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Optimal allocation strategies for prioritized geographical vaccination for Covid-19

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ABSTRACT

While SARS-CoV-2 vaccine distribution campaigns are underway across the world communities, these efforts face the challenge of effective distribution of limited supplies. We wonder whether suitable spatial allocation strategies might significantly improve a campaign’s efficacy in averting damaging outcomes. In the context of a limited and intermittent COVID-19 supply, we investigate spatial prioritization strategies based on six metrics using the SLIR compartmental epidemic model. We found that the strategy based on the prevalence of susceptible individuals is optimal especially in early interventions and for intermediate values of vaccination rate. It minimizes the cumulative incidence and consequently averts most infections. Our results suggest also that a better performance is obtained if the single batch allocation is supplemented with one or more updating of the priority list. Moreover, the splitting of supply in two or more batches may significantly improve the optimality of the operation.

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1. Introduction

In 2020, novel coronavirus broke out in the world [1–6]. It causes, in two years, millions of confirmed cases and deaths. Great efforts in the world have been made for controlling COVID-19 pandemic, but unfortunately, this latter continues to pose serious challenges to global health.

In another respect, the mathematical modeling gives epidemiologists a powerful tool in order to understand the virus propagation mechanism and consequently try to control it with different means [7–12]. In this regard, many standard models have been proposed especially those based on population compartments of different epidemic state. Among them, we cite essentially, the SLIR (Susceptible –Latent –Infectious –Recovered/Removed) model. A more realistic modeling approach try to adapt the SLIR model to take into account the geographical or spatiotemporal dimension [13–16]. In addition to their ability to introduce local characteristics in the model such as population density, these works have the advantage of including the mobility flux between different areas which is a major factor driving the geographical virus propagation.

In severe situations such that imposed by the COVID-19 pandemic, the development and use of vaccines is of a great hope to control COVID-19 epidemic. However, given the scarcity of the vaccine doses, researchers have made a great effort to establish prioritization strategies for COVID-19 vaccination. The most common approaches typically focused on prioritizing individuals with higher transmission or with higher risk using age-stratified deterministic models [8,17–23]. Some studies have focused on whether we should prioritize the essential workers or the older people and present the
benefits of targeting essential workers [24,25]. In the same context, Babus et al. proposed an allocation strategy taking into account different ages and occupations [26].

On the other hand, many prospective studies have addressed the question of vaccine prioritization based on the standard epidemic model using a spatiotemporal treatment [27–29]. Although there is little literature on the subject, in most recent works, scientists suggested optimal spatial allocation strategies and recommended to allocate the vaccine doses where they have the most beneficial impact on the epidemic dynamics [27,30,31] based on different local criteria.

In this context, our work is a contribution to the investigation of geographically based allocations of vaccine doses. For this purpose, we used a geographical adapted SLIR (Susceptible–Latent–Infectious–Recovered/Removed) model to quantify the impact of our COVID-19 vaccine prioritization strategies on cumulative incidence, under a limited supply of COVID-19 vaccine doses.

The efficacy of the spatial allocation strategies is measured by the cumulative incidence (Cumulative number of individuals that contracted the virus in the course of the simulation time divided by the total population number). The simulations are done for different values of the intervention time \( t_0 \), that is the time of the first dose administration as well as vaccination rate \( V_R \) which represents the vaccine rollout speed as a percentage of the total population vaccinated per day. We found that, among the six strategies studied in this work, the optimal strategy is the one based on the metric of the prevalence of susceptible individuals: \( S/N \), which results in high reduction of the cumulative incidence in function of early intervention time and average values of vaccination rate. However, the efficacy of the vaccination campaign depends highly on the optimal allocation of vaccine supplies. In fact, we found that the vaccination is more efficient if the vaccine is allocated in one single batch, but provided that the priority list is updated more than one time in the period of vaccine coverage.

In Section 2 we formulate the spatiotemporal SLIR model and we propose the methods of the implementation of this model with real population and mobility data from USA. Then, in Section 3, we discuss the vaccine allocation strategies and the different metrics used for prioritization. Section 4 is devoted to the presentation of the results of the numerical simulation corresponding to the established vaccination strategies and as well as the discussion of their implications. We end with a conclusion section.

2. Virus propagation model

To model the COVID-19 transmission and vaccination, we use the compartmental model SLIR. The dynamics assume classic compartmentalization in which each individual is classified by one of the discrete states such as Susceptible, Latent, Infectious and permanently Recovered/Removed. The model transition parameters between compartments are labeled \( \beta \), \( \alpha \) and \( \lambda \). \( \alpha \) and \( \lambda \) are set respectively at 0.33 and 0.2 and \( \beta \) is deducted from the reproductive number \( R_0 \) value which is 1.5 representing substantial virus growth in the case of COVID-19 [18]. The idea of spatial vaccination allows us to integrate the geographical, demographic and mobility dimensions into the standard SLIR model following the work in [15,16]. The combination of these three dimensions allows for the subdivision of the studied area of population \( N \) into \( Z \) geographical regions, each one has a population \( N_i \). The infection dynamics take place within each subpopulation and can be transmitted through commuting flows between different areas. The mobility flows represent a network of connections with fluxes \( \omega_{ij} \) and among subpopulations that express the number of individuals who go from subpopulation \( i \) to subpopulation \( j \). We assume that everyone commuting from location \( i \) to location \( j \), stays at location \( j \) for an average time \( \tau^{-1} \); where \( \tau \) is the rate of return. We point out that the commuting database used in this work contains essentially statistics about commuting workers and that every worker stays at its destination an average time of 8 h (from 24), corresponding to \( \tau = 3 \) day\(^{-1} \); this value was used also by D.Balcan et al. (ref. [15]). The commuting databases have been collected from The U.S. Census Bureau of the states of the country. The full dataset comprehends more than 300 million of commuters over 51 states and their counties [32]. The target of our study is the population of the US where subpopulations/regions \( i \) are just the \( Z = 51 \) states with \( i = 1, \ldots, Z \). The model is based on the following dynamics in each subpopulation \( i \):

\[
\begin{align*}
\frac{dS_i}{dt} &= -\frac{\beta S_i}{N_i} \left[ \frac{1}{\tau} \sum_{j \in n(i)} \psi_{ji} \right] \\
\frac{dL_i}{dt} &= -\alpha L_i + \beta S_i \left[ \frac{1}{\tau} \sum_{j \in n(i)} \psi_{ji} \right] \\
\frac{dI_i}{dt} &= \alpha L_i - \lambda I_i \\
\frac{dR_i}{dt} &= \lambda I_i
\end{align*}
\]

where: \( \bar{N}_i = N_i + \sum_j N_j \frac{\omega_{ij}}{\tau} \frac{1}{\tau + \gamma_j} \) stands for the stationary average population in region \( i \) taking into account commuting individuals from neighbors; and \( \psi_{ji} = \gamma_j + \gamma_j \frac{N_i}{\bar{N}_j} \) is a transfer factor from area \( j \) to area \( i \); with \( \gamma_j = \frac{\sigma_j}{\tau + \gamma_j} \), \( \sigma_j = \frac{\omega_j}{\bar{N}_j} \), \( \sigma_i = \sum_{j \in n(i)} \sigma_{ij} \).

In this work, we simulate up to 600 days of disease dynamics using sufficiently small time step integration. The initial conditions are set such that all population is in the susceptible state except one individual considered in the infectious state. The seed case was chosen to be in the state of Alabama (Other choices of the seeded location do not substantially affect the relative optimality of the different strategies considered in this work).
3. Vaccination strategies

The vaccine is assumed, for simplicity, to have a protective efficacy of 100%. Furthermore, no vaccine hesitancy is supposed. The principle of the COVID-19 vaccination strategy used here consists in prioritizing the allocation of COVID-19 vaccines using spatial epidemic information. We fix a maximal objective of 70% of the total population to be vaccinated by the end of the vaccination campaign. This may not always be strict given that in some regions the number of susceptible individuals may be less than the targeted objective depending on the local epidemic situation. However, as our prioritization strategy is implemented under limited supply assumptions, due to logistic challenges, we assume that only a limited stock of COVID-19 vaccine doses is available, that is 35% of the total population, which covers 115 Million of the US population.

To implement the vaccination strategies we set a priority list of the regions to vaccinate in descending order of some metric values. In this work, we adopt six standard strategies in vaccine prioritization based on different metrics: strategy 1: infectious incidence $I$, strategy 2: number of susceptibles $S$, strategy 3: population $N$, strategy 4: prevalence of infectious $I/N$, strategy 5: prevalence of susceptibles $S/N$, strategy 6: Total in-flux of individuals $\Omega$ (For region $i$, $\Omega_i = \sum_j \omega_{ij}$). Afterwards, we allocate the vaccine doses to at most 70% of each region population in the ordered list according to one of the allocation scenarios detailed below, until the supply is exhausted. If the supply is contiguous, vaccines are administered in a single batch. Otherwise, if the supply is intermittent, vaccines are administered in multiple separated batches. In our approach, we vary three parameters that can affect the outcome of vaccine distribution decisions. First, we make use of the vaccinestockinanoptimalway.Ourvaccinationstrategiesfollowmode2(theparalleloone)andreduce

One can distinguish two vaccination modes: mode 1 (sequential mode): where vaccination starts in the top region in the list; and only after reaching the 70% goal on that region (in the limit of its susceptible population), that we proceed with the following one on the list and so on ... until the stock is exhausted. In mode 2 (parallel mode): we proceed by a parallel vaccination of all the regions that are in the priority list until the stock is exhausted. Clearly the sequential mode does not make use of the vaccine stock in an optimal way. Our vaccination strategies follow mode 2 (the parallel one) and reduce to mode 1 only if the stock available is less than that needed for one single region.

In this respect, we distinguish between the planning/allocation time and the execution/vaccination time. During the planning time, we begin from the region at the top of the priority list and allocate to that region the equivalent of 70% of its population, then 70% to the next one ... etc, until the stock is exhausted; the remaining regions (those with lower metric values) are not assigned any vaccine doses. During the execution time, all allocated doses are actually administered to individuals and the concerned regions perform their vaccination operations independently and simultaneously with a vaccination rate (percentage of local population vaccinated per day) $V_R$ which is proportional to local population. The execution/vaccination starts at $t_0$ and is interrupted only when the current stock is exhausted; but whenever a new supply is available, it restarts again...until the end of the simulation time. The regions at the bottom of the list that are considered as having low priority will not be allocated any vaccine doses unless all the regions on the top have received their share.

We consider especially $V_R$ ranging from 0.005% to 2% fraction of each population region in the priority list vaccinated per day and an intervention time $t_0$ in the interval from 50 to 500 days. After each supply, the vaccination operation starts immediately and the regions that have received their allocated doses are vaccinated in parallel. Across all strategies
considered, we assume that vaccinated individuals acquire immunity that lasts for the remaining simulation time window. The number of individuals vaccinated in each region in every time step are subtracted from the number of susceptible individuals of that region and added to a new compartment $V_i$ used for tracking the number of vaccinated individuals. From the simulated results, we compute the cumulative incidence, which is used as outcome to compare the efficacy of different vaccine prioritization strategies.

The implementation of the model is performed via the pseudo code corresponding to a strategy with M update points and K supply points:

BEGIN
Set the input parameters of the model.
Load data from input files (populations $N_i$ and mobility fluxes $\omega_{ij}$).
Compute variables appearing in the equations of the dynamics: $\bar{N}_i$, $\sigma_{ij}$, $\sigma_i$, $\gamma_{ij}$ and $\psi_{ij}$.
Set intervention points:
Update points: $U = \{ t_u[i], 1 <= i <= M \}$
Batch/supply points: $B = \{ t_b[i], 1 <= i <= K \}$
Set time $t=0$, CurrentStock=0 and initialize SLIR variables of the epidemic state.
WHILE ($t \leq t_{max}$):
  if($t \geq t_0$) Vaccinate()
  if($t \in B$): Add new supply and update CurrentStock= CurrentStock+NewSupply
  if($t \in U$) Reallocate()
  ComputeTimelyOutputData()
  Advance timestamp $t = t + h$
END WHILE
ComputeGlobalOutputData ()
END

FUNCTION Reallocate():
  For each region: Recompute metric value
  Sort regions in descending order of the metric and store them in List[
  WHILE (CurrentStock > 0):
    For each region $i$ in List[]: Alloc[$i$]=Min(CurrentStock, 0.7*$N[i]$, $S[i]$)
  END WHILE

FUNCTION Vaccinate():
  FOR each region $i$:
    Define Dose=Min($V_R*N[i]*h$, Alloc[$i$],$S[i]$)
    $S[i]= S[i]-Dose$
    $V[i]=V[i]+Dose$
    CurrentStock= CurrentStock-Dose
  END FOR

4. Results and discussion

In order to measure the potential impact of our spatial allocation strategies on the epidemic situation, we compute the cumulative incidence of the COVID-19 Infections under various values of the vaccination rate $V_R$ and the intervention time $t_0$. We apply the scenario 3b with an initial supply of 14% of the total population which amounts to 46 Million doses provided at time $t_0$. The second and third supplies are allocated at $t_0 + \Delta t$ and $t_0 + 2 \Delta t$ respectively. They cover another 14%, (46 Million) and 7% (23 Million) of the total population respectively.

In Fig. 1, we plot the total number of infectious individuals for the case without vaccination compared to the case with vaccination considering four intervention times ($t_0 = 50, 100, 300$ and 350 days). We see that the number of infectious individuals as a function of time reaches a peak that is higher for late vaccination. In particular, for intervention time $t_0 = 350$ days, it approaches the case with no vaccination. In contrast, for early intervention times, the peak becomes very low and at the same time, we observe a shift in the position of the peak towards high time values meaning a delay of the disease cycle and consequently the avoidance of the overload of care services.

In order to compare the strategies of vaccination, we use as outcome the cumulative incidence (Percentage of the total cumulative number of infectious cases from the total population). This measure permits to show the impact of the vaccination rate $V_R$ and of the intervention time $t_0$ on the efficacy of the vaccination campaign.
Fig. 1. The fraction of infectious individuals for the case without vaccination and the case with vaccination using four different intervention times ($t_0 = 50, 150, 300$ and $350$ days) and a vaccination rate $V_R = 1\%$ of the total population vaccinated per day.

From Fig. 2, we can clearly see that all the prioritization strategies of vaccination show a reduction of the cumulative incidence as a function of the vaccination rate but with different degrees of efficacy. We notice that the prioritization based on the prevalence of the susceptible (Strategy S/N) minimizes the cumulative incidence under vaccination rates (0.4\% to 1.2\% vaccinated per day) compared to the strategies using other metrics. The prioritization based on the prevalence of the infectious (Strategy I/N) presents a slight advantage for small vaccination rates (less than 0.4\%). However, a less performance is observed for the strategy $N$ based on the prioritization of regions of large population sizes. This can be understood by the fact that this latter metrics is a static one and does not make use of any information about the epidemic situation. On the contrary, prioritization of regions of high prevalence of susceptible individuals can be beneficial, especially because this vaccination strategy targets the susceptible population giving them a protection against the disease.

However the strategies: I, S and S/N, are characterized by a minimum and then an increase in the cumulative incidence indicating an apparently counterintuitive result: a slow vaccination operation may be more optimal than a faster one. As an explanation, we should keep in mind that we are comparing vaccination strategies with the same total population to be vaccinated at the end of the campaign; the only difference is the rate at which the vaccine rollout is carried out due to differences in space–time distribution. Consider the two points in Fig. 2 corresponding to $V_R = 0.7\%$ and $1.4\%$ vaccinated per day respectively, having moderate and very fast vaccination rates. Simple calculations show that, for $V_R = 0.7\%$, the first vaccine batch for example, will last 100 days approximately (to reach the objective of the maximal 70\% of the population). While for $V_R = 1.4\%$, the same first batch will last 50 days. Given that the period between two consecutive batches is $\Delta t = 50$ days, in the $V_R = 1.4\%$ case, almost all the vaccine doses of the first batch are used, while for $V_R = 0.7\%$, half of the doses of the first batch remains unused and are consequently re-planned along with the second batch and distributed for a new priority list. The same goes for the second batch. This re-planning of the remaining doses is performed under a new current epidemic situation, making the allocation strategy more optimal for moderate vaccination rates. For very slow vaccination, the advantage of stock re-planning does not overcome the rapid epidemic expansion. In contrast, static strategies ($N$ and $\Omega$) do not show this behavior and a moderate vaccination speed will not have any advantage in this case.

In Fig. 3, we plot values of the cumulative incidence as a function of the intervention time $t_0$ (start time of the vaccination campaign) with a vaccination rate of 1\% of the total population vaccinated per day. Globally, we note that the earlier we start the vaccination, the more we reduce the cumulative incidence further. Very late vaccination (beyond 400 days) is absolutely ineffective and all vaccination strategies become equally worse and almost equivalent to no vaccination at all. Moreover, for all values of the intervention time $t_0$, the strategy S/N is again the best one especially at early $t_0$, while the strategy $N$ is the worst one.
Fig. 2. Cumulative incidence as a function of the vaccination rate $V_R$ in the scenario 3b and for an intervention time $t_0 = 150$ days using six different metrics: I, S, N, I/N, S/N, $\Omega$ (see text).

Fig. 3. Cumulative incidence as a function of the intervention time $t_0$ in the scenario 3b for a vaccination rate of 1% vaccinated per day using six different metrics: I, S, N, I/N, S/N, $\Omega$ (see text).
COVID-19 prioritization strategies may not be equally effective across all vaccine supply scenarios described above in preventing infection or disease. To evaluate the impact of different vaccine supply scenarios on strategies efficacy, we vary the interval $\Delta t$ between consecutive interventions (new vaccine supply or simple updating of the priority list). For all supply scenarios, we compute the cumulative incidence as a measure of the efficacy of each allocation strategy. In Fig. 4, we plot the cumulative incidence as a function of $\Delta t$ for different values of the intervention time $t_0$ and for a vaccination rate of 1% vaccinated per day, considering the scenario 1b2u (1 batch with two updates). The Fig. 4.a and 4.b correspond to the strategy S/N and the strategy I/N respectively. For early intervention time ($t_0 = 150$ days), the two strategies are shown to be optimal for intermediate values of the update time up to $\Delta t \approx 70$ days. This special value corresponds to the approximate time where the supply intended for each region is exhausted; considering that a maximal of 70% of its population is vaccinated with a rate of 1% vaccinated per day. So the optimal value of $\Delta t$ is situated around the middle of this interval (35 days). For $\Delta t < 35$ days only one update is performed before the stock is exhausted; the other update is ineffective. This explains the increase of the cumulative incidence resulting in the decrease of the efficacy. For $\Delta t > 70$ days, the two updates are now outside the vaccine coverage time window. So the procedure becomes equivalent to the case with no update (Cumulative Incidence=0.29) corresponding to the limit $\Delta t = 0$ days (where the priority list is updated twice at the time when the list is first created). Therefore, the curves are flattening at the same level of this point.

For late intervention times, we can clearly see that the region of optimality decreases with increasing intervention time $t_0$. Consequently, the two strategies converge to the case with no vaccination, meaning that all strategies become equally ineffective when the supply comes very late.

Interestingly, we note that the S/N strategy is clearly more effective compared to the I/N strategy. This is shown by the minimal value attained in each case by the cumulative incidence in the optimal regime.

We can observe irregularities in the curves of Fig. 4.a and 4.b which are due to the non-continuous character of the prioritization strategy. Indeed a small change in some parameter may induce a considerable change in the priority list given that the geographical regions have very different sizes.

In order to confirm the efficiency of the S/N strategy observed in the scenario 1b2u we compare it to the other supply scenarios. This is achieved by plotting the curves of the cumulative incidence as a function of $\Delta t$ for the early interventions, i.e. $t_0 = 150, 300$ days (Figs. 5 and 7).

Fig. 5 represents the cumulative incidence as a function of $\Delta t$ with an intervention time $t_0 = 150$ days for the S/N vaccination strategy implemented using five supply scenarios of vaccine in addition to the no vaccination case for comparison. For small interval $\Delta t$, the scenario 1b is less optimal; this is obvious because S/N is a dynamical metric.
which gets updated following the epidemic situation. But for scenario 1b, it loses its advantage and behaves like a static metric being evaluated only once at $t = t_0$ without any subsequent updating. In general, the interval $0 < \Delta t < 70$ days is found to be the region of optimality of the strategy S/N in all scenarios compared to the standard scenario 1b (without update). This interval is exactly the time where the first batch is consumed. In this interval, the scenario 1b2u is clearly the more optimal compared to all other scenarios. For $\Delta t > 70$ days the two scenarios 1b2u and the scenario 1b1u join the standard scenario 1b, meaning that when the update operations come after 70 days they are inefficient.

In order to support the preceding conclusions implied by the results of Fig. 5, we plot in Fig. 6 the time evolution of the vaccine stock and the fraction of infectious individuals for the scenario 2b considering values of $\Delta t = 100$, 250 and 350 days. For $\Delta t = 100$ days (Fig. 6.a), the second vaccine batch comes after the consumption of the first one. Although there is a time interval not covered by vaccination, the number of infectious individuals remains very low. This explains the first plateau observed in Fig. 5. For $\Delta t = 250$ days (Fig. 6.b), the second vaccine batch comes during the epidemic wave. The vaccine doses are used to mitigate the epidemic. The larger is the interval between the two supplies, the larger is the cumulative incidence. For $\Delta t = 350$ days (Fig. 6.c), the second batch comes very late after the epidemic cycle has already ended. The second supply of vaccine doses is useless although they are actually used but very late.

In Fig. 7, we plot the cumulative incidence as a function of $\Delta t$ with an initial intervention time $t_0 = 300$ days of the S/N vaccination strategy implementation using five supply scenarios of vaccine compared to the no-vaccination case. The results are in line with those of Fig. 5, and confirm that the scenarios 1b2u and 1b1u are optimal for $\Delta t$ ranging from 0 days to 70 days. For $\Delta t > 70$ days the cumulative incidence curves of these two scenarios converge to the 1b standard scenario level. The less optimal scenario is the scenario 3b for all the values of $\Delta t$. The optimality interval shrinks for
Fig. 6. Time evolution of the vaccine stock (pink curves) and the fraction of infectious (green curves) individuals for the supply scenario 2b. Data are computed for values of time interval $\Delta t$: (a) $\Delta t = 100$ days, (b) $\Delta t = 250$ days and (c) $\Delta t = 350$ days.

Fig. 7. Plots of the cumulative incidence as a function of $\Delta t$ ranging from 0.1 to 200 days with an intervention time $t_0 = 300$ days and a vaccination rate 1% vaccinated per day. The data are plotted for the S/N vaccination strategy. The supply scenarios represented in the figure are 1b, 1b1u, 1b2u, 2b and 3b. The scenario without vaccination is also represented for comparison.
the scenario 2b and it disappears for the scenario 3b. The curves of cumulative incidence corresponding to the scenarios 2b and 3b saturate at the values 0.41 and 0.46 respectively, corresponding to the cumulative incidence value of the first vaccine supply as a single batch; i.e. 21%, 14% respectively. We note that in the cumulative incidence curve corresponding to scenario 2b, there is only one plateau this time, compared to the curve of the cumulative incidence of the same scenario in Fig. 5. This can be explained by the fact that the epidemic wave has already taken place because of the late intervention time. Consequently, any delay between the two batches induces an increase of the cumulative incidence.

5. Conclusion

In summary, in this study the question of optimal COVID-19 vaccine allocation is investigated by using spatial prioritization strategies submitted to supply limitations based on USA population and mobility data. Our main findings show that the strategy S/N, based on the prevalence of susceptible individuals, is optimal compared to alternative strategies and shows good performance in reduction of the cumulative incidence and mitigating the epidemic as well, especially in intermediary vaccine rates and early interventions. Moreover, we studied five scenarios and showed that the best supply scenario to implement the optimal strategy S/N is the scenario 1b2u with a single batch and two updates of the priority list. The optimality of the scenario is manifest when the time interval between two interventions does not exceed 70 days.

We found that a one-time rigid planning of vaccine allocation might result in a sub-optimal scenario. The optimality can be improved if we make one or more updating of the priority list (as in scenario 1b1u and 1b2u) to make sure that the rest of the supply will be allocated taking into consideration the constantly changing epidemic situation. And if we act early with respect to the epidemic outbreak we can improve the optimality by splitting the vaccine batch in two or more batches (as in scenario 2b and 3b) separated by suitable time intervals.

We believe that these conclusions can be generalized to other countries and can be applied also at the regional level. Despite not being exhaustive, we believe that our findings can be used as a benchmark with which other strategies can be compared and further developed.

CRediT authorship contribution statement

Ikram Ghazal: Conceptualization, Idea, Discussion, Writing, Software. Abdeljalil Rachadi: Conceptualization, Idea, Discussion, Writing, Supervision. Hamid Ez-Zahraouy: Conceptualization, Discussion, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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