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Spatio-temporal spread of the Ebola 2014 outbreak in Liberia and the effectiveness of non-pharmaceutical interventions: a computational modelling analysis

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Authors' contributions

SM, MA, LF, MG, AP, DC, AV provided the data. SM, MA, LF performed the computational experiments. SM, AV conceived the study. All authors analyzed, discussed the results, edited and commented the manuscript draft. All authors read and approved the final manuscript.

Declaration of interests

All authors declare no conflict of interest.

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Summary

Background—The 2014 Ebola epidemic in West Africa defines an unprecedented health threat. We developed a model of Ebola transmission that integrates detailed geographical and demographic data from Liberia to overcome the limitations of non-spatial approaches in projecting the disease dynamics and assessing non-pharmaceutical control interventions.

Methods—We use a spatial agent-based model calibrated using a Markov chain Monte Carlo approach. The model is used to estimate Ebola transmission parameters and investigate the effectiveness of interventions such as availability of Ebola Treatment Units, safe burials procedures and household protection kits.

Findings—Through August 16, 2014, we estimate that 38·3% (95%CI 17·4-76·4) of infections were acquired in hospitals, 30·7% (95%CI 14·1-46·4) in households, and 8·9% (95%CI 3·3-11·8) while participating in funerals. The movement and mixing of Ebola and non-Ebola patients in hospitals at the early stage of the epidemic is found to be a sufficient driver of the observed pattern of spatial spread. The subsequent decrease of incidence at country and county level is ascribable to the increasing availability of Ebola treatment units – which in turn contributed to drastically decrease hospital transmission – safe burials, and distribution of household protection kits.

Interpretation—The model allows evaluating intervention options and disentangling their role in the decrease of incidence observed since September 7, 2014. High-quality data - e.g. to estimate household secondary attack rate, contact patterns within hospitals, and effects of ongoing interventions - are needed to reduce uncertainty in model estimates.

Introduction

The exponential increase of Ebola cases in Sierra Leone, Liberia and Guinea during the months of August and September 2014 defines an unprecedented health threat to the West African region. A massive international response requiring the large-scale deployment of human and capital resources is needed to stop the epidemic. Such efforts would benefit from quantitative predictions about the growth of the epidemic and the effectiveness of potential containment or mitigation strategies. According to World Health Organization (WHO) and Liberian Ministry of Health & Social Welfare reports[1,2], 7069 cases and 2964 deaths were recorded in Liberia by November 17, 2014, with 341 cases and 170 deaths among health care workers (HCW). Since September 2014, the recorded number of cases has not followed the initial exponential growth trend observed in the early phase of the outbreak and the epidemic may be waning in parts of Liberia.[2] In recent years, mathematical modelling at very detailed spatial resolutions, sometimes down to the level of single individuals, has been tailored to make projections for policy makers using population specific socio-demographic features of the population.[3–8]

Recently published works on EVD transmission[9–13], have been key in motivating and informing the strong international response to the epidemic. Here we propose an approach

that can overcome some of the limitations of those early approaches, namely homogenous mixing assumption in all settings relevant to EVD transmission and lack of spatial structure, that might result in overestimating EVD incidence. We developed a spatial agent-based model that integrates socio-demographic data of Liberia to estimate the relative importance of the main settings for Ebola virus disease (EVD) transmission, which are within households, in the general community (mainly corresponding to close relatives, in the case of EVD), in hospitals, and at funerals during burial ceremonies. We simulated the EVD epidemic in a synthetic population in which every household in Liberia is explicitly represented. The model includes hospitals and clinics treating Ebola cases up to mid August and Ebola treatment units (ETUs) in the subsequent period and the risk of spread to HCW working at them. We used the model to project the spatio-temporal spreading of the disease and disentangle the impact of ETUs availability, safe burials procedures, and the distribution of household protection kits in averting EVD cases.

Methods

Model Structure

The EVD natural history model is adopted from Legrand and colleagues[14]: susceptible individuals can acquire infection after contact with an infectious individual and become exposed without symptoms; at the end of the latent period infectious and symptomatic individuals can transmit infection at home to both household members and close relatives. Infectious individuals at home then may either be hospitalized, die, or recover. Hospitalized individuals may also either die or recover. Deceased individuals may transmit infection during their funeral (to household members and relatives belonging to additional households) and are then removed from the model. To account for the spatial spread of the epidemic, we explicitly model the movements of individuals, including non-Ebola patients, seeking assistance in health care facilities, the movements of individuals taking care of Ebola patients not hospitalized, and the attendance of funerals. Individuals are grouped into randomly assigned households whose size is based on Demographic Health Survey data and are geographically placed to match population density estimates on a grid of 3,157 cells covering the country. A full description of the synthetic population and the transmission model is in the SI.

Disease Transmission

Most EVD transmission parameters used in the model were from a study of the current outbreak by the WHO-led team[15] and are summarized in Table 1. The model accounts for three routes of transmission: transmission in households and in the general community (corresponding to additional households) when the infected individuals are at home; transmission in hospitals; and transmission during funerals (to household and additional household members). (See SI for details on the transmission model). In general hospitals both HCW and non-Ebola patients are exposed to the risk of contracting the disease. Starting from August 15, 2014, the model accounts for the increasing number of hospital beds specific for Ebola patients in ETUs. The number of available beds in ETUs increases over time according to data reported by the WHO (data reported in the SI). Importantly, after August 15, 2014 Ebola patients are no longer admitted to general hospitals but only to ETU

where they can transmit the infection only to HCW (with probability 0.05% with respect to general hospitals). Moreover we assume that safe burials increase linearly over time from 0% on August 15 to 90% on October 15. In the model three key parameters have to be estimated for the current outbreak, namely β_h (transmission rate in hospitals), β_f (transmission rate between household members, including their contacts with the deceased during burial ceremonies), and σ (scaling factor for the transmission rate in the general community relative to β_f).

Model Calibration

Simulations were calibrated to begin with 24 initial Ebola-related deaths by June 16, 2014, matching an early report from the WHO. To estimate the three key model parameters, we used a Markov chain Monte Carlo (MCMC) approach exploring the likelihood of the recorded number of deaths among HCW and in the general population based on official reports through August 16, 2014.[1,2] In principle, it would be possible to use also more recent data for model calibration. The drawback of this approach lies in the fact that parameter estimate would depend on the simulated effects of all ongoing interventions, whose impact is still uncertain. In the baseline scenario, we set the reporting rates of deaths both among HCW and in the general population to be equal to 100%. In addition, to provide an upper bound to our predicted number of cases and deaths, we investigate a second scenario (underreporting scenario) where we still assume a 100% reporting in HCW but a 50% reporting in the general population -- accounting for the possibly elevated rate of underreporting of Ebola deaths. Random-walk Metropolis-Hastings sampling is used to explore the parameter space, checking convergence by using chains of 10,000 iterations (after a 2,000 burn in period) starting from several different initial values of the parameters set. The MCMC analysis, and the identifiability of parameters are described in detail in the SI.

Role of the funding source

The funders had no role in study design, data collection and analysis, interpretation, or preparation of the manuscript. The corresponding author had full access to all the data in the study and had final responsibilities for the decision to submit for publication.

Results

The early transmissibility of EVD in different social settings

The model calibration yields 830 cases (95%CI: 695–969) and 402 deaths (95%CI: 332–478) in Liberia by August 16, 2014, assuming perfect reporting of EVD cases and deaths (the baseline scenario). If we assume 50% underreporting in the general population and no underreporting in HCW, the model estimates 1,571 cases (95%CI: 1,315–1,849) and 805 deaths (95% CI: 672–947) by that date. The actual reporting rate in Liberia is unknown, so these two extreme scenarios are used to cover the uncertainty of the surveillance data. The estimated cases and deaths over time for both of these reporting scenarios are shown in Fig. 1A. The estimated basic reproduction number is R_0=1·84 (95%CI: 1·60-2·13) for the baseline scenario and R_0=1·9 (95%CI: 1·62-2·14) for the underreporting scenario (see Table 2 for estimates, and SI for the calculation procedure). Basic reproduction number estimates

are in agreement with recent estimates obtained with different mathematical modelling approaches.[12,15–20] Under the baseline scenario we estimated a generation time of 18.1 days (SD: 12.3 days). The growth rate of the simulated epidemics is 0·038 $days^{-1}$ (95%CI: 0·028-0·048), corresponding to a doubling time of 18·6 days (95%CI: 14·3-24·3). In the underreporting scenario, the generation time is 17·2 days (SD: 12·4 days) and the growth rate is 0·043 $days^{-1}$ (95%CI: 0·031-0·052), corresponding to a doubling time of 16·5 days (95%CI: 13·2-22·4). Such values are in agreement with those reported by the WHO-led team [15], namely an estimated generation time of 15·3 days (SD: 9·1 days) and doubling time of 15·8 days (95%CI: 14·4-17·4) in Liberia.

The model was used to estimate the fraction of EVD transmission attributable to different settings. As of August 16, 2014, under the baseline scenario, we estimate that 52·9% (95%CI: 20·3-71·3) of infections occurred in households or in the general community (of which 30·7%, 95%CI 14·1-46·4 were within households), 38·4% (95%CI: 17·4-76·4) in hospitals, and 8·6% (95%CI: 3·2-11·8) at funerals (Fig. 1B, 1C and Table 2). The estimated household secondary attack rate (SAR), or the probability that an infected person will infect a susceptible household member, is 19·4% (95%CI 7·2-34·8), in agreement with values reported in Dowell and colleagues[21] for the 1995 outbreak in the Democratic Republic of the Congo (16%). For the underreporting scenario, 72% (95%CI: 60·2-79·8) of infections occurred in households or in the general community (of which 41·7%, 95%CI 32·9-57·4, were within households), 17·5% (95%CI: 9·3-29·8) in hospitals, and 10·4% (95%CI: 8·8-12) at funerals (Fig. 1B, 1C and Table 2). The household SAR was estimated to be 36·1% (95%CI 21·8-55·9). The higher estimated household SAR in the underreporting scenario stems from the fact that unreported cases can be accounted for only by enhancing transmission in households and the general community, because the finite hospital capacity limits the number of transmissions occurring in that specific setting. EVD transmission attributable to funerals has been estimated by others using case report data to be 9%[15], in good agreement with our transmission model-based estimates. The lower uncertainty in the estimated values for the underreporting scenario can be explained by considering that the number of cases in the general population is higher than in the scenario assuming 100% reporting, while the number of cases among HCW remains the same (see Fig. 1C). This poses an upper constraint on the transmissibility in hospitals.

The spatio-temporal spread of EVD

The calibrated model was used to investigate the features and drivers of the spatial spread of EVD in Liberia. Figure 1D and 1E show the geographic diffusion of the EVD outbreak up to August 16, 2014 in the model (see SI for a full spatio-temporal analysis). Although the model was initialized with a few localized cases, EVD is widespread across most of the country by early August. The spatial drivers of EVD spread in our model are contacts across households and infected individuals travelling to hospitals and clinics. We tested different maximum distances between households with frequent contacts from 2.5 to 20 km, but they had little impact on the model results (see SI). While this result does not rule out the possible effects from other long-range mobility process, it indicates that up to the initiation of intervention a sufficient driver for the geographic spread of EVD is hospitals, where Ebola and non-Ebola patients from a large catchment area can interact. In the SI we show

that the model consistently predicts the week of the first Ebola case and number of cases over time by county.

The impact of non-pharmaceutical interventions

The model can be used to provide projections of the future burden of the outbreak, at least in the near future, and to analyse the potential effectiveness of non-pharmaceuticals interventions. Figure 2A shows projections for January 1, 2015 (18 weeks after the last data used for model calibration), assuming that after early August the available beds in ETUs increases over time according to data reported by the WHO and safe burials are progressively implemented as described in the Methods section. In the model calibrated to the baseline scenario, there are 11,806 cases (95%CI: 2,387-60,856) and 4,032 deaths (95%CI: 1,085-11,446) in the general population and 230 deaths (95%CI: 153-324) among HCW by January 1, 2015. More cases are projected by the model calibrated assuming 50% underreporting, with 321,127 cases (95%CI: 56,058-828,797) and 34,751 deaths (95%CI: 11,639-78,826) in the general population and 305 deaths (95%CI: 192-426) among HCW. The numbers provided by the underreporting scenario seems hardly compatible with the actual data reported so far in official reports and suggest that underreporting could not be as high as 50%.

Thanks to the availability of an increasing number of Ebola beds in ETUs after mid August, in all investigated scenarios hospital transmission drastically decreases over time. In particular, as of January 1, 2015 the fraction of infection from hospital-based transmission decreases to 17% (95%CI: 0·9-59·8) and 0·5% (95%CI: 0·1-1.9) in the baseline and underreporting scenarios. We stress that after mid August only a negligible number of cases are generated in hospitals, as we assume that Ebola patients are admitted only to ETUs. According to the WHO estimates, there have been 2,373 safe burials in Liberia as of November 12, 2014, consistent with model estimates, namely 1,462 on average (95%CI 310–3,293).

Figure 2B shows the number of admission in ETUs and the number of Ebola patients in treatment over time. In agreement with observed data, the model predicts an increase of admissions and treated Ebola cases from mid August to mid September and a subsequent decrease. WHO reports following September 7, 2014 have shown a decreasing number of cases, suggesting that local chains of transmission have been broken in some districts. This is consistent with model simulations characterized by a high proportion of cases generated in hospitals in the initial phase of the outbreak and a consequent later decrease of transmission in hospitals. Although both Fig. 2B and 2C, point out that more high quality data, e.g. to provide field estimates of household secondary attack rate and contact patterns within hospitals and ETUs, are needed to reduce uncertainty of model estimates, the decrease of incidence after September 2014 is widespread. This is very clear in Fig. 2C, showing that the growth of the cumulative number of cases over time deviates from exponential growth and eventually flattens in all the most affected counties of Liberia.

In order to quantify the contribution of ETUs deployment and safe burials in Table 3 we report the EVD cases projected by the model, along with the number of averted cases when compared with a no interventions scenario (see also Fig. 3A). As shown in Table 3, in the

absence of interventions the model predicts a total of 36,775 cases (95%CI: 12,279-107,913) on January 1, 2015. We considered the distribution of household protection kits to a certain fraction of households where a case is identified. According to CDC estimates, the protection kit, together with the increased awareness in households where the kit is distributed, could reduce transmission in a household by 90%.[13] This is modelled by reducing the transmission rate β_f by 90% (the 50% reduction scenario is analysed in the SI) for all infectious individuals in the household where the protection kit is supplied. This implies a reduction of the force of infection to which individuals living in both that household and its additional related households are exposed. The same reduction is assumed for funeral transmission.

As no estimates of the coverage achieved in Liberia are currently available – this is the reason why we did not include the effects of protection kits in the baseline scenario – we model the effectiveness of deploying protection kits starting from a coverage of 30% of households receiving protection kits up to a 90%. The deployment is assumed to increase linearly from 0% on August 15 to the maximum level on October 15, 2014. Results are shown in Fig. 3B. Deployment of protection kits to about 50% of households might have contributed to further reduce incidence from about 30 daily new cases in November 2014 to about 10 daily cases, a value consistent with WHO reports.

Discussion

The agent-based model presented here can be used for projections of the number of cases as well as the potential effects of interventions during the current EVD outbreak. Early modelling approaches to the epidemic projected a larger number of cases, but they were focusing on the early exponential growth phase of the disease with models that assume the population of Liberia is homogeneous and well-mixed.[13,15,17] The projections obtained here are closer to the number of EVD cases reported by the WHO as they take advantage of the population structure and more detailed data on intervention policies. The presented results demonstrate the impact of ETUs and safe burials in the decrease of incidence observed in Liberia after early September 2014. ETUs may have contributed to halve the number of cases and deaths (see Fig. 3A) and safe burial may have contributed an additional 50% reduction compared to a scenario with no intervention. Although it is not possible to quantitatively assess efficacy and coverage of protection kits, our results support the hypothesis that the observed decreasing trend of incidence in Liberia might be partly ascribable to this mitigation policy. Interestingly it seems that increasing the coverage of protection kits above the 50% threshold produces marginal improvements with less than a 4% increase in the number of averted case but a nearly doubling of the effort and cost of deploying protection kits.

Although the presented model is informed by the most recent data available on the EVD outbreak in Liberia, there are important limitations in data availability, and a number of assumptions should be kept in mind when considering the results of this study. An estimate that is obtained from previous outbreaks is the 80% hospitalization rate. However, even a lower assumed hospitalization rate of 60%, as well as different assumed transmission models in hospitals, do not change the results substantially (see SI). Model estimates also do

not vary substantially when the case fatality ratio is increased to 70.8%, according to more recent, though highly variable, estimates[15] (see SI), as well as by assuming key natural history parameters derived from the analysis of previous outbreaks[12,14] (see SI). Our results also suggest that the reporting rate is likely much greater than 50%. However, the uncertainty of model estimates and sensitivity of results to assumptions about the reporting rate call for urgent field estimates of the reporting rate, as it is likely lower than 100%. Uncertainty of model estimates and sensitivity of results to the values of the transmission rates in households and hospitals (see Fig. 1B) indicate that more high quality data to provide field estimates of the household secondary attack rate and contact patterns within hospitals are needed to reduce uncertainty of model estimates. Finally, model estimates would benefit from quantitative estimates of efficacy of the ongoing interventions, especially for protection kits. Moreover, it would also be key to inform model with detailed estimates of practical implementation of policies, as simply providing supplies of equipments might not be sufficient.[23]

As detailed in the manuscript we assume that each infectious individual can transmit the infection in the general community on a daily basis to a limited number of individuals (corresponding to two additional households, in the reference scenario) living inside a circle (of 10 km radius, in the reference scenario) around the household of each Ebola case. This choice derives from the fact that there is no evidence of pre-symptomatic EVD transmission so far. Thus it is very unlikely that Ebola infectious individuals would be in the condition to travel long distances, except for those strictly necessary for seeking hospital care. On the other hand it is reasonable to think that susceptible individuals coming in contact with Ebola cases would mainly correspond to visiting relatives and friends. The reliability of such hypotheses is supported by our analysis, presented in detail in the SI, showing that even a model accounting for EVD transmission in the community only at 2.5 km at most is able to reproduce the observed pattern of spatial spread, and our projections are fairly insensitive to such an extreme assumption. Our findings are also robust with respect to increasing the number of contacts in the general community (here modelled as additional households in the network of daily contacts of each individual) and to the distance at which contacts are made (see SI). Therefore, although we cannot rule out that local population mobility could represent a possible driver of EVD dynamics in the future, for the moment there is no evidence that such mobility is necessary to explain what has been observed so far. However, we warn that we do not consider explicitly mobility due to commuting patterns or other business travel. Although this kind of mobility should not play a very important role in Ebola transmission - mobile people are generally not symptomatic thus have nearly zero or very low infectivity - we cannot rule out their relevance in increasing the geographical dispersion of the outbreak.

Finally, this modelling approach can be extended to other countries in West Africa and consider more detailed policies for the isolation of cases, ETUs management, and funeral preparation. We did not investigate pharmaceutical interventions such as vaccines, as data on their efficacy are not available. The presented model could however be used to analyse the potential effectiveness of these interventions and their deployment strategies as data become available.

Panel: Research in context

Systematic Review—We queried PubMed and Google Scholar for manuscripts describing Ebola transmission models. The manuscripts by Legrand et al.[14] introduces a homogeneous mixing model accounting for the main routes of Ebola transmission, namely community, hospitals and funerals. Models with similar epidemiological structure have been recently developed to provide estimates for the ongoing Ebola epidemic in West Africa,[9,10,13] and for predicting the international spread.[11,12] Models with simplified compartmental structure have been used to estimate the reproduction number of the epidemic. [16-19] Here we aim at improving estimates by explicitly accounting also for transmission in households and spatial structure of the population, an approach similar to that previously used to study the spread of other infectious diseases, e.g. influenza.[3-8] We rely on official Liberian Ministry of Health and WHO reports [1,2] for the epidemic data and the paper by the WHO Ebola Response Team [15] for the disease natural history parameters.

Interpretation—This is the first study based on a microsimulation approach to evaluate the relative importance of different settings relevant to EVD transmission and the spatial dynamics of the epidemic. The approach allows a thorough assessment of the effectiveness of intervention options. However, our study highlights that, given the current uncertainty of model estimates, high quality data – e.g. quantitative estimates of household secondary attack rate, contact patterns within hospitals, and effects of the ongoing interventions – are needed to improve model estimates. The model could be used to assess strategies and effectiveness of pharmaceutical interventions such as vaccines as data become available.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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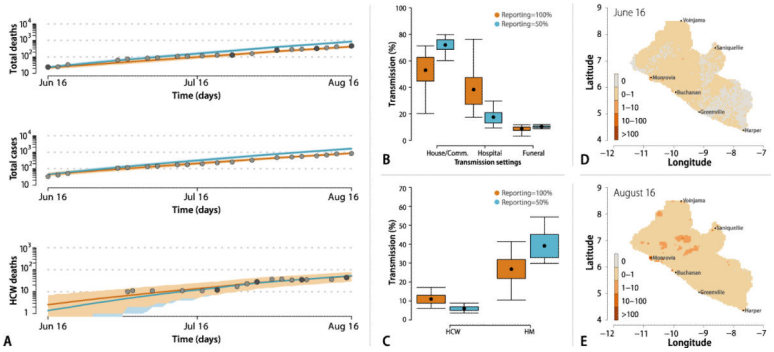

Figure 1.

Early spread of EVD in Liberia **A** Top panel: cumulative number (on a log scale) of EVD deaths over time in the general population of Liberia. Dots refer to the data reported by the WHO (dark dots indicating data used for model initialization and calibration). Lines and shaded areas refer to estimated average and 95% CI model predictions, respectively. The scenario assuming 100% reporting is shown in orange, and the 50% underreporting scenario is shown in blue. The hospitalization rate was assumed to be 80%. Middle panel: cumulative number (on a log scale) of EVD cases (confirmed, probable, and suspected) over time in the general population. Colours as in top panel. Bottom panel: cumulative number (on a log scale) of EVD deaths over time among health care workers. Colours as in top panel. **B** Proportions of infections occurring within households and the community, in hospitals, and during funerals as of August 16, 2014. Results assuming 50% and 100% reporting rates in the general population are shown. **C** Proportion of cases among HCW and proportion of cases due to contacts between household members (HM) as of August 16, 2014 by assuming 50% and 100% reporting rates in the general population. **D** Simulations of the spatial spread of EVD in Liberia as of June 16, 2014. Predicted cumulative number of EVD cases per cell over time in Liberia by assuming a 100% reporting rate and 80% hospitalization rate. Each cell corresponds to an area of about 25 km^2. **E** As **D** but as of August 16, 2014.

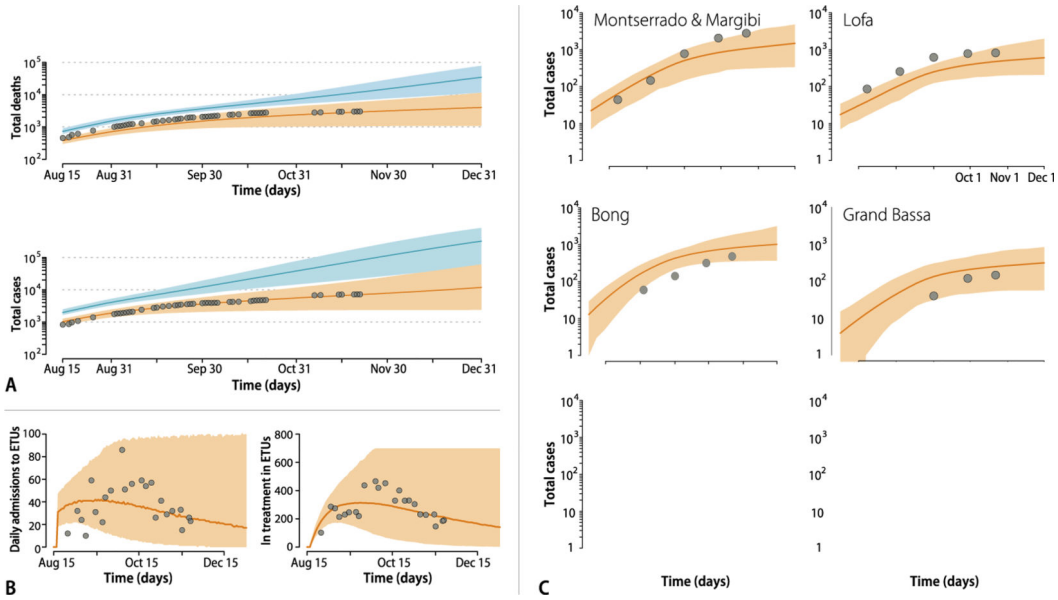

Figure 2.

Spatio-temporal dynamics after mid August 2014 **A** Number of deaths (top panel) and cases (bottom panel) in the general population. Dots refer to the data reported by the WHO. Lines and shaded areas refer to estimated average and 95% CI model predictions, respectively. Orange refers to the 100% reporting scenario, blue to 50% reporting scenario. An 80% hospitalization rate was assumed. **B** Left panel: daily number of admission to ETUs by assuming the 100% reporting scenario. Lines and shaded areas refer to estimated average and 95% CI model predictions, respectively. Dots refer to the data reported by the WHO. An 80% hospitalization rate was assumed. Right panel: as left panel but for the number of Ebola patients in treatment in ETUs. **C** Cumulative number of cases in the general population in the most affected counties of Liberia (the seven counties account for about 97% of overall cases) by assuming the 100% reporting scenario. Dots refer to the data reported by the WHO. Lines and shaded areas refer to estimated average and 95% CI model predictions, respectively.

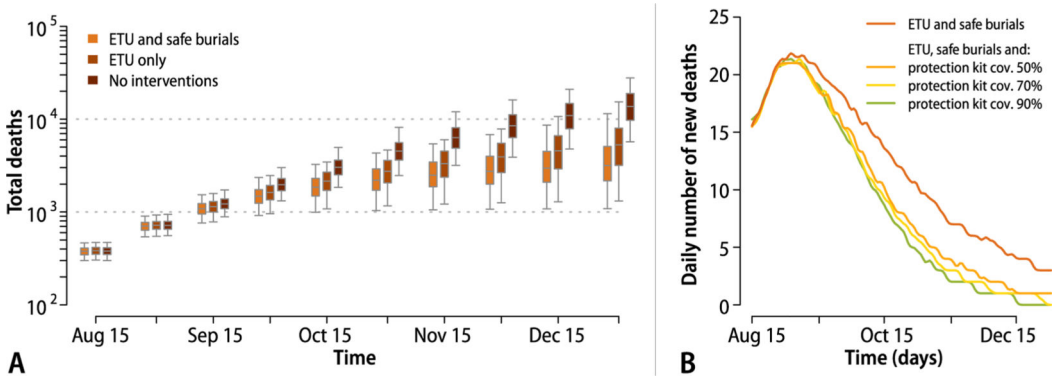

Figure 3.

Impact of non-pharmaceutical interventions. **A** Estimated cumulative number of deaths (boxplot show 2·5%, 25%, 75% and 97·5% quantiles of the predicted distribution) as predicted by the model by assuming the 100% reporting scenario and considering different degrees of interventions. An 80% hospitalization rate is assumed. **B** Estimated median number of daily deaths by assuming the 100% reporting scenario, the effects of both ETUs and safe burials, and by varying the coverage of protection kits from 50% to 90%. An 80% hospitalization rate is assumed.

Table 1

Values for the base set of parameters. In the SI it is possible to find the results of sensitivity analyses.

parameter	value	reference
average duration of incubation period	11·4 days	[15]
average time from symptom onset to death	7·5 days	[15]
average time from symptom onset to recovery for survivors	7·9 days	[12]*
average time from symptom onset to hospitalization	5 days	[15]
proportion of cases hospitalized	80%	[12, 22]
average time from hospitalization to death	4·2 days	[15]
average time from hospitalization to recovery for survivors	4·6 days	[12]*
average time from hospitalization to dismissal for survivors	11·8 days	[15]
average time from death to burial	2 days	[14]
overall case fatality ratio	54%	[2]

* refers to values resulting as the difference between the time from symptom onset/hospitalization to death and time from symptom onset/hospitalization to the end of infectiousness as reported in Gomes et al. [12]

Table 2

Parameter estimates by assuming that 80% of cases are hospitalized.

parameter	100% reporting mean (95%CI)	50% reporting mean (95%CI)
β_f (days^{-1})	0·15 (0·04–0·28)	0·37 (0·18–0·65)
β_h (days^{-1})	0·33 (0·15–0·67)	0·21 (0·11–0·39)
σ	0·73 (0·27–0·99)	0·56 (0·14–0·98)
household and community transmission* (%)	52·9 (20·3–71·3)	72 (60·2–79·8)
hospital transmission* (%)	38·4 (17·4–76·4)	17·5 (9·3–29·8)
funeral transmission* (%)	8·6 (3·2–11·8)	10·4 (8·8–12)
R_0	1·84 (1·60–2·13)	1·9 (1·62–2·14)
household SAR (%)	19·4 (7·2–34·8)	36·1 (21·8–55·9)

* as of August 16, 2014.

Table 3

Number of projected cases and average number of averted cases as of January 1, 2015 by assuming 100% reporting and 90% efficacy of household protection kits.

Intervention	cases in the population mean (95%CI)	averted cases mean
no interventions	36,775 (12,279-107,913)	–
ETU only	21,479 (2,761-103,295)	15,296
ETU and safe burials	11,806 (2,388-60,857)	24,969
ETU, safe burials and protection kits (50% coverage)	6,185 (2,367-13,523)	30,590
ETU, safe burials and protection kits (70% coverage)	5,456 (2,350-10,488)	31,319
ETU, safe burials and protection kits (90% coverage)	4,993 (2,286-8,770)	31,782