

JOINT DOE LABORATORY MODELING AND ANALYSIS CAPABILITY COVID-19 MEDICAL RESOURCE DEMANDS

May 12, 2020

Pat Finley, Melissa Finley, Walt Beyeler, Dan Krofcheck, Chris Frazier, Laura Swiler, Teresa Portone, Erin Acquesta, Paula Austin, Drew Levin, Robert Taylor, Katherine Tremba, Monear Makvandi, Sean DeRosa, Ann Hammer, Chad Davis

OUTLINE

INTRODUCTION

GOAL

MODELING APPROACH

LOCALIZED DECISION SUPPORT

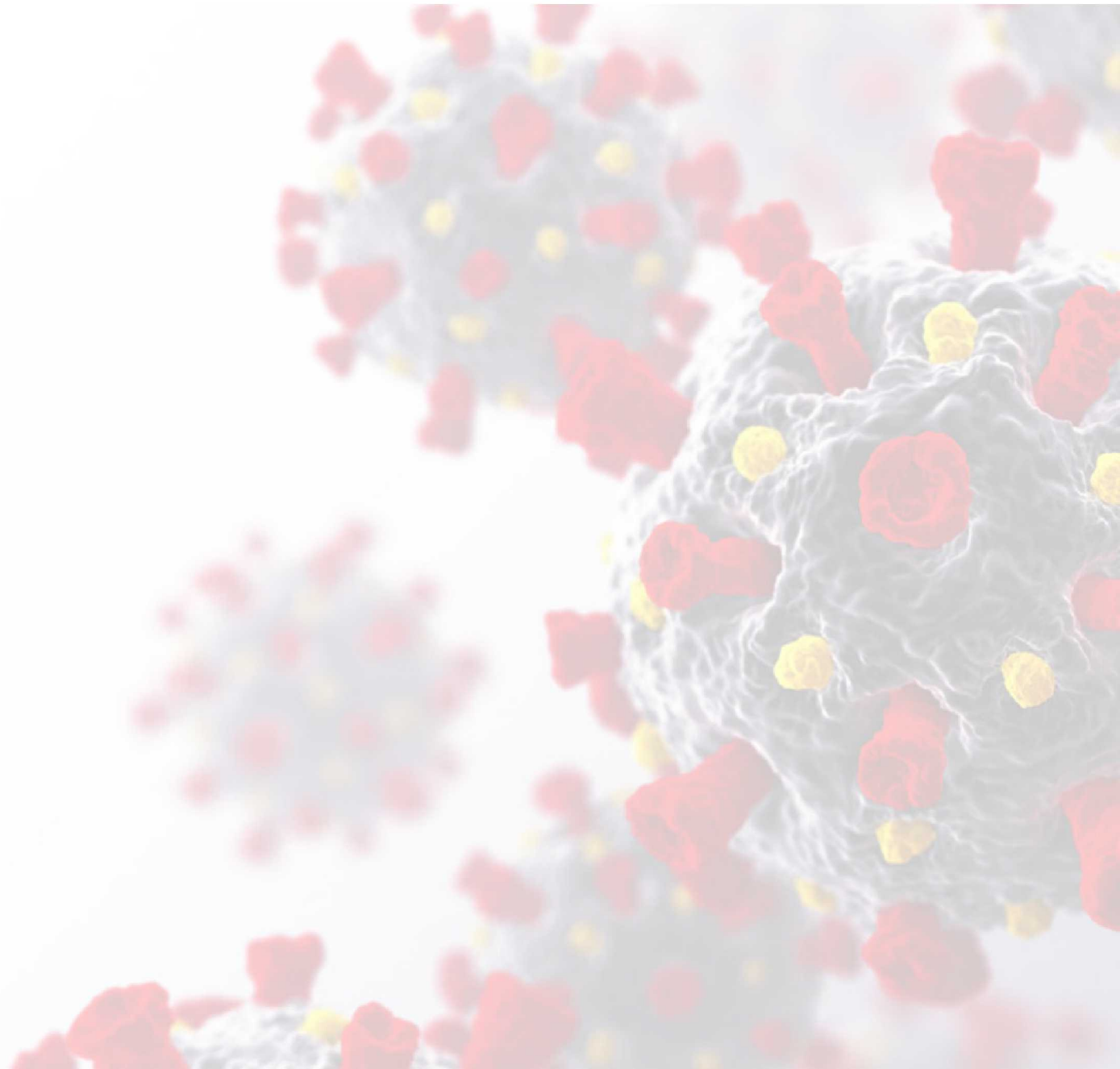
NATIONAL RESULTS (RISK INDICATORS)

CURRENT STATUS / NEXT STEPS

DETAILED MODEL FORMULATION

DATA, PARAMETERS, AND ASSUMPTIONS

UNCERTAINTY ANALYSIS



DETAILED SURGE MODELING OF MEDICAL RESOURCE DEMANDS

Goal

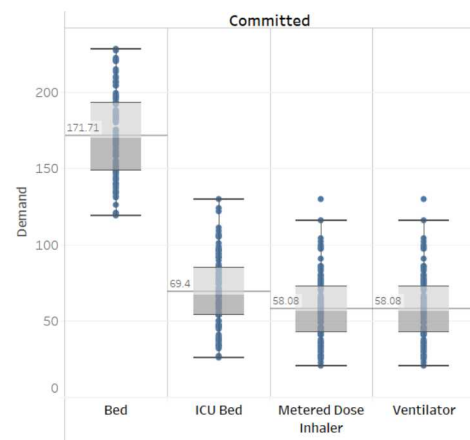
- Calculate resource demands for treating COVID-19 patients based on disease spread projections from epi models
- Anticipate possible times and locations of medical resource shortfalls throughout the pandemic

Approach

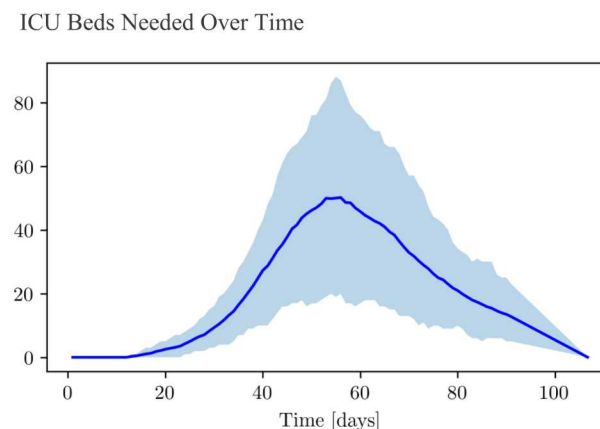
- Use discrete event mathematical model to track patient progress through a hospital treatment system
- Incorporate uncertainty in patient treatment pathways and ranges of resource use per patient to provide risk indicators
- Inputs are patient arrival stream projections from epidemiological models at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

Results

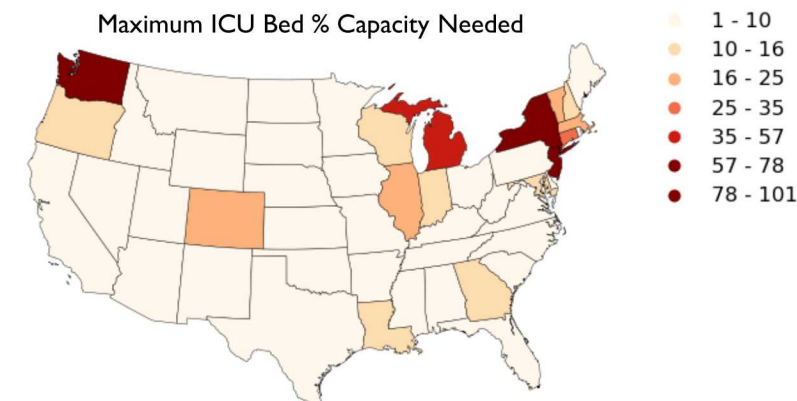
Maximum number of resource needs with a range of **uncertainty**



Resource needs **over time** with a range of uncertainty



State or county **risk** indicators



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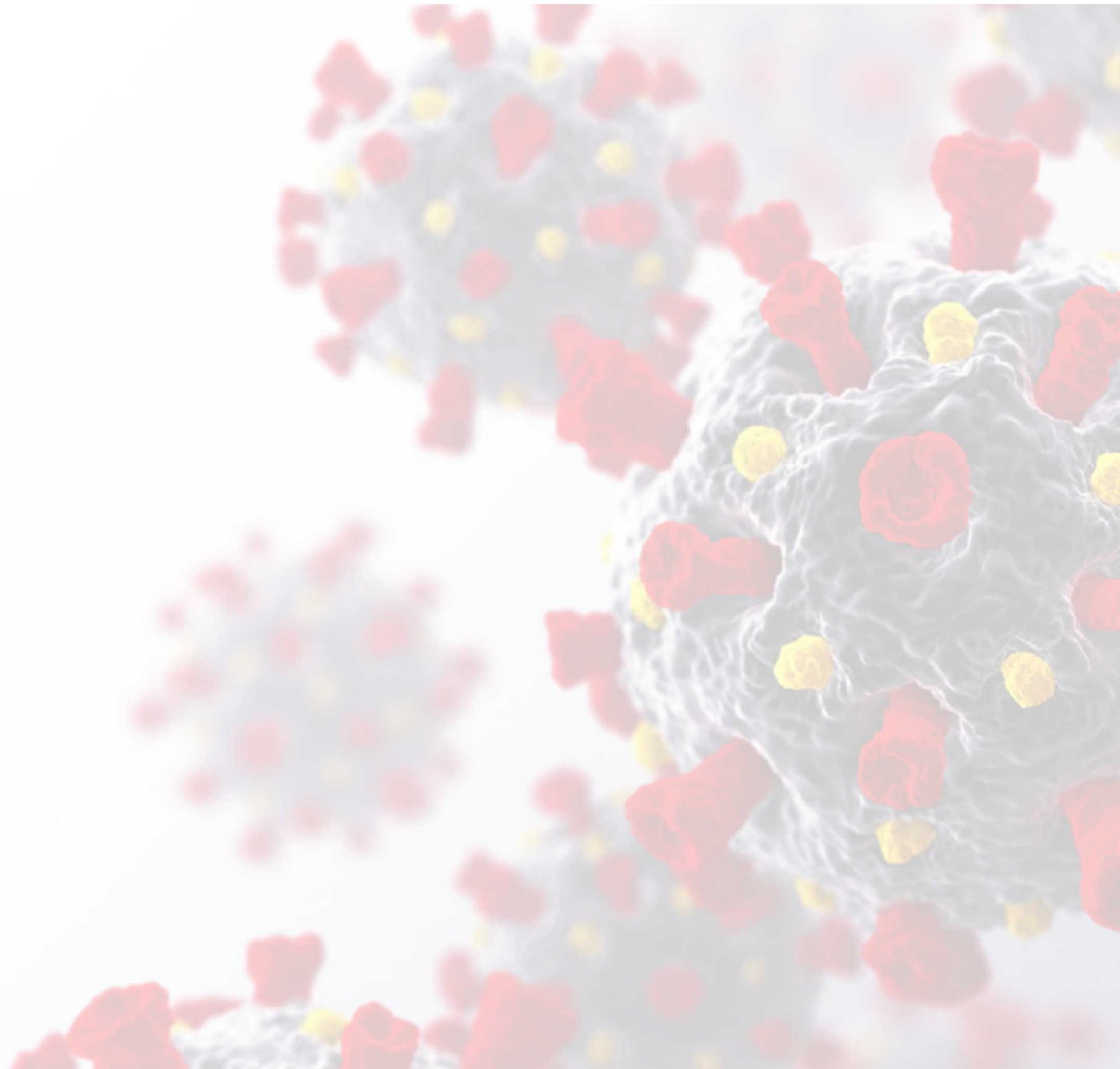
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Objectives

- 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
- Integrate extant information about epidemiological parameters, regional medical resources, and demographics

Questions of Interest for Decision-Makers

1. Do I have a problem? If so, where (which states)?
2. How localized is my problem? County-level? State-level?
3. How many key resource demands are exceeding capacity?
4. When does the issue become critical?
5. Where can I go for help? (Which states have excess capacity, and might be able to lend resources?)
6. What does it look like if I change social distancing guidance?

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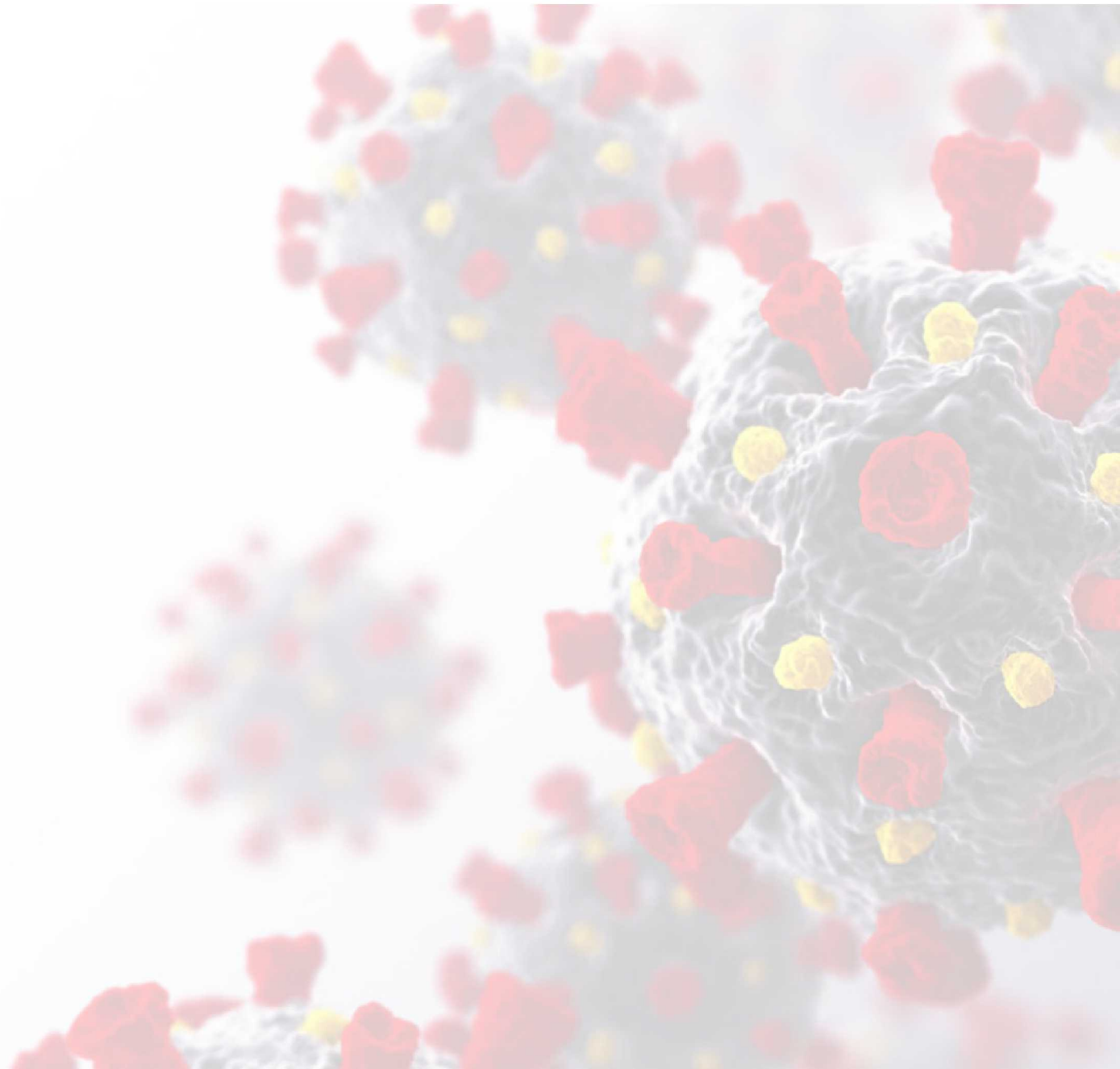
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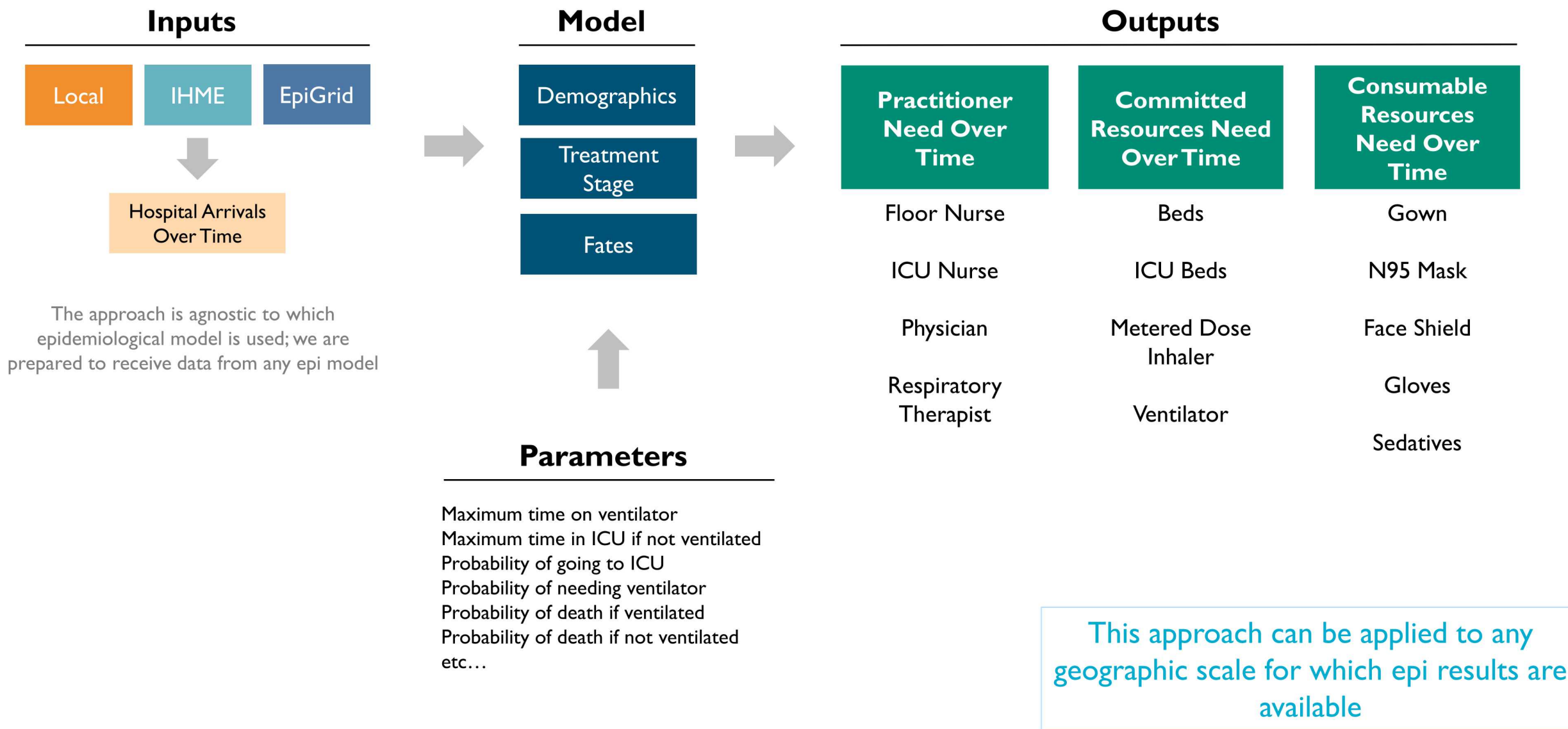
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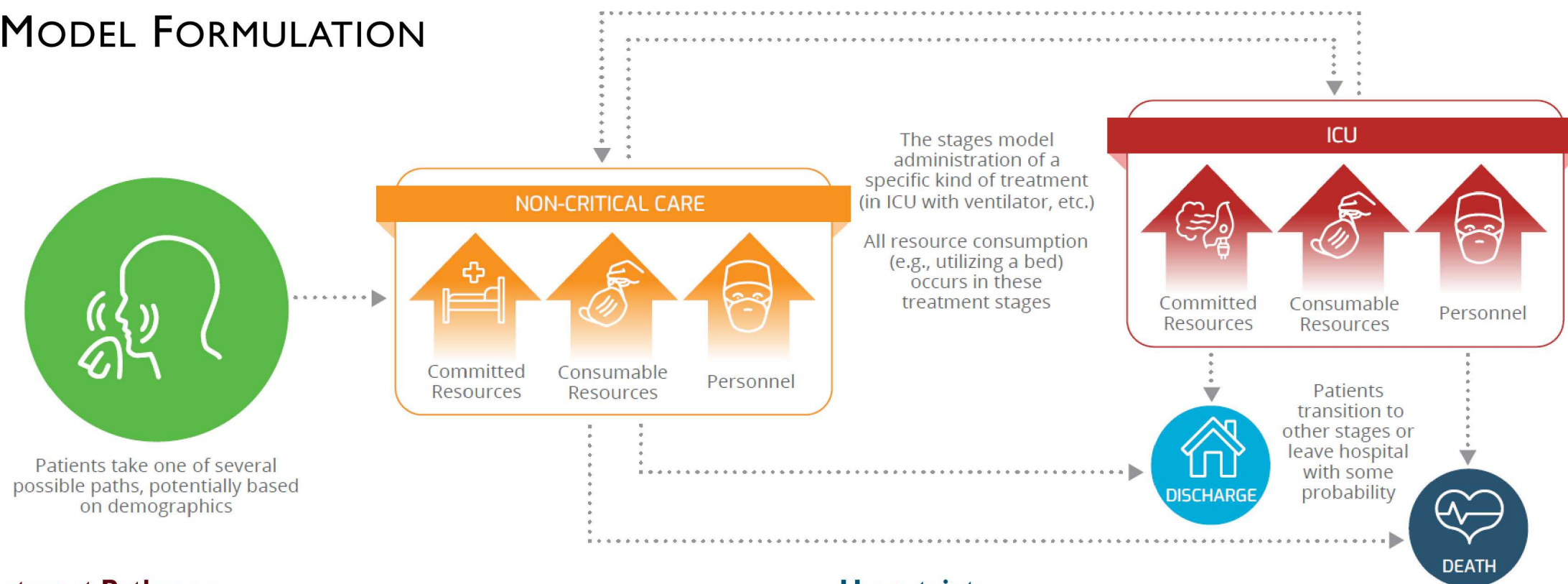
UNCERTAINTY ANALYSIS



APPROACH



MODEL FORMULATION



Treatment Pathways

- Patients take a treatment pathway through the system
- Spend time in *stages* of the system (in a regular or ICU bed, on a ventilator, etc.)
- Each stage requires different levels and types of resource consumption

Configuration Information

- Possible treatment trajectories and probabilities
- Types of resources to track
- How committed, consumable, and practitioner resources are used
- Scalable to hospital, county, state, or national regions

Uncertainty

- Probability that a patient moves to a specific stage
- Time spent in each treatment stage
- Medical providers (how many patients they can treat in a shift, amount of PPE used per patient, etc.)

Demographic Information

- Each patient's pathway and fate could be conditional on patient demographics to refine parameter ranges
- This demographic information is not currently available from any epi model, but the model is designed to accommodate these inputs when available

UNCERTAINTY ANALYSIS OVERVIEW

Goal: Characterize uncertain inputs and propagate them to uncertainty in the resulting resource projections.

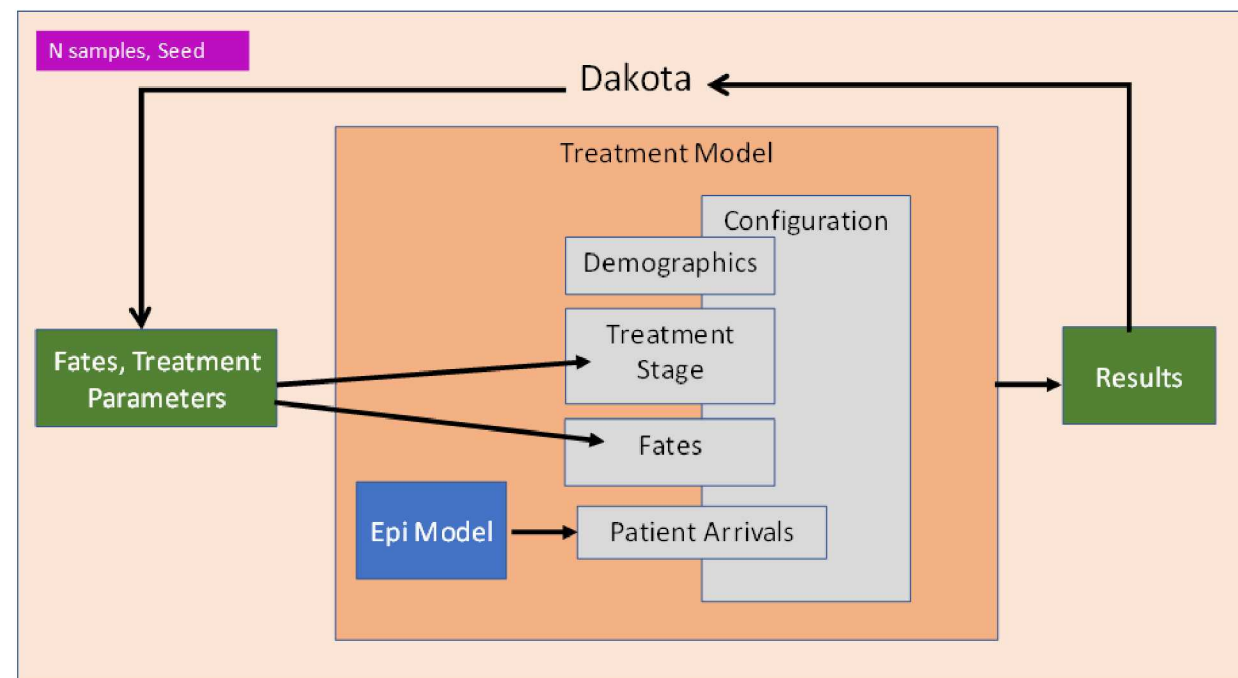
Uncertainties in the model include:

- Probability that a patient moves to a specific stage
- Time spent in each treatment stage
- Medical providers (how many patients they can treat in a shift, amount of PPE used per patient, etc.)

Used Latin Hypercube Sampling (LHS) in Dakota software framework

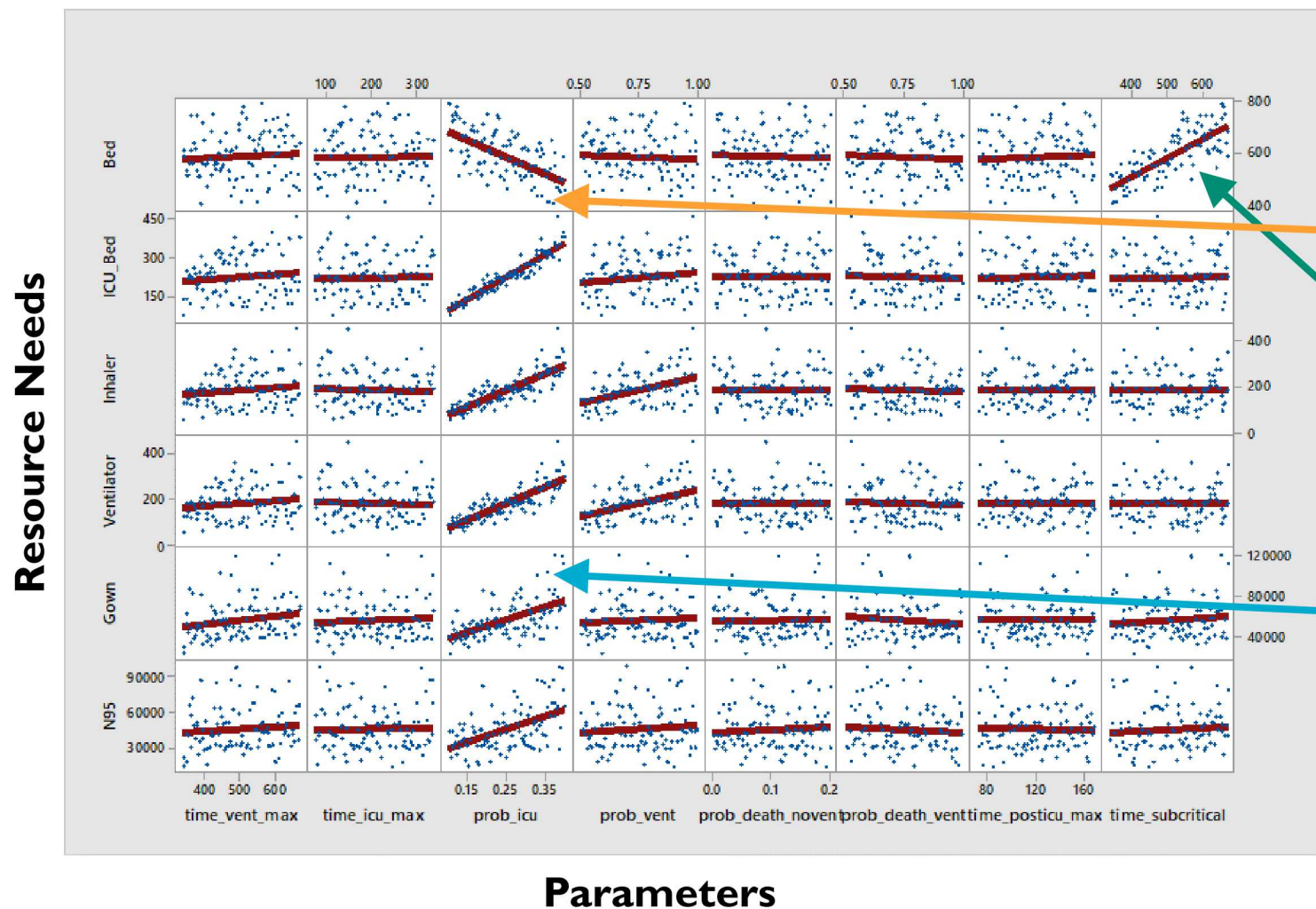
- 8 continuous parameters
- 18 discrete parameters

Uncertainty quantification process for the resource demand model



SENSITIVITY ANALYSIS

Goal: Identify most influential parameters to assess model performance



Positive and negative correlations are expected

- Probability that a patient goes to the ICU is positively correlated with ICU beds needed but negatively correlated with regular beds needed
- Maximum time the patient spends in non-ICU care is strongly positively correlated with the number of regular beds needed

Probability that a patient goes to the ICU is a strongly influential parameter on resources such as the number of ICU beds

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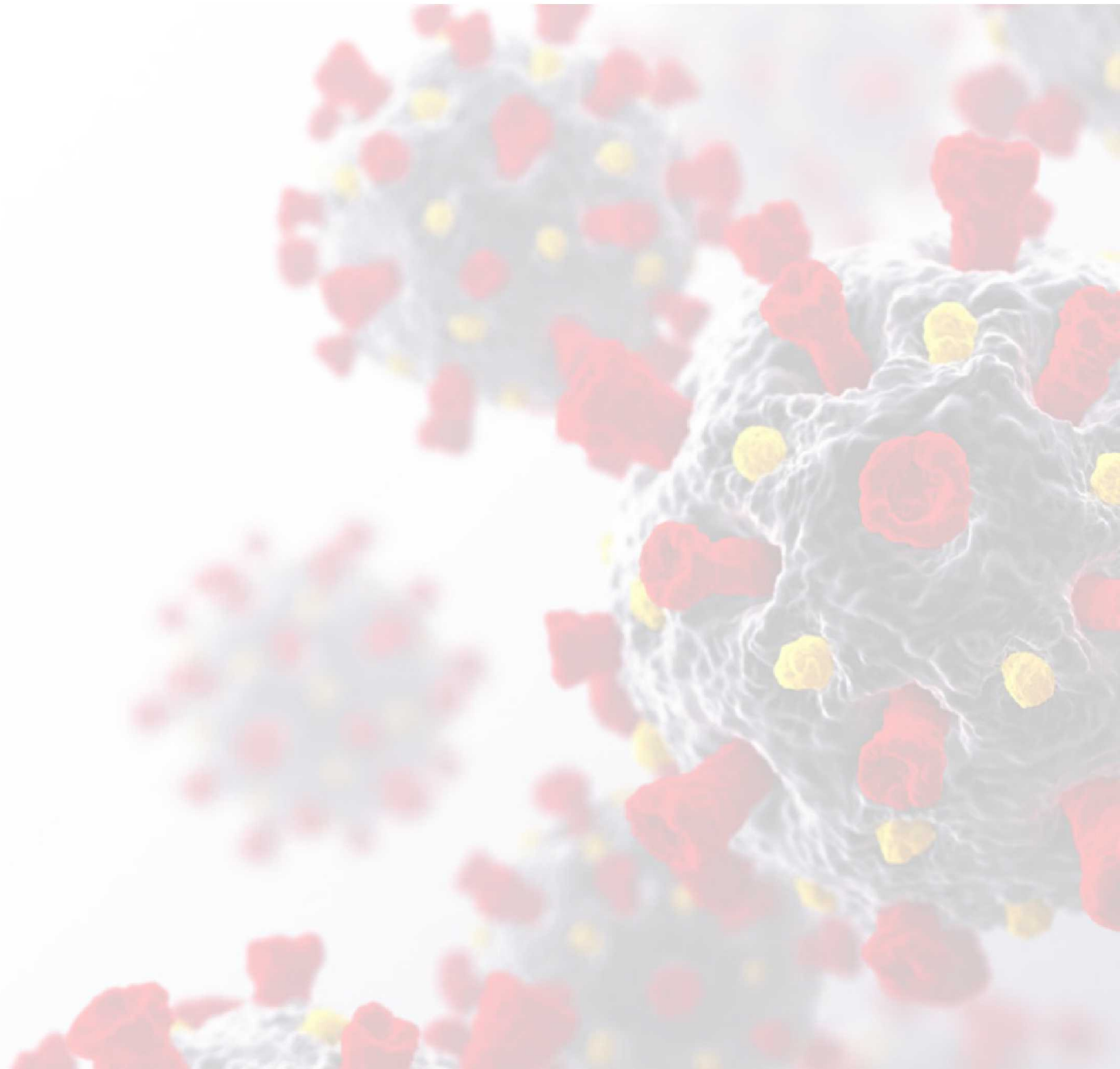
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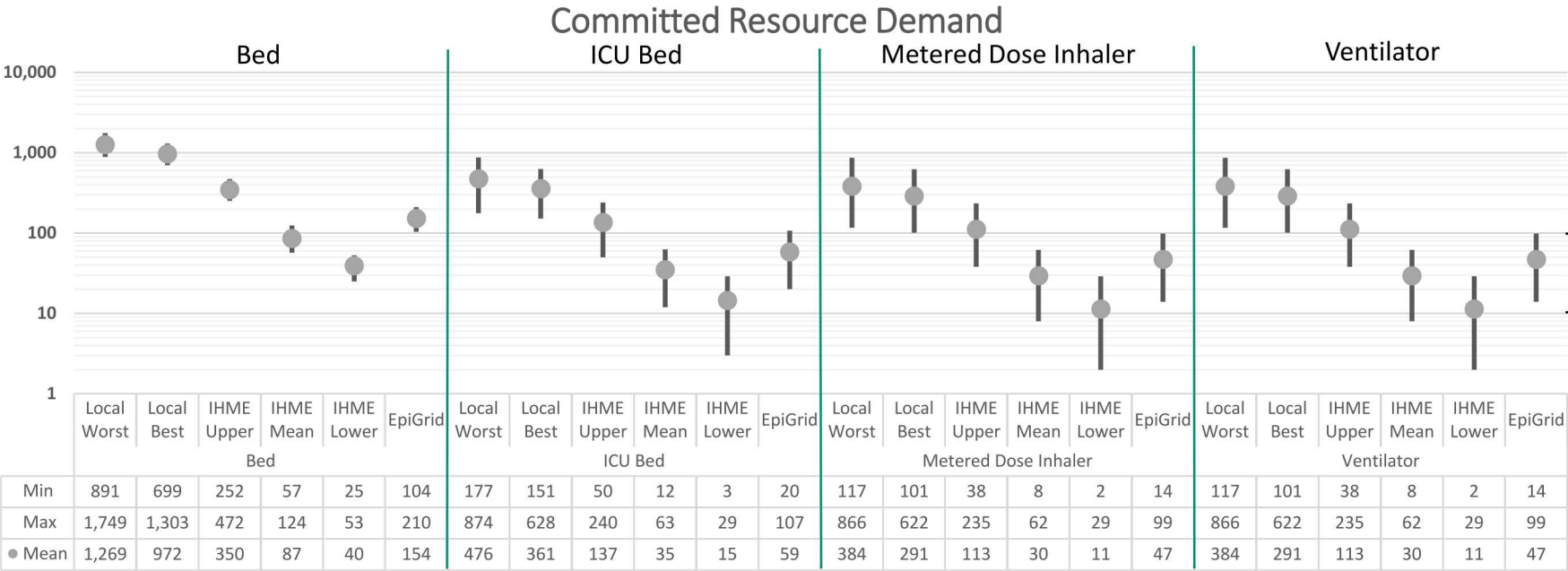
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UNCERTAINTY ANALYSIS



DETAILED ANALYSIS FOR INDIVIDUAL LOCATIONS

Compare maximum resource demand across different epi models and different scenarios



Ranges in demand are dictated by **uncertainties in parameters** (e.g., probability the patient goes into the ICU, needs a ventilator, length of stay)

DETAILED ANALYSIS FOR INDIVIDUAL LOCATIONS

Plan for resource needs over time

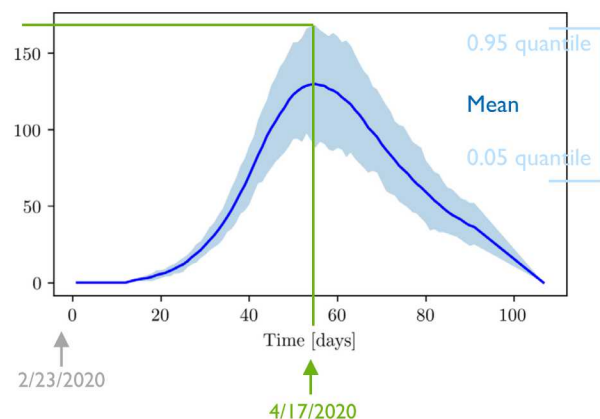
Inputs



Outputs

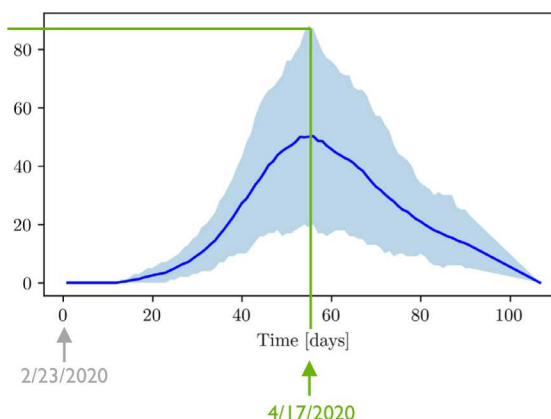


Bed



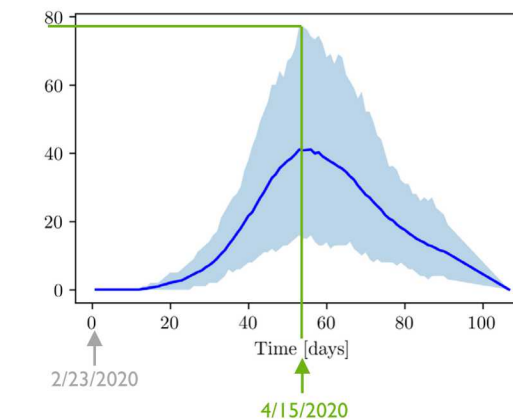
There is a 95% probability that 168 or fewer beds are needed by **4/17**

ICU Bed



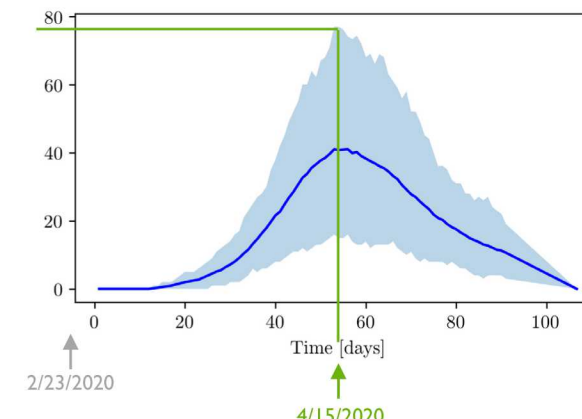
There is a 95% probability that 88 or fewer ICU beds are needed by **4/17**

Metered Dose Inhaler



There is a 95% probability that 77 or fewer metered dose inhalers are needed by **4/15**

Ventilator



There is a 95% probability that 77 or fewer ventilators are needed by **4/15**

Ranges in demand (illustrated by the light blue quantiles) are dictated by **uncertainties in parameters** (e.g., probability the patient goes into the ICU, needs a ventilator, length of stay)

DETAILED ANALYSIS FOR INDIVIDUAL LOCATIONS

Plan for weekly ordering needs of PPE and other consumable resources

Inputs

Local

IHME

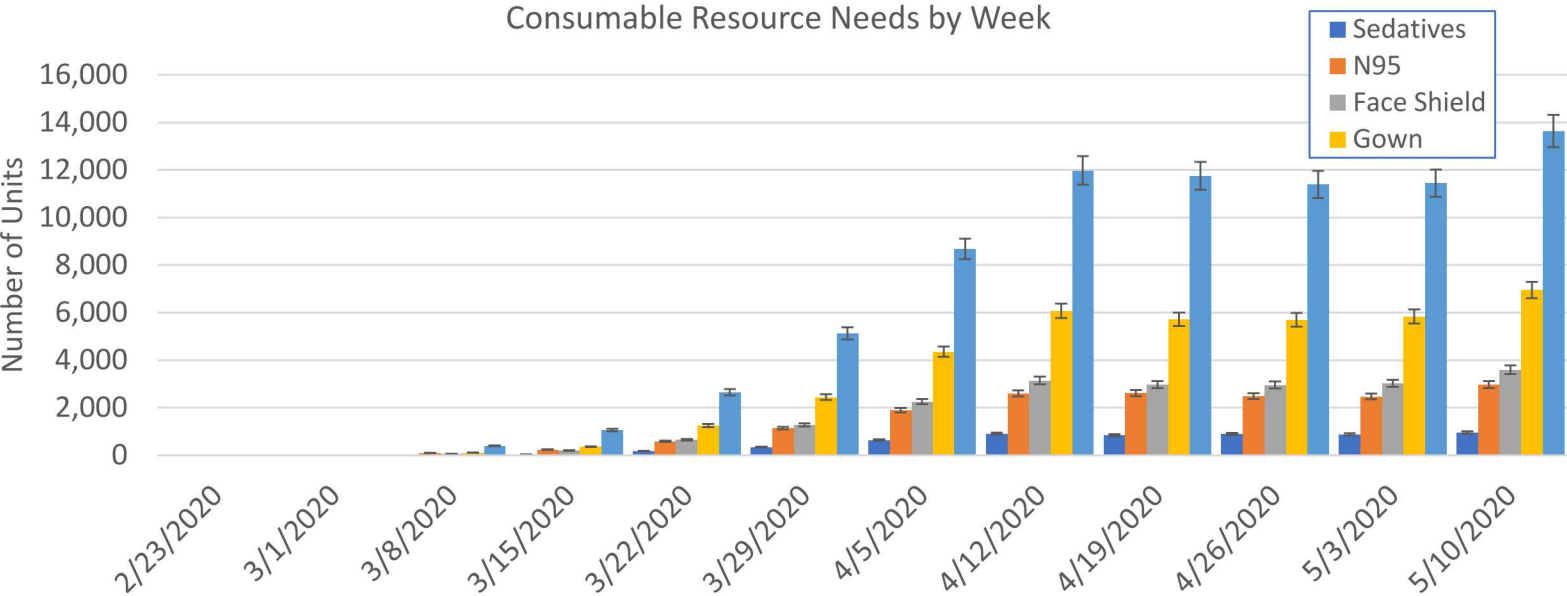
EpiGrid

Outputs

Committed
Resources Need
Over Time

Consumable
Resources
Need Over Time

Practitioner
Need Over Time



Week	Mean Weekly Demand				
	Sedatives	N95	Face Shield	Gown	Gloves
2/23/2020	0	0	0	0	0
3/1/2020	0	0	0	0	0
3/8/2020	0	97	63	111	398
3/15/2020	39	241	202	361	1,057
3/22/2020	183	592	652	1,248	2,645
3/29/2020	347	1,141	1,275	2,443	5,129
4/5/2020	643	1,894	2,259	4,355	8,676
4/12/2020	912	2,602	3,148	6,074	11,980
4/19/2020	839	2,616	2,968	5,714	11,749
4/26/2020	896	2,489	2,957	5,696	11,392
5/3/2020	882	2,473	3,028	5,841	11,446
5/10/2020	963	2,977	3,593	6,949	13,639
TOTAL	5,704	17,122	20,145	38,792	78,111

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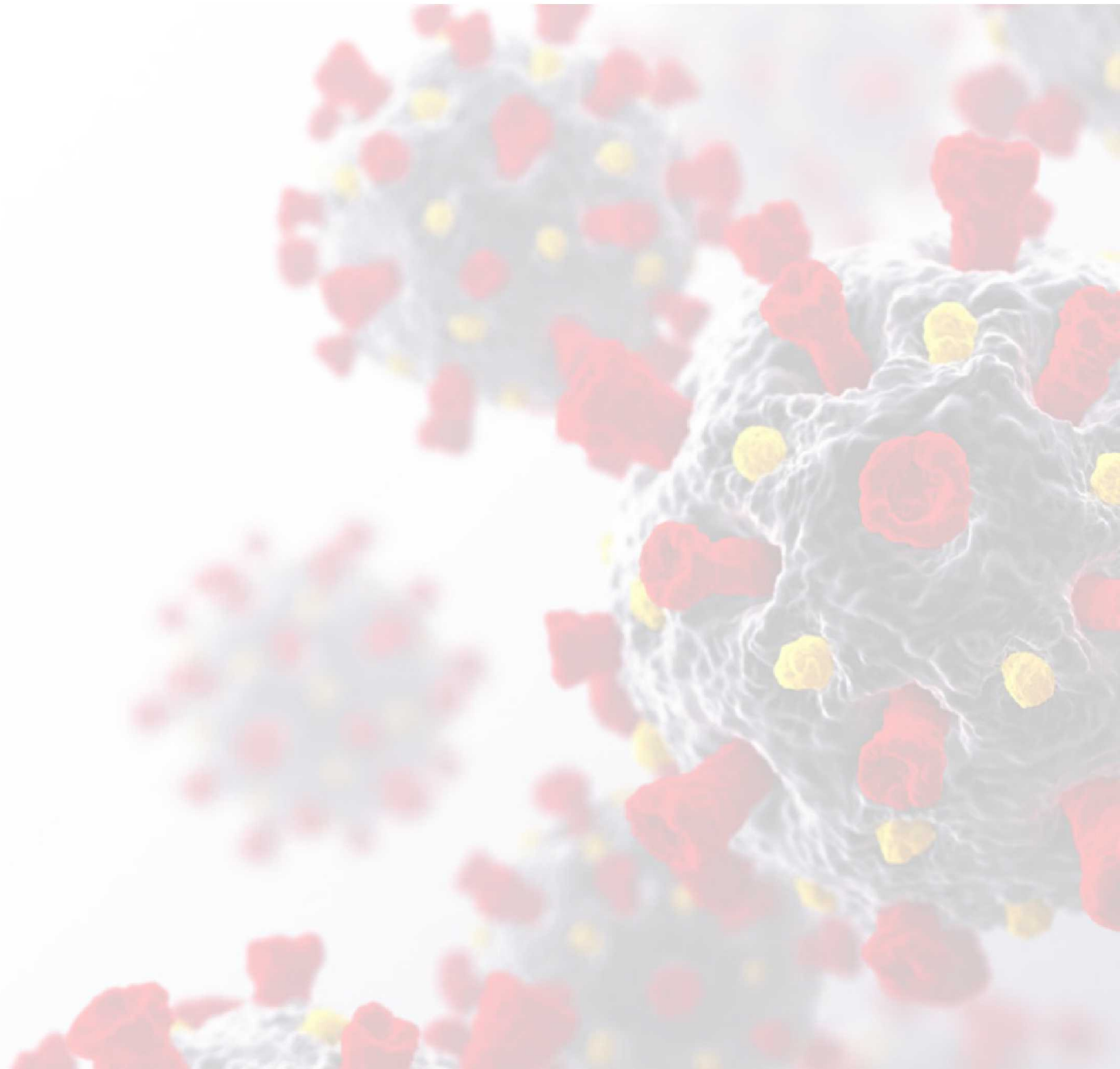
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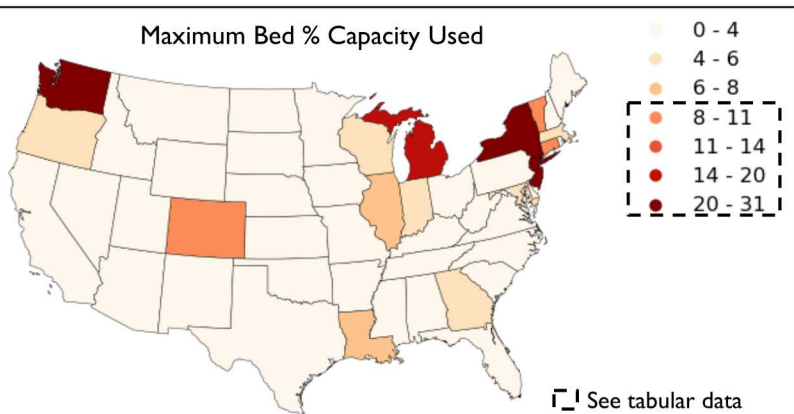
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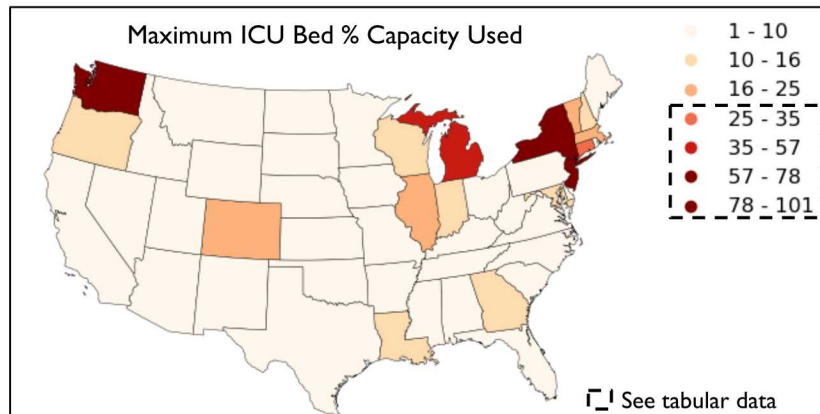
UNCERTAINTY ANALYSIS



NATIONAL SUMMARY: STATE RESOURCE SUFFICIENCY

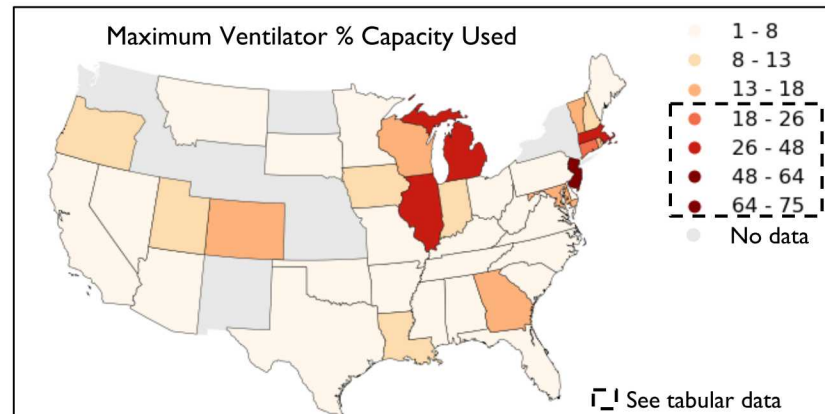


States with Resource Utilization >8% Capacity	Maximum Bed % Capacity Used
Washington	41.0
New York	33.4
New Jersey	31.0
Michigan	26.9
Connecticut	14.5
Illinois	13.7
Colorado	12.4
Vermont	11.0
Louisiana	10.4
Indiana	9.3
Wisconsin	8.4
Massachusetts	8.2



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



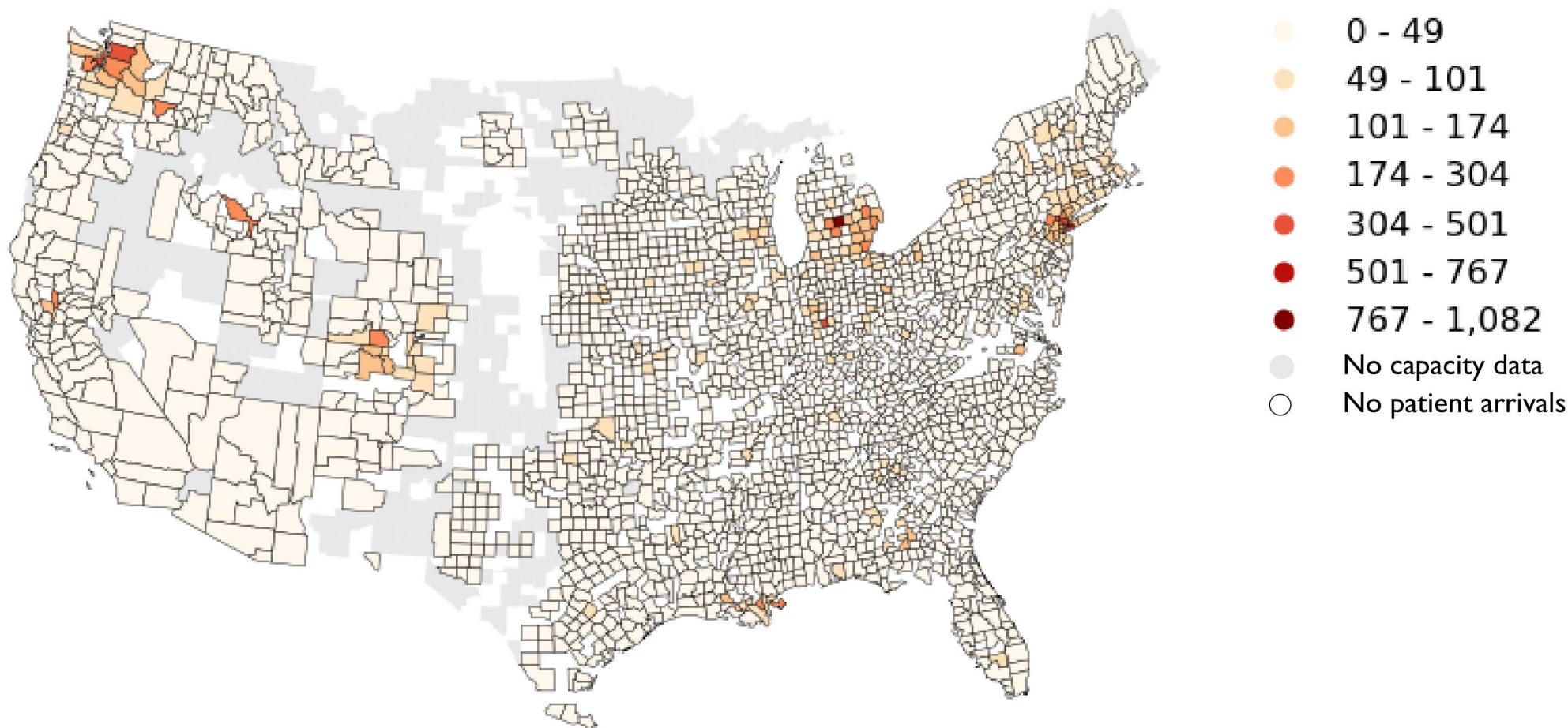
States with Resource Utilization >18% Capacity	Maximum Ventilator % Capacity Used
New Jersey	75.0
Michigan	64.3
Illinois	48.1
Massachusetts	42.3
Connecticut	24.5
Rhode Island	23.3
Wisconsin	23.2
Vermont	22.4
Georgia	22.1
Maryland	22.0
Colorado	20.6
Indiana	18.4

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, $\beta = 0.3$
 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).

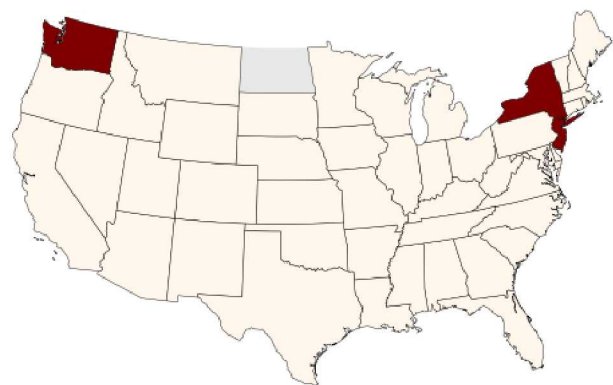
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Using EpiGrid patient streams, 4/26/2020 dataset, $\beta = 0.3$
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NATIONAL SUMMARY: EXCEEDANCE OF CAPACITY, SOCIAL DISTANCING

Probability of Exceeding ICU Bed Capacity

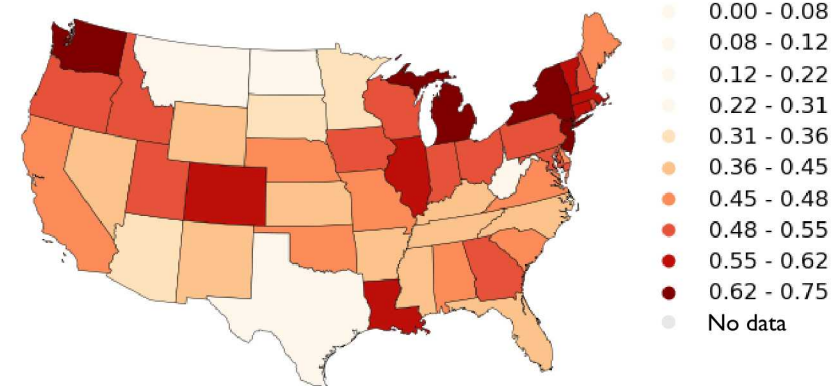
Maximum Social Distancing
From 4/11/20 to the end of the simulation,
likelihood of infections spreading is discounted 80%
relative to doing nothing



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

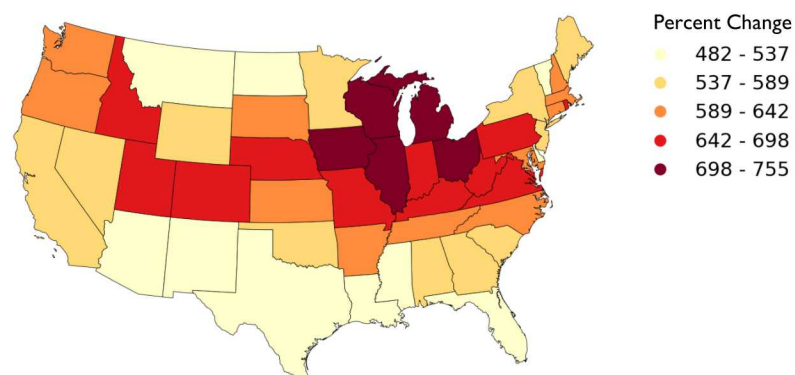


Note that with decreasing degree of social distancing (from left to right in above maps), the probability of exceeding capacity of ICU beds across the country increases significantly.

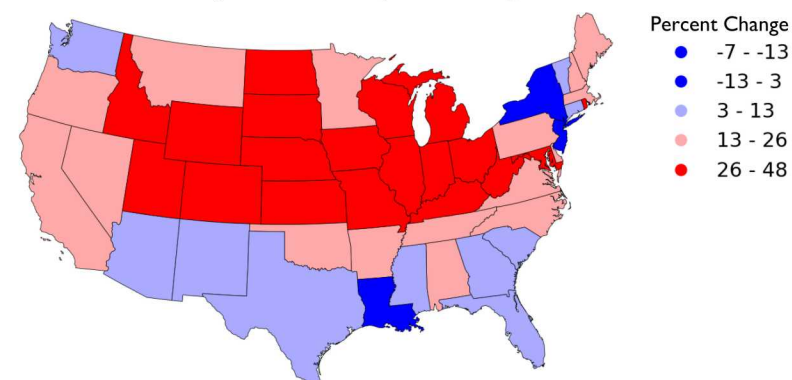
NATIONAL SUMMARY: TIMESERIES OF INCREASE/DECREASE IN DEMAND

Sequence of maps show increase/decrease of demand from month to month, March – July.
Shading in the “red” family show increases; shading in the “blue” family show decreases.

March to April Change in Bed Demand

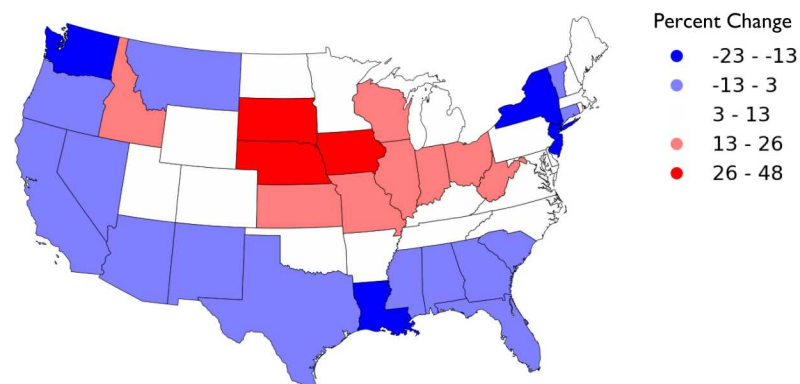


April to May Change in Bed Demand



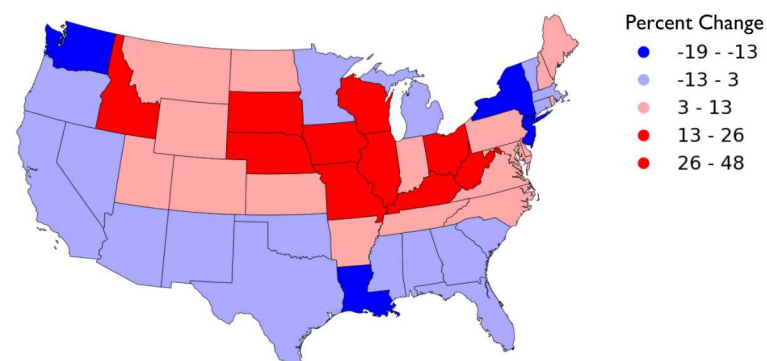
Going into May is the first time some states start to decrease their bed demands

May to June Change in Bed Demand



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

June to July Change in Bed Demand



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

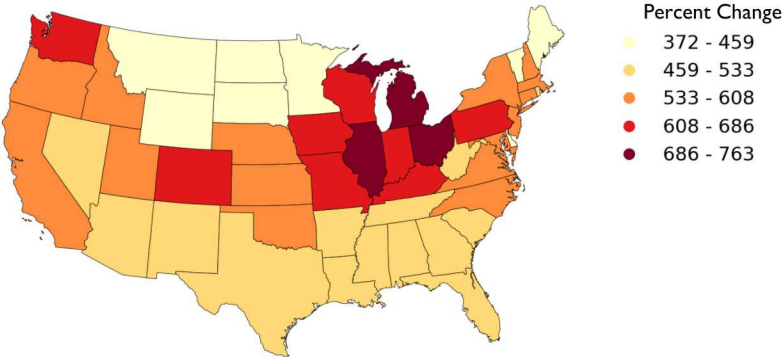
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Using EpiGrid patient streams, 4/26/2020 dataset, $\beta = 0.3$
Analysis horizon: 3/3/2020 – 7/20/2020

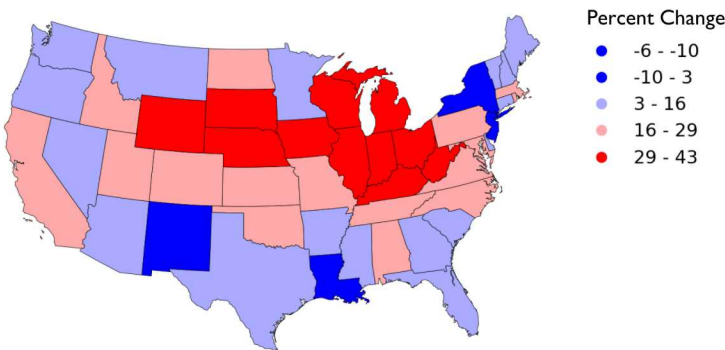
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March to April Change in ICU Bed Demand

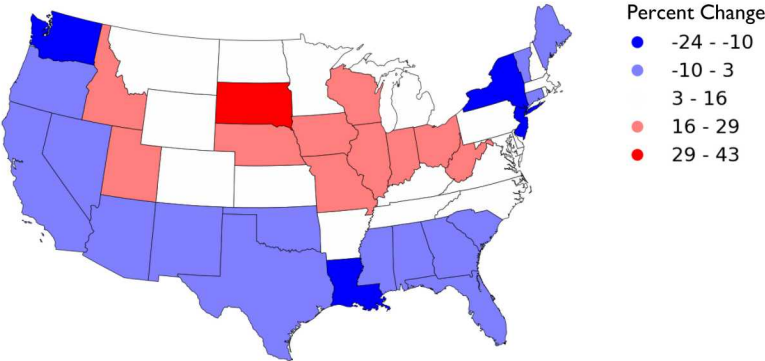


April to May Change in ICU Bed Demand



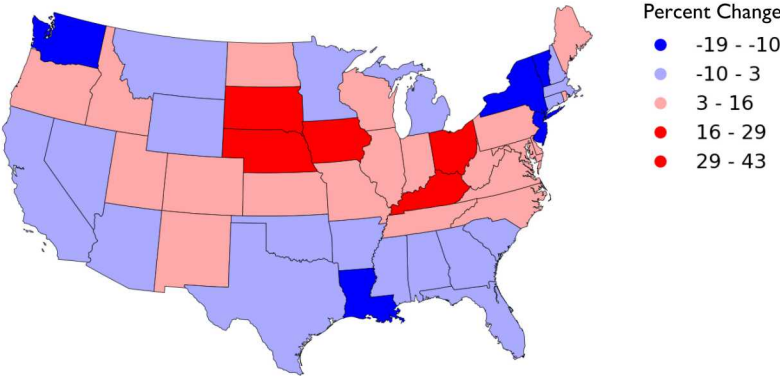
Similar national pattern to non-ICU beds, but more states show a decrease in ICU bed demand compared to non-ICU beds

May to June Change in ICU Bed Demand



Similar pattern as non-ICU bed demand

June to July Change in ICU Bed Demand



Different states (e.g., Oregon, New Mexico) show increases in ICU bed demand compared to non-ICU bed demand

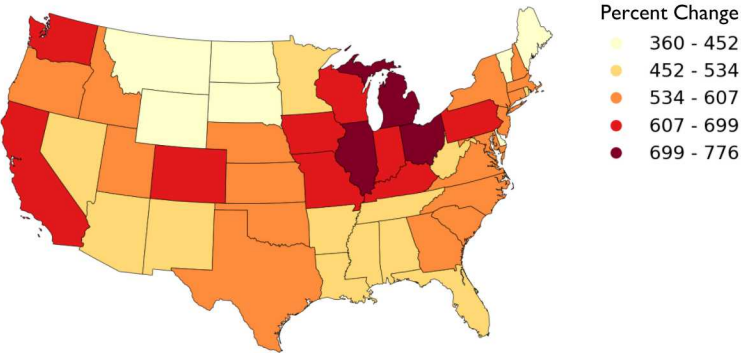
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Analysis horizon: 3/3/2020 – 7/20/2020

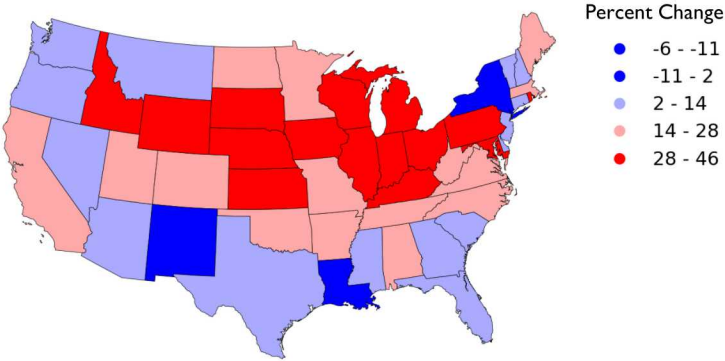
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March to April Change in Ventilator Demand

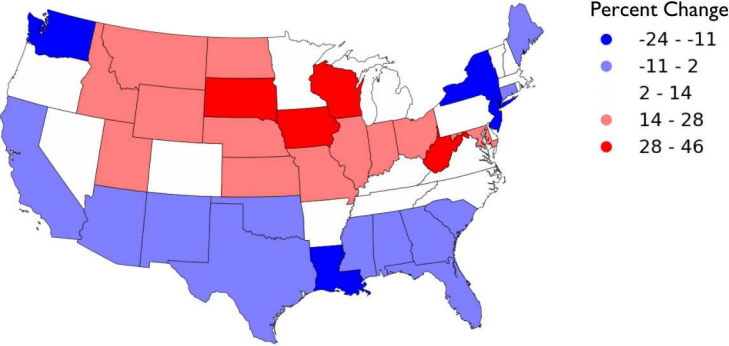


April to May Change in Ventilator Demand



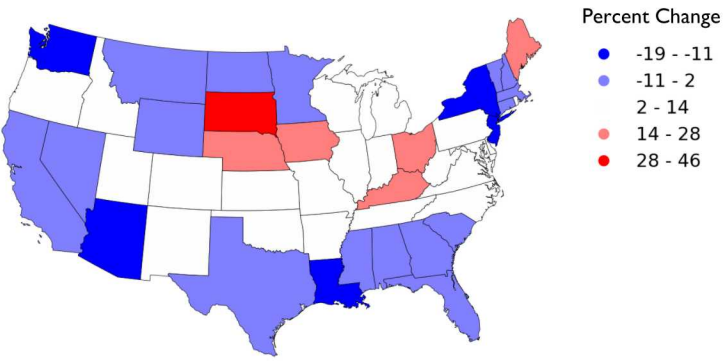
Going into May is the first time some states start to decrease their bed demands

May to June Change in Ventilator Demand



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

June to July Change in Ventilator Demand



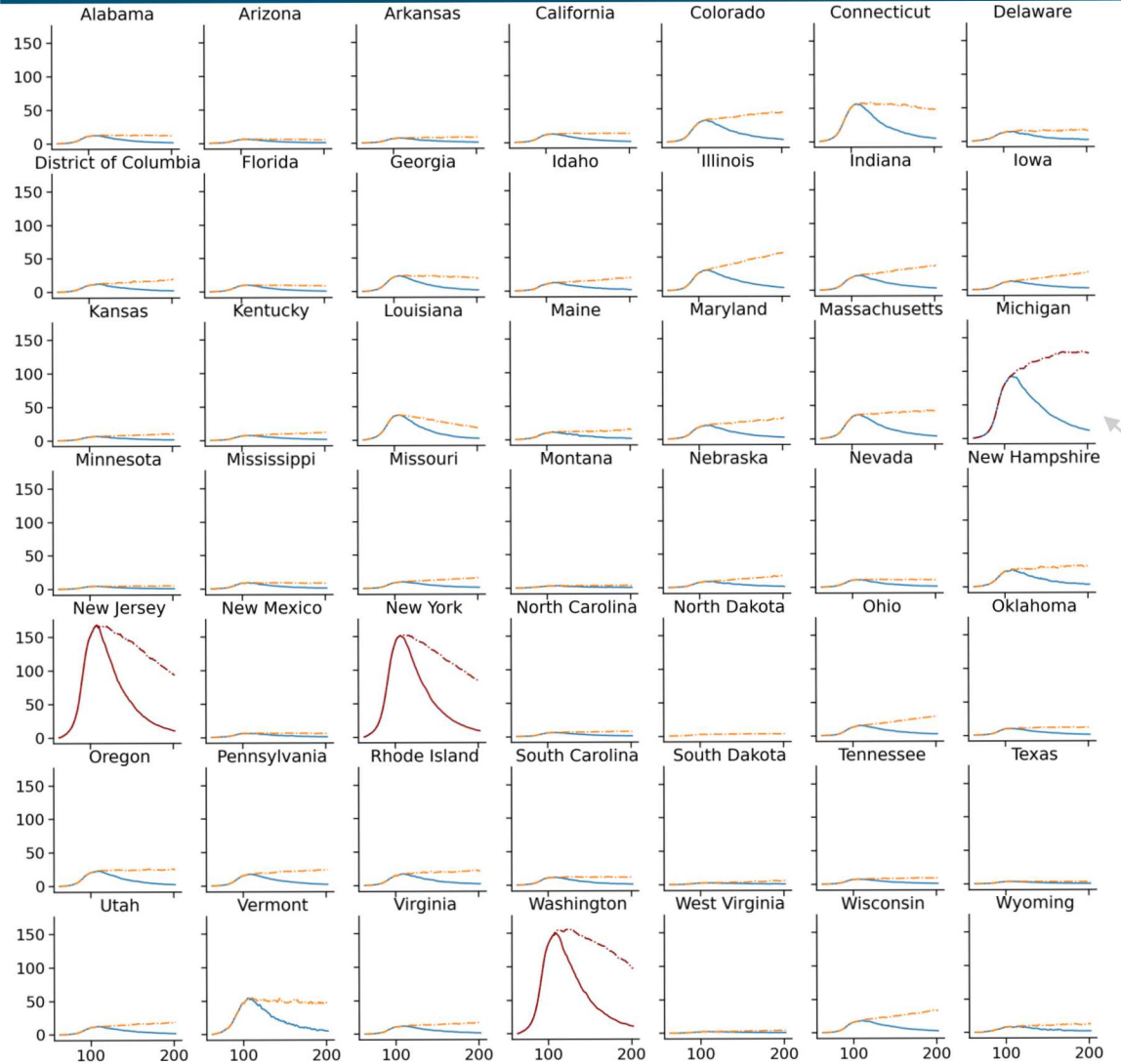
Slightly less change in ventilator demand than change in bed demand for central states

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 for all states, 3/3-7/20



	Maximum Social Distancing, $\beta = 0.2$	From 4/11/20 to the end of the simulation, likelihood of infections spreading is discounted 80% relative to doing nothing
	Moderate Social Distancing, $\beta = 0.3$	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

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, $\beta = 0.2$ and 0.3
Analysis horizon: 3/3/2020 – 7/20/2020

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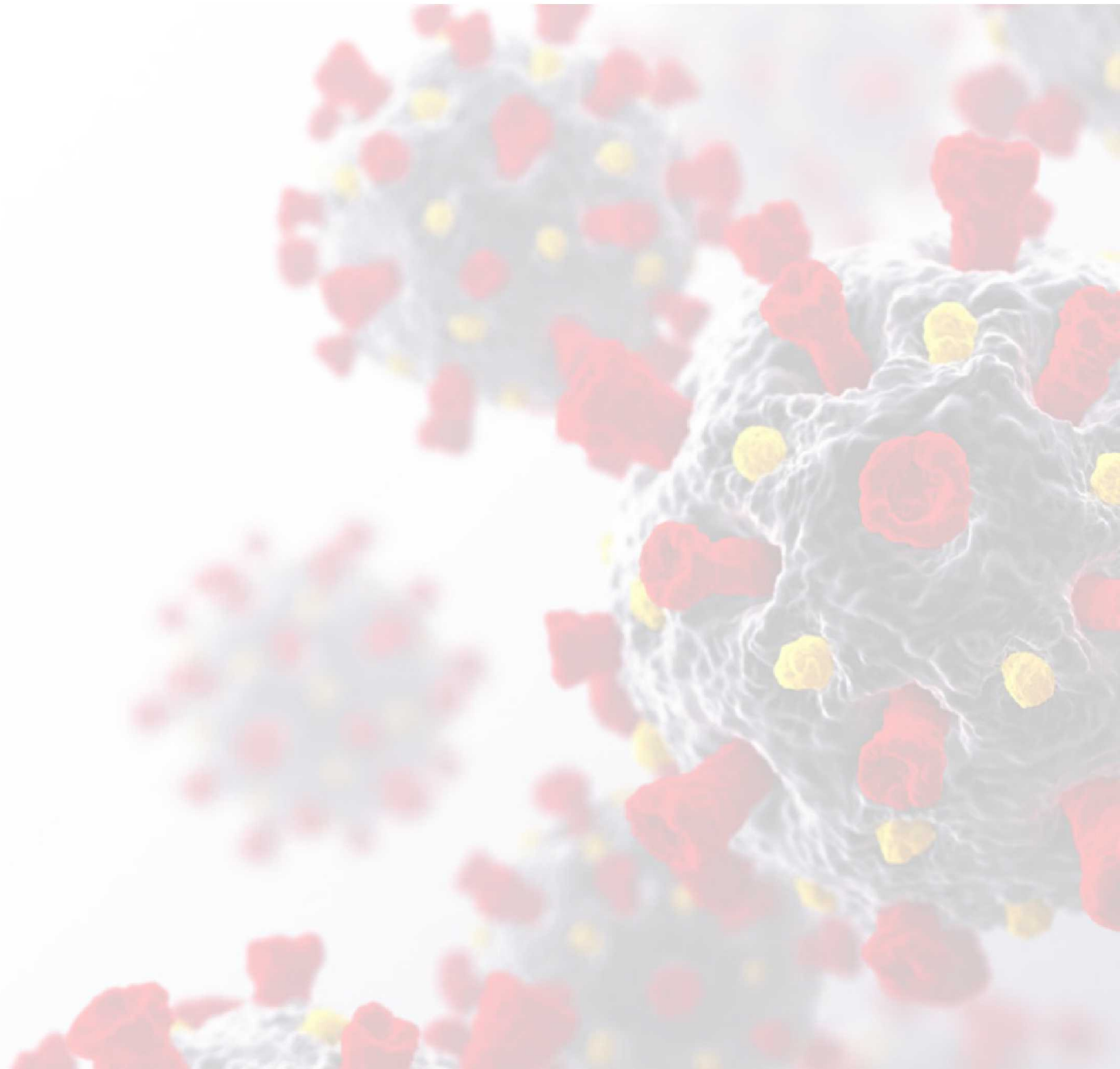
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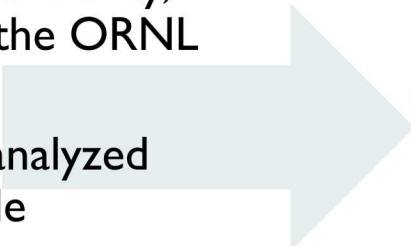
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STATUS

Current Status (Phase I)

- Phase I work focused on model development and testing needed to generate national-scale resource estimates at county-wide granularity, and test-delivery of resulting data to the ORNL dashboard
 - The resource model can be run and analyzed when new EpiGrid results are available
 - The current results are being incorporated into the ORNL dashboard
- 

Next Steps (Potential DOE Phase 2)

- Focus on designing and implementing the high-throughput data pipeline needed to **rapidly generate** national scale resource analysis outputs on a production scale. Include validation using actual resource utilization tracking where possible.
- **Rapid updating** of detailed resource supply information and spatially varying demand-model parameters to better estimate anticipated shortfalls and uncertainties, incorporating hospital service areas as applicable

Next Steps (Targeting FEMA/Tiger Team)

- With resource constraints/strained hospital systems, identify resource allocation strategies
- The methodology is developed and tested, just need stakeholder engagement to continue

Potential future COVID-19 resurgence scenarios (as standard hospital admissions return to normal) will necessitate continued risk indicator tracking and development of associated mitigation strategies

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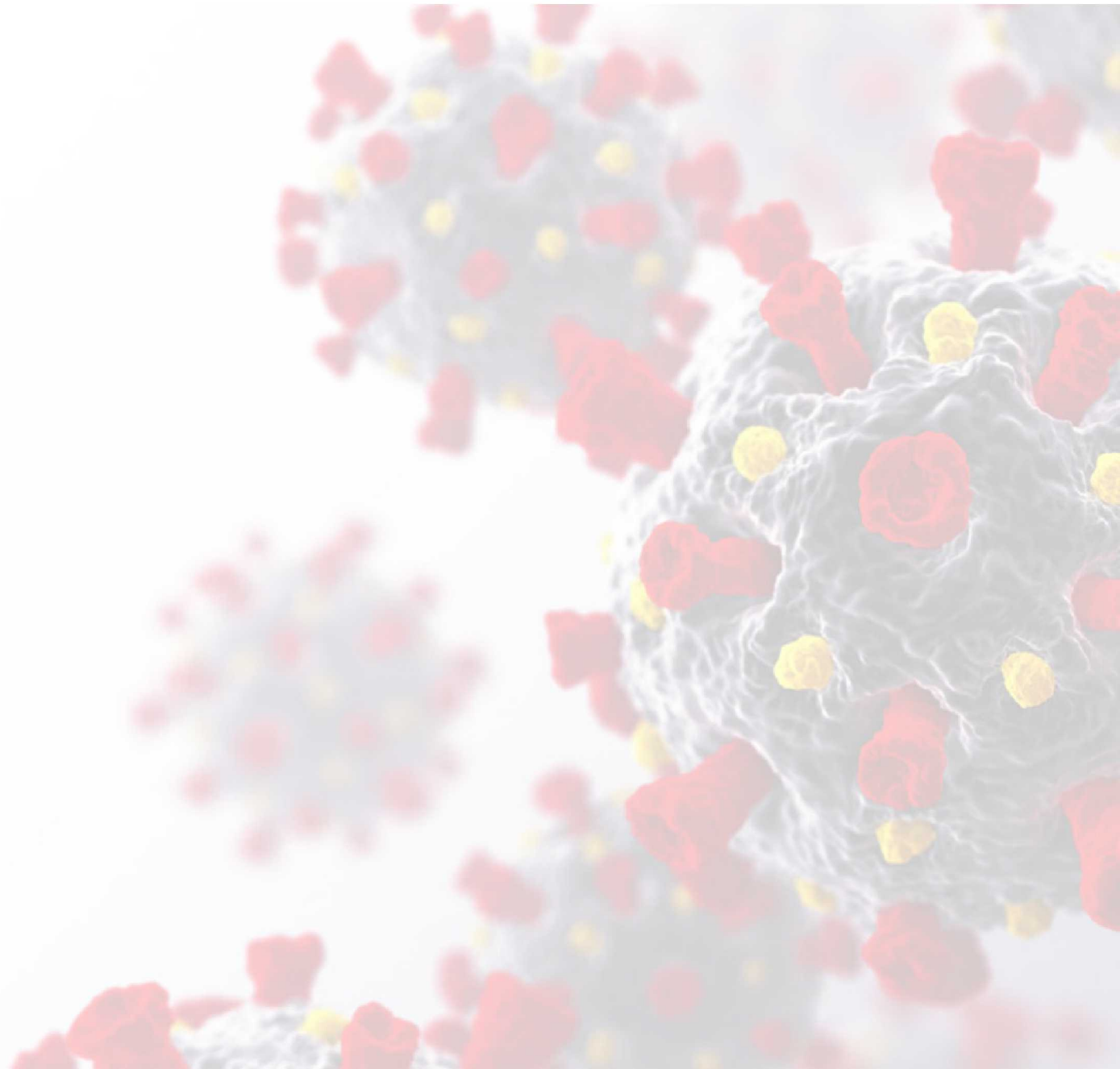
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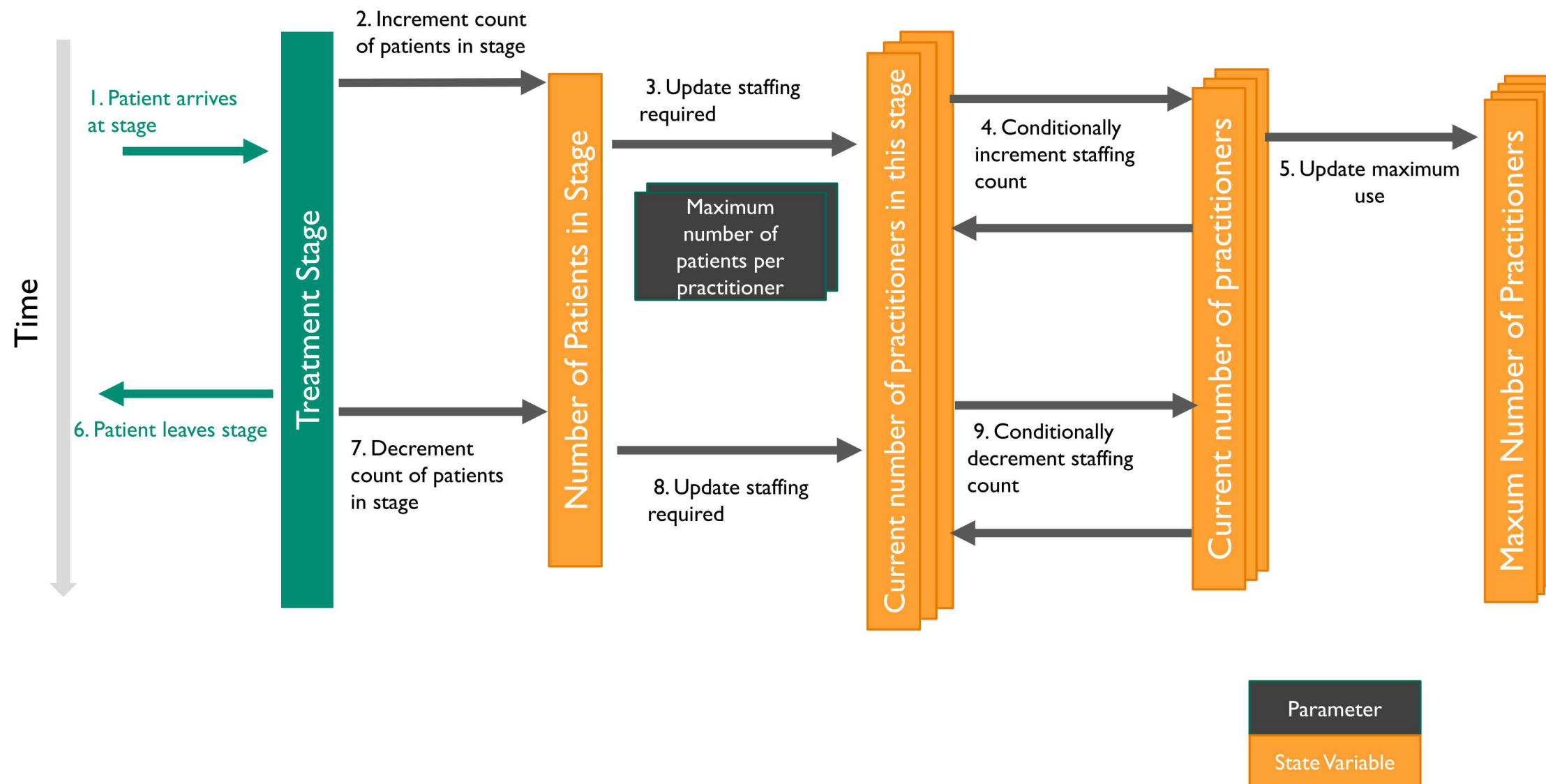
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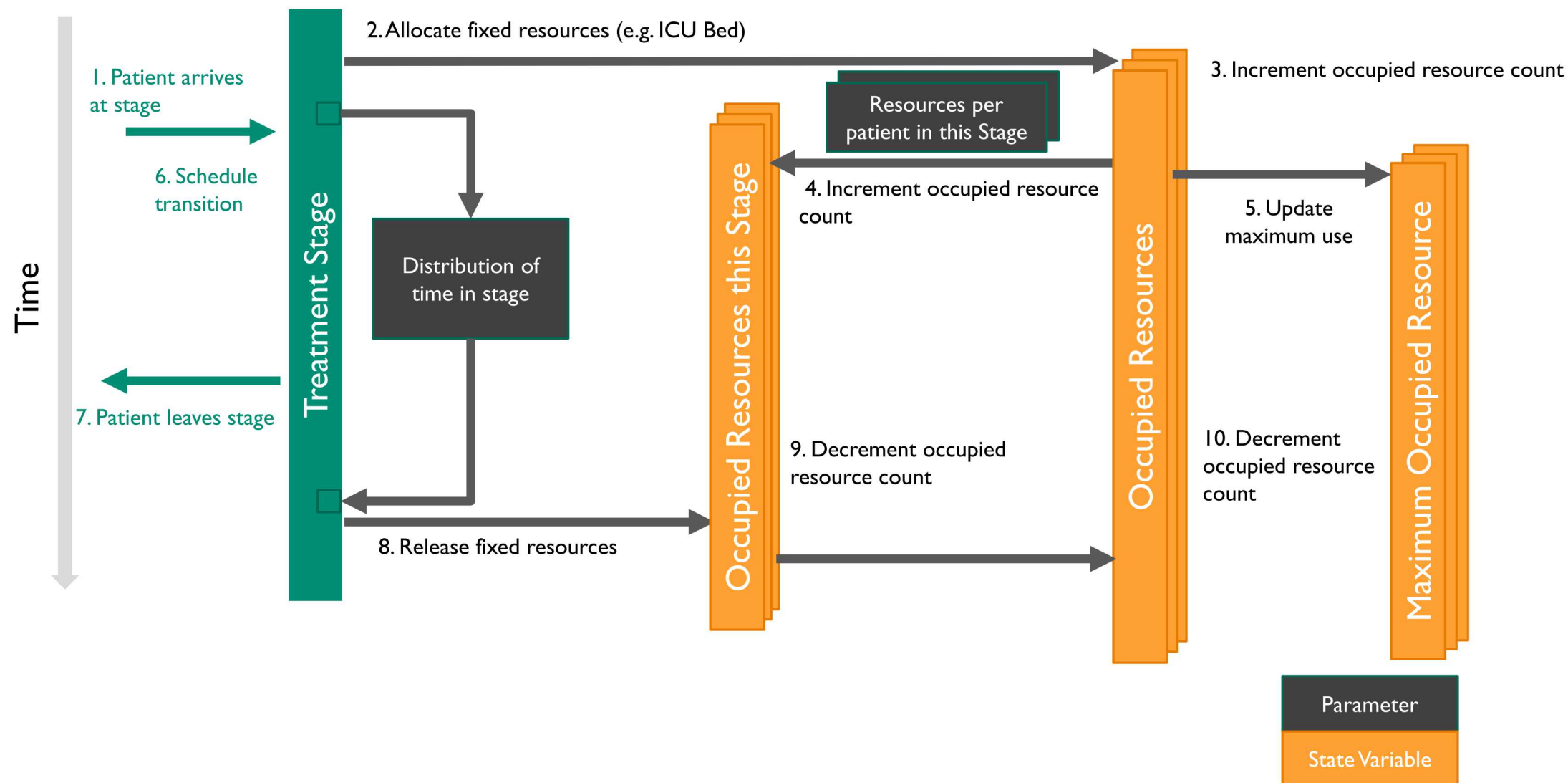
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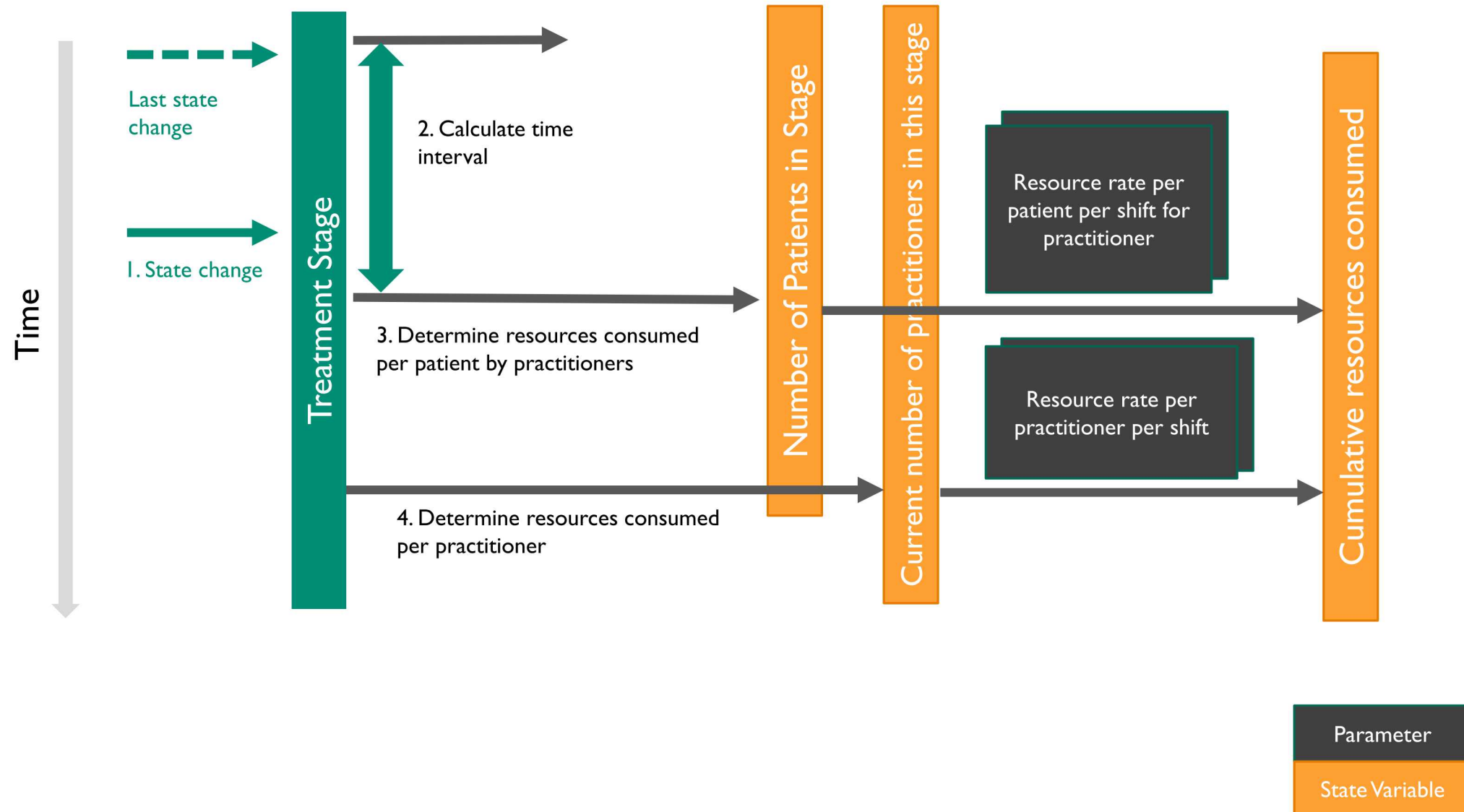
CALCULATING RESOURCE BURDENS - PRACTITIONERS



CALCULATING RESOURCE BURDENS - COMMITTED



CALCULATING RESOURCE BURDENS - CONSUMABLE



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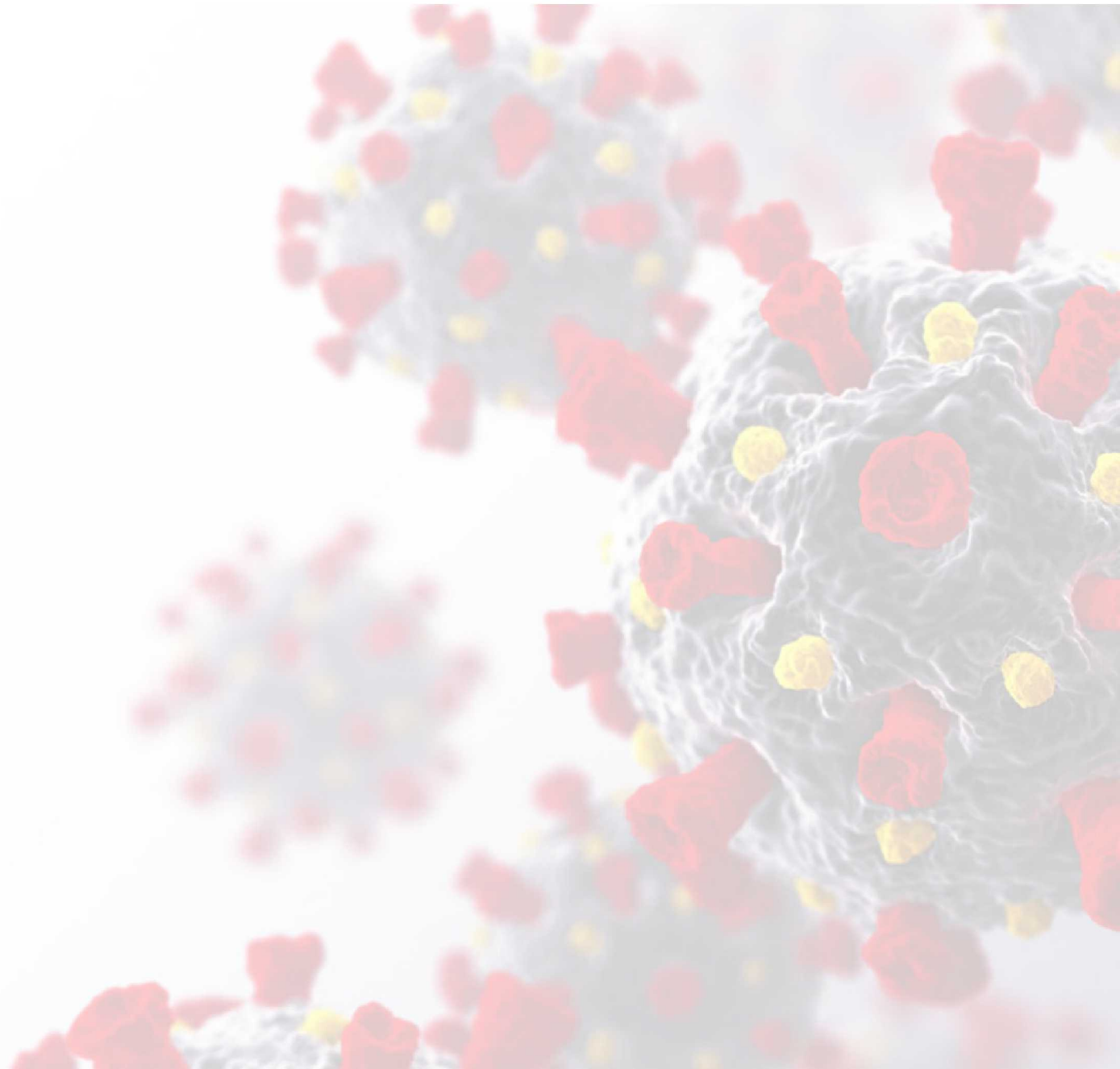
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MODEL PARAMETERS

Group	Parameter	Range	Source
Treatment paths, probabilities, times	Probability of going to ICU	10% to 40%	Guan WJ, Ni ZY, Hu Y, et al; China Medical Treatment Expert Group for Covid-19. Clinical characteristics of coronavirus disease 2019 in China. <i>N Engl J Med</i> . doi: 10.1056/NEJMoa2002032 Wang D, Hu B, Hu C, et al. Clinical Characteristics of 138 Hospitalized Patients With 2019 Novel Coronavirus–Infected Pneumonia in Wuhan, China. <i>JAMA</i> . 2020;323(11):1061–1069. doi:10.1001/jama.2020.1585 Clinical course and outcomes of critically ill patients with SARS-CoV-2 pneumonia in Wuhan, China: a single-centered, retrospective, observational study. Yang X, Yu Y, Xu J, Shu H, Xia J, Liu H, Wu Y, Zhang L, Yu Z, Fang M, Yu T, Wang Y, Pan S, Zou X, Yuan S, Shang Y
	Probability of needing a ventilator (if in ICU)	50-100%	
	Maximum time any patient would require ventilation	14 to 28 days	
	Maximum time in ICU if not on a ventilator	3 to 14 days	

Staffing		Location	
		ICU	General
Practitioner	ICU Nurse	Uniform 1-2	N/A
	Doctor	Uniform 2-10	Uniform 20-50
	Nurse	N/A	Uniform 4-10
	Respiratory Therapist	Uniform 2-6	N/A

Units used per shift in ICU		Resource			
		Gowns	N95 Mask	Gloves	Face Shield
Practitioner	ICU Nurse	2-4	1-4	4-12	1-4
	Doctor	1-2	1	1-12	1
	Nurse	N/A	N/A	N/A	N/A
	Respiratory Therapist	1-2	1	6-12	1

Units used per shift in General		Resource			
		Gowns	N95 Mask	Gloves	Face Shield
Practitioner	ICU Nurse	N/A	N/A	N/A	N/A
	Doctor	1-2	1	1-12	1
	Nurse	2-3	1-3	3-12	1
	Respiratory Therapist	N/A	N/A	N/A	N/A

Epi inputs drive results more than these parameter values

REFERENCES

Treatment Paths and Outcomes

- Guan WJ, Ni ZY, Hu Y, et al; China Medical Treatment Expert Group for Covid-19. Clinical characteristics of coronavirus disease 2019 in China. *N Engl J Med*. doi:[10.1056/NEJMoa2002032](https://doi.org/10.1056/NEJMoa2002032)
- Wang D, Hu B, Hu C, et al. Clinical Characteristics of 138 Hospitalized Patients With 2019 Novel Coronavirus–Infected Pneumonia in Wuhan, China. *JAMA*. 2020;323(11):1061–1069. doi:10.1001/jama.2020.1585
- Clinical course and outcomes of critically ill patients with SARS-CoV-2 pneumonia in Wuhan, China: a single-centered, retrospective, observational study. Yang X, Yu Y, Xu J, Shu H, Xia J, Liu H, Wu Y, Zhang L, Yu Z, Fang M, Yu T, Wang Y, Pan S, Zou X, Yuan S, Shang Y.
- Severe Outcomes Among Patients with Coronavirus Disease 2019 (COVID-19) — United States, February 12–March 16, 2020 - CDC
- Clinical Characteristics of Coronavirus Disease 2019 in China; Wei-jie Guan, Ph.D., Zheng-yi Ni, M.D., et al. doi: 10.1056/NEJMoa2002032; 10.1056/NEJMoa2002032; New England Journal of Medicine; Massachusetts Medical Society; 0028-4793; UR - <https://doi.org/10.1056/NEJMoa2002032;2020/04/04>
- Preliminary Analysis of case data from Canada and New Mexico

Usage Rates

- Planning estimates provided by a local New Mexico health service
- Preliminary Analysis of hospital usage and staffing reports provided by NMHA
- CDC guidance cited in: Potential Demand for Respirators and Surgical Masks During a Hypothetical Influenza Pandemic in the United States; Cristina Carias, Gabriel Rainisch, Manjunath Shankar, Bishwa B. Adhikari, David L. Swerdlow, William A. Bower, Satish K. Pillai, Martin I. Meltzer, and Lisa M. Koonin

NMHA DATA

Staffing – Number of patients per practitioner

Context		
Role	ICU	General
ICU Nurse	1 to 2	N/A
Doctor	2 to 4	21
Nurse	N/A	4 to 7
Respiratory Therapist	4	
Lab Tech		
Environmental Services		
Radiology		
ECG Tech		
Healthcare Assistant		

PPE

ICU				
Units used per shift				
Practitioner	Gowns	N95 Mask	Gloves	Face Shield
Floor Nurse				
ICU Nurse	4	4	4	4
Doctor	1	1	1	1
Healthcare Assistant				
Environmental Services				
Lab Tech				
RT				
Radiology				
ECG Tech				

PPE

General				
Units used per shift				
Practitioner	Gowns	N95 Mask	Gloves	Face Shield
Floor Nurse	3	3	3	1
ICU Nurse				
Doctor	1	1	1	1
Healthcare Assistant				
Environmental Services				
Lab Tech				
RT				
Radiology				
ECG Tech				

Supplies					
Hospital	Practitioner	Units used per patient per shift		Context	Comments
		Sedatives/drugs: Succinylcholine/ rocuronium Etomidate; Propofol Metered Dose Inhalers – Albuterol, (Ventolin); Azithromycin Plaquenil (hydroxychloroquine) Fentanyl; hydromorphone; IV fluids; TPN (Total Parenteral Nutrition) Lipids; dopamine	Equipment intubation tubes, supply tubing, suction catheters; oxygen, oxygen masks, oxygen supply tubing, nebulizing equipment; IV supplies		Drugs and routinely administered meds were separated out from equipment Some drugs are administered more often than others, while equipment may be just 1 per person until they need a new one
Cibola Grants	ICU Nurse	1 - 4 (dose dependent)/patient; Maybe 6-8/patient (shortage)	1 or less/patient NA (IV pump)	ICU	4 bed ICU; 21 non-ICU beds
LLMC		1 - 4 (dose dependent)/patient; Maybe 6-8/patient (Shortage)	1 or less/patient NA (IV pump)	ICU	263 total beds; unknown # ICU beds
SJRM		NA	NA		
Roosevelt		Shortage	IV pump possibly		2 ICU beds; 22 non-ICU
LCMC		NA	Yes (6)		
Artesia Gen		NA	NA		
Eastern NM Med Center		Shortage	NA		
Rust		Etomidate			

LOCAL HEALTH SERVICE PLANNING NUMBERS

Staffing – Number of patients per practitioner

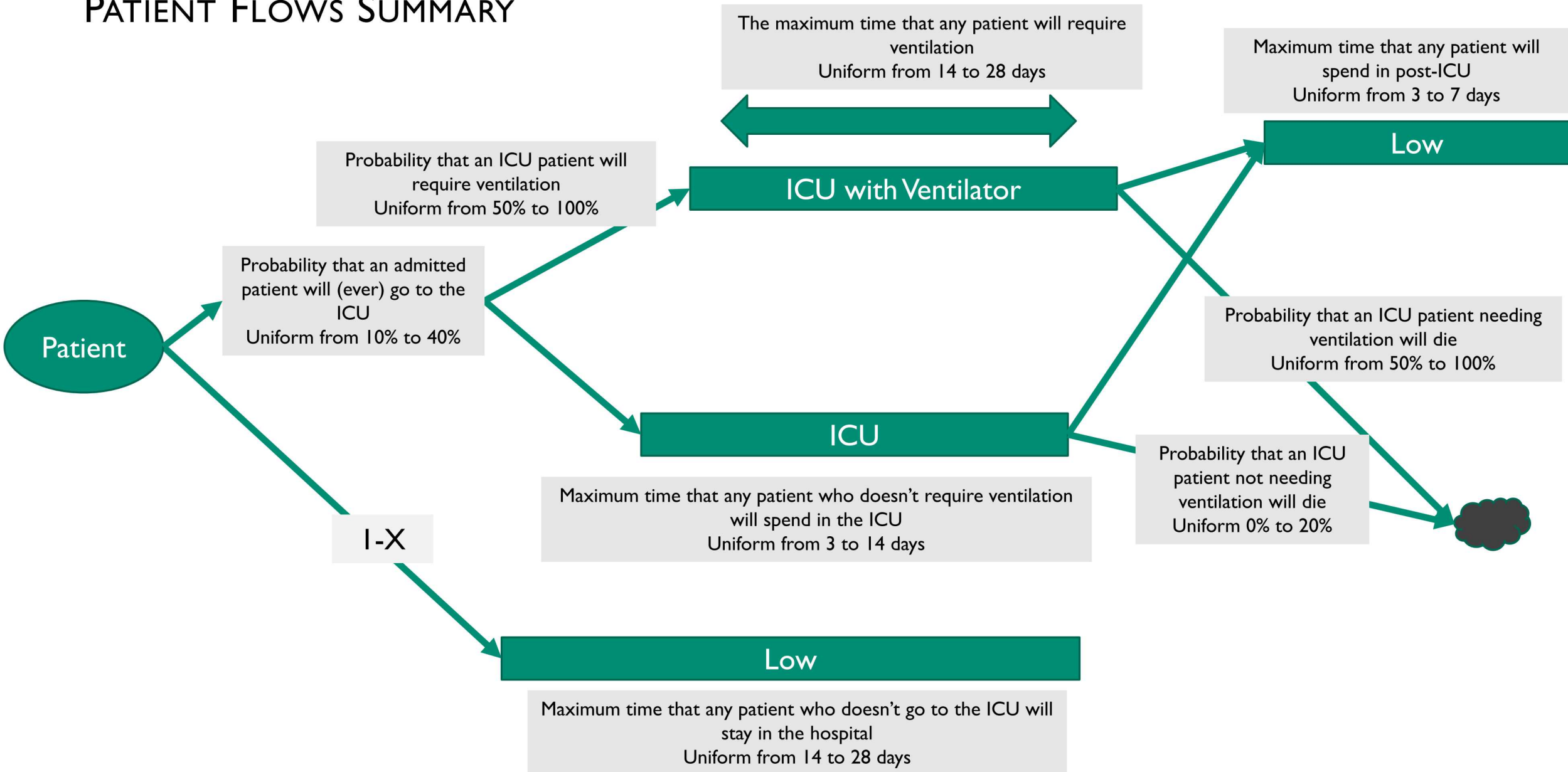
Context			
Role	ICU	General	
ICU Nurse	2	N/A	
Doctor	10	20 to 50	Imputed from staffing and nurse/patient ratios assuming 2 docs ICU, 4 general
Nurse	N/A	4 to 10	
Respiratory Therapist			
Lab Tech			
Environmental Services			
Radiology			
ECG Tech			
Healthcare Assistant			

PPE

ICU				
Units used per shift				
Practitioner	Gowns	N95 Mask	Gloves	Face Shield
Floor Nurse	2	1	8	1
ICU Nurse	2	1	12	1
Doctor	2	1	12	1
Healthcare Assistant	2	1	8	1
Environmental Services	4	1	16	1
Lab Tech	2	1	12	1
RT	2	1	8	1
Radiology	2	1	8	1
ECG Tech	2	1	8	1

General				
Units used per shift				
Practitioner	Gowns	N95 Mask	Gloves	Face Shield
Floor Nurse	2	1	8	1
ICU Nurse	2	1	12	1
Doctor	2	1	12	1
Healthcare Assistant	2	1	8	1
Environmental Services	4	1	16	1
Lab Tech	2	1	12	1
RT	2	1	8	1
Radiology	2	1	8	1
ECG Tech	2	1	8	1

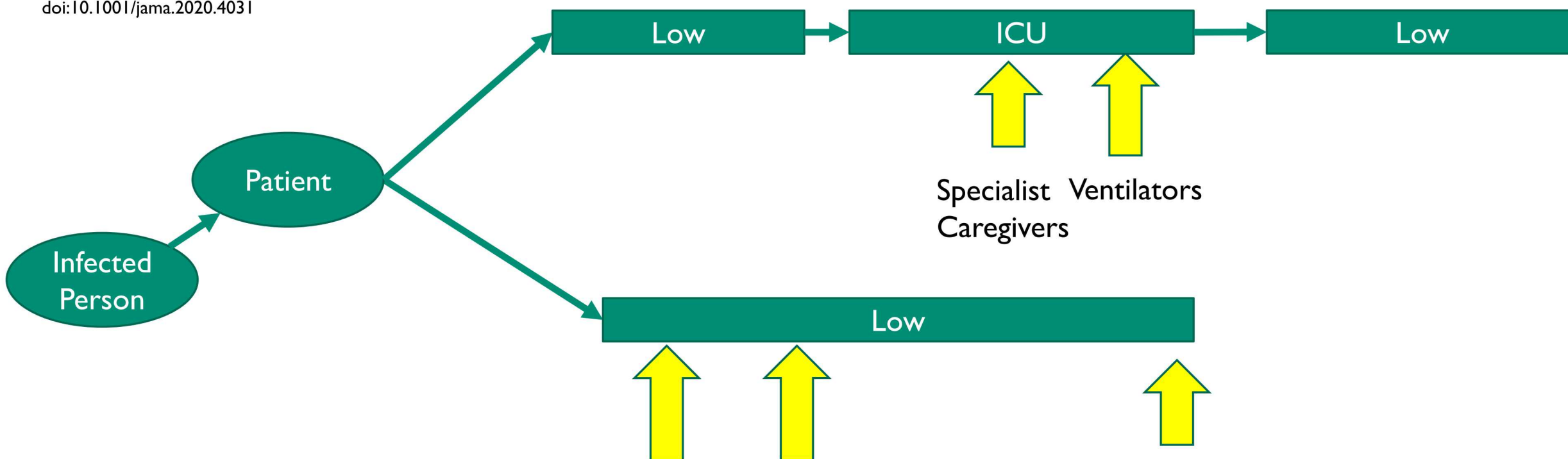
PATIENT FLOWS SUMMARY



PATIENT TREATMENT PATHWAY REFERENCES

As of March 7, the current total number of patients with COVID-19 occupying an ICU bed (n = 359) represents 16% of currently hospitalized patients with COVID-19 (n = 2217); The proportion of ICU admissions represents 12% of the total positive cases, and 16% of all hospitalized patients. Grasselli G, Pesenti A, Cecconi M. Critical Care Utilization for the COVID-19 Outbreak in Lombardy, Italy: Early Experience and Forecast During an Emergency Response. *JAMA*. Published online March 13, 2020. doi:10.1001/jama.2020.4031

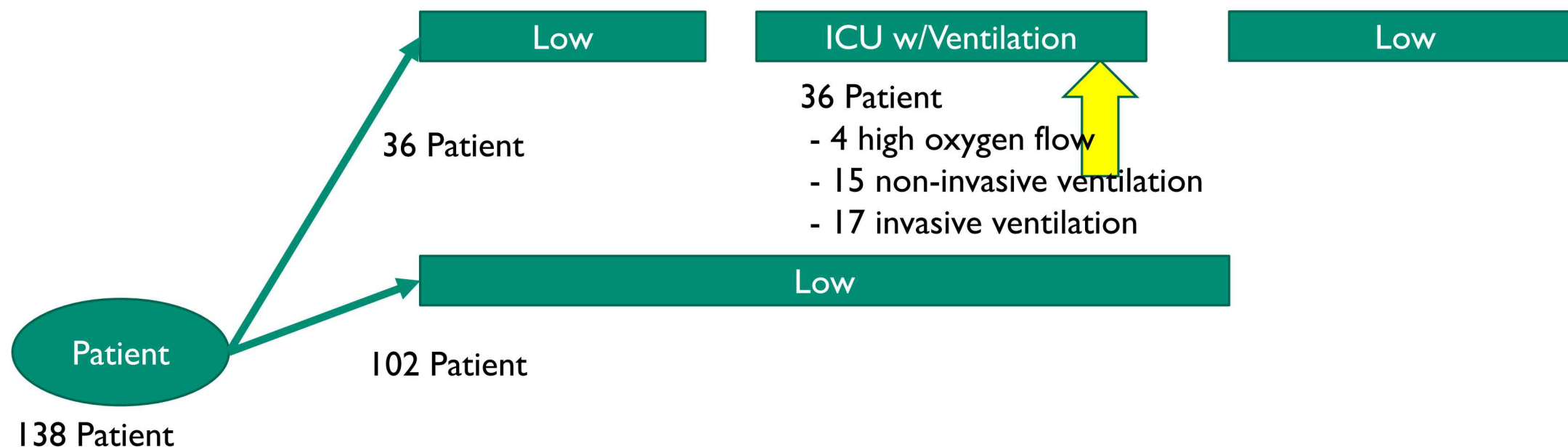
In this single-center case series involving 138 patients with NCIP, 26% of patients required admission to the intensive care unit and 4.3% died.; Wang D, Hu B, Hu C, et al. Clinical Characteristics of 138 Hospitalized Patients With 2019 Novel Coronavirus–Infected Pneumonia in Wuhan, China. *JAMA*. 2020;323(11):1061–1069. doi:10.1001/jama.2020.1585



Guan WJ, Ni ZY, Hu Y, et al; China Medical Treatment Expert Group for Covid-19. Clinical characteristics of coronavirus disease 2019 in China. *N Engl J Med*. doi:[10.1056/NEJMoa2002032](https://doi.org/10.1056/NEJMoa2002032)

PATIENT TREATMENT PATHWAY REFERENCES

Wang D, Hu B, Hu C, et al. Clinical Characteristics of 138 Hospitalized Patients With 2019 Novel Coronavirus–Infected Pneumonia in Wuhan, China. *JAMA*. 2020;323(11):1061–1069. doi:10.1001/jama.2020.1585

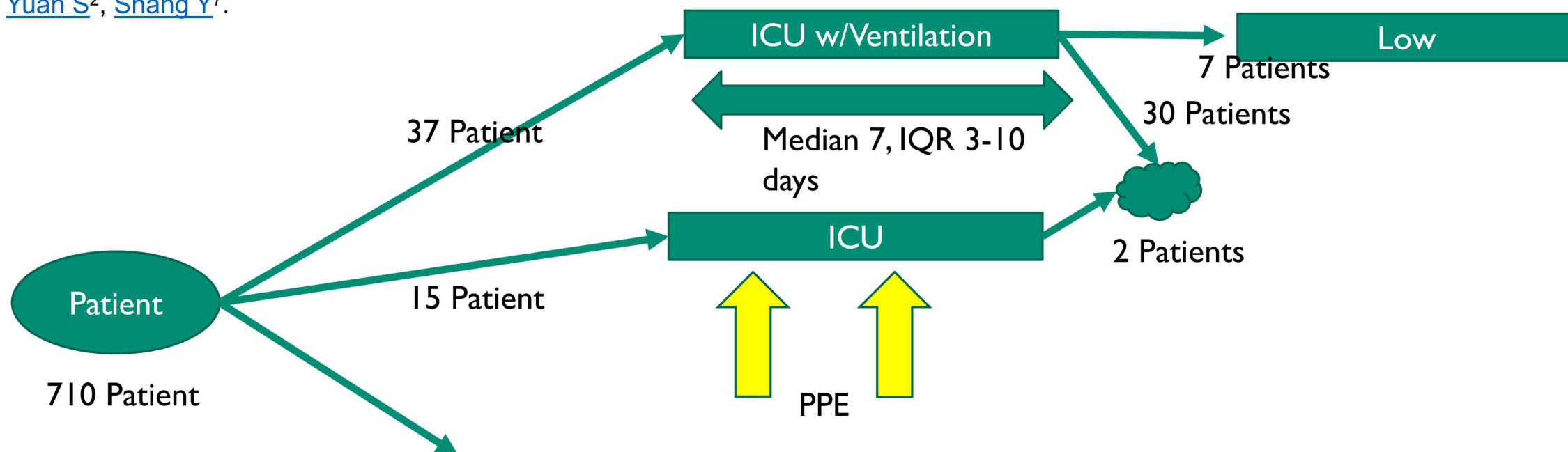


Of 138 hospitalized patients with NCIP, the median age was 56 years (interquartile range, 42-68; range, 22-92 years) and 75 (54.3%) were men. Hospital-associated transmission was suspected as the presumed mechanism of infection for affected health professionals (40 [29%]) and hospitalized patients (17 [12.3%]). Common symptoms included fever (136 [98.6%]), fatigue (96 [69.6%]), and dry cough (82 [59.4%]). Lymphopenia (lymphocyte count, $0.8 \times 10^9/L$ [interquartile range {IQR}, 0.6-1.1]) occurred in 97 patients (70.3%), prolonged prothrombin time (13.0 seconds [IQR, 12.3-13.7]) in 80 patients (58%), and elevated lactate dehydrogenase (261 U/L [IQR, 182-403]) in 55 patients (39.9%). Chest computed tomographic scans showed bilateral patchy shadows or ground glass opacity in the lungs of all patients. Most patients received antiviral therapy (oseltamivir, 124 [89.9%]), and many received antibacterial therapy (moxifloxacin, 89 [64.4%]; ceftriaxone, 34 [24.6%]; azithromycin, 25 [18.1%]) and glucocorticoid therapy (62 [44.9%]). **Thirty-six patients (26.1%) were transferred to the intensive care unit (ICU) because of complications**, including acute respiratory distress syndrome (22 [61.1%]), arrhythmia (16 [44.4%]), and shock (11 [30.6%]). The median time from first symptom to dyspnea was 5.0 days, to hospital admission was 7.0 days, and to ARDS was 8.0 days. Patients treated in the ICU ($n = 36$), compared with patients not treated in the ICU ($n = 102$), were older (median age, 66 years vs 51 years), were more likely to have underlying comorbidities (26 [72.2%] vs 38 [37.3%]), and were more likely to have dyspnea (23 [63.9%] vs 20 [19.6%]), and anorexia (24 [66.7%] vs 31 [30.4%]). Of the 36 cases in the ICU, **4 (11.1%) received high-flow oxygen therapy, 15 (41.7%) received noninvasive ventilation, and 17 (47.2%) received invasive ventilation (4 were switched to extracorporeal membrane oxygenation)**. As of February 3, 47 patients (34.1%) were discharged and 6 died (overall mortality, 4.3%), but the remaining patients are still hospitalized. Among those discharged alive ($n = 47$), the median hospital stay was 10 days (IQR, 7.0-14.0).

PATIENT TREATMENT PATHWAY REFERENCES

Clinical course and outcomes of critically ill patients with SARS-CoV-2 pneumonia in Wuhan, China: a single-centered, retrospective, observational study.

[Yang X](#)¹, [Yu Y](#)², [Xu J](#)², [Shu H](#)², [Xia J](#)³, [Liu H](#)¹, [Wu Y](#)², [Zhang L](#)⁴, [Yu Z](#)⁵, [Fang M](#)⁶, [Yu T](#)³, [Wang Y](#)², [Pan S](#)², [Zou X](#)², [Yuan S](#)², [Shang Y](#)⁷.



Of 710 patients with SARS-CoV-2 pneumonia, 52 critically ill adult patients were included. The mean age of the 52 patients was 59.7 (SD 13.3) years, 35 (67%) were men, 21 (40%) had chronic illness, 51 (98%) had fever. 32 (61.5%) patients had died at 28 days, and the median duration from admission to the intensive care unit (ICU) to death was 7 (IQR 3-11) days for non-survivors. Compared with survivors, non-survivors were older (64.6 years [11.2] vs 51.9 years [12.9]), more likely to develop ARDS (26 [81%] patients vs 9 [45%] patients), and more likely to receive mechanical ventilation (30 [94%] patients vs 7 [35%] patients), either invasively or non-invasively. Most patients had organ function damage, including 35 (67%) with ARDS, 15 (29%) with acute kidney injury, 12 (23%) with cardiac injury, 15 (29%) with liver dysfunction, and one (2%) with pneumothorax. 37 (71%) patients required mechanical ventilation. Hospital-acquired infection occurred in seven (13.5%) patients.

PATIENT TREATMENT PATHWAY REFERENCES

Severe Outcomes Among Patients with Coronavirus Disease 2019 (COVID-19) — United States, February 12–March 16, 2020 - CDC

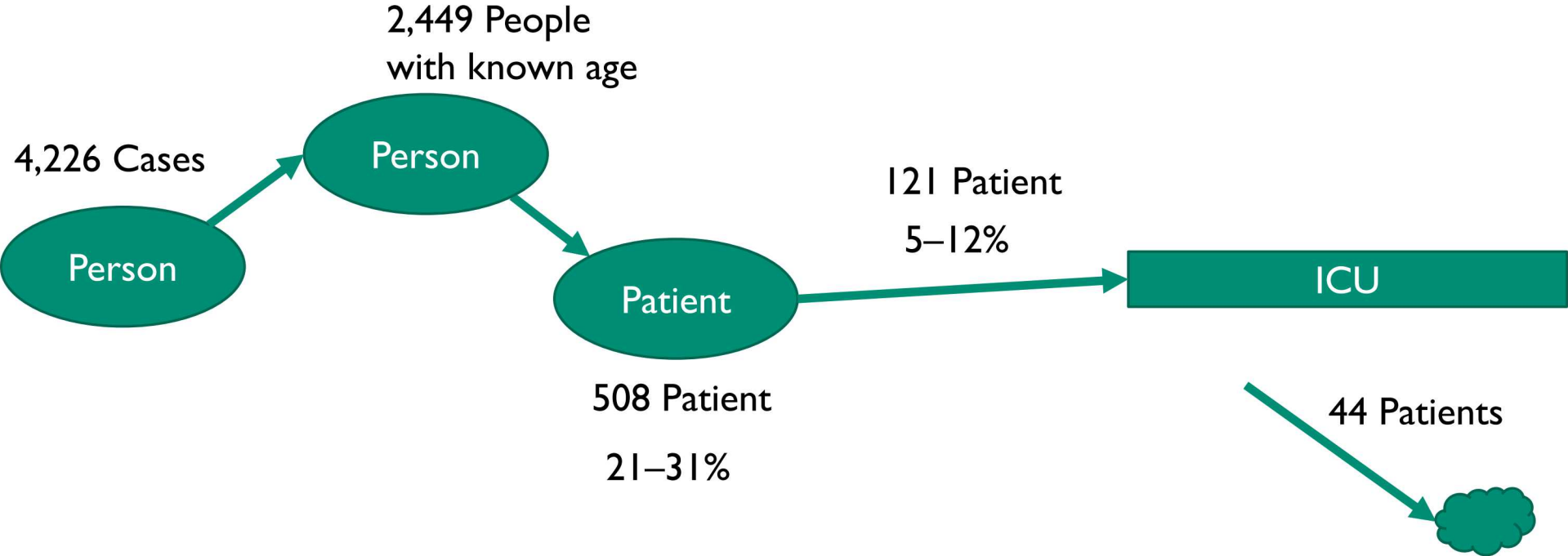


TABLE. Hospitalization, intensive care unit (ICU) admission, and case– fatality percentages for reported COVID–19 cases, by age group — United States, February 12–March 16, 2020 Age group (yrs) (no. of cases) %* Hospitalization ICU admission Case-fatality 0–19 (123) 1.6–2.5 0 0 20–44 (705) 14.3–20.8 2.0–4.2 0.1–0.2 45–54 (429) 21.2–28.3 5.4–10.4 0.5–0.8 55–64 (429) 20.5–30.1 4.7–11.2 1.4–2.6 65–74 (409) 28.6–43.5 8.1–18.8 2.7–4.9 75–84 (210) 30.5–58.7 10.5–31.0 4.3–10.5 ≥85 (144) 31.3–70.3 6.3–29.0 10.4–27.3 Total (2,449) 20.7–31.4 4.9–11.5 1.8–3.4 * Lower bound of range = number of persons hospitalized, admitted to ICU, or who died among total in age group; upper bound of range = number of persons hospitalized, admitted to ICU, or who died among total in age group with known hospitalization status, ICU admission status, or death.

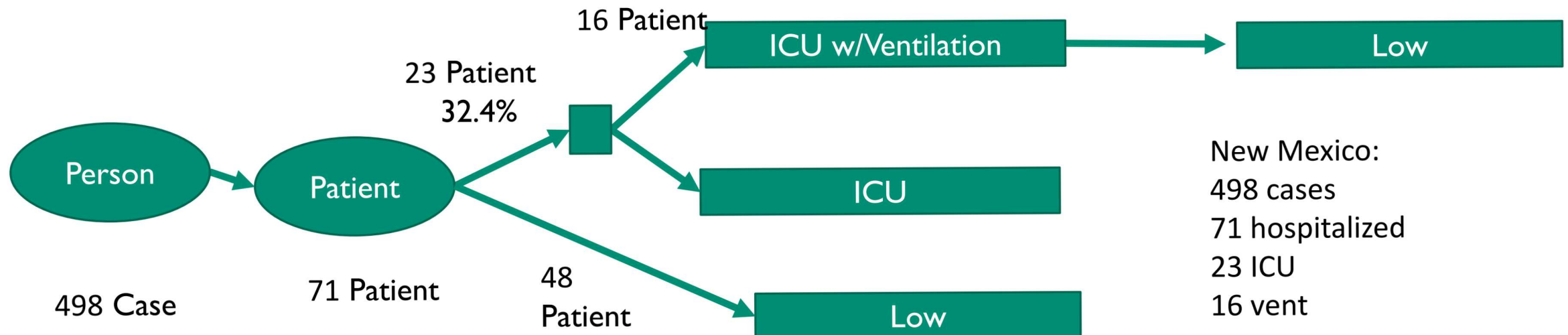
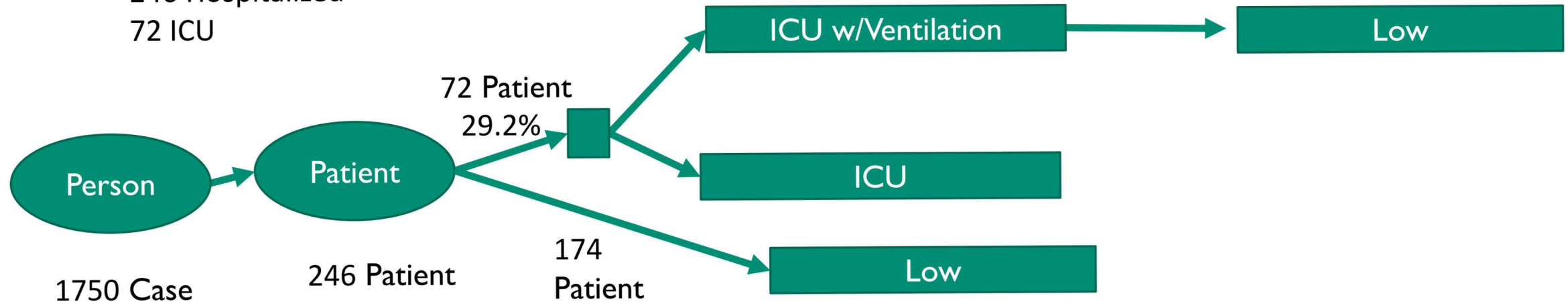
PATIENT TREATMENT PATHWAY REFERENCES

Canada:

1750 Cases with outcomes

246 Hospitalized

72 ICU

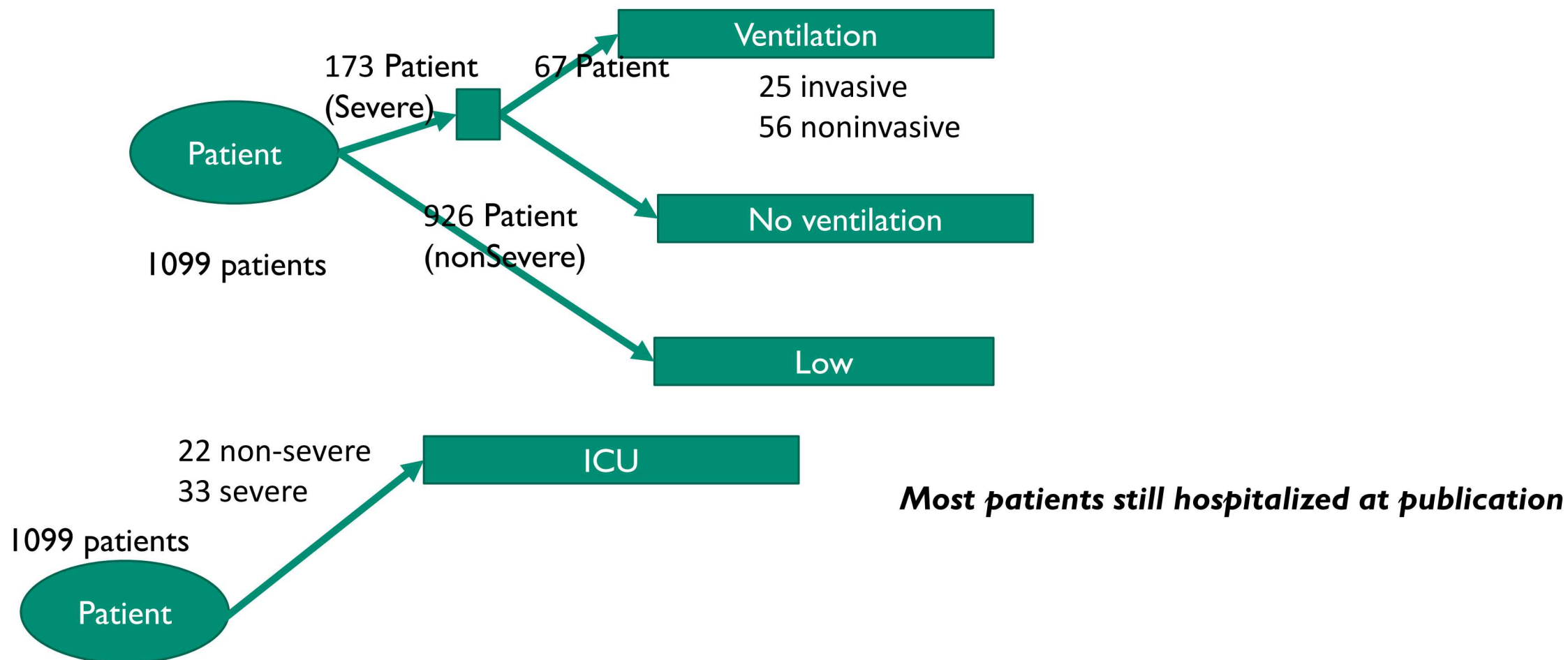


New Mexico:
498 cases
71 hospitalized
23 ICU
16 vent

PATIENT TREATMENT PATHWAY REFERENCES

Clinical Characteristics of Coronavirus Disease 2019 in China

.Wei-jie Guan, Ph.D., Zheng-yi Ni, M.D., et al. doi: 10.1056/NEJMoa2002032; 10.1056/NEJMoa2002032; New England Journal of Medicine; Massachusetts Medical Society; 0028-4793; UR - <https://doi.org/10.1056/NEJMoa2002032;2020/04/04>



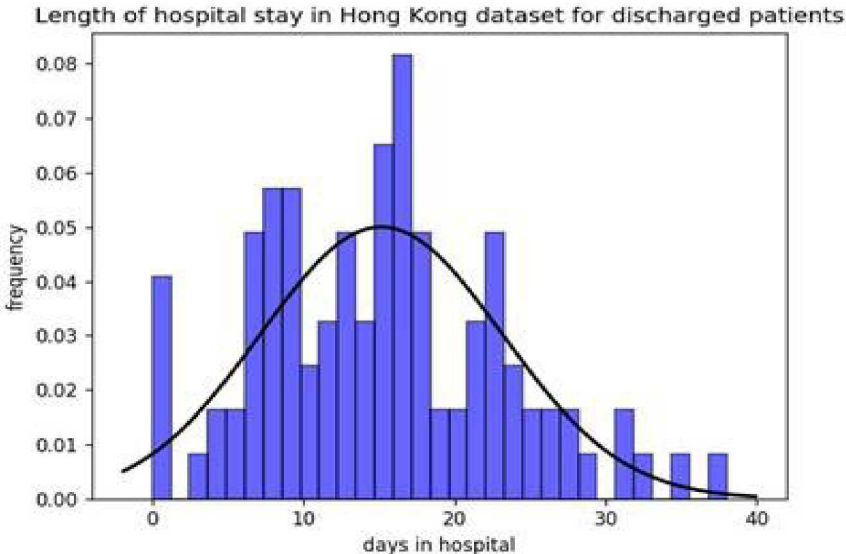
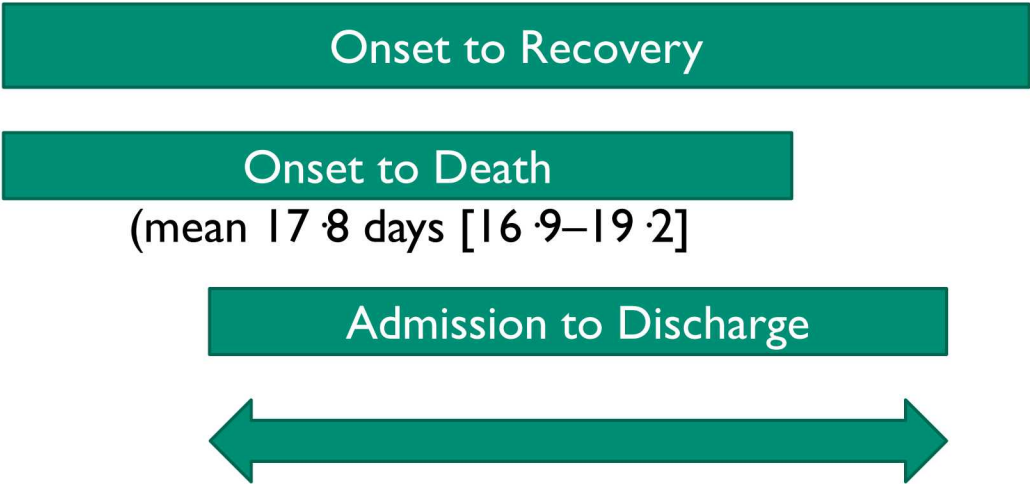
PATIENT TREATMENT PATHWAY REFERENCES

Estimates of the severity of coronavirus disease 2019:
a model-based analysis
Robert Verity*, Lucy C Okell*, Ilaria Dorigatti*, Peter Winskill*, Charles Whittaker*, Natsuko Imai, Gina Cuomo-Dannenburg, Hayley Thompson, Patrick G T Walker, Han Fu, Amy Dighe, Jamie T Griffin, Marc Baguelin, Sangeeta Bhatia, Adhiratha Boonyasiri, Anne Cori, Zulma Cucunubá, Rich FitzJohn, Katy Gaythorpe, Will Green, Arran Hamlet, Wes Hinsley, Daniel Laydon, Gemma Nedjati-Gilani, Steven Riley, Sabine van Elsland, Erik Volz, Haowei Wang, Yuanrong Wang, Xiaoyue Xi, Christl A Donnelly, Azra C Ghani, Neil M Ferguson*

In the subset of 24 deaths from COVID-19 that occurred in mainland China early in the epidemic, with correction for bias introduced by the growth of the epidemic, we estimated the mean time from onset to death to be 18·8 days (95% credible interval [CrI] 15·7–49·7; figure 2) with a coefficient of variation of 0·45 (95% CrI 0·29–0·54). With the small number of observations in these data and given that they were from early in the epidemic, we could not rule out many deaths occurring with longer times from onset to death, hence the high upper limit of the credible interval. However, given that the epidemic in China has since declined, our posterior estimate of the mean time from onset to death, informed by the analysis of aggregated data from China, is more precise (mean 17·8 days [16·9–19·2]; figure 2).

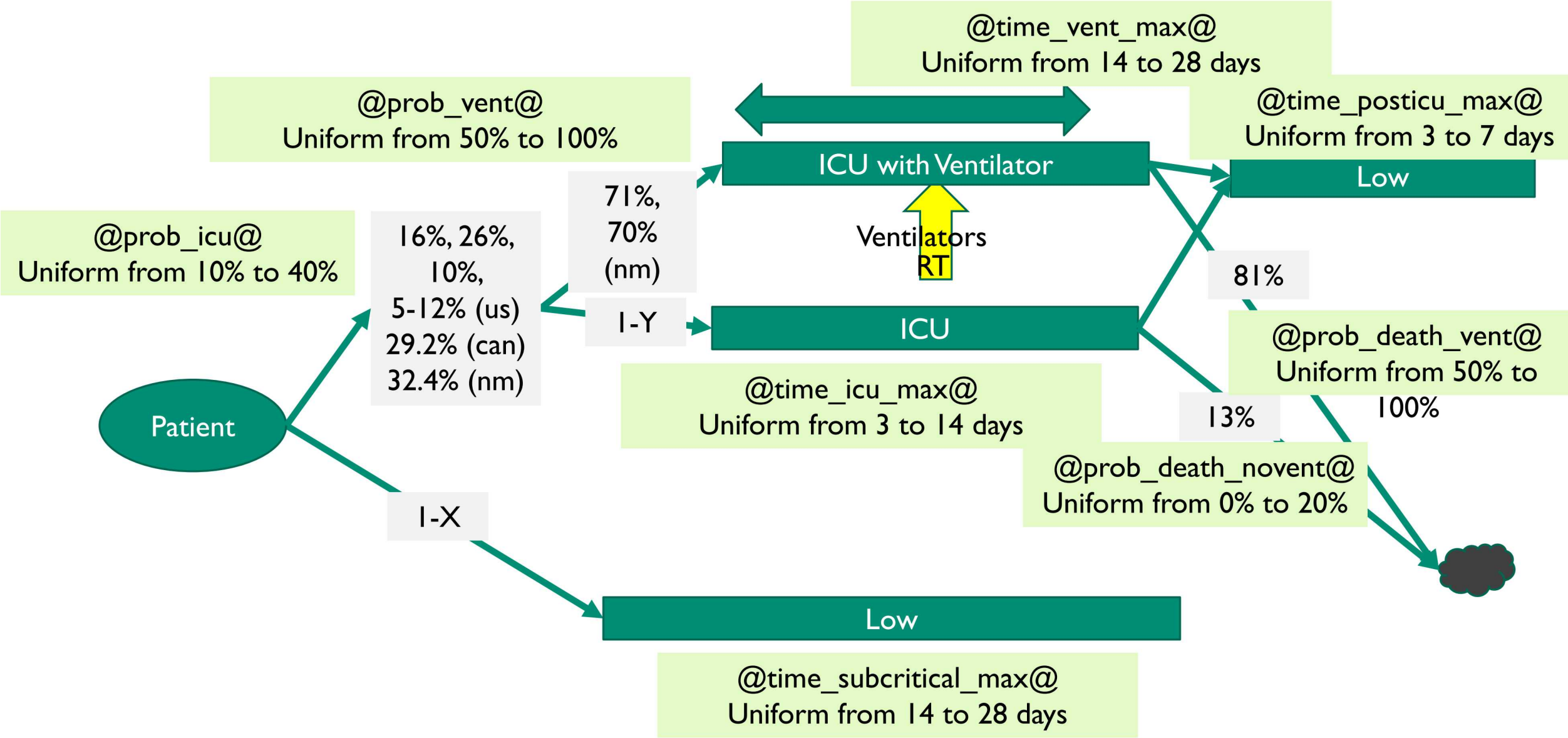
Using data on the outcomes of 169 cases reported outside of mainland China, we estimated a mean onset-to-recovery time of 24·7 days (95% CrI 22·9–28·1) and coefficient of variation of 0·35 (0·31–0·39; figure 2). Both these onset-to-outcome estimates are consistent with a separate study in China.

24·7 days (95% CrI 22·9–28·1)



HOSPITAL_ICU_STimeInHospita	Im(D)
TAY	
No	0
No	0
No	1
Yes	2
Yes	2
No	2
No	2
	3
Unknown	3
Yes	4
No	4
	4
Unknown	7
No	8
Yes	14
	19

PATIENT TREATMENT PATHWAY CONSOLIDATED DURATIONS

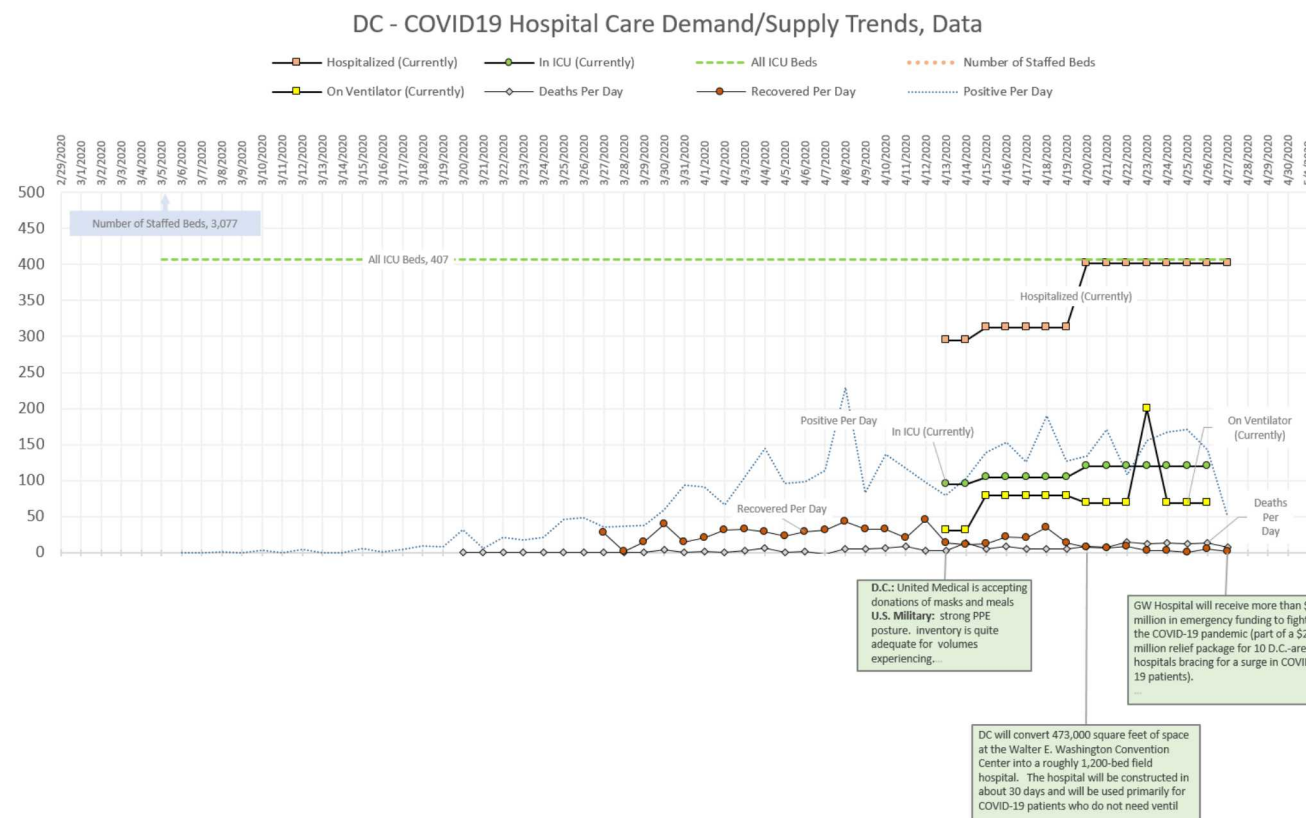


VALIDATION PLAN: COMPARISON TO REALIZED RESOURCE USES

Goal: Leverage observations of actual utilization to constrain uncertainty in future projections

A team tracked real resource utilization for DC, NY, MI, LA, and NM. There are two steps in this validation:

1. For locations with similar EpiGrid projected patient streams as observed, compare the observed resource utilizations to resource estimates from the model to update parameter ranges and reduce future uncertainty.
2. Use the observed patient arrival streams for these states as inputs to the model to calculate projected resource utilization. Compare to the observed resource use to update parameter ranges and reduce future uncertainty.



Validation plan to be completed in Phase 2: Compare actual resource utilization numbers (where this data is available) to the model predictions

OUTLINE

INTRODUCTION

GOAL

MODELING APPROACH

LOCALIZED DECISION SUPPORT

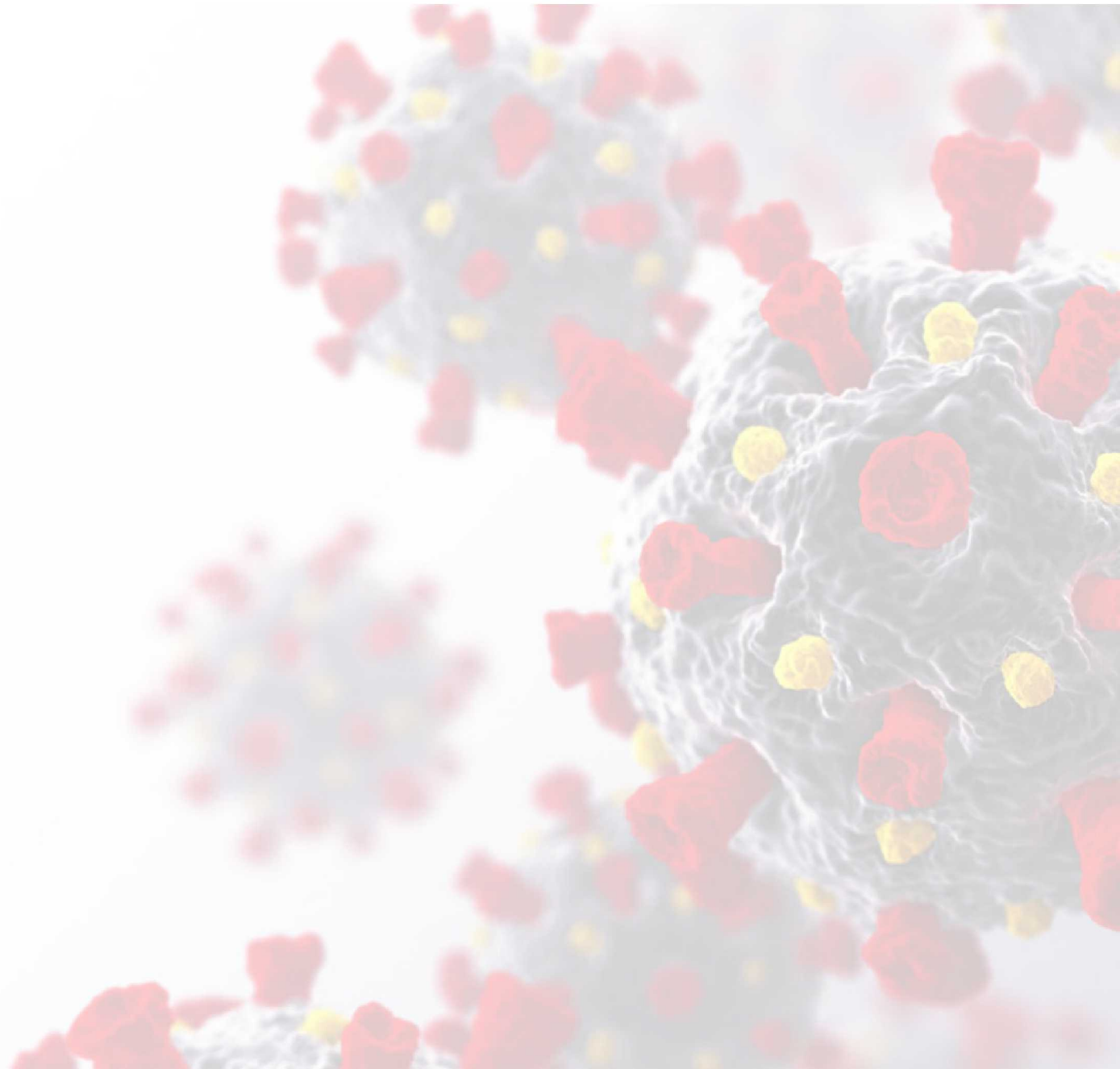
NATIONAL RESULTS (RISK INDICATORS)

CURRENT STATUS / NEXT STEPS

DETAILED MODEL FORMULATION

DATA, PARAMETERS, AND ASSUMPTIONS

UNCERTAINTY ANALYSIS



UNCERTAINTY ANALYSIS OVERVIEW

Uncertainties in the model include:

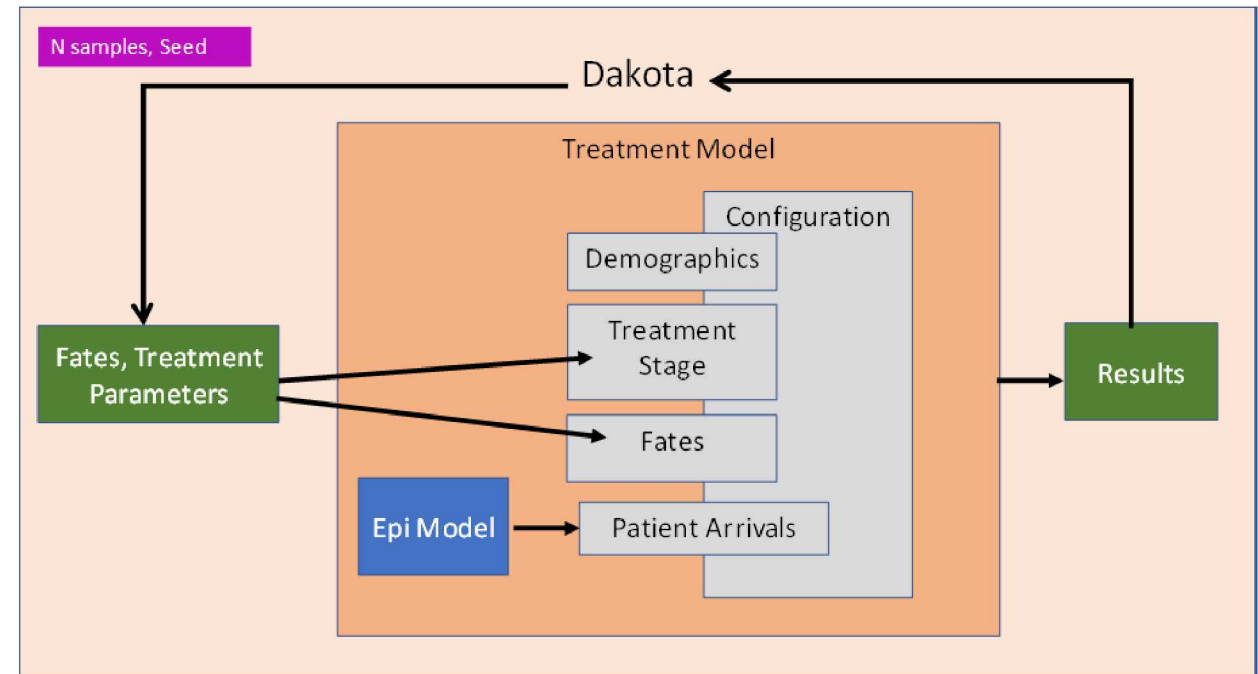
- Probability that a patient moves to a specific stage
- Time spent in each treatment stage
- Medical providers (how many patients they can treat in a shift, amount of PPE used per patient, etc.)

Goal: characterize these uncertain inputs and propagate them to uncertainty in the resulting resource projections.

Used Latin Hypercube Sampling (LHS) in Dakota software framework

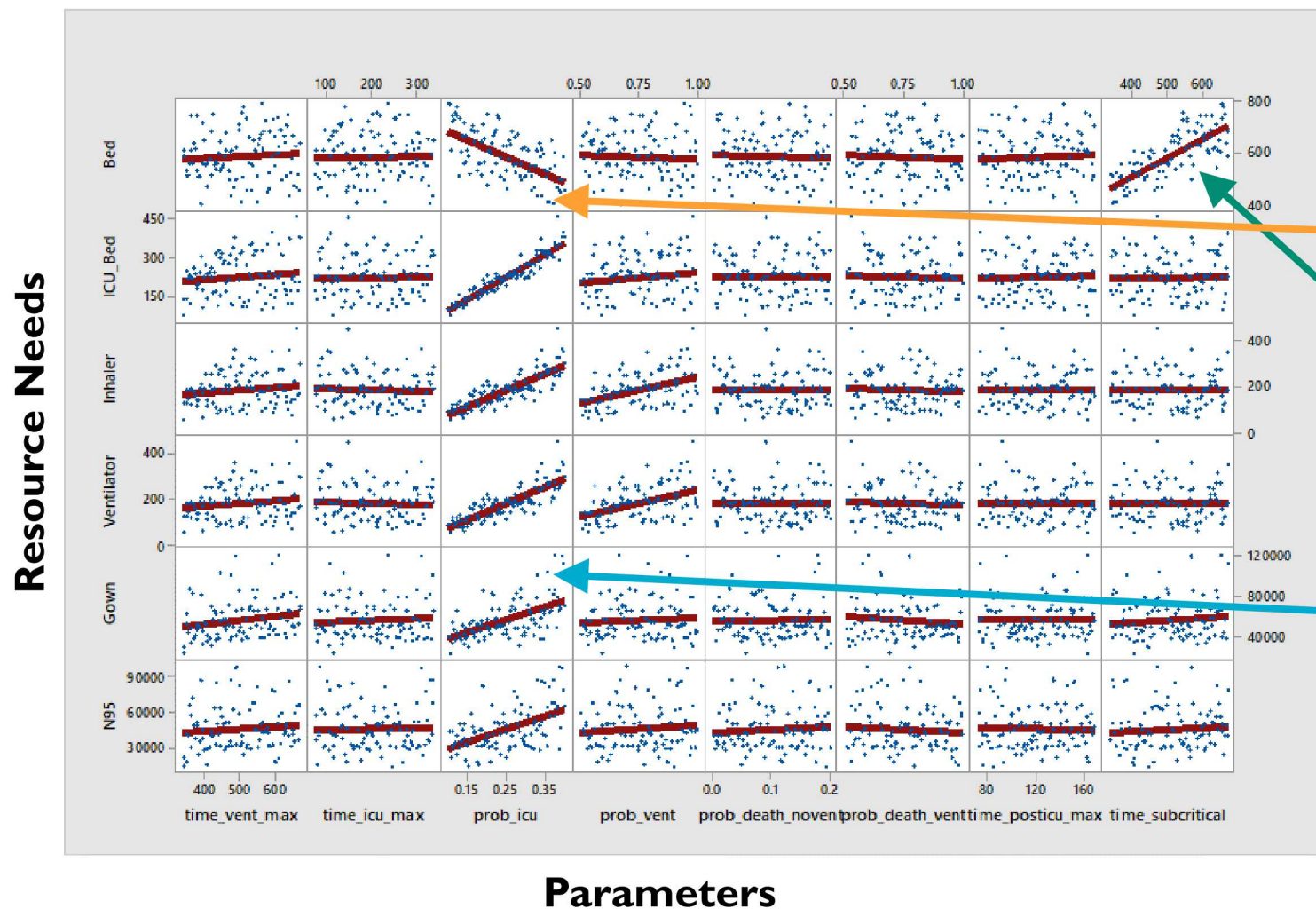
- 8 continuous parameters
- 18 discrete parameters

Uncertainty quantification process for the resource demand model



SENSITIVITY ANALYSIS

Goal: Identify most influential parameters



Positive and negative correlations are expected

- Probability that a patient goes to the ICU is positively correlated with ICU beds needed but negatively correlated with regular beds needed
- Maximum time the patient spends in non-ICU care is strongly positively correlated with the number of regular beds needed

Probability that a patient goes to the ICU is a strongly influential parameter on resources such as the number of ICU beds

REPLICATE ANALYSIS

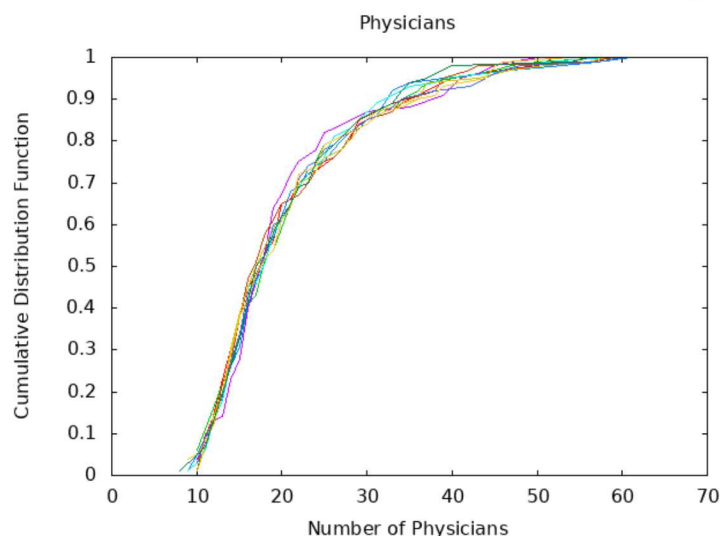
Determine how many samples are enough for the LHS

Work with decision maker to determine if the associated level of uncertainty in the statistics is acceptable

Analysis of Spread of Cumulative Distribution Functions

Compare range of the medians versus range of the 95th percentiles to determine if level of uncertainty in 95th percentiles is acceptable

Result: Confidence interval for the mean of the medians is tighter than the confidence interval on the mean of the 95th percentiles.



Example of replicate statistical analysis:

Range of 95th percentiles is [35, 43]
 Mean of 95th percentile is 38.5
 Confidence interval on the mean 95th percentile is [36.9, 40.1]

Range of Medians is [17, 18]
 Mean of medians is 17.7
 Confidence interval on mean of medians is [17.4, 18]

Analysis of Number of Samples

Generate LHS samples of size N=100, N=500, and N=1000

Perform t-tests and F-tests to compare means and variances, respectively

Result: N=100 is sufficient to obtain reasonably accurate estimates of mean and variance

NumSamples	Statistic	FloorNurseMax	ICUNurseMax	PhysicianMax	RespiratoryTherap	BedMax	ICU_BedMax
100	Mean	27.30	52.02	21.00	17.00	171.71	69.40
	Std. Dev.	9.59	24.37	9.70	8.57	27.46	23.30
	Min	14	14	10	5	119	26
	Max	56	124	58	40	228	130
500	Mean	27.40	52.39	20.90	17.26	172.68	69.51
	Std. Dev.	9.66	25.30	9.89	9.93	28.01	23.37
	Min	13	15	8	3	108	29
	Max	61	137	70	58	254	137
1000	Mean	27.46	52.07	21.00	17.12	172.88	69.20
	Std. Dev.	9.71	24.89	10.15	9.71	28.05	23.21
	Min	12	14	8	3	112	25
	Max	62	130	69	64	249	134