

# Environmental Inequality and Heavy Metal in Birmingham Canals: A Quantitative

Analysis

A dissertation submitted by

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#### Abstract

#### Purpose

Studies on environmental inequality have been conducted for decades, however, the relationship between water quality and deprivation is weak and needs to be updated. Although there is evidence showing there has been a lot of heavy metal usage, and the corresponding heavy metal pollution in Birmingham canals, very little has been done to assess such conditions and the linkage between heavy metal pollution and deprivation. As a result, this project is aimed to provide a current view on heavy metal pollution in Birmingham canals, and the associated potential environmental inequality concerning deprivation.

#### Methods

A quantitative approach is employed to gather primary data and secondary data. The heavy metal concentration in the canal water is obtained through sampling and laboratory tests by ICP-MS. In contrast, the data of canal sediment is obtained by inquiry to Canal and River Trust. Statistical tests are performed by SPSS and 90% conference level is adopted.

## Findings

Surface water Hg exceeds the EQS limit by 23% to 203%, while the remaining heavy metals in Birmingham canals have a low concentration. However, the sediments are extremely polluted by mixed types of heavy metals Cr, Cd, Cu, Ni, Pb, As, Zn. Although statistical tests do not suggest a significant difference between heavy metal pollution and the area of deprivation in Birmingham, this cannot imply there is no issue of environmental inequality of heavy metal pollution among the wards in Birmingham due to low statistical power. Further studies would be required to confirm the possible environmental inequality of heavy metal pollution in the canals of Birmingham.

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# Glossaries

ADM	Absolute deviation from mean
DEFRA	Department for Environment, Food and Rural Affairs
EI	Environmental Inequality
EJ	Environmental Justice
EQS	Environmental Quality Standard
FEW	Family-wise-error
ICP-MS	Inductively Coupled Plasma Mass Spectrometry
IMD	Index of Multiple Deprivation
IOD	Index of Deprivation
ISO	International Organization for Standardization
LC50	Lethal Concentration 50
LSOA	Lower Layer Super Output Areas
MAC	Maximum Allowable Concentration
PE-HD	High-density polyethylene
QC	Quality Control
RBMPs	River Basin Management Plans
SCHEER	Scientific Committee on Health, Environmental and Emerging Risks
SEPA	Scottish Environmental Protection Agency
SPSS	Statistical Package for the Social Science
TWI	Tolerable weekly intake
USEPA	United States Environmental Protection Agency
WFD	Water Framework Directive
WHO	World Health Organisation

#### **CHAPTER 1**

## **Introduction and Literature Review**

#### 1.0 Introduction

Healthy rivers are essential for biodiversity, as well as closely related to human physical and mental health. Rivers provide habitats for wildlife, which could be used to combat flooding and provide a place for recreational use (UK Parliament, 2022). According to the latest statistic from the Department for Environment, Food and Rural Affairs (DEFRA, 2023), only 16% of the surface water bodies assessed in the UK were in high and good ecological status under the definition of the Water Framework Directive (WFD). Agriculture and rural land management, the water industry, and urban and transport pressures are the main reasons for interrupting the mediations of the surface water. *Figures 1 and 2* illustrate the status of surface water bodies, canals and rivers in the UK under the WFD definition from 2009 to 2019.

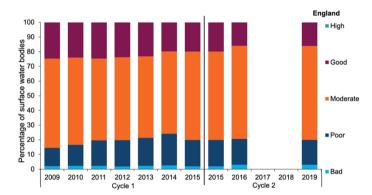


Figure 1. Ecological status of surface water bodies in the UK from 2009 to 2019

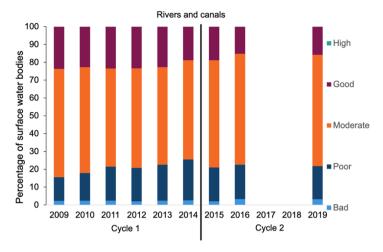


Figure 2. Ecological status of rivers and canals from 2009 to 2019

Environment Agency (2022) reported metals, such as cadmium, lead, nickel, zinc, and the organo-metal tributyl tin are the chemical substances found in the river that often exceed the environmental quality standard (EQS). Heavy metals are toxic to both flora and fauna even with a very low concentration, as well as nonbiodegradable in nature (Madhav et al., 2022). As a result, it would be necessary to monitor the concentration of heavy metals in rivers.

## 1.1 Water Quality and Surface Water Status

Ritchie and Schiebe (2000) defined water quality as "a general term used to describe the physical, chemical, thermal, and/or biological properties of water". Enshrined in the UK legislation, surface water was defined as "inland waters, except groundwater; transitional waters and coastal waters, except in respect of chemical status for which it shall also include territorial waters", while surface water status is determined by the poorer of its ecological status and its chemical status (*Directive 2000/60/EC of the European Parliament and of the Council*). Based on the definition above, good water quality of surface water means to achieve a certain level in chemical, physical, and biological dimensions, hence, standards are required to be established for this purpose.

On top of that, based on the usage of water, various water standards were established, including drinking water standards, bathing water standards, and recreational water standards. The guideline of the World Health Organisation (WHO)(2021) recognised rivers and canals as one kind of recreational water usage, listing out possible risks and standards to follow.

## 1.2 Water Framework Directive and UK implementation

Council Directive 2000/60/EC (2000), also known as the Water Framework Directive (WFD), was established by the EU in 2000 to protect both the qualitative and quantitative health of water, aiming to reduce and remove pollutants from the water and to ensure there is enough water to support both wildlife and humans needs, as well as creating a unified approach to the management of the water resources on the river basin (Battersby, 2022). For surface water, article 4 required member states to use River Basin Management Plans (RBMPs) to not only protect, enhance, and restore all bodies of surface water, but also require necessary measures and aim to achieve good ecological potential and surface water chemical status at the latest 15 years from the date that enforce the Directive (2000). Nevertheless, the WFD requires member states to establish a management plan for each river basin, and update it every six years (Battersby, 2022).

The Water Environment (Water Framework Directive) (England and Wales) Regulations 2017 (WFD Regulation) was established in England and Wales to provide a framework to manage the water environment in England and Wales and was retained as UK law after exiting the EU (Environment Agency, 2022; DEFRA, 2023). England finished the first RBMPs 6-year cycle in 2015 and started the second cycle with new monitoring and classification standards to assess the ecological status of surface water (DEFRA, 2023). According to DEFRA (2014), the number of specific pollutants added to the regulatory list increased from 19 to 29 in 2014, to

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include heavy metals such as copper, manganese, and zinc. Currently, England started the third cycle of RBMPs, and expected to be finished in 2027, alongside the RBMPs is the 25-Year Environment Plan, which was driven by the Environment Act 2021 (DEFRA, 2021; Environment Agency, 2022).

## **1.3** Environmental Quality Standard (EQS)

Under the requirement of WFD, the Environmental Quality Standard (EQS) should be applied for polluting substances, if the results exceed the limits stated in EQS, it would cause adverse effects to the environment (SEPA, 2020). *Table 1* summarises the EQS of heavy metals that are under concern, as well as the statuary status of each pollutant.

# 1.4 Sediments – Environment Impact and Standard

Sediments are polluted by various human activities, including industrial and wastewater discharges, agricultural runoff, and urban stormwater (Rangel-Buitrago et al., 2023). The major pollutants of sediment are metals, hydrocarbons, and microplastics, causing serious adverse consequences to both the aquatic environment and human health (Rangel-Buitrago et al., 2023). However, due to insufficient toxicology data, monitoring, and analysis methods, there is currently no in-river sediment standard in the UK (Mokwe-Ozonzeadi, 2014; Environment Agency, 2019).

Substance	Statutory status	EQS Lin	EQS Limit (Fresh Water) (µg/L)		Remark
		Annual Average	Maximum Allowable	95%-ile	
			Concentration		
Aluminium	Non-Statutory	15 (pH>6.5)	10 (pH≤6.5)	-	
			25 (pH>6.5)		
Arsenic	Non-Statutory	50	-	-	
Cobalt	Non-Statutory	3 (Dissolved)	100 (Dissolved)	-	
Cadmium	WFD PS/PHS/OP	≤0.08 (Class 1)	≤0.45(Class 1)	-	< 40 mg CaCO3/l
		0.08 (Class 2)	0.45 (Class 2)		40 to < 50 mg CaCO3/l
		0.09 (Class 3)	0.6 (Class 3)		50 to < 100 mg CaCO3/1
		0.15 (Class 4)	0.9 (Class 4)		100 to < 200 mg
		0.25 (Class 5)	1.5 (Class 5)		CaCO3/l
					$\geq$ 200 mg CaCO3/l
Chromium III	WFD UK Specific Pollutant	3.4 (Dissolved)	-	-	
Chromium IV	WFD UK Specific Pollutant	4.7 (Dissolved)	-	32	
Copper	WFD UK Specific Pollutant	1 (Bioavailable)	-	-	
Iron	WFD UK Specific Pollutant	1000 (Dissolved)	-	-	
Lead	WFD PS/PHS/OP	1.2	14	-	
Manganese	WFD UK Specific Pollutant	123 (Bioavailable)	-	-	
Mercury	WFD PS/PHS/OP	-	0.07	-	
Nickel	WFD PS/PHS/OP	4 (Bioavailable)	34 (Dissolved)	-	
Silver	Non-Statutory	0.05 (Dissolved)	0.1 (Dissolved)	-	
Sodium	Non-Statutory	No EQS	No EQS	-	
Tin	Non-Statutory	25	-	-	
Zinc	WFD UK Specific Pollutant	10.9 (Bioavailable)	-	-	

*Table 1.* Environmental Quality Standard (EQS) of heavy metals that under concern (SEPA, 2020)

# 1.5 Effect of heavy metal on human health

It has been proven that heavy metal toxicity poses a major threat to humans, which can harm the human body by interfering with metabolic processes and proper functioning (Jaishankar *et al.*, 2014). It is reported that the most common heavy metals found in wastewater include arsenic, cadmium, chromium, copper, lead, nickel, and zinc, these elements not only can cause risks for humans, but also threaten the environment (Lambert, Leven and Green, 2000). Moreover, heavy metal enters the environment by natural means and through human activities, such as mining, urban runoff, sewage discharge, and industrial activities, causing significant pollution and toxicity to the environment across the globe (Jaishankar *et al.*, 2014). In addition, it is important to identify the adverse effects of heavy metals on humans, and the corresponding sources of intake, *Table 2* summarises this information on common heavy metals found in the environment.

Element	Adverse Health Effect	Potential Sources of Uptake
Arsenic (As)	Expose to low levels of arsenic will cause nausea and vomiting,	Air and soils contaminated by pesticides and fertilisers.
	reduce the production of erythrocytes and leukocytes, abnormal	Food and drinking water contaminated by arsenical chemicals,
	heart beat, pricking sensation in hands and legs, damaging blood	pesticides or natural mineral deposits. (Jaishankar et al., 2014)
	vessels. (Jaishankar et al., 2014)	
	Long-term exposure will cause the formation of skin lesions,	
	internal cancers, neurological problems, pulmonary disease,	
	peripheral vascular disease, hypertension and cardiovascular	
	disease, and diabetes mellitus. (Jaishankar et al., 2014)	
Selenium (Se)	Selenium plays important role to maintain various physiological	Selenium presents in various form in environmental, including
	processes, pathogenesis and pathophysiology of various disorders.	soil, air, water, plants, and food, which could be possible route of
	Excess daily intake would cause diarrhea, nausea, and	uptake for human. (Mehdi et al., 2013)
	vomiting.(Kieliszek, Bano and Zare, 2022)	
Silver (Ag)	Chronic exposure of silver could induce permanent bluish-gray	The major exposure route of silver is through ingestion of drinking
	discoloration of the skin (argyria) or eyes (argyrosis), while	water and food, and occupational exposure. (Drake and
	exposure to soluble silver compounds may induce toxic effects	Hazelwood, 2005)
	including liver and kidney damage, irritation of the eyes, skin,	
	respiratory, and intestinal tract, as well as changes in blood cells.	
	(Drake and Hazelwood, 2005)	
Aluminium (Al)	Aluminium poisoning has wide range effects on enzymes activities,	Aluminium is widely used by human, residue aluminium
	protein synthesis, and DNA repairing. It also affects the blood	compounds could be found in drinking water, food, air, medicine,
	content, musculoskeletal system, kidney, liver, and respiratory and	deodorants, cosmetics, packaging, buildings, and aerospace
	nervous system. (Rahimzadeh et al., 2022)	industry. (Rahimzadeh et al., 2022)

Barium (Ba)	Absorbing large amount of barium that dissolves in water can cause	Inhalation from the site that make or use barium compound.
	change in heart rhythm or paralysis. Absorbing small amount of	Inhalation of dust, eating soil or plants near hazardous waste sites.
	barium that dissolves in water can cause vomiting, abdominal	(Agency for Toxic Substances and Disease Registry, 2007)
	cramps, diarrhea, difficulties in breathing, change in blood pressure,	
	and muscle weakness. (Agency for Toxic Substances and Disease	
	Registry, 2007)	
Cadmium (Cd)	Highly toxic to the kidney and accumulates in the proximal tubular	Fossil fuels, natural resources, iron and steel production, cement,
	cells in higher concentrations, and causing bone mineralisation.	non-ferrous metal production, cadmium products, waste
	(Jaishankar et al., 2014)	incineration. (Jaishankar et al., 2014)
	Inhaling high level of cadmium will cause severe damage to the	
	lung. (Jaishankar et al., 2014)	
Cobalt (Co)	Excess intake of cobalt could induce neurological, cardiovascular	The exposure route of cobalt can be characterised into four
	and endocrine deficits. (Leyssens et al., 2017)	components, which are occupational, environmental, dietary and
		medical exposure. (Leyssens et al., 2017)
Chromium (Cr)	Cr (III) and Cr (IV) is the most prevalent form of Cr which reported	Chromium is widely used on industrial, domestic, agricultural,
	to have potential toxic and direct toxicities on skin, respiratory	medical, and technological applications. The exposure route of
	system and gastrointestinal tract. DNA damage has been reported	chromium included dermal contact, inhalation, and ingestion.
	as well. (Shin et al., 2023)	(Shin et al., 2023)
Copper (Cu)	Excess copper exposure would result in gastrointestinal symptoms,	Exposure of copper can be in different ways, including ingestion
	liver and kidney damage, neurological symptoms, cardiovascular	of contaminated water and food, ,soil, occupational exposure,
	effect. Long term exposure would induce Wilson's disease. (Bost et	dietary supplements. (Bost et al., 2016)
	<i>al.</i> , 2016)	

Iron (Fe)	Excess intake of iron could induce nausea and vomiting, abnormal	Iron is the essential element for human metabolic processes,
	pain on stomach, iron overload, cellular and organ damage,	sources of excess iron could be from supplements, dietary intakes,
	cognitive impairment, and hypotension. (Nazanin, Richard and	and hereditary conditions.(Nazanin, Richard and Roya, 2014)
	Roya, 2014)	
Manganese (Mn)	The accumulation of manganese in human body could induce	Manganese presents in wide range of food, fertilisers, paints,
	adverse neurological effects, pneumonia, decreased libido, and	fireworks, and cosmetics. The major route of manganese intake is
	sperm damage. (Miah et al., 2020)	via food consumption.(Miah et al., 2020)
Nickel (Ni)	No nutritional value is identified for human, exposure to nickel can	Nickel is extensively distributed in the environment, water, air,
	induce allergy, cardiovascular and kidney diseases, lung fibrosis,	and soil. Exposure route included ingestion or inhalation of
	lung and nasal cancer. (Genchi et al., 2020)	polluted air, water, or food by industrial activities. (Genchi et al.,
		2020)
Lead (Pb)	Lead will deposit in blood, skeletal bones, and soft tissues. (Halmo	Lead-based paints, gasoline, cosmetics, toys, household dust,
	& Nappe, 2023)	contaminated soil, industrial emissions. (Gerhardsson et al., 2002)
	Miscarriage, stillbirths or premature births. (PHE, 2016)	Contaminated drinking water by lead pipe. (Jaishankar et al., 2014)
	Lower IQ, behavioural problems, nerve damage or delayed growth	
	of children. (PHE, 2016)	
Zinc (Zn)	Intoxication by excess intake of zinc is rare, excess zinc intake could	Sources of excess zinc could be from supplements, dietary intakes,
	induce copper deficiency and neurological effects. (Plum, Rink and	and occupational exposure. (Plum, Rink and Haase, 2010)
	Haase, 2010)	
Mercury (Hg)	Exposure to elevated levels of mercury could damage the brain,	Present in most foods and beverages ranged from $<1$ to 50 µg/kg,
	kidneys, and the developing fetus. (Alina et al., 2012)	higher level in marine foods. (Jaishankar et al., 2014)

	Present in soil and water in form of methyl mercury. (Jaishankar et al., 2014)
	Fossil fuels, dental amalgams, old latex paint, incinerators, thermometers. (Jaishankar <i>et al.</i> , 2014)

*Table 2*. The health effects and potential sources of uptake of various kind of heavy metals

#### **1.5** Birmingham Canals – Brief History and Water Quality

Birmingham encompassed River Tame, Rea, and Cole, these rivers were used for domestic purposes and sources of fish and waterfowl for thousands of years until occupied by infrastructures, including canals, at the end of the 19<sup>th</sup> century (Dutton, 2007). Canals in Birmingham played an important role in Industrial Revolution transportation, after the completion of the central Birmingham canal system in 1772, industries associated with metal manufacturing and engineering built rapidly alongside the banks of the canals, chemical works and a coal wharf were also located near to the canal, these industrial activities together with intensive boat traffic led to the accumulation of heavy metal in sediments deposits on the canal bed (Bromhead, 1994). In the mid-19<sup>th</sup> century, the arrival of the railway in Birmingham gradually superseded canal transportation, and by the mid-20<sup>th</sup> century, resulting from the decline of the canal transportation and manufacturing industry, the canal network was abandoned or lacked maintenance (Gibbons, Peng and Tang, 2021; Birmingham City Council, No date). Henceforward, the canals were restored, and the function altered from commercial transport to leisure and recreational purposes (Gibbons, Peng and Tang, 2021).

A study three decades ago analysed toxic metals content within the sediment of Birmingham canals, including arsenic, lead, cadmium, chromium, copper, nickel, and zinc, whereas 80% of the analyses exceeded the Dutch C guideline values, showing a severe contamination by heavy metal at that period (Bromhead, 1994). In 2022, a water monitoring report was established by Severn Trent Water, Affinity Water, and Canal & River Trust, focusing on the monitoring results of the Grand Union Canal. Within the report, two sites from the Birmingham and Fazeley Canal were included, and heavy metals including cobalt, manganese, nickel, and zinc were tested and compared with WFD EQS. and drinking water standards. Based on the testing

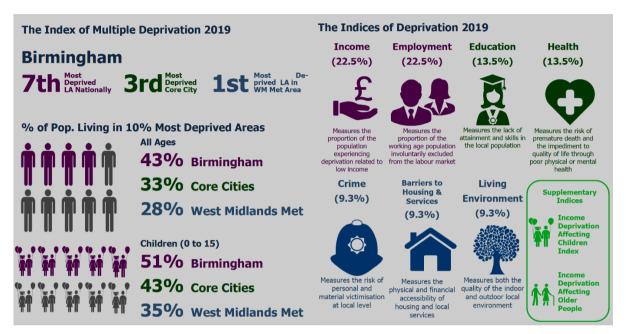
results, nickel and zinc were reported to exceed 2 times and 1.5 times of the annual average of the standard on the upper Grand Union Canal, respectively (Atkins Limited, 2022).

## **1.6 Deprivation in Birmingham**

The Industrial Revolution in Birmingham lead to an economic boom in the 18<sup>th</sup> and 19<sup>th</sup> centuries. Aimed to seek decent employment opportunities, numerous immigrants moved into Birmingham which soared the population to over 500,000 by 1901, the rapid population growth, however, resulted in social and public problems associated with poor housing and sanitation conditions (Birmingham City Council, 2007). In 1970s to 1980s, due to the joint impact of industrial decline and recession, the unemployment rate for Birmingham rose to over 20% (Birmingham City Council, 2007). Since then, the City Council proposed a series of economic strategies to suppress the boost of the unemployment rate, including restructuring the economy by supporting local businesses and encouraging inward investment, and building science park to support the development of high technology industries, nevertheless, as most of the residents in Birmingham were absence or had inappropriate skills, they were not able to access the job, and the outcomes were limited, many parts of the city were still suffering from high level of unemployment and deprivation (Birmingham City Council, 2007).

In 2019, Birmingham City Council researched the deprivation within the city, and established the Index of Deprivation (IOD), illustrating the Index of Multiple Deprivation (IMD) and income deprivation. The IMD was determined by seven domains, including income, employment, education, health, crime, barriers to housing and services, and living environment. *Figures 3* and *4* show a summary of deprivation in Birmingham based on demography and locations. Nevertheless, it was reported that Birmingham was the third most deprived core city in the UK after Liverpool and Manchester, with 43% and 51% of the population and children,

respectively, living in the 10% most deprived areas (Birmingham City Council, 2019). Regarding the deprivation by wards, a significant deprivation could be observed across the city, it was reported that the east of the city centre, and the south, west, and northeast of the outer city are mostly suffering from deprivation (Birmingham City Council, 2019).



*Figure 3*. The Index of Multiple Deprivation (IMD) of Birmingham in 2019 (Birmingham City Council, 2019)

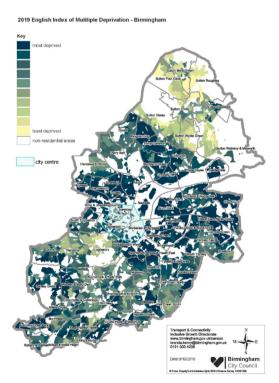


Figure 4. Deprivation by LSOA in Birmingham (Birmingham City Council, 2019)

## 1.7 Environmental Justice (EJ) and Environmental Inequality

The US Environmental Protection Agency (USEPA) defined environmental justice as "the fair treatment and meaningful involvement of all people regardless of race, colour, national origin, or income with respect to the development, implementation and enforcement of environmental laws, regulations and policies", and fair treatment means "means no group of people should bear a disproportionate share of the negative environmental consequences resulting from industrial, governmental and commercial operations or policies."(Environment Agency, 2008). In general, the research of environmental justice aims to investigate and "redress the disproportionate environmental burdens and benefits associated with social inequalities", matching the growing concern of income inequality (Banzhaf, Ma and Timmins, 2019; Chakraborty, Collins and Grineski, 2016).

Environmental Agency (2008) identified the elements of EJ and provided definition for each element, stating that the works on EJ can recognise all the components, or take a more restricted and focused view. *Table 3* summarises the elements and the definition of EJ.

On the other hand, the Environment Agency (2008) stated environmental inequality is a subcomponent of environmental justice, meaning that an environmental aspect is distributed unevenly within different social class, ethnicity, gender, age, and location. An environment aspect could be one of the below.

- Negative aspects (e.g. exposure to pollutants)
- Positive aspects (e.g. access to green space)
- Procedural aspects (e.g. information accessibility, involvement in decision-making processes)

Elements	Definition
Distributive Justice	Concern with how environmental goods (such as access to green space) and
	environmental bads (such as pollution and risk) are distributed amongst
	different groups and the fairness or equity of this distribution
Procedural Justice	Concern with the fairness or equity of access to environmental decision-
	making processes and to rights and recourse in environmental law.
Policy Justice	Concern with the principles and outcomes of environmental policy decisions
	and how these have impacts on different social groups.
Intranational Justice	Concerned with how these distributions and processes are experienced and
	operate within a country.
International Justice	Extends the breadth of concerns to include international and global issues,
	such as climate change
Intergenerational Justice	Encompasses issues of fairness and responsibility between generations, such
	as emerge in debates over the protection of biodiversity. Such concerns are
	particularly important in relation to waste management policy, as the impacts
	of waste management facilities such as landfills may last for hundreds of
	years.

Table 3. Elements of EJ and definition of each element (Environment Agency, 2008)

# 1.8 Researches on Environmental Inequality and Social Inequality

Environmental Inequality was actively being researched in the early 1990s, however, due to the political support in the 2000s, the progress towards EJ is slower than expected (Mitchell, 2019). The report by Mitchell (2019), furthermore, provided a picture of the EJ research and development in the UK. Rather than focus on ethnicity as in the US, the EJ research in the UK focused on deprivation, which is widely perceived as a major reason for social exclusion (Mitchell, 2019).

A study by the European Environmental Agency shows that exposure to air pollution, noise, and extreme temperatures does not affect everyone in the same way in Europe, and the effects of exposure are hugely reflected in the socio-demographic differences within the society, including the personal characteristics (i.e. age or health) and socio-economic status (i.e. income, employment status, or education level) (Kaźmierczak, European Environment and European Topic Centre for Air Pollution and Climate Change, 2018). Studies revealed that vulnerable groups, such as older people, children, people having material disadvantage, and people bad in health would be more vulnerable to air pollution, noise, and extreme temperatures due to a lack of financial ability or having less power to determine their own life (Kaźmierczak, European Environment and European Topic Centre for Air Pollution and Climate Change, 2018). This indicates environmental inequality is associated with social vulnerability in European countries.

Environmental inequality exists in the US as well. A study examines the race-based and income-based disparities from the air toxics in Cancer Alley, LA, US, a preponderance place of petrochemical industries built in this region (James, Jia and Kedia, 2012). Study shows that people in low-income tracts have 12% more cumulative risk of cancer than those in high-income tracts, while people in black-dominant areas have 16% more risk of cancer than people in white-dominant areas, the study also implies a worsened disparity in the poorest and most highly concentrated black areas (James, Jia and Kedia, 2012).

On the other hand, for a case in the UK, the Grenfell Tower fire tragedy revealed the social inequality in the UK. On 14<sup>th</sup> June 2017, a block of 24 stories public housing flats in North Kensington, London, was on fire due to a faulty fridge freezer, and the fire spread rapidly and caused at least 72 people died (Clancy, 2020). After the investigation, it was suspected that the rapid spread of fire was caused by the cladding material on the exterior of the building, which has a combustible nature and was decided to put on the exterior of the building result from the constraint of budget during building refurbishment (Watt, 2017). This tragic incident raised fundamental policy issues regarding safety regulation, providing "stark evidence on the social

and political determinants of health inequality", as well as the need for appropriate policies and action by both national and local governments to deal with the housing crisis (Watt, 2017).

However, in the UK, due to the constraints of time, budget, and availability of data, studies in the UK often simply consider the proximity of people surrounding the pollution sources, and straightforward conclusions are supported with available data, which reveal little about the outcomes of the concerns (Mitchell, 2019). In addition, the research gap on EJ was recognised years ago, and craving for research on the EJ associated health outcomes, the understanding of health impacts from long-term low-level exposure, and the potential cumulative effects of the pollutant mixes (Mitchell, 2019).

# 1.9 Environmental Inequality and Social Deprivation in the UK

There is massive evidence of environmental inequality and the association with social deprivation across the UK. For green space, studies showed that people with lower social-economic status generally less visit parks, woodlands, and social recreational areas resulting from lower green space quality and accessibility (Barbosa *et al.*, 2007; O'Brien and Morris, 2014). Another report (Walker *et al.*, 2003) summarised that the waste facilities, including waste recycling and transfer sites, and waste incinerators, are more likely to be located in the areas with higher social deprivation.

Moreover, the linkage between environmental inequality and social deprivation has been studied two decades ago, and a clear relationship has been proved. Walker *et al.* (2003) studied the environmental quality and social deprivation across the UK, and reported that there were eight times more people in the deprived area than those least deprived living within the tidal

floodplain, seven times more emission sources for the most deprived wards than least deprived wards, and have the highest air pollutant concentration in the most deprived wards.

However, although massive evidence of environmental inequality exist, the relationship between water quality and social deprivation remains anecdotal, and the studies between them are narrow (Environment Agency, 2008). An analysis around two decades ago showed that for the residents who live within 600m of a river, the deprived populations are much more likely to live near a river with poor chemical and biological status, and this effect concentrated in the North West, Yorkshire and the Humberside, and London (Environment Agency, 2008). This study reveals the environmental inequality in certain regions in the UK, yet, considering environmental inequality can occur at different levels, within the country, region, and city (Mitchell, 2019), and the study was about two decades ago, thus, the latest situation about environmental inequality should be updated.

#### **1.10** Frameworks – The Marmot Review and Doughnut Economic Model

The Marmot Review is one of the key literature that catalysed the actions of health inequality in the UK (Mitchell, 2019). In the policy objectives, Marmot *et al.* (2010) indicated that the health and well-being of individuals are affected by the communities that they are living in, including the lack of access to green spaces in deprived areas, thus, accessing to good water quality, recreational and green space will contribute to reducing inequalities, and to help to create sustainable communities. However, although concepts and frameworks were proposed in the Marmot Review, the situation seems getting worse. In the Marmot Review 10 years on, Marmot *et al.*(2020) revealed that the deprivation level and social exclusion in many places have been intensified, these could be found in the places of post-industrial areas and big towns, such as Manchester and Birmingham. Result from the cut of funding in the most deprived areas, it was found that the most deprived areas have five times less amount of quality green space, as well as higher levels of pollutants than the other urban areas, which would lead to a serious of direct and indirect negative health effects (Marmot *et al.*, 2020).

Raworth (2012) proposed the Doughnut Economic model, which applies to the public health model, shown in *Figure 5*. This model aims to reach the needs of all human beings within the "just boundaries", while no one will either fall short of the essential elements of life or overshoot the ecological ceiling (Raworth, 2012). In addition, this model illustrated the linkage between the economic systems, human health and well-being, and environmental health, as well as the dynamics between different stresses and politics, highlighting the extreme inequalities and inefficiencies of resource use (Raworth, 2012).

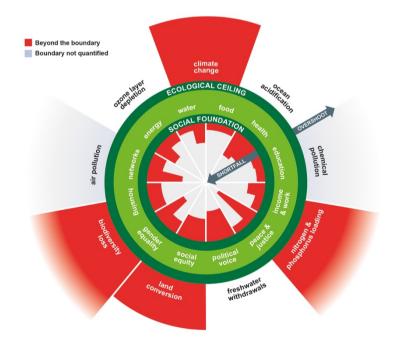


Figure 5. The Doughnut Economic model (Raworth, 2012)

## 1.11 Research Gap

Studies on environmental inequality have been conducted for decades, and massive evidence exists, the research on environmental inequality has been slowed down, as well as the relationship between water quality and deprivation is weak and needs to be updated. In addition, considering the negative effects of environmental inequality would be magnified for vulnerable groups in the deprived areas, it would be necessary to give a general view of the environmental inequality in the deprived areas. Yet, although there is evidence showing there has been a lot of heavy metal usage, and the corresponding heavy metal pollution in Birmingham canals, very little has been done to assess such conditions and the linkage between heavy metal pollution and deprivation. As a result, this study design focuses on the environmental inequality of health metal in the canals of Birmingham, UK.

## 1.12 Aims and Objective

This project aims to provide a current view of the heavy metal pollution within Birmingham canals and sediment, as well as investigate the association between the canal heavy metal pollution and deprivation in Birmingham. This project has the following objectives:

- Perform heavy metal screening tests for the canals' water and sediment within Birmingham.
- 2. Compare the test result and the current available standards.
- 3. Identify the characteristics of heavy metal contamination in Birmingham canals.
- 4. Investigate the potential environmental inequality of heavy metal pollution with demographic differences, i.e. location, deprived and wealthy area.

# **Research Questions**

- 1. What is the level of heavy metal pollution in the canals of Birmingham?
- 2. Are the concentration of heavy metals in the canals exceed the limit of current standards?
- 3. Is there potential environmental inequality of heavy metal pollution with demographic differences?

# **Chapter Summary**

Environmental Quality Standard (EQS) was established for heavy metal content in water but not sediment. Studies on Environmental Justice (EJ) and environmental inequality found negative impacts on human health and well-being for those who have lower socio-economic status and are excluded. Massive evidence exists to illustrate the relationship between environmental inequality and deprivation at the regional level, but lacks a general view of the environmental inequality in the deprived areas at the city level.

# **CHAPTER 2**

# Methodology

#### 2.0 Overview

This chapter outlines the methodology of this project, a quantitative approach is chosen to determine the association of environmental inequality in Birmingham canals. Sediment data is collected from both inquiry from the Canal and River Trust. Furthermore, the data are processed by SPSS for statistical analysis.

# 2.1 Research Setting and Sampling Sites

This project investigates the association of environmental inequality and heavy metal contents in Birmingham canals, quantitative method would be the best approach to provide a solid ground for discussion. Furthermore, it is necessary to define the boundary of the city. Birmingham City Council (2018) provided a ward map, indicating the boundary of the city and the composition of 69 wards in Birmingham. *Figure 6* shows the latest Birmingham ward map.

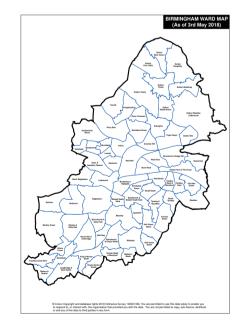


Figure 6. Birmingham ward map (Birmingham City Council, 2018)

Based on the boundary on the map, 7 canals are included within the area of Birmingham city, which are;

- 1. Birmingham & Fazely Canal
- 2. Tame Valley Canal
- 3. New Main Line
- 4. Old Main Line
- 5. Worcester & Birmingham Canal
- 6. Grand Union Canal
- 7. Digbeth Brach

Sampling sites are located from the canals within the area, three criteria are considered for the selection of the sampling sites:

- A) Reference from the monitoring station by the Canal and River Trust
- B) Junction / reasonable distance apart from another sampling site
- C) Can be used to represent a ward in Birmingham

Figure 7 and Table 3 provide details of the canals and each sampling site for this project.

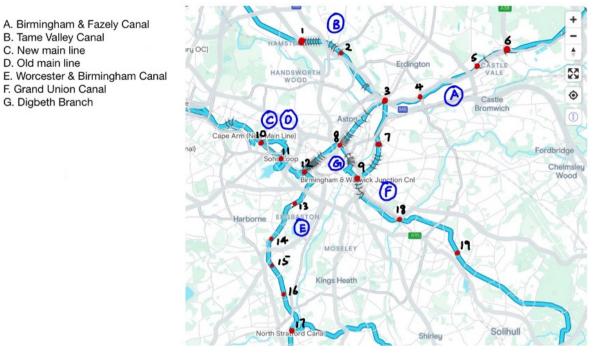


Figure 7. Graphical illustration of sampling sites

Site Code	Site	Ward
S1	Perry Barr Lock 1, Top Lock	Perry Barr
S2	Perry Barr Lock 11	Perry Barr
S3	Salford Junction	Nechells
S4	Bromford Bridge 2, Bromford Lane	Bromford & Hodge Hill
S5	Lock 1, Minworth	Pype Hayes
S6	Lock 3, Minworth, Wiggins Hill Rd	Sutton Walmley & Minworth
S7	Lock 5, Garrison Bottom Lock	Alum Rock
S8	Aston Junction, Rocky Lane	Nechells
S9	Bordesley Junction	Bordesley & Highgate
S10	Turnover Bridge, End of Soho Loop	Soho & Jewellery Quarter
S11	Rotton Park Junction	North Edgbaston
S12	Old Turn Junction	Ladywood
S13	Bridge 85, St. James Road	Edgbaston
S14	Bridge 82, University Avenue	Edgbaston
S15	Bridge 79, Selly Oak Railway Bridge	Bournbrook & Selly Park
S16	Bridge 77, Maryvale Road	Stirchley
S17	King's Norton Junction	King's Norton North

S18	Bridge 88F, Foot Bridge Armoury Road	Sparkbrook & Balsall Heath East
S19	Bridge 85, Lincoln Road	South Yardley

Table 4. Location of sampling sites

# 2.2 Data Collection

Heavy metal data of both water and sediment are collected for quantitative analysis separately. However, due to the time constraint and limited budget, sediment data would be provided by the Canal & River Trust as secondary data, while water data would be collected by on-site sampling and laboratory analysis as primary data. The secondary data provided by the Canal & River Trust was collected to a high standard, providing precise and solid-ground evidence for this project.

#### 2.2.1 Sediment Data

Sediment data is collected by inquiry of data from the Canal & River Trust, the concentration of each element of heavy metals stated in *Table 1*, and the sampling locations are required.

## 2.2.1.1 Ethical Consideration

The participant from the Canal & River Trust consented to the collection of data, and the purpose of the project and the intended use of the data were informed, a brief explanation of the study would be provided to the participant after the project is conducted and summarised.

## 2.2.2 Water Data

Water data is collected by on-site sampling and laboratory analysis, ICP-MS is used for the quantitative analysis to determine the concentration of heavy metals, the quality control (QC)

would be performed to ensure the precision and accuracy of the test results. The ISO standards used for water sampling and laboratory testing are stated below.

- 1) BS EN ISO 5667-1:2023, Water quality Sampling Part 1: Guidance on the Design of sampling programmes and sampling techniques
- 2) BS EN ISO 5667-3:2018, Water quality Sampling Part 3: Preservation and handling of water samplings
- BS EN ISO 5667-6:2016+A11:2020, Water quality Sampling- Part 6: Guidance on sampling of rivers and streams
- BS EN ISO 17294-1:2024, Water quality Application of inductively coupled plasma mass spectrometry (ICP-MS) – Part 1: General requirements
- 5) BS EN ISO 17294-2:2023, Water quality Application of inductively coupled plasma mass spectrometry (ICP-MS) Part 2: Determination of selected elements including uranium isotopes

#### 2.2.2.1 Water Sampling, Transportation and Storage

Canal waters are collected from the sampling locations specified in *Table 3*. Based on the guidance of preparation of sampling from ISO (2016), lone working is avoided to ensure the health and safety of the sampler, gloves are worn to avoid contamination, and a sampling plan is provided with the information of each sampling site (See Appendix 1). For the sampling of canal water to determine heavy metal, 500 ml PE-HD bottles are preferred as the sampling container (ISO, 2018). Furthermore, to avoid any source of contamination or loss of trace metals, each bottle is rinsed three times by canal water and is filled directly from the body at around 30 cm under the surface (ISO, 2016). Labels are given to each sample with the information of sampling date, site code, and name of sampling personnel.

Furthermore, the samples are stored in an icebox during transportation to ensure the temperature is below 8°C, and stored in a cold room in the laboratory (ISO, 2018). Considering the maximum storage time of the samples, laboratory tests would be conducted as soon as possible.

### 2.2.2.2 Laboratory Analysis – The Procedure

With the capability of simultaneous multielement analysis and high sensitivity, the concentration of heavy metals in this project is determined by ICP-MS, and the low detection limit in trace level allows comparison between the test results and existing standards (Jia, Li and Li, 2011).

The laboratory test is carried out in accordance with ISO 17294-2:2023. The calibration curve is prepared by Five-point external calibration, where multi-element calibration solutions are prepared by diluting the stock solution of each element with 2% nitric acid. For each calibration solution, 25  $\mu$ l of 100 ppm gold solution is added for the determination of mercury. The concentration of each element and the final volume are listed in *Table 5*.

Elements		Con	centration (	ppb)		Final
	Std 0 (Blank)	Std 1	Std 2	Std 3	Std 4	Volume (ml)
As, Se	0	10	20	40	50	50
Ag, Al, Ba, Ca, Cd, Co,	0	5	10	20	25	
Cr, Cu, Fe, Mn, Ni, Pb,						
Zn						
Sn	0	10	20	40	50	
Hg	0	2	4	8	10	

Table 5. Concentration of each elements in standard solutions for the calibration curve

For the sample preparation, the samples are filtered with  $0.45\mu m$  membrane filter, and 5ml of each sample is pipetted for testing. For each 5ml sample, 25  $\mu$ l of nitric acid and gold solution are added, and a duplicate sample would be prepared for quality check.

After that, the instrumental parameters of the ICP-MS system would be adjusted in accordance with the manufacturer's manual. After 30 minutes of warm-up prior to the measurement and performance check, the instrumental testing would be performed in the order of standard solutions and samples, and the intensities and concentration of each element could be obtained after the test.

## 2.3 Deprivation Category

To provide a meaningful result, instead of conducting statistical tests and comparisons for a large number of separate areas, it is recommended to categorise smaller areas into different clusters into deprivation quantiles (Office for Health Improvement and Disparity, 2024). The cluster of an area is determined by two steps, the first step is to arrange the deprivation rank of each area and sort them from most to least, the second step is to divide the number of areas by the number of deprivation categories required, where in this case is 4 (Office for Health Improvement and Disparity, 2024). *Table 6* summarised that the categories should be assigned additional areas based on the fractional part of the number.

Quartiles	
Number after decimal point	Quartiles receiving an extra area
.0	None
.25	1
.5	1,3
.75	1,2,3

*Table 6.* Deprivation categories (Quartiles) receiving additional small areas (Office for Health Improvement and Disparity, 2024)

#### 2.4 Statistical Testing

The data are processed by the IBM Statistical Package for the Social Sciences (SPSS). To determine the association between the area of deprivation and heavy metal contents, the data, both water and sediment, will be presented in two ways, which are descriptive statistics and statistical tests respectively. For the statistical tests, Kolmogorov-Smirnow (K-S) tests and Levene's homogeneity of variance test will be performed to test whether the assumptions of normality and common variance are satisfied. If the assumptions are not satisfied, nonparametric tests will be performed and compared clusters based on the deprivation ranking. In this project, the Wilcoxon test is the suitable test to determine whether there is a difference between two clusters. However, "Family-wise error" (FWE), which is a type I error would be occurred when performing multiple statistical analyses, and null hypothesis would be rejected even though it is true, and a correction method or factor should be applied to reduce such error (Lee and Lee, 2018). As a result, Bonferroni method would be performed in this project, in which the significant level is corrected by dividing by the number of comparisons. Yet, as the adjusted conference level is often smaller than the required, the Bonferroni method is reported to be over-conservative and fails to detect real differences (Lee and Lee, 2018). The test result would be considered as significant if the conference level reaches or higher than 90% ( $p \le 0.1$ ).

## **Chapter Summary**

This project uses a quantitative approach to determine the association between environmental inequality and heavy metal content in Birmingham canals. The sediment data are provided by the Canal and River Trust, while the water data are obtained by water sampling and laboratory analysis. SPSS is used to process the data for statistical analysis.

#### **CHAPTER 3**

### Result

#### 3.0 Overview

This chapter is divided into two sections to report the results, respectively. The first section reports the results of canal water, and the second section reports the results of sediment data. Both sections report the level of concentration for each heavy metal from laboratory testing and the statistical testing concerning the association between heavy metal content and deprivation.

### 3.1 Result of the Canal Water

*Tables 7a & 7b* summarise the results of canal water from laboratory testing. 17 elements are tested by ICP-MS. Among the tested elements, 11 of them are tested positive in ppb level from the samples, including Barium (Ba 138), Mercury (Hg 202), Lead (Pb 208), Chromium (Cr 52), Manganese (Mn 55), Iron (Fe 56), Cobalt (Co 59), Nickel (Ni 60), Copper (Cu 63) , Zinc (Zn 66), Arsenic (As 75), and Selenium (Se 82); 3 of them are tested none or the concentration were below the detection limit, including Silver (Ag 107), Cadmium (Cd 111), and Tin (Sn 138); 2 of them are rejected from the further discussion as the coefficient of determination (R<sup>2</sup>) of the calibration curve is low, including Aluminium (Al 27, R<sup>2</sup> = 0.456) and Calcium (Ca 43, R<sup>2</sup> = 0.685).

Furthermore, 69 wards are divided into four different clusters based on their deprivation ranking in Birmingham, and fit into the table below, appendix 2 summarised a full table of which cluster each ward in Birmingham belongs to based on the calculation with deprivation

ranking, whereas cluster one represents the most deprived areas while cluster four represents the least deprived areas. In addition, of the 19 samples collected from different areas, 2 of them are Cluster One, 5 of them are Cluster Two, 6 of them are Cluster Three, and the remaining 6 are Cluster Four.

Ward Name	Depriva	Cluster	Ag 107	Cd 111	Sn 138	Ba 138	Hg202	Pb 208	Al 27	Ca 43	Cr 52	Mn 55	Fe56	Co59
	tion ranking	(Quartile)	(ppb)	(ppb)	(ppb)	(ppb)	(ppb)	(ppb)	(ppb)	(ppb)	(ppb)	(ppb)	(ppb)	(ppb)
Alum Rock	5	1	-0.059	-0.071	-0.086	50.252	0.212	0.488	-12.856	-23701.649	0.251	1.465	11.908	0.173
Sparkbrook & Balsall Heath East	1	1	-0.091	-0.060	-0.024	61.443	0.167	1.578	5.551	-19516.153	0.246	1.671	20.505	0.356
Bordesley & Highgate	19	2	-0.080	-0.034	-0.009	55.759	0.099	1.673	3.969	-19471.649	0.175	2.377	14.051	0.188
Nechells	24	2	-0.080	-0.060	-0.076	59.453	0.102	0.044	-8.815	-23130.745	0.059	11.527	5.909	0.235
Nechells	24	2	-0.085	-0.027	0.107	56.454	0.130	2.120	4.202	-16267.044	0.284	6.385	14.489	0.176
Bromford & Hodge Hill	33	2	-0.080	-0.020	-0.008	54.435	0.114	1.374	-4.261	-18325.801	11.554	1.837	16.717	0.105
Soho & Jewellery Quarter	29	2	-0.088	-0.041	0.051	44.621	0.162	1.110	1.862	-17006.640	0.207	4.159	25.835	0.120
Pype Hayes	39	3	-0.082	-0.063	-0.007	48.322	0.123	0.823	-1.483	-17513.113	15.364	1.804	14.714	0.111
North Edgbaston	41	3	-0.080	-0.033	0.003	48.393	0.141	0.639	4.173	-15033.408	0.479	4.790	13.423	0.194
Ladywood	42	3	-0.076	-0.051	0.013	46.917	0.138	0.981	20.039	-15594.140	0.472	6.055	14.749	0.221
Stirchley	46	3	-0.084	-0.030	-0.040	45.993	0.132	0.404	24.728	-17926.345	0.178	1.845	10.068	0.132
King's Norton North	44	3	-0.091	-0.036	0.008	53.364	0.149	0.378	8.310	-17303.063	0.159	1.502	7.034	0.083
South Yardley	48	3	-0.091	-0.069	-0.008	55.002	0.122	1.513	0.079	-14671.290	0.320	6.250	31.515	0.393
Perry Barr	56	4	-0.013	-0.059	-0.045	46.429	0.114	-0.019	-7.386	-15536.403	0.024	1.270	10.464	0.143
Perry Barr	56	4	-0.078	-0.071	-0.058	51.061	0.093	-0.077	-6.993	-15803.300	0.024	2.540	8.521	0.076
Edgbaston	61	4	-0.053	-0.027	-0.016	55.564	0.130	0.256	-1.139	-17164.375	0.316	1.240	3.950	0.084
Edgbaston	61	4	-0.065	-0.059	-0.019	47.289	0.150	0.052	0.565	-16972.754	0.292	0.819	1.179	0.071
Bournbrook & Selly Park	60	4	-0.069	-0.054	-0.039	46.575	0.144	0.082	3.880	-17665.364	0.228	1.283	2.813	0.076
Sutton Walmley & Minworth	64	4	-0.080	-0.056	0.002	48.912	0.152	1.884	4.843	-18024.719	4.342	3.361	21.510	0.175

Table 7a. Result of canal water from laboratory testing

Ward Name	Deprivation	Cluster	Ni 60	Cu 63	Zn 66	As 75	Se 82
	ranking	(Quartile)	(ppb)	(ppb)	(ppb)	(ppb)	(ppb)
Alum Rock	5	1	11.879	7.318	-1.820	2.931	0.924
Sparkbrook & Balsall Heath East	1	1	20.585	4.691	5.470	2.561	1.283
Bordesley & Highgate	19	2	16.799	11.768	42.758	2.806	1.985
Nechells	24	2	4.238	0.908	11.900	1.780	0.742
Nechells	24	2	10.058	7.036	5.939	3.156	-0.223
Bromford & Hodge Hill	33	2	19.754	8.405	39.530	2.945	1.340
Soho & Jewellery Quarter	29	2	5.189	4.820	9.752	3.113	0.531
Pype Hayes	39	3	15.079	4.761	21.487	2.259	1.042
North Edgbaston	41	3	6.450	5.762	13.105	4.199	0.351
Ladywood	42	3	7.666	8.425	4.301	4.218	-0.439
Stirchley	46	3	13.296	6.478	26.688	3.074	0.714
King's Norton North	44	3	12.878	6.376	28.102	3.233	0.011
South Yardley	48	3	12.744	2.462	6.664	1.731	1.564
Perry Barr	56	4	6.176	0.917	0.894	2.700	-0.810
Perry Barr	56	4	5.022	0.644	0.625	2.114	0.309
Edgbaston	61	4	10.216	10.271	27.487	2.596	-0.088
Edgbaston	61	4	10.113	5.501	14.875	2.471	0.404
Bournbrook & Selly Park	60	4	10.472	4.753	9.536	2.733	0.518
Sutton Walmley & Minworth	64	4	-0.080	-0.056	0.002	48.912	0.152

Table 7b. Result of canal water from laboratory testing

### 3.1.1 Descriptive Statistic

*Table 8* shows the descriptive statistics of different heavy metals in canal water, while *Figures* 8 to 19 shows the box plots of each heavy metal in canal water tested against the clusters, where Cluster One and Four represent the most and least deprived areas, respectively. The dots in the box plot represent the outliner in the data. In general, most of the heavy metals from the tested canal water show a descending order across the clusters. However, three metals, which included chromium, manganese, and zinc, show an extremely low concentration in cluster one.

	Ν	Minimum	Maximum	Mean	Std. Deviation
Ba138	19	44.621	61.443	51.38095	4.943852
Hg202	19	.093	.212	.13547	.027806
Pb208	19	.000	2.120	.81047	.704379
Cr52	19	.024	15.364	1.84074	4.250186
Mn55	19	.819	11.527	3.27263	2.710141
Fe56	19	1.179	31.515	13.12389	7.841769
Co59	19	.071	.393	.16379	.090125
Ni60	19	4.238	20.585	11.33368	4.915627
Cu63	19	.644	11.768	5.68232	3.021737
Zn66	19	.000	42.758	15.62632	13.107829
As75	19	1.731	4.218	2.79105	.658783
Se82	19	.000	1.985	.68200	.599095
Valid N (listwise)	19				

Descriptive Statistics of Heavy Metal in Canal Water

Table 8. Descriptive statistics of heavy metal in canal water

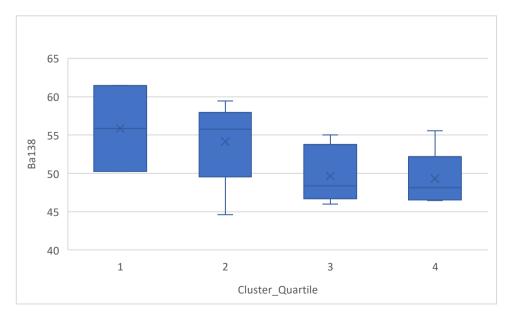


Figure 8. A box plot for barium in canal water by clusters

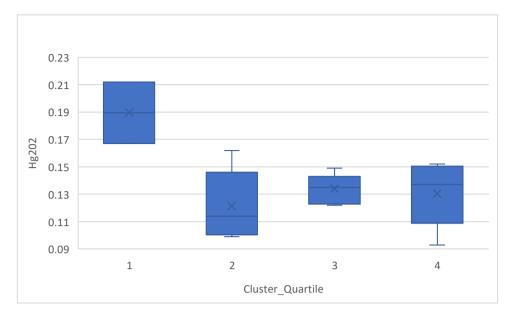


Figure 9. A box plot for mercury in canal water by clusters

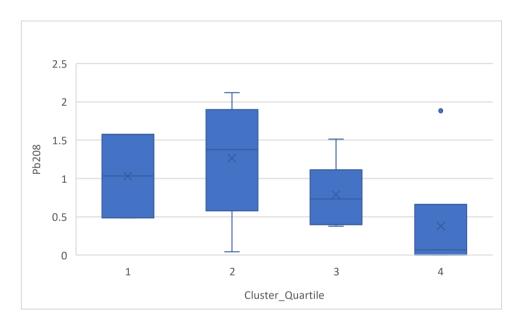


Figure 10. A box plot for lead in canal water by clusters

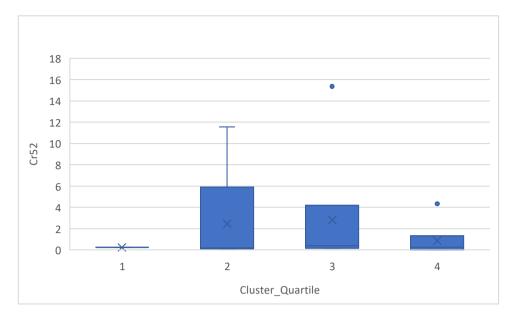


Figure 11. A box plot for chromium in canal water by clusters

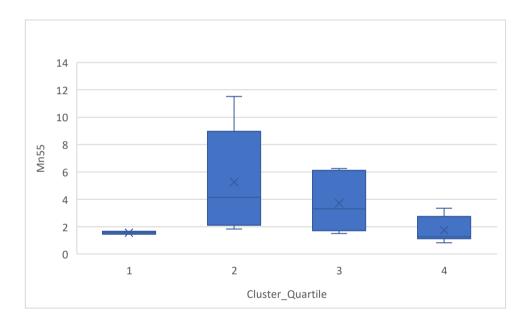


Figure 12. A box plot for manganese in canal water by clusters

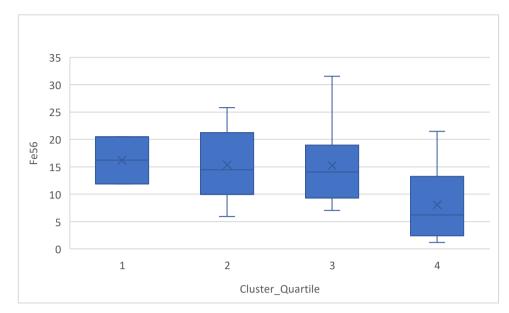


Figure 13. A box plot for iron in canal water by clusters

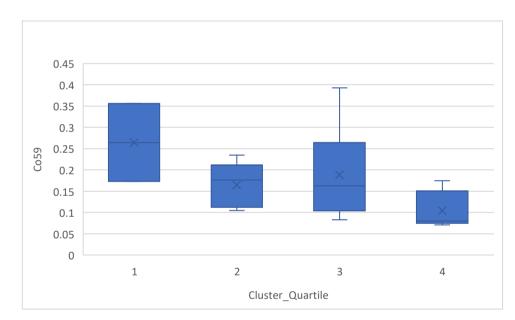


Figure 14. A box plot for cobalt in canal water by clusters

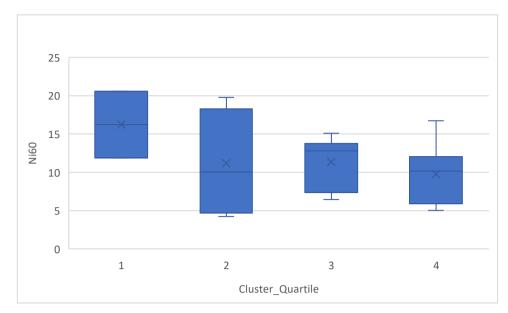


Figure 15. A box plot for nickel in canal water by clusters

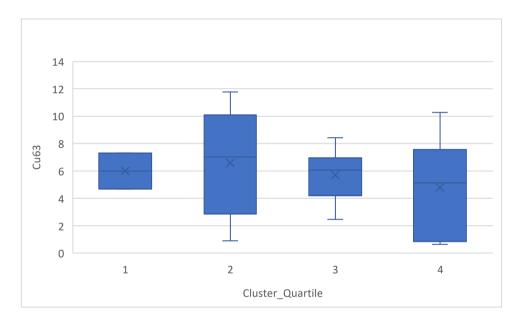


Figure 16. A box plot for copper in canal water by clusters

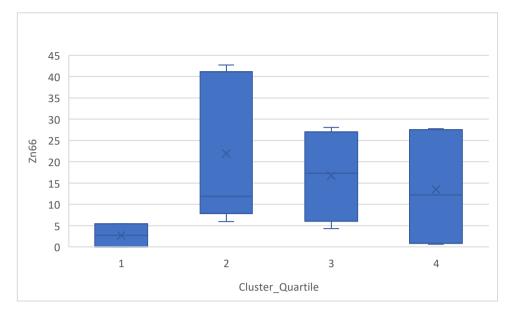


Figure 17. A box plot for zinc in canal water by clusters

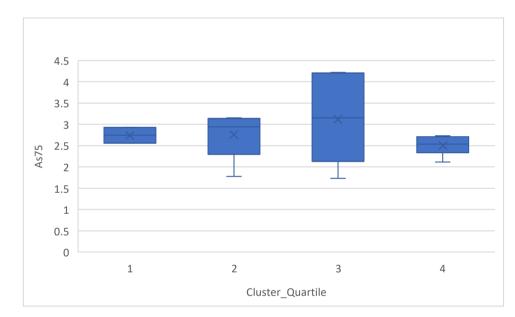


Figure 18. A box plot for arsenic in canal water by clusters

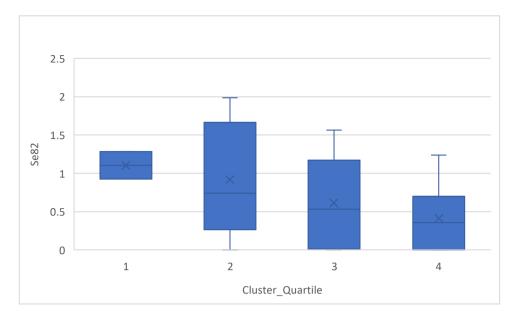


Figure 19. A box plot for selenium in canal water by clusters

### 3.1.2 Statistical Test

The statistical tests are performed by SPSS. The statistical test results show that the normality and common variance assumptions of this set of data are not satisfied (See Appendix 4), therefore, the Wilcoxon test would be performed to determine whether there is a difference among the deprivation clusters. To minimise the type I error, the Bonferroni correction factor would be applied. For a test to be statistically significant at 0.1 level,  $p < 0.1 \div 6 = 0.0167$  for four decimal places.

*Tables 9* to *14* show the statistical test result of comparison for each cluster with each element. However, at 90% conference level, none of the results of the canal water has significant differences among the comparison.

## 3.1.3 Quality Control

The quality control of the test result is controlled by the duplicate analysis. The absolute deviation from mean (ADM) is required to be lower than 10% in order to pass the quality control. In addition, the calculation from S17 and S17 duplicate suggested that no ADM exceeded 10%, thus, the test result passed the duplicate analysis.

				Cius	ster 1 v Q	Juster 2	<u> </u>					
	Ba138	Hg202	Pb208	Cr52	Mn55	Fe56	Co59	Ni60	Cu63	Zn66	As75	Se82
Mann-Whitney U	4.000	.000	4.000	4.000	.000	5.000	3.000	2.000	4.000	.000	3.000	4.000
Wilcoxon W	19.000	15.000	7.000	19.000	3.000	20.000	18.000	17.000	7.000	3.000	6.000	19.000
Z	387	-1.936	387	387	-1.936	.000	775	-1.162	387	-1.936	775	387
Asymp. Sig. (2-tailed)	.699	.053	.699	.699	.053	1.000	.439	.245	.699	.053	.439	.699
Exact Sig. [2*(1-tailed	.857ª	.095 <sup>a</sup>	.857ª	.857ª	.095ª	1.000 <sup>a</sup>	.571ª	.381ª	.857ª	.095ª	.571ª	.857ª
Sig.)]												

Cluster 1 v Cluster 2

Table 9. Wilcoxon test of Cluster 1 v Cluster 2 for canal water

# Cluster 1 v Cluster 3

	Ba138	Hg202	Pb208	Cr52	Mn55	Fe56	Co59	Ni60	Cu63	Zn66	As75	Se82
Mann-Whitney U	2.000	.000	4.000	4.000	1.000	5.000	4.000	4.000	6.000	1.000	4.000	3.000
Wilcoxon W	23.000	21.000	25.000	7.000	4.000	26.000	25.000	25.000	27.000	4.000	7.000	24.000
Z	-1.333	-2.000	667	667	-1.667	333	667	667	.000	-1.667	667	-1.000
Asymp. Sig. (2-tailed)	.182	.046	.505	.505	.096	.739	.505	.505	1.000	.096	.505	.317
Exact Sig. [2*(1-tailed	.286ª	.071ª	.643ª	.643ª	.143ª	.857ª	.643ª	.643ª	1.000ª	.143ª	.643ª	.429ª
Sig.)]												

Table 10. Wilcoxon test of Cluster 1 v Cluster 3 for canal water

				Clus	ster 1 v (	Cluster 4	ŀ					
	Ba138	Hg202	Pb208	Cr52	Mn55	Fe56	Co59	Ni60	Cu63	Zn66	As75	Se82
Mann-Whitney U	2.000	.000	2.000	6.000	4.000	2.000	1.000	1.000	5.000	2.000	3.000	1.000
Wilcoxon W	23.000	21.000	23.000	27.000	25.000	23.000	22.000	22.000	26.000	5.000	24.000	22.000
Z	-1.333	-2.000	-1.341	.000	667	-1.333	-1.677	-1.667	333	-1.333	-1.000	-1.677
Asymp. Sig. (2-tailed)	.182	.046	.180	1.000	.505	.182	.094	.096	.739	.182	.317	.094
Exact Sig. [2*(1-tailed	.286ª	.071ª	.286 <sup>a</sup>	1.000 <sup>a</sup>	.643 <sup>a</sup>	.286ª	.143 <sup>a</sup>	.143 <sup>a</sup>	.857ª	.286ª	.429 <sup>a</sup>	.143 <sup>a</sup>
Sig.)]												

Table 11. Wilcoxon test of Cluster 1 v Cluster 4 for canal water

				Clus	ster 2 v (	Cluster 3	3					
	Ba138	Hg202	Pb208	Cr52	Mn55	Fe56	Co59	Ni60	Cu63	Zn66	As75	Se82
Mann-Whitney U	7.000	8.000	8.000	10.000	10.000	14.000	14.000	14.000	12.000	13.000	11.000	11.500
Wilcoxon W	28.000	23.000	29.000	25.000	31.000	35.000	29.000	29.000	33.000	34.000	26.000	32.500
Z	-1.461	-1.278	-1.278	913	913	183	183	183	548	365	730	640
Asymp. Sig. (2-tailed)	.144	.201	.201	.361	.361	.855	.855	.855	.584	.715	.465	.522
Exact Sig. [2*(1-tailed	.177ª	.247ª	.247ª	.429ª	.429ª	.931ª	.931ª	.931ª	.662ª	.792ª	.537ª	.537ª
Sig.)]												

Table 12. Wilcoxon test of Cluster 2 v Cluster 3 for canal water

				Clus	ster 2 v (	Cluster 4						
	Ba138	Hg202	Pb208	Cr52	Mn55	Fe56	Co59	Ni60	Cu63	Zn66	As75	Se82
Mann-Whitney U	7.000	12.000	7.000	15.000	4.000	6.000	4.000	15.000	10.000	10.000	6.000	7.000
Wilcoxon W	28.000	27.000	28.000	36.000	25.000	27.000	25.000	36.000	31.000	31.000	27.000	28.000
Z	-1.461	550	-1.464	.000	-2.008	-1.643	-2.013	.000	913	913	-1.643	-1.474
Asymp. Sig. (2-tailed)	.144	.582	.143	1.000	.045	.100	.044	1.000	.361	.361	.100	.140
Exact Sig. [2*(1-tailed	.177ª	.662 <sup>a</sup>	.177ª	1.000 <sup>a</sup>	.052ª	.126ª	.052ª	1.000 <sup>a</sup>	.429 <sup>a</sup>	.429 <sup>a</sup>	.126ª	.177ª
Sig.)]												

Table 13. Wilcoxon test of Cluster 2 v Cluster 4 for canal water

# **Cluster 3 v Cluster 4**

	Ba138	Hg202	Pb208	Cr52	Mn55	Fe56	Co59	Ni60	Cu63	Zn66	As75	Se82
Mann-Whitney U	18.000	17.000	6.000	11.000	6.000	8.000	7.000	12.000	14.000	15.000	11.000	14.000
Wilcoxon W	39.000	38.000	27.000	32.000	27.000	29.000	28.000	33.000	35.000	36.000	32.000	35.000
Z	.000	160	-1.925	-1.123	-1.922	-1.601	-1.764	961	641	480	-1.121	645
Asymp. Sig. (2-tailed)	1.000	.873	.054	.261	.055	.109	.078	.337	.522	.631	.262	.519
Exact Sig. [2*(1-tailed Sig.)]	1.000ª	.937ª	.065ª	.310 <sup>a</sup>	.065ª	.132ª	.093ª	.394ª	.589ª	.699 <sup>a</sup>	.310ª	.589ª

Table 14. Wilcoxon test of Cluster 3 v Cluster 4 for canal water

### 3.2 Result of Sediment

*Table 15* shows the secondary data of the sediment provided by the Trust, data were tested by accredited laboratories between the period of 2014 to 2023. The sampling sites were required to be as near to the sampling sites of canal water as possible to ensure consistency and comparability with the result of canal water. However, due to the lack of monitoring stations or undesirable sampling locations, only 14 samplings are included in further discussion.

9 elements were tested positive by ICP-MS, including arsenic, cadmium, chromium, copper, lead, mercury, nickel, selenium, and zinc, the pH of the tested samples ranged from 6.7 to 8.9. Moreover, among the 14 sampling sites, 2 of them are Cluster One, 4 of them are Cluster Two, 3 of them are Cluster Three, and the remaining 5 are Cluster Four.

Ward Name	Cluster	pН	Arsenic	Cadmium	Chromium	Copper	Lead	Mercury	Nickel	Selenium	Zinc
	Quantile		(As)	(Cd)	(Cr)	(Cu)	(Pb)	(Hg)	(Ni)	(Se)	(Zn)
			(ppm)	(ppm)	(ppm)	(ppm)	(ppm)	(ppm)	(ppm)	(ppm)	(ppm)
Alum Rock	1	8.3	17.4	7.37	226	1609	224.5	0.46	243.7	3.1	3278
Sparkbrook & Balsall Heath East	1	7.3	43.5	11.28	475.8	1614	376.7	0.82	317.2	2.5	3132
Nechells	2	7.5	70.7	13.91	653.7	4254	927.5	1.78	322.6	10	5712
Nechells	2	7.9	51.6	17.45	801.7	3450	625.1	2.82	458.9	3.4	3540
Bordesley & Highgate	2	7.8	78.6	25.19	4090	9210	953.8	3.22	514.9	5.8	6270
Soho & Jewellery Quarter	2	7.8	19.7	12.34	728.6	3204	332.1	0.98	246.5	2.7	2966
Stirchley	3	7.3	14.8	1.8	32	84.6	73.1	<0.5	24.7	<0.5	162.7
King's Norton North	3	7.5	43.4	11.96	543.5	2707	428	1.07	327.4	2.7	3259
South Yardley	3	7.4	56.3	15.76	1160	3730	675.5	1.74	500.4	3.7	3980
Perry Barr	4	7.3	33.5	11.72	695.2	2658	693.2	1.29	1063	6.8	3424
Sutton Walmley & Minworth	4	8.1	16.6	2.25	84	533.2	129	0.14	131	0.5	907.4
Edgbaston	4	7.3	52.3	24.87	869.7	4477	518.2	1.51	401.7	4.3	5923
Edgbaston	4	6.7	7.9	1.1	25.6	69.5	91.6	<0.5	53.8	0.5	395.3
Bournbrook & Selly Park	4	8.1	20.8	5.09	44	309.5	161.5	0.33	102.4	3.6	1880

Table 15. Secondary data of sediment provided by Canal & River Trust

### 3.2.1 Descriptive Statistic

*Table 16* shows the descriptive statistics of different heavy metals in sediments, while *Figures* 20 to 28 show the box plots of the elements in sediment samples against the clusters. Surprisingly, cluster one shows low concentrations across all the elements, while cluster two shows the highest concentration of heavy metals among the clusters, and the concentration level descends in Clusters Three and Four. The consistency of this trend could be observed across all the elements in sediment data.

	Ν	Minimum	Maximum	Mean	Std. Deviation
As	14	7.90	78.60	37.6500	22.32149
Cd	14	1.10	25.19	11.5779	7.70823
Cr	14	25.60	4090.00	744.9857	1027.60958
Cu	14	69.50	9210.00	2707.8429	2423.76296
Pb	14	73.10	953.80	443.7000	297.82025
Hg	14	.00	3.22	1.1543	.99713
Ni	14	24.70	1063.00	336.3000	262.71602
Se	14	.00	10.00	3.6857	2.75314
Zn	14	162.70	6270.00	3196.3857	1927.53847
Valid N (listwise)	14				

Descriptive Statistics of Heavy Metal in Sediment

Table 16. Descriptive statistics of heavy metal in sediment

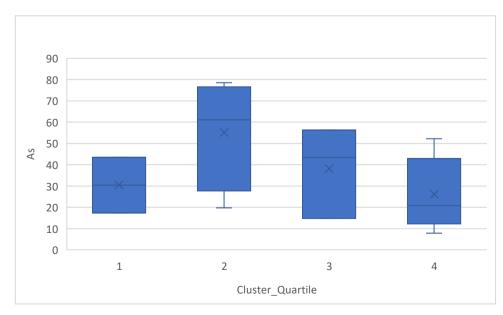


Figure 20. A box plot for arsenic in sediment by clusters

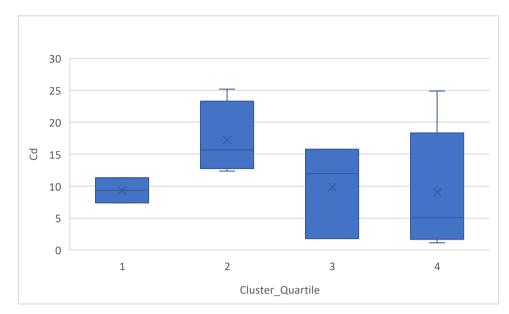


Figure 21. A box plot for cadmium in sediment by clusters

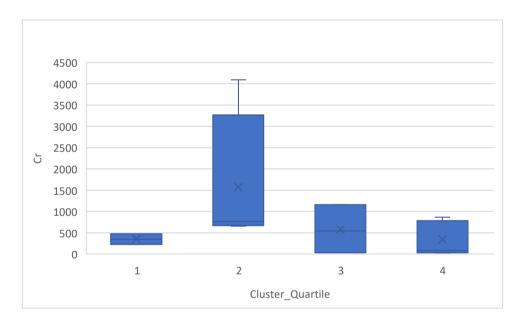


Figure 22. A box plot for chromium in sediment by clusters

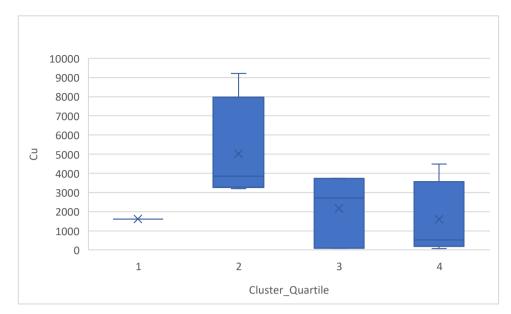


Figure 23. A box plot for copper in sediment by clusters

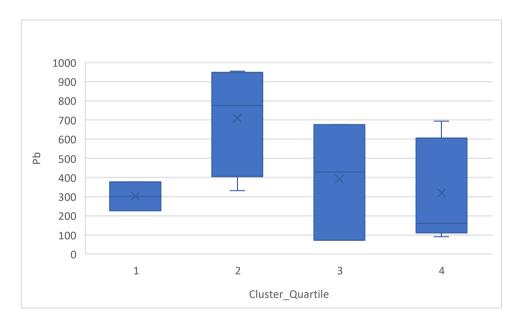


Figure 24. A box plot for lead in sediment by clusters

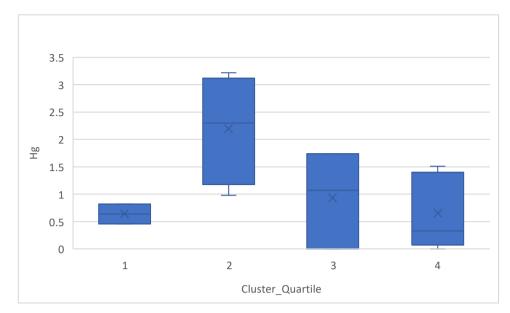


Figure 25. A box plot for mercury in sediment by clusters

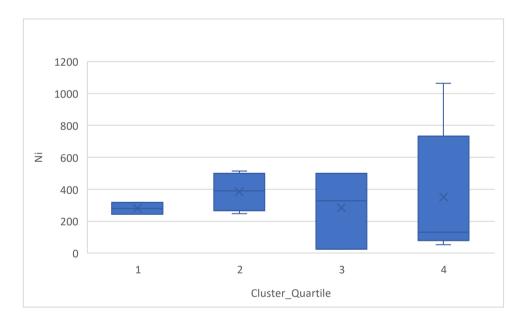


Figure 26. A box plot for nickel in sediment by clusters

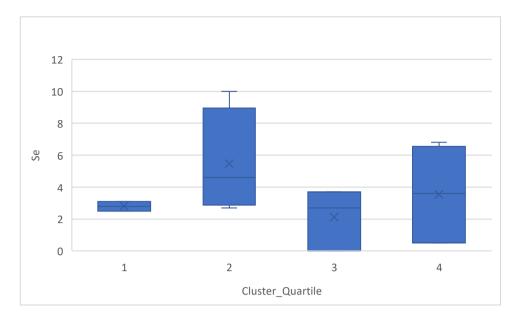


Figure 27. A box plot for selenium in sediment by clusters

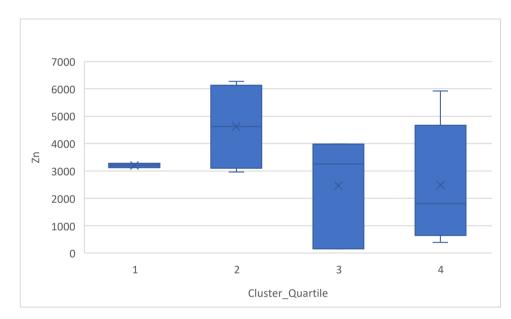


Figure 28. A box plot for zinc in sediment by clusters

### 3.2.2 Statistical Test

Similar to the data of canal water, the statistical test results show that that the normality and common variance assumptions are not satisfied, the test results can be found in Appendix 4. Wilcoxon tests are performed to determine any significant difference in the level of concentration between clusters, and the Bonferroni correction factor is applied again to for the

determination of significant difference, where for a test to be statistically significant at 0.1 level, p < 0.0167 for four decimal places. *Tables 17* to 22 show the statistical test results of 6 comparisons between clusters.

Although a trend could be observed from the descriptive statistics, however, at 90% conference level (p < 0.0167), none of the results of the sediment has a significant difference among the comparison of clusters.

	As	Cd	Cr	Cu	Pb	Hg	Ni	Se	Zn
Mann-Whitney U	1.000	.000	.000	.000	1.000	.000	1.000	1.000	2.000
Wilcoxon W	4.000	3.000	3.000	3.000	4.000	3.000	4.000	4.000	5.000
Z	-1.389	-1.852	-1.852	-1.852	-1.389	-1.852	-1.389	-1.389	926
Asymp. Sig. (2-tailed)	.165	.064	.064	.064	.165	.064	.165	.165	.355
Exact Sig. [2*(1-tailed Sig.)]	.267	.133	.133	.133	.267	.133	.267	.267	.533

Table 17. Wilcoxon test of Cluster 1 v Cluster 2 for sediment

# Cluster 1 v Cluster 3

	As	Cd	Cr	Cu	Pb	Hg	Ni	Se	Zn
Mann-Whitney U	3.000	2.000	2.000	2.000	2.000	2.000	2.000	3.000	3.000
Wilcoxon W	9.000	5.000	5.000	5.000	5.000	5.000	5.000	9.000	9.000
Z	.000	577	577	577	577	577	577	.000	.000
Asymp. Sig. (2-tailed)	1.000	.564	.564	.564	.564	.564	.564	1.000	1.000
Exact Sig. [2*(1-tailed Sig.)]	1.000	.800	.800	.800	.800	.800	.800	1.000	1.000

Table 18. Wilcoxon test of Cluster 1 v Cluster 3 for sediment

	Cluster 1 v Cluster 4								
	As	Cd	Cr	Cu	Pb	Hg	Ni	Se	Zn
Mann-Whitney U	4.000	4.000	4.000	4.000	4.000	4.000	4.000	4.000	4.000
Wilcoxon W	19.000	19.000	19.000	19.000	19.000	19.000	19.000	7.000	19.000
Z	387	387	387	387	387	387	387	391	387
Asymp. Sig. (2-tailed)	.699	.699	.699	.699	.699	.699	.699	.696	.699
Exact Sig. [2*(1-tailed Sig.)]	.857	.857	.857	.857	.857	.857	.857	.857	.857

# Cluster 1 v Cluster 4

Table 19. Wilcoxon test of Cluster 1 v Cluster 4 for sediment

	As	Cd	Cr	Cu	Pb	Hg	Ni	Se	Zn
Mann-Whitney U	3.000	2.000	3.000	2.000	3.000	2.000	5.000	2.500	3.000
Wilcoxon W	9.000	8.000	9.000	8.000	9.000	8.000	11.000	8.500	9.000
Z	-1.061	-1.414	-1.061	-1.414	-1.061	-1.414	354	-1.249	-1.061
Asymp. Sig. (2-tailed)	.289	.157	.289	.157	.289	.157	.724	.212	.289
Exact Sig. [2*(1-tailed Sig.)]	.400	.229	.400	.229	.400	.229	.857	.229	.400

# Cluster 2 v Cluster 3

Table 20. Wilcoxon test of Cluster 2 v Cluster 3 for sediment

## Cluster 2 v Cluster 4

	As	Cd	Cr	Cu	Pb	Hg	Ni	Se	Zn
Mann-Whitney U	4.000	3.000	4.000	3.000	3.000	2.000	6.000	8.000	4.000
Wilcoxon W	19.000	18.000	19.000	18.000	18.000	17.000	21.000	23.000	19.000
Z	-1.470	-1.715	-1.470	-1.715	-1.715	-1.960	980	492	-1.470
Asymp. Sig. (2-tailed)	.142	.086	.142	.086	.086	.050	.327	.623	.142
Exact Sig. [2*(1-tailed Sig.)]	.190	.111	.190	.111	.111	.063	.413	.730	.190

Table 21. Wilcoxon test of Cluster 2 v Cluster 4 for sediment

# Cluster 3 v Cluster 4

	As	Cd	Cr	Cu	Pb	Hg	Ni	Se	Zn
Mann-Whitney U	5.000	6.000	6.000	6.000	7.000	6.500	7.000	5.000	7.000
Wilcoxon W	20.000	21.000	21.000	21.000	13.000	21.500	13.000	11.000	13.000
Z	745	447	447	447	149	300	149	750	149
Asymp. Sig. (2-tailed)	.456	.655	.655	.655	.881	.764	.881	.453	.881
Exact Sig. [2*(1-tailed Sig.)]	.571	.786	.786	.786	1.000	.786	1.000	.571	1.000

Table 22. Wilcoxon test of Cluster 3 v Cluster 4 for sediment

## **Chapter Summary**

17 elements were tested from 19 samples for canal water, while 11 of them were tested positive in ppb level which included in further discussion. Based on the statistical analysis by cluster, most of the heavy metals show a descending order across the clusters from the box plot, however, none of the results of the canal water has significant differences among the comparison. On the other hand, 9 elements tested positive from 14 samples for sediment, and surprisingly, the most deprived areas (cluster one) show a low concentration across all the elements, and cluster two shows the highest concentration, and descends in Cluster Three and Four. In addition, none of the results of the sediment has significant differences among the comparisons.

#### **CHAPTER 4**

### Discussion

#### 4.0 Overview

The section discusses the objectives and research questions of this project, including the comparison of the test results and the current available standards, the identification of characteristics of heavy metal conditions in Birmingham canals, as well as the determination of potential environmental inequality of heavy metal pollution with the clusters of deprivation in Birmingham.

### 4.1 Comparison of the Test Results and Standards

The water quality standards provide "the desired condition of a water body, and the means by which that condition will be protected or achieved", and to protect human health and aquatic life in these water (USEPA, 2023). A range of water standards are available for the comparisons, the comparison could be against UK provisions, or WHO guidelines. In addition, three sets of standards are summarised and compared with the test results of the canal water, these standards included the EQS standard under the requirement of WFD, the WHO recreational water standard, as well as the drinking water standards from the UK provision.

### 4.1.1 EQS Standard

The EQS standard specified the limits of 16 elements that are under concern for both statutory and non-statutory, and the test results could be compared with the maximum allowable concentration stated in the standard. However, the comparability of this set of standards with the test results of the canal water is low, and only 6 of the elements could be compared, including cobalt, cadmium, lead, mercury, nickel, and silver. The remaining elements are not comparable for two reasons, for aluminium, it is excluded from discussion due to the poor performance of the calibration curve, and for the rest of the elements, there is no stated limit of maximum allowable concentration for the elements.

*Table 23* shows the limit of the maximum allowable concentration of inland fresh water for the elements that could be compared, which could be comparable with the test result of canal water (*Table 7a* and *7b*). Although the concentration of cobalt, cadmium, lead, nickel, and silver in all of the tested samples is below the limits, the concentration of mercury in all samples exceeded the limit ranging from 23% to 203%.

Element	Statutory status	EQS Limit (Inland Fresh Water) (µg/L)
		Maximum Allowable Concentration (MAC)
Cobalt	Non-Statutory	100 (Dissolved)
Cadmium and its compounds	WFD PS/PHS/OP	≤0.45(Class 1)
		0.45 (Class 2)
		0.6 (Class 3)
		0.9 (Class 4)
		1.5 (Class 5)
Lead	WFD PS/PHS/OP	14
Mercury and its compounds	WFD PS/PHS/OP	0.07
Nickel and its compounds	WFD PS/PHS/OP	34 (Dissolved)
Silver	Non-Statutory	0.1 (Dissolved)

Table 23. 6 elements in EQS standard is comparable with the test result

Mercury is a volatile compound that naturally occurs in the environment, however, it is highly toxic to humans which would accumulate in the human body and may have toxic effects on the nervous, digestive, and immune systems (Environmental Agency, 2019).

According to Scientific Committee on Health, Environmental and Emerging Risks (SCHEER)(2022), the limit of 0.07 µg/L was set with the consideration of tolerable weekly

intake (TWI) of human consumption, and the multiplication of the application factor of the lowest acute toxicity test that currently available, which is the 8 days LC50 on Carassius auratus of  $0.7 \ \mu g \ L^{-1}$ . Furthermore, it is reported that a low concentration of mercury in surface water can lead to a high concentration in insects, birds, and fishes (Environmental Agency, 2019). As a result, the exceed of the limit is not only harmful to aquatic life but also causes bioaccumulation and biomagnification in animals, activities such as fishing in the canal could lead to heavy metals entering the food chain, causing adverse effects on the human body (Environmental Agency, 2019).

On the other hand, under the WFD framework, if the water body fails one or more substances when determining the chemical status, the water body is classified as failing to achieve good chemical status (*Directive 2000/60/EC of the European Parliament and of the Council*). Therefore, a conclusion could be drawn that the canals in Birmingham fail to achieve a good chemical status under the WFD framework.

#### 4.1.2 WHO Recreational Water Standard and Drinking Water Standard

The EQS standard takes different factors into account, such as the calculation of bioavailability, pH, and the hardness of the water, however, these factors set up a boundary to this project which makes the standard have a low comparability with the test results. Thus, in order to give a general picture of the test results, the WHO recreational water standard would be used for comparison as well.

The WHO recreational water standard provides screening values for indicative chemicals in recreational waters, and the standard is derived from the WHO drinking water standard by

multiplying the limits by 20 times (WHO, 2021). Hence, this standard will be compared with the test results alongside the drinking water standard. *Table 24* summarises the guideline values and limits of heavy metals stated in the WHO recreational water standard and the UK drinking water standard.

Element	UK Drinking Water Standard	WHO Recreational Standard
	(ppb)	(ppb)
Arsenic	10	200
Cadmium	5	60
Chromium	50	1000
Copper	2000	40000
Lead	10	200
Manganese	50	8000
Nickel	20	1400
Mercury	1	-
Selenium	10	-
Iron	200	-

Table 24. The UK drinking water standard and WHO recreational standard

Comparing *Tables 7a & 7b* and *Table 24*, under the UK drinking water standard, apart from the sample from Sutton Walmley and Minworth exceeding the limit of arsenic, and the sample from Sparkbrook and Balsall Heath East exceeds the limit of nickel, the remaining test results are below the limits of both UK drinking water standard and WHO recreational water standard. Yet, as this project only provided a single screening test instead of long term monitoring, this finding can only be an initial reference and cannot imply that the canal water is safe or in good status.

### 4.2 Characteristics of Heavy Metal Condition in Birmingham Canals

Comparing the results with the legislation limits and guideline values indicated whether the water bodies or sediments are in good status or not. However, in the UK, only 16% of the surface water bodies assessed were in high and good ecological status under the definition of the WFD (DEFRA, 2023). Therefore, to identify the characteristics of the heavy metal conditions in Birmingham canals, it would be necessary to compare with the results from different regions. Hence, this section is divided into two parts, identifying the characteristics of heavy metals for both water and sediments respectively.

### 4.2.1 Heavy Metal Condition in Canal Water

Zhou *et al.* (2020) collected past sampling data of the concentration of 12 heavy metals in surface water bodies (rivers and lakes) from 1972 - 2017 around the globe, the data was summarised and categorised based on the demography. It is reported that the heavy metal pollutants changed from single pollution to mixed pollution over time, and the sources of contamination changed from mining and manufacturing to rock weathering and waste discharging (Zhou *et al.*, 2020). Furthermore, *Table 25* shows the mean and standard deviation of the data from *Zhou et al* and this project for comparison.

Through the comparison, apart from the concentration of mercury is the mean of Europe, the concentration of the remaining 11 heavy metals in Birmingham canals is much lower than in other regions. Consequently, combining the findings from section 4.1, although the water quality in Birmingham canals cannot reach a good chemical status under the WFD framework due to the exceeding of the limit by mercury, the mean concentration of mercury in Birmingham canals is the mean of the surface water bodies in Europe, and the concentration

of the rest of the heavy metals compared are much lower than the rivers and lakes in other regions. Thus, in terms of the characteristics of heavy metals, it is not a special case for the surface water in Birmingham canals to exceed the limit by mercury, in contrast, the canals have a high overall performance.

Metals	Africa	Asia	Europe	North America	South America	Birmingham
						Canals
Cadmium	$45.04 \pm 14.99$	$17.75\pm3.96$	$5.69 \pm 5.05$	$1.12\pm0.85$	$63.54\pm35.81$	-
Lead	$83.82\pm22.50$	$92.70\pm17.35$	$14.31\pm3.58$	$163.28 \pm 163.28$	$332.93 \pm 196.14$	$0.81\pm0.70$
Chromium	$388.77 \pm 170.20$	$383.93 \pm 240.44$	$13.61 \pm 3.77$	$5.42\pm3.80$	$903.78 \pm 894.61$	$1.84\pm4.25$
Mercury	$528.50 \pm 488.70$	$4.17 \pm 1.60$	$0.15\pm0.12$	1.00	40.00	$0.14\pm0.28$
Zinc	$1169.00 \pm 680.68$	889.57 ± 448.85	$1338.99 \pm 979.86$	86.94 ± 48.51	$680.49 \pm 608.37$	$15.63 \pm 13.11$
Copper	$190.79 \pm 67.22$	$345.85 \pm 246.43$	$14.63\pm2.75$	$15.90 \pm 9.75$	$142.64 \pm 70.62$	$5.68\pm3.02$
Nickel	$131.69 \pm 85.61$	$54.84 \pm 18.52$	$137.47\pm51.39$	$10.93 \pm 6.04$	$33.55\pm22.47$	$11.33 \pm 4.92$
Manganese	$945.48 \pm 613.26$	967.77 ± 533.27	$257.87 \pm 76.87$	57.26 ± 44.83	$89.36 \pm 63.15$	$3.27 \pm 2.71$
Iron	$483.54 \pm 176.85$	$3152.78 \pm 2375.54$	$243.75 \pm 126.21$	$274.06 \ \pm 467.54$	$1203.83 \pm 1561.26$	$13.12\pm7.84$
Arsenic	$33.46 \pm 13.35$	$178.30 \pm 112.25$	$18.54 \pm 4.60$	-	-	$2.79\pm0.66$
Cobalt	$12.60 \pm 10.31$	$28.83 \pm 17.59$	$0.36\pm0.01$	-	$6.78\pm2.12$	$0.16\pm0.09$

Table 25. Table for comparison for heavy metal in canal water (Zhou et al., 2020)

### 4.2.2 Heavy Metal Condition in Sediment

As aforementioned, there is no statutory standard for sediments in the UK. Therefore, comparing the data with the other studies could be a way to identify the characteristics of heavy metal conditions in sediment.

A meta-analysis by Shammin *et al.* (2024) tested 6 heavy metals in sediment in Bangladesh from 1998 to 2021, it was reported that the sediments were severely contaminated by nickel, copper, cadmium, lead, and arsenic. On the other hand, Sojka and Jaskla (2022) tested 6 heavy metals in sediments of 47 rivers in Europe, and the result indicated that one-third of the

sediments tested were contaminated. *Table 26* summarises the mean and standard deviation of the sediment data, as well as the sediment data in this project.

Comparing the data from other studies with the result of this project, could imply that the concentration of heavy metals in Birmingham canals is extremely high, ranging from 3.36 times for arsenic to 247.97 times for copper. In addition, the sediments have extremely high concentrations of heavy metals which could be a potential threat to aquatic life and humans.

Metals	Shammin et al. (2024)	Sojka and Jaskla (2022)	Birmingham Canals
	Bangladesh (ppm)	Europe (ppm)	(ppm)
Chromium	$61.22 \pm 69.05$	$16.1 \pm 22.1$	$744.99 \pm 1027.61$
Cadmium	$1.74 \pm 2.80$	$0.168 \pm 0.321$	$11.58 \pm 7.71$
Copper	$44.45 \pm 60.74$	$10.92 \pm 14.96$	$2707.84 \pm 2423.76$
Nickel	$57.09 \pm 62.56$	8.21 ± 11.0	$336.30 \pm 262.72$
Lead	$46.62 \pm 137.77$	$18.0 \pm 37.4$	$443.70 \pm 297.82$
Arsenic	$11.22 \pm 19.48$	-	$37.65 \pm 22.32$
Zinc	-	$57.9 \pm 86.9$	$3196.39 \pm 1927.54$

Table 26. Table for comparison for heavy metal in sediment (Shammi *et al.*, 2024; Sojka and Jaskuła, 2022)

### 4.2.3 Characteristics - and the Linkage with Politics

By combining the findings from Section 4.2.1 and 4.2.2, although the surface water of the Birmingham canal has a low concentration of heavy metals, the sediments are extremely polluted by mixed types of heavy metals. Guan *et al.* (2018) stated that heavy metals in sediment is always considered to have a distinct anthropogenic origin, hence, the high concentration of heavy metals in sediment is considerably caused by the historical canal activities and usages during the period of the Industrial Revolution. Moreover, this finding aligns with the study three decades ago which shows severe contamination by heavy metals (Bromhead, 1994).

On the other hand, heavy metals tend to sink in sediments, and accumulate in the lower layer of the sediment, over time, heavy metals are released back into the water as the hydrodynamic conditions change (Singh *et al.*, 2005; Shammi *et al.*, 2024). Nevertheless, sediments can be a bed that contributes to the bio-magnification of heavy metals by aquatic organisms (Shammi *et al.*, 2024). As a result, sediment is a crucial part in order to protect the aquatic environment.

In the UK government 25-Year Environmental Plan, the government said to minimise the risk of chemical contamination in water by several actions, including implementing chemical strategy with framework and cooperating with different stakeholders (HM Government, 2018). However, sediment is a critical part of securing the water quality, which seems to be ignored. In addition, there should be a focus on the interaction of chemicals between the sediment and the environment in the UK, as well as establishing statutory limits and monitoring by delegated agencies.

### 4.3 Heavy Metal Pollution and Deprivation in Birmingham - Limitation

The statistical tests show no significant difference between heavy metal pollution and the area of deprivation in Birmingham for both canal water and sediment, however, this cannot imply a result that there is no issue of environmental inequality of heavy metal pollution among the wards in Birmingham. This could be a result of the limitation of this project, which could be discussed in two aspects, the first is the monitoring period and the sample size of this project, and the second is the limitation of the statistical test.

To begin with, due to constraining of time and budget, the result could only be obtained by a single-time screening instead of a long period of monitoring, and only 19 sampling sites were

selected to do the sampling. In addition, this little amount of data can only give an insight into the concentration of heavy metal in a particular instant, instead of sufficient evidence that could solidly represent a certain area in Birmingham.

Secondly, the limitation of the statistical test, which is the consequence of the above, could provide statistical errors for further discussion. It is being recognised that a small sample size within a short period of time can induce type I and type II errors, which decrease the statistical power and prevent the findings from being extrapolated (Faber and Fonseca, 2014). On the other hand, it is reported that the Bonferroni method that this project used is unnecessarily conservative with weak statistical power, where the adjusted p is often smaller than the required by conference level, this would be magnified if there are many tests for comparison (Lee and Lee, 2018). As a result, although there is no significant difference between heavy metal pollution and the area of deprivation in Birmingham, the statistical power of this result is low, and possible findings may still be undercover.

However, although no conclusion could be drawn on the issue of environmental inequality, most of the heavy metals in both canal water and sediment show a descending order across the clusters of deprivation, as well as an extremely low concentration of heavy metals could be found in cluster one of the sediments results. These results provided an initial finding and reference, and no potential environmental inequality should be ignored. Further studies would be required to confirm the possible environmental inequality of heavy metal pollution in Birmingham canals and the association with the areas of deprivation in Birmingham, as well as the potential effects on surrounding environments and human health.

## **Chapter Summary**

The results are compared with EQS, the WHO recreation water standard, and the UK drinking water standard, mercury is found to be exceeding the surface water EQS limit, it is, however, still the mean concentration of Europe. Furthermore, although the surface water of the Birmingham canal has a low concentration of heavy metals, the sediments are extremely polluted by mixed types of heavy metals, which could be a potential threat to aquatic life and humans. On the other hand, no conclusion could be drawn on the issue of environmental inequality of heavy metal pollution and the association with areas of deprivation in Birmingham due to the low statistical power of this project, however, this project provided an initial finding and reference on environmental inequality in Birmingham. Further studies would be required to confirm the possible environmental inequality of heavy metal pollution in Birmingham canals, and the potential effects on surrounding environments and human health.

### **CHAPTER 5**

### **Conclusion and Recommendation**

### 5.1 Conclusion

To conclude, this project aims to provide a current view of heavy metal within Birmingham canals and sediment, as well as investigate the association between the canal heavy metal pollution and deprivation in Birmingham. Findings suggested that although the surface water of the Birmingham canal has a low concentration of heavy metals, the sediments are extremely polluted by mixed types of heavy metals, which could be a potential threat to aquatic life and humans. Nevertheless, the finding suggested that there is no association between heavy metal pollution and deprivation in Birmingham, however, this cannot imply that there is no issue of environmental inequality due to low statistical power.

## 5.2 Recommendation

### 5.2.1 Policy

The findings suggested the sediment in Birmingham canal is heavily contamination by a wide range of heavy metals. Other studies suggested that sediment is a curial part crucial part of secure water quality, thus, the importance of sediment should not be ignored. Focus should be put on the interaction of chemicals between the sediment and the environment in the UK, as well as establishing statutory limits and monitoring by delegated agencies.

# 5.2.2 Further Studies

This project provided initial findings on environmental inequality of heavy metal pollution in the Birmingham canal, and the association with deprivation concerning the wards in Birmingham. Further studies would be required to confirm the possible environmental inequality of heavy metal pollution in Birmingham canals and the association with the areas of deprivation in Birmingham, as well as the potential effects on surrounding environments and human health.

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# **Appendix 1 - Sampling Plan**

# Heavy Metals in Birmingham Canals - Sampling Sheet

Site Code	Ward	Site	Parking	Post Code	Remark
S1	Perry Barr	Perry Barr Lock 1, Top Lock	109 Rowdale Road	B42 2DQ	Walk along the pathway
S2	Perry Barr	Perry Barr Lock 11	3 Elmbridge Road	B44 8AP	3 mins walk to bp
S3	Nechells	Salford Junction	4-19 Jameson Road	B6 7SJ	Main road→down the bdg
S4	Bromford & Hodge Hill	Bromford Bridge 2, Bromford Lane	Canal Lane	B24 8DX	Go down at the bridge
S5	Pype Hayes	Lock 1, Minworth,	Oakenhayes Cres	B76 9RP	Walk to 34 then path
S6	Sutton Walmley & Minworth	Lock 3, Minworth, Wiggins Hill Rd	Cuttle Bridge Inn	B76 9DP	Park Outside
S7	Alum Rock	Lock 5, Garrison Bottom Lock	Wing Yip	B7 5NT	15 mins walk
S8	Nechells	Aston Junction, Rocky Lane	Wing Yip	B7 5NT	10 mins walk
S9	Bordesley & Highgate	Bordesley Junction	St Andrew's shp park	B10 0XA	15 mins walk
S10	Soho & Jewellery Quarter	Turnover Bridge, End of Soho Loop	-	-	Walk
S11	North Edgbaston	Rotton Park Junction	-	-	Walk
S12	Ladywood	Old Turn Junction	-	-	Walk
S13	Edgbaston	Bridge 85, St. James Road	-	-	Walk
S14	Edgbaston	Bridge 82, University Avenue	-	-	Walk
S15	Bournbrook & Selly Park	Bridge 79, Selly Oak Railway Bridge	-	-	Walk
S16	Stirchley	Bridge 77, Maryvale Road	-	-	Walk
S17	King's Norton North	King's Norton Junction	-	-	Walk
S18	Sparkbrook & Balsall Heath East	Bridge 88F, Foot Bridge Armoury	100 Armoury Road	B11 2RJ	Walk through the path
		Road			
S19	South Yardley	Bridge 85, Lincoln Road	Olton Croft	B27 6PA	Post Code for Lincoln Road

# Appendix 2 -

# Deprivation Ranking of Birmingham 69 Wards in 2019 and the Corresponding Cluster

Name	2019 Deprivation Ranking	Cluster 4 Quartile
Sparkbrook & Balsall Health East	1	1
Bordesley Green	2	1
Lozells	3	1
Castle Vale	4	1
Alum Rock	5	1
Newtown	6	1
Hearlands	7	1
Gravelly Hill	8	1
Balsall Heath West	9	1
Birchfield	10	1
Shard End	11	1
Kingstanding	12	1
Garretts Green	13	1
Aston	14	1
Glebe Farm & Tile Cross	15	1
Handsworth	16	1
Ward End	17	1
Kings Norton South	18	1
Bordesley & Highgate	19	2
Tyseley & Hay Mills	20	2
Small Heath	21	2
Frankley Great Park	22	2
Holyhead	23	2
Nechells	24	2
Druids Heath & Monyhull	25	2
Stockland Green	26	2
Yardley West & Stechford	27	2
Perry Common	28	2
Soho & Jewellery Quarter	29	2
Sparkhill	30	2
Bartley Green	31	2
Allens Cross	32	2
Bromford & Hodge Hill	33	2
Billesley	34	2
Weoley & Selly Oak	35	2
Acocks Green	36	3
Rubery & Rednal	37	3
Erdington	38	3

Pype Hayes	39	3
Longbridge & West Heath	40	3
North Edgbaston	41	3
Ladywood	42	3
Moseley	43	3
Kings Norton North	44	3
Sheldon	45	3
Stirchley	46	3
Highter's Heath	47	3
South Yardley	48	3
Yardley End	49	3
Hall Green North	50	3
Quinton	51	3
Oscott	52	3
Brandwood & King's Heath	53	4
Handsworth Wood	54	4
Harborne	55	4
Perry Barr	56	4
Bournville & Cotteridge	57	4
Sutton Reddicap	58	4
Northfield	59	4
Bournbrook & Selly Park	60	4
Edgbaston	61	4
Hall Green South	62	4
Sutton Trinity	63	4
Sutton Walmley & Minworth	64	4
Sutton Vesey	65	4
Sutton Mere Green	66	4
Sutton Wylde Green	67	4
Sutton Four Oaks	68	4
Sutton Roughley	69	4

# Appendix 3 - Statistical Test Results for Normality and Common Variance Assumption for Canal Water

### Normality Test

Cluster 1

### One-Sample Kolmogorov-Smirnov Test<sup>a</sup>

			Ba138	Hg202	Pb208	Al2 7	Cr52	Mn55	Fe56	Co59	Ni60	Cu63	Zn66	As75	Se82
Ν			2	2	2	2	2	2	2	2	2	2	2	2	2
Normal Parameters <sup>b,c</sup>	Mean		55.84750	.18950	1.03300	2.77550	.24850	1.56800	16.20650	.26450	16.23200	6.00450	2.73500	2.74600	1.10350
	Std. Deviation		7.913232	.031820	.770746	3.925150	.003536	.145664	6.078997	.129401	6.156072	1.857570	3.867874	.261630	.253851
Most Extreme Differences	Absolute		.260	.260	.260	.260	.260	.260	.260	.260	.260	.260	.260	.260	.260
	Positive		.260	.260	.260	.260	.260	.260	.260	.260	.260	.260	.260	.260	.260
	Negative		260	260	260	260	260	260	260	260	260	260	260	260	260
Test Statistic			.260	.260	.260	.260	.260	.260	.260	.260	.260	.260	.260	.260	.260
Asymp. Sig. (2-tailed) <sup>d</sup>			.e	.e	.e	.e	.e	.e	.e	.e	.e	.e	.e	.e	.e
Monte Carlo Sig. (2- tailed) <sup>f</sup>	Sig.		1.000	1.000	1.000	.694	.051	.024	1.000	1.000	.429	.455	.708	.044	.489
tailed)'	99% Confidence Interval	Lower Bound	1.000	1.000	1.000	.682	.045	.020	1.000	1.000	.416	.442	.697	.039	.477
		Upper Bound	1.000	1.000	1.000	.706	.057	.027	1.000	1.000	.442	.468	.720	.049	.502

a. Cluster\_Quartile = 1

b. Test distribution is Normal.

c. Calculated from data.

d. Lilliefors Significance Correction.

e. Significance can not be computed because sum of case weights is less than 5.

f. Lilliefors' method based on 10000 Monte Carlo samples with starting seed 2000000.

### Cluster 2

### One-Sample Kolmogorov-Smirnov Test<sup>a</sup>

			Ba138	Hg202	Pb208	Al27	Cr52	Mn55	Fe56	Co59	Ni60	Cu63	Zn66	As75	Se82
Ν			5	5	5	5	5	5	5	5	5	5	5	5	5
Normal Parameters <sup>b,c</sup>	Mean		54.14440	.12140	1.26420	2.00660	2.45580	5.25700	15.40020	.16480	11.20760	6.58740	21.97580	2.76000	.91960
	Std. Deviation		5.632540	.025764	.778497	2.046008	5.086692	3.930066	7.130086	.052855	6.899731	4.053480	17.664737	.565280	.764858
Most Extreme Differences	Absolute		.321	.213	.221	.237	.465	.210	.227	.202	.208	.144	.316	.332	.192
	Positive		.173	.213	.141	.237	.465	.210	.227	.202	.208	.127	.316	.242	.192
	Negative		321	192	221	231	319	192	225	184	191	144	240	332	118
Test Statistic			.321	.213	.221	.237	.465	.210	.227	.202	.208	.144	.316	.332	.192
Asymp. Sig. (2-tailed) <sup>d</sup>			.102	.200 <sup>f</sup>	.200 <sup>f</sup>	.200 <sup>f</sup>	<.001	.200 <sup>f</sup>	.115	.074	.200 <sup>f</sup>				
Monte Carlo Sig. (2-	Sig.		.095	.665	.597	.477	<.001	.690	.554	.756	.703	.982	.109	.068	.826
tailed) <sup>e</sup>	99% Confidence Interval	Lower Bound	.088	.653	.585	.464	.000	.678	.541	.745	.691	.979	.101	.061	.816
		Upper Bound	.103	.677	.610	.490	.000	.702	.567	.767	.715	.986	.117	.074	.835

a. Cluster\_Quartile = 2

b. Test distribution is Normal.

c. Calculated from data.

d. Lilliefors Significance Correction.

e. Lilliefors' method based on 10000 Monte Carlo samples with starting seed 2000000.

f. This is a lower bound of the true significance.

### Cluster 3

### One-Sample Kolmogorov-Smirnov Test<sup>a</sup> Ba138 AI27 Cu63 Hg202 Pb208 Cr52 Mn55 Fe56 Co59 Ni60 Zn66 As75 Se82 6 6 6 6 N 6 6 6 6 6 6 6 6 6 Normal Parametersb,c 49.66517 .13417 .78967 9.55483 2.82867 3.70767 15.25050 .18900 11.35217 5.71067 16.72450 3.11900 .61367 Mean Std. Deviation 3.650285 .010572 .424697 10.504692 6.142572 2.240684 8.518007 .112458 3.451151 1.992858 10.198608 1.005521 .617326 Most Extreme Differences Absolute .303 .188 .166 .214 .482 .297 .357 .221 .323 .183 .180 .192 .169 Positive .160 .214 .482 .221 .137 .169 .303 .188 .297 .357 .191 .183 .171 -.173 -.192 -.160 Negative -.178-.142 -.166 -.182 -.332 -.186 -.167 -.323 -.177 -.180 Test Statistic .303 .188 .166 .214 .482 .297 .357 .221 .323 .183 .180 .192 .169 Asymp. Sig. (2-tailed)<sup>d</sup> .090 .200<sup>f</sup> .200<sup>f</sup> .200<sup>f</sup> <.001 .106 .016 .200<sup>f</sup> .049 .200<sup>f</sup> .200<sup>f</sup> .200<sup>f</sup> .200<sup>f</sup> Monte Carlo Sig. (2-.489 .709 .873 Sig. .085 .743 .889 .542 <.001 .099 .017 .047 .775 .804 tailed)<sup>e</sup> 99% Confidence Interval Lower Bound .078 .731 .881 .529 .000 .091 .013 .476 .041 .765 .793 .697 .865 Upper Bound .092 .754 .897 .555 .000 .106 .020 .502 .052 .786 .814 .720 .882

a. Cluster\_Quartile = 3

b. Test distribution is Normal.

c. Calculated from data.

d. Lilliefors Significance Correction.

e. Lilliefors' method based on 10000 Monte Carlo samples with starting seed 2000000.

f. This is a lower bound of the true significance.

### Cluster 4

### One-Sample Kolmogorov-Smirnov Test<sup>a</sup>

			Ba138	Hg202	Pb208	Al27	Cr52	Mn55	Fe56	Co59	Ni60	Cu63	Zn66	As75	Se82
N			6	6	6	6	6	6	6	6	6	6	6	6	6
Normal Parameters <sup>b,c</sup>	Mean		49.30500	.13050	.37900	.74083	.87100	1.75217	8.07283	.10417	9.78750	4.79233	13.53400	2.50400	.41183
	Std. Deviation		3.527084	.023253	.743313	1.554389	1.705249	.979259	7.465447	.043861	4.114701	3.640455	12.182187	.228625	.457598
Most Extreme Differences	Absolute		.216	.219	.399	.378	.461	.351	.210	.344	.267	.190	.207	.174	.242
	Positive		.216	.178	.399	.378	.461	.351	.210	.344	.267	.190	.184	.158	.242
	Negative		207	219	305	317	310	170	178	225	198	162	207	174	184
Test Statistic			.216	.219	.399	.378	.461	.351	.210	.344	.267	.190	.207	.174	.242
Asymp. Sig. (2–tailed) <sup>d</sup>			.200 <sup>e</sup>	.200 <sup>e</sup>	.003	.007	<.001	.020	.200 <sup>e</sup>	.025	.200 <sup>e</sup>				
Monte Carlo Sig. (2- tailed) <sup>f</sup>	Sig.		.527	.502	.004	.008	<.001	.021	.573	.026	.208	.726	.593	.845	.350
tailed)'	99% Confidence Interval	Lower Bound	.514	.489	.002	.005	.000	.017	.560	.022	.197	.715	.580	.835	.338
		Upper Bound	.540	.515	.005	.010	.000	.024	.585	.030	.218	.738	.605	.854	.362

a. Cluster\_Quartile = 4

b. Test distribution is Normal.

c. Calculated from data.

d. Lilliefors Significance Correction.

e. This is a lower bound of the true significance.

f. Lilliefors' method based on 10000 Monte Carlo samples with starting seed 2000000.

# Common Variance Test

### Tests of Homogeneity of Variances

Statisticdf1df2Sig.Ba138Based on Median.847315.489Based on Median and with adjusted off.535.310.482.568Based on trimmed mean.775.3.15.220Based on Median.652.3.15.424Based on Median and with adjusted off.3.15.424Based on Irimmed mean.1.579.3.15.236P2020Based on Median and with adjusted off.3.15.6863Based on Irimmed mean.1.217.3.9.694.8822Based on Median and with adjusted off.3.15.0264Based on Irimmed mean.3.12.3.15.0.02Based on Irimmed mean.3.12.3.15.0.02Based on Irimmed mean.7.588.3.15.0.02Based on Irimmed mean.7.588.3.15.0.02Based on Irimmed mean.1.254.3.15.0.22Based on Irimmed mean.1.254.3.15.0.02Based on Irimmed mean.1.254.3.15.0.02Based on Irimmed mean.1.254.3.15.0.02Based on Irimmed mean.1.254.3.15.0.02Based on Irimmed mean.0.33.3.5.0.22Based on Irimmed mean.0.33.3.5.0.22Based on Irimmed mean.0.33.3.5.0.22Based on Irimmed mean<			Levene			
Based on Median         5.335         3         1.5         6.665           Based on Median and with adjusted df         5.335         3         10.482         6.668           Based on Mean         7.755         3         1.5         5.226           Based on Mean         1.652         3         1.5         4.224           Based on Mean         9.900         3         9.446         4.339           Based on Mean         3.843         1.5         7.266           Based on Mean         3.844         3         1.5         .882           Based on Mean         3.844         3         1.5         .882           Based on Mean         3.12         3         1.5         .882           Based on Mean         4.407         3         1.5         .026           Based on Mean         4.4095         3         5.713         .071           Based on Mean         1.613         3         1.5         .026           Based on Mean         1.613         3         1.5         .027           Based on trimmed mean         1.254         3         1.5         .024           Based on trimmed mean         1.254         3         1.5         .024				df1	df2	Sig.
Based on Neclan and with adjusted df.535.310.482.6668Hg202 Based on trimmed mean.775.3.15.526Hg202 Based on Median.990.3.9446.439Based on Median and 	Ba138	Based on Mean	.847	3	15	.489
with adjusted afansweranswerBased on trimmed mean7.7753155.260Hg2Q2 Based on Median9.90039.4464.319Based on Median and with adjusted df9.90039.4464.319Based on Median and with adjusted df315.226Based on Median2.17315.236Based on Median2.1739.694.882Based on Median2.17315.0026Based on Median4.095315.0026Based on Median4.095315.0026Based on Median4.09535.713.071Based on Median1.813315.827Based on Median2.297315.827Based on Median2.297315.026Based on Median2.399315.026Based on Median2.399315.024Based on Median2.399315.024Based on Median2.399315.024Based on Median0.36315.990Based on Median0.36315.991Based on Median0.36315.992Co52Based on Median0.36315.224Based on Median1.62931.5.224Nith adjusted df1.26231.5.224Based on Median		Based on Median	.535	3	15	.665
Hg202 Based on Mean1.65231.5.220 Act on Based on Median and with adjusted df.99039.446.439Based on Median and with adjusted df.99039.446.439Based on Median.1.57931.5.236Pb208 Based on Median.21731.5.883Based on Median.21739.694.882Based on Median.21731.5.002Based on Median.409531.5.002Based on Median.40953.5.713.071Based on Median.40953.5.713.071Based on Median.40953.5.713.071Based on Median.7.58831.5.003Cr52 Based on Median.7.58831.5.827Based on Median.2.573.5.625.172Based on Median.2.3993.5.625.172Based on Median and with adjusted df.0.363.15.990Based on Median and with adjusted df.0.363.15.991Based on Median and with adjusted df.0.363.15.224F56 Based on Median and with adjusted df.0.36.3.15.224F67 Based on Median and with adjusted df.0.36.3.15.224F56 Based on Median and with adjusted df.3.31.5.224F56 Based on Median and with adjusted df			.535	3	10.482	.668
Hg202 Based on Mean1.65231.5.220 Act on Based on Median and with adjusted df.99039.446.439Based on Median and with adjusted df.99039.446.439Based on Median.1.57931.5.236Pb208 Based on Median.21731.5.883Based on Median.21739.694.882Based on Median.21731.5.002Based on Median.409531.5.002Based on Median.40953.5.713.071Based on Median.40953.5.713.071Based on Median.40953.5.713.071Based on Median.7.58831.5.003Cr52 Based on Median.7.58831.5.827Based on Median.2.573.5.625.172Based on Median.2.3993.5.625.172Based on Median and with adjusted df.0.363.15.990Based on Median and with adjusted df.0.363.15.991Based on Median and with adjusted df.0.363.15.224F56 Based on Median and with adjusted df.0.36.3.15.224F67 Based on Median and with adjusted df.0.36.3.15.224F56 Based on Median and with adjusted df.3.31.5.224F56 Based on Median and with adjusted df		Based on trimmed mean	.775	3	15	.526
Based on Median	Ha202					
Based on Median and with adjusted df.990.39.446.4.339Based on trimmed mean1.579.3.15.2.36Pb208 Based on Median.2.17.3.15.8.83Based on Median.2.17.3.15.8.83Based on Median and with adjusted df.2.17.3.15.8.817Al27 Based on Median and with adjusted df.2.17.3.15.0.02Based on Median and with adjusted df.4.095.3.5.713.0.071Based on Median and with adjusted df.2.27.3.5.713.0.03Cr52 Based on Median.2.27.3.15.8.827Based on Median.2.297.3.5.19.8.27Based on Median.2.399.3.5.625.1.72Based on Median.2.399.3.5.625.1.72Based on Median.2.399.3.5.625.1.72Based on Median.3.399.3.5.625.1.72Based on Median and with adjusted df.3.33.15.992Co54 Based on Median and with adjusted df.3.3.15.992Co54 Based on Median and with adjusted df.3.3.15.2.274Based on Median and with adjusted df.3.3 <td< td=""><td></td><td></td><td></td><td>-</td><td></td><td></td></td<>				-		
Based on trimmed mean         1.579         3         115         2.36           Pb208         Based on Median         .217         3         15         .683           Based on Median         .217         3         15         .683           Based on Median and with adjusted df         .217         3         15         .6817           Al27         Based on Median and with adjusted df         4.095         3         15         .0026           Based on Median         4.095         3         5.713         .0071           Based on Median         .297         3         15         .0026           Based on Median         .297         3         15         .038           Based on Median         .297         3         15         .038           Based on Median         .297         3         15         .038           Based on Median         .239         3         5.625         .172           Based on Median         .339         .5.625         .172           Based on Median         .036         3         13.029         .990           Based on Median         .036         3         13.029         .990           Based on Median		Based on Median and		-		
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Based on Median and with adjusted df	Pb208	Based on Mean	.384	3	15	.766
with adjusted df         item         item         item         item           Based on Irimmed mean         3.12         3         15         0.002           Based on Median         4.095         3         15         0.002           Based on Median         4.095         3         5.713         0.071           Based on Median         4.095         3         5.713         0.071           Based on Irimmed mean         7.588         3         15         0.033           Cr52         Based on Median         2.97         3         15         8.827           Based on Median         2.97         3         15         0.19           Based on Median         2.399         3         15         0.19           Based on Median         2.399         3         5.625         1.172           Based on Median         0.366         3         15         0.990           Based on Median         0.366         3         15         9.990           Based on Median         0.366         3         15         9.990           Based on Median         0.366         3         15         2.274           Based on Median         0.366         3		Based on Median	.217	3	15	.883
Al27 Based on Median8.487315.002Based on Median and with adjusted df4.095315.026Based on trimmed mean7.588315.003Cr52 Based on Median and with adjusted df315.003Based on Median and with adjusted df.297315.827Based on Median and with adjusted df.297315.325Based on Median.297315.325Mn52 Based on Median and with adjusted df.399315.109Based on Irimmed mean1.254315.021Based on Irimmed mean.239935.625.172Based on Median and with adjusted df.036315.990Based on Median and with adjusted df.036313.029.990Based on Median and with adjusted df.036313.029.990Based on Median and with adjusted df.225.225.225Based on Median and with adjusted df.203.3.3.224N60 Based on Median and with adjusted df.203.3.3.3.224N60 Based on Median and with adjusted df.203.3.3.3.3Cu52 Based on Median and with adjusted df.203.3.3.3.3Based on Median and with adjusted df.203.3.3.3.3Based on Median and with adjusted df.20			.217	3	9.694	.882
Based on Median4.095315.026Based on Median and madysted df4.09535.713.071Based on trimmed mean7.588315.003Cr52 Based on Median1.813315.188Based on Median and with adjusted df.297315.827Based on Irimmed mean1.254315.325Based on Median and with adjusted df.297315.325Based on Median and with adjusted df.2399315.109Based on Median and with adjusted df.33935.625.172Based on Irimmed mean4.218315.947Based on Median and with adjusted df.336315.990Based on Irimmed mean.036313.029.990Based on Irimmed mean.033315.922Co59 Based on Median and with adjusted df.337.274Based on Median and with adjusted df.347.3.15Based on Irimmed mean.1631315.224Nife Based on Irimmed mean.16313.15.224Nife Based on Irimmed mean.16313.15.224Nife Based on Irimmed mean.16313.15.224Nife Based on Irimmed mean.16313.15.224Nife Based on Median and with adjusted df.203.15.343Based on Irimmed mean<		Based on trimmed mean	.312	3	15	.817
Based on Median and with adjusted df4.09535.713.071Based on trimmed mean7.588315.003Cr52 Based on MedianBased on Median.297315.827Based on Median and add df.29739.519.827Based on Mean1.254315.019Based on Mean4.532315.019Based on Meal.239935.625.172Based on Median.239935.625.172Based on Median.036315.999Based on Median.036313.029Based on Median.036313.029Based on Median.036313.029Based on Median.036313.029Based on Median.036313.029Based on Median.033315Based on Median.1629315Based on Median.1629315Based on Median.1631315Based on Median.1629315Based on Median.1629315Based on Median.1631315Based on Median.1631315Based on Median.1629315Based on Median.1631315Based on Median.1631315Based on Median.1631315Based on Median.163131	Al27	Based on Mean	8.487	3	15	.002
with adjusted dfinitial initialinitial initialinitial initialBased on trimmed mean7.5883150.03Cr52Based on Median.2973158.827Based on Median.29739.519.827Based on Median.297315.325Mn55Based on Median2.399315.109Based on Median.239935.625.172Based on Median.239935.625.172Based on Median.036315.990Based on Median.036315.992Based on Median.036315.992Co59Based on Median.036315.225Based on Median.1629315.225Based on Intimmed mean.1631315.225Based on Median.14263.9065.298Based on Mean.1629315.224Ni60Based on Mean.1631315.224Ni60Based on Mean.1631315.224Ni60Based on Mean.1629315.225Based on Inimmed mean.1631315.224Ni60Based on Mean.1629315.224Ni60Based on Mean.16293.5.274Based on Inimmed mean.1631315.224Ni60 <td></td> <td>Based on Median</td> <td>4.095</td> <td>3</td> <td>15</td> <td>.026</td>		Based on Median	4.095	3	15	.026
Cr52 Based on Meain1.813315.188 Based on MedianBased on Median and Madjusted df.29739.519.827Based on Median.29739.519.827Based on Median.2397315.019Based on Median2.399315.109Based on Median2.39935.625.172Based on Median.239935.625.172Based on Median.036315.990Based on Median.036315.992Based on Median.036315.992Co59 Based on Median.036315.2274Based on Median.1426315.2274Based on Median.1426315.2274Based on Median.1426315.224Ni60 Based on Median1.631315.224Ni60 Based on Median.1631315.224Ni60 Based on Median.1631315.224Ni60 Based on Median.1631315.343Based on Median.1631315.343Based on Median.1631315.343Based on Median.1631315.224Ni60 Based on Median.812315.343Based on Median.1631315.224Ni60 Based on Median.8123			4.095	3	5.713	.071
Based on Median		Based on trimmed mean	7.588	3	15	.003
Based on Median	Cr52					
Based on Median and with adjusted df				-		
Based on trimmed mean1.254315.325Mn55Based on Mean4.532315.019Based on Median and with adjusted df2.39935.625.172Based on trimmed mean4.218315.024Fe56Based on Mean.044315.987Based on Median.036313.029.990Based on Median and with adjusted df.036313.029.990Based on Median and with adjusted df.036315.922Co59Based on Median1.426315.224Based on Median1.426315.343Based on Median1.623315.344Based on Median1.203315.347With adjusted df.1203315.440Cu63Based on Mean.954315.440Cu64Based on Mean.954315.022Based on Mean.761315.025As75Based on Mean.761315.025Based on M		Based on Median and				
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Based on Median2.399315.109Based on Median and with adjusted df2.39935.625.172Based on trimmed mean4.218315.024Fe56 Based on Median0.044315.987Based on Median0.036313.029.990Based on Median and with adjusted df0.036313.029.990Based on Median and with adjusted df1.629315.225Based on Median1.629315.225Based on Median1.42639.065.298Based on Median1.631315.224Ni60 Based on Median1.631315.224Based on Median1.203315.343Based on Median1.203315.182Based on Median1.203315.182Based on Median1.203315.190Cu33Based on Median1.800315.190Cu44Based on trimmed mean.812315.191Cu54 Based on Median.812315.507Based on Median.812315.507Based on Median.812315.512Based on Median.812315.533Based on Median.761315.533Based on Median.761315.553Based on Median	Mn55					
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Based on trimmed mean4.218315.024Fe56 Based on Median.044315.987Based on Median and with adjusted df.036313.029.990Based on trimmed mean.033315.992Co59 Based on Median1.629315.225Based on Median1.426315.224Based on Median1.42639.065.298With adjusted df1.631315.224Ni60 Based on Median1.631315.182Based on Median1.203315.343Based on Median1.203315.343Based on Median1.203315.445Based on Median.812315.507Based on Median.812315.507Based on Median.812315.507Based on Median.812315.512Based on Median.812315.523Based on Median.761315.523Based on Median.761315.525Based on Median.761315.025AszBased on Median.761315.025Based on Median.761315.025Based on Median.785315.077Based on Median.2.412315.025Based on Median		Based on Median and		-		
Based on Median.036315.990Based on Median and with adjusted df.036313.029.990Based on trimmed mean.033315.992Co59 Based on Median1.629315.274Based on Median1.42639.065.298Based on Median and with adjusted df1.42639.065.298Based on Median and with adjusted df1.426315.224Ni60 Based on Median1.847315.182Based on Median1.203313.349.347With adjusted df1.203315.190Cu63 Based on Median and with adjusted df.812315.190Cu63 Based on Median and with adjusted df.812315.507Based on Median and with adjusted df.812315.022Based on Median.812315.022Based on Median and with adjusted df.76136.272.554Based on Median and with adjusted df.761315.025As75 Based on Median.2.412315.025As75 Based on Median and with adjusted df.2.412315.025As75 Based on Median and with adjusted df.3.412315.025Based on Median and with adjusted df.2.4123.15.025Based on Median and with adjusted df.3.			4.218	3	15	.024
Based on Median and with adjusted df $.036$ $3$ $13.029$ $.990$ Based on trimmed mean $.033$ $3$ $15$ $.992$ Co59         Based on Median $1.629$ $3$ $15$ $.225$ Based on Median $1.426$ $3$ $15$ $.225$ Based on Median and with adjusted df $1.426$ $3$ $9.065$ $.298$ Ni60         Based on Median and with adjusted df $1.426$ $3$ $15$ $.182$ Based on Median and with adjusted df $1.203$ $3$ $15$ $.182$ Based on Median and with adjusted df $1.203$ $3$ $15$ $.142$ Based on Median and with adjusted df $.1203$ $3$ $15$ $.190$ Cu63         Based on Median and with adjusted df $.812$ $3$ $15$ $.190$ Cu64         Based on Median and with adjusted df $.812$ $3$ $15$ $.022$ Based on Median and with adjusted df $.812$ $3$ $15$ $.022$ Based on	Fe56	Based on Mean	.044	3	15	.987
with adjusted dfand a baseBased on trimmed mean.033315.992Co59Based on Mean1.629315.225Based on Median1.426315.274Based on Median and with adjusted df1.42639.065.298Based on trimmed mean1.631315.224Ni60Based on Median and with adjusted df1.203315.343Based on Median1.203315.343Based on Median and with adjusted df1.203315.445Based on Median and with adjusted df.812315.190Cu63Based on Median and with adjusted df.812315.507Based on Median and with adjusted df.812315.507Based on Median and with adjusted df.812315.022Based on Median and with adjusted df.761315.022Based on Median and with adjusted df.761315.025As75Based on Median and with adjusted df.761315.025As75Based on Median and with adjusted df.761315.025Based on Median and with adjusted df.761315.007Based on Median and with adjusted df.761315.007Based on Median and with adjusted df.761315.007Based on Median and <br< td=""><td></td><td>Based on Median</td><td>.036</td><td>3</td><td>15</td><td>.990</td></br<>		Based on Median	.036	3	15	.990
Co59 Based on Mean1.629315.225Based on Median1.426315.274Based on Median and with adjusted df1.42639.065.298Based on trimmed mean1.631315.224Ni60 Based on Median1.847315.182Based on Median1.203315.343Based on Median and with adjusted df1.203315.343Based on Median and with adjusted df.203315.445Based on Median and with adjusted df.812315.190Cu63 Based on Median.812315.507Based on Median.812315.507Based on Median.812315.507Based on Median.812315.022Based on Median.761315.022Based on Median and with adjusted df.76136.272.554Based on Median and with adjusted df.761315.025As75 Based on Median and with adjusted df.2412315.007Based on Median and with adjusted df.2697315.083Se82 Based on Median and with adjusted df.830315.449Based on Median and with adjusted df.6.9773.15.083Se82 Based on Median and with adjusted df.830315.498 <td< td=""><td></td><td></td><td>.036</td><td>3</td><td>13.029</td><td>.990</td></td<>			.036	3	13.029	.990
Based on Median         1.426         3         15         .274           Based on Median and with adjusted df         1.426         3         9.065         .298           Based on trimmed mean         1.631         3         15         .224           Ni60         Based on Mean         1.847         3         15         .182           Based on Median         1.203         3         15         .343           Based on Median and with adjusted df         1.203         3         13.349         .347           Based on Median and with adjusted df         .942         3         15         .445           Based on Median and with adjusted df         .812         3         15         .507           Based on Median and with adjusted df         .812         3         15         .507           Based on Median and with adjusted df         .812         3         15         .507           Based on Median and with adjusted df         .812         3         15         .022           Based on Median and with adjusted df         .812         3         15         .022           Based on Median and with adjusted df         .761         3         15         .025           As75         Based on Median an		Based on trimmed mean	.033	3	15	.992
Based on Median and with adjusted df1.42639.065.298Based on trimmed mean1.631315.224Ni60Based on Mean1.847315.182Based on Median1.203315.343Based on Median and with adjusted df1.203313.349.347Based on trimmed mean1.800315.190Cu63Based on Median.812315.445Based on Median.812315.507Based on Median and with adjusted df.812311.731.512Based on Median and with adjusted df.812315.440Zn66Based on Mean.954315.022Based on Median and with adjusted df.761315.533Based on Median and with adjusted df.761315.025As75Based on Median and with adjusted df.761315.025As75Based on Median.2.412315.007Based on Median and with adjusted df.2.412315.007Based on Median.2.412315.025As75Based on Median.2.412315.007Based on Median.2.412315.007Based on Median.2.412315.007Based on Median.2.412315.003Based on Median.2.697 <td>Co59</td> <td>Based on Mean</td> <td>1.629</td> <td>3</td> <td>15</td> <td>.225</td>	Co59	Based on Mean	1.629	3	15	.225
with adjusted df         1.100         0.000         1.000           Based on trimmed mean         1.631         3         15         .224           Ni60         Based on Mean         1.847         3         15         .182           Based on Median         1.203         3         15         .343           Based on Median and with adjusted df         1.203         3         13.349         .347           Based on trimmed mean         1.800         3         15         .190           Cu63         Based on Median         .942         3         15         .445           Based on Median         .812         3         15         .507           Based on Median and with adjusted df         .812         3         11.731         .512           Based on Median and with adjusted df         .812         3         15         .022           Based on Median and with adjusted df         .6272         .554         .533           Based on Median and with adjusted df         .761         3         15         .025           As75         Based on Mean         2.785         3         15         .077           Based on Median and with adjusted df         2.412         3         9.382 <td></td> <td>Based on Median</td> <td>1.426</td> <td>3</td> <td>15</td> <td>.274</td>		Based on Median	1.426	3	15	.274
Ni60 Based on Mean1.847315.182Based on Median1.203315.343Based on Median and with adjusted df1.203313.349.347Based on trimmed mean1.800315.190Cu63 Based on Mean.942315.445Based on Median.812315.507Based on Median and with adjusted df.812311.731.512Based on Median and with adjusted df.812315.022Based on Median and with adjusted df.761315.022Based on Mean4.317315.022Based on Median and with adjusted df.761315.533Based on Median and with adjusted df.761315.025As75Based on Mean2.785315.077Based on Median and with adjusted df.2412315.025As75Based on Median and with adjusted df.2412315.077Based on Median and with adjusted df.2412315.083Se82Based on Mean.2497315.330Based on Median and with adjusted df.830311.648.503Based on Median and with adjusted df.830311.648.503			1.426	3	9.065	.298
Based on Median1.203315.343Based on Median and with adjusted df1.203313.349.347Based on trimmed mean1.800315.190Cu63 Based on Mean.942315.445Based on Median.812315.507Based on Median and with adjusted df.812315.507Based on Median and with adjusted df.812315.440Zn66 Based on Median.954315.022Based on Median.761315.533Based on Median and with adjusted df.761315.025Based on Median.761315.025Based on Median and with adjusted df.761315.025Based on Median and with adjusted df.785315.027Based on Median and with adjusted df.785315.025Based on Median and with adjusted df.785315.025Based on Median and with adjusted df.78335.330.330Based on Median and with adjusted df.830315.498Based on Median and with adjusted df.83031		Based on trimmed mean	1.631	3	15	.224
Based on Median1.203315.343Based on Median and with adjusted df1.203313.349.347Based on trimmed mean1.800315.190Cu63 Based on Mean.942315.445Based on Median.812315.507Based on Median and with adjusted df.812315.507Based on Median and with adjusted df.812315.440Zn66 Based on Median.954315.440Zn66 Based on Median and with adjusted df.761315.022Based on Median and with adjusted df.761315.025Based on Median and with adjusted df.761315.025Based on Median and with adjusted df.761315.027Based on Median and with adjusted df.761315.025Based on Median and with adjusted df.761315.025Based on Median and with adjusted df.761315.027Based on Median and with adjusted df.785315.027Based on Median and with adjusted df.785315.025Based on Median and with adjusted df.783315.083Se82 Based on Median and with adjusted df.830315.498Based on Median and with adjusted df.830311.648.503	Ni60	Based on Mean	1.847	3	15	.182
with adjusted df1.0000.0001.000Based on trimmed mean1.800315.190Cu63Based on Mean.942315.445Based on Median.812315.507Based on Median and with adjusted df.812311.731.512Based on trimmed mean.954315.440Zn66Based on Mean.954315.022Based on Median.761315.533Based on Median and with adjusted df.76136.272.554Based on Median and with adjusted df.761315.025As75Based on Mean2.785315.077Based on Median2.412315.025As75Based on Median and with adjusted df2.412315.025Based on Median2.412315.025Based on Median and with adjusted df.697315.083Se82Based on Median and with adjusted df.830315.498Based on Median.830311.648.503.503				3	15	.343
Cu63 Based on MeanBased on Mean.942315.445Based on Median and with adjusted df.812315.507Based on Median and with adjusted df.812311.731.512Based on trimmed mean.954315.440Zn66 Based on MedianBased on Median.761315.022Based on Median.761315.025Based on Median and with adjusted df.761315.025Based on Median.2.412315.025Based on Median and with adjusted df.2.412315.025Based on Median and with adjusted df.2.412315.025Based on Median and with adjusted df.2.412315.083Se82 Based on Median and with adjusted df.3.30315.498Based on Median.8.30311.648.503			1.203	3	13.349	.347
Cu63 Based on MeanBased on Mean.942315.445Based on Median and with adjusted df.812315.507Based on Median and with adjusted df.812311.731.512Based on trimmed mean.954315.440Zn66 Based on MedianBased on Median.761315.022Based on Median.761315.025Based on Median and with adjusted df.761315.025Based on Median.2.412315.025Based on Median and with adjusted df.2.412315.025Based on Median and with adjusted df.2.412315.025Based on Median and with adjusted df.2.412315.083Se82 Based on Median and with adjusted df.3.30315.498Based on Median.8.30311.648.503		Based on trimmed mean	1.800	3	15	.190
Based on Median Based on Median and with adjusted df.812315.507Based on Median and with adjusted df.812.311.731.512Based on trimmed mean.954.3.15.440Zn66 Based on Median.761.3.15.022Based on Median and with adjusted df.761.3.533.533Based on Median and with adjusted df.761.3.554.554Based on trimmed mean4.153.3.025.554Based on Median and with adjusted df.761.3.15.025As75 Based on Median.2.412.3.15.027Based on Median and with adjusted df.2.412.3.15.017Based on Median and with adjusted df.2.697.3.15.083Se82 Based on Median.3.60.3.15.330Based on Median.830.3.15.498Based on Median and with adjusted df.830.3.11.648.503	Cu63	Based on Mean	.942	3	15	.445
with adjusted df         No.12		Based on Median	.812	3	15	.507
Zn66         Based on Mean         4.317         3         15         .022           Based on Median         .761         3         15         .533           Based on Median and with adjusted df         .761         3         15         .533           Based on Median and with adjusted df         .761         3         6.272         .554           Based on trimmed mean         4.153         3         15         .025           As75         Based on Mean         2.785         3         15         .027           Based on Median         2.412         3         15         .077           Based on Median and with adjusted df         2.412         3         9.382         .131           Based on Median and with adjusted df         2.697         3         15         .083           Se82         Based on Mean         1.240         3         15         .330           Based on Median         .830         3         15         .498           Based on Median and with adjusted df         .830         3         11.648         .503			.812	3	11.731	.512
Zn66         Based on Mean         4.317         3         15         .022           Based on Median         .761         3         15         .533           Based on Median and with adjusted df         .761         3         15         .533           Based on Median and with adjusted df         .761         3         6.272         .554           Based on trimmed mean         4.153         3         15         .025           As75         Based on Mean         2.785         3         15         .027           Based on Median         2.412         3         15         .077           Based on Median and with adjusted df         2.412         3         9.382         .131           Based on Median and with adjusted df         2.697         3         15         .083           Se82         Based on Mean         1.240         3         15         .330           Based on Median         .830         3         15         .498           Based on Median and with adjusted df         .830         3         11.648         .503			.954	3	15	.440
Based on Median         .761         3         15         .533           Based on Median and with adjusted df         .761         3         6.272         .554           Based on trimmed mean         4.153         3         15         .025           As75         Based on Median         2.785         3         15         .027           Based on Median         2.412         3         15         .007           Based on Median and with adjusted df         2.412         3         9.382         .131           Based on trimmed mean         2.697         3         15         .083           Se82         Based on Mean         3.607         3         15         .330           Based on Median and with adjusted df         3.697         3         15         .083           Based on Mean         3.607         3         15         .083           Based on Mean         3.607         3         15         .083           Based on Median         830         3         15         .498           Based on Median and with adjusted df         .830         3         11.648         .503	Zn66			-		
Based on Median and with adjusted df.76136.272.554Based on trimmed mean4.153315.025As75Based on Mean2.785315.077Based on Median2.412315.107Based on Median and with adjusted df2.41239.382.131Based on trimmed mean2.697315.083Se82Based on Median.830315.498Based on Median and with adjusted df.830311.648.503				-	-	
Based on trimmed mean         4.153         3         15         .025           As75         Based on Mean         2.785         3         15         .077           Based on Median         2.412         3         15         .107           Based on Median and with adjusted df         2.412         3         9.382         .131           Based on trimmed mean         2.697         3         15         .083           Se82         Based on Median         1.240         3         15         .330           Based on Median         .830         3         15         .498           Based on Median and with adjusted df         .830         3         11.648         .503		Based on Median and				
Based on Median Based on Median and with adjusted df2.412315.107Based on Median and with adjusted df2.41239.382.131Based on trimmed mean2.697315.083Se82Based on Median Based on Median.830315.498Based on Median and with adjusted df.830311.648.503			4.153	3	15	.025
Based on Median and with adjusted df2.41239.382.131Based on trimmed mean2.697315.083Se82Based on Mean1.240315.330Based on Median.830315.498Based on Median and with adjusted df.830311.648.503	As75	Based on Mean	2.785	3	15	.077
Based on Median and with adjusted df2.41239.382.131Based on trimmed mean2.697315.083Se82Based on Mean1.240315.330Based on Median.830315.498Based on Median and with adjusted df.830311.648.503		Based on Median	2.412	3	15	.107
Based on trimmed mean2.697315.083Se82Based on Mean1.240315.330Based on Median.830315.498Based on Median and with adjusted df.830311.648.503		Based on Median and		-		
Se82         Based on Mean         1.240         3         15         .330           Based on Median         .830         3         15         .498           Based on Median and with adjusted df         .830         3         11.648         .503			2.697	3	15	.083
Based on Median.830315.498Based on Median and with adjusted df.830311.648.503	Se82			-	-	
Based on Median and with adjusted df.830311.648.503	5002			-		
		Based on Median and		-	-	
			1.223	3	15	.336

# Appendix 4 - Statistical Test Results for Normality and Common Variance Assumption for Canal Sediment

## Normality Test

Cluster 1

### One-Sample Kolmogorov-Smirnov Test<sup>a</sup>

			As	Cd	Cr	Cu	Pb	Hg	Ni	Se	Zn
N			2	2	2	2	2	2	2	2	2
Normal Parameters <sup>b,c</sup>	Mean		30.4500	9.3250	350.9000	1611.5000	301.6000	.6400	280.4500	2.8000	3205.0000
	Std. Deviation		18.45549	2.76479	176.63527	3.53553	106.20744	.25456	51.97235	.42426	103.23759
Most Extreme Differences	Absolute		.260	.260	.260	.260	.260	.260	.260	.260	.260
	Positive		.260	.260	.260	.260	.260	.260	.260	.260	.260
	Negative		260	260	260	260	260	260	260	260	260
Test Statistic			.260	.260	.260	.260	.260	.260	.260	.260	.260
Asymp. Sig. (2-tailed) <sup>d</sup>			.e	.e	.e	.e	. <sup>e</sup>	.e	.e	.e	.e
Monte Carlo Sig. (2-	Sig.		.339	1.000	1.000	1.000	.053	.095	.793	1.000	.788
tailed) <sup>f</sup>	99% Confidence Interval	Lower Bound	.327	1.000	1.000	1.000	.048	.087	.782	1.000	.777
		Upper Bound	.351	1.000	1.000	1.000	.059	.102	.803	1.000	.799

a. Cluster\_Quartile = 1

b. Test distribution is Normal.

c. Calculated from data.

d. Lilliefors Significance Correction.

e. Significance can not be computed because sum of case weights is less than 5.

f. Lilliefors' method based on 10000 Monte Carlo samples with starting seed 2110151063.

## Cluster 2

### One-Sample Kolmogorov-Smirnov Test<sup>a</sup>

			As	Cd	Cr	Cu	Pb	Hg	Ni	Se	Zn
N			4	4	4	4	4	4	4	4	4
Normal Parameters <sup>b,c</sup>	Mean		55.1500	17.2225	1568.5000	5029.5000	709.6250	2.2000	385.7250	5.4750	4622.0000
	Std. Deviation		26.21075	5.72551	1682.08556	2822.83847	292.55230	1.01482	123.02998	3.29583	1614.21436
Most Extreme Differences	Absolute		.223	.234	.426	.358	.272	.229	.224	.236	.250
	Positive		.185	.234	.426	.358	.202	.161	.196	.236	.249
	Negative		223	197	293	259	272	229	224	200	250
Test Statistic			.223	.234	.426	.358	.272	.229	.224	.236	.250
Asymp. Sig. (2-tailed) <sup>d</sup>			.e	.e	. <sup>e</sup>	.e	.e	.e	.e	.e	.e
Monte Carlo Sig. (2-	Sig.		.736	.678	.002	.078	.391	.703	.733	.671	.569
tailed) <sup>†</sup>	99% Confidence Interval	Lower Bound	.724	.666	.001	.071	.379	.692	.722	.659	.556
		Upper Bound	.747	.690	.003	.085	.404	.715	.745	.683	.582

a. Cluster\_Quartile = 2

b. Test distribution is Normal.

c. Calculated from data.

d. Lilliefors Significance Correction.

e. Significance can not be computed because sum of case weights is less than 5.

f. Lilliefors' method based on 10000 Monte Carlo samples with starting seed 2110151063.

# Cluster 3

### One-Sample Kolmogorov-Smirnov Test<sup>a</sup>

			•	-							
			As	Cd	Cr	Cu	Pb	Hg	Ni	Se	Zn
Ν			3	3	3	3	3	3	3	3	3
Normal Parameters <sup>b,c</sup>	Mean		38.1667	9.8400	578.5000	2173.8667	392.2000	.9367	284.1667	2.1333	2467.2333
	Std. Deviation		21.23919	7.21742	564.81391	1880.26824	302.79146	.87763	240.77887	1.91398	2028.08177
Most Extreme Differences	Absolute		.264	.282	.191	.278	.214	.227	.238	.283	.319
	Positive		.198	.206	.191	.204	.187	.190	.193	.207	.228
	Negative		264	282	182	278	214	227	238	283	319
Test Statistic			.264	.282	.191	.278	.214	.227	.238	.283	.319
Asymp. Sig. (2-tailed) <sup>d</sup>			.e	.e	.e	.e	.e	.e	.e	.e	.e
Monte Carlo Sig. (2-	Sig.		.597	.508	.897	.528	.806	.753	.707	.504	.341
tailed) <sup>†</sup>	99% Confidence Interval	Lower Bound	.585	.495	.889	.515	.796	.742	.696	.491	.329
		Upper Bound	.610	.521	.905	.540	.816	.764	.719	.517	.353

a. Cluster\_Quartile = 3

b. Test distribution is Normal.

c. Calculated from data.

d. Lilliefors Significance Correction.

e. Significance can not be computed because sum of case weights is less than 5.

f. Lilliefors' method based on 10000 Monte Carlo samples with starting seed 2110151063.

### Cluster 4

### One-Sample Kolmogorov-Smirnov Test<sup>a</sup>

			As	Cd	Cr	Cu	Pb	Hg	Ni	Se	Zn
Ν			5	5	5	5	5	5	5	5	5
Normal Parameters <sup>b,c</sup>	Mean		26.2200	9.0060	343.7000	1609.4400	318.7000	.6540	350.3800	3.5400	2489.9400
	Std. Deviation		17.25332	9.77900	405.79553	1906.69414	270.33444	.69536	420.72627	3.03035	2237.53971
Most Extreme Differences	Absolute		.223	.256	.339	.314	.320	.279	.299	.242	.221
	Positive		.223	.256	.339	.314	.320	.279	.299	.242	.221
	Negative		144	209	217	210	200	220	240	219	175
Test Statistic			.223	.256	.339	.314	.320	.279	.299	.242	.221
Asymp. Sig. (2-tailed) <sup>d</sup>			.200 <sup>e</sup>	.200 <sup>e</sup>	.062	.121	.105	.200 <sup>e</sup>	.164	.200 <sup>e</sup>	.200 <sup>e</sup>
Monte Carlo Sig. (2-	Sig.		.579	.357	.055	.110	.095	.242	.161	.439	.597
tailed) <sup>f</sup>	99% Confidence Interval	Lower Bound	.566	.345	.049	.102	.087	.231	.152	.426	.585
		Upper Bound	.592	.370	.060	.118	.102	.253	.171	.451	.610

a. Cluster\_Quartile = 4

b. Test distribution is Normal.

c. Calculated from data.

d. Lilliefors Significance Correction.

e. This is a lower bound of the true significance.

f. Lilliefors' method based on 10000 Monte Carlo samples with starting seed 2110151063.

### Levene Statistic df2 df1 Sig. As Based on Mean 3 .807 .326 10 Based on Median .257 3 10 .855 Based on Median and .257 3 8.662 .855 with adjusted df Based on trimmed mean .325 3 10 .808 Cd Based on Mean 3 .398 1.089 10 Based on Median .355 3 10 .787 Based on Median and .355 3 6.819 .788 with adjusted df .436 Based on trimmed mean .991 3 10 3 Cr Based on Mean 3.729 10 .049 Based on Median .408 3 10 .751 Based on Median and .408 3 3.586 .757 with adjusted df .093 Based on trimmed mean 2.826 3 10 Cu Based on Mean 1.979 3 10 .181 3 Based on Median .751 .408 10 Based on Median and 3 .408 7.371 .752 with adjusted df Based on trimmed mean 1.623 3 10 .246 Pb Based on Mean 1.105 3 10 .392 Based on Median .325 3 10 .807 Based on Median and .325 3 7.768 .808 with adjusted df Based on trimmed mean 1.048 .414 3 10 Based on Mean Hg 1.975 3 10 .182 Based on Median 3 .905 10 .473 Based on Median and 8.425 .905 3 .478 with adjusted df Based on trimmed mean 1.926 3 10 .189 Ni Based on Mean 1.777 3 10 .215 Based on Median .487 3 10 .699 Based on Median and 3 .487 4.643 .707 with adjusted df Based on trimmed mean 1.604 3 10 .250 Based on Mean 3 .254 Se 1.587 10 3 Based on Median 1.271 10 .337 Based on Median and 1.271 3 7.780 .350 with adjusted df Based on trimmed mean .253 1.588 3 10 Based on Mean 3 .148 Zn 2.221 10 Based on Median .770 3 10 .537 Based on Median and 3 .770 6.243 .550 with adjusted df Based on trimmed mean 2.042 3 10 .172

## **Tests of Homogeneity of Variances**