Epidemiological model of the spread of COVID-19 in Hawaii's challenging fight against the disease

Title: Epidemiological model of the spread of COVID-19 in Hawaii's challenging fight against the disease

Authors: Monique Chyba, Yuriy Mileyko, Oleksandr Markovichenko, Richard Carney, Alice E. Koniges

Presenter: Monique Chyba

Dept. of Mathematics, University of Hawai`i at Manoa
Honolulu, Hawai`i
e-mail: chyba@hawaii.edu

Presenter’s resume:

Prof. Monique Chyba's is a mathematician at the University of Hawaii, Manoa. Her main expertise is the development of geometric methods to solve optimal control problems. One of her central objectives is to understand the role of singular extremals in optimal strategies for nonlinear control systems. Her research is oriented towards applications such as the motion planning problem for multi-agents using spectral graph theory, and geometric approaches to navigation for autonomous underwater vehicles and quadcopters or morphogenesis. She also works on data-driven problem and modeling applied to microbiomes diversification, disease spread and more. Her PhD is from the University of Geneva in Switzerland in Mathematics.

University of Hawai’i at Manoa Team

Faculty: **Monique Chyba** & **Yuriy Mileyko**
Grad Students: **Richard Carney** & **Christopher Gray** & **Oleksandr Markovichenko**
Undergrad Students: **Alan Tong** & **Elizabeth Swantek** & **Dikshika Shrestha**
Department of Mathematics
University of Hawai’i at Manoa
Faculty: **Thomas Lee**
Office of Public Health Studies
University of Hawai’i at Manoa
Faculty: **Alice E. Koniges**
Hawai’i Data Science Institute
University of Hawai’i at Manoa
Grad Student: **Victoria Kala**
Department of Mathematics
University of California, Los Angeles
Grad Student: **Katherine Guo**
Monte Vista High School
Danville, California

The team is growing with a large R_0 number :-) and not everyone is on the picture

Global Health Challenges GLOBAL HEALTH 2020

October 2020

Epidemiological model of the spread of COVID-19 in Hawaii's challenging fight against the disease

Monique Chyba & Yuriy Mileyko & Oleksandr Markovichenko & Richard Carney & Alice Koniges

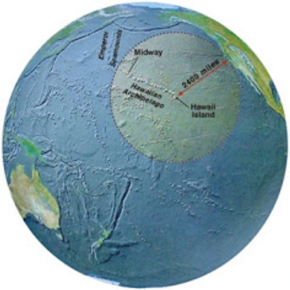
chyba@hawaii.edu

University of Hawaii at Manoa, Honolulu, Hawaii

Presentation Content

- Project Overview
- Mathematical Modeling
- Revisiting the Past
- Simulating Forward Scenarios
- Conclusion and Future Work

Hawai'i Island Chain



Primary Goal of Our Work

To capture peculiarity of the situation in Hawai'i and provide detailed modeling of current virus spread patterns aligned with dates of lockdown and similar measures. We use this analysis to formulate scenario outcomes moving forward.

Isolated Geographic Location

Hawai'i and other US Islands have been noted by the media as COVID-19 hotspots in August after a relatively calm period of low case rates. U.S. Surgeon General Jerome Adams came in person on August 25 to Oahu to address the alarming situation.

Isolated: Good or Bad?

Hawai'i finds itself in a unique position due to its **extremely isolated geographic location**, mostly linear population distribution along the coast, and a **heavy dependence on the tourism and hospitality sectors** of the economy.

- While the first two factors appeared advantageous in the fight against the disease, the latter one creates a tempering effect on feasible long-term mitigation efforts, since too stringent an approach may lead to a catastrophic impact on the economy.
- We study the unique aspects of Hawai'i from both a social and data-driven modeling perspective to understand and recommend the critical intervention measures that make the most impact on spread of the disease while mitigating societal adversities.

Course of COVID-19 in Hawai'i

Hawai'i crushing COVID-19

The March stay-at-home order brought applause when the epidemic was stomped flat but as a result Hawai'i remained extremely vulnerable to the disease exemplified by the following alarming situation in which the islands saw a very significant second wave of infections.

COVID-19 crushing Hawai'i

The state's seven day average case rate per 100,000 of populations went from months at the bottom of the US list to holding a clear spot in the top 15 as of the ending days of August 2020[a]

[a] Covid in the U.S.: Latest Map and Case Count - The New York Times

Epidemiological Models

Compartmentalized SEIR models of the COVID-19 provide the basis for much of the current epidemiological modeling efforts world-wide, however variants in the compartmental choices and corresponding variables allow for parameter matching and optimizations, thus providing useful predictive information specific to our Island population

What can they do?

Making a good model for a pandemic is difficult, but it is even harder to use it properly. There is no reliable data on how the coronavirus spreads, and people turn out to be really, really complicated![a]

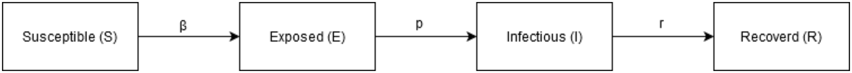
- Understand the past
- "What-If" scenarios!
- Who should received vaccine first?

[a] Maggie Koerth, Coronavirus Models Were Always About More Than Flattening The Curve

SEIR

To model the spread of COVID-19, we employ a compartmentalized model[a], which is based on a standard discrete SEIR model. As in the standard SEIR model, we partition a given population into four compartments: **Susceptible** (not currently infected), **Exposed** (infected with no symptoms), **Infected** (infected with symptoms), **Removed** (recovered or deceased).

[a] Curtailing transmission of severe acute respiratory syndrome within a community and its hospital, Lloyd-Smith & al.



- β transmission rate
- p probability to develop symptoms
- r recovery rate

GSEIR - Generalized SEIR Model

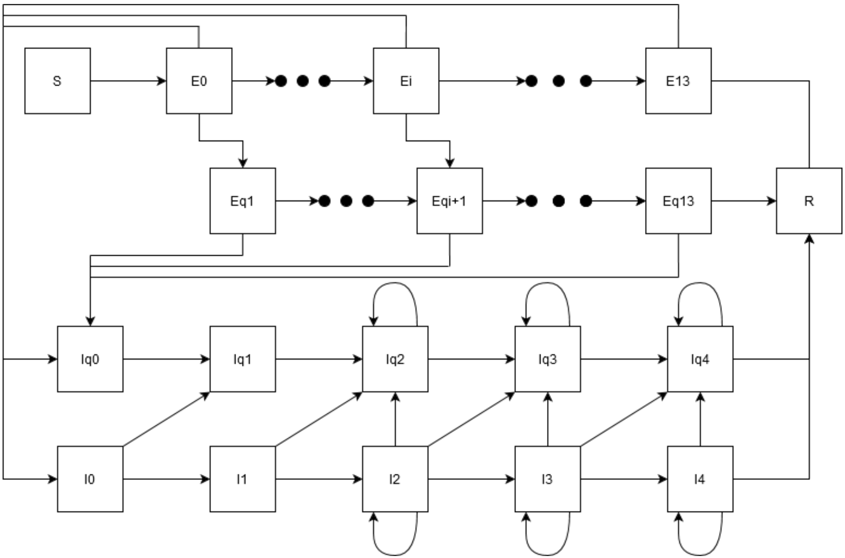
To better capture the dynamics of the infection, we divide the whole population into two population groups: **the general community** and **healthcare workers** (healthcare workers play a vital role and are exposed in different ways than the general community.

In addition, compartments Exposed and Infected (in each population group) are split into multiple stages to better reflect the progression of the disease. The dynamics of each population group have two distinguished parts: the dynamics of Susceptible individuals, and the dynamics of the rest of the compartments. The former is governed by the **hazard rate**.

Variables

Variable $S(t)$. The number of susceptible individuals.
Variables $E_i(t)$**.** The number of asymptomatic infected individuals i days after exposure who are not quarantined.
Variables $E_{q,i}(t)$**.** The number of quarantined asymptomatic infected individuals i days after exposure.
Variables $I_j(t)$**,** $i = 0, 1$**.** The number of symptomatic infected individuals i days after the onset of symptoms who are not quarantined.
Variables $I_j(t)$**,** $j = 3, 4, 5$**.** The number of symptomatic infected individuals at the nominal stage i of the illness. Note that a person can stay at a given stage for several days.
Variables $I_{q,j}(t)$**,** $j = 0, 1$**.** The number of quarantined symptomatic infected individuals, with j representing either the number of days after the onset of the symptoms ($j = 0, 1$), or the stage of the illness ($j = 2, 3, 4$).
Variable $R(t)$**.** The number of removed (recovered or deceased) individuals.

GSEIR Diagram



Dynamics Equations

The equations for the dynamics of the two population groups are essentially the same. Only the hazard rate and the parameters determining transition rates into quarantine may be different between the two groups.

$$
\begin{aligned}
S(t+1) &= e^{-\lambda(t)} S(t) \\
E_0(t+1) &= (1 - e^{-\lambda(t)}) S(t) \\
E_i(t+1) &= (1 - p_{i-1})(1 - q_{a,i-1}) E_{i-1}(t), \\
&\qquad i = 1, \ldots, 13 \\
E_{q,i}(t+1) &= (1 - p_{i-1})(q_{a,i-1} E_{i-1}(t) + \\
&\quad + E_{q,i-1}(t)), \quad i = 1, \ldots, 13 \\
I_0(t+1) &= \sum_{i=0}^{13} p_i (1 - q_{a,i}) E_i(t) \\
I_1(t+1) &= (1 - q_{s,0}) I_0(t) \\
I_2(t+1) &= (1 - q_{s,1}) I_1(t) + (1 - r)(1 - q_{s,2}) I_2(t)
\end{aligned}
$$

Dynamics Equations-Continued

$$
\begin{aligned}
I_j(t+1) &= r(1-q_{s,j-1})I_{j-1}(t) + \\
&+ (1-r)(1-q_{s,j})I_j(t), \quad j = 3,4 \\
I_{q,0}(t+1) &= \sum_{i=0}^{13} p_i(q_{a,i}E_i(t) + E_{q,i}(t)) \\
I_{q,1}(t+1) &= I_{q,0}(t) + q_{s,0}I_0(t) \\
I_{q,2}(t+1) &= I_{q,1}(t) + q_{s,1}I_1(t) + \\
&+ (1-r)(q_{s,2}I_2(t) + I_{q,2}(t)) \\
I_{q,j}(t+1) &= r(q_{s,j-1}I_{j-1}(t) + I_{q,j-1}(t)) + \\
&+ (1-r)(q_{s,j}I_j(t) + I_{q,j}(t)), \quad j = 3,4 \\
R(t+1) &= R(t) + rI_4(t) + rI_{q,4}(t) + \\
&+ (1-p_{13})E_{13}(t) + (1-p_{13})E_{q,13}(t)
\end{aligned}
$$

Hazard Rate and Mixing Pool

The hazard rate, $\lambda(t)$, depends on time and essentially determines the probability, $1 - e^{-\lambda(t)}$, of an individual becoming exposed at time t. It is different for different population groups and takes into account interactions between the groups, thus coupling their dynamics.

Hazard Rate Community

$$\begin{aligned}\lambda_c(t) = \quad & \beta\Big[(I_c + \varepsilon E_c) + \gamma((1-\nu)I_{c,q} + \varepsilon E_{c,q}) + \\ & \rho[(I_h + \varepsilon E_h) + \gamma((1-\nu)I_{h,q} + \varepsilon E_{h,q})]\Big]/N_c,\end{aligned}$$

with

$$N_c(t) = S_c + E_c + I_c + R_c + \rho(S_h + E_h + I_h + R_h).$$

Hazard Rate Health Care Workers

$$\lambda_h(t) = \rho\lambda_c + \beta\eta\Big[(I_h + \varepsilon E_h) + \kappa\nu(I_{h,q} + I_{c,q})\Big]/N_h,$$

with

$$N_h(t) = S_h + E_h + I_h + R_h$$

Oahu Island

Oahu

Oahu is the most populated island in the chain, providing an appropriate data set for interpretation of our models as well as guidance for the entire state.

Island specific regulations

We focus specifically on Oahu, the most-affected by COVID-19 Island as of now, since each island (or group of islands in the case of Maui) has its own mayor and thus restrictions and governmental actions may vary slightly within the entire state as they are determined not only uniformly by the Governor but also by the Mayors and local governments of the outer islands.

Variable and Parameters for Oahu Model

Parameter, meaning	Value
β, basal transmission rates	optimized to fit data
Factors modifying transmission rate	
ε, asymptomatic transmission	0.75
ρ, reduced healthcare worker interactions	0.8
γ, quarantine	0.2
κ, hospital precautions	0.5
η, healthcare worker precautions	0.5
ν, symptomatic hospitalization	0.08

Variable and Parameters for Oahu Model

Population fractions	
p_i, $i = 0, \ldots, 13$, onset of symptoms after day i	0.000792, 0.00198, 0.1056, 0.198, 0.2376, 0.0858, 0.0528, 0.0462, 0.0396, 0.0264, 0.0198, 0.0198, 0.0198, 0
$q_{a,i}$, $i = 0, \ldots, 13$, asymptomatic quarantine after day i	0 before June 10, then $q_5 = q_6 = q_7 = 0.05$
$q_{s,i}$, $i = 0, \ldots, 4$, symptomatic quarantine after day/stage i	C: 0.1, 0.4, 0.8, 0.9, 0.99; H: 0.2, 0.5, 0.9, 0.98, 0.99
r, transition to next symptomatic day/stage	0.2

Choice of Parameters

The model depends on a large quantities of parameters. The p_i (probability for the onset of symptoms to appear after day i) and r the probability for the illness to evolve and eventually recover are chosen to reflect some CDC estimations.

Asymptomatic

It is based top reflect the assumption that 40% of all infections remain asymptomatic:

$$0.4 = \sum_{i=0}^{13} \frac{(i+1)p_i \prod_{j=0}^{i-1}(1-p_j)}{1-\prod_{i=0}^{13}(1-p_i)}.$$

Length of Illness

It is base on the assumption that the average length of illness is 17 days:

$$17 = 2 + \sum_{n=3}^{\infty} \frac{n(n-1)(n-2)}{2} r^3 (1-r)^{n-3} = 2 + \frac{3}{r}.$$

Initial Conditions

The initial values of most variables are zero. The only non-zero values are the number of susceptible individuals in the general community and the healthcare worker community, $S_c(0) = 937711$, $S_h(0) = 15000$.

First COVID-19 case, March 6, 2020

In addition, we assume a single not quarantined symptomatic individual, reflecting the first detected case of COVID-19 on Oahu: $I_{c,0}(0) = 1$.

Fitting the Curve from March 6 to August 31, 2020

Except for the basal transmission rate β of SARS-CoV-2, our model parameters are fixed to correspond to available information about the virus and the disease.

The primary task is to determine model's parameters necessary for an accurate data fit of Oahu data from March 6th to August 27. We use data from the Hawaii Data Collaborative for the count of daily cases as well as active hospitalisations and active ICU beds [a].

[a] https://www.hawaiidata.org/covid19

The basal rate of transmission is adjusted in time to reflect non-pharmaceutical measures taken by state of Hawai'i during this pandemic.

Basal Transmission Rates

They are obtained by optimizing the fit to the data using the Levenberg–Marquardt algorithm.

Optimized Transmission Rates

Here are the optimized transmission rates to fit Oahu data. They reflect the State and Oahu non-pharmaceutical mitigation measures.

March 6 - April 2	April 2 - May 20	May 20 - May 30
$\beta = 0.3657$	$\beta = 0.0491$	$\beta = 0.1133$
May 30 - June 10	June 10 - Aug 11	Aug 11 - Aug 27
$\beta = 0.2109$	$\beta = 0.1694$	$\beta = 0.1086$

Daily Cases Fit

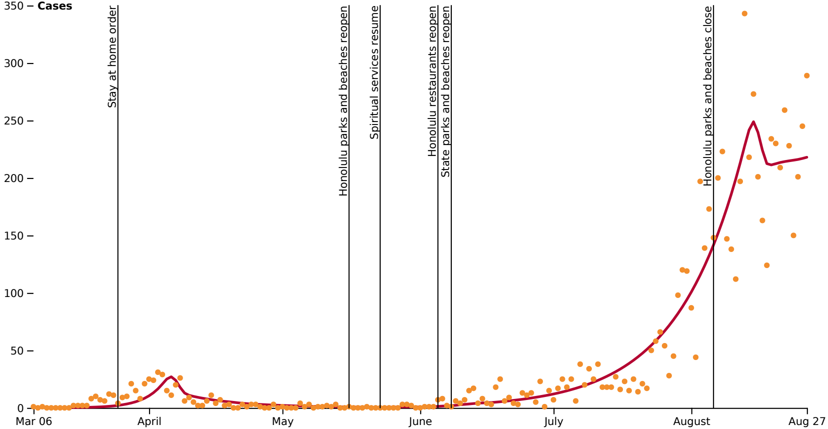


Figure: Daily cases. Dots are the actual data and the plain line represents the model. We also delineate the various mitigation measures that took place during that period.

Data Fit for Data on Active Hospitalization and ICU Beds

An important quantifier in COVID-19 is the number of hospitalization and ICU beds. Since we have seen hospitals throughout the world being overwhelmed by the number of COVID-19 patients, it is a critical element of mitigation strategy. The data are shown starting July 18, since the numbers for earlier dates have not been released by the Department of Health.

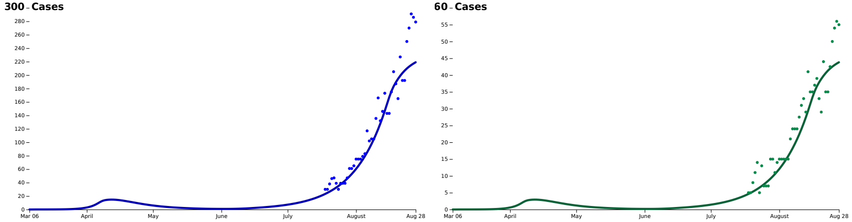
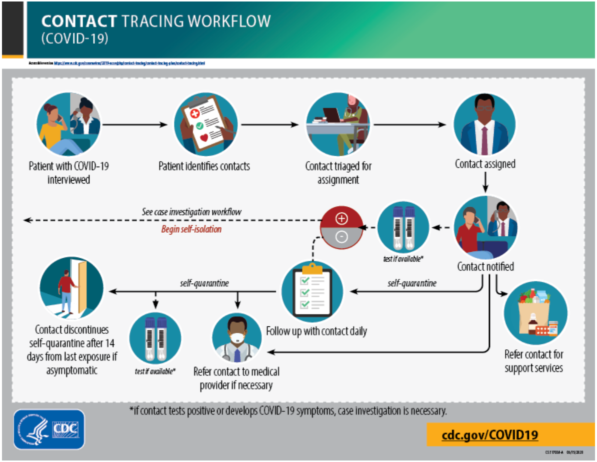


Figure: Data fit for data on active hospitalization (blue) and ICU beds (green). Real data are dots (State) and model predictions are lines (Oahu).

Revisiting the Past

We first retrospectively predict the impact on the number of hospitalisations and ICU beds if proper testing/contact tracing and quarantine measures would have been in place on June 10, corresponding to the date when many of the Hawai'i stay-at-home restrictions were lifted.



Contact Tracing Assumption

In our data fit, we assumed that starting June 10, 15% of the asymptomatic people are going into quarantine as the result of testing and contact tracing. More precisely, we assume we catch about 14.3% of asymptomatic population as follows: 5% after day 5 of being exposed, then 5% of the remaining after day 6 of exposure, and then another 5% of the remaining after day 7.

We will denote this scenario as $5 : 0.05, 6 : 0.05, 7 : 0.05$ (days 5,6 and 7, each at 5%).

Impact Factors

There are several factors which affect the number of asymptomatic individuals going into quarantine, thus slowing down the spread of the virus: **improved testing with more rapid turn around, increased contact tracing, and dedicated quarantine facilities.**

Impact of early asymptomatic quarantine

Table below shows the impact of the earlier detection on the total number of cases from June 10 to August 27 as well as on the cumulative number of active hospitalisations and active ICU patients for the two and a half month period. These cumulative numbers are computed by summing up the number of all hospitalized (ICU) patients for each day.

Testing/Contact Tracing	Total Cases	Cum act Hospt.	Cum act ICU
5:0.05, 6:0.05, 7:0.05	6517	4721	944
3:0.05, 4:0.05, 5:0.05	5658	4163	833
2:0.05, 3:0.05, 4:0.05	5102	3799	760
5:0.1, 6:0.1, 7:0.1	5760	3953	791
3:0.1, 4:0.1, 5:0.1	4346	3088	618
2:0.1, 3:0.1, 4:0.1	3551	2590	518

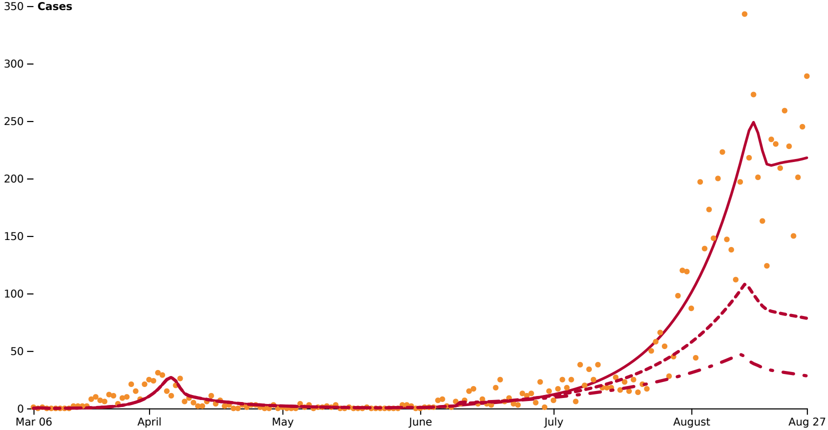
Impact of the volume of asymptomatic quarantine

The actual percentage of detected asymptomatic individuals is affected by the amount of testing done, by the amount of contact tracing resources available, and in large part, by quarantine facilities. Quarantine facilities are particularly important for the Oahu modeling, since a large number of residents live in multi-generational and non-family member shared households. Note that the quarantine fraction of 0.1 on each of the three days leads to the overall 27% detection of asymptomatic cases, 0.2 reaches 48.8%, and 0.3 reaches 65%.

Testing/Contact Tracing	Total Cases	Cum act Hospt.	Cum act ICU
5:0.05, 6:0.05, 7:0.05	6517	4721	944
5:0.1, 6:0.1, 7:0.1	5760	3953	791
5:0.2, 6:0.2, 7:0.2	4499	2865	573
5:0.3, 6:0.3, 7:0.3	3573	2175	435

Alternate scenarios

Our model suggests a larger benefit when asymptomatic individuals are caught early. Combining both of the above factors, we create various scenarios to predict how the total hospitalisation and ICU beds would have been affected.



Hospitalisation and ICU variations for different scenarios

Testing/Contact Tracing	Total Cases	Cum act Hospt.	Cum act ICU
5:0.05, 6:0.05, 7:0.05	6517	4721	944
3:0.15, 4:0.2, 5:0.1	3249	2269	454
2:0.15, 3:0.3, 4:0.2	1667	1208	242

Updated hospital capacity as of March 30, 2020:

Number of OHCA licensed beds	2,757
Number of ICU beds	338
Number of ventilators	534
Number of beds excluding ICU beds	2,419
Number of beds occupied-32%	893
Number of ICU beds occupied-37%	126
Number of ventilators in use-11%	58
Source: Healthcare Association of Hawaii	

Discussion

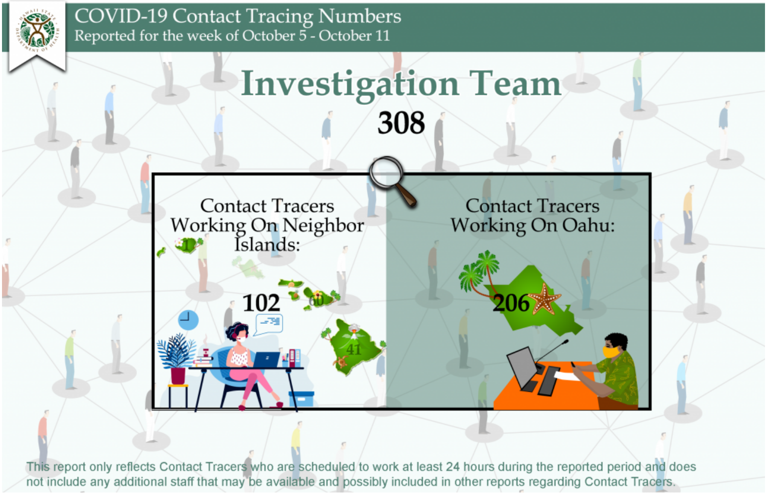
Data Fitting

A zoom on the data fit for dates between March 6 and May 30 demonstrates the efficiency and good timing of the first stay-at-home order, Hawai'i even being referred at the time as the safest state. Starting in mid-June we see the daily cases increasing and following an exponential trend for a 40 day period to become one of the worst states in dealing with the pandemic.

Contact Tracing/Testing and Quarantine

We show that with an increased structure of testing/contact tracing and quarantine facilities, we could have dramatically impacted the outcome as of August 27. Our results show that earlier detection of asymptomatic individuals has the most effect on the behavior of the model. Assuming we traced and quarantine successfully 52% of the asymptomatic population after days 2, 3 and 4 (more dominantly after day 3 of being exposed), we would have seen a reduction of 4850 total daily cases, 3513 cumulative active hospitalisation and 702 cumulative active ICU beds which is equivalent to a reduction of about 74% for total daily case, and for both hospitalisation and ICU beds.

Oahu Improved Contact Tracing



Forecasting Scenarios

The data fitting and parameter matching specific to our Oahu data allows us to better understand the effects of the various parameters as well as the transmission rate fits. We then use this to provide scenarios past August 27, 2020 that are dependant on testing/contact tracing and quarantine measures.

The transmission rate is adjusted for each scenario depending on various societal events: stay-at-home order (we assume β slightly higher than during the first stay-at-home order due to community spread); Labor day holiday weekend (increase in transmission rate for a few days); lifting the stay-at-home order on October 5 (varies depending on population behavior), Thanksgiving holiday.

Scenario 1

Assumptions

Very aggressive testing/contact tracing and facility quarantine but moderate compliance in individual behavior. Assumes catching a total of 78% of asymptomatic individuals between days 2 and 4 of exposure. We assume the population will behave similarly to what happened after June 10 once the stay-at-home order is lifted.

Transmission rates for Scenario 1		
Aug 30 - Sep 11 $\beta = 0.09$	Sep 11 - Sep 14 $\beta = 0.12$	Sep 14 - Oct 5 $\beta = 0.09$
Oct 5 - Dec 1 $\beta = 0.17$	Dec 1 - Dec 5 $\beta = 0.2$	Dec 5 - Dec 31 $\beta = 0.17$
Testing/Tracing for Scenario 1: 2:0.4, 3:0.4, 4:0.4		

Scenarios 2 and 3

Transmission rates for Scenario 2 and 3		
Aug 30 - Sep 11 $\beta = 0.09$	Sep 11 - Sep 14 $\beta = 0.12$	Sep 14 - Oct 5 $\beta = 0.09$
Oct 5 - Dec 1 $\beta = 0.145$	Dec 1 - Dec 5 $\beta = 0.2$	Dec 5 - Dec 31 $\beta = 0.145$
Testing/Tracing for Scenario 2: 0.2, 3:0.2, 4:0.2		
Testing/Tracing for Scenario 3: 3:0.2, 4:0.2, 5:0.2		

Assumptions

More realistic testing/contact tracing and facility quarantine but higher compliance in individual behavior starting after lifting the stay-at-home order on October 5. Assumes catching a total of 49% of asymptomatic individuals between days 2 and 4 of exposure. We assume the population will behave in a more compliant way than what happened after June 10 once the stay-at-home order is lifted. The transmission rate is thus reduced from 0.1694 to 0.145. Scenario 3 is identical to scenario 2 but with more a relaxed testing/contact tracing and facility quarantine.

Simulating Scenarios 1,2 and 3: Daily Cases

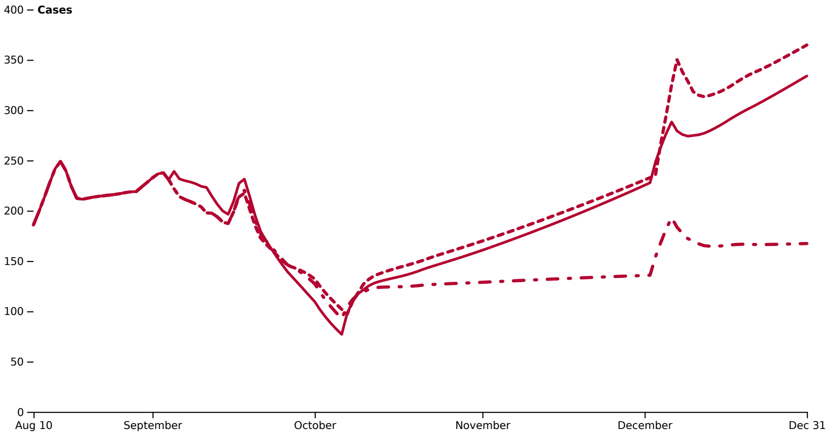


Figure: Scenario 1: plain line. Scenario 2: dot-dash line. Scenario 3: dash line. Scenario 1 is better at first but scenario 2 is provides the best outcome over the long run.

Simulating Scenarios 1,2 and 3: Daily Cases

Peak for Each Scenario

It is important to note that the wave for scenario 2 starts to decrease in early 2021, while the number of daily cases for scenarios 1 and 3 keeps increasing, with a peak of 594 daily cases on April 3 for scenario 1, and a peak of 541 daily cases on April 23 for scenario 3.

1. For scenario 2, the maximum daily cases will not exceed 193 and the peak will occur in early December due to an assumed increase in non-compliance during the Thanksgiving holiday
2. For scenario 3 we are looking at 541 cases in early April
3. We reach 594 cases in late April for scenario 1.

Discussion

We demonstrate how different transmission rates and testing/contact tracing, quarantine facilities affect the future of the curve. The take away from these results is that to succeed in controlling the curve, we need a combination of aggressive testing/contact tracing, quarantine facilities as well as compliance from individual to keep the transmission rate to lower levels.

Contact Tracing/Testing and Quarantine

Scenario 1 assumes almost perfect success in quarantining exposed individuals but transmission rates comparable to what we had after the State lifted the first stay-at-home order. Scenario 2 assumes better compliance from the population (lower transmission rate β) and aggressive but doable contact tracing; it provides the best outcome. Scenario 3 with same transmission rate as scenario 2 but shifting the contact tracing by one day shows significantly more cases.

The conclusion is that to control the curve long term we need both: aggressive contact tracing and high compliance from the population.

Conclusion

If provided contact tracing was in place with quarantine facilities as well as explicit guidance for the public on how to behave and compliance to those, we would be now under 50 daily cases and a second stay-at-home would not have been necessary

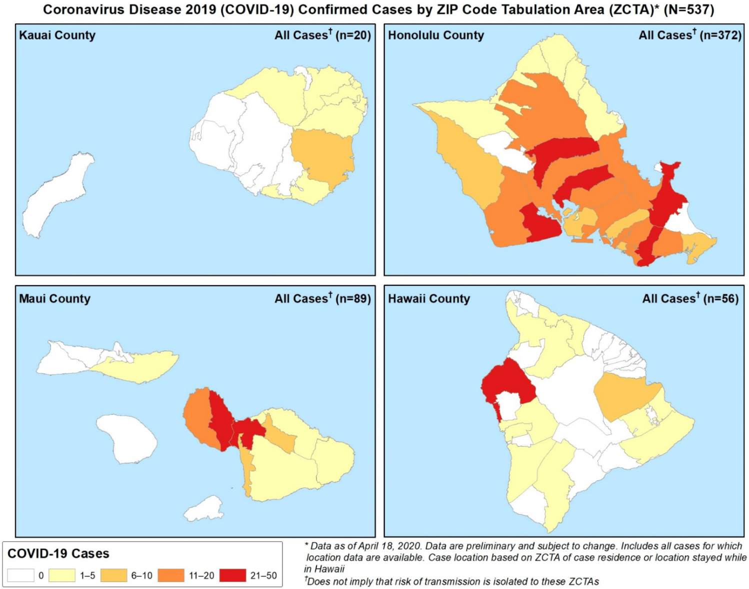
Economic Impact

The best alternate scenario reduces the total hospitalisation and ICU beds by 74% which amount to almost $10 million. Contact tracing, as well as quarantine facilities also have a cost, but it will be quite lower. Comparing the forecasting scenario, we obtain that as of December 31, scenario 2 saves more than $12 million compared to scenario 3 and scenario 1 saves almost $4 million compared to scenario 3. Those amounts increase quite dramatically after December 31, 2020.

Future work

- The State of Hawai'i is, since March 26, 2020, in an effective isolation bubble following the mandatory 14-day traveler quarantine that has not yet been lifted. The interisland quarantine was lifted on June 16 and then partially reinstated on August 11. This is the reason why travelers are not explicitly included in our work; they are currently virtually nonexistent (counts dropped to the lower hundreds from a historical norm of about 30,000 a day). Traveling is reopening again, we are working to add tourists and traveler residents in the model.
- Current work is introducing a new variable category of individual that reflect vaccination. Indeed, our compartmental model can be used to account for the additional sub-population of the vaccinated.
- Understanding how the flu is going to interact with COVID-19 is another big unknown.

MAHALO!



*Data as of April 18, 2020. Data are preliminary and subject to change. Includes all cases for which location data are available. Case location based on ZCTA of case residence or location stayed while in Hawaii

†Does not imply that risk of transmission is isolated to these ZCTAs


THANK YOU