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Modeling and Analysis in Support of Organizational Decisions during the COVID-19 Pandemic

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Abstract: The 2019 coronavirus disease (COVID-19) disrupted economic and social systems on an unprecedented scale. Organizational leaders faced unstructured problems that required novel analysis and evidenced-based decision-making approaches. This paper explains several analytical tools and problem-solving methodologies used at the United States Military Academy at West Point to support decision-making related to operational activities and future planning. While many of the tools apply basic analytical methods, the novelty of this paper lies in the unique application of the tools, visual presentation of data analytics, and the explanation of the contextual circumstances that prompted the development of these tools.

Keywords: Visual Analytics, Monte Carlo Simulation, COVID-19

1. Introduction

The 2019 coronavirus disease (COVID-19) required leaders and policymakers across society to make hard decisions across numerous environments and systems. The virus created a need for unstructured and unprecedented problem solving and decision-making under novel conditions. The novelty and severity of this pandemic, coupled with non-linear disease growth that varied across time and space, created a highly complex decision-making environment. Decision problems and systems rife with variability and interdependencies are difficult to represent with analytical models, and these systems often require simulation to create a reasonable representation of their behavior (Harrell et al. 2012, p.38). Shortly after the onset of the pandemic, many world-class epidemiologists and modelers developed disease projections based upon characteristics of early COVID-19 dynamics and classical models of epidemiology, with many using the Susceptible-Exposed-Infectious-Removed (SEIR) model as a foundation (Adam, 2020). While these analytic models served national, state, and large metro leaders well, many sectors and systems within society could not project the pandemic's high-level forecasts and potential impacts onto their specific systems of concern. Colleges and universities landed in this latter category. Colleges and universities traditionally manage familiar and structured problems, and they now faced novel and unstructured problems. For some institutions of higher learning, COVID-19 presented an existential crisis.

In many ways, colleges and universities became ideal systems to promote the spread of COVID-19. The typical American university system fosters an environment that encourages continual social interactions amongst young adults, with many of these interactions in a large group setting. In most universities, students disperse for recess at different times throughout the year and travel home for short periods. During a pandemic, student dispersion creates vectors of infection opportunities, with these student vectors then returning to campus and spreading the virus further. As students return to campus, go back into congregate housing, and mix across classes and extracurricular activities, an unmitigated university environment creates near-ideal conditions for a disease like COVID-19 to flourish. The COVID-19 asymptomatic rate and mild severity amongst young adults created further opportunity for undetected, rapid disease spread. To make matters worse, colleges and

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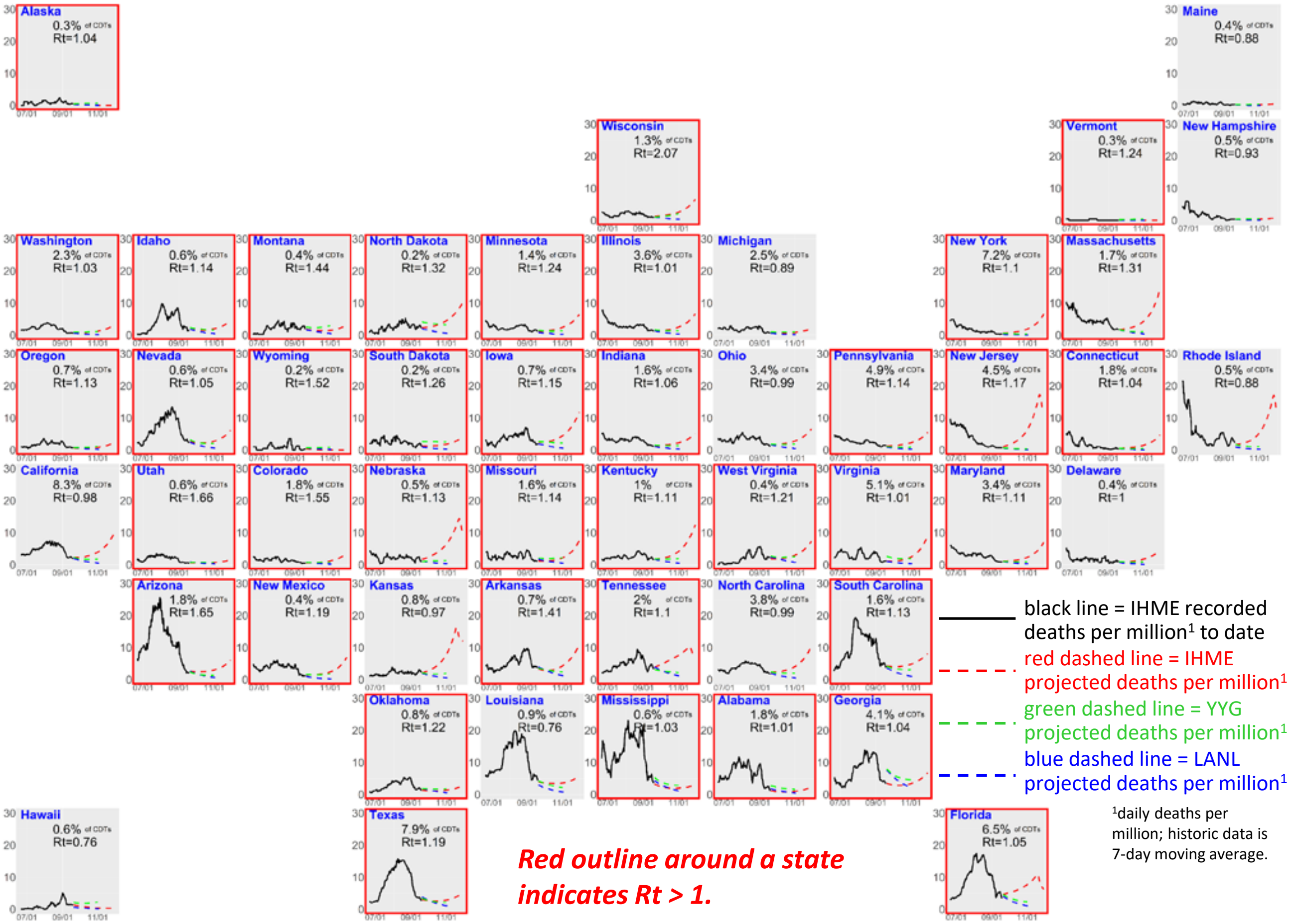
universities now represented a considerable threat to local communities—the communities that traditionally form symbiotic relationships with these institutions.

Based on the dynamics of the disease and the susceptibility of campus environments, many universities operated in a remote learning environment during the latter part of the Spring 2020 semester. However, numerous forces pressured university leaders to open their institutions for in-person learning during the fall of 2020. Universities quickly developed mitigation strategies that included extensive disease testing programs, hybrid learning systems, outdoor learning environments (e.g., tents), wastewater testing programs, and contact tracing systems. Despite these efforts, many universities experienced substantial outbreaks, and some were forced to revert to distance learning after attempting in-person modalities.

This paper presents several modeling and analysis methods used at the United States Military Academy (USMA) to mitigate COVID-19 and provide information to decision makers to enact policies that prevented the spread of the disease. Prevention of infections mattered significantly to support force protection. However, USMA leaders needed to balance the tradeoffs for critical in-person developmental experiences that support the mission of the Academy to educate and train the Army's future leaders. This paper describes analyses that helped achieve a balance in these trades.

2. Modeling and Analysis Methods

Modeling and analysis methods employed to support leader decisions centered on three analytical threads: maintaining situational awareness, predicting USMA-specific impacts, and modeling in support of COVID-19 mitigation strategies.



black line = IHME recorded deaths per million[1] to date

red dashed line = IHME projected deaths per million[1]

green dashed line = YYG projected deaths per million[1]

blue dashed line = LANL projected deaths per million[1]

[1]daily deaths per million; historic data is 7-day moving average.

Red outline around a state indicates Rt > 1.

Figure 1. Historical records and projections derived from the Institute for Health Metrics and Evaluation (IHME), Youyang Gu (YYG) covid19-projections.com, and Los Alamos National Labs (LANL) (IHME, 2020; Gu, 2020; LANL 2020).

2.1 Maintaining Situational Awareness

Awareness of COVID-19 dynamics, based on both empirical evidence from public data and the science of the disease, provided leaders perspective and a basis to support decisions. Analytical products used at USMA that supported situational awareness ranged from simple Bayesian analysis to extensive discrete-event simulation models. Map-based products were particularly helpful since the impact of COVID-19 changed across space and time. An example of an early map-based product is shown Figure 1, depicting the impact of the disease through September 20, 2020. The tile plots in Figure 1 were generated using `ggplot` from the `R` programming language (Wickham, 2016), and the geospatial layout of state tiles was accomplished using the `raster` package from `R` (Hijmans, 2020). The minimal structure of the code to generate a state tesselate plot has been included in the appendix of this article.

Tessellated plots with a geospatial reference, similar to Figure 1, provide leaders with detailed awareness of disease dynamics across space and time. The graphic creates a dashboard of detailed information which is easily updated using web-based data sources and scripts that require minimal updating and maintenance.

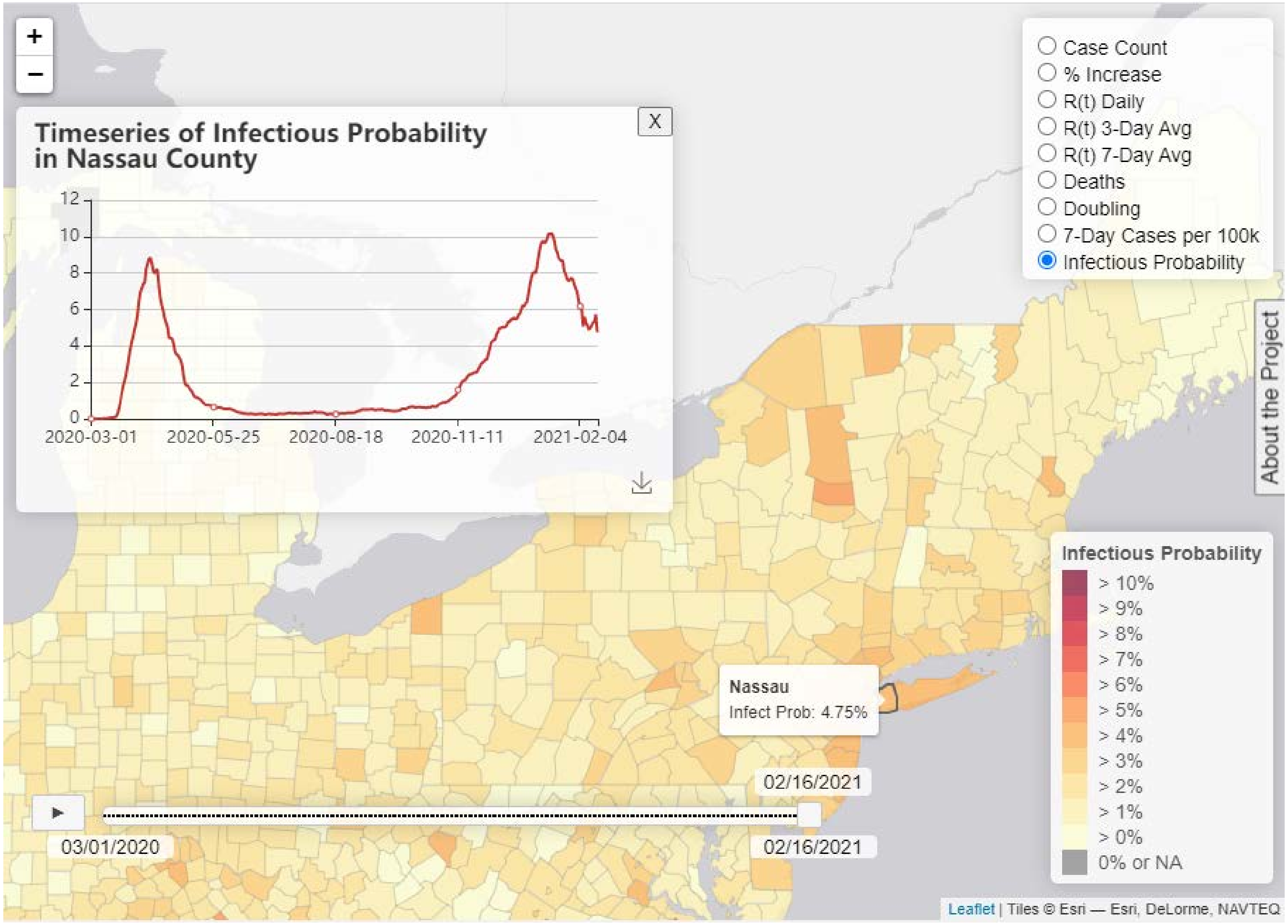


Figure 2. A screen-shot of Kloo's BigMap project, a dynamic county-level web-based interface that provides real-time awareness of COVID-19 dynamics (https://iankloo.github.io/bigmap/).

In addition to the spatio-temporal tile plots shown in Figure 1, a web-based spatio-temporal graphic emerged from this work. The BigMap project, highlighted in Figure 2, provided spatio-temporal COVID-19 dynamics awareness at the county level, for every county in the United States. While the concept of a map visualization of COVID-19 statistics was not unique, the study team found that existing frameworks were missing key features for individual decision making. First, it was important to present statistics on the finest granularity possible with reliable data sources. Second, we needed to account for time to get a sense of the trajectory of the pandemic. BigMap provides individual timeseries graphs for each county and also allows the user to change the date for the entire map at once with a time slider. Finally, existing map projects seemed to focus on case count statistics and/or deaths. Our team found the *effective reproduction number* or R(t) (Nishiura and Chowell, 2009) and *infectious probability* (an internally developed metric measuring the probability of encountering a person currently infectious with COVID-19) to be the most useful tools to inform risk analyses.

2.2 Predicting COVID-19 positivity for returning cadets

USMA released cadets for spring break in mid-March of 2020, the same week that the COVID-19 pandemic emerged as a significant threat. USMA administrators decided to extend spring break, not realizing at the time that this extension would last until July of 2020 for many of the cadets. There was an urgent need, however, to return the graduating class, as it needed to complete requirements and graduate in May of 2020, a critical component of the USMA mission and a statutory requirement. Bringing cadets back to West Point during the pandemic invited the previously mentioned risk—introducing potentially infectious cadets that could spread the disease amongst other cadets and the installation staff and faculty. Mitigating this risk became a focal point for USMA leaders and planners.

A critical question surrounded the decision to return cadets: how many cadets would be COVID-19 positive upon return? Leaders needed to quarantine infected cadets and guard against further spread of the disease. These two objectives hinged upon the number of infected cadets that would return. Fortunately, it was possible to test 100% of the returning population. Cadets that tested positive would remain in quarantine lodging for at least 14 days and would return to duty if symptom-free. Quarantine requirements presented a logistical challenge, and if the positivity was too high, graduation would have to be delayed.

Estimating the number of COVID-19 positive cadets presented an opportunity for Monte Carlo simulation. Coupling our knowledge of cadet locations across the country with disease prevalence created the information needed to build a simple simulation. Estimating regional prevalence of the disease, and projecting prevalence in the future, remains a complicated problem. The prevalence of a disease is the proportion of people currently infected. There were two statistics used to derive disease prevalence: confirmed infections and confirmed COVID-19 related deaths. Both statistics provided an unambiguous signal of disease presence; however, building a prevalence estimate from either statistic is challenging.

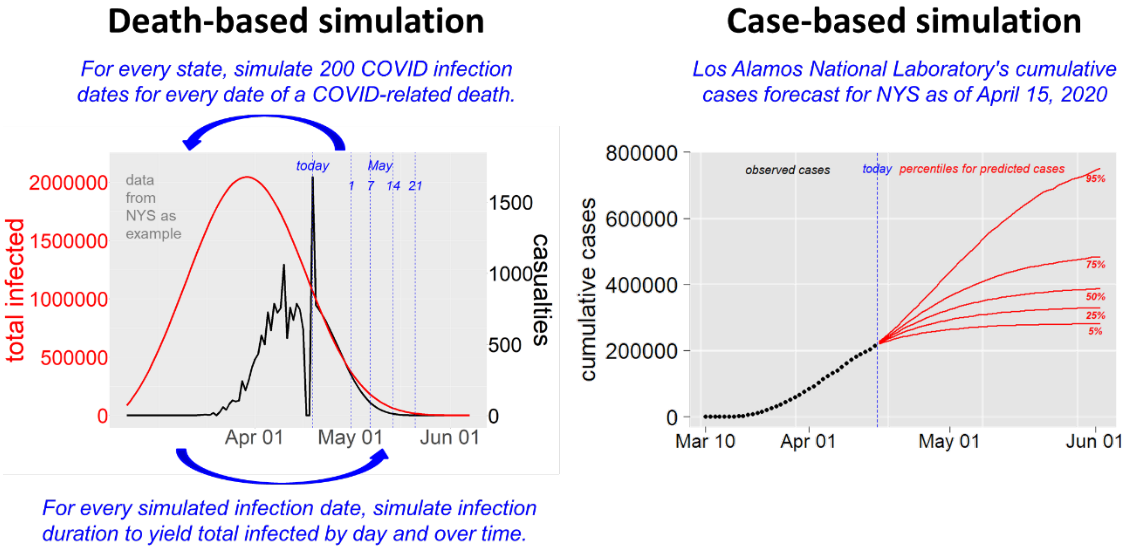


Figure 3. Examples of prevalence projections that supported the Monte Carlo simulations used to estimate the number of COVID-19 positive cadets from the Class of 2020.

Two approaches were taken to build the prevalence estimate. The first approach involved using a projection model from Los Alamos National Laboratory based on confirmed cases (LANL, 2020). We will refer to this as the case-based prevalence estimation method. The case-based method explored various levels of under-ascertainment from confirmed infections. Confirmed infections reflect a fraction of actual infections, and estimates of this fraction during the spring of 2020 ranged between 5% and 90% (Russell et al., 2020). This extreme variation clearly introduces problems with prevalence estimation, but fortunately the LANL modelers took much of this variation into account in building their case-based estimates.

The second prevalence estimation method involved using death-based projections from IHME (IHME, 2020). The death-based prevalence model required estimating the infection fatality rate (IFR). Early studies of the IFR estimated the rate to be between 0.5 and 0.78 (Meyerowitz-Katz and Merone, 2020). The rate used in the Monte Carlo simulation for the death-based prevalence estimate was 0.5 and was based on the early studies of COVID-19.

The LANL model provided a direct estimate of confirmed cases seven weeks into the future. LANL modelers admit the problem of under-ascertainment; however, they remained committed to forecasting confirmed cases in order to maintain a method to validate results. The authors of this paper applied various under-ascertainment levels to explore an estimated realm of possible outcomes. Prevalence estimation from the IHME death projections involved application of the IFR. Given an IFR of 0.5, one COVID-related death casted 200 simulated infections into a previous point in time, randomly distributed based upon reported time periods between infections and deaths, which was estimated with a triangular distribution with a minimum of 5 days, a maximum of 60 days, and a mean of 21 days. Once infections were seeded in the model, the duration of the infections followed a triangular distribution with a minimum of 5 days, a maximum of 42 days, and a mean of 14 days. Fortunately, IHME continued to project deaths into the future since the onset of the COVID-19 pandemic, and this provided a means to estimate prevalence.

Once prevalence was estimated using either the case-based model or the death-based model, a common Monte Carlo simulation framework was used to project the number of infected cadets. Given a state-level estimate for the total infected population on any given day, we calculate the state probability of infection on day i—the estimate of the total infected population on day i divided by the total population, and represent this as $P(infection_i)$. Once we have an estimate for prevalence by day, $P(infection_i)$, for every state, it is possible to simulate the number of infected cadets from every state on every day using a binomial distribution where the probability of success is $P(infection_i)$ and n is the number of cadets in the state. Replicating this simulation hundreds of times, which is a relatively trivial computation, provided interval estimates for the expected number of cadets that would test positive for COVID-19 upon their return to the Academy. For the window of time that the Class of 2020 needed to return to West Point, the case-based model estimated between 1 and 19 positive cases, and the death-based model estimated between 6 and 18 positive cases. The actual number of infected cadets was on the high side of these intervals, but it was contained within them.

The success of this modeling effort created two important dynamics at USMA. First, logistical planners found themselves in a comfortable situation where their planning estimates aligned with reality. Second, the Academy leadership's trust in the modeling and analysis grew. The leaders also understood the value of these modeling efforts as an important planning tool.

2.3 Guiding the Testing Policy

Once USMA leaders decided to resume in-person learning, the development of a COVID-19 surveillance testing strategy emerged as a priority. Through the use of modeling and simulation, USMA leaders and planners developed confidence and committed to a strategy that ultimately protected cadets, staff, and faculty from a widespread COVID outbreak. The model will be presented in summary with emphasis on concepts. The source code and instructions for running the model are available at https://github.com/evangelistapaul/COVID_testing_perl.

To explore the decision space related to testing cadets and understand the potential outcomes across this space, the authors developed a custom computer simulation model that represents the typical dynamics of cadet life during an academic term. These dynamics include time spent in a barracks room, company area, team or club practice area, and classrooms or instructional spaces. As cadets pursue activities across these spaces, mixing and interactions between cadets occur, presenting opportunities for COVID-19 to spread given an infection exists. Administrators hold several policy levers capable of detecting and preventing disease spread. The most powerful levers include testing protocols and activity prohibitions. To understand the effect of various policy configurations, the authors explored an efficient design of experiments (DOE), an experimental construct that systematically and intelligently spans the decision space. The simulation model methodology and simulated COVID-19 testing strategies seek to minimize the number of tests and the number of infections.

Results of the computer simulation model and the DOE show that testing only symptomatic cadets will not protect against an outbreak of COVID. Promising testing strategies include adaptive testing that results in 100% testing of close contacts of a symptomatic cadet that tests positive for COVID-19. Close contacts include cadets in the same company, team, or instructional section.

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2.3.1 Testing Simulation Model Methodology

The simulation model centers on three activity categories for every cadet: company activities, educational activities, and athletic or club activities. As cadets spend time in each of these activities, they mix and interact broadly amongst each other. A cadet with a COVID-19 infection has many opportunities to spread the infection given the dynamic nature of a cadet's typical day. The presented model seeks to create a reasonable representation of these dynamics. All models are abstract representations of reality and rely on simplifications and assumptions. Simplifications in this model exist where it is believed that these simplifications do not invalidate results. Many simplifications will be apparent in the discussion of the basic model construct that follows, and key assumptions will be explicitly stated in a future section.

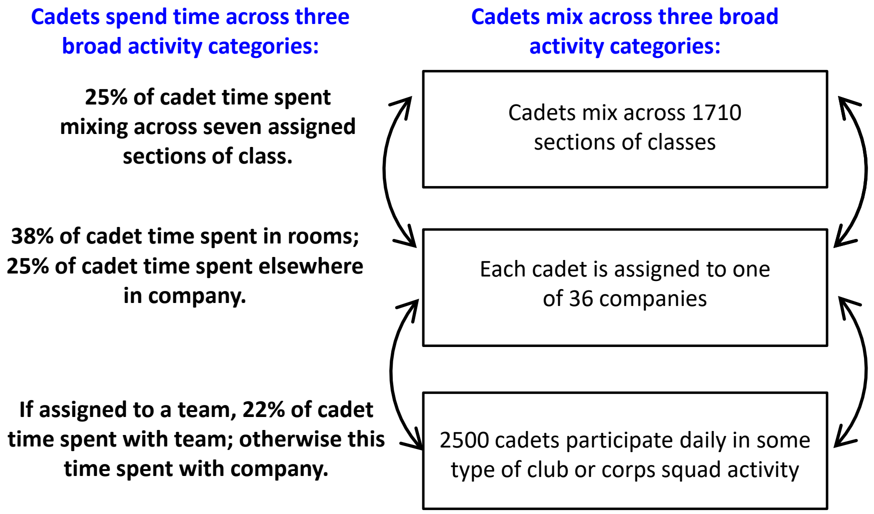

Figure 4. Testing simulation model concept.

The basic model construct follows. Every cadet is assigned to one of 36 companies, with 122 cadets in each company. Companies consist of upper-class cadets (juniors and seniors) and under-class cadets (freshmen and sophomores). Rooms are expected to average 2.5 cadets each, with upper-class cadets receiving priority on 2-person rooms. Cadets spend 38% of their time in their rooms, including sleep, and they spend 25% of their time elsewhere in the company. Cadets also spend 25% of their time mixed across seven assigned sections of class. These seven sections represent five academic classes, one military science class, and one physical education class. One-half of the sections include only upper-class cadets, and the other half includes only under-class cadets. Cadets also spend time in corps squad (i.e., NCAA sports team) or club activities. It is assumed that 2,500 cadets participate in a daily team or club activity, with 50 cadets in each of 50 teams or clubs. If cadets do not participate in a team or club activity, this time is spent with their company. The model is time-based, using weekly iterations. Opportunities for disease spread occurs within a room, company, section, or team/club.

The key assumptions of the model follow:

- The period of analysis is 16 weeks (length of a typical semester).
- The model starts with two randomly infected cadets.
- 100% testing of cadets occurs prior to the start of every semester (hence only two positive cadets as a starting condition).
- Infections last two weeks.
- Infected cadets may infect up to 1 other cadet per week.
- Infection opportunities occur randomly based upon the distribution of time spent in each activity category.
- Immune cadets exist, either as a function of starting conditions or recovery from an infection.
- USMA knows which cadets are immune, and it does not test them (critical to reduce test costs).
- If an infection opportunity targets an immune cadet, the opportunity fails and does not persist.
- 70% of infected cadets are asymptomatic.
- Asymptomatic cadets spread the disease at the same rate as symptomatic cadets.
- Symptomatic cadets receive a PCR test.

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- PCR sensitivity (true positive rate) is 95%.
- PCR specificity (true negative rate) is 99%.
- After a period of analysis, the conditions, including the number of infected cadets, reset.

Beyond expected non-pharmaceutical interventions (NPI), USMA leaders possess three primary policy levers in the model, namely:

1) Random testing: Select *n* cadets from the Corps to test randomly each week. This includes the option to test n=4,392 cadets or 100% of the Corps.
2) Adaptive testing: Test a proportion of the company / team / class sections associated with a PCR positive cadet.
3) Company lockdown: After surpassing an infection threshold in the Corps, cadets will be locked down in their company areas and rooms. Within the model, this restricts transmission to within company only, isolating spread.

2.3.2 Testing Simulation Model Results

Initial results showed that the mixing and common dynamics of the cadet population created susceptibility for an outbreak if prudent testing measures and controls were not implemented. We expected a small proportion of our cadets to be symptomatic if infected, which we estimated at 30%. To date, we have been unable to validate this estimate, however several studies indicate that the estimate is reasonable. Symptoms provide a first line of detection against COVID, and without symptoms the disease remains hidden without a test. If the testing policy only includes cadets that present symptoms, we are likely to miss asymptomatic cadets and create conditions for an outbreak. For this reason, various surveillance strategies are recommended. The model assumes that USMA has awareness of the immune status of cadets via antibody testing. This is an important assumption that reduces overall testing costs.

Visualization of results significantly helped with model verification and interpretation of various policies. The visualizations help us verify that the model runs as intended and enables a more complete interpretation of results. A series of shaded tiles, representing the cadet categories of activities, serves as one of the primary visualization techniques. An example of one week of simulation results and a brief explanation of the graphic has been included in Figure 5. Figures 6 and 7 show the results from two different strategies: symptomatic testing only and adaptive testing. The adaptive testing policy showed the most promise in the simulated results.

USMA ultimately followed recommendations from the model related to the random sampling method and followed a modified version of the adaptive sampling. However, the most significant result from the simulation did not relate to any of the statistical analysis or nuanced simulation results. The most significant result emerged as a productive dialogue that used the simulation to build confidence in a testing strategy, iterate on some alternative testing strategies, and ultimately understand the realm of possible outcomes related to the spread of the disease. The simulation model supported the implementation of a testing strategy that allowed USMA to minimize disruption to mission requirements.

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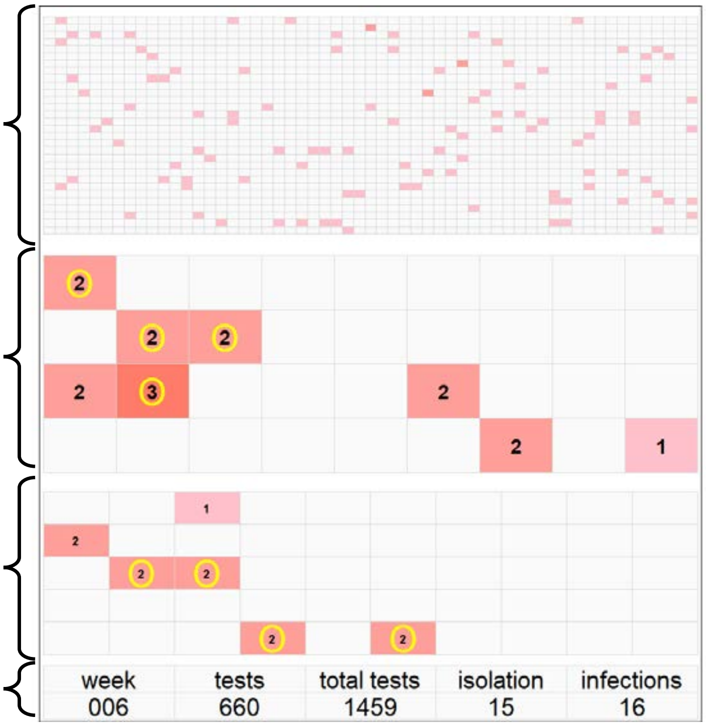


Cadet sections: Pink represents 1 infection, and royal red represents 5 or more. The same scale applies for company and club/team cells.

Cadet companies: The shading follows from above. The number represents currently infected cadets in the company. Isolated cadets are removed from this count. A circle represents a company-wide (100%) test during the associated week based on detection of infection.

Cadet teams/clubs: The coloring and notation formats are identical to the companies.

This table shows the simulation week, tests that week, cumulative tests to date, number of isolated cadets, and total current infections.

Figure 5. COVID-19 testing simulation visualization tool.

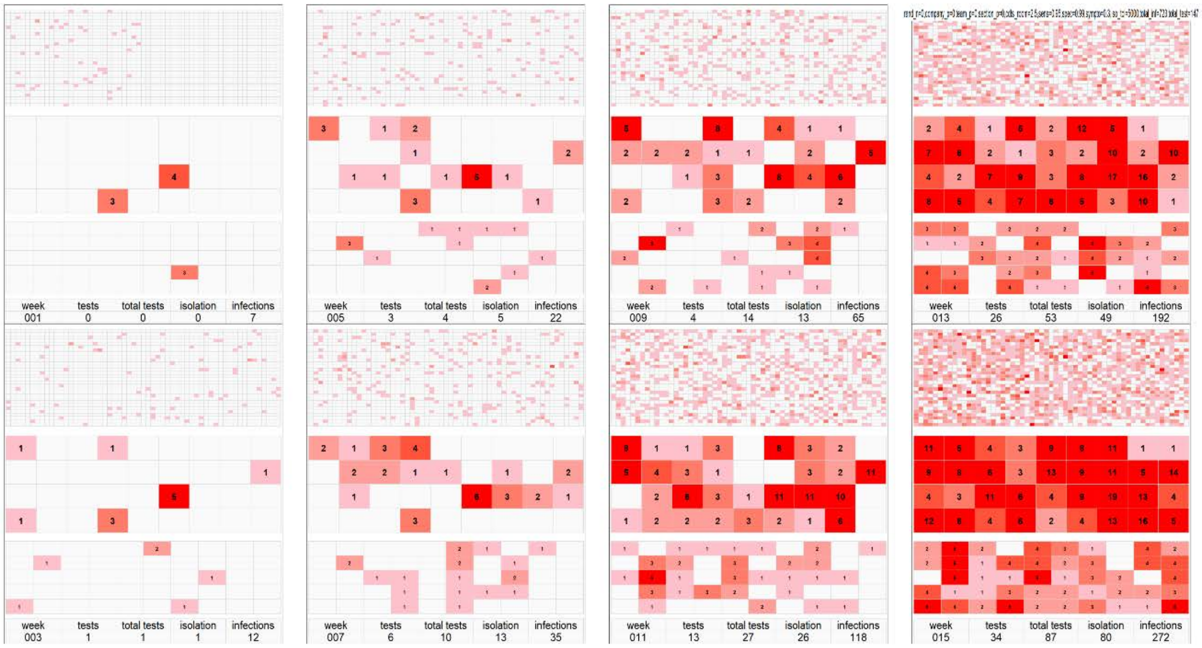


Figure 6. COVID-19 visualization tool showing simulated infections with symptomatic testing only.

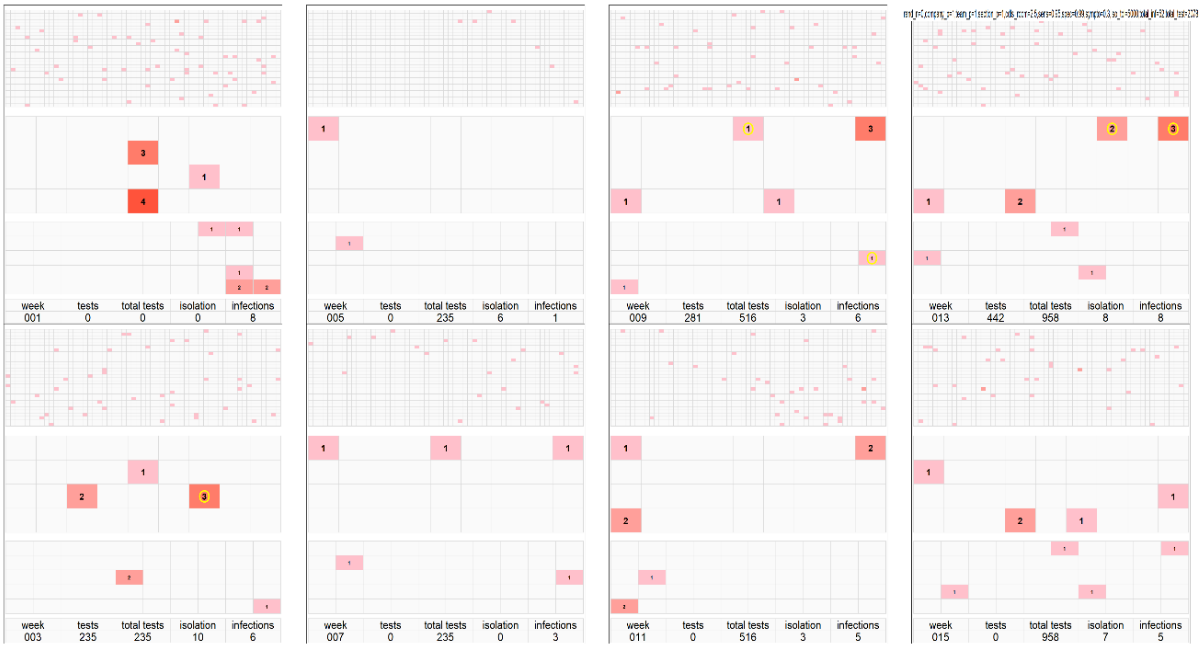
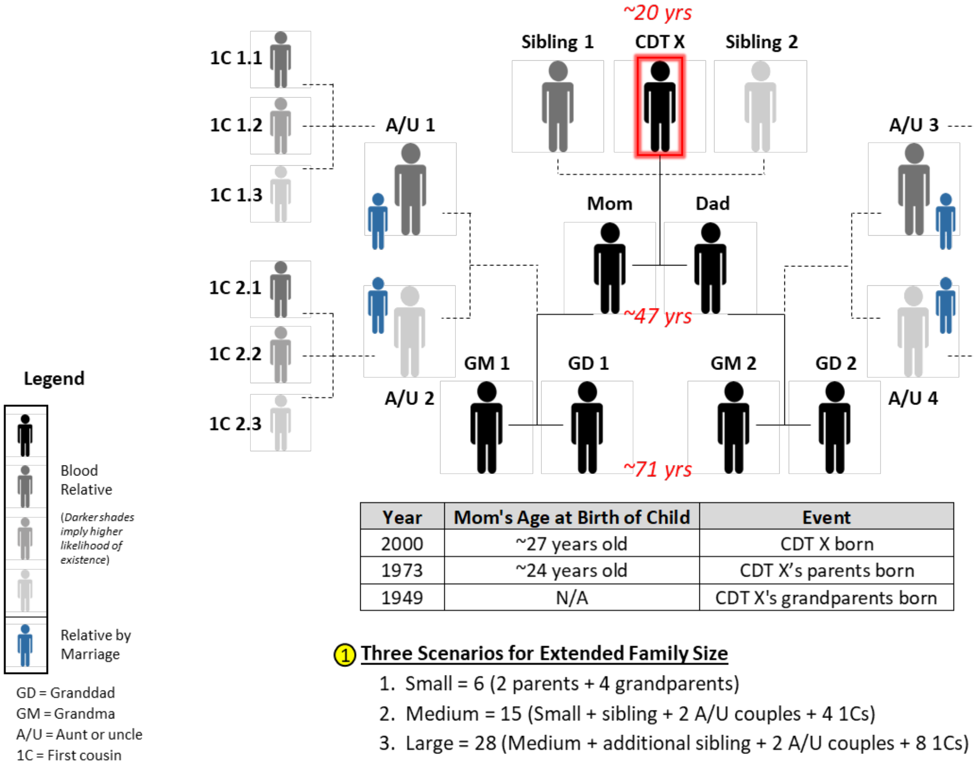


Figure 7. COVID-19 visualization tool showing simulated infections with adaptive testing.

2.4 Assessing the Potential Psychological Impact of COVID-19 on Cadets

In addition to guiding the development of USMA’s testing policy, the authors provided the Academy’s leadership with estimates for the probability that a cadet would be dealing with the most significant mental stressor associated with the pandemic – the death of a loved one or friend. To this end, Figure 8 represents a cadet’s extended family, where a hypothetical cadet – dubbed “Cadet X” (CDT X) – is assumed to be 20 years old. Born in 2000, a CDC National Vital Statistics Report (Matthews and Hamilton, 2002) suggests CDT X’s mother was roughly 27 years old at the time of his delivery. Based on the same report, in 1973, when CDT X’s mother was born, his grandmother would have been about 24. Assuming CDT X’s parents and grandparents are still alive, CDT X’s smallest extended family is six people. If we further apply the US fertility rate of roughly two births per woman, CDT X gains a sibling and two aunts or uncles, and if the aunts or uncles get married and have children, CDT X adds four first cousins, increasing the size of his extended family to 15. Finally, if we add a third child per mother, CDT X adds two more aunt and uncle couples and eight first cousins, totaling 28 extended family members. As seen near the yellow circle with a 1 inside it, we refer to these extended family scenarios as small, medium, and large.



Year	Mom's Age at Birth of Child	Event
2000	~27 years old	CDT X born
1973	~24 years old	CDT X's parents born
1949	N/A	CDT X's grandparents born

① Three Scenarios for Extended Family Size

1. Small = 6 (2 parents + 4 grandparents)
2. Medium = 15 (Small + sibling + 2 A/U couples + 4 1Cs)
3. Large = 28 (Medium + additional sibling + 2 A/U couples + 8 1Cs)

Figure 8. Scenarios for the size of a typical cadet's extended family

Moving to CDT X's acquaintance network, we leverage the results from two papers that estimate the average number of people a person knows. The first article, written by Bernard et al. (2001), estimates an average network size of 290, a number they note is a minimum but "demonstrably correct in many cases" (p. 21). The second article, written by McCormick et al. (2010), applies sophisticated statistical techniques to correct several issues when estimating the size of one's personal network, including one's ability to remember the names of the people one knows. Based on their analysis, the average network size is 611. We will refer to these acquaintance network scenarios as small and large.

We are now ready to estimate the probability CDT X knows someone who has succumbed to COVID-19. Adapting an intuitive result from Moody's 2005 paper "Fighting a Hydra: A Note on the Network Embeddedness of the War on Terror," we apply the equation $p = 1 - (1 - d/t)^c$, where *d* represents the number of COVID-19 deaths, *t* is the size of the population the *d* deaths are embedded in, and *c* is the size of CDT X's network. Applying algebra of events and substituting in age-based death statistics and population numbers from the CDC (2021), total deaths from USAFacts (2021), and network sizes from the previously discussed scenarios yielded sobering results. For example, as of January 5, 2021, in a classroom of 18 cadets there was a 99.5% chance that at least one cadet had lost an acquaintance to COVID-19. Similarly, in a cadet company of 125 cadets, there was more than a 90% chance that at least one cadet had lost an extended family member, and we expected roughly 32 to have lost an acquaintance. Figure 9 visually communicates the latter results, and it was used to emphasize the significant and expanding psychological impact of the pandemic on the cadets.

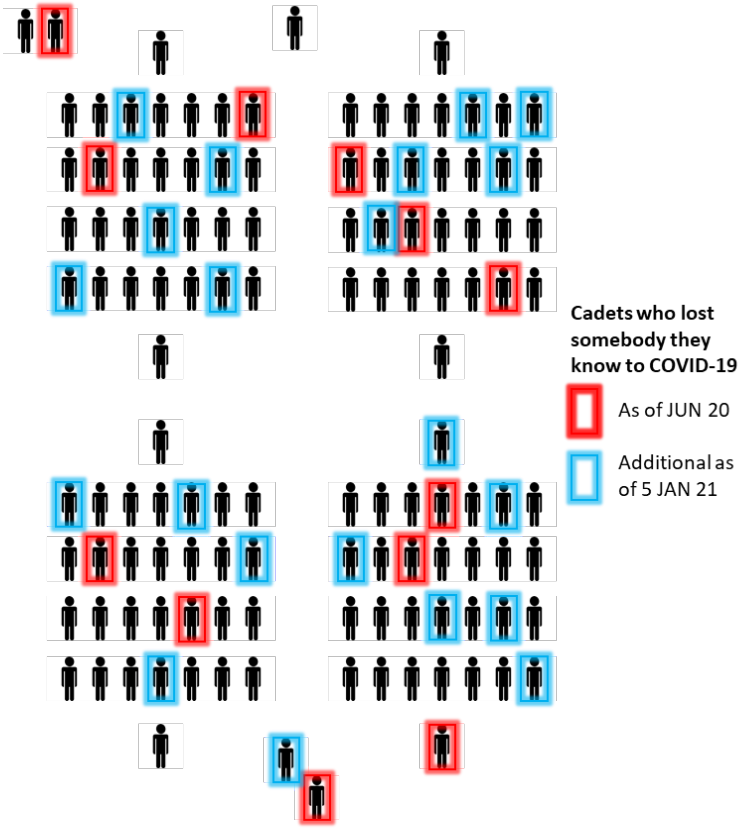


Figure 9. Estimated number of cadets in a cadet company who had lost an acquaintance to COVID-19 as of June 2020 and January 5, 2021

3. Conclusion

In March of 2020, scientists and health officials sounded alarms and validated the globe-shaking severity of the COVID-19 disease. Leaders at the United States Military Academy responded in a manner familiar to any service member that has been involved in a military contingency operation: planning ensued, a new task organization formed, staff responsibilities emerged, and an order was written and published. Military leaders have consistently relied upon upon military operations research practioners to support military decisions with science, logic, and analysis (Bates et al., 2015). Consistent with historical precedent and from the earliest days of USMA's response to COVID-19, leaders recognized the importance of integrating modeling, analysis, and logic deduced from science to address the novel decision problems presented by the pandemic. The results discussed in this paper present some of the modeling and analysis that supported important decisions at USMA.

Most of the methods used to support decisions did not require new discoveries or the implementation of cutting-edge analytical methods. However, the analysis did require two important intellectual ingredients: deep contextual understanding of the problems under investigation and broad competency in modeling and analysis methods that had potential to address these problems. As decision makers grew increasingly confident in the availability of these two ingredients, trust emerged, and decisions underpinned by analysis became an important part of the overall USMA response.

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5. Appendix

State Tessellation Plot

```
#load needed packages
lapply(c("ggplot2","raster","png"), require, character.only = TRUE)

#the loop below contains the detailed plotting script for each tile
for(i in 1:length(state.abb)){
  fname = paste(state.name[i],".png",sep = "")
  png(fname)
  p <- ggplot() + ggtitle(state.abb[i])#build tile plot for each state
  print(p)
  dev.off()
}

#each of 50 states will be aligned in a specific row and column,
#creating the geospatial layout
state_row <- c(7,1,6,6,5,5,4,5,8,7,8,3,3,4,4,6,5,7,1,5,3,3,3,7,5,3,5,4,2,4,6,3,
                      6,3,4,7,4,4,4,6,4,6,8,5,2,5,3,5,2,4)

state_col <- c(7,1,2,5,1,3,10,10,9,8,1,2,6,6,5,4,6,5,11,9,10,7,5,6,5,3,4,2,11,9,
                      3,9,7,4,7,4,1,8,11,8,4,6,4,2,10,8,1,7,6,3)

png("myMap.png", width = 11000, height = 8000, units = "px")
dev.off()
myMap_raster <- readPNG("myMap.png")
png("tesselate.png", width = 11000, height = 8000, units = "px")
plot.new()
rasterImage(myMap_raster,0,0,1,1)

row_max <- 8
col_max <- 11
state_row <- (row_max+1) - state_row

for(i in 1:length(state.name)){
  image_fname <- paste(state.name[i],".png",sep = "")
  img<- readPNG(image_fname)
  raster_x_min <- (state_col[i]-1)/col_max
  raster_y_min <- (state_row[i]-1)/row_max
  raster_x_max <- raster_x_min + 1/col_max
  raster_y_max <- raster_y_min + 1/row_max
  rasterImage(img, raster_x_min, raster_y_min, raster_x_max, raster_y_max)
}
dev.off()
```

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