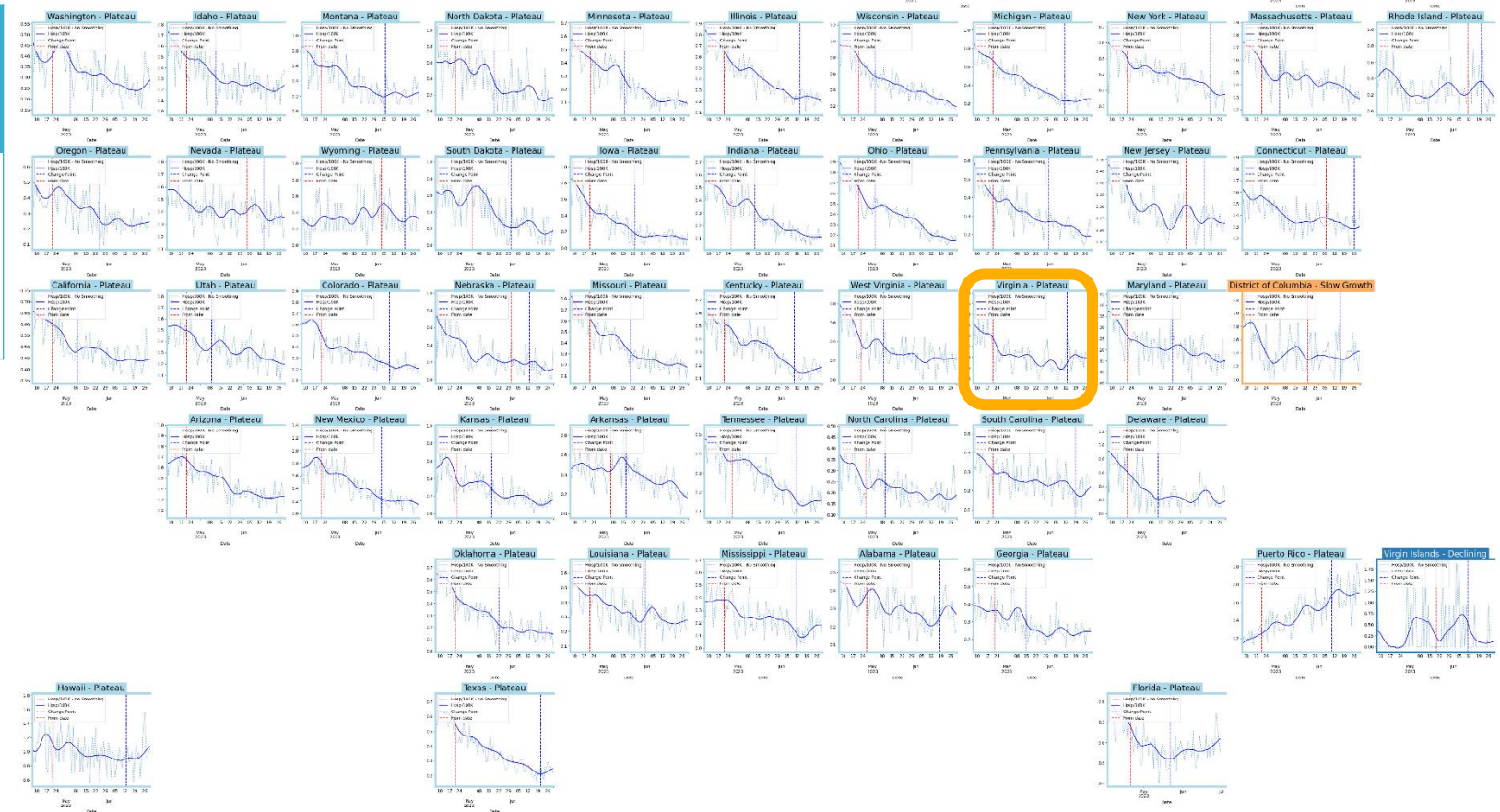
- The counties south of Richmond are now tracking the IncreasedTemp scenario closer than the Adaptive scenario. Last month they tracked both scenarios equally.
- Smyth County is now tracking IncreasedPerm more closely (previously IncreasedTemp).
- Other areas of the Commonwealth are largely the same as last reported, mostly tracking Adaptive.

COVID-19 Broader Context

United States Hospitalizations



Status	Current Week	Last Month
Declining	1	(1)
Plateau	51	(48)
Slow Growth	1	(3)
In Surge	0	(1)

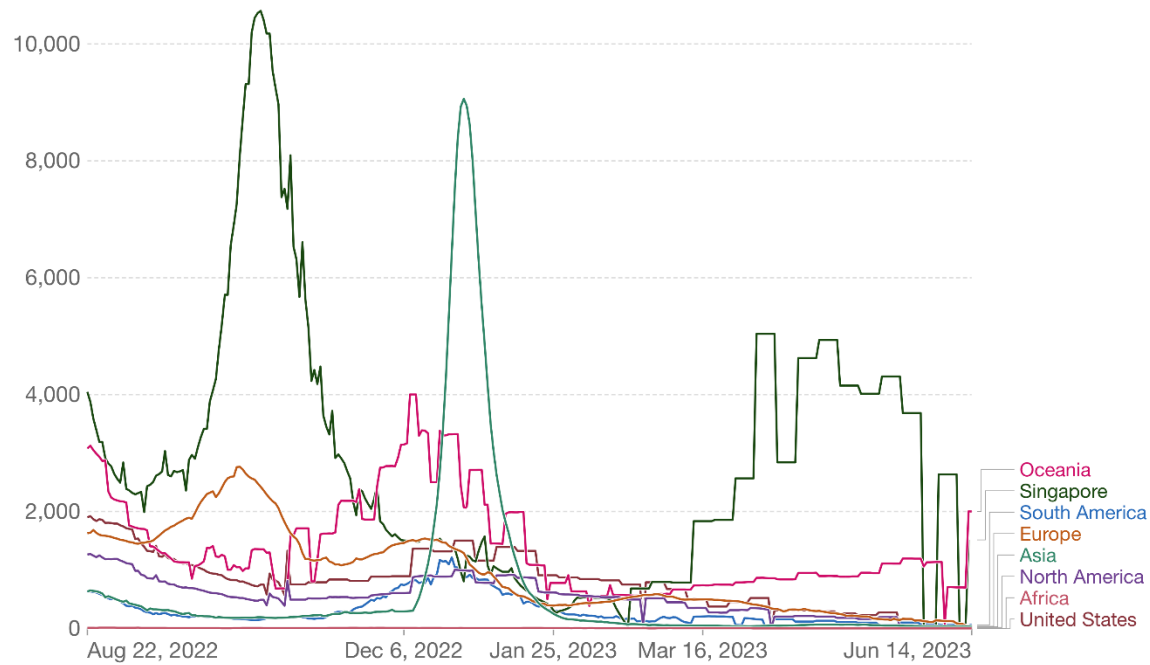


Around the World – Various trajectories

Confirmed cases

Weekly confirmed COVID-19 cases per million people

Weekly confirmed cases refer to the cumulative number of confirmed cases over the previous week.



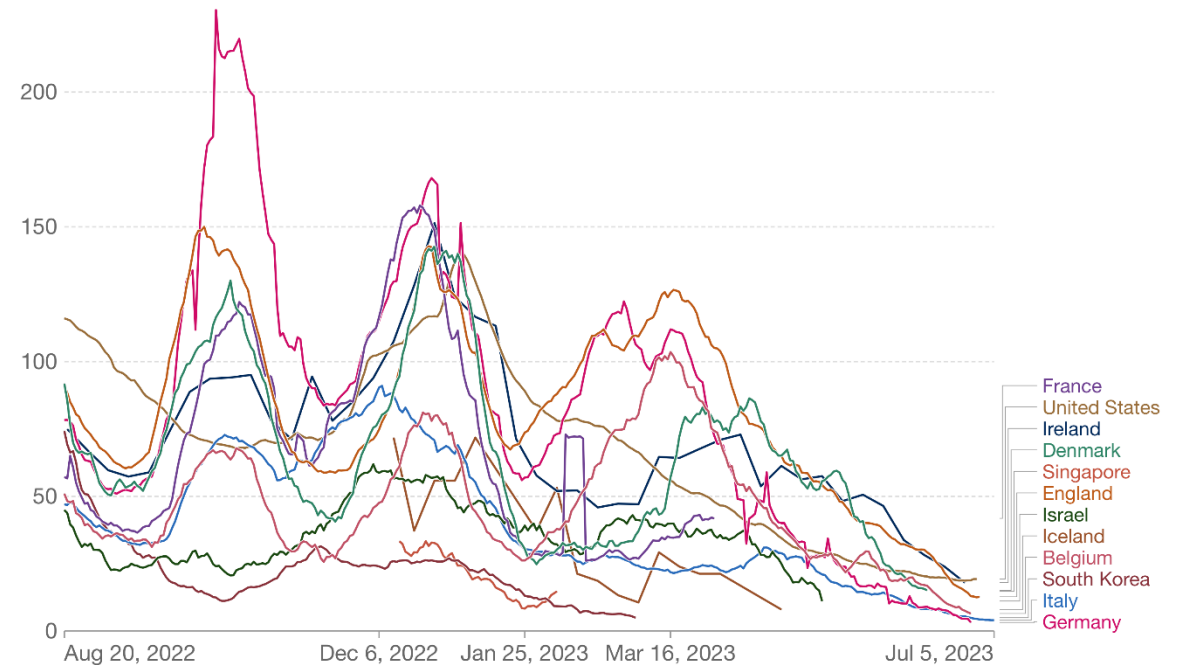
Source: WHO COVID-19 Dashboard

CC BY

Hospitalizations

Weekly new hospital admissions for COVID-19 per million people

Weekly admissions refer to the cumulative number of new admissions over the previous week.



Source: Official data collated by Our World in Data

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[Our World in Data](https://ourworldindata.org)

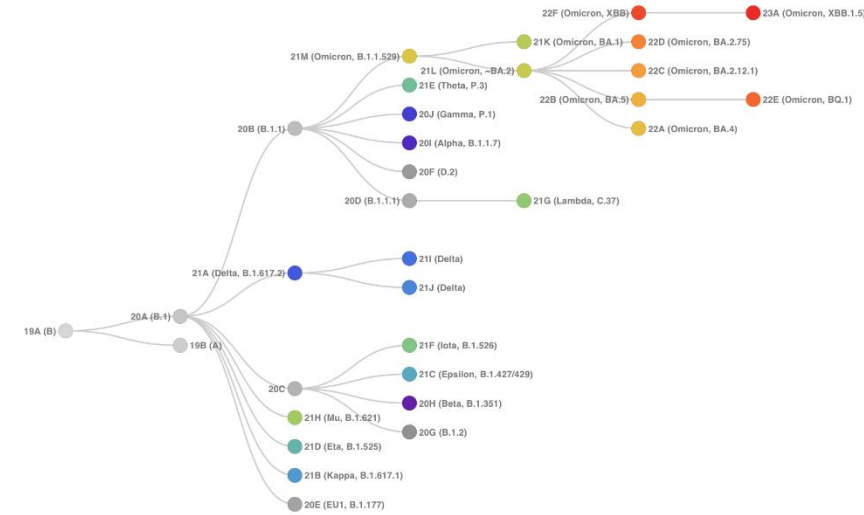


COVID-19 Genomic Update

SARS-CoV2 Variants of Concern

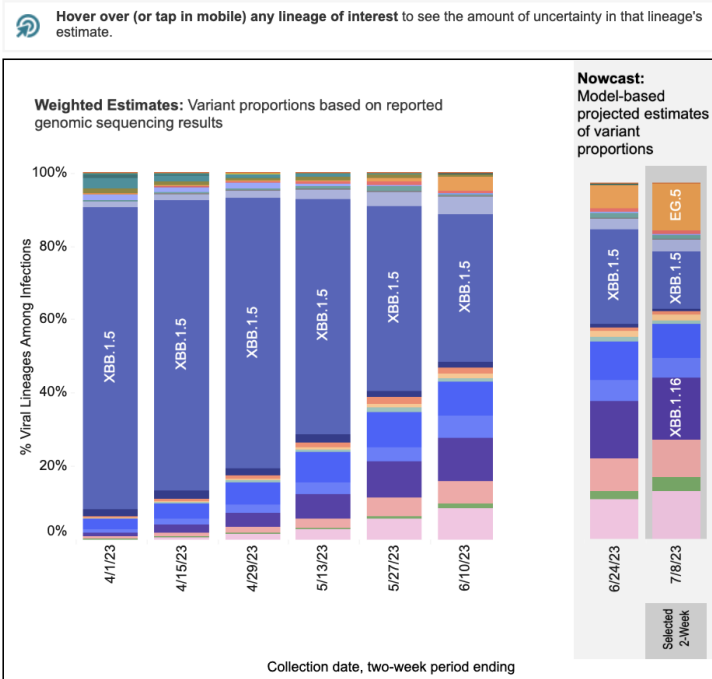
Emerging variants have potential to continue to alter the future trajectories of pandemic and have implications for future control

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



Weighted and Nowcast Estimates in United States for 2-Week Periods in 3/19/2023 – 7/8/2023

Nowcast Estimates in United States for 6/25/2023 – 7/8/2023



USA			
WHO label	Lineage #	%Total	95%PI
Omicron	XBB.2.3	13.4%	11.3-15.8%
	XBB.1.9.2	5.6%	4.0-7.7%
	XBB.1.9.1	9.4%	8.1-10.9%
	XBB.1.5.68	1.0%	0.6-1.9%
	XBB.1.5.59	1.6%	1.0-2.6%
	XBB.1.5.10	0.8%	0.4-1.5%
	XBB.1.5.1	0.7%	0.5-1.0%
	XBB.1.5	16.1%	13.8-18.6%
	XBB.1.16.6	4.1%	2.0-7.9%
	XBB.1.16.1	10.4%	8.4-12.8%
	XBB.1.16	17.5%	15.2-20.0%
	XBB	3.6%	2.5-5.1%
	FE.1.1	1.3%	0.6-2.7%
	FD.2	0.1%	0.1-0.3%
	EU.1.1	1.1%	0.6-1.7%
	EG.5	13.0%	7.5-21.1%
	CH.1.1	0.2%	0.1-0.4%
	BQ.1.1	0.0%	0.0-0.0%
	BQ.1	0.0%	0.0-0.0%
	BN.1	0.0%	0.0-0.0%
BF.7	0.0%	0.0-0.0%	
BA.5	0.0%	0.0-0.0%	
BA.2.75	0.0%	0.0-0.0%	
BA.2	0.0%	0.0-0.0%	
Other	Other*	0.0%	0.0-0.1%

<https://clades.nextstrain.org>

Omicron Updates*

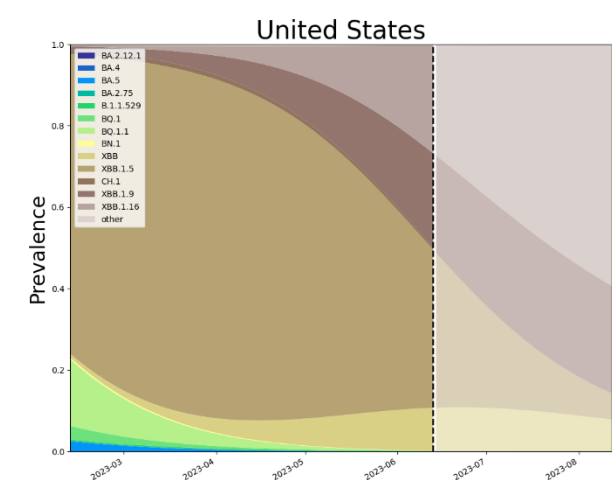
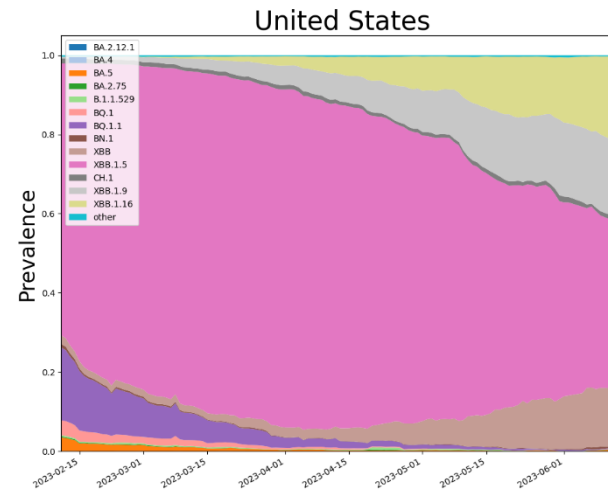
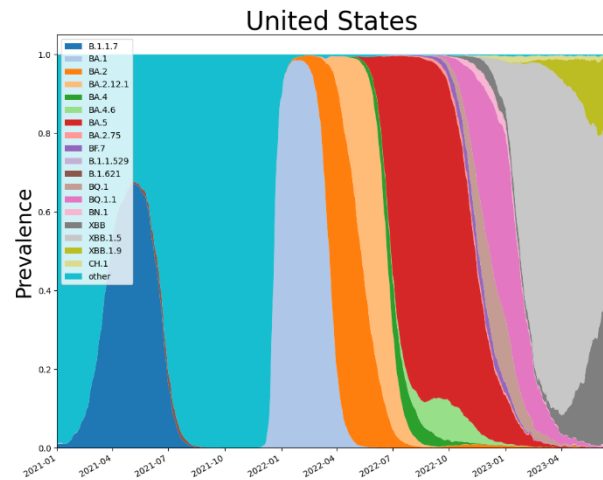
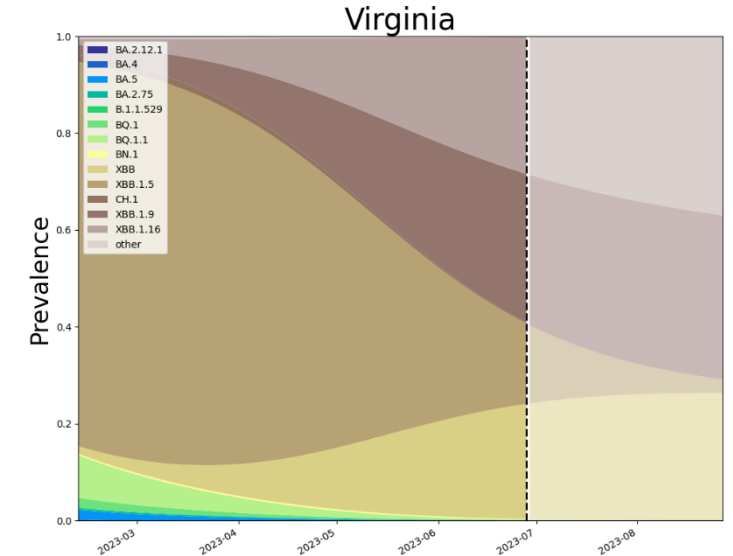
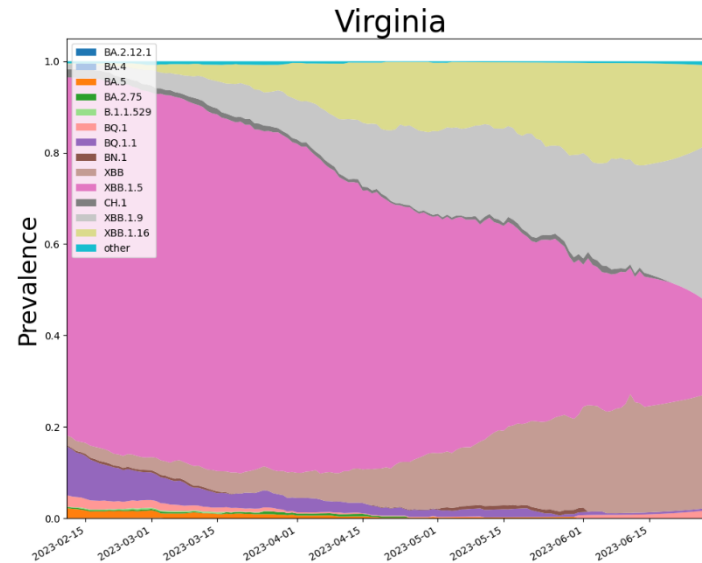
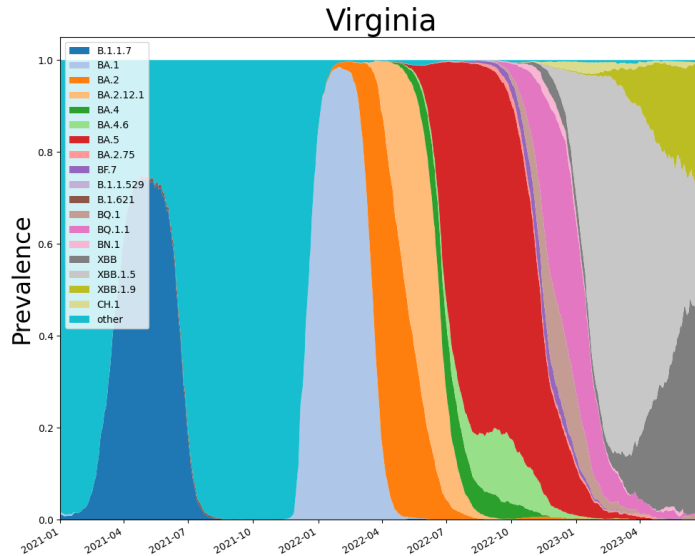
- XBB.1.5.* proportions have fallen to 20%
- XBB.1.16.* has grown to 32%
- XBB.1.9.* remains steady at 15%
- XBB.2.3 continues to grow at 13.4%

*percentages are CDC NowCast Estimates

SARS-CoV2 Omicron Sub-Variants

As detected in whole Genomes in public repositories

VoC Polynomial Fit Projections



Note:
Everything
from dotted
line forward is
a projection.

SARS-CoV2 Omicron Sub-Variants

COV-spectrum

“Editor’s choice”
Variants to watch

Known variants

Which variant would you like to explore?

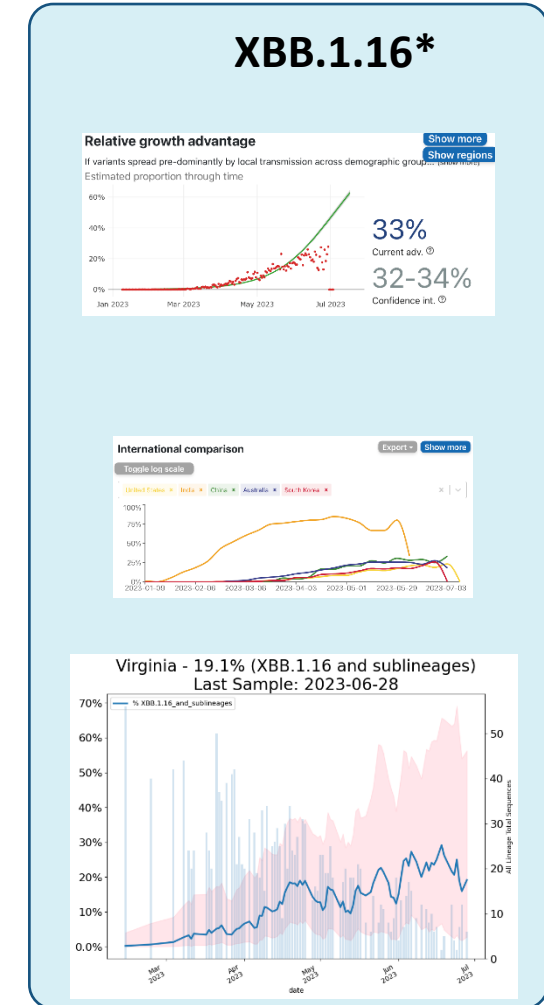
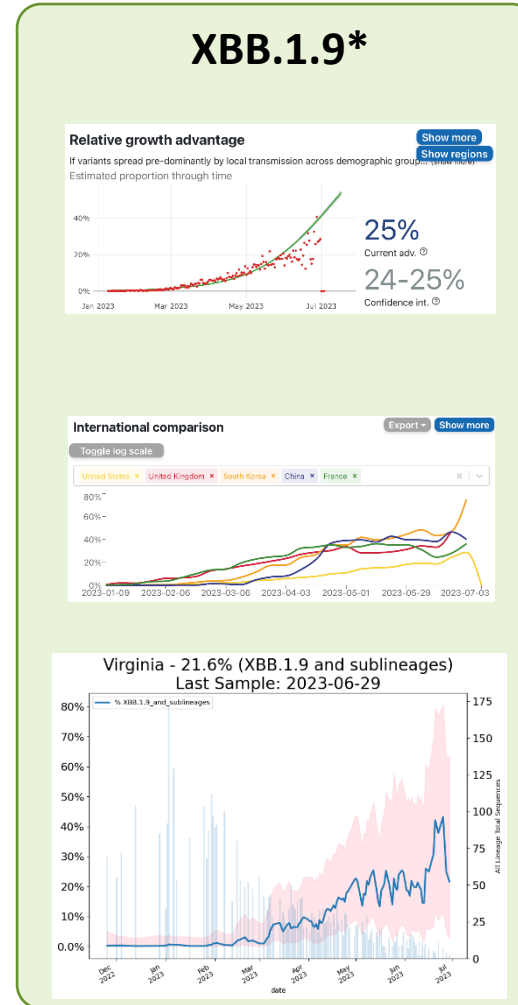
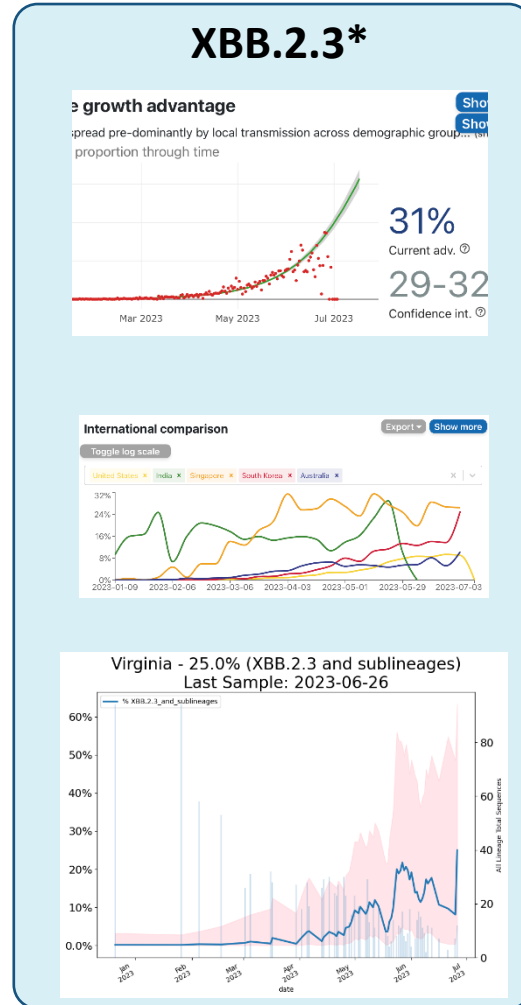
Editor's choice ▼



covSPECTRUM

Enabled by data from 

14-Jul-23

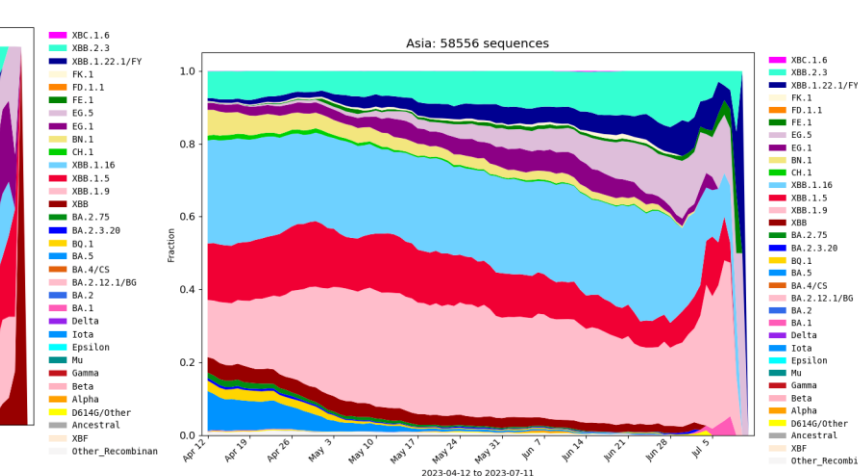
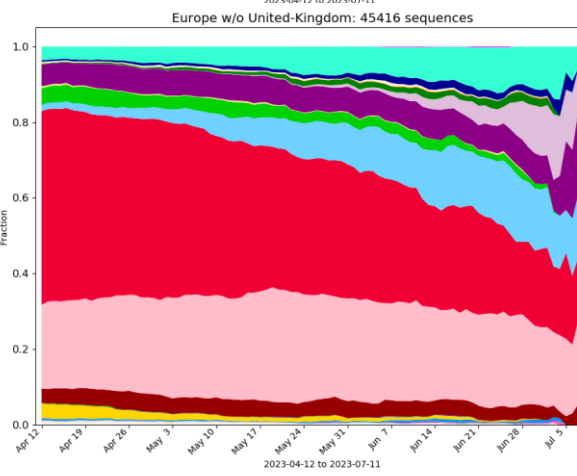
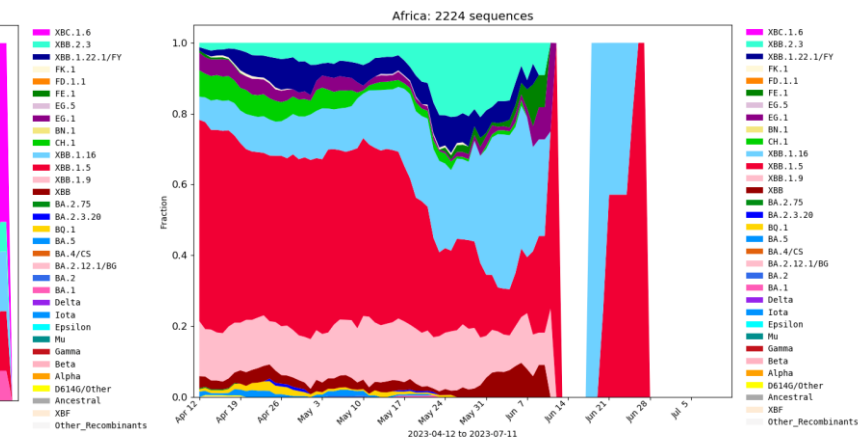
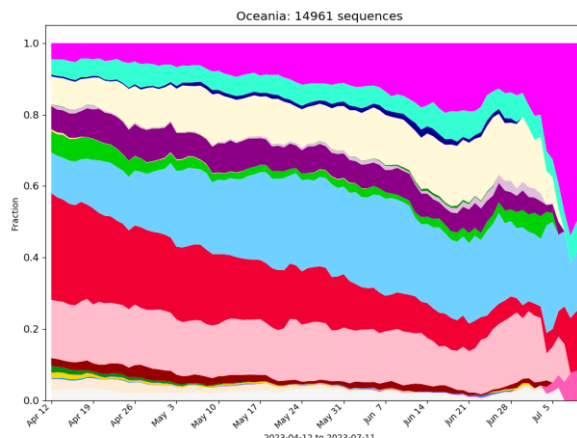
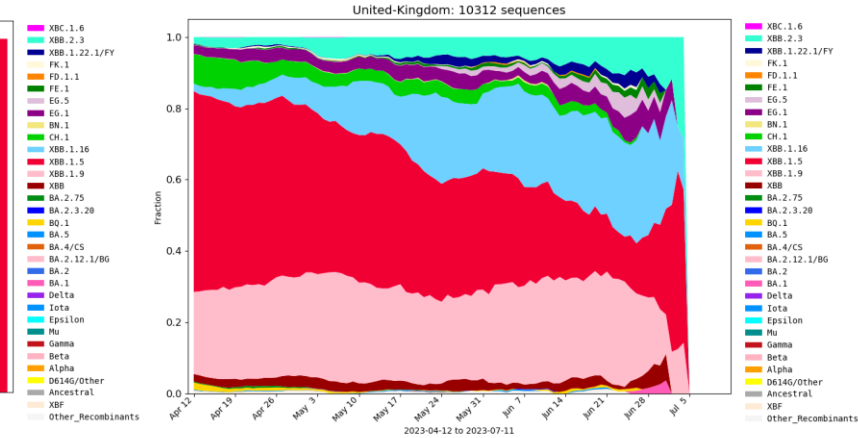
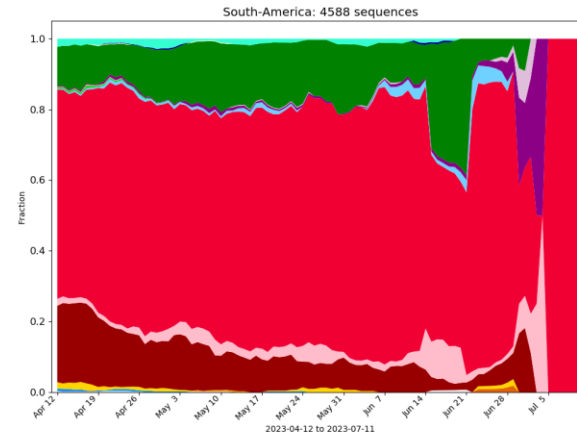
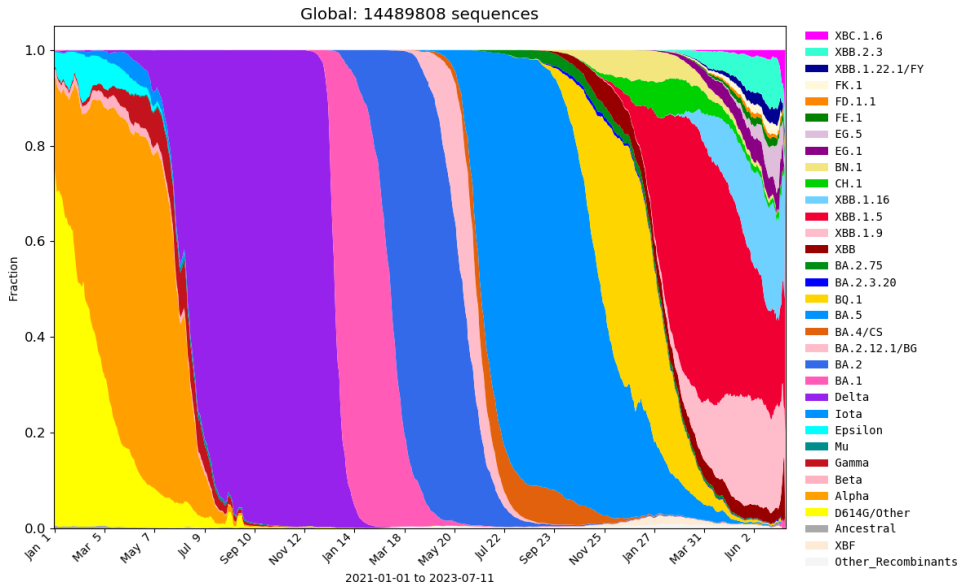


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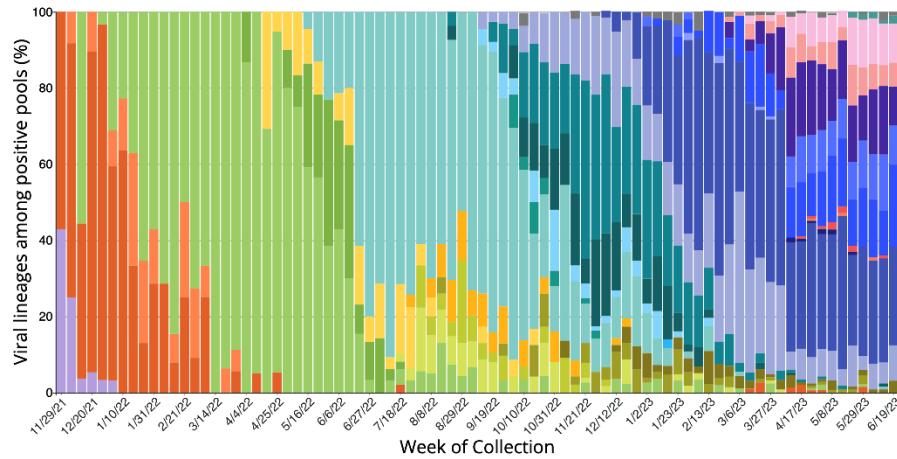
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Global SARS-CoV-2 Variant Status



Variants Detected, by Collection Week

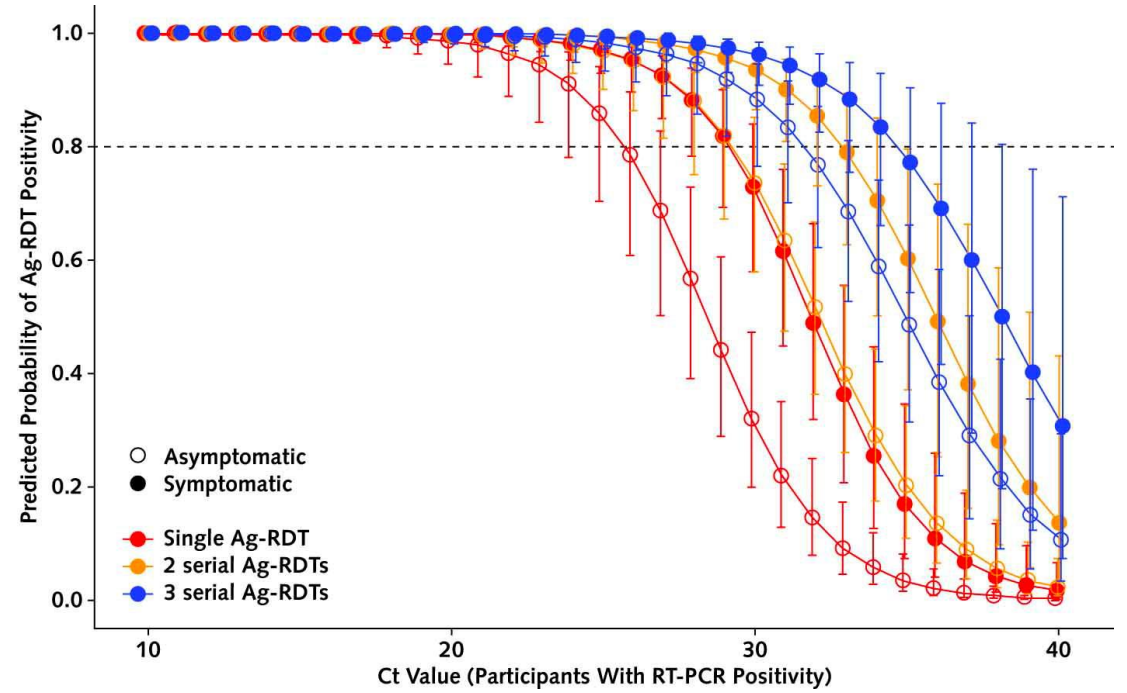


<https://cov.lanl.gov/components/sequence/COV/sparks.comp>

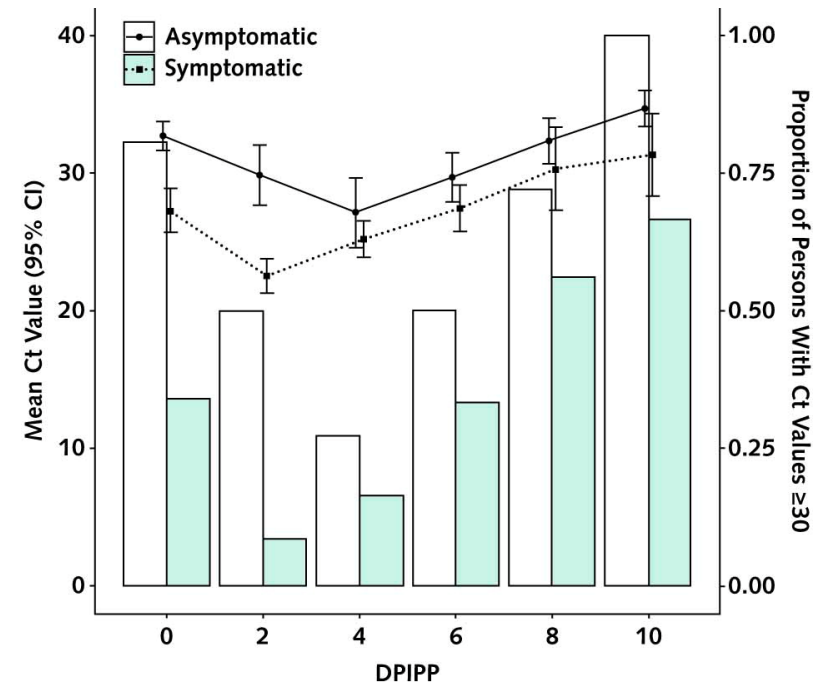
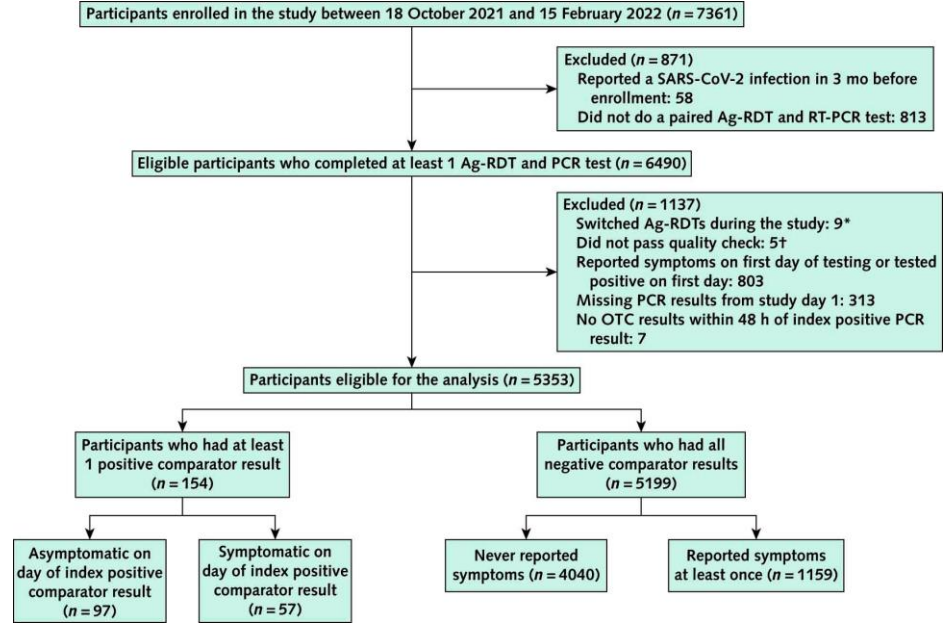
<https://github.com/gerstung-lab/SARS-CoV-2-International> (03/29/23)

Pandemic Pubs (July 12th, 2023)

1. Large prospective cohort study suggests use of at home antigen tests should include repeated testing. Antigen test performance was optimized when asymptomatic participants tested 3 times at 48-hour intervals and when symptomatic participants tested 2 times separated by 48 hours.



This article describes primary findings from a large study designed in coordination with the National Institutes of Health, FDA, and 3 major Ag-RDT manufacturers to evaluate the performance of serial testing using Ag-RDTs for detection of SARS-CoV-2 among asymptomatic persons within the first week of infection. Of 7361 participants in the study, 5353 who were asymptomatic and negative for SARS-CoV-2 on study day 1 were eligible. In total, 154 participants had at least 1 positive RT-PCR result. The analysis was repeated for different days past index PCR positivity (DPIPPs). Serial testing with Ag-RDTs twice 48 hours apart resulted in an aggregated sensitivity of 93.4% (95% CI, 90.4% to 95.9%) among symptomatic participants on DPIPPs 0 to 6. When singleton positive results were excluded, the aggregated sensitivity on DPIPPs 0 to 6 for 2-time serial testing among asymptomatic participants was lower at 62.7% (CI, 57.0% to 70.5%), but it improved to 79.0% (CI, 70.1% to 87.4%) with testing 3 times at 48-hour intervals.

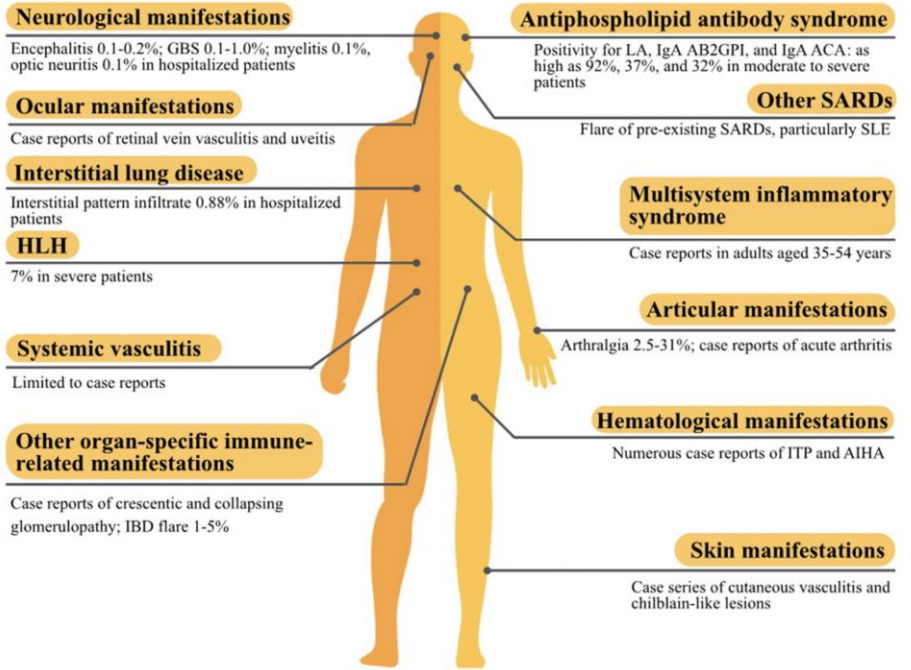


Pandemic Pubs (June 8th, 2023)

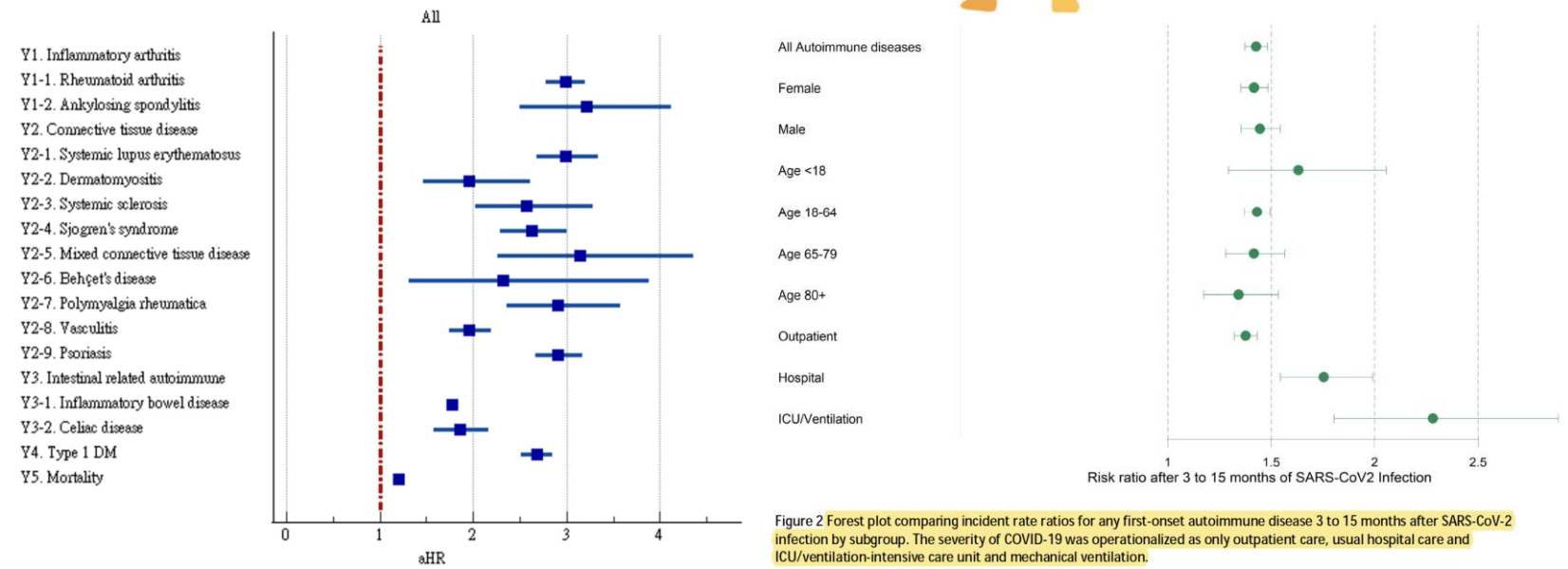
1. Several large cohort studies from three different countries indicate an increased risk (20-30%) for new auto-immune disease following COVID-19 infection. One study shows increased risk based on severity of initial infection.

Study	N with Covid	N Controls No Covid	Increased Risk of New Autoimmune Disease	Citation
US	884,463	2,926,016	19-47%*	Chang R, eClinical Medicine, 9 January 2023
Germany	641,704	1,560,357	43%	Tesch F, MedRxiv, 26 January 2023
UK	458,147	1,818,929	22%	Syed U, MedRxiv 7 October 2022

*range dependent on specific autoimmune condition, adjusted for competing risks, before this adjustment 100-200% increased risk @erictopol



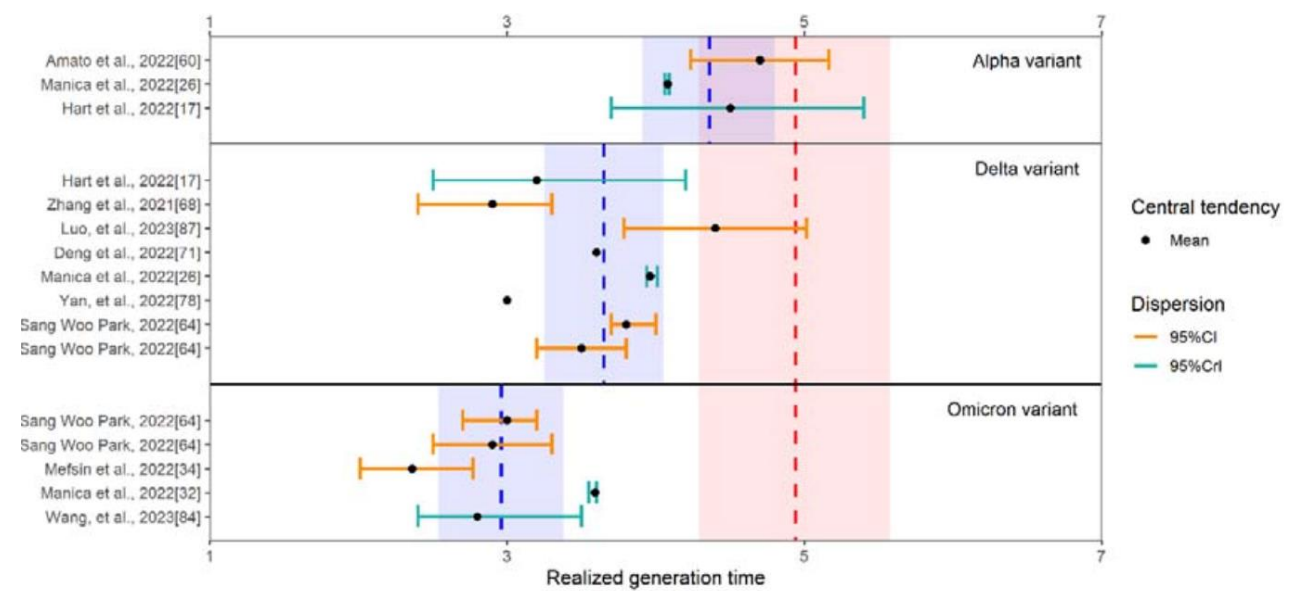
Severe COVID-19 cases have demonstrated a substantial inflammatory response with pro-inflammatory cytokines and chemokines that stimulate pulmonary inflammation. As the burden of COVID-19 cases increases worldwide, so does our understanding of the condition. Owing to worldwide vaccination efforts, mortality due to COVID-19 has been decreasing, but we continue to witness considerable morbidity and increased rates of post-COVID-19 conditions and in particular, new-onset autoimmune and inflammatory diseases in individuals who have had COVID-19. The range and incidence of these post-COVID-19 disorders have now been highlighted in two large retrospective cohort studies.



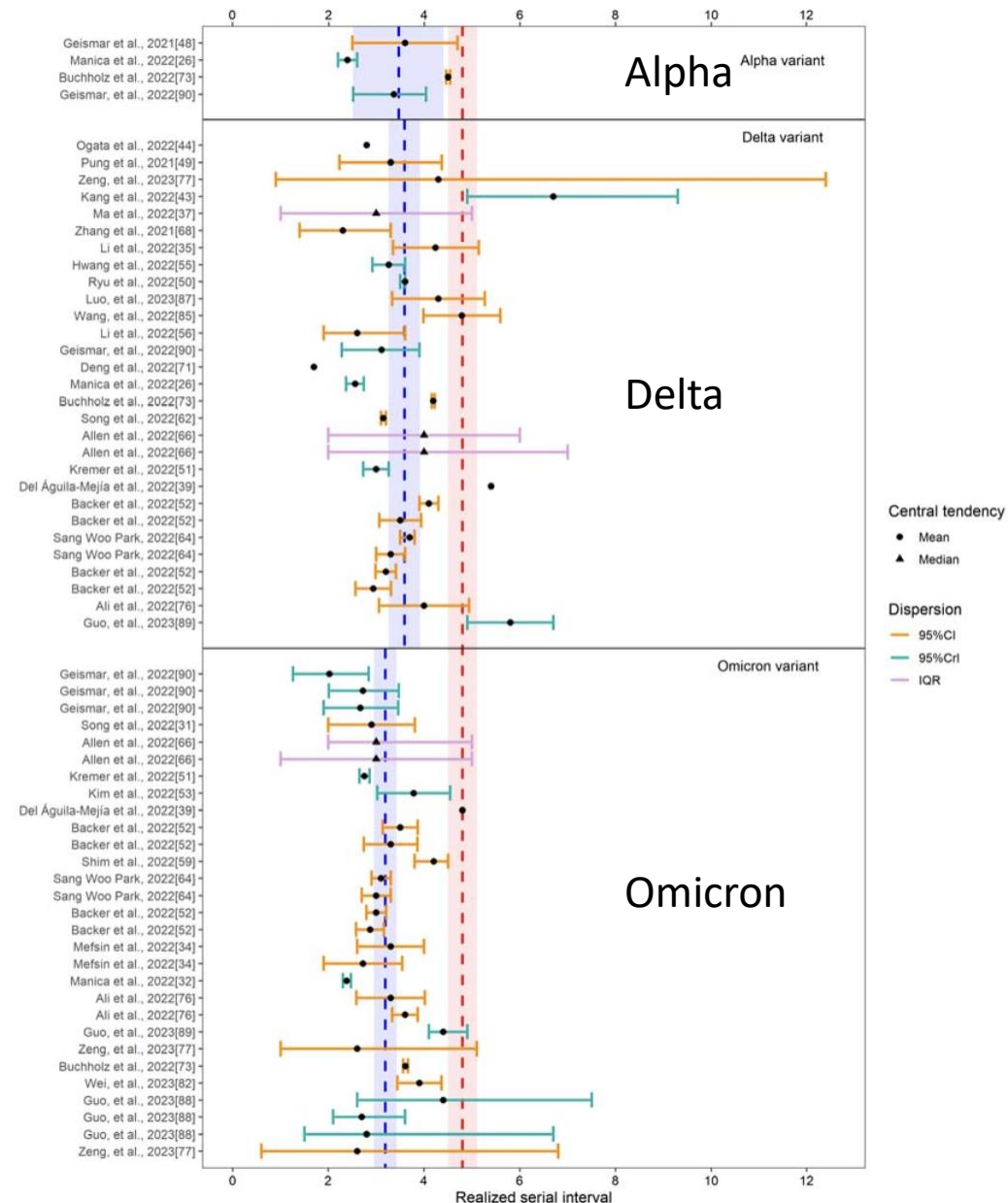
[Nature Reviews Rheumatology](https://www.nature.com/articles/s41584-023-00964-y)
<https://www.nature.com/articles/s41584-023-00964-y>
 via [Eric Topol](#)

Pandemic Pubs (May 25th, 2023)

1. Meta-analysis derived pool of many household or contact tracing studies with well observed case series to further quantify the shortening of incubation and serial interval (time between infections) over time during the pandemic and across variants. Omicron's serial interval is shorter than Delta which was similar to Alpha.



Omicron had the shortest pooled estimates for the incubation period (3.63 days, 95%CI: 3.25-4.02 days), serial interval (3.19 days, 95%CI: 2.95-3.43 days), and realized generation time (2.96 days, 95%CI: 2.54-3.38 days) whereas the ancestral lineage had the highest pooled estimates for each of them. We found considerable heterogeneities ($I^2 > 80\%$) when pooling the estimates across different virus lineages, indicating potential unmeasured confounding from population factors (e.g., social behavior, deployed interventions).



[MedRxiv](https://www.medrxiv.org/content/10.1101/2023.05.19.23290208v1)

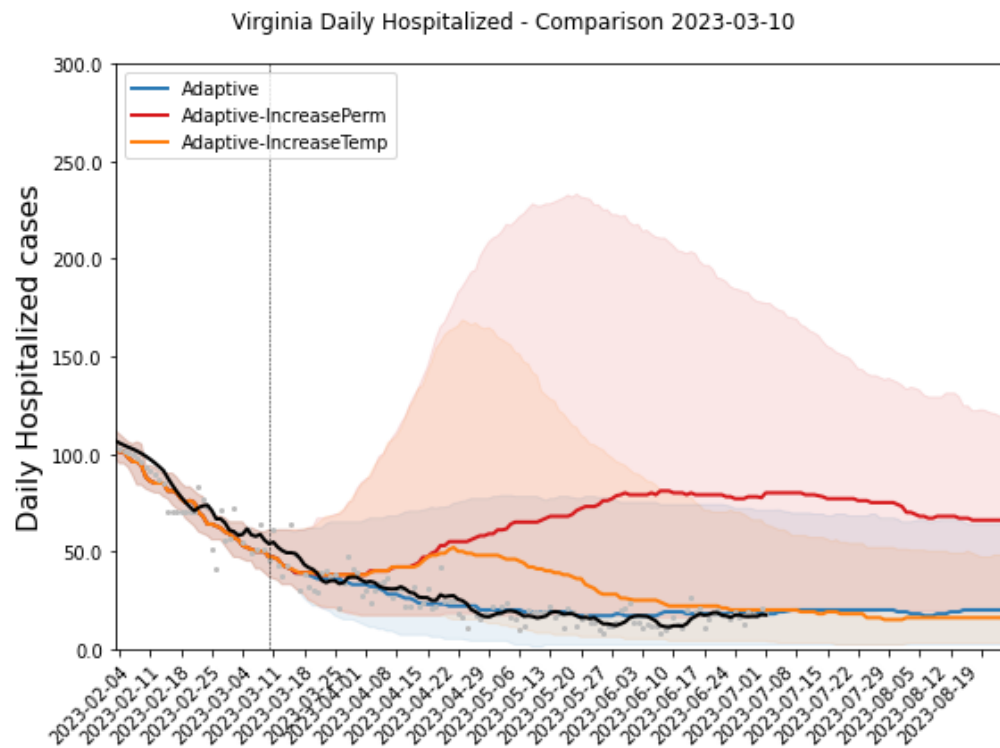
<https://www.medrxiv.org/content/10.1101/2023.05.19.23290208v1>

Model Results

Past projections – Hospitalizations

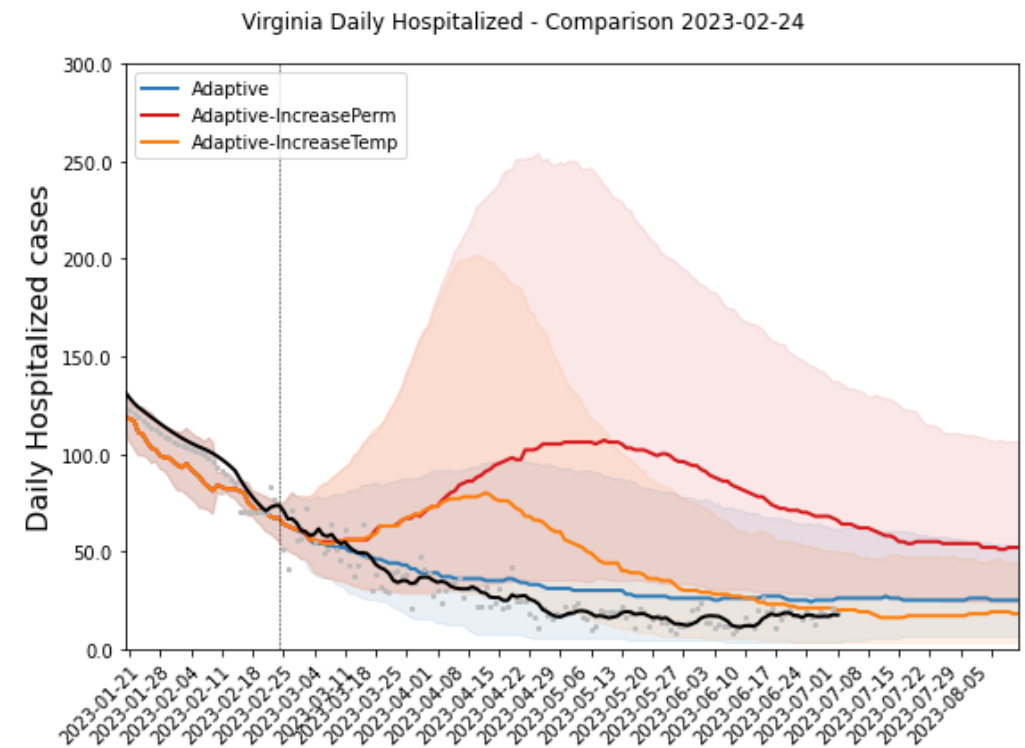
- Previous projections remain on target with recent observations
- Past 14 weeks have stayed steady and indicate possibility of slight upward trend in coming weeks

Previous round – 14 weeks ago



14-Jul-23

Previous round – 16 weeks ago



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National Modeling Hub Updates

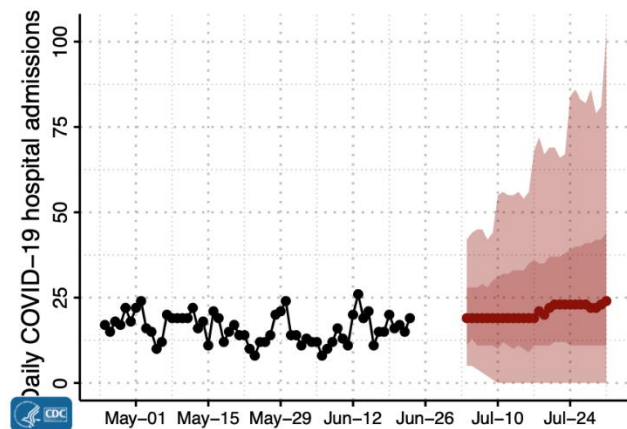
Current COVID-19 Hospitalization Forecast

Statistical models for submitting to CDC COVID Forecasting Hub

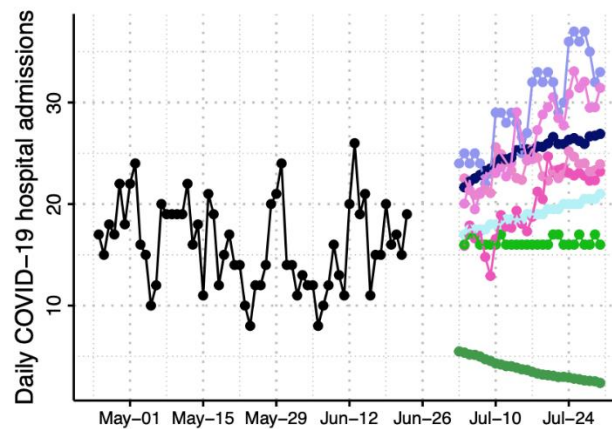
- Uses a variety of statistical and ML approaches to forecast weekly hospital admissions for the next 4 weeks for all states in the US

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

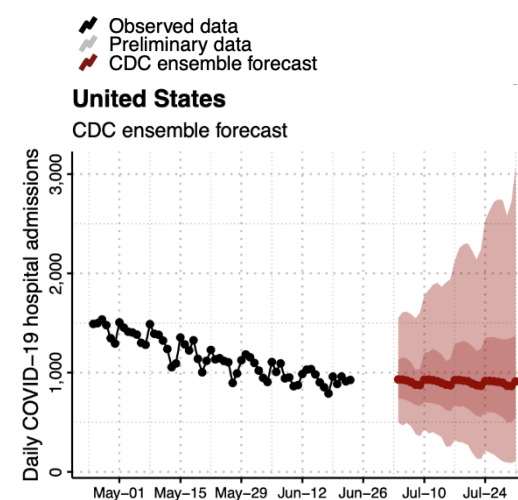
Virginia
CDC ensemble forecast



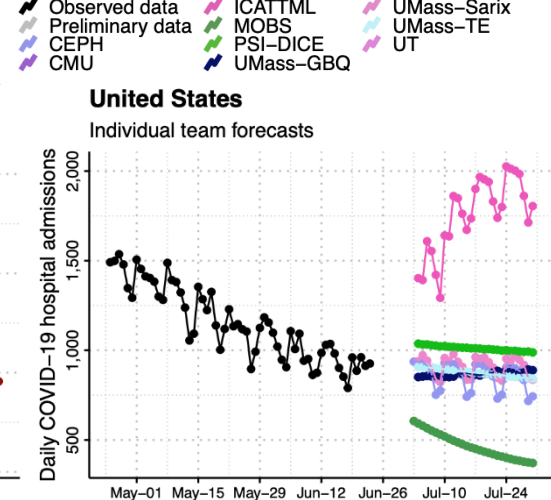
Virginia
Individual team forecasts



United States
CDC ensemble forecast



United States
Individual team forecasts



- Observed data
- Preliminary data
- CEPH
- CMU
- ICATML
- MOBS
- PSI-DICE
- UMass-GBQ
- UMass-Sarix
- UMass-TE
- UT

Scenario Modeling Hub – COVID-19 (Round 17)

Collaboration of multiple academic teams to provide national and state-by-state level projections for 6 aligned scenarios

<https://covid19scenariomodelinghub.org/viz.html>

- Preliminary Results
- Round Designed to explore different seasonal vaccination levels and the impact of Immune Escape

Scenario Dimensions:

Immune Escape (IE):

Slower IE (20%/yr) vs.
Faster IE (50%/yr)

Vaccination levels:

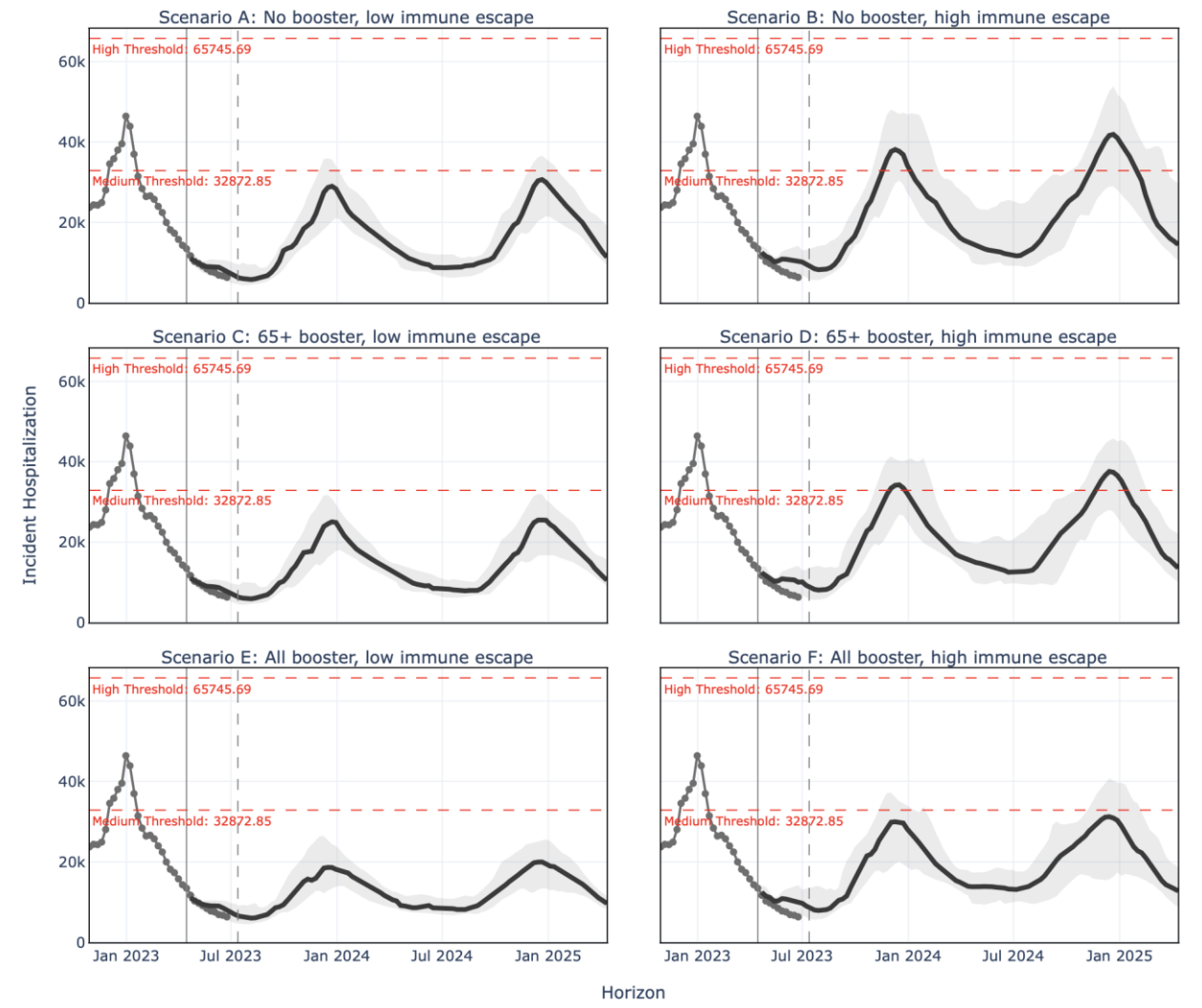
None vs.
Vulnerable and 65 + vs.
Broader population of eligible

	Low immune escape <ul style="list-style-type: none"> • Immune escape occurs at a constant rate of 20% per year 	High immune escape <ul style="list-style-type: none"> • Immune escape occurs at a constant rate of 50% per year
No vaccine recommendation <ul style="list-style-type: none"> • Uptake negligible or continues at very slow levels based on existing 2022 booster trends 	Scenario A	Scenario B
Reformulated annual vaccination recommended for 65+ and immunocompromised <ul style="list-style-type: none"> • Reformulated vaccine has 65% VE against variants circulating on June 15 • Vaccine becomes available September 1 • Uptake in 65+ same as first booster dose recommended in September 2021 • Uptake in individuals under 65 negligible or continues to trickle based on 2022 booster trends 	Scenario C	Scenario D
Reformulated annual vaccination recommended for all currently eligible groups <ul style="list-style-type: none"> • Reformulated vaccine has 65% VE against variants circulating on June 15 • Vaccine becomes available September 1 • 65+ uptake same as first booster dose recommended in September 2021 • Coverage in individuals under 65+ saturates at levels of the 2021 booster (approximately 34% nationally) 	Scenario E	Scenario F

SMH – COVID-19 (Round 17) - Results

- Peak timing and size can oscillate over the longer term
- These scenarios are very unlikely to remain stable over longer term, nonetheless, some of these patterns may remain
- Scenarios with faster immune escape (dashed) converge more quickly than the slower immune escape

Projected Incident Hospitalization by Epidemiological Week and by Scenario for Round 17
 (- Start Projection Epiweek; -- Current Date)

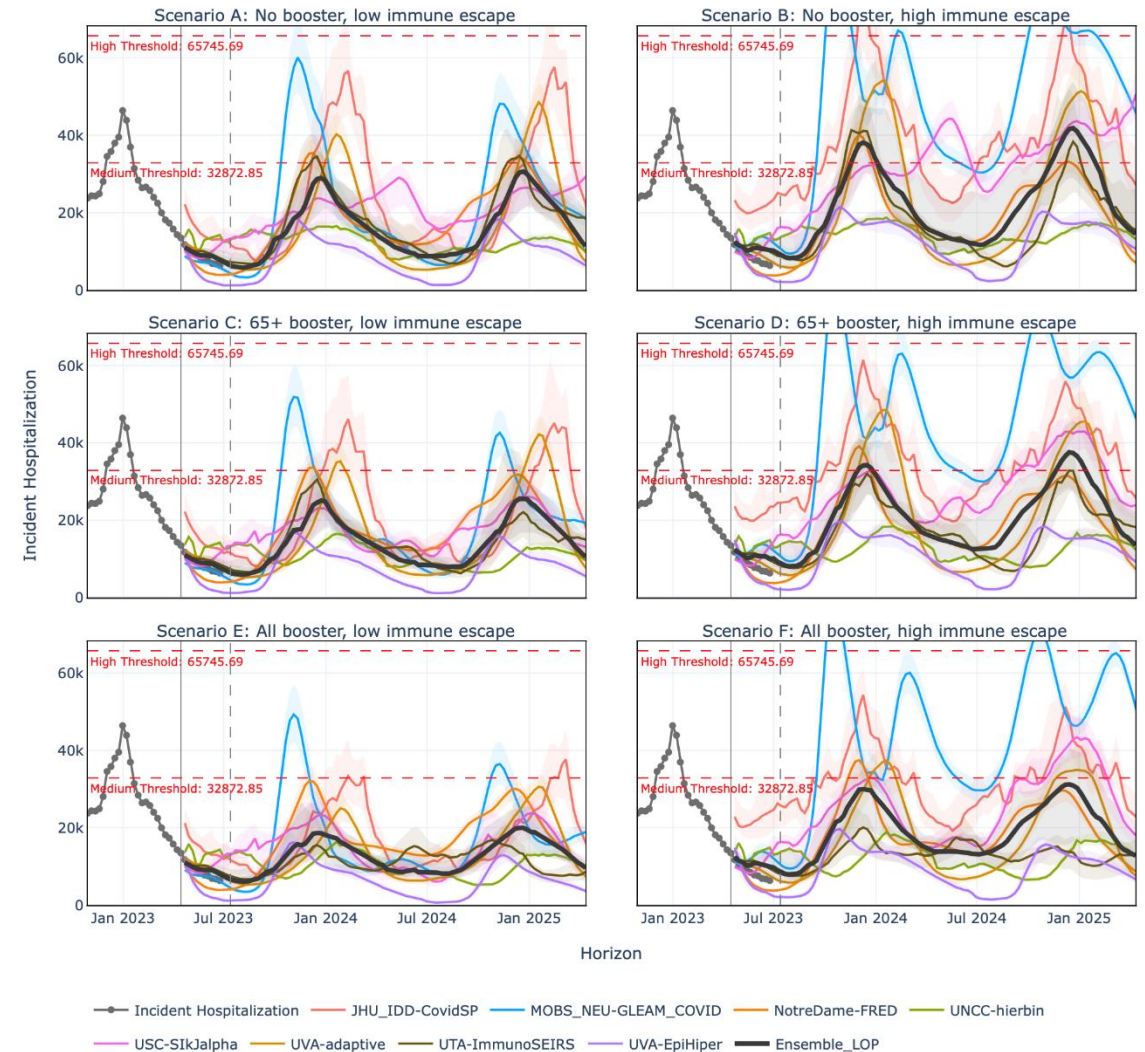


Slower Immune Escape (20%) Faster Immune Escape (20%)

SMH – COVID-19 (Round 17) - Results

- Faster Immune Escape leads to higher estimated seasonal peaks
- Wider booster coverage (all age groups) leads to lower peaks and overall reduction in hospitalizations and deaths
- Peak timing and size can oscillate over the longer term
- These scenarios are very unlikely to remain stable over longer term, nonetheless, some of these patterns may remain
- Not all models follow same trajectory, though the Ensemble has performed well in the past (when scenarios match what eventually happens)

Projected Incident Hospitalization by Epidemiological Week and by Scenario for Round 17
 (- Start Projection Epiweek; -- Current Date)

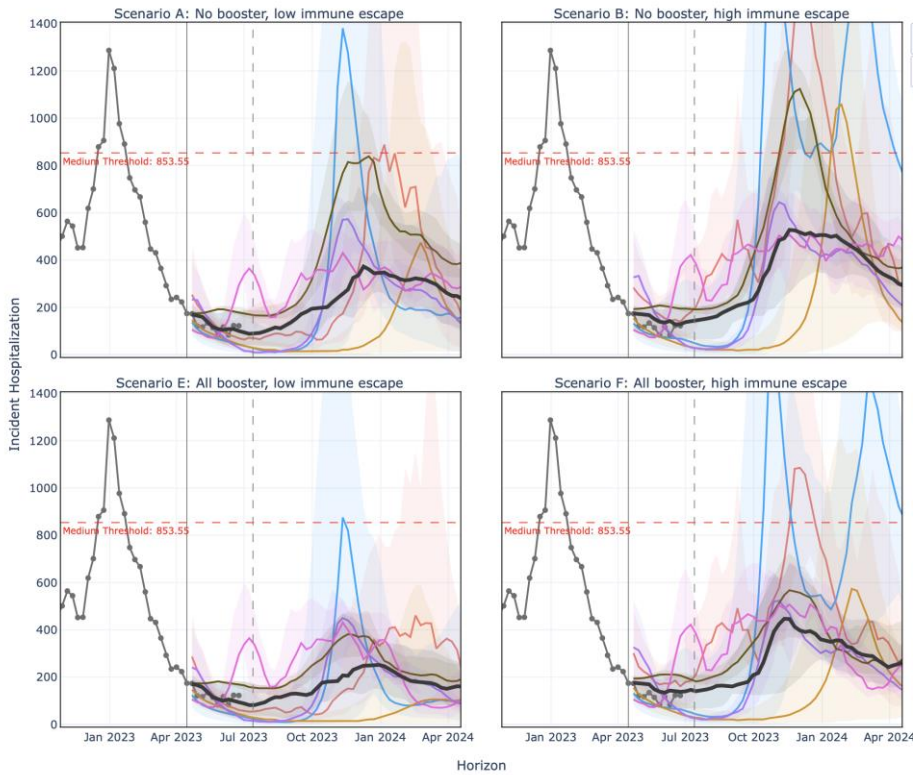


Slower Immune Escape (20%) Faster Immune Escape (20%)

SMH – COVID-19 (Round 17) – Virginia Results

- To date, immune escape evolution has been slow. Booster campaign size remains unknown

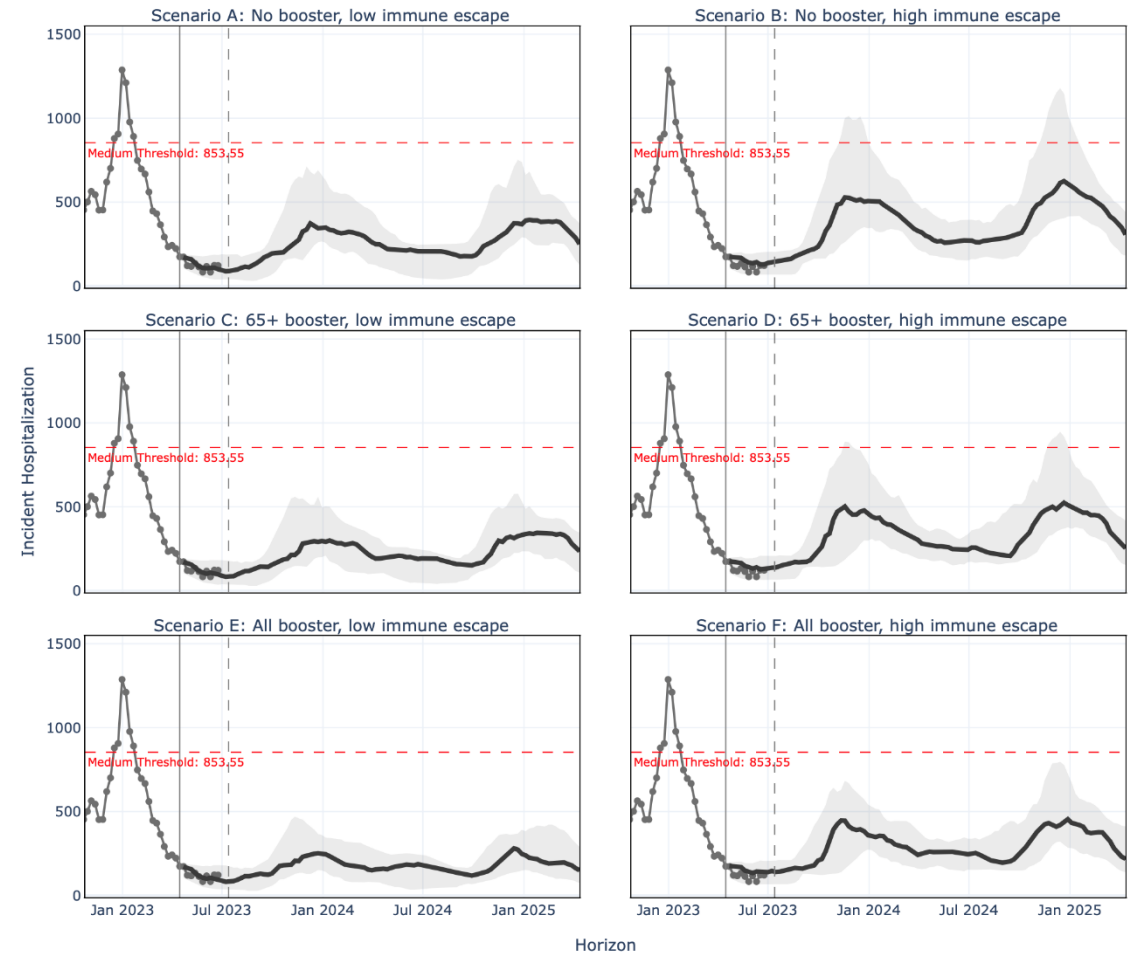
Projected Incident Hospitalization by Epidemiological Week and by Scenario for Round 17
(- Start Projection Epiweek; -- Current Date)



Incident Hospitalization JHU_IDD-CovidSP MOBS_NEU-GLEAM_COVID NotreDame-FRED UNCC-hierbin
 UVA-adaptive UVA-EpiHiper UTA-ImmunoSEIRS USC-SIKAlpha Ensemble_LOP

14-Jul-23

Projected Incident Hospitalization by Epidemiological Week and by Scenario for Round 17
(- Start Projection Epiweek; -- Current Date)



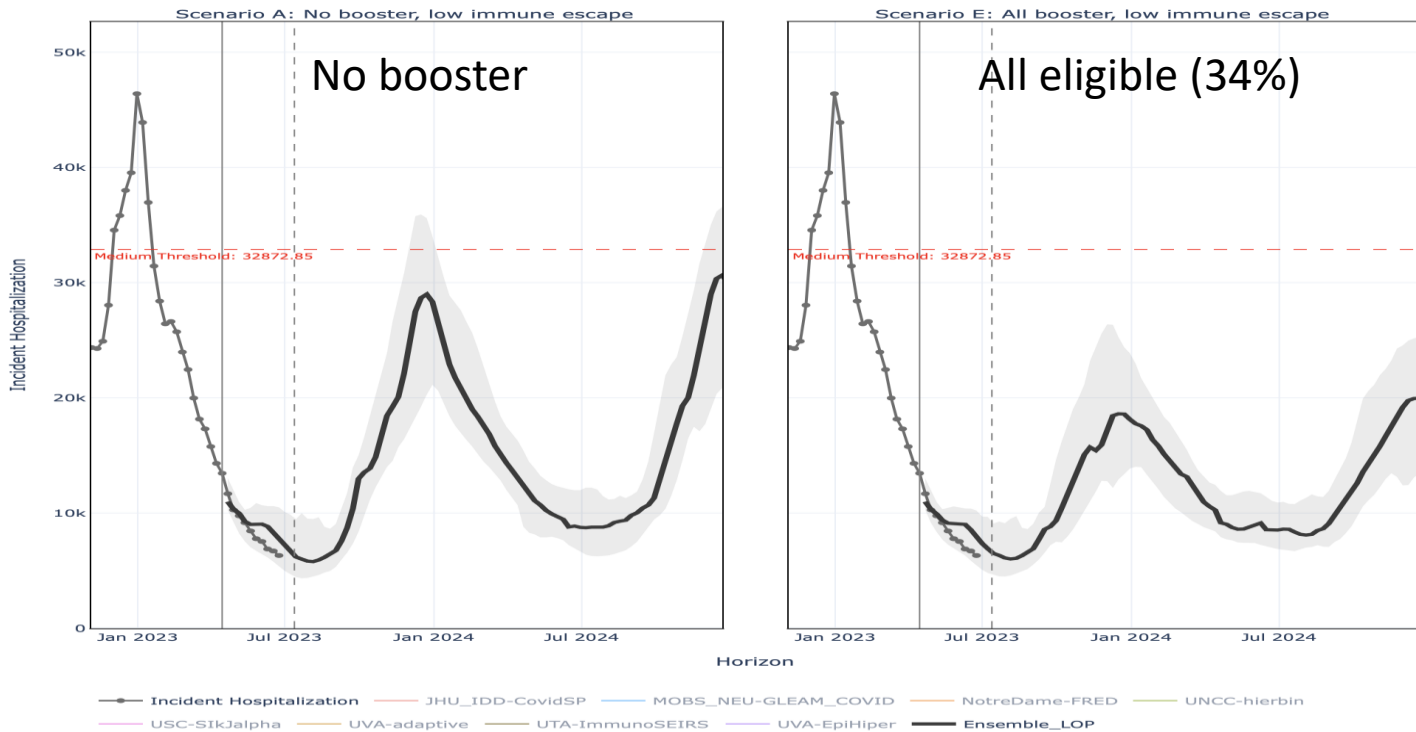
Slower Immune Escape (20%) Faster Immune Escape (20%)

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SMH – COVID-19 (Round 17) – Results – Booster Impact

- Comparing A and E (low immune escape, no booster vs. all eligible for booster)
 - Total booster coverage similar to last booster campaign (34% national coverage)
- Significant reductions in peak sizes

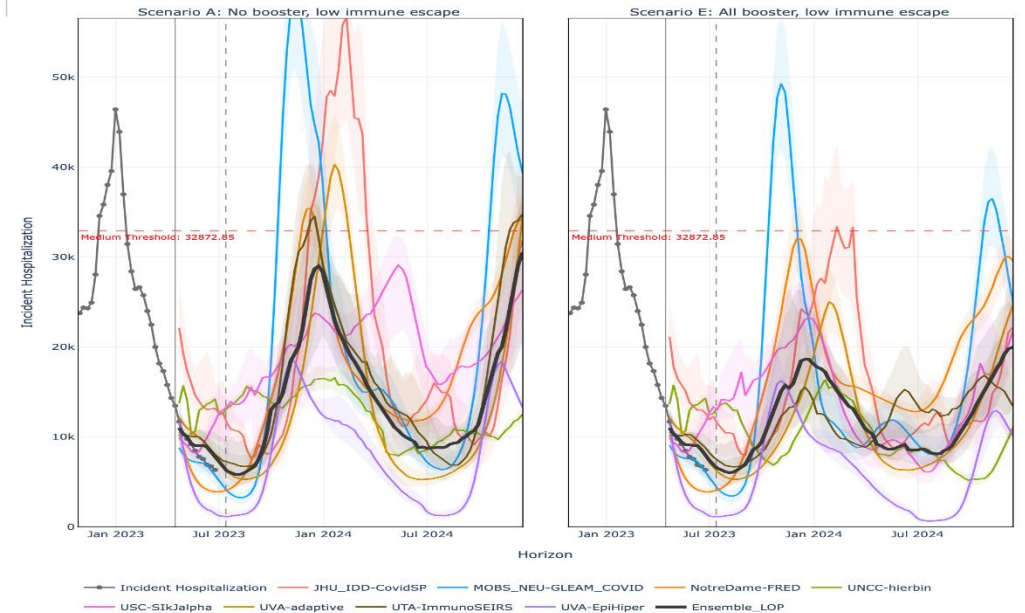
Projected Incident Hospitalization by Epidemiological Week and by Scenario for Round 17
 (- Start Projection Epiweek; - Current Date)



14-Jul-23

Ensemble Only

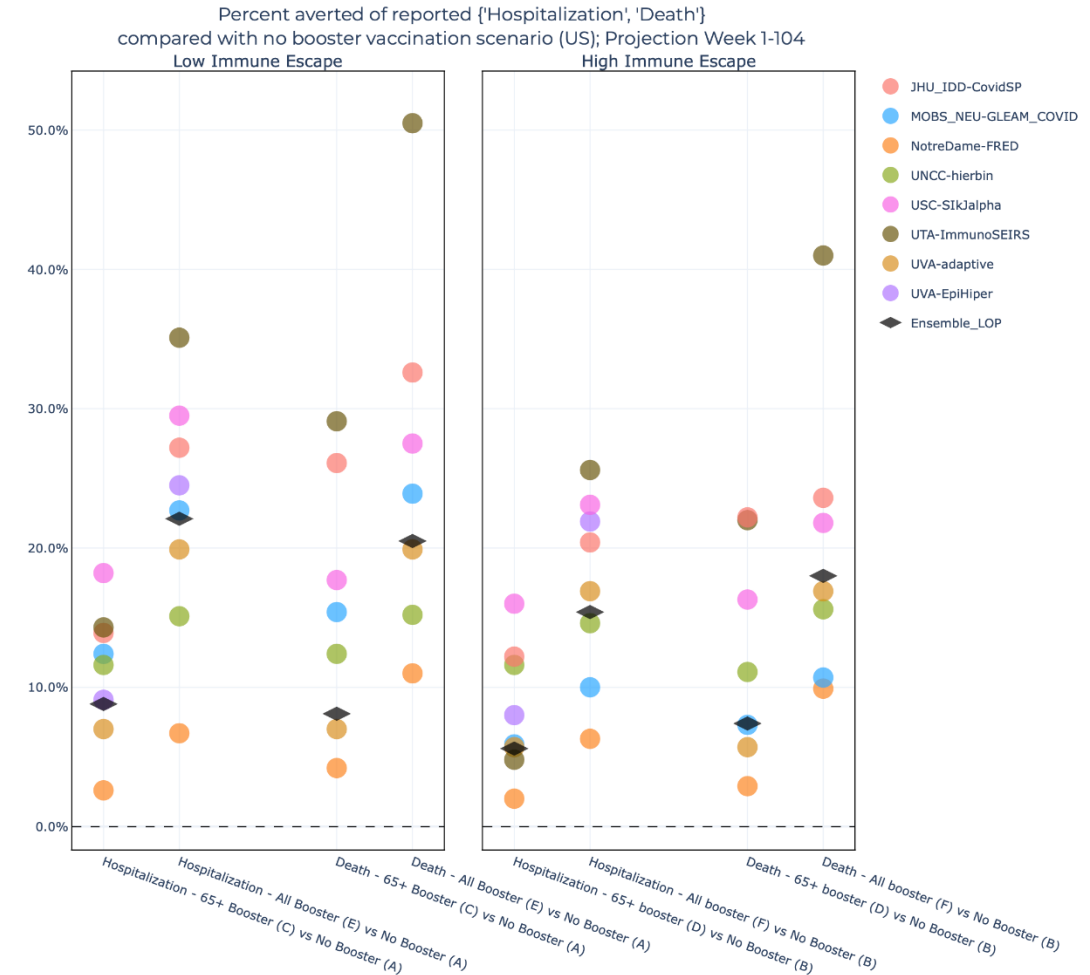
Projected Incident Hospitalization by Epidemiological Week and by Scenario for Round 17
 (- Start Projection Epiweek; - Current Date)



All Model Variability

SMH – COVID-19 (Round 17) – Results – Booster Impact

- Models estimate potential reduction in hospitalizations ranging from 35% - 15% for a whole population campaign and 8% - 18% for a 65+ only campaign
- Reductions in deaths are higher with ensemble estimates of 22% reduction for whole population and 18% reduction for 65+
- Reductions are smaller for the high immune escape scenarios



SPHINX Project Update

Strengthening **P**ublic **H**ealth **I**nformatics using **N**e**X**t-generation tools

CSTE OUTBREAK TOOLS PROJECT

- Project started in February 2023
- Objective: Pilot test, evaluate, and deploy analytic tools with identified partners from STLT health departments



Funding Opportunity Announcement:
Development of forecast, analytic, and visualization tools to improve outbreak response and support public health decision-making

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Ajay
Sanjeevan



Aniruddha
Adiga



Benjamin
Hurt



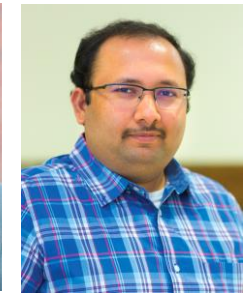
Bryan Lewis



Gursharn
Kaur



Madhav
Marathe



Srin
Venkatramanan



VDH VIRGINIA DEPARTMENT OF HEALTH
Foresight and Analytics,
Office of Emergency Management
BIOCOMPLEXITY INSTITUTE



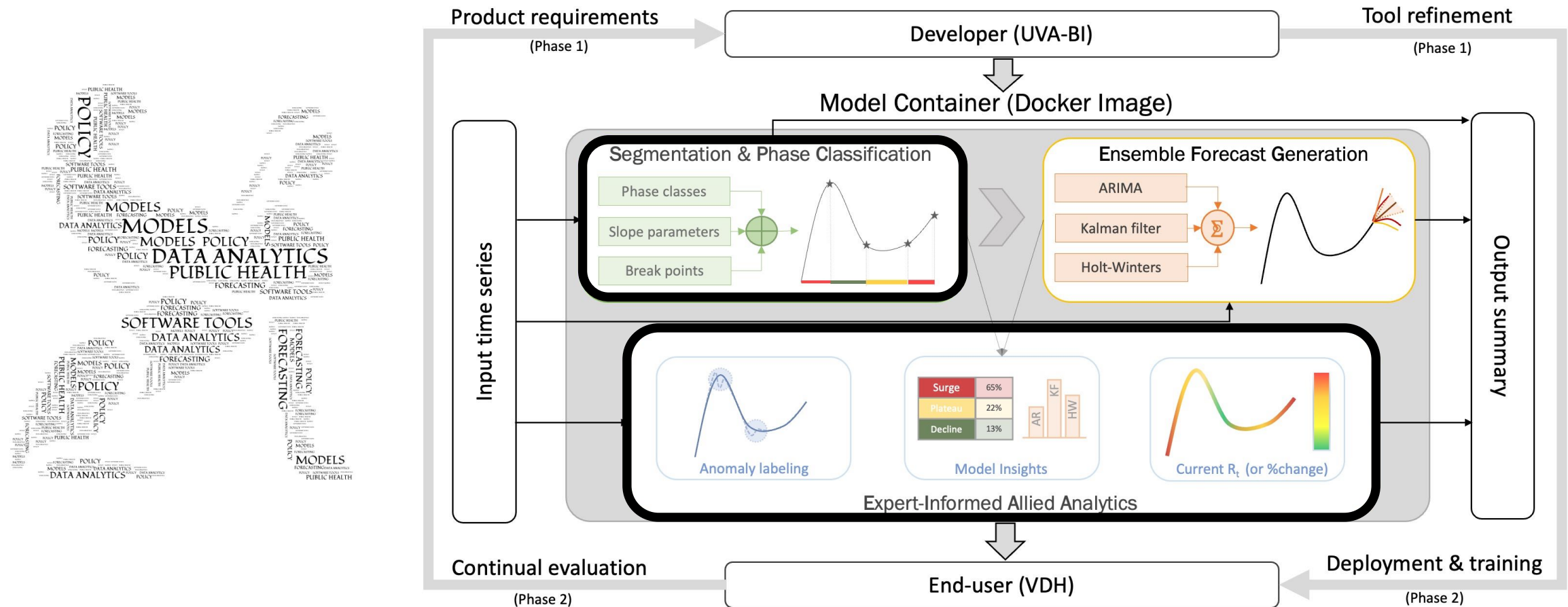
Justin Crow



Alex Telionis

PROPOSED FRAMEWORK

Strengthening **P**ublic **H**ealth **I**nformatics using **N**eXt-generation tools





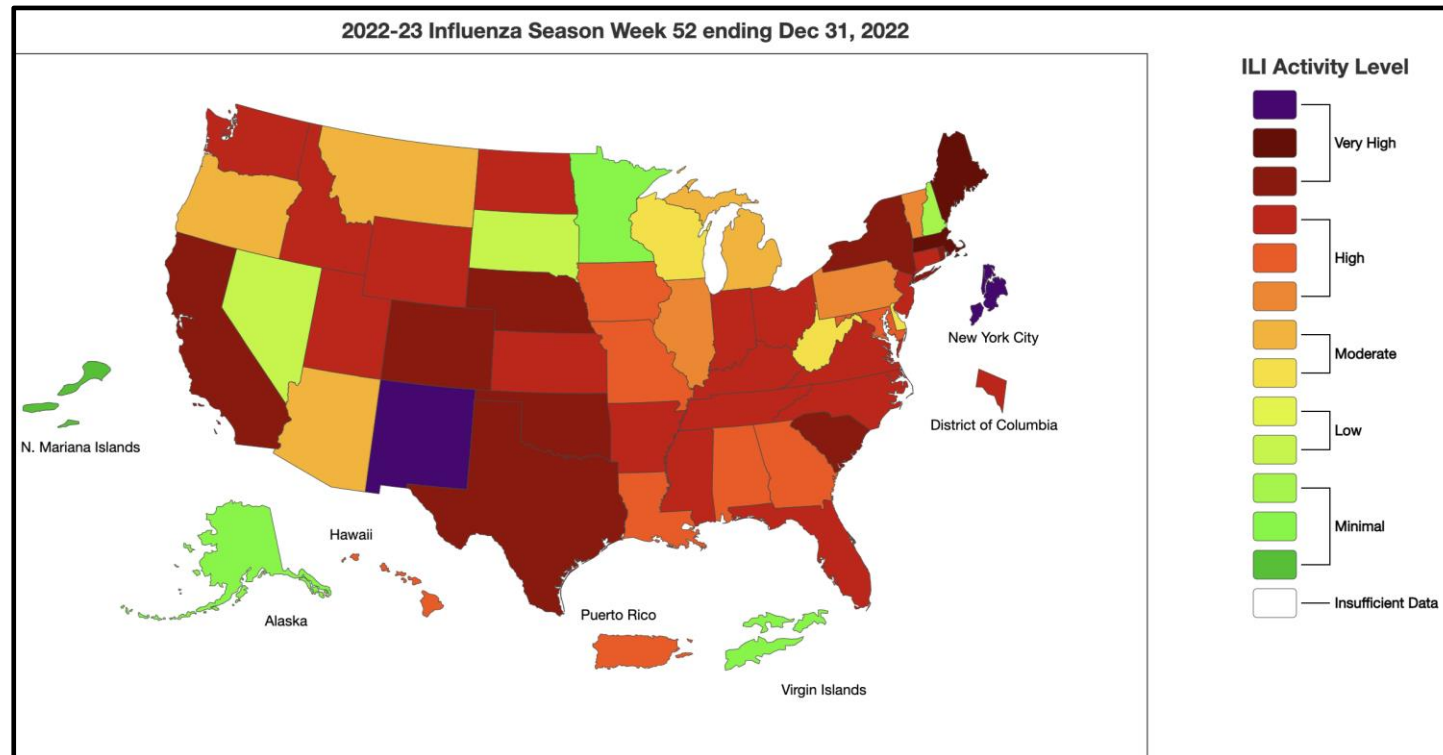
CATEGORICAL INDICATORS



CATEGORICAL INDICATORS FOR EPIDEMICS

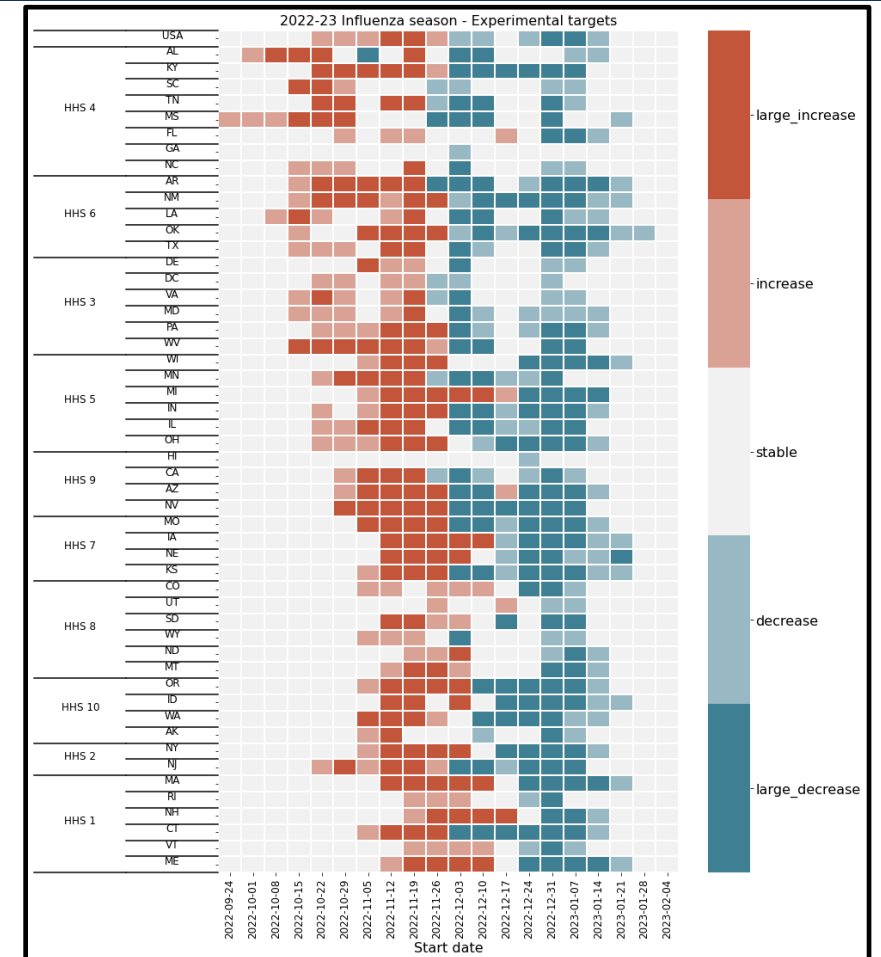
- What do we mean by categorical indicators?
 - Indicators of current level of activity (e.g., **High**, **Medium**, **Low**)
 - Indicators of current trend in the activity (e.g., **Surging**, Plateau, **Declining**)
 - Could be based on the raw time series or other derived quantities (e.g., R_t)
- Why categorize?
 - Useful summary of epidemic activity for situation assessment and prognosis
 - Valuable for decision makers as well as public communication
- Challenges
 - Various definitions and lack of standardization
 - Sensitivity to anomalies and dynamic range
- Opportunities
 - Correlating across multiple signals
 - Aggregating across scales

EXAMPLES FROM INFLUENZA SURVEILLANCE



ILINet State Activity Indicator Map

Source: <https://gis.cdc.gov/grasp/fluview/main.html>

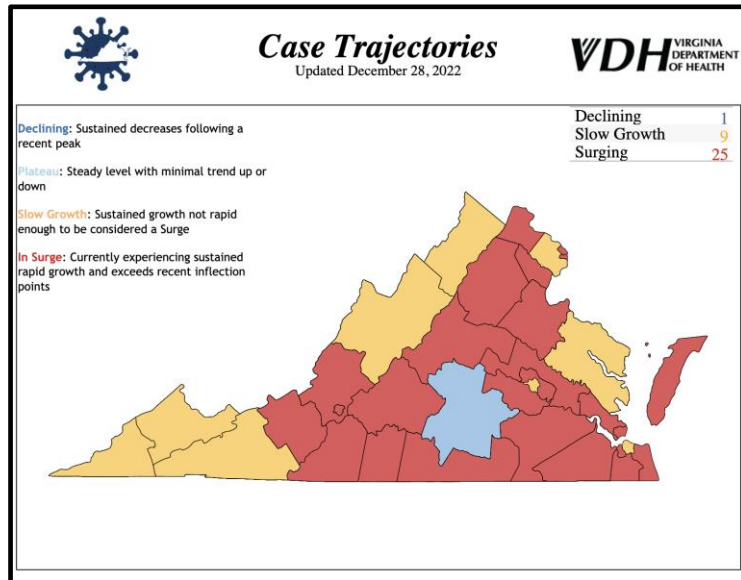


HHS hospitalizations trend indicators (FluSight 2022-23)

<https://github.com/cdcepi/Flusight-forecast-data/tree/master/data-experimental>

EXAMPLE FROM COVID-19: CASE SURVEILLANCE

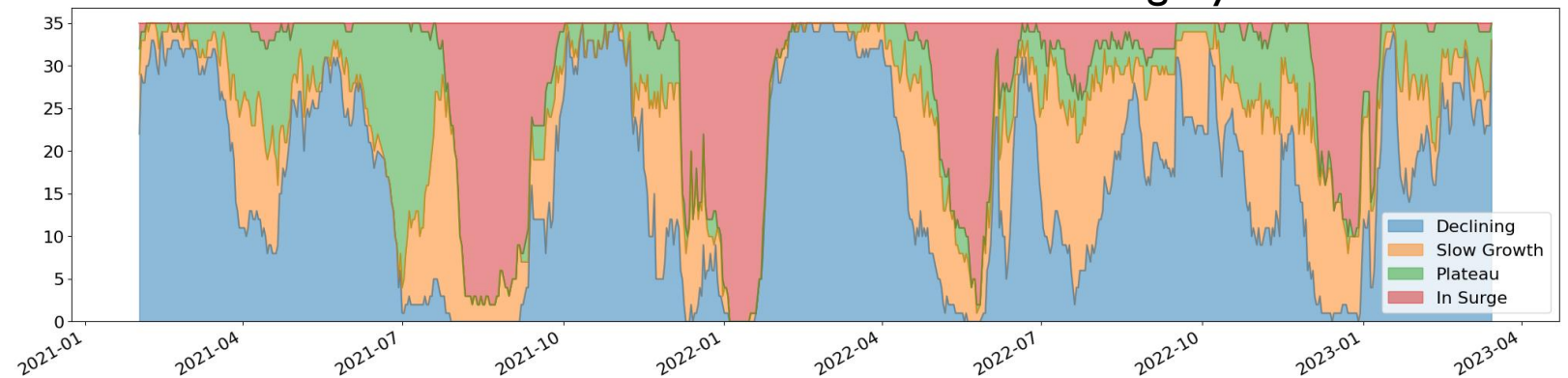
Customized slope thresholds for category definitions



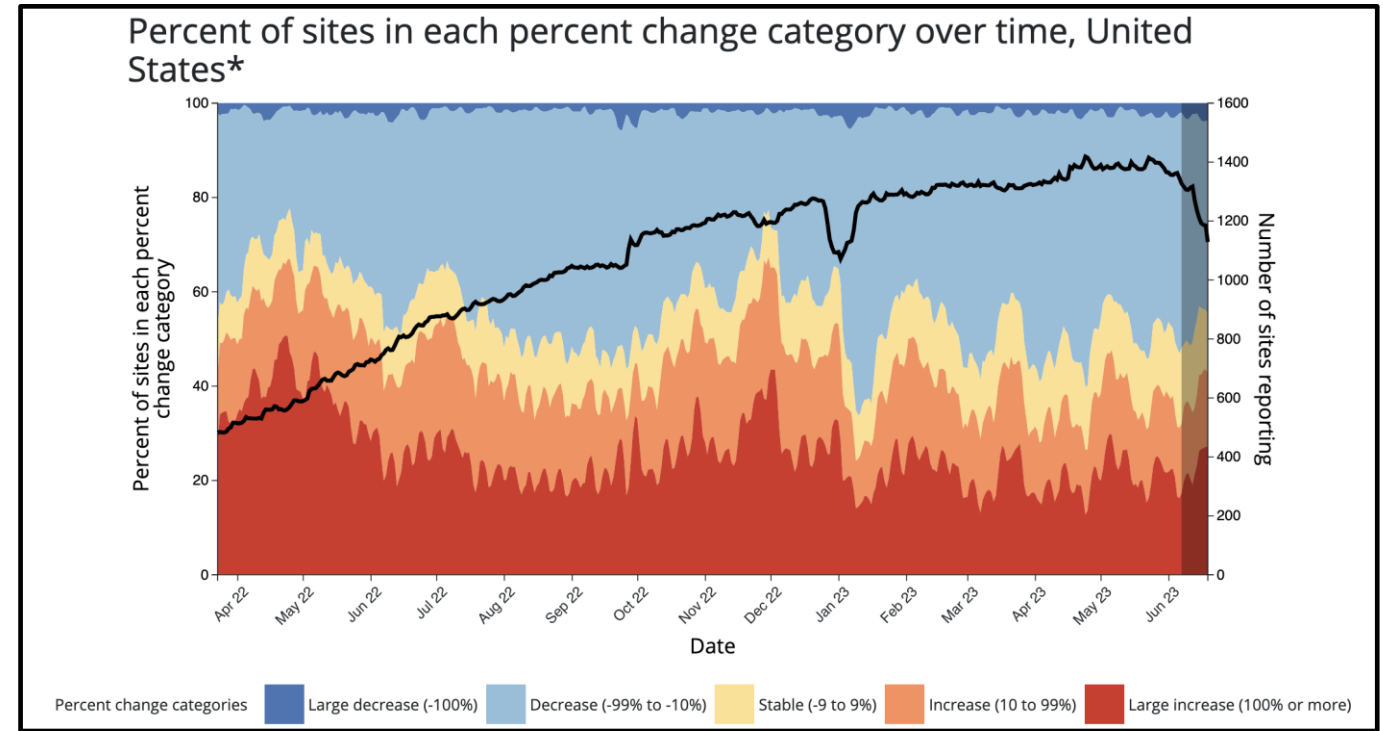
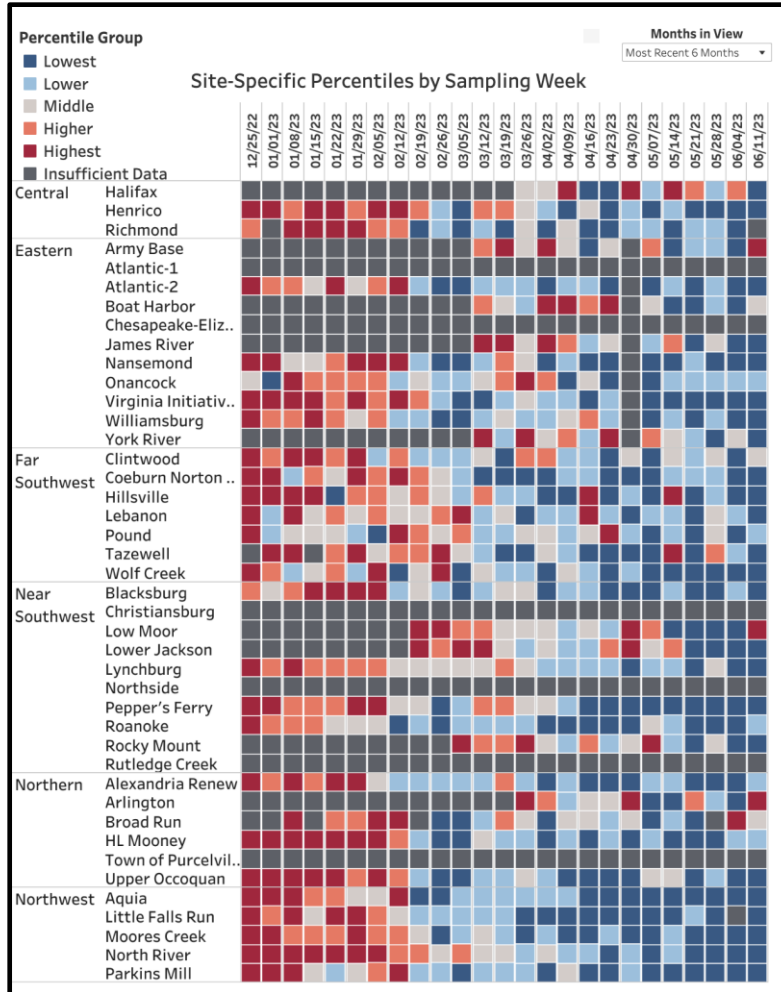
<https://www.vdh.virginia.gov/coronavirus/see-the-numbers/covid-19-modeling/district-trajectory-map/>

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

Number of health districts in each category



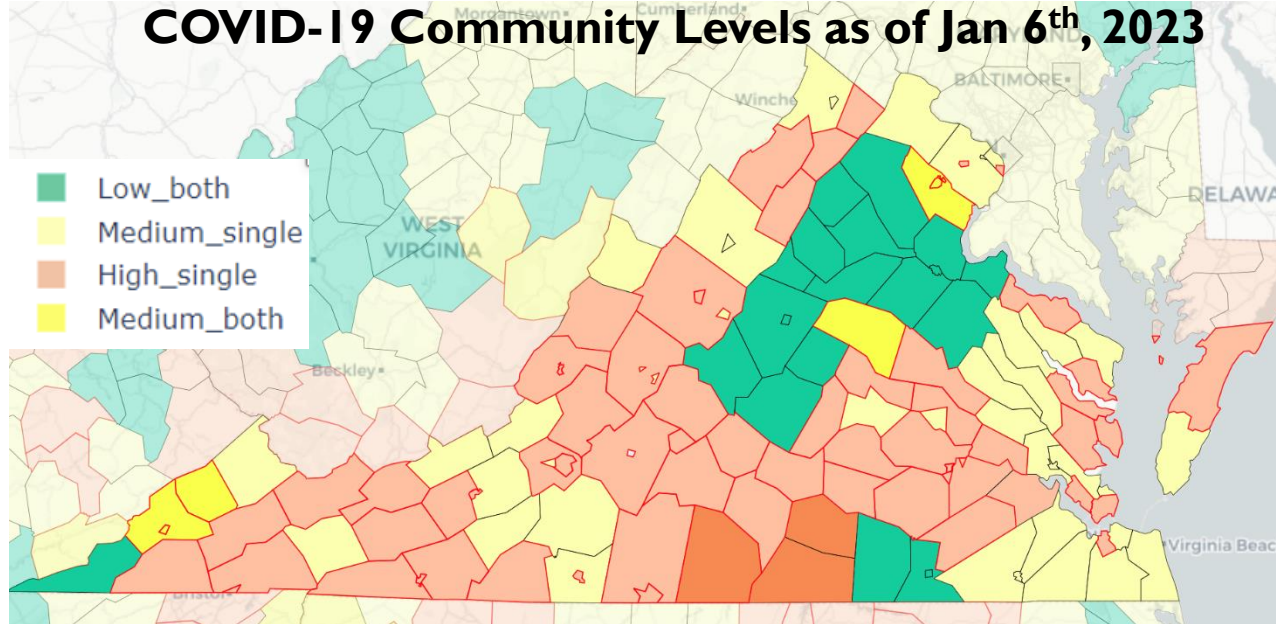
EXAMPLES FROM COVID-19: WASTEWATER SURVEILLANCE



UNIVERSITY of VIRGINIA <https://www.cdc.gov/covid-data-tracker/#wastewater-surveillance>

MULTIVARIATE CATEGORY DEFINITIONS

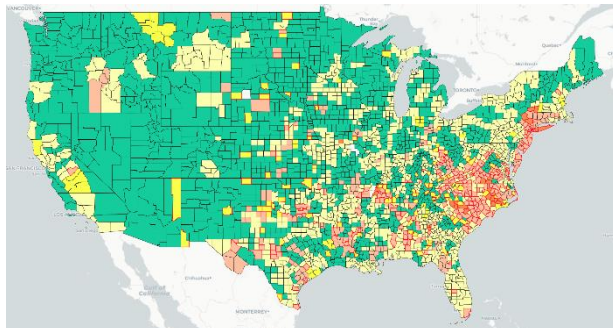
COVID-19 Community Levels as of Jan 6th, 2023



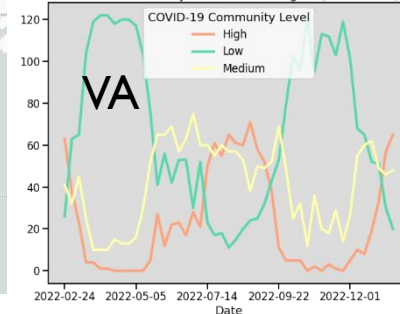
Red outline indicates county had 200 or more cases per 100k in last week

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

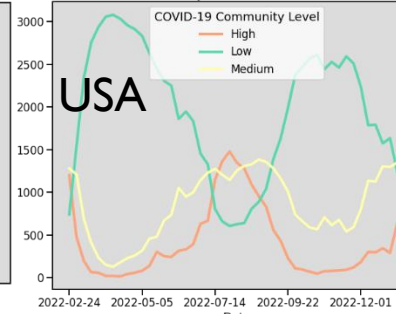
Dark color indicates both beds and occupancy set the level for this county



COVID-19 Community Level Trends - Virginia [2023-01-12]



COVID-19 Community Level Trends - USA [2023-01-12]



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%

Data from: [CDC Data Tracker Portal](#)

MULTI-TIME SERIES ANALYTICS: COVID-19 IN VIRGINIA

■ Source data:

- WW viral load by sewershed
- Cases mapped to sewershed catchment (from line list)
- CLI% available per health district
- Hospitalizations by health district (from state level)

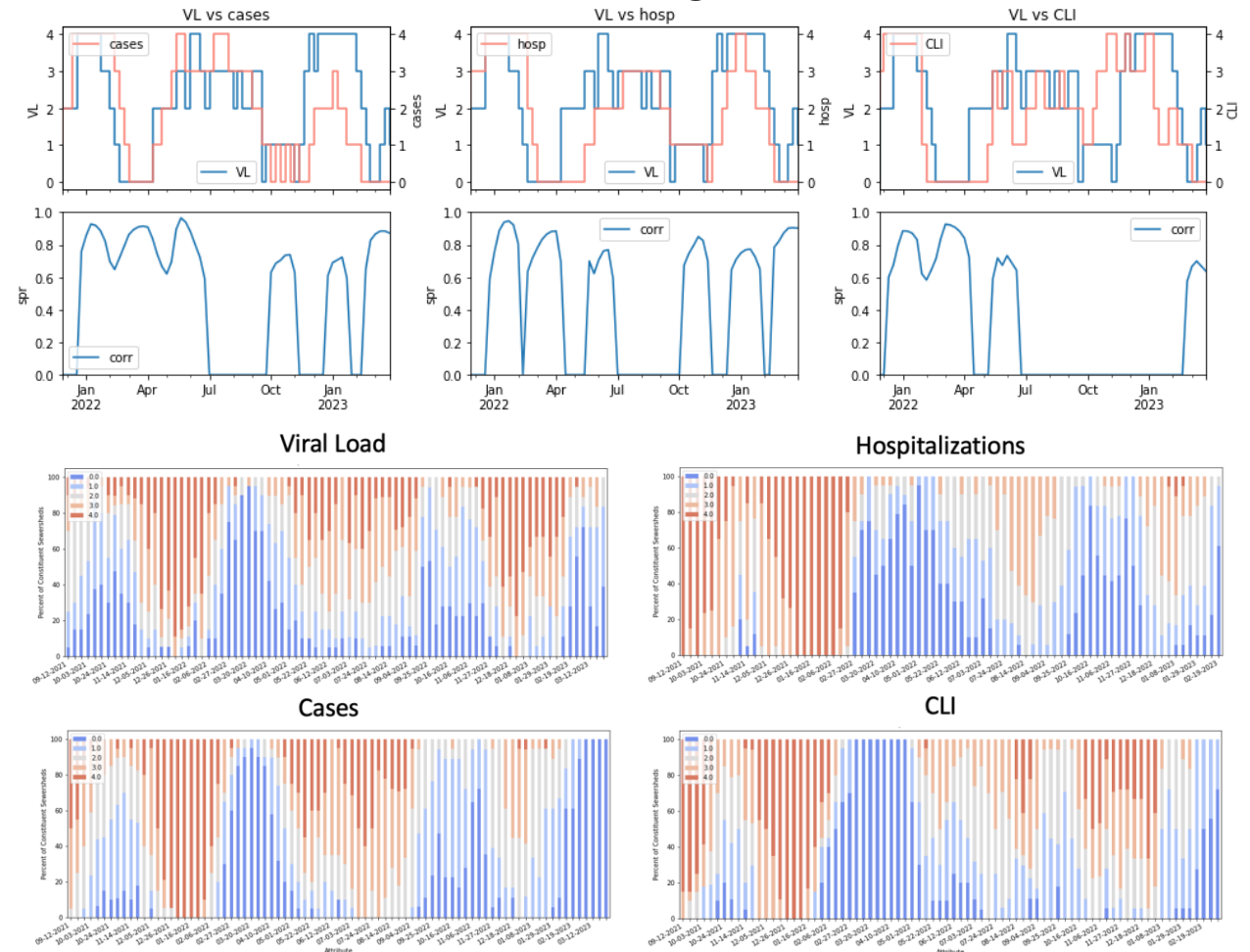
■ Categorization:

- Obtain quintiles from entire time series (per signal, location)
- Categorize to level 0 through 4

■ Multi-timeseries analytics:

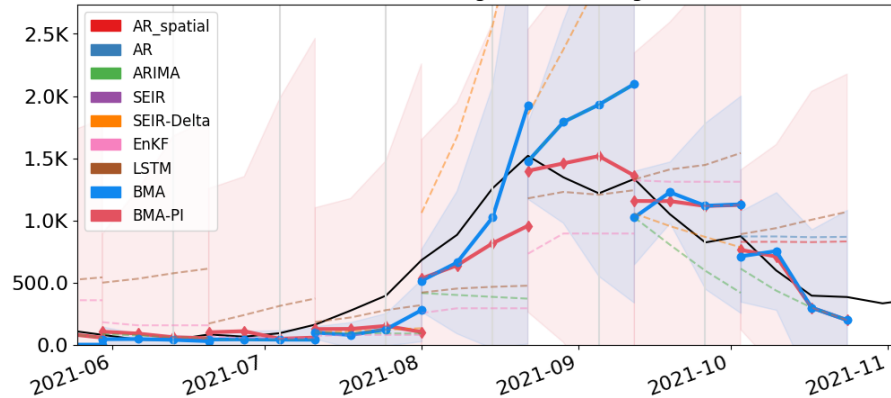
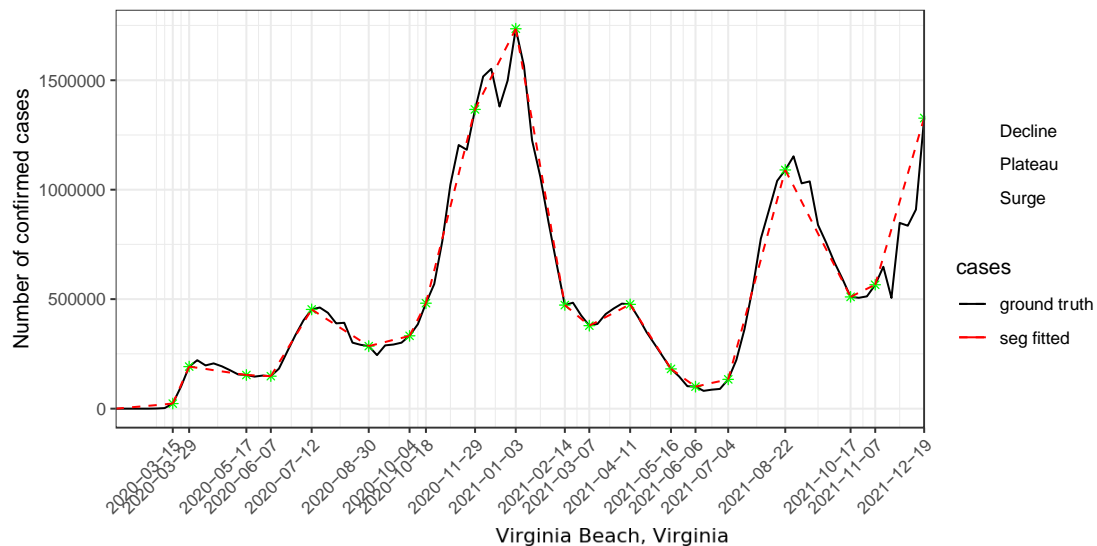
- Pairwise Spearman correlation
- % locations at various quintiles by signal

State level categorical correlation

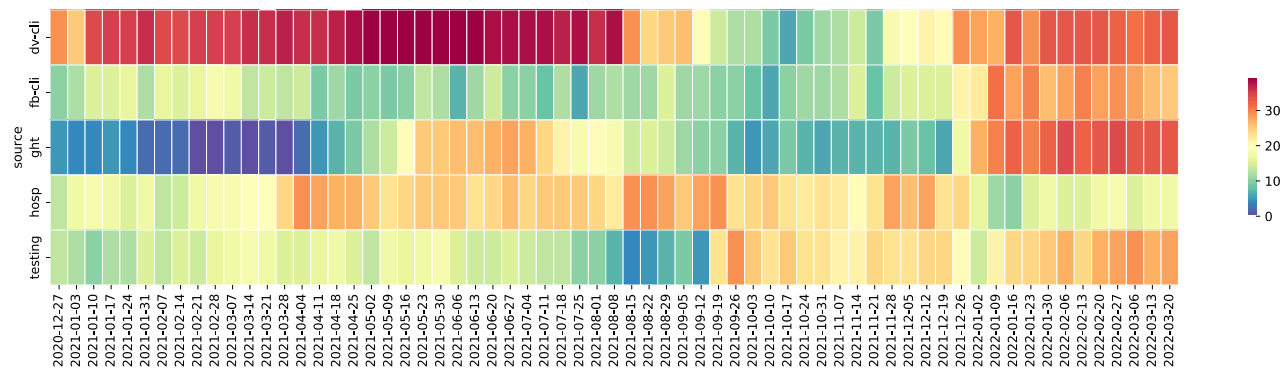


BEYOND ANALYTICS: PHASE-INFORMED FORECASTING

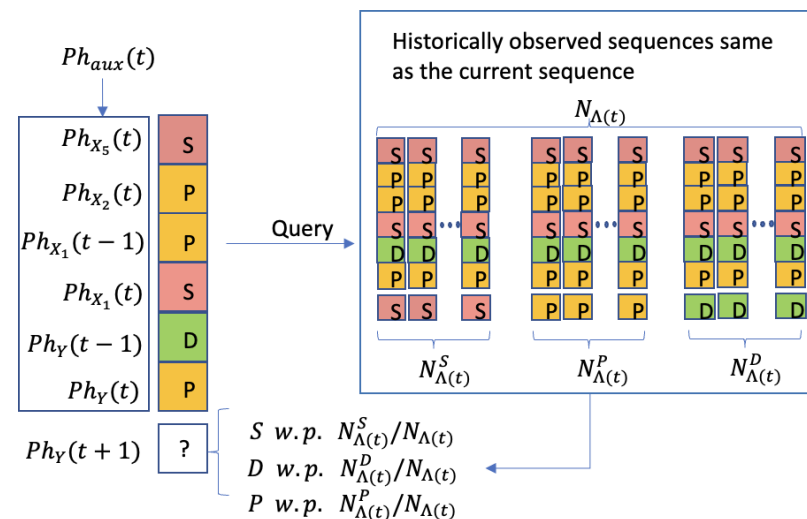
Phase-informed model ensembles



Phase prediction using leading indicators



of states for which an individual signal was identified as a leading indicator





TOOL INTRODUCTION



TAXONOMY OF CATEGORIZATION RULES

- Level-based categories
 - Using equal-width intervals for the data range (e.g., ILINet Activity Indicator)
 - Using quantiles of the data to inform category bins (e.g., VDH COVID-19 wastewater surveillance)
- Trend-based categories
 - Rate change over a fixed length window (HHS hospitalization trends)
 - Rate change over automatically detected segments (VDH case trajectories)
 - Percent change in activity over a fixed length window (CDC NWSS dashboard)
- Combined rules
 - Multi-signal-based categories (e.g., CDC Community Levels)

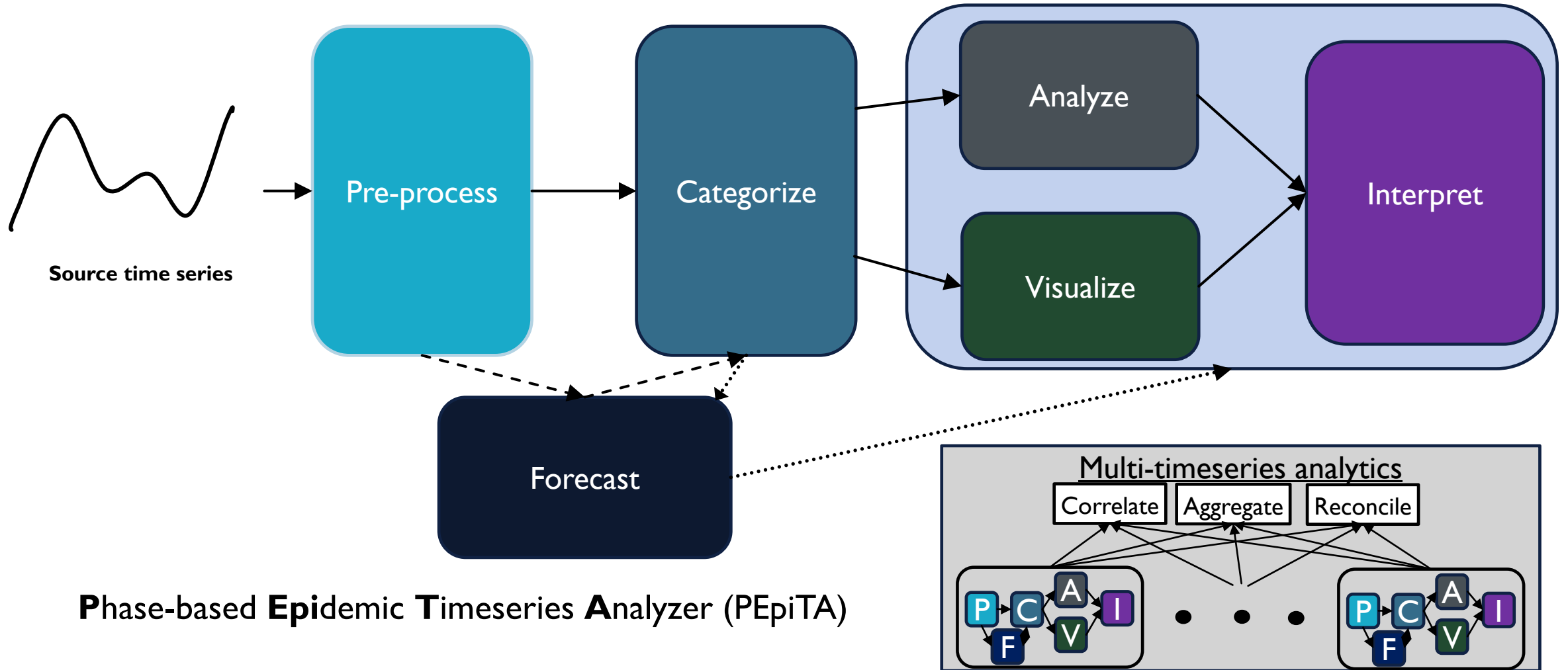
How to decide on the appropriate categorization for a given signal or region?

PEpiTA: Phase-based Epidemic Timeseries Analyzer

Phase-based Epidemic Time-series Analyzer (PEpiTA)

- Upload or choose a publicly-available time series for analysis
- Perform standard preprocessing (e.g., interpolation, smoothing)
- Choose among pre-defined rules for category extraction
- Customize analytical parameters such as number of bins, range, trend windows
- Download visualizations and analytical summaries

PEpiTA - WORKFLOW



Phase-based Epidemic Timeseries Analyzer (PEpiTA)

PEpiTA - INTERFACE

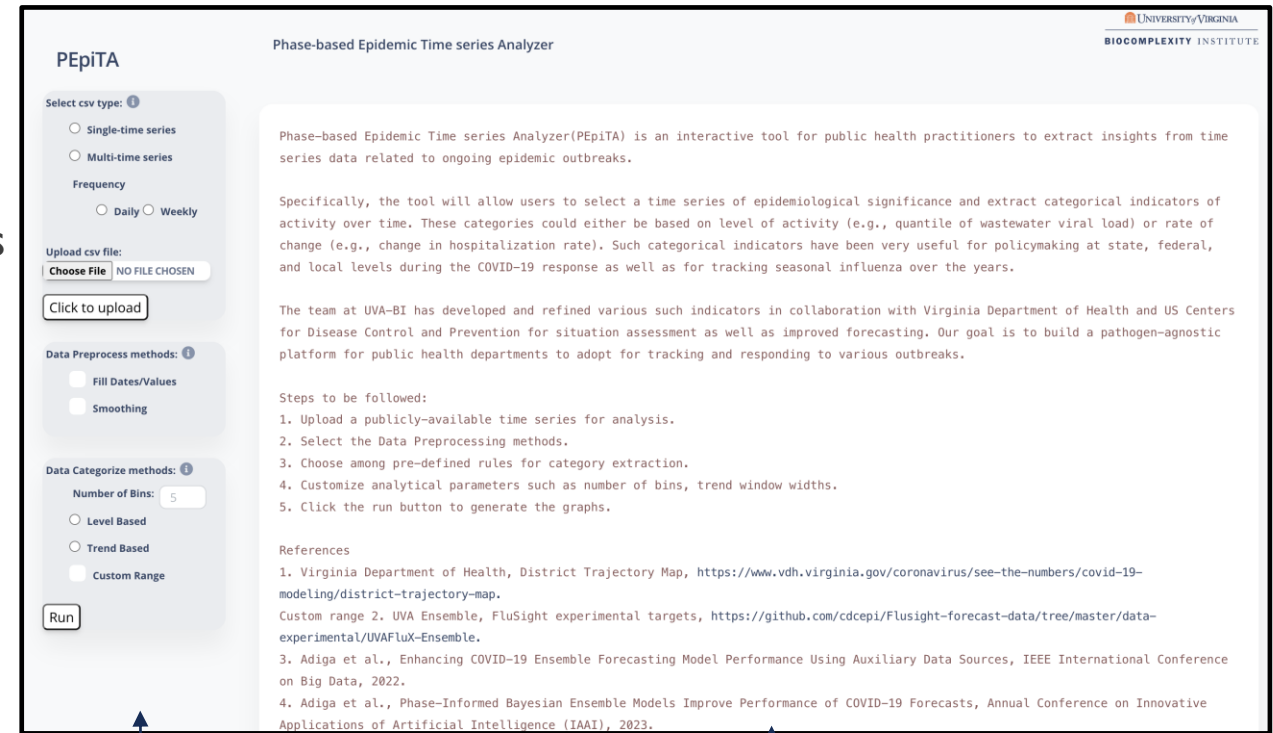
- Browser-based interface using Django framework
- Codebase in Python (using pandas, matplotlib)
- Setup for headless mode; Exploring installation options

<https://github.com/NSSAC/PEpiTA>

```

/Users/vsriniv/Documents/Research/Github/PEpiTA
(base) vsriniv@Srinivasans-MacBook-Pro PEpiTA % cd webdesign
(base) vsriniv@Srinivasans-MacBook-Pro webdesign % python manage.py runserver
Watching for file changes with StatReloader
Performing system checks...

System check identified no issues (0 silenced).
June 23, 2023 - 18:15:37
Django version 4.2.1, using settings 'webdesign.settings'
Starting development server at http://127.0.0.1:8000/
Quit the server with CONTROL-C.
  
```



Input pane

Landing page

PEpiTA - INTERFACE

Input file properties

Preprocessing method

Categorization method

Visual Summary

Analytical Summary

PEpiTA

Select csv type: ⓘ

Single-time series
 Multi-time series

Frequency

Daily Weekly

Upload csv file:

Choose File NO FILE CHOSEN

Click to upload

File in memory:
va_covid_occupancy.csv
Last Updated: June 23, 2023, 6:23 p.m.

Data Preprocess methods: ⓘ

Fill Dates/Values

Method

Linear Forward

Smoothing

Window:

Data Categorize methods: ⓘ

Number of Bins:

Level Based

L-cut

Trend Based

Custom Range

Run

Phase-based Epidemic Time series Analyzer [View CSV Data](#)

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Single time series - Level-based categories

Analytical summary [[↓](#)]

CATEGORY	BIN BOUNDARIES	NUMBER OF OCCURRENCES	PERCENT TIME SPENT	AVERAGE DURATION SPENT
C1	(147.13, 895.69)	536	48.59%	107.2
C2	(895.69, 1640.51)	389	35.27%	48.6
C3	(1640.51, 2385.34)	93	8.43%	18.6
C4	(2385.34, 3130.17)	53	4.81%	13.2
C5	(3130.17, 3875.0)	32	2.9%	16.0

[Download Categorical Time Series csv \[↓ \]](#)

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ONGOING AND FUTURE WORK

- Incorporating stakeholder feedback from VDH and other STLT agencies (like you!)
- Expanding categorization rules and making them *FAIR*
Findable, **A**ccessible, **I**nteroperable, and **R**eusable
- Interoperability with other analytical tools (e.g., epiprocess, EpiNow2)
- Improved analytics and interactive visualizations
- Nowcasting and forecasting capabilities; Advanced multi-time series workflows

If you're interested in testing and providing feedback, please reach out to
srini@virginia.edu

Key Takeaways

Projecting future cases precisely is impossible and unnecessary.

Even without perfect projections, we can confidently draw conclusions:

- Case rates are in an undulating plateau, currently in an upswing
- Hospitalization rates remain in plateau, with very slight growth
- Most indicators still point to continued plateaus, though some indicate slow growth
- Scenerio Modeling Hub, round 17 results published, impact of fall booster is high

VDH – UVA Updates

- SPHINX project update – PePITA tool piloted at CSTE conference in Salt Lake City
- Projected Trajectories from previous rounds remain on target, no new projections made this round

Questions?

Biocomplexity COVID-19 Response Team

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