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Utilizing Covid-19 Models In Humanitarian Crisis Settings

Duane Barksdale
dbarksdale95@gmail.com

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Duane Barksdale

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Yale School of Public Health

Primary Reader: Robert Heimer, PhD

Secondary Reader: Gregg Gonsalves, PhD

Abstract

Since the emergence of the COVID-19 pandemic in late 2019, several researchers and decision-makers have turned to statistical modeling to inform predictions of the severity of the burden of infection and disease in various settings. While it is understood that no model can perfectly describe the transmission of a novel and highly transmissible pathogen, there still lies the potential for models to be useful tools for local and international decision makers to act proactively to mitigate the burden of disease. In Syria, these challenges are compounded by humanitarian crises resulting from the ongoing civil war in the region. This conflict has led to significant decreases in health system capacity and public health data collection, and has increased the number of internally displaced populations in the country, who are particularly at risk of severe COVID-19-related morbidity and mortality. These factors make ensuring the reliability of transmission dynamic models more challenging, as models often rely on observed data for the estimation of key model parameters (e.g., force of infection, mortality rates) that describe factors contributing to the transmission of SARS-CoV-2. In response, researchers intending to apply modelling techniques to settings hosting active humanitarian crises should tailor models to rely upon a smaller number of parameters for which reasonably plausible estimates can be obtained, and leverage the ability of models to simulate various scenarios (e.g., efficacy of interventions, infectiousness of variants) to inform decision-making in these regions.

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Table of Contents

Introduction

As is routine when developing models to pathogens responsible for novel outbreaks, there are several challenges to developing SARS-CoV-2 models that are generalizable to settings with different populations who are dealing with a host of region-specific circumstances (Holmdahl et al., 2020). In settings of humanitarian crisis, the SARS-CoV-2 outbreak has been exacerbated by population displacement resulting from violent conflicts that had been ongoing years before the initial outbreak in late 2019. Specific challenges to modeling SARS-CoV-2 include variation in the reproduction number across time and geographic locations, implementation and uptake of non-pharmaceutical interventions, underlying medical risk factors of populations, environmental risk factors, and sociopolitical contexts (Bertozzi et al., 2020). While previous studies have attempted to forecast the transmission of the virus in settings such as refugee camps (Truelove et al., 2020), authors have noted a host of social consequences that complicate the ability of models to produce reliable predictions, often resulting in underestimations of the true burden of infection and disease (Alwan, 2020). This paper will describe the unique burden of COVID-19 faced by regions experiencing ongoing humanitarian crises, describe challenges to ensuring accuracy when modeling outbreaks in these settings, and identify strategies to be utilized by modelers and decision-makers to interpret COVID-19 models in these settings, using the ongoing Syrian crisis as an example.

Background

COVID-19 in Humanitarian Settings

Since the emergence of the pandemic in late 2019, there have been over 100 million cases of COVID-19 reported globally, and over 2.6 million reported deaths. In settings where humanitarian crises, such as violent political conflict and natural disaster-induced property destruction, are ongoing, the burden of COVID-19 has been especially high. Humanitarian crises are often accompanied by forced population displacement after conflict or severe weather. According to the United Nations High Commissioner for Refugees, there are approximately 80 million forcibly displaced individuals worldwide, with about 45.7 million being internally displaced, and 26.3 million being refugees (UHNCR, 2021). Regarding COVID-19, forcibly displaced populations are considered particularly vulnerable to the burden of COVID-19 due to factors that are both environmental and related to the health status of these populations.

Environmental factors that result in increased risk of COVID-19 morbidity and mortality in humanitarian settings include forced population displacement and migration triggered by major conflict or severe weather events, and decreases in the quality of living conditions during periods of conflict and instability. Internally displaced populations (IDPs) and refugees are believed to be at an increased risk of COVID-19 morbidity and mortality as a result of unsustainable living conditions in unstable political regions and camp settings; common issues faced in these settings include overcrowding and inadequate sanitation infrastructure (Singh et al., 2020). During the initial global spread of the SARS-CoV-2, observers at refugee camps in Somalia, Bangladesh, and Greece reported concerns that social distancing would not be possible in camp settings, and that medical staff equipped to treat and test for COVID-19 were not available (Subbaraman, 2020).

In addition, increasing instances of major adverse weather events have the potential to increase the number of displaced populations globally, and have already been devastating for populations who are already displaced (Yonetani, 2016; Potsdam, 2020). The health status of internally displaced populations is also of particular concern, since SARS-CoV-2 infection can exacerbate existing chronic conditions and infectious diseases in individuals, and since some of these chronic conditions can increase the severity of COVID-19-related disease. Studies have indicated that co-infection with SARS-CoV-2 and bacterial pathogens are associated with a higher likelihood of mortality than those without coinfections (Lansbury et al., 2020).

Concerns around the burden of COVID-19 among displaced populations are not purely speculative, as evidence has indicated an increasing burden of several infectious diseases among these populations. A review of reported outbreaks between 1996 and 2016 suggests that annual rates of outbreaks among forcibly displaced populations have been increasing (Desai, 2020). Internally displaced populations in various countries are believed to be at a greater risk of infectious diseases including tuberculosis, HIV, and other infectious respiratory diseases (Castañeda-Hernández et al., 2018; UNAIDS, 2007; Bellos et al., 2010). The risk of co-infection involving COVID-19 is further exacerbated by the reported disruption of routine vaccination activities for measles, mumps, rubella, polio, diphtheria, pertussis, and other vaccine preventable illnesses (VPIs) (Lassi et al., 2021). The potential resurgence of VPIs resulting from disrupted vaccination programs combined with the ongoing spread of SARS-CoV-2 could result epidemics of co-infection involving COVID-19, further increasing the risk among these already vulnerable populations. In turn, it is crucial that global public health efforts focus on studying and mitigating the effects of the virus among forcibly displaced populations.

COVID-19 Transmission Dynamic Models

Transmission dynamic models have been some of the most powerful tools infectious disease-oriented public health experts and decision-makers have developed and wielded in recent years. This form of statistical modeling allows researchers and professionals to leverage existing data on rates of disease, pathogen-specific characteristics, populations characteristics in order to develop mathematical equations designed to predict the spread of pathogens throughout populations temporally. Modelers often abide by the adage that "all models are wrong, but some are useful," which summarizes the idea that models are more useful as decision-making tools than as perfect predictors of the spread of infectious diseases. This alludes to both the inability of any statistical model to perfectly capture all factors that contribute to a set of given outcomes in real-world settings, and the potential for well-constructed and properly interpreted models to provide useful information for proactive decision-making. Since the emergence of COVID-19 in late 2019, models have been developed to predict rates of infection, identify potential targets for intervention, and estimate the efficacy of interventions in various international settings.

The majority of COVID-19 compartmental models described in literature are SIR and SEIR models, which contain components for individuals who are susceptible (S), exposed and non-infectious (E), infectious (I), and recovered (R) (Guan et al., 2020). COVID-19 models vary in the subcategorization of these compartments, with some models including various states of infectiousness given the varying presentations of SARS-CoV-2 infection among individuals. For example, several researchers have studied models that include separate compartments for infectious individuals who are asymptomatic, individuals with symptoms, and individuals who require hospitalization as a result of severe infection (Guan et al., 2020). Advantages to sub-compartmentalizing the infectious compartment include allowing for the integration of different rates of mortality dependent on each infectious state and the potential for individuals to transition between infectious states, as can occur in the real world (Radulescu et al., 2020). The addition of model compartments can be a disadvantage if sufficient data are not available to inform estimates of the length of time individuals are expected to stay in model compartments (i.e., the latent period).

Model parameters are variables estimated based on existing data, and ultimately tailor models to specific pathogen- and region-specific factors. Common parameters in transmission dynamic models include: the transmission parameter (represented using β), which quantifies the likelihood that a given individual who is susceptible to infection will become infected after coming into contact with a member of the population who is infected and infectious; the progression rate (ω), which quantifies the likelihood that an asymptomatic infectious individual in a population will progress to symptomatic disease after one unit of time; and the recovery rate (σ), which quantifies the likelihood that an infected and infectious individual will recover from the infection and no longer be infectious after one unit of time (Del Valle et al., 2013). In addition, researchers have calculated estimates of the force of infection (λ) and the serial interval of infection for COVID-19 models based on data on serological screening for SARS-CoV-2 antibodies, observed symptomatic cases, and PCR-based test results among several other types of data (Subramanian et al., 2021; Rai et al., 2021). Other parameters such as the death rate (μ) may also be included. Depending on the number and type of compartments selected to be included in a model, there may be few or several parameters involved in model development. In a meta-analysis of COVID-19 models, authors found that the number of model parameters ranged from six to 29 across 63 studies (Guan et al., 2020).

In addition to data-based parameters, assumptions are crucial to ensuring an accurate interpretation of model results. Model assumptions are conditions that may or may not reflect real-world settings with the ultimate purpose of facilitating model development. Assumptions are generally identified during the development of models, and describe characteristics of populations and infectious diseases. Assumptions typically serve the function of either tailoring models to specific pathogens and settings, or for the sake of simplifying model inputs. One assumption encoded in models used for COVID-19 is that individuals who are asymptomatic and infectious are believed to be less infectious than symptomatic individuals, but have a longer period of infectiousness as suggested by the notion that asymptomatic individuals will not self-isolate (Sayampanathan et al., 2021; Morozova et al., 2020; Childs et al., 2020). This assumption allows for model equations, key components used for tailoring models to specific infectious agents, to take into account differences in infectiousness that one would observe in real-world settings. Regarding model simplification, one common assumption embedded in COVID-19 models is that population sizes remain constant and mix homogenously, resulting in relatively stable and predictable dynamics of interactions between individuals within populations (Cooper et al., 2020).

Conflict in Syria

Since 2011, the protracted conflict in Syria has resulted in the forced displacement of more than half of the pre-conflict population of 22 million. In addition to this displacement, the conflict has resulted in widespread destruction of health systems throughout the country, particularly in the northern region of the country, which for much of the conflict was not under control of the Damascus government. The most current data indicates that countrywide, about 6.1 million individuals are internally displaced, representing over one-third of the total population of 17 million (Human Rights Watch; World Bank).

[Figure 1 Map Identifying Territorial Control in Syria (The Economist, 2020)]

Only about 50% of Syrian hospitals remaining fully functional (Health Sector, 2020). Attacks on health facilities totally 628 by Syrian government forces, Russian government forces, the Islamic State, and other coalition forces and unknown groups have occurred since 2016 (Physicians).

Intentionally targeting of healthcare workers, been common in conflict zones, has left at least 930 medical professionals killed since 2011 (PHR). Disruptions in the delivery of healthcare have had significant impacts on the health of displaced populations, most notably outbreaks of polio and leishmaniasis that have occurred in the years since the emergence of the conflict (Mbaeyi et al., 2017; Al-Salem, 2016). Concerns related to the delivery of care during the COVID-19 pandemic have already been raised, as the lack of stable health infrastructure has led to difficulties in testing and surveillance of COVID-19, as well as delivering care for severe cases (Amnesty, 2020). Given this host of challenges, researchers seeking to utilize transmission dynamic modeling in settings where humanitarian crises are ongoing should strive to ensure that models, and their outputs, take into account these obstacles.

Developing COVID-19 Models for Humanitarian Crisis Settings

Infectious Disease Surveillance and Data Availability

Violent conflict and humanitarian crises are known to increase the risk of infectious disease transmission, morbidity, and mortality due to effects including forced population displacement, the disruption of routine vaccination activities, the destruction of sewage and water sanitation systems, and direct attacks on healthcare workers and facilities (Ekzayez et al., 2020). These effects, in conflict-affected settings, imperil surveillance of infectious diseases and other activities critical to protecting the health of impacted populations. Initial outbreak detection in conflict-affected regions largely relies upon clinical identification of patients who have symptoms consistent with infection of known pathogens (Ismail et al., 2016). While this method is advantageous in settings lacking laboratory diagnosis, it does not detect asymptomatic infections, novel infectious pathogens, and infection in individuals who do not present to health facilities. As a suspected outbreak progresses, the need for diagnostic testing rapidly becomes a necessity, which can present significant challenges in conflict-affected settings. In the northern regions of Syria, conflict dynamics including fluctuations in governmental and non-governmental control of regions, targeted attacks on healthcare facilities and workers, and inconsistent access to hard-to-reach areas have made it especially difficult to establish a consistent system for infectious disease reporting and surveillance (Ismail et al., 2016). For RT-PCR COVID-19 testing specifically, surveillance is even more difficult as patient samples may require transport across national borders, a process which has resulted in injury and death during previous outbreaks (WHO Europe).

Further complicating the establishment of a robust infectious disease surveillance system is the need for collaborative and integrated data sharing protocols. In Syria, this challenge is compounded by regional variation in health system oversight with the World Health Organization, Turkey's Assistance Coordination Unit, and different governmental and opposition-based entities having responsibility for coordinating health-based activities in different regions throughout the country (Coutts et al., 2015). Efforts geared towards collaboration between these entities have varied in their success over the past nine years, but have been challenging due to the number of actors involved, and unpredictable changes in organizational capacity and geographic control throughout the region (Ismail et at., 2016).

The vast majority of health surveillance in northern Syria is conducted by the Assistance Coordination Unit (ACU)'s Early Warning and Response Network (EWARN) based in Turkey in collaboration with the WHO and CDC. Early warning systems for disease outbreaks have been critical in identifying and addressing gaps in public health surveillance in conflict affected regions. ACU's EWARN was specifically designed to provide public health surveillance in areas of northern Syria occupied by government opposition groups, and has been critical in providing data on several diseases where standardized reporting systems were otherwise unavailable (Cordes et al., 2017). In addition to enhancing data collection efforts, EWARN conducts training for internal staff every three months, as well as for health workers in non-governmental organizations throughout Syria. EWARN has operated in northern Syria since the collapse of the health system in mid-2013, and was responsible for reporting the first cluster of polio cases in the region that same year (Ekzayez et al., 2020).

Surveillance of COVID-19 in humanitarian settings is plagued by a host of disease-specific challenges. Since most cases of COVID-19 either produce mild symptoms or are asymptomatic, relying solely on syndromic surveillance would result in significant underestimates, and potentially misdiagnoses of the disease (Alawa et al., 2020). This being the case, tests involving laboratory confirmation of the SARS-CoV-2 virus are preferred to more accurately capture the burden of disease in populations. This makes surveillance of COVID-19 especially challenging, since humanitarian settings that contain refugee camps and populations with high rates of internal displacement are known to have inadequate access to testing equipment, health workers trained to conduct testing, and laboratories required to process samples (Lau et al., 2020). While there have been efforts by local and international stakeholders to use limited resources to test high-risk populations in these settings, case counts are generally thought to be underestimates given the increased risk of transmission and lack of consistent and widespread testing.

Estimating Model Parameters

Population Mobility Dynamics

In northern Syria, where most camps for the internally displaced are located. there is no system of civil registration and no comprehensive mortality surveillance system. Data on both of these measures are necessary for calculating birth and death rates in the population, therefore those attempting to parameterize changes in this population must make the decision to use existing sources on Syrian populations with incomplete data, use estimates for regions other than Syria (e.g., global death rate), or make assumptions about the changes in the size of the population. Another common assumption of models describing the transmission of COVID-19 is that individuals within populations are assumed to mix homogenously over time (Britton et al., 2020). This assumption is made in models describing several infectious diseases, despite existing knowledge on the potential effects of non-homogenous population mixing on the final size of epidemics (Cui et al., 2018). This assumption is typically made since attempting to account for all factors that describe non-homogenous population mixing across populations would result in models that are more complex than particularly useful. Despite its common appearance in descriptions of transmission dynamic models, this assumption has been the subject of critique among epidemiologists, who are often concerned with how heterogeneity of exposures within populations can lead to different health outcomes (Bansal et al., 2007).

When attempting to more accurately describe population movement, modelers have used network-based models to encode characteristics of population mixing (e.g., clustering of individuals within the same age group) to produce more reliable model results (Pastor-Satorras, 2001). While network-based models are particularly useful for the goal of encoding heterogenous population mixing, their reliability depends on the availability of data on population mixing and clustering, as well as the likelihood that target populations will behave predictably over time. In the context of forced displacement, fluctuations in migration following major violent conflict or climate events are difficult to anticipate in models not specifically designed to address such a scenario. Mass migration following violent conflict events and natural disasters can make it particularly difficult to produce reliable estimates to inform the development of network-based models (IOM, 2020). One alternative to network modeling has been explored for COVID-19 by adjusting the number of expected contacts a given individual will have based on their level of socialization, which could be a useful strategy in settings where detailed population data is not available (Britton et al., 2020).

Estimating the Force of Infection

One of the key parameters included in epidemiologic transmission dynamic models is the force of infection, commonly denoted using λ. This parameter describes the rate at which susceptible individuals are expected to become infected, and is estimated using data on new infections, exposure of susceptible individuals to infectious individuals, and the average duration of exposure in outbreak settings (Hens, 2009). Calculations of the force of infection differ based on whether the transmission of pathogens is believed to be density- or frequency-dependent. For models assuming density-dependent transmission, in which the force of infection increases with population size, the equation is as follows, with *t* indicating a unit of time, β indicating the transmission parameter, and *I* representing the number of infectious individuals at a given time.

$$\lambda(t) = \beta * I(t)$$

For models assuming frequency-dependent transmission, in which the force of infection is primarily dependent on the proportion of infectious individuals in the population, the calculation is as follows.

$$\lambda(t) = \beta * I(t)/N(t)$$

While the transmission parameter, β, is used to describe the average number of people an infected individual is expected to expose to disease over a given unit of time, the force of infection more directly accounts for the likelihood than an exposed susceptible individual will become infected. In general, estimates of the force of infection for a given pathogen are only as reliable as the data being used in calculations.

Obtaining rates on the number of new COVID-19 infections to inform estimates of infection has generally been challenging for epidemiologists, as unreported infection is believed to have been a significant contributor to the rapid spread of SARS-CoV-2 (Li et al., 2020). Some models designed to predict COVID-19 have included parameters identifying rates of case detection and reporting to account for gaps in testing and reporting (Centre, 2020). This can be a useful method of better predicting the burden of COVID-19 within populations, but in the Syrian context producing a reliable estimate of under-detection presents a set of challenges. Cases may go undetected when infected individuals who receive a test receive false-negative results, or when infected individuals do not undergo testing at all (Reese et al., 2020). While data on false-negative results may be transferable across various contexts if all parties are using the same test, data on uninfected untested individuals is not readily available for internally displaced populations living in Syria. One strategy to collect data to inform these estimates would be to conduct antibody-based seroprevalence surveys to identify the prevalence of individuals who have ever had COVID-19, however these studies require significant amounts of staffing, resources, and coordination (including having access to individuals during appropriate sampling times), all of which are documented challenges for Syrian health system (Angulo et al., 2021; Douedari & Howard, 2019).

Encoding Risk of Asymptomatic Infection

Given existing data on the differential impacts of symptomatic versus asymptomatic disease on COVID-19 morbidity, mortality, and infectiousness, COVID-19 models often contain multiple infectious states to differentiate between different stages of infection (Subramanian, 2021). As addressed above, the distinction between these states is important not only to more accurately reflect how the disease manifests among members of the population, but also allows modelers to account for differences in mobility and mixing trends between the two groups (e.g.., asymptomatic populations may engage in more mixing than symptomatic populations who self-isolate). One challenge for applying models that contain multiple compartments for distinct infectious states it that data involved in the estimation of these parameters has primarily been collected in settings that are not currently experiencing humanitarian crises to the degree of conflict-affected settings (Faskianos, 2020).

Estimating the number of susceptible individuals exposed in a given unit of time is complicated by the fact that approximately 17-20% of COVID-19 infections are asymptomatic, while asymptomatic cases are believed to be responsible for at least half of transmission events based on a meta-analysis of relevant studies (Byambasuren et al., 2020; Johansson et al., 2021). Determining the rate at which members in a given population will become infected and asymptomatic as opposed to symptomatic is another challenged faced by COVID-19 models. Although studies have identified smoking, pre-existing lung damage and disease, obesity, and older age as risk factors for developing symptomatic COVID-19, research is still being conducted on what factors are associated with the development of either symptomatic or asymptomatic disease (Tao et al., 2020; Hopkinson et al, 2021; Tartof et al., 2020).

Mortality Estimates

Mortality surveillance is a key component of any properly functioning health system. A comprehensive system of mortality surveillance can allow rapid detection of health crises occurring in specific geographic regions, age-groups, and other subpopulations, while also serving as a reference for healthcare workers and decision-makers to assess the efficacy of interventions designed to reduce the burden of mortality (Fottrell, 2009). In addition, mortality surveillance data can serve as a reference from which health services and equipment can be allocated following major events that result in the death of several individuals, including violent conflict events. Challenges in ensuring adequate mortality surveillance typically fall under two categories: (1) reliably capturing the number of deaths in particular regions over time, and (2) ensuring accurate reporting of the cause of death for individuals (Checchi, 2018). In conflict-affected settings, several context-specific factors have negative impacts on the collection of robust, reliable data on mortality due to factors such as forced population displacement, changing dynamics of geopolitical control across geographic regions, and a lack of trained staff dedicated to collecting data, among several other factors (Levy et al., 2016).

During an ongoing crisis in which mortality data has not been collected for significant period of time, it would be advantageous to collect retrospective mortality data as well as to establish a protocol for collecting mortality data prospectively (Checchi, 2018). Retrospective mortality data is critical for estimating a baseline mortality rate to which prospective mortality data can be compared. Several strategies for collecting both retrospective and prospective mortality data in conflict-affected settings have been described in public health literature, which also identifies key context-dependent strategies. For example, in refugee camps or urban settings where populations are relatively stationary and easy to reach, data collection in the form of a survey administered by home visitors is generally advised as a method of collecting both retrospective and prospective data on mortality (Checchi, 2018). Additionally, in crisis-affected settings where nutritional surveillance that utilizes small-site-based surveys is ongoing, survey tools can be modified to capture data on mortality within these regions (Checchi, 2018). Ultimately, the selected method for mortality data collection should be the most feasible given the conflict and migration dynamics of targeted regions.

To assess the impact of COVID-19 on mortality, calculating an estimate for excess mortality attributable to the disease would be ideal (Setel et al., 2020). However, in humanitarian settings, producing this calculation is particularly challenging due to difficulties in obtaining a reliable estimate of pre-COVID and mortality due to the challenges described above, as well as a reliable estimate of mortality mid-pandemic. Without a standardized system for capturing mortality data that remains somewhat consistent during pandemic and non-pandemic periods, estimates of excess death will likely be unreliable.

Strategies for Model Adaptation

Parameter Estimation

As described above, using forecasting models to estimate of the number of COVID-19 cases over time in settings with unstable population dynamics and limited data on infection and other related health and socioeconomic factors is likely to result in unreliable estimates that will likely have limited utility. This notion highlights the importance of parameter selection and quantification in models, which have direct implications on model estimates and behavior. Parameters should be selected based on an assessment of the necessity of the parameter for model function (e.g., duration of infectiousness is likely a key parameter), and the reliability and availability of data used to inform parameter estimates in a given region. The inclusion of too few parameters may result in models that are not specific enough to describe the transmission dynamics of COVID-19 specifically, and the inclusion of too many parameters, especially in cases where data used to inform parameter estimates is not sufficiently validated, may result in increases in the uncertainty of model estimates. An example of how including too many parameters for which there are not sufficient data to produce reliable parameter estimates can be observed in the case of the CovidSim model.

CovidSim is an epidemiological model by the Imperial College COVID-19 Response Team, designed to predict the transmission dynamics and burden of COVID-19. This model was used to guide COVID-19-related policy development in the United Kingdom at the onset of the outbreak in March 2020, highlighting the impact that transmission dynamic models have on public health decision-making in the real world (Edeling et al., 2021). CovidSim contains over 900 input parameters, ranging from COVID-19-specific disease parameters, like the latent period and duration of infectiousness, to intervention parameters, such as the average length of time individuals self-isolate after testing positive for infection (Edeling et al., 2021). Given the large number of parameters included in the model, concerns surrounding parameter uncertainty are relevant to the assessment of the model's reliability. Uncertainty in this case refers to the inclusion of parameter estimates that are probabilistic and uncertain, since estimates are often based upon available, and potentially biased, data sources (Briggs et al., 2012). Other sources of uncertainty in CovidSim relate to the model structure (e.g., the impact of including an 'Exposed' state on model results), and scenarios in which models are applied (e.g., the appropriateness of including intervention measures as model paramters). To address the effect of these sources of uncertainty on CovidSim estimates, Edeling and colleagues conducted a parametric sensitivity analysis and uncertainty quantification on 19 parameters, and found that model outputs were impacted by up to 300% based on scenarios observed by the authors (Edeling et al., 2021). Overall, the authors found that biases in observed data, which directly informed parameter estimates, had a significantly negative impact on model reliability.

The lessons learned from CovidSim are particularly relevant in settings hosting active humanitarian crises, such as Syria, given inconsistent data collection and availability on important factors used to inform parameter estimation, including population dynamics that may vary between regions and types of settings (e.g., urban centers, camp settings). As such, those seeking to develop and utilize models in Syria, and settings facing similar challenges, should attempt to strike a balance between the inclusion of an adequate number of estimable parameters to tailor models to COVID-19, while avoiding including so many unknown parameters that model estimates become too unreliable. In addition to the careful selection of parameters to include in model equations, modelers and decision-makers should leverage the flexibility of models to analyze the predicted outcomes of models relative to various potential scenarios.

Modeling Multiple Scenarios

Rather than using models to produce estimates of the expected number of cases, researchers attempting to use models in crisis settings should focus on how variations in parameter estimates can describe various real-world scenarios. With this strategy, modelers can simulate a variety of potential scenarios by adjusting parameter estimates, and analyze model outputs relatively to support decision-making and policy recommendations. Models that are designed with the primary purpose of predicting the number of COVID-19 cases within a given population are typically known as statistical models, although compartmental models often contain components that are based on statistical estimation as well (Becker et al., 2021). Given significant gaps in data on infection related statistics, several parameters in models describing rates of transmission among populations in humanitarian settings rely on estimates that are based on incomplete data, or calculated using data from other settings that may not be applicable. In response to these concerns related to data reliability, studies involving model-based simulations of outbreak scenarios in Syria, and similar settings, would likely benefit from reporting estimates for a number of different scenarios encoded by varying model estimates.

For example, one study conducted by faculty at the London School of Economics and Political Science presented results of a COVID-19 model geared towards forecasting the burden of disease presented the results of various SIR model simulations with differing R_0 (and by extension β) values (Mehchy & Turkmani, 2020). For this study, the authors modeled three scenarios describing different levels of public awareness and public health intervention, each encoded by R_0 values ranging from 1.5 to 3; in addition, the authors modeled a phased approach in which assumed R_0 values decreased from 3 to 1.5 over the period of one month. As anticipated, an R_0 value representing no action (3) resulted in high rates of infection and death, while R_0 values representing increasing levels of intervention and public awareness (1.5) resulted in lower rates of infection and death; the phased model indicated that increasing levels of intervention over time would lead to increases in the proportion of recovered individuals in the population.

Although this model produced results forecasting an actual number of COVID-19 cases, the authors' observation of the behavior of the model was perhaps the main takeaway. By observing the relationships between the number of infected, susceptible, and deceased individuals observed in different model scenarios, the authors illustrate the fact that swift and properly implemented interventions likely have significant impacts on the number of people expected to be impacted by the virus in addition to the expected outcomes of the population of individuals who become infected. This case is a prime example of how models can be used to inform decisions around intervention strategies and timing, despite concerns around data reliability and parameter estimation. Given that these concerns are common to several regions hosting ongoing humanitarian crises, the idea approaching and using models as malleable and observable tools rather than a static set of equations and outputs should be kept in mind by those seeking to use models for research and decision-making. This strategy has already been utilized in studies observing different effects based on the timing of lockdowns and varying levels of mask use within populations, and can be utilized to study other factors affecting transmission dynamics that are becoming increasingly relevant as the pandemic continues (Oraby et al., 2021; IHME, 2021).

Future Directions

At the current stage of the COVID-19 pandemic, three areas of study will become particularly relevant to model construction and analysis. First, the efficacy and adherence to non-pharmaceutical interventions (e.g., social distancing, travel restrictions) is a critical parameter to define and quantify, since the success of evidence-based interventions are reliant upon the extent to which populations actually participate. In Syria, and other settings hosting ongoing humanitarian crises, this is a particularly important area for research given challenges in ensuring adequate resources and staffing in order to fully implement interventions such as wearing face masks and self-isolating after receiving a positive test result. In camp settings hosting large numbers of internally displaced individuals, even seemingly simple prevention measures such as social distancing are not possible due to high population density (Subbaraman, 2020). Given these challenges, it may be advantageous for COVID-19 modelers to assess the relative impacts of multiple interventions, with parameter estimates that indicate low levels of adherence to a series of interventions. Using this strategy, researchers may be able to determine a set of interventions that, when implemented concurrently, would have a high likelihood of mitigating the burden of disease even if interventions suffered issues related to adherence. This strategy echoes findings published by the Imperial College COVID-19 Response team in March 2020, which suggest that multiple concurrent interventions have a higher likelihood of having an impact on transmission than one intervention alone (Ferguson et al., 2020).

Second, the increasing availability of vaccines with different levels of efficacy at preventing infection, transmission, severe disease morbidity, and mortality will likely result in a decreased risk for each of these factors, dependent on the types of vaccines delivered and the rate of coverage in a given population. In Syria, the first batch of vaccines are expected to be allocated to the most vulnerable populations who are accessible in the region (e.g., the oldest individuals in zones not experiencing active conflict) (Human Rights Watch, 2021). Analyzing variations in coverage and types of vaccines may provide information on the proportion of individuals in high-risk groups that need to be vaccinated in order for notable reductions in disease burden to occur. This information could be used to inform vaccine distribution strategies to ensure that an adequate number of vaccines are distributed across regions.

Third, the emergence of new variants must be taken into account, especially considering the increased risk of mortality documented for the B.1.1.7 variant in the United Kingdom, and the uncertainty surrounding the efficacy of vaccines against newly emerging variants (Collins, 2021). For each of these topics, data to inform parameter estimates are still being collected as the pandemic unfolds. Given the lack of comprehensive data in each of these areas, it is likely that models that assess different scenarios characterized by variations in said parameters (e.g., efficacy of interventions, vaccination rates in a given region, infectiousness of new strains) will be able to provide more useful information than models that attempt to forecast the burden of disease using one scenario based on fixed parameter estimates.

Conclusion

It is important for model developers to communicate regularly with decision-makers who may not have a strong foundation in statistical analysis for two reasons. First, modelers must ensure that model results are interpreted correctly, as to avoid misunderstandings about the reliability of model outputs compared to real-world scenarios. These discussions should make clear that models will rarely be able to provide an exact number of cases that will occur in the future, but that models have the potential to describe how one or several factors may significantly exacerbate or mitigate the burden of infection and disease. Second, modelers should construct models based on answerable questions that come from decision-makers to ensure that modelling remains a useful tool in policy development and intervention design. An example of this can be seen in reports describing results of the OCHA-Bucky Model, which is designed to model COVID-19 cases and deaths in countries hosting active humanitarian crises. Weekly reports include estimates of new cases alongside recommendations for the intensity of control efforts to be enacted by local public health stakeholders and decision-makers (Centre, 2020). In settings of humanitarian crisis where the burden of disease is expected to be high, but model reliability is limited by a host of conflict-related factors, it is especially important to ensure that any models used to inform decision-making are constructed and utilized in ways that acknowledge the nature of these conflicts and potential statistical limitations.

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