IDENTIFYING GEOGRAPHIC AREAS WHERE CHILDREN MAY BE AT-RISK OF LEAD POISONING AND ASSESSING THE NEED FOR LEAD ABATEMENT IN URBAN AREAS: A CASE STUDY IN HAMILTON, ONTARIO

IDENTIFYING GEOGRAPHIC AREAS WHERE CHILDREN MAY BE AT-RISK OF LEAD POISONING AND ASSESSING THE NEED FOR LEAD ABATEMENT IN URBAN AREAS: A CASE STUDY IN HAMILTON, ONTARIO

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ABSTRACT

Thirty years since the removal of lead from gasoline, lead still poses a health risk. Children are most at-risk for adverse health outcomes caused by lead toxicity due to both behavioural (e.g., hand-to-mouth behaviour) and physiological differences (i.e., increased intake of lead by body weight, higher uptake rate and a higher vulnerability to the effects of lead) compared to adults (Yeoh et al., 2009). As a result, governments must identify children that may be at-risk of lead poisoning and develop practical methods to mitigate lead exposure.

Before a government can develop a policy to help mitigate exposure of lead for children, we need to understand the spatial distribution of lead within the city. A popular spatial model used within air pollution research may allow more accurate, and more localized predictions than the most common interpolation method, kriging. Land use regression (LUR) is a technique leveraging multiple predictor variables to help estimate the spatial distribution of the dependent variable. By using historical sources of lead, LUR can be used to model soil lead levels (SLL) with localized variation. Unfortunately, spurious relationships can be the basis of a LUR model, which may lead to an overfitted spatial model resulting in a model with little generalizability and questionable ability to estimate the dependent variable at unobserved locations. Ultimately, Empirical Bayesian Kriging may be the best option for soil contamination research due to its ability to provide a smoothed prediction surface and its dependence on the spatial structure of the data to provide estimations.

The benefit to society and the return on investment (ROI) is often the justification for lead remediation. Gould (2009) estimates a $17 to $221 ROI for every dollar spent on lead hazard control. One of the main components of this estimate of ROI comes from the decrease in intelligence quotient (IQ) that a child may experience as a consequence of lead toxicity. There are three main ways that a decrease in IQ can negatively impact the economy, (i) lower potential lifetime earnings, (ii) reduced tax revenues, and (iii) higher spending on special education (Gould, 2009). Since IQ has such a significant role in the ROI estimates, chapter 3 seeks to achieve a greater understanding of the relationship between blood lead levels (BLLs) and IQ. The loss of IQ points for an increase in blood lead concentration proposed by Lanphear et al. (2005) and referenced by Gould (2009) is significantly higher than what we found in our meta-analysis. Thus, the projected ROI proposed by Gould (2009) may be much lower than previously calculated.

In the final chapter, the cost associated with permanent lead abatement is investigated based on ROI projections as a case study in Hamilton, Ontario. We show that, in most cases, permanent lead remediation is far too expensive for a municipal government. Furthermore, the capital initially invested may not be distributed back into the local economy, as the ROI suggests. We suggest that municipal governments make decisions based on need, rather than basing remediation decisions on ROI projections. Furthermore, we recommend the use of hazard quotient maps to help justify lead remediation as a more accurate representation of potential lead toxicity, instead of only looking at SLL exceedances across the city.

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PREFACE

This thesis dissertation contains five chapters, which includes: an introduction, three main chapters, and a conclusion. The first paper (chapter 2) examines a relatively new interpolation method for heavy metal soil contamination research and discusses the inherent flaws in using land use regression compared to the traditional method of kriging. The second paper (chapter 3) is a meta-analysis exploring the relationship between blood lead levels in children and intelligence quotient (IQ). This paper presents a thorough investigation into the relationship between BLLs and IQ using modern meta-analysis techniques to synthesize unstandardized beta coefficients. Lastly, the third paper (chapter 4) presents a cost-benefit analysis of lead remediation in Hamilton, consisting of soil, water, and paint abatement. Despite significant return on investment projections, the paper discusses reasons why a city should reconsider investing in such a large project.

The first chapter is a methodological paper that contributes to a broader research audience (e.g., air pollution research) that uses land use regression for spatial modelling. The second chapter contributes to the literature by quantifying the relationship between blood lead levels in children and intelligence quotient by pooling results from 13 papers. Finally, the last paper contributes to the literature by examining the feasibility of lead remediation at a municipal-level and discussing alternatives to permanent lead abatement. This dissertation seeks to challenge the necessity and benefit of lead remediation in urban cities by providing a case study in Hamilton, Ontario.

The first author of each paper reviewed the literature, completed the analysis, interpreted the results, and wrote the manuscripts. The first author also collected, cleaned, and prepared a historical data set for the first paper (chapter 2). Dr. Bruce Newbold co-authored each of the three manuscripts, providing guidance from initial concept development to analysis, submission and revision. For the first paper, Dr. Niko Yiannakoulias also guided concept development and analysis. The three chapters presented in this thesis dissertation are as follows:

Chapter 2:

Mackay, K.P., Yiannakoulias, N., and Newbold, K.B. (2018). A critical assessment of land use regression for interpolating soil lead (Pb) levels: a case study in Hamilton, Ontario.

Chapter 3:

Mackay, K.P., and Newbold, K.B. (2019). The relationship between childhood blood lead levels and Intelligence Quotient: a meta-analysis.

Chapter 4:

Mackay, K.P., and Newbold, K.B. (2018). A critical assessment of the return on investment of permanent lead hazard control: a case study in Hamilton, Ontario.

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LIST OF ABBREVIATIONS

95% CI	95% Confidence interval
AV	All variables
BLL	Blood lead level
CDC	Centers for Disease Control and Prevention
DR	Discount rate
EBK	Empirical Bayesian Kriging
EBL	Elevated blood lead level
FIRE	Finance, insurance and real estate
HEV	Hold-out evaluation
HOME	Home Observation for Measurement of the Environment Inventory
HQ	Hazard quotient
HWDSB	Hamilton-Wentworth District School Board
IQ	Intelligence Quotient
LUR	Land Use Regression
OCR	Optical Character Recognition
OK	Ordinary Kriging
OLV	Only lead-related variables
Pb	Lead
RMSE	Root mean square error

ROI	Return on investment
SES	Socio-economic Status
SLL	Soil lead level
UBC	Unstandardized beta coefficient

Chapter 1 Introduction

1.1 Justification of research topic

Despite declining blood lead levels (BLLs) among Canadians (Government of Canada, 2013; O'Grady et al., 2011), lead (Pb) remains a problem in cities across Canada (Richardson et al., 2011). The Canadian Health Measures Survey (CHMS) reported a BLL of 1.34 µg/dL (geometric mean) for Canadians aged 6 to 79 (Health Canada, 2013). In Hamilton, the geometric mean of blood lead from tested children was 2.18 µg/dL (converted from 0.11 µmol/L). Although less than 1% of Canadians aged 6 to 79 exceed the guidance value of 10 µg/dL, BLLs lower than the actionable reference level have been shown to cause adverse health outcomes (Health Canada, 2013). In 2013, Health Canada released a risk management strategy for lead that concluded by stating that there are areas within the literature that require more research to investigate lead toxicity and its impact on human health and the environment. Additionally, Health Canada stated that there is a need to characterize sources of exposure, exposure levels for Canadians, and toxicity at low blood lead levels (Health Canada, 2013).

Lead contamination in urban cities is mostly attributed to three primary sources, (i) leaded gasoline, (ii) lead-based paint, and (iii) leaded pipes. The introduction of unleaded gasoline was first introduced in 1972 and phased out by 1990 (Health Canada, 2013), but the combustion of leaded fuel has left lead particulates in the soil. Similarly, lead-based paint has been regulated in Canada since 1978 and eliminated in 1991

(Abelsohn et al., 2010), yet it remains in older houses that used lead-based paint for its durable properties (Gilbert et al., 2006). Lastly, leaded pipes were widely used within cities until phased out pre-1990s in favour of non-toxic materials (Health Canada, 2013), but lead pipes remain in many older homes that have not been renovated. In older cities, these three primary sources of lead may pose a significant risk to the population.

This dissertation focuses on Hamilton, Ontario, Canada as a case study because Hamilton is a relatively old city with an old housing stock (Richardson et al., 2011) and has had a long industrial past that may increase exposure to lead within the city. There have been many businesses located in Hamilton's downtown core over the past 100 years that worked with lead products, which may have contaminated the air, water and soil within the city (see Section 2.2.3). In Chapter 2, we identify seven business categories, in addition to the road network, that may have resulted in environmental lead contamination since 1920, (i) automobile garages (n=1,464), (ii) automobile painters (n=142), (iii) battery and service stations (n=142), (iv) gasoline stations (n=1,443), (v) junk and salvage yards (n=230), (vi) lead manufacturing (n=16), and (vii) paint manufacturing (n=21). This dissertation builds on a study by Richardson et al. (2011), which explains that the downtown core is also home to a concentration of disadvantaged individuals with lower average household income, poorer health status, and lower education levels as compared to the city's periphery. Disadvantaged populations are often more exposed to lead poisoning (Hanchette, 2008), which means governments must develop policies and programs to help mitigate exposure for these vulnerable groups.

Lead can enter the body of a child in three main ways, (i) ingestion, (ii) skin absorption, and (iii) inhalation (Cleveland et al., 2008). Although absorption of lead through the skin can occur, ingestion of lead-based paint or lead-contaminated soil or inhalation of lead-contaminated dust is a more significant threat to children since the gastrointestinal tract is more efficient at absorbing the lead as opposed to the skin (Cleveland et al., 2008). Additionally, a mother with lead within the body (i.e., lead in the blood or stored within the bones) can transfer lead to the fetus during gestation or transfer lead to the child during breastfeeding (Abelsohn et al., 2010; Cleveland et al., 2008; Laidlaw et al., 2008). At moderate to high concentrations, lead poisoning can have a significant effect on the body, causing paralysis or encephalopathy at higher concentrations, and fatigue, headaches, abdominal pain and weight loss at moderate concentrations (Advisory Committee on Childhood Lead Poisoning Prevention, 2013; David C Bellinger et al., 2006; Cleveland et al., 2008). These adverse health outcomes are rare in Canada since the average blood lead level has declined about 70% since the 1970s (i.e., the percentage of Canadians exceeding 10 µg/dL dropped from 27% in 1978-1979 to less than 1% in 2007-2009) (Health Canada, 2013). However, an emerging field of research suggests that even at low blood lead concentrations (i.e., <10 µg/dL), lead exposure amongst children may result in decreased learning and memory abilities, lowered IQ, decreased verbal ability, impaired speech and hearing functions, and early signs of hyperactivity or attention deficit hyperactivity disorder (Chiodo et al., 2007; Cleveland et al., 2008; Ragan et al., 2009; World Health Organization, 2011).

Since lead still poses a threat in many urban cities in Canada (Health Canada, 2013), there is a risk for children to develop an intellectual impairment from low-level lead poisoning. At a population level, intellectual impairment can have a significant impact on the economy, with estimates ranging from $1.5 billion to $9.4 billion (2010 Canadian dollars) per year in Canada (Health Canada, 2013). Intellectual impairment causes economic stress through the loss of potential lifetime wages and tax revenue, increased need for special education, increased incidence of violent crime, and reduced school and work performance (Brown, 2002; M. S. Burns et al., 2014; Nevin, 2000). Gould (2009) argues that “for every dollar spent on controlling lead hazards, $17 to $221 would be returned in health benefits, increased IQ, higher lifetime earnings, tax revenue, reduced spending on special education, and reduced criminal activity” (p. 1166).

1.2 Thesis Objectives and Research Questions

The overarching goal of this dissertation is to identify geographic areas in Hamilton, Ontario, Canada, where children may be at-risk of lead poisoning and characterize sources of lead that may increase the risk of lead exposure and poisoning. This dissertation builds on a study developed by Richardson et al. (2011) by determining the risk of lead poisoning to children by exploring the spatial distribution of lead. In the report by Richardson et al. (2011), the authors collected most of the data (see Chapter 2, Section 2.2: Data sets and sources of lead) used within this dissertation, but mainly focused on a qualitative approach to analysis and public health education for solutions. Spatial analysis was limited to descriptive statistics, and median values by neighbourhood, which are problematic for three main reasons, (i) neighbourhoods are too large for a continuous variable (i.e., soil lead levels), (ii) boundaries create abrupt changes in value, and (iii) neighbourhoods vary in shapes and sizes. Soil lead levels are a continuous variable, which means that they change across space. If a continuous variable such as soil lead levels is grouped into an areal unit, there will be a loss of information that can be important when trying to identify children that may be at-risk of lead poisoning. Additionally, by grouping a continuous variable into areal units, there may be abrupt changes in values between adjacent neighbourhoods (i.e., an areal unit with high soil lead levels adjacent to an areal unit with low soil lead levels). Continuous variables should be grouped with caution because the specific way a variable (e.g., soil lead levels) changes across space is vital to identify at-risk children and to develop strategies to mitigate exposure. Lastly, the neighbourhoods in Hamilton are not consistent in shape nor size, which limits the information that can be extracted from the analysis. Neighbourhood soil lead ranges are far too broad for a problem that has a continuous distribution. In other words, lead contamination varies across space, and merely categorizing large swathes of the city into arbitrary spatial segments (i.e., neighbourhoods) will not capture the threat to children adequately. Therefore, this dissertation seeks to develop a greater understanding of the spatial distribution of soil lead levels within the downtown core of Hamilton by employing better methods of spatial modelling.

More specifically, this dissertation seeks to determine the need for lead remediation within the city and discuss how feasible permanent lead abatement would be for a municipal government. In the study by Richardson et al. (2011), the results mostly focused on public health education as a method to reduce exposure to lead contamination. The authors found that about half of participants within the highest risk areas were aware of the public health campaign offering free water service pipe inspection. However, awareness of exposure reduction campaigns and the threat of lead exposure in the home was lower among participants with relatively low household incomes, tenants in rented dwellings, families that did not speak English or French at home, and parents without a post-secondary education. Additionally, Richardson et al. (2011) found that most (82%) of participants were interested and willing to comply with follow-up study components (e.g., blood lead retesting, medical follow-up, and public health inspections of the home). The report argues that there is a broad audience for public health campaigns to spread awareness about lead exposure mitigation, and targeting specific populations may improve lead exposure reduction (Richardson et al., 2011). As discussed previously, there are plenty of studies promoting permanent lead abatement strategies (see Burns & Gerstenberger, 2014; Korfmacher, Ayoob, & Morley, 2012; Schnur & John, 2014), promising substantial returns on investment for the government and boosts to the overall economy (Brown, 2002; Gould, 2009; Health Canada, 2013). Despite these encouraging policy recommendations, this dissertation seeks to understand the real-world feasibility of lead remediation at the municipal level by (i) understanding the spatial distribution of lead within the city, (ii) determining the relationship between blood lead levels and IQ, (iii) estimating the projected costs and return on investment for lead hazard control in

Hamilton, Ontario, and (iv) determining the need for lead abatement in Hamilton, Ontario.

1.3 Dissertation Contents

In order to address some of the issues declared by Health Canada (2013), chapter 2 investigates Land Use Regression (LUR) as a viable alternative to kriging. If LUR worked as intended, the spatial model could have both identified historical sources of lead, in addition to providing localized soil lead estimations. The second chapter evolved into an essential investigation of LUR methodology, identifying various issues with the spatial modelling technique, and a recommendation to use kriging in future studies with heavy metal contamination. We show that LUR can be overfitted based on spurious relationships and suggest that a parsimonious model with global smoothing (i.e., Empirical Bayesian Kriging) is likely a better option for soil contamination research. As a result of this chapter, we utilize Empirical Bayesian Kriging as the primary interpolation technique for the spatial modelling found in chapter 4.

In chapter 3, we explore the relationship between blood lead levels and IQ by completing a meta-analysis of the literature. The decline of IQ as blood lead levels increase is a common justification for lead remediation, so it is crucial to explore the literature to understand this relationship. Furthermore, chapter 4 examines the return on investment projections suggested by Gould (2009), which are partially dependent on the relationship between blood lead levels and IQ. In chapter 3, we show that the loss of IQ points as a result of an elevated blood lead level is much smaller than suggested by Lanphear et al. (2005) and referenced by Gould (2009). Thus, the ROI projections by Gould (2009) may be much lower than first calculated.

Building on the findings of chapters 2 and 3, chapter 4 investigates the cost to remove lead from the natural and built environment permanently, calculates the return on investment, and discusses the need for lead remediation within the lower city of Hamilton, Ontario. First, chapter 4 estimates the cost to replace lead-contaminated soil, leaded pipes from older homes, and screen or remove lead-based paint from homes. As we discover, the cost to permanently remove lead from the natural and built environment is staggering, and the returns on investment are in the millions and billions of dollars. In order to determine if there is a need for lead remediation within the city, we also use hazard quotient maps to investigate the threat to children further. Finally, we discuss alternatives to permanent lead abatement as a means to mitigate lead exposure for children, while also considering budget constraints for a municipal government.

In chapter 5, we conclude the dissertation by discussing the main contributions we have made to the literature. The references for this section can be found at the end of chapter 5.

Chapter 2 A critical assessment of land use regression for interpolating soil lead (Pb) levels: a case study in Hamilton, Ontario

2.1 Introduction

Soil lead (Pb) contamination continues to pose a significant risk to children in many post-industrialized cities (Hanna-Attisha et al., 2016). Given the adverse health risks associated with lead exposure, soil lead contamination is hazardous in areas where children play in the soil or close to the ground and consume the leaded soil through normal hand-to-mouth behaviour (Cleveland et al., 2010; Landrigan et al., 2011). Low blood lead levels (<10μg/dL) in children have been linked to many adverse health and social outcomes including cognitive, auditory, and behavioural impairments, as well as "increased health care costs, increased incidence of violent crime, increased need for special education services, reduced school and work performance, and reduced lifetime earning potential" (Burns and Gerstenberger, 2014, p. 27). As a result, knowing soil lead concentration in the environment is necessary to identify and target areas where contamination has exceeded regulatory guidelines set by governing bodies. Soil sampling is often used to measure concentrations of lead that have accumulated in the soil at specific locations, but spatial modelling is necessary to interpolate lead concentrations between sampled locations.

For the last several decades, lead interpolation has depended on kriging for spatial modelling due to its ability to smooth the model when data are sparse. Kriging is a general term used to describe a variety of different techniques reliant on the spatial structure of the data. Research on heavy metal contamination has often relied on two forms of kriging known as Empirical Bayesian Kriging (see Finzgar, Jez, Voglar, & Lestan, 2014; Pandey et al., 2015) and Ordinary Kriging (see Amini, Afyuni, Fathianpour, Khademi, & Flühler, 2005; Liu, Wu, & Xu, 2006). Although background levels of lead naturally vary within the environment, anthropogenic sources of lead are more limited in areas distant from urban and suburban development. As a result, kriging is an ideal choice for interpolation in rural areas where sources of lead are limited to few sources, and the spatial distribution of values is more uniform than in urban areas (i.e., the values of lead change gradually across space). In urban areas where sources of lead are more common, and the prediction of soil lead levels (SLLs) becomes more complex and heterogeneous (Cattle et al., 2002), land use regression (LUR) may provide better predictions.

Land use regression, first introduced by Briggs et al. (1997), is a common interpolation technique in air pollution research (see Arain et al. 2007; Melymuk et al. 2013; Sahsuvaroglu et al. 2006; Saraswat et al. 2013; Wang et al. 2013), but its use in the soil sciences has been limited (see, for example, Deschenes, Setton, Demers, & Keller, 2013; Wu, Edwards, He, Liu, & Kleinman, 2010). LUR works by determining how well various land use variables (also known as predictor variables) can estimate the spatial variation of the dependent variable by using regression analysis. Theoretically, there are two main reasons why LUR may be superior to kriging in urban areas. Firstly, LUR maximizes the amount of information available for spatial modelling. LUR can use a wide variety of land use predictor variables that are often easily obtained from a municipal government, whereas kriging is limited to the sampled information. Secondly, since LUR can use a multitude of explanatory variables that vary at a small scale, it can predict localized variation more effectively than kriging (Arain et al., 2007).

The use of LUR as an interpolation technique for SLLs is limited. Wu et al. (2010) explored land use regression as a method to explain SLLs; however, they did not evaluate the model as an interpolator. The authors exclusively evaluated the ability of road type to explain SLLs in different types of land use and had mixed results. In commercial areas, the road network was only able to explain 16% of the variation in SLLs, whereas residential areas, freeways and major arterials were able to explain 61% of SLL variation. In a more comprehensive evaluation of land use regression as an interpolation technique, Deschenes et al. (2013) explained 78% of the variation in SLLs using four variables: industrial land use within 5km, industrial emissions within 25km, industrial emissions within 10km and presence of closed mines within 50km. However, these previous uses of LUR in SLL prediction (see Deschenes et al., 2013; Wu et al., 2010) have not used historical data as predictor variables. Since modern soil lead contamination in urban areas was likely caused by the long history of lead used throughout the last century, in addition to the fact that lead can remain within the soil for decades (Schnur et al., 2014), historical data are more likely to explain the spatial variation of SLLs than any modern source. For example, the use of lead for residential and commercial products has been regulated for nearly thirty years (CMHC, 2005), which means modern sources of lead are very likely a poor proxy for historical sources of lead. Furthermore, despite literature indicating that aerosol lead can travel vast distances before being deposited into the soil (ATSDR, 2007; Mielke et al., 2010), the true explanatory power of aerosol lead from distant sources for the spatial distribution of SLLs in an urban area is uncertain.

Based on soil lead levels from Hamilton, Ontario, and the results of Wu et al. (2010) and Deschenes et al. (2013), this paper will address three objectives. First, it will examine the relationship between the spatial distribution of SLLs and historical lead-related businesses in Hamilton, Ontario. Second, it will compare the prediction accuracy for LUR and two baseline kriging models (OK and EBK). Third, it will consider the practicality of LUR as a means to address the complexity of interpolating lead in an urban center. In doing so, this paper will provide a critical review of the use of LUR in general, and more specifically, for predicting SLLs. This paper will operate under the null hypothesis that there is no relationship between the number of historical lead-related businesses and soil lead levels for objective one and that LUR will not provide more accurate predictions of SLLs than Ordinary Kriging or Empirical Bayesian kriging.

2.2 Data sets and sources of lead

2.2.1 Study area

The study area consists of the lower city of Hamilton, Ontario. This older part of the city falls between Hamilton Harbour to the north and the Niagara Escarpment, which bisects the city and runs east to west (see Figure 2.1). The city of Hamilton is known as ‘steel city’ due to the presence of two of the largest steel mills in Canada. Beyond steel, the city was also home to many other businesses over the last century that handled leaded products. The ‘lower city’ mostly consists of an older housing stock (Richardson et al., 2011), which means lead service pipes and deteriorating lead-based paint that continues to pose a threat for residents. Although lead service pipes, leaded gasoline and lead-based paint are the most common sources of lead, many other sources may explain the spatial distribution of SLLs in the city, which will be described below. Hamilton is an optimal area to explore the spatial distribution of SLLs for three main reasons, (i) Hamilton has a long history of lead use and the spatial distribution of lead is likely complex, (ii) understanding which sources can be attributed to soil lead contamination can help mitigate exposure within the city, and (iii) localized SLL estimations can help target areas most exposed to soil lead contamination.

2.2.2 Soil lead samples

This paper will utilize a soil lead level data set, in addition to a rich historical data set that was collected for this study. As part of a more extensive study conducted by Hamilton Public Health Services in 2008-2009 (Richardson et al., 2011), the city collected soil lead samples from sites around the old lower city. The data set comprises of 187 soil lead samples throughout the downtown core of Hamilton. Sample locations were chosen based on the home location of a parent or guardian attending a participating clinic, as well as the age of the housing. The SLL data set was collected and processed by the Ministry of the Environment during the summer of 2009 (Richardson et al., 2011). Soil samples were collected using a tube-type soil corer up to a five-centimetre depth "from a household's front, back or side yard depending on where the child played most frequently and/or where there was sufficient conditions to sample" (Richardson et al. 2011). Samples were analyzed using atomic absorption spectrophotometry to determine lead content with a limit detection of 5µg/g dry weight at the MOE Phytotoxicology Laboratory in Toronto, Ontario.

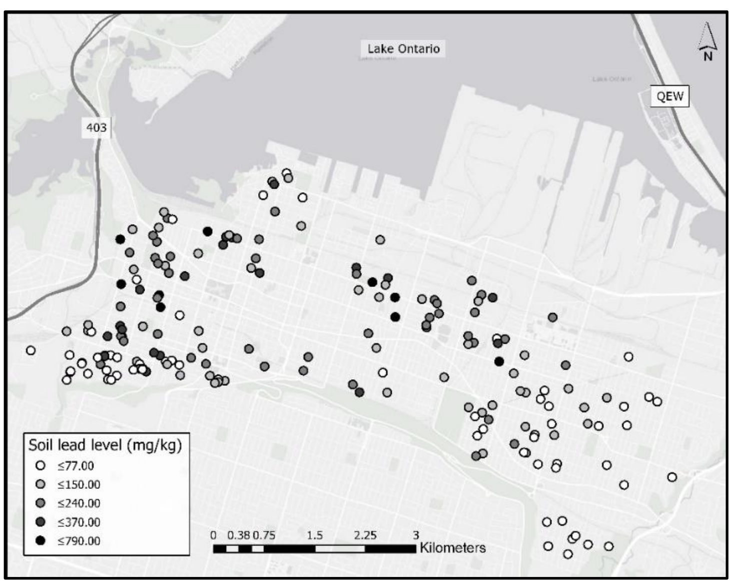

Figure 2.1: Depiction of the study area in Hamilton, Ontario, Canada (see Appendix A)

2.2.3 Historical independent variables

Historically, lead was used in a wide range of applications, including paint, plumbing products, batteries, gasoline, and other products. In the last few decades, researchers have identified lead-contaminated soil as a source of lead poisoning, particularly amongst young children (Ryan et al., 2004). However, the use of historical data to understand the spatial distribution of lead has not been explored in previous research. Historical businesses that manufactured or used lead-based products in Hamilton were collected as a means to explain the spatial distribution of SLLs in this study.

Historical data were collected from three sources: (i) Vernon's Business Directories, (ii) Bell Canada's Telephone Book (Yellow Pages), and (iii) a modified DMTI road network. Vernon's business directories were searched from 1925 to 1975, at which time the business directories were no longer printed. Between the years 1980 and 1990, Bell Canada's Yellow Pages were searched to collect the remaining ten years of businesses. In order to capture the most detailed data while also accommodating time limitations, the two business directories were searched at 5-year intervals. The DMTI road network was compared to a scanned map from 1990 and digitally modified to accurately represent the historical road network in Hamilton. In total, eleven types of lead-related variables were collected (i.e., automobile painters, automobile garages and repair shops, battery service stations, gasoline stations, junk and salvage yards, lead product manufacturers, paint manufacturers, local roads, major roads, highways, and expressways), in addition to five business types that are used as controls (i.e., dental offices, wholesale trade, retail trade, finance, insurance and real estate (FIRE), and public administration). Dental offices were collected from the same historical sources as above, and the other controls were collected from the DMTI Enhanced Points of Interest shapefile (i.e., wholesale trade, retail trade, FIRE, and public administration). Data collected for each business included: opening year, closing year, business type (variable name), business name, street number (from), street number (to), street name, street direction, street type and any comments associated with the business. Once the businesses were collected and transcribed, businesses with the same location and category were consolidated, and the closing year extended accordingly. Next, the data were geocoded using a Bing Maps API Key, and any unmatched records were located manually.

The 1925 to 1990 period was chosen for two main reasons. First, this period reflects the most significant use of lead (i.e., leaded gasoline and lead-based paint) in Canada. As Mielke (1999) explains, "the amount of lead in gasoline over only the 57 years of its use [in the United States] from 1929 to 1986 roughly equals all of the lead in paints in 94 years of lead-paint production" (p. 3). Second, the data collection process was time-intensive. In 1921, the addition of tetraethyl lead to gasoline was discovered as a method to curb engine knock. In addition to leaded gasoline, lead-based paint followed a similar trajectory of use in Canada. Lead-based paint had already been in use for decades by the time lead was added to gasoline, with the addition of lead into paint popularized by its useful properties, which included: durability, pigment and anticorrosive characteristics (ATSDR, 2007; Levin et al., 2008). Despite the useful properties of lead, the addition of lead was eliminated from all paint by the Canadian government after lead-based paint was linked to cases of child lead poisoning in 1991 (Abelsohn et al., 2010; O'Grady et al., 2011). Due to time constraints, data collection began with 1925, following the sale of leaded gasoline.

We collected eleven historical predictor variables that capture the potential for soil contamination, including lead manufacturing, automobile painters, automobile garages, battery and service stations, junk and salvage yards, paint manufacturing, gasoline stations, major roads, expressways, local roads and highways. Historically, the automotive industry has been a significant source of lead exposure, mostly due to the combustion of leaded gasoline and the use of lead in paint as well as various automotive components, especially lead-acid batteries (Ohio Environmental Protection Agency, 2010).

As explained above, the sale of leaded gasoline lasted for nearly seventy years, with the sale of leaded gasoline capturing 90% of all gasoline sales in the US (Gilbert et al., 2006), having a significant impact on SLLs and BLLs currently seen today. Based on the recommendation by the United States Environmental Protection Agency, leaded gasoline was phased out in 1986 and later banned in 1990 (Gilbert et al., 2006). After removing tetraethyl lead from gasoline, "average childhood blood lead levels in the U.S. plummeted from approximately 16 μg/dL in 1976 to 3.2 μg/dL in 1994" (Gilbert &

Weiss, 2006, p. 695). Moreover, Meyer, Brown, & Falk (2008) explain that 80%-90% of airborne lead pollution can be attributed to the use of leaded gasoline in large, urban cities. In order to capture the effects of leaded gasoline use, a modified road network was utilized.

The DMTI road network was modified to reflect the 1990 road network to ensure traffic flows were represented accurately. The downtown core of Hamilton, Ontario has not changed significantly in the last century; however, there has been significant development in the suburban areas surrounding the core, and two new expressways have been built since 1990. A paper map was scanned and used to manually edit the road network in order to reflect historic road infrastructure in 1990. The road network was further divided into road types (categorized by DMTI) to act as a surrogate for traffic flows and, thus, the total amount of leaded fuel being burned. The road network contains four road types, which include: expressways, highways, major roads and local roads.

Another possible source of lead within the environment could be the result of activity from junk and salvage yards, metal merchants and automobile wreckers. Historically, automobiles were a significant source of lead from the use of lead-based paint, lead batteries, lead wheel weights and the combustion of leaded gasoline. Block (2009) explains that lead has been recovered from scrap yards by scavenging old automobiles and other materials, leading to lead deposition in the soil. Additionally, Genaidy et al. (2008) describe lead as an emission hazard from recycling, municipal waste and salvage facilities due to automobile wrecking. Moreover, the Occupational Safety and Health Administration states that "an employee may be exposed to lead [from] demolition or salvage, new construction, alteration, repair, transportation, disposal, storage or containment of lead or materials containing lead on the construction site" (Lampo et al. 2009).

Lead-based paint has been one of the most significant sources of lead historically and was eventually banned in Canada in 1991 (Abelsohn et al., 2010). Production of lead-based paint soared during the early 1900s; however, usage declined after studies began to link lead-based paint with adverse health effects in children. In addition to lead-based paint being used in residential areas, the automotive industry also used lead-based paint as a durable option for automobile bodies and thus, airborne lead could be deposited into the soil surrounding automobile paint shops (Enander et al., 2004; Wahid et al., 1997). Similarly, home renovations or deteriorating painted surfaces, and paint manufacturing plants could also result in soil contamination. A study by Gottesfeld (2015) found that workers in paint manufacturing plants are exposed to dangerous levels of lead, and often transport lead outside via contaminated dust and clothing.

Another potential source of lead contamination in Hamilton is the historical manufacturing of lead products. The City of Hamilton has been home to considerable industrial activity that includes leaded product manufacturing. There have been several different lead-based product manufacturing plants in the last century, producing various leaded products (e.g., leaded glass, antimonial lead alloys, lead diver weights, sheet lead, lead boat keels and sand castings). During the importing, processing and exporting of leaded products, there is a potential for soil lead contamination.

2.2.4 Control variables

In order to test the validity of land use regression for use as an interpolation technique for SLLs, we collected data on five control variables. Dental offices were chosen as the historical control variable (i.e., 1925-1990) since this business type should have no causal association with soil lead contamination. Dental offices have also been present in the study area throughout the past century, which ensured an extensive data set for a control variable. Additionally, we used four other modern control variables from the DMTI (2010) Enhanced Points of Interest shapefile, which included: (i) wholesale trade, (ii) retail trade, (iii) finance, insurance, and real estate (FIRE), and (iv) public administration.

2.3 Methodology

In soil contamination research, kriging is often the choice for interpolating heavy metals (see Ha et al. 2014; Yang et al. 2015; Zhou et al. 2016), but in recent years, land use regression has been tested as a method to predict soil lead levels (see Deschenes et al. 2013). As the name suggests, land use regression uses the environment as a way to estimate the value of a dependent variable at an unobserved location using regression modelling. In LUR modelling, various predictor variables (i.e., automobile garages, battery and service stations, etc.) are tested and eliminated through the process of forward selection.

In general, LUR models for different applications are built using the same methodology, although slight variations have been developed since Briggs et al. (1997) first developed the technique. Based on the methodology used by Sahsuvaroglu et al. (2006), the first step was to subset the soil lead samples into a training set (i.e., a subset to develop the LUR models using R-squared values) and a test set (i.e., a randomly chosen subset to test the accuracy of the LUR and kriging models using RMSE). Next, the Point Distance tool in ArcMap 10.3.1 was used to measure the distance between every SLL sample and every lead-related business. The Point Distance tool output a table that was imported into R, whereby a script was used to calculate the cumulative sum of businesses, or length of the road, by category (e.g., automobile painters, automobile garages, etc.) and distance interval (i.e., 500 distance buffers, ranging from 10 meters to 5,000 meters, at 10-meter intervals). Spearman correlation values were calculated between the cumulative sums of businesses or summed length of roads by type and distance interval, and the SLLs. The Spearman correlation values were used to determine at which distance the cumulative sum of businesses or summed length of roads produced the highest correlation between each independent variable and the SLL samples. Spearman correlation is a rank-order correlation coefficient, which is beneficial when using data that are not normally distributed, and may contain outliers (Mukaka, 2012). As can be seen in Table 2.1, each of the sixteen variables correlates highest at a specific distance (e.g., lead manufacturing correlates with the spatial distribution of SLLs at a distance of 2,010 meters). Based on these distances, each variable was manually entered into a bivariate regression model to explain log-transformed SLLs (training set). Once the bivariate model with the highest R-squared was determined, each of the remaining independent variables were entered using forward selection. This process of building and entering the remaining independent variables to improve the regression model was continued until the final model was constructed. Variables entered into the model must improve the R-square value by at least 1% (Wang et al., 2013), while also retaining a statistical significance of at least 95% and maintaining a variance of inflation factor of less than 2. As a result, two LUR models were developed, (i) only lead-related variables (OLV) and (ii) all variables, which included lead-related variables and control variables (AV) The final LUR model can be defined mathematically as follows:

$$\hat{Z}(X_0) = \beta_1 + \beta_2 X_n + \varepsilon$$

In this model, $\hat{Z}$ is the predicted value at point X_0, β_1 is the y-intercept, β_2 is the slope coefficient of variable X, *n* is the number of variables, and ε represents the error term.

In order to compare the different interpolation techniques, the LUR and kriging models were developed using the training subset of the SLLs. As described by Wang et al. (2013), HEV is the preferred method to test the accuracy of predictions if the sample is large enough to split the dependent variable into two groups, (i) the training set, and (ii) the test set. As the names imply, the training set is used to develop the model, and the test set is used to determine the accuracy of the predictions. There is no consensus on the size of the test set, but since this paper utilizes a relatively large sample size of 187 soil samples, 20% (n=38) of the soil lead samples were randomly selected to achieve a test set higher than 30 observations.

This paper also includes the results of two popular kriging techniques used in soil contamination research, known as Empirical Bayesian Kriging (EBK) and Ordinary Kriging (OK). These models are not included as a comparison to LUR but will act as a baseline to determine the efficacy of the LUR predictions. Both kriging techniques have been explained extensively elsewhere (see Krivoruchko, 2012; Verdin, Rajagopalan, Kleiber, & Funk, 2015), but a brief description will be discussed here. EBK can provide accurate predictions by compensating for the uncertainty associated with estimating the semivariogram. EBK creates subsets of the total sample and estimates semivariograms for each subset, which allows the model to account for local and global trends (Zoellick, 2016). EBK estimates the semivariogram by simulating data, estimating a new semivariogram based on the previous model and generating weights to compensate for uncertainties (Krivoruchko, 2012).

The result of this process has been shown to predict heavy metal concentrations with a high degree of accuracy in past soil contamination studies (Aelion et al., 2009; Finzgar et al., 2014; Pandey et al., 2015). Next, OK relies on the spatial structure of the data and can utilize detrended data. The residuals output by the detrending function can then be used to develop weights based on a variogram (Anderson et al., 2005). In this case, a trend analysis determined a third-order trend removal best fits the SLL samples. The fundamental model for kriging (EBK and OK) can be defined as follows:

$$\hat{z}(x_0) = \sum_{i=1}^{n} \lambda_i z(x_i)$$

In this calculation, $\hat{Z}$ is the predicted value at point X_0, z is the observed value at the sampled location X_i, λ_i is the weight assigned to the sampled location, and *n* is the number of sampled points used in the calculation (Li et al., 2014).

2.4 Results

2.4.1 Distance profiles

Spearman correlations were generated between each independent variable and the soil lead samples at distances from 10 meters to 5,000 meters, at 10-meter intervals. Next, we determined the distance at which the highest correlation was achieved between each independent variable and the soil lead samples. In Table 2.1, the independent variables are shown in descending order of the Spearman correlation value. All sixteen variables correlated with the dependent variable significantly ($p < 0.001$ or $p < 0.05$), and Spearman correlations ranged from -0.231 to 0.601. As a result of a negative and unexpected correlation with SLLs, the highway variable was not used in the development of the regression model.

As shown in Table 2.1, lead manufacturing correlated highest with SLLs with a Spearman correlation value of 0.601 at a distance of 2,010 meters. Interestingly, automobile painters, automobile garages and wholesale trade businesses (a control variable) had the second, third, and fourth highest correlations with SLLs, with Spearman correlation values of 0.587, 0.548 and 0.541, respectively. Similarly, dental offices (a control variable) and gasoline stations correlate nearly identically with SLLs, achieving Spearman correlation values of 0.466 and 0.465 at 1700 and 1,780 meters, respectively. Lastly, the remaining three road network variables correlated the lowest with Spearman correlation values of 0.286 (major roads at 170m), 0.267 (expressways at 1,090m), and 0.182 (local roads at 30m).

Table 2.1: Relationship between independent variables and soil lead levels by distance

Independent variables	Year(s) of data	Distance of highest correlation (meters)	Spearman correlation value	*p*-value
Lead manufacturing	1925-1990	2,010	0.601	<0.001
Automobile painters	1925-1990	1,380	0.587	<0.001
Automobile garages	1925-1990	2,260	0.548	<0.001
Wholesale trade*	2010	1,360	0.541	<0.001
Battery and service stations	1925-1990	2,270	0.535	<0.001
Junk and salvage yards	1925-1990	4,380	0.532	<0.001
Paint manufacturing	1925-1990	1,990	0.514	<0.001
Dental offices*	1925-1990	1,700	0.466	<0.001
Gasoline stations	1925-1990	1,780	0.465	<0.001
Retail trade*	2010	1,440	0.460	<0.001
Finance, insurance and real estate (FIRE)*	2010	590	0.457	<0.001
Public administration*	2010	470	0.341	<0.001
Major roads	1990	170	0.286	<0.001
Expressways	1990	1,090	0.267	<0.001
Local roads	1990	30	0.182	0.026
Highways	1990	3,220	-0.231	0.005

Note: * indicates which variables are controls

Distance profiles displaying the Spearman correlation at different distances for each independent variable are illustrated in Figure 2.2 and Figure 2.3. Figure 2.2 shows the distance profiles for the lead-related variables, whereas Figure 2.3 shows the distance profiles for the control variables. The information presented in Table 2.1 corresponds to the distances with the highest correlation, but these peaks are not as apparent when observed graphically. Nearly all distance profiles, except local and major roads, have a similarly shaped curve, in which the correlation values plateau after a relatively short distance (typically less than 1,000 meters). Additionally, the distance and strength of the correlations are closely related in the thirteen distance profiles, and the distance at which the highest correlation value is achieved often occurs at a relatively large distance in the profile. Major roads has a similarly shaped distance profile but plateaus at a lower and insignificant correlation value after an initial correlation peak at around 150m. Local roads present a unique distance profile among the fifteen others. Local roads peaks initially at 30m, correlating at the 95% confidence level, but later correlates negatively and more significantly (p = 0.001) at around 2,250m.

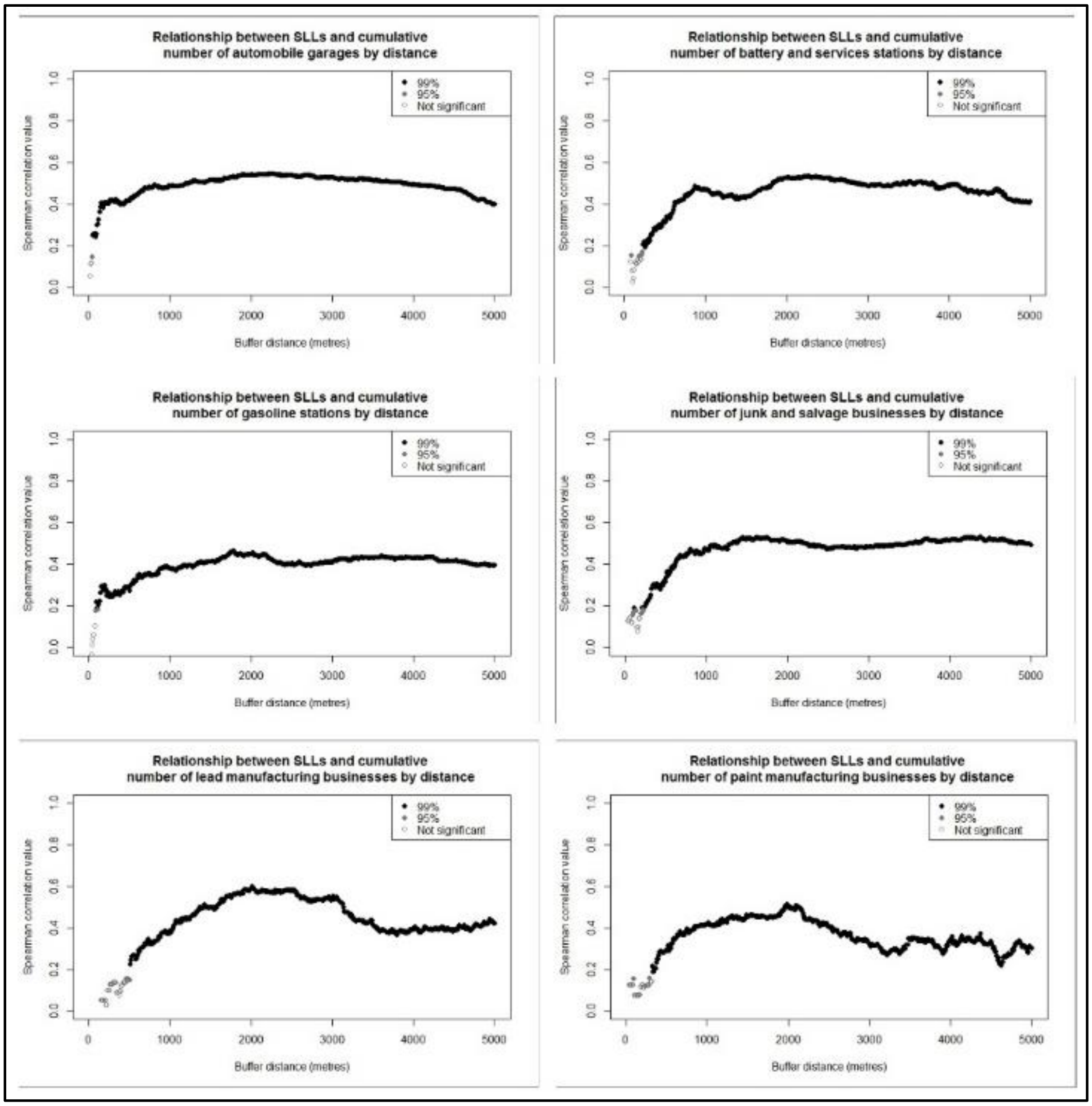

Figure 2.2: Distance profiles for the relationship between the cumulative sum of each independent, lead-related variable and SLLs (see Appendix B)

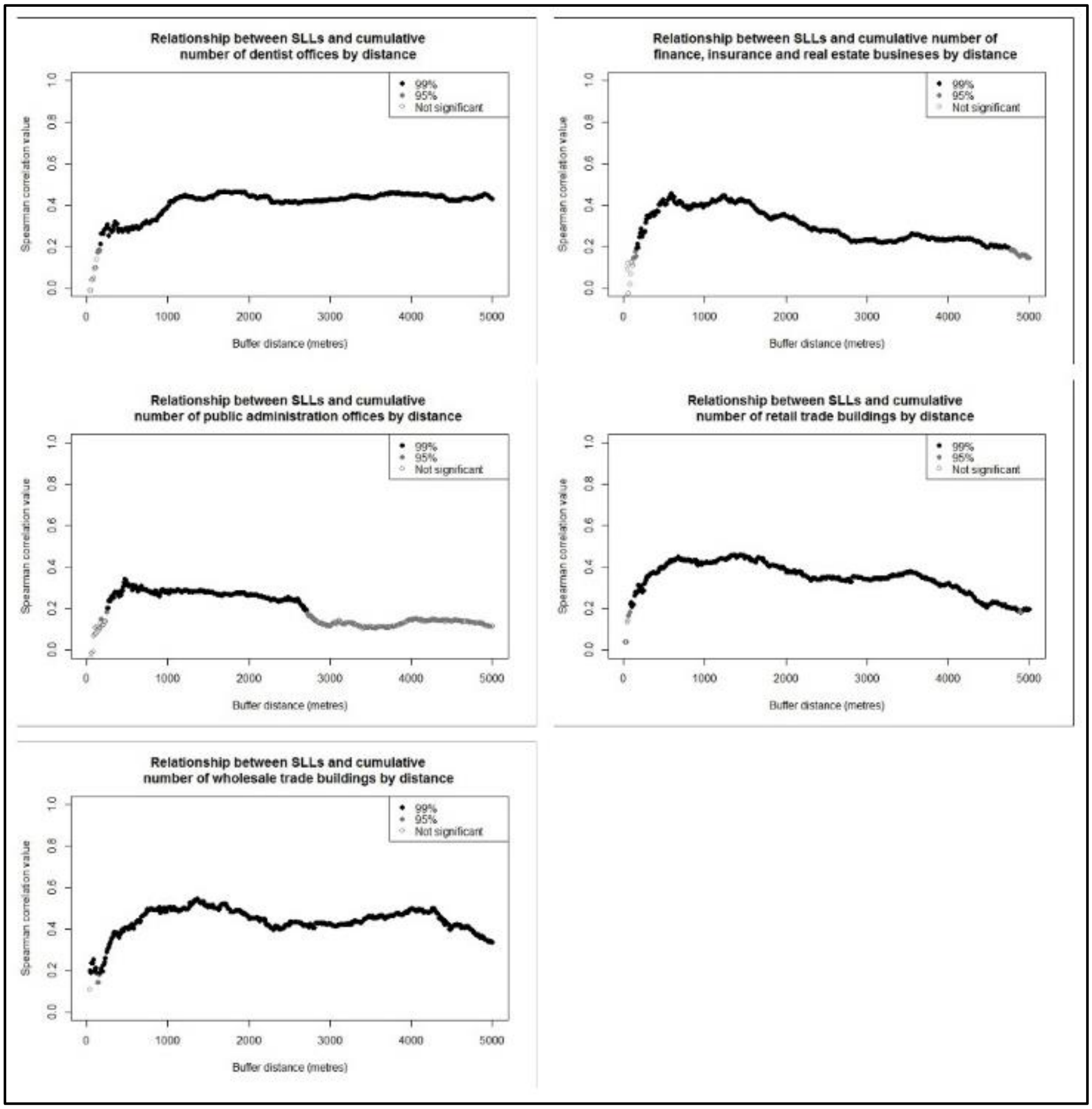

Figure 2.3: Distance profiles for the relationship between the cumulative sum of each independent control variable and SLLs (see Appendix C)

2.4.2 Interpolation models

We also developed a LUR model in order to understand how it may perform using control variables, as well as variables with spurious relationships with the dependent variable. In order to fully understand how the use of uncertain predictor variables can influence the prediction accuracy of a LUR model, two models were created: (i) a LUR model with only lead-related variables (OLV), and (ii) a LUR model with all variables (AV) (i.e., both the lead-related predictor variables, in addition to the control variables). The final OLV model included lead manufacturing, expressways, local roads and automobile painters, and achieved an adjusted R-squared value of 0.24 and acceptable variance of inflation factors of 1.8, 1.0, 1.0 and 1.8, respectively. The AV model was constructed second and included lead manufacturing, wholesale trade buildings, local roads and public administration buildings. The AV model achieved an adjusted R-squared value of 0.26 and acceptable variance of inflation factors of 1.3, 1.5, 1.0 and 1.2, respectively.

In the case of the four SLL spatial models (see Figure 2.4), an RMSE value was calculated using the prediction errors to compare the accuracy of each interpolator. The OK, EBK, OLV and AV models received an RMSE value of 76.7, 82.6, 209.0 and 182.1, and average errors of -7.1, -0.6, -141.8 and -113.2, respectively. The RMSE values suggest that we cannot reject the null hypothesis that LUR does not provide more accurate predictions of SLLs than OK or EBK. Furthermore, the distance profiles suggest some model over-fitting, since the best LUR model also includes some covariates without a plausible causal influence on SLL.

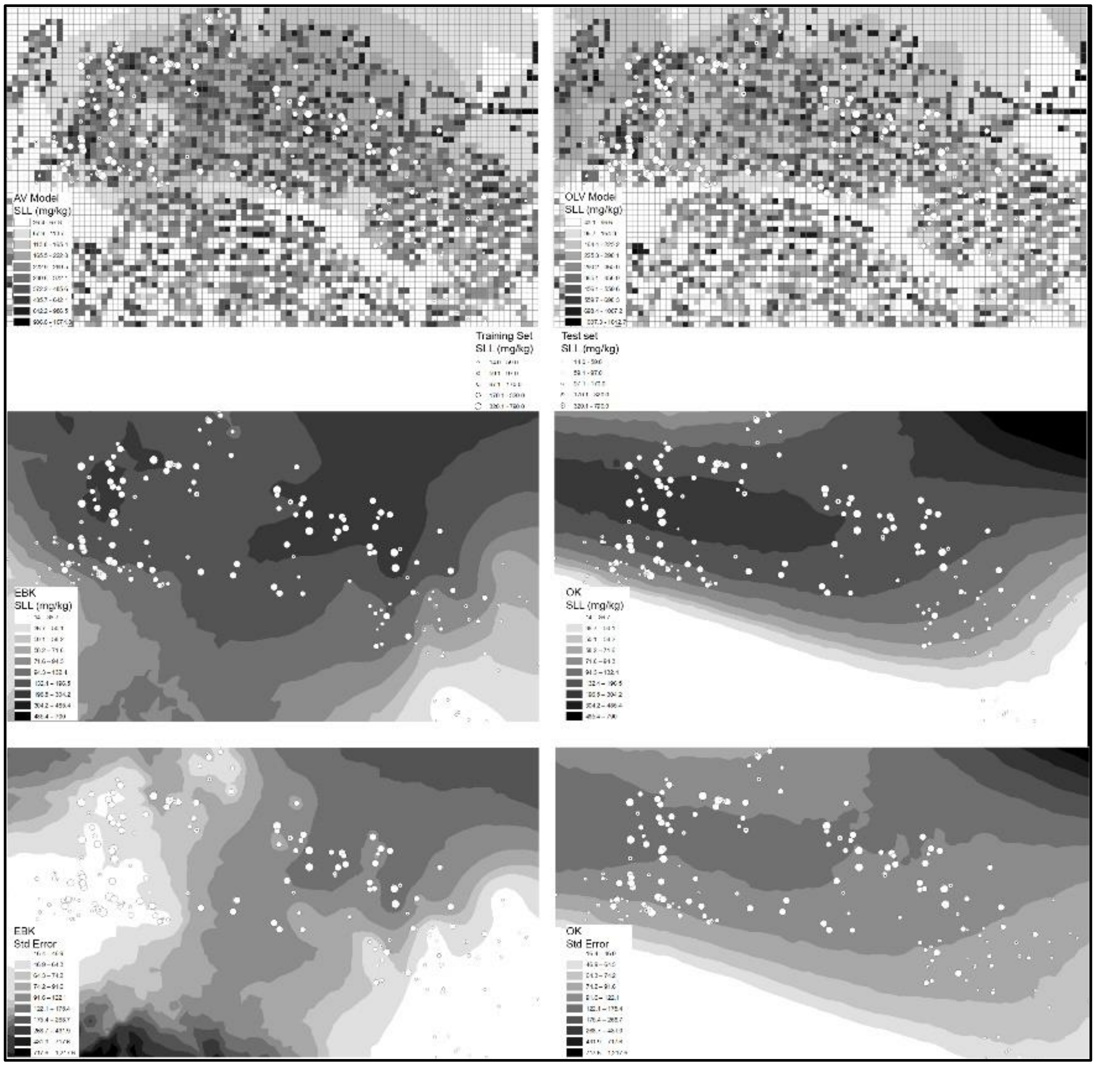

Figure 2.4: SLL predictions for LUR AV, LUR OLV, EBK and OK, and standard error for EBK and OK (see Appendix D)

2.5 Discussion

By visually comparing the graphs for each lead-related variable and the control variables, the results are not consistent with the hypothesis that there is a relationship between the number of historical lead-related variables and soil lead levels. The shape of the distance profiles is very similar across the vast majority of the variables, which indicates that there does not seem to be a relationship between the number of cumulative lead-related businesses or the summed length of roads, and the spatial distribution of SLLs in Hamilton, Ontario. The distance at which the independent variable correlates highest with SLLs suggests a spurious relationship. In other words, the distance profiles do not illustrate an expected relationship between the independent and dependent variables. For example, paint manufacturing seems to plateau around 1,000 meters, but the variable correlates highest at 1,990 meters, before quickly returning to the original plateaued correlation value at about 2,200 meters. Similarly, battery and service stations peaks at approximately 900 meters but does not achieve the highest correlation value until 2,270 meters. All of the variables (i.e., historical lead-related businesses, the historical control and the modern controls) illustrate distance profiles that do not seem consistent with the literature.

In the process of exploring a comparatively new method to address the complexity of interpolating lead in an urban center, this paper has uncovered some challenges with using land use regression more generally. Estimating accurate SLL concentrations in urban areas will often be a concern for municipal governments that have limited resources to explore and abate lead contamination. Resource management at a municipal level is an important consideration that will ultimately limit the time and money that can be invested in accurately predicting soil lead contamination for urban areas. As a result, there are three main critiques of LUR in general and specifically for

SLL prediction in an urban area, which include (i) the resource-intensiveness of data collection, (ii) the risk of confounding factors, and (iii) the risk of spurious relationships.

First, historical data collection was a particularly time-intensive task for this study and would not be reasonable for most municipal governments that lack historical digital business information. The process of transcribing businesses from microfilm business directories and cleaning the database took approximately 500 hours. As technology improves, Optical Character Recognition (OCR) could be utilized to digitize the analog business directories and avoid the transcribing process entirely. However, these technologies still have digitizing error rates of 5% for modern sources and much higher error rates for historical sources (Singh, 2013).

Second, this study shows that conceptually unrelated variables can have a statistically significant correlation with the dependent variable, in addition to increasing the perceived explanatory power and decreasing the RMSE of LUR models. This is not surprising given the process used in LUR models for including variables; a large number of possible distance thresholds are explored, with the one that is most highly correlated being favoured for use in the model. This amounts to a form of data mining in which a nearly exhaustive search of possible distance thresholds will find a 'highest' correlation with little substantive importance in explaining the real pattern of lead dispersal in the environment. The use of several such spurious variables may cause an over-fitting problem in LUR, improving the apparent performance of the model, but at the expense of generalizability and parsimony. Since it is difficult to be sure about the genuine relationship between each independent variable and the dependent variable, simpler models may be preferable. Creating parsimonious models are essential for contamination research because one of the main goals of developing an accurate spatial model is for remediation efforts. A model that explains less spatial variation of the contaminant, but contains only a few predictor variables will be much more useful for targeting the contaminants efficiently with remediation plans than an over-fitted model with a marginally higher degree of explanatory power.

Third, the results of the Spearman correlations suggest that relationships between all predictor variables and SLLs should be interpreted with caution. To the knowledge of the authors, the distance profiles used to illustrate the correlations between SLLs and the cumulative counts of businesses (or summed length of roads) have not been visualized in past LUR studies. In regards to soil lead contamination, the area most directly surrounding the source seems likely to have the highest concentrations of lead, with decaying SLLs as the distance from the source increases (Clark et al., 2014). Based on this idea, the distance profiles should have the highest correlations at the shortest distances and decrease as the buffer size increases. However, in this study, the distance profiles reveal weak correlations at the shortest distances and highest correlations at relatively large (but somewhat arbitrary) distances from the sources. Displaying these distance profiles is critical to understand if the relationship between the contaminant and predictor variables are consistent with the known or suspected diffusion pattern, and could be an essential tool for critically assessing the appropriateness of LUR in other research. Indeed, the distance profiles for the control variables and the predictor variables are similar enough to suggest that there is a weak relationship between the historical sources of lead and the spatial distribution of SLLs.

Kriging has been criticized for its inability to detect localized variation of the dependent variable (Arain et al., 2007; Kerckhoffs et al., 2015), but producing a smooth model is one of its best qualities. Kriging can reduce noise and avoid over-fitting a model based on the vagaries of a data set, which is vital for generalizability. Furthermore, kriging has the benefit of estimating error, which can be used to determine the accuracy of estimations at unobserved locations. Additionally, kriging offers a quick and intuitive process for developing an OK or EBK model. In ArcMap 10.3.1, a user can quickly develop an OK or EBK model using the geostatistical wizard and test the predictions using HEV with relative ease. In regards to resource-intensity, there was no comparison between the two methods—OK and EBK was significantly more efficient.

2.6 Conclusion

Since the introduction of land use regression by Briggs et al. (1997), air pollution researchers have been modelling air pollutants in cities all over the world, including through the use of LUR. LUR has been used extensively in air pollution research to predict NO_x and NO_2 concentrations (see Lee et al., 2014; Su et al., 2009), PM2.5 concentrations (see Beckerman et al., 2013; Olvera et al., 2012), SO_2

concentrations (see Chen et al., 2012) and many more air pollutants. More recently, LUR has been used in soil contamination research.

Although LUR is praised for its ability to detect localized variation in urban settings (see Arain et al., 2007; Hoek et al., 2008; Sahsuvaroglu et al., 2006), this paper has uncovered two potential problems with LUR that can harm the value of the LUR model. First, predictor variables that have no plausible relationship with the independent variable (i.e., the control variables) may cause over-fitting. In practice, this means that novel variables (i.e., variables tested for the first time or not seen in the literature) can be falsely identified as contributors to the spatial distribution of a contaminant. For policymakers, false identification of contaminant sources can waste valuable resources, especially at the municipal level, where budgets for abatement efforts are much smaller. Second, this paper has shown that graphing distance profiles should be an integral part of future LUR studies to ensure that model selection is based on reasonable science rather than data mining. This paper has shown that using Spearman correlations alone can result in the selection of unintuitive predictor variables. Distance profiles will help researchers determine whether or not the relationship between predictor variables and the dependent variable exhibit expected relationships in regards to distance, helping to identify spurious relationships and reduce the chance of confounding factors.

Based on the work by Deschenes et al. (2013), this study attempted to use LUR as a method to accurately predict SLLs in the urban core of Hamilton, Ontario. This paper explored three main objectives to, (i) examine the relationship between the number of historic lead-related variables and the spatial distribution of soil lead contamination, (ii) compare two baseline kriging models (OK and EBK) and LUR in terms of prediction accuracy, and (iii) consider the practicality of using LUR as a means to predict SLLs in an urban area. In both cases, the null hypotheses were not able to be rejected, which suggests there is no relationship between SLLs and historical sources of lead and that LUR will not provide more accurate soil lead estimates than OK or EBK in Hamilton, Ontario.

As a result of this study, several issues associated with LUR were identified. Despite every attempt to explain the spatial distribution of SLLs using historical sources of lead, the results of this paper suggest that OK or EBK could be a better choice to predict SLLs in an urban area than LUR.

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Chapter 3 The relationship between childhood blood lead levels and Intelligence Quotient: a meta-analysis

3.1 Introduction

Since anthropogenic sources of lead were first linked to lead poisoning, research began to associate lead poisoning with various physical and mental outcomes among children (Riva et al., 2012). Once lead enters the body through inhalation, oral consumption, skin absorption, or through a mother's breastmilk or umbilical cord, it can cause a myriad of adverse health outcomes. At first, doctors and researchers were only able to identify health outcomes caused by significant acute and chronic exposures to lead. In children, acute exposure to lead can cause "vomiting, diarrhea, convulsions, coma and death" (Richardson et al., 2011, p. 61). In contrast, chronic exposure was initially associated with physical symptoms related to the renal system, peripheral nervous system, central nervous system, hematologic system, and gastrointestinal system (Cleveland et al., 2008). As time progressed, ambient levels of lead within the environment began to fall as leaded-gasoline and lead-based paint were phased out, causing average blood lead levels (BLLs) to decline (Schnur et al., 2014). Although the physical symptoms of lead poisoning in children began to diminish, researchers discovered adverse health outcomes relating to the brain at low (i.e., <10 μg/dL) BLLs. One of the most researched effects of low-level blood lead concentration in children has been the decrease in intelligence.

3.1.1 Measuring intelligence quotient

Childhood intelligence can be measured using several different tests that evaluate a child's cognition of specific tasks (see below), which are combined to create a full-scale Intelligence Quotient (IQ) score. A full-scale IQ score is the combination of smaller subsets of the IQ test, measuring various forms of cognition (e.g., performance, verbal, patterns, etc.). The combination of subsets is dependent on the type of IQ test, as well as the language of the test. Some IQ tests do not require the use of language, which can be useful for children without language skills, or in countries where multiple languages may be common (Oller et al., 2000). Each IQ test reviewed in this paper is standardized to a normal distribution with a mean score of 100 within a population. Different IQ tests have been developed over the years; however, these IQ tests have been standardized to ensure comparability across the various tests (Wasserman et al., 2000).

Since the discovery that lead poisoning may cause negative cognition in children, researchers have maintained the notion that elevated BLLs lower IQ in children. For example, in the paper by Menezes-Filho et al. (2018), the authors found that an increase in BLLs from 0.5 µg/dL to 5.0 µg/dL caused a decline in IQ by 8.6 points for children. In other cases, studies have found a less significant loss of 0.5 IQ points per 1 µg/dL in four-year-old children (Crump et al., 2013). In some research, a distinction is made at different levels of BLLs. In the paper by Canfield et al. (2013), researchers found the children lost 7.4 IQ points as average lifetime blood lead levels increased from 1 µg/dL to 10 µg/dL, whereas children with a blood lead level increase from 10 µg/dL to 30 µg/dL exhibited an IQ loss of 2.5 points.

3.1.2 Social outcomes

Researchers have continued to demonstrate a link between BLLs and a decline in IQ in children. At first, a decrease in IQ was associated with high BLLs in children (Ernhart et al., 1988; Schilling et al., 1988; Schroeder et al., 1985), but as time progressed, researchers found that even children with low BLLs exhibited a decline in IQ (Alvarez-Ortega et al., 2017; Schnaas et al., 2006; Taylor et al., 2017). The decline of IQ from lead poisoning is often small—only amounting to a loss of a few points in many cases (Hornung et al., 2009; Min et al., 2009), but the loss of IQ has been linked to an increase of many adverse social outcomes, including violent crime, healthcare costs, need for special education, and a loss of potential lifetime earnings and tax revenue (Brown, 2002; Gould, 2009; Health Canada, 2013; Nevin, 2000).

According to an analysis by Health Canada (2013), the negative social consequences of lead poisoning and IQ loss has a significant impact on the economy. In Canada, it is estimated that decreasing the average BLL from 1.5 µg/dL to 0 µg/dL would save the economy $35 billion per cohort from changes in lifetime earnings per child (i.e., based on the July 1, 2009, to June 30, 2010 cohort). At an 8% discount rate, Canadians can expect to save $1.5 billion, and up to $9.4 billion with a 3% discount rate (Health Canada, 2013). The loss of lifetime earnings has been calculated based on two assumptions, (i) an increase of 1 µg/dL in blood lead levels is associated with a 1 IQ point deficit, and (ii) a one IQ point deficit is associated with a 1.66% decline in potential lifetime earnings (Health Canada, 2013). Considering the projected impact on the economy, the two assumptions to calculate potential savings are vital to produce an accurate prediction. Thus, the relationship between BLLs and IQ is necessary to accurately quantify the negative impact of lead poisoning on the economy. In order to help researchers accurately quantify the impact on the economy, this paper seeks to synthesize the literature relating BLLs and IQ with a meta-analysis of all UBCs available within the literature, in addition to exploring smaller populations with subgroup analysis.

3.1.3 Past meta-analyses

To the knowledge of the authors, there have only been three meta-analyses investigating the relationship between BLLs in children and IQ. We will investigate the past three meta-analyses before discussing how this meta-analysis will build on and develop a more robust approach to measuring the relationship. Needleman et al., (1990) completed one study, one by Schwartz (1994), and another most recently by Wu et al. (2018). Each of these three meta-analyses have summarized the relationship using different methodologies, and aggregating various types of information (i.e., correlations, and regression coefficients). In the paper by Needleman et al. (1990), tooth (n=5) and blood (n=7) lead levels were separately compared to IQ. First, blood and tooth lead studies were divided into two respective groups to achieve homogeneity among the pooled studies. Homogeneity was further investigated within the two groups using the

Rosenthal method of comparing *p* values, "which is based on the sum of the squared deviations of the *t* values for lead from the group mean" (Needleman et al., 1990, p. 674). Next, the authors created separate weights for the two groups based on the sample size of each study using two techniques developed by Fisher, and Mostellar and Bush (Needleman et al., 1990). The effect size for studies was then calculated by converting the *t* value to *z* scores using Fisher's transformation and compared with the χ^2 statistic. Partial correlation coefficients were then explored in order to see if one study was having an influential effect on the pooled effect size using the method described in a paper by Gatsonis et al. (1989), and the definition of a small effect from Cohen (i.e., partial r = 0.14). Needleman et al. (1990) found that the pooled effect sizes were homogenous, meaning that the sampled children among included studies had baseline characteristics that were similar enough to not significantly influence the result (Rücker et al., 2008). For example, differences caused by the country of origin did not significantly affect the pooled result. The pooled effect of partial r was -0.15 ± 0.05 for the blood lead group, and -0.08 ± 0.05 for the tooth lead group. Furthermore, the authors performed a leave-one-out sensitivity analysis. However, they did not find any studies that had a significant overall effect on the pooled result, nor did the authors find any significant bias from excluding 12 studies from the pooled result, which were eliminated for various reasons (Needleman et al., 1990).

Schwartz (1994) included eight studies in a meta-analysis of loss of IQ points when BLLs increased from 10 µg/dL to 20 µg/dL. Additionally, the meta-analysis investigated the threshold of BLLs and the effect on IQ. By estimating a linear regression function with different ranges of blood lead data, the authors were able to estimate the threshold at which the relationship between BLLs and IQ no longer exists. Additionally, this process was further explored using a prospective lead study with the lowest mean BLL within the available studies in order to investigate the possibility of a toxicity threshold for lead poisoning. The residuals from two regression models were used to construct a third model showing the adjusted relationship between IQ and BLLs. In the first regression model, full-scale IQ was regressed against a set of confounding variables (e.g., age, race, child stress score, HOME score, maternal IQ, etc.), and the second regression model regressed blood lead at 24 months against the same set of confounding variables from the first regression model. Seven studies were synthesized in the baseline meta-analysis showing a decrease in IQ of 2.57 ± 0.41 points for an increase in BLLs between 10 µg/dL to 20 µg/dL. After a sensitivity analysis was completed (i.e., removing the study with the largest effect size, and removing the study with the most significant finding), the authors did not see a significant effect on the pooled result. A further sensitivity analysis was included in which the authors included eight studies with a non-result that decreased the estimated loss in IQ points by half, but the pooled result remained statistically significant. Next, Schwartz (1994) added studies that did not meet the initial criteria for study selection, including studies with different ages of children, in addition to a study with children living solely in disadvantaged areas. Even with these additional studies included in the pooled effect, the authors did not find a significantly different result. Lastly, the authors found that the slope between BLLs and IQ was steeper at lower levels of blood lead (i.e., 3.23 ± 1.26 IQ points below 15 μg/dL) than at higher levels of blood lead (i.e., 2.32 ± 0.40 IQ points greater than 15 μg/dL). Additionally, the author found that a relationship between IQ and BLLs still exists at BLLs lower than 5 μg/dL (Schwartz, 1994).

The most recent meta-analysis discussing the relationship between IQ and BLLs was published in 2018 using much more up-to-date methods to pool the results of studies. Wu et al. (2018) used a variety of inclusion criteria, some of which included only using studies that used the Wechsler intelligence scale, which is a full-scale IQ test measuring cognitive abilities in five categories: verbal comprehension, visual/spatial, fluid reasoning, working memory, and processing speed (Wechsler, 2014). Additionally, inclusion criteria also dictated that the study must be either a prevalence (i.e., the total number of cases during a specific time) or case-control study, as well as excluding studies with a low sample size (n < 10). Researchers used RevMan 5.2 and Stata 12.0 software to pool and estimate the relationship between BLLs and IQ for case-control studies using a significance cut-off of p =< 0.05. Cochran's Q and Higgins & Thompson's I^2 statistics provided a measurement of evaluating heterogeneity within the pooled results, which allows researchers to determine if the population under examination is the same (i.e., the population cannot be divided into smaller subgroups by various characteristics of the individuals). The weighted mean difference was used to pool the results, including 95% confidence intervals. A sensitivity analysis was used to test the robustness of the pooled result, in addition to the use of funnel plots to investigate publication bias. There were a total of 22 case-control studies, and seven prevalence studies included in the meta-analysis that were analyzed using a systematic review. Wu et al. (2018) found significant heterogeneity within the 22 studies (i.e., I^2 = 85.8%), and explain that the heterogeneity was likely not a result of differences in the year, study site, sample size, or age, so a random-effects model was chosen for the meta-analysis. After pooling the 22 studies with a random-effects model, the weighted mean difference was -6.60 (95% CI: -9.01 to -4.20, $p < 0.0001$) for every one µg/L of blood lead (-0.66, 95% CI -0.90 to -0.42 for every one µg/dL of blood lead), which was significantly lower than the children within the control group. The leave-one-out sensitivity analysis showed that the pooled result did not change significantly, but the heterogeneity remained high. Researchers also found that publication bias was not present within the pooled results through the use of a Bgger [sic] (i.e., Egger) test and funnel plots (Wu et al., 2018).

Past meta-analyses have achieved a reasonable understanding of the relationship between BLLs and IQ; however, this paper will address their shortcomings. First, in the paper by Needleman et al. (1990), pooled partial r values suggest a relationship may exist, but the relationship was not quantified using regression coefficients. Next, the meta-analysis by Schwartz (1994) uses relatively simple regression analysis to pool effect sizes of the current body of literature. The result showed that at higher blood lead levels, lead had a lower impact on a child’s IQ than at lower blood lead levels. In the most recent meta-analysis by Wu et al. (2018), researchers used a much more modern approach to synthesizing the data using the RevMan software.

Building on the paper by Wu et al. (2018), this meta-analysis will address three main limitations of past meta-analyses by: (i) using R software, (ii) using a much larger pool of beta coefficients, and (iii) including a general and subgroup analysis. One of the limitations of the RevMan software is that the only estimator for pooled effect sizes is the DerSimonian-Laird estimator, which is less robust than other estimators, such as the Hartung-Knapp-Sidik-Jonkman method. More specifically, the DerSimonian-Laird estimator is more likely to create false-positives as a result of a small number of studies, and when there is substantial heterogeneity present within the pool (Harrer et al., 2019). In order to address the second and third limitations, we will use all available unstandardized beta coefficients, in addition to doing a subgroup analysis to explore the presence of differences between smaller populations with varying characteristics. In the past three meta-analyses on this topic, researchers have only used the final, adjusted model to include in the meta-analysis. Thus, past meta-analyses have generated pooled results based on a small number of UBCs, and lack a subgroup analysis. By utilizing every UBC reported in each paper included in this meta-analysis, we are able to generate more accurate pooled results, in addition to including a thorough subgroup analysis. In the past, meta-analyses have collected data according to subgroups based on certain criteria (e.g., only using the final adjusted model, or only using studies that used the WISC IQ test). In this meta-analysis, we will use all UBCs available to create a comprehensive pooled result, and explore any subgroups that may exist within the population.

3.1.4 Objectives

Over the last several decades, researchers have tried to measure the link between BLLs in children and intelligence. The relationship between BLLs and IQ has been essential to policymakers because IQ can be further linked to potential lifetime wages of an individual, the need for special education, the likelihood a child will graduate from high school and post-graduate education, and increases in violent crime. In the context of lead poisoning research, a decrease of one IQ point has been associated with a specific value of potential lifetime wage loss within a population (Gould, 2009), which can be used to justify the substantial capital investment of permanent lead abatement. The relationship between BLLs and IQ in children is vital to develop cost-effective policies, in addition to developing programs that target children with low BLLs. This paper aims to identify the relationship between BLLs and IQ among children more robustly by leveraging all available data from past studies. Specifically, this paper has three main objectives, (i) more accurately quantify the relationship between full-scale intelligence quotient and blood lead levels in children in a general context, (ii) identify the heterogeneity of the relationship between full-scale intelligence quotient and blood lead levels in children within the literature, and (iii) identify and explore the existence of subgroups that may influence the relationship between intelligence quotient and blood lead levels in children.

3.2 Methods

3.2.1 Data sources and search strategy

In November 2018, the PubMed database was searched for English-language studies relating to the association between BLLs and IQ. The PubMed database was chosen because the repository catalogues journal articles from Medline, PubMed Central (PMC), and the National Center for Biotechnology Information (NCBI). Furthermore, PubMed is managed by the U.S. National Library of Medicine, which is also responsible for running the Medline database. Additionally, PubMed has been shown to produce the most search results for the same search query among five Medline platforms (i.e., PubMed, ProQuest, EBSCOhost, Web of Science, and Ovid). Although Ovid was shown to produce similar results to PubMed most consistently, the Ovid platform still returned fewer results than PubMed when the results differed (Burns et al., 2019). The following search terms for titles and abstracts published during any year were included: blood lead, blood Pb, lead poisoning, Pb poisoning, IQ, intelligence quotient, child, children, toddler, youth, adolescent, teenager, infant. The full search term can be seen below:

"(\"blood lead\" [Title/Abstract] OR \"blood pb\" [Title/Abstract] OR \"lead poisoning\" [Title/Abstract] OR \"pb poisoning\" [Title/Abstract]) AND (iq [Title/Abstract] OR \"intelligence quotient\" [Title/Abstract]) AND (child [Title/Abstract] OR children [Title/Abstract] OR toddler [Title/Abstract] OR youth [Title/Abstract] OR adolescent [Title/Abstract] OR teenager [Title/Abstract] OR infant [Title/Abstract])"

The “RISmed” package for R was used to search the PubMed database API (application programming interface). Initially, 180 papers were identified using the search query listed above. First, titles and abstracts were read and categorized into three groups, (i) ‘yes’: papers that discuss the relationship between IQ and lead poisoning, (ii) ‘maybe’: papers that might discuss the relationship between IQ and lead poisoning, and (iii) ‘no’: papers that do not discuss IQ and lead poisoning. After the initial screening process of reading titles and abstracts, 84 papers were categorized into the ‘yes’ group, 48 papers were categorized into the ‘maybe’ group, and 48 papers were categorized into the ‘no’ group. Papers that were categorized as ‘yes’ or ‘maybe’ totalled 132 and were selected to download and read carefully. During the download process, an additional 12 papers were eliminated because they were not accessible (i.e., available to McMaster University), and nine papers were eliminated because they were not written in the English language (i.e., 111 papers remained). During the final phase of elimination, the 111 papers were read carefully to extract data and eliminate any other papers that did not meet the inclusion criteria. After the final screening process, 98 papers were removed because they did not meet the inclusionary requirements. Thirteen papers were identified for inclusion and met the following requirements, (i) English-language, (ii) peer-reviewed, (iii) contains an unstandardized beta coefficient (UBC) to describe the relationship between blood lead levels and intelligence quotient, (iv) uses full-scale IQ score measured on a normal distribution with a mean score of 100 within a population, (v) children are younger than 18 years of age, (vi) blood samples were taken using venous puncture, (vii) blood lead levels were either not transformed, log-transformed or natural log-transformed, (viii) reported 95% confidence intervals or standard error, and (ix) contains primary or secondary research.

3.2.2 Data extraction

After collecting the 13 papers for review, we tabulated the following information: study location, type of study (i.e., cohort, or case-control), study years, number of children in the final sample, age of children, type of blood sample, units of measure for blood lead concentration, type of full-scale IQ test(s), mean of blood lead level, mean of full-scale IQ, statistical tests (i.e., regression, or crude correlation), transformation, regression type, confounding variables controlled for in model(s), blood lead level categories, correlation and regression coefficient, 95% confidence intervals, standard error, and *p*-value. See Table 3.1 for descriptive statistics of the papers included in this meta-analysis.

3.2.3 Pooling beta coefficients

In order to leverage all UBCs available within the literature, in addition to developing a robust pooled estimate, we will use a two-group approach in this meta-analysis. First, we will use all untransformed UBCs to formulate the main group (i.e., the linear group). The results of the linear group will be the true estimates since they have a one-to-one relationship between BLLs and full-scale IQ in children. Second, we will standardize all available (i.e., log, natural log, and untransformed) UBCs to one unit of measure (i.e., the non-linear group) that we can use to verify the results and trends we see within the linear group. We standardized the coefficients transformed with log, natural log, in addition to untransformed UBCs to ensure the coefficients are on the same scale. A paper by Rodríguez-Barranco et al. (2017) describes a method to standardize UBCs from a regression model using $\log_{10}$, natural log and untransformed variables to prepare the coefficients for meta-analysis. In the context of this paper, a UBC where BLLs have been log-transformed is converted using $LOG_{10}(1.5)$ * UBC, and LN(1.5) * UBC when the BLLs have been natural log-transformed, where 1.5 is used to convert to a 50% scale. Standardized UBCs using this method can be interpreted as a 50% increase in BLLs will cause a loss (if negative) of IQ points equal to the standardized beta coefficient. For models where BLLs have not been transformed, we are still required to standardize the beta coefficients. In a linear model, we can use 0.5 * n * UBC, where 0.5 is to convert to a 50% scale, and n represents the sample size of the regression model. In cases where the BLLs were not transformed), the sample size of the regression model is required. Not all UBCs collected for this meta-analysis include sample size, so any UBCs without a reported sample size were dropped from the pooled result (n=12).

Rodríguez-Barranco et al. (2017) report that by testing the conversion calculation for linear models using simulated data, the accuracy of the untransformed beta coefficients depends on the symmetry of the independent and dependent variables (i.e., BLLs and IQ). The normality of each variable distribution is not known; however, BLLs are often left-skewed, and IQ is often normally distributed. Warne et al. (2013) show through the analysis of IQ results from a wide range of countries and tests, consisting of adults and children, that the distribution of IQ among a population is most commonly normal. In contrast, BLLs have been consistently asymmetrically left-skewed (i.e., most children are in the lowest blood lead groups) in the United States for many years (CDC, 2019). Many other countries around the world exhibit this same left-skewed distribution of BLLs among children (see Colombia: Alvarez-Ortega, Caballero-Gallardo, & Olivero-Verbel, 2017; Iran: Nakhaee et al., 2019; Sweden: Skerfving, Lofmark, Lundh, Mikoczy, & Stromberg, 2015), which leads us to believe the BLLs in this meta-analysis will also exhibit a left-skewed distribution. As a result of normally distributed IQ (dependent variable) and asymmetrically distributed BLLs (independent variable), we can expect a variance of 0.52 to 0.63% between the true UBC and the UBC calculated with the formula proposed by Rodríguez-Barranco et al. (2017). Additionally, for models where BLLs have been transformed using log or natural log, variances between true and converted UBCs are predicted to be between 0.24 and 0.34% (Rodríguez-Barranco et al., 2017). In order to use all UBCs available in the literature, we will use the calculations proposed by Rodríguez-Barranco et al. (2017) to convert all UBCs to one standardized form that can generate a more robust pooled result. In past meta-analyses, only one UBC has been used per included study, which limits the predictive power of the pooled result. Using the method outlined by Rodríguez-Barranco et al. (2017), we will be able to leverage all UBCs presented within each study. As a result of using this technique, we will be able to generate accurate trends and relative differences among pooled results that can be used to compare with the results of the linear group.

The remainder of the analysis within this paper will employ the methods outlined by Harrer et al. (2019), which explains the most modern approaches to meta-analyses. In order to pool the beta coefficients, we are first required to decide between using a fixed-effects model or a random-effects model. A fixed-effects model is used when the study populations across pooled papers are the same, whereas a random-effects model is used when the study population cannot be assumed to be the same (Harrer et al., 2019). In this paper, we employ the random-effects model for two reasons, (i) study populations are derived from countries around the world, and (ii) blood lead samples come from children of different ages. The random-effects model we employ is stated as follows:

$$\theta_k = \mu + \epsilon_k + \zeta_k$$

In the random-effects model, θ_k is the beta coefficient for study k, μ is the average of all beta coefficients, ϵ_k is the error associated with sampling, and ζ_k is the study-specific random effect (i.e., the difference between the beta coefficient for study k and the average of all beta coefficients). The ζ_k term is derived using τ^2, which can be calculated using different estimators that calculate between-study variance using slightly different approaches. There are eight different methods to calculate τ^2 in the R package that we will use for this paper, which includes (i) DerSimonian-Laird, (ii) Paule-Mandel, (iii) Restricted Maximum-Likelihood, (iv) Maximum-likelihood, (v) Hunter-Schmidt, Sidik-Jonkman, (vi) Hedges, (vii) Empirical Bayes, and (viii) Hartung-Knapp-Sidik-Jonkman. The DerSimonian-Laird method is often used in meta-analyses performed using the RevMan software; however, the Hartung-Knapp-Sidik-Jonkman (HKSJ) estimator has been shown to outperform DerSimonian-Laird (DS) in most cases (Harrer et al., 2019). The method of calculating τ^2 using the HKSJ and DS approaches were described in detail in a paper by (Mathes et al., 2018). In meta-analyses with heterogeneity, the average error rates were consistently higher with DS than with the HKSJ estimator (Inthout et al., 2014). As a result, we will utilize the HKSJ estimator since our meta-analysis is expected to have heterogeneity, as discussed above. Additionally, pooling the UBCs requires a weight to reflect the strength of each relationship (i.e., the robustness of the sample to determine a relationship capable of being generalized to a population). Weighting was generated using the standard error for each UBC, which is a value derived using the standard deviation and size of the population associated with each UBC.

3.2.4 Between study heterogeneity

Heterogeneity is an essential aspect of a meta-analysis because it informs us of the differences between studies within the initial pooled results. If the heterogeneity within the pooled results is high, there are likely subgroups that may explain variation that was missed, or extreme values are present within the pooled result. For example, high heterogeneity within the pooled results may mean that a child with high prenatal BLLs has a different effect on IQ than a child with high BLLs at five years old. There are three main ways to calculate heterogeneity within pooled results, which include: (i) Cochran's Q, (ii) Higgins & Thompson's I^2, and (iii) Deeks, Higgins & Altman's τ^2. Cochran's Q is ideal when there is a large number of studies, and the sample size of studies is large. As a result, Cochran's Q is influenced by statistical power, which is not ideal to rely on for a meta-analysis solely. Similarly, Higgins and Thompson's I^2 also depends on the statistical power of studies but is more favourable because I^2 includes a 'rule of thumb' to interpret the amount of heterogeneity within the results (i.e., I^2 = 25%: low heterogeneity, I^2 = 50%: moderate heterogeneity, I^2 = 75%: high heterogeneity). Lastly, Deeks, Higgins & Altman's τ^2 is better than Cochran's Q and Higgins & Thompson's I^2 in that the heterogeneity measure is not dependent on the number of studies or statistical power; however, τ^2 can be more difficult to interpret since the measure uses a prediction interval (Harrer et al., 2019). For example, if the prediction interval includes zero, or a positive value, it would be difficult to conclude that BLLs influence IQ.

Outliers may also cause high heterogeneity in the data, or that the pooled result is being heavily influenced by one study. In order to detect outliers in the pooled result, we will search for studies with confidence intervals that do not overlap the pooled confidence interval (Harrer et al., 2019). If a UBC has an upper confidence interval that is lower than the low-end of the prediction interval, the UBC is considered an outlier. Similarly, if the lower confidence interval of the UBC is higher than the high-end of the prediction interval, the UBC is considered an outlier. Once outliers have been removed, we will conduct a sensitivity analysis to examine how the pooled result changes. Another essential type of sensitivity analysis is detecting influential studies within the pooled result. The significance of a pooled result may be influenced by one study, that when removed, can drastically alter the outcome of the pooled result. In order to conduct a more rigorous sensitivity analysis, we will use the leave-one-out method to consecutively calculate the pooled result after removing one study at a time until all studies have been removed once.

The Baujat plots are the first method to investigate the influence of UBCs in the overall pooled result. On the y-axis, influence is shown, whereas the x-axis shows the overall heterogeneity contribution. Therefore, UBCs shown in the upper-right corner could be considered potential outliers since they have a strong influence and high heterogeneity contribution to the pooled result.

After investigating influence with the Baujat plots, we will use a set of influence characteristic graphs to identify potential outliers within the pool. Each point on the graphs represents a pooled result when the corresponding UBC has been omitted from the pooled result (i.e., leave-one-out analysis). Red points represent the UBC(s) that have been identified as influential studies (i.e., outliers) based on exceedance of two thresholds, (i) DFFITS, and (ii) hat. In the calculations below, k represents the number of UBCs within the pooled result.

$$| \mathrm{DFFITS} | > 3 \times \sqrt{(1 / (k - 1)}$$

$$hat > 3 \times (1 / k)$$

DFFITS and *hat* are calculated each time a study has been omitted during the leave-one-out analysis. When a pooled result (omitting one paper) has exceeded the threshold of either DFFITS or *hat*, the paper that has been eliminated will be identified on the influence analysis graphs as red. The DFFITS graph describes the change in the predicted pooled UBCs when omitting each study (measured in standard deviations). Similar to the standard residuals graph, DFFITS shows the significant changes in the predicted pooled UBCs when the two outliers are removed (Harrer et al., 2019).

The graph showing standardized residuals (of heterogeneity) shows the amount of heterogeneity caused by each study. Next, Cook's Distance is a measure to quantify the influence a particular data point has on the pooled result. In the graph showing covariance ratio, UBCs with a covariance ratio less than one could be removed to generate a more precise estimate of the model coefficients, and data points exhibiting a covariance ratio significantly less than one may be seen as outliers within the data (Viechtbauer et al., 2010). The graphs showing hat and weight on the y-axis show the leverage (i.e., the weight) of each unstandardized beta coefficient within the pooled coefficients. The graph with τ^2 on the y-axis shows the value of τ^2 for a pooled result when each study has been omitted individually. Similarly, the graph with Q on the y-axis shows the change in Cochran's Q if each unstandardized beta coefficient was removed from the pooled result.

Lastly, we will use a Graphic Display of Heterogeneity (GOSH) plot to explore the heterogeneity within the pooled result further. A GOSH plot allows us to examine the pooled result on the x-axis and the heterogeneity along the y-axis. Through the use of the GOSH plots, we will identify potential patterns that may exist within the pooled result. If the GOSH plot shows more than one cluster, this will indicate that the pooled result may be describing more than one subpopulation (Harrer et al., 2019). In order to ensure a thorough analysis, we will perform a subgroup analysis regardless of the results of the GOSH plot to explore common subgroups identified within the literature.

Subgroup analysis is used to determine how the pooled result changes when studies are grouped by different characteristics (e.g., study design, time of blood sample, etc.). Similar to the original pooled beta coefficients, we will use the random-effects model to pool the beta coefficients for each subgroup. Next, Harrer et al. (2019) explain that we will be required to calculate the significance of the differences between each subgroup by computing the Standard Error of the differences between pooled results. The result of this calculation will inform us if the differences between subgroups are significant. Cochran's Q can determine a statistically significant difference between subgroups among each group (i.e., non-linear and linear). A significant Q means that the differences in pooled UBCs are statistically significant, suggesting that the subgroups are influencing the results.

3.2.5 Publication bias

In the last step of the analysis, we will investigate the possibility of publication bias, which can happen when journals or researchers do not publish non-results (e.g., non-significant results, or results with a neutral or unexpected regression coefficient). Avoiding the publication of non-results is also known as the file-drawer problem, which states that studies with better results are more likely to be published than studies with a less significant result (Harrer et al., 2019). Thus, in a meta-analysis, it is important to investigate possible publication bias to identify limitations that may be present in the pool of literature. One method to investigate the possibility of publication bias is through the use of a funnel plot. A funnel plot is used to explore the symmetry of the UBCs by plotting standard error on the y-axis and effect size on the x-axis. If publication bias is not present, we expect to see points plotted in a symmetrical pattern (i.e., points with high, medium and low standard error). The Egger's test will be used to further investigate the potential asymmetry of the UBCs in the pooled result by determining if any asymmetry in the funnel plot is statistically significant. If statistically significant asymmetry is found using the funnel plots and Egger's test, we will proceed to a Duval & Tweedie's trim-and-fill procedure to add 'missing' UBCs to the funnel and recalculate the pooled result. Asymmetry in a funnel plot is indicative of a pooled result missing unpublished results (i.e., non-results). Thus, using the trim-and-fill procedure, the pooled result includes simulated UBCs that act as a proxy for unpublished results (Harrer et al., 2019).

One issue with the trim-and-fill procedure is that the result is only valid for publication bias as a result of effect size discrimination, but not non-significance (Simonsohn et al., 2014a). In addition to the trim-and-fill procedure, we will use a *p*-curve analysis to provide another pooled result to mitigate the potential of *p*-hacking. The practice of *p*-hacking is most likely to occur when researchers have not determined the exact methodology before analysis begins (i.e., decisions about outlier removal, measures to analyze, covariates to use, etc.), which may lead to self-serving decisions that increase publishing odds. As a result of *p*-hacking, a statistically significant outcome may be indicative of selective reporting, rather than a genuine relationship (Simonsohn et al., 2014a). A *p*-curve analysis will allow us to analyze the presence of publication bias by measuring the distribution of *p*-values included in the pooled result in two ways, (i) right-skewedness, and (ii) flatness. If a pooled result contains evidential value (i.e., the collective pooled result has meaning), the *p*-curve will exhibit a significantly right-skewed and non-flat curve. If a *p*-curve is not right-skewed, it may suggest that the pooled result is noisy, imprecise, or lacking certainty. Second, the *p*-curve of the pooled UBCs will be compared to a curve with 33% power (i.e., 2 out of 3 studies fail). If the *p*-curve of the pooled UBCs are significantly flatter than a curve with 33% power, we will conclude that the pooled result lacks evidential value. As a result of these two measurements, the *p*-curve analysis will determine if an evidential value exists within the pooled UBCs (Simonsohn et al., 2014a). Furthermore, the *p*-curve analysis will also be used to estimate the true effect size. In this meta-analysis, estimating true effect size using the *p*-curve method will attempt to correct for inflated UBCs as a result of *p*-hacking by only relying on the statistically significant UBCs (Simonsohn et al., 2014b).

The last method to identify any publication bias within the pooled literature is a risk of bias summary. This meta-analysis will look at the following factors to determine if any of the included papers exhibit a risk of bias, (i) selective outcome reporting, (ii) population sampling, (iii) measurement of confounders, (iv) IQ testing, (v) incomplete outcome data, (vi) blood lead collection, and (vii) blood lead analysis. In each of the seven factors, we will flag a paper with a low, medium, or high risk of failing to explain each factor adequately, or enacting appropriate methodologies.

3.3 Results

3.3.1 Descriptive statistics

In the initial tests, we will include two pooled results, (i) all UBCs with a non-linear transformation (non-linear), (ii) only untransformed UBCs (linear). By presenting the results of the meta-analysis with these two groups, we will be able to robustly explain the relationship between blood lead levels and IQ within a linear and non-linear pooled result. The purpose of including a non-linear result is to incorporate all current literature relating blood lead levels and IQ in children.

This meta-analysis will draw from 13 studies published between 1992 and 2018, which can be seen in Table 3.1. The 13 studies presented in this study have collected data from a wide range of countries, including Australia, the United States, South Korea, Chile, Italy, Brazil, China, the United Kingdom, and Yugoslavia. Similarly, the ages of children during blood sampling ranges widely from prenatal to 16 years old, and BLLs range from 0.4 µg/dL up to an average of 17.1 µg/dL. Mean IQ ranges from 75.4 to 116; however, one study does not report an average. In Table 3.1, the pooled result groups and the number of UBCs that each paper has contributed is shown. Some papers contribute multiple UBCs to each pooled result since many papers analyze the relationship between BLLs and IQ among different subgroups (e.g., age groups, unadjusted and adjusted models, etc.). Lastly, all papers explored in this meta-analysis use linear regression; however, in the paper by Min et al. (2009), nonlinear models were used to test the relationship between IQ and BLLs. The authors did not find that a nonlinear relationship existed and proceeded to use linear regression models to estimate the relationship between IQ and BLLs.

Table 3.1: Descriptive statistics for papers included in this meta-analysis

Authors & publishing year	**Type of Study**	**Total UBCs**	**Country**	**Age of children (years)**	**Mean blood lead levels (μg/dL)**	**Mean IQ**	**Original unit of BLLs**	**Transformation of blood lead levels**	**Regression type**
(Bellinger et al., 1992)	Cohort	32	US	6 months to 10	3 to 7.8	116	μg/dL	None	Linear
(Canfield et al., 2013)	Cohort	48	US	3 to 5	0.7	89.8	μg/L	None	Linear
(Dietrich et al., 1993)	Cohort	18	US	6.5	5 to 17.1	86.9	μg/dL	None	Linear
(Hong et al., 2015)	Cohort	4	South Korea	8 to 11	1.8 (geometric)	110.1	μg/dL	Log	Linear
(Iglesias et al., 2011)	Cohort	4	Chile	7 to 16	3.5 to 10.8	104.1	μg/dL	None	Linear
(Lucchini et al., 2012)	Cohort	1	Italy	11 to 14	1.7	106.3	μg/dL	Natural log	Linear
(Menezes-Filho et al., 2018)	Cohort	2	Brazil	7 to 12	1.6	75.5	μg/dL	Log	Linear
(Min et al., 2009)	Cohort	6	US	4 to 11	7	81 to 86	μg/dL	None	Linear, and nonlinear (testing)
(Pan et al., 2018)	Case-Control	2	China	9 to 11	0.7 (geometric)	103.4	μg/L	None	Linear
(Taylor et al., 2017)	Cohort	6	UK	Prenatal to 8	3.7	103.1 to 104.8	μg/dL	None	Linear
(Tong et al., 1996)	Cohort	20	Australia	11 to 13	0.4 to 1.0	100	μmol/L	Natural log	Linear
(Wasserman et al., 2000)	Cohort	5	Yugoslavia	Prenatal to 7	1.0 to 1.3	Not reported	μg/dL	Log	Linear
(Wasserman et al., 2003)	Cohort	3	Yugoslavia	10 to 12	0.8 to 1.5	75.4 to 75.9	μg/dL	Log	Linear

*Note: Mean blood lead levels have been converted to a one-unit increase in μg/dL where necessary, although, the original unit of measure shown

3.3.2 Pooled unstandardized beta coefficients

In the context of this paper (see Table 3.2 for pooled UBCs), UBCs in the non-linear group describes the IQ point loss (if negative) for a 50% increase in BLLs. For example, a UBC of -0.40 would mean that for a 50% increase in BLLs, we expect a loss of 0.40 IQ points. On the other hand, UBCs in the linear group describes an IQ loss (if negative) for a one-unit increase in BLLs. In the same example, a UBC of -0.40 would mean that for an increase of one unit in BLLs (e.g., 1 µg/dL to 2 µg/dL), we expect a loss of 0.40 IQ points. Indeed, a linear pooled result is much easier to interpret, nor is it sensitive to different BLL ranges; however, the non-linear pooled result will allow the inclusion of significantly more literature (i.e., of the 13 papers included in this meta-analysis, six papers exhibit transformations, whereas seven papers do not include a transformation).

As can be seen in Table 3.2, the pooled result for the non-linear group was -0.40 (95% CI: -0.54 to -0.27) with a prediction interval of -1.96 to 1.16. Heterogeneity measures were 0.62 (τ^2), 92.4% (I^2), and 1,809 (Q). In the linear group, the pooled result was -0.20 (95% CI: -0.26 to -0.15), with a prediction interval of -0.71 to 0.30. Heterogeneity measures in the linear group were 0.06 (τ^2), 47.7% (I^2), and 220 (Q). A forest plot has been generated for both groups to visually represent the pooled result, which can be found in Appendix E.

Table 3.2: Pooled results for non-linear and linear groups, including heterogeneity measures

Group	Pooled result	95% confidence interval			Prediction interval		τ^2	I^2	Q	
		Lower	Upper	p	Lower	Upper				p
Non-linear Papers: 13 UBCs: 139	-0.40	-0.54	-0.27	< 0.0001	-1.96	1.16	0.62	92.4%	1,809	< 0.0001
Linear Papers: 7 UBCs: 116	-0.20	-0.26	-0.15	< 0.0001	-0.71	0.30	0.06	47.7%	220	< 0.0001

3.3.3 Influence, heterogeneity, and outlier detection

Next, we will look more closely at heterogeneity and influence by detecting potential outliers within the data sets. The first outlier detection method identified 49 UBCs from six papers in the non-linear group, ranging from -0.19 to 1.16, which can be seen in Table 3.3. Once the 49 outliers were removed, 90 UBCs remained from 11 papers. The pooled result decreased to -0.73 (95% CI: -0.94 to -0.53) with a prediction interval of -2.53 to 1.06. Heterogeneity measures have changed to 0.81, 93.8% and 1,428 for τ^2, I^2 and Q, respectively. In the linear group, three UBCs were identified as outliers from two papers, resulting in a pool of 113 UBCs from 6 papers. The pooled result from the linear group was -0.22 (95% CI: -0.27 to -0.17), and a prediction interval of -0.70 to -0.27. The heterogeneity measures were 0.06 (τ^2), 30.2% (I^2), and 160 (Q). Results of the first outlier detection method will be discussed below, and the forest plots produced omitting outliers can be seen in Appendix F.

Table 3.3: Pooled results omitting outliers using simple detection method, including heterogeneity measures

Group	Pooled result	95% confidence interval			Prediction interval		τ^2	I^2	Q	
		Lower	Upper	p	Lower	Upper				p
Non-linear Papers: 11 UBCs: 90	-0.73	-0.94	-0.53	< 0.0001	-2.53	1.06	0.81	93.8%	1,428	< 0.0001
Linear Papers: 6 UBCs: 113	-0.22	-0.27	-0.17	< 0.0001	-0.70	0.27	0.06	30.2%	160	< 0.01

3.3.3.1 Baujat plots

The Baujat plot for the non-linear group (see Appendix G), shows two UBCs (ID: 294 and 295) within the upper-right quadrant, both from the paper by Wasserman et al. (2000). Three more UBCs (ID: 268, 269, and 270) from the paper by Tong et al. (1996) can be seen distant from the main group with relatively high influence, but low heterogeneity contribution. In contrast, the Baujat plot for the linear group illustrates a more gradual dispersion of UBCs from the primary grouping in the bottom-left quadrant. There are twelve UBCs (ID: 107, 91, 142, 156, 10, 179, 211, 210, 9, 141, 8 and 209) that are relatively distant from the main group, and the two UBCs that are furthest into the top-right quadrant with high influence and heterogeneity have IDs: 141 and 209.

3.3.3.2 Influence Characteristics

First, we will explore the influence characteristics for the non-linear group, which identifies the two UBCs (ID: 294 and 295) from the Wasserman et al. (2000) paper as potential outliers. All eight graphs for the three groups can be seen in Appendix H. As shown in the first graph, the two red points have high, negative standard residuals relative to the rest of the UBCs. Cook's distance depicts the strong influence that the two red points have on the pooled result. Similarly, when these two red points are individually omitted from the pooled result, the τ^2 value is reduced significantly. Other UBCs will also reduce the τ^2 (shown as negative peaks on the graph); however, they do not have as much weight within the pooled result, which will be discussed below. In the graph showing Cochran's *Q* on the y-axis, the two red points are the only UBCs that significantly reduce the value of *Q* once removed from the pooled effect in the leave-one-out analysis. The graph with DFFITS shows the two red points as relatively distant from the rest of the UBCs and depicts a similar shape as the graph illustrating the covariance ratio. Although difficult to see on the graph, covariance ratios range from 0.94 to 1.03, and the two red points have a covariance of 0.95 and 0.96 for ID numbers 294 and 295, respectively. Lastly, and perhaps most importantly, the *hat* and weight groups illustrate the weight each UBC has within the pooled result. The weights are based on the standard error, which is generated using the sample size used to generate each UBC. The larger the sample size, the smaller the standard error. Thus, studies with high weight will have more influence on the pooled result, and the two UBCs shown in red are shown to have high weight within the pooled result. Indeed, UBCs identified by threshold exceedance (shown in red) is not a guarantee that they are outliers, but careful analysis of each graph in combination can be used to identify outliers successfully. In the non-linear group, the two UBCs identified using the threshold exceedance do seem to be outliers within this pool, showing high heterogeneity and high influence on the result. Other UBCs depict strong influence or high heterogeneity, but none as consistently as the two UBCs shown in red on the graphs. Additionally, two forest plots (see Appendix I) were generated to investigate further the influence of each UBC within the pooled result. First, the graph showing the pooled result when each UBC has been omitted depicts a significant difference when the two UBCs (ID: 294 and 295) from the Wasserman et al. (2000) paper have been removed. Similarly, the I^2 value decreases significantly when these two UBCs have been omitted from the pooled result. As a result of the influence analysis, we believe the outliers have been correctly identified, and they will be removed from the pooled result.

Interestingly, the influence characteristics for the linear group has not identified any outliers within the pool of UBCs. The *hat* threshold for the linear group was calculated as 0.03; however, the range of *hat* values was between 0.00 and 0.02. Similarly, the DFFITS threshold was ±0.28, whereas the range of DFFITS values in the linear group was -0.26 and 0.13. The graph showing standard residuals depicts multiple UBCs causing heterogeneity, but there does not seem to be any UBCs that are influencing the heterogeneity more than others. In the linear group, multiple UBCs are lower than one, but the lowest covariance ratio value is only 0.93. Although nineteen UBCs are lower than one, the values are not significantly lower. On the τ^2 and Q graphs, there are multiple, negative peaks, but there is not a significant difference when observing the change in τ^2 and Q. After analyzing all graphs in conjunction, we can see that there are UBCs that contribute to heterogeneity; however, these UBCs have little influence on the pooled result. Thus, we agree with the influence characteristics that have not identified any additional outliers within the pooled result. The final pooled result of the UBCs can be seen in Table 3.4 below.

Table 3.4: Pooled results omitting additional outliers identified through influence analysis, including heterogeneity measures

Group	Pooled result	95% confidence interval			Prediction interval		τ^2	I^2	Q	
		Lower	Upper	p	Lower	Upper				p
Non-linear Papers: 11 UBCs: 88 Removed: 2	-0.64	-0.82	-0.45	< 0.0001	-2.29	1.02	0.68	70.7%	297	< 0.0001
Linear Papers: 6 UBCs: 113 Removed: 0	-0.22	-0.27	-0.17	< 0.0001	-0.70	0.27	0.06	30.2%	160	< 0.01

3.3.3.3 GOSH plots

The final method to identify heterogeneity within the pooled result is the use of a Graphic Display of Heterogeneity (GOSH) plot. The GOSH plot is a means to detect patterns within the data and determine if there is more than one ‘population’ group. The GOSH plot informs the subgroup analysis by identifying the number of potential subgroups. The GOSH plots generated for the two groups can be seen in Appendix J. The GOSH plot for the non-linear group shows one large grouping, but on the left side of the mass, there is a slight indentation in the group, which may represent two subgroups in the pooled result. In contrast, the GOSH plot for the linear group distinctly shows one primary grouping. Although the linear group plot seems to suggest that the pooled result is the product of one population, the literature suggests multiple subgroups that affect the relationship between BLLs and IQ. The next section of this paper will explore the relationship based on the subgroups identified in the literature.

3.3.4 Subgroup analysis

After exploring the pooled result from both groups (i.e., non-linear and linear), we will now investigate any differences that may exist between subgroups. From the GOSH plot, we have identified two potential subgroups for the non-linear group, whereas the linear group did not suggest the presence of subgroups; however, we will still explore both groups in the subgroup analysis for a thorough investigation of the UBCs.

In Table 3.5, we can see the pooled results for the UBCs with and without adjustment for confounders. Although the pooled results for the non-linear group seems to suggest a large difference, the *p*-value for subgroup differences between unadjusted and adjusted pooled results are not significant, but the differences between subgroups for the linear group was significant. When the linear UBCs were adjusted for confounders, we can see that the pooled result was -0.14 (95% CI: -0.20 to -0.08), whereas the pooled result for the unadjusted UBCs was -0.31 (95% CI: -0.39 to -0.22). In the unadjusted subgroup for the linear UBCs, heterogeneity was moderate with 0.07 (τ^2), 41.8% (I^2), and 91 (Q). Interestingly, the adjusted subgroup for the linear UBCs has no heterogeneity with values of 0.04 (τ^2), 0.0% (I^2), and 54 (Q).

Table 3.5: Pooled results for the subgroup analysis of UBCs by unadjusted and adjusted regression models, including heterogeneity measures

Group	Subgroup	Pooled result	95% confidence interval		τ^2	I^2	Q	Subgroup differences	
			Lower	Upper				Q	p
Non-linear	**Unadjusted** Papers: 6 UBCs: 39	-0.80	-1.13	-0.47	0.81	63.6%	104	2.16	0.14
	Adjusted Papers: 10 UBCs: 49	-0.52	-0.73	-0.30	0.53	73.3%	180		
Linear	**Unadjusted** Papers: 5 UBCs: 54	-0.31	-0.39	-0.22	0.07	41.8%	91	11.10	< 0.01
	Adjusted Papers: 6 UBCs: 59	-0.14	-0.20	-0.08	0.04	0.0%	54		

In Table 3.6, we have created subgroups for infants (prenatal to 6 months), toddlers (7 months to 47 months), and children (48 months to 204 months) to reflect the age groupings (i.e., defined by Health Canada, 2013) when the individual's BLLs were measured. As can be seen in Table 3.6, the differences between infant, toddler, and child are significantly different within the non-linear group with pooled results of -0.22, -0.59, and -0.83, respectively. Additionally, we have a τ^2 of 0.55, an I^2 of 0.0% and a Q of 22 for the infant subgroup, a τ^2 of 0.63, an I^2 of 57.5% and a Q of 73 for the toddler subgroup, and a τ^2 of 0.63, an I^2 of 82.7% and a Q of 185 for the child subgroup. In the linear group, the pooled result for infants, toddlers, and children was -0.03, -0.19, and -0.29, respectively, τ^2 values of 0.07, 0.03, and 0.07, I^2 values of 0.0%, 12.3%, and 50.2%, and Q values of 8, 49, and 94, respectively. The differences between age groups for the linear UBCs were statistically significant. Interestingly, the heterogeneity measures for both the non-linear and linear groups increase as the age of the child at blood lead testing increases.

Table 3.6: Pooled results for the subgroup analysis of UBCs by child age at blood lead sampling, including heterogeneity measures

Group	Subgroup	Pooled result	95% confidence interval		τ^2	I^2	Q	Subgroup differences	
			Lower	Upper				Q	p
Non-linear	**Infant** Papers: 4 UBCs: 23	-0.22	-0.49	0.04	0.55	0.0%	22	9.50	< 0.01
	Toddler Papers: 4 UBCs: 32	-0.59	-0.90	-0.27	0.63	57.5%	73		
	Child Papers: 10 UBCs: 33	-0.83	-1.15	-0.52	0.63	82.7%	185		
Linear	**Infant** Papers: 3 UBCs: 21	-0.03	-0.13	0.08	0.07	0.0%	8	15.91	< 0.01
	Toddler Papers: 3 UBCs: 44	-0.19	-0.26	-0.12	0.03	12.3%	49		
	Child Papers: 5 UBCs: 48	-0.29	-0.38	-0.20	0.07	50.2%	94		

In Table 3.7, we show the pooled results for two publishing year subgroups, which include, (i) 2009-2019, and (ii) pre-2009. This subgroup analysis has shown significant differences for both main groups (i.e., non-linear and linear). In the non-linear group, there is a pooled result of -0.29 (95% CI: -0.51 to -0.07), and -1.00 (95% CI: -1.26 and -0.74) for the 2009-2019, and pre-2009 subgroups. Also, we have a τ^2 of 0.39, an I^2 of 45.0% and a Q of 67.33 for the 2009-2019 subgroup, and 0.70, 77.1%, and 213.86, for the τ^2, I^2, and Q, respectively. In the linear group, the pooled results were -0.15 (95% CI:

-0.51 to -0.07) and -0.29 (-1.26 to -0.74) for the 2009-2019, and pre-2009 subgroups and the subgroup differences were statistically significant. Additionally, the heterogeneity measures for 2009-2019 and pre-2009 were 0.03 and 0.08 (τ^2), 12.0% and 39.1% (I^2), and 70 and 81 (Q), respectively.

Table 3.7: Pooled results for the subgroup analysis of UBCs by publishing year, including heterogeneity measures

Group	Subgroup	Pooled result	95% confidence interval		τ^2	I^2	Q	Subgroup differences	
			Lower	Upper				Q	p
Non-linear	**2009-2019** Papers: 6 UBCs: 38	-0.29	-0.51	-0.07	0.39	45.0%	67.33	17.48	< 0.0001
	Pre-2009 Papers: 5 UBCs: 50	-1.00	-1.26	-0.74	0.70	77.1%	213.86		
Linear	**2009-2019** Papers: 4 UBCs: 63	-0.15	-0.21	-0.09	0.03	12.0%	70	7.31	< 0.01
	Pre-2009 Papers: 2 UBCs: 50	-0.29	-0.38	-0.21	0.08	39.1%	81		

Lastly, we used a subgroup analysis to investigate possible differences between countries (see Table 3.8). Unfortunately, there were not enough papers for each country, so as a means to overcome this issue, we have grouped the countries by G7 membership (i.e., G7 countries, and non-G7 countries). The Group of Seven (G7) encompasses the seven most economically dominant countries worldwide, which include Canada, France, Germany, Italy, Japan, the United Kingdom, the United States, and the European Union. The G7 forum is a chance for leaders, ministers and policymakers to discuss both international and domestic issues (Government of Canada, 2020). In both the non-linear and linear groups, we do not find a statistically significant difference between the G7 and non-G7 subgroups.

Table 3.8: Pooled results for the subgroup analysis of UBCs by G7 membership, including heterogeneity measures

Group	Subgroup	Pooled result	95% confidence interval		τ^2	I^2	Q	Subgroup differences	
			Lower	Upper				Q	p
Non-linear	**G7** Papers: 6 UBCs: 74	-0.58	-0.79	-0.36	0.76	50.9%	148.68	2.11	0.15
	Others Papers: 5 UBCs: 14	-0.86	-1.21	-0.51	0.25	90.9%	142.40		
Linear	**G7** Papers: 6 UBCs: 109	-0.21	-0.26	-0.16	0.05	28.4%	150.87	1.34	0.25
	Others Papers: 1 UBCs: 4	-0.50	-1.28	0.29	0.18	64.8%	8.53		

3.3.5 Publication bias

3.3.5.1 Funnel plots

The funnel plots included in this paper (see Appendix K) also depict the points from the trim-and-fill procedure, which are shown as clear circles, and the original UBCs are shown in dark grey. The funnel plot for the non-linear group (including UBCs identified as outliers) shows a large group of UBCs at the top of the pyramid, with most points shown as negative values. Four UBCs are shown in the centre of the funnel plot, and four more are shown in the bottom-left of the plot. This funnel plot illustrates a significant number of UBCs within the upper segment of the pyramid, in addition to lateral asymmetry, suggesting the possibility of publication bias. Similarly, the funnel plot for the linear group depicts a large cluster of UBCs in the top-most portion of the plot, with a secondary grouping along the dotted line. At the bottom of the plot, there is a dispersed grouping of UBCs.

In addition to the visual analysis of the funnel plots, we used the Egger's test of symmetry to determine if publication bias exists. As can be seen in Table 3.9, asymmetry is present in both (i.e., non-linear and linear groups) funnel plots. The intercept for the non-linear group was -1.33 (90% CI: -2.11 to -0.54, $p < 0.01$), and -0.87 (90% CI: -1.27 to -0.48, $p = 0$) for the linear group. The Egger's test suggests that there is statistically significant asymmetry in both groups, which means that publication bias might be present within the pooled results.

Table 3.9: Egger's test of symmetry and publication bias

Group	**Intercept**	**90% Confidence Interval**		**t**	***p***
		Lower	**Upper**		
Non-linear	-1.33	-2.11	-0.54	-3.29	< 0.01
Linear	-0.87	-1.27	-0.48	-5.67	0

After identifying that publication bias might be present within the pooled results, we used the trim-and-fill procedure to add the 'missing' UBCs that may influence the pooled result. A visual representation of the 'missing' UBCs that have been added can be seen in Appendix K, where the clear circles represent added UBCs from the trim-and-fill procedure, and the dark grey circles represent the original UBCs. In the non-linear funnel plot, UBCs have been added as a small cluster in the uppermost segment of the pyramid, one in the middle section, and four in the bottom segment. Similar to the non-linear group, UBCs were added to the upper and lower quadrants. As a result of adding 29 ‘missing’ UBCs to the non-linear group, and 47 UBCs to the linear group, the pooled results became statistically non-significant. Pooled results and heterogeneity measures for the trim-and-fill procedure can be seen in Table 3.10 below.

Table 3.10: Pooled results using Duval & Tweedie’s trim-and-fill procedure, including heterogeneity measures

Group	Pooled result	95% confidence interval			Prediction interval		τ^2	I^2	*Q*	
		Lower	Upper	*p*	Lower	Upper				*p*
Non-linear Papers: 13 UBCs: 168 Added: 29	-0.13	-0.31	0.05	0.16	-2.41	2.15	1.32	95.1%	3,433	0
Linear Papers: 7 UBCs: 163 Added: 47	-0.04	-0.11	0.02	0.20	-0.80	0.71	0.14	65.1%	465	< 0.0001

3.3.5.2 *P*-curve analysis

As a final method to explore the risk of publication bias in the pooled results, we can use a *p*-curve analysis. Table 3.11 shows the results of the *p*-curve analysis, and Appendix L contains the *p*-curve plots. In the non-linear group, the *p*-curve plot shows that 62% of UBCs have a *p*-value of 0.01, 16% at 0.02, 9% at 0.03, and 7% at 0.04 and 0.05, in addition to 94 UBCs excluded with a *p*-value > 0.05. The non-linear group generated a power of 95% and a pooled result of -0.61. In the linear group, the plot shows that 64% of UBCs have a *p*-value at 0.01, 16% at 0.02, 8% at 0.03, 12% at 0.04, and 0% at 0.05%, with 91 UBCs with a $p > 0.05$. The *p*-curve for the linear group had a power of 71%, and a pooled result of -0.67.

Table 3.11: *P*-curve analysis of linear and non-linear UBC groups

Group	Total number of UBCs included in the analysis		Power estimate			Evidential value		*p*-curve estimate
			Power estimate	95% CI		Evidential value present	Evidential value absent and/or inadequate	
	p<0.05	*p*<0.025		Lower	Upper			
Non-linear *p* < 0.05: 45 *p* > 0.05: 94	45 (34.4%)	36 (25.9%)	95%	91.1%	97.6%	Yes	No	-0.61
Linear p < 0.05: 25 p > 0.05: 91	25 (21.55%)	21 (18.1%)	71%	52%	84.3%	Yes	No	-0.67

3.3.5.3 Risk of bias summary

The last step in the meta-analysis is summarizing the risk of bias for papers included in the study. A visual representation of the risk of bias summary can be found in Appendix M. Seven types of bias were reported in this meta-analysis, including, (i) selective outcome reporting, (ii) population sampling, (iii) measurement of confounders, (iv) IQ testing, (v) incomplete outcome data, (vi) blood lead collection, and (vii) blood lead analysis. None of the 13 papers included in this study exhibit any signs of selective outcome reporting, or population sampling issues. Hong et al. (2015) and Menezes-Filho et al. (2018) did not fully explain the process of collecting confounding variables, which were identified as ‘unclear’ in the risk of bias summary. The papers by Wasserman et al. (2003) and Min et al. (2009) only briefly describe the process of administering IQ testing, so the risk of bias in these papers is ‘unclear’. Three of the thirteen papers were identified as ‘high’ for incomplete outcome data for not reporting some necessary data. Bellinger et al. (1992) did not report the mean BLL for children at ten years old, Dietrich et al. (1993) did not report mean BLL for children at age 6, nor did the authors report mean BLLs for children between 0 and 6 years old, and Min et al. (2009) did not report mean BLL for children at 9 and 11 years old. Reporting the specific steps for blood lead collection was mostly an issue in older papers (see Bellinger et al., 1992; Dietrich et al., 1993; Tong et al., 1996), but Canfield et al. (2013) also neglected to specify how blood lead samples were collected. Lastly, Dietrich et al. (1993) and Tong et al. (1996) were marked as ‘unclear’ for blood lead analysis bias because these two papers did not detail the process of analysis.

3.4 Discussion

In this meta-analysis, we have created two groups to generate a robust analysis of the available literature by incorporating as many UBCs from the literature as possible with the non-linear and linear groups. First, the non-linear group will incorporate all 139 UBCs from 13 papers, whereas the linear group will provide a smaller pool of UBCs (i.e., 116 UBCs from 7 papers) that are easy to interpret. The non-linear group benefits from incorporating all data into the meta-analysis, by utilizing a relatively new method to standardize UBCs that were generated from transformed (e.g., log, natural log, etc.) BLLs. In contrast, the linear group only incorporates UBCs that have not been generated using transformed BLLs to keep a consistent linear relationship between full-scale IQ and blood lead levels in children.

As mentioned above, the non-linear group poses a fairly significant limitation of generating a result that is difficult to interpret. The pooled results from the non-linear group means that for every 50% increase in blood lead levels, we can expect an IQ loss (if negative) equal to the UBC. The main problem with this method of standardizing UBCs is that the pooled results will be susceptible to the blood lead range chosen to present the IQ loss in a practical example. In other words, the absolute change in blood lead levels can vary widely while still presenting a 50% change, which is problematic to quantifying IQ loss. For example, the following three blood lead ranges all present a 50% change, but vary drastically in absolute change: (i) 0.10 µg/dL to 0.15 µg/dL, (ii) 1 µg/dL to 1.5 µg/dL, and (iii) 10 µg/dL to 15 µg/dL. In the three examples, the absolute change is 0.05 µg/dL, 0.5 µg/dL, and 5 µg/dL, respectively. Thus, using the non-linear pooled results is difficult, but it serves as a meaningful sensitivity analysis to provide confidence to the linear pooled results. Since the non-linear group contains more UBCs from a wider range of literature, the trends seen in the subgroup analysis and the *p*-values associated with each pooled result will help to verify the legitimacy of the linear results. As a result, the two groups provide a more robust result than using either the non-linear or linear group alone. For the remainder of the discussion, we will use the results of the non-linear group as a method to provide confidence to the pooled results from the linear group.

In the initial pooled results, both the non-linear and linear groups achieved statistical significance. The pooled result for the linear group was -0.20 (95% CI: -0.26 to -0.15) with a moderate level of heterogeneity. After using a simple outlier detection method using confidence intervals, the pooled result decreased marginally to -0.22 (95% CI: -0.27 to -0.17). The omission of the 3 UBCs identified by the simple outlier method also decreased the I^2 value to 30.2% (from 47.7%). In addition to the simple method of outlier detection using confidence intervals, we also employed a more rigorous method to remove outliers from the pooled results. The Baujat plots and influence characteristics were used to investigate extreme values that may have considerable influence over the result. These methods employ visual representation, along with statistical tests, to help identify potential outliers. After the influence analysis, no outliers were detected in the linear group, so the pooled result remained the same. In the non-linear group, the pooled result was -0.40, -0.73, and -0.64 for the original, simple outlier detection, and influence analysis, respectively. In relative terms, the change was 182% between -0.40 and -0.73, and 160% between -0.40 and -0.64. Thus, based on these relative changes in the pooled result for the non-linear group, we might see pooled results slightly higher, if more literature was available in the linear group; however, these values would still be well within the lower and upper bounds of the prediction interval of -0.70 to 0.27 for the linear group.

Next, we investigated the heterogeneity with GOSH plots to explore the possibility of subgroups present in the pooled results. The literature suggests that subgroups exist for differences in BLLs, and thus, there will likely be subgroups present within a pool of UBCs relating BLLs to IQ. If BLLs are influenced by specific characteristics like child age, publication year, study origin, or presence of confounding variables, we expect to see a scatterplot with visually distinct clusters of points. In the non-linear plot, we can see that there is potentially the presence of two subgroups within the data. In contrast, the linear group does not visually show the presence of subgroups within the UBCs; however, the additional UBCs present in the non-linear group may suggest that if more literature were present in the linear group, we would see a second cluster emerge. The literature also suggests that subgroups exist for the relationship between BLLs and IQ. For example, a large number of studies use age as a method to subdivide the population (see Iglesias et al., 2011; Taylor et al., 2017; Tong et al., 1996). Although the GOSH plots depict a weak clustering, we proceeded to a subgroup analysis to gather further insight.

Based on the literature and the information available for each study, we investigated four potential subgroups, (i) adjustment for confounding variables in the regression model, (ii) age of the child at blood lead measurement, (iii) year of publication, and (iv) data collected in countries with and without G7 membership. Interestingly, the differences between adjusted and unadjusted regression models are not significant for the non-linear group, yet statistically significant for the linear group, which suggests that if more literature was available for the linear group, we might see a non-significant pooled result. Furthermore, the unadjusted pooled result decreases to -0.31 with more heterogeneity, but the adjusted pooled result increases to -0.14 with virtually no heterogeneity. The relative difference between the subgroups between the non-linear and linear groups is close, so we expect to see similar pooled results if more literature was added to the linear group. In this case, it is difficult to suggest the confounding variables (e.g., age, HOME score, maternal IQ, etc.) are influencing the pooled results since the subgroup differences are not significant for the non-linear group, despite being significant for the linear group. We suggest more research to make a robust conclusion about the influence of confounders on the relationship between full-scale IQ and blood lead levels.

In the subgroup analysis for the age of the child at blood testing, we can see a statistically significant difference for age among both the non-linear and linear groups. The pooled results decrease following the relationship suggested by the literature (see Chen et al., 2005; Hornung et al., 2009). In other words, as a child increases in age, a child's IQ is more negatively influenced by BLLs. Interestingly, the heterogeneity measures also increase with age, suggesting that older children may have more divergent influences confounding their full-scale IQ scores. The pooled results in the linear group changed from -0.03, to -0.19, to -0.29, when a child's age group changes between infant, toddler, and child, respectively. The relative change between the infant and toddler (i.e., 633%) or child (i.e., 967%) subgroup is quite significant, but if we look at the relative change between the toddler and child subgroups, the difference is similar between the non-linear (41%) and linear (53%) groups. Thus, we expect the pooled result for the infant subgroup to be marginally higher to reflect the relative change between the infant and toddler subgroups depicted in the non-linear group (i.e., a 268% increase) if there was more literature to add to the linear group.

Next, the subgroup analysis for the publishing year illustrates that the pooled result has lowered since studies published in pre-2009. The linear group generated a pooled result of -0.29 in pre-2009 studies and -0.15 in studies published between 2009 and 2019. Also, the 2009 and 2019 subgroup had less heterogeneity than the pre-2009 subgroup. Similarly, the same trend can be seen in the non-linear group, but the relative difference between the newer and older studies is significantly higher (345%) than in the linear group (193%). If more literature was available in the linear group, we might see a more negative value for the pre-2009 pooled result, which may suggest that the relationship between BLLs and IQ is smaller than once thought since methods to measure BLLs and IQ have improved within the last few decades.

As a final subgroup analysis, we examined the differences in pooled results for countries with and without G7 membership. In both the non-linear and linear groups, we did not find a statistically significant difference between G7 and non-G7 countries. Although the pooled results are not significantly different, we can see that the number of studies with data collected from countries without G7 membership is much lower than countries with G7 membership. We suggest more research to be conducted in countries that do not have G7 membership to generate a clearer understanding of how the relationship between full-scale IQ and blood lead levels may vary by country.

As discussed above, publication bias can occur when smaller studies without a large enough sample size (i.e., lower statistical power), or studies with non-results are not published. The next set of statistical methods is used to both identify the presence of publication bias, in addition to controlling for the lack of smaller studies and non-results. The results of Egger's test of symmetry seems to suggest that publication bias may be plausible as an outcome of the 'file drawer' problem; however, the trim-and-fill procedure was not statistically significant for either group (i.e., non-linear or linear). Egger's test of symmetry can be indicative of the 'file drawer' problem, but it may also suggest that the pool of UBC values is homogenously negative. The notion that most UBCs are negative (i.e., elevated blood lead levels negatively influence full-scale IQ) is not unreasonable. In the original pool of 116 UBCs in the linear group, nine UBCs were greater than zero, and in the trim-and-fill procedure, 47 additional UBCs were added. Based on the outcome of Egger's test of symmetry and Duval & Tweedie's trim-and-fill procedure, we have no reason to believe that the 'file drawer' problem has influenced the pooled result.

As a final measure to explore publication bias, we used a *p*-curve analysis to determine if researchers used '*p*-hacking' to increase the statistical power of their results. The graphs showing the *p*-curve for the non-linear and linear groups suggests that the distribution of *p*-values within each group is natural and expected. In fact, the *p*-curve for the linear group shows that 0% of *p*-values are within the 0.05 bin, and 91 values exceed 0.05. Although the *p*-curve analysis shows that evidential value is present, we do not think there is reason to believe *p*-hacking occurred considering the distribution of *p*-values within each group.

Based on other meta-analyses published on this topic in the past, this paper encompasses far more UBCs than any other meta-analysis. This paper uses a two-group approach to incorporate as many UBCs as possible. First, we created one group of UBCs that have not been transformed as the main group, which contained 116 UBCs from 7 papers. Second, we used a new technique to back-transform UBCs to a standardized format, which allowed us to create a non-linear group utilizing all UBCs available within the literature. The non-linear group incorporated all 139 UBCs available from 13 papers, but the standardizing process of UBCs in this group makes it difficult to interpret results. Thus, we leveraged the more robust results of the non-linear group to inform the interpretation of pooled results from the linear group. Additionally, we did not select a specific subgroup to analyze, allowing us to examine the relationship between BLLs and full-scale IQ more robustly. Instead, we narrowed our UBCs within the subgroup analysis phase of the meta-analysis to incorporate all UBCs initially, then explored the existence of potential subgroups within the original pool of UBCs.

Indeed, pooling multiple UBCs per study does differ significantly from past meta-analyses. Meta-analyses typically use one UBC, or in the case of the paper by Needleman et al. (1990), partial r, per study to represent the findings of each paper; however, we have utilized all UBCs reported in each paper. Researchers in the past have avoided using all UBCs reported within the literature for two main reasons, (i) inability to standardize UBCs across papers using different transformations, and (ii) researching a more specific subgroup. First, the inability to standardize UBCs derived from data that had been transformed using different methods (e.g., log, natural log, etc.) has been a significant factor for researchers not being able to collect a larger sample of UBCs to include in a meta-analysis. In this paper, we have utilized a relatively new technique generated by Rodríguez-Barranco et al. (2017) that has allowed us to use UBCs reported in studies using a wide range of transformations. Second, this paper avoids using a more specific subgroup to eliminate UBCs based on certain characteristics (e.g., age at blood drawn, presence of confounders, country of data collection, etc.), and uses a subgroup analysis to identify the existence of any groups within the main population with similar relationships. Additionally, meta-analyses may examine the relationship between BLLs and IQ using cross-sectional or cohort studies separately, but a subgroup analysis may suffice. In the context of this paper, we did not differentiate between cross-sectional studies and cohort studies since individual UBCs reported from cohort studies can still be considered cross-sectional as independent UBCs.

This meta-analysis has incorporated far more UBCs than any other meta-analysis about the relationship between BLLs and full-scale IQ for children, resulting in a statistically significant pooled result of -0.22 (95% CI: -0.27 to -0.17; prediction interval: -0.70 to 0.27). In the introduction of this meta-analysis, we discussed how Health Canada (2013) predicts that the Canadian government will save $35 billion per cohort from changes in lifetime earnings as a result of decreasing the average BLLs in children from 1.5 µg/dL to 0 µg/dL. Projected savings were based on the assumption that a one unit (i.e., µg/dL) increase in BLLs is associated with a one IQ point deficit in children under six years old, but this meta-analysis suggests that relationship is significantly lower (i.e., closer to zero). The pooled result of this meta-analysis suggests a five-fold difference between the pooled result found in this meta-analysis and the one used by Health Canada. If we use the pooled result (i.e., -0.22) generated in this meta-analysis, the Canadian government could only expect $7.7 billion per cohort by decreasing the average BLLs in children from 1.5 µg/dL to 0 µg/dL, and the average IQ per child would only increase by approximately 0.33 points. At an 8% discount rate, we could only expect a savings of $330 million, and at a 3% discount rate, we could expect a savings of about $2.1 billion per cohort. If we use the pooled result of the adjusted UBCs in the linear group (i.e., -0.14), the savings per cohort would decrease to a mere $4.9 billion, or $210 million at an 8% discount rate and $1.3 billion at a 3% discount rate. Similarly, for the literature that has been published between 2009 and 2019, the pooled result was -0.15, which would produce nearly identical savings projections. Lastly, if we use the pooled results for infants (-0.03), toddlers (-0.19), and children (-0.29), we can calculate the projected savings by age group using the percent of the population that each age group contributes to the total population under six years old. In the 2016 census, Statistics Canada (2019) reported 369,730 children under one-year-old (16.1%), 1,529,060 children one to four years old (66.7%), and 394,530 children five years old (17.2%). Unfortunately, the age groups do not align directly with the age groups outlined in this meta-analysis; however, they will provide a reasonable estimate. If the BLLs of children under six years old decreased from 1.5 µg/dL to 0 µg/dL, the projected savings by age group would be approximately $169.1 million, $4.4 billion, and $1.7 billion for infants, toddlers, and children, respectively. At an 8% discount rate, we could expect a savings of $7.2 million (infants), $190.1 million (toddlers), and $74.8 million (children), and at a 3% discount rate, we could expect a savings of $45.4 million (infants), $1.2 billion (toddlers), and $468.9 million (children). Based on the findings of this meta-analysis, we can see that the projected savings due to the relationship between elevated BLLs and full-scale IQ are significantly lower than the projections made by Health Canada (2013). Unfortunately, the new savings projections in this meta-analysis may not be enough to justify the large capital investment of lead abatement.

3.5 Limitations

There are two main limitations specific to this meta-analysis, (i) the relative difference between non-linear pooled results may not be comparable to the linear group, and (ii) using all UBCs from each paper may dilute findings of smaller studies. The non-linear group is useful to incorporate more UBCs into the pooled result to show upward and downward trends for comparison in the subgroup analysis. However, the relative differences (i.e., percent change between pooled results) among the non-linear pooled results may not accurately represent the relative changes we would see in the linear group with a larger pool of UBCs. Next, using all UBCs reported in each paper may cause papers with multiple UBCs to dilute the findings of papers with fewer UBCs. For example, if a paper reports 20 UBCs, it may dilute the findings of a paper only reporting 2 UBCs. Although some studies may report more UBCs than others, the sample size between interstudy regression models often changes due to data collection limitations (i.e., variability in subgroup data collection). Thus, the weights of each UBC should limit the ability of studies reporting more UBCs from diluting the findings of studies reporting fewer UBCs.

In addition to the limitations specific to the study, there are more generalized criticisms of the meta-analysis process. Firstly, meta-analysis is a product of the data included in the analysis. As a means to capture all available literature into the pool of research, the search process is a vital process of the meta-analysis. This meta-analysis used a pre-determined search term to collect literature from the PubMed database, which may have missed literature on the topic. Thus, it is possible that influential studies were excluded, which may have changed the result of this meta-analysis. Second, all steps for this meta-analysis were completed by one investigator, which means there is a more significant chance of human error. Although steps were taken to address the possibility of human error (i.e., reviewing processes, double-checking values, etc.), there is still a chance that things (e.g., an erroneous value) were overlooked. Meta-analyses also invite a higher degree of uncertainty in the sense that uncertainties from individual studies and UBCs are added together in a meta-analysis. As a result, there is more uncertainty with the results of a pooled outcome. This meta-analysis mitigates uncertainty by providing a 95% confidence interval and a prediction interval with the pooled results. Another concern with meta-analyses is pooling data from different populations, using different confounding variables. Pooling data that were derived using different populations (i.e., groups of people with different identifying characteristics), in addition to models that have either been unadjusted or adjusted using variable confounders can make it difficult to produce reliable comparisons and pooled results. Although these limitations exist, the meta-analysis process is still the best way to synthesize the literature to estimate the collective relationship between BLLs and full-scale IQ in children.

3.6 Conclusion

As shown in this meta-analysis, the impact of BLLs on IQ may not be as strong as once thought within the broader literature. Indeed, an elevated BLL for a child can be linked to a loss of IQ, but the magnitude of intellectual loss is not as high as suggested by other meta-analyses linking BLLs and IQ. By utilizing a recent transformation technique to standardize the UBCs, we were able to develop a two-group method to generate more robust linear pooled results. Additionally, by using a subgroup analysis, this meta-analysis was able to synthesize far more information than previously done in past meta-analyses. The result of this meta-analysis may have a significant impact on future cost-benefit analyses, and reduce the return on investment projections for lead abatement.

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Chapter 4 A critical assessment of the return on investment of permanent lead hazard control: a case study in Hamilton, Ontario

4.1 Introduction

Lead (Pb) abatement and awareness continues to be important in many post-industrialized societies where lead poisoning remains a problem (Hanna-Attisha et al., 2016). Lead can be a risk to children through three primary sources, which include lead-based paint, water contaminated by lead pipes, and lead-contaminated soil. Children are at increased risk to lead poisoning since children often play close to the ground and can consume contaminated soil through normal hand-to-mouth behaviour (Cleveland et al., 2010; Landrigan et al., 2011). Low-dose lead poisoning (<10 µg/dL) has been linked to several adverse social and economic outcomes, which can place a cost burden on society, with Health Canada (2013) estimating that the impact of lead accounts for approximately $920.4 million (M) to $5.7 billion (B) (2006 USD) [$1.5B to $9.2B (2018 CAD)] per year. As a note to the reader, the currency is in 2006 USD, and currency listed within square brackets is in 2018 CAD for the introduction unless otherwise stated (i.e., $1.00 2006 USD = $1.6190 2018 CAD). Additionally, since this paper will switch to 2018 CAD and Gould's paper is in 2006 USD, the values of return on investment will remain in 2006 USD to preserve the ratio of investment and return (i.e., we will use 17 times and 221 times capital investment cost to calculate return on investment).

4.1.1 Mitigating lead exposure

Public health intervention and permanent lead abatement are two options that can be considered to reduce lead exposure for children. Public health interventions can be used to help mitigate children's exposure to lead by educating parents of exposure risks, how to make crucial behavioural changes, blood lead testing, and professional risk assessments within the home. There are many types of behavioural changes families can make, and some examples may include: proper hygiene, allowing water taps to run before drinking, frequent wet mopping and vacuuming, leaving shoes outside, and giving more attention to children as they play. Public health policies and awareness campaigns are often less expensive and reach a much wider audience, but their total dependence on families to enact these mitigation strategies may result in poor health outcomes.

Alternatively, permanent remediation strategies, namely soil removal and replacement, paint remediation, and the replacement of lead water pipes can be used to eradicate lead from the environment, either within a building, on the property of a structure, or in an open space. Remediation strategies can be used on public or private property, including residential homes, parks, schools, or any other location that children may be exposed to contamination. Permanent lead remediation is preferred since the chance of lead exposure will be removed entirely, but this strategy can be a source of significant economic burden for families or government entities. Capital investment is an important consideration when developing a lead abatement strategy. However, the literature has shown that lead hazard control can produce a return on investment (ROI) in the form of health care and special education savings, increased lifetime earnings and tax revenues, and a reduction in crime (Gould, 2009).

4.1.2 Cost of lead remediation and social benefits

The cost and efficacy of permanent lead abatement can vary widely based on the type of hazard control and location. Mielke et al. (2011) discuss remediation efforts in New Orleans where they replaced lead-contaminated soil at childcare centres across the city. Researchers found that the replacement of soil at each childcare centre, in addition to an interior environment assessment, would cost less than $100 [$161.90] per child. At a total estimated cost of $700,500 [$1.1M], Mielke et al. (2011) explain that over ten years, the cost per child will lower to a mere $10 [$16.19]. As a result of the soil replacement, soil lead levels decreased significantly from a median of 558 mg/kg (range 14.1-3692 mg/kg) to an acceptable and safe median of 4.1 mg/kg (range 2.2-26.1 mg/kg) (Mielke et al., 2011). A 1998 study estimates the average cost of remediation at $1,700 [$2,752] per household with a total of $5M [$8.1M] for the entire study (Yeoh et al., 2009). In Rochester, New York, Korfmacher, Ayoob, & Morley (2012) explain that in December 2005, a law was passed requiring any rental property built before 1978 to be inspected for lead risks within the home. Researchers report that the city spends $600,000 [$971,428] per year on lead dust wipes, inspectors, and additional administrative needs. Compliance with Rochester's Lead Law imposes additional costs on landlords. Korfmacher et al. (2012) report results from a telephone survey of 183 landlords that had to comply with the Rochester Lead Law. The average repair cost per unit was approximately $1,726

[$2,794], but the median cost was only $300 [$485.71]) and 34% of respondents reported they did not have to spend anything. As a result of the Rochester Lead Law, researchers found that "94% of units passed visual inspections and that 89% of tested units passed dust-wipe inspections during the first 4 years" (Korfmacher et al., 2012, p.315). Additionally, Korfmacher et al. (2012) explain the evaluation of the project suggests that the new lead laws contributed to a decline in children's blood lead levels by mitigating exposure to lead hazards within the home. In contrast, Farrell, Brophy, Chisolm, Rohde, & Strauss (1998) explain that soil was replaced with lead-free soil (less than 50 ppm) and re-sodded in either the front yard, back yard, or both if the soil lead level exceeded 500 ppm. Interestingly, a year after soil replacement, BLLs dropped, but there was no significant difference between the BLLs of remediation and control groups (i.e., no soil abatement). Furthermore, soil samples showed that after two years, SLLs increased significantly (Farrell et al., 1998). In addition to the high capital investment outlined within the literature, a meta-analysis by Yeoh et al. (2009) explains that research often does not include the costs associated with paying researchers and educators for lead remediation programs.

A consensus within the literature states that the return on investment (ROI) for lead hazard control is relatively high compared to other programs such as vaccinations. A study by Gould (2009) has reported a return of $17 to $221 [$27.52 to $357.81] for every dollar [$1.6190] invested in lead hazard control. The ROI is estimated to save the United States about $181B to $269B [$293B to $435B]. Gould (2009) argues that lead-based paint remediation alone has a return of $12 to $155 [$19.43 to $250.95] for every dollar [$1.6190] spent and $124B to $188B [$200B to $304B] in net savings. The author explains that capital returns are a result of less pressure on the health care system to treat lead poisoning, increased Intelligence Quotient (IQ), higher lifetime earnings, tax revenues, reduced spending on special education, and reduced criminal activity (Gould, 2009). Gould (2009) explains that the ROI for lead hazard control is significantly higher than vaccination programs to fight the most common childhood diseases ($5.30 to $16.50 [$8.58 to $26.71] returned for every dollar spent [$1.6190]). Specific to this study, permanent lead abatement has been shown to benefit the economy by saving $110B to $319B [$178B to $516B] for a single cohort (Taylor et al., 2011). A study by Brown (2002) suggests savings of over $46,000 [$74,476] per building, over ten years, with at least one child under the age of six years old within the home.

Permanent lead abatement is undoubtedly the best way to eliminate the risk of a child being exposed to lead hazards. This paper will address three main objectives to explore lead abatement, return on investment, and discuss any concerns with projected ROI estimates. Objective one will explore the cost for permanent lead abatement in Hamilton, Ontario, and discuss how reasonable this approach would be for residents and the municipal government. Objective two will determine the projected ROI from permanent lead abatement in Hamilton based on the estimates presented by Gould (2009), and objective three will explore the need for soil lead abatement.

4.2 Datasets

4.2.1 Study area

The City of Hamilton is a post-industrialized city along the southwestern edge of Lake Ontario. The study focuses on the downtown core of Hamilton (see Figure 2.1, p.14), surrounded by the escarpment (south), highway 403 (west), Lake Ontario (north) and the Red Hill expressway (east). Hamilton has had a long history of steel production, in addition to a flourishing manufacturing district, including paint factories, which may have attributed to soil contamination within the city. The City of Hamilton was chosen to explore permanent lead abatement for three main reasons: (i) Hamilton has an old housing stock and may contain leaded pipes, as well as lead-based paint on the interior and exterior walls, (ii) Hamilton is a relatively old city with a busy downtown core which means soil lead contamination from leaded gasoline combustion is likely high, and (iii) its industrial history.

4.2.2 Target land uses for lead abatement

In Hamilton, there are four primary land uses that may require lead abatement, which includes: residential land parcels, parks, elementary schools, and nursery- and pre-schools. Residential land parcels will require three types of lead abatement (i.e. soil, paint, and lead pipes) to remediate lead fully. Parks were included since children may spend time on the ground playing and have a chance to consume soil at these locations. Parks were divided into two sub-categories to determine the cost per child, (i) low-volume parks, and (ii) high-volume parks. Low-volume parks are any community- or neighbourhood-level park that will typically only draw children from the immediate proximity, whereas high-volume parks are often larger and draw children from all over the city. Both low- and high-volume parks may include general open space, sports facilities, and trails. Elementary schools, in addition to nursery- and pre-schools, were included since children may spend a significant amount of time at school during the day. Unfortunately, data were difficult to obtain for nursery- and pre-schools, so only soil abatement cost was included in the analysis.

4.2.3 Soil samples

This paper uses a data set collected by Hamilton Public Health Services in 2008-2009 that contains soil, water and dust samples measuring lead content (Richardson et al., 2011). These data were collected as part of a more extensive study that also collected BLLs, in addition to survey variables. The dataset is comprised of 187 soil lead samples that were collected throughout the downtown core of Hamilton. Soil samples were collected from the lower city based on the location of the household (i.e., industry-adjacent zone, middle zone, escarpment-adjacent zone, and old recycling plant zone) and the age of the dwelling (i.e., before 1950, and after 1950). The soil samples were collected and processed by the Ministry of the Environment during the summer of 2009. A tube-type soil corer, at a depth of 5 centimetres, was used to sample the soil “from a household’s front, back or side yard depending on where the child played most frequently and/or where there was sufficient conditions to sample” (Richardson et al. 2011).

Samples were then analyzed using atomic absorption spectrophotometry to determine the lead content with a limit detection of 5 μg/g dry weight.

4.3 Methodology

4.3.1 Predicting cost of lead abatement

Objective one will explore the cost associated with permanent lead abatement from four central locations where lead is likely to pose a threat to children, which includes: residential homes, parks, elementary schools, and nursery- and pre-schools. A permanent lead abatement strategy often requires a high capital investment in the short-term but completely removes lead from the environment. Permanent lead abatement strategies are often expensive because they may require special materials, machinery, or individuals to remove contaminates.

In order to estimate SLLs within the lower city, Empirical Bayesian Kriging was used to understand the spatial distribution of SLLs. Soil and sod remediation has been calculated for two thresholds, (i) 70 mg/kg, and (ii) 140 mg/kg, which represent the human health guidelines for agricultural (i.e., soil and food ingestion), and residential/parkland (i.e., soil ingestion) land uses, respectively (Canadian Council of Ministers of the Environment, 1999). Lead-based paint is mostly an issue for homes built before 1960 (Government of Canada, 2017), but since the housing stock in Hamilton is quite old, the vast majority of homes built in downtown Hamilton may contain lead-based paint (Richardson et al., 2011). Lastly, lead pipes are most prevalent in homes that were built before 1945 (Richardson et al., 2011); however, Hamilton schools were recently checked for water lead levels, so schools needing lead pipe replacement was known based on the results of that report (Leitner, 2018). Since this paper is a case study in Hamilton, Ontario, we will use 2018 Canadian dollars for the analysis, results, and discussion.

In addition to the total projected cost, the cost per child was also calculated to provide a more contextual projection. Total abatement cost is likely to be quite expensive, so it is crucial to understand how that cost relates to the children it will help. Cost per child was calculated simply by dividing the total cost of abatement by the number of children (in the 2016 age cohort) affected by the abatement (Statistics Canada, 2018). For residential homes, cost per child was estimated by determining the percent of residential land parcels per dissemination area that are targeted for lead remediation and multiplying by the total number of children in the dissemination area. As previously discussed, parks were divided into two categories (i.e., low-volume and high-volume) to project cost per child estimates more accurately. Total lead abatement costs for parks were divided by the total children within Hamilton for high-volume parks and divided by the total children within the specific dissemination area for low-volume parks. The cost per child for elementary schools was calculated by dividing total cost by the number of children enrolled in junior kindergarten and kindergarten (Hamilton Wentworth District School Board, 2018), which are the most vulnerable age groups to lead poisoning. Lastly, the cost per child for nursery- and pre-schools was determined by using an estimate of 43% of children being enrolled in daycare in Ontario (Statistics Canada, 2011).

4.3.1.1 Sod and soil replacement

For objective one, the replacement cost of sod and soil, paint, and lead pipes was calculated for at-risk land parcels (i.e., homes, parks, elementary schools, and nursery- and pre-schools) within the study area. First, at-risk land parcels for soil contamination were determined by using Empirical Bayesian Kriging and the SLL samples. Land parcels situated in the soil that exceeded 70 mg/kg and 140 mg/kg were selected for soil and sod replacement at a depth of six inches (Mielke et al., 2011). Sod and soil costs were determined by finding the least expensive sod and soil companies within Hamilton and using the best possible discounted prices. The least expensive price for sod within Hamilton is $0.26 per square foot (Green Horizons Sod Farms, 2018) and $137.62 per cubic yard for soil (Big Yellow Bag, 2018). Labour cost to replace the sod and soil was determined by contacting local landscaping companies. Despite contacting multiple companies, only one responded with a quote of 0.012 hours per square foot of sod and soil replacement, at a rate of $68/man-hour (Jerome, 2018). Total abatement costs for objective one can be seen in Table 4.1.

4.3.1.2 Paint abatement

According to The President's Task Force on Environmental Health Risks and Safety Risks to Children (see Gould, 2009), controlling lead-based paint hazards requires screening structures pre-dating 1960 (Government of Canada, 2017) to determine if complete lead abatement is necessary. Age of dwelling was not available at the household level, but we were able to access the median age of dwelling by census tract to predict at-risk homes within the study area (City of Hamilton, 2017). Lead-based paint screening is estimated to cost $1,943 per home, and if further lead abatement is necessary, phase two will cost up to $17,485 per home (Gould, 2009). The median size of homes referenced in the study was not disclosed, so we used the median size of homes within the United States at the time of the study (i.e., 2,057 square feet) (United States Census Bureau, 2010) and the median size of homes in Hamilton in 2018 (i.e., 1,200 square feet) (Webster, 2018). Based on the difference in square footage, the $1,943 to $17,485 cost estimates were changed accordingly (i.e., $1,133 to $10,200 per Hamilton home). Similarly, square footage of elementary schools, by room, were acquired from the Hamilton-Wentworth District School Board (HWDSB) (Webster, 2018). Square footage of schools was determined by identifying which rooms are most likely to pose a risk to children (i.e., boys' and girls' washroom, gymnasium, classrooms, learning commons, kindergarten, kitchen, stage, daycare, foyer, girls and boys changeroom, computer lab, literacy centre, special education, music room, health room, common area, multi-purpose room and nutrition room) and the resulting square footage was used to determine the cost of screening and complete lead-based paint abatement per school.

4.3.1.3 Lead-pipe abatement

The City of Toronto (about an hour east of Hamilton) generated a cost estimate of roughly $1,942 to $2,914, depending on the characteristics of the property, to remove and replace lead-pipes (City of Toronto, 2018). Residential homes built before 1945 were used to calculate the cost to replace lead-pipes within the study area (Richardson et al.,

2011) and similar to paint abatement, we used median age of dwelling by census tract as a proxy to determine at-risk homes (City of Hamilton, 2017). Fortunately, recent lead testing of water fountains in Hamilton identified schools that exceeded safe levels of lead in drinking water (Leitner, 2018). Schools listed with water lead exceedances were used to calculate the total cost for lead-pipe removal in Hamilton; however, the median square footage of Toronto homes was not able to be obtained, so the cost of lead pipe remediation was based on the median square footage of Hamilton homes. The total cost of lead pipe remediation was $1.65 to $2.48 per square foot, which was multiplied by the square footage of schools (see above) and summed.

4.3.2 Calculating return on investment

Objective two required us to calculate the ROI for lead hazard control. In other words, when a dollar is spent on lead hazard control, society saves money from reduced spending on health outcomes caused by lead poisoning. Gould (2009) argues that a conservative estimate would return $17 (2006 USD), up to an optimistic $221 (2006 USD). Additionally, Gould (2009) estimates that lead-based paint remediation returns $12 (2006 USD) to $155 (2006 USD) for every dollar spent. Unfortunately, the author does not outline how soil and lead pipe abatement factors into the ROI evaluation; however, a study from the Arizona Department of Health Services breaks down exposure pathways causing elevated BLLs (see Levin et al., 2008). The study suggests that exposure from soil and paint accounts for 24% and 17% of childhood elevated BLLs, respectively. Contaminated water from lead pipes was not identified as a direct exposure pathway by Arizona Department of Health Services, but a category named "miscellaneous other sources" was identified with an exposure rate of 19% (see Levin et al., 2008). As a means to calculate ROI for all types of remediation, we will use the ROI estimated by Gould (2009) and estimate soil and pipe replacement ROI using the study by the Arizona Department of Health Services (see Levin et al., 2008). Based on the study by Arizona Department of Health Services, we will use $4.08 to $53.04 (2006 USD) (24% of $17 to $221) for soil and sod replacement, and $1.02 to $13.26 (2006 USD) (remaining 6%) for lead pipe abatement. Based on these values, a conservative and optimistic ROI was calculated using the total cost of remediation for each land use and abatement type.

When discussing project costs and return on investment, it is essential to consider the present and future values using a discount rate (DR). The discount rate is used to determine the value of money accumulating in a bank over a predetermined amount of time and interest rate. In order to understand the value of a project, we can use this information to compare the discounted costs and ROI to generate an informed decision. Different projects require different discount rates and timespans, but Health Canada (2013) suggests that a discount rate between 3% and 8% since the outcomes of lead abatement are both social and financial. Furthermore, Health Canada (2013) also explains that a lifetime for a working child spans from 15 to 67 years old, so we will use 52 years for the discount rate calculation. Unfortunately, Gould (2009) did not disclose the number of years, nor the discount rate used for the ROI projections; however, the author does describe the savings concerning a child's lifetime. Thus, we assume that the number of years used in the discount rate calculation was similar to the 52 years used by Health Canada (2013). Since the true values used in the discount rate calculations for the ROI projections are not known, we suggest using caution when comparing the discounted project costs and the ROI projections.

4.3.3 Understanding the threat to children

In addition to soil lead level thresholds regulated by the government, we can also calculate hazard quotients to determine the threat to children. A hazard quotient (HQ) is the ratio between the potential exposure of a contaminate to the threshold at which no adverse health effects are expected (EPA, 2018). The HQ can be calculated as follows, where C_s is the concentration of contaminant in soil (mg/kg), IR_s is the soil ingestion rate (kg/day), RAF_{oral} is the relative absorption factor from the gastrointestinal tract, D_2 is the days per week the child is exposed (divided by 7 days), D_3 is the weeks per year the child is exposed (divided by 52 weeks), and BW is the bodyweight of the child (Health Canada, 2010):

$$\text{Hazard Quotient} = \frac{\text{Estimated Exposure (Dose) (mg/kg bw/day)}}{\text{Tolerable Daily Intake (TDI) (mg/kg bw/day)}}$$

$$\underset{\text{(mg/kg bw/day)}}{\text{Estimated Exposure (Dose)}} = \frac{C_s * IR_s * RAF_{oral} * D_2 * D_3}{BW}$$

An in-depth look at the Hazard Quotient and Estimated Exposure calculations can be found in Appendix N. This paper will create three hazard quotient maps with a tolerable daily intake of 0.0015 mg/kg bw/day, for each age group: (i) infants (0 – 6 mo.), (ii) toddlers (7 mo. – 4 yr.), and children (5 – 11 yr.) (see Appendix N). In Canada, the current blood lead intervention level is 10 µg/dL (Health Canada, 2013), but the United States uses a much lower blood lead intervention level of 5 µg/dL (M. S. Burns et al., 2014). For this paper, we will use the blood lead intervention level from the United States since adverse health effects have been observed in children well below 10 µg/dL (Health Canada, 2013). A tolerable daily intake of 0.0015 mg/kg bw/day will result in a blood lead level of 5 µg/dL (based on SNC-Lavalin, 2012; World Health Organization, 2011; see Appendix N). In combination with ArcMap and a prediction surface, we can use the Raster Calculator tool to create a hazard quotient map. An HQ map will allow us to more accurately understand the threat to children and determine the need to remediate contaminated soil.

4.4 Results

4.4.1 Cost of permanent lead abatement

Objective one required estimation of the cost of permanent lead abatement for four land use types, which included (i) residential, (ii) parks, (iii) elementary schools, and (iv) nursery- and pre-schools. Two SLL thresholds were used for abatement (i.e., greater than 70 mg/kg and greater than 140 mg/kg), which can be seen in Table 4.1. At the SLL thresholds of >140 mg/kg and >70 mg/kg, soil and sod replacement will cost $112.3M to

$174.7M for residential homes ($25,700 to $31,700 per child), $24.2 to $38.1M for high-volume parks ($853 to $1,300 per child), $12.5M to $18.4M for low-volume parks ($9,100 to $10,700 per child), $7.6M to $9.9M for elementary schools ($4,500 to $4,700 per child), and $43,900 for nursery- and pre-schools ($8 per child). Additionally, lead-based paint abatement will cost $30.6M to $275.6M for residential homes ($4,400 to $39,500 per child), and $28,300 to $255,000 for elementary schools ($16 to $147 per child). Lastly, lead pipe removal will cost $47.3M to $70.9M for residential homes ($8,100 to $12,100 per child), and $14,300 to $21,500 for elementary schools ($52 to $78 per child).

Table 4.1: Cost of lead abatement and cost per child

Land use type	**Type of abatement**	**Total cost**	**Cost per child**
Residential	Soil >70 mg/kg	$174,708,760	$31,707
	Soil >140 mg/kg	$112,322,261	$25,791
	Paint (Screening vs. removal)	$30,620,666 to $275,585,988	$4,389 to $39,510
	Lead pipes (Range estimate)	$47,261,661 to $70,892,492	$8,100 to $12,149
Parks (High Volume)	Soil >70 mg/kg	$38,072,010	$1,345
	Soil >140 mg/kg	$24,165,812	$853
Parks (Low Volume)	Soil >70 mg/kg	$18,395,300	$10,663
	Soil >140 mg/kg	$12,512,398	$9,067
Elementary schools	Soil >70 mg/kg	$9,875,431	$4,655
	Soil >140 mg/kg	$7,626,521	$4,566
	Paint (Screening vs. removal)	$28,333 to $255,000	$16 to $147
	Lead pipes (Range estimate)	$14,319 to $21,478	$52 to $78
Nursery- and pre-schools	Soil >70 mg/kg	$43,941	$8
	Soil >140 mg/kg	$43,941	$8

4.4.2 Return on investment (ROI)

Based on the cost estimates from objective one, conservative and optimistic ROI projections were calculated for the second objective (see Table 4.2). At the 140 and 70 mg/kg SLL thresholds, soil and sod abatement would return \$458.3M to \$712.8M (conservatively) and \$6.0B to \$9.3B (optimistically) for residential homes, \$98.6M to \$155.3M (conservatively) and \$1.3B to \$2.0B (optimistically) for high-volume parks, \$51.1M to \$75.1M (conservatively) and \$663.6M to \$975.7M (optimistically) for low-volume parks, \$31.1M to \$40.3M (conservatively) and \$404.5M to \$523.8M (optimistically) for elementary schools, and \$179,300 (conservatively) to \$2.3M (optimistically) for nursery- and pre-schools. Screening and abatement for lead-based paint will return \$623.9M to \$5.6B (conservatively) and \$8.1B to \$73.0B (optimistically) for residential homes, \$337,200 to \$3.0M (conservatively) and \$4.4M to \$39.4M (optimistically) for elementary schools. Finally, lead pipe replacement will return \$48.2M to \$72.3M (conservatively) and \$626.7M to \$940.0M (optimistically) for residential homes, and \$13,600 to \$21,900 (conservatively) and \$189,900 to \$284,800 (optimistically) for elementary schools.

Table 4.2 also shows the discounted project costs at a 3% and 8% discount rate (DR). As can be seen, the 3% discounted project costs exceed the conservative ROI values for all abatement types, except for paint abatement in residential homes (\$142.4M to \$1.3B) and elementary schools (\$131,800 to \$1.2M). Indeed, the optimistic ROI values far exceed the total project costs discounted at 3%, but the project costs discounted at an 8% rate has the same result as the project costs discounted at 3%.

Table 4.2: Discounted rates of lead abatement cost and ROI of permanent lead abatement

Land use type	Type of abatement	Total cost with a 3% DR	Total cost with an 8% DR	Return on investment (per dollar spent)	
				Conservative	Optimistic
Residential	Soil >70 mg/kg	$812,550,508	$9,557,624,559	$712,811,742	$9,266,552,652
	Soil >140 mg/kg	$522,398,019	$6,144,706,197	$458,274,822	$5,957,572,694
	Paint (Screening vs. removal)	$142,413,224 to $1,281,718,985	$1,675,135,405 to $15,076,218,313	$623,855,488 to $5,614,699,517	$8,110,121,336 to $72,991,093,721
	Lead pipes (Range estimate)	$219,808,593 to $329,712,891	$2,585,498,357 to $3,878,247,562	$48,206,894 to $72,310,340	$626,689,622 to $940,034,433
Parks (High Volume)	Soil >70 mg/kg	$177,068,574	$2,082,768,934	$155,333,799	$2,019,339,393
	Soil >140 mg/kg	$112,392,434	$1,322,015,898	$98,596,513	$1,281,754,662
Parks (Low Volume)	Soil >70 mg/kg	$85,554,441	$1,006,334,033	$75,052,827	$975,686,743
	Soil >140 mg/kg	$58,193,735	$684,503,756	$51,050,584	$663,657,592
Elementary schools	Soil >70 mg/kg	$45,929,503	$540,245,732	$40,291,758	$523,792,861
	Soil >140 mg/kg	$35,470,079	$417,216,769	$31,116,204	$404,510,645
	Paint (Screening vs. removal)	$131,774 to $1,185,976	$1,549,986 to $13,950,040	$337,167 to $3,034,506	$4,383,175 to $39,448,574
	Lead pipes (Range estimate)	$66,596 to $99,892	$783,336 to $1,174,976	$13,611 to $21,907	$189,867 to $284,800
Nursery- and pre-schools	Soil >70 mg/kg	$204,365	$2,403,838	$179,277	$2,330,609
	Soil >140 mg/kg	$204,365	$2,403,838	$179,277	$2,330,609

4.4.3 Hazard quotient

Three hazard quotient maps were created to show the differences between an infant, toddler and child, with 52 weeks of exposure and a tolerable daily intake of 0.0015 mg/kg bw/day (based on SNC-Lavalin, 2012; World Health Organization, 2011). Additionally, one hazard quotient map was created to show the difference in HQ distribution for a toddler with 40 weeks of exposure to represent cold and snow-covered winter months. Table 4.3 shows the descriptive statistics of HQ among the three age groups (i.e., infant, toddler, and child), and two exposure durations (i.e., 52 weeks, and 40 weeks) in Hamilton, Ontario. The spatial distribution of hazard quotient for all six age groups and exposure combinations yielded maximum hazard quotients lower than 1, which means no children, on average, will be at-risk of adverse health effects of soil lead exposure in Hamilton. Toddlers are at the highest risk level because they inadvertently consume four times more soil per day (i.e., 80 mg/day) than both infants and children (i.e., 20 mg/day). The average hazard quotients in Hamilton were 0.195, 0.388, and 0.049, with 52 weeks of exposure, and 0.150, 0.299, and 0.037, with 40 weeks of exposure for infants, toddlers and children, respectively. The maximum hazard quotients in Hamilton were 0.396, 0.786, and 0.099, with 52 weeks of exposure, and 0.304, 0.605, and 0.076 with 40 weeks of exposure for infants, toddlers and children, respectively.

Toddlers are the highest-risk age group, and based on the hazard quotient calculations; this age group may be at risk of exceeding the blood lead threshold of 5 µg/dL if further exposed to lead through contaminated water, dust and paint chips. In order to remediate homes in this area (n=666), it would cost \$3,107,394 to replace soil and sod, \$754,578 to \$6,793,200 to replace paint, and \$1,293,372 to \$1,940,724 to replace pipes. Although the square footage of apartments is unknown, to replace sod and soil for the 80 apartments within the lower city, it would cost $706,030.

Table 4.3: Hazard Quotient for different age groups, based on weeks of exposure and a tolerable daily intake of 0.0015 mg/kg bw/day in Hamilton, Ontario

Age Group	**Weeks of exposure**	**Hazard Quotient**			
		Minimum	**Maximum**	**Mean**	**Standard Deviation**
Infant	52	0.043	0.396	0.195	0.078
Toddler	52	0.086	0.786	0.388	0.156
Child	52	0.011	0.099	0.049	0.020
Infant	40	0.033	0.304	0.150	0.060
Toddler	40	0.066	0.605	0.299	0.120
Child	40	0.008	0.076	0.037	0.015

4.5 Discussion

In 2018, Hamilton released its gross capital spending budget for the year, totalling $256.3M. More specifically, Hamilton's budget for waste management initiatives and open space development is $4.4M and $7.8M, respectively (City of Hamilton, 2018a). Based on these allowances, many of the lead abatement options seen in Table 4.1 are unrealistic within current budget constraints. Indeed, some of these expenses could be subsidized by the provincial or federal government, but many other urban cities in Canada are facing similar levels of lead contamination (Health Canada, 2013).

For objective one, we explored the cost of permanent lead remediation in Hamilton and found that the cost far exceeds any reasonable solution for the municipal government to implement. Aside from nursery- and pre-schools, soil and sod replacement is significantly more expensive than any other permanent remediation strategy. Elementary schools are the least expensive target for soil and sod replacement, but still require a substantial capital investment of $7.6M that exceeds the repairs and minor renovations budget of $3.8M for HWDSB during the 2018/2019 school year (Zucker et al., 2018). Soil and sod replacement for elementary schools may be possible with federal and provincial subsidies, or multi-year investment from HWDSB. Arguably, the cost of soil and sod replacement may be reasonable for elementary schools and high-volume parks, when considering the cost per child (per age cohort). High-volume parks would cost roughly $850 to $1,300 per child to remediate, but the initial investment is staggering. Furthermore, soil contamination does not ubiquitously pose a threat to children. Dangerous SLLs only pose a threat to children where they are playing (e.g., running around, sitting, etc.), so total soil remediation may not be needed. As an alternative to complete soil replacement, the city, or parents, could construct designated play areas where children can safely play without any exposure to contaminated soil (e.g., the ground covered with mulch, a sandbox, or a paved area). Children at-risk of lead poisoning (i.e., ages 0 to 4 yr.) will require constant supervision, so designated play areas would likely be sufficient to eliminate exposure to contaminated soil.

Lead-based paint is one of the most likely pathways of exposure for many children, but can also be one of the easiest to mitigate. Hamilton's downtown has an old housing stock, and there are still schools within the study area that pre-date 1960, which indicates the potential for lead-based paint exposure. Lead-based paint remediation can cost anywhere from $30.6M for initial screening efforts, and up to $275.6M for complete removal of lead-based paint in homes; however, in a residential home, permanent lead-based paint removal cannot be completed at a reduced cost by homeowners since construction can cause an increase of lead within the home (O'Grady et al., 2011). Elementary schools can be screened and fully remediated for anywhere between $28,300 and $255,000, which is a reasonable expense given the cost per child is only $16 to $147 for the current age cohort. Furthermore, the ROI for paint remediation in residential homes and elementary schools is higher than the 3%, and 8% discounted project costs for conservative and optimistic estimates, respectively. Lead-based paint abatement is the only type of remediation with a positive ROI when the project costs have been discounted to future value; however, professional screening and lead-based paint remediation is often not required because contaminated walls can be painted over with lead-free paint as an effective method of mitigating exposure (CMHC, 2005; Korfmacher et al., 2012; Nevin, 2000).

Finally, lead pipes pose a risk to any resident living in a home that pre-dates 1945 (Richardson et al., 2011). Lead pipes can be present as a service line (i.e., the pipe connecting the house to the main supply), or as the internal piping within the home. For complete remediation, the capital investment to replace lead pipes for residential homes in Hamilton would cost the municipal government between $47.3M to $70.9M, which far exceeds a reasonable capital investment for the city. As recently identified by the city, there are three elementary schools within the study area that require lead pipe replacement with an estimated cost of $14,300 to $21,500. Lead pipe replacement would likely be a viable option for these schools; however, it may not be needed after an update to the municipal water supply. In late 2018, Hamilton began adding orthophosphate to the city water supply, which coats the insides of pipes to reduce lead from leaching into the water significantly. Hamilton added the orthophosphate to the water supply after implementation in seven other Canadian cities (i.e., Toronto, Winnipeg, Sudbury, St. Foy, Dartmouth, Bathurst, and Campbellton) and six U.S. cities (i.e., Washington D.C., New York City, Detroit, Chicago, Atlanta, and Nashville), as well as a successful two-year pilot study in Hamilton. Implementation of orthophosphate to Hamilton's water supply costs approximately $4.9M and an additional $307,619 per year in operating costs (City of Hamilton, 2018b). Hamilton's decision to add orthophosphate to the water supply to mitigate lead exposure is an excellent alternative to the substantial capital investment required to replace lead pipes from homes within the study area.

Objective two determined the projected ROI estimates for permanent lead abatement in Hamilton. The ROI estimates for lead hazard control outlined by Gould (2009) are complicated and consider many different avenues for possible savings, both directly and indirectly, as a result of adverse health outcomes of lead exposure. As can be seen in Table 4.2, the conservative and optimistic ROI estimates are incredibly high for nearly all land type and abatement strategies covered in this paper, but the discounted project costs match the ROI estimates for all lead abatement categories, aside from lead-based paint abatement. The ability to profit, break-even, or take a loss from a lead abatement project is only half of the information that municipalities must consider when approving a remediation project. The second half of the decision is based on the capital investment needed to complete the project. Furthermore, the savings returned from lead hazard control are not straightforward, and thus, we argue that there are two main reasons why using ROI projections are unrealistic to make policy and program decisions at the municipal level, (i) capital investment, and (ii) recipient of savings.

As we have shown with this case study, the capital investment required to abate lead exposure in Hamilton permanently is far too expensive for a municipal government. Even with federal or provincial subsidies, the costs are high, and the reduction in exposure is likely not high enough to justify the investment. As suggested in the study by Farrell et al. (1998), contaminated soil replacement did not reduce child BLLs significantly between abatement and control groups. Although the return on investment will allow the municipal government to either break even, take a small loss or profit on the various lead abatement strategies presented in this paper, the capital investment is still too high. There are only a few lead abatement options presented in this study that could be reasonably achieved by the municipal government. Municipal governments do not have the budget to be basing decisions solely on projected future savings. Policy and program initiatives must comply with strict budgets that can even be restrictive for multi-year projects.

Second, the return on investment does not explain how savings will benefit stakeholders. As previously discussed, four main factors will result in a return on investment from lead hazard control, which includes: (i) less pressure on the health care system, (ii) IQ increases, (iii) reduced spending on special needs education, and (iv) reduced criminal activity (Gould, 2009). In Canada, health care and education budgets are provided by the provincial government (Fedeli, 2019). Therefore, the province of Ontario will benefit most from a reduction of special needs education and pressure on the health care system. Furthermore, a reduction in criminal activity will reduce pressure on the municipal justice system (e.g., prisons and court). However, the cost savings will mostly transfer to the provincial and federal justice systems with an additional reduction in violent crime (Burns et al., 2014).

Objective three explored the need for soil lead abatement by investigating hazard quotients within the City of Hamilton. Many factors influence a hazard quotient and can differ based on the characteristics of a child or the environment; however, Health Canada (2010) has set estimations for each factor, across the three age groups. The two factors that change in the hazard quotient calculations presented in this paper are the soil lead level and weeks of exposure. As shown in Table 4.3, Appendix O, and Appendix P, the soil lead levels across the city and the weeks of exposure can have a significant impact on the hazard quotients. The two scenarios (i.e., 52 weeks of exposure, and 40 weeks of exposure) show that the average child within the city is not at-risk of adverse health effects from SLLs. Since these calculations are based on averages for child characteristics, it is still possible that a child who consumes more soil per day or weighs less than the average may be at-risk for adverse health outcomes. As stated above, this risk could be mitigated by developing designated play areas to reduce or eliminate exposure to contaminated soil.

Additionally, the municipality should offer complete soil, paint and service pipe remediation to the households that exceeded a hazard quotient of 0.5 with 40 weeks of exposure. The addition of exposure to lead-contaminated paint, water and dust may put these children at-risk of exceeding a blood lead level of 5 µg/dL. The areas in which toddlers are at the highest risk also contain a relatively high percentage of households below the poverty line, ranging from 24.7% to 42.3% of households (Statistics Canada, 2016). Considering a significant portion of households in this area are living under the poverty line, the government should help this vulnerable population to preserve environmental equity within the city and eliminate the economic burden on low-income households.

We propose that governments make lead policy decisions based on need and cost, rather than savings or returns on investment. ROI projections can help policymakers decide between different program initiatives, but the estimates can also be misleading.

There are too many factors and assumptions that are used to calculate a return on investment and can inflate values to make capital investment seem more cost-effective.

4.6 Conclusion

As Hamilton's housing stock continues to age, many of the older buildings will eventually be gentrified or demolished and replaced with new structures. By implementing construction policies that require permits for safe lead removal, this process will eventually eradicate the threat of lead-based paint and leaded pipes from Hamilton. However, there are many less expensive alternatives to permanent lead remediation that municipal governments and residents can use to reduce exposure for children. Designated play areas can be constructed in backyards of homes, parks and schools to eliminate the threat of exposure for supervised children. Second, lead-based paint can be contained using inexpensive methods such as painting over old lead-based paint and lastly, lead pipe removal may not be necessary after the addition of orthophosphate to the water supply (City of Hamilton, 2018b).

4.7 References

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Chapter 5 Conclusions and future research

This dissertation sought to understand the spatial distribution of soil lead levels in an urban area better, identify the necessity for lead abatement and challenge the current recommendations for lead remediation in urban cities. The purpose of this thesis is to help policymakers make informed decisions at the municipal level by investigating current challenges, rather than focusing on projections developed by cost-saving models. The literature recommends lead remediation in urban cities on the basis that the return on investment is high, but permanent abatement poses significant challenges for municipalities and residents. Presented as a case study in Hamilton, Ontario, this dissertation challenges standard methodologies, relationships and predictions within the literature, and illustrates that remediation may not always be feasible or necessary for municipal governments. Chapter five of this dissertation seeks to identify the main contributions of this thesis within the literature.

5.1 Contributions

As a result of the three manuscripts presented in this dissertation, the contributions to the literature are as follows:

1. Predictive models should remain parsimonious

A key component of lead remediation is identifying areas that exceed contamination thresholds. Since soil testing can be expensive, we are required to estimate the lead levels between sampled points across space. In heavy metal contamination research, the standard approach is to use an interpolation method called kriging, which relies on the spatial structure of the sampled data set to make estimations at unobserved locations. One of the perceived downfalls of kriging is that estimations are globally smoothed (Arain et al., 2007), which means local variation is lost. In chapter 2, the paper attempts to utilize a different approach to interpolation that focuses on localized prediction for soil lead levels. This approach, called Land Use Regression (LUR), is a commonly used interpolator within the air pollution literature (see Arain et al. 2007; Melymuk et al. 2013; Sahsuvaroglu et al. 2006; Saraswat et al. 2013; Wang et al. 2013), and uses pollution sources as predictor variables in a regression model to estimate the contaminate in unobserved locations. Chapter 2 provides the results of both LUR and kriging, in addition to uncovering three flaws with land use regression as an interpolation technique.

As discussed in chapter 2, a LUR model may include predictor variables that do not have a real relationship with the dependent variable. The method of selecting predictor variables is inherently flawed since correlations between predictor and dependent variables are selected based on the highest correlation coefficient without considering the physical relationship between the contamination source and the dependent variable. As a result of this variable selection method, the LUR model can overfit the data and lead to a model that cannot be generalized over space or time. A LUR model with multiple predictor variables also poses a problem for remediation efforts. Predictor variables that explain the spatial distribution of the contaminate may be targeted by governments for remediation, policy, or program initiatives, despite having no real relationship with the dependent variable. Remediation and program initiatives that target a variable that does not relate to the contaminate can pose a serious concern within cities where the municipal government has limited resources. Additionally, policies may falsely limit commercial businesses or industries that are not contributing to the contaminate. At the local scale, predictor variables that are overfitted to the data can have a significant financial impact on the residents, businesses, industry, and government, and the solution may not reduce exposure to the contaminate.

In the case of interpolation, we found that kriging is a better solution for remediation efforts because kriging focuses on the spatial structure of the data. As Tobler's first law dictates, near things are more related than distant things, which is an integral component of kriging. Kriging uses a semivariogram to understand the spatial relationship between observed points within the data set. This method does not require external predictor variables to estimate the level of contamination at unobserved locations, and thus, the predicted surface is more trustworthy than estimations made by LUR. Specifically for lead (Pb) remediation, the contamination is typically from historical sources of lead (e.g., combustion of leaded fuel, and lead-based paint), so understanding where the contamination came from is less important to a government entity. One of the most important aspects of spatial modelling for a government is the ability to understand the spatial distribution of the contaminate across space. Areas within a city that pose a significant threat to the public can be remediated, or secondary soil testing can be done within the area of concern to understand the distribution of the contaminate better.

2. Any uncertainties will be exaggerated in a model

In contamination research, a key component of developing a remediation plan is to understand the spatial distribution of the contaminate across space and determine whether an abatement project is worth the financial investment. In chapter 2, we saw that LUR could rely on relationships with spurious and uncertain relationships. An interpolation model that relies on relationships that may not directly exist can have a significant effect on the remediation efforts and policy decisions developed to mitigate exposure to the contaminate. In chapter 2, we showed that a more simplistic model (i.e., kriging) might be preferred since the model depends on the spatial structure of the data, rather than a dependence on uncertain relationships. One of the problems outlined in chapter 2 is that many of the relationships between predictor variables and the dependent variable are spurious and unintuitive; thus, the model becomes overfitted to the specific data set. As a result, the LUR model has little value to a municipal government that may require new predictions over time or may waste resources targeting sources that have no direct influence on the contaminate.

In chapter 3, we examined the relationship between blood lead levels in children, and its influence on full-scale IQ. We found that the relationship between BLLs and full-scale IQ is lower than previously suggested, but explain that the meta-analysis method may present some limitations that are important to consider. One of these limitations discusses how the meta-analysis process then exaggerates the uncertainties present in each study. In other words, any variability that cannot be explained by the regression models in individual studies are still present in the unstandardized beta coefficients (UBCs) that are pooled in the meta-analysis. Thus, the pooled results have more uncertainty than each UBC on its own. Similarly, there is uncertainty when pooling UBCs from different populations (i.e., children with different characteristics) and regression models that have been constructed with a different set of confounders. In a meta-analysis, heterogeneity measures can help determine if pooled UBCs have similar characteristics (e.g., sample size, UBC value, confidence intervals, etc.); however, the underlying uncertainties embedded in the UBCs (e.g., demographic variation in the population, the process of IQ testing, confounding variables used, etc.) may influence the results. Additionally, publication bias may also add uncertainty into the pooled result, but fortunately, some tests can help identify and correct for publication bias.

Additionally, in chapter 4, the inherent uncertainties within the Gould (2009) ROI model are illustrated with the vast discrepancies between the conservative and optimistic ROI predictions. The ROI projections presented by Gould (2009) were based on the National Health and Nutritional Examination Survey (NHANES) administered by the CDC to children (n = 194,000) living in the United States. Despite a large sample size, many factors can affect lead exposure, which will vary based on the characteristics of a population and the environmental variances across space. Population size and density, and the number of children living within the city will affect the ROI a municipality can expect from lead abatement efforts. In other words, a city with a high density of children living in a lead-contaminated area can expect a higher ROI than a city with a lower density of children living in a lead-contaminated area. Additionally, cities with a higher density of low-income households may benefit more from lead abatement intervention by the government, since lower-income individuals have less financial autonomy to implement lead mitigation efforts (e.g., painting over lead-based paint or replacing lead service pipes). Furthermore, there are environmental factors that can affect the potential exposure to lead for a child. First, cities in warmer climates are at higher risk of lead exposure due to “greater exposures to soil lead, dispersion of dust when lead-painted windows are opened and shut, and remobilization of lead on interior surfaces as air moves through open windows and doors” (Levin et al., 2008, p. 1290). Warmer climates also encourage children to play outdoors for longer, increasing exposure to soil and airborne lead exposure, and variations in Vitamin D throughout the year (i.e., from sun exposure) can cause variations in susceptibility to lead poisoning in children (Levin et al., 2008).

Lastly, fallen leaves during autumn and snow during the winter can cause physical barriers to lead exposure for children, and rain can also help reduce exposure to lead-laden dust within a city.

3. The best approach is not always the most feasible approach

In an ideal world, we would always take the best possible approach to every problem; however, governments have financial limitations and require solutions that provide a balance between capital investment and efficacy. Regarding lead remediation, often, it is not possible to permanently remove lead from the environment because the capital investment is far too substantial for a government budget.

In chapter 1, we recommended kriging for interpolation, rather than using LUR. In addition to more accurate predictions, kriging is also significantly faster and easier to use when compared to LUR. At the municipal level, a government may not have the resources to collect data, maintain a database, develop a regression model, and use mapping software to create a prediction surface. In contrast, a kriging model can be developed quickly and easily using the Geostatistical Wizard in ArcGIS, which requires a rudimentary level of understanding to create the prediction surface.

In chapter 4, we showed that a significant portion of the downtown core in Hamilton exceeds the 70 and 140 mg/kg thresholds set by the federal government (Canadian Council of Ministers of the Environment, 1999). Despite enormous return on investment projections for lead remediation in Hamilton, we discussed how the government would not be able to afford such significant capital investment in most cases. Permanent solutions are the best way to mitigate lead exposure for children, but in an urban setting with large areas contaminated by lead, the capital investment is just too large for a government with limited resources. Multi-year investment plans are also possible for governments to pay for lead remediation, but the ROI associated with most lead abatement strategies in Hamilton did not overcome the future discounted project costs. Moreover, the cost savings associated with lead abatement do not necessarily transfer to the municipal government. Thus, it may be more advisable for a city to promote cheaper alternatives that mitigate exposure either spatially or temporally. For example, a city could spatially mitigate lead exposure by replacing contaminated soil only for playgrounds, rather than replacing soil for the entire park. A temporal example may be forcing landlords to apply a fresh coat of paint to older homes every few years to cover old lead-based paint. These examples provide an adequate level of lead exposure mitigation and cost a significantly lower amount of money to implement. In addition to smaller, city-wide approaches to reduce lead exposure, we also recommend eliminating lead contamination in the highest risk areas in the city to reduce adverse health outcomes and preserve environmental equity. Chapter 4 also suggests that in some cases, permanent lead abatement is recommended if the remediation project benefits a relatively large number of children. For example, we showed that the daycare centres in Hamilton would be a relatively small capital investment and would benefit a significant number of children. Lastly, soil lead level thresholds set by the government are typically ten times lower than the actual safe threshold to account for differences in populations (U.S. Food & Drug, 2019). Hazard quotient calculations showed that, on average, children are not at-risk of adverse health effects in Hamilton, Ontario. Despite having large swathes of soil exceeding the regulatory threshold for lead, hazard quotient maps can help policymakers decide whether or not lead remediation is necessary to reduce the risk of lead poisoning for children.

5.2 Limitations

In Chapter 2, we used the soil lead levels to estimate contamination levels at unobserved locations with some success, but the sampling method left large areas without soil samples. The method of data sampling provided measured soil lead levels for participating residents, which means broad, business-dense areas of the downtown core do not have soil lead levels. As a result, spatial modelling techniques will have more difficulty determining the relationship between observed data locations and the environment. For example, Empirical Bayesian Kriging uses the spatial structure of the data set to determine the relationship of distance between observed locations, so having a more grid-like data set is ideal for developing a better predictive model. Similarly, land use regression would also benefit from more grid-like data set to determine the relationship between predictor variables and observed locations. Ideally, the original data collection would have included grid-like soil sampling for residential, commercial and industrial properties across the lower city of Hamilton. Furthermore, better predictive models may have been possible using a more powerful workstation to develop and use the land use regression model. Developing and using a land use regression model at a high resolution (i.e., <100-meter cell size) was not possible using the computer available for analysis. A higher-end workstation may have allowed a more predictive land use regression model. Lastly, time was a major constraint in this chapter because data collection was primarily done manually by searching historical business directories and inputting the data into a database. Manually collecting data limited the number of business directories that could be searched (i.e., we searched business directories at 5-year intervals: 1925, 1930, 1935, etc.) to include in the database. More time could afford a more representative data set (i.e., searching business directories at a 1-year interval) and we could have also included other historical predictive variables such as land use and zoning, weather and wind patterns, and road networks that changed at the same year interval as the business directories.

In Chapter 3, we were limited by access to particular journal articles based on two main factors. First, we were not able to read journal articles that were not written in English, which may have eliminated important studies from the meta-analysis. Second, some journal articles were not available through McMaster’s journal database, which further limited the pool of journals available for analysis. In addition to accessibility limitations, we were also limited by the fact that not all papers reported a UBC with an untransformed independent variable (i.e., BLLs), so we were not able to pool as much literature for the two groups. Furthermore, not all papers reported other key information, such as an unstandardized beta coefficient, sample size per regression model, or the methods of data collection.

In Chapter 4, we were not able to access household-level information regarding the age of dwelling, which could have been used as a proxy for both lead-based paint and lead-pipe presence within the home. The highest resolution we could access was the median dwelling age by census tract. Additionally, homes within the study area could have been renovated, eliminating lead-based paint and lead pipes. Access to construction permits could have allowed us to develop more accurate projections for abatement costs and return on investment estimates. Next, in chapter 4, we did not have the square footage of homes in Toronto, even though the cost was based on a Toronto home, so the cost to remove lead pipes from a residency was not converted to account for the difference in square footage between Toronto and Hamilton houses. Lastly, in the hazard quotient calculations, we did not have the data necessary to estimate full exposure to lead (i.e., we did not have lead-contaminated water or lead-based paint data for all homes to predict hazard quotients better). Furthermore, we did not know the travel patterns of children to estimate exposure. For example, we did not know if a child spent time in the backyard, and more time at a local park during an average day.

5.3 Future work

As a result of this dissertation, we encourage researchers to explore distance profiles for current air pollution research that utilizes land use regression as a spatial modelling technique and to recommend better solutions to municipal governments for mitigating lead exposure with consideration for capital investment, rather than return on investment. Second, we recommend a comprehensive set of public health initiatives to spread awareness, encourage the use of preventative measures for mitigating lead exposure, and generate crowd-sourced data for better soil lead predictions.

As discussed in chapter 2, we recommend the use of distance profiles to understand the relationship between the dependent and independent variables at each buffer distance. We found that the distance profiles are imperative to a land use regression model to verify that each relationship is intuitive and the distance profile decays appropriately. We encourage air pollution researchers to integrate distance profiles into the initial selection process for predictor variables and eliminate predictor variables that do not exhibit an expected distance profile.

Second, we encourage researchers to focus on reasonable solutions for lead poisoning mitigation efforts for municipalities without fixating too heavily on return on investment predictions. Ideally, we would remove all sources of anthropogenic lead from the environment, but as we have shown in chapter 4, the cost of abatement may be too high for a municipal government. We encourage researchers to investigate the need for lead abatement on a case-by-case basis to determine whether or not children are at-risk of developing lead poisoning before recommending costly mitigation strategies. By utilizing the hazard quotient, researchers can assess the risk of lead contamination to children in different populations and cities before recommending mitigation strategies or full abatement initiatives.

Next, we encourage municipalities with large-scale lead contamination to develop two main public health initiatives to spread awareness, promote preventative measures, and to help collect more data. First, a web app to access lead poisoning information and available resources for lead mitigation. In Hamilton, Ontario, Statistics Canada (2019) reported that 81.8% of residents used the internet in 2009, which increased from 71.2% in 2005. Although the next Internet use study has not been released, the CRTC (2019) reports that in 2017 99.1% of Ontario residents had broadband internet, and 99.8% of Ontario residents had a mobile data plan. Additionally, residents of Hamilton have free access to the internet at any public library, which is likely a service provided by most municipalities in Canada and the US. A web app (i.e., a website using a map as a starting point to disseminate information to a targeted audience) would make the information more accessible for residents. A web app could be used in three main ways: (i) view maps, (ii) provide education, and (iii) request services. First, maps of soil lead levels, hazard quotient, and age of structures and lead pipes could be viewed by parcel (if available). Online maps should include error rates by land parcel with a brief explanation to help parents interpret the information. Additionally, online maps could also include a hazard quotient calculator to allow parents to input specific measures for their child (e.g., body weight and soil lead level, or additional sources of exposure including lead-contaminated water or dust) to view more accurate hazard quotient estimates by land parcel. Based on this information, the municipality may promote specific preventative measures dependent on the level of risk to a child (e.g., exceeding a soil lead or hazard quotient threshold). Preventative measures may include creating a designated play area for their child, repainting with latex paint, wet mopping, flushing taps, and child hygiene (i.e., washing hands and taking off shoes before entering the house). Additionally, a web app could offer a streamlined approach to requesting services and crowd-sourcing data for better predictive power. The City of Hamilton and likely many other municipalities offer free or inexpensive services to identify or reduce lead exposure for residents. A web mapping interface would allow residents to view specific information about their land parcel and request relevant services that may be required. For example, viewing information about a land parcel with a dwelling age predating 1945 could prompt the user to request a lead-pipe service check by the city. Other services may include a home check to identify potential sources of lead-based paint or soil lead and water lead testing. Ideally, municipalities could use this system to collect subsidized data to improve soil lead predictions, in addition to lead-based paint and lead pipe information. Municipalities could offer subsidized, professional soil, paint and water testing to residents, which would reduce the cost of testing for both residents and the municipality. As the city collects more data, predictions will become more accurate, and targeting high-risk areas will become easier.

Next, we encourage municipalities to canvass high-risk areas to disseminate information and bring awareness of potential sources of contamination, in addition to resources and methods to reduce exposure to lead. Once a web app has been built, the municipality must create awareness, which will require an advertisement campaign. In Hamilton, the study by Richardson et al. (2011) reported that half of the participating residents in the highest risk areas were aware of the free services provided by Hamilton. In order to spread awareness of a web app designed to help residents reduce their exposure to lead, municipalities should canvass the highest risk areas to promote the web app and disseminate information about lead poisoning risks and methods to mitigate exposure.

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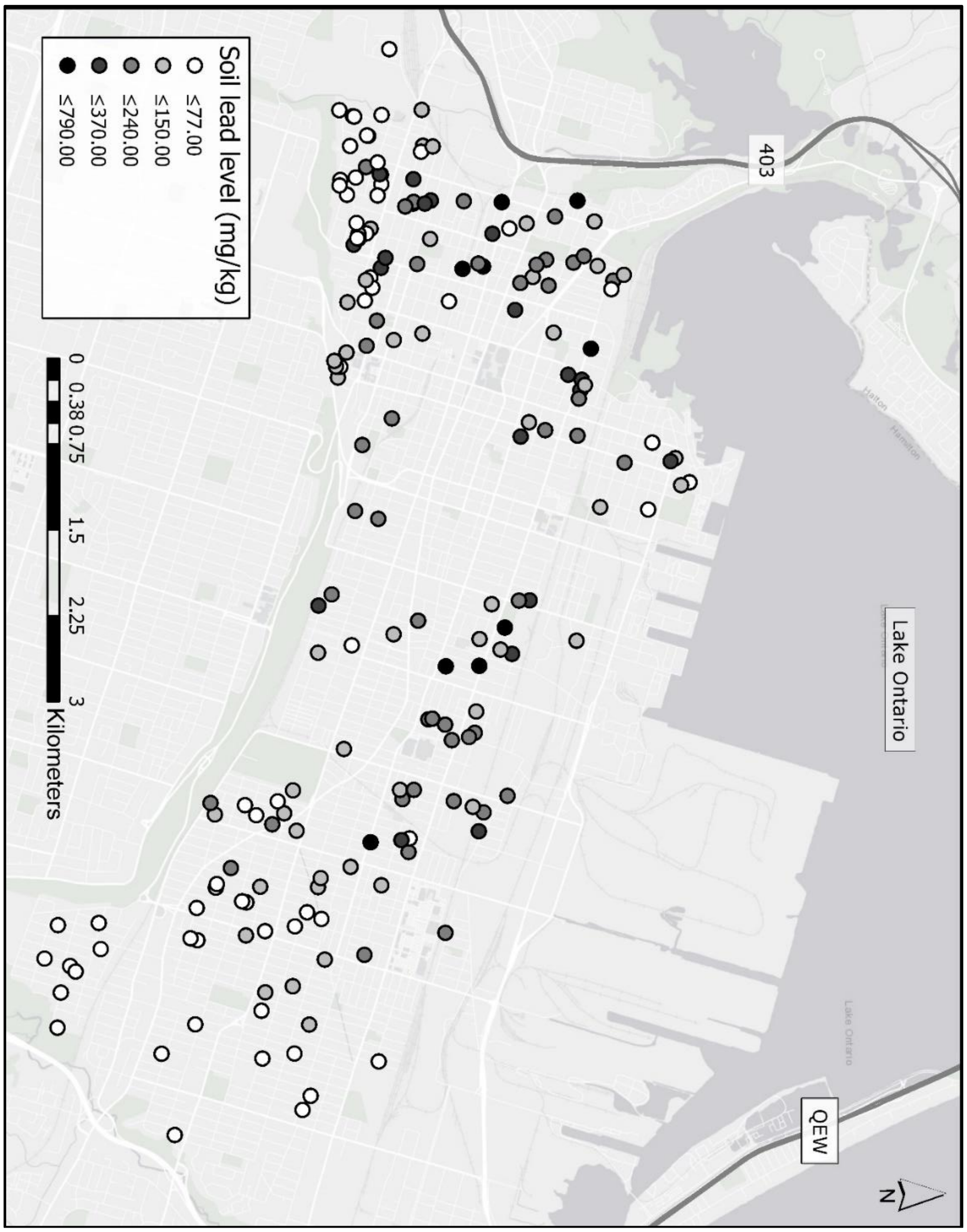
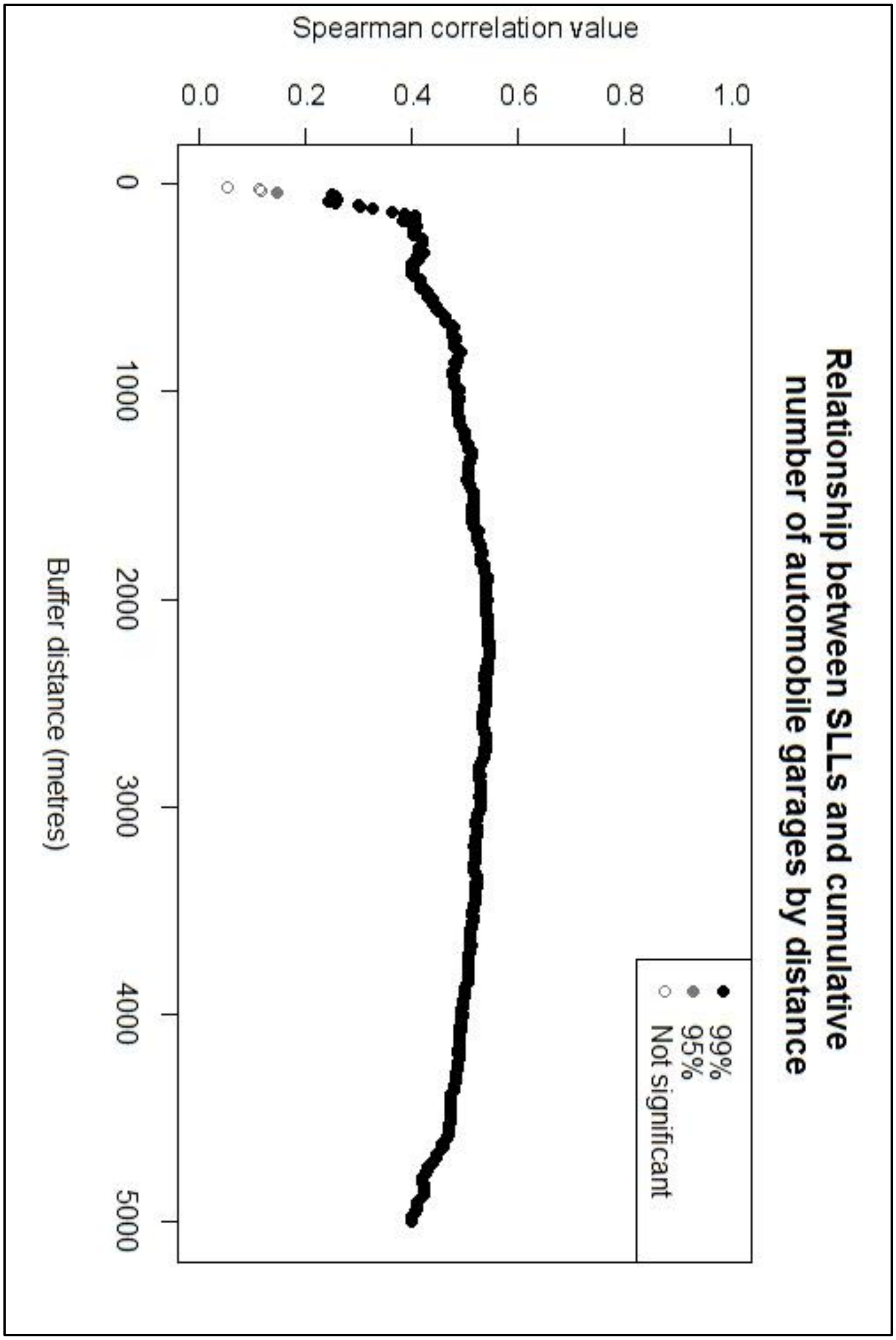
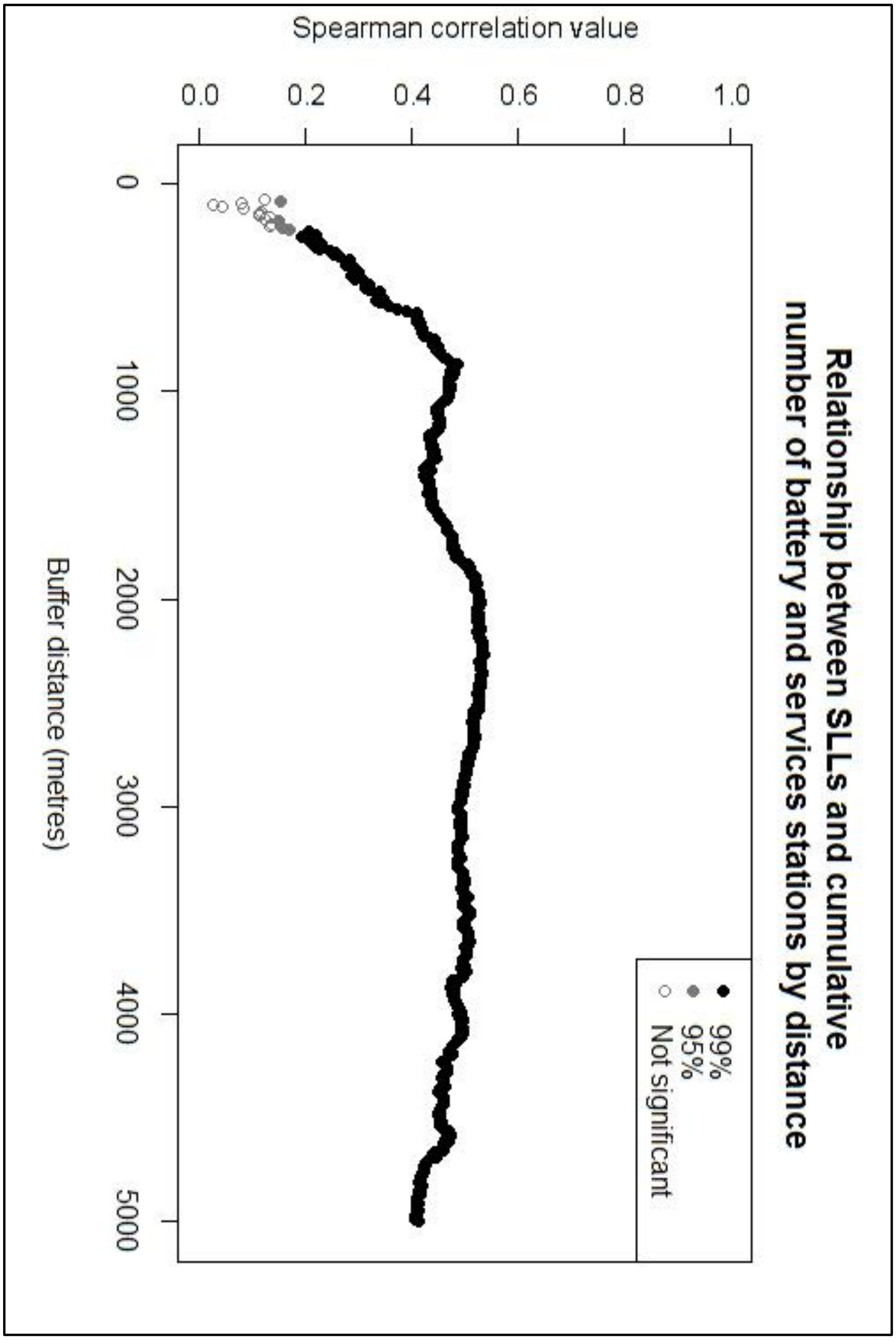
Chapter 6 Appendix

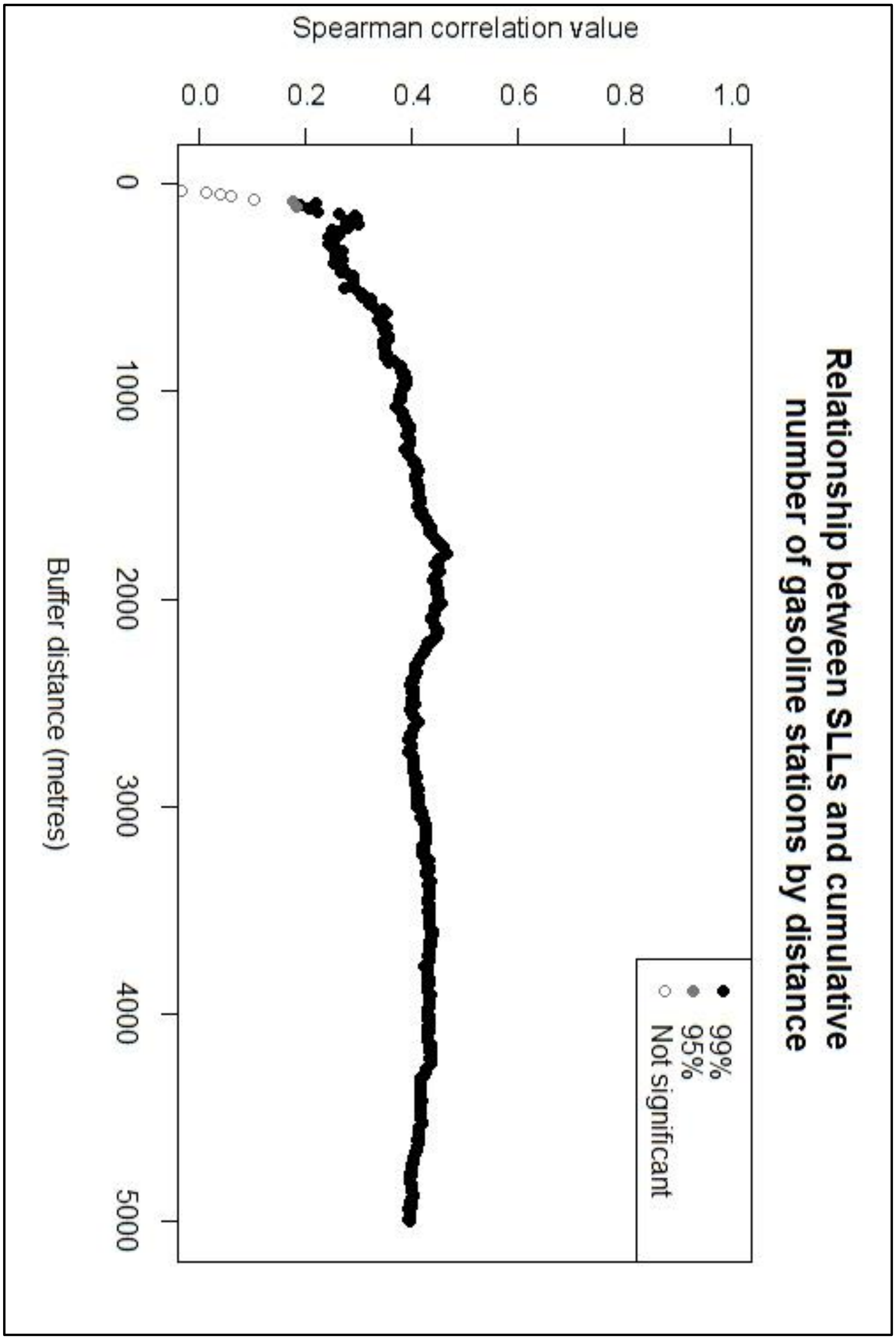
6.1 Appendix A: Depiction of the study area in Hamilton, Ontario, Canada

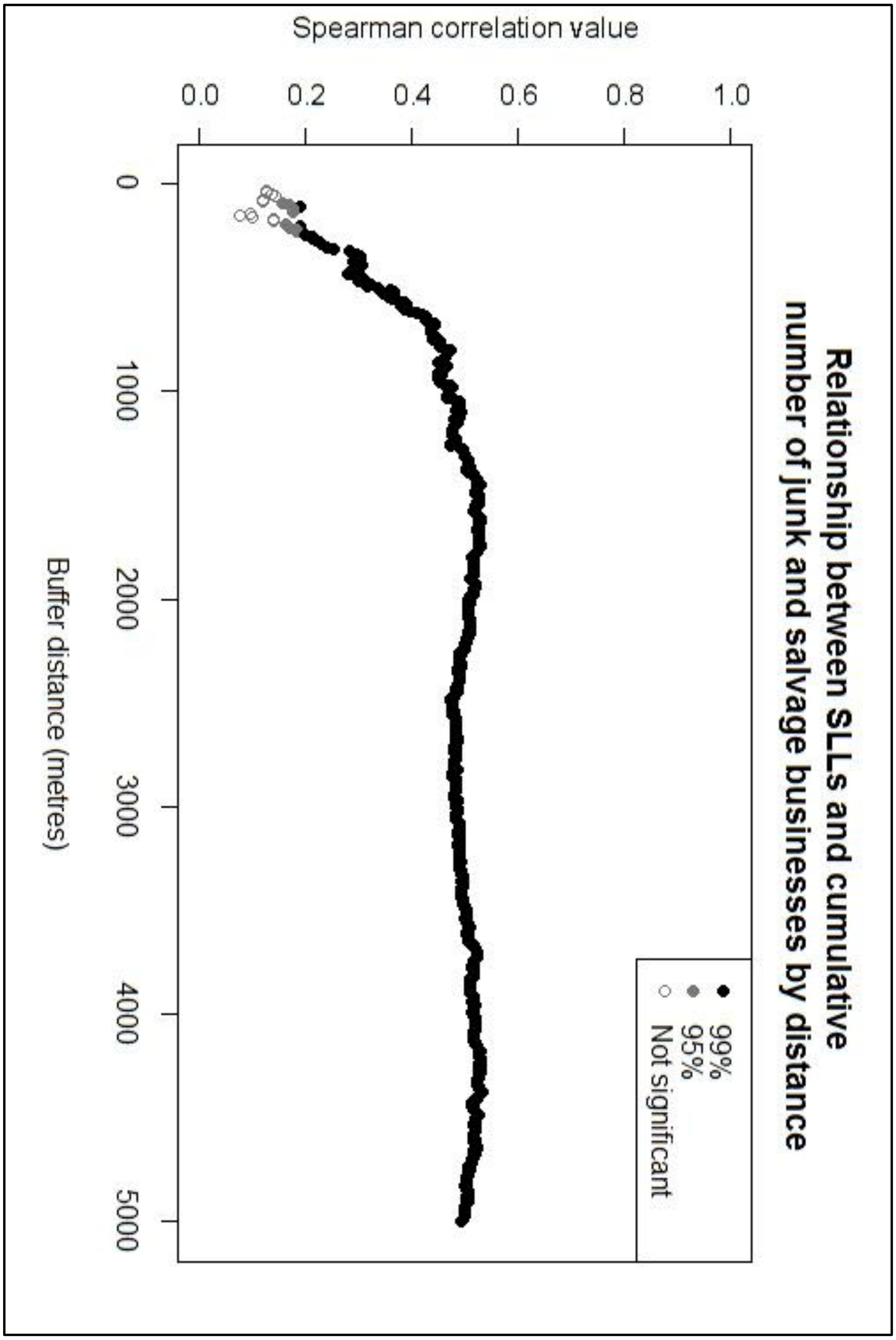


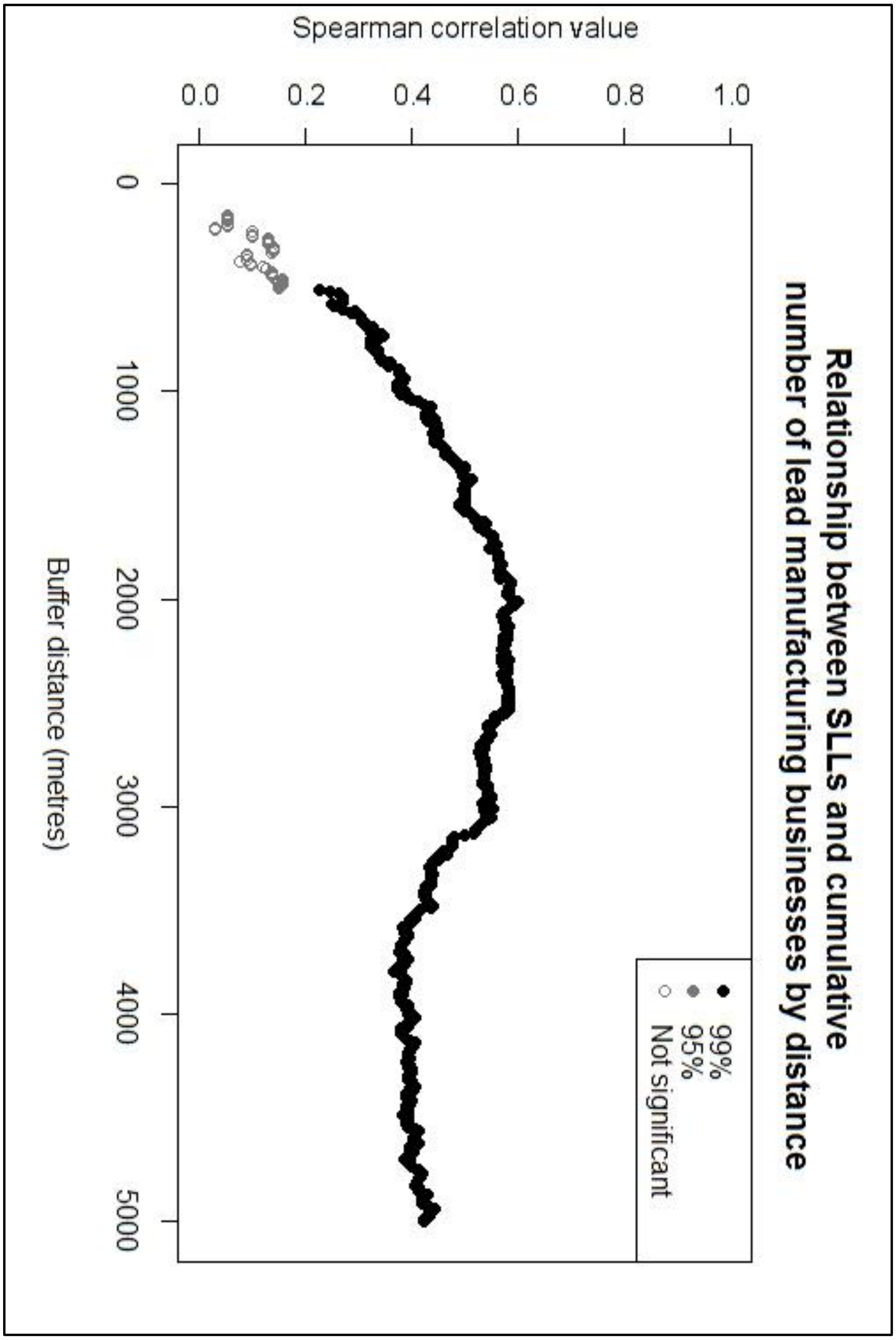
6.2 Appendix B: Distance profiles for the relationship between the cumulative sum of each independent, lead-related variable and SLLs

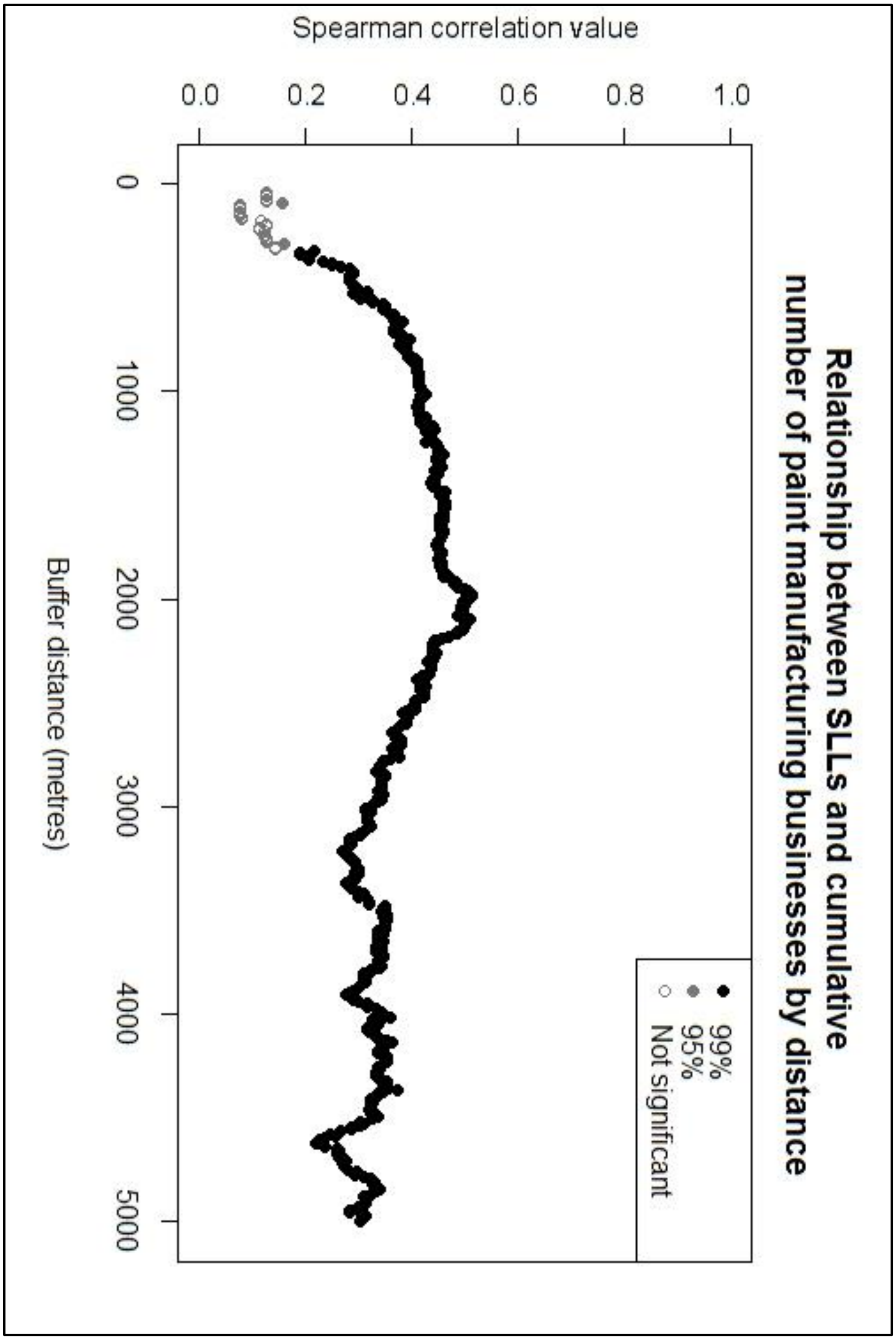



Relationship between SLLs and cumulative number of battery and services stations by distance
Spearman correlation value
0.0
0.2
0.4
0.6
0.8
1.0
0
1000
2000
3000
4000
5000
Buffer distance (metres)
99%
95%
Not significant

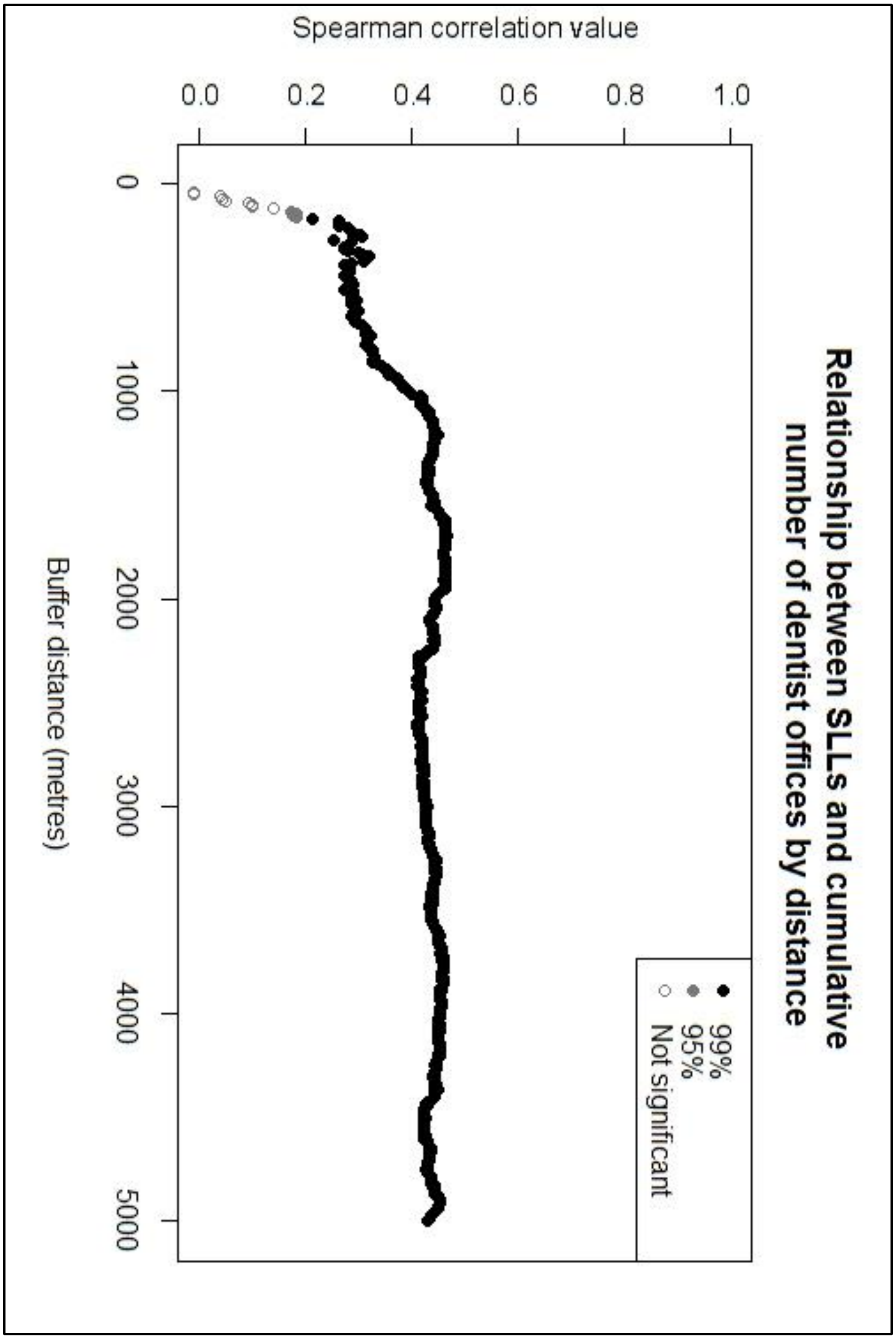

Relationship between SLLs and cumulative number of gasoline stations by distance
Spearman correlation value
0.0
0.2
0.4
0.6
0.8
1.0
Buffer distance (metres)
0
1000
2000
3000
4000
5000
99%
95%
Not significant

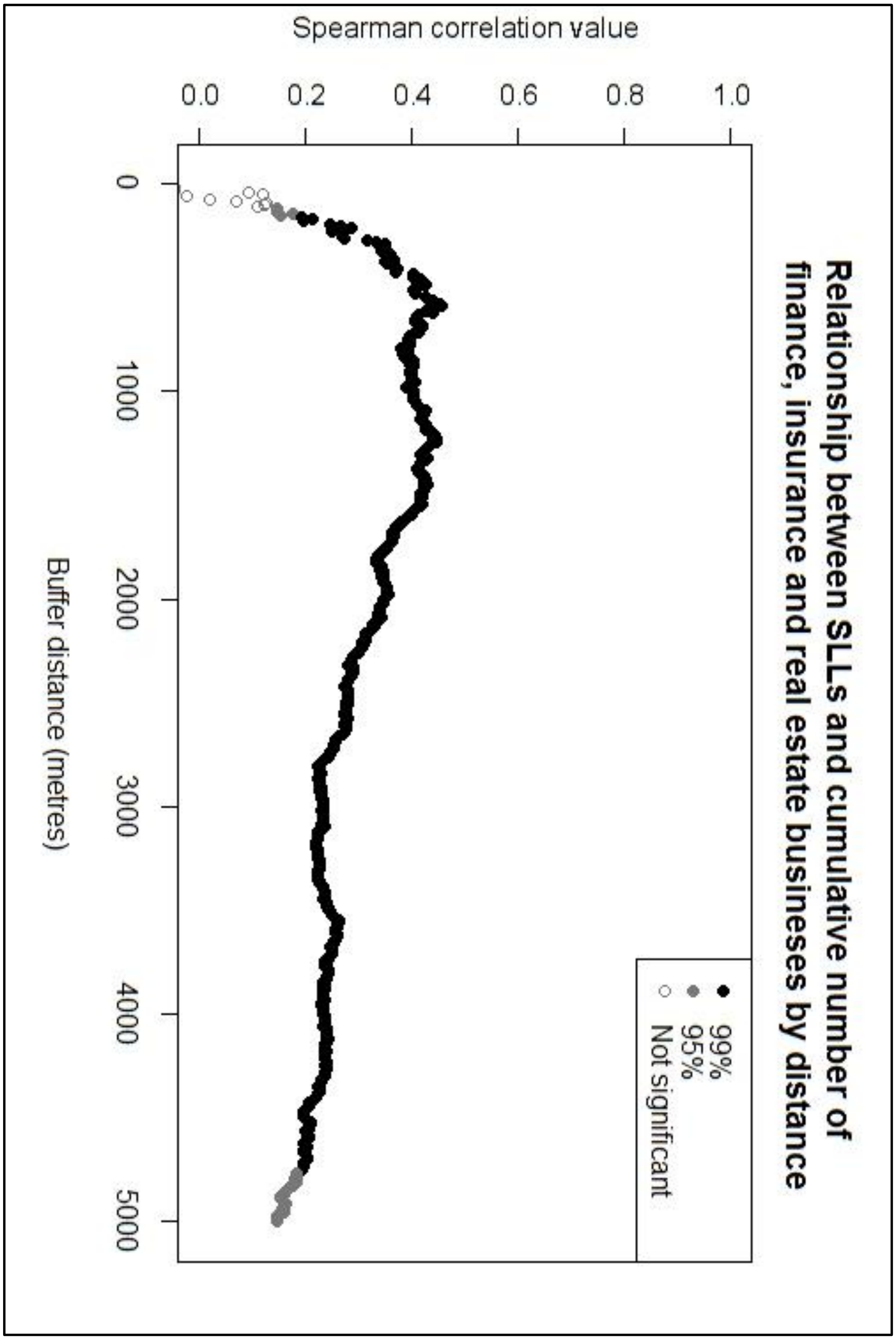

Relationship between SLLs and cumulative number of junk and salvage businesses by distance
Spearman correlation value
0.0
0.2
0.4
0.6
0.8
1.0
Buffer distance (metres)
0
1000
2000
3000
4000
5000
99%
95%
Not significant

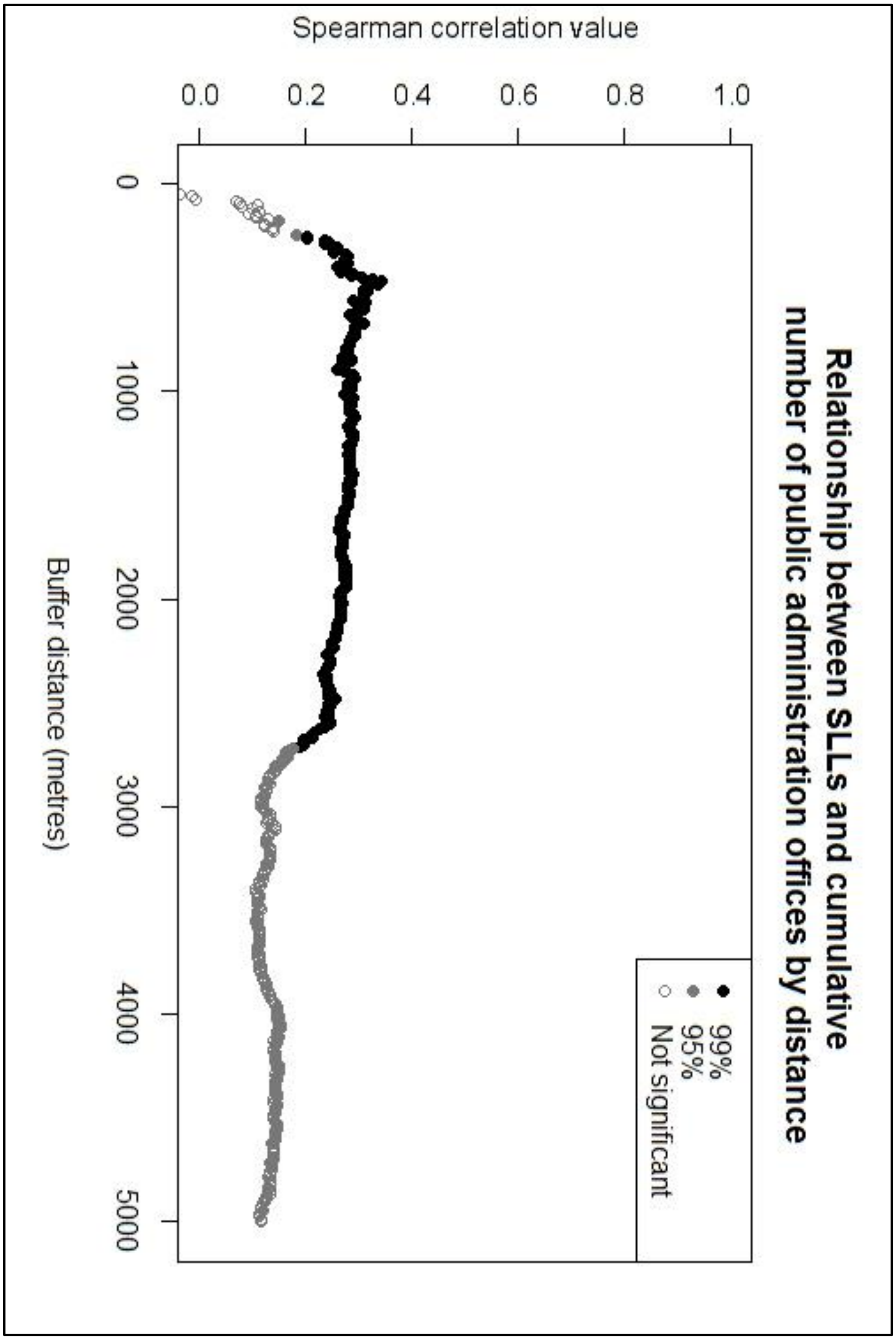

Relationship between SLLs and cumulative
number of lead manufacturing businesses by distance
Spearman correlation value
0.0
0.2
0.4
0.6
0.8
1.0
Buffer distance (metres)
0
1000
2000
3000
4000
5000
99%
95%
Not significant

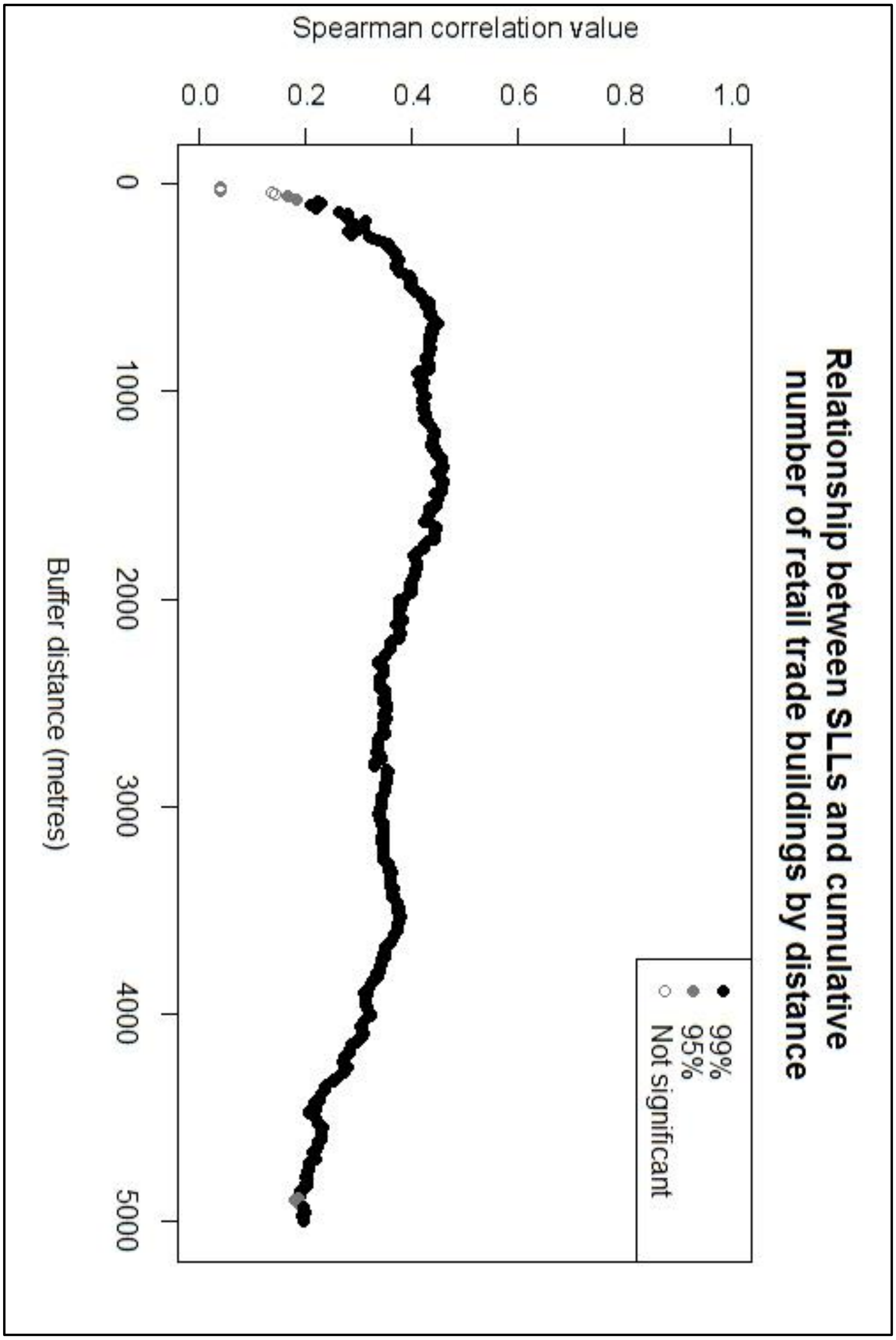

Relationship between SLLs and cumulative number of paint manufacturing businesses by distance
Spearman correlation value
0.0
0.2
0.4
0.6
0.8
1.0
0
1000
2000
3000
4000
5000
Buffer distance (metres)
99%
95%
Not significant

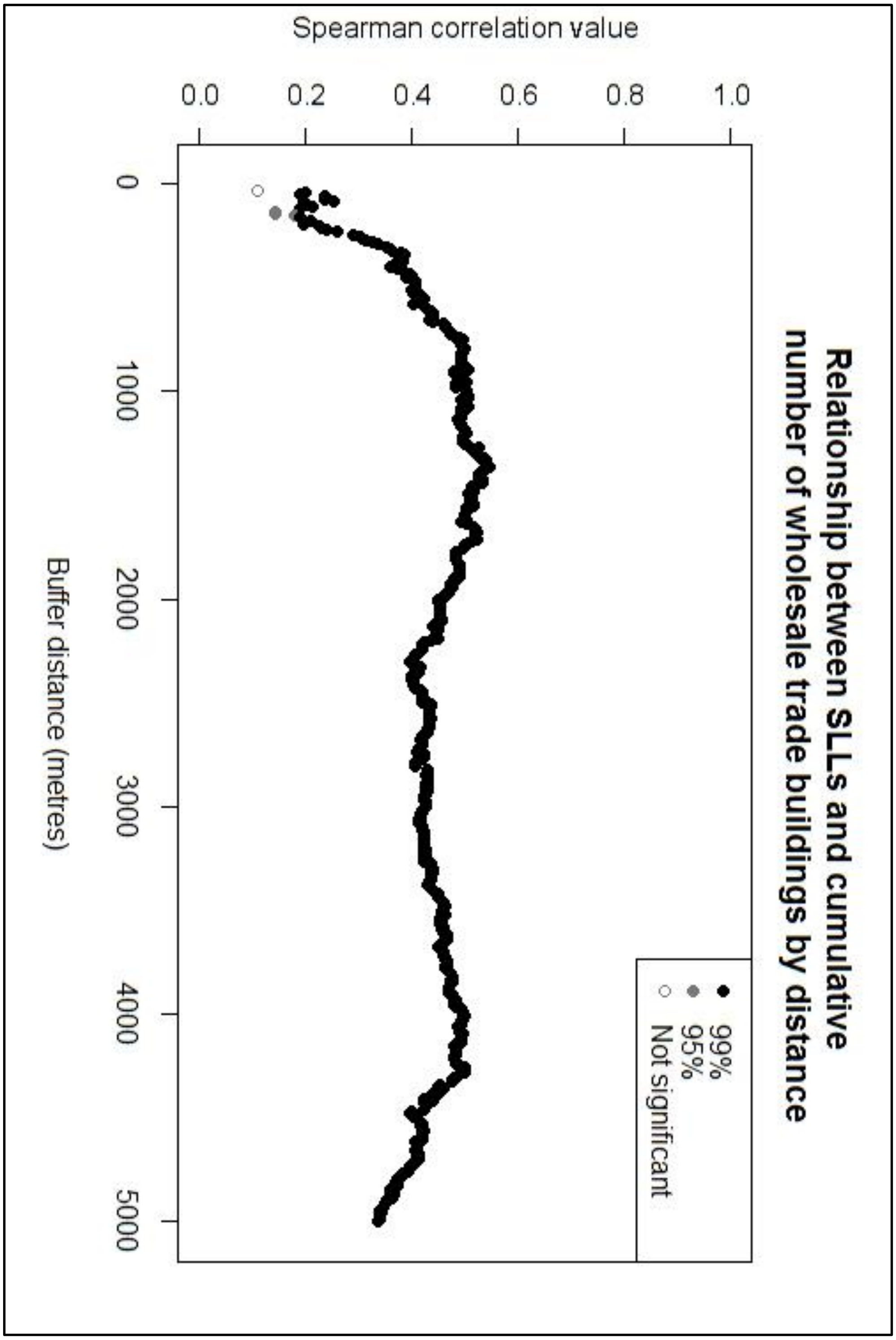
6.3 Appendix C: Distance profiles for the relationship between the cumulative sum of each independent control variable and SLLs



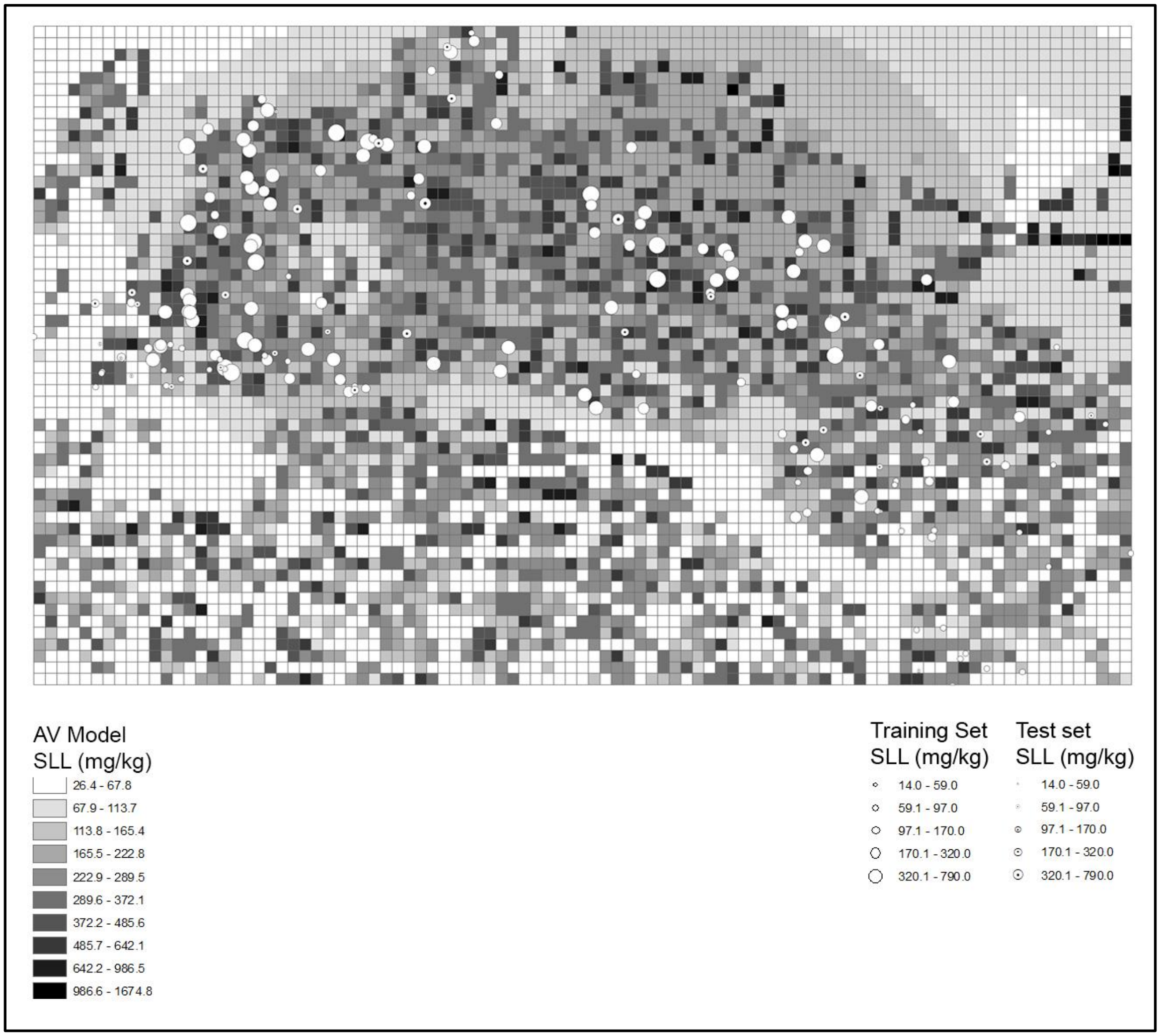

Relationship between SLLs and cumulative number of finance, insurance and real estate businesses by distance
Spearman correlation value
0.0
0.2
0.4
0.6
0.8
1.0
0
1000
2000
3000
4000
5000
Buffer distance (metres)
99%
95%
Not significant

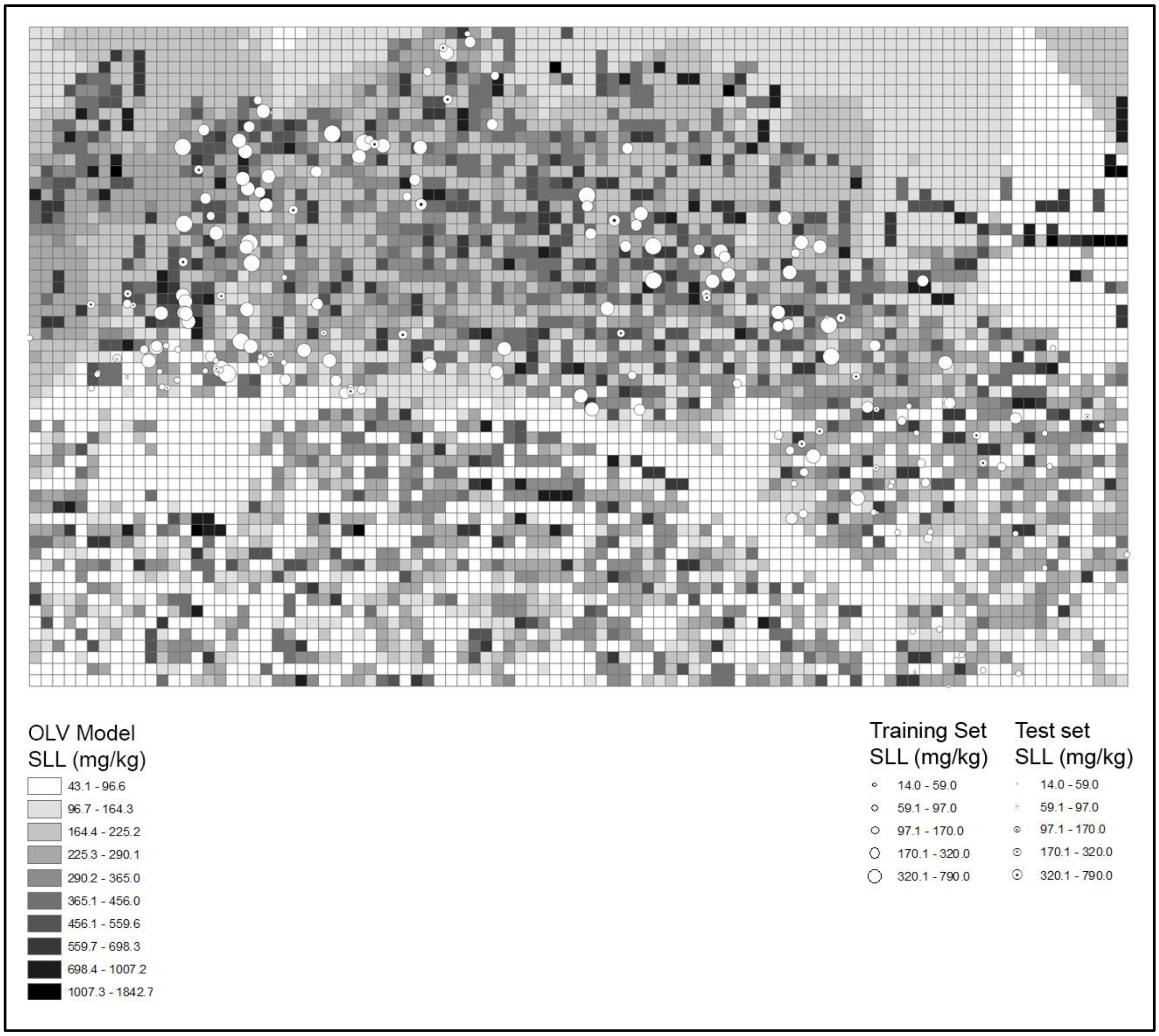

Relationship between SLLs and cumulative number of public administration offices by distance
Spearman correlation value
0.0
0.2
0.4
0.6
0.8
1.0
0
1000
2000
3000
4000
5000
Buffer distance (metres)
99%
95%
Not significant

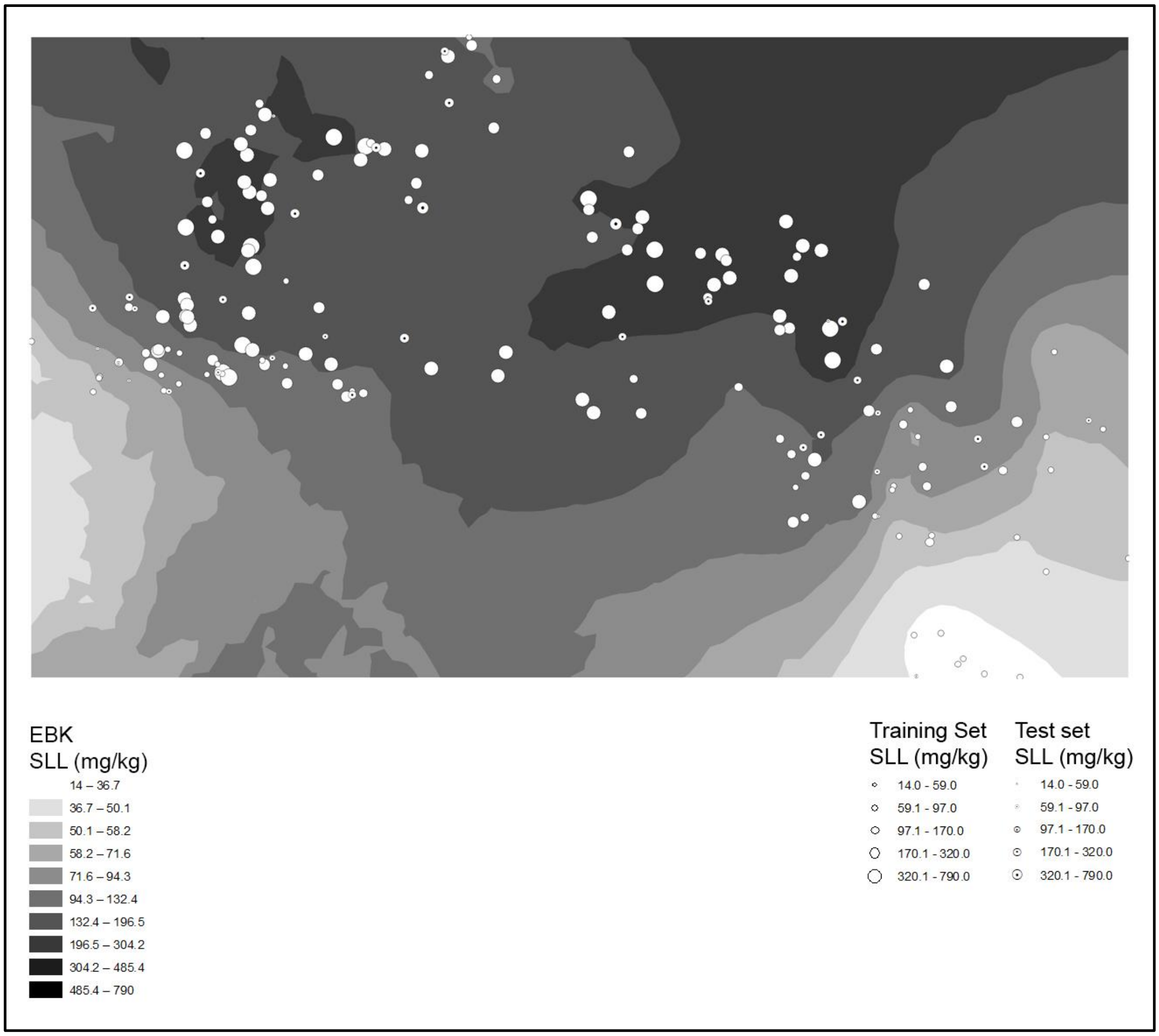

Relationship between SLLs and cumulative number of retail trade buildings by distance
Spearman correlation value
0.0
0.2
0.4
0.6
0.8
1.0
Buffer distance (metres)
0
1000
2000
3000
4000
5000
99%
95%
Not significant

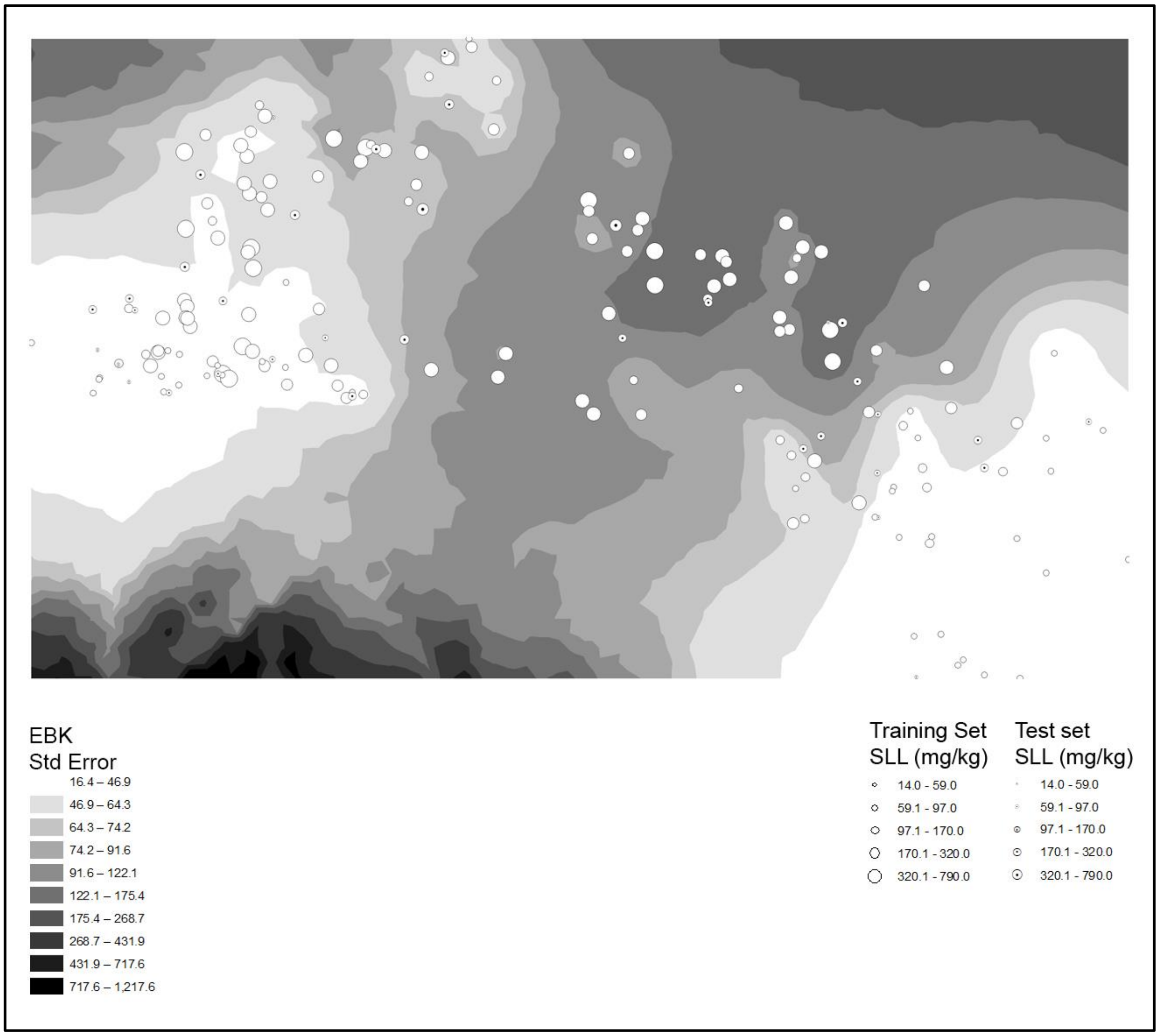

Relationship between SLLs and cumulative number of wholesale trade buildings by distance
Spearman correlation value
0.0
0.2
0.4
0.6
0.8
1.0
Buffer distance (metres)
0
1000
2000
3000
4000
5000
99%
95%
Not significant

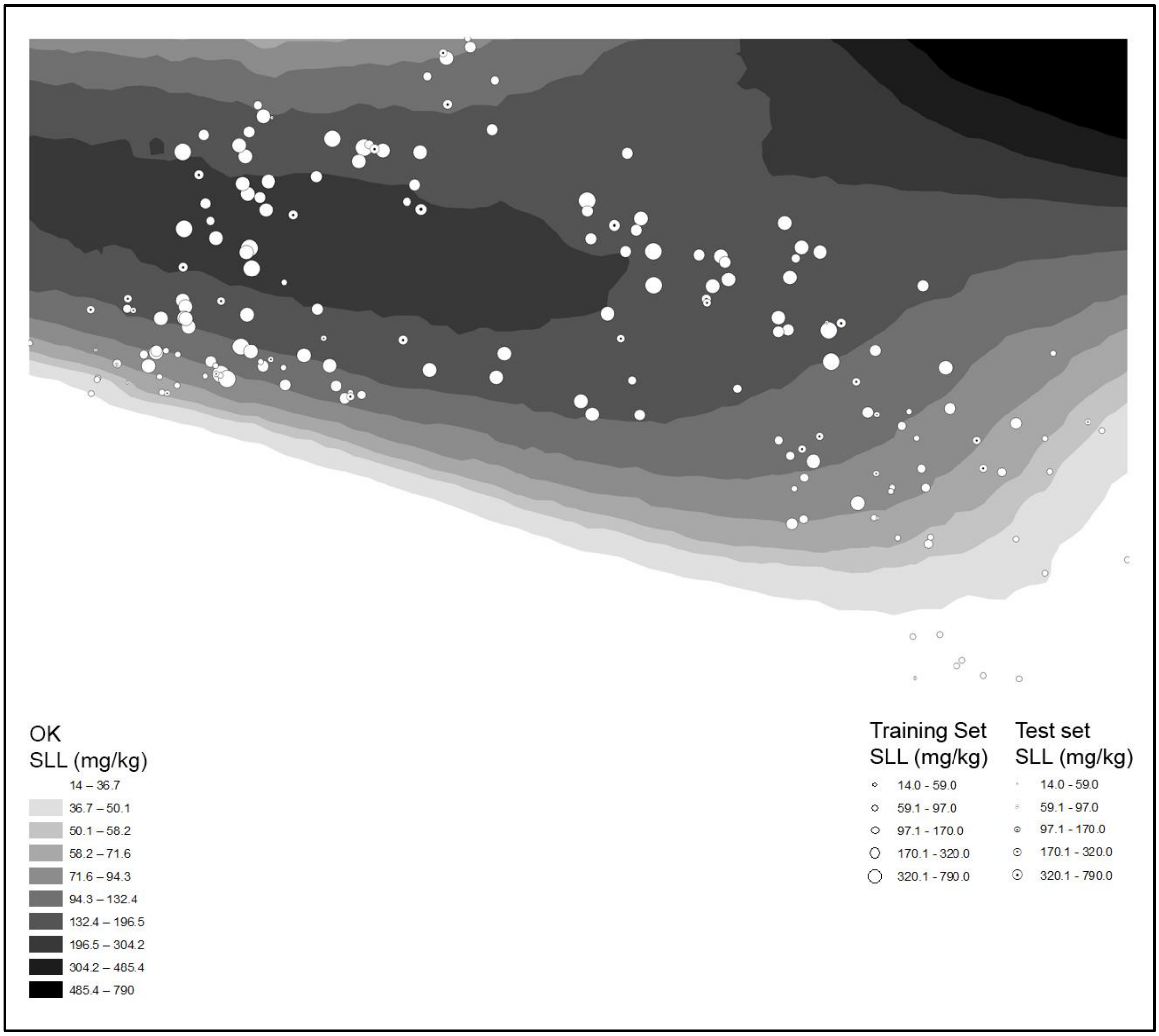
6.4 Appendix D: SLL predictions for LUR AV, LUR OLV, EBK and OK, and standard error for EBK and OK

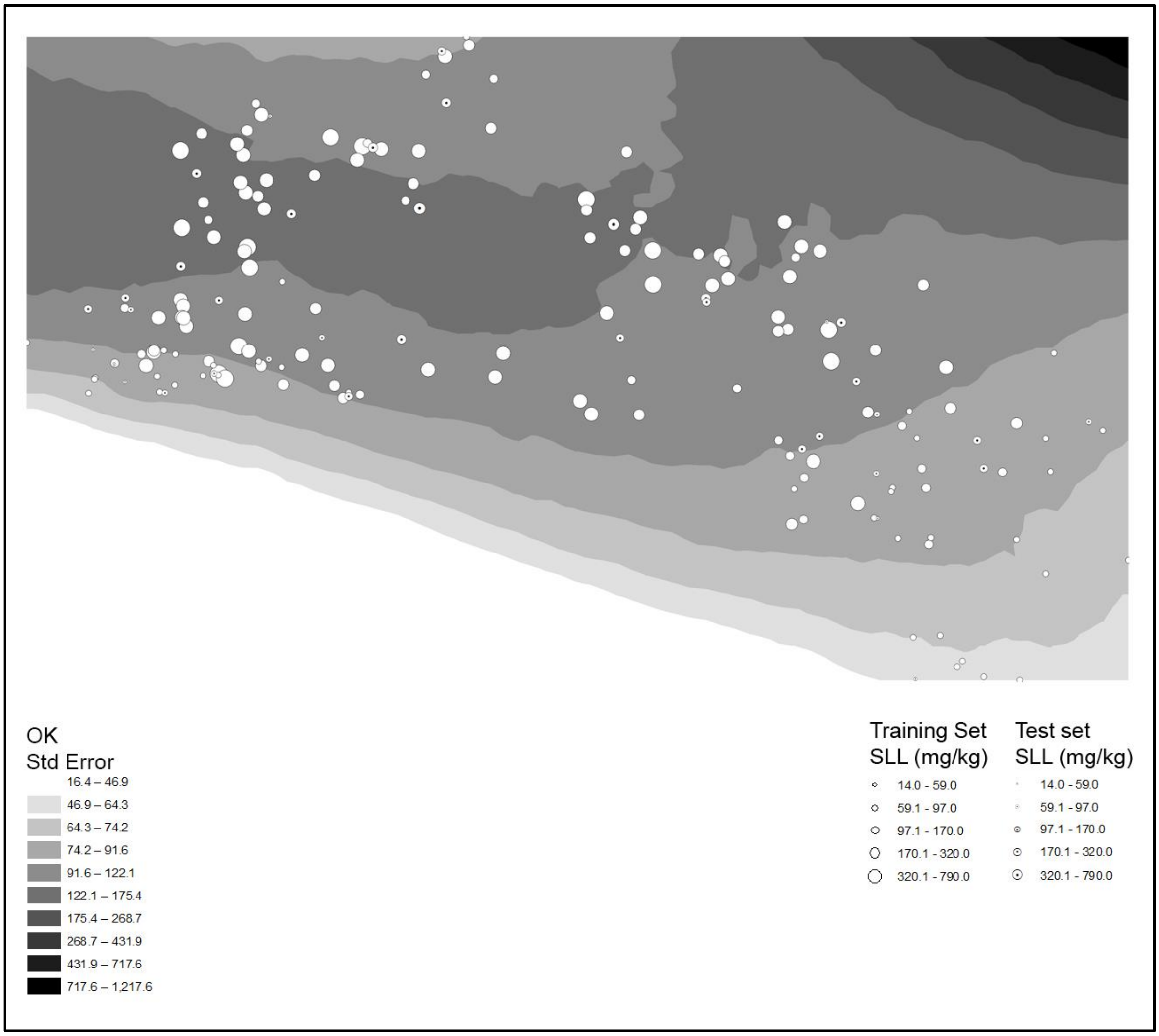



OLV Model
SLL (mg/kg)
43.1 - 96.6
96.7 - 164.3
164.4 - 225.2
225.3 - 290.1
290.2 - 365.0
365.1 - 456.0
456.1 - 559.6
559.7 - 698.3
698.4 - 1007.2
1007.3 - 1842.7
Training Set
SLL (mg/kg)
14.0 - 59.0
59.1 - 97.0
97.1 - 170.0
170.1 - 320.0
320.1 - 790.0
Test set
SLL (mg/kg)
14.0 - 59.0
59.1 - 97.0
97.1 - 170.0
170.1 - 320.0
320.1 - 790.0


EBK
SLL (mg/kg)
14 – 36.7
36.7 – 50.1
50.1 – 58.2
58.2 – 71.6
71.6 – 94.3
94.3 – 132.4
132.4 – 196.5
196.5 – 304.2
304.2 – 485.4
485.4 – 790
Training Set
SLL (mg/kg)
14.0 - 59.0
59.1 - 97.0
97.1 - 170.0
170.1 - 320.0
320.1 - 790.0
Test set
SLL (mg/kg)
14.0 - 59.0
59.1 - 97.0
97.1 - 170.0
170.1 - 320.0
320.1 - 790.0

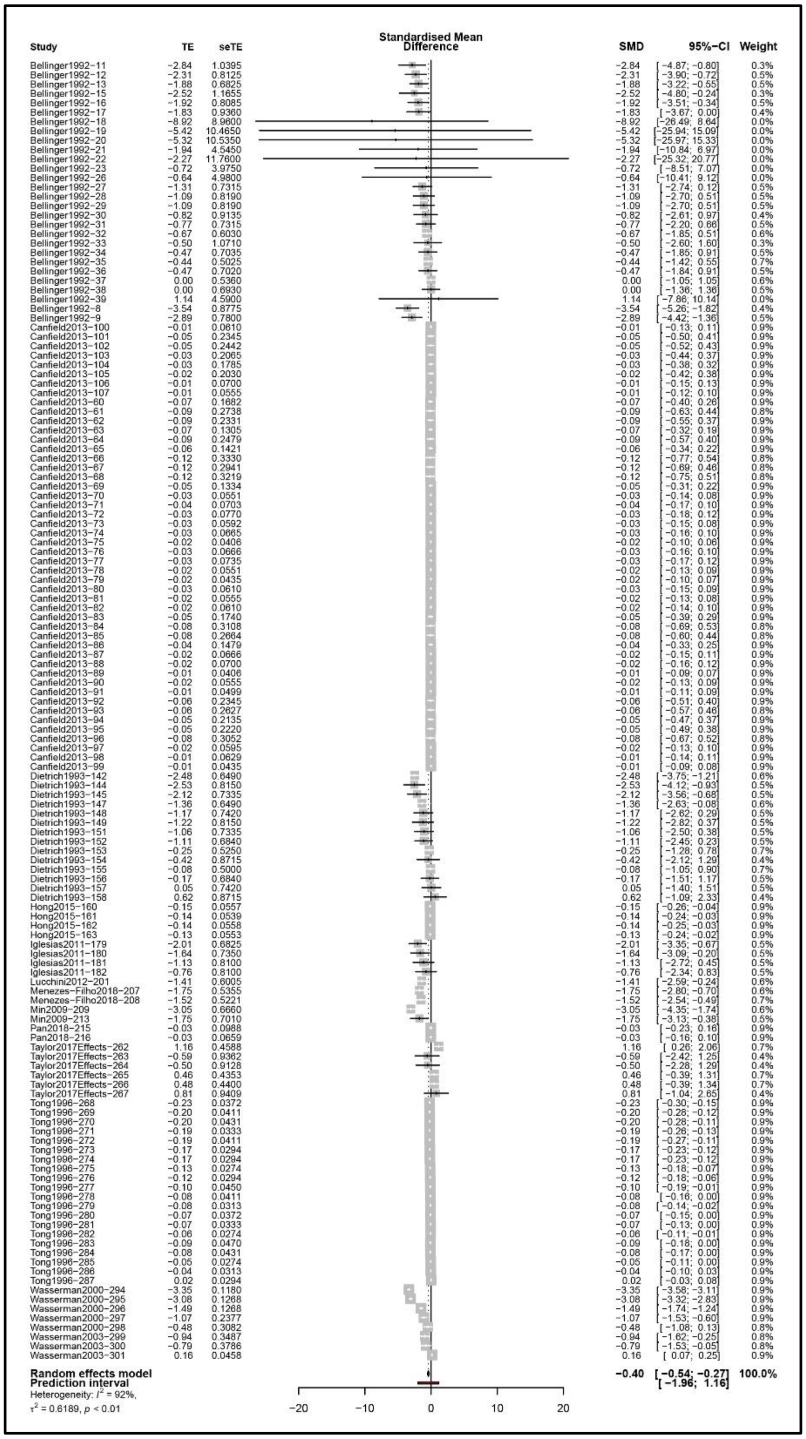

EBK
Std Error
16.4 – 46.9
46.9 – 64.3
64.3 – 74.2
74.2 – 91.6
91.6 – 122.1
122.1 – 175.4
175.4 – 268.7
268.7 – 431.9
431.9 – 717.6
717.6 – 1,217.6
Training Set
SLL (mg/kg)
14.0 - 59.0
59.1 - 97.0
97.1 - 170.0
170.1 - 320.0
320.1 - 790.0
Test set
SLL (mg/kg)
14.0 - 59.0
59.1 - 97.0
97.1 - 170.0
170.1 - 320.0
320.1 - 790.0


OK
SLL (mg/kg)
14 – 36.7
36.7 – 50.1
50.1 – 58.2
58.2 – 71.6
71.6 – 94.3
94.3 – 132.4
132.4 – 196.5
196.5 – 304.2
304.2 – 485.4
485.4 – 790
Training Set
SLL (mg/kg)
14.0 - 59.0
59.1 - 97.0
97.1 - 170.0
170.1 - 320.0
320.1 - 790.0
Test set
SLL (mg/kg)
14.0 - 59.0
59.1 - 97.0
97.1 - 170.0
170.1 - 320.0
320.1 - 790.0

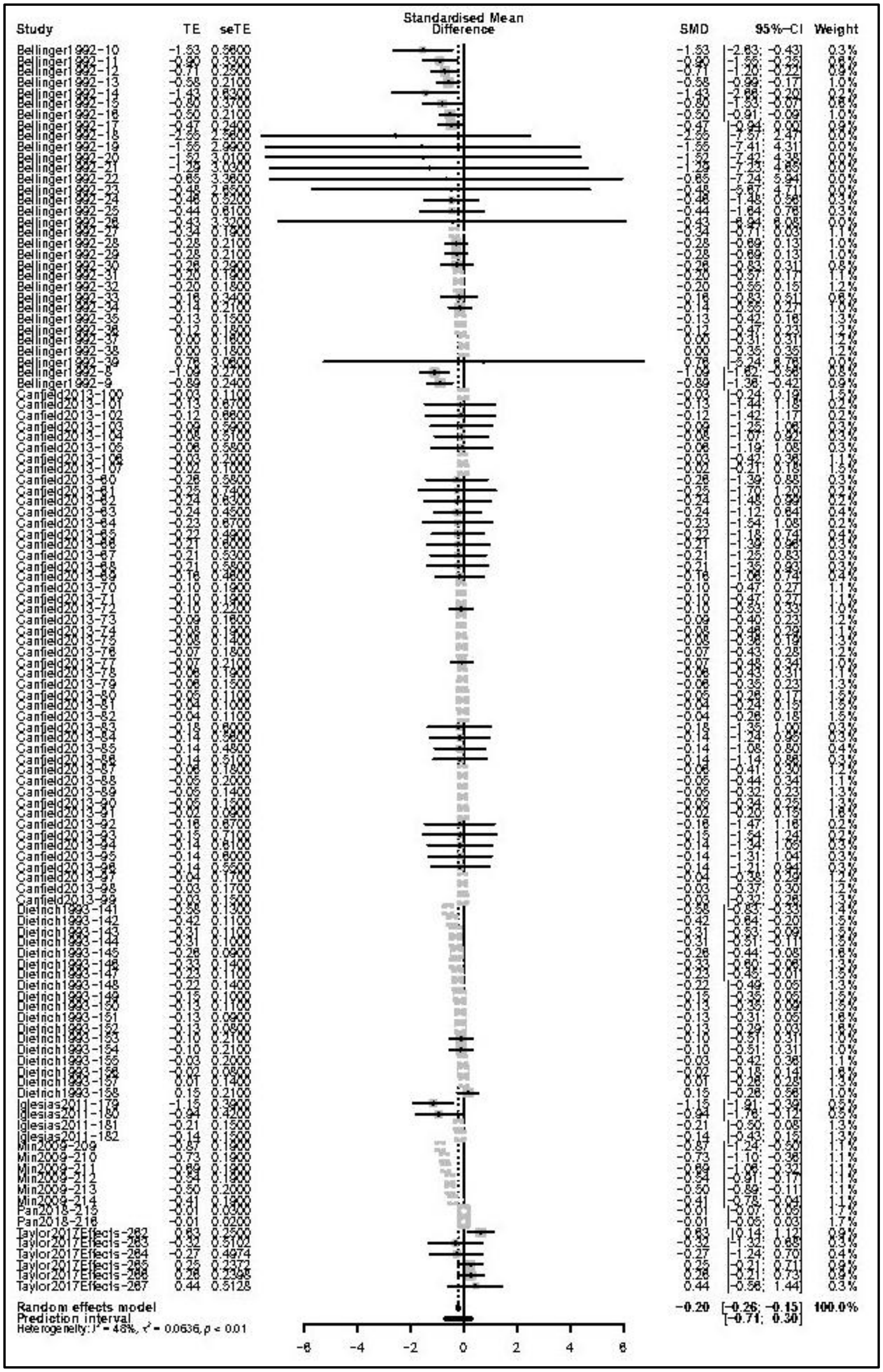

OK
Std Error
16.4 – 46.9
46.9 – 64.3
64.3 – 74.2
74.2 – 91.6
91.6 – 122.1
122.1 – 175.4
175.4 – 268.7
268.7 – 431.9
431.9 – 717.6
717.6 – 1,217.6
Training Set
SLL (mg/kg)
14.0 - 59.0
59.1 - 97.0
97.1 - 170.0
170.1 - 320.0
320.1 - 790.0
Test set
SLL (mg/kg)
14.0 - 59.0
59.1 - 97.0
97.1 - 170.0
170.1 - 320.0
320.1 - 790.0

6.5 Appendix E: Forest plots

6.5.1 Non-linear

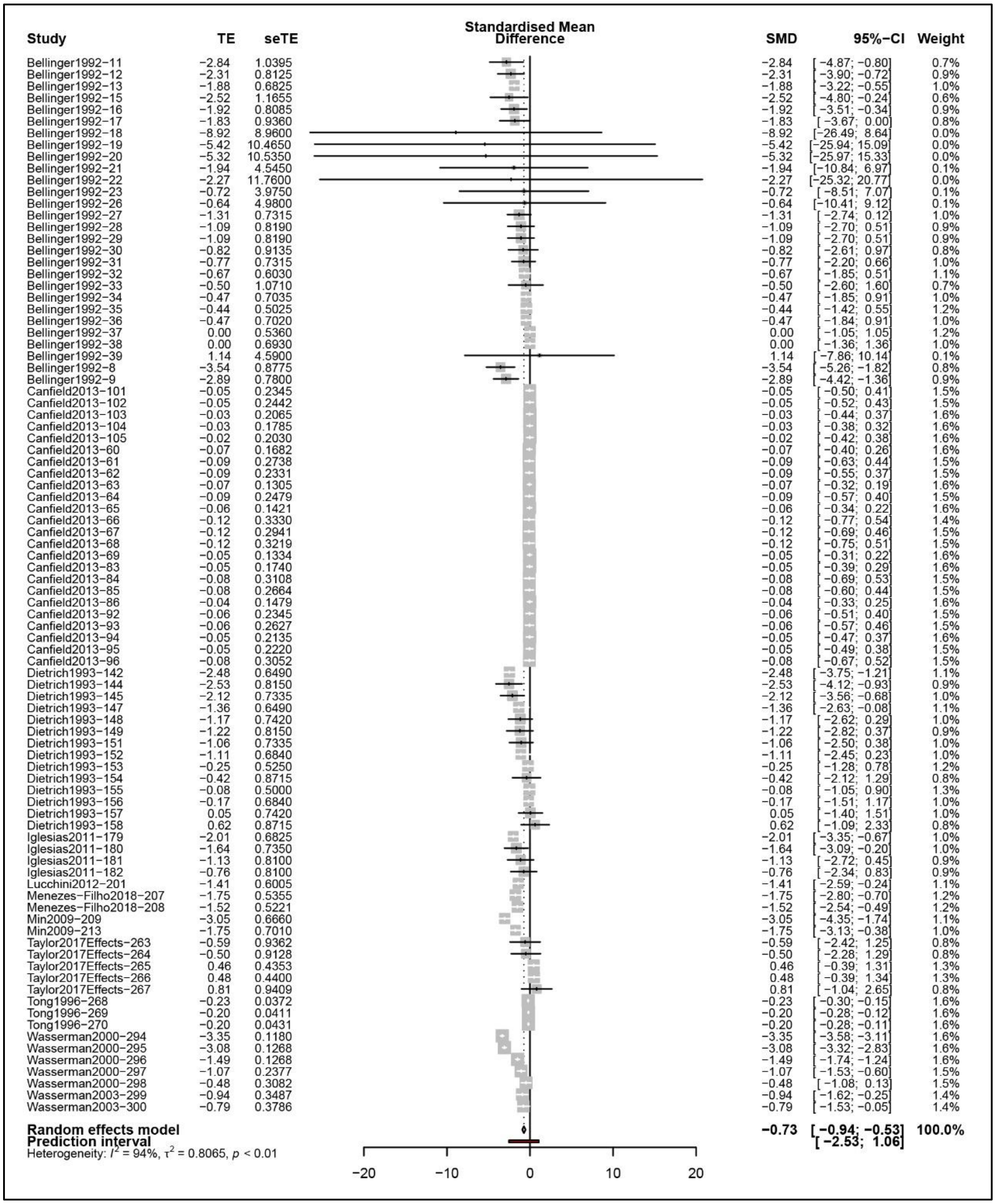


6.5.2 Linear

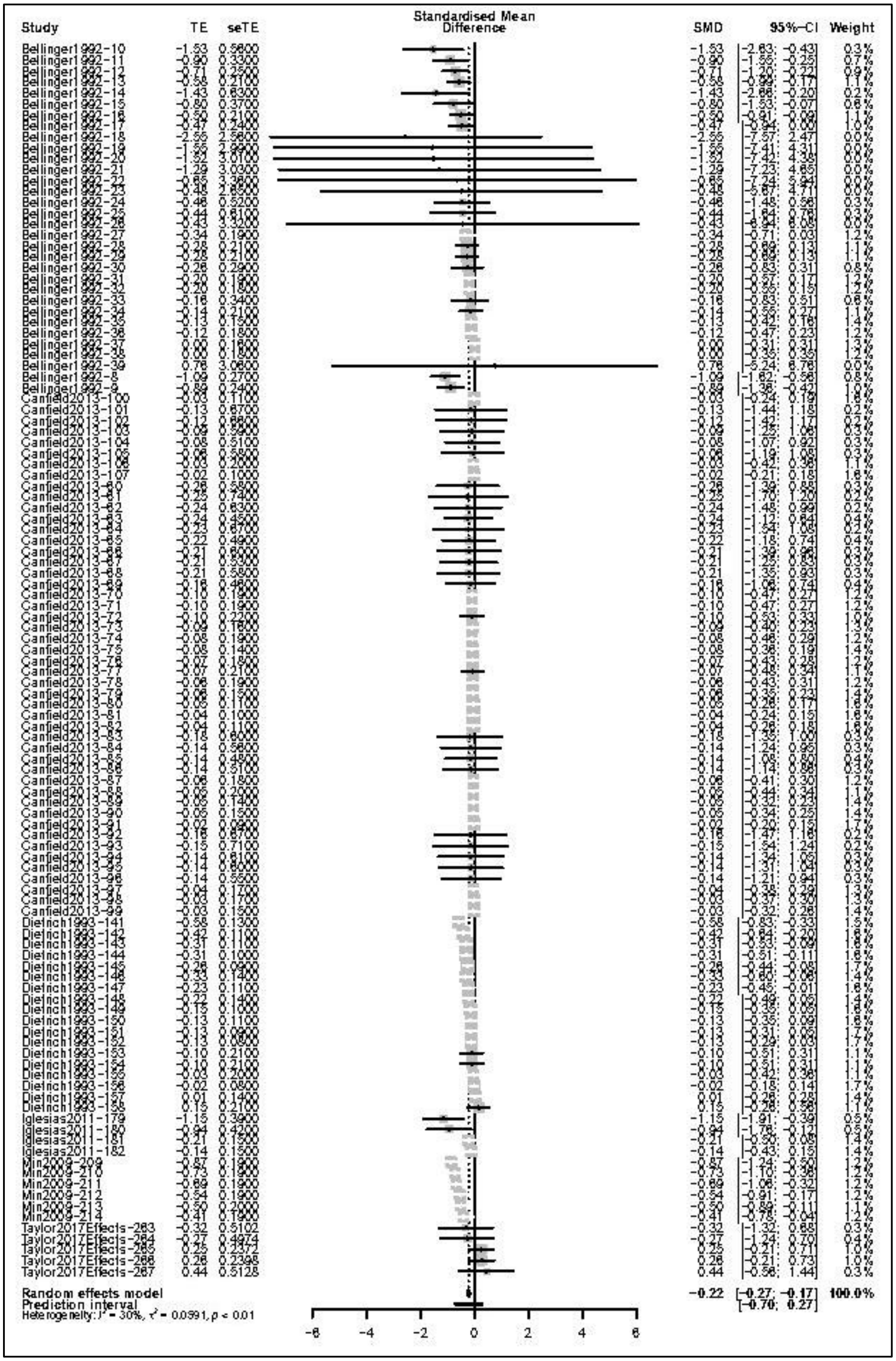

Study
TE
seTE
Standardised Mean Difference
SMD
95%-CI
Weight
Random effects model
Prediction interval
-0.20
[-0.26; -0.15]
100.0%
[-0.71; 0.30]
-6
-4
-2
0
2
4
6

6.6 Appendix F: Forest plots after simple outlier detection and removal

6.6.1 Non-linear

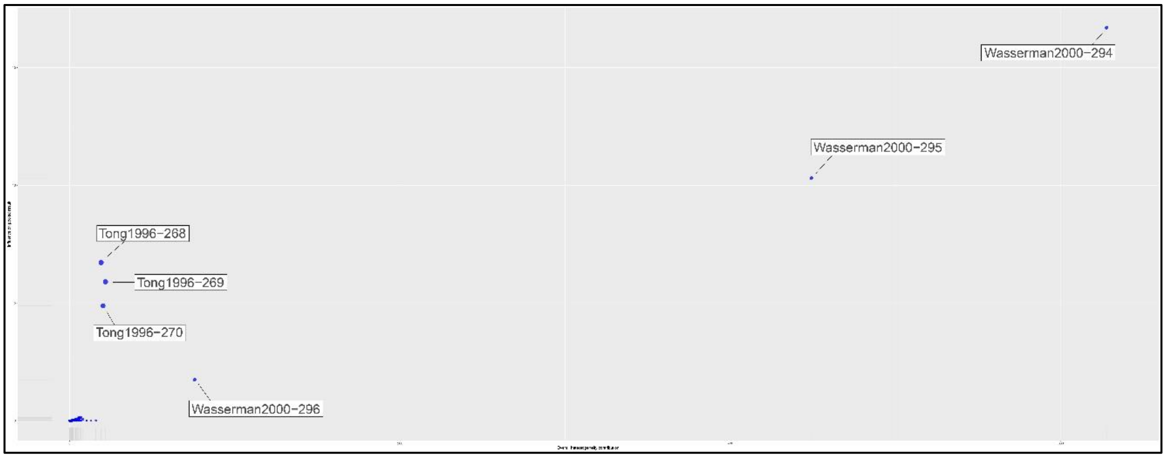


6.6.2 Linear

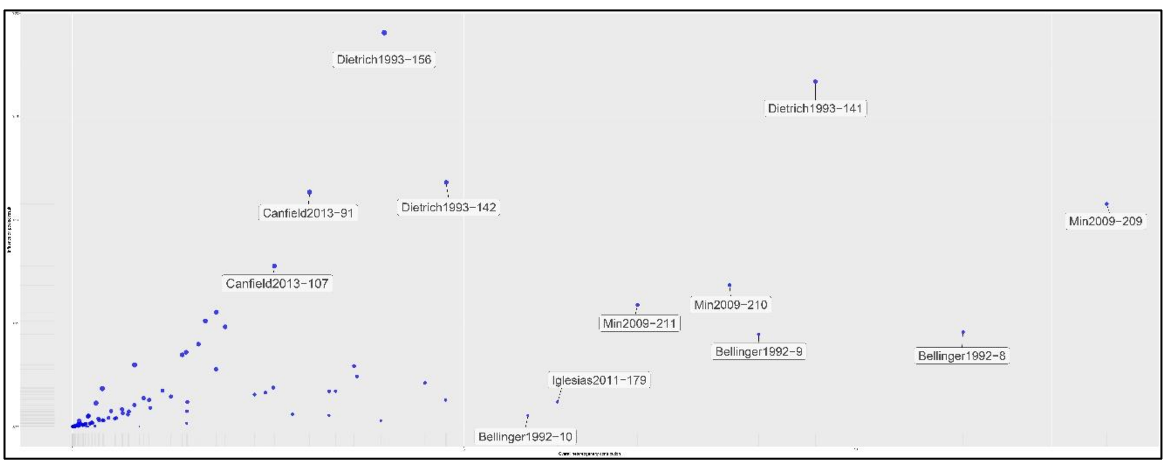

Study
TE
seTE
Standardised Mean Difference
SMD
95%-CI
Weight
Random effects model
Prediction interval
Heterogeneity: I^2 = 30%, τ^2 = 0.0391, p < 0.01
-0.22
[-0.27; -0.17]
100.0%
[-0.70; 0.27]
-6
-4
-2
0
2
4
6

6.7 Appendix G: Baujat plots

6.7.1 Non-linear

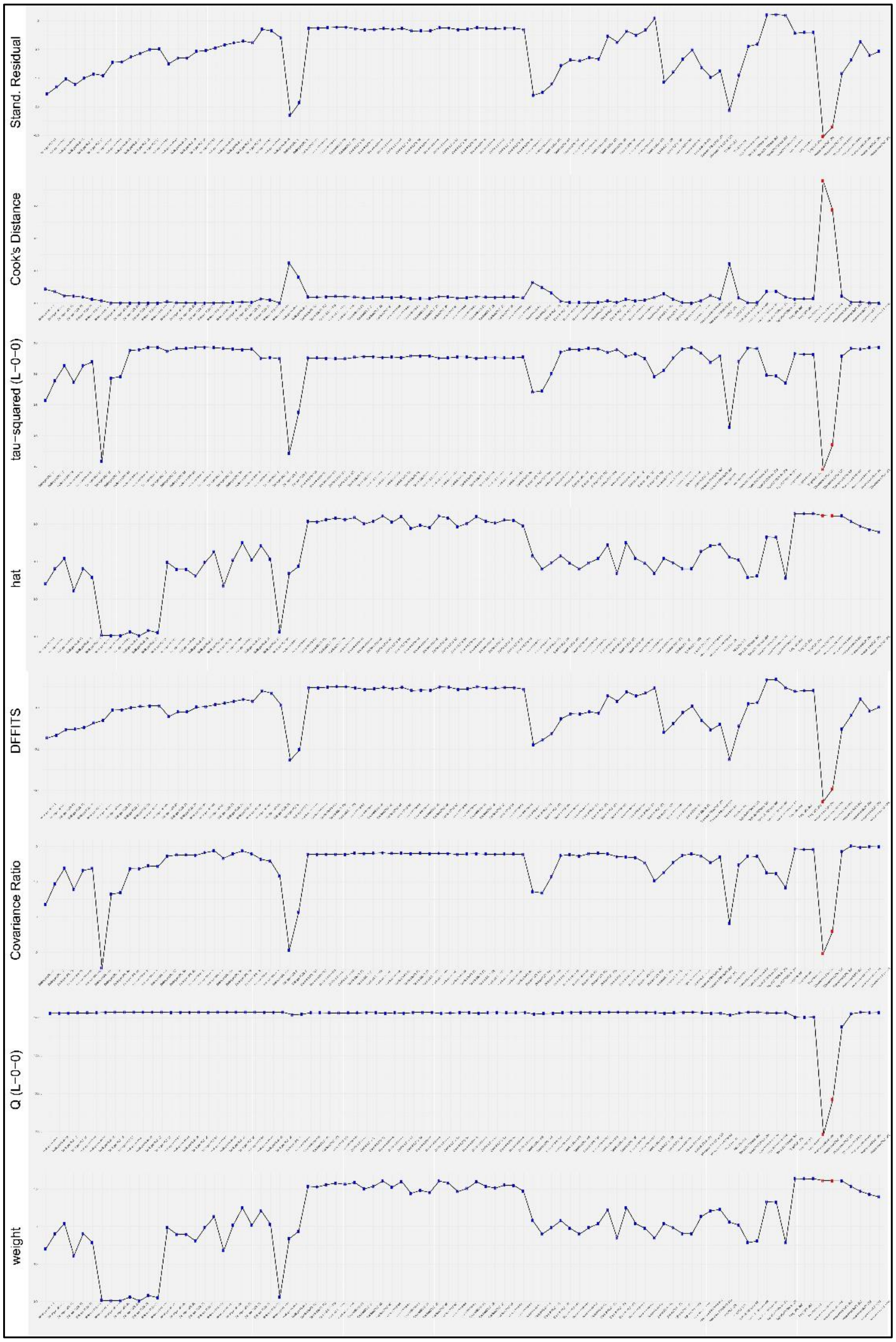


6.7.2 Linear

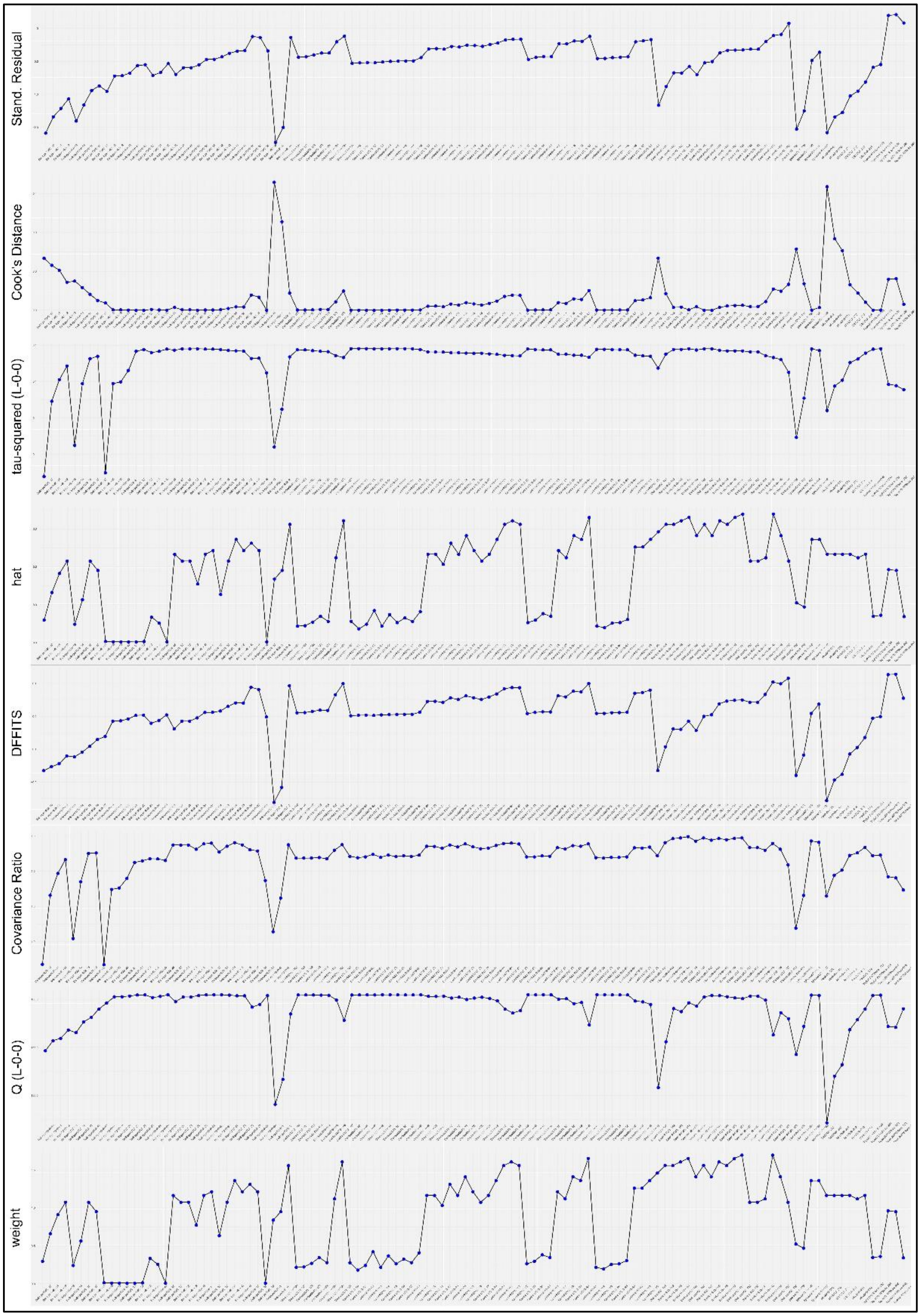


6.8 Appendix H: Influence characteristic graphs

6.8.1 Non-linear

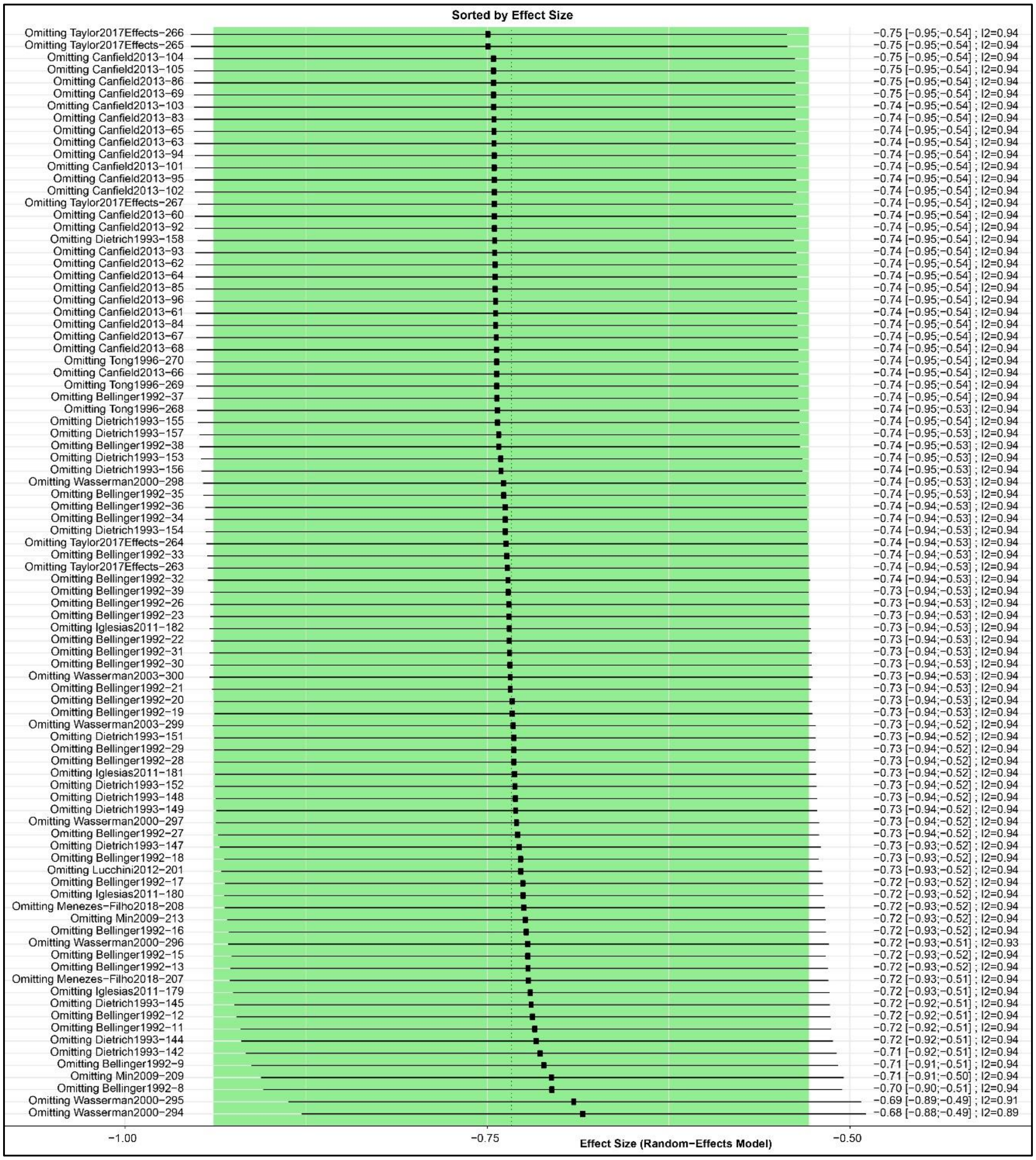


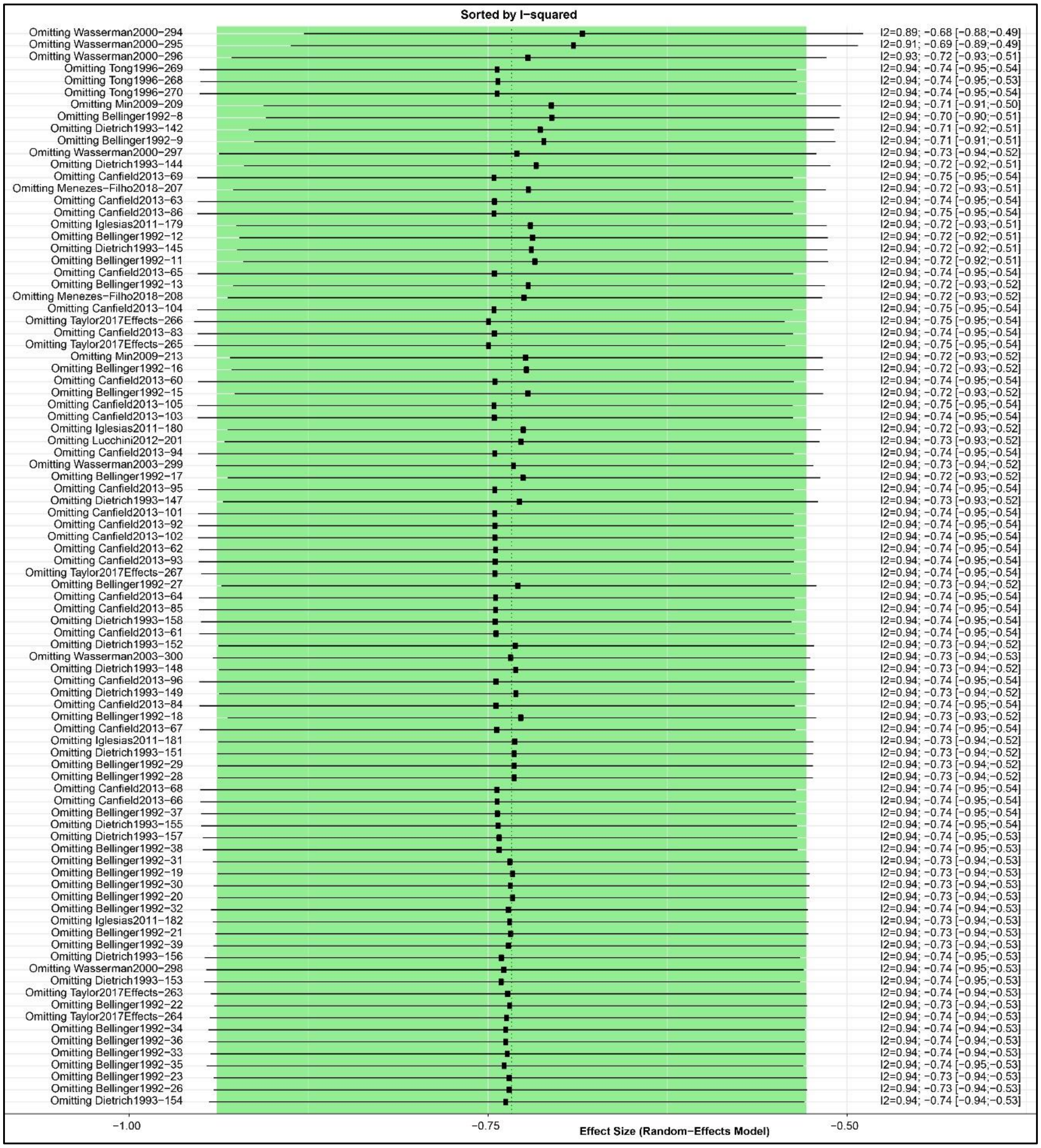
6.8.2 Linear


Stand. Residual
Cook's Distance
tau-squared (L-0-0)
hat
DFFITS
Covariance Ratio
Q (L-0-0)
weight

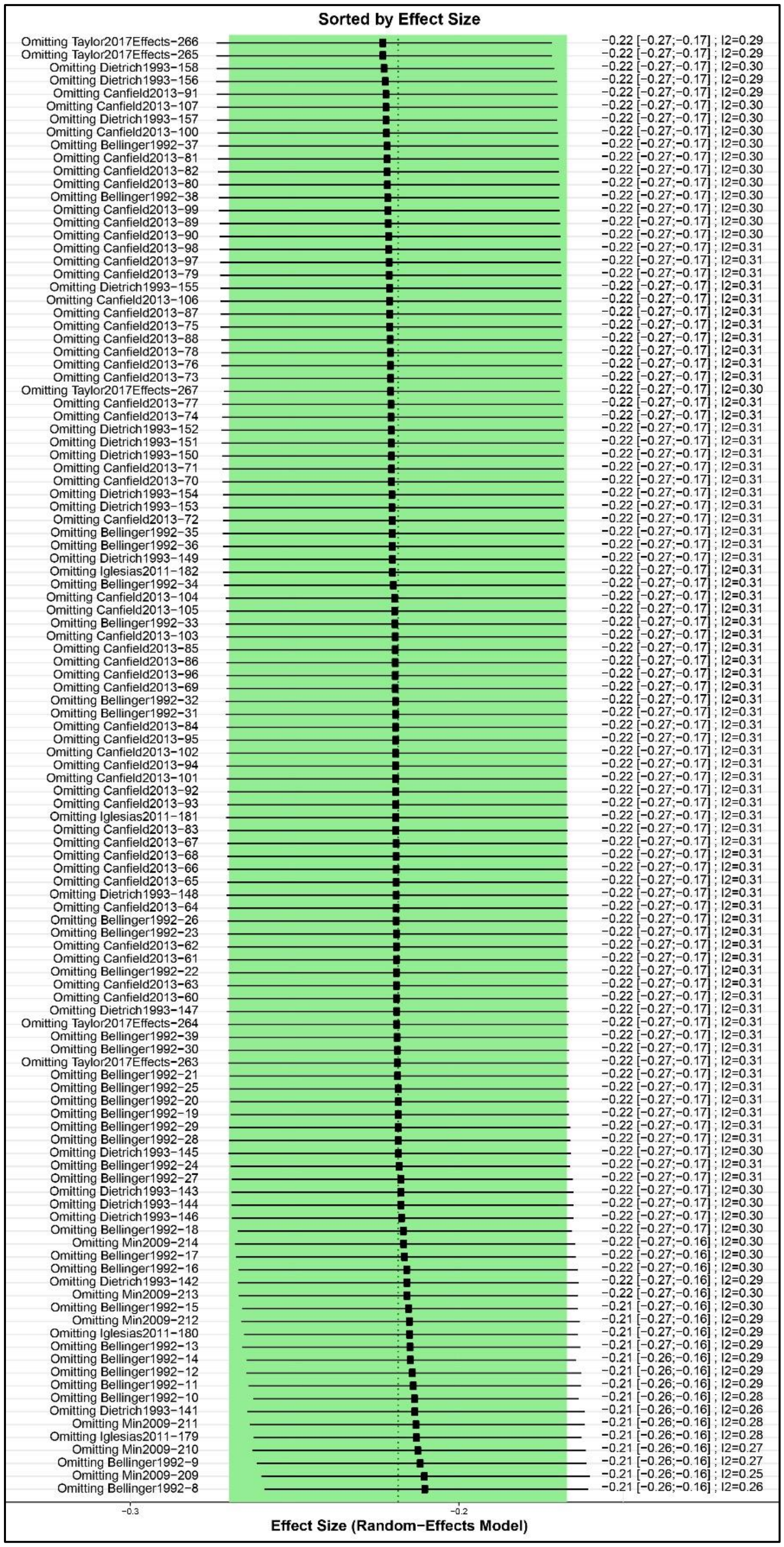
6.9 Appendix I: Forest plots for leave-one-out analysis, sorted by pooled result and I^2

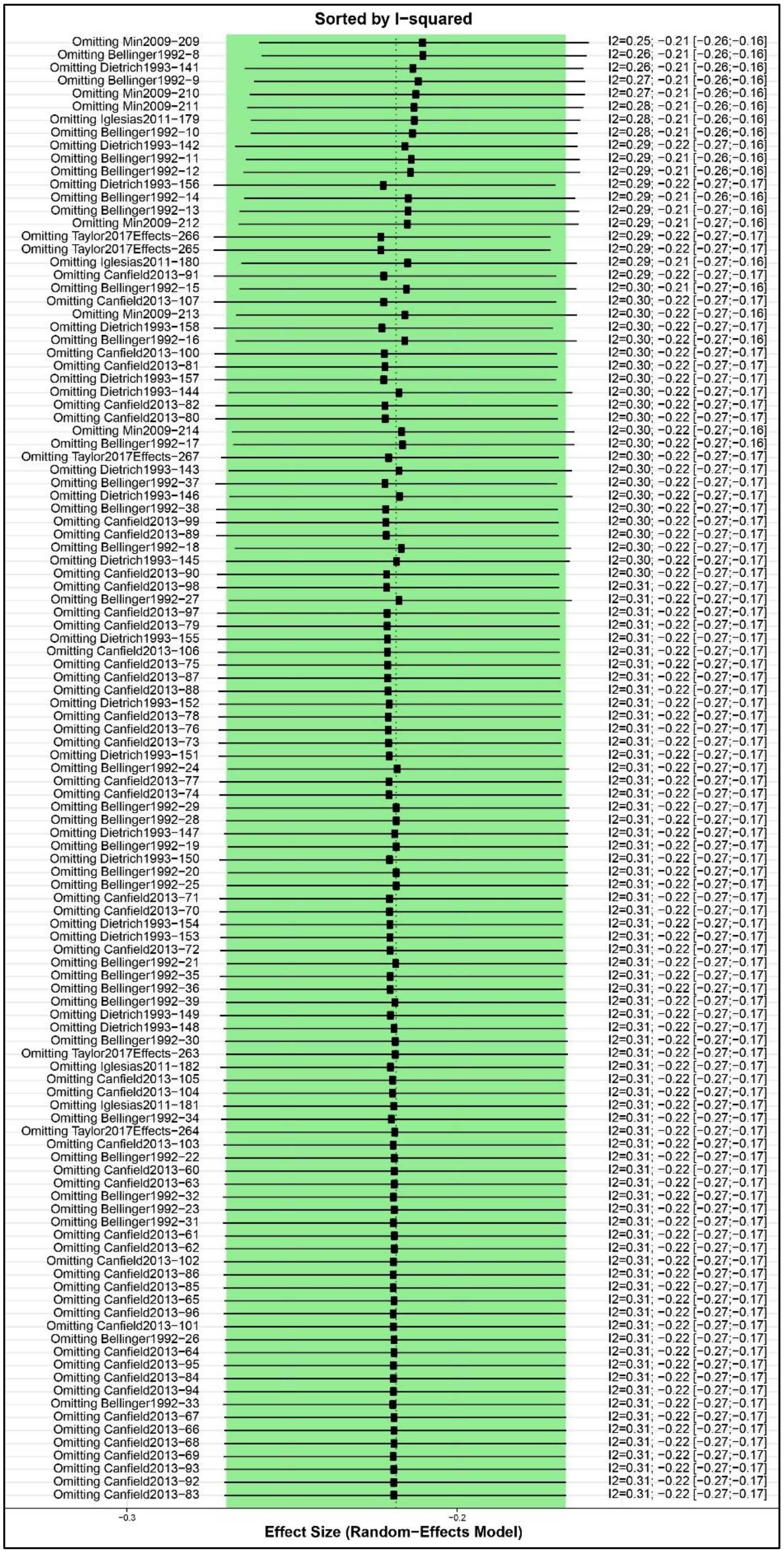
6.9.1 Non-linear




Sorted by I−squared
Effect Size (Random−Effects Model)

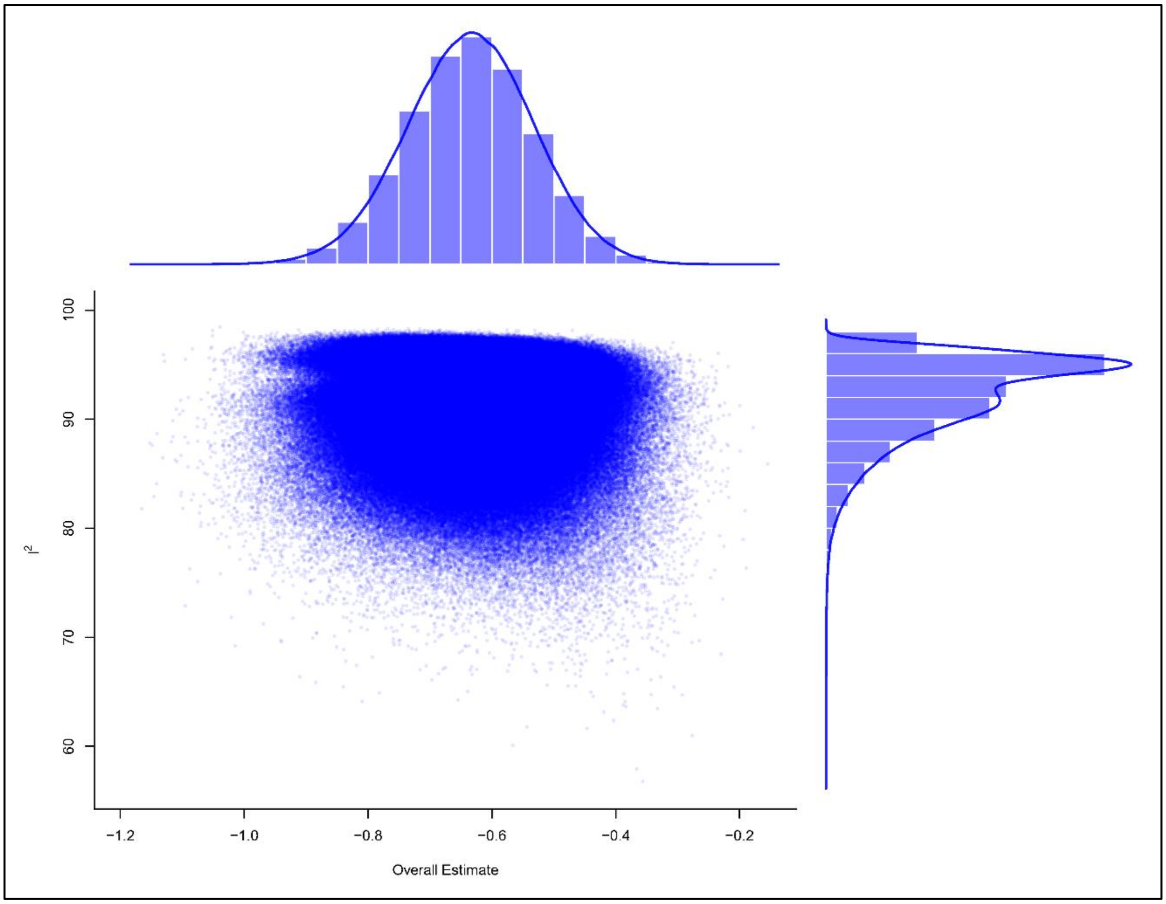
6.9.2 Linear


Sorted by Effect Size
Omitting Taylor2017Effects−266 −0.22 [−0.27;−0.17] ; I2=0.29
Omitting Taylor2017Effects−265 −0.22 [−0.27;−0.17] ; I2=0.29
Omitting Dietrich1993−158 −0.22 [−0.27;−0.17] ; I2=0.30
Omitting Dietrich1993−156 −0.22 [−0.27;−0.17] ; I2=0.29
Omitting Canfield2013−91 −0.22 [−0.27;−0.17] ; I2=0.29
Omitting Canfield2013−107 −0.22 [−0.27;−0.17] ; I2=0.30
Omitting Dietrich1993−157 −0.22 [−0.27;−0.17] ; I2=0.30
Omitting Canfield2013−100 −0.22 [−0.27;−0.17] ; I2=0.30
Omitting Bellinger1992−37 −0.22 [−0.27;−0.17] ; I2=0.30
Omitting Canfield2013−81 −0.22 [−0.27;−0.17] ; I2=0.30
Omitting Canfield2013−82 −0.22 [−0.27;−0.17] ; I2=0.30
Omitting Canfield2013−80 −0.22 [−0.27;−0.17] ; I2=0.30
Omitting Bellinger1992−38 −0.22 [−0.27;−0.17] ; I2=0.30
Omitting Canfield2013−99 −0.22 [−0.27;−0.17] ; I2=0.30
Omitting Canfield2013−89 −0.22 [−0.27;−0.17] ; I2=0.30
Omitting Canfield2013−90 −0.22 [−0.27;−0.17] ; I2=0.30
Omitting Canfield2013−98 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−97 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−79 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Dietrich1993−155 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−106 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−87 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−75 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−88 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−78 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−76 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−73 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Taylor2017Effects−267 −0.22 [−0.27;−0.17] ; I2=0.30
Omitting Canfield2013−77 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−74 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Dietrich1993−152 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Dietrich1993−151 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Dietrich1993−150 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−71 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−70 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Dietrich1993−154 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Dietrich1993−153 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−72 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Bellinger1992−35 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Bellinger1992−36 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Dietrich1993−149 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Iglesias2011−182 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Bellinger1992−34 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−104 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−105 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Bellinger1992−33 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−103 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−85 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−86 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−96 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−69 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Bellinger1992−32 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Bellinger1992−31 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−84 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−95 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−102 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−94 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−101 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−92 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−93 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Iglesias2011−181 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−83 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−67 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−68 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−66 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−65 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Dietrich1993−148 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−64 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Bellinger1992−26 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Bellinger1992−23 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−62 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−61 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Bellinger1992−22 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−63 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Canfield2013−60 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Dietrich1993−147 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Taylor2017Effects−264 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Bellinger1992−39 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Bellinger1992−30 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Taylor2017Effects−263 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Bellinger1992−21 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Bellinger1992−25 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Bellinger1992−20 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Bellinger1992−19 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Bellinger1992−29 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Bellinger1992−28 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Dietrich1993−145 −0.22 [−0.27;−0.17] ; I2=0.30
Omitting Bellinger1992−24 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Bellinger1992−27 −0.22 [−0.27;−0.17] ; I2=0.31
Omitting Dietrich1993−143 −0.22 [−0.27;−0.17] ; I2=0.30
Omitting Dietrich1993−144 −0.22 [−0.27;−0.17] ; I2=0.30
Omitting Dietrich1993−146 −0.22 [−0.27;−0.17] ; I2=0.30
Omitting Bellinger1992−18 −0.22 [−0.27;−0.17] ; I2=0.30
Omitting Min2009−214 −0.22 [−0.27;−0.16] ; I2=0.30
Omitting Bellinger1992−17 −0.22 [−0.27;−0.16] ; I2=0.30
Omitting Bellinger1992−16 −0.22 [−0.27;−0.16] ; I2=0.30
Omitting Dietrich1993−142 −0.22 [−0.27;−0.16] ; I2=0.29
Omitting Min2009−213 −0.22 [−0.27;−0.16] ; I2=0.30
Omitting Bellinger1992−15 −0.21 [−0.27;−0.16] ; I2=0.30
Omitting Min2009−212 −0.21 [−0.27;−0.16] ; I2=0.29
Omitting Iglesias2011−180 −0.21 [−0.27;−0.16] ; I2=0.29
Omitting Bellinger1992−13 −0.21 [−0.27;−0.16] ; I2=0.29
Omitting Bellinger1992−14 −0.21 [−0.26;−0.16] ; I2=0.29
Omitting Bellinger1992−12 −0.21 [−0.26;−0.16] ; I2=0.29
Omitting Bellinger1992−11 −0.21 [−0.26;−0.16] ; I2=0.29
Omitting Bellinger1992−10 −0.21 [−0.26;−0.16] ; I2=0.28
Omitting Dietrich1993−141 −0.21 [−0.26;−0.16] ; I2=0.26
Omitting Min2009−211 −0.21 [−0.26;−0.16] ; I2=0.28
Omitting Iglesias2011−179 −0.21 [−0.26;−0.16] ; I2=0.28
Omitting Min2009−210 −0.21 [−0.26;−0.16] ; I2=0.27
Omitting Bellinger1992−9 −0.21 [−0.26;−0.16] ; I2=0.27
Omitting Min2009−209 −0.21 [−0.26;−0.16] ; I2=0.25
Omitting Bellinger1992−8 −0.21 [−0.26;−0.16] ; I2=0.26
−0.3
−0.2
Effect Size (Random−Effects Model)

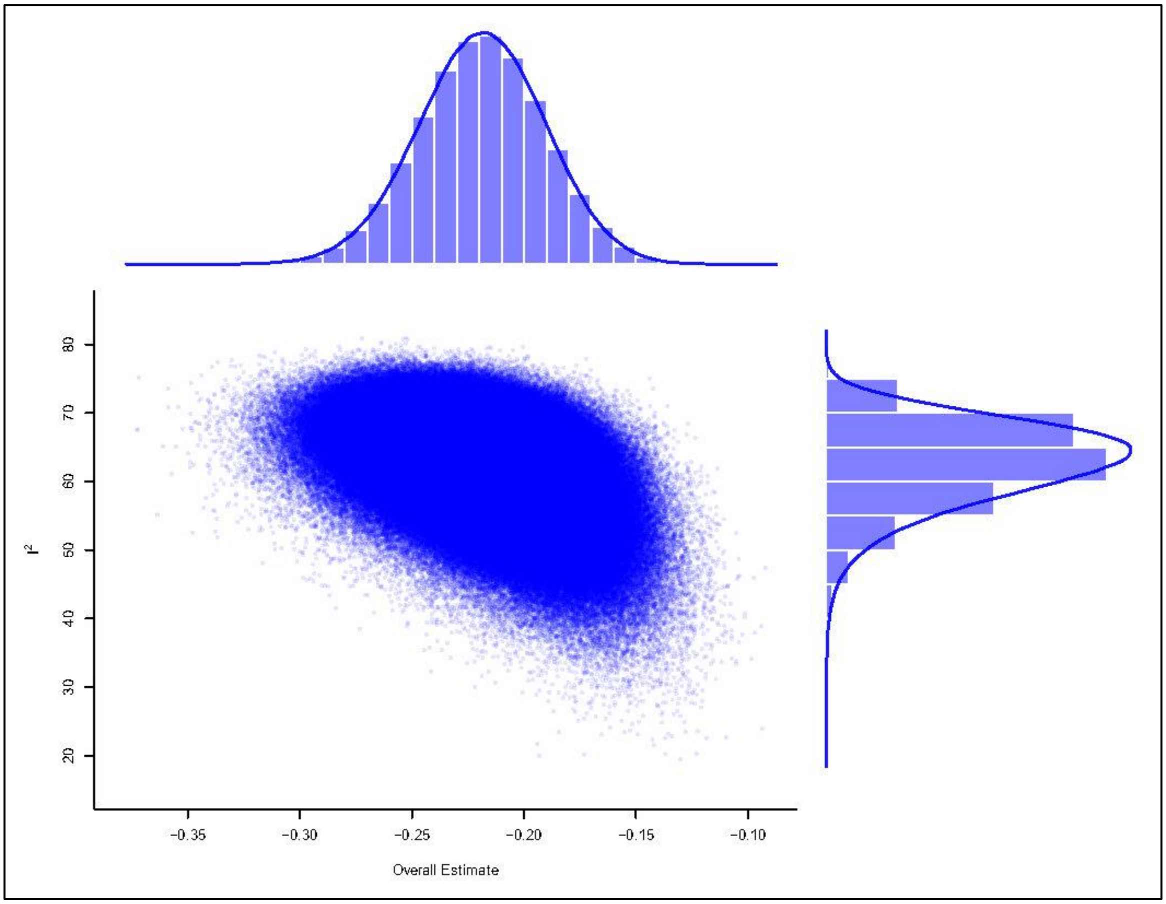

Sorted by I−squared
Effect Size (Random−Effects Model)
−0.3
−0.2

6.10 Appendix J: GOSH plots

6.10.1 Non-linear

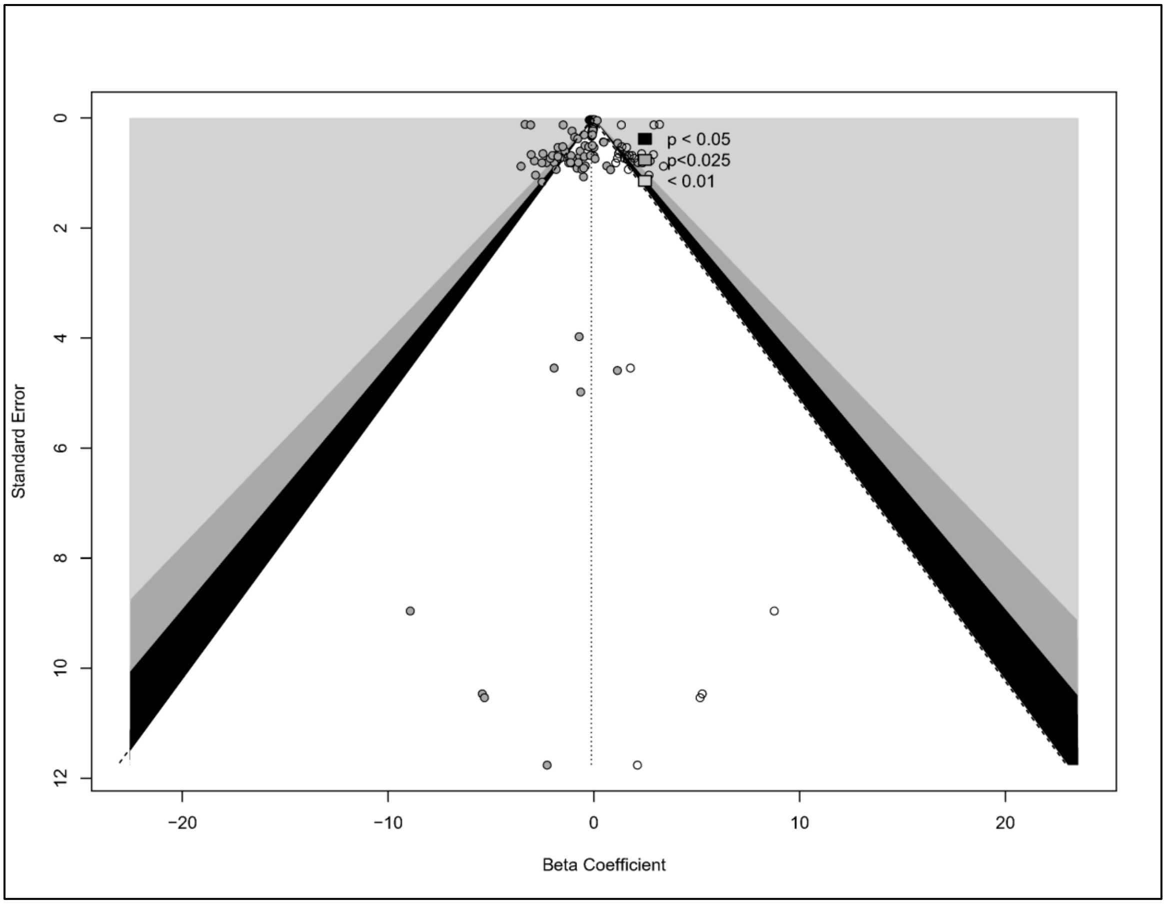


6.10.2 Linear

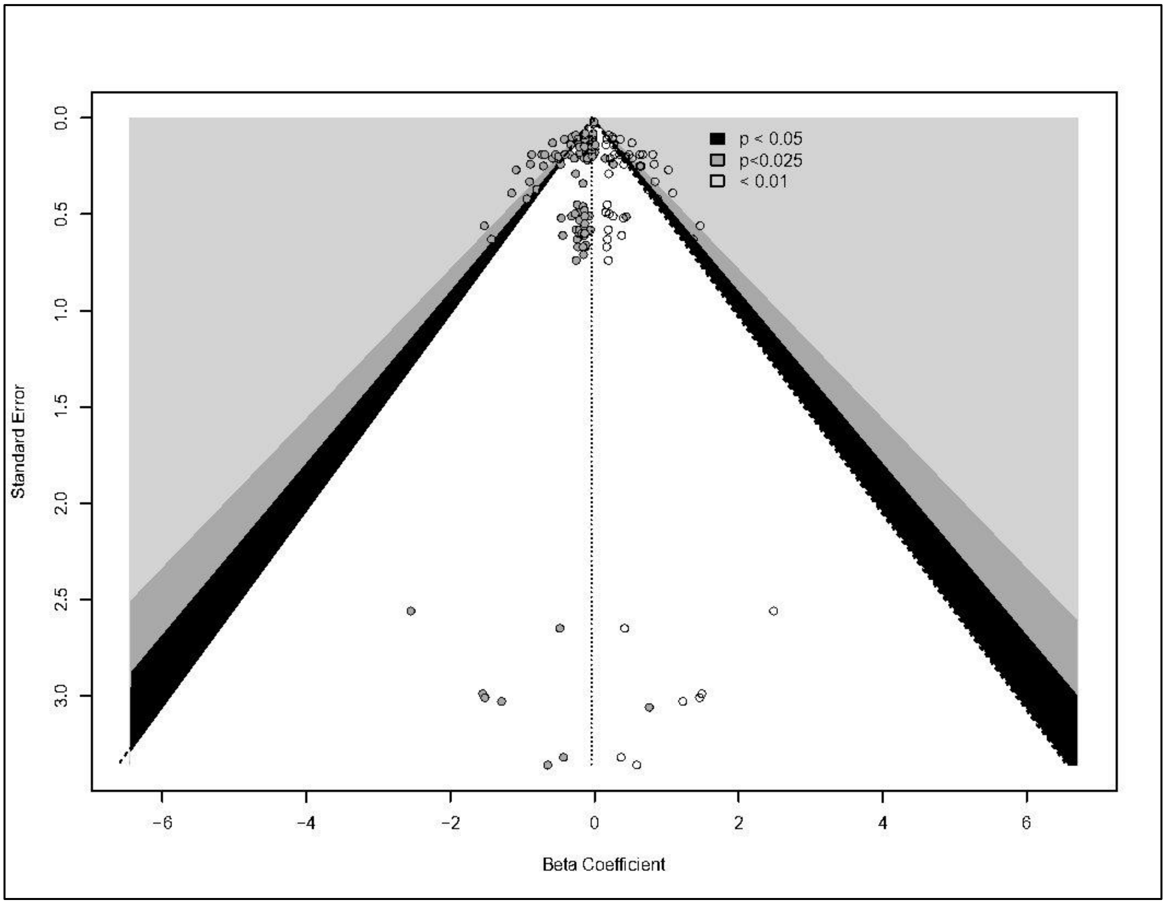


6.11 Appendix K: Funnel plots with *p*-value and trim-and-fill points

6.11.1 Non-linear

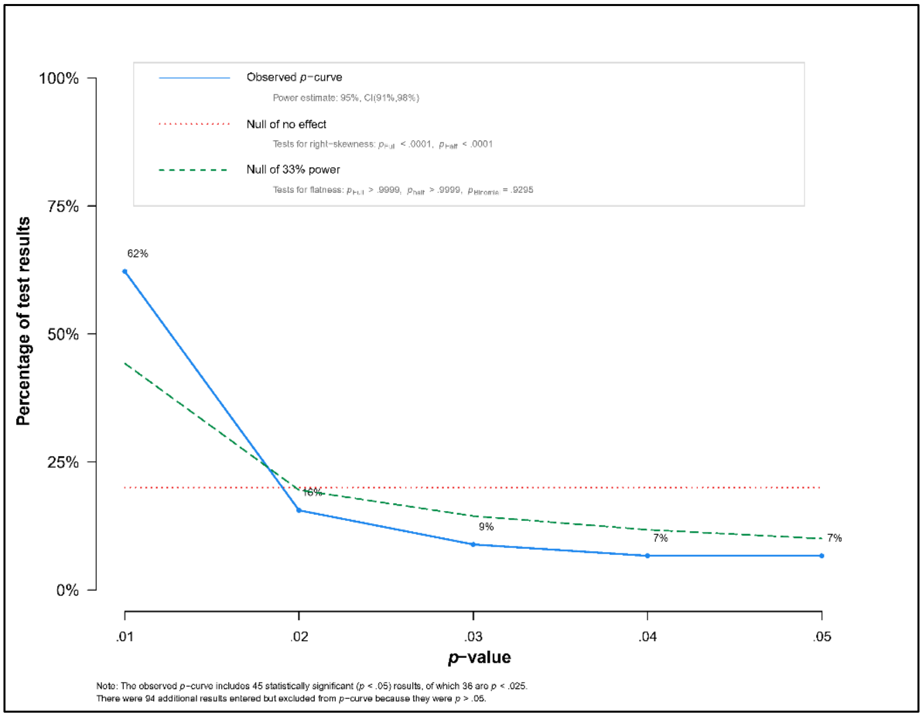


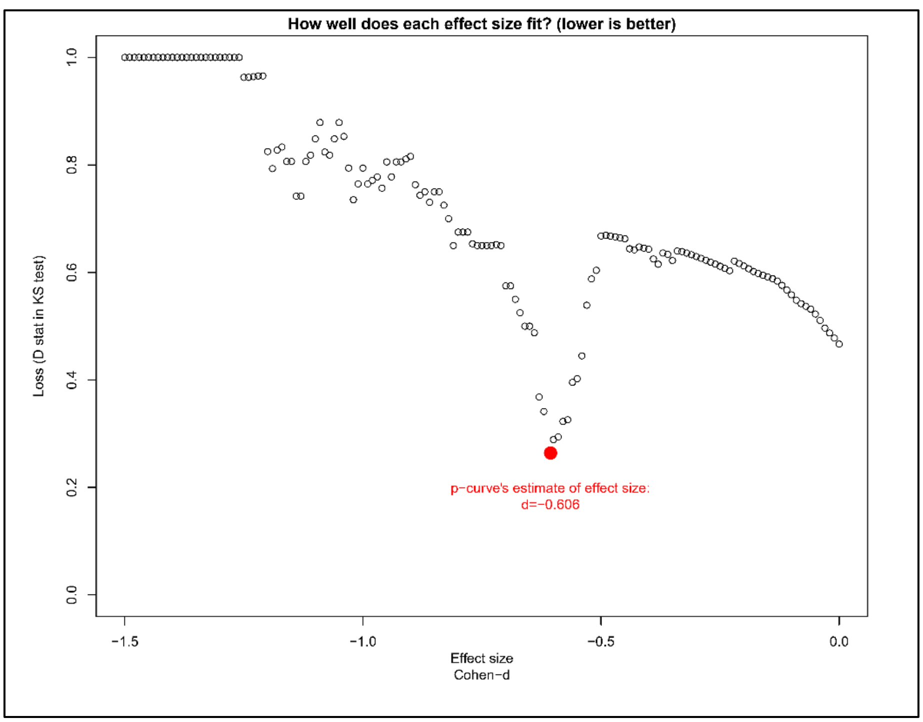
6.11.2 Linear


p < 0.05
p<0.025
< 0.01
Standard Error
0.0
0.5
1.0
1.5
2.0
2.5
3.0
−6
−4
−2
0
2
4
6
Beta Coefficient

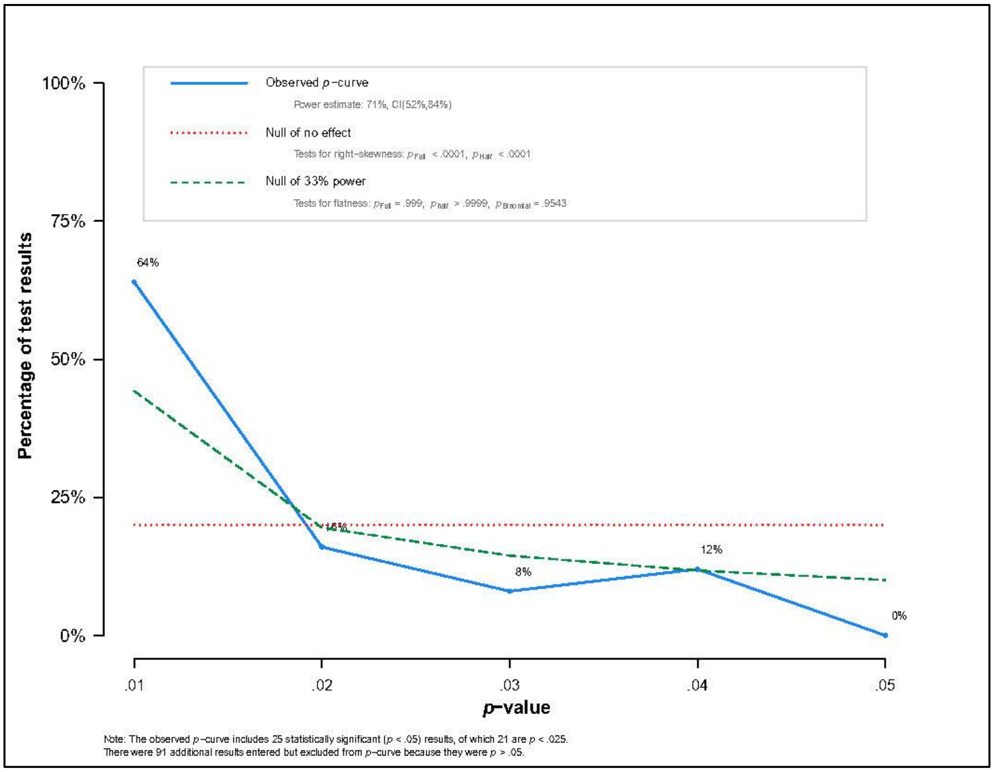
6.12 Appendix L: *P*-curve analysis

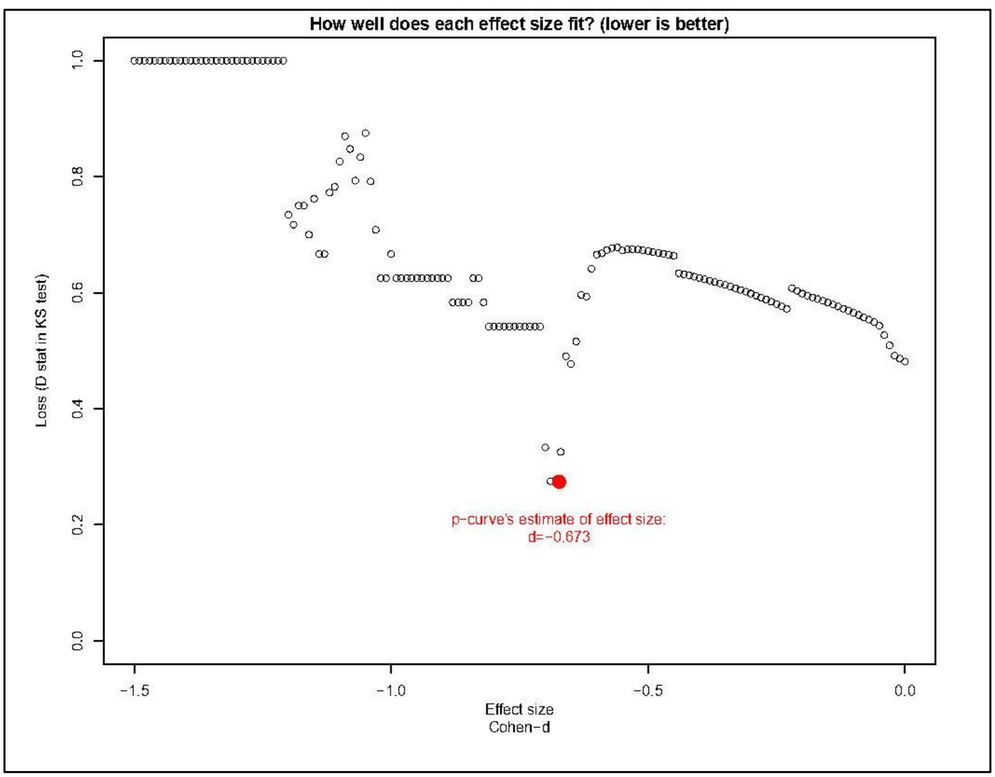
6.12.1 Non-linear



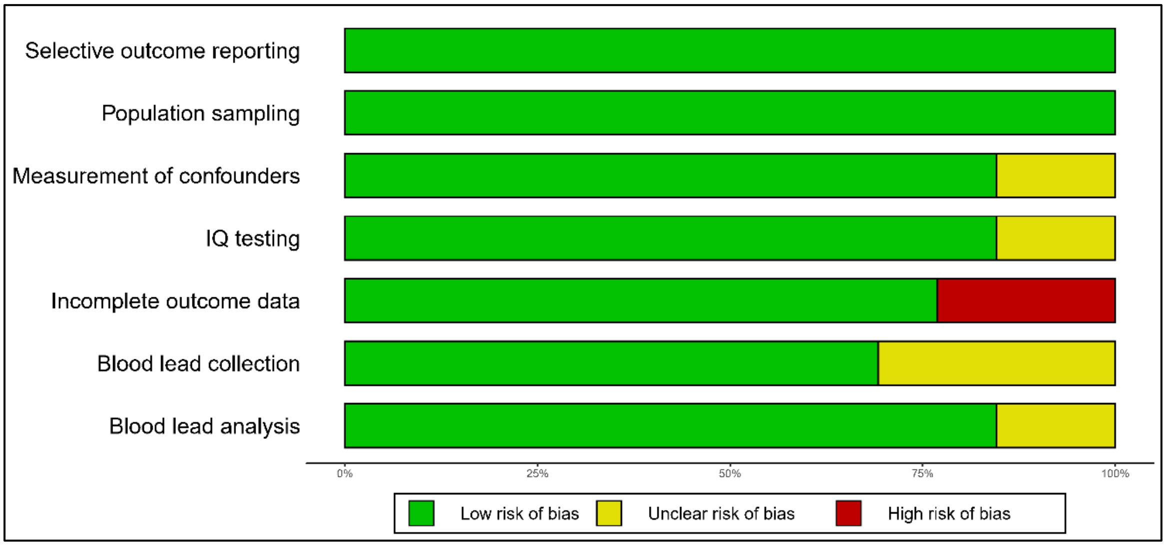


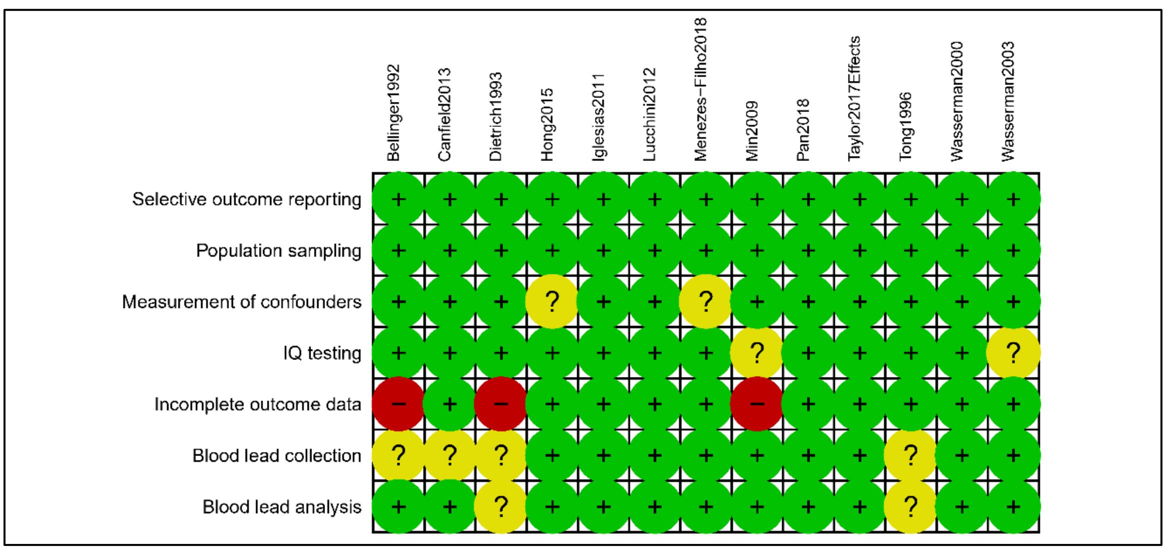
6.12.2 Linear


Observed p−curve
Power estimate: 71%, CI(52%,84%)
Null of no effect
Tests for right−skewness: pFull < .0001, pHalf < .0001
Null of 33% power
Tests for flatness: pFull = .999, pHalf > .9999, pBinomial = .9543
100%
75%
50%
25%
0%
Percentage of test results
64%
16%
8%
12%
0%
.01
.02
.03
.04
.05
p−value
Note: The observed p−curve includes 25 statistically significant (p < .05) results, of which 21 are p < .025.
There were 91 additional results entered but excluded from p−curve because they were p > .05.


How well does each effect size fit? (lower is better)
Loss (D stat in KS test)
1.0
0.8
0.6
0.4
0.2
0.0
p−curve's estimate of effect size:
d=−0.673
−1.5
−1.0
−0.5
0.0
Effect size
Cohen−d

6.13 Appendix M: Risk of bias summary





6.14 Appendix N: Hazard quotient calculation

6.14.1 Functions and assumptions

$$\text{Hazard Quotient} = \frac{\text{Estimated Exposure (Dose) (mg/kg bw/day)}}{\text{Tolerable Daily Intake (TDI) (mg/kg bw/day)}}$$

$$\underset{\text{(mg/kg bw/day)}}{\text{Estimated Exposure (Dose)}} = \frac{C_s * IR_s * RAF_{oral} * D_2 * D_3}{BW}$$

Where (Health Canada, 2010):
C_s = Concentration in soil (mg/kg)
IR_s = Soil ingestion rate (kg/day)
RAF_{oral} = Relative absorption factor from the gastrointestinal tract
D_2 = Days per week exposed (divided by 7 days)
D_3 = Weeks per year exposed (divided by 52 weeks)
BW = Body weight (kg)

Tolerable Daily Intake (TDI):
TDI relating to a blood lead level of 2 µg/dL = 0.0006 mg/kg bw/day (SNC-Lavalin, 2012)

Conversion factor for 5 µg/dL = 5 µg/dL / 2 µg/dL = 2.5

TDI relating to a blood lead level of 5 µg/dL = 0.0006 * 2.5 = 0.0015 mg/kg bw/day

Assumptions (Health Canada, 2010):

Characteristic	Infant	Toddler	Child
Age	0 – 6 mo.	7 mo. – 4 yr.	5 – 11 yr.
C_s (mg/kg)	SLL varies across space	SLL varies across space	SLL varies across space
IR_s (kg/day)	0.00002	0.00008	0.00002
RAF_{oral}	1.0	1.0	1.0
BW (kg)	8.2	16.5	32.9

6.14.2 Example hazard quotient calculation for a toddler without winter soil exposure

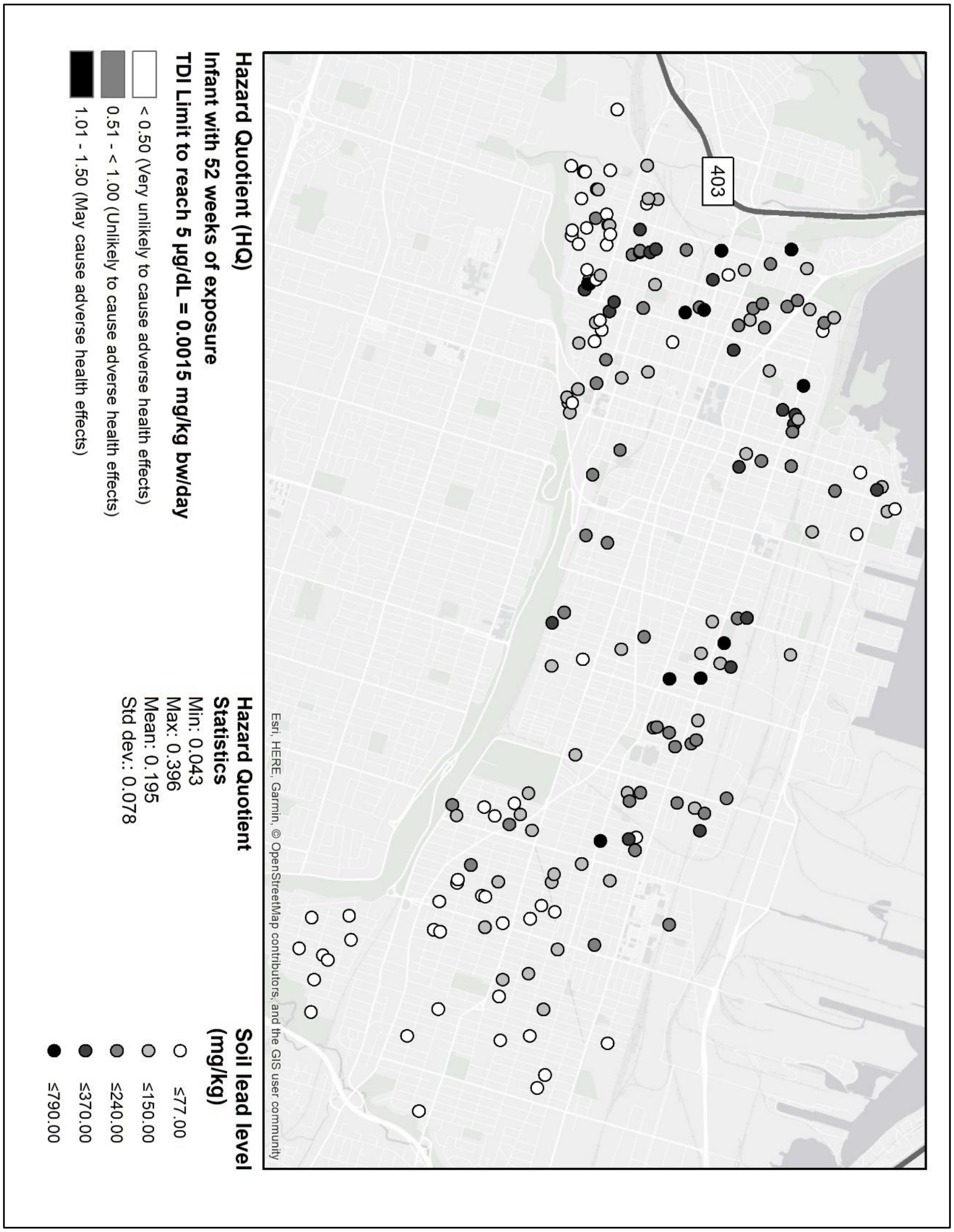
Given:
C_s = 250 mg/kg
IR_s = 0.00008 kg/day
RAF_{oral} = 1
D_2 = 7 days / 7 days = 1
D_3 = 40 weeks / 52 weeks = 0.769
BW = 16.5 kg
TDI relating to a blood lead level of 5 µg/dL = 0.0015 mg/kg bw/day

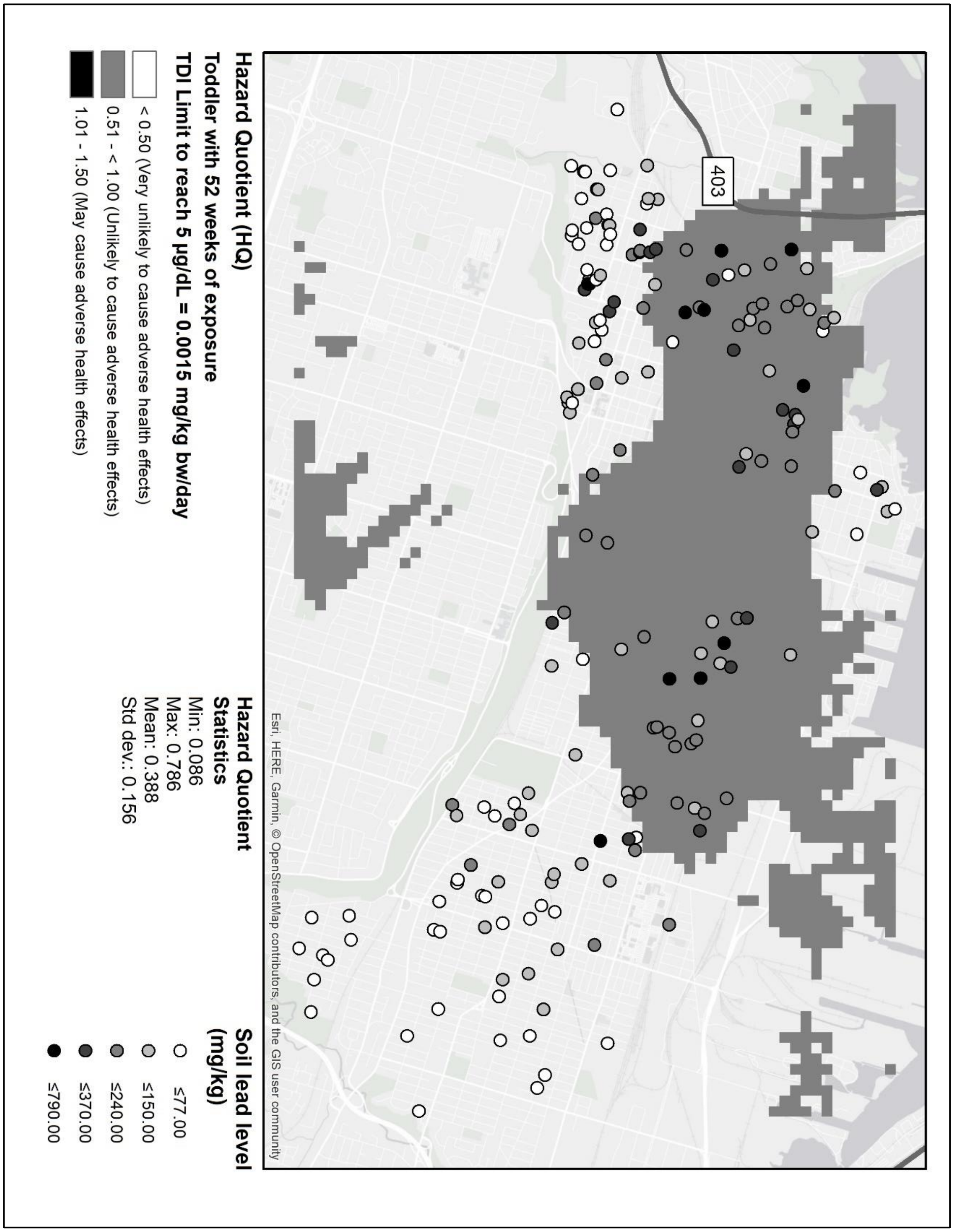
$$\text{Estimated Exposure (Dose)} = (\text{mg/kg bw/day}) \quad \frac{250 * 0.00008 * 1 * 1 * (40/52)}{16.5} = 0.00093240093$$

$$\text{Hazard Quotient} \quad \frac{0.00093240093}{0.0015} = 0.62160062$$

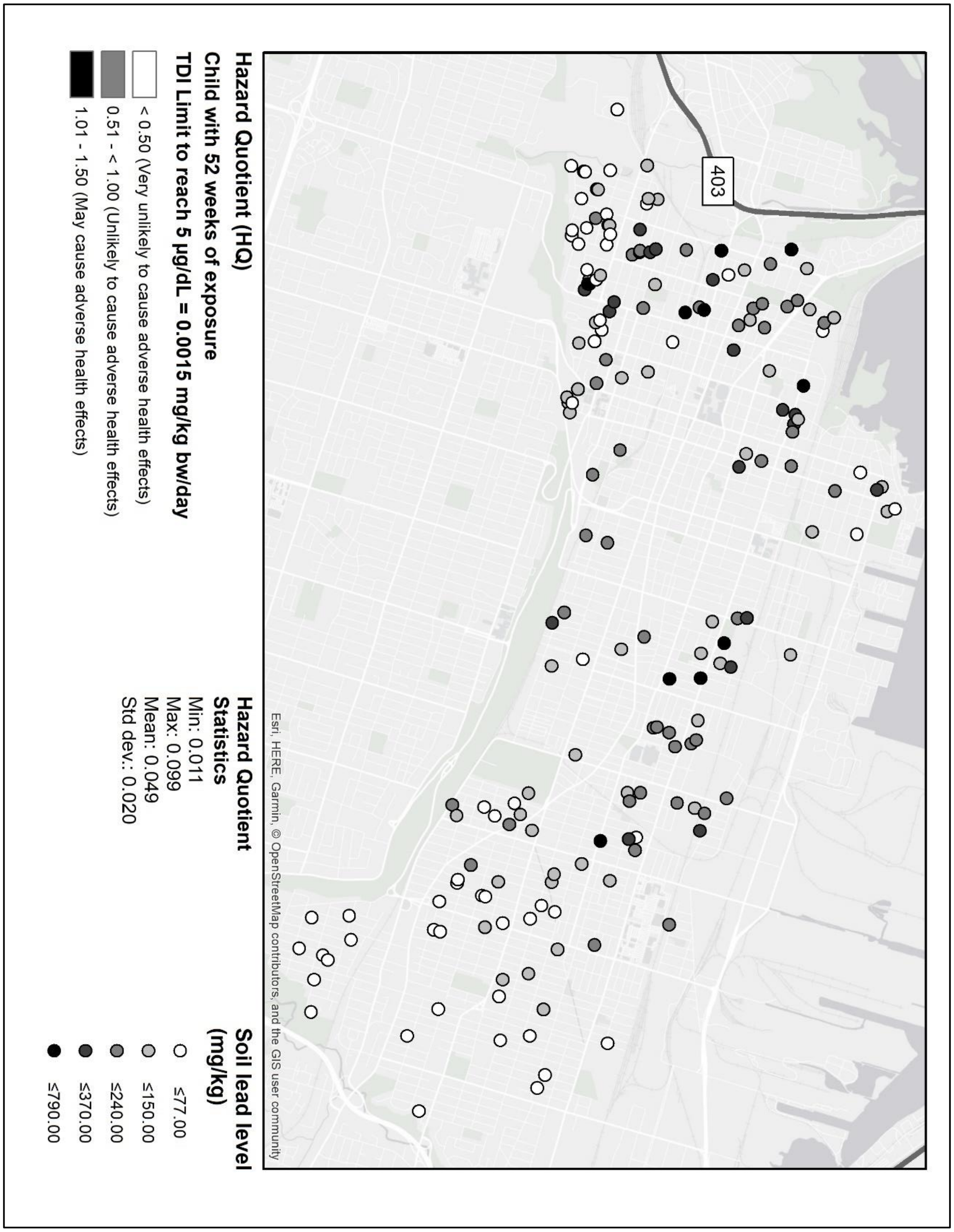
Therefore, the Hazard Quotient for a toddler without winter exposure is 0.62. In this example, the toddler will not likely be at-risk of developing adverse health effects associated with a blood lead level of 5 µg/dL or greater from soil exposure.

6.15 Appendix O: Hazard quotient maps with 52 weeks of exposure and TDI relating to 5 µg/dL





Hazard Quotient (HQ)
Toddler with 52 weeks of exposure
TDI Limit to reach 5 µg/dL = 0.0015 mg/kg bw/day
< 0.50 (Very unlikely to cause adverse health effects)
0.51 - < 1.00 (Unlikely to cause adverse health effects)
1.01 - 1.50 (May cause adverse health effects)
Hazard Quotient Statistics
Min: 0.086
Max: 0.786
Mean: 0.388
Std dev.: 0.156
Soil lead level (mg/kg)
≤77.00
≤150.00
≤240.00
≤370.00
≤790.00
403
Esri, HERE, Garmin, © OpenStreetMap contributors, and the GIS user community


403
Esri, HERE, Garmin, © OpenStreetMap contributors, and the GIS user community
Hazard Quotient (HQ)
Child with 52 weeks of exposure
TDI Limit to reach 5 µg/dL = 0.0015 mg/kg bw/day
< 0.50 (Very unlikely to cause adverse health effects)
0.51 - < 1.00 (Unlikely to cause adverse health effects)
1.01 - 1.50 (May cause adverse health effects)
Hazard Quotient Statistics
Min: 0.011
Max: 0.099
Mean: 0.049
Std dev.: 0.020
Soil lead level (mg/kg)
≤77.00
≤150.00
≤240.00
≤370.00
≤790.00

6.16 Appendix P: Hazard quotient map for a toddler with 40 weeks of exposure and a TDI relating to 5 µg/dL