Network Systems
Science & Advanced
Computing

Biocomplexity Institute
& Initiative

University of Virginia

# Estimation of COVID-19 Impact in Virginia

May 27, 2020

(data current to May 26)

Biocomplexity Institute Technical report: TR 2020-067

UNIVERSITY of VIRGINIA

BIOCOMPLEXITY INSTITUTE

biocomplexity.virginia.edu

# Who We Are

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


**Points of Contact**

Bryan Lewis
brylew@virginia.edu

Srini Venkatramanan
srini@virginia.edu

Madhav Marathe
marathe@virginia.edu

Chris Barrett
ChrisBarrett@virginia.edu


**Biocomplexity COVID-19 Response Team**

Aniruddha Adiga, Abhijin Adiga, Hannah Baek, Chris Barrett, Golda Barrow, Richard Beckman, Parantapa Bhattacharya, Andrei Bura, Jiangzhuo Chen, Clark Cucinell, Allan Dickerman, Stephen Eubank, Arindam Fadikar, Joshua Goldstein, Stefan Hoops, Sallie Keller, Ron Kenyon, Brian Klahn, Gizem Korkmaz, Vicki Lancaster, Bryan Lewis, Dustin Machi, Chunhong Mao, Achla Marathe, Madhav Marathe, Fanchao Meng, Henning Mortveit, Mark Orr, Przemyslaw Porebski, SS Ravi, Erin Raymond, Jose Bayoan Santiago Calderon, James Schlitt, Aaron Schroeder, Stephanie Shipp, Samarth Swarup, Alex Telionis, Srinivasan Venkatramanan, Anil Vullikanti, James Walke, Amanda Wilson, Dawen Xie

# Overview

- **Goal**: Understand impact of COVID-19 mitigations in Virginia
- **Approach:**
  - Calibrate explanatory mechanistic model to observed cases
  - Project infections through the end of summer
  - Consider a range of possible mitigation effects in "what-if" scenarios
- **Outcomes:**
  - Ill, Confirmed, Hospitalized, ICU, Ventilated, Death
  - Geographic spread over time, case counts, healthcare burdens

# Key Takeaways

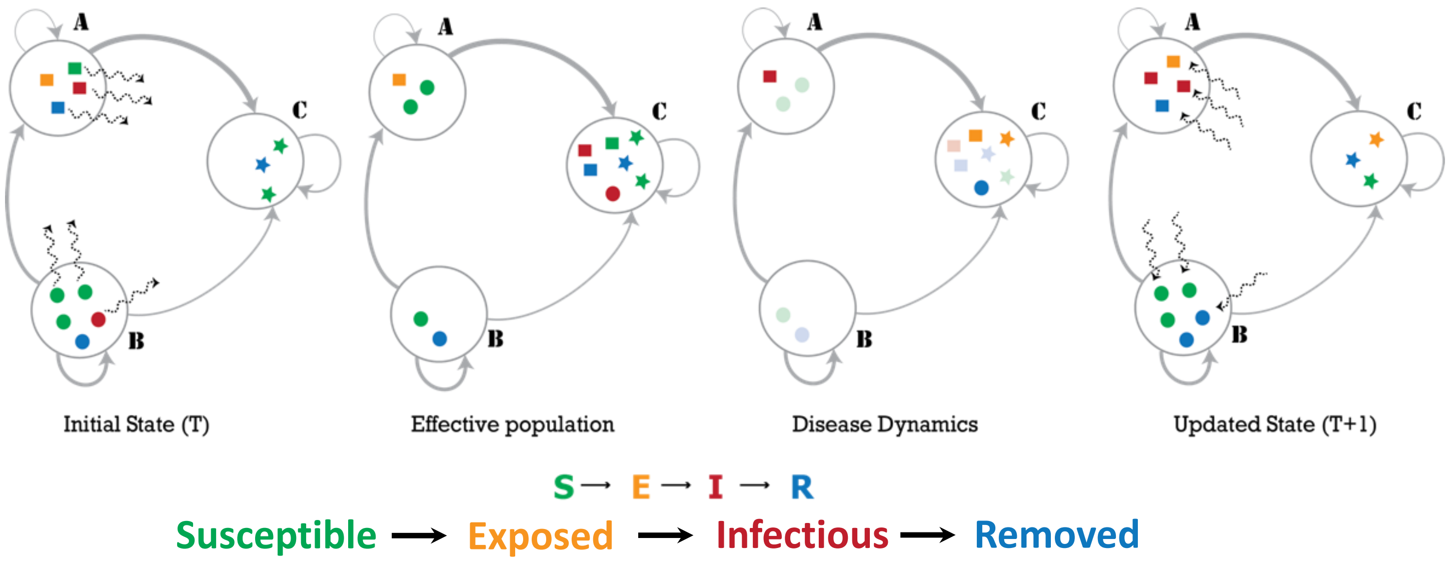
Projecting future cases precisely is impossible and unnecessary.
Even without perfect projections, we can confidently draw conclusions:

- **We are entering a period of transition, shifting to sustaining control through test and trace and other mitigations rather than strict social distancing.**
- Model update this week shows possible paths forward, rebounds with and without new mitigations, uncertainty remains on timing of this transition.
- Data show fewer people “stay home”, as well as progress towards better detection.
- **Intensity of rebound** depends on degree of social distancing relaxation; **intensity of new mitigations** depends on testing volumes and tracing effectiveness.
- The situation is changing rapidly. Models will be updated regularly.

# Model Configuration and Data Analysis

# Simulation Engine – PatchSim

- Metapopulation model
  - Represents each population and its interactions as a single patch
  - 133 patches for Virginia counties and independent cities
- Extended SEIR disease representation
  - Includes asymptomatic infections and treatments
- Mitigations affect both disease dynamics and population interactions
- Runs fast on high-performance computers
  - Ideal for calibration and optimization




Venkatramanan, Srinivasan, et al. "Optimizing spatial allocation of seasonal influenza vaccine under temporal constraints." *PLoS Computational Biology* 15.9 (2019): e1007111.

# Model Configuration

- **Transmission:** Parameters are calibrated to the observed case counts
  - **Reproductive number:** 2.1 - 2.3
  - **Infectious period** (time of infectiousness before full isolation): 3.3 to 5 days
- **Initial infections:** Start infections from confirmed cases by county
  - Timing and location based on onset of illness from VDH data
  - Assume 15% detection rate, so one confirmed case becomes ~7 initial infections
- **Mitigations:** Intensity of social distancing rebound and control sustaining mitigations into the future are unknowable, thus explored through 5 scenarios

# Mitigation Scenarios:
## Rebound Intensity x Detection Levels + Unmitigated

**Pause from Social Distancing:** Began on March 15th

- Lifted on May 15th (61 days), with two-week delay (75 days) for select counties*
- **Intensity**: Social distancing pauses and significantly reduces case growth

**Intensity of Rebound:** Relaxation of social distancing measures increases interactions in society, leading to two levels of transmission rates:

- **Light:** Interactions return to 1/6th of pre-pandemic levels, moderate increase in transmission
- **Strong:** Interactions return to 1/3rd of pre-pandemic levels, stronger increase in transmission

**Detection Control**: Increased Testing Capacity coupled with infection control measures

- **Better Detection**: Plays a role by limiting the period of infectiousness before isolation

**Unmitigated:** No social distancing or other types of mitigation

* Select counties as mentioned by recent releases from Governor Northam's office
https://www.governor.virginia.gov/newsroom/all-releases/2020/may/headline-856741-en.html
https://www.governor.virginia.gov/newsroom/all-releases/2020/may/headline-856796-en.html

# Five Mitigation Scenarios

| Scenario | Rebound Intensity | Better Detection | Name | Description |
|---|---|---|---|---|
| 1 | Strong | No | Strong | Strong Rebound, Detection same |
| 2 | Light | No | Light | Light Rebound, Detection same |
| 3 | Strong | Yes | Strong – BetterDetection | Strong Rebound, Detection improved |
| 4 | Light | Yes | Light – BetterDetection | Light Rebound, Detection improved |
| 5 | NA | | Unmitigated | No mitigation |

# Full Model Parameters

| | Parameter | Values | Description |
|---|---|---|---|
| Transmission | Transmissibility ($R_0$)[1] | 2.2 [2.1 – 2.3] | Reproductive number |
| | Incubation period[1] | 5 days | Time from infection to infectious |
| | Infectious period[1] | 3.3 - 5 days | Duration of infectiousness |
| | Infection detection rate[3] | 15% | 1 confirmed case becomes ~7 initial infections |
| | Percent asymptomatic[1] | 50% | Infected individuals that don't exhibit symptoms |
| Resources | Onset to hospitalization[1] | 5 days | Time from symptoms to hospitalization |
| | Hospitalization to ventilation[1] | 3 days | Time from hospitalization to ventilation |
| | Duration hospitalized | 8 days | Time spent in the hospital [4] |
| | Duration ventilated[2] | 14 days | Time spent on a ventilator |
| | Percent hospitalized[1] | 5.5% (~20% of confirmed) | Symptomatic individuals becoming hospitalized |
| | Percent in ICU[1] | 20% | Hospitalized patients that require ICU |
| | Percent ventilated[1] | 70% | ICU patients requiring ventilation |

1 CDC COVID-19 Modeling Team. "Best Guess" scenario. Planning Parameters for COVID-19 Outbreak Scenarios. Version: 2020-03-31.
2 Up-to-date. COVID-19 Critical Care Issues. https://www.uptodate.com/contents/coronavirus-disease-2019-covid-19-critical-care-issues?source=related_link (Accessed 13APRIL2020)
3 Li et al., *Science* 16 Mar 2020:eabb3221 https://science.sciencemag.org/content/early/2020/03/24/science.abb3221 (Accessed 13APRIL2020)
4 Personal communications, UVA Health and Sentara (~500 VA based COVID patients)

# Recent Parameter Validation

**New York State announced sero-prevalence survey results on May 2nd**

- 15,000 antibody tests conducted randomly through the state at grocery stores
- **Total Attack Rate**: 12.3%

**Estimation of undetected infections**

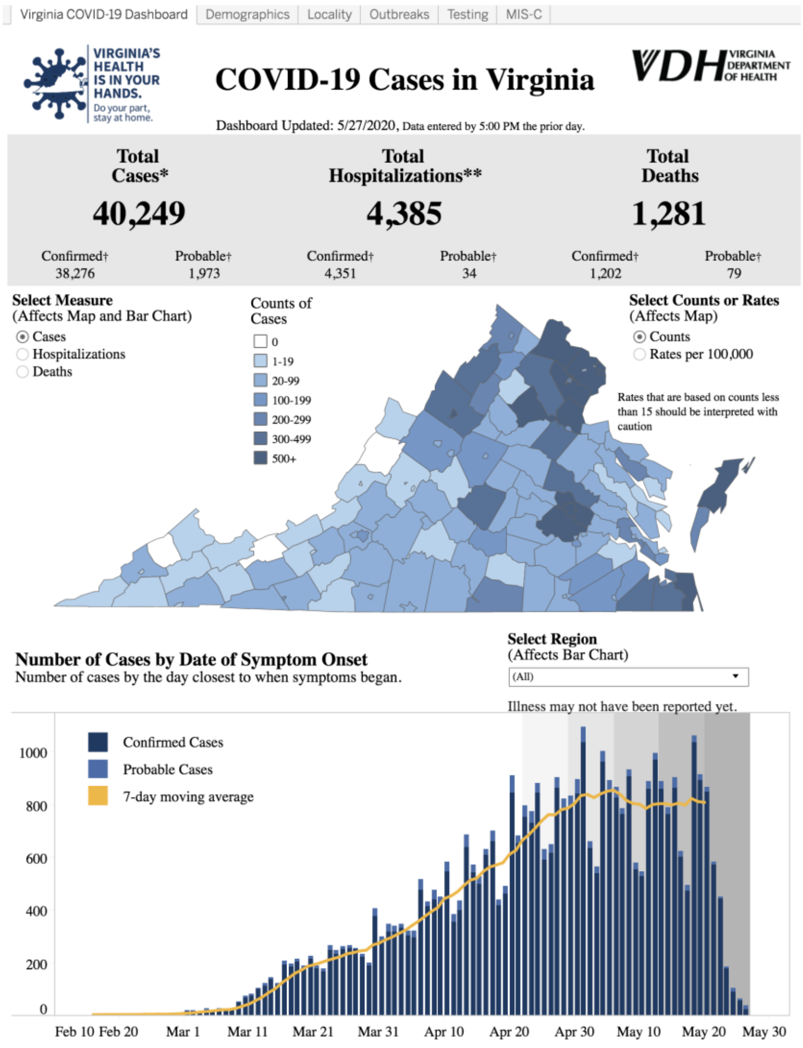
- Total infections in NY = 2.46M, total of 300K confirmed cases
- Confirmed case detection = 12% of infections (close to 15% used in model)

**Estimation of hospitalizations from infections**

- Total infections in NY = 2.46M, total of 66K hospitalizations
- Hospitalizations = 2.7% of infections (close to 2.25% used in model)

# Calibration Approach

- **Data:**
  - County level case counts by date of onset (from VDH)
  - Confirmed cases for model fitting
- **Model:** PatchSim initialized with disease parameter ranges from literature
- **Calibration:** fit model to observed data
  - Search transmissibility and duration of infectiousness
  - Markov Chain Monte Carlo (MCMC) particle filtering finds best fits while capturing uncertainty in parameter estimates
- **Project:** future cases and outcomes using the trained particles



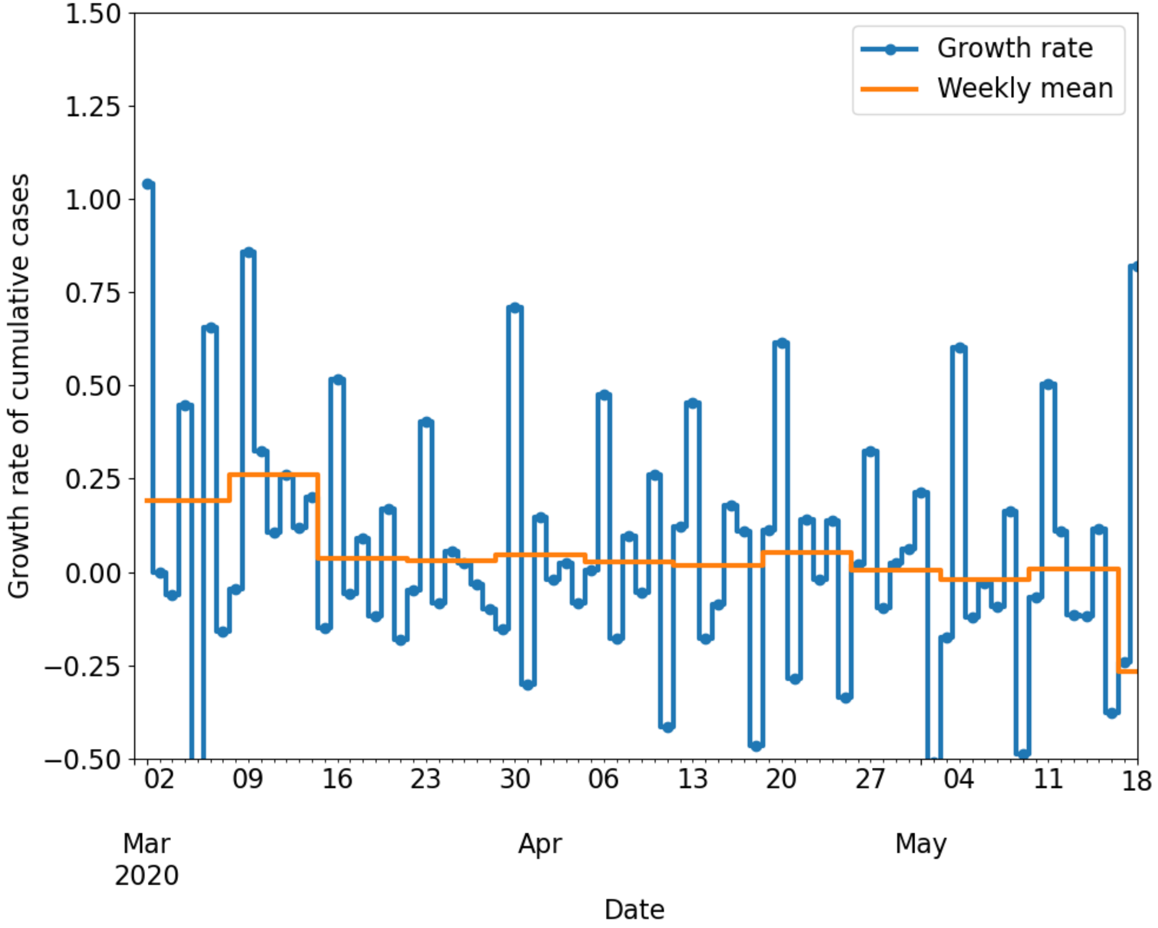

Accessed 9:30am May 27, 2020
https://www.vdh.virginia.gov/coronavirus/

UNIVERSITY of VIRGINIA
BIOCOMPLEXITY INSTITUTE

# Impact of Interventions

# Estimating Effects of Social Distancing

## VDH data shows reductions in growth rate starting in mid-March



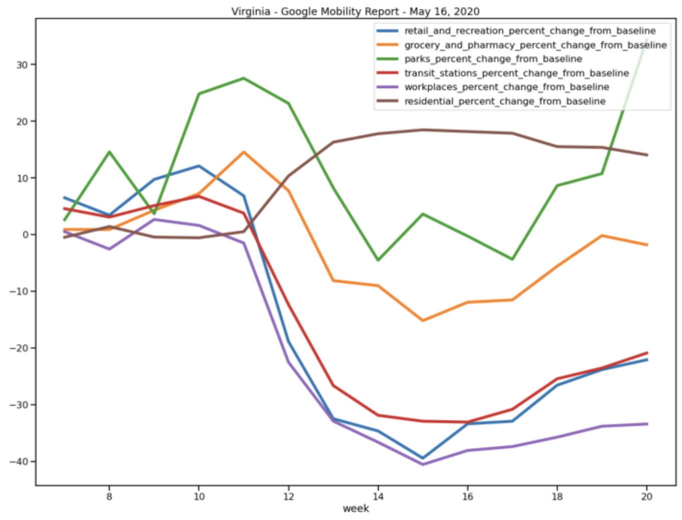

Weekly growth rate by date of onset

- Week before March 15 = 0.3
- Week after March 15 = -0.02 to 0.04

Crude reproductive number estimates

- 2.2 before March 15th
- 0.91 to 1.19 after March 15th

**Google Mobility data shows VA greatly reduced activities, though is rebounding:** [https://www.google.com/covid19/mobility/](https://www.google.com/covid19/mobility/) (as of May 16th)



# Estimating Effects of Better Detection

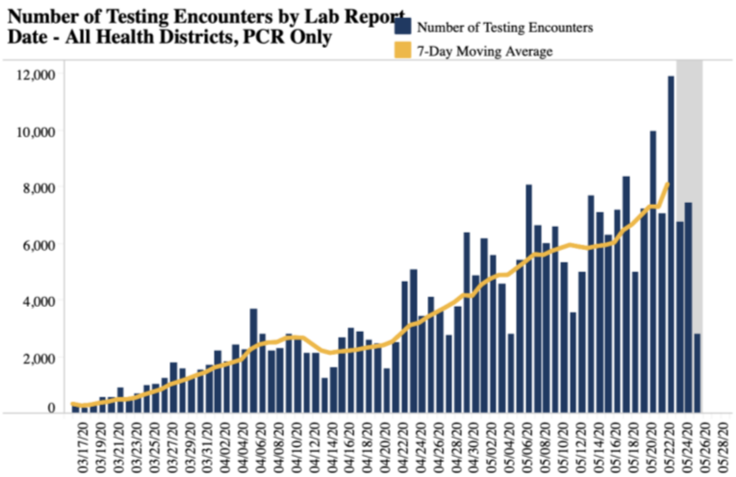
## VDH data shows reductions in time from Symptom Onset to Diagnosis

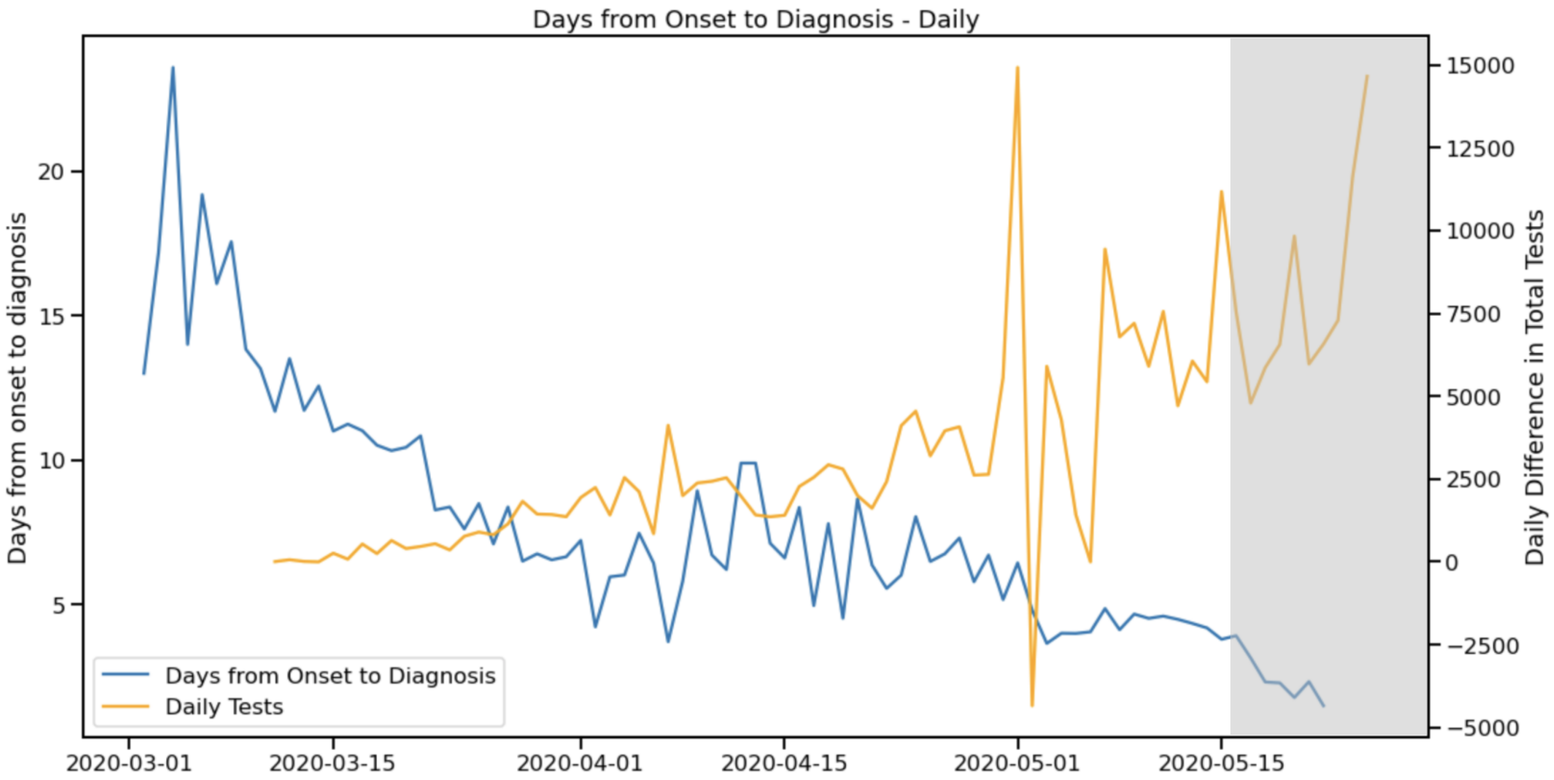
Days to Diagnosis drops ~30% in recent weeks

- Mid March to Late April = 6.8 days
- Late April to Mid May = 4.7 days

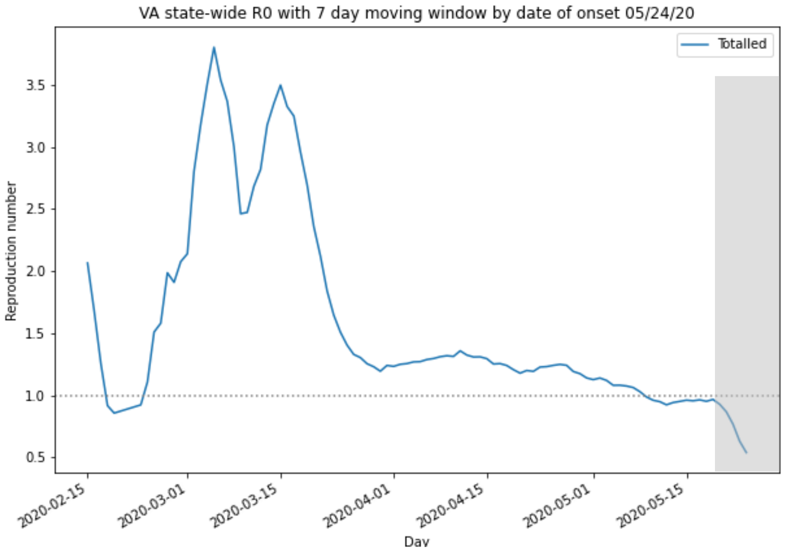
Testing Encounters increase

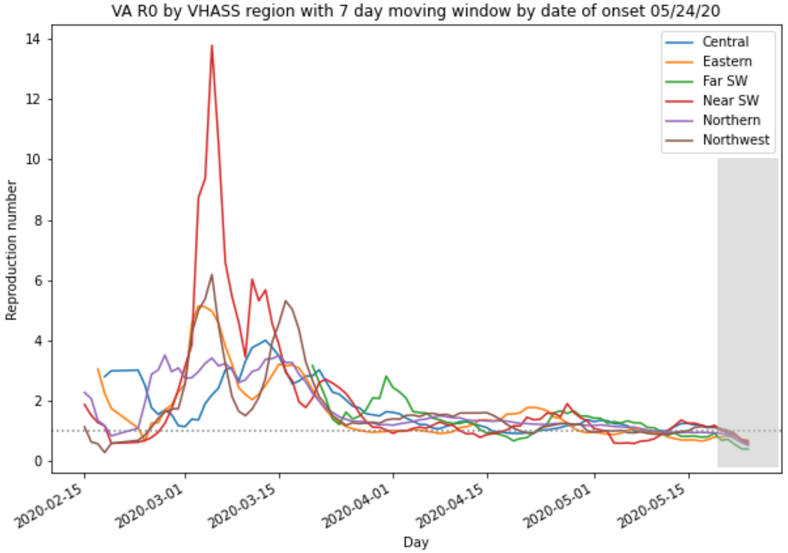
- Late April = ~4K / day
- Mid May = ~7K / day



# Estimating Daily Reproductive Number




**Statewide and most regions follow similar pattern**

- Spike, followed by a decline, to plateau, with recent decline
- This week: overall decline, some regions up

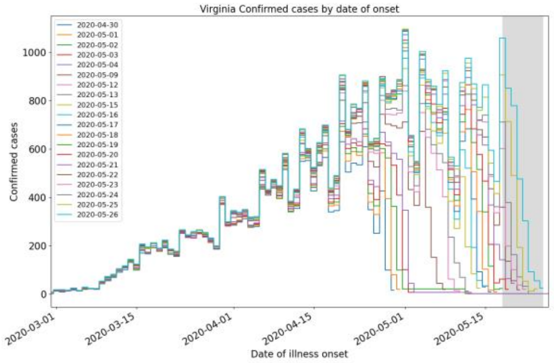
## Methodology

- Wallinga-Teunis method as implemented in EpiEstim[1] R package
- Based on Date of Onset of Symptoms
- Uses serial interval to estimate $R_e$ over time: 6 days (2 day std dev)

**Recent Estimates subject to revision as more data comes in**

- Date of onset unstable in last 7-14 days

May 16th Estimates




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

# Future Interactions Drive Future Cases

**Adherence to Social Distancing measures and Individual Choices about Personal Disease Control Practices will drive the next phase of the Epidemic**

**Challenges**:

- Assessing the adherence with policies as actual behavior drives the epidemic
- Translating future policies to changes in transmission dynamics

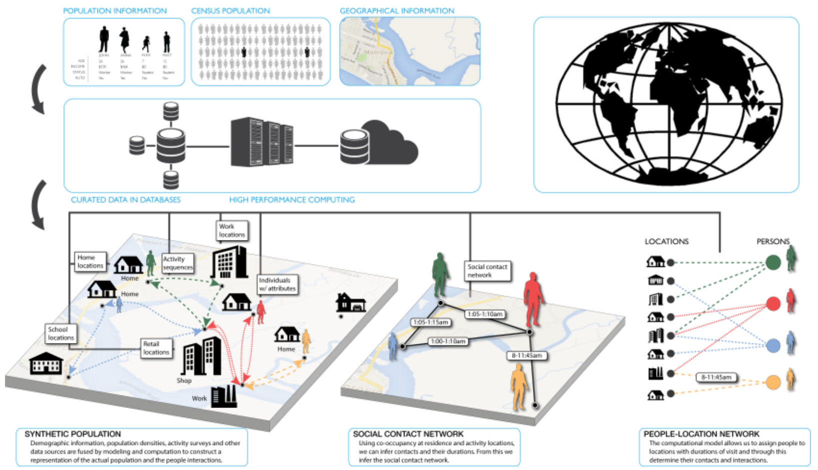
**Interactions can increase and cases can be driven lower, sustaining control**

- Policies must carefully weigh local risk of spread, monitor local epidemiology, and tune policies and guidance to changing conditions
- Individuals must be ready to adhere to changes in policies and continue to practice good personal disease control practices

# Agent-based Model Aided Policy Assessment

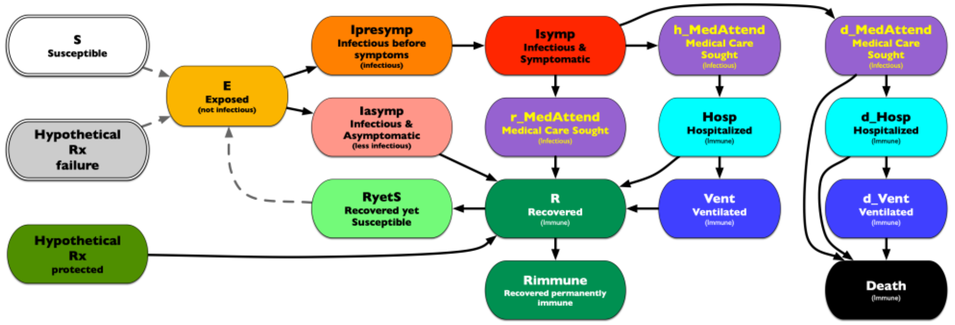
## EpiHiper: Distributed network-based stochastic disease transmission simulations

- Assess the impact on transmission under different conditions
- Translate changes in social interactions to transmission risk




### Synthetic Population

- Census derived age and household structure
- Time-Use survey driven activities at appropriate locations



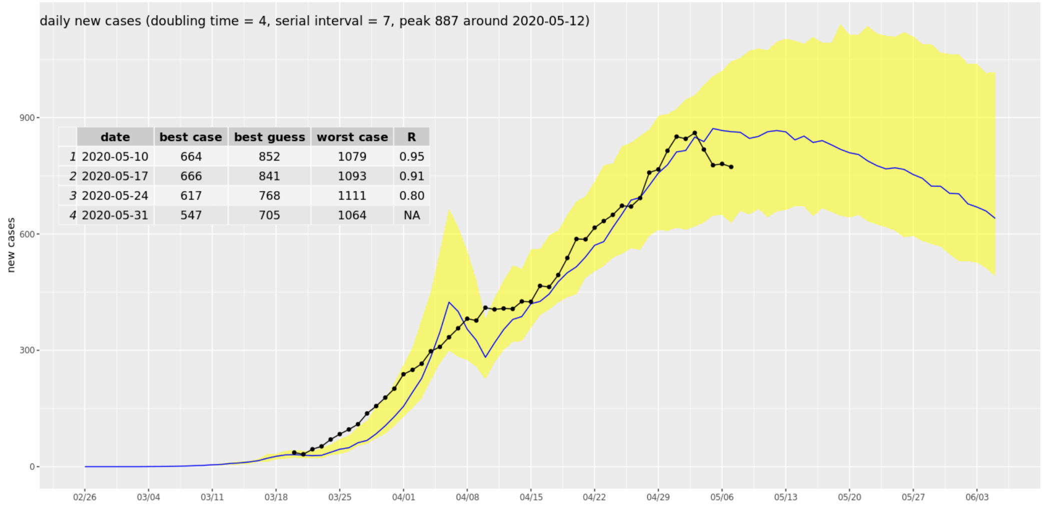

### Detailed Disease Course of COVID-19

- Literature based probabilities of outcomes with appropriate delays
- Varying levels of infectiousness
- Hypothetical treatments for future developments

# Agent-Based Model Design

**Study of ”Stay Home” policy adherence**

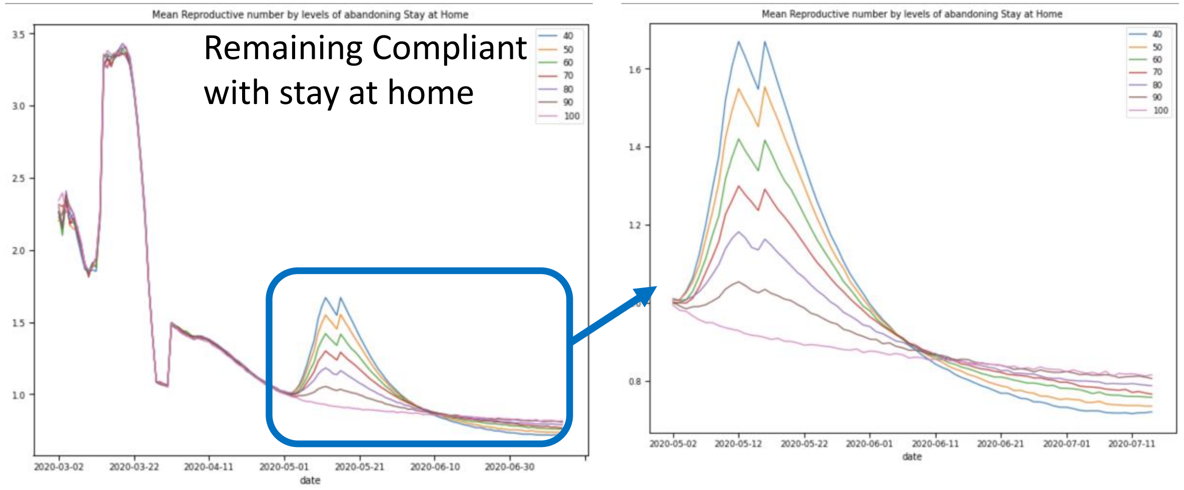
- Calibration to current state in epidemic
- Implement “release” of different proportions of people from ”staying at home”




| | date | best case | best guess | worst case | R |
|---|---|---|---|---|---|
| 1 | 2020-05-10 | 664 | 852 | 1079 | 0.95 |
| 2 | 2020-05-17 | 666 | 841 | 1093 | 0.91 |
| 3 | 2020-05-24 | 617 | 768 | 1111 | 0.80 |
| 4 | 2020-05-31 | 547 | 705 | 1064 | NA |

**Calibration to Current State**

- Adjust transmission and adherence to current policies to current observations
- For Virginia, with same seeding approach as PatchSim

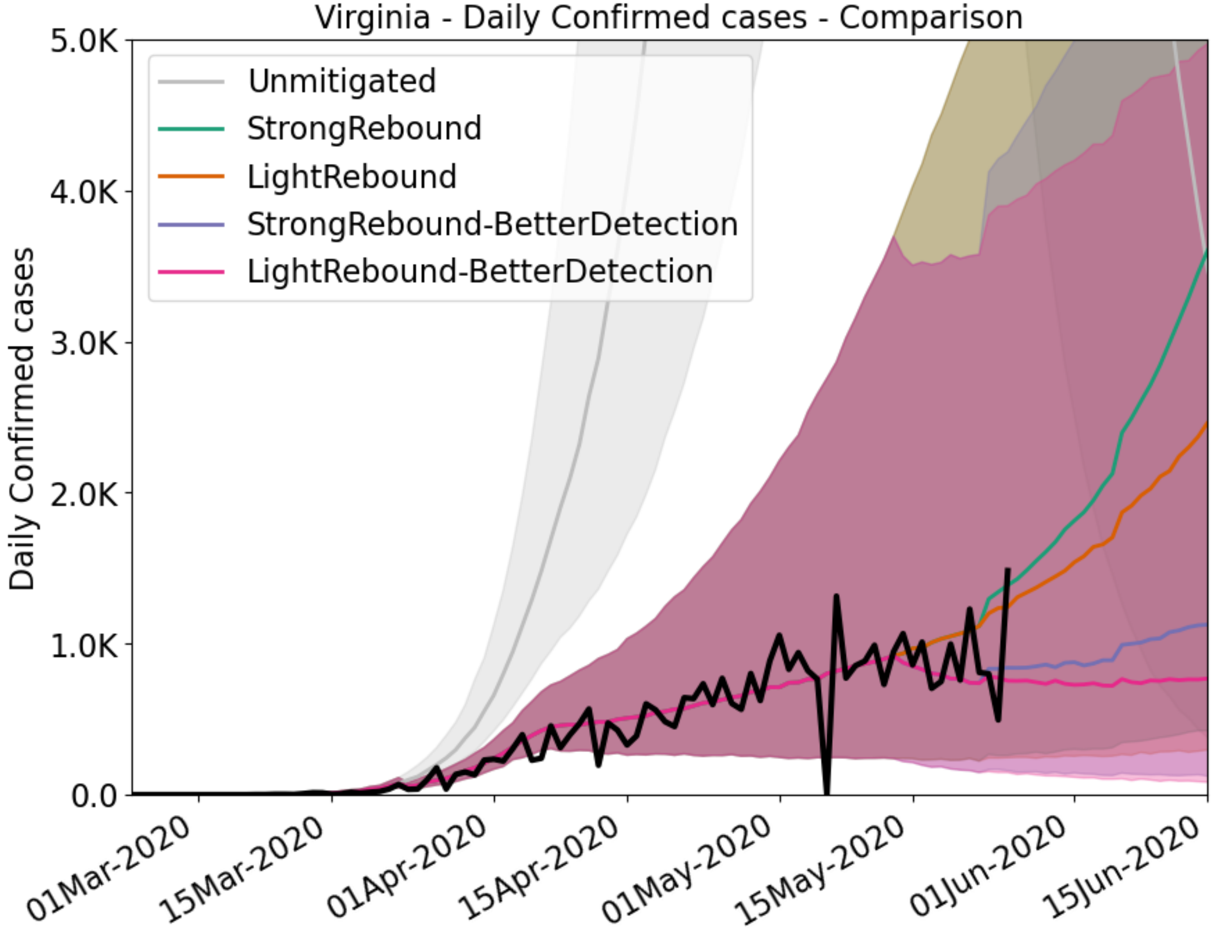



**Impacts on Reproductive number with release**

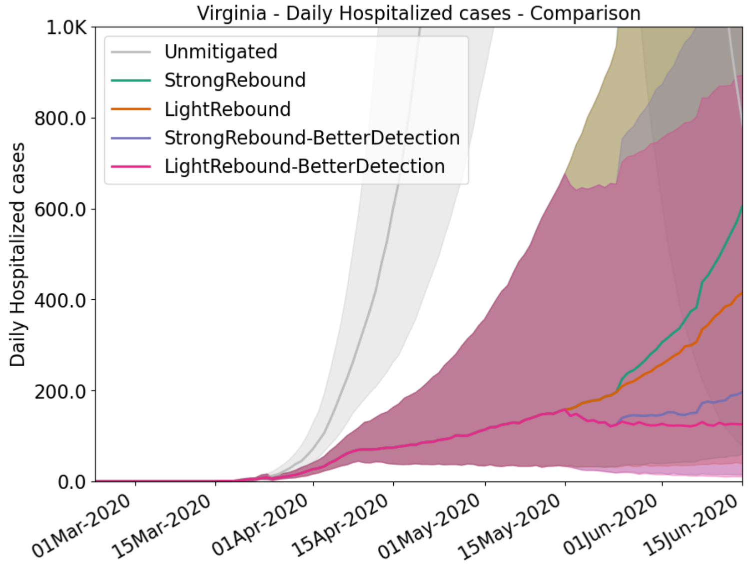
- After release, spike in transmission driven by additional interactions at work, retail, and other
- At 25% release (70-80% remain compliant)
- Translates to 15% increase in transmission, which represents a 1/6$^{th}$ return to pre-pandemic levels

# Short-term Projections

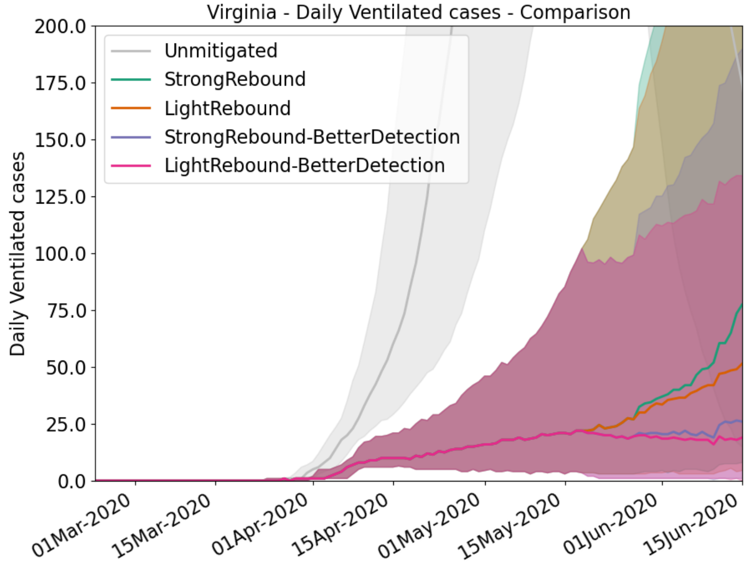
## Confirmed cases




## Hospitalizations

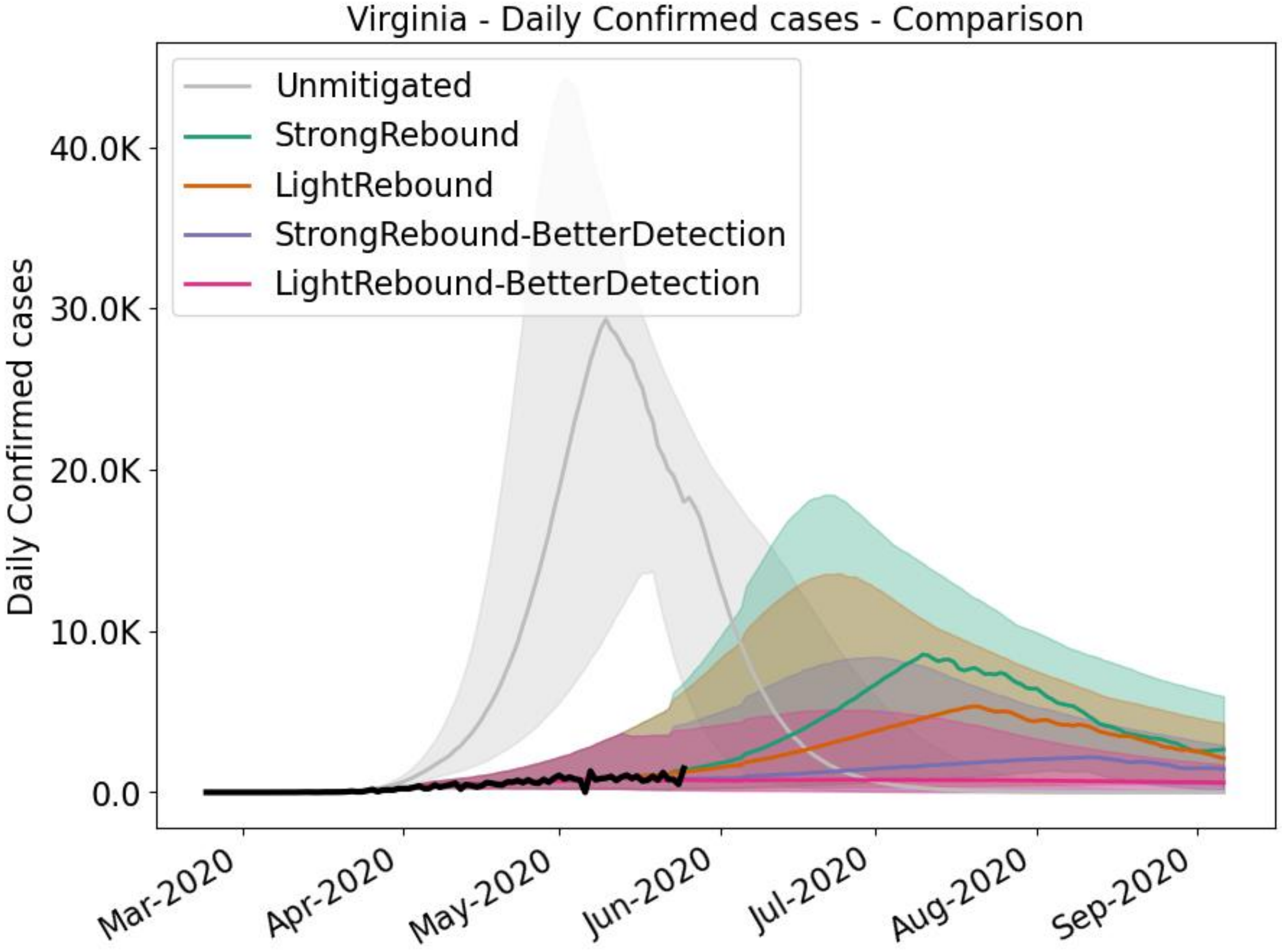



## Ventilations




UNIVERSITY of VIRGINIA
BIOCOMPLEXITY INSTITUTE

# Period of Transition: Sustaining Control




**Weekly New Confirmed Cases***

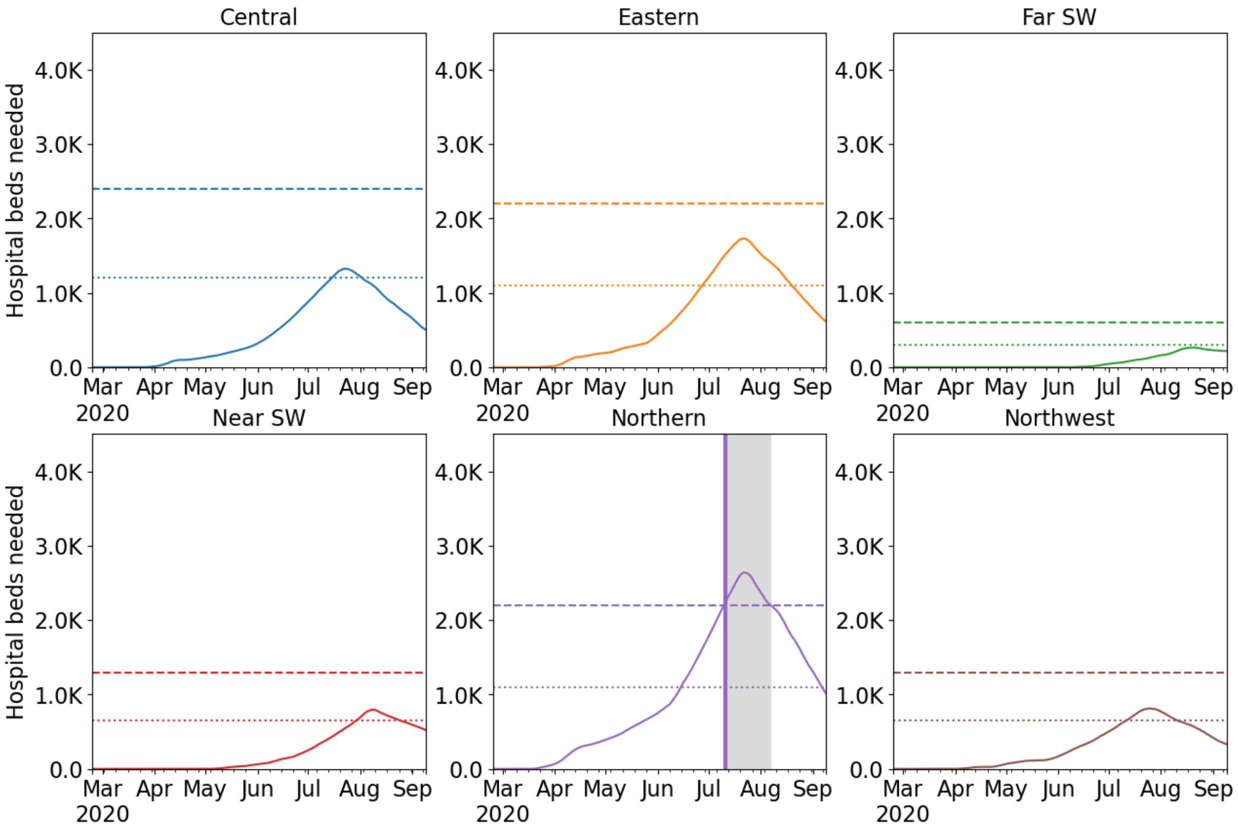
| Week Ending | Unmitigated | Light | Light – Better Detection |
|---|---|---|---|
| 5/24/20 | 159,643 | 5,339 | 5,339 |
| 5/31/20 | 126,034 | 5,774 | 5,229 |
| 6/7/20 | 77,114 | 6,030 | 5,052 |
| 6/14/20 | 43,790 | 7,075 | 5,232 |
| 6/21/20 | 22,734 | 7,960 | 5,280 |
| 6/28/20 | 11,108 | 8,916 | 5,314 |
| 7/5/20 | 5,432 | 9,941 | 5,314 |
| 7/12/20 | 2,630 | 10,919 | 5,246 |
| 7/19/20 | 1,266 | 11,896 | 5,183 |
| 7/26/20 | 586 | 12,849 | 5,143 |
| 8/2/20 | 266 | 13,651 | 5,046 |
| 8/9/20 | 95 | 14,176 | 4,934 |

*Numbers are medians of projections

# Hospital Demand and Capacity by Region

**Capacities by Region – Light Rebound**

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




* Assumes average length of stay of 8 days

**Date ranges when regions are estimated to exceed surge capacity**

| | Scenario | Date Ranges |
|---|---|---|
| 1 | Strong | Late June to Mid August |
| 2 | Light | Mid July to Early Aug |
| 3 | Strong – Better Detection | None |
| 4 | Light – Better Detection | None |
| 5 | Unmitigated | Mid April to Late June |

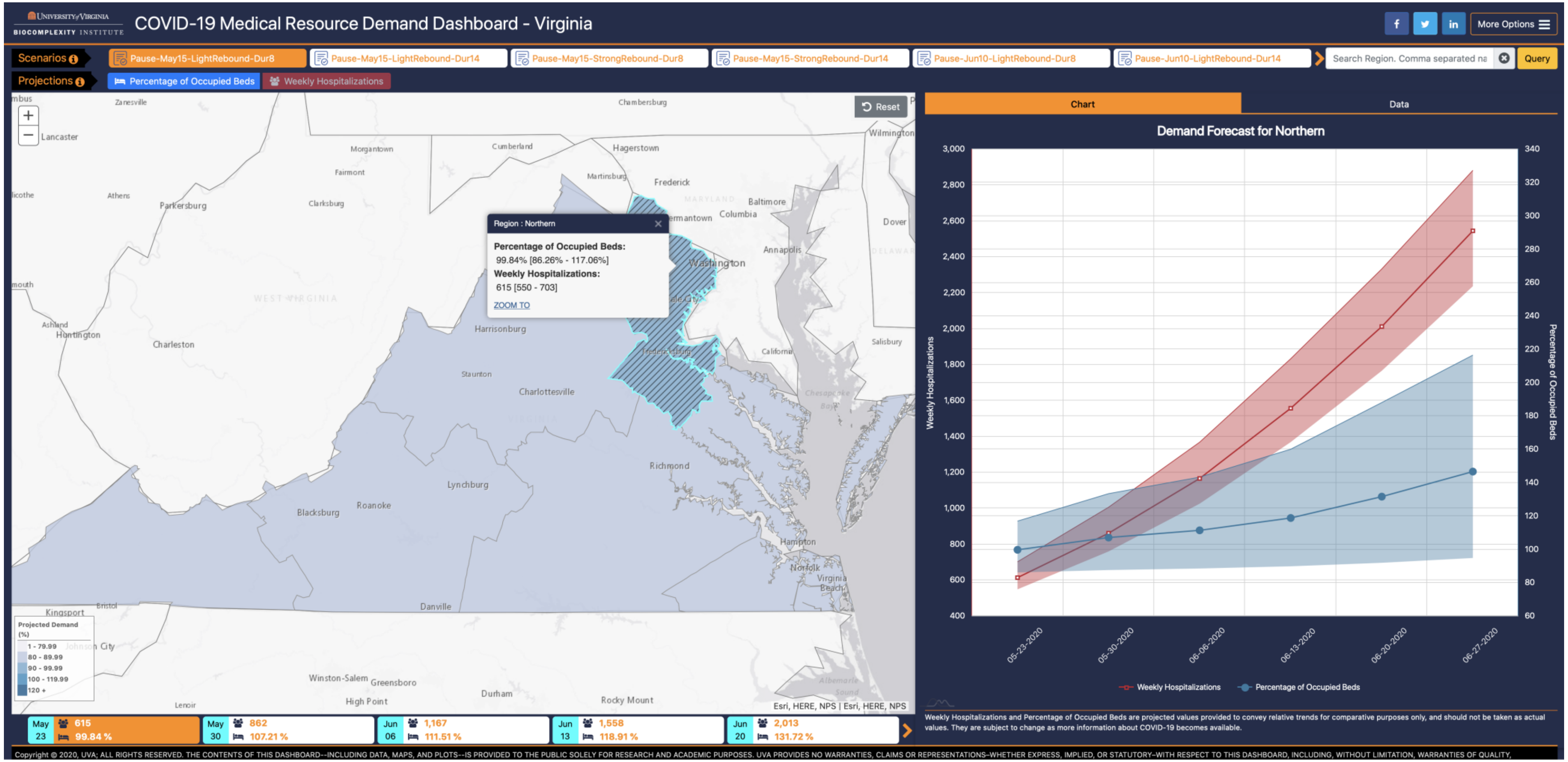
**Social Distancing has postponed the time to when capacity could be exceeded 1 to 2 months**

UNIVERSITY of VIRGINIA

BIOCOMPLEXITY INSTITUTE

# Medical Resource Demand Dashboard

https://nssac.bii.virginia.edu/covid-19/vmrddash/



# Key Takeaways

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

- **We are entering a period of transition, shifting to sustaining control through test and trace and other mitigations rather than strict social distancing.**
- Model update this week shows possible paths forward, rebounds with and without new mitigations, uncertainty remains on timing of this transition.
- Data show fewer people “stay home,” as well as progress towards better detection.
- **Intensity of rebound** depends on degree of social distancing relaxation; **intensity of new mitigations** depends on testing volumes and tracing effectiveness.
- The situation is changing rapidly. Models will be updated regularly.

# References

Venkatramanan, S., et al. "Optimizing spatial allocation of seasonal influenza vaccine under temporal constraints." *PLoS computational biology* 15.9 (2019): e1007111.

Arindam Fadikar, Dave Higdon, Jiangzhuo Chen, Bryan Lewis, Srinivasan Venkatramanan, and Madhav Marathe. Calibrating a stochastic, agent-based model using quantile-based emulation. SIAM/ASA Journal on Uncertainty Quantification, 6(4):1685–1706, 2018.

Adiga, Aniruddha, Srinivasan Venkatramanan, Akhil Peddireddy, et al. "Evaluating the impact of international airline suspensions on COVID-19 direct importation risk." *medRxiv* (2020)

NSSAC. PatchSim: Code for simulating the metapopulation SEIR model. https://github.com/NSSAC/PatchSim (Accessed on 04/10/2020).

Virginia Department of Health. COVID-19 in Virginia. http://www.vdh.virginia.gov/coronavirus/ (Accessed on 04/10/2020)

Biocomplexity Institute. COVID-19 Surveillance Dashboard. https://nssac.bii.virginia.edu/covid-19/dashboard/

Google. COVID-19 community mobility reports. https://www.google.com/covid19/mobility/

Cuebiq: COVID-19 Mobility insights. https://www.cuebiq.com/visitation-insights-covid19/

Biocomplexity page for data and other resources related to COVID-19: https://covid19.biocomplexity.virginia.edu/

# Questions?

**Biocomplexity COVID-19 Response Team**


**Points of Contact**

Bryan Lewis
brylew@virginia.edu

Srini Venkatramanan
srini@virginia.edu

Madhav Marathe
marathe@virginia.edu

Chris Barrett
ChrisBarrett@virginia.edu



Aniruddha Adiga, Abhijin Adiga, Hannah Baek, Chris Barrett, Golda Barrow, Richard Beckman, Parantapa Bhattacharya, Andrei Bura, Jiangzhuo Chen, Clark Cucinell, Allan Dickerman, Stephen Eubank, Arindam Fadikar, Joshua Goldstein, Stefan Hoops, Sallie Keller, Ron Kenyon, Brian Klahn, Gizem Korkmaz, Vicki Lancaster, Bryan Lewis, Dustin Machi, Chunhong Mao, Achla Marathe, Madhav Marathe, Fanchao Meng, Henning Mortveit, Mark Orr, Przemyslaw Porebski, SS Ravi, Erin Raymond, Jose Bayoan Santiago Calderon, James Schlitt, Aaron Schroeder, Stephanie Shipp, Samarth Swarup, Alex Telionis, Srinivasan Venkatramanan, Anil Vullikanti, James Walke, Amanda Wilson, Dawen Xie