2021

MULTI-SCALE DYNAMIC HUMAN MOBILITY FLOW PATTERNS FOR SPATIO-TEMPORAL EPIDEMIOLOGY MODELING

Awase Khirni Syed, Zahid A. Butt, Saied Pirasteh, Jonathan Li

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University of Waterloo

NSERC

PERSONAL IDENTIFICATION NO (PIN) FAMILY NAME OF APPLICANT:

Application: Discovery Grants Program	Individual
Identification	
Applicant	
Family Name:	First Name:
Middle Name:	
Current Position:	

Administering Organization

Organization:

Department/Division:

Application

Application Title:	MULTI-SCALE DYNAMIC HUMAN MOBILITY FLOW PATTERNS FOR SPATIO-TEMPORAL EPIDEMIOLOGY MODELING	
Language of the Application:	English	French
Suggested Evaluation Group:		

Hours per month to be devoted to the research/activity or use of equipment or facility:

PERSONAL IDENTIFICATION NO (PIN) FAMILY NAME OF APPLICANT:

Institutional Identifier	FORM 101	Date
	APPLICATION FOR A GRANT	2021/01/15
System-ID (for NSERC use only)	PART I	

Family name of the applicant	Given Name	Initial(s) of all given names	Personal Identification No. (PIN)

Department

Institution that will administer the grant:

Language of the application:

English French

Time (in hours per month) to be devoted to the proposed research/activity

Hours:

Type of grant applied for

Title of proposal:

Provide a maximum of 10 keywords that describe this proposal. Use commas to separate them.

Research subject code(s)		Area of application code(s)	
Primary	Secondary	Primary	Secondary

Certification Requirements

If this proposal involves any of the following, check the box(es) and submit the protocol to the university or college's certification committee

Research involving:	Humans	Humans pluripotent stem cells	Animals	Biohazards

Indicate if the proposed research takes place outdoors and if you answered YES to a), b) or c) – Appendix A (Form 101) must be completed: YES / NO

TOTAL AMOUNT REQUESTED FROM NSERC

YEAR 1	YEAR 2	YEAR 3	YEAR 4	YEAR 5

I certify that this project will involve only industry partners with whom no prior research partnership has taken place:

SIGNATURES(Refer to instructions" What do signatures mean?")

It is agreed that the general conditions governing grants as outlined in the NSERC Program Guide for Professors apply to any grant made pursuant to this application and here by accepted by the applicant's employing institution.

Applicant

PROTECTED WHEN COMPLETED

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Applicant's department, Institution, tel, fax and e-mail

HEAD OF THE DEPARTMENT

DEAN OF FACULTY

PRESIDENT OF INSTITUTION
(OR REPRESENTATIVE)

SUMMARY OF PROPOSAL FOR PUBLIC RELEASE (USE PLAIN LANGUAGE)

BUSINESS TELEPHONE
EMAIL:

Travel has traditionally been a major determinant in the transmission of diseases throughout documented history. Human migration has been the pathway for transmitting infectious diseases, and their mobility will continue to shape the emergence, frequency, and spread of infections in various geographic areas and populations. Spanish flu of 1919 and Covid-19 are the best examples that exhibit transmission of an infectious disease due to human mobility. The increase in the number of travellers and their spatial mobility have eliminated microbial geographic barriers and heightened the potential for the spread of infectious diseases. In an era of a globally interconnected ecosystem, human mobility plays a predominant role in the transmission of diseases. Existing technology infrastructure enables us to monitor the trajectory and evolution of highly infectious diseases in real-time, yet little effort has been made to capture, collate, and predict models of outbreaks in real-time. Many technology firms have collected anonymous "human mobility data" at postcode granularity, which could have served to predict growth clusters ahead of time at various geographic locations and to devise data-driven policy decisions for the governing agencies. By collating, highly accurate mobile datasets, vehicle tracking data, industrial data (chamber of commerce, real-estate), we can define critical aspects of social behavior of individuals between periods of latency and outburst using a time-varying network model. This project aims to develop a multi-scale modeling and simulation platform for human mobility flow patterns for Spatio-temporal epidemiology modeling. These machine learning models/agent-based simulation models would serve to present a deeper understanding of the spatial transmission of the disease across a network of human contacts. Furthermore, with the availability of the data in real-time, it would help us create a disease risk profile for a specific population and serve real-time interventions that might limit an individual's or a population's susceptibility to a given disease. It further evaluates the efficacy of different mathematical models in curbing the spread of the disease in real-time.

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Commented [ZB2]: Are we talking about datasets related to mobility or data from mobile phones using gps to track mobility?

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OTHER LANGUAGE VERSION OF SUMMARY(OPTIONAL)

PROPOSED EXPENDITURES

	CASH	IN-KIND
1. Salaries and benefits		
a. Students		
b. Postdoctoral fellows		
c. Technical/professional assistants		
d.		
e.		
2. Equipment or facility		
a. Purchase or rental		
b. Operation and maintenance costs		
c. User fees		
d.		
e.		
3. Materials and supplies		
a. Hard drive		
b. Office supplies		
c.		
d.		
4. Travel		
a. Conferences		
b. Field work		
c. Project-related travel		
d.		
e.		
5. Dissemination		
a. Publication costs		
b.		
c.		
6. Technology transfer activities		
a. Field trials		
b. Prototypes		
c.		
d.		
Total Proposed Expenditures:		
Total support from industry:		
Total support from university:		
Amount Requested from NSERC		

Supporting organizations are not required to make cash or in-kind contributions for this grant. However, if there are any contributions, please report them in the following table, and describe any in-kind contributions provided in the budget justification.

Name of the Supporting Organization

Cash contributions to direct costs of research (Transfer amounts to page three(3); except those for the Ship Time Program).

In-kind contributions to direct costs of research

1. Salaries for scientific and technical staff
2. Donation of equipment, software
3. Donation of material
4. Field work logistics
5. Provision of services
6.

Total of in-kind contributions to direct costs of research

In-kind contributions to direct costs of research

1. Use of organization's facilities
2. Salaries of managerial and administrative staff
3.

Total of all in-kind contributions

Contribution to post-secondary institution overhead

Remarks:

1. Salaries and Benefits (Sub Total: $)

2. Equipment and Facilities(Sub Total: $)

3. Materials and supplies(Sub Total: $)

MULTI-SCALE DYNAMIC HUMAN MOBILITY FLOW PATTERNS FOR SPATIO-TEMPORAL EPIDEMIOLOGY MODELING

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1. Background and Rationale:

Humans by nature are social and exhibit interactions not only with the environment but also between different species that have evolved alongside them. From foraging for food to travelling across geographies, they have been a primary source of transmission of diseases throughout documented history. Human migration and travel has been the pathway for transmitting infectious diseases, and their mobility will continue to shape the emergence, frequency and spread of infections in various geographic areas and populations. The increase in the number of travellers and their spatial mobility have eliminated microbial geographic barriers and heightened the potential for the spread of infectious diseases. With the recent trends in urbanization and globalization, human mobility across various geographies is extremely dynamic. Geographically, scale refers to large levels of descriptions from closed spaces/building to communities, towns, regions and nations, that describe the different critical aspects of human social behavior. Alessandretti *et al., (*2020) state that day-to-day human mobility does indeed contain significant dimensions, corresponding to spatial 'containers' that limit mobility behaviour. They argue that a person's trajectory infers to their neighbourhood, city and so on, as well as the size of these geographical containers. Manivannan *et al.,* (2020) argues that the data used to study human activity can be grouped into two extreme conditions a.) natural and b.) laboratory. "*while the former concerns data collected during real-life activities of people in a given city or country, and might thus be affected by complex environmental factors and all kinds of unknown conditions",* these natural datasets tend to fit the specific needs to understand, model and predict disease transmissions due to human activity.

Human activity can be understood by studying three key components, which are motion tracking, recognizing the type of activity and analyzing the obtained patterns (Manivannan *et al.,* 2020). They are rooted in interactions between multiple species navigating through different habitats. Understanding the ecology and lifecycle of the vector helps us model infectious diseases. When there is an interaction between pathogen, host and a vector in a favourable environment, the transmission of a vector-borne disease occurs. There is a growing need for data that describes how species are moving and interacting with humans across these ecological habitats that would help epidemiologists understand and model transmissions in real-time. With the availability of drones and hyper-spectral imaging technology, we can now seamlessly acquire Spatio-temporal resolution data for a geographic region on a temporal frame that can serve as an input dataset for modelling interactions in real-time. Many public and private enterprises have collected anonymous "human mobility data" at postcode granularity which could have served to predict growth clusters ahead of time at various geographic locations. By collating these datasets with hyper-spectral imaging technology, new Spatio-temporal perspectives, which are well suited for parameterizing disease spread metapopulation models or measuring temporal changes in interactions between population groups spread in different regions (e.g. postcode).

The fusion of these disparate, diverse and sometimes incomplete data with varying granularity is crucial for urban-planning, socio-psychology, political sciences, and epidemiology (Moreau *et al.,* 2020). Moureau *et al.,* further argues that by mining and analyzing semantic mobility sequences from these data sets would help to identify coherent information and human behaviours. Alharthi *et al.,* (2020) argues that by analyzing social data as a participatory sensing system, it provides a deep understanding of city dynamics, which mimics people's mobility patterns, social patterns and event detection. Their study predicts the potential number of visitors for specific venues based on the analysis of mobility patterns of individuals. This ability to accurately predict the number of visitors to a venue allows authorities to better understand the behavior of people. In the past, Spanish flu of 1919 has presented some insights to devise compartmental epidemiology models, which have been vital in modeling current outbreak of Covid-19 transmission initially. Despite using these mathematical models, scientists and policy makers are unable to curb the wide spread transmission of COVID-19. Unfortunately, our policy decisions are purely

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Commented [ZB5]: You would need to explain what growth clusters are. Are you talking about disease clusters?

Commented [ZB6]: Is this social media data?

Commented [ZB7]: Behaviour related to mobility and travel

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based on transmission rates and reported deaths. We need to create new mathematical models of human interaction with parameters that best describe the phenomenon in real-time. The new mathematical models not only need to address the goals of "*containing the disease"* but also "*sustaining the economy*". Furthermore, the mathematical models do not factor "*human mobility data*" across geographies of space and time and their interactions with other species for instance, interaction of zookeepers with animals, that has spread Covid-19 to Chimpanzees in the zoo. The rapid spread of COVID-19 across the country/countries, can be regarded as an epidemiological network, where the nodes are the cities and the interconnections are the roads. In the recent days, the pandemic has now reached new transmission levels, where, without the help of machine learning tools, it is difficult to make optimal decisions. Machine learning models can serve to address these challenges by sifting through large volumes of data in real-time for optimal data-driven policy decisions.

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2. Research Objectives and Methodology

The objective of this project is to investigate and develop new Spatio-temporal epidemiological models by collating disparate, diverse highly accurate mobile datasets, vehicle tracking data, industrial data (chamber of commerce, real-estate, change of address data from postal records) with hyper-spectrometry image data. Spatial epidemiology is the "*description and analysis of geographic variations in disease with respect to demographic, environmental, behavioural, socioeconomic, genetic and infectious risk factors" (*Elliott *et al.,*2004). They further argue that with the "*recent advances in geographic information systems, statistical methodology and availability of high-resolution, geographically referenced health and environmental quality data have created unprecedented new opportunities to investigate environmental and other factors in explaining local geographic variations in disease".* Linard and Tatem (2012) argue that building Spatio-temporal epidemiology models would assist public health decision making process. These models should reflect interactions between pathogens, vectors, hosts and between these agents and their habitat. The environment determines the spatial variations in disease risk and makes the transmission of vector-borne and other infectious diseases an intrinsically spatial process. Early epidemiology mathematical models were compartmentalized and assumed the total population to be constant for a geographic region. This, however, does not reflect the "*spatial nature of infectious diseases, and particularly spatial heterogeneities in transmission and spread, make risk maps and spatially-explicit models of disease incidence valuable tools for understanding disease dynamics and planning public health interventions (Elliot et al, 2004; Riley 2007; Linard and Tatem, 2012) '.*

GIS has been widely use to merge spatial and aspatial data to classify the various factors of diseases from disparate and diverse sources, to perform spatial analysis by geo-referencing the data. Any real-time Spatio-temporal analysis of diseases needs to take into account the population flows in and out of a specific geographic region (either post-code level or county level) over a granular temporal frame. The veracity of spatial and aspatial demographic data is of utmost importance for deriving insights into populations at risk and infection rate on a Spatio-temporal frame. Many different interpolation methods have been typically used to estimate population density such as Areal weighting and Pycnophylactic interpolation etc, which consider uniform distribution of the population across an administrative district. Our interest lies in using Dasymetric modelling techniques that use hyperspectral imaging land cover data to distribute populations within administrative units, more importantly the dynamic flow of human mobility across administrative units. Balcan *et al.,* (2009) argues that accurate multi-scale human mobility data is difficult to obtain, but with the availability of transport network data from air, train and intercity bus service data would serve as feeder inputs at a coarse level. Lenormand *et al.,*(2020) argues that "*individual human mobility is a complex phenomenon, involving various mechanisms interacting at different spatial and temporal scales. These dynamic are the product of individual behaviours, governed by decisions that may*

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depend on multiple contextual factors such as economic resources, geography, culture, norms, habits, or life experience and quality of life".

Research Objectives:

i. To build a new data-driven framework that combines satellite, meteorological, census, human-mobility and consumption data to predict disease propagation on a Spatio-temporal frame?
ii. To build a realistic model incorporating host, pathogen and inter-species interaction on a Spatio-temporal frame compared to the traditional compartmental epidemiological models?
iii. How do agent-based simulations help us reveal change points in the transmission of a disease across Spatio-temporal time frame across geographies?
iv. What role did population density play in transmission of a disease across Spatio-temporal time frame across geographies?
v. How does urbanization and greater mobility pattern contribute to the spread of disease?
vi. How do interventions impact the spread of transmission of disease?
vii. What impact does data uncertainty have on model selections?
viii. To determine whether citizen's attitudes and behaviours contributed to the rapid transmission of Covid-19 across geographies?
ix. What metrics define the robustness of the scaling relationship observed in human-mobility data and Spatio-temporal interaction behaviours?
x. How human mobility patterns with Social Network data (Facebook/Tinder/Twitter) using Hidden Markov Models help us simulate and predict potential transmission of vector borne diseases?
xi. What techniques reduce uncertainty in epidemiological modeling?
xii. To explore the feasibility of generating an on-demand real-time Spatio-temporal map based visualization for each variable of interest by creating a global socio-demographic repository.
xiii. To investigate spatial origin-destination flow imputation using graph convolution networks for epidemiological modeling
xiv. How is the absence of contemporary, detailed and reliable origin-destination flow data in low income countries has an impact on Spatio-temporal epidemiology modeling? Can transport spatial network data help us build graph structured data to predict flow data from a network learning perspective?
xv. What disparate models of movement best reflects the interaction and mobility patterns of humans?
xvi. What deep learning models for human mobility help us predict accurate transmission rates across a specific geography, irrespective of the scale?
xvii. What spatial activity models help us predict transmission rates across various landscapes?
xviii. How does trip destination, predict the likelihood contraction of covid-19? What simulation techniques can serve to programmatically segregate, sequence human mobility in a highly contagious Spatio-temporal environment?
xix. How does satellite sensing of nighttime light emissions across geographies serve as to provide early detection of disease?
xx. How does satellite sensing of nighttime light emissions in urban areas, help us measure insomnia and long-term changes in our nervous systems?

Commented [ZB12]: These are a lot of objectives. I would suggest arranging them in themes and within the themes, we can have objectives and sub-objectives. For example: Social network analysis, Mobility analysis as themes and within these themes a main objective and several sub-objectives.

Commented [ZB13]: Need to explain what is consumption data?

Commented [ZB14]: More details are required as how we would model this interaction

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Commented [ZB16]: How are we thinking of collecting data about behavior's and attitudes? Are we going to do surveys or social media data?

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xxi. How does satellite sensing of nighttime light emissions help us assess the social economic impacts across a specific geography?

xxii. How does satellite sensing of nighttime light emissions help us measure the effectiveness of containment policy actions such as lockdown protocols, curfews?

xxiii. How does hyperspectral imaging help us measure air pollution across geographies and it's correlation with transmission rate of any disease?

xxiv. How can we measure health inequities (7 determinant of health inequalities such as natural, biological variation, health damaging behaviour, transient health advantage of one group over another, Health damaging behaviour-lifestyles, exposure to unhealthy, stressful living and working conditions, inadequate access to essential health and other basic services) on a Spatio-temporal scale across a geographic area and its role in predicting disease transmission rates?

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xxv. How does social gradient of health help us in predicting geographic areas likely to increase the spread of infectious disease on a Spatio-temporal scale?

xxvi. What social determinants of health factors shape health and well being of population in predicting geographic areas likely to increase the spread of infectious disease on a Spatio-temporal scale?

xxvii. To study the impact of infectious disease on mental health of people across geographies using social network sentiment analysis?

xxviii. What are the spatial and temporal characteristics derived from different geotagged activity patterns of social network data to perform sentiment analysis during the outbreak of a disease?

xxix. Can geotagged tweets be used as a proxy to approximate the human mobility patterns of different behavioural groups during the outbreak of a disease?

Table 1: Project activities and milestones

Milestones	Month1-2				Month3-4				Month5-6				Month7-8				Month9-10				Month11-12			
Project kickoff meeting																								
Literature review																								
Data collection and modeling																								
Spatio-temporal socio-demographic repository Design																								
Machine Learning Mathematical Models																								
Prescriptive Analysis Tools																								
Evaluation																								
Results and Writing																								

i. Short-term objectives

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The short-term objective of this research is to build a real-time Spatio-temporal analytical platform for epidemiological models and robust tools for the Canadian Geography in particular.

a. Understanding the error and uncertainty in collating heterogeneous data set and hyperspectral imaging to predict potential Spatio-temporal area of vector-borne diseases
b. Select optimal parameters to control the transmission of disease and orchestrating a data-driven policy for governing agencies
c. Provide a comparative analysis of policies and scenarios across various Spatio-temporal geographies along socio-demographic parameters.

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Commented [ZB21]: For prevention and control of diseases?

ii. Long-term objectives

The long-term objective of this research is to build a global real-time Spatio-temporal analytical platform for epidemiological models and robust tools for

a. Understanding the error and uncertainty in collating heterogeneous data set and hyperspectral imaging to predict potential Spatio-temporal area of vector-borne diseases
b. Select optimal parameters to control the transmission of disease and orchestrating a data-driven policy for governing agencies
c. Provide a comparative analysis of policies and scenarios across various Spatio-temporal geographies along socio-demographic parameters.

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iii. Innovations and Milestones

The objective of this project is to create a real-time data collation, modeling and simulation platform, that would serve to define data-driven policy for containing the outbreak of diseases.

iv. Research competence

The research team consists of the applicant, 2 Ph.D., 2 graduate research , 2 bachelor students and three senior research scientist at the university of waterloo. The applicant has well-established experience and skills in the areas of Geographic Information Systems, Spatial Analytics, Classification algorithms, deep learning and in working with international government and industry partners. The application is reviewer for Journals. The senior research scientist will actively engage in designing , architecting and building a real-time data analytics platform for capturing, collating, modelling, simulation studies and presenting Spatio-temporal visualizations.

v. Creation of New Collaborative Relationship

vi. Industrial Relevance

This project would serve as real-time analytical platform for devising data-driven policy making and assessing its impact on a national and global scale. In phase one, it's focus is on designing a resilient framework for North America which can further be expanded to the European and Asian continents.

d. Study Areas and Data Set

COVID-19 has evolved as pandemic on a global scale, from a localized vector borne disease to a planetary pandemic. We need a multi-dimensional perspective to tackle it. We need to monitor and measure these rate in real-time:

- Spatio-temporal incidence rates that identity the rate of development of disease over time in the population at risk for disease on a Spatio-temporal frame for a geographic region.

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- The proportion of people infected in a total population at risk, at a point in time and over a period of time.
- The proportion of people who develop the disease after confirmed exposure to the people with disease.

The availability of data on rates of development and deaths, can also indicate where, how and for how long Spatio-temporal interventions are required. By collating Spatio-temporal Socio-demographic datasets across geographies of space and time, a real-time data-driven framework would serve as an effective tool to guide policy makers. The underlying table:2 outlines various categories of demographic data that is available at our disposal at various levels of granularity at various geographies either collected by public or private agencies.

Commented [ZB25]: Are we talking about prevalence here?

Commented [ZB26]: Are we talking about R0?

Table 2: Spatio-Temporal Demographic Datasets.

Category	Description	Level of Granularity	Source
Census Data (pre-covid, post-covid)	-sociodemographic statistical data	County/postcode granularity	National Statistical Agencies
Real-Estate (pre-covid, post-covid)	-Occupancy dataset in house/apartments - new sale registrations -rental listings	County/postcode granularity	National Real Estate Registrar
Post services (pre-covid, post-covid)	Mail redirection data	County/postcode granularity	Postal Agency
Energy consumption data (pre-covid, post-covid)	Night time hyper spectral images vs day time spectral images	County/postcode granularity	Electricity Distribution Board
E-Commerce Data (pre-covid, post-covid)	- Online food ordering data (instacart data, ubereats data, skipmydishes data) - Online grocery ordering data - Postcode delivery data - Fedex, Bluedart, ups data	County/postcode granularity	Amazon, Walmart, Grofers
Travel data (pre-covid, post-covid)	- Urban Rail Transit system data - Intercity/interstate/intercountry transit system data - Air travel data - Immigration data - Interurban and intra-urban trip data -	State/county granularity	
Consumption aata (pre-covid, post-covid)	- Product Consumption data (market basket analysis dataset) - Petrol Consumption	County/postcode granularity	
Healthcare data	- Frequency of consultations - Severity of infection	County/postcode granularity	

(pre-covid, post-covid)	- Mental health consultations		
Chamber of commerce data (pre-covid, post-covid)	- International import category by volume, origin-destination - International export category by volume, origin-destination - Product demand - Bankruptcy filing - Open business hours - Employee data - Credit and Debit Card Transaction Data	State/county /postcode granularity	
Social life (pre-covid, post-covid)	- Divorce rate - Marriage data from registrar of marriages - Night life/pub visitation datasets - Online dating (Tinder/Facebook) - Working hours - Cinema and Theatre occupancy rates - Webinar enrollment (Eventbrite data) - Bi-weekly earnings - Governmental Support (e.g.: CERB payments)	State/county/postcode granularity	
Crime (pre-covid, post-covid)	- Hate crime - Theft - Road accidents - Homicide incidents - Domestic disputes - Tickets /Penalty (Covid-19 breakdown)	State/county/postcode granularity	
Activities Data (pre-covid, post-covid	- Stadium visits - Gym visits - Event sales data - Zoo / Entertainment Parks Visitation rate -		
Insurance (pre-covid, post-covid)	- Accident - Health - Dental - Medical - Car	State/county/postcode granularity	

Education (pre-covid, post-covid)	- Online schooling enrollment - In-person school enrollment	State/county/postcode granularity	
Garbage Data (pre-covid, post-covid)	- Organic waste - Inorganic waste - Plastic	State/county/postcode granularity	
Social Network (pre-covid, post-covid)	- Mobile phone gps trajectory - Geo-tagged image data (instagram, facebook) - Geotagged Tweets - Sentiment Analysis Data	State/county/postcode granularity	
Health Inequity Survey (pre-covid, post-covid)	- Socio-Demographic Surveys to capture Health inequity data	State/county/postcode granularity	

One of the key challenges is to secure highly accurate data for each category, that could serve to provide multi-dimensional perspectives and design new mathematical models that not only take into socio-demography, but also Spatio-temporal aspects in real-time. This project aims to create real-time data collation framework from numerous open data platforms, public, private agencies and online questionnaire to record the exposure assessment of occupational and environmental epidemiological studies.

e. Anticipated Impact and Significance

f. Technology Transfer

The University of Waterloo team will be working closely with national and international partners on developing Spatio-temporal epidemiological models and tools for data-driven policy making. Devising frameworks to assess the efficacy of these data-driven policies in real-time. The tool will be licensed to the governing bodies through a annual subscription platform.

g. Knowledge Dissemination

This work will significantly benefit to Canadian governing agencies and its economy by revolutionizing the way we capture, collate, synthesize and simulate potential scenarios for Spatio-temporal socio-demographic epidemiological modeling.

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h. Training plan

This section outlines the rationale for the training program to equip, doctorate, graduate and bachelor students with skills and tools to successfully build a real-time Spatio-temporal analytical platform. It also identifies various workshops that would serve to build competence in the field of Spatial endemics, Spatio-temporal analytics, Geostatistics and Remote Sensing using hyper spectral imaging.

Commented [ZB28]: Better to specify what kind of things they will be learning-machine learning, deep learning, Bayesian spatio-temporal modeling.

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