Modelling SARS-CoV-2 disease progression in Australia and New Zealand: an account of an agent-based approach to support public health decision-making

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Abstract

Objective: In 2020, we developed a public health decision-support model for mitigating the spread of SARS-CoV-2 infections in Australia and New Zealand. Having demonstrated its capacity to describe disease progression patterns during both countries' first waves of infections, we describe its utilisation in Victoria in underpinning the State Government's then 'RoadMap to Reopening'.

Methods: Key aspects of population demographics, disease, spatial and behavioural dynamics, as well as the mechanism, timing, and effect of non-pharmaceutical public health policies responses on the transmission of SARS-CoV-2 in both countries were represented in an agent-based model. We considered scenarios related to the imposition and removal of non-pharmaceutical interventions on the estimated progression of SARS-CoV-2 infections.

Results: Wave 1 results suggested elimination of community transmission of SARS-CoV-2 was possible in both countries given sustained public adherence to social restrictions beyond 60 days' duration. However, under scenarios of decaying adherence to restrictions, a second wave of infections (Wave 2) was predicted in Australia. In Victoria's second wave, we estimated in early September 2020 that a rolling 14-day average of <5 new cases per day was achievable on or around 26 October. Victoria recorded a 14-day rolling average of 4.6 cases per day on 25 October.

Conclusions: Elimination of SARS-CoV-2 transmission represented in faithfully constructed agent-based models can be replicated in the real world.

Implications for public health: Agent-based public health policy models can be helpful to support decision-making in novel and complex unfolding public health crises.

Key words: COVID-19, infection, agent-based model, ABM, policy

The first notification of SARS-CoV-2 infections in Australia and New Zealand (NZ) [1] were 26 January and 26 February 2020, respectively.[2,3] The public health response to managing the pandemic in both countries involved the testing of individuals showing symptoms of SARS-CoV-2 infection, isolating individuals with a positive polymerase chain reaction (PCR) test, and tracing and quarantining contacts. On a country scale, comprehensive physical distancing strategies were in place from 28 March in Australia[3] with people asked to remain at home other than for essential purposes and maintain a 1.5-metre distance between one another when in public; these had been lifted or re-imposed at varying times by states and territories since mid-May 2020. In New Zealand, similar mass home quarantine was initiated on 26 March 2020,[4] which placed even tighter restrictions on individual movements than in Australia, with staged lifting commenced in mid-May.[5] Both countries have ongoing enhancements of the health system capacity and continue (as of October 2021) extensive travel restrictions including the closure of country borders to non-residents and 14-day quarantine for the small number of international arrivals still permitted. For the state of Victoria, Australia, a second wave of infections sparked by hotel quarantine breaches occurred in July, which led to the implementation of 'Stage 4' restrictions through to late October 2020.

The public health response implemented in Australia and New Zealand initially focussed on suppression ('flattening the curve'). Later, the New Zealand strategy explicitly became that of elimination.[6,7] In Australia, the stated goal waxed between that of 'suppression/elimination'[8] before transitioning to 'aggressive suppression leading to zero community transmission'.[9]

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A limitation of population-level macro-simulation models that informed government decision-making in Australia and New Zealand in the early stages of the pandemic in 2020 was their inability to efficiently combine the three major dynamics affecting disease progression: biomedical, social and spatial.[10,11] Modelling conducted in early 2020 by the Australian and New Zealand governments using the susceptible-exposed-infected-recovered (SEIR) concept[12,13] was useful in publicly communicating and comparing the health impact of unmitigated and/or suppressed pandemic scenarios. However, this simplified approach left important public health policy questions unanswered that may have benefitted from investigation through alternative methods able to more faithfully represent population heterogeneity and behavioural mechanisms driving disease transmission and progression through societies. For example, macro-simulation models could not easily capture the heterogeneity of individuals across important, interacting variables such as gender, age, health status, worker status, stage of infection or illness, infectiousness, social networks, illness duration, asymptomatic status, over-dispersion of contacts and forward transmission, compliance with public health directions, location, travel behaviour or other phenomena without quickly becoming intractable;[14] yet these interacting factors remained no less important to understanding disease spread through a society and the likely success of public health interventions, whether they were easily modelled or not.[15] Similarly, although micro-simulation models[16] can capture some of the heterogeneity described above, they remain limited in their ability to represent both spatial phenomena and behavioural dynamics representative of interactions between individuals or between individuals and institutions,[17] which are important in the consideration of practical public health policy delivery. At the time, our research group's contention was that Agent-Based Models (ABMs) that could represent small-scale interactions of individuals constructed in artificial or 'synthetic' populations might provide additional, useful insight into how behaviour affects disease progression and also how public health policy options available to government might affect the progression of infections and COVID-19 cases. We considered that by modelling not just the disease dynamics, but the social and spatial elements that lead to its transmission, it would be possible to better understand the impact of available public health policy options and likely patterns of disease progression across a society.

Our practical aim in these early stages was to demonstrate to public health decision-makers and policy-makers that the nature of existing macro-models excluded the consideration of potentially valuable policy options and strategies (e.g. elimination of local community transmission). Further, we contended that ABMs could assist policy-makers to more effectively investigate the effect of existing public health strategies, interventions, and/or assist the exploration of strategies for when restrictions could be safely halted or partially removed in response to declining SARS-CoV-2 infection numbers and/or the introduction of vaccination programs.

We therefore provide here a historical account of the development and progression of two, linked research efforts that were aimed at informing Australia and New Zealand's public health response to the pandemic. Firstly, we describe the construction and application of an ABM incorporating biomedical, social and spatial factors to estimate the probability of elimination of community transmission of SARS-CoV-2 under: i) strict distancing policies implemented in New Zealand and Australia on 26 and 28 March 2020, respectively, continuing indefinitely (counter to fact); and ii) the same policy, but with physical distancing decaying over 60 days post 26 and 28 March (but ongoing border closure, testing and contact-tracing; crudely approximating policy that actually played out). Secondly, we describe the subsequent adoption and practical application of this model by the Victorian State Government, which used it to assist in developing its plan for exiting from a significant second wave of infections from July to October 2020.[18,19]

Methods

We created an agent-based, dynamic policy model similar in structure to those described elsewhere,[2,11,20,21] but specifically designed to be conceptually transparent enough for comprehension by, and interaction with, policy-makers. We also built it to be flexible enough to be rapidly adapted and tuned to a broad range of domestic and international demographic and policy scenarios. All programming, documentation, data and details related to the calculations, estimations and assumptions for the Wave 1 model are available for download from the online repository (https://bit.ly/2XI3v3z). A brief model description covering key inputs and model design is included below, however, a comprehensive description of the model following the standards of the Overview, Design concepts and Details (ODD)[22] protocol for ABMs is provided as a Supplementary File. This ODD protocol is not static and develops alongside the ongoing expansion and refinement of the model itself.

The model was scaled to the entire Australian (25 million) and New Zealand (5 million) populations and included a suite of parameters for the purposes of investigating the likelihood of SARS-CoV-2 progression and/or elimination of community transmission in both countries under two primary public health intervention scenarios (e.g. enacting or relaxation of social restrictions). We determined the elimination of community transmission to be when zero cases of COVID-19 were observed in either modelled population. This modelled definition can be more certain than in a real-life context[7] as the model user has perfect information about the presence of active cases in the model (in reality, New Zealand and Australia adopted an informal definition of 28 days without a case arising from community transmission as a working definition of local elimination).

Model development context

In an unfolding pandemic, evidence can and does change rapidly and the time scales for critical public policy decision-making may be measured in hours or days rather than months.[23] Therefore, the model was built using parameters from the pandemic in Australia and New Zealand understood at the time of construction and application. The model was/is capable of taking account of contemporary and dynamic evidence surrounding important factors that influence SARS-CoV-2 infection patterns such as physical distancing measures, school, workforce and public movement restrictions, as well as infection transmission characteristics, and the time it takes to recover from and clear infection. The model was built to simulate the dynamics of SARS-CoV-2 at either a country, state or local level. More recent iterations also incorporate vaccine effectiveness and distribution strategies, though these functions were not used in the applications described here because, at the time of development, vaccines were not available.

For each selected jurisdiction (e.g. country or state), individual agents making up a synthetic population representing residents of either Australia, New Zealand or Victoria were produced. Each agent possessed demographic, behavioural, and social policy response characteristics uniquely assigned to them. Agents moved and interacted in the model environment based on stochastic processes and/or in response to policies reflecting exogenous restrictions or individual decisions. Their aggregate behaviour, experiences (for example of infection and recovery) and actions were used to assess the effect of SARS-CoV-2 disease progression and suppression strategies across populations.

The computing demands and development time required to build and run a 1:1 scaled agent-based model representing potentially millions of people can be considerable. This makes analysis associated with rapid changes in policies and time-critical decision-making difficult in an unfolding pandemic. Hence, published individual and agent-based models used to inform policy in the early stages of the pandemic in both the United Kingdom and Australia were often adapted from existing influenza models.[2,24] Despite their influence and utility, they have also been criticised from the perspective of transparency (e.g. the model code is not available), scale (e.g. local vs. national dynamics), and limited incorporation of social and behavioural dynamics related to adherence that either facilitate or suppress SARS-CoV-2 spread.[25] Their ability to be easily applied outside their specific countries of origin is also limited.

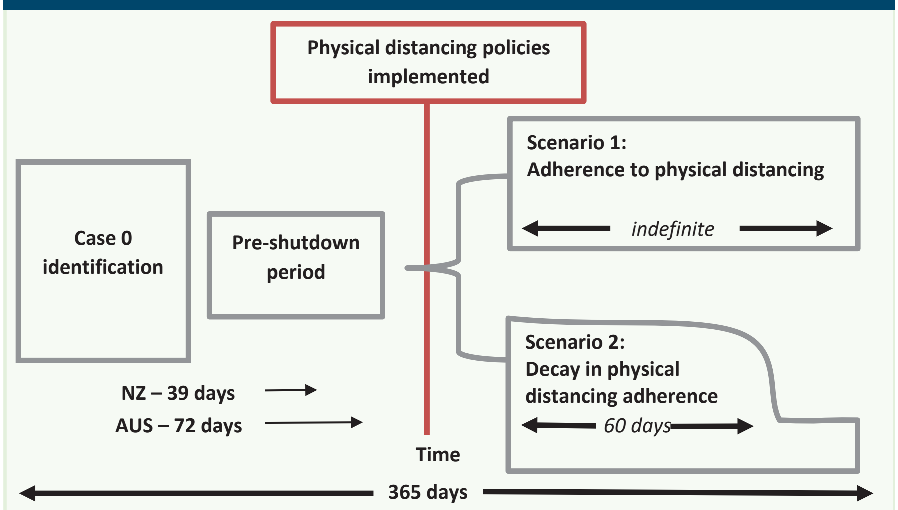
Therefore, instead of representing the entire population of individuals (e.g. 25,000,000 for Australia), the total number of agents in the model did not change, however, the number of people that each agent in the model represented did. This dynamically aligned the scale of the model with the likely scale of public interest and public health policy decision-making at the time. For example, in the early and late stages of Wave 1 infections in Australia and New Zealand, single identified COVID-19 cases (e.g. hotel quarantine workers, doctors, etc), exposure sites (e.g. hospitals) and circumstances were described by public health authorities in great detail, with infection control measures targeted at these manageable outbreak sites (e.g. localised testing and tracing, deep cleaning, etc). However, as daily reported infections reach(ed) 300 per day at the peak in Australia in around late March 2020, or upwards of 700 in Victoria during August 2020, the scale of pattern description, policy and public interest similarly scales up; individual circumstances and cases are no longer policy-relevant and instead, broad-based population health measures are described and required. At the tail-end of the epidemic curve, the model returns again to a small scale and representation of interest that identifies individual cases and locations (e.g. one infected agent represents one infected person).

Exploration of public health policy scenarios during Wave 1 in Australia and New Zealand

As the first wave of infections took hold in Australia and New Zealand, we explored two scenarios for each country, namely: i) strict physical distancing policies implemented in New Zealand and Australia on 26 and 28 March, respectively, continuing indefinitely; and ii) the same policy, but with public adherence to physical distancing decaying over 60 days post-implementation (see Figure 1) to a residual level of 20% of maximum, reflecting medium- to long-term behaviour shifts as a result of the pandemic but with continued tracking, tracing and isolation of infected individuals by the health system. All model iterations ran for 300 simulated days. Estimated median time to elimination with 95% simulation intervals (SI) was reported for Australia and New Zealand, alongside estimated dates for elimination with 80 and 90% likelihood. Because it is underpinned by stochastic processes, we analysed results from 1,000 model runs.

The model used for Australia and New Zealand's Wave 1 was initially populated by 2,500 people with 2,498 people susceptible. Time was scaled to one day per model time-step. Two people were classified as infected with SARS-CoV-2 and could potentially infect others. In the early stages of model runs, people moved in random directions throughout the simulated community (i.e. this is a 'drifting' model, as opposed to constructions that include origins and destinations of specific types such as cafes, workplaces, or supermarkets).[26] If an infected person encountered a susceptible person in any location, there was a probability of disease transmission from the infected to the susceptible person. This probability was tuned to produce early-stage (e.g. day 10–30) country-level doubling patterns approximating those reported for SARS-CoV-2 in each country and approximating a basic reproduction number (R_0) value of between 2.2 to 2.7.[27,28] The Wave 1 model also adjusted for infected overseas arrivals, the proportion of which ranged from 70% for New Zealand in the early stages of the pandemic, to 45% in the latter stages,[4] and 62% for Australia throughout the epidemic[3] (this feature was later disabled in modelling Victoria's second wave as international arrivals were diverted away from Melbourne to ease pressure on its hotel quarantine system). Infected international arrivals (imported cases) began their illness duration in an advanced state compared with those who acquired their infection in the community, equivalent to their incubation period minus a mean of 1 day and standard deviation of 0.5 days. This reflected the acquisition of the illness prior to arrival and appreciated a

Figure 1: Representation of the 2 scenarios modeled for Australia and NZ during wave 1.



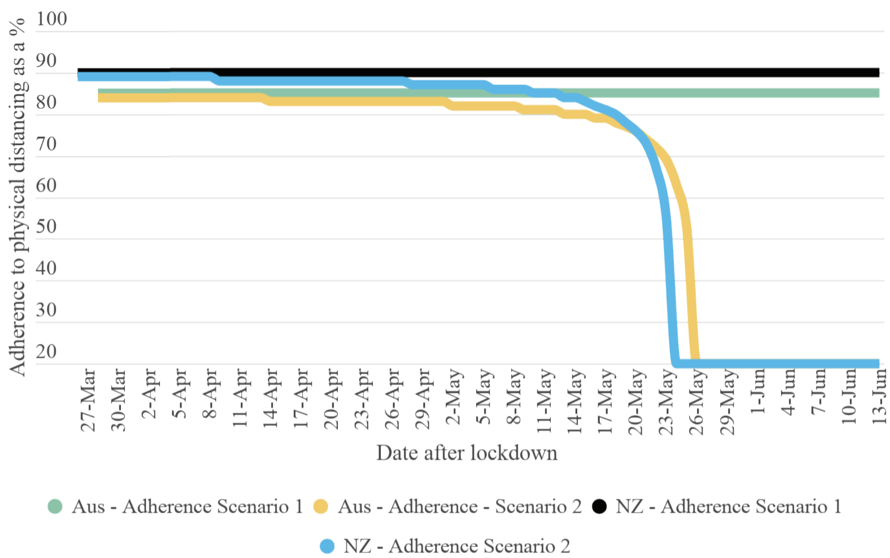
few days in transit to Australia and/or New Zealand. Based on estimates of asymptomatic case proportions, 20% of cases were classified as asymptomatic[7,29] and demonstrated a transmission likelihood that was one-third[30] that of symptomatic cases (the remaining 80%). Testing regimes were not modelled.

Infected people experienced a uniquely assigned incubation period (e.g. to symptom onset) drawn from a log-normal distribution with a mean (μ) of 5.1 days and standard deviation (σ) of 1.5 days.[31] Infected people were also assigned a period of illness duration that followed a log-normal distribution with a μ of 20.8 days and σ of 2 days.[29] If infected, each person had a likelihood of complying with isolation requests drawn from a beta distribution with a median of 93.3% (α=28, β=2). Infected individuals also had a likelihood of death based on their age group.[32] Deceased people were effectively 'hidden' from interacting with the remaining susceptible, infected and recovered population. Effective reproduction number (R*t*) values were calculated and reported on an individual basis for each person on the last day of their infectious period before either recovery or death.

The timing of the introduction of public health and physical distancing restrictions were mapped to that observed in each country. For Australia, Day 0 was estimated to be 16 January 2020, 10 days prior to the first reported case (i.e. incubation period for first case, plus three days for detection). For New Zealand, Day 0 was estimated to be 16 February. Physical distancing policies were enacted in the model for Australia on day 72 (28 March) and for New Zealand on day 39 (26 March).[5] In anticipation of the application of restrictions, people began physical distancing measures 14 days prior to policy implementation up to the maximum settings for each country (see Table 1). The increase in physical distancing behaviours prior to policy implementation followed a power-law determined by the number of days between the current day (e.g. ti – 14) and the day of implementation and is consistent with observed mobility trends in Australia and New Zealand.[33] Table 1 provides a summary of the parameters and 'agent' characteristics of this original conceptualisation (a more comprehensive table of parameters is available in the ODD protocol, section 2.1 to 2.3).

The decay in adherence to physical distancing over the 60-day period in Scenario 2 followed a power-law determined by the number of days between the expected day the current public health response was removed (ti^) and the current day in each country (e.g. $t_{i\wedge} - t_i$). That is, as the date of removing restrictions at the end of Wave 1 approached, people began reducing their levels of physical distancing in anticipation of the date, returning to a residual baseline at day 60 of 20%, reflecting ongoing efforts or reduced opportunities to make contact in the period after restrictions had been eased. A period of 60 days was selected in accordance with what we (and other social and economic policy analysts at the time)[34] regarded as a likely maximal tolerance for law-makers and the public to stay under social and economic restrictions. Rates of adherence over time in each scenario are depicted in Figure 2. It should also be noted that these exponential patterns of decay did *not* play out as expected. Instead, a more linear decline was observed.[35]

Figure 2: Modeled percentage of public adherence to physical distancing restrictions over time for Australia and NZ under each scenario.



The behaviour of simulated people in the Australian model in response to the use of physical distancing restrictions was that, where possible (i.e. 85% of the time in Australia), people avoided either being in or moving to locations occupied by other people. The remainder did not. In the New Zealand example, this was increased to 90%, consistent with observed increased stringency measures at the beginning of the lockdown period.[5] The selection of people who actively avoided others was updated at each time-step (i.e. there were no high- or low-adherence individuals who always acted pro- or anti-socially). Adherence resulted in an increased distancing between agents in the model, and a reduced movement and ability of people to transmit the virus. Under conditions of physical distancing, people only moved if others who did not observe distancing rules (e.g. through necessity or non-adherence) moved into the location they were currently occupying. In such circumstances, people adhering to the distancing policy moved away by identifying the closest unoccupied location in their surrounding area and moved to that location.

To initially calibrate/validate the model, we ran both an unmitigated scenario for Australia to compare against publicly available Commonwealth Government modelling and compared our model results to the SARS-CoV-2 infection data from Wuhan, Hubei Province, China. The primary parameters that were adjusted during this procedure to achieve a target reproductive rate approximating that observed in China (~2.5)[28] were those that contributed to: a) the frequency of close contact between people (i.e. the 'speed' of agents in the environment); and b) transmission rates of the disease per close contact (i.e. the mean infectiousness of individuals); see ODD protocol, section 2.1. Details of the initial validation are reported in the online repository (https://bit.ly/2XI3v3z). Results reflected both the observed (China) and modelled (Australia) disease trajectories as reported in the literature.[13,27,28] This target reproductive rate was higher, however, than observed in Australia and New Zealand, requiring an associated reduction in modelled contact and infectiousness parameters to match observed early-stage case-load data. Observed differences in Australasia may have been due to a combination of social context (e.g. household structures), timing and vigilance (i.e. existing population knowledge of the risk having observed the overseas experience) and lower population density.

Wave 2 model description (Victorian outbreak)

In August 2020, the state of Victoria, Australia, entered a significant second wave of infections and metropolitan Melbourne entered a strict stage-4 lockdown involving school and business closures, night-time curfews, physical distancing, mandatory mask-wearing and stay-at-home orders, exceptions to which were limited to essential work, groceries, health service attention and limited periods (e.g. 1–2 hours) of exercise. The Victorian Department of Health and Human Services (now 'Victorian Department of Health') requested assistance from our research team to assist in estimating the likely trajectory of SARS-CoV-2 cases under variously eased public health policy settings using an adaptation of our Wave 1 agent-based policy model, which had been since adapted to estimate the likelihood of achieving elimination in Victoria given various lockdown restrictions.[37] The goal of this engagement with the Victorian Department of Health and Human Services was to assist in returning Victoria to a 'COVID-Normal' state that enabled suppression of new cases and a return of economic and social activities while preventing the emergence of a serious 'third wave' that would again require an extended lockdown.

Working with departmental representatives, we constructed a set of policy triggers that reflected various times and conditions that policy-makers might choose to either tighten or loosen social restrictions. For example, under a 'loose suppression' strategy, policy-makers might decide to move from stage 4 restrictions (most restrictive) to stage 3 when confirmed cases remained at 100 per day, and they might decide that any two-day period where that level is reached was adequate to ease restrictions. Conversely, pursuing more aggressive policy settings might dictate that restrictions should not be eased at all until 28 days of no community transmission had been recorded. All options between such extremes were also available.

Table 1. Parameter estimates and 'agent' characteristics used in the wave 1 model (a full list of parameters and model description is available in the ODD protocol, section 2.1 to 2.322).[a]

Key Parameters	Parameter Estimates (Australia)	Parameter Estimates (NZ)
Physical distancing (% of people limiting movement and maintaining a distance of 1.5m (Aus) or 2.0m (NZ) in public) [5,33]	85%	90%
Physical distancing - time (% of time that people successfully maintain a distance of 1.5m (Aus) or 2.0m (NZ) in public) [5,33]	85%	90%
Proportion of essential workers[b]	30% of working age-people	20% of working age-people
Mean incubation period (days, log-normal)[31]	m = 5.1, sd = 1.5	m = 5.1, sd = 1.5
Mean illness period (days, log-normal)[29]	m = 20.8, sd = 2	m = 20.8, sd = 2
Mean adherence with isolation of infected cases (%, beta distribution[28,2,b]	m = 0.93, sd = 0.05	m = 0.93, sd = 0.05
Super-spreaders as a proportion of population[c]	10%	10%
Number of days after infection that new cases are publicly reported[b]	8	8
Date of case 0 (Day 0)	January 16th, 2020	February 16th, 2020
Days from case 0 to policy enactment	72 (March 28th, 2020)	39 (March 26th, 2020)
Asymptomatic cases (% of cases) [7,29]	20%	20%
Infectiousness of asymptomatic cases vs symptomatic cases[30]	33%	33%
Physical distancing anticipation time-window[33]	14 days	14 days
Decay in physical distancing adherence window[34]	60 days (May 26th)	60 days (May 28th)
Public compliance with isolation orders[b]	95%	95%
Proportion of imported cases pre and post lockdown[3,4]	62% pre, 62% post	70% pre, 45% post
Agent Characteristics	**Definition**	
Infection status	Infected, susceptible, recovered, deceased	
Time now	The number of days (integer) since an infected person first became infected with SARS-CoV-2	
Age-range	The age-bracket (categorical) of the person, calibrated to census data deciles from 0 to 100.	
Risk of death	The overall risk of death (float) for this person based on their age-profile	
Location	The current location of the simulated person (agent) in the model interface	
Pace	The speed at which the person moves around the environment – higher speeds resulted in more close contact with other people (agents) in the model	
Heading	The direction of travel of the person at the current time-step. In conjunction with the scaling approach, the heading variable was used to create local communities and control interaction between and across communities	
Contacts	A count (integer) of contacts the person (agent) had interacted with in the past day as they moved within the model's environment	
Student Status	A dynamic, Boolean variable that indicated whether people under 20 years of age were current students or not and might therefore return to face-to-face learning should schools be re-opened.	
Essential Worker Status	A dynamic, Boolean variable that indicated whether people of between 20 years of age and 69 years of age were classified as essential workers or not and might therefore return to face-to-face work should industries re-open.	

Notes:
a: Additional parameter uncertainty was introduced into the model in subsequent representations and made available for the Wave 2 representation36
b: Assumed parameter based on expert opinion
c: 10% of the population potentially transmit infections widely through occasional travel to random locations.

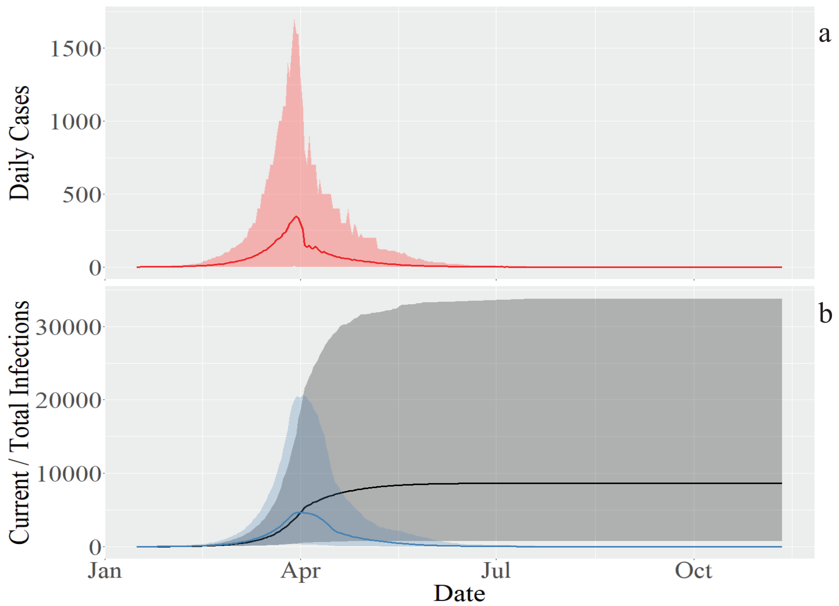
The Victorian model was initialised with a set of existing infections (scaled to 2400 as of 31 August 2020) and seeded with a seven-day run of new infections that were estimated from a 14-day declining exponential curve leading into 1 September 2020 (244 * [0.914 ^ $^{(ti + 15)}$]) where t_i represents the current time-step of the model. Stages of restrictions from level 4 to 3 and 2 were also triggered in the Victorian model under various 14-day rolling averages to determine the likelihood of a resurgence in cases of >30 cases per day, leading to a third wave and possible re-imposition of 'stage-3-like' conditions prior to 25 December 2020. Stages of eased restrictions represented in the model were devised alongside Departmental representatives, accounting for gradual re-opening of schools and industry, of movement and interaction among citizens and between households, mask-wearing and mask efficacy, tracking and tracing efficacy, quarantine and isolation efficacy, movement and interaction of essential workers, and the extent of lockdown fatigue (characterised by non-compliance with stay-at-home orders) estimated among the population over time. Details of model assumptions were released publicly at the time the Roadmap was announced and were made available on the University of Melbourne's website (https://msd.unimelb.edu.au/news/emerging-from-lockdown-modelling,-outputs-and-assumptions). These details as they were released to the public are also included in Supplementary File 1 alongside results from one-at-a-time sensitivity analyses related to major variables of interest including transmissibility, track and trace efficiency, mask-wearing, social/physical distancing adherence, essential worker classifications and illness period duration.

Results

We present results in two parts. Firstly, we show results for Wave 1 in Australia and New Zealand as modelled and understood up to 8 June 2020 using an initial conceptualisation of the presented model developed in early 2020 as the pandemic unfolded. We then present results relating to Australia's second wave of infections in which we describe how the model developed for Wave 1 was applied by the Victorian Government in planning its way out of lockdown through its 'Roadmap to Reopening'.[18] The findings for Wave 2, therefore, focus less on the quantitative analysis of the model and its predictions, and more so on the context in which this model was used for decision support and applied by government in planning and executing its public health response.

At the time that our analysis of Australia and New Zealand first wave was conducted (8 June 2020), there had been a total of 7,265 confirmed SARS-CoV-2 infections in Australia, including a total of 102 deaths, 446 current infections and 6,708 recovered individuals.[3] In New Zealand, these figures were 1,151 confirmed cases (1,504 confirmed and probable), 22 deaths, 0 current infections and 1,482 recovered individuals.[4] To 8 June 2020, 62% of reported cases in Australia had originated from outside country borders, arriving by air and sea.[3] For New Zealand, this figure was 45%.[4] Since that time (24 February 2021), Australia recorded an additional 21,674 COVID-19 cases and 807 deaths. More than 70% of total cases and deaths had occurred in the southern state of Victoria. After achieving an initial period of 100 days without a recorded community transmission, New Zealand (as of 24 February) had recorded a total of 2,368 cases (2012 confirmed and probable) and a total of 26 deaths.[4] At the time of writing (October 2021), both countries had maintained very low to negligible levels of community transmission until June 2021, when an outbreak that began in NSW seeded into Victoria and New Zealand, triggering a significant third wave. Prior to this time, both jurisdictions had avoided subsequent waves by quickly quelling small outbreaks generated from occasional quarantine facility breaches through effective tracking and tracing, and/or 'snap' local lockdowns of minimal duration.

Figure 3: Estimated Australian disease progression under consistent adherence with physical distancing policies (average number of new daily (panel a) and current and cumulative (panel b) cases from 1000 simulations) with shaded areas representing 95% simulation intervals. Solid lines represent mean values.



Australia – Wave 1

The findings from our Wave 1 ABM reflected the SARS-CoV-2 infection experience in early June 2020 (see the comparison of estimated vs. observed data in ODD protocol section 4.4.1). We estimated that although elimination was possible given Australia's then-current policy settings, it would be comparatively delayed when compared to New Zealand by virtue of: Australia's deferred start to physical distancing restrictions from the date of identification of Case 0 (72 days), a greater starting caseload prior to intervention, a greater number of ongoing imported cases as a proportion of total cases, and a less stringent lockdown regime, estimated to be 76% the strength of New Zealand's. Nonetheless, the estimates from the model under consistent public adherence to physical distancing settings of 85%, suggested Australia's median estimated date for elimination under the full adherence scenario 1 was 12 July (95%SI: 5 June to 28 August) (see Figure 3). We estimated an 80% probability of elimination in Australia by 3 August (95%SI: 30 July to 8 August) and 90% likelihood by 17 August (95%SI: 8 August to 30 August) (see Figure 5). Statistics for the non-adherence scenario 2 for Australia were not calculated due to the frequency of null values (i.e. multiple model runs where elimination did not occur by the end of the simulation). Comparison of the physical distancing adherence vs. decay scenarios showed an estimated likelihood of elimination at 100 days post lockdown in Australia (6 July) of 40% and 10%, respectively (see Figure 4).

In June 2020, we therefore estimated that Australia was far less likely to eliminate SARS-CoV-2 from the population if adherence to physical distancing policies decayed over the 60-day intervention period (to 28 May) from an initial estimated 85% to 20% during the onset of the 60-day implementation period (see Figure 4). We predicted a 25% chance that Australia would eliminate local

SARS-CoV-2 community transmission up to 300 days post-initial lockdown under the decay adherence scenario 2. Moreover, at a 20% residual physical distancing level, a significant second wave of infections was estimated to occur (and did). For Australia to maintain a >80% chance of elimination in the simulated timeframe and avoid a second wave of infections, we estimated that physical distancing would need to remain at or above 70% lower than the pre-pandemic baseline (see ODD protocol section 4.4.2).

New Zealand – Wave 1

Modelled results for New Zealand produced in early 2020 also demonstrated a pattern of disease progression consistent with that observed between 26 February and 8 June 2020[4] (see ODD protocol, section 4.4.1.2). Prior to implementation of the New Zealand Government's physical distancing policy on 26 March 2020, growth in new cases appeared exponential but flattened through to 5 April, whereupon the pattern became one of sharp decline. Growth in SARS-CoV-2 infections was exacerbated by a significant import of cases from international arrivals.[4] These observed patterns were also reflected in the model results, providing confidence that the representation of disease transfer mechanisms between individuals, case import, and public health interventions such as physical distancing were reasonably represented by the behaviour of our modelled synthetic population.

Based on consistent application of, and adherence to, physical distancing policies associated with New Zealand's strategy, we estimated a median date for elimination under the adherence scenario to be 3 June 2020 (95%SI: 4 May to 27 June). There was an estimated 80% probability of eliminating SARS-COV-2 in New Zealand by 14 June (95%SI: 12 June to 17 June) and a 90% likelihood of elimination by 21 June (95%SI: 17 June to 28 June) (see Figure 5). Under conditions of gradual decay in adherence from 85% to 20% over the 60 days from the implementation of restrictions to 26 May, we estimated that New Zealand was still a more than likely (94% chance) of achieving local elimination of community transmission by the end of the simulation interval (300 days) (see Figure 6). Comparison of the physical distancing adherence vs. decay scenarios showed a likelihood of elimination 100 days post lockdown in New Zealand (4 July) of 99% and 68%, respectively. A summary of findings for Australia and New Zealand as estimated using our Wave 1 model as of 8 June 2020 is reported in Table 2.

Application of the model to Wave 2 in Victoria, Australia

Figure 7 shows the estimated 14-day rolling average reported SARS-CoV-2 infections for Victoria between mid-September and late October 2020 accounting for the estimated effect of eased restrictions contained within the Victorian Government's 'Roadmap for Reopening'.[18,19,38] Victoria reached a rolling 14-day average of <5 cases per day on 25 October,[39] which was consistent with the median date estimated by the model (26 October). Each 'trace' in this chart represents a single run from one of 1,000 individual trials and demonstrates the wide variability in estimates for reaching a rolling 14-day average of <5 cases/day. These results demonstrating the range of possible outcomes were also released to the public to communicate levels of uncertainty associated with the model estimates.[18]

In the context of decision support for public health policy-makers, the most important questions were associated with when and under what circumstances areas of the economy and social life could return to less restricted or pre-pandemic conditions without risking re-entry into greater restrictions or worse, lockdown. It was designed to prevent the oscillation pattern observed in countries around the world that had released restrictions too early, prior to

Figure 4: Estimated Australian disease progression with decay in adherence to physical distancing (average number of new daily (panel a) and current and cumulative cases (panel b) from 1000 simulations with 95% confidence intervals) with shaded areas representing 95% simulation intervals, estimated on June 8th, 2020. Solid lines represent mean values.

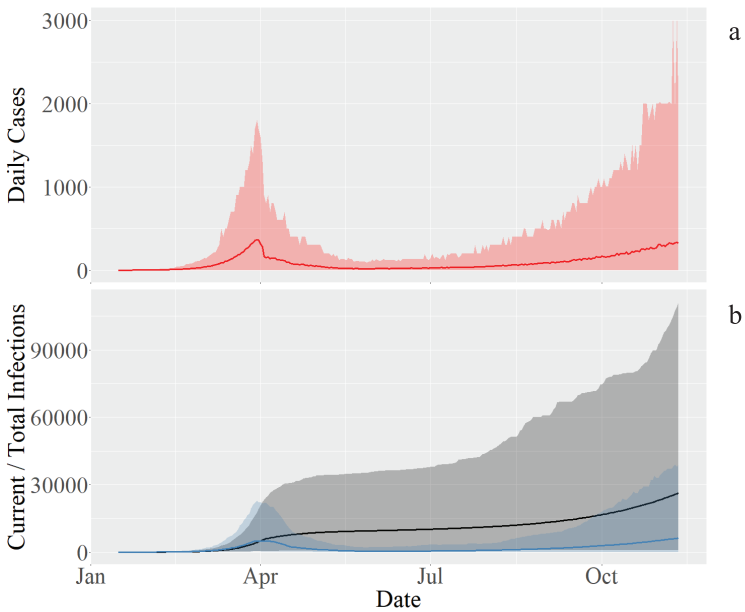


Table 2: Summary of findings for Australia and New Zealand using the agent-based model originally estimated on 8 June, 2020.

Scenario 1. Adherence condition	Australia	NZ
Median estimated elimination date	12 July (95% SI: 28 May to 5 September)	3 June (95%: SI 29 April to 1July)
80% estimated probability of elimination	3 August (95% SI: 30 July to 8 August)	14 June (95% SI: 12 June to 17 June)
90% estimated probability of elimination	17 August (95% SI: 8 August to 30 August)	21 June (95% SI: 17 June to 28 June)
Scenario 2. Adherence decay condition		
Median estimated elimination date	Uncalculable – 25% likelihood[a]	June 15th[a]
80% estimated probability of elimination	nil	September 3rd[a]
90% estimated probability of elimination	nil	November 13th[a]
Effective reproductive number	1.8 - 1.9	1.8 - 1.9

Note:
a: Estimates and/or simulation intervals cannot be calculated due to null values of elimination dates extending beyond the simulation time-window.

Figure 5: Estimated NZ disease progression under consistent adherence with physical distancing policies (average number of new daily (panel a) and current and cumulative (panel b) cases from 1000 simulations with 95% confidence intervals) with shaded areas representing 95% simulation intervals estimated on June 8th, 2020. Solid lines represent mean values.

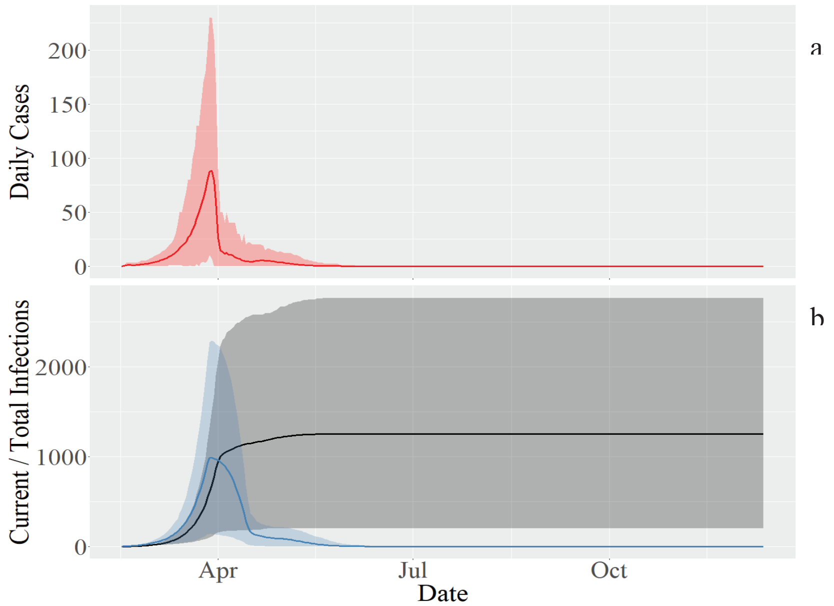
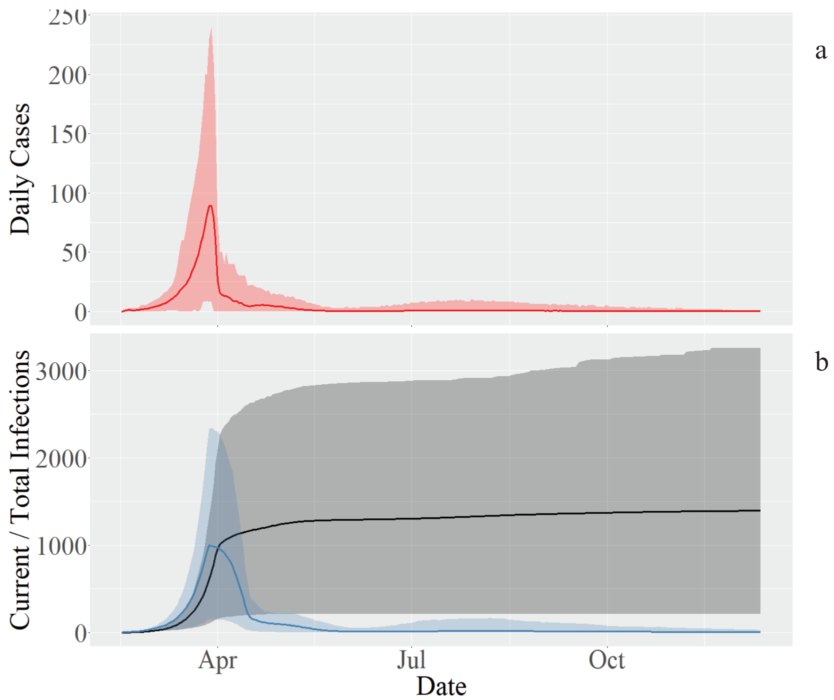


Figure 6: Estimated NZ disease progression with decay in adherence to physical distancing (average number of new daily (panel a) and current and cumulative cases (panel b) from 1000 simulations with 95% confidence intervals) with shaded areas representing 95% simulation intervals, estimated on June 8th, 2020. Solid lines represent mean values.



bringing cases fully under control (see Figures 8a and 8b). The most important finding of our Wave 2 model used in Victoria was the demonstration that the trigger conditions chosen for when to significantly ease restrictions, and the planned extent of those eased restrictions (e.g. school re-openings, returns to work and increased expected movement and close interactions), greatly affected the risk of a modelled resurgence in SARS-CoV-2 cases resulting in a projected third wave of infections and a potential risk of returning to lockdowns or other social restrictions. If a fortnightly case average of 25 cases per day was used when moving from Stage 3 to Stage 2, the predicted risk of a resurgence that would lead to a subsequent repeat of a Stage 3-style lockdown (i.e. >30 recorded cases per day over a 14-day period) prior to 25 December 2020 was estimated at just over 60% (see Figure 8). A more stringent five cases per day threshold lowered that estimated risk to just 3%. This was due not only to the reduction in new cases per day but also the reduced total number of 'active infections' present in the community produced by waiting longer for new case numbers to decline over time.

The second important finding was that settings that failed to suppress cases adequately resulted in a distinct, longer-term oscillation pattern where Victoria was projected to move in and out of lockdowns as a result of experiencing third, fourth and fifth (and more) infection waves over time; patterns that have since been widely observed.[18] The clear communication of these modelled results was a central feature of the Victorian Government's justification of its adopted strategy and they were publicly released in conjunction with its announcement of the Victorian Government's 'Roadmap for Reopening'.[18,19,38] A detailed description of the Victorian Government's RoadMap, results of the modelling exercise and the modelled assumptions that underpin it are available in the Supplementary File and ODD protocol, section 7.

Discussion

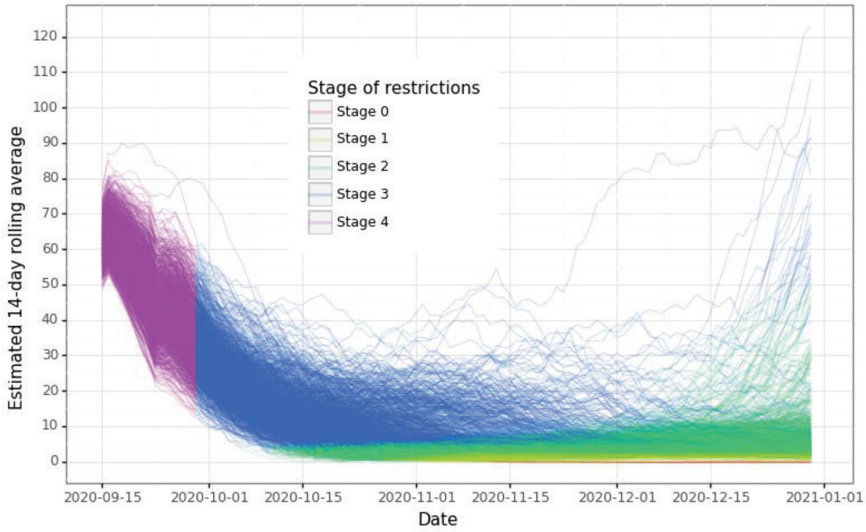
The findings of this study are two-fold. Firstly, we demonstrate the development and utility of a dynamic, agent-based policy model drawn from complex systems science to assist governments and public health policy-makers to consider and communicate the potential effects of a range of public health policies.

This work and its adoption by policy-makers in real-world public-health policymaking is a demonstrable example of an incorporation of complexity science in public health that has been consistently called for in the public health, systems, and complexity modelling literature,[40,41] but that has so far produced few tangible examples.

Secondly, the core results of our Wave 1 model reiterate that for island nations such as Australia and New Zealand, the potential to eliminate community transmission of SARS-CoV-2 (and other viruses and/or variants of similar transmissibility) or at least experience prolonged periods of negligible community transmission remained high if borders could be secured and public will could be preserved. Under maintained stringent physical distancing, we estimated a median probability of achieving elimination of community transmission in Australia during the first wave of infections by 12 July 2020 and a 90% probability of achieving elimination by 17 August. In contrast, the modelled median probability of achieving elimination of community transmission in New Zealand was 3 June 2020 with a 90% probability by 21 June. In fact, as of 8 June 2020 when our original estimates were devised, New Zealand had no known active cases and the New Zealand Government had declared local elimination of SARS-CoV-2. However, under the scenario of decaying adherence to physical distancing (closer to what actually played out in both countries), we estimated that elimination of community transmission in Australia was unlikely and a second wave of SARS-CoV-2 infections was probable. This second wave occurred in Victoria and was considerably larger and more deadly than the first.

Our finding that island jurisdictions have the potential to eliminate community transmission of SARS-CoV-2 was also reflected by successes observed in Taiwan in 2020. Taiwan acted at least 6–8 weeks before both Australia and New Zealand by imposing border controls on 25 January. An extensive public health response ensued including the testing of individuals showing symptoms of SARS-CoV-2 (Taiwan instituted one of the most comprehensive testing regimes per case of SARS-CoV-2),[42] isolating individuals (and their close contacts), extensive contact tracing, and the wearing of face masks while in public. Together, New Zealand, Taiwan and Australia consistently ranked among the best-performing countries, globally, with regard to managing their policy responses to COVID-19, especially during the early stages of the pandemic.[43]

Figure 7: Estimated outcomes from 1,000 model runs from mid-September to 25 October, 2020. Each colour represents different stages as set out in the Victorian Roadmap.[38]



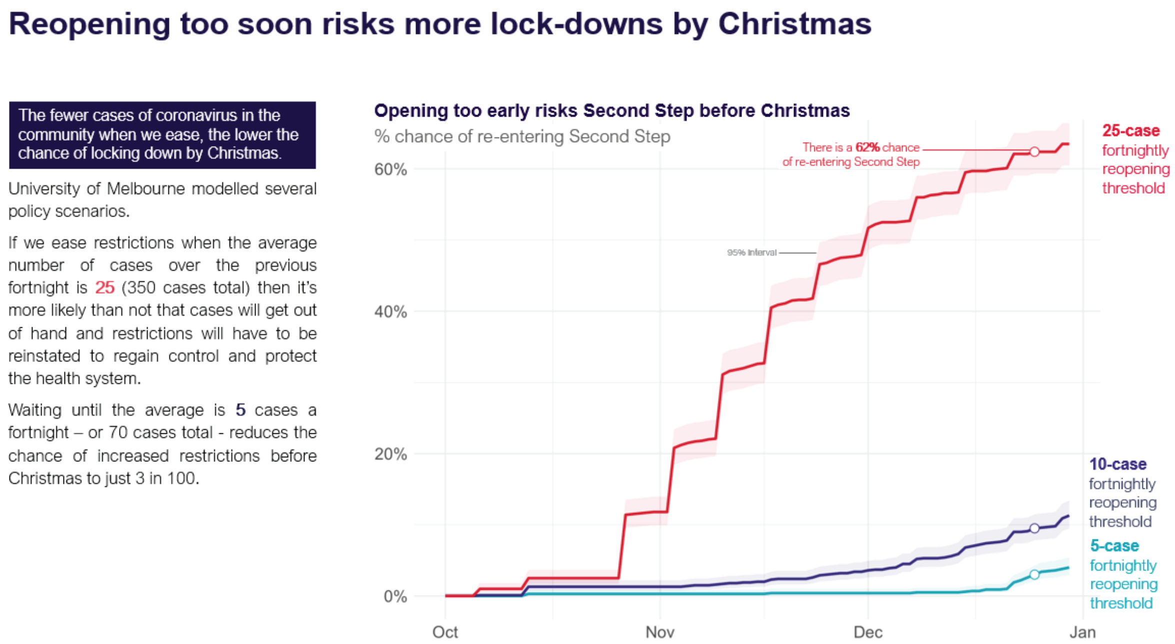
A limitation of our findings is the level of uncertainty associated with results. This is not unusual given that infectious diseases and circumstances surrounding transmission dynamics are inherently stochastic. The wide simulation intervals are the net outcome of many possible timings and amplitudes of a second wave, in addition to stochastic variability scenarios that may play out. This has implications for how closely one might expect any model of this kind to be validated by closely matching real-world data. It also highlights an important principle of agent-based and broader dynamic modelling exercises in that representing the mechanisms of change generally takes precedence over efforts to precisely forecast or match numerical results.[44,45] Having said that, our model's adaptation to Victoria's second wave of infections proved to be highly predictive, demonstrating a 14-day rolling average of within one case per day of the actual average as of 26 October, despite the model being devised more than 50 days earlier when rolling averages were just under 200 cases per fortnight (Victoria's 14-day rolling average on 26 October 2020 was just 3.6 cases per day).[19] Upon reaching this target, the Victorian Government released restrictions to 'Level 2'. As of 1 January 2021, Victoria had recorded no locally transmitted COVID-19 infections for 60 consecutive days, maintaining this record into the new year until two small outbreaks occurred through hotel quarantine breaches – and were subsequently quashed – in January and February 2021.

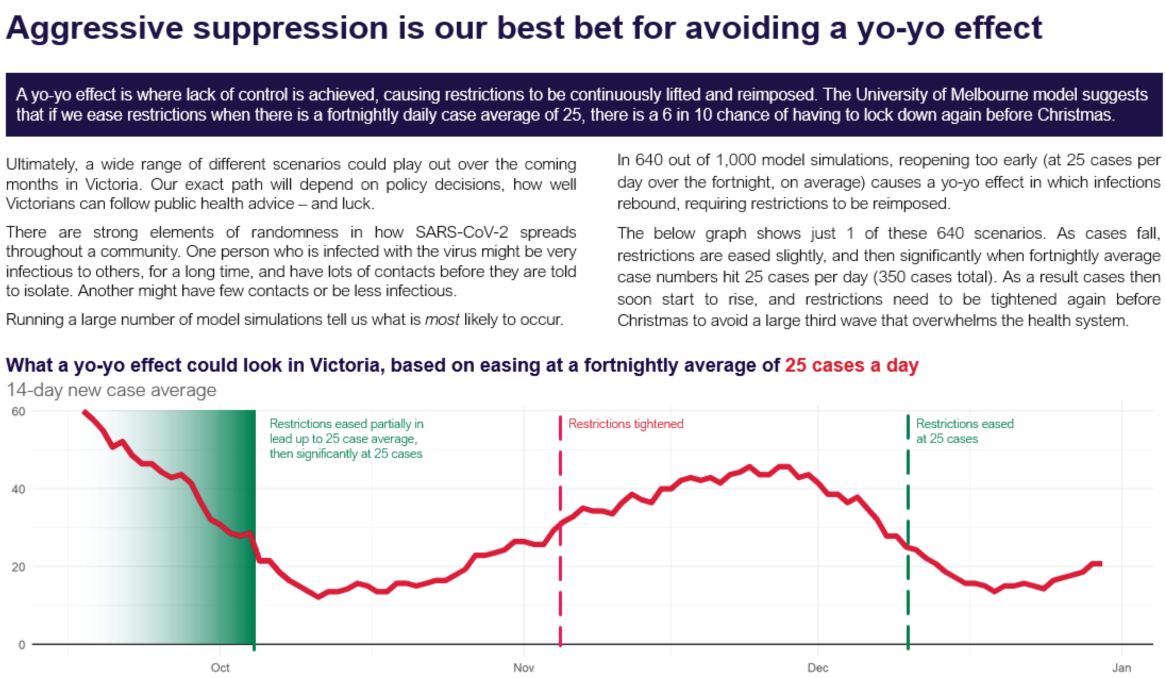
Further limitations and challenges

The model and approach we describe here have many strengths including the ability to run policy experiments that assess changes in behaviour and contact patterns as demonstrated in its Wave 2 utilisation for Victoria. Despite this, the model also omits many potentially important factors. It does not include changes to individual hygiene behaviours (hand washing and cough etiquette, etc) or associated environmental transfer that may alter rates of transmission (e.g. through surfaces). Further, it also does not include accurate geographic representation of towns, cities, or other locations whose proximity may alter transmission patterns (e.g. commuting or transport routes). Its representation of demographic and workplace heterogeneity is also limited. It, therefore, remains an abstraction in many respects. However, it has been built flexibly and can be extended to include adjustments to assumptions or inclusion of these and other public health considerations such as school and public transport closures, mask-wearing, expansion of tracking, tracing and testing regimes, changes to the understanding of the demographic, workforce, and movement patterns given new empirical data (e.g. linear vs. exponential decays), and advances in the use of digital technologies for rapid and more efficient contact tracing.[46] More recently, it has also been adapted to consider the additional challenges of the Delta variant and expanded to include vaccination roll-out strategies, including vaccine effectiveness and targeting of vulnerable groups in staged administration among other improvements. Our model code continues to evolve, is open for use and adaptation by any other jurisdiction around the world who may wish to use or adapt it for their own immediate and/or longer-term planning purposes (https://bit.ly/2XI3v3z). Model speed has also been enhanced through deployment on high-performance computing clusters, enabling a greater exploration of the policy phase space.[47]

From a methodological and research application perspective, it is very important to note that the development of this model and its application to the Victorian context did not occur 'cold'. As model authors and contributors, we worked closely with representatives from the Department of Health and Human Services to construct and deploy new, policy-relevant functions

Figure 8a and 8b: Demonstration of the use of the model (publicly released slide-pack[18]) by the State Government of Victoria to communicate risk associated with various opening trigger settings when exiting wave 2. A full set of slides is available in the ODD protocol (see section 7).





and features, sometimes under extreme time pressure. The results of these models and trials were sometimes publicly released within only a day or two of their completion. It is acknowledged that had this development occurred in a more deliberate manner and given more time, this would have afforded greater consideration of the model architecture and/or some model features including more efficient coding practices or closer calibration to real-world data or dynamics. More attention may also have been directed to model validation and verification activities, and sensitivity analyses. Practically, however, we did not always have that opportunity, but such are the realities of developing and deploying models in crises conditions. We made a judgement at the time alongside our academic and government collaborators that potential issues were more likely 'mice than tigers'.[48] Thankfully, however, time has provided the opportunity to re-visit the model with clear eyes and improve both performance and robustness. Already, this has resulted in considerable improvements in speed (>1000x original) and design that will continue to be openly documented in the model's ODD protocol and online repository as well as online policy and decision support tools developed with co-authors and collaborators (e.g. https://populationinterventions.science.unimelb.edu.au/pandemic-trade-offs-july-2021).

Finally, we also acknowledge that real-world evidence also indicates that some assumptions governing behaviour and mechanisms – especially in our Wave 1 conceptualisation – did not operate in the model as they did in the real world. For example, increases in mobility showed a more linear recovery after cessation of lockdowns than exponential.[35] Also, testing, tracking and tracing mechanisms are not realistically represented as 'likelihoods of being traced per day', but follow both up and downstream chains of enquiry. The likely positive case reporting bias in the early stages of the pandemic directed toward presenting and/or hospitalised cases and returned travellers and their contacts is also not accounted for. The duration of illness estimated for agents in this model was also arguably longer than necessary, however, this did not result in an estimated extension of generation time or serial intervals (mean = 5.4 days, sd = 0.6 days) beyond observed empirical estimates.[49,50] Our contemporary models and representations now incorporate such improvements while also benefitting from better publicly available data.

Conclusions

There are multiple factors countries must consider in weighing up the benefits of individual infectious disease suppression strategies or preparing themselves to be resilient in the face of second and subsequent waves of infections in the absence of adequate vaccine coverage. Such factors include the probability of re-entry of the virus after initial elimination (and the probability that any such outbreaks can be successfully controlled); the time to produce and availability of a vaccine or highly effective antivirals; and the cost-benefit ratio of any strategy when taking into account other health, economic and social factors.[51] Here, we present a model that was both robust and flexible enough to assist decision-makers think through and analyse critical public health policies and their consequences in real-time. As indicated by the Victorian Government's Chief Health Officer, Professor Brett Sutton, in his public address on Sunday 8 November 2020, the evidence provided through this work was "extraordinarily helpful" in assisting the government to chart Victoria's course to safety in 2020.

"We backed the modelling … and that's what it told us [getting to <5 cases per day was possible] … and we are very pleased that it has been validated and vindicated … If there's a lesson for anyone, it's that science-based disciplines use empirical data and other inputs to try to make the best decisions … it's not perfect, nothing is perfect, but it has been extraordinarily helpful to get us here." – Professor Brett Sutton.

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Supporting Information

Additional supporting information may be found in the online version of this article:

Supplementary File 1: Modeling Victoria's escape from COVID-19.