

Modeling pandemics and vaccine and equity issues

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ABSTRACT

We present some recent activity in Ontario on the mathematical modeling of COVID-19 and the development of optimal strategies for vaccine distribution that take into account equity issues.

Keywords: Compartment model, economic impact, equity issues, hurricane model, lockdown trade-offs, vaccine distribution

Introduction

This article contains a summary and discussion of information and insights presented at the Canada–India Health Summit in May 2021. The three topics in the title, namely modeling, vaccine, and equity issues, cover a very broad area, and it is essentially impossible to do justice to them in a brief report or discussion. Moreover, we are dealing with a dynamic situation around the world. We will therefore confine ourselves to a very high-level description of some of the issues connected to these topics. It should be obvious to anyone who has been following the pandemic that all three topics are of critical importance when understanding and moving forward in the pandemic, especially in our current state around the world.

As a result of our work during the past year, we would like to highlight three aspects of the pandemic from the perspective of modeling, namely the importance of reliable data, the development of an integrative approach to modeling that takes into account the full impact of the pandemic, and the need for an effective balance of measures to minimize disease spread while maintaining

societal functions and building a more equitable and effective vaccination plan.

Mathematical Models

In trying to understand and give useful information about the dynamics of the pandemic, mathematical modeling is obviously an important tool. This tool has been used for at least several centuries in developing our understanding of the spread of infectious diseases. For example, Bernoulli in 1760 introduced a mathematical model to study the spread of smallpox.^[1] In the 19th century, Ronald Ross developed a mathematical model of malaria. Ross was actually born in India and did his research on identifying the malaria parasite in Secunderabad. The model that he worked with is an early example of a compartmental model.

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In compartmental models, the population is divided into several subsets or compartments. In the SIR model, for example, the S denotes the part of the population that is susceptible to infection, the I denotes the part that is infected, and the R denotes the part that is recovered. The SIR model puts forward a set of differential equations relating the three quantities in terms of several parameters related to the disease such as transmission probability and recovery rate. The SIR model was formulated in 1927 by Kermack and McKendrick. The text of Bailey^[2] is a good reference for the classical theory of infectious disease modeling.

The basic SIR model has been refined in several ways and there is a large literature on this subject. One of the refinements that was developed during the pandemic was to consider an age-stratified version of the model.^[3] This was necessary because it was observed that (at least in the early waves) the virus affected different age populations differently (for example, the elderly was the most susceptible and children were either not being infected or were experiencing less severity). The latest variants have caused us to re-evaluate this, but the need for age-stratified compartment models continues to be present.

In practice, SIR models have to be regularly recalibrated as the underlying parameters might change, for example as a result of public health measures or vaccinations. As an illustration of how these models are used, Figure 1 shows a graph produced by the McMaster research group of David Earn (which uses an susceptible-exposed-infectious-removed model, with the E denoting the compartment of exposed population) that shows past and projected case numbers under various assumptions about vaccinations and public health measures. The shaded bands indicated 95% confidence intervals.

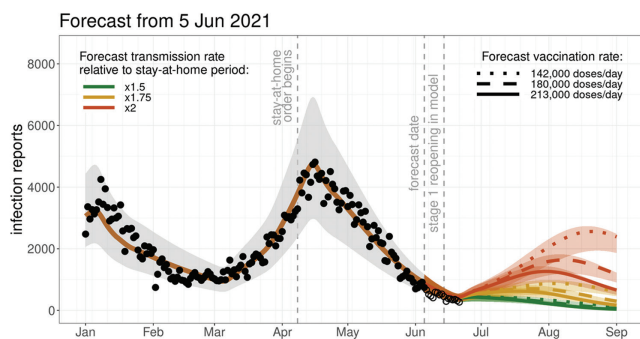


Figure 1: <https://mac-theobio.github.io/forecasts/outputs/McMasterOntarioForecastsBlog2021-06-05>

In trying to visualize the dynamics of the pandemic, a research group led by the Fields Institute has been working on a new approach which we call the hurricane model. This is a data-driven model which considers not only the caseload at a given time but also how quickly the case numbers are changing. If we think of the total number of cases at time t being represented by a function $f(t)$, then the incidence is the derivative $f'(t)$, and the rate of change of incidence is the second derivative $f''(t)$. We term the pair $(f'[t], f''[t])$ as growth and acceleration. In the hurricane model, we track this vector in time. Weather systems are tracked in terms of their latitude and longitude, and by analogy, we use growth and acceleration to track the pandemic.

In Figure 2, which was computed on May 16, 2021, we can see how the pandemic has progressed in Ontario. We see that the growth and acceleration have been following a cyclical trend. The model predicts the possible situations of how we will move forward and these are the three scenarios indicated in purple, gold, and red. The upper graph on the left indicates the weekly growth rate, while the lower graph on the left indicates the weekly acceleration.

In Figure 3, we have plotted the growth and acceleration vector for each province as of May 16, 2021. You can see that at that point in time, Manitoba was an outlier, and we also saw the movement of the Atlantic provinces which until then had had quite low numbers.

COVID-19 Lockdown Trade-Offs

The pandemic is not only a health issue but affects many other aspects of society including economic aspects. The company Riskthinking.AI is developing tools to display these interrelated aspects. One of these tools, developed with a grant from the Canadian Supercluster initiative, is called COVIDWISDOM and it

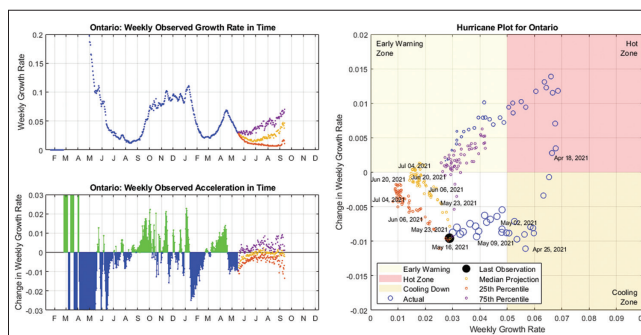


Figure 2: Hurricane plot for Ontario as of May 16, 2021

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is a way to visually and statistically compare lockdown interventions/procedures against economic impact of those procedures [Figure 4]. COVIDWISDOM™ trades off epidemiological-based outcomes with economic impacts under different lockdown regimes and compliance scenarios for COVID-19. The risk factors are compliance with mask wearing, handwashing, distancing, and hygiene. The algorithm coordinates between an epidemiological model to understand health impacts and an economic model to understand economic impacts. Uncertainty in the risk variables is uncovered using Structured Expert Judgment. The data feeding this model come from publicly available, almost real-time data. The development of such models requires an interdisciplinary team of data scientists, economists, epidemiologists, and software engineers.

According to Riskthinking.AI, a more effective instrument than lockdown might be the managing of compliance with mask wearing. Investigators from Riskthinking.AI felt that we might have achieved results as good or better than were actually achieved with various lockdown regimes through active enforcement of mask wearing everywhere. The social and economic value of such a strategy, they felt, would far outweigh the social and economic costs we experienced under lockdown. More analysis, discussion, and debate are clearly warranted on this important question.

A look under the hood of the workflow and architecture of the CLIMATEWISDOM™ product shows the data required to operate it and the microservices needed to run it [Figure 5]. The product was completed and operational in November 2020.

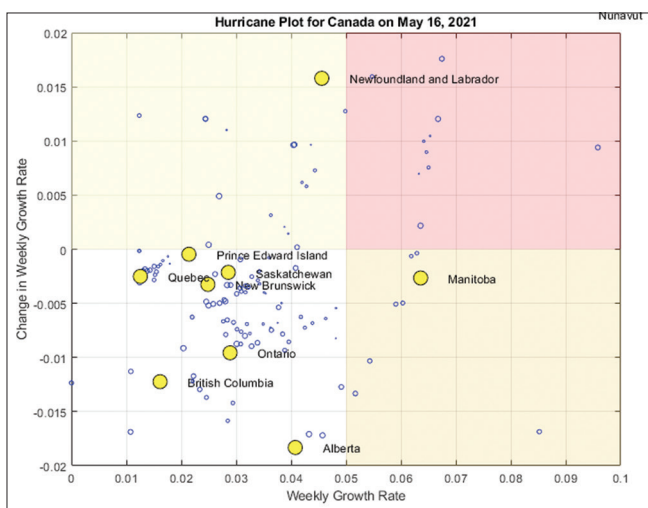


Figure 3: Growth and acceleration of Canadian provinces on May 16, 2021

Further to the idea of simultaneously modeling economic and health parameters, the Fields Institute and University of Toronto research group developed an analysis of balancing caseloads against unemployment.^[4] In Figure 6, we plotted (on a logarithmic scale) caseloads versus unemployment, computed against a number of different scenarios. Each dot in this plot represents a sequence of public health measures applied over a number of months. What is striking about this plot is the “efficient frontier” that emerges to suggest that there is an optimal strategy for minimizing caseloads and unemployment.

Vaccine distribution: Sociodemographics and ethical considerations in ontario

We have witnessed almost a miraculous development over <12 months of effective vaccines to combat the COVID-19 disease. While rapid deployment is essential to reduce morbidity and mortality, the science of vaccine effectiveness continues to evolve. For example, early studies demonstrated reduced hospitalizations and deaths among vaccinated individuals, so priority populations correctly included those at highest risk for these outcomes, including older people and those living and working in long-term care. However, there are many other communities at high risk. This population is comprised largely of people from marginalized communities including visible minorities, those unable to work from home, in lower-paying jobs, and living in crowded conditions, often in multigenerational households. Hence, the principles of equity and justice were crucial in planning a vaccine distribution strategy.

Analysis from the Ontario Science Advisory Table noted that 30% of Ontario cases of COVID-19 occurred in 10% of neighborhoods and 50% occurred in 20%.

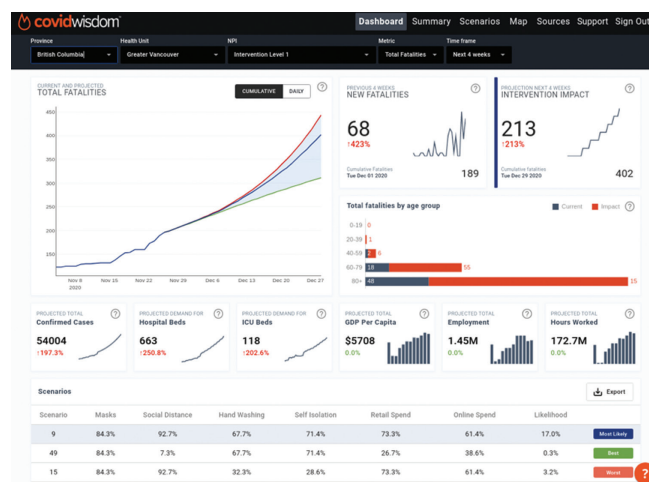


Figure 4: A screenshot of COVIDWISDOM produced by Riskthinking.AI Corp

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These neighborhoods reflect a high incidence of the high-risk populations as noted above. Deaths occurred predominantly in high incidence neighborhoods. Moreover, with later knowledge that the messenger ribonucleic acid vaccines were effective in preventing infection, attention turned toward prioritizing the populations who lived in “hot-spots” where both transmission and disease severity were highest.

As of March 29, 2021, the highest coverage was among those aged ≥ 80 years. However, coverage for all ages was lowest in the highest risk communities, depicted here on the left column of Figure 7. Residents of communities with the lowest risk of SARS-CoV-2 infections were 1.5 times more likely to have received one COVID-19 vaccine, compared to those in communities with the highest risk. For example, among those aged ≥ 80 years, vaccine coverage ranged from 50% to 72%. High levels of coverage among younger adults in low-risk areas likely represented greater uptake by health-care workers; however, the consistently lower coverage among all age groups in areas with the greatest risk suggested the presence of barriers to vaccination (e.g., access challenges due to inability to leave work, transportation issues, and lack of vaccine confidence).

Some of the likely reasons for the early high vaccination coverage rates in low-risk areas might include: higher socioeconomic status with better access to mass vaccination clinics – booking, private transportation/better mobility, fewer economic and time constraints, a low proportion of low paid essential workers who have difficulty getting time off to obtain the vaccine, and a low proportion of racialized communities who may be vaccine hesitant due to legitimate distrust for government and public health authority related to colonization, discriminatory, or abusive history. There may be other factors and causes as well.

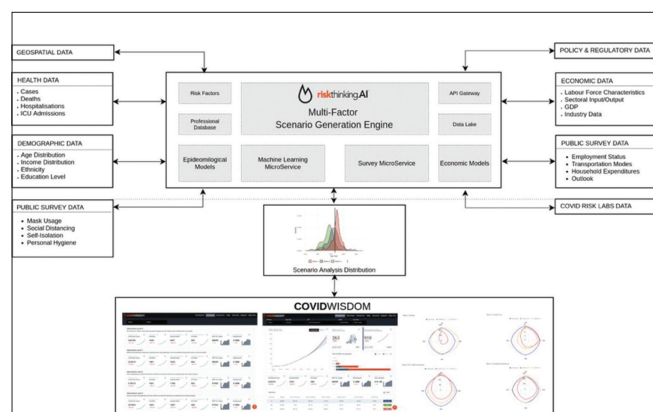


Figure 5: Architecture of COVIDWISDOM developed by Riskthinking.AI Corp.

The analysis of Mishra *et al.* from the Ontario Science Advisory Table [Figure 8]^[5] showed that allocating 50% of vaccines in Ontario to the 74 neighborhoods comprising the highest 2 deciles of disease over a 30-day period would result in 18% fewer cases of COVID-19 compared with 100% allocation according to age only.

This corresponds to 14% fewer hospitalizations and intensive care unit admissions and 11% fewer deaths. Over the course of the month of April, the disparity between the highest and lowest risk neighborhoods narrowed, as shown in Figure 9.

Vaccine distribution and equity issues in India

India started its national vaccination program on January 16, 2021. Technology was used to ensure a targeted and phased distribution through the Co-Win application. The distribution program was also guided by the National Expert Group on Vaccine Administration for COVID-19.

The first phase of the distribution program targeted health-care and other frontline workers, Phase 2 included those individuals over the age of 50 and those with comorbidities, and Phase 3 targeted individuals $> 18-45$ years of age. Three kinds of vaccines were available in India: Covishield (Serum Institute of India – Rs. 150/dose to the central government, Rs. 300/dose to states, and Rs. 600/dose to private hospitals), Covaxin (Bharat Biotech and Indian Council of Medical Research scientists – Rs. 150/dose for central government and Rs. 400 for state governments), and Russian Sputnik V (Dr. Reddy’s Lab, Rs. 995).

As of May 2021, approximately 142 million people had received their first dose of the vaccine and 40 million had received their second dose. India is also proudly

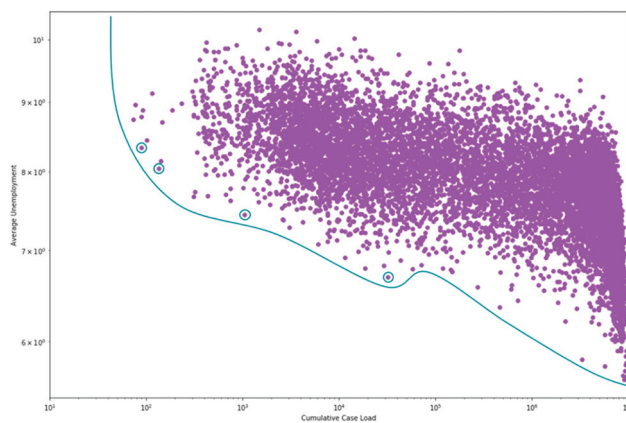


Figure 6: Case load versus unemployment (from the Fields Institute-University of Toronto research group)

Age group	Neighbourhood Risk*										Overall
	1 = high incidence of COVID-19 infections					10 = low incidence of COVID-19 infections					
80+	50%	55%	59%	66%	66%	66%	65%	72%	69%	70%	64%
75-79	37%	43%	43%	46%	45%	46%	40%	40%	30%	29%	39%
70-74	13%	19%	19%	18%	19%	21%	17%	17%	10%	9%	16%
65-69	8%	10%	10%	11%	10%	11%	10%	10%	7%	8%	9%
60-64	18%	23%	22%	21%	21%	21%	19%	18%	14%	20%	20%
55-59	7%	9%	9%	10%	11%	11%	10%	11%	10%	12%	10%
50-54	6%	7%	7%	8%	9%	8%	9%	9%	10%	11%	8%
45-49	8%	7%	6%	8%	8%	8%	8%	9%	10%	11%	8%
40-44	5%	6%	6%	7%	8%	7%	8%	8%	9%	10%	7%
16-39	4%	5%	5%	6%	6%	6%	6%	7%	8%	8%	6%
Overall	8%	10%	10%	11%	11%	12%	11%	12%	11%	13%	13%

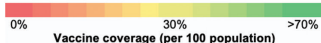


Figure 7: Vaccine coverage (per 100 population) organized by age group and neighbourhood risk (excluding long term care) as of March 29, 2021. Source: ICES

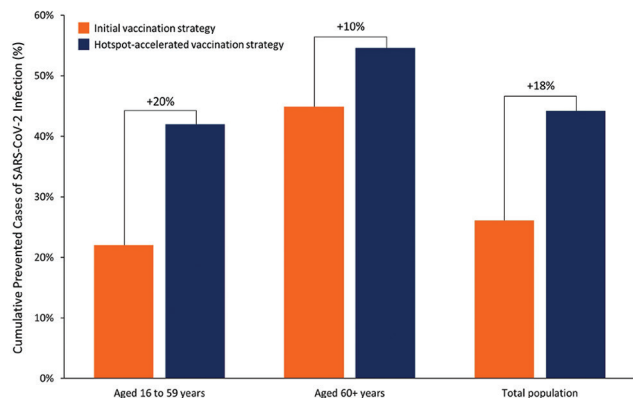


Figure 8: Infections prevented by a strategy of vaccinating residents and essential workers in hotspots. Source: <https://covid19-sciencetable.ca/sciencebrief/covid-19-vaccination-strategy-for-ontario-using-age-and-neighbourhood-based-prioritization/>

Age group	Neighbourhood Risk*										Overall
	1 = high incidence of COVID-19 infections					10 = low incidence of COVID-19 infections					
80+	69%	72%	75%	78%	79%	81%	82%	83%	85%	85%	79%
75-79	70%	73%	76%	78%	80%	81%	82%	82%	83%	80%	79%
70-74	68%	72%	74%	75%	77%	77%	78%	79%	78%	71%	75%
65-69	64%	67%	67%	64%	65%	65%	68%	66%	61%	48%	63%
60-64	61%	64%	62%	58%	59%	58%	62%	56%	54%	48%	58%
55-59	49%	50%	48%	43%	41%	42%	43%	41%	39%	35%	43%
50-54	44%	45%	38%	32%	27%	27%	28%	25%	23%	22%	31%
45-49	23%	30%	22%	22%	23%	23%	23%	23%	21%	21%	23%
40-44	19%	24%	20%	21%	22%	23%	22%	21%	20%	19%	21%
16-39	11%	12%	10%	11%	11%	11%	11%	11%	12%	13%	11%
Overall (16+)	32%	37%	33%	34%	33%	34%	35%	35%	36%	35%	34%

Figure 9: Vaccine coverage (per 100 population) organized by age group and neighbourhood risk (excluding long term care) as of April 26, 2021. Source: ICES

hosting the Vaccine Maitri Initiative as the largest vaccine manufacturer in the world, in which it provides vaccines to nations across the world. More details can be found in the article by Dr. J. S. Thakur in this volume.

Conclusion

The modeling of the pandemic clearly evolved during the course of the pandemic. Based on our discussion above, there are three aspects that we would like to draw attention to.

First, it is evident (especially in models such as the Hurricane) that reliable global data are key to having well-constructed

models and for deducing meaningful and impactful conclusions. Reliable data are necessary for testing hypotheses and for designing appropriate public health measures.

Second, we need to develop an integrative approach to modeling. The pandemic cannot be seen only from a public health perspective but has to be understood and responded to while taking into account many different aspects of society. This includes the economic aspect (both from the point of view of impact on commercial activity and the differential impact based on the socio-economic status of individuals) and the social aspect (such as mental health, and the desire and the need for people to interact with each other). Traditional models tend to see these aspects separately, but it should be evident that they impact each other and so need to be included in a single model.

And third, we have found that modeling has driven important public health actions such as better defining an effective balance of measures to minimize disease spread while maintaining societal functions, and building a more equitable and effective vaccination plan. Models can further assist in building resilience in preparing for the next contagion, for example in the transportation sector. Given the interconnectedness of society and the world, contagion can spread very rapidly. Air travel especially makes it possible for an epidemic to become a pandemic in matter of days. More thought has to be given to resilience in the face of such hyperconnectivity. We do not want to lose the benefit of connectivity and ease of movement. Can we address the design of transportation and other systems to build in more resilience?

Recommendations

Given the context of the Health Summit providing an opportunity for Canada–India collaboration, we recommend that a small group of modelers and public health experts in both countries establish an ongoing research partnership to continue to investigate the three aspects indicated above, namely the collection of reliable data, integrative modeling, and improving resilience in social organization. We recommend that a follow-up Health Summit be convened on an annual basis to present and discuss findings on these important topics.

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Nil.

Conflicts of interest

There are no conflicts of interest.

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