VOLUME V | Issue 1 | 2017 | CIEO

Guest-Editor: Eric Vaz
Editor-in-Chief: Patrícia Pinto

Journal of Spatial and Organizational Dynamics

Novel Approaches in Geographic Information Systems

TECHNICAL INFORMATION

Volume V, Issue 1, 2017

JOURNAL OF SPATIAL AND ORGANIZATIONAL DYNAMICS

Novel Approaches in Geographic Information Systems

Authors:
Akeem Foster
Eric Vaz
Georgios Efthimiou
Jessica Miki
Konstantinos Ntouras
Michael Cusimano
Sina Tehranchi
Teresa de Noronha
Thomas Panagopoulos

Guest-Editors: Eric Vaz
Editor-in-Chief: Patrícia Pinto

Publisher:
Research Centre for Spatial and Organizational Dynamics - CIEO
Campus de Gambelas, Faculdade de Economia, Edifício 9
8005-139, Faro
cieo@ualg.pt
www.cieo.pt

Editorial Board:
Teresa de Noronha, Faculty of Economics, University of Algarve, Portugal (mtvaz@ualg.pt)
André Torre, Institut National de la Recherche Agronomique, Agro Paris Tech, France (andre.torre@wanadoo.fr)
Charlie Karlsson, Jönköping International Business School, Jönköping University, Sweden (Charlie.Karlsson@ihh.hj.se)
Eric Vaz, Department of Geography, Ryerson University, Canada (evaz@GEOGRAPHY.Ryerson.Ca)
Helen Lawton Smith, Department of Management - Birkbeck, University of London, U.K (helen.lawtonsmith@ouce.ox.ac.uk)
Jafar Jafari, School of Hospitality Leadership, University of Wisconsin-Stout, USA (jafari@uwstout.edu)
Purificación Galindo, Department of Statistics, University of Salamanca, Spain (purivic@yahoo.com)
Rafael Alberto Peres, Universidad Complutense de Madrid, Spain (estrategia@rafaelalbertoperez.com)
Saul Neves de Jesus, Faculty of Human and Social Sciences, University of Algarve, Portugal (snjesus@ualg.pt)
Thomas Panagopoulos, Faculty of Sciences and Technology, University of Algarve, Portugal (tpanago@ualg.pt)

Open Access Policy:
This is a blind peer-reviewed journal.
Articles submitted to this journal should not have been published before in their current or substantially similar form.
The JSOD is diffused by all links related to the Research Center for Spatial and Organizational Dynamics and is continually online (http://www.cieo.pt/discussion_papers_editions.php)
This journal is supported by the Portuguese Foundation for Science and Technology (FCT).

Indexation:
RePec-Ideas
Directory of Open Access Journals
Emerging Sources Citation Index (ESCI) - Thomson Reuters
Latindex
Academia.edu

Networking and Indexing:
Silvia Fernandes

Page Layout:
Marlene Fernandes

Design and Cover Concept:
Bloco D, Design e Comunicação

Quarterly Edition
ISSN: 2183-1912
CIEO, Faro, Portugal

TABLE OF CONTENTS

KNOWLEDGE AND ATTITUDES OF FORESTRY STUDENTS ON NATURE AND PROTECTED AREAS IN GREECE

Georgios Efthimiou[1]
Konstantinos Ntouras[2]
Thomas Panagopoulos[3]

ABSTRACT

The study and academic training of citizens in issues of forest and protected areas shapes the environmentally friendly attitudes to graduates. Attitudes include public beliefs and assessments of ecosystem management activities. In education it is necessary to redefine our values and ethical norms and obligations towards man and the natural environment. The field of study and gender have an impact on environmental attitudes and behaviors of students. The protected areas are subject to ample scientific research and have educational interest. The purpose of this research is to measure attitudes on Protected Areas (PA) of Forestry students in Greece. The questionnaire used as a research tool, based on the scale FVS (Forest Values Scale) which is suitably adapted for PA. Based on the results of this survey it was found that the majority of the sampled students showing more biocentric attitude to Protected Areas which is largely due to the subject of their studies. With regard to gender on the positive attitude towards the environment was found to be statistically significant in favor of women. Students largely support positive environmental attitudes and found that there is a relationship between the level of knowledge about protected areas and the attitude towards the environment.

Keywords: Protected Areas, Environmental Attitudes, Environmental Education.

JEL Classification: Q20, I29

1. INTRODUCTION

Education is the tool of citizens shaping based on critical and research thinking. The study and academic training of citizens in issues of forest and nature shapes the environmentally friendly attitudes to the graduates. According to Jobes (1991) the young and educated citizens often have romantic attitude to the naturalness of a region such as the national park of Yellowstone. Essential role in education for cultivating attitudes and behavior play the family and the school (Ajzen & Fishbein, 2000; Frick *et al.,* 2004; Matzanos *et al.,* 2012). This educational framework seeks to establish a sustainable school (Breiting *et al.*, 2005; Gough, 2006), promotes collective learning (Henderson & Tilbury, 2004), encourages participatory processes (Sutton & Kemp, 2002), prepares students for action (Huckle, 2010), assist in the formation of responsible environmental behavior (Hwang *et al.,* 2000). Attitudes include public beliefs and assessments of ecosystem management activities (Reading *et al.,* 1994). In

[1] Department of Forestry and Natural Environment Management, Technological Educational Institute of Sterea Hellas, 36100, Karpenissi, Greece, efthimiou@teiste.gr
[2] Economist foresters, Secondary Education, 43100, Karditsa, Greece, dourask@sch.gr
[3] Centro de Investigação sobre o Espaço e as Organizações, Universidade do Algarve, 8005-139 Faro, Portugal, tpanago@ualg.pt

education it is necessary to redefine our values and ethical norms and obligations towards man and the natural environment (Flogaiti, 2006).

It is an important aspect of educational research and psychology to study science education (Lavonen *et al.,* 2008). The scientific field of study and gender has have an impact on environmental attitudes and behaviors of students. In many surveys referred environmentally friendly attitudes of students studying objects on the environment (Ntouras, 2013).

The protected areas are subject to much scientific research and educational interest (Mose & Weixbaumer, 2007; Efthimiou, 2015). According to Prato and Fagre (2005), protected areas are harmonious human and nature coexistence spaces (Mantzaros *et al.,* 2012). Greece has a large number of protected areas which are developed and support many environmental education programs at all levels of education (Papapanagou *et al.,* 2005; Efthimiou, 2015). Curricula for protected areas is scarce and there are only courses for training people involved in their management (Matzanos *et al.,* 2012). In higher education there is a corresponding course and students are educated in schools with forestry and environmental studies subject. The experiential use of protected areas in the context of environmental education can contribute to the enrichment of knowledge, the development of environmentally friendly attitudes and perceptions on protected areas (Matzanos *et al.,* 2010; Papadomarkakis, 2011; Matzanos *et al.,* 2012).

The purpose of this research is to measure attitudes on Protected Areas (PA) of Forestry students in Greece using a questionnaire based on the Forest Values Scale (FVS) suitably adapted for PA.

2. METHODS AND MATERIALS

The survey was conducted during the first 2 months of 2016, and 143 students of the Forestry Department of Central Greece took part. As a research tool the survey used self-report questionnaire which consisted of two parts. The first part is related to demographics of the sample, such as sex, age, urbanity region of origin, preference-selection line of the section and further containing two control questions of the students' knowledge on protected areas, which accept as answer the "Correct" "False" and "Do not know". These questions have created a knowledge survey variable, which graded with 1 each correct answer, and graded with zero each incorrect or the answer "Do not know". Therefore those who have not answered any question properly graded to zero, those who answered correctly only one question scored one, and those who correctly answered both questions were scored with two.

The second part concerned the FVS scale (Steel *et al.,* 1994), which covers forests and forest areas. The questionnaire was modified and adapted so as to respect IP, but without changing the spirit and the target of the questionnaire, which is to investigate the sample attitude towards the subject matter and to determine whether this is a humanistic (Anthropocentric), that is oriented to human needs and requirements, without paying emphasis to the environment, Intermediate, where the focus is on human and environmental needs and Biocentric balanced, which special emphasis is given on the environment and stated in this research with the variable FVS. The scale consists of eight statements Likert-type proposals from 1 (strongly disagree) to 5 (strongly agree). For the total score of the scale, the statements-sentences 1, 3, 4 and 5 has been reversed so that higher scores indicate biocentric attitude. The data is then aggregated, and ratings range from 8 to 40. Lower scores indicate anthropocentric attitude, mean score indicates balanced attitude, and a higher score shows biocentric attitude to PA and their use.

Three individual subscales can also be created for this global scale: humanistic, Intermediate, and biocentric. The humanistic subscale consists of items 1, 3, 4 and 5 and measures the anthropocentric attitude. The scores are summed and ranges from 4 to 20. Lower scores indicate more humanistic attitude. The Intermediate subscale comprised of the elements 2 and 6. The scores on this scale are summed and range from 2 to 10. Higher scores indicate neutral or stopover. The subscale Biocentric consists of items 7, 8 and measures the biocentric attitude. The scores are summed and range from 2 to 10. Higher scores indicate more biocentric attitude.

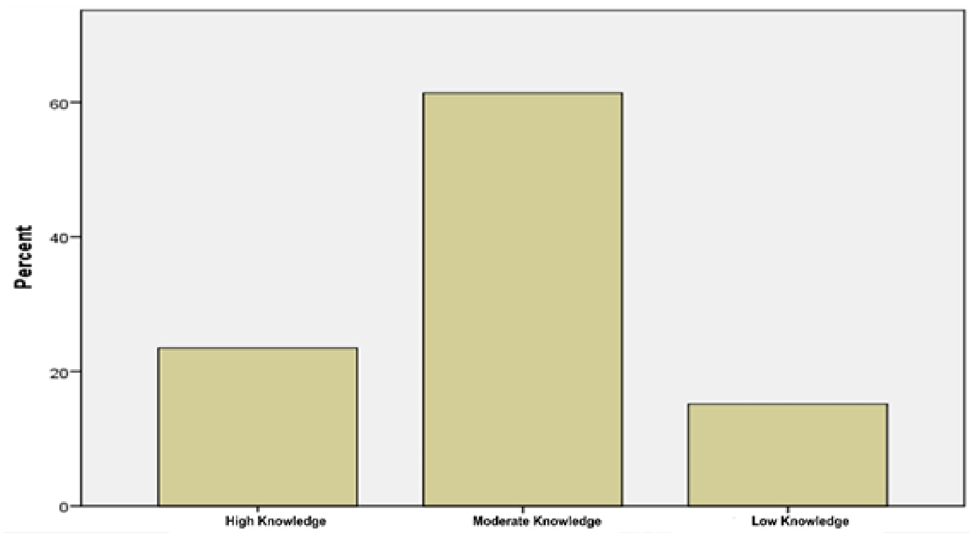
Cronbach a reliability index calculated above 0.80 in the initial study, meanwhile, for the sample this ratio was 0.43 and was considered low. Low alpha value may be due to the low number of questions-statements or low correlated or non-existence of data homogeneity (Tavkol & Dennick, 2011). Correcting reliability was done by excluding statements-proposals 2 and 3 of the FVS scale, bringing the Cronbach a to 0.71, which is a high value for the credibility of the research tool. Then an adjustment of the scoring scale, which now consists of six statements proposals, with a minimum score of 6 and a maximum 30 was made. This variable describes the three categories and the overall range from 6 to 30, is 24, therefore, the width of each class is 8. Scores in the range of 6-14 relate to anthropocentric attitude, scores between 15 and 22 relate to Intermediate and scores between 23 and 30 relate to Biocentric attitude. Finally, a sub scaling was carried out after remodeling concerning the following scales: Anthropocentric at 3-15, Intermediate 1-5, and biocentric 2 to 10.

3. RESULTS

In total 143 students participated in the research. Of these 90 (62.9%) were male, and 53 (37.1%) were female. The 19.3% resides in a settlement under 1500 inhabitants, the same percentage resides in the range of 1500 to 5000 inhabitants and 61.4 in settlement of over 5000 people. Attending the 1st, 3rd, 5th and 7th semester, respectively 28%, 39.9%, 18.9% and 13.3%. Students in order of preference of the department was from 1 to 5 choice in 42.1%, from 6 to 10 to 31.4% over the 26.4% 10th.

At questions of the students' knowledge on protected areas, from all the valid answers, 23.5% did not respond properly to any question, the 61.4% responded correctly to one question, while 15.2% answered correctly on two questions as shown in Figure 1. We can define, respectively, three knowledge categories as low, moderate and high knowledge as shown in Figure 1.

Figure 1: Knowledge Categories for Protected Areas



Source: Own Elaboration

Since all of the FVS-scale proposals statements, the answers cover the spectrum from Anthropocentric to biocentric attitude. If this variable describes the three categories, with a total range of 24, from 6 to 30, shows that scores of 6-14 related humanistic attitude, scores from 15 to 22 relate Stopover and scores from 23 to 30 relate biocentric attitude. Based on the categories of scores achieved, results that 7 people (4.9%) had a humanistic attitude, 61 (42.7%) had intermediate attitude and 75 (52.4%) had biocentric attitude, as shown in Table 2.

Table 2: Scores of FVS

Score	Freq.	%
12	5	3,5
13	1	,7
14	1	,7
16	3	2,1
17	1	,7
18	8	5,6
19	7	4,9
20	9	6,3
21	10	7,0
22	23	16,1
23	14	9,8
24	11	7,7
25	17	11,9
26	24	16,8
27	4	2,8
28	2	1,4
29	2	1,4
30	1	,7
Total	143	100,0

Source: Own Elaboration

A similar result occurs when separately examine each subscale. Specifically humanistic attitude based on the variable Anthropocentric, has 4.9% of the sample, while based on the variable Biocentric 52.4% have biocentric attitude, as shown in Table 3.

Table 3: Attitude FVS

	Freq.	Percent
Antropocentric	7	4,9
Intermediate	61	42,7
Biocentric	75	52,4
Total	143	100,0

Source: Own Elaboration

Demographic differences among of students were examined in FVS. After Levene control for gender variations, it was found that fluctuations were equal. It was found statistically significant differences in the averages of the scale in terms of gender, with females F = 4.05, p <0.05, in average. The average for men (M = 2.40, SD = 0.60) was lower than that of women (M = 2.60, SD = 0.57). Women show more biocentric attitude than men. It was not found statistically significant differences in the averages of the FVS variable for the other demographic characteristics examined.

There were differences of averages in the variable FVS regarding the level of knowledge, which is related to the attitude of the students towards the environment. After Levene control for gender variations, it was found that fluctuations were unequal and t test was used to correct it. We found statistically significant differences in the averages of the scale to the level of knowledge about Protected Areas (F = 4.99, p <0.05) in average. The average of those with a low level of knowledge (M = 2.19, SD = 0.75) was lower than those with medium level of knowledge (M = 2.58, SD = 0.50). Those who have a low level of knowledge about Protected Areas, have more humanistic attitude towards those who have moderate knowledge level (Table 4). It was not found statistically significant differences in the averages of the variable FVS sample for other knowledge levels tested.

Table 4. Control of averaging differences of FVS regarding sex

<table>
<tr><td>FVS/Knowledge</td><td>N</td><td>Mean</td><td>SD</td><td colspan="4">FVS - Bonferroni</td></tr>
<tr><td>Low Knowledge</td><td>31</td><td>2,19</td><td>0,749</td><td rowspan="2">(I)
Low
Knowledge</td><td rowspan="2">(J)
Moderate
Knowledge</td><td>(I-J)</td><td>Sig.</td></tr>
<tr><td>Moderate Knowledge</td><td>81</td><td>2,58</td><td>0,497</td><td>-0,387*</td><td>0,05</td></tr>
<tr><td>High Knowledge</td><td>20</td><td>2,45</td><td>0,605</td><td></td><td></td><td></td><td></td></tr>
</table>

*. The mean difference is significant at the 0.05 level

Source: Own Elaboration

There were differences of averages controls the variable FVS regarding the level of knowledge. The other demographic characteristics of the sample were investigated without finding statistically significant differences.

4. CONCLUSIONS

The results of this survey revealed that the majority of the sampled students show more biocentric attitude to Protected Areas which is largely due to the object of their studies. Differences between male and female respondents are statistically significant. Women were more sensitized towards the environment, showing more biocentric attitude than men. This result is in agreement with results of analogous investigations where «Girls tend to have more favorable attitude towards the environment» (Ntouras, 2013). These findings are consistent with those of other researcher, indicating that such behavior could be seen as a way to take care of their children and socialization based on family (Tikka *et al.,* 2000; Sutton & Kemp, 2002). According to Tikka, Kuitunen & Tynys, (2000), "the concern felt by women for nature and the environment could be seen as a way to take care of their children, because a clean and safe environment is a prerequisite for prosperity and survival" (Ntouras, 2013). According to Müderrisoğlu & Altanlar (2011) female undergraduate students tend to hold significantly more positive attitudes towards the environment. According to the results of this study, students largely support positive environmental attitudes.

Alp, Ertepinar, Tekkaya and Yilmaz (2006) showed a statistically significant effect of the degree of environmental knowledge in environmental attitudes of students (Ntouras, 2013) corroborating with the results of the present study.

The oldest conceptions of Protected Areas was the absolute protection of them and the exclusion of human activities (Hatziharalambous, 2006). This perception gradually proved exaggerated or even wrong (Karavellas *et al.,* 2003). Gradually, new attitudes have emerged in relation to strategies which aimed to facilitating of local participation, where the competent authorities manage natural resources with local value (Francis, 1996; Conway, 1997; Mehta & Heinen, 2001; Nepal, 2002; Tampakis, 2009). Perceptions of local people contain useful information's that could be incorporated into the decision making process and lead to the reduction of conflicts (Trakolis, 2001).

4.1 Limitations and future research

Although we used both online survey and paper pencil format, we did not succeed in accessing as large a sample of farmers as we had wished. We should aim to conduct interviews with farmers to gain more information about meadow management in practice. About the research of knowledge's level although we didn't use a comprehensive and complete research tool, there were only two questions with three possible answers. Therefore the probability of accidental correct response is important and can influence all of the answers which given. Further research with comprehensive research tool of knowledge is required to be implemented. Nevertheless, despite the limitations mentioned, the existence of a relationship between the level of knowledge about Protected Areas and the attitude towards the environment, agree with the results of other investigations. Specifically, the research of Hausbeck, Milbrath & Enright (1992), found that although the students had rather low scores on questions of knowledge, showed higher scores for awareness and concern for the environment.

This study examined the attitudes and knowledge of students studying the natural and forest environment. The next step will be a comparison of the current results with students of Landscape Architecture that have more anthropocentric field of study and then link the findings of the research with the environmental education practice. The findings have important value for teachers of secondary and higher education who study and teach environmental issues. Experience has shown that the development and design of appropriate educational material to high school students in Cyprus increased positive attitudes of students towards the environment (Chatzichampis *et al.,* 2016).

REFERENCES

Ajzen, I. and Fishbein, M. (2000). Attitudes and the attitude-behaviour relation: reasoned and automatic processes. *European Review of Social Psychology*. 11(1): 1-33.

Alp, E., Ertepinar, H., Tekkaya, C. and Yilmaz, A. (2006). A statistical analysis of children's environmental knowledge and attitudes in Turkey. *International Research in Geographical and Environmental Education*. 15(3): 210-223.

Breiting S., Mayer, M. and Morgensen, F. (2005). *Quality Criteria for ESD-Schools*. ENSI, Vienna.

Chatzichampis, A., Manolis, K., Johnson, B. and Mappouras, D. (2016). National results for the conceptual understanding of the trophic relationships of organisms to environmental attitudes of pupils in first grade under the new detail programs Biology of Cyprus. In: P.

Stasinakis (ed.), *Proceedings 9th Panhellenic Congress "Environment and Man"*. Greek Alliance Biosciences, Athens, 1: 126-131.

Conway, K. (1997). *Gender and culture influences on attitudes towards National Park Punta Izoto, Honduras: An Assessment for Participatory Conservation and Management*. Master Thesis. University of Florida, Gainesville.

Efthimiou, G. (2015). The protected areas management in Greece. In: E. Manolas (ed.), *Environmental Policy: Theory and Practice*. School of Forestry and Environmental Management and Natural Resources, Democritus University of Thrace, Orestiada. Greece. 1: 64-75.

Flogaiti, E. (2006). *Education for the environment and sustainability*. Athens Greek letters.

Francis, M. (1996). Community involvement and the management of vegetation in selected communal areas in Zimbabwe. In: Bihini Won wa Musiti (ed.), *1996 Pan African symposium on sustainable use of natural resources and community participation*. IUCN, Harare.

Frick, J., Kaiser, F.G. and Wilson, M. (2004). Environmental knowledge and conservation behavior: Exploring prevalence and structure in a representative sample. *Personality and Individual Differences*. 37(8): 1597-1613.

Gough, A. (2006). Sustainable schools in the UN decade of education for sustainable development: meeting the challenge? *Southern African Journal of Environmental Education.* 23: 48-63.

Hatziharalambous, E. (2006). *Protected areas of Drama: Valuable natural capital for sustainable development of the county.* Developmental Drama Conference, 3rd Thematic Field Environment - Tourism Culture. Drama.

Hausbeck, K., Milbrath, W.L. and Enright, M.S. (1992). Environmental knowledge, awareness and concern among 11th-grade students: New York State. *The Journal of Environmental Education*. 24(1): 27-34.

Henderson, K and Tilbury, D. (2004). *Whole-School approaches to sustainability: an international review of sustainable school programs*. Report prepared by the Australian Research Institute in Education for Sustainability (ARIES) for the Department of the Environment and Heritage, Australian Government, Melburn.

Huckle, J. (2010). ESD and the Current Crisis of Capitalism: Teaching beyond Green New Deals. *Journal of Education for Sustainable Development*. 4: 135-142.

Hwang, Y.H., Kini, S.I. and Jeng, J.M. (2000). Examining the causal relationships among selected antecedents of responsible environmental behaviour. *The Journal of Environmental Education*. 31(4): 19-25.

Jobes, P. (1991). The Greater Yellowstone social system. *Conservation Biology*. 5(3): 387-394.

Karavellas, D., Katsadorakis, G., Maragou, P., Nantsou T. and Svoronou, E. (2003). *Protected Areas Management: Best Practice Guide*. WWF ELLAS. Athens.

Lavonen, J., Byman, R., Uitto, A., Juuti, K. and Meisalo. V. (2008). Students' interest and experiences in physics related themes: Reflections based on ROSE-survey in Finland. *Themes in Science and Technology Education*. 1(1): 7-36.

Matzanos, D., Xanthaki, Y., Papavasileiou, B., Papadomarkakis, I. and Nezam, J.J. (2012). Knowledge and attitudes graduate high school students in protected areas. *5th National Conference on Environmental Policy and Management*. Department of Environment, University of the Aegean, 25-27 May 2012, 94-112.

Matzanos, D., Xanthaki, Y., Papavasileiou, B. and Papadomarkakis, I. (2010). Protected Areas: knowledge and students 'attitudes of primary school Archangel - Rhodes'. *1st National Conference on Local Communities and Higher Education Programs: Coexistence of*

Sustainable Management. Rhodes, 23-24, April 2010. (Acceded in 8 of August 2016, on the Web site: http://www.rhodes.gr/userfiles/f3d32225-c364-4819-aea4-00cf65c58887/MatzanosDimitrios.pdf

Mehta, J.N. and Heinen, J.T. (2001). Does community-based: conservation shape favorable attitudes among locals. An empirical study from Nepal. *Environmental Management*. 28: 165-177.

Mose, I. and Weixlbaumer, N. (2007). A new paradigm for protected areas in Europe? In: I. Mose (ed.), *Protected areas and regional development in Europe: towards a new model for the 21st century.* Ashgate, Aldershot, 3-20.

Müderrisoğlu, H. and Altanlar, A. (2011). Attitudes and behaviors of undergraduate students toward environmental issues. *International Journal of Environmental Science and Technology.* 8(1): 159-168.

Nepal, S.K. (2002). Involving indigenous peoples in protected area management: Comparative perspectives from Nepal. Thailand, and China. *Environmental Management*. 30: 748-763.

Ntouras, K. (2013). *Environmental Attitudes of Larisa's Technological Education*. T.E.I. of Thessaly, Karditsa.

Reading, R.P., Clark, T.W. and Kellert, S.R. (1994). Attitudes and knowledge of people living in the greater Yellowstone ecosystem. *Society and Natural Resources*. 7: 349-365.

Papadomarkakis, I., Xanthacou, Y., Matzanos, D., Papavasileiou, V. and Simina, V. (2011). Field study of the valley of Aithona in Rhodes: postgraduate students' knowledge and attitudes. *Proceedings of the 12 International Conference on Environmental Science and Technology.* Rhodes, Greece, 8-10 September 2011, 1: 1424-1431.

Papapanagou, E., Tiniakou, A. and Georgiadis, T. (2005). Environmental education as a management tool in protected areas: the Messolongi wetlands example (Western Greece). In: Lekkas, T.D. (ed.), *Proceedings of the 9th International Conference on Environmental Science and Technology.* Rhodes, Greece, 1-3 September, 688-693.

Sutton, S.E. and Kemp, S.P. (2002). Children as partners in neighborhood place making: Lessons from intergenerational design charrettes. *Journal of Environmental Psychology*. 22: 171-189.

Steel, B.S., List, P. and Schindler, B. (1994). Conflicting values about federal forests: A comparison of national and Oregon publics. *Society and Natural Resources*. 7: 137-153.

Tampakis, S. (2009). Protected Areas: The policies of yesterday and today. In: Manolas, E. (ed.), *Issues of Forestry and Management of the Environment and Natural Resources*. Democritus University of Thrace, Orestiada, 1: 151-165.

Tavakol, M. and Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education*. 2: 53-55.

Tikka, P.M., Kuitunen, M.T. and Tynys, S.M. (2000). Effect of educational background on students' attitude, activity levels and knowledge concerning environment. *The Journal of Environmental Education*. 31(3): 12-19.

Trakolis, D. (2001). Perceptions, preferences and reactions of local inhabitants in Vikos-Aoos National Park, Greece. *Journal of Environmental Management*. 28: 665-676.

NEW METHODS FOR RESILIENT SOCIETIES: THE GEOGRAPHICAL ANALYSIS OF INJURY DATA

Eric Vaz[1]
Jessica Miki[2]
Teresa de Noronha[3]
Michael Cusimano[4]

ABSTRACT

In this paper an empirical assessment of injury patterns is supplied as an example of social endurance - resilient societies can be built by means of geographical analysis of injury data, providing better support for decision makers regarding urban safety. Preventing road traffic collisions with vulnerable road users, such as pedestrians, could help mitigate significant loses and improve infrastructure planning. In this sense, the geographical aspects of injury prevention are of clear spatial analog, and should be tested regarding the carrying capacity of urban areas as well as vulnerability for growing urban regions. The application of open source development tool for spatial analysis research in health studies is addressed. The study aims to create a framework of available open source tools through Python that enable better decision making through a systematic review of existing tools for spatial analysis. Methodologically, spatial autocorrelation indices are tested as well as influential variables are brought forward to establish a better understanding of the incremental concern of injuries in rural areas, in general, and in the Greater Toronto Area, in particular. By using Python Library for Spatial Analysis (PySAL), an integrative vision of assessing a growing epidemiological concern of injuries in Toronto, one of North America's fastest growing economic metropolises is offered. In this sense, this study promotes the use of PySAL and open source toolsets for integrating spatial analysis and geographical analysis for health practitioners. The novelty and capabilities of open source tools through methods such as PySAL allow for a cost efficiency as well as give planning an easier methodological toolbox for advances spatial modelling techniques.

Keywords: Open Source, Spatial Analysis, Resilience, Geographic Analysis, Spatial Decision Support Systems, Python.

JEL Classification: I10, I18, C31

1. INTRODUCTION

Since the late 1960s GIS and spatial analysis statistics has been used to effectively model, study, and interpret results of geographic phenomena with spatial dimensions and associated attributes (Burrough, 2001). They are commonly used in the City of Toronto (2014) for informed and enhanced decision making through: (i) evaluating suitability and capability,

[1] Department of Geography and Environmental Studies, Ryerson University, Toronto, ON, Canada. Research Centre for Spatial and Organizational Dynamics, University of the Algarve, Faro Portugal. evaz@ryerson.ca
[2] Department of Geography and Environmental Studies, Ryerson University, Toronto, ON, Canada. jessica.miki@ryerson.ca
[3] Faculty of Economics, University of the Algarve, Faro, Portugal. Research Centre for Spatial and Organizational Dynamics, University of the Algarve, Faro Portugal. mtvaz@ualg.pt
[4] Department of Neurosurgery University of Toronto, Toronto, ON, Canada. St. Michael's Hospital, Toronto, ON, Canada. cusimanom@smh.ca

(ii) estimating and predicting, and, (iii) interpreting and reorganizing of information. In this sense, further implementation of geographical analysis can be brought by integration of spatial analysis standards, where implementation of better decisions geared towards protection of citizens and fostering better analytics may have a leading role in mitigation of injuries (Vaz *et al.*, 2016). Cost efficiency of exploring novel techniques for adapting new tools must be considered, given the budgetary constraints of commercial software licenses, open source may become important analytical tools to mitigate the concerns of injuries in a growing region.

Every year close to 1 per cent of Canadians are injured in a road traffic incident (Andrey, 2000). Within Canada, Toronto has the highest motor vehicle collision injury rate, in the past decade alone, there were more than 20 deaths per year, and the pedestrian and cyclists' collisions with cars generated direct costs of $62 million (IndEco Strategic Consulting Inc., 2012). Road traffic accidents strain social, infrastructure, and health care systems and represent thus an incremental cost to society. Per Transportation Canada (2014) in 2009 a total of 2009 fatalities and 1145 serious injuries were registered in road traffic accidents. The city of Toronto (Toronto Public Health, 2012) identified road traffic accidents as the leading cause of death in youth for 2010. Approximately 25% of all road traffic fatalities in Canada are described as vulnerable road users, with 13% of all fatalities being pedestrians (Transport Canada, 2014).

We present three distinct spatial analytical applications as to address the complexity of injuries within the study region. Our paper is structured as follows: (i) In a first section we test the capability to visualize and describe collision information and visualize the data. Due to the sensitivity of the health information, collision points were aggregated as injury counts within Toronto neighbourhoods. The second part focuses on efficient assessment of high and low descriptives of collision neighbourhoods, followed by applications of spatial autocorrelation through the implementation of Global and Local Moran's I statistics. Finally, and most importantly, we establish a framework for Toronto on the socio-economic profile of neighbourhoods, adopting a Geographically Weighted Regression (GWR) model. For the definition of the socioeconomic study the factors were derived by the city of Toronto's open data portal, much in line with the avenue this study procures, in addressing a open source framework for spatial analysis. The following sections lead to a discussion of findings as well as conclusions, were we incorporate the broader picture of applications within public health participation with more advanced spatial analysis tools to efficiently plan regions.

Ours is a Python based modelling approach. These have proven efficient to answer social, economic and environmental concerns. While many of these programming languages require an advanced knowledge of programming and scripting making the learning curve steep, novel geocomputational methods are steering towards simplified syntaxes that allow laymen work together with experts and bring efficient and simple solutions. The Python Spatial Analysis Library (PySAL) was used to develop the study and generate tools to widen scientific applications (Rey *et al.*, 2008). This paper takes a systematic approach to understand the contribution of such tools for public health. PySAL is used as to integrate spatial analysis methods and assessing this instrument for the applied public health sector. Open source software and practices offer major advantages for applying spatial analysis to multifaceted research activities. The variety of open source tool sets can be used to further explore, educate, and empower researchers and general users. The openness cultivates a greater culture of knowledge sharing through transparent, adaptable, portable, and modularity coded processes (Ertz, Rey & Joost, 2014). PySAL and other open source software can be freely installed on personal and institutional devices, offering greater access than traditional predesigned software packages. Within a growing body of digital data, where spatiotemporal availability and locational accuracy is exponentially growing, such tools may set new benchmarks for the general public as well as very specific silos of application. This study focused on car collisions and the resulting injuries on pedestrians. The complexity of this problem represents the ideal laboratory to forward a clear geographical analytical application of a concern that has not been explored in the Greater Toronto Area from a spatial analysis stance.

2. STUDY AREA

The study will focus on the neighbourhoods of the municipality of Toronto. In the year 2011, the city of Toronto had an estimated population of 2,615,060 residents (Statistics Canada, 2014). The City of Toronto composes of 630.21 square kilometers, and has a population density of 4,150 persons per square kilometres (Statistics Canada, 2014). The population densities are significantly greater than the national value of 4 persons per square kilometers (Statistics Canada, 2014), and creates a strong activity center for Canada. The Greater Toronto Marketing Alliance (2011) describes the Greater Toronto Area as the fourth largest business and manufacturing region in North America. This economic region supports the second largest automotive centre in North America, and 21 out of Canada's top 30 law firms. These are key industries that can benefit from collision mapping and prevention to improve automotive safety and insurance claims. Improving road safety has long established economical and holistic benefits as the 25-year capital program includes a $50 billion rapid transit plan with Metrolinx to spread the transit systems within 2 kilometers within 80% of the city's residents (Greater Toronto Marketing Alliance, 2011). Improving transit infrastructure is a key priority as regional planning will have to accommodate for demographic changes. A prominent population trend observed by Statistics Canada (2015) is the increasing immigrant population that maintains Toronto's population and urban growth (Vaz & Arsanjani, 2016). Their report suggests that immigrant population growth will have an impact on the regional infrastructure and planning demands (Vaz *et al.*, 2016). The growth in population and development can be observed through the 10.5% growth of private dwellings, to 1,989,705 Toronto dwellings, from 2006 to 2011 (Statistics Canada, 2014). This is a larger growth than the national change of 7.1% in private dwellings usually occupied by residents (Statistics Canada, 2014), and show cases Toronto's strong demand for strategic and sustainable infrastructure planning. In order to generate more information for better decision and policy making in the dynamic city of Toronto the neighbourhoods will be used as they study boundaries.

3. DATA

Collision data from 2002 to 2013 were collected by the Canadian Institute for Health Information (CIHI). Inconsistent entries for the year 2013 are also included, and lack geographical referenced coordinates as well as other key values. The information helps to support effective healthcare systems management, distribute health information, and raise awareness for public health initiatives (Canadian Institute for Health Information, 2015). As health data contains sensitive information rounding values can be used to generalize the information. In this data set International Classification of Diseases (ICD) has been used to describe the injury incident. The ICD are World Heath Organization (2015) standard diagnostic tools used in epidemiology, health management, and clinical processes to classify health problems by type and severity. These ICD tags were used to identify and select the desired collision entries for this analysis. ICDs for motor vehicle collisions with pedestrian, and motor vehicle collisions with pedestrians for 2010 were selected using a SQL query and exported into separate data sheets. The georeferencing information from the data sheets, described as 'x' and 'y' coordinate values, was input into ArcGIS for visualization and to spatially join the collision incidents to their respective Toronto neighbourhoods. Neighbourhood shapefiles were obtained from the City of Toronto's Open Data catalogue (Toronto Open). The City of Toronto (2015) and Statistics Canada census tracts use these neighbourhood boundaries to statistically report and perform longitudinal studies as the boundaries do not change over time. Neighbourhoods offered a meaningful geographic area for effective community planning and aggregation level for the health data. Neighbourhoods built from the Statistics Canada census tracts cover several city blocks with 7,000 to 10,000 residents, and respect existing boundaries (The City of Toronto, 2015a). These boundaries are used for the Wellbeing Toronto web application, released to also help users visualize and evaluate community social development datasets (The City of Toronto, 2015b). The year 2010 was chosen as it complements the study completed by the City of Toronto and associated public health analysis. As a guiding framework for spatial analysis of public health data it was important to utilize open source data sets and tools. All the methodology and data steps were completed in open sours programs. The socio-economic data was collected from Toronto open data portal. As identified in the literature review, gender, education levels, employment status, annual income, and age can influence the number and frequency of pedestrian road collisions. Socio-demographic data was collected from the Toronto Open. The data was collected from the 2006 and 2011 census, and processed into Toronto neighbourhood boundaries (The City of Toronto, 2014). The neighbourhood identity numbers were used to join socio-demographic files to the geographic shapefiles of Toronto neighbourhoods, also provided by the Toronto Open data team. The data has been processed from the census values, and have been processed by Statistics Canada (2010 source) to normalize the data. To identify any correlated socio-economic factors that may add statistic bias to the study analysis the database file with the determinant factors and neighbourhood identities were standardized and correlated through R studio statistic software. R studio is another open source development platform that utilizes coding for statistical analysis.

4. METHODS

The study outlines an effective and feasible framework for spatially analyzing health data. It utilizes PySAL and R packages, followed by QGIS for visualization purposes. Initially QGIS is used to map collision frequency of Toronto neighbourhoods. Global spatial autocorrelation was then generated in PySAL to identify patters of collision frequency and severity. PySAL was also used for the local Moran's I spatial autocorrelation analysis to identify patterns of collisions correlation within the neighbourhoods. To identify any explanatory factors R studio was used to select socio-economic factors for the geographic weighted regression (GRW) analysis testing in PySAL. PySAL has multiple geographical weighted regression models available. To maintain simplicity for users, the Ordinal Lease Squares (OLS) with geographic weight matrix method was used to measure the similarity of the socio-economic factors to model the collision frequencies. The results can be used to identify potentially vulnerable road users and areas that can be targeted for improving road safety. The framework can then be used to help introduce spatial analysis tools into healthcare analysis, as well as other industries that would greatly benefit from affordable and accessible toolsets.

4.1 Visualizing neighbourhood collision incidents

Before using the code based statistical packages it is useful to visualize the collision data. Map visualization helps users evaluate geographic datasets and better comprehend community health indicators (The City of Toronto, 2015b). This initial objective was completed through spatially joining collisions to their respective neighbourhoods and demographic profiles. From the database file as a spreadsheet or attribute table ArcMap application, the rate of traffic collisions per residential population count could be calculated (Table 1).

Table 1. Top 13 collision counts in neighbourhoods from 2010

Neighbourhood identity number	Neighbourhood name	Residential population	Pedestrian collisions	Collision frequency rate	Collisions per 1000 residents
1	West Humber-Clairville	32265	23	0.0007	1
136	**West Hill**	**25635**	**21**	**0.0008**	**1**
70	**South Riverdale**	**24430**	**19**	**0.0008**	**1**
73	**Moss Park**	**15480**	**18**	**0.0012**	**1**
116	Steeles	24705	18	0.0007	1
132	Malvern	44315	18	0.0004	0
75	Church-Yonge Corridor	24370	17	0.0007	1
126	Dorset Park	24365	17	0.0007	1
137	Woburn	40845	17	0.0004	0
2	Mount Olive-Silverstone-Jamestown	32130	16	0.0005	0
26	Downsview-Roding-CFB	32010	16	0.0005	0
93	Dovercourt-Wallace Emerson-Juncti	34725	16	0.0005	0
129	Agincourt North	30160	16	0.0005	1

Source: Own Elaboration

In order to make the rate more comparable the frequency of collisions per resident was then applied to identify how many collisions would occur for every 1,000 residents. The largest 10 values of collision count and collision frequencies was organized into table 2. The summary table demonstrates that neighbourhoods with high collision counts do not consistently have a high frequency of residential and motor vehicle collisions. Of the highest values observed in 13 and 11 neighbourhoods, only the West Hill (136), South Riverdale (70), and Moss Park (73) have high collision counts and frequencies. This may be because Toronto has a high transient population that is not counted within the residential population. Toronto has a high commuting population, and as previously identified many trips can be achieved through active transportation modes. Research also suggests that in areas with high active transportation concentration there are less motor vehicles to cause collisions. The map and regression analysis can help to further identify any contributing collision factors and areas that can be targeted for improving conditions.

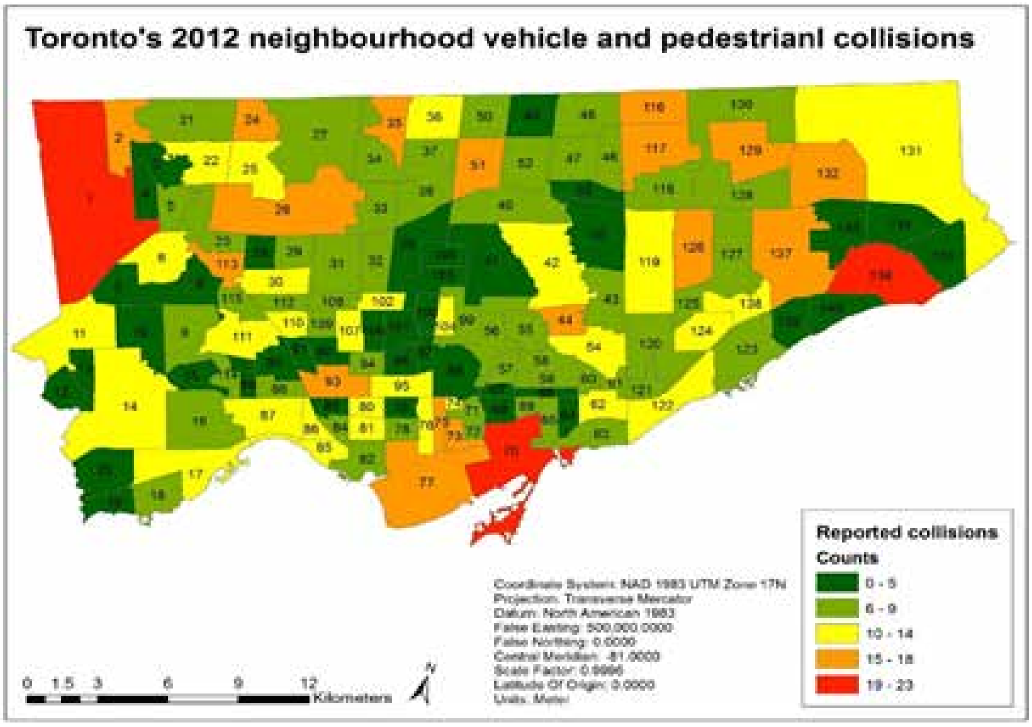
Table 2. Top 11 collision frequencies in neighbourhoods from 2010

Neighbourhood identity number	Neighbourhood name	Residential population	Pedestrian collisions	Collision frequency rate	Collisions per 1000 residents
73	**Moss Park**	**15480**	**18**	**0.0012**	**1**
110	Keelesdale-Eglinton West	11225	11	0.0010	1
113	Weston	16470	14	0.0009	1
22	Humbermede	14780	13	0.0009	1
114	Lambton Baby Point	7780	7	0.0009	1
112	Beechborough-Greenbrook	6530	6	0.0009	1
136	**West Hill**	**25635**	**21**	**0.0008**	**1**
70	**South Riverdale**	**24430**	**19**	**0.0008**	**1**
44	Flemingdon Park	21290	16	0.0008	1
30	Brookhaven-Amesbury	17325	13	0.0008	1
86	Roncesvalles	14650	11	0.0008	1

Source: Own Elaboration

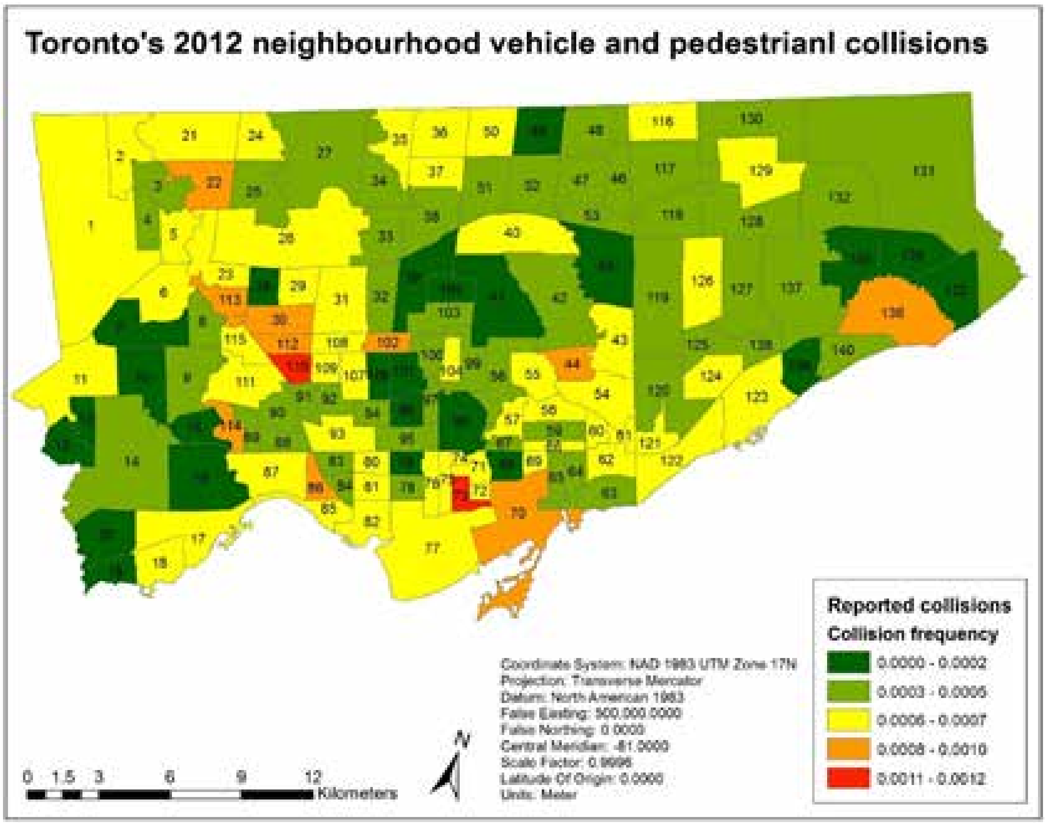
The collision counts and frequencies were mapped in ArcMap to produce figures one and two. Figure 1 maps the collision counts in each neighbourhood, while figure 2 maps the rate of collisions over the residential population. The maps effectively colour the regions with equal interval values that can be used to start to generate trend conceptual trends. Without more information, an accurate conclusion cannot be made about the pedestrian and vehicle collisions, a more thorough statistical analysis is needed to determine if the collision distribution is random or has any contributing factors.

Figure 1. ArcMap generated counts of the 2010 reported vehicle and pedestrian collisions in Toronto neighbourhoods



Source: Own Elaboration

Figure 2. ArcMap generated residential frequencies of the 2010 reported vehicle and pedestrian collisions and neighbourhoods' residential population



Source: Own Elaboration

4.2 Spatial weights in PySAL

In order to effectively run a spatial analysis, spatial weights will have to be used to give the location values of the data set a contextual meaning. As PySAL Developers (2015) data, spatial weights are central components for some spatial analysis techniques as the spatial weights matrix describes the potential for interaction between observations given their locations. Within the PySAL environment, spatial weight matrices can be generated through contiguity based weights, distance based weights, and kernel weights. In order to store the large datasets with a full matrix, and mitigate memory constraints, PySAL stores the matrices in two main dictionaries, respectively for neighbours and weights of each observation (PySAL Developers, 2014). This allows for PySAL to effectively generate weights for and accurate global spatial autocorrelation analysis. PySAL also allows for topology to accurately represent by generating spatial weights from shapefiles, as empirical research and non-topological vector data can be used to construct the weights before an analysis (PySAL Developers, 2014).

The queen contiguity spatial weight matrix was used to calculate the Moran's I value. The Geoda workbook by Anselin (2005) outlines that the queen contiguity is effective for areal or polygon data. This matrix type was able to include more wards in the analysis than the alternative spatial weight matrixes. In order to maintain accuracy, the weight matrix was generated from the shapefile.

4.3 Global Spatial Autocorrelation

Spatial autocorrelation can be used to identify spatial patterns and geographic relationships between features in space. Spatial autocorrelation techniques have been developed and used to measure non-random spatial patterns of attribute values (PySAL Developers, 2014). Two commonly used techniques focus on observing the global spatial autocorrelation and the local spatial autocorrelation. Global spatial autocorrelation reviews variable values to identify any patterns of clustering across the study area (Chun & Griffith, 2013). Local spatial autocorrelation reviews regions within global patterns of clusters (Bivand, 2015), described as hot or cold spots for high and low respective values (Ord & Getis, 1995). Relationships that cluster similar values have a positive autocorrelation; while negative autocorrelations have clusters of dissimilar values (PySAL Developers, 2014). If there is not a significantly positive or negative correlation, then the arrangement of values can be concluded as random.

Ord-Getis (1995) and Chun and Griffith (2013) identify that global Moran's I can be used to effectively measure the correlation of spatial features. PySAL's Moran's I for global spatial autocorrelation has been described in equation 1. Where n is the total number of features, y the attribute, the attribute's deviation from feature i, and i's mean generates z_i (equation 2), $w_{i,j}$ is the spatial weight between features i and j, S_0 is the aggregate of all the spatial weights, calculated as a Moran's I value from -1 to 1. A Moran's I value of 1 indicates that features are positive autocorrelation; and a -1 value indicates that features are dispersed in a negative spatial autocorrelation (Bivand, 2015). While a value of 0 suggests that features have no significant relationship, and are randomly distributed with no spatial autocorrelation. The significance of the Moran's I can be described through the z-score value. A z-score greater than 1.96 or less than -1.96 concludes that the spatial autocorrelation has a significance level of 5% (0.05) (ESRI, 2009). If the significance level is above 5% it is unlikely to be a result of a random distribution. The Moran's I pseudo significance level (p-value) can also be used to determine if a sample has statistical significance (Anselin, Exploring Spatial Data with GeoDA: A Workbook, 2005); with a confidence level of less than 0.05. If the p-value is greater than 0.05 then the sample is random and does not have a statistically significant spatial autocorrelation.

Equation 1. Global Moran's I (PySAL Developers, 2014)

$$I = n/S_0 \frac{\Sigma_i \Sigma_j z_i w_{i,j} z_j}{\Sigma_i z_i^2}$$

Equation 2. Global Moran's I attribute information (PySAL, 2014)

$$z_i = \gamma_i - \overline{\gamma}$$

To further identify statistically significant collision clustered areas, objective two utilized global and local spatial autocorrelation Moran's I analyses. The results (table 3) suggest that the collisions occur randomly with low spatial autocorrelation patterning. Global significance from the instance was measured through the z-score as 0.72, and the positive spatial autocorrelation has a 0.47 p-value confidence, suggesting that the pattern is randomly distributed. The numeric values are extremely direct in conveying the low statistical significance of the collision incidents. PySAL returned 14 significant digits, offering a very precise and statistical analysis for a variety of study applications.

Table 3. Global Moran's I Summary Statistics

Global Moran's tests	Value	Interpretation
I	0.028	Weak positive spatial autocorrelation
Expected I	-0.007	Weak negative spatial autocorrelation
Z-score	0.722	Likely to be random distribution
Pseudo P-value	0.470	Random insignificant spatial autocorrelation

Source: Own Elaboration

4.4 Local Spatial Autocorrelation

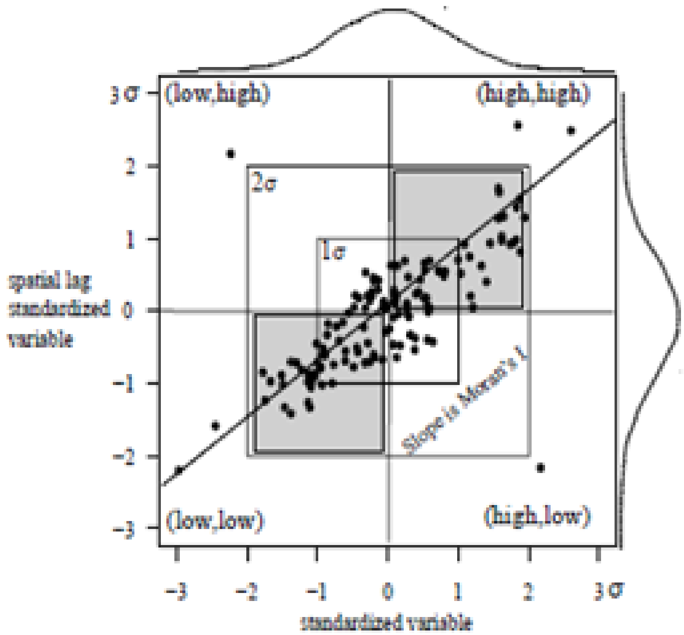
To utilize PySAL in localized clusters local Moran's I statistical analysis was generated. Local Moran's I can be used to evaluate local measures of spatial variation and association (Anselin, 1995). The local Moran's I counts the collisions within a dissemination area and identifies if they are high or low cluster values. PySAL local Moran's I (equation 3) uses the same variables as the global statistic, described above.

Equation 3. Local Moran's I (PySAL, 2014)

$$I_i = \Sigma_j z_i w_{i,j} z_j / \Sigma_i Z_i Z_j$$

PySAL generates Local Indicators of Spatial Autocorrelation (LISA) statistics to quantitatively measure local spatial autocorrelation for Moran's I tests. LISA was used to indicate how many points were statistically significant (less than 0.05), with inferences of the collision values calculated through pseudo-p values for each LISA. The "Numpy" module extension was used to identify significant LISAs and then the indexing was used to find the quadrant of a Moran's scatter plot where each of the significant values would be placed. Figure 3 displays a positive autocorrelation of standardized sample of the scatter-plot, where the variable of interest (collisions) average against the neighboring values. The Moran's I value would be the slope of the line of best fit in the scatter plot (Ward & Gleditsch, 2007).

Figure 3. Standardized Moran's I scatter plot (Ward & Gleditsch, 2007)



Source: Own Elaboration

When running the local Moran's, I analysed all 140 wards were considered, then 16 statistically significant wards were identified through their LISA p-values (less than 0.05). These significant wards were selected though PySAL, and their respective plot quadrants were returned. As the majority of the significant values are in the third quadrant there is a significant amount of low values surrounding low observations. It can be concluded that the collisions are not concentrated in one geographic region. The regression analysis can be used to identify if there are any contributing factors within the neighbourhood.

4.5 Geographic Ordinal Lease Squares Regression

Spatial regression was used to identify any correlation between socio-demographic factors and collision rates. Factors that may influence collision rates include levels of; gender, age, education, income, occupation (get stats). In order to compare the collision frequency and socioeconomic factors the samples were transformed into percentages of the ward population. In PySAL spatial regression can be diagnosed through Anselin, Bera, Florax and Yoon (1996) Lagrange multiplier (LM) test. They used the Jarque-Bera method to develop a test for spatial dependency and heteroskedasticity that can be applied in socio-economic studies and urban environments.

In PySAL the Ordinal Least Square (OLS) spatial regression analysis is a Geographic Weighted Regression (GRW) analysis used to test for spatial autocorrelation of the collisions and socio-demographic variables. The OLS has been adapted with geographic weighted regression (GRW) considerations for local parameters, rather than global parameters to calculate the strength of fit a model has to a hypothesis (Gao & Li, 2011). The GWR equation calculates R^2 as the goodness of fit from 0 to 1, where 1 and high values represent a better fit model than 0 and low values. The geographic OLS (GOLS) statistics were generated from the queen weight matrix was used in Moran's I method to optimize the ward polygons. From the CSV file of the collisions (dependant) and independent variables were transformed into nx1 (dependant) and nx2 (independent or explanatory variables) arrays. Spatial weight from the Moran's I statistics was used to weight the CVS objects; no row-standardization was applied as the samples are already estimated.

The GOLS analysis offers insight into factors that contribute to collision rates. The R^2 and the adjusted R^2 value of 0.52 and 0.49 respectively, suggest that the model is not a strong fit for the study. In this simple application GOLS was applied to several different socio-economic factors to demonstrate the PySAL process. The socio-economic features included estimated populations of age groups, average family income, education levels, gender, and employment statuses. Each factor's correlation with collision injuries were measured through the GOLS analysis (table 4). The co-efficient and probability values suggest the strength and type of relationship the variables have on collision frequency (ESRI, 2009). Complimentary to the review of literature, the model identifies that collisions will increase by 82 counts for every one percent of growth in the population that has a grade 9 and below education. All education based factors had strong positive relationship with the collision counts, they had the largest respective coefficient value of all explanatory factors. Average family income had the smallest coefficient value, and negatively affected the collision frequency. Comparatively, all the other factors have a moderate influence on the collision counts; when all other variables remain constant (ESRI, 2009). Although only male, youth, adults, and employment rates had statistically significant probabilities that the explanatory factors were not random outcomes. All the other probabilities are greater than the designated 0.05 p-value, and may be random outcomes of this incident.

Table 4. GOLS Collision Factor Summary Statistics

Factor	Co-efficient	Probability	Interpretation
Men	20.4	0.05	Higher populations of men moderately increased collisions, statistically significant
Women	-11.1	0.31	Lower populations of women weakly increased collisions
Youth (19 years old and younger)	46.6	0.1×10^{-8}	Higher populations of youth moderately increased collisions, statistically significant
Adults (20 to 64 years old)	49.6	6.09×10^{-4}	Higher population of adults moderately increased collisions, statistically significant
Seniors (65 years old and over)	18.4	0.18	Higher populations of seniors moderately increased collisions
Grade 9 and below education	**82.1**	**0.16**	**Higher education levels strongly increased collisions**
College and certificate education	73.5	0.21	Higher education levels strongly increased collisions
Bachelor's degree and more education	80.7	0.17	Higher education levels strongly increased collisions
Employed	-27.9	0.03	Lower employment levels moderately increased collisions, statistically significant
Unemployed	9.87	0.79	Higher unemployment levels weakly increases collisions
Average Family Income	**-1.25×10^{-5}**	**0.21**	**Lower average income weakly increased collisions**

Source: Own Elaboration

4.6 PySAL Regression Diagnostics

In the OLS regression report diagnostic statistics are also included. The diagnostic statistics can be used to quantify the confidence the GOLS method has in modeling the collision patterns and factors. As the multicollinearity condition number is 779.33 and the regression diagnostic statistics are irregular, it can be concluded that this model offers a weak fitted regression analysis (table 5). The Jarque-Bera normality of errors (JB) describes if residuals are normally distributed; a value under 0.05 (probability) identifies that the residuals are not normally distributed and the results have unreliable model misspecification (ESRI, 2009). In this incident the JB has a p-value of 0.29, meaning the GOLS model results are trustworthy and can be used to describe linear regression correlations. Supplementary to this diagnostic statistic, the Breusch-Pagan (BP) and Koenker-Bassett (KB) tests diagnostics for heteroskedasticity (Bivand, 2015). The random coefficients can be used to determine if the independent (explanatory) variables have a consistent relationship with the collision (dependant) counts (ESRI, 2009). As the BP p-value is significant (0.04) and the KB is not significant (0.11) the heteroskedasticity and non-stationary conditions cannot confidently be accepted.

Table 5. GOLS Regression Diagnostics Summary

Test	Degrees of freedom	Statistical value	P-value	Interpretation
Jarque-Bera normality of errors	2	2.41	0.29	Acceptable GOLS report
Breusch-Pagan test diagnostics for heteroskedasticity random coefficients	11	20.3	0.04	Acceptable GOLS report
Koenker-Bassett test diagnostics for heteroskedasticity random coefficients	11	16.9	0.11	Flawed GOLS report

Source: Own Elaboration

PySAL generates multiple OLS regression statistics, as well as additional test linear regression a spatial diagnostic test can be generated. All of the PySAL LM tests run in the residuals to identify the presence of remaining spatial autocorrelation of an OLS model, and suggest an accurate spatial model (PySAL Developers, 2014). In PySAl there are 5 types of spatial models: simple and robust spatial lag; simple and robust spatial error; and joint presence of spatial lag with spatial error model (PySAL Developers, 2014). Each tests in the residuals return the statistic and p-value that can be used to identify an alternative model with a better fit for more accurate analysis (PySAL Developers, 2014).

5. DISCUSSION AND CONCLUSIONS

While this study explores research relevant to car collision prevention within a neighbourhood scale the methods can be adapted into areas such as physical sciences, social sciences, health, tourism, planning, tourism, and more. This study of neighbourhood collisions may contribute to the trends in net health studies for trends of public health studies are identified as: social or racial health inequalities; health policy development and disease control; sense of individual-based analysis for poor health; and exploration into GIS data (Diez Roux & Mair, 2010). These resources can be used to benefit policies and communities with targeted neighbourhood level features (Diez Roux & Mair, 2010).

Developing and active transportation network will improve infrastructure and connectivity of the participating GTA municipalities. Increased connectivity boosts the bike-ability and walkability of areas that have poor planning attributes, and associated negative effects. This planning strategy may also qualify municipalities for federal and provincial funding for long-term and larger scale building projects than previously possible. Larger scale funding and projects will have increased benefits for community and individual health (The City of Toronto, 2012). The city of Toronto (2012) describes large scale active transportation project as being able to decrease car collisions and noise pollution, while improving air quality.

The investments into improving road safety represent a small fraction of the estimated costs, and projects can be paired with other government structures for funding and strategies to control health care costs. For example, the Greater Toronto Area (GTA) municipalities can work with Metrolinx to construct and active transportation network (The City of Toronto, 2012). The City of Toronto (2012) also recommends projects for investing in active transportation infrastructure, lowering speed limits, and implementing advanced traffic signal systems. Better data collection and analysis should guide infrastructure improvements for promoting safer active transportation.

The sense of safety within a neighbourhood has been observed to positively influence the health and economic stability of an area. As forms of physical activity have positive effects on cases of mental illnesses and stress, the City of Toronto (2012) identifies stress reduction as a value-added asset of active transportation. Within Toronto, 27% of the population 15 years old and under in 2001 surveyed most days in their life were quite stressful or extremely stressful (The City of Toronto, 2012). Promoting active transportation lifestyles can introduce daily stress relieving forms of physical activity, and reduce the risk of chronic diseases (The City of Toronto, 2012). Real estate values are also dependent on the neighbourhood quality of life.

Finally, this study was designed to demonstrate the benefits of using PySAL and open source applications for spatial analysis methods. The functional method can be applied to different datasets types for exploring global and local spatial autocorrelation, and spatial regression. In this application, neighbourhood collision and wellbeing levels were examined to identify vulnerable road users and target infrastructure solutions within the neighbourhoods. The data was analyzed through python based spatial analysis library techniques, and utilized other ooen source software packages. This makes the study highly accessible to others for reviewing and building on the research presented.

Our research goals have been achieved: 1) To develop a PySAL based analysis for modeling collision condition; 2) To identify spatial patterns for injuries; 3) To measure pedestrian collisions within Toronto neighbourhoods. The first objective of spatially enabling the collision data introduces geovisualzition and the impact of spatial analysis for identifying regional trends. The second objective demonstrates the difference of global and local spatial autocorrelation of collision patterns. Areas of high and low collision frequencies were quickly identified, and accurately described using the statistics and unique weight file. The third objective generates an informative regression report for measuring the relationships that the socio-economic factors have with collision frequency. The regression report offers a strong selection of statistical tests that can be used to measure the fit of the model to the observed values. From the report it can be concluded that the study model can be improved with including more observations of collisions and contributing factors.

The city of Toronto and other planning authorities can use this information to design targeted traffic collision solutions. Other studies can also benefit from this process, Anselin, Syabri, and Kho (2006) have designed GeoDa open sourced examples for dealing with public health planning, economic development, demographic development, real estate analysis, and criminology reports. All these applications can help the City of Toronto to develop with a higher level of social wellbeing, and have been packaged into an open web based mapping platform. The City of Toronto (2015) promote the map portal as a tool for users to gain a better understanding of the neighbourhoods and community level planning initiatives. As Toronto continues to grow and develop it will need sustainable strategic planning for more accessible active transportation networks to accommodate the working and residential population demands. Active transportation has become a prominent feature in Toronto Public Health reports for road safety. The Toronto City Clerk (2012) identifies that several safety measures will be introduced over the next few years to try to mitigate vehicle collisions. Reducing speed limits and traffic calming features have been implemented in some residential neighbourhoods, and new target sites can be identified using spatial analysis methods demonstrated in this study.

As technologies and data continue to increase the demand and opportunities for spatial analysis will increase. Goodchild (2010) predicts that with the greater interaction of boundary domains and scientific disciplines spatial information will become more desirable and necessary. Previous studies suggest that this integration of spatial statistical methods is most effectively done through designing a framework (Anselin, Syabri & Kho, 2006). In line with these observations this paper aims to contribute to the increasing field of open source spatial analysis toolsets. The framework and commands can be used to desmonstrate the impact, feasibiliy, and overall necessity of PySAL and spatial analysis methods.

REFERENCES

Andrey, J. (2000). The automobile imperative: Risks of mobility and mobility-related risks. *The Canadian Geographer*. 387-400.

Anselin, L. (2005, March 6). *Exploring Spatial Data with GeoDA: A Workbook*. Retrieved from Geoda Center: http://geodacenter.asu.edu/systems/files/geodaworkbook.pdf

Anselin, L., Syabri, I. and Kho, Y. (2006). GeoDA: An Introduction to Spatial Data Analysis. *Geographical Analysis*. 5-2.

Bivand, R. (2015). *The Problem of Spatial Autocorrelation: forty years on*. CRAN.

Burrough, P. (2001). GIS and geostatistics: Essential partners for spatial analysis. *Environmental and Ecological Statistics*. 361-377.

Burrows, S., Auger, N., Gamche, P. and D., H. (2012). Individual and area socioeconomic inequalities in case-specific unintentinal injury mortality: 11-year follow-up study of 2.7 million Canadians. *Accident Analysis and Prevention*. 99-106.

Canadian Institute for Health Information (2015). *Vision and Mandate*. Retrieved from CIHI ICIS: https://www.cihi.ca/en/about-cihi/vision-and-mandate

Chun, Y. and Griffith, D. (2013). *Spatial statistics and geostatistics*. SAGE, Los Angeles, CA.

Ertz, O., Rey, S. and Joost, S. (2014). Open source dynamics in geospatial research and education. *Journal of Spatial Information Science.* 67-71.

ESRI (2009, April 25). *Interpretating OLS Results*. Retrieved from ESRI Resources: http://resources.esri.com/help/9.3/arcgisengine/java/gp_toolref/spatial_statistics_tools/interpreting_ols_results.htm

Gao, J. and Li, S. (2011). Detecting Spatially Non-Stationary and Scale-Dependent Relationships Between Urban Landscape Fragmentation and Related Factors Using Geographically Weighted Regression. *Applied Geography.* 292-302.

Goodchild. (2010). Twenty years of progress GIScience in 2010. *Journal of Spatial Information Science.* 3-20.

Greater Toronto Marketing Alliance. (2011). *Doing Business in the GTA*. Retrieved from Greater Toronto Marketing Alliance: http://www.greatertoronto.org/why-greater-toronto

IndEco Strategic Consulting Inc. (2012). *Road to health: Improving walking and cycling in Toronto*. Retrieved from IndEco: http://www.indeco.com/www.nsf/Ideas/road2health

PySAL Developers. (2014, July 25). *User Guide*. Retrieved from Pysal: https://pysal.readthedocs.org/en/v1.8/users/introduction.html

Statistics Canada. (2014, April 17). F*ocus on Geography Series, 2011 Census*. Retrieved from Statistics Canada Catalogue: https://www12.statcan.gc.ca/census-recensement/2011/as-sa/fogs-spg/Facts-csd-eng.cfm?LANG=Eng&GK=CSD&GC=3520005

The City of Toronto. (2012). *Road to Health: A Healthy Toronto by Design Report*. Staff Report Action Required, Toronto.

The City of Toronto. (2014, December 17). *Well Being Toronto*. Retrieved from Toronto Open Data Portal.

The City of Toronto. (2015a). *Neighbourhood Profiles*. Retrieved from Toronto demographics/

The City of Toronto. (2015b, May 10). *Wellbeing Toronto*. Retrieved from Toronto Social Development.

Transport Canada. (2014, 07 11). *Road Safety in Canada*. Retrieved from Government of Canada.

Vaz, E. and Arsanjani, J. (2015). (2015). Predicting Urban Growth of the Greater Toronto Area-Coupling a Markov Cellular Automata with Document Meta-Analysis. *Journal of Environmental Informatics.* 25(2): 71-80.

Vaz, E., Zhao, Y. and Cusimano, M. (2016). Urban habitats and the injury landscape. *Habitat International.* 56: 52-62.

Vaz, E., Anthony, A. and McHenry, M. (2017) The Geography of Environmental Injustice. *Habitat International*, accepted.

Ward, M. and Gleditsch, K. (2007, June 15). *An Introduction to Spatial Regression Models in the Social Sciences*. Retrieved from Web Duke: https://web.duke.edu/methods/pdfs/SRMbook.pdf

A LOCAL SPATIAL ANALYSIS CRITERION OF POST-TRAUMATIC BRAIN INJURY AND ACCESSIBILITY TO PUBLIC TRANSPORTATION

Eric Vaz[1]
Akeem Foster[2]
Michael Cusimano[3]

ABSTRACT

Reported cases of traumatic brain injuries are increasing among the Canadian population. With an annual rate of 187,000 reported cases a year and growing, there is an extrapolated growth of 239,000 cases of traumatic brain injuries occurring annually by 2036.

As Ontario intends to be a completely accessible province for those with disabilities by 2025, this paper utilizes GIS to visualize and better understand the relationship between post-TBI residents living in Brampton and their accessibility to public transportation. As Brampton is currently the most expensive city to insure a vehicle because of frequent collisions occurring within the city, creating a more accessible, reliable, and efficient public transportation system can integrate those who have experienced a traumatic brain injury back into society while reducing the required use of a personal vehicle. This will contribute to a safer city, as there are fewer vehicles on the road at risk of being involved in a road accident. There are also further benefits to this, as it will also reduce levels of congestion in the foreseeable future.

Keywords: GIS, Post-Traumatic Brain Injury, Public Transportation.

JEL Classification: I10, I18, C31

1. INTRODUCTION

Traumatic brain injuries are an issue as there are over 187,000 incidents reported among annually among Canadians. The incidents in which head injuries occur, such as transportation collisions, work and home environments, violent or from participating in recreational activities pose a health challenge for the Canadian population as it costs over \$6.8 billion dollars annually directly and indirectly (Caro, 2011). Caro (2011) mentioned that the numbers of TBI cases in Canada are extrapolated to grow to more than 239,000 annually by the year 2036 with 66% percent of those cases projected in the high growth provinces of Alberta, British Columbia and Ontario. Having a sustainable system in place to provide effective care for post-traumatic brain injury patients will likely ensure that the tragic incidents would be reduced, as there are common cases of sequelae involved with head injuries.

In Cullen *et al.* (2013) article, neuropsychometric tests were used to predict return to driving after a traumatic brain injury. The participants in this study were drawn from an acquired

[1] Department of Geography and Environmental Studies, Ryerson University, Toronto, ON, Canada and Research Centre for Spatial and Organizational Dynamics, University of the Algarve, Faro Portugal. evaz@ryerson.c
[2] Department of Geography and Environmental Studies, Ryerson University, Toronto, ON, Canada. akeem.foster@ryerson.ca
[3] Department of Neurosurgery University of Toronto and St. Michael's Hospital, Toronto, ON, Canada. cusimanom@smh.ca

brain injury database (ABI) that was established in 1999 at the Toronto Rehabilitation Institute University Health Network (TRI-UHN). This article addressed Hopewell's (2002) study that determined, among many patients, the possibility of having their ability to drive restricted is of a greater concern than any other functional limitation. Driving is a complex task that requires the person operating the vehicle to be able to process sensory information and make timely decisions but impairments in the speed of processing and information are commonly found among those that suffered a traumatic brain injury (Cullen *et al.,* 2013). To further support this finding, A return to driving after a brain injury has been correlated with a better overall quality of life, such as returning to employment, maintaining social relationships as well as reintegrating themselves back into society (Rapport *et al.,* 2006).

Bivona *et al.* (2012) determined an increased probability of being involved in a road collision with personal responsibility among drivers that returned to driving after a traumatic brain injury. Based on the results of the sixty participants in the survey, the main finding was that those who returned to driving after a traumatic brain injury had a statistically significantly greater risk (more than twice as likely) to be involved in a road accident while being at fault than they did before the injury. The results confirmed that driving ability is impaired after a traumatic brain injury. Though the limitations of this article is that it is a relatively small number of participants, to their knowledge at the time, the article is one of the few long-term follow up studies investigating the risk of being involved in road accident after a traumatic brain injury compared with pre-traumatic brain injury data (Bivona *et al.,* 2012).

Elsayed's (2011) research paper took an approach using surveys completed by staff working with clients from Community Head Injury Resource Service of Toronto (CHIRS), an organization that provides services to adults in Toronto that have acquired brain injuries (ABI). The survey consisted of yes/no multiple choice questions that examined if the client has applied for Wheel-Trans before and if they were declined, why? The assistive devices the clients would use, issues that would impact the client's ability to use conventional public transit, their current method of transportation and whether or not clients miss activities or appointments because they have no reliable transportation (Elsayed, 2011). The purpose of this was to look into accessible public transportation for those who are suffering from brain injuries within Toronto and this study identified that clients were declined from being able to use Wheel-Trans, as they did not have any physical apparent disabilities or rely on the use of assistive devices. Also, it was found that among those surveyed, people who never use public transportation miss more appointments/activities than those who do use a public transit service such as the TTC.

What was derived from these articles was that those who suffer from head injuries are likely to suffer impairments depending on the severity. This has many drawbacks as it affects how they operate within society and ways to better accommodate them should be considered. Though, driving is associated with an increase in personal independence, those that experience a traumatic brain injury are at greater risk of being involved in a collision and being at fault when driving (Bivona *et al.,* 2012; Cullen *et al.*, 2011). An efficient and accessible public transportation service as well as assistive public transportation service (such as Wheel-Trans) can be used to increase the well being and better implement those that suffer from traumatic brain injuries back into society while reducing the need for them to return to driving and being an increased risk.

2. STUDY AREA

Brampton is Canada's fourth fastest growing city and as the population increases the importance on becoming a more accessible city rises. Traumatic Brain Injuries (TBI) are a concern for Canadian healthcare systems as they pose significant challenges related to the financial sustainability and safety within a society. A current estimate constructed from US data suggests that that there are approximately 500 in every 100,000 Canadians per year that are likely to experience a TBI (North Eastern Ontario Brain Injury Network, 2015). Based on those results there is a projected total number of 187,000 TBIs reported to be inflicted on Canadians each year along with the possibilities of severe head injuries not being reported or going underreported. There is an estimated $6.8 billion in costs to serving TBI patients both direct and indirectly across Canada (Caro, 2011) as TBIs are the most common type of injury resulting in death and disability for those aged 45 years and younger.

The challenges associated with helping patients with TBIs vary depending on the severity of the head injury but those that experienced a TBI in moderate and severe cases are likely to require further adaptations to help assist them effectively in society as their lifestyle will require changes to accomplish daily tasks (Sherer *et al.*, 2000). Individuals that experienced a moderate to severe TBI commonly encounter complications affecting their cognitive, physical and psychological abilities as it becomes more difficult for them to perform adequately as they did before the injury was sustained (Lundqvist & Alinder, 2007). Sequelae associated with moderate and severe cases of TBIs are the increased susceptibility to having a seizure, the loss of muscle control, speech, vision, and hearing plus in some cases, resulting in paralysis. The cognitive abilities that endure impediments as a result of a post-TBI comprise of an increased difficulty in concentration as well as short-term and long-term memory loss. Suffering from these conditions lead to the increased difficulty of mentally and physically impaired individuals that endured a moderate or severe TBI to perform adequately within society (Community Head Injury Resource Services, 2013).

In this sense, the unexpected nature of post-TBI incidents must be carefully monitored at all scales. Particularly when dealing with complex tasks where additional and often incremental risk may exist. Driving is such a complex task that requires the use of motor skills, cognitive abilities, along with behavioral management. Potential impediments caused by coping with a TBI, patients that were able to previously travel on their own accord before having received the injury are faced with the possibility of driving restrictions as it is essential for drivers being able to process information to problem solve quickly, making important and timely decisions while on the road (D'apolito *et al.*, 2012). As a result of post-TBI sequelae impairing the ability for patients to drive commendably, driving is considered an unsafe task for the patients suffering from conditions of post-TBIs (Cullen *et al.*, 2012). In the United States, the reported rates of individuals that had experienced a moderate to severe TBI returning to driving are between 40% to 60%. The use of an automobile is known to be associated with the multiple aspects of independence and well-being. Having detained someone's ability or privilege to drive has been correlated with lowered rates of employment, community integration and life satisfaction (Labbe *et al.*, 2014). Respective studies have been done pertaining to the relationship between road traffic accidents following TBIs. This study revealed that individuals with severe TBI that resume driving pose a greater risk of being involved in a road accident than those that did before acquiring a severe TBI (Bivona *et al.*, 2012).

Based on the cities high insurance rates, AllState Insurance claims that drivers travelling within the city of Brampton were more likely to get into a car accident than anywhere else in Ontario as the city of Brampton holds the highest frequency of collisions (680 News, 2010). A safe and effective alternative to driving an automobile after enduring a TBI is an area of importance as Brampton is a sub-urban city where most households own and rely on the use of automobiles (Vaz & Arsanjani, 2015). Based on the statistics of post-TBI victims and Brampton's current structure, the likelihood of individuals driving after a TBI and getting into a motor vehicle accident is further increased when returning to driving.

Referring to the Accessibility for Ontarians with Disabilities Act (AODA), Ontario has a goal for making public services (including transportation) to be accessible for all by the first of January 2025 (AccessON, n.d.). The aim of this paper is to offer a spatial analysis with the location of reported patients that experienced a TBI and their accessibility to public transportation within the city of Brampton. The questions that the spatial analysis intends to address through visualization are:

- Which post-TBI residents are within reasonable walking distance from a bus stop?
- Where are there clusters of post-TBI residents?
- What is the average family income of census tracts where TBI patients reside?

3. METHODOLOGY

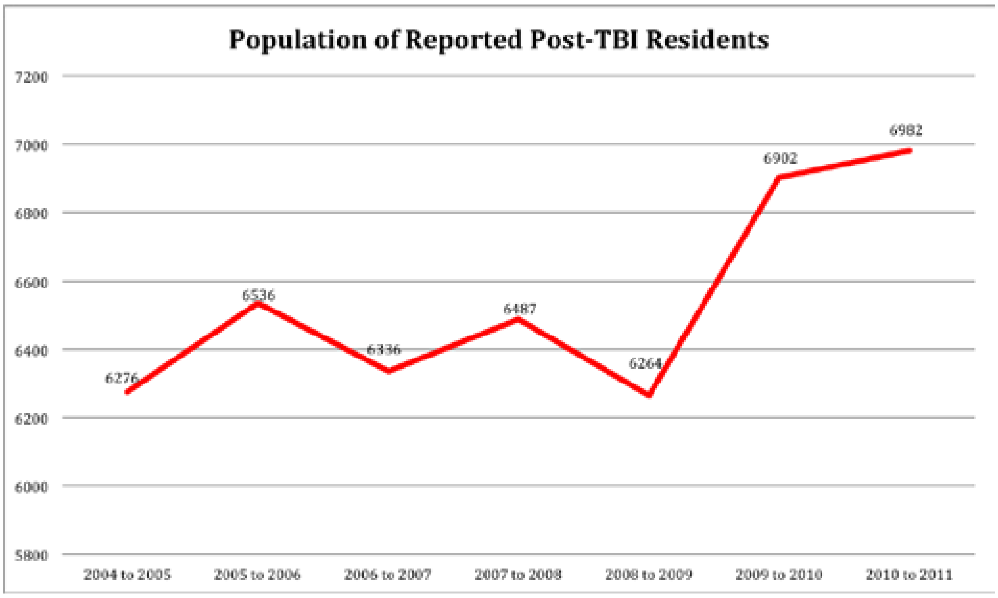
3.1 Description of Data

Based on research that recognized post-TBI patients having an increased risk of being involved in a road accident while driving (Bivona *et al.*, 2012) and post-TBI patient's that have had their ability or privilege to drive seized with correlations to lowered rates of employment, community integration and life satisfaction (Labbe *et al.*, 2014), it is of importance to create a more safe and accessible public transportation service in a city that experiences the highest rates of vehicle collisions in the country because Brampton relies heavily on private forms of transportation. The purpose of this research paper is to provide a spatial analysis to aid in better understand how accessible post-TBI patients residing in Brampton are to public transportation.

Head injury data was obtained by Dr. Eric Vaz, co-investigator of the project from the Canadian Institutes of Health Research (CIHR) grant "STAIRS TBI and Violence Project" with St. Michael's Hospital and partnered with the Ontario Ministry of Health. It includes the records of residence of all patients that have been hospitalized with reported trauma to the head. It is ordered annually throughout the years 2004 and 2011. This particular dataset has attributes that contain information indicating where the patient resides through the use of their postal code, as well as the patient's gender and if other injuries were sustained in conjunction with the head injury. This data is significant as it uses real life incidents that were conveyed and then organized to provide a spatial representation to be visualized with the use of GIS.

The data provided by St. Michael's Hospital is confidential and contains hundreds of thousands of reported cases of head injuries that have been registered within hospital databases across Canada. Narrowed down to the city of Brampton, there are over 6000 cases of head injuries being reported that happen every year with a total of n = 45,783 that occurred throughout the seven years (Figure 1). The data utilizes problem codes that can be identified through the use of the International Statistical Classification of Diseases and Related Health Problems (ICD-10-CA). The ICD-10-CA is a descriptive catalog used to categorize diseases, injuries, and causes of death along with the external causes of injury and poisoning. It contains 23 chapters with alphanumeric categories and subcategories that are not limited to diseases but also risk factors to health such as occupational and environmental factors (Vaz *et al.*, 2015). The ICD-10-CA is used to organize the information pertaining to each patient's injury by having a main problem code, which is a TBI for the case of this paper, that indicates the primary injury and additional problem codes that contribute in providing further detail relating to the injury. These problem codes contain useful information such as whether or not the injury occurred in an industrial or construction area, a place of trade, while engaged in sports or recreational activity, or if a vehicle was involved.

Figure 1. Post-TBI population in Brampton (2004-2011)



Source: Own Elaboration

Information pertaining to the public transportation system for the city of Brampton was retrieved directly from Brampton Transit's database along with additional data, which was extracted through the use of Overpass Turbo, a web-based data-mining tool for OpenStreetMap. The information provided by Brampton Transit contains records of each bus route and its traces that are displayed as lines within ArcMap. Brampton Transit also provided a list containing the location of all 2776 bus stops linked to Brampton Transit as well as the description of each stop indicating the street they are on and the bus route each stop belongs to.

Brampton Transit offers Züm, which is its Bus Rapid Transit (BRT) service that derived from the city's response to improved transportation options, as Brampton is the fourth fastest growing city in Canada.

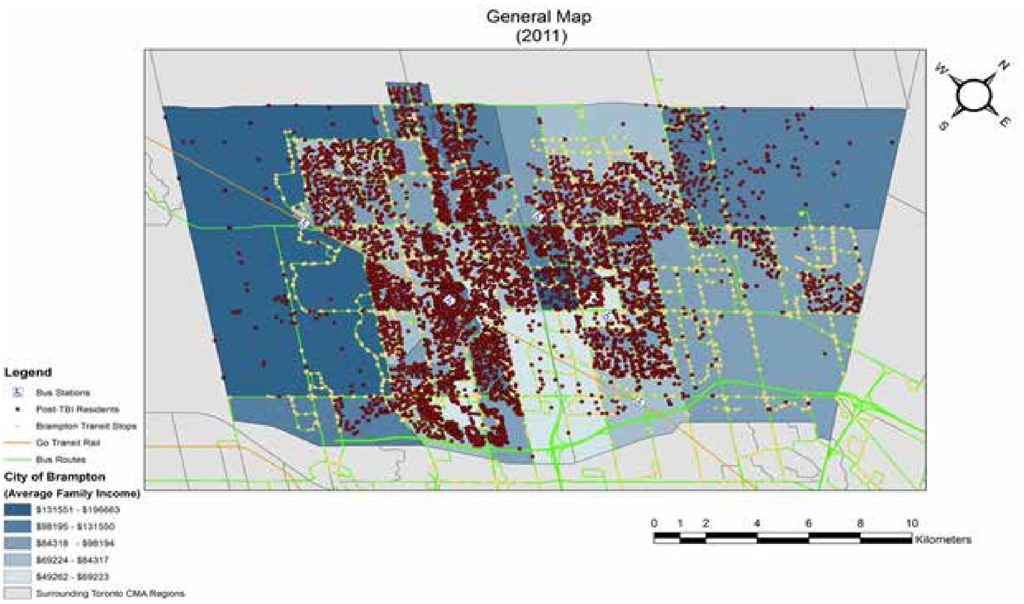
Three separate maps were used to display the spatial locations of post-TBI residents recorded in 2004 between 2011 and how they are dispersed throughout the city of Brampton in 2006, 2008, and 2011 (Figure 2). This process was done by using a spatial join to add the attributes of the head trauma data to a map of Ontario. The clip feature was then used to isolate the city of Brampton from the map of Ontario and the post-TBI in that city as well. For further detail, census 2006 data was also added and was used as a choropleth to display the average family income for each census tract across Brampton.

Figure 2. Maps displaying the spatial distribution of post-TBI residents across Brampton in 2006, 2008 and 2011

Source: Own Elaboration

In addition to Figure 1, public transportation data obtained from OpenStreetMaps through the use of Overpass Turbo along with the data attained from Brampton Transit's database provided the opportunity to add route traces and its respective bus stop locations to the map. Figure 3 offers a direct visualization to present an idea of where the post-TBI residents are located in relation to the route traces, bus stops, bus stations and the average family income of each census tract.

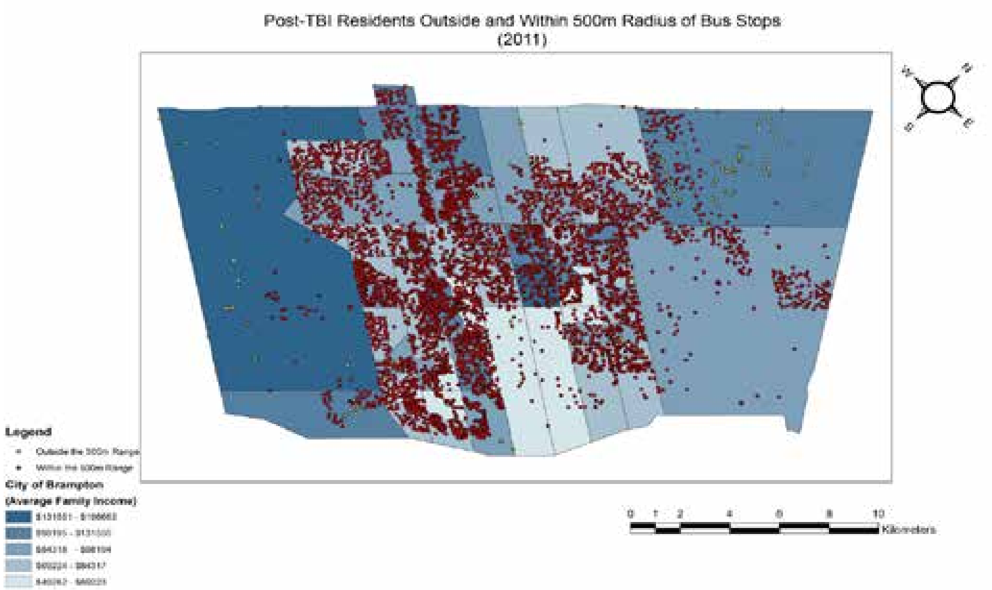
Figure 3. Post-TBI residents in Brampton displayed with bus routes, bus stops/stations and average family income



Source: Own Elaboration

People with disabilities have difficulties walking long distances. UK guidelines suggest that stops should ideally be placed so that no one should have to walk more than 400m along a route to reach a bus stop near amenities (International Best Practice in Accessible Public Transportation for Persons with Disabilities, 2010). To identify which post-TBI patients were in an optimum range to be considered either accessible or least accessible a radius of 500m from each bus stop was chosen. An extra 100m was used was used to keep minor detours into account such as a need to cross the road at a stop light or to walk around a fence. Also, the points displaying the positions of post-TBI residents are based on postal codes and this can result in there being a difference of a few meters from the actual location of their home. A map was created to deduce the population of post-TBI residents to show those that fall within and outside a 500m radius of bus stop locations (Figure 4). This was done by using the buffer tool set at 500m for each bus stop and then the clip tool to filter the selected post-TBI residents within the 500m radiuses.

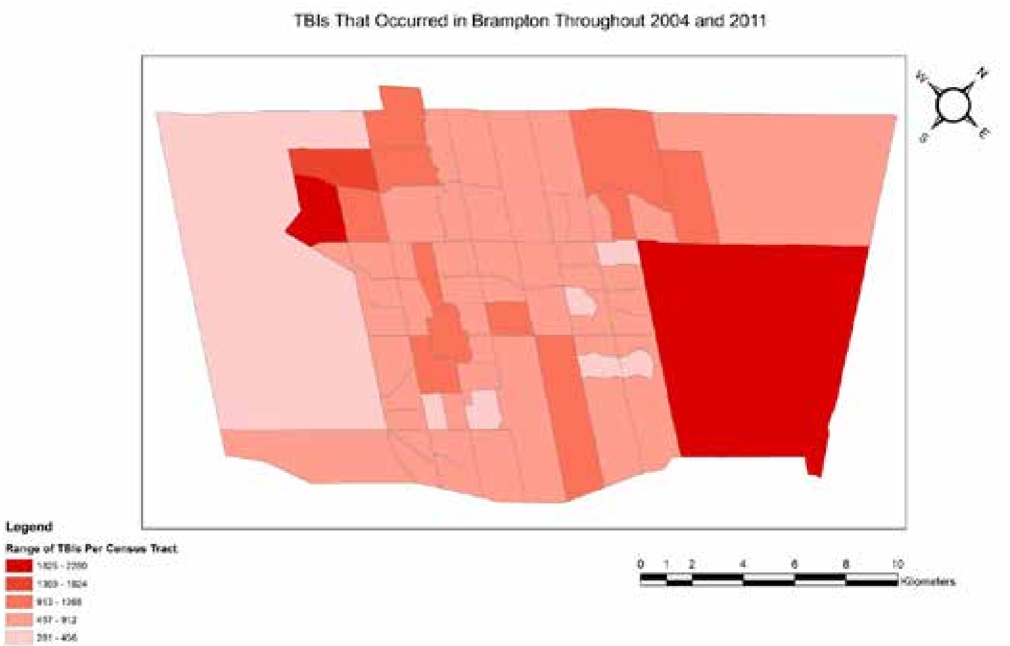
Figure 4. Map displaying post-TBI residents within and outside 500m radiuses of bus stops



Source: Own Elaboration

Since there can be multiple post-TBI residents belonging to a single postal code and the map can only shows one point per postal code, a choropleth map was used with the purpose of revealing the density of post-TBI residents that had been reported between 2004 and 2011 dwelling within each census tract (Figure 5). The lowest population of post-TBI residents residing in a census tract is 281 and the highest is 2280. The values were classified using an equal distribution of 20% per colour gradient.

Figure 5. Choropleth map showing clusters of post-TBI residents in Brampton



Source: Own Elaboration

4. DISCUSSION

4.1 Population

This research paper highlights the occurrences of residents that have been reported to sustain a TBI dwelling in Brampton. Using the locations of post-TBI residents in Brampton and bus stops, accessibility to public transportation among post-TBI residents could be assessed. As the fourth fastest growing city in Canada, the populations of those that have experienced a TBI are increasing as well (Figure 1). Brampton held the highest growth rate between 2006 and 2011 among Canada's largest 20 cities in 2011. This has been consistent since 1981 and has been so at a higher rate than the Toronto Census Metropolitan Area (CMA) (Statistics Canada, 2011). As more housing became available to support the increasing population of Brampton, the reported locations of where those that experienced a TBI began to expand further from the centre of the city and more to the northern and western parts of the city from 2006 and 2011 (Figure 2). The clusters of post-TBI residents are located in the northwestern area, city centre, as well as the north and southeastern areas of Brampton (Figure 5). Brampton is notorious for its high vehicle insurance cost as collisions are most frequent among residents within this city (680 News, 2010). With knowledge obtained from a study that identifies the higher relative risk for drivers that have experienced a TBI to be 2.3 times more likely to be involved in a collision while driving than those who have never suffered a TBI (Bivona *et al.*, 2012).

4.2 Accessibility

Using GIS to display the locations of patients that had experienced a TBI was effective in getting an idea to determine how accessible public transportation was to them within the city of Brampton. The suggested walking distance to a bus stop is 400m based on UK public transportation planning guidelines (International Best Practice in Accessible Public Transportation for Persons with Disabilities, 2010) and keeping in mind both the occurrences of obstacles such as a fence or road intersection not allowing for a direct path as locations based on postal codes can vary a few meters from the point placed on the map. The extra 100m was added to create a 500m buffer of post-TBI patients within a 500m radius of bus stops. This provided the result of there being 45,198 reported post-TBI residents that are well within the 500m walking distance of a bus stop and 585 reported post-TBI residents that are not. 99% of post-TBI residents have access to public transportation and many of them are dwelling in a census tract with an average household income of $69,224 or more. The 1 percent that is not within the 500m radiuses of bus stops is located mostly to the western and northern parts of Brampton. Those that are among the 1 percent outside of the 500m radiuses of bus stops that are located in the city centre are still fairly close and fall just outside of the radius. Many of the post-TBI residents among the 1% that fall outside of the 500m radiuses of bus stops reside in a census tract that has a family income earning $84,318, or above.

5. CONCLUSION

There are limitations associated with the data that has been used in this research. Because the data retrieved from St. Michael's database is confidential, personal information regarding the patient's age, marital status, education, and whether they were currently licensed to drive in Ontario at the time of the injury are unavailable. Furthermore, the severity of their injury is not disclosed so the condition of the patient could be much better or worse from when the injury was reported. This resulted in every reported patient that experienced a TBI to be treated the same, regardless of the severity of the TBI and whether it resulted in a permanent disability or not. Each reported TBI patient is considered to have further difficulty coping with rehabilitating themselves back into society as they were pre-injury and are also considered an increased risk while driving post-TBI relative to other drivers that have not sustained a TBI. In addition, public transportation data is as of 2015 and the reported TBI residents were recorded from 2004 to 2011. A possibility of them relocating when this research paper was constructed is present but still does not negate the implementation of a more accessible public transportation system.

In conclusion, 99% of reported post-TBI residents residing in Brampton are within the 500m walking distance of a bus stop that provides access to public transportation system that can take them to many key locations in the city. In theory, creating a more reliable, accessible public transportation system would be able to provide a much more safe and convenient alternative for post-TBI residents as well as current and future citizens living in Brampton to travel and avoid driving. This would allow for those who suffer from symptoms of post-TBI to assimilate themselves back into society in a safe and effective way that also reduces congestion and decreases the increased risk of a collision, as they are not driving with impairments.

REFERENCES

"A Review of International Best Practice in Accessible Public Transportation for Persons with Disabilities." *UNDP in Malaysia, Singapore & Brunei Darussalam*. Department for International Development (DFID) and TRL, 1 June 2010. Web. 13 Dec. 2015.

"Accessibility for Ontarians with Disabilities Act (AODA)." *Ontario*. Ministry of Community and Social Services, 2008. Web. 11 Dec. 2015.

Bivona, U., D'Ippolito, M., Giustini, M., Vignally, P., Longo, E., Taggi, F. and Formisano, R. (2012). Return To Driving After Severe Traumatic Brain Injury. *Journal of Head Trauma Rehabilitation.* 1.

Caro, D. (2011). Towards Sustainable Traumatic Brain Injury Care Systems: Healthcare Leadership Imperatives in Canada. *Healthcare Management Forum*. 25-30.

"Census Profile." *Statistics Canada*. 2011. Web. 10 Dec. 2015.

Classen, S., Levy, C., Mccarthy, D., Mann, W.C., Lanford, D. and Waid-Ebbs, J.K. (2009). Traumatic Brain Injury and Driving Assessment: An Evidence-Based Literature Review. *American Journal of Occupational Therapy.* 580-91.

Cullen, N., Krakowski, A. and Taggart, C. (2013). Early Neuropsychological Tests as Correlates of Return to Driving after Traumatic Brain Injury. *Brain Inj Brain Injury*. 38-43.

D'Apolito, A.-C., Massonneau, A., Paillat, C. and Azouvi, P. (2013). Impact of Brain Injury on Driving Skills. *Annals of Physical and Rehabilitation Medicine*. 63-80.

Elsayed, N. (2011). A Look into Accessible Public Transportation for People in Toronto Who Have Acquired Brain Injuries. *Social Care Neurodisability Social Care and Neurodisability.* 138-46.

Hopewell, C. A. (2002). Driving Assessment Issues for Practicing Clinicians. *Journal of Head Trauma Rehabilitation*. 48-61.

Hulme, J. (2008). Resuscitation of Patients after Traumatic Brain Injury. *Trauma*. 55-63.

"ICD-10-CA." *ICD-10-CA*. 2015. Web. 13 Dec. 2015.

Labbe, D.R., Vance, D.E., Wadley, V. and Novack, T.A. (2014). Predictors of Driving Avoidance and Exposure Following Traumatic Brain Injury. *Journal of Head Trauma Rehabilitation*. 185-92.

Lundqvist, A. and Alinder, J. (2007). Driving after Brain Injury: Self-awareness and Coping at the Tactical Level of Control. *Brain Inj Brain Injury*. 1109-117.

"Prevalence and Incidence | North Eastern Ontario Brain Injury Network (NEOBIN)." *Prevalence and Incidence | North Eastern Ontario Brain Injury Network (NEOBIN)*. 2015. Web. 10 Dec. 2015.

Rapport, L.J., Hanks, R.A. and Bryer, R.C. (2006). Barriers to Driving and Community Integration after Traumatic Brain Injury. *Journal of Head Trauma Rehabilitation*. 34-44.

Sherer, M., Madison, C.F. and Hannay, H.J. (2000). A Review of Outcome after Moderate and Severe Closed Head Injury with an Introduction to Life Care Planning. *Journal of Head Trauma Rehabilitation*. 767-82.

Vaz, E. and Arsanjani, J. J. (2015). Predicting Urban Growth of the Greater Toronto Area-Coupling a Markov Cellular Automata with Document Meta-Analysis. *Journal of Environmental Informatics*. 25(2): 7.

Vaz, E., Cusimano, M. and Hernandez, T. (2015). Land use perception of self-reported health: Exploratory analysis of anthropogenic land use phenotypes. *Land Use Policy*. 46: 232-240.

SPATIAL ASSESSMENT OF ROAD TRAFFIC INJURIES IN THE GREATER TORONTO AREA (GTA): SPATIAL ANALYSIS FRAMEWORK

Eric Vaz[1]
Sina Tehranchi[2]
Michael Cusimano[3]

ABSTRACT

This research presents a Geographic Information Systems (GIS) and spatial analysis approach based on the global spatial autocorrelation of road traffic injuries for identifying spatial patterns. A locational spatial autocorrelation was also used for identifying traffic injury at spatial level. Data for this research study were acquired from Canadian Institute for Health Information (CIHI) based on 2004 and 2011. Moran's I statistics were used to examine spatial patterns of road traffic injuries in the Greater Toronto Area (GTA). An assessment of Getis-Ord Gi* statistic was followed as to identify hot spots and cold spots within the study area. The results revealed that Peel and Durham have the highest collision rate for other motor vehicle with motor vehicle. Geographic weighted regression (GWR) technique was conducted to test the relationships between the dependent variable, number of road traffic injury incidents and independent variables such as number of seniors, low education, unemployed, vulnerable groups, people smoking and drinking, urban density and average median income. The result of this model suggested that number of seniors and low education have a very strong correlation with the number of road traffic injury incidents.

Keywords: Spatial Analysis, Geographic Information Systems, Injury Analytics, Traffic Injuries, Geographically Weighted Regression.

JEL Classification: I10, I18, C31

1. INTRODUCTION

Road traffic accidents are the leading and the most frequent cause of death and injury worldwide (Morency *et al.*, 2012). Injuries sustained in road traffic accidents are a major burden on healthcare system in terms of emergency treatment, chronic care, and rehabilitation (Ramage-Morin, 2008). In 2009, road traffic accidents accounted for about 2300 fatalities and 11450 serious injuries which required hospitalization (Transport Canada, 2011). According to World Health Organization (WHO) report in 2005, currently road traffic injuries are the leading cause of death and injuries, the 10th leading cause of all deaths and 9th leading contributor to the burden of disease worldwide. It has been predicted that by 2030, road traffic injuries will become the third largest contributor to the burden of disease worldwide (Chisholm *et al.*, 2012).

[1] Department of Geography and Environmental Studies, Ryerson University, Toronto, ON, Canada. Research Centre for Spatial and Organizational Dynamics, University of the Algarve, Faro Portugal. evaz@ryerson.ca
[2] Department of Geography and Environmental Studies, Ryerson University, Toronto, ON, Canada. sina.tehranchi@ryerson.ca
[3] Department of Neurosurgery University of Toronto and St. Michael's Hospital, Toronto, ON, Canada. cusimanom@smh.ca

Moreover, WHO also reports that majority of road traffic injuries are among "*pedestrians, cyclists, and motorcyclist who are the most vulnerable road users*". For instance, according to Transport Canada (2011), in total about 25% of all road traffic fatalities are among vulnerable road users, of which 13% of fatalities are among pedestrian alone. According to Schuurman and others (2009) pedestrian safety is often overlooked, primarily because smooth movement of motorized vehicle remains a priority for engineers in road design (Schuurman *et al.*, 2009).

Consequently, one of the major contributing causes of road traffic accidents is urban sprawl (Ewing, Schieber & Zegeer, 2003). The reason being is because since cities have spread outward into rural areas (de Noronha & Vaz, 2015), residents of sprawled cities tend to commute by a vehicle to their job in the city. This as a result increase the use of motor vehicles, which ultimately leads to an increase in the road traffic accidents.

Road traffic accident, is a global occurrence, which results in increased injury and mortality rates (World Health Organization, 2005). Increase in the number of motorized vehicle over the past few decades has been accompanied by an increasing number of road traffic injuries (Ameratunga, Hijar & Norton, 2006). According to Ashokbhai (2014) road traffic injuries have become a threat to the public health in many countries as it contributes to "*poverty by causing death, injuries, disabilities, grief and loss of productivity*". The reason being is because the victim may take time off from work which would result in loss of income due to their injuries.

In general, it is important to study road traffic injuries as it is a major problem and it is not well recognized in many countries. For the purpose of this study, road traffic injury data from 2004 and 2011 was acquired from the Canadian Institute for Health Information (CIHI). The purpose of this study is as follow,

- To investigate and determine the spatial pattern of road traffic injuries throughout the study area.
- To identify areas of hotspots with high frequency of road traffic injury
- To develop a spatial explanatory model for underlying causes of road traffic injury.
- And lastly, to understand and determine contributing factors behind the spatial pattern using geographic weighted regression (GWR).

2. INTRODUCTION

2.1 Socioeconomic Factors

Road traffic accidents have been recognized as one of the major causes of disability and death among people every day (Scheidt *et al.*, 1995). There have been several literatures in the field of road traffic injury, however majority of research studies have been focused on the vulnerable road users, as they consider to have the highest number of injury and mortality (Pratte, 1998). Studies have also focused on the factors that contribute to the increase in the number of road traffic injuries and mortality.

According to the study by Link and Phelan (1995) and Camilloni and others (2013), socioeconomic status (SES) can play a major role as a fundamental determinants of injuries and deaths. For instance, study by Camilloni and others (2013) suggested that people with lower income are more likely to get involve in a road traffic injury, primarily due to their lack of access to new and safer mean of transportation. Similarly, low socioeconomic status is highly correlated with each of the "*14 major causes of injury and death in the International Classification of Diseases (ICD)*" (Link & Phelan, 1995). Study by Cubbin, LeClere and Smith (2000) discovered that risks for motor vehicle related fatalities can vary by occupation. People with lower status job are more prone to motor vehicle related fatalities (Cubbin, LeClere & Smith, 2000). The high risk of motor vehicle related fatalities among people with lower job status, may possibly reflect the fact that due to lower income, they are more likely to live in outer city-core (rural areas), which would result in greater distance commute by car, and thus be exposed to higher risk of road traffic injury. Similarly, it is possible that due to lower income, they are less likely to be able to afford newer and safer vehicle, which would put them at a great risk in the event of an accident.

In addition to socioeconomic factors, some studies have suggested that both urban and rural environment can have an impact on the road traffic injuries as well. Afukarr, Antwi and Ofosu-Amaah (2003) explain that majority of road traffic injuries occur on rural areas, where roads are deteriorated and driving rules and regulations are frequently tend to be ignored by drivers (Jacob & Sayer, 1983). As a result the chances of getting into an accidents are much higher than in urban areas. On the contrary, other studies have suggested otherwise. For instance, study by Al-Omari and Obaidat (2013) showed that the rates of casualties occurring in urban areas among vulnerable road users are relatively higher compare to rural areas. In fact, pedestrians constitute a higher proportion of road traffic injuries in urban area (Jacob & Sayer, 1983) among vulnerable road users, followed by cyclist (WHO, 2005). Urban areas tend to have a higher risk of road traffic injuries due to several reasons. Concentration of vehicles and population in city center which causes congestion and heavy traffic, lack of attention to traffic rules by both drivers and pedestrians (jaywalking), as wells as lack of segregated pedestrian and bicycle facility (bike lane) on the road network (Pratte, 1998) are the main reason of high rate of road traffic injury in urban setting.

2.2 Global and Local Spatial Analysis

Road traffic accidents causing injury have increased throughout the years (Odero, Garner & Zwi, 1997), as a result it has become the main motivation behind the analysis of motor vehicle accident pattern. Due to the importance of road traffic accidents, number of studies have focused their attention to road traffic accident hotspot identification (Flahaut *et al.*, 2003; Geurts & Wets, 2003; Manepalli, Bham & Kandada, 2011) in order to reduce and prevent the increase in road traffic injuries. Martin, Crandall and Pilkey (2000) explained that road traffic studies have focused on identifying past, present and future injury patterns from motor vehicle accidents, in order to help researchers establish injury prevention priorities. However, to address these priorities, spatial analysis could be joined with road traffic injury data for the analysis.

The growth in spatially references datasets, advance visualization, rapid data retrieval and ability to manipulate data in geographic information system (GIS) (Vaz & Khaper, 2016), have allowed new techniques to thrive for spatial data analysis (Anselin, 1995). Spatial autocorrelation is one of those methods that has been widely used to evaluate the interconnectedness of values in a geographic area to those nearby (Jackson & Waller, 2005). Spatial autocorrelation is important because the outcome in one area can greatly influence the outcome of its neighboring areas (Anselin, 1995). According to the Tobler's first law of geography, "*everything is related to everything else, but near things are more related than distance things*" (Tobler, 1970). Number of studies in the field of road traffic injury (LaScala, Gerber & Gruenewald, 1999; Aguero-Valverde & Jovanis, 2006) have implemented this method to examine the distribution of incidents in space, and conduct analysis accordingly.

Study of hotspots which also is referred to as "*black spots or high risk locations*" (Geurts & Wets, 2003) are sites with significantly higher frequency of injuries or accidents compare to neighboring locations (Hakkert & Mahalel, 1978). However, to reduce the number of road traffic injuries, a feasible solution is to identify hotspots (Geurts & Wets, 2003; Montella, 2010). Some of the commonly used hotspot identification methods are local spatial autocorrelation, known as Getis-Ord Gi* Statistics (Ord & Getis, 1995), and Kernel density estimator (Flahaut *et al.*, 2003). Among the existing methods, Getis-Ord Gi* Statistics is preferred to be used for hotspot identification (Manepalli, Bham & Kandada, 2011). Though, both Getis-Ord Gi* Statistics and Kernel density estimator have different conceptualization, both produce similar results under specific conditions of the selected parameters (Manepalli, Bham & Kandada, 2011).

Number of researchers have made the link between road traffic injury and spatial analysis using hot spot analysis. Erdogan (2009) conducted a study in Turkey aiming at road traffic accidents using global and local spatial autocorrelation analysis, to examine whether provinces in Turkey with high rate of road traffic accident are clustered or are located close to each other randomly. Additionally, Gi* Statistics and Z-score of statistics were used to identify hotspots that may not be visible with global spatial autocorrelation (Getis and Ord, 1992). More recently, Truong and Somenahalli (2011) used Moran's I statistics to examine spatial patterns of pedestrian-vehicle crash data. Getis-Ord Gi* Statistics was also used to identify the clustering of low and high values, and also to generate a pedestrian vehicle crash hotspot map. It is apparent that global and local spatial autocorrelation is well known method and is used by many researchers in different fields, especially in the field of road traffic accidents.

2.3 Geographic Weighted Regression (GWR)

One of the main objectives in spatial analysis is the identification of relationships that exist among different variables (Helbich *et al.*, 2013). In order to analyze the relationship among variables, it is important to conduct regression analysis. Regression analysis is a popular method of analysis among researchers when it comes to estimating effects of explanatory variables on the dependent variable (Charlton, Fotheringham & Brunsdon, 2006). Moreover, regression analysis allows researchers to study and explore spatial relationships, to understand the influencing factors that may affect the spatial patterns, and also to predict outcomes based on that understanding (Moutinho & Hutcheson, 2011: 225). For that matter, several techniques have already been implemented. For instance, ordinary least square (OLS) which is one of the most basic and most commonly used techniques, is a generalized linear modelling technique which is used to estimate regression models at a global level (Moutinho & Hutcheson, 2011: 224). Geographic weighted regression (GWR), however, is another technique to estimate regression with spatially varying relationships at a local level (Brunsdon, Fotheringham & Charlton, 1996). According to Lu, Charlton and Fotheringham (2011), in the last few years, there have been an increasing interest in the local forms of spatial analysis methods that produces results locally rather than globally. As a result, GWR has been identified to be the most popular, reliable and accurate method for exploring the spatial relationships among variables (Zhang *et al.*, 2004).

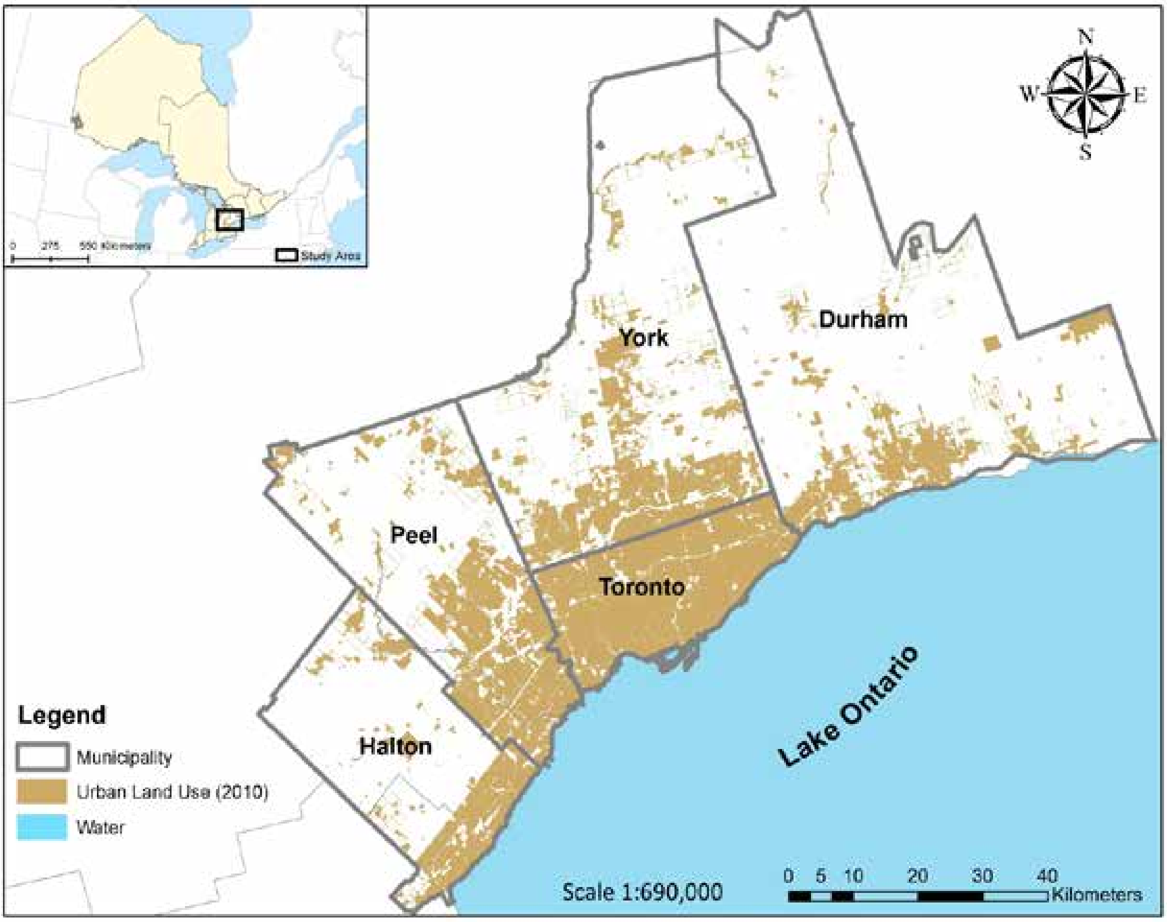
In addition, geographic weighted regression technique has been widely used in different research fields such as economics (Huang, Wu & Barry, 2010), ecology and environment (Zhang *et al.*, 2004), urban analysis (Gao & Li, 2011) and health analysis (Nakaya, 2005; Vaz, Cusimano & Hernandez, 2015). According to Zhang and others (2004), one of the advantages of using GWR is that it significantly improves the model fitting over ordinary least square (OLS). Also, since GWR produces results at a local level, the result are more accurate and reliable compare to global regressions.

3. STUDY AREA

The Greater Toronto Area (GTA), which is the focus for this study, is comprised of the City of Toronto and the four surrounding regional municipalities of Durham, Halton, Peel and

York, which are located along the northern shore of Lake Ontario (Figure 1). The GTA has a population of over six million people, of which more than half of that population live in the surrounding regional municipalities (GTA Alliance, 2011). The GTA is considered to be the fourth largest populated area in North America (GreaterToronto, 2013). Furthermore, the GTA is bounded by Lake Simcoe to the north, Lake Ontario to the south, Kawartha Lake to the east and Niagara Escarpment to the west. The region covers an area of over 7000 km^2 with the newly amalgamated City of Toronto at its urban core. This urban core includes the former cities of Toronto, North York, Etobicoke, Scarborough, and the District of East York. The GTA is the largest urban area in Canada and one of the largest in North America. The GTA continues to experience rapid growth with the region adding nearly 100,000 new residents each year. This growth is expected to continue over the coming decades with the GTA becoming home to nearly 9.4 million people by 2041 (MetropolisIQ, 2012).

Figure 1. Urban land use cover in the Greater Toronto Area (GTA), located in southern Ontario, Canada



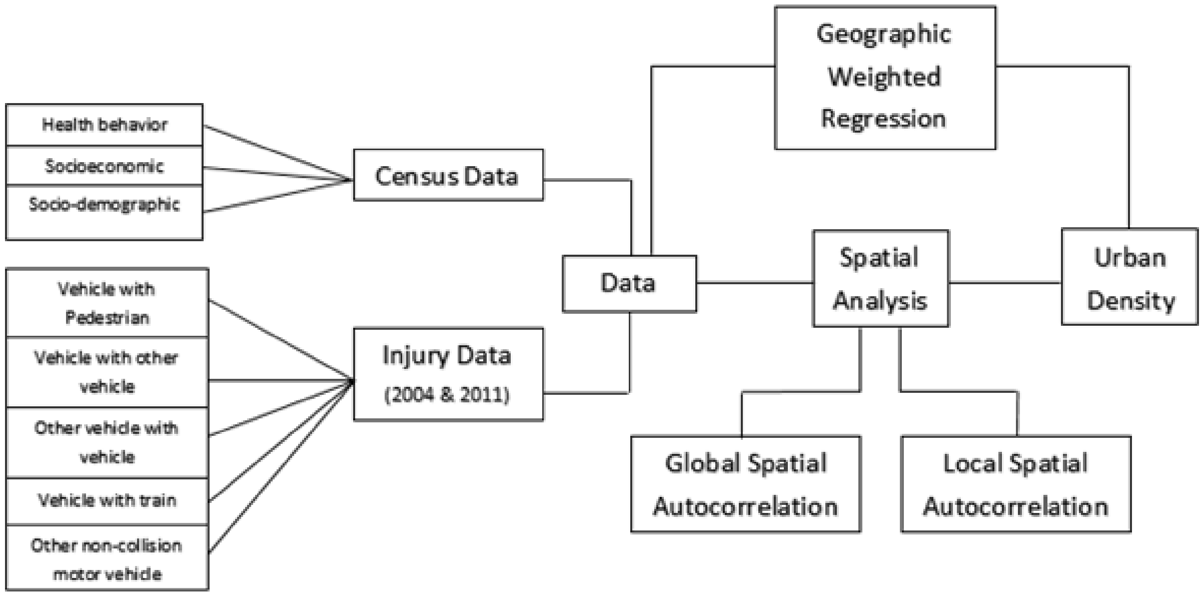
Source: Own Elaboration

4. METHODOLOGY

4.1 Data

In terms of the data analysis, number of census variables and injury data types were aggregated to conduct the analysis (Figure 2). These data variables were then used to perform global and local spatial autocorrelation and perform geographic weighted regression along with urban density data to identify factors that may contribute to the increase of road traffic injury in the Greater Toronto Area.

Figure 2. Construction of road traffic injury spatial analysis



Source: Own Elaboration

Road traffic injury data were acquired from The Canadian Institute for Health Information (CIHI). The CIHI which was founded in 1994, is an independent and non for profit organization created by Canada's federal, provincial and territorial governments (Statistics Canada, 2011). Their goal is to coordinate, develop and improve Canadian health and health care system by providing and distributing health information from hospitals and other organizations all over the country. The CIHI also provides information that are required for effective healthcare management, enable sound policy and raise public awareness of the factors that could contribute to affect health (Statistics Canada, 2011; CIHI, 2014). The CIHI manages and holds about 27 different databases of health information. Some of these databases are on health personnel, health spending and health services such as ambulatory care and discharge abstract.

To extract motor vehicle injury data from a larger dataset, a tabular search of International Classification of Diseases (ICD) codes was conducted to search for data of interest. International Classification of Diseases (ICD) codes are the "standard diagnostic tool for epidemiology, health management and clinical purposes" (WHO, 2014). ICD codes are used to classify diseases and other health problems, based on their type and severity. Motor vehicle injury data related to traffic were extracted from the 2004 and 2011 National Ambulatory Care[4] (NAC) dataset using set of SQL queries in Microsoft Access. After retrieving the desired data, they were categorized into five primary injury types, such as motor vehicle collision with pedestrian, motor vehicle collision with other vehicle, other motor vehicle collision with motor vehicle, motor vehicle collision with train and finally, other non-collision motor vehicle accidents (Figure 2). However, since the extracted data were not spatially defined, the data sets were geocoded[5] using postal codes available in the dataset. The geocoded

[4] The National Ambulatory Care (NAC) contains data for all hospital-based and community-based ambulatory care on day surgery, outpatient clinics, and emergency departments.
[5] Process of transforming non spatial data into spatial data that can be displayed as features on a map

incidents, which now contained x and y coordinates were then georeferenced[6] using ArcGIS built-in tools to display the incident in each category on a map.

Following that, statistical analysis CHASS (Computing in the Humanities and Social Sciences) from the University of Toronto was used to provide census information for the Greater Toronto Area. Number of socioeconomic and socio-demographic factors that affect road traffic injury according to previous studies were selected from the census. Variables such as low education, number of unemployed, average median income, mobility, and number of seniors are used in statistical analysis to quantify their significance to the number of road traffic injury incidents (Figure 2). For effective statistical analysis, all variables were transformed to the square root, in order to reduce skewness that existed within the data.

Last but not least, for health behavior analysis, 2010 Ontario health survey from Canadian Institute Health Research (CIHR) were retrieved for statistical analysis. Data such as number of people smoking and drinking alcohol were collected for the Greater Toronto Area (Figure 2). Similar to the socioeconomic and socio-demographic data, health behavior data were used in statistical analysis to measure their significance to the number of road traffic injury incidents. They were also transformed to the square root for an effective and accurate outcomes.

4.2 Global Spatial Autocorrelation

Spatial patterns is defined by the arrangement and distribution of features in space and the geographic relationship among them (Gatrell *et al.*, 1996). Accordingly, in order to be able to measure the relationship among features according to their spatial arrangement, it is necessary to conduct spatial autocorrelation (Cliff & Ord, 1973). There are two types of spatial autocorrelation. Global spatial autocorrelation identifies whether the values of a variable show a significant pattern of regional clustering (Vaz, 2016). In contrast, local spatial autocorrelation identifies the location of high and low value clusters, usually known as hotspots and cold spots (Ord & Getis, 1995). In global measures, the relationship among features may be described as positive correlation if similar values are spatially close to each other (clustered), negative correlation if different values are located near one another (dispersed) and random if spatial pattern cannot be distinguished from the arrangement of values (Getis, 2008). In order to understand and measure such pattern, statistical tools such as Moran's I (Anselin, 1995; Ord-Getis, 1995) can be used to measure the dispersal or clustering of the features in space. As a result, Moran's I value can be computed as,

$$I = \frac{n}{S_0} \frac{\sum_{i=j}^{n} \sum_{j=1}^{n} w_{i,j} \, z_i z_j}{\sum_{i=1}^{n} z_i^2} \tag{1}$$

where z_i is the deviation of an attribute for feature i from its mean $(x_i - X)$, $w_{i,j}$ is the spatial weight between features i and j, and n is the total number of features (Anselin, 1995). S_0 is the aggregate of all the spatial weights, which is calculated as,

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} \tag{2}$$

Moran's I value are ranged from -1 to 1. A Moran's I value of +1 indicates that features are clustered and there is a positive autocorrelation; conversely, a Moran's I value of -1 indicates that features are dispersed and there is a negative spatial autocorrelation. Moran's I value

[6] Process of aligning geographic data to a known coordinate system so it can be viewed, queried, and analyzed with other geographic data.

of 0 indicates that features are distributed randomly and therefore, spatial autocorrelation would not exist (Slocum *et al.*, 2009: 52). However, before calculating Moran's I, a spatial weight matrix was defined using queen contiguity, which outlines a locations neighbor with either a shared border or vertex (Anselin, 1995).

Moreover, the statistical significance for Moran's I can be calculated using z-score method (Erdogan, 2009). This is primarily used to see whether the outcome is the result of random distribution or not. Z-score greater than 1.96 or less than -1.96 indicates that there is a spatial autocorrelation at a 5% significant level; thus the outcome is not as a result of random distribution.

4.3 Local Spatial Autocorrelation

In order to evaluate the spatial variation and the spatial association, it is necessary to conduct local measures such as local Moran's I (Anselin, 1995) or Getis-Ord Gi* statistics (Getis & Ord, 1992). This is carried out by counting the number of road traffic injury incidents in each dissemination area within the study area. This will allow us to determine whether the features contain high or low clustering value. Unlike measures of global spatial autocorrelation, which gives only one value indicating the degree of regional clustering across the whole study area, Getis-Ord Gi* statistics gives a value for each location which indicates the degree of high or low value clusters (Getis & Ord, 1992). Also, Getis-Ord Gi* statistics is used to measure the degree of association from a concentration of weighted point (Ord & Getis, 1995). For the purpose of this study, the local statistics were carried out by using queen contiguity weight matrix in relation to the number of road traffic injury incidents which was calculated earlier. Higher Getis-Ord Gi* statistics value indicates that spatial clustering among features is significant (Vaz, 2013). This value is highly correlated with the z-score or significance level. For instance, higher value of z-score indicates the intensity of clustering among higher value known as hot spot, and low z-score value indicates the intensity of clustering among lower values known as cold spot (Ord & Getis, 1995). The Getis-Ord Gi* statistics is computed as,

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} \; - \; \bar{X} \; \sum_{j=1}^{n} w_{i,j}}{S\sqrt{\dfrac{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \tag{3}$$

where x_j is the attribute value for feature j, $w_{i,j}$ is the spatial weight between features i and j and n is the total number of features (Ord & Getis, 1995).

4.4 Level of Urbanization

According to studies, one of the main contributing factors influencing road traffic injury is urban density. It has been found that many of the road traffic injuries occur on urban roads where population is higher and traffic congestion is at its peak. This could be due to the lack of attention on the road or the way roads have been designed (Pratte, 1998). GTA has seen a significant growth in urban development in the past 30 years. As a result of urban growth (Vaz *et al.*, 2012; Vaz & Nijkamp, 2015), population has increased which has led to higher rate of road traffic injuries (Atubi, 2012). Urban density is defined as areas that are continuously being or have been developed with a population of 50,000 or more. These areas are usually considered to be developed and densely settled (Carlino, Chatterjee & Hunt, 2007). To evaluate the influence of urban density on road traffic injuries, a model was carried out by measuring the urban size and the geographic size of each census tract. As a result, urban density in each census tract was computed as,

$$Urban\ Density = \frac{\sum_{i=1}^{n} U_i}{A} \tag{4}$$

where U_i is the size of each urban area and A is the geographic size of each census tract. However, urban areas were developed by combining urban categories such as commercial, residential, industrial, parks/recreation and government/institutions. The importance of evaluating the urban density in this research, is to explain if the increase in urbanization has any influence on the road traffic injuries (Vaz *et al.*, 2017).

4.5 Geographic Weighted Regression

According to number of studies (Camilloni *et al.*, 2013; Pratte, 1998; Link & Phelan, 1995), several factors have contributed in the increase of road traffic injuries worldwide. In order to investigate the relationship between the number of road traffic injuries and other related factors such as income, education, unemployment and etc., geographic weighted regression (GWR) method was used. GWR is an extension of classical standard regression (OLS) with a difference that GWR allows local parameters to be estimated rather than global parameters (Gao & Li, 2011). The main reason that GWR is used in the study is because results are more reliable and more accurate since they are at a local level. The results in GWR is similar to the classical standard regression (OLS) in which R^2 represents the goodness of fit. Similar to OLS, R^2 value ranges from 0 to 1, and the higher the R^2 value is, the better the model fits the hypothesis. Geographic weighted regression can be expressed as,

$$y_i = \beta_0(\mu_i, v_i) + \sum_{k=1}^{p} \beta_k(\mu_i, v_i) x_{ik} + \varepsilon_i \tag{5}$$

where y_i is the dependent variable at location i, β_0 (μ_i, v_i) is the intercept parameter at location i, (μ_i, v_i) is the coordinate of location i, $\beta_k(\mu_i, v_i)$ is the local regression coefficient for the k-th explanatory variable at location i, X_{ik} is the value of the k-th explanatory variable at location i and lastly, ε_i are random errors at point i terms (Lu, 2011).

In addition, in order to be able to estimate the parameters in GWR, all observations must be weighted. Observations closer to point i have higher impact on the local parameter and therefore are weighted more than data that are located further away (Gao & Li, 2011). As a result the parameters are computed as,

$$\hat{\beta}_{(\mu,v)} = (X^T W_{(\mu,v)} X)^{-1} X^T W_{(\mu,v)} y \tag{6}$$

where $\hat{\beta}_{(\mu,v)}$ represents the unbiased estimate of β, $W((\mu,v)$ is the weighting matrix which acts to ensure that observations near to the specific point have bigger weight value (Lu, Charlton & Fotheringham, 2011). The weighting functions which are also called kernel are being implemented using the Gaussian distance decay which is computed as

$$W_{ij} = \exp(-\frac{d_{ij}^2}{h^2}) \tag{7}$$

where W_{ij} represents the weight of observation j for location i, h is a non-negative parameter known as bandwidth which produces a decay of influence with distance and d_{ij} is the measure of Euclidean distance between location of observation i and j and is computed as (Brunsdon, Fotheringham & Charlton, 1998),

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{8}$$

where (x_i, y_i) and (x_j, y_j) are point coordinates. As a result, if observation j coincide with i, the weight value is one, and if the distance is greater than the kernel bandwidth then the weight will be set to zero. Moreover, as Huang, Wu and Barry (2010) explain, there are two weighting methods that can be used in GWR, fixed and adaptive kernel. In fixed kernel, distance is constant, though the number of adjacent neighbors vary. In adaptive kernel, distance among features vary but the number of neighbors remains constant. For instance, in adaptive kernel if feature contain dense distribution, then the spatial context is smaller, and if the feature have sparse distribution then the spatial context is larger. For the purpose of this study, adaptive kernel was chosen for the analysis.

5. RESULTS AND DISCUSSION

5.1 Road Traffic Injury Incidents Statistics

The result of this research study follows the three stream of analysis as defined earlier, defining spatial pattern of road traffic injuries, identify areas of hotspots and cold spots, and determine variables that contribute and influence the increase in road traffic injuries. Table 1 is a summary statistics comparing the number of road traffic injury incident between Ontario and GTA between 2004 and 2011.

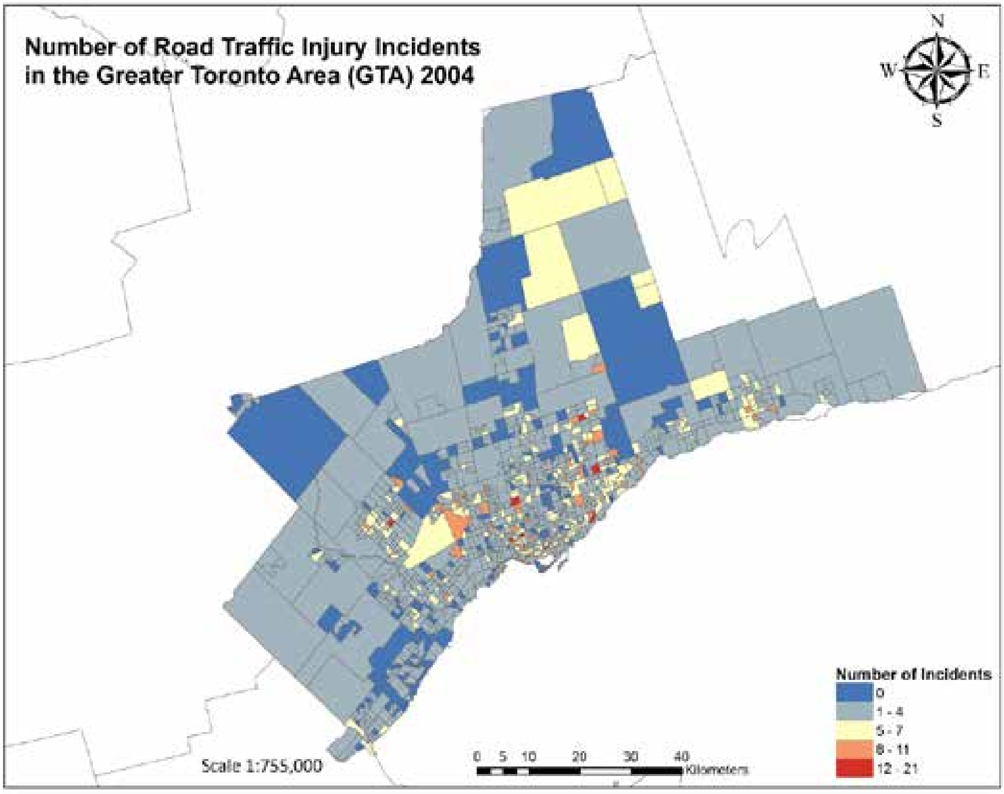
Table 1. Summary statistics of road traffic injury incidents statistics

	2004		2011		Change (%)	
	Ontario	**GTA**	**Ontario**	**GTA**	**Ontario**	**GTA**
Motor vehicle collision with pedestrian	3916	1837	4132	1892	6	3
Motor vehicle collision with other vehicle	137	53	139	61	1	15
Motor vehicle collision with train	196	24	76	14	-61	-42
Other motor vehicle collision with motor vehicle	3522	1621	4488	2224	27	37
Other non-collision vehicle accidents	102	25	61	16	-40	-36
TOTAL	**7873**	**3563**	**8896**	**4207**	**13**	**18**

Source: Own Elaboration

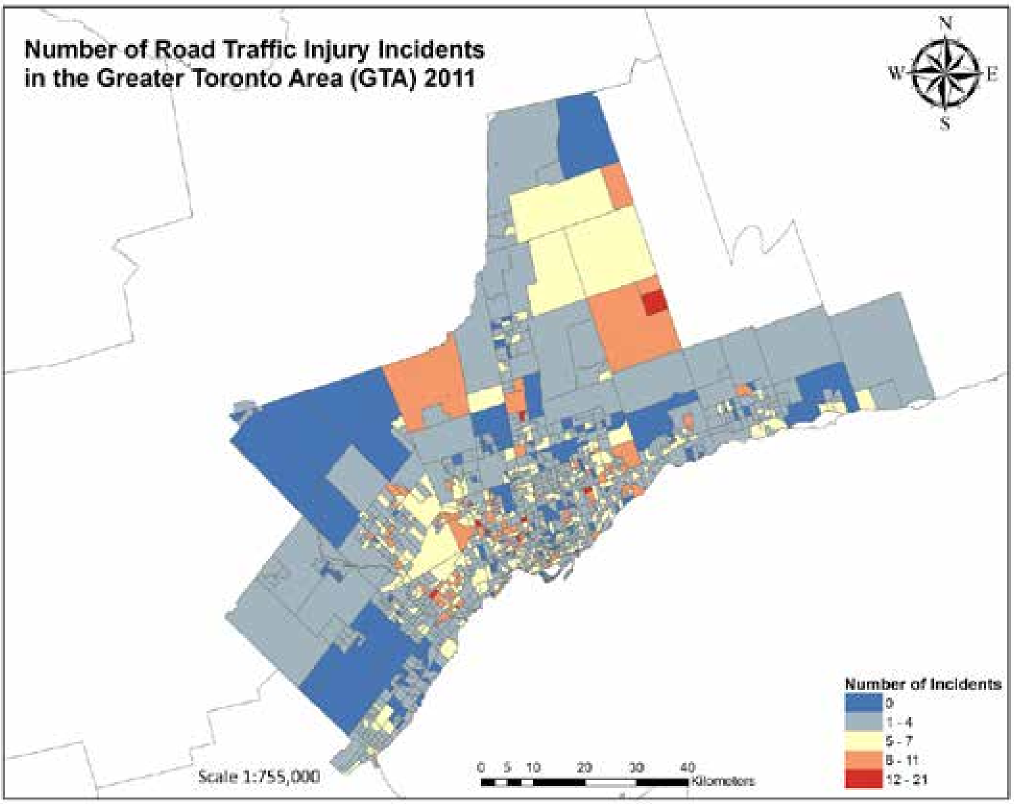
As Table 1 shows, there has been an 18% increase in the total number of road traffic injuries just within GTA between 2004 and 2011. The table also illustrates that nearly 50% of all traffic injury incidents in Ontario occur within Greater Toronto Area (GTA), and therefore this establishes a huge threat to the public. The change and increase in the number of road traffic injury incidents between 2004 and 2011 can clearly be seen in Figures 3 and 4 below.

Figure 3. Number of road traffic injury incidents in the Greater Toronto Area (GTA) 2004



Source: Own Elaboration

Figure 4. Number of road traffic injury incidents in the Greater Toronto Area (GTA) 2011



Source: Own Elaboration

This significant growth in the total number of road traffic injury in the GTA from 2004 to 2011 is primarily due to the population increase that had occurred in the GTA. However after normalizing the data by total population, it was observed that there was about 17% increase in the terms of the total number of road traffic injuries in both Ontario and the GTA between 2004 and 2011. Moreover, increase in the use of motor vehicle and vehicle dependability as a result of urban sprawl can be one of the factors of this significant change in the total number of road traffic injury in the GTA.

5.2 Global Pattern of Road Traffic Injury in the Greater Toronto Area

The Moran's I analysis indicates a statistically significant clustering pattern of vehicle collision with pedestrian, and other motor vehicle collision with motor vehicle in the Greater Toronto Area (Table 2). With z-scores above 1.96, we know that there is a positive spatial autocorrelation with 95 percent confidence, and therefore the outcomes are not as a result of random distribution.

Table 2. Summary table of global spatial autocorrelation

	2011		
	Moran's I	**Z-score**	**Pattern**
Motor vehicle collision with pedestrian	0.24	10.88	Cluster
Motor vehicle collision with other vehicle	0.08	0.66	Random
Motor vehicle collision with train	0.69	1.78	Cluster
Other motor vehicle collision with motor vehicle	0.20	10.45	Cluster
Other non-collision vehicle accidents	-0.15	-0.20	Random

Source: Own Elaboration

One of the reasons that could explain the clustering pattern of pedestrian collision with a motor vehicle is population density. According to the study by Clark (2003), there is a positive relationship when it comes to traffic fatalities and population density. As for the GTA, majority of Ontario's population is concentrated in the GTA which increases the risk of traffic injury and fatalities among people. In addition, pedestrian safety is often overlooked in the main cities, because smooth movements of motor vehicles has become a priority of engineers in road design (Schuurman *et al.*, 2009).

5.3 Greater Toronto Area Hotspots

Local approaches were also used for analyzing spatial association to identify locations with highest number of incidents compare to other locations which is also known as hot spots. The results revealed that majority of motor vehicle collisions with pedestrian occur in urban areas of GTA where population density is higher. In contrast, motor vehicle collision with other vehicle hotspots are mostly concentrated on the southern part of GTA, with majority of hotspots in the Toronto region. On the contrary, Peel region and western part of Durham region have seen a significant existence of hotspots when it comes to other motor vehicle collision with motor vehicle. The result indicates that these two regions have the highest rate of injury as a result of vehicle collision compare to other regions in the study area. Compare to other three collision types, motor vehicle collision with train had the lowest number of road traffic injury incidents. However, according to the hotspot analysis results, majority of this types of incidents happen on the northern part of Toronto region where there is a rail track that pass by. In addition to all these, other non-collision vehicle accidents hotspots have occurred on the outskirt of the city where areas are rural and population is lower.

5.4 Contributing Factors to Road Traffic Injury in the Greater Toronto Area

Though the road traffic injury contributing factors do not affect the identification of hotspots, some of the key factors can be considered. For this research, eight geographic weighted regression models have been developed based on their category (Table 3). For socio-demographic factors, variables such as age, mobility and employment status were selected. For socioeconomic factors, variables such as income and education were selected, and for health behavior factors, variables such as number of smokers and alcohol drinkers were selected for the analysis. In addition, the urban size in each census tract was also included in the analysis to see whether level of urbanization has any effect on the number of road traffic injuries. The strength of each model is evaluated by considering the R^2 value which is created after the model is executed.

Table 3. Summary statistics of geographic weighted regression

	Variables	R^2	Interpretation
Socio-Demographic	Seniors	0.93	Very strong
	Vulnerable Groups	0.60	Moderately strong
	Unemployed	0.67	Moderately strong
Socio-Economic	Average Median Income	0.58	Moderate
	Low Education	0.80	Very strong
Health Behavior	Smoke	0.53	Moderate
	Drink	0.57	Moderate
Land use cover	Urban	0.61	Moderately strong

Source: Own Elaboration

Based on the results presented in Table 3, both seniors and low education have a very strong correlation with the dependent variable, number of road traffic injury incidents. This result suggest that areas with higher number of seniors and higher number of population with lower education leads to higher number of road traffic injury incidents. Following that, number of unemployed, urban land use (Vaz & Arsanjani, 2015) cover and vulnerable groups explained 67, 61 and 60 percent of the model respectively. Surprisingly, according to these results, health behavior factors such as smoking and drinking does not have a strong correlation with number of road traffic injuries, which conveys that there should be other health behavior factors that should correlate with the number of road traffic injuries.

With seniors and low education being identified as main factors that contribute to the increase of road traffic injuries, some policies should be implemented in order to alleviate road traffic injury accidents in major cities with high population density such as Greater

Toronto Area. As an example, in London UK a congestion pricing project was implemented in the highest vehicular congested area which would force people to pay a fee in order to be able to drive in those congested areas (Mackie, 2005). This has reduced congestion significantly, allowing people to walk, shop and live in a more pleasant and safer environment. Moreover, according to the study by Mackie (2005), this policy has also reduced personal injury accidents in central London by 5%.

6. CONCLUSION

6.1 Findings

This research presented an approach based on the global spatial autocorrelation of road traffic injury for identifying the spatial pattern, and local spatial autocorrelation for identifying traffic injury hotspots. Global spatial autocorrelation allowed us to examine the pattern of injury incidents and determine whether they are clustered or dispersed in the study area. This was measured by using Moran's I value. On the other hand, local spatial autocorrelation or Getis-Ord Gi* statistics, was used to identify hot spots in the study area. The hot spots were measured by using z-score value. Identification of hot spots are important because the results reveal areas where governments should pay more attention when it comes to road injury preventions. In addition to these two methods, geographic weighted regression (GWR) was also used in determining factors that would influence the increase in road traffic injury. One of the benefits of using GWR was that it allowed locational information to be included in the analysis, and thus the results became more accurate and reliable.

6.2 Limitations

Furthermore, different geographic units were used in the analysis. For instance, in both global and local spatial autocorrelation, dissemination areas (DA) were used, primarily due to the accuracy and reliability of the results in smaller areas. In contrast, census tracts (CT) geographic units were used for statistical analysis, because since DA geographic units are small in size, they tend to create more variance and as a result skew the results in regression analysis. Therefore, a larger geographic unit such as CT was applied in the statistical analysis to avoid skewness in the result. However, using CT geographic unit had its own limitation. As an example, the north western municipalities of Durham region (Scugog and Brock) which are considered as secluded and rural area, were excluded from the analysis, due to the lack of CT geographic units, and thus they were not included in the regression analysis. In addition to this, there were some issues within the census data as well. For example, 17 instances of null data or no data values were present within the GTA census tracts, and as a result they were also not included in the regression analysis.

6.3 Future Research

Identification of road traffic injury hotspots and determining influencing factors in road traffic injury can definitely be beneficial in injury prevention measures. The findings of this research supports those of other studies which associate low education and urban density with road traffic injury. In addition, number of seniors was also found to be a factors in road traffic injury. Consequently, these results provide a foundation for extending road traffic injury research. Future studies should definitely analyze and study the road design and visibility in urban areas. Road design is widely acknowledged in several studies. For instance studies have found that motor vehicle speed and fatality frequencies are higher on wider major arteries, and as a result there are more crashes and injuries at main intersections. Also, study by Morency (2012) examined how road design can increase the rate of pedestrian and cyclist injuries within an urban areas. The results of this study suggested that arterial roads with increased turning range and free-flow right turn lanes may threaten pedestrian and cyclist. Therefore, to better orient street level environment and prevent such incidents to occur, further studies should include more detailed measures of street design and visibility. Furthermore, since health behaviors factors such as smoking and drinking demonstrated a moderate relationship with road traffic injury incidents, future studies should examine physical factor such as time and the distance travelled in relation to road traffic injury incidents. Some studies have found that distance travelled can pose a great risk to pedestrian and other drivers (Chapman, 1973; Lassarre *et al.*, 2007). Study by Lassarre and others, examined the relationship between road accidents and distance travelled. The results explained that drivers that travel a greater distance, are more likely to driver at a higher speed and be prone to exhaustion and thus threaten the safety of other motorists and pedestrians. Study by Chapman (1973) also found that driving time can also be an exposure to road traffic injury. For instance, driving between day and night can greatly impact the risk of road injuries. Drivers with poor visions are more prone to get in an accident since they would not be able to see and distinguish the objects clearly at night time. Having said this, to prevent and alleviate the rate of road traffic injury, further studies should include more detailed examination and analysis on time and distance travelled.

REFERENCES

Afukarr, F.K., Antwi, P. and Ofosu-Amaah, S. (2003). Pattern of Road Traffic Injuries in Ghana: Implications for Control. *Injury Control and Safety Promotion*. 10(1-2): 69-76.

Aguero-Valverde, J. and Jovanis, P.P. (2006). Spatial Analysis of Fatal and Injury Crashes in Pennsylvania. *Accident Analysis and Prevention*. 38: 618-625.

Al-Omari, B.H. and Obaidat, E.S. (2013). Analysis of Pedestrian Accidents in Irbid City, Jordan. *The Open Transportation Journal*. 7: 1-6.

Ameratunga, S., Hijar, M. and Norton, R. (2006). Road Traffic Injuries: Confronting Disparities to Address a Global-Health Problem. *The Lancet*. 367: 1533-1540.

Anselin, L. (1995). Local Indicators of Spatial Association – LISA. *Geographical Analysis.* 27(2): 93-115.

Ashokbhai, P.V. and Jain, A.M. (2014). Road Safety Audit: An Identification of Black Spots on Busy Corridor Between Narol-Naroda of Ahmedabad City. *International Journal of Engineering and Technical Research*. 2(3): 86-89.

Atubi, A.O. (2012). Determinants of Road Traffic Accident Occurrences in Lagos State: Some Lessons for Nigeria. *International Journal of Humanities and Social Science*. 2(6): 252-259.

Brunsdon, C., Fotheringham, A.S. and Charlton, M.E. (1996). Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity. *Geographical Analysis.* 28(4): 281-298.

Brunsdon, C., Fotheringham, S. and Charlton, M. (1998). Geographically Weighted Regression-Modelling Spatial Non-Stationarity. *Journal of the Royal Statistical Society.* 47(3): 431-443.

Camilloni, L., Farchi, S., Chini, F., Rossi, P.G., Borgia, P. and Guasticchi, G. (2013). How Socioeconomic Status Influences Road Traffic Injuries and Home Injuries in Rome. *International Journal of Injury Control and Safety Promotion*. 20(2): 134-143.

Carlino, G.A., Chatterjee, S. and Hunt, R.M. (2007). Urban Density and the Rate of Invention. *Journal of Urban Economics*. 61: 389-419.

Chapman, R. (1973). The concept of exposure. *Accident Analysis and Prevention*. 5: 95-110.

Charlton, M., Fotheringham, S. and Brunsdon, C. (2006). Geographically Weighted Regression. Discussion Paper. Unpublished. ESRC National Center for Research Methods.

Chisholm, D., Naci, H., Hyder, A.A., Tran, N.T. and Peden, M. (2012). Cost effectiveness of strategies for reducing road traffic injuries in sub-Saharan Africa and South East Asia: mathematical modelling study. *BMJ*. 344(612): 1-9.

CIHI (2014). *Vision and Mandate*. Retrieved May 15, 2014, from http://www.cihi.ca/CIHI-ext-portal/internet/EN/SubTheme/about+cihi/vision+and+mandate/cihi010703

Clark, D.E. and Cushing, B.M. (2003). Rural and urban traffic fatalities, vehicle miles, and population density. *Accident Analysis and Prevention*. 36: 967-972.

Cliff, A.D. and Ord, J.K. (1973). *Spatial Autocorrelation*. Pion:London.

Cubbin, C., LeClere, F.B. and Smith, G.S. (2000). Socioeconomic Status and the Occurance of Fatal and Nonfatal Injury in the United States. *American Journal of Public Health.* 90(1): 70-77.

Erdogan, S. (2009). Explorative Spatial Analysis of Traffic Accident Statistics and Road Mortality among the Provinces of Turkey. *Journal of Safety Research*. 40: 341-351.

Ewing, R., Schieber, R.A. and Zegeer, C.V. (2003). Urban Sprawl as a Risk Factor in Motor Vehicle Occupant and Pedestrian Fatalities. *American Journal of Public Health*. 93(9): 1541-1545.

Flahaut, B., Mouchart, M., Martin, E.S. and Thomas, I. (2003). The Local Spatial Autocorrelation and The Kernel Method for Identifying Black Zones: A Comparative Approach. *Accident Analysis and Prevention*. 35: 991-1004.

Gao, J. and Li, S. (2011). Detecting Spatially Non-Stationary and Scale-Dependent Relationships Between Urban Landscape Fragmentation and Related Factors Using Geographically Weighted Regression. *Applied Geography*. 31: 292-302.

Gatrell, A.C., Bailey, T.C., Diggle, P.J. and Rowlingson, B.S. (1996). Spatial point pattern analysis and its application in geographical epidemiology. *Transaction of the Institute of British Geographers*. 21(1): 526-274.

Getis, A. and Ord, J.K. (1992). The Analysis of Spatial Association by Use of Distance Statistics. *Geographical Analysis*. 24(3): 189-206.

Getis, A. (2008). A History of the Concept of Spatial Autocorrelation: A Geographer's Perspective. *Geographical Analysis*. 40: 297-309.

Geurts, K. and Wets, G. (2003). *Black Spot Analysis Methods: Literature Review*. Flemish Research Center for Traffic Safety. Diepenbeek, Belgium.

Greater Toronto Marketing Alliance (2011). *Population Forecast and Growth Rate*. Retrieved April 27, 2014, from http://www.greatertoronto.org/why-greater-toronto/economic-overview/population

Hakkert, A.S. and Mahalel, D. (1978). Estimating the Number of Accidents at Intersections from a Knowledge of the Traffic Flows on the Approaches. *Accident Analysis and Prevention.* 10: 69-79.

Huang, B., Wu, B. and Barry, M. (2010). Geographically and Temporally Weighted Regression for Modeling Spatio-Temporal Variation in House Prices. *International Journal of Geographical Information Science*. 24(3): 383-401.

Jackson, M.C. and Waller, L.A. (2005). Exploring Goodness-of-Fit and Spatial Correlation Using Components of Tango's Index of Spatial Clustering. *Geographical Analysis*. 37: 371-382.

Jacob, G.D. and Sayer, I. (1983). Road Accidents in Developing Countries. *Accident Analysis and Prevention*. 15(5): 337-353.

LaScala, E.A., Gerber, D. and Gruenewald, P.J. (1999). Demographic and Environmental Correlates of Pedestrian Injury Collision: A Spatial Analysis. *Accident Analysis and Prevention*. 32: 651-658.

Lassarre, S., Papadimitriou, E., Yannis, G. and Golias, J. (2007). Measuring accident risk exposure for pedestrians in different micro-environments. *Accident Analysis and Prevention*. 39: 1226-1238.

Link, B.G. and Phelan, J. (1995). Social Conditions as Fundamental Causes of Disease. *Journal of Health and Social Behavior*. 35: 80-9.

Lu, B., Charlton, M. and Fotheringham, A.S. (2011). Geographically Weighted Regression Using a Non-Euclidean Distance Metric with a Study on London House Price Data. *Procedia Environmental Science*. 7: 92-97.

Mackie, P. (2005). The London congestion charge: A tentative economic appraisal. *Transport Policy*. 12: 288-290.

Manepalli, U.R., Bham, G.H. and Kandada, S. (2011). Evaluation of Hotspots Identification Using Kernel Density Estimation (k) and Getis-Ord (Gi*) on I-630. In: *International Conference on Road Safety and Simulation*.

Martin, P.G., Crandall, J.R. and Pilkey, W.D. (2000). Injury Trends of Passenger Car Drivers in Frontal Crashes in the USA. *Accident Analysis and Prevention*. 32: 541-557.

MetropolisIQ (2012). *GTA Population, Employment and Household Projections to 2041*. Retrieved April 27, 2014, from https://metropolisiq.com/blog/entry/updated-gta-population-employment-and-household-projections-to-2041

Montella, A. (2010). A Comparative Analysis of Hotspots Identification Method. *Accident Analysis and Prevention.* 42: 571-581.

Morency, P., Gauvin, L., Plante, C., Foumier, M. and Morency, C. (2012). Neighborhood Social Inequalities in Road Traffic Injuries: The Influence of Traffic Volume and Road Design. *American Journal of Public Health*. 102(6): 1112-1119.

Moutinho, L.A.M. and Hutcheson, G.D. (2011). The SAGE Dictionary of Quantitative Management Research. London: SAGE Publications Ltd.

Nakaya, T., Fotheringham, A.S., Brunsdon, C. and Charlton, M. (2005). Geographically Weighted Poisson Regression for Disease Association Mapping. *Statistics in Medicine.* 24: 2695-2717.

Odero, W., Garner, P. and Zwi, A. (1997). Road Traffic Injuries in Developing Countries: A Comprehensive Review of Epidemiological Studies. *Tropical Medicine and International Health*. 2(5): 445-460.

Ord, J.K. and Getis, A. (1995). Local Spatial Autocorrelation Statistics: Distributional Issues and an Application. *Geographical Analysis*. 27(4): 286-306.

Pratte, D. (1998). Road to Ruin: Road Traffic Accidents in the Developing World. *NEXUS.* 13: 46-62.

Ramage-Morin, P.L. (2008). Motor Vehicle Accident Death, 1979 to 2004. *Statistics Canada Health Reports*. 19(3) :1-7.

Scheidt, P.C., Harel, Y., Trumble, A.C., Jones, D.H., Overpeck, M.D. and Bijur, P.E. (1995). The Epidemiology of Nonfatal Injuries among US Children and Youth. *American Journal of Public Health*. 85(7): 932-938.

Schuurman, N., Cinnamon, J., Crooks, V.A. and Hameed, S.M. (2009). Pedestrian Injury and the Built Environment: An Environmental scan of hotspots. *BMC Public Health.* 9(233): 1-10.

Slocum, T.A., McMaster, R.B., Kessler, F.C. and Howard, H.H. (2009). *Thematic Cartography and Geovisualization*. Upper Saddle River, N.J.: Pearson Prentice Hall.

Statistics Canada (2011). *About the Canadian Institute for Health Information (CIHI)*. Retrieved May 7, 2014, from http://www.statcan.gc.ca/pub/82-221-x/2011002/abc-eng.htm

Tobler, W.R. (1970). A Computer Movie Simulating Urban Growth in the Detroit Region. *Economic Geography*. 46(2): 234-240.

Transport Canada (2011). *Road Safety in Canada*. Retrieved May 22, 2014, from http://www.tc.gc.ca/eng/motorvehiclesafety/tp-tp15145-1201.htm

Truong, L.T. and Somenahalli, S.V. (2011). Using GIS to Identify Pedestrian-Vehicle Crash Hot Spots and Unsafe Bus Stops. *Journal of Public Transportation*. 14(1): 99-114.

Vaz, E., Nijkamp, P., Painho, M. and Caetano, M. (2012). A multi-scenario forecast of urban change: A study on urban growth in the Algarve. *Landscape and Urban Planning*. 104(2): 201-211.

Vaz, E. and Jokar Arsanjani, J. (2015). Crowdsourced mapping of land use in urban dense environments: An assessment of Toronto. *The Canadian Geographer/Le Géographe canadien*. 59(2): 246-255.

Helbich, M., Brunauer, W., Vaz, E. and Nijkamp, P. (2013). Spatial heterogeneity in hedonic house price models: the case of Austria. *Urban Studies*. 0042098013492234.

Vaz, E. (2016). The future of landscapes and habitats: The regional science contribution to the understanding of geographical space. *Habitat International*. 51: 70-78.

Vaz, E., Lee, K., Moonilal, V. and Pereira, K. (2017). Potential of Geographic Information Systems for Refugee Crisis: Syrian Refugee Relocation in Urban Habitats. *Habitat International*.

Vaz, E. and Khaper, M. (2016). New Resources For Smart Food Retail Mapping. A Gis And The Open Source Perspective. *Journal of Spatial and Organizational Dynamics*. 4(4): 305-313.

Vaz, E., Cusimano, M. and Hernandez, T. (2015). Land use perception of self-reported health: Exploratory analysis of anthropogenic land use phenotypes. *Land Use Policy*. 46: 232-240.

de Noronha, T. and Vaz, E. (2015). Framing urban habitats: the small and medium towns in the peripheries. *Habitat International*. 45: 147-155.

Vaz, E. (2013). The spatial business landscape of India. *Journal of Spatial and Organizational Dynamics*. 1(4): 241-253.

Vaz, E. and Nijkamp, P. (2015). Gravitational forces in the spatial impacts of urban sprawl: An investigation of the region of Veneto, Italy. *Habitat International*. 45: 99-105.

World Health Organization (2005). *World Report on Road Traffic Injury Prevention*. Retrieved May 3, 2014, from http://siteresources.worldbank.org/EXTTOPGLOROASAF/Resources/WHO_full_report_en.pdf

World Health Organization (2014). *International Classification of Diseases (ICD)*. Retrieved May 16, 2014, from http://www.who.int/classifications/icd/en/

World Web (2013). *Greater Toronto Area*. Retrieved April 27, 2104, from http://www.greatertoronto.worldweb.com/

Zhang, L., Bi, H., Cheng, P. and Davis, C.J. (2004). Modeling Spatial Variation in Tree Diameter-Height Relationships. *Forest Ecology and Management*. 189: 317-329.

ISSN: 2183-1912

Authors

Akeem Foster
Eric Vaz
Georgios Efthimiou
Jessica Miki
Konstantinos Ntouras
Michael Cusimano
Sina Tehranchi
Teresa de Noronha
Thomas Panagopoulos

UAlg
UNIVERSIDADE DO ALGARVE

CIEO
Centro de Investigação sobre o Espaço e as Organizações

FCT
Fundação para a Ciência e a Tecnologia
MINISTÉRIO DA CIÊNCIA, TECNOLOGIA E ENSINO SUPERIOR