

# Modeling and Foresight during the COVID-19 Pandemic

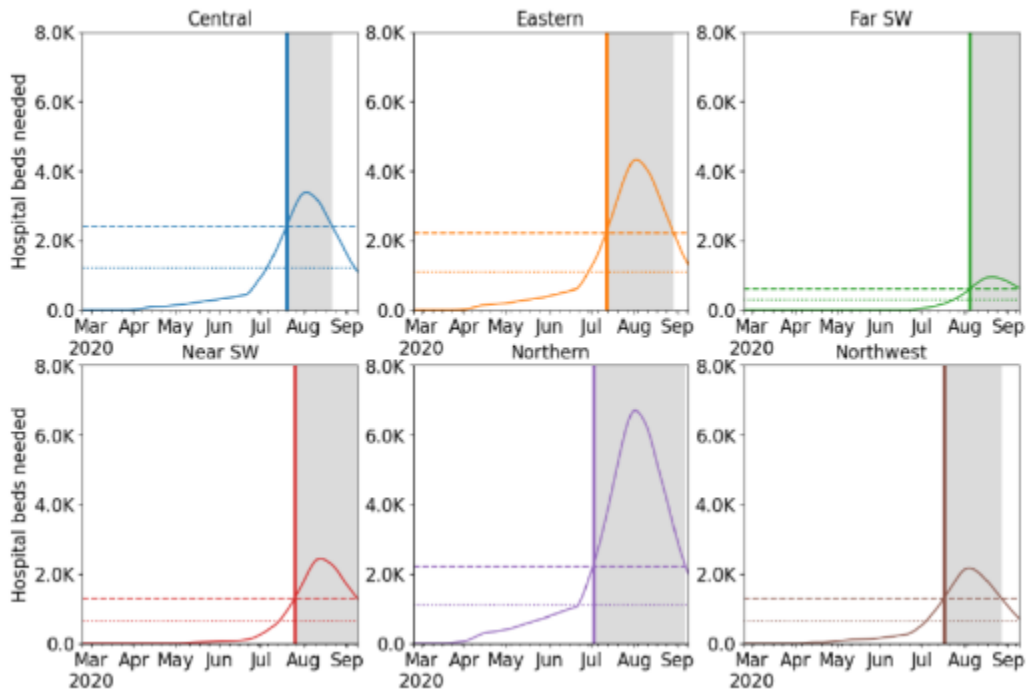
Prepared by

Virginia Department of Health

March 29, 2022

## Capacities by Region – Pause June 10

COVID-19 capacity ranges from 80% (dots) to 120% (dash) of total beds



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## Definitions

Forecasts are a ubiquitous part of our lives but it is difficult to nail down a standard set of definitions for thinking about the future. Rather, several words are used interchangeably to mean very different things. For this project we have adopted the following terminology:

**Model:** A Quantitative tool that aids in understanding complex phenomena. Models have a wide array of uses during a pandemic, including forecasting, program design, and policy analysis.

**Estimate:** An educated approximation of a *current* unknown value or situation.

**Projection:** Past trends projected forward, usually with models of varying degrees of complexity and under different assumptions.

**Forecast:** A projection or judgment about future values or outcomes that includes a recognition of uncertainty. Uncertainty may be expressed by confidence intervals, alternate scenarios, or expressed as probabilities.

**Prediction:** A certain statement about the future. “Mark my words...X will happen.”

The future is filled with uncertainty. Professional forecasting results in estimates, projections, and forecasts. Models have a wide array of uses during a pandemic, including forecasting, program design, and policy analysis.

## Executive Summary

Coronavirus disease 2019 (COVID-19) was an unprecedented threat to public health. As COVID-19 began to appear in the United States, Virginia’s policymakers and public health officials faced a great deal of uncertainty. The Virginia Department of Emergency Management (VDEM) and the Virginia Department of Health (VDH) turned to Carter Price, of RAND Corporation, and the University of Virginia Biocomplexity Institute (UVA-BI) to provide expertise, and Virginia-specific models. These resources quickly proved instrumental in the decision to pause the field hospital process, resulting in substantial savings to the state.

UVA-BI has continued to provide model projections, foresight, and expert analysis, resulting in over 92 slides sets and weekly briefs, numerous updates to stakeholders, over 1.3 million views to the main projection dashboard, and citations in over 360 local media reports. The projections and foresight assist local health officials, school administrators, businesses, and individuals to assess risk and plan for the future. UVA-BI has improved and updated the models throughout this period, including undertaking innovative projects to improve forecasts.

Additionally, UVA-BI has applied their modeling expertise to support policy-making, program design, and early warning systems. Among other areas, their work has supported safe return to

schools, contact tracing, genetic surveillance, hotspot identification, and community mitigation policies.

Through FY2021 this work was funded by the Coronavirus Relief Fund (CRF) pursuant to the federal Coronavirus Aid, Relief, and Economic Security Act (CARES Act). VDH sought and received additional funding through the federal Epidemiology and Laboratory Capacity - Enhanced Detection Expansion grant (ELC-EDx) to continue COVID-19 model projections, and to support the expanded modeling for program design and planning. This funding is currently scheduled to end in July, 2023. The contract for the expanded work is pending.

## Introduction

### Background

Coronavirus disease 2019 (COVID-19) was an unprecedented threat to public health. SARS-CoV-2 was a new virus, introduced into a universally naive population, without any available vaccine or pharmaceutical available, and with unknown treatment protocols. COVID-19 quickly overwhelmed health systems in China and Italy, driving an unprecedented response in these countries. As COVID-19 began to appear in the United States, Virginia's policymakers and public health officials faced a great deal of uncertainty. They naturally turned to existing pandemic models to understand how COVID-19 may affect the Commonwealth, and how best to respond.

Unfortunately, to those unfamiliar with them, these models provided little certainty. Two models included in an April 7, 2020 presentation to Virginia policymakers included vastly different projections of COVID-19 hospitalizations in Virginia. The University of Washington IHME Model projected a peak of 2,854 Virginia hospitalizations occurring in April 2020. The University of Pennsylvania's CHIME model projected a peak of 38,590 Virginia hospitalizations occurring in late May 2020 - a peak thirteen times higher and a month later.

The Virginia Department of Emergency Management (VDEM) and the Virginia Department of Health (VDH) turned to two resources to manage this uncertainty. Carter Price, of RAND Corporation, provided expert consultation on models and their uses. The University of Virginia Biocomplexity Institute (UVA-BI) created Virginia-specific models, at the local level, using COVID-19 case data provided by VDH. These resources quickly proved instrumental in guiding the COVID-19 response. While other states, working with the US Army Corps of Engineers, were setting up field hospitals (often at great expense), Virginia paused this effort based on the model projections and guidance provided by UVA-BI and RAND. For the most part, field hospitals built in the US stood empty, as mitigation efforts were successful in "flattening the curve". This pause resulted in substantial savings to the state.

Contracts with UVA-BI and RAND were initially managed by VDEM, while VDH coordinated the work. Beginning in January 2021, VDH assumed the contract management role as well. The work was funded by the Coronavirus Relief Fund (CRF) pursuant to the federal Coronavirus Aid, Relief, and Economic Security Act (CARES Act) to support this work in 2021 and the federal

Epidemiology and Laboratory Capacity - Enhanced Detection Expansion grant (ELC-EDx) Additionally, the work described below leveraged funding and relationships with other federal and local health agencies. In particular, the development and improvement of models was carried out using funds from VDH, NSF Expeditions program, DTRA funding and several NSF Rapid grants. Furthermore, the work has supported regular forecasting and scenario-based projection activities coordinated by the CDC. In June of 2021, VDH decided not to renew RAND's contract, as UVA-BI was providing modeling and analysis for Virginia. The work associated with this funding is currently managed by Justin Crow, the Director of the Division of Social Epidemiology, in the Office of Health Equity (Classified), supported by Alex Telionis, Public Health Modeling Coordinator (Contractor).

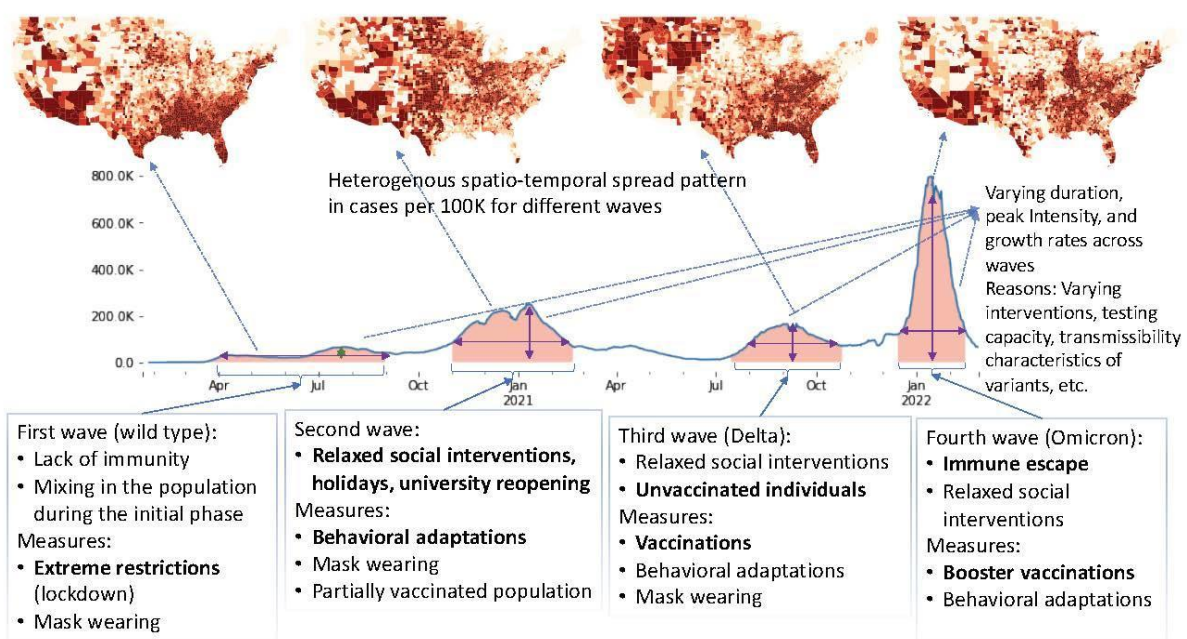
## Purpose of Modeling & Foresight

Models can serve multiple purposes during a pandemic. One purpose of models is to assist policymakers, planners, and the public to anticipate the future course of a pandemic. In many cases this can include specific projections about cases, hospitalizations, or deaths, or other factors of interest such as resource demands. When used as forecasts, these types of projections are most useful in the short term. Over longer periods of time, models can help us understand the implications of *potential* future environments, such as the impact of new variants, vaccination uptake, or seasonal changes. Model scenarios, which reflect different parameter profiles to anticipate potential future environments, can also help policymakers understand the impact of policy choices. When Virginia policymakers decided to pause field hospitals, they relied on model scenarios projecting the impact of mitigation policies.

Similarly, models can assist with program design and resource allocation. UVA models have been used to prioritize contacts for tracing and investigations, design testing regimes for universities, develop blueprints for genetic sequencing samples, and target neighborhoods for mobile testing and vaccination clinics. Similarly, models can be used to allocate resources by estimating the relative impact and cost effectiveness of programs. See references [9,18,19] for further details.

Another class of use for models is to integrate available data for situation assessment. UVA models were used to provide situation assessment as the pandemic evolved. Models in this class included, case ascertainment rate, days to detection, vaccine hesitancy, mask usage, mobility changes, vaccine uptake, and immunity profiles at the population level. Comparative analysis was also performed to see how VA was doing compared to its neighboring states and the country as a whole.

*Challenges:* Modeling to support pandemic response is challenging; these challenges stem from lack of timely and accurate data, multiple uses of the same models, and social, economic, spatial and temporal heterogeneities. COVID-19, like earlier pandemics, posed these challenges. But, in addition, all modelers faced challenges that were quite unique including: (i) the causal reasons for each wave were different; (ii) the state of the underlying social systems was different; (iii) different individuals were affected physically, socially and economically, furthermore different social, behavioral and political considerations were at play during each phase, (iv) the shape of the curves, the intensity, peak and the growth was different for each phase and (v) the advent of social media, international trade and travel and prevailing political polarization introduced new challenges in the form of misinformation, breakdown of global supply chains, reduced compliance, and created higher levels of hesitancy than one would have anticipated. The figure shows the



different underlying causal reasons that were at play during each wave of the COVID-19 pandemic. See [9] for further details.

UVA-BI’s projection models have been one of the main resources for anticipating the course of the pandemic in Virginia. Even the most complex models, however, are simple tools. Models can anticipate the implications of potential future environments, but are often less effective at predicting which environment will come to pass. Models require human interpretation, and function best when considered as part of a portfolio of information sources. One of the most important functions of the collaboration with RAND and UVA-BI was providing these sources. Among other projects, the modeling and foresight team provided national and international scanning, developed early warning tools, and provided advance warning on the characteristics of new variants. VDH and UVA-BI also collaborated with the Metaculus forecasting platform, to augment foresight and forecasting capabilities.

Using all of these tools, VDH was able to provide modeling and foresight during the pandemic that was not available to any other state. The activities of the modeling and foresight unit described below fit into the following categories:

- Model projections and forecasts
- Early warning & ancillary analysis
- Reporting and public education
- Bespoke modeling

Additionally, this report describes key uses of the modeling work, feedback received, and next steps.

## Overview of Activities

### Model Projections and Forecasts

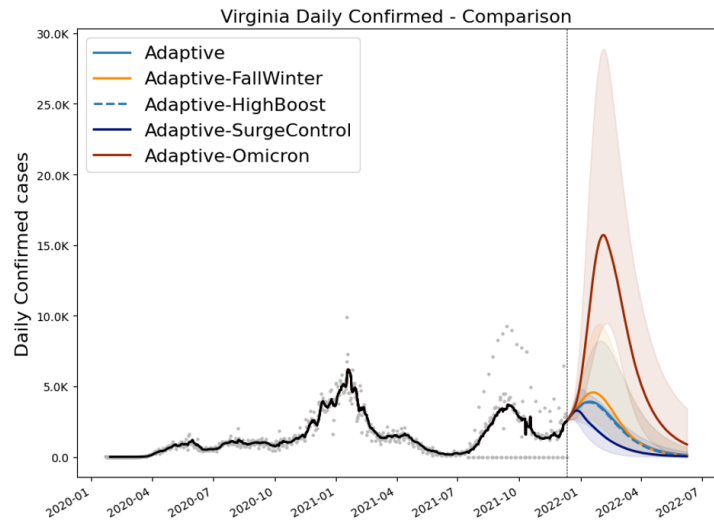
Evidence-based policymaking hinges upon the use of state-of-the-art approaches to integrate the latest data, emerging insights, and domain knowledge. The science of epidemics has benefited largely from a long history of mathematical models and recent advances in computational approaches. The team at UVA-BI leveraged these techniques and developed various epidemiological models to inform and support policymakers. These models differ in their complexity, underlying assumptions, and are chosen based on the question at hand, phase of the epidemic, and available data. The team has benefited from and contributed to various multi-model consortiums organized at the federal level, where modeling assumptions and parameters are discussed to encourage a healthy diversity across different approaches.

For instance, some of the modeling techniques used by the team include: (i) statistical and machine learning models for short-term forecasting of the epidemic, (ii) aggregate compartmental models to provide flexibility for medium-range projections under various scenarios, (iii) detailed agent-based models for studying specific questions that involve individual level variations and impact of social and societal structure. These models have been used for studying various questions such as: (i) the impact of social distancing and phased reopening during various stages of the pandemic, (ii) behavioral adaptations and the role of seasonality in generating COVID-19 waves, (iii) threat assessment for novel variants in terms of transmission and severity, and, (iv) population level benefits of vaccinations. The models have helped formalize and distill prevailing assumptions about disease characteristics (such as incubation period, infection fatality rate), testing and surveillance systems (underreporting of cases, delay from symptom onset to detection), and human behavior (mobility across regions, mask wearing, vaccine acceptance). This section summarizes the core modeling pipeline that has produced scenario-based projections that have been central to public communication and policy guidance over the past two years. Other modeling activities are discussed later in the report.

**Short-term forecasts:** Epidemic dynamics, unlike weather, are influenced by decisions of individuals, organizations, and communities. However, due to inherent delays in disease dynamics (from exposure to symptoms) and reporting process (from symptom to detection), one can leverage allied signals to provide highly reliable short-term forecasts. Further, for outcomes

such as hospitalizations, current cases can be used to provide robust forecasts 2-4 weeks into the future. The team at UVA-BI has leveraged sophisticated machine learning tools to integrate various signals from social media, mobility, and weather, to provide 1-4 week ahead short-term forecasts of cases and hospitalizations at the county/state level for Virginia and the United States. In addition to being part of the CDC ForecastHub, these have also been used within VDH and by our projection models. See [8,9,11] for further details.

**Scenario-based projections:** While predicting human behavior is inherently difficult, population level trends can be projected forward in time with reasonable confidence. However, these projections still require assumptions about what changes (e.g., seasonality) and what does not (e.g., variant mixture) in the future. The team, in collaboration with VDH and fellow experts from the infectious disease modeling community, has crafted various scenarios for medium-term projections at the county level for Virginia since April 2020. One of the earliest projections involved comparing



different timelines and intensities for the stay-at-home executive order during the first wave. These were compared against an “Unmitigated” baseline scenario for evaluating the impact of these interventions. At different stages of the pandemic, various counterfactual conditions pertaining to non-pharmaceutical interventions, vaccinations, seasonality, novel variants, etc. were codified as scenarios and provided support for planning and preparedness efforts. Since some of these policies (e.g., vaccination rollout in the general population) or disease evolution (e.g., emergence of novel variants) do provide some lead time, the scenarios are constructed sufficiently in advance anticipating the potential changes to the time course of the pandemic.

One of the earliest applications of the model involved the stay-at-home scenarios that helped delay the setting up of field hospitals in Virginia. As another example, scenarios pertaining to vaccine rollout for 5-11 year olds were constructed in mid-August (12 weeks prior to their ultimate administration) and were impactful in guiding decision making even at the federal level. Based on the Delta experience in countries like India, the late summer wave of 2021 was projected under one of the scenarios as early as mid-June. Similarly, UVA-BI created an Omicron scenario based on early evidence from South Africa and Europe in early December, weeks prior to a significant surge in cases in Virginia.

An advantage of the projection-based approach is the ability to combine knowledge of the world with the quantitative model to assess potential futures. As early news of the Omicron variant was being gathered in South Africa as well as preliminary experience in Europe, the UVA team was able to construct an Omicron projection for the Commonwealth of Virginia. The Omicron scenario helped Virginia’s hospitals and health systems understand that, though Omicron would drive an unprecedented number of cases, hospitalizations and deaths would be more subdued, pressuring but not overwhelming capacity.

**Ancillary projections:** While case projections have garnered the most attention, these are informed in turn by forecasts of variables that drive the disease dynamics. The team has built statistical models to leverage social media surveys and search trends to estimate vaccine acceptance in the population, and thus the rate of vaccine uptake given current levels of supply. This approach was central to evaluating the impact of vaccine rollout in 5-11 year olds and the need for boosters during the recent Omicron wave. Similarly using case curves from outside the United States, separate models were developed to predict how quickly a novel variant will spread in Virginia. This model was especially useful in projecting and subsequently tracking the evolution of the Alpha, Delta, and Omicron variants in Virginia. Further, the model projections have also been translated to more intuitive metrics such as population immunity by integrating the latest evidence about the rate of waning and protection conferred by prior infection and vaccination. Such estimates have been crucial at various stages to serve as cautionary notes for subsequent waves of the epidemic.

**Human judgment in forecasting:** While computer models are useful for capturing complex relationships among available datasets, it is tough to incorporate human insights into such a framework. Humans, either a group of experts, or a community of informed individuals, can produce quite reliable forecasts of certain aspects of the pandemic (i.e., wisdom of the crowds). Through a unique partnership with the community forecasting platform, Metaculus, VDH and UVA-BI conducted a series of forecasting tournaments (Keep Virginia Safe, Lightning Tournament, Real Time Pandemic Decision Making) to solicit forecasts for various epidemiological, socioeconomic, and behavioral variables. These forecasts have been incredibly valuable during times of high uncertainty (e.g., Omicron surge) by providing reliable forecasts and crowd-sourced parameter estimates and in capturing the 'pulse-of-the-public' at various stages of the pandemic.

## Ancillary Metrics, Situation Assessment & Early Warning Indicators

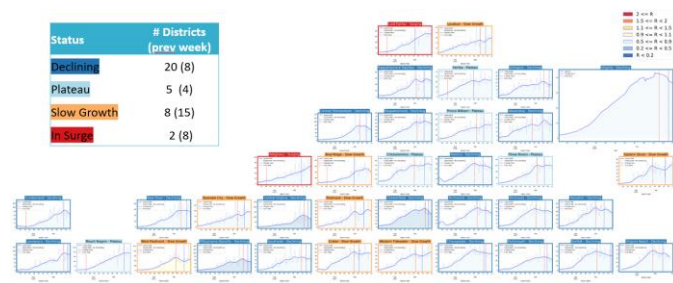
The team has developed various Metrics and Indicators (M&I) derived from publicly available datasets for both situation assessment and early warnings. Such M&I have been crucial in distilling the multidimensional data streams, and have yielded actionable insights for policymakers. Further, they have been integral to effective communication of complex information to the general public. In this section, we briefly summarize a few such metrics along with how they were used.

**Effective Reproduction Number:** Knowing how quickly the epidemic is growing in various parts of Virginia is central to understanding the impact of different interventions and tracking the pandemic through the phases. Effective reproduction number, which is the average number of new cases created by each infection, succinctly captures the growth of cases in a region. Whether the number is greater or less than 1 indicates if the epidemic is growing or shrinking in size. The team has generated this estimate on a weekly basis at the statewide, regional, and district level. It is presented in the weekly public report, and has provided warnings of surging/cresting of a wave.

**Days from Symptom Onset to Diagnosis:** This metric obtained from case data allows quantifying the effectiveness of the testing and surveillance apparatus. While in the early days, due to testing limitations, this was around 5-6 days, through subsequent ramp-up it stabilized at

around 2-3 days. It also helped characterize swift changes in the epidemic, like the onset of a new variant which stressed the testing system.

**Trajectory classification:** In addition to the Effective Reproduction Number, the team used recent case time series to classify the 35 health districts of Virginia into four different phases namely: Surge, Slow Growth, Plateau, Decline. Maps and district grids were produced to show the current phase of various districts within the Commonwealth as well as at the national level to compare Virginia to her neighbors.



**Variant tracking:** The emergence of novel variants has preceded at least three of the COVID-19 waves at the national level. Genomic surveillance is critical to know what fraction of cases currently in circulation are due to a particular variant. However, they are limited due to sample size and incur delays in processing especially in the middle of a surge. The team used publicly available information from GISAID and other sources to provide up-to-date information on variant prevalence as well as model-based projections of how they could change over time. Such estimates were useful in planning for potential surges as well as for communicating the importance of vaccinations (during Delta surge) and boosters (during the Omicron surge).

**Hotspots:** Using high resolution data available at zip code level, the team produced maps summarizing spatiotemporal hotspots of COVID activity. At various points of time, these aligned with correctional facilities, food processing plants, university/college towns, and highlighted the localized surges taking place across Virginia.

**Health care worker prevalence:** The team combined data from the general population as well as from health care workers (HCWs) to measure the relative rate of infections in the HCW population. Since the healthcare workforce availability is crucial for pandemic management, this provided insights into communities where they were adversely affected, as well as additional context for issues such as vaccine resistance, pandemic fatigue, and workforce shortage in this critical subpopulation.

**Exposure risk by group size:** While local case rates are useful in tracking at population level, for individuals trying to decide on attending events and conducting various activities, it is quite abstract. The team used modeling assumptions to convert local case rates into an estimate of exposure risk when in a group of individuals of a particular size. When combined with other factors such as indoor/outdoor settings, vaccine status of individuals, this provides effective communication of risk under various activities and can inform mitigation strategies.

**Socioeconomic breakdown:** The pandemic has inflicted a heavy toll over the past two years, and this impact has been especially pronounced in some subpopulations by social, demographic, and economic characteristics. The team has summarized the case and hospitalization data by race and ethnicity across Virginia health districts. Highlighting disparities assists with understanding risks and disease progression, and suggests targeting strategies. A similar variation across income quantiles in terms of the pandemic experience was also observed. Finally, the team leveraged age-stratified data on cases, hospitalizations, and deaths to observe marked shifts due to changing mixing patterns and vaccine uptake.

**Comparison to previous peaks:** Contextualizing the current experience in terms of historical activity is a useful tool in guiding individual and collective decision making. The team provided intuitive maps for comparing a county's case activity to past peaks and the previous seasonal experience.

**Vaccine Acceptance and Uptake:** Since the availability of vaccines in December 2020, the rollout has been staggered across age and priority groups. As Virginia ramped up its efforts in vaccinating the general population, it was important to know the current demand and to identify pockets of vaccine resistance. The team used data from surveys administered on social media to summarize prevailing vaccine sentiments across age groups and regions. They also compared it to current uptake, and provided projections of uptake based on acceptance.

**Mask wearing and Mobility:** Until vaccines became available, the spread of COVID-19 was mostly controlled through non-pharmaceutical interventions including mask-wearing, social-distancing, remote work, etc. Various indicators at the state and county level captured the level of compliance to these measures. The team summarized trends in mask-wearing through the course of the pandemic as observed through social media surveys. The team has also used metrics based on foot traffic to various activity locations to capture the impact of social distancing and stay-at-home orders, as well as for tracking economic recovery during the reopening phases.

**Literature Reviews:** The past two years of pandemic have also seen an explosion in the amount of information generated by the scientific community studying COVID-19 from various angles. Since early 2021, the team at UVA-BI has continued the role of RAND in summarizing the latest findings in clinical, epidemiological, and biological aspects of COVID-19. In addition to informing the models, these discussions have helped policymakers stay abreast of the current science. Especially since the emergence of novel variants, these literature reviews have succinctly summarized the experience across countries and provided the latest updates on clinical factors pertaining to vaccine-induced and natural immunity.

## Reporting & Public Education

Models and forecasts are essential tools for anticipating the course of a pandemic. UVA-BI provided raw projections to VDH, VDEM, VHHA and other stakeholders throughout the pandemic. Data was also available to the public on the Virginia Open Data Portal. Model results often require interpretation and guidance. In addition to releasing raw projections, the UVA-BI and the VDH Modeling and Foresight team provided regular updates and discussion, dashboards, slides, and briefs interpreting the data.

### Regular Meetings & Updates

UVA-BI and RAND provided regular updates to VDH, VDEM, the Secretary of Health and Human Resources (SHHR), and the Virginia Hospital and Healthcare Association (VHHA) beginning in April 2020. RAND ceased providing updates when their contract was not renewed. At this time Deloitte, working with the VDH Office of Epidemiology, began providing regular surveillance and vaccination updates. The VDH Modeling & Foresight team also provided regular updates to Local Health Districts and others using information gathered from these meetings. Regular meetings and updates included:

- Weekly meetings with VDH Modeling team and Office of Epidemiology staff
- Biweekly meetings organized by the SHHR for Cabinet Offices and Agency Heads. Through January 13, 2022
- Weekly or biweekly updates to VHHA and other stakeholders.
  - Biweekly in early Summer 2021, and Winter 2021/2022 onwards
  - Originally for VHHA only, expanded to all stakeholders in March 2021
  - There are currently 214 individuals on the invite list for this meeting, and dozens attend these updates regularly
- Biweekly Variant Surveillance meetings beginning in July 2021
- Ad hoc meetings that covered a range of topics that were critical at various time points. Examples include: (i) meeting to assess contact tracing protocols, (ii) meetings to design strategies for mobile vaccine clinics placement, (iii) meetings to decide testing regimes and protocols, (iv) meetings to coordinate Table Top exercise, (v) meetings to study establishing field hospitals and other logistical challenges and (vi) meetings to study questions related to biosurveillance.

UVA-BI and VDH modeling team members also participated in numerous media interviews to update the public on model projections, variants, and other factors influencing the anticipated course of the pandemic. Information from modeling results and presentations has been cited in over 360 media articles. A sampling of articles includes:

[“Biocomplexity Institute Unveils COVID-19 Model”](#) Apr 14, 2020. Bacon’s Rebellion.

[“Could Virginia be heading for a new COVID-19 case peak?”](#) Oct 21, 2020. Virginia Mercury.

[“University of Virginia scientists wield statistics to prep for coronavirus’ next moves”](#) Sept 5, 2021. The Virginian Pilot.

[“UVa report: Virginia on rapid decline after wild COVID-19 roller coaster ride, but Southside lags”](#) Feb 20, 2022. Danville Register & Bee.

### Briefs, Slides and Reports

Accompanying weekly meetings, UVA-BI and RAND/Deloitte provided extensive slide sets displaying model results, situational reports, ancillary analysis, and literature reviews providing extensive insight into the state and potential course of the pandemic, in Virginia, nationally, and internationally. The slide sets were posted for the public on VDH’s COVID-19 [Data Insights](#) blog every Friday beginning in April, 2020. The briefs were also distributed widely across the state, including to staff at VDH, VDEM, DoE, VHHA, Local health districts, and several universities.

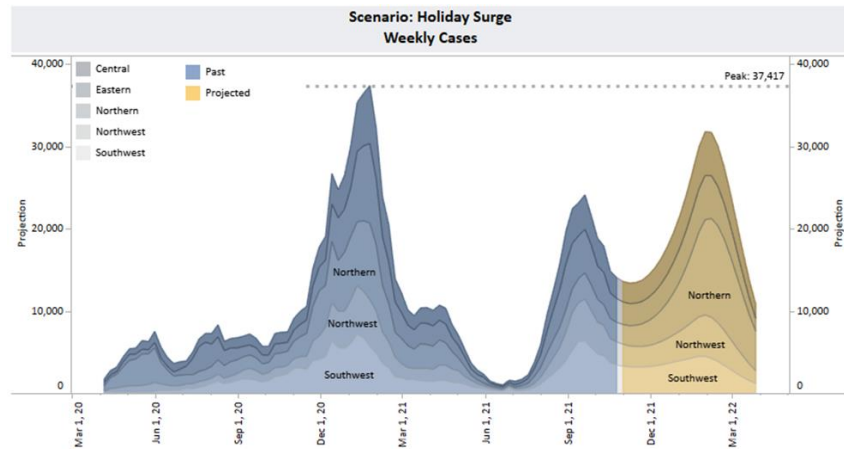
Each blog post also included a 2-3 page weekly report written by VDH staff that highlighted key statistics, graphs, and talking points, and provided a discussion of the current situation, model results, and modeling and forecasting concepts. Information from these public resources was often amplified by local media outlets, which regularly cited these resources.

Dashboards:

UVA-BI, the VDH modeling team, and partners, created a number of dashboards to improve access to model projections, and to assist with exploring and interpreting the results.

**The UVA COVID-19 Model Explorer:**

Created by the VDH Modeling and Foresight team and hosted on the VDH COVID-19 Data Insights page, the Model Explorer displays model results at the local health district and metropolitan area levels. It includes dynamic text to assist with interpretation of local results. Pages within the dashboard include maps of weekly projections, projections of regional caseloads, and a surge trajectory map. The dashboard also includes a brief overview describing models, how they work, and how the UVA model should be interpreted. First published May 1, 2020, the dashboard has had over 1.37 million views as of March 22, 2022.

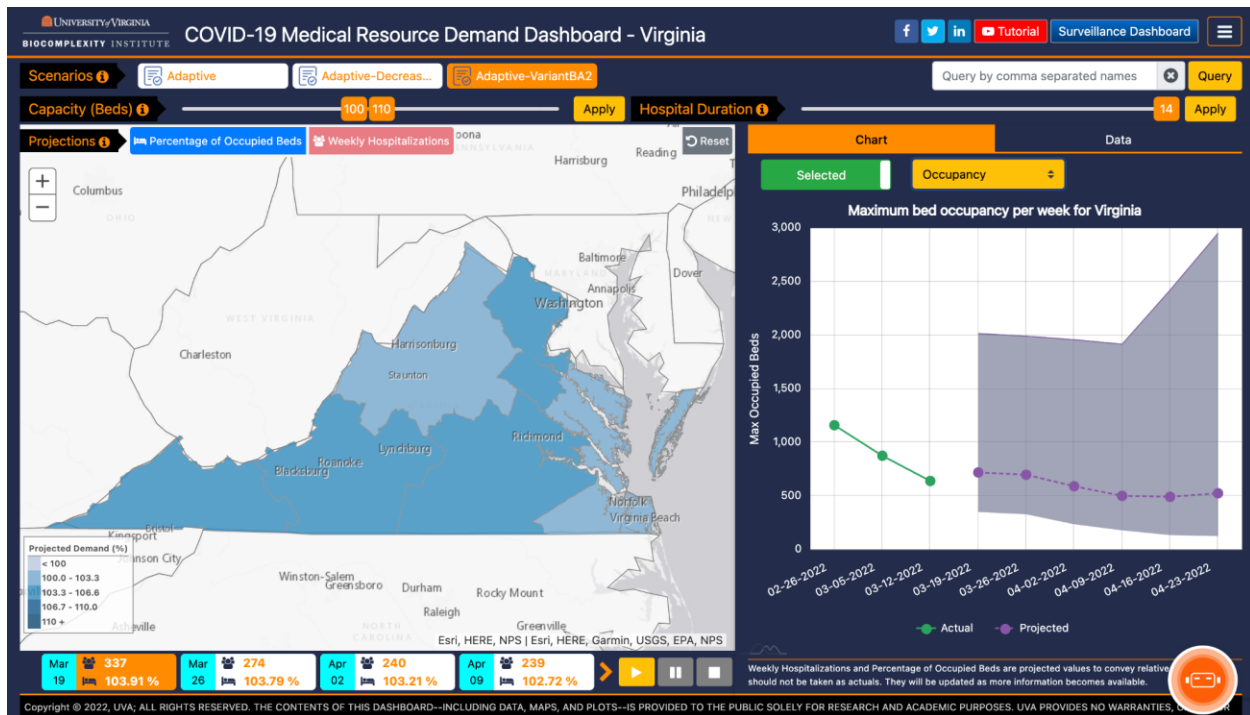


**Mobile Clinic Dashboard:**

This tool uses anonymized cell phone mobility data made available through SafeGraph’s Data for Academics program to assist with locating mobile clinics. Unlike similar tools, this shows where people who reside in different Census Tracts tend to travel to, and the days they tend to do so. This makes clinic resources available to people when they are already outside of their homes, shopping, working, or running errands. By including Census Tract-level demographic data, clinics are able to target certain demographics, including persons of different race or ethnicity, age groups, or vaccination status. See [6] for further details.

**Medical Resource Demand Dashboard:**

The Medical Resource Demand Dashboard (MRDD), published by UVA-BI in May 2020, uses multiple visualizations and timelines to provide spatiotemporal representations of where hospital capacities are likely to be sufficient, tested or exceeded under multiple epidemic scenarios.



**VaxStat Dashboard:** VaxStat provides insights on Vaccine Deployment and Acceptance in Virginia. It includes information on vaccine acceptance by region, vaccine uptake, graphs correlating vaccination rates vs. recent COVID-19 confirmed cases, and projections of vaccine administrations.

**Mobility Intervention Impact Analysis Dashboard:** Developed with partners at Stanford University, this decision-support tool utilizes large-scale data and epidemiological modeling to quantify the impact of changes in mobility on infection rates. Using a fine-grained, dynamic mobility network from SafeGraph’s Data for Academics program, this tool allows policymakers to understand the regional implications of mitigation measures in different venues on disease progression. See [20] for further details.

**Biocomplexity Forecasting Dashboard:** One of the challenges in analyzing data for public health response is the variety of analytical models available. This dashboard allows the user to compare short-term models at the county level and thus provide a range of projections for COVID-19 and influenza. It also displays median and mean model projections, which often provide the best insights.

## Bespoke Modeling Studies

**Contact tracing:** The COVID-19 Contact Tracing team worked collaboratively with the UVA-BI during the first half of 2021 to consider and research key questions regarding the impact and effectiveness of contact tracing as an intervention strategy for controlling an epidemic. The team met weekly to align on the study questions, approach, and parameters. The scalable agent-based model, together with a detailed model of Virginia’s social contact networks, developed as an

outcome of these efforts, provided important insights into how Virginia should dedicate and focus contact tracing resources. Three key findings included: (i) contact tracing helps further reduce cases/hospitalizations/deaths even with ongoing vaccinations; (ii) contact tracing helps us to reach the targeted threshold much earlier, and (iii) tracing more contacts earlier may potentially lead to fewer people in quarantine later on. See [17] for further details.

**Vaccine allocation:** The question of allocating a limited supply of vaccines was considered by the UVA team in January 2021. The question was revisited again multiple times as the situation on the ground changed. UVA-BI used agent-based models to assess several strategies, including age-based distribution, social interaction-based distribution, and prevalence-based distribution. See [15,16] for further details.

**University reopening/operations:** Using agent-based models, UVA-BI supported local universities to study the impact of campus reopening and various mitigation strategies (mask wearing, class sizing, hybrid teaching, testing strategies, etc.). A novel methodology was developed to harness real-time mobility data to understand the impact of mobility on campus spread. Using a realistic agent-based model of a University campus UVA-BI assessed various interventions to reduce spread on a University campus. These included: (i) hybrid learning, (ii) social distancing, (iii) use of masks and other protective equipment, (iv) odd/even class schedule, and (v) delayed openings of the campus. UV-BI also assessed various protocols for isolation upon detection, role of increased testing and testing-prevalence trade-off. UVA-BI also used detailed mobility traces to generate an understanding of surges on the campus when campuses would reopen and connected this to prevalence in the community, assessing the connection of increased mobility with increased campus cases. See [13,14] for further details.

**Genomic surveillance modeling:** UVA-BI meets regularly with analysts from VDH and the Division of Consolidated Laboratory Services to monitor, assess, and provide modeling support for variants, including prevalence projections, sequence sample design, time-to-detect analysis, and a genomic volatility indicator. To date the team has generated sequencing allocation profiles for emergence scenarios to help calibrate ongoing sequencing efforts at DCLS; characterized the dynamics of detection and its relationship to prevalence; processed ongoing sequence surveillance in Virginia and its neighbors to identify natural selective pressure in circulating virus; and used synthetic populations of Virginia and agent-based models to analyze sensor deployment scenarios under varying budget conditions. Importantly, these studies can leverage modeling efforts to guide an adaptive genomic surveillance program that will improve the ability to detect and track variants and their impact on Virginia.

**Tabletop Exercise:** The team worked closely with partners at the McChrystal Group to develop a scenario and narrative for a tabletop exercise carried out to understand the possible surge in cases due to a novel variant. The exercise included senior officials from the state, including the Secretary of Health, State Health Commissioner and others. The tabletop exercise helped leadership think through responses to a new, vaccine-resistant variant, identify gaps, and develop policies. Specifically, the VEST team developed a simulated scenario, the “*Omega Variant*”. The exercise was facilitated by McChrystal Group analysts.

# Evaluation

## Key Statistics

- Invitees to the Surveillance & Modeling Stakeholder Meeting: 214
- Average Stakeholder Meeting Attendance, Dec - Mar 2022: 110
- Weekly Reports/UVA Slide Sets Posted: 93
- Total Views of UVA Model Explorer: 1.37 million
- Media Stories Identified (as of March 9): 360+

## Key Uses

The modeling and foresight work has impacted the work of VDH, state agencies, and partners in numerous ways. As noted in the introduction, UVA-BI's model projections and advice were referenced in the decision to pause field hospital standup in the earliest days of the COVID-19 pandemic. Projections were also used to support decisions to temporarily expand hospital and health workforce capacity in advance of case and hospitalization surges caused by variants and seasonal factors.

Projections are also used to anticipate resource needs. VDH's testing program uses UVA-BI case projections to anticipate testing needs by Local Health Districts. Efforts are underway to use the projections to anticipate demand for therapeutics as well. In a recent feedback survey, discussed in detail below, Local Health Districts cited preparing contact tracers and case investigators for case surges as a key use.

Ancillary and bespoke analysis was also used for policymaking and program planning. For instance, group size risk analysis, discussed on page 9, was used to inform capacity limits at different times during the pandemic. Metaculus forecasts were used to anticipate the number of samples the CDC would require for sequencing in spring 2021. UVA-BI modeling has taken over this role, identifying the number of sequences needed, and assisting with prioritizing samples for sequencing. Agent-based modeling was used to target contact tracing resources and prioritize contacts, and several universities used it to guide reopening processes at various points in the pandemic.

## Next Steps

### Challenges

The Modeling and Foresight program has been an essential and unique resource for Virginia throughout the pandemic. However, the pandemic was a trial by fire for this work. There are a number of areas offering opportunities for improvement.

**Staffing:** There was no staff dedicated to modeling or forecasting in VDH or VDEM at the beginning of the pandemic. Initially, the modeling and foresight unit was staffed by one director on loan from the Office of Health Equity, with temporary support from staff from other units at different times throughout the pandemic. ELC-EDx funding allowed the unit to add two contractors, including a full-time public health modeling coordinator. Overstretched staff, in the modeling unit and VDH generally, made it difficult to address some of the challenges mentioned below.

**Data Sharing:** Although VDH was a willing partner in sharing data with UVA-BI, data governance at VDH was not yet mature during the pandemic. As new datasets were needed (e.g., vaccinations, genomic sequencing) the process and responsibilities for securing data sharing agreements was shifting and unclear. Staffing challenges in informatics and data units added additional pressures. VDH has created a new Center for Public Health Informatics, which is working on streamlining these processes. Nevertheless, data governance issues have created delays and affected the timeliness of UVA-BI products.

**Communication:** While models and other foresight tools are essential resources during a pandemic, they can be confusing and generally require expert interpretation to use effectively. Model projections were sometimes viewed as predictions (a definitive statement of what will happen) rather than as tools to aid in understanding, analysis, and anticipation. Others saw multiple scenarios and wide confidence intervals and wondered what was the point. In the worst cases, this sometimes led to distrust or accusations of “gaming” the projections to drive behavior, even among VDH staff. More work needs to be done to socialize these tools, and to communicate results in a way that is meaningful and effective for a wider array of audiences.

**Policy Gaps:** One of the best uses of modeling and foresight tools is to assist policymakers with decision making and program design. The mechanistic and agent-based models used by UVA-BI excel in this use case. Despite some notable successes, there was often a gap between policy questions and answers. The policy question sphere was often opaque or vague to the modeling team, while the answers provided by the modeling team could be academic, couched in uncertainties and contingencies when staff “just need a number”. To get the most out of modeling and foresight tools, efforts should be made to bridge these gaps.

## Next Steps

**Organizational Changes:** The VDH modeling and foresight team was initially housed in VDH's Office of Epidemiology, Division of Surveillance and Investigation, managed by staff on loan from other offices. In summer of 2021, responsibility for the team moved to the planning unit of the Covid Task Force, operated by staff from the VDH Office of Emergency Preparedness (OEP). Seeing the value in this work beyond COVID-19, OEP sought and received funding for a full-time program supervisor for modeling, foresight and informatics within the CDC Public Health Workforce Grant. This role is expected to be filled in spring of 2022, and the modeling and foresight team will move permanently to OEP.

**Endemic Stage:** The modeling work thus far has been performed in the context of an ongoing pandemic, with the immediate needs of the response taking precedence. As we progress to an endemic phase, the modeling and foresight work will progress as well. Some key early strategies for this period include:

- Integration with other communicable disease threats, including respiratory diseases such as influenza
- Improving and streamlining public communication, with a focus on risk-based forecasting and CDC Community Transmission Levels and mitigation guidance
- Knowledge consolidation for future public health emergencies:
  - Transferring some products to VDH, creating direct links to VDH data and code that can be run internally, shortening turnaround times
  - Improving data sources and structures, including data-sharing documents that support quick ramp-up of products and modeling in diverse circumstances
  - Linking of data products to decision and planning needs in VDH's endemic planning and after-action reviews

## Conclusion

The CRF funding directed to UVA-BI and RAND provided the Commonwealth with state-specific modeling, advanced analytic, and foresight capabilities that few – if any – other states had access during the pandemic. The work performed by these entities proved instrumental in the decision to pause field hospitals, and has provided essential support throughout the pandemic. VDH sought and received additional funding through the federal ELC-EDx grant to continue, improve and expand on these activities, leveraging insight provided as we move to the endemic phase and prepare for new variants and other emerging public health threats.

## Articles published:

UVA scientists have written over 50 articles related to the ongoing COVID-19 pandemic response. The following articles have benefitted from work funded by VDH, and have enhanced the work being done to support VDH response efforts.

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7. Wang L, Adiga A, Chen J, Sadilek A, Venkatramanan S, Marathe M. CausalGNN: Causal-based Graph Neural Networks for Spatio-Temporal Epidemic Forecasting. *Proceedings of the Thirty-Sixth Annual Conference on Artificial Intelligence (AAAI-22)*. <https://www.aaai.org/AAAI22Papers/AISI-6475.WangL.pdf>
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