GeoAnalytics Project Evaluation

Report on Test of Change Project: Address health inequities and enhance population health management strategies through Geographical Information Systems(GIS) technology (GeoAnalytics)

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This report is an evaluation of the *Test of Change Project: Address health inequities and enhance population health management strategies through Geographical Information Systems (GIS) technology (GeoAnalytics)* undertaken by Southlake Community Ontario Health Team.

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Executive Summary

The link between communities, places, and health is well established in the scientific and public health literature, and differences in the characteristics of places can help explain differences in health inequalities. Place-based analysis, as illustrated in this project, offers a lens to better understand the health needs of local communities, evaluate gaps in health service accessibility, and show where opportunities to intervene exist.

The Ontario health system has become more locally oriented with the introduction of Ontario Health Teams, providing a vital link between health policy makers, health service providers, and local communities. OHTs are sources of expertise in data collection, analysis, and evidence-based approaches to improve population health and health equity. As such, there is tremendous potential for these organizations to conduct analyses that are relevant and impactful for local health services and health outcomes.

This report serves to review the potential role of geoanalytics for Ontario Health Teams via an examination of place-based analytic approaches at the local level, examination of use-case scenarios for emergency department visits and mammography screening, and an evaluation of the potential for geoanalytics within a population health framework.

Importantly, we are concerned here with how the analytic results can be used in health system planning and point-of-care, with the goal of improving the health of local populations. For this project, use-cases have been selected to make use of existing data available to Southlake Community OHT and for those that can lead to impactful interventions and upstream engagement strategies in the short-term.

The final evaluation further discusses the potential for spread and scale of the analytic frameworks, data systems, and tools at the Provincial level. Looking towards future digital infrastructure, a geoanalytics approach has strong potential to integrate with existing health data systems and provide a much-needed link between often-inaccessible health administrative data and locally relevant population statistics.

Summary of Recommendations

Southlake's geo-analytics project shows how place-based analysis and geospatial tools can provide insight into targeted health interventions at a local level. This project provides an example of how a data-centred, place-based approach enhances understanding of Southlake's attributable population.

Evaluation found that this project is aligned with objectives of Ontario OHTs, with strong potential for transformative change. Southlake has shown potential to improve population health outcomes and facilitated collaboration and knowledge exchange across OHTs using innovative, web-based mapping applications.

Evaluation of this project has resulted in the following specific recommendations:

Geocode data consistently to ensure that data from different sources link appropriately.

Follow analytic protocols that were developed *a priori*.

Support internal expertise from within its organization and with aligned partners.

Retain and grow new expertise with the potential for long-term contracts.

In considering how this project can be scaled and spread to other OHTs, there are several evidence-based recommendations:

Do things differently – where changes in local health care systems usually result from pilot studies or limited trials which expose local services to "doing things differently" and building capacity as leaders and participants in innovation and reform.

Strengthen local champions – where imagination and creativity of good ideas are recognized, including recruitment and retention of highly skilled individuals that can not only fit the needs of a specific project, but also adapt to future projects.

Support local innovations – that build knowledge of what is possible and evaluate options in terms of their fit to the needs of the community, recognizing that what might work elsewhere may not work here.

Health geoanalytics can support public health organizations in making informed decisions, optimizing resource allocation, and improve the efficiency of their operations. This leads to cost savings by reducing waste, targeting interventions effectively, and improving overall health outcomes in the population. The most lasting contribution of this project is the potential for a geoanalytics approach to be integrated at the OHT level in Southlake.

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Section 1: Project Background

Our health is highly dependent upon where we live, work, or play.[1] It is well understood that most health and human service problems exist in a geographic context, and any analysis must consider this context.[2,3] Risks of environmental contamination, whether air or water quality, are not uniform across space; access to health services or primary health providers are geographically differentiated; and, availability of disease screening differs between regions.

Never has there been such a focus on equity as it relates to health, especially to ensure that health and human services organizations address the social determinants of health and gaps in social equities.[4] These inequities involve poverty, age, living conditions, and education, and it's important to understand the connection between where things are happening and where service gaps exist.

Place-based analysis, as illustrated in this project, offers a lens to better understand the health needs of local communities, evaluate gaps in health service accessibility, and show where opportunities to intervene exist.[5] Ultimately, this approach is more population-centric, providing for evidence-based monitoring and responding to the distinct health care needs of diverse communities.

To obtain a thorough knowledge of the population, population health management needs reliable data management systems and integration of these systems.[6] Utilization patterns for healthcare are analyzed, visualized, and related to services at the neighbourhood level using GIS technology.[7]

By tackling use-cases like access to care and services, preparedness and response, disease surveillance and control, and population and community health, this project seeks to strengthen analytic capabilities for Southlake Community Ontario Health Team (OHT)[i], with a view to the potential for scaling to other OHTs across Ontario. Indeed, best-practice for place-based initiatives support not only integrating projects across domains *within* a neighbourhood, but also *vertically* with city and provincial policy levers and resources.[8,9]

[i] Referred to as *Southlake* in the remainder of the report.

Place-Based Analysis

Place-based analysis can significantly improve processes for connecting residents with health services, ensuring health care for all who need it. The foundation of this analysis is geographically based data, from which the locations of health-related services are in the paths of people, ultimately improving access. Decades of use have provided examples where geographic analysis has been used to align health and health care to population needs, address disparities in accessibility, provide health organizations with key metrics, and inform and educate patients.

To deliver programs and services that align with community needs, it is critical to understand the local population and how it may change the future. Using demographic, socioeconomic, and lifestyle data, GIS can be used to build a more complete picture of communities, understand health disparities, analyze public health trends, and prepare for future needs.

GIS is more than a technology; it is a way of thinking about the spatial relationships that drive health inequities where people live, work, learn, and play.[10]

Health information is useful in helping people to understand public health, mitigate disease outbreaks, and analyze disease etiology. However, most public health agencies typically collect data as needed and maintain it locally, and this unavoidably limits the access to important public health data for health researchers and the public.[11,12] Indeed, evidence and experience indicates that geographically referenced health information should serve as a basis for decision-making.[2]

Maps are powerful tools to classify, visualize, communicate, and navigate space and/or spatial relations in the data which would be hard to explore otherwise.[13] With maps, it is easy to discover adjacent neighborhood similarities as well as spatial patterns that are hidden in health data.[11] GIS technologies are a key tool to accomplish these tasks, allowing for the connection between health inequities, determinants, services, and the geographic data with which planners can make strategic decisions supporting change.

Increasingly complex problems in the health field require increasingly sophisticated computer software, distributed computing power, and standardized data sharing. To address this need, Web-based mapping is now emerging as an important tool to enable health practitioners, policy makers, and the public to understand spatial health risks, population health trends and vulnerabilities.[11]

Geographic analysis has been used by community health organizations to characterise the local patient mix, understand demographic shifts, and identify outlying populations to detect service gaps. GIS provides the tools to analyze service areas, examine where access is strong, and pinpoint underserved neighborhoods. Further, web-based dashboards can be used to map performance goals and present opportunities to improve service levels.

OHTS AND PLACE-BASED ANALYSIS

OHTs are central organizations in the effort to build a better public health system designed to improve access to care and address the foundational causes of poor health.[14] Crucially, these organizations provide a vital link between health policy makers, health service providers, and local communities. OHTs are sources of expertise in data collection, analysis, and evidence-based approaches to improve population health and health equity.

OHTs are a new model of delivering healthcare in Ontario, Canada. They are designed to bring together healthcare providers and organizations in a specific geographic region to work together as a team to provide coordinated, patient-centered care.

The aim of OHTs is to improve the quality of care, patient outcomes, and the patient and provider experience while also making the healthcare system more efficient and sustainable. The teams are made up of a variety of healthcare providers, such as doctors, nurses, social workers, and other allied health professionals, as well as organizations such as hospitals, community health centers, and mental health and addiction service providers. These organizations are expected to provide a range of services, including primary care, mental health and addiction services, and home care. They are also responsible for coordinating care across different healthcare settings, such as hospitals, long-term care facilities, and community-based care.

Given the renewed role of OHTs in the Ontario health care landscape, they are uniquely poised to enact place-based public health initiatives.

MOVING FROM ANALYSES TO INITIATIVES

Place-based health initiatives are public health interventions that focus on improving the health outcomes of individuals and communities by addressing the social determinants of health in a specific geographic area. These initiatives recognize that where people live, work, and play can have a significant impact on their health and wellbeing and seek to create supportive environments that promote health and prevent disease.[9]

Place-based health initiatives have become increasingly popular in recent years as public health professionals recognize the importance of addressing the social determinants of health to improve health outcomes and reduce health disparities.

> The Healthy Neighborhoods program in Baltimore[48] was launched in 2015 with the goal of improving the health of residents in six low-income neighborhoods. The project focussed on the social determinants of health, such as access to healthy food, safe and affordable housing, and community resources.
>
> This successful program used a multi-sectoral approach that prioritized collaboration between residents, government agencies, and community organizations, to create healthy places where people can thrive. Some of the key strategies used in this program included promoting healthy food options, increasing access to physical activity, and creating safe and walkable neighborhoods.[49]

Place-based health initiatives have advantages over traditional interventions, including:

1. **Focus on upstream determinants:** Place-based health initiatives target upstream determinants of health, such as social and environmental factors, that have a significant impact on health outcomes. By addressing these factors, place-based initiatives can create sustainable changes that improve health outcomes in the long term.
2. **Community engagement:** Place-based health initiatives involve residents and community organizations in the design and implementation of interventions, which helps to ensure that interventions are appropriate and meet community needs.
3. **Multi-sectoral approach:** Place-based health initiatives bring together stakeholders from a variety of sectors, including healthcare, education, housing, and transportation, to address the social determinants of health. This approach can lead to comprehensive and coordinated interventions that have a greater impact on health outcomes.
4. **Scalability:** Place-based health initiatives can be scaled up or down depending on the needs of the community. This flexibility allows initiatives to be tailored to the unique needs of each community and can lead to more effective interventions.

Despite these advantages, place-based health initiatives also face several challenges:

1. **Data collection and Evaluation:** Place-based health initiatives require rigorous data collection and evaluation to measure their impact on health outcomes. This can be challenging, especially in resource-limited settings where data collection and analysis may be difficult.
2. **Funding:** Place-based health initiatives require consistent resources to implement, which can be a barrier for many communities, especially those with limited resources. Higher-level government agencies often fund projects for short time periods of 1-2 years, which is generally insufficient to realize meaningful and measurable change.
3. **Sustainability:** Place-based health initiatives require ongoing organizational support, human resources, and community relationships to maintain their impact over time. Without sustained direction, interventions may not be effective in the long term.

Place-based health initiatives are an important strategy for improving health outcomes and reducing health disparities. These initiatives recognize the impact of social determinants of health on individual and community health and seek to create supportive environments that promote health and prevent disease. While place-based health initiatives face several challenges, they have significant potential to create sustainable changes that improve health outcomes in the long term.

POPULATION HEALTH MANAGEMENT FRAMEWORK

A PHM approach was employed by Southlake in developing their geoanalytics test of change project and related use-case scenarios. The primary aim of PHM is to optimize health outcomes for entire groups of individuals, rather than just individual patients. This approach involves analyzing data on the health of a population, understanding the social determinants of health, and implementing interventions to improve health outcomes.

PHM involves a range of activities, including identifying the health needs of a population, implementing interventions to address those needs, and monitoring and evaluating the outcomes of those interventions. PHM also involves collaboration between healthcare providers, public health professionals, and community organizations to address the social and environmental factors that contribute to poor health outcomes.

One of the key principles of PHM is the use of data and analytics to inform decision-making. By analyzing data on the health of a population, healthcare providers can identify high-risk populations and develop targeted interventions to improve health outcomes. PHM also involves the use of technology, such as electronic health records, to improve care coordination and facilitate communication between healthcare providers.

The primary objective of this project was to leverage advanced geoanalytics to inform decision-making, identify high-risk populations, and design targeted interventions. The use of technology and data analytics was central to this project, and it integrated data from multiple sources, including from OHT partners, provincial data resources, and locally adapted Census-based data.

A PHM framework founded on a geospatial data system can be used to address a range of questions, including:

Identifying high-risk populations for certain health conditions and use this information to target interventions and preventive measures towards those populations.

Monitoring health outcomes such as hospitalization rates, readmission rates, and mortality rates over time to identify trends and patterns that can be used to improve care delivery.

Assessing socio-economic factors to understand the underlying social determinants of health that impact health outcomes and develop targeted interventions to address health disparities.

Analyzing healthcare utilization including emergency department visits, hospitalizations, and outpatient services to identify areas where healthcare resources can be better allocated.

Predictive modeling can be used to identify individuals, or groups of individuals at high risk of developing certain health conditions and develop targeted interventions to prevent or manage health conditions.

Developing local interventions that demonstrate benefit to local populations in collaboration with health and community stakeholders

Data and information were integrated within a geospatial data framework, where health, demographic, socioeconomic, and infrastructure data were combined geographically. This approach allowed for data collected at multiple geographic levels, from multiple providers, and across multiple domains, to be combined into a single database and analytic model.

Data limitations are often the largest challenge for conducting evidence-based analyses at a local level. Local organizations are generally limited in what data can be used to analyse specific issues and are thus forced to “make do” with what data is available. Given this, it’s useful to view how data systems, particularly those linked to geospatial data, can be used within a PHM framework.

DATA SYSTEMS AND POPULATION HEALTH MANAGEMENT

Geospatial data systems are powerful tools that can be used in population health management to analyze health data within a geographic context.[15] Through a geospatial data approach, healthcare providers can identify areas with the greatest health needs and develop targeted interventions to improve health outcomes.

While health data systems have been widely discussed in the context of health system transformation and the introduction of OHTs in Ontario, geospatial data systems have perhaps been overlooked.

The key components of a geospatial *health* data system include:

1. **GIS:** A GIS is more than a single piece of software but is rather a *system* that allows for the creation, visualization, analysis, and sharing of geographic data. The system utilizes a framework of data management that integrates geographically-referenced health data with multiple spatial data resources
2. **Health data:** A geospatial data system for population health management requires health data that is geocoded, meaning that each data point is associated with a specific geographic location.
3. **Spatial analytic tools:** These allow users to easily perform spatial data analysis including clustering or hotspot analysis. Importantly advances in spatial regression analysis allow for prediction and identification of risk measures.
4. **Integration with other data sources:** A key benefit of a geospatial data system is the potential to integrate with other data sources, such as environmental, demographic, and socioeconomic data.
5. **Visualization Tools:** Visualization tools allow users to create maps and visualizations that communicate complex data in a simple and understandable way. These tools can include heat maps, choropleth maps, and scatter plots. By visualizing health data, users can identify patterns and relationships that may not be apparent through tabular data.

This geo-analytic project demonstrates how a single OHT can integrate data from multiple sources into a geospatial data system and use these data to provide evidence for targeted health interventions. Indeed, the flexibility by which data can be incorporated is one of the key features that can allow scaling outside the OHT and into other contexts.

REALIZATION OF ECONOMIC AND HEALTH BENEFITS

Prior research and knowledge illustrate how a geospatial data management approach using a population health management framework can yield several economic benefits. The benefits of a geospatial approach to PHM include:

1. **Targeted Resource Allocation:** Geospatial data linked to health data can provide valuable insights into inequalities of health resource usage. This can include questions such as the factors affecting specialist referrals by primary care physicians.[16] Using this information, organizations can identify specific geographic areas that require targeted interventions, resulting in a cost savings to the public.[17]
2. **Improved Health Outcomes:** Increased understanding of the social determinants of health and their spatial patterns enables organizations to develop targeted interventions to address upstream determinants of health such as access to healthcare, environmental factors, socioeconomic conditions, and more.[18]
3. **Enhanced Preventive Care:** Geospatial data can help identify areas with higher risks of chronic diseases or health conditions and leverage to implement proactive preventive care strategies. For example, this has been used to identify community clusters of bladder and kidney cancer in Nova Scotia.[19] These measures can reduce the incidence of preventable diseases, lowering costs associated with acute care, hospitalizations, and long-term management.
4. **Optimal Resource Planning:** Analyzing patterns of access and usage of health resources, organizations can ensure better accessibility for those in need. This approach can minimize healthcare inefficiencies,[20] and potentially decreases emergency department visits and hospital admissions, resulting in cost savings. For instance, detailed analyses have been conducted on the spatial accessibility of primary health care services. [21]
5. **Evidence-Based Decision Making:** Organizations can use linked geospatial data to prioritize interventions and policies based on the specific needs and characteristics of different geographic areas. Evidence-based decision making helps allocate resources more effectively, avoid wasteful spending, and achieve better health outcomes while maximizing economic benefits.[22]

These examples illustrate how organizations have leveraged geospatial approaches to understand the impact of social determinants of health and develop targeted interventions. By analyzing geospatial data, organizations can identify areas with higher health inequities, allocate resources effectively, and implement strategies to address the underlying social factors influencing health outcomes.

Context of Southlake

The attributable region for Southlake covers a wide area including northern York Region and southern Simcoe County in central Ontario (Figure 1). Centrally located in Southlake's attributable region is the Town of Newmarket (population 88,000), served by Southlake Regional Health Centre, which is the major hospital in the region. The Southlake region also includes several other towns, villages, and rural areas.

As shown in Table 1, Southlake's attributable population is estimated at just over 340,000 (50.7% female), with a median age of 41 years. About half (50.6%) of the population resides in urban areas, 46.2% reside in small towns, and 2.9% reside in rural areas, while province-wide 19% of the population resides in small towns and 7% in rural areas, calculated by the Rural Index of Ontario (RIO).

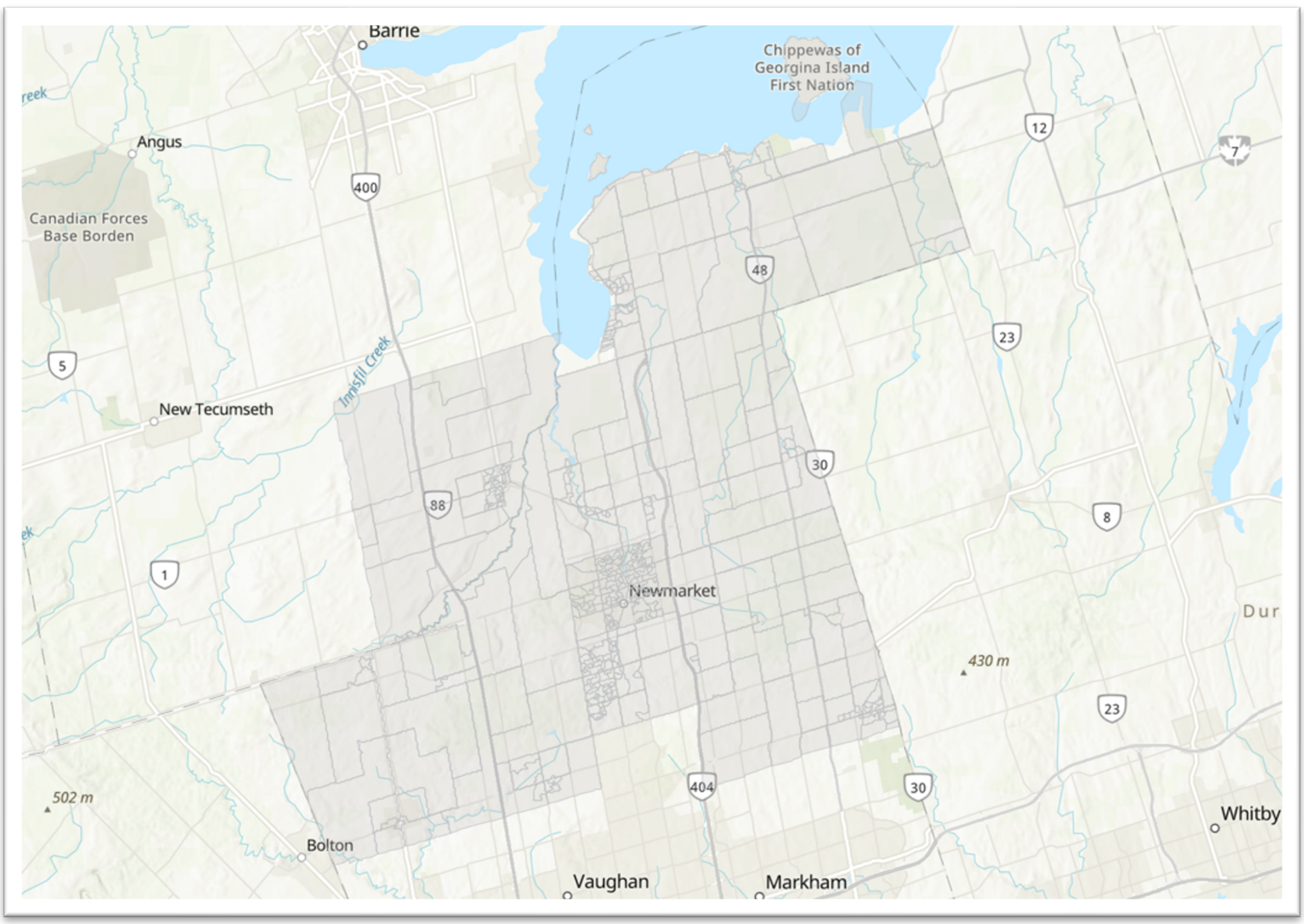


Figure 1:Map of OHT Region, Dissemination Area Boundaries, 2021.

Table 1: Socio-Demographic Characteristics, Southlake Attributed Population (2020) and Ontario, 2022

		Southlake OHT		Ontario		
Variable	**Value Label**	**Number**	**Percent (%)**	**Number**	**Percent (%)**	**Difference (%)**
	Total Population	341,382	2.2%	14,957,511		
RIO index	a. Urban (0-9)	172,760	50.6%	10,887,221	72.8%	**22.18**
	b. Small town (10-39)	157,828	46.2%	2,848,012	19.0%	**(27.19)**
	c. Rural (40+)	9,805	2.9%	1,051,315	7.0%	4.16
	d. Missing	989	0.3%	170,963	1.1%	0.85
Income quintile	a. Low (1)	28,049	8.2%	2,888,437	19.3%	**11.09**
	b. 2	41,274	12.1%	2,921,219	19.5%	7.44
	c. 3	66,684	19.5%	3,027,019	20.2%	0.70
	d. 4	120,803	35.4%	3,054,409	20.4%	**(14.97)**
	e. High (5)	84,128	24.6%	3,024,814	20.2%	(4.42)
Marginalization: Instability	a. Lowest instability (1)	90,680	26.6%	3,313,674	22.2%	(4.41)
	b. 2	95,668	28.0%	2,832,825	18.9%	**(9.08)**
	c. 3	70,379	20.6%	2,723,133	18.2%	(2.41)
	d. 4	47,357	13.9%	2,622,356	17.5%	3.66
	e. Highest instability (5)	35,756	10.5%	3,316,424	22.2%	**11.70**
Marginalization: Deprivation	a. Lowest deprivation (1)	80,635	23.6%	3,476,020	23.2%	(0.38)
	b. 2	118,576	34.7%	3,136,360	21.0%	**(13.77)**
	c. 3	69,019	20.2%	2,815,709	18.8%	(1.39)
	d. 4	45,233	13.2%	2,667,841	17.8%	4.59
	e. Highest deprivation (5)	26,377	7.7%	2,712,482	18.1%	**10.41**
Marginalization: Dependence	a. Lowest dependence (1)	139,247	40.8%	4,218,866	28.2%	**(12.58)**
	b. 2	71,483	20.9%	3,012,372	20.1%	(0.80)
	c. 3	59,967	17.6%	2,566,308	17.2%	(0.41)
	d. 4	34,793	10.2%	2,448,410	16.4%	6.18
	e. Highest dependence (5)	34,350	10.1%	2,562,456	17.1%	7.07
Marginalization: Ethnic concentration	a. Lowest concentration (1)	37,340	10.9%	2,270,948	15.2%	4.24
	b. 2	60,914	17.8%	2,404,194	16.1%	(1.77)
	c. 3	79,855	23.4%	2,625,922	17.6%	(5.84)
	d. 4	98,939	29.0%	3,151,657	21.1%	**(7.91)**
	e. Highest concentration (5)	62,792	18.4%	4,355,691	29.1%	**10.73**

Data Source: Ontario Community Health Profiles Partnership, Primary Care Data Reports

The attributed population of Southlake is comparatively well-off economically, with 60.1% of the attributed population in the top-two income quintiles. As these quintiles are calculated at the provincial level, this compares to 40.6% of the Ontario population in the top-two income quintiles. This is supported by the Ontario Index of Marginalization deprivation component, where only 20.1% of the attributed population are in the two most-deprived quintiles compared to 35.9% in Ontario, while 58.6% are in the two least-deprived quintiles compared to 44.2% provincially.

Considering instability, which is a measure of population mobility and dependence, 24.4% of Southlake's attributed population resides in areas for the two highest instability quintiles, compared to 39.7% provincewide.

The dependency component of the marginalization index considers the demographic dependency ratio, percentage of seniors, and labour force participation. Southlake's population has much lower dependence with 61.7% residing in areas from the lowest two dependency quintiles compared to 48.3% of the Ontario population.

The ethnic concentration component illustrates a more nuanced view of the Southlake attributable population. While the population residing in areas from the top-two quintiles is lower at 47.7% compared to 50.2% provincially, there are fewer people in areas with a low ethnic concentration (28.7% compared to 31.3%). This suggests that while there are fewer areas with high ethnic concentration, there are also fewer areas with low concentrations.

In comparing the overall profiles of Southlake's attributable population, to those who had at least one visit to the emergency department in Table 2, there are some clear significant differences. The deprivation component of the Ontario Marginalization Index shows that while residents from neighbourhoods with the lowest deprivation quintiles had higher percentages of ED visits, those in the 2nd and 3rd quintile had lower ED visit percentages. A pattern emerges with the ethnic concentration component, where areas with the lowest concentration had higher percentages of ED visits, while those with the highest ethnic concentration had lower percentages of ED visits. This pattern suggests that residents from ethnically concentrated areas are using the ED to a lesser extent than residents from less ethnically concentrated neighbourhoods.

The clearest pattern of difference between residents with an ED visit and the broader attributed population is with the dependency component. This component includes the proportion of the population 65 years and older, the dependency ratio, and the proportion of the population not in the labour force. Neighbourhoods with lower dependence scores had significantly lower percentages of ED visits, while those with higher dependence scores had significantly higher percentages of ED visits. This pattern is likely due to the proportion of the population in these areas over the age of 65 and under the age of 15, two populations with high ED visit rates.

Table 2: Characteristics of Total Attributed Population versus Population with an ED Visit, 2020

		Southlake OHT		ED Visit		
Variable	**Value Label**	**Number**	**Percent (%)**	**Number**	**Percent (%)**	**Difference (%)**
	Population	341,382		124,720		
RIO index	a. Urban (0-9)	172,760	50.6%	58,403	46.8%	(3.78)
	b. Small town (10-39)	157,828	46.2%	61,246	49.1%	2.87
	c. Rural (40+)	9,805	2.9%	4,657	3.7%	0.86
	d. Missing	989	0.3%	414	0.3%	0.04
Income quintile	a. Low (1)	28,049	8.2%	11,875	9.5%	1.31
	b. 2	41,274	12.1%	15,947	12.8%	0.70
	c. 3	66,684	19.5%	25,531	20.5%	0.94
	d. 4	120,803	35.4%	42,466	34.0%	(1.34)
	e. High (5)	84,128	24.6%	28,743	23.0%	(1.60)
Marginalization: Instability	a. Lowest instability (1)	90,680	26.6%	34,494	27.7%	1.09
	b. 2	95,668	28.0%	26,832	21.5%	(6.51)
	c. 3	70,379	20.6%	18,414	14.8%	(5.85)
	d. 4	47,357	13.9%	30,310	24.3%	**10.43**
	e. Highest instability (5)	35,756	10.5%	14,081	11.3%	0.82
Marginalization: Deprivation	a. Lowest deprivation (1)	80,635	23.6%	42,098	33.8%	**10.13**
	b. 2	118,576	34.7%	26,289	21.1%	**(13.66)**
	c. 3	69,019	20.2%	17,671	14.2%	(6.05)
	d. 4	45,233	13.2%	26,818	21.5%	8.25
	e. Highest deprivation (5)	26,377	7.7%	11,255	9.0%	1.30
Marginalization: Dependence	a. Lowest dependence (1)	139,247	40.8%	25,943	20.8%	**(19.99)**
	b. 2	71,483	20.9%	22,222	17.8%	(3.12)
	c. 3	59,967	17.6%	13,195	10.6%	(6.99)
	d. 4	34,793	10.2%	48,695	39.0%	**28.85**
	e. Highest dependence (5)	34,350	10.1%	14,076	11.3%	1.22
Marginalization: Ethnic concentration	a. Lowest concentration (1)	37,340	10.9%	23,799	19.1%	**8.14**
	b. 2	60,914	17.8%	29,665	23.8%	5.94
	c. 3	79,855	23.4%	34,262	27.5%	4.08
	d. 4	98,939	29.0%	15,515	12.4%	**(16.54)**
	e. Highest concentration (5)	62,792	18.4%	20,890	16.7%	(1.64)

Data Source: Ontario Community Health Profiles Partnership, Primary Care Data Reports

Section 2: Use Case Scenarios

Through stakeholder and community engagement, Southlake developed two use-case scenarios under the test of change project: mammography screening, and ED admissions. These use-cases are aligned with the Southlake OHT collaborative quality improvement plan to improve access to primary care and cancer screening. At the foundation of this process is a commitment to community-inclusion and a place-based approach, where issues relevant to the local population are addressed.

To develop these specific use cases, the Southlake project team applied a logic model to refine an analytic and intervention plan. The steering committee and stakeholders assisted in developing the hypotheses, indicators, test of change, feasible interventions with partners and the health outcome benefit realizations (Figure 2).

Hypothesis	• Development of testable hypotheses for use-case scenarios
Inputs	• Determination of data sources and indicators for use-case analysis
Test of Change	• Activities required for analysis, interpretation, engagement, intervention, and evaluation
Examples	• Details of steps identified in Test of Change
Local Interventions	• Potential local interventions informed by use-case analyses for program delivery, servicing, or planning
Health Outcome Benefits	• Linkage between interventions and potential local health outcome benefits

Figure 2: Project logic model for health outcome benefit realization.

Two separate hypotheses were developed through stakeholder engagement and relate to the goals and collaborative quality improvement plan of Southlake. Inputs include socio-demographic variables, key infrastructure locations, and health outcome data requirements. The test of change is sub-divided into four phases: 1) data preparation, analysis, and visualization; 2) determination of causation through stakeholder engagement; 3) intervention; and 4) evaluation of interventions and measurement. Building from the two scenarios, local interventions were developed for each, and potential health outcome benefits were identified.

As can be seen from the business case requirements for the geo-analytics project, the requirements for success are all possible to be achieved locally within Southlake's region. Indeed, a primary objective of this project was that it leverages existing data and expertise to address questions relevant to local stakeholders.

Data Sources and Methods

This section provides a description of the data sources included in this project, the specific variables calculated, and the general methods employed for use-case analysis.

DATA SOURCES

This project integrated data from a range of sources and data types, using a GIS framework to facilitate data linkage and combined analysis.

DEPENDENT VARIABLES

Mammography Screening Rates

Breast cancer screening rates were provided to Southlake by Cancer Care Ontario via a health system planning data request. De-identified record-level data of individuals who received a mammogram in the 2020-21 and 2021-22 fiscal years were provided at the Forward Sortation Area (FSA) and Dissemination Area (DA) geographic levels. These data were transferred as a data worksheet in a Microsoft Excel Workbook.

Screening rates were calculated as the percentage of the eligible population (females over the age of 65) who were screened for breast cancer in 2020-21 and 2021-22.

Emergency Department Visits

Individual-level patient records for emergency department visits for 2020 – 2021 were obtained from Southlake Regional Hospital and stored in an Excel workbook. Each patient record contained the postal code of residence provided on admission, the CTAS score, and other relevant information. Data were extracted from hospital records and contained *all* individuals who visited the emergency department, regardless of where their place of residence was located.

To link ED visits to geographic data, patient records were first geocoded using the ePCCF (described below). Those records that were within the Southlake geographic region and were indicated as CTAS 4 or 5 were selected, and summarized by DA. To calculate a standardized rate, the number of visits by DA was divided by the total DA population, and then multiplied by 1,000 persons. This resulted in a standardized rate of ED visits per 1,000 persons.

INDEPENDENT VARIABLES

Sociodemographic Variables

Sociodemographic variables were obtained from two sources: the Ontario Marginalization Index and the DemoStat product from Environics Analytics (Table 3). The Ontario Marginalization Index was developed using 2016 census data and is provided as a set of component scores and quintiles for the dimensions of deprivation, dependency, ethnic concentration, and instability.[23] These scores can be used individually or combined into a single index. Scores are calculated at the Dissemination Area (DA) level. While both a quintile and a component score are provided for each DA, it is not recommended that the quintile be used in a regression with continuous variables, but rather be used for mapping or data summary purposes.

Table 3: Area-based analytic variables considered for use-case scenario analyses.

Variable	Source	Description
Mammography	CCO	Percent of eligible females screened
CTAS_4_5	Southlake	Rate of ED usage for CTAS 4&5 per 100 people
MedianIncome	Environics	Median income
Education	Environics	Percent of population with bachelor's degree or higher
LFPart	Environics	Labour force participation
Immigration	Environics	Percent of population who are immigrants
NoEnglish	Environics	Percent of adults who speak non-official language at home
Female65	Environics	Percentage of population over 65 years who are female
FamKids	Environics	Percentage of families with kids at home
LiveAlone	Environics	Percentage of adults living alone
TransitDistance	Calculated	Distance to transit stop
ProvidorDist	Calculated	Distance to 3 nearest primary care providers
OBSP_Dist	Calculated	Distance to screening centre
Instability	ONmarg	Index of Marginalization – Instability
Deprivation	ONmarg	Index of Marginalization – Deprivation
Dependency	ONmarg	Index of Marginalization – Dependency
EthnicConcen	ONmarg	Index of Marginalization – Ethnic concentration

The DemoStat product from Environics was also used as it contains a wide range of census-based indicators that have been calculated at the DA level and scaled for inter-censal periods. From this file, it is possible to calculate additional detailed socio-demographic indicators such as the percentage of females over the age of 65 or the percentage of families with kids living in the home. A list of variables calculated from the DemoStat table is included in Table 3.

Spatial Data Files

Dissemination area boundary files were obtained from Statistics Canada. Transit stop locations were obtained from the Town of Newmarket. Ontario Breast Cancer Screening Program locations were created by Southlake using the known address locations of OBSP facilities.

Postal Code Geocoding

To facilitate geocoding of patient records, the Enhanced PCCF (ePCCF) was obtained from Environics Analytics. This set of files allows for a link between 6-character postal codes from Canada Post and standard census geographic identifiers from Statistics Canada. The ePCCF includes a unique PCCF link file and an enhanced rural PCCF file that includes postal code and place name.

ANALYTIC METHODOLOGY

DATA EXPLORATION AND EXPLORATORY DATA ANALYSIS

A best practice in geoanalytics is to begin projects by undertaking an Exploratory Spatial Data Analysis (ESDA). ESDA is a set of analytical techniques used to study and describe spatial patterns and relationships in data. This set of methods can help researchers better understand the distribution of phenomena across geographical areas, identify areas of high or low values of a variable of interest, and identify spatial clusters or patterns that may not be evident through traditional statistical methods.

The primary steps in conducting ESDA are as follows:

1. **Data preparation:** ESDA begins with the collection and preparation of spatial data. This may involve geocoding, cleaning, and transforming the data to ensure it is in a format suitable for analysis.
2. **Data visualization:** The next step involves creating visual representations of the data to identify patterns, clusters, and outliers. This may include maps, scatterplots, histograms, and other graphical displays.
3. **Spatial autocorrelation analysis:** Spatial autocorrelation analysis helps identify the presence of spatial dependence in the data, which can help identify areas with similar or dissimilar values of a variable of interest.
4. **Spatial clustering analysis:** Spatial clustering analysis is used to identify spatial patterns or clusters in the data. This can help identify areas of high or low values of a variable and can be useful for identifying areas of concern in health research.

ESDA is widely used in health research to study the spatial patterns of health outcomes or health resources, such as hospitals or clinics, and identify areas where access to healthcare may be limited. This information can be used to inform policy decisions and improve healthcare delivery in underserved areas.

GENERALIZED LINEAR REGRESSION

A global predictive model was developed using generalized linear regression methods, using in the ArcGIS software. While this is not an inherently spatial method, for these scenarios we have included distance features within this model with distance to transit stops. The results of this approach are then used to inform a spatial regression model.

GEOGRAPHICALLY WEIGHTED REGRESSION

Geographically Weighted Regression (GWR) is a spatial regression technique that extends traditional regression analysis by accounting for spatial variations in the relationship between variables. It is particularly useful in situations where the relationship between variables varies across space and cannot be adequately captured by a single global regression model.

In traditional regression analysis, a single regression model is fitted to the entire dataset, assuming a constant relationship between the variables throughout the study area. However, this assumption may not hold true in many real-world scenarios, especially in spatial contexts where relationships can vary due to spatial heterogeneity or local interactions.

GWR overcomes this limitation by estimating local regression models for each location in the study area. It assigns different weights to neighboring observations based on their spatial proximity and performs regression analysis for each location using these weighted observations. As a result, GWR produces a set of local parameter estimates that reflect the spatially varying relationship between the variables.

GWR is widely used in health research to explore spatial patterns and relationships between health outcomes and various determinants or risk factors. It allows researchers to examine how the relationships between health outcomes and predictors vary across different regions within a study area. This can be particularly valuable in understanding the spatially specific factors that influence health outcomes, identifying areas with high or low risk, and designing targeted interventions or policies.

By incorporating spatial information and capturing local variations, GWR provides insights that may be missed by traditional regression analysis. It enables researchers to detect spatial non-stationarity, identify areas with different relationships between variables, and generate localized predictions or maps of health outcomes. GWR is commonly used in epidemiology, public health, and spatial health research to investigate factors influencing disease patterns, access to healthcare, environmental health, and health inequalities, among other areas of interest.

DATA EXPLORATION

CORRELATION ANALYSIS

One of the first steps in developing the use-case analyses was to calculate linear correlation coefficients between each of the potential independent variables. This simple procedure allows for an understanding of which variables could be included concurrently in a statistical model. As can be seen from Table 4, there is strong bivariate correlation between many of the variables, as indicated by values less than -0.7 or greater than 0.7. In general, variables with either a moderate or strong linear correlation should not be included simultaneously.

Table 4: Correlation coefficients for potential independent variables.

	INS	*DEP*	*DPY*	*ETH*	*KID*	*LF*	*INC*	*LONE*	*PUNI*	*PIMM*	*ENG*	*FEM*
INS	1.00											
DEP	0.54	1.00										
DPY	0.39	-0.02	1.00									
ETH	-0.10	0.05	-0.44	1.00								
PKIDS	-0.69	-0.25	-0.70	0.50	1.00							
LF	-0.32	-0.22	-0.64	0.15	0.57	1.00						
INC	-0.65	-0.63	-0.25	0.14	0.60	0.29	1.00					
ALONE	0.66	0.21	0.64	-0.36	-0.66	-0.35	-0.42	1.00				
PUNI	-0.27	-0.57	-0.13	0.32	0.40	0.19	0.62	-0.18	1.00			
PIMM	-0.06	-0.14	-0.03	0.55	0.21	0.02	0.11	-0.09	0.38	1.00		
ENG	-0.19	-0.19	-0.21	0.64	0.39	0.17	0.29	-0.23	0.44	0.77	1.00	
FEM65	0.38	-0.09	0.81	-0.50	-0.52	-0.33	-0.06	0.62	0.05	-0.09	-0.26	1.00

Based on the correlation table, there are a limited number of variables that could potentially be included simultaneously. These were limited by selecting variables with a coefficient value greater than -0.5 and less than 0.5.

For mammography screening, the following could be included:

- Deprivation score
- Ethnic concentration score
- Percent of females over 65 years of age

For emergency department rates, only the following could be included:

- Deprivation score
- Ethnic concentration score

EXPLORATORY SPATIAL DATA ANALYSIS

OUTLIER ANALYSIS

The first step that was conducted was to determine if there were any potential outliers for our analytic variables and if there are any features that have values that are significantly different from their neighbours. The results of this analysis are shown in Figure 3 and Figure 4, where a *High-High Cluster* indicates that there is a statistically significant cluster of high values, a *High-Low Cluster* is a high value outlier surrounded by low values, a *Low-High Cluster* is a low-value outlier surrounded by high values, and a *Low-Low Cluster* is a cluster of low values.

The results of the outlier analysis the Emergency Department visits show that indeed, there is significant local spatial variation for both high and low values. Unsurprisingly, there is a large region of high-high clusters in the town of Newmarket, but there are some clear high value outliers along the periphery of the SLOHT region. The low-low values are also potentially due to proximity of other hospitals where people seek care. In the absence of combining ED utilization from neighboring hospitals, cold spots may appear, though the rate of ED utilization may still be within the expected norm or high if the full picture was available.

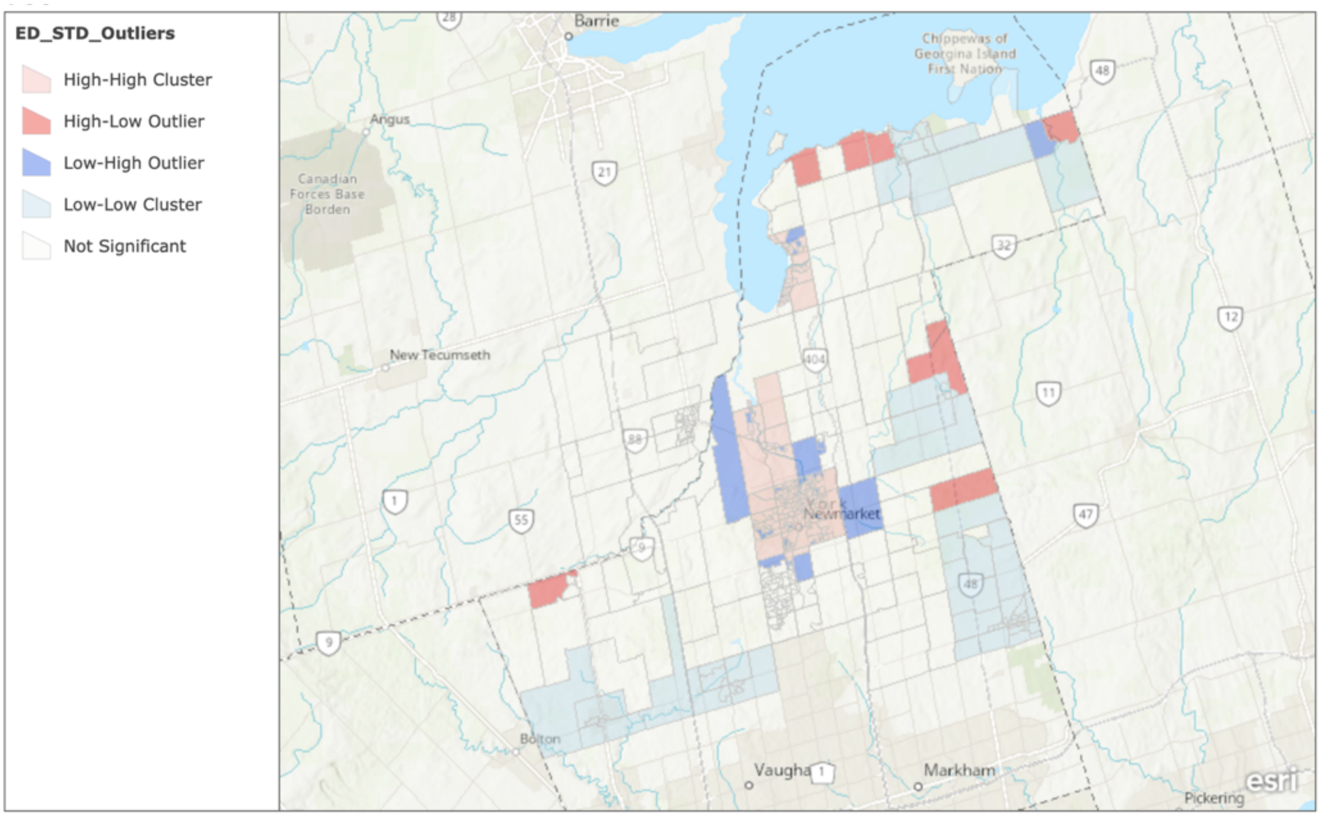


Figure 3: Outlier Analysis for Emergency Department Visits, CTAS 4 & 5, 2021-2022, per 1000 Persons.

The results of the outlier analysis for mammography screening rates show that indeed, there is significant local spatial variation for both high and low values. As with emergency department visits, there is a large high-high cluster in the town of Newmarket. However, there are also clearly some lower than expected values within the urban area. This suggests that some local areas in Newmarket have lower mammography screening rates than would be expected given the rates in neighbouring areas.

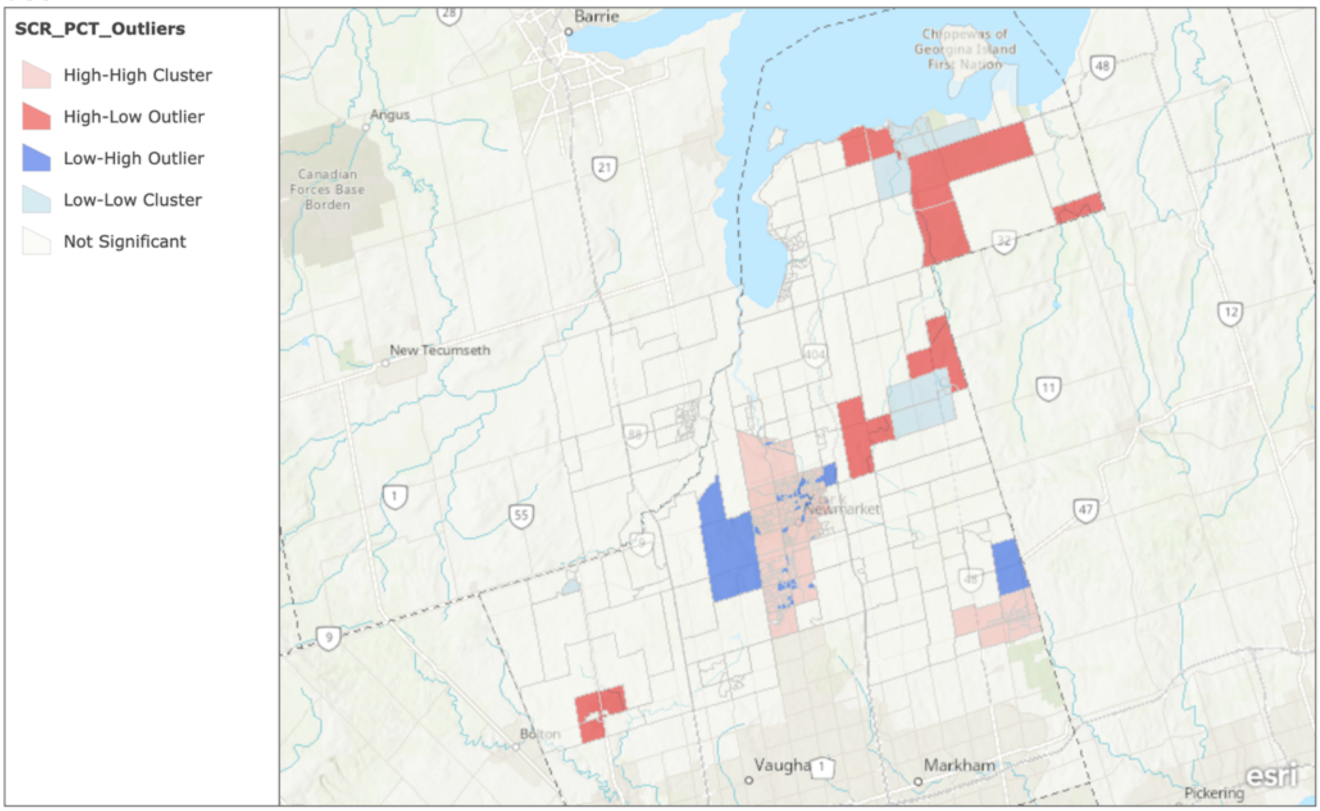


Figure 4: Outlier Analysis for Mammography Screening, Percent of Eligible Population, 2021-2022.

HOT-SPOT ANALYSIS

Furthering our analysis of outliers, spatial analysis allows for the calculation and visualization of *hot spots* for each dependent variable (*Getis-Ord Gi* indicator*). In this analysis, each DA is analyzed in the context of neighboring DAs. Improving on the above outlier analysis, a DA with a high outlier value is interesting but may not be a statistically significant hot spot. To be a statistically significant hot spot, a feature will have a high value and be surrounded by other features with high values. When the local sum of values is different from the expected local sum, and when that difference is too large to be the result of random chance, a statistically significant value is obtained.

As can be seen in Figure 5, there are several areas with statistically significant hot spots or cold spots. The central urban area of Newmarket shows a large hot spot area for ED visits, as well as a hot spot in the Village of Keswick to the north.

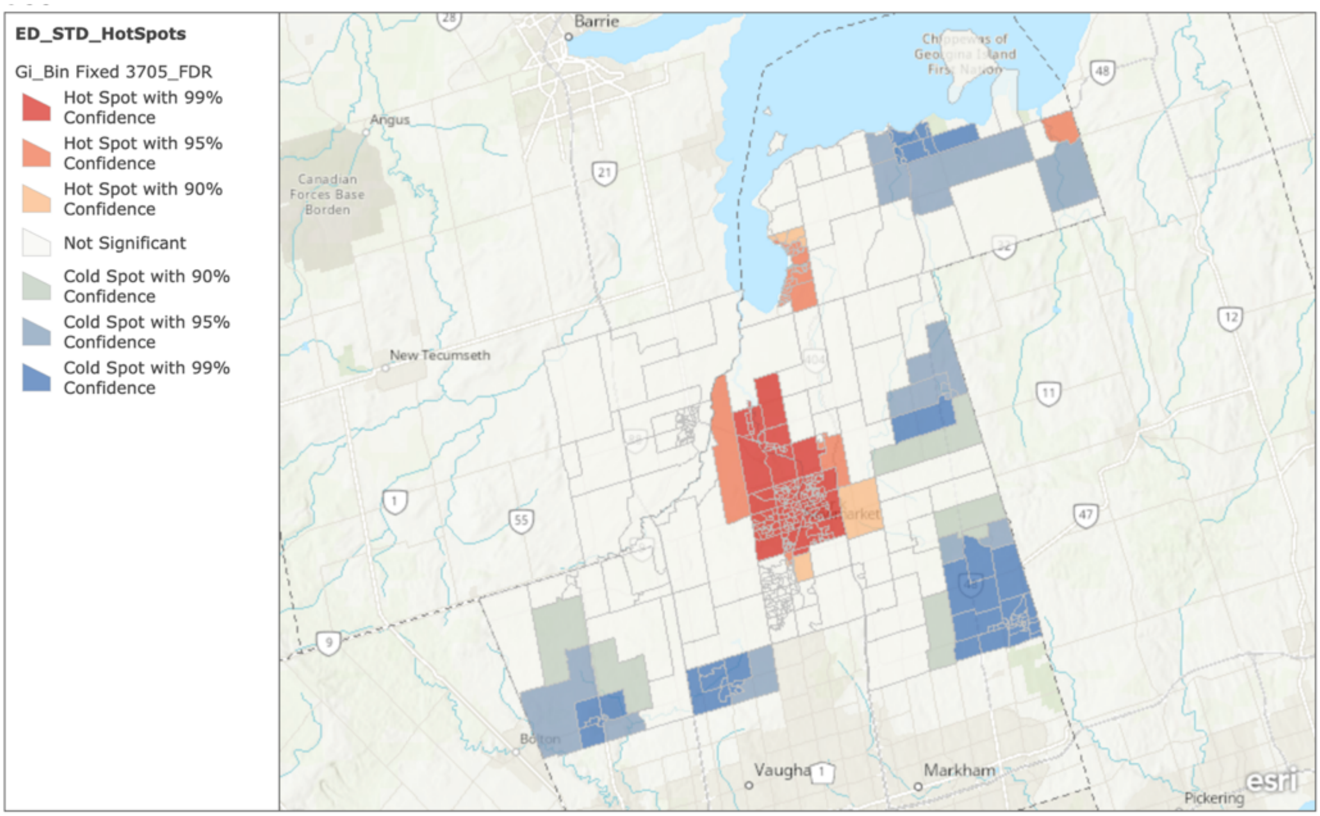


Figure 5: Hot-Spots of Emergency Department Visits, CTAS 4 & 5, 2021-2022, Standardised per 1000 Persons.

There are several cold-spots (areas with lower than expected rates) near Mossington Park in the northeast, Whitchurch-Stouffville in the southeast, and Nobleton / King City in the southwest. This is useful for understanding ED usage, as it suggests that rural residents are using the ED at Southlake Hospital to a lower degree than those in central Newmarket. Again, without information from surrounding hospitals, the full degree of hospital utilization cannot be ascertained.

A similar pattern can be seen in the hot spot analysis for mammography screen rates (Figure 6), where the largest hot spot is located in central Newmarket. However, unlike with ED usage, there is also a hot spot of higher than expected screening rates in Whitchurch-Souffville. Cold spots with lower than expected rates cover a wide part of the northeast along Lake Simcoe, centrally in the east of the region, and in the southwest around Nobleton.

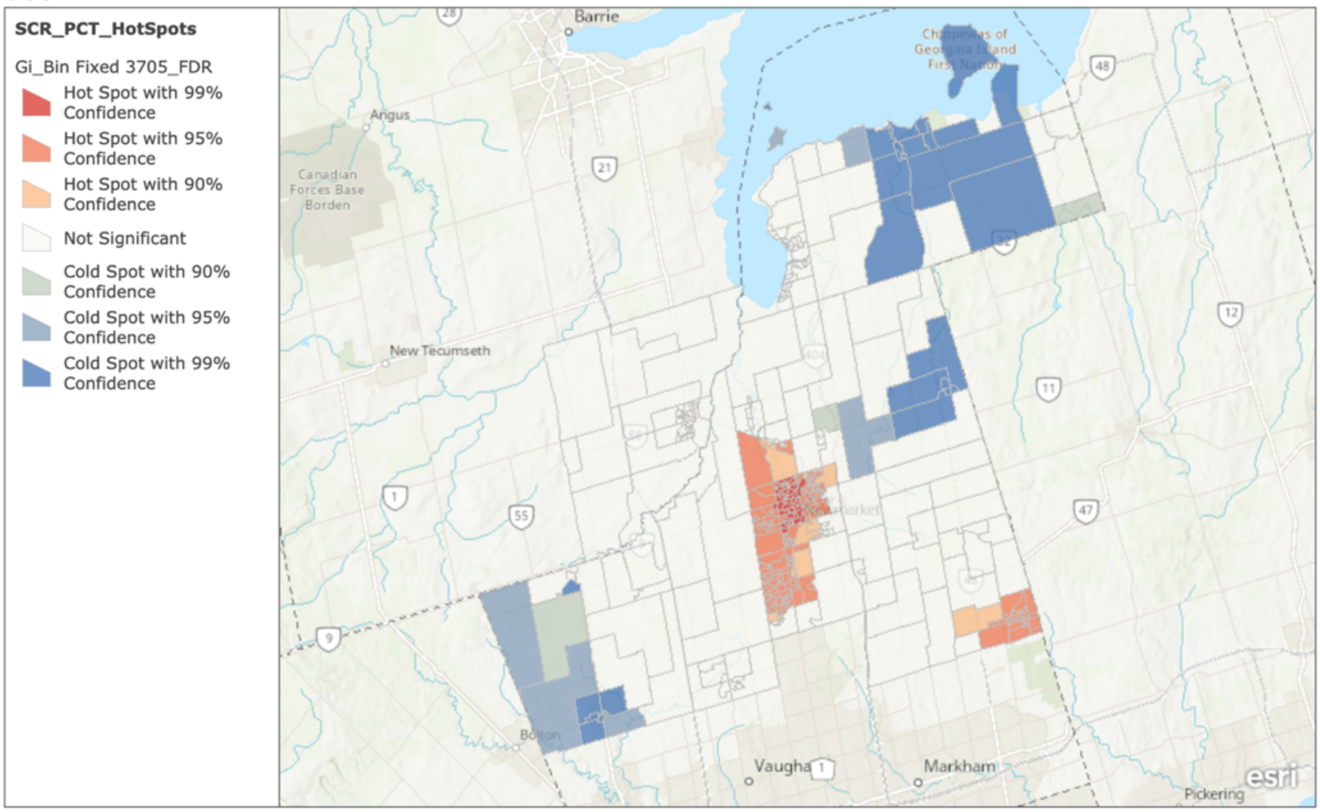


Figure 6: Hot-Spots of Mammography Screening Rates, Percent of Eligible Population, 2021-2022.

The above analysis provides additional strong evidence that the dependent variables for both selected use case scenarios exhibit statistically significant local variation. As such, interventions should be geographically targeted to specific regions within the Southlake attributed region.

While the results of the above analyses alone could be used to geographically target interventions, further analysis can enhance understanding of what factors contribute to higher or lower than expected rates. The following section presents an exploration of the independent variables through local bivariate analyses.

LOCAL BIVARIATE RELATIONSHIPS

Local Bivariate Relationships allow the relationship between two variables to be quantified by determining if the values of one variable are dependent on or are influenced by the values of another variable and if those relationships vary over geographic space. This measure calculates an *entropy* statistic for this relationship that quantifies the amount of shared information between the two variables.

The results of a local bivariate analysis can be:

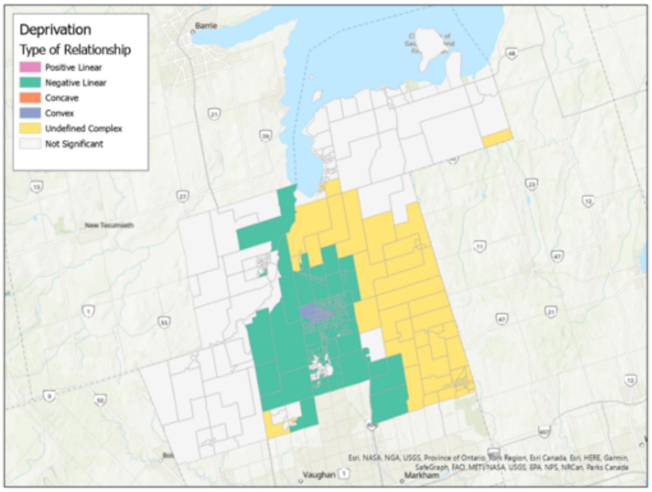
- **Not Significant:** The relationship between the variables is not statistically significant.
- **Positive Linear:** Dependent increases as the explanatory variable increases.
- **Negative Linear:** Dependent decreases as the explanatory variable increases.
- **Concave:** Dependent changes by a concave curve as the explanatory variable increases.
- **Convex:** Dependent changes by a convex curve as the explanatory variable increases.
- **Undefined complex:** Variables are significantly related, but the type of relationship cannot be reliably described by any of the other categories.

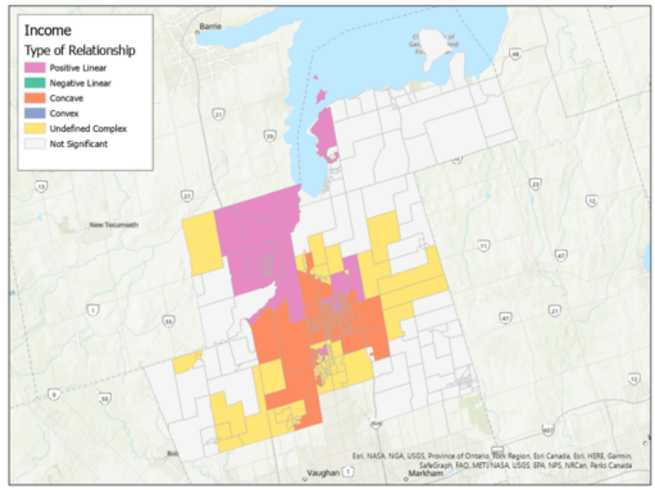
For both the use-case scenarios, local bivariate statistics were calculated between the dependent variable (screening or ED visits) and all potential independent variables. Only the variables with *statistically significant* results are presented here.

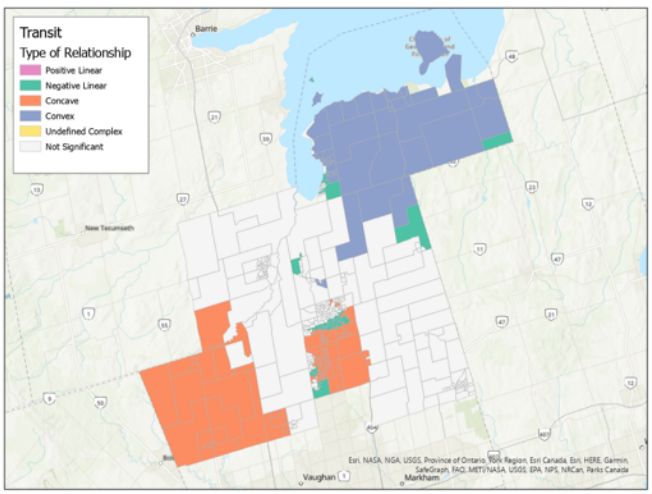
Mammography Screening

The first variable with results of local significance is the deprivation score from the Ontario Marginalization Index. The results indicate that for much of the Southlake region, there is a negative linear relationship between rates of mammography screening and deprivation (green areas), so screening rates decrease when deprivation rates increase. For areas in yellow or blue, there is either a convex or complex relationship, indicating a strong non-linear relationship.

The second variable with local significance is median income. This is not surprising given the clear results with the deprivation score and that income is a component of this score. There is a positive linear relationship to the northwest of Newmarket, where mammography screening rates increase as the median income increases. This also matches the results from the deprivation score for this area. The remainder of the areas of statistical significance show either concave or complex relationships. Given the linear relationship for these areas with the deprivation score, it is anticipated that these would be non-linear positive relationships.







A – Deprivation score

B – Median income

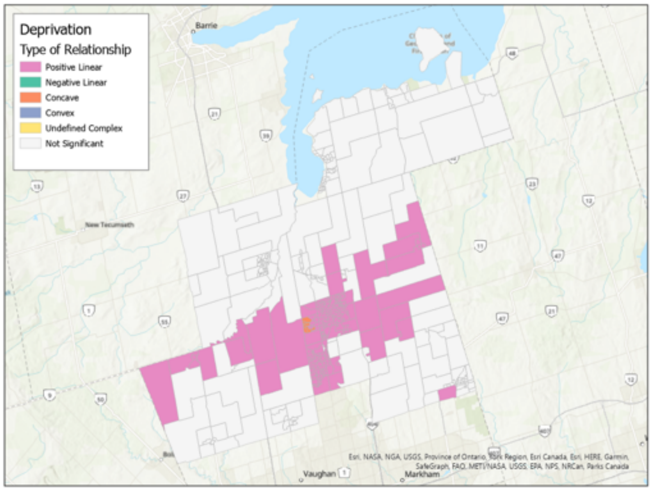
C – Distance to transit stops

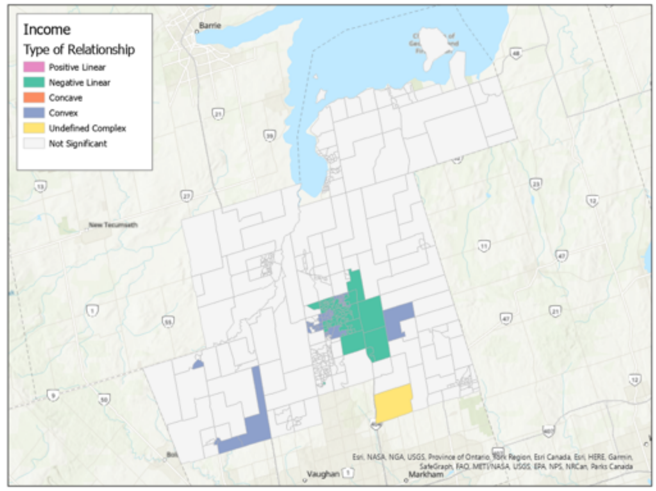
Figure 7: Bivariate analysis results, screening, and significantly related independent variables.

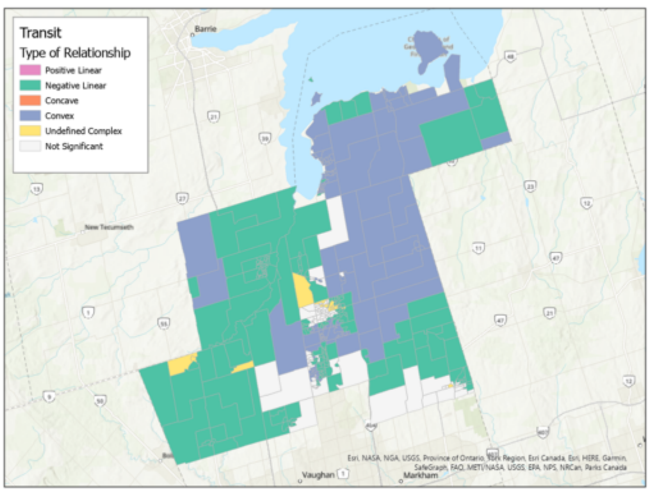
The third variable with local significance is distance to transit stops (Figure 7). The relationship between screening rates and distance to transit is more difficult to decipher. However, given the significance results are only seen in the northeast and southwest rural areas, it is logical that this relationship is a proxy for distance to the primary urban centre of Newmarket. For those areas with a convex relationship (blue), it is likely that this indicates that the further from Newmarket, the lower the mammography screening rates. While the areas with a concave relationship (orange), these have higher relative screening than rural areas.

Emergency Department Visits

The first variable with results of local significance is the deprivation component score from the Ontario Marginalization Index. The only local areas with local significance are across the central area of Southlake's attributable region, where there is a strong positive linear relationship. This indicates that for these areas, when the deprivation rate increases, so too does the standardized rate of CTAS 4&5 ED visits.







A – Deprivation score

B – Median income

C – Distance to transit stops

Figure 8: Bivariate analysis results, ED visits and significantly related independent variables.

Bivariate results indicate significant local relationships between ED visits and income, where increases in neighbourhood median income are negatively related to the rate of ED visits.

The distance to transit variable shows significant local relationships across much of the region, where a negative linear relationship indicates that increases in distance to transit stops results in decreases in ED visits. It is difficult to discern how this may impact ED rates uniformly across the region, given the range of urban and rural areas compared to the concentration of transit stops in the Town of Newmarket.

Use Case 1: Mammography Screening

Breast cancer is accountable for most cancer related deaths among women of all ages. Organized population-based mammography screening programs, such as the Ontario Breast Screening program aim to reduce the morbidity and mortality of breast cancer.[24,25] Through screening, breast cancer can be detected at an early stage, allowing for patients to engage with more effective treatment options, have a better chance of going into remission, and have a better survivability probability than those who are clinically detected because they are symptomatic.[26,27]

The Ontario breast screening program aims to encourage eligible women ages 50 to 74 be screened with a mammogram every 2 years. This is assuming that the women have not had any new breast cancer symptoms, personal history of breast cancer, no current breast implants, have not had a mastectomy, and have not had a mammogram screening in the last 11 months.

Some individuals between the ages of 30 to 69 may also be at increased risk if they are known to have a gene mutation that increases their risk for breast cancer, have a first-degree relative that has a gene mutation and have not done the genetic testing themselves, are assessed to have a 25% or greater chance of having breast cancer based on family history, or have had radiation to the chest to treat another cancer or condition before the age of 30 and at least 8 years ago are encouraged to be screened every year as they are considered high risk.

Breast cancer screening programs are an important tool for reducing the overall burden of this disease. However, there are numerous challenges to encouraging eligible women to participate in the screening program. By investigating and monitoring geographic variations in mammography screening participation, the OHT can assist in improving promotion strategies for areas that appear to have lower than expected screening rates.

In a previous application of small-area spatio-temporal analysis of participation rates in mammography screening programs in Dortmund, Germany, researchers aimed to the intra-urban variation of screening participation at the neighbourhood level. This was done to identify demographic and socioeconomic risk factors that contribute to non-response to screening invitations. It was found that although participation in screening programs rose throughout the city, the districts in the inner city, those with low-income groups, immigrant populations, and those who existed in the lower socio-economic gradient were the least likely to participate in screening.[28]

Similar results were found in a comparable analysis in a individual-level analysis from Geneva, Switzerland.[29] Although this analysis was conducted at the individual level, and researchers were able to trace the individual's pathway through their cancer experience over time, something we were unable to do given the data available, it does present the fact that socio-economic factors may contribute to lower rates of screening, and we incorporated such analysis into our own.

In another study, geographic access, socio-demographic and built environment factors were assessed to see if they were predictive of breast cancer screening service utilization in Greater Sydney Australia.[30] In this study individuals were found to be more likely to engage in mammography if they spoke English, had a university level of education, and if they had a personal vehicle.[31] If the screening centre was mobile, women we less likely to go to screening if they worked and if the venue was collocated (within 500 meters) of a bus stop or a hospital but were more likely to go if it was collocated with their family practitioner and shops[12]. If the screening venue was fixed, individuals were more likely to use the screening services if they were collocated with a train station or a hospital but were less likely to attend if the fixed screening location was close to a bus stop, family practitioner or shops.

Like our analysis, this analysis was conducted at the neighbourhood level. Although individual level rates of screening, indicators, and changes over time were not available, this analysis shows the strength of conducting neighbourhood level analysis, and how this information can be used to profile areas or neighbourhood in need of tailored health promotion efforts. As well, it shows the direct in which further built environment analysis should be conducted, seeing the proximity of screening location to other neighbourhood features, to see if they factor into likelihood of screening participation.[32] These are great examples of geo-analytical techniques used for a mammography screening population, and identifying those who are not being screened, with the hope of better tailoring health promotion programs to reach these populations.

This project aims to do the same for the Southlake Community OHT, applying similar geo-spatial analysis with socio-economic factors, travel times, neighbourhood factors including rurality and rates of screening participation based on the regions dissemination areas. A dissemination area is a small area composed of one or more neighbouring dissemination blocks and is the smallest standard geographic area for which all census data are disseminated.

This use-case scenario shows the strengths of applying geo-analytics to this setting. It also shows limitations in the data we available to conduct the necessary analysis to fully identify those who are not being screened for breast cancer when they should be. By doing so we can properly target these populations through public health initiatives, and in turn reduce the morbidity and mortality of breast cancer for these individuals.

ANALYTIC RESULTS

The first step in the analysis was to conduct a global regression using a gaussian (continuous) generalized linear regression model. The global model results in Table 5 provide some insight into how the potential independent variables help explain variation in mammography screening rates. Model 1 included the deprivation and ethnicity scores from the Ontario Marginalization Index as well as the percent of females over the age of 65. Deprivation and ethnicity were significant, where decreasing deprivation was related to an increase in mammography screening. The opposite was found with the ethnicity score, where increases in the ethnicity score were related to increases in mammography screening rates. However, the adjusted R^2 for this model indicated that it only explained about 6.6% of the variation in mammography screening rates.

Interestingly, in Model 2, when distance to transit was included, the ethnicity score was no longer significant, and the effect became slightly negative. However, distance to transit was significant, where the results showed that the closer areas were to transit, mammography screen rates increased. This model was significantly stronger, explaining about 51.3% of the variation in mammography screening rates.

Given the above, Model 3 was run with only the deprivation score and distance to transit. This model remains strong, with an adjusted R^2 of 0.515. The strength of this model is supported by the AICc values, where Model 3 has the lowest AICc values.

Table 5: Global regression model results, mammography screening use case scenario.

	Model 1	**Model 2**	**Model 3**
Constant	48.57 (3.31)	59.523 (2.462)	59.164 (0.759)
Deprivation	-4.603*** (1.178)	-5.602*** (0.852)	-5.606*** (0.847)
Ethnicity	7.109*** (1.848)	-0.862 (1.402)	
Percent Females >65yrs	0.299 (0.178)	-0.025 (0.130)	
Distance to Transit		-0.003*** (0.000)	-0.002*** (0.000)
R^2	0.073	0.518	0.517
Adjusted R^2	0.066	0.513	0.515
AICc	3218.80	2971.22	2967.50
No. of Observations	382	382	382

Standard errors are reported in parentheses.
*** indicates significance at the 99% level.

Building on the results from the exploratory spatial data analysis and global regression results, a continuous Geographically Weighted Regression (GWR) was performed with the mammography screening rate as the dependent variable using the number of neighbours as the neighbourhood type in the analysis.

The first map is the local R^2 values, which shows the goodness of fit for the local GWR models, interpreted as the proportion of the variance for the dependent variable accounted by the local regression models. As can be seen from Figure 9, there is a large variation in the local R^2 across the study region. Areas in green show values ranging from 0.55 to 0.94, indicating that between 55% and 94% of the variance of the dependent variable is accounted by the specified model. This compares to the global regression model, which had an adjusted R^2 of 0.515.

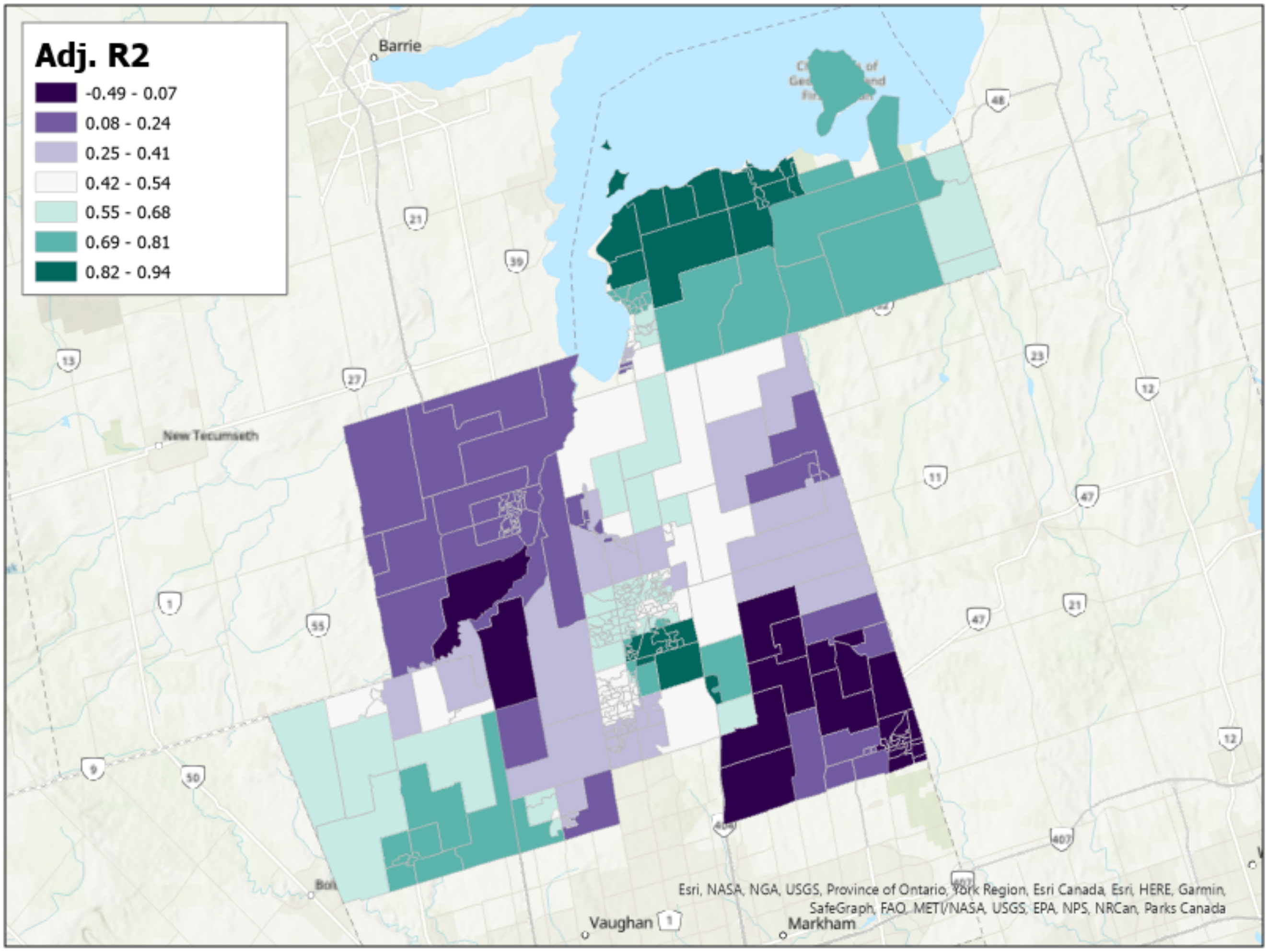


Figure 9: GWR locally adjusted R^2, mammography screening model.

The purple shaded areas of the local R^2 map indicate where the model is weak, or even where the selected model performs *worse* than a model that predicts the mean. Given this, the results suggest that the specified model is most valid in regions that have R^2 values over 0.42, and potentially in areas with an R^2 between 0.25 – 0.41 (light purple).

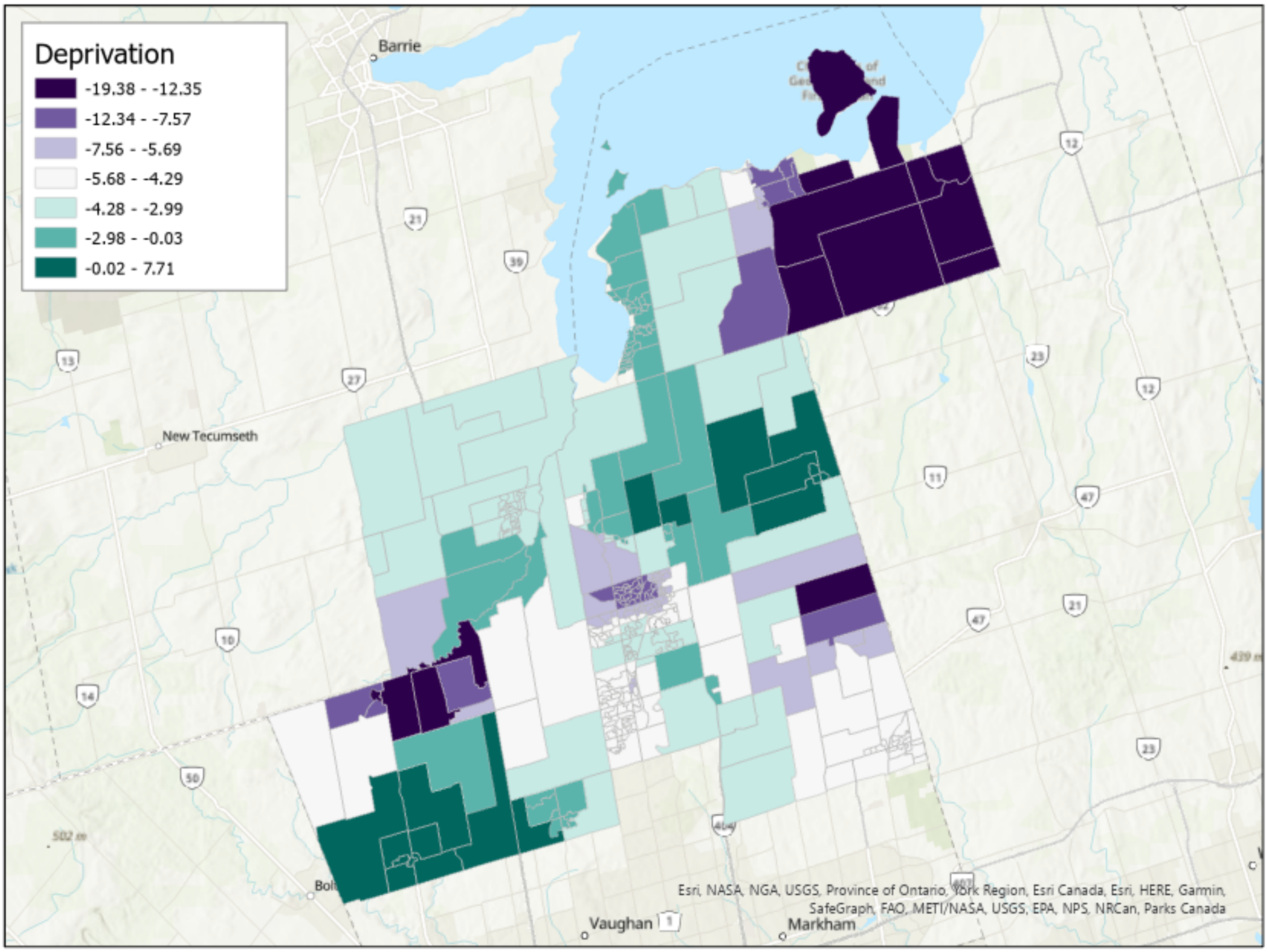


Figure 10: GWR local parameter estimates, deprivation score, mammography screening model.

Turning to the parameter estimates, Figure 10 shows the local parameter estimates for the deprivation score. Estimates range from -19.38 to 7.71, with negative values showing areas where higher deprivation scores are related to lower screening rates. Positive values show areas where lower deprivation scores result in higher screening rates.

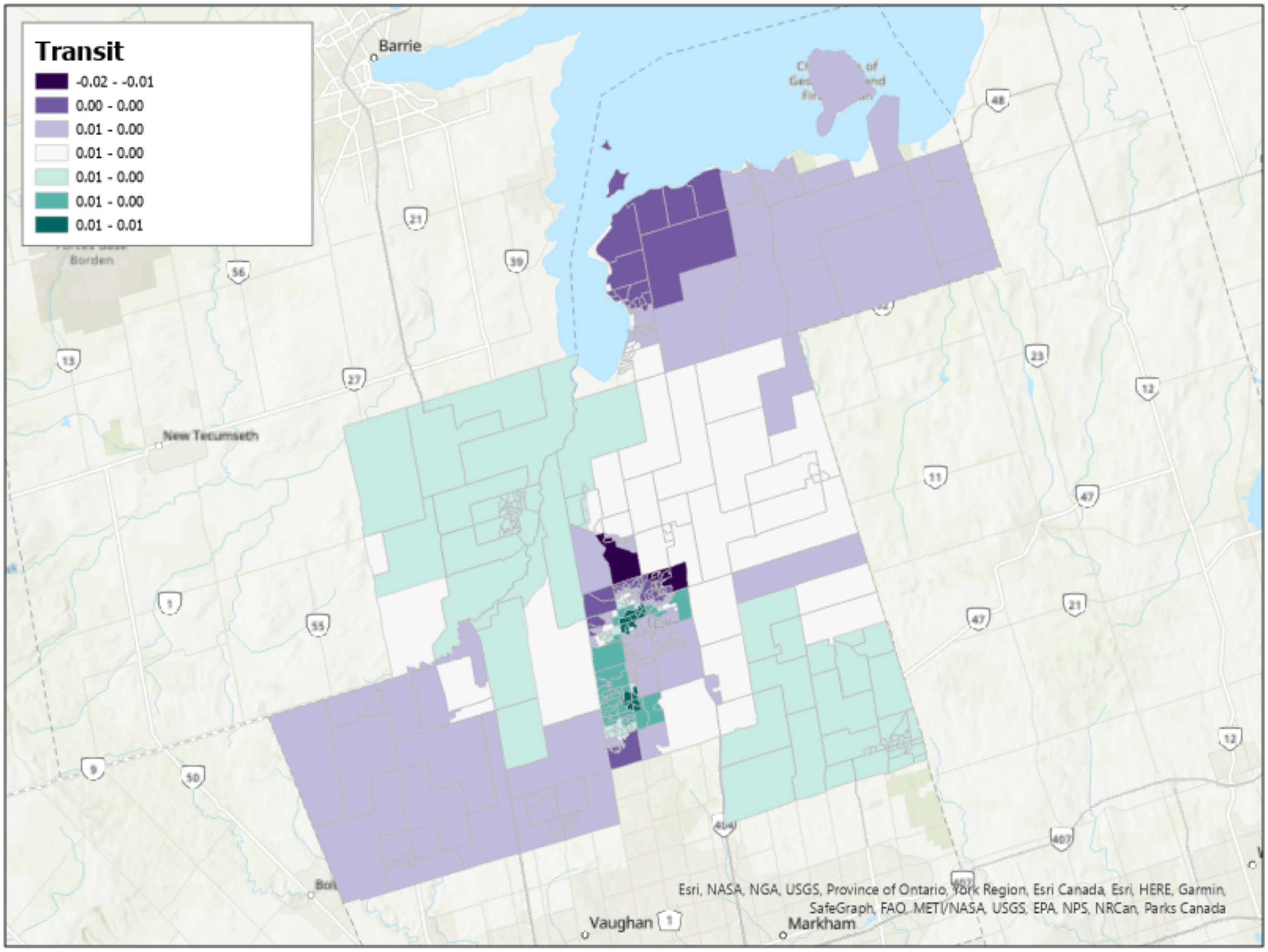


Figure 11: GWR local parameter estimates, distance to transit, mammography screening model.

The local parameter estimates for distance to transit stops in Figure 11 show how screening rates may be influenced by the distance to transit stops. Given the clustering of transit within the Town of Newmarket, these estimates are most valid in this area. Moving from purple to green shows how increasing distance to transit increases screening rates. Importantly, the darkest shades of purple show areas where an *increase* in distance to transit *reduces* screening rates.

Use Case 2: ED Admissions with CTAS 4 & 5

The Canadian Triage and Acuity Scale (CTAS) was first introduced in 1999 to simplify the prioritizing of patients in the Canadian Healthcare system.[33] It attempts to accurately define patient needs and provide timely care in the Emergency Department (ED). The CTAS is divided into levels 1-5, with 1 being the most acute or "emergent" and 5 representing the lowest acuity patients.

One of the greatest stressors on Canadian EDs is the presentation of low-acuity patients with conditions that can treated by primary care resources.[34] Low-acuity patients can contribute to delayed entry into the healthcare system for patients with critical presentations and add strain to the limited resources in the ED.[35] In 2021-2022, CTAS 4 and 5 patients accounted for 35.9% of ED visits in Canada. While this is down from 45.6% in 2011-2012, this still represents a significant proportion of ED visits.[36]

Socioeconomic status (SES) has previously been linked to low-acuity emergency department use in Canada as well as Australia and the United States.[37–39] A 2014 study on ED visits in Ontario found that 25.4% of ED visits were represented by the population in the highest material deprivation quintile, compared to 13.3% in the lowest quintile.[37]

Since SES factors are often spatially related, mapping SES alongside CTAS 4 and 5 ED use can enable us to visualize relationships between SES and low-acuity ED use to identify opportunities for intervention. The University of Virginia Health System is currently facilitating a project that follows this logic. Spatially analysing SES and medical record data enabled the identification of neighbourhoods where community health intervention could be most effectively implemented to decrease low-acuity ED usage.[40] This led to the creation of the WellAWARE program, which aims to reduce barriers to health living and connect people with primary care.

The objective of this project is to examine spatial patterns non-urgent ED usage, with the goal of identifying specific geographic areas where higher than expected ED usage is related to specific socio-demographic or infrastructure factors.

ANALYTIC RESULTS

The first step in the analysis was to conduct a global regression using a gaussian (continuous) generalized linear regression model. The global model results in Table 6 provide some insight into how the potential independent variables help explain variation in rates of ED admissions for CTAS 4&5 conditions.

Model 1 included the deprivation, ethnicity, and dependency scores from the Ontario Marginalization Index. In this model, only the deprivation score was significant, where increased deprivation was related to an increase in CTAS 4&5 ED visits. However, the adjusted R^2 for this model indicated that it only explained about 8.7% of the variation in CTAS 4&5 ED admissions.

Table 6: Global regression model results, emergency department use case scenario.

	Model 1	**Model 2**	**Model 3**
Constant	67.260 (3.146)	75.60 (3.070)	78.058 (2.692)
Deprivation	18.989*** (3.255)	17.690*** (3.003)	17.571*** (3.005)
Ethnicity	3.151 (4.947)	-6.227 (4.700)	
Dependency	-5.209 (3.380)	-4.608 (3.115)	
Distance to Transit		-0.004*** (0.000)	-0.004*** (0.000)
R^2	0.094	0.233	0.228
Adjusted R^2	0.087	0.225	0.223
AICc	3997.28	3935.87	3934.57
No. of Observations	382	382	382

Standard errors are reported in parentheses.
*** indicates significance at the 99% level.

Interestingly, in Model 2, when distance to transit was included, the effect of the ethnicity score became negative, although it remained not statistically significant. However, distance to transit was significant, where the results showed that the closer areas were to transit, ED rates increased. This model was significantly stronger, explaining about 23.3% of the variation in CTAS 4&5 ED admission rates.

Given the above, Model 3 was run with only the deprivation score and distance to transit. This model remains moderate, with an adjusted R^2 of 0.223. The strength of this model is supported by the AICc values, where Model 3 has the lowest AICc values.

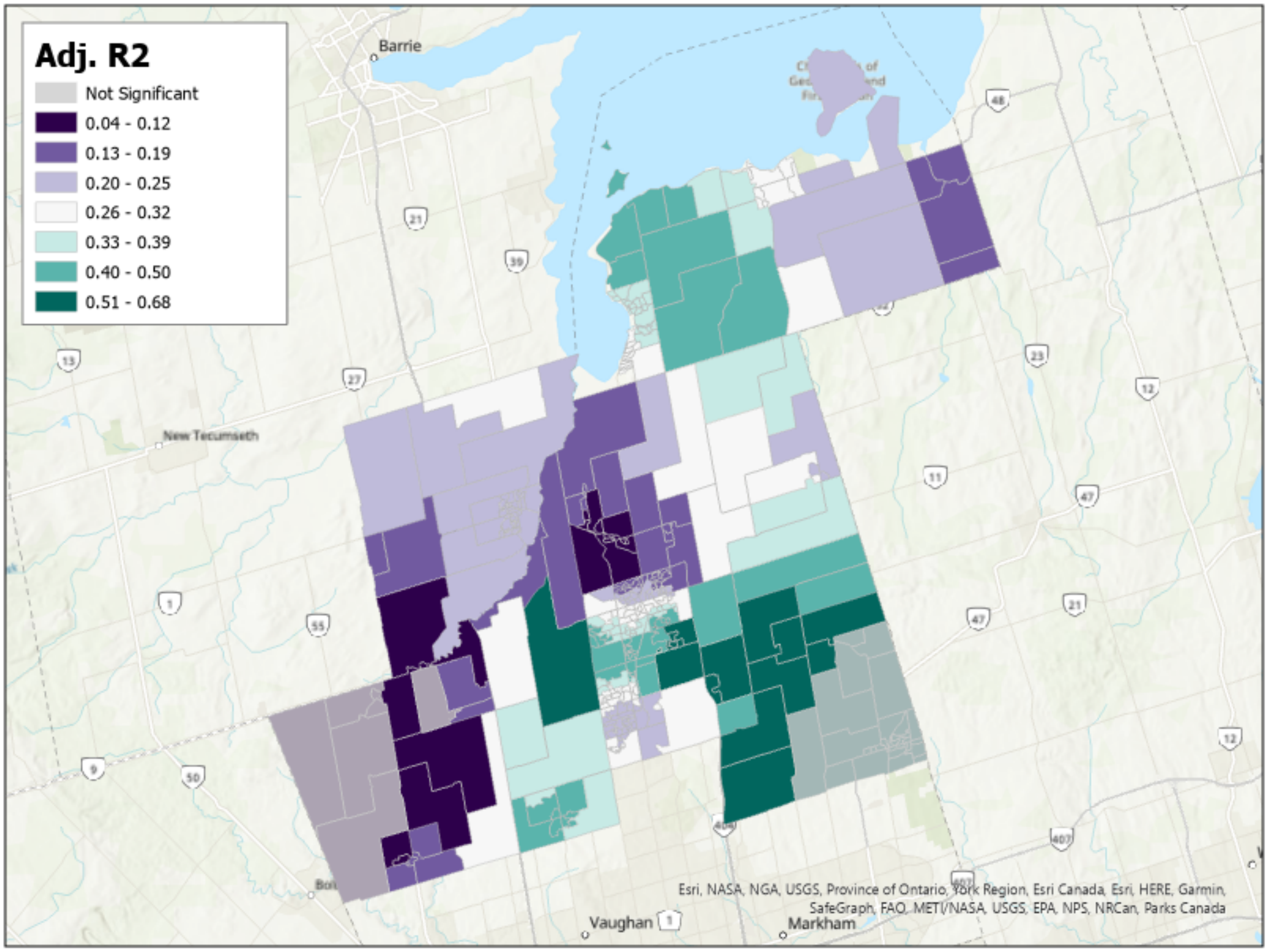


Figure 12: GWR locally adjusted R^2, CTAS 4&5 visits model.

Turning to the results of the GWR models, the map of adjusted R^2 values in Figure 12 show significant spatial variation across the study region. The areas with the strongest predictive powers are in the north from Island Grove south to Keswick as well as in the east of Newmarket to Ballantree and southwest to King City.

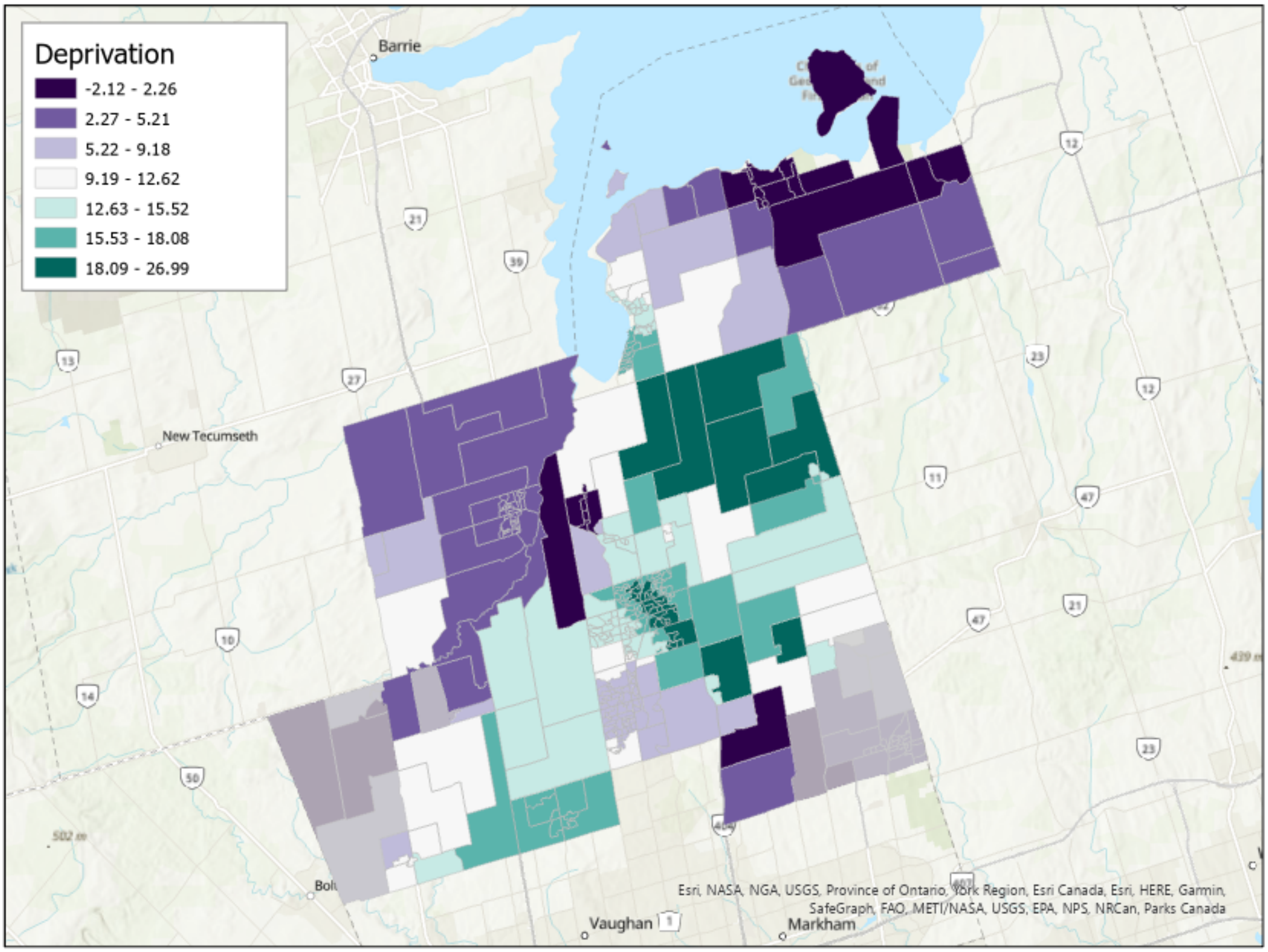


Figure 13: GWR local parameter estimates, deprivation score, CTAS 4&5 model.

The parameter estimates for the deprivation score in Figure 13 also show significant spatial variation, with high positive values in the northeast of Newmarket and the rural northeast between Keswick and Uxbridge. The interpretation of these values would be that for the highest category, for each 1 unit increase in the deprivation score, the rate of CTAS 4&5 ED visits would increase by between 18 and 27 per 1,000 persons.

For some parts of the study area, there also appears to be a *negative* relationship with the deprivation score. In the north of the region along lake Simcoe, including Georgina Island, it suggests that when deprivation decreases, the ED visit rate would increase. However, this effect is quite small and should instead be interpreted that deprivation does not necessarily influence ED rates for these areas.

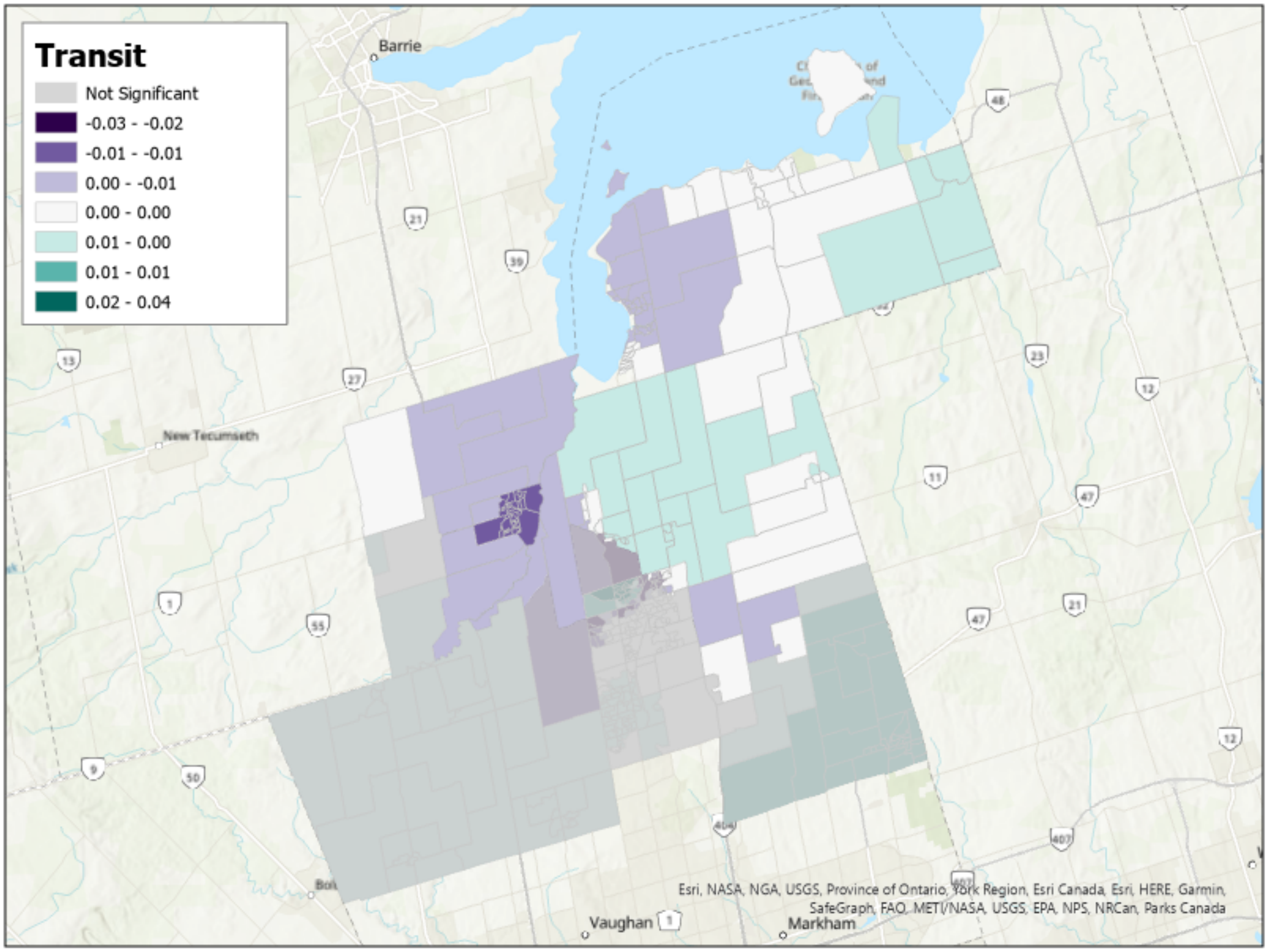


Figure 14: GWR local parameter estimates, distance to transit, CTAS 4&5 model.

The parameter estimates for the distance to transit variable are not as clear as with the mammography screening variable. For a large part of the study area this variable is not significant. The strongest results are around the community of Bradford West Gwillimbury, where there is a small negative relationship between distance to transit and ED rates.

Overall, the GWR results for this use case indicate that there are clear areas across Southlake where the level of deprivation in an area may influence ED visits for CTAS 4&5.

Data Visualization and Web Apps

A key aspect of this Test of Change project is the development of knowledge translation or knowledge exchange tools. Most knowledge translation materials focus on reports, presentations, or infographics. For this project, Southlake embarked on a web mapping exercise to not only present the results of the analytic project, but also to provide an interactive tool whereby health professionals and planners could investigate key population health indicators in relation to the two use case scenarios (see Figure 15 and Figure 16 below).

To facilitate this web-mapping exercise, Southlake partnered with Eastern Toronto OHT to replicate one of the use case analyses and enable comparison between two different OHT environments. Tools were developed with assistance from ESRI Canada, the leading global GIS software vendor, with their Experience Builder™ application. This collaboration provided a link between Southlake and industry, through ESRI Canada's interest in expanding capacity in public health.

Due to software licenses expiring, Southlake was unable to remain hosting these web applications once the project was completed. However, in partnership with Carleton University, these applications will be hosted on their servers.

The web applications will be accessible through:

https://carleton.ca/determinants/2023/southlake-oht-web-mapping/

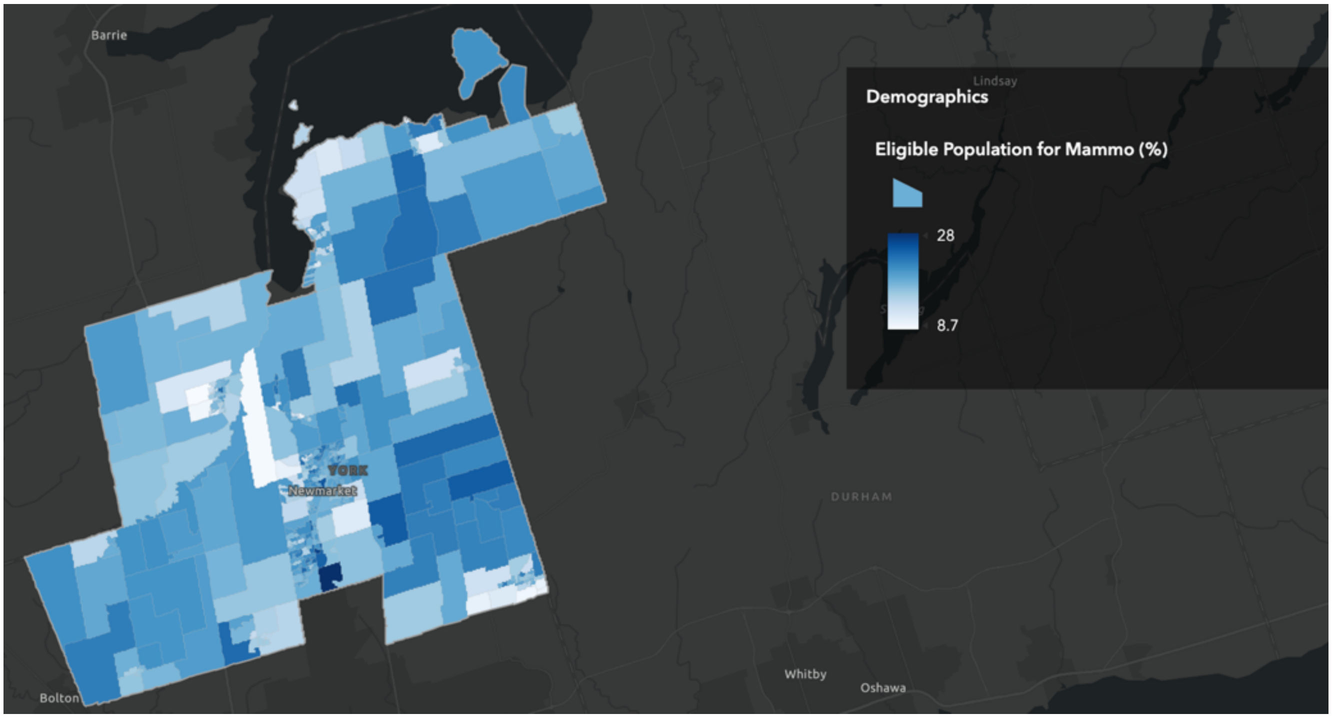


Figure 15: Web mapping application example: population eligible for screening.

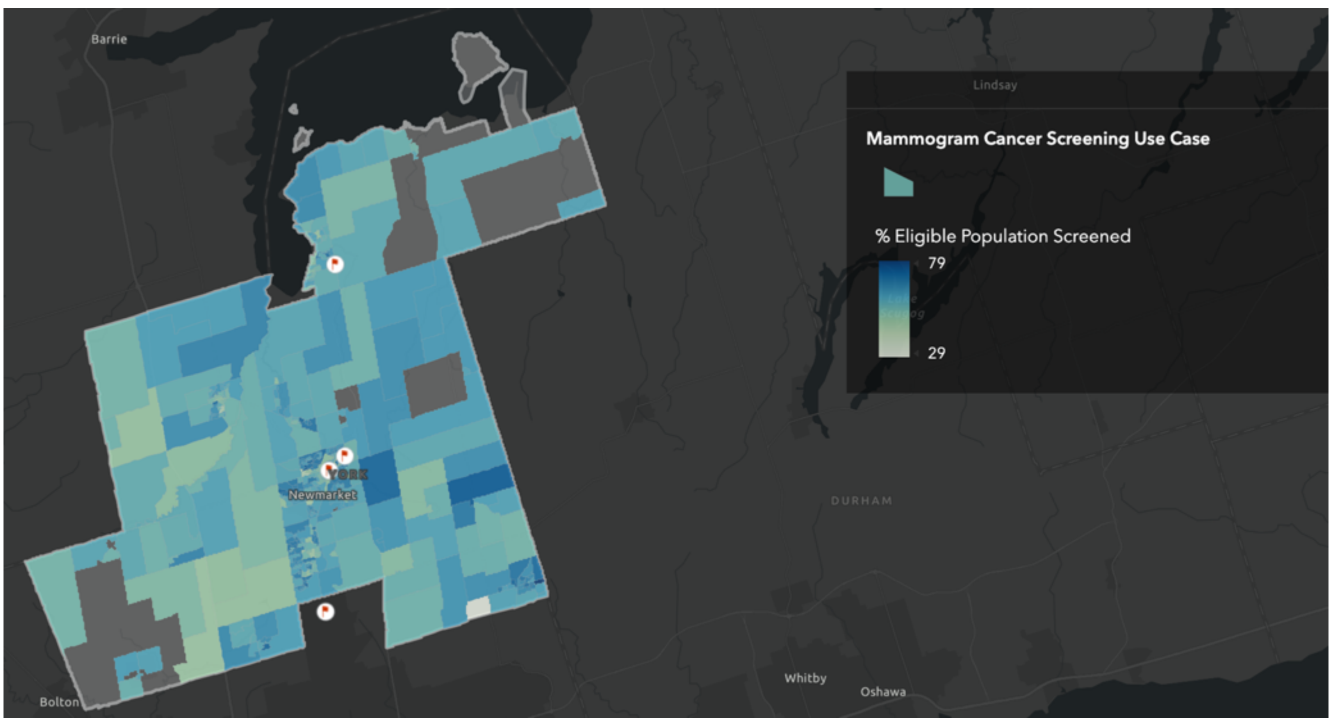


Figure 16: Web mapping application example: mammography screening rate.

Section 3: Critical Evaluation

Evaluation of Southlake's geo-analytics project illustrates how place-based analysis and geospatial tools can provide insight into developing targeted health interventions at a local level. Central to this test of change is the use of available health and socio-demographic data resources to examine key local health issues through a rigorous and defensible methodology. Overall, this project provides an example of how a data-centred, place-based approach can provide a comprehensive understanding of Southlake's underlying attributable population.

Throughout the project, evaluation is a key component. As such, this report has been developed to provide a thorough evaluation of the objectives, methods, and conclusions of the geo-analytics project.

Given the objectives of this test of change project it can be seen as an overall success. This conclusion is supported by the findings that:

The development of this project is aligned with OHT objectives.

The objectives for OHTs in general and Southlake include improving the quality of care, patient outcomes, and the patient and provider experience while also making the healthcare system more efficient and sustainable.

There is potential for transformative change.

A geospatial approach to population health management has the potential to transform how health services and health outcomes are evaluated within Southlake and other OHTs.

There is potential to improve population health outcomes.

The two use-case scenarios have provided strong evidence to support local health interventions to increase cancer screening and shift emergency department usage patterns.

The project has facilitated collaboration and knowledge exchange across OHTs.

Southlake has collaborated with other OHTs, including East Toronto OHT, numerous community partners, and other health service organizations. They have also demonstrated a capacity to develop innovative knowledge exchange through internet mapping.

GEOANALYTICS PROJECT REVIEW

The overall objective of this project was to design and develop a digitally enabled innovation with the potential to improve patient access, experience, and health outcomes. Southlake transformational project with potential for spread and scale.

FROM ANALYSIS TO INTERVENTIONS – POSTCARD CAMPAIGN

Based on the results of the mammography screening use-case scenario, Southlake in partnership with the Central Regional Cancer Program developed a breast cancer screening campaign targeting residents in the community of Keswick. Located on the south shores of Lake Simcoe, Keswick is home to around 27,000 residents.

Geographic analysis of mammography screening rates indicated clustering of higher than expected low rates (Figure 4) via outlier analysis and statistically significant “cold spots” (Figure 5) of mammography screening rates in this area. Further analysis via GWR indicated a statistically robust model fit, with an inverse relationship to the Ontario Marginalization deprivation score, where increases in deprivation were related to decreases in mammography screening.

Southlake and the regional cancer program office selected to implement a postcard campaign to encourage cancer screening for older women in this area. Using Canada Post, 1,115 postcards were mailed to households within 3 DA clusters in 3 Postal Code Forward Sortation areas. Postcards showed locations for screening as well as a link to an online survey.

Given the short timeframe of the test of change project, the campaign was implemented in less than 2 months. As such, there were significant limitations to this intervention in terms of measurable efficacy. While postcard campaigns can be useful, evidence shows that they are best used as *part* of a larger information campaign integrating multiple stakeholders and potential points of contact.[41,42]

Despite the limitations, several individuals responded to the survey and indicated when booking a screening that they had received information via the postcard campaign. As such, there is strong potential for change via this targeting approach and it is anticipated that had there been sufficient time in the test of change project, more impactful results could be measured.

POTENTIAL ECONOMIC BENEFITS

The realization of specific economic benefits for a short-term test of change project are difficult to evaluate. Projects that focus on interventions to reduce health inequities, target specific populations, and focus on upstream determinants of health see cost savings on a much longer-term.[43,44] However, there is potential from this project to reduce health costs via addressing upstream determinants of health, which can include increases in cancer screening or reductions in emergency department usage.[45]

The most lasting contribution of this project is the potential for a geoanalytics approach to be integrated at the OHT level in Southlake. Health geoanalytics can support public health organizations in making informed decisions, optimizing resource allocation, and improving the efficiency of their operations. This leads to cost savings by reducing waste, targeting interventions effectively, and improving overall health outcomes in the population.

Five key areas where Southlake and other OHTs can use health GIS in the future are:

1. **Resource Allocation:** By efficiently targeting interventions and allocating resources where they are most needed, Southlake can reduce costs associated with ineffective or inefficient resource distribution.
2. **Disease Surveillance:** As seen throughout the COVID-19 pandemic, GIS allows for real-time monitoring and analysis of disease outbreaks and patterns. Public health organizations can respond more effectively, reducing the economic impact of epidemics, facilitate timely allocation of healthcare resources, targeted vaccination campaigns, and implementation of preventive measures.
3. **Planning and Decision Making:** Southlake can use GIS to identify gaps in healthcare services, assess the accessibility and coverage of existing facilities, and strategically plan for new facilities or services. This helps optimize healthcare delivery and minimize unnecessary costs.
4. **Risk Assessment and Emergency Response:** By identifying vulnerable populations and areas prone to natural disasters or other emergencies, public health organizations can develop proactive strategies, emergency response plans, and evacuation plans.
5. **Program Evaluation:** GIS can be used to assess the effectiveness and cost-efficiency of interventions by analyzing their spatial distribution and impact on health outcomes. This helps inform future program planning, ensuring resources are allocated to the most effective interventions.

RECOMMENDATIONS

Based on the evaluation of the geo-analytics test of change project, there are several recommendations to guide future projects and potential project scale and spread. These fall under the headings of data systems and data access, analytic process and statistical modelling, partnerships and expertise, and sustainability and scalability.

DATA SYSTEMS AND ACCESS

There are several recommendations for improvements in the data system and data access procedures and methods.

Document input data: Input data should be documented and with complete metadata including access rules, timelines for retention, and data versioning. Input data were provided from multiple partners in multiple formats but were not necessarily documented consistently nor stored in the same location. The same data was sometimes duplicated in different folders with no details as to any differences.

Use consistent data types: Data files should use a consistent data type that is accessible across the organization. Analytic and interim data files were sometimes in different formats, or in formats only readable by specific software packages (such as the ArcGIS geodatabase file format).

Utilise clear data storage rules: Raw data should be stored separately from analytic data, with analytic data files created using a consistent formatting and naming convention.

Set data interoperability guidelines: As data for analysis come from multiple sources, it is key that guidelines for how data can link are developed. This includes selection of common data types, the software used to develop data linkages, and any limitations on data transformation imposed by the data provider.

Geocode data consistently: This recommendation is perhaps the most critical step in ensuring that data from different sources are linked appropriately for area-based analysis. It is well-known that individual-level health administrative data do not contain codes that link between small-area geographic units for analysis. As such, several geocoding methodologies have been developed by different providers. It is essential that the most appropriate method is identified and followed consistently throughout the analytic process.

For this project, the geocoding methodology from Environics Canada was selected; however, individual-level records were not processed following this method, resulting in miscalculation of the area-based rates of emergency department usage.

ANALYTIC PROCESS AND STATISTICAL MODELLING

Follow analytic protocols and best-practices: A clear process was identified for developing analytic models, but in reviewing the model results it was determined that these were not always followed correctly. For instance, it was recognized that a first step in developing statistical models is to perform exploratory analysis. When exploratory results were reviewed, it was found that several selected variables were significantly correlated and thus should not be included in the same model. Had the protocol been followed, these would have been excluded.

Statistical review: The models developed by the analysts, while comprehensive, had some fundamental errors in statistical calculations. For instance, counts for emergency department visits were used in statistical models rather than using population standardised rates (expressed as visits/1,000 persons). These errors could have been avoided by tighter review by other internal experts at Southlake.

Document analyses: Analysts and managers should maintain continual documentation of the analytic steps undertaken. This documentation should include reference to data transformations, calculations, and specific locations for input and output files.

Use accessible analytic techniques: Analyses should make use of techniques that can be followed and replicated easily by other analysts in the organization. Analysts in Southlake used advanced Python programming within ArcGIS Pro to perform analyses. As such, replication of the analysis would only be interpretable by other experts in geoanalytics and would likely not be possible to replicate by others within the Southlake organization.

Provide accessible interpretation of results: Analytic results generated from interim analyses and final model results need to be presented in a manner that is accessible to a broad audience who may not have technical expertise in geoanalytics. Presentation of results to the internal working group included statistical results without interpretation that would be accessible to all the members.

PARTNERSHIPS AND EXPERTISE

Drawing from successful projects elsewhere, Southlake has recognized that partnerships would be critical to the success of this project. This aspect of the evaluation has been largely successful, where Southlake has initiated or strengthened collaboration with community groups, other regional health organizations, other OHTs in Southern Ontario, and with external research groups.

Support internal expertise: Southlake has significant internal expertise both within its organization and with aligned partners. As such, there is strong potential to draw from existing expertise (significant) and growing new expertise.

Retain and grow new expertise: the ability to grow new expertise and retain highly qualified personnel is limited by the short time-durations of the test of change project funding and unclear sustainability moving forward. A highly qualified GIS and statistical analyst was retained for this project who left for stable employment elsewhere given the short-term nature of the Southlake contract.

SUSTAINABILITY AND SCALABILITY

Sustainability and scalability of health intervention projects is difficult and fraught with numerous challenges. Indeed, Canada has been described as a land of “perpetual pilot projects” where successful targeted interventions are not scaled to provide benefit elsewhere.[46] This has clear implications on economic costs and on the potential to exact measurable change in the health system.

Reviews of the literature and experience from examining other rural health interventions has shown that features of successful implementation include a level of local autonomy, strong service-community connections, a capacity for change, a flexible approach to implementation, and a realistic recognition of differences in local communities.[47] Some of these features are present at the OHT level, while some are limited by constraints at higher levels.

Do things differently: In highly regulated systems such as health it may be difficult for services to act locally to implement initiatives that have not been centrally mandated. However, changes in local health care systems usually result from pilot studies or limited trials which expose local services to "doing things differently" from neighboring services and building capacity as leaders and participants in innovation and reform.

Move away from one-size-fits-all: There have been endless calls for moves away from "one size fits all" service models, with assertions that policy which focuses on outcomes (accessibility and health outcomes) is likely to be more effective than policy which focuses on inputs.

Local champions: There also needs to be local leadership and champions where imagination and creativity allowed local actors to recognize good ideas when they see them and coordinated their implementation and ongoing operation. This includes the recruitment and retention of highly skilled individuals that can not only fit the needs of a specific project, but also adapt to future projects.

Local innovations: Innovation capacity is about building knowledge of what is possible and evaluating options in terms of their fit to the needs of the community. Such knowledge should equally recognize why particular initiatives that appear successful elsewhere might not work in a particular location.

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