Sandia National Laboratories

SAND2020-6848PE

COVID-19 Pandemic Modeling

Phase I Project Final Report

May 21, 2020

Joint DOE Laboratory Modeling and Analysis Capability

Partners: Los Alamos, Oak Ridge, and Argonne National Laboratories

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia LLC, a wholly owned subsidiary of Honeywell International Inc. for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

COVID-19 Modeling and Analysis Activities

Medical Resource Demands

State and county risk indicators of medical resource shortfalls

Economic Impacts

GDP impact of the COVID-19 event and associated reopening scenarios

Medical Resource Routing

Optimal distribution of limited resources and feasibility of national sharing strategies

Comorbidity Analysis

How do comorbidities affect infection severity?

Recovery Analysis

Testing and contact tracing needs for different levels of reopening

Epidemiological Forecasting

Data-driven, short-term forecasts of new cases by state and region

COVID-19 Modeling and Analysis Activities

Medical Resource Demands

State and county risk indicators of medical resource shortfalls

Economic Impacts

GDP impact of the COVID-19 event and associated reopening scenarios

Medical Resource Routing

Optimal distribution of limited resources and feasibility of national sharing strategies

Comorbidity Analysis

How do comorbidities affect infection severity?

Recovery Analysis

Testing and contact tracing needs for different levels of reopening

Epidemiological Forecasting

Data-driven, short-term forecasts of new cases by state and region

Detailed Surge Modeling of Medical Resource Demands

Goal

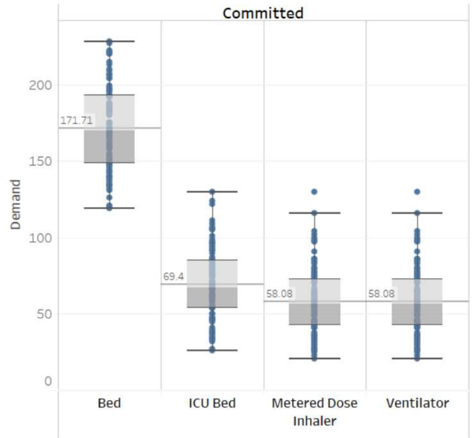
- Calculate resource demands for treating COVID-19 patients based on disease spread projections from epidemiological models
- Anticipate possible times and locations of medical resource shortfalls throughout the pandemic

Approach

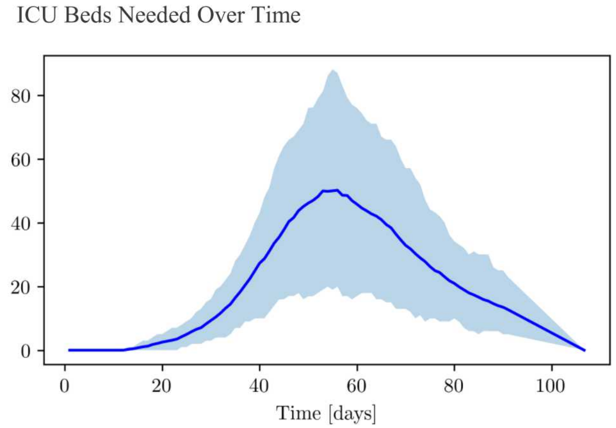
- Use discrete event mathematical model to track patient progress through a hospital treatment system
- Incorporate uncertainty in patient treatment pathways and ranges of resource use per patient to provide risk indicators
- Inputs are patient arrival stream projections from epidemiological models at varying spatial or temporal scales

Results

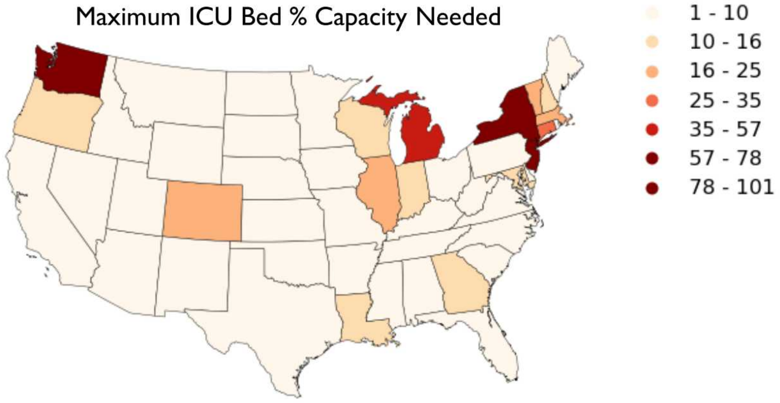
Maximum number of resource needs with a range of uncertainty



Resource needs over time with a range of uncertainty



State or county risk indicators



Approach

Inputs

Local | IHME | EpiGrid

Hospital Arrivals Over Time

The approach is agnostic to which epidemiological model is used; we are prepared to receive data from any epidemiological model

Model

- Demographics
- Treatment Stage
- Fates

Parameters

Maximum time on ventilator
Maximum time in ICU if not ventilated
Probability of going to ICU
Probability of needing ventilator
Probability of death if ventilated
Probability of death if not ventilated
etc…

Outputs

Practitioner Need Over Time

- Floor Nurse
- ICU Nurse
- Physician
- Respiratory Therapist

Committed Resource Need Over Time

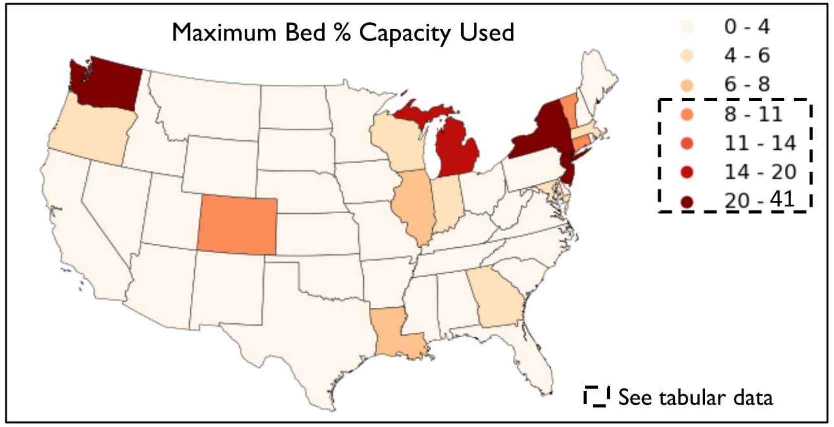
- Beds
- ICU Beds
- Metered Dose Inhaler
- Ventilator

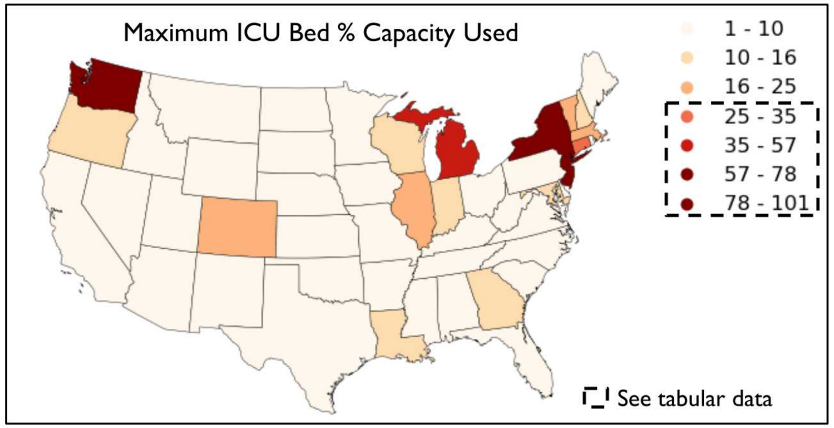
Consumable Resource Need Over Time

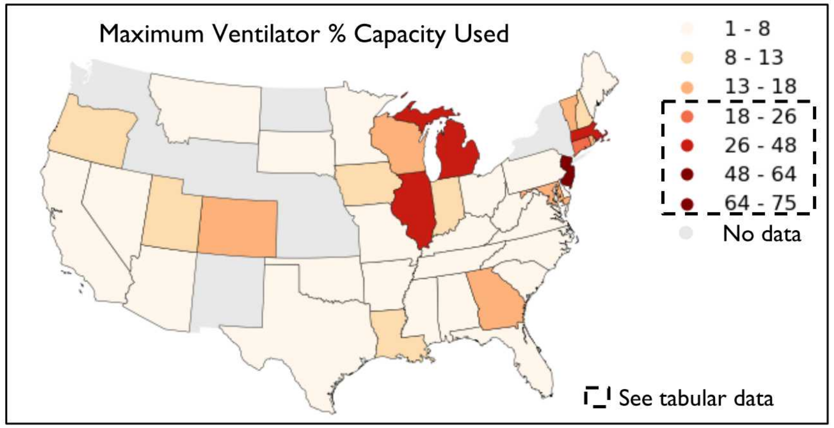
- Gown
- N95 Mask
- Face Shield
- Gloves
- Sedatives

- Uncertainties in parameters are propagated throughout the model to provide a range of resource projections
- This modeling approach can be applied to any geographic scale for which epidemiological results are available

National Summary: State Resource Sufficiency







States with Resource Utilization >8% Capacity	Maximum Bed % Capacity Used
Washington	41.0
New York	33.4
New Jersey	31.0
Michigan	26.9
Connecticut	14.5
Illinois	13.7
Colorado	12.4
Vermont	11.0
Louisiana	10.4
Indiana	9.3
Wisconsin	8.4
Massachusetts	8.2

States with Resource Utilization > 25% Capacity	Maximum ICU Bed % Capacity Used
New Jersey	100.9
Washington	92.8
New York	92.7
Michigan	77.9
Illinois	34.6
Connecticut	34.5
Vermont	31.6
Colorado	26.7

New Jersey % Capacity for ICU Beds

> 100% from 4/17 – 4/25

> 95% from 4/11 – 5/9

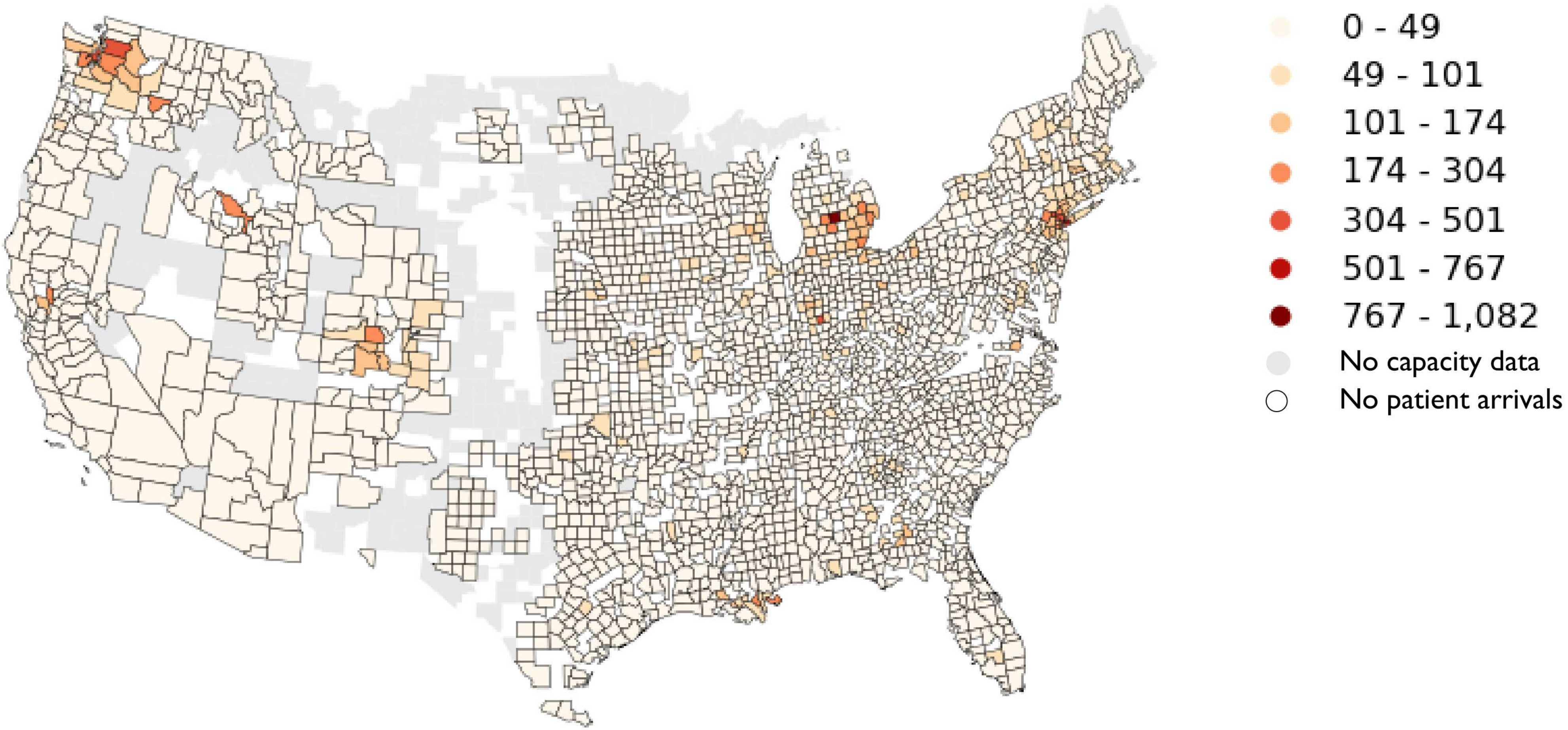
States with Resource Utilization >18% Capacity	Maximum Ventilator % Capacity Used
New Jersey	75.0
Michigan	64.3
Illinois	48.1
Massachusetts	42.3
Connecticut	24.5
Rhode Island	23.3
Wisconsin	23.2
Vermont	22.4
Georgia	22.1
Maryland	22.0
Colorado	20.6
Indiana	18.4

Resource utilization presented here is the mean value. This can be adjusted based on the level of acceptable risk tolerance.

Using EpiGrid patient streams, 4/26/2020 dataset, β = 0.3
Analysis horizon: 3/3/2020 – 7/20/2020

National Summary: County Resource Sufficiency, ICU Beds

Maximum ICU Bed % Capacity Used



County detail provides specificity for state level, and mirrors the same areas of concern.

Significant difference in color scale values driven by comparison of county demand to county capacity (vs. state capacity).

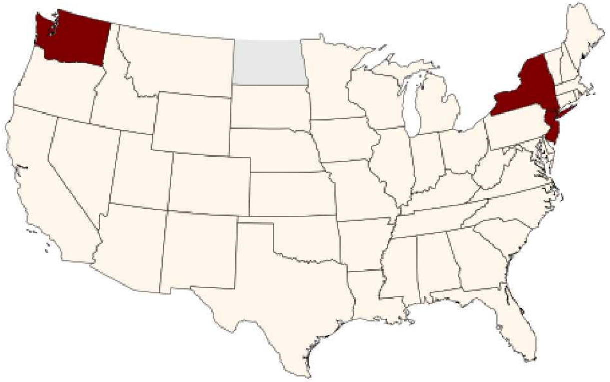
Resource utilization presented here is the mean value. This can be adjusted based on the level of acceptable risk tolerance.

Using EpiGrid patient streams, 4/26/2020 dataset, β = 0.3
Analysis horizon: 3/3/2020 – 7/20/2020

National Summary: Exceedance of Capacity, Social Distancing

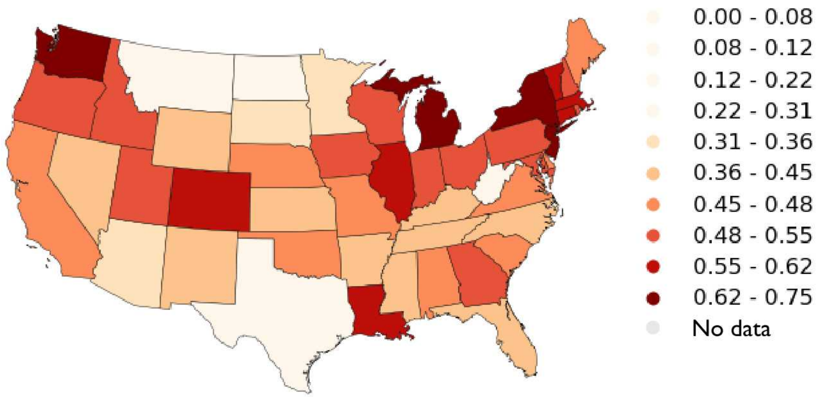
Probability of Exceeding ICU Bed Capacity

Maximum Social Distancing
From 4/11/20 to the end of the simulation, likelihood of infections spreading is discounted 80% relative to doing nothing



Moderate Social Distancing
From 4/11/20 to the end of the simulation, likelihood of infections spreading is discounted 70% relative to doing nothing

Minimal Social Distancing
From 4/11/20 to the end of the simulation, likelihood of infections spreading is discounted 40% relative to doing nothing



Note that with decreasing degree of social distancing (from left to right in above maps), the probability of exceeding capacity of ICU beds across the country increases significantly.

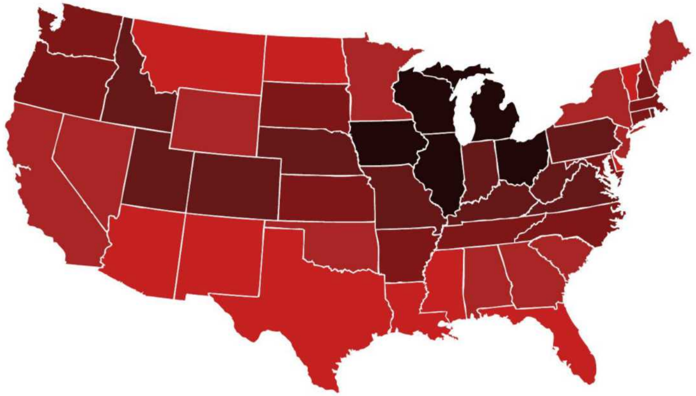
Resource utilization presented here is the mean value. This can be adjusted based on the level of acceptable risk tolerance.

Using EpiGrid patient streams, 4/26/2020 dataset
Analysis horizon: 3/3/2020 – 7/20/2020

National Summary: Timeseries of Increase/Decrease in Demand

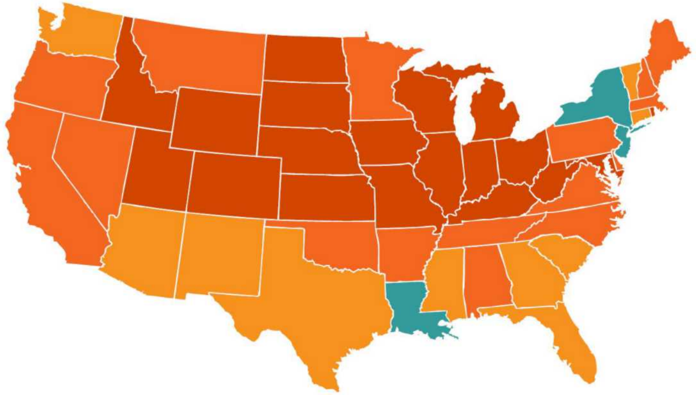
Month-to-month change in bed demand

MARCH-APRIL



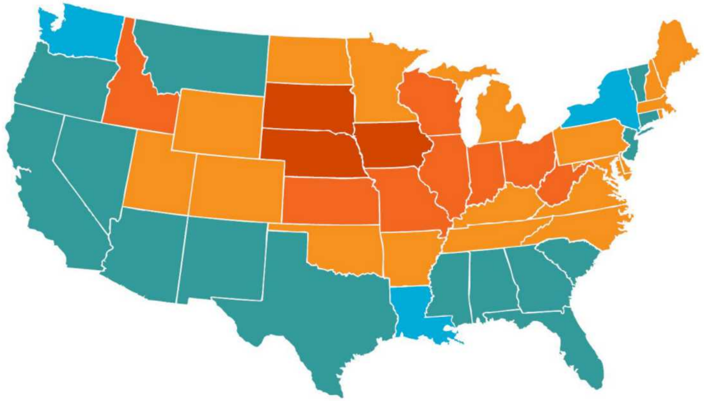
The entire country is showing an increase in bed demand, but the Great Lakes area shows the greatest increase

APRIL-MAY



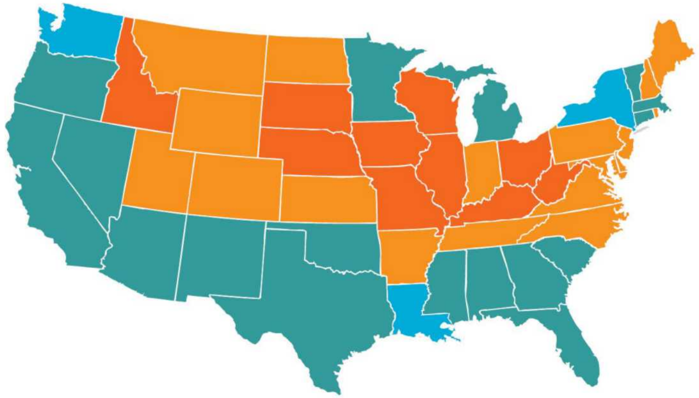
Going into May is the first time some states start to decrease their bed demands

MAY-JUNE



South Dakota, Nebraska, and Iowa will see the largest percent increases in bed demand

JUNE-JULY



Idaho and parts of the central U.S. will continue to see increases in bed demand into July

% INCREASE

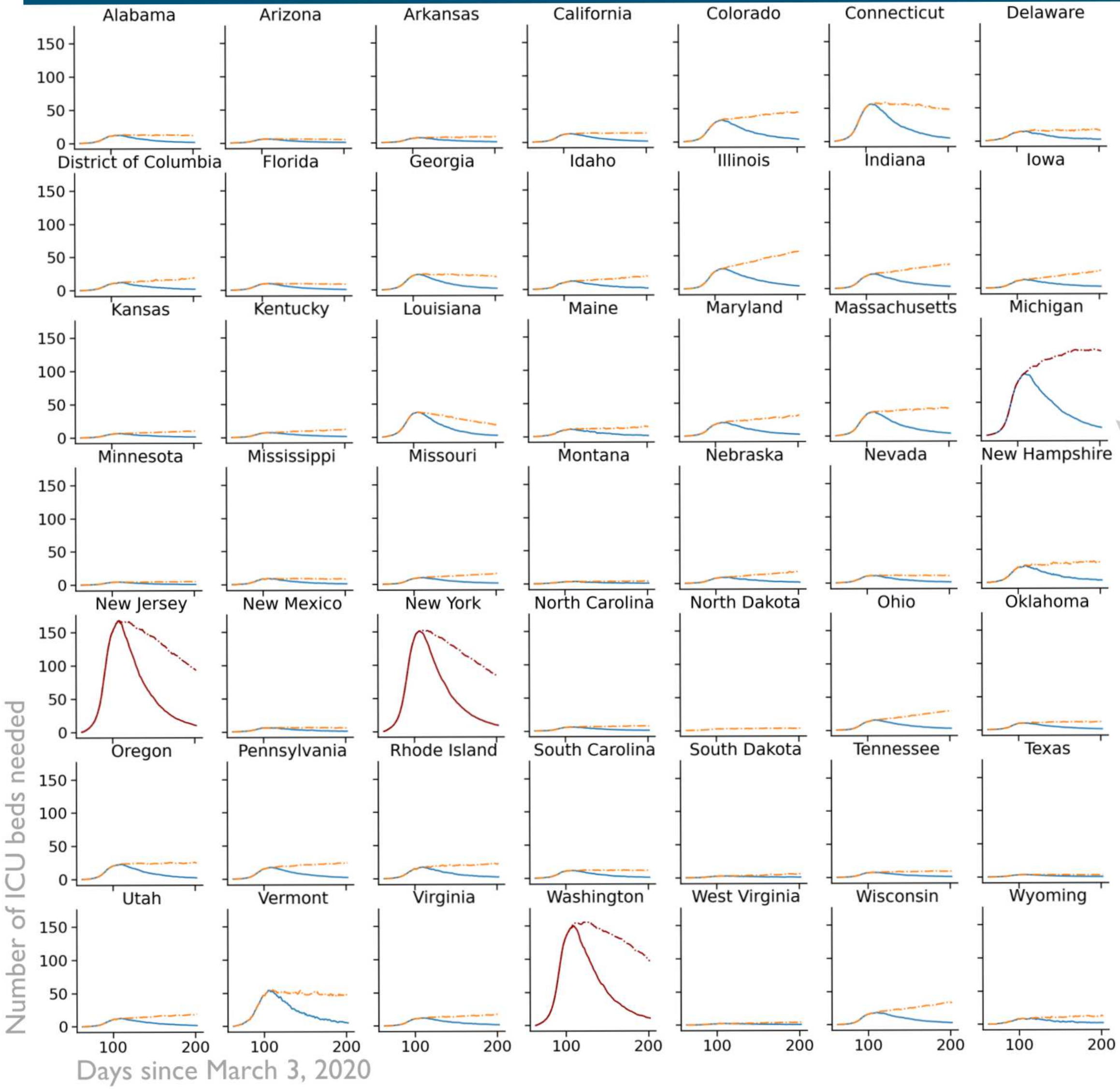
- 698-755
- 642-698
- 589-642
- 537-589
- 482-537
- 26-48
- 13-26
- 3 to 13
- -13 to -3
- -23 to -13

Resource utilization presented here is the mean value. This can be adjusted based on the level of acceptable risk tolerance.

Using EpiGrid patient streams, 4/26/2020 dataset, $\beta = 0.3$
Analysis horizon: 3/3/2020 – 7/20/2020

National Summary: Timeseries of State Patterns

Sparklines of ICU bed demand by state*, 3/3-7/20



	Maximum Social Distancing	*From 4/11/20 to the end of the simulation, likelihood of infections spreading is discounted 80% relative to doing nothing*
	Moderate Social Distancing	*From 4/11/20 to the end of the simulation, likelihood of infections spreading is discounted 70% relative to doing nothing*
	State exceeds ICU Bed capacity	

Enable quick visual indicators of differences in temporal patterns between states and impacts of social distancing scenarios

- Michigan, Illinois, Colorado, etc. experience very different ICU bed demand depending on extent of social distancing

*Contiguous 48 states plus Washington DC
Resource utilization presented here is the mean value. This can be adjusted based on the level of acceptable risk tolerance.

Using EpiGrid patient streams, 4/26/2020 dataset, β = 0.2 and 0.3
Analysis horizon: 3/3/2020 – 7/20/2020

COVID-19 Modeling and Analysis Activities

Medical Resource Demands

State and county risk indicators of medical resource shortfalls

Economic Impacts

GDP impact of the COVID-19 event and associated reopening scenarios

Medical Resource Routing

Optimal distribution of limited resources and feasibility of national sharing strategies

Comorbidity Analysis

How do comorbidities affect infection severity?

Recovery Analysis

Testing and contact tracing needs for different levels of reopening

Epidemiological Forecasting

Data-driven, short-term forecasts of new cases by state and region

Integrated Medical Resource Supply/Demand Routing Model

Goal

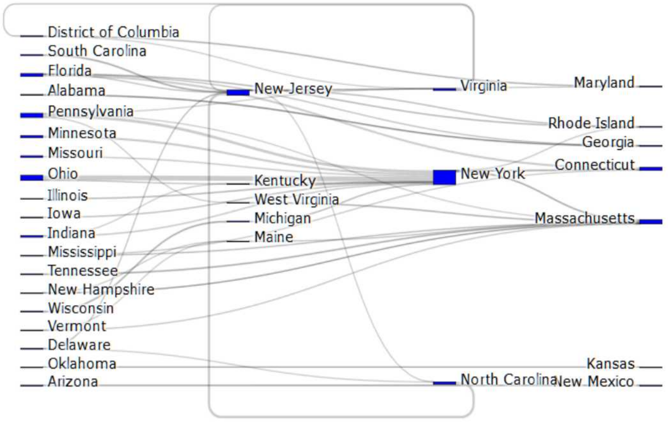
- Provide insights into the patterns and scale of routing recommendations to show the feasibility of specific routing strategies

Approach

- Use an optimization model which determines routing paths for medical resources to match supply with demand
- The model incorporates travel costs and seeks to minimize the number of regions with unmet demand

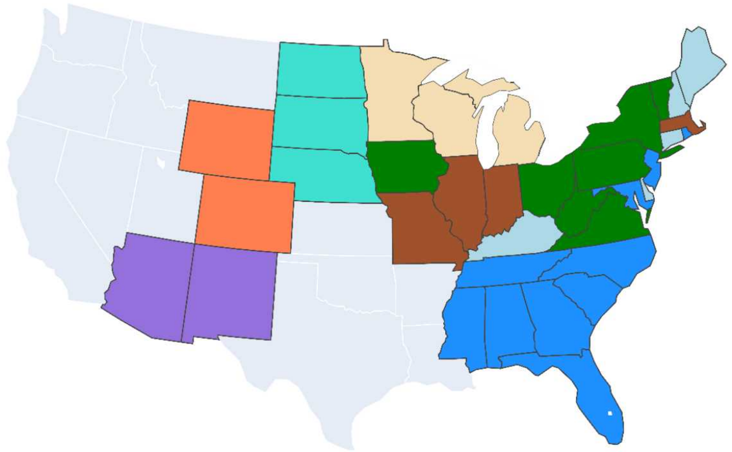
Results

Resource sharing feasibility to minimize shortfalls experienced by any state



Detailed routing recommendations at time points throughout the event

Integrated planning framework to combine multiple scenarios and assess uncertainty

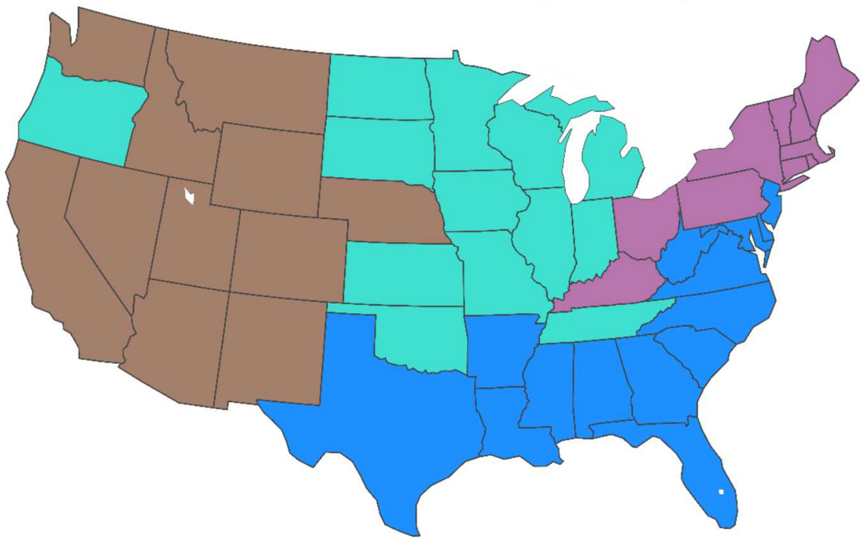


Resource Sharing Example Results

Ventilator Routing

Ventilator routing recommendations to minimize the shortfall experienced by any state for a single time point. Arrows represent the direction of resource flow, weighted by the magnitude of the shipment.

Communities that would benefit by sharing ventilators



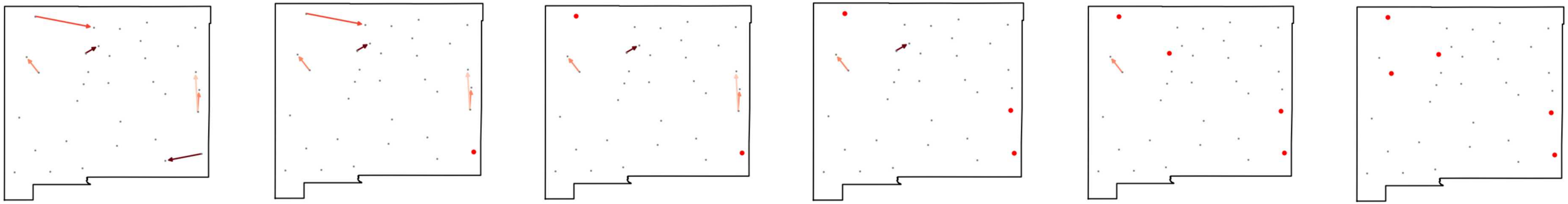
Communities detected for ventilator movements between states for a specific epidemiological scenario. States that belong to the same sharing community have the same color.

Provide insights into the patterns and scale of routing recommendations to show the *feasibility* of specific routing strategies, and to understand the implications of making policy based on specific forecasts

Resource Location Analysis

Example: where should ICU beds be placed to minimize patient travel within New Mexico?

With no added ICU beds	**Choose 1 location to add ICU beds**	**Choose 2 locations to add ICU beds**	**Choose 3 locations to add ICU beds**	**Choose 4 locations to add ICU beds**	**Choose 5 locations to add ICU beds**
	Lea	Lea; San Juan	Lea; Roosevelt; San Juan	Lea; Roosevelt; San Juan; Sandoval	Lea; Roosevelt; San Juan; Sandoval; Cibola
23 people must travel between counties	13 people must travel between counties	10 people must travel between counties	7 people must travel between counties	2 people must travel between counties	0 people must travel between counties



Arrows show direction patients must travel to overcome a shortfall in ICU beds (darker color = more travel)
Red dot shows optimal county to place more ICU beds

Evaluate feasibility of new resource placement incorporating uncertainty in patient needs

COVID-19 Modeling and Analysis Activities

Medical Resource Demands
State and county risk indicators of medical resource shortfalls

Economic Impacts
GDP impact of the COVID-19 event and associated reopening scenarios

Medical Resource Routing
Optimal distribution of limited resources and feasibility of national sharing strategies

Comorbidity Analysis
How do comorbidities affect infection severity?

Recovery Analysis
Testing and contact tracing needs for different levels of reopening

Epidemiological Forecasting
Data-driven, short-term forecasts of new cases by state and region

Recovery Modeling and Analysis

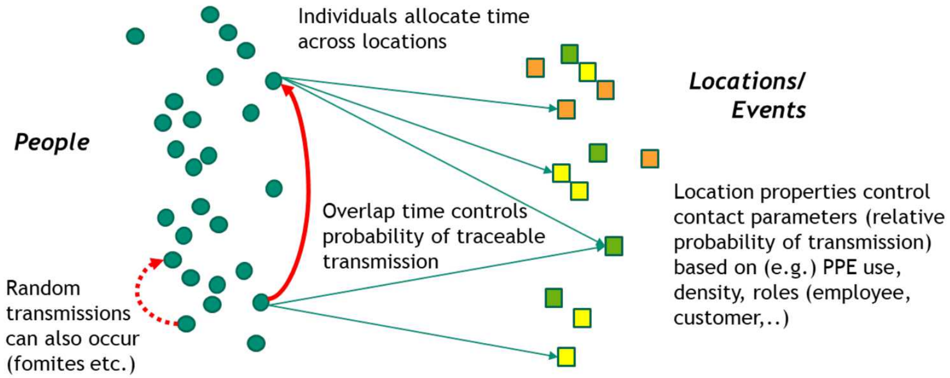
As social distancing is relaxed, develop optimized testing and contact tracing strategies to enable effective outbreak management given resource constraints

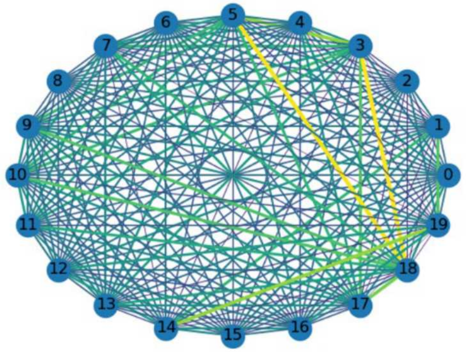
Approach

- Integrate a contact network into a deterministic differential equation model to understand how location-based interactions impact virus spread and associated contact tracing requirements

Current Status

- Initial formulation and implementation is complete. Phase 2 work will expand the contact network representation, generation of results for real-world contact network





Notional location-informed contact network. Location characteristics lead to different transmission probabilities, designated by different colors

COVID-19 Modeling and Analysis Activities

Medical Resource Demands
State and county risk indicators of medical resource shortfalls

Economic Impacts
GDP impact of the COVID-19 event and associated reopening scenarios

Medical Resource Routing
Optimal distribution of limited resources and feasibility of national sharing strategies

Comorbidity Analysis
How do comorbidities affect infection severity?

Recovery Analysis
Testing and contact tracing needs for different levels of reopening

Epidemiological Forecasting
Data-driven, short-term forecasts of new cases by state and region

Economics Analysis Overview

The COVID-19 pandemic could cause $2-3.4 trillion loss in 2020 U.S. Gross Domestic Product (GDP)

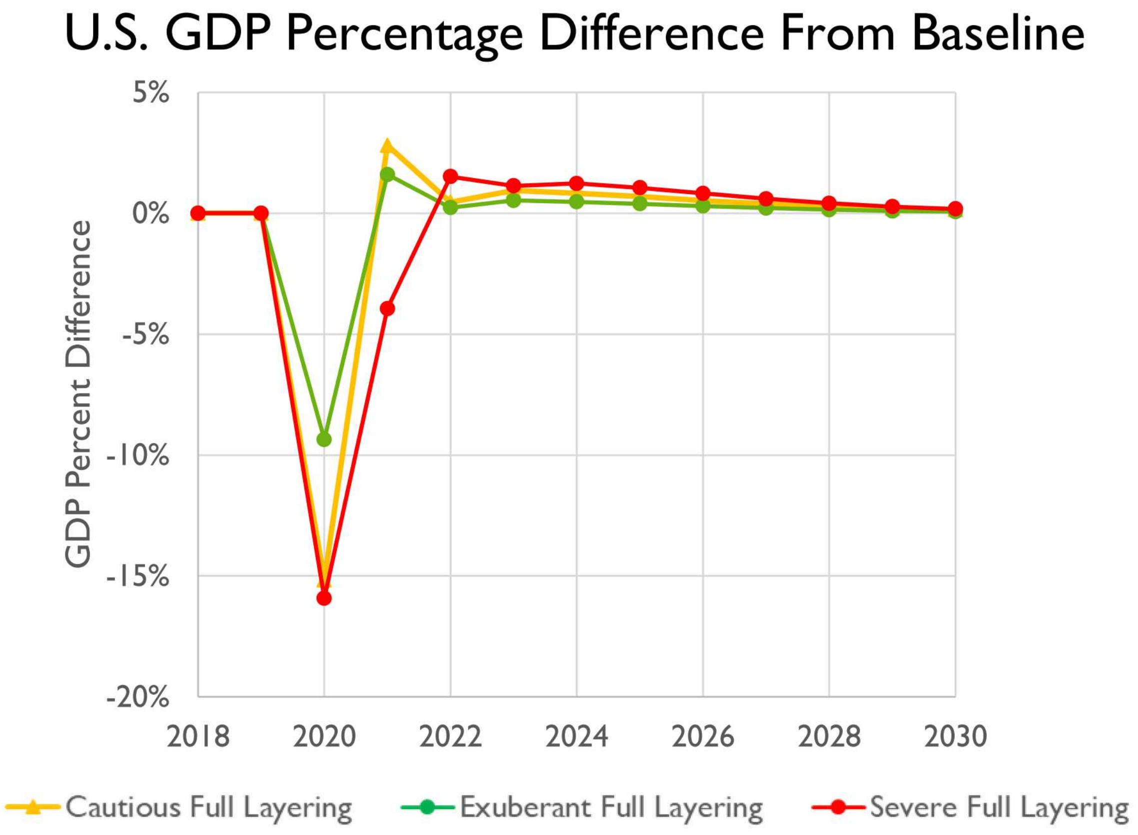
Our goal is to estimate the cumulative economic impacts of COVID-19 and recovery strategies.

Our approach is to generate a national baseline forecast with the REMI model, then modify the baseline to reflect national COVID-19 impacts, then examine response and recovery strategies.

The impact is sizeable, according to our analysis:

- Using data as of April 24th with assumptions about the duration of the COVID-19 event as projected now combined with scenario assumptions about recovery results range from 9.2% to 15.9% reduction in 2020 gross domestic product (GDP)
- That is equivalent to ~$2 to $3.4 trillion loss (annualized)

Potential response and recovery strategies should be carefully examined for effectiveness.



Economics Methodology

Using the REMI code, modify a baseline national forecast to reflect national COVID-19 impacts

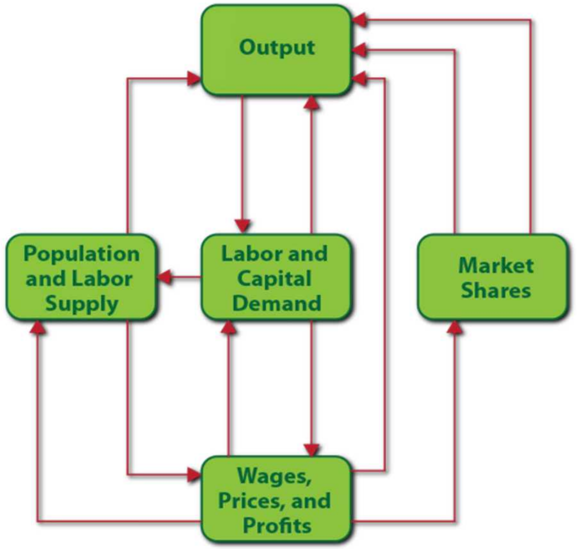
- Supply and demand shocks
- Results in new national COVID baseline forecast
- Slowdown or recession scenario

Test mitigation strategies

- Epidemiological
- Economic
- Resource model
- State and federal

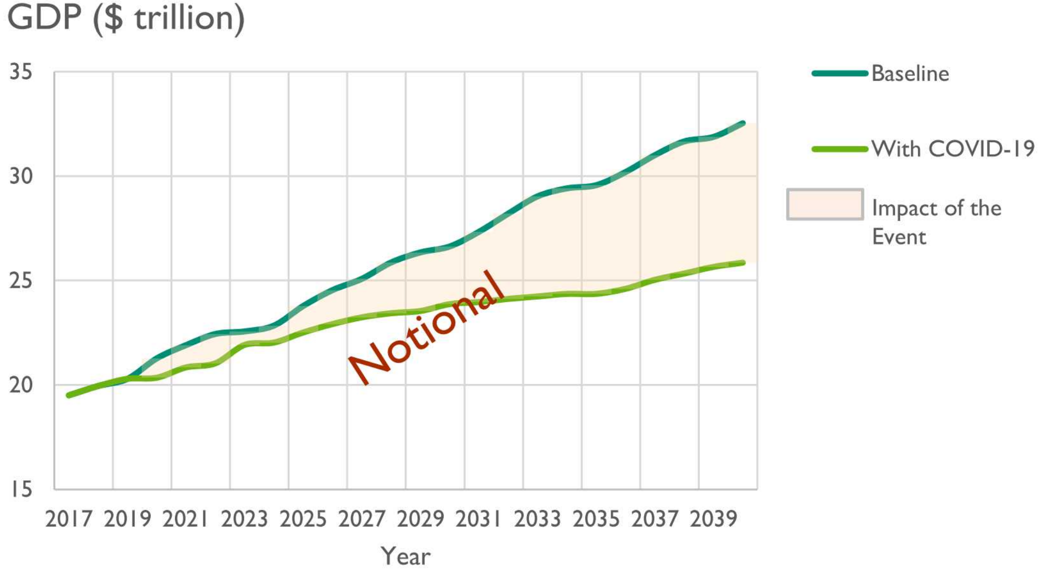
Overall

- All weekly, monthly, or quarterly data is scaled to annual
- Stimuli +/- will occur over the year at differing time intervals
- Base year in model for inflation is 2017
- Output will be reported in 2020 dollars
- Perform sensitivity analysis on principal parameter estimates or uncertainty quantification analysis



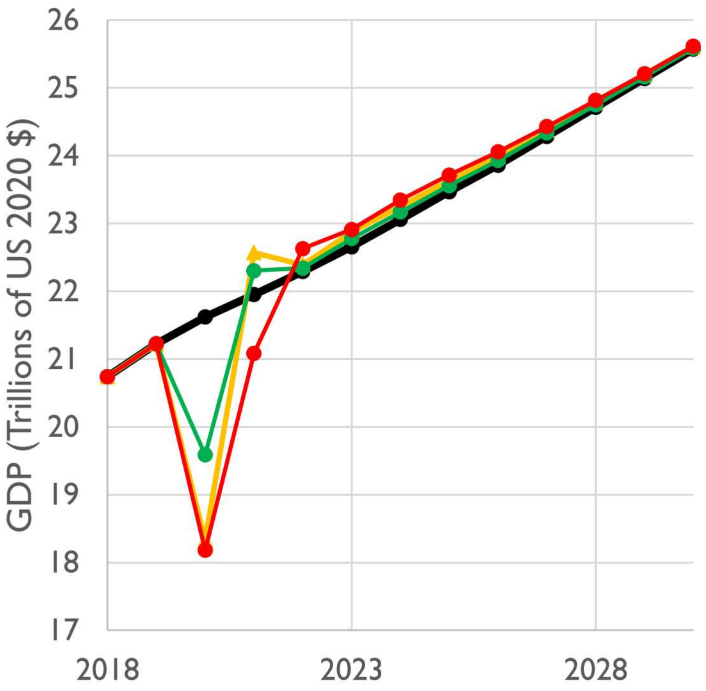
Representation of the circular nature of the economy which the model captures

Example Output

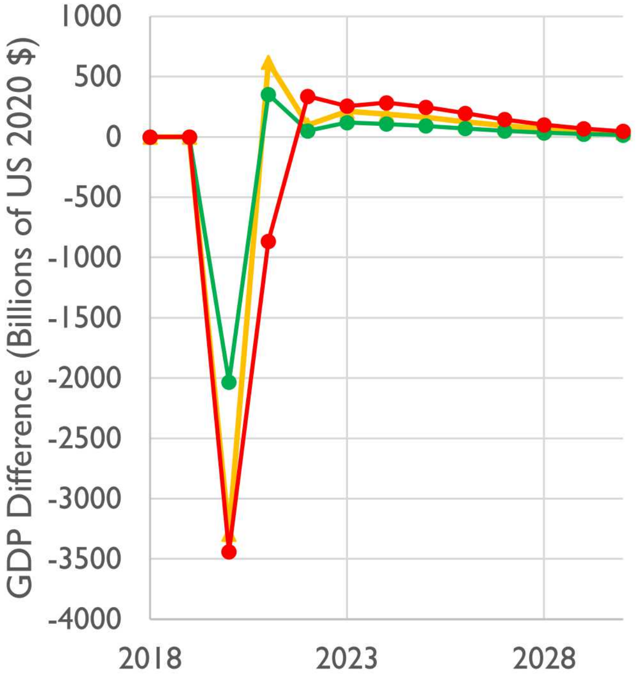


Results for Economic Scenarios
All categories combined, full layering approach applied

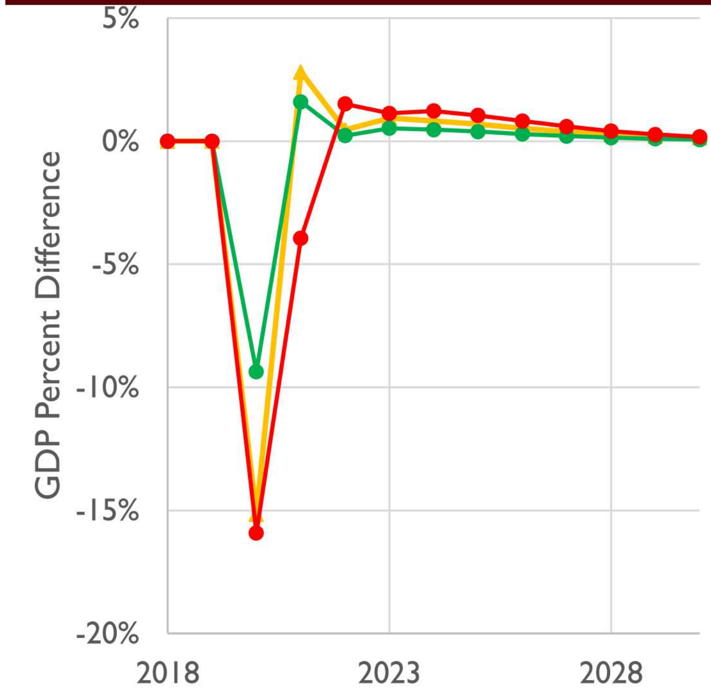
US GDP Levels



US GDP Difference from Baseline



US GDP Percentage Difference From Baseline



The pre-COVID baseline forecast is shown in red. "New COVID" baseline forecast is in purple. The interactions between supply and demand shocks, exogenous changes in economic transactions, and transfer payments are all captured in the purple result.

We are experiencing both demand and supply side shocks. It is the net of these effects that we are "experiencing" as economic losses. The economic situation will continue to evolve as either the event continues (i.e. healthcare spending) or mitigations (i.e. work from home; CARES Act) take a effect.

Depicted is the percent change from baseline. The shocks depress labor and commodity prices across the economy. Once the shock is gone it causes demand to more than bounce back in 2021. This expansion drives prices back up, creating a slow return to baseline in the years after 2021.

The Cautious Scenario results in 15.2% reduction or $3.2 trillion loss in 2020 U.S. GDP from the pre-COVID baseline.

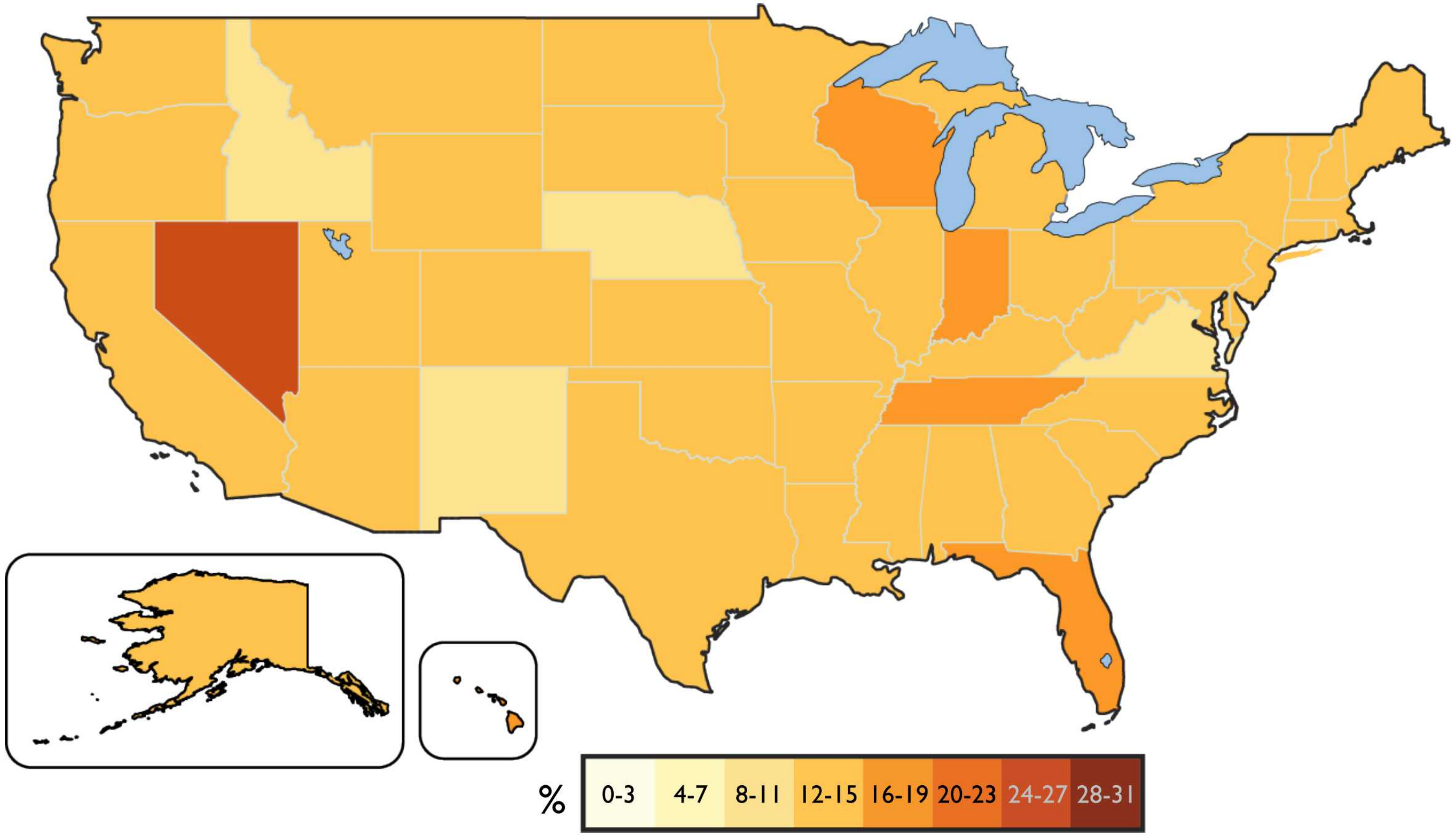
Cautious Scenario, this is a national scale event with possibly long-term negative economic impacts

Unprecedented event

- Unlike previous "disaster" events this is not a regional event
- Every state is negatively affected
- The longer the "event" continues the larger the economic impact

State-by-state impacts

- Overall closures to retail, food and drinking places, and entertainment affect all states
- Manufacturing closures are concentrated in specific states
- The energy sectors in every state are negatively affected due to declining demand



Decrease in state GDP in the cautious scenario

Every state is negatively affected.
States with diverse economies experience slightly less severe impacts.

Cautious Scenario, Impacts by State

Manufacturing

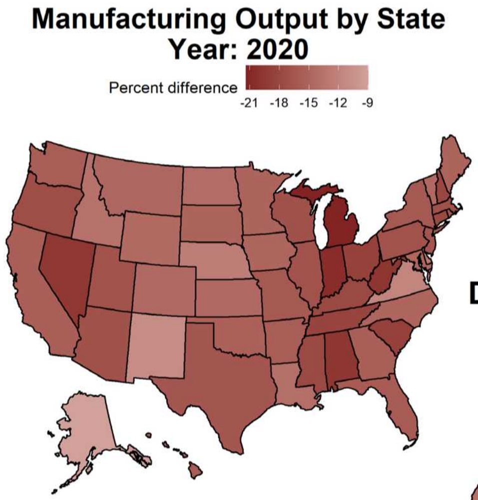
- Manufacturing is not a large industry in every state
- Makes up a significant portion of output in:
  - Michigan, Indiana, and Alabama
- Linked to automotive manufacturing sectors

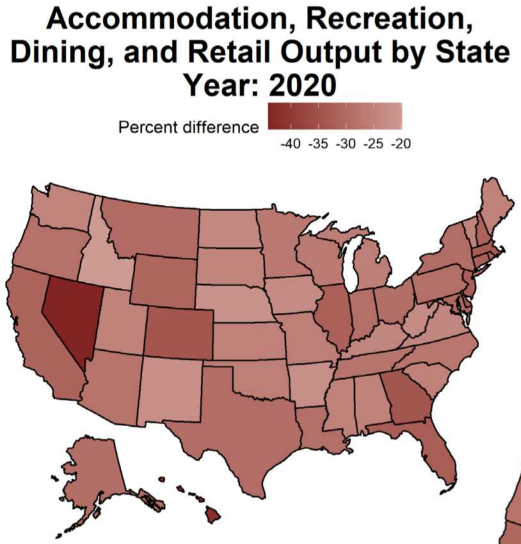
Accommodation, Recreation, Dining, and Retail

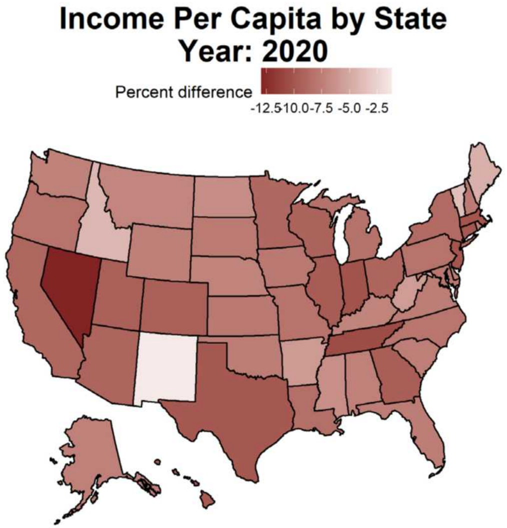
- These industries are a large source of jobs and output in every state
- The effect is very similar across almost all states
- Nevada is more reliant on tourism relative to other states

Income

- Nevada's loss in income is expected given the large concentration of labor in tourism-related industries
- New Mexico historically experiences economic downturns on a lag; overall is a very small economy







COVID-19 Modeling and Analysis Activities

Medical Resource Demands

State and county risk indicators of medical resource shortfalls

Economic Impacts

GDP impact of the COVID-19 event and associated reopening scenarios

Medical Resource Routing

Optimal distribution of limited resources and feasibility of national sharing strategies

Comorbidity Analysis

How do comorbidities affect infection severity?

Recovery Analysis

Testing and contact tracing needs for different levels of reopening

Epidemiological Forecasting

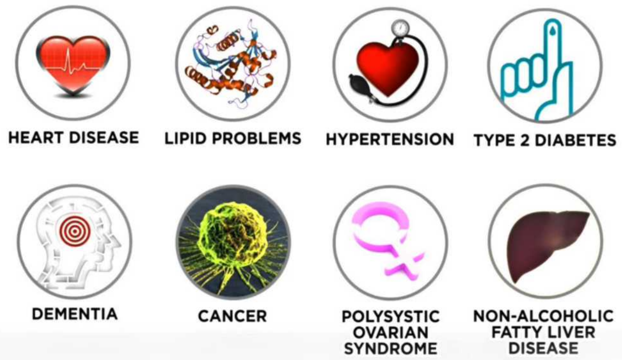
Data-driven, short-term forecasts of new cases by state and region

Comorbidity Analysis Overview

Machine learning and data science applied to electronic health record (EHR) medical data to improve risk prediction for severe COVID-19 symptoms

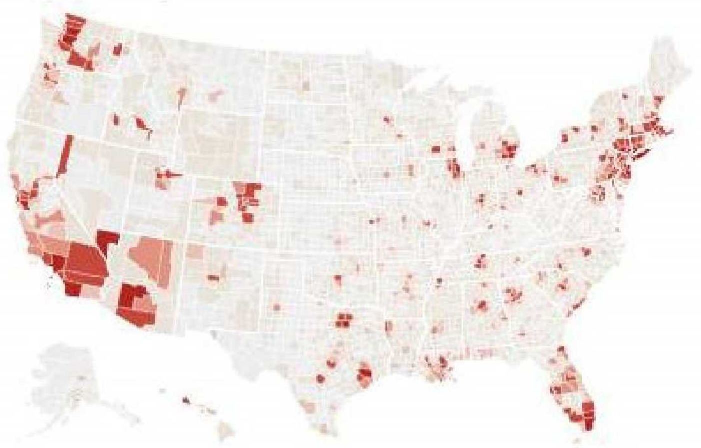
How do comorbidities affect infection severity?

- Our county-level model fits will reveal the effects of individual demographic and comorbidity features on infection outcomes



Which patients are most at risk?

- Longitudinal EHR analysis will train an improved deep Convolutional Neural Network/Recurrent Neural Network model to more accurately predict infection severity based on a patient's full medical history
- We will produce an interpretable model based on our findings for use in clinical settings



How will disease progression differ by US county?

- Local county-level models will be extensible to all US counties as broad demographic and comorbidity prevalence data is available
- Nuanced effects can then be incorporated into our epidemiological models

Exemplar - Regression to Parameterize Risk By Age

Data from public sources:

- China
- South Korea
- Hong Kong
- United States

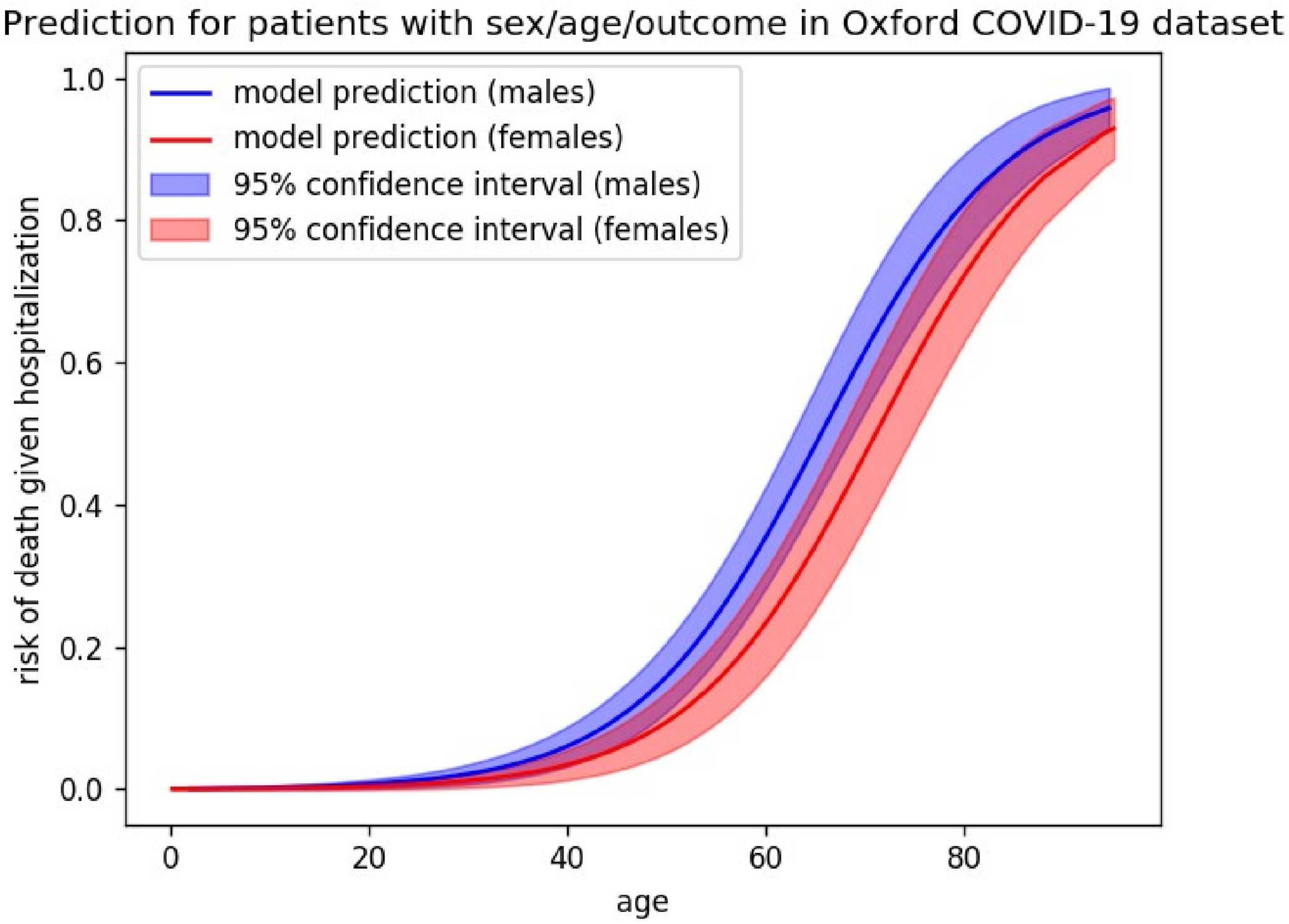
Logistic Regression Fit

- Reveals risk curves with uncertainty
- Also provides model parameters for use in other projections

Can be extended to explore comorbidity risk with additional data

Analysis Conclusion:

- Mortality risk increases with age
- Men at higher risk than women



Characterize mortality risk based on patient demographics and history to potentially discover unknown risk factors

Preliminary Results – Socio-Economic Status Proxy Predicts County Mortality Growth

Using California health survey data, we trained a model with all available features to fit the COVID Mortality growth rate.

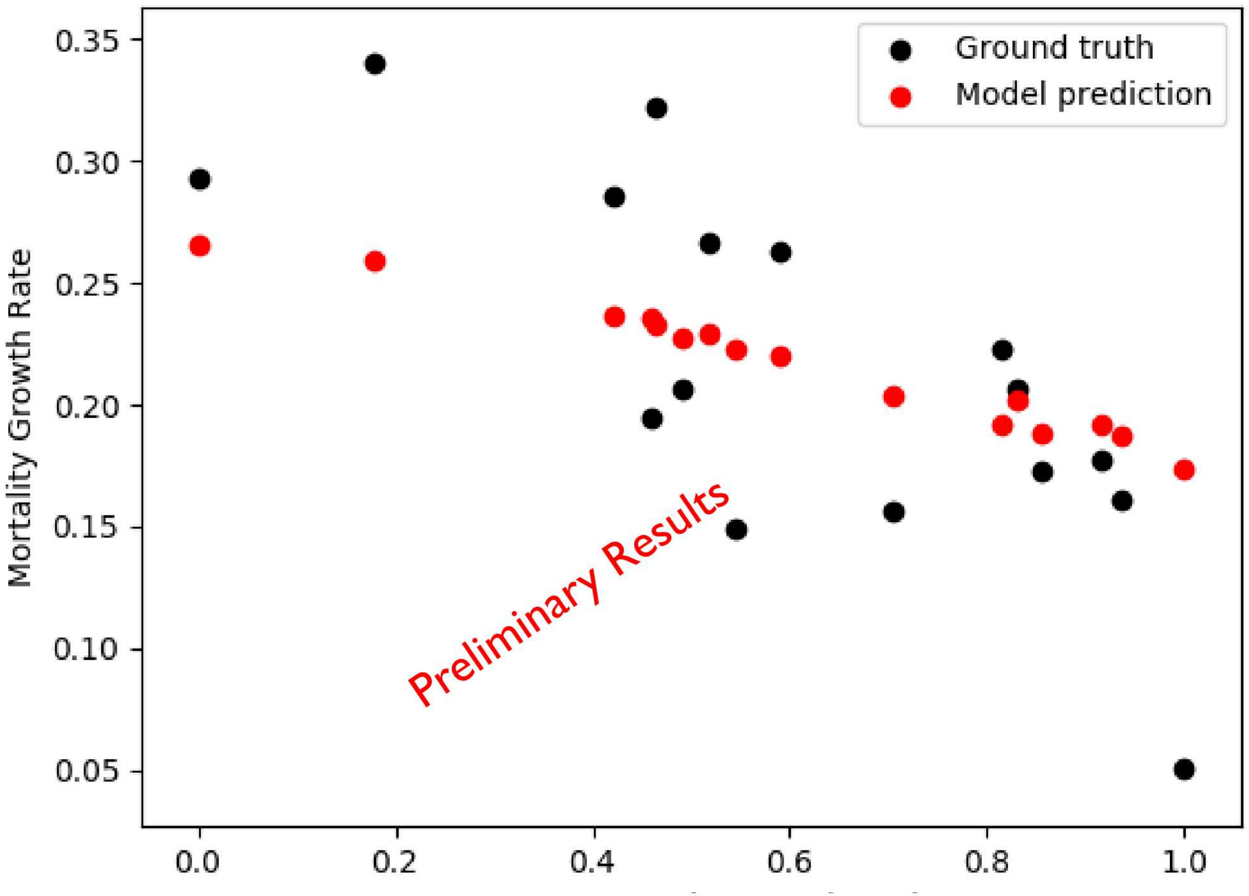
Over 16 training examples:

- Training R^2 Score: 0.43
- Training Mean Absolute Error: 0.045
- Cross Validation Mean Test Error: 0.061 +/- 0.040
- Cross Validation Mean Train Score: 0.45 +/- 0.07

This figure shows the relationship between ***the most significant feature*** in the model (the highest coefficient in the trained model) to the outcome.

Lasso regression merges similar features into one, **it is likely that the feature shown is representative of the % of county residents with employment based insurance.**

Model Predictions vs. Most Significant Feature



% Children Covered by Employment Health Ins.

COVID-19 Modeling and Analysis Activities

Medical Resource Demands
State and county risk indicators of medical resource shortfalls

Economic Impacts
GDP impact of the COVID-19 event and associated reopening scenarios

Medical Resource Routing
Optimal distribution of limited resources and feasibility of national sharing strategies

Comorbidity Analysis
How do comorbidities affect infection severity?

Recovery Analysis
Testing and contact tracing needs for different levels of reopening

Epidemiological Forecasting
Data-driven, short-term forecasts of new cases by state and region

COVID-19 Forecasting via COVID-19 Modeling and Bayesian Forecast (COMBO)

COMBO: An SNL-developed, data-driven method to forecast an outbreak

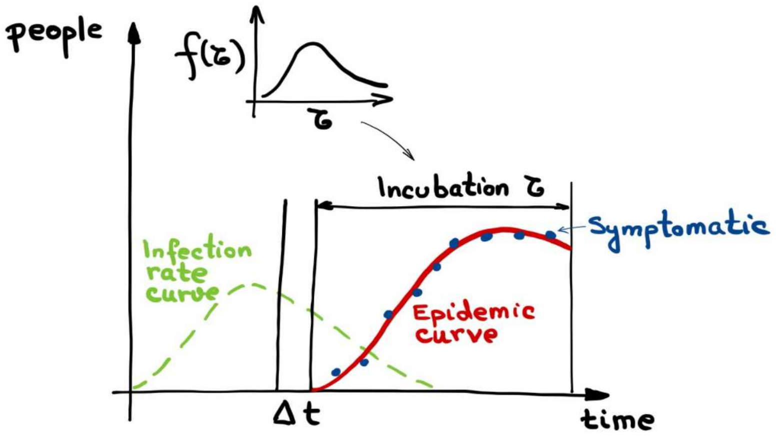
- LDRD in 2009, hardened with DTRA funds, unused since 2011

How it works: Infers a time-dependent infection rate model from the epidemic curve

- Inverse problems solved via Bayesian inference
- 10-day-ahead forecasts generated from inferred infection curve

Technical details – the model:

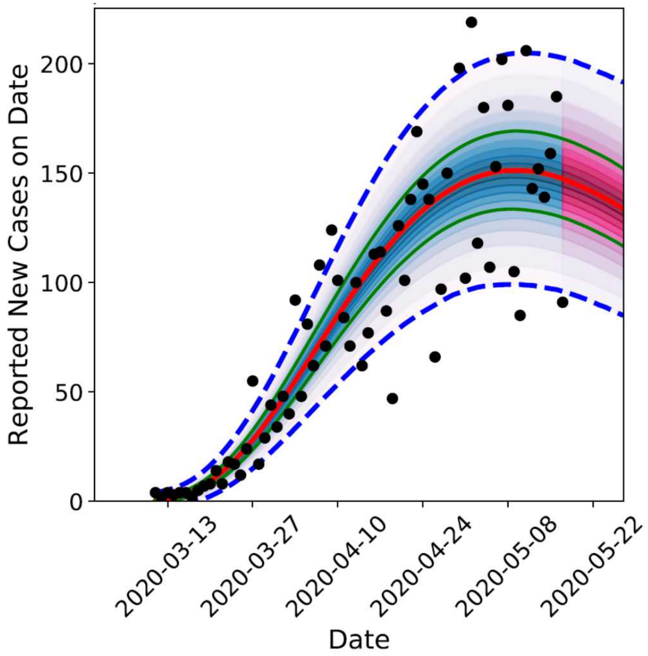
- Infected cases observed on a given day are a consequence of people infected at an earlier time coming out of incubation and presenting symptoms
- The incubation period is drawn from COVID19 incubation period distribution
- Infection rate model is a parameterized curve



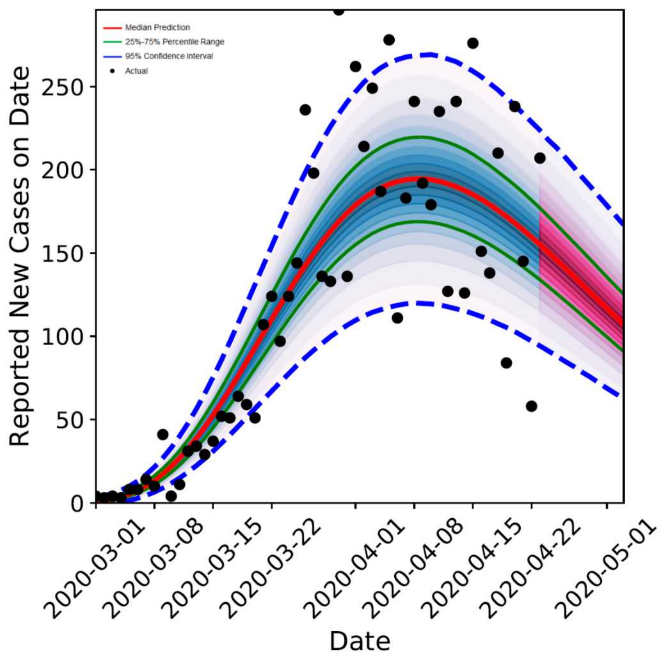
Provide 10-day forecast of new cases from inferred infection curve based on case data

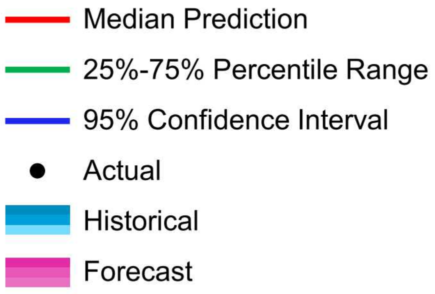
Example State and Regional Results

New Mexico Daily New Case Forecast 5/17/20



San Francisco Bay Area New Case Forecast 4/23/20





- Forecast new cases at country, state and regional scales
  - Technique uses Bayesian inference; always true to data/evidence
  - Uncertainty quantification built into the model
- Detects/infers "flattening" of the infection curve due to countermeasures
  - Changes forecasts accordingly & automatically; no special calibration/model change needed
  - Infers effect of countermeasures when signal is evident in data (time-lag ~1.5x incubation period)

Team

Patrick Finley (Co-PI)
Danny Rintoul (Co-PI)
Melissa Finley (Co-PI)
Walter Beyeler (Task Lead)
Vanessa Vargas (Task Lead)
Drew Levin (Task Lead)
Scott Collis (Director)
Dean Jones (Senior Manager)
Bradley Dickerson (Senior Manager)
Benjamin Brodsky (Project Manager)
Sean DeRosa (Project Manager)
Erin Acquesta
Paula Austin
Patrick Blonigan
Michael Bynum
Thomas Catanach
Kamaljit Chowdhary
Chad Davis

Bert Debusschere
Anne Descour
Christopher Frazier
Edgar Galvan
Jared Gearhart
Brian Geiger
Ann Hammer
Aundre Huynh
John Jakeman
Jessica Jones
Mohammad Khalil
Katherine Klise
Thomas Kroeger
Daniel Krofcheck
Monear Makvandi
Carianne Martinez
Taylor McKenzie
Teresa Portone

Jaideep Ray
Cosmin Safta
Asael Sorensen
Laura Swiler
Robert Taylor
Katherine Tremba
Lawrence Trost
Bernadette Watts
Jonathan Whetzel
Justin White
Michael Ford
Gianluca Geraci
Desmond Harmon
Meghan Othart
Julia Potter