Simulation of safe and dignified burial for control of Bundibugyo Ebola virus epidemics

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Motivation

The importance of safe and dignified burial

The ongoing epidemic of Ebola Bundibugyo Virus Disease (BVD) in the eastern Democratic Republic of Congo (DRC) and Uganda appears to be propagating. Just as during the previous large DRC epidemic (2018-2020), there have been concerning reports of a breakdown in community trust and violence surrounding the burial of hospitalised cases. These reports underscore the importance of ensuring culturally appropriate, accessible, compassionate inhumation of people who die from BVD, the bodies of whom remain infectious after their death. Safe and dignified burial (SDB) is a recognised pillar of Ebola response and is supported by evidence [1–5] as a superior alternative to either (i) no support for safe burial, which can result in unchecked propagation [6–9]; or, perhaps worse still, (ii) militarised, coercive approaches to patient isolation and burial management: these impede grief, worsen mental health, have been shown to result in mistrust and can disincentivise care-seeking [10–13]. At least in DRC, SDB has previously been offered presumptively, i.e. for any deaths in the community regardless of whether they had received an Ebola test or diagnosis.

SDB and Ebola transmission

An epidemic evolves as a function of how transmissible the pathogen is. We use the reproduction number, or R, to quantify this property. For example, an R of 2.0 means that on average each case will lead to two further cases. Thankfully, past Ebola epidemics in DRC have, on average, featured an R well below 2.0 [4, 14], though this number varies over time, across locations and between epidemics.

Now suppose that on average each case of BVD results in 0.9 further cases while they are alive and infectious, and that cases who die cause 0.8 further cases before they are buried (let's call this quantity R_D). If we assume that every other case is fatal, on average half of cases will only result in 0.9 further cases, while the half who pass away will result in (0.9 + 0.8 = 1.7). The average R therefore will be (0.9 + 1.7) / 2 = 1.3. This means each new generation of cases will, on average, be greater than the previous one. However, if SDB were to completely cancel out transmission from bodies, in this example all cases would have an average R of 0.9, i.e. the new generations of cases would be smaller than those preceding: in other words, any value of R < 1 should, in the long term, result in the epidemic going extinct – a very important insight when considering the potential contribution of different interventions.

We can use a simple transmission model to explore different scenarios of how SDB could affect the epidemic's trajectory, and thus inform decisions about which targets the SDB service should set out to achieve. The estimates below are not predictions of how the epidemic will evolve (many other factors will determine this), but rather illustrative projections under different conditions. We take as our analysis unit an average-sized health zone in eastern DRC in which SDB is implemented once the outbreak reaches a certain size. Methods are summarised at the end of the document.

Exploring scenarios

A simple comparison

Let's first consider a set of extreme scenarios: no SDB versus perfectly implemented SDB for all deceased cases, under three levels of R and R_D, the number of cases resulting from an average dead case before burial (Figure 1). What is apparent is that under these simple scenarios SDB makes a serious difference in terms of lowering the caseload. As we would expect, under 100% coverage the epidemic will progress very slowly or not at all, as long as R_D is sufficiently large relative to R.

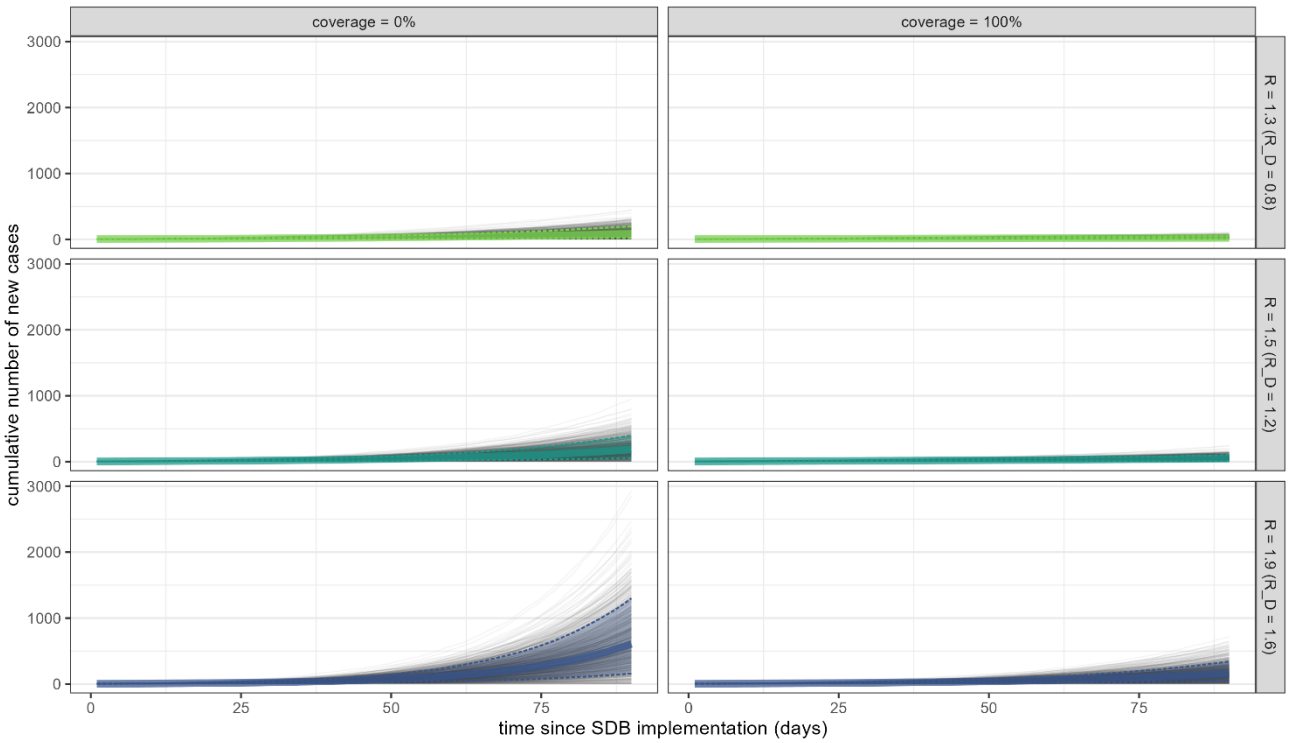

Figure 1. Projected number of cumulative cases over 90 days, starting with 5 prevalent infections, under 0% and 100% SDB coverage and increasing transmissibility ($\boldsymbol{R}$), after 1000 simulation runs and assuming 100% SDB effectiveness. Thick lines indicate median projections; dotted lines contain 80% of simulation run results. Individual simulation runs are plotted as light grey lines.

More realism: varying levels of coverage and effectiveness

In reality these extreme scenarios are unrealistic. Some BVD deaths may be missed by SDB teams, i.e. the coverage of SDB will probably be <100%. Moreover, SDB is only fully effective if three key tasks are accomplished: securing the body, safe burial and environmental disinfection: in previous work, we estimated that the SDB service during the 2018-2020 epidemic in DRC averaged 61% effectiveness (with an unknown but probably high coverage) [5]. Effectiveness was higher when community-led groups were supported to carry out SDB, and lowest when insecurity disrupted the Ebola response.

We can explore different combinations of SDB coverage and effectiveness (Figure 2). This suggests that there is no clear-cut set of targets one could adopt: the higher the coverage and effectiveness, the better. Both indicators, but perhaps coverage in particular, may depend heavily on community trust: after all, coverage depends on community members feeling able to call in the SDB service without being stigmatised or otherwise harmed.

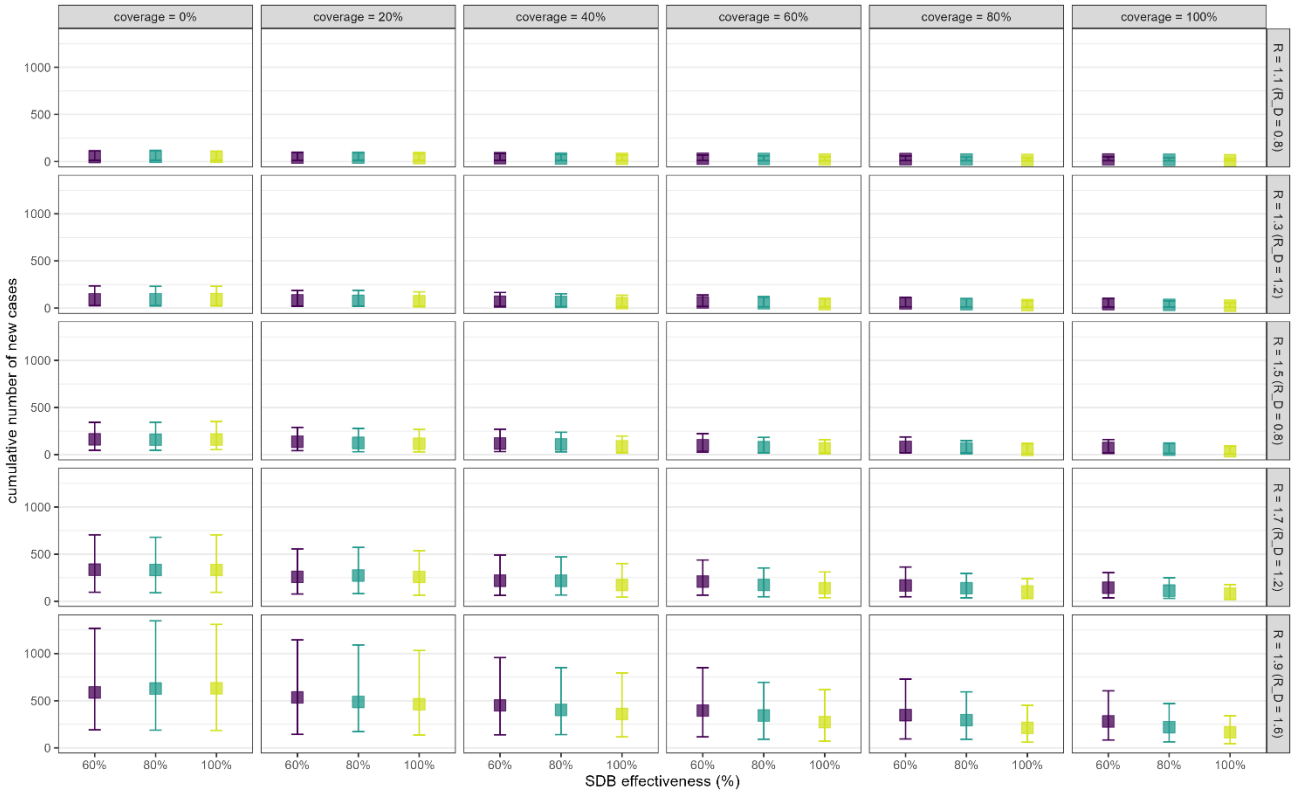

Figure 2. Median projected number of cumulative cases over 90 days, starting with 5 prevalent infections, under varying scenarios of SDB coverage, SDB effectiveness and $\boldsymbol{R}$, after 1000 simulation runs. Error bars contain 80% of simulation run results.

Can SDB contain outbreaks?

We can also look at a different metric of SDB's impact, namely whether it can on its own tilt the epidemic's trajectory towards extinction or contain outbreaks before they propagate. This is illustrated in Figure 3. Unsurprisingly, extinction is much more likely when R is relatively low. At these marginal levels of transmissibility, SDB conducted with high coverage and effectiveness can potentially increase the chances of extinction substantially, irrespective of other interventions.

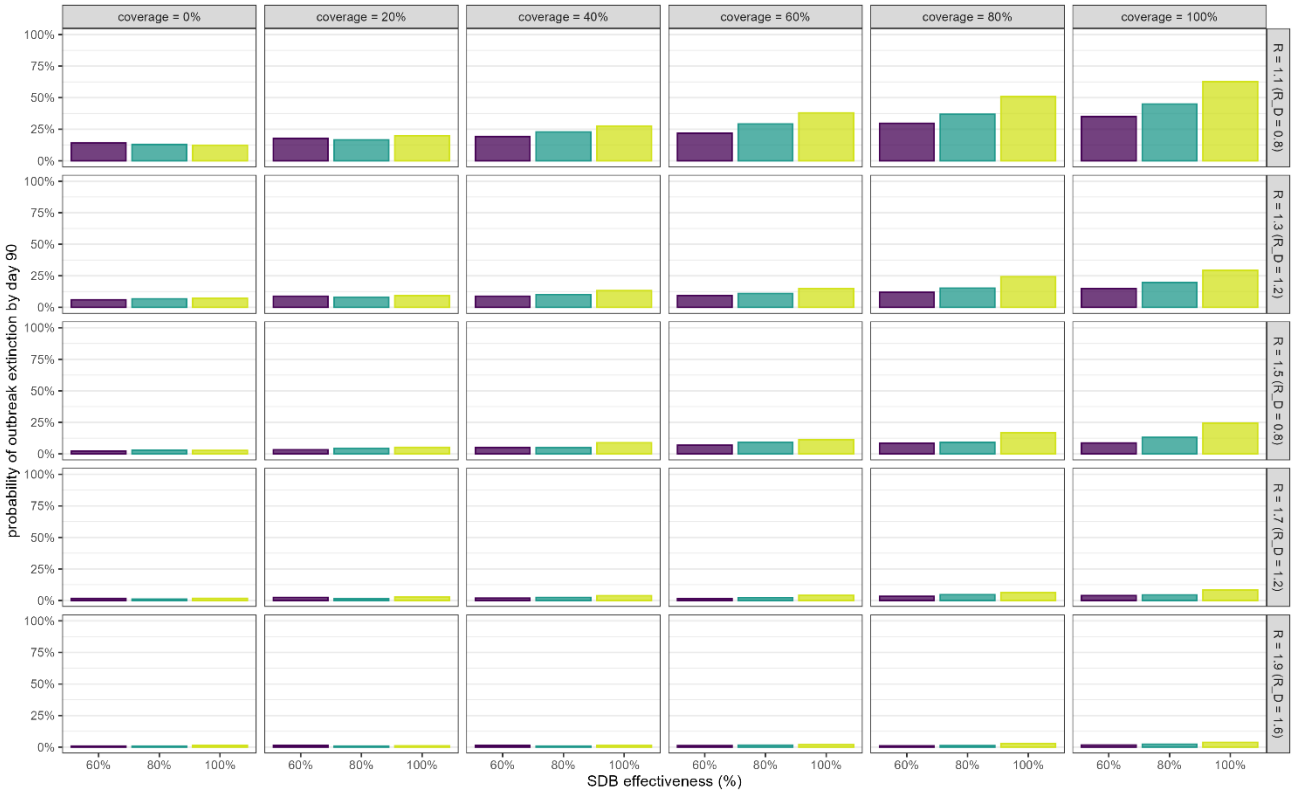

Figure 3. Percentage of simulation runs (n = 1000) in which no new cases were projected during the last 21 days of the 90-day simulation period, starting with 5 prevalent infections, under varying scenarios of SDB coverage, SDB effectiveness and R.

Implementing SDB when the epidemic is more or less advanced

Lastly, we have assumed above that the SDB service kicks in at a point in the local (health zone) outbreak's maturity when five cases are already prevalent. This, too, turns out to be a key parameter, as illustrated in Figure 4. If SDB only becomes operational once the health zone has a large number of prevalent cases, it is unrealistic to expect that it alone will bring the epidemic under control quickly: of course this is not a point against implementing SDB, but merely signifies that control will require a longer timeframe when looking at large population units where the epidemic is well-established; SDB on its own might contain only very small localised outbreaks, such as new importations from neighbouring zones.

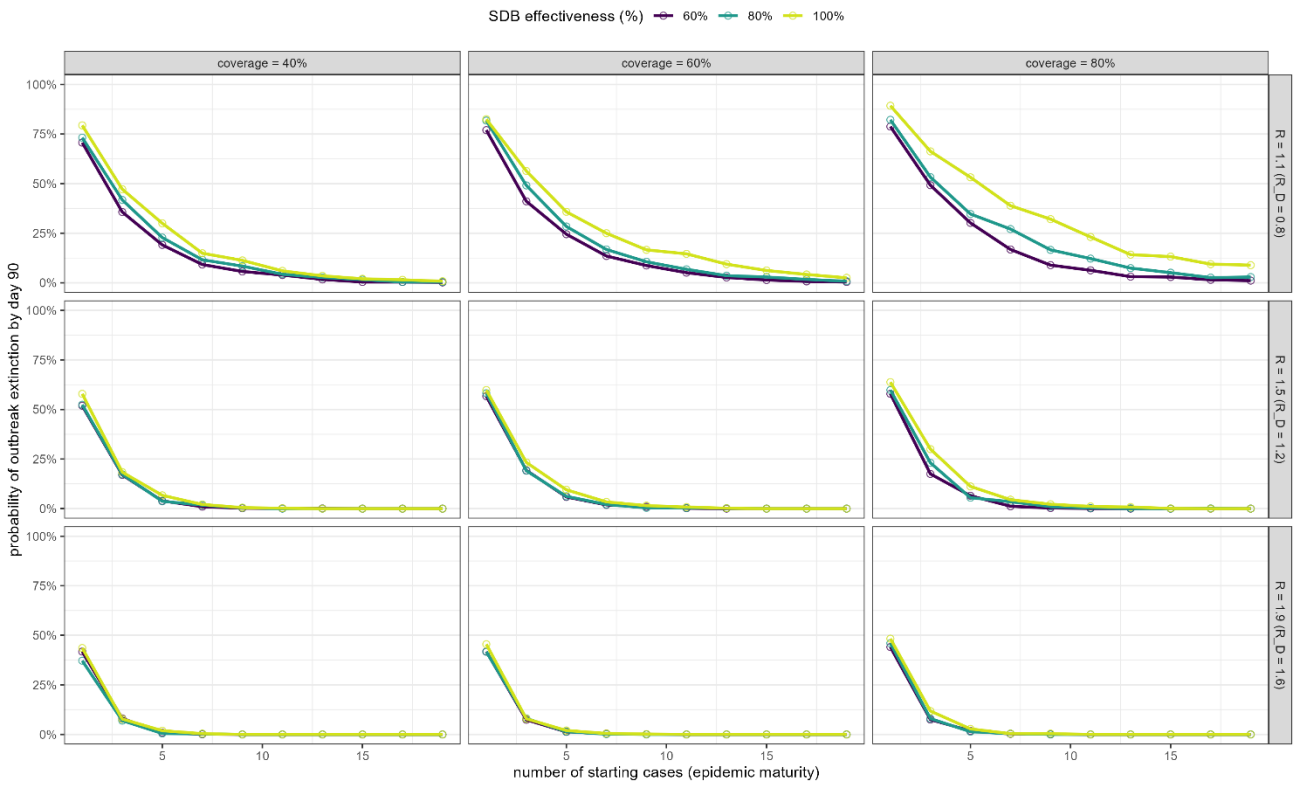

Figure 4. Percentage of simulation runs (n = 1000) in which no new cases were projected during the last 21 days of the 90-day simulation period, under varying scenarios of SDB coverage, SDB effectiveness, $\boldsymbol{R}$ and the starting number of prevalent cases.

Conclusions

A few conclusions can be drawn from the above modelling insights:

1. Achieving high SDB coverage and effectiveness is very important, underscoring the need for community engagement and trust-building, as well as strong collaboration between the SDB service and other response pillars (in particular surveillance/contact tracing†). Maintaining a presumptive approach may help to maximise coverage, albeit at a cost that needs to be weighted against other response priorities. It is, incidentally, very unlikely that a coercive approach would achieve a coverage similar to SDB's, as it is instead shown to lead to low care-seeking and body occultation [2, 13, 15].
2. Under certain conditions of low transmissibility, SDB could make the difference between outbreak propagation and extinction. We have assumed here no other interventions are ongoing. However, the combination of highly performant SDB and, say, isolation and case management would probably make a formidable contribution to transmission [16]. Moreover, SDB as a trust-building measure is likely to encourage care-seeking and case reporting, and could thus act synergistically with other interventions.
3. The longer it takes for SDB to get underway, the harder it will take to bring outbreaks under control. With this in mind, it may be efficient to preposition and activate SDB even in areas where no transmission is yet observed: while we have not explored the spatial dynamics of the epidemic here, such a strategy may prevent geographic spillover.

† Measuring the coverage of SDB is difficult, as it implies estimating the number of unseen deceased cases. However, it can be done if all data collection systems use and cross-communicate a harmonised case ID: a technique called capture-recapture analysis or multiple systems estimation can be used in real time to estimate unseen deaths and thus coverage [17].

Methods

Model structure

For this simulation, we constructed a simple stochastic transmission dynamic model of BVD, using a standard compartmental structure and a random mixing assumption, modified only to allow for deceased cases to contribute to transmission before they are buried (Figure 5). Susceptible cases move to the incubating state based on a force of infection λ; they become symptomatic and thus infectious with flow rate r_1: while in this state they influence λ based on R_I, mean transmissibility during this state. They move out of the infectious period when their illness ends (r_2), either dying (case-fatality ratio μ) or surviving $(1-\mu)$. Of those who die, a proportion γ (coverage) receive SDB and influence λ based on an R_D attenuated by the effect of SDB (δ_φ) at whatever level of effectiveness φ it is being implemented with (see below), while the remainder $(1-\gamma)$ influence λ based on an unattenuated R_D. All dead persons are eventually buried with rate r_3, thereby joining survivors in the Removed state.

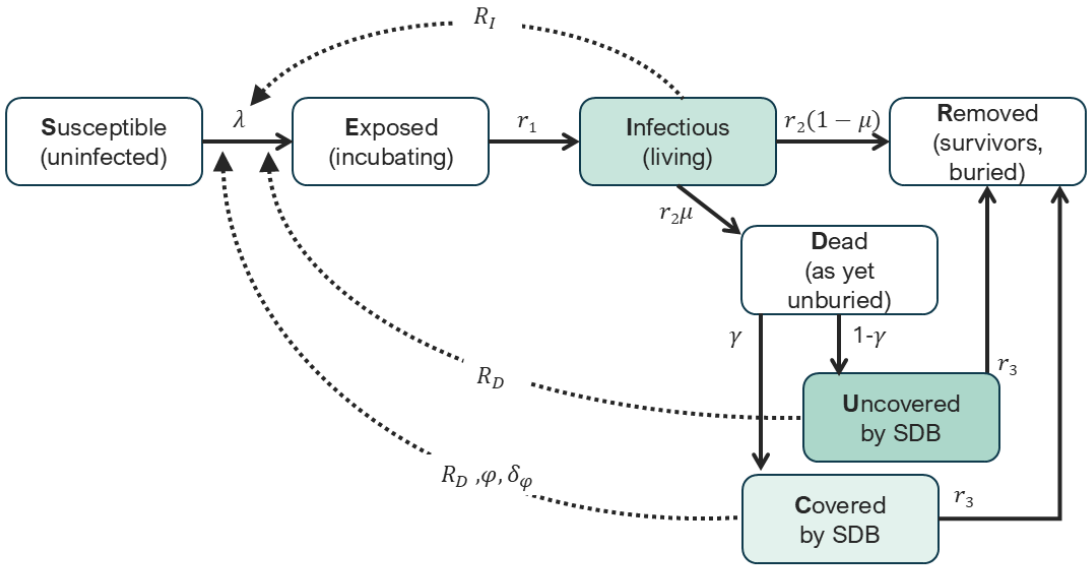

Figure 5. Schematic of the model's structure.

The effect of SDB

The reproduction number can be decomposed into the sum of transmissions resulting from effective contacts made by a living case during their infectious period (R_I) and the number of transmissions from the same case before they are buried (R_D), conditional on the case being fatal:

$$R = R_I + \mu R_D$$

R_D can be reduced as a function of the coverage γ and effectiveness φ of SDB. We previously evaluated the effectiveness of the SDB service supported by the Congolese Red Cross and International Federation of Red Cross and Red Crescent Societies (IFRC) during the 2018-2020 EVD epidemic in the eastern DRC [5]. We also estimated the *absolute* reduction δ_φ in R corresponding to varying levels of φ in the

same setting, after accounting for plausible confounders (including concurrent interventions) through two methods of propensity score analysis [4]. Here we average findings from both methods to yield a $\delta_\varphi \sim f(\varphi)$ function as model input (Figure 6). Note that γ in 2018-2020 is unknown, but likely to have been high during most of the epidemic [4]. For simplicity and to err on the side of a conservative estimate of SDB's potential effect, we assume that the estimated δ_φ occurred at $\gamma = 1$. If SDB is operational, we can accordingly write

$$R = R_I + (1-\gamma)\mu R_D + \gamma\left(\mu R_D - \delta_\varphi\right)$$

whereby the proportion γ of deceased cases that receives SDB experiences a reduction of δ_φ in their transmissibility. This imposes the minimum constraint that $R_D \geq \frac{\delta_{\varphi,\max}}{\mu}$, but does not suggest a maximum. There is limited empirical evidence on the precise contribution of unsafe burials to overall Ebola transmissibility. During the West Africa (2013-2016) epidemic, R_D was estimated at about 2.6 for unsafe burials [18]. A separate analysis of the same epidemic suggests that R_D was about 0.3 after accounting for large-scale interventions [19]. Our own analysis of the previous large DRC epidemic suggests a $\delta_{\varphi,\max}$ of up to 0.4 may be realistic (Figure 6), i.e. that $R_D \geq 0.8$. We have explored a range of $R_D$values in this paper so as to cover a realistic range, but stress the importance of better characterising this quantity.

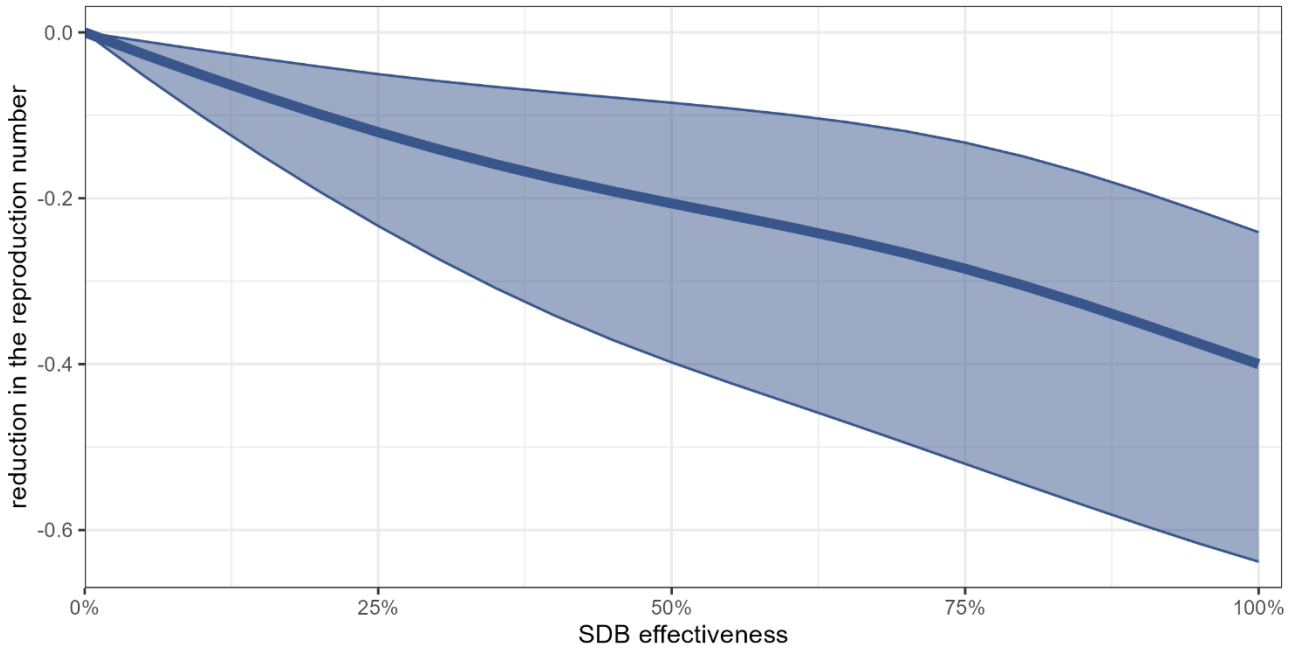

Figure 6. Estimates of the absolute reduction in $\boldsymbol{R}$ resulting from varying levels of SDB effectiveness, for cases that do benefit from SDB (i.e. assuming 100% coverage).

State transitions

The model was implemented using daily time steps Δt, with the number of transitions $n_t^{A\to B}$ between any states A and B occurring during the time step is governed by random binomial draws $\mathrm{bin}(n_t^A, p_t^{A\to B})$, where n_t^A is the number of people at risk of transitioning from A at the start of t and $p_t^{A\to B}$ is the probability of the transition occurring, assuming exponential delays. In detail:

$$n_t^{S\to E} \sim \text{bin}\left(S_t, 1-\exp\left(-\left(\frac{R_I}{T_I}\frac{I_t}{N_t}+\frac{R_D}{T_B}\frac{U_t}{N_t}+\frac{R_D-\frac{\delta_\phi}{\mu}}{T_B}\frac{C_t}{N_t}\right)\Delta t\right)\right)$$

$$n_t^{E\to I} \sim \text{bin}\left(E_t, 1-\exp\left(-\left(\frac{1}{T_E}\right)\Delta t\right)\right)$$

$$n_t^{I\to F} \sim \text{bin}\left(I_t, 1-\exp\left(-\left(\frac{1}{T_I}\right)\Delta t\right)\right)$$

$$n_t^{F\to D} \sim \text{bin}(n_t^{I\to F}, \mu)$$

$$n_t^{I\to R} = n_t^{I\to F} - n_t^{F\to D}$$

$$n_t^{D\to C} \sim \text{bin}(n_t^{F\to D}, \gamma)$$

$$n_t^{D\to U} = n_t^{F\to D} - n_t^{D\to C}$$

$$n_t^{C\to R} \sim \text{bin}\left(C_t, 1-\exp\left(-\left(\frac{1}{T_B}\right)\Delta t\right)\right)$$

$$n_t^{U\to R} \sim \text{bin}\left(U_t, 1-\exp\left(-\left(\frac{1}{T_B}\right)\Delta t\right)\right)$$

Note that state F (not pictured in Figure 5) denotes the end of the infectious period, whereupon cases divide into survivors and decedents. Similarly, D also partitions instantly into C or U. At the end of Δt, the number of people in each state is:

$$S_{t+1} = S_t - n_t^{S\to E}$$

$$E_{t+1} = E_t + n_t^{S\to E} - n_t^{E\to I}$$

$$I_{t+1} = I_t + n_t^{E\to I} - n_t^{I\to F}$$

$$C_{t+1} = C_t + n_t^{D\to C} - n_t^{C\to R}$$

$$U_{t+1} = U_t + n_t^{D\to U} - n_t^{U\to R}$$

$$R_{t+1} = R_t + n_t^{I\to R} + n_t^{C\to R} + n_t^{U\to R}$$

Input parameters

Parameter input values are listed in Table 1. Analysis was in R software, but the model was compiled in C++ using the `pomp` package [20] and associated guidance. The analysis is entirely reproducible, and input parameters can be modified, from the following repository: https://github.com/francescochecchi/bvd_sdb_sim .

Table 1. List of parameters and input values.

Parameter	Value	Description	Source and notes
R	variable	Overall reproduction number.	Range assumed based on health zone-specific R values in Checchi et al. [4].
R_D	variable	Reproduction number of *deceased* cases, before burial.	See text.
R_I	variable	Reproduction number of *living* infectious cases.	$R_I = R - \mu R_D$
Incubation period (T_E)	6.3	Days from infection to symptoms.	Mean of Table 5, van Kerkhove et al. [21].
Infectious period (T_I)	10.0	Days from symptoms to death or recovery.	Table 5, van Kerkhove et al. [21]. Infectiousness starts at symptom onset.
Burial period (T_B)	1.5	Days before person is buried.	Assumed. Similar to values adopted by other models.

Parameter	Value	Description	Source and notes
Case-fatality ratio (μ)	50%	Proportion of cases who die of BVD.	Table 5, van Kerkhove et al. [21]. Assume 10% higher as available sources reported mainly on hospitalised (treated) cases.
SDB coverage (γ)	variable	Proportion of burials attended to by an SDB team.	
SDB effectiveness (φ)	variable	Proportion of burials for whom all required SDB steps are accomplished.	Known as 'success' in Checchi et al. [4].
δ_φ	variable	Absolute reduction in R_D at a given level of φ assuming γ = 1.	Read from Figure 6. Assumed point estimates.
Number of seeds	5	Number of prevalent cases at the start of the simulation.	Varied in sensitivity analysis.
Population (N)	211,121	Population size. $N = S + E + I + C + U + R$	Mean DRC health zone population (Ituri, South Kivu, North Kivu provinces only), based on UN-OCHA projections.

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