A Stochastic Model of COVID-19 Infections During a Large-Scale Canadian Army Exercise

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ABSTRACT

The Canadian Army's largest and most complex training exercise is Exercise MAPLE RESOLVE which occurs annually in the spring. Several thousand soldiers from Canada and allied countries participate in the exercise ensuring high readiness to deploy on operational missions. In 2021, the COVID-19 pandemic imposed significant additional challenges on the exercise, particularly with the increasing prevalence of more-transmissible variants of the virus and the impending rollout of vaccines at the time of planning. In these circumstances, the potential magnitude of COVID-19's impact on the exercise was highly uncertain. We present a stochastic model of COVID-19 transmission for military contexts based on the Susceptible-Exposed-Infected-Recovered (SEIR) compartment approach that estimates the number of infections that may occur over time. The model implements several features of continued relevance to planning and risk mitigation strategies related to COVID-19 in military settings including: interactions between populations with different transmission dynamics, the risk associated with the prevalence of the virus in the local general population, dividing populations into cohorts to reduce transmission potential, multiple infection paths for different variants of the virus, the scheduling of vaccinations, and a dynamic model of vaccine efficacy from the time of the first dose. We show the results of the model applied to Exercise MAPLE RESOLVE 2021. This analysis quantified the potential scale of COVID-19 infections during the exercise and was used to support the Canadian Army's decision to proceed with the exercise under strict adherence to a comprehensive COVID-19 risk mitigation strategy.

1.0 INTRODUCTION

The Canadian Army's largest and most complex annual training exercise, Exercise MAPLE RESOLVE (Ex MR), is a key event ensuring combat readiness and the opportunity to practice interoperability with international partners [1]. Historically, approximately 5000 soldiers from Canada and allied nations gather in Wainwright, Alberta, Canada, from April to June to attend Ex MR and related exercises called Agile RAM I and Agile RAM II [2][1]. Although scheduled as an annual event, Ex MR 2020 was cancelled by the Commander of the Canadian Army in response to the SARS-CoV-2 (COVID-19) pandemic.

With no end to the pandemic on the horizon, the Canadian Army proceeded with planning Ex MR 2021, incorporating a comprehensive COVID-19 risk mitigation strategy. However, during the final planning phases of the exercise, an acceleration of COVID-19 infections was occurring across Canada. This third wave was driven by the B.1.1.7 strain, known as the Alpha variant. In the context of this paper, the term

[1] Unless otherwise stated, we will use the term "Ex MR" to refer to the collection of all three exercises.

"variant of concern" (VOC) refers to the Alpha variant. Figure 1-1 shows reported COVID-19 infections across Canada and the rise of the third wave immediately prior to Ex MR 2021 (green shaded region):

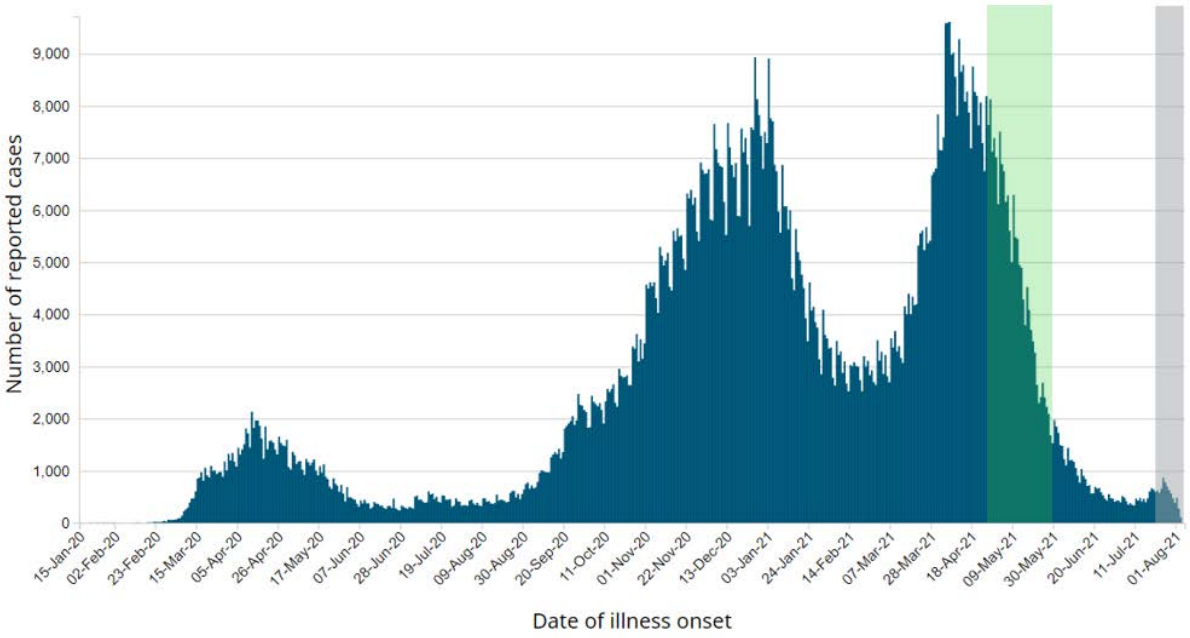

Figure 1-1: Reported COVID-19 infections across Canada, highlighted in green is the timeframe for Exercise MAPLE RESOLVE [3].

To mitigate the risk of a COVID-19 outbreak at the exercise, planners developed a layered risk mitigation strategy, including: limiting international participation, reducing the number of Canadian participants, isolated work zones, cohorting within zones, physical distancing, masks, and vaccination. During early spring, the majority of the Canadian population was unvaccinated, including the Canadian Armed Forces (CAF); however, vaccines were starting to become more widely available. CAF members were to be supplied with the Moderna vaccine starting in April 2021; therefore, exercise participants were offered their first dose of the vaccine while at Ex MR.

However, despite these measures, the potential magnitude of COVID-19's impact on the exercise was uncertain and therefore difficult to plan for. For example, how many medical staff, contact tracing resources and quarantine facilities would be required? Are the planned risk mitigation strategies, like zones and cohorting, sufficient to reduce the risk to an acceptable level? And, ultimately, should the exercise proceed in the present COVID-19 environment? Additional concerns included the increasing spread of the Alpha variant, the impact of first dose vaccination while at the exercise, and whether there would be a need to quarantine post-exercise to reduce the potential for community infections arising from departing exercise participants. A collaboration between Defence Research and Development Canada (DRDC) and Canadian Forces Health Services group (CFHS) had been established to develop a modelling and simulation capability to inform the CAF's response to COVID-19. Under this collaboration, in order to respond to the questions related to the planning of Ex MR, the Susceptible-Exposed-Infected-Recovered (SEIR) compartment modelling approach was employed.

The SEIR model [4] is a well-established modelling approach used in epidemiology. In its simplest form, the SEIR model divides a population into four compartments (susceptible, exposed, infected, and recovered) and defines the flows between these compartments using mathematical rate equations. However, to model a

military exercise whilst in an evolving pandemic environment, additional compartments, flows and features were required. Key factors that were included in the model of Ex MR were the presence of multiple COVID-19 variants, vaccinations, isolated work zones, cohorting, and the staggered arrivals and departures of exercise participants.

The model was created using the PyCoMod Python package, a compartment modelling framework developed by DRDC [5] which has been used to model the impact of COVID-19 at CAF training schools and during a CAF deployment to assist in combatting COVID-19 outbreaks in Canadian long-term care homes. For Ex MR, the framework was used to create a model that considers the risk of COVID-19 entering the training population and then simulates its spread during the exercise. The analysis sought to quantify the potential scale of COVID-19 infections occurring at Ex MR, as well as assessing the impact of the new Alpha variant and the vaccination plan. It also sought to quantify the potential for infectious individuals to leave the exercise and spread COVID-19 to their home communities.

The results of this analysis informed the final planning for the exercise, allowing the planning team to make decisions regarding its level of response to COVID-19 with knowledge of the likely impact of the virus under various scenarios.

2.0 MILITARY SETTING AND MODELLING APPROACH

For Ex MR 2021, the exercise was scaled back to approximately 2500 personnel. Different groups of personnel, involved in different aspects of the exercise, arrived and departed at various times. The first arrivals were in early April, and the last departures were in early June. Most participating soldiers were based in Edmonton, Alberta, as such, the prevalence of COVID-19 in the Edmonton area was used to estimate of the probability that an infected individual enters the exercise population.

All exercise personnel were required to quarantine for seven days and obtain a negative COVID-19 test immediately prior to arriving at the exercise. Personnel were assigned to one of three zones and interaction between zones was minimized. The three zones were the primary training zone, the base zone, and the support zone, with the majority of participants active in the primary training zone.

Within the zones, exercise personnel were further divided into cohorts of a specified size. Most person-to-person interactions would stay within the cohorts; however, some interaction was possible between cohorts. At all times, even within cohorts, protective measures (including physical distancing, masking and sanitizing) were employed to the greatest extent possible.

On-site medical staff and facilities were present to quarantine and treat suspected and confirmed COVID-19 cases. The on-site vaccination clinic was conducted from April 27th to 30th, providing CAF members with their first dose of the Moderna vaccine on a voluntary basis.

Finer details about the physical space participants would be operating in, organizational structures, the nature of person-to-person interactions, and the number of interactions were not available. Therefore, a high-level modelling approach was required, based on aggregate population and infection characteristics. We employed the SEIR compartment modelling approach as it is appropriate for this type of problem, but with additional compartments and flows to account for the distinctive features of the Ex MR setting.

2.1 SEIR Model Structure

Although Ex MR participants were divided into three zones, because the support and base zones (SBZ) consisted of more-controlled work settings resembling regular base operations, we simplified these two zones into a single zone. In the SBZ, the risk of COVID-19 transmission was assumed to be similar to other

general CAF work settings which have experienced lower transmission rates than the general Canadian population [6]-[8]. The primary training zone (PTZ) was considered to be a higher-risk zone for COVID-19 transmission because the number of person-to-person interactions is likely to be larger, and the nature of the interactions is less-easily controlled due to the requirements of the training activities.

Both the SBZ and PTZ were modelled using identical compartment structures but with different parameters. We assumed, based on information provided by the exercise planners, that interactions between zones were negligible.

Within each zone, we modelled vaccinated and unvaccinated individuals and the presence of both the original COVID-19 strain and the Alpha variant. Therefore, each zone model contained four different infection paths with unique characteristics:

- Unvaccinated, original strain infection
- Unvaccinated, alpha variant infection
- Vaccinated, original strain infection
- Vaccinated, alpha variant infection

Figure 2-1 shows the full compartment structure of the model used for each zone. There are multiple susceptible compartments on the left, representing various states with respect to vaccination, leading into the four infection paths proceeding to the right. The compartment notation is summarized in Table 2-1.

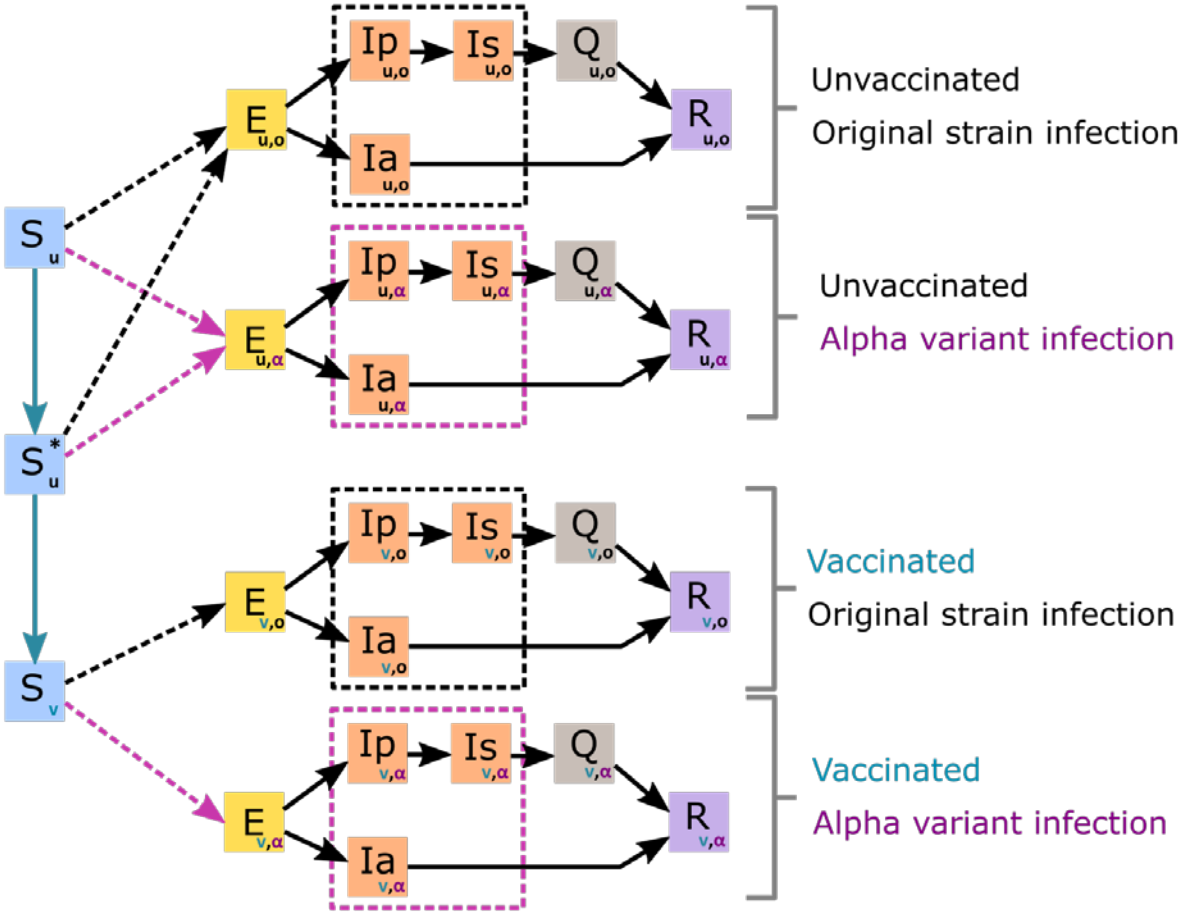

Figure 2-1: Compartment flow diagram for each zone model.

The susceptible compartments are S_u(susceptible, unvaccinated), S_u^* (susceptible, received vaccine dose) and S_v (susceptible, vaccinated). The model of vaccination consists of first moving individuals from S_u to S_u^*, corresponding to when the first dose is administered. Being in the S_u^* compartment does not yet confer immune resistance to COVID-19, and exposure while in this compartment leads to the same infection paths as those who are unvaccinated. However, once in the S_u^* compartment, individuals gradually flow to the S_v compartment after an exponential delay, modelled as a flow rate proportional to the population in S_u^*. The lag introduced by the S_u^* compartment models the time required for the vaccine to produce immune resistance to COVID-19.

If a susceptible individual is infected, the infection paths consist of first moving to an exposed compartment (E), leading to either an asymptomatic infection (Ia) or pre-symptomatic infection (Ip). Pre-symptomatic individuals eventually become symptomatic (Is), which will be detected and lead to quarantine (Q). Asymptomatic infections remain in the population for the duration of their infection and then enter the recovered compartment (R). Quarantined individuals are removed from the population and are therefore unable to infect others; they enter the recovered compartment once the infection has cleared. The compartments in the four infection paths are distinguished by the subscripts i,j where i represents the vaccination status which is either u (unvaccinated) or v (vaccinated), and j represents the virus variant which may be either o (original strain) or α (Alpha variant).

Table 2-1: Compartment notation.

Symbol	Description
S_i	Susceptible
S_i^*	Susceptible (received vaccine dose, delay until vaccinated)
$E_{i,j}$	Vaccinated
$Ia_{i,j}$	Infected asymptomatic
$Ip_{i,j}$	Infected pre-symptomatic
$Is_{i,j}$	Infected symptomatic
$R_{i,j}$	Recovered
$Q_{i,j}$	Quarantined

Where i ϵ {u, v} and j ϵ {o, α}.

Asymptomatic, pre-symptomatic and symptomatic infections from any infection path can spread the disease. Contact with any individual infected with either the original strain (black dashed box) or Alpha variant (purple dashed box) produces new exposures to the original strain (black dashed arrows) or Alpha variant (purple dashed arrows), respectively. The Alpha variant was assumed to be 50% more transmissible than the original strain [9], [10].

New exposures were modelled stochastically using a binomial distribution wherein each susceptible individual has a probability of being exposed given by $B_{i,j} \cdot I/N$, where $B_{i,j}$ is the appropriate transmission rate given the individual's vaccination status and the variant in question, and I/N is the proportion of the population (excluding quarantined individuals) that is infectious with the given strain. The transmission rate also varies randomly from day to day around a nominal mean value according to a beta distribution. This additional variation models the fact that certain days will see higher transmission than others.

We considered two effects of the vaccine on transmission (affecting those that reach the S_v compartment), namely a reduction in the probability of having a symptomatic infection (the vaccine's efficacy) and a

reduction in the probability of transmitting the disease. These effects were applied to the transmission rate parameters in the model.

Each zone model, as shown in Figure 2-1, was replicated in parallel based on the number of cohorts. Person-to-person interactions mostly occur within the same cohort; however, cohorts are not perfectly isolated, so we introduced a probability of being exposed based on the overall proportion of infected people within the entire zone. This reflects the probability of transmission occurring in common areas, such as eating facilities.

Ex MR participants arrive and depart in groups at specified times. Arrivals are assumed to have isolated for a period of time and have tested negative for COVID-19 immediately prior to arrival. The majority of new arrivals enter the model in the S_u compartment. However, despite testing and depending on the local prevalence of the virus and the duration of pre-quarantine, there remains a small probability that an asymptomatic infection will enter the Ex MR population in one of the Ia compartments. Such break-through events may be infected with either the original strain or the Alpha variant depending on the relative prevalence of the Alpha variant in the Edmonton area. The probability of a break-through infection was determined by the Missed Infection Calculator developed by Guillouzic et al. [11].

In early 2021, the total number of COVID-19 cases in Canada, even accounting for a large proportion of undetected infections, was still only a small percentage of the total Canadian population, and the rate of COVID-19 cases among CAF members was known to be even smaller than that in the general population. We therefore assumed that the number of participants that had already recovered from a prior COVID-19 infection and gained natural immunity was negligible.

The groups departing Ex MR were removed proportionally from all compartments within the model, according to the departure schedule. Therefore, with every departure, there was a chance that an individual with an asymptomatic or pre-symptomatic infection could produce community infections traceable to departing Ex MR participants.

2.2 Validation of the vaccination model

Vaccination in SEIR models, is sometimes simply modelled by moving individuals directly to the recovered compartment, for example [12], [13]. However, vaccinated individuals are not immune to COVID-19; they are still capable of being infected and spreading the infection, which is not possible from the recovered compartment. A more elaborate approach involves moving the vaccinated population to a second susceptible compartment within which the probability of infection is reduced, as in [14]. However, vaccination does not produce immediate resistance to infection, which is relevant for analyses over short time scales, as was the case for Ex MR. To account for the delay in the development of the vaccine's effectiveness, we first move individuals to the intermediate compartment, S_u^*, upon receiving the injection. Individuals in S_u^* then gradually move to the vaccinated compartment, S_v, at a rate proportional to the S_u^* population. This produces an exponential delay before the benefits of the vaccine are acquired. We validated this model of vaccination against Pfizer's trial data [15]. Pfizer's published trial results include data describing how the vaccine's efficacy develops over time from the first dose. Although the Ex MR participants were provided with the Moderna vaccine, Moderna's published trial results [16] do not clearly show how efficacy develops over time. But the Moderna and Pfizer vaccines are similar in mechanism and efficacy, therefore we assumed that the efficacy of the Moderna vaccine over time follows a similar pattern to that of the Pfizer vaccine. Figure 2-2 contains a reproduction of the figure from Pfizer's report showing the incidence rate of COVID-19 in their placebo and vaccine groups over time starting from the first dose [15]. This shows that for approximately the first 11 days after the first dose, the vaccine group (red line) performed no better than the placebo group (blue line), but after this point the incidence rate in the vaccine group flattens and eventually attains the headline efficacy of 95%. Overlaid on the figure is the result of fitting our vaccination model to Pfizer's data using an average delay in the S_u^* compartment of 11 days. We can see that our vaccination

model closely matches Pfizer's trial data in terms of the time dependence of the vaccine's efficacy[2].

Pfizer's trial included providing the second dose 21 days after the first. Although the second dose was not provided during the exercise, the CAF was allotted sufficient vaccine supply to provide two doses to the entire military population. So it was known that the second dose would be administered within a reasonable timeframe. Therefore, we used the full two-dose efficacy as the long-term vaccine efficacy in our model. But because the timeframe for the exercise was short and the vaccine was provided several weeks into the exercise, the short-term dynamics of the vaccine's efficacy were important, and our model captures this aspect of its performance.

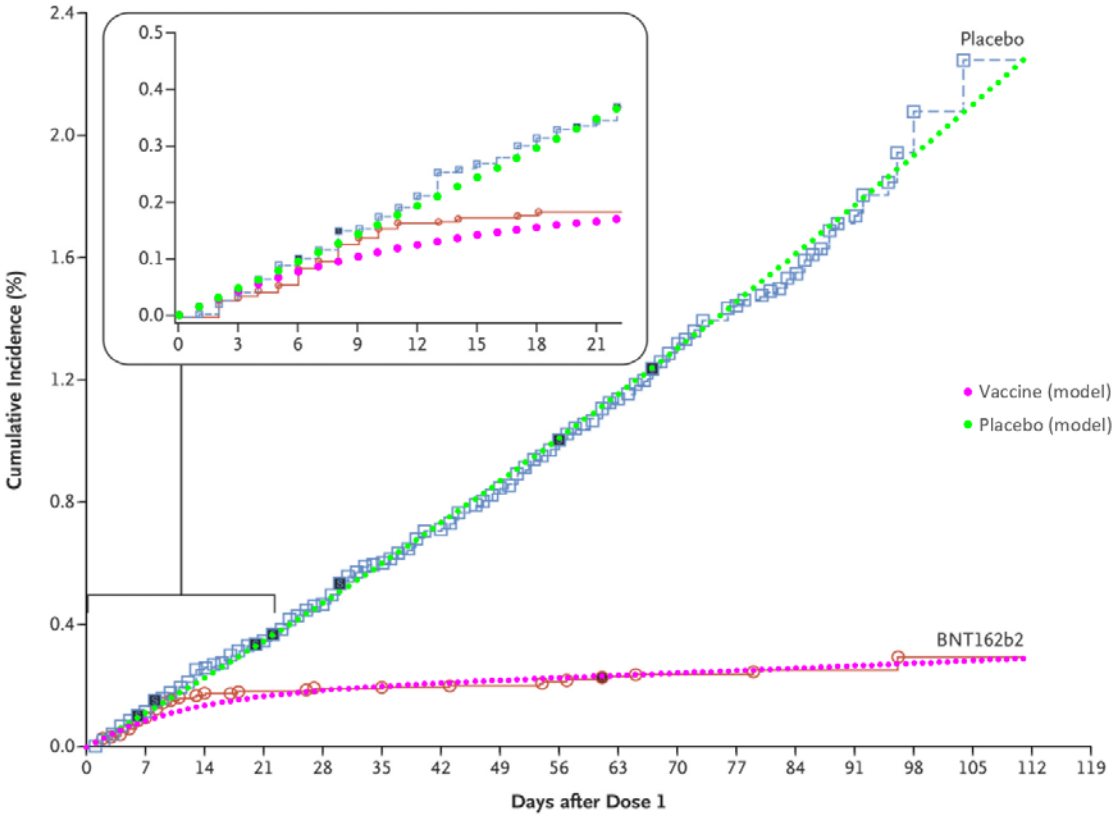

Figure 2-2: Vaccination efficacy model validated against Pfizer's vaccine trial data [15]

2.2 Model Parameters

Many of the exercise-related parameters were provided by the Ex MR planning team and relate to how the exercise was to be conducted. The model was constructed to take into account the possibility that an infection could be introduced at any time by arriving individuals, and that an infection at the exercise could be introduced to the community by departing individuals. Groups of exercise participants were scheduled to arrive and depart each zone at specific times. Figure 2-3 illustrates the attendance over time for the PTZ (blue line) and the SBZ (orange line). Each rise in the lines corresponds to a group of participants arriving, and each fall corresponds to a group departing.

[2] It is possible to achieve even closer agreement between the model and the vaccine trial data by using a series of two or more exponential delay compartments rather than one. However, the fit achieved with a single delay compartment is acceptable and we did not believe that this addition to the model would have a tangible impact on results or conclusions.

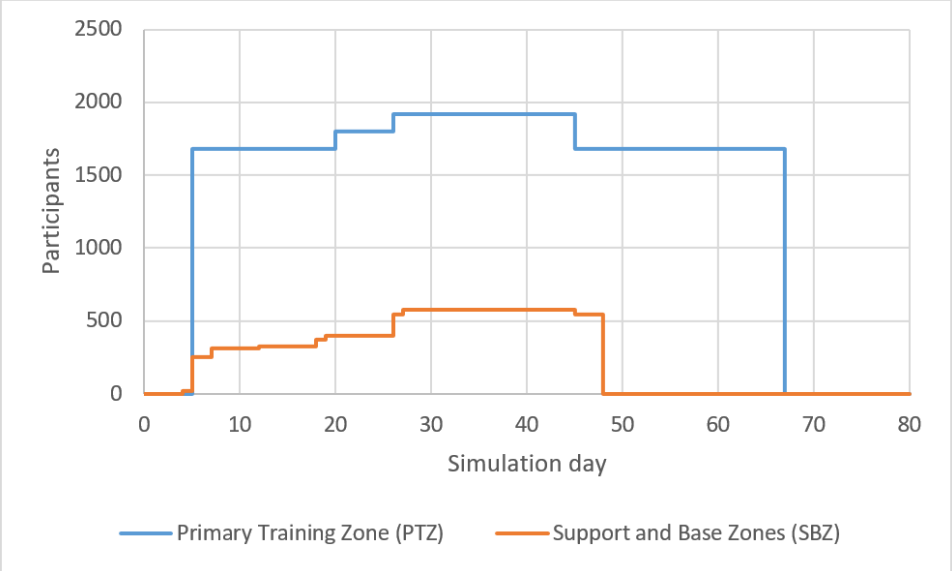

Figure 2-3: Exercise attendance schedules for the PTZ and SBZ.

As previously described, the COVID-19 risk mitigation strategy included: limiting the movement and interactions between participants, cohorting, quarantine, testing, and vaccination. These measures were the principal elements in the risk mitigation strategy that were modelled using the SEIR framework. Some measures were not considered because their impact is already controlled by other parameters. For example, isolation of close contacts through contact tracing was not explicitly modelled because this effectively reduces the transmission rate, which is a parameter we can already control in the model.

For the purposes of this analysis, the Ex MR planners indicated that each zone would be divided into cohorts containing approximately 40 individuals each, however the final cohort sizes used at Ex MR may differ from this number. To account for the restricted contacts between cohorts and zones, we have two mixing parameters, Pmix_cohort and Pmix_zone, respectively. These parameters are multiplied by the nominal transmission rate. For example, Pmix_cohort is 0.1, meaning the probability of transmission between cohorts is one tenth the regular probability of transmission within a cohort. As previously noted, the probability of mixing between zones was assumed to be zero.

Upon the availability of vaccines, a four-day vaccination clinic was added to the Ex MR COVID-19 strategy, where it was estimated by the planning team that 80% of participants would be willing to receive their first dose of the vaccine. To observe the impact of the vaccine, we ran the model at both zero and 80% vaccine uptake. The vaccination and population mixing parameters had to be chosen based on subjective information provided by the planners. A summary of these risk mitigation parameters can be found in Table 2-2.

Table 2-2: Risk mitigation parameters.

Symbol	Description	Value	Source
num_cohorts	Number of individuals in a cohort	40	Provided
Pmix_zone	Mixing factor between zones	0	Assumed
Pmix_cohort	Mixing factor between cohorts	0.1	Assumed
quarantine	Length of pre-quarantine period in days	7 days	Provided
test	PCR test before arrival	Yes	Provided
vac_rate	Vaccination rate in population (April 27th - 30th)	500 people per day	Provided
vac_uptake	Vaccine uptake	0%, 80%	Assumed

Parameters describing the disease dynamics of COVID-19 were sourced from publicly available data and publications. The definitions, values, and sources of these parameters are listed in Table 2-3.

Estimates of point prevalence (PP) by geographic region across Canada can be found via DRDC's point prevalence map [17]. For the model, we used a PP of 2.5% as this was the PP in the Edmonton area on April 6th, 2021, when the exercise was about to commence. Although individuals would be arriving from various areas around Canada and partner nations having different PP, we assumed that the PP in Edmonton would be characteristic of most of the participants' exposure risk.

The number of COVID-19 cases reported is not characteristic of the total number of infections within the population, as individuals may experience mild to no symptoms and may not seek testing or treatment and will therefore be excluded from case data. In Canada, the estimated rate of reported cases relative to total infection has ranged from 18-69% over time [18]. To account for these undetected individuals, we assumed 40% of COVID-19 infections are reported, lending to an under-ascertainment factor of 2.5 (for each reported case, there are 2.5 unreported infections).

The timing of the exercise coincided with the increasing circulation of the more transmissible Alpha variant in Canada. During exercise planning, it was not known exactly how prevalent the Alpha variant would be among total COVID-19 infections. To account for this unknown, we estimated the Alpha variant prevalence (PVOC) at various levels (50%, 75% and 100%). It was later reported that the estimated Alpha variant prevalence in Canada during the last weeks of the exercise ranged from 40-55% [19].

A key parameter is the probability of an individual entering with an infection. This parameter is a function of PP, quarantine time, testing, and disease dynamics. Higher PP results in an increase in the probability of importing an infection, while quarantine and testing reduce it. To obtain this parameter, we used DRDC's Missed Infection Calculator [11], where we consider an individual completing a 7-day imperfect quarantine and getting a PCR test at the end of quarantine. Here, imperfect quarantine means the individual quarantines at home and takes precautions to minimize their exposure to the community and members of their household. The calculator provides the probability that the individual escapes the quarantine and test protocols with an undetected infection.

At the time of analysis, the efficacy of the vaccines in preventing symptomatic infection was known from vaccine trials [15], [16], and further research had shown that vaccinated individuals who become infected are less likely to transmit to others [20]. As such, our model of the vaccine was based on these two properties. However, there is now evidence that the vaccine's efficacy is the result of both resistance to infection (whether symptomatic or not), and resistance to symptoms if infection occurs [10]. The delay from receiving

the first vaccine dose to the development of immune resistance to COVID-19 was modelled using an average delay of 11 days. This resulted in the best fit to Pfizer's trial data, shown in Figure 2-2, as well as being qualitatively the point at which the Pfizer report's authors note that the vaccine begins to take effect.

There are many factors that can affect disease transmission in a population, such as public health measures, adherence to rules, frequency and proximity of interactions with other people, ventilation, etc. These factors can vary significantly from one setting to another. At the time of this analysis, COVID-19 case data in CAF operational settings did not exist in sufficient quantity to infer transmission parameters. We therefore derived the transmission rate from three documented COVID-19 outbreaks in the US military:

1. COVID-19 transmission among US Marine recruits [21];
2. COVID-19 transmission among US Air Force trainees [22]; and
3. A COVID-19 outbreak aboard the U.S.S. Theodore Roosevelt [23].

These instances represented the best available data of which we were aware of COVID-19 transmission in military settings.

The US Marine and US Air Force scenarios are most comparable to Ex MR. Both employed a risk mitigation approach similar to the planned strategy at Ex MR, where participants were required to pre-quarantine and obtain a negative PCR test immediately prior to arrival. Cohorts, physical distancing and masks were also employed in the training environments. In both the US Marine and US Air Force trainees, the pre-quarantine and testing procedure discovered and isolated COVID-19 cases in approximately 1% of the incoming training population. Once training commenced, it was found that COVID-19 had nonetheless entered the populations and the infection had spread to an additional 2% of US Marine recruits and an additional 1% of US Air Force trainees after 14 days. From these data, and using a simple SEIR model, we inferred a transmission rate of 0.19 for the US Marine scenario and 0.11 for the US Air Force scenario. In the absence of additional data sources, we used these two transmission rates in our model of the PTZ, one representing a "high" transmission scenario, and the other representing a "low" transmission scenario.

The U.S.S. Theodore Roosevelt, being an aircraft carrier, was not directly comparable to the Army exercise setting of Ex MR, however it experienced a significant outbreak in which 26% of the crew ultimately tested positive for COVID-19 and where new case numbers were reported daily for an extended period. We did not assume that the U.S.S. Roosevelt outbreak would be indicative of the transmission rate at Ex MR. However, the higher-quality data from this incident enabled us to employ Bayesian methods to infer the parameters of a beta distribution modelling the daily variation in the transmission rate. We specified the beta distribution in terms of its mean, μ, and weight, ω, where $\mu = \alpha/(\alpha + \beta)$ and $\omega = \alpha + \beta$, using the standard α and β parameters of the beta distribution. The weight term controls the spread of the beta distribution, and in the case of the U.S.S. Roosevelt, we inferred a weight of 7.5, which represents a relatively high degree of variability from day to day as one might expect in an operational setting. The data from the US Marines and the US Air Force were not amenable to this Bayesian inference as daily case data was not available. We were only able to estimate the mean transmission rate in those scenarios, but we used the U.S.S. Roosevelt incident to estimate the daily variation in the transmission rate around those mean values.

It was assumed that individuals in the SBZ would have a lower COVID-19 transmission risk than those participating in the PTZ because they would be performing work in a more-controlled setting similar to

normal day to day operations of the CAF. Therefore, the transmission rate for SBZ was assumed to be that of the general CAF population. However, only the total number of COVID-19 infections since the start of the pandemic is reported by the CAF [7]. This makes it difficult to directly infer the transmission rate occurring among CAF members, but the per-capita infection rate has been consistently around 40% of the general Canadian population [6]. Therefore, to estimate the transmission rate for the SBZ, we used the previous 60 days of COVID-19 case data for the Canadian population, adjusted for under-ascertainment and the 40% relative incidence of COVID-19 cases in the CAF. Using this approach allowed us to infer both the mean (0.10) and weight (278) of the beta distribution describing the transmission rate for the SBZ. This mean transmission rate is only slightly less than the low transmission scenario in PTZ, but the higher weight corresponds to less daily variability in the transmission rate, consistent with the more-controlled environment in the SBZ.

Transmission rates are further affected by the Alpha variant, which has been estimated to be 50% more transmissible than the original strain [9], [10]. The transmission rate associated with exposure to the population infected with the Alpha variant is multiplied by this factor to account for the increased infectiousness.

Additional disease parameters originate from studies examining the dynamics of COVID-19, such as the latent period, recovery rate, asymptomatic rate, under-ascertainment and quarantined delay are summarized in Table 2-3.

Table 2-3: Parameters relating to disease dynamics.

Description	Value	Source
Latent period - days between contracting the disease and becoming infectious	3.3 days	[24]
Probability of asymptomatic infection	30%	[25]
Transmission rate in PTZ: beta(mean, weight)	Low: beta(0.11, 7.5) High: beta(0.19 7.5)	[21]-[23]
Transmission rate in SBZ: beta(mean, weight)	beta(0.1, 278)	[6]-[8]
Days before no longer infectious (I.e. recovered)	10 days	[26], [27]
Reduction in onwards transmission for infected vaccinated individuals	0.60	[10], [20]
Increase in transmission due to Alpha variant	50%	[9], [10]
Point Prevalence (PP) - proportion of infected individuals in the population at a point in time	2.5%	[17]
Probability of an individual entering with an infection	0.35%	[11]
Prevalence of the Alpha variant - proportion of infections that are the Alpha variant	50%, 75%, 100%	Assumed
Days an individual is symptomatic before they enter quarantine	2 days	Assumed
Days an individual is infectious but not yet symptomatic. I.e. pre-symptomatic	2 days	[24], [25]

Under-ascertainment	2.5	Assumed
Delay in immunity from time of dose to protection	11 days	[15]
Vaccine efficacy: probability of preventing symptoms in individuals with 1 dose of vaccine	0.95	[15]

2.3 Python modelling framework

The compartment model of Ex MR was implemented using a Python package called PyCoMod. PyCoMod (Python Compartment Modelling) was developed by several scientists within the Centre for Operational Research and Analysis (CORA), including the authors of this work, to support this and other studies of COVID-19's impact on the CAF. PyCoMod is publicly available as an open source project on github [5].

PyCoMod was developed as a general-purpose compartment modelling framework that allows complex compartment structures and flow equations to be built using simple, pure-Python syntax. It does not implement a specific model of COVID-19 but facilitates the creation of such models. Its key features include stochastic compartment flows, Monte-Carlo simulation, input and output data management, and plotting of time series output distributions. PyCoMod models also support vectorization such that a single model can run on vector inputs allowing multiple parallel models to be executed at once. The model's initial conditions, parameter values and run settings can be specified using a Python dictionary or an Excel file, facilitating the management of different run scenarios.

One of PyCoMod's more powerful features is that models are defined as object-oriented classes, and instances of PyCoMod models can be nested. This allows larger, complex models to be built up from simpler, re-usable sub-models. Any existing model can thus be incorporated into future, more-elaborate models.

For the Ex MR scenario, the complex compartment structure, stochastic infections, multiple infection paths, cohorts, and varying levels of interaction between individuals and cohorts necessitated the more advanced features available in PyCoMod. Additional information and code examples are available on the project's github site.

3.0 RESULTS

We varied three key parameters in our simulations of COVID-19 spread at Ex MR: transmission rate, vaccine uptake, and Alpha variant prevalence.

The transmission rates include the "low transmission" and "high transmission" scenarios in the PTZ derived from the range of transmission rates that we were able to infer from documented outbreaks in the US military. These represented the only comparable scenarios of which we were aware at the time where published case data was available. We note that the number of such published outbreak events in military settings was quite limited at the time, and additional data sources, including those from CAF operations, would have been preferable.

To examine the impact of vaccination, we show results for scenarios where no vaccinations are provided to participants, and where 80% of participants received their first dose of vaccine over the four-day vaccination clinic in late April.

Finally, we include three scenarios covering a range of possibilities for the prevalence of the Alpha variant relative to the original strain. Our results cover Alpha variant prevalence of 50% (the best estimate at the

time), 75% and 100% (worst case scenario).

Using PyCoMod's built-in Monte Carlo simulation capability, we ran 200 simulations of each combination of scenarios to obtain the median (dark line) alongside the 25th and 75th percentiles (shaded region) of the COVID-19 infections occurring over time at Ex MR. We reported on three categories of infections that were of interest to military planners:

1. cumulative infections – total infections at Ex MR, including both symptomatic and asymptomatic infections;

2. outgoing infections – total exposed, asymptomatic and pre-symptomatic infections leaving Ex MR; and

3. detected infections – total symptomatic infections at Ex MR.

The following subsections detail these results for the aforementioned combination of parameters ranging from the best-case scenario (low transmission, low Alpha prevalence, high vaccination) to the worst-case scenario (high transmission, high Alpha prevalence, no vaccination).

3.1 Cumulative infections

Modelling cumulative infections provides a measure of the total scale of COVID-19 transmission that could occur during the exercise; this includes both detected (symptomatic) and undetected (asymptomatic and pre-symptomatic) infections from both the SBZ and the PTZ. As such, cumulative infections will report higher counts than the number of cases actually detected during the exercise, which will be predominantly symptomatic infections. This effect will be even more pronounced if the population has a high vaccine uptake as we assumed that vaccination protects strongly against symptomatic infections.

The resulting effect of PP, cohort size, Alpha prevalence, vaccination, and transmission rates on the number of cumulative infections is shown in Figure 3-1 and summarized in Table 3-1. The figure shows the median number of infections from the Monte Carlo simulation and the 25th and 75th percentiles, providing an indication of the potential variability in outcomes. The table shows the range of the median total infections from low to high transmission for the various scenarios of Alpha prevalence and vaccine uptake. The final column shows the difference (i.e. the reduction in total infections) that the vaccine produces.

In the high-transmission scenario, increasing the prevalence of the Alpha variant produces a significant increase in the number of infections. However, the impact of the Alpha variant is not as pronounced in the low-transmission scenario. The vaccination clinic, with 80% uptake, results in an average 22% reduction in cumulative infections if transmission is low, compared to a 47% reduction in cumulative infections if transmission is high. Figure 3-1 provides a good visualization of this effect, where vaccination is shown to flatten the infection curve, especially in the high-transmission scenario.

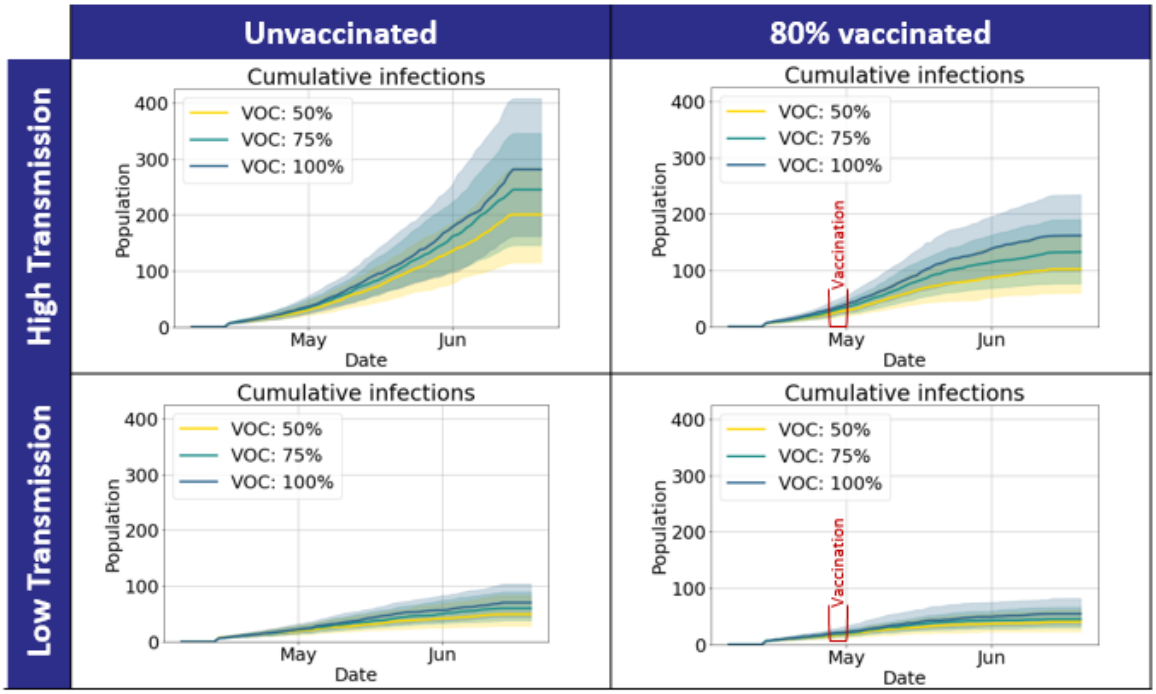

Figure 3-1: Median number of cumulative infections alongside the 25th and 75th percentiles for different scenarios of Alpha (VOC) prevalence, vaccination and transmission.

Table 3-1: Range of median cumulative infections from low to high transmission for different scenarios of Alpha (VOC) prevalence and vaccination.

Point Prevalence (PP)	VOC Prevalence	Range of median # of cumulative infections		
		Cumulative infections		
		No vaccination	Vaccination	**Difference**
2.5%	**50%**	49 – 203	40 – 102	**9 – 101**
	75%	60 – 253	45 – 134	**15 – 119**
	100%	70 – 282	54– 162	**16 – 120**

3.2 Outgoing infections

Modelling outgoing infections provides a measure of the scale of infections that could leave the exercise. As we assume that symptomatic infections would be quarantined and unable to depart until recovered, outgoing infections are those exposed or infected participants with an undetected (asymptomatic or pre-symptomatic) infection. These individuals contracted COVID-19 during the exercise and, once home, could spread it to their households and communities.

Similar to cumulative infections, Figure 3-2 and Table 3-2 show that an increase in transmission and/or Alpha prevalence results in an increase in the number of outgoing infections. The high-transmission scenarios produced up to 82% more outgoing infections, on average, compared to the low-transmission scenario. Vaccination significantly reduces the number of outgoing infections, having a larger impact in the high-transmission scenario (60% reduction), compared to the low-

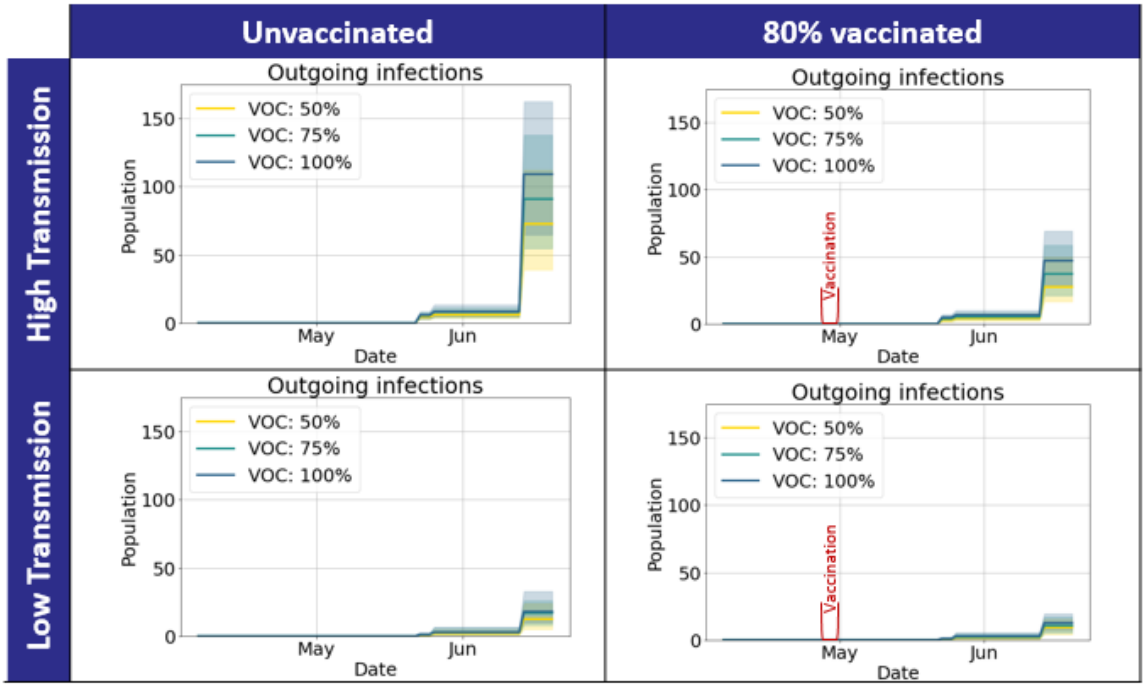

Figure 2-2: Median number of outgoing infections alongside the 25th and 75th percentiles for different scenarios of Alpha (VOC) prevalence, vaccination and transmission.

transmission scenario (31% reduction).

Table 3-2: Range of outgoing infections from low to high transmission for different scenarios of Alpha (VOC) prevalence and vaccination.

Point Prevalence (PP)	VOC Prevalence	Range of median # of outgoing infections		
		Outgoing infections		
		No vaccination	Vaccination	Difference
2.5%	50%	13 – 73	9 – 28	4– 45
	75%	17 – 91	11 – 37	6 – 54
	100%	18 – 110	13 – 47	5 – 63

3.3 Detected infections

Modelling detected infections provides a measure of the scale of infected individuals that will have to be quarantined and treated while at the exercise. This can assist in estimating the demand for health services resources needed to ensure the safety of participants; for example: quarantine space, hospital beds, medical

staff and personal protective equipment (PPE). Additionally, the detected infections can be compared to the actual COVID-19 case counts reported at the exercise.

Following a similar pattern to the previous results, we observe more detected infections as transmission and/or Alpha prevalence increases. However, vaccination reduces infections, especially in the high-transmission scenario where the results show a 54% reduction in the median number of detected cases, compared to a 38% reduction for the low-transmission scenario. Detected infections are counted within the cumulative infections discussed previously, and the results are qualitatively identical, but at a reduced scale. Therefore, we did not include the figure, but the median number of detected cases occurring during the exercise is provided in Table 3-3.

Table 3-3: Range of detected infections from low to high transmission for different scenarios of Alpha (VOC) prevalence and vaccination.

Point Prevalence (PP)	VOC Prevalence	Range of median # of detected infections		
		Total detected cases		
		No vaccination	Vaccination	**Difference**
2.5%	**50%**	8 – 34	5 – 15	**3 – 19**
	75%	10 – 41	6 – 19	**4 – 22**
	100%	11 – 47	7 – 22	**4 – 25**

4.0 CONCLUSION

Operating in a COVID-19 environment has become the new reality for militaries worldwide, and ensuring operational readiness for the CAF and allied forces while managing risks associated with COVID-19 is essential. This work quantified the potential scale of COVID-19 infections at Ex MR, the Canadian Army's largest annual exercise involving thousands of military personnel. The results of this analysis assisted military planners in preparing for the exercise and in making an informed decision to proceed with the exercise, given the present COVID-19 environment and the need to ensure the safety of participants. A stochastic SEIR compartment model was developed in the publicly available PyCoMod Python package to examine the impact of COVID-19 on the exercise and the effectiveness of risk mitigation strategies, such as on-site vaccination, within military settings.

The model showed that vaccination, the strongest available protective measure against COVID-19, can significantly decrease the burden of infections, even over short timeframes from the time of administering the first dose. The impact of vaccination is even more evident in high-transmission scenarios, whether due to circumstances where transmission is harder to control or to the presence of more transmissible variants of the virus. As vaccines were just starting to become available to the CAF during Ex MR, senior military officials made the decision to pause the exercise in order to provide participants the opportunity to receive their first dose of vaccine.

There were noted concerns that departing Ex MR participants might spread COVID-19 to their communities upon returning from the exercise. To assess whether a post-exercise quarantine period may be advised, we modelled the number of outgoing infections and found that, given the estimated transmission risk and the planned vaccination clinic, the number of outgoing infections was likely to be small. In fact, because the Ex MR participants were to be offered the vaccine ahead of the general Canadian population with an expected high uptake, it was unlikely that the returning CAF members posed any increased threat to their communities. The exercise planners concluded that participants would be permitted to return home after the exercise without quarantine.

A comparison of our results with actual infection rates during the exercise is not presented because the CAF has not publicly released these numbers. However, a small number of COVID-19 infections was recorded during the exercise and these fell within the range of our model's predicted detected infections. This broadly validates that the assumptions and methods employed in this work were appropriate for Ex MR and potentially other military exercise scenarios.

This work helped quantify several important risk factors associated with conducting a large-scale military exercise in a pandemic situation. The results were used to inform key considerations about the exercise including: the importance of zones, cohorting and other protective measures to maintain low transmission, the impact of vaccination even over short timeframes, the potential demand for COVID-19 quarantine and treatment resources, and the risk of exporting infections back to the communities. Ultimately, this work provided the Ex MR planning team with COVID-19 risk information necessary to make an informed decision about proceeding with the exercise during the ongoing pandemic.

4.0 FUTURE WORK

This modelling framework can be applied to a multitude of disease transmission scenarios, including those that employ alternate risk mitigation strategies and vaccination procedures, and that take place in different environments. The public availability of the PyCoMod modelling package enables other researchers to efficiently develop similar models customized to the specific nature of future outbreaks, whether due to COVID-19 or other infectious diseases.

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