Modelling the impact of detection on COVID-19 transmission dynamics in Ghana

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ABSTRACT
Recently, due to the global increase in new cases of infections, the World Health Organisation declared COVID-19 disease a pandemic. We present a deterministic model to investigate the impact of detection of infected individuals on the transmission dynamics of COVID-19. The model is extended to capture the role of immigration, governmental interventions and public perception of risk regarding the number of critical cases and deaths. The model is fitted to the currently available data on cumulative COVID-19 cases in Ghana and trends of outcomes quantitatively estimated. Results suggest that intervention in the form of lockdown lengths the period of reaching the peak of infection, thereby giving time for policymaking and management of pandemic. Simulation results suggest that detection of exposed individuals has great potential to reduce daily detected cases and flatten the cumulative curve during the early stages of the pandemic. Thus, more effort should be targeted towards increasing contact tracing and detection of those suspected to be exposed to COVID-19 in order to curtail the spread of the disease. Results from this study would be useful in informing government policy direction and management regarding the control of COVID-19 in Ghana and other countries.

1. Introduction
The novel coronavirus COVID-19, also named the severe acute respiratory syndrome coronavirus (SARS-CoV-2), is one of the many coronaviruses known to exist (Ndairou et al., 2020). COVID-19 is believed to have originated from...
Wuhan in early December 2019 (World Health Organization et al.). It is also believed to have been found in seafood, and the earliest patients of COVID-19 reported access to seafood in Wuhan. As of 25 May 2020, COVID-19 had affected 213 countries globally with 5,165,481 confirmed cases and 336,430 deaths recorded (Worldometer, 2020). Africa accounted for 107,747 confirmed cases of the recorded global cases with 3,257 deaths and 42,924 recoveries. South Africa has been the most hit with 22,583 confirmed cases and 429 deaths as of 25 May 2020 (Worldometer, 2020).

Most of the first reported cases in Africa have been attributed mainly to international travel. This has resulted in most governments enforcing several intervention measures meant to curb the further spread of COVID-19. These measures included lockdowns, testing and screening individuals, recommending social distancing and wearing of face masks and use of hand sanitizers. On 12 March 2020, Ghana recorded its first two COVID-19 cases and noted a rapid increase in the daily reported number of cases. In response, the government of Ghana implemented a 21-day lockdown that started on 30 March 2020 and ended on 19 April 2020. The Ghananian government banned all public gatherings, closed all schools, universities and borders. It also encouraged strict hygiene practices on businesses that were allowed to operate. Furthermore, the government set up a COVID-19 response committee responsible for enforcing measures to reduce the spread of infection, contain the spread of infection within the country, provide enough care to those infected and mitigate the impact of the virus on the social and economic life (Danquah & Schotte, 2020).

Mathematical modelling provides a framework for finding solutions to emerging and re-emerging viruses such as COVID-19. For instance, Ivorra et al. (Ivorra et al., 2020) developed a 9-SEIHRD mathematical model describing COVID-19 dynamics in China. The model took into account undetected COVID-19 cases and results from this study established that enhancing detection of COVID-19 cases in China could be beneficial in ascertaining the number of hospital beds required for managing critical cases (Ivorra et al., 2020). Chen et al. (Chen & Yu, 2020) developed a second derivative model for assessing the detection rate of COVID-19 during a certain 2-month period. It was established that as soon as an outbreak of a disease or infection is detected it is important to closely monitor and assess the responses of individuals to the interventions put in place so as to reduce the spread of infection. Lin et al. (Lin et al.) developed a preliminary conceptual model taking into account the public perception of the disease together with governmental action effects to assess the spread of COVID-19 disease in Wuhan City of China.

In this study, we extend the model developed for the COVID-19 outbreak in Wuhan by Lin et al. (Lin et al.) to incorporate the class of detected and quarantined infected individuals so as to capture the disease dynamics in Ghana. The study seeks to investigate the impact of undetected cases on the COVID-19 disease spread in Ghana since low coverage of testing has been linked to the continued spread of the disease (Kim et al.). We thus capture the impact of varying detection rates on COVID-19 dynamics and propose a six-state SEIQRD compartmental model for the spread of COVID-19 in Ghana. Results from this study will be of great help in the fight against COVID-19 in Ghana as well as other countries.

The paper is arranged as follows; in Section 2, we formulate and establish the basic properties of the model. The model is analysed for stability in Section 3. In Section 4, we carry out some numerical simulations. Parameter estimation and numerical results are also presented in this section. The paper is concluded in Section 5.

## 2. Model formulation

The model developed in this paper comprises infection dynamics amongst humans only. Thus, the human population comprises of the following distinct compartments: $S(t)$, $E(t)$, $I(t)$, $Q(t)$, $R(t)$ and $D(t)$. The class $S(t)$ represents individuals susceptible to COVID-19 infection, $E(t)$ represents the exposed individuals, $I(t)$ represents the infected individuals, $Q(t)$ represents the detected and quarantined individuals, $R(t)$ represents recovered individuals and $D(t)$ represents deceased individuals. Upon being infected susceptible individuals join the class of exposed individuals at a rate given by

$$\lambda = \beta \left( \frac{I + \eta Q}{N} \right).$$

(2.1)

The parameter $\eta$ accounts for the relative infectivity of individuals in class $Q(t)$ as compared to individuals in class $I(t)$. Assuming that the infectivity rate of individuals in $I(t)$ is higher than that of individuals in $Q(t)$, it follows that $0 < \eta < 1$. This is due to the fact that these individuals reduce their contacts either through self-isolation measures or due to hospitalization these individuals will have contact only with healthcare personnel who in most cases have protective gear. Exposed individuals join the class $I$ of infectives after completing their incubation for an average period of $\gamma^{-1}$ days. We consider the class $I(t)$ to include pre-symptomatic undetected individuals, asymptomatic undetected individuals and symptomatic (mild and severe) undetected individuals. Once individuals are in class $I(t)$, they can
either recover naturally at a rate given by $\rho_1$ to join the class $R(t)$, experience disease-related death at a rate given by $\delta_1$ to join the class $D(t)$ of the deceased or are detected and quarantined to join the class $Q(t)$. In this paper, we assume that individuals in class $E$ who are suspected to have been exposed to COVID-19 are detected at a rate given by $\sigma_1$ joining the class $Q$ whereas individuals in class $I$ are detected at a rate given by $\sigma_2$ to join the class $Q$. Upon entering the class $Q(t)$ individuals will either recover at a rate given by $\rho_2$ or can experience disease-related death at a rate given by $\delta_2$ to join the class $D(t)$ of the deceased. We assume that people who recover do not go back to the susceptible class. The total human population is thus given by

$$N(t) = S(t) + E(t) + I(t) + Q(t) + R(t) + D(t).$$

The flow diagram for the COVID-19 model is given in Figure 1.

The description of model variables, parameters and assumptions combined with the model flow diagram (Figure 1) leads to the following set of nonlinear ordinary differential equations:

\[
\begin{align*}
S' &= -\lambda S, \\
E' &= \lambda S - (\sigma_1 + \gamma)E, \\
I' &= \gamma E - (\sigma_2 + \rho_1 + \delta_1)I, \\
Q' &= \sigma_1 E + \sigma_2 I - (\rho_2 + \delta_2)Q, \\
R' &= \rho_1 I + \rho_2 Q, \\
D' &= \delta_1 I + \delta_2 Q,
\end{align*}
\]

where all model parameters are assumed to be positive.

3. Model analysis

3.1. Positivity of solutions

We consider the positivity of system (2.2). We prove that all the state variables remain non-negative and the solutions of system (2.2) with positive initial conditions will remain non-negative for all $t > 0$. We state the following.

**Theorem 1** Given that the initial conditions of system (2.2) are $S(0) > 0, E(0) > 0, I(0) > 0, Q(0) > 0, R(0) > 0, D(0) > 0$. There exists $S(t), E(t), I(t), Q(t), R(t), D(t) : (0, \infty) \to (0, \infty)$.

Proof. Assume that

$$\dot{i} = \sup \{t > 0 : S > 0, E > 0, I > 0, Q > 0, R > 0, D > 0 \} \in [0, t].$$

Thus $\dot{i} > 0$ and it follows from the first equation of system (2.2) that

$$\frac{dS}{dt} + \lambda S = 0.$$

Thus

$$\frac{d}{dt} \left[ S(t) \exp \int_0^t \lambda S ds \right] = 0.$$

So

$$S(i) \exp \int_0^i \lambda S ds - S(0) = C,$$

giving

$$S(i) = S(0) \exp \left[ -\int_0^i \lambda S ds \right] + C \exp \left[ -\int_0^i \lambda S ds \right] > 0.$$

From the second equation of system (2.2), we have

$$\frac{dE}{dt} = \lambda(t)S - (\sigma_1 + \gamma)E \geq -(\sigma_1 + \gamma)E$$

$$E(i) \geq E(0)e^{-((\sigma_1 + \gamma)i)} > 0.$$

In a similar way, it can be shown that $I(t) > 0$, $Q(t) > 0, R(t) > 0, D(t) > 0$ for all $t > 0$ and this completes the proof.

3.2. Invariant region

Adding the first five equations of (2.2) gives

$$\frac{dN}{dt} = 0.$$

Then $\lim_{t \to \infty} \sup N \leq N_0$. It follows from system (2.2) of equations that $S + E + I + Q + R + D = N$ is invariant. Thus we have the feasible region for system (2.2) defined by

$$\Omega = \{(S, E, I, Q, R, D) \in \mathbb{R}_+^6 | 0 \leq N \leq N_0 \}.$$

It is easy to verify that the region $\Omega$ is positively invariant with respect to system (2.2).
3.3. The disease-free equilibrium point and the basic reproductive number

The model has a disease-free equilibrium

\[ C_0 = (S_0, E_0, I_0, Q_0, R_0, D_0) = (N_0, 0, 0, 0, 0, 0), \]

resembling a scenario without disease in the community. The basic reproduction number is defined as the average number of new infections produced by a single infectious individual in a completely susceptible population over the duration of the infectious period. Usually denoted \( R_0 \), the basic reproductive number tells whether the disease under study will persist or die out. In general, for values of \( R_0 < 1 \), the disease will die out and if \( R_0 > 1 \) the disease will persist in the community. Following the next-generation matrix approach by Van den Driessche and Watmough (Van den Driessche & Watmough, 2002) we have

\[
R_0 = \frac{\beta \gamma}{(\sigma_2 + \delta_1 + \rho_1) \beta \eta \sigma_1 (\delta_1 + \rho_1)} + \frac{(\sigma_2 + \rho_2)(\gamma + \sigma_1)(\delta_1 + \rho_1 + \sigma_2)}{\beta \eta \sigma_2} + \frac{(\delta_2 + \rho_2)(\delta_1 + \rho_1 + \sigma_2)}{\beta \eta \sigma_2} = R_1 + R_2 + R_3. \tag{3.1}
\]

\( R_1 \) indicates that a fraction \( \frac{\gamma}{(\gamma + \sigma_1)} \) of exposed individuals progress to the infective class and will spend an average time of \( \frac{1}{\sigma_2 + \delta_1 + \rho_1} \), the contact rate is \( \beta \), \( R_2 \) indicates that a fraction \( \frac{\sigma_1}{\sigma_2 + \delta_1 + \rho_1} \), from the exposed class will progress to the quarantined class and spend an average time of \( \frac{1}{(\delta_2 + \rho_2)} \), the contact rate is \( \beta \eta \) and finally \( R_3 \) indicates that a fraction \( \frac{\delta_1}{\sigma_2 + \delta_1 + \rho_1} \), of infected individuals will progress to the quarantined class and spend an average time of \( \frac{1}{(\delta_2 + \rho_2)} \), and the contact rate of infection is \( \beta \eta \).

4. Numerical simulations

4.1. A case study for COVID-19 spread in Ghana

In this section, we perform numerical simulations of system (1). We model the COVID-19 outbreak in Ghana, which started on 12 March 2020 as officially confirmed by the government of Ghana. We include the governmental action of lockdown as a stepwise function that takes zero before lockdown and non-zero for different lockdown stages. We adopt the transmission rate given in Lin et al. (Lin et al.) that includes both the impact of governmental actions (such as lockdown, wearing of face masks, encouraging hygienic practices, etc.) and the public perception (represented by \( P(t) \)) of risk regarding the number of critical cases and deaths. Thus, the transmission rate is given as follows:

\[
\lambda(t) = \beta(t) \left( \frac{I + \eta Q}{N} \right) \text{ where } \beta(t) = \beta_0 (1 - \alpha) \left( 1 - \frac{P}{\bar{N}} \right) . \tag{4.1}
\]

The term \( (1 - P/N)^\kappa \) captures the effects of public perception of the risk to contract the disease based on severe cases reported. Here, \( \kappa \) is a parameter controlling the strength of the response. \( \beta_0 \) is the baseline transmission rate and \( \alpha \) is the efficacy of “governmental actions”. A value of \( \alpha \) close to one implies high efficacy and the reverse is true for values of \( \alpha \) close to zero. Thus, we now have the following set of nonlinear ordinary differential equations:

\[
\begin{align*}
S' &= (1 - P) \Lambda - \lambda(t) S, \\
E' &= \rho \Lambda + \lambda(t) S - (\sigma_1 + \gamma) E, \\
I' &= \gamma E - (\sigma_2 + \rho_1 + \delta_1) I, \\
Q' &= \sigma_1 E - \sigma_2 I - (\rho_2 + \delta_2) Q, \\
R' &= \rho_1 I + \rho_2 Q, \\
D' &= \delta_1 I + \delta_2 Q, \\
P' &= \sigma_1 E + \sigma_2 I + \delta_2 Q - \omega P,
\end{align*}
\tag{4.2}
\]

where \( \omega^{-1} \) is the mean duration of public reaction. The flow diagram for the extended COVID-19 model is now given in Figure 2.

After the official confirmation of COVID-19 outbreak in Ghana on 12 March 2020, the initial lockdown was instituted starting on Monday 30 March 2020 and ended on 19 April 2020. From then onwards the lockdown was relaxed but social distancing and wearing of face masks continue to be enforced by the government. We include the governmental action of lockdown as a stepwise function which takes zero before lockdown

![Figure 2. Model flow diagram.](image-url)
and non-zero for different lockdown stages. We also capture immigration of people before the lockdown where we assume that these people might have been susceptible or exposed to COVID-19 upon their entering into the country. Due to the travel restrictions imposed when the lockdown started, we assume that there was no more immigration of people after 30 March 2020. Thus, we set

$$\begin{cases} \Lambda \neq 0 \text{ before the lockdown,} \\ \alpha = 0 \text{ before the lockdown,} \end{cases} \quad \begin{cases} \Lambda = 0 \text{ after the lockdown,} \\ \alpha \neq 0 \text{ after the lockdown.} \end{cases}$$  \quad (4.3)

The COVID-19 data for Ghana used in this study was obtained from the reports presented by the government of Ghana Figure 3 and reported by Worldometer, 2020. We perform curve fitting using the data given in Table 1. Estimates of unknown parameter values and intervals used are shown in Table 2. Curve fitting process allows us to quantitatively estimate the trend of the outcomes of COVID-19 in Ghana. We make use of the least-squares curve fit routine (lsqcurvefit) in Matlab with optimization to estimate our unknown model parameters. Cumulative cases for COVID-19 in Ghana are estimated using the function

$$\text{prev} = \int_{t_{k-1}}^{t_k} [\sigma_1 E(t) + \sigma_2 I(t)] dt, \quad (4.4)$$

where $t_{k-1}$ and $t_k$ denote the start and end of the time interval, respectively. We fit the model to the cumulative cases of COVID-19 in Ghana before, during and after the lockdown. In order to obtain the optimal fit under this combined scenario, we set the conditions as given in (4.3). We use the optimal value for $\alpha$ during the lockdown to measure the potential impact of lockdown in reducing the peak of cumulative cases.

Figure 4 illustrates the trends in the cumulative COVID-19-detected cases in Ghana. We observe from Figure 4 that system (4.2) fits well with the data from Table 1. Estimated parameter values are shown in Table 2.

The baseline value of the basic reproduction number $R_0 = 2.0497$.

To explore the impact of immigration, governmental intervention and public perception of risk regarding the number of COVID-19 critical cases and deaths in Ghana, we will simulate model (4.2) using parameter

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**Table 1. Data for COVID-19 cases in Ghana**

| Date  | 12/3/20 | 13/3/20 | 14/3/20 | 15/3/20 | 16/3/20 | 17/3/20 | 18/3/20 | 19/3/20 |
|-------|---------|---------|---------|---------|---------|---------|---------|---------|
| Date  | 2       | 2       | 2       | 6       | 6       | 7       | 7       | 11      |
| Total cases | 20/3/20 | 21/3/20 | 22/3/20 | 23/3/20 | 24/3/20 | 25/3/20 | 26/3/20 | 27/3/20 |
| Date  | 16      | 21      | 23      | 27      | 53      | 68      | 132     | 137     |
| Total cases | 28/3/20 | 29/3/20 | 30/3/20 | 31/3/20 | 1/4/20  | 2/4/20  | 3/4/20  | 4/4/20  |
| Date  | 141     | 152     | 152     | 161     | 195     | 204     | 205     | 205     |
| Total cases | 5/4/20  | 6/4/20  | 7/4/20  | 8/4/20  | 9/4/20  | 10/4/20 | 11/4/20 | 12/4/20 |
| Date  | 214     | 214     | 287     | 313     | 378     | 378     | 408     | 566     |
| Total cases | 13/4/20 | 14/4/20 | 15/4/20 | 16/4/20 | 17/4/20 | 18/4/20 | 19/4/20 | 20/4/20 |
| Date  | 566     | 636     | 641     | 641     | 641     | 834     | 1042    | 1042    |
| Total cases | 21/4/20 | 22/4/20 | 23/4/20 | 24/4/20 | 25/4/20 | 26/4/20 | 27/4/20 | 28/4/20 |
| Date  | 1042    | 1154    | 1154    | 1279    | 1279    | 1550    | 1550    | 1671    |
| Total cases | 29/4/20 | 30/4/20 | 30/4/20 | 31/5/20 | 3/5/20  | 4/5/20  | 5/5/20  | 6/5/20  |
| Date  | 1671    | 2074    | 2074    | 2169    | 2169    | 2719    | 2719    | 3091    |
| Total cases | 7/5/20  | 8/5/20  | 9/5/20  | 10/5/20 | 11/5/20 | 12/5/20 | 13/5/20 | 14/5/20 |
| Date  | 3091    | 4012    | 4263    | 4263    | 4700    | 5127    | 5408    | 5530    |
| Total cases | 15/5/20 | 16/5/20 | 17/5/20 | 18/5/20 | 19/5/20 | 19/5/20 | 19/5/20 | 19/5/20 |
| Total cases | 5638    | 5735    | 5735    | 5737    | 6096    | 6096    | 6096    | 6096    |
values in Table 2. The total population of Ghana was assumed to be 31 million. Some of the parameter values were obtained from the literature on COVID-19 and the remaining unknown parameters were estimated within plausible range of values from data fitting so as to capture the current COVID-19 transmission dynamics in Ghana. According to Worldometer, 2020, Ghana had a total of 193705 tests done at the time of drafting this manuscript with an average of 6249 tests per 1 million which translates to 6.249 tests per 1,000. The following initial conditions were used: \( S(0) = (1 - p) \Lambda + N - E(0) - I(0) - Q(0) - R(0) \) where \( N = 31 \times 10^6 \), \( E(0) = p \Lambda, I(0) = 0, Q(0) = 2, R(0) = 0, D(0) = 0, \) and \( P(0) = 20 \) with \( \Lambda \) and \( \alpha \) set as given in (4.3).

**Table 2.** Description of parameters used in system (4.2)

| Description                                      | Symbol | Range          | Baseline value | Source                        |
|--------------------------------------------------|--------|----------------|----------------|-------------------------------|
| Baseline disease transmission rate               | \( \beta_0 \) | 0.9011 – 1.400 | 1.0598         | (Nyabadza et al., 2020)       |
| Modification factor                              | \( \eta \) | 0 – 1          | 0.205          | Data fit                      |
| Governmental action strength                     | \( \sigma \) | 0 – 1          | 0.35           | (Lin et al.)                  |
| Intensity of response                            | \( k \) | 695.1 – 2254.1 | 1117.3         | (Lin et al.)                  |
| Mean latent period                               | \( y^{-1} \) | 3–5 days       | 5              | (Lin et al.)                  |
| Detection rate of exposed individuals            | \( \sigma_1 \) | 0 – 0.0037     | 2.4131 \times 10^{-7} | Data fit |
| Detection rate of infected individuals           | \( \sigma_2 \) | 0 – 0.037      | 0.0000867917   | (Worldometer, 2020)           |
| Recovery rate of undetected                      | \( \rho_1 \) | 0.2 – 0.5      | 0.4345 days    | (Nyabadza et al., 2020)       |
| infectious individuals                           |        |                |                |                               |
| Recovery rate of quarantined individuals         | \( \rho_2 \) | 0.4 – 0.7      | 0.62           | Data fit                      |
| Disease-related death rate for                    | \( \delta_1 \) | 0 – 0.5        | 0.00102        | Data fit                      |
| undetected infectious individuals                |        |                |                |                               |
| Disease-related death rate for detected          | \( \delta_2 \) | 0 – 1          | 0.0050549      | (Worldometer, 2020)           |
| individuals                                      |        |                |                |                               |
| Mean duration of public reaction                 | \( \omega^{-1} \) | 4.90–21.00    | 11.2           | (Lin et al.)                  |
| Proportion of exposed immigrants                 | \( \rho \) | 0 – 1          | 1.1752 \times 10^{-4} | Data fit |
| Daily rate of immigration                        | \( \Lambda \) | 400 – 800      | 595            | (Mettle et al., 2020)         |

**Figure 4.** Model system (4.2) fitted to data for cumulative COVID-19 cases in Ghana. The blue circles indicate the actual data, and the solid red line indicates the model fit to the data.

**Figure 5.** Simulation of cumulative cases in the presence of lockdown.
Figures 5–8 illustrate the simulation of cumulative cases in the absence and presence of 21-day lockdown. Figure 6 clearly shows the scenario that had there not been any intervention instituted then the number of cumulative COVID-19 cases might have reached close to 22000 cases by 21 May 2020. We observe from Figure 8 that in the absence of any form of intervention the curve will flatten approximately at the end of April 2021 whereas in the presence of intervention the curve will flatten at around the end of July 2021. It should be noted that the form of intervention considered is in the form of a 21-day nationwide lockdown. Figure 8 indicates that the lockdown lengthens the period of reaching peak infections thereby giving time for policymaking and management of the pandemic.

Figures 9 and 10 illustrate the simulation of daily detected cases in the absence and presence of 21-day lockdown assuming a constant detection rate for the entire time period under consideration. Figure 9 indicates the daily detected cases for a shorter time period whilst Figure 10 is projected for a longer period of time. Figure 10 shows that in the absence of intervention, the peak daily detected cases may reach approximately 12500 around October 2020 whereas in the presence of intervention the peak daily detected cases may reach approximately 11500 around February 2021.

Figures 11 and 12 illustrate the effect of varying the parameters \( \sigma_1 \) and \( \sigma_2 \), respectively, on the number of daily detected cases. Figure 11 illustrates how an increase of \( \sigma_1 \) by levels of 10% and 20% can influence the number of daily detected cases in the presence of a 21-day lockdown. We observe that if the detection rate had been at levels 10% or 20% higher than the current rate then the daily reported cases would have dramatically reduced to less than 50 cases by 21 May 2020. As can be seen, detection of exposed individuals has more impact as compared to detection of infectious individuals. This emphasizes the need for more contact tracing of those suspected to have been exposed to COVID-19 disease so as to reduce the spread of the disease. This is a reflection that individuals in class \( E \) are the main drivers of the pandemic. Thus, more effort should be directed towards increasing efficient test kits and contact tracing of exposed individuals so as to reduce the number of detected cases.
Figure 8. Simulation of cumulative cases (projected) in the absence and presence of 21-day lockdown.

Figure 9. Simulation of daily detected cases in the absence and presence of 21-day lockdown.

Figure 10. Simulation of daily detected cases (projected) in the absence and presence of 21-day lockdown.

Figure 13 shows that a 10% increase in the level of $\sigma_1$ flattens the curve on approximately 21 May 2020 with close to about 11000 cases whereas a 20% increase in the level of $\sigma_1$ flattens the curve on approximately 5 May 2020 with close to about 10500 cases. As observed in Figure 8, the current level of $\sigma_1$ will flatten the curve at approximately the end of July 2021.

Figures 14–16 show that the parameter $\sigma_2$ has less impact on the number of daily detected cases and cumulative detective cases as compared to $\sigma_1$. As can be observed in Figures 14–16, $\sigma_2$ is observed to impact in the later stages of the pandemic unlike $\sigma_1$ which has greater impact in the earlier stages of the pandemic.
5. Conclusion

In this paper, a deterministic model to investigate the impact of detection of exposed and infected individuals on the transmission dynamics of COVID-19 in Ghana was formulated. The model was developed with the aid of principles drawn from the huge literature of mathematical epidemiology and current knowledge about the disease as presented by WHO. The model was extended to incorporate governmental actions (such as lockdown, policy on wearing of face masks, etc.), immigration and public perception of risk emanating from the number of infections and death toll. The extended model is applied to a case
study of the disease spread in Ghana. The least-squares curve fit routine is used to fit the model to the available cumulative COVID-19 cases in Ghana and trends of outcomes quantitatively estimated. Estimates of important parameters were obtained within plausible ranges. Different case scenarios on the impact of the 21-day lockdown were analysed by considering a step-wise function, which takes zero before lockdown and non-zero for different lockdown stages.

Using estimated and known parameter values of the model, we performed numerical simulations for cumulative and daily detected cases of COVID-19 in Ghana in the absence and presence of lockdown. Results from this study confirmed with the existing data from Ghana.
would be useful in informing government policy direction and management regarding the control of COVID-19 in Ghana and other countries.

The model can be extended to incorporate asymptomatic infectious, mildly infected and severely infected individuals so as to specifically capture the contributions of these individuals to the disease dynamics.

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**PUBLIC INTEREST STATEMENT**

The paper proposes a system of ordinary differential equations to model COVID-19 transmission dynamics in Ghana. The model investigates the impact of detection of infected individuals on the transmission dynamics of COVID-19. The model framework is modified to capture the role of immigration, governmental interventions and public perception of risk regarding the number of critical cases and deaths. Application of the model is done through fitting the system of equations to the currently available data on cumulative COVID-19 cases in Ghana. Enhancing detection mechanisms of exposed individuals is highly beneficial in controlling this pandemic. Results drawn from this study would be useful in informing government policy direction and management regarding the control of COVID-19 in Ghana and other countries.

**References**

Chen, X., & Yu, B. (2020). First two months of the 2019 coronavirus disease (COVID-19) epidemic in China: Real-time surveillance and evaluation with a second derivative model. *Global Health Research and Policy*, 5(1), 1–9. [https://doi.org/10.1186/s41256-020-00137-4](https://doi.org/10.1186/s41256-020-00137-4)

Danquah, M., & Schotte, S., *COVID-19 and the socioeconomic impact in Africa* 2020. [https://doi.org/10.35188/UNU-WIDER/WBN/2020-5](https://doi.org/10.35188/UNU-WIDER/WBN/2020-5)

Ivorra, B., Ferrández, M. R., Vela-Pérez, M., & Ramos, A. (2020). Mathematical modeling of the spread of the coronavirus disease 2019 (COVID-19) taking into account the undetected infections. The case of China. *Communications in Nonlinear Science & Numerical Simulation*, 88, 105303. [https://doi.org/10.1016/j.cnsns.2020.105303](https://doi.org/10.1016/j.cnsns.2020.105303)

Kim, G.-U., Kim, M.-J., Ra, S. H., Lee, J., Bae, S., Jung, J., & Kim, S.-H. (2020). Clinical characteristics of asymptomatic and symptomatic patients with mild COVID-19. *Clinical Microbiology and Infection*.

Lin, Q., Zhao, S., Gao, D., Lou, Y., Yang, S., Musa, S. S., Wang, M. H., Cai, Y., Wang, W., Yang, L., et al. A conceptual model for the outbreak of coronavirus disease 2019 (COVID-19) in Wuhan, China with individual reaction and governmental action. *International Journal of Infectious Diseases*, 93, 211–216. [https://doi.org/10.1016/j.ijid.2020.02.058](https://doi.org/10.1016/j.ijid.2020.02.058)

Mettle, F. O., Osei Affi, P., & Twumasi, C. (2020). Modelling the transmission dynamics of tuberculosis in the Ashanti region of Ghana. *Interdisciplinary Perspectives on Infectious Diseases*, 2020, 1–16. [https://doi.org/10.1155/2020/4513854](https://doi.org/10.1155/2020/4513854)

Ndairou, F., Area, L., Nieto, J. J., & Torres, D. F. (2020). Mathematical modeling of COVID-19 transmission dynamics with a case study of Wuhan. *Chaos, Solitons, and Fractals*, 135, 109846. [https://doi.org/10.1016/j.chaos.2020.109846](https://doi.org/10.1016/j.chaos.2020.109846)

Nyabadza, F., Chirove, F., Chukwu, W. C., & Visaya, M. V. (2020). Modelling the potential impact of social distancing on the COVID-19 epidemic in South Africa. *medRxiv*.

Van den Driessche, P., & Watmough, J. (2002). Reproduction numbers and sub-threshold endemic equilibria for compartmental models of disease transmission. *Mathematical Biosciences*, 180(1–2), 29–48. [https://doi.org/10.1016/S0025-5564(02)00108-6](https://doi.org/10.1016/S0025-5564(02)00108-6)

Qianying, L., Shi, Z., Dazhou, G., Yijun, L., Shu, Y., Salihu, S. M., Maggie, H. W., Yongli, C., Weiming, W., Lin, Y., Daihai, H. (2020). *Coronavirus disease 2019 (COVID-19): Situation report, 80*. Worldometer, D. (2020). *Covid-19 coronavirus pandemic*. [https://www.worldometers.info/coronavirus/country/ghana/](https://www.worldometers.info/coronavirus/country/ghana/)