Modeling Report 2

Arizona Department of Health Services
COVID-19 Modeling Working Group 1
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April 20, 2020

Executive Summary

Since Arizona confirmed its first case of COVID-19 on January 26, 2020, the state has activated public health and emergency management capabilities. The Arizona Department of Health Services (ADHS) convened the COVID-19 ADHS Modeling Working Group to develop models and predictions focused on Arizona. This second report of that Working Group updates the current current epidemiology in Arizona and provides updated estimates of future cases as of April 20.

At the present time, Arizona is showing signs of being at or near the peak of infections and hospitalizations based on current testing practices and continuation of current non-pharmaceutical interventions including social distancing. The projected peak appears to have a flattened and longer-duration shape, consistent with efforts toward physical distancing. All signs indicate that Arizona's aggressive actions to limit COVID-19 spread were effective at preventing a surge of patients that exceeded medical resources. This report aims to provide an evidence base consistent with the White House Guidelines for Opening Up America Again. Projections are based on a dynamic disease transmission model developed by the authors for the purpose of estimating COVID-19 transmission in Arizona.

This report provides projections of new cases and deaths from COVID-19, based on the best available science and Arizona case data. It produces daily counts for infected individuals and daily counts for deaths for five plausible scenarios, last updated on April 20. It also provides scenario-based estimates of resource needs for hospital beds, ICU beds, and ventilators. This report does not include a capacity assessment at this time. It is a resource estimate of the beds and ventilators that would benefit a COVID-19 patient if it were available.

Background and Overview of Working Group

Arizona confirmed its first case of COVID-19 on January 26, 2020. Between January and the present time, the state of Arizona has activated their public health and emergency management response capabilities in preparation for a potential surge in cases. The Arizona Department of Health Services (ADHS) and the Office of the Arizona Governor, Doug Ducey, have been working in concert with federal guidance from the Centers for Disease Control and Prevention (CDC) and the Federal COVID-19 Task Force to respond to individual cases and enact policies to protect the health of Arizonans.

At the time of this analysis, Arizona has measurable COVID-19 community spread across all 15 counties and the state is under orders to limit social contact and remain at home other than conducting essential activities. Businesses and schools are closed. Essential businesses including grocery stores, pharmacies, gas stations, and take-out/drive-through restaurants remain open under social distancing guidelines. Governor Ducey issued a Declaration of Public Health Emergency on March 11, 2020, and a Stay-at-Home Executive Order on March 30, 2020 outlining essential businesses, with the list of essential businesses updated on April 3, 2020. The Executive Order expires on April 30, and it is unknown at the present time if it will be safe to re-open businesses and schools at that time.

In an effort to improve the statewide and local pandemic response in Arizona, ADHS is seeking input from the scientific community in Arizona to help inform key planning assumptions and decisions. A number of COVID-19 related issues confronting public health officials will benefit from scientific input to enable appropriate planning and decision-making, including resource acquisition, business and public service closures, social movement restrictions, and government planning for future budgeting and planning the resumption of normal public activities and services. The COVID-19 ADHS Modeling Working Group was convened by ADHS to bring together the relevant scientists in the state to inform the state's response decisions and planning. The Working Group consists of experts in clinical medicine, epidemiology, mathematical modeling, public health, policy analysis, industrial engineering, and economics.

Tasking of the Working Group

ADHS convened the COVID-19 ADHS Modeling Working Group to coordinate the appropriate subject matter experts and modelers to develop estimates for these requirements:

i. A projection of new cases and deaths from COVID-19 - going out at least 2 to 4 weeks into the future. This will need to be continuously updated and adjusted as new data come in.
ii. Projection of the hospital capacity tipping point
iii. Projections of PPE needs, taking into account alterations in use of PPE for current best practice, and changes in the patient case loads
iv. Projections of ventilator demand and supply in AZ by region
v. Economic impact of current public health interventions.

The Modeling Working Group (MWG) has been meeting weekly since March 26 to discuss the request and review new information and models. Sub-groups formed to address each analysis. ADHS sent multiple emails to the group with information and data resources. The MWG distributed internally via email several summaries and information resources for discussion and analysis. ADHS held two training sessions on MEDSIS and the syndromic surveillance system for MWG members to ensure members can access up-to-date information. ADHS convened a meeting on April 2 for the MWG to present initial model results at which the MWG agreed on a modeling approach to address each of the areas.

This report – Report 2 of the Modeling MWG – provides updates to Item i: A projection of New Cases and Deaths from the COVID-19. It produces daily counts for newly infected individuals and daily counts for deaths for five plausible scenarios. It also provides updated scenario-based estimates of resource needs for hospital beds, ICU beds, and ventilators (items ii, iii, and iv). This report does not include a capacity assessment at this time. It is a resource estimate of the space and equipment that would benefit a COVID-19 patient if it were available. In other words, this assessment assumes unlimited resources in order to predict the total need or requirement.

This preliminary modeling report was developed by Arizona State University with input from Working Group members at the University of Arizona and ADHS.

Current situation

As of April 20, 2020, there were 5,064 reported cases and 187 deaths in Arizona.

20-Apr	Positive	Negative	Deaths	Total
ADHS	5,064	31,838	187	54,500
COVID tracking (daily)	2,489	1,038	3	21,125
Total	5,064	49,436	187	54,500

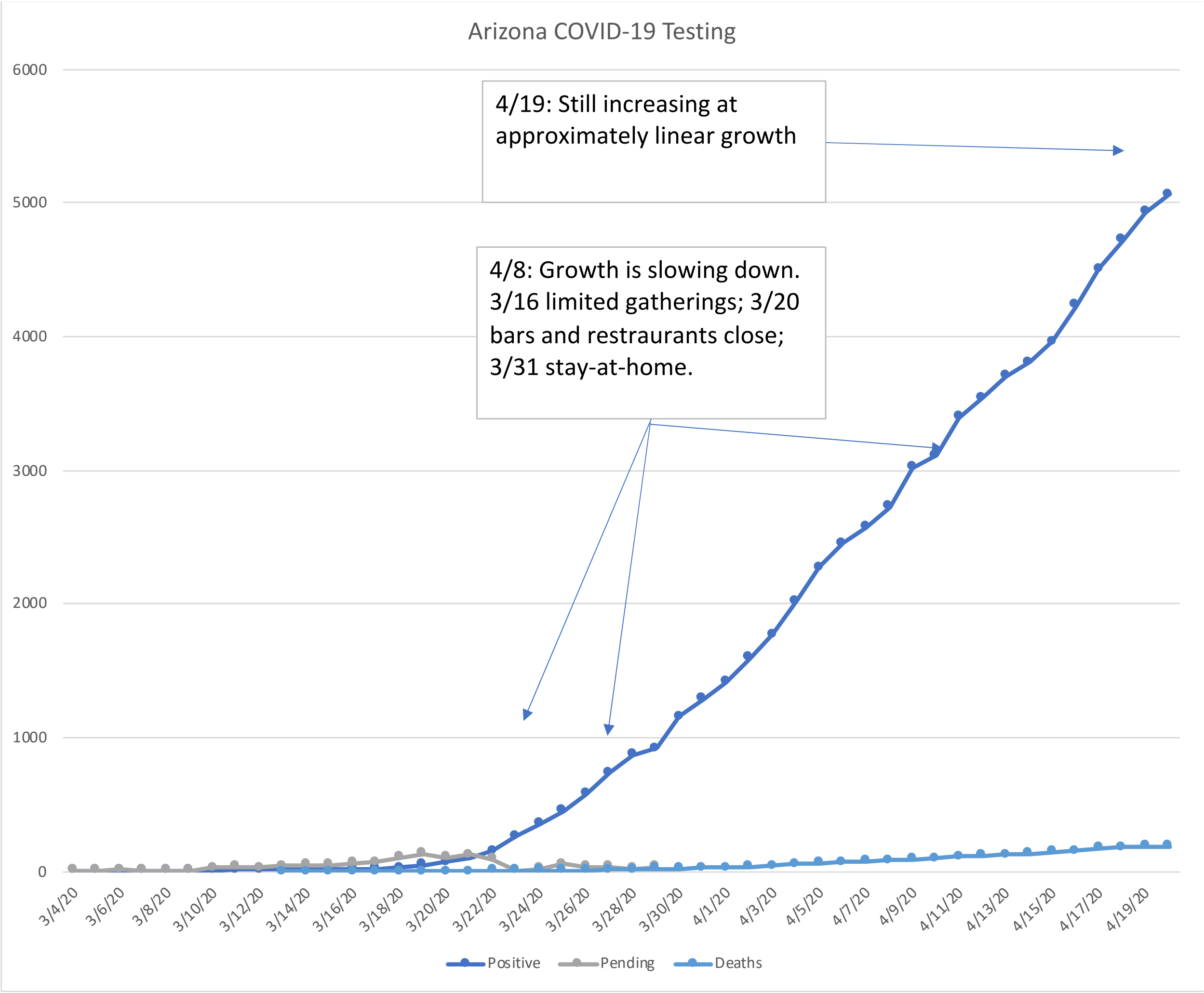


Figure 1: Cumulative COVID-19 Cases Detected by molecular RT-PCR tests in Arizona.

The COVID-19 “epi curve” is based on the cumulative number of cases of disease that are positively detected within the population. The growth rate of new confirmed cases is marked by three distinct periods of transmission. The initial growth period prior to March 17th appears to follow stochastic transmission effects with low level of disease incidence in the population, but with community spread. This means that the resulting people who are infected are due to random or chance occurrence.

The epi-curve likely has considerable biases in estimating disease prevalence since tests were scarce and reserved for individuals at high-risk under CDC criteria for “Persons Under Investigation.” Additional bias was introduced in preliminary data prior to and including March due to the reporting of positive cases only. The result of these biases is that the true disease prevalence and trajectory have been unknown during much of this time, and we are reliant on new data to recapture the trends. Data from clinical studies are used to piece together epidemiological data that is unknown in Arizona.

The period from March 18th through approximately March 24 shows exponential growth. The exponential growth coincides with the increased testing that began the week of March 23rd and the increase in reporting results on March 27. The increase in newly identified cases reflects cases that were newly infected in the 3-10 days prior to received confirmation of a positive test and subsequent entry into the state's tracking database. The period from March 18th to March 24 also predates Governor Ducey's initial stay-at-home order issued on March 30th, but follows decisions by Mayors in Flagstaff, Phoenix, and Tucson to close bars and dine-in restaurant services in their respective cities, followed closely by an Executive Order from Governor Ducey on March 19th to close bars, movie theaters, gyms, and dine-in restaurants in counties with confirmed COVID-19 cases.

Newly confirmed case data from positive PCR tests during the period from April 3 to April 20 can be interpreted in several ways, and only additional data will reveal the correct interpretation. New cases have been hovering at a consistent level between 100 and 300 tested and confirmed cases per day. See Figure 2. Although the data appears to have plateaued over the last three weeks, there is significant variability in the data that makes it impossible to confirm or refute that new cases have peaked. Contemplation of a future peak is dependent heavily on whether contact patterns change significantly and scientific uncertainties about the level of undetected disease currently in the population.

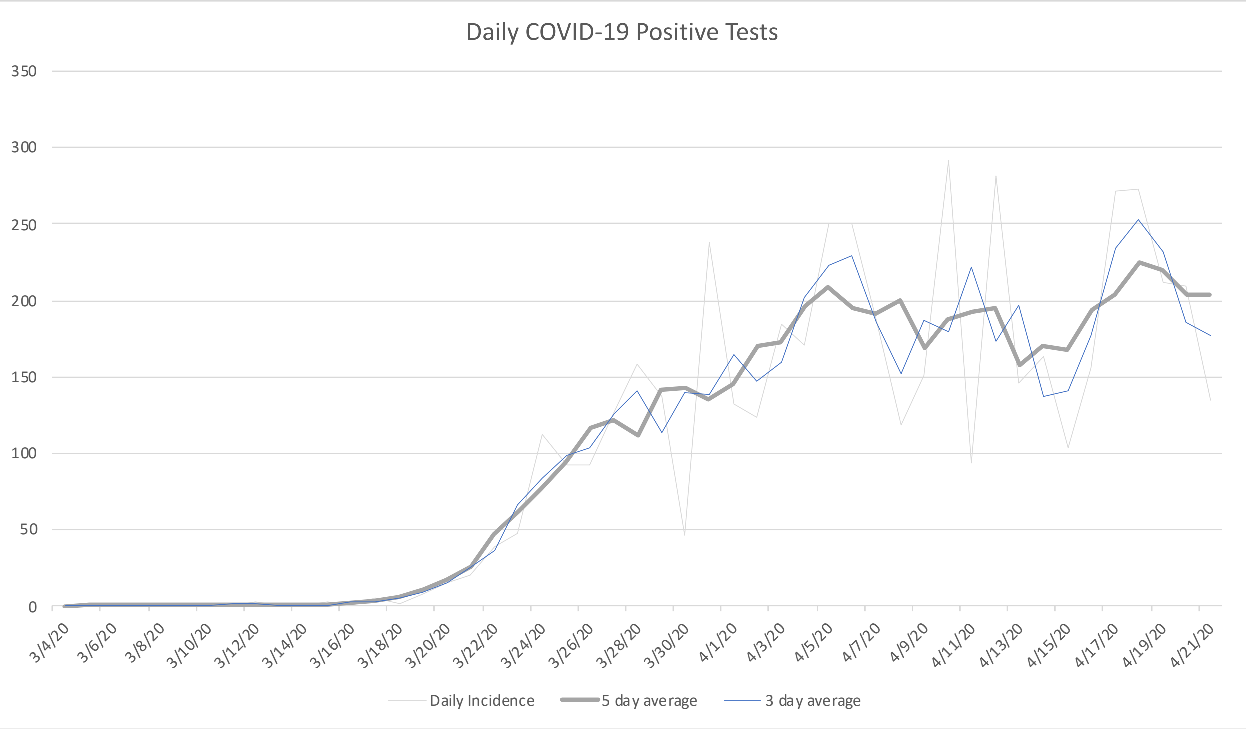
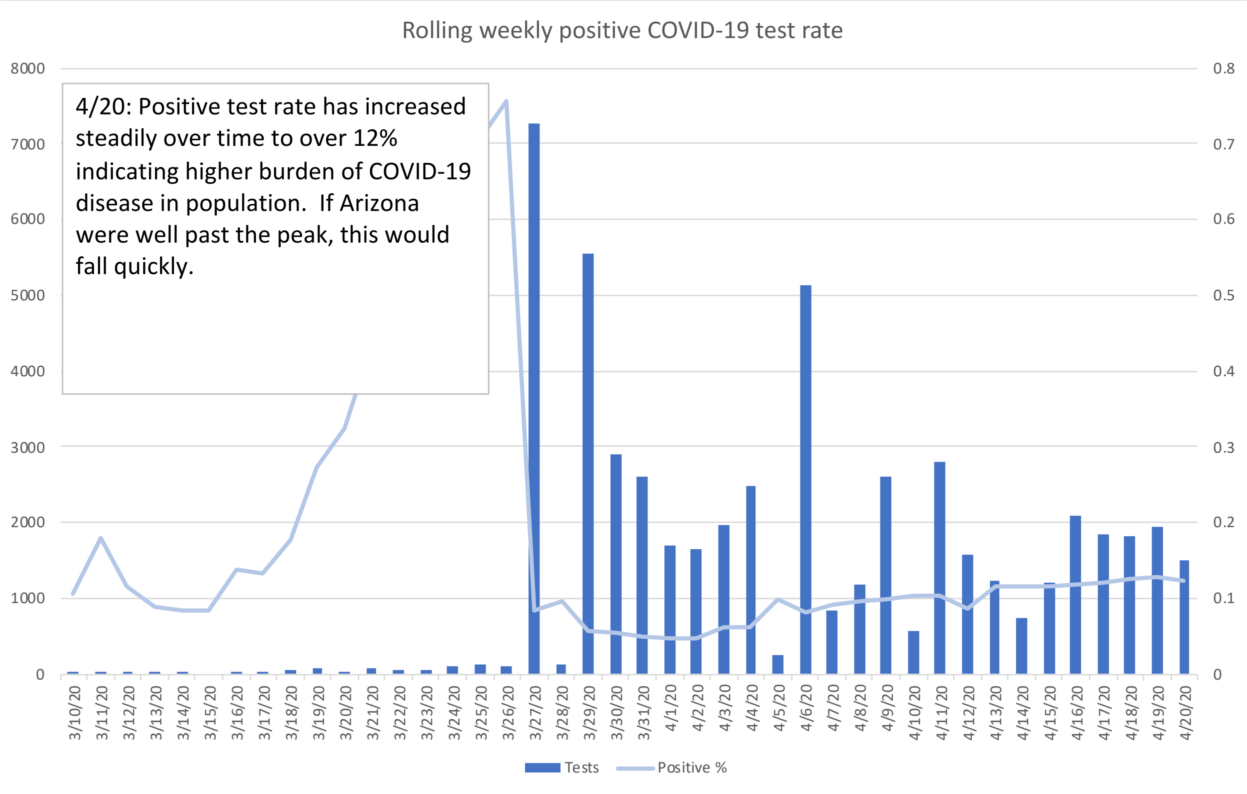


Figure 2: Daily Positive COVID-19 PCR tests and moving averages

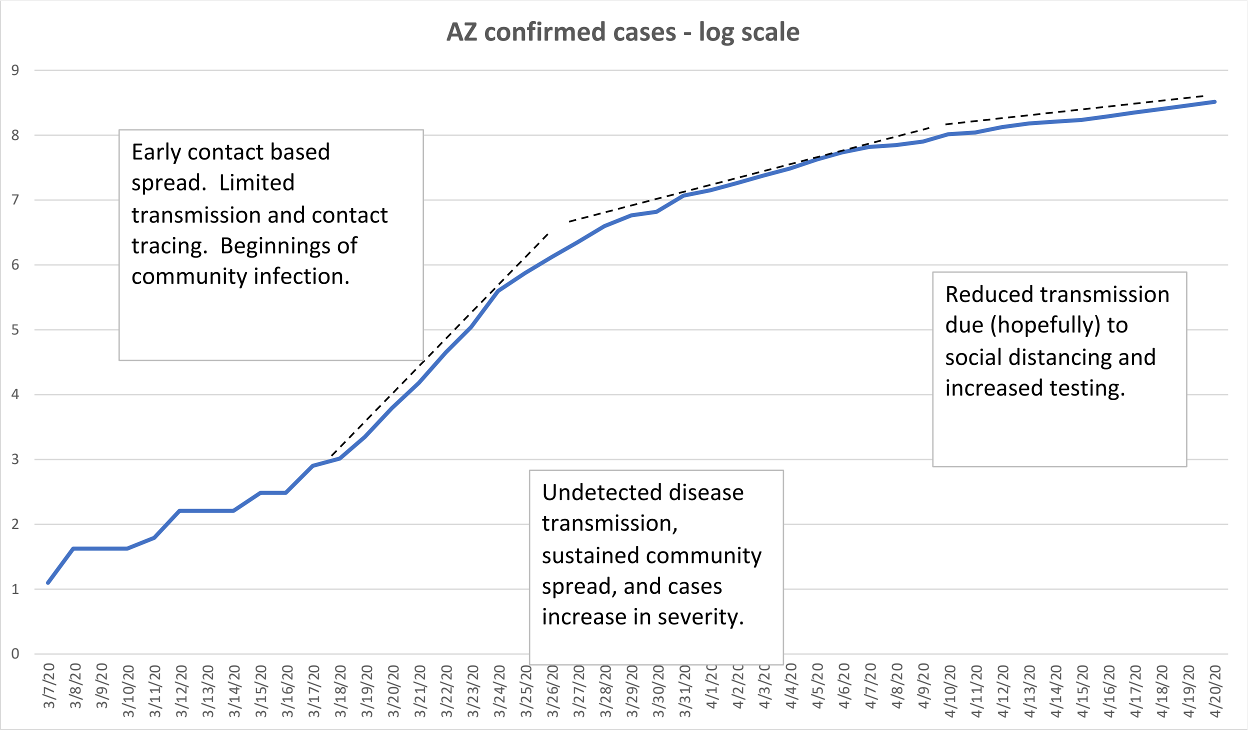
Testing capacity in Arizona is currently between one thousand and three thousand tests per day with peaks in the five thousand to seven thousand range that may be attributable to surges in test processing or to delays in reporting test results. See Figure 3. Positive test rate has been increasing steadily from a low of less than 5% in early April to above 12% presently.


Rolling weekly positive COVID-19 test rate

4/20: Positive test rate has increased steadily over time to over 12% indicating higher burden of COVID-19 disease in population. If Arizona were well past the peak, this would fall quickly.

Figure 3: Test throughput and positive sample rate

Figure 4 shows the exponential growth rate of the epi curve. If this graph is well-estimated by a straight line, we can observe exponential growth in new cases with growth rate equal to the slope of this curve. This graph changes its slope around March 25th which does coincide with reduced transmission due to social distancing following a series of local and statewide orders for business closures. The data suggests that transmission has slowed down significantly.



Early contact based spread. Limited transmission and contact tracing. Beginnings of community infection.

Undetected disease transmission, sustained community spread, and cases increase in severity.

Reduced transmission due (hopefully) to social distancing and increased testing.

Figure 4: natural logarithm of cumulative case count is used to approximate transmission rate over time.

There is a clear, continued pattern of bending the curve downward, indicating further reduced transmission. Once we have achieved an effective R value of less than one, the pandemic will begin to die out locally.

We estimated the current growth rate (April 7 – April 20) of the pandemic with a line Figure 4 and Figure 5. The implied growth rate of the current growth is 0.05 with a doubling time of 13.9 days. The prior period (March 25 thru April 7) had a slope (pandemic growth rate) of 0.13 (R^2 = .974) and a doubling time of 5.3 days.

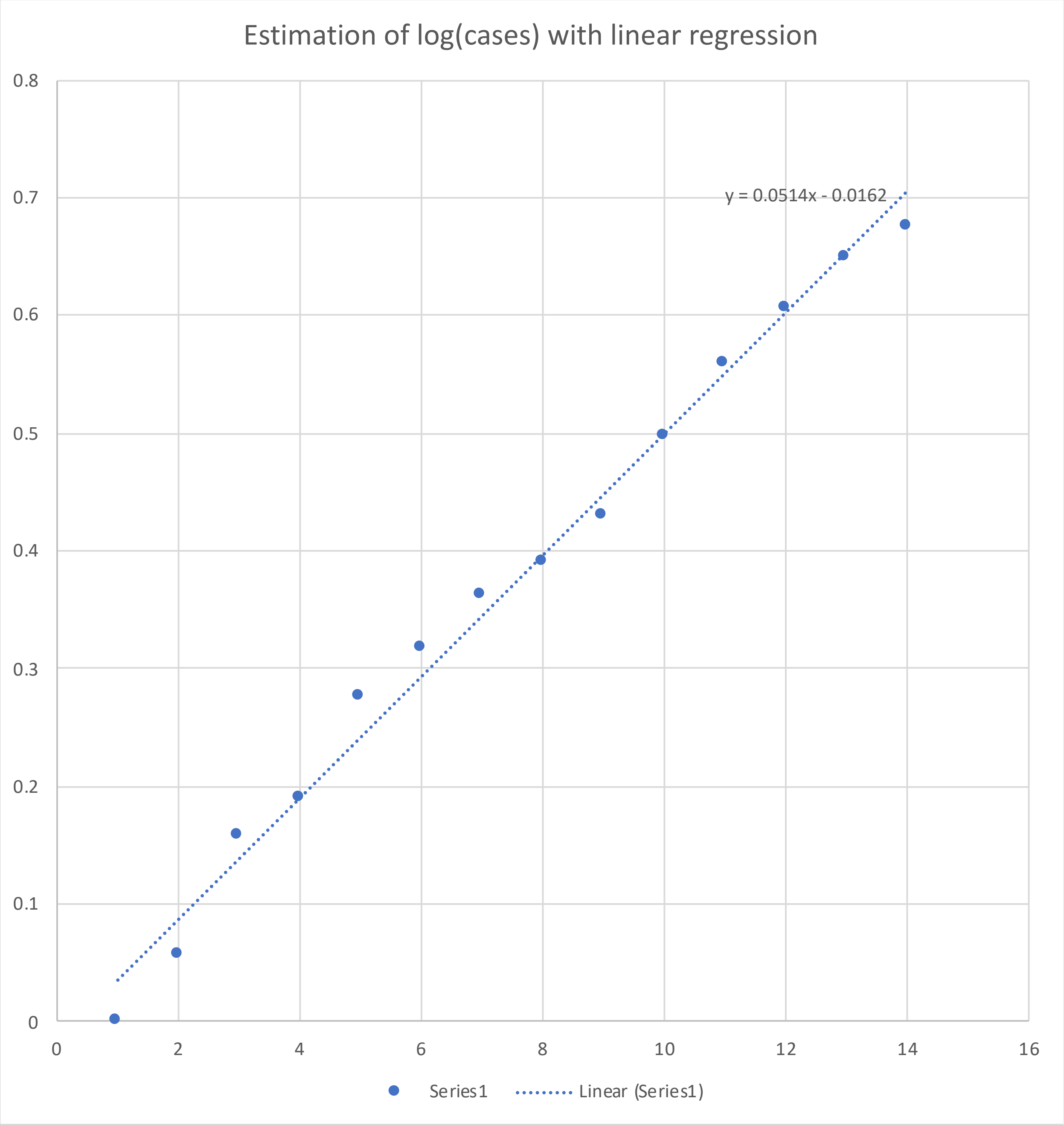


Figure 5: Estimation of transmission rate for April 7-20.

Between March 17 and March 24, growth rate of 0.42 with (R^2 = .998). Doubling time of 1.7 days. This upward trend in doubling time indicates continued slowing of transmission.

In summary, the recent measures put in place to limit contact and increase social distancing are showing an effect of reducing the growth rate from 0.42 persons/day to 0.13 persons/day to 0.05 persons/day. The data are confounded by significant measurement challenges resulting from limited test data and changes to test criteria. The future trajectory of new cases may continue to grow at the current rate. It might also increase or decrease. Additional challenges in interpreting this data include the time-delay between contact and transmission of COVID-19 to a susceptible person and the time the test result of that person is positively confirmed (if at all). Estimates of under-reporting of infected cases range from a case ascertainment rate below 10% (Perkins, et al), to an ascertainment rate of 14% in China (Shaman) and 0.09% in the US (Shaman, CDC modeling coordination group or paper on website). With a current case count of 5,064 cases in Arizona as of April 20, 2020, applying these estimates to Arizona result in range from 35 thousand to 55 thousand infected individuals to date, including many who are asymptomatic or mildly symptomatic.

Modeling approach and problem assignment

The Working Group decided to develop an AZ specific model, and to compare results to models on popular COVID websites. The IHME model is currently predicted that the peak hospitalization period occurred in Arizona the first week of April.

There are several reasons to develop our own Arizona specific model: The first is that Arizona's situation is unique. We have different epi data, different testing rates, and a unique climate (meteorological and political) that will differentially impact disease transmission. We might borrow results from other studies, but they need to be assembled with care if they are going to have value. The second, is that we need to be able to use the models as new data becomes available, and this requires an Arizona-specific model to be connected to the Arizona-specific response process.

Using the most up-to-date Arizona data on cases, deaths, and hospital capacity including ventilator use, and learning from the experience of other regions most similar to Arizona, our model provides a two- to four-week future projection specific to Arizona that can be continuously updated as social isolation measures begin to flatten the curve. This model can serve as an actionable management tool to guide ongoing policy response to manage risk at local and state levels.

1. We created five scenarios. The scenarios are based on the currently available case count data as of April 20, 2020. Each scenario is based on a plausible future outcome. The differences in each scenario are due to variables that are key drivers of the model output: transmission rate, β of symptomatic individuals (transmission rates of other infected types are functions of this parameter), disease characteristics that are scientifically unknown (epistemic uncertainty), rate of transmissions by asymptomatic patients, seasonal effects, and random variability (aleatory uncertainty).

2. Our models are developed around key issues that are presently unknown, but can cause the predictions to have significantly different outcomes. Examples to such issues are the COVID-19 testing and the prevalence of asymptomatic cases. The lack of testing and uncertainty around burden of disease in the population makes forecasting particularly challenging. It is important to point out that even the question of whether to forecast an unknown but

accurate number is different than forecasting an estimate that is known to be biased/wrong.

3. This update (4/20) is the second major revision of the model and updates the prior projections issued 4/8. We aim to update our model weekly or when data trends change significantly, which will be useful in coming months both as a resource to guide state and local policy changes related to nonpharmacological interventions (i.e. social distancing), and to better characterize the nature and behavior of the novel coronavirus infection in retrospective study.

4. This model can be useful for resource planning and tracking progress as the number of active cases fall. It could also have some utility in the coming months to guide public policy related to non-pharmacological interventions, and particularly to assess for a second increase in infection rates due to changes in social distancing behavior or seasonal fluctuations. At the time this model is being created, there is significant concern within public health and scientific communities about a subsequent wave of infections, possibly in the autumn months. This model is designed to assist in decisions about how and when to re-open of schools and businesses without creating a wave of new infections that overwhelms the healthcare system. The key to doing this is to observe the unbiased growth rate of new cases and connect that through the timeline of disease progression to measure the efficacy of each intervention on new cases. Intense social distancing, as is now being practiced in Arizona, will have an immediate effect on transmission, but it will take several days for exposures to incubate the disease, develop symptoms, be tested, and become confirmed cases. It will take even more time - in some cases weeks - for these cases to be treated and released from the hospital. This model will help track multiple interventions and their cumulative ability to mitigate the burden of this disease.

5. Model updates. We don't anticipate the model to stay stagnant for long. We intend to update model assumptions and scenarios as scientific evidence and consensus become available from ongoing studies. We will publish a list of the updates since the last published model.

6. Working Group products. The models produced by the ADHS COVID-19 Modeling WG are living documents controlled by MWG membership. The aim of the MWG is to produce consensus products with adequate scientific justification. Over time, we anticipate the evidence base for MWG projections to change and the MWG is responsible for coordinating model updates.

7. Forward looking: The models will be developed so that we can track changes in disease transmission, account for time delays, and update projections based on observations from testing data. The model is being built around the paradigm of gradual re-opening with controlled relaxation of social distancing restrictions to ensure that we do not have an additional wave of infections that overruns hospital capacity.

Model Assumptions

We use customized SEIR models with additional infected compartments to represent the diversity of disease progression in infected individuals.

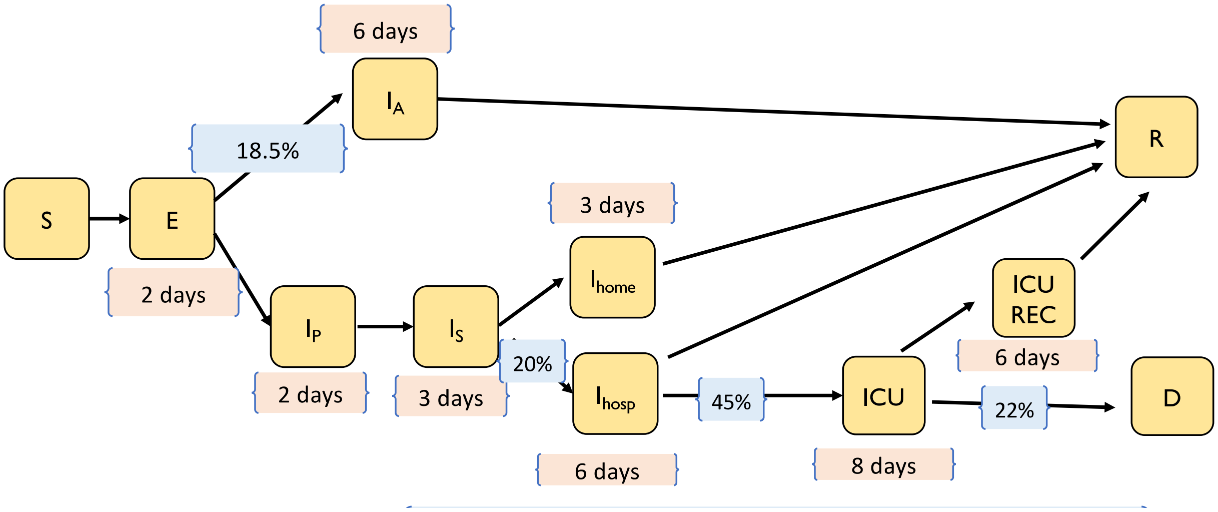


Figure 6. AZ SEIR model with ICU compartments

The SEIR model and the indicated parameters given in Figure 1 represents an update of the Model0 that was used to generate some initial estimates on 4/1/2020. The following paragraphs explain our rationale for the parameter choices made in the model.

Asymptomatic cases: We have chosen to use the proportion of asymptomatic cases identified by Mizumoto and his colleagues (Mizumoto et al., 2020) onboard the Diamond Princess. In particular, we assume that 18.5% of exposed individuals a symptomatic, and do not exhibit clinical symptoms that can be detected. Repeat testing of passengers provided enough information to allow better tracking of asymptomatic infections than other available studies (as of April 1, 2020). Because the population of the Diamond Princess was older than average, it is possible the proportion of asymptomatic cases was lower than in other populations based on public health reports from other affected populations with more normal age distributions.

While a study of returning Japanese patients (Nishiura et al., 2020) found a higher rate (33%), the number of asymptomatic, virus-positive people was very small (N=5). A study of nursing home patients found 30% of patients were “asymptomatic or presymptomatic” on the day of testing (Kimball et al., 2020), however the combining of categories makes this proportion less useful for our model. Given the potential of assumptions about the asymptomatic portion to raise the number of cases, a conservative estimate of asymptomatic proportion is prudent in these circumstances.

We assumed that asymptomatic cases represent mild infections that patients recover on an average of 6 days (Wolfel et al., 2020; Tindale et al., 2020).

Transmission rate by asymptomatic individuals: A critical reason for modeling asymptomatic patients explicitly is the observation that these individuals transmit the disease, but at a lower rate (Ferguson et al., 2020). Based on this observation, we assumed that asymptomatic individuals, and individuals who are presymptomatic transmit at a rate that is 55% of the rate of transmission by symptomatic individuals.

Undetected Infections: Several studies have pointed to the fact that a large fraction of infections remain undetected. We used these studies along with the daily data on confirmed cases in Arizona to impute the total number of infected individuals whose infections may be undetected due to the fact that they are asymptomatic or have only mild symptoms, or are not tested for a COVID19 infection. In particular, two reliable studies predict that the actual number of infections is about 11 times the current number of documented cases (Li et al., 2020 and Ferguson et al., 2020). We use this estimate to calibrate our models based on the daily confirmed case data in the State. In the prior version of the model, we reported undetected cases (estimated) as infections. In this version, we load undetected cases into the initial conditions of the model where they contribute to the transmission term as undetected and potentially asymptomatic cases. The number we report for infections is inversely proportional to the undetected proportion of cases so that it is consistent across scenarios and with reporting data. It should be noted that there is a major advantage to this model approach because we can estimate the recovered individuals who have acquired some level of immunity under each scenario, and therefore can use the model to forecast re-opening scenarios that rely on herd immunity.

Rates of Hospitalization, ICU Admission: We used a CDC provided modeling guideline document to set hospitalization rates and ICU admission rates in our model (CDC COVID response team, 2020). In particular, we assumed that symptomatic patients will be seeking healthcare on their 5th day of symptom onset, and 12% of these individuals will be hospitalized. The remaining patients take an average of 3 days to recover at home, which mirrors our assumption on the recovery duration of asymptomatic cases. Several other model parameters used come directly from CDC modeling documentation, including expectations of time in hospital, ICU admissions, transmission rates, and rates of symptomatic patients.

The probability that an ICU patient will die is an ensemble average of the estimates obtained from a number of sources. In particular, rates of mortality on mechanical ventilators are found to be relatively high for COVID-19. We adopted a value of 22% for probability since it results in an overall mortality rate of 2% among symptomatic individuals.

The proportion of ICU patients who need mechanical ventilators has been estimated as 88% in Arizona. We used this estimate to obtain estimates for the required number of ventilators under each scenario.

Time in Each Disease Phase: Length of disease phases was compiled from Ferguson (2020), CDC planning documents, Wang (200) and Chen (2020). Some phases were estimated from overall disease length and known symptomatic time.

Several studies point to the difference between the ICU stays by patients who eventually recover, and ICU patients who die. In particular, time to death from symptom onset is estimated to be 17.4 days and time to recovery from symptom onset is estimated to be 24.7 days by Verity et al. (2020). We used this estimate to estimate the durations in each phase of the disease in the hospital, assuming that 45% of the hospitalized patients will need ICU care, and among those, 88% will require mechanical ventilation.

Table 1. Estimated parameters for COVID-19 clinical progression, and literature sources

Quantity	**Parameter**	**Value**	**Source**
Incubation Period	$E+I_P$	4 days	Cai et al., 2020; Laio et al., 2020; Lauer et al., 2020;
Proportion of Asymptomatic Infections	A	18.5%	Mizumoto et al., 2020
Asymptomatic viral shedding		0.55	Li et al., 2020
Duration of mild/presymptomatic phase of infection	I_P	2 days	Wei et al., 2020
Infection rate for I_S and I_H cases		0.30	Pei & Shaman, 2020
Duration of LR symptoms before hospital admission	I_S	3 days	Zhou et al., 2020
Duration of infection (Time from symptoms to hospitalization)	I_P+I_S	5 days	Tindale et al., 2020; Ferguson et al., 2020; Chen et al., 2020; Wang et al., 2020; Zhou et al., 2020
Hospitalization rate of Is cases	p_H	12%	Wu et al., 2020
Proportions of hospitalizations that go to the ICU	p_{ICU}	45%	Guan et al., 2020; Wu & McGoogan, 2020
Proportion of mild infections	$1-p_H$	80%	Wu et al., 2020; Yang et al., 2020
Duration of illness from symptom onset		23 days	Verity et al., 2020
Time from symptom onset to death		17 days	Verity et al., 2020; Wu et al. 2020
Case Fatality Rate		2%	Wu et al., 2020
Overall ICU Mortality	p_D	22%	Grasselli et al., 2020

Projections Produced by AZ SEIR Model

We solve the model as a homogeneous model for the entire state of AZ (with population size 7,728,717) to analyze the dynamics of transmission over time.

To account for the above-mentioned uncertainties, we produce projections under five different scenarios that are likely to represent the spread in relevant measures such as hospitalizations over time, number of deaths due to the outbreak, etc. The five scenarios allow us to produce a range of estimates that between best case and worst case.

	beta = 0.15	beta = 0.2	beta = 0.25
1X	**1**		**2**
4X		**3**	**4**
11X		**5**	

Figure 7: Scenarios are drawn from parameterizations for undetected cases and transmission rate, beta.

We use a multiple for the number of undetected cases in the population: 1X, 4X, and 11X. A multiple of 11X assumes that there is significant undetected COVID-19 in the community that continues to transmit. A multiple of 1X assumes that 100% of COVID cases are detected. For each scenario, we report only the cases that are detected – meaning that we divide the number of infections by the multiple as an estimate of positive reported cases. Beta = 0.02 is the best fit to the slope of the cumulative cases curve.

Table 2. Details on the scenarios considered for the projections

Scenario	Description
Scenario 1.	**Best case scenario.** Assumes “high” effective social distancing with an low effective transmission rate (beta = 0.15). Assumes that asymptomatic transmission is negligible with a 1X unconfirmed multiple. A beneficial Summer effect is modeled by reducing beta by half (to 0.075) on May 1.
Scenario 2.	**Moderate transmission; no underreporting.** Assumes continued social distancing with moderate compliance (beta = 0.25) Summer effect is modeled by reducing beta by half on May 15.

Scenario 3.	**Best fit**: Assumes undetected cases are 4X known cases and can transmit asymptomatically (beta = .20). Summer effect is modeled by reducing S by half on May 15. Assumes no additional mitigation, but high compliance with current social distancing orders. This scenario is the current best fit to the data.
Scenario 4.	**Limited re-opening scenario.** Limited asymptomatic transmission, limited re-opening. This scenario assumes a slightly increased transmission consistent with limited re-opening and congregation of small groups(beta = 0.25). Assumes 4X undetected cases as initial infections. Summer effect is modeled by reducing S by half on May 15. Same as scenario 3 with increased transmission.
Scenario 5.	**Late testing scenario:** Assumes a high number of infectious, undetected cases (11X) that would be consistent with rolling out testing in the middle of a large outbreak (similar to Wuhan or Italy). Current social distancing (beta =0.2). Summer effect of reduced transmission rate, beta to 0.10 after May 15.

The current transmission rate, β is a result of the social distancing measures taken all across the state. It is perfectly possible that the social distancing measures resulted in a lower transmission rate (i.e., β=0.15). While that results in a lower number of people getting infected, we should note that this also means that after the social distancing measures are relaxed, and transmission rate is higher than this current transmission rate, due to the fact that there is a large number of remaining susceptible individuals in the population, we may get a second wave of infections.

Figure 7 presents projections for the total number of confirmed infected individuals under each scenario. Note that the total infected projection includes individuals who are asymptomatic or pre-symptomatic on a given day at the testing rate assumed for each scenario.

A major determinant of the peak time in our models is summer effects by reducing the transmission rate by one half. In the coming weeks, we will be monitoring data and literature to modify this assumption as needed. In Figure 7, we present projections under each scenario. The peak is hit around mid-May according to our model, which is dependent on summer effects originating around May 15.

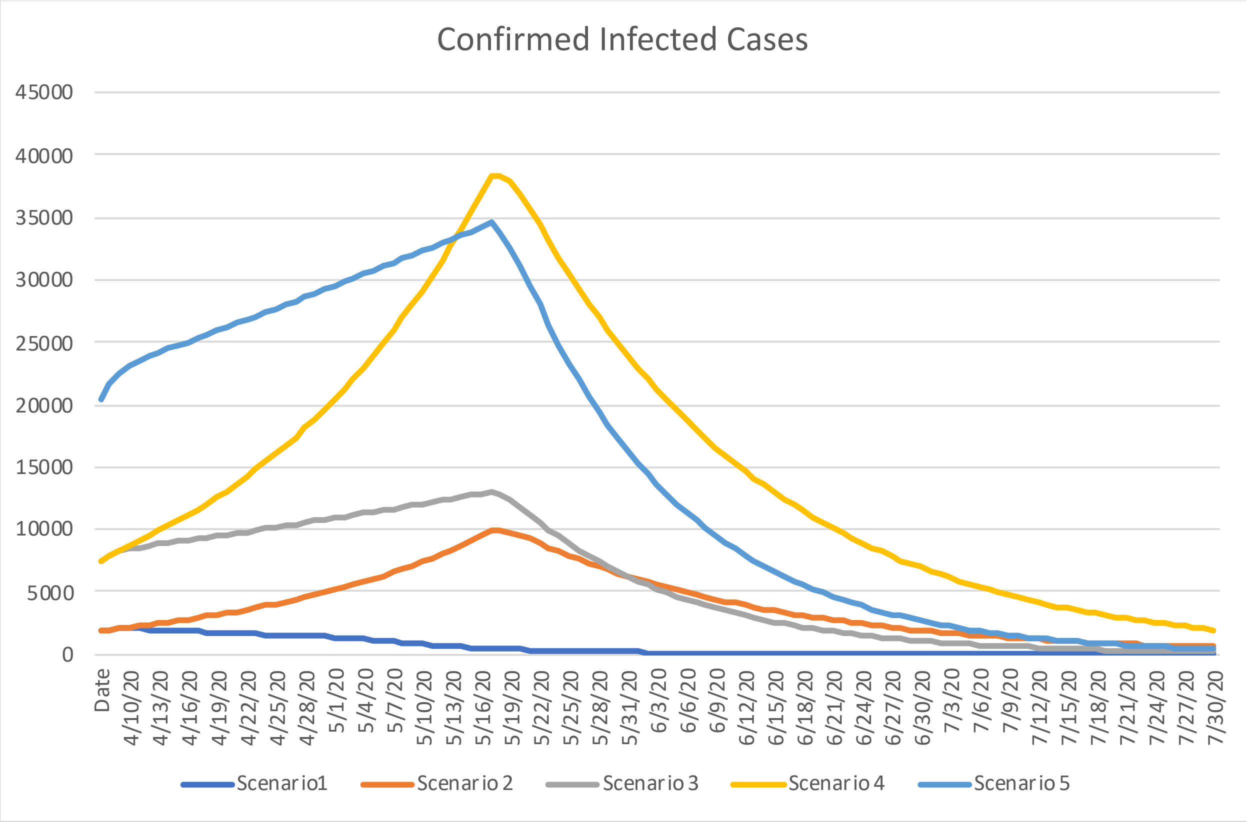


Figure 7. Total number of infected persons for each scenario.

The projections produced by the model under each of the five scenarios are presented in Figure 7. Scenarios 4 and 5 are based on assumptions that are likely to be untrue: specifically, that there is a very high level of undetected disease currently transmitting and that re-opening will occur even if it causes transmission to increase significantly.

Figure 8 compiles the scenarios into a feasible estimates for ongoing COVID-19 infections. The shaded blue area under the curve represents the range of infections that we can anticipate under current restrictions based on current rates of disease. The area in gray represents potential infections from scenarios that have a very high rate of undetected transmission and cases that relax social distancing for example under a re-opening scenario.

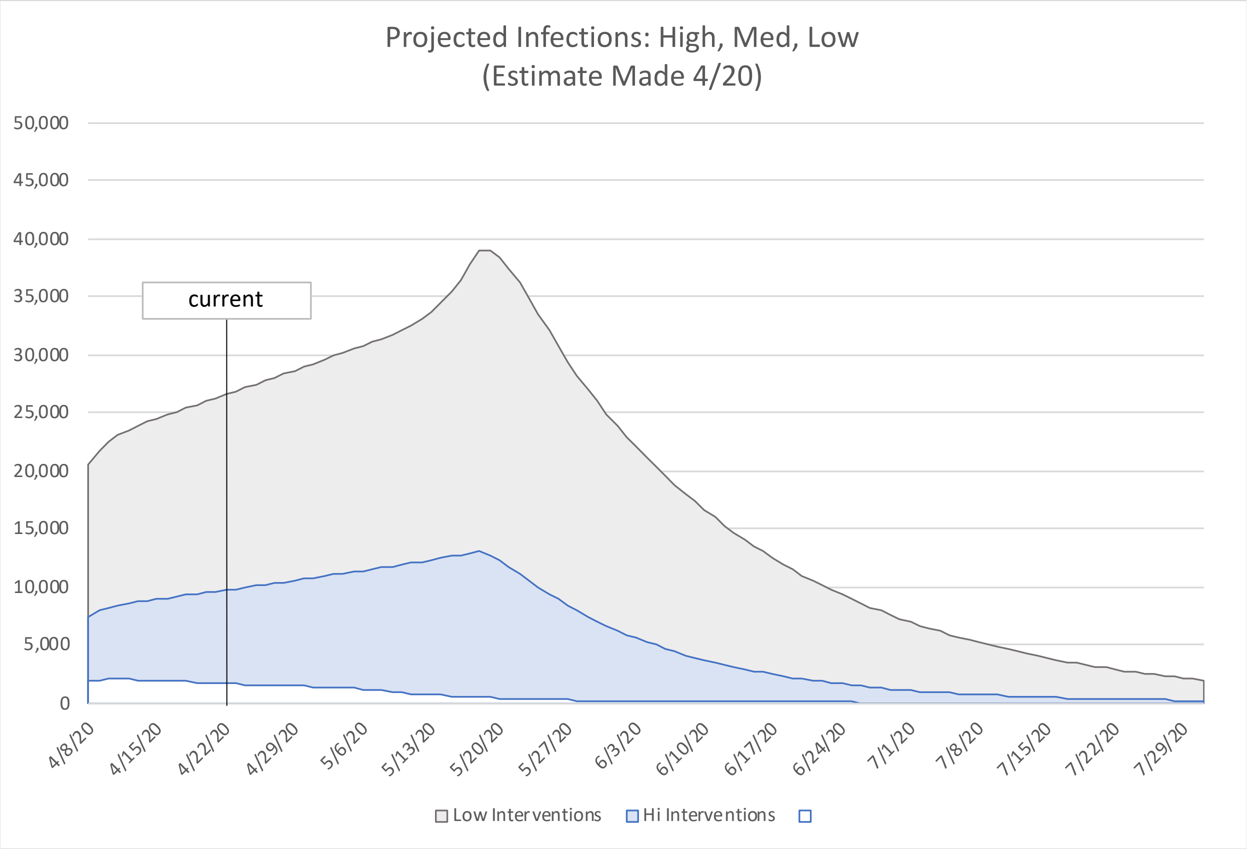


Figure 8: Estimates for infections with Low and High efficacy of non-pharmaceutical interventions.

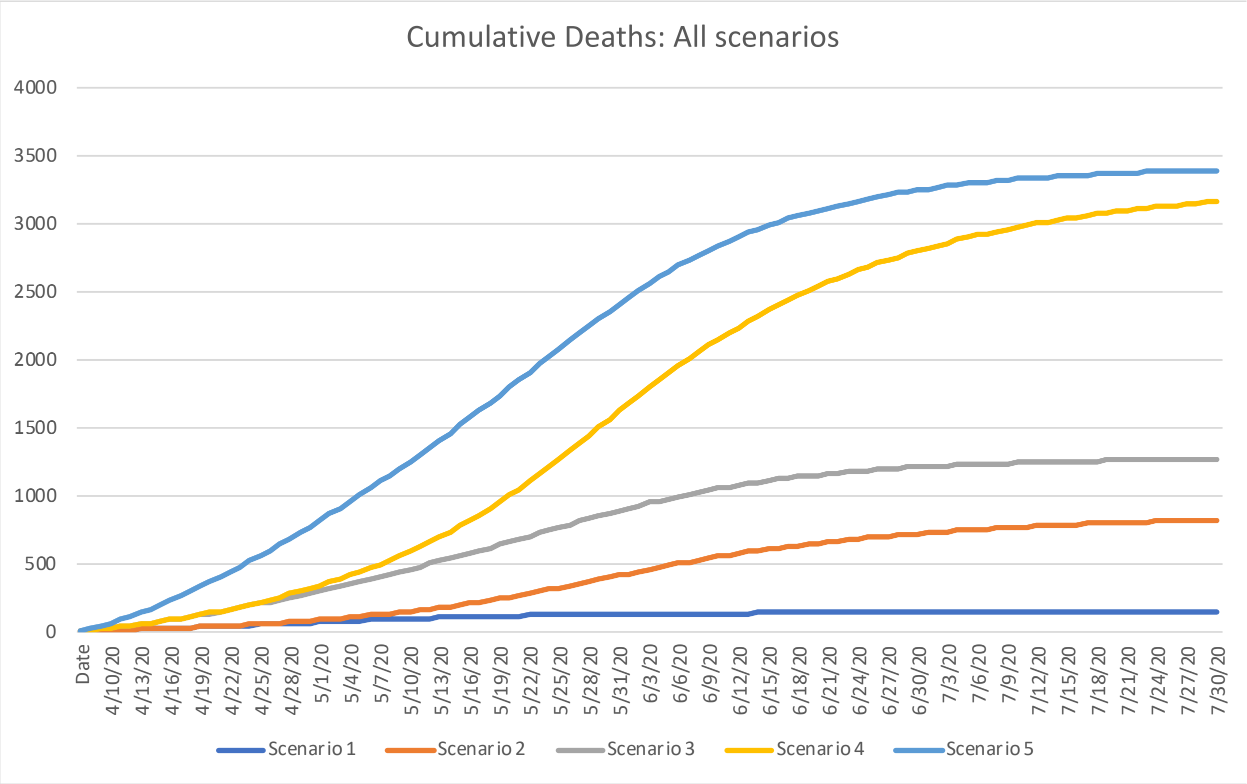


Figure 9.

The number of deaths projected under each scenario.

Deaths are handled similarly in the model. (Figure 9).

Figure 10 identifies ranges for mortality from COVID-19 between April 8 and July 31, 2020. We identify scenarios that have increased transmission due to a large number of unidentified individuals and/or have a higher rate of transmission that can sustain community spread. These estimates are conditionally predictive – meaning that if events unfold according to the assumptions of the model, they are plausible outcomes based on the known science.

Deaths (April 8 - July 31)		
	Point	Range
With Mitigation		**200-1500**
Scenario I	136	
Scenario II	817	
Scenario III	1,264	
Without Mitigation		**2000-4000**
Scenario I	3,157	
Scenario II	3,389	

Figure 10: mortality ranges

A critical quantity to project is the number of hospitalizations due to COVID-19. Due to the fact that we have different bins to track the number of patients in the hospital in the AZ SEIR Model1, we can obtain separate projections for the number that are hospitalized over time. In

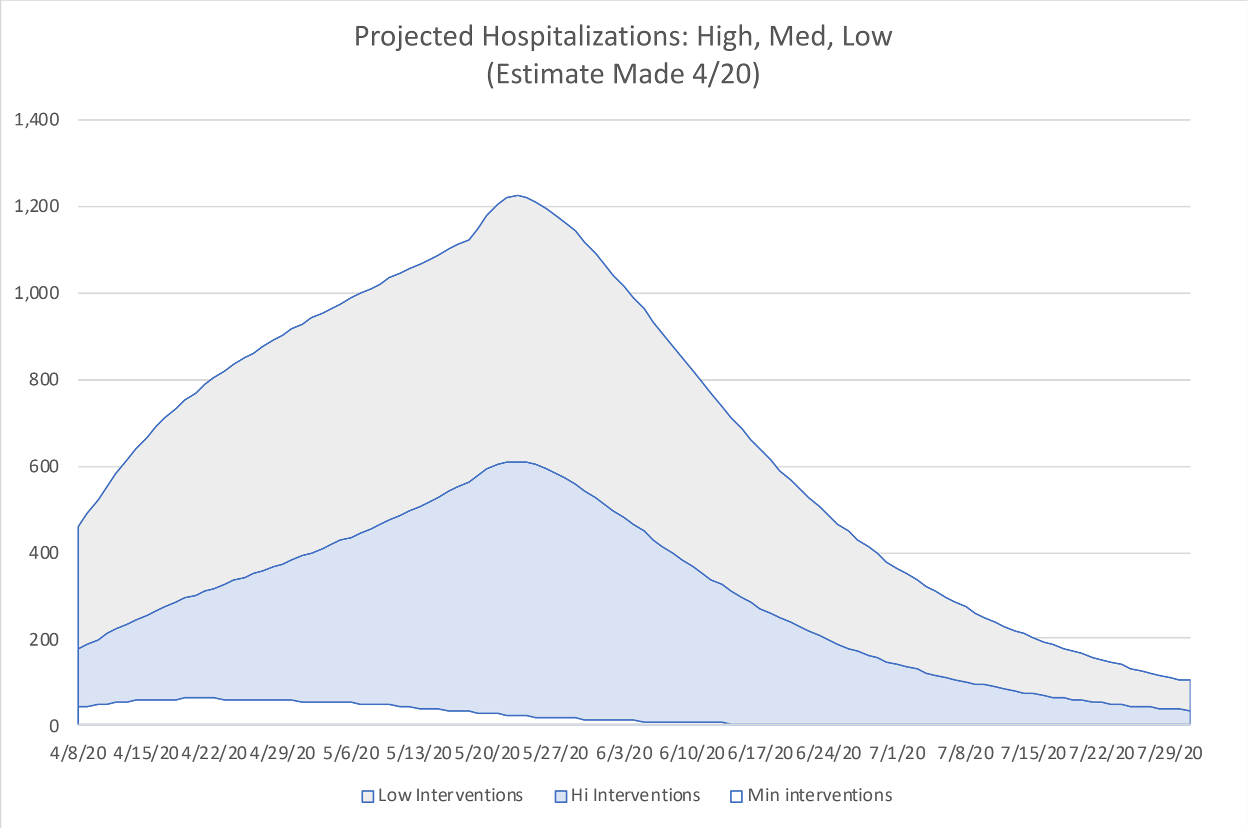


Figure 11. Number of hospitalized patients (including regular bed and ICU) projected under each scenario

Projections for the number in the ICU and patients on mechanical ventilators are given in Figures 11 and 12. Our calculations for the number of ventilators are driven by the probability of ventilation among patients in ICU, which was estimated as 88% by the University of Arizona workgroup.

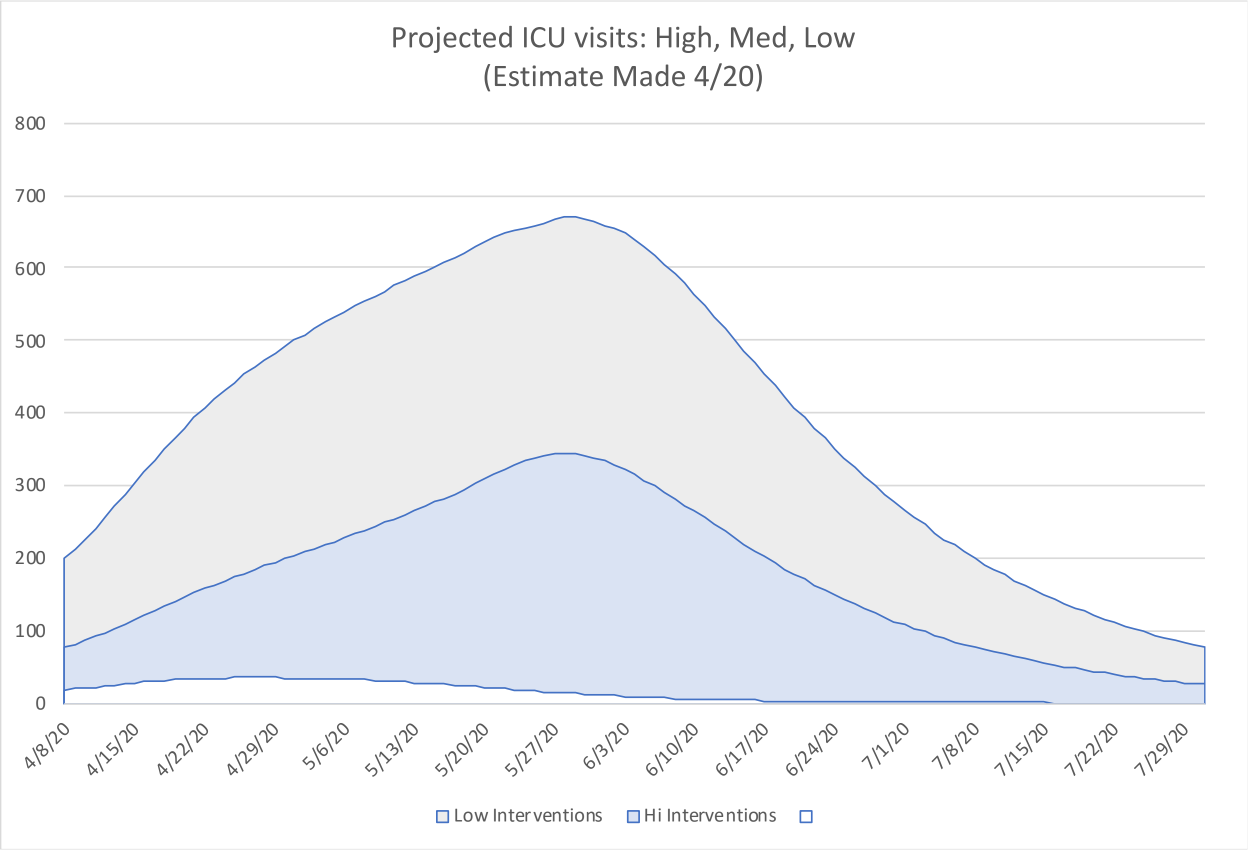


Figure 12. Projections for number of patients in the ICU and patients on mechanical ventilators.

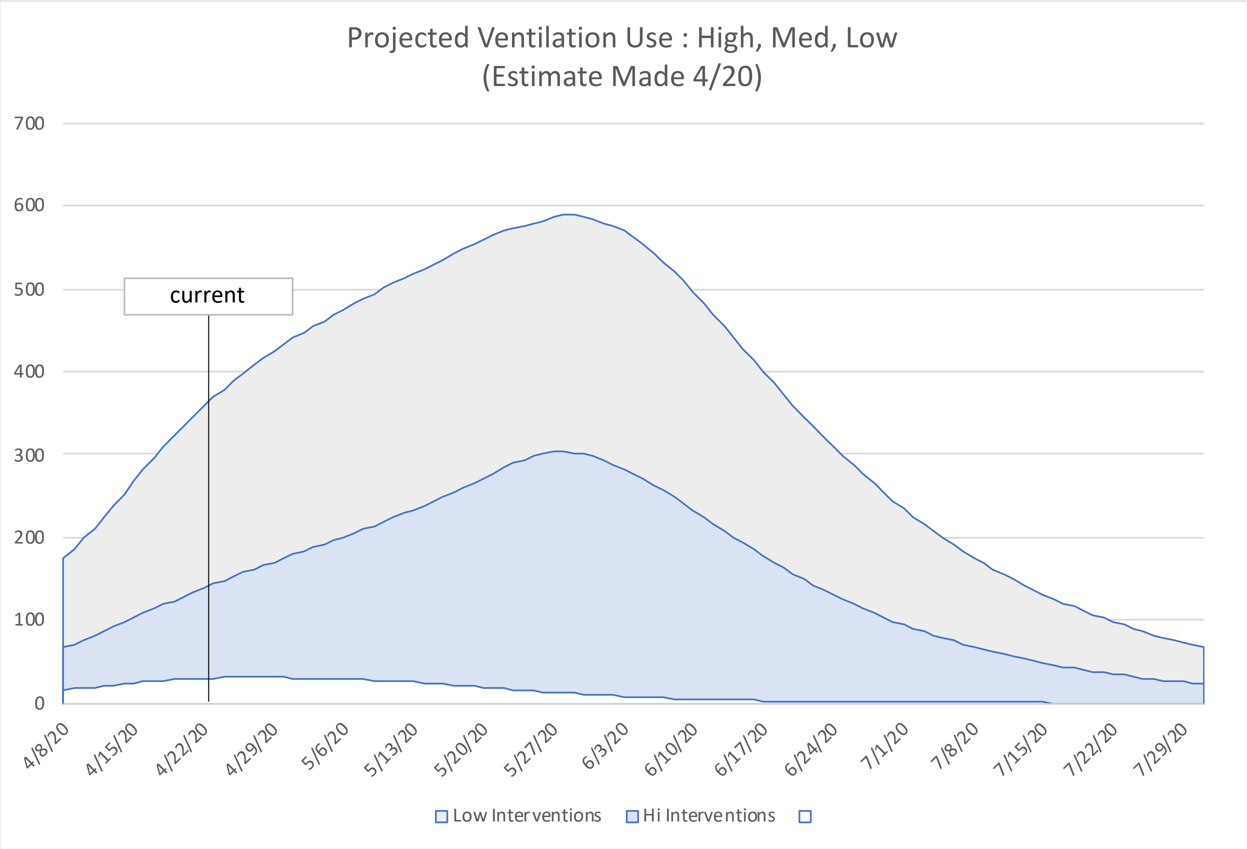


Figure 13: Ventilator needs - all scenarios.

Acknowledgements

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Supplemental Data

Appendix A: AZ SEIR Model1 Details

We consider two values, 0.30 and 0.25 for the transmission rate. Asymptomatic and presymptomatic patients transmit at a rate that is equal to 55% of the transmission rate of symptomatic patients. Similarly, we assumed that patients isolated in their homes or in ICU transmit at a lowered rate that is equal to 20% of the transmission rate of symptomatic patients. The differential equations that correspond to the model are as follows:

$$\begin{aligned}
\dot{S} &= -\Big[\beta_A \frac{I_A}{N} + \beta_P \frac{I_P}{N} + \beta_S \frac{I_S}{N} + \beta_{\text{home}} \frac{I_{\text{home}}}{N} + \beta_{\text{hosp}} \frac{I_{\text{hosp}}}{N} + \beta_{\text{ICU1}} \frac{I_{\text{ICU1}}}{N} + \beta_{\text{ICU2}} \frac{I_{\text{ICU2}}}{N}\Big] S \\
\dot{E} &= \Big[\beta_A \frac{I_A}{N} + \beta_P \frac{I_P}{N} + \beta_S \frac{I_S}{N} + \beta_{\text{home}} \frac{I_{\text{home}}}{N} + \beta_{\text{hosp}} \frac{I_{\text{hosp}}}{N} + \beta_{\text{ICU1}} \frac{I_{\text{ICU1}}}{N} + \beta_{\text{ICU2}} \frac{I_{\text{ICU2}}}{N}\Big] S - E\,\omega \\
\dot{I}_A &= p_A E\,\omega - I_A\,\gamma_A \\
\dot{I}_P &= (1-p_A) E\,\omega - I_P\,\gamma_P \\
\dot{I}_S &= I_P\,\gamma_P - I_S\,\gamma_S \\
\dot{I}_{\text{home}} &= (1-p_H) I_S\,\gamma_S - I_{\text{home}}\,\gamma_{\text{home}} \\
\dot{I}_{\text{hosp}} &= p_H\, I_S\,\gamma_S - I_{\text{hosp}}\,\gamma_{\text{hosp}} \\
\dot{I}_{\text{ICU1}} &= p_{\text{ICU}} I_{\text{hosp}}\,\gamma_{\text{hosp}} - I_{\text{ICU1}}\,\gamma_{\text{ICU1}} \\
\dot{I}_{\text{ICU2}} &= (1-p_D) I_{\text{ICU1}}\,\gamma_{\text{ICU1}} - I_{\text{ICU2}}\,\gamma_{\text{ICU2}} \\
\dot{R} &= I_A\,\gamma_A + I_{\text{home}}\gamma_{\text{home}} + (1-p_{\text{ICU}})\, I_{\text{hosp}}\gamma_{\text{hosp}} + I_{\text{ICU2}}\,\gamma_{\text{ICU2}} \\
\dot{D} &= p_D\, I_{\text{ICU1}}\,\gamma_{\text{ICU1}}
\end{aligned}$$

where the parameters are set as

$$\begin{aligned}
&\omega = 1/2\ ,\ \gamma_A = 1/6,\ \gamma_P = 1/2,\ \gamma_S = 1/3,\ \gamma_{\text{home}} = 1/3, \\
&\gamma_{\text{hosp}} = 1/6,\ \gamma_{\text{ICU1}} = 1/8,\ \gamma_{\text{ICU2}} = 1/6,\ p_A = 0.185,\ p_H = 0.20, \\
&p_{\text{ICU}} = 0.45,\ p_D = 0.22
\end{aligned}$$

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