Chapter 205

Wearing Masks in COVID-19 pandemic: Mathematical model and simulation for evaluating the impact of non-pharmaceutical intervention strategy associated with social distancing on pandemic behavior in Minas Gerais/Brazil

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ABSTRACT
The COVID-19 pandemic has caused health system collapse and led governments to implement non-pharmaceutical interventions, such as wearing a mask and social distancing. In this study, the SEIR (susceptible-exposed-infected-recovered) model is proposed for assessing the effects of social distancing and wearing a mask on the prediction of COVID-19 transmission dynamic in Minas Gerais – Brazil. This work presents a theoretical-computational study and the mathematical modeling simulations of COVID-19 transmission dynamics. The model describes eight population groups: susceptible, confined, exposed, asymptomatic, symptomatic, hospitalized, recovered, and dead. The mask-wearing is inferred by the following parameters: mask aerosol reduction (M_red), mask availability (M_ava), and proper mask-wearing (M_cov). Different scenarios are simulated for evaluating the effect of the parameters on the pandemic evolution. Simulations demonstrate a reduction of around 99% compared to the no-mask-wearing scenario when masks are available for 80% of the population. Professional masks, such as N95 and FFP2 (M_red=97%), reduce by 98,9% of the number of deaths. The proper mask-wearing shows a significant impact on pandemic development, by reducing considerably M_cov it could even overcome the total number of deaths and infections than those in a no-mask-wearing scenario, if the social distancing measures were not intensified. Wearing a mask is extremely efficient and required in the fight against the COVID-19 pandemic. A combination of social distancing and wearing a mask, if properly performed, allows controlling the pandemic more efficiently, minimizing the total and the daily number of deaths and infections, and avoiding a greater health system overload.

Keywords: COVID-19, SEIR model, Non-pharmaceutical interventions, Behavior Changes.

1 INTRODUCTION

The novel coronavirus disease (COVID-19), caused by severe acute respiratory syndrome 2 (SARS-CoV-2), was identified in Wuhan, Hubei province, China, at the end of 2019. The disease outbreak has rapidly spread to other countries and has been causing a great problem for the public health system and socioeconomic impacts around the world [1], [2]. According to Johns Hopkins University, until August 2021, over 200 million cases of COVID-19 were confirmed worldwide.

The first COVID-19 case in Brazil was confirmed on February 26, 2020, in São Paulo. Since then, the disease has spread to the rest of the country, reaching more than 20 million cases until the first semester of 2021[3]. In the State of Minas Gerais, social isolation measures were implemented at the beginning of the pandemic and the average rate of social distancing in the state capital varied between 30 and 50% during the first months[4]. However, the restrictions have been lifted in several cities over time.

Currently, even in face of the global vaccination progress, non-pharmaceutical interventions such as wearing masks, hand hygiene, and social distancing policies must still be adopted. Those measures are very important for pandemic control since the new virus variants tend to have higher transmissibility, leading to a greater number of infections [5].

Throughout history, mathematical models have been widely applied to pandemic studies, providing a realistic and dynamic vision of the disease spread as well as preventing the timing and costs required to disease containment [6]. The first work about infectious diseases' spread was proposed by Daniel Bernoulli, related to smallpox in 1760 [7]. In the 1900s, Sir Ronald Ross and Kermack-McKendrick also studied the transmission dynamics and control of infectious diseases [1].

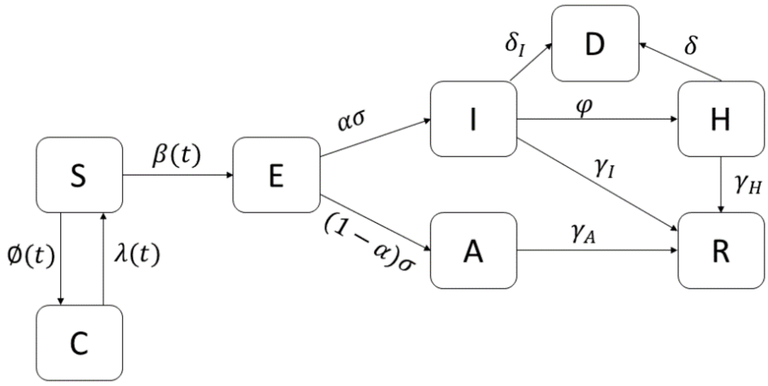
Epidemiological mathematical modeling has helped in understanding the dynamics of several diseases, such as H1N1 [8], dengue [9], and viral hepatitis B (HBV) [10] For COVID-19, many studies have been proposed to better understand the disease spread, control, and mitigation measures such as social distancing policies [11], [12], the impact of wearing masks on public spaces[2], [13], and impact on the health system [12].

The present work aims to analyze the effects of wearing masks on the transmission dynamics and control of COVID-19 in the State of Minas Gerais, Brazil, using the SEIR (susceptible-exposed-infected-recovered) model. The model is developed considering the influence of two non-pharmaceutical interventions, wearing a mask and social distancing, currently adopted in the state. The model validation is based on real data provided by the State Health Department (SES). Different scenarios based on mask-wearing are evaluated to define the effects of each parameter on the pandemic progression.

2 METHODS

In this work, an SEIR model was developed to represent the COVID-19 pandemic behavior in Minas Gerais – Brazil. The model describes the dynamic behavior of eight population groups: Susceptible ($S(t)$), Confined ($C(t)$), Exposed ($E(t)$), Asymptomatic ($A(t)$), Symptomatic ($I(t)$), Hospitalized ($H(t)$), Recovered ($R(t)$), and Deaths ($D(t)$). The interactions among these epidemiological classes in the model are illustrated in Figure 1.

Figure 1: Transition states of epidemiological classes in the mathematical model.



Numerical analysis has evaluated the population and it did not consider the effects of age, gender, or regional demographic characteristics. Migration and birth effects are also ignored [11], [14]. Since asymptomatic patients rarely progress to severe diseases, this group was not considered to account for deaths. The model has considered two non-pharmaceutical interventions: social distancing and wearing a mask. The mathematical model is given by the following Equations 1-8.

$$\frac{dS(t)}{dt} = -\frac{\beta(t)S(t)}{N}(1 - M_{eff})\big(I(t) + \eta A(t)\big) - \frac{\beta(t)S(t)}{N}\big(lH(t)\big) - \emptyset(t)S(t) + \lambda(t)C(t) \qquad (1)$$

$$\frac{dC(t)}{dt} = \emptyset(t)S(t) - \lambda(t)C(t) - \frac{\beta(t)S(t)}{N}(1-\varepsilon)(1 - M_{eff})(I(t) + \eta A(t))C(t) \qquad (2)$$

$$\frac{dE(t)}{dt} = \frac{\beta(t)}{N}\big(1 - M_{eff}\big)\big(I(t) + \eta A(t)\big)(S(t) + (1-\varepsilon)C(t)) + \frac{\beta(t)S(t)}{N}lH(t) - \sigma E(t) \qquad (3)$$

$$\frac{dI(t)}{dt} = \alpha\sigma E(t) - \varphi I(t) - \gamma_I I(t) - \delta_I I(t) \qquad (4)$$

$$\frac{dA(t)}{dt} = (1-\alpha)\sigma E(t) - \gamma_A A(t) \qquad (5)$$

$$\frac{dH(t)}{dt} = \varphi I(t) - \delta H(t) - \gamma_H H(t) \qquad (6)$$

$$\frac{dR(t)}{dt} = \gamma_I I(t) + \gamma_A A(t) + \gamma_H H(t) \qquad (7)$$

$$\frac{dD(t)}{dt} = \delta H(t) + \delta_I I(t) \qquad (8)$$

Mask effectiveness is defined by $M_{eff} = M_{ava}M_{cov}M_{red}$, which expresses the following parameters: the mask availability as the population proportion who has access to a mask (M_{ava}), the mask coverage as the population proportion who has access to mask and properly use it, and the aerosol reduction rate indicating the effective pathogenic organisms filtering by a mask (M_{red}) [15].

$\beta(t)$ is time-dependent in this study, representing the contact transmission rate as shown in Equation 9. Based on data provided by the Minas Gerais State Department of Health, $\beta(t)$ was established differently at each stage of the pandemic.

$$\beta(t) = \begin{cases} \beta_0 & t \leq t_0 \\ \beta_{min} + (\beta_0 - \beta_{min})e^{-r(t-t_0)}, & t_0 < t \leq 4t_0 \\ 0{,}9\beta_0 & 4t_0 < t \leq 5t_0 \\ 1{,}035\beta_{min} + 0{,}9(\beta_0 - \beta_{min})e^{-r(t-4t_0)}, & 5t_0 < t \end{cases} \quad (9)$$

Where t_0 is the first time point in the pandemic when $\beta(t)$ has decreased, β_{min} is the lowest transmission rate value achieved during the pandemic, and r is the transmission decay rate. For $t > 4t_0$, the coefficients that multiply β_0, β_{min}, and $(\beta_0 - \beta_{min})$ were defined by real data fitting.

Social distancing is described through a balance between people entering and lifting the isolation class, defined by the parameters φ and λ, which correspond to the entering and exiting rate, respectively [16]. These parameters are considered time-dependent, based on the following studies Castilho et al. [16], Jia et al. [17], and Lyra et al. [18]. The number of people in social distancing was defined based on the movements of individuals among classes S and C, for $\emptyset$ e λ rates, according to Equations 10 and 11.

$$\emptyset(t) = a_0 . e^{\delta_c(t - t_{lock})} \quad (10)$$

$$\lambda(t) = b_0 . e^{\delta_c(t - t_{lift})} \quad (11)$$

Where $_{block}$ and t_{lift} are the average time of entering and lifting social distancing, in days, respectively.

The control reproduction number (R_c), represented by Equation 12, quantifies the average number of new COVID-19 cases generated by an infectious individual introduced in a population with partial protection. The R_c is calculated by adding the reproduction number of new cases generated by symptomatic individuals (R_{I_s}), given in Equation 13, and asymptomatic individuals (R_{I_a}), as stated by Equation 14 [1].

$$R_c = R_{I_s} + R_{I_a} \quad (12)$$

where:

$$R_{Is} = \frac{\alpha\beta(1 - M_{ava}M_{red}M_{cov})}{\varphi + \delta_I + \gamma_I} \quad (13)$$

$$R_{Ia} = \frac{(1-\alpha)\sigma\beta(1 - M_{ava}M_{red}M_{cov})}{\gamma_a} \quad (14)$$

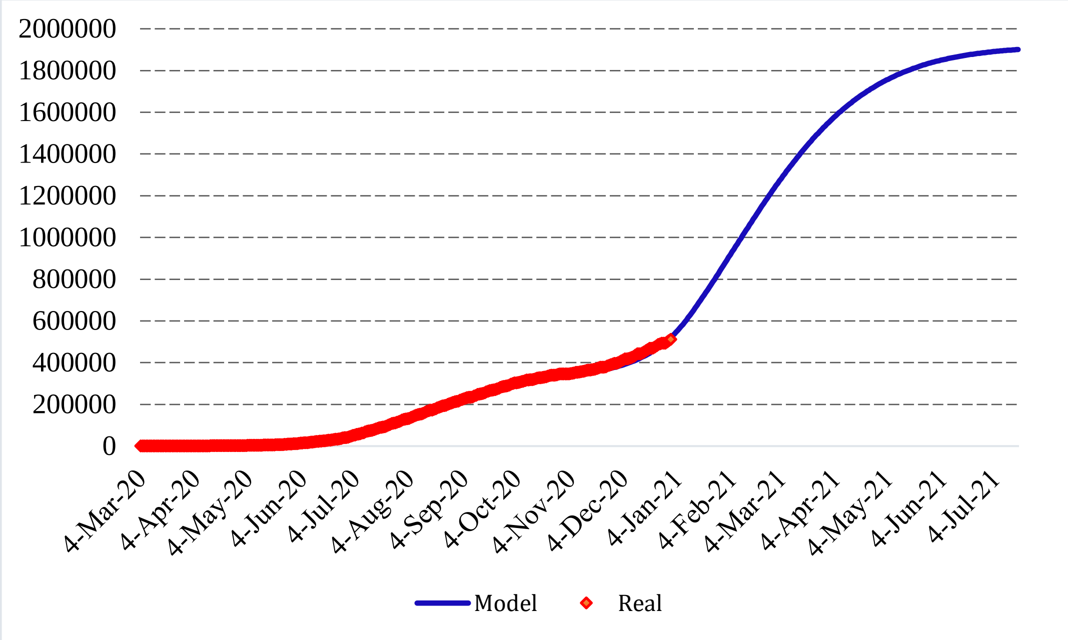
According to the epidemiological behavior, if the reproduction number is less than unity, a small influx of COVID-19 cases will not result in a disease outbreak. It should be noted that the epidemiological condition $R_c < 1$ is sufficient but not necessary for reducing or eliminating the epidemic [1].

3 RESULTS

The proposed model was validated using data provided by the Minas Gerais State Department of Health up to December 31, 2020. Table 1 details the parameters and initial conditions considered in the simulation. The parameters with no reference were fitted based on data.

The model was fitted and applied to the pandemic projection up to July 17, 2021, accounting for 500 days. Figures 2 and 3 show the curves of the total number of infections and deaths, respectively.

Figure 2: Real data and simulation infections for Minas Gerais/Brazil.



The model has achieved suitable results for real data. The determination coefficients (R^2) were equal to 0.9942 for the total number of deaths and 0.9986 for the total number of infections during the period analyzed.

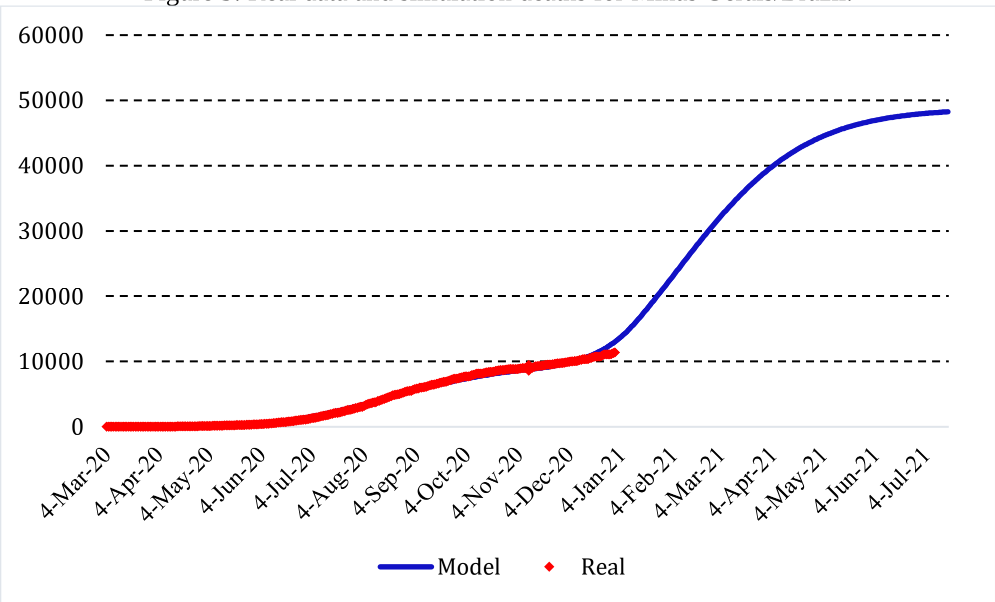
Table 1:Parameters and Initial Conditions.

Parameter	Description	Value	Reference
$\boldsymbol{\beta_{min}}$	Minimum contact transmission rate	$0.18\ day^{-1}$	-
$\boldsymbol{\beta_{0,1}}$	Initial contact transmission rate	$0.65\ day^{-1}$	-
$\boldsymbol{r}$	Contact transmission decay rate	$0.01\ day^{-1}$	-
$\boldsymbol{t_0}$	The first time the transmission rate decreased	$62\ days$	-
$\boldsymbol{\eta}$	Coefficient of relative transmission for asymptomatic about symptomatic	0.5	[19]
$\boldsymbol{l}$	Coefficient of relative transmission for hospitalization concerning symptomatic	0.5	[19]
$\boldsymbol{\sigma}$	The transition time between exposed and infectious	$1/5.1\ day^{-1}$	[1]
$\boldsymbol{\alpha}$	Infections proportion that becomes symptomatic	0.18	[20]
$\boldsymbol{\varphi}$	Symptomatic hospitalized rate	$1/5\ day^{-1}$	[19]
$\boldsymbol{\gamma_I}$	Symptomatic recovery rate	$1/10\ day^{-1}$	[2], [13]
$\boldsymbol{\gamma_A}$	Asymptomatic recovery rate	$1/14\ day^{-1}$	[2], [13]
$\boldsymbol{\gamma_H}$	Hospitalization recovery rate	$1/7\ day^{-1}$	[2], [13]
$\boldsymbol{\delta}$	Hospitalization death rate	$2.8.10^{-2}\ day^{-1}$	[2]
$\boldsymbol{\delta_I}$	Symptomatic death rate	$7.5.10^{-3}\ day^{-1}$	-

t_{lock}	Average time for entering in social distancing	$15\ days$	-
t_{lift}	Average time for lifting social distancing	$42\ days$	-
a_0	Initial factor of people's adherence to social distancing	37.2 %	[21]
b_0	The initial factor behind people leaving social distancing	78%	-
δ_c	Social distancing adherence and leaving growth rate	$1.10^{-2}\ day^{-1}$	-
M_{red}	Aerosol reduction factor by a properly mask-wearing	68.5%	[15]
M_{cov}	Population proportion that has access to and properly mask-wearing	84.5%	[22]
M_{ava}	Mask availability to the population	45.1%	[22]
Initial conditions			
$N(0)$	14754647		[23]
$S(0)$	14754521		[13]
$E(0)$	120		[24]
$I(0)$	6		[25]
$A(0)$	0		-
$H(0)$	0		-
$Q(0)$	4470658		[21], [23]

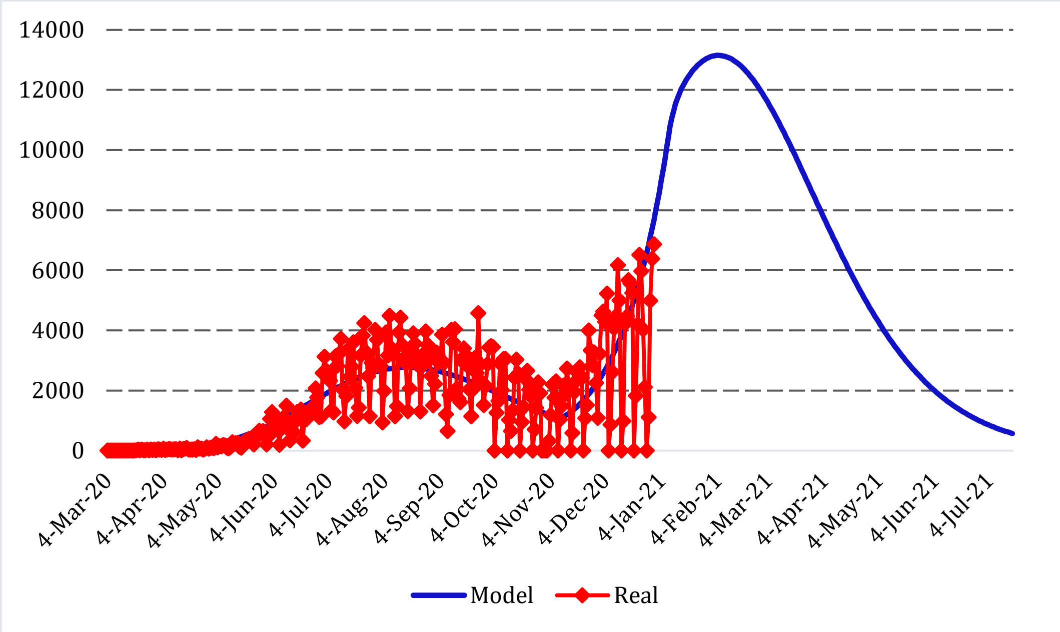
The model-fitting has estimated an amount of 1,900,554 infections up to July 17, 2021. The number of confirmed cases on this date was equal to 1,900,420 (SES, 2021) which represents an error of 0.007% from the model prediction compared to real data. The number of deaths was 48,249 during that period, with an error of 0.38% compared to available data.

Figure 3: Real data and simulation deaths for Minas Gerais/Brazil.

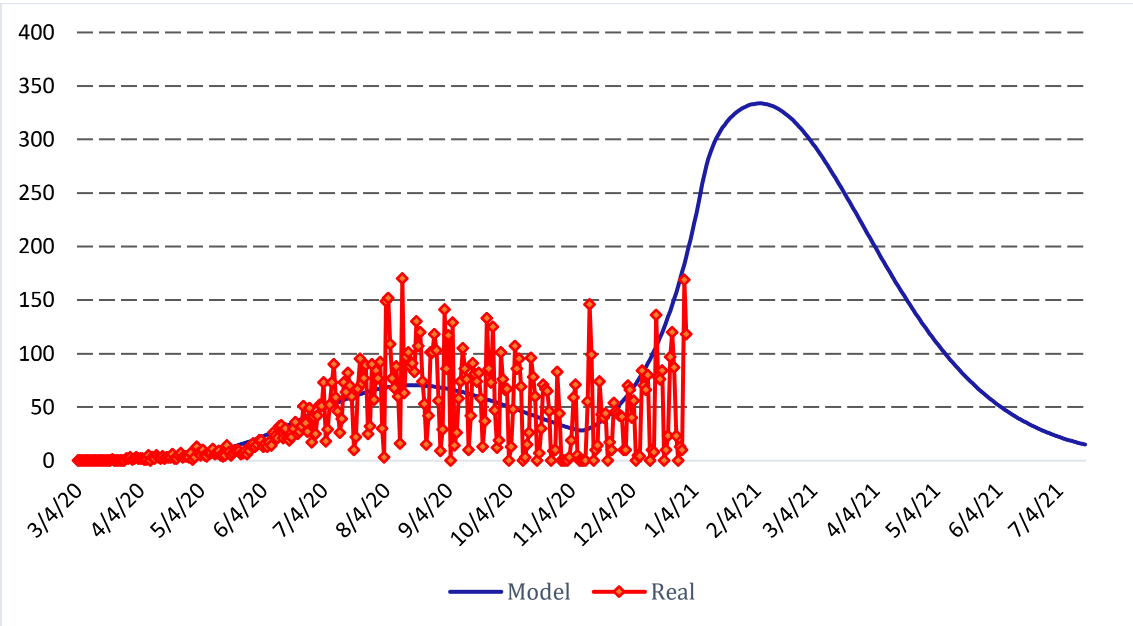


Figures 4 and 5 show the curves of the daily number of infections and deaths, respectively.

Figure 4: Real data and model predictions of daily infection rates for Minas Gerais/Brazil.



Considering the model predictions, the first wave of COVID-19 reached its peak on August 17, 2020, reporting 2,772 infections and 70 deaths. According to data released by SES, this peak was reached on August 20, 2020. The second wave would have peaked at the beginning of February, achieving 334 daily deaths on February 05, 2021, if no measures were introduced to change the simulated scenario. From October 04, 2020, the SES/MG started to update the daily data corresponding to Saturdays, Sundays, and holidays on the next business day, which changed the daily profile.



The proposed model has evaluated the effects of each parameter on mask effectiveness. Social distancing conditions have remained constant and the scenarios were simulated up to September 19, 2021.

The parameters M_{red}, M_{cov}, and M_{ava} were evaluated separately, considering the individual impact on the pandemic curve. Table 2 provides the parameter variation range considered in this study.

Table 2: Mask effectiveness parameters for the simulated scenarios.

Parameter	**Real Condition**	**Lower Limit**	**Upper Limit**
M_{red}	68.5%	40%	97%
M_{cov}	84.5%	8%	84.5%
M_{ava}	45.1%	10%	80%

The standard condition has remained constant for all scenarios, representing the current scenario of the pandemic. The parameters M_{red} and M_{ava} were changed to the lower limit, upper limit, and real condition as presented in Table 2. The parameter M_{cov} was changed to both limits and its average value. For each parameter change, the others remained in their real condition. In addition, another scenario considering no mask-wearing was also simulated.

Initially, different types of masks were evaluated by M_{red} variation. For M_{red} equals 40%, the entire population that wears a mask would choose homemade cloth masks made of cotton, while for M_{red} equals 97%, the N95 or FFP2 face masks would be adopted.

Table 3 shows the results for the total number of infections and deaths, respectively, considering the aerosol reduction efficiency variation M_{red}.

Table 3: Model prediction infections and deaths for permutations in M_{red}

$\boldsymbol{M_{red}}$	**Total of infections**	**Total of deaths**
No mask-wearing	14,127,983	358,803
40%	10,475,564	266,043
68.5%	1,908,323	48,463
97%	113,723	2,888

For the total number of infections, it is possible to note that wearing a mask with a 40% of aerosol reduction rate by the entire individuals that currently wear a mask, has reduced the total number of infections by 25.85%. This has corresponded to 3,652,420 fewer infections than the scenario in which no one would wear a mask. M_{red} equals 68.5% and has achieved a decrease of around 86%. Considering the number of deaths, M_{red} equals 97% has reported a reduction of around 16 times compared to the current condition. When the same comparison has considered in the no mask-wearing scenario, the reduction in the number of deaths was approximately 99.2 %.

It also analyzed the influence of mask availability, M_{ava}. For this analysis, it was assumed three different values for the parameter M_{ava}, were: 10%; 45.1%, and 80%. Table 4 presents these results.

Table 4:Model prediction infections and deaths for permutations in M_{ava}

M_{ava}	Total of infections	Total of deaths
No mask-wearing	14,127,983	358,803
10%	14,094,268	357,946
45.1%	1,908,323	48,463
80%	17,778	451

The results indicate that the number of deaths and infections decreased by 2.39% when mask availability was 10%, compared to the no-mask-wearing scenario. In contrast, the results have achieved a significant decrease when masks are available for 80% of the population, reporting 99.87% and 99.1% reductions compared to the no mask-wearing scenario and the real scenario, respectively.

The effect of proper mask-wearing on the population with available masks was also analyzed. Table 5 summarizes the results for the total number of deaths and infections.

Table 5: Model prediction infections and deaths for permutations in M_{cov}

M_{cov}	Total of infections	Total of deaths
No mask-wearing	14,127,983	358,803
8%	14,153,772	359,458
46.25%	11,149,826	283,167
84.5%	1,908,323	48,463

From Table 5, proper mask-wearing has proved to be effective in reducing the total number of infections and deaths for M_{cov} values at 46.25% and 84.5%, respectively. The first case has reported a reduction of 2,978,157 infections and 75,636 deaths, compared to the no mask-wearing scenario, while M_{cov} equals 84.5% reduced 12,219,660 infections and 310,340 deaths. However, M_{cov} equals 8% has increased by 0.183% compared to the no mask-wearing scenario.

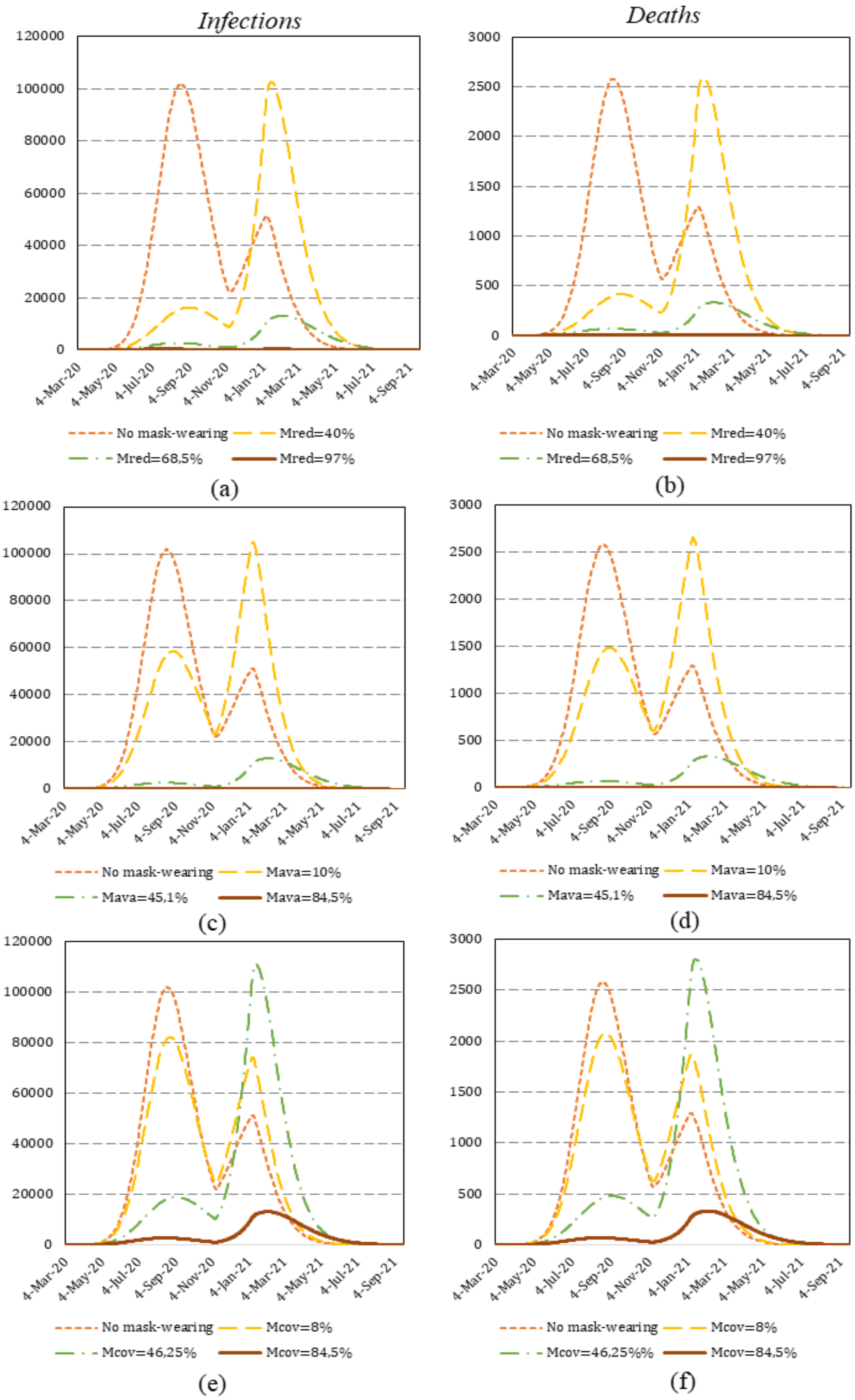
Figure 6 presents the curves of the daily number of infections and deaths for the simulated scenarios.

Figure 6 (a) shows that no mask-wearing has achieved a peak of 101,717 infections in the first wave, while for M_{red} at 40%, 68.5%, and 97 % the number of infections was 16,371; 2,771; and 482, respectively. These results indicate the mask effectiveness in the pandemic daily numbers. Considering the number of deaths, for the no mask-wearing scenario, in Figure 6 (b), a daily death accounting for 2,579 would be achieved in the first wave of the pandemic. The number of masks has reduced the number of deaths by 83.9%, 97.3%, and 99.5%, for M_{red} at 40%, 68.5, and 97%, respectively.

In this case, it is also important to note that social distancing is a key role as a preventive measure in the COVID-19 pandemic. Although M_{red} at 40% has achieved successful results in the first wave, this did not repeat in the second wave prediction. Daily numbers were higher than those of the no mask-wearing. This is due to a greater number of people did not keep social distancing, at that moment, since social distancing tends to decrease over time. Thus, the number of susceptible was higher during the second wave.

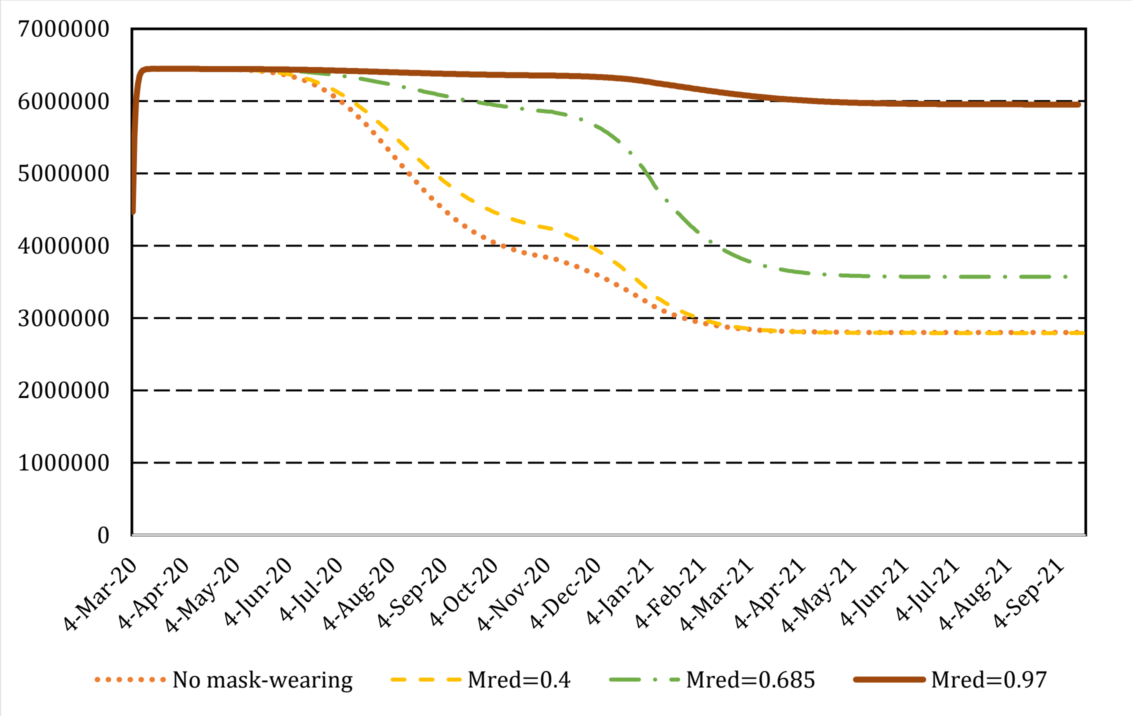
Mask availability for only 10% of the population would achieve around 1,485 daily infections in the first wave, while in the second wave around 2,650 could be infected (see Figure 6 (c)). For only 10% of the population wearing a mask, the total number of deaths and infections did not significantly decrease and it would not be sufficient to prevent the health system collapse unless the isolation measures were intensified. It is just verified a postponement of this moment when compared to the no mask-wearing scenario. On the other hand, if masks are available to 80% of the population, the maximum number of daily infections will be 122, while the number of daily deaths will achieve a peak of 3, as presented in Figure 6 (d).

Figure 5:Simulations of daily infection and death rates for permutations in M_{red} (a)-(b), M_{ava} (c)-(d), and M_{cov} (e)-(f)



In Figures 6 (e) and (f), unlike the earlier cases, it is observed a reduction of 19.38% compared to the first wave peak in the no mask-wearing scenario when the lower limit for M_{cov} was considered in the simulations. In the second wave peak, the scenario for M_{cov} at 8% was about 44% higher. Although apparently, no mask-wearing scenario is the worst, it should be considered that social distancing has reduced during the second wave, as shown in Figure 7.

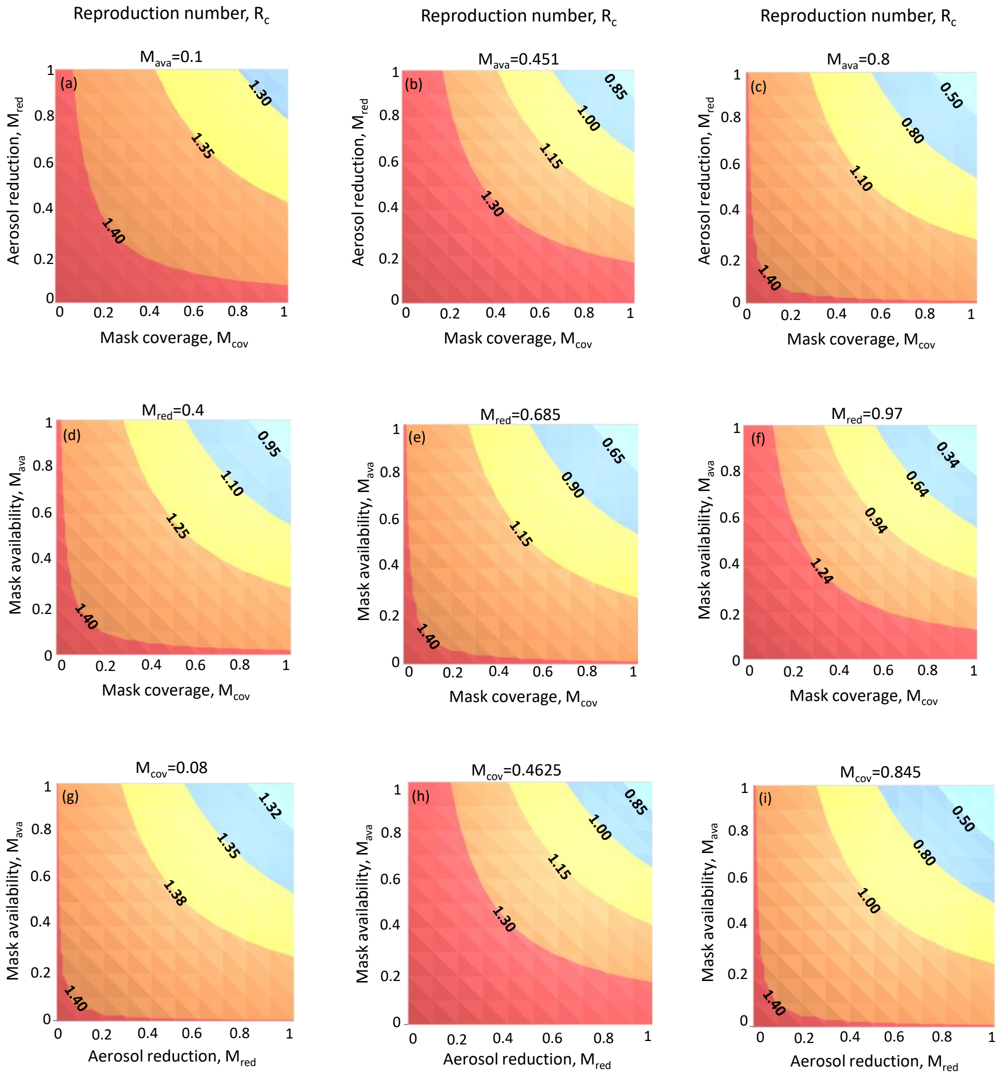
Figure 6: Individuals in social distancing to different $\boldsymbol{M_{cov}}$.



Lifting social distancing was similar for both situations. However, analyzing the daily number of infections, for the no mask-wearing scenario, a greater number of individuals have been infected and have already recovered, while for M_{cov} at 8%, this number was smaller. In the second wave, the number of individuals not infected was higher for this scenario, since the number of people who did not keep the social distancing also increased.

Figure 8 presents the control reproduction number (R_c) variation as a function of the parameters variation: mask availability (M_{ava}), aerosol reduction rate (M_{red}), and mask coverage (M_{cov}) using an effective contact rate as $\beta = \beta_0$.

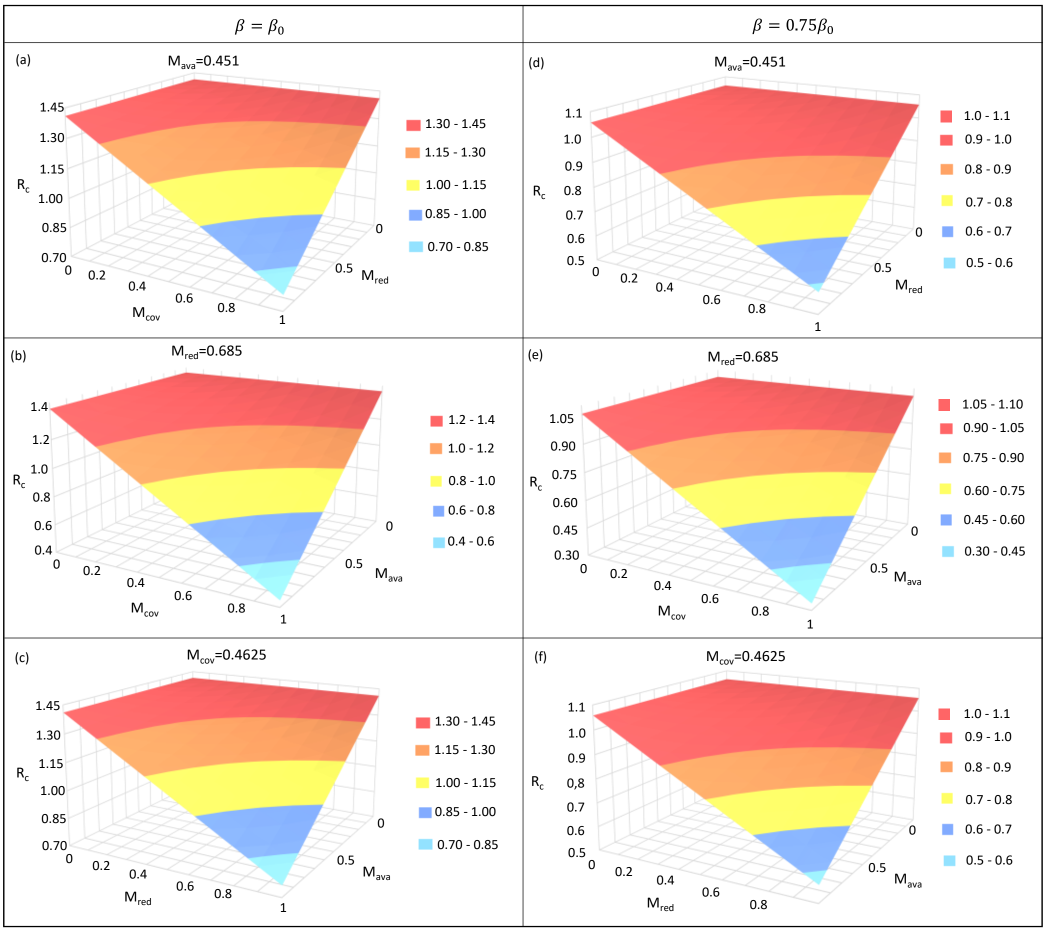
Figure 7:Contour plots of the control reproduction number (R_c), as a function of mask availability (M_{ava}), aerosol reduction (M_{red}), and mask coverage (M_{cov}). (a)-(c) Constant parameter M_{ava}, (d)-(f) Constant parameter M_{red}, (g)-(i) Constant parameter M_{cov}. The effective contact rate $\beta = \beta_0$



From the results, it can be noted that a change in the mask parameters values has significantly affected the reproduction number (R_c). From Figure 8 (a), (d), and (g), in which one of the parameters was set below 40%, even if the remaining values were at 100%, the pandemic would not end, since $R_c > 1$, for all cases. The scenarios considering M_{ava}, M_{red}, and M_{cov} fixed between 40% and 70% are presented in Figures 8 (b), (e), and (h), respectively. In this case, for the pandemic to end ($R_c < 1$), the M_{ava}, M_{red}, and M_{cov} should be greater than 70%, which is not a reality in most countries. At last, in Figure 8 (c), (f), and (i), the reproduction number was lower than 1 for parameters higher than 50%, but, for that, the fixed parameter should be higher than 80%.

Mask parameters variation was combined with social distancing strategies through effective contact rate (β) reduced to 25% of the initial value, evaluating its effect on R_c. Figure 9 provides these results. The mask parameters were the real condition ones.

Figure 8: Profile of the control reproduction number (R_c), as a function of mask availability (M_{ava}), aerosol reduction (M_{red}), and mask coverage (M_{cov}), for different percentages in the baseline value of the effective contact rate (β). (a)-(c) $\beta = \beta_0$ and (d)-(f) $\beta = 0.75\beta_0$.



It is possible to note that the effective contact rate reduction has significantly affected the reproduction number. Comparing Figure 9 (a)-(c) with Figure 9 (d)-(f), the maximum reproduction number value has reduced from around 1.45 to 1.1. It shows that mask-wearing combined with social distancing leads to an important reduction in the transmission rate. It should be highlighted that from the results presented in Figure 9 (d)-(e), it was necessary to set the mask availability and the aerosol reduction at around 40% as well as the proper mask-wearing at 30% to mitigate the COVID-19 transmission, i.e., $R_c < 1$, from a feasible scenario.

4 CONCLUSIONS

The COVID-19 pandemic has caused a world crisis. Preventive measures such as vaccines, wearing a mask, and social distancing have helped to mitigate the pandemic effects on the health public system. Although there are still ongoing discussions about it, this study proposes to better understand the importance of non-pharmaceutical interventions, mainly, wearing a mask, to fight against the coronavirus pandemic.

Our results indicate that wearing a masking impact directly the death and hospitalization rate peak in all scenarios in the first wave of the pandemic. These rates significantly decrease as far as masks are available for the population, achieving 99% when masks are available for 80% of the population. However, at least around 30% of the population should have access to masks so that the second wave peak does not exceed the estimated value for the first wave when there is no mask-wearing, maintaining the same social distancing profile.

By checking the mask aerosol reduction effect, a significant decrease is already achieved by wearing only homemade cloth masks (40%) when compared to the no mask-wearing scenario. However, a great increase in the daily cases and deaths in the second wave is reached. In the current scenario, this reduction is around 85%.

Proper mask-wearing is also a relevant factor in its efficiency. If mask availability is only 45.1%, proper use by the population can avoid health system overload. In the simulated scenarios, the first and second wave peak of the pandemic decreases only if 84.5% of the population properly wears a mask. For the remaining scenarios, since the social distancing predicted tends to decrease, not even mask-wearing will reduce the health system overload risks. This highlights the importance of associating two preventive measures for an effective fight against the pandemic.

Reproduction Number (R_c) analysis provides important information for the pandemic slowdown. Simulations indicate that wearing a mask tends to decrease the R_c value. However, to achieve $R_c < 1$, it will be possible only followed by other measures such as social distancing.

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REFERENCES

E. Iboi, o. O. Sharomi, c. Ngonghala, and a. B. Gumel, “mathematical modeling and analysis of covid-19 pandemic in nigeria,” *medrxiv*, p. 2020.05.22.20110387, jan. 2020, doi: 10.1101/2020.05.22.20110387.

C. N. Ngonghala, e. Iboi, and s. Eikenberry, “mathematical assessment of the impact of non-pharmaceutical interventions on curtailing the 2019 novel coronavirus,” *math. Biosci.*, vol. 325, p. 108364, 2020, doi: 10.1016/j.mbs.2020.108364.

Ministério da saúde, “painel de casos de doença pelo coronavírus 2019 (covid-19) no brasil pelo ministério da saúde,” 2021. Https://covid.saude.gov.br. (accessed aug. 26, 2021).

L. H. Duczmal *et al.*, “vertical social distancing policy is ineffective to contain the covid-19 pandemic,” *cad. Saude publica*, vol. 36, no. 5, may 2020, doi: 10.1590/0102-311x00084420.

Fiocruz, “boletim do observatório covid – 19,” 2021. Https://portal.fiocruz.br/noticia/covid-19-boletim-confirma-reducao-de-casos-internacoes-e-obitos-pela-oitava-semana (accessed aug. 28, 2021).

R. Padmanabhan, h. S. Abed, n. Meskin, t. Khattab, m. Shraim, and m. A. Al-hitmi, “a review of mathematical model-based scenario analysis and interventions for covid-19,” *comput. Methods programs biomed.*, vol. 209, p. 106301, sep. 2021, doi: 10.1016/j.cmpb.2021.106301.

R. S. Barbosa, a. S. S. Soares, d. A. Coelho, and d. A. Santos, “software de simulações dos modelos sir e seir como ferramenta de gerenciamento ambiental de doenças epidemiológicas,” *sci. Cum ind.*, vol. 4, no. 2, pp. 114–118, 2016, [online]. Available: https://doi.org/10.18226/23185279.v4iss2p114.

S. Kim, j. Lee, and e. Jung, “mathematical model of transmission dynamics and optimal control strategies for 2009 a/h1n1 influenza in the republic of korea,” *j. Theor. Biol.*, vol. 412, pp. 74–85, jan. 2017, doi: 10.1016/j.jtbi.2016.09.025.

H. M. Yang and c. P. Ferreira, “assessing the effects of vector control on dengue transmission,” *appl. Math. Comput.*, vol. 198, no. 1, pp. 401–413, apr. 2008, doi: 10.1016/j.amc.2007.08.046.

A. Goyal, l. E. Liao, and a. S. Perelson, “within-host mathematical models of hepatitis b virus infection: past, present, and future,” *curr. Opin. Syst. Biol.*, vol. 18, pp. 27–35, dec. 2019, doi: 10.1016/j.coisb.2019.10.003.

A. O. Cardoso, n. G. Sousa, r. F. Cardoso, and a. G. Utsumi, “análises de estratégias de isolamento social para o enfrentamento da pandemia covid-19 em minas gerais/brasil,” *holos*, vol. 5, pp. 1–19, 2020.

P. H. T. Schimit, “a model based on cellular automata to estimate the social isolation impact on covid-19 spreading in brazil,” *comput. Methods programs biomed.*, vol. 200, p. 105832, mar. 2021, doi: 10.1016/j.cmpb.2020.105832.

S. E. Eikenberry *et al.*, “to mask or not to mask: modeling the potential for face mask use by the general public to curtail the covid-19 pandemic,” *infect. Dis. Model.*, 2020.

N. G. Sousa, a. O. Cardoso, r. F. Cardoso, and a. G. Utsumi, “análise da dinâmica de transmissão da covid-19 em minas gerais: modelagem e simulação,” *res. Soc. Dev.*, vol. 9, no. 8, pp. 1–17, 2020.

T. Li, y. Liu, m. Li, x. Qian, and s. Y. Dai, “mask or no mask for covid-19: a public health and market study,” *plos one*, vol. 15, no. 8 august, aug. 2020, doi: 10.1371/journal.pone.0237691.

C. Castilho, j. A. M. Gondim, m. Marchesin, and m. Sabeti, “assessing the efficiency of different control strategies for the coronavirus (covid-19) epidemic,” *arxiv prepr. Arxiv2004.03539*, 2020.

J. Jia *et al.*, “modeling the control of covid-19: impact of policy interventions and meteorological factors,” *arxiv prepr. Arxiv2003.02985*, 2020.

W. I. Lyra, j. -dias do nascimento jr, j. Belkhiria, l. I. De almeida, p. M. Paulo chrispim, and i. De andrade, “covid-19 pandemics modeling with modified determinist seir, social distancing, and age stratification. The effect of vertical confinement and release in brazil,” 2020, doi: 10.1371/journal.pone.0237627.

C. N. Ngonghala, e. A. Iboi, and a. B. Gumel, “could masks curtail the post-lockdown resurgence of covid-19 in the us?,” *math. Biosci.*, vol. 329, p. 108452, nov. 2020, doi: 10.1016/j.mbs.2020.108452.

R. Subramanian, q. He, and m. Pascual, “quantifying asymptomatic infection and transmission of covid-19 in new york city using observed cases, serology, and testing capacity,” *proc. Natl. Acad. Sci.*, vol. 118, no. 9, mar. 2021, doi: 10.1073/pnas.2019716118.

Inloco, “mapa brasileiro da covid-19,” 2020. Https://mapabrasileirodacovid.inloco.com.br/pt/ (accessed jul. 13, 2012).

E. Stanislau *et al.*, “estudo observacional sobre adesão ao uso de máscaras faciais em uma região metropolitana,” *brazilian j. Infect. Dis.*, vol. 25, p. 101153, jan. 2021, doi: 10.1016/j.bjid.2020.101153.

Instituto brasileiro de geografia e estatística (ibge), “população estimada,” 2019. .

P. V. Savi, m. A. Savi, and b. Borges, “a mathematical description of the dynamics of coronavirus disease (covid-19): a case study of brazil,” apr. 2020, accessed: jul. 10, 2020. [online]. Available: http://arxiv.org/abs/2004.03495.

Secretaria estadual de saúde (ses), “boletim epidemiológico,” 2020. [online]. Available: http://coronavirus.saude.mg.gov.br/boletim.

Secretaria estadual de saúde (ses), “boletim epidemiológico 20/07/2021,” 2021. [online]. Available: https://coronavirus.saude.mg.gov.br/images/1_2021/07-julho/covid-19_-_boletim20210720.pdf.

Online]. Available: https://coronavirus.saude.mg.gov.br/images/1_2021/07-julho/COVID-19_-_BOLETIM20210720.pdf.