VIMC Model Method

**Underlying spatial incidence rate estimates**

We use the 5 km by 5 km spatial incidence rate estimates from a published study (<https://doi.org/10.1016/S0140-6736(17)33050-7>) for the 35 countries in sub-Saharan Africa. These countries are as follows: Angola, Burundi, Benin, Burkina Faso, Central African Republic, Côte d'Ivoire, Cameroon, Democratic Republic of the Congo, Republic of the Congo, Ethiopia, Ghana, Guinea, Guinea-Bissau, Kenya, Liberia, Madagascar, Mali, Mozambique, Mauritania, Malawi, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Somalia, South Sudan, Chad, Togo, Tanzania, Uganda, South Africa, Zambia, and Zimbabwe.

As for the other 10 countries outside of sub-Saharan Africa that we also involve in this study, including Afghanistan, Algeria, Haiti, Iran, Iraq, Nepal, Pakistan, Philippines, Thailand, and Yemen, we adopt the country-level annual cholera case reported by the WHO Weekly Epidemiological Record (WER) and process them. We first calculate the mean of the annual cholera cases from the 5 most recent and available years, then divide it by the mean population averaged over the 5 corresponding years using demographic data provided by VIMC, which gives us an annualized incidence rate for each country. Subsequently, we assume cholera incidence rate is spatially homogeneous across the country and use the singular annualized incidence rate for the whole country area.

For Bangladesh and India specifically, we generate the spatial incidence rate layer in a different way. We have an internal dataset with spatial incidence rate estimates for Bangladesh in the same 5-by-5 resolution, which is used for Bangladesh. The singular population-weighted mean incidence rate calculated from this dataset is then used for India given the consideration that India doesn’t keep a good record of cholera cases and the assumption that India may face a similar cholera infection risk as Bangladesh.

To add stochasticity to this process, we draw random spatial layers from the 1000-layer spatial incidence rate data for the sub-Saharan African countries and Bangladesh; in the other countries with singular annualized incidence rate estimate, we assume the annualized cholera cases follow the Poisson distribution and generate random layers of spatial incidence rate accordingly.

**Time-varying incidence rate trend**

Over a period of 101 years (from 2000 to 2100) to simulate in the model, the underlying incidence rate is unlikely to remain constant, we implement the incidence rate trend to factor in the time-dependent variance in the underlying spatial incidence rates.

We assume a deterministic log-linear relation between time (in years) and annual incidence rates using Poisson regression model: . To estimate the model coefficients, a dataset comprises WHO-reported annual cholera cases for all available countries and the corresponding time is developed initially. For each individual country among the countries with at least 5 years of WHO annual cholera case data, we use the model coefficients estimated from the regression model, assume the coefficients remain constant over the whole simulation period, then calculate and project their annual incidence rates from 2000 to 2100. These countries include Angola, Burundi, Benin, Burkina, Central African Republic, Côte d’Ivoire, Congo – Brazzaville, Algeria, Ghana, Guinea, Guinea-Bissau, Madagascar, Mali, Mozambique, Mauritania, Malawi, Namibia, Niger, Rwanda, Sierra Leone, South Sudan, Chad, Togo, Tanzania, Uganda, Zambia, Afghanistan, Iran, Nepal, Pakistan, Philippines, and Thailand. For countries with inadequate WHO data (< 5 years) or with extreme annual incidence rate projections using the coefficients from the Poisson regression model, we develop another Poisson regression model that aggregates all available case data in the WHO dataset without categorizing different countries : . This regression model allows us to derive a single global annual incidence rate projection that can be used in these countries uniformly, including Cameroon, Congo – Kinshasa, Ethiopia, Iraq, Kenya, Liberia, Nigeria, Senegal, Somalia, Yemen, South Africa, Zimbabwe, Haiti, Bangladesh, and India.

To use the year-dependent incidence rate trend for each country on top of their underlying spatial incidence rate, we assume the yearly incidence rate trend and spatial incidence rates converge in year 2014—for year 2014, the original spatial incidence rate suffices; for any year other than 2014, we calculate a multiplicative multiplier for the projected yearly incidence rate trend relative to its 2014 projected estimate and multiply it to the spatial incidence rate to make a new spatial estimate for that year. The plot for the year-dependent incidence rate trend multiplier can be found in the supplementary material.

**Outbreak pattern**

The cholera cases are usually reported when a district-level outbreak happens. The static spatial incidence rates along with the incidence rate trend disregards the temporal outbreak dynamics and the district-level variance in the dynamics—some high-risk districts may experience outbreaks that drive up the cholera cases to an extreme degree and surpass other districts in certain years.

We implement the district-level stochastic cholera outbreak spatial multiplier on top of the layers mentioned above. We adopt a dataset from a published paper (<https://doi.org/10.1101/2021.10.25.21265347>) that has the outbreak data across different spatial scales in multiple countries from 2010 to 2020, including Angola, Benin, Côte d’Ivoire, Cameroon, Congo – Kinshasa, Congo - Brazzaville Ethiopia, Ghana, Guinea, Guinea-Bissau, Kenya, Mali, Mozambique, Malawi, Namibia, Niger, Nigeria, Sierra Leone, South Sudan, Chad, Tanzania, Uganda, Zambia, Zimbabwe, and Somalia. Different districts across spatial scales with outbreak data are summarized in tables as part of the supplementary material. For countries and districts without outbreak data, we assume that there is no time-varying outbreak pattern. Among all the countries with outbreak data for different spatial scales, we only focus on the 476 level-2 administration districts because level-2 districts provide the most available data, which narrows down to 21 countries to implement outbreak pattern: Benin, Côte d’Ivoire, Cameroon, Congo – Kinshasa, Congo - Brazzaville Ethiopia, Ghana, Guinea, Guinea-Bissau, Kenya, Mali, Malawi, Namibia, Niger, Nigeria, Sierra Leone, South Sudan, Chad, Tanzania, Zambia, Zimbabwe, and Somalia.

This published dataset has quantitative information about each individual outbreak, including the outbreak attack rate, the name and spatial scale of the district where the outbreak happened, the threshold incidence rate, which is used to determine whether an outbreak happened in one district—an outbreak should have an attack rate well above the threshold incidence rate (more detailed definition of an outbreak period can be found in the paper), the outbreak start time, and the outbreak duration. Because outbreaks do not last for a full year, we need to convert the short-term-based outbreak attack rate to an annualized outbreak-year incidence rate weighted on durations of outbreak periods and non-outbreak periods for the outbreak years. We also calculate the 10-year mean incidence rate across outbreak years as well as non-outbreak years for all level 2 districts. We then divide the annualized outbreak-year incidence rate and the threshold incidence rate by the 10-year mean incidence rate to calculate outbreak multiplier and threshold multiplier for each district. The annual probability of outbreak in each district is calculated by dividing the number of unique outbreaks recorded in that district by the 10-year period observed and summarized by the study.

For each level-2 administration district, the spatial outbreak multipliers are generated over the first decade in the period from 2000 to 2100 and repeatedly used for the rest of the years following the decennial pattern, e.g., the same outbreak multiplier is applied to 2001, 2011, 2021, etc. Given there are 50 sets of stochastic simulations to implement outbreak pattern into, different stochastic draws of the outbreak multipliers are generated in correspondence to each simulation individually. Prior to assigning the outbreak multiplier value, a set of 50 empty spatial multipliers is initialized with the default value “1”. In the process of generating an outbreak spatial multiplier for a certain layer of spatial incidence rate during a given year in a given level-2 administration district, an outbreak check is passed first based on the outbreak probability: if an outbreak is supposed to happen, then the pre-calculated outbreak multiplier value will be applied to where that specific district belongs to on the spatial outbreak multiplier while the other districts remain unchanged; if an outbreak is not supposed to happen, the pre-calculated threshold multiplier value will be applied instead. It’s worth noting that for districts without any temporal outbreak patterns, the initial value “1” will remain constant on the spatial outbreak multiplier.

**Vaccination campaign strategy, indirect effects, and waning effectiveness**

The vaccination campaign is hypothesized to be undertaken on the district level in each country. First, the level-2 administration districts are ranked based on the size of population affected by cholera. The affected population size is calculated by multiplying the 5 km by 5 km spatial population data in 2020 with the mean spatial incidence rate in each district, which is from the published study (<https://doi.org/10.1016/S0140-6736(17)33050-7>) as well. Second, the vaccines are given to the highest-ranking districts to fully cover their population until no vaccine is left. The vaccination coverage data is provided by VIMC, including vaccination year, target population, coverage, and fully vaccinated people (target population times coverage). In each vaccination campaign year, given the limited vaccines, not all level-2 districts can have their whole population fully vaccinated, there are almost always districts not receiving any vaccines and one district partially vaccinated because of the vaccination strategy we implement. Due to the incomplete coverage of the vaccination campaign intended to fully vaccinate the overall population in a district, we assumed arbitrarily that only 80% of the population will receive the vaccines in all supposedly fully vaccinated districts. Additionally, if the vaccination campaigns are undertaken in adjacent years, we will not vaccinate a vaccinated (fully or partially) district again during the following three years.

The vaccines are assumed to directly reduce the proportion of population susceptible to cholera infection, in the meanwhile, the indirect protection of the vaccines and the waning effectiveness are also considered. To facilitate the mechanism of vaccination campaign bringing indirect protection to the unvaccinated, we assume that a certain vaccination coverage level will reduce the underlying spatial cholera incidence rate among susceptible people in each level-2 administration district. We select two published studies (10.1093/cid/cit009; <https://doi.org/10.1093/inthealth/ihy085>) that reported a range of cholera vaccine coverage levels and the corresponding incidence rates in each unvaccinated sub-population, combine their data, and develop a logistic regression model based on the data, which will inform us the degree of reduction in the spatial incidence rate given a coverage value from any districts. As for the waning effectiveness of the cholera vaccine, we use the data from a published meta-analysis (<https://doi.org/10.1016/S1473-3099(17)30359-6>) that reported both effectiveness and efficacy. First, we subset the data with no missing value for mean efficacy, upper bond of efficacy, lower bond of efficacy, standard error, and the period over which the efficacy was measured after people were fully vaccinated. Second, a simple linear regression is developed with middle time point of the measurement period as the explanatory variable, mean efficacy as the response variable, and the inverse of the standard error squared (variance) as the weight. This model is then used to inform the remaining proportion of protected population a certain number of years after the vaccination campaign. It’s worth noting that we assume the protection from vaccines doesn’t last for more than 5 years.

**Simulation, different settings, and model output**

The simulation is done on the yearly basis from 2000 to 2100 across two counterfactual scenarios: vaccination campaign scenario and no vaccination scenario, each with 50 stochastic runs. For each year, different layers of spatial data and scalars are aligned together and multiplied to estimate the number of cholera cases, including spatial population (integrated with the temporal change from the VIMC population data), spatial default cholera incidence rate, spatial susceptible population proportion (derived from vaccine coverage data), spatial relative reduction in incidence rate due to the indirect protection from vaccination campaign, spatial outbreak-related incidence rate multiplier, and the incidence rate temporal trend scalar. The stochastic simulations are facilitated by multi-layer spatial data, including the spatial incidence rate and the spatial outbreak-related incidence rate multiplier. Each layer is used for one stochastic run. Under the no vaccination scenario and among the years when the vaccines have no protective effects on the population under the vaccination campaign scenario, the overall population is assumed to be susceptible to cholera infection.

We consider four different settings, each of which has two scenarios and 100 stochastic simulations in total (50 simulation for each scenario). These four settings are different in terms of whether the outbreak-related incidence rate multiplier and the incidence rate temporal trend scalar are applied. Additionally, they also have different underlying spatial incidence rate given 50 new layers of spatial incidence rate data are randomly drawn from the source for each setting. On the side note, the same set of outbreak-related incidence rate multipliers are used for the two settings that have the outbreak-related incidence rate multiplier applied for the purpose of efficiency.

With the estimated number of cholera cases in each country, we can then calculate the number of death and disability-adjusted life years (DALYs) related to cholera infection. The country-specific case fatality ratio (CFR) data is from WHO WER as well, which is used to multiply with the number of cases to calculate the number of deaths. For the countries without CFR data or with CFR data higher than 0.07, we aggregate all the cholera case and death data from WHO and calculate an overall CFR, which is then used on those countries. Cholera-related DALYs is calculated using the data provided by VIMC.

Our code and relevant data to this study can be found at GitHub (<https://github.com/HopkinsIDD/gavi_vimc_cholera.git>).