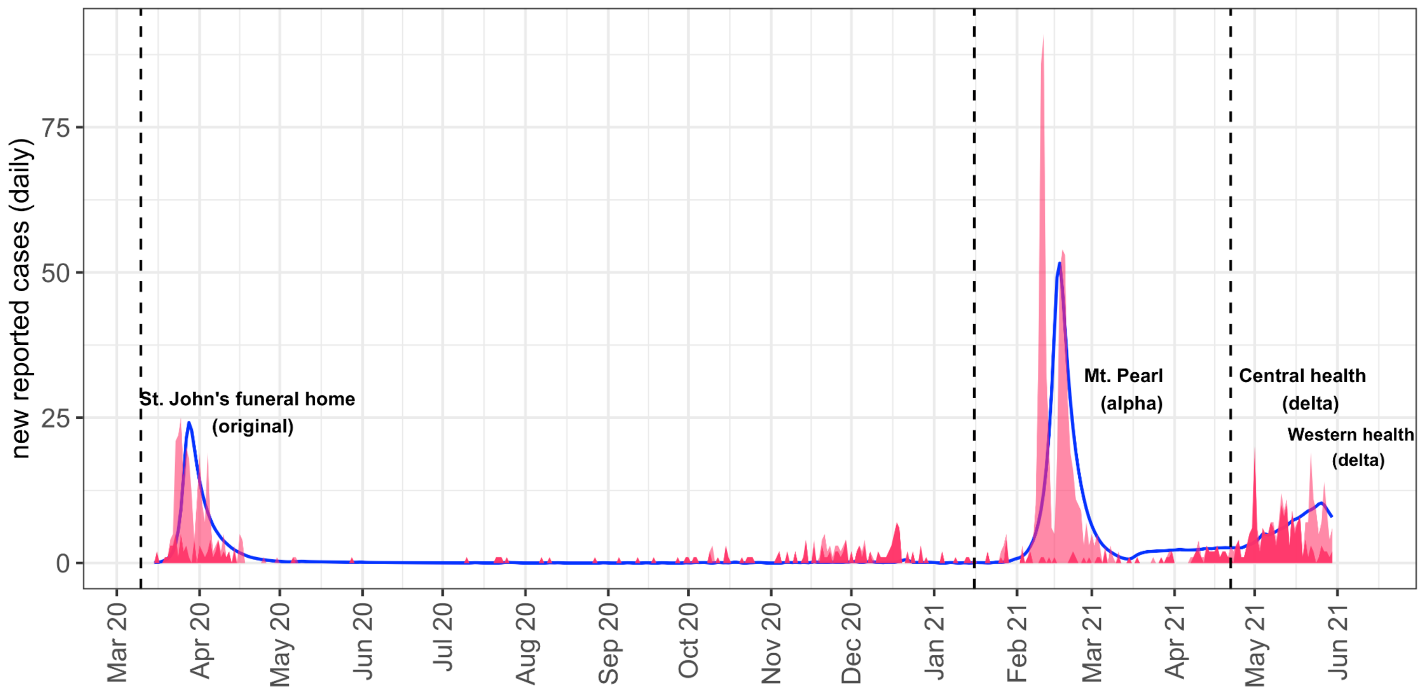
Pandemic preparedness needs modelling preparedness

highlighting the role of mechanistic models and the gap in supporting Canadian small jurisdictions

Amy Hurford

COVID-19 cases reported in Newfoundland and Labrador



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Newfoundland & Labrador Centre for Health Information
CANMOD
MATHEMATICS FOR PUBLIC HEALTH
AARMS Atlantic Association for Research in the Mathematical Sciences
OMNI | RÉUNIS
Public Health Agency of Canada
NSERC CRSNG

Pandemic preparedness needs modelling preparedness

1. There was high demand for modelling during the pandemic

2. Mechanistic and statistical models have different roles in pandemic decision support

3. The modelling needs of small jurisdictions can be different than the modelling needs of large jurisdictions.

4. Building capacity in mathematical biology and statistics in Atlantic Canada

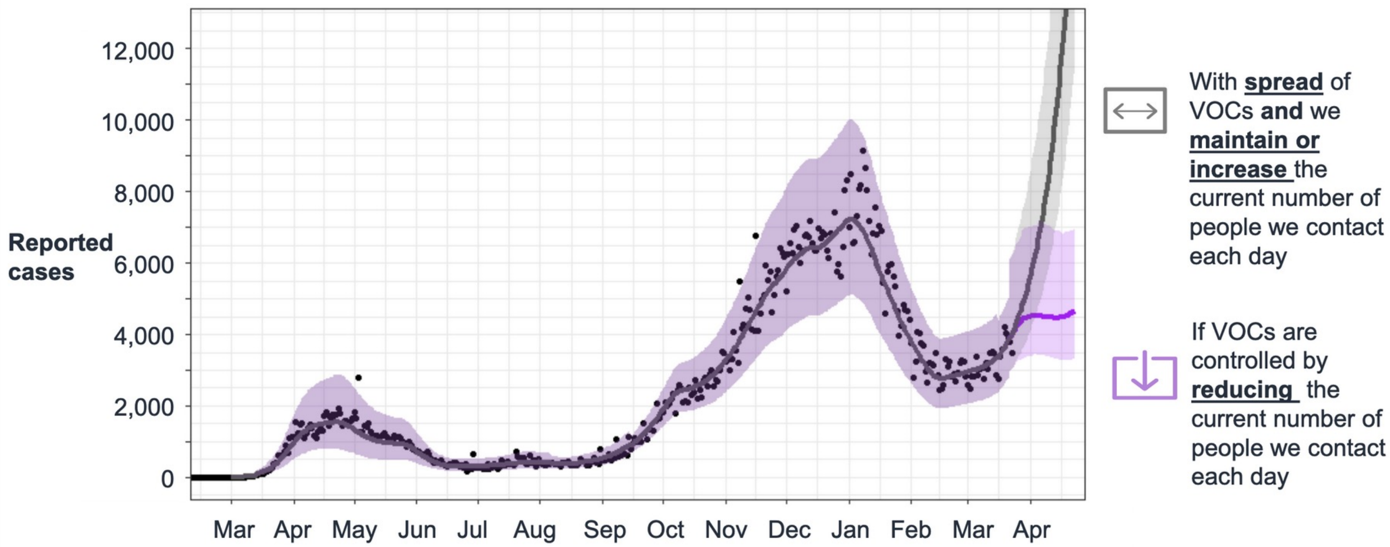
1. High demand for modelling during the pandemic

- Forecasting
- Counterfactual scenarios
- Public health communication
- Quantities to inform decisions

Forecasting and scenarios

PHAC report involving `McMasterPandemic`

Longer-range forecast shows stronger public health measures will be required to counter more transmissible variants of concern

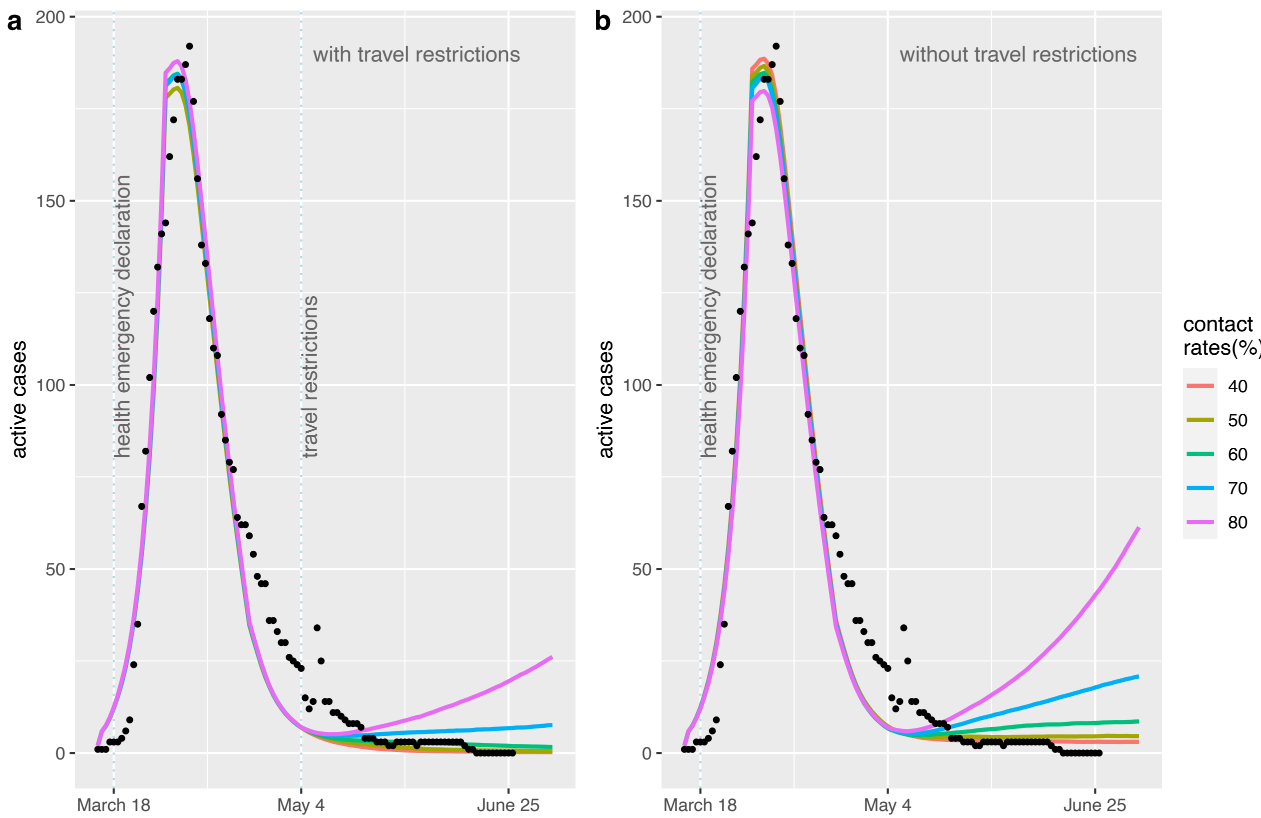


Data as of March 24, 2021
Note: *Ensemble of output from PHAC-McMaster and Simon Fraser University models*

The PHAC McMaster forecast is based on current estimates transmission rates fitted to reported cases. It assumes VOCs are introduced in mid-Dec (~1 week prior to first detected case in Canada) at very low prevalence; VOCs (all VOCs known to date) are 50% more transmissible than wild-type; growth rate AND replacement rate are negatively correlated with the strength of public health measures. Proportion of VOC is obtained by a combination of calibrating to surveillance data as well as information on proportions of cases that are VOC. Recent changes in testing rates are not taken into account in this forecast. SFU methods are at https://www.sfu.ca/magpie/blog/variant-simple-proactive.html

Slide by Steve Walker (https://canmod.github.io/macpan2/)

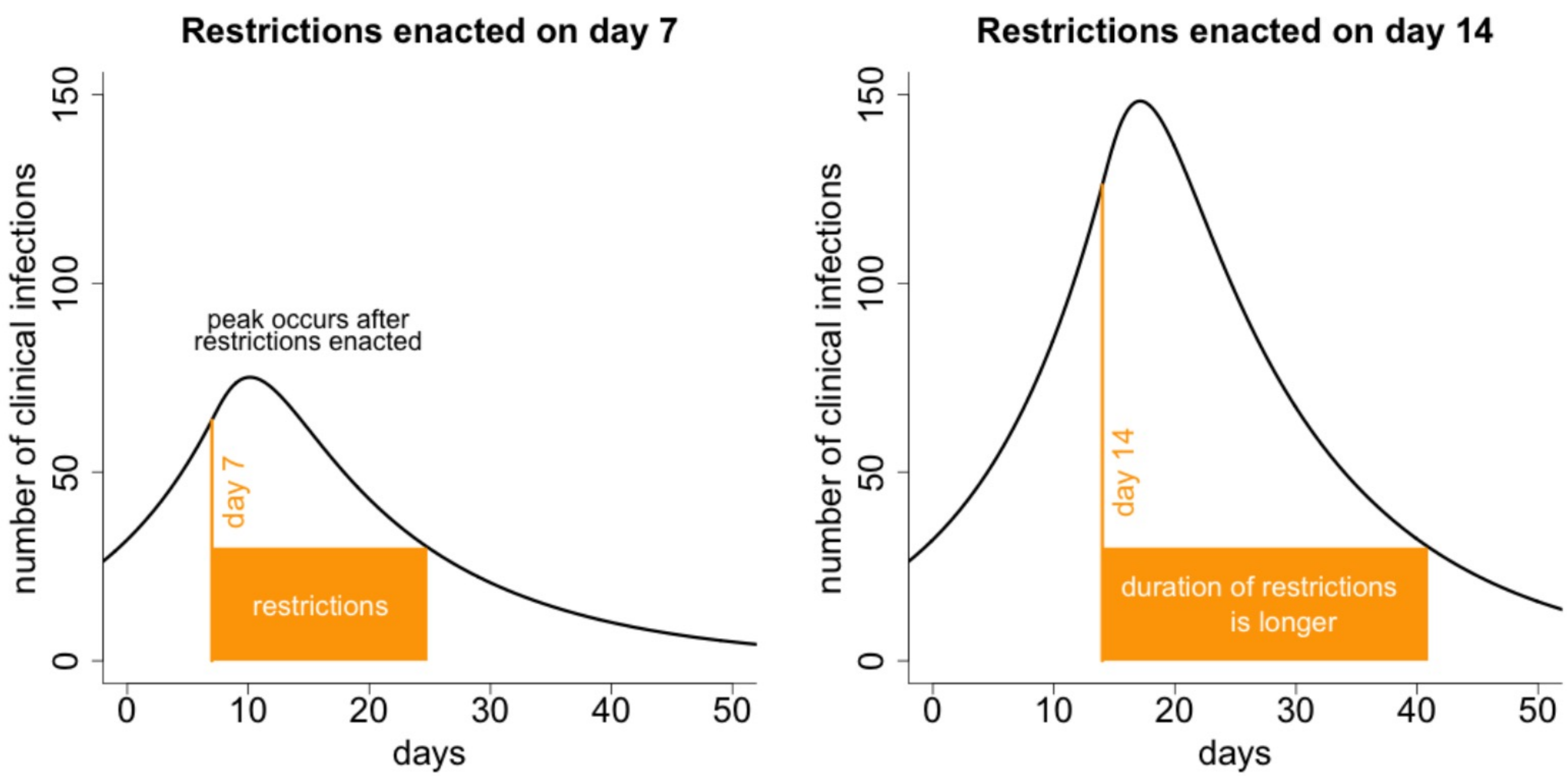
Counter-factual scenarios



Hurford, A., P. Rahman, J. C. Loredo-Osti. 2021. Modeling the impact of travel restrictions on COVID-19 in Newfoundland and Labrador. J Roy Soc Open.

Public health communication

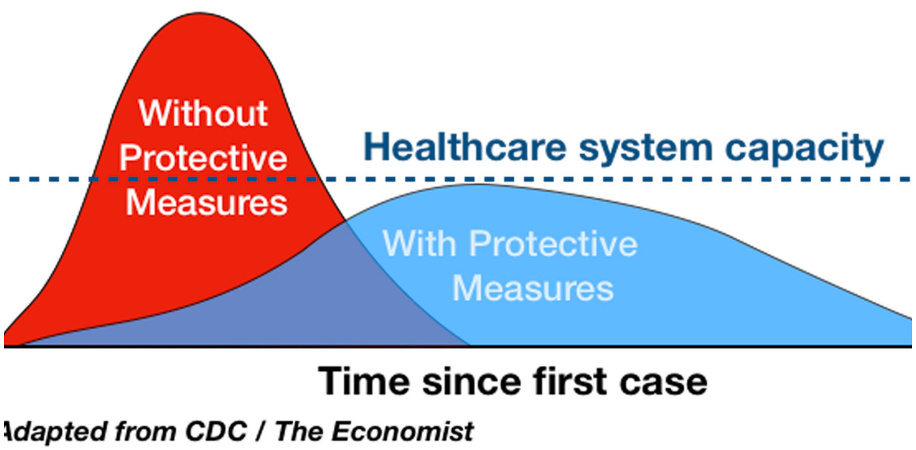
Simple models are valuable as “stylized facts” for communication to non-modellers



Hurford and Watmough. 2021. Don’t wait, re-escalate: delayed action results in longer duration of COVID-19 measures. MedRxiv

Public health communication

Flatten the curve

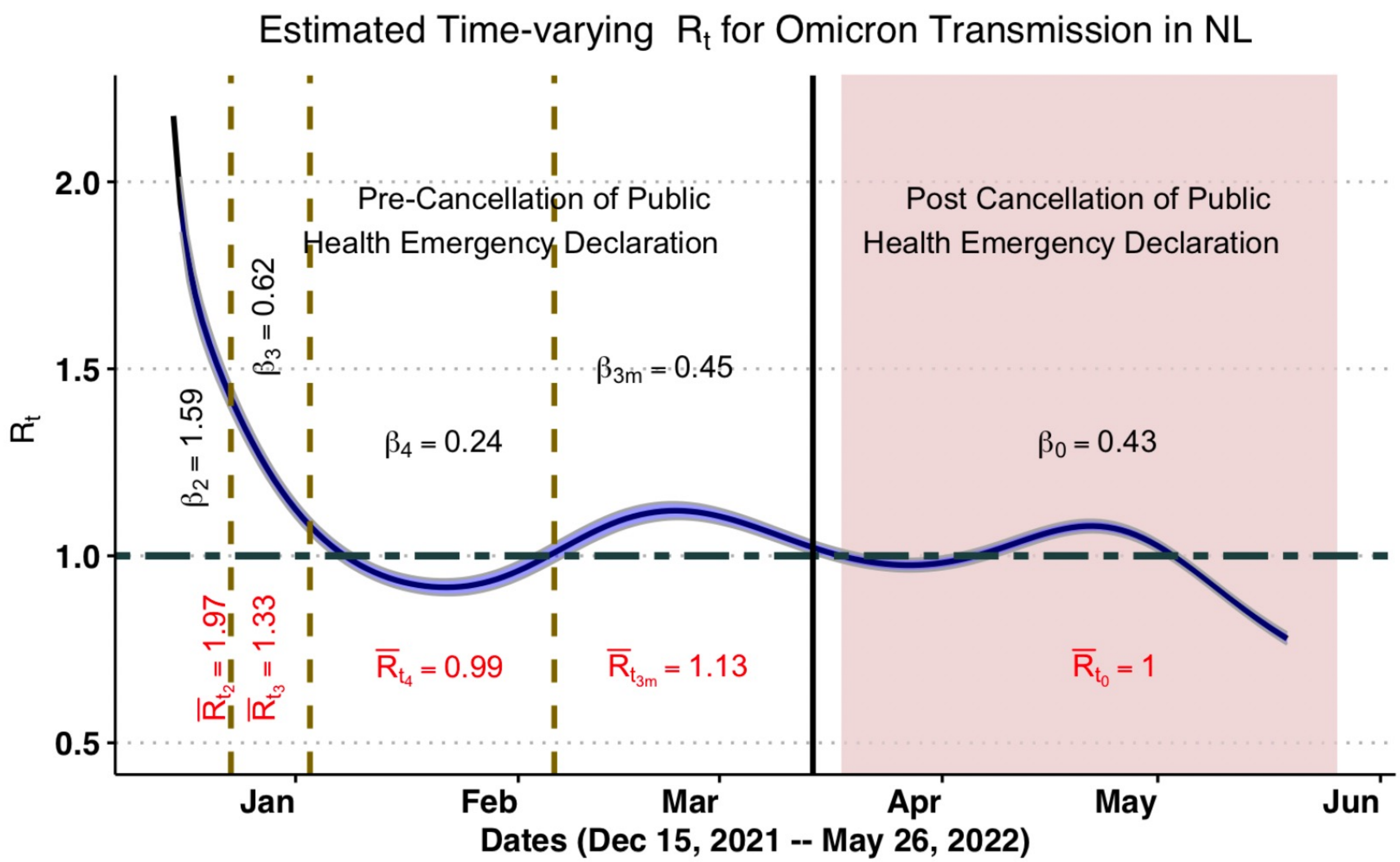


Omicron (less severe, more transmissible) was forecast to place an extreme burden on the healthcare system

CoVaRR-Net Pillar 6 (Computational Biology and Modelling)[1]

Executive summary: The current epidemiological, experimental, and computational evidence to date points to a clear growth advantage of the Omicron variant of SARS-CoV-2. Canada should therefore be prepared for another large pandemic wave within the next month. Even if Omicron disease severity remains the same, or even less severe than previous variants (due to viral changes and/or increased immunity), the exponential growth that is forecast will result in a large number of cases in a very short period of time, placing an extreme burden on the medical care system.

Quantities to inform decisions



Anokye et al. Reconstruction of Omicron (B.1.1.529) transmission dynamics in Newfoundland and Labrador. In prep

2. Mechanistic and statistical models

- Definitions
- Mechanistic and statistical models have different roles in decision support

2. Mechanistic and statistical models

Mechanistic model (epidemiology):

- A mathematical or computer simulation model that describes the ***processes*** of infectious disease spread. For example, transmission, recovery, and control measures.
- Types: mathematical compartmental models or agent-based models
- Distinct from statistical models in:
  - Emphasizing biological realism in describing processes (rather than variables and prediction)
  - That many parameters are independently estimated
- However, mechanistic and statistical (phenomenological) models exist on a continuum

Mechanistic models have independently estimated parameters

COVID-19 Epidemiological and Modelling Parameters Report - April 15th, 2020

Current to Daily Scan of April 13th, 2020 (citations added since report of April 8th marked in blue text; citations with updated values since report of April 8th marked in red text)

References within this report are taken from the Daily Scan of COVID-19 Scientific Publications (contact: lisa.waddell@canada.ca)
> Foci included in data extraction: Epidemiological; Clinical Data; and Modelling/Prediction
> Data extracted by Public Health Risk Sciences Division | NML | PHAC
>> Inquiries related to the enclosed tables are to be directed to ainsley.otten@canada.ca

Notes of Caution: N
19. These works, if
evolve beyond the
have been reviewe
This report is not a

Interpret With Caution (IWC) - noted in the table to indicate data is extracted and the researcher has assumed it is a reasonable proxy of the parameter at this time.

Parameter	Units	Description	Cau
Basic Reproduction Number, R_o *	-	The basic reproduction number (R_o) is defined as the average number of secondary cases caused by a single infectious individual in a totally susceptible population.	
Case Number Doubling Time	days	Time it takes for the number of cases to double.	
Case Fatality Rate (CFR)	%	Number of deaths divided by the number of cases for a certain period of time.	Tra be The
Serial interval*	days	Serial interval describes the duration of time between the onset of symptoms in a primary case and the onset of symptoms in a secondary case infected by the primary case.	
Incubation period*	days	The incubation period represents the time period between the occurrence of infection (or transmission) and the onset of disease symptoms.	
Latent period*	days	The latent period is definied as the period of time between the occurrence of infection and the onset of infectiousness	
Infectious Period	days	The time during which an infected person can transmit an infectious agent to another person. May also be referred to	In n extr
Proportion asymptomatic but infective*	%	Proportion of cases in which the infected individual does not and will not exhibit symptoms, but are capable of infecting others.	Ma Val ass
Proportion Hospitalized	%	Proportion of cases admitted to hospital divided by total number of cases	Par

Definitions sourced/amended from:

* - Moghadas, S. and Milwid, R. Glossary of Terms for Infectious Disease Modelling. National Collaborating Centre for Infectious Diseases. 2016. Available at: https://nccid.ca/publications/glossary-terms-infectious-disease-moc

About | R_o | Doubling Time | CFR | Serial Interval | Incubation Period | La | +

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Mechanistic models have independently estimated parameters

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Incubation Period (days)

Author	Title	MLV	Plausible Range	N	Population	Location
Chen, L., Lou, J., Bai, Y., et al	COVID-19 Disease With Positive Fecal and N	6		1	Clinically Confirmed (fecal sample +)	Wuhan
Fan, C., Lei, D., Fang, C., et al	Perinatal Transmission of COVID-19 Associa	7		Case 1	Two confirmed cases during third trimester of pregnancy	Wuhan
Liang, J. & Yuan, H.	The impacts of diagnostic capability and pre	5.57	2.67 - 7.95 (95% CI)		confirmed cases	Wuhan
Sun, D., Li, H., Lu, X.X., et al	Clinical features of severe pediatric patients		5 - 10	4	Confirmed severe pediatric cases (family cluster and single nosocomial cas	Wuhan
Zhang, B., Zhou, X., Qiu, Y., et	Clinical characteristics of 82 death cases wit	7	5 - 10	7	Hospitalized confirmed cases	Wuhan
Zhang, l., wan, k., chen, j., et a	When will the battle against novel coronavir	3		(modelled)	confirmed cases	Wuhan
Lin, Y., Ji, C., Weng, W., et al	Epidemiological and Clinical Characteristics c	7	5 - 10	124	Confirmed and suspected elderly outpatient cases	Wuhan
Lin, Y., Ji, C., Weng, W., et al	Epidemiological and Clinical Characteristics c	7	5 - 10	60	Confirmed and suspected elderly outpatient cases, male	Wuhan
Lin, Y., Ji, C., Weng, W., et al	Epidemiological and Clinical Characteristics c	7	4.75 - 9	64	Confirmed and suspected elderly outpatient cases, female	Wuhan
Li,Q.;Guan,X.;Wu,P.;Wang,X.;	Early Transmission Dynamics in Wuhan, Chi	5.2	4.1 - 7.0 (95% CI)	10	first 425 confirmed cases in Wuhan	Wuhan
Xie, M., Tian, J., Hun, M., et a	Analysis of Epidemiological and Clinical Char	6.78		9	Confirmed children cases	Wuhan
Jiang, X., Rayner, S. & Luo, M	Does SARS-CoV-2 has a longer incubation p	4.9	4.4 - 5.5 (95%CI)	50	Confirmed cases	Wuhan
Bao, H., Fang, Y., Lai, Q., et al	Comprehensive Comparisons to Demonstra	5	4 - 7.75 (IQR)	101	Confirmed hospitalized cases, All patients	Wuhan
Bao, H., Fang, Y., Lai, Q., et al	Comprehensive Comparisons to Demonstra	4	3.25 5.25 (IQR)	12	Confirmed hospitalized cases, Severe cases	Wuhan
Bao, H., Fang, Y., Lai, Q., et al	Comprehensive Comparisons to Demonstra	5	4 7.75 (IQR)	89	Confirmed hospitalized cases, Mild cases	Wuhan
Lytras, T., Panagiotakopoulo:	Estimating the ascertainment rate of SARS-C	4.38	4.34 - 4.41 (95% CI)	49948	confirmed cases	Wuhan
Zhou, F., Yu, X., Tong, X., et al	Clinical features and outcomes of 197 adult	6.14	(SD±9.27)	283	confirmed hospitalized cases who were discharged from hospital	Hubei
Ai, J., Chen, J., Wang, Y., et al	The cross-sectional study of hospitalized co	8.09 (SD±4.99)	1 - 20	44	Hospitalized confirmed cases	Hubei
Linton, N.M., Kobayashi, T., Y	Incubation Period and Other Epidemiologica	5	4.2 - 6.0 (95% CI)	52	Cases diagnosed outside of Wuhan excluding Wuhan residents	China (except Wuhan)
Linton, N.M., Kobayashi, T., Y	Incubation Period and Other Epidemiologica	5.6	5 - 6.3 (95% CI)	158	Cases diagnosed outside of Wuhan including Wuhan residents	China (except Wuhan)
Han, H.	Estimate the incubation period of coronavir	5.84	(SD ± 2.93)	59	confirmed, chain-of-infection	China (except Hubei)
Han, H.	Estimate the incubation period of coronavir	6.73	(SD ± 3.20)	32	confirmed, chain-of-infection, >=40 years old	China (except Hubei)
Han, H.	Estimate the incubation period of coronavir	4.84	(SD ± 2.28)	25	confirmed, chain-of-infection, <40 years old	China (except Hubei)
Miao, C., Zhuang, J., Jin, M., e	A comparative multi-centre study on the clir	7	3 - 9	62	Confirmed and suspect cases (incubation period based on confirmed case	China (except Hubei)
Sanche, S., Lin, Y.T., Xu, C., et	High Contagiousness and Rapid Spread of S	4.2	3.5 - 5.1 (95% CI)	24 case reports	publicly available case reports, 140	China (except Hubei, r
Leung, C.	The difference in the incubation period of 2(	1.8	1 - 2.7	175	Confirmed case in travelers to Hubei	China (excluding Hub
Leung, C.	The difference in the incubation period of 2(	7.2	6.1 - 8.4	175	Confirmed case in non-travelers to Hubei	China (excluding Hub
Lauer,Stephen A.;Grantz,Kyra	The incubation period of 2019-nCoV from p	5.2	4.4 - 6.0 (95% CI)	101	Confirmed cases	China (except Hubei)
Li, M., Chen, P., Yuan, Q., et a	Transmission characteristics of the COVID-1	7.2	(SD ± 4.11)	(modelled)	Confirmed cases	China (except Hubei)
Sanche,Steven;Lin,Yen Ting;X	The Novel Coronavirus, 2019-nCoV, is Highl	4.2	3.5 - 5.1	140	first case reports in Chinese provinces other than Hubei	China
Leung, C.	Estimating the distribution of the incubatior	1.8	1 - 2.7	152	Travelers to Hubei and non-travellers	China
Leung, C.	Estimating the distribution of the incubatior	6.9	5.5 - 8.3	152	Non-travellers to Hubei	China
Backer,Jantien A.;Klinkenberg	The incubation period of 2019-nCoV infecti	6.4	5.6 - 7.9 (95% CI)	88	Travellers from Wuhan with confirmed COVID-19	China
Guan, W., Liang, W., Zhao, Y.,	Comorbidity and its impact on 1,590 patien	3.6	0 - 7.8	1590	Hospitalized confirmed cases	China
Guan, W., Liang, W., Zhao, Y.,	Comorbidity and its impact on 1,590 patien	3.7	0 - 8	1191	Hospitalized confirmed cases, patients without comorbities	China
Guan, W., Liang, W., Zhao, Y.,	Comorbidity and its impact on 1,590 patien	3.5	0 - 7.4	399	Hospitalized confirmed cases, patients with comorbidities	China
Liu,Tao;Hu,Jianxiong;Kang,M	Transmission dynamics of 2019 novel coror	4.8 (±2.2)	2 - 11		confirmed cases	China
Guan,Wei-jie;Ni,Zheng-yi;Hu,	Clinical characteristics of 2019 novel corona	3	0 - 24	1099	patients with laboratory-confirmed cases from 552 hospitals	China

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Mechanistic modelling for pandemic preparedness

- Support decisions on resource needs for "hypothetical-yet-plausible" future pandemics
- Ready-to-go methods that can be adapted and used for long-range forecasting and to explore scenarios to support public health decisions on the use of interventions

Ogden NH et al. ***Mathematical modelling for pandemic preparedness in Canada: Learning from COVID-19***. Can Commun Dis Rep 2024;50(10):345–56. https://doi.org/10.14745/ccdr.v50i10a03

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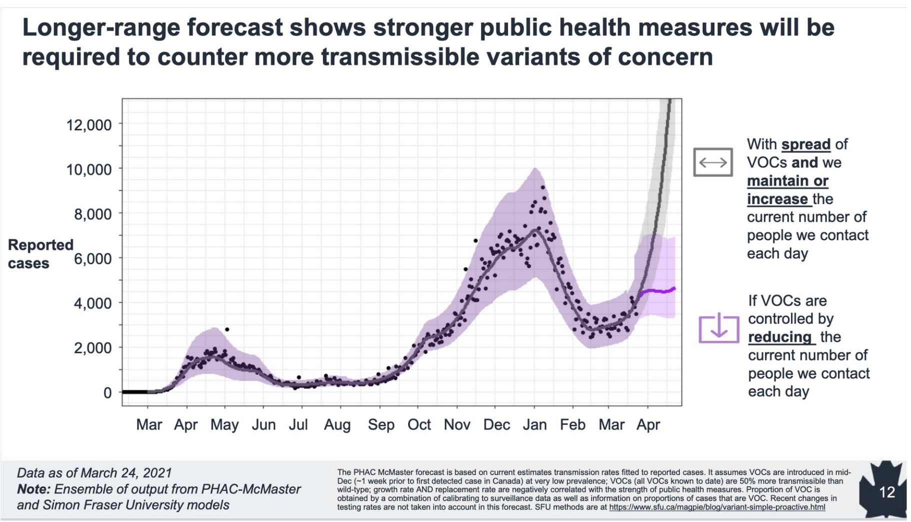
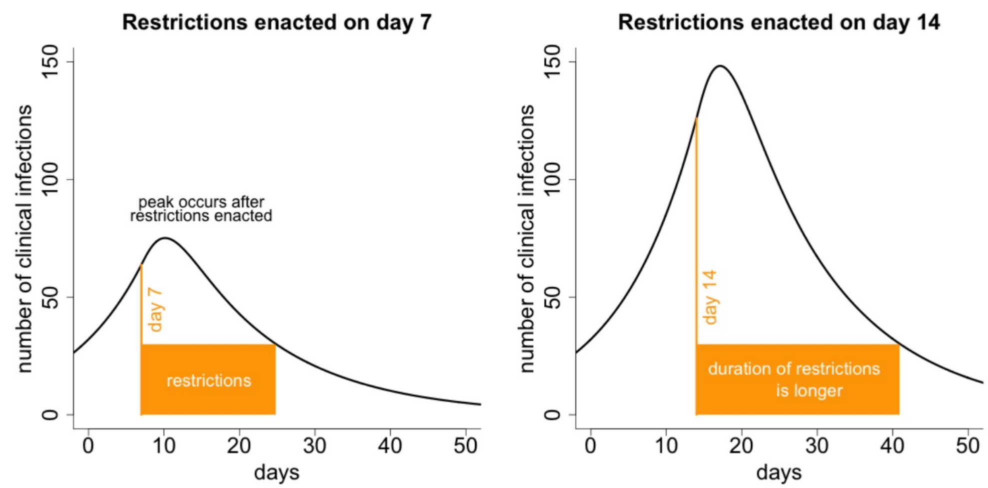
Mechanistic models

PHAC report involving McMasterPandemic



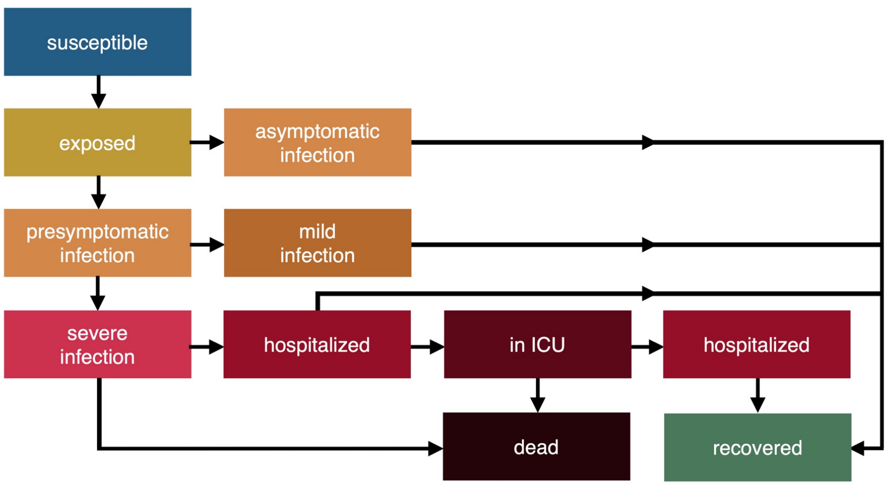


Slide by Steve Walker (https://canmod.github.io/macpan2/)

Hurford and Watmough. 2021. Don’t wait, re-escalate: delayed action results in longer duration of COVID-19 measures. MedRxiv

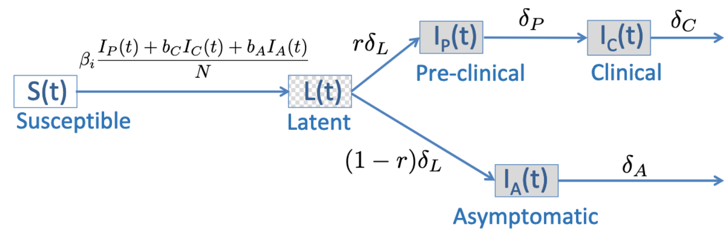
Mechanistic models

McMasterPandemic COVID-19 (Mechanistic) Model



Slide by Irena Papst/Steve Walker (https://canmod.github.io/macpan2/)

COVID-19 model



$$
\begin{aligned}
\frac{dS(t)}{dt} &= -\beta_i S(t)\frac{I_P(t) + b_C I_C(t) + b_A I_A(t)}{N},\\
\frac{dL(t)}{dt} &= \beta_i S(t)\frac{I_P(t) + b_C I_C(t) + b_A I_A(t)}{N} - \delta_L(t),\\
\frac{dI_P(t)}{dt} &= r\delta_L L(t) - \delta_P I_P(t),\\
\frac{dI_C(t)}{dt} &= \delta_P I_P(t) - \delta_C I_C(t),\\
\frac{dI_A(t)}{dt} &= (1-r)\delta_L L(t) - \delta_A I_A(t),
\end{aligned}
$$

Hurford and Watmough. 2021. Don't wait, re-escalate: delayed action results in longer duration of COVID-19 measures. MedRxiv

Mechanistic and statistical models have different roles

	Fast results	Realistic assumptions	Few cases	Insight	Reference
Agent-based model	No	Yes	Yes	A little	Adams 2020
Stochastic model	Depends	Depends	Yes	Moderate	Bertozzi et al. 2020
Compartmental model	Yes	No	No	Yes	Arino et al. 2006; Adams 2020; Saltelli et al.; Bertozzi et al. 2020
	Short-term predictions		**Scenarios**		
Statistical model	Yes		No		Holmdahl and Buckee 2020
Mechanistic model	Maybe		Yes		Funk and King 2020
Ensemble model	Yes		Yes		Adam 2020; Shea et al 2020

Fast results matters

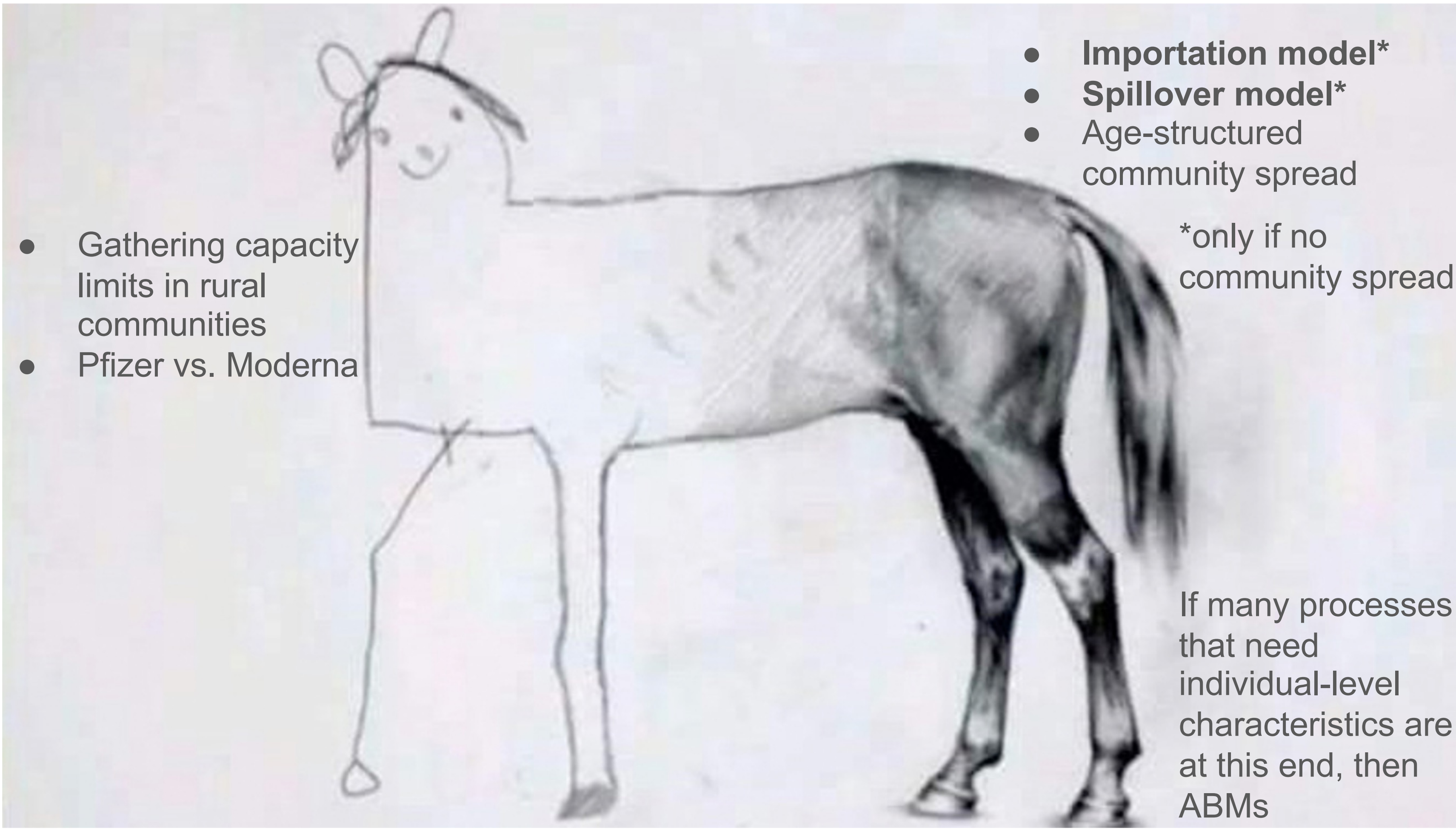
Feasibility of fitting and sensitivity analysis is a strength of fast models, i.e. ODEs
Consider a model:

- 20 parameters (no means unusual in ecology/epidemiology)
- 10 values of each parameter
- 1 second per model run

Number of required runs: 10^{20} = 100,000,000,000,000,000,000
Start time: immediately after Big Bang
Current status: 0.4% complete

Argument is from Dietz (2017) Ecological forecasting, p140

ABM vs. compartmental - conflation with model complexity

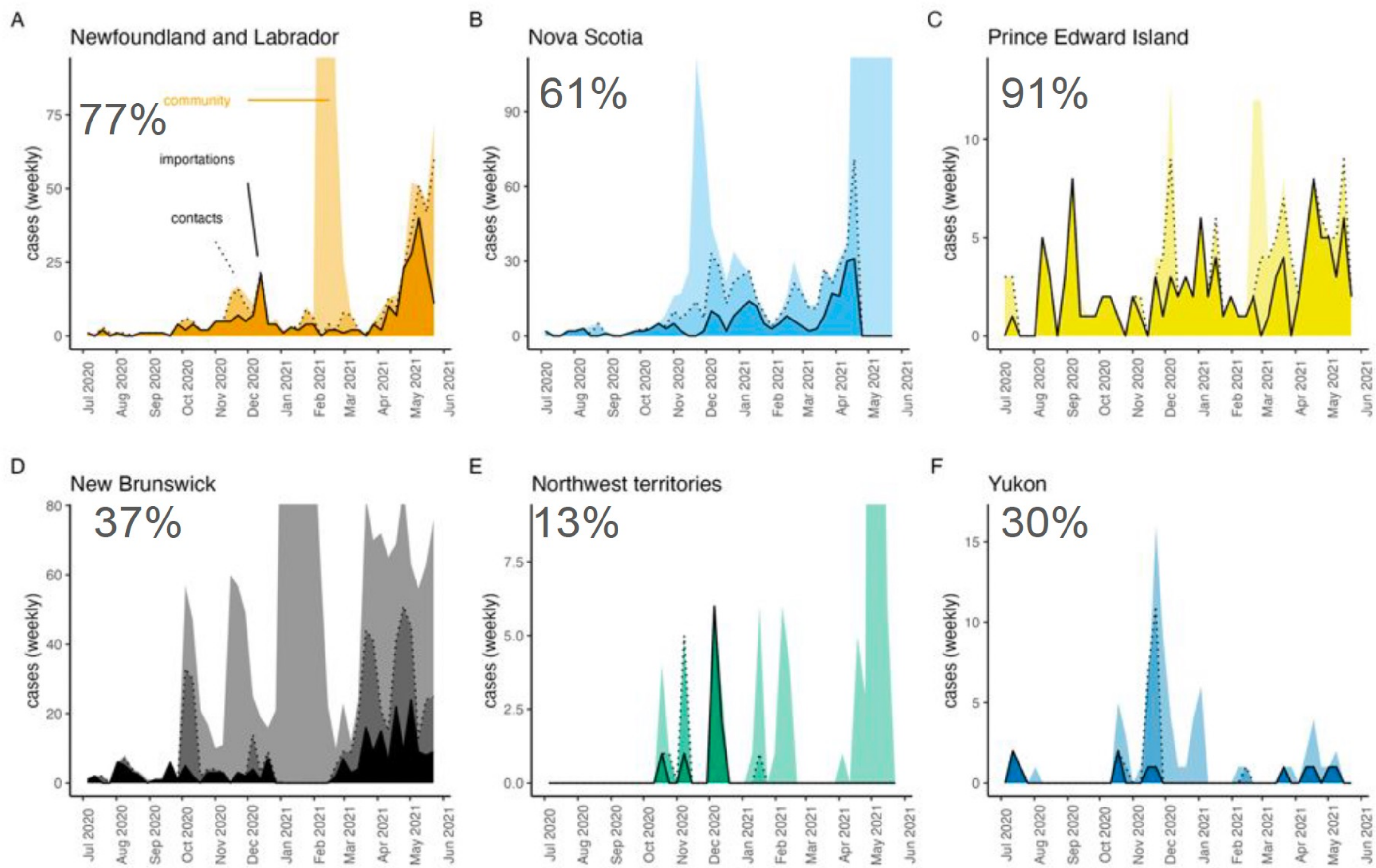


3. Different modelling needs of small jurisdictions

- Small jurisdictions had different epidemiology during COVID-19
- Small jurisdictions may have different best public health responses
- Common pitfalls that affect small jurisdictions modelling

Small jurisdictions had different epidemiology

Mean daily % of reported cases that are travel-related



Hurford et al. *Pandemic modelling for regions implementing an elimination strategy*. Journal of Theoretical Biology. 2023.

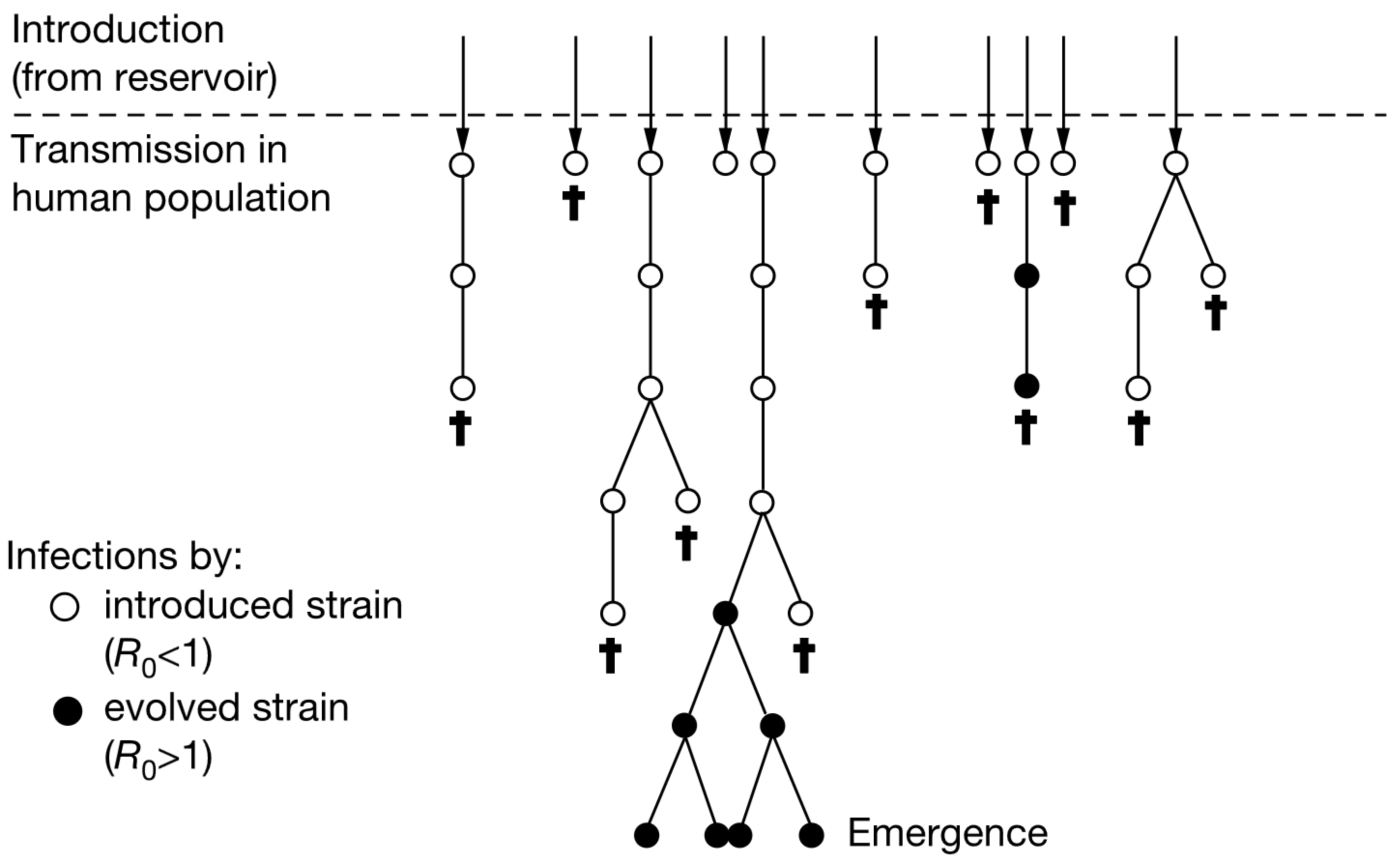
Small jurisdictions had different epidemiology

- No cases: with no confirmed cases
- Sporadic cases: with one or more cases, imported or locally detected
- Clusters of cases: experiencing cases, clustered in time, geographic location and/or by common exposures
- Community transmission: experiencing larger outbreaks of local transmission defined through an assessment of factors including, but not limited to: large numbers of cases not linkable to transmission chains; large numbers of cases from sentinel lab surveillance; and/or multiple unrelated clusters in several areas of the country/territory/area
- Pending: transmission classification has not been reported to WHO

Reporting Country/ Territory/Area	Total confirmed cases	Total confirmed new cases	Total deaths	Total new deaths	Transmission classification[i]	Days since last reported case
Hungary	4 114	7	576	3	Community transmission	0
Kyrgyzstan	3 954	228	43	1	Clusters of cases	0
Bosnia and Herzegovina	3 675	88	172	1	Community transmission	0
Greece	3 310	8	190	0	Clusters of cases	0
Croatia	2 388	22	107	0	Sporadic cases	0

WHO coronavirus (COVID-19) situational report 157 – June 25 2020

Clustered cases (Stage III: Stuttering transmission)



Antia et al. 2003. The role of evolution in the emergence of infectious disease; Lloyd-Smith et al. 2009. Epidemic dynamics at the human-animal interface.

Small jurisdictions may have different best PH responses

2021 Updated WHO recommendations

Risk-assessment approach to the implementation of risk mitigation measures for international travel

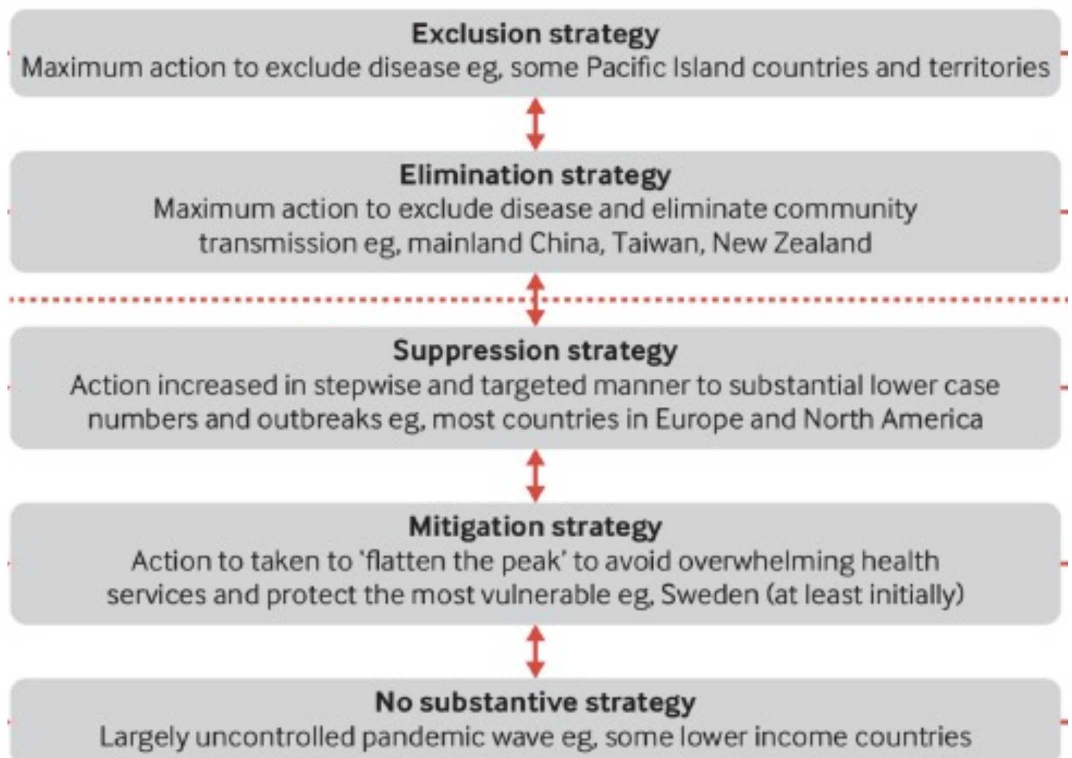
National authorities should conduct thorough, systematic and regular risk assessments as new information emerges to inform the introduction, adjustment and discontinuation of risk mitigation measures in the context of international travel.

For international inbound travel, the following factors should be considered:

- the local epidemiology (8) in departure and destination countries
- the volume of travellers between countries and existing bilateral and multilateral agreements between countries to facilitate free movement
- public health and health services performance and capacity (7) to detect and care for cases and their contacts in the destination country, including among vulnerable travellers, such as refugees, migrants and temporary or seasonal workers whose livelihoods largely depend on cross-border activities
- public health and social measures implemented to control the spread of COVID-19 in departure and destination countries and available evidence on adherence and effectiveness of such measures in reducing transmission
- contextual factors, including economic impact, human rights and feasibility of applying measures.

Technical considerations for implementing a risk-based approach to international travel in the context of COVID-19 2 July 2021

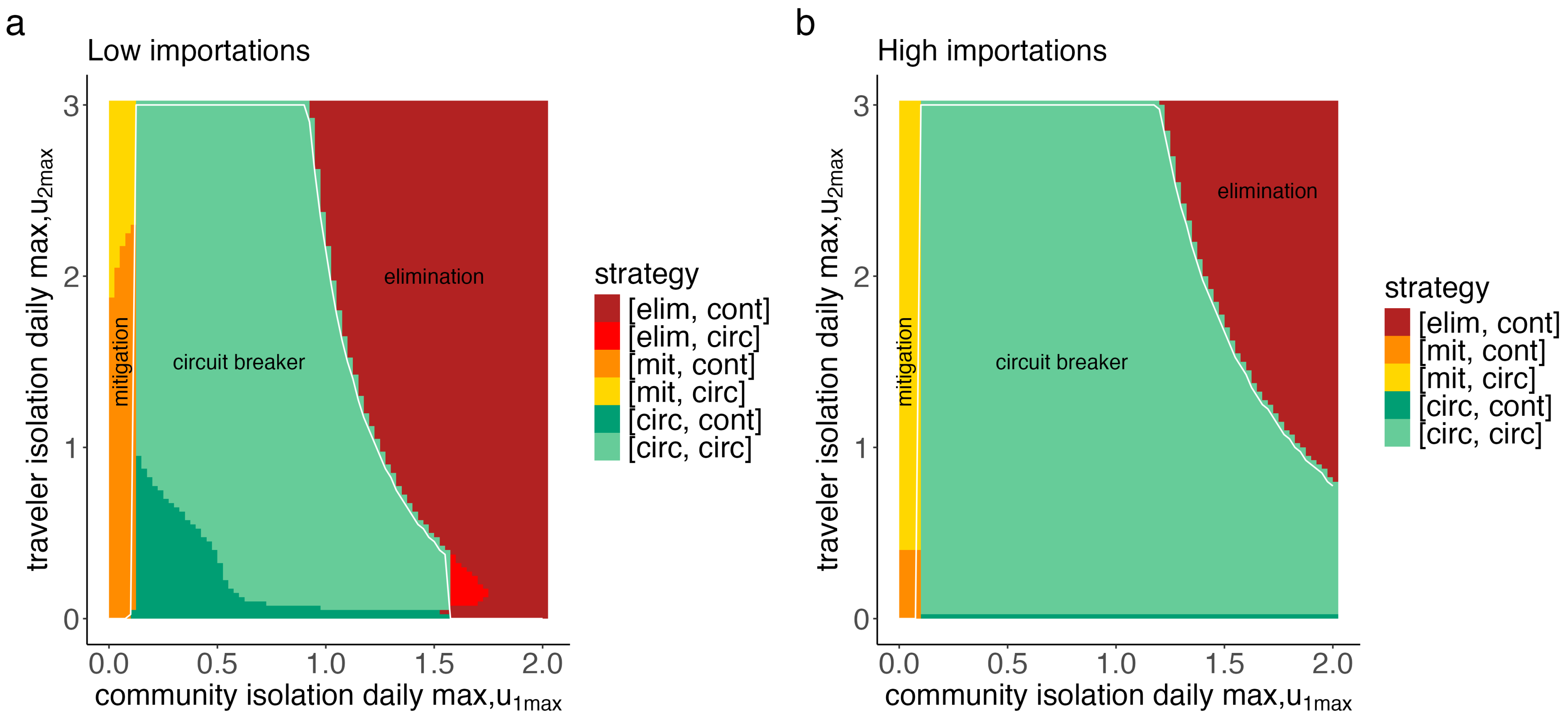
Small jurisdictions may have different best PH responses



A mitigation strategy can be continuous or circuit breaker

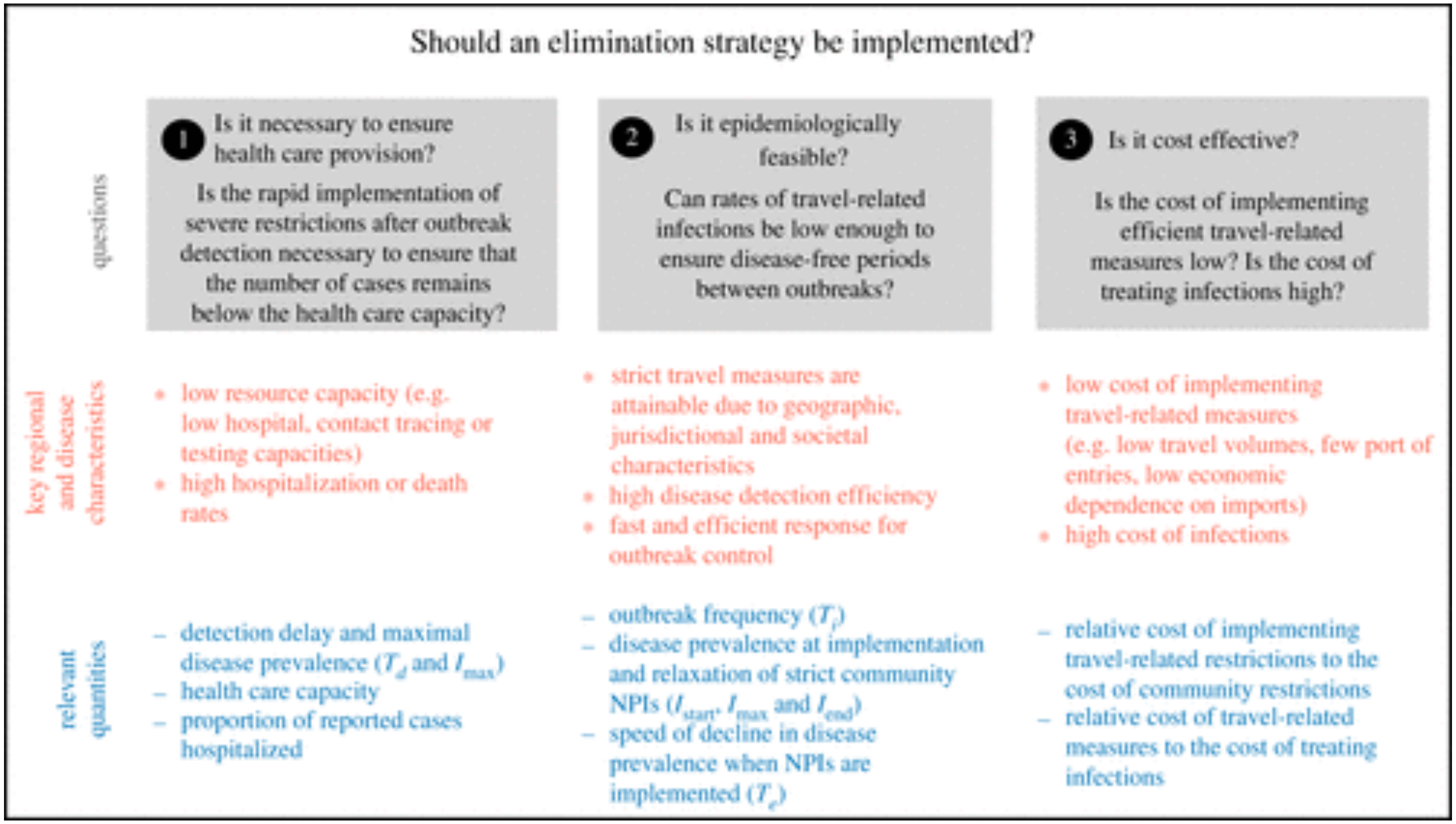
Baker et al. 2020. Elimination could be the optimal response strategy for covid-19 and other emerging pandemic diseases

Small jurisdictions may have different best PH responses

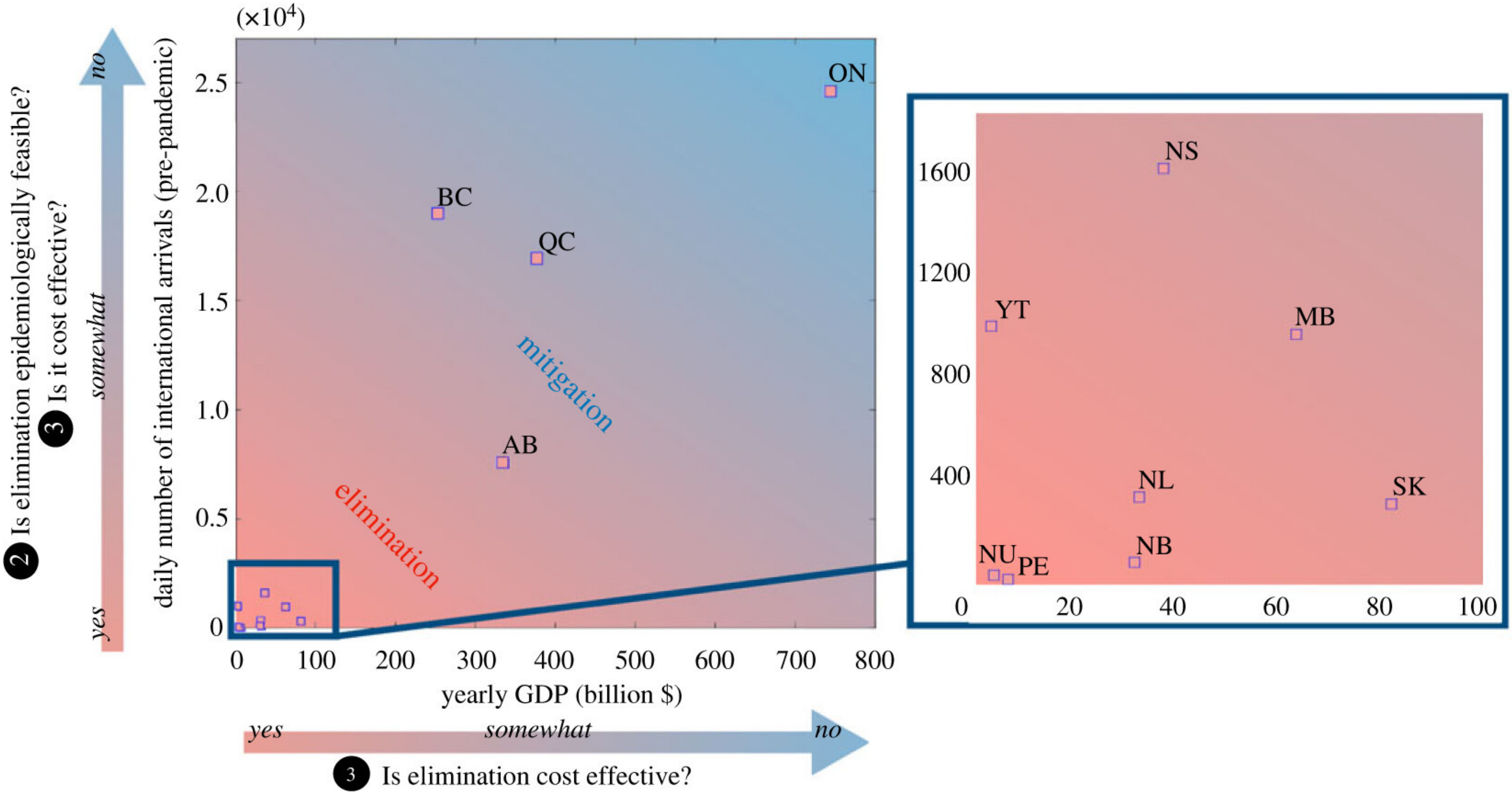


G. Adu-Boahen. Optimal Control Strategies in Epidemic Models: Analysis of Community and Traveler Isolation Strategies Under Resource Constraints. MSc thesis. 2025. Model based on Hansen and Day. 2011. Optimal control of epidemics with limited resources

Small jurisdictions may have different best PH responses



Martignoni et al. *Is SARS-CoV-2 elimination or mitigation best? Regional and disease characteristics determine the recommended strategy.* Royal Society Open Science. 2024.

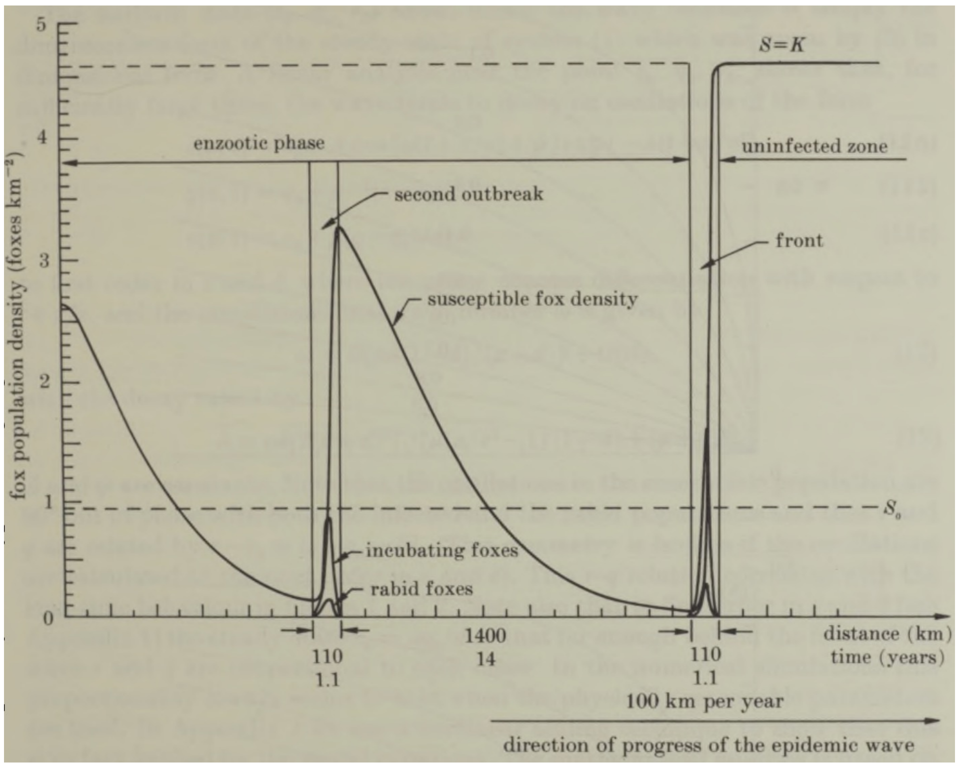


Martignoni et al. 2024. Is SARS-CoV-2 elimination or mitigation best? Regional and disease characteristics determine the best strategy

Common pitfalls that affect small jurisdiction modelling

- Pitfall 1: Atto-fox
- Pitfall 2: Island of Transmithica
- How we addressed these problems
- The problem of over-generalizing results from large jurisdictions

Murray et al. 1986: rabies would re-appear in south England 6 years later



Murray et al. 1986. On the spatial spread of rabies among foxes

- Main conclusions of Murray et al. 1986 are based on a technical error: the atto-fox (Mollison 1991)
- Aside from the error, Murray et al. 1986 is quite inspiring

Continuous dependent variables cause the atto-fox problem

- "As to the second wave, close inspection shows that the explanation lies not so much in the determinism of the model as in its modeling of the population as continuous rather than discrete and its associated inability to let population variables reach the value zero"

- ".. The density of infected [foxes] … declines to a minimum of around one atto-fox (10^{-18} of a fox) per square kilometer. The model then allows this atto-fox to start the second wave as soon as the susceptible population has regrown sufficiently."

Mollison, 1991. Dependence of epidemic and population velocities on basic parameters

Pitfall 1: atto-fox

- Concerns models where population variables never reach zero, enabling rebounds from very small values (i.e., 10^{-18})

- Affects modelling concerning:
  - Public health measures that are released
  - Elimination strategies, and travel measures
  - Transmission dynamics involving clusters of cases

- Solutions
  - End the outbreak when a small value is reached (Hansen and Day 2011)
  - Modelling outbreak duration and time between outbreaks (Martignoni et al. 2024)
  - Importation-community spread switch model

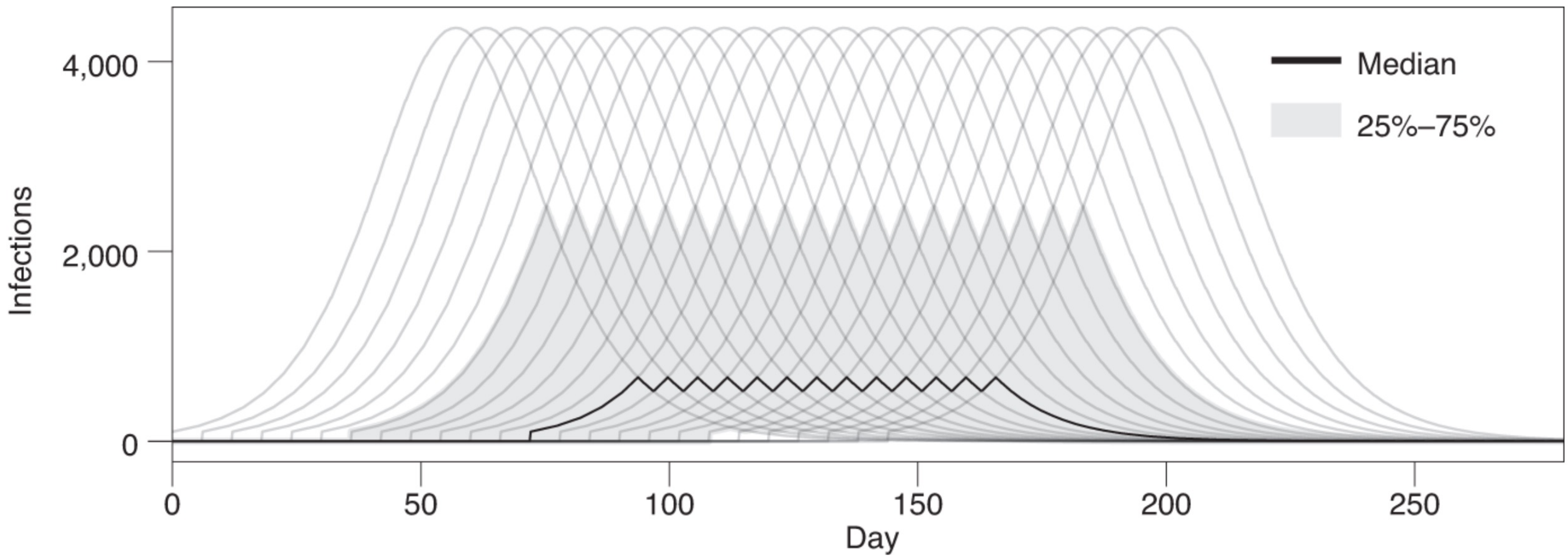
Hansen and Day. 2011. Optimal control of epidemics with limited resources; Martignoni et al. 2024. Is SARS-CoV-2 elimination or mitigation best? Regional and disease characteristics determine the best strategy

Pitfall 2: Island of Transmithica

On the island of Transmithaca, one million people lived in complete isolation from the rest of the world. A virus had ravaged the outside world, and, in the process, all viral parameters had become known with perfect precision. As Transmithaca slowly opened up for outside visitors, the inhabitants knew everything about the virus – except when it would arrive. The leaders of Transmithaca asked their epidemiologists to estimate how the disease would impact society. The epidemiologists simulated a number of scenarios, all with perfect choices of parameters, but different starting dates for the epidemic. Their simulations produced an ensemble of epidemic curves and, thinking that the individual simulated epidemic trajectories might clutter the picture, they presented the fixed-time summary statistics shown in grey and black in Fig. 1. Thus, the islanders prepared for an outbreak that might infect between 2,000 and 3,000 individuals at peak impact. As we can inspect, however, from the ensemble of time-displaced curves, the actual peak impact in every single case is more than 4,000 cases.

Juul et al. 2021 Fixed-time descriptive statistics underestimate extremes of epidemic curve ensembles

Pitfall 2: Island of Transmithica



Simulations of the outbreak on the island Transmithaca (created using a deterministic compartmental model). Grey curves show individual simulations. Median and confidence intervals calculated using fixed-time statistics are defined in the legend. Simulations are identical except for the date on which the outbreak starts. The fixed-time descriptive statistics do not capture peak numbers of infections.

Juul et al. 2021. Fixed-time descriptive statistics underestimate extremes of epidemic curve ensembles

Pitfall 2: Island of Transmithica

- Concerns uncertain start dates

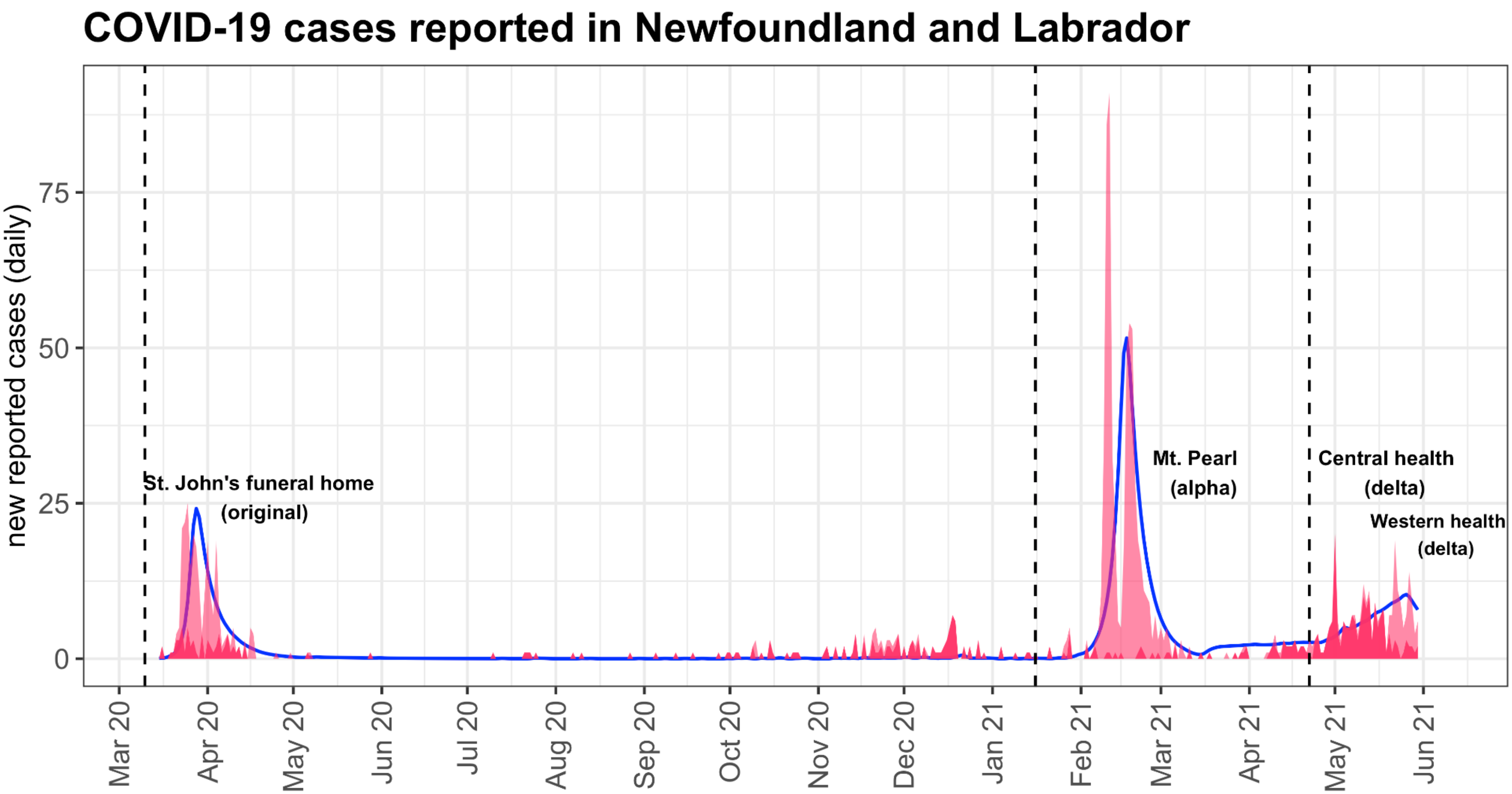
- Affects:
  - Deterministic, stochastic, and agent-based models;
  - Regions that have no community outbreaks;
  - Models linking importation models to community spread models;
  - Ensemble forecasts of hospitalizations during the COVID-19 pandemic in the Netherlands (Juul et al. 2021)

- Solutions (see Juul et al. 2021 for details):

  (1) curve-based summary statistics

  (2) summarizing estimated likelihoods of specific scenarios of interest

How we addressed these problems



Model fitting: importation-community spread switch model

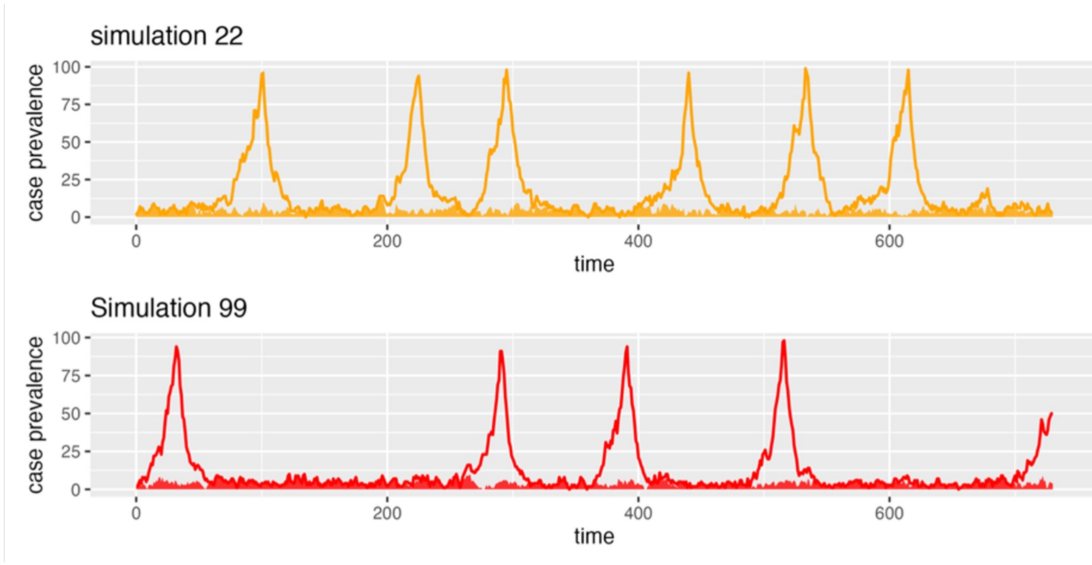
- Data: incidence of travel-related cases (dark shading) and community cases (light shading)
- Include a model variable that is travelers in isolation
- 10 days before a reported community outbreak, briefly allow the rate that an isolating traveler infects a susceptible community members to be positive (vertical dashed line)
  - All other times this rate is 0
- When infection incidence is less than a small threshold, set to 0.

Features of the importation-community spread switch model

Overcomes:

- Pitfall 1 (atto-fox) by setting low incidence to 0
- Pitfall 2 (Island of Transmithica) by fixing the community outbreak start dates (vertical dashed lines). Start date is not treated as uncertain.

Scenario modelling, i.e. following from the switch model



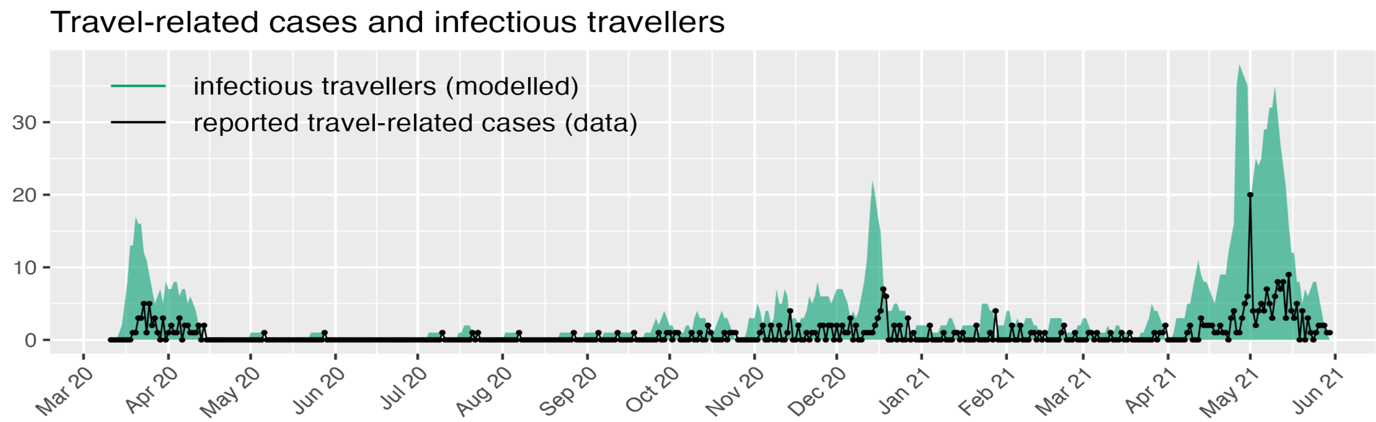
- Community outbreak dates determined by travel-related cases (details next slide)

- $R_t > 1$ except from when community cases ≥ 100 until elimination

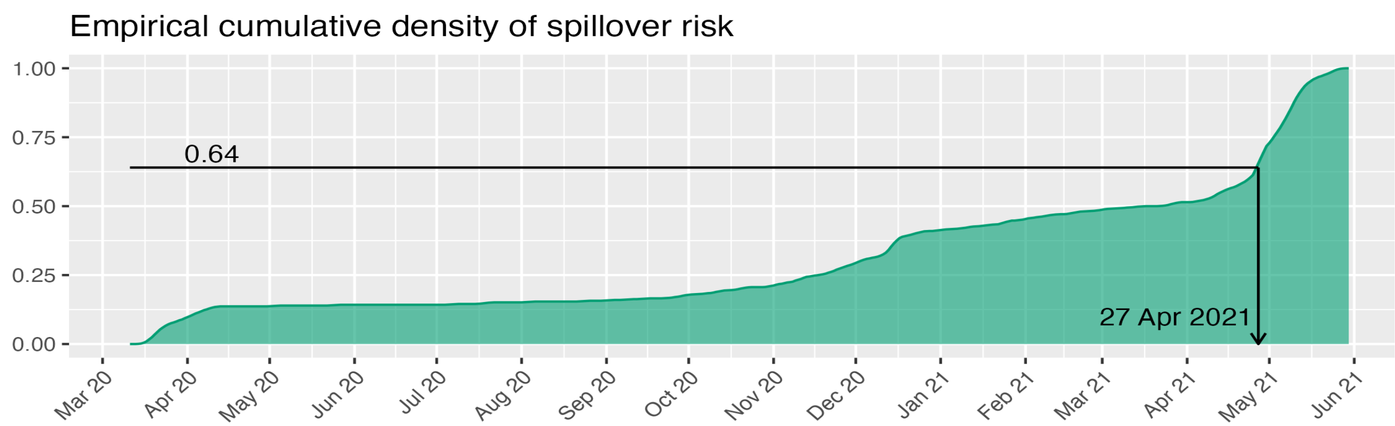
Multiple realizations
DO: • Av. number of community outbreaks • Av. size of community outbreak • Av. days without community cases DO NOT: • Av. prevalence at a given time • Put too much significance in the start date of an outbreak

Determining when the outbreaks start for the scenario modelling

Use travel-related case data and a model to estimate infectious travelers (prevalence)



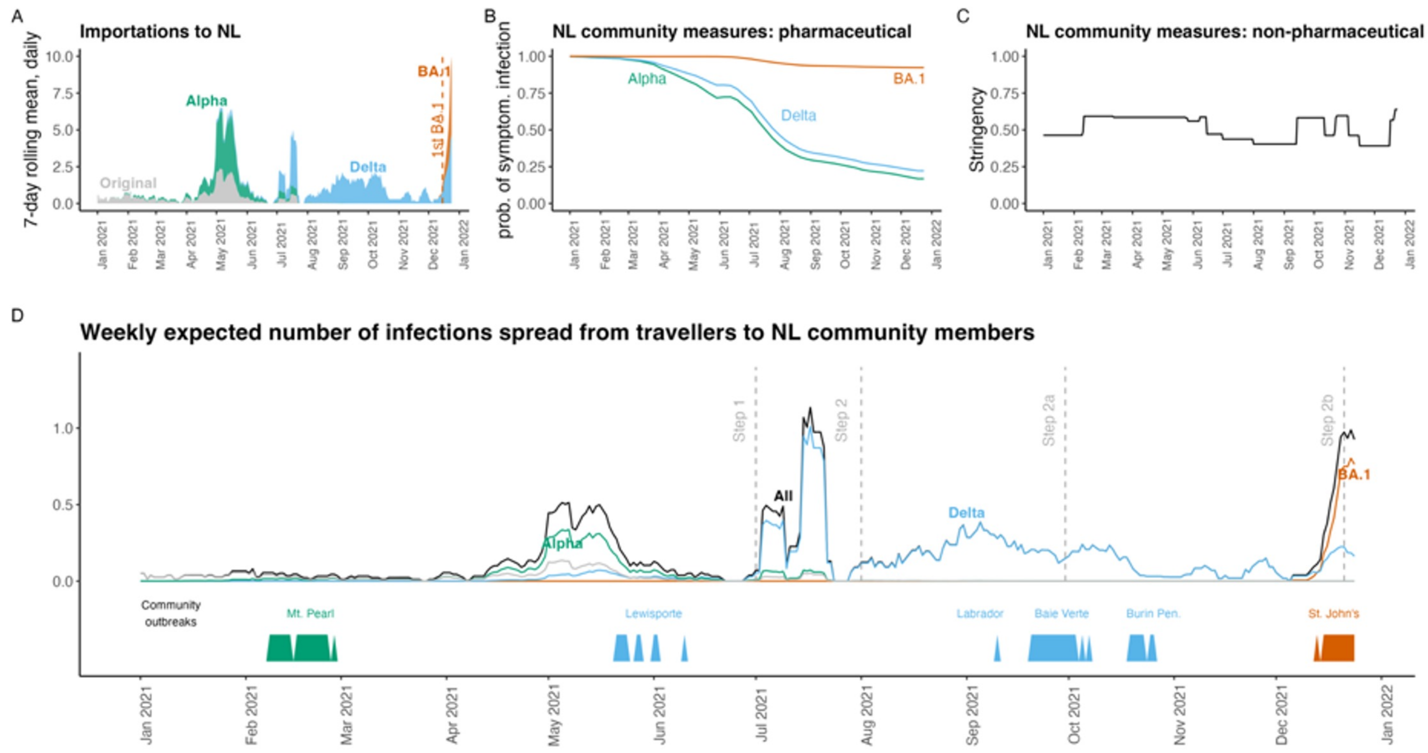
Use the inverse cumulative method to sample the start dates for community outbreaks from the empirical density of infectious travelers (prevalence)



Determining when the outbreaks start for the scenario modelling

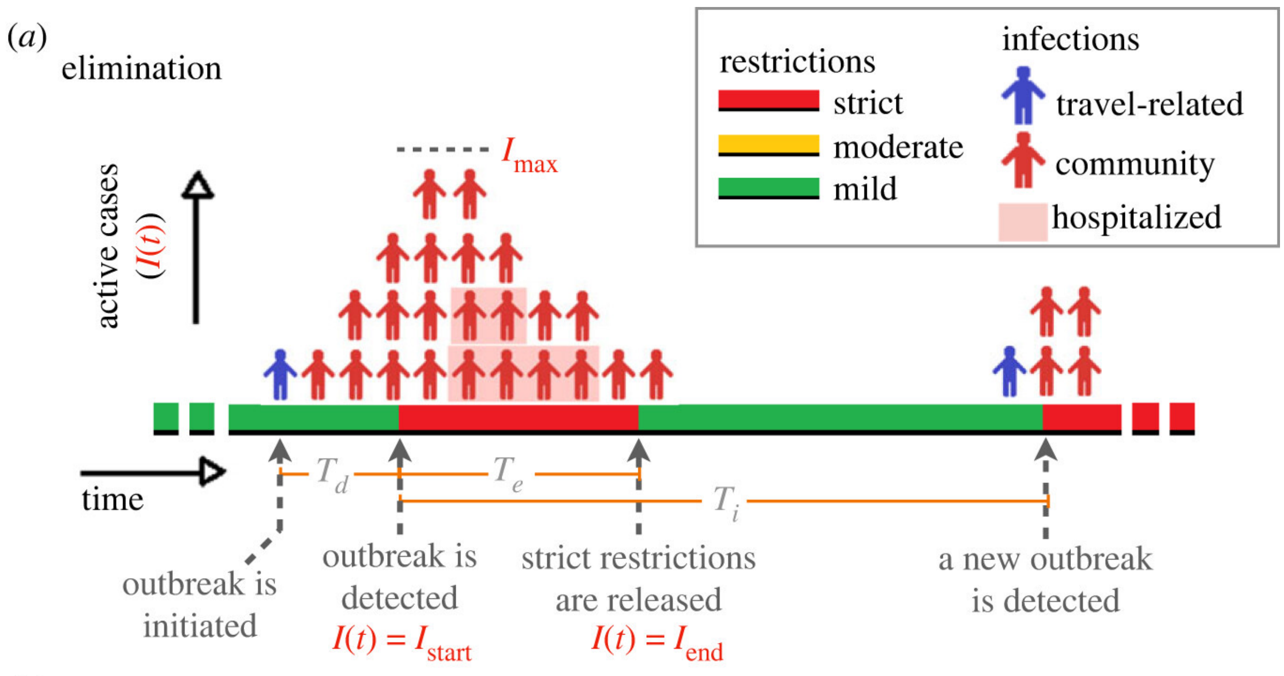
Extend this idea by using the same method for a more detailed spillover model

i.e., make D into a cumulative density and use inverse method



Hurford et al. 2023. Pandemic modelling for regions implementing an elimination strategy

Fixes: Modelling outbreak duration and time between outbreaks

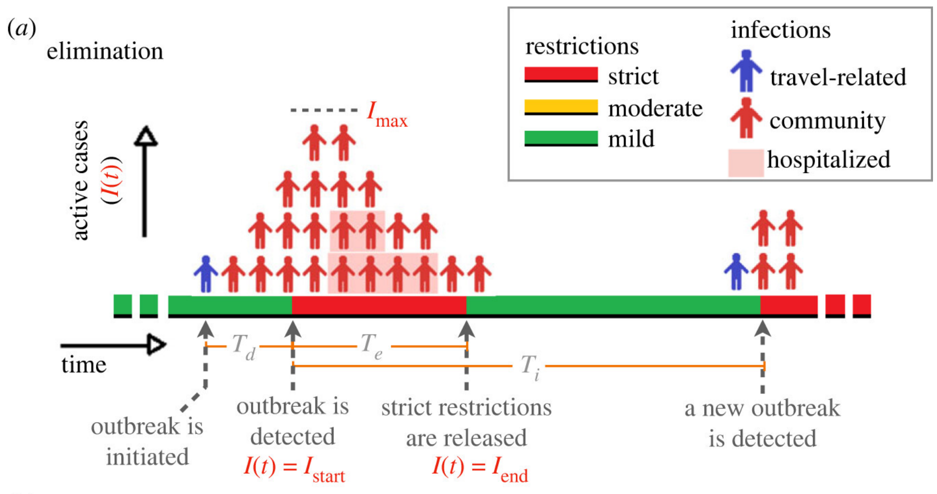


Dr. Maria Martignoni

Could be modelled as a branching process or an agent-based model, but atto-fox problem is “not so much about the determinism”.

Martignoni et al. 2024. Is SARS-CoV-2 elimination or mitigation best? Regional and disease characteristics determine the best strategy

Fixes: Modelling outbreak duration and time between outbreaks



Percentage of days with mild restrictions, $T_e < T_i$

$$\frac{T_i - T_e}{T_i} \times 100$$

$$T_e = \frac{\ln(I_{\mathrm{start}}/I_{\mathrm{end}})}{\gamma(1 - R_c)}$$

Martignoni et al. 2024. Is SARS-CoV-2 elimination or mitigation best? Regional and disease characteristics determine the best strategy

Problem: Over-generalization from large jurisdictions

Concerns using community spreads models (i.e., SIR) and resulting recommendations in regions where community spread is not occurring

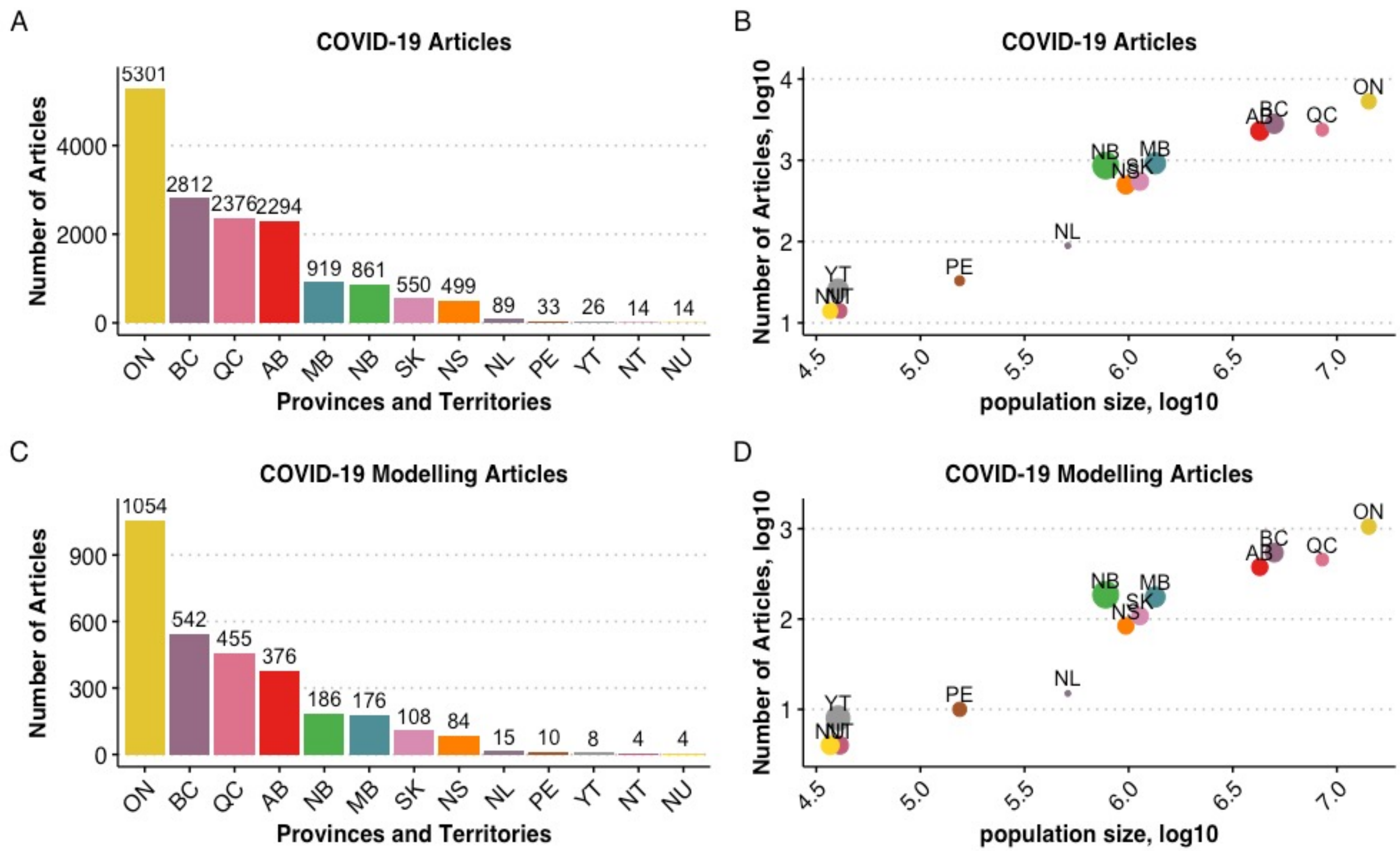
Affects:

- Regions without community spread
- Underserved and under-resourced jurisdictions

Solutions:

- Do the modelling correctly
- Multijurisdictional representation
- Serving and resourcing all jurisdictions
- Canadian small jurisdictions modelling group (CanSJ)

Small jurisdictions are under-resourced



Small jurisdictions are under-resourced

“the need for additional public health physicians is most acute in rural areas, the Atlantic provinces, the territories and areas served by Health Canada’s First Nations and Inuit Health Branch".

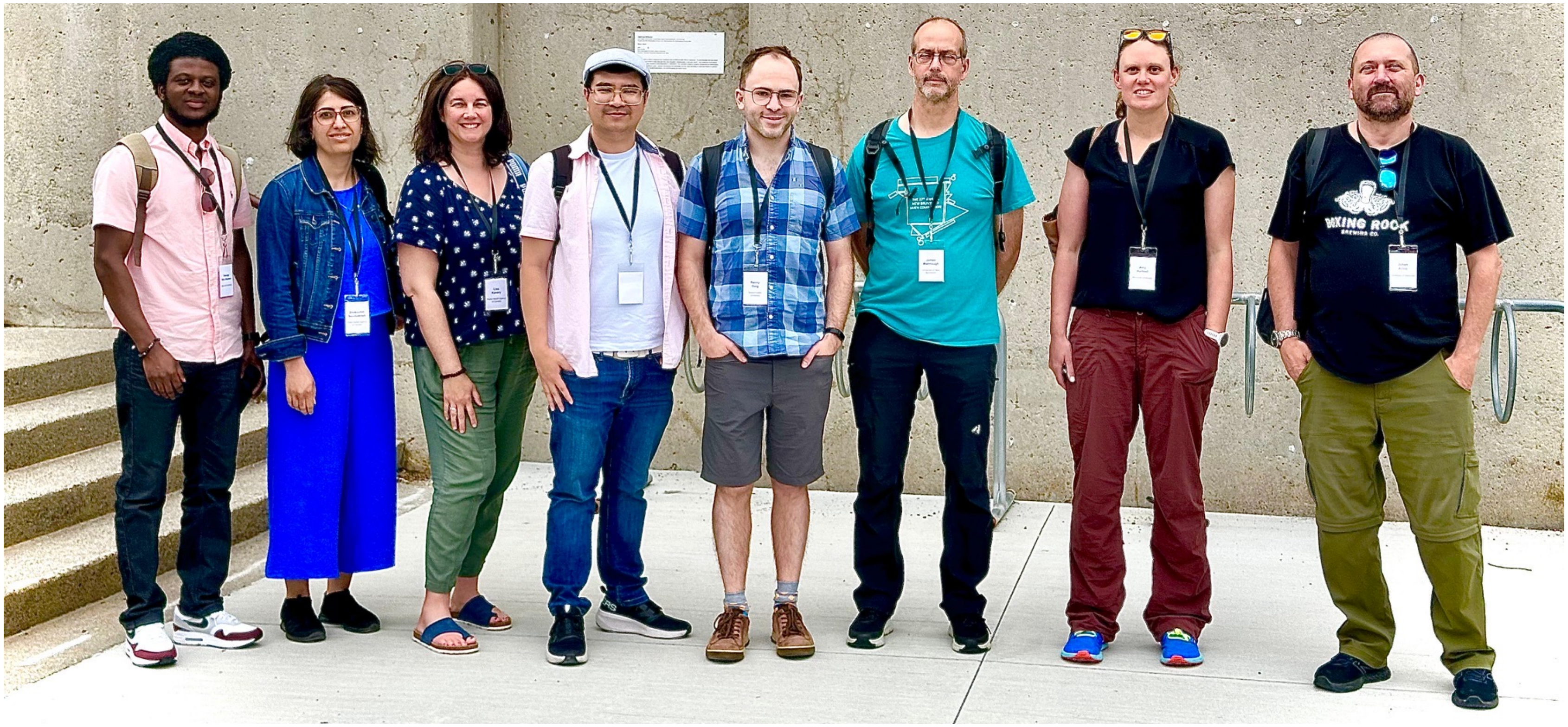
--- 2003 report by the National Advisory Committee on *SARS and Public Health*

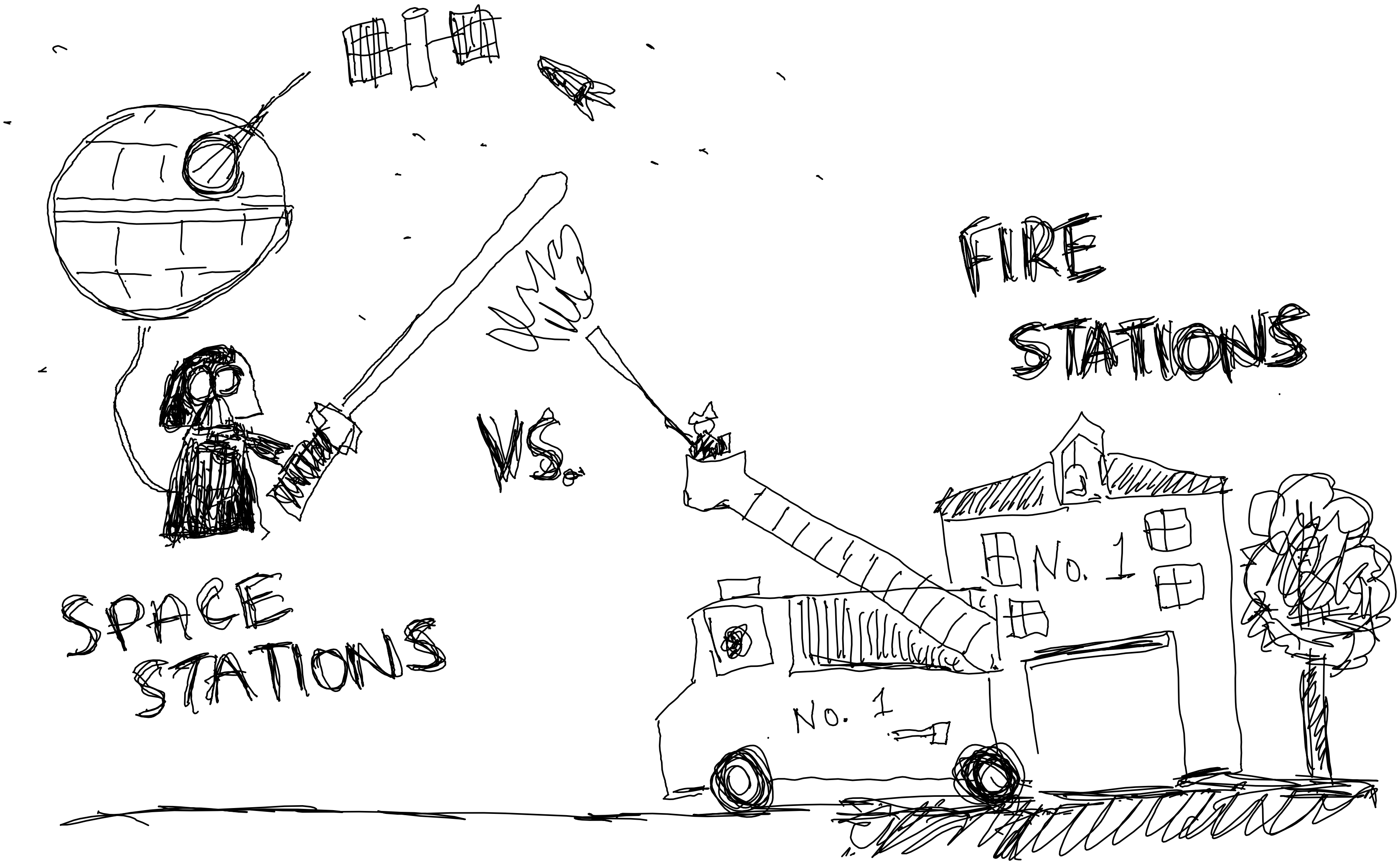
Small jurisdictions can be overlooked

- American Samoa was one of the few places to report no mortalities from the 1918 influenza pandemic
- Maritime quarantine, including several day wait period before disembarking maintained until at least 1920
- Outbreak in 1926 resulted in clinical infections in 25% of the population;
- 1/1000 residents died, ~200 lower than overall mortality in nearby Western Samoa

Shanks and Bundage. 2012. Pacific islands which escaped the 1918–1919 influenza pandemic and their subsequent mortality experiences

Canadian Small Jurisdictions Working Group (CanSJ)




SPACE STATIONS
VS.
FIRE STATIONS
No. 1
No. 1

Reasons for fire stations

- Most of us experienced the COVID-19 public health emergency in primarily one place. Anecdotally, you need some local expertise or critical errors are likely (no slides on this – just recounting my observation)

- Regional characteristics determine the best public health response

- Small jurisdictions are under-resourced and their needs can be overlooked, or falsely assumed, in bigger conversations

Reasons for space stations

- Under-resourced jurisdictions need access to the best experts too!

Changing contact patterns in Newfoundland and Labrador, Canada in response to public health measures during the COVID-19 pandemic

Renny Doig[1*], Amy Hurford[2,3*], Liangliang Wang[1], Caroline Colijn[4]

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Reasons for space stations

macpan2 1.16.7

macpan2

McMasterPandemic was developed to provide forecasts and insights to Canadian public health agencies throughout the COVID-19 pandemic. Much was learned about developing general purpose compartmental modelling software during this experience, but the pressure to deliver regular forecasts made it difficult to focus on the software itself. The goal of this `macpan2` project is to re-imagine `McMasterPandemic`, building it from the ground up with architectural and technological decisions that address the many lessons that we learned from COVID-19 about software.

The Public Health Risk Sciences Division at the Public Health Agency of Canada uses `macpan2` (for example, here).

Authors

Steve Walker. Maintainer, author.

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Jen Freeman. Author.

Ben Bolker. Author.

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Irena Papst. Contributor.

Michael Li. Contributor.

Kevin Zhao. Contributor.

Our current projects using macpan2

- *Estimating the undiagnosed fraction of Hepatitis C in NL*
  Collaborators: Laura Bruce and Peter Daley (Memorial U)

- *Estimating human infections of avian influenza*
  Collaborators: Josh Mack, Joseph Baafi, Andrew Lang, Kathryn Hargan (Memorial U), Randy Green (Miauwpkek FN), ECCC, Govt of Nunatsiavut, Nunatukavut CC

- *Building a general modelling framework for pandemic and non-pandemic SARS-CoV-2 and Avian influenza, malaria, Arctic rabies, and Lyme disease*
  Collaborators: Michael Li (PHAC) and Memorial U

Pandemic preparedness needs modelling preparedness

1. There was high demand for modelling during the pandemic
2. Mechanistic and statistical models have different roles in pandemic decision support
3. The modelling needs of small jurisdictions can be different than the modelling needs of large jurisdictions.
4. Building capacity in mathematical biology and statistics in Atlantic Canada

Acknowledgments

Memorial U Proton Rahman; J.C. Loredo-Osti; Maria Martignoni; Francis Anokye; Joshua Renault; Joesph Baafi; George Adu-Boahen

Guelph U Zahra Mohammadi; Monica Cojocura

PHAC Michael WZ Li; Nicholas Ogden; Lisa Kanary

McMaster U Steve Walker

NLHS – Digital Health Kendra Lester; Alicia Blackmore

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U New Brunswick James Watmough

Simon Fraser U Caroline Colijn; Renny Doig; Liangliang Wang

NLHS Suzette Spurrell; Andrea Morrissey

CanSJ