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A call for caution and transparency in the calculation of land use mix: Measurement bias in the estimation of associations between land use mix and physical activity

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ABSTRACT

There is evidence that land use mix based on the Shannon (1948) entropy formula may be misspecified in some studies. The aim of this study was to quantify the bias arising from this misspecification. Spatial coordinates were obtained from Statistics Canada for 9348 unique point locations. Five hundred-metre polygon-based network buffers were drawn around each coordinate (ArcGIS 10.1). Land use mix was calculated for each buffer using the true and misspecified land use mix formulas. Linear regression models were used to estimate the associations between a simulated dataset of daily steps and the true and misspecified measures. Misspecification of the land use mix formula resulted in a systematic underestimation of the true association by 26.4% (95% CI 25.8–27.0%). To minimize measurement bias in future studies, researchers are encouraged to use a constant definition of *N* in the denominator of the Shannon entropy formula.

1. Introduction

In the last decade there has been an increase in the number of studies conducted on the associations between neighbourhood designs and physical activity (Ding and Gebel, 2012; Feng et al., 2010). Recent reviews have highlighted inconsistencies across studies, with variability in demonstrated effects (Feng et al., 2010; McCormack and Shiell, 2011; Ferdinand et al., 2012). While the important contributory factors that constitute walkability are conceptually well-defined, inconsistencies in their associations with physical activity may be partly attributable to differences in walkability measurement and computation of indices (Hess et al., 2001; Brownson et al., 2009). One example of this is in the current method of calculating land use mix – a component of walkability.

Land use mix is a measure of the diversity of land uses contained in a neighbourhood (Leslie et al., 2007; Manaugh and Kreider, 2013). While many studies suggest that higher land use mix is associated with higher levels of physical activity, others suggest null effects (Feng et al., 2010; McCormack and Shiell, 2011; Grasser et al., 2013). In the neighbourhoods and health literature, land use mix is most commonly calculated using a variation of an entropy formula introduced in 1948 by Claude E. Shannon as part of his work on the mathematical theory of communication (Shannon, 1948). It is defined as $(-\sum_k (p_k \ln p_k))/\ln N$, where p is the proportion of land area within a predefined geographical zone devoted to a specific land use and N is the total number of land use categories (Leslie et al., 2007; Manaugh and Kreider, 2013). The resulting values range from 0 to 1 where 0 represents complete homogeneity and 1 represents complete heterogeneity in land uses within a neighbourhood.

When calculating land use mix via the Shannon entropy formula, the value of N should remain constant. Misspecification of the entropy formula arises when N is defined as the number of land uses that fall into each neighbourhood buffer (i.e., variable for each neighbourhood). This is problematic as it results in an overestimation of land use mix in some neighbourhoods and does not allow for meaningful comparisons of land use mix within a study. Take, for example two hypothetical neighbourhoods, for simplicity defined here by polygonal buffers around two home addresses (Fig. 1). Neighbourhood A is comprised of two types of land uses (i.e., residential and commercial) while Neighbourhood B is comprised of three types of land uses (i.e., residential, commercial and governmental). Assuming that there are three land uses of interest in total, Neighbourhood A should have an entropy score less than 1, and Neighbourhood B should have an entropy score equal to 1 (i.e., the most amount of diversity in land uses possible given three land uses

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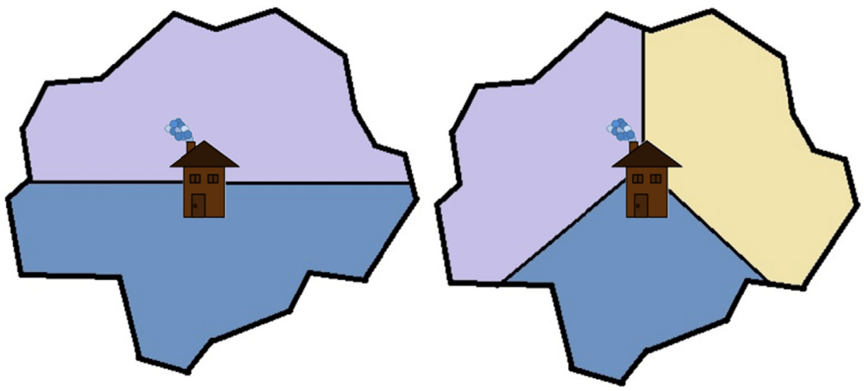

Fig. 1. Two hypothetical neighbourhoods with one representing a 50–50% split between two types of land uses (Neighbourhood A) and one representing a 33–33% split between three types of land uses (Neighbourhood B).

of interest). However, when N is defined as the number of land uses in each buffer (i.e., 2 for Neighbourhood A; 3 for Neighbourhood B), the resulting entropy scores for Neighbourhoods A and B are both 1 – an overestimation of the land use mix in Neighbourhood A.[1] It is only when N is constant and equivalent to the *total* number of land uses of interest (i.e., 3) that meaningful comparisons of land use mix can be made across neighbourhoods within a study. In this example, use of a constant N results in entropy scores of 0.63 and 1 for Neighbourhoods A and B, respectively[2] – a more accurate reflection of the diversity of land uses in each of the neighbourhoods.

While previous studies may have used a constant definition of N (Frank et al., 2004; Hajna et al., 2013; Frank et al., 2007; Coffee et al., 2013), because N has not been explicitly defined in some studies and there is evidence that a variable definition of N may have been used (Frank et al., 2005, 2006), the possibility of exposure misclassification arising from the incorrect calculation of entropy cannot be ignored. The objective of this study was to quantify the amount of bias arising from using a variable definition of N in the Shannon entropy formula and to argue that careful consideration of how the entropy score is calculated is required in future studies.

2. Methods

2.1. Data

Anonymized spatial coordinates were obtained from Statistics Canada for 9348 unique point locations from across Canada. The point locations corresponded to the postal code addresses of individuals who participated in Cycle 1 (2007–2009) of the Canadian Health Measures Survey. The Canadian Measures Survey is a survey conducted on a nationally representative sample of Canadians aged 6–79 years. Individuals living on reserves, in institutions and full-time members of the Canadian Forces were not represented in the sample Statistics Canada (2011). Access to the data was granted by Statistics Canada.

2.2. Exposure measurement: land use mix

Neighbourhoods were approximated using 500-m polygon-based network buffers drawn around each point location (ArcGIS 10.1; ESRI; Redlands, CA). The areas of four land uses, identified *a priori* as important predictors walking, were calculated for each buffer. These included residential, commercial, institutional-governmental, and recreational land uses. Land uses that were not considered important predictors of walking were excluded (open/vacant, industrial, agricultural, railway, transportation and utility land) (Christian et al., 2011).

Land use mix was calculated for each neighbourhood buffer using a constant and a variable definition of N in the denominator of the Shannon entropy formula (herein referred to as $\text{LUM}_{\text{constant}}$ and $\text{LUM}_{\text{variable}}$, respectively). For both measures, the numerator was equal to $(-1)\sum_k(p_k \ln p_k)$ where p was the proportion of land area devoted to a specific land use (k) in the polygon-based network buffers (Leslie et al., 2007). For $\text{LUM}_{\text{constant}}$, the numerator was divided by ln(4), representing the four land uses of interest. For $\text{LUM}_{\text{variable}}$, the numerator was divided by ln(N), where N represented the number of the land types that fell into each buffer (i.e., 0, 1, 2, 3 or 4).

2.3. Outcome measurement: simulated daily step counts

Walking is the most common and preferred form of physical activity among adults (Gilmour, 2007). It is commonly assessed using pedometers, small devices that are worn on the hip and that capture the number of steps taken (Tudor-Locke et al., 2011; Marshall et al., 2009; Schneider et al., 2004). Daily step counts reflect overall physical activity levels in adults (Marshall et al., 2009)). Cut-points developed by Tudor-Locke and Bassett are commonly used to classify the activity levels of adults (sedentary: <5000 steps/day; low active: 5000–7499 steps/day; somewhat active: 7500–9999 steps/day; active: 10,000–12,500 steps/day; highly active: $>12{,}500$ steps/day) (Tudor-Locke and Bassett, 2004). Because higher daily steps counts have been linked to important health outcomes, including lower blood pressure, haemoglobin A1C, and anthropometric measures (Manjoo et al., 2010, 2012; Dwyer et al., 2011), they are an outcome of interest in the neighbourhood and health literature.

Data from Cycle 1 (2007–2009) of the Canadian Health Measures Survey indicate that, on average, Canadian men and women accumulate 9544 and 8385 steps/day, respectively (Colley et al., 2011) – placing them in the '*somewhat active*' category. Assuming that Canadian adults accumulate an average of 7000 steps/day when land use mix is zero, we created four linear regression models with varying assumptions regarding the associations between steps/day and the true land use mix score (i.e., $\text{LUM}_{\text{constant}}$). These included a 1000, 2000 and 3000 decrement in daily counts, a null effect, and a 1000, 2000 and 3000 increment in steps/day when comparing

[1] Land use mix (Neighbourhood A) $= -1((0.5 \ln 0.5)+(0.5 \ln 0.5)/\ln 2)=1$; land use mix (Neighbourhood B) $= -1((0.33 \ln 0.33)+(0.33 \ln 0.33)+(0.33 \ln 0.33)/\ln 3)=1$.

[2] Land use mix (Neighbourhood A) $= -1((0.5 \ln 0.5)+(0.5 \ln 0.5)/\ln 3)=0.63$; land use mix (Neighbourhood B) $= -1((0.33 \ln 0.33)+(0.33 \ln 0.33)+(0.33 \ln 0.33)/\ln 3)=1$; *Note:* The third term in the numerator is omitted given that the third land use is not present in the buffer and taking the natural logarithm of 0 is invalid.

Table 1
Per cent underestimation of steps/day by $LUM_{variable}$, overall and by rural/urban location.

Model ($y = \alpha + \beta x$)	Increment in daily step counts (95% CI)		Percent underestimation (95% CI)
	$LUM_{constant}$ standard	$LUM_{variable}$ biased association	
Overall			
Steps = 7000 − 3000 ($LUM_{constant}$)	−3000	−2209 (−2226 to −2191)	26.4% (25.8–27.0)
Steps = 7000 − 2000 ($LUM_{constant}$)	−2000	−1472 (−1484 to −1461)	26.4% (25.8–27.0)
Steps = 7000 − 1000 ($LUM_{constant}$)	−1000	−736 (−742 to −730)	26.4% (25.8–27.0)
Steps = 7000 + 0 ($LUM_{constant}$)	0	0 (0–0)	0
Steps = 7000 + 1000 ($LUM_{constant}$)	1000	736 (730–742)	26.4% (25.8–27.0)
Steps = 7000 + 2000 ($LUM_{constant}$)	2000	1472 (1461–1484)	26.4% (25.8–27.0)
Steps = 7000 + 3000 ($LUM_{constant}$)	3000	2209 (2191–2226)	26.4% (25.8–27.0)
By location			
Rural: steps = 7000 − 3000 ($LUM_{constant}$)	−3000	−1982 (−2024 to −1940)	33.9% (32.5–35.3)
Urban: steps = 7000 − 3000 ($LUM_{constant}$)	−3000	−2208 (−2227 to −2189)	26.4% (25.8–27.0)
Rural: steps = 7000 − 2000 ($LUM_{constant}$)	−2000	−1321 (−1349 to −1293)	34.0% (32.5–35.4)
Urban: steps = 7000 − 2000 ($LUM_{constant}$)	−2000	−1472 (−1485 to −1459)	26.4% (25.8–27.1)
Rural: steps = 7000 − 1000 ($LUM_{constant}$)	−1000	−661 (−675 to −647)	33.9% (32.5–35.3)
Urban: steps = 7000 − 1000 ($LUM_{constant}$)	−1000	−736 (−742 to −730)	26.4% (25.8–27.0)
Rural: steps = 7000 + 0 ($LUM_{constant}$)	0	0 (0–0)	0
Urban: steps = 7000 + 0 ($LUM_{constant}$)	0	0 (0–0)	0
Rural: steps = 7000 + 1000 ($LUM_{constant}$)	1000	661 (647–675)	33.9% (32.5–35.3)
Urban: steps = 7000 + 1000 ($LUM_{constant}$)	1000	736 (730–742)	26.4% (25.8–27.0)
Rural: steps = 7000 + 2000 ($LUM_{constant}$)	2000	1321 (1293–1349)	34.0% (32.5–35.4)
Urban: steps = 7000 + 2000 ($LUM_{constant}$)	2000	1472 (1459–1485)	26.4% (25.8–27.1)
Rural: steps = 7000 + 3000 ($LUM_{constant}$)	3000	1982 (1940–2024)	33.9% (32.5–35.3)
Urban: steps = 7000 + 3000 ($LUM_{constant}$)	3000	2208 (2189–2227)	26.4% (25.8–27.0)

neighbourhoods with maximal to neighbourhoods with minimal heterogeneity in land uses (i.e., $LUM_{constant} = 1$ versus $LUM_{constant} = 0$). The steps counts produced by these models were used to quantify the bias resulting from using $LUM_{variable}$ under each of the varying effects.

2.4. Rural/urban location

Point locations were linked to Canadian postal codes in ArcMap 10.1 using the 2009 Platinum Postal Suite Forward Sortation Areas file (DMTI Spatial)™. Rural and urban locations were classified according to the Canada Post classification system where rural locations were defined as postal codes in which the second character was equal to 0 and urban locations were defined as postal codes in which the second character was greater than or equal to 1.

2.5. Statistical analysis

The mean difference between the two measures of land use mix was calculated and the amount of measurement error in the $LUM_{variable}$ score was defined as the percentage by which it overestimated the $LUM_{constant}$ score. Univariate linear regression models were used to assess the associations between daily steps counts and the two measures of land use mix, overall and by rural location. Measurement bias was calculated as the percentage difference in the parameter estimates between the true and the biased models. All analyses were conducted using SAS 9.2 (SAS 9.2; SAS Institute Inc., Cary, NC, USA). 95% Confidence intervals (CI) were used in the interpretation of results.

3. Results

The average value for $LUM_{constant}$ was 0.21 with a standard deviation (SD) of 0.22. This was comparable to the average value for $LUM_{variable}$ (0.28, SD = 0.28). Ninety-one per cent (91.1%) of the neighbourhoods were located in urban centres. Zero, one, two, three and four of the land uses of interest were contained in 11.1%, 25.9%, 24.2%, 21.8% and 17.1% of the neighbourhood buffers, respectively.

The mean difference between $LUM_{variable}$ and $LUM_{constant}$ (0.07, 95% CI −0.11 to 0.07) represented a 32.9% overestimation of the true raw score (95% CI −52.6% to 34.0%). The parameter estimates of the linear models for the two LUM variables and steps/day overall and by rural/urban location are presented in Table 1. Use of the $LUM_{variable}$ measure resulted in a systematic underestimation of the true association by 26.4% (95% CI 25.8–27.0%). The underestimation was 7.5% greater in rural compared to urban neighbourhoods.

4. Discussion

While many studies assess land use mix via the Shannon entropy formula (Hess et al., 2001; Leslie et al., 2007; Coffee et al., 2013; Cervero 1997; Duncan et al., 2010; Muller-Riemenschneider et al., 2013), few provide a clear definition of the denominator that is used in the calculation of this score. Given that these studies serve as guides for other researchers and there is evidence that the entropy formula may have been previously misspecified (Frank et al., 2005), it is important to revisit the original formula and encourage its appropriate use. To our knowledge, this is the first study to quantify the bias associated with misspecifying the Shannon entropy formula. We demonstrated that using a variable rather than a constant definition of N systematically underestimated by 26.4% the association between the actual land use mix scores of 9348 Canadian home neighbourhoods and a corresponding simulated dataset of daily step counts. The underestimation was 7.5% greater among rural compared to urban neighbourhoods, suggesting that the bias may be greater in studies of neighbourhoods that contain fewer land use categories.

It is important to note that even when land use mix is calculated correctly, the entropy score only accounts for the proportion of land uses in a given geographical region. As noted by others (Hess et al., 2001; Manaugh and Kreider, 2013), it does not account for the relative importance of different land uses, the interaction between land uses, or the shape configurations of these land uses. For example, a neighbourhood containing 80%

commercial and 20% residential areas would be given the same land use mix score as a neighbourhood containing 80% residential and 20% commercial areas. In theory, however, the former should be given greater weight as it would provide residents with more walking opportunities. In terms of land use interaction, take for example, two neighbourhoods that both contain a 50–50% split between residential and commercial land area. In one neighbourhood, the residential land area may be grouped in half of the neighbourhood and the commercial land area in the other half. In the second neighbourhood, the residential areas may be interspersed throughout the commercial areas. In theory, the latter neighbourhood should be given more weight on the land use mix scale, given that the maximized interaction between the residential and commercial areas would be provide more opportunities for walking than if the two land uses were highly segregated. Manaugh and Kreider (2013) have proposed an interaction measure that captures this level of detail. Lastly, even though certain land area shapes may be more conducive to walking than others, the entropy score does not account for the shapes of the land use areas. For example, a polygon-shaped piece of commercial land would be expected to be more conducive to walking than a circular piece of commercial land of the same area. This may be because a polygon-shaped piece of land would allow for greater interactions with other land uses, but also because a more maze-shaped land area may encourage more exploration of the area. Although this issue may be addressed in part by the interaction measure proposed by Manaugh and Kreider (2013), tools such FRAGSTATS may also be used (McGarigal and Marks, 1994).

Despite the limitations inherent in the Shannon entropy score, it remains the most common method for capturing land use mix in the health geography literature, and, if calculated correctly, is a valuable tool for assessing relative land use mixes within neighbourhoods. Because of this, it is important that researchers who choose to use the score calculate it correctly and in a way that minimizes bias. When interpreting the results of this study, it is important to note that, while $LUM_{constant}$ is referred to as the unbiased estimate of land use mix, there are other sources of measurement bias that may affect the accuracy of the measurement (e.g., the quality of the land use data) Brownson et al., 2009; Tim, 1995). Nevertheless, because these biases are not expected to be differential across neighbourhoods, the impact on the effect estimates is expected to be minimal. Strengths of this study included a large sample size and a wide variety of neighbourhoods from across Canada.

In conclusion, land use mix is a component of walkability that is suggested to be associated with lower cardiometabolic risk (Coffee et al., 2013; Muller-Riemenschneider et al., 2013). It is commonly assessed in the health geography literature using a variation of the Shannon entropy formula and studied as a potential predictor of physical activity, the variable believed to mediate the association between land use mix and improved health outcomes. Despite its common use, there is a lack of transparency in the calculation of land use mix. In this study we argue that misspecification of the denominator in the commonly entropy score may systematically bias the associations between land use mix and physical activity towards the null. In order to reduce measurement bias in the estimation of these associations, we encourage researchers who choose to use the Shannon entropy formula, to use a constant value for N and to provide a clear definition of their land use mix calculation in future publications.

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References

Brownson, R.C., Hoehner, C.M., Day, K., Forsyth, A., Sallis, J.F., 2009. Measuring the built environment for physical activity: state of the science. Am. J. Prev. Med. 36 (4 Suppl) (S99–S123 e112).

Cervero, R., 1997. Travel demand and the 3Ds: density, diversity, and design. Transp. Res. 2 (3), 199–219.

Christian, H.E., Bull, F.C., Middleton, N.J., et al., 2011. How important is the land use mix measure in understanding walking behaviour? Results from the RESIDE study. Int. J. Behav. Nutr. Phys. Act. 8, 55.

Coffee, N.T., Howard, N., Paquet, C., Hugo, G., Daniel, M., 2013. Is walkability associated with a lower cardiometabolic risk? Health Place 21, 163–169.

Colley, R.C., Garriguet, D., Janssen, I., Craig, C.L., Clarke, J., Tremblay, M.S., 2011. Physical activity of Canadian adults: accelerometer results from the 2007 to 2009 Canadian Health Measures Survey. Health Rep. 22 (1), 7–14.

Ding, D., Gebel, K., 2012. Built environment, physical activity, and obesity: what have we learned from reviewing the literature? Health Place 18 (1), 100–105.

Duncan, M.J., Winkler, E., Sugiyama, T., et al., 2010. Relationships of land use mix with walking for transport: do land uses and geographical scale matter? J. Urban Health 87 (5), 782–795.

Dwyer, T., Ponsonby, A.L., Ukoumunne, O.C., et al., 2011. Association of change in daily step count over five years with insulin sensitivity and adiposity: population based cohort study. Br. Med. J. 342, c7249.

Feng, J., Glass, T.A., Curriero, F.C., Stewart, W.F., Schwartz, B.S., 2010. The built environment and obesity: a systematic review of the epidemiologic evidence. Health Place 16 (2), 175–190.

Ferdinand, A.O., Sen, B., Rahurkar, S., Engler, S., Menachemi, N., 2012. The relationship between built environments and physical activity: a systematic review. Am. J. Public Health 102 (10), e7–e13.

Frank, L., Sallis, J.F., Conway, T.L., Chapman, J.E., Saelens, B.E., Bachman, W., 2006. Many pathways from land use to health: associations between neighborhood walkability and active transportation, body mass index, and air quality. J. Am. Plan. Assoc. 72 (1), 75–87.

Frank, L.D., Andresen, M.A., Schmid, T.L., 2004. Obesity relationships with community design, physical activity, and time spent in cars. Am. J. Prev. Med. 27 (2), 87–96.

Frank, L.D., Schmid, T.L., Sallis, J.F., Chapman, J., Saelens, B.E., 2005. Linking objectively measured physical activity with objectively measured urban form: findings from SMARTRAQ. Am. J. Prev. Med. 28 (2 Suppl. 2), S117–S125.

Frank, L.D., Saelens, B.E., Powell, K.E., Chapman, J.E., 2007. Stepping towards causation: do built environments or neighborhood and travel preferences explain physical activity, driving, and obesity? Soc. Sci. Med. 65 (9), 1898–1914.

Gilmour, H., 2007. Physically active Canadians. Health Rep. 18 (3), 45–65.

Grasser, G., Van Dyck, D., Titze, S., Stronegger, W., 2013. Objectively measured walkability and active transport and weight-related outcomes in adults: a systematic review. Int. J. Public Health 58 (4), 615–625.

Hajna, S., Dasgupta, K., Halparin, M., Ross, N.A., 2013. Neighborhood walkability: field validation of geographic information system measures. Am. J. Prev. Med. 44 (6), e51–55.

Hess, P.M., Moudon, A.V., Logsdon, M.G., 2001. Measuring land use patterns for transportation research. Transp. Res. Rec.: J. Transp. Research Board 1780, 17–24.

Leslie, E., Coffee, N., Frank, L., Owen, N., Bauman, A., Hugo, G., 2007. Walkability of local communities: using geographic information systems to objectively assess relevant environmental attributes. Health Place 13 (1), 111–122.

Manaugh, K., Kreider, T., 2013. What is mixed use? Presenting an interaction method for measuring land use mix. J. Transp. Land Use 6 (1), 63–72.

Manjoo, P., Joseph, L., Pilote, L., Dasgupta, K., 2010. Sex differences in step count-blood pressure association: a preliminary study in type 2 diabetes. PloS One 5 (11), e14086.

Manjoo, P., Joseph, L., Dasgupta, K., 2012. Abdominal adiposity and daily step counts as determinants of glycemic control in a cohort of patients with type 2 diabetes mellitus. Nutr. Diabetes 2, e25.

Marshall, S.J., Levy, S.S., Tudor-Locke, C.E., et al., 2009. Translating physical activity recommendations into a pedometer-based step goal: 3000 steps in 30 minutes. Am. J. Prev. Med. 36 (5), 410–415.

McCormack, G.R., Shiell, A., 2011. In search of causality: a systematic review of the relationship between the built environment and physical activity among adults. Int. J. Behav. Nutr. Phys. Act. 8, 125.

McGarigal, K., Marks, B.J., 1994. Fragstats: Spatial Pattern Analysis Program for Quantifying Landscape Structure. Forest Science Department, Oregon State University, Corvallis, OR.

Muller-Riemenschneider, F., Pereira, G., Villanueva, K., et al., 2013. Neighborhood walkability and cardiometabolic risk factors in australian adults: an observational study. BMC Public Health 13, 755.

Schneider, P.L., Crouter, S., Bassett, D.R., 2004. Pedometer measures of free-living physical activity: comparison of 13 models. Med. Sci. Sports Exerc 36 (2), 331–335.

Shannon, C.E., 1948. A mathematical theory of communication. Bell Syst. Tech. J. 27, 379–423.

Statistics Canada, 2011. Canadian Health Measures Survey (CHMS) Data User Guide: Cycle 1. Statistics Canada, Ottawa, ON.

Tim, U.S., 1995. The application of GIS in environmental health sciences: opportunities and limitations. Environ. Res. 71, 75–88.

Tudor-Locke, C., Bassett Jr., D.R., 2004. How many steps/day are enough? Preliminary pedometer indices for public health. Sports Med. 34 (1), 1–8.

Tudor-Locke, C., Craig, C.L., Brown, W.J., et al., 2011. How many steps/day are enough? For adults. Int. J. Behav. Nutr. Phys. Act. 8, 79.