Simulating spread of COVID-19 in New Zealand (DRAFT V1.0)

A Manual for an ODE Model

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Code available at: https://gitlab.com/tpmcovid/ode-model
Documentation last updated in: July 2023

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Introduction

Covid-19 Modelling Aotearoa (CMA) developed and used an ODE (ordinary differential equation) model to simulate the spread of the Omicron variants of COVID-19 in Aotearoa New Zealand and to provide policy advice for the New Zealand Government during the period of July 2022 - June 2023.

The model is an age-structured model that includes the following processes and mechanisms:

1. Vaccination according to Ministry of Health data on the number of vaccine doses given in each five-year age group
2. Waning of vaccine-derived and infection-derived immunity and consequent reinfection
3. Differential levels of immunity against infection compared to severe disease and death
4. Simplified model for the effect of new variants of SARS-CoV-2
5. Change in age-specific contact rates and case ascertainment rates over time
6. Model for the effect of antiviral medications on infection fatality rate according to Ministry of Health data on antiviral prescriptions.

An earlier version of this simulation model is described in the published paper (Lustig et al. 2023). Most key assumptions remain valid in the current version of code implementation. The model's code repository was continuously updated with new assumptions and parameters after publication. This documentation is a breakdown of the current version of the model code, and a mapping from code implementation to model description in both the paper and the updated supplementary materials (which is a comprehensive description of model assumptions stored in the git repository). The goal of creating this document is to facilitate technical users who are not familiar with this model and are without strong epidemiology/mathematics background, to get started quickly.

Requirements

The ODE model was developed and run with the following software and dependencies in Matlab:

- Matlab R2023a
- Statistics and Machine Learning Toolbox
- Deep Learning Toolbox
- Parallel Computing Toolbox

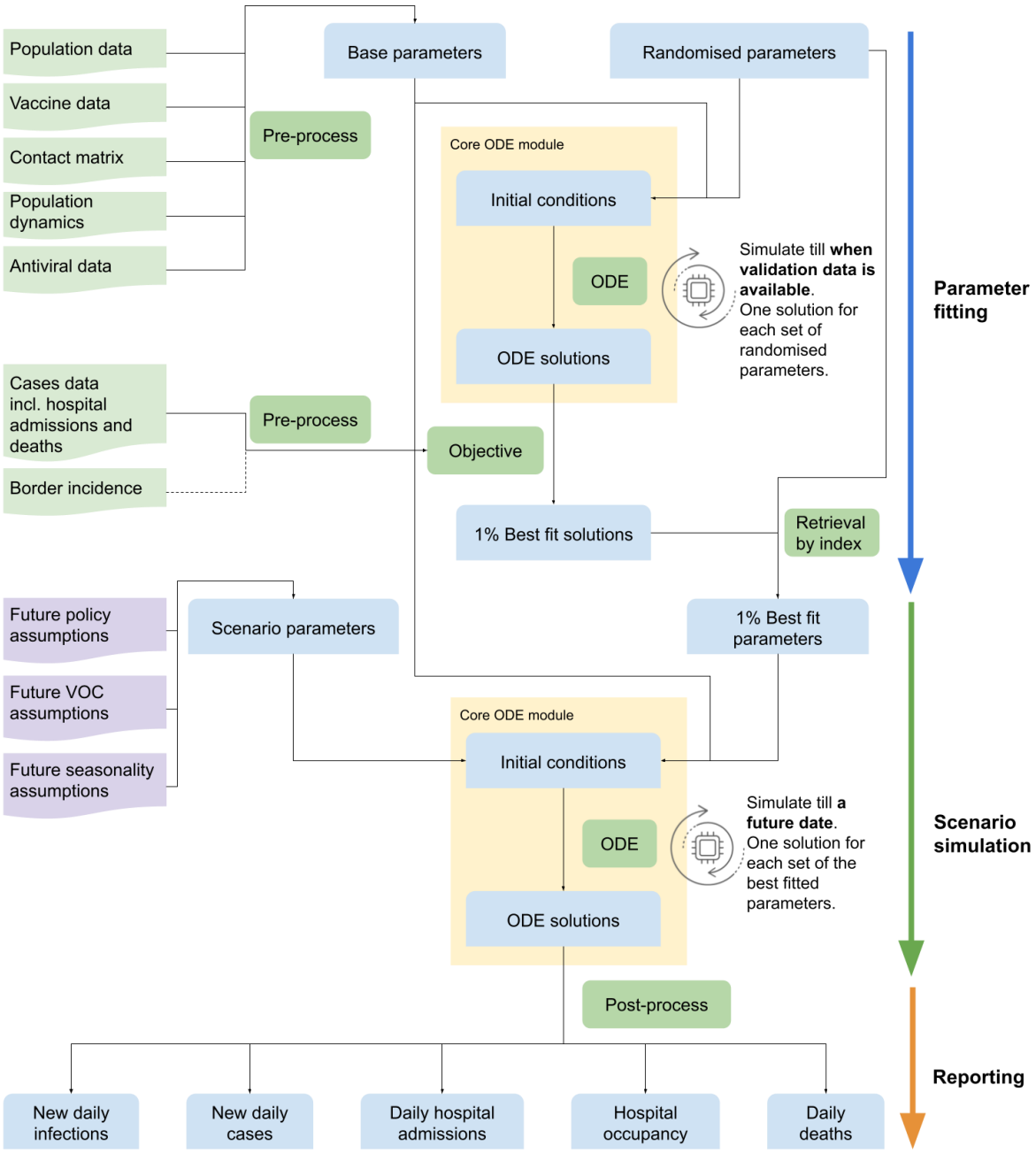
Data sources

Running the ODE model simulation requires the following data sources.

Table 1: Data sources

Data	File name in code	Provided by	Used for	Note
Vaccine rollout	*TPM_vaccine_[YYYY-MM-DD].csv*	Ministry of Health	Base parameter setting	Data updated every two weeks or so. Last update on 6 June 2023.
Population size	*popsize_national.xlsx*	StatsNZ	Base parameter setting	Data updated in 2022.
Population dynamics	NA (embedded in code)	StatsNZ	Base parameter setting	Infoshare 2019.
Age-dependent contact matrix for New Zealand	*nzcontmatrix.xlsx*	Research (Prem et al.)	Base parameter setting	
Antiviral data	*therapeutics_by_age_[DD-MM-YYYY].mat*	Ministry of Health	Base parameter setting	Last updated on 6 June 2023.
Daily cases	*TPM_comm_cases_info_[YYYY-MM-DD].csv*	Ministry of Health	Parameter fitting, reporting and plotting	Including hospital admission date and death flag for cases. Data updated every two weeks or so. Last update on 18 June 2023.
Border incidence	*border_incidence.xlsx*	Research (M. Plank, Github repository)	Reporting and plotting	Originally used for parameter fitting but no longer used in the later development stage. Data last updated on 09 Sep 2022.
Hospital occupation	*hospOccDataTotals_MOH_[YYYYMMDD].xlsx*	Ministry of Health (MOH Github repository)	Reporting and plotting	Originally used for parameter fitting but no longer used in the later development stage. Updated daily.

Simulation process


Population data
Vaccine data
Contact matrix
Population dynamics
Antiviral data
Pre-process
Base parameters
Randomised parameters
Core ODE module
Initial conditions
ODE
ODE solutions
Simulate till when validation data is available. One solution for each set of randomised parameters.
Parameter fitting
Cases data incl. hospital admissions and deaths
Border incidence
Pre-process
Objective
1% Best fit solutions
Retrieval by index
Future policy assumptions
Future VOC assumptions
Future seasonality assumptions
Scenario parameters
1% Best fit parameters
Core ODE module
Initial conditions
ODE
ODE solutions
Simulate till a future date. One solution for each set of the best fitted parameters.
Scenario simulation
Post-process
New daily infections
New daily cases
Daily hospital admissions
Hospital occupancy
Daily deaths
Reporting

Major code modules

Core ODE module

The core ODE module is repeatedly called and executed in both the parameter fitting and scenario simulation processes. This will be described in three parts: the initial conditions, the ODE, and the solutions.

Initial conditions

The initial conditions contain in total 2,288 compartments or variables. These are eventually flattened and concatenated into an array of the shape 2,288*1, before being sent into the solver of ODE.

Table 2: Compartments table

Compartments	Shape	Description	Reference
N0	16*1	Initial population size in each age group	
V0	(16+16+16)*1	Initial number of people vaccinated (and immunised) with at least 1 dose, 2 doses and 3+ doses on Day 1 in each age group	
S0	(16*14) * 1	Initial number of people in each of 14 susceptible compartments (age-dependent) on Day 1.	Paper 2.1 Immunity model, Figure 1. The order of the compartments in S0 is as shown in Figure 1: 0 dose, 1 dose, 2 doses followed by 3 lower immunity level compartments, 3+ doses followed by 3 lower immunity level compartments, and 4 empty post-infection susceptible compartments. The lower level immunity is due to waning.
E0	(16*14) * 1	Empty exposed compartments	Same order as above.

Compartments	Shape	Description	Reference
I0	(16*14) * 1	Empty infectious (clinical cases) compartments	Same order as above.
A0	(16*14) * 1	Empty subclinical (asymptomatic cases) compartments	Same order as above.
R0	(16*14) * 1	Empty recovered compartments	Same order as above.
C00, C10, C20, C30, Cr0	16*3*1	Empty confirmed cases compartments for different immunity groups - 0 dose, 1 dose, 2 doses, 3+doses, and reinfected. Each of the third 16*1 compartments are the observed compartments, aka the cumulative reported cases that are unvaccinated, had 1 dose, 2 doses, 3+ doses, and previously infected.	Supplementary materials 6. Clinical pathways and fitting to data
H00, H10, H20, H30, Hr0	16*5*1	Empty hospitalisation compartments for different immunity groups - 0 dose, 1 dose, 2 doses, 3+doses, and reinfected. Each of the fourth and fifth 16*1 compartments are the observed compartments - the number of cases currently in hospital and the cumulative number of hospital discharges, respectively	Supplementary materials 6. Clinical pathways and fitting to data
F00, F10, F20, F30, Fr0	16*6*1	Empty fatalities compartments for different immunity groups - 0 dose, 1 dose,	Supplementary materials 6. Clinical pathways and fitting to data

Compartments	Shape	Description	Reference
		2 doses, 3+doses, and reinfected. Each of the sixth 16*1 compartments are the observed compartments - the cumulative number of fatalities.	

Note:
0 dose and 1 dose are treated the same in terms of immunity effect. In the code, however, there are still separate compartments to differentiate them. Part of the reason is to keep track of the flow between those compartments, and to retain the potential to simulate separate immunity effects if future research indicates that there are significant differences.

Relevant script

- getIC.m

ODE model

The model applies one of Matlab's most versatile ODE solvers, ode45, to a set of ordinary differential equations that are defined in myODEs2.m, to simulate the continuous dynamic system of disease spreading. Equations defined in myODEs2.m reflect the real world spread of COVID-19 in a mathematical format, in particular how the population flows between different compartments over time.

Relevant scripts

- myODEs2.m - supplementary formula (1-5, 8-20, 21, 27-29)
- getFOI.m - supplementary formula (6)
- getNGMtimeDep.m - supplementary formula (7) and the un-indexed formula between (6) and (7)
- calcPopnDynamics.m - supplementary formula (22-24)
- getDosesPerUnitTime.m
- getPTestPerUnitTime.m
- getAntiviralsTreatedPerUnitTime.m
- get_dCdt.m - supplementary formula (27, 31)
- get_dHdt.m - supplementary formula (28, 31)
- get_dFdt.m - supplementary formula (29, 31)

ODE solution

The ode45 solver produces the solution array Y, which is restructured by function extractEpiVarsCompact or extractEpiVarsCompact_vaxSplitInf into a compact structure containing a set of matrices of epidemiological variables over time and corresponding to 16 age groups. The size of each matrix is length of simulation (nDays) * 16.

Related scripts

- naiveABCSEIR.m
- extractEpiVarsCompact.m
- extractEpiVarsCompact_vaxSplitInf.m
- condenseSusLevels.m

Table 3: Solution matrices table

Matrices	Shape	Description	Note
N	nDays * 16	Total population size in each age group each day	
V1, V2, V3	nDays * 16	Number of people vaccinated with at least 1, 2, 3 doses in each age group each day	
S	nDays * 16	Summed number of people in all the susceptible compartments in each age group each day.	Summed over 14 susceptible compartments.
Sw	nDays * 16	Average susceptibility in each age group each day.	The average is weighted by vulnerability to infection (1 - immunity to infection) in each susceptibility class.
E1	nDays * 16	Summed number of people exposed for the first infections in each age group each day.	Summed over the exposed compartments corresponded to the susceptible compartments 1-10.
E2	nDays * 16	Summed number of people exposed for re-infections in each age group each day.	Summed over the exposed compartments corresponded to the susceptible compartments 11-14.
Ev01	nDays * 16	Summed number of people exposed for the first infections who are unvaccinated or had one dose in each age group each day.	Summed over the exposed compartments corresponded to the susceptible compartments 1-2. Extracted by extractEpiVarsCompact_v

Matrices	Shape	Description	Note
			axSplitInf only.
Ev2	nDays * 16	Summed number of people exposed for the first infections who had 2 doses in each age group each day.	Summed over the exposed compartments corresponded to the susceptible compartments 3-6. Extracted by extractEpiVarsCompact_vaxSplitInf only.
Ev3	nDays * 16	Summed number of people exposed for the first infections who had 3 doses in each age group each day.	Summed over the exposed compartments corresponded to the susceptible compartments 7-10. Extracted by extractEpiVarsCompact_vaxSplitInf only.
I	nDays * 16	Total number of infectious and clinical (symptomatic) cases in each age group each day.	Summed over 14 I compartments.
A	nDays * 16	Total number of infectious and subclinical (asymptomatic) cases in each age group each day.	Summed over 14 A compartments.
C0, C1, C2, C3, Cr	nDays * 16	Cumulative number of confirmed cases in each immunity category with 0, 1, 2, 3 doses and reinfections, in each age group each day.	For each matrix, only values in the third case compartment which is the observed case compartment are retrieved.
H0occ, H1occ, H2occ, H3occ, Hrocc	nDays * 16	Current hospital occupancy in each immunity category with 0, 1, 2, 3 doses and reinfections, in each age group each day	These correspond to the fourth hospitalisation compartments.

Matrices	Shape	Description	Note
H0dis, H1dis, H2dis, H3dis, Hrdis	nDays * 16	Cumulative number of hospital discharges in each immunity category with 0, 1, 2, 3 doses and reinfections, in each age group each day.	These correspond to the fifth hospitalisation compartments.
F0, F1, F2, F3, Fr	nDays * 16	Cumulative number of deaths in each immunity category with 0, 1, 2, 3 does and reinfections, in each age group each day.	These correspond to the sixth fatality compartments.

Randomised parameters

An approximate Bayesian computation (ABC rejection) approach is taken to fit the model to actual data. A set of parameters are randomised to introduce some reasonable noise to particular simulation components. In this document, one set of these randomised parameters is named as Theta, and they will introduce randomness to some variables in the complete set of parameters for each simulation run, which is documented as parInd later.
All the randomised values are drawn from a uniform distribution in the interval (0,1).

Relevant scripts

- naiveABCSEIR.m line 13, 49, 61-62
- getParUnified.m

Table 4: Randomised parameters

Variable name (in Theta) as a randomised value	Variable name (in parInd) where randomness is introduced	Affected simulated component	Note
Theta.dateSeed	parInd.dateSeed	When the first case appeared in NZ	Around 19 Jan 2022
Theta.Cstart	parInd.Ct	The control function, which is a scaling factor reflecting the relative daily transmission affected by various factors, e.g. policy change	Baseline between 0.58 and 0.78
Theta.Cramp	parInd.Ct	The control function, which is a scaling factor reflecting the relative daily transmission affected by various factors, e.g. policy change	After the first ramp-up Ct increases to between 0.89 and 1.31.
Theta.rampDays	CtRampDays (eventually parInd.Ct)	How many days for the reproduction number to linearly increase (for the first time)	The first ramp-up period is 35-75 days, the second ramp-up period is 1-19 days
Theta.rampStart	CtRampStarts (eventually parInd.Ct)	When the reproduction number increase starts (for the first time)	The first ramp-up around 10 Mar 2022, the second ramp-up around 15 Sep 2022

Variable name (in Theta) as a randomised value	Variable name (in parInd) where randomness is introduced	Affected simulated component	Note
Theta.pTestMult	parInd.pTestCline, parInd.pTestSub	Testing probability for clinical and subclinical groups (age and date stratified)	Prior distribution of 3 age groups are as described in supplementary Table 1. Between the two dates 01 May 2022 and 01 Jan 2023, the testing probabilities are linearly interpolated (see getBasePar.m line 150 - 181. These prior values are further multiplied by the randomised parameter pTestMult between 0.8 and 1.2.
Theta.IFR	parInd.IFR	Infection fatality rate	See more details in Base parameters. The global IFR multiplier is between 0.5 and 1.5.
Theta.IHR	parInd.IHR	Infection hospitalisation rate	See more details in Base parameters. The global IHR multiplier is between 0.5 and 1.5.
Theta.relaxAlpha	parInd.relaxAlpha (eventually parInd.contactPar)	Relaxation of contact matrix back to Prem *et al.* (0=not at all, 1=fully)	Between 0 and 0.8
Theta.MRampDays	parInd.contactPar.change Window	The time window for relaxation of contact matrix (linear change)	The contact matrix changes in a window of 50-90 days from around 10 Mar 2022 as indicated by CtRampStarts(1).
Theta.vocWane	parInd.vocWaneAmount	The scale of immunity waning for each post-infection susceptible compartments, or BA.5 immunity escape (relative to BA.2)	Between 0.1 and 0.7

Variable name (in Theta) as a randomised value	Variable name (in parInd) where randomness is introduced	Affected simulated component	Note
Theta.waneRate	parInd.waneRateMult (eventually waneRate_StoS and waneRate_RtoS)	A multiplier on waning rate - rate of moving from one susceptible compartment to the next one with lower immunity, or from a recovered compartment to a susceptible compartment.	Base waning rate S to S is 0.0045. The multiplier is between 0.5 and 1.5.
Theta.Cramp2	parInd.Ct	The control function, controlling the relative daily transmission	After the second ramp-up further multiplied by a value between 1.1 and 1.3.
Theta.ramp2Days	CtRampDays (eventually parInd.Ct)	How many days for the reproduction number to linearly increase (for the second time)	The first ramp-up period is 35-75 days, the second ramp-up period is 1-19 days
Theta.ramp2Start	CtRampStarts (eventually parInd.Ct)	When the reproduction number increase starts (for the second time)	The first ramp-up around 10 Mar 2022, the second ramp-up around 15 Sep 2022

These parameters are mostly reflected in supplementary Table 1.
Note that if needed, more reproduction number ramp-up parameters can be added, in a similar way as shown in getParUnified.m line 39-45.

Base parameters

These are pre-fixed parameters, reflecting the reality (or at least a best guess for the reality), which stay the same for all simulation runs. Some of these parameters are based on historical data, and some are manually tuned by experiments during model development.
These parameters are wrapped in a struct as an output of the getBasePar function. In this document the struct is named as parBase.

Relevant scripts

- getBasePar.m - supplementary formula (25-26) implemented here
- getDemogPars.m
- getHerreraRatesOmi.m
- getVaccineData.m
- getImmPars.m
- getATCmatrices.m

Table 5: Base parameters

Variable name	Description	Default value	Note
Simulation parameters			
parBase.date0	Simulation start date	2021 March 05	The model runs from the beginning date of the vaccine roll out in NZ, to ensure waning of vaccine-derived immunity is correctly captured.
parBase.tEnd	Simulation end date, either defined by user, or a default value is used	3*360 days (~3 years)	For parameter fitting purposes, simulate till the date of the latest reported cases; for scenario simulation purposes, simulate till a future date.
parBase.tBase	Time vector from simulation start date to end date	A datenum array of length tEnd	tEnd is noted as nDays hereafter.
Disease spreading parameters			
parBase.R0	Basic reproduction number without intervention	3.25	

Variable name	Description	Default value	Note
parBase.cSub	Relative infectiousness of subclinical cases	0.5	Subclinical cases are 50% infectious compared with clinical (symptomatic) cases.
parBase.tE	Latent period from exposure to being infectious	1 day	
parBase.tI	Infectious period	2.3 days	
Compartmental model parameters / Population structure parameters			
parBase.nAgeGroups	Number of different age groups of the population	16	Every 5 years till 75+, in total 16 groups
parBase.nSusComp	Number of susceptible compartments	14	See details in paper 2.1 Immunity model, Figure 1.
parBase.nVaxComp	Number of vaccination status classes	3	Corresponding to 0/1 dose, 2 doses, and 3+ doses
parBase.nCaseComp	Number of confirmed cases compartments	3	See details in supplementary material 6. Clinical pathways and fitting to data
parBase.nHospComp	Number of hospitalised cases compartments	5	See details in supplementary material 6. Clinical pathways and fitting to data
parBase.nDeathComp	Number of deaths compartments	6	See details in supplementary material 6. Clinical pathways and fitting to data
Population structure parameters - Region specific population			
parBase.popCount	Population size of each age group of the specified region	An array of size 16*1	Based on data provided by StatsNZ (updated in 2022). By default the region is "national". The 16 age groups are as in parBase.nAgeGroups.
parBase.totalPopSize	Total regional population, a sum of par.popCount	5,233,646	Total population of NZ by default

Variable name	Description	Default value	Note
parBase.popDist	Regional population percentage per age group	An array of size 16*1	Age-specific population divided by total population
Population structure parameters - Other level population			
parBase.popSize_NR	Northern region (NR) population size	1,937,700	Only used to calculate hospitalisation rates per 100,000 according to NR data
parBase.popDistBench	National population percentage per age group	An array of size 16*1	Used for contact matrix adjustment
Contact matrix parameters			
parBase.C_detBal	An age-specific contact matrix adjusted for New Zealand population	A 16*16 matrix	Based on Prem *et al.*
parBase.ageBlockSizes	The number of 5-yr age groups contained in each age block	A 1*6 array	The age groups are divided into 0-14, 15-24, 25-34, 35-49, 50-59, 60+ blocks, for the purpose of contact matrix adjustment
parBase.nAgeBlocks	The number of age blocks	6	As above
parBase.Cw1	Weighting matrix for adjusting the initial contact matrix	A 6*6 matrix	The values in this matrix were manually tuned to make the modeled age-splitted case numbers best match with the actual age-splitted case numbers
Population dynamics parameters			
parBase.popnDeathRate (Mu)	Death rate per 1000 per day for 16 age groups	A 16*1 array	StatsNZ infoshare 2019
parBase.popnBirthRate (b)	Total births per day	163.3	StatsNZ infoshare 2019. Total births divided by 365.24 days

Variable name	Description	Default value	Note
parBase.popnAgeingRate	The daily rate moving to the next 5 year age group	0.00055	1/(5*365.25)
Seeding parameters			
parBase.seedDur	Time window (in days) when community seed cases appear	7	This is to approximate the seeding of the initial Omicron cases in NZ over a period in late Jan 2022 (see parInd.dateSeed)
parBase.initialExp	Number of seed cases appearing in the community seeding window for each age group	A 16*1 array	0.1% of the population size in each age group. These cases appear in about 7 days around par.dateSeed (normal distribution) - see getFOI.m line 7-12.
parBase.borderTime	Date when border cases start getting seeded	2022 March 01	This is approximately corresponding to the initial relaxation of NZ border policies in 2022
parBase.borderSeeds	Number of daily border seed cases appearing from borderTime	300	This is an approximation from the number of border arrivals in previous years
Disease rate parameters			
parBase.pClin	Probability of developing symptoms for individuals with no immunity per age group	A 16*1 array	See descriptions in Supplementary Table 2
parBase.ui	The susceptibility of each age group relative to the 60-64 years age group	A 1*16 array	See descriptions in Supplementary Table 2
parBase.IHR0	Age-split infection hospitalisation rates adjusted for the Omicron variant and NZ data	A 16*1 array	Adjusted to reflect Omicron specific IHR, pICU and IFR in NZ. See manual tuning note in getBasePar.m line 117-120. Supplementary Table 2 describes more details about hospitalisation and death rates based on Herrera-Esposito and de Los

Variable name	Description	Default value	Note
			Campos (2022) and NZ observed data.
parBase.IFR0	Age-split infection fatality rates adjusted for the Omicron variant	A 16*1 array	
Testing and lag parameters			
parBase.tLatentToTest	Delay from onset of infectiousness to test in days	4	See Supplementary Table 1
parBase.tTestToHosp	Delay from test to hospital admission in days	1	See Supplementary Table 1
parBase.tLOS	Length of stay per age group	A 16*1 array	Based on NZ data
parBase.tDeath	Days from admission to death	14	See Supplementary Table 1
parBase.pTest1_030	Testing probability before 1 May 2022 for clinical cases 0-29 yrs	0.5	Manually tuned, Supplementary Table 1. The testing probability linearly decreases between 1 May 2022 to 1 Jan 2023, to reflect the effect of public health strategy change and voluntary behavioural change.
parBase.pTest2_030	Testing probability after 1 Jan 2023 for clinical cases 0-29 yrs	0.25	
parBase.pTest1_3060	Testing probability before 1 May 2022 for clinical cases 30-59 yrs	0.6	
parBase.pTest2_3060	Testing probability after 1 Jan 2023 for clinical cases 30-59 yrs	0.4	
parBase.pTest1_60p	Testing probability before 1 May 2022 for clinical cases 60+ yrs	0.75	Manually tuned, Supplementary Table 1. For the elderly population, testing probability is assumed to stay high.
parBase.pTest2_60p	Testing probability after 1 Jan 2023 for clinical cases 60+ yrs (stay the same)	0.75	
parBase.pTestClin0	Age-dependent testing probability for clinical cases.	A nDays*16 matrix	Calculated using pTest1_030, pTest2_030, pTest1_3060, pTest2_3060,

Variable name	Description	Default value	Note
			pTest1_60p and pTest2_60p and the two case ascertainment rate (CAR) change dates - 1 May 2022 and 1 Jan 2023.
parBase.subClinPtestMult	Scaling factor for testing probability of subclinical cases	0.4	Testing probability of subclinical cases is assumed to be 40% of the testing probability of clinical cases. Supplementary Table 1.
Vaccination parameters			
parBase.vaccImmDelay	Delay from vaccination to immunity in days	14	
parBase.doses1	Daily cumulative number of dose 1 given to people in each of the 16 age groups	A nDays*16 matrix	Based on actual vaccine roll-out data (and the projection of the roll-out if needed). Given the delay for developing immunity from vaccine, the data is shifted by vaccImmDelay (14) days and cropped to match the simulation start and end. The vaccination data is truncated by the simulation window if there are more dates than the simulation window, or padded with a flat tail (the last number) if there are fewer dates.
parBase.doses2	Daily cumulative number of dose 2 given to people in each of the 16 age groups	A nDays*16 matrix	
parBase.doses3	Daily cumulative number of dose 3 given to people in each of the 16 age groups.	A nDays*16 matrix	
parBase.doses4plus	Daily cumulative number of dose 4 given to people in each of the 16 age groups.	A nDays*16 matrix	
parBase.nDose1Smoothed	Smoothed daily number of dose 1 having immunity in each of the 16 age groups.	A nDays*16 matrix	Data is smoothed over a 56 days sliding window, to make it sufficiently smooth for not breaking the ODE.
parBase.nDose2Smoothed	Smoothed daily number of dose 2 having immunity in each of the 16 age groups.	A nDays*16 matrix	
parBase.nDose3Smoothed	Daily number of dose 3 having immunity in	A nDays*16 matrix	

Variable name	Description	Default value	Note
	each of the 16 age groups.		
parBase.nDose4Smoothed	Daily number of dose 4 having immunity in each of the 16 age groups.	A nDays*16 matrix	
Antivirals parameter			
parBase.daily_treatcaseratio	The daily ratio of treated cases in cases receiving antiviral therapy for each of the 16 age groups.	A nDays*16 matrix	Calculated using antivirals data. The effects of antivirals were added to the model in June 2023 with more details in supplementary material 3. Vaccination, waning, and antivirals.
Immunity parameters			
parBase.waneRateMean	Mean daily immunity waning rate	0.0045	Assumed. This is the middle value of the range of waning rates tested.
parBase.relRate_RtoS	Relative rate of moving from recovered compartments to susceptible compartments	1.85	Supplementary Table 1. Assumed
parBase.VEi	Immunity against infection for each of the 14 susceptible compartments	A 1*14 array	Calculated from neutralizing titre based on Khoury et al. 2021, Golding and Lydeamore 2022. See getBasePar.m line 225-254.
parBase.VEh	Immunity against hospitalisation for each of the 14 compartments	A 1*14 array	Calculated from neutralizing titre based on Khoury et al. 2021, Golding and Lydeamore 2022. Minimum immunity of 0.5 is applied to the compartments that had 2, 3+ doses or previously infected (compartments 3:end). See getBasePar.m line 225-254.

Variable name	Description	Default value	Note
parBase.VEt	Immunity against transmission for each of the 14 compartments	A 1*14 array of zeros	
parBase.VEs	Immunity against symptoms for each of the 14 compartments	A 1*14 array	For simplicity this is set equal to VEi
parBase.VEf	Immunity against death for each of the 14 compartments	A 1*14 array	For simplicity this is set equal to VEh
parBase.waneNet_StoS	Fluxes between susceptible compartments as a result of immunity waning	A 14*14 matrix	0 stands for no movement, and -1 / 1 stands for flux out of / into a compartment. See the flow between compartments in paper Figure 1.
parBase.waneNet_RtoS	Fluxes (proportions) moving from the recovered compartment to the post-infection susceptible compartments.	A 14*14 matrix	The recovered cases with 0/1 and 2+ doses had different proportions moving into the 4 post-infection susceptible compartments (compartments 11-14). These proportions are calculated by solving an ODE so that the average titre drop matches with a specified amount.
parBase.vaxNet	Fluxes between susceptible compartments as a result of vaccination	A 14*14 matrix	0 stands for no movement, and -1 / 1 stands for flux out of / into a compartment. See the flow between compartments in paper Figure 1.
Variant of Concern (VOC) parameters			
parBase.vocWaneDate	Date of new variant (BA.5) being predominant	20 June 2022	This is a manually tuned date. For simplicity it is assumed that all infections before this date are BA.2 and all infections after this date are BA.5
parBase.vocWaneWindow	Variant transition window (in days)	2	Due to immunity escape of the new variant, movement of people to a lower post-

Variable name	Description	Default value	Note
			infection immunity compartment is assumed to take place in a short time window from 20 June 2022
parBase.VOC_logTitreDrop	The drop in log neutralizing titre for VOC (BA.5) relative to BA.2	log(0.4)	This is to model the reduction in vaccine effectiveness.
parBase.VEi_VOC	Immunity against VOC infection for each of the 14 susceptible compartments	A 1*14 array	Calculated based on the drop in log titre for VOC and Khoury et al.
parBase.VEh_VOC	Immunity against hospitalisation post infection by VOC for each of the 14 compartments.		Calculated based on the drop in log titre for VOC and Khoury et al. Minimum immunity constraint (0.5 as above) applied to compartments that had 2, 3+ doses or previously infected (compartments 3:end).
parBase.VEt_VOC	Immunity against transmission post infection by VOC.	A 1*14 array of zeros	
parBase.VEs_VOC	Immunity against developing symptoms post infection by VOC	A 1*14 array	Equal to VEi_VOC
parBase.VEf_VOC	Immunity against death after infection by VOC	A 1*14 array	Equal to VEh_VOC

Note:
In the final stage of delivering stakeholder requests and code refinement, some scenario parameters reflecting New Zealand specific situations were moved into the getBasePar.m script. However, as they are not part of the key assumptions of the model, and are not used in parameter fitting, those parameters are not included in the table above. Instead, they are included in the next table - Scenario parameters.

Scenario parameters

Relevant scripts

- getBasePar.m
- getParUnified.m

Table 6: Scenario parameters

Variable name	Description	Default value	Note
Default settings wrapped in base parameters			
parBase.scenarios.Properties.VariableNames	Variable names that define each scenario	{'cRampDeltaPolicy', 'VOC2active', 'seasonMultAmp', 'antiviralsEffectIHRmult', 'policyDate', 'VOC2date', 'scenarioNumber'}	
parBase.scenarios.scenarioNumber	Index of different scenarios	A nScenarios*1 array starting from 1	
parBase.scenarios.policyDate	An array of policy change dates	A nPolicy*1 array	Note that the current code only explores different seasonality effects in 3 scenarios with the same policy change date ('15-May-2023'). However, different policy change dates can be added if required.
parBase.scenarios.cRampDeltaPolicy	Relative transmission changes due to policy changes	A nScenarios*1 array	Value greater than 1 means transmission increase and value below 1 means transmission decrease. This is a multiplier that applies to Ct.
parBase.scenarios.VOC2active	Boolean to switch on or off the second variant arriving scenario (besides the BA.5 VOC)	A nScenarios*1 array of ones	By default a second VOC is included to simulate what had happened in Nov 2022 so all scenarios have a value 1 to switch on this effect.

parBase.scenarios.VOC2date	Date when a new VOC becomes predominant (besides the BA.5 VOC)	A nScenarios*1 array	15 November 2022 is the assumed date when a second VOC became predominant.
parBase.scenarios.seasonMultAmp	Amplitude of the seasonality multipliers applied to Ct	A nScenarios*1 array	0 - no seasonality; 0.1 - relatively weak seasonality; 0.2 - relatively strong seasonality. This is to simulate the variety in time-dependent transmission due to seasonality, and the value controls the amplitude of the seasonality wave. See supplementary material 2. Control function.
parBase.scenarios.antiviralsEffectIHRmult	Effect multipliers of antivirals on IHR	A nScenarios*1 array with zeros	0 - no effect; 1 - full effect. No effect on IHR is assumed in the default scenarios.
parBase.nScenarios	Total number of scenarios	3	This is based on the parBase.scenarios settings above.
parBase.scenario_names	Scenario names	A nScenarios*1 array of string values	This is used as a suffix of the output file names
Default settings wrapped in individual simulation runs			
CtRampStarts (eventually affecting parInd.Ct)	Transmission ramp up dates: ○ 10 Mar 2022 ± 5 days. This is the end of period 1, and beginning of the first ramp up:, - start seeing actual cases bump up, related to policy change ○ 15 Sep 2022 ± 5 days. Beginning of the second ramp up. ○ The end date of the simulation. This is a placeholder for future policy change,	A 3*1 array of datenum values	1. There were a number of policy changes in early March 2022 including relaxed border rules. As a result of relaxation of public health measures and of voluntary risk-reduction behaviours, a gradual increase in reproduction number excluding immunity □□□ over a 1-2 months window is assumed, and this is consistent with the observed bump-up in reported cases starting around this date.

	with no effect on time-dependent Ct values currently.		2. The COVID-19 Protection Framework (traffic lights) ended at 11.59pm 12 Sep 2022. Mandatory mask-wearing ended too. Isolation rules were relaxed and vaccination mandates ended soon in late Sep. Similarly these are reflected by a gradual increase in reproduction number over a time window. 3. An additional policy change date can be passed in via scenPar (if defined) and replace the placeholder date.
CtRampDays (eventually affecting parInd.Ct)	Transmission ramp-up window lengths: ○ 55 ± 20 days. Ramp window from period 1 to period 2, where the reproduction number excluding immunity increase linearly from $\square_{\square\square,1}$ to $\square_{\square\square,2}$ ○ 10 ± 20 days. Ramp window for second ramp up. ○ 0 days. Placeholder for future policy change.	A 3*1 array	See supplementary material Table 1. If a third policy change date is passed in by scenPar, the default ramp window for this third ramp up will be reset to 30 days by default.
CtRamp (eventually affecting parInd.Ct)	Ct values in different periods: ○ 1.1 ± 0.21. ○ Further multiplied by a value between 1.1 and 1.3. ○ Placeholder for future policy change, same as the second value	A 3*1 array	After the first ramp up, Ct values would change to a value between 0.89 and 1.31. After the second ramp up, Ct values would be (0.89-1.31)*(1.1*1.3). The Ct values after the third ramp up can be modified by scenPar.cRampDeltaPolicy as customised.

seasonMultAmpl (eventually affecting parInd.Ct)	The amplitude of the seasonality wave	0.1	Seasonality effect of increased transmission in winter and reduced transmission in summer, is simulated by applying a sin curve multiplier to Ct values since its start date. The multiplier oscillates between 0.9-1.1 by setting seasonMultAmpl as 0.1. This value can be reset as customised in scenPar.
seasonStart (eventually affecting parInd.Ct)	The start date of seasonality effect	01 Apr 2023	The seasonality effect was added mainly for simulating future spreading (when the model was developed).
CtSeasonMult (eventually affecting parInd.Ct)	The time-dependent seasonality multiplier	A nDays*1 array	Controlled by seasonMultAmpl. A time-dependent multiplier, whose value is constantly 1 before seasonStart, and fits a sin curve after seasonStart ->1 around winter and <1 around summer.

Apart from the policy changes, new VOC effect, antivirals effect (on IHR), and seasonality effect, the end date of simulation is also an important variable for scenario simulation. This is until when in the future users would like to run the simulation and get insights about the disease spread. By default it is set to 30 June 2024 in naiveABCSEIR.m (line 142). Note that model assumptions and parameter values are likely to become invalid over time as the epidemiological situation changes. Therefore, any long term simulation results must be interpreted with caution, and model review and update is strongly recommended in future use.

Wrapped parameters per simulation run

For each simulation run (each time solving the core ODE), the randomised parameters, the base parameters and additional scenario parameters (if any) are wrapped into one struct, to construct the initial conditions for the ODE solver.
In this document, this structure is named as parInd. The combination of each set of randomised parameters, the base parameters, and each set of the scenario parameters, is referred to as one sample.

Relevant script

- getParUnified.m

Table 7: Wrapped parameters per simulation run

Variable name	Description	Value	Note
parInd (iSample)	Parameter structure of individual run at the ith sample		For simplicity, the index iSample will not be noted later.
Seeding parameters			
parInd.dateSeed	A date around which the initial Omicron cases appear	Randomised around 19 Jan 2022 A date near 19 Jan 2022 (± 3 days)	Initial Omicron cases are seeded in a short window of about 7 days (parBase.seedDur) around this date (see paper 2.1 Immunity model and supplementary Table 1)
Control function			
parInd.Ct	The control function, which is a scaling factor reflecting the relative daily transmission affected by various factors, e.g. policy change, and seasonality.	A 1*nDays array, initial value randomised between 0.58 and 0.78	Daily values will soon be updated according to ramp up settings (getParUnified.m line 27-53), to reflect the impact of public health interventions, voluntary behavioural change, and seasonality effect.
Testing and lag parameters			
parInd.pTestClin	Age-dependent testing probabilities for clinical cases.	A 16*nDays matrix	The baseline testing probability (see parBase.pTestClin0)

Variable name	Description	Value	Note
			multiplied by a scaling constant from the randomisation (see Theta.pTestMult).
parInd.pTestSub	Age-dependent testing probabilities for subclinical cases	A 16*nDays matrix	40% of the probabilities for clinical cases.
parInd.pTestTS	Age-dependent overall testing probability	A 16*nDays matrix	Calculated from parInd.pTestClin, parInd.pTestSub and parBase.pClin.
Disease rate parameters			
parInd.IHRmult	A scaling constant for the infection hospitalisation rates	A randomised value between 0.5 and 1.5	
parInd.IFRmult	A scaling constant for the infection fatality rates	A randomised value between 0.5 and 1.5	
parInd.IHR	Age-dependent infection hospitalisation rates.	A 16*1 array	Using rates adjusted for Omicron, tuned by actual and modeled data (see parBase.IHR0) and further multiplied by the scaling factor parInd.IHRmult.
parInd.IFR	Age-dependent infection fatality rates.	A 16*1 array	Using rates adjusted for Omicron, and further multiplied by the scaling factor parInd.IFRmult.
Antivirals effect parameters			
parInd.antiviralsEffectIHRmult	A multiplier for the effect of antivirals on IHR	0 or customised value as part of scenario parameters	0 - no effect; 1 - full protection from hospitalisation.
parInd.antiviralsEffectIFRmult	A multiplier for the effect of antivirals on IFR	A randomised value between 0.4 and 0.6	0 - no effect; 1 - full protection from fatality.
Contact matrix parameters			

Variable name	Description	Value	Note
parInd.relaxAlpha	Amount by which the contact matrix (M0) relaxes back to the pre-pandemic matrix (M1) estimated by Prem *et al.* 2017	A randomised value between 0 and 0.8	0 - no relaxation at all; 1 - fully relaxed. See more description in supplementary materials about formula (7)
parInd.contactPar.weights	Weighting matrix to adjust the initial contact matrix	A 16*16 matrix	Expanded from age blocks to age groups using parBase.Cw1.
parInd.contactPar.weightsChange	Weighting matrix to adjust the contact matrix for relaxation	A 16*16 matrix	Calculated based on parBase.Cw1 and parInd.relaxAlpha, and expanded from age blocks to age groups.
parInd.contactPar.changeDate	Start date for the change of contact matrix	10 Mar 2022 (± 5 days)	Same as the first ramp-up start date
parInd.contactPar.changeWindow	Ramp window for the contact matrix to change	Randomised between 50-90 days	Contact matrix relaxes linearly in this window from the start date.
VOC parameters			
parInd.vocWaneAmount	The scale of immunity waning for each post-infection susceptible compartments, or BA.5 immunity escape (relative to BA.2)	A randomised value between 0.1 and 0.7	This determines what fraction of each post-infection susceptible compartment moves to the next lower immunity class
parInd.VOC2active	A switch to control modelling for a second VOC in the future	False by default	Can be updated by the scenario parameters if needed
parInd.vocWaneDate2	Date of a second new variant being predominant	A date	Optional. Dependent on scenario settings
parInd.vocWaneAmount2	Amount of a second new variant immune escape	0.25 by default	Dependent on scenario settings.
Immunity parameters			

Variable name	Description	Value	Note
parInd.waneRateMult	A multiplier on waning rates	A randomised value between 0.5 and 1.5	
parInd.waneRate_StoS	Rate of moving from one susceptible compartment to the next one with lower immunity	A value between 0.0022 and 0.0067	Calculated using parBase.waneRateMean and parInd.waneRateMult
parInd.waneRate_RtoS	Rate of moving from the recovered compartment to the post-infection susceptible compartment	A value between 0.0042 and 0.0125	Calculated using parBase.waneRateMean, parBase.relRate_RtoS and parInd.waneRateMult

Use of major code modules

Parameter fitting

To make the simulation match the reality as much as possible, an ABC (approximate Bayesian computation) approach is taken to tune some parameters as "best guesses" of the reality.
The core modules introduce randomness to some base parameters by generating a large amount of the randomised parameters sets. Each set of randomised parameters together with the base parameters and scenario parameters (only those reflecting the past scenarios) are jointly used to construct one set of initial conditions for the ODE model solver. By solving the ODE iteratively using each of the parameter sets, a large number of simulation results sets are produced, and can be compared with observed data. NOTE that these simulations would only run until when the observed data is available (which is a date in the past).
By doing so, the model will then perform two actions to ensure the parameters are best guesses and can be further used to reasonably indicate what could happen in the future and/or in other scenarios.

- Action 1: Filtering
    - Based on the distance between the simulation results and the observed data (the objective), the model will select 1% of the best simulations (with smallest distances), and correspondingly the 1% of fitted parameter values
- Action 2: Plotting
    - Violin plots of the randomised parameters are produced using the 1% selected parameter values. By this visualisation, researchers and model users can quickly check whether the corresponding base parameter setting is sensible - if any of the distributions is strongly skewed to one end, we may need to consider fine tuning the base parameter.

Relevant scripts:

- naiveABCSEIR.m line 80-83 (objective)
- calcErrorWithAgeCurrent.m - supplementary formula (32)

- getVarsToPlot.m
- combineBands.m
- violinplot.m

Objective

The objective is the distance or error from the ODE solution to actual data for a given parameter set. All errors from different metrics are summed with equal weights.

Error calculation

Set-up

- Only fit to cases after 14 Feb 2022
- Only fit to other data after 1 Feb 2022
- Exclude 10 days of data for deaths to account for reporting lag
- Exclude 40 days of hospital admission data to account for reporting lag

Metrics

Data to compare/fit include:

- Daily new cases (total)
- Daily deaths (total)
- Daily new hospital admissions (total)
- Daily new cases (per age group) - This is fit to fractions of admissions of age groups rather than absolute numbers.
- Daily new hospitalisation admissions (per age group) - This is fit to fractions of admissions of age groups rather than absolute numbers.
- Daily incidence per capita - This is compared with the incidence in border workers with known data limitations.

See more details in supplementary material 6. Clinical pathways and fitting to data.

The actual data are smoothed over a 7-day window for better comparison. As a result, the mean squared error for each metric is returned as the distance. A sum of all the distances, equally weighted across these metrics, is calculated for one simulation run, corresponding to one set of parameters.

Scenario simulations

To get insights about future transmission and impact, the model uses the 1% best fitted parameters and scenario specific parameters that represent future assumptions to run simulations for an extended period of time.
For each of the scenarios, the core ODE solving is executed using each set of parameters in the 1% best fitted parameter sets, and metrics are retrieved and saved in output files.

Relevant scripts:

- naiveABCSEIR.m line 117-125, 137-252

Supporting modules

Pre-processing

CMA developed some preprocessing scripts to transform raw data files into the format that the major code modules can consume more easily.
The git repository README file has described how to run preprocessing in **3. How to process the unit record data** and **4. How to process the vaccination data**.

Relevant scripts

- Epi_data_cleaning.m
- processVaxDataNational.m

Post-processing

Post-processing involves translating the scenario simulation outputs into a format that is easy to interpret by stakeholders, usually in summary tables and plots. More details here.

Relevant scripts

- naiveABCSEIR.m line 255-276
- getAllData.m
- plotTrajModelTiled.m
- plotTrajModelAgeSplit.m
- writeMOHspreadsheetsTrajAndBands.m
- writeRMarkdownSpreadsheets.m
- writeRMarkdownSpreadsheetsCompare.m

Version control

Git was applied to keep track of changes in the code base, and for collaboration between multiple model contributors.