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EDITORIAL

Modeling spatial and temporal expansion of COVID-19 in Goias State: lessons for advising health policies

Modelando a expansão espacial e temporal da COVID-19 em Goiás: lições para subsidiar políticas públicas

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In the context of a global expansion of the COVID-19 pandemic, predictive models have become a fundamental tool for helping to inform public policies toward mitigating the effects of the disease[(1)]. Classic epidemiological models that belong to the SIR (susceptible, infected, and recovered individuals) class and their variations have been widely used[(2)] in this context, indicators related to the transmission of the disease among the population, such as the reproduction number *R*[(3)], which was discussed exclusively by scientists before the COVID-19 pandemic, gained public recognition and began being publicized in the media.

Although SIR models can be easily implemented analytically, more complex models that evaluate disease progress at an individual level over time are more realistic[(4)]. These models, named agent-based models (ABM), are especially useful because of the ease with which they incorporate the heterogeneity of a population and the possibility of assessing interventions in complex scenarios[(5)]. In contrast, they are more difficult to be calibrated and adjusted to empirical data and their implementation requires great computational power[(6)]. Applying these complex dynamic models requires interdisciplinary integration between scientists from different areas.

In this context, with the onset of the COVID-19 pandemic in Brazil at the beginning of 2020 and, more specifically in Goias state in March, we developed an ABM that can evaluate the spatial and temporal dynamics of the pandemic in the state. The ABM-COVID-GO model, designed by a research group at the Federal University of Goias (www.covid.bio.br), simulates COVID-19 progression by considering each individual in a population of susceptible people in a metapopulation framework, in which Goias state is a population and each one of its municipalities, with their demographic specificities (especially age structure), is a subpopulation. In this model, individuals from each municipality get infected gradually according to the place's internal dynamics and its geographic and demographic relationships. The model simulates the disease progression based on several parameters and their statistical distributions, including incubation period, transmissibility time and period, proportion of infected individuals that developed symptoms, probabilities of progression to more severe conditions that require hospitalization, admission to intensive care units, and probability of evolution to death, with all these items stratified by age group. Having the number and transmission of infections in the population as a starting point, it is possible to progressively estimate the number of events (people admitted to hospital and intensive care units and number of deaths caused by COVID-19) and the demand for hospital beds at each time, already taking into account the mean length of hospital stay. It is important to emphasize that the models project an effective number of events, regardless of problems related to underreporting or delays in information systems or the confirmation of cases and deaths.

The main parameter related to the progression of an epidemic is the basic reproduction number (R_0 at the beginning of the epidemic), which expresses the average

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number of secondary infections that an infected individual originates in a population of susceptible people[7]. This number decreases with the gradual reduction in the number of susceptible individuals in the population and especially as a result of intervention measures implemented over time, which made it necessary to define another parameter designated effective reproduction number (*Re*). In ABM-COVID-GO III, *Re* is estimated directly from the social distancing index measured by mobile telephony and generated *in loco* (https://mapabrasileirodacovid.inloco.com.br/pt/) for each municipality in Goias. Several modeling studies have assumed that implementing social distancing measures reduces *Re*[8]. The values estimated empirically by using the EpiEstim package based on the COVID-19 indeed confirmed cases in Goias state showed a strong relationship with the social distancing index, considering a temporal delay of seven days between the beginning of social distancing and the generation of new cases (r=-0.72). This is important to validate ABM-COVID-GO assumptions and shows the need to keep social distancing in addition to recommended nonpharmacologic measures such as diagnosis of potential cases, isolation of confirmed cases, and screening and quarantine of contacts to mitigate the impacts of COVID-19.

Improving the model calibration gradually has been possible by using local data, to reproduce the progression of the curve that shows the growth of hospitalizations and deaths caused by COVID-19 in Goias more accurately. Among these data, we included the infection prevalence estimates obtained from population-based serologic surveys carried out in Goiania (0.75% and 2.1% on 05/30 and 06/20, respectively[9], according to the Goiania Municipal Health Secretariat) and the number of patients with COVID-19 who are hospitalized in Goiania.

A well-calibrated model means that it is possible to accurately capture the main past tendencies and, by applying inductive reasoning, one may project future events under different scenarios. This can be done by considering different levels of social distancing in the future or evaluating counterfactual situations (for instance, assessing what would have occurred if no measure had been implemented). By exploring different scenarios, it is possible to obtain contrasting estimates for events and demand for hospital beds for COVID-19 patients in the future. For example, the low levels of social distancing recorded in June 2020, which led to a high *Re* (between 1.4 and 1.5), when used as input, could help predict an extremely high number of deaths (around 18,000) in the long run. Although long-term continuous growth scenarios usually do not materialize, since measures to reduce the transmission rate are implemented on an emergency basis to prevent health systems from collapsing, the perception of the magnitude of the accumulated events that originated from a quasi-exponential growth in the long run can be useful, because it can be a warning about the need to adopt stricter measures to fight the pandemic. Additionally, taking into account the difficulty involved in implementing a new prolonged quarantine, it is possible to test the effect of alternative scenarios, such as carrying out stricter social distancing measures intermittently (with 14-day cycles, for example), which would reduce the number of deaths in the long term up to 61.5%. Most importantly, when we consider an additional strategy of substantial reinforcement of epidemiological surveillance based on the implementation of screening and quarantine of case contacts to interrupt secondary transmission chains, there is a further impact of around 15% in the decrease of hospitalizations and deaths caused by COVID-19 in the long run[10]. Reality is undoubtedly more complex than any of these scenarios, and it is indisputable that the effectiveness of any adopted measure depends on several factors, especially adherence of the population and the society and the existence of effective conditions to implement and keep this type of strategy over time.

In short, applying an ABM in the evaluation of COVID-19 progression has been useful for understanding the evolution of the disease and inform public policies in the municipality of Goiania and the state of Goias. These policies have been systematically proposed, discussed, and validated by the Committee for Emergency Operations in Public Health in the municipality of Goiania and the state of Goias. It is worth emphasizing that the answer to the question "what may happen?" is different from the answer to the question "what must be done?". Models answer the former and, by doing so, can be useful for providing those who have to answer the latter with resources. Defining what has to be done is the responsibility of managers who coordinate with public authorities, public health agencies, and society.

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