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Modeling the role of public health education in Ebola virus disease outbreaks in Sudan

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A B S T R A C T

Public involvement in Ebola Virus Disease (EVD) prevention efforts is key to reducing disease outbreaks. Targeted education through practical health information to particular groups and sub-populations is crucial to controlling the disease. In this paper, we study the dynamics of Ebola virus disease in the presence of public health education with the aim of assessing the role of behavior change induced by health education to the dynamics of an outbreak. The power of behavior change is evident in two outbreaks of EVD that took place in Sudan only 3 years apart. The first occurrence was the first documented outbreak of EVD and produced a significant number of infections. The second outbreak produced far fewer cases, presumably because the population in the region learned from the first outbreak. We derive a system of ordinary differential equations to model these two contrasting behaviors. Since the population in Sudan learned from the first outbreak of EVD and changed their behavior prior to the second outbreak, we use data from these two instances of EVD to estimate parameters relevant to two contrasting behaviors. We then simulate a future outbreak of EVD in Sudan using our model that contains two susceptible populations, one being more informed about EVD. Our finding show how a more educated population results in fewer cases of EVD and highlights the importance of ongoing public health education.

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1. Introduction

The Ebola Virus Disease (EVD) has posed a serious health threat to African countries since the mid 1970s. The disease was first detected in Sudan in 1976, but 21 additional outbreaks have since occurred in Central and Western Africa resulting in over 28,000 total cases (Ebola Virus Disease, 2015; Moghadam, Omidi, Bayrami, Moghadam, & SeyedAlinaghi, 2015). While past

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outbreaks each produced less than 500 cases, the recent 2013 occurrence of EVD in West Africa produced over 28,000 cases, the most cases of EVD to date (Ebola Virus Disease, 2015). The stark difference in the number of cases between various outbreaks makes predicting the severity of future outbreaks difficult. Specific transmission dynamics and resulting case counts are dependent on a number of factors including the specific strain of EVD, the population size of a given region, and specific human behavior that can either reduce, or contribute to, the spread of the disease (Dietz, Jambai, Paweska, Yoti, & Ksaizek, 2015).

The reservoir for Ebola is believed to be animals such as bats and monkeys (Olival & Hayman, 2014; World Health Organization,); outbreaks of Ebola begin after an animal from the reservoir infects a human. The disease has an incubation period of 2–21 days (World Health Organization Ebola Response, 2014; World Health Organization,). Once the virus is in the human population, individuals can contract the disease after coming in contact with the bodily fluids of an infected individual, which can include contact with someone who has died from EVD. This transmission route is exacerbated by the virus as additional bodily fluids are produced by the disease resulting in vomiting, deification, and bleeding. Since there is not yet a vaccine available, patients are treated with oral or intravenous fluids in addition to treating specific symptoms (World Health Organization,).

Cultural practices in West Africa play a large role in the transmission of Ebola (Dietz et al., 2015). When a family member becomes ill, it is common practice to forgo seeking medical treatment and instead see a traditional herbalist or be cared for at home. This is especially true in the case of Ebola as early symptoms are similar to those of influenza. Being cared for by family members often results in numerous relatives contracting the disease (Fitzpatrick et al., 2014). Another highly affected area outside the home is in health care settings. In fact, if protocols are not followed, hospital settings can produce a significant number of cases during Ebola outbreaks (Cook et al., 2015; Olu et al., 2015). It is common practice for deceased individuals to be washed, embraced, kissed, and prepared for burial by family members (Brainard, Hooper, Pond, Edmunds, & Hunter, 2015). This is problematic as deceased individuals still carry, and are capable of spreading, the virus. Even highly educated individuals who are aware of an ongoing Ebola outbreak may participate in such cultural practices. As a result, burial practices also play a major role in spreading the disease (Cook et al., 2015).

From past outbreaks it is clearly evident that taking precautions against spreading Ebola can quickly reduce or eliminate an outbreak (Brainard et al., 2015). For example, early projections during the 2014 outbreak of EVD in West Africa estimated that, without any intervention, as many as 1.4 million cases could be produced over the course of the epidemic (Meltzer et al., 2014). However, the World Health Organization declared the outbreak to be an “international health emergency” (IHR Emergency,). As a result, a significant international intervention was launched that coordinated aid from numerous entities and included massive information campaigns to educate the general public about preventing the spread of EVD. The aid included health care resources for the affected countries, and the information campaigns altered individual behavior, which quickly contained the outbreak and limited the total number of infections immensely (Chowell, Simonsen, Viboud, & Kuang, 2014). Additionally, considering the cases of Ebola that occurred in the United States and Europe during the 2014 outbreak in West Africa, careful precautions were taken by the European and American population and governments, which prevented secondary outbreaks from occurring.

The effects of public health education on the evolution of a disease have been studied in the cases of HIV (Bhunu, Mushayabasa, Kojouharov, & Tchuenche, 2010; Del Valle, Hethcote, Hyman, & Castillo-Chavez, 2005; Mukandavire & Garira, 2007; Mukandavire, Garira, & Tchuenche, 2009), drinking dynamics (Xiang, Song, & Huo, 2016), Hepatitis C virus transmission dynamics (Mushayabasa & Bhunu, 2012), and Ebola (Fast, Mekaru, Brownstein, Postlethwaite, & Markuzon, 2015; Shen, Xiao, & Rong, 2015). Mathematical models have been used to evaluate the potential role of interventions against the Ebola virus disease. Interventions aimed at reducing the burden of the 2014 Ebola virus disease epidemic were incorporated into mathematical models, see for instance (Agusto, Teboh-Ewungkem, & Gumel, 2015; Djiomba Njankou & Nyabadza, 2016; Drake et al., 2015; Kucharski et al., 2015; Pandey et al., 2014; Rachah & Torres, 2015; Tambo, Ugwu, & Ngogang, 2014; Browne et al., 2014).

Studies have shown that the prevalence of any epidemic is strongly dependent on the social behavior of individuals in a population (Del Valle et al., 2005; Xiang et al., 2016). This is evident in two early Ebola outbreaks in Sudan where the relative magnitude of each outbreak was a reflection of preparedness of health care providers and knowledge of the general public about the disease (Baron, McCormick, & Zubeir, 1983; Report of a WHO/International Study Team, 1978). Our goal was to assess how behavior change induced by education can alter the dynamics of an outbreak of EVD. We approach this question by formulating a deterministic model in which a community has two types of individuals: one that is educated about Ebola and takes precautions to avoid contracting the disease, and a second that does not take precautions against contracting or spreading the disease. Our results illustrate the importance of education as a preventative measure against contracting Ebola.

We partition the susceptible population into two groups: individuals who have not yet been influenced by public health education and those who have been educated. Unlike previous models which simply reduce various rates as a result of public health education (Fast et al., 2015; Shen et al., 2015), we estimate different parameters for each group. This approach is similar to specific preceding models in (Joshi, Lenhart, Albright, & Gipson, 2008, Joshi, Lenhart, Hota, & Agusto, 2015). We use data from the aforementioned Ebola outbreaks in Sudan to parameterize our model and also include the effect of information on increasing the rate of infected individuals seeking professional health care (Baron et al., 1983; Report of a WHO/International Study Team, 1978).

In the next section we formulate a model for the case with an educated class and an uneducated class. In section three, parameters are estimated separately for each class using a reduced version of our model. The parameters governing the uneducated class are obtained using data from the Sudan 1976 outbreak and the parameters for the educated class are estimated using data from the Sudan 1979 outbreak. The fourth section contains numerical results for a future outbreak of EVD in Sudan, and includes varying key parameters such as the education rate. Our findings illustrates how public health education and resulting behavior change can greatly impact an outbreak of Ebola. We close with some conclusions and final thoughts.

2. Model formulation

We formulate a model with the susceptible class partitioned into two groups. We use the subscript "*edu*" to denote the class that is takes appropriate precautions during an EVD outbreak due to public health education. There are two a susceptible classes (S_{edu} and S), which contain the number of individuals in each group. Correspondingly, there are two classes (I_{edu} and I) that contain the number of infected individuals that exist in the community. Both I_{edu} and I can transition into a second infected class we consider to be the number of people in a health care setting (H), where individuals are being cared for by trained professionals. Note that we consider the health care professionals themselves to be in S_{edu}. Since infections arise in the community as well as in health care locations, transmission will occur in both settings. The model also includes a recovered class (R) and class of dead bodies (D), both of which also have units of numbers of individuals. Finally, there is an environment class (B), which represents the density of Ebola virus in the environment. Recovered individuals no longer experience acute symptoms of Ebola and are immune to reinfection as we will be only be considering a short time frame. The class of the dead is needed because it is common practice in West Africa for family members to come in contact with deceased relatives, which makes this transmission route for Ebola particularly unique and interesting. The environment class represents all possible contamination in the general community including the existence of bodily fluids, dirty linens, and any potential animal which may be a source of infection. Table 1 presents a complete list and description of all parameters in the model. A flow diagram characterizing the full model is depicted in Fig. 1. In the diagram, solid lines represent flow between compartments, the dashed lines represent the infected classes contaminating the environment, and the curved dashed lines represent new infections coming from interaction of susceptibles with the environment.

The full model takes the following form:

$$\begin{aligned}
&S' = \pi - \mu S - \theta S - (\beta_{0a}B + \beta_{1a}I + \beta_{3a}I_{edu} + \beta_{4a}D + \beta_{2a}H)S\\
&S'_{edu} = \theta S - \mu S_{edu} - (\beta_{0b}B + \beta_{1b}I + \beta_{3b}I_{edu} + \beta_{4b}D + \beta_{2b}H)S_{edu}\\
&I' = \left(\beta_{0a}B + \beta_{1a}I + \beta_{3a}I'_{edu} + \beta_{4a}D + \beta_{2a}H\right)S - \gamma(\alpha_{1a}, \alpha_{2a}, H_{total})I - \phi_1 I - \delta_1 I\\
&I'_{edu} = (\beta_{0b}B + \beta_{1b}I + \beta_{3b}I_{edu} + \beta_{4b}D + \beta_{2b}H)S_{edu} - \gamma(\alpha_{1b}, \alpha_{2b}, H_{total})I_{edu} - \phi_2 I_{edu} - \delta_2 I_{edu}\\
&H' = \gamma(\alpha_{1b}, \alpha_{2b}, H_{total})I_{edu} + \gamma(\alpha_{1a}, \alpha_{2a}, H_{total})I - \delta_3 H - \phi_3 H\\
&R' = \phi_1 I + \phi_2 I_{edu} + \phi_3 H - \mu R\\
&D' = \delta_1 I + \delta_2 I_{edu} + \delta_3 H - \omega D\\
&B' = \xi(I + I_{edu} + H + D) - dB
\end{aligned} \tag{1}$$

where

Table 1
Parameters found in the model.

Parameter	Description
β_{0a}	Transmission rate from uneducated interaction with the environment
β_{1a}	Transmission rate from uneducated interaction with uneducated infected
β_{2a}	Transmission rate from uneducated in hospitals
β_{3a}	Transmission rate from uneducated interaction with educated infected
β_{4a}	Transmission rate from uneducated interaction with dead bodies
β_{0b}	Transmission rate from educated interaction with the environment
β_{1b}	Transmission rate from educated interaction with uneducated infected
β_{2b}	Transmission rate from educated in hospitals
β_{3b}	Transmission rate from educated interaction with educated infected
β_{4b}	Transmission rate from educated interaction with dead bodies
α_{1a}	Sigmoidal constant that governs uneducated infected movement into hospital
α_{2a}	Sigmoidal constant that governs uneducated infected movement into hospital
α_{1b}	Sigmoidal constant that governs educated infected movement into hospitals
α_{2b}	Sigmoidal constant that governs educated infected movement into hospitals
ϕ_1	Recovery rate for infected uneducated individuals in the community
ϕ_2	Recovery rate for infected educated individuals in the community
ϕ_3	Recovery rate for infected individuals in hospitals
δ_1	Death rate for uneducated infected individuals in the community
δ_2	Death rate for educated infected individuals in the community
δ_3	Death rate for infected individuals in hospitals
ω	Burial rate of dead bodies
ξ	Environmental contamination rate
d	rate of decay of ebola in the environment
π	Growth of uneducated susceptible
μ	Natural death rate
θ	Rate of education

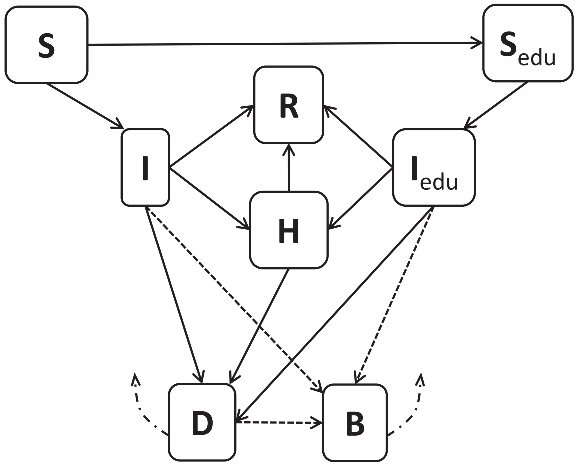

Fig. 1. A flow diagram for the full Ebola model. Solid lines represent flow between compartments, the dashed lines represent the infected classes contaminating the environment, and the curved dashed lines represent new infections coming from interaction of susceptibles with the environment.

$$\gamma(\alpha_{1i}, \alpha_{2i}, H) = \frac{1 - e^{\frac{-H}{\alpha_{1i}}}}{1 + \alpha_{2i} e^{\frac{-H}{\alpha_{1i}}}}.$$

Recall that it is common in West African countries for sick individuals to forgo seeing a doctor and instead be cared for at home, especially in the case of a minor illness. Since EVD initially has flu-like symptoms, the number of individuals seeking care at the beginning of an outbreak is especially low. However, as more cases of an outbreak are detected, the awareness of the disease increases in the community through the media, government, and even word of mouth. Increased awareness results in people seeking help sooner and thus an increased rate of transfer to health care settings. We capture this characteristic with the sigmoidal shaped function γ, which ranges from 0 (no one going to the hospital) to 1 (the maximum rate of seeking medical attention). The parameter α_2 sets the point at which the function begins its sharp increase and α_1 determines the steepness of the increase. Since γ is a function of H, as more hospitalizations occur, general awareness of the epidemic increases and the rate of individuals seeking treatment in a hospital will increase. There are two different sets of α values for the educated and uneducated populations because educated individuals will be more likely to understand the significance of an outbreak and the ramifications of failing to seek treatment compared with the uneducated population. We have also included different death rates (δ_1, δ_2, δ_3) and recovery rates (ϕ_1, ϕ_2, ϕ_3) to distinguish between rates for those who take precautions versus those who do not, as well as individuals in the community versus those in the hospital. We also include a rate of burial ω and environmental contamination rate ξ so we can properly model these transmission routes.

The transmission coefficients ($\beta_{i,j}$) are different for educated individuals than those for uneducated to reflect the fact that individuals who are educated about the disease will take more precautions as opposed to those who are not. We expect that the differences in behavior exhibited by educated individuals will reduce their interaction with infectious individuals, dead bodies, and environmental contamination resulting in reduced transmission when compared with those who do not take precautions. We also allow for the flow from the uneducated susceptible class to the educated susceptible class via the parameter θ to represent change in behavior which could result from increased awareness of the epidemic via media coverage, word of mouth, and/or dissemination of information by health care agencies.

3. Parameter estimation

In order to estimate the transmission coefficients, we use data from Sudan where an outbreak occurred in the same location at two separate instances. The initial outbreak occurred in 1976, and was the first recorded outbreak of Ebola (Ebola Virus Disease, 2015; Report of a WHO/International Study Team, 1978); the second outbreak occurred in 1979 in the same general location (Baron et al., 1983; Ebola Virus Disease, 2015). We take the initial 1976 outbreak to be a population entirely uneducated about the disease as it was the initial documented occurrence of Ebola in the world. As a result of media coverage and public health education, we assume that during the 3 years following the initial outbreak the remaining population became aware of EVD and how to avoid it. As a result, we take the second outbreak to be a population of individuals who behavior differently as a result of various forms of public health education. Our assumptions are supported by the fact that, under nearly identical transmission conditions, there were significantly more cases in the first outbreak compared to the second (see Tables 2 and 3). Additionally, there were many more infections that took place in hospitals in the 1976 outbreak.

Table 2
Data from the 1976 outbreak of Ebola in Sudan.

	July	August	September	October	November
Cumulative Cases	8	38	176	260	280
Cumulative Recovered	4	17	90	121	133
Cumulative Deaths	4	21	86	139	147
New Cases	8	30	138	84	20
New Recovered	4	13	73	31	12
New Deaths	4	17	65	53	8
% infections that occurred in the community				% infections that occurred in the hospital	
38.5%				61.5%	

Table 3
Data from the 1979 outbreak of Ebola in Sudan.

	End July & August	September	October
Cumulative Cases	16	33	34
Cumulative Recovered	2	11	12
Cumulative Deaths	13	20	22
New Cases	16	17	1
New Recovered	2	9	1
New Deaths	13	7	2
% infections that occurred in the community		% infections that occurred in the hospital	
85%		15%	

To estimate parameters for these contrasting behaviors, we reduce our model to a single population and use a least squared optimization approach to find the set of parameters that best match the data.

In each reduced model we only consider a single population-one either educated about the EVD or uneducated about the disease. Since we are simulating an epidemic scenario that takes place during a short time frame, we take the natural death rate (μ) and birth rate (π) to be zero. This yields the following system that describes the 1976 outbreak:

$$\begin{aligned}
S' &= -(\beta_{0a}B + \beta_{1a}I + \beta_{4a}D)S - \beta_{2a}SH \\
I' &= (\beta_{0a}B + \beta_{1a}I + \beta_{4a}D)S + \beta_{2a}SH - \gamma(\alpha_{1a}, \alpha_{2a}, H)I - \phi_1 I - \delta_1 I \\
H' &= \gamma(\alpha_{1a}, \alpha_{2a}, H)I - \delta_2 H - \phi_2 H \\
R' &= \phi_1 I + \phi_2 H \\
D' &= \delta_1 I + \delta_2 H - \omega D \\
B' &= \xi(I + H + D) - dB.
\end{aligned}$$

In the first scenario, we consider is the Sudan 1976 outbreak that took place in the towns of Nzara and Maridi, which had a combined population totaling 35,000 (Report of a WHO/International Study Team, 1978). The outbreak began when workers of a cotton factory in Nzara became ill on June 27, 1976 and lasted until the end of November. The disease spread to Maridi in early August when a patient infected in Nzara was admitted to a hospital in Maridi. The majority of total cases took place in Maridi with the hospital cited as an amplification factor (Report of a WHO/International Study Team, 1978). The first international response took place on October 29, 1976 when the World Health Organization sent an emergency response team to investigate and assist with the new disease (Report of a WHO/International Study Team, 1978). By this time the outbreak was nearly over as the number of new cases had been declining for over a month (Report of a WHO/International Study Team, 1978).

The 1976 outbreak provides an example in which EVD was introduced to a system where the entire population is uneducated about Ebola and therefore does not take appropriate precautions against spreading the disease. This includes not following accepted health care protocol, which is reflected in the large number of new infections that took place in health care settings. Therefore we will use data from the 1976 outbreak to estimate parameters related to a population that is uneducated about EVD and a health care setting entirely unprepared to handle an outbreak. The World Health Organization's report from this outbreak includes the data seen in Table 2 (Report of a WHO/International Study Team, 1978).

In the second scenario, we consider the 1979 Sudan outbreak (Baron et al., 1983). This occurrence of EVD took place in the towns of Nzara and Yambio, which is nearly the identical location as the 1976 outbreak. The report from this outbreak includes the data show in Table 3 (Baron et al., 1983). The outbreak began on July 31 1979 in Nzara and later spread through family members to the nearby town of Yambio (Baron et al., 1983). The disease was active from the last few days of July through to the first week of October. Since the 1979 outbreak took place in the same location as the previous outbreak and only three years later, the population is composed of mostly the same individuals as the 1976 outbreak. We therefore assume the population was more educated about the disease, that individuals took precautions against contracting the disease, and that sick individuals sought medical attention at a higher rate. However, despite having recently dealt with EVD, the health care facilities were not prepared to deal with another outbreak. The hospital was understaffed, did not have a quarantine policy, and the staff was not trained on proper disinfecting and sterilization techniques (Baron et al., 1983). As a result, 15% of new infections took place in a health care setting. Only after the World Health Organization intervened on September 22 was proper protocol put in place, which helped extinguish the outbreak (Baron et al., 1983). Since the second outbreak took place only 3 years later, we will take the population size to be the same.

To estimate parameters using the reduced model, we find the set of values that best matched the data by creating a minimization scheme that relates model output to data from the outbreak. We use the MultiStart algorithm and fmincon from the optimization toolbox in MATLAB to implement all optimization schemes. The fmincon algorithm accepts as input the unknown parameters with a scalar value to be minimized ($J(x)$), while also imposing inequality constraints. Since fmincon is a local solver, the MultiStart algorithm generates a large number of starting points to test, which ensures we were finding the global minimum. For all parameter estimation simulations, we use a population size of 35,000 and begin with one infected individual in the community, and one in the health care setting. We assume an initial value of zero for the recovered, dead body, and environment classes, as these compartments do not become populated until the disease is present in the population.

To help understand appropriate bounds to impose on the parameters, we first simply minimize the difference between the number of new cases in the data and the number of new cases produced by the model:

$$\underset{x}{\text{Minimize}}\, J(x) = \|NC - NC^*\|_2,$$

where NC represents the 1×5 vector of new cases produced each month in the model, NC^* represents the 1×5 vector of new cases from each month in the data, and x represents all possible values of the unknown parameters.

After determining appropriate bounds to impose on the parameters in order to limit the search area, we run the scheme again but this time matching the number of new cases as well as the percent of infections that came from the community and health care settings, respectively:

$$\underset{x}{\text{Minimize}}\, J(x) = \|NC - NC^*\|_2 + \|100*(PC - PC^*)\|_2 + \|100*(PH - PH^*)\|_2,$$

where PC represents the percentage of new cases arising in the community and PH represents the percent of new cases arising in health care settings. We multiply by 100 in order to weight the values appropriately.

This allows us to refine the parameter bounds further. We then fit new cases, new deaths, new recoveries and the percent of infections that came from the community and hospital:

$$\underset{x}{\text{Minimize}}\, J(x) = \|NC - NC^*\|_2 + \|100*(PC - PC^*)\|_2 + \|100*(PH - PH^*)\|_2 + \|100*(NR - NR^*)\|_2 \\ + \|100*(ND - ND^*)\|_2,$$

where NR represents the 1×5 vector of new monthly recoveries and ND represents the 1×5 vector of new monthly deaths.

First, the step-wise procedure described above was used with the data from the 1976 Sudan outbreak to estimate the parameters associated with individuals who do not take precautions against contracting and spreading EVD. Estimated parameter values are shown in Table 4.

By taking a step-wise approach to fitting the parameters, we were able to fit the data from the 1976 outbreak as depicted in Fig. 2. Since individuals who are not aware of the risks associated with Ebola are more likely to be treated at home, the number of infections in the community initially increases more rapidly than those in hospitals. Once enough individuals have

Table 4
Parameter estimation results obtained by fitting 1976 Sudan data to the reduced model.

Parameter	Description	Value
β_{0a}	Transmission rate from uneducated interaction with the environment	9.90×10^{-08}
β_{1a}	Transmission rate from uneducated interaction with uneducated infected	4.40×10^{-06}
β_{2a}	Transmission rate from uneducated in hospitals	0.012
β_{4a}	Transmission rate from uneducated interaction with dead bodies	1.84×10^{-07}
α_{1a}	Sigmoidal constant that governs uneducated infected movement into hospitals	18.8
α_{2a}	Sigmoidal constant that governs uneducated infected movement into hospitals	15
ϕ_1	Recovery rate for infected uneducated individuals in the community	0.04
ϕ_3	Recovery rate for infected uneducated individuals in hospitals	0.011
δ_1	Death rate for uneducated infected individuals in the community	0.077
δ_3	Death rate for uneducated infected individuals in hospitals	0.07
ω	Burial rate of dead bodies	0.07
ξ	Environmental contamination rate	0.43
d	rate of decay of Ebola in the environment	0.87

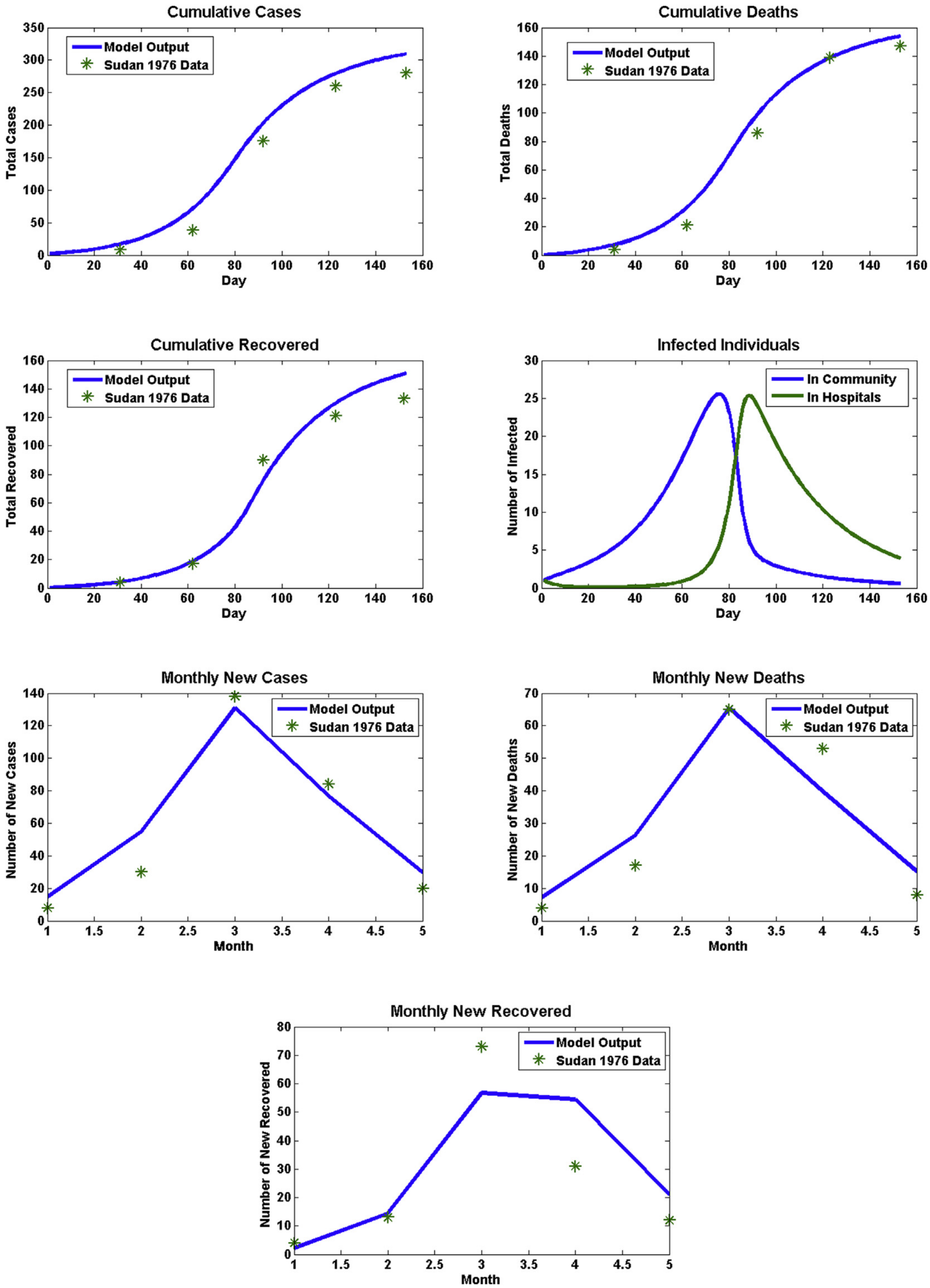

Fig. 2. Results from fitting the reduced model to the 1976 Sudan data.

been admitted to hospitals an outbreak is declared and information is disseminated to the public, which increases general awareness of the disease resulting in more individuals seeking medical attention. The two distinct peaks in the graph depicting infected individuals capture this effect. The number of infections in the community increases more rapidly than the number of infections in hospitals until a threshold of awareness is reached at which point individuals begin going to the hospitals at a higher rate, which ultimately extinguishes the outbreak.

Table 5
Parameter estimation results obtained by fitting 1979 Sudan data to the reduced model.

Parameter	Description	Value
β_{0b}	Transmission rate from educated interaction with the environment	1.96×10^{-18}
β_{2b}	Transmission rate from educated in hospitals	2.07×10^{-06}
β_{3b}	Transmission rate from educated interaction with educated infected	2.23×10^{-06}
β_{4b}	Transmission rate from educated interaction with dead bodies	3.77×10^{-13}
α_{1b}	Sigmoidal constant that governs educated infected movement into hospitals	4
α_{2b}	Sigmoidal constant that governs educated infected movement into hospitals	3
ϕ_2	Recovery rate for infected educated individuals in the community	0.02
ϕ_3	Recovery rate for infected educated individuals in hospitals	0.02
δ_2	Death rate for educated infected individuals in the community	0.02
δ_3	Death rate for infected educated individuals in hospitals	0.02
ω	Burial rate of dead bodies	0.09
ξ	Environmental contamination rate	0.2
d	rate of decay of Ebola in the environment	0.8

Now we turn our attention to the model for 1979 Sudan outbreak:

$$\begin{aligned}
S'_{edu} &= -(\beta_{0b}B + \beta_{1b}I_{edu} + \beta_{4b}D)S_{edu} - \beta_{2b}S_{edu}H \\
I'_{edu} &= (\beta_{0b}B + \beta_{1b}I_{edu} + \beta_{4b}D)S_{edu} + \beta_{2b}S_{edu}H - \gamma(\alpha_{1b}, \alpha_{2b}, H)I_{edu} - \phi_1 I_{edu} - \delta_1 I_{edu} \\
H' &= \gamma(\alpha_{1b}, \alpha_{2b}, H)I_{edu} - \delta_2 H - \phi_2 H \\
R' &= \phi_1 I_{edu} + \phi_2 H \\
D' &= \delta_1 I_{edu} + \delta_2 H - \omega D \\
B' &= \xi(I + H + D) - dB
\end{aligned}$$

We again use the same optimization tools and approach to estimate parameters related to those who take precautions against contracting and spreading EVD. By taking the previously described step-wise approach to fitting the parameters we were able to fit the data from the 1979 Sudan outbreak. Results from this procedure are shown in Table 5 and model output is depicted in Fig. 3. Since there was a much shorter outbreak with far fewer cases the data is more coarsely fit, but we were still able to capture the dynamics seen in the data. Notice that since this population seeks medical treatment at a higher rate, very few infections are present in the community at a given time. Instead, individuals seek professional medical attention almost immediately.

Table 6 presents the list of parameters which could not be estimated from the two single-population data sets, including transmission rates that govern the interaction between those educated about EVD and those who are not. We assume that the interaction between susceptible uneducated and infected educated would be the same as susceptible uneducated and infected uneducated. Similarly, we assume the interaction between susceptible educated and infected uneducated would be the same as susceptible educated and infected educated. We therefore assume that $\beta_{3,a} = \beta_{1,a}$ and $\beta_{1,b} = \beta_{3,b}$ will best represent the behavior being modeled in each class. The rate of education, θ, is an unknown parameter that controls flow from the S class into the S_{edu} class. By varying this rate, we can analyze the importance of interventions such as public health education as well as general public education about EVD in preventing or reducing an outbreak.

4. Numerical simulations

By considering two distinct populations, each with their own behavior that impacts transmission dynamics, we are in position to simulate a potential future outbreak of an EVD in Sudan. The parameters estimated from the Sudan 1976 data captures transmission dynamics in a population uneducated about EVD and therefore takes few precautions against contracting the disease in a community setting as well as inadequate protocol in health care settings. The coefficients derived from the Sudan 1979 data capture dynamics in a setting where the general population is aware of Ebola and individuals take preventative measures against transmission, which represents our educated population. However, since health care workers were still not properly trained to handle EVD, transmission rates in this setting remained relatively high. By combining estimated parameters in the full model while varying others, we can analyze the relevance of individual behavior, cultural practices, and proper health care protocol in reducing or preventing an outbreak of EVD.

In the following scenarios we model an outbreak of EVD in present day towns of Nzara, Maridi, and Yambio using the full moden shown in (1). The most recent population estimates for these towns are 73,800 (Nzara), 18,000 (Maridi), and 40,382 (Yambio) for a total of 132,182 (Maridi, 2011; Nzara, 2014; Yambio, 2011). See Table 7 for a description of all parameters used in the following simulations. In all simulations we begin with one uneducated infected in the community, one educated infected in the community, and one infected in the hospital. All remaining individuals will begin in one of the susceptible classes. We assume an initial value of zero for the recovered, dead body, and environment classes. We use most of the estimated transmission rates ($\beta_{1a}, \beta_{3a}, \beta_{4a}, \beta_{1b}, \beta_{3b}, \beta_{4b}$) and all sigmoidal constants ($\alpha_{1a}, \alpha_{2a}, \alpha_{1b}, \alpha_{2b}$) shown in Tables 4–6 in our simulations. The transmission rate in the health care setting (β_{2a}, β_{2b}) will depend on how prepared the facilities are for an outbreak of EVD. Since EVD has been established in Africa for 40 years, we can assume the transmission rate in the health care

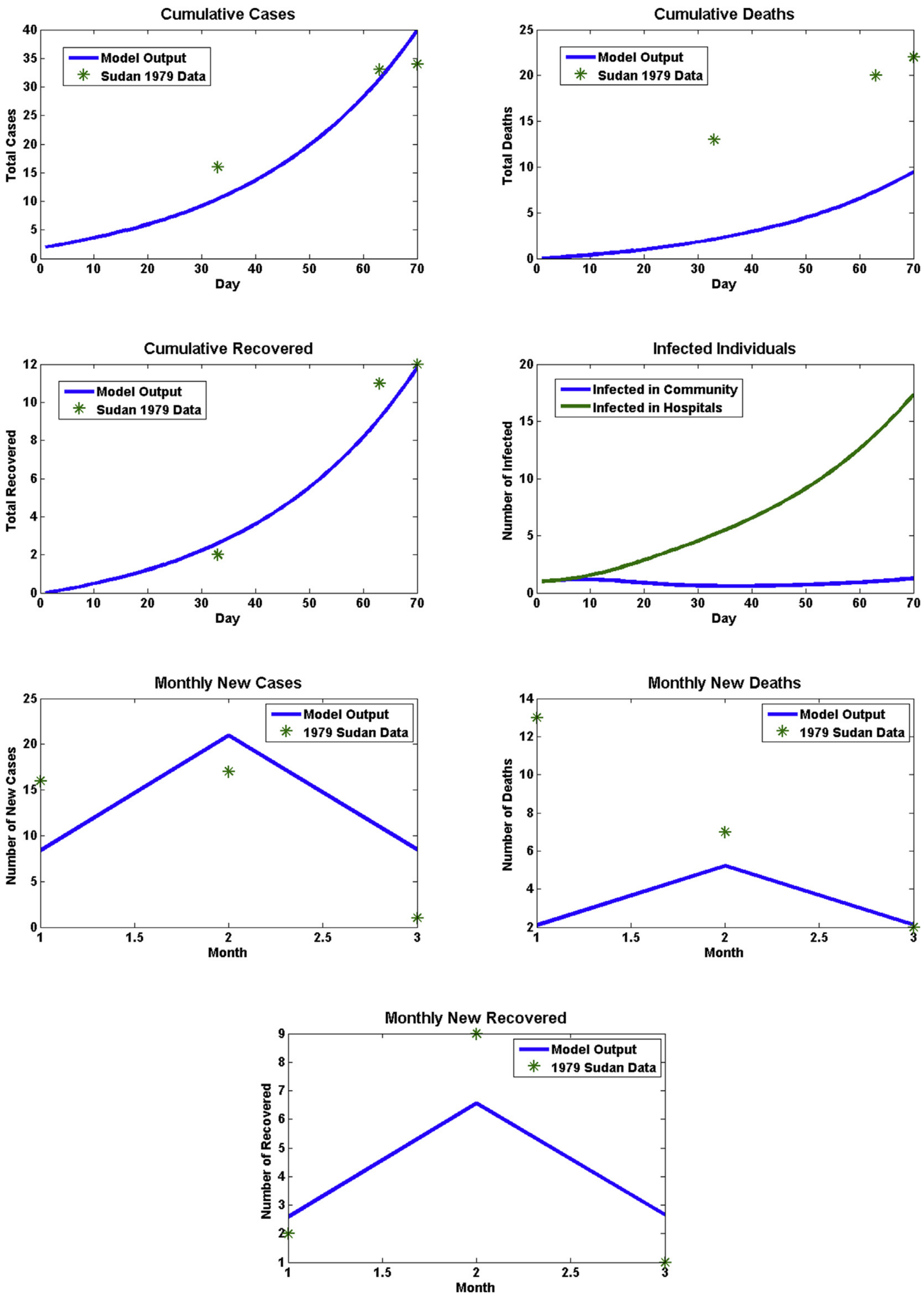

Fig. 3. Results from fitting the reduced model to the 1979 Sudan data.

setting will be no worse than that of the 1979 Sudan outbreak. For the environmental contamination rate (ξ) and decay rate (d), we took the average of the two estimated rates found in Tables 4 and 5 For the burial rate of dead bodies (ω), we used the estimate from the 1979 outbreak, which is a more rapid burial rate compared to the 1976 outbreak. Since we are simulating over a short time frame, we take the growth rate (π) and death rate (μ) to be 0.

Table 6
Parameters that could not be estimated from the data.

Parameter	Description	Value
β_{3a}	Transmission rate from uneducated interaction with educated infected	$\beta_{3,a} = \beta_{1,a}$
β_{1b}	Transmission rate from educated interaction with uneducated infected	$\beta_{1,b} = \beta_{3,b}$
θ	Rate of education	

Table 7
A list of all parameters used in simulations including the data used for estimation, if applicable.

Parameter	Description	Source	Value Used
β_{0a}	Transmission rate from uneducated interaction with the environment	Sudan 1976	9.90×10^{-08}
β_{1a}	Transmission rate from uneducated interaction with uneducated infected	Sudan 1976	4.40×10^{-06}
β_{2a}	Transmission rate from uneducated in hospitals	$\leq \beta_{2b}$	$\leq 2.07 \times 10^{-06}$
β_{3a}	Transmission rate from uneducated interaction with educated infected	$= \beta_{1a}$	4.40×10^{-06}
β_{4a}	Transmission rate from uneducated interaction with dead bodies	Sudan 1976	1.84×10^{-07}
β_{0b}	Transmission rate from educated interaction with the environment	Sudan 1979	1.96×10^{-18}
β_{1b}	Transmission rate from educated interaction with uneducated infected	$= \beta_{3b}$	2.23×10^{-06}
β_{2b}	Transmission rate from educated in hospitals	Sudan 1979	$\leq 2.07 \times 10^{-06}$
β_{3b}	Transmission rate from educated interaction with educated infected	Sudan 1979	2.23×10^{-06}
β_{4b}	Transmission rate from educated interaction with dead bodies	Sudan 1979	3.77×10^{-13}
α_{1a}	Sigmoidal constant that governs uneducated infected movement into hospitals	Sudan 1976	18.8
α_{2a}	Sigmoidal constant that governs uneducated infected movement into hospitals	Sudan 1976	15
α_{1b}	Sigmoidal constant that governs educated infected movement into hospitals	Sudan 1979	4
α_{2b}	Sigmoidal constant that governs educated infected movement into hospitals	Sudan 1979	3
ϕ_3	Recovery rate for infected individuals in hospitals	Historic Average (Magill et al., 2013, p. 332)	$0.12 - 0.20$
ϕ_1	Recovery rate for infected uneducated individuals in the community	Based on ϕ_3	$= .5\phi_3$
ϕ_2	Recovery rate for infected educated individuals in the community	Based on ϕ_3	$= .5\phi_3$
δ_3	Death rate for infected individuals in hospitals	Historic Average (Singh & Ruzek, 2013)	$0.09 - 0.14$
δ_1	Death rate for uneducated infected individuals in the community	Based on δ_3	$= 2\delta_3$
δ_2	Death rate for educated infected individuals in the community	Based on δ_3	$= 2\delta_3$
ω	Burial rate of dead bodies	Sudan 1979	0.09
ξ	Environmental contamination rate	Sudan 1976 & 1979	$.5(.43 + .2)$
d	rate of decay of EVD in the environment	Sudan 1976 & 1979	$.5(.87 + .8)$
θ	Rate of education	Will Vary	$0 - 0.2$

We begin by comparing how different ratios of educated and uneducated individuals results in varying levels of infections. Specifically, how they impact the length of the outbreak and the number of infected individuals. To consider this, we compare the percent of the total population infected in the two simulations of the historic outbreaks in Sudan with the total percent of population infected in a simulation of an outbreak in present day Sudan with a mixed population. In the simulations of past outbreaks in Sudan we assume the population is either entirely educated or uneducated. In the simulation of present day Sudan we take 50% of the population to be educated, 50% of the population to be uneducated, and use the recovery and death rates in hospitals of $\phi_3 = 0.16$ and $\delta_3 = 0.09$ as these values ensure all death and recovery rates fall within the historic averages (Magill, Hill, Solomon, & Ryan, 2013, p. 332; Singh & Ruzek, 2013). Results from these simulations are show in Fig. 4. The completely uneducated population has the highest percent of the population infected due to the high number of infected individuals that forgo seeking medical attention and instead remain in the community. On the other hand, the entirely educated population transitions in the hospital at a much quicker rate, which extinguishes the outbreak. The simulation of present day Sudan falls in between the two other simulations as we take only 50% of the population to be educated. This simulation has the steepest initial increase in infected individuals due to the significantly larger population size. However, individuals will move to the hospital at a quicker rate than the entirely uneducated population, which extinguishes the outbreak.

Different strains of EVD will result in varying recovery rates and death rates. The historic average time to death for EVD has ranged from 6 to 16 days (Singh & Ruzek, 2013) while the historic average recovery time has ranged from 7 to 14 days (Magill et al., 2013, p. 332). Since the specific strain of EVD in a future outbreak would play a significant role in the specific recovery and death rate, we will consider a range of both values in our full model simulations that span the values of the historic rates. Additionally, since proper care can improve the likelyhood of survival, we assume that the death rate in the community is twice death rate in a health care settings ($\delta_1 = \delta_2 = 2\delta_3$) and that the recovery rate in the community is half the recovery rate in a health care setting ($\phi_1 = \phi_2 = .5\phi_3$). Other unknown inputs in the full model include the rate of education (θ) and the transmission rate in health care settings (β_{2b}) as well as the proportion of initial susceptible population that are educated and uneducated about preventing the spread of EVD. These inputs are particularly important for illustrating the need to train health care workers about proper EVD protocol and educate the general public about EVD before, and during, outbreaks. The Sudan 1976 outbreak saw 0.008% of the total population becoming infected (Report of a WHO/International Study Team,

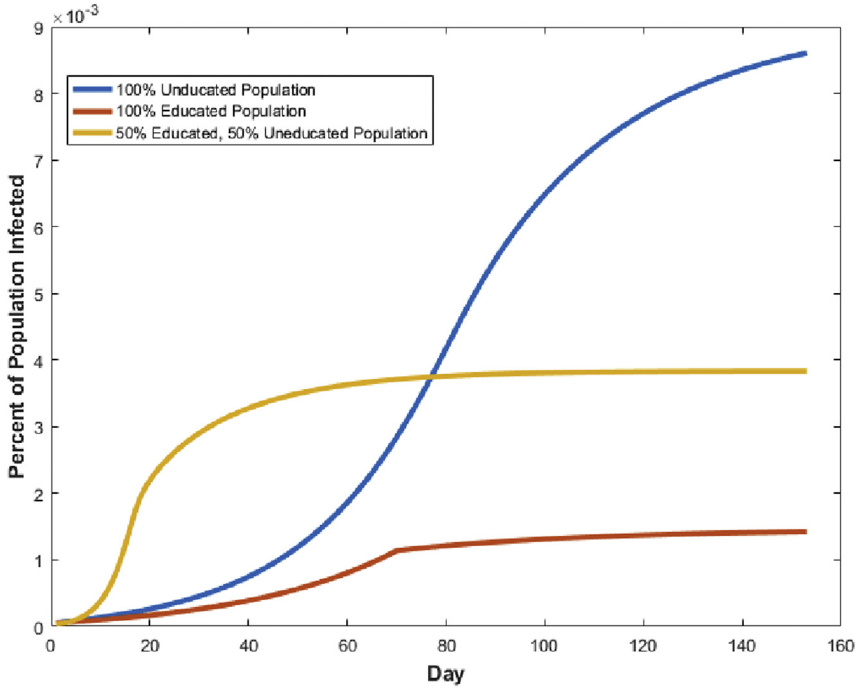

Fig. 4. Various levels of education lead to different percent of total population infected.

1978) and the 2014 EVD outbreak in West Africa saw 0.001% of the total population becoming infected (World Health Organization Ebola Response, 2014). For comparison in the current simulations, 0.008% of the total population of 132,182 would be 1058 cases and 0.001% of the total population would be 185 cases.

Using a ratio of uneducated:educated susceptibles of 1:3, a θ value of 0, and the health care transmission coefficient estimated from the Sudan 1979 data, we simulate an outbreak of EVD using a time span of 365 days. In this scenario, an unprecedented outbreak takes place for most values of ϕ_3 and δ_3 as seen in the top two plots in Fig. 5, where most total case counts were well over 1000. This simulation represents a scenario with a relatively high percent of educated individuals in the community but no public health education takes place ($\theta = 0$). By using the health care transmission coefficient from the 1979 outbreak, this simulation also represents a case where health care workers are not properly trained on appropriate EVD protocol. This results in high incidence rates for low death and recovery rates because individuals begin to fill up the health care facilities as the outbreak goes on, which is volatile in this setting. Even if the entire initial population is educated, a high transmission rate in health care settings still results in a massive outbreak takes place for most recovery and death rate values (ϕ_3 and δ_3), as seen in the top two plots in Fig. 5. However, if β_{2a} and β_{2b} values are reduced by 0.5, the total number of cases is reduced to reasonable levels, as seen in the bottom plot in Fig. 5. These simulations illustrate the fact that reducing transmission in a health care setting and/or educating individuals about EVD prior to an outbreak can significant reduce the total cases during an epidemic.

To help inform interventions used to mitigate a future outbreak, we aim to capture the dynamics of public health education and resulting behavior change in our model. We capture these dynamics using the θ parameter, which controls flow from the uneducated susceptible compartment into the educated susceptible compartment. Increasing values of θ will represent a higher rate of behavior change. We can also analyze the importance of timing of public health education by adjusting the time at which θ becomes nonzero. Note that the delay between implementation of a public health campaign and large-scale behavior change will depend upon many factors including the specific methods being used to disseminate information. In the present paper we only wish to model how behavior change itself can impact an outbreak. We therefore consider the activation of θ to represent the time at which large-scale behavior change begins to take place rather than when the public health education began. Since we are considering a hypothetical future outbreak of EVD in Sudan, we assume that the hospital setting will have a 75% reduced transmission rate estimated from the 1979 outbreak and we run our model for one year. We use an initial ratio of uneducated:educated susceptibles of 3:1, which will change over time depending on the value of θ used.

Fig. 6 displays results when no intervention takes place, which means that $\theta = 0$ in all simulations. In this case, the outbreak peaks between 40 and 50 days, with new cases appearing as long as 5 months after the initial case. There were 350–650 total cases of EVD, or 0.0026–0.0049% of the total population becoming infected. Fig. 7 displays results when an intervention begins 60 days after the start of the outbreak. There were 347–628 total cases of EVD, or 0.0026–0.0048% of the

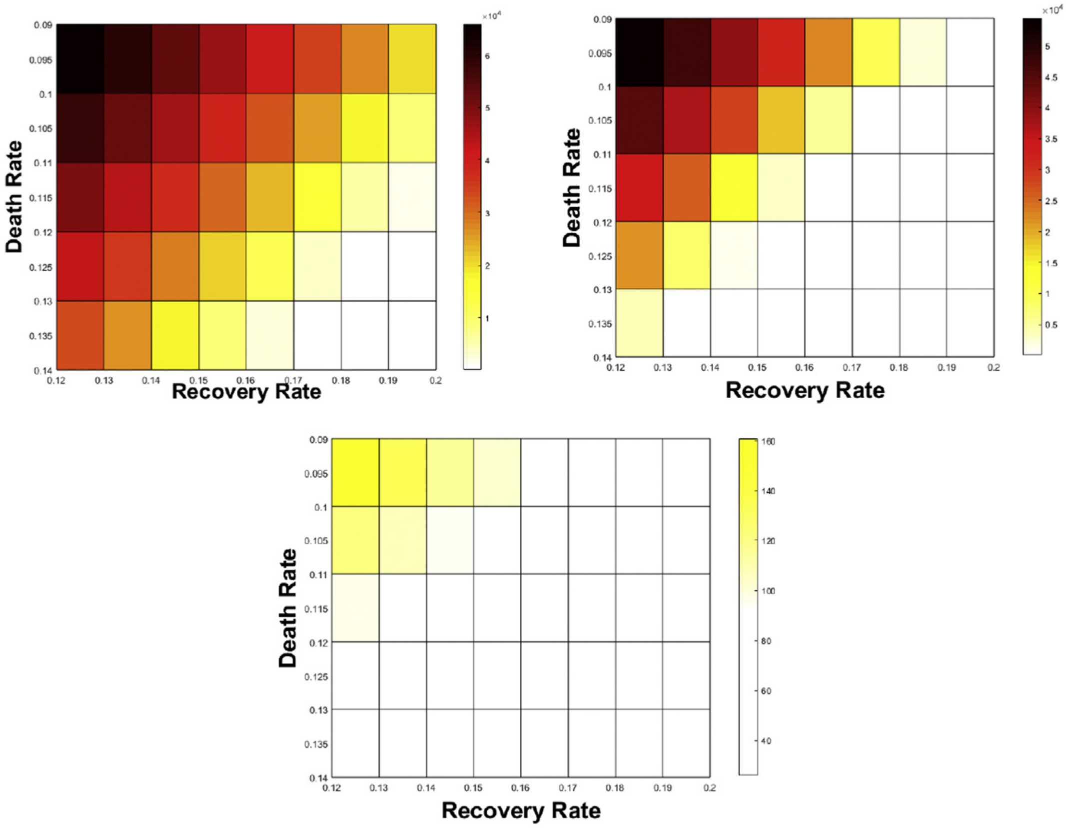

Fig. 5. Results of a potential outbreak in Sudan for various recovery and death rates with a rate of education θ of 0 in all simulations. The color bar gives the total number of infections. The top left plot has a ratio of uneducated:educated susceptibles of 1:3 and the transmission rate in health care settings is high. The top right plot has 100% of the population educated and the transmission rate in health care settings is high. The bottom plot has a ratio of uneducated:educated susceptibles of 1:3 and the transmission rate in health care settings is reduced by 0.5.

total population becoming infected. In this scenario, since the outbreak had already peaked, there was only a slight reduction in total cases of EVD. Fig. 8 displays results when an intervention begins 30 days after the start of the outbreak. Since the information campaigns were introduced before the total number of infections peaked we see a more significant reduction in total cases ranging from 295 to 538 total cases of EVD, or 0.0022–0.0041% of the total population becoming infected. Fig. 9

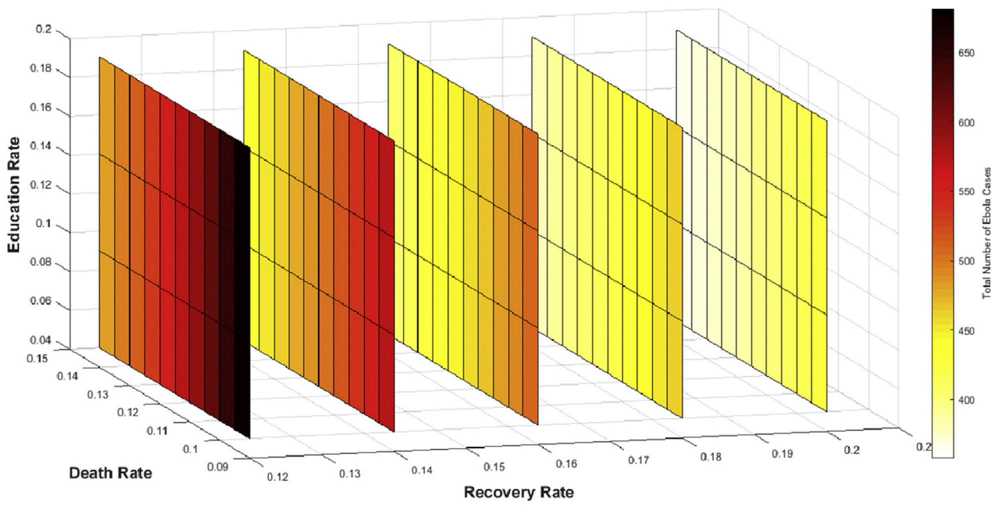

Fig. 6. Results of a simulated outbreak in Sudan displaying the total cases of EVD for various recovery, death, and education rates. These figures reflect the absence of public health education as $\theta = 0$ in all cases.

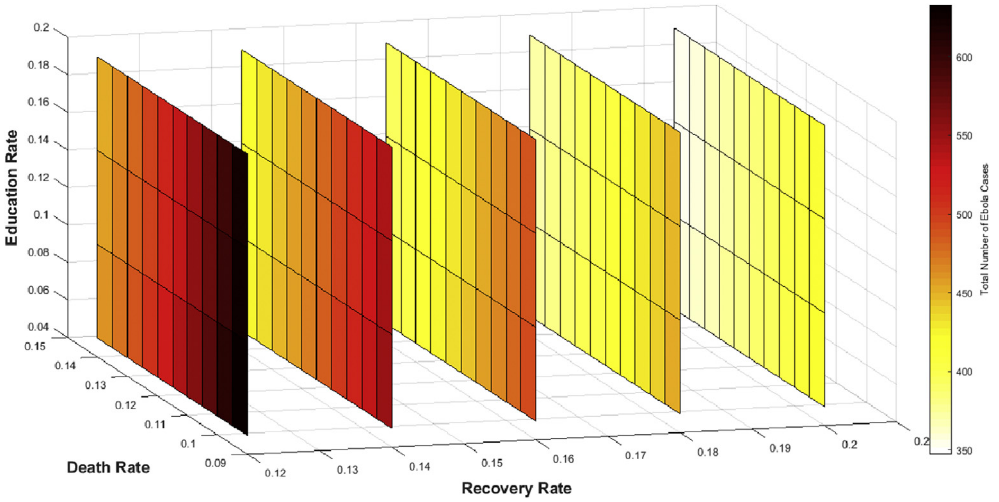

Fig. 7. Results of a simulated outbreak in present day Sudan displaying the total cases of EVD for various recovery, death, and education rates. These figures reflect public health education starting 60 days afters the initial case, which is past the peak of the outbreak.

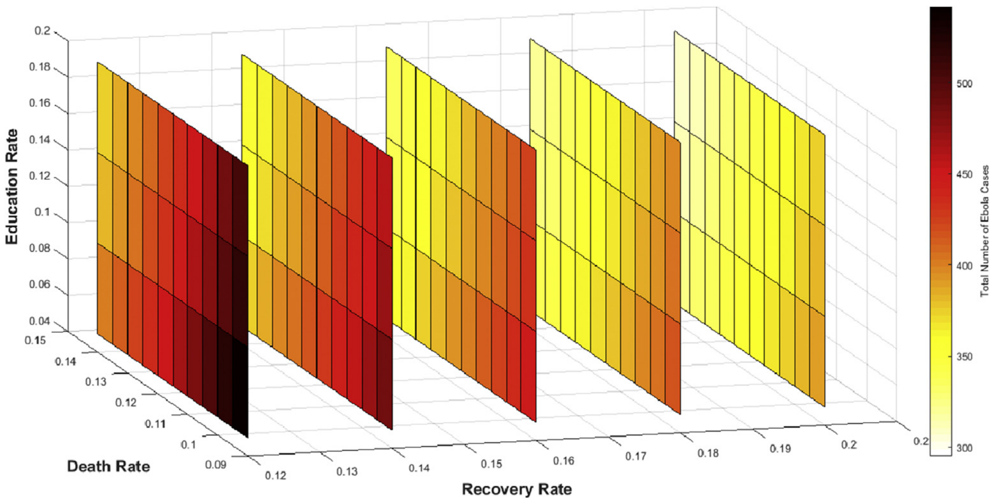

Fig. 8. Results of a simulated outbreak in present day Sudan displaying the total cases of EVD for various recovery, death, and education rates. These figures reflect public health education starting 30 days afters the initial case, which is immediately prior to the peak of the outbreak.

displays results when an intervention begins 14 days after the start of the outbreak, which is well before outbreak peaks. As a result, there were 107–420 total cases of EVD, or 0.0008–0.0032% of the total population becoming infected. Fig. 10 displays results when the θ value is nonzero from the start of the outbreak. This simulation represents the best possible scenario where public health education begins immediately after the first case of EVD is detected. In this case there were 16–143 total cases of EVD, or 0.0001–0.0011% of the total population becoming infected. These results clearly illustrate not only the importance of public health education that lead to behavior change, but also the timing of such campaigns. The earlier behavior change begins to take place as a result of public health education, the more lives that can be saved. To illustrate this, we consider the case where the population is educated about EVD prior to an outbreak, so that the initial ratio of uneducated:educated susceptibles is inverted to 1:3 and no public health education is implemented. Results from this simulation are shown in Fig. 11. In this scenario, the number of cases ranges from 20 to 66 total cases or 0.0002–0.0005% of the total population, which is a significant reduction from all previous simulations.

The histogram in Fig. 12 displays the total number of cases of EVD from numerical simulations in Figs. 6 through 11. The histogram clearly shows that the timing of public health education is important in reducing the number of cases of EVD. Specifically, the earlier an educational campaign is implemented, the fewer cases that result. It may be difficult to organize an educational campaign during an outbreak, as resources are already limited. As a result, ongoing education of the population will not only result in fewer cases, but is also the most reasonable approach.

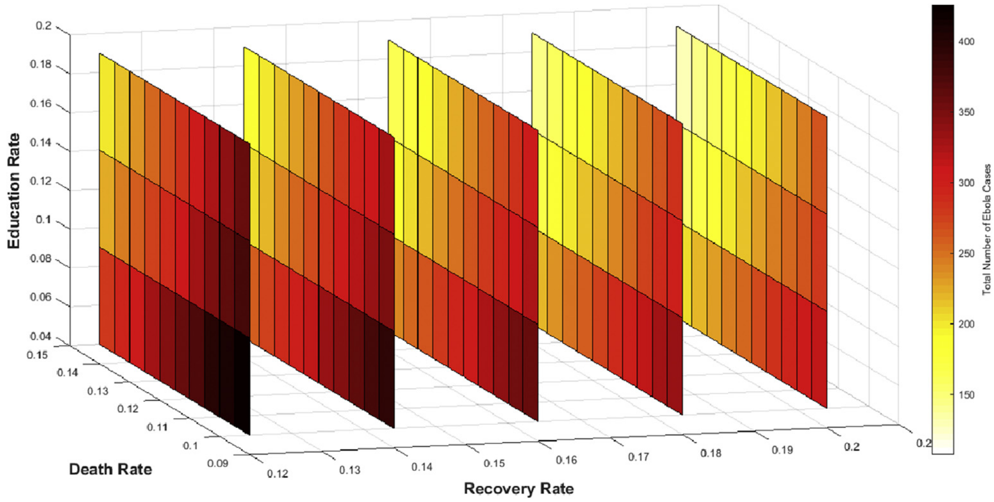

Fig. 9. Results of a simulated outbreak in present day Sudan displaying the total cases of EVD for various recovery, death, and education rates. These figures reflect public health education starting 14 days afters the initial case, which is well prior to the peak of the outbreak.

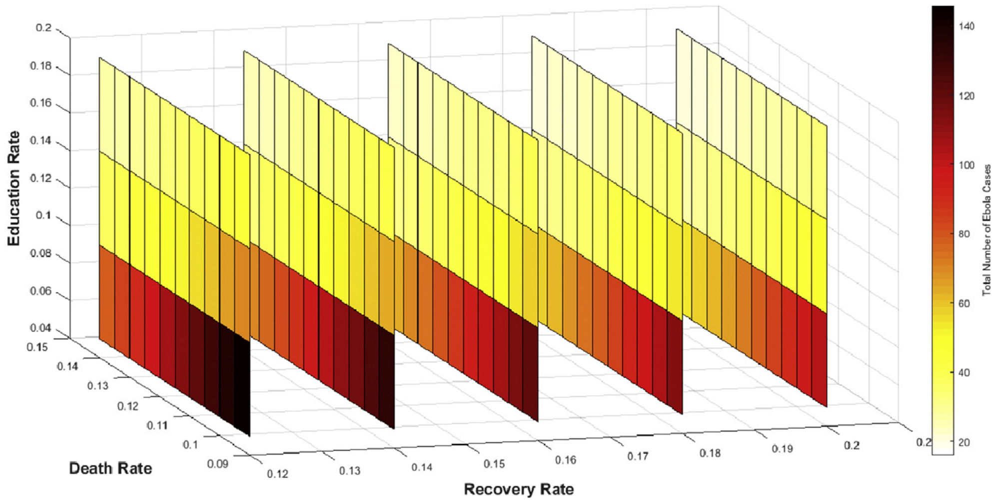

Fig. 10. Results of a simulated outbreak in Sudan displaying the total cases of EVD for various recovery, death, and education rates. These figures reflect public health education starting immediately after the initial case.

5. Sensitivity analysis

We performed a sensitivity analysis on the full model using the total number of infections as the outcome of interest. Parameter values to test were sampled using Latin Hypercube Sampling (LHS), and Partial Rank Correlation Coefficients (PRCC) were used to evaluate how sensitive the total number of infections is to changes in each parameter value (Blower & Dowlatabadi, 1994; Marino, Hogue, Ray, & Kirschner, 2008). We included all the parameters from Table 7, except for β_{3a}, β_{1b}, ϕ_1, δ_1, δ_2, β_{0b}, and β_{4b} as these inputs are either dependent on other parameters or their estimated values are less than 1.0×10^{-10}. We also treated the percentage of the initial population that begins in the uneducated susceptible class as a parameter, denoted as S_0. To construct intervals for the LHS sampling, we chose to select from values 50% above and below the baseline values given in Table 7 with uniform probability distributions used for each interval. We used the suggested number of draws provided in (McKay, Beckman, & Conover, 1979), which resulted in $N > 4K/3$ draws of the LHS design, where K is the number of input parameters and N is the number of LHS draws. In our case, $K = 18$ and $N = 50$.

PRCC is a tool with which we can evaluate the impact of changes in each parameter on the outcome of interest, even when the relationship is non-linear. Note that we can apply the Fisher transformation to the PRCC as described in (Fieller & Pearson, 1961; Macklin, 1982). To determine the significance of the PRCC for each parameter, we calculated a p-value for each using the

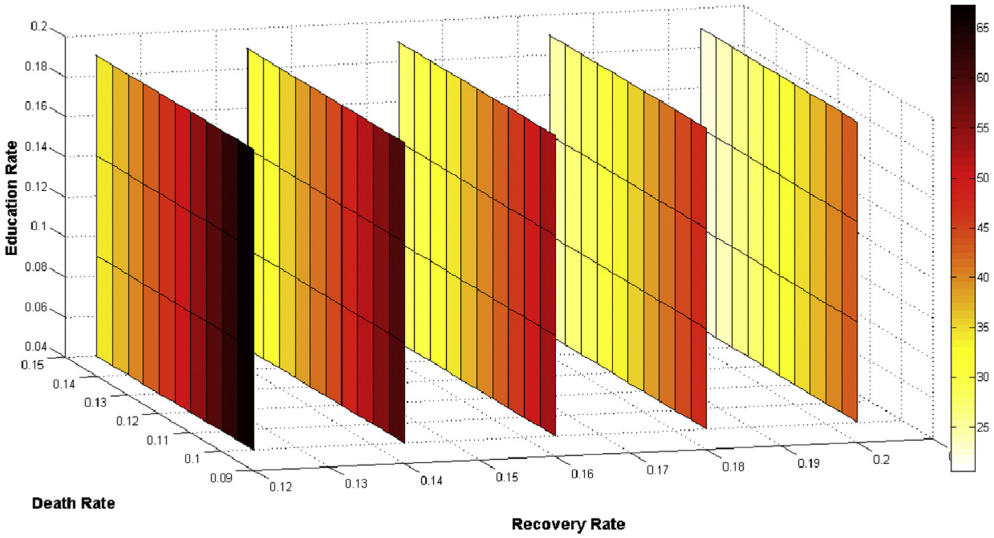

Fig. 11. Results of a simulated outbreak in Sudan displaying the total cases of EVD for various recovery, death, and education rates. These figures reflect an initial ratio of uneducated:educated susceptibles of 1:3 and no public health education ($\theta = 0$). These figures illustrate how educating the population prior to a case of EVD can prevent an outbreak from occurring.

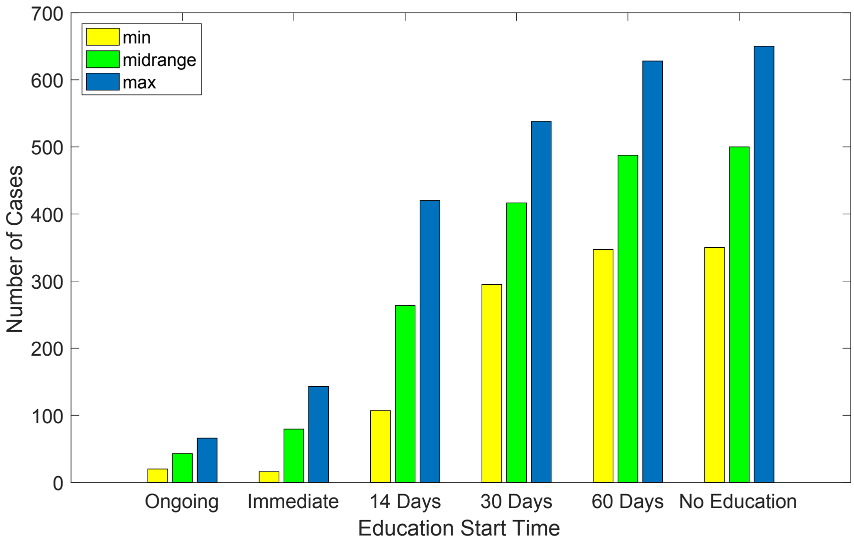

Fig. 12. This histogram summarizes the simulated future outbreaks in Sudan. Specifically, it displays the maximum, minimum, and midrange of the total number of cases of EVD from the numerical simulations in Figs. 6 through 11. Each simulation considered implementing public health education at a different time and the education rates, death rates, and recovery rates were varied in each case.

methods described in (Marino et al., 2008). Since we are performing $K = 18$ hypothesis tests, we corrected the resulting p-values for false discovery using the FDR method of (Benjamini & Hochberg, 1995).

PRCC values with an adjusted p-value less than 0.01 are considered significantly different from 0. The results of the sensitivity analysis are displayed in Table 8, where statistically significant PRCC values are shown in bold.

Based on the adjusted $p-$ value, six of the PRCC values are deemed not significant including β_{0a}, β_{1a}, β_{2a}, β_{4a}, α_{2a}, and ξ. All other PRCC values are deemed statistically significant, with positive values indicating a positive correlation between the parameter and total number of infections and a negative value indicates a negative correlation. The following parameters therefore have a statistically significant PRCC value and a positive influence on the number of infections: β_{3b}, β_{2b}, α_{1b}, ω, and S_0. Each of these values makes sense based on their role in the system. The following parameters have a statistically significant PRCC value and a negative influence on the number of infections: α_{1a}, α_{2b}, ϕ_2, ϕ_3, δ_3, d, and θ.

Using the twelve parameters whose PRCC values were found to be significant, pairwise comparisons with Fisher transformed values (Fieller & Pearson, 1961) produces the results given in Table 9. The PRCC values that are significantly different

Table 8
Model parameters and the corresponding PRCC and FDR adjusted p-values resulting from the sensitivity analysis. Significant values are less than 0.01 and are highlighted in bold.

Variable	PRCC	p-value
β_{0a}	−0.086030	7.162e−01
β_{1a}	0.282820	1.431e−01
β_{2a}	0.035981	8.437e−01
β_{4a}	0.322470	9.279e−02
β_{3b}	0.884460	**1.878e−13**
β_{2b}	0.917910	**0.000e+00**
α_{1a}	−0.387030	**3.799e−02**
α_{2a}	−0.063951	7.685e−01
α_{1b}	0.525560	**3.550e−03**
α_{2b}	−0.443820	**1.618e−02**
ϕ_2	−0.712940	**4.494e−06**
ϕ_3	−0.655080	**6.291e−05**
δ_3	−0.840170	**1.323e−10**
ω	0.467430	**1.102e−02**
ξ	−0.088059	7.162e−01
d	−0.414850	**2.554e−02**
θ	−0.587120	**6.792e−04**
S_0	0.489260	**7.607e−03**

Table 9
Pairwise PRCC Comparisons with FDR Adjusted *P*-values. A bold Y indicates the *P*-value is significant ($\mathbf{P} < \mathbf{.01}$) and a normal N indicates the *P*-value is not significant.

	β_{3b}	β_{2b}	α_{1a}	α_{1b}	α_{2b}	ϕ_2	ϕ_3	δ_3	ω	d	θ	S_0
β_{3b}		N	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
β_{2b}			**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
α_{1a}				**Y**	N	N	N	**Y**	**Y**	N	N	**Y**
α_{1b}					**Y**	**Y**	**Y**	**Y**	N	**Y**	**Y**	N
α_{2b}						N	N	**Y**	**Y**	N	N	**Y**
ϕ_2							N	N	**Y**	N	N	**Y**
ϕ_3								N	**Y**	N	N	**Y**
δ_3									**Y**	**Y**	N	**Y**
ω										**Y**	**Y**	N
d											N	**Y**
θ												**Y**
S_0												

($p < .01$) are shown in bold. Pairs whose PRCC values are not significantly different indicate cases where there is no evidence showing that the outcome changes differently in response to changes in the two parameters. There is a significant difference between β_{3b} and β_{2b} with each of the remaining parameters, which stands out the most in these results. These two parameters represent transmission rates among the educated class and have the strongest PRCC values as seen in Table 8. In essence, β_{3b} and β_{2b} reflect the strength of behavior change in reducing an outbreak of EVD. If the educated portion of the populations does not take precautions against spreading the disease (ie, high β_{3b} and β_{2b} values), then a significant number of cases will be produced. Since the pairwise comparison between β_{3b} and β_{2b} was not significant, it is not clear which parameter is more influential. Further evidence for this point is provided by the fact that the percent of the population that starts in the uneducated class (S_0) is also significantly different than most other parameters and is negatively correlated with the total number of infections. While recovery rates ϕ_2 and ϕ_3 as well as death rate δ_3 were both negatively associated with the outcome in a significant way as individual parameters, the pairwise comparison of each was non-significant rendering the relative importance of each inconclusive.

6. Conclusions

Unnecessary interactions with infected individuals and poor health care protocol each contribute to the duration and spatial spread of an EVD outbreak (Brainard et al., 2015; Chowell et al., 2014; Cook et al., 2015; Dietz et al., 2015). Some of these causes result from cultural practices, while others are due to a lack of awareness about EVD. Such behavior is clearly evident in the 1976 outbreak of EVD in Sudan as this initial documented outbreak of Ebola lasted for five months, infected a large portion of the population, and produced most new infections in a health care setting. For this reason we estimated parameters related to the uneducated population using data from the 1976 outbreak (Report of a WHO/International Study Team, 1978).

We then used the Sudan 1979 data to estimate parameters related to the educated population, as we assume this outbreak consisted of individuals who were more educated about EVD. This is a fair assumption as the outbreak lasted for less time and had fewer cases, and health care professionals had an improved medical understanding of the disease. Considering these facts about the EVD outbreak in Sudan in 1979, our model illustrated fewer cases due to having more knowledgeable suspectibles with respect to medically appropriate interactions with infecteds. The knowledge of the general community as well as health care workers in that situation also results in lower estimated transmission rates.

Public health education has been used in the past to alter an epidemic by improving the general population's understanding of a disease (Bhunu et al., 2010; Del Valle et al., 2005; Joshi et al., 2008, 2015). We model the impact of such behavior changes on an outbreak by considering two sub-populations and estimating parameters related to each separately before viewing the interplay between the two groups in our full model. In simulations of the full model, the initial proportion of educated and uneducated susceptibles as well as the timing of behavior change play major roles in reducing the magnitude of the outbreak. Specifically, the sooner changes in behavior take place and the more educated susceptibles that exist, the fewer cases that result. The model is highly sensitive to various inputs such as transmission rates, recovery rates, and death rates as illustrated in our simulations and sensitivity analysis. Our model indicates that the severity of a future outbreak will be governed by the preparedness of health care facilities as well as the specific strain of EVD.

Our conclusions echo what was seen in the 2014 outbreak of EVD in West Africa: the severity of an outbreak is directly tied to the level of prior knowledge and education of the general population as well as preparedness of health care facilities. For instance, a high proportion of educated individuals results in far lower incidence levels of EVD. The education in this context includes breaking some of the cultural practices assumed to contribute significantly to the spread of the disease. The study further identifies the timing of behavior change to be one of the determining factors in the success of a control strategy. Delayed implementation can cause establishment of the epidemic leading to complication in reducing the burden of the disease. Another key takeaway is the need for ongoing public health education. This fact is supported by this work as having a higher percent of educated individuals results in a far lower percent of the population becoming infected. This was also evident in the 2014 outbreak in West Africa, as by the time public health campaigns were launched the number of incidents had already reached a record size, which made it difficult to quell the epidemic. Simulation and sensitivity results show that the outcome of the epidemic is highly sensitive to various rates. Thus, the severity of future outbreaks of EVD are governed by the level of education present in the population as well as preparedness of health care facilities. Capacity to handle large numbers of hospitalizations due to high education response rates, trust in health care systems, and well-strained health professionals will contribute significantly to the reduction in the burden of the Ebola disease.

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