Reacting to outbreaks at neighboring localities

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We study the dynamics of epidemics in a networked metapopulation model. In each subpopulation, representing a locality, disease propagates according to a modified susceptible-exposed-infected-recovered (SEIR) dynamics. We assume that individuals reduce their number of contacts as a function of the weighted sum of cumulative number of cases within the locality and in neighboring localities. The susceptible and exposed (pre-symptomatic and infectious) individuals are allowed to travel between localities undetected. To investigate the combined effects of mobility and contact reduction on disease progression within interconnected localities, we consider a scenario with two localities where disease originates in one and is exported to the neighboring locality via travel of undetected pre-symptomatic individuals. We associate the behavior change at the disease-importing locality due to the outbreak size at the origin with the level of preparedness of the locality. Our results show that restricting mobility is valuable if the importing locality is increasing its level of preparedness with respect to the outbreak size at the origin. Moreover, increased levels of preparedness can yield lower total outbreak size by further reducing the outbreak size at the importing locality, even when the response at the origin is weak. Our results highlight that public health decisions on social distancing at localities with less severe outbreaks should strongly account for potential impact of neighbouring localities with a poor response to the outbreak rather than localities with successful responses.

Keywords: Epidemiology, networked metapopulation, nonlinear dynamics, social distancing.

I. INTRODUCTION

Early detection of disease outbreaks at their location of origin provide a chance for local containment and time to prepare in other locations. Such preparation may enable locations connected to the origin to become more aware of the outbreak and develop a stronger response to the disease especially when it is not contained. The success of containment strategies is highly dependent on the ability of promptly detecting most infectious individuals in a given location. The recent outbreak of the COVID-19 virus has shown that successful containment efforts are highly challenging when many infectious individuals remain asymptomatic and can travel undetected between locations [1].

In the ongoing COVID-19 outbreak, localities in the US are beginning to see alarming surges in their number of cases and hospitalized individuals at different times, likely because the introduction times of the disease to the local communities differ [2]. While reducing mobility between localities can delay the overall epidemic progression, the epidemic trajectory, e.g., the final outbreak size, is not strongly affected by the travel restrictions unless they are combined with a strong reduction in transmission within the locality [3–6]. In the US, local authorities are implementing non-pharmaceutical interventions, e.g., declaring emergency or issuing stay at home orders, at different times. Community response to these interventions differ across localities [7]. The premise of this work is to assess— in a generalized model —the combined effects of mobility, local response to disease prevalence, and the level of alertness prior to disease surge in a locality.

Here, we consider a networked-metapopulation model [8–11] where the disease progresses according to susceptible-exposed-infected-recovered (SEIR) dynamics within each population or locality (similar to [12]). Within each population, susceptible individuals can become exposed, i.e., pre-symptomatic, by being in contact with individuals in exposed and infected compartments. Recent experiments on temporal viral shedding of COVID-19 estimate near half of the secondary cases happen by being in contact with individuals in pre-symptomatic stage [13]. The difference between pre-symptomatic infected and infected individuals is that pre-symptomatic individuals can travel between localities undetected. In our model, the exposed individuals progress to being infected and then to being recovered.

That is, we do not make a distinction between symptomatic and asymptomatic infected individuals; further extensions could incorporate such differences, e.g., [1, 14].

Our focus is on the role of behavior changes in different localities and the effects of behavior changes on local disease progression. We assume individuals change their behavior and reduce their contacts proportional to disease severity, i.e., the ratio of infected and recovered, in the population [15, 16]. In addition, behavior in a locality can be affected by the disease severity in neighboring localities. That is, individuals in a locality take protective measures, e.g., social distancing, based on disease severity in a neighboring locality. In particular, we consider a scenario between two localities in which the disease originates in one, and moves to the other locality by mobility of exposed individuals. In this scenario, we interpret initial behavior changes at the locality neighboring the origin as 'preparedness-based' behavior change. Our aim is to quantify the combined effects of inter-locality mobility, preparedness-based behavior change, and behavior changes in response to local disease prevalence. Our analysis focuses on delay in peak times between two localities, total outbreak size and the outbreak size at localities neighboring the origin as a function of mobility, preparedness, and population response.

II. MODEL

We consider a networked meta-population model. At each population, the disease propagates according to SEIR dynamics, that assumes a homogeneously mixed population. In addition, we assume there is constant travel in and out of each population. At midst of containment efforts, the flow of travelers are only healthy (susceptible), and those that are infectious without symptoms (exposed). The dynamics at locality i is given as follows:

$$\dot{S}_i = -\beta_i \frac{S(I+E)}{N_i} + \sum_{j\in\mathcal{N}_i} \lambda_{ji} \frac{S_j}{S_j+E_j} - \frac{S_i}{S_i+E_i} \sum_{j\in\mathcal{N}_i} \lambda_{ij} \tag{1}$$

$$\dot{E}_i = \beta_i \frac{S(I+E)}{N_i} - \mu E_i + \sum_{j\in\mathcal{N}_i} \lambda_{ji} \frac{E_j}{S_j+E_j} - \frac{E_i}{S_i+E_i} \sum_{j\in\mathcal{N}_i} \lambda_{ij} \tag{2}$$

$$\dot{I}_i = \mu E_i - \delta I_i \tag{3}$$

$$\dot{R}_i = \delta I_i, \tag{4}$$

where β_i is the transmission rate at location i, λ_{ij} is the flow of individuals from location i to neighboring location j, μ denotes transition rate from exposed (pre-symptomatic) to infected (symptomatic), and δ is the recovery rate. We denote the neighboring localities of i with $\mathcal{N}_i$. We assume total flow in and out of a location are equal, i.e., $\lambda_{ij} = \lambda_{ji}$. The total mobility flow from i to j include susceptible and exposed individuals proportional to their size in the population. We assume infected individuals cannot move without being detected.

The transmission rate at location i depends on the inherent infectivity rate β and social distancing due to disease prevalence,

$$\beta_i = \beta \left(1 - \omega_{ii} \frac{I_i + R_i}{N_i} - \sum_{j\in\mathcal{N}_i} \omega_{ij} \frac{I_j + R_j}{N_j}\right)^{\alpha_i}. \tag{5}$$

In the social distancing model, individuals reduce their interaction with others proportional to the ratio of cumulative cases, defined as the ratio of infectious and recovered in the population, individuals at locality i and neighboring localities of i. The term inside the parentheses is the awareness at locality i caused by disease prevalence. The weight constant $\omega_{ii} \in [0,1]$ determines the importance of disease prevalence at locality i versus the importance of disease prevalence at neighboring $\mathcal{N}_i$ localities, $\omega_{ij} \in [0,1]$. We assume the weights sum to one, i.e., $\sum_{j\in\mathcal{N}_i \bigcup i} \omega_{ij} = 1$. The exponent constant α_i represents the strength of response to the disease awareness. It determines the overall distancing at locality i based on the awareness. If $\alpha_i = 0$, there is no distancing response to the awareness at locality i. Note that the awareness term inside the parentheses is always less than or equal to 1. Thus, the larger α_i is, the larger is the distancing response at locality i to disease prevalence. We refer to the case with $\alpha_i = 1$ as the linear distancing model.

In the following, we consider two localities with equal population sizes $N_1 = N_2$. The disease starts at locality 1 with 0.1% infected, and spreads over to locality 2 via undetected exposed individuals traveling from 1 to 2. We set $\beta = \frac{1}{2}$, $\mu = \frac{1}{2}$, and $\delta = \frac{1}{3}$ based on the rates estimated at [1] for the COVID-19 outbreak in China. Note that we have the standard SEIR model in both localities when $\alpha_i = 0$ and $\lambda_{ij} = 0$ for all localities.

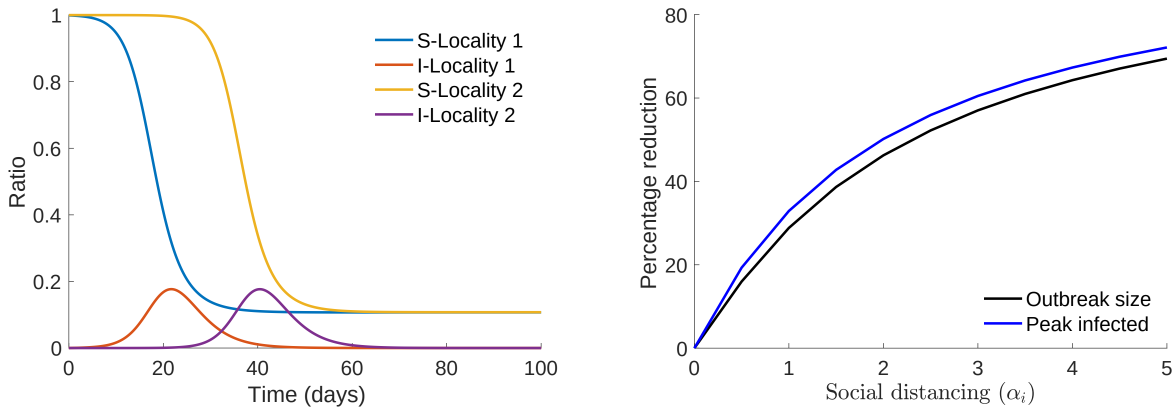

FIG. 1: (Left) SEIR model at localities 1 and 2 with no-distancing. The difference in time of peaks is the 19 days. Final outbreak sizes of localities 1 and 2 are almost identical. (Right) Percentage reduction in outbreak size and ratio of infected at peak with respect to increasing social distancing exponent (α_i) at Locality 2. We measure the reduction with respect to the no-distancing case ($\alpha_i = 0$). In both cases, we have the mobility per day $\lambda_{12} = \lambda_{21} = 0.01\%$ of the population.

III. MOBILITY AND SOCIAL DISTANCING

As a baseline we consider no distancing response, i.e., $\alpha_i = 0$ for all $i = \{1, 2\}$—see Figure 1 (Left). Final sizes at localities are almost the same. The difference in peak times of two localities increases from 19 days to 31 days as λ_{ij} decreases from 0.01% to 0.0001%. Next, we consider the effect of social distancing. For this, we assume localities only put weight on disease prevalence at their own locality, i.e., $\omega_{ii} = 1$ for $i \in \{1, 2\}$. Figure 1 (Right) shows the reduction in final outbreak size and peak ratio of infected at Locality 2 as localities become more responsive, i.e., as α_i increases. When the distancing is linear $\alpha_i = 1$, the reductions in peak and outbreak size are slightly above 20%. Reduction in both metrics reaches above 60% when $\alpha_i = 5$. While both metrics continue to decrease with α_i increasing, there does not exist a critical threshold of α_i that stops the outbreak from happening [15–17]. We observe a slight decrease in time of peak from day 37 to day 35 as α_i increases from 0 to 5. The results mentioned above for Locality 2 are very similar for Locality 1 which observes the outbreak on average 19 days earlier. This similarity is expected when $\omega_{12} = \omega_{21} = 0$, and $\alpha_1 = \alpha_2$. Next, we analyze when localities respond differently to the outbreak.

IV. ADOPTED AWARENESS

We analyze the effect of awareness at Locality 2 caused by the outbreak in Locality 1. We denote the weight ω_{21} associated with this awareness as the adopted awareness weight. Locality 1, the origin of the outbreak, faces the outbreak first. We assume Locality 1's awareness is not shaped by the outbreak at Locality 2, i.e., $\omega_{11} = 1$. Figure 2 (Left) and (Right) show the outbreak size at Locality 2 with respect to the weight Locality 2 puts on the size of the epidemic at Locality 1 respectively for weak linear ($\alpha_2 = 1$) and strong ($\alpha_2 = 3$) responses at Locality 2. In each plot, we consider both weak ($\alpha_1 = 1$) and strong ($\alpha_1 = 3$) responses by Locality 1, and low ($\lambda_{ij} = 0.0001\%$) and high ($\lambda_{ij} = 0.01\%$) mobility rates.

In Figure 2 (Left) and (Right), the outbreak size at Locality 2 monotonically decreases starting from no adopted awareness case, as adopted awareness w_{21} increases irrespective of the strength of response α_2 at Locality 2. The starting point is higher on the left figure since the response to awareness at Locality 2 is weak (linear) while the strength of response on the right is strong with $\alpha_2 = 3$. In both figures, the decrease of the outbreak size at Locality 2 with respect to the adopted awareness constant is faster when the response at Locality 1 is weak. The reason for this is that a weaker response at Locality 1 results in a higher ratio of cumulative cases, which means higher awareness at Locality 2.

Indeed, Locality 2 is always better off adopting the awareness at Locality 1, as this will lead to an early strong response to the disease. The mobility across localities amplifies the effect of response at Locality 1 on the outbreak size at Locality 2. When mobility is low, the difference in time when disease takes-off at Locality 2 compared to Locality 1 is very large ($\approx$ 31 days), which means the contribution of the ratio of cumulative cases at Locality 1 to the awareness at Locality 2 is high. This translates to a stronger response at Locality 2. When the response at Locality 2 is high, we observe that high awareness caused by the outbreak at Locality 1 can suffice in stopping disease transmission at

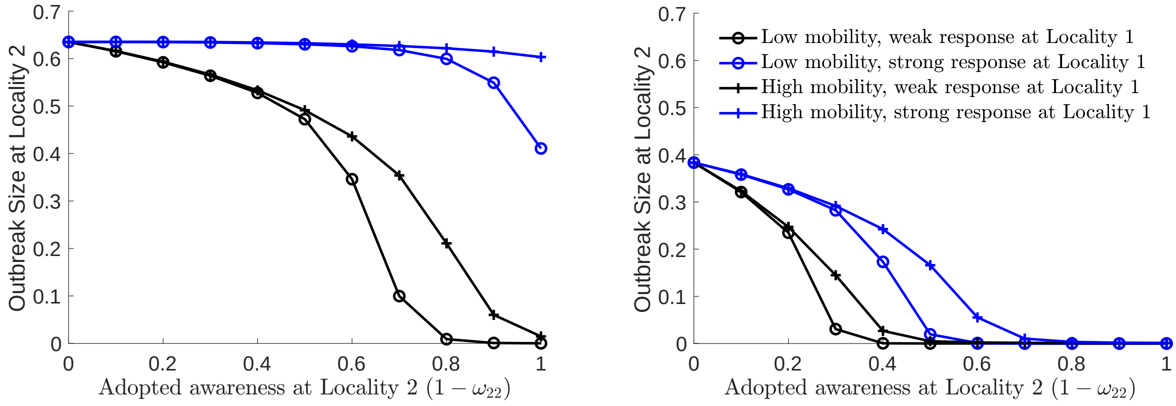

FIG. 2: Outbreak size at Locality 2 with respect to mobility and response at origin for (Left) weak ($\alpha_2 = 1$) and (Right) strong ($\alpha_2 = 3$) response at Locality 2. Low and high mobilities are set as $\lambda = 0.0001\%$ and $\lambda = 0.01\%$, respectively. Weak and strong response at Locality 1 correspond to ($\alpha_1 = 1$) and ($\alpha_1 = 3$), respectively. Weak mobility and weak response at Locality 1 is the best setting for reducing the outbreak size at Locality 2 by increasing adopted awareness.

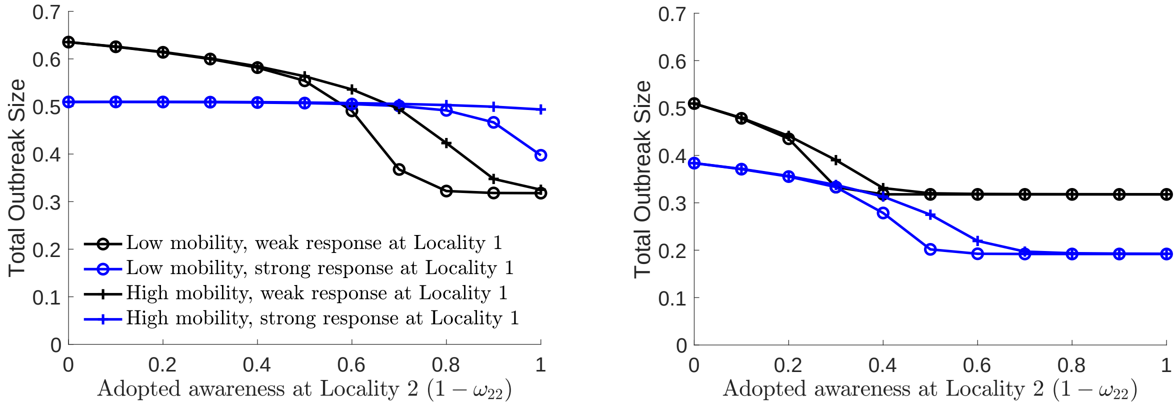

FIG. 3: Total outbreak size with respect to mobility and response at origin for (Left) weak ($\alpha_2 = 1$) and (Right) strong ($\alpha_2 = 3$) response at Locality 2. Low and high mobilities are set as $\lambda = 0.0001\%$ and $\lambda = 0.01\%$, respectively. Weak and strong response at Locality 1 correspond to ($\alpha_1 = 1$) and ($\alpha_1 = 3$), respectively. There exists a critical adopted awareness constant value in (Left) where the total outbreak size is lower in the scenario where both localities respond weakly compared to the scenario where Locality 1 has a strong response. The critical value for the adopted awareness constant value can be found by looking at the intersection of the black line with the blue line for the corresponding mobility value. When both localities respond strongly to the disease in (Right) figure, a critical adopted awareness constant value does not exist.

Locality 2—see Figure 2 (Right) for $w_{21} > 0.4$ for low mobility and weak response at Locality 1. We note that the adopted awareness should be interpreted as individuals in Locality 2 reducing contacts, i.e., practice social distancing, based on the awareness that the outbreak at Locality 1 creates. That is, when the disease starts in one location (locality 1) and moves to a neighboring locality (locality 2) via travel of exposed or asymptomatic infectious individuals from the origin, the adopted awareness distancing term at locality 2 is a measure of the preparedness at Locality 2.

While the above analysis shows that Locality 2 can benefit from a heightened awareness due to a weak response at Locality 1, this awareness is a direct result of the lack of control at Locality 1. In Figure 3, we analyze the total outbreak size given the same setting as in Figure 2. In Figure 3 (Left), we consider a weak (linear) response at Locality 2. In this scenario, for adopted awareness smaller than 0.6 ($\omega_{21} < 0.6$), we observe that the total outbreak size is smaller in the cases that Locality 1 responds strongly, i.e., $\alpha_1 = 3$ (shown by blue lines). For adopted awareness larger than 0.6 ($\omega_{21} > 0.6$), we see that the total outbreak size is smaller in the cases that Locality 1 responds weakly, i.e., $\alpha_1 = 1$ (shown by black lines). An intuition for this result follows. When the response at Locality 1 gets weaker, the outbreak size at Locality 1 increases. This increase results in a higher level of preparedness at Locality 2, which yields a smaller outbreak size at Locality 2. Figure 3 (Left) shows that there exists a level of preparedness ($\omega_{21} \approx 0.6$) above which the increase in severity of the outbreak at Locality 1 is smaller than the reduction in the outbreak size

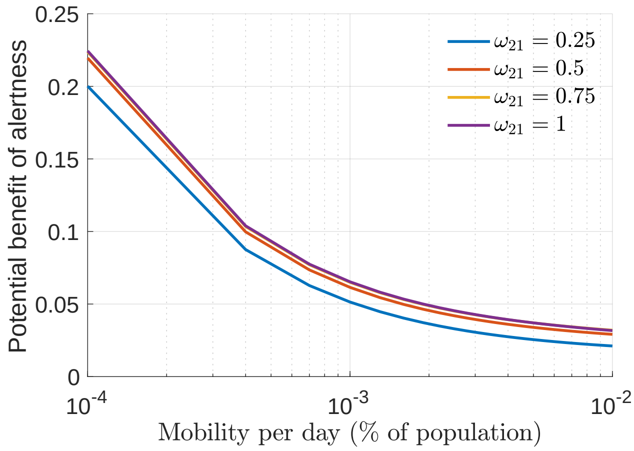

FIG. 4: Benefit of adopted awareness with respect to mobility. Locality 1 shows a strong response $\alpha_1 = 3$, while the response at Locality 2 is weak $\alpha_2 = 1$. The benefit is measured as the reduction in final size with respect to the zero-adopted awareness constant scenario $\omega_{21} = 0$. Let $F_2(\omega_{21}, \lambda_{12})$ denote the final outbreak size at Locality 2 with respect to ω_{21} and λ_{12}. The benefit of alertness is defined as $F_2(0, \lambda_{12}) - F_2(\omega_{21}, \lambda_{12})$.

at Locality 2. We note that the critical level of preparedness needed is higher when mobility is high. In contrast, when the response at Locality 2 is strong in Figure 3 (Right), there does not exist an adopted awareness constant value where a weak response at Locality 1 can be better in terms of total outbreak size. This is because even a small outbreak at Locality 1 triggers a strong level of preparedness at Locality 2 because the response constant is $\alpha_2 = 3$.

Comparing Figures 3 (Left) and (Right), the total outbreak size is always lower on the right figure, i.e., when the response at Locality 2 is strong. These observations indicate that we obtain the best outcome in terms of total outbreak size when both localities respond strongly, and Locality 2 has an adopted awareness constant value near $\omega_{21} \approx 0.5$. Recall, ω_{21} represents a measure of preparedness at Locality 2. In other words, the best outcome in terms of total outbreak size is when a locality balances its reaction to its own state and that of others.

We further demonstrate the effects of mobility rate on the outbreak size at Locality 2 in Figure 4. We measure the benefit in outbreak size with respect to the outbreak size when adopted awareness constant is zero, i.e., $\omega_{21} = 0$. As is evident from Figure 4, it is better to have a high adopted awareness constant for all mobility rate values. Given positive adopted awareness constant values $\omega_{21} > 0$, the potential benefit of adopted awareness reduces as mobility increases. The intuition for this is that when the mobility increases, the delay in start times of the outbreaks between localities is reduced. This implies the adopted awareness at Locality 2 is lower as the full impact of the outbreak at Locality 1 is not yet realized.

V. DISCUSSION

We developed a mathematical model to analyze the impact of social distancing efforts on disease dynamics among interconnected populations. We assumed that social distancing efforts at a given location is a function of both disease prevalence within the population and outbreak dynamics at neighboring localities. Our analysis showed that it is beneficial to reduce travel between localities given the inability to detect asymptomatic infectious individuals (consistent with recent findings [1]). However, this benefit is contingent on how prepared neighboring localities are for the importation of cases. We used the term adopted awareness to determine the level of preparedness at neighboring localities as an increasing function of the outbreak size at the origin. The increasing function assumption implied that neighboring localities increase their levels of preparedness as the severity of the disease at the origin increased. That is, as the severity of the outbreak at the origin increases, this triggers increased social distancing efforts at neighboring localities by local authorities making non-pharmaceutical interventions, e.g., declaring state of emergency, or issuing stay at home orders. Our analysis showed that slow mobility will provide the lead time for increased alertness levels and will result in higher levels of preparedness. Indeed, low mobility reduces the critical level of preparedness needed to stop the outbreak from becoming a pandemic at a neighboring locality (Figure 2).

It is not surprising that increased levels of preparedness reduces the outbreak size at localities neighboring the origin. However, the level of preparedness is contingent on the outbreak size at the origin. Thus, in order for the level of preparedness to increase at a locality, its neighbor should incur a larger outbreak size. In order to assess whether the level of preparedness, and thus, reduction in outbreak size at neighboring localities can make up for the increased outbreak size at the origin, we looked at the total outbreak size as a function of strength of response to local disease prevalence. Our results show that increased levels of preparedness at neighboring localities can yield lower total outbreak sizes even when the response at the origin is weak (Figure 3(Left)). These findings imply that if there are multiple localities with outbreaks, the jurisdictions with less severe outbreaks should be looking at their worse-off neighbor rather than their best-off neighbor, and implementing social distancing measures accordingly. Given the continuing threat of COVID-19, the present study provides additional support for viewing pandemics in a connected, rather than isolated, context.

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Materials

The code is available at `https://github.com/ceyhuneksin/reacting_outbreaks_neighboring_localities`.