Network Systems
Science & Advanced
Computing

Biocomplexity Institute
& Initiative

University of Virginia

Estimation of COVID-19 Impact in Virginia

June 10th, 2020

(data current to June 9th)

Biocomplexity Institute Technical report: TR 2020-073

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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

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Biocomplexity COVID-19 Response Team

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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

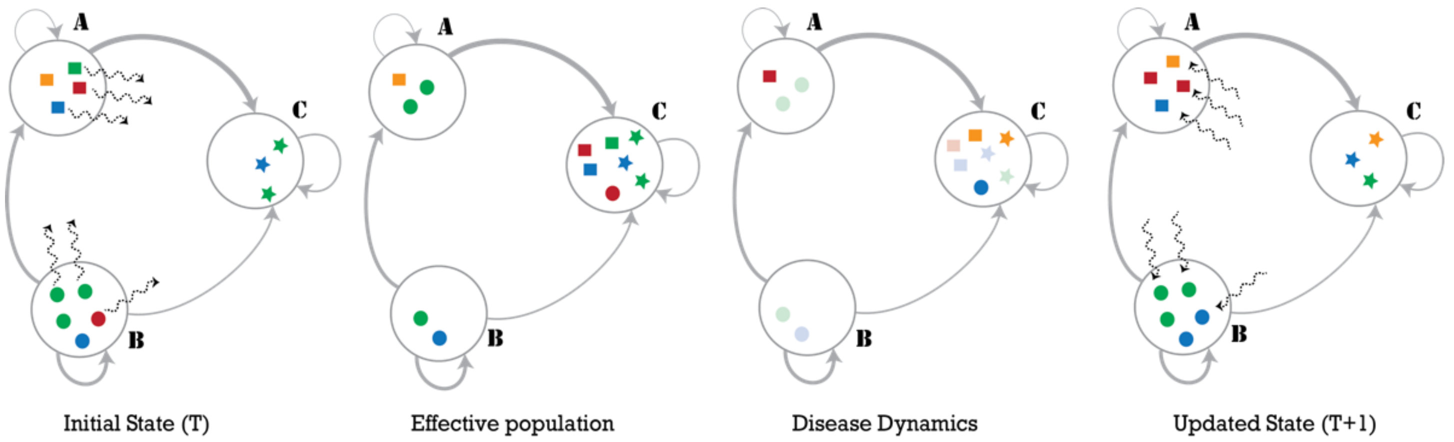
Projecting future cases precisely is impossible and unnecessary.
Even without perfect projections, we can confidently draw conclusions:

- **We remain in 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.
- Impact of better detection and isolation are showing, uncertainty of timing remains.
- **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



S → E → I → R

Susceptible → Exposed → Infectious → Removed

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

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 <u>significantly reduces case growth</u>

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
- **Full Rebound**: Interactions return completely (100%) to pre-pandemic levels, as a reference

Tracing and Isolation: Increased Testing Capacity coupled with infection control measures can limit the period of infectiousness without isolation

- **Better Detection**: Observed relative reductions in days from onset to diagnosis applied to infectious period and remain stable into future for projections

* 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	Full	No	Full Rebound	Return to 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
	Percent Fatality	1.75%	Symptomatic individuals who die

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

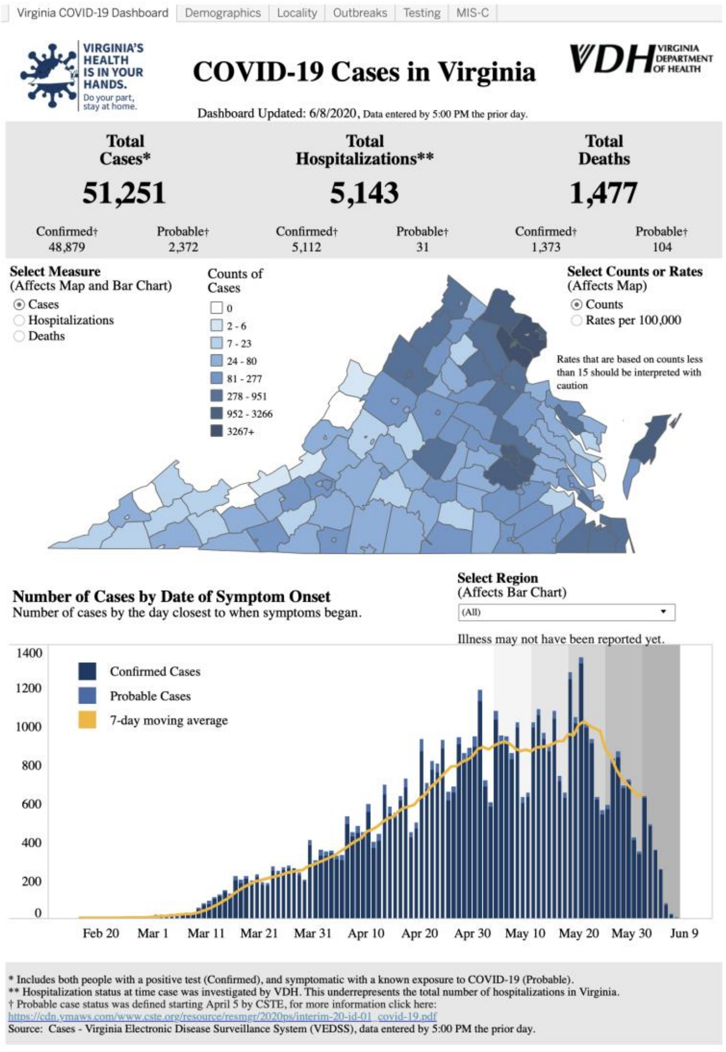
- Total infections in NY = 2.46M, total of 300K confirmed cases
- Confirmed case detection = 12% of infections (close to 15% used in model)

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 3pm June 9, 2020
https://www.vdh.virginia.gov/coronavirus/

Impact of Interventions

Estimating Effects of Social Distancing

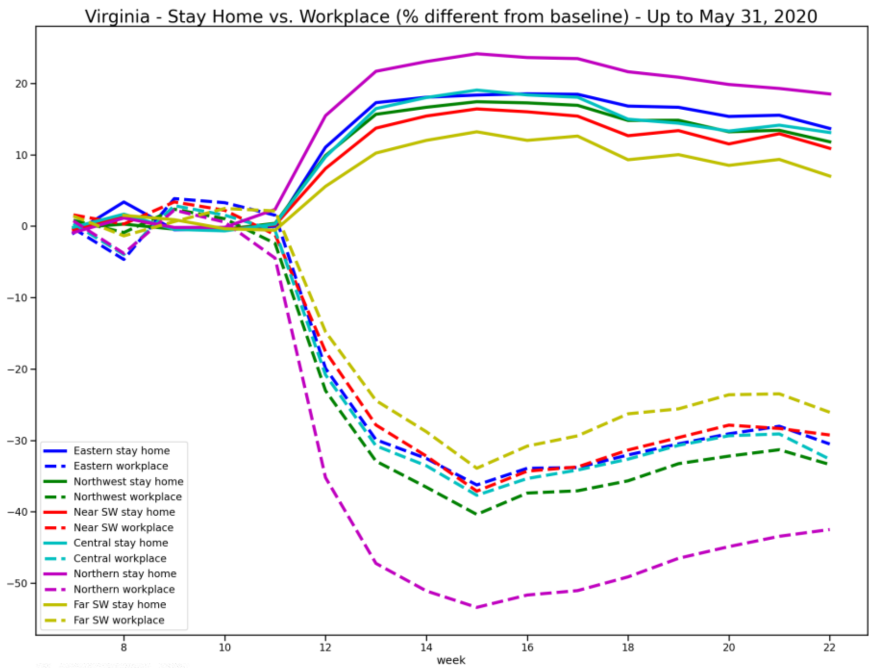
Mobility data shows pause mid-March, slow rebound starting in May

Google Mobility data shows continued slow rebound

(as of May 31st)

https://www.google.com/covid19/mobility/

- Regional levels of Stay at home vs. Workplace
- 30% reduction of those staying at home
- **Trends**: Very slow and stable reductions in stay home

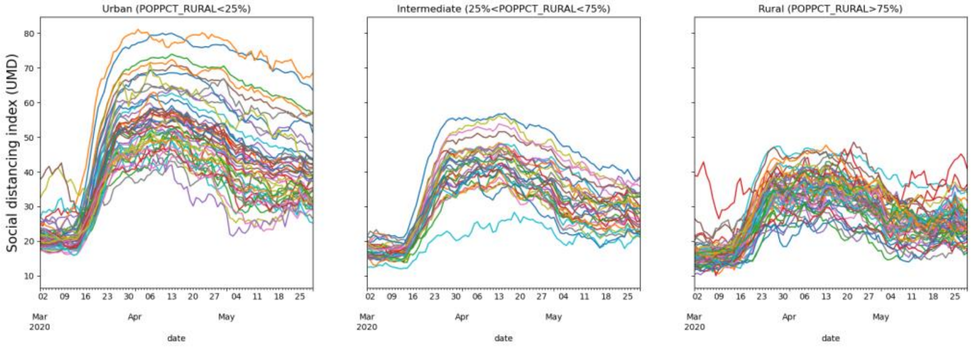


Weekly growth rate by date of onset

- Week before March 15 = 0.3
- Week after March 15 = -0.03 to 0.04

Crude reproductive number estimates

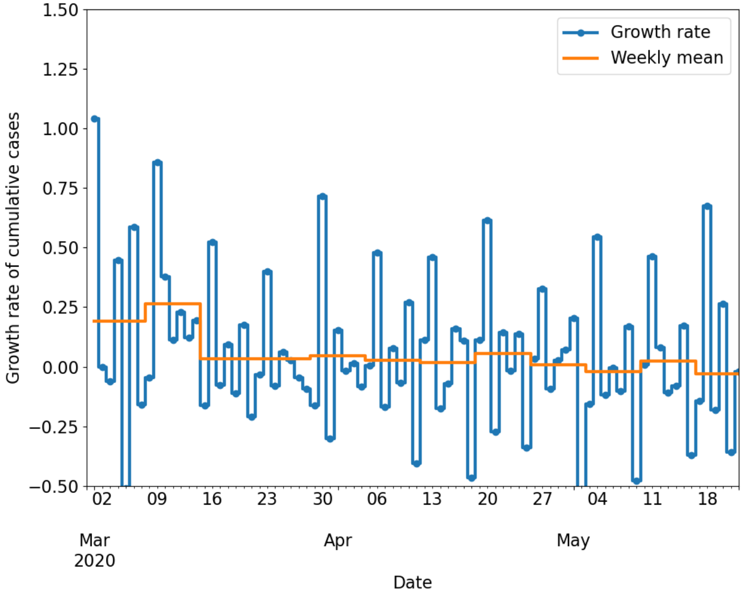
- 2.2 before March 15th
- 0.81 to 1.10 after March 15th



Urban – Rural divide shows in level of social distancing

https://data.covid.umd.edu

- Urban counties show more social distance, rural counties show less
- This is a biased measure, lower mobility accesses more services in urban areas



Estimating Effects of Better Detection

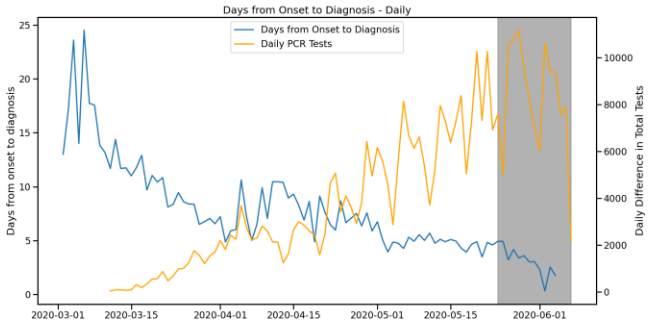
VDH data shows reductions in time from Symptom Onset to Diagnosis

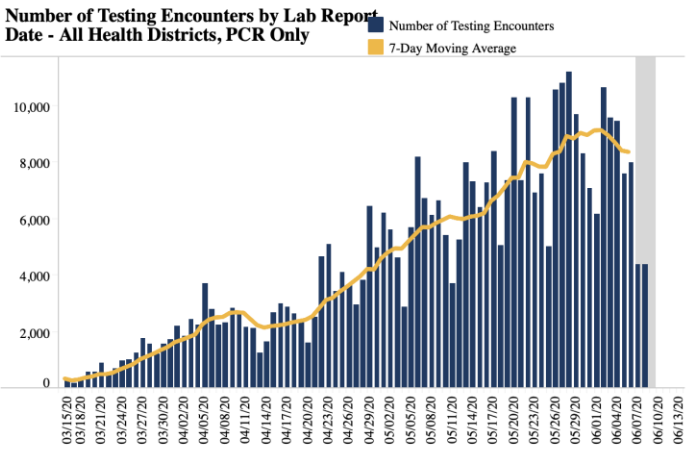
Days to Diagnosis drops ~30% in recent weeks

- Mid March to Late April = 7.5 days
- Late April to Mid May = 5.3 days
- Mid May to end of May = 4.0
- Slight shift up from last week (7.2 and 5.1)

Testing Encounters increase:

~4K/day (late April) to ~8K/day (early June)





Accessed 5pm June 9, 2020

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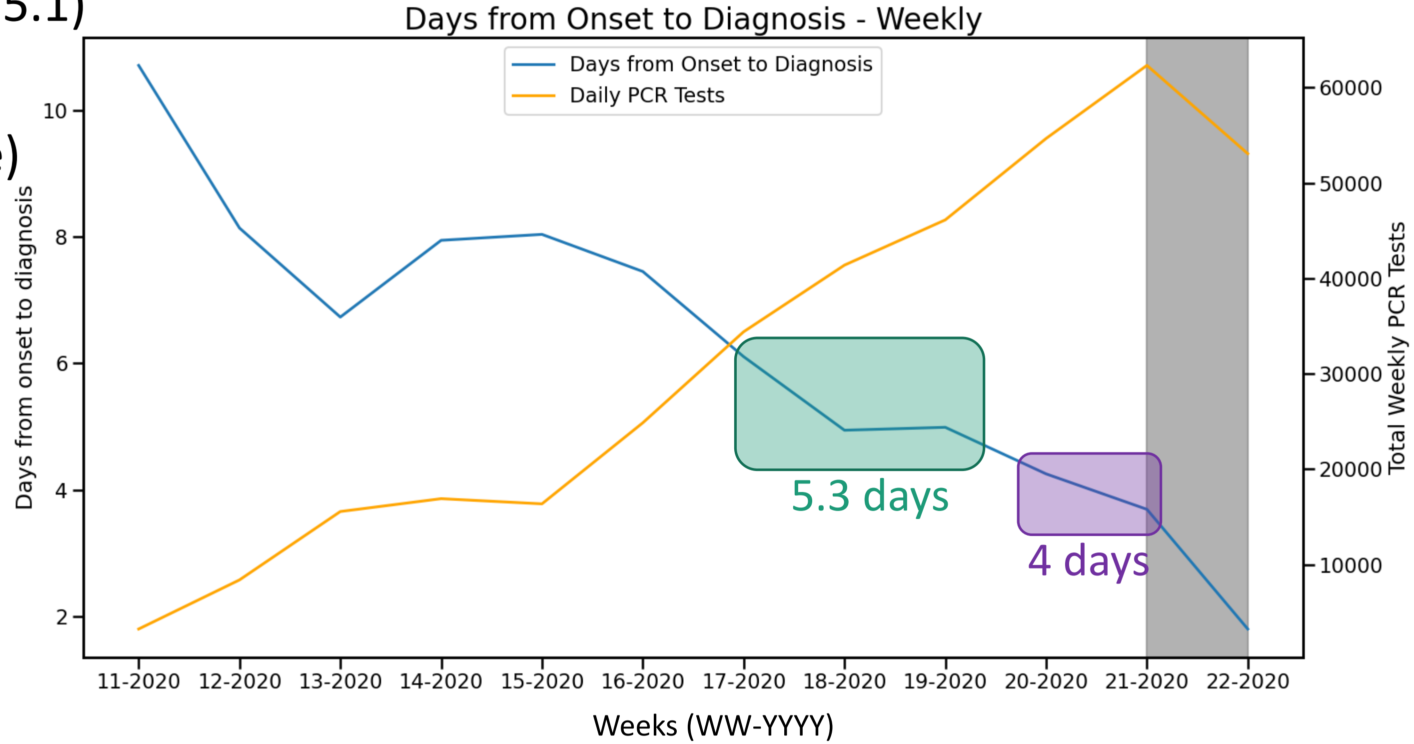
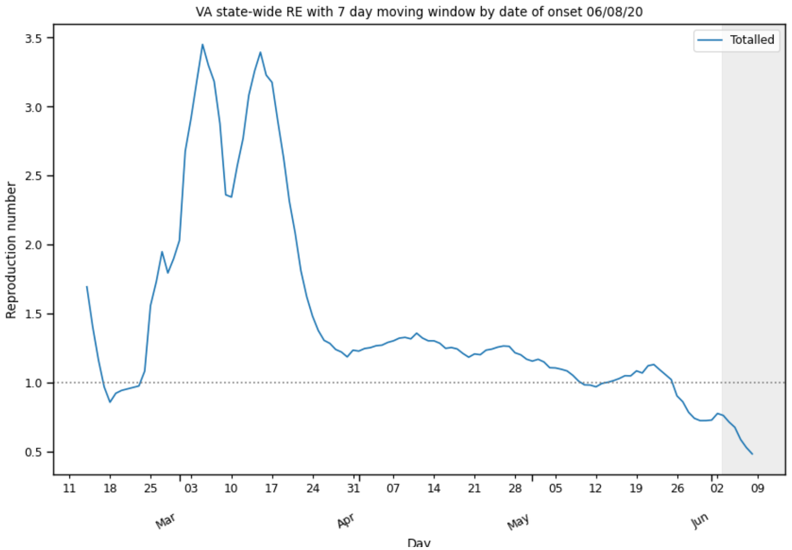
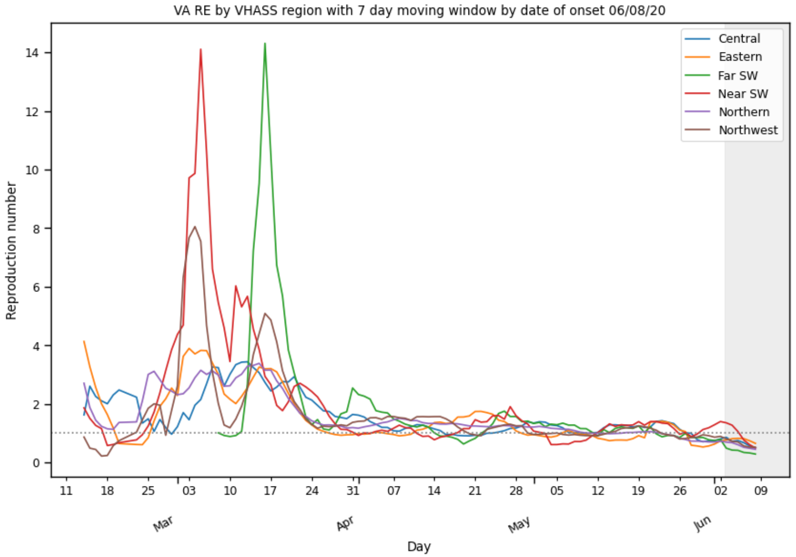


Estimating Daily Reproductive Number





Statewide and most regions follow similar pattern

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

Methodology

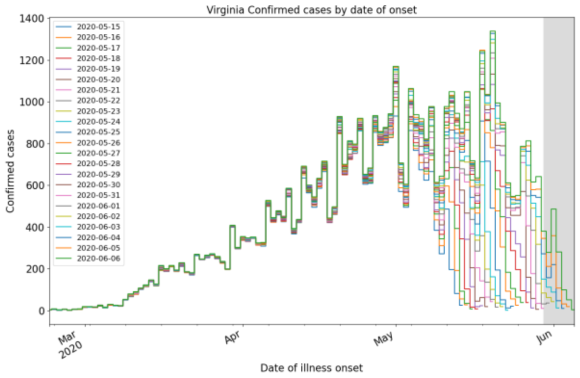
- Wallinga-Teunis method as implemented in EpiEstim[1] R package
- Based on Date of Onset of Symptoms
- Uses serial interval to estimate R_e over time: 6 days (2 day std dev)

Recent Estimates subject to revision as more data comes in

- Date of onset unstable in last 7-14 days

May 30th Estimates

Region	Current R_e	Diff Last Week
State-wide	0.724	-0.336
Central	0.704	-0.585
Eastern	0.528	-0.786
Far SW	0.852	-0.080
Near SW	1.122	-0.160
Northern	0.715	-0.268
Northwest	0.944	0.008

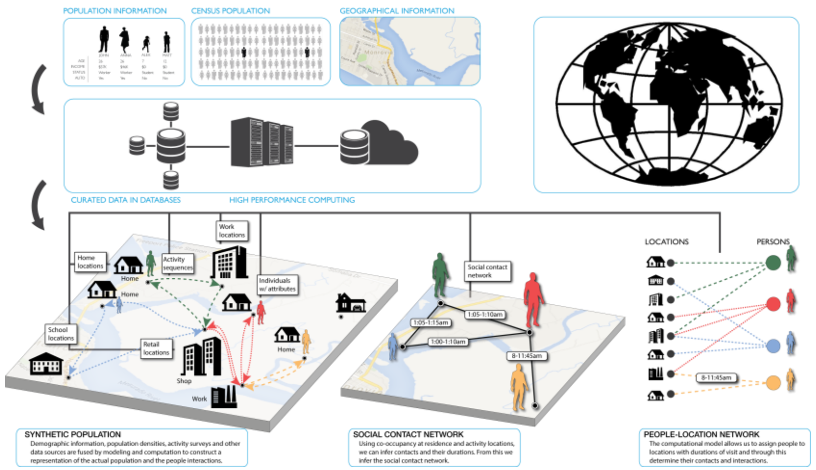


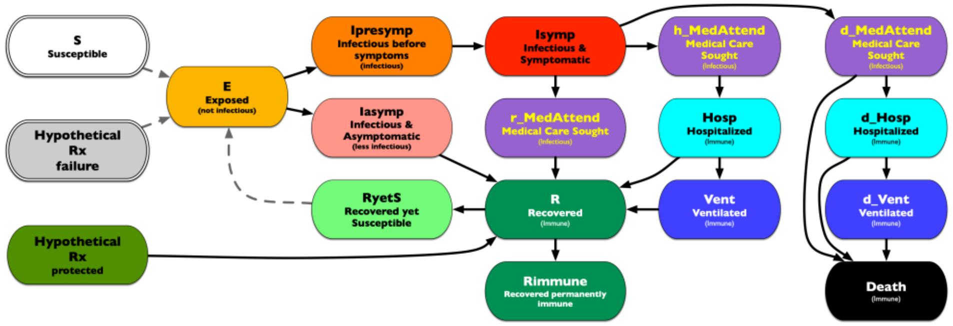
1. Anne Cori, Neil M. Ferguson, Christophe Fraser, Simon Cauchemez. A New Framework and Software to Estimate Time-Varying Reproduction Numbers During Epidemics. American Journal of Epidemiology, Volume 178, Issue 9, 1 November 2013, Pages 1505–1512, https://doi.org/10.1093/aje/kwt133

Agent-based Model (ABM)

EpiHiper: Distributed network-based stochastic disease transmission simulations

- Assess the impact on transmission under different conditions
- Assess the impacts of contact tracing





Synthetic Population

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

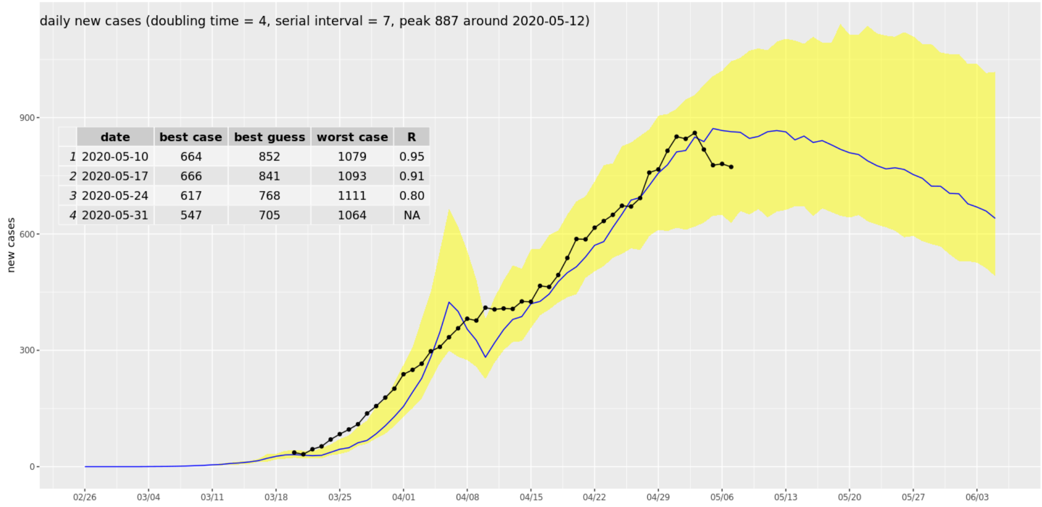
Detailed Disease Course of COVID-19

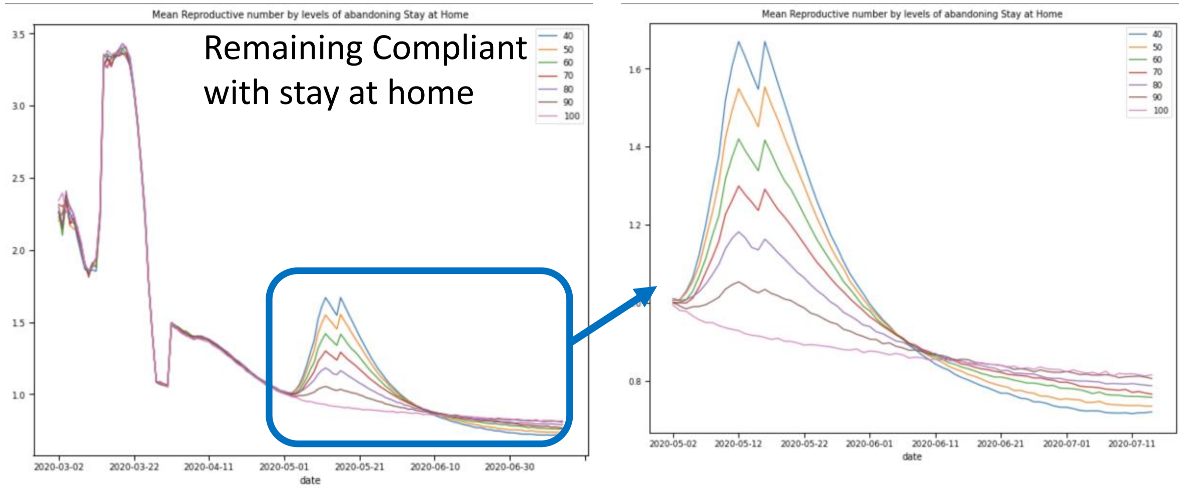
- Literature based probabilities of outcomes with appropriate delays
- Varying levels of infectiousness
- Hypothetical treatments for future developments

ABM Social Distancing Rebound Study Design

Study of ”Stay Home” policy adherence

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





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

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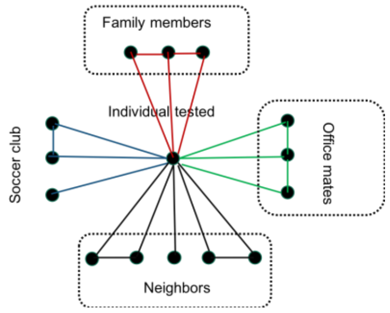
Preliminary ABM Contact Tracing Study

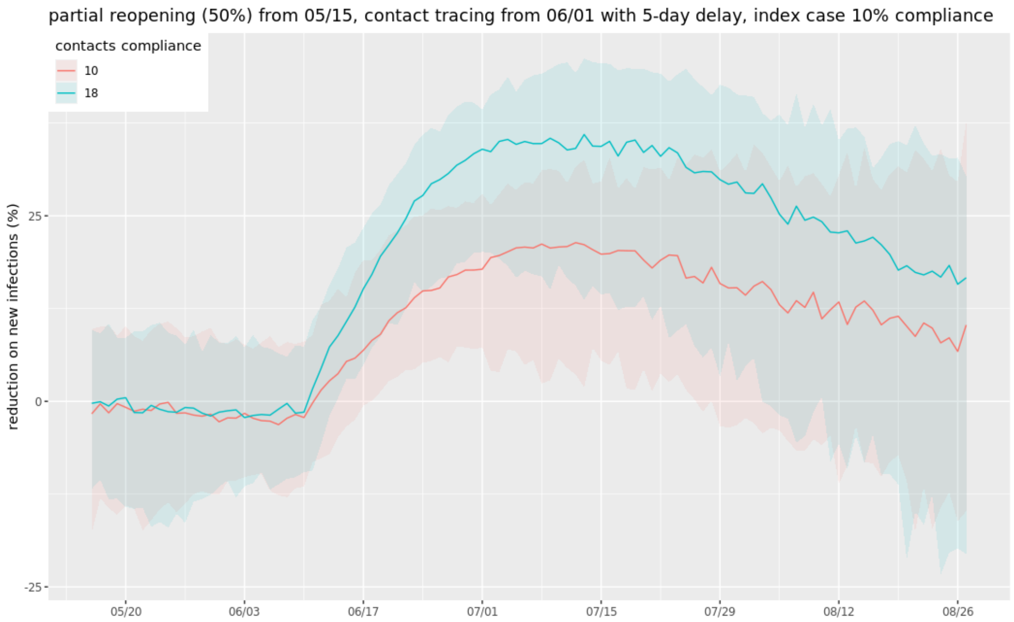
What reductions in cases can enhanced case and contact isolation achieve?

- Preliminary results suggest modest levels of compliance will have benefits
  - Must increase case finding and their compliance with isolation
  - Must have sufficient tracers to find contacts and urge isolation
- *Preliminary estimates* suggest the numbers of new infections can be reduced 20-30% with improved isolation of cases (10% more) and moderate compliance (10-18%) of contacts

name	description	timing
VHI (voluntary home isolation)	40% of symptomatic cases stay home for 14 days	throughout the pandemic
SC (school closure)	all schools are closed	from 03/13 to 08/28
RO (partial reopening)	a fraction of people who used to stay home continue doing so	from 05/15
CT (contact tracing)	a fraction f_1 of symptomatic cases are identified (as index cases) and isolated; a fraction f_2 of their close contacts (at least 2 hours every day) are traced and isolated at home	from 06/01



Isolation of the tested person, and tracing of their family and close contacts.



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:

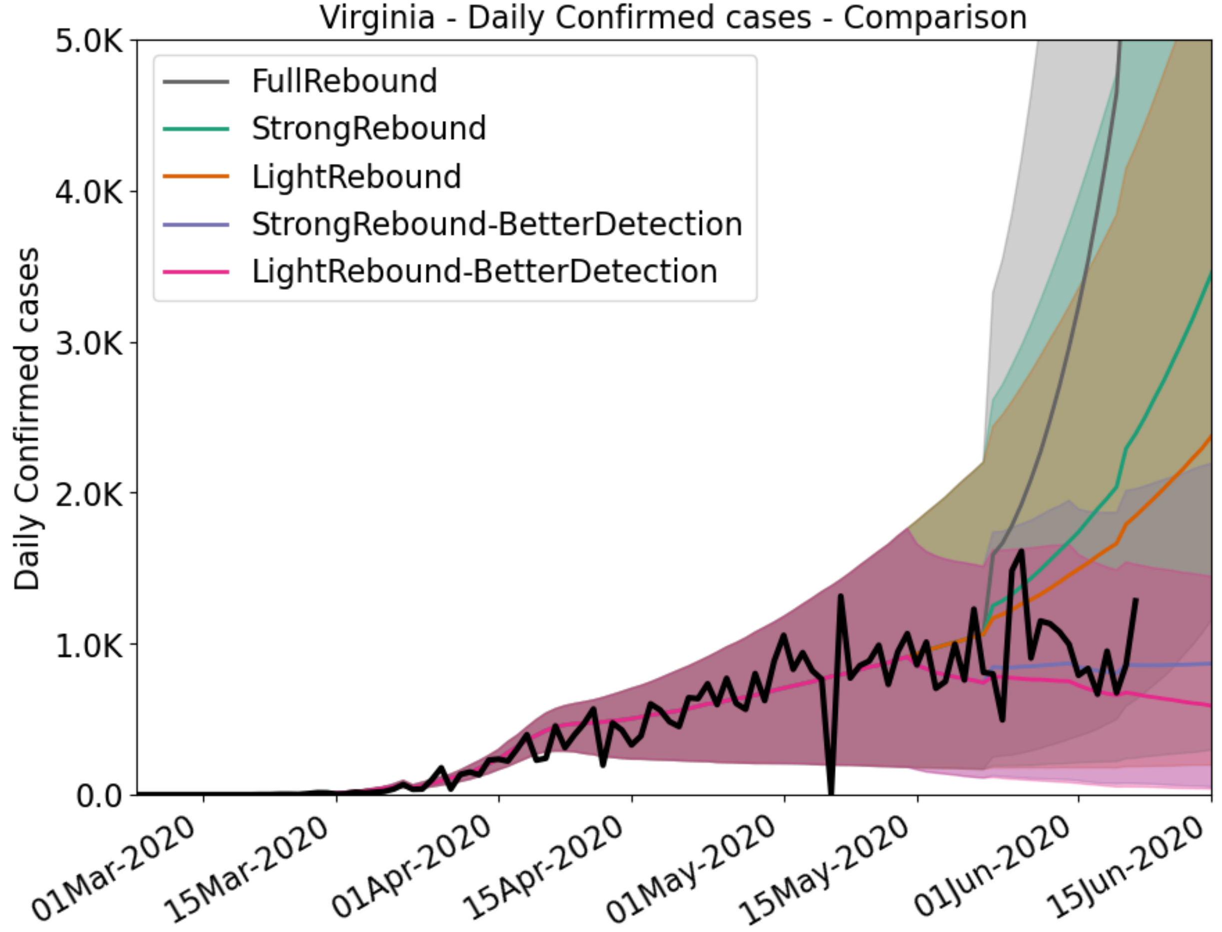
- Assessing the adherence with policies as actual behavior drives the epidemic
- Translating future policies to changes in transmission dynamics

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

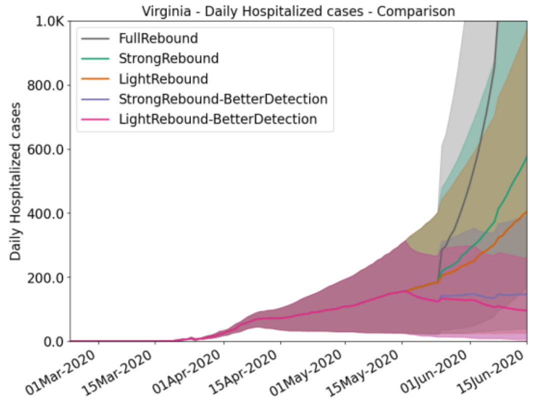
- Policies must carefully weigh local risk of spread, monitor local epidemiology, and tune policies and guidance to changing conditions
- Individuals must be ready to adhere to changes in policies and adopt good personal disease control practices

Short-term Projections

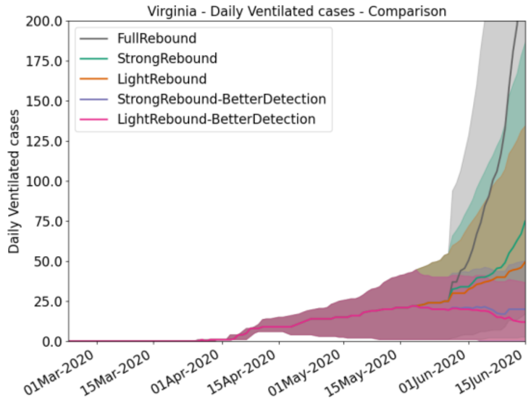
Confirmed cases



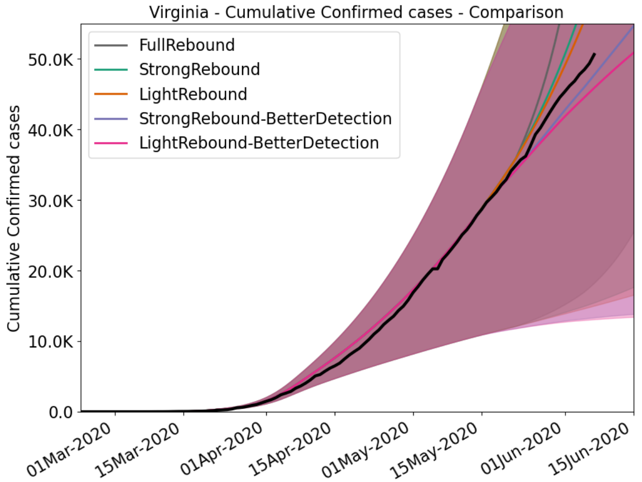
Hospitalizations



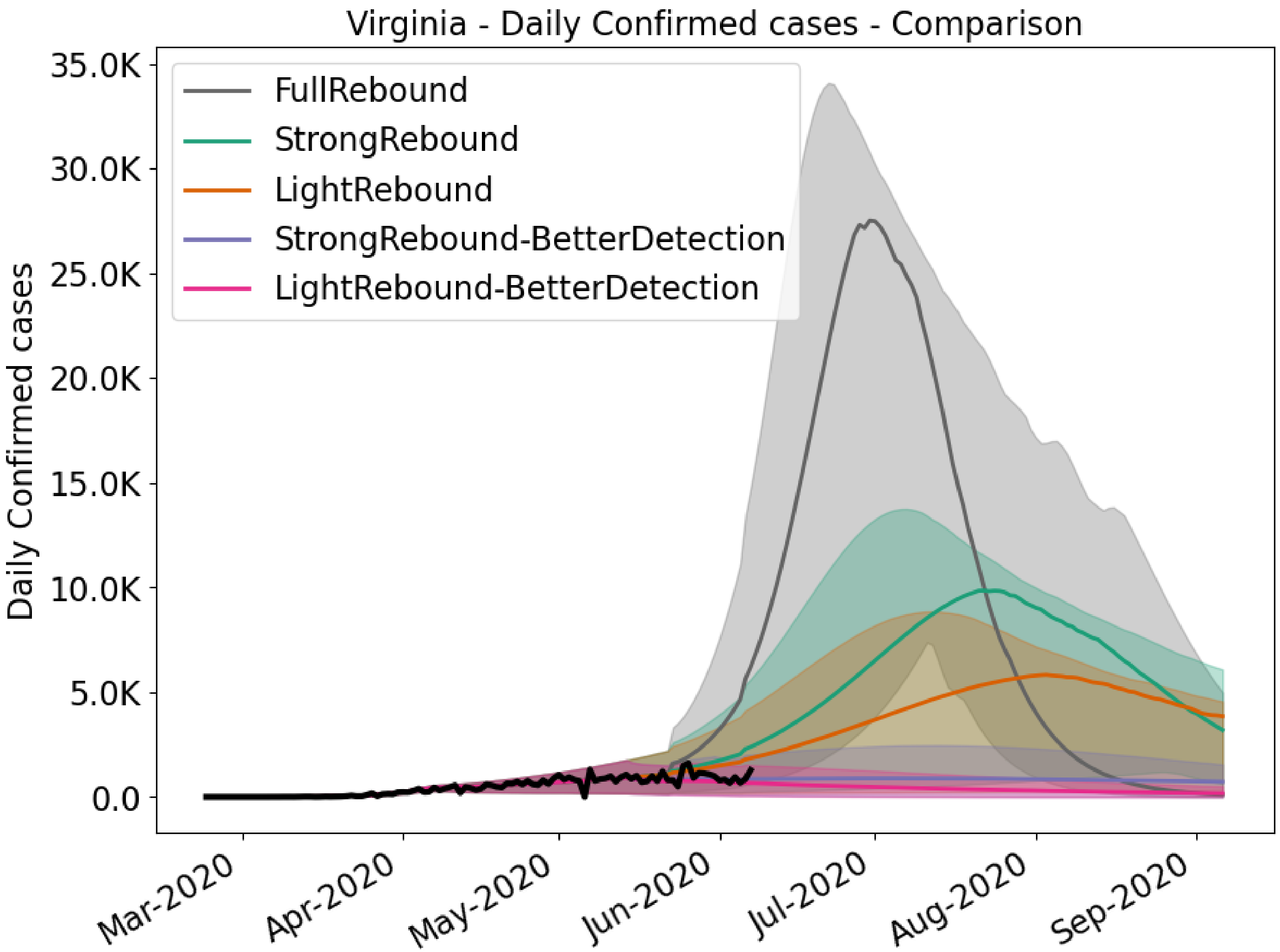
Ventilations



Cumulative Confirmed cases



Period of Transition: Sustaining Control



Weekly New Confirmed Cases*

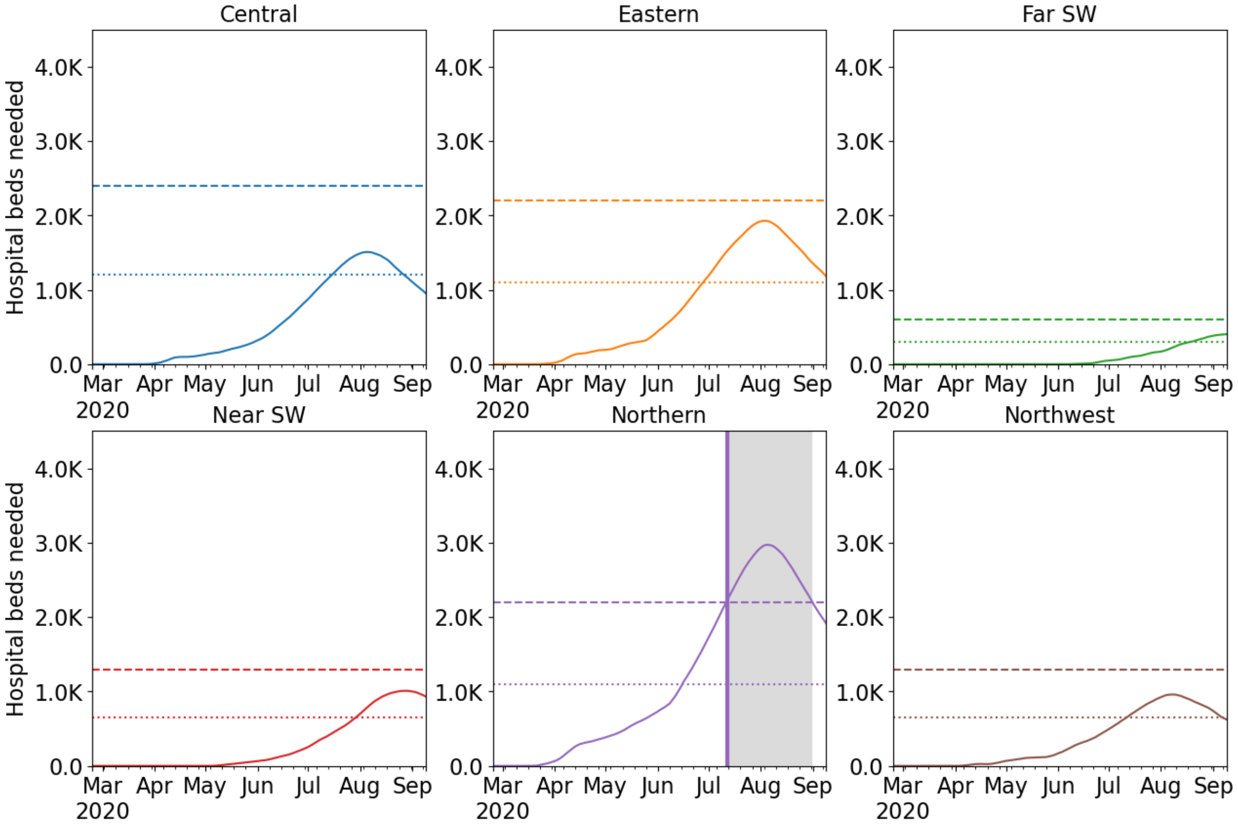
Week Ending	Full Rebound	Light	Light – Better Detection
5/31/20	25,286	10,756	4,938
6/7/20	53,960	13,790	4,509
6/14/20	100,397	17,150	4,058
6/21/20	157,448	21,024	3,722
6/28/20	187,920	25,215	3,361
7/5/20	172,825	29,545	3,044
7/12/20	126,878	33,624	2,765
7/19/20	76,472	37,130	2,484
7/26/20	41,327	39,554	2,264
8/2/20	21,252	39,692	2,016
8/9/20	10,609	38,036	1,784
8/16/20	5,289	35,534	1,600

*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

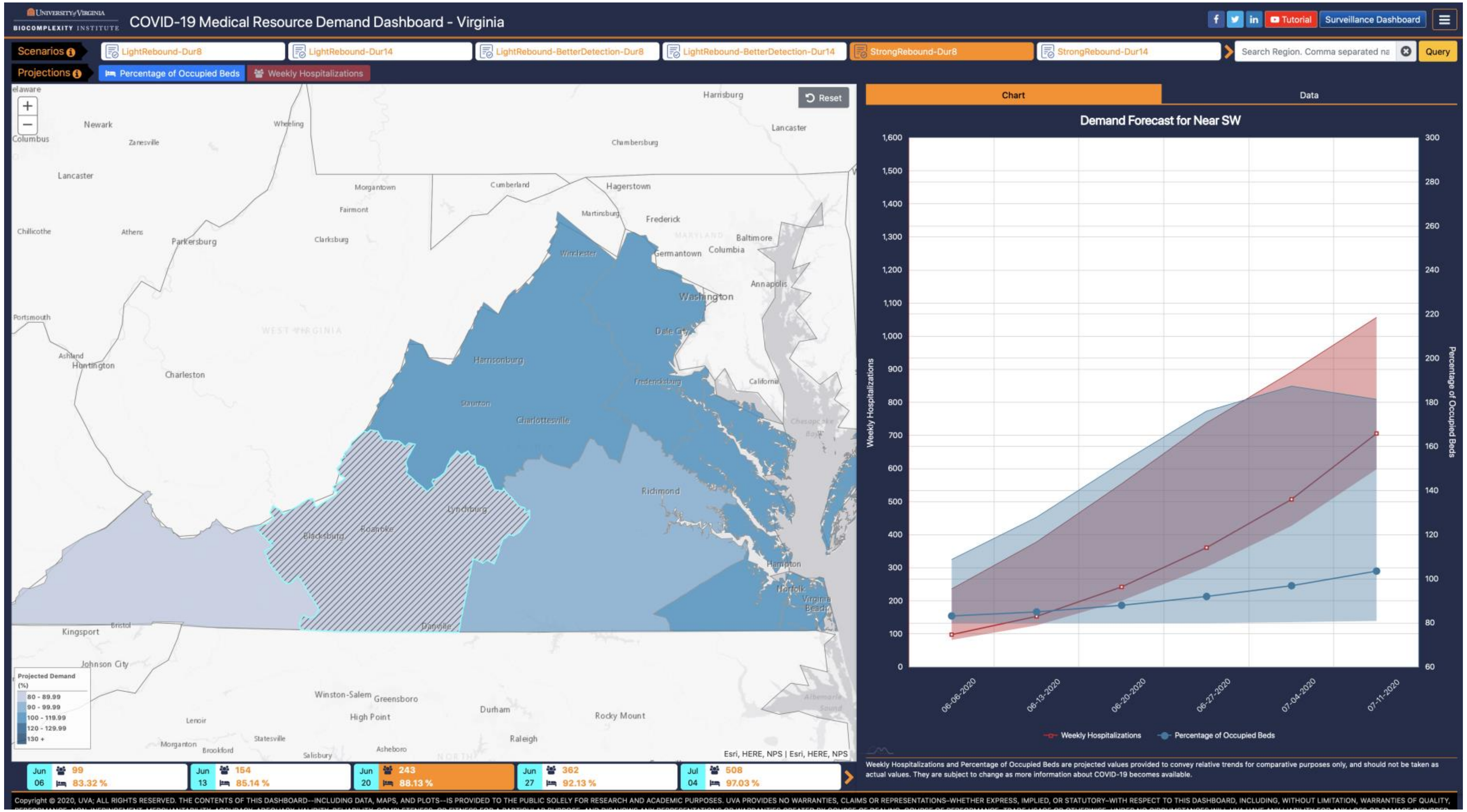
Date ranges when regions are estimated to exceed surge capacity

	Scenario	Date Ranges
1	Strong	Late June to Early Sept
2	Light	Mid July to Late Aug
3	Strong – Better Detection	None
4	Light – Better Detection	None
5	Full Rebound	Mid June to Early August

Social Distancing postponed the time to when capacity could be exceeded, but without other measures we may still reach it in some areas

Medical Resource Demand Dashboard

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



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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?

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