Title:	**Comparing Social Capital and Spatial Use Patterns in Three Hamilton Census Tracts**

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Abstract

The Social Imaging Study uses a new social capital measurement instrument (Social Capital General Social Survey – SCGSS) developed for neighbourhood level measurement of social network and trust levels. This instrument is paired with Global Positioning System data to measure spatial behaviour of a random sample of participants across three East Hamilton Census Tracts differentiated by income – median and a standard deviation above and below the median for adults aged 18-64 years. The spatial statistics of the GPS data is analyzed and summarized for comparison with the SCGSS data to determine if the hypothesis that greater movement correlates with higher levels of social capital. Early results show some statistical significance for the income and marital status dependent variables interacting with Nearest Neighbour Z-scores and the Directional Rotation of the spatial ellipsis across all three Census Tracts. There is also significant interaction between Census Tract pairs on the mode of contact with relatives and number of acquaintances dependent variables and range of independent spatial variables. Finally, there are single Census Tract interactions between the dependent variables of trust in city officals and frequency of contact with close friends and three different independent spatial variables.

Keywords: social capital, spatial statistics, General Social Survey, GPS

Comparing Social Capital and Spatial Use Patterns in Three Hamilton Census Tracts

Introduction

It can be difficult and expensive to measure social capital levels and charateristics at neighbourhood scales across urban areas. Like other approaches in science, it may be possible to find an economical measurement that can serve as a proxy for social capital levels. Given Tobler's First Law of geography that all things are related but near things are more related (Miller, 2004), the Social Imaging Project is exploring the merits of spatial use patterns as a proxy for social capital levels in aggregate form at Census Tract levels (serving as rough geographic boundaries for neighbourhoods).

The Social Capital GSS (SCGSS) instrument is a new synthetic survey tool based on General Social Survey questions that has been developed to meet neighbourhood level social capital measurement that allows for comparision with larger scale and lower resolution measurements already exist. The SCGSS acts as control with spatial use (GPS) functioning as a proposed proxy measure – not for individuals but as an aggregate, statistical representation of the whole population (each Census Tract which is the population from which the sample is drawn). All of the factors that the SCGSS measures (age, demographics, trust, networks) give us information about individuals and the aggregate Census Tract. The spatial use is another type of information about individuals and the aggregate Census Tract. These can in turn be compared with each other *across* Census Tracts. Ten different spatial statistical measures of the GPS data tracks are utilized to summarize spatial characteristics of the participants.

The Social Imaging Study involved identification of three Census Tracts in Hamilton, ON based on a set of criteria: one Census Tract at the median income level (adults aged 15-64), and one each a standard deviation above and below the median. The choice of Census Tracts was then refined to locate three that met the above criteria in addition to being as close to each other as possible for similarities in urban form, access to transportation, and so on (Table 1).

Position	Census Tract	$/yr income	**Adjusted CT (Name)**	**$/yr income**
Median	*5370073.00*	*26,340*	**5370025.00 (McQueston)**	**26,671**
Std. Dev. Above	*5370131.00*	*32,191*	**5370030.00 (Delta)**	**31,238**
Std. Dev. Below	*5370053.00*	*20,620*	**5370071.00 (Rosedale)**	**19,178**

Table 1: Census Tract selection based on 2011 Statistics Canada Census Data.

The area being studies is located on the eastern edge of the lower city of Hamilton between the industrial area and the Niagara Escarpment (a geological feature comprised of a limestone cliff that runs through the city)(Figure 1).

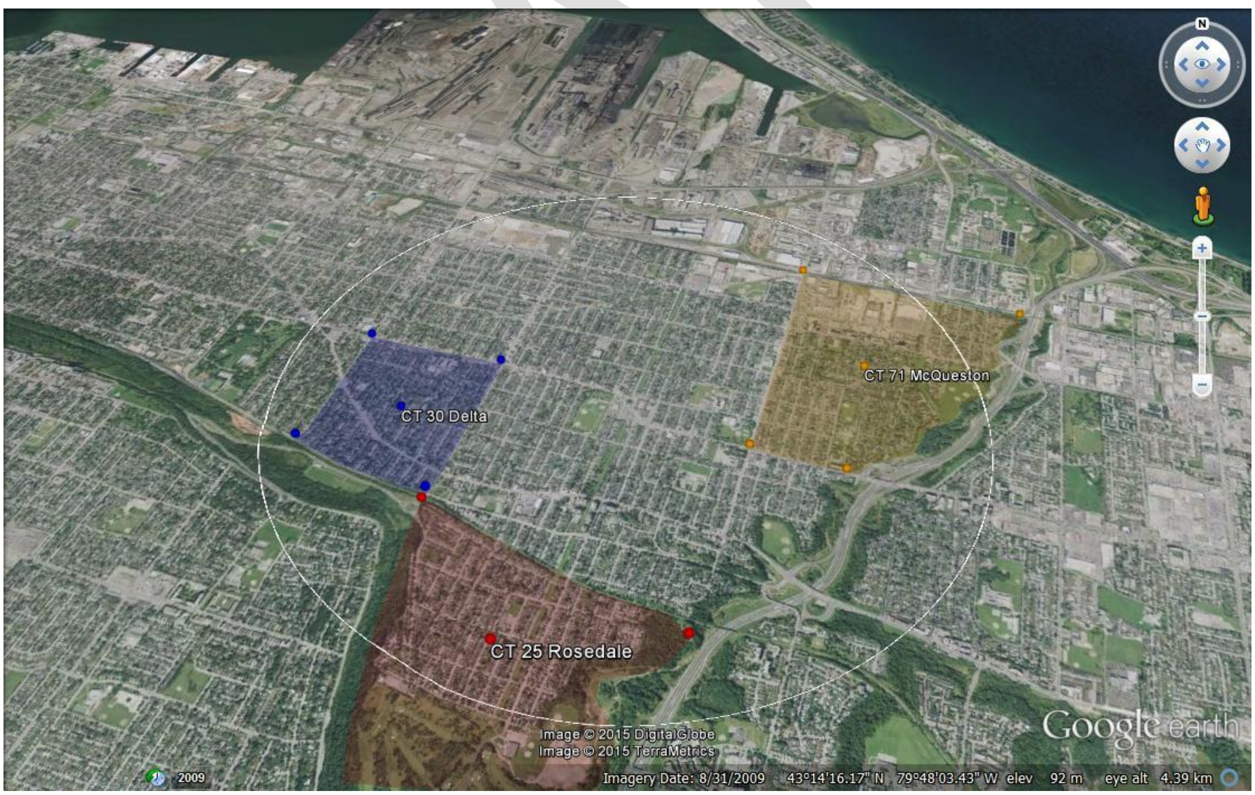


Figure 1: Google image of the research area showing a 2 km circle (white) that encompasses Delta (blue), McQueston (yellow) and Rosedale (red) Census Tracts.

Random Digit Dialing between January –May 2016 was used to recruit participants for both the SCGSS and the spatial data collection. Spatial data was generated by survey respondents carrying a Global Positioning System (GPS) data logging device with them for a seven day period. This double collection of data enables the core exploration of spatial use and social captial levels with consideration for the extent to which spatial data characteristics can be used as a proxy for measuring variances in social capital levels across geographic areas.

There were significant challenges in recruiting representative samples from each Census Tract and additional Census Tracts were added that met the criteria of each of the three Census Tracts selected (Table 2).

Position	Adjusted CT (Name)	Eligible Population	**Additional CT**	**Eligible Population**
Median	5370025.00 (Rosedale)	1840	**5370028.00** **5370055.00**	**2849** **2943**
Std. Dev. Above	5370030.00 (Delta)	2880	**5370031.00**	**2098**
Std. Dev. Below	5370071.00 (McQueston)	4350	**5370059.00**	**3173**

Table 2: Additional Census Tracts and population figures.

6099 call attempts were made with 151 responses to the request for both survey and GPS data logging participation (Appendix A: Call centre audit data). The 151 responses were further reduced and resulted in 97 useable completes (survey and GPS data logging portions, n=97). Despite a Human Research Ethics (University of Waterloo) approved honorarium strategy, devices were lost, not returned and calls unaswered. After significant follow-up, 23 of the 91 devices used for the data collection were unaccounted for upon completion of the project.

The data collected from the SCGSS formed a matrix of 97 observations across 41 variables. The data collected from the GPS data logging portion comprised a dataset of 2,100,000 observations across 97 participants after being adjusted for seven day collection period consistency.

Social Capital and the General Social Survey

Significant sholarly attention has been paid to social capital research with more than 9164 sources listed in the Web of Science database alone across dozens of disciplines (Friesen, 2016b). The phenomena of social capital is comple x involving intricate and often difficult to measure social and cultural interactions from individual to societal scales. This has resulted in dozens of social capital measurement scales being developed to explore facets such as loneliness (Russell, 1996), employment (Leana & Van Buren, 1999), health (Carpiano, 2007) and trust (Chow & Chan, 2008).

Two key charateristics of social capital are social networks and trust. In an effort to more explicitly link new social capital research with existing datasets, a new instrument was developed. The Social Capital GSS instrument was designed to integrate questions from more than 30 years of national social survey work in Canada. That work is in turn linked with the International Social Survey Programme (ISSP) that has an international scope (Lauer & Yodanis, 2004). The Canadian GSS program began in 1985 with Cycle 1 and continues to the present. Using "social networks" and "trust" as rubrics for selection, Cycles 1-27 spanning 1985-2013 were reviewed for questions that could be included in a new instrument. Demographic questions from prior GSS cycles were also reviewed and considered to achieve a balance in the instrument between efficiency and information yield. In addition, the Personal Social Capital Scale 16 (Chen, Stanton, Gong, Fang, & Li, 2009) instrument was used as an external reference point given the established scholarly review of its function and consonance with social networks and trust.

The standard GSS cycles are lengthy and expensive surveys to administer with a typical n=13,000-25,000 across Canada. For neighbourhood measures of social capital, considerable refinement was needed. However, making use of existing well-studied and field tested GSS questions allows borrowing of that investment along with possible comparison on a question-by-question basis between localized results and national patterns which may be of value to other researchers.

Three cycles were identified from the possible 27 cycles as particularly relevant and were selected for further refinement – Cycle 17, 22, and 27. These are comprised of 138 modules (modules are comprised of themed sets of questions). After careful review, 114 modules were excluded. The 24 relevant modules were reviewed and 130 questions were selected from them. When compared against social networks and trust, 54 questions were excluded. The core of 66 questions was then subjected to refinement and 32 were identified as non-core questions, leaving a final set of 41 questions for the SCGSS instrument. Slight adjustments were made to some questions and answer frameworks but efforts focussed on leaving the questions intact (Figure 1).

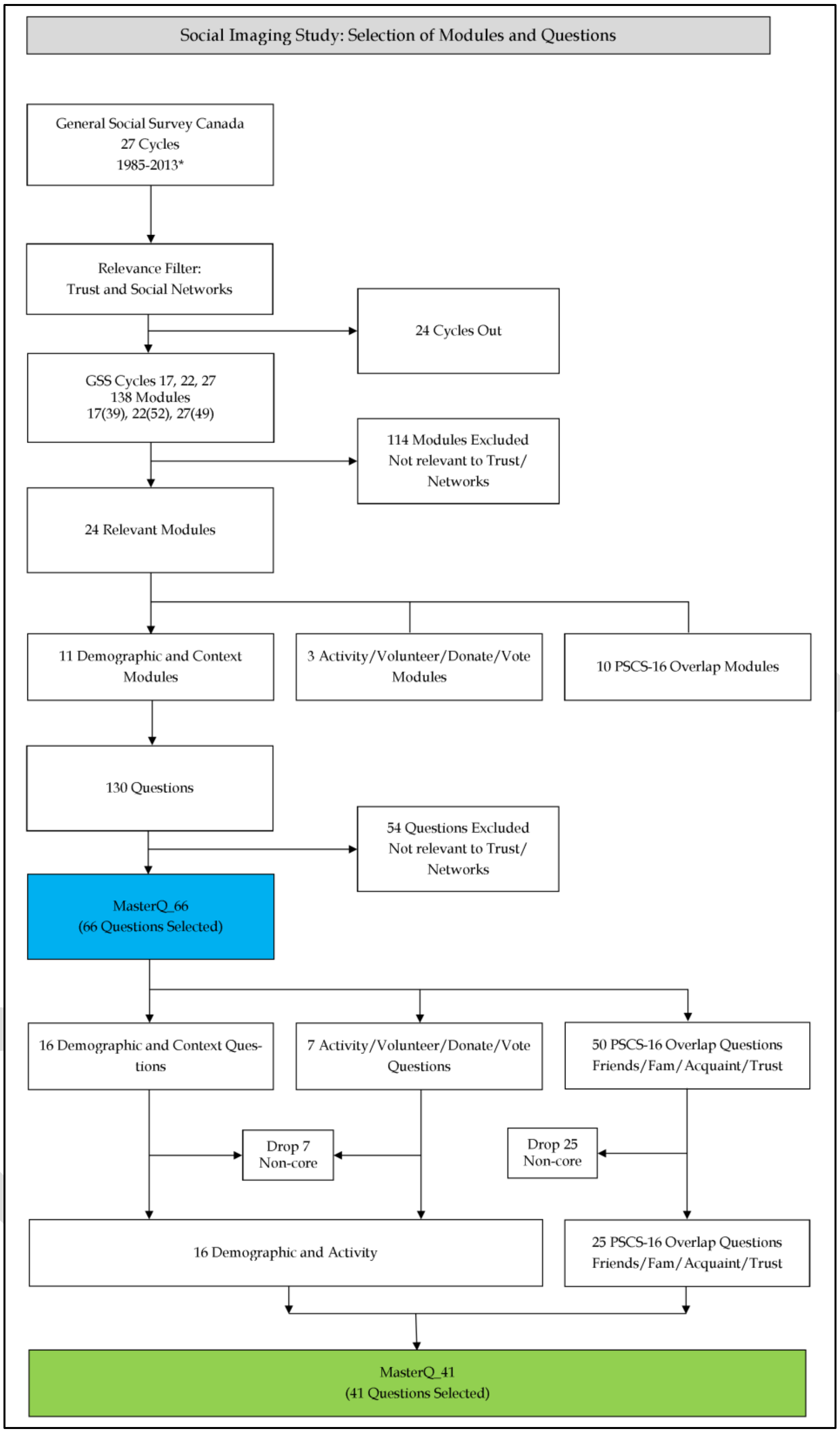


Figure 2: Social Capital General Social Survey question development and selection rubric. Original cycle background data from: Statistics Canada http://www5.statcan.gc.ca/cansim/a31?lang=eng

The result of the GSS cycle review and question selection is a social capital survey instrument with 41 questions: 16 Demographic and Context questions, 12 questions on Social Networks, and 13 questions on Trust (Friesen, 2016a). The questions on social networks and trust capture both individual and institutional perceptions of trust and relational context.

Global Positioning System Spatial Data

In order to begin exploration of spatial use patterns at aggregate Census Tract levels, participants in the Social Imaging Study completed both the SCGSS instrument and carried a Global Positioning System (GPS) data logging device with them for seven days. The devices used were the QStarz BT-Q1000X Travel Recorder. The device uses a MTK II GPS module with 66 channel tracking, -165dBm antenna sensitivity, and +200,000 observation memory capacity (see Appendix 2). Custom GPS data logging devices were also developed in conjunction with the study. The objective was to meet feature requirements that minimized human factor variables such as forgetting to charge the device, removable memory, and the addition of other custom sensors to add further dimensions to the data collection (see Appendix 3). These custom devices were not ready for production at the time of study deployment so the BT-Q1000X units were generously loaned by Prof. Darren Scott, Faculty of Science, School of Geography and Earth Science (McMaster University).

The GPS devices were set to record a position every 15 seconds regardless of motion with participants taking them with them if they left their home. They were also asked to recharge them every night. A very brief travel diary page was also provided for participants to record the degree to which the week of the spatial data collection was considered normal. They also filled in simple time use graphs based on primary activity in a six hour blocks and added additional comments. The averages of these time use blocks indicated a significant center weighting of “normal” with a slight “less active” skew (Figure 2).

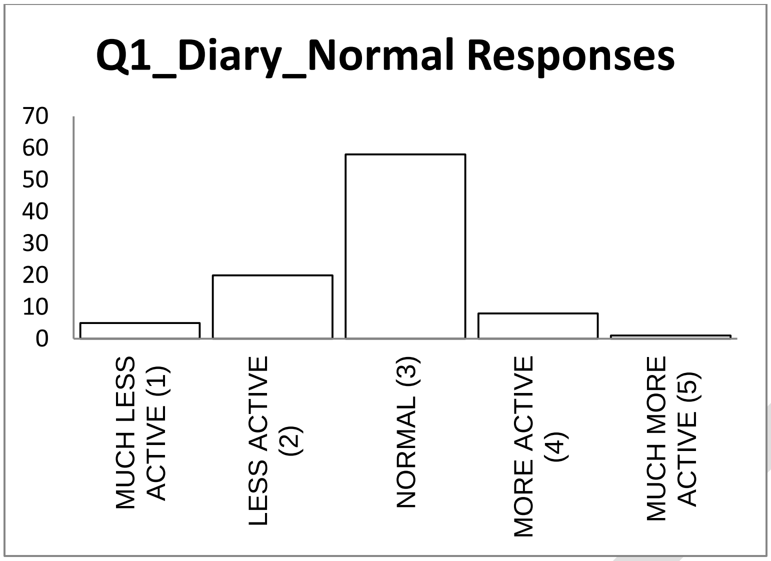
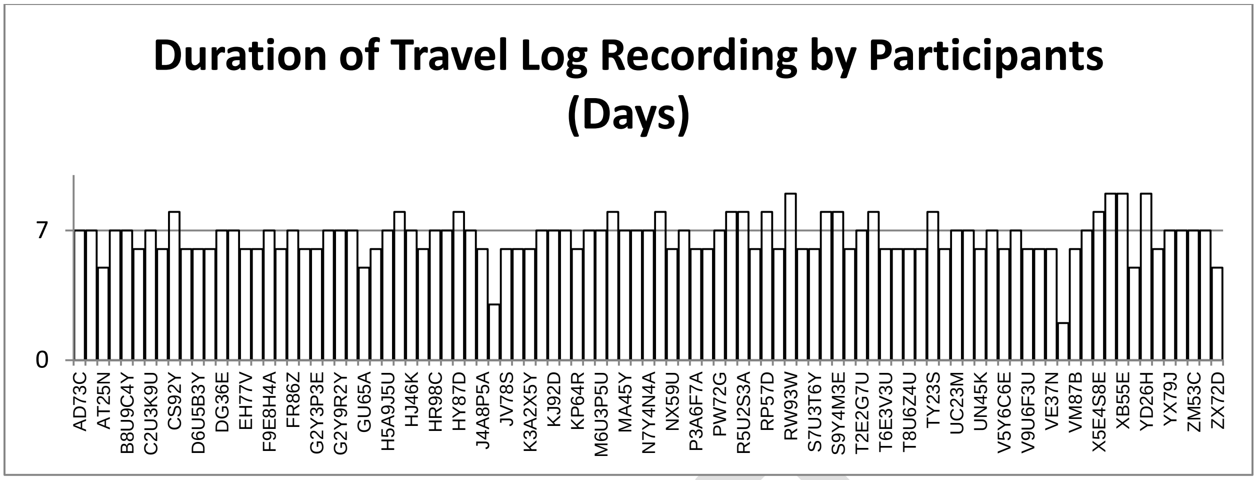


Figure 3: Results of time use diary for GPS data logging users.

Data collection ran from January 20, 2016 to March 23, 2016 with several devices showing up until May 4, 2016. All returns in this time period were included. There were time variations in the duration of data collection as the begin and end times were dependent on participants. Some participants carried devices far longer than the seven days. Other participants noted they seldon left home and turned on the device only when they did leave. Three files were included where the survey notes and travel diary data verified why there was intermittent data and where corroboration was not possible, participants were removed from consideration for the study. Where data collection went beyond seven days, a block of seven days which had the most consistency of collection based on observations per day, was selected for consideration.

Average number of days for participants (N=97) yielded a mean of 6.7 days and the average (mean) number of data logging points (observations after standardization was 21,657 with median of 22,194. Total number of observations after adjustments was 2,100,690 (Figure 4).



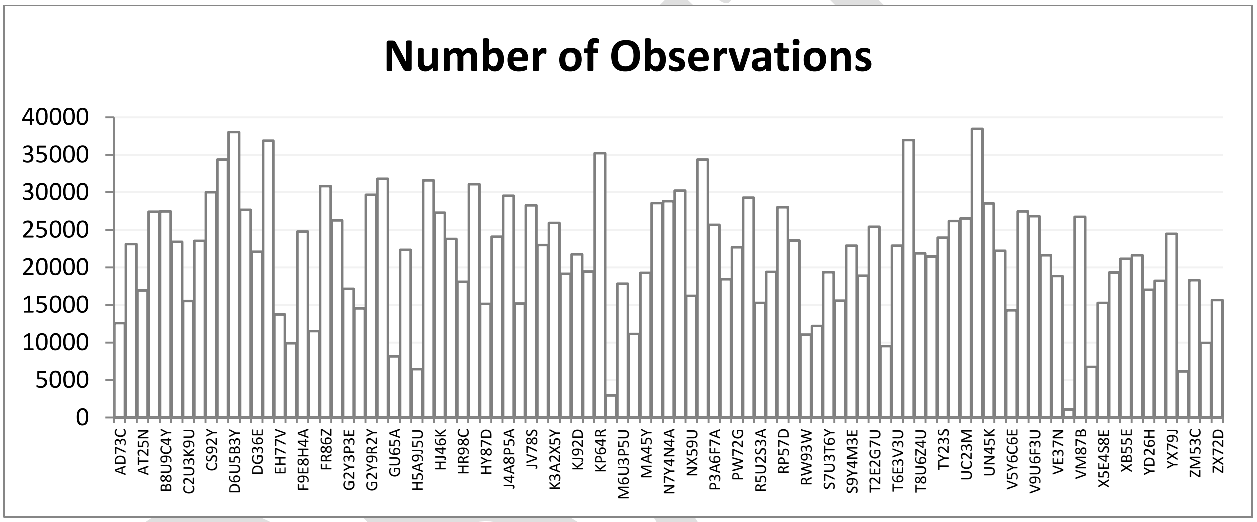


Figure 4: Duration (above) and Number of Observations (below) of Social Imaging Study participants (sorted alphabetically).

Mapping of an individual track reflects that general nature of the distribution patterns that the logging devices yielded (Figure 4).

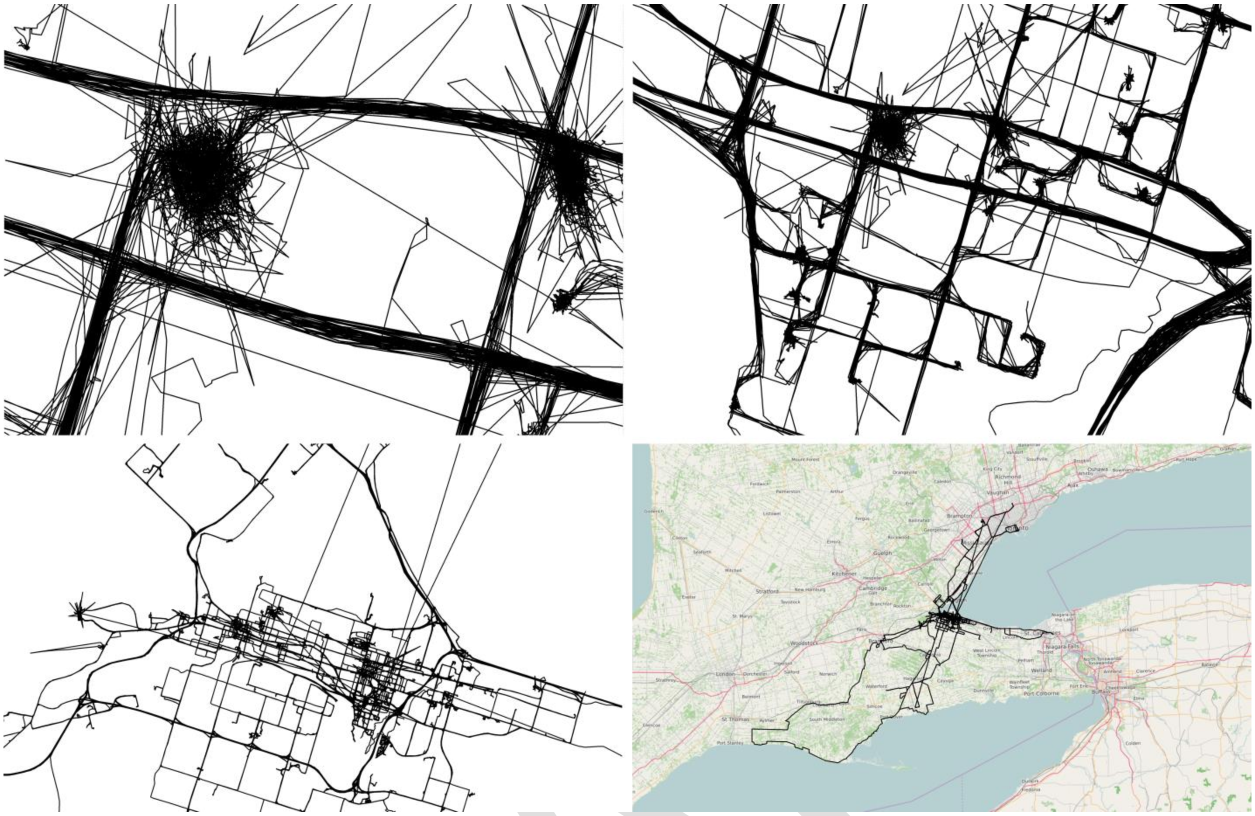


Figure 5: Example of Census Tract aggregated GPS data logging tracks for seven day period at various resolutions with and without map details (ESRI, ArcGIS 10.3.1 Desktop).

Raw data was processed for importing to ArcGIS to facilitate spatial analysis using a custom Excel macro designed to format, organize, remove unwanted columns, and standardize time codes. In addition, there were cases where the devices recorded a position every second or every five seconds. These files were sequentially reduced to 15 second intervals with another custom Excel macro that removed every nth line as required. Data was projected from Latitude/Longitude format to UTM 17N (Southern Ontario) using the ArcGIS "Project" tool. Ten spatial variables were synthesized from the analysis process (Table 3).

Variable	**Explanation**	**ArcGIS Tool Used**	**Example of Measurement Output**
Total Distance	Length of line generated by GPS tracks	Points to Line	71509.07 meters

Radius of the Standard Distance from the Mean	The distance from the mean geographic center of a set of coordinates to the outer edge of a circle representing one standard deviation from the mean	Standard Distance	469.15 meters
Difference between the Mean and the Median	Distance between the location of the geographic mean and the median set of coordinates.	(Distance between mean and median calculated manually using Exce)	63 meters
Rotation of the Standard Distance Ellipsis	The rotation clockwise from North (0 degrees) of the standard deviation of the x axis when calculated as a value of the standard deviation of the y axis	Directional Distribution	80.6 degrees
Ratio of the X and Y axis of the Standard Deviational Ellipse	Length of standard deviation of the X axis divided by the standard deviation of the Y axis where a perfect circle would equal 1.	(Calculated manually using Excel)	7.4 (indicating a distribution with a significant x axis distribution compared with the y axis)
Nearest Neighbour Observed Median Distance	Computes the average distance from one point to all others for the whole set and then identifies the median distance.	Average Nearest Neighbour	0.540 meters
Nearest Neighbour Ratio	Compares how close the next nearest point is compared with a random distribution of points. Clustered < 1 < Dispersed	Average Nearest Neighbour	o.050

Nearest Neighbour Z-score	Measures how likely it is that a given distribution of points is random. Low scores equal very unlikely distribution is random.	Average Nearest Neighbour	-278.89
Nearest Neighbour Area	Area of the smallest rectangle that encloses all points – does not necessarily align with x and y axes.	Average Nearest Neighbour	10960790.29 square meters
Standard Speed	Calculations of all the speed values carried into the dataset from the GPS devices expressed as standard deviation.	Summary Statistics	3.52 km/h

Table 3: Spatial variables utilized and with descriptions, tools of analysis, and outputs explained.

The Spatial data, after the above-noted cleaning, processing, and analysis, yields a matrix of 97 observations (N=97) with 10 secondary variables arising out of analysis of the original GPS data logging points following the preceeding calculations and tools. It should be noted that the measures are relative within the group given that tools like “Integrate” and “Collect” werenot used prior to analysis. GPS data logging devices will generate distances even when stationary given that the fixes bounce. While this could be corrected, it is more important that the data is handled consistently as a whole whether collected and cleaned or processed in a closer-to-raw state. Statistical means will be used to describe, explore and begin to infer results. The variables above have visual dimensions as well and this is an additional means of analysis that has significant further potential (Figure 5).

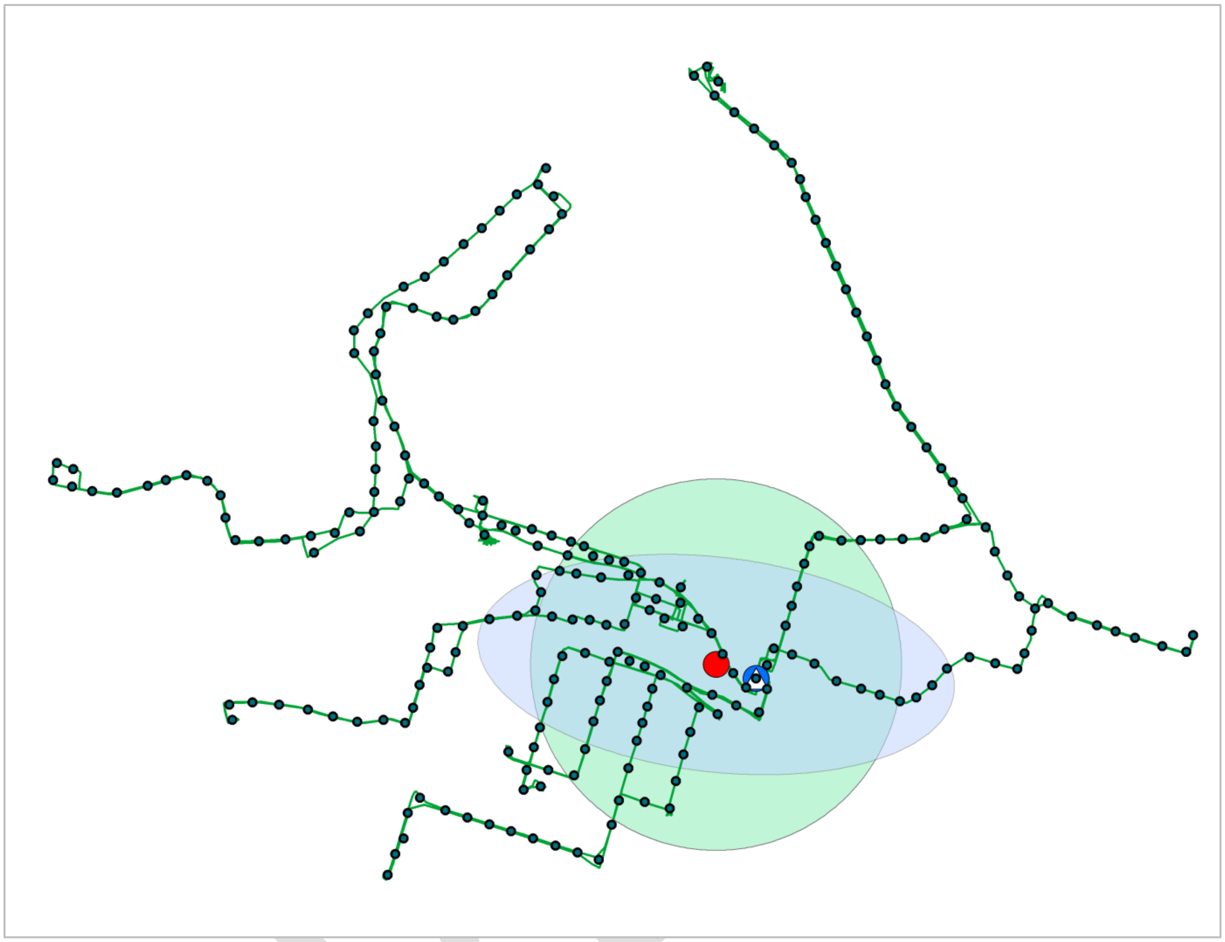


Figure 6: Image with map details omitted showing features of a mapped GPS data track. Features include: mean center(red), standard deviation (green circle), median feature (white on blue), directional ellipse(blue ellipse), pathway with points collected and emphasized for clarity and joined in a line (green - total distance).

Initial Results

Demographics and Context Compared with Spatial Variables

(16 dependent variables).

For Demographic/Context dependent variables, focus will be limited to those variable interactions that showed modest statistical significance across all three neighbourhoods. The two dependent variables are "income" and "marital.status". One result is that there is less p-value significance (*) is highest across all the variable interactions. A second result is that there is more overlap across all three neighbourhoods. There are two dependent variables that show notable interaction with independent variables (Table 3).

Neighbourhood	Dependent Variable	Independent Variables	Significance	P-value
Delta	income	+spatial	nn.zscore	0.0382
McQueston	income	+spatial	nn.zscore ellips.rotat ellips.xyrat	0.0730 0.0179 0.0147
Rosedale	income	+spatial	ellips.rot	0.0379
Delta	marital.status	+spatial	ellipsis.rotat	0.0514
McQueston	marital.status	+spatial	nn.ratio nn.zscore	0.0820 0.0158
Rosedale	marital.status	+spatial	standis.radius allpointsarea.rectangle	0.0506 0.0277

Table 4: Dependent variable interactions with indpendent spatial variab les across all three neighbourhoods.

There were also dependent variables that occurred in two neigbhourhoods with p-values lower than 0.05 (Table 4).

Neighbourhood	Dependent Variable	Independent Variables	Significance	P-value
Delta	dwell.type	+spatial	ellips.rotat ellips.xyrat	0.0394 0.0525

McQueston	dwell.type	+spatial	ellips.rotat diff.memed	0.0514 0.0453
Delta	vote.freq		nn.ratio	0.0822
Rosedale	vote.freq	+spatial	nn.ratio ellips.xyrot	0.0188 0.0706
Delta	donate	+spatial	ellips.rot nn.ratio	0.0509 0.0186
Rosedale	donate	+spatial	nn.ratio	0.0617
McQueston	education	+spatial	total.distance	0.0552
Rosedale	education	+spatial	total.distance dif.memed nn.obmedist nn.ratio nn.zscore standard.speed	0.0258 0.0266 0.0078 0.0327 0.0090 0.0310

Table 5: Dependent variables with spatial data significance shared by two neighbourhoods.

“Income” and “marital.status” have notable interactions with ellipsis variables and nn.zscores. This encourages the possiblity that income differentiation may be a meaningful social capital factor. The limitation is that “income” and “marital.status” are both demographic features rather than social capital factors. It would appear their role is secondary at best and would require further investigation.

This represents a complex mix of variables interacting across a variety of dynamics. The challenge trying to identify meaningful patterns as they relate to the actual structures of the phenomena being investigated. Before those conclusions can be ventured, it is necessary to examine the nature of the interaction between the Social Capital dependent variables and the Spatial variable set.

Social Capital Compared with Spatial Variables

The challenge of comparing spatial and social datasets is the complex nature of the variables and their interactions. The reason for including this analysis is that the search for meaningful signals at an exploratory stage must be careful that it is open to uncover significance that is peripheral but which could be analyzed and understood in such a way that insight and information are the result. It may be that important signals will show up differently from one neighbourhood to another given the sample size and subtle but important confounding variables.

The interaction of the 25 dependent Social Capital variables with independent Spatial variables yielded two result patterns . The first are interaction models that yieled statistically significant results but which occured in only one of the three neighbourhoods (Table 5).

Neighbourhood	Dependent Variable	Independent Variables	Significance	P-value
Delta	trust.city	+spatial	standis.radius dif.memed	0.0095 0.0084
Rosedale	close.freq	+spatial	nn.obmedist	0.0069

Table 6: Single Neighbourhood significant interactions between Social Capital and Spatial variables.

Model potential may be refined to reveal wider usefulness than was initially the case. The second interactions worth noting are the variables that showed statistical significance in two neighbourhoods (Table 6). There were no dependent variables that occurred across all three neighbourhoods at p-value significance levels beyond (** = 0.001)

Neighbourhood	Dependent Variable	Independent Variables	Significance	P-value
Delta	relative.contact	+spatial	nn.zscore	0.0100
Rosedale	relative.contact	+spatial	standis.radius dif.memed nn.obmedist nn.ratio allpointsarea.rectangle	0.0097 0.0197 0.0296 0.0848 0.0387
McQueston	acquaint.number	+spatial	nn.zscore	0.0877
Rosedale	acquaint.number	+spatial	total.distance standis.radius nn.obmedist nn.ratio allpointsarea.rectangle standard.speed	0.0523 0.0226 0.0726 0.0843 0.0061 0.0211

Table 7: Significant p-values for Social Capital dependent variables and Spatial data variables.

It appears that “z-scores” and “relative.contact” variables interact in important ways in Delta but a much more extensive list of variables (not including “nn.zscore”) contribute in the Rosedale dataset. It is not clear what the relationship is between Nearest Neighbour Z-scores and “relative.contact” (the mode of contact most used with relatives who do not live in the same home) but it appears, by inference, that the lower income Census Tract (McQueston) shows less interaction on these variables. However, the "number.acquaintances" (number of acquaintances someone has – people who are not friends and are not related but which they know at least the first name of) in Rosedale, the median income tract, shows considerable and meaningful variabel interaction on "stand.dis" (standard distance from the mean measured spatially), "nn.obmedist" (Observed Mean Distance), "nn.ratio" (Nearest Neighbour Ratio), and "allpointsarea.rectangle" (area of a rectangle drawn around all points). These do not show up on McQueston or Delta at significant levels. Model tuning may identify that those patterns are there but require additional analysis and techniques to understand.

When analysis was performed on the dataset as a whole without neighbourhood segmenting, many of the p-value signals were not visible. Development of a more carefully specified model based on feedback and fine-tuning will result in greater clarity about which spatial features are the most critical indicators of social capital levels.

Limits

The significant number of interactig variables across multiple modes makes the detection of meaningful signals challenging. Multi-variate linear regression has provided an initial orientation to the possibility of signal amid the noise but requires further testing and strategic analysis.

Demographic and context data was treated in aggregate form as direct numeric values without analysis of the content behind those variables. This is suitable for pattern detection but a more fullsome explanation of the particpant poplulation by Census Tract would be needed to provide a link between the statistical data and the human groups being described.

Descriptive, exploratory and inferential modes of exploration are appropriate for the datasets that are being utilized but more concrete conclusions remain for future consideration. As such, the current paper provides one means of approaching the problems of social capital measurement by proxy using an originally generated dataset. It may well be that there are other data elements that are needed to support further extension of the social capital/spatial movement hypothesis.

Care must be exercised in this process to avoid oversimplification of a complex phenomena by means of a simplified proxy measurement. It is not clear that there is such a measurement or that if found, it would be adequate to anything more than a very selective aspect of the phenomena.Awareness that these boundaries exist is critical.

A full review of other possible proxy measures for social capital and spatial patterns was not undertaken here. While measurement of social capital has been considered elsewhere, identifying a range of proxies measures is a very distinct undertaking and should be kept in mind.

Disucssion

There is clearly more information in the data tracks themselves – eg. Route Choice Analysis(Papinski & Scott, 2011) or developing data mining algorithms that can find time/location/social interaction patterns from large datasets (Eagle, 2005). There is also more information in the relationships between the Spatial Data variables and the Demographic/Context and Social Capital variables than has been possible to explore here. Candidates for further examination have been identified but there are almost certainly other features and combinations that should be considered.

Given the sizes of the samples, the results of spatial use and social capital be generalized do not appear generalizable. The intention of the study ws to be descriptive, exploratory and to begin to infer possible correlations between spatial use patterns and levels of trust and social network based aspects of social capital in local neighbourhoods. However, there are information patterns in the data that warrant further investigation, including applications in contexts where social capital levels are already well-known and to which spatial data could be added and analyzed as above.

Complex social phenomena will never be easy to decipher. Social capital remains a new field (Ostrom & Ahn, 2003) that has significant scope for continued growth. This growth will take place through a combination of disciplined investigation that makes use of rigorous statistical and emperical processes along with exploratory connections and leaps that will prevent locally optimized solutions that are far below a globalized optimum (Goldberg, 1989).

The hope is that if a more cost-effectiveproxy measure for social capital can be found using ubiquitous , organic, dynamic spatial pattern data generated by billions of mobile devices and the Internet of Things, wewill have been able to move from rudimentary visual maps of social infrastructure to much moreextensive and accurate maps of the invisble landscape of social capital.

Formal causal relationships will be unlikely given that the phenomena being investigated cannot be isolated in a lab setting and the entities involved exercise agency, leaving greater room for non-stochastic behaviour. This should not, however, dissuade use from seeking greater clarity concerning social capital measurement including possible proxy measures. In natural science, temperature is an aggregate measure. We can't know the position and velocity of every molecule of a gas but we can usefully predict the behaviour of the gas as an emergent property we call temperature, pressure, etc. Our search for such proxy measures in the social sciences field must continue to press forward building on what has already been accomplished.

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Appendices

Appendix 1

Code	Call Status - Overall	Total		1		2		3	
				1 Delta		2 McQueston		3 Rosedale	
I	10_Not_in_Service	**974**	16%	**193**	13%	**409**	19%	**372**	15%
I	11_Fax/Modem_Line	**36**	1%	**9**	1%	**10**	0%	**17**	1%
I	12_Wrong_Number/Business_vs._Household	**38**	1%	**11**	1%	**13**	1%	**14**	1%
R	-1_Completion	**153**	3%	**57**	4%	**48**	2%	**48**	2%
IS	20_Household/Gatekeeper_Refusal	**400**	7%	**119**	8%	**134**	6%	**147**	6%
IS	21_Respondent_Refusal	**1368**	22%	**360**	24%	**465**	22%	**543**	22%
IS	22_Second_Refusal/Do_Not_Call_Back	**1**	0%	**1**	0%	**0**	0%	**0**	0%
R	23_Non-Qualifier	**956**	16%	**218**	15%	**289**	14%	**449**	18%
U	29_RECEPTION_ONLY_Received_Call	**1**	0%	**0**	0%	**0**	0%	**1**	0%
U	30_Busy_Signal	**30**	0%	**2**	0%	**9**	0%	**19**	1%
U	31_No_Answer	**374**	6%	**90**	6%	**129**	6%	**155**	6%
U	32_Answering_Machine_-_Message_Left	**207**	3%	**79**	5%	**62**	3%	**66**	3%
U	33_Answering_Machine_-_No_Message_Left	**1184**	19%	**268**	18%	**406**	19%	**510**	21%
U	39_Soft_Appointment	**34**	1%	**4**	0%	**21**	1%	**9**	0%
U	40_Hard_Appointment	**11**	0%	**3**	0%	**5**	0%	**3**	0%
U	41_Moved/Left_Toll-Free_Number	**1**	0%	**0**	0%	**0**	0%	**1**	0%
U	42_Call_Answered_-_Call_Again	**175**	3%	**42**	3%	**62**	3%	**71**	3%
IS	43_Communication_Problem_-_Non-Language	**8**	0%	**1**	0%	**4**	0%	**3**	0%
IS	44_Language_Barrier	**109**	2%	**18**	1%	**59**	3%	**32**	1%
U	45_Language_Appointment	**6**	0%	**3**	0%	**2**	0%	**1**	0%
IS	56_Serious_Illness/Incapable	**7**	0%	**0**	0%	**4**	0%	**3**	0%
IS	57_Travel_Within_Canada/US	**1**	0%	**1**	0%	**0**	0%	**0**	0%
U	99_Supervisor_Review	**25**	0%	**10**	1%	**3**	0%	**12**	0%
	Total	**6099**	**100%**	**1489**	**24%**	**2134**	**35%**	**2476**	**41%**
	Average Number accessed per complete	**39.86**		**26.12**		**44.46**		**51.58**	

	Total	1 Delta	2 McQueston	3 Rosedale
R = Responding Units	1109	275	337	497
U = Unresolved	2048	501	699	848
IS = Non Responding	1894	500	666	728
Response Rate (MRIA)	**21.96%**	**21.55%**	**19.80%**	**23.97%**
Completes	153	57	48	48
Terminates	0	0	0	0
Not Qualified	956	218	289	449
Over Quota	0	0	0	0
Incidence Calculation	**13.80%**	**20.73%**	**14.24%**	**9.66%**

	Total	1 Delta	2 McQueston	3 Rosedale
Gross Response Rate	**2.51%**	**3.83%**	**2.25%**	**1.94%**
Gross Refusal Rate	**29.00%**	**32.24%**	**28.07%**	**27.87%**
Gross NQ Rate	**15.67%**	**14.64%**	**13.54%**	**18.13%**

Appendix 2

QStarz BT-Q1000X Travel Recorder

Further information available on website:

http://www.qstarz.com/Products/GPS%20Products/BT-Q1000X-S.htm

General		**Accuracy (none DGPS)**	
GPS solution	MTK II GPS Module	Position	
Frequency	L1, 1575.42MHz	Without aid: 3.0m 2D-RMS < 3m CEP(50%) without SA(horizontal) DGPS (WAAS, EGNOS, MSAS): 2.5m): 2.5m	
C/A Code	1.023MHz chip rate	**Velocity**	Without aid: 0.1m /s, DGPS(WAAS, EGNOS, MSAS): 0.05m /s
Channels	66 CH performance tracking	Time	50 ns RMS
Antenna (Intemal)	Built-in low noise antenna	Datum	WGS-84
Sensitivity		**Dynamic Conditions**	
Tracking -165 dBm		Altitude	< 18,000m
Acquisition Rate		Velocity	< 515m /sec
Cold Start	35 sec, average	Acceleration	< 4g
Warm Start	33 sec, average	Update	1Hz as default (1~ 5Hz changeable by software utility)
Hot Start	1 sec, average	**Interface**	
Reacquisition	< 1 sec.	Bluetooth	V1.2 compliant (SPP profile)
AGPS	< 15 sec.		Class 2 (10 meters in open space)
Power			Frequency: 2.4~2.4835 GHz
Built-in rechargeable Li-ion battery		Power On/Off	Slide switch (Off-Nav-Log)
Input Voltage	Vin: DC 3.0-5.0V	Power Charge	Mini USB
Backup Voltage	DC 1. 2 ± 10%	**GPS Protocol**	
Charging time	3hrs. (Typical)	NMEA-0183 (V3.01) - GGA, GSA,GSV, RMC(default); VTG, GLL(Optional), Baud rate 115200 bps, Data bit : 8, stop bit : 1(Default)	
Environmental			
Operating Temperature	- 10 C to + 60 C		
Storage Temperature	- 20 C to + 60 C		
Charging	0 C to + 45 C	**Device Size**	
Accessories			
Car Charger	USB Cable	72.2 (L) X 46.5 (W) X 20 (H) mm	
Rechargeable Battery	Software CD	**Device Size**	
Multi-language Quick Guide		Standard	Fully Compliant with USB2.0
		Full - Speed	12Mbps

Disassembled device showing primary components – BT-Q1000 shown and is physically identical to the R and X models which have larger memory and other non-used features.

Appendix 3

TRIAT (Tiny Researcher In A Tube)

by Milton Friesen

Software

GPS logging – TinyGPS as base

Sleep Function – coded into TinyGPS core

Vibration/Accelerometer – coded into TinyGPS core

Hardware

Atmega 328P IC (bare) running code directly

Arduino Pro Mini (alternate)

OpenLog – SparkFun / SDmicro cardholder (alternate)

UP501 GPS module / G635 / LS20031 (alternates)

Batteries – Lithium Thionyl Chloride non-rechargeable

Assembly – conversion of testing bench to small production line

On/Off switch – simple, SPST micro switch

Accelerometer

Piezo vibration sensor – small, weighted, high sensitivity

Data Review

- How many days logged

- Quality of the returned data

- Conversion to Google Maps

- Failure/Error rate

- Usefulness for network analysis

Hardware Review

- Battery levels

- Component function and condition

- Failure rate