Table S2: Sensitivity Analysis

Table S2 shows the sensitivity analysis results for all exogenous parameters and initial values using Sobol Sequence and Random Sampling. A base case run is given below, and each sensitivity run utilizes these values and changes one of the values in normal and incremental distribution within a preset range. Table S2 is split in two parts: SIR and intervention structures. A brief discussion about the insights of the sensitivity analysis follows the results for each tested parameter.

Table A. Summary of sensitivity test. (Click the parameters for further analysis results)

No	Parameters	Numerical	Behavioral	Interventions
1	**connectedness of aquifers**			
2	**time to affect water in aquifers**			
3	**ratio of asymptomatic**			
4	**average incubation time**			
5	**average duration of illness asymptomatic**			
6	**susceptible population**			
7	**recently infected population**			
8	**asymptomatic population**			
9	**recovered asymptomatic population**			
10	**severe infected population**			
11	**normal ratio of severe disease**			
12	**time progress to next stage**			
13	**average duration of illness symptomatic**			
14	**average asymptomatic infection acquired immunity period**			
15	**fraction mildly infected seeking care**			
16	**fraction severe infected seeking care**			
17	**treated fatality fraction**			
18	**bacteria shedding from asymptomatic**			
19	**bacteria shedding from mildly infected**			
20	**bacteria shedding from severely infected**			
21	**effect of the fraction of infected on the fraction ofcontaminated water**			

Indicators:

	Sensitive		Highly sensitive

No	Parameters	Numerical	Behavioral	Interventions
22	time to increase distribution capacity			
23	desired water distribution capacity			
24	vaccination start time			
25	desired number of vaccines			
26	time to procure vaccines			
27	desired sewage plant treatment			
28	degradation time			
29	effect of sewage plant treatment on sanitary condition			
30	time to increase treatment capacity			
31	weight of sewage plant support			
32	weight of latrine use			
33	ratio sewered population			
34	ratio open defecation			
35	building latrine start time			
36	time to build latrine			
37	people per latrine			
38	desired number of new latrine			
39	effect of sanitary on contaminated water			
40	building ORC start time			
41	time to build ORC			
42	desired number of ORC			
43	effect of ORC strain on fraction of severe disease			
44	desired number of DTC			
45	building DTC start time			
46	desired time to update system			

Indicators:

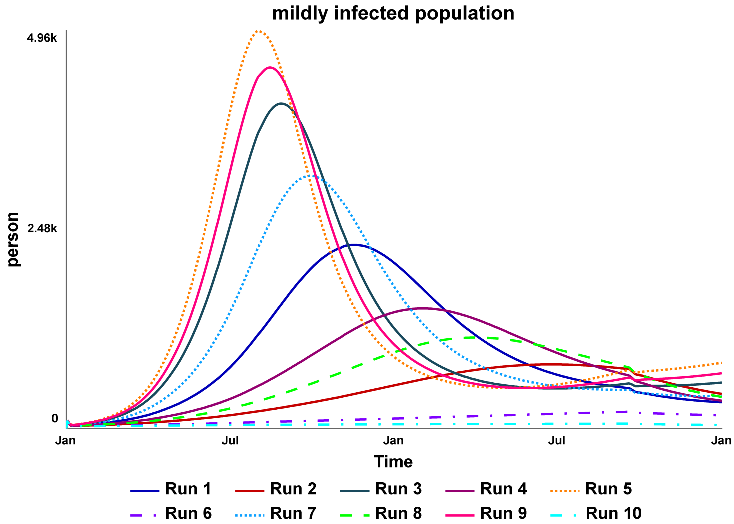
	Sensitive		Highly sensitive

1. SIR Model Component Structures:

[Back to summary]

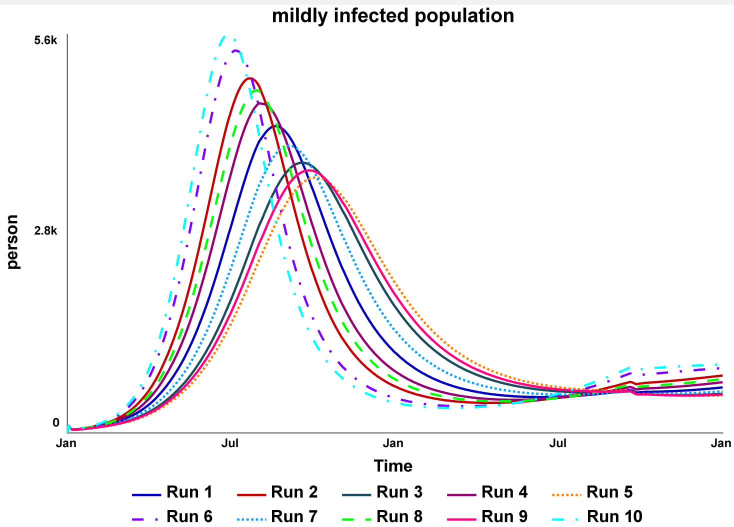
Sensi parameter | **Result: Behavior over time graphs**

	connectedness of aquifers
Run 1	0.12
Run 2	0.10
Run 3	0.13
Run 4	0.11
Run 5	0.14
Run 6	0.09
Run 7	0.12
Run 8	0.10
Run 9	0.14
Run 10	0.08



The model is strongly (numerically and behaviourally) sensitive to changes in the value of "connectedness of aquifers" as expected. According to Pruyt's [1] cholera model, this is an abstract concept related to the amount of reservoir water consumed. Adapting from Pryut's cholera model, this variable is a simplified and uncertain factor indicating the contact rate (susceptible population) with contaminated water. Higher connectedness values, higher impact on the infection rate (likewise). The variable is calibrated to the historical data, amounting to 13% in the base model.

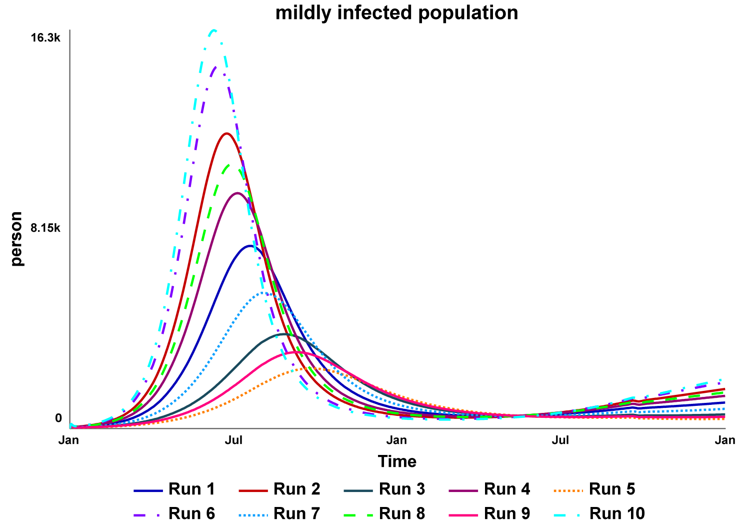
	time to affect water in aquifers
Run 1	14
Run 2	11
Run 3	17
Run 4	12.5
Run 5	18.5
Run 6	9.5
Run 7	15.5
Run 8	11.75
Run 9	17.75
Run 10	8.75



The model is numerically sensitive to changes in the value of "time to affect water in aquifers" as expected. The variable controls the delay in "smoothed fraction of contaminated water". Hence, if the delay is short, the contaminated water reached or used by the susceptible population faster through the "indirect degree of infection" variable.

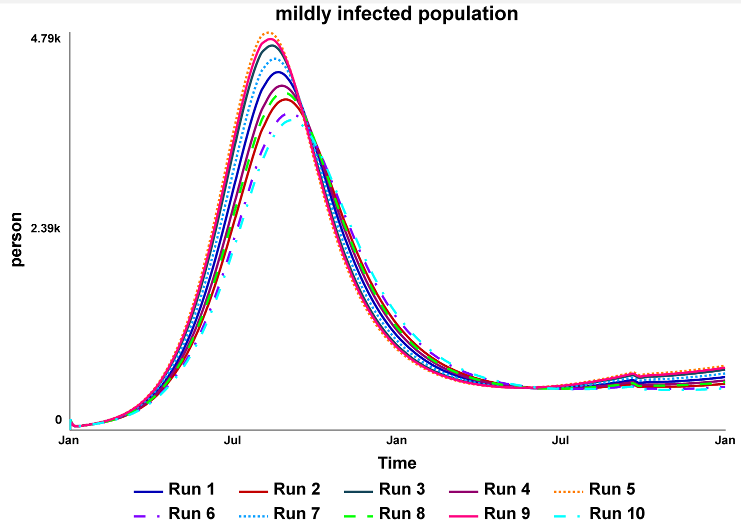
[Back to summary]

	ratio of asymptomatic
Run 1	0.68
Run 2	0.59
Run 3	0.76
Run 4	0.63
Run 5	0.81
Run 6	0.54
Run 7	0.72
Run 8	0.61
Run 9	0.78
Run 10	0.52



The model is strongly (numerically and behaviourally) sensitive to changes in the value of "ratio of asymptomatic" as expected. Since 75% of infections remain clinically unapparent, they are the 'silent spreader' in the communities.

	average incubation time
Run 1	1.00
Run 2	0.75
Run 3	1.25
Run 4	0.88
Run 5	1.38
Run 6	0.63
Run 7	1.13
Run 8	0.81
Run 9	1.31
Run 10	0.56

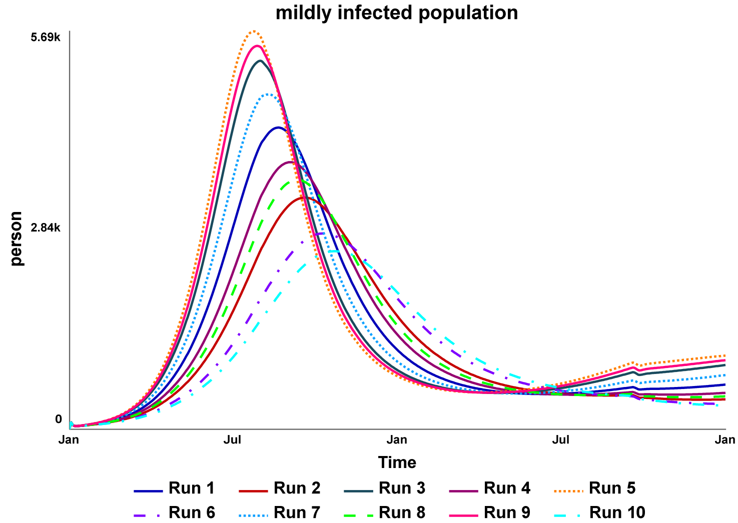


The model is numerically sensitive to changes in the value of "average incubation time" as expected. The value determines the infection progression rate to different stages of the disease; hence, it determines the differences of bacteria sheddings on the water contamination rate. The longer the incubation time, the longer the individuals stay in the recently infected population stock instead of moving on the severely infected population stock with higher bacteria shedding rate.

[

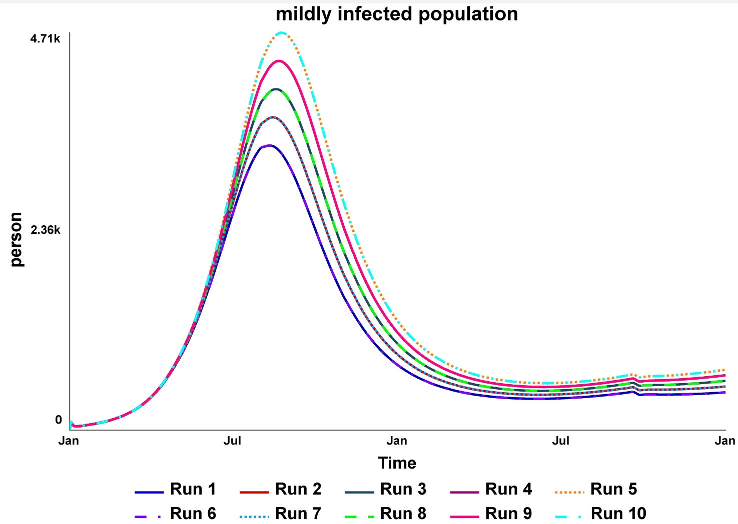
[Back to summary]

	average duration of illness asymptomatic
Run 1	5
Run 2	4
Run 3	6
Run 4	4.5
Run 5	6.5
Run 6	3.5
Run 7	5.5
Run 8	4.25
Run 9	6.25
Run 10	3.25



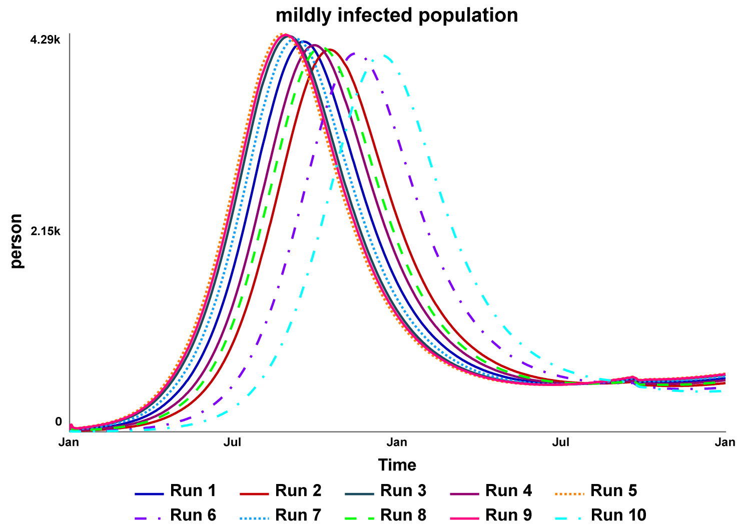
The model is strongly (numerically) sensitive to changes in the value of "average duration of illness asymptomatic" as expected. Since 75% of infections remain clinically unapparent, they are the 'silent spreader' in the communities. The faster the silent spreaders recovered, the lesser the bacteria shedding in contaminating the water source.

	susceptible population
Run 1	2500000
Run 2	2750000
Run 3	3000000
Run 4	3250000
Run 5	3500000
Run 6	2500000
Run 7	2750000
Run 8	3000000
Run 9	3250000
Run 10	3500000



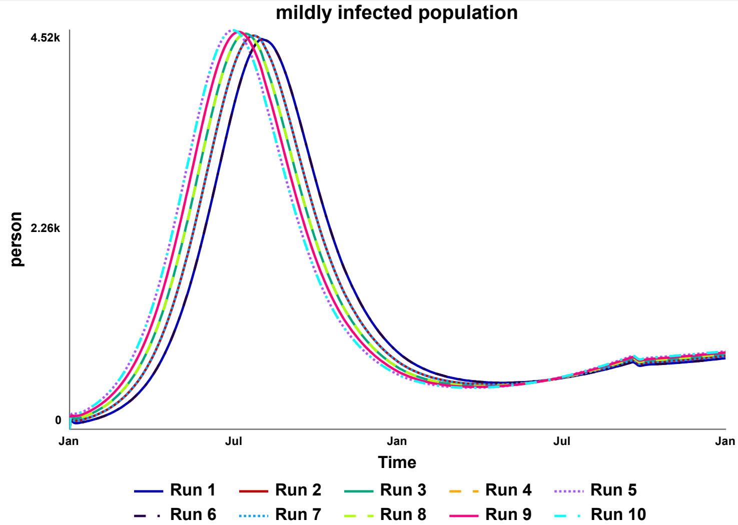
The model is numerically sensitive to changes in the value of "susceptible population" (initial value) as expected. The infection rate depends on the number of susceptible individuals. If the initial population value is lower, the scale of the infected population is smaller. On the other hand, the sensitivity of the susceptible population stock also indicated a leverage point for interventions. Interventions targeting to reduce the susceptibility can strengthen the balancing feedback loop and flatten the infection curve.

	recently infected population
Run 1	500.50
Run 2	250.75
Run 3	750.25
Run 4	375.63
Run 5	875.13
Run 6	125.88
Run 7	625.38
Run 8	313.19
Run 9	812.69
Run 10	63.44



The model is numerically sensitive to changes in the value of "recently infected population" (initial value) as expected. A higher number of infected individuals in the population increases the strength of the infection reinforcing feedback loop. Hence, one of the leverage points is to prevent people from getting infected in the first place.

	asymptomatic population
Run 1	500
Run 2	778
Run 3	1056
Run 4	1333
Run 5	1611
Run 6	1889
Run 7	2167
Run 8	2444
Run 9	2722
Run 10	3000

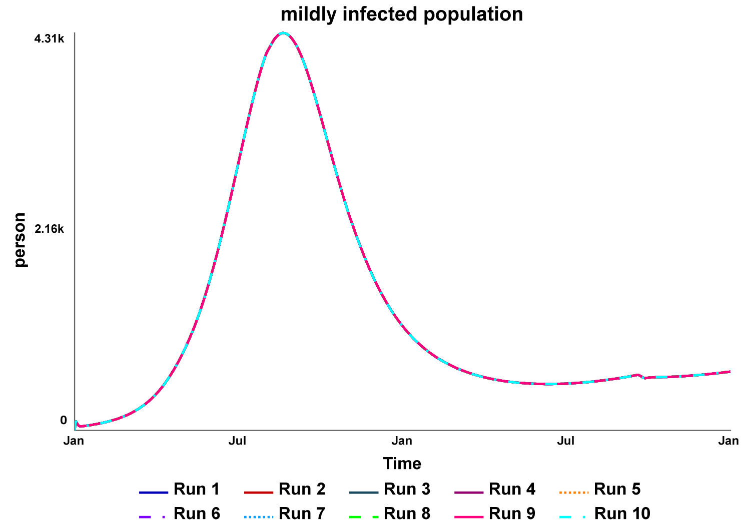


The model is numerically sensitive to changes in the value of "asymptomatic population" (initial value) as expected. Similar results were found with tests on "mildly infected population", "untreated mildly infected population", and "treated mildly infected population". A higher number of asymptomatic and mild infected individuals in the population increases the strength of the infection reinforcing feedback loop. Among the infected individuals, 75% are asymptomatic, and 15% are mildly symptomatic [2,3]. This underscores a key challenge in stopping the epidemic: If people do not know they are infected, they are probably not taking steps to prevent transmitting it (treated mildly infected population might not be identified as cholera patients because it is clinically indistinguishable from other causes of diarrheal illness). To prevent bacteria shedding from silent spreaders in contaminating water sources, policies must focus on improving sanitary conditions (infrastructures) and preventing people from getting infected in the first place.

[Back to summary]

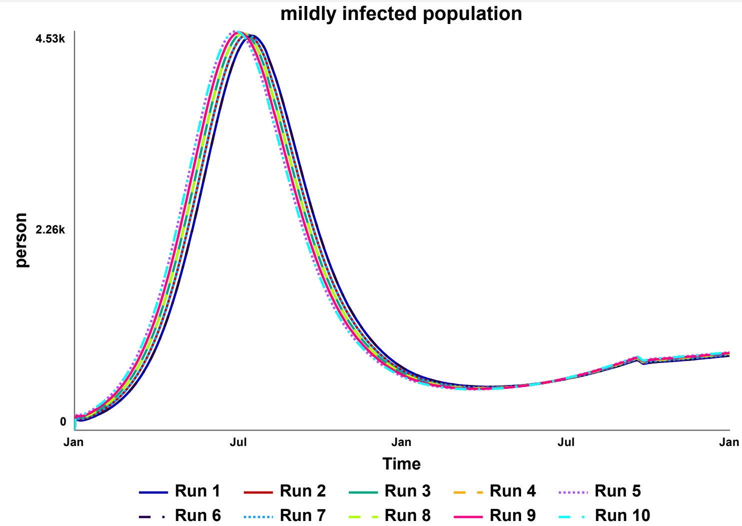
[Back to summary]

	recovered asymptomatic population
Run 1	500.50
Run 2	250.75
Run 3	750.25
Run 4	375.63
Run 5	875.13
Run 6	125.88
Run 7	625.38
Run 8	313.19
Run 9	812.69
Run 10	63.44



The model is insensitive to changes in the value of "recovered asymptomatic population" (initial value) as expected. Similar results were found with tests on "recovered immune untreated population", "treated severe population", "recovered immune treated population". These sub-population are part of the balancing feedback loops in the model.

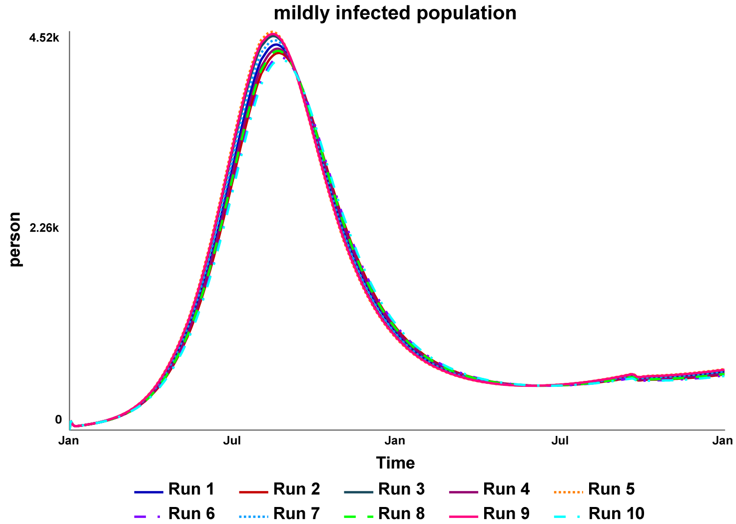
	severe infected population
Run 1	500.50
Run 2	250.75
Run 3	750.25
Run 4	375.63
Run 5	875.13
Run 6	125.88
Run 7	625.38
Run 8	313.19
Run 9	812.69
Run 10	63.44



The model is slight numerically sensitive to changes in the value of "severe infected population" (initial value) as expected. A similar result was found with a test on "untreated severe population". Although only 10% of all infected individuals progress into a severe disease state, bacteria shedding is highest among the severely infected individuals [2]. Hence, it is crucial to treat these individuals, more importantly to prevent deaths, and prevent them from contaminating water sources.

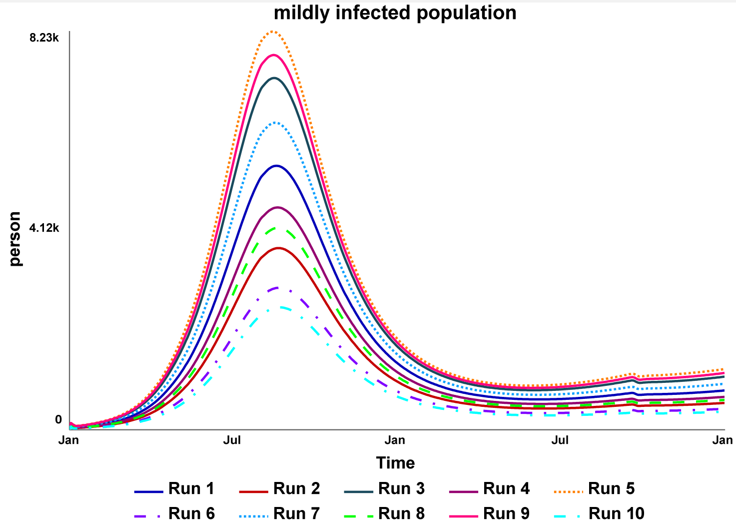
[Back to summary]

	normal ratio of severe disease
Run 1	0.35
Run 2	0.28
Run 3	0.43
Run 4	0.31
Run 5	0.46
Run 6	0.24
Run 7	0.39
Run 8	0.29
Run 9	0.44
Run 10	0.22



The model is insensitive to changes in the value of "normal ratio of severe disease" as expected. The testing range is small, between 9-11% of all infected individual because this parameter is determining the flow from mild infection to severe infection. Hence, 0.4 (40%) of the mild infected population progresses into severe infected population. From the previous test, it shows that the model is less sensitive to this subpopulation due to the small ratio among the total infected population. However, the total death is more sensitive towards the ratio of severe disease as this population could progress to death.

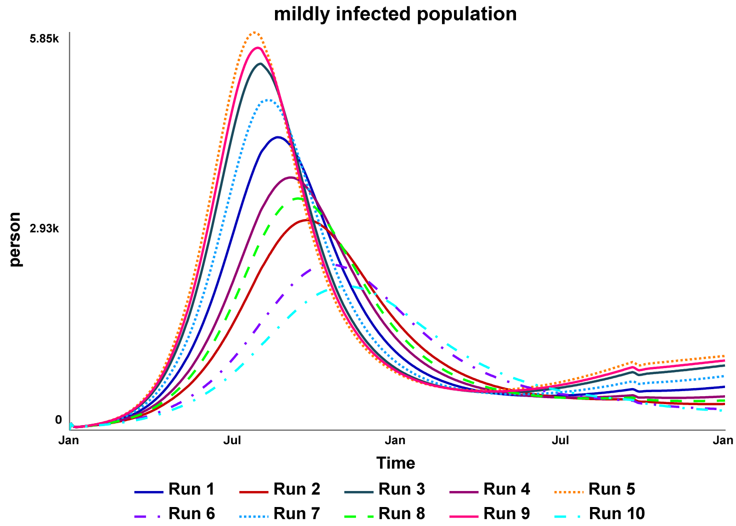
	time progress to next stage
Run 1	1.25
Run 2	0.88
Run 3	1.63
Run 4	1.06
Run 5	1.81
Run 6	0.69
Run 7	1.44
Run 8	0.97
Run 9	1.72
Run 10	0.59



The model is strongly (numerically) sensitive to changes in the value of "time progress to next stage" as expected. The faster the infected individuals leave the mild and severe infected stocks, the faster they move to the recovery state, attributing to the balancing feedback loops.

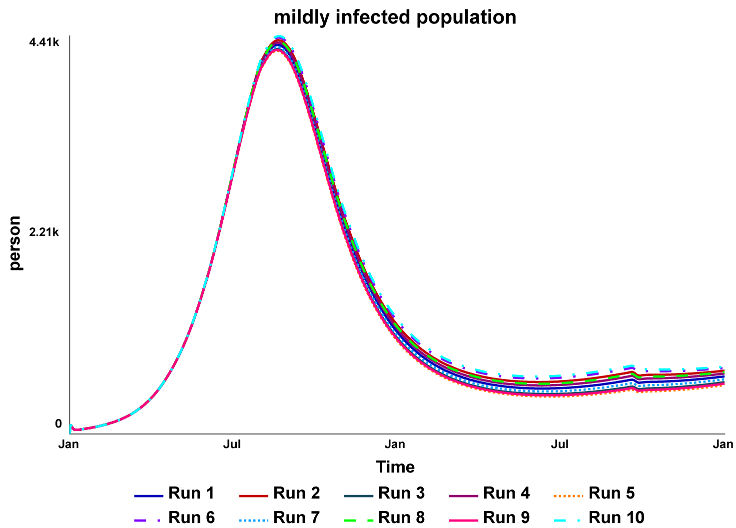
[Back to summary]

	average duration of illness symptomatic
Run 1	9
Run 2	7
Run 3	11
Run 4	8
Run 5	12
Run 6	6
Run 7	10
Run 8	7.5
Run 9	11.5
Run 10	5.5



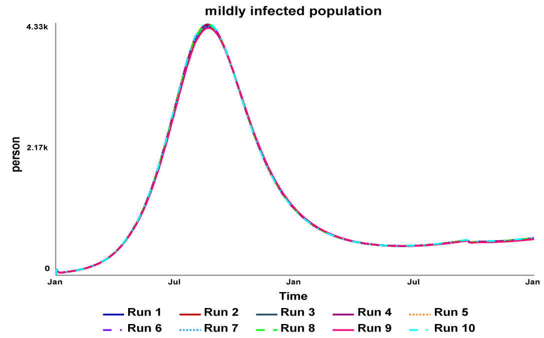
The model is strongly (numerically) sensitive to changes in the value of "average duration of illness symptomatic" as expected. The faster the infected individuals leave the infectious stocks into the recovery stocks, the stronger the strength of the balancing feedback loops.

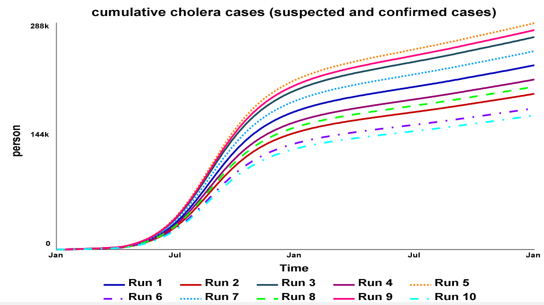
	average asymptomatic infection acquired immunity period
Run 1	180
Run 2	165
Run 3	195
Run 4	172.5
Run 5	202.5
Run 6	157.5
Run 7	187.5
Run 8	168.75
Run 9	198.75
Run 10	153.75



The model is slight sensitive to changes in the value of "average asymptomatic infection acquired immunity period" as expected. A similar result was found with a test on "average symptomatic infection acquired immunity period. When individuals stay in the recovered stocks longer, more individuals are accumulated in the recovered stocks, strengthening the balancing feedback loops. Hence, the behavior changes after the tipping point of shift from infection reinforcing feedback loops to balancing feedback loops.

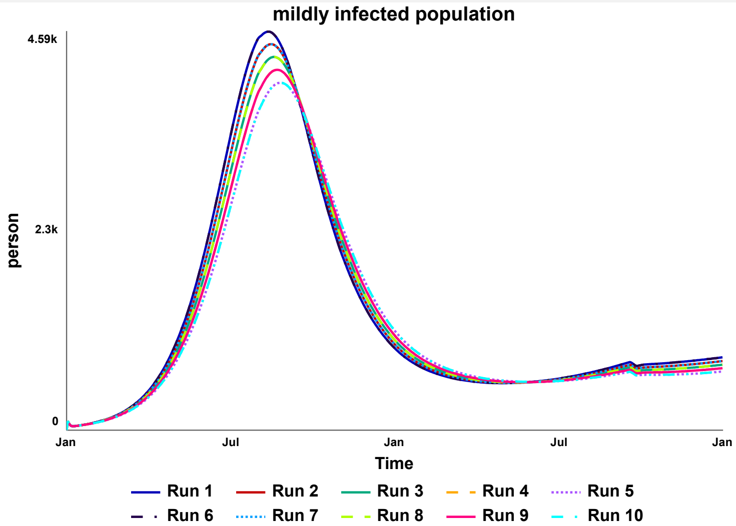
	fraction mildly infected seeking care
Run 1	0.20
Run 2	0.15
Run 3	0.25
Run 4	0.18
Run 5	0.28
Run 6	0.13
Run 7	0.23
Run 8	0.16
Run 9	0.26
Run 10	0.11





The model is insensitive to changes in the value of "fraction mildly infected seeking care" as expected. For mildly infected cases, individuals are provided with oral rehydration treatment that is not helping to prevent bacteria shedding into the environment. On the other hand, the reported cholera cases are numerically sensitive to this parameter change. The surveillance system relies on reported cases from ORC and DTC in Yemen. Hence, if more people seek treatment (demand) and more treatment centers are available (supply), the reported cholera cases are higher.

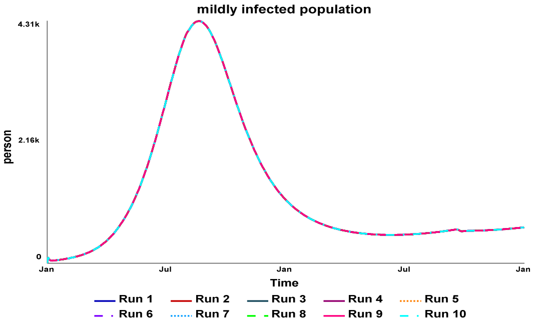
	fraction severe infected seeking care
Run 1	0.20
Run 2	0.23
Run 3	0.27
Run 4	0.30
Run 5	0.33
Run 6	0.37
Run 7	0.40
Run 8	0.43
Run 9	0.47
Run 10	0.50

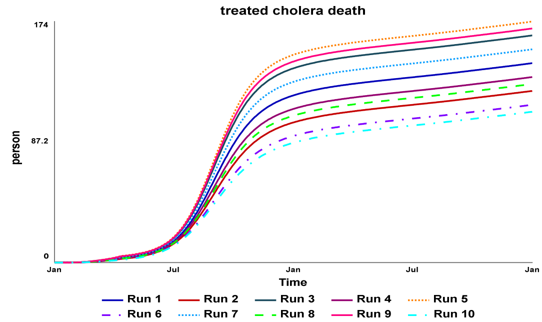


The model is numerically sensitive to changes in the value of "fraction severe infected seeking care" as expected. A ratio of severely infected individuals required emergency treatment at DTC, where the excretion of the individuals at the centers is treated before entering the sewage system. Hence, reducing the risk of water contamination by cholera bacteria shedding.

[Back to summary]

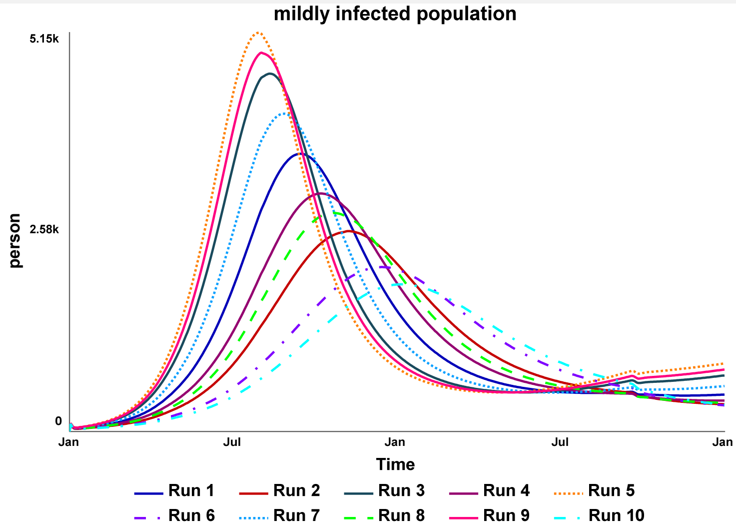
	treated fatality fraction
Run 1	0.0013
Run 2	0.0009
Run 3	0.0016
Run 4	0.0011
Run 5	0.0018
Run 6	0.0007
Run 7	0.0014
Run 8	0.0010
Run 9	0.0017
Run 10	0.0006





The model is insensitive to changes in the value of "treated fatality fraction" as expected. Similar results were found with tests on "untreated fatality fraction", "treated fatality fraction", "service capacity sensitivity", and "service strain fatality fraction". All these parameters are sensitive to the cholera deaths.

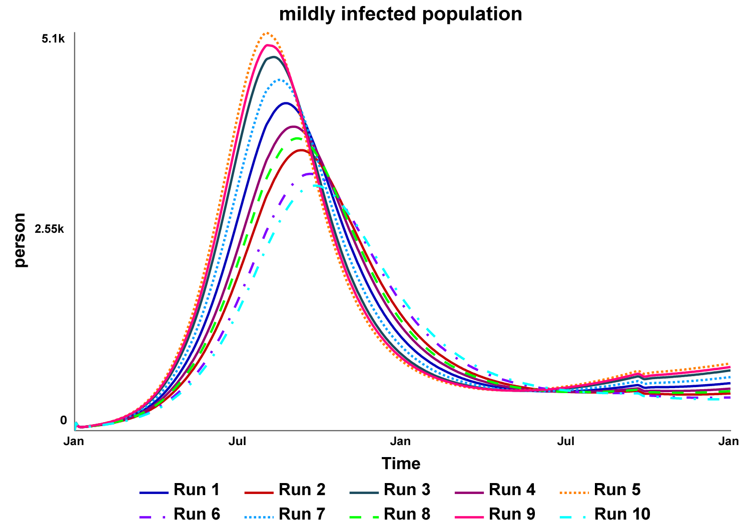
	bacteria shedding from asymptomatic
Run 1	0.60
Run 2	0.50
Run 3	0.70
Run 4	0.55
Run 5	0.75
Run 6	0.45
Run 7	0.65
Run 8	0.53
Run 9	0.73
Run 10	0.43



The model is strongly (numerically) sensitive to changes in the value of "bacteria shedding from asymptomatic" as expected. Although the tested values are the lowest among the three infectious levels of bacteria sheddings, the highest number of asymptomatic individuals (75%) attribute to the high sensitivity of this parameter value.

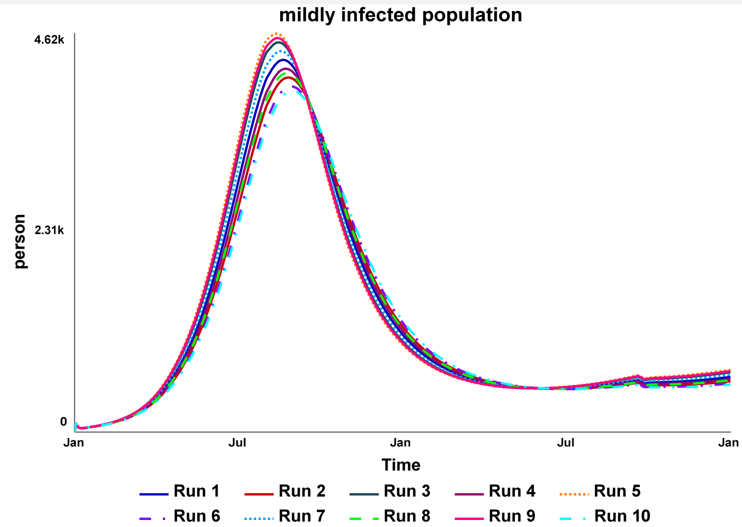
[Back to summary]

	bacteria shedding from mildly infected
Run 1	1.30
Run 2	1.15
Run 3	1.45
Run 4	1.23
Run 5	1.53
Run 6	1.08
Run 7	1.38
Run 8	1.19
Run 9	1.49
Run 10	1.04



The model is numerically sensitive to changes in the value of "bacteria shedding from mildly infected" as expected. For mildly infected cases, they shed bacteria into the environment with and without treatment.

	bacteria shedding from severely infected
Run 1	2.00
Run 2	1.75
Run 3	2.25
Run 4	1.88
Run 5	2.38
Run 6	1.63
Run 7	2.13
Run 8	1.81
Run 9	2.31
Run 10	1.56

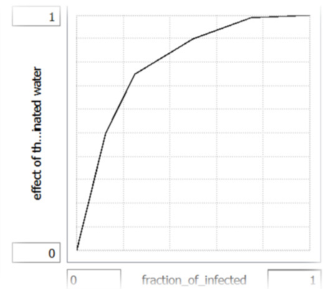


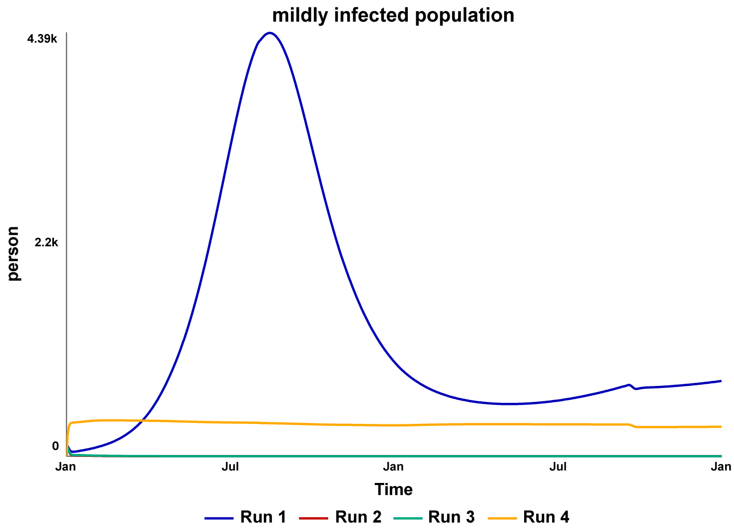
The model is numerically sensitive to changes in the value of "bacteria shedding from severely infected", and least sensitive compared to the other two infectious level of bacteria shedding, as expected. First, the number of severely infected individuals is only account for 10% of the total infected population. Second, among this 10% severely infected individuals, those who received treatment at DTC are assumed to not contribute to the bacteria shedding into the environment as the excretion of the individuals at the centers is treated before entering the sewage system.

[Back to summary]

effect of the fraction of infected on the fraction of contaminated water

Run 1 – logarithmic growth
Run 2 – exponential growth
Run 3 – linear growth
Run 4 – S-shape growth





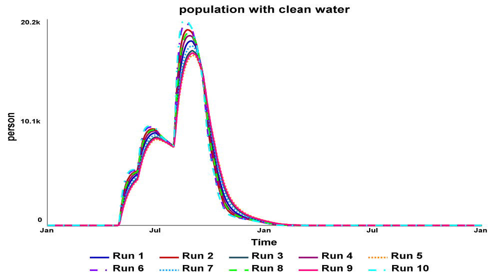
The model is strongly (numerically and behaviourally) sensitive to changes in the graphical function shape of "effect of the fraction of infected on the fraction of contaminated water", as expected. This effect refers to Pryut's cholera model [1]. The effect of the fraction of infected on the fraction of contaminated water is a graphical function: if the fraction of infected is 0% then the fraction of contaminated water is assumed to be 0%, if it is 12.5% then the fraction of contaminated water is assumed to be 5%, if it is 25% then the fraction of contaminated water is assumed to be 75%, if it is 50% then the fraction of contaminated water is assumed to be 90%, if it is 75% then the fraction of contaminated water is assumed to be 99%, and if it is 100% then the fraction of contaminated water is assumed to be 100%. This relationship is also an assumption in Pryut's cholera model. Compared to other curves in the graphical function, the assumption from Pryut's model shows a behavior that is expected from the model.

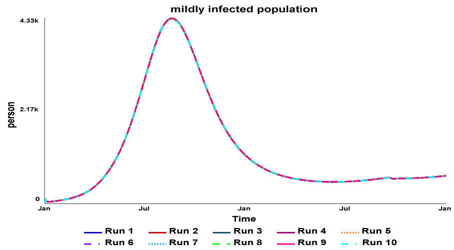
2. Intervention Component Structures:

[Back to summary]

Clean water provision
Vaccination

	time to increase distribution capacity
Run 1	13
Run 2	9
Run 3	17
Run 4	11
Run 5	19
Run 6	7
Run 7	15
Run 8	10
Run 9	18
Run 10	6

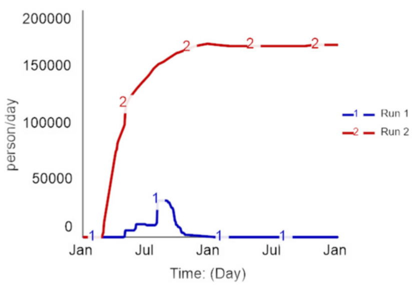


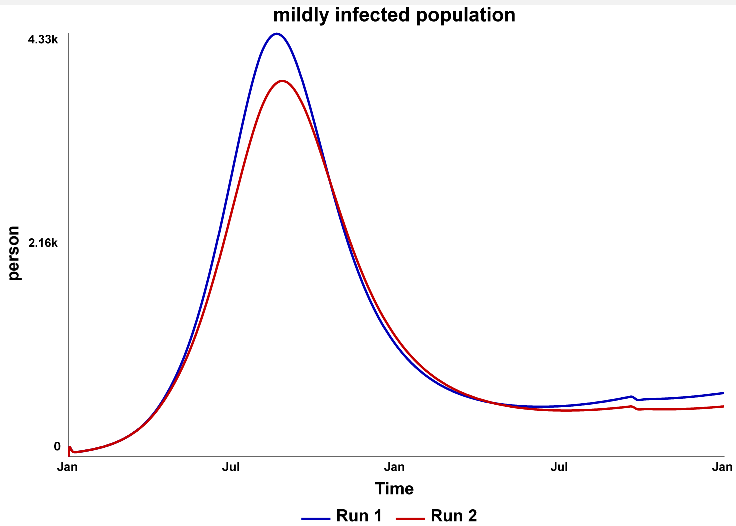


The population with clean water represents the population who, through the Clean Water Provision Intervention, is provided with sachets to purify water, trucked clean water, and installed, fixed and cleaned out sanitation facilities such as toilets in affected areas. The model is insensitive to changes in the value of "time to increase distribution capacity" as expected because the model is simulated on the historical data of intervention. The intervention barely showed an impact because the resources were limited. However, the population with clean water is numerically sensitive to the delay of this parameter. If the supply of water is provided faster, more individuals move from the susceptible stock into the population with clean water stock faster, increasing the strength of the balancing feedback loop.

desired water distribution capacity

Run 1 - historical data in 2017
Run 2 – test

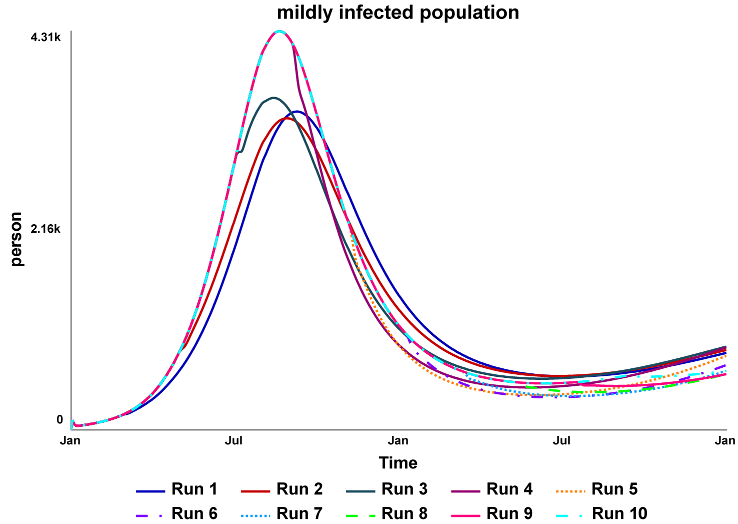




The model is numerically sensitive to changes in the value of "desired water distribution capacity" as expected. When more individuals move from the susceptible stock into the population with clean water stock, the strength of the balancing feedback loop increases.

[Back to summary]

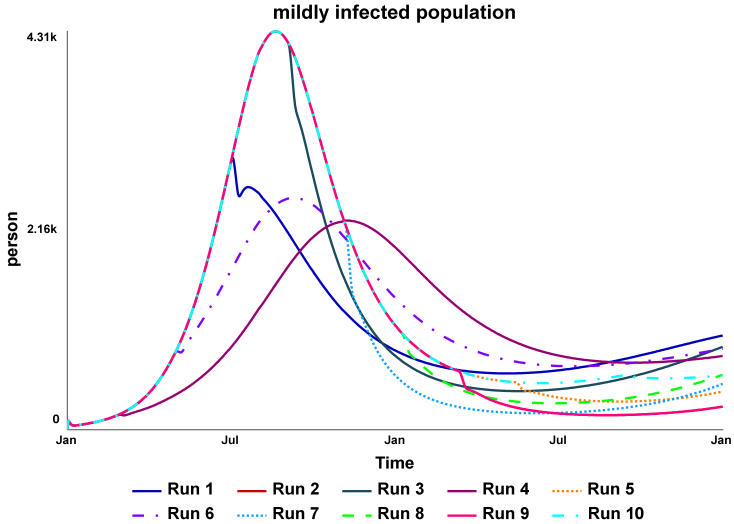
	vaccination start time
Run 1	30
Run 2	93
Run 3	157
Run 4	220
Run 5	283
Run 6	347
Run 7	410
Run 8	473
Run 9	537
Run 10	600



The model is numerically sensitive to changes in the value of "vaccination start time" as expected. With the same amount of vaccine provision in Al-hudaydah (260,000 vaccines - intervention historical data), an earlier vaccine campaign shows a significant reduction of infected population.

	vaccination start time	desired number of vaccines
Run 1	156	890000
Run 2	410	1000000
Run 3	220	450000
Run 4	30	780000
Run 5	473	560000
Run 6	93	560000
Run 7	283	1000000
Run 8	346	450000
Run 9	410	1000000
Run 10	600	340000

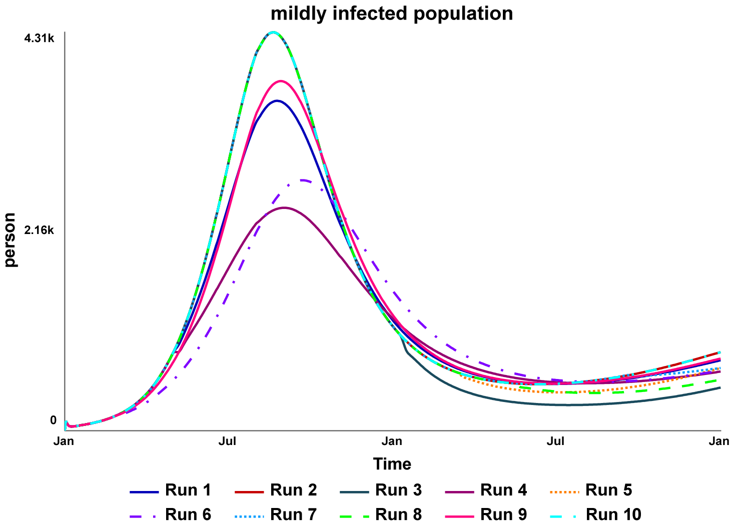
One vaccine dose policy



The model is strongly (numerically and behaviourally) sensitive to changes in the values of "vaccination start time" and "desired number of vaccines". For example, Run 4 (780,000 vaccines on day 30) shows the most promising outcome. However, it is unrealistic to implement such vaccine procurement in such a short amount of time. Run 6 (560,000 vaccines on day 93) shows a more realistic approach, with a low number of vaccines but earlier vaccine provision to the population reduces the mildly infected population profoundly. Run 9 (1,000,000 vaccines on day 410) shows the least favorable impact. Even though there are one million vaccines, providing vaccines very late in the epidemic gives minimal impact.

[Back to summary]

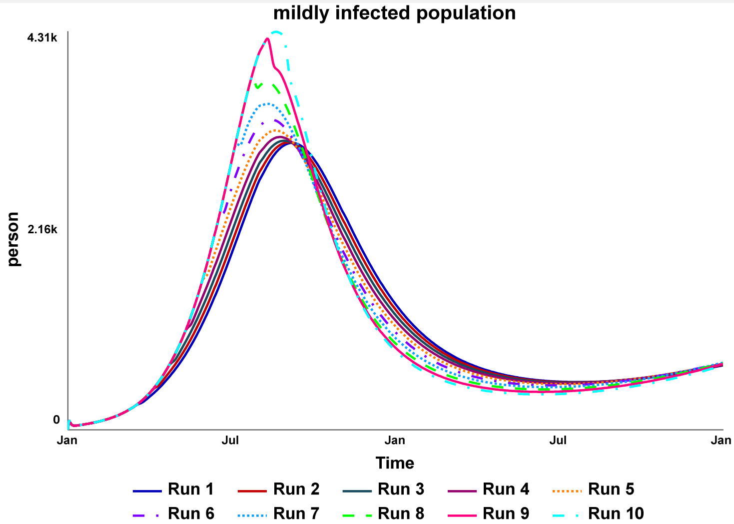
	vaccination start time	desired number of vaccines
Run 1	93	340000
Run 2	537	10000
Run 3	347	670000
Run 4	93	1000000
Run 5	410	230000
Run 6	30	780000
Run 7	600	340000
Run 8	473	450000
Run 9	30	230000
Run 10	537	10000



Two vaccine dose policy

The model is strongly (numerically and behavioral) sensitive to changes from one-dose to a two-dose policy with the same testing range in the one-dose policy. The two-dose policy provides three years of protection compared to one year in one dose vaccination. When the individuals are protected longer, it contributes to the balancing feedback loops. The oscillation in late 2018 is dampened more in two dose policy compared to one dose policy.

	time to procure vaccines
Run 1	15
Run 2	33
Run 3	52
Run 4	70
Run 5	88
Run 6	107
Run 7	125
Run 8	143
Run 9	162
Run 10	180



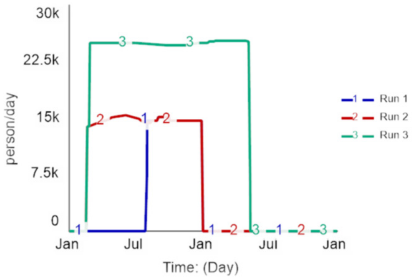
By setting the model at two doses policy, 560,000 vaccines, and starting on day 60: the model is numerically sensitive to changes in the value of "time to procure vaccines" as expected. This delay takes into consideration of implementation challenges of capacity building. The delay attributes to the delay in providing vaccines to the population. Hence, the sooner the vaccine provision starts in an epidemic, the faster the balancing feedback loop is strengthened, reducing the infected population.

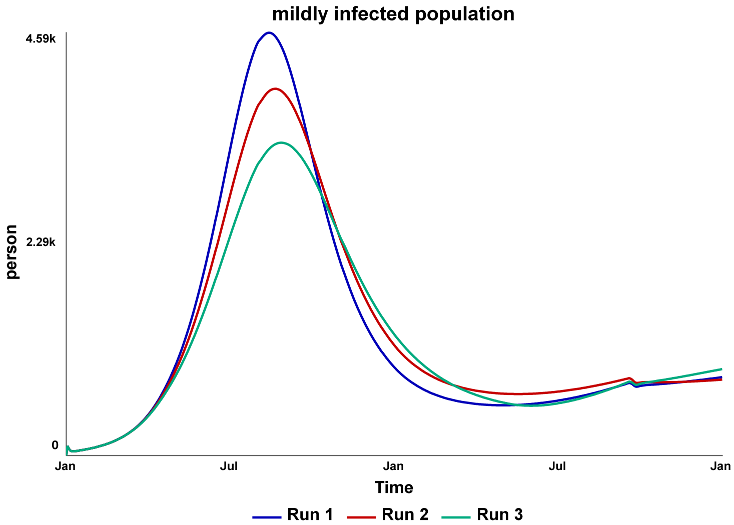
Sanitation infrastructure conditions

[Back to summary]

desired sewage plant treatment

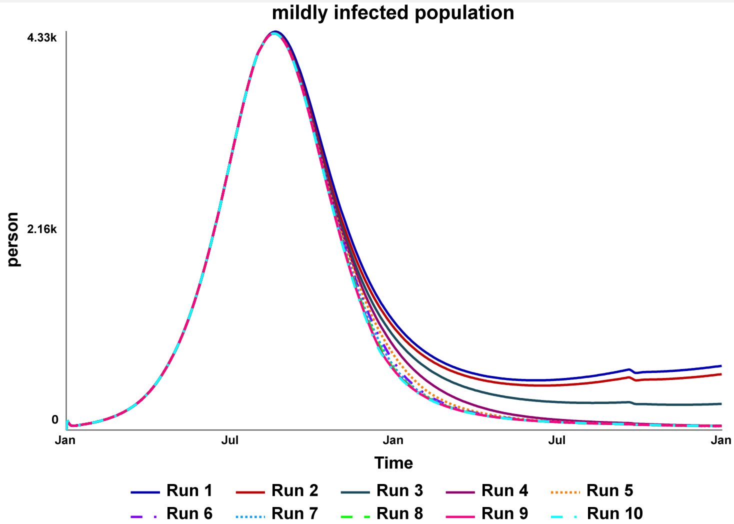
Run 1 – historical data
Run 2 – earlier intervention
Run 3 – double the intervention





The model is strongly (numerically) sensitive to changes in the values of "desired sewage plant treatment" as expected. The infection reinforcing feedback loop is affected by the water source contamination by the infected individuals. If the current sewage plant treatment is well supported, there is less water contamination by cholera.

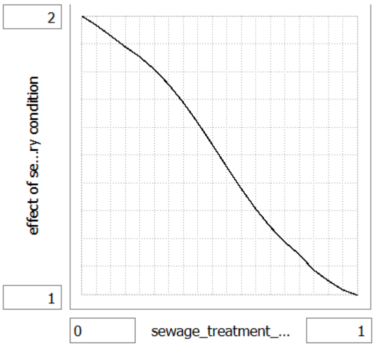
	degradation time
Run 1	10
Run 2	49
Run 3	89
Run 4	128
Run 5	168
Run 6	207
Run 7	247
Run 8	286
Run 9	326
Run 10	365

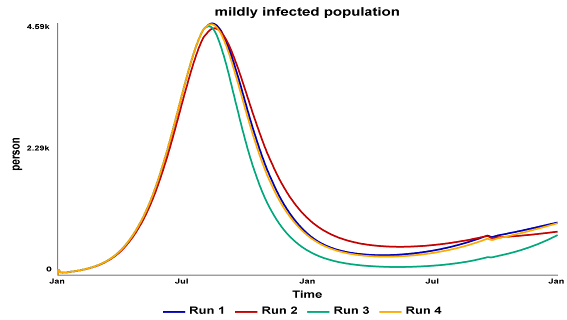


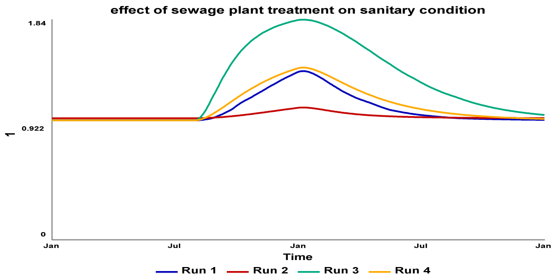
The model is numerically sensitive to changes in the value of "degradation time" as expected. Assuming a sewage treatment plant needs maintenance after a certain period (degradation time). If the degradation time is longer, the resources (intervention historical data) to support the treatment plant could have reached more treatment plants. As a result, there is a reduction in water contamination by cholera.

effect of sewage plant treatment on sanitary condition

Run 1 – S-shape decay
Run 2 – exponential decay
Run 3 – logarithmic decay
Run 4 – linear decay

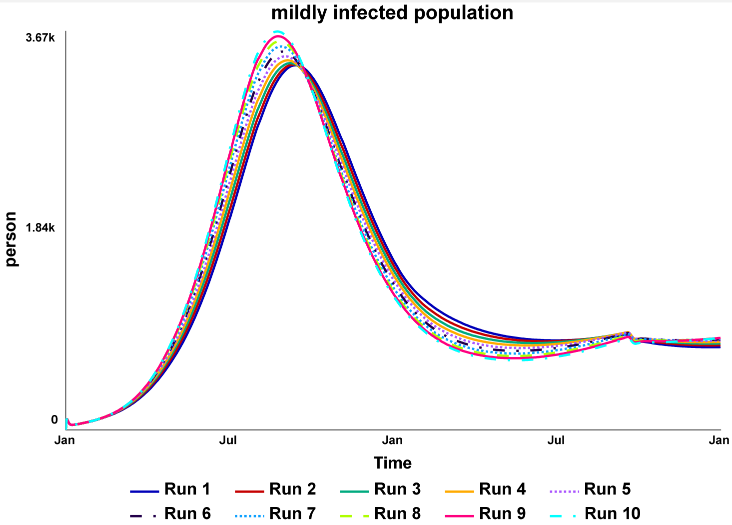






The model is numerically sensitive to changes in the graphical function shape of "effect of sewage plant treatment on sanitary condition", as expected. Run 1 (S-shape decay) and Run 4 (linear decay) show similar behavior. However, very few relationships are linear due to the problem's complexity. Hence, non-linear S-shape decay is assumed to represent the effect of sewage plant treatment on sanitary conditions.

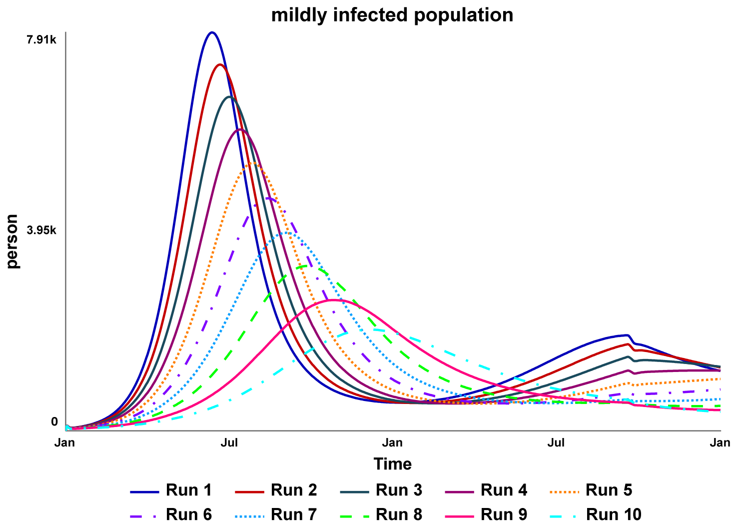
	time to increase treatment capacity
Run 1	10
Run 2	20
Run 3	30
Run 4	40
Run 5	50
Run 6	60
Run 7	70
Run 8	80
Run 9	90
Run 10	100



The model is numerically sensitive to changes in the value of "time to incrase treatment capacity" as expected. This delay takes into consideration of implementation challenges of capacity building. Hence, the faster the intervention begins, the sooner the balancing feedback loop being strengthened (reducing water contamination), decreasing the infected population.

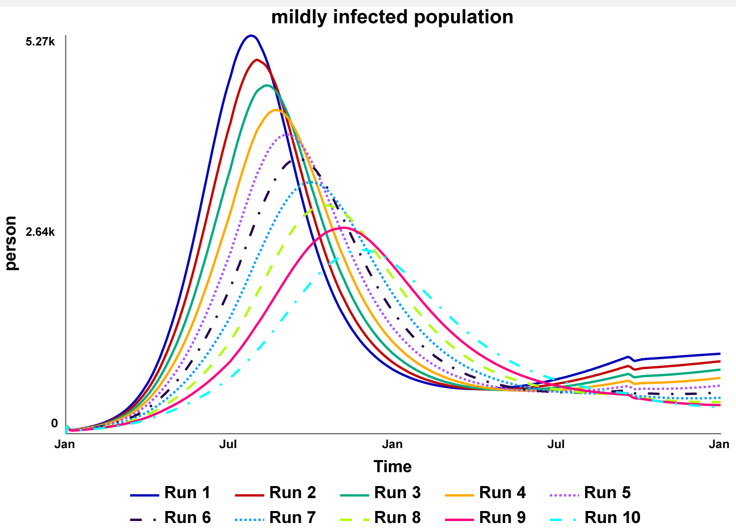
[Back to summary]

	weight of sewage plant support
Run 1	0.20
Run 2	0.26
Run 3	0.31
Run 4	0.37
Run 5	0.42
Run 6	0.48
Run 7	0.53
Run 8	0.59
Run 9	0.64
Run 10	0.70



The model is strongly (numerically) sensitive to changes in the values of "weight of sewage plant support" as expected. This is one of the crucial leverage points on the sanitary condition as the highest numbers of cholera cases have been reported in places where sewage treatment plants are non-functional. Without working sewage treatment plants, raw sewage is often diverted to poor neighborhoods and agricultural lands (leads to contamination of the shallow aquifers and wells) where local civilians and private tankers collect drinking water. The value is conceptualized with a higher weight than "latrine use" and "other infrastructure states" on the highly sensitive effect of sanitary on contaminated water (strong leverage point).

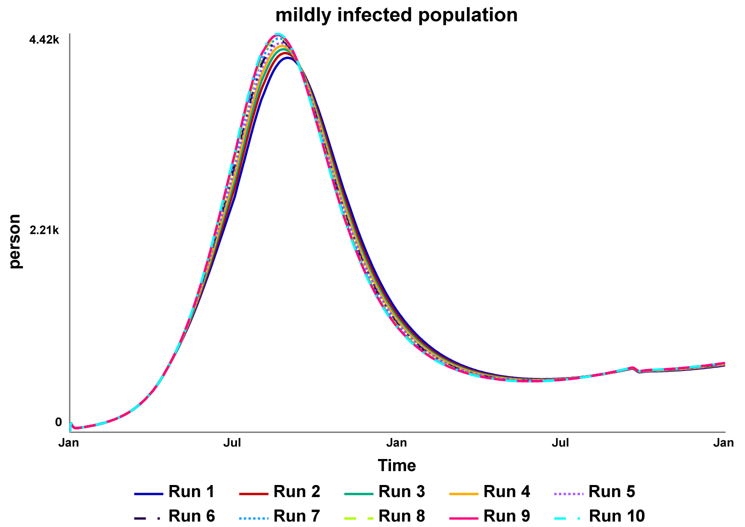
	weight of latrine use
Run 1	0.10
Run 2	0.13
Run 3	0.17
Run 4	0.20
Run 5	0.23
Run 6	0.27
Run 7	0.30
Run 8	0.33
Run 9	0.37
Run 10	0.40



By setting the model at 500 additonal latrines, and starting on day 100: the model is strongly (numerically) sensitive to changes in the value of "weight of latrine use" as expected. This intervention affects the sanitary condition substantially as open defecation can lead to contamination of the shallow aquifers and wells.

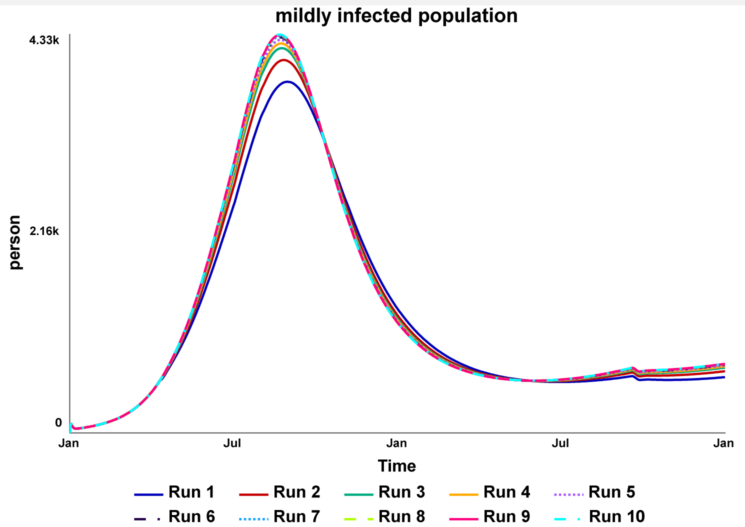
[Back to summary]

	ratio sewered population
Run 1	0.4
Run 2	0.45
Run 3	0.5
Run 4	0.55
Run 5	0.6
Run 6	0.65
Run 7	0.7
Run 8	0.75
Run 9	0.8
Run 10	0.85



The model is slight numerically sensitive to changes in the value of "ratio sewered population" as expected. Assuming that the sewage treatment plant intervention (historical data) remains the same but the ratio value differs, the impact would also differ following the changing needs for sewage plant treatment.

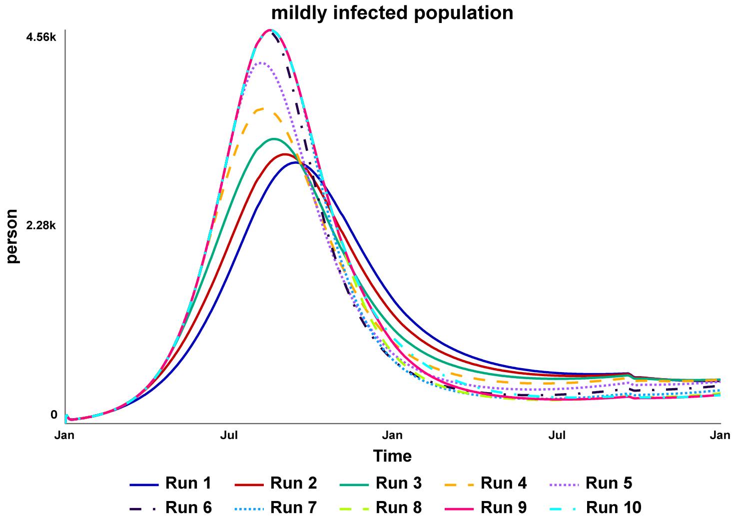
	ratio open defecation
Run 1	0.005
Run 2	0.006
Run 3	0.007
Run 4	0.008
Run 5	0.009
Run 6	0.011
Run 7	0.012
Run 8	0.013
Run 9	0.014
Run 10	0.015



The model is slight numerically sensitive to changes in the value of "ratio open defecation" as expected. Assuming that the number of latrine building remains the same but the ratio of open defecation differs, the impact would also differ following the changing needs for latrines.

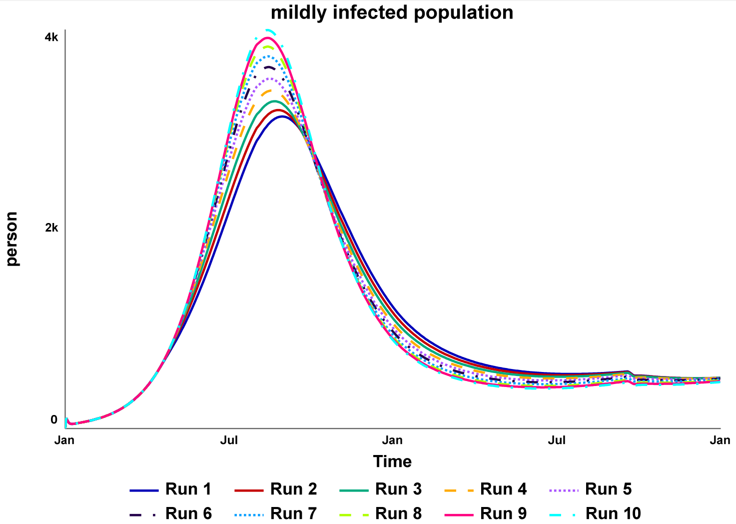
[Back to summary]

	building latrine start time
Run 1	30
Run 2	67
Run 3	104
Run 4	142
Run 5	179
Run 6	216
Run 7	253
Run 8	291
Run 9	328
Run 10	365



By setting the model at 1000 additional latrines: the model is numerically sensitive to changes in the value of "building latrine start time" as expected. With the same amount of latrine provision in Al-hudaydah, an earlier vaccine campaign shows a significant reduction of infected population.

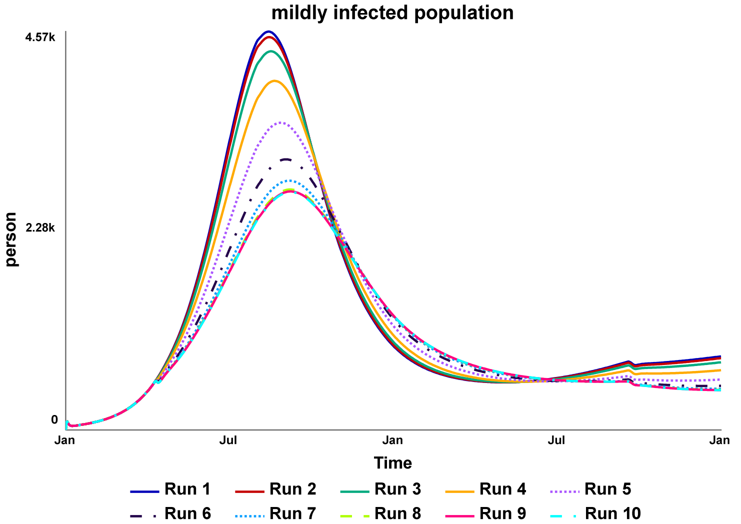
	time to build latrine
Run 1	15
Run 2	23
Run 3	32
Run 4	40
Run 5	48
Run 6	57
Run 7	65
Run 8	73
Run 9	82
Run 10	90



By setting the model at 1000 additional latrines, and starting on day 100: the model is numerically sensitive to changes in the value of "time to build latrine" as expected. This delay takes into consideration of implementation challenges of capacity building. Hence, the faster the intervention begins, the sooner the balancing feedback loop being strengthened (reducing water contamination), decreasing the infected population.

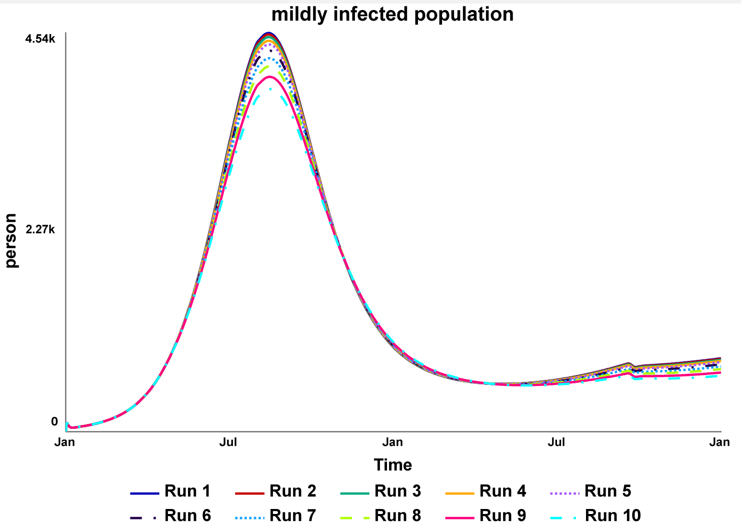
[Back to summary]

	people per latrine
Run 1	10
Run 2	20
Run 3	30
Run 4	40
Run 5	50
Run 6	60
Run 7	70
Run 8	80
Run 9	90
Run 10	100



By setting the model at 500 additional latrines, and starting on day 100: the model is numerically sensitive to changes in the value of "people per latrine" as expected. The higher the value, the more Al-hudaydah population would be covered by latrine and sewage system (assuming the latrines are well maintained).

	desired number of new latrine
Run 1	250
Run 2	306
Run 3	361
Run 4	417
Run 5	472
Run 6	528
Run 7	583
Run 8	639
Run 9	694
Run 10	750

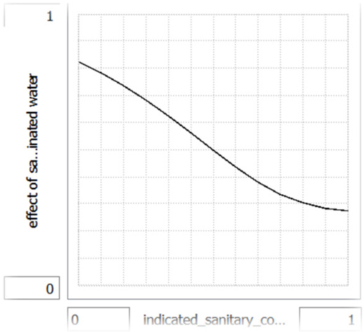


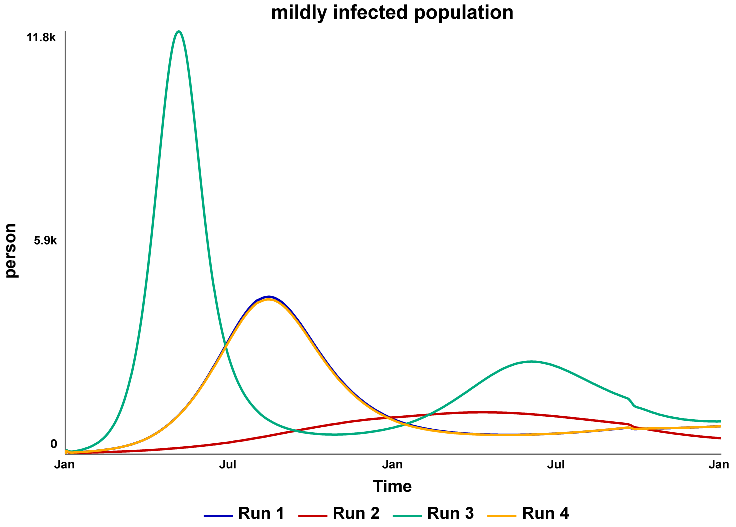
By setting the model at 500 additional latrines, people per latrine at 20, and starting on day 100: the model is numerically sensitive to changes in the value of "desired number of new latrine" as expected. The higher the value, the more Al-hudaydah population would be covered by latrine and sewage system (assuming the latrines are well maintained).

[Back to summary]

effect of sanitary on contaminated water

Run 1 – S-shape decay
Run 2 – exponential decay
Run 3 – logarithmic decay
Run 4 – linear decay

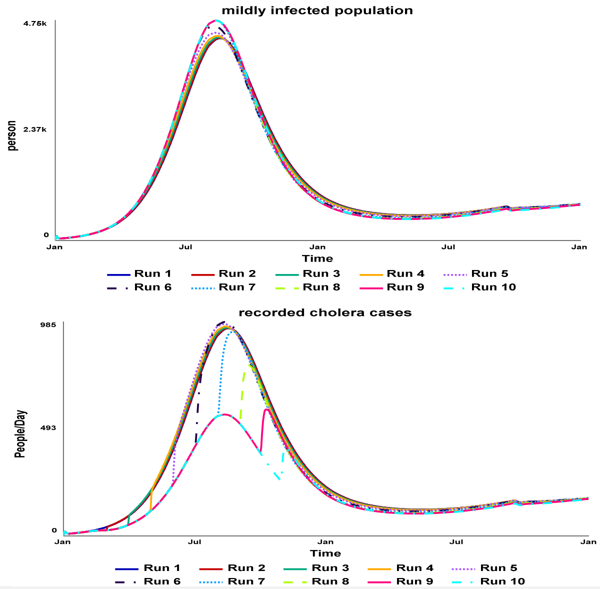




The model is strongly (numerically and behavior) sensitive to changes in the graphical function shape of "effect of sanitary on contaminated water", as expected. Run 1 (S-shape decay) and Run 4 (linear decay) show similar behavior. However, very few relationships are linear due to the problem's complexity. Hence, a non-linear S-shap decay is assumed to represent a sanitary effect on contaminated water.

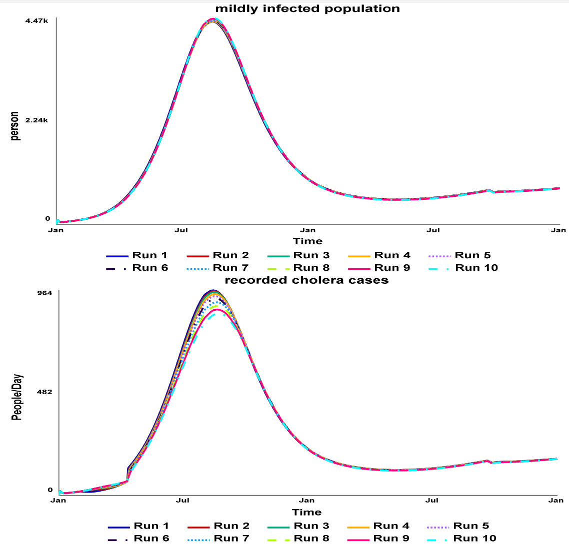
[Back to summary]

	building ORC start time
Run 1	30
Run 2	60
Run 3	90
Run 4	120
Run 5	150
Run 6	180
Run 7	210
Run 8	240
Run 9	270
Run 10	300



The model is slight numerical sensitive to changes in the value of "building ORC start time" as expected because the model is simulated on the historical data of intervention. The intervention showed minimal impact because the resources were limited to accommodate the need of Al-hudaydah infected individuals and mildly infected individuals might not be aware they are infected. However, the recorded cholera cases are highly (numerically) sensitive to the values. If the ORC service starts earlier, more individuals receive treatment earlier (prevention on progressing to severe state), so does the surveillance system can function earlier to provide crucial information for cholera emergency response.

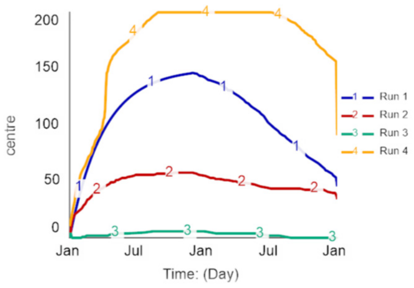
	time to build ORC
Run 1	30
Run 2	67
Run 3	104
Run 4	142
Run 5	179
Run 6	216
Run 7	253
Run 8	291
Run 9	328
Run 10	365

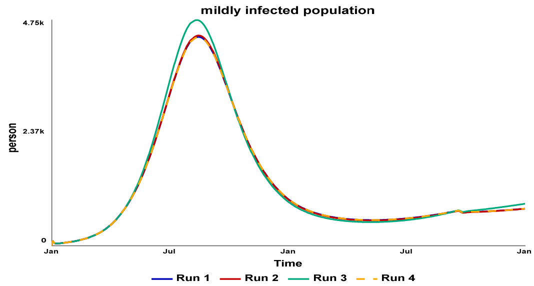


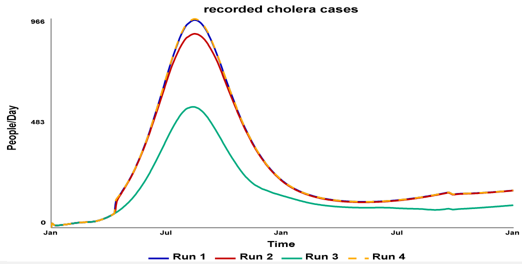
The model is insensitive to changes in the value of "time to build ORC" as expected with the historical data as the intervention was not sufficient to meet the population need (supply and demand issues). This delay takes into consideration of implementation challenges of building ORC. Hence, the faster the intervention begins, the sooner the infected individuals receive treatment (prevention on progressing to severe state), and the surveillance system can function earlier to provide crucial information for cholera emergency response.

[Back to summary]

desired number of ORC



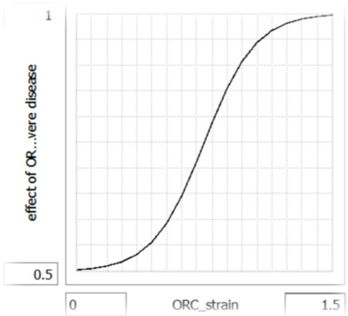


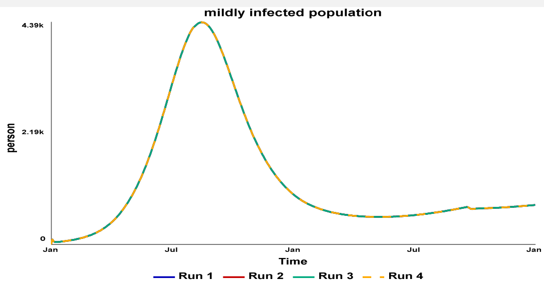


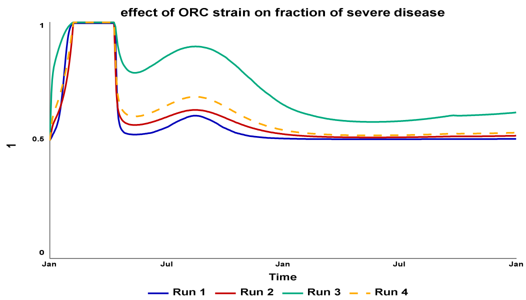
The model is numerically sensitive to changes in the value of "desired number of ORC" as expected. A similar result was found on "patient treated". Run 1, 2, and 4 show similar results, indicating a lack of need (or demand) from the infected individuals. Increasing the demand (health-seeking behavior) among the mildly infected individuals is one of the leverage points and should be further explored as the next steps.

effect of ORC strain on fraction of severe disease

Run 1 – S-shape growth
Run 2 – exponential growth
Run 3 – logarithmic growth
Run 4 – linear growth



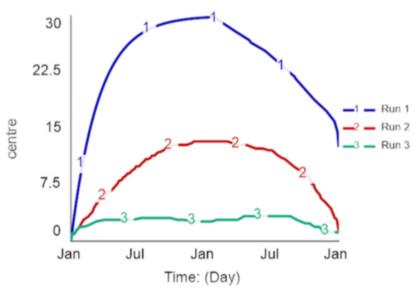


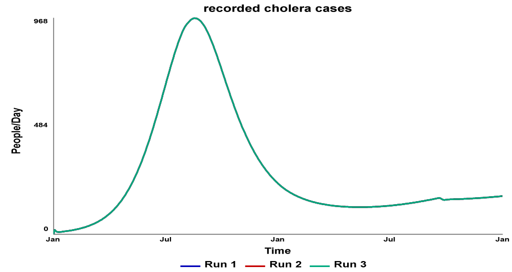


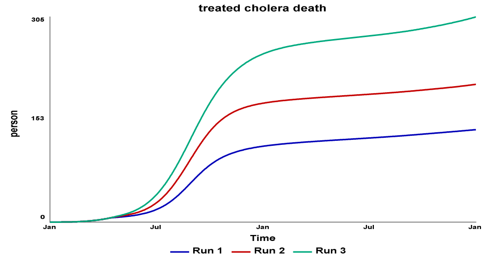
The model is insensitive to changes in the graphical function shape of "effect of ORC strain on fraction of severe disease", as expected. Based on the historical data of ORC, the impact is minimal towards the overall infection reinforcing feedback loop. However, the effect impacts the number of progressing into severe disease states as mildly infected individuals receive early treatment helps to prevent progressing to a severe state. When the severely infected increases (only during the initial months before the ORC were built), cholera deaths slightly increase.

[Back to summary]

desired number of DTC

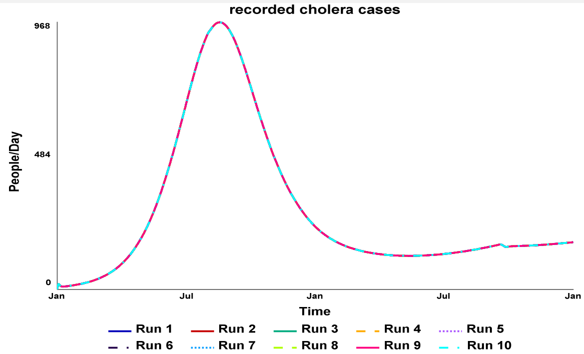


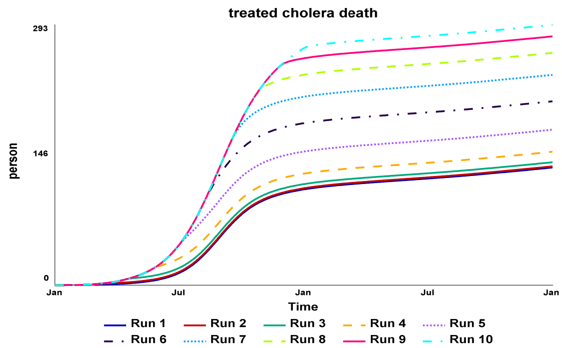




The model is insensitive to changes in the value of "desired number of DTC" as expected. A similar result was found on "bed". Severely infected individuals seeking treatment are very low relative to the total infected population. Even though the DTC treats the human waste before releasing it into the sewage system as the desired action to decrease water contamination, the impact is minimal. However, the teated cholera death is highly (numerically) sensitive to treatment at DTC.

	building DTC start time
Run 1	30
Run 2	67
Run 3	104
Run 4	142
Run 5	179
Run 6	216
Run 7	253
Run 8	291
Run 9	328
Run 10	365

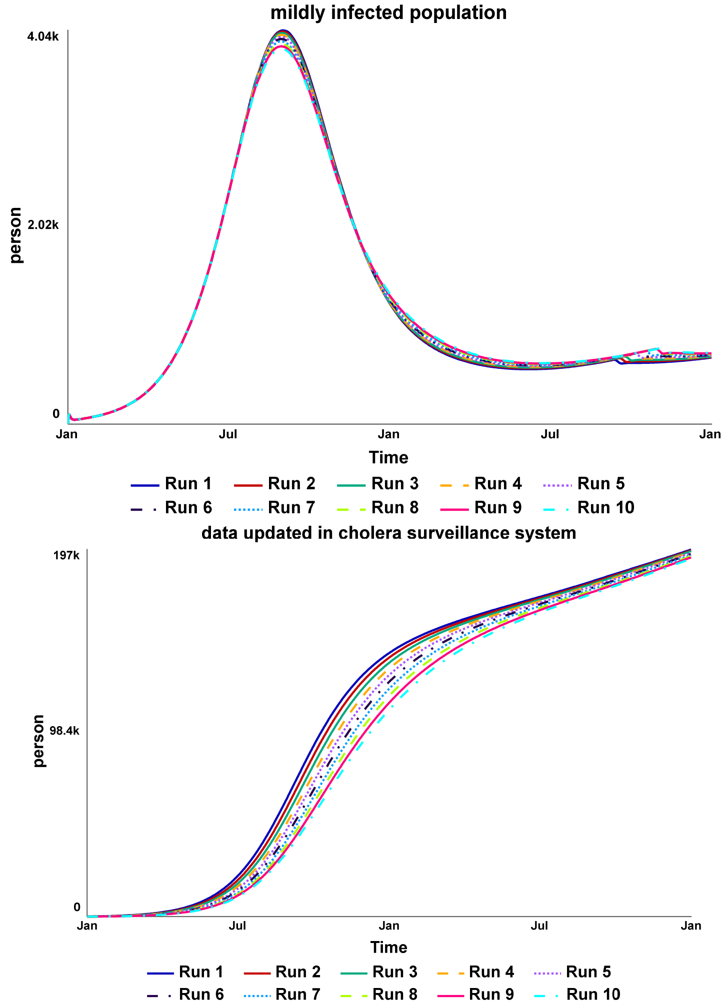




The model is insensitive to changes in the value of "building DTC start time" as expected. A similar result was found with "time to build DTC". However, the teated cholera death is highly (numerically) sensitive to both parameters.

[Back to summary]

	desired time to update system
Run 1	7
Run 2	13
Run 3	19
Run 4	25
Run 5	31
Run 6	36
Run 7	42
Run 8	48
Run 9	54
Run 10	60



The model is slight numerical sensitive to changes in the value of "desired time to update system" as expected in the scenario based on historical intervention data. It assumes that if the surveillance system is delayed, the emergency response based on the collected cholera prevalence data experiences a delay in the start time (policy structures). Likewise, if the surveillance system is highly responsive, the start time of the intervention will be earlier.

References

1. Pruyt, E. *Small System Dynamics Models for Big Issues: Triple Jump towards Real-World Complexity*; TU Delft Library: Delft, The Netherlands, 2013.