Coupled models of structured contagion processes in human-environment systems

Peter C. Jentsch

Department of Applied Mathematics, University Of Waterloo

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Supervised by Chris T. Bauch and Madhur Anand

Introduction

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Chapter 1

Studying COVID-19 vaccination

- Model-based analyses are exploring which group should be the first to get the vaccine [Bubar et al., 2020, Buckner et al., 2020].
- The epidemiological landscape will change throughout the remainder of the pandemic
- Perception of risk due to the virus, and therefore perception of benefit of physical distancing, also fluctuates
- The group to vaccinate first, to most reduce mortality, is a function of this landscape

Compartmental model overview

Disease Compartments

$S_i(t)$: Susceptible

$S_{2,i}(t)$: Vaccinated but still susceptible

$V_i(t)$: Vaccinated and immune

$E_i(t)$: Exposed

$P_i(t)$: Pre-symptomatic

$I_{a,i}(T)$: Infectious and asymptomatic

$I_{s,i}(t)$: Infectious and symptomatic

$R_i(t)$: Recovered

where $i = 1 \ldots 16$ comprises age structure

Social compartments

$x(t)$: Uses NPIs

$1 - x(t)$: Does not use NPIs

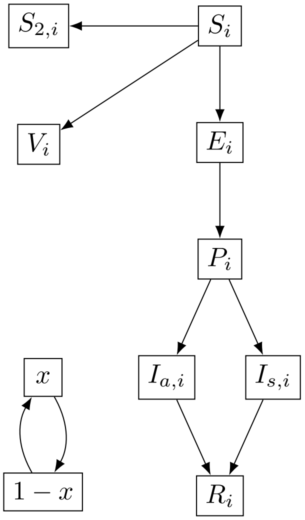


Figure: Compartments

Parameterization

- We used an approximate bayesian method to fit the model to case data from Ontario, Canada from March 12 to Nov 12, 2020.
- $x(t)$, proportion of people using NPIs was fit to google mobility data for Ontario
- Also fit the population seroprevalence to a point estimate from June 2020 for Ontario
- Provincial shutdowns (school and workplace) that occurred in Ontario were also implemented at their respective dates
- The efficacy of work shutdowns were fit to google mobility to account for work that could not be moved to remote
- Results were evaluated with 400 points sampled from the posterior distributions from this method

Results

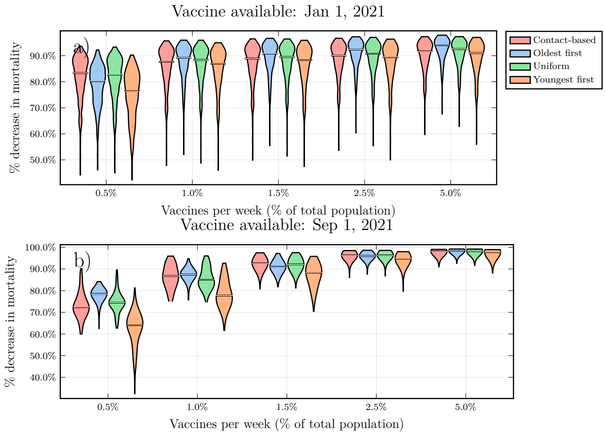
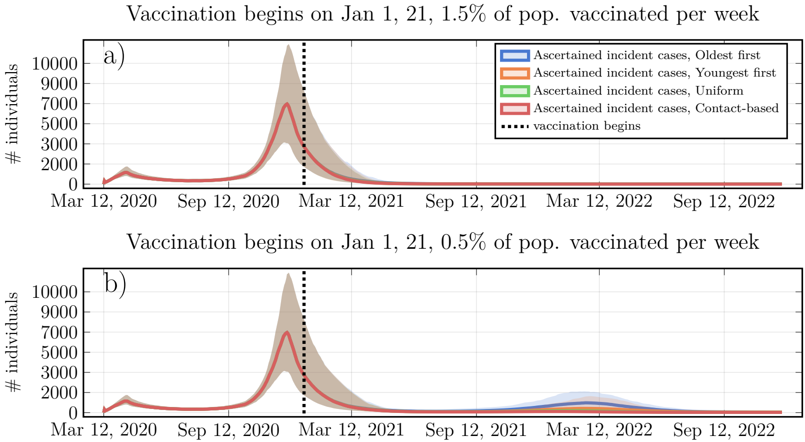
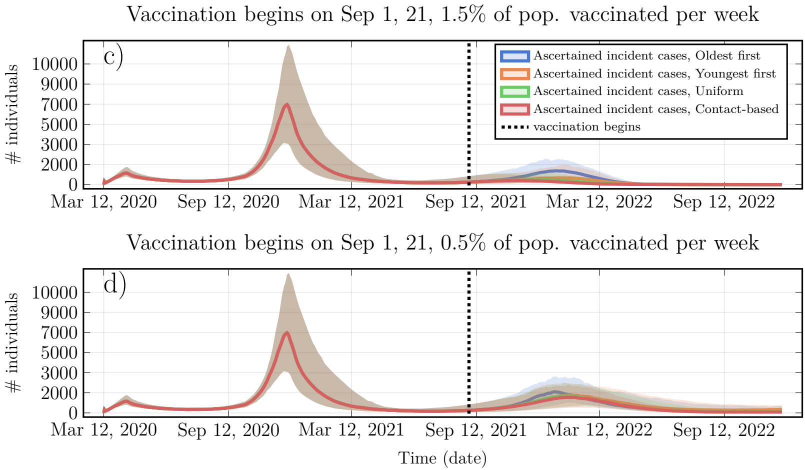


Figure: Percentage reduction in cumulative mortality due to COVID-19 after 5 years with respect to *psi*, expressed as a percentage of the total population per week. Here $v_{D_i} = v_{T_i} = 0.75$, shutdown at 200% of first wave. Percentage reductions are relative to no vaccination.


Vaccination begins on Jan 1, 21, 1.5% of pop. vaccinated per week
a)
individuals
10000
9000
7000
5000
3000
2000
0
Mar 12, 2020
Sep 12, 2020
Mar 12, 2021
Sep 12, 2021
Mar 12, 2022
Sep 12, 2022
Ascertained incident cases, Oldest first
Ascertained incident cases, Youngest first
Ascertained incident cases, Uniform
Ascertained incident cases, Contact-based
vaccination begins
Vaccination begins on Jan 1, 21, 0.5% of pop. vaccinated per week
b)
individuals
10000
9000
7000
5000
3000
2000
0
Mar 12, 2020
Sep 12, 2020
Mar 12, 2021
Sep 12, 2021
Mar 12, 2022
Sep 12, 2022


Vaccination begins on Sep 1, 21, 1.5% of pop. vaccinated per week
c)
individuals
10000
9000
7000
5000
3000
2000
0
Mar 12, 2020
Sep 12, 2020
Mar 12, 2021
Sep 12, 2021
Mar 12, 2022
Sep 12, 2022
Ascertained incident cases, Oldest first
Ascertained incident cases, Youngest first
Ascertained incident cases, Uniform
Ascertained incident cases, Contact-based
vaccination begins
Vaccination begins on Sep 1, 21, 0.5% of pop. vaccinated per week
d)
individuals
10000
9000
7000
5000
3000
2000
0
Mar 12, 2020
Sep 12, 2020
Mar 12, 2021
Sep 12, 2021
Mar 12, 2022
Sep 12, 2022
Time (date)

Results

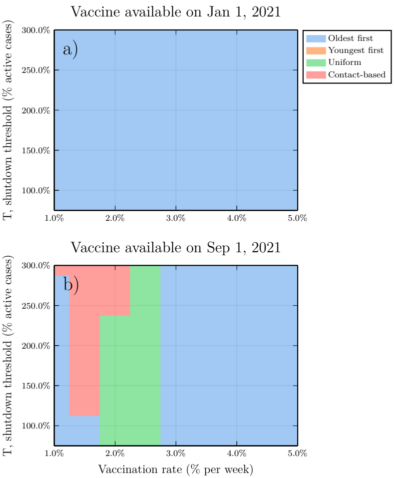


Figure: Each parameter pair is colored according to the strategy that prevents most deaths on average, over all realizations of the model.

Results

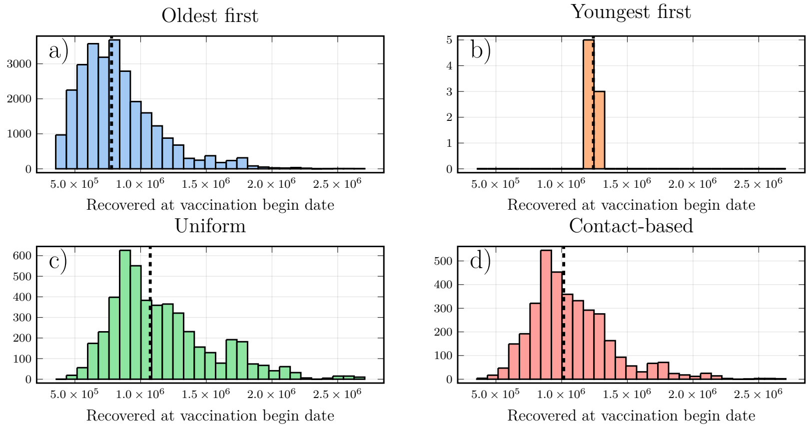


Figure: Histogram of no. recovered at vaccination begin date, according to best strategy for that realization, over all parameter values in sensitivity analysis. Vertical lines are the median.

Discussion

- We described an age structured compartmental model of Sars-CoV-2 infection and vaccination coupled to a social model
- Showed that sometimes transmission interrupting strategies can be more effective
- Depends on the pre-existing immunity in the population

Chapter 2

policy modelling

Invasive species

Model

$$\frac{dS_i}{dt} = \underbrace{rS_i\left(1 - \frac{(S_i + I_i)}{K}\right)}_{\text{Logistic Growth Of Forest}} - \underbrace{AS_i(I_i + B_i)\theta_k(I_i - I_a)}_{\text{Infestation term}} \tag{1}$$

$$\frac{dI_i}{dt} = \underbrace{-\gamma I_i}_{\substack{\text{Death of}\\ \text{infested trees}}} + \underbrace{AS_i(I_i + B_i)\theta_k(I_i - I_a)}_{\text{Susceptibles become infested}} - \underbrace{d\sum_{j=1, j\neq i}^{N} P_{j,i}(1 - C_e)(1 - L_i)I_i}_{\substack{\text{Total infested wood}\\ \text{leaving due to transport}}} \tag{2}$$

$$\frac{dB_i}{dt} = \underbrace{-\gamma B_i}_{\text{Decay of firewood}} + \underbrace{d\sum_{j=1, j\neq i}^{N} P_{i,j}(1 - C_e)(1 - L_j)I_j}_{\text{Import of fallen wood}} \tag{3}$$

$$\frac{dL_i}{dt} = \sigma L_i(1 - L_i)(\underbrace{U}_{\substack{\text{Net cost to}\\ \text{transport firewood}}} + \underbrace{s(2L_i - 1)}_{\text{Social influence term}} + \underbrace{fI_i}_{\text{Impact of infestation}}) \tag{4}$$

Data

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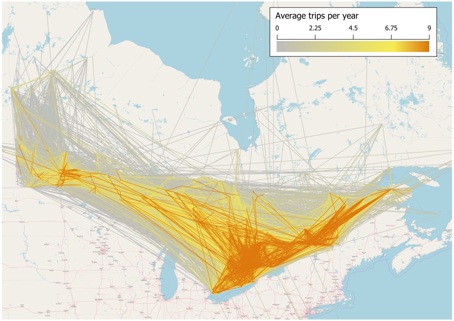

Results

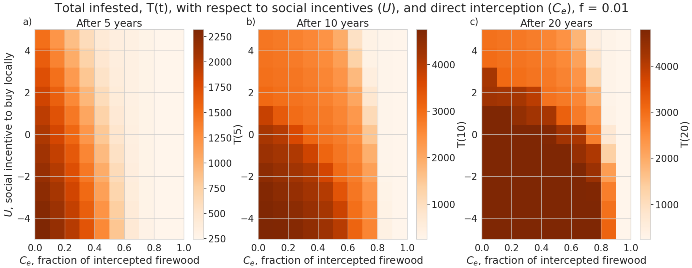

Figure: Total number of infested trees per node over 5 (a), 10 (b), and 20 (c) years

Results

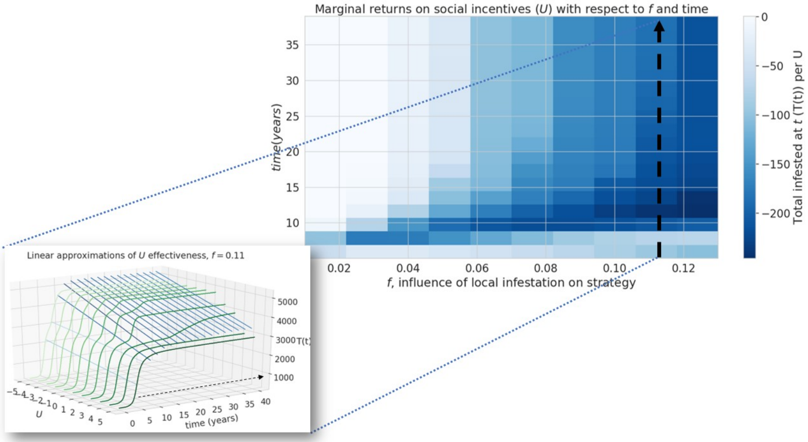

Figure: Efficacy of social incentives on infestation after time T. Inset graph shows an example of cross-section along the line $f = 0.11$

Results

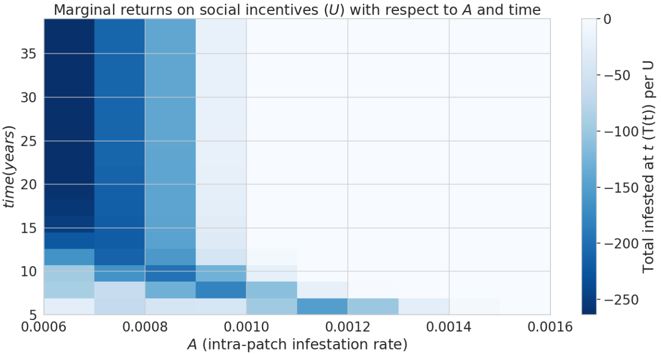

Figure: Efficacy of social incentives on infestation after time period T with respect to A, the intra-patch infestation parameter.

Results

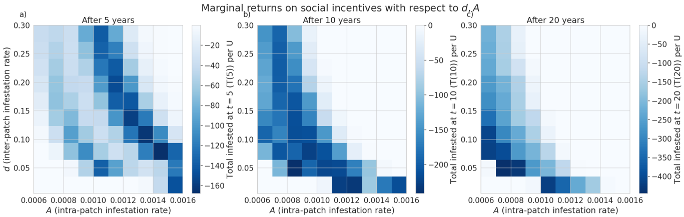

Figure: Efficacy of social incentives on infestation after time T intra-patch spreading rate A, affects infestation outcomes.

Results

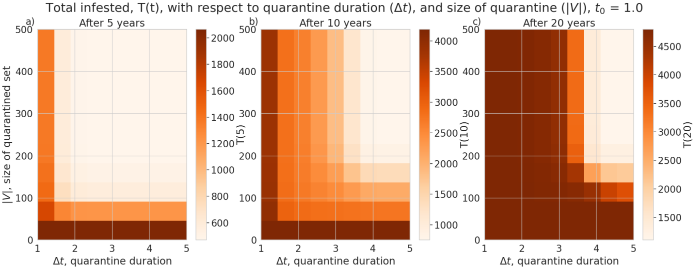

Figure: Average total infested trees ($T(t)$) after 5, 10 and 15 years (panels a), b), and c) respectively), assuming the quarantine begins one year after the pest is introduced.

Chapter 3

Model

$$j_{n+1,1} = dJ_n + I_{n-2} + F_n \tag{5a}$$

$$j_{n+1,k} = (1-d)j_{n,k-1} - \frac{\alpha_1}{T} P_n j_{n,k-1}, \qquad k = 2 \ldots K-1, K \tag{5b}$$

$$S_{n+1} = S_n + (1-d)j_{n,K} - \left(I_n + \frac{\alpha_2}{T} P_n I_n\right) - \frac{\alpha_2}{T} P_n \left(S_n + (1-d)j_{n,K}\right) - \sigma_F \gamma_n \tag{5c}$$

$$I_{n+1} = r_1 I_n e^{-\beta_1 (T - S_{n+1})} - \frac{\alpha_2}{T} P_n I_n + \sigma_I \xi_n \tag{5d}$$

$$F_{n+1} = P_n \left[\frac{\alpha_1}{T} \sum_{k=1}^{K-1} j_{n,k} + \frac{\alpha_2}{T} \left(S_n + (1-d)j_{n,K}\right) + \frac{\alpha_2}{T} I_n\right] + \sigma_F \gamma_n \tag{5e}$$

$$P_n = T - \sum_{i=1}^{n} F_i e^{-\kappa(n-i)} \tag{5f}$$

Results

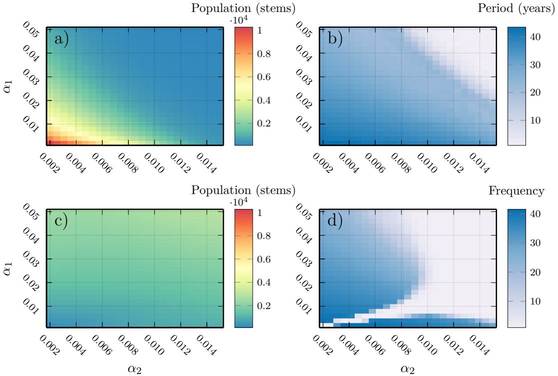

Figure: Panels: a) Average size of largest MPB population, b) Average frequency of MPB outbreaks, c) Average size of largest fire season, d) Average frequency of severe fire seasons. All measured at equilibrium.

Results

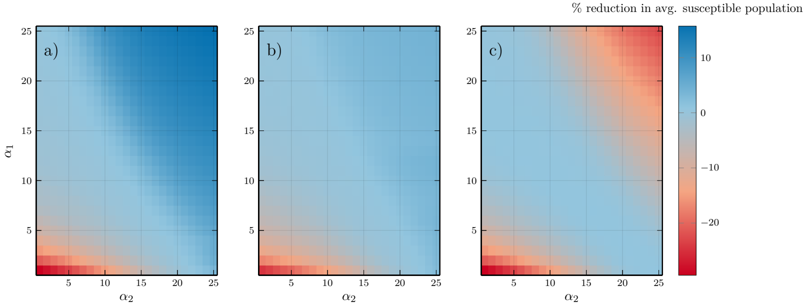

Figure: Percentage change in average susceptible (mature) forest population compared to no FTP with a) $\tau = 0.15, m = 8$, b) with $\tau = 0.15, m = 8$ applied every 5 years, c) controlled burning with $\tau = 0.15, m = 8$, with respect to burning rates α_1, α_2.

Results

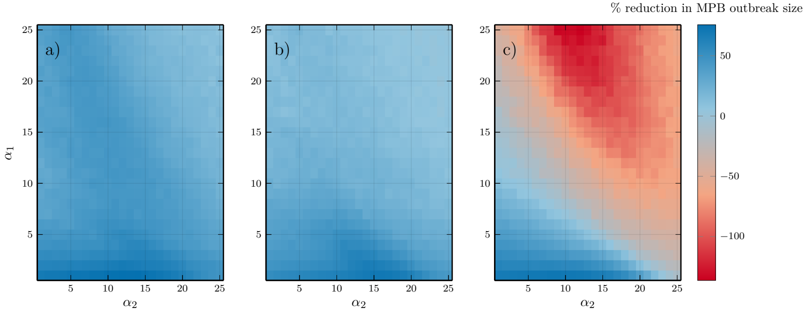

Figure: Percentage change in maximum MPB infestation size within 500 year period under FTP with a) $\tau = 0.15, m = 8$, b) with $\tau = 0.15, m = 8$ applied every 5 years, c) controlled burning with $\tau = 0.15, m = 8$, with respect to burning rates α_1, α_2.

Conclusion

Bubar, K. M., Kissler, S. M., Lipsitch, M., Cobey, S., Grad, Y., and Larremore, D. B. (2020).
Model-informed COVID-19 vaccine prioritization strategies by age and serostatus.
medRxiv.

Buckner, J. H., Chowell, G. H., and Springborn, M. R. (2020).
Optimal dynamic prioritization of scarce COVID-19 vaccines.
medRxiv.

Model Equations

$$
\begin{aligned}
\frac{dS_i^1}{dt} &= -r\rho_i s(t) S_i^1 \sum_{j=1}^{16} C_{ij}(t) \left(\frac{I_{s_j} + I_{a_j} + P_j}{N_j} \right) - \tau S_i^1 && (6) \\
\frac{dS_i^2}{dt} &= -r\rho_i s(t) S_i^2 \sum_{j=1}^{16} C_{ij}(t) \left(\frac{I_{s_j} + I_{a_j} + P_j}{N_j} \right) - \tau S_i^2 && (7) \\
\frac{dE_i}{dt} &= r_i s(t)(S_i^1 + S_i^2) \sum_{j=1}^{16} C_{ij}(t) \left(\frac{I_{s_j} + I_{a_j} + P_j}{N_j} \right) - \sigma_0 E_i + \tau(S_i^1 + S_i^2) && (8) \\
\frac{dP_i}{dt} &= \sigma_0 E_i - \sigma_1 P_i && (9) \\
\frac{dI_{a_i}}{dt} &= \eta \sigma_1 P_i - \gamma_a I_{a_i} && (10) \\
\frac{dI_{s_i}}{dt} &= (1-\eta)\sigma_1 P_i - \gamma_s I_{s_i} && (11) \\
\frac{dR_i}{dt} &= \gamma_a I_{a_i} + \gamma_s I_{s_i} && (12) \\
\frac{dx}{dt} &= \kappa x(1-x) \left(\frac{\sum_{i=1}^{16} \alpha_i (I_{a_i} + I_{s_i})}{\sum_{i=1}^{16} N_i} - cx \right) + p_{ul}(1-2x) && (13) \\
C_{ij}(t,x) &= C_{ij}^W(t) + C_{ij}^S(t) + (1 - \epsilon_P x)\left(C_{ij}^O + C_{ij}^H \right) && (14)
\end{aligned}
$$