Modelling the impact of respiratory syncytial virus (RSV) vaccine and immunoprophylaxis strategies in New Zealand

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Highlights (85 characters): A maternal RSV vaccine or mAb would effectively reduce RSV disease burden in New Zealand.

Abstract

Background

Mathematical models of respiratory syncytial virus (RSV) transmission can help describe seasonal epidemics and assess the impact of potential vaccines and immunoprophylaxis with monoclonal antibodies (mAb).

Methods

We developed a deterministic, compartmental model for RSV transmission, which was fitted to population-based RSV hospital surveillance data from Auckland, New Zealand. The model simulated the introduction of either a maternal vaccine or a seasonal mAb among infants aged less than 6 months and estimated the reduction in RSV hospitalizations for a range of effectiveness and coverage values.

Results

The model accurately reproduced the annual seasonality of RSV epidemics in Auckland. We found that a maternal vaccine with effectiveness of 30-40% in the first 90 days and 15-20% for the next 90 days could reduce RSV hospitalizations by 18-24% in children younger than 3 months, by 11-14% in children aged 3-5 months, and by 2-3% in children aged 6-23 months. A seasonal infant mAb with 40-60% effectiveness for 150 days could reduce RSV hospitalizations by 30-43%, 34-48% and by 14-21% in children aged 0-2 months, 3-5 months and 6-23 months, respectively.

Conclusions

Our results suggest that either a maternal RSV vaccine or mAb would effectively reduce RSV hospitalization disease burden in New Zealand. Overall, a seasonal mAb resulted in a larger disease prevention impact than a maternal vaccine.

1 Introduction

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2 Respiratory syncytial virus (RSV) is the leading cause of acute respiratory tract infections (ARI) 3 in children worldwide [1]. Almost all children have an RSV infection by two years of age [2], 4 with infants aged less than six months experiencing the greatest burden of severe disease [1]. The 5 monoclonal antibody (mAb), Palivizumab, is currently the only licensed preventative strategy for 6 RSV. However, due to its requirement of monthly dosing and high costs, its use is limited to 7 high-risk infants [3] and is rarely used in New Zealand (NZ) [4]. 8 Several RSV vaccines and mAbs are in clinical development [5]. The RSV F nanoparticle 9 maternal vaccine is currently the most advanced vaccine candidate. In a Phase 3 trial, the vaccine 10 did not meet its primary endpoint of reducing RSV lower respiratory tract infections (LRTI), 11 despite an overall efficacy of 39.4% (95% confidence interval [CI], 5.3-61.2) against RSV LRTI 12 for 90 days after vaccination. However, the vaccine did meet secondary objectives of reducing 13 RSV LRTI hospitalizations and severe hypoxemia with benefits through to 180 days after 14 vaccination [6]. Consequently, the vaccine is being assessed in an ongoing Phase 3 trial. In terms 15 of new immunoprophylaxis through mAbs, the candidate Nirsevimab, which is administered 16 once seasonally, demonstrated a 70.1% (95% CI 52.3–81.2) efficacy in reducing RSV LRTI in 17 healthy pre-term infants over the 150 day follow-up period [7]. Nirsevimab is currently being 18 trialled for use in all infants. 19 Several mathematical modelling studies assessing the impact of potential RSV vaccination and 20 mAbs have been published. In particular, Cromer et al. [8] and Rainisch et al. [9] compared the

22 respectively. While informative, these studies assumed effectiveness values that were higher than

impact of RSV mAbs and maternal vaccination, using a cohort model and decision tree model

those reported from recent clinical trials, limiting their application. Additionally, differences in
climate, demographics, and contact patterns can impact RSV transmission [10], emphasising the
need to develop and fit RSV models to specific regions. Moreover, as RSV is not a notifiable
disease, the quality of surveillance methods and RSV burden data varies considerably by location
[1].

In this study, we estimated the impact of an RSV maternal vaccine and a seasonal infant mAb on
RSV hospitalizations, under varying levels of coverage and effectiveness, using a mathematical
model fitted to population-based RSV hospital surveillance data from Auckland, NZ.

31 Methods

32 Setting and population-based data

33 Data for this study were sourced from the Southern Hemisphere Influenza Vaccine Effectiveness 34 Research and Surveillance (SHIVERS) project [11]. SHIVERS was an active ARI surveillance 35 project conducted in two public hospitals serving the central, southern, and eastern regions of Auckland from 30th April 2012 to 31st December 2015. These regions have a combined 36 37 population of approximately one million, including 36,000 children aged less than two years 38 [12], and are predominantly urban with a sub-tropical climate. The SHIVERS hospital sites 39 provide all respiratory inpatient services for the population residing in these regions. Ethical 40 approval for the SHIVERS project was obtained from the NZ Health and Disabilities Ethics 41 Committee (NTX/11/11/102).

During the study, research nurses reviewed daily records to identify all admissions with a
suspected ARI. All patients meeting the World Health Organization severe acute respiratory
infection (SARI) case definition (cough and fever within the last 7 days in 2012 and within 10

| 45 | days from 2013 onwards) were included [13]. Nurses obtained consent and collected |
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| 46 | nasopharyngeal swabs/aspirates from patients. To provide an understanding of the respiratory |
| 47 | virus burden among patients with an ARI that did not meet the SARI definition (cough and/or |
| 48 | fever but not both within last 10 days), study nurses enrolled a sample of non-SARI respiratory |
| 49 | patients from 2013 to 2015. Sampling of non-SARI respiratory patients in 2013 was during the |
| 50 | peak winter/spring period (mid-August to October) and included weekly selection of two |
| 51 | paediatric and two adult inpatients at each hospital. During 2014 and 2015, this surveillance was |
| 52 | extended to enrol approximately six paediatric and six adult non-SARI respiratory patients |
| 53 | weekly between April and September at each hospital. |
| 54 | In addition to the SHIVERS testing protocol, hospital laboratories provided results from clinical- |
| 55 | ordered tests performed on patients hospitalized with an ARI. These results were included after |
| 56 | validation of the hospital PCR assay performance. Collected specimens were tested for RSV |
| 57 | using the United States Centers for Disease Control and Prevention real-time reverse |
| 58 | transcription (RT)-PCR protocol at the Institute of Environmental Science and Research or using |
| 59 | the AusDiagnostic PCR protocol and real-time PCR assays at hospital laboratories [11]. |
| 60 | To account for changes in testing criteria and to correct for non-testing, we applied the |
| 61 | proportion positive for RSV among SARI and non-SARI cases to non-tested SARI and non- |
| 62 | SARI patients for each age group by study week. |
| 63 | Model structure and parameters |
| 64 | We modelled RSV transmission in a population using a deterministic, compartmental |
| 65 | Susceptible (S) – Exposed (E) – Infectious (I) – Recovered (R) – Susceptible (S) transmission |

66 (SEIRS) model, similar to work by Hogan et al [14]. The model divided the population into four

age groups: children aged 0–2 months (S₁, E₁, I₁, R₁), children aged 3–5 months (S₂, E₂, I₂, R₂), children aged 6–23 months (S₃, E₃, I₃, R₃), and individuals aged two years and older (S₄, E₄, I₄, R₄). Schematic representations of the models are presented in Figure 1 and all equations are provided in Supplementary Material S1. The transmission function λ_i (t), representing the force of infection on age group *i* over time t, with indices *i* and *j* representing the four age cohorts, was calculated as:

73
$$\lambda_i = \beta_0 (1 + \beta_1 \cos(\frac{2\pi t}{52} + \varphi)) \frac{1}{N_i} \sum_{j=1}^4 M_{i,j} I_j,$$

where β_0 is the transmission coefficient. The seasonal fluctuations in RSV transmission observed in temperate/sub-tropical climates including NZ [15], were captured through a cosine function [10]. The parameter β_1 is the amplitude of seasonal forcing, and φ represents the phase shift. The mixing matrix $M_{i,j}$ is the number of contacts that an individual in age group *j* has with individuals in age group *i*.

79 Mixing between age groups was based on NZ-specific contact rates as reported by Prem et al.

80 [16]. We adapted the contact matrix to match the age structure used in our model and converted

81 daily values to weekly (Supplementary Material S2). As these rates were in five-year age groups,

82 we also assessed the impact on model outcomes when using more finely stratified contact data

from the United Kingdom as reported by Fumanelli et al.[17].

There are on average 279 live births per week in Auckland [18], informing the birth rate in the model. The average life expectancy for an Auckland resident is 81 years [19]. We assumed that deaths only took place in the older age group, thus the weekly ageing/death rate in age group 4 (η_4) was equal to 1/ (52*79). The weekly ageing rates from age group 1 to 2, age group 2 to 3, and age group 3 to 4 were 1/13, 1/13, and 1/78 respectively. Epidemiological parameters were based on data published in the peer reviewed literature or estimated during model fitting (Table 1). Drawing on previous observation and modelling studies, we assumed average values for a latent period $(1/\sigma)$ of four days, a duration of infectiousness $(1/\gamma)$ of ten days, and immunity following infection $(1/\nu)$ of 230 days [14, 20, 21].

We assumed that infants are born with temporary immunity to RSV infection though

94 transplacental transfer of antibodies, however the level of protection conferred is uncertain [22].

95 Based on data from serological studies of RSV specific antibodies [23, 24], we initially reduced

96 susceptibility to infection by 33% in infants younger than three months ($\alpha_{1=}0.66$) and included

97 this as a fitted parameter. As this parameter is derived from limited observations, we also

assessed the impact on fitted parameters and model outputs when assuming no natural maternallyderived immunity in the model.

100 Model fitting

101 Our model output represents the total number of RSV infections in the population while our data 102 are RSV hospitalizations. We therefore scaled our model results by parameters P_1 , P_2 , P_3 , and P_4 103 which represent the proportion of RSV infections in each age class that are hospitalized and 104 detected with RSV. This was estimated as the sum of all cases in the data for an age group 105 divided by the sum of the modelled incidence over 209 weeks, the SHIVERS surveillance time 106 period.

107 We estimated parameters β_0 , β_1 , φ and α_1 by fitting the model to weekly hospitalizations for the 108 four age groups in our model. We fitted the model in R software by maximum likelihood 109 estimation using the bbmle package [25]. We assumed that the number of RSV hospitalizations each week represented Poisson samples with expectation pI, where p is probability of a case being hospitalized and RSV detected, and I is the true incidence in each age group. Confidence intervals for fitted parameter estimates were based on the quadratic approximation at the maximum likelihood estimate [25].

114 Model with vaccination or immunoprophylaxis

We considered two RSV preventative strategies: first, a maternal vaccination where infants are born with maternal vaccine derived protection, and secondly, a seasonal immunoprophylaxis in the form of a single dose mAb, administered to infants aged less than six months. Recent Phase 3 trials for RSV maternal vaccines and mAbs have assessed efficacy against medically significant LRTI. As the majority of infants are reported to have symptomatic RSV infections [26], we assumed in our analysis that the effectiveness of maternal vaccines or mAbs against all RSV infections in infants could be similar.

122 For maternal vaccination, we assumed the duration of protection from a maternal vaccine to be 123 180 days, which was the duration of follow-up to assess efficacy in the recent RSV-F maternal 124 vaccine trial [6]. Immunized infants were born into a P_i group and had susceptibility to infection 125 reduced by factor 1 - ve, where ve is a proxy for vaccine effectiveness. While the RSV-F 126 maternal vaccine phase 3 trial did not meet its primary endpoint [6], it is possible that the newer 127 maternal vaccine products, which utilise the more antigenic pre-fusion F protein, may lead to 128 higher neutralizing titres in mothers and greater protection for the infant [27]. Moreover, 129 considering the stated minimal criteria for an RSV maternal vaccine efficacy against RSV-130 associated LRTI was 60% [28], we tested a default scenario where effectiveness against infection 131 waned over time starting at 40% and halved after 90 days. However, we also tested scenarios

where vaccine effectiveness was initially 30% and then waned to 15% after 90 days, and where
effectiveness remained at 40% throughout the 180-day period.

134 To investigate the impact of an RSV mAb, we assumed infants aged less than six months were 135 administered the mAb two months prior to or during the NZ winter season. The duration of 136 protection from RSV mAb was 150 days, which was the duration of follow-up used to assess 137 efficacy in the recent Nirsevimab trial [7]. Like maternal vaccination, immunized infants had 138 susceptibility to infection reduced by factor 1 - ve, based on mAb effectiveness. Informed by the 139 Phase 3 Nirsevimab trial, which showed a 70.1% efficacy against medically attended LRTI 140 among pre-term infants, who have a greater risk of severe RSV-associated outcomes [29], we 141 tested a default scenario of 50% effectiveness against infection among all infants. We also tested 142 scenarios where mAb effectiveness against infection was 40% and 60%.

For both preventative strategies, the default coverage was set at 50%, informed by recent
maternal vaccination coverage data from NZ [30], however we also tested scenarios of 30% and
80% coverage. Model equations with maternal vaccination or seasonal mAb are provided in
Supplementary Material S1.

147 Model outputs

The number and proportion of hospitalizations averted in children aged less than two years was estimated, stratified by age group, for each of the default strategies, and when coverage and effectiveness levels were varied. We assessed the public health impact during the first ten years following vaccine or mAb introduction, as well as the impact once the intervention was wellestablished within the population. Uncertainty in model outputs was estimated from the 153 distribution of 500 model simulations, each using a different combination of parameter values

154 based on the fitted parameter uncertainty from maximum likelihood estimation (Table 1).

155 **Results**

156 Model fit

Figure 2 shows the model fitted to RSV hospitalizations for children younger than two years by age group. When testing the assumption of no natural maternally derived protection, we found that our model was unable to fit to the data. Additionally, we found model outcomes were not markedly different when using more finely age-stratified contact data (Supplementary Material S3), and as such, we chose to present results using NZ-specific contact rates. Both the base and intervention model outputs demonstrated a seasonal pattern of RSV infections (Figure 3). Fitted parameter values with 95% confidence intervals (CIs) are shown in Table 1.

164 Averted hospitalizations

165 Both RSV preventative strategies modelled reduced the number of hospitalizations compared to 166 baseline among children less than two years of age (Table 2). At default values, the RSV 167 maternal vaccine had a reduced impact in the first year following implementation. By the second 168 year, the vaccine showed a consistent reduction in hospitalizations compared to baseline among 169 children aged less than six months. It also showed a small impact among children aged 6-23 170 months (Figure 3). A seasonal RSV mAb at default values had a small impact on hospitalizations 171 among children aged less than two years in the first year but had a larger impact in the second 172 year following implementation (Figure 3).

Once well-established in the population, the default maternal vaccine scenario of 50% coverageand 180 days duration of protection with 40% effectiveness for the first 90 days, and a 20%

175 effectiveness, thereafter, resulted in a 24% reduction in hospitalizations per 1000 children aged 176 0–2 months, a 14% reduction among children aged 3–5 months, and a 3% reduction among 177 children aged 6–23 months, compared to baseline. If coverage of a vaccine with our default 178 effectiveness values was increased from 50% to 80%, there was an additional 14%, 9%, and 3% 179 reduction in hospitalizations among children aged 0-2 months, 3-5 months, and 6-23 months 180 respectively, compared to the default scenario. The impact of a maternal vaccine was greatest in 181 children aged 0-2 months, except in scenarios in which it was assumed there was no waning 182 vaccine effectiveness, where the impact was similar in both children aged 0-2 months and 3-5 183 months (Table 2, Supplementary Material S4). 184 A seasonal mAb among infants aged less than six months at default values of 50% coverage and 185 50% effectiveness for 150 days, resulted in a 37% reduction in hospitalizations per 1000 children 186 aged 0–2 months, a 41% reduction among children aged 3–5 months, and a 17% reduction 187 among children aged 6-23 months, compared to baseline. If coverage of a mAb with 50% 188 effectiveness was increased from 50% to 80%, there was an additional 3%, 3%, and 2% 189 reduction in hospitalizations among children aged 0-3 months, 3-5 months, and 6-23 months 190 respectively, compared to the default scenario. The impact of a seasonal mAb on averted 191 hospitalizations was greatest in children aged 3–5 months for all scenarios.

192 **Discussion**

We report the potential impact of an RSV maternal vaccine or a seasonal infant RSV mAb on
RSV hospitalizations, given a range of coverage and effectiveness measures and using a dynamic
transmission model. This model assumed effectiveness and duration of protection values

informed from recent Phase 3 trial results and found both preventative strategies to reducehospitalizations in children aged less than two years.

198 When assuming a similar coverage to that for existing maternal vaccination programmes in NZ, 199 an RSV maternal vaccine with waning effectiveness that approximates the recent RSV F vaccine 200 Phase 3 results could reduce RSV hospitalizations by 24%, 14%, and 3% in children aged 0-2 201 months, 3-5 months, and 6-23 months, respectively. In contrast, a seasonal mAb administered to 202 infants aged less than six months with 50% effectiveness could reduce RSV hospitalizations by 203 37%, 41%, and 18% in the same age groups. Overall, a seasonal mAb showed a greater health 204 impact due to its ability to protect a wider age range of children than a maternal vaccine, 205 although this finding should be interpreted within the context of our assumptions about the 206 effectiveness and durability of the two interventions modelled.

207 RSV is the leading cause of ARI hospitalizations in young children, highlighting the need for 208 new pharmaceutical interventions to reduce health system burden and cost. Given the challenges 209 of active immunization in early infancy, either an RSV maternal vaccination or an infant RSV 210 mAb are realistic public health strategies. Maternal vaccination strategies for influenza and 211 pertussis currently exist, thus the same systems can be leveraged for implementation of an RSV 212 maternal vaccine. However, such a strategy will require access to and acceptability of 213 vaccination among pregnant women. While no newborn monoclonal antibodies are currently 214 recommended in NZ [4], the previous success of licensed immunoprophylaxis for RSV 215 (Palvizumab) may aid in the licensure and acceptability of a new candidate. Moreover, producers 216 of Nirsevimab expect the product to have vaccine-like pricing [31]. As the modelled health 217 impacts from both strategies in our study were not substantially different, pricing of these

interventions together with comprehensive cost-effectiveness analysis will be crucial forimplementation.

220 In our model, a maternal vaccine providing protection for a 180-day period showed a small 221 impact in terms of averted hospitalizations among children aged 6-23 months, suggesting some 222 indirect effects. This contrasts with a related mathematical modelling study from Western 223 Australia that found the effect of an RSV maternal vaccine to be negligible for children 6-23 224 months of age [14]. It is possible that this impact may be due to our adaptation of contact rates 225 from 0-4-year old children to infants, however, in a sensitivity analyses using more finely age-226 stratified contact data, we still observed a small indirect effect of maternal vaccination. Another 227 possible explanation is that our inclusion of RSV ARI hospitalization data among all ages may 228 have resulted in a better capture of RSV transmission and disease among older children and 229 consequently shown greater impact of a modelled preventative strategy. Additionally, the 230 Western Australian model used cohort ageing to model transitions between age groups, whereas 231 we applied continuous ageing, which due to the exponential distribution of the duration of each 232 compartment, could result in a larger modelled indirect effect.

233 Previous studies comparing RSV vaccines and/or mAbs have assumed effectiveness values 234 higher than recent clinical trial results. In terms of the relative impact of RSV mAb and maternal 235 vaccinations on hospitalizations, in studies by Rainisch et al. and Cromer et al., when assuming 236 100% uptake of both candidates, a mAb was estimated to prevent approximately 1.7–1.8 times 237 more hospitalizations than a maternal vaccine among infants aged less than six months [8, 9]. In 238 our study, if assuming 100% uptake at the default effectiveness values for each candidate, a 239 seasonal mAb prevented 1.1 times more hospitalizations than a maternal vaccine among infants 240 aged less than six months. The greater impact of maternal vaccination in our study is likely due

to our longer assumed duration of protection, informed by recent clinical trial results.

Additionally, we noted a greater impact on hospitalizations with increased coverage for a maternal vaccine than for a seasonal mAb. Such findings suggest that a maternal vaccine may be more cost-effective than previously estimated. It also highlights the strengths of our study, which incorporates characteristics of RSV preventative strategies currently in Phase 3 trials and validates the model against comprehensive RSV surveillance data.

247 Our study also has several important limitations. Firstly, the starting values for our fitted 248 parameter for maternally derived immunity were based upon limited data. We found our model 249 was unable to fit to data if we assumed no such immunity and our fitted values aligned closely 250 with previous seroprevalence and modelling studies [14, 23, 24]. Secondly, we utilized scaling 251 parameters to fit the modelled incidence to the number of RSV hospitalizations reported in our 252 data. Due to limited information on the proportion of RSV infections that are hospitalized by 253 age, validation of these parameters was challenging. Examination of emergency care 254 presentation and hospitalization rates due to RSV in NZ show that infants aged 0-2 months are 255 three times as likely to be hospitalized than those aged 6–11 months [32], which supports our 256 assumptions. Nevertheless, better data on RSV disease burden in the community and 257 hospitalization risk will be valuable for future RSV modelling and are needed to assess the 258 potential benefit of pharmaceutical interventions more comprehensively. Finally, our modelling 259 relied on hospitalization data, thus did not assess the health impact of preventive strategies in 260 other settings. Furthermore, an RSV vaccine or mAb may have benefits that extend beyond 261 preventing direct RSV-associated events, as evidence suggests that severe RSV in infancy is 262 associated with recurrent wheeze and development of asthma later in life [33]. Additionally, data 263 from the recent RSV F nanoparticle maternal vaccine Phase 3 trial reported a reduction in "all

cause" medically significant LRTI events (i.e. without a requirement of RSV) [6]. As these
additional benefits of an RSV preventative strategy were not accounted for in our model,
findings from our study are likely to be a conservative estimate of the true health and economic
impact.

268 Our study suggests that both an RSV maternal vaccination and a seasonal mAb could effectively 269 reduce RSV hospitalization burden in young children. A seasonal mAb had a greater modelled 270 impact than a maternal vaccine as it provided protection to a wider age range, however a year-271 round maternal vaccination demonstrated a small indirect effect among children aged 6-23 272 months and had greater impact with increased coverage. Additional data on the burden of RSV in 273 the community and in other health care settings together with cost-effectiveness analyses will be 274 vital for assessing the impact of future possible implementation of these interventions. Finally, as 275 RSV vaccine candidates are also being developed for older children and adults, further 276 modelling, and cost-effectiveness work to estimate the impact of combined strategies will be 277 important.

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| Parameter | Definition | Fixed/Fitted | Value(s) | Reference |
|-----------------------|--|--------------|--|-----------|
| 1/σ | Latent period (days) | Fixed | 4 | [21] |
| 1/γ | Infectious period (days) | Fixed | 10 | [20, 21] |
| 1/v | Duration of immunity following infection (days) | Fixed | 230 | [14, 21] |
| β₀ | Transmission coefficient | Fitted | 0.054 (0.053 - 0.056) | |
| β1 | Amplitude of seasonal forcing | Fitted | 0.451 (0.431 – 0.471) | |
| φ | Phase of seasonal forcing | Fitted | -1.546 (-1.595 – -1.497) | |
| α1 | Reduced susceptibility in 0–2 months age group due to RSV-natural maternal antibodies | Fitted | 0.684 (0.614 – 0.747) | [23, 24] |
| P_{I} | Proportion of infected that are hospitalized and detected in age group 0–2 months | | 0.55 | |
| P ₂ | Proportion of infected that are hospitalized and detected in age group 3–5 months | | 0.29 | |
| <i>P</i> ₃ | Proportion of infected that are hospitalized and detected in age group 6–23 months | | 0.03 | |
| P4 | Proportion of infected that are hospitalized and detected in age group ≥24 months | | 0.0002 | |
| pv | Vaccine/mAb coverage | Fixed | 50% ^a | [30] |
| 1/ω | Duration of mAb ^b induced protection (days) | Fixed | 150 | [6, 7] |
| | Duration of vaccine induced protection (days) | Fixed | 180 | [6,7] |
| ve | Vaccine effectiveness mAb ^b effectiveness | Fixed | 40% - 20% ^a 50% ^a | [6, 7] |

Table 1: Model parameter values

^a Default values, ^b mAb; monoclonal antibody. 95% Confidence intervals are for fitted parameters

Table 2: Annual hospitalizations in terms of cases per 1,000 children and percentage reduction in hospitalizations for each age

group compared to baseline (no intervention) for a range of scenarios among children aged less than two years.

| | Annual hospitalizations | | | | | | |
|---|-------------------------|--------|-------------------------|--------|---------------------------|-------|--|
| | Infants aged 0–2 months | | Infants aged 3–5 months | | Children aged 6–23 months | | |
| | Cases per 1,000 | (%) | Cases per 1,000 | (%) | Cases per 1,000 | (%) | |
| Baseline | 30.0 (26.3-34.1) | | 22.9 (21.3-24.5) | | 10.1 (9.6-10.7) | | |
| Maternal vaccine impact with protection of 180 days | | | | | | | |
| Expected coverage (50%) | | | | | | | |
| Default effectiveness (40% first 90 days, 20% next 90 days) | 22.8 (20.0-25.8) | (24.1) | 19.6 (18.3-20.9) | (14.3) | 9.8 (9.2-10.3) | (3.4) | |
| Lower effectiveness (30% first 90 days, 15% next 90 days) | 24.6 (21.6-27.9) | (17.9) | 20.5 (19.1-21.9) | (10.5) | 9.9 (9.4-10.4) | (2.1) | |
| Sustained protection (40% for 180 days) | 22.1 (19.5-25.1) | (26.2) | 17.0 (15.8-18.1) | (25.7) | 9.6 (9.1-10.1) | (5.4) | |
| Higher coverage (80%) | | | | | | | |
| Default effectiveness (40% first 90 days, 20% next 90 days) | 18.6 (16.4-21) | (38.0) | 17.6 (16.4-18.7) | (23.1) | 9.5 (9-9.9) | (6.5) | |
| Lower effectiveness (30% first 90 days, 15% next 90 days) | 21.4 (18.8-24.2) | (28.8) | 18.9 (17.7-20.2) | (17.2) | 9.7 (9.2-10.2) | (4.4) | |
| Sustained protection (40% for 180 days) | 17.8 (15.7-20.1) | (40.6) | 13.7 (12.8-14.6) | (40.1) | 9.2 (8.7-9.6) | (9.6) | |
| Lower coverage (30%) | | | | | | | |
| Default effectiveness (40% first 90 days, 20% next 90 days) | 25.7 (22.6-29.2) | (14.2) | 21.0 (19.6-22.5) | (8.1) | 10.0 (9.4-10.5) | (1.4) | |
| Lower effectiveness (30% first 90 days, 15% next 90 days) | 26.9 (23.6-30.5) | (10.4) | 21.6 (20.1-23.1) | (5.7) | 10.1 (9.5-10.6) | (0.6) | |
| Sustained protection (40% for 180 days) | 25.3 (22.2-28.7) | (15.6) | 19.4 (18-20.7) | (15.3) | 9.9 (9.3-10.4) | (2.6) | |

| Seasonal mAb‡ impact with duration of protection of 150 days | | | | | | |
|--|------------------|--------|------------------|--------|---------------|--------|
| Expected coverage (50%) | | | | | | |
| Default effectiveness (50%) | 18.9 (16.7-21.4) | (36.9) | 13.5 (12.6-14.4) | (41.0) | 8.3 (7.9-8.8) | (17.7) |
| Lower effectiveness (40%) | 20.9 (18.4-23.6) | (30.3) | 15.2 (14.2-16.2) | (33.6) | 8.7 (8.2-9.2) | (13.9) |
| Higher effectiveness (60%) | 17.1 (15.1-19.3) | (43.0) | 11.9 (11.2-12.7) | (47.9) | 8.0 (7.5-8.4) | (21.4) |
| Higher coverage (80%) | | | | | | |
| Default effectiveness (50%) | 17.9 (15.8-20.2) | (40.2) | 12.8 (12-13.7) | (43.9) | 8.2 (7.7-8.6) | (19.2) |
| Lower effectiveness (40%) | 20.0 (17.7-22.7) | (33.2) | 14.6 (13.6-15.6) | (36.1) | 8.6 (8.1-9.0) | (15.1) |
| Higher effectiveness (60%) | 16.0 (14.1-18.0) | (46.6) | 11.2 (10.5-11.9) | (51.0) | 7.8 (7.4-8.2) | (23.1) |
| Lower coverage (30%) | | | | | | |
| Default effectiveness (50%) | 20.3 (17.9-23) | (32.2) | 14.5 (13.5-15.5) | (36.6) | 8.6 (8.1-9.0) | (15.5) |
| Lower effectiveness (40%) | 22.1 (19.5-25.1) | (26.2) | 16.1 (15-17.1) | (29.8) | 8.9 (8.4-9.4) | (12.1) |
| Higher effectiveness (60%) | 18.7 (16.5-21.1) | (37.7) | 13.1 (12.2-13.9) | (43.0) | 8.2 (7.8-8.6) | (18.8) |

^a The public health impact shown in the table is once an intervention is well-established within a population. ‡ mAb; monoclonal antibody



Figure 1. Schematic diagram for model assessing impact of a maternal RSV vaccine and a seasonal newborn monoclonal antibody (mAb).

The compartments S_i , E_i , I_i , R_i , and P_i represent the susceptible, exposed, infectious, recovered, and protected populations respectively for each age group *i*. The parameters λ_i represent transmission rates in each age group *i* while parameters σ , γ , and ν represent the latent, recovery, and immunity rates respectively. Reduced susceptibility to infection due to either maternally derived antibodies is represented by α_1 . Vertical lines represent births and ageing. The parameter *pv* represents the proportion vaccinated or administered a mAb. Infants protected by immunization or mAb have susceptibility to infection reduced by factor 1 - ve. A seasonal mAb was given to all infants aged less than 6 months and had a duration of protection of 150 days (with the waning mAb protection rate represented by ω). All model equations are presented in the Supplementary Material S1.



Figure 2: Model output with 95% Confidence Intervals against RSV hospitalization data (dots) for each age group. The shaded area represents 95% confidence intervals for model outputs which were estimated from the distribution of 500 model simulations, each using a different combination of parameter values based on the fitted parameter uncertainty from maximum likelihood estimation, as shown in Table 1.



Figure 3: Weekly RSV hospitalizations per 1000 children by age group for baseline, default maternal vaccine, and default seasonal infant monoclonal antibody (mAb) scenarios for five years following implementation.

The black line represents the base model while the blue and red lines represent outputs of the seasonal mAb and vaccination model at default values, respectively



Figure 4: Estimated annual RSV hospitalizations per 1000 children aged less than two years for baseline and different vaccination and seasonal monoclonal antibody (mAb) effectiveness and

coverage scenarios.

Distribution (2.5%, 25%, 75%, and 97.5% quantile and median) of each modelled scenario, which were estimated from the distribution of 500 model simulations, each using a different combination of parameter values based on the fitted parameter uncertainty from maximum likelihood estimation, as shown in Table 1. Figures by finer age groups among children aged less than two years are provided in Supplementary Material S4

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Supplementary Material

S1. Model equations

As stated in the main text, the force of infection for age group *i* was calculated as:

$$\lambda_{i} = \beta_{0}(1 + \beta_{1}\cos(\frac{2\pi t}{52} + \varphi))\frac{1}{N_{i}}\sum_{j=1}^{4}M_{i,j}I_{j}$$

This was chosen to represent the distinct seasonality of RSV. Similar seasonal forcing has been shown to accurately model RSV seasonality in temperate climates and accounts for the increase in observed RSV infections during winter periods. In the equation above, β_0 is the transmission coefficient, β_1 is the amplitude of seasonal forcing, and φ represents the phase shift. The mixing matrix $M_{i,j}$ is the number of contacts that an individual in age group *j* has with individuals in age group *i*.

In the equations below, λ_i represents the force of infection in each age group *i* while parameters σ , γ , and ν represent the latent, recovery, and immunity rates respectively. Live births are represented by μ . Reduced susceptibility to infection due to maternally derived antibodies is represented by α_1 . Ageing is represented by η_i .

$$\frac{dS_1}{dt} = \mu - \alpha_1 \lambda_1 S_1 - \eta_1 S_1 + \nu R_1$$
$$\frac{dE_1}{dt} = \alpha_1 \lambda_1 S_1 - \eta_1 E_1 - \sigma E_1$$
$$\frac{dI_1}{dt} = \sigma E_1 - \eta_1 I_1 - \gamma I_1$$
$$\frac{dR_1}{dt} = \gamma I_1 - \eta_1 R_1 - \nu R_1$$

$$\frac{dS_i}{dt} = \eta_{i-1}S_{i-1} - \lambda_i S_i - \eta_i S_i + \nu R_i$$
$$\frac{dE_i}{dt} = \eta_{i-1}E_{i-1} + \lambda_i S_i - \eta_i E_i - \sigma E_i$$
$$\frac{dI_i}{dt} = \eta_{i-1}I_{i-1} + \sigma E_i - \eta_i I_i - \gamma I_i$$
$$\frac{dR_i}{dt} = \eta_{i-1}R_{i-1} + \gamma I_i - \eta_i R_i - \nu R_i$$

Note: Differential equations for S_i, E_i, I_i, R_i represent equations for age groups 2 to 4.

Model equations with maternal vaccination

The force of infection λ_i was calculated the same as for the baseline (no intervention) models. Immunized infants had susceptibility to infection reduced by factor 1 - ve, where *ve* represents maternal vaccine effectiveness. The proportion vaccinated is represented by *pv*. Protection from vaccination is assumed to last for up to 180 days (six months), therefore vaccine effectiveness was set to 0 in age groups 3 and 4. The model equations are:

$$\begin{aligned} \frac{dS_1}{dt} &= (1 - pv)\mu - \alpha_1\lambda_1S_1 - \eta_1S_1 + vR_1 \\ \frac{dE_1}{dt} &= \alpha_1\lambda_1S_1 + (1 - ve)\alpha_1\lambda_1P_1 - \eta_1E_1 - \sigma E_1 \\ \frac{dI_1}{dt} &= \sigma E_1 - \eta_1I_1 - \gamma I_1 \\ \frac{dR_1}{dt} &= \gamma I_1 - \eta_1R_1 - vR_1 \\ \frac{dP_1}{dt} &= (pv)\mu - (1 - ve)\alpha_1\lambda_1P_1 - \eta_1P_1 \\ \frac{dS_2}{dt} &= \eta_1S_1 - \lambda_2S_2 - \eta_2S_2 + vR_2 \end{aligned}$$

$$\begin{aligned} \frac{dE_2}{dt} &= \eta_1 E_1 + \lambda_2 S_2 + (1 - ve)\lambda_2 P_2 - \eta_2 E_2 - \sigma E_2 \\ \frac{dI_2}{dt} &= \eta_1 I_1 + \sigma E_2 - \eta_2 I_2 - \gamma I_2 \\ \frac{dR_2}{dt} &= \eta_1 R_1 + \gamma I_2 - \eta_2 R_2 - v R_2 \\ \frac{dP_2}{dt} &= \eta_1 P_1 - (1 - ve)\lambda_2 P_2 - \eta_2 P_2 \\ \frac{dS_3}{dt} &= \eta_2 S_2 - \lambda_3 S_3 - \eta_3 S_3 + v R_3 \\ \frac{dE_3}{dt} &= \eta_2 E_2 + \lambda_3 S_3 + (1 - ve)\alpha_3 \lambda_3 P_3 - \eta_3 E_3 - \sigma E_3 \\ \frac{dI_3}{dt} &= \eta_2 I_2 + \sigma E_3 - \eta_3 I_3 - \gamma I_3 \\ \frac{dR_3}{dt} &= \eta_2 P_2 - (1 - ve)\lambda_3 P_3 - \eta_3 P_3 \\ \frac{dS_4}{dt} &= \eta_3 S_3 - \lambda_4 S_4 - \eta_4 S_4 + v R_4 \\ \frac{dE_4}{dt} &= \eta_3 I_3 + \sigma E_4 - \eta_4 I_4 - \gamma I_4 \\ \frac{dR_4}{dt} &= \eta_3 R_3 + \gamma I_4 - \eta_4 R_4 - v R_4 \\ \frac{dP_4}{dt} &= \eta_3 P_3 - (1 - ve)\lambda_4 P_4 - \eta_4 P_4 \end{aligned}$$

Model equations with seasonal mAb

Immunized infants had susceptibility to infection reduced by factor 1 - ve, where ve is a proxy for mAb effectiveness. The proportion immunized is represented by pv. To investigate the impact of a seasonal mAb, equations were numerically solved with a condition that pv = 0 for weeks that were not two months prior to or within the winter season period (where the winter season was defined as weeks 18–39 of each year), and pv = pv otherwise. The model equations are:

$$\begin{aligned} \frac{dS_1}{dt} &= \mu - \alpha_1 \lambda_1 S_1 - \eta_1 S_1 + \nu R_1 - p\nu S_1 + \omega P_1 \\ \frac{dE_1}{dt} &= \alpha_1 \lambda_1 S_1 + (1 - \nu e) \alpha_1 \lambda_1 P_1 - \eta_1 E_1 - \sigma E_1 \\ \frac{dI_1}{dt} &= \sigma E_1 - \eta_1 I_1 - \gamma I_1 \\ \frac{dR_1}{dt} &= \gamma I_1 - \eta_1 R_1 - \nu R_1 \\ \frac{dP_1}{dt} &= p\nu S_1 - (1 - \nu e) \alpha_1 \lambda_1 P_1 - \eta_1 P_1 - \omega P_1 \\ \frac{dS_2}{dt} &= \eta_1 S_1 - \lambda_2 S_2 - \eta_2 S_2 + \nu R_2 - p\nu S_2 + \omega P_2 \\ \frac{dE_2}{dt} &= \eta_1 E_1 + \lambda_2 S_2 + (1 - \nu e) \lambda_2 P_2 - \eta_2 E_2 - \sigma E_2 \\ \frac{dI_2}{dt} &= \eta_1 I_1 + \sigma E_2 - \eta_2 I_2 - \gamma I_2 \\ \frac{dR_2}{dt} &= \eta_1 R_1 + \gamma I_2 - \eta_2 R_2 - \nu R_2 \\ \frac{dP_2}{dt} &= p\nu S_2 + \eta_1 P_1 - (1 - \nu e) \lambda_2 P_2 - \eta_2 P_2 - \omega P_2 \\ \frac{dS_3}{dt} &= \eta_2 S_2 - \lambda_3 S_3 - \eta_3 S_3 + \nu R_3 + \omega P_3 \end{aligned}$$

$$\begin{aligned} \frac{dE_3}{dt} &= \eta_2 E_2 + \lambda_3 S_3 + (1 - ve) \alpha_3 \lambda_3 P_3 - \eta_3 E_3 - \sigma E_3 \\ \frac{dI_3}{dt} &= \eta_2 I_2 + \sigma E_3 - \eta_3 I_3 - \gamma I_3 \\ \frac{dR_3}{dt} &= \eta_2 R_2 + \gamma I_3 - \eta_3 R_3 - v R_3 \\ \frac{dP_3}{dt} &= \eta_2 P_2 - (1 - ve) \lambda_3 P_3 - \eta_3 P_3 - \omega P_3 \\ \frac{dS_4}{dt} &= \eta_3 S_3 - \lambda_4 S_4 - \eta_4 S_4 + v R_4 + \omega P_4 \\ \frac{dE_4}{dt} &= \eta_3 E_3 + \alpha_4 \lambda_4 S_4 + (1 - ve) \lambda_4 P_4 - \eta_4 E_4 - \sigma E_4 \\ \frac{dI_4}{dt} &= \eta_3 I_3 + \sigma E_4 - \eta_4 I_4 - \gamma I_4 \\ \frac{dR_4}{dt} &= \eta_3 R_3 + \gamma I_4 - \eta_4 R_4 - v R_4 \\ \frac{dP_4}{dt} &= \eta_3 P_3 - (1 - ve) \lambda_4 P_4 - \mu_4 P_4 - \omega P_4 \end{aligned}$$

S2. Contact matrices used in models

We used the following contact matrix in our model. It was adapted from New Zealand specific contact rates as reported by Prem et al.[1], and daily values were converted to weekly values.

| | <3m | 3-5m | 6-23m | 24m+ |
|-------|--------|--------|--------|--------|
| <3m | 1.371 | 1.371 | 1.371 | 0.225 |
| 3-5m | 1.371 | 1.371 | 1.371 | 0.225 |
| 6-23m | 8.225 | 8.225 | 8.225 | 1.348 |
| 24m+ | 65.802 | 65.802 | 65.802 | 89.191 |

As contact rates provided by Prem et al. were in five year age groups, which were used to estimate contact rates in infants, we also undertook sensitivity analyses using contact data below from the United Kingdom as reported by Fumanelli et al.[2] which was in one-year age bands.

| | <3m | 3-5m | 6-23m | 24m+ |
|-------|--------|--------|--------|--------|
| <3m | 0.484 | 0.484 | 0.474 | 0.193 |
| 3-5m | 0.484 | 0.484 | 0.474 | 0.193 |
| 6-23m | 2.777 | 2.777 | 2.728 | 1.112 |
| 24m+ | 68.020 | 68.020 | 66.429 | 89.191 |

Prem K, Cook AR, Jit M. Projecting social contact matrices in 152 countries using contact surveys and demographic data. PLoS Comput Biol. 2017;13:e1005697.

 Fumanelli L, Ajelli M, Manfredi P, Vespignani A, Merler S. Inferring the Structure of Social Contacts from Demographic Data in the Analysis of Infectious Diseases Spread. PLoS Comput Biol. 2012;8:e1002673. S3. Sensitivity analyses: Weekly RSV hospitalizations per 1000 children by age group for baseline, default maternal vaccine, and default seasonal infant monoclonal antibody (mAb) scenarios for five years following implementation using contact rates from Fumanelli et al.



- Baseline - mAb - Vaccination

S4a-c: Estimated annual RSV hospitalizations per 1000 children aged less than two years (by age groups) for baseline and different vaccination and seasonal monoclonal antibody (mAb) effectiveness and coverage scenarios.



a. Children aged 0-2 months

b. Children aged 3-5 months



c. Children aged 6-23 months



Distribution (2.5%, 25%, 75%, and 97.5% quantile and median) of each modelled scenario by age group, which were estimated from the distribution of 500 model simulations, each using a different combination of parameter values based on the fitted parameter uncertainty from maximum likelihood estimation, as shown in Table 1.