Low-Infection Re-open Sequence of Canada Using GLEaM Model

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Abstract

The COVID-19 pandemic has pressed the pause button for almost every economic entity in the world and Canada is no exception. While the curve has been flattened by the joint effort of the people, the decision to re-open Canada requires caution against another wave of the epidemic. This is a decision that can only be harder than the initial lock down order and so far there has not been a clear path for the academia and the government. This paper aims to explore a reasonable re-open sequence of Canadian cities that can minimize the infection number while balancing the economic trade off. As this problem is of paramount importance, numerous statistical simulations have been conducted using the Global Epidemic and Mobility (GLEaM) model to forecast the outlooks of different re-open decisions. The GLEaM model has been praised for its accuracy in infectious disease modeling and flexibility in the scope of spatial data. A viable model also requires fine tuning of its parameters. We trained our GLEaM model with the 125-day Canadian COVID-19 time series along with population-distance weighted mobility matrix, then utilized Bayesian Optimisation to enhance forecasting abilities. Our GLEaM is able to help building a policy model that eventually suggests policy makers to re-open cities with lower populations before cities with high populations. The policy model can provide detailed re-opening date of each region.

Keywords
GLEaM model, statistical simulation, Bayesian optimisation, public health policy

1 Introduction

By the end of 30 May, 2020, there are 90190 reported COVID-19 cases in Canada nation wide [1]. Since the lock down introduced at a federal level in March, the economic devastation as the trade off for the public health priority might incur further damage to the Canadian households and businesses financially. Based on the simulation results, if the lock down continues at current level without any degree of relaxation, it will take more than one year to reduce infection number to a single digit. Therefore, the re-open of Canada is an imminent and inevitable task that the government and all Canadians need to take on. Currently, a lot of effort have been made towards descriptive analysis of this pandemic to explain what have already happened, including time series dashboards [2] and World Health Organization (WHO) situation reports [3], but it is certainly the time for us to look forward. The subsequent problem leads to the thesis of this paper, the re-open sequence of Canada that focuses on minimizing infection number. To solve such a problem, we believe it involves relatively accurate forecasting and statistical simulation. Traditionally, the SEIR model [4] has been a standard to analyze epidemics using partial differential equation approach. However, its assumptions might not coincide with the geographic property or demographic features of Canada. Thus, we decided to extend SEIR model to the Global Epidemic and Mobility (GLEaM) model [5] to capture the spatial and demographic factors that will affect the spread of the disease, which we consider it would be more Canadian oriented. As GLEaM is a multi-parameter model, we utilized Bayesian Optimisation to select parameters so that the simulation results largely agree with the historical data. The GLEaM model is further used to infer re-open policy outlooks and eventually determines the re-opening date of each region described in (). This implies that government should consider re-open regions with lower population ahead of re-opening larger cities.

2 Materials & Methods

2.1 Materials & Data

As it might be universally acknowledged that the more realistic the assumptions and data are, the more trustworthy the statistical simulations, GLEaM in our case, will be.

For training and optimisation purposes, we utilized the historical time series of confirmed COVID-19 cases in Canada from 22 January, 2020, to 25 May, 2020, by provinces/territories provided by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University [6].

As for the Canadian demographic data, we obtained population amounts and spherical coordinates of 247 Canadian municipal regions as of December, 2019 [7].

To set up initial conditions to train our model, we further collected detailed COVID-19 confirmed cases by municipal regions from 22 January, 2020, to 11 March, 2020, [8] to make the simulation assumption as realistic as possible.

2.2 GLEaM Model

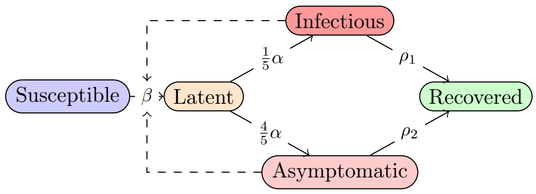
The Global Epidemic and Mobility (GLEaM) model is an extension of the Susceptible-Exposed-Infected-Recovered (SEIR) model, where population and mobility factors are better represented in the simulation. The traditional SEIR model is a compartment-based model for epidemics. Any individual in a compartment-based model belongs to a compartment, which is the stage of infection. The SEIR model has four compartments and is represented using 4 differential equations indicating the time-dependent evolution of each compartment.[1]

We model the spread of COVID-19 using a SEIR-based model with 5 compartments, corresponding to the 5 states a person can be in:

- Susceptible (susc): In this stage, the person is healthy but can contract the virus.
- Latent (latent): The person has contracted the virus. According to WHO, the median incubation period is 5 to 6 days, which corresponds to a daily incubation probability of $\alpha := 1/10$ [3].
- Infectious (infect): The person develops a symptom.
- Asymptomatic (asympt): In 80% of the cases a patient only develops mild to no symptom [3].
- Recovered (recov): The person has acquired immunity. From WHO data, the daily transition probabilities from Infectious (resp. Asymptotic) to Recovered is $\rho_1 := 1/30$ (resp. $\rho_2 := 1/20$), based on the median of a geometric distribution.

[1]The code for this model can be found at https://github.com/Stochastica/CovidPolicySim

Figure 1: The five compartments of the model with their transition probabilities.



Let S_t be the state of a person at time t (in units of days). Then we have

$$\Pr(S_{t+1} = j | S_t = i) = T_{i,j}$$

$$\boldsymbol{T} = \begin{array}{cl} \begin{bmatrix} 1-\beta & \beta & 0 & 0 & 0 \\ 0 & 1-\alpha & 0.2\alpha & 0.8\alpha & 0 \\ 0 & 0 & 1-\rho_1 & 0 & \rho_1 \\ 0 & 0 & 0 & 1-\rho_2 & \rho_2 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} & \begin{array}{l} \mathsf{susc} \\ \mathsf{latent} \\ \mathsf{infect} \\ \mathsf{asympt} \\ \mathsf{recov} \end{array} \end{array}$$

The spread pressure β is dependent on the proportion of people infected:

$$\beta := \eta \cdot \frac{\mathsf{p}_{\mathsf{latent}} + \mathsf{p}_{\mathsf{infect}} + \mathsf{p}_{\mathsf{asympt}}}{\mathsf{p}_{\mathsf{tot}}}$$

where η is a proportionality constant. We assume that under quarantine, the $\mathsf{p}_{\mathsf{infect}}$ population cannot spread COVID-19.

Additionally, the GLEaM model incorporates population layer and mobility layer.

2.2.1 Population Layer

The population layer is defined by dividing Canada into $n_{\mathsf{regions}} = 247$ municipal regions using the data from [7]. We assume that the population is completely mixed in each region. Then, let p_i be the population of region i.

2.2.2 Mobility Layer

The mobility layer is defined to model the spatial distribution of coronavirus cases by simulating human travel among the regions defined in the population layer. The population is allowed to move in between regions. Let R_t be the region of a person at time t. Then

$$\Pr(R_{t+1} = j | R_t = i) = M_{i,j}$$

The matrix $\boldsymbol{M}$ is defined as

$$M_{i,j} := \begin{cases} \mu(1-\mu_{\mathsf{pop}}\mathsf{p}_i/\mathsf{p}_{\mathsf{tot}}) & \text{if } i=j \\ (1-M_{i,i})D_{i,j}/\sum_k D_{i,k} & \text{otherwise} \end{cases}$$

where

$$D_{i,j} := \frac{\mathsf{p}_j/\mathsf{p}_i}{\mathrm{dist}(i,j)}$$

This models the three types of actions a person can take in a time step:

- Stay in the city with probability $M_{i,i}$. The **mobility coefficient** μ dictates the probability for a person to leave.
- Move to city j because of j's proximity to i. This is modeled using the $\mathrm{dist}(i,j)$ parameter, which is the distance between cities i and j
- Move to city j because of j's economic impact. This is modeled using the ratio $\mathsf{p}_j/\mathsf{p}_i$.

The transmission and mobility matrices $\boldsymbol{T}$ and $\boldsymbol{M}$ may be different for each day due to quarantine policies. Let $\boldsymbol{T}$ (resp. $\boldsymbol{T}^\star$) be the transmission matrix when a quarantine is not imposed (resp. imposed), and likewise for $\boldsymbol{M}$. $\boldsymbol{T},\boldsymbol{T}^\star$ are parametrised by $\eta,\eta^\star$ and $\boldsymbol{M},\boldsymbol{M}^\star$ are parametrised by $\mu,\mu^\star$. A quantity with a star indicates quarantine being imposed.

Since each person is identified by two variables, R and S, the simulation is calculated on a 2-dimensional array $\boldsymbol{A}$ of data, where $A_{i,j}$ represents the number of individuals in compartment i and region j. We specify the detail of the GLEaM model as in Algorithm 1. In each time step, the population $\boldsymbol{A}^{(t)}$ in the compartments of a city are updated to $\boldsymbol{A}^{(t+1)}$ using the rule (where $\boldsymbol{A}_{:,j}$ is the jth column of $\boldsymbol{A}$)

$$\boldsymbol{B}^{(t)}_{:,j} := \boldsymbol{A}^{(t)}_{:,j} + \sum_{i=1}^{5} \boldsymbol{\Delta}^{(i)}_T$$
$$\boldsymbol{\Delta}^{(i)}_T \sim \mathrm{Multinom}(A_{j,i}, \boldsymbol{T}_{j,:})$$

and the population is migrated using the rule

$$\boldsymbol{A}^{(t+1)}_{i,:} := \boldsymbol{B}^{(t)}_{i,:} + \sum_{j=1}^{n_{\mathsf{regions}}} \boldsymbol{\Delta}^{(j)}_M$$
$$\boldsymbol{\Delta}^{(j)}_M \sim \mathrm{Multinom}(A_{j,i}, \boldsymbol{M}_{i,:})$$

Algorithm 1: GLEaM Model

procedure SIMULATE($t_{\mathsf{begin}}, t_{\mathsf{max}}$)
  $\boldsymbol{A} \leftarrow$ initial-population
  for $t = t_{\mathsf{begin}}, \ldots, t_{\mathsf{max}}$
    $\boldsymbol{T} \leftarrow$ TRANSMISSION-MATRIX(t)
    $\boldsymbol{M} \leftarrow$ MOBILITY-MATRIX(t)
    for $i = 1, \ldots, n_{\mathsf{regions}}$
      Calculate transmission on $\boldsymbol{A}_{:,i}$ using multinomial distribution with probabilities $\boldsymbol{T}$
    end for
    for $j = 1, \ldots, 5$
      Calculate migration on $\boldsymbol{A}_{j,:}$ using multinomial distribution with probabilities $\boldsymbol{M}$
    end for
  end for
end procedure

The initial time t_{begin} is set to the time at which the 100th coronavirus case appeared in Canada. Since the number of people in the latent compartment is unknown, we assume the number of latent cases is proportional to the number of active cases by a proportionality constant λ.

The following 6 parameters shall be determined by optimisation: $\eta,\eta^\star,\mu,\mu^\star,\mu_{\mathsf{pop}},\lambda$.

2.3 Bayesian Optimisation

To estimate the various constants in the GLEaM model, we use Bayesian Optimisation.

Bayesian optimisation is considered to be free of the form of the objective function while optimising it to select most promising hyperparameters. The approach builds a probability model that evaluates the performances of hyperparameters. Theoretically, it reduces the cost of optimisation as it restores the information from the past trials and incorporates it to the next round of search. After each iteration, the updated model becomes a better approximation of the original objective function.

In our optimisation process, we employed the BayesianOptimization python library [9]. In particular, we adopted the method of Gaussian Process-Upper Confidence Bound (GP-UCB) [10]. The optimiser assumes the objective function

$$f(\boldsymbol{x}) \sim \mathcal{N}\left(\mu_t(\boldsymbol{x}), \sigma^2_t(\boldsymbol{x})\right)$$

with particular initial conditions μ_0, σ_0. For each iteration, the upper conditional bound function is

$$\varphi_t = \mu_{t-1} + \sqrt{\beta_t}\sigma_{t-1}$$

then, we choose $\mathbf{x}_t = \text{argmax}_x \varphi_t(\mathbf{x})$ and resample $y_t = f(\mathbf{x_t}) + \epsilon_t$ and update μ_t, σ_t correspondingly for next iteration. Through active learning relies on this heuristic approach, we maintain a balance from the exploration and exploitation trade off in the hyperparameter optimisations while minimizing the number of objective function evaluations.

2.4 Training

Let

- t_0 be 22 January, the beginning of the COVID-19 pandemic data in Canada.
- t_{begin} be the day on which the 100th coronavirus case was confirmed.
- t_{train} be the 115th day after t_{begin}, i.e. 17 May.
- t_{test} be the 124th day after t_{begin}, i.e. 26 May.

The historical data is separated into three parts:

- Preliminary period: The time frame $[t_0, t_{\mathsf{begin}})$ is the when the initial stage of confirmed patients data being prepared for model training [8].
- Training period: The time frame $[t_{\mathsf{begin}}, t_{\mathsf{train}})$ is the data segment used to calibrate the model.
- Testing period: The time frame $[t_{\mathsf{train}}, t_{\mathsf{test}})$ is the data segment used to test the model.

In order to perform Bayesian optimisation, we normalise the range of some model parameters in Table 1:

Parameter	Lower bound	Upper bound
$\log_{10} \eta$	-3	0
$\log_{10} \frac{\eta^\star}{\eta}$	-4	0
$\log_{10} \mu$	-4	-0.3
$\frac{\mu^\star}{\mu}$	-3	0
$\log_{10} \mu_{\mathsf{pop}}$	-3	-0.3
$\log_{10} \lambda$	0	3

Table 1: Range of Model Parameters

The loss function is designed so it covers both small scale and large scale errors in the prediction. Suppose $y_{k,t}$ and $\hat{y}_{k,t}$ are the total number of cases in province k at time t. (Regional-level data is currently not available) The **historical loss** is

$$L_{\mathsf{hist}}(\boldsymbol{y}, \hat{\boldsymbol{y}}) := \sum_k \sum_{t=t_{\mathsf{begin}}}^{t_{\mathsf{train}-1}} (\log y_{k,t} - \log \hat{y}_{k,t})^2$$

2.5 Policy Optimisation

After the model is trained, we determine the optimal policy for re-opening. Order the region indices $1, \ldots, n_{\mathsf{regions}}$ in ascending or descending order with respect to their population. Region j should open when

$$j \leq \left(\frac{t - t_{\mathsf{policy}}}{\pi_D} \right)^{\pi_P}$$

By sequentially re-opening, we avoid spikes in latent infected individuals caused by opening the cities in rapid succession.

Let t_{policy} be June 1st, on which day the policy would go into effect. We simulate the pandemic to 22 Jan. 2021 in Canada and we minimise on two objectives:

- $C(\hat{\boldsymbol{y}})$: The number of total COVID-19 cases at the end of simulation, since this value is directly linked to the number of deaths.
- $Q(\hat{\boldsymbol{y}})$: The number of people in quarantine multiplied by the duration of quarantine. This value represents the economic loss.
- ϵ: The trade-off between $C(\hat{\boldsymbol{y}})$ and $Q(\hat{\boldsymbol{y}})$.

The policy loss function is

$$L_{\mathsf{policy}}(\hat{\boldsymbol{y}}) := C(\hat{\boldsymbol{y}}) + \epsilon \cdot Q(\hat{\boldsymbol{y}})$$

with the understanding that the cases before t_{policy} are not included. L_{policy} is then also optimised using Bayesian optimisation, with the parameter ranges in Table 2

Parameter	Lower bound	Upper bound
π_D	90	235
π_P	-1	1

Table 2: Range of Policy Parameters

The result of this optimisation is dependent on the value of ϵ, which we select to be $\frac{1}{365 \cdot 2}\text{Day}^{-1}$, i.e. quarantining two individuals for 365 days and one individual case for COVID-19 are considered equivalent.

3 Results

3.1 Model Training Result

Based on the model assumptions above and Bayesian Optimisation, our GLEaM model parameters have been summarized as in Table 3.

Parameter	Estimate
$\log_{10}\eta$	-0.5332
$\log_{10}\frac{\eta^\star}{\eta}$	-0.8031
$\log_{10}\mu$	0.1501
$\frac{\mu^\star}{\mu}$	-1.5378
$\log_{10}\mu_{\mathsf{pop}}$	-1.1481
$\log_{10}\lambda$	-1.2187

Table 3: GLEaM Model Parameters Results

3.2 Policy Result

Based on our GLEaM model parameters provided in Table 3, we further identified our policy model parameters as shown in Table 4.

Parameter	Estimate
π_D	229.7
π_P	-0.2331

Table 4: Policy Parameters Results

The suggested re-open date for each region has been disclosed in Appendix 6: Table 6 along with a geographical visualization of the reoing process in Appendix 6: Figure 7.

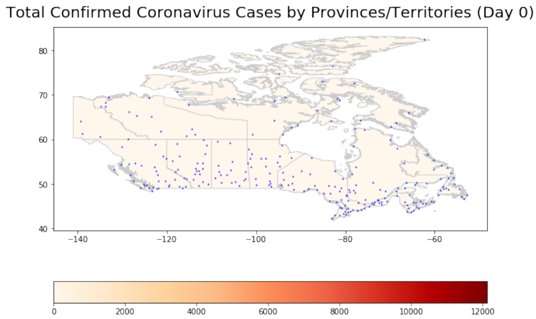
4 Discussion

4.1 Model Training

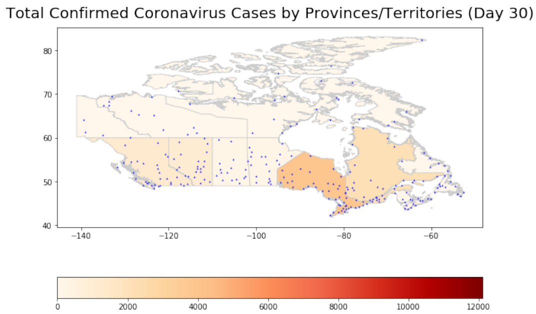
After applying Bayesian Optimisation, our model resembles the actual confirmed COVID-19 cases in Canada as a whole, which has been shown in the Figure 3.

Moreover, simulation on confirmed cases displays a similar process at the aggregated provincial/territorial level, as displayed in Figure 4 and visualized geographically by Figure 2 on the day 0, 30, 60, 80 since the simulation starts hypothetically on 11 March, 2020[2].

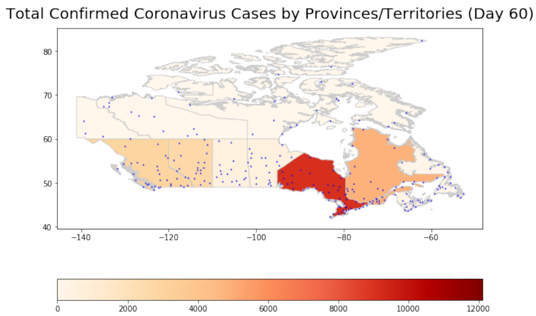
[2]The code to generate this set of graphs can be found at `https://github.com/WeixiSilhouetteZed/Big-Data-Challenge/blob/master/BDC.ipynb`



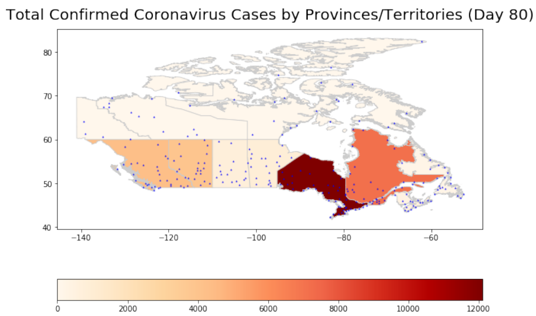
(a) Simulation Day 0



(b) Simulation Day 30



(c) Simulation Day 60



(d) Simulation Day 80

Figure 2: Simulated Confirmed Coronavirus Cases by Provinces/Territories From Day 0 to Day 80. Table data support is given by Table 5 in Appendix B

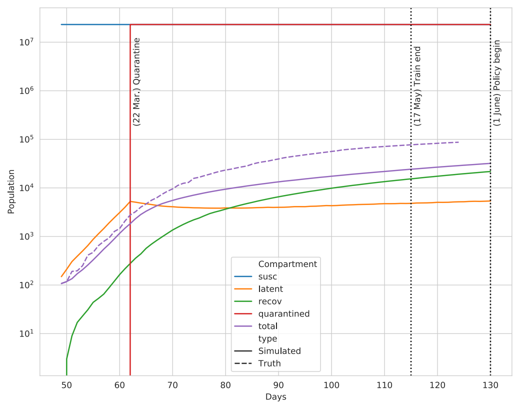


Figure 3: Simulated and Real infection numbers before 1 June.

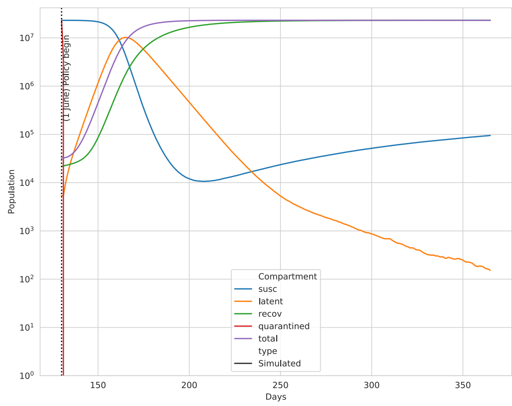


Figure 6: Infection numbers under no imposed quarantine. The wedge between total number of cases and recovered is a huge stress on the healthcare system.

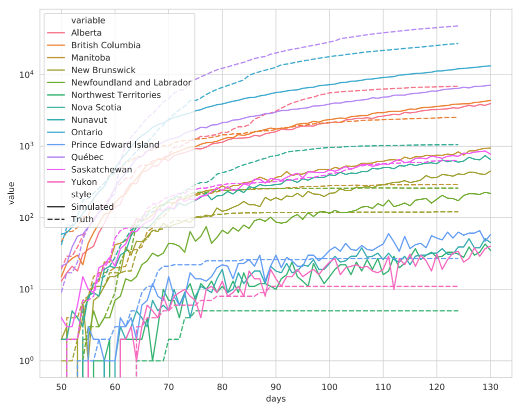


Figure 4: Simulated and Real infection numbers before 1 June (provincial/territorial level).

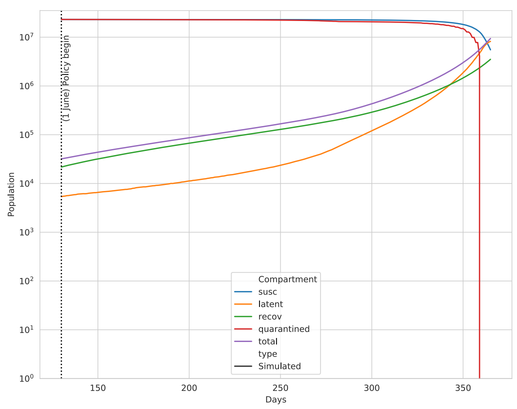


Figure 5: Infection numbers of the optimal policy

Figure 3 suggests that the GLEaM model is a relatively accurate model for the spread of COVID-19. Compared to homogeneous spread models such as SEIR, the model takes into account the spatial separation of infection cases. However, the model's performance is limited by the amount of data available. The model is trained using Bayesian optimisation, which is a methodology that is robust but slower compared to Gradient Descent.

4.2 Policy Selection

The results from Bayesian optimisation for policy are in Figure 5 (cf. Figure 6 with no quarantine). Based on the policy optimisation process, we suggest reoing regions with smaller population prior to regions with higher population.

One interesting observation is that regardless of the quarantine policy, the number of latent cases does not diminish appreciably until the majority of the population is infected. This suggests that herd immunity is inevitable. We have also attempted to find a policy based on the number of infections and date using the formula

$$\mathsf{p}_{j,\mathsf{infect}} \le (1-c_1)^{t-t_{\mathsf{policy}}} c_2 \left(1-\frac{\mathsf{p}_{j,\mathsf{tot}}}{\mathsf{p}_{\mathsf{tot}}}\right)^{c_3} \mathsf{p}_{j,\mathsf{tot}}$$

but such attempts proved futile in generating a policy other than quarantining indefinitely or immediately lifting the quarantine.

5 Conclusions

Based on the above simulations, we recommend that the quarantine be lifted in order with small communities reoing sooner than larger communities. The opening dates can be found in Appendix 6. If more data become available, they can be used to calibrate the model even further. We hope this analysis can provide a methodology to tackle such an intriguing yet extremely delicate matter as the future of Canadian households and businesses depends on it.

5.1 Possible Improvements

Due to the limitation of our computational devices, it is prohibitively expensive to test more flexible policies, such as one with a specific reoing date for each region. If more computational power and more data are available, the topic of more flexible policy may be feasible. The model also does not take into account the influx and out-flux of COVID-19 cases across the border, but such cases are minimised by the strict travel restrictions and border closures imposed by the federal government.

The objective function could be modified so it instead accounts for the maximal stress on the healthcare system. This may lead to more useful results since herd immunity requires a substantial portion of the population to be infected in order to be effective.

6 Acknowledgements

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Appendix A: Definition of Variables

- β: Spread pressure
- η: Infectiosity
- $\eta^{\star}$: Infectiosity under quarantine.
- μ: Mobility
- $\mu^{\star}$: Mobility under quarantine
- μ_{pop}: Mobility due to population
- λ: Latent ratio
- p: Population. p_i is the population of ith region, and $\mathsf{p}_{\mathsf{tot}}$ is the total population.
- $t_0, t_{\mathsf{begin}}, t_{\mathsf{train}}, t_{\mathsf{test}}, t_{\mathsf{policy}}$: Dates
- ϵ: The trade off in value between quarantining one person for one day compared to a person being infected.

Appendix B: Table Data For Visualization of Simulation Results

Province	Day 0			Day 30			Day 60			Day 80		
	Susceptible	Latent	Confirmed	Susceptible	Latent	Confirmed	Susceptible	Latent	Confirmed	Susceptible	Latent	Confirmed
Alberta	2902226	32	13	2809545	461	1134	2809628	552	2640	2806326	674	3952
British Columbia	3338638	28	15	3097485	549	1253	3097735	632	2939	3097579	747	4356
Manitoba	687568	7	2	652698	105	279	652607	83	616	651701	146	943
New Brunswick	308393	2	2	312581	56	123	313634	72	290	313295	72	450
Newfoundland and Labrador	171507	0	0	157894	21	67	157893	27	146	157670	32	219
Northwest Territories	27193	0	0	25766	7	11	25808	10	16	25255	3	35
Nova Scotia	527867	6	2	518670	74	205	517663	124	501	518205	128	652
Nunavut	31659	0	0	30465	5	19	30257	7	26	30565	7	45
Ontario	9714611	93	59	9658963	1617	3896	9653390	2006	9127	9646031	2193	13302
Prince Edward Island	42342	0	0	42163	8	22	42012	8	43	42204	10	58
Quebec	4711803	37	21	5167193	857	2135	5158412	1063	4859	5160265	1208	7151
Saskatchewan	632539	6	4	611580	113	240	613022	145	569	612135	151	773
Yukon	24412	0	0	22201	3	13	22311	5	19	22045	4	40

Table 5: Simulated Data Support for Figure 2

Appendix C: Re-opening Sequence From Optimal Policy

Municipal Region	Estimated Re-open Date	Municipal Region	Estimated Re-open Date	Municipal Region	Estimated Re-open Date	Municipal Region	Estimated Re-open Date	Municipal Region	Estimated Re-open Date
Toronto	2021-01-17	Weyburn	2020-11-04	Amherst	2020-09-04	Marathon	2020-07-17	Coral Harbour	2020-06-15
Montreal	2021-01-16	Iqaluit	2020-11-03	Kapuskasing	2020-09-03	Kindersley	2020-07-17	La Scie	2020-06-14
Vancouver	2021-01-14	Meadow Lake	2020-11-02	Dauphin	2020-09-01	Channel-Port aux Basques	2020-07-16	Watson Lake	2020-06-14
Ottawa	2021-01-12	Thunder Bay	2020-10-31	Dryden	2020-08-31	Saint-Augustin	2020-07-15	Taloyoak	2020-06-13
Calgary	2021-01-11	Saint John	2020-10-30	Revelstoke	2020-08-30	Digby	2020-07-14	Natashquan	2020-06-13
Edmonton	2021-01-09	Nanaimo	2020-10-28	Happy Valley	2020-08-29	Hay River	2020-07-13	Buchans	2020-06-12
Hamilton	2021-01-08	Saint-Jerome	2020-10-27	Banff	2020-08-28	Windsor	2020-07-13	Hall Beach	2020-06-12
Winnipeg	2021-01-06	Red Deer	2020-10-26	Yarmouth	2020-08-27	La Ronge	2020-07-12	Mingan	2020-06-11
Quebec	2021-01-05	Lethbridge	2020-10-25	La Sarre	2020-08-26	Deer Lake	2020-07-11	Kangirsuk	2020-06-11
Oshawa	2021-01-03	Kamloops	2020-10-23	Stephenville	2020-08-25	Atikokan	2020-07-10	Sandspit	2020-06-10
Kitchener	2021-01-01	Prince George	2020-10-22	Flin Flon	2020-08-24	Gander	2020-07-10	Deline	2020-06-10
Halifax	2020-12-31	Medicine Hat	2020-10-21	The Pas	2020-08-23	Shelburne	2020-07-09	Fort Smith	2020-06-10
London	2020-12-29	Chicoutimi	2020-10-19	Vegreville	2020-08-22	Inuvik	2020-07-08	Cartwright	2020-06-09
Windsor	2020-12-28	North Bay	2020-10-18	Peace River	2020-08-21	Lillooet	2020-07-07	Holman	2020-06-09
Victoria	2020-12-26	Joliette	2020-10-17	Creston	2020-08-20	Chapleau	2020-07-07	Lynn Lake	2020-06-09
Saskatoon	2020-12-25	Sydney	2020-10-15	Sioux Lookout	2020-08-19	Burns Lake	2020-07-06	Trout River	2020-06-08
Barrie	2020-12-23	Orillia	2020-10-14	Cochrane	2020-08-18	Biggar	2020-07-05	Fort Resolution	2020-06-08
Regina	2020-12-22	Rimouski	2020-10-13	Liverpool	2020-08-17	Wiarton	2020-07-04	Forteau Bay	2020-06-07
Sudbury	2020-12-20	Timmins	2020-10-12	Melville	2020-08-16	Hudson Bay	2020-07-04	Hopedale	2020-06-07
Abbotsford	2020-12-19	Prince Albert	2020-10-10	Deer Lake	2020-08-15	Matagami	2020-07-03	Pukatawagan	2020-06-07
Sarnia	2020-12-17	Saint-Georges	2020-10-09	Jasper	2020-08-14	Attawapiskat	2020-07-02	Trepassey	2020-06-06
Sherbrooke	2020-12-16	Sept-Iles	2020-10-08	Fort Chipewyan	2020-08-13	Red Lake	2020-07-02	Chesterfield Inlet	2020-06-06
Saint John's	2020-12-14	Owen Sound	2020-10-07	Lac La Biche	2020-08-12	Moosonee	2020-07-01	Eastmain	2020-06-06
Kelowna	2020-12-13	Corner Brook	2020-10-05	Baie-du-Poste	2020-08-11	Tofino	2020-06-30	Dease Lake	2020-06-05
Trois-Rivieres	2020-12-11	Val-d'Or	2020-10-04	Gimli	2020-08-10	Igloolik	2020-06-30	Paulatuk	2020-06-05
Kingston	2020-12-10	New Glasgow	2020-10-03	Athabasca	2020-08-09	Inukjuak	2020-06-29	Fort Simpson	2020-06-05
Moncton	2020-12-08	Terrace	2020-10-02	Nelson House	2020-08-08	Little Current	2020-06-28	Brochet	2020-06-05
Peterborough	2020-12-07	North Battleford	2020-09-30	Rankin Inlet	2020-08-07	Pond Inlet	2020-06-28	Cat Lake	2020-06-04
Drummondville	2020-12-05	Cranbrook	2020-09-29	Port Hardy	2020-08-06	Cap-Chat	2020-06-27	Radisson	2020-06-04
Fredericton	2020-12-04	Edmundston	2020-09-28	Wawa	2020-08-05	Cambridge Bay	2020-06-26	Port-Menier	2020-06-04
Chilliwack	2020-12-02	Camrose	2020-09-27	Arviat	2020-08-04	Thessalon	2020-06-26	Resolute	2020-06-04
Shawinigan	2020-12-01	Pembroke	2020-09-26	Baker Lake	2020-08-03	Bella Bella	2020-06-25	Upper Hay River	2020-06-03
Cornwall	2020-11-29	Yorkton	2020-09-24	Cape Dorset	2020-08-02	Cobalt	2020-06-24	Port Hope Simpson	2020-06-03
Belleville	2020-11-28	Swift Current	2020-09-23	Lake Louise	2020-08-01	Pangnirtung	2020-06-24	Tsiigehtchic	2020-06-03
Charlottetown	2020-11-27	Prince Rupert	2020-09-22	Repulse Bay	2020-07-31	Dawson	2020-06-23	Ivujivik	2020-06-03
Victoriaville	2020-11-25	Williams Lake	2020-09-21	Arctic Bay	2020-07-30	Kugluktuk	2020-06-23	Stony Rapids	2020-06-03
Grande Prairie	2020-11-24	Brooks	2020-09-20	Fort Good Hope	2020-07-29	Geraldton	2020-06-22	Alert	2020-06-02
Penticton	2020-11-22	Quesnel	2020-09-18	Schefferville	2020-07-29	Gillam	2020-06-21	Fort Severn	2020-06-02
Campbell River	2020-11-21	Thompson	2020-09-17	Kimmirut	2020-07-28	Kuujjuaq	2020-06-21	Rigolet	2020-06-02
Courtenay	2020-11-19	Dolbeau	2020-09-16	Saint Anthony	2020-07-27	Nipigon	2020-06-20	Lansdowne House	2020-06-02
Orangeville	2020-11-18	Powell River	2020-09-15	Oxford House	2020-07-26	Nain	2020-06-20	Salluit	2020-06-02
Moose Jaw	2020-11-17	Nelson	2020-09-14	Parry Sound	2020-07-25	Gjoa Haven	2020-06-19	Uranium City	2020-06-02
Brandon	2020-11-15	Mont-Laurier	2020-09-13	Antigonish	2020-07-24	Fort McPherson	2020-06-19	Burwash Landing	2020-06-02
Brockville	2020-11-14	Kenora	2020-09-11	Fort Nelson	2020-07-23	Argentia	2020-06-18	Grise Fiord	2020-06-02
Rouyn-Noranda	2020-11-12	Dawson Creek	2020-09-10	Smithers	2020-07-22	Norman Wells	2020-06-18	Island Lake	2020-06-02
Whitehorse	2020-11-11	Amos	2020-09-09	Bathurst	2020-07-22	Churchill	2020-06-17	Big Beaverhouse	2020-06-02
Fort McMurray	2020-11-10	Baie-Comeau	2020-09-08	Norway House	2020-07-21	Tuktoyaktuk	2020-06-17	Ennadai	2020-06-01
Yellowknife	2020-11-08	Hinton	2020-09-07	Stettler	2020-07-20	Berens River	2020-06-16		
Fort Saint John	2020-11-07	Selkirk	2020-09-06	New Liskeard	2020-07-19	Shamattawa	2020-06-16		
Wetaskiwin	2020-11-06	Steinbach	2020-09-05	Hearst	2020-07-18	Baddeck	2020-06-15		

Table 6: Re-open Sequence by Estimated Dates

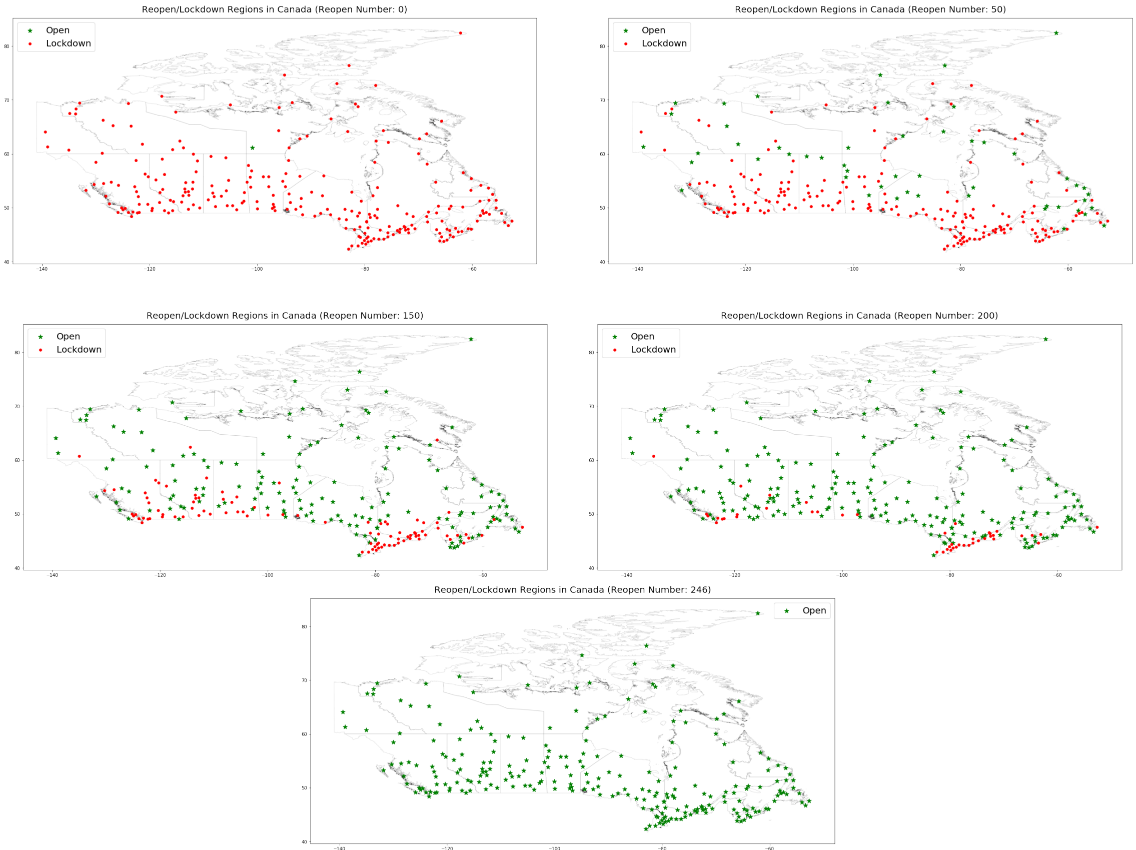

Figure 7: Visualization of the Re-open Sequence