What makes for effective pandemic policy?

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Abstract

In light of the COVID-19 pandemic, understanding the impact of public health interventions on epidemic spread has become crucial for managing future outbreaks. A common framework for pandemic modelling is the SIR (Susceptible/Infected/Recovered) model which uses differential equations to model disease spread. There are numerous extensions of this model that add more groups (such as SIVQR – Susceptible/Infected/Vaccinated/Quarantined/Recovered), and there innumerable different policy interventions/characteristics one can consider in the model. This report aims to determine which policy measures are most important in managing disease spread.

1. Introduction

You need to say enough to understand the problem and objectives and a quick guide to your approach. At the end of the introduction, give a brief outline of what the following sections will cover, e.g., "The rest of the report is as follows. Details of the experimental design will be given in Section 2, . . ." Probably we will cite here Turkyilmazoglu, 2022

2. The experimental design

In the `MATLAB` code there are eight parameters of interest that we can tune. They are in no particular order: `prob_spread`, `recovery_rate`, `vac_eff`, `prob_sympt`, `isolation`, `vac_rate`, `quar_dur`, `num_daily`.

These represent (respectively) the probability that an unvaccinated individual will catch the disease from a single interaction with an infectious individual, the average rate of recovery for an infected individual in days, the proportional effectiveness of the vaccine (for example 0.1 means that vaccinated individuals are 10% as likely to get infected compared to if they were unvaccinated), the probability that an infected individual shows symptoms, the rate at which the susceptible population is vaccinated in days, the duration that symptomatic individuals are quarantined in days, the average number of daily interactions that an individual has per day.

The first of four of these parameters were randomized in simulation for each observation. This choice was made to reduce the number of effective runs, and because these

parameters would be hard (or potentially impossible) to measure in the real world. More detail is given in Appendix A. The last four of these parameters were considered as treatments and their levels were thus pre-designed and recorded.

The response of interest is ____. A complete description of the data is contained in Appendix B

For a summary of the experimental factors, see Table 1. These levels were chosen based on ____.

The design is a full 3^4 factorial and our model is

$$Y_{ijk\ell} = \mu + \alpha_i + \nu_j + \kappa_k + \eta_\ell + (\alpha\nu)_{ij} + (\alpha\kappa)_{ik} + (\alpha\eta)_{i\ell} + (\nu\kappa)_{jk} + (\nu\eta)_{j\ell} + (\kappa\eta)_{k\ell}$$
$$+ (\alpha\nu\kappa)_{ijk} + (\alpha\nu\eta)_{ij\ell} + (\alpha\kappa\eta)_{ik\ell} + (\nu\kappa\eta)_{jk\ell} + (\alpha\nu\kappa\eta)_{ijk\ell} + E_{ijk\ell}$$

where $i, j, k, \ell = 1, 2, 3$ and:
- μ is a main effect common to all observations
- α_i is the effect on `load` of `soc.iso` at level i
- ν_j is the effect on `load` of `vac.rate` at level j
- κ_k is the effect on `load` of `quar.dur` at level k
- η_ℓ is the effect on `load` of `num.daily` at level ℓ
- $(\alpha\nu)_{ij}$ is the "interaction effect" on `load` of `soc.iso` and `vac.rate` at levels i, j
- and similarly for other higher order effects
- $E_{ijk\ell} \sim \mathcal{N}(0, \sigma^2)$

3. Analysis

Try to be specific about your findings, and present numerical estimated effects, recommended levels, the estimated response at the recommended levels, etc. "The high level of temperature was better at the 5% significance level" does not summarize well: the reader would have to make some more calculations to assess whether the result is practically significant. Instead, "We are 95% confident that the effect of changing temperature from 15 to 25°C is an increase in mean (a response variable) of (a confidence interval)" tells the reader immediately whether there is a result of concern.

If interaction effects are reported you should be careful to interpret them. Numerical estimates of interaction effects are not easy to understand. Rather, refer to a table of averages or an interaction plot. Talk about how the estimated effect of one factor depends on the level of another.

Do not give excessive digits for estimates, etc. Two significant digits are usually sufficient for a standard error. Give the corresponding estimate to the same accuracy, e.g., 14.37 kg with standard error 0.54 kg, 14.4 kg with standard error 5.4 kg, or 14 kg with standard error 54 kg. Always give units of measurement for estimates and standard errors.

If a transformation has been applied you will often want to convert predictions on the transformed scale back to the original scale.

2

4. Conclusions

The conclusions are often essentially a summary of the important results.

Evaluate what you did. What would you do differently next time if a similar experiment were conducted?

References

Turkyilmazoglu, M. (2022). An extended epidemic model with vaccination: Weak-immune sirvi. *Physica A: Statistical Mechanics and its Applications*, 598, 127429. https://doi.org/https://doi.org/10.1016/j.physa.2022.127429

Appendix

A. Discussion of simulation

The model considers five distinct groups: S, I, V, Q, and R; which are the number of susceptible, infected, vaccinated, quarantined and recovered individuals respectively. If N is the total population, we can define $s = S/N$, $i = I/N$, $v = V/N$, $q = Q/N$, $r = R/N$ and work with these population proportions. The system of differential equations is

$$\begin{cases} ds/dt = -\beta_0 si - \nu s \\ di/dt = \beta_0 si + \beta_1 vi - \mathbb{I}_Q P_{\text{sympt}} i + (1 - \gamma_Q)\kappa q - \gamma i \\ dv/dt = \nu s - \beta_1 vi \\ dq/dt = \mathbb{I}_Q P_{\text{sympt}} i - \kappa q \\ dr/dt = \gamma i + \gamma_Q \kappa q \end{cases} \tag{1}$$

where

- β_0 and β_1 are the transmission rate ($\#$ daily interactions $\times \mathbb{P}[\text{spread per interaction}]$) for unvaccinated and vaccinated individuals respectively
- ν is the vaccination rate of susceptible individuals
- $\mathbb{I}_Q$ is an indicator variable equalling 1 if there is a quarantine policy and 0 if there is no quarantine policy
- P_{sympt} is the probability that an infected individual is symptomatic
- γ and γ_Q are the average rates [1/(average recovery duration)] of recovery for infected individuals and individuals who just came out of quarantine respectively
- κ is the average rate [1/(average quarantine duration)] at which we take people out of quarantine

The `MATLAB` code uses Euler's method with time steps of size `k = 0.001` to simulate the dynamics of these groups over 90 days from an initial condition of 1% infected and everyone else susceptible. Parameters mentioned to be randomized in Section 2 were done so using the built in functions `randn()` and `rng(404)` for reproducibility. The response was measured as `load = max(i + q)`.

B. Description of data

Description goes here

C. Tables and figures

Factor	Levels	Symbol
Isolation	Low (0), Medium (0.5), High (1)	`soc.iso`
Vaccination rate	0 ppd, 1 ppd, 2 ppd	`vac.rate`
Quarantine duration	0 days, 7 days, 14 days	`quar.dur`
Average number of daily interactions	15 ipd, 30 ipd, 45 ipd	`num.daily`

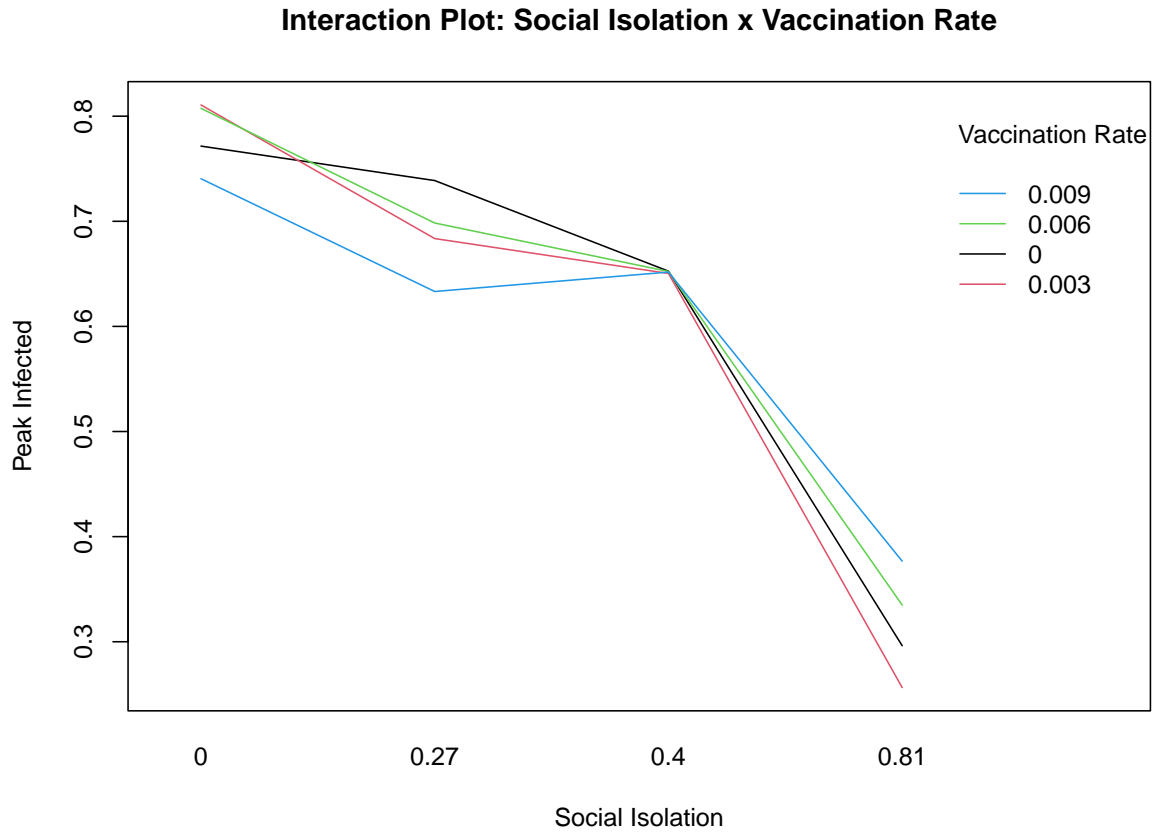Table 1: ppd is "percent population vaccinated per day" and ipd is "average number of daily interactions per day"

Figure 1: Interaction plot