Statement of guidance and recommendations to African Union Member States on the epidemic modelling of the COVID-19 pandemic

Table of Contents

Introduction

Global perspective on epidemic modelling: Mathematical models of COVID-19 have been used widely across the globe to understand the dynamics of the COVID-19 pandemic, prepare the health system response and inform policy decisions. However, in many African countries, many of the more severe projections for the potential impact of the disease have not yet been observed, even when accounting for the age-gradient of severity and relatively young demography in many countries.

Why 'all models are wrong, some models are useful': In part, the fact that attempts at 'reasonable worst-case scenarios' have not come to pass is to be expected and welcomed. Unlike, for example, models for producing weather forecasts – something you cannot change – the trajectory of COVID-19 is something that can be rapidly altered by both policy decisions and individual behavior. As a result, even if there were a perfect model, its projections could not, nor even should, predict the future if it aims to inform decision-making. Instead, *the aim of modelling infectious disease is to provide a dynamic real-time guide for decision-makers on the range of plausible scenarios likely to occur given the available policy options.*

What models got right in the African context: Many African countries were amongst the most rapid to respond to the emerging threat of COVID-19, implementing large-scale interventions at very early stages of their epidemic. As demonstrated in this document using very simple models, this rapid mobilization and timeliness of implementing control measures is likely to be an important determinant of their success. Indeed, as these measures were relaxed, subsequent waves of disease have been observed in many countries including South Africa[1], Kenya[2], Tunisia[3], Morocco[4], Sudan[5] and the Democratic Republic of Congo (DRC)[6] where such waves have severely impacted the health system by straining the supply of oxygen and ICU beds and inflicting a heavy toll on healthcare workers, often necessitating the re-imposition of control measures.

Importantly, although models have typically highlighted the high burden associated with unmitigated epidemics, in most African countries where control measures such as curfews, travel restrictions and prohibition of large gatherings were implemented, such measures were applied prior to any known model-based projections of likely COVID-19 impact in Africa. Such measures were arguably very effective in stalling the transmission of the virus. At the writing of this report (June 2021) many African countries have experienced multiple waves of the outbreak highlighting the extent to which control measures can slow down viral transmission, but also underscoring the fine balance that must be struck between the imposition of control measures and their subsequent release. Given the emergence of new SARS-CoV-2 variants and the slow global vaccine rollout, it is clear that the epidemic remains far from over[7].

What we currently don't know: Undoubtedly, many other factors have contributed to the relative lower mortality observed in many African countries. These could include a younger population (median age 19)[8], varying profile of comorbidities[9], and the potential for pre-existing immunity due to pre-exposure to related coronaviruses[10]. Of course, non-pharmaceutical interventions (often referred to as social distancing or 'lockdown' measures) have been an important feature of the mitigation response. The extent to which each of these factors has contributed to the relative success of African countries in managing the health crisis is yet unknown and remains to be studied in depth.

Despite acknowledging the apparent lower mortality in Africa, it is worth noting that most countries have lagged considerably in tracking the COVID-19 mortality data. As is increasingly recognized in many parts of the world, the confirmed deaths due to COVID-19 appear to represent only a fraction of the actual mortality of this disease, with many countries in Europe, Latin America and Asia experiencing substantially higher levels of excess mortality, with trends that mirror the course of the pandemic. In South Africa (to our knowledge the only country in Africa where such estimates are available) the latest excess mortality estimates from 3rd May 2020 to 12th June 2021 stand at 170,091 in comparison to the reported 57,706 confirmed deaths (Figure 1)[11]. Whilst not all of these deaths are necessarily directly due to the virus, these data along with reports of large unexplained spikes in all-cause excess mortality in Nigeria[12], Sudan[13] and Somalia[14] suggest that COVID-19 is capable of causing impact comparable to that witnessed in most other regions of the world[15]. This is particularly worrying given the continued threat of new SARS-CoV-2 variants which could be more transmissible, more pathogenic and potentially more deadly.

Figure 1

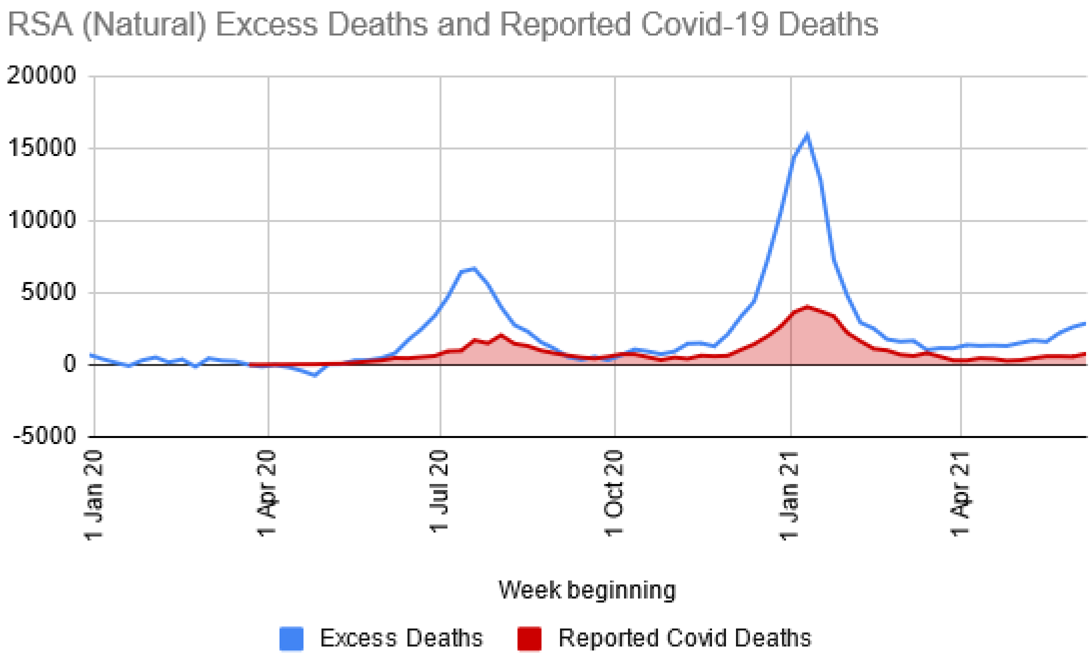

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Figure 1: Comparison of the estimated weekly excess deaths with the number of daily COVID-19 deaths reported by the Ministry of Health of the Republic of South Africa. Although more data are needed on the underlying causes of death, the observation that excess mortality deaths mirror the trend of COVID-19 deaths is strongly supportive of the notion that a significant proportion of the excess mortality observed in South Africa is attributable to COVID-19.

Where models have failed and why: In the words of the statistician George Box 'all models are wrong but some models are useful'. Indeed, given the multiple waves of the COVID-19 epidemic in many African countries, and the difficulties associated with measuring true mortality, it remains to be seen precisely how wrong transmission models have been. Nevertheless, it is clear that transmission models applied to African countries have been crude, to say the least, and have yet to explain the relatively low levels of severity observed to date in many African countries[16].

During the early stages of the pandemic, most models of COVID-19 spread in Africa included significant extrapolations of estimates of transmissibility and age-dependent severity witnessed in Asia and Europe. It can be argued that this was probably unavoidable due to the prior establishment of the disease in those regions before seeding in Africa. It can also be argued that the general unwillingness of Europe to believe such extrapolations from China at the beginning of the pandemic contributed substantially to the relatively slow reaction of decision-makers and the subsequent high mortality in many European countries at the beginning of the epidemic.

Furthermore, the characteristics of the virus were not known at the beginning of the pandemic and are still yet to be fully understood. For instance, at the beginning of the pandemic, the apparent lower contribution of young children to COVID-19 transmission than is typically observed in other respiratory infections was not known. Neither was the relative contribution of aerosolized transmission resulting in increased transmissibility indoors versus limited transmission outdoors. Such unknowns made it far more difficult to forecast COVID-19 transmission with any degree of accuracy. This is in addition to the myriad other biological, environmental, social, demographic and other contextual factors that have yet to be adequately characterized that explain the different trajectories of the disease across different countries globally.

What is abundantly clear is that the pandemic has exposed stark inequities in global investments in infectious disease epidemiology, modelling and analytics. These inequities range from a dearth of studies collecting data on contact patterns relevant to the transmission of respiratory infections in most African countries – data that is crucial to adequately parametrize transmission prior to an epidemic, to infrastructure and funding for serosurveillance, to data on community-based measures of mortality which remain largely absent across the continent even at this advanced stage of the pandemic[17], as well as a worrying lack of commitment to developing sustainable African-driven modelling capacity.

The power of epidemic modelling: Epidemic modelling uses data-driven approaches to forecast the potential course of an epidemic, estimate the impact of mitigation strategies and propose potential future scenarios, all of which should guide policy makers in attenuating the health and economic consequences of an outbreak. When parametrized to the contextual realities of a region, epidemiological models can be a powerful tool for guiding the outbreak response, optimizing the distribution of resources with each phase of the epidemic, and minimizing disruptions to healthcare and the economy.

Purpose of this document: While this document highlights scientific recommendations drawn within the context of the COVID-19 pandemic, it is important to emphasize that these guidelines and recommendations are broadly applicable to other infectious disease outbreaks, and should *guide policy makers in understanding epidemic modelling and investing the necessary resources to improve public health surveillance and epidemic control in Africa for this and future outbreaks.*

Importantly, this is a call to African decision-makers to prioritize investments in African academic institutions and African scientists who must lead the way in advancing our understanding of the local drivers of disease transmission and outcomes.

With regard to epidemic modelling, there is a critical need to invest in a common data space, at a country level, regional level and continental level that integrates and harmonizes multiple data sources, clinical protocols and scientific outputs as this would promote robust capacity for regional disease surveillance and outbreak response. In fact, epidemiological models derived from an interconnected knowledge ecosystem would be far more likely to reflect the regional realities faced by African States.

Specifically, this document describes:

(i) The importance of modelling the COVID-19 pandemic in Africa
(ii) Understanding epidemiological modelling and the types of epidemiological models in use
(iii) Illustrating how epidemiological models use data to forecast scenarios and measure the impact of mitigation options and trade-off scenarios
(iv) Factors to consider in choosing an epidemiological model
(v) Range of policy questions that can be addressed by epidemiological models
(vi) Strengths and limitations of epidemiological models
(vii) Data sharing and privacy concerns

Importance of modelling the COVID-19 pandemic in Africa

In a pandemic, guiding the outbreak response is of paramount importance. Effective responses must be sufficiently informed by data and local insights drawn from the social, demographic, biological, environmental and political realities of a region. In this regard, Africa has unique characteristics that shape the trajectory of disease transmission which ought to be integrated in designing context-appropriate epidemic forecasting models[18]. More than a year into the COVID-19 pandemic, the general consensus is that the early projections of morbidity and mortality in Africa were neither sufficiently informed by local data, nor contextually nuanced enough to capture the realities of this region which is remarkably different from the rest of the world.

As different phases of the COVID-19 pandemic unfold, particularly with the emergence of new SARS-CoV-2 variants, policy makers are questioning which strategies to favour to contain virus transmission and safeguard the health of their populations while maintaining economic stability:

- how, where and when to avail critical healthcare resources (airports, land borders, urban zones)
- if, when and where to expand clinical healthcare capacity (reinforcing health workforce, availing personal protective equipment, access to oxygen and critical care beds)
- planning the next phases of the pandemic, in particular anticipating the rollout and distribution process for the COVID-19 vaccine
- how to balance the allocation of resources to the COVID-19 response with other health priorities and avoid rolling back gains made in fighting other diseases – a major concern in Africa
- how to shape post-lockdown strategies that minimize the health risk, re-open economies and safeguard socio-economic stability
- how to react to the risks and opportunities emerging in the global pandemic

Epidemiologic modelling is an important scientific tool that uses data insights to guide reflection around these issues, assess the range of policy options available and measure their impact on population health and socio-economic stability. For decision makers, these insights are vital in choosing strategies that address the needs of their populations.

Epidemiological models

Epidemiological models assess the course of an epidemic in a population by integrating various complex parameters, such as the properties of viral propagation, health system data, population demographics, decisions on testing, quarantine, restricted movement and lockdown, all of which impact the timeline and magnitude of the outbreak. Epidemiological models thus range in complexity based on their capacity to integrate these parameters in their computations.

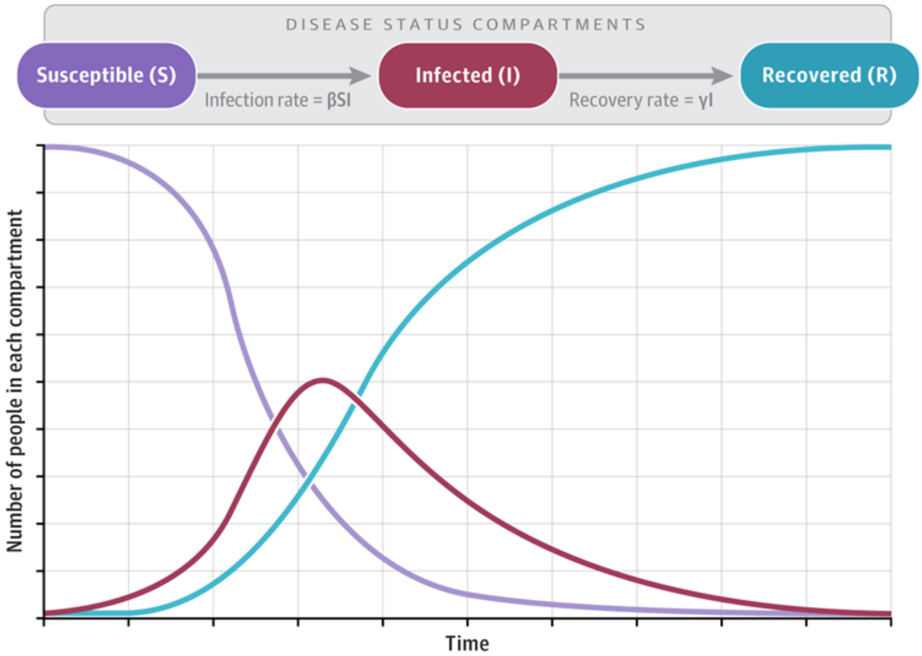
A common approach to epidemic modelling is to divide the population into different compartments, representing disease status, and then mathematically define the movement of the population from one compartment to another, often integrating reasonable assumptions into these computations.

I. The SIR Model

The simplest epidemiological model that allows monitoring of the most basic elements of an epidemic is the SIR model[19] which describes the flow of individuals through three mutually exclusive compartments: Susceptible, Infected, and Recovered.

Figure 2 shows the epidemic trajectory predicted by a simple Susceptible-Infected-Recovered (SIR) Model[20]. At the beginning of the epidemic, 100% of the population is in the susceptible compartment, assuming there is no existing immunity to the virus. As individuals are exposed to the virus, they move from the susceptible compartment to the infected compartment. The infected compartment includes both asymptomatic and symptomatic individuals, and does not distinguish mild disease from severe disease requiring hospitalization.

Figure 2



Source: Tolles J, Luong T. JAMA 2020, 323

The rate of disease transmission (movement from susceptible to infected) is calculated as a function of the parameter β (effective contact rate). Mitigation strategies such as lockdowns, quarantines, social distancing, hand washing and use of sanitizer lower the value of β. Transition from infected to recovered compartments depends on the characteristics of the contagion, the human biological response to it, population demographics, comorbidities, etc. and is calculated as a function of the parameter γ (rate of recovery).

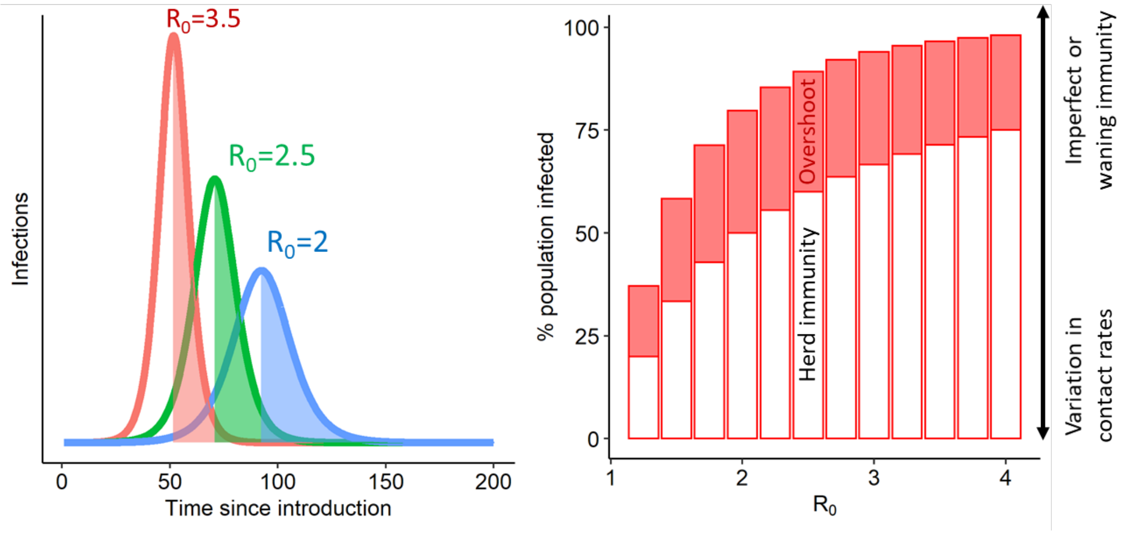
The basic reproduction number R_0 is the ratio between β and γ and describes the mean number of new infections caused by a single infected individual. Decreasing the effective contact rate (β) decreases the R_0 thereby lowering the rate of infections (flattening the curve).

II. Understanding R0 and herd immunity

In infectious disease epidemiology, R_0 is defined as the average number of secondary infections caused by an infection in a wholly susceptible population in the absence of interventions. It helps to determine the spread of disease in an unmitigated epidemic. Every infectious disease which attempts to invade a population has an R_0 and this value must be above 1 for an epidemic to occur.

For COVID-19, R_0 may vary by region due to factors that are hard to predict but may include contact patterns, population density and time normally spent indoors. In Figure 3, the left panel shows the trajectory of an unmitigated epidemic for different values of R_0 of a simple SIR model parametrised to approximate for COVID-19. For a higher R_0 the disease will infect more people in total but will peak and decline more rapidly than a lower R_0 which will pass through a population more slowly but will infect fewer people.

Figure 3



In an unmitigated epidemic, the eventual peak and decline of the infection curve is due to the acquisition of immunity within the population – at some point this becomes high enough so that newly infectious people begin to transmit infections to less than 1 person on average and infections start to drop. The level of immunity at which this occurs is known as the "***herd immunity threshold***". It is the level of immunity often aimed for by vaccination campaigns because at this level, even if the disease were to start again at zero, it would not be able to cause an epidemic.

For naturally acquired COVID-19 immunity, we cannot be sure of the proportion of infected people at which the herd immunity threshold would be reached – high variation within contact rates across the population (e.g. people living alone vs people in large households, those who work outside vs those who work in crowded spaces indoors) can move this threshold downwards, whereas imperfect or waning immunity will move it upwards. However, given the high transmissibility of the SARS-CoV-2 virus, it is reasonable to expect the proportion of the population who would need to be infected to achieve this level of immunity would be high. The right panel on Figure 3 shows this threshold for our simple model. Increasing values of R_0 correspond with an increasing herd immunity threshold.

In an unmitigated epidemic, there is a strong possibility of overshooting the herd immunity threshold, as shown by the shaded areas in Figure 3 (both panels). This is because when this threshold is reached the number of active infections is very high, leading to a period where the epidemic 'overshoots' the herd immunity threshold.

The infections occurring as a result of this overshoot are the most avoidable of all infections that would occur during an unmitigated epidemic. This is because they can only occur if control measures are completely abandoned whilst the disease is still transmitting. Therefore, ***even if current measures have not successfully suppressed the disease they will still be saving many lives if they remain in place until a vaccine is widely available or the epidemic wanes.***

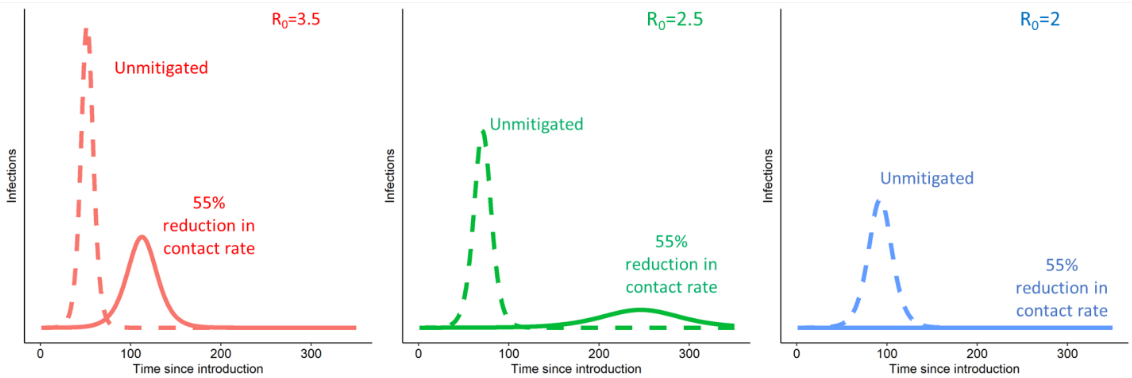
For these reasons, it must be emphasized that herd immunity is a desirable goal only within the context of vaccinations. Attempts to achieve herd immunity through an unmitigated epidemic would result many avoidable deaths that are preventable with the appropriate mitigation measures.

III. *Modelling the impact of interventions*

In epidemic modelling, R_0 also helps to determine the impact of interventions aimed towards reducing the rate of contact between infectious and susceptible people. In Figure 4, for three different values of R_0 (comparing mitigated to the unmitigated scenarios from Figure 3), we simulate in our simple model an intervention that results in halving of contact rates two weeks after the virus is first introduced (solid lines).

In our simulation, for the lowest R_0 (R_0=2) this is enough to suppress the disease and maintain infection at low levels. For higher values of R_0 (at R_0=3.5 and R_0=2.5) the disease would not be suppressed but would be mitigated, still spreading but more slowly, peaking later but at much lower levels than an unmitigated epidemic.

Figure 4

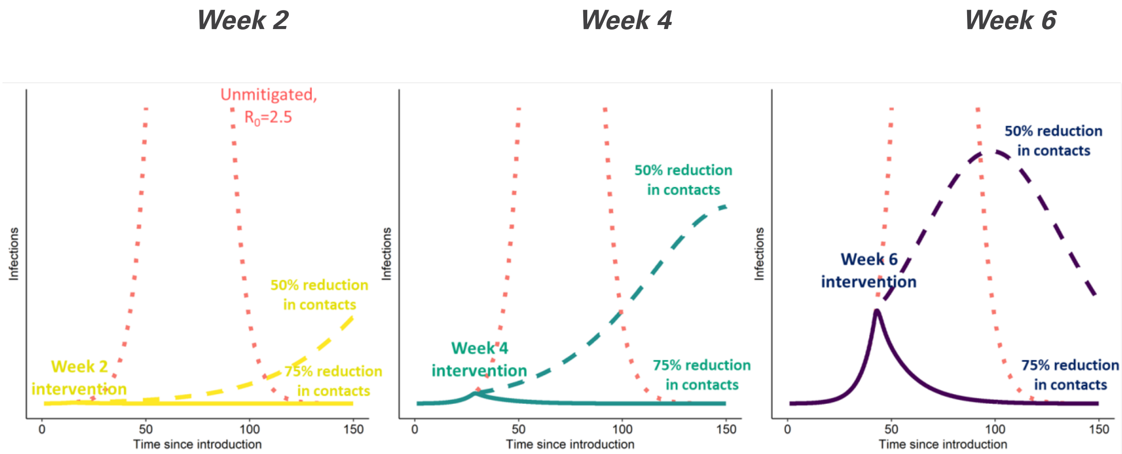


R_0 is defined as being in the absence of interventions – this is necessary in order to understand the need and extent of interventions. However, as a result, it is difficult to estimate R_0 using data collected after interventions have been implemented. Many existing estimates of R_0 for COVID-19 come from data in countries such as China and those in Western Europe which were heavily affected by the disease before measures to suppress the disease were implemented. In many African countries, interventions were implemented very early in the epidemic and during a period with low availability of testing. As a result, in African countries it is very difficult to estimate R_0 with any confidence.

Models suggest that the speed of response in many African countries is likely to have been a major factor in substantially reducing the impact of the virus to date. This is illustrated in Figure 5, which simulates an epidemic of R_0=2.5 under two intervention scenarios: (1) a reduction in contact rates of 50% (dashed lines) or (2) a reduction of 75% (solid lines). For reference, the dotted red line shows the unmitigated scenario (Note: this reference line exceeds the limit of the y-axis).

The three panels show interventions implemented at 2, 4 or 6 weeks following the disease's introduction. In this simulation a 50% reduction in contact rates does not suppress the disease entirely but acting at an earlier stage where there are fewer infections still markedly slows the spread of the disease. In contrast, a 75% reduction in contact rates leads to dramatically fewer infections and is enough to suppress the virus especially when implemented earlier.

Figure 5



IV. Modelling disease severity and risk of mortality

There remains a great deal of uncertainty in the typical level of severity of disease caused by the outbreak in many countries, including the average risk of severe disease requiring hospitalisation and the average risk of mortality (often referred to as the IFR, infection fatality rate).

In many countries the number of reported deaths remains relatively low. Younger populations are likely to provide protection from severe disease, as could lower prevalence of relevant comorbidities. On the other hand, in many countries, individuals may not be able to access care or diagnosis, even with severe disease, and subsequently deaths may be going unreported. There are also an increasing number of examples of African countries such as South Africa, Kenya, Tunisia, Libya, Morocco, Tunisia and Algeria, where health services have come under strain, or been temporarily overwhelmed, as a result of the disease.

Nevertheless, in the absence of widespread mass-testing in many African countries, studies assessing the seroprevalence of anti-SARS-CoV-2 antibodies in populations in Kenya[21], Congo[22], Malawi[23] and Nigeria[24] among others have been instrumental in estimating the extent of viral exposure within communities. Most of these studies show that viral transmission is much more extensive than has been reported, providing crucial data for better estimating the dynamics of viral transmission, modelling the next phases of the outbreak and guiding policy responses[25].

Non-pharmaceutical interventions are extremely disruptive and carry significant economic, social and psychological costs. These variables are unlikely to be captured within a transmission model but need to be carefully considered when making balanced decisions around future strategies to control the pandemic. As Figure 6 illustrates, in countries where the disease has been controlled well by such interventions to date, abandoning control measures, or lifting them too rapidly, can largely undo progress that has been achieved to date, resulting in a similar degree of 'overshoot' to an unmitigated epidemic and additional excess morbidity and mortality associated with healthcare strain (solid purple line).

Figure 6

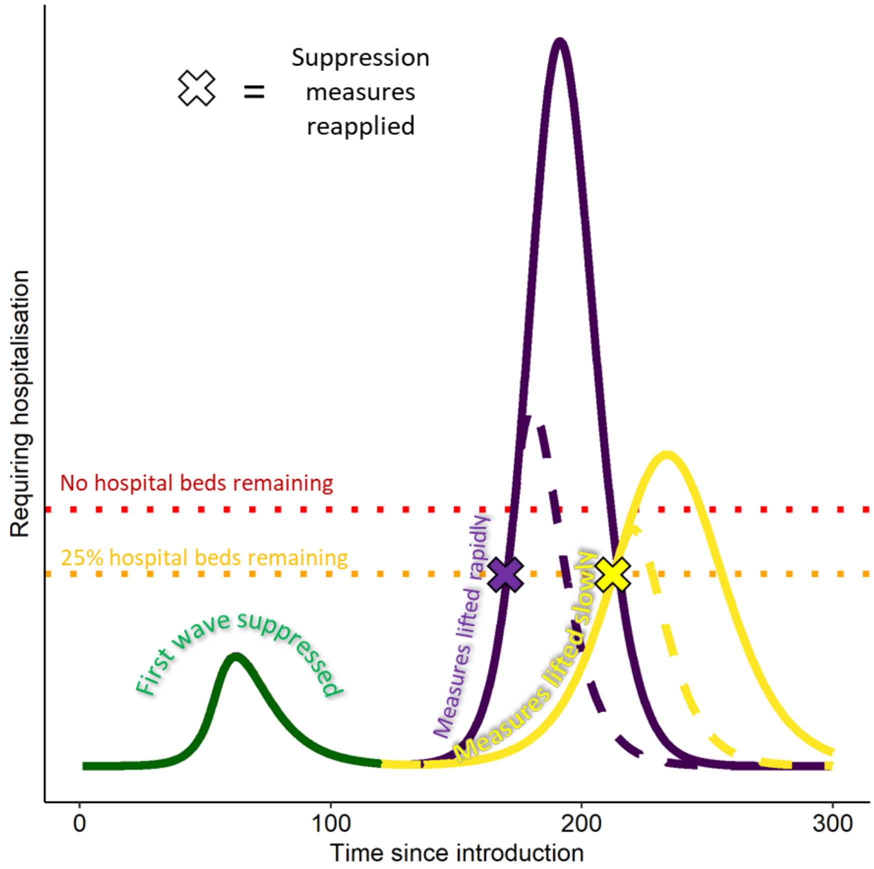


Figure 6 illustrates a hypothetical example in which a country has successfully suppressed a first wave of COVID-19 and avoided excess mortality associated with healthcare strain. Uncertainty in both the underlying severity and degree of immunity within the population makes the impact of lifting measures difficult to predict. However, a phased approach to lifting restrictions (illustrated using the yellow line), both reduces the extent to which a subsequent wave risks straining the health system and the likelihood of 'overshoot' where the direct benefits of suppressing the first wave of infection would be largely lost (purple line). Moreover, given the lag between infection and hospitalisation, a more gradual approach provides more opportunity for a country to redeploy suppression measures in the face of a subsequent wave leading to healthcare strain (dashed yellow line) than in a scenario where measures are lifted more rapidly (dashed purple line).

Meanwhile, the lag between infection and the development of severe disease (often around two weeks) means that there will always be a delay between the imposition of control measures and the impact of these measures being felt within the health system. As a result, if severe cases are rising rapidly, implementing measures as a result of health systems coming under strain may not prevent them going over capacity (dashed purple line). In contrast, a slower, more phased approach is likely to both minimise any overshoot and provide a great window of opportunity within which to respond to any subsequent wave of severe cases.

V. *Extensions of the SIR model in use for monitoring the COVID-19 pandemic*

For COVID-19, several modelling groups have extended the classical Susceptible-Infected-Recovered (SIR) model to include additional compartments representing other important stages of disease transmission. Depending on the complexity of the model, these compartments could include exposed, asymptomatic, symptomatic, tested (confirmed), quarantined, hospitalized, critical care patients and dead patients.

As with the SIR model, transitions from one compartment to another are determined by a host of factors related to disease transmission, detection and treatment, population demographics, as well as the decisions made by individuals, organizations and authorities.

Extensions of the SIR model used for COVID-19 epidemic modelling range from the SEIR model (Susceptible, Exposed, Infected, Removed)[26], the SIRD model (Susceptible, Infected, Recovered, Dead)[27], the SEIRD model (Susceptible, Exposed, Infected, Recovered, Dead) to models with increasing layers of granularity (such as the SIDARTHE model[28] and the South African National COVID-19 Epi Model[29]).

The choice of model and the availability of data inputs greatly influence the resulting forecasted scenarios. The more sophisticated the model, the more granular the input data required, and the more 'context-aware' the resulting scenarios will be.

Whichever model is chosen, the outputs ought to guide authorities to optimize the allocation of limited resources and to identify critical gaps to address in the health sector and the economy. This minimizes the chances of overwhelming the health system and avoids pitting health considerations against economic ones, instead merging these considerations as part of an integrated whole.

It is worth noting that because epidemiological models capture ongoing trends and are subject to reasonable assumptions which could change over time, they provide projections that vary over a wide range of uncertainty. Models must be adjusted continuously to reflect the rapidly changing nature of the outbreak, our increasing knowledge of the disease-causing agent (SARS-CoV-2), the human biological response to it and the social response to policy decisions taken by authorities.

Nevertheless, ***when interpreted with caution and in their proper context, epidemiological models are a powerful tool to accompany decision-makers in shaping appropriate real-time policy responses*** to the outbreak. Epidemiological modelling must therefore be viewed as a dynamic process of estimating disease transmission and projecting potential future scenarios that provides policy makers with the critical data needed to adapt their policy choices in order to manage the outbreak and avoid the worst-case scenario. Naturally, this process requires recalibration and fine-tuning as the epidemic evolves and more data and knowledge emerges.

Factors to consider in choosing an epidemiological model in Africa

Local contextual relevance

The epidemiological model chosen must be adaptable to the structural nuances of countries and local regions. In Africa, this is particularly important because the use of continent-wide data or nationally aggregated data sets tends to obscure socio-economic realities of local regions, resulting in unreliable forecasts and misinformed decisions that have consequences for millions.

To propose contextually relevant scenarios, data-driven approaches to epidemiological modelling must be applicable at a granular level, utilizing local data to dynamically model the propagation of the virus, its severity, and its impact on the health system and the economy.

Near-term versus long-term forecasting

Given an ongoing outbreak such as the COVID-19 pandemic, rather than provide long-term forecasts of cumulative infections, hospitalizations and deaths, the most useful epidemiologic models project a range of near-term scenarios to accompany authorities in planning and shaping real-time adaptive approaches to control the outbreak and inform decisions on the easing or tightening of lockdown restrictions.

Adapting to the needs of decision makers

Data outputs should speak to the articulated needs of decision makers. The epidemiological model should be designed to answer specific questions that a government agency may have. Because there is no one-size-fits-all model, the most useful models are able to adapt to the questions deemed important by national and local authorities, integrating locally relevant data into the modelling in order to accompany decision makers in choosing the best course of action.

Expertise, scientific rigor and transparency of modelling

Epidemiological modelling overseen by interdisciplinary teams of professionals in public health and epidemiology, mathematics and data science, virology, immunology, and the social sciences is likely to achieve greater success and should be preferred over singular groups. Furthermore, collaborations with businesses, technology companies and research partners are extremely beneficial and foster a framework for the sharing of protected data responsibly. Importantly, transparency in the use of data, analytical methods, algorithms and representation of key recommendations, as well as the openness to public scrutiny is a key indicator of trustworthy knowledge partners[30].

Availability of data inputs

To yield the benefits of a data-driven approach, governments have a duty to provide access to reliable data. Based on the current understanding of the human-to-human transmission dynamics of SARS-CoV-2, data that would be particularly relevant in the African context includes, but is not limited to:

(i) Population demography and distribution of known comorbidities
(ii) Confirmed cases, testing rates, diagnostic testing methods, contact tracing
(iii) Health system capacity, including the availability of equipment (e.g. ICU beds, ventilators), staffing, locations of facilities, capacity to expand or redirect resources
(iv) Local mobility patterns, including air and ground transportation
(v) Local public markets, in particular locations and density of traffic
(vi) Social housing distribution patterns of formal and informal settlements
(vii) Lockdown decisions taken by the authorities and organizations to curb the disease outbreak

These data are available from several existing sources, including government agencies and national statistics bureaus; international organizations and databases such as WorldPop, the World Bank, the United Nations; private companies such as telecommunications companies, Facebook and Google.

Range of policy questions addressed by the epidemiological models

Depending on the availability of quantitative and qualitative data inputs, computational modelling can guide in crafting policies on a range of issues, including:

Health impact

- How many cases and deaths of COVID-19 at the country, regional, administrative levels?
- What will be the demands on the health system (hospital beds, intensive care units, ventilators...) at the administrative level?
- How, where and when should the available resources be directed to optimize their impact?

(*For example, should we convert a local stadium into a makeshift hospital, should we mobilize container clinics, how many, how soon, where should they be located…*)

Virus propagation

- Where are the inherent vulnerabilities regionally and which areas are virus propagation hotspots
- Which are the most impactful measures to mitigate the outbreak within these zones?

Testing and tracing

- What are the targets for optimal testing capacity for effective containment of the outbreak?
- What is the best estimate for the number of untested COVID-19 positive people in the population?
- How much capacity to trace contacts will be needed?

Lockdown measures

- How long can we keep the (lockdown, curfew and physical distancing) measures in place? What has been the impact of these measures in containing the virus so far, what has been their impact on the economy? Should we lift these measures or continue?
- Which are the most impactful measures in slowing down and suppressing the virus? Are the current social distancing measures adequate to contain the outbreak?

Economic impact

- Quantify the economic impact (by economic sector or administrative level) of different measures that aim to slow and suppress the virus.
- Compare lockdown measures using a cost-benefit analysis for the country taking account of the economy, livelihoods and well-being of the citizens (*How can the economy reopen and workers return safely back to work while keeping the risk of viral propagation low*?)

Vaccine distribution

- Who should get the vaccine first? (*Prioritizing amongst health care professionals, essential workers, vulnerable groups, etc. especially where there are limited vaccine doses*)
- Given the trajectory of the outbreak, what proportion of the population will need to be vaccinated to achieve herd immunity?
- How should authorities prioritize regional vaccine roll out in the country? (*Regional hotspots, urban cities versus rural settlements, vulnerable zones such as transport corridors*)
- How widely can the vaccine be distributed given existing logistical realities? What measures are needed to promote equitable distribution of the vaccine especially to remote populations?

Best practice

- What are the likely scenarios over the next several months taking into consideration what is also going on with our neighbours and around the world?
- What are the immediate, medium-term, and long-term risks and opportunities to consider?
- What measures are needed to safely reopen borders locally and internationally?

Strengths and limitations of computational models for epidemics

Epidemic models can deliver a practical decision-support tool to authorities for:

1) monitoring the propagation of the virus and mapping hot-spots that warrant immediate attention
2) forecasting a range of scenarios capturing the likely course of the epidemic in the country and the potential impact on the health and social systems
3) guiding decision-making on how, where and when available resources should be directed to optimize their impact
4) weighing the health and socio-economic impact of mitigation strategies, thereby guiding decisions on optimal disease control strategies e.g. determining which lockdown measures are effective, which to lift, which population categories should be vaccinated first etc.
5) planning for the different phases of an epidemic by guiding continuous impact analysis of the virus and response measures, identifying parameters that have the greatest influence on disease spread, setting targets for testing and tracing, and providing insights on the immediate, medium-term, and long-term risks and opportunities

Limitations of computational models for epidemics

1) As the COVID-19 epidemic is still ongoing, our knowledge on the biological and sociological dynamics influencing disease spread is incomplete. Current models rely on reasonable assumptions and must be dynamic enough to adjust to evolving knowledge
2) The quality of the forecasted scenarios is determined by the quality of data inputs. Incomplete, incorrect, overly-aggregated or poorly defined data is unlikely to yield accurate forecasts as it would obscure regional nuances, thereby creating a false sense of security or panic

Data sharing and privacy concerns

COVID-19 has presented an urgent need for data collection and sharing among authorities, healthcare practitioners, scientists and the general public. Information on confirmed case counts and locations, testing rates, diagnostic testing methods, contact tracing, health system capacity, population demographics and mobility patterns is crucial to tracking the course of the outbreak, mobilizing resources and directing them appropriately, measuring the effectiveness of interventions, and forecasting the reopening of economies.

Illustrative example

Human mobility data collected from mobile phones and digital surveillance tools has immediate privacy concerns. In many cases, this data is already within the domain of non-institutional actors and private companies, therefore how they share this data and with whom they share it is particularly important. For COVID-19, this data is especially valuable for visualizing and forecasting the geographical spread of the outbreak. However, privacy concerns require that only the necessary information is shared with authorized users. Given the importance of mobility data to COVID-19 epidemic modelling, government authorities have a duty to develop a legal framework that governs the collection and use of such data.

Because there are several stakeholders, each with different but complementary interests in curbing the outbreak, government authorities have a duty to set the rules of the game with respect to data sharing and privacy, encouraging the emergence of an ecosystem that would promote the circulation of open protected data and avoid needlessly exposing private information.

Data collection and processing should be justified by reasons of public interest and abide by the principle of proportionality[31]. This means that the data collected must (a) be proportional to the seriousness of the public health threat, (b) be limited to what is absolutely needed to achieve the intended purpose, and (c) be scientifically justified. All data exchange should follow strict ethical guidelines and be in compliance with applicable laws.

Conclusion

In the global urgency provoked by the COVID-19 pandemic, countries have a lot more to gain from sharing data than they do by keeping these resources under lock and key. No doubt there are geopolitical complexities to consider, including matters of national security, economic competition, inter-operability of data systems and differing privacy regulations all of which can be arbitrated to embed shared values. A shared data open space is a cause worth exploring given the enormous upside to public health and socio-economic stability. Indeed, if there was ever a time to prove the public interest utility of collecting and storing these vast amounts of data, this global pandemic is the moment. Open anonymized data, or sensitive data provided under strict data-sharing agreements with authorized users would allow scientists and public health professionals to generate insights that guide decisions on the policies and strategies a country should undertake to stem this and future outbreaks.

Finally, African Union member states should reach consensus on the principles and systems to apply in sharing data during a health emergency. There will almost certainly be future infectious disease outbreaks. The African continent can and must be better equipped to track and forecast the course of these outbreaks by investing now in a robust pipeline for African-driven modelling capacity and epidemic surveillance in order to protect the health and livelihoods of African §populations.

Acknowledgements

Principal author: Yvonne K. Mburu, PhD. Immunologist and Founder, Nexakili, Paris, France.

Notable contributions: Patrick Walker, PhD. Lecturer, MRC Centre for Global Infectious Disease Analysis, Department of Infectious Disease Epidemiology, Imperial College London, London, UK; the Africa CDC Science, Standards and Regulations Technical Working Group; and the Africa CDC Modelling group.

Endnotes

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African Union

AFRICA CDC
Centres for Disease Control and Prevention
Safeguarding Africa's Health

Addis Ababa, ETHIOPIA P. O. Box 3243 Tele: +251-115 517 700
Fax: +251-11-5 517844 Website: www.africa-union.org

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