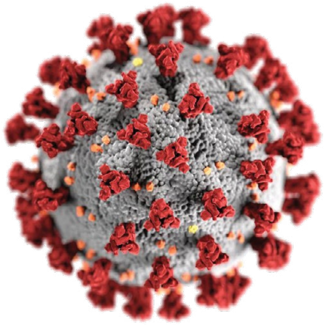

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Toward a Science-Based Management Approach to Stealth Threats: A Case Study Using The Novel Coronavirus

By Thomas J. Mackin

Abstract

The modest early stage impact of slow-moving threats makes it easy to underestimate their impact. These threats grow and evolve unnoticed until reaching dramatic impacts in both scope and scale. Since slow-moving threats can grow to catastrophic magnitudes that threaten our very survival, they are more aptly identified as 'stealth threats'. The geographic range of stealth threats combined with their impact across multiple sectors impose potentially existential costs to the Nation. As such, we must re-focus the mission of DHS to identify and combat stealth threats. When dealing with stealth threats, there is no instinctive approach that can relate the facts of today to the consequences of tomorrow. Preparing for, and responding to, stealth threats requires a commitment to validated science-based models that predict the impact of the threat. We illustrate these points, and the role of mathematical modeling in emergency response, using the SIR growth model of epidemics applied to Covid-19.

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Introduction

The Coronavirus pandemic makes clear that natural catastrophes present a much larger threat than non-state terrorism. Furthermore, our response is hamstrung by both social-media disinformation as well as the 'slow moving' nature of these threats. In a report from the United Nations Office for Disaster Risk Reduction Staupe-Delgado[1] elaborated upon six key features of slow-moving threats, reproduced here:

1. Early warning technologies do not necessarily secure proactive response to slow-onset disasters due to political and practical obstacles in the way of timely action.
2. Generic all-hazards DRR strategies, while best practice in the context of sudden-onset disasters, are generally inappropriate for the management of slow-onset disasters.
3. Slow-onset disasters often fall outside the mandate of specialized disaster management agencies.
4. The geographically dispersed nature of slow-onset disaster impacts reduces their perceived severity and political salience.
5. The concept of disaster is often equated with sudden-onset disasters.
6. The vast majority of disaster research and theory revolves around sudden-onset disasters, generally the largest and most destructive historical events.

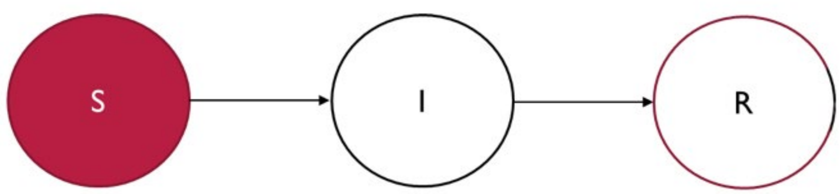
The slowly emergent nature of such threats makes them less urgent to the general public. As a result, threats emerge and grow outside the priority-box of prevention planning until reaching a tipping point of exponential risk. The magnitude of consequence posed by these slow-moving threats requires a name commensurate with the consequences, which is why I propose the more insidious label of 'stealth threats'. This characteristic of modest early stage impact makes it easy to underestimate the catastrophic nature of stealth threats. Our collective lack of action, described by Robert Gifford (Gifford, 2011)[2] as 'The Dragons of Inaction," is rooted in psychological barriers to slow moving threats. Put simply, our evolution programmed us to respond to threats of immediate impact. Yet, though we have progressed beyond an environment that presents daily threats to life, we have not adjusted our threat- mentality. Since stealth threats can grow, if unchecked, to tipping points of enormous magnitude[3], we must re-focus the mission of DHS to identify and combat these emerging threats. These are the so-called 'fat tail' or Black Swan events discussed by Talib.[4] The geographic range of stealth threats combined with their impact across multiple sectors imposes potentially existential costs to the Nation.

Certain natural hazards, such as pandemics, disinformation, mass migrations, food and water shortages, and climate change, are compounded by the inherent delay time between the onset of the threat and the experience of significant consequences. It is because these hazards lack an immediately significant consequence that they engender a false sense of security. Worse, the lack of immediate consequence subjects many of these threats to outright dismissal: think climate change as well as the current pandemic. A large number of social-media postings, news reports, radio personalities and government officials have deemed both climate change and the Coronavirus a hoax. In the case of Coronavirus, the disinformation is so pervasive to have earned it a special name: "infodemic." [5] This disinformation landscape makes it especially difficult to mount a proper response. If there is anything to be learned from the Coronavirus pandemic it is that planning and response must be based in science *and* believed by the public. There is no instinctive approach that can relate the facts of today to the consequences of tomorrow. Preparing for, and responding to, emerging stealth threats requires a science-based approach that builds predictive models of the phenomenon. These models rely on fundamental physics, chemistry, and biology to generate predictions of the future. Such models are analogous to weather forecasting, a complex science that enjoys widespread public support. Weather models predict the future using complex computer simulations rooted in sophisticated mathematical models, presented using forecast graphics that are easy to understand and widely acceptable. Analogous efforts are underway in the current pandemic, but have failed to achieve the same level of public support.

Even though nearly every aspect of our modern society depends upon scientific principles to enable their function, Barry, Han and McGinty[6] report that nearly half of the U.S. adult population does not trust science. Yet, two of the keys to emergency response are[7]: 1) identify potential emergencies and, 2) develop a plan. Clearly, this requires forecasting, which is the science of predicting future events. The most broadly applicable tool for this is Systems Dynamics[8], a field of study created by Jay Forester in the 1950s[9]. Anyone interested in developing sound models to predict the outcomes of response policies should read Forester. The goal of the present article is to introduce the reader to this field using the example of a systems dynamics model applied to the Coronavirus pandemic.

Mathematical models of epidemic growth can be used to demonstrate the broader utility of model-based predictions for emergency response planning. From the emergency response perspective, it is important to note that these models do not have to be 100% accurate to be useful as a planning tool. All they must do is predict the proper course of events and establish worst-case outcomes to enable staging and preparation. For the reader interested in a comprehensive overview of a broad range of epidemic models, see, for instance, Chowel, et. al.[10] From the planner's perspective, the well-established SIR model[11] offers a sufficiently predictive method to show how the growth of a pandemic is affected by stay-at-home orders, the wearing of masks, vaccinations and quarantine. Armed with these models, planners can make informed decisions concerning opening and closure plans to manage the load on medical facilities while buying time to develop treatments and vaccines.

The SIR model, Figure 1, includes three key components: (1) The population of individuals who are susceptible to infection, S; (2) The number of infected people, I that are circulating among the susceptible population, and (3) those who are removed from the population, R, either through death or recovery from the illness. Each of these populations is represented by a circle in Figure 1 where each circle represents a bucket that holds the number of individuals in each category. At the start of the epidemic, the population is not infected and resides entirely in the S-bucket. We begin the model by introducing an infected individual into the susceptible population, then use the related equations to predict how the number of infections will grow over time. Though this is a rather simple approach to modeling the growth of infections, it works remarkably well. The graphic, alone, provides a simple visual way to understand how the epidemic is influenced by the size of the population and the numbers of infected and recovered individuals.



$$\dot{S} = -\frac{\beta}{N} \cdot S \cdot I \qquad \dot{I} = \frac{\beta}{N} \cdot S \cdot I - b \cdot I \qquad \dot{R} = b \cdot I$$

Figure 1: The simple SIR model consists of three basic populations: the population of people susceptible to the virus, S, the number of infected people, I, and the number who have either recovered or died, R. Changes in the numbers in each category are represented by the equations below each circle.

The fundamental problem of epidemiology is to understand how the populations in the S, I and R buckets are changing over time. The rate at which these numbers change is indicated by $\dot{S}, \dot{I}, and\ \dot{R}$, where the dot above the symbol indicates a rate of change. Since we generally compile and report daily cases, all of these changes are daily rates of change. In an epidemic, people move from the susceptible bin, *S*, to the infected bin, *I*, and finally to the removed bin, *R*. To predict the number of people in each category, we must know the probability of catching the disease when exposed to an infected individual, □, and the probability of recovery from the disease after being infected, ***b***, as well as the total size of the starting population, ***N***. The parameters β and ***b*** calibrate the model to the current pathogen. The equations below each bin in Figure 1 are the standard equations for the SIR model.

Using this simple model, we can calculate the number of infections over time for a particular population, N, if you can measure the transmissivity, □, and the recovery term, ***b***. This is where the model needs data so one can determine these important parameters. As such, we can't run predictive models in the first weeks of a pandemic because we need to measure the number of infections as well as the number of people who have recovered or died. In models calibrated by the author, the South Korean data was used to fit the SIR model to the measured number of infections, allowing an experimental measure of the parameters □ and ***b***. Figure 2 shows the resulting SIR model predictions for the United States, using □ and ***b*** from South Korea, and starting the model with 1 infected person on January 20th of 2020. It is important to state that these model predictions presume that <u>no mitigation</u> measures would be taken to control the spread, representing the case of free spreading of the infection. It is also worth noting that these results were calculated using an Excel spreadsheet, a program that is readily available to any and all responders/emergency planners. The initial runs of the SIR model predicted 2.16 million deaths, consistent with the 2.2 million deaths predicted by the Ferguson group at Imperial College[12]. Far from being wrong, these jaw dropping numbers motivated the lockdowns that successfully suppressed the number of infections. Unfortunately, rather than cheering this success, certain public figures maligned the models as unhinged warnings that the sky was falling.

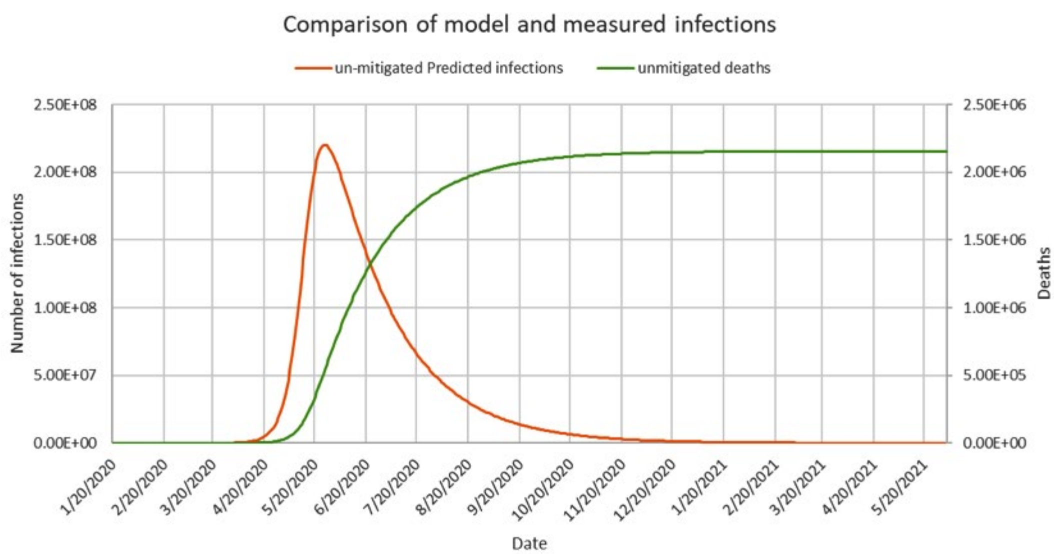


Figure 2: The SIR model allows calculation of daily infection and mortality numbers.

Aside from numbers, though, a good basic model provides a clear understanding of how one can manage epidemics. It does so by offering a prediction of the future based upon current conditions. If you can lower the transmissivity, □, you will reduce the number of people who become infected. The vectors of infection include touch transfer to the nose, eyes and mouth or through inhaling virus-laden respiratory droplets. To avoid touch transmission through fingers to face, we wash our hands. To prevent inhaling virus we must avoid sharing breathable air with infected people. This means you either stay away from those who are infected (social distancing or self-quarantine) or you wear a mask that is capable of filtering out the respiratory droplets. Outdoor interaction, if distanced, dilutes the concentration of potential virus by mixing respiratory droplets with large volumes of non-shared breathable air, reducing the need for masks. We can show these effects by plotting the SIR model with different values of transmissivity (Beta=0.21, 0.10 and 0.08), Figure 3. The model shows two important effects from decreasing transmissivity: first, the infection curve is pushed out in time and, second the maximum number of infections decreases.

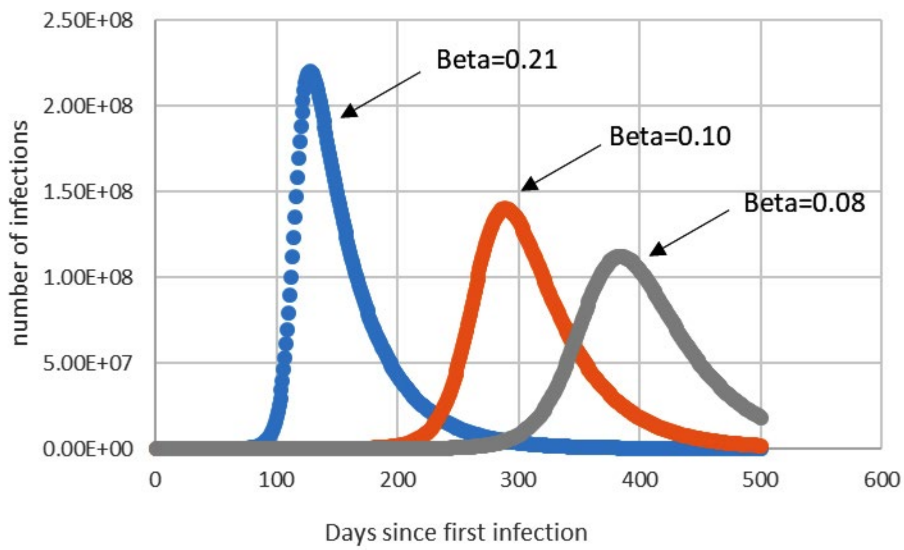


Figure 3: decreasing transmissivity either by wearing a mask and/or social distancing reduces the peak.

We use the model to measure the effect of self-quarantine by reducing the size of the susceptible population, S. Since this population is reduced, the number of potential infections is likewise reduced. Again, the simple model captures the effect and allows us to model the results. Figure 4 shows how a 60-day lock-down with 70% compliance changes the infection curve. In this case, the lock-down was initiated on day 106 and kept in place for 60 days. The black curve shows how the un-mitigated curve is 'flattened' with lock-down. Notice, however, that when the lock down has ended and if there is still virus circulating, then the infections renew their aggressive growth, but to a lower peak number. The models show that a lock-down is a temporary pause in epidemic growth intended to buy time for increasing preparedness and testing. The minute it is lifted, the epidemic cycle starts anew.

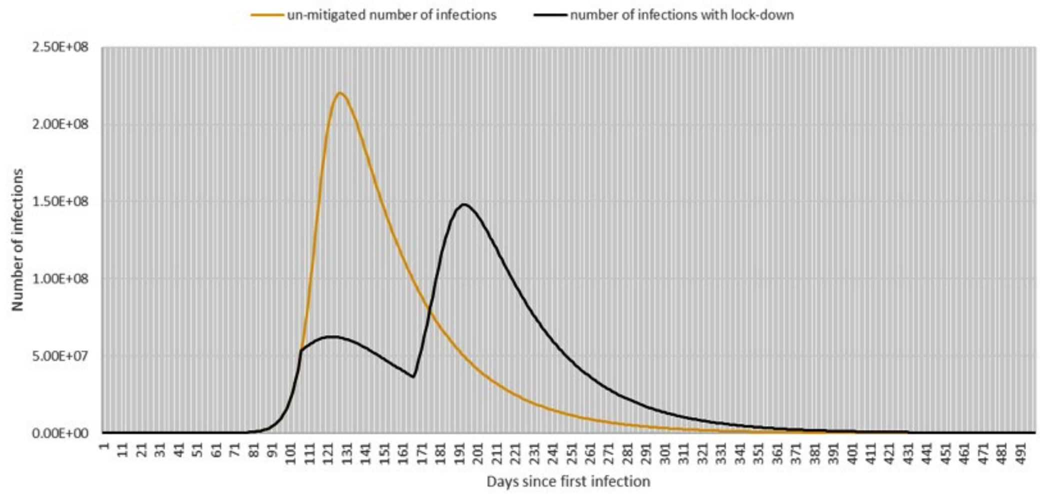


Figure 4: Lockdowns, black curve, flatten the curve during the duration of the lock down.

The single most effective method, short of vaccines, to limit epidemic growth is to identify and quarantine those who are infected. The number of new infections per day is given by the following equation:

$$\dot{S} = \frac{\beta}{N} \cdot S \cdot I \qquad (1)$$

In order for the infection to grow, we must have infected individuals circulating among the uninfected. If we were able to test and quarantine all infected people, *I*, we could keep them from circulating among the susceptible population, *S*. In terms of the model, it means that *I*=0 in Equation (1) and the number of newly infected people would then be zero. That means we could stop entirely the growth of infections if we could test and identify every person who was infected. This is what testing, contact tracing, and quarantine can accomplish and is precisely why so many countries have dramatically outperformed the United States. Unfortunately, the U.S. has not adopted this approach as a national strategy and, until we do, absent a vaccine, we will lose the battle.

It is admittedly impossible to identify and quarantine ***all*** infected people. However, we can explore how profound the effect is by simply looking at the model, with an aggressive testing program that identifies and quarantines 10% of all infected individuals. Results of such a model are shown in Figure 5, where a dramatic drop in the number of infections has occurred. The effectiveness of this approach is precisely why so many people have been pressing for testing…it allows us to identify and isolate infected individuals and remove them from circulation.

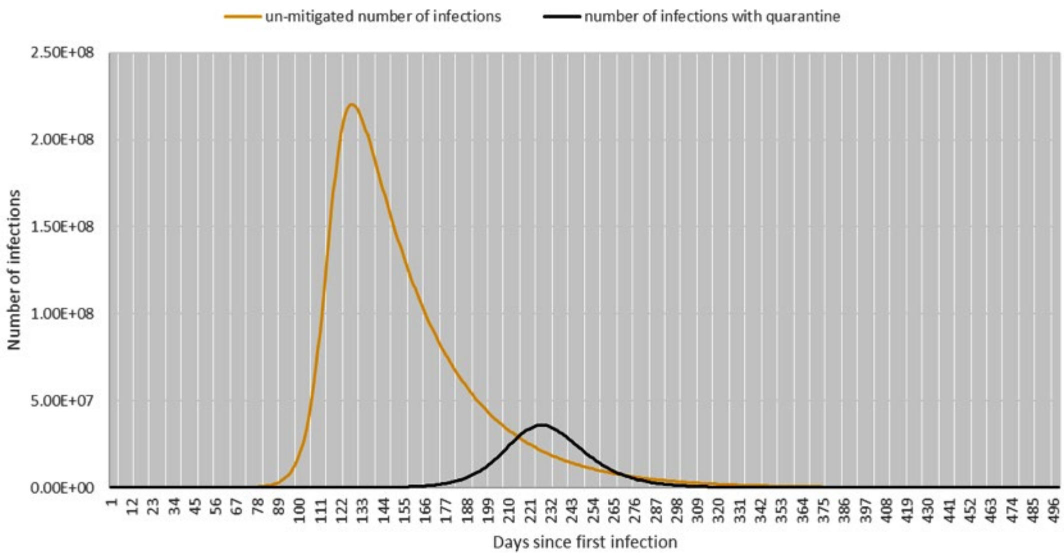


Figure 5: Plot of infection curves comparing unmitigated (yellow) to quarantine of 10% of all infected individuals. Quarantine of infected individuals is a very effective approach to reducing the impact of a pandemic.

Conclusion

It is worth emphasizing that the goal of risk management is to *predict* the future. This idea is not new or radical. We do this by understanding the science of the problem at hand and building models to predict future outcomes. Those models inform prevention and response actions, based upon key parameters in the model, to mold the future into a more palatable outcome. If the actual numbers fall short of the predictions, we have likely implemented successful strategies to decrease the consequences. It does not mean that the model is bad; it means that we have changed the inputs to the model and, therefore, changed the outputs. This, too, is an important aspect of modeling and planning that must be communicated to the public. The short of it is this: our citizens must believe in the actions we take and they must trust that those actions are in the public interest. Over the next 20 years our nation will face a large number of stealth threats. Identifying and planning for these threats is the precise wheelhouse of emergency management. We need to carve out priorities for long-term, slow-moving threat management to avoid future disasters, and we must develop ways of communicating those plans and actions to the public using forecasting methods that they can trust. In short, we must embark on a new effort to ensure scientific integrity and believability, speaking about it whenever possible to ensure public understanding. Furthermore, we must assure that any of our short-term response actions do not derail long-term planning.

About the Author

Tom Mackin is Professor of Mechanical Engineering at the California Polytechnic State University in San Luis Obispo California, Adjunct Professor in the Center for Homeland Defense and Security at the Naval Post Graduate School, former Chief Science Officer at Synbotics, Inc., and founding member of the Board at Mission Street Manufacturing. He received his Ph.D. in Engineering Science and Mechanics from Penn State in 1991. From 1991 to 1993 he worked as a research engineer in the Materials Department at UC Santa Barbara. In 1993 he joined the faculty in Mechanical and Industrial Engineering at the University of Illinois. From 2002-2003 he served as an ASME Executive Office Fellow in the White House Office of Science and Technology Policy, where he served as a technology policy analyst and White House Liaison to the National Nanotechnology Initiative, and White House Liaison to the Networking and Information Technology Research and Development program. In 2004 he became the Founding Director of the Illinois Homeland Security Research Center, and an affiliate faculty member in the Arms Control, Disarmament and International Security program at the University of Illinois. In 2005 he was hired as Chair of the Mechanical Engineering Department at Cal Poly. In 2008 he co-founded the Center for Collaborative Engineering Research and Education (CCERE) with UCSB, and the Center for Renewable Energy and Alternative Transportation Technologies at Cal Poly. He was product development lead and project manager on four start-ups, served as on-screen and technical expert for the Discovery Channel show "The Colony", and currently serves as engineering consultant for the Small Business Development Center and the Center for Innovation and Entrepreneurship in San Luis Obispo. He may be reached at tmackin@calpoly.edu .

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