Water Metabolism of Large Cities:

Assessing the Vulnerabilities of Water Systems

By Ehud Kirsh

Submitted for the Degree of Doctor of Philosophy from

The Department of Chemical and Process Engineering

University of Strathclyde, Glasgow

University of
Strathclyde
Engineering

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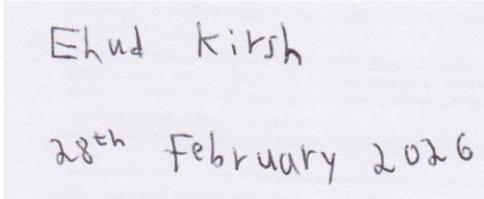
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Abstract

Large cities are rapidly growing as an increasing portion of humanity moves into urban settings. Among the concerns this trend raises are the vulnerabilities of drinking Water Supply Systems (WSS) and the risk of water shortages similar to electricity outages.

There appears to be a gap in the literature for a framework that best captures overlooked aspects of the vulnerabilities that WSS face, including a supplier-focused method for selecting indicators that track vulnerabilities and correlation analysis of these indicators. The few published WSS Multi-Criteria Analysis (MCA) indices include numerous indicators that are less relevant to the resiliency of WSS.

To address this gap in water systems literature, this research aims to develop a framework that identifies and assesses the vulnerabilities of WSS. This can guide decision-makers to enhance the resiliency of WSS through improved governance and investments in infrastructure.

The results include a methodology with a list of criteria for selecting indicators, a novel custom index of a set of said indicators, and a newly programmed MCA Solver to run the index. Several of the indicators can be customised with special formulae and nested into sub-indicators.

The software incorporates a variety of methods from the MCA literature, an ability to process and store large sets of user data, and features that existing software lacks, for example, calculating uncertainties and correlation matrix analysis. It effectively computes as a complex yet specialised calculator and is designed for general MCA applications besides WSS vulnerabilities.

Significant further results were also yielded. Correlations across dozens of case study cities globally suggest some indicators measure the same vulnerability and hence should merge, while conversely others potentially represent different vulnerabilities than those which were suspected.

These results advance the current tools, methods, and understanding of indicators and vulnerabilities in this field of WSS research.

Layman's Summary

In the last several years, there have been severe incidents that caused water shortages similar to power outages or electricity blackouts, meaning that people opened up their taps and no water came out, or its quality was not suitable for drinking. It is possible to learn from these incidents as they each leave a clue as to what likely caused it.

This research aims to develop tools to understand these clues better. This will allow decision-makers to improve management and make appropriate investments in infrastructure to reduce the risk of future incidents.

This research studies cities that experienced such incidents and creates a new method to rank cities globally to determine which are most vulnerable and in which aspects. This comparison helps water suppliers understand how they compare to others globally and where they are weakest, so they know where and how to improve their resiliency against future incidents.

This comparison is called a custom index, while the causes of incidents are known as vulnerabilities, and the clues that track the vulnerabilities are referred to as indicators. To compare scores of the water systems of various cities globally, a new specialised software tool was developed for this research, which includes useful features that existing software lacks, for example, correlation analysis and uncertainties.

The main results of this research are a list of indicators, a methodology for selecting them, and a new software application.

Acknowledgements

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Note that this thesis features cross-references as interactive text links when referring to headings and caption labels of figures. When reading the thesis as a .pdf file, these cross-references can be clicked on to jump to where the mentioned heading or figure is internally within the document. Not to confuse with the blue underlined hyperlinks in the References and types of licenses in the caption labels of cited figures, which open up URLs externally in a browser. Despite the cross-references, this thesis was written in a way that allows a reader to print it out on paper and read it statically. The cross-references always explicitly write which heading number they point to within the thesis.

List of Tables

Note that captions that begin with an 'S' are in the Appendices. 'S' stands for Supplementary.

List of Equations

List of Scripts

Every script's caption starts by specifying its programming language for clarity.

Scripts tend to be typed text rather than screenshots to easily allow to select and copy them as text, maximise their quality resolution, and overall reduce the size of this document.

List of Graphical User Interfaces (GUIs)

Every GUI is of the MCA solver unless labelled otherwise.

List of Maps

Every map's caption starts with its location scope if known.

Map 5 and Map 7 are included thanks to an explicitly written permission from the Public Utilities Board (PUB), Singapore's National Water Agency. Map 8 is included thanks to an explicitly written permission from Hong Kong's Water Supplies Department (WSD) / 水務署.

List of Pictures

The front page cover of Singapore's Merlion and Marina Bay Sands Hotel Tower is a photo captured by Uwe Schwarzbach [1], used under a CC BY-NC-SA 2.0 license.

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List of (General) Figures

Every figure's caption starts with its type if it is standard.

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Nomenclature

The nomenclature tables below are sorted alphabetically, except where some terms are grouped together:

Table 1 – Nomenclature: Multicriteria Analysis (MCA) Abbreviations

Abbreviation	Denotes	Meaning
AHP [3], [4], [5], [6]	Analytical Hierarchy Process	A weighting method where criteria are sorted into an importance hierarchy matrix and are weighted by relative pairwise comparison between each neighbouring criterion.
MCA [7]	Multi-Criteria Analysis	MCA and MCDA are synonyms. These are a family of methods that rank alternative scenarios based on how they score on two or more criteria.
MCDA [8]	Multiple Criteria Decision Analysis	
PROMETHEE [9]	Preference Ranking Organization METHod for Enrichment of Evaluations	An outranking method where final scores for alternatives are outranks. There are at least five PROMETHEE versions, each with different final scoring algorithms, but all sort the criteria into a normalised decision matrix.
WPM [10]	Weight Product Model	A ranking method where the final rank scores are equal to the product of the criteria scores to the power of the weights.
WSM [11]	Weight Sum Model	A ranking method where the final rank scores are equal to the sum product of the criteria weights and scores.

Table 2 – Nomenclature: Software Abbreviations

Abbreviation	Denotes	Abbreviation	Denotes
API	Application Programming Interface	HTML	HyperText Markup Language
		JPG	Joint Photographic Group
CSS	Cascading Style Sheets	JS	JavaScript
CSV	Comma-Separated Values	JSON	JavaScript Object Notation
DOM	Document Object Model	SVG	Scalable Vector Graphics
GUI	Graphical User Interface	XML	Extensible Markup Language

Table 3 – Nomenclature: Water Systems Abbreviations

Abbreviation	Denotes	Meaning and Notes
BOD [12]	Biological Oxygen Demand	The amount of dissolved oxygen needed by aerobic organisms to break down organic material present in a given water sample at certain temperature over a specific time period.
CPE	Chemical and Process Engineering	An engineering discipline focused on designing and optimising the bulk processing and production of fluids and fine solids.
IWA	International Water Association	A self-governing nonprofit organization and knowledge hub for the water sector
LF	Location Factor	The ratio of purchasing power of a given locality relative to a benchmark reference
MCM	Million Cubic Meter	Unit of volume. 10^6 m^3 = 10^9 L (One Billion Litres).
MGD	Million Gallons per Day	Unit of volumetric flow rate. 10^6 Gallons/Day. Gallons can be either Imperial or US.
O&M	Operation and Maintenance Cost	The cost of operating and maintaining a processing or treatment plant for a period of time. Excludes capital (construction) and distribution costs.
VA	Vulnerability Analysis	Process of identifying, quantifying, and prioritising the vulnerabilities in a system
WDN	Water Distribution Network	A network of mains pipelines and pumps that distribute drinking water. This excludes water treatment plants.
WSS	Water Supply System	A system that supplies drinking water. Includes water treatment plants as well as the WDN of pumps and mains pipelines.
WDS	Water Distribution System	These phrases are used interchangeably in the literature, see the titles of some Studied Papers in Appendix A – Literature, but not otherwise used by this research project.
WSN	Water Supply Network	
WQI [13]	Water Quality Index	An MCA index where the concentrations of undesirable substances are indicators to quantify the quality of water. Typically, in reference to Tap Water Quality and not Source Water Quality.

Table 4 – Nomenclature: Non-Abbreviations Terms

Term	Definition	References
Accuracy	The closeness of agreement between a measured quantity value and a true quantity value of a measurand	[14], [15]
Error	The difference between the true and the measured value	[16], [17]
Precision	The level of agreement of a particular measurement with itself when it is repeated	[14]
Random Error	A statistical error that is due to chance and does not recur	[16]
Systematic Error	An error that is not determined by chance but is introduced by an inaccuracy (as of observation or measurement) inherent in the system	[16]
Uncertainty	Non-negative parameter characterising the dispersion of the quantity values being attributed to a measurement	[17]

Term	Definition	References
Affordability	State of being cheap enough for people to be able to buy	[14]
Cost	The expenses incurred in producing or providing a product	[16]
Price	The amount of money a customer pays for a product	[16]

Term	Definition	References
Aggregate/ Composite Index	A single index that combines multiple individual indicators, with the goal of measuring complex concepts that are too multidimensional for a single indicator to capture	[18]
Normalisation	Transforming values to a standard scale	[19]
Weight	Relative Importance	[14], [16]

Term	Definition	References
Aqueduct	A structure for carrying water across land, especially one like a high bridge with many arches that carries pipes or a canal across a valley	[14]
Aquifer	A layer of rock, sand, or earth that contains water or allows water to pass through it	[14]

Term	Definition	References
Blue Water	Consumptive water that is not directly returned to its source	[20]
Green Water	Rainwater that stays on the surface, including vegetation	[20]
Grey Water	Water that has been used before	[14]

Drought	A long period when there is little or no rain	[14]
Water Stress	Freshwater withdrawn as a percentage of the total available locally	[21]

Evaporation	The process of a liquid changing to a gas. Excludes transpiration in the context of WSS.	[14]
Evapotranspiration	Combined evaporation and transpiration	
Transpiration	Water loss as vapour from the surface of a plant or skin	

Iteration	Repetition of computer instructions in a loop	[16]
Recursion	A software function that calls itself	

Risk	= Severity x (Likelihood OR Frequency of an incident)	[22]
Vulnerability	Weakness of a system that could cause an incident	

Embankment	An artificial slope made of earth and/or stones. Also known as a levee, dike, dyke, floodbank, and stop bank	[14]
Impervious	Not allowing liquid to go through	
Metering Water	Percentage of households whose water consumption is metered (as opposed to the amount of water which is metered)	[21]
Potable	Clean and safe to drink	[14]
Precipitation	Water that falls from the clouds towards the ground, e.g. rain, snow, hail, and sleet	
Runoff	Water from rain or melting snow, or liquid from an industrial or farming process that flows away from high areas to low areas into a place such as a river	
Soil Moisture Content	Content of liquid water in a surface soil layer of 2 to 5 cm depth	[23]
Virtual Water	The amount of water required to produce a commodity	[24]
Water Dependency	Importation of water by a country from another country	[25]

Thesis Outline Structure

The structure of this thesis is depicted in Figure 1 below, and each chapter is briefly discussed thereafter:

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                    │ Chapter 1: Introduction      │
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        ┌──────────────────────────────────────────────────────┐
        │ Chapter 2: Literature Review of WSS Assessment        │
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┌──────────────────────┐                         ┌──────────────────────┐
│ Chapter 3: MCA Solver │                         │ Chapter 4:           │
│ Software Tool         │                         │ Custom Index         │
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        │ Chapter 5: Conclusions and Further Work               │
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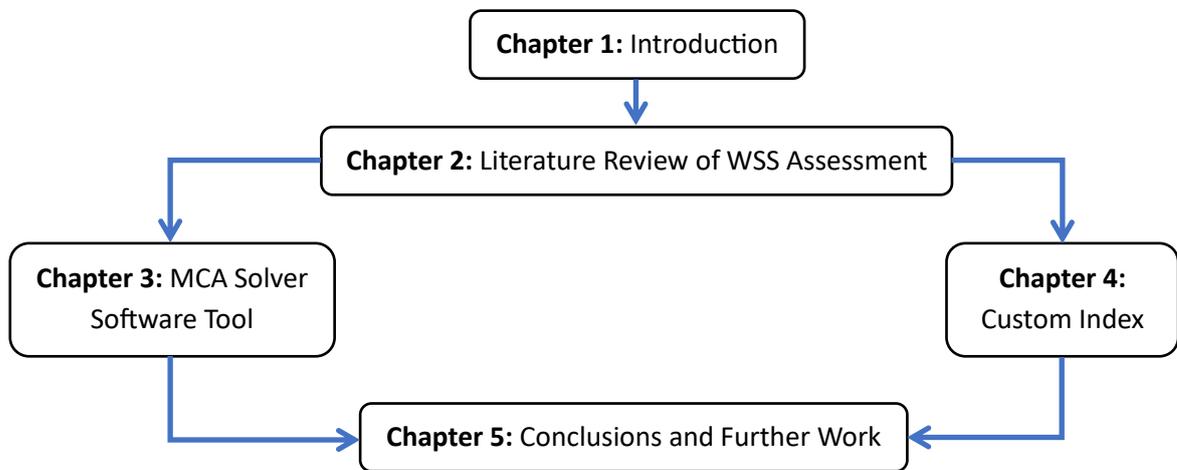
Figure 1 – Flowchart of the Thesis Outline Structure

Chapter 1: Introduction

Section 1.1 introduces the background of water systems, their vulnerabilities, current research, the problems they currently face, and their relevance. It also describes the inspiration from the literature for carrying out this research. Section 1.2 documents past supply disruption incidents.

Section 1.3 describes the relation to Chemical and Process Engineering of water research. It is a unique perspective considering that water research tends to be a minor topic for a PhD in Chemical and Process Engineering, compared to other topics such as reactions and molecular simulations.

Sections 1.4 and 1.5 lay out the gaps in the WSS literature and the Hypothesis, Objective, and Novelty for this research. These include the two novel aspects of this project, which have a chapter dedicated to each in Chapter 3: MCA Solver Software Tool and Chapter 4: Custom Index.

Chapter 2: Literature Review of WSS Assessment

Section 2.1 introduces the Literature Review of WSS Assessment by stating its aims and methodology, and lists some of the searched keywords and the explored publication sources.

Sections 2.2 and 2.3, respectively, present and discuss the methodologies and results of water systems research papers and literature reviews. Including statistics of papers, existing software, and indices, and discussing the most notable papers.

Lastly, section 2.4: Summary, describes which gaps in the literature were found, the methods that were selected for conducting this research, and why. For this reason, the Literature Review of WSS Assessment in Chapter 2 is placed at the beginning of this thesis, because these gaps, methods, papers, and terms need to be understood before researching further to fill these gaps in the literature by producing novel work reported in the following chapters 3 and 4.

Chapter 3: MCA Solver Software Tool

Chapter 3 introduces MCA as a family of methods and mathematically compares the methods within the MCA family. As MCA is explained, this chapter also presents the newly created MCA Solver Software Tool by presenting its equations, scripts, and Graphical User Interfaces (GUIs).

This chapter is placed before the Custom Index chapter because it explains MCA to a reader who might be unfamiliar with MCA, which can help to understand the MCA Custom Index later in Chapter 4. Having said that, the MCA solver does not depend on the custom water index because the MCA Solver Software Tool is a general-purpose calculator application, which happens to be very useful for creating a water vulnerability index; hence, the software is placed in a chapter before the index.

Chapter 4: Custom Index

Despite being positioned after Chapter 3 for a reader unfamiliar with MCA, this Custom Index is written such that it can be understood without the context of the MCA Solver Software Tool and only with the context of the Introduction and Literature Review, as shown above in Figure 1.

Sections 4.2: Case Study Cities, 4.3: Vulnerability Indicators, and 4.5: Selecting Weighting and Ranking Methods cover user choices. Scores and Rankings results are in sections 4.4 and 4.6, respectively. Some results can already be calculated in section 4.4 before all user choices are made in section 4.5. This is a structure unique to MCA, as is explained in Figure 12 in sub-section 2.2.4.

Chapter 5: Conclusions and Further Work

Section 5.1 presents the results of this research from all the previous chapters and discusses how they connect. It begins with the main expected findings, followed by sub-section 5.1.1: Further Findings, which respectively confirm the results that were anticipated and the other important and interesting results that were found unintentionally.

Sections 5.2 and 5.3 discuss likely further work for the two novel aspects, the MCA Solver Software Tool and the Custom Index, respectively, including more and enhanced features, methods, and data.

1. Introduction

1.1. Water Systems and Vulnerabilities

Large cities are rapidly growing as an increasing portion of humanity moves into urban settings [21], [26]. Such changes may benefit from economies of scale, but may also suffer from diseconomies of scale. To protect society, it may prove useful to investigate how to mitigate some of the diseconomies of scale. Among the concerns this trend raises are the vulnerabilities of drinking water supply systems, which risk facing water shortages similar to electricity blackouts.

For example, a well-known water shortage was the Cape Town Water Crisis. It occurred between 2015 and 2020 and peaked in 2017-2018. During it, a term referred to as "Day Zero" was used to describe a projected date on which the water supply would have to shut off completely [27]. Day Zero never happened thanks to the combined efforts of the water supplier, citizens, and rainfall. The crisis was due to falling levels of stored water, as shown below in Figure 2 [28], because of water stress, caused by highly wasteful consumption and drought.
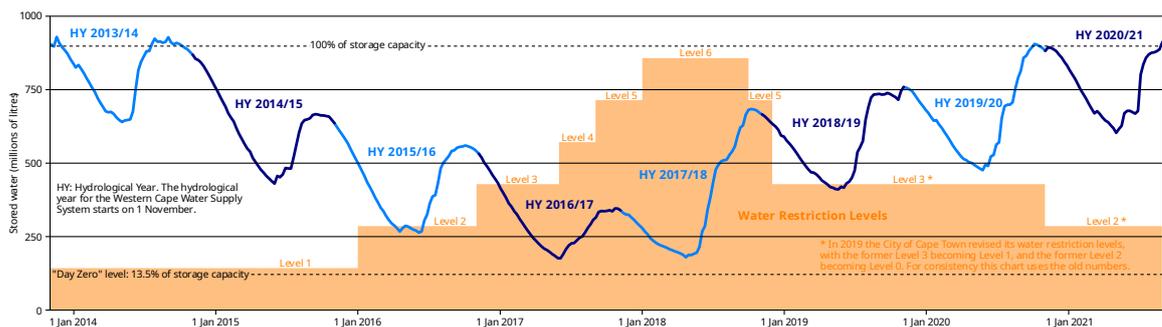
Figure 2 – Cape Town stored water and consumption restrictions by year [28], CC BY-SA 4.0

Picture 1 – Capetonians fill up water bottles at the peak of the crisis [28], CC BY-SA 4.0

It is common to think, "It would not happen here or to me", but for the sake of security, there is a need to prepare in advance. If Cape Town had imposed water restrictions earlier, it could have mitigated or prevented the crisis, and photos such as Picture 1 [28] above would not exist.

The water shortage incidents this research addresses can be regional, temporary, and of various natures and causes. What they all have in common is the disruption of the regular supply of reasonably affordable potable water to consumers, such that turning on the tap and water would not come out for an entire region for a significant period of time. The term 'potable' refers to water quality that is sufficiently clean to be suitable for drinking. All 'distributed' water is potable, but not all of it is used for drinking. Some of it is used in industry, and some is for other residential uses.

Referring to the title, the word 'Metabolism' tends to refer to the biological concept and would not normally be associated with the stationary concrete structures of urban settings, which give off the opposite impression of living organisms by being still. Despite water infrastructure not moving, it can have similar properties to living creatures. Distribution mains and aqueducts may be immobile, but they enable water flow through them, similar to the flow of water and blood in living beings.

The idea of analysing cities similarly to organisms was inspired by the book 'Scale' [29] by Geoffrey West, in which, among other systems, cities and organisms are compared as networks, such as blood vessels, nerves, and neurons of organisms, to be similar to electricity, gas, and water pipelines of cities. Cities live like organisms. The borders of a city can be viewed as the skin boundaries of an organism's body, being mostly at a steady state (no accumulation over time), with respect to water, energy, and other supplies constantly entering, existing, and being produced and consumed. A city's inhabitants and buildings are equivalent to a body's cells and organs, while roads and pipes are equivalent to blood vessels.

Related to the book 'Scale' by Geoffrey West, the initial idea for this project was to research population growth as a vulnerability, as it relates to the Malthusian theory. This, however, was replaced in light of the gap found in the next Chapter 2: Literature Review of WSS Assessment by constructing a list of indicators to assess multiple vulnerabilities, because evidently, not all case studies have growing populations, and some have other severe vulnerabilities which cause water shortage incidents, hence this research is now more all-encompassing.

In addition, this research was inspired by a previous research of this author, exploring the bottlenecks of the affordability of water supply systems [30]. The aforementioned research focused on the consumer side, whereas this research focuses on the supplier's viewpoint.

The term 'Large City' has a debatable meaning with no universally agreed-upon definition. For the purpose of this research, a large city must at least have a minimum population density of a thousand people per square kilometre or a million people in total, as is recorded in Table S7 – Case Study Cities Basic Statistics in Appendix C – Index. Large cities are the focus because, as the inspiration book Scale has shown, larger cities have diseconomies of scale, which make them more vulnerable, and these can affect more people. Furthermore, larger cities have more published data.

'Assessing' refers to quantifying and understanding the vulnerabilities of water systems to assist decision-makers in better mitigating said vulnerabilities to lower the risk of water shortage. Note that this research solely focuses on the potable water distribution aspect of water systems, even though there are overlaps in vulnerabilities with wastewater, as discussed in sub-section 5.3.3: Wastewater, because including both would be too complicated.

As documented in the studied papers of the Literature Review of WSS Assessment in Appendix A – Literature, the terms Water 'System' and 'Network', as well as Water 'Supply' and 'Distribution', are often used interchangeably. This includes their acronyms WSS, WDN, WSN, and WDS as tabulated above in the Nomenclature. There is a subtle distinction, however, which this research project refers to consistently. In the context of potable water, 'Water Distribution Network' (WDN) refers to a network of mains pipelines and pumps that distribute potable water and excludes the treatment plants, whereas 'Water Supply System' (WSS) refers to both the WDN and the treatment plants together. This distinction is important for later calculating the Operation and Maintenance (O&M) costs of water treatment plants of WSS in the Affordability indicator in sub-section 4.3.8, excluding the WDN. The word 'Network' implies a complex web of pipelines of a certain total length, which are mapped by some water providers [31].

As mentioned below in Chapter 2: Literature Review of WSS Assessment in sub-section 2.3. Discussion, the current research on water systems revolves around Multi-Criteria Analysis (MCA) indices that rank water systems of cities globally by listing indicators that track vulnerabilities. There are also non-literature review papers, each exploring a specific case study by location, as well as literature reviews of those papers. These are tabulated in Table S2 and Table S1, respectively, in Appendix A – Literature.

These papers assess vulnerabilities in a variety of methods, such as graphical, network, economic, and probabilistic, not merely MCA. These methods are discussed in section 2.2: Methods used in Water Supply Assessment. Lastly, past incidents are analysed in section 1.2 below to study the vulnerabilities to better understand which set of indicators MCA indices should have.

1.2. Past Water Supply Disruption Incidents

Table 5 below documents several notable past water supply disruption incidents. It is, of course, a limited list, but its focus here is to present a variety of circumstances and locations where water supply failed, each due to different vulnerabilities. The documented vulnerabilities are Source Water Quality, Tap Water Quality (both pathogen and high lead heavy metal concentrations), Lead Pipes, Storage Capacity, Water Stress, Water Loss, and Flood Risk. Arguably, Soil Moisture Content indirectly also acts as a proxy for Water Stress.

Table 5 – Past Water Supply Disruption Incidents

#	Year	Location	Description and Vulnerabilities	References
1	2000	Ontario, Canada	Pathogens in tap water due to floods	[32]
2	2015	Hong Kong	High concentrations of lead in tap water	[33], [34]
3	2017	Hong Kong	36 bursts of WDN mains pipelines	[35]
4	2017	Cape Town	Water stress, drought, and wasteful consumption	[27]
5	2024	Dubai, UAE	Flooding from rare heavy rain	[36], [37], [38]
6	2024	South-East USA	Hurricane Helene, floods caused water outages	[39], [40]
7	2025	Los Angeles, USA	Palisades Wildfires: water shortage and unsafe quality alert	[41], [42]

Bear in mind that even though certain cities publish less of their data than others, this does not necessarily mean they are worse than others, though they are more likely to be. Particularly in developing cities, incidents either go without substantial press coverage or discussion is suppressed due to their controversial and embarrassing nature.

For this reason, among others, case studies for this research are required to be developed cities, see point 3) in sub-section 4.2.1: Case Study Cities Selection Requirements. This is an imperfect decision considering that some incidents still may go unnoticed, as well as the fact that developing cities are not any less important, and a universal index would still need to be capable of analysing them eventually. However, it is easier to understand complicated systems by starting with simpler systems, and developed cities are simpler to understand as a result of more abundant data and a more transparent track record of incidents.

Considering the nature of the references in Table 5 above, it is an unfortunate reality that incidents are always first reported by news agencies and even private individuals, as opposed to academic papers. Hence, several references may be more informal. Having said that, the most important aspect of finding important information is that it is published and verified by multiple sources, even if not in the most formal settings. Readers can then form their own opinions. Research into these incidents follows with time. Academic sources are not as fast to report incidents as news agencies, which have the most financial incentive and specialisation to do so. Academic research does, however, assess the causes of incidents and where systems failed more so than the speculations on social media.

What's special about the Dubai incident is that such heavy rains were not expected or seen for many decades, so there was little to no preparation. More on it in sub-section 4.3.6: Flood Risk below. The flooding in Dubai caused electricity outages and fatalities, meaning that the Custom Index of this research will not only directly assess the vulnerabilities of water systems, but interestingly also the vulnerability of other systems by proxy. Therefore, understanding these past incidents helps to emphasise the importance of this research and assessing the vulnerabilities of water systems.

Granted, not every vulnerability of one utility is also that of another. For example, there were no reports of electricity outages during the Hong Kong 2015 and 2017 incidents of high concentrations of lead and pipeline bursts. In the future, it could be interesting and potentially useful to develop a universal index for assessing overall risk for all utilities, not only water supply, probably starting with wastewater due to its similarity and overlap of vulnerabilities with water supply.

The cause of the 2024 Los Angeles wildfires is unclear, though what is clear is that they spread through strong winds and were challenging to stop because of a severe water shortage, resulting in less water available for firefighters to combat the fires. The cause of the water shortage may have been due to poor governance [41]. Regardless, the fires easily spread due to fast winds, dry warm climate, and high population density, see Table S7 – Case Study Cities Basic Statistics in Appendix C – Index under the Water Supplier Sources sub-section. Beyond the fact that burnt homes lose access to the water supply because their water infrastructure is destroyed, the wildfires caused the local water supplier to issue an 'Unsafe Water Alert' over water quality concerns related to this incident [42].

Addressing the 2000 Ontario Tap Water Quality incident, insufficient treatment of floodwater after heavy rainfall resulted in E. coli contamination that caused 2300 people to become sick and seven to pass away [32]. This is appalling, but also interesting for several reasons:

Firstly, this took place in a small town by the Great Lakes. One would expect water quality there would be among the highest in the world, both due to society being highly developed there and also due to the nearby naturally large freshwater bodies of the Great Lakes. This teaches the moral to always be on guard and not be complacent.

Secondly, it shows how at least two, possibly three vulnerabilities caused this incident. These are Flood Risk and Tap Water Quality for certain, with Source Water Quality potentially as well. It would have required the water system to merely be resilient to a single one of the indicators in the vicious chain to prevent this incident. The concept of setting up many defences, and strengthening them as much as possible, against every realistic vulnerability within reason, is referred to as the 'Swiss Cheese Model' in the CPE safety mindset. It is visually illustrated below in Figure 3 [43]:
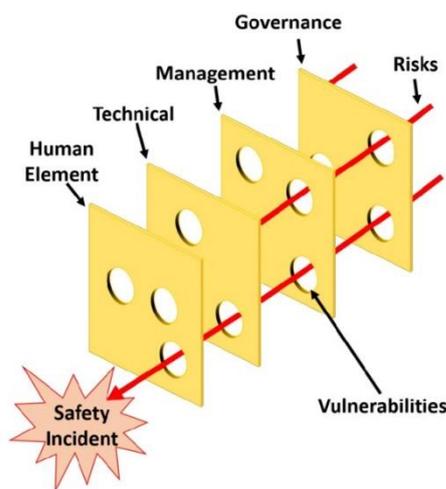
Figure 3 – CPE Safety Swiss Cheese Model [43], CC BY-NC-ND 4.0

Bear in mind that it is often impossible to prevent certain incidents, particularly natural disasters such as hurricanes. It is, however, more often than not possible to limit the severity of the damage and casualties caused. The layers in the Swiss Cheese Model in Figure 3 above are not only to prevent an incident but also to limit and contain it after it occurs.

The following sub-sections will discuss individual vulnerability indicators and potential solutions to reduce their risks, but two such possible mitigation strategies are discussed here because the 2000 Ontario incident involves multiple indicators. Those safety precautions include using water filters and boiling water before drinking it. The former is relatively common for numerous people and environments, as a water filter is a cost-effective means of separating out microbes and other contaminants. The latter can be used in emergencies where the safety of tap water is put in question (Boil Water Alert Notice) or used in general as a precautionary benefit for hot drinks, soups, etc.

1.3. Relation to Chemical and Process Engineering

Considering that water research is a minor subtopic within Chemical and Process Engineering, it is important to express why this research is conducted within a Chemical and Process Engineering department. Chemical and Process Engineering (CPE) is an engineering discipline focused on designing and optimising the bulk processing and production of fluids and fine solids. Although this is an unofficial definition, it includes virtually every application that is widely recognised as CPE while also excluding any other applications that are not recognised as CPE. Specifically, this definition covers crystallisation, polymers, catalysts, adsorption, gasification, and pyrolysis, among others. The bulk processing and production of larger solids, especially while utilising a conveyor belt assembly line, is typically covered under Manufacturing Engineering. To understand the properties of the materials themselves to detect, design, and utilise them, other disciplines such as Chemistry, Materials Engineering, and Mechanical Engineering are employed. Besides powders, bulk production of solids can still be considered as CPE applications if they also involve significant processing of fluids, such as pharmaceutical pills and tablets with their liquid ingredients.

An analogy for introducing CPE to an unfamiliar reader is by comparing it to cooking. A pressure cooker manipulates the temperature and pressure for a given volume, time, and ingredients in order to cook in batch reactions. This analogy is limited because although there are many chemical plants that run in batch mode, many others run continuously to capitalise on economies of scale and often also involve reversible reactions, unlike home cooking.

Water is a fluid that is processed and treated in bulk, similar to the other fluids in CPE, such as hydrocarbons, detergents and cleaning agents, dyes and paints, etc. In fact, being the most processed industrial fluid in terms of rate of generation by weight or volume, water is almost always produced continuously in treatment plants for large cities. Hence, the engineering of water treatment is similar to other well-known continuous processes in CPE, such as those involving oil and gas, as opposed to low-volume productions such as high-purity chemicals, for example, certain solvents and resins, which are often produced in batch, similar to the aforementioned cooking analogy. Water is unique not only for being the most continuously processed fluid by flow rate but also for having rainwater and wastewater sewage systems that process water separately from each other and from potable water, all at very high flow rates compared to industrial fluids. The processes of water treatment share the same fundamental engineering principles of risk management and vulnerability mitigation, material balances, and financial calculations. Hence, the relation of WSS research to Chemical and Process Engineering.

Figure 4 below presents the process for conventional water treatment [44]. The three steps are Coagulation, Flocculation, and Sedimentation. This method is used for both treating potable water for consumption as well as wastewater for safe discharge or use as grey water. Grey water has numerous uses, for example, irrigation, firefighting, humidification, toilet flushing (see Figure 6 below), groundwater recharge, construction concrete mixing, and a cold utility for cooling in industries such as CPE plants [45]. There are variations of this 3-step process that include recycling for increased filtration as well as Ultraviolet (UV) radiation to destroy microbes (disinfection) [44].
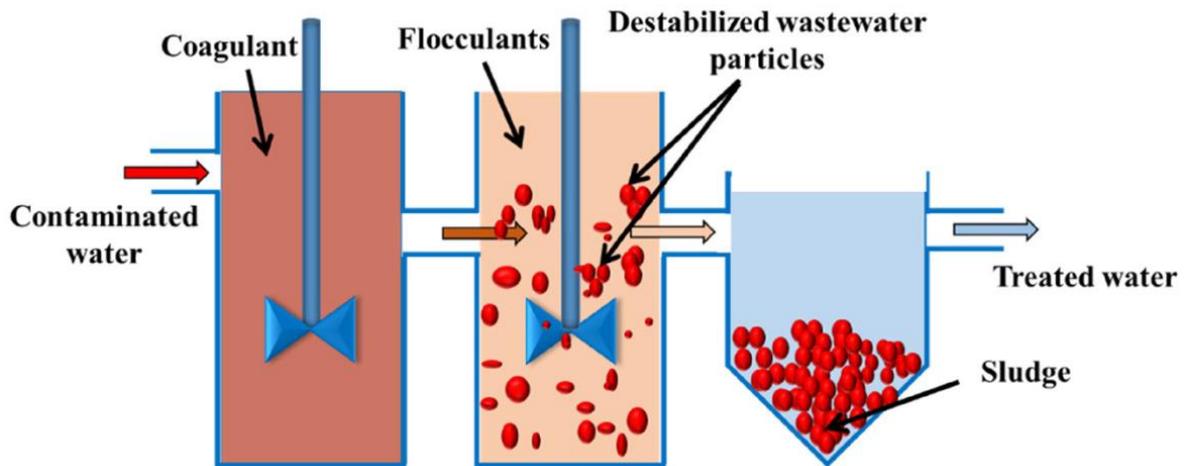
Figure 4 – Side Visual of Coagulation, Flocculation, and Sedimentation [44], CC BY-NC-ND 4.0

Other CPE separation processes which treat water include the methods of Thermal Distillation, Reverse Osmosis (RO) filtration, and the newly anticipated Electrodialysis [30].

Another common subtopic in CPE is the water quality of effluent. It involves measurements of Biological Oxygen Demand (BOD) and Dissolved Oxygen (DO), and is discussed in this research as a part of a major indicator called Source Water Quality in sub-section 4.3.4.

There are, of course, numerous other disciplines that contribute to WWS research, but CPE principles offer a unique perspective on Control Volumes, as demonstrated in the case studies of this research, being WDN pipelines with well-defined borders. A previous research project by the author of this research, which inspired this research, constructed water material balances in Figure 5 and Figure 6 below to better understand these unique water systems and reveal where the bottlenecks for consumer affordability are [30]. The dashed boundaries represent control volumes, with the circles 'I' and 'E' representing Inlets and Exits for streams, respectively. The Sankey Material Balance Diagrams were sketched out in a freeware software called STAN [46]. The units shown for water flow rates are Million Tonne/Year, MGD, and MCM/Year. Note that these flow rates are rounded to whole numbers.
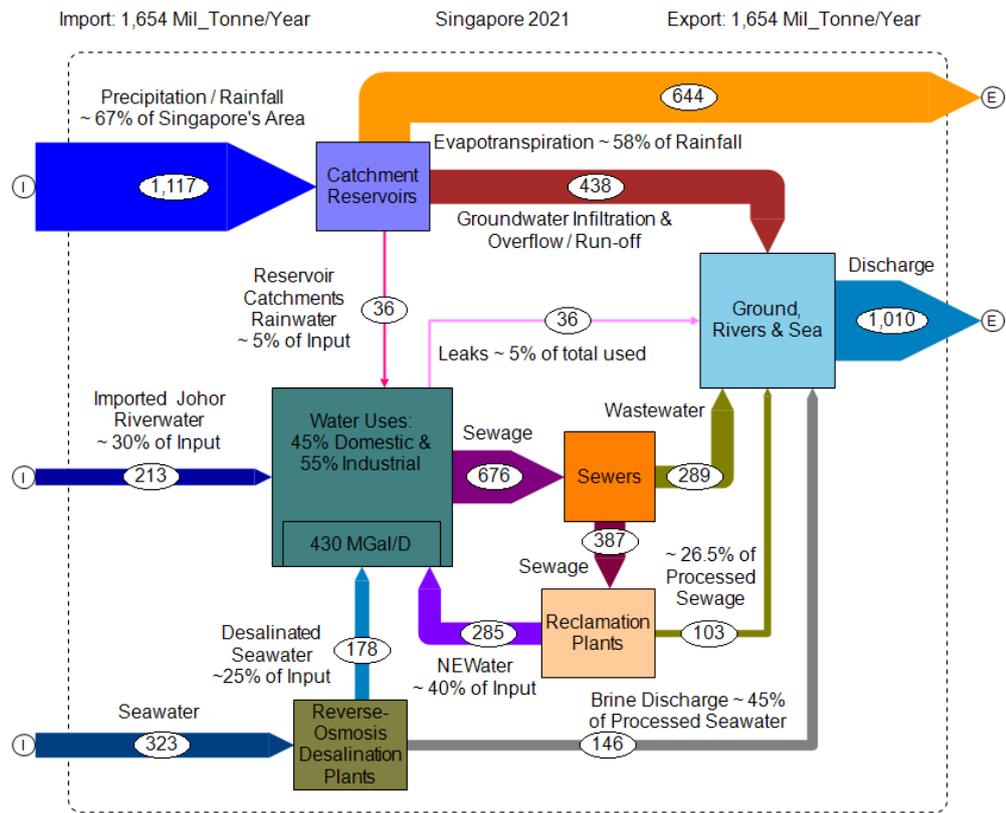
Figure 5 – Sankey Diagram of Singapore's Water Material Balance [30]
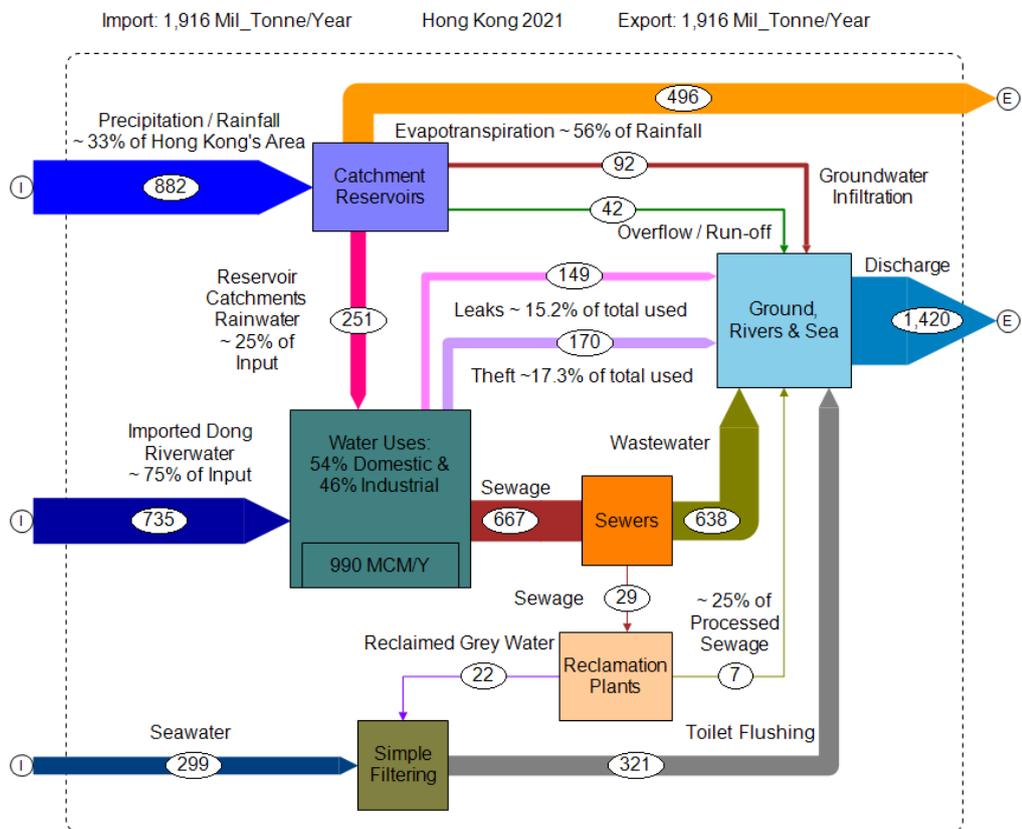
Figure 6 – Sankey Diagram of Hong Kong's Water Material Balance [30]

1.4. Current state-of-the-art and research gaps

The current state-of-the-art for assessing the vulnerabilities of Water Supply Systems (WSS) is dominated by the use of Multi-Criteria Analysis (MCA). For decades, WSS papers compared neighbouring municipalities and water resources with MCA, as is documented in sub-section 2.3.1: Statistics and Table S2 in Appendix A – Literature. Over the last decade, this MCA approach has expanded to comparing WSS worldwide. The two prominent indices that rank the resilience of WSS globally were published by Arcadis in 2016 [21] and by DuPont in 2021 [47]. Comparing cities worldwide allows for a deeper analysis, taking into consideration unique aspects of WSS such as water reclamation, catchments, seawater for toilet flushing, and so on and so forth. Another advantage of conducting MCA globally is that it allows for a simple, universal way to estimate the resilience of WSS by comparing its various aspects against other WSS abroad, thereby revealing where the greatest vulnerabilities of a WSS are so they can be addressed with an investment or better management.

Despite the promising potential of global WSS MCA indices, the current literature is largely limited to the two mentioned in the previous paragraph. There is a gap in the MCA and WSS literature for a framework that will include an MCA solver that incorporates criteria correlations and calculates uncertainties, and a methodology for constructing a WSS global index that includes clear selection requirements for indicators. Also missing from the WSS literature is a worldwide WSS index that focuses only on the vulnerabilities that can cause water supply disruptions. The 2016 Arcadis and 2021 DuPont indices have scopes that are too broad and do not focus solely on vulnerabilities that are likely to disrupt the water supply. Their structures are also needlessly complex, for example, due to divisions into multiple nested layers of sub-indices, and some of their data seems unreliable.

On all of these counts, this research project aims to improve upon by programming a new MCA Solver Software Tool and a new Custom Index methodology. These two contributions are methodological and application-based and are covered in Chapters 3 and 4, respectively, and discussed in section 1.5: Hypothesis, Objective, and Novelty below. The improvements of this new Custom Index over the existing indices in the literature are further detailed in section 4.6: Rankings Results.

Chapter 2 presents the various analysis methods used in the WSS literature, including MCA, but also Probabilistic and Economic methods, as well as other methods which are exclusively software-based. It compares the features of existing MCA software packages, as well as research papers in the WSS literature.

1.4.1. Summary of MCA Weighting and Ranking Methods

While the fundamentals of MCA are introduced in sub-section 2.2.4, specific methods employed in MCA, as well as scripts to demonstrate how they are efficiently programmed, are covered in Chapter 3: MCA Solver Software Tool. As defined in Table 1 in Nomenclature, Multi-Criteria Analysis (MCA) is "a family of methods that rank alternative scenarios based on how they score on two or more criteria". MCA compares case studies or alternative scenarios against each other to calculate an overall final score for each and ranks them. Criteria are attributes of alternatives.

In MCA, each criterion is assigned a weight. A weight is defined in Table 4 in the Nomenclature as 'relative importance' assigned to each criterion. There are two types of methods used in MCA: weighting and aggregating/ranking. Weighting methods determine the weights, while aggregating/ranking methods determine the final scores or ranks of the alternatives.

The simplest weighting method is to assign each criterion an equal weight as any other. This requires the least user input and is good to quickly calculate an estimate and learn how MCA works, but unless all criteria are equal in importance, it typically makes sense to move to another weighting method. The second simplest weighting method, which is often the default to be used, is to manually assign weights. This requires expertise on a topic and is often handled by a panel of experts in a given topic [47]. In events where the differences of case studies from each other matter the most, the Standard Deviation becomes the default method to stand out. There are other weighting methods which are variations of these three most fundamental weighting methods, which are listed. The Analytical Hierarchy Process (AHP) is a mathematically inconsistent weighting method by design that would simply default to Manual Assignment of weights were it consistent. The purpose of AHP is to test human psychology [4], [48].

Ranking methods input the weights generated by weighting methods, so they are also calculated in this sequence. The simplest and often default ranking method is the Weight Sum Model (WSM) [11]. WSM is the Sum Product Statistics function. Similarly, another simple ranking method that is often seen in the MCA literature is called the Weight Product Model (WPM) [10]. WPM's equation might have been called 'Product Power' unofficially, as it would describe its nature compared to WSM. WPM tends to be seen as inferior to WSM because it becomes illogical for inputs of the number 0. Lastly, there is a family of ranking methods called Preference Ranking Organization METHod for Enrichment of Evaluation (PROMETHEE) [9] which is more complicated, but it 'outranks' case studies directly to each other instead of to maximum and minimum scores like WSM and WPM which some prefer as final scores are negative and positive and a final score of 0 becomes the middle baseline.

1.5. Hypothesis, Objective, and Novelty

The hypothesis of this research is that by constructing a methodology to quantify and therefore better understand the vulnerabilities of water supply systems, decision-makers can better manage and invest in them to increase the resilience against the risk of water supply disruptions. As defined in the Nomenclature, 'Risk' is the severity of an incident times its frequency or likelihood. This risk needs to be reduced, i.e. as low as reasonably possible (ALARP).

The objective of this research is to develop a methodology to assess the vulnerabilities of water supply systems in large cities.

The two novel contributions of this research are an application-based custom index of indicators and the programming of a methodological solver software tool to run it.

This MCA Solver functions as a Decision Support System (DSS) for assessment. While many DSS are designed for optimisation, which means deciding how to address a known vulnerability [49], this tool has a different purpose, which precedes that stage. It is not a competing alternative approach, but rather it serves the necessary prerequisite assessment stage, whose added value is to first quantify the systemic vulnerabilities of WSS to subsequently inform an additional complementary DSS tool designed for management and investment decisions.

The Custom Index evaluates vulnerabilities of case study cities worldwide, and the software solver correlates and ranks them. The Custom Index seeks to improve upon professional indices studied from the WSS literature to be more aware of how a water system of interest compares to others, and to know where it is most lacking and needs improvement.

The methodology of constructing the Custom Index has various parts, including lists of criteria for selecting the case study cities and indicators that measure the vulnerabilities, as well as a decision-making process for selecting the weighting and ranking methods.

The Custom Index features a novel perspective of concentrating its focus on the supplier side and aiming only to assess water systems based on vulnerabilities that pose risks to the current supply of drinking water. In contrast, other indices in the WSS literature have generic scopes that include nutrient recovery, protecting threatened species, water access, consumer affordability, and eco-friendly green space. Although the latter are also important and have their place, they leave a gap in the literature that could be useful to fill to better understand the vulnerabilities of the water supply.

The strict supplier-side perspective of this research addresses a gap in the WSS literature. Existing indices have a generic scope, mixing critical supply vulnerabilities with unrelated consumer-focused or environmental metrics, such as green space or consumer affordability. This broad approach dilutes the focus. A water supplier, which is the entity naturally most concerned with and responsible for preventing supply disruptions, is left with an unclear assessment of risk. This research provides a novel framework that narrows the focus, enhancing WSS resilience by concentrating resources only on those vulnerabilities prone to causing a supply disruption.

To achieve this, the Custom Index includes a novel supplier-side Affordability indicator using a pioneer Operation and Maintenance (O&M) equation for estimating the cost of water treatment compared to the GDP as a measure of the financial well-being of the local water supplier.

In addition, two more novel indicators are included in the Custom Index, which are Tap and Source Water Qualities. They are each designed as a separate sub-index with their own nested sub-indicators that include concentrations of substances and other simple measures in water to estimate quality accurately, even in cases where some data may be lacking. Unlike existing water quality indices, which may involve many measures, the water quality sub-indices indicators utilised by the Custom Index of this research are designed to input only a few measures. These should be moderately uncomplicated to collect from yearly reports published by water suppliers, estimates based on satellite data, or measured analytically with laboratory equipment.

Tap Water Quality specifically uses a new scores normalisation approach created by this research project called 'Mixed Compliance'. It penalises concentrations of contaminants linearly, but only starting from half the maximum recommended guideline and above, not from concentrations of zero (undetectable). This aims to be fairer and not penalise low but still detectable concentrations of contaminants, making perfect scores realistically achievable and improvement efforts more motivating.

The software has useful and unique features to run the Custom Index, which existing software packages in the literature lack, namely, calculating uncertainties and correlations between the selected indicators. Understanding the uncertainties and correlations from the analysis improves the understanding of the indicators in order to create, modify, and even remove or combine indicators that have high uncertainty or that correlate strongly with each other. These are in addition to more elementary features which are reasonable to expect from modern software, which current analysis application programs lack, but the new solver programmed for this research project delivers.

2. Literature Review of WSS Assessment

Table of Contents

2.1. Introduction

Following the contextual background in sections 1.2: Past Water Supply Disruption Incidents and 1.4: Current state-of-the-art and research gaps, as well as the Hypothesis, Objective, and Novelty of this research project in section 1.5 above, this review aims to understand the current literature on the topic of assessing the vulnerabilities of water supply systems. Of particular focus are developed large cities, to be considered from the perspective of water suppliers. Of interest are assessment methodologies and models.

This chapter covers the methods and sources from the literature that inspired the application-based and methodological contributions of this research project, which are the MCA Solver Software Tool and Custom Index, respectively, as was mentioned in sections 1.4 and 1.5 above. The main relevant sections in this chapter that cover these inspirational methods and sources are 2.2.4: Multi-Criteria Analysis (MCA) Methods and 2.3.2: Most Notable Sources. These are summarised in section 2.4: Summary.

The starting search points are meta-analyses and systematic reviews that compare numerous existing papers and tools. The papers most relevant to this topic are the inspiration for the generation of the new Custom Index. The novelty of this Custom Index will be its supplier-focused set of indicators and methodology for selecting them for assessing the vulnerabilities of WSS that can specifically cause supply disruption events.

The focus is to be initially narrowed down as much as possible for simplicity and relevance, so papers are specifically searched for 'assessing the vulnerabilities of water systems in large, developed cities'. Only once the Custom Index is created and its methodology assessed can it be further generalised to other types of case studies.

2.1.1. PRISMA Methodology

This review utilises the PRISMA methodology (Preferred Reporting Items for Systematic Reviews and Meta-analyses [8], [50], [51]) for filtering through publications to find and study high-quality papers needed for accurate and useful discussion and conclusions. Figure 7 below presents the flowchart steps for filtering through the publications. The major publisher sources were, but not limited to, ResearchGate, Elsevier/ScienceDirect, Springer, MDPI, Google Scholar, and the IWA.
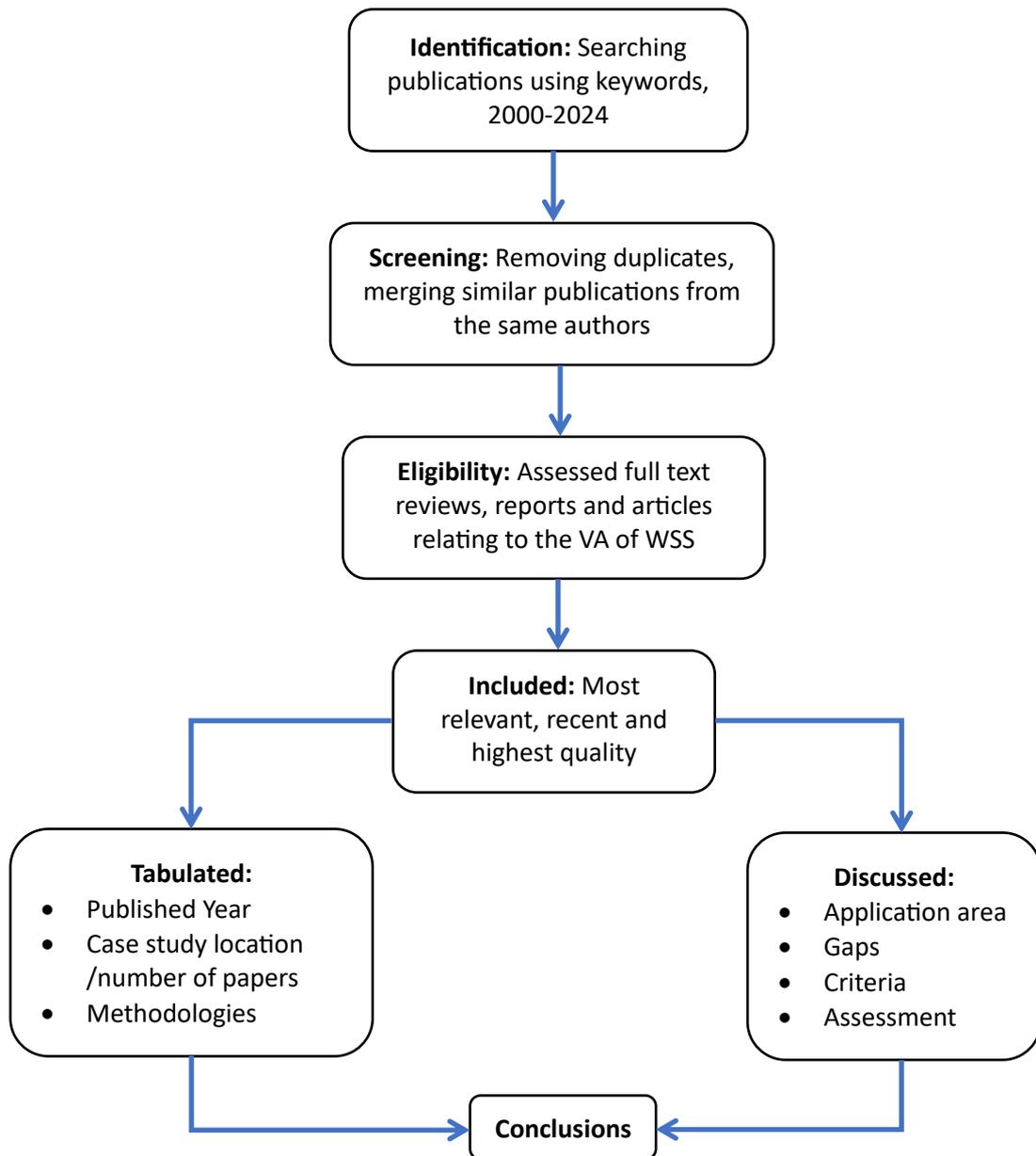
Figure 7 – Flowchart of the Literature Review PRISMA Methodology

The keywords searched varied, but included 'water supply/distribution systems/networks' and 'vulnerability assessment'. The focus was to search for papers that mainly list vulnerabilities that can result in water supply disruptions, and what methods were used to assess these.

The papers are tabulated in Table S1 and Table S2 in Appendix A – Literature, which accompanies this chapter. As can be seen in Table S2, several papers in the water systems literature research water "resources". Water resources refer to the locations where water is sourced from, such as aquifers, wells, surface rivers, and lakes. Very few of the papers in Table S2 are not strictly speaking water-related, but focus on MCA to better understand it, and hence are included. This is because it was discovered early on in the search for papers that numerous water papers use MCA methods.

When comparing analysis methods, and especially their outcomes, it is important to note that there are several ways to decide between them, and there are not always right or wrong choices. As a matter of fact, as several titles in this literature review show, there are new methodologies being invented, including modifications of the methods below. This is different from other scientific, engineering, and mathematical applications, where the formulae and algorithms used are clear and objectively the only ones that should be used.

The scientific method is about repeatability, but considering that different applications receive different results from the use of different analysis methods, it can be said that the preference of some methods over others is mostly based on the opinions and preferences of researchers.

There is no simple way to figure out with certainty which methods are more suitable to analyse an application. Hence, it may be best to either combine several methods or allow a user to pick inside the tool's software which to use. At any rate, reasonable justifications for a selection must be made. The methods chosen for the Custom Index are discussed, selected, and justified in section 4.5: Selecting Weighting and Ranking Methods.

The sub-sections below provide an overview of several of the main methodologies used in water research in the papers studied in this literature review. These methods include economic, probabilistic, graphical, and multicriteria analysis. A few papers also developed their own customised methodologies, but these are rarer.

2.2. Methods used in Water Supply Assessment

2.2.1. Probabilistic Methods

Fault Tree Analysis (FTA) and Bayesian Networks (BN) are two separate and distinct methods, though they do have a similarity. They are both top-down, systemic, and macro analysis methods. They estimate the chances of events occurring using probabilities [52]. FTA utilises Boolean logic gates such as 'AND' and 'OR' as shown below in Figure 8 [53]. BN uses more specific chances, as shown below in Figure 9 [54]. BN is, therefore, more flexible, but FTA is simpler.
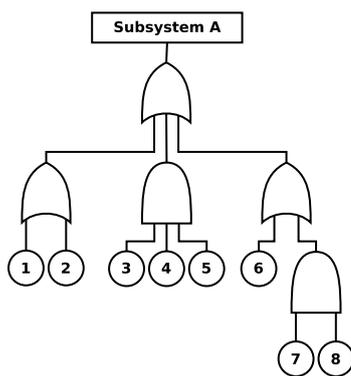
Figure 8 – Flowchart of a Fault Tree Analysis (FTA) [53], CC0 1.0
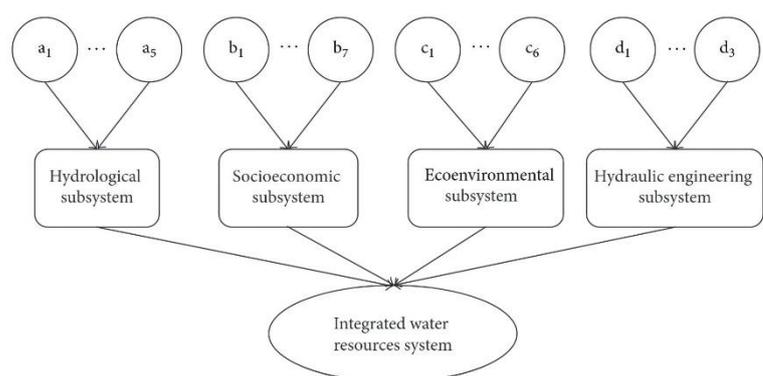
Figure 9 – Flowchart of a Bayesian Network (BN) [54], CC BY 3.0

Having said that, neither seems to be suitable for the creation of the desired Custom Index. The purpose is to assess the vulnerabilities currently, compare water systems of large cities globally, and lead to improved management to minimise the vulnerabilities. Predictions and forecasts are not the aim of this research, though it is interesting to see it used in the WSS literature.

Table S2 in Appendix A – Literature lists several water research papers that utilise probabilistic methods. These include the use of BN in a 2021 paper, 'Hierarchical Bayesian Approach For Assessing WDS' in Tennessee [55]. A fuzzy variant of FTA was used by the 2019 paper 'An Approach to Estimating Water Quality Changes in WDS' [56], which is too complex for the purpose of this research project. Some papers use both for comparison, namely the 2021 'Development of Multi-Hazard Risk Assessment Model for Agricultural WSS' in Isfahan [57].

2.2.2. Economic Methods

In economics, making a single policy change can alter incentives and market signals and therefore shift the market's supply and demand curve, thereby creating externalities, as shown below in Figure 10 [58]. Partial Equilibrium Analysis (PEA) is an economics method for analysing which changes are most likely to result in a supply and demand curve that maximises profit [59].
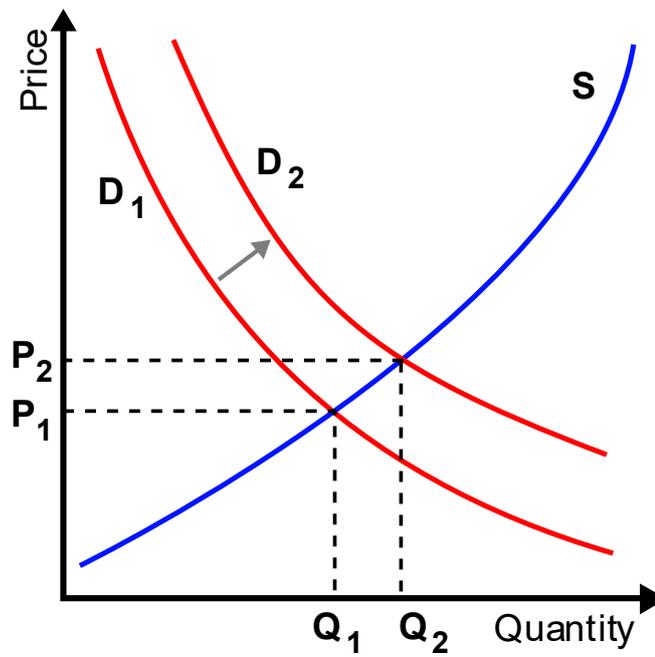
Figure 10 – Graph of supply and demand curves shifting [58], CC BY 2.5

In this review, the only paper that used PEA for assessing WSS is an Australian 2010 conference paper [60]. The interesting fact is that this is a paper by the Australian government, which shows that their perspective is from a governance and economic perspective, as opposed to a private supplier or investor perspective. It appears as though PEA is not a suitable method for the creation of a new Custom Index because it exclusively focuses on a single indicator, which is finance, while the Custom Index will also address other indicators.

Besides PEA, a 2018 Uganda-studied paper [61] also uses finance equations to calculate which circumstances may result in the highest profitability. It combines Capital Expenditure (CAPEX) and Net Present Value (NPV) with MCA, illustrating an ability to combine seemingly different methods.

PEA is used for a single criterion, profit or finance, whereas the possible adjustments of the policy could be numerous. The complex nature of PEA is in measuring the economic impact itself, whereas MCA can be used in applications where the complex analysis is in the criteria or preferable features of the system itself, which would be the equivalent of the policy changes in PEA.

2.2.3. GIS and EPANET Methods

Various papers utilise predominantly software packages as VA methodologies, such as the Geographic Information System (GIS), as shown below in Figure 11 [62], and EPANET, as shown in Map 1 [63], to visualise the vulnerabilities of water systems and highlight where they lie, such as contaminations, human impact, blockages, breakages/leaks, etc. EPANET is named after the United States Environmental Protection Agency (EPA), with the added 'net' at the end to symbolise the network aspect of the software. Some of these methods are also 'continuous', meaning they are constantly updated by sensors and manual inspections. The advantage of these methods is that they are very detailed and accurate, so they can pinpoint the exact locations of issues and know where to send maintenance support and what kind.

The problem is that these methods require significant amounts of recent data and are therefore beyond the measuring resources of this research. It also means they cannot easily compare and rank water systems globally because not every city has a sophisticated network of sensors and reporting of incidents that are all recorded on an interactive software map of the WDN. They also only measure certain vulnerabilities, but not every vulnerability that is likely to cause a water outage, for example, affordability and water dependency/reliance on importation are not mapped. This means that alone, these methods cannot assess the overall vulnerability of a WSS for water outages unless they are combined with methods that can assess the other important vulnerabilities as well.

These methods can also make forecasts and predictions, similar to the aforementioned Probabilistic Methods in sub-section 2.2.1 above. Again, though, for the same reason as was explained previously in sub-section 2.2.1, this research does not make predictions, so this functionality is not useful for this research.

Studied papers from Table S2 in Appendix A – Literature that employ EPANET as a sole method include two virtually simulated case study cities in a 2021 'Simulation and VA of WDNs Under Deliberate Contamination Attacks' [64] and a 2007 'VA of a Drinking WDS' [65]. There are other papers that researched EPANET of physical locations with real statistics as input data, but in papers that simulated case studies, EPANET is used disproportionately. A 2019 Egyptian paper, 'Flood-Hazard Assessment Modelling' [66], combines GIS with another type of method in the form of AHP MCA to make predictions. Another paper that combines another kind of method, but also combines both EPANET and GIS, is a 2014 'BN VA Tool For WDS Under Extreme Events' in Italy [67].
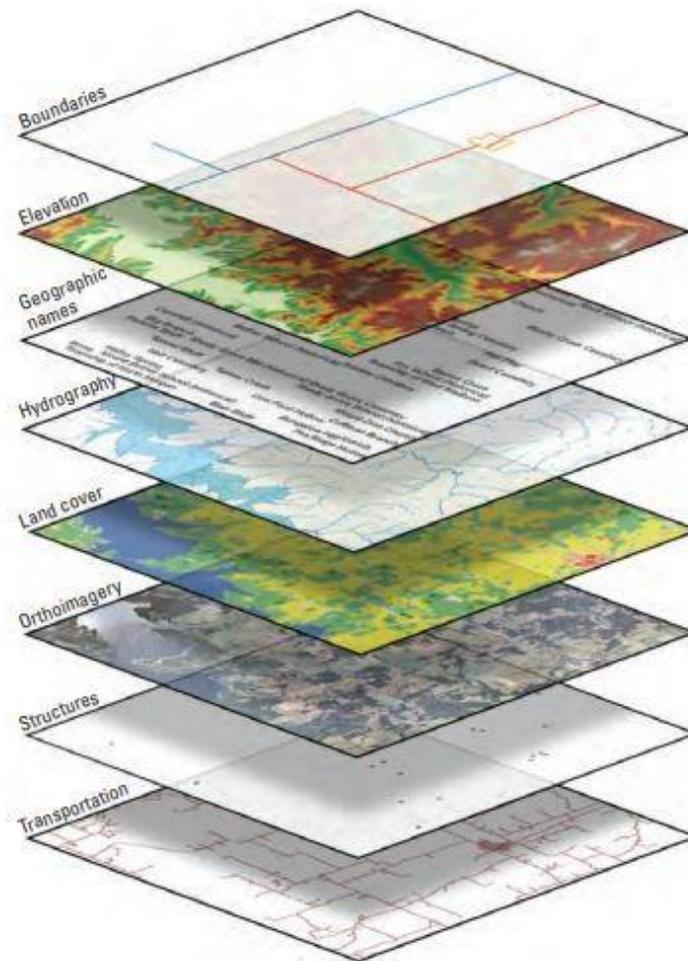
Figure 11 – Layers of GIS maps [62], Public Domain
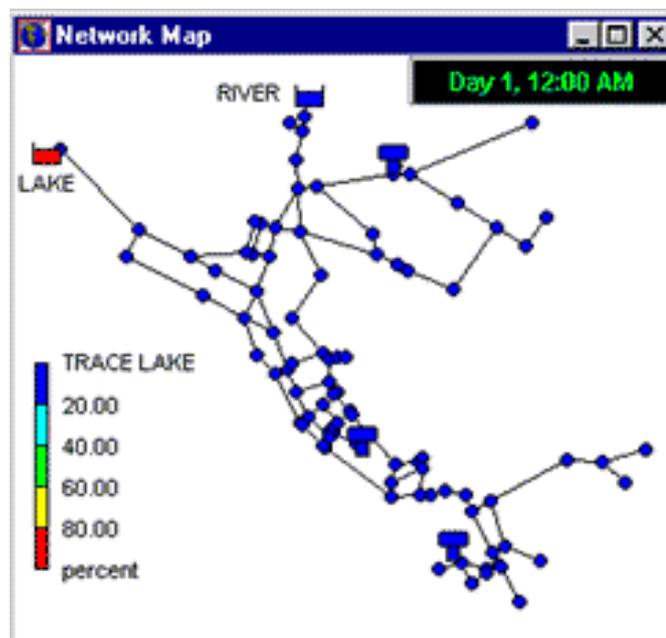
Map 1 – A network utilising the EPANET app [63], Public Domain

2.2.4. Multi-Criteria Analysis (MCA) Methods

An index is a list of scores or ranks of case studies or alternative scenarios. For example, the Quality of Life Index of countries by the European Commission [68]. As defined in Table 4 in the Nomenclature and according to the OECD, an aggregate or composite index is a compilation of individual indicators into a single index on the basis of an underlying model designed to measure multidimensional concepts that cannot be captured by a single indicator [18].

As defined in Table 1 in Nomenclature, Multi-Criteria Analysis (MCA) is "a family of methods that rank alternative scenarios based on how they score on two or more criteria". It is also known by the name Multiple Criteria Decision Analysis (MCDA). MCA methods are used to compute aggregate indices. MCA compares case studies or alternative scenarios against each other to calculate an overall final score for each and ranks them. The final score each alternative receives is a function of a list of scores it has on a list of criteria or indicators, hence the name 'multicriteria'. Criteria are attributes of alternatives. If alternatives were to only have a single criterion between them that scores differently, it would be very easy and virtually automatic to rank whichever alternative is best. However, due to the complex nature of several alternatives scoring higher on some criteria but lower on others, it is necessary to use analysis methods to rank alternatives to select the best ones.

Table S3 in Appendix B – Software shows examples from the literature of alternatives being available for laptop models, while the criteria are the specifications and features of the laptops. The purpose of this comparison is to determine which laptop models are the best to purchase for particular user preferences.

In MCA, each criterion is assigned a weight. A weight is defined in Table 4 in the Nomenclature as 'relative importance' assigned to each criterion. In the laptop examples, this would compare the importance of certain specifications, such as storage versus price, where a higher weight signifies greater importance. There are two types of methods used in MCA: weighting and aggregating/ranking. Each index utilises one of each. Weighting methods determine the weights, while aggregating/ranking methods determine the final scores or ranks of the alternatives.

Figure 12 below presents the relation between inputs, methods, and outputs in MCA. Arrows represent dependence on inputs. Arrows originate from inputs, point at outputs, and go through a method if applicable. Whenever an arrow does not go through a method, it is because it is merely a matter of filling in numbers, from literature, for example. A blue arrow is always applied, whereas a red arrow is optional and method-dependent.
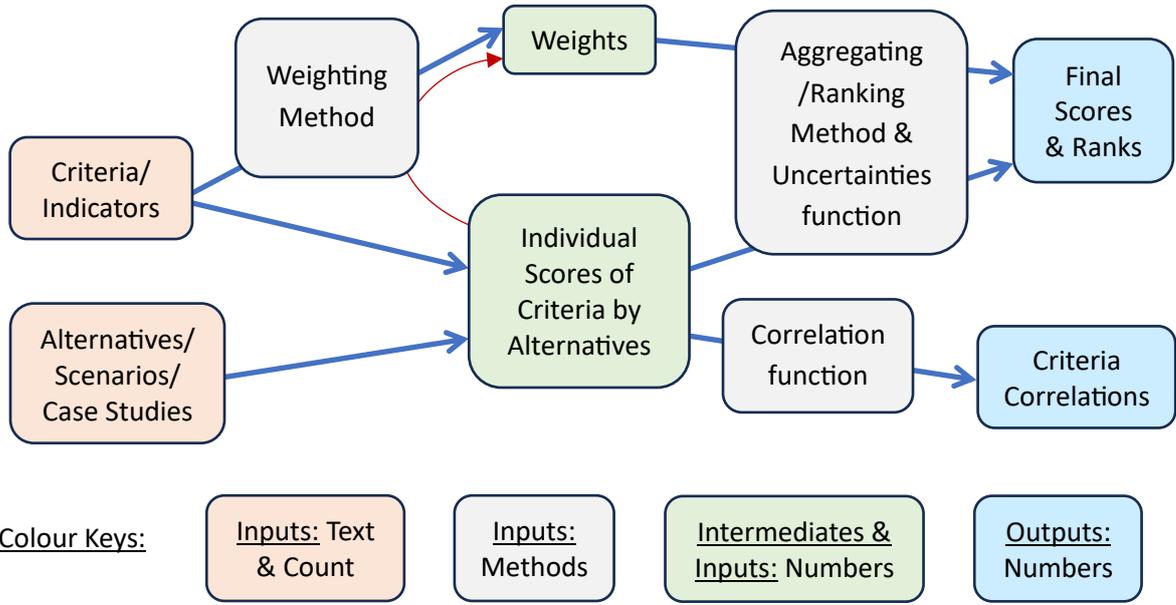
Figure 12 – Flowchart of MCA inputs, methods, and outputs

There are two major outputs for MCA: the final scores/ranks and the correlations between the criteria. Although the former is the main output and is more important, the latter is part of what sets aggregate indices apart from single indicator indices. The correlations measure whether two criteria might potentially correlate too highly with each other. In the case of water systems, this would mean two indicators might measure the same vulnerability. In other words, this could be explored further to determine potential causality between the indicators. "Correlation does not imply causation", but it is an inexpensive way to suggest where to explore next.

All correlation methods are functions, as can be seen in Equation 8 and Equation 9 in section 3.4: Criteria Correlations Matrix, so Figure 12 specifies 'Correlation function'. However, several methods are not single functions, meaning they do not have an equation or traditional inputs. Namely, the 'All Equal' and Manual Assignment weighting methods, covered in sub-section 3.2.2.

Any criterion can be its own nested index, also referred to as a sub-index. Such a criterion has the same list of alternatives as the main index, but its own list of sub-criteria, weighting method, and ranking method, to yield an overall score for that criterion for each alternative in the main index.

Different criteria can be measured in different units. In the laptop examples, cost is measured in the unit of currency, while memory and storage are measured in gigabytes. To put together the criteria scores in different units into the same index, there needs to be an algorithm that standardises all the units into the same single unit. This algorithm step in MCA is called 'Normalisation'. The normalisation of weights and scores is done inside their respective green squares in Figure 12.

The normalisation functions of weights and scores are shown in Script S4 in Appendix B – Software. For weights, they are each divided by their sum total, so that the new sum total of the normalised weights is equal to exactly one. Weights technically do not need to be normalised because they are always in the same units as each other, but it makes the final score numbers more convenient and often in the range of between 0 and 1 or 0% to 100%. As for normalising scores, although they can often be normalised into common units, it is typically simpler to convert all the scores to be unitless and in the range of between 0 and 1 or 0% to 100%. This is the commonality of normalising weights and scores, that they may share the same range. With scores, several indicators are already natively measured in the units of percentages or are from other sub-indices, hence they are already normalised in this range to begin with. A 'Normalised' matrix, for instance, is a matrix where the initial scores of each alternative by each criterion have been converted to the range of between 0 and 1, as shown in GUI 7 in section 4.4: Scores Results.

Besides weighting and ranking methods, MCA methods can be organised into other categories, for example, Continuous and Discrete, as presented in Figure 13 [7] below:
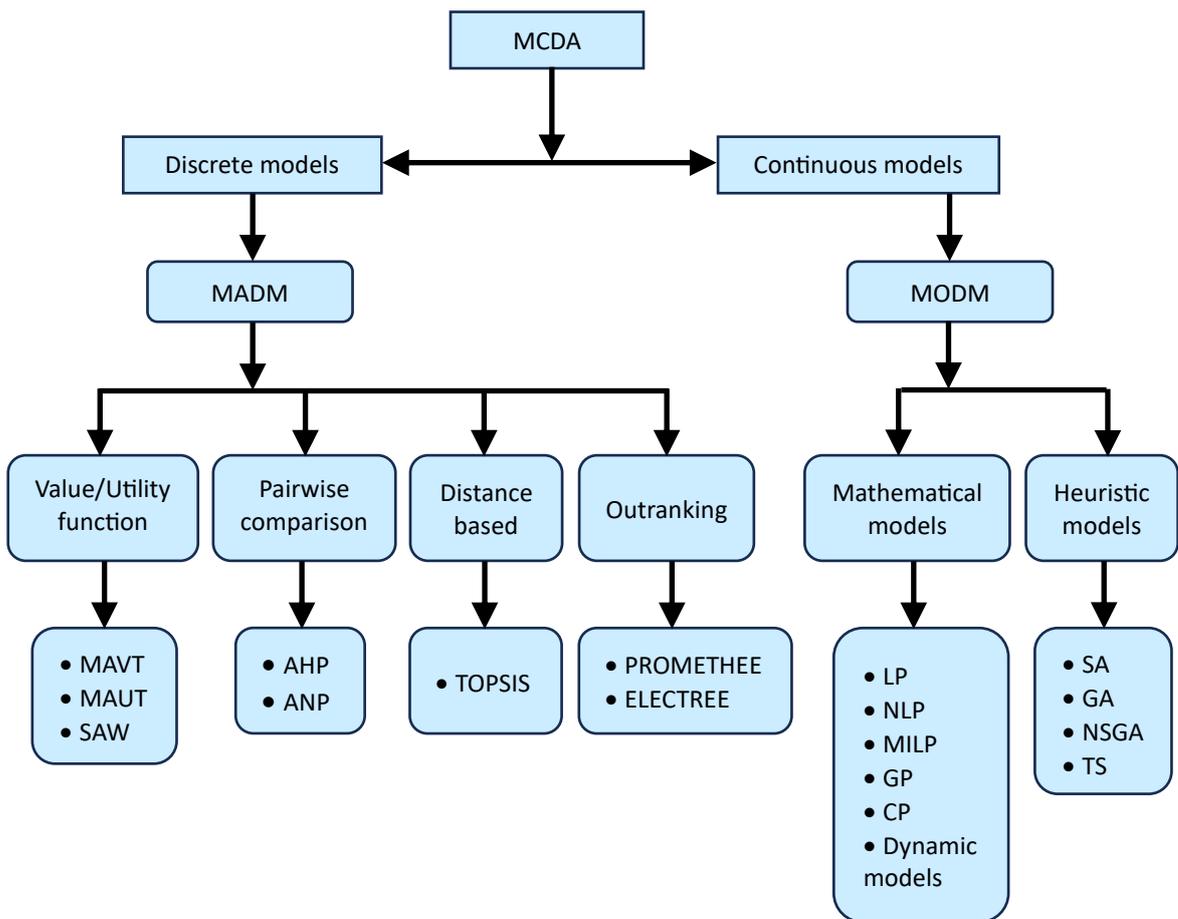
Figure 13 – Flowchart of the MCA family of methods [7], CC BY 4.0 remixed

The MCA methodologies in Figure 13 above are divided into two main branches based on the nature of the decision space [7], [69]. The first, Multi-Attribute Decision-Making (MADM), is applied to problems with a finite and pre-determined set of alternatives. The second, Multiple-Objective Decision-Making (MODM), is used for continuous optimisation problems where the alternatives are not pre-defined but must be designed or discovered.

Within the discrete MADM branch, methods are either known as "weighting" or as "aggregate ranking". These were introduced and discussed in the paragraphs above.

The only weighting methods that appear in Figure 13 are the Analytic Hierarchy Process (AHP) and its extension, the Analytic Network Process (ANP). AHP structures a decision problem into a simple hierarchy and uses pairwise comparisons to derive numerical weights for each criterion. See sub-section 3.2.3. This process provides a robust way to translate qualitative preferences into quantitative priorities. ANP advances this concept by allowing for complex interdependencies and feedback loops between criteria, forming a network rather than a strict hierarchy.

Other weighting methods not shown in Figure 13 are discussed in section 3.2, while aggregate ranking methods are discussed in section 3.3.

The Simple Additive Weighting (SAW) is the default and simplest ranking method in MCA. It is known by other names, such as the Weight Sum Model (WSM) and Sum Product in Statistics. See Table 7 in sub-section 3.3.1, which documents another similar ranking method from the literature that is absent in Figure 13, the Weight Product Model (WPM). The Multi-Attribute Value Theory (MAVT) and Multi-Attribute Utility Theory (MAUT) are more comprehensive frameworks. Distance-based methods, such as TOPSIS, rank alternatives based on their proximity to an ideal solution. Outranking methods like ELECTRE and PROMETHEE establish a dominance relationship by comparing pairs of alternatives, which is then used to construct a final ranking.

In contrast to the MADM branch, the MODM paradigm operates on a different principle entirely. MODM is fundamentally a tool for design and optimisation, not for ranking a pre-defined list. It is applied to problems with a continuous or infinite set of potential solutions defined by a set of constraints. The goal of MODM is to find a set of optimal solutions by optimising multiple objective functions simultaneously, representing the best possible compromises among conflicting goals. This makes MODM suitable for strategic planning and design problems where the optimal course of action must be created rather than simply selected from a list.

2.2.4.1. Existing MCA Software

Table 6 below summarises the comparison of three existing MCA Solvers from the Literature in Appendix A – Literature.

Table 6 – Existing MCA Solvers from the Literature

Software \\ Criteria	2003 Analytical Hierarchy Process (AHP) [3]	2023 MCDA-KIT [70]	2024 Decerns MCDA [71]
Free to use	Unclear	✔/✖ Commercially Licensed, otherwise free for non-profit	✖ Licensed for all: Commercial, Academic, or Personal uses
A wide variety of weighting methods (Including AHP & STDEV)	✖ Only AHP	✔/✖ No Standard Deviation	✔
Text areas for comments	Unclear	✔ Yes, but requires pressing on elements to see comments	✔
Download & Upload User Inputs & Results as a file	Unclear	✔ .xml file	✔ .dcm file
Graphing: Shows the contribution of each criterion towards the ranks	Unclear	✔ GUI S2 in Appendix A – Literature	✖
Uncertainties and Correlations features	✖	✖	✖ Interestingly, plots graphs, but does not actually calculate correlations. Not even a zooming-in feature.

Considering the limitations of each software package, there is clearly a gap for MCA solver software. Specifically, one that is free and open source for non-commercial uses, but of high enough quality that it could be sold. A software with a variety of weighting and ranking methods that performs correlation analysis, handles uncertainties, and shows the contribution to the ranks of alternatives by each criterion.

2.3. Discussion

Whereas most papers presented models for assessment, few offer resiliency improvement suggestions. Interestingly, the papers that offered improvement suggestions are non-MCA economic and dynamic models. These are the Australian 2010 conference paper [60] with PEA and a 2006 Fire Flows Micropolis paper [72].

Network methods, including some papers that combine with MCA, also tend to be integrated with the GIS and EPANET methods, though typically to give probabilistic estimates for incident events as opposed to giving general overall performance or sustainability scores, such as with MCA. Such notable papers include a 2012 VA of WSN in Algeria, which uses general statistical estimates and graphical presentations [73]. A 2014 paper assessed extreme events in Italy using BN, integrated it with fuzzy numbers, and presented it graphically [67]. A 2021 paper presented a flowchart and graphs of a hierarchical approach using BN [55]. A 2021 paper combined Fuzzy FTA with Hybrid BN in Iran [57].

A 2019 paper assessed nodes using a Network Entropy method in an eastern China city [74]. A 2017 paper used the centrality metric for a topological analysis in Cyprus [75]. A 2016 paper innovated a Resilience Index for assessing the performance of networks in Italy [76]. Others include a 2012 Weighted and Directed Network Models in an American paper [77]. 2020 and 2021 papers in Hungary assessed the probabilities of pipe failure events using graphical network statistics [78], [79].

Few papers had interesting combinations of network and MCA methods. A 2020 paper in Canada integrated FTA and PROMETHEE [80]. A 2015 paper in China combined BN with AHP MCA [54].

Many MCA papers can be criticised for not clearly stating some of the following: their weighting and ranking methods, weights, criteria, and even case studies. Even if a paper mentions these, it is typically difficult to search for this information because instead of dedicating headings to each of these, they are only mentioned once briefly in the discussion with other, less important information.

For instance, the 2023 MCA applied to rank rehabilitation strategies of WDNs paper [81] can be praised for having the dedicated heading 'Case Study', although it is unfortunate that it does not mention the location of the case study and instead only describes it. The WDN is cited, so only when following the reference does its source explain that this case study is a simulation.

On the other hand, the 2022 paper on Integrated strategic planning & MCA framework should be praised not only for explaining its methods of AHP and Fuzzy TOPSIS (MCA), but also for clearly attaching numerous maps of the studied case study of Sefidroud, Iran [82]. It inspired this research to share several maps; see the List of Maps.

There is also room for simulation case studies, but such papers should clarify to the reader that their case studies are simulated. For example, the 2020 Evaluation of Different Natural Wastewater Treatment Alternatives paper [83] focuses too much on the details of its PROMETHEE methodology calculations with no apparent mention of its specific case study location.

2.3.1. Statistics

Table S2 in Appendix A – Literature tabulates the publication year of each of the studied papers. As presented in Figure 7 in sub-section 2.1.1: PRISMA Methodology, the papers in this literature review were published since the year 2000. And yet, the majority of the papers studied in this literature review were published within the last decade, since 2015, to research with significantly more recent data. This can be seen in Figure 14 below, which presents the number of papers studied in this literature review by their year of publication:
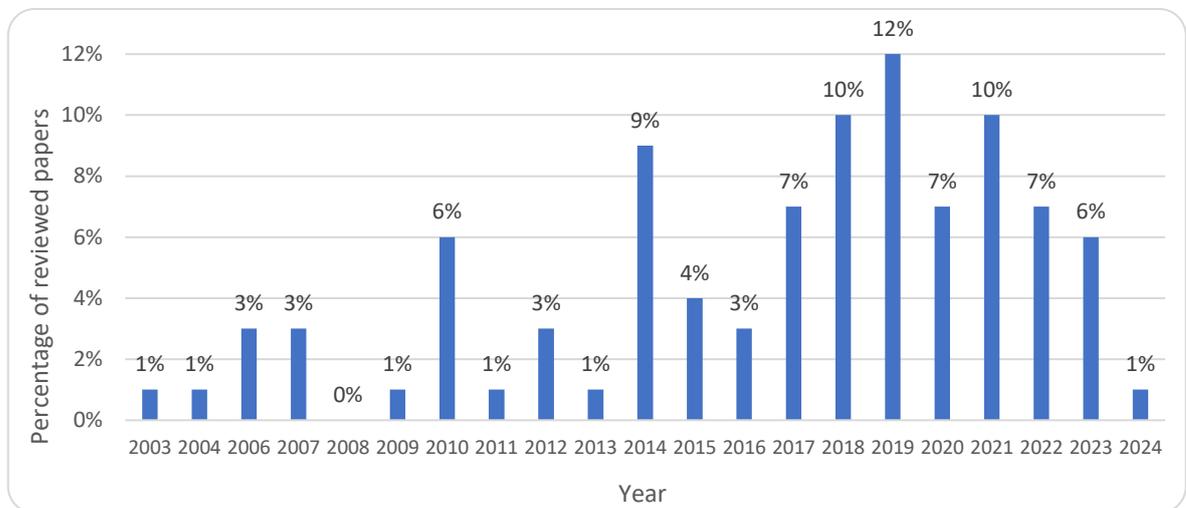
Figure 14 – Bar Chart of the percentage of water papers reviewed by year

Note that Figure 14 rounds the percentages to whole numbers for convenience.

There is no apparent trend across time among these papers, other than that the more recent ones were selected more disproportionately for this literature review study. The lack of apparent trends makes it challenging to accurately determine the direction this research field is heading in.

Having said that, considering the recent and current advancements in Artificial Intelligence (AI), it is expected that the direction this research field will head in will involve the incorporation of AI, as do numerous other fields. It is a new and vitally useful technology, like the advent of electricity and computer software, and it is expected to revolutionise a number of topics. A considerable limiting factor specifically for water systems research is the availability of data and its reliability. Currently, AI is not considered sufficiently reliable to determine whether data is accurate or not, but it can help find sources and give ideas of what keywords to search for. AI can also help in programming. In the future, AI may help with validating calculations and assist in employing more complex assessment methods, which were discussed in section 2.2. More on AI in sub-section 5.3.10: Artificial Intelligence (AI) Data in section 5.3: Further Work – Index.

Following section 2.2: Methods used in Water Supply Assessment, the prevalence of methods employed by the studied papers in this literature review is shown in Figure 15 below by their types:
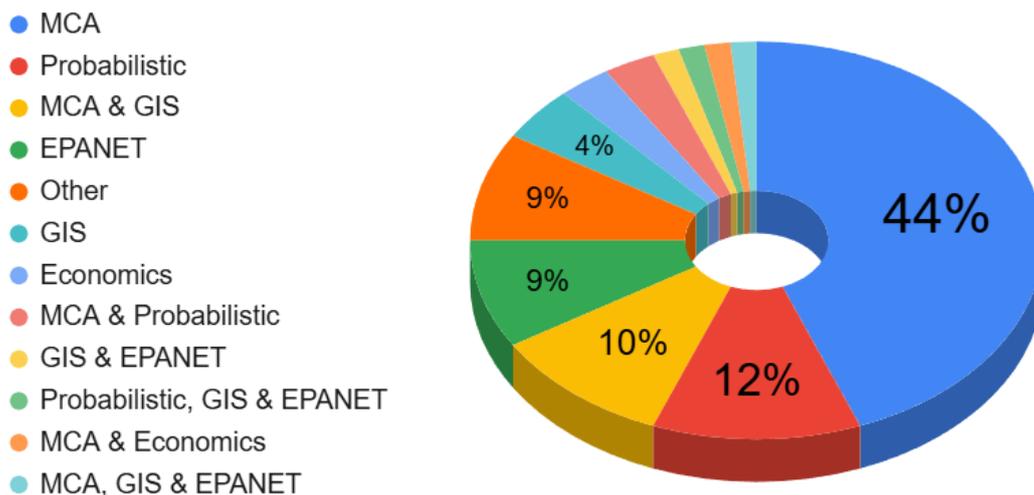
Figure 15 – Pie Chart of the methods in the WSS research papers

The popularity of MCA compared to other methods can be explained by the fact that water systems are multifactorial, as there are various vulnerabilities that water systems face. MCA is relatively simple to apply, whereas the GIS and EPANET methods can be more complex and require greater availability of data. Assessing the resiliency of water systems can be done without making forecasts, so probabilistic methods also may not be as useful as MCA.

A few papers developed their own custom methods, but without MCA, they cannot ideally compare alternatives with multiple criteria. Map 2 and Figure 16 below show the global distribution of the papers researched by this literature review by country as a percentage of the total studied. Italy and Iran top the list of locations with the most studied papers, at roughly 10% of the total each.

Considering the water research conducted in Canada and Brazil, it is clear that water systems are also researched in countries that experience low water stress, meaning it is important there as well.
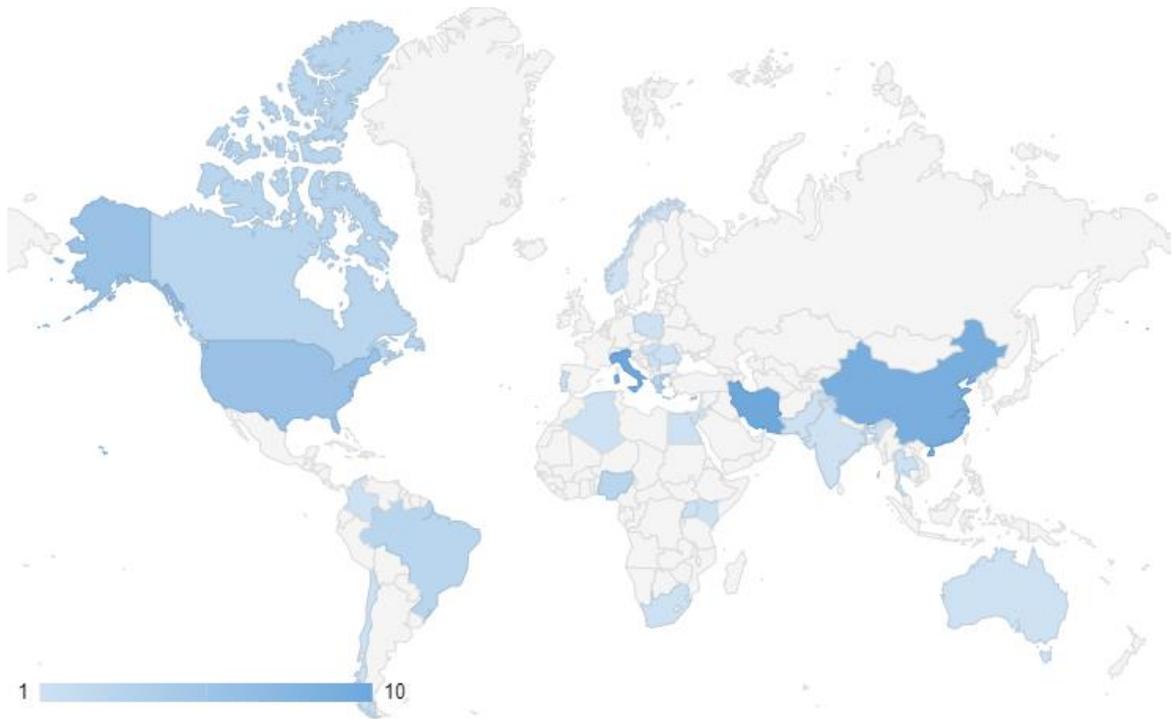
Map 2 – World countries by the percentage of reviewed papers
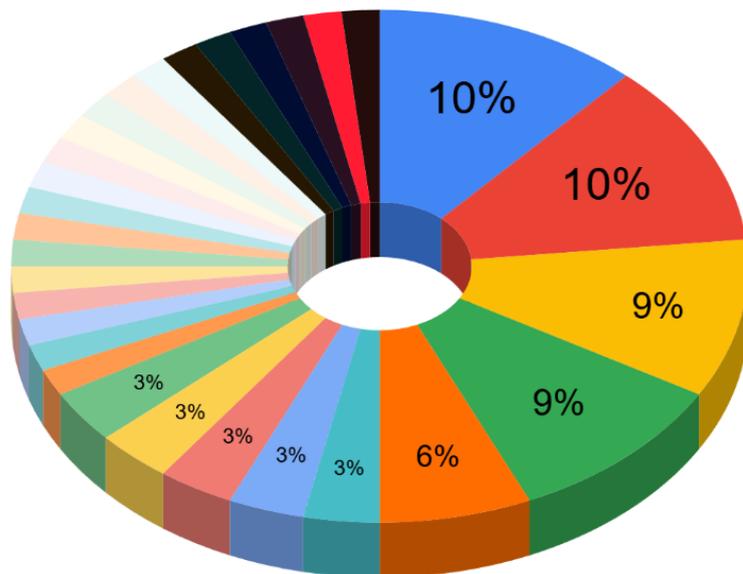
Figure 16 – Pie Chart of the countries in the WSS research papers

2.3.2. Most Notable Sources

Among the sources studied in this literature, a few stand out the most.

They are documented here by their type:

- Indices: Arcadis 2016 Sustainable Cities Water Index [21], DuPont 2021 City Water Index [47]

- Literature Reviews: 2021 MCA Methods to Address Water Allocation Problems [7], 2019 Analysis of Water Resources VA Tools [51]

- Academic Papers: 2022 Urban Water Security [19], 2020 Assessing Water Security [48], 2019 Urban Water Security [84]

- Reports: 2023 National Performance Report [85]

- Website: IB-NET [86]

- MCA Software Solver Applications: 2003 Analytical Hierarchy Process (AHP) [3], 2023 MCDA-KIT [70], 2024 Decerns MCDA [71]

Besides these specific literature reviews and academic papers, the other papers studied throughout this literature review are tabulated in Table S1 and Table S2, respectively, in Appendix A – Literature. These two literature reviews and three academic papers are bookmarked in Table S1 and Table S2 with a comment to easily locate them for reading convenience.

The 2021 'MCA Methods to Address Water Allocation Problems' literature review listed MCA methods by their categories as shown in Figure 13 in sub-section 2.2.4: Multi-Criteria Analysis (MCA). The 2019 'Analysis of Water Resources VA Tools' literature review laid out the PRISMA methodology and demonstrated well how to perform it, as illustrated in Figure 7 in sub-section 2.1.1: PRISMA Methodology. Both presented statistics of papers, such as publication year, locations, and the MCA methods used.

These three academic papers list indicators that assess vulnerabilities of water systems, which most other papers do not. Most other papers instead focus on a specific vulnerability, such as flooding, affordability, etc. This is why a number of papers, though as Figure 15 in sub-section 2.3.1: Statistics shows only a minority, use assessment methods that are not MCA. These three papers use MCA, specifically the AHP weighting method, which is also helpful because they demonstrate how to apply it.

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Similar to these three academic papers, the IB-NET website [86] and the 2023 National Performance Report [85] are also helpful for studying which lists of indicators are used to assess the vulnerabilities of water systems in large cities. These helped pick indicators in section 4.3: Vulnerability Indicators. IB-NET also provides data, and so it is cited throughout section 4.3.

As for the indices, the most pertinent index discovered in the WSS literature is the 2016 Sustainable Cities Water Index [21] written by Arcadis, based on data researched by the Centre for Economics and Business Research (CEBR) in affiliation with the IWA. It features a number of the same indicators used in this paper's custom index, particularly under its 'Resiliency' sub-index. Another relevant index is the 2021 City Water Index by DuPont [47]. There were not many other indices found, namely, ones that assess the water systems of cities globally using MCA and a list of indicators. Therefore, these two demonstrated how it is possible to do so.

The difference between these two indices and the academic papers that also use the same MCA family of methods is that these papers study in depth either a single location or a small number of locations, whereas the indices study in breadth dozens of case study cities globally. Both the 2016 Arcadis and 2021 DuPont indices use MCA, whereas most but not all the papers use MCA. The exact method of every paper is also tabulated in Table S2 in Appendix A – Literature.

The three programs studied from sub-section 2.2.4.1: Existing MCA Software provide a general layout for programming an MCA solver. The main reason for programming a new software as opposed to using any existing other is that they lack a correlation matrix and uncertainty features. Besides, they are not very convenient to use, because none of them even has a zoom-in feature. They are also not free or open-sourced. Lastly, they are not programmed in HTML, so they cannot be uploaded as webpages in browsers, although they could have easily been scripted in HTML and JavaScript. Theoretically, any program that can be written in HTML and JS, probably should be. This allows for fast and convenient access to the program without having to download and install it; to use it by merely accessing a website instead, hence there is an opportunity here.

The 2003 Analytical Hierarchy Process (AHP) only features AHP as the weighting method [3]. 2023 MCDA-KIT does not feature a simple Standard Deviation weighting method and costs money to purchase a license to use commercially [70]. 2024 Decerns MCDA costs money to purchase a license for any use, including academic [71]. The new MCA solver scripted for this research is designed to surpass the quality of the current commercially licensed aforementioned programs because it will include all the features that the others lack.

2.3.3. Validation and Assessment

The process of testing whether a tool is reliable and therefore valid is called validation [87].

An MCA Solver Software Tool, being essentially a calculator, though a specialised one, is validated in the same way a regular hand calculator would be validated: by testing a series of math problems and checking it yields exactly the correct answers that are known in advance.

For an index, testing its reliability is more complicated. Similar to how there is no one objective way to configure camera lenses and filters [88], there is no one objective way to configure an MCA index. Multiple camera configurations can record pictures that appear slightly different from each other in terms of brightness and contrast, for example, by using a wide-angle lens and a polarising filter, which can improve image quality in some environments but not in others. This subjectivity means that the use of the word 'validating' may not be as applicable in the context of testing the quality of cameras or indices in the same way that a calculator solver can be validated by calculating exact answers from known calculations in the literature. For this reason, the Custom Index of this research project is said to be 'assessed' as opposed to 'validated'.

The MCA solver is only considered reliable if it computes all the answers for mathematical calculations correctly, whereas the Custom Index is assessed by a correlation against an existing index from the literature, and it is subjective to determine how strong the correlation needs to be.

Assessing an index involves both its method and data together, making it more complicated than validating a solver, which only involves its data, as the math behind its method is known in advance from the literature. In the case of an MCA solver, the method is the list of known weighting and ranking methods from the MCA literature. The solver is validated using MCA papers from the literature in the sub-section Validated MCA exercises from the literature in Appendix B – Software. The Custom Index, on the other hand, is assessed for its reliability in section 4.6: Rankings Results, where it is correlated against the 2016 Arcadis Resiliency sub-index.

There is another method for validation found in this literature review that was not employed in this research project, which is prediction. Forecasting the likelihood of incident events in certain geographies and then over time, comparing them to the statistics of the actual events. Notably, the Flood-Hazard Assessment Modelling paper in Ras Gharib, Egypt, used the GIS methodology for this purpose and has an impressive 83.3% successful prediction rate [66]. Prediction methods were not implemented due to time constraints and the need to study another complicated method to make forecast predictions. Therefore, the Custom Index assesses statistics from the past instead.

2.4. Summary

There seems to be a gap in the water systems literature for indices that assess the vulnerabilities of water systems of cities, as shown in the Most Notable Sources sub-section 2.3.2 above. The two studied indices do not have a clear, focused method for selecting their indicators. This research aims at producing a Custom Index with clear Indicators Selection Requirements as covered in sub-section 4.3.1.

Among the most important requirements that these indices miss are to employ a unique perspective of the supplier as opposed to a consumer, to list indicators that can be improved by investments and better management, and to calculate correlations and uncertainties. These two indices mix numerous supplier-focused indicators, such as water loss, stress, and quality, with consumer-focused indicators of water access, threatened species, and green space (2016 Arcadis [21]) and nutrient recovery (2021 DuPont [47]). Evidently, their selection of indicators is somewhat confusing, perhaps because their aim is unfocused. The new Custom Index of this research has a clear aim of assessing how vulnerable water systems are to supply disruption incidents.

The lack of a Criteria Correlations Matrix in these indices is unbecoming, considering that both indices employ lengthy arrays of indicators, especially the 2021 DuPont [47]. Therefore, statistically, it is quite likely that several indicators may correlate too highly with one another, suggesting they measure the same vulnerability. To implement this correlation feature, along with others that these indices miss, this research outputs another novelty in the form of a newly developed MCA Solver Software Tool to run the Custom Index. The features of correlations and uncertainties, among others, are missing in these indices as well as in the Existing MCA Software covered on page 2.2.4.1. These are two separate novel contributions of this research project: a Custom Index, being the application-based contribution and an MCA Solver Software Tool, being the methodological contribution.

It is clear from Figure 15 in sub-section 2.3.1 that the majority of water research papers employ MCA. Considering that this research aims to develop tools that will assess multiple vulnerabilities, it makes sense for it to use MCA as well. The reason for the wide utilisation of MCA in this field is that there are multiple vulnerabilities in WSS, so using other methods may not cover the full picture.

The other methods, such as supply and demand economics, probabilistic forecasting, and GIS and EPANET, have their own complexities, while their advantages do not typically compensate for the constraints of analysing single indicators. They can be paired with MCA, as is shown in Figure 15. However, combining methods not only increases the complexity but also may require additional data that may not be available.

Regarding discrete versus continuous methods, Figure 13 in sub-section 2.2.4: Multi-Criteria Analysis (MCA) lists examples of such methods. Continuous methods require the availability of continuously updating data [72]. This would be unnecessary, as this Custom Index aims to view the WSS as a big picture that is relatively at a steady state, at least from one year to the next. Leakage rates, flood risk, and other vulnerabilities of WSS do not alter substantially year by year, and their data often requires at least months to accumulate and report on accurately.

Furthermore, continuous methods are barely used in the water systems literature, and when they are, it is mostly regarding improving the economics [7]. Continuous methods would be unnecessarily complicated; hence, discrete methods are selected for the Custom Index of this research project. Recall from section 1.5: Hypothesis, Objective, and Novelty that the Custom Index aims to be able to produce accurate results even with moderate to low availability of data, while continuous methods are the opposite and would require constant streams of data.

3. MCA Solver Software Tool

Table of Contents

3.1. Introduction

Following the introduction to MCA in sub-section 2.2.4, it is clear that a universal index for assessing water systems would benefit from MCA methods to aggregate multiple vulnerability indicators. Following sub-section 2.2.4.1: Existing MCA Software, there seems to be a gap in the literature regarding MCA software that can compute correlations and uncertainties and have other features.

The purpose of this chapter is to present a newly programmed MCA solver software tool and delve deeper into the MCA methods included in it and how they are scripted. This software can also be used outside of WSS research for broader MCA comparisons, making it quite a useful output of this research project.

Examples of this software tool solving MCA exercises from the literature that validate it are included in Appendix B – Software. Appendix B – Software accompanies this chapter and contains other important scripts and GUIs that are too long to include here in Chapter 3. Most notably, GUI S8 in the Supplementary GUIs sub-section in Appendix B – Software shows the MCA solver's HTML & CSS when JS is turned off. This clarifies the different sections of the solver and their natural flow as demonstrated in Figure 12 in sub-section 2.2.4 Existing MCA Software.

Weighting Methods and Ranking Methods are discussed by their names in sections 3.2 and 3.3, respectively. The solver allows the user to select a weighting method and a ranking method of their choosing from a list of methods included in the tool. The applications of these methods in the literature are presented in the studied papers in Table S2 in Appendix A – Literature and validated worked examples by the solver software in Table S3 in Appendix B – Software.

The weighting methods implemented in the MCA solver are 'All Equal' weights, Manual Assignment, Analytical Hierarchy Process (AHP), Standard Deviation and Entropy. These are featured in the dropdown menu in GUIs in sub-sections 3.2.1 to 3.2.3 below. The aggregate ranking methods implemented in the MCA solver are the Weight Sum Model (WSM), Weight Product Model (WPM) and the Preference Ranking Organization METHod for Enrichment of Evaluations (PROMETHEE) I and II. These are featured in the dropdown menu in GUI 4 in sub-section 3.3.2.

The features, Criteria Correlations Matrix and Uncertainties, that necessitate this new software are in sections 3.4 and 3.5, respectively. Section 3.6: Technical Aspects of Software Development explains the decision to program in JS and HTML, the secondary features of this software, and goes through the development environment and journey. Lastly, section 3.7 is the Summary.

3.2. Weighting Methods

Recall from sub-section 2.2.4 and from the Nomenclature that weights are the relative importance of criteria, where a higher weight implies greater significance. Weighting methods select weights for criteria. Each of the following sub-sections introduces and explains a weighting method that is included in the software. The last sub-section in this section, 3.2.6, compares the weighting methods.

3.2.1. All Equal

'All Equal' is the simplest weighting method, as all criteria are equal in weight, as shown in GUI 1 below. It is important to emphasise that there is nothing inherently wrong with this simplistic method; it has its use cases. In an event when a user does not know which criterion to value more, or believes all criteria are equal in worth, which may be the case for some comparisons and applications, this method provides simplicity and quick calculations with minimal input from a user.

A user can start with this weighting method to begin getting results, and then change to another weighting method, so this method helps to get started. This method also serves as a benchmark to compare with the weights of other methods when deciding on which weighting method correlates the best with another existing index, see Table 16 in sub-section 4.5.1: Sensitivity Analysis.

GUI 1 – All Equal Weights hoverable comment

3.2.2. Manual Assignment

Manual Assignment is another straightforward method, arguably the second simplest. The user assigns a single number for each criterion. Theoretically, this can be any positive number, including both integers and decimals, see GUI 2 below.

The higher the number, the higher the weight. Assigning zero to any criterion effectively turns it off and does not take it into account mathematically at all, no matter what its scores are, as if this criterion were not there at all.

Criteria Weighting

Number of Criteria = 6

User Inputs: Criteria Preferences

Weighting Method: -Manual-

-All Equal-
-Manual-
AHP
STD
Entropy

Manual Weights (-Manual-)
Manually assign weights

Recommended Use
This is the default weighting method for most cases. It is recommended when the user understands which criteria are valued more. For example, high uncertainty criteria should typically be assigned low weight, but this may be subjective.

Criteria	Criteria1Name	Criteria2Name	Criteria3Name	Criteria4Name	Criteria5Name	Criteria6Name
Raw Weights	3.5	2.25	7	1	0	
Normalised Weights	0.25	0.16	0.51	0.07	0.00	0.00

Reset Criteria Names   Reset Weights

GUI 2 – Manually Assigned Weights hoverable comment

3.2.3. Analytical Hierarchy Process (AHP)

Similar to Manual Assignment, though more complicated, the Analytical Hierarchy Process (AHP) weighting method requires additional user input numbers to generate weights. It is the weighting method that requires the largest amount of additional user input numbers, more so than any other. In fact, the only other weighting method that requires any additional user input numbers is Manual Assignment.

Consider the following analogy: If criterion A is valued twice as much as criterion B and criterion B is valued thrice as much as criterion C, how much more would criterion A be valued than criterion C? With the Manual Assignment weighting method, criterion A would be 6 times (2x3) more valued than criterion C.

With AHP, however, this can be different. AHP is by design mathematically inconsistent in order to test the inconsistent preferences of human judgment. This often involves calculating a Consistency Ratio (CR) to determine the extent of mathematical inconsistency [4], [48]. In this example, a user would be asked how much more they value criterion A over criterion C, even if they already provided the ratios of A:B and B:C. To deal with this inconsistency, a so-called pairwise matrix is introduced, where each criterion is both a row and a column and is compared against all others, see GUI 3 below:

Criteria Weighting

Number of Criteria = 4

User Inputs: Criteria Preferences

Weighting Method: AHP
- -All Equal-
- -Manual-
- AHP
- STD
- Entropy

Analytic Hierarchy Process (AHP)
Generates weights based on pairwise comparison. The ratio in each cell represents how much the column criteria matters more than the row criteria (please fill it).

Recommended Use
Typically not recommended, as it is purposefully mathematically inconsistent and complicated compared with manual weights. It is used to test the inconsistencies of human preferences.

Criteria	Criteria1Name	Criteria2Name	Criteria3Name	Criteria4Name
Criteria1Name	1 / 1	5 / 1	4 / 1	7 / 1
Criteria2Name	1 / 5	1 / 1	1 / 2	3 / 1
Criteria3Name	1 / 4	2 / 1	1 / 1	3 / 1
Criteria4Name	1 / 7	1 / 3	1 / 3	1 / 1
Raw Weights	2.41	0.55	0.78	0.26
Normalised Weights	0.60	0.14	0.20	0.06

Reset Criteria Names Reset Weights

GUI 3 – AHP Weights hoverable comment

The number of unique pairwise comparisons T_n among n criteria in the AHP matrix is calculated by Equation 1 – Triangular Numbers below [89], [90]. This represents a second-order polynomial, or in other words, parabolic complexity. Likewise, T_n can be calculated by considering the third (blue) layer of Figure 17 – Pascal's Triangle below. The second (green) layer of Pascal's Triangle is the row number n, and the first (gold) layer is always equal to 1.

$$T_n = \frac{n \cdot (n-1)}{2}$$

Where:

n = number of criteria ,

T_n = number of unique pairwise comparisons

Equation 1 – Triangular Numbers
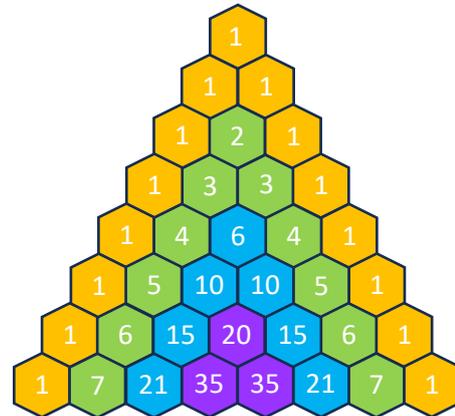
Figure 17 – Pascal's Triangle

For the special cases of n being 0, 1, 2, and 3, which do not show T_n in the third layer of Pascal's Triangle, T_n is 0, 0, 1, and 3, respectively, as calculated by the Triangular Numbers equation. There are six unique pairwise comparisons between the four criteria in the above example of GUI 3. This excludes the diagonal line of correlations of 1 between a criterion and itself, as well as the mirrored cells on the opposite side of the diagonal. This rule is also the same for the number of correlations between criteria. The difference is that the mirrored cells across the diagonal are reciprocals of each other or one over (1/) in AHP, but are the same number in a Criteria Correlations Matrix. This is shown in GUI 5 in section 3.4: Criteria Correlations Matrix.

It is designed this way to be more efficient, because unlike other weighting and ranking methods, AHP is unique for being the only method in the MCA solver to have synchronicity such that editing one 'number'-type input field automatically updates a mirrored input field to have the same number digit, see GUI S6 in Appendix B – Software. This means that it makes more sense to read the inputs directly from the HTML input fields rather than a matrix, as can even be done in NodeJS without HTML at all, because this way the synchronicity ensures the consistency of the mirrored reciprocal values along the diagonal of the preference matrix. Script 1 below demonstrates the efficiencies of the way AHP was programmed. This script for AHP is different from that of other JS functions in this thesis, as it is integrated into the HTML front-end element 'WeightsTable', as can be seen where the inputs are read using '.value' and the outputs are inserted using '.textContent'.

```
/*---------------Parts of a greater Weighting() function---------------*/
const ColSums=Array.from({length:Criteria}).fill(0)
for(let Col=0;++Col<=Criteria;){
    for(let Row=0;++Row<=Criteria;){
        const Cell=WeightsTable.rows[Row].cells[Col],N=Cell.firstChild.value
      ,D=Cell.lastChild.value
        if(N==0||D==0){break}else{ColSums[Col-1]+=N/D}
    }
}
for(let RelativeWeight,Weight=0;++Weight<=Criteria;){
    RelativeWeight=0
    for(let Col=0;++Col<=Criteria;){
        const Cell=WeightsTable.rows[Weight].cells[Col],N=Cell.firstChild.value
      ,D=Cell.lastChild.value
        RelativeWeight+=N/D/ColSums[Col-1]
    }
    WeightsTable.tFoot.rows[0].cells[Weight].textContent=RelativeWeight.toFixed(2)
    RelativeWeights.push(RelativeWeight)
}

/*---------------Standalone related functions---------------*/
,Num1Cloner=()=>{
    const NumClone=Create('input');NumClone.type='number'
    NumClone.value=1;NumClone.readOnly=true
    return NumClone
}
,InsertAPHtBodyRow=Criteria=>{
    WeightsTable.tBodies[0].insertRow().insertCell()
        .append(TextAreaCloner(Criteria,'C_'))
    for(let Row=0;++Row<Criteria;){
        const N='N_R'+Criteria+'C'+Row,D='D_R'+Criteria+'C'+Row
        WeightsTable.rows[Row].insertCell()
            .append(RatioNumCloner(D),' / ',RatioNumCloner(N))
        WeightsTable.tBodies[0].lastChild.insertCell()
            .append(RatioNumCloner(N),' / ',RatioNumCloner(D))
    }
    WeightsTable.rows[Criteria].insertCell()
        .append(Num1Cloner(),' / ',Num1Cloner())
}
```

Script 1 – JS AHP functions

All other weighting and ranking methods and correlations JS functions in this software application do not use HTML-specific syntax, as can be seen in Script 2 in sub-section 3.2.4, Script 9 in section 3.4, and the scripts in Table 7 in sub-section 3.3.1: Absolute Ranking Methods.

3.2.4. Standard Deviation

Standard Deviation [91], [92] as a weighting method is straightforward. It does not require any additional user inputs like the All Equal and Manual Assignment methods do. Instead, it only asks to insert all scores, not even uncertainties or best and worst possible scores. The weight of any criterion is equal to the sample standard deviation of the scores of that criterion. Therefore, even if not all scores are entered, it is possible to compute the weights of specific criteria that have entered all their scores and therefore know the relative importance of criteria relative to each other as scores are entered by the user.

Due to most scores being samples and not whole populations, the exact standard deviation equation is sample STDEV, shown below in Equation 2 and Script 2 for n number of alternatives:

$$s = \sqrt{\frac{\sum(x_i - \bar{x})^2}{n-1}}$$

$$= \sqrt{\frac{(\sum x_i^2) - \frac{(\sum x_i)^2}{n}}{n-1}}$$

Equation 2 – Sample Standard Deviation

```
,VAR_S=X=>{//Sample Variance S²
    const n=X.length;let Σx=0,Σx2=0
    for(let i=-1;++i<n;){
        const x=X[i];Σx+=x;Σx2+=x*x
    }
    return Number(((Σx2-Σx*Σx/n)/(n-1)).toFixed(3))
}// e.g. VAR_S([9,2,5,4,12,7]) //→ 13.1

,STDEV_S=X=>Number(Math.sqrt(VAR_S(X)).toFixed(3))
// e.g. STDEV_S([9,2,5,4,12,7]) //→ 3.619
```

Script 2 – JS Sample Standard Deviation function

This idea of using standard deviation as a weighting method is to penalise deviations from the mean in applications where precision is important. Such applications may include, but are not limited to, production lines, etc.

3.2.5. Entropy

So-called 'Entropy' is a custom weighting method from the literature [93]. It is similar to Standard Deviation and is designed to correlate with it. The idea behind it is that it theoretically better tracks deviation from the mean. It penalises deviation from the mean average. Unlike Standard Deviation, which can calculate individual raw weights with individual arrays of scores for given criteria, Entropy requires all scores to be entered to calculate all weights together. Hence, Entropy is stricter.

Equation 3 and Script 3 of Entropy below demonstrate why this weighting method does not work for scores of the number zero, as Entropy uses logarithms, and the logarithm of zero is undefined.

In order to prevent unnecessary calculations, the very first loop in Script 3 checks for zeros and stops the function if any are detected by returning a comment.

This brings up another crucial point to make: if Entropy as a method completely fails if any score is zero, it surely also becomes very imprecise at scores very close to zero, even if it does not show to the user as a function failure, which could lead to a user trusting unreliable results. In general, it is best to avoid methods that fail when using scores of zero.

$$\text{Weight} = \frac{100 \cdot \left(1 - e(x_i)\right)}{\sum_{i=1}^{A}(1 - e(x_i))} \text{, where: } e(x_i) = \frac{1 + \sum_{i=1}^{A}(x_i \cdot \ln(x_i))}{-\ln(A)} \text{, where: } x_i = \frac{\text{Score i}}{\sum_{i=1}^{A}(\text{Scores})}$$

Keys: x_i − Normalised score of alternative i   ,   A − Number of Alternatives

Equation 3 – 'Entropy' Weighting Method

```
,Entropy=S=>{// S = Matrix of scores, where
    # Rows = # Criteria Weights , # Cols = # Alternatives
    let C=S.length,e=C // C = # Criteria
    const A=S[0].length,h=Math.log(A) // A = # Alternatives
    ,W=Array.from({length:C}).fill(0) // W = Weights Array []

    for(let c=C,s,Σ=0;--c>=0;Σ=0){//Σ = Sum total of each criterion's scores
        for(let a=A;--a>=0;Σ+=s){
            s=S[c][a]
            if(s===0)return'Entropy is undefined for scores of 0'
        }
        for(let a=A;--a>=0;e+=s){s=S[c][a]/Σ;s=s*Math.log(s)/h;W[c]+=s}
        ++W[c]
    }
    while(--C>=0)W[C]=Math.round(W[C]*100/e) // You can comment out this
line if you want to use NormaliseWeights(W) instead

    return W
}/* These weights are already normalised, so they sum up to exactly 100
        Entropy([[250,200,300,275,225],[16,16,32,32,16],[12,8,16,8,16],[5,3,
4,4,2]]) //➜ [6,38,29,27]
        Entropy([[20,25,18,22],[15,27,20,18],[20,18,21,20],[55,65,45,50],[5,
3,7,5],[9,5,7,5]]) //➜ [6,21,1,8,36,28]
*/
```

Script 3 – JS 'Entropy' function

Note that Script 3 is inefficient compared to Script 2 above of Standard Deviation because of the four 'for' and 'while' loops and the use of logarithms.

3.2.6. Comparison of Weighting Methods

Following the initial introduction to weighting methods in sub-section 2.2.4, the red arrow in Figure 12 in sub-section 2.2.4: Multi-Criteria Analysis (MCA) Methods uses scores as inputs to generate weights in the specific weighting methods of Standard Deviation and Entropy covered in sub-sections 3.2.4 and 3.2.5, respectively. Most other weighting methods covered in this section, All Equal, Manual Assignment, and AHP, do not require scores as inputs. This can be argued as an advantage of the former methods for their convenience, as well as the fact that the weights for Standard Deviation and Entropy are "volatile" and change as the scores update. Unlike Standard Deviation, which only requires the scores of a specific criterion to generate its weight independently of others, Entropy requires inputting all scores to calculate the weights. The use of four loops and two logarithms in Script 3 – JS 'Entropy' function is also computationally expensive, but so is Script 1 – JS AHP functions.

Of course, 'All Equal weights' is the simplest and requires no user inputs, but at the cost of not using the weighting functionality at all. Hence, in most cases, it is best to start with All Equal at first, and then either select Manual Assignment if it is known which criteria matter more or occasionally select Standard Deviation where deviation from the norm and precision are important. Entropy is a method that fails at scores of zero (due to the logarithm of zero) and arguably very small-number scores (close to zero) as well, due to inaccuracies; hence, it should be used sparingly. Lastly, AHP is essentially the same as Manual Assignment, but with a psychological twist, testing the consistency of the user. Therefore, it should preferably be used as a psychological test, as opposed to attempting to derive the most accurate results possible, such as when choosing how to invest money.

In conclusion, weighting methods each have advantages and disadvantages, but some tend to generally outperform their competition in their area. Manual Assignment tends to outperform AHP due to AHP's mathematical inconsistency; hence, AHP should only be used to test the user's memory or psychology. Methods that correlate with deviation from the mean tend to be dominated by Standard Deviation, so selecting alternatives such as Entropy should be done with a reason and perhaps by comparing it to the weights of Standard Deviation. Generally speaking, though, to merely get started with an MCA aggregate index, it is best to begin with Manual Assignment for simplicity and quickly getting results, and then select either Standard Deviation if deviation from the mean matters, or use Manual Assignment if the user knows roughly the relative importance of the criteria themselves. In most cases, deviation from the mean does not matter, hence Manual Assignment is generally the most ideal weighting method.

3.3. Ranking Methods

Also known as 'Aggregating' in literature [19], 'Ranking methods' input the weights of criteria and the scores of alternatives and criteria as shown in Figure 12 in sub-section 2.2.4: Multi-Criteria Analysis (MCA) Methods, and output a single array of numbers called 'ranks', one rank for each alternative. The ranks identify which alternatives are overall the best scoring and which are the lowest. The lower the rank number, the better. Rank number 1 is the best, followed by 2, etc.

Not to be confused with the two ranking functions in Script 9 in section 3.4, Aggregation methods in this MCA research are referred to as ranking methods because it is a clearer term. These methods combine all the scores of all the criteria for each alternative scenario and, using the weights, generate a final score to compare or rank with all the other alternative scenarios. Hence the name. In the literature, methods such as PROMETHEE are known as 'outranking methods', so it is a similar and clearer name to refer to these aggregation methods as ranking methods.

Ranking methods have two specific types: absolute and relative. Absolute ranking methods are simpler and tend to be straightforward equations, while relative methods tend to involve complicated matrices. Absolute ranking methods rank from zero up to a positive number, typically an integer such as the number one. Hence, absolute ranking methods each have a clear maximum and minimum possible score, 0% and 100%.

Relative ranking methods hover above and below zero with no clear maximum or minimum or benchmark other than the middle line of zero, hence the name 'relative', because they only compare to each other and nothing else, similar to the concept of enthalpy within a reference state in thermodynamics not being able to be measured directly [94]. Similarly, with relative ranking methods, the term 'outranking' is sometimes used instead of 'ranking' and sometimes as a synonym for it [7].

Note that the collective use of the term 'Ranking Methods' is context-dependent, as it can include or exclude outranking methods. It is used collectively because there can only be a single ranking or outranking method for any index, similar to how there can only be a single weighting method. For this reason, this research mostly uses the terms 'relative outranking' and 'absolute' ranking methods, such that the term 'Ranking Methods' can be used collectively to include both.

An interesting difference between weighting and ranking methods is that ranking methods never require user inputs specific to the selected method itself, unlike some weighting methods, such as Manual Assignment or AHP, which require a different number of user inputs depending on the exact method selected. Scores do not count as required user inputs specific to ranking methods, because they are also used to calculate correlations.

Furthermore, changing the ranking method in MCA only changes the final ranks, which is, of course, crucially important, but changing the weighting method always changes both the weights and the ranks.

3.3.1. Absolute Ranking Methods

The Weight Sum Model (WSM) is both the most basic of the ranking methods and the most used in literature (See Appendix A – Literature). The exact equation of WSM is identical to Sum Product in statistics, as shown in Equation 4 below, which inputs two arrays of numbers of equal length and outputs a single number. Similarly, the Weight Product Model (WPM) from the MCA literature also has an equation shown below in Equation 7, appropriately named 'Product Power' in statistics terminology.

This MCA research also compares two hypothetical methods similar to the aforementioned two, using the same two array inputs and one number output, and also using basic arithmetic, for comparison. These are Sum Power (Equation 5) and Product (Equation 6), also shown below in Table 7, which also shows the names, equations, and scripts of these four possible absolute ranking methods:

Table 7 – Absolute Ranking Methods

Keys: R – Rank, S – Score, W – Weight, n – number of criteria, a – alternative, c – criterion, A – Array

Statistics Function Name	MCA Method Name	Equation	JavaScript
Sum Product [91], [92]	Weight Sum Model (WSM) [11]	$$R_a = \sum_{c=1}^{n} S_{ac} \cdot W_c$$ *Equation 4 – Sum Product*	```,SumProduct=(A1,A2)=>{ let L=A1.length,R=A1[--L]*A2[L] while(--L>=0)R+=A1[L]*A2[L] return R }// e.g. SumProduct([1,3],[4,7]) //➜ 25 , 1*4 + 3*7``` *Script 4 – JS Sum Product function*
Sum Power	N/A	$$R_a = \sum_{c=1}^{n} S_{ac}{}^{W_c}$$ *Equation 5 – Sum Power*	```,SumPower=(A1,A2)=>{ let L=A1.length,R=A1[--L]**A2[L] while(--L>=0)R+=A1[L]**A2[L] return R }// e.g. SumPower([1,3],[4,7]) //➜ 2188 , 1**4 + 3**7``` *Script 5 – JS Sum Power function*
Product [91], [92]	N/A	$$R_a = \prod_{c=1}^{n} S_{ac} \cdot W_c$$ *Equation 6 – Product*	```,Product=A=>{// ∏ let L=A.length,P=A[--L];if(P===0)return 0 while(--L>=0){const a=A[L] if(a===0)return 0;P*=a} return P }// e.g. Product([1,3,4,7]) //➜ 84 , 1*3*4*7``` *Script 6 – JS Product function*
Product Power	Weight Product Model (WPM) [10]	$$R_a = \prod_{c=1}^{n} S_{ac}{}^{W_c}$$ *Equation 7 – Product Power*	```,ProductPower=(A1,A2)=>{ let L=A1.length,R=A1[--L] if(R===0)return 0;R**=A2[L] while(--L>=0){const a=A1[L] if(a===0)return 0;R*=a**A2[L]} return R }// e.g. ProductPower([1,3],[4,7]) //➜ 2187 , 1**4 * 3**7``` *Script 7 – JS Product Power function*

Script 6 and Script 7 efficiently terminate further iterations and return 0 as soon as they detect a score of zero. Moreover, Product is the only formula of these four that has a Statistics name of only a single word and fittingly has a single array as an input. To calculate the product of an array of scores and an array of weights, they may easily concat in JS, i.e. 'ScoresArray.concat(WeightsArray)' or vice versa.

3.3.2. Relative Outranking Methods

The purpose of having different methods that have the same task is to get the best comparative results, and perhaps to also alternate between the methods so some rank several alternatives higher in some applications, while other methods rank other alternatives higher in other applications. Various methods might always rank some alternatives higher than others, but the exact method may determine whether the absolute or relative difference in rank would be small or large.

In contrast to this, if two seemingly different methods yield the same relative results every time, they can be said to be the same method.

This is the case for the Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE) I & II. PROMETHEE II is identical in its complicated algorithm to PROMETHEE I except for one final step that PROMETHEE II applies only for styling and does not change the relative outranks at all, which is that it divides all final outrank numbers by the number of alternatives minus one, as is explained in GUI 4 below and is written in Script 8 below:

GUI 4 – PROMETHEE I & II hoverable comments

Script 8 below is the script of the PROMETHEE I & II methods. It includes an example from the literature [95], which is detailed in Appendix B – Software.

```javascript
,Rank=A=>{const S=A.slice().sort((a,b)=>b-a);return A.map(v=>S.indexOf(v)+1)}
// ranks values from biggest to smallest, e.g. Rank([0, -1.4, 7.6]) //→ [2, 3,
1]
,PROMETHEE=(W,S,II)=>{
    // II: if(II===true){PROMETHEE II}else{PROMETHEE I}; W = Array of weights,
S = Matrix of normalised scores between 0 and 1, with 0 being worst and 1 being
best. # Rows = # Alternatives , # Cols = # Criteria Weights.

    /*---------------------Checks---------------------*/
    if(!W.every(s=>s>=0))
        return'Every weight needs to be either a positive number or 0'
    if(!S.flat(Infinity).every(s=>s<=1&&s>=0))
        return'Every score needs to be pre-normalised between 0 and 1. Please
consider using the NormaliseScores function.'
    const C=W.length // C = # Criteria
    if(S[0].length!==C)return'#Criteria must equal the #Weights'

    /*---------------------Preparations---------------------*/
    const A=S.length // A = # Alternatives
    ,F=Array.from({length:3},()=>Array(A).fill(0))
      // F has 3 cols for flows: Leaving, Entering, and Net Total
    II=II===true?A-1:1

    /*---------------------Calculations---------------------*/
    for(let Am=A;--Am>=0;)// Am = Minuend Alternative
        for(let As=A;--As>=0;)// As = Subtrahend Alternative
            if(Am!==As)
                for(let c=C;--c>=0;){// c = Column
                    const Flow=Number((Math.max(0,W[c]*(S[Am][c]-
S[As][c]))/II).toFixed(2))
                    F[0][Am]+=Flow;F[1][As]+=Flow;F[2][Am]+=Flow;F[2][As]-=Flow
                }
    for(let c=3;--c>=0;) // rounding to 2 decimal places
        for(let a=A;--a>=0;)F[c][a]=Number(F[c][a].toFixed(2))
    F[3]=Rank(F[2]) // last col is ranks with #1 being the best

    return F // returns a matrix of 4 columns with # Rows = # Alternatives
}
/* e.g.
PROMETHEE([0.38,0.09,0.05,0.22,0.17,0.08,0.02],[[0,0,0,0,0,1,0],[0.5,0.5,1/3,0,
2/3,0.14286,0],[0.5,1,1,0.5,2/3,0.71429,1/3],[1,1,1,1,1,0,1],[0.5,0.5,1,0.5,2/3
,1,1],[0,0,1/3,0,2/3,0.42857,0]],true) //→
    [[0.04,0.12,0.27,0.6,0.25,0.03],[0.48,0.21,0.07,0.06,0.09,0.4],[-0.44,-
0.09,0.2,0.54,0.16,-0.37],[6,4,2,1,3,5]]
*/
```

Script 8 – JS PROMETHEE I & II function

3.3.3. Comparison of Ranking Methods

A fundamental flaw of Sum Power and WPM is that by using the weights as powers, they take into account criteria with weights of zero. The Product method completely fails with both weights and scores of zero, so in this aspect, it is the worst. This is a clear advantage of WSM, as weights of zero essentially turn off a criterion, while still showing it and not deleting it for the convenience of the user. Regardless of the ranking method, by definition, a weight of zero should always mean that it cancels out in the calculations, so that criterion is completely irrelevant for ranking or decision-making, and non-WSM absolute ranking methods do not reflect that.

Sum Power and WPM are taking weights too much into account for weights of zero; it necessarily means that any small weights that are close to zero are still taken too much into account. This is not just due to being small relative to other weights, but also because weights are powers and that takes them disproportionately too much into account relative to their actual importance, the smaller a weight becomes in number and the closer to zero.

Another important aspect of the number zero is when scores are zero. As mentioned in a previous paragraph, the Product method fails for scores that happened to have a zero, but this is also the case for WPM for the same reason. WPM is only slightly better than the Product method because at least it is only slightly inaccurate and does not completely fail for weights of zero. Perhaps, for this reason, WPM is used in literature, and Product is not. Both might seem to have efficient scripts (Script 6 and Script 7 in sub-section 3.3.1), but these are only for detecting scores of zero to save unnecessary calculations, so the software is efficient, but an index using these would not be.

As an aside, recall that there are also weighting methods that fail with scores of zero, most notably Entropy.

Table 7 in sub-section 3.3.1: Absolute Ranking Methods documents that there are no standard MCA names for Product or Sum Power equations. These two equations were only included in Table 7 due to a keen observation as part of this MCA research for their similarities to WSM and WPM, especially considering that WSM is identical to Sum Product from Statistics. After this analysis, another interesting observation is in fact that Sum Power is a superior method to WPM, despite not being mentioned in the literature. This is because, despite both mishandling zero and near-zero weights, only WPM completely fails with scores of zero. In this aspect, Sum Power is more similar to WSM than WPM.

As for outranking relative methods, they are complicated, computationally expensive, and exponentially so for every extra alternative and criterion due to their matrix nature, while absolute ranking methods are computationally cheap due to their linear equations. Outranking methods cannot display the exact fractional contribution of each criterion to the final rank score of each alternative, while, in contrast, every absolute ranking method can. See Figure 32 for a visual illustration.

Relative outranking methods also cannot compare a single alternative against a benchmark such as 0% and 100% or any percentage in between, only against at least another alternative. One can argue that although MCA fundamentally aims to compare alternatives, the ability to compare maximum and minimum theoretical boundaries is also very useful and is a valid MCA application. In fact, consider the acronym MCA – Multi-Criteria Analysis, see Table 1 in the Nomenclature. One advantage of outranking relative methods is that they nearly always accept scores and weights of zero well, but this can also be said for WSM.

In conclusion, WSM appears to be the best ranking method. It is the simplest, used extensively in the literature, does not fail scores or weights of zero or near zero, and in fact excels in precision for these. After WSM, PROMETHEE is quite an upstanding methodology, although it requires at least two alternatives to work, and it cannot be compared using 0% and 100% boundaries.

PROMETHEE's complexity makes it challenging for less technical users to understand, as well as computationally expensive parabolically with an increased number of alternatives and criteria. Non-WSM absolute ranking methods should only ever be used when it is guaranteed that there are no weights or scores of zero. Absolute ranking methods have the following hierarchy from worst to best: Product, WPM, Sum Power, and WSM.

3.4. Criteria Correlations Matrix

A fundamental feature of this MCA solver is a matrix that automatically calculates the correlations between all the criteria, as shown in GUI 5 below:

Criteria Correlation Analysis

These are the Pearson's 'R' correlations between the scores of each criterion.
If the scores between any two criteria correlate too strongly,
it raises the concern that they both measure a very similar or even the same indicator.

| |R| < 0.3 : Low Correlation | |R| < 0.5 : Moderate Correlation | |R| ≥ 0.5 : High Correlation |

\Criteria Criteria	Affordability (10⁴ m³/Capita·Year)	Flood Risk (1-5)	Water Stress (1-5)	Soil Moisture Content (%)	Source Water Quality (0-10)	Tap Water Quality (%)	Water Loss (%)
Affordability (10⁴ m³/Capita·Year)	1	-0.20	-0.25	0.41	0.22	0.18	-0.14
Flood Risk (1-5)	-0.20	1	0.13	0.00	0.19	-0.33	-0.18
Water Stress (1-5)	-0.25	0.13	1	-0.68	-0.35	-0.41	0.37
Soil Moisture Content (%)	0.41	0.00	-0.68	1	0.31	0.36	-0.22
Source Water Quality (0-10)	0.22	0.19	-0.35	0.31	1	-0.09	-0.44
Tap Water Quality (%)	0.18	-0.33	-0.41	0.36	-0.09	1	0.01
Water Loss (%)	-0.14	-0.18	0.37	-0.22	-0.44	0.01	1

Normalised Scores

\Criteria Alternatives	Affordability (10⁴ m³/Capita·Year)	Flood Risk (1-5)	Water Stress (1-5)	Soil Moisture Content (%)	Source Water Quality (0-10)	Tap Water Quality (%)	Water Loss (%)
Amsterdam, Holland	0.47 ± 0.27	0.25 ± 0	1 ± 0	0.39 ± 0.02	0.24 ± 0	0.74 ± 0.01	1 ± 0.03
Bahrain	1 ± 0	0.5 ± 0	0 ± 0	0.86 ± 0.02	0.21 ± 0	0.25 ± 0.01	0.44 ± 0.03

GUI 5 – Criteria Correlations Matrix

Correlation matrices are simple, useful, and common, as seen in a variety of indices in the literature [68]. Despite this, neither of the water indices in the Literature Review of WSS Assessment in sub-section 2.3.2: Most Notable Sources calculated any correlations. For this reason alone, there is a gap in the literature to publish a WSS vulnerability index that includes this fundamental feature.

A correlation matrix works automatically without requiring any additional user input. It inputs the individual scores of each alternative by each criterion and can output correlations without the weights or the need to specify the weighting and ranking methods. Its simplicity, convenience, and usefulness make it a foundational part of what every MCA software and index should implement.

This means that, beyond the approach of deriving value only from the final ranks, this MCA solver can independently suggest which indicators highly correlate with each other as another useful output, as can be seen in Figure 12 in sub-section 2.2.4.

Correlation does not imply causation, but it does raise inquiries that may lead to further investigation. More data points or case studies allow for a less sensitive and thus more reliable correlation. If two indicators correlate strongly, it can mean that they measure the same phenomenon, such as vulnerability; hence, this is useful for investment decisions so as not to double-spend and invest in two supposedly independent criteria that aim to address and improve the resilience against the same vulnerability.

Correlations can also suggest whether it is better to implement more or less of an indicator, such as a governance policy. This could then inform whether the best possible score should be higher or lower than the worst possible score, so it is best to start with correlations first when that is unclear.

One of the major selection requirements for potential criteria indicators is having a low correlation with others, hence being unique and not measuring the same thing twice, or double-counting. Even if the weights are adjusted, a double-counted indicator would clutter the list, which, for simplicity, should be concise.

Script 9 below presents Pearson's r correction function as shown in Equation 8 below [91], [92], [96]. It also shows the Rank function that is used for the final ranking of the alternatives, see GUI 8 in section 4.4.

$$r = \frac{\sum\left((x_i - \bar{x}) \cdot (y_i - \bar{y})\right)}{\sqrt{\sum(x_i - \bar{x})^2 \cdot \sum(y_i - \bar{y})^2}}$$

$$= \frac{n \cdot (\sum x_i \cdot y_i) - (\sum x_i) \cdot (\sum y_i)}{\sqrt{\left(n \cdot (\sum x_i^2) - (\sum x_i)^2\right) \cdot \left(n \cdot (\sum y_i^2) - (\sum y_i)^2\right)}}$$

Equation 8 – Pearson's r Correction

$$\rho = 1 - \frac{6 \cdot \sum\left(d_i^2\right)}{n \cdot (n^2 - 1)}$$

Where: $d_i = \text{Rank}(x_i) - \text{Rank}(y_i)$

n = number of criteria

Equation 9 – Spearman's ρ Correlation

Also included in Script 9 below is the function for Equation 9 – Spearman's ρ Correlation [96] above, which is an alternative correlation function. It is more complicated as it uses a modified 'FractionRank' function. The plan is to integrate and add Spearman's ρ Correlation as an option for the criteria correlations table in GUI 5 above for the additional convenience and optionality to better serve the user, see sub-section 5.2.1 Correlation Method Selection under Further Work – Software Features. The MCA solver currently only utilises Pearson's r correction for the correlation matrix.

The first line in Equation 8 above is the most common and famous, but the second line uses n, which is the number of items, or case studies, in MCA. This expanded equation is the one used in Script 9 below because it is more efficient and therefore faster, as it only loops over n once, whereas calculating mean averages would require an additional loop unnecessarily.

Both Pearson's r and Spearman's ρ correlations input two arrays of equal length, which contain x and y coordinates. They output a single coefficient number between -1 and 1.

```javascript
,Rank=A=>{const S=A.slice().sort((a,b)=>b-a);return A.map(v=>S.indexOf(v)+1)}
/* Purpose: rank values from biggest to smallest,
    e.g. Rank([5,62,5,0,4,-3.4,5,62]) //➞ [3,1,3,7,6,8,3,1]
*/
,FractionRank=A=>{// Adds (#occurrences-1)/2 for each tied rank
    const R=Rank(A),L=R.length,C=new Map()
    for(let i=-1;++i<L;){const r=R[i];C.has(r)||C.set(r,0);C.set(r,C.get(r)+1)}
    for(let i=-1;++i<L;)R[i]+=(C.get(R[i])-1)/2
    return R
}// e.g. FractionRank([5,62,5,0,4,-3.4,5,62]) //➞ [4,1.5,4,7,6,8,4,1.5]

,SpearmanCorrelation=(A1,A2)=>{// Coefficient 'ρ': 1 ≥ ρ ≥ -1
    const n=A1.length,Rank1=FractionRank(A1),Rank2=FractionRank(A2);let Σd2=0
    for(let L=n;--L>=0;)Σd2+=(Rank1[L]-Rank2[L])**2 // d = difference in ranks
    return(1-(6*Σd2/(n*(n*n-1)))).toFixed(2)
    // ρ = 1 - 6Σd²/n(n²-1)
}// e.g. SpearmanCorrelation([1,6,4,3,4],[9,5,9,7,2]) //➞ -0.48

,PearsonCorrelation=(X,Y)=>{// Coefficient 'r': 1 ≥ r ≥ -1
    const n=X.length
    if(n<2)return -Infinity // to prevent error in the console when used in
some apps that may not accept NaN
    let Σx=0,Σy=0,Σx2=0,Σy2=0,Σxy=0
    for(let i=-1;++i<n;){
        const x=X[i],y=Y[i]
        Σx+=x;Σy+=y;Σx2+=x*x;Σy2+=y*y;Σxy+=x*y
    }
    return((n*Σxy-Σx*Σy)/Math.sqrt((n*Σx2-Σx*Σx)*(n*Σy2-Σy*Σy))).toFixed(2)
}// e.g. PearsonCorrelation([1,6,4,3,4],[9,5,9,7,2]) //➞ -0.52
```

Script 9 – JS Ranking and Correlations functions

Note that the more alternatives (and therefore by extension, scores) there are, the less likely it is for extremely strong correlations to occur due to anomalies by chance. On the same note, any strong correlation needs to be addressed and discussed, and only as a last resort, justified as a coincidence due to having too few case studies in a correlation calculation. It is to be expected that there will be moderate to strong correlations in many indices, some by chance and others not.

Script 10 below presents the efficient algorithms of the above GUI 5 – Criteria Correlations Matrix. After programming and testing the correlation matrix to work well by calculating the correlation at each cell, further efficient algorithms were programmed to reduce the number of calculations which are being made.

Firstly, for any cell whose row index is equal to its column index, its correlation is simply assigned to be 1. Such cells are known as the 'Diagonal' positions [97], and they can be taken as an array equal in length to the square matrix for certain other matrix functions in mathematics.

Secondly, a correlations matrix is known as a 'Symmetric Matrix' [97], meaning that all values which are not part of the diagonal M[x][x] or M[y][y], or so-called off-diagonal positions, are mirrored along the diagonal and equal those on the other side, such that M[x][y] == M[y][x]. By definition, a Symmetric Matrix is equal to its transpose, such that $M = M^T$ [97].

To make the programming more efficient, it is sufficient to calculate only the values on one side of the diagonal and, in the same line of script, assign the same value on the other side as well.

Script 10 below uses this same efficient concept of a symmetrical or at least mirrored square matrix as was described in sub-section 3.2.3 for the AHP weighting method and shown in Script 1 – JS AHP functions.

```
for(let Row=Criterias+1;--Row>0;){

    for(let Col=Criterias+1;--Col>0;){

        if(Row<=Col){// do away with unnecessary checks

            const Cell=ScoresCorrelationsTable.rows[Row].cells[Col]

            if(Row==Col){// No need to calculate

                Cell.textContent=1;Cell.style.backgroundColor='RGBA(255,0,0,0.2)'

            }else{// if(Row<Col) Calculate only once for every 2 cells

                const Cor=PearsonCorrelation(Scores[Row],Scores[Col])

                ,Mag=Math.abs(Cor)

                ,MirrorCell=ScoresCorrelationsTable.rows[Col].cells[Row]

                Cell.textContent=MirrorCell.textContent=Cor

                if(Mag<0.3){//Low Correlation

                    Cell.style.backgroundColor =

                        MirrorCell.style.backgroundColor='RGBA(0,255,0,0.05)'

                }else if(Mag<0.5){//Moderate Correlation

                    Cell.style.backgroundColor =

                        MirrorCell.style.backgroundColor='RGBA(0,0,255,0.05)'

                }else//High Correlation

                    Cell.style.backgroundColor =

                        MirrorCell.style.backgroundColor='RGBA(255,0,0,0.05)'

            }

        }

    }

}
```

Script 10 – JS Correlations Matrix: efficient algorithms

Despite MCA criteria being correlated in numerous applications, such as EU indices [68], it appears to be lacking in the WSS literature, as covered in Chapter 2. Considering the simplicity of calculating correlations and their usefulness, both of which can be seen in this section, it begs the question: why have the 2016 Arcadis and 2021 DuPont indices not incorporated a correlation matrix? Are there any drawbacks to implementing one? Should novel formulae be innovated to address such drawbacks?

Although it is impossible to prove, it is highly likely that the only two limitations that prevented these two indices from implementing correlation analysis are that they have not considered it deeply enough, perhaps due to not understanding its potential utility, and their lack of a solver such as this MCA tool software that can automatically calculate the correlations easily without any additional user input.

Therefore, the novel solutions to solve these two limitations are exactly the two novel outputs of this research project: an MCA solver that features a correlation matrix and a Custom Index that demonstrates an example of indicators from the literature that highly correlate with each other that showcasing the utility of this feature. Other than this, there are no drawbacks to a correlation analysis, as it can be calculated automatically and simply ignored. There are no new formulae to innovate to solve drawbacks that do not exist.

It is important to reemphasise that the correlation function is completely separate from the weighting and aggregate ranking methods in an MCA index, see Figure 12 – Flowchart of MCA inputs, methods, and outputs in sub-section 2.2.4. This means that correlating indicators is completely optional and is done in addition to these two types of methods, not instead of them.

The purpose of correlating indicators is to produce a separate output from the list of final scores and rankings, which is the list of correlations. Again, see Figure 12 in sub-section 2.2.4. These correlations can have a positive feedback loop by detecting indicators that correlate too highly with each other, and therefore, these can be combined for simplicity to prevent double-counting and fairer weight distribution.

For example, consider the use of the 'All Equal' weighting method with an index that has multiple indicators that highly correlate with each other, and in essence, measure the same property. By having the largest number of indicators for the same aspect, it unfairly receives a larger weight and unfairly shifts the decision-making that would result from the final rankings of the MCA index.

This can also occur with the AHP weighting method, considering that it is mathematically inconsistent by design to test user psychology [4], [48], and therefore, this unnecessary complexity of having more indicators than is needed can cause a user to assign illogical preferences because there are more input fields that can be filled, which can go wrong.

Therefore, contrary to the prejudice that performing a correlation analysis could have drawbacks, with this MCA solver, the only drawbacks are when an MCA index lacks a correlation analysis.

3.5. Uncertainties

There are several types of errors in measurements and corresponding methods for correcting and estimating them. Understanding errors is important for calculating final uncertainties for an index.

The two main kinds of errors in measurements are Random Errors and Systematic Errors [15], [17]. A random error is unpredictable and has no consistent pattern, whereas Systematic Errors are consistent and repeatable deviations from the true value in measurements. Both types of errors undermine the accuracy, but only Random Errors also undermine the precision.

Accuracy is defined as 'the closeness of agreement between a measured quantity value and a true quantity value of a measurand' [14], [15]. Precision is defined as 'the level of agreement of a particular measurement with itself when it is repeated' [14].

A Systematic Error, also known as Bias, skews the results in either direction, up or down. Skewing is known as an 'Offset Error' if it is additive [15]. Skewing is known as a 'Scale Factor error' if it is multiplicative [15]. A 'Zero Error' is a specific kind of Offset Error when a measuring instrument should read zero, and it reads another number instead [15]. Systematic Errors can theoretically be completely eliminated if the measuring tool is properly calibrated, meaning it is adjusted so its skewness is corrected [17].

Random Errors cannot be eliminated via calibration, but they can be mitigated with repeated measurements [15]. While the measured quantity is estimated to be the average of the measurements, the uncertainty of a measured quantity is typically calculated as the standard deviation of the repeated measurements [15], [17].

As such, the uncertainty tends to be smaller than individual measurement errors. Repeated measurements also help to detect anomaly readings so they can be safely discarded. Hence, multiple independent measurements are encouraged for getting a more reliable and accurate estimate.

When a variable is calculated based on the value of another or multiple other variables that have uncertainties, a concept by the name 'Error Propagation' or 'Propagation of Uncertainty' is employed to calculate the uncertainty of the output variable based on the input uncertainties. The exact calculation depends on the formula used for calculating the main quantity, such as addition, multiplication, logarithm, etc [15], [17].

In the MCA solver, each aggregation ranking method has its own equation for calculating final overall weights for final overall scores, one for each alternative scenario or case study in MCA. The uncertainty equations are based on the differentiations of aggregation ranking functions [17].

The final uncertainties for WSM and WPM are derived below in Equation 10 and Equation 11:

$$\Delta S = \sqrt{\sum_{i=1}^{n}(W_i \cdot \Delta C_i)^2 + \sum_{i=1}^{n}(C_i \cdot \Delta W_i)^2}$$

<u>Derivation</u>

Where: $W_i = \dfrac{\partial S}{\partial C_i}$, $C_i = \dfrac{\partial S}{\partial W_i}$

Equation 10 – WSM Uncertainty

$$\Delta S = S \cdot \sqrt{\sum_{i=1}^{n}\left(W_i \cdot \frac{\Delta C_i}{C_i}\right)^2 + \sum_{i=1}^{n}(\ln(C_i) \cdot \Delta W_i)^2}$$

<u>Derivation</u>

Where: $\dfrac{W_i}{C_i} = \dfrac{\partial \ln(S)}{\partial C_i}$, $\ln(C_i) = \dfrac{\partial \ln(S)}{\partial W_i}$

Equation 11 – WPM Uncertainty

Where: W = Weight , C = Criterion Score , S = Final Score , Δ = Uncertainty, n = number of criteria

Note how the final uncertainty ΔS is equal to a square root or a multiple of a square root, which makes sense because the result of a square root is plus-or-minus (±), the same as uncertainties. The summed-up brackets inside the square root are squared, so they are equal to zero or positive. Hence, the inside of the square root is never negative and will never result in an imaginary uncertainty.

Half of these two equations are cancelled out because weights are not assigned an uncertainty in the MCA solver ($\Delta W_i = 0$). This is for simplicity and because there is no need to assign an uncertainty to numbers that themselves may be user-assigned. The input scores have uncertainties based on how they are measured, such as the error associated with water meters for the water loss rate. All Equal, Manually inserted weights and AHP are subjective, so it makes no sense to assign them with uncertainties. There are naturally no uncertainties in the all-equal weighting method.

An uncertainty calculation example is shown in Equation 17 in section 4.4: Scores Results.

For the sake of simplicity, PROMETHEE methods were omitted from the uncertainties feature because they are complicated to differentiate. PROMETHEE uncertainties may be added as further work. The simplicity of calculating their uncertainties is yet another advantage for absolute ranking methods over relative outranking methods.

3.6. Technical Aspects of Software Development

The following sub-sections detail the technical side of developing the MCA software. These include decisions that increase speed and performance, which are covered in sub-sections 3.6.1: Efficient Algorithms, 3.6.2: Choice of Programming Language, and 3.6.3: Efficient Syntax. Efficient Syntax is covered after the Choice of Programming Language because this depends on the specific programming language, but Efficient Algorithms can be covered first because they are independent of programming languages. The development and testing tools and environments are detailed in sub-section 3.6.4: Development Apps and Extensions.

Bear in mind that although all of these choices are principled and justified, they are ultimately based on personal preferences. The most important of these decisions is the programming language because, unlike specific algorithms and syntax that can be relatively easily changed, changing a programming language is substantially more tedious and affects all the syntax. The programming language determines the environment where the program can run; most notably, JS and HTML web apps can run as websites on the client-side of browsers. Arguably, the least important choice, but nevertheless interesting and useful to know, is the development environment apps because they do not ultimately affect how the final product runs.

Sub-sections 3.6.5 and 3.6.6 cover the Classes and Clones as well as the User Data Storage aspects of the programming, respectively. Lastly, Challenges and Bugs are discussed in sub-section 3.6.7.

3.6.1. Efficient Algorithms and Practices

Every scripting language can benefit from an efficient practice called 'minification'. It is the practice of copying the original script files and creating parallel files that have the exact same functionality but reduced byte size as much as possible. The original files are referred to as the 'formatted' version of the software, and they are most readable to humans, while minified files are readily readable for computers; hence, the software will execute faster. Minification removes all comments ('//' & '/**/'), unnecessary spaces (' ') and line breaks ('\n'), renames variables to single-byte characters and performs a number of other actions to reduce the byte size without altering or breaking the original functionality of the programme. The idea is that the software developers work directly on the formatted version and export it to publish and run it as a minified version. The formatted version can also be published as open source for users to read the scripts, but it is also nearly always that programs run as the minified versions to be lighter in byte size for storage and memory, as well as to launch and run faster.

There are three more examples of efficient algorithm practices in the scripts in this MCA solver: using the least number of loops possible, early terminations, and mirroring pairwise matrices.

When reading scripts, it is easy to assume subconsciously that each line roughly takes as much time to compute as the other, but a line that contains a loop may actually compute the equivalent of many regular lines, as many as the number of repetitions of that loop. Therefore, even though it is efficient to limit any unnecessary lines of operations in general, it is especially important to limit the number of loops. Similarly, limiting computationally expensive operations like logarithms compared to more basic algebra, like multiplication.

There are a number of statistical equations that can be rearranged so that they can be calculated without calculating a mean average. The issue with calculating a mean is that it takes a whole extra loop to calculate the sum total, only for the sum to then be divided by the length of the loop to be used in another loop as a mean variable. The MCA solver includes the Standard Deviation weighting method and Pearson's r correlation in the second form of their formulae in Equation 2 and Equation 8 to yield Script 2 and Script 9, respectively, which have each only a single loop (sub-section 3.2.4 and Section 3.4 and respectively).

Some equations fail with specific inputs, most notably the number zero causes problems with equations that divide by the scores or calculate their logarithms because the logarithm of zero and the division by zero are both mathematically undefined.

The examples of the Entropy, Product, and WPM functions terminate whenever they detect a score of zero, preventing further unnecessary calculations, see Script 3, Script 6, and Script 7 in sub-sections 3.2.5: Entropy and 3.3.1: Absolute Ranking Methods, respectively. Technically, these scripts may be modified to also detect infinity, minus infinity, and non-numbers, but the 'number' type input fields prevent such data from being inserted, so these further modifications could be unnecessary.

There are two square matrices in the MCA solver for pairwise comparisons. These are the AHP weighting method and the Criteria Correlations Matrix. Firstly, for cells along the diagonal line with equal row and column index numbers (row # = col #), there is no calculation, and these cells are filled automatically with the number 1. Secondly, the values in each non-diagonal cell can be mirrored across the diagonal line, hence only needing to be calculated once. During development, there were calculations in every cell to ensure the script was initially calculating correctly.

3.6.2. Choice of Programming Language

As for file formats used by the MCA solver, it is scripted in HTML, JS, and CSS. The bar chart is in SVG, as opposed to other solutions such as Canvas, for simplicity. Sub-section 3.6.6.2 covers the ability to export user input data as JSON and CSV.

Following the explanation of minification in sub-section 3.6.1 above, one of the major reasons for selecting JS and HTML as the programming languages is that, in HTML minification specifically, the CSS, JS, SVG, and other text file formats can all be combined into a single HTML file. Thereby not only increases the convenience of being able to send and open the whole program as a single file as opposed to a whole folder, but it also saves on the byte size of the main HTML file by removing the lines that call all the secondary CSS, JS, SVG, and other files that are part of the program. For example, HTML calls JS by using the syntax 'src' as shown in Script 12 in sub-section 5.2.3.

JS has the advantage of being the only programming language besides WebAssembly that can make calculations on the client-side (the computer of the user) for web pages on all the most popular modern browsers. As a result, HTML is the most cross-compatible format for an app to run on any operating system. However, WebAssembly cannot be minified into a single HTML page like JavaScript. WebAssembly is also more complicated and time-consuming to learn to use and to verify each function works properly, so the MCA solver does not use WebAssembly at all. The only advantage of WebAssembly is its speed, but the MCA solver is fast enough with only JS because all the calculations are simple arithmetic, on top of all the other Efficient Syntax and Efficient Algorithms and Practices.

Regarding speed, JS was also chosen because it is faster than alternative scripting languages. Because MCA calculations are simple and the entire program can execute within less than a second in JS, it makes sense to program it in JS. JS has a balance between being easy to program and having fast execution.

Another useful aspect of JS is its 'Eager Evaluation' ability, which allows it to predict results before pressing Enter in the console of browsers in the Developer Tools (F12) area or in NodeJS in a terminal. Other languages, namely Python, lack this ability. This allows JS fast software development, testing, and even the ability to tell which syntax is less efficient than others, because some syntax can block Eager Evaluation.

JS has a C-like syntax, which most programmers are familiar with, if not outright generally prefer over Python's forced indentation. JS can use optional extensions to mimic Python's indentation for those who prefer it; see sub-section 3.6.4 below for more about Development Apps and Extensions. JS can minify away line breaks '\n' and empty spaces ' ', which Python, by design, cannot. JS also has the tertiary operators '?:', which are more minified than 'if' and 'else' in Python. The minified syntax of JS also includes arrow functions, which Python lacks; these can be seen in every JS script in the List of Scripts except Script 10 and Script 11. Furthermore, JS can have minified declarations using a single 'let' or 'const' with follow-up commas ',' to replace subsequent 'let' or 'const' and without mandatory semi-colons ';'.

Note that all scripts in JS can be classified as one of three: those that work in both HTML and NodeJS, and those that work in either. This is unique to JS as a programming language because, as was highlighted before, JS is the only programming language that runs on the client-side of websites and that can change elements on the front end, also known as manipulating the DOM. This solver is in HTML, not NodeJS, hence no script in this project is in the category of NodeJS-only. NodeJS was, however, used as a testing environment for most functions, as sub-section 3.6.4 below discusses.

To determine whether a script can work in both environments or only in either is fairly simple; look for syntax that could possibly only work in either, look it up, and try to use the script in either environment. For example, Script 1 – JS AHP functions from sub-section 3.2.3 was integrated directly into the HTML solver to manipulate the DOM. This involved using syntax that only works in HTML and not NodeJS, including '.rows[]', '.cells[]', '.lastChild', '.value', '.textContent', '.append', '.type='number'', '.readOnly', and '.insertRow().insertCell()'. Similarly with Script S5 under Supplementary Scripts in Appendix B – Software and '.addEventListener'.

On the other hand, Script 2 in sub-section 3.2.4: Standard Deviation works in both HTML and NodeJS. A common theme to note is that shorter scripts and functions in general are more likely to be possible to run in both environments, whereas longer scripts and non-functions or non-variables tend to be more specialised and only run in either environment.

3.6.3. Efficient Syntax

Below are notable examples of efficient syntax in JS by different natures. Some syntax is considered more efficient because it is faster or better performant than another, but some syntax is considered more efficient because it saves on bytes and therefore storage size.

Starting with the latter, it is possible to define multiple variables and constants simultaneously with the same 'let' or 'const' declarations, respectively, to save on having to repeat writing them for each newly declared variable and constant, by simply using a comma to separate the new declarations. This can also be done by declaring functions as constant arrow functions as opposed to using the 'function' declaration. This replaces the eight-byte string of 'function' with a single-byte comma for any function declared except the first. Examples of these are Script 1, Script 2, Script 8, Script 9, Script S4, and Script S5, see the List of Scripts.

Regarding Script S5, event listeners in HTML's JS are added using the '.addEventListener' syntax, not only because that is the only way to attach multiple event listeners to a given element or to use certain types of triggering events, but also to increase efficiency. The use of '{passive:1}' increases performance by guaranteeing that the syntax 'event.preventDefault()' will not be used. Using the '.addEventListener' syntax also allows for faster launching of the program because they are placed later in the JS file after the launching of the document, since they are not visually needed in the first few seconds of loading the HTML file.

Regarding loops, the '.reduce()', 'for(in)' and 'for(of)' types of loops are all slower than 'for(;;){}', 'while(){}' and 'do{}while()' [98], and so the former types are not used at all in the MCA solver. Instead, only the latter types are used, with slight advantages and disadvantages for each type against the other two. This raises an important and interesting question: why does a programming language feature any syntax that is less efficient whatsoever?

The answer is that this is a matter of debate and criticism, but the idea is that introducing a wide variety of syntax allows a software developer to choose a syntax that is more readable and easier for them to understand, and therefore faster to program at the expense of the speed of the final product. The counterargument is that all the various types of syntax are roughly equally simple to use, so it is best to only include in a programming language the fewest syntax that is actually needed and that which is the most efficient. Regardless, the most efficient syntax for loops was used in this MCA solver.

3.6.4. Development Apps and Extensions

The scripts were edited in Visual Studio Code (VS Code), which is a popular code-editing application that supports many programming languages and file formats, features, and extensions. Unlike simple text editing applications such as Notepad, VS Code highlights syntax in various colours depending on its type and nature, such as a function, variable, etc. It also counts lines, displays indentation, highlights parentheses pairs, displays hoverable comments over syntax, and more.

VS Code and similar code-editing applications also feature extensions, which are add-on programs that provide extra features. To showcase the development environment of the MCA solver, two examples of free open-source VS Code extensions that assisted in the development of this solver are detailed here. They are by no means the only extensions, but they are the most notable two.

These are 'SonarLint' [99] and 'EditCSV' [100]. SonarLint highlights potential mistakes, inefficiencies, and deprecated (obsolescent) syntax in JS scripts and offers efficient alternatives. EditCSV visualises CSV text files as spreadsheets, as Table S5 shows in Appendix B – Software. It is also immensely useful for programming the 'Export Data as .csv' button shown in GUI S8 in the Supplementary GUIs sub-section in Appendix B – Software.

On the browser side, which is the running and testing environment of the solver tool, the browser 'Brave' was chosen. Brave is based on Chromium and its fast and efficient Blink and V8 engines. The Brave browser was selected for its exceptional speed, as well as having the same engine as the Popular Google Chrome [101], [102], as well as its terminal console (F12) and generality of the same syntax, so it would render the same visual as in the Google Chrome browser.

Despite the standardisation of JavaScript syntax across all major browsers, it is not complete; hence, it is useful for any web application to be tested on a Chromium-based browser to see how most users would view the software as it is rendered in testing.

Examples of useful web extensions for this research include 'Toggle JavaScript' [103] and 'Awesome Screen Recorder & Screenshot' [104]. The former turns off JS completely, which allows for a better understanding of how the HTML and CSS interact without any JS on, as shown in GUI S8 in the Supplementary GUIs sub-section in Appendix B – Software. The latter captures high-definition screenshots of the MCA Solver Software Tool that are too long or wide for a regular-sized monitor. These can all be seen as the GUIs throughout this document.

3.6.5. Classes and Clones

In HTML, a textarea is an element that allows the user to input text. HTML elements may have attributes such as classes. A class is a group of elements with a collective name (string). In the MCA solver, each criterion and alternative has its own class, which is named after its type (criterion or alternative) and index number in the tables.

The use of classes in the MCA solver is specifically to automatically synchronise the text between all textareas of the same criterion or alternative, such that when one text is edited, it is instantly the same in all. Such a group of identical textareas is known as clones of each other. In object-oriented programming, the term 'cloning' refers to recreating identical or nearly identical duplicates of elements which share the same fundamental attributes [105] such as style (CSS), input types (e.g. 'number'), and classList.

Besides synchronising user inputs, for example, numbers of weights and scores or names of alternatives and criteria, classes of element clones are also useful to highlight to the user which class is currently being hovered over or focused on. This also shows the user which elements are clones of the same class and will therefore change text to synchronise with each other upon changes to the element that is currently in focus.

GUI 5 in section 3.4 demonstrates how a focused textarea 'Water Loss (%)' is highlighted using CSS in the colour of 'YellowGreen' while the hovered textarea 'Affordability (10^4 m3/Capita·Year)' is highlighted in the CSS colour of 'Aqua'. Focusing or hovering over any textarea clone highlights all clones of that class at the same colour for as long as the hover or focus lasts. Note that this is not only in the same table of 'Scores Correlations', but also in all other tables, including 'Normalised Scores'.

Script S5 under Supplementary GUIs in Appendix B – Software shows the functions used in the MCA solver to clone input and textarea elements. The decision to use cloning functions as opposed to the JS cloneNode() method is due to the fact that cloneNode() does not copy event listeners [105]. Script S5 also shows the functions that highlight hovered and focused elements, 'Aqua' and 'YellowGreen' respectively.

The use of different colours also allows conveying useful information to the user without overwhelming them with unnecessary information. Another colour, red, warns that highlighted cells are about to be reset or deleted, see sub-section 3.6.6.3: Resetting User Data below and Buttons' Red Highlights & Comments GUIs in Appendix B – Software.

3.6.6. User Data Storage

Many aspects of the MCA solver software are automatic. For example, there are no 'run' buttons.

Another similar aspect is the automatic saving of user data. This means that when a user refreshes the page (F5) or closes it and then reopens the page, all the data will remain in place. Any changes the user makes, including deleting, adding, or changing data and changing preferred options settings (dropdown lists, toggle checkboxes, etc), will be remembered. This is very convenient, especially for applications that involve many user input numbers as well as long texts like descriptions. It would be unreasonable to expect the user to fill hundreds of input fields every time the solver is refreshed or closed, including by mistake.

3.6.6.1. Automatic Data-Saving Methods

There are a number of ways to store variables in HTML and JS. Besides adding text to the DOM, JS can temporarily store parameters that are declared as 'const', 'let', or 'var' and 'sessionStorage'. The issue with these is that they are cleared when the HTML page is refreshed or closed. Another storage method is using cookies. The problem with cookies is that they tend to be blocked or cleared automatically by users' browsers and extensions. Furthermore, they are less secure, and they do not work offline for the offline downloaded version of the MCA solver as a single minified HTML file.

This leaves JS with mainly two native syntaxes for storing data locally, offline, and automatically. These are 'localStorage' and 'IndexedDB'. IndexedDB is optimised as it is asynchronous and is stored in binary format to reduce byte size. It is slightly more complicated than localStorage, which is synchronous, so localStorage was used instead for the MCA solver. localStorage is sufficient and possibly even optimised to be faster for the limited data of only a several hundred data fields, whereas IndexedDB is more suitable for substantially larger sets of data, like databases.

localStorage is simple to use. Its main syntaxes are: 'localStorage.setItem(,)', 'localStorage.getItem()', 'localStorage.removeItem()' and 'localStorage.clear()'. The first three of these target-specified items, so localStorage does not require reading or overriding all the stored data, which would be inefficient.

3.6.6.2. Exporting Data File Formats

Besides storing the user data locally, it makes sense to store it in dedicated files that can be downloaded or exported from the solver. This will allow a number of uses:

Firstly, localStorage by itself only saves the data of a single index, but it makes sense to store multiple files of various MCA indices in a folder to load them up and save changes to each of them separately using the same tool.

Secondly, as the name suggests, localStorage only stores data locally, so in order to share user data with others, the data would need to be downloaded as a file, and then that file can be shared with others so they can open up the user data on their computer using their copy of the MCA solver.

But for that, a specific file format needs to be selected. Table 6 in sub-section 2.2.4.1 notes that the Existing MCA Software: 2023 MCDA-KIT and 2024 Decerns MCDA store and export their user data in the file format of '.xml' and '.dcm' respectively.

The MCA solver uses the '.json' file format. The main reason is that this is the format that localStorage is natively in, so exporting and uploading user data is as simple as using 'JSON.stringify(localStorage)' and 'JSON.parse(localStorage)' syntaxes, respectively. It is also more convenient to program the demonstration examples in GUI S4 in Appendix B – Software as JS objects {} inside the solver's own script, which can then be tried out by the user by simply replacing the localStorage with these demo examples that share the same format as JSON.

As for other file formats, JSON is more efficient at storing data compared to XML, as it uses fewer bytes as part of its format. XML has a structure similar to HTML, while JSON has a structure similar to JS. This is another regard in which this new MCA solver bests Existing MCA Software.

The solver also exports data as CSV, which has the advantage of potentially being even more byte-efficient than JSON while also allowing the user to input data to be displayed as a spreadsheet, as shown in sub-section CSV & JSON Data Storage Files in Appendix B – Software. Between JSON and CSV, it is advantageous that the MCA solver has the flexibility to export user input data as multiple file formats for the convenience of the user to enjoy and benefit from.

3.6.6.3. Resetting User Data

Here is a simple challenge: if there are dozens and even hundreds of input fields, how would a user conveniently delete their data if they want to redo the index or part of it, or create another index?

The issue here is actually the aforementioned automatic saving of user data, because, without it, refreshing the page (F5) or closing and reopening the page would reset all the data by itself. A user might also only want to delete data of some types but keep others, for example, delete all the weights but keep the scores.

A very simple solution was implemented, which is creating 'reset' buttons. Each reset button highlights in red the input fields it will reset as the user hovers the mouse cursor over the button. These buttons are shown in sub-section Buttons' Red Highlights & Comments in Appendix B – Software, in GUI S9 to GUI S14.

They delete data from specific groups of input fields while leaving others alone. They also delete simultaneously the localStorage of these input fields, so refreshing or relaunching the software does not reupload the unwanted numbers into empty input fields, and also saves up on storage.

This solution is better than the alternatives of leaving the user with either having to manually delete text and numbers from many input fields, deleting all the localStorage, or using the range sliders or their 'number' type input fields to remove as many criteria and alternatives as possible to delete cells before re-introducing them. It makes sense to have dedicated tools if they are simple and efficient, as they are in this case.

3.6.7. Challenges and Bugs

As is the nature of software development, there have been numerous challenges and bugs.

The most significant bug encountered during the development of the MCA solver was an infinite loop when using some features of the software, such as certain weighting methods. Typically, when encountering an infinite loop while making calculations, it is due to a badly designed algorithm where a loop in a single function does not change its condition. However, that infinite was not tied to one specific function or an iterative loop expression like 'while()', 'do{}while()', or 'for(,,)'.

After deeper analysis, it was discovered that the custom functions 'Plot()', 'Ranking()', and a couple of others were calling each other in a vicious cycle. It is generally fine for a function to call another every time it is triggered by an EventListener. However, if function 'A' always calls function 'B', while 'B' also always calls function 'A', this creates an infinite loop. This was the case for the MCA solver, with roughly four or five functions that trigger each other indefinitely in a vicious cycle whenever any is triggered, even though at least one of these clearly did not need to call another. This also points to another problem, which is that on occasion, one function calls another without any need, which is inefficient and increases processing times, but this is only detected when it creates an infinite loop. This, however, can be excused away by justifying that some functions update some numbers and visuals by making calculations, and normally, this does not hurt the overall performance too much for a function to trigger another.

The solution was simple. Sketch on paper which functions trigger which others by drawing arrows that point from any function to whichever it triggers, and then deciding when an arrow is most unnecessary, to then cut open this loop.

After researching this phenomenon, it appears not to be named as either iterative or recursive in nature. As is written in Table 4 in the Nomenclature, Recursion is defined as a "software function that calls itself", while the definition for Iteration is "repetition of computer instructions in a loop" [16]. Both iteration and recursion are designed to stop when a specific condition is met. This is typically manifested with a simple 'if(){}else{}' for recursion, whereas iteration uses 'while(){}', 'do{}while()' or 'for(,,){}' in JS and 'Until' in other programming languages.

This type of infinite loop is more similar to a recursive infinite loop because it continues to call another function rather than a simple for or while loop. However, because it calls other functions that call it, it is debated as to whether this can truly be labelled as recursive. At any rate, it is mostly uncommon for functions to call each other in a loop, hence why it was harder to detect.

3.7. Summary

The MCA Solver is a software tool programmed entirely from scratch in HTML and JS. This is done so it can be uploaded as a website and use some of the HTML syntax, for example, 'localStorage' for storing user input data. Following the gaps in the literature on MCA software explored in sub-section 2.2.4.1, the aim of this program is to include the features missing in existing MCA applications. The quality of this MCA solver is aimed to be high enough for it to be possible to be licensed or sold, but it could also be open-sourced in the future.

This chapter discussed the mathematics and programming of the various methods included in this solver, from the basic features of an MCA tool of weighting and ranking methods to those uniquely included in this software of correlations and uncertainties. A comparison was made between the AHP weighting method and the correlations feature because they both use a square matrix of a length equal to that of the number of criteria and a unique number of pairwise comparisons found in Figure 17 in sub-section 3.2.3. Similarly, there is a comparison between Entropy and WPM because both fail completely if even a single score is zero, at least in the case of WPM, unless it is the desire of the user to completely fail an alternative that has a score of zero for even only a single criterion. This highlights how the mathematical use of logarithms (ln) and product (Π) in MCA methods can result in scores of zero or even close to it, unlike methods that sum (Σ) scores.

Comparing weighting and ranking methods shows how some methods may be unnecessarily complicated, such as Entropy, AHP, and PROMETHEE. Still, these methods are used in literature, and so they are included in this solver because they are too complicated to be calculated in a spreadsheet application, as they need significant manual adjustment with any newly added or removed alternative scenario or indicator; therefore, this MCA solver is ideal for running them.

It is most efficient to program software that acts as a specialised calculator and is dedicated to ranking case studies while conveniently requiring the least amount of user input for both simplicity and saving time. It is also more professional to present the use of dedicated engineering software that calculates correlations, uncertainties, and complicated methods quickly by itself, as opposed to using a spreadsheet. Therefore, the complicated methods actually justify the need for MCA software the most, more than any other convenient feature in this specialised software.

This chapter also made an interesting further finding, which is that there are two additional theoretical absolute ranking methods called 'Sum Power' and 'Product', the former likely outperforming an existing method, WPM.

4. Custom Index

Table of Contents

4.1. Introduction

"All models are wrong, but some are useful" – statistician George E. P. Box [106]

The aim of this chapter is to construct a custom MCA index model that will be able to shed light on which indicators are the most likely to reflect the vulnerabilities of WSS that can lead to water supply disruptions, so they can be addressed to prevent such incidents.

This new 'Custom Index' is inspired by the 2016 Sustainable Cities Water Resiliency Sub-Index [21] and aims to improve upon it. The improvements of this new Custom Index over the 2016 sub-index are a better selection of indicators that have a novel perspective of focusing on the supplier-side of water supply, as well as calculating correlations and uncertainties.

This chapter begins with section 4.2 discussing the Selection Requirements of Case Study Cities in sub-section 4.2.1 and then carrying out a Comparison and Selection of them in sub-section 4.2.2.

Following this, section 4.3 details the Vulnerability Indicators. Similar to section 4.2 before it, section 4.3 lists Indicators Selection Requirements in its first sub-section: 4.3.1. The remaining sub-sections in section 4.3 are discussions of the individual indicators themselves. This includes how these indicators track genuine vulnerabilities of WSS, their sources of data, potential paths for resiliency improvements against the vulnerabilities, and even analogies to biology due to the theme of water metabolism.

The indicators covered in this section are both the ones that end up being included in the Custom Index, but also the ones that were not. They are compared, categorised, and selected in sub-section 4.3.17.

After sections 4.2 and 4.3 cover the Case Study Cities and Vulnerability Indicators, which are the MCA criteria and alternatives, respectively, scores and uncertainties can be tabulated in GUI 6 in section 4.4: Scores. It also allows calculating the correlations in GUI 5 – Criteria Correlations Matrix shown in section 3.4.

Recall Figure 12 in sub-section 2.2.4: Multi-Criteria Analysis (MCA) Methods, which explains that scores and correlations can be inserted and calculated, respectively, as soon as all criteria and alternatives are gathered, before selecting a weighting or ranking method or weights. Figure 12 points out how certain weighting methods, such as Standard Deviation and Entropy, use the scores as inputs to generate weights. Therefore, it makes sense to strategically cover the scores in section 4.4 before considering what the weighting method should be based on the scores in section 4.5: Selecting Weighting and Ranking Methods. The general deviations from the mean that scores have can determine which weighting method to use. Even if neither Standard Deviation nor Entropy is selected, it is a good MCA practice to structure this order of filling in an MCA index.

Following is the final section 4.6: Rankings Results. Sub-section 4.6.1 covers Methodology Assessment and Discussion, whereas sub-section 4.6.2 summarises.

Lastly, this chapter is accompanied by Appendix C – Index. It features sources of data for the indicators in the forms of Interactive Maps and Case Studies Basic Statistics, to better understand the Case Study Cities and to verify they each fit the Selection Requirements of a "large city".

4.2. Case Study Cities

4.2.1. Selection Requirements

The following are the selection requirements for a city to become a case study in the Custom Index:

1) Appear in the 2016 Sustainable Cities Water Index [21] for an assessment correlation.

2) Be a "Large City", meaning having a population of at least a million or a density of a thousand people per square kilometre, and having its own water treatment plants. This was reasoned in Chapter 1: Introduction. See Table S7 – Case Study Cities Basic Statistics in Appendix C – Index.

3) Be at least somewhat 'developed'. This means high literacy rates, access to electricity, and no war zones, all of which would needlessly complicate the Custom Index and make it controversial.

4) Have well-defined borders, preferably city-states, especially islands. It makes for a clearer picture, and city-states and island nations tend to be more interesting and have unique water system features.

5) Have accessible public data. Bear in mind that for different MCA indices, some indicators are bottlenecks for data availability. In this case, it is Tap Water Quality that requires dedicated reports. Tap Water Quality Reports are published roughly yearly by water suppliers and vary greatly in structure, the included substances, and language. All of these, although language to a smaller extent, can pose a hurdle for a researcher to gather the necessary data for comparison. On the other hand, the least bottlenecked vulnerability indicator with the most widely available recent and reliable data is Soil Moisture Content, as it is based on satellite data.

Gathering the necessary data needed in order to calculate scores for a case study city in the MCA solver can require about an hour. However, it could take longer to achieve more reliable data, i.e. lower uncertainty. Again, finding dedicated data for Tap Water Quality Reports is what takes the most time due to complexity, whereas satellite-derived Soil Moisture Content and others can use the same universal sources, such as Interactive Maps, as other case studies, saving on research time.

Unlike the Vulnerability Indicators, which are relatively few in number and very distinct from each other in their nature, case study cities are more numerous and are analysed here in breadth, not depth, because this is their nature. Hence, case studies are discussed in this section without dedicating subheadings for each case study. More case studies produce stronger and more reliable correlations, but not so with more indicators, because it is the indicators that are cross-correlated.

4.2.2. Comparison and Selection

Singapore and Hong Kong were already explored in depth by the author of this research previously in Figure 5 and Figure 6 in section 1.3 [30], as well as being assessed in the 2016 Sustainable Cities Water Index [21]; hence, they were the natural first two choices. They are unique cases, having very well-defined borders as being island city-states and being developed, hence having a significant amount of public information, such as Tap Water Quality Reports, and in general having unique features such as Hong Kong's seawater for flushing and Singapore's NEWater reclamation.

These cities possess significant vulnerabilities, including a lack of self-reliance, also known as dependence on water importation from their immediate neighbours of Malaysia and Mainland China. Hong Kong also had very well-documented incidents of high concentrations of lead in its water supply in 2015, which halted the WDN in a specific part of the city [33], [34], and then another major incident in 2017 of 36 burst water distribution mains pipelines [35]. These are exactly the sorts of major events that this Custom Index primarily aims to understand. Singapore, interestingly and famously, has what it calls its 'Four National Taps' [107], which are its four sources of water: Precipitation Catchment Reservoirs, Desalination, 'NEWater' Reclamation/Recycling, and Importation. Ironically, the last 'tap' is international and not really national. Singapore plans to phase out importation completely by 2061 when its agreement with Malaysia ends [108], [109].

Speaking of island city-states with well-defined borders, this research naturally chose a path for selecting as many case study cities as possible in breadth, not depth, due to its MCA nature and ability to compare many cities using the MCA solver tool. Hence, after Singapore and Hong Kong, other jurisdictions were sought, which were not too hard to find despite there being only two hundred counties or thereabouts currently.

Bahrain was selected as another case study example due to its being a developed, population-dense city-state island that is water-stressed. Unfortunately, Bahrain was not included in the 2016 Sustainable Cities Water Index. However, all this means that Bahrain would not be present in the correlation comparison between this Custom Index and the resiliency sub-index for assessment (Figure 33 and Figure 34), and in fact, it shows this Custom Index is universalisable and may assess cities besides those that Arcadis covered.

Another interesting case study is London, England. Despite being in a more temperate climate zone and having one of the highest Soil Moisture Content of the case studies (31% v/v, see GUI 6 in section 4.4), it is the most water-stressed region in the UK [110]. This is due to being close to the east coast, which receives less precipitation from moist air that comes from the Atlantic Ocean, being in the south, which also reduces precipitation, and being the most densely populated region in the UK. London however, being a historic and economic hub, is the benchmark for numerous measures such as Greenwich Time, but in the interesting context of water systems, it is by definition a benchmark of 1.00 for Faithful+Gould 2014-22 location factors [111], [112] which are used for the Affordability indicator, hence London was selected as an interesting city case study to include.

Another UK city, Manchester, was selected for being where some of this research was conducted, which allowed for on-the-ground Tap Water Quality analysis to compare with quality reports, see sub-section 4.3.3.3: Analytical Observations. Manchester is also unique for having a 96-mile-long aqueduct system to supply water from its north [113]. This system is named Thirlmere after the reservoir from which it withdraws water. It was built in the Victorian era and inspired by the gravity aqueducts of the Romans.

Amsterdam was selected because it is the capital of the Netherlands, a country famous for building dykes for centuries as its major flood-mitigating measure. This is due to much of the territory of the Netherlands being below sea-level elevation, with the capital city of Amsterdam being entirely below sea-level elevation, see Map 6 in sub-section 4.3.6: Flood Risk.

Riyadh was selected to explore two interesting aspects. Firstly, unlike other desert cities, which meet their water demands from their adjacent coast using local desalination plants, Riyadh is a landlocked city and imports its water from desalination plants well over two hundred miles away. Secondly, despite the previous statement, the water price in Riyadh is among the lowest in the world [114], because it is heavily subsidised at about 70% [115].

The next step was to select other small city-states that are similar because they have well-defined borders, but also include non-islands, as long as they are coastal, to assess desalination as an option. Hence, several case studies are coastal. Case studies in this research were selected to give variety to spot interesting trends based on different geographies, climate zones, coastal access or landlocked, political status, and any other interesting characteristics which set cities apart from each other. In total, 24 case studies were selected for this Custom Index, of which 21 are in common with the 50 Arcadis assessed [21]. For the complete list of 21 cities both indices share in common, see Figure 33 and Figure 34 in sub-section 4.6.1: Methodology Assessment and Discussion.

Cities which were not selected from the 2016 Sustainable Cities Water Index tend to be either insufficiently developed, lacking clear borders, such as metropolis mega-cities, lacking data, particularly Tap Water Quality Reports, or were limited in numbers to keep the Custom Index with a manageable number of only a couple of dozen case study cities, enough to analyse its methodology.

The three case studies that are included in this Custom Index but were not by Arcadis are Taipei (Taiwan), Kuwait City, and Bahrain. These were chosen for being coastal small jurisdictions with well-defined borders, and it can be argued that the 2016 index by Arcadis could have benefited from incorporating these. Map 3 below shows where the 24 case study cities are geographically located [116]. In terms of proximity, they are sorted into four groups from west to east:

- <u>North America (6, in blue):</u> Los Angeles, Mexico City, Dallas, Houston, Toronto, Washington DC
- <u>Europe (8, in red):</u> Manchester, London, Paris, Brussels, Amsterdam, Rome, Copenhagen, Berlin
- <u>Gulf Peninsula (5, in green):</u> Riyadh, Kuwait City, Bahrain, Doha, Dubai
- <u>East Asia and Australia (5, in yellow):</u> Singapore, Hong Kong, Shanghai, Taipei, Melbourne
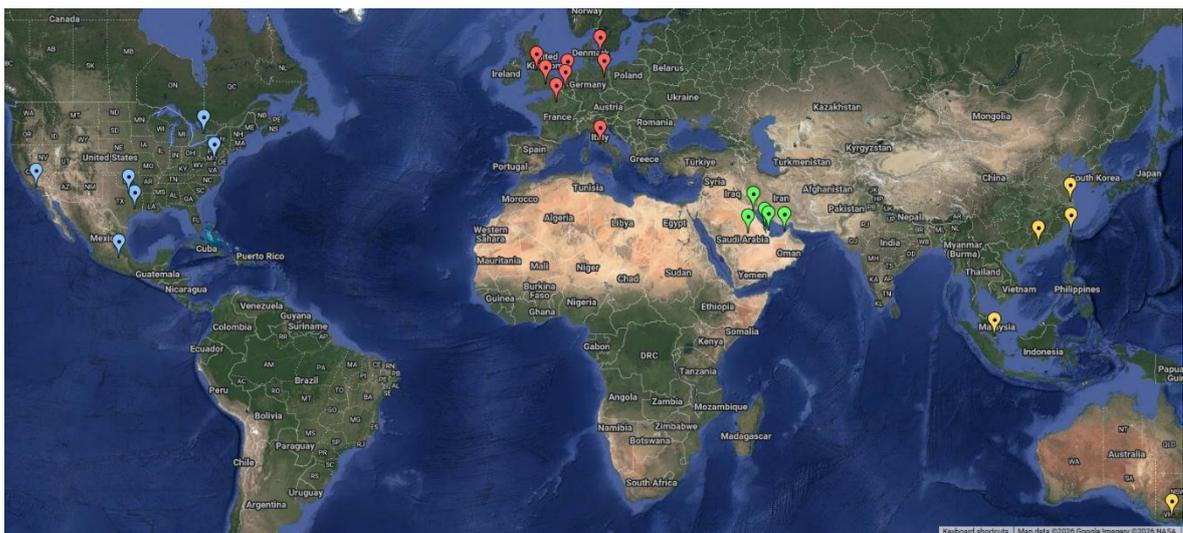
Map 3 – World Case Study Cities Pinned [116], © Google & NASA

Of course, considering there are other ways to group the case studies, such as along the lines of culture, development index, and climate zones, there is no single best way to group the case studies. In some sense, having variety is best to allow for experimentation to determine which group, if any, correlates the most with certain results. Refer to Table S7 in Appendix C – Index for the Case Studies Basic Statistics of population, area, and water consumption. It is sorted alphabetically by the names of cities, the same as all the lists and tables of statistics in this document that list the case studies.

4.3. Vulnerability Indicators

4.3.1. Indicators Selection Requirements

Water systems experience numerous vulnerabilities, and it is crucial to select which of these are best to include in the Custom Index to estimate the overall vulnerability to WSS. The key is to only include a few indicators for simplicity and the ability to assess many case studies while still producing accurate results.

An indicator does not necessarily need to be a vulnerability, even if vulnerabilities and indicators are often referred to interchangeably as synonyms. In the context of the Custom Index, for the sake of simplicity, many, if not most, indicators are, in fact, direct vulnerabilities. This index may be thought of as a list of patient blood test results, where some indicators might be directly bad while others are only proxies (potentially even strong) of problems. A proxy tracks a problem but is not the problem itself. In other words, a proxy is a symptom. Proxies are used as indicators because they tend to be easier and more reliable to measure than the actual problems they correlate with.

For consistency, indicators are selected using the following strict and principled requirements:

1) Relate to WSS, including either water distribution pipelines or reservoirs, and be analogous to 'Metabolism', see Figure 5 and Figure 6 in section 1.3. Ideally, all vulnerabilities that affect WSS should be factored in, while all those that do not directly affect WSS should not be factored in. Both aspects create the possibility of both types I and II errors, meaning factoring in false vulnerabilities or ignoring real vulnerabilities, respectively.

2) Be mentioned in the WSS literature (see Appendix A – Literature). The evidence for this is by using citations to WSS literature, where indicators are discussed.

3) Have readily available and reliable recent data.

4) Do not correlate strongly with other indicators to prevent double-counting, see GUI 5 – Criteria Correlations Matrix in section 3.4.

5) Focus on the perspective of water suppliers, not consumers.

6) Preferably be documented as contributing to or being the cause of Past Water Supply Disruption Incidents. See sub-section 1.2.

7) It can realistically be improved to be more resilient with intervention, for example, investment or better management. To further limit the potentially long list of possible indicators for simplicity, the focus should be exclusively on indicators that not only are relevant as mentioned in point 1) above, but also indicators that can be improved with investments. Meaning, investing in the infrastructure of the WSS to mitigate vulnerabilities. Put simply, focus on the vulnerabilities that can be controlled, as presented below in Figure 18:
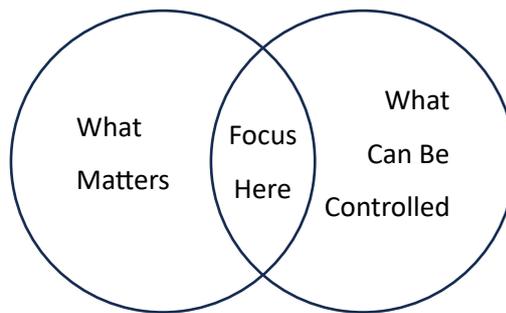
Figure 18 – Venn Diagram of What Matters and What Can Be Controlled

The idea is that water suppliers that employ the framework of the Custom Index should be able to clearly find which vulnerabilities are bottlenecked and should receive funding to improve their resiliency most urgently. There needs to be a balance, though, between this requirement and providing accurate final rankings in general, because theoretically, it is possible for an indicator to be highly relevant as a vulnerability yet cannot improve its resiliency with investments, e.g. some natural and artificial disasters. For simplicity, it is assumed the developed case study cities are not subject significantly to these disasters, save for flood risk, which is a whole topic on its own in water systems literature and hence is a standalone indicator.

8) Preferably, be measured in percentages from 0% to 100% or fractions from 0 to 1; otherwise, the Custom Index will have to be normalised. Even so, indicators with these boundaries are clearer and can be considered to be more concrete. While technically not a requirement, this is very convenient and allows for an easier understanding of the data, which makes it more natural and universalisable and therefore more easily accepted by potential users of the Custom Index. Although normalisation can exist in other units, percentages or fractions are effectively unitless and have clear boundaries of 0% to 100% and 0 to 1.

4.3.2. Water Loss

Also known as 'Non-Revenue Water', the term 'Water Loss' refers to the percentage of potable water distributed that the water supplier is not paid for. In many case study cities, water loss only refers to water leaked. This is most notably the case for Singapore, which has all of its water metered [86](7.1). For other Case Study Cities, such as Hong Kong, water loss also includes water theft [117], which is also euphemistically referred to as 'unbilled' and 'unauthorised' consumption. These two types of water losses are presented separately in Figure 6 in section 1.3. Table 8 below documents the percentage of water lost in distribution for each case study city, supported by references from data by local water suppliers. The decimal places are based on the numbers in the original sources.

Table 8 – Water Loss rates of Case Study Cities (%)

Case Study City	Water Loss Rate (%)	References	Case Study City	Water Loss Rate (%)	References
Amsterdam, Holland	4	[107], [118]	Los Angeles, California	9.9	[119]
Bahrain	24	[120]	Manchester, England	24.4	[121]
Berlin, Germany	5	[118]	Melbourne, Australia	10	[122]
Brussels, Belgium	26	[86] (6.1)	Mexico City, Mexico	40	[123]
Copenhagen, Denmark	7.22	[124]	Paris, France	6	[119]
Dallas, Texas	8.8	[125]	Riyadh, Saudi Arabia	30	[126]
Doha, Qatar	26	[127]	Rome, Italy	27.8	[128]
Dubai, UAE	5.3	[129]	Shanghai, China	17.6	[119]
Hong Kong	32.5	[117]	Singapore	5	[118]
Houston, Texas	16.87	[130]	Taipei, Taiwan	17.73	[131]
Kuwait City, Kuwait	10	[132]	Toronto, Canada	10	[133]
London, England	26.7	[119]	Washington DC	25	[134]

This vulnerability affects the WSS as a whole, but also specific areas that may suffer from unpredictable distribution and other types of damage due to localised leaks.

4.3.2.1. Analogy to Biology

Referring to the perspective of 'Water Metabolism' of large cities, water leakage is analogous to bleeding. Similarly, maintenance that seals leaks is analogous to bandages and platelets in blood. In contrast to biological bodies, Table 8 above illustrates that WSS can have very high leakage rates constantly and very high statistical variance. This is a diseconomy of scale, meaning increased inefficiency as a percentage with increasing capacity. It is said that undesirable things rise to the level they are tolerated, and clearly, the human body cannot tolerate leaks as much as WDNs, so it is unsurprising to witness the differences in structure and size in both, leading to such disparities.

It is more likely that a smaller WDN would be better at finding and sealing leaks than a larger one. This is due to the engineering principle, which is that the more parts a system has, the more likely any one of them is to go wrong. The more places there are to look for leaks, the longer it takes to detect them. This is similar to cracking a longer password. Having said that, there are also economies of scale in supporting large cities, so if it requires much water to be lost in order for a water system to support a large city, it is most likely worth it. Still, it seems to be possible to achieve a less than 10% water loss rate; hence, for numerous cities, it should be a realistic target to aim for.

4.3.2.2. Resiliency Improvement Suggestions

Sensors and cameras can be used to detect locations of leakage and where maintenance crews should go to fix the leakages. Level and flow rate sensors can be placed in junction points where major pipes split and combine, and centralised software can calculate which areas are most likely in need of maintenance. For reference, see Picture S4 in Appendix C – Index for the appearance of water meters. Cameras, as well as reports of detected leaks or flooding from local communities, can also help detect points of water loss in the system. In general, investing in strong pipes makes it less likely that they will be subject to accidental breakages.

As is written in Table 4 in the Nomenclature, 'Metering water' is defined as the 'percentage of households whose water consumption is metered' [21]. This can likewise be defined as the 'flow rate of potable water which is measured as reaching the consumers as a percentage of total distributed'. Whichever definition is picked, the more metering, the more useful information there is regarding where and how much water is lost. This means that metering could have been used as uncertainty to Water Loss or as a standalone indicator. It was not used because it would require gathering even more data, and because it was easier to automatically generate uncertainty for water loss as a decimal for the given reported data of each city. For example, the uncertainty of Singapore's 5% water loss rate would be ±1% whereas 8.8% for Dallas yields a ±0.1% uncertainty.

4.3.3. Tap Water Quality

Also known as drinking water quality, tap water quality is one of the most fundamental vulnerabilities of WSS, which can lead to incidents that cause supply shortages [33], [34], [135]. Being the tap itself, it is the final stage in the WDN, which can cause a failure that may cut the flow. There are entire studies solely examining tap water quality incidents by their type of failed quality (e.g. pathogen, heavy metals, etc) [136].

Unlike tap water quality, Water Loss above is an indicator that is easy enough to estimate from a material balance over the distributed water relative to the water metered by consumers, hence it is conveniently in the units of percentages because it is natively normalised. On the other hand, Water Quality varies on more dimensions, so it is a sub-index where each sub-indicator measures a different concentration of a contaminant substance in the drinking water or a similar measurement.

The Canadian Water Quality Index (CWQI) [137] provides scores based on the percentage of water samples that pass testing. In this sense, this is conveniently in the units of percentages, where 0% is the worst, with no samples passing, and 100% is the best, with all samples passing. There are several issues with this approach:

Firstly, this method cannot assess WSS globally with publicly available data, because the number of samples taken and passed is typically not published. Furthermore, not every water supplier tests for the exact same list of contaminants, so there needs to be an exact, agreed-upon universal list of contaminants to allow for objective universal comparison. Such a list would have to be small because many entities realistically do not agree on many things in common.

Secondly, several contaminants are worse than others on a concentration basis, and this approach of the percentage of tests passed does not take this into account. It also does not take into account which tests fail on a single contaminant and which on multiple.

Hence, it is paramount to focus on creating a sub-index of concentrations of substances in the drinking water as sub-indicators. Each contaminant is given its own weight based on its severity, so failing on any specific one or multiple contaminants will be more fair. Instead of counting failed tests, the maximum concentrations should be counted relative to a maximum allowed guideline, as this is stricter and lets the consumer know the worst values they can reasonably expect. This is also better because if a few samples fail, say three, that means there is an issue of repeated failures, which is important to penalise with a lower score. This cannot be captured by comparing a WSS with a 100% pass rate to a WSS with a nearly perfect score, say 99.7%.

Looking at the literature, it appears that different organisations, such as the WHO, estimate water quality based on tests for acceptable levels of various contaminants, such as heavy metals, plastics, nitrates, cyanide, bacteria, etc.

Map 4 [13] below presents which Water Quality Indices (WQIs) are employed globally:
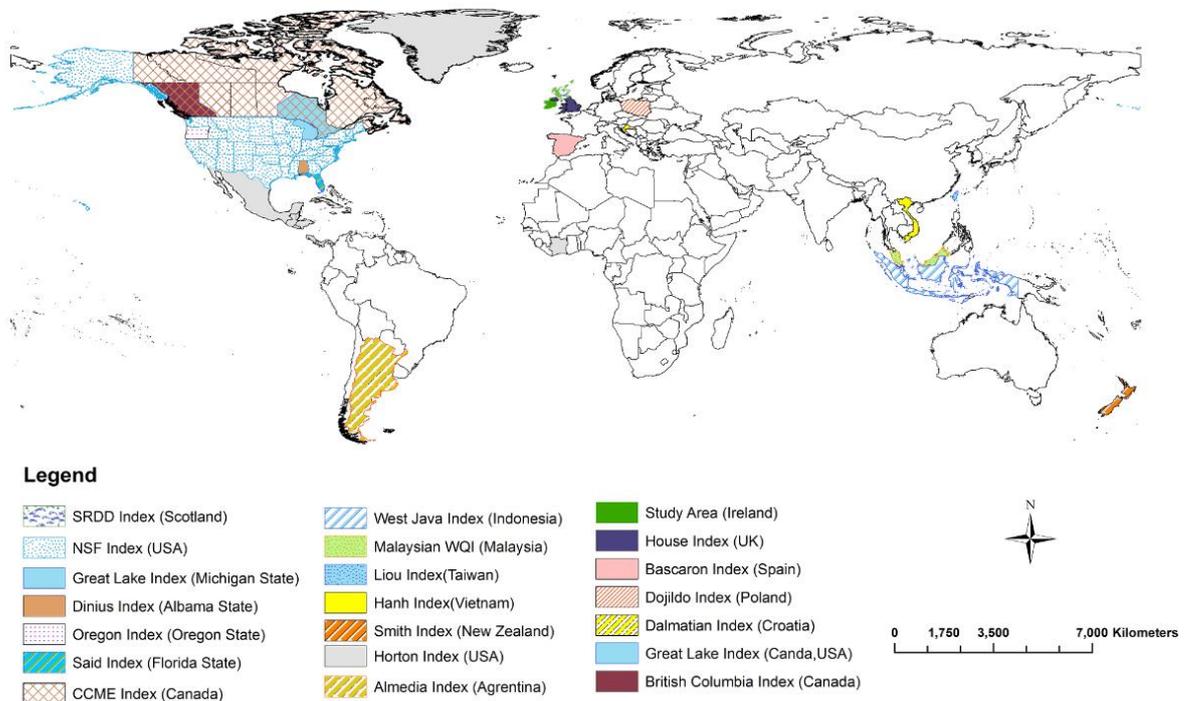
Map 4 – World Water Quality Indices [13], CC BY-NC-ND 4.0

Data for this research is extracted from self-reported Tap Water Quality Reports, which are published regularly, typically yearly, by water suppliers, see sub-section 4.3.3.1 below. There does not seem to be an alternative universal source of data. Even so, several water suppliers publish tap water quality reports irregularly, if at all. Some also omit seemingly fundamental measurements such as common heavy metals, which is suspicious. Conversely, some contaminants are not naturally present in some water sources in any meaningful amounts; hence, the local water suppliers may purposefully measure for these to appear good in their published testing reports.

In some locations, the local water suppliers may have lower standards, such as higher maximum tolerance concentrations than recommended by the WHO [138], but boast about passing tests based on their twisted standards and their higher standards for other, less prevalent contaminants. On top of all of this is the assumption that the published data is not fabricated or distorted and that regulators and inspectors are trustworthy in all localities.

For these reasons, it may be best to form two categories of important water systems sub-indicators:

1) The universal sub-indicators, which are easy to estimate and hence are widely available as data.

2) The sub-indicators which may be lacking in data due to difficulty measuring them, or are only available to some (confidential), or are not universal in standards or reliability.

There is no universally agreed upon best WQI or way to estimate the quality of drinking water; there are numerous WQIs [13], [139], [140]. Even if there was, it would require too much publicly available data, which might be lacking in some locations; hence, a universal WQI would require a few simple sub-indicators with data that is universally available. The concentrations of measured substances will be compared to guidelines of respected institutions such as the WHO. The WHO documented a lengthy list of substances with recommended maximum allowed concentrations in drinking water [137].

Considering that there are many possible contaminants, only the most significant ones will be assessed at first, while others can follow in future work. The WHO has a list of the top "10 Chemicals of Major Public Health Concern" [141] shown below in Figure 19. These are Arsenic, Asbestos, Benzene, Cadmium, Dioxins (and similar), (insufficient or excess) Fluoride, Lead, Mercury, Pesticides, and Air Pollutants:
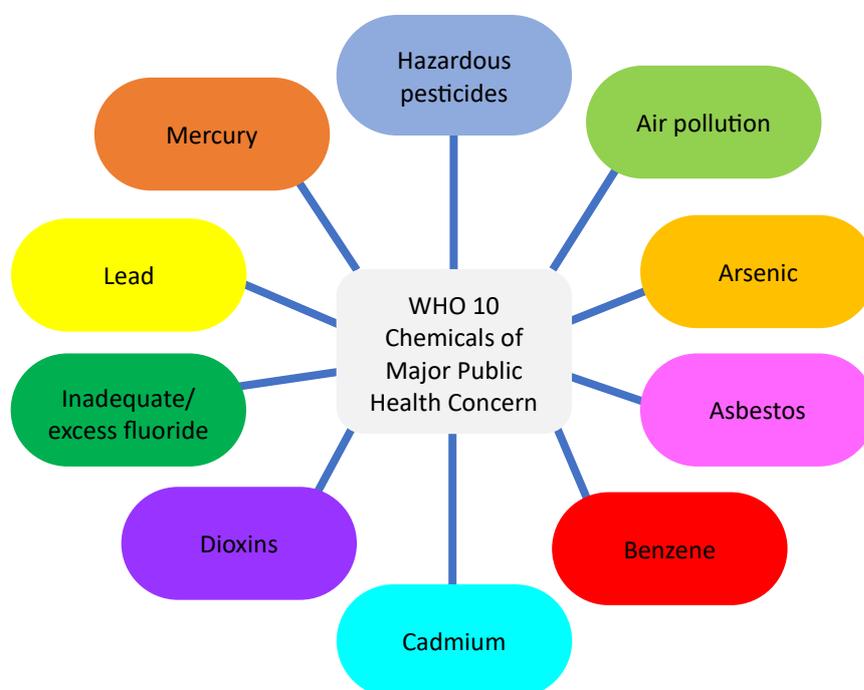
Figure 19 – WHO's 10 Chemicals of Public Health Concern [141], CC BY-NC-SA 3.0 IGO remixed

Of these, Asbestos, Dioxins, Pesticides, and Air Pollutants are all groups of substances, hence are not assessed due to their complexity, lack of data, and lack of WHO guidelines. Fluoride would also not be assessed due to its lower risk relative to other substances, as it is added intentionally to drinking water, and due to its politicised, controversial nature. Benzene is also omitted due to a lack of sufficient data in Tap Water Quality Reports.

The four heavy metals of Arsenic, Cadmium, Lead, and Mercury are selected to be assessed. They are very common and basic to test for, especially lead, which historically was used as the material water pipes and joint fittings were constructed out of. Lead also makes an appearance in sub-section 1.2: Past Water Supply Disruption Incidents.

Besides these heavy metals selected from the WHO's Figure 19 above, other fundamental water quality indicators are taken into account. Nitrates and nitrites also have WHO guidelines [138] and are commonly discussed in the topic of water quality, hence are included as well. Conductivity is simple to measure; hence, data is widely available, and it is potentially telling of both hardness (calcium) and removal filtering of salt (sodium) from the source, or contamination, such as from coastal flooding.

If any city omits tests for any of these basic substances, its score is penalised as though it violated the WHO's maximum recommended guideline concentrations. This is because omitting such basic tests is suspicious, as if the results are purposefully hidden. Ultimately, a future user of this Custom Index will be able to adjust it to decide which substances are included, their weights, and the exact way to penalise non-compliance or omission of data.

Table 9 and Table 10 in sub-section 4.3.3.1: Tap Water Quality Reports below tabulate the scores of Case Study Cities for each contaminant with references and explanations of how the weights were objectively assigned based on the severity of each contaminant.

4.3.3.1. Tap Water Quality Reports

Table 9 below references Tap Water Quality sub-indicators where data is available. The lower the score, the better. The weights are assigned based on the CDC's 'Immediately Dangerous To Life or Health (IDLH)' metric [142] in ppm, except for Electrical Conductivity, which was assigned a weight based on an educated guesstimate equivalent. These reports range from Bahrain's EWA being the oldest from 2014 [143] and Manchester's United Utilities being the most recent from 2023 [144].

Five case studies: Mexico City, Dubai, Kuwait City, Riyadh, and Shanghai are omitted from Table 9 and Table 10 to save space due to their complete lack of available tap water quality reports. Their Tap Water Quality score is 0.

Out of interest, the Median Lethal Dose LD_{50} is also written here, which was considered initially but later replaced by IDLH due to its greater availability of guideline values.

Table 9 – Tap Water Quality sub-indicators scores

Indicator / Case Study City	Source by most recent dates	Arsenic (µg/L OR ppb)	Lead (µg/L OR ppb)	Mercury (µg/L OR ppb)	Cadmium (µg/L OR ppb)	Nitrate (NO3-) (mg/L OR ppm)	Nitrite (NO2-) (mg/L OR ppm)	Electrical Conductivity @ ~25°C (µS/cm)
Max Guideline (and Worst Possible Score)	• WHO [138] • EU	10	10	6	3	50	3	2500 EU [145]
IDLH (ppm) [142]	CDC's IDLH	5	100	10	9	200	400	1000 (guesstimate)
Weight		1	0.05	0.5	0.556	0.025	0.013	0.005
Median Lethal Dose LD_{50} [142] (mg/kg)		-	450	-	-	120		N/A
Amsterdam, Holland	Waternet [146]	2.32	0.2	0.01		5.97	0.007	604
Bahrain	EWA [143]	50	10	1	5	2	0.1	1800

Berlin, Germany	BW [147]	2	5	0.1	0.5	4.09	0.03	1040
Brussels, Belgium	Vivaqua [148]	0.5	0.3	0.05	0.06	22.6	0.02	709
Copenhagen, Denmark	HOFOR [149]	0.57	0.025	0.001	0.003	2.8	0.0013	968
Dallas, Texas	-City of- [125]		0			0.666	0.032	
Doha, Qatar	Kahramaa [150]	2	5	1	2	1	0.035	
Hong Kong	WSD [151]	3	8	0.05	1	14	0.02	321
Houston, Texas	Public Works [152], [153]	7.6	15			0.4		
London, England	Thames Water [154]	1.2	0.9	0.07	0.4	34.4	0.382	629
Los Angeles, California	SCV Water [155]	2	5			0.4		2200
Manchester, England	United Utilities [144]	0.48	0.91	0.13	0.09	2.21	0.0115	136
Melbourne, Australia	GWW [156]		17	0.2	0.2	0.37		620
Paris, France	eau de Paris [157]					36		698
Rome, Italy	Acea [158]	2.9	2		2	37.9	0.1	896
Singapore	PUB [159]	0.69	0.5	0.03	0.2	3.67	0.13	468
Taipei, Taiwan	TWD [160]	1.7	1.1	0.03	0.8	0.34	0.3	
Toronto, Canada	-City of- [32]	0.9	3.86	0	0.02	0.59	0.009	389
Washington DC	DC Water [161]	0.4	15			2		

Table 10 below documents the Tap Water Quality normalised scores for each case study. The scores for each sub-indicator are the highest yearly recorded measurements. The worst possible score for each sub-indicator is the maximum recommended upper limit from Table 9 above, for example, 10 µg/L for Lead. The normalisation function for scores is found in Script S4 in Appendix B – Software under sub-section Supplementary Scripts.

Instead of using zero as the best possible score, a new normalisation implementation is employed for this custom indicator called 'Mixed Compliance'. The way it functions is that the best possible score for each sub-indicator is equal to half of the maximum recommended upper limit, or, in other words, half of the worst possible score. This innovative approach is done to be fairer, where concentrations of contaminants are low but still detectable, by rewarding case studies with perfect scores for those sub-indicators. This is considered fairer because a perfect score would otherwise be nearly impossible to achieve, as measurements of contaminants are very likely still to be detectable even in small concentrations, and it may not be fair to penalise what may be unavoidable.

The Mixed Compliance score for each case study is between zero and seven, with seven being the number of sub-indicators. A higher score is better. This is then normalised in the range of 0-7 to percentages of 0-100% or fractions of 0-1, which is then the final score for this indicator.

Regardless, case studies receive a score of 0 for this indicator where no data is published. This is applicable to any indicator where data is lacking, considering that these measurements are considered to be fundamental and expected to be published by all water suppliers.

Table 10 – Tap Water Quality final scores spreadsheet

City\Score	Water Supplier	Report Reference By Most Recent Dates	Mixed Compliance Score (higher is better)	Normalised Mixed Compliance Score (higher is better)
Best Possible Score		-	2.148	100%
Worst Possible Score			0.000	0%
Amsterdam, Holland	Waternet [146]	10/2022-12/2022	1.593	74%

Bahrain	EWA	2015 [143]	0.540	25%
Berlin, Germany	BW [147]	2022	2.148	100%
Brussels, Belgium	Vivaqua [148]	09/2023	2.148	100%
Copenhagen, Denmark	HOFOR [149]	07/2022-01/2023	2.148	100%
Dallas, Texas	-City of-	2021 [125]	0.088	4%
Doha, Qatar	Kahramaa	2014 [150]	1.958	91%
Hong Kong	WSD [151]	10/2021-09/2022	2.118	99%
Houston, Texas	Public Works	2021 [152], [153]	0.505	24%
London, England	Thames Water	2023 [154]	2.139	100%
Los Angeles, California	SCV Water [155]	2021	1.076	50%
Manchester, England	United Utilities	17/03/2023 [144]	2.148	100%
Melbourne, Australia	GWW [156]	2022-23	1.086	51%
Paris, France	eau de Paris	2021 [157]	0.019	1%
Rome, Italy	Acea	2018 [158]	1.450	68%
Singapore	PUB [159]	07/2021-06/2022	2.148	100%
Taipei, Taiwan	TWD	2022 [160]	2.143	100%
Toronto, Canada	-City of- [32]	2022	2.148	100%
Washington DC	DC Water	2023 [161]	1.025	48%

4.3.3.2. Median Lethal Dose

To improve upon the WHO recommendations, the possibility of using a concept called 'Median Lethal Dose' (LD_{50}) [162] was considered to penalise lack of compliance with heavy metal levels more so than nitrates and nitrites and conductivity, which would make intuitive sense. Even adhering to the WHO guidelines, heavy metals are measured in ppb, nitrates and nitrites in ppm, while conductivity has no WHO guideline, meaning that heavy metals are more lethal. Regarding conductivity, incidentally, the EU guideline of 2500 µS/cm @ 20°C [163] is adopted.

The LD_{50} of a substance is the dose required to kill half of those who ingest it within a specified period of time and is typically in the units of g-substance/kg-bodymass·day [162]. Using LD_{50} to either generate weights or replace the guidelines was not selected for several reasons:

There is a lack of human data for certain substances, such as Arsenic [164]. The extent to which animal data is translated to humans has been argued, and still, there is no standard way to compare a value for a specific animal, such as a dog, rat, or mouse, to a human. Merely multiplying by a constant coefficient would not work well because results vary significantly not only between different LD_{50} values of different substances but also between repeated measurements of the same substances [165].

Moreover, different members of the same species may widely vary in their health status, and to get an accurate LD_{50}, many large samples would have to be tested repeatedly, which would be expensive and invoke ethical concerns; hence, data on even animals is limited and has high uncertainty.

There is also no value for conductivity, hence a linear LD_{50} comparison could not be used completely regardless.

4.3.3.3. Analytical Observations

As the only analytical experimental analysis of this research, tap water samples were taken in the case study of Manchester, England, on Friday, the 26th of January 2024, after one of several maintenance procedures carried out by the local water supplier, United Utilities. The water supplier only notified a generic notice months ahead of time (see Figure S1 in Appendix C – Index), so the exact moment came as somewhat surprising, and claimed the maintenance event was essential and unavoidable. Picture 2 and Picture 3 below visually demonstrate the differences in turbidity of the tap water during the maintenance procedure (samples in the centre and left) against the water taken hours after the maintenance was over (sample on the right). There were also sediments accumulating at the bottom of the maintenance samples.

Picture 2 – Tap water samples without flash   *Picture 3 – Tap water samples with flash*

This illustrates that, indeed, even an impressively highly ranked case study such as Manchester, with a score of effectively 100% based on self-reported tap water quality statistics, does not appear to be so flawless in real life. "Regular maintenance procedures" can technically also be seen as a euphemism for water supply disruption incidents, as these could theoretically be done less frequently and would have a lesser impact on turbidity if the infrastructure and management were to improve.

However, there is clearly a high uncertainty here due to the nature of self-reporting by the supplier, which would not be the case for other vulnerability indicators, such as satellite data Soil Moisture Content.

One has to wonder if this research had more budget, more samples could have been taken of tap water quality directly inside all the case studies, and given a more accurate tap water quality analysis, such as more of these discolouration events. If these events occur in a high-scoring case study, it is likely to happen in others and perhaps even more in lower-scoring case studies. See sub-section 5.3.5: Analytical Experimental Verifications in the Further Work – Index section for further details.

4.3.3.4. Resiliency Improvement Suggestions

Considering that to get a higher score in Table 10 – Tap Water Quality final score in sub-section 4.3.3.1, a case study city would need to at least measure most of the substances listed as sub-indicators in Table 9 in sub-section 4.3.3.1, a good first aim for increasing the score of a case study city would be to list every substance in its Tap Water Quality Reports. These are universally standard to measure, especially the four heavy metals of Arsenic, Lead, Mercury, and Cadmium, which hold the highest weights in this custom Tap Water Quality sub-index.

Of course, measurements alone do not improve tap water quality directly, but they can indirectly by measuring which substances are at too high concentrations and then addressing the root cause, such as a source of contamination. For example, if lead concentrations are too high but only lead and no other contaminants, this may indicate the use of old lead water pipes. In case the materials of the pipes were not recorded when they were installed, it is possible to find their location by measuring the quality of the water in different sections of the mains pipelines to pin down where the lead pipes are in order to replace them.

A major risk for contamination of drinking water is leaching from the water pipes themselves and their joints. This is especially the case because the lengthy journey from the supplier to the consumer may cover different materials from which water pipes are composed, allowing plenty of opportunity for some of the material to leach out. Water mains pipelines are primarily made of three types of materials: concrete, metal, and plastic. Each material can leach, but some are more likely to, and some leached substances are more dangerous to health than others.

Of the metal pipes, lead is the most adverse to health as it is a dietarily non-essential heavy metal with its WHO maximum recommendation guideline of 10 µg/L | ppb [138], whereas copper and iron are both dietarily essential minerals. The WHO set a maximum guideline of 2 mg/L | ppm for copper [138] and no maximum guideline for iron. For reference, though, the WHO does mention that 0.3 mg/L | ppm of iron in drinking water is most likely safe, as it is roughly typically the average concentration in drinking water [166].

The UN also referenced these exact recommendation guideline numbers, including a comment that iron's guideline is about taste more so than health [137]. Too much of any substance can be toxic, as the saying goes, "the dose makes the poison". Even so, both copper and iron have more bioavailable forms, such as heme-iron [167], [168], [169] found in food, hence no amount of leaching should be deemed desirable.

The 2015 Hong Kong incident covered in section 1.2 involved residential lead pipes [33], [34]. The water mains pipelines that distributed water around the city were not composed of lead, which was most of the length the water travelled. Rather, the lead pipes were specifically in certain neighbourhoods.

This goes to show the importance of considering the materials of water pipes to limit leaching. Sub-section 'Types of water pipe materials' in Appendix C − Index compares the advantages and disadvantages of the various materials of water pipes. As a summary of the comparisons there, it appears that all three main types of materials for mains water pipes, metal, plastic, and concrete, leach into the water they distribute. Having said that, microplastics seem to be of serious concern, so it probably makes sense to prioritise using metal and concrete for WDN mains pipelines and to keep plastic pipes for inside residential areas instead. This may limit the length of the journey distributed drinking water has to be exposed to plastic. On the other hand, the 2015 Hong Kong incident shows that the small distance of residential pipes is all that is required for contamination. This can potentially be due to a lack of proper maintenance by the local neighbours, whereas the water supplier might be more keen to perform maintenance on pipes that are directly under its responsibility, i.e. the WDN mains.

Inside homes, pipes can be either plastic polymers or metal alloys, but not concrete, because concrete pipes have wide minimum diameters. Steel has the advantage of being able to be detected via a magnetic metal detector if pipes are hidden inside walls and roofs, to prevent drilling or striking nails into them. It can also be used as an electrical ground/earth in some places for various applications. Both polymers and alloys are cost-effective and are simple to connect, hence they are often preferred not only for potable water but also for wastewater.

There is indeed a trend towards more demand for the polymer PVC and HDPE pipes with sustained demand for the conventional materials of concrete and metal alloys, most notably Ductile Iron Steel [170], [171]. Interestingly, there is little mention of lead pipes in the projection of investments; hence, it appears that whatever lead pipes are still used are being phased out, while no new pipes are made out of lead.

4.3.4. Source Water Quality

Following the above sub-section 4.3.3: Tap Water Quality, source water quality was chosen to be a sub-index for the same reasons. The weighting and ranking methods of the Water Quality sub-indices are also Manual Assignment and WSM for simplicity. Considering that there is no need to be concerned with either method not working for scores of zero, the score ranges for BOD, Total Nitrogen, and Electrical Conductivity were decided to be 0-4 as opposed to 1-5 for convenience and simplicity. The weights were decided based on the general understanding of which indicators are most critical, though they are mostly used for illustration.

Similar to Water Stress and Flood Risk, it is based on data in interactive maps. See Source Water Quality Interactive Maps in Appendix C – Index. An interesting observation is that the more detailed data for Dissolved Oxygen, Nitrates, and Total Phosphates is actually less recent and originates from 2010. This means that the overall weight of this indicator of source water quality in the Custom Index should be lower than that of tap water quality.

One challenge with measuring source water quality is with Case Study Cities that import or otherwise transport their water from miles away, some over a hundred miles away. These include, for example, Manchester, Riyadh, and Mexico City. The problem is that the data in the Source Water Quality Interactive Maps in Appendix C – Index could be misleading if they estimate different scores for the locations of the source and the city. This problem can be both type I and II errors, i.e. a bad quality source can rank highly if the target city has good satellite data, and vice versa. The solution which was implemented here is simple, and that is to harshly record the worst score on any of these maps for any point in the transport journey. This means that whether the worst estimated score is the source, the city, or anywhere in between, that will be noted as the source water quality score.

This addresses the fact that the quality of the transported water can alter along the way, especially due to wastewater effluent. This idea can, however, be challenged in terms of the boundary condition requirement set up in sub-section 4.3.1: Indicators Selection Requirements. This naturally poses a disadvantage for those transporting water from further away, but this is indeed in line with disadvantages in real life. Importing water for over a hundred miles is generally unfavoured due to the complex journey it takes and the capital costs required for setting it up. Longer length closed systems of pipelines spend more energy pumping distributed water and are more susceptible to leaks, either by accident or by malice. Longer open channels, such as rivers and aqueducts, experience increased evapotranspiration and a greater chance for contamination.

Table 11 below documents the scores for six sub-indicators for the source water quality sub-index:

Table 11 – Source Water Quality sub-index scores spreadsheet

Indicator Case Study City	BOD	Total Nitrogen	Electrical Conductivity	Dissolved Oxygen (DO)	Nitrates	Total Phosphates	Source Water Quality Score
Interactive Maps Sources	Map S10 in Appendix C – Index WWF 3.1.1 [172]			Map S11 in Appendix C – Index Quality Unknown [12]			-
Year of Data	2019			2010			-
Weight	3.00	1.00	1.00	1.00	2.00	2.00	10.00
Best Score	0	0	0	10.5	0	0	10.00
Worst Score	4	4	4	5	4	0.95	0.00
Amsterdam, Holland	3	4	3	7	3	0.38	3.06
Bahrain	4	4	4	5.2	0.75	0.35	2.92
Berlin, Germany	4	4	3	10.5	1.4	0.22	4.09
Brussels, Belgium	4	4	4	7.5	2.8	0.55	1.90
Copenhagen, Denmark	2	4	3	9	1.3	0.24	5.32
Dallas, Texas	2	4	3	7.5	0.7	0.18	5.48
Doha, Qatar	4	4	4	5	0.75	0.43	2.72
Dubai, UAE	0	3	3	5	1	0.43	6.09
Hong Kong	2	3	2	5	0.8	0.3	5.22
Houston, Texas	1	3	2	7	0.7	0.15	6.70

Kuwait City, Kuwait	3	4	3	5	0.75	0.34	3.91
London, England	3	4	4	9.5	4	0.6	2.31
Los Angeles, California	1	3	4	7	0.65	0.2	6.12
Manchester, England	2	4	3	10	3	0.37	4.38
Melbourne, Australia	1	3	3	9	0.75	0.17	6.74
Mexico City, Mexico	4	4	3	5	1.6	0.41	2.59
Paris, France	3	4	3	9	1.2	0.27	4.56
Riyadh, Saudi Arabia	3	4	4	5.5	0.8	0.41	3.58
Rome, Italy	4	4	3	9	1.2	0.17	4.02
Shanghai, China	3	4	3	6	1.3	0.3	3.90
Singapore	2	3	2	6	0.6	0.2	5.71
Taipei, Taiwan	1	4	1	6	1.1	0.2	6.21
Toronto, Canada	4	4	3	9	1	0.19	4.08
Washington DC	0	4	2	9.5	0.7	0.95	5.97

4.3.4.1. Resiliency Improvement Suggestions for Effluent Discharge and Saltwater Intrusion

Indicators such as Nitrates, Phosphates, and BOD can be the result of discharged untreated wastewater effluent [173]. In the 'BBC Panorama: The Water Pollution Cover-Up' Documentary [174], the release of untreated wastewater was clearly shown to be the result of a lack of proper inspections. This documentary raises an issue with water suppliers such as United Utilities, which is incidentally the same water supplier as in the case study of Manchester, England.

The issue is that although water companies can treat wastewater properly before discharging it, they often discharge untreated sewage to rivers and the sea, as it is more economical for them if they can legally evade penalties. They manage to avoid detection legally because the days of inspections are known to them in advance, and therefore they discharge the majority of the waste after, and not right before, the inspections. The BBC Panorama documentary uncovered how notifying a water treatment company in advance alters its behaviour to wait to discharge its untreated waste only after the inspection. A simple and basic reform would be to replace scheduled inspections with surprise inspections.

Another issue is incentives. Not only on the part of the inspected water company, but also the inspectors themselves. Monopolies lead to lower quality-per-price ratios due to insufficient competition. Similar to how there can be a monopoly in manufacturing if only a single company produces a certain good, there can be a monopoly with regard to inspections. A for-profit company could be more likely to discover an actual breach of environmental regulations by its competitor than government inspectors, both thanks to the profit motive of a competitor and also because a competitor, being themselves a proven expert in their field, understands the practicality of how to circumvent due diligence.

No entity spends its money as responsibly as the money it earns, and companies work harder to generate revenue so they are less likely to waste it. Therefore, another simple reform is to allow multiple competitors in the same regions, as well as private companies in general, the license to conduct surprise inspections of each other, which will be financially rewarded for discoveries of breaching protocol, along with negative advertising and fines for the polluter. This does not need to completely replace government inspectors, but considering their inspections are often insufficient on their own, it may prove productive to partly supplement with private inspectors as well.

Besides the discharge of untreated effluent, water sources also face a vulnerability from a concept known as Saltwater Intrusion. It is the migration of saltwater, for example, brackish and seawater, into freshwater bodies such as aquifers, rivers, and lakes. See Figure 20 below for an illustration [175]:
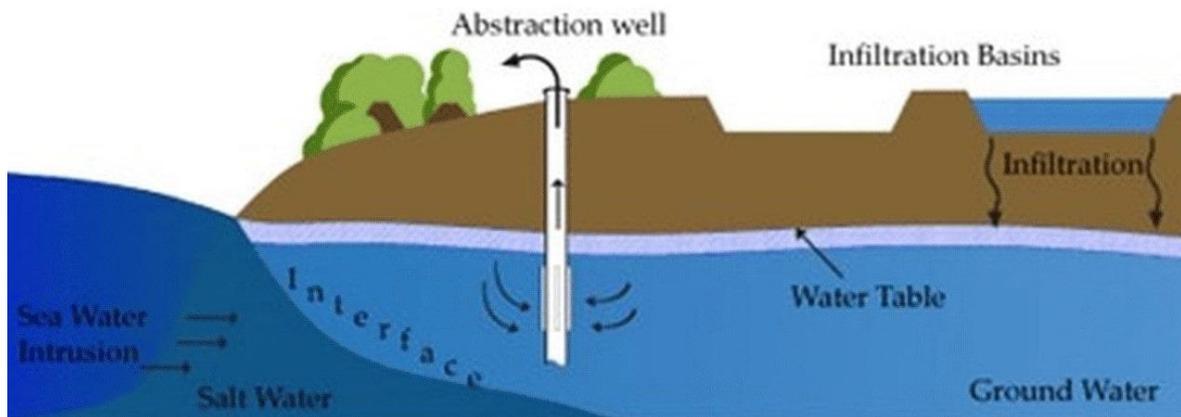
Figure 20 – Side Visual of Saltwater Intrusion [175], CC BY 4.0 cropped

Beyond harming the natural biodiversity [176], it can cause sources of water to require more extensive treatment and lead to water shortages, as conventional treatment cannot produce drinking quality water from sources of water over certain thresholds of salinity [177]. An affected region of south New Orleans, Louisiana [178], which left thousands without a local water supply due to Saltwater Intrusion from the Gulf of Mexico into the Mississippi River. Other susceptible regions include Maryland [179] and numerous others globally.

Possible solutions include building dams, dykes, and considering nanofiltration and reverse osmosis [177] desalination methods over conventional microfiltration. Dams and dykes can be expensive, and desalination is more expensive than conventional treatment. Affordability is a vulnerability in and of itself; more on that and desalination versus conventional treatment in sub-section 4.3.8: Affordability. Desalination also filters out desirable minerals, for example, magnesium [177].

Another issue with embracing desalination, or hybrid methods, is that it takes time to adapt, while Saltwater Intrusion in the environment has already occurred in the aforementioned regions faster. While local water suppliers weigh their options and work to adapt, Saltwater Intrusion has already caused water shortages, leading the locals to rely on water from neighbouring regions.

4.3.5. Water Stress

Water stress is defined as the "freshwater withdrawn as a percentage of total available locally" [21]. In other words, it is a ratio that should be kept as low as possible. A small denominator for this ratio is referred to as water scarcity, or a small absolute amount of water available.

This relates to mm Water Balance (Storage Change [19], [86], [117], [180] IB-NET 7.1), and in fact, these two indicators measure the same vulnerability; hence, Water Stress was preferred due to more abundant data, as shown in Water Stress Interactive Maps in Appendix C – Index. An online interactive map named the 'Water Balance App' was found while researching, though its soil moisture content data was inconsistent compared to the aforementioned ECMWF Satellite data from Map S1 in Appendix C – Index, hence this app and indicators were eventually selected against being used for its questionable 'Change in Storage' data. See Water Balance Change in Storage Interactive Map in Appendix C – Index for further details on Water Balance.

Due to the availability of specific Interactive Maps and the nature of data for both this and the indicator of Flood Risk in sub-section 4.3.6 below, both indicators are measured in the range of 1-5. This is because data is given in the interactive maps as five possible scores of 'Low', 'Low-to-medium', 'Medium-to-high', 'High', and 'Extremely-high'. These are normalised mathematically in a 1-5 range, where 1 is best or 'Low' and 5 is worst or 'Extremely-high'. Initially, the Custom Index normalised this data in a range of 0-4, but it caused a mathematical problem where a specific weighting method known as 'Entropy' does not work at all for scores of zero, as it causes division by zero. 'Entropy' is a custom weighting method taken from the MCA literature designed to correlate with standard deviation, and presumably improve upon it. See sub-section 3.2.5: Entropy.

4.3.5.1. Resiliency Improvement Suggestions

Considering that water stress is the ratio of withdrawal to available water, as also specifically defined in the Water Stress Interactive Maps, it can be mitigated by addressing both aspects. It is easier to understand using Sankey diagrams, as shown in Figure 5 and Figure 6 in section 1.3 for reference.

To maximise renewal, it is important to increase the effective catchment area. Map 5 [181] below presents Singapore's effective catchment area. Besides rain that drops directly into the reservoirs (dark blue), rain that drops in the rest of the "effective catchment" (light blue) is drained into the reservoirs through a pipeline system separate from that of wastewater sewage, as shown in Figure 21 [182] below. Rainwater from gutters can also be harvested for personal use and stored in water tanks.

Map 5 – Singapore's Catchment Reservoirs [181], PUB, Singapore's National Water Agency
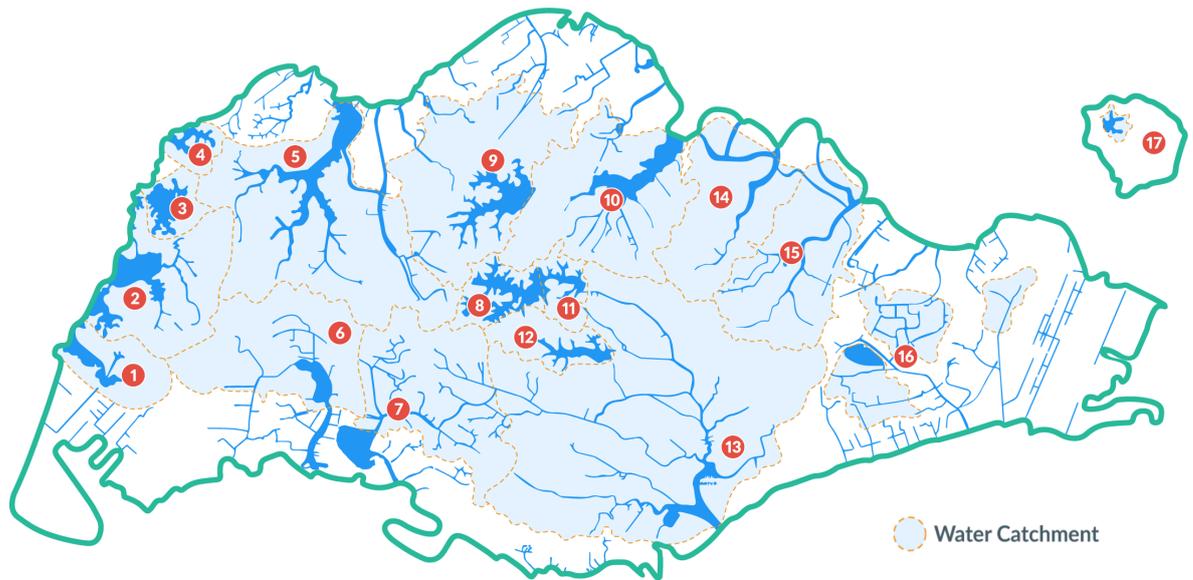
1 Tengeh Reservoir	5 Kranji Reservoir	9 Upper Seletar Reservoir	13 Marina Reservoir	16 Bedok Reservoir
2 Poyan Reservoir	6 Jurong Lake	10 Lower Seletar Reservoir	14 Punggol Reservoir	17 Tekong Reservoir
3 Murai Reservoir	7 Pandan Reservoir	11 Lower Peirce Reservoir	15 Serangoon Reservoir	
4 Sarimbun Reservoir	8 Upper Peirce Reservoir	12 MacRitchie Reservoir		
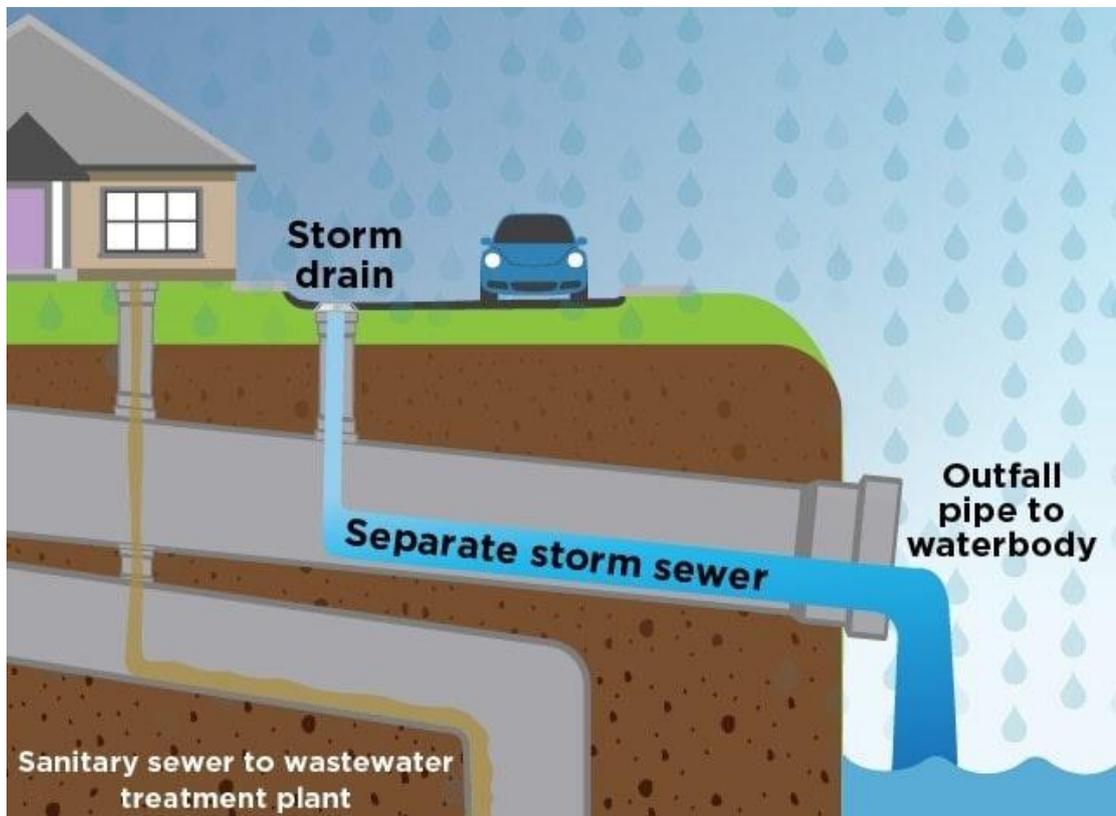
Figure 21 – Side Visual of separate wastewater and rainfall drain systems [182], Public Domain

To limit withdrawal, water needs to be conserved more. With regard to conserving the use of any resource, there is the concept of the three 'R's to consider: Reduce, Reuse, and Recycle. Water 'Reuse' is referred to as 'Grey water'. Refer to section 1.3 for a detailed list of grey water applications. 'Recycle' produces a new product, whereas 'Reuse' reuses an existing product; hence, recycling is the most energy-intensive and therefore expensive. Refer to Figure 5 in section 1.3, which presents Singapore's water recycling called 'NEWater'.

There are numerous water reuse and recycle applications in industry, agriculture, and domestically, though it is not always certain which of the two terms best describes an application, considering that reuse and recycle are a spectrum where recycle requires extensive filtration treatment, while reuse requires minimal treatment.

Regarding 'Reduce', there are numerous methods. Picture 4 [183] below shows how conventional sprinklers not only use up more water than drip irrigation in Picture 5 [184] but are also not as targeted, considering the gaps between rows of vegetation, furthering the waste of water. Some plants do require more water than others, but even so, it can be accomplished with drip irrigation.

Picture 4 – Sprinkler Irrigation [183], CC0 1.0   *Picture 5 – Drip Irrigation [184], generated using DeepAI*

A similar method to conserve, or 'Reduce', water use is the timing. Strategically watering plants during darker hours, namely when cloudy and during early mornings and late afternoons, as opposed to at noon, to save up a significant amount of water from transpiration [185].

Another method is limiting the flow rates of taps by designing taps that only allow for a moderate maximum flow rate, as well as self-reset taps, especially in public places where there is no financial incentive for water consumers to conserve water.

Other methods of reducing water use include high water prices (or at least no subsidies), not decreasing water prices with increasing consumption (avoiding a so-called 'decreasing block tariff' to "incentivise" industries), importing products that require a lot of water to produce instead of producing them locally (both industrially and agriculturally), smart metering systems and utilising seawater for toilet flushing [186] as shown in Figure 6 in section 1.3.

Another way to preserve precious water is to focus on saving blue water, which is the most expensive type of water, even at the expense of more green water if available. In the example of Figure 22 below [187], it may make sense to grow legumes instead of maize or vineyards instead of all other crops in water-stressed regions where blue water is scarce. Figure 22 measures the volume of water required to grow one ton of various crops; however, the bar chart could have been rearranged to have other units depending on alternative considerations, including the nutritional and economic values of different crops.
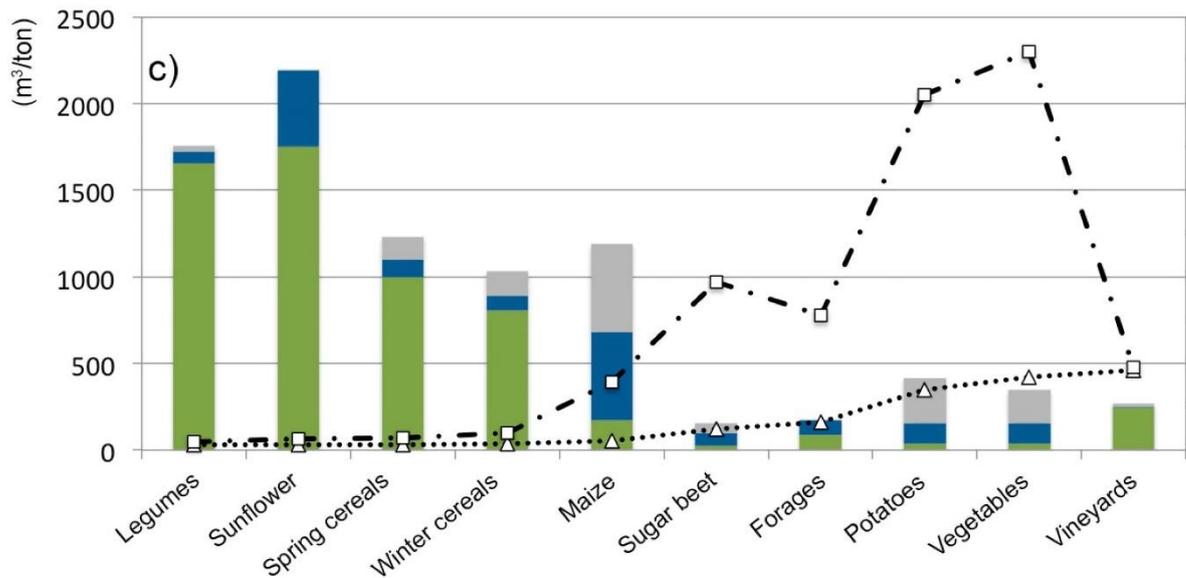
Figure 22 – Bar Chart of blue, green, and grey waters demands [187], <u>CC BY 4.0</u> cropped

Regarding more uses of rainwater, Picture 6 below displays a rare but unique application in Japan, which stores drained rainwater and uses small sprinklers in the roads for two purposes: cleaning the road and replacing salt to melt snow and ice using hot water [188]. For the latter use, this would only be useful in areas that are not too cold so that the water would not freeze. This is a use of water that would otherwise not be used and might save on blue water to perform the same task.

Picture 6 – Road Sprinklers [188], <u>CC BY 3.0</u>

4.3.6. Flood Risk

Floods pose a risk to WSS because they can contaminate the distributed water and corrode metal pipes with salinity, as well as rupture pipes due to the force of waves. Floods can be salty due to the overflowing of saline surface bodies of water, typically a sea, but can also be a river.

Because of these two sources from which water can overflow and cause flooding, unlike the indicator of Water Stress above, Flood Risk is quantified in this Custom Index as the harshest risk between coastal and riverine flooding, as data is presented in Flood Risk Interactive Maps in Appendix C – Index. Multiple papers mention floods separately from natural disasters (See Table S2 in Appendix A – Literature) and several focus specifically on flooding as the major risk to water systems [4], [21], [66], [48], [189].

A 2024 incident of deadly flooding in the case study of Dubai caused both water and electricity outages, along with fatalities [36], [37], [38]. It is a classic example of saying as was described in Chapter 1: Introduction: "It would never happen here or to me". Being the worst flooding event in decades for the region, there was no preparation because, as a low precipitation area, the local authorities did not pay enough attention to flood-preventing and mitigating measures. Had they invested ahead of this incident, the lives could have been saved and the outages prevented.

4.3.6.1. Resiliency Improvement Suggestions

Firstly, it is important to prevent overflow from seas and rivers. Learning from the experiences of others, no culture is more well-known for fending off the sea than the Dutch. Map 6 [190] below maps out two-thirds of the Netherlands territory, which is susceptible to coastal flooding from the North Sea. The city of Amsterdam is fully below sea level and is right off the coast. The primary solution the Dutch have had for centuries has been constructing dykes, as shown below in Picture 7 [191]. A dyke is defined as "an artificial slope made of earth or stones" [14], see the Nomenclature.

Picture 7 is specifically a dyke of the River Irwell in the case study city of Manchester. It demonstrates how flood prevention measures can increase the total green surface area of a city and therefore produce more clean oxygen to breathe. Note that it is safer to build houses and lines of their utilities (gas and water pipes, and electricity cables) further away from the dyke, and place a medium buffer in between, for example, a secondary road, as is the case in Picture 7. Another safety practice is to keep the apartment buildings even further away from the river than the attached homes, to limit the potential number of those affected by flooding per area.
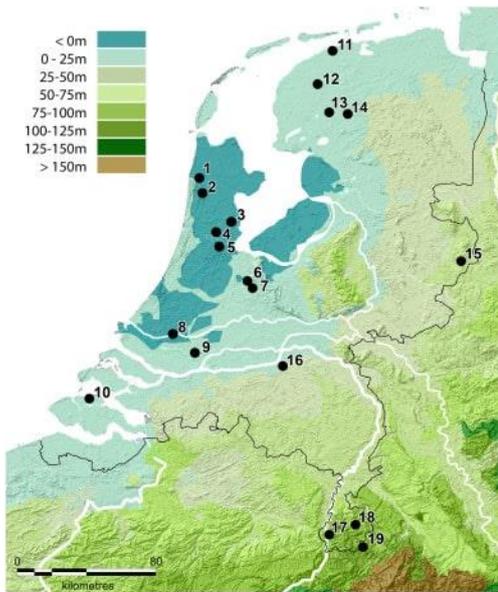
Map 6 – The Netherlands' elevation [190], CC BY 4.0

Picture 7 – River Dyke [191], © Google & partners

Resiliency investments against sea and river overflow can also include setting up automatic self-closing floodgates using the overflow water itself as the hydraulic fluid [192], shown below in Figure 23 [193]:
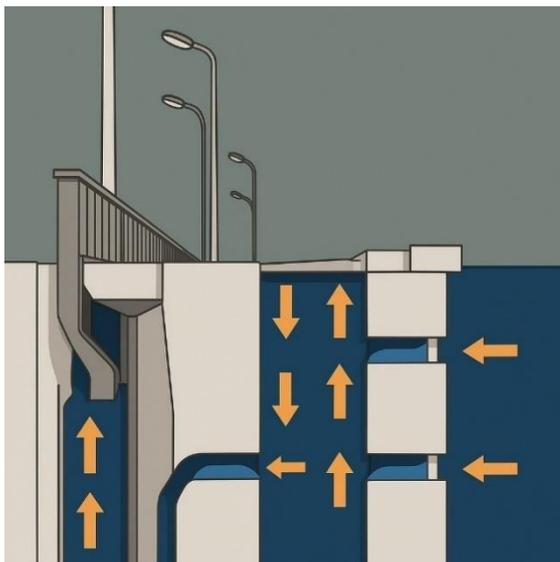
Figure 23 – Side Visual of self-closing hydraulic floodgate [193], generated using ChatGPT
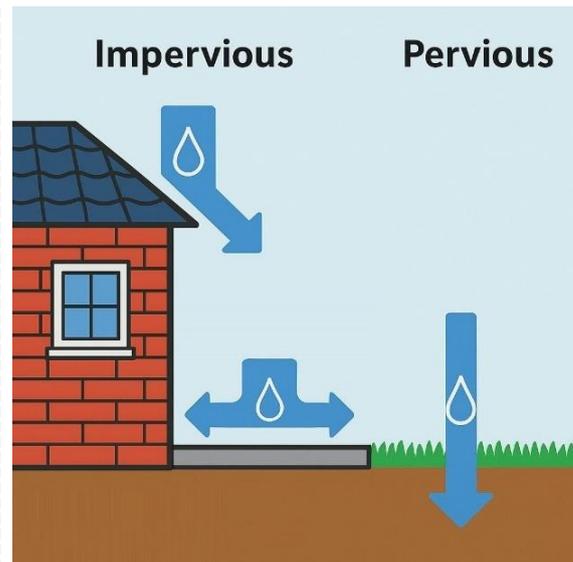
Figure 24 – Side Visual of pervious/impervious surfaces [193], generated using ChatGPT

As the Dubai incident demonstrated, flooding can occur not only due to high waves of the seas or overflow of rivers, but also due to heavy rains. When too much water from any source is introduced to an urban environment that lacks proper flood-preventing and mitigating measures, this water can accumulate. This accumulation is known as 'Runoff'. This is written arithmetically using the general balance CPE formula in Equation 12 below:

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Accumulation = In – Out + Generation – Consumption

Flooding-specific Water Balance, in the units of volumetric flow rate:

Runoff = Precipitation + River & Sea Overflow – Evapotranspiration – Ground Infiltration

Equation 12 – Flooding Water Balance

Figure 24 [193] above presents that a significant cause for the accumulation of runoff is impervious artificial surfaces, typically composed of concrete, such as buildings, roads, and sidewalks. These define cities and urban areas, yet they limit water from infiltrating into the soil and instead accumulate into runoff and exacerbate floods. It is intuitive that concrete is impervious, considering water pipes are made out of it.

Figure 25 [194] below illustrates the portions of evapotranspiration, ground infiltration, and runoff based on the type of environment, whether natural or urban.
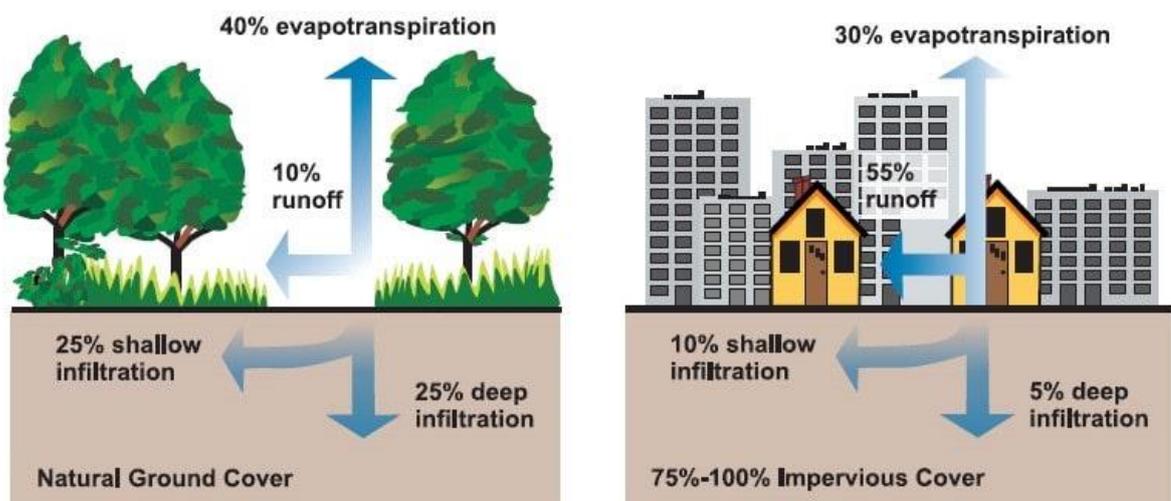
Figure 25 – Sankey Diagrams of natural versus urban runoff [194], Public Domain

An interesting observation regarding Figure 25 is that evapotranspiration is higher for a natural environment compared to an urban area, despite there being more runoff in the urban area. At first, this is unintuitive because the more water infiltrates, the less one would expect to be available to evaporate from the surface. This is the case because this is not evaporation as much as it is transpiration. This means that plants absorb the rainwater and it transpires from them without running off onto impervious artificial surfaces such as roads and pavements.

A natural environment has less runoff and is therefore better. A solution can be a mixed urban area with much of the surface area being both green and pervious, for example, grass, bushes, and trees. These not only reduce runoff by allowing more infiltration but also produce oxygen and thus improve air quality and mood, and therefore health. These green pervious solutions include some of the existing infrastructure that takes up much of the surface area, for example, car parking spaces and tram rails, as shown respectively below in Picture 8 [195] and Picture 9 [184]:

Picture 8 – Pervious Semi-Paved Grass Car Park [195],
CC BY-SA 4.0
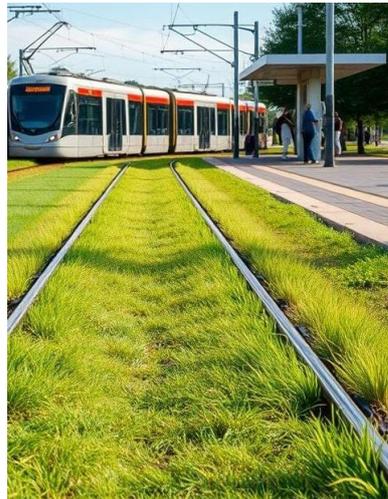
Picture 9 – Pervious Grass Tram Rail [184], generated using DeepAI

Picture 10 – Green Roofing [184], generated using DeepAI

Green car parks also enhance safety by lowering speed due to being semi-paved. The UK, which includes two Case Study Cities in this Custom Index, namely Manchester and London, has set a regulation requiring planning permission to construct a new driveway in private homes only if a proposed driveway is more than five square meters in impervious area [196]. Thereby incentivising the construction of the semi-concrete grassy driveways in Picture 8 as driveways that do not require the hustle of having to obtain a planning permission.

Green roofing, as shown in Picture 10 above [184], can also contribute to the air quality and green aesthetic, but referring back to the focus at hand, which is decreasing runoff by increasing ground infiltration, green roofing can only assist here to a limited extent. This is because any water it cannot absorb will be drained down in gutters to potentially become runoff, because roofs do not have the thickness that soil has, again referring to pervious grass car parks and tram rails.

An important criticism here of the 2016 Sustainable Cities Water Index [21] is its use of green space as an indicator. That index might have thought of green roofing as a good flood mitigation measure, though it did not clearly specify. It is inadequate to use a resiliency improvement solution for an existing indicator as another separate indicator because both measure the same vulnerability twice unnecessarily. Should all other solutions to indicators also be included as indicators? It would be too complicated. Moreover, green roofing specifically is the least effective solution for flooding of the ones discussed so far in this sub-section, due to it being thin and not able to absorb as much water.

Another solution for draining runoff from accumulating that is more effective than green roofing is called 'Kerb Drain', as shown below in Picture 11 [197]:
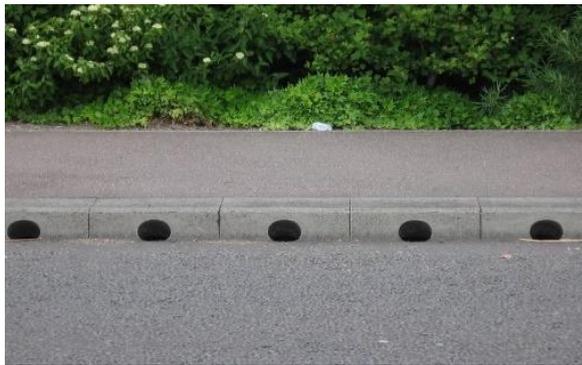
Picture 11 – Kerb Drain [197], CC BY-NC 2.0

Unlike conventional storm drain holes that are installed in the roads themselves, which are very uncomfortable and also insecure to drive and ride on, the kerb drain is on the side; hence, there is no need to drive or ride over it.

The holes of the kerb drain also decrease the amount of concrete needed per block, so they save on material. The holes can be made to be smaller than a conventional drain to prevent items from being dropped and lost down into the drain, for example, phones and keys. Maintenance is also important to ensure drainage holes are kept clear of garbage that could block the capacity to drain.

Kerb Drain can be combined with solutions that maximise pervious green areas, such as medians and roundabouts, as opposed to traffic lights, as shown above in Picture 11. Kerb Drain can be designed to be a high kerb or low enough to walk, ride, and drive on, as is also shown in Picture 11.

Conventional storm drains, being fewer and less distributed, are more likely to be accidentally placed in an elevated position and therefore inefficiently leave runoff undrained, as shown below in Picture 12 [193]. Even with a lot of runoff, the level of the runoff itself only rises a little and not enough to reach the drain. Even if some water reaches an elevated drain, the vast majority will not.

A storm drain, as shown below, should be sufficient to drain all the runoff, yet it does not because of its elevation and a bad construction design. Similar elevated storm drains can be spotted in parks.

Picture 12 – Elevated Conventional Storm Drain [193], generated using ChatGPT

The most important positions to place traditional storm drain holes would be the lowest elevations, as virtually all runoff flows down to elevation local minimums. These are where runoff accumulates in floods and causes the most damage. It makes sense to employ a mixed approach where conventional storm drain holes are strategically located in local minimum elevations, but all other flood-mitigating solutions discussed are also utilised. The combination of solutions maximises the effective catchment surface area as was described in the previous sub-section 4.3.5.1: Water Stress Resiliency Improvement Suggestions in Map 5 and Figure 21.

This distribution helps to ensure no one area lacks the means to drain water or is overwhelmed by the flow rate. There are other aspects of a mixed approach, namely the beauty of pervious grass dykes, car parks, tram rails, roundabouts and medians, and kerb drains, as well as the clean air from the grass. These solutions effectively manage to drain water into a dedicated drainage system separate from wastewater, as also shown in the previous sub-section in Figure 21 for a number of other uses already discussed.

Lastly, if pipes break during a flood, the leaks can add to the runoff and exacerbate the situation. Hence, it is important to strengthen pipes. See the 'Types of water pipe materials' sub-section in Appendix C – Index for material considerations for water pipes, including strength.

Clearly, there is a variety of effective flood-mitigating measures. They are all simple, and yet, those in charge need the foresight to take the time to set them up to prepare for floods, including from heavy rainfall, as was in the Dubai incident [36], [37], [38]. As the saying goes: "*It wasn't raining when Noah built the Ark.*"

4.3.7. Soil Moisture Content

Soil Moisture Content is defined by the ECMWF as the "content of liquid water in a surface soil layer of 2 to 5 cm depth" [23], see Table 4 in the Nomenclature. It is a proxy for drought [198]. Table 12 below documents the v/v yearly average and the lowest soil moisture contents of Case Study Cities for any calendar month. This data is taken from ECMWF's interactive map [199] as shown in Map S1 in Appendix C – Index. This data is based on satellite recording observations and models.

Table 12 – Soil Moisture Contents of Case Study Cities (%)

Case Study City	Yearly Average	Yearly Lowest	Case Study City	Yearly Average	Yearly Lowest
Amsterdam, Holland	40	37	Los Angeles, California	16	15
Bahrain	15	13	Manchester, England	42	32
Berlin, Germany	29	21	Melbourne, Australia	19	13
Brussels, Belgium	19	13	Mexico City, Mexico	13	8
Copenhagen, Denmark	50	42	Paris, France	39	30
Dallas, Texas	31	27	Riyadh, Saudi Arabia	9	6
Doha, Qatar	14	11	Rome, Italy	25	15
Dubai, UAE	11	10	Shanghai, China	58	46
Hong Kong	38	36	Singapore	28	29
Houston, Texas	37	34	Taipei, Taiwan	59	57
Kuwait City, Kuwait	15	12	Toronto, Canada	44	36
London, England	39	31	Washington DC	42	34

The majority of the soil moisture data makes sense, such as arid regions having lower yearly soil moisture contents compared to temperate climates. This indicator is considered good, meaning that a higher numerical score is better. It is advantageous to have a good availability of universal, reliable, recent, and accurate data, but also specificity regarding water supply vulnerability. It is logical to assume that places with lower soil moisture would struggle more with evaporation of their water reserves and generally increased water demand, especially for agriculture.

Soil moisture is important for plants and agriculture, as well as recharging underground water reserves, as opposed to having precipitation evaporate.

Map S1 in Appendix C – Index calculated yearly average soil moisture contents using data only from the year 2022, whereas yearly lowest soil moisture contents are calculated from data collected from the years 2003-2022. Therefore, even though both yearly lowest and average numbers utilise recent data, only the yearly lowest numbers are based on a wide range of two decades and therefore are more reliable. Despite this, all numbers from this app are given in the resolution of the nearest percentage or two decimal places, considering the data is given in the units of 'm^3 m^{-3}' as can be seen in Map S1. Thus, the uncertainty for the numbers in Table 12 above is ±1%. Moreover, the yearly lowest soil moisture contents are more critical than the yearly lowest because it is at the peak of drought when a water system is most vulnerable, hence it is decided to use the yearly lowest soil moisture contents from Table 12 above, not yearly averages, for the Custom Index in GUI 6 in section 4.4: Scores Results.

It is interesting to compare soil moisture content to the percentage of a person's body mass or volume which is water, considering the analogy of cities to organisms implied by the word 'Metabolism' in the title of this research, and as was mentioned in Chapter 1: Introduction by the inspirational book 'Scale'. Both Water Body Composition and Soil Moisture Content are measured in the same unit of percentage (%), cannot be physically less than 0% or more than 100% and must be within a narrow range for the person or city to survive, although a city being non-biological is more flexible. Also, even though neither is a perfect measure, they are excellent proxy indicators for large vulnerabilities. A low Water Body Composition can indicate low muscle mass, which famously holds at least 3g of absorbed water in 1g of glycogen [200], and potentially can be a symptom of other conditions as well. Compared to satellite data and ground measurements, Water Body Composition has its own measurement methods, for example, BIA, DEXA, and MRI [201].

4.3.7.1. Resiliency Improvement Suggestions

Both Soil Moisture Content and Water Body Composition can be improved, the latter with lifestyle choices. Due to a high correlation of Soil Moisture Content with Water Stress, as can be seen in GUI 5 – Criteria Correlations Matrix in section 3.4, the resiliency improvement suggestions for Soil Moisture Content would be largely the same as those above in sub-section 4.3.5.1: Water Stress Resiliency Improvement Suggestions. Another interesting consideration is the use of pervious surfaces as discussed above in sub-section 4.3.6.1: Flood Risk Resiliency Improvement Suggestions, to allow for ground infiltration and therefore soil moisture recharge.

4.3.8. Affordability

Since all indicators in this Custom Index are from the perspective of the supplier, so should this indicator of affordability. The affordability of the supplier is more centred around economics compared to traditional consumer affordability, which revolves around personal finance, particularly considering that a large portion of case studies have a single governmental water supplier. Even though 'Affordability' typically refers to the consumer side, it can also apply to the supplier side to measure the general wellness state of the economy as a whole. Affordability is defined as a condition where a product in question is cheap enough for a buyer to purchase, see Nomenclature. Therefore, supplier-focused affordability would focus on the cost of treating water.

Affordability as a consumer-focused indicator in water research is often measured in the number of hours someone who is being paid the minimum wage would have to work to afford a certain amount of water [202]. The idea is to care for the lowest paid in society, to ensure they can afford enough water to live decently. There are a number of issues with this approach. Firstly, several countries do not have a minimum wage, and they negotiate wages through unions [203].

Some countries that do have minimum wages may not enforce them in some cases. This approach also does not take into account unemployed people, some of whom may meet part of their water needs from various free sources, such as public taps. Furthermore, there are several legal ways to pay less than minimum wage, for example, requiring employees to work overtime, requiring lengthy preparation and commute times, which are unpaid, volunteer work, etc. As the minimum wage rises, so does unemployment [204]. This makes sense because if theoretically the minimum wage was set too high, it would force either breaking the law or laying off less productive workers to maintain profitability. This means that this metric does not take into account the unemployment rate and only rewards a high minimum wage with no limit, assuming all people can secure a job. On top of all these criticisms, this metric is not selected here because the focus of this research is on vulnerabilities that can cause disruptions in the distribution of water. A lack of affordability for the most vulnerable in society is not such a vulnerability, even though it can be devastating to those affected.

The first thought regarding the challenge of quantifying the affordability of water suppliers is to look at the water prices. These are known as 'Tariffs' [205], not to be confused with taxation on international trade. 'Water Tariff' tends to refer to the price of both drinking water and wastewater services, while the term 'Wastewater Tariff' exclusively refers to the fee for wastewater services. Although this is an imperfect measure, higher water prices could indicate high treatment costs.

Therefore, this cost is passed to consumers. The issue is that low water prices can be either due to having efficient infrastructure and management as well as plentiful sources of water, or it could be that water prices are occasionally low at the point of sale to consumers because they are subsidised, meaning the water supplier makes a financial loss. Governments subsidise products which they see as basic fundamentals, or in this case, specifically as a 'public utility' that needs to be affordable to all. This connects to the previous paragraph about the affordability of water to minimum-wage workers. Possibly the best illustrating example is the case study of Riyadh, which has by a considerable margin the lowest tap water price at £0.03/m³ [114] despite experiencing among the worst water stresses due to relying on both desalination and importation of water from over two hundred miles away. This is due to water being subsidised at roughly 70% [115].

Since both minimum wage and water prices are inadequate indicators for the supplier-focused affordability approach the Custom Index aims to employ, a new metric was developed. This metric is similar to the minimum wage metric but uses average GDP per capita instead because all countries have GDPs, which are relatively easily accessible statistics, and it shifts the focus away from socio-economics, which consumer-focused affordability indicators often revolve around in water research. This shifts the focus from price to cost. As noted in the Nomenclature, the difference in definitions between cost and price is that cost is the amount of money required to produce a product, whereas price is the amount of money required to purchase an existing product. Therefore, cost rather than price is more supplier-focused.

Therefore, this new affordability indicator replicates the consumer indicator of the number of hours working minimum wage indicator. Referring back to the beginning of this sub-section, a supplier-side affordability indicator would capture the general wellness state of the economy. But because it cannot use the water price, it has to use the water cost. This begs the question: how to measure the cost of producing drinking water? This is not a straightforward question, but breaking down the various costs associated with running a water system helps. Reflecting on the definitions of WDN and WSS as previously discussed in the Nomenclature and section 1.1, there is a distinction in terms of the treatment plants and the network of pumps and distribution mains pipelines. This new affordability indicator will focus on the treatment plants and not on the distribution costs. The reasons for this are twofold: One is to simplify, similar to narrowing the focus of this research to water supply as opposed to wastewater and other possible aspects. Two is because other indicators, such as Water Loss, already focus solely on the WDN. Now there is a need to make considerable focus on the other aspect of the WSS, which is the treatment plants that produce potable water.

Next, there needs to be a consideration as to whether to include the cost of constructing the water treatment plants, i.e. capital cost. The issue with this is that some plants are very old, while some are newer; hence, there is no fair universal method of comparison. Consider the case study of Toronto, which has four conventional water treatment plants commissioned between the years of 1941–1979 [206]. Even if adjusted for inflation, it is not clear that the cost of constructing these plants should be taken into the calculation of the total cost needed to treat water today.

An alternative approach is to pick a 'cut-off' period of 30 years, for example, and the cost of any plant constructed before that point would not be calculated in this indicator. The issue again is that this would be an arbitrary number, which would penalise plants that were constructed 29 years ago and reward those built 31 years ago. This can be argued to actually be the opposite, and older infrastructure could be seen as a vulnerability; read more on this in sub-section 4.3.10: Ageing Infrastructure. Therefore, capital costs of treatment plants are omitted from this indicator, the same as WDN costs. Instead, the focus is on the Operation and Maintenance Costs (O&M).

O&M is also a better choice to select because there is more data available for it. To estimate the O&M of case studies, some assumptions had to be made. Firstly, some case studies publish data on their expenses that allow for estimating their water costs directly. The special case study of Hong Kong imports the majority of its water from Mainland China in a fixed agreement of 820 MCM/year for 4.5 billion HKD/year, irrespective of actual consumption, in reference to the year 2015 [180]. Therefore, an estimate for the cost of water in Hong Kong is presented in Equation 13 below:

$$\frac{4.5 \times 10^9 \ \text{HKD}}{\text{year}} \times \frac{\text{year}}{820 \times 10^6 \ \text{m}^3} \times \frac{\text{USD}}{7.79 \ \text{HKD}} = \$0.70/\text{m}^3$$

Equation 13 – Hong Kong's cost of importing water from Mainland China

As shown below in Table 13, \$0.7/m³ is considered actually quite expensive. To calculate water cost as treatment O&M for the rest of the case studies requires other numbers and assumptions. It is fair to assume in the literature that the O&M in various locations worldwide can be estimated based on the cost of certain reference locations if the scale of treated volumetric flow rate is known, as well as a 'Location Factor' (LF). The purpose of LFs is to compare the purchasing power of certain locations to others to make educated estimates when data is lacking, as is the case here. For a location-based correction of purchasing powers, this indicator uses LFs by Faithful+Gould [111], [112]. As discussed previously in section 4.2: Case Study Cities, London was partly selected because it is the benchmark reference for Faithful+Gould's ENR at exactly 1.00 by definition.

This is similar to London also being the world's reference for Greenwich Mean Time (GMT). It is an advantage for Water Finance Research to utilise Chemical Engineering, as Chemical Engineers are experienced at gathering LFs for chemical and processing plants, and water treatment plants are very similar. Considering that LFs already take purchasing power into account, the GDP data does not need to be Purchasing Power Parity (PPP), as that would be double-counting, so nominal GDP numbers are used instead.

Next is estimating water costs in other case studies besides Hong Kong. Due to the limited reference sources of water costs, rough cost estimates were generated. A few sources report estimates for expected water costs based on the technology of the treatment plant. The following sources have a large uncertainty, and therefore so are the resultant indicator scores. However, the focus here is on methodology and directional accuracy. This means that these sources output numbers that make sense, i.e., the more expensive technology in practice is also that in the calculations.

The two main water treatment technologies considered here are conventional and desalination. To understand what conventional water treatment is, refer to Figure 4 – Side Visual of Coagulation, Flocculation, and Sedimentation in section 1.3. These two technologies each have estimates that were based on different reference sources, but what they both have in common is that the nominal figures calculated for any case study city, no matter which technology it uses, are multiplied by its LF divided by 100 to account for disparities in purchasing power. Faithful+Gould lists LFs in ENR around the 100 number, so the division by 100 is to turn it into a fraction for multiplication, as opposed to keeping it as a percentage. The smaller the LF, the better and more affordable a location. LF of less than 100 is more affordable and therefore has more purchasing power than the benchmark reference of London.

Starting with desalination, there is a paper that estimates that the most affordable seawater desalination costs $0.45 [207] for large-scale Reverse Osmosis (RO) of $+100,000 - 320,000$ m^3/day, which is well within the consumption rates statistics of the Case Study Cities that are recorded in Table S7 in Appendix C – Index. Several more papers also agree with this rough estimate [208], [209]. RO and economies of scale are assumed not only because they are more realistic, but also to note the most optimistic cost estimate for desalination, because it is still significantly more expensive than the conventional treatment estimate in the following paragraph:

One source estimates the O&M of conventional water treatment plants on a logarithmic graph [210]. A major assumption is made here, which is that several plants have the same cost per unit volume as a single large one.

This is done to simplify the comparison between Case Study Cities, as some have more treatment plants than others per volumetric flow rate. This assumption is probably realistic, as for any plant, economies of scale eventually reach a peak beyond a certain large capacity, hence why cities build multiple plants. Cities build multiple plants not only for safety in case one plant fails temporarily, so the others cover for it, but also to lower distribution costs as plants are spread around a city.

With this in mind, this source graphs O&M in 10^6/year against plant capacity in the units of 10^6 Imperial Gallons/Day (MGD). Performing dimensional analysis, the gradient of this graph interestingly comes out to the units of money per volume, which is the interest here. This is interesting because, unlike the previous desalination estimate, this estimate for conventional treatment does not require an estimated consumption rate, but rather only calculates a gradient to the log-log graph. The gradient comes out as ($7×10^6$/year)/(2,700 MGD). Adjusting units provides a $/m^3$ estimate below in Equation 14:

$$\frac{\$7 \cancel{\times 10^6}}{\cancel{year}} \times \frac{\cancel{Day}}{2,700 \cancel{\times 10^6} \cancel{Imp\ Gallons}} \times \frac{220 \cancel{Imp\ Gallons}}{m^3} \times \frac{\cancel{year}}{365 \cancel{Days}} = \$1.6 \times 10^{-3}/m^3$$

Equation 14 – Conventional water treatment cost estimate in $/m³

It would be amiss not to mention that this estimate for conventional water treatment is magnitudes cheaper than the above estimate for desalination. Again, this estimate is also supported by another reference source with a similar logarithmic approach [211]. Of course, these are only rough cost estimates from a few reference sources, but the focus here again is methodology and directional accuracy. A water supplier utilising this indicator may have access to more reliable data or examine more papers, but this will not guarantee the results will be any different. It makes sense that desalination is more expensive because it is more energy-intensive.

Considering that the source for this graph [210] is over a decade older than the desalination sources, this was further adjusted for inflation using the Engineering News-Record (ENR) Cost Index [212]. This price index was selected as opposed to a generalist inflation alternative, most notably the Consumer Price Index (CPI), because the source for this graph mentions an ENR number of 6,500. It was decided not to adjust desalination because its source did not provide an ENR number.

Moreover, a counterbalance assumption that in reality the advancements in desalination were developed faster than conventional technology; therefore, there is no need to further adjust for inflation.

Recall again that this indicator is more about generic rough estimates for costs to capture a larger picture and invent a new methodology, as opposed to spending a substantial amount of time obsessing over making very accurate estimates. With this in mind, 6,500 ENR corresponds to the year 2002. The most recent ENR estimate of 13,300 was taken in the last month of this index, which is May 2023. Taking ENR into account, the conventional water treatment cost is multiplied by the unitless ratio of 13,300/6,500 ≈ 2. Unsurprisingly, an adjustment for inflation still does not bring the estimate significantly closer to the same magnitude as desalination.

The final score for this indicator is nominal GDP per capita divided by the cost of water production, where higher is better. It may sound like a complicated unit, but it may very well measure the affordability of producing drinking water for the supplier relative to the amount of local purchasing power. It would be unsustainable if a location had too high water production costs.

GDP per capita is an objective measure of the general wealth and well-being of an economy, hence why it is utilised here. The reason nominal GDP is used instead of Purchasing Power Parity (PPP) is that the cost of water is estimated using LFs; hence, it is not desirable to correct for location twice in the estimate. Nevertheless, if different technologies yield costs of different magnitudes, it will make the decision between Nominal and PPP irrelevant to prove that the financial bottleneck is truly the technologies themselves. In future work, the use of PPP GDP instead of nominal GDP could do away with LFs for simplicity, although it does make sense to utilise LFs in an engineering context.

Looking at the results in Table 13 below, unsurprisingly, the largest disparity in water costs is due to the sources and technologies used as opposed to LFs. Desalination is more expensive than conventional treatment, even with the advancements in reverse osmosis technology and electro-dialysis around the corner. Had capital costs been considered as well, it is highly likely that this disparity would have been even greater. This is because conventional plants tend to be old [206], as advancements in conventional technologies are not as great (or need to be) as those in desalination, such as the shift from evaporative crystallisation techniques (MSF & MED) to Reverse Osmosis.

This means that cities which rely on desalination tend to have newer (built in the last ~30 years) and thus more expensive plants. For example, Hong Kong is currently developing its first desalination plant [213]. As desalination proves to be more reliable, cities that rely on it grow in population faster than cities that rely on conventional treatment; hence, even more capital costs are spent on building more desalination plants to meet growing demands.

Equation 15 below calculates the Affordability scores for Case Study Cities in Table 13 below:

$$\text{Location Factor} \times \text{GDP} / \text{Water Treatment O\&M Cost} = \text{Supplier Affordability}$$

Equation 15 – Custom Supplier-Focused O&M Affordability

Table 13 – Affordability calculations spreadsheet

Case Study City	Location Factor (LF)	Nominal GDP Per Capita ($/Capita·Year)	O&M Cost of Water Treatment ($/m3)	Nominal GDP Per Capita/Cost of Water Treatment (m3/Capita·Year)
References	Faithful+Gould [111], [112]	IMF [214]	[207], [208], [209], [210], [211]	-
Year Of Data	2014-22	2023	2000-2013	-
Best Score	Min	Max	Min	Max
Worst Score	Max	Min	Max	Min
Amsterdam, Holland	1.12	$61,100	$0.004	1.7E+07
Bahrain	0.81	$28,400	$0.36	7.8E+04
Berlin, Germany	0.97	$50,800	$0.003	1.6E+07
Brussels, Belgium	0.86	$81,400	$0.003	3.0E+07
Copenhagen, Denmark	1.04	$68,800	$0.003	2.1E+07
Dallas, Texas	0.93	$80,000	$0.003	2.7E+07
Doha, Qatar	0.81	$83,900	$0.36	2.3E+05
Dubai, UAE	0.65	$49,500	$0.29	1.7E+05
Hong Kong	1.38	$52,400	$0.70	7.5E+04
Houston, Texas	0.93	$80,000	$0.003	2.7E+07
Kuwait City, Kuwait	0.97	$33,600	$0.44	7.7E+04
London, England	1.00	$76,100	$0.003	2.4E+07
Los Angeles, California	0.93	$86,500	$0.003	2.9E+07

Manchester, England	0.90	$46,400	$0.003	1.6E+07
Melbourne, Australia	1.08	$70,500	$0.003	2.0E+07
Mexico City, Mexico	0.62	$12,700	$0.002	6.4E+06
Paris, France	1.06	$44,400	$0.003	1.3E+07
Riyadh, Saudi Arabia	0.79	$29,900	$0.36	8.4E+04
Rome, Italy	0.80	$36,800	$0.003	1.4E+07
Shanghai, China	0.40	$26,700	$0.001	2.1E+07
Singapore	0.87	$91,100	$0.39	2.3E+05
Taipei, Taiwan	0.53	$33,900	$0.002	2.0E+07
Toronto, Canada	0.92	$52,700	$0.003	1.8E+07
Washington DC	0.93	$95,600	$0.003	3.2E+07

Although the best efforts were made to ensure the most accurate data was gathered, ultimately, some data is rare in the literature, especially some updated recent data. Therefore, this indicator uses high uncertainty. The purpose of this index is to present a method to a user who might wish to re-create it as their own index, using more up-to-date and reliable data, should they have access to it.

4.3.8.1. Resiliency Improvement Suggestions

To improve a metric that is calculated by an equation, it is important to consider every variable in the equation. This is also the case with Water Stress. Improving the economy should increase the LF by reducing the cost of living, and of course, by raising the GDP. As for the cost of water treatment, water plants need to be more affordable to build and run, which can be done by improving the efficiency of their operation and construction. The running cost can be reduced with improved technologies, but ultimately, it may be the unfortunate reality for some arid water systems that desalination will always be more expensive for them than conventional water treatment.

Referring to the previous research, which inspired this project [30], it also concluded that the employed technology, whether conventional treatment or desalination, is a major bottleneck for affordability, though it is interesting to see that this is probably the case for both customer and supplier affordability.

4.3.9. Blockages

Similarly to 4.3.2: Water Loss, this is also an indicator documenting the prevalence of mains pipeline malfunctions. Water Loss can be measured as a material balance as a percentage of the total volume metered at the consumer ends relative to the volume distributed from the plants.

However, measuring blockages is more complicated. The difference here is that no water is leaked; it is, however, stopped from flowing to its intended destination. This actually makes it harder to quantify and lower priority because no water is lost, and as the saying goes, "water finds its way" around.

A Blockages indicator can represent the percentage of the WDN's pipes that are blocked either completely or in significant part. It can also represent the number of blockages per unit length or per unit length·time, as seen in literature [19], [48], [86](IB-NET 10.1).

To measure blockages, water meters would need to be installed throughout the WDN. These will gather data that will intelligently detect localised lower-than-expected flow rates. This approach will not only detect the locations of blockages but also of leaks. Metering only the consumer ends and water treatment plants allows calculating the total Water Loss rate, but not finding the locations of the leaks or the prevalence and locations of blockages.

This metric can measure either only the potable water distribution pipelines or also potentially include wastewater as well. This is because blockages in the sewage collection pipelines can cause issues with clogging, which can affect the ability to use distributed water. Wastewater, however, is more likely due to non-organic solids that consumers flush that they were not meant to, which complicates the nature of wastewater blockages relative to distributed potable water.

To protect pipes from earthquakes and other natural disasters, they would have to be strengthened by being built out of resilient materials. To protect from extreme weather such as freezing, they would have to be built deep enough to be further away from the freezing air above ground, but not too deep that they would reach permafrost [215]. Similarly, heating up water and pumping it at high velocity also helps to protect against freezing. Lastly, increasing the diameters of pipes and insulating them can also make them more resilient to being blocked or frozen and typically still allow for high flow rates, even though capital costs can be more expensive.

This indicator was not adopted for the Custom Index due to a lack of publicly available data, probably because it is harder to measure, and water suppliers are less keen to share such data.

4.3.10. Ageing Infrastructure

The idea of using the age of pipelines as a vulnerability seems logical. One would expect old pipes to be more likely to be blocked, leaked, corroded, contaminated, or made of contaminating materials, particularly lead. As for the last point, the materials pipes are composed of should have been known since the moment they were installed. The rest can be discovered based on local reports of leaks, bad water quality, or abnormalities in pressure.

Another aspect regarding the age of infrastructure is related to rainwater and wastewater systems. Older systems tend to combine rainwater and wastewater drainage for simplicity, but newer systems tend to separate these [216]. See Figure 21. The downside of a separated system is having twice the length of water pipelines, but the upside is having less volumetric flow rate of sewage to process, which can overflow the sewage system during heavy rains [216]. Separate systems allow the discharging of rainwater to the environment with no treatment or minimal treatment to generate potable water. See Map 5 in sub-section 4.3.5, which harvest rain for potable water.

As an MCA indicator, older pipes would most likely be penalised, due to being more likely to suffer from any of the aforementioned points. This, however, may not be completely the case every time in real life. Some older pipes might be more reliable as they have proven to withstand the test of time, while there are always risks with anything new. Nevertheless, there is clear evidence that some pipeline failures may appear to be due to ageing, such as in the Hong Kong 2017 incident, in which 36 main pipeline bursts were reported [35].

This potential vulnerability indicator was decided to be omitted mostly due to a lack of data availability. This research only found the city of New Orleans in Louisiana as a city that publishes a detailed and up-to-date interactive map of its major water pipelines by their date of installation [31]. It maps generations of 20-year intervals, but no pipes younger than 2019 or older than 1900, despite the fact that the city of New Orleans was established substantially earlier in 1718, and its modern water system started construction in 1879 [217].

As an aside, despite the availability of data for New Orleans, especially regarding its ageing pipelines, it was not selected as a case study, mostly due to not being in the 2016 Sustainable Cities Water Index [21]. Furthermore, there was nothing special to explore regarding New Orleans as far as water systems are concerned, besides the data on ageing pipelines, which, as mentioned, was decided to be omitted for future work.

The issue is the availability of data. Not only do very few cities have such interactive maps or similar data, but much of the data is over a century old and getting older, which is unique. This would require an exception to the requirement of 'recent' data in the 4.3.1: Indicators Selection Requirements.

There is also the matter of how to rank pipes exactly. Should it be similar to a WSM ranking, where older pipes receive a lower weight? How will the weights be given exactly? A score of 1 for those built within the last two decades and a score of 0 for the oldest, and linearly in between? What about the exact groups? Different cities may have different brackets for generations. If more cities were to publish such maps, software would be needed to count the exact length of pipelines by each age group. Even then, their widths and, therefore, maximum flow rates would also need to be taken into account.

Ultimately, in life, there are two types of ideas that sound good: the ones that are good without a doubt, and the more they are pursued, the better, and the ones that are at best experimental and are not clearly good. Having a low leakage rate, the least amount of blockages, and the lowest percentage of pipes being made out of lead are all unambiguously good ideas, which is why they would make for good indicators if data were available. But scoring pipes badly for their age is not an unequivocally good idea.

If they work, there are surely bigger priorities than constantly incentivising and replacing them, which is costly. Recall that aqueducts, which are centuries old, still function well, so even if data were available, which it is not, why bother discriminating against pipes only because of age?

4.3.11. Lead Pipes

Lead pipes have been used for centuries for plumbing water, so much so that its symbol Pb originates from this fact [218]. Lead pipes have been proven time and again to leach the lead heavy metal into drinking water and directly harm consumers [138], [141], [218], [219]. Lead is considered a 'forever chemical' [219]. A 'forever chemical' is one that does not decay, yet still poses risks in whichever environment it pollutes. Because lead particles are so small and do not decay, they can accumulate in factories, landfills, etc. No material is perfect, but lead specifically is very bad for leaching, as is discussed in sub-section 4.3.3.4: Tap Water Quality Resiliency Improvement Suggestions and Table S6 – Water Pipes Materials Comparison in Appendix C – Index.

The idea of this indicator is to count the percentage of mains pipelines as well as smaller water pipes in residential building blocks, which are composed of lead as well as potentially other highly contaminating materials or are fitted with connecting joints. Lead pipes leach lead, which is harmful to health, so they need to be replaced and kept out of use completely. Unlike Tap Water Quality, which addresses multiple contaminants and therefore is a sub-index, this indicator would be more conveniently native in the units of percentage, where 0% is best with no lead pipes and 100% is worst with all pipes being of lead.

The measured length will include both the public WDN and also private water pipes in residential building blocks because this seemed to have caused the incident in Hong Kong in 2015 of high concentrations of lead in tap water, which disturbed the water supply [33], [34], [135].

The data required is a map similar to that which was published for the city of New Orleans [31], but where pipes are categorised by their material rather than age. This indicator was omitted here because no such data was found to be publicly available.

4.3.11.1. Resiliency Improvement Suggestions

Lead pipes and joint connection fittings need to be replaced and kept out of use completely. This has been accomplished in some developed cities but not in all. It is easier to replace water lines that belong to water suppliers, though consumer pipes should be upgraded as well. Priority must be given to areas that currently suffer from high lead concentrations in tap water. Additionally, tap filters can also add an additional 'Swiss Cheese' layer of safety for individual domestic consumers.

4.3.12. Storage Capacity

Consider two possible water systems, both roughly consume as much water yearly as their sources renewably replenish. One water system has a large storage capacity that can last for years, such as surface rivers and lakes, while the other barely has a few wells and underground aquifers or artificial storage vessels such as tanks. Using Water Stress as an indicator would not alone measure this clear vulnerability. Each locality can have a 'bad year' or even several consecutively, as presented in Figure 2 in Chapter 1: Introduction. For this reason, an additional independent indicator can be considered, which is the storage capacity.

To allow for a universal comparison between water systems globally, instead of using the units of absolute volume storage, for example, MCM, the units of storage capacity as an indicator should be the number of years a water system can solely rely on its reserves. In other words, the Volume stored is divided by yearly consumption to get the number of years. The unit of time was chosen in years as opposed to months because consumption and replenishment are different by season, so it is important to think in terms of years and calculate yearly averages and minimums.

This indicator faces several challenges. Firstly, and as mentioned, a decision needs to be made as to whether to pick the maximum capacity or the lowest yearly mean-average stored. The maximum capacity could be significantly higher than it is ever filled and therefore does not indicate much about the severity of actual low storage, whereas a low measured storage amount could lose focus on whether there is currently even the extra capacity to store any significant additional volume.

In localities such as Singapore, catchment volume data is sensitive and confidential [30]. The uncertainty would also be high because water bodies change shapes with time, for example, rivers change course and area through erosion and the formation of meanders and ox-bow lakes [220].

Even coastlines do not have a universal method to reliably, objectively, and accurately have their parameter measured, despite being 2-dimensional and measured from above the water surface using satellite imaging. This is known as the 'Coastline Paradox' [221]. Therefore, why would a 3-dimensional indicator, which will require underwater imaging, be considered accurate and reliable?

The storage capacity of some localities would be magnitudes larger or smaller than that of others, hence some may question this indicator altogether. This would be especially the case if water reserves were slow to replenish or non-renewable whatsoever, such as with desert underground water, which does not replenish due to a lack of precipitation. Some cities may also share their water reserves with others, especially importing cities by some definitions, which would disqualify this indicator due to being unable to keep it within a consistent control volume.

Some reserves can have large capacities but do not actually save enough water to live up to the large reserves, hence rendering the large storage capacity useless. Imagine ranking highly the finances of an entity merely because it has a high credit limit or even because it has no maximum limit on the amount of money it is legally allowed to save in bank accounts, but in reality, it has no savings.

It would make no sense to only take into account the total volume storage capacity and not the regular amounts put into savings, as well as the amount already kept in savings. Furthermore, similar to unspent cash experiencing inflation, water saved in a reservoir can experience both evaporation and degradation in quality with time, hence disincentivising saving, which this simple indicator alone will not take into account.

Clearly, this initially seemingly simple indicator not only lacks available reliable data but also raises other complex questions; hence, it was not selected for this new Custom Index.

4.3.13. Importation Water Dependency

As mentioned above in the Storage Capacity vulnerability, it is risky for a water system to lack sufficient water storage relative to its consumption. The Storage Capacity vulnerability is similar to Water Stress, yet clearly distinct. Water Stress is a unitless ratio of the rate of consumption to the rate of renewable replenishment, namely from precipitation, whereas Storage Capacity is in the units of years' worth of consumption reserved. A water system experiencing Water Stress can still potentially replenish all the water it needs on its own if it has efficient governance. However, some water systems are in a significantly worse position, because they do not withstand their Water Stress and rely on importing water from other jurisdictions, typically their border neighbours.

When a country imports its water from another, it is called 'Water Dependency' [25]. As is required by the Indicators Selection Requirements of this index, Water Dependency or importation is mentioned as a vulnerability indicator in literature [7], [48]. Also, as suggested by the same method for this Custom Index, water dependency is conveniently naturally normalised in percentages from 0% which is best and means self-reliance, to 100% which is worst and means all water is imported.

Cities such as Singapore and Hong Kong heavily rely on their neighbours for water importation. Map 7 [108] and Map 8 [222] below present the routes where Singapore imports roughly 30% of its potable water from the Johor River, and Hong Kong imports approximately 75% of its potable water from the Dongjiang and through Shenzhen [223], see Figure 5 and Figure 6 in section 1.3.

Map 7 – Singapore's Water Importation Route [108],

PUB, Singapore's National Water Agency

Map 8 – Hong Kong's Water Importation Route [222],

The Water Supplies Department/水務署

Table 14 below presents the water dependency and the rate at which water replenishes per capita. The sources of these statistics are predominantly from worldometer [25], Statista [224], and OurWorldInData [225]. These are given by country, not city, due to the nature of the published statistics. This highlights the advantage written in sub-section 4.2.1: Case Study Cities Selection Requirements for selecting city-states with well-defined borders. Because some statistics, such as those of worldometer, are collected at the national level, it is more advantageous to select a whole country as a city-state case study for more availability of data.

Table 14 – Water Dependency & Renewable Water per inhabitant by country

Country	Water Dependency (%)	Renewable Water Rate per Inhabitant (m³/person/year)	Country	Water Dependency (%)	Renewable Water Rate per Inhabitant (m³/person/year)
Australia	0	19,000 – 20,000	Kuwait	100	5
Bahrain	97	78	Mexico	12	3,500 – 3,600
Belgium	34	1,600 – 1,900	Netherlands	88	5,000 – 5,300
Canada	2	79,000 – 89,000	Qatar	3	22
China	1	2,000	Saudi Arabia	0	73
Denmark	0	1,000 – 2,800	Singapore	30 [Figure 5 in section 1.3]	110
France	5	3,200 – 3,000	Taiwan	0 [226]	No Data
Germany	31	1,900 – 2,100	UAE	0	16
Hong Kong	75 [223], [Figure 6 in section 1.3]	No Data	United States	8	7,400 – 9,500
Italy	5	3,200	United Kingdom	1	2,200 – 2,500

It is interesting to note that the wide disparities between the Renewable Water rates per Inhabitant of different countries, which span multiple magnitudes apart, suggest that the wide disparities in water treatment costs estimated in sub-section 4.3.8: Affordability are not as inaccurate as may seem at first sight. This is similar to how benchmark scores of software can also vary in magnitude.

It is also important to keep a number of technicalities in mind regarding the Water Dependency and Renewable Water rate per Inhabitant:

Firstly, there is a substantial distinction concerning desalination based on climate zones. In contrast to arid regions, other environments may have hydroelectricity generation capabilities thanks to significant precipitation. This is significantly more sustainable because the former costs energy to treat water, while the latter generates electricity, which is the opposite. Yet, this difference is not distinguished here.

Secondly, for countries with very high Renewable Water rates per inhabitant, it is very important to note that much of it is inaccessible. Meaning that there is no infrastructure in place to merely open up a tap and watch as all this amount of clean, renewable water on paper arrives at the consumer and generates hydroelectricity along the way. Most notably, much of Canada's 79,000 – 89,000 m³/person/year Renewable Water per Inhabitant is mapped in Map 9 [227] below to be in Canada's rivers and lakes in low-population-density regions in the colder north of the country, excluding the Great Lakes, which Canada shares with the United States. Similarly, the majority of Iceland's 450,000 – 510,000 m³/person/year Renewable Water per Inhabitant [25], [224], [225] is located within their rivers, lakes, and glaciers as mapped in Map 10 [228] below:
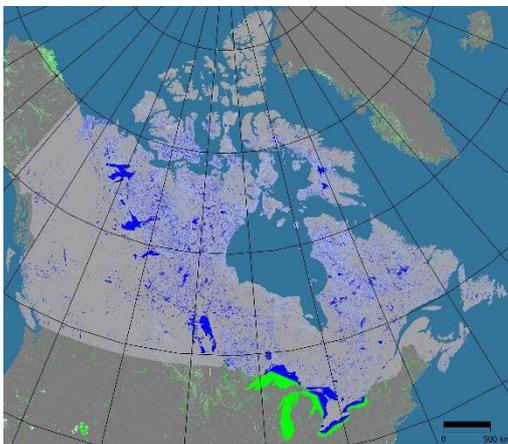
Map 9 – Canada's freshwater rivers and lakes [227], <u>CC BY 4.0</u> cropped
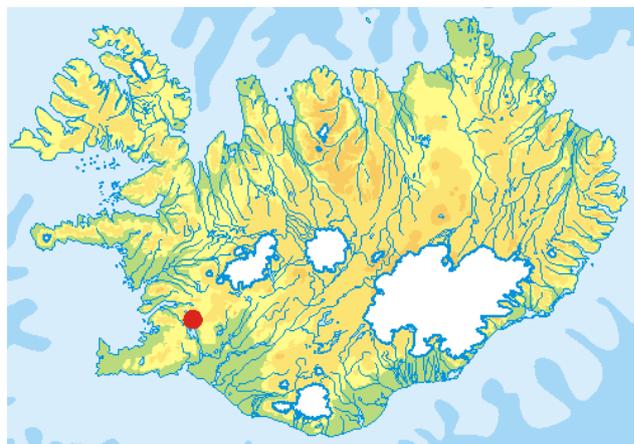
Map 10 – Iceland's freshwater rivers, lakes, and glaciers [228], <u>CC BY-SA 3.0</u> cropped

Thirdly, it is important to verify values with more than one source, because in some cases, some statistics do not make substantial sense and yet are left unexplained. For example, where is Israel importing 58% of its water [25] from? This is too much to deliver in water bottles, and this statistic does not include virtual water. Israel exports at least 50 MCM/year of potable water to Jordan as part of their 1994 peace treaty [229], so how is it that Jordan's Water Dependency stands at a lower 27% [25]? Clearly, worldometer [25] alone is unreliable.

Additionally, even if Water Dependency is not directly used as a vulnerability indicator, it does raise important information for another existing indicator: Source Water Quality. As shown above in Table 14, some countries barely depend on others for importing their water, while others depend almost completely, and of course, it is a spectrum with some countries in between.

Source Water Quality needs to assess the quality at the source, and perhaps all the way up until and including the area where it is consumed, because transported water can be contaminated at any point in canals, rivers, and aqueducts along the way. A high Water Dependency raises the concern of needing to increase the control volume for the Source Water Quality scores, and vice versa.

Similar to official bilateral water agreements between countries, there is also the matter of constructing dams that block rivers from naturally flowing water from one country to another. This includes from Ethiopia to Egypt's Nile through North Sudan in Map 11 [230] and from Turkey to Iraq's Euphrates and Tigris Rivers through Syria in Map 12 [231] below. Naturally, each country would like to keep water from its territory to itself, but there are also reasons not to.

Egypt threatened Ethiopia with military action if Ethiopia constructed a dam [232]. Imagine being in a poor country and spending a lot of money you do not have and cannot afford, only for a strong country to threaten that your project would be blown up in a military operation. This was seemingly a sufficient deterrent.

Moreover, governments do not wish to gain notoriety for causing water shortages and even fatalities in another country. What's more, if a country is in the middle of a river, if it builds a dam to shut off the flow downstream, another country can build its own dam upstream and prevent it from getting any water in retaliation, hence another deterrence.

In Iraq and Syria, there were and are other factions besides their governments, most notably the autonomous Kurdish regions and previously ISIS. The several factions that fought over the territory in Syria and Iraq posed a direct risk to the Euphrates and Tigris, the two major rivers in these countries, as well as a risk to their dams.

Dams pose a vulnerability not only because the rivers are relied upon for drinking water, but also for discharging effluent and wastewater, as well as the fact that if a dam is opened or blown, it can result in a tremendous flow of accumulated water and therefore deadly flooding downstream in lower elevations.

Map 11 – Nile River's borders [230], <u>CC BY-SA 3.0</u>

Map 12 – Euphrates and Tigris Rivers' dams [231],

<u>CC BY-NC-SA 2.0</u> *cropped*

Map 13 [233] below zooms out of the two regions described above and presents which states around the world rely on rivers that originate in other states. Considering that there are only roughly 200 countries, and several of them are island nations, there are only so many rivers where this applies.

In this polarised world, it is best for any entity to be self-sufficient. This is especially the case when one neighbour is dependent on another with whom they may not always get along well. Hong Kong, for example, receives the majority of its water from the Chinese mainland [180], [234] though this is concerning to many Hong Kong residents who distrust the Chinese government over issues such as the past Hong Kong protests. Residents who do not trust the quality of the imported water or the exporter often resort to bottled water, which is more wasteful [135].

Even when neighbours do get along better, such as with Singapore and Malaysia, water deals can be costly and have an expiry date [108], [109] which raises insecurities.

4.3.13.1. Virtual Water

Another aspect of water importation and external dependency is the concept of so-called 'Virtual Water'. Virtual Water is defined as the amount of water required to produce a commodity, see Nomenclature. This water is classified as industrial or agricultural, not domestic. 'Imported Virtual Water' refers to virtual water used for manufacturing in foreign countries where products are imported from. This is the amount of water that would have been used to manufacture products locally if they were not imported, hence a potential water dependence. Map 14 [235] below illustrates the various importation routes of virtual water by the types of products. A water-stressed country can strategically focus on exporting low virtual water products while importing high virtual water products and vice versa for a low Water Stress country, whichever is most economical.
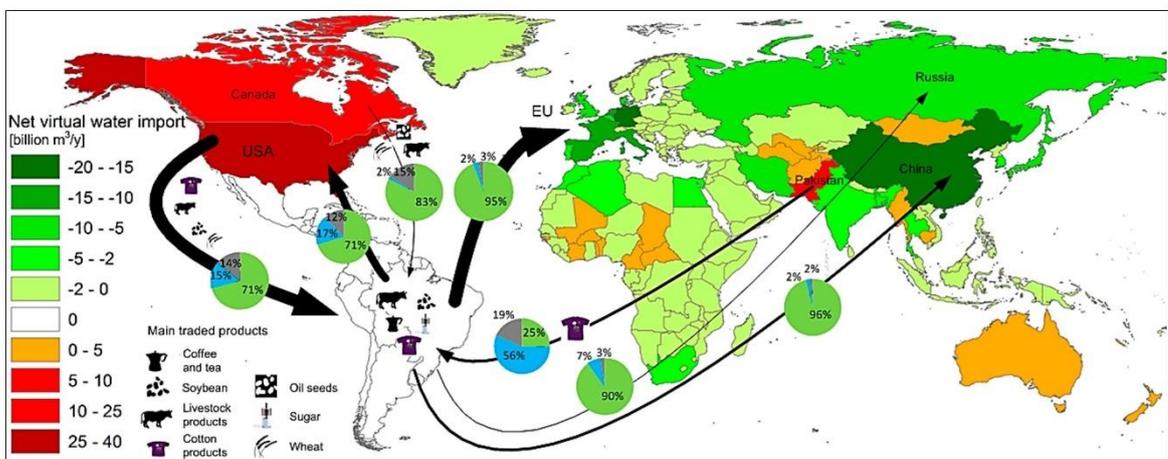
Map 14 – World Countries Virtual Water Net Imports [235], <u>CC BY 4.0</u>

4.3.13.2. Summary of water importation discussion

In summary, importation water dependency is a good indicator due to the availability of public data, its direct relevance to water systems, its discussion in the literature, and because it is natively normalised between 0% and 100%.

Importation as an indicator was not included because of its complexity. There needs to be a clear measurement definition for this indicator. To simplify, it is best to avoid measuring 'Virtual Water'. Instead, it is best to measure the percentage of water consumed, purchased, or otherwise contracted from a border neighbour. The uncertainty for this would be lower; it is natively normalised between 0% and 100% and direct water dependence is more expensive and is a greater vulnerability than a virtual dependence. There are fewer trade partners to rely on with direct import as opposed to virtual import, hence having to purchase at monopoly prices like Hong Kong or having expiring agreements like Singapore.

4.3.13.3. Resiliency Improvement Suggestions

Improving the self-reliance of water supply is not only theoretical but practical. Both of the aforementioned Asian cities and Singapore in particular have set plans in motion to become self-reliant. Singapore aims for full water independence by 2060-2061, which is when its water agreement with Malaysia for importing water from the Johor River expires [236]. Singapore is working on expanding its NEWater and desalination, while Hong Kong has begun setting up its first desalination plant in Tseung Kwan O [237].

For coastal cities, all their water can theoretically be generated via desalination, although at a cost of money, energy, and ecological damage from making discharge regions too salty for marine life. An interesting aspect is that it is economically feasible for coastal cities to be energy-dependent but water-independent, because fossil fuels may be imported via oil tankers from far away in a way that would not be feasible for importing water, because water is consumed in magnitudes more per capita than oil.

The political instability of relying solely on a single neighbour for water may be alleviated and replaced by relying on others for energy, including 'allies' as opposed to potential 'political rivals'. This competition is also better economically because it does not necessitate fixed monopoly prices, such as those in the agreement of 820 MCM/year for 4.5 billion HKD/year between Mainland China and Hong Kong, irrespective of the actual consumption of Hong Kong [180].

The best-case scenario is having one's own reservoir that has no expiry date and can constantly generate new clean water via precipitation. This is in contrast to treaties with expiry dates and therefore an uncertain future, for example, the Singapore-Malaysia contract set to expire in 2061, which is a continuation of previously expired agreements [108].

However, it is not unwise to also diversify water sources. Hong Kong is currently developing its first desalination plant [213], which it estimates could generate water more affordably than the current package deal it has with China.

It is always good for a city to be able to generate as much of its own water as bargaining power to negotiate a better deal with its exporter. It would also mean that China may have less power to interfere in Hong Kong politics if it has fewer resources to offer, which Hong Kong would depend on. This may improve the image of the governing authorities of Hong Kong and its political system in the eyes of its residents.

4.3.14. Non-Renewable Primary Energy

Energy is the key to obtaining just about anything. Energy is the currency of nature, with which most wealth can be exchanged. Having access to energy in the form of oil in landlocked deserts allows for the pumping of water from further away reservoirs. The availability of oil allows coastal cities to desalinate, which is where numerous cities, primarily nowadays, get their drinking water from.

Certain WSS are at risk of eventually running out of oil in the future. This can be a gradual issue or a volatile market issue, where, suddenly, although oil will still exist, its price may suddenly become unaffordable to some cities. It is unclear whether all cities will manage to cope and find alternative sources of energy. This is an issue for both developing and developed cities alike.

This indicator is convenient due to the high reliability and availability of data. It is naturally normalised from 0% to 100%. With enough energy, any endeavour can be pursued using 'brute force' as opposed to efficiency. Reflecting on every single other indicator, with no exception, they are all regarding efficiency and how to improve it. Here, generating more energy, including renewable energy, is less about the efficiency of the water supply system and more about being able to desalinate, reclaim/recycle water, and pump water from further distances instead. Further, lacking energy makes basic aspects of society challenging to power, never mind intensive water practices.

4.3.14.1. Resiliency Improvement Suggestions

Energy independence is key. Solar, wind, nuclear, geothermal, hydropower, and other experimental technologies are all potential solutions. Some of these solutions are geography-dependent, and there will need to be solutions for less geographically fortunate cities. Hydroelectricity is especially good to have not only because it is a way to generate electricity as opposed to spending it to treat water, but it is also a sign of the abundance of water due to the necessity of significant precipitation needed to implement hydroelectricity.

Note that 'Primary Energy' refers to the total amount of energy used in a society. It is interesting to note that no country in the world has yet to source all of its primary energy from renewables [238]. This is due to challenges such as fully adopting electric vehicles due to a shortage of lithium and its lower energy density. Only two developed countries generating more than 4,000 kWh/capita managed to generate all of their electricity from renewables: these are Norway and Iceland [239], [240]. Both countries have an abundance of water due to generating most of their electricity from hydro. Iceland also utilises geothermal [241] while Norway utilises wind [242].

4.3.15. Groundwater Reliance

Similar to the Importation Water Dependency discussed above, it raises the question: what other sources of water are less reliable due to higher costs? Even if those other alternatives are self-reliant. The case study of Singapore is highlighted due to its diverse water sources known as the four national taps, best presented in Figure 5 – Sankey Diagram of Singapore's Water Material Balance in section 1.3. Desalination and water reclamation are more expensive than catchments, but they are at least renewable.

Unlike Singapore, some cities that rely on wells and underground aquifers suffer from Groundwater Depletion if they withdraw too much water through wells than is replenished through precipitation. This again reminds of Water Stress and Storage Capacity; however, there is an important distinction.

Groundwater can and does replenish itself in a number of locations over time via rainfall, but the issue is that deserts barely receive rain. It is both important and interesting to realise that the water which is stored underneath deserts came from rains thousands of years ago, when the earth and the sun were oriented differently as part of a great cycle, when the Sahara was green [243]. Low-precipitation desert cities rely in part on groundwater sources that have little to no replenishment, meaning that they are as non-renewable and ancient as the oil they rely on.

This means that, unlike with Water Stress and Storage Capacity, where limiting consumption can maintain a water source indefinitely, some ground sources are effectively non-renewable, which raises an even more dire vulnerability. This is without even mentioning the salinity [244] and other minerals in groundwater, which can, over time, pose a greater threat to water quality compared to surface sources, for example, lakes.

This non-renewable nature of groundwater is similar to non-renewable energy, as discussed in sub-section 4.3.14: Non-Renewable Primary Energy.

Therefore, a potential vulnerability indicator can score groundwater as more vulnerable than surface lakes. This indicator would also be conveniently natively normalised in percentages between 0% of sources being non-renewable groundwater, which is best, to 100% which is the worst. This indicator is also mentioned in the literature [48].

4.3.15.1. Resiliency Improvement Suggestions

To the extent that groundwater cannot replenish itself, it should be preserved and only used as a last resort. Alternative water sources, such as piping and desalination, should be used instead. Some groundwater reserves have been drained for decades [244] and may also need decades to replenish, so plans should be considered and implemented to get started on turning this trend around.

4.3.16. Water Reused & Recycled

Ideally, the source of water would be local and completely more than fully regenerate itself through precipitation. This is discussed above in sub-sections 4.3.13 and 0. To the extent that this ideal is not met, this metric of Reuse and Recycle is important.

These two R's are used in the literature [189], [245] and were discussed as part of the Resiliency Improvement Suggestions of Water Stress in sub-section 4.3.5.1, with only one R being omitted, which is Reduce. The rationale of potentially having an indicator of only Reuse and Recycle is that they are the two most similar R's, which utilise water again. They are easy to measure and can be measured conveniently and natively in percentages from 0% to 100% of water being reused, recycled, or both since the moment it is used as potable water until the moment it is discharged.

Recycling water, specifically, is known as reclamation. In Singapore specifically, reclaimed water for potable purposes is called NEWater. This idea is also shown in the material balance Sankey diagrams of Figure 5 and Figure 6 in section 1.3. These show how Singapore uses recycled water for drinking water and Hong Kong reuses grey water for toilet flushing, combined with seawater.

This indicator would be imperfect because surely both reusing water and then recycling is better than only either, and there is no universal objective way to factor in this difference or even directly compare which alone is better, Reuse or Recycle. Moreover, if much of the water that goes towards being either reused or recycled evaporates along the way, will this count towards the combined reuse and recycle? This query is likely simpler than the previous, and the answer would be no, because the results are what truly matter as opposed to goodwill intentions. This means water would need to be metered where it is used, not where it is distributed from, to account for losses.

The main concerns for making this indicator would not only be that very few case studies practice any significant recycling or reusing of water, with the exception of some grey water, but more importantly, that it tends to be those case studies that resort to expensive reusing and recycling that are water-scarce. Therefore, it is Water Stress that needs to be the indicator, and incidentally, as covered in its sub-section 4.3.5, the 3 R's are included in it as Resiliency Improvement Suggestions.

4.3.17. Indicators Comparison and Selection

Table 15 below compares the Vulnerability Indicators that were discussed above. These are grouped into economic, environmental and technical infrastructure, distinct thematic domains.

Key: Asterisk * means an indicator was selected for the Custom Index.

Table 15 – Indicators Comparison

Economic					
Indicator Criterion Name, Units, and References to Literature	Definition and Units	Higher OR Lower measured number is better	Direct Vulnerability OR Proxy, and what of?	Sources of Data	How these values are measured in reality
*Affordability	Amount of potable water that can be afforded per capita per year (10^4 m3/Year· Capita)	Higher is better	Proxy for general economic well-being	GDP: IMF [214]. LF & cost of water treatment from reports.	GDP formula, government data, and cost estimates.
Non-Renewable Primary Energy	Percentage (%) of total energy used, which is non-renewable	Lower is better	Direct Vulnerability	'Our World In Data' [238] and other	Wattmeters and multimeters
Importation Water Dependency	The percentage (%) of total water used, which is imported			Water Suppliers Reports	Water Meters

Environmental					
Indicator Criterion Name, Units, and References to Literature	Definition and Units	Higher OR Lower measured number is better	Direct Vulnerability OR Proxy, and what of?	Sources of Data	How these values are measured in reality
*Flood Risk	The portion of the population that is expected to be significantly adversely affected by flooding in an average year. Normalised as 1-5.	Lower is better	Direct Vulnerability	Interactive Maps in Appendix C – Index	"cascade of models within the Global Flood Risk with IMAGE Scenarios (GLOFRIS) modelling framework"
*Water Stress	The ratio of total water withdrawals to available renewable surface and groundwater supplies. Normalised as 1-5.				"global hydrological model, PCRaster Global Water Balance (PCR-GLOBWB 2)"
*Soil Moisture Content	content of liquid water in a surface soil layer of 2 to 5 cm depth (%)	Higher is better	Proxy for Drought, and by extension, Water Stress		Spectroscopy Satellite Footage
Water Reused & Recycled	Percentage (%) of total water used that is reused or recycled			Water Suppliers Reports	Water meters
*Source Water Quality	Sub-index, normalised as 0-10		Proxy for downstream quality issues	Interactive Maps in Appendix C – Index	Hand-held Meter Tools

Technical Infrastructure – relates to the physical infrastructure, like the mains pipelines.					
Indicator Criterion Name, Units, and References to Literature	Definition and Units	Higher OR Lower measured number is better	Direct Vulnerability OR Proxy, and what of?	Sources of Data	How these values are measured in reality
*Tap Water Quality	Sub-index, normalised as %	Higher is better	Direct Vulnerability	Tap Water Quality Reports	Hand-held Meter Tools
Storage Capacity	The volume capacity of the water storage			Water Suppliers Reports	Radar, laser, satellites
Blockages	Count per length of WDN mains pipes	Lower is better			Water meters, reports, and inspections
*Water Loss	Percentage (%) of potable water lost throughout distribution. Combined leakage and even theft, and evapotranspiration				Water meters
Groundwater Reliance	Percentage (%) of the total water used, which is groundwater				
Lead Pipes	Percentage (%) of WDN mains pipes			Water Supplier Map Records [31]	
Ageing Infrastructure	The sum product of the portions of mains pipes and their ages	Arguably, lower is better	Proxy for Blockages, Lead Pipes, and other contaminants		

Having detailed the potential indicators for the Custom Index in Table 15 above, and having discussed them each individually in a dedicated sub-section, here is their comparison to select which indicators to include in the Custom Index and which to omit:

Firstly, any indicator that serves as a proxy for another should not be selected if the direct vulnerability indicator has at least as much availability of data. The main reason for the use of proxy indicators is their advantage of being widely available, recent, and reliable data. Having said that, 'Water Reused & Recycled' is a proxy for Water Stress, but its data availability is not better than Water Stress.

In fact, Water Reused & Recycled can also be looked at as a resiliency improvement suggestion for Water Stress, similar to Green Spaces being a mitigation measure for Flood Risk. Green Spaces is an indicator in the 2016 Sustainable Cities Water Index [21], as was discussed in sub-section 4.3.6: Flood Risk. Similar to how Green Spaces is not selected as an indicator for this Custom Index because it is a mitigation measure for another indicator, so is Water Reused & Recycled omitted.

It was decided to include Soil Moisture Content as an indicator, despite it being a proxy for drought, which Water Stress also discusses, because it has very widely available recent data using satellite observations. Clearly, Water Stress is pivotal as it was discussed in connection to other potential indicators, so it is decided to also include Water Stress.

Similarly, although 'Lead Pipes' is a direct vulnerability indicator by itself, it was decided to be excluded, while Tap Water Quality is included instead, because of a lack of data availability. Tap Water Quality is its own direct vulnerability indicator, but it can serve as a proxy for Lead Pipes because it measures lead as a sub-indicator. It is a particular shame to exclude this indicator, considering that 'Lead Pipes' would be natively normalised in the unit of percentages from 0% to 100%, so it would be ideal to include it in future work if data becomes available.

'Ageing Infrastructure' is excluded because it is a proxy for Blockages and Lead Pipes, which are both themselves excluded, all due to a lack of sufficient data available. As sub-section 4.3.10 notes, Ageing Infrastructure is generally a problematic indicator because it penalises a measure that constantly becomes "worse" with time (age), and potentially unjustifiably so.

As sub-section 4.3.9 notes, Blockages are more difficult and less critical to measure than Water Loss; hence, Water Loss, which, for both these reasons, has more data published, is selected as an indicator for the Custom Index.

Storage Capacity is omitted due to poor availability and even confidentiality of data, and the general complication of deciding how to measure it. It may be beneficial to include it in future work if data is available.

Considering the study of Past Water Supply Disruption Incidents in section 1.2, Table 5 documents Water Stress, Flood Risk, Source Water Quality, and Tap Water Quality. These four are very fundamental indicators in water research and have sufficient data availability, hence they are selected for the Custom Index. It should be noted that Tap Water Quality is the bottleneck for data availability, so it is also a major factor when deciding which Case Study Cities to choose.

This is the case because, unlike other indicators that have a single value or can be gathered from satellite data/Interactive Maps, Tap Water Quality requires multiple values for each alternative for an overall score, therefore making it a sub-index. It also relies on published reports from water suppliers that could be less reliable and verifiable than satellite data. Some water suppliers do not even seem to publish Tap Water Quality Reports.

Similar to Tap Water Quality, Source Water Quality is also a sub-index. However, Source Water Quality relies on Interactive Maps whose data is gathered from satellite observations, hence Source Water Quality is not the bottleneck for data availability that Tap Water Quality is. Both are also included to be correlated against each other to figure out whether the quality at the source statistically could potentially affect the quality at the tap.

Lastly, Affordability is selected to give an economic perspective on the water supplier. Affordability tends to be consumer-focused in the water systems literature, but to fit the unique approach of analysing all indicators from the supplier's perspective, this would be no different.

Only seven indicators were selected for this Custom Index, for simplicity and to demonstrate the methodology of the Custom Index as simply and quickly as possible. More indicators can be added later as future work to better capture the vulnerability of WSS, see sub-section 5.3.7: Introducing Other Indicators in section 5.3: Further Work – Index.

Three of the seven indicators that were selected have been customised. Tap and Source Water Qualities being sub-indices are customised in the form of selected lists of sub-indicators, while Affordability has a new custom supplier-focused equation (see Equation 15 in sub-section 4.3.8).

4.3.18. Other Indicators

This sub-section discusses several indicators that were excluded from the Custom Index. Bear in mind that because this is a new Custom Index constructed from scratch, several indicators were omitted for simplicity, as very few indicators are needed to illustrate the methodology.

Firstly, Water Metered is an indicator in water systems literature. Its discussion and the justification for its exclusion are in sub-section 4.3.2.2: Water Loss Resiliency Improvement Suggestions.

Secondly, population growth can cause increased vulnerability in the form of increased water demand. It was excluded because it is a prediction, which is different from all the other indicators that measure existing statistics instead. The risk of water demand is already covered in Water Stress. Increased water demand does not necessarily equate to a vulnerability, because it can be. Cities next to large bodies of fresh water, such as the case study of Toronto and the Great Lakes, can withstand an increased demand. Likewise, with enough energy, water supply can match demand through desalination, hence sub-section 4.3.14: Non-Renewable Primary Energy.

4.3.18.1. Other Economic Indicators

It is unsustainable for any entity to continuously make a financial loss. If it makes a loss, it means it is wasteful in terms of purchasing power and real resources. A water supplier can make a profit whether it is private, public/nationalised, or mixed as a private-public-partnership.

The main issue with most economic indicators is that they focus on the consumer as opposed to the supplier, which is common but does not fit the approach of this research. One example that is focused on the supplier is non-revenue water. However, it is already being taken into account through Water Loss as well as GDP Per Capita/Water Costs in Affordability. Metering levels of Case Study Cities globally also lack sufficient availability of data.

Other potential economic indicators include the amount or percentage of the budget left to improve the resiliency to vulnerabilities, as well as the percentage of shareholders who are satisfied. The idea is that if the discretionary budget is too limited, there would not be enough for a genuine emergency, such as the incidents discussed in section 1.2: Past Water Supply Disruption Incidents. If shareholders are unsatisfied, they can sell too many shares of the stock at the same time and cause uncertainty that can exacerbate an incident when one happens.

There is, of course, a lengthy list of other potential risks in the finances or management of any corporation. Regardless, focusing on these aforementioned two:

Consultants must consider solutions for the budget. Water fees can be raised, but that strategy is naturally limited, reduces the affordability of vulnerable consumers, and overall upsets the customers, who are the very group the water supplier wishes to satisfy. Taxes can also be increased and granted to water suppliers, though again, this is a limited strategy that leaves hard-working people financially behind. An upside, however, of raising costs is that it promotes conservative and responsible water usage. Alternatively, cutting down on unnecessary expenses may also yield a sufficient budget by improving the efficiency of spending.

As for the shareholders, it is too difficult to accurately and universally measure the thoughts and feelings of people. Furthermore, some water suppliers are private while others are public, so it is not universally fair to compare which water suppliers have satisfied shareholders when some have few to none. Therefore, this potential indicator was not selected for the Custom Index.

At any rate, one solution can be nationalising the water supplier so shares are not traded. Alternatively, having strict trading rules such as the shares having no voting power, disallowing a hostile takeover, or requiring more time to trade, thereby making their trade more illiquid. Of course, if the water supplier is also profitable and performs well in terms of quality and has no outage incidents, this indicator would be less risky.

Shareholders today are also concerned about ethical practices, as well as general transparency in regularly published reports. Reflecting on the Tap Water Quality Reports in Table 9 in sub-section 4.3.3.1, some case studies did not report certain very important substances included in Figure 19 in sub-section 4.3.3. Some case studies do not seem to publish any drinking water quality reports.

Likewise, there are also financial reports in which water suppliers and public companies in general discuss their earnings and losses as well as trends in their strategy [246]. Such financial reports can be published more frequently to some shareholders' liking, for example, quarterly as opposed to yearly. Transparency is indeed important for stability and can help to protect the equity against speculators shorting and selling the stock.

Ultimately, profit as an indicator, as well as satisfied shareholders and a discretionary budget, were omitted because there is already a financial indicator of supplier-side Affordability. Moreover, unlike other indicators, this one would be improved in terms of business management as opposed to physical improvements of the water system, such as better distribution mains pipelines. Besides, there is a variety of other potential finance indicators, so it makes sense to only focus on a single one for simplicity to start off with.

4.4. Scores Results

GUI 6 below tabulates the scores and uncertainties of each indicator in the Custom Index:

\Criteria Alternatives	Affordability (10⁴ m³/Capita·Year)	Flood Risk (1-5)	Water Stress (1-5)	Soil Moisture Content (%)	Source Water Quality (0-10)	Tap Water Quality (%)	Water Loss (%)
Amsterdam, Holland	1700 ± 850	4 ± 0	1 ± 0	37 ± 1	3.06 ± 0.01	74 ± 1	4 ± 1
Bahrain	7.8 ± 3.9	3 ± 0	5 ± 0	13 ± 1	2.92 ± 0.01	25 ± 1	24 ± 1
Berlin, Germany	1600 ± 800	4 ± 0	4 ± 0	21 ± 1	4.09 ± 0.01	100 ± 0	5 ± 1
Brussels, Belgium	3000 ± 1500	2 ± 0	5 ± 0	13 ± 1	1.90 ± 0.01	100 ± 0	26 ± 1
Copenhagen, Denmark	2100 ± 1050	1 ± 0	3 ± 0	42 ± 1	5.32 ± 0.01	100 ± 0	7.22 ± 0.01
Dallas, Texas	2700 ± 1350	5 ± 0	2 ± 0	27 ± 1	5.48 ± 0.01	4 ± 1	8.8 ± 0.1
Doha, Qatar	23 ± 11.5	4 ± 0	5 ± 0	11 ± 1	2.72 ± 0.01	91 ± 1	26 ± 1
Dubai, UAE	17 ± 8.5	5 ± 0	5 ± 0	10 ± 1	6.09 ± 0.01	0 ± 0	5.3 ± 0.1
Hong Kong	7.5 ± 3.75	5 ± 0	3 ± 0	36 ± 1	5.22 ± 0.01	99 ± 1	32.5 ± 0.1
Houston, Texas	2700 ± 1350	4 ± 0	3 ± 0	34 ± 1	6.70 ± 0.01	24 ± 1	16.87 ± 0.01
Kuwait City, Kuwait	7.7 ± 3.85	4 ± 0	5 ± 0	12 ± 1	3.91 ± 0.01	0 ± 0	10 ± 1
London, England	2400 ± 1200	4 ± 0	4 ± 0	31 ± 1	2.31 ± 0.01	100 ± 0	26.7 ± 0.1
Los Angeles, California	2900 ± 1450	4 ± 0	5 ± 0	15 ± 1	6.12 ± 0.01	50 ± 1	9.9 ± 0.1
Manchester, England	1600 ± 800	2 ± 0	2 ± 0	32 ± 1	4.38 ± 0.01	100 ± 0	24.4 ± 0.1
Melbourne, Australia	2000 ± 1000	4 ± 0	4 ± 0	13 ± 1	6.74 ± 0.01	51 ± 1	10 ± 1
Mexico City, Mexico	640 ± 320	4 ± 0	5 ± 0	8 ± 1	2.59 ± 0.01	0 ± 0	40 ± 1
Paris, France	1300 ± 650	4 ± 0	3 ± 0	30 ± 1	4.56 ± 0.01	1 ± 1	6 ± 1
Riyadh, Saudi Arabia	8.4 ± 4.2	2 ± 0	5 ± 0	6 ± 1	3.58 ± 0.01	0 ± 0	30 ± 1
Rome, Italy	1400 ± 700	3 ± 0	5 ± 0	15 ± 1	4.02 ± 0.01	68 ± 1	27.8 ± 0.1
Shanghai, China	2100 ± 1050	5 ± 0	5 ± 0	46 ± 1	3.90 ± 0.01	0 ± 0	17.6 ± 0.1
Singapore	23 ± 11.5	4 ± 0	1 ± 0	29 ± 1	5.71 ± 0.01	100 ± 0	5 ± 1
Taipei, Taiwan	2000 ± 1000	4 ± 0	2 ± 0	57 ± 1	6.21 ± 0.01	100 ± 0	17.73 ± 0.01
Toronto, Canada	1800 ± 900	2 ± 0	1 ± 0	36 ± 1	4.08 ± 0.01	100 ± 0	10 ± 1
Washington DC	3200 ± 1600	2 ± 0	2 ± 0	34 ± 1	5.97 ± 0.01	48 ± 1	25 ± 1
Best Possible Score	3200	1	1	57	6.74	100	4
Worst Possible Score	7.5	5	5	6	1.90	0	40

GUI 6 – Custom Index scores

GUI 7 below shows the normalised scores of GUI 6:

Normalised Scores

\Criteria Alternatives	Affordability (10⁴ m³/Capita·Year)	Flood Risk (1-5)	Water Stress (1-5)	Soil Moisture Content (%)	Source Water Quality (0-10)	Tap Water Quality (%)	Water Loss (%)
Amsterdam, Holland	0.53 ± 0.27	0.25 ± 0	1 ± 0	0.61 ± 0.02	0.24 ± 0	0.74 ± 0.01	1 ± 0.03
Bahrain	0 ± 0	0.5 ± 0	0 ± 0	0.14 ± 0.02	0.21 ± 0	0.25 ± 0.01	0.44 ± 0.03
Berlin, Germany	0.5 ± 0.25	0.25 ± 0	0.25 ± 0	0.29 ± 0.02	0.45 ± 0	1 ± 0	0.97 ± 0.03
Brussels, Belgium	0.94 ± 0.47	0.75 ± 0	0 ± 0	0.14 ± 0.02	0 ± 0	1 ± 0	0.39 ± 0.03
Copenhagen, Denmark	0.66 ± 0.33	1 ± 0	0.5 ± 0	0.71 ± 0.02	0.71 ± 0	1 ± 0	0.91 ± 0
Dallas, Texas	0.84 ± 0.42	0 ± 0	0.75 ± 0	0.41 ± 0.02	0.74 ± 0	0.04 ± 0.01	0.87 ± 0
Doha, Qatar	0 ± 0	0.25 ± 0	0 ± 0	0.1 ± 0.02	0.17 ± 0	0.91 ± 0.01	0.39 ± 0.03
Dubai, UAE	0 ± 0	0 ± 0	0 ± 0	0.08 ± 0.02	0.87 ± 0	0 ± 0	0.96 ± 0
Hong Kong	0 ± 0	0 ± 0	0.5 ± 0	0.59 ± 0.02	0.69 ± 0	0.99 ± 0.01	0.21 ± 0
Houston, Texas	0.84 ± 0.42	0.25 ± 0	0.5 ± 0	0.55 ± 0.02	0.99 ± 0	0.24 ± 0.01	0.64 ± 0
Kuwait City, Kuwait	0 ± 0	0.25 ± 0	0 ± 0	0.12 ± 0.02	0.42 ± 0	0 ± 0	0.83 ± 0.03
London, England	0.75 ± 0.38	0.25 ± 0	0.25 ± 0	0.49 ± 0.02	0.08 ± 0	1 ± 0	0.37 ± 0
Los Angeles, California	0.91 ± 0.45	0.25 ± 0	0 ± 0	0.18 ± 0.02	0.87 ± 0	0.5 ± 0.01	0.84 ± 0
Manchester, England	0.5 ± 0.25	0.75 ± 0	0.75 ± 0	0.51 ± 0.02	0.51 ± 0	1 ± 0	0.43 ± 0
Melbourne, Australia	0.62 ± 0.31	0.25 ± 0	0.25 ± 0	0.14 ± 0.02	1 ± 0	0.51 ± 0.01	0.83 ± 0.03
Mexico City, Mexico	0.2 ± 0.1	0.25 ± 0	0 ± 0	0.04 ± 0.02	0.14 ± 0	0 ± 0	0 ± 0.03
Paris, France	0.4 ± 0.2	0.25 ± 0	0.5 ± 0	0.47 ± 0.02	0.55 ± 0	0.01 ± 0.01	0.94 ± 0.03
Riyadh, Saudi Arabia	0 ± 0	0.75 ± 0	0 ± 0	0 ± 0.02	0.35 ± 0	0 ± 0	0.28 ± 0.03
Rome, Italy	0.44 ± 0.22	0.5 ± 0	0 ± 0	0.18 ± 0.02	0.44 ± 0	0.68 ± 0.01	0.34 ± 0
Shanghai, China	0.66 ± 0.33	0 ± 0	0 ± 0	0.78 ± 0.02	0.41 ± 0	0 ± 0	0.62 ± 0
Singapore	0 ± 0	0.25 ± 0	1 ± 0	0.45 ± 0.02	0.79 ± 0	1 ± 0	0.97 ± 0.03
Taipei, Taiwan	0.62 ± 0.31	0.25 ± 0	0.75 ± 0	1 ± 0.02	0.89 ± 0	1 ± 0	0.62 ± 0
Toronto, Canada	0.56 ± 0.28	0.75 ± 0	1 ± 0	0.59 ± 0.02	0.45 ± 0	1 ± 0	0.83 ± 0.03
Washington DC	1 ± 0.5	0.75 ± 0	0.75 ± 0	0.55 ± 0.02	0.84 ± 0	0.48 ± 0.01	0.42 ± 0.03

GUI 7 – Custom Index normalised scores

Equation 16 below was used to derive the normalised scores (and uncertainties) from their inputs:

$$\text{Normalised Score} = \frac{\text{Input Score} - \text{Worst Possible Score}}{\text{Best Possible Score} - \text{Worst Possible Score}}$$

Equation 16 – Normalisation of scores and uncertainties

It was taken from the MCA literature [47], [93], [247], [248] and is programmed in Script S4 in Appendix B – Software. Note that in the literature, the terms max and min scores are used.

Alternatives Ranks

Ranking Method: (WSM)

Alternatives	Final Scores (Out Of 1)	Absolute Ranks (1 Is Best)
Amsterdam, Holland	0.65 ± 0.02	6
Bahrain	0.27 ± 0.01	19
Berlin, Germany	0.59 ± 0.02	8
Brussels, Belgium	0.53 ± 0.03	9
Copenhagen, Denmark	0.83 ± 0.02	1
Dallas, Texas	0.44 ± 0.03	14
Doha, Qatar	0.34 ± 0.01	18
Dubai, UAE	0.27 ± 0.00	20
Hong Kong	0.41 ± 0.00	16
Houston, Texas	0.47 ± 0.03	11
Kuwait City, Kuwait	0.26 ± 0.01	21
London, England	0.47 ± 0.03	13
Los Angeles, California	0.47 ± 0.03	12
Manchester, England	0.67 ± 0.02	5
Melbourne, Australia	0.49 ± 0.02	10
Mexico City, Mexico	0.08 ± 0.01	24
Paris, France	0.42 ± 0.02	15
Riyadh, Saudi Arabia	0.24 ± 0.01	23
Rome, Italy	0.39 ± 0.02	17
Shanghai, China	0.26 ± 0.02	22
Singapore	0.69 ± 0.01	3
Taipei, Taiwan	0.67 ± 0.02	4
Toronto, Canada	0.79 ± 0.02	2
Washington DC	0.62 ± 0.04	7

GUI 8 – Custom Index final ranks

Equation 17 below demonstrates by example how the uncertainties of WSM are calculated using Equation 10 – WSM Uncertainty from section 3.5, normalised weights from GUI 10 in sub-section 4.5.4: Selecting Weights and normalised uncertainties from GUI 7 above. This example is for the case study of Amsterdam shown in GUI 8 to the left:

$$\pm\sqrt{\begin{array}{c}(0.27 \cdot 1/14)^2 \\ +(0.02 \cdot 1/14)^2 \\ +(0.01 \cdot 3/14)^2 \\ +(0.03 \cdot 3/14)^2\end{array}} = \pm 0.02$$

(rounded to 2 decimal places)

Equation 17 – Uncertainty Calculation Example

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Both the Case Study Cities and Vulnerability Indicators are sorted alphabetically ascendingly, with the exception of Water Stress, which was placed between Flood Risk, with which it shares the same 1-5 range and sources of data [110], [249], and Soil Moisture Content, with which it strongly correlates, as discussed below in sub-section 4.4.1: Indicators Correlations.

When the same indicator has multiple sources of data, which on occasion do not entirely agree, there must be an objective, consistent way to choose which numbers to use in the index. One option is to average out the inputs and perhaps increase the uncertainty for that data point. The other option, which was actually implemented in this Custom Index, is to pick the harshest number to stay on the safe side. On the same harsh principle, the Soil Moisture Content indicator selects the yearly lowest single-month reading, not the yearly average. At any rate, data sources must generally agree with each other, or at least one must be discarded as being unreliable. Besides the single case study city of Amsterdam in Water Loss (Table 8 in sub-section 4.3.2), Water Stress and Flood Risk are the only indicators that rely on the harshest reading of multiple sources, which they also happen to share. These are ResourceWatch [110], [250], [251] and ThinkHazard [249], [252], [253]. They are presented in the Interactive Maps sources sub-section in Appendix C – Index.

Both the Vulnerability Indicators and Case Study Cities are sorted alphabetically in GUI 6 because, at this point, their final scores are yet to be calculated. The one exception is Water Stress, which is better grouped with Flood Risk, with which it shares data sources (cited in the above paragraph) and Soil Moisture Content, with which it shares a strong correlation and the same nature of measuring drought, more on this in sub-section 4.5.4: Selecting Weights.

4.4.1. Indicators Correlations

The correlations between the indicators are displayed in GUI 5 in section 3.4: Criteria Correlations. The scores for these correlations cover all 24 Case Study Cities using the data from GUI 6 above.

Note that mathematically, a minimum number of case studies is required to provide reliable correlation data, and the more the better. Correlations decrease in sensitivity with every additional case study. This is a result of the definitions of the correlation equations as shown in Equation 8 – Pearson's r Correction and Equation 9 – Spearman's ρ Correlation in section 3.4.

Initially, the purpose of scripting GUI 5 was to look for any correlations that are too high between any two indicators, which would indicate double-counting, which is a concern raised in sub-section 4.3.1: Indicators Selection Requirements.

The most apparent correlations to look for are similarly-sounding indicators such as tap and source water qualities. As shown in GUI 5, these have a correlation of -0.09, which is among the lowest and clearly suggests effectively no statistically significant correlation. This observation has profound implications, as it was initially speculated there might be a correlation because the quality of the source water could theoretically affect the quality at the tap for the same level of treatment, especially considering the perilous domino effect in the 2000 Ontario incident documented in section 1.2: Past Water Supply Disruption Incidents. This is the first and most comprehensive correlation in WSS literature to clearly suggest the other logical possibility, which is that with aggressive treatment, even low-quality source water can have very high quality at the tap and vice versa.

One cannot help but wonder what other interesting and possibly strong correlations could be discovered. Indeed, there is a strong negative correlation between Soil Moisture Content and Water Stress of -0.68. Much like "correlation does not imply causation", a strong correlation between two indicators does not imply they necessarily are measuring the same vulnerability. Yet, with Soil Moisture Content and Water Stress, it is apparent that they both measure drought.

The negative sign also makes sense, because a high Water Stress would be expected to strongly correlate with low Soil Moisture Content. In MCA in general, it is ill-advised to use multiple criteria that strongly correlate, as it risks double-counting the same indicator and causing an unnecessary complication. It was decided to keep both indicators for illustration, but not in future work. However, weights are adjusted accordingly, as will be discussed in sub-section 4.5.4: Selecting Weights below.

For future work on this Custom Index, Water Stress is expected to be retired in favour of keeping Soil Moisture Content. In theory, if multiple indicators measure the same vulnerability, they can be combined. However, it is to eliminate all but one instead. It also makes sense to keep the indicator with the more recent, accurate, widely available data, which in this case is Soil Moisture Content, as it derives its data from direct satellite observations, as noted in sub-section 4.3.7. This suggestion is covered more comprehensively in sub-section 5.3.11 in the Further Work – Index section.

Having discussed all these correlation calculations, it is probably a prudent conclusion to suggest that any congregate MCA index should have a criteria correlation analysis as a fundamental requirement. It is very simple to implement, and in fact, automatic in the new MCA Solver Software Tool. It clearly can be very useful and suggests relations and lack, therefore, which, although they can seem self-evident looking back, were not so when predicted initially. Therefore, understanding correlations helps to better understand the nature of the criteria themselves.

Besides these two main indicator correlations, it can be informative to understand the remaining indicator correlations or lack thereof. At effectively no correction of 0.01 between Tap Water Quality and Water Loss, it appears that there is no relation between the quality of distributed drinking water and Water Loss through leakages or otherwise. In sharp contrast, Water Loss moderately negatively correlates with Source Water Quality at -0.44, which could suggest that leakages could cross-contaminate into water reservoirs and adversely affect their quality.

However, there is a positive, yet low, 0.19 correlation between Source Water Quality and Flood Risk, which is the opposite of what would be expected from potential cross-contamination of flooding with water resources, especially flooding of waste or saline waters. Flood Risk and Water Loss share a low negative -0.18 correlation, meaning that WSS happened to not suffer from both at the same time.

Considering the high negative correlation of -0.68 between Soil Moisture Content and Water Stress, it can be expected that all of their correlations, moderate or low, would be of the same strength and with opposite signs. For example, there are practically no correlations between Flood Risk on the one hand and Soil Moisture Content and Water Stress on the other hand at 0.00 and 0.13, respectively, meaning they probably do not relate, and that Flood Risk is probably equally likely in both arid and temperate climate zones alike.

Similarly, Affordability correlates at a low -0.25 with Water Stress and a moderate 0.41 with Soil Moisture Content. This could mean that poorer regions suffer more from Water Stress and drought, or that these correlations are not sufficient to imply a relation, and this trend between the correlations of Soil Moisture Content and Water Stress is only due to the strong correlation between them. This trend continues with the correlations of -0.35 and 0.31 that Water Stress and Soil Moisture Content, respectively, have with Source Water Quality, and again with the correlations of -0.41 and 0.36 that Water Stress and Soil Moisture Content, respectively, have with Tap Water Quality, and lastly with 0.37 and -0.22, respectively, with Water Loss.

There is a moderately positive correlation of 0.41 between Affordability and Soil Moisture Content, which could indicate that temperate climate zones tend to be wealthier, which would make sense. Soil Moisture Content also has 0.31 and 0.36 moderate correlations with sources and tap water qualities respectively, further suggesting that water quality tends to be better in temperate Case Study Cities, although, considering that Affordability only has a 0.22 and 0.18 low correlations with sources and tap water qualities respectively, these moderate correlations between Soil Moisture Content and water quality may not necessarily be due to a good state of an economy.

Moreover, Water Stress moderately correlates at 0.37 with Water Loss, while it negatively correlates with source and tap water qualities at -0.35 and -0.41, respectively. Likewise, Flood Risk negatively moderately correlates with Tap Water Quality at -0.33. Those moderate correlations could mean that Case Study Cities that suffer from any of these particular vulnerabilities might be more likely to suffer from several of these at the same time. The reason could be bad management, the economy, or even geography.

Affordability weakly negatively correlates with Flood Risk and Water Loss at -0.20 and -0.14, respectively, which could be due to the availability of funding or lack thereof to mitigate these vulnerabilities.

Moderate correlations could suggest that there are some indicators that tend to score similarly or opposite from each other due to possible effects they may have on each other in real life, or effects they experience from a commonality in real life. Moderate correlations are not strong enough to suggest that they measure the same vulnerability and are therefore not merged to prevent double-counting. It can be expected that some moderate correlations would, in fact, appear as low correlations, and vice versa, as statistics and the list of case studies are updated with time.

It is also important to consider the technical reasons for these correlations, namely, the sources of data. For this Custom Index, Water Stress and Flood Risk share the same sources of data [110], [250], [249], [252], and this could theoretically affect their low 0.13 correction somehow. Similarly, as Tap Water Quality relies on Tap Water Quality Reports, it is the bottleneck indicator for data availability in this index, so several Case Study Cities have a score of 0 for it, which also affects correlations.

4.4.2. Selecting Types of Uncertainties

There is an order of priorities regarding which uncertainty type to use for each application.

Firstly, if uncertainties are provided by a reliable data source along with its values, if they seem reasonable, it is best to use them. Secondly, for indices with short ranges such as 1-5, uncertainties are assumed to be zero so as not to be unreasonably high. This is not ideal, hence indices should be avoided where there are reliable alternatives. Thirdly, if each value is acquired via multiple measurements, it is best to use the standard deviation of each set of measurements as the uncertainty of the corresponding value, as it would be smaller and more accurate than alternatively using the decimal figure of the reading or presumably the resolution of the metering device. Lastly, if there is only a single measurement provided per value, typically, such as when measuring lengths, it is best to use the resolution of the meter used or a decimal figure corresponding to the decimal figures provided for the value itself.

The Affordability indicators were manually assigned to ±50% because these scores are very rough estimates, and it was realised that the final uncertainties are not much influenced by this decision.

Referring back to GUI 6 above, the uncertainties of Flood Risk and Water Stress were manually assigned as zero, because in the range of 1-5, they would be too large in a bar chart. It is assumed that any value in this narrow range is reliable with negligible uncertainty. The other indicators have automatically generated uncertainties, except for scores of 0 and 100 in Tap Water Quality, because zero uncertainty is a standard assumption for any scores that are on hard boundary limits, such as 0% and 100%.

GUI S16 under the Buttons' Red Highlights & Comments sub-section in Appendix B – Software explains that scores that are equal to the best and worst possible scores receive an uncertainty of zero because a value is fairly certain when it is equal to the limit. None of the uncertainties in Affordability, Soil Moisture Content, Source Water Quality, and Water Loss are zero, because the best and worst scores in each are not the maximum and minimum possible values, but rather are merely the maximum and minimum values within these arrays of values.

Standard Deviation was not used to generate uncertainties because none of the sources for the data of the indicators provide multiple measurements, see Table 15 in sub-section 4.3.17: Indicators Comparison and Selection. Standard Deviation could be used for future research if data is measured analytically as opposed to being sourced from online reports and interactive maps, as discussed in sub-section 5.3.5: Analytical Experimental Verifications.

4.5. Selecting Weighting and Ranking Methods

To determine which analysis methods any index should use, the first step is to rule out incompatible methods. As was previously discussed in Chapter 3, several methods mathematically fail when there is even a single score with the value zero, regardless of the units. In the Custom Index, several Case Study Cities do not publish Tap Water Quality Reports and therefore score zero on Tap Water Quality.

The 'Entropy' weighting method from sub-section 3.2.5 calculates the logarithm of a score, which is mathematically undefined for a score of zero. The WPM aggregate ranking method from sub-section 3.3.1 multiplies all the scores to the power of their weights, so it also would fail because even a single score of zero for any indicator would result in a final score of zero for that case study city. Similarly, the AHP weighting method from sub-section 3.2.3 is mathematically inconsistent by design [4], [48], and attempting to fill in user preferences consistently defaults to the Manual Assignment method from sub-section 3.2.2.

Therefore, it makes sense to exclude the Entropy, AHP, and WPM methods. Besides Manual Assignment, this leaves the 'All Equal' and Standard Deviation weighting methods from sub-sections 3.2.1 and 3.2.4, respectively, and the WSM and PROMETHEE ranking methods from sub-sections 3.3.1 and 3.3.2, respectively. Bear in mind that PROMETHEE I and II are effectively the same method, and due to their relative nature, they yield identical correlations, so they will be considered together for the purpose of the Sensitivity Analysis below.

4.5.1. Sensitivity Analysis

To determine whether the calculated scores by the Custom Index are reasonably accurate, they were correlated to the closest index from the WSS literature, the 2016 Resiliency Sub-Index by Arcadis. The rationale is that by conducting a sensitivity analysis, which tests different weighting and ranking methods and weights, it is possible to figure out how sensitive the Custom Index is to changes in these. This would suggest which changes would yield the highest correlation with an established similar index in the literature and, therefore, could be seen as making the Custom Index more reliable, as it would suggest that it measures the same concept of the resiliency of WSS.

Regarding the Standard Deviation weighting method, there are two approaches to implementing it. The first approach is to consider all 24 Case Study Cities of the Custom Index for calculating the weights and then only the 21 that both indices have in common in the Sensitivity Analysis. This would mean three Case Study Cities that affected the weights were left out of the correlations themselves.

The second approach is to only consider the 21 Case Study Cities that both indices share in common, but then calculate another set of weights with all the 24 considered for the final scores in sub-section 4.6.1, should this method be selected. Having calculated the normalised weights, both approaches yield the exact same normalised weights when rounding to two decimal places. See GUI 9 below, which considers all 24 Case Study Cities for the Raw Weights:

Criteria Weighting

Number of Criteria = (7)

User Inputs: Criteria Preferences

Weighting Method: (STD)

Criteria	Affordability (10⁴ m³/Capita·Year)	Flood Risk (1-5)	Water Stress (1-5)	Soil Moisture Content (%)	Source Water Quality (0-10)	Tap Water Quality (%)	Water Loss (%)
Raw Weights	1111.08	1.14	1.5	13.7	1.46	43.01	10.53
Normalised Weights	0.94	0.00	0.00	0.01	0.00	0.04	0.01

Reset Criteria Names   Reset Weights

GUI 9 – Standard Deviation Weights

Note that while three indicators in GUI 9 above have an effective weight of zero, one indicator, Affordability, is almost exclusively the only indicator that is considered. This is clearly not ideal, and it undermines the utility of a Multi-Criteria Analysis in the first place. Although there are existing research papers that analyse only a single indicator like Flood Risk, see Table S2 in Appendix A – Literature, this research would not be as novel if it attempted to repeat this approach. Specifically regarding Affordability, there could have been a potentially more dedicated method to analysing finances as was discussed in sub-section 2.2.2: Economic Methods.

Regarding the Manual Assignment weighting method, any change to any weight yields a completely different correlation. The exact number of possible correlations for the Manual Assignment weighting method is equal to the number of possible weights for any indicator to the power of the number of indicators. This is the same calculation as calculating the strength of a password, cryptographic private key, or padlock combination, which is measured in the number of possibilities.

Using quite conservatively only three possible weights (1, 2, or 3) for each of the modestly short list of merely seven indicators yields 3^7=2187 possibilities. This would form a 27 by 81 ($3^3 \times 3^4$) matrix, which would be too unnecessarily large to display on a page, and would either necessitate too many manual calculations or having to spend time to expand the MCA solver to include a feature to calculate these automatically. While the latter may make sense for future work (see sub-section 5.2.4), it would not be necessary for this initial implementation of the Custom Index.

A simpler approach, which would be just as valid, is to test each indicator's weight individually up and down (3 and 1) while maintaining all the remaining weights constant in the middle (2). This assumes that the higher and lower the score of any indicator is, the higher or lower the correlation always is, meaning a simple relation without maximum and minimum stationary points. This is relatively safe to assume, considering the nature of Equation 4 – Sum Product in sub-section 3.3.1.

This means that the number of calculated correlations for this Sensitivity Analysis is equal to twice the number of indicators, plus one for the use of the 'All Equal' weighting method, plus another one for the Standard Deviation weighting method, and then double this amount because there are two ranking methods: WSM and PROMETHEE. This gives: 2(2×7+1+1) = 32 correlations in total.

Table 16 below documents the calculated Pearson's r correlations between the Custom Index and the 2016 Sustainable Cities Water Resiliency Sub-Index based on the weighting method and weights:

Table 16 – Correlations between indices by weighting method and weight

Indicator	Weight	r	Indicator	Weight	r	Method	Weight	r
Affordability	3	0.51	Soil Moisture Content	3	0.50	Water Loss	3	0.46
	1	0.50		1	0.51		1	0.51
Flood Risk	3	0.51	Source Water Quality	3	0.50	All Equal	2	0.50
	1	0.52		1	0.44			
Water Stress	3	0.48	Tap Water Quality	3	0.57	Standard Deviation	N/A	0.24
	1	0.51		1	0.54			

The final scores for the 'All Equal' and Standard Deviation weighting methods are plotted in Figure 26 to Figure 31 below. Figure 26 and Figure 29 display the contribution of each indicator to the final score of each of the 24 Case Study Cities of the Custom Index. The other four figures plot the 21 Case Study Cities that both indices share in common. These figures normalise the scores such that the highest scoring case study city scores 100 by definition, and zero is the lowest possible score. Figure 28 and Figure 31 are sorted based on the rankings of the Custom Index, not the 2016 Arcadis Resiliency sub-index.
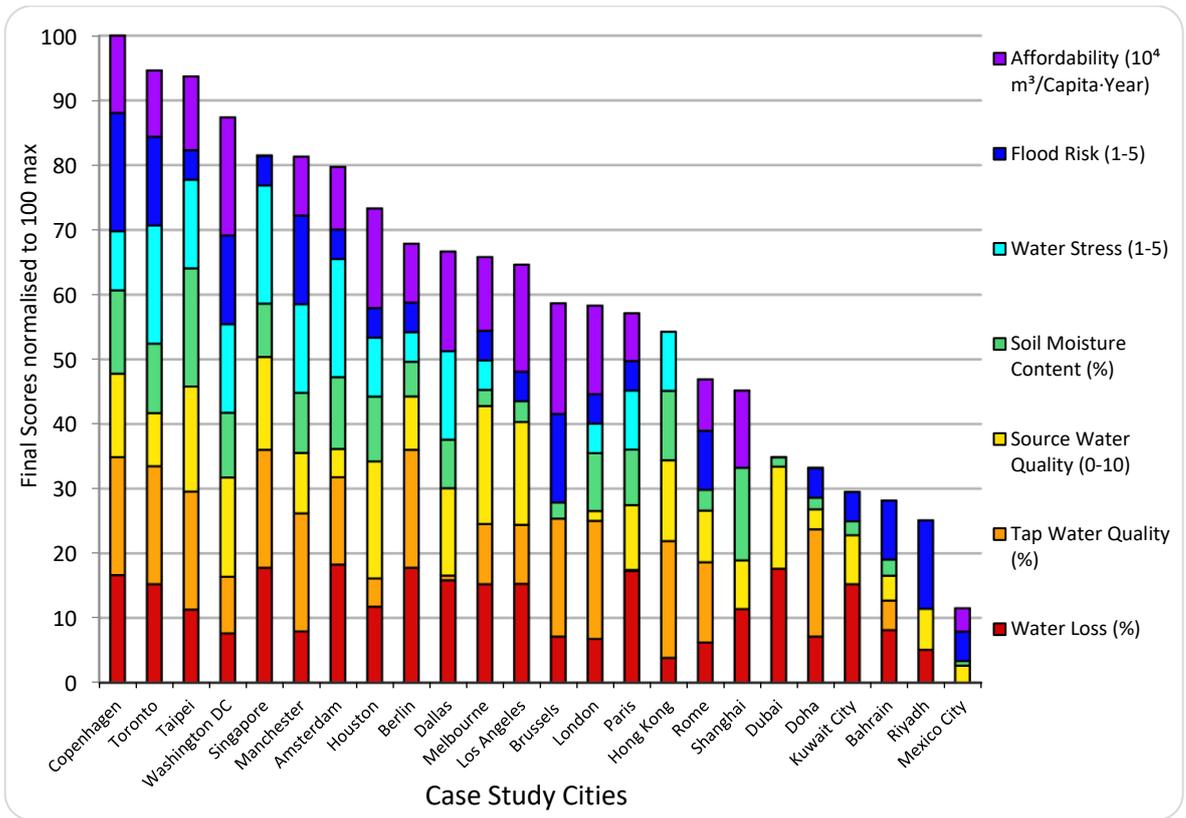
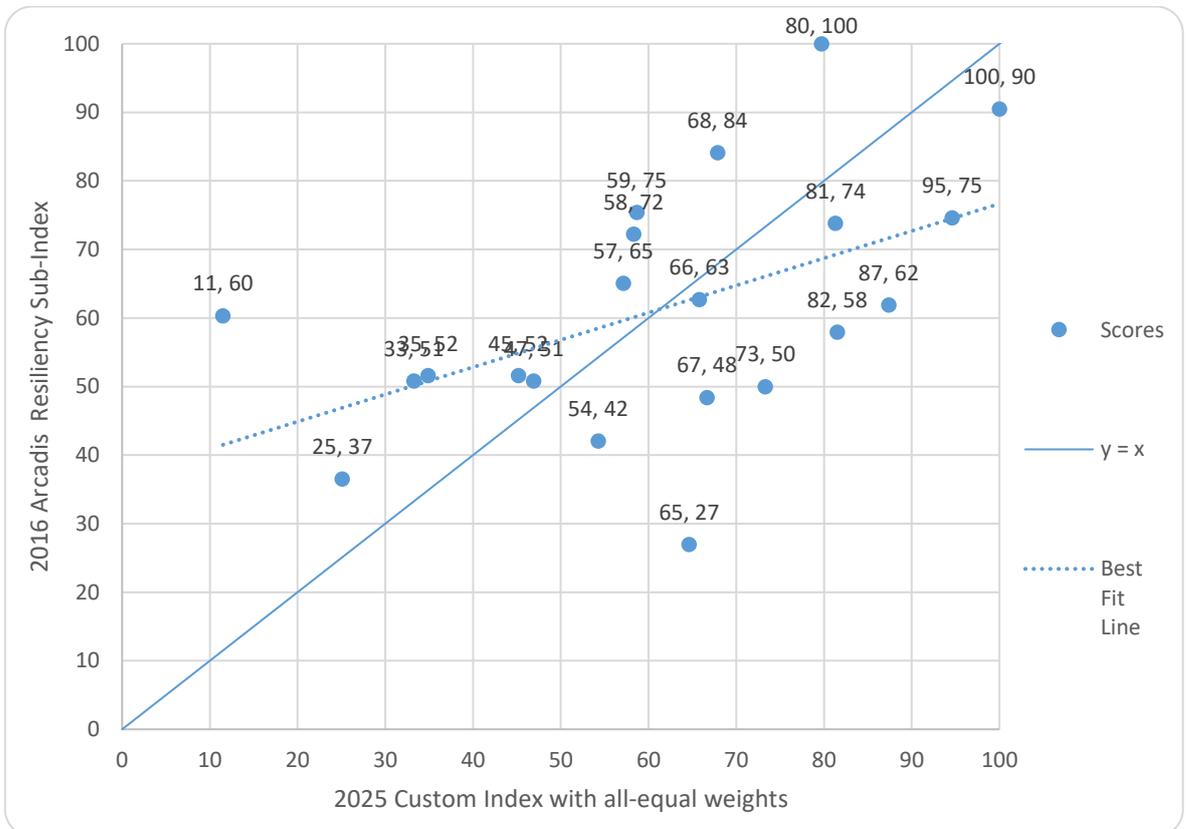*Figure 26 – Bar Chart of the Final Scores with all-equal weights*

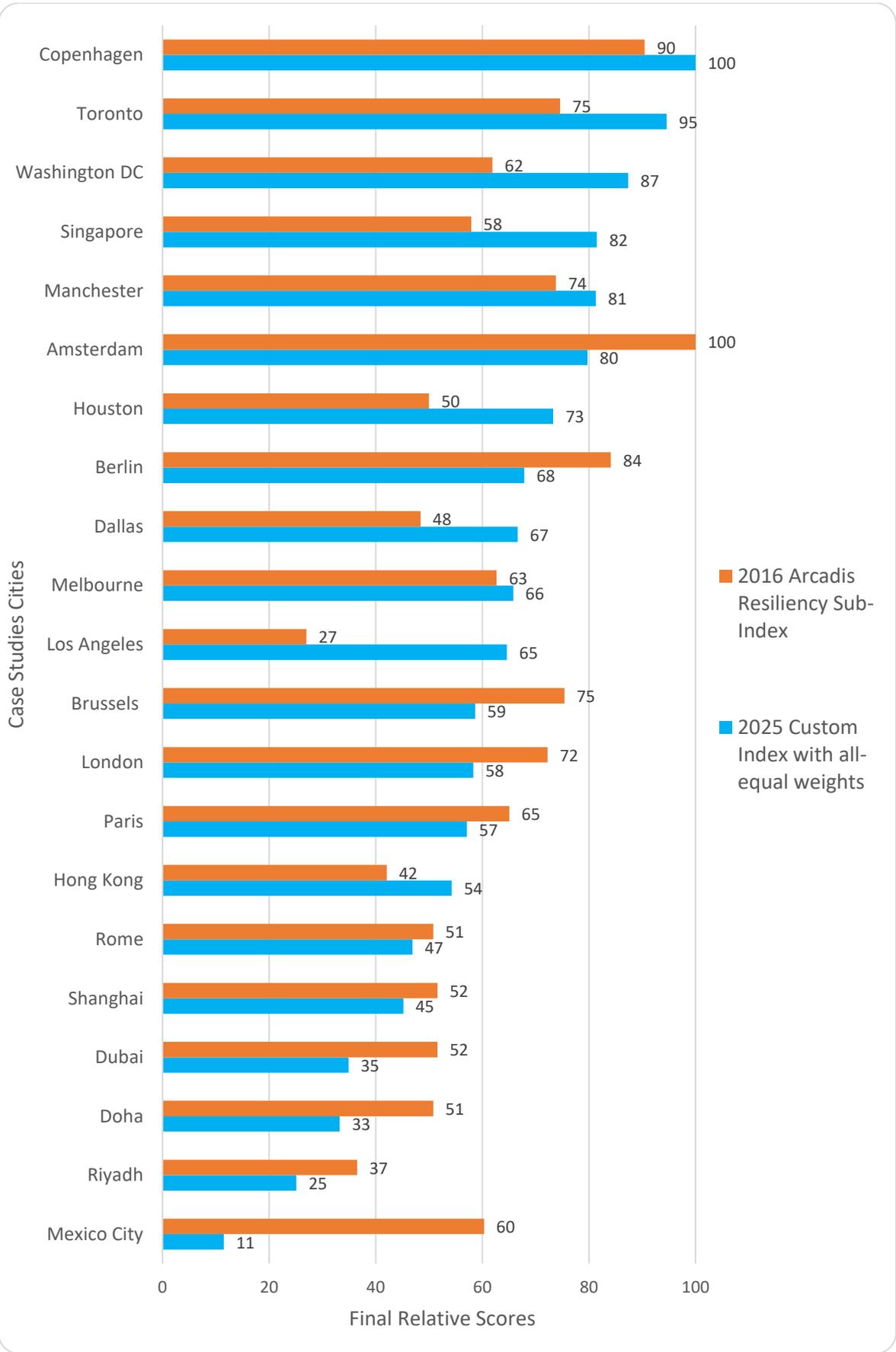*Figure 27 – Graph correlating the 2016 Resiliency Sub-Index with all-equal weights*

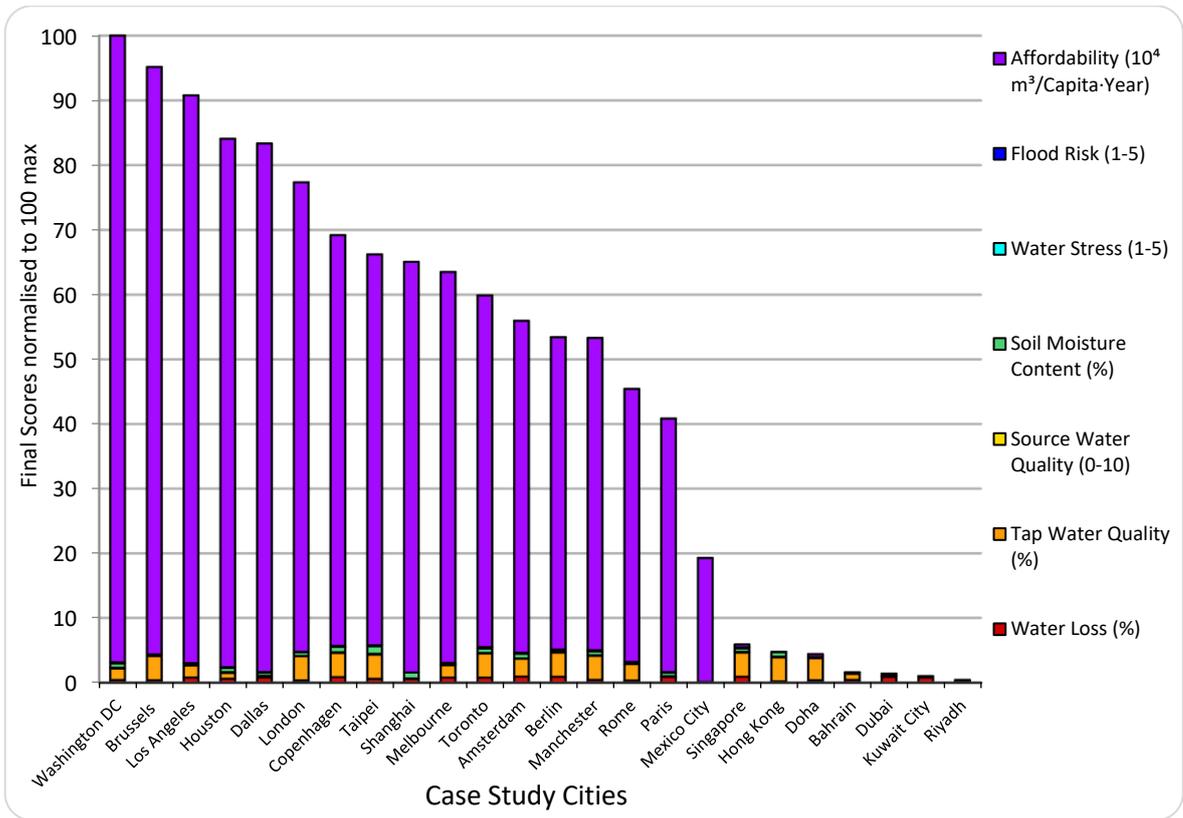*Figure 28 – Bar Chart of the 2016 Resiliency and Custom indices with all-equal weights*

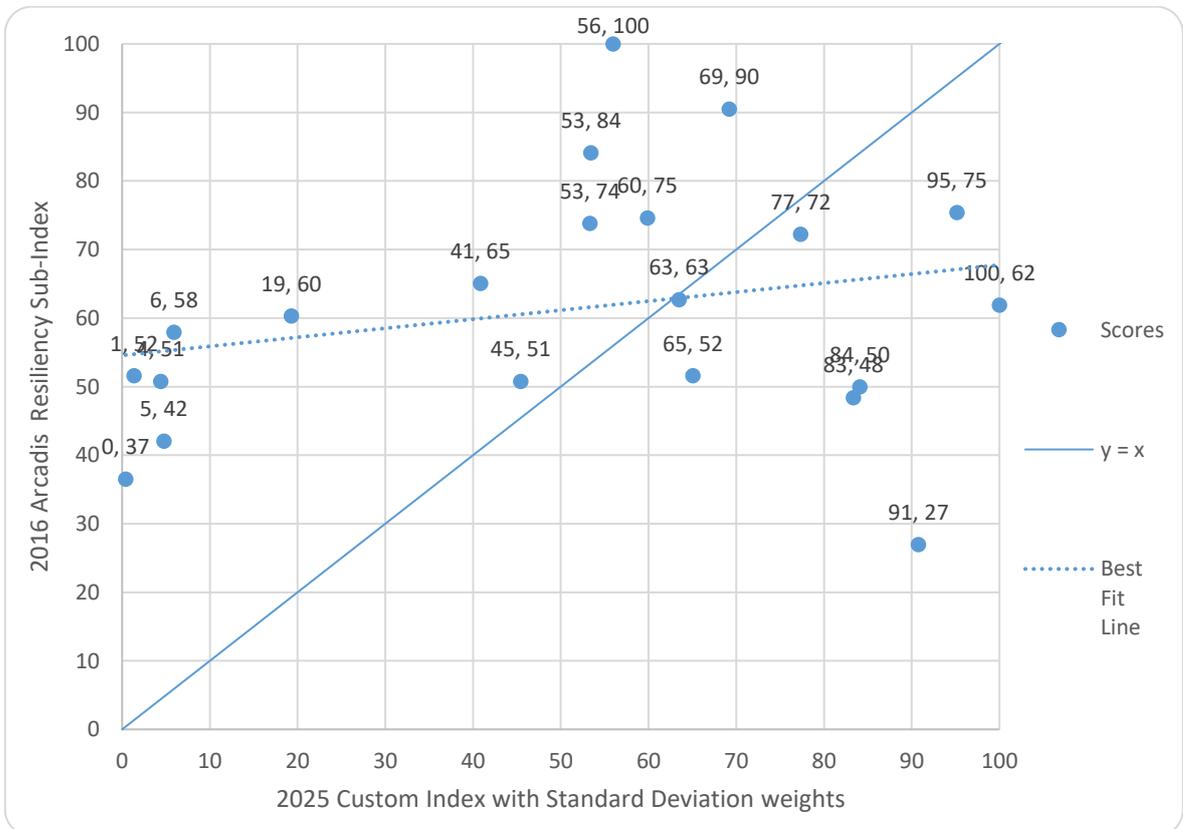*Figure 29 – Bar Chart of the Final Scores with Standard Deviation weights*

Figure 30 – Graph correlating the 2016 Resiliency Sub-Index with Standard Deviation weights
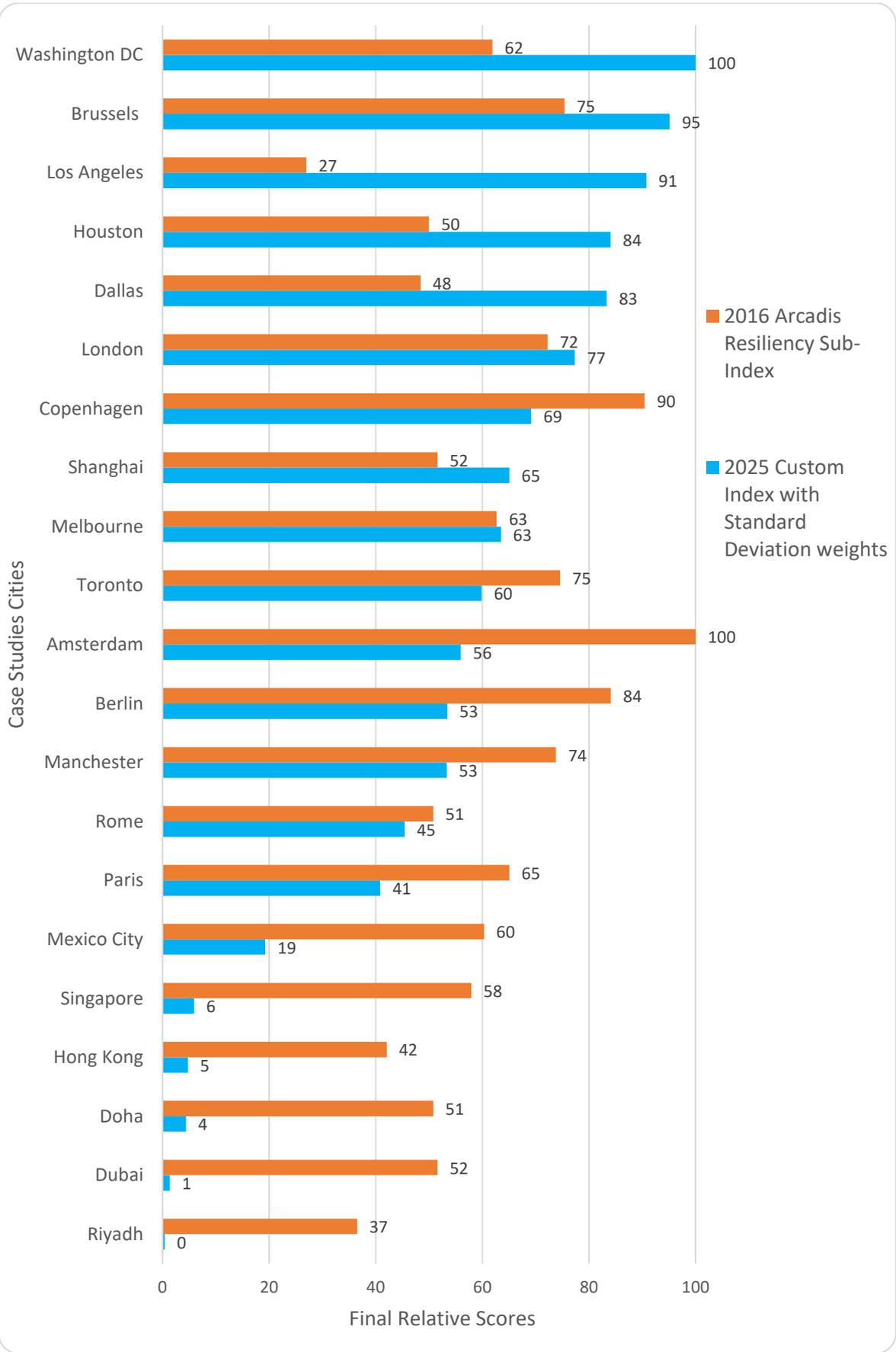
Figure 31 – Bar Chart of the Arcadis and Custom indices with Standard Deviation weights

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4.5.2. Selecting a Ranking Method

Both aggregate rank methods, WSM and PROMETHEE, resulted in very close correlations, always within ±0.01 of each other, so Table 16 above only displays half of the calculated correlations, specifically the WSM ones.

Following the explanations in the Comparison of Ranking Methods (3.3.3), it is apparent that WSM is the most ideal ranking method in general by default for most MCA applications. This is apparent because absolute ranking methods, unlike outranking methods, have the ability to display exactly the contribution of each criterion to the final rank score of each alternative, as was described in sub-section 3.3.3 and as is shown in Figure 32 in sub-section 4.6.1: Methodology Assessment and Discussion. Therefore, an outranking method would be inadequate, especially as the MCA Solver Software Tool will be upgraded to show the exact contribution of each criterion as is described in Bar Chart Improvements, sub-section 5.2.3 of the Further Work – Software Features section.

WSM is also more suitable for this Sensitivity Analysis than PROMETHEE because with WSM the final score of each case study city is calculated independently of any other, so it is possible to display in Figure 26 and Figure 29 above all the 24 Case Study Cities of the Custom Index, while in Figure 27, Figure 28, Figure 30 and Figure 31 only the 21 Case Study Cities that both indices have in common are displayed, and the scores of these 21 Case Study Cities that in common stay the same consistently across all these plots. With PROMETHEE, it would be either confusing or inconsistent.

Lastly, it is more visually appealing to normalise all the final scores such that the highest ranking is 100, and the minimum theoretical final score is 0. With PROMETHEE, the final scores would include negative values, making it impossible to visualise the Best Fit Line against the y = x line in Figure 27 and Figure 30.

4.5.3. Selecting a Weighting Method

Starting with Standard Deviation, it results in by far the lowest correlation in Table 16 above of 0.24, about half of all the other correlations, which are around 0.50. The reason for this is very visually clear from GUI 9 and Figure 29 above. The Standard Deviation weighting method is heavily distorted by the large variance between the estimated O&M costs of water treatment between on the one hand, the group of Case Study Cities that mainly rely on affordable conventional water treatment, as illustrated in Figure 4 in section 1.3, and on the other hand, the group of Case Study Cities that mainly rely on expensive desalination. Considering that water is generally a cheap substance, this variance is not as critical as is automatically weighted by the Standard Deviation weighting method.

The Affordability indicator has a high uncertainty due to the nature of the calculation and, therefore, should ideally be assigned a lower weight. There are other considerations when it comes to what weight each indicator should be assigned, such as the age of the data itself. These considerations are the reason that it makes more sense to use the Manual Assignment weighting method over the automatically assigning weighting methods of Standard Deviation and 'All Equal'. Moreover, the 2021 DuPont index also manually assigns weights based on the understanding of experts [47].

Considering these reasons, it is fair to suggest that Manual Assignment is the most appropriate weighting method for this Custom Index, and it is therefore selected.

The 'All Equal' weighting method results in a strong 0.50 correlation, which is a good sign that the Custom Index indeed measures the resilience of WSS against vulnerabilities, as the 2016 Arcadis Resiliency sub-index attempted to measure as well. The small variations in the weight of each indicator in Table 16 are expected to result in a significant change in the overall correlation if all are changed to maximise the correlation.

Having said that, it is also a good sign that there is low sensitivity in the variation of individual weights. It indicates that even if the relative importance of indicators subjectively changes, the final scores for Case Study Cities would be challenging to manipulate on purpose to be inaccurate or unrealistic.

4.5.4. Selecting Weights

Having chosen Manual Assignment as the weighting method in the previous sub-section 4.5.1 above, the exact weights now need to be selected. There are two principles to go by when manually selecting weights. Firstly, criteria with older, less unreliable, or higher uncertainty data receive a lower weight.

Secondly, Criteria that can increase the correlation with the compared 2016 Arcadis Resiliency sub-index may receive higher weights, especially if they can be rationalised to indicate a greater and more direct vulnerability than others. It is important to note here that the results of the Custom Index are important to suggest that the methodology of the Custom Index is reliable. These results are not only the final scores but also the correlation between the two indices. Therefore, it is important to see how high the correlation between the two indices can go within reason.

It is important to re-emphasise that this Custom Index is mostly aimed at illustrating to water suppliers how to best construct a WSS index, but publicly available data is not always the most reliable, hence the exact weights for this Custom Index are also mostly for illustration purposes of this methodology. For future research, water suppliers, experts, and researchers may select different weights or even a different weighting method entirely to satisfy their needs.

A re-assessment of the weights in the future would be necessary should more indicators be added or existing ones be altered, and should the Manual Assignment weighting method remain in use. See sub-sections 5.3.7: Introducing Other Indicators and 5.3.8: More sub-indicators in section 5.3: Further Work – Index.

Hence, due to not needing to be exceedingly accurate, for the purpose of this Custom Index, it was decided to select weights in the simple integer range of 1-3 for the sake of simplicity. This is despite the ability of the MCA solver to support fractional weights for Manual Assignment.

Affordability has the highest uncertainty data, so it receives the lowest weight of 1.

Water Loss is weighed at 3 as it contributed to the correlation of 0.60 in Table 16 above, and also because, despite relying on various different sources, i.e. local water supplier data, it is very recent and accurate, often measured in tenths of percentages, see Table 8 in sub-section 4.3.2. Hence, it has low uncertainty. What's more, it is convenient and natively normalised in the units of percentages from 0% to 100%.

As is shown in GUI 5 in section 3.4: Criteria Correlations Matrix, there is a very high |-0.68| correlation between Water Stress and Soil Moisture Content. Correlation does not imply causation, but in this case, it would make sense for both indicators to measure the same vulnerability: drought. This makes sense because the correlation is negative. This is what would be expected. An arid environment with low Soil Moisture Content due to low precipitation would be expected to also have a low replenishment of its water sources relative to withdrawals.

It was decided to keep both indicators in the Custom Index to present the usefulness of the correlations table feature of the MCA Solver Software Tool. In fact, the very high correlation between them actually suggests that Soil Moisture Content might be a superior indicator for drought despite being a proxy. This is because it can be generated natively normalised in the units of percentages from 0% to 100% and its data is recent and accurate using satellites anywhere in the world, which is highly verifiable, repeatable, and falsifiable, and does not rely on potentially dubious statistics from local water suppliers, such as withdrawal rate, as with Water Stress.

For this reason, in future work, Water Stress would likely be removed and its weight would be added to Soil Moisture Content. It is important to note that the current implementation of the Custom Index focuses on showcasing the novel methodology, while the results themselves would likely change in the future with other data.

Considering that the 0.60 correlation increased with a moderately higher Water Stress weight and decreased with Soil Moisture Content weight, Soil Moisture Content is weighted at 1, and Water Stress is weighted at 2. Soil Moisture Content is a relatively novel way to measure drought in WSS literature, which typically uses a ratio of withdrawals to replenishment as Water Stress. Therefore, it may also be wise to assign Soil Moisture Content a low weight because it is a new approach, and potentially increase it in the future if it ever replaces Water Stress completely.

Source and tap water qualities are weighted 1 and 3, respectively, because Source Water Quality relies on older data, see Table 11 and Table 15 in sub-sections 4.3.4 and 4.3.17, respectively. Tap Water Quality Reports, however, are published yearly and so are significantly more recent and detailed. Source Water Quality is also more varied in terms of water sources, such as lakes, rivers, underground aquifers, and wells, and most crucially, coastal water for desalination, which affects a number of the case studies. Furthermore, some case studies, such as Manchester, Riyadh, and Mexico City, import their water from far away; hence, measuring local catchments misses a larger picture, which is not the case with Tap Water Quality.

Tap Water Quality is also more likely to cause a water shortage [33], [34] than Source Water Quality, due to their order in the supply chain. A badly scoring water source can still rank highly in tap quality without enough treatment, and vice versa. This is, in fact, one of the most important unintended findings of this research. See sub-section 5.1.1.2: Correlation Between Vulnerabilities and one of the lowest correlations between any two indicators in GUI 5 of merely |-0.09|.

Flood Risk receives a high weight of 3, considering the recent Past Water Supply Disruption Incidents tabulated in section 1.2. For the same reason as Past Water Supply Disruption Incidents, Tap Water Quality and Water Stress receive moderate and high weights as opposed to 1. The weight of Water Stress being 2, combined with the weight of Soil Moisture Content, which is 1, gives an overall effective weight of 3 for drought, which, for the Custom Index, is considered high.

It is important to emphasise again that Soil Moisture Content and Water Stress can work in unison despite being opposites. This is achievable by setting opposing best and worst values, as shown in GUI 6 in section 4.4: Scores Results.

These selected weights are summarised in GUI 10 below:

Criteria Weighting

Number of Criteria = (7)

User Inputs: Criteria Preferences

Weighting Method: (-Manual-)

Criteria	Affordability (10⁴ m³/Capita·Year)	Flood Risk (1-5)	Water Stress (1-5)	Soil Moisture Content (%)	Source Water Quality (0-10)	Tap Water Quality (%)	Water Loss (%)
Raw Weights	1	3	2	1	1	3	3
Normalised Weights	0.07	0.21	0.14	0.07	0.07	0.21	0.21

Reset Criteria Names   Reset Weights

GUI 10 – Selected weights for vulnerability indicators

Using Pearson's r correlation as was previously used in Table 16 in sub-section 4.5.1: Sensitivity Analysis, these weights yield a strong 0.60 correlation between the Custom Index and the 2016 Arcadis Resiliency sub-index. The difference of 0.10 between this and the 'All Equal' weighting method indicates that although a manual selection of the weights results in a moderately significant increase in the correlation, it was not too large. This is a positive sign, as it means the Custom Index is not too sensitive.

4.6. Rankings Results

4.6.1. Methodology Assessment and Discussion

Following sub-section 2.3.3: Validation and Assessment, to assess the Custom Index, it needs to be correlated against the most similar existing index in the literature. From sub-section 2.3.2: Most Notable Sources, the 2016 Sustainable Cities Water Resiliency Sub-Index [21] was selected, as it was explained that it has the closest combination of indicators in common with the Custom Index. It also has a foreword from the reputable IWA. As both indices effectively attempt to measure the resiliency of WSS to vulnerabilities, a high correlation of above 0.5 is sufficient. Attempting to achieve too high a correlation would likely come into conflict with the aim of improving upon the current indices in the WSS literature by reproducing an existing index instead.

The majority of Case Study Cities, which were studied in this Custom Index, 21 out of 24, are also included in the 2016 Sustainable Cities Water Index, to generate the most reliable correlation using a sizable number of case studies. The other three cities were selected out of specific interest in them, as well as testing the repeatability of the method of the Custom Index with cities that are not included in the 2016 Sustainable Cities Water Index.

The data for the Custom Index is gathered from various sources. These sources are mentioned in the dedicated sub-sections for each indicator in section 4.3: Vulnerability Indicators, in Table 15 in sub-section 4.3.17: Indicators Comparison and Selection, and are presented in Appendix C – Index under sub-sections Interactive Maps.

The final aggregated scores of the Case Study Cities of the Custom Index are listed in GUI 8 in section 4.4, and these scores are plotted in Figure 32, Figure 33, and Figure 34 below. They follow the same structure as the figures in sub-section 4.5.1: Sensitivity Analysis. These three figures do not plot the uncertainties because the uncertainties are low, as documented in GUI 8. Figure 32 and Figure 34 are sorted from the best-scoring Case Study City on the Custom Index. Figure 32 lists all the 24 Case Study Cities, while Figure 33 and Figure 34 only list the 21 that both indices share in common for correlating them.

The 2016 Index does not specify exact score numbers the same way the Custom Index does in GUI 6 in section 4.4: Scores. In order to generate score numbers for Figure 33 and Figure 34, a software 'ruler' app was used against the bar chart in the original index publication [21] to measure their lengths relative to each other in centimetres for a certain zoom setting. These numbers were then correlated using Equation 8 – Pearson's r Correction from section 3.4 for the 21 Case Study Cities, both indices share in common. These numbers are drawn below in Figure 34.

The contributions of each indicator's score for the final aggregate score of each of the 24 case study cities are highlighted in Figure 32 below. The result correlation is plotted below in Figure 33.

These figures normalise all final scores such that the best case study of each index scores 100, which are Copenhagen for the Custom Index and Amsterdam for the 2016 Sustainable Cities Water Resiliency Sub-Index. It is worth noting here that Singapore scored highly in the Custom Index due to its very well-documented Tap Water Quality Reports and low Water Loss, despite its Affordability challenges due to reliance on importation, desalination, and NEWater reclamation. Normalisation to 100 does not affect the correlation and is only for visual convenience, as well as noting which case study ranks highest in either index. The main consideration here is the strong correlation of 0.60 between the two indices plotted in Figure 33.
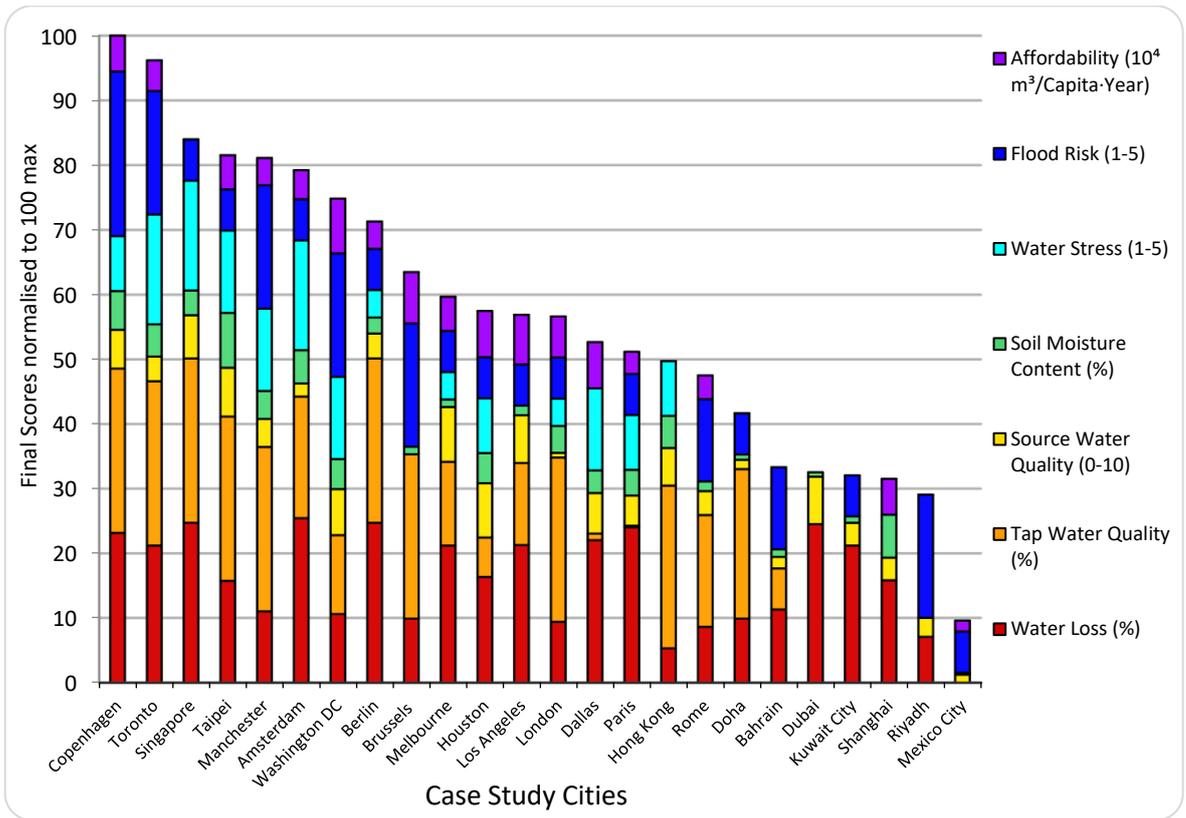
Figure 32 – Bar Chart of the Final Scores of Case Study Cities in the 2025 Custom Index
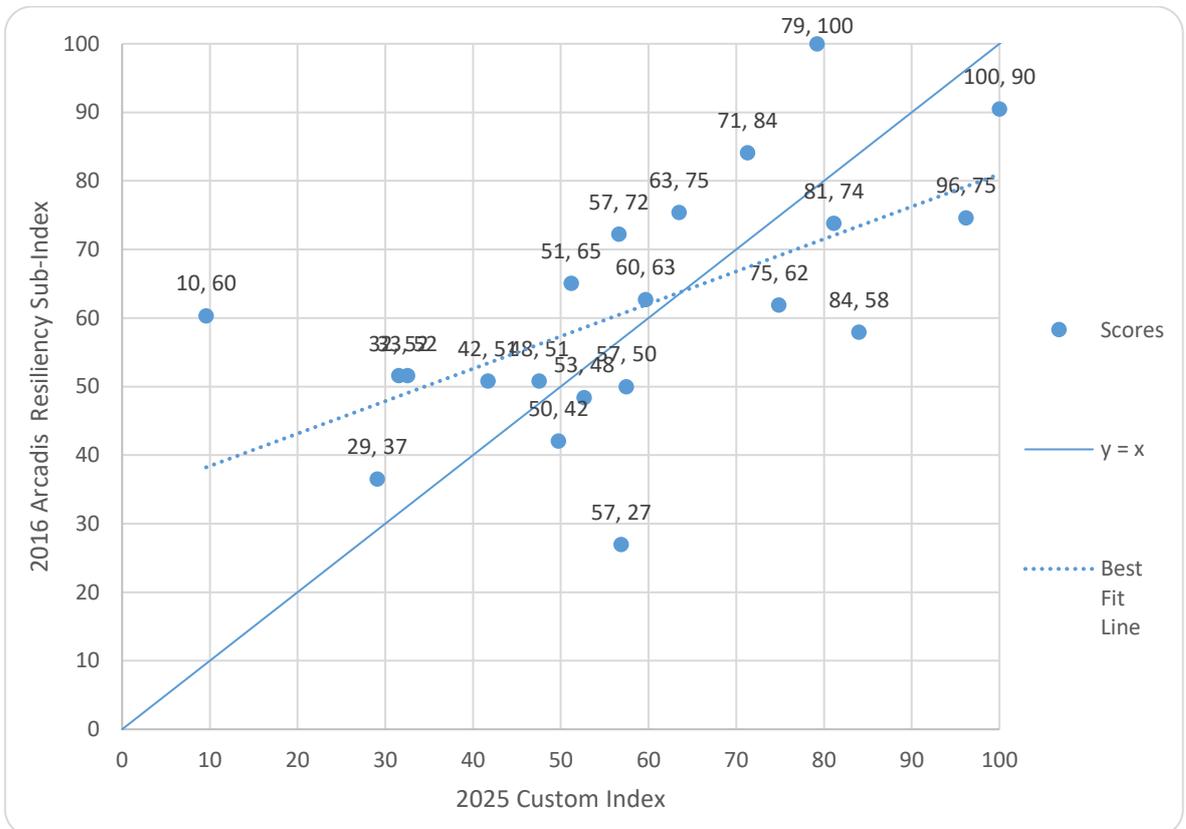

Figure 33 – Graph correlating the 2016 Resiliency Sub-Index with the Custom Index
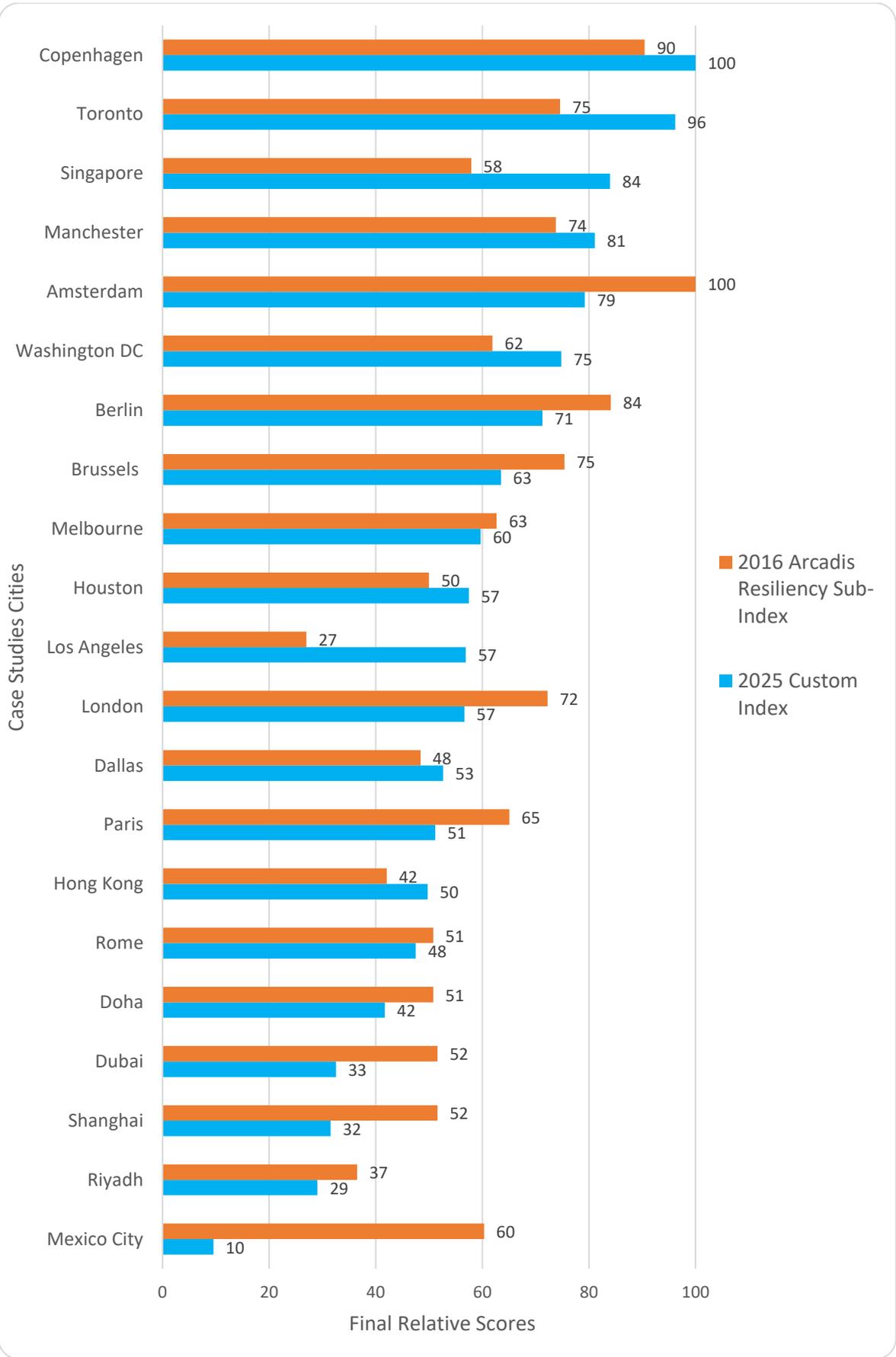
Figure 34 – Bar Chart of the 2016 Resiliency Sub-Index and Custom Index

The three main constructive criticisms that come to mind for the 2016 Sustainable Cities Water Resiliency Sub-Index are its usage of the 'Water-related disaster risk', 'Green Space', and 'Water Balance' indicators, its complicated usage of three subindices, including 'Efficiency' and 'Quality', and some of its questionable data.

Starting with 'Water-related disaster risk', its definition includes Flood Risk and drought [21], both of which are already covered in its Flood Risk and Water Stress indicators, respectively. It is inadequate that no Criteria Correlations Matrix was conducted to ensure no double-counting occurred; however, it is worse if, by the definition of the indicators, they are unnecessarily complicating the index by double-counting on what appears to be on purpose.

The usage of 'Green Space' as an indicator is incredible in terms of how much it contributes to the final scores of most of the case studies, as shown by Arcadis [21]. It raises a critical question: why would more green spaces be valuable for the resiliency of water systems at all? More to the point, what evidence or even theory is there to suggest that green spaces protect water systems from preventing or mitigating water shortages? The closest answer to these questions appears to be that water is absorbed in vegetation, which lowers the flow rate of rainfall runoff and limits flooding. This was discussed in sub-section 4.3.6.1, along with numerous significantly more effective flood-mitigation solutions. Moreover, the amount of water green roofs can absorb is very limited because they are thin. Consequently, this vulnerability is already being taken into account as part of flood risk. It seems as though this indicator was added merely to appear "greener" and more sustainable.

Focusing on Hong Kong, the 2016 Resiliency Sub-Index gave it a low score. A major contributor to this low score is a score of 0 for 'Green Spaces'. Hong Kong is covered in woodland hills and parks. It is confusing as to why Arcadis awarded the desert city of Riyadh a relatively large green score, while Hong Kong was awarded nothing. Was this for the effort to produce green areas, as opposed to the actual percentage of the land that is green? It does not seem to be the effort, considering that the percentage of a city's area which is green is exactly the definition provided by Arcadis [21].

In fact, considering how simple this definition is, it should be easy enough to measure a rough score for every case study using satellite imagery applications, for example, Google Earth or Maps [191]. Performing such measurements would dispute the Green Spaces scores in the 2016 Resiliency Sub-Index. It seems as though the referenced source for the Green Spaces scores was unreliable.

In terms of data points, it is unclear why some European cities, such as Paris and Rome, score so poorly in resiliency to flood risk, despite having excellent scores in most sources. Moreover, Dubai received a significant score for flooding resiliency, despite a 2024 severe flooding incident proving that Dubai should not receive any score for flooding resiliency. This flooding incident caused electricity and water outages [36], [37] and resulted in three deaths [38]. This is in contrast to no such recently recorded events in the case studies of Berlin and Copenhagen, which, although the 2016 Sustainable Cities Water Resiliency Sub-Index correctly scores highly overall, clearly do not take into account any resiliency to flood risk for these two case studies.

Regarding Water Balance and Reserve Water, the two Texas cities of Dallas and Houston, as well as Toronto, scored poorly on Water Balance. Conversely, the desert city of Riyadh scored highly here. By the definition given by Arcadis [21], this means a deficit of rainfall. But considering these cities have large lakes [125], [254], [255], [152], particularly Toronto's great lakes [32], this Water Balance indicator must be put into question. It is misleading, considering that as long as the large lakes remain, only Water Stress truly matters in this regard. Water Stress can occur in such cities if their treatment does not meet demand, despite the large capacity of stored water. Water Balance sounds as though it refers to the reserved capacity of stored water; hence, even its name is misleading.

The case study city of Mexico City received a high 'Green Spaces' score. This is the opposite of Hong Kong, which received a low 'Green Spaces' score as was previously discussed; this, too, is based on questionable data, considering that a smaller percentage of Mexico City's area appears to be green compared to Hong Kong's [191]. Mexico City is ranked above Chicago for having less Water Stress in the 2016 Resiliency Sub-Index, but not only is this disputed with the source of data of the Custom Index [110], but this also makes little sense, considering that Chicago borders the Great Lakes. The unnecessarily complicated 3 sub-indices of the 2016 sub-index means that the substantial 40% Water Loss Mexico City experiences [123] is not taken into account in the Resiliency sub-index at all.

The 2016 Arcadis covers twenty indicators. Six of these are in the 'Resiliency' sub-index, seven 'Efficiency' indicators, and seven 'Quality' indicators [21].

The 2021 DuPont index also features three cumbersome categories: 'Reliability', 'Accessibility', and 'Sustainability' [47]. Yet, the 2021 DuPont index is even more complicated as it subdivides into lists of sub-indicators.

Moreover, the Custom Index calculated uncertainties, unlike the 2016 and 2021 indices.

The first important note to make about comparing the 2021 DuPont index to the Custom Index of this research is that the 'Accessibility' sub-index does not aim at assessing the vulnerabilities of WSS against potential future incidents, but rather, the current equitable access and connectivity.

In this sense, the Custom Index innovates beyond the 2021 DuPont index, because it fills a gap in the literature, which is assessing the vulnerabilities of WSS from the perspective of the supplier alone. Both the 2016 Arcadis and 2021 DuPont indices assess a mixture of indicators, some of which are consumer-focused, while in the Custom Index, these all have the unique perspective of only being supplier-focused, more notably, the new, novel supplier Affordability indicator.

The Custom Index opted to cover only a few indicators, not only for the simplicity of demonstrating the methodology works and applying an innovative supplier-focused perspective, but also to avoid double-counting the same vulnerability twice or more via two or more separate indicators. Unlike the 2016 Arcadis and 2021 DuPont indices, the Custom Index implemented a Criteria Correlations Matrix, which was discussed in section 3.4. It is quite likely that much like was previously discussed for Arcadis, DuPont also employed criteria that highly correlate, though this can only be speculated, considering that neither calculated correlations nor has Arcadis published exact score numbers for each case study for each indicator, which is why a correlation with it in Figure 34 and Figure 33 required a software 'ruler' app as was previously mentioned.

The 2021 DuPont index covers 13 indicators and not one but two nested levels of sub-indicators. This is the only example of any index in the literature review of this research where an index has two nested levels of sub-indicators, making it unnecessarily complicated. For example, how would these sub-indicators be correlated against one another? Would they all be correlated against one another on an equal basis to produce a quadratically larger Criteria Correlations Matrix of a length of a few dozen indicators? Recall Equation 1 – Triangular Numbers in sub-section 3.2.3 for the number of unique pairwise correlations based on the number of indicators. This is why it is important to narrow down the focus of an index, to limit the number of assessed indicators. The indicators of Water Connectivity/Coverage and Nutrient Recovery, although important, do not assess the vulnerabilities that could lead to disruptions of the current water supply.

While both the 2016 Arcadis and 2021 DuPont indices include indicators that may not be relevant for the vulnerabilities of WSS, as well as duplicate indicators that measure the same vulnerabilities, they lack actually important indicators which this research discusses and considers to include in future revisions. These include the mix of sources for water supply in percentages, meaning reliance on imports, non-renewable groundwater, and expensive desalination and reclamation.

As was mentioned at the opening of this chapter, *"All models are wrong, but some are useful"* – statistician George E. P. Box [106]. No aspect illustrates this better than at the extremes of any model, not only MCA. It is for this reason that boundary conditions are often considered in CPE. One need only consider what would be the case if any alternative received the worst possible score for any given vulnerability.

Consider the possibility of a case study having a leakage rate at or near 100%. Even if it scores highly in all other criteria, such a high leakage rate would be sufficient to cause a complete failure of the WSS. If a WSS index reflected this, it would give a final score of 0 for such a case study. And yet, the current implementation of the Custom Index, as well as the 2016 and 2021 WSS indices from the literature (sub-section 2.3.2), do not reflect this reality mathematically.

This is a broad issue with MCA and other models. A possible solution is to increase weights exponentially the closer a score is to the extreme worst possible score. More on better weighting methods for further work in sub-section 5.2.4 in the next Chapter.

It is also important and interesting to raise an analogy here. Some weighting methods, such as Entropy (3.2.5), fail completely with scores of zero, but also fail realistically with scores close to zero. This represents an opposite error, one when the WSS still functions, but the mathematical model indicates a failure. Hence, the Entropy weighting method was not selected for this Custom Index.

Beyond the choice of the weighting method selected, it is the exact definition of each criterion that determines whether the index model is realistic and sufficiently accurate.

On top of this, some indicators are not even considered in the index, due to a lack of data, as mentioned in sub-sections 4.3.17 and 4.3.18. Meaning that without data to measure the resiliency of case studies for certain other vulnerabilities, it cannot be known whether there is a case study that is at a high risk of failure for those vulnerabilities. Hence, the model is imperfect.

As the saying goes: *"If you are so clever, why aren't you rich?"* If MCA models were so accurate, they would win in the stock market. It was famously suggested that blindfolded monkeys are better at investing than financial analysts [256], [257], [258]. It is therefore prudent to be humble and to recognise that small improvements to a model will still not make it completely accurate, but perhaps accurate enough to be useful and beat competing existing models, and therefore provide utility in the real world. The Custom Index can still be useful because, in realistic conditions, no case study has any score that is too extreme. *"Do not let the perfect be the enemy of the good."*

4.6.2. Summary

The 2016 Arcadis and 2021 DuPont WSS indices published lists of Case Study Cities and Vulnerability Indicators, which are the basis of developing an MCA index for the vulnerabilities of WSS.

The 2016 Arcadis index can be improved by sharing the exact numbers for the scores and weights, which both the 2021 DuPont index and the Custom Index of this research specified. Several scores in the 2016 Arcadis seem unintuitive and unreliable, so its data needs to be revised and better cited with multiple references per indicator, if possible. The 2016 Arcadis index should discard the indicators 'Water-related disaster risk', 'Green Space', and 'Water Balance', which are already taken into account through the Flood Risk and Water Stress indicators.

Both the 2016 Arcadis and 2021 DuPont indices can improve by implementing uncertainties and correlations, as the Custom Index has, using the MCA Solver Software Tool. They should clarify their perspective since they are not exclusively supplier-focused. By extension, what commonality do all their indicators share? Both indices should combine all three categories into one, and the 2021 DuPont index should especially do away with the two nested layers of sub-indicators.

The Custom Index was developed in the order specified in Figure 12 in sub-section 2.2.4 Existing MCA Software. The Case Study Cities and Vulnerability Indicators have their dedicated novel lists of selection requirements. These selection requirements include clear WSS boundaries for the Case Study Cities, realistically possible to improve the resilience against the Vulnerability Indicators, and moderate availability of data for both.

The Custom Index assessed twenty-four Case Study Cities, which were sufficient to conduct the Criteria Correlations Matrix and illustrate the methodology. The 2016 Arcadis and 2021 DuPont indices assessed 50 and 51 Case Study Cities, respectively, which is even better for calculating more reliable correlations; unfortunately, they did not calculate any. The twenty-four Case Study Cities are varied and represent different cultures, climate zones, land and sea boundaries, and unique features such as catchments and reclamation.

The Vulnerability Indicators of the Custom Index include the new supplier-focused Affordability and the Tap and Source Water Quality indicators with a novel selection of sub-indicators and the "mixed-compliance" equation to assess water quality in the fairest manner. The list of indicators which were selected and constructed for this Custom Index is its most important output, as any fork of this model can use an entirely different set of Case Study Cities, but the indicators and their implementation would be quite similar due to their supplier-centred focus.

The novel output of the Custom Index is its guideline methodology of selection requirements for case studies, indicators, and sub-indicators, as well as the exact set of indicators and sub-indicators, not the exact final scores.

Regarding the uncertainties, they were important to demonstrate that even if a user manually assigns the affordability uncertainties as high as ±50%, the final uncertainties are still at most ±4%, see GUI 7 and GUI 8 in section 4.4. This further emphasises that despite there being no statistically significant correlation between the Custom Index and the 2016 Resiliency Sub-Index, several case studies scored highly and poorly in both indices, as would be expected. Examples are Amsterdam, Berlin, Copenhagen, Manchester, and Toronto, which all scored above 70% in both indices, while Hong Kong and Riyadh scored at 50% or less in both indices, see Figure 34.

A future user can allocate the uncertainties differently, for example, by fundamentally inspecting each variable in Equation 15 – Custom Supplier-Focused O&M Affordability in sub-section 4.3.8 and calculating an Affordability propagation uncertainty for each case study city. Estimating uncertainties is complicated, and there are no solutions, only trade-offs.

Similarly, constructing the Custom Index involved wisely selecting the weighting and ranking methods, as well as uncertainties, which, for this index, the simplest of these methods were the most fitting. As for which Case Study Cities scored the highest, it is unsurprising that cities that rely on local conventional large bodies of surface water, particularly lakes, scored the best. Cities that rely on desalination, or even worse than desalination, importation, if they are landlocked, scored poorly. Similarly, cities located in temperate environments have higher soil moisture contents and experience lower Water Stress.

Recall the hypothesis of this research project from section 1.5, which is that by constructing a methodology to quantify and therefore better understand the vulnerabilities of WSS, decision-makers can better manage and invest in the WSS to increase the resilience against the risk of water supply disruptions. The purpose of this research was to lay the groundwork to build a future researcher regarding how to apply this framework. Therefore, this research can be said to be theoretical. It was assessed by comparing the final scores of the Case Study Cities by the Custom Index to an existing example in the literature, which is the 2016 Resiliency Sub-Index. As was discussed above, there is a strong correlation between the two indices at 0.60.

5. Conclusions and Further Work

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5.1. Conclusions

This research project assessed the vulnerabilities of WSS in large cities. This is due to the observation that humanity is becoming increasingly urbanised [21], [26] and therefore, the vulnerabilities of water systems are increasingly becoming major vulnerabilities for humanity as a whole.

Following section 2.2: Methods used in Water Supply Assessment in chapter 2: Literature Review of WSS Assessment, Multi-Criteria Analysis (MCA) was identified as the most appropriate family of methods for analysing WSS. MCA methods are the most common types of methods used in the WSS literature, because water systems face multiple vulnerabilities; hence, their resiliency is multi-factorial. MCA is needed to best capture all the major vulnerabilities WSS have.

Sub-section 2.3.2 details the Most Notable Sources studied in Chapter 2: Literature Review of WSS Assessment. These include papers that list indicators that measure the vulnerabilities of WSS and two indices that compare the WSS of cities worldwide. There were only very few such indices found in the water systems literature review. The advantages of comparing cities worldwide include learning from both their failure incidents and successes, giving perspective to water suppliers on how their city compares to others that might have handled vulnerabilities better, and correlating indicators to prevent the use of indicators that correlate too strongly, suggesting they may measure the same vulnerability unnecessarily, and thereby complicating an MCA index.

However, the two studied indices from sub-section 2.3.2 do not include correlations, uncertainties, or even a specific aim. A number of their indicators address environmental and socio-economic issues, which, although important, shift the focus from the vulnerabilities of WSS that can realistically cause water shortages, as documented in section 1.2: Past Water Supply Disruption Incidents. For example, Nutrient Recovery and Water Connectivity/Coverage are both important, but an index that includes them no longer solely focuses on the vulnerabilities that can disrupt the existing water distribution.

Therefore, to fill this gap in the WSS literature, this research project constructed a novel MCA Custom Index, detailed in Chapter 4. It has a unique list of Indicators Selection Requirements, detailed in sub-section 4.3.1. It revolves around a unique approach of only selecting indicators that are supplier-focused, as opposed to focusing on the customer or the environment. This is due to the 'Water Metabolism' innovative perspective of this research, which views the vulnerabilities of water systems of large cities similarly to the vulnerabilities of organisms and their metabolism.

This Custom Index concludes that the best indicators to assess the vulnerabilities of WSS are: Water Loss (4.3.2), Tap Water Quality (4.3.3), Source Water Quality (4.3.4), Flood Risk (4.3.6), Soil Moisture Content (4.3.7), Affordability (4.3.8), Lead Pipes (4.3.11), Importation Water Dependency (4.3.13), Non-Renewable Primary Energy (4.3.14) and Groundwater Reliance (4.3.15). The last four were excluded from the Custom Index due to a lack of data and to simplify this initial version of the Custom Index to only include a few indicators that are sufficient to assess it.

The only indicator that was included in this Custom Index but actually expected to be omitted in a future revision is Water Stress (4.3.5). Water Stress is extremely important, but so is the methodology by which it is measured. Water Stress was included in this initial Custom Index to illustrate its strong correlation with Soil Moisture Content; hence, only one of these two should remain. Soil Moisture Content is a proxy indicator, but has the advantage of having reliable recent and widely available data based on satellite observations, hence it is preferred to remain. Tap and source water qualities are sub-indices with their own set of sub-indicators, and affordability also innovated its own supplier-focused equation for this research.

The Custom Index also outputs a set of weights, uncertainties, and weighting and ranking methods.

Page 2.2.4.1 details the Existing MCA Software programs by their advantages and disadvantages, for the sake of carrying out a new MCA Custom Index for WSS. Considering the lack of fundamental features, specifically uncertainties and correlations, as well as other basic features, namely zooming in and being free and open source, it was decided to program a new MCA Solver Software Tool as another output of this research project, alongside the WSS Custom Index, which this solver will run. This new MCA solver is detailed in Chapter 3. It can be used for any MCA index, not merely WSS.

Sub-section 2.3.3: Validation and Assessment discusses how both the MCA Solver Software Tool from Chapter 3 was validated and the Custom Index from Chapter 4 was assessed, meaning what evidence was used to test their credibility. As was noted in the introduction sections to both chapters, their respective validation and assessment are in the section Validated MCA exercises from the literature of Appendix B – Software and in sub-section 4.6.1: Methodology Assessment and Discussion. The operation of the MCA solver as a specialised software calculator was validated by comparing its results to example calculations from the MCA literature. The assessment of both the methodology and data of the Custom Index was achieved with a strong correlation against the existing 2016 Sustainable Cities Water Resiliency Sub-Index from the literature [21] in Figure 33.

5.1.1. Further Findings

Throughout the history of scientific discoveries, certain important findings were not originally aimed at being tested for. The following important discoveries are the further findings of this research:

5.1.1.1. New Ranking Methods Discovered and Compared

Firstly, after analysing the equations and scripts of the two Absolute Ranking Methods from MCA literature, it appears that WSM and WPM can be forked into two similar methods: Product and Sum-Power, as Table 7 shows in sub-section 3.3.1. While WSM is the well-known Sum-Product statistics equation, Product is also a familiar statistics formula. These four make a clear two-by-two table of sum and product, and product and power, of the scores and weights. Ultimately, it was justified in sub-section 3.3.3: Comparison of Ranking Methods that WSM is the superior method of these four, but the discovered Sum-Power method was found to be superior to WPM. This means that this research suggests a new, yet simple, replacement method for an existing MCA method in the literature.

5.1.1.2. Correlation Between Vulnerabilities

Secondly, GUI 5 – Criteria Correlations Matrix in section 3.4 demonstrates the novelty of the correlations across the twenty-four Case Study Cities between indicators that were never-before-seen correlated in the WSS literature. There are two fascinating correlations that stand out the most:

A very low correlation of -0.09 between tap and source water qualities means that even a bad quality at the source can be adequately purified at water treatment plants. The inverse can also be true, that a good quality at the source can be contaminated along the WDN from the plant until it reaches domestic taps, or that the treatment is inadequate at the plant to begin with. Tap and source water qualities were included as separate indicators to allow for calculating this correlation. Initially, it was speculated that they would strongly correlate due to their similar natures, with the latter being the downstream of the former. Therefore, this low correlation is quite meaningful.

The strongest correlation of all is -0.68 between Water Stress and Soil Moisture Content. As the negative sign suggests, it is logical that the lower the Soil Moisture Content, the higher the drought and therefore the Water Stress. This is potentially quite an important discovery for future MCA of WSS vulnerability, because it may mean that it is most reliable and accurate to use Soil Moisture Content as a proxy for Water Stress, because Soil Moisture Content gathers consistent and reliable data from satellite observations, see Map S3 in Appendix C – Index.

5.2. Further Work – Software Features

There are software features that seem like good ideas but have yet to be developed during this research project, for simplicity. Should the MCA attract significant interest, the following suggested improvements would likely be implemented in future work:

5.2.1. Correlation Method Selection

Have an option to select between Spearman's ρ or Pearson's r correlations, of Equation 8, Equation 9, and Script 9 from section 3.4. This could be as simple as a toggle button, as these are the two most notable correlation methods; hence, a dropdown selection list would not be necessary. Currently, the only correlation function implemented by the MCA solver is Pearson's r.

5.2.2. Uncertainties Options

Currently, there are only two options for uncertainties in the software, besides turning them off: Either manually assigning absolute numbers in the same unit as the scores or clicking the 'auto-gen' button, which generates such absolute uncertainties in any fields that are empty. The auto-gen button is shown in GUI S15 under the section Buttons' Red Highlights & Comments in Appendix B – Software. Script 11 below documents how JS bases the automatic uncertainties on the decimal of the scores:

```
const DecFigs=StringScore.includes('.')?StringScore.split('.')[1].length:0
,Gen=Uncertainty.value=10**-DecFigs;localStorage.setItem(Uncertainty.id,Gen)
```

Script 11 – JS automatically generated uncertainties feature

Firstly, as GUI S15 shows, it could be improved by only highlighting the empty uncertainty input fields and only those that have a filled-in score to their left, in order to base the auto-generated uncertainty on the decimal placement of the score. The MCA software works correctly this way; however, it does not limit the red highlighting exclusively to the input fields that are currently subject to being filled.

Secondly, some users may prefer to input the uncertainties as relative values, as opposed to absolute values. This means either percentages (%) or fractions, instead of the same unit as the input scores. Introducing this option, either for specific scores, may be beneficial for some users who enjoy more flexibility and user preference settings. Some scores may have relative uncertainty in the literature, so it would be time-consuming and prone to user errors to require the user to convert to absolute uncertainties themselves in order to input the uncertainties into the solver.

5.2.3. Bar Chart Improvements

5.2.3.1. Custom Plotting Script

Google Charts is the only external library package that the MCA solver uses. It is free to use and open source under the Apache 2.0 License [259]. The main issue with using libraries, in general, is that even if they have many features and customisation capabilities, and even if the syntax is understood and tolerated for the purpose of integrating them with the rest of the scripts, it is challenging to minify them into a single HTML file that will be able to run offline. Libraries are large to suit a wide variety of users, while only several features are needed for each use.

Even the official minimised version of libraries can be considered too large, with file sizes often larger than the rest of the program combined. In fact, the main JS file for the MCA solver has a formatted size of 58.9kB while the official Google Charts library has a size of 61.1kB. It is therefore a balanced compromise between the performance time to run and launch a program and the time needed to write and test an alternative custom script.

The MCA solver was developed because Existing MCA Software programs lacked essential features, namely correlations and uncertainties. However, Google Charts was used for simplicity, because although plotting a chart was important for plotting uncertainties, the actual plotting was not the fundamental focus of the MCA Solver Software Tool.

Libraries may be imported for use via a link, but this requires an internet connection, uses up bandwidth, and risks the page not being available due to it having been taken down or under a denial-of-service attack, etc. Currently, the MCA solver uses this option with the following HTML line, as shown below in Script 12:

```
<script src='https://www.gstatic.com/charts/loader.js'></script>
```

Script 12 – HTML line importing the Google Charts library

Alternatively, a library may be downloaded and referenced without needing an internet connection. The issue is that this increases the file size substantially and therefore its upload and download speeds. It even increases the loading time, because Google's CDN (Content Delivery Network) is geographically distributed [260], meaning users download the library from the servers closest to them, thereby minimising latency. Most browsers aggressively cache resources downloaded from CDNs, so subsequent page loads might not even need to download the library again if it is already cached.

Another issue for the use of libraries in general and Google Charts, in particular, is the inconvenient warnings it creates in the console and its hit on performance. These can be due to poor scripting when the library was programmed, bad integration, or incompatibility with the custom software it was integrated into, or the library's use of deprecated (obsolescent) syntax. Script 13 below demonstrates how, despite the software without Google Charts requiring only an eighth of a millisecond to load, an incompatibility with passive EventListeners on the part of Google Charts causes an unacceptable 53ms delay.

```
Upload: 0.1279296875 ms                              Formatted_MCA.js:540

[Violation] Forced reflow while executing JavaScript took 53ms

▶[Violation] Added non-passive  jsapi_compiled_default_module.js:157
event listener to a scroll-blocking 'mousewheel' event. Consider
marking event handler as 'passive' to make the page more responsive.
See https://www.chromestatus.com/feature/5745543795965952

>
```

Script 13 – DevTools Console (F12) browser messages when the MCA solver is launched

A monitor that refreshes 60 times every second (60Hz) would be delayed by more than 3 frames (60 frames/sec x 0.053 sec = 3.18 frames), and most people could notice and potentially be annoyed by this delay. This software aims to be exceptionally fast, and clearly, using an external library goes against the ethos of unparalleled execution speed, along with the software being fully scripted from scratch. Therefore, it may prove advantageous to customise a script for chart-plotting for this solver.

5.2.3.2. Baseline

An interesting yet simple idea is to allow the user to pick a 'baseline' or 'benchmark' for the final scores bar chart. This is similar to the OECD charts that highlight a mean average for an index across the OECD countries. Such a line would appear horizontal in Figure 32, vertical in Figure 34, and both in Figure 33 in sub-section 4.6.1. In other words, perpendicular to the bars in bar charts.

All alternatives below it will be considered as failed, and all above it as succeeded or passed. Failed and passed alternatives may be coloured in red and green, respectively.

5.2.3.3. Display Each Criterion's Contribution

Another idea regarding plotting the final scores of alternatives is to plot the contribution of each criterion. This is clearly possible and common for absolute ranking methods, for example, WSM and WPM, but more challenging, if not impossible, for outranking methods, namely PROMETHEE. See Figure 32 in sub-section 4.6.1: Methodology Assessment and Discussion for illustration.

5.2.4. More Weighting and Ranking Methods

An interesting idea that was suggested is the possibility of adding another weighting method, particularly an algorithm that attempts via trial and error to maximise the correlation between this new index and an existing one, say the 2016 Sustainable Cities Water Resiliency Sub-Index. This is inspired by the application of the Manual Assignment weighting method in section 4.5: Selecting Weighting and Ranking Methods.

Beyond the fact that it would be complicated to program and may take over a minute to run to generate meaningful results, this interesting idea of a weighting method was abandoned due to another potentially greater reason: This new index aims to improve upon potential flaws of previous indices before it, and in fact, offer them constructive criticism. This means that attempting to correlate the results of a new index as closely as possible to an existing index may not make the most sense.

Instead, it may be better to manually assign weights based on situational awareness and allow future users to either manually assign their own weights or generate them using several existing weighting methods that are already programmed into the MCA Solver software tool. This research utilises Equation 8 – Pearson's r Correction from section 3.4 to ensure that the Custom Index and the 2016 Sustainable Cities Water Resiliency Sub-Index are at least moderately correlated (R ≥ 0.3) if not strongly correlated (R ≥ 0.5) to ensure some level of credibility. See Figure 33 in sub-section 4.6.1: Methodology Assessment and Discussion.

In fact, it would probably be better to have a new feature first that correlates an existing index with another, before expanding it to automate weights. That would require adding another red arrow to Figure 12 in sub-section 2.2.4 Existing MCA Software.

As for the idea of introducing more complicated weighting and ranking methods than those incorporated already in the solver, it is worth noting that the Custom Index employs the simplest weighting and ranking methods: Manual Assignment and WSM, as was justified in section 4.5: Selecting Weighting and Ranking Methods. Complicated methods refer to Entropy, AHP, and PROMETHEE.

Potential complicated MCA methods that can be included in future improvements of the solver can be other matrix methods, such as TOPSIS and ANP or even more complicated methods, such as Fuzzy ones. These were not included for simplicity. They need to be studied, programmed, and tested to be validated, see the section Validated MCA exercises from the literature in Appendix B – Software.

It is also arguable as to whether more complicated methods would yield better results. The Comparison of Weighting Methods and the Comparison of Ranking Methods in sub-sections 3.2.6 and 3.3.3, respectively, both concluded that, of the existing methods, the simplest are the best.

There is an expression: *"If you are so clever, why aren't you rich?"* Looking at many investment 'techniques' that attempt to pick the best stocks, some very complicated methods might fool naive investors, but these still do not beat diverse index funds or even a set of stocks picked at random [256], [257], [258]. If complicated MCA methods were so successful, they would be famous for making people predict the stock market and become rich, yet they are not.

This puts into question the very idea of having overly complex methods requiring a matrix sequence algorithm and cannot be written as a traditional equation, as shown in Table 7 – Absolute Ranking Methods in sub-section 3.3.1, or are complicated to Display Each Criterion's Contribution, as was discussed in paragraph 5.2.3.3 above. Nevertheless, once a method is understood, programmed, and verified, there are no major reasons not to include it in the MCA Solver Software Tool, because some users may appreciate their inclusion.

5.2.5. Use a faster coding language

Thanks to the optimisations in section 3.6: Technical Aspects of Software Development, the MCA solver loads up and solves all calculations and plots within a millisecond. See Script 13 in sub-section 5.2.3.1. Therefore, however tempting it may be to continue to optimise and make the software faster, such as using WebAssembly or another programming language altogether, such as Rust, it is simply unnecessary.

This idea of optimising the execution speed of the software is fundamental for any software project, hence it was worth noting here. Any optimisation for speed should start with removing the dependency on an external library first, as was discussed in sub-section 5.2.3.1: Custom Plotting Script above.

5.2.6. Show Math Working Step By Step

Showing all the math step by step may be complicated for a user to follow, but if they strongly wish to verify the math and not skip any step behind the scenes, it may be a good idea to show all the math in the front end. Of course, this feature will be possible to turn on and off for those who want simplicity, and in fact, it is likely to be turned off by default.

GUI S17 in the Buttons' Red Highlights & Comments sub-section in Appendix B – Software already presents some work in the form of normalising scores and calculating the final scores, but excludes the more complicated calculations of PROMETHEE and final uncertainties. To simplify the math, cloned nodes can show the working for values that the user hovered over, similar to highlighted textareas when selected or hovered on, see sub-section 3.6.5: Classes and Clones.

5.2.7. User Data Storage Optimisations

The efficiency of file formats that store data refers to their ability to store as much data as possible while maintaining their byte sizes as low as possible. This can be done by doing away with unnecessary indentation and shortening delimiters to single-byte characters. Sub-section CSV & JSON Data Storage Files in Appendix B – Software discusses the use of the JSON and CSV file formats for downloading user input data, and how CSV is more efficient than JSON. JSON itself is typically more efficient than other file types, such as XML.

Having said that, further simple optimisations can be made. Namely, by adopting the Tab-Separated Values (TSV) file format. TSV is more efficient than CSV because its delimiter is a tab character '\t' as opposed to a comma ','. Data tends to include more commas than tabs. See Script S1 in Appendix B – Software, which includes commas when storing the names of Case Study Cities, for example: London, England, and Houston, Texas. Script S1 addresses the commas by using quotation marks ` " " `, but this adds more bytes unnecessarily, which TSV files do not need to add.

Note that both CSV and TSV also use line breaks '\n' to separate values, but the advantage CSV and TSV have over JSON and other file formats is their spreadsheet/table structure, which helps to organise data into rows and columns, as shown in Table S4 and Table S5 in Appendix B – Software. Both CSV and TSV can be viewed and edited in both a spreadsheet app and the VS Code 'EditCSV' extension [100] that was discussed in sub-section 3.6.4: Development Apps and Extensions. The reason TSV was not implemented is that, as simple as it is, it was only discovered by the author at the end of this research project. Even with CSV, the programming could have been more efficient by not applying quotation marks to values with no commas, for example, numbers.

5.3. Further Work – Index

5.3.1. Decision Support Systems (DSS)

As described in the Layman's Summary, the applicability of the Custom Index is to help decision-makers address the vulnerabilities of WSS through better management and investments. As established in section 1.5: Hypothesis, Objective, and Novelty, the MCA solver that was developed in this thesis functions as an assessment-DSS. The added value of this research is, therefore, the construction of this validated assessment framework, which fills a gap in the WSS literature.

This assessment-DSS is complementary to, and not a competing alternative approach to, the Optimisation-DSS tools that are often applied to manage known vulnerabilities. An Optimisation-DSS supports the decision-making on how to mitigate risks [49], but it first requires a robust assessment to identify what to mitigate. This research has successfully constructed the preceding assessment tool.

A significant avenue for future work is to formally integrate this assessment-DSS with a future Optimisation-DSS. Such a framework would create a complete, end-to-end strategic tool. It would first use the Custom Index to identify and rank vulnerabilities, and then use that output to model the costs and benefits of various mitigation strategies, such as investments in WSS infrastructure or enhancements to governance.

5.3.2. Plastic Bottled Water

Besides the increased use of plastic bottles during incidents [40], [42], [135], their use could, in theory, be considered as a proxy vulnerability indicator for water systems for two reasons:

Firstly, the health of the people and the environment. Bottled water increases industrial water consumption because plastic bottles require multiple times more water to manufacture than the amount of water they contain [261]. This can lead to increased Water Stress. It is also unhealthy to drink from plastic bottles due to the leaching of microplastics [262], [263], especially when water is left in plastic bottles for long durations and in hot settings. Bottled water also costs fuel to ship from far away and increases plastic waste, which is bad for the environment.

Secondly, when water systems objectively fail or fail to earn the trust of the consumers, many opt for bottled water. This can be due to bad taste, hard water, colour (turbidity), smell, lack of trust in quality due to politics or lead pipes, as well as existing Water Stress, which requires importation.

Importation of bottled water is mostly virtual water, again, considering that most of the water that is required to manufacture bottled water is in the production of the plastic as opposed to the contained water. See Map 14 – World Countries Virtual Water Net Imports in sub-section 4.3.13.1.

Importation of water can also be temporary, such as in local water outages. For example, bottled water was donated in the 2024 Hurricane Helene flooding incident [40], which was documented in Table 5 in section 1.2. This means that in this vicious chain reaction, one vulnerability, Flood Risk, leads to another, specifically increased bottled water consumption.

Moreover, part of the demand for bottled water is due to convenience, cultural norms, and marketing of alkaline or mineral water. But the bottleneck is the Tap Water Quality.

Solutions may include filtering tap water for better quality. Potential issues with water filters are that they can be expensive for some people, so not everyone will install them, and therefore, it is bad to have a system that relies on them. Some contaminants can still remain unfiltered, and several important minerals, such as magnesium, will be filtered out [177]. The counterargument is that these very few minerals should be ingested either from food or supplements. Even though bottled water is not used as an indicator, it is curious to imagine how its prevalence would correlate with other indicators, particularly Tap Water Quality, with which it is speculated to strongly negatively correlate.

5.3.3. Wastewater

There are case studies, such as Singapore, where they recycle their drinking water; hence, an issue with wastewater treatment, such as a lack of pumping of wastewater or leakages, would mean there is not enough water incoming to treat to make into NEWater, and would be a vulnerability for the drinking water distribution network as well. This is an aspect overlooked in this index, mainly because it is not universal and is mostly applicable to only a few such case studies where drinking water is recycled from wastewater.

Another unavoidable aspect is that because waste and drinking water pipes often pass next to each other, if pipes are damaged in a location simultaneously, there could be cross-contamination. Drinking water leakages are so frequent that they are actually an indicator statistic. This means cross-contamination is likely enough to occur, so it is probably wise to take leaks of wastewater into consideration. This is related to other indicators, which can cause the leaks to begin with, such as floods, as well as other natural and artificial disasters, which could be another vulnerability indicator.

Lastly, there can be backflow due to imbalances of pressure. Imagine wastewater from a sink being pumped up into the sink and overflowing it, thereby interfering with the proper function of using it for drinking water. This is a simple example, but it could occur in a more complicated water system or treatment plant.

Ultimately, wastewater would have been too complicated to consider along with the water supply for the purpose of this focused research. Wastewater can include aspects such as nutrient recovery and other physical and biological separation processes. It is a topic too complex and important, and it would be unjust for it to be covered in this index only in breadth.

The closest indicator, which was discussed in this research, to wastewater is Source Water Quality in sub-section 4.3.4. This is because its sub-indicators include BOD and the concentrations of phosphates and nitrates.

5.3.4. Climate Change

Global warming is constantly being discussed in the contemporary water systems literature. For example, see the paper Vulnerability of Urban Water Infrastructures to Climate Change at City Level [264] in Table S2 in Appendix A – Literature. The main reasons for not focusing on climate change as a central focus of this research are twofold:

Firstly, plenty of other researchers have already discussed global warming, including from the perspective of water systems; hence, if this research focused on it as well, it would not have been quite so novel. Secondly, this research already has central focuses, which are the supplier-focused indicators, making an MCA index in a new MCA software, etc. Similar to Plastic Bottled Water and Wastewater in sub-sections 5.3.2 and 5.3.3, respectively, such a focus would cause unnecessary complications to this research, which needed to remain brief as it only scratches the surface of WSS vulnerabilities as it is.

Similarly, the title of this thesis and the focus of Chapter 2: Literature Review of WSS Assessment and Chapter 4: Custom Index are on 'Vulnerabilities', not 'Sustainability', which is the term used in the context of the discussion of climate change. These may sound as direct opposites, but rather, 'resiliency' is the opposite of 'vulnerability'. Sustainability is different, and it is used in various ways in the literature. Furthermore, focusing on it would likely not be considered novel.

In terms of sustainability, it is important to note that this research project focused on 'Clean Water and Sanitation' as opposed to 'Climate Action'. These are two separate UN Sustainable Development Goals out of a list of seventeen in total. They are the 6th and 13th goals, respectively [21], [68], [265].

5.3.5. Analytical Experimental Verifications

As mentioned in sub-section 4.3.3.3: Analytical Observations, there was barely any physical analytical experimentation in this research project. It may prove useful for a future study that puts greater emphasis on the accuracy of the data arising from testing the tap water quality of Case Study Cities in real life to verify the Tap Water Quality Reports. This approach would lower uncertainty and increase the reliability of a future index by calculating the standard deviation of arrays of measured data, as mentioned in sub-section 4.4.2: Selecting Types of Uncertainties. The downside is that it would consume more time and resources to manually test samples in every case study city.

Analytical experimental verifications can also be done with other indicators, but not Soil Moisture Content, because a future researcher would probably still not have access to their own satellites.

5.3.6. More Case Study Cities

This research focused on both large and developed cities. See sub-section 4.2.1. Case Study Cities Selection Requirements. It would be interesting to see further research on either less densely populated areas or with lower standards of living.

Some indicators rely on data that is often missing, namely, Tap Water Quality, not to mention the omitted indicators. In developing cities, this is because these statistics would be embarrassing to publish or because the authorities are not resourced or motivated to gather and publish the data.

However, other indicators, especially those reliant on Interactive Maps for data such as Soil Moisture Content, make it still theoretically possible to assess at least in part most places around the world. These Interactive Maps often rely on much more reliable satellite data as opposed to potentially biased self-reported data from a single source, the water supplier, which has a vested interest.

On the other hand, and to be fair to developing cities, in certain developed cities, some data is confidential for geopolitical and security reasons, namely Singapore's total volume of catchment reservoirs [30]. It is also possible to fork a specialised index that includes such indicators with confidential data and leave it for the water suppliers to assess their own water system for themselves internally.

The idea of assessing large cities, as was explained in the Introduction of this report, is that large cities are increasingly becoming more important because more people migrate to cities, large cities tend to have more publicly available data, and because the inspirational book Scale has a unique perspective on cities' metabolism, similar to that of organisms. Having said that, low-density areas also 'metabolise' water similarly to large cities and have significant numbers of people living in them, and if data is locally available in these regions, there is no reason why this Custom Index could not also extend to assess them as well. It would be interesting to plot correlations such as Water Loss against population or population density, as theoretically, it should be lower in less populated areas for the rationale explained in paragraph 4.3.2.1. Analogy to Biology.

This research studied 24 case studies, whereas the 2016 Arcadis and 2021 DuPont indices discussed in sub-section 2.3.2 assessed 50 and 51 cities, respectively [21], [47]. It is a shame they did not plot a Criteria Correlations Matrix, considering that the more case studies, the more reliable the correlations are. However, this therefore presents an opportunity for the Custom Index and the MCA Solver Software Tool.

5.3.7. Introducing Other Indicators

Referring back to sub-section 4.3.17: Indicators Comparison and Selection, four excellent indicators that were omitted from the Custom Index are detailed in Table 15. These are:

- 4.3.11: Lead Pipes
- 4.3.13: Importation Water Dependency
- 4.3.14: Non-Renewable Primary Energy
- 4.3.15: Groundwater Reliance

All of these four indicators are conveniently natively normalised in percentages, where 0% is the best and 100% is the worst. This is consistent with the third column in Table 15.

Published data should be readily available to all of them, except perhaps the first indicator, 4.3.11: Lead Pipes. The percentage of the mains pipelines which were constructed from or fitted with lead should be known in the water distributor's records for the WDN, even if the records are not published. This makes it challenging to include this indicator in a universal index that compares WDNs globally, though it still means that a water supplier with data can use this indicator for their own use if they have data.

The two main reasons these indicators were omitted are to simplify this first revision of the Custom Index and for simplicity. The MCA Solver Software Tool was more than capable of accounting for these four additional indicators and several more than that.

5.3.8. More sub-indicators

Not to be confused with the similarly-sounding above sub-section 5.3.7: Introducing Other Indicators, yet similar to it, this section adds more sub-indicators to specifically the two indicators, which are themselves sub-indices or nested indices, which are source and tap qualities. Much like it is possible to add more indicators to the main index, it is possible to add more sub-indicators to these sub-index indicators.

Tap and source water qualities are themselves standalone indices that measure the concentrations of several hazardous substances of great importance. If data were more widely available, reliable, and recent, these could have been made into more comprehensive indices of longer lists of substances, each with its own weight.

5.3.8.1. More Tap Water Quality Sub-Indicators

For Tap Water Quality, there are three additional notable metrics to consider adding: Fluoride (mg/L | ppm), Benzene (µg/L | ppb), and Total Organic Carbon (mg/L | ppm). Fluoride and Benzene are two substances that are regularly measured in various water suppliers' Tap Water Quality Reports, and they are most importantly chosen among the WHO's top list of "10 chemicals of public health concern" as shown in Figure 19 in sub-section 4.3.3: Tap Water Quality [141].

For Fluoride vulnerability, the WHO lists specifically as "Inadequate or excess fluoride". This means that although being less toxic per the same concentration as other substances that can be found in drinking water, considering the high concentrations of Fluoride (mg/L | ppm) compared to many others, including Benzene (µg/L | ppb), Fluoride can also pose a very real health risk.

As for other contaminants in the WHO's top 10 list, such as Asbestos and Dioxins, these pose an exposure threat mostly through respiration and food consumption, respectively, hence are therefore less adequate to explore in water vulnerability research.

Total Organic Carbon is a proxy for a list of other substances; hence, a larger concentration of mg/L | ppm is listed in the few Tap Water Quality Reports that do list it. Alternatively, a vastly more comprehensive water quality sub-index would include potentially dozens of substances, though this would limit the potential for being universalisable due to a lack of data.

The main reason for leaving out these potential sub-indicators is the lack of available data, while the reader of the Custom Index should already understand the method of customising sub-indices with only a few sub-indicators, as well as having fewer case studies which report these in their Tap Water Quality Reports compared to the arguably more hazardous heavy four metals in Figure 19 which were indeed all included in the final Tap Water Quality sub-index.

5.3.8.2. Artificial & Natural Disasters (other than flood risk)

Flood Risk was already selected as the only natural disaster risk indicator because it tends to predominantly appear in the WSS literature as a major vulnerability on its own [21]. However, there are other possible disasters that can threaten a WSS, both natural and artificial. A possible idea is to turn the Flood Risk indicator into a sub-index with a variety of other external threats as sub-indicators. It will better capture the overall vulnerability, but at the cost of additional complexity and the need for more data to be collected and analysed.

5.3.9. Broader Utilities Vulnerability Index

Following the discussion from sections 1.2: Past Water Supply Disruption Incidents and 5.3.3: Wastewater, it is clear that the vulnerabilities of water supply overlap with the vulnerabilities of other utilities of large cities, including wastewater and electricity, as the 2024 Dubai incident showed [36], [37]. This raises an interesting question: would there be a use for an index that analyses the vulnerabilities of all utilities? This would include water supply, wastewater, electricity, gas, communications, and others.

This idea may sound complicated; however, most of the indicators are already shared in common. Moreover, there are indices that rank countries on their affordability, quality of life, human development, and so on. Therefore, it would not be far-fetched to suggest such an index. Not only are the same vulnerabilities shared among the multiple utilities, but so is the budget allocated by the authorities to address them, therefore making the utilities even more interconnected.

It was not implemented ultimately because the purpose of this research was to construct a WSS index and to demonstrate the credibility of its methodology. Such a broad model would likely have greater uncertainty and a more limited demand. Nevertheless, it could prove interesting and useful in the future. Were it to ever be implemented, it would make sense to start with including Wastewater before incorporating any non-water utilities for simplicity. This would form a combined drinking water and wastewater index.

5.3.10. Artificial Intelligence (AI) Data

Artificial Intelligence (AI) models proved themselves recently as very helpful tools for researchers. It was used in this research for one task, which was to generate text-to-image pictures, which helped circumvent the default IP restrictions of online photos.

They are increasingly capable of various tasks, for example, writing and correcting scripts, answering complex CPE questions, and searching for sources of data to reference. While the former two can be tested for their accuracy by merely testing the scripts AI generates or the calculated numerical results it arrives at, the latter currently requires follow-up manual checks by normal web searches to be verified.

Water research, as well as other research topics, is expected to increasingly incorporate AI even more and potentially be essential for certain future projects. In the future, AI could theoretically be sufficiently reliable to ask for sources of data to cite.

5.3.11. Comprehensive Indicators Correlations

As was highlighted in the Abstract and Conclusion, among the greatest novel aspects and findings of this research project are the correlations between the indicators in GUI 5 – Criteria Correlations Matrix in section 3.4. This is because correlations between tap and source water qualities, as well as Water Stress and Soil Moisture Content, are missing from the WSS literature.

As was stated before, the fascinating aspect of correlations between indicators is that they can raise interesting questions and thoughts, all without determining any weighting or ranking methods, selecting weights, and calculating final ranking scores. Recall Figure 12 in sub-section 2.2.4 Existing MCA Software.

Hence, in Chapter 4: Custom Index, the selection of the weights and weighting and ranking methods came in a later section 4.5: Selecting Weighting and Ranking Methods, after sub-section 4.4.1: Indicators Correlations.

Many indicators were not added, not only due to a lack of reliable data but also to maintain a low number of indicators for the simplicity of illustrating the methodology of designing a WSS vulnerabilities custom MCA index.

Following sub-section 5.3.7 above: Introducing Other Indicators, GUI 5 – Criteria Correlations Matrix in section 3.4 would grow quadratically larger with every added indicator, as is calculated by Equation 1 – Triangular Numbers in sub-section 3.2.3. However, it is necessary to test for correlations that are too strong and could indicate accidentally double-counting the same vulnerability using multiple indicators.

Incidentally, another decision that would probably be wise to make before adding additional indicators is to remove existing indicators with strong correlations, probably removing Water Stress, again, as previously discussed and justified. Soil Moisture Content is an accurate and reliable proxy for Water Stress using recent satellite data.

Having said that, it may also be beneficial to correlate sub-indicators for the same purpose as the main indicators, following the above sub-section 5.3.8: More sub-indicators. This can be implemented by having a single large correlation matrix and having more data, or simplifying by only correlating sub-indicators of the same sub-index and not correlating indicators and sub-indicators of different levels. This may depend on the nature of the particular MCA index, so it should probably be up to the user to decide.

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Key – Ac: Accessed date. The date before it is the date published or last updated.

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Appendices

Table of Contents

Appendix A – Literature

Studied Papers

Notes:

- The titles of the papers below have been shortened with the use of acronyms and cutting the latter half of the titles that are too long. This is done here for the sake of simplicity and shortening the size of Table S1 and Table S2 below. The References do, however, contain the full titles.

- Two literature reviews in Table S1 and three papers in Table S2 are marked with an asterisk (*) next to their titles. This note is to bookmark them. They are discussed in sub-section 2.3.2: Most Notable Sources. The three bookmarked papers in Table S2 contain detailed lists of indicators.

Table S1 – Reviewed literature reviews, sorted by published year

#	Review Description	# Papers	Year	Methodologies	Ref
1	Risk analysis methods of WSSs	68	2022	Custom	[266]
2	An Overview of MCDA Application in Managing Water-Related Disaster Events	149	2021	PRISMA	[8]
3	A Review Of 80 Assessment Tools Measuring Water Security	80	2021	Custom	[267]
4	A Systematic Review of the State of Cyber-Security in Water Systems	64	2021	PRISMA	[50]
5	*MCA Methods to Address Water Allocation Problems	49	2021	Custom	[7]
6	*Analysis of Water Resources VA Tools	32	2019	PRISMA	[51]
7	A Systematic Review of Water VA Tools	20	2012	Custom	[268]

Table S2 – Reviewed model papers, sorted by published year

#	Paper Description	Locations	Year	Methodologies	Ref
1	Flood vulnerability assessment in the flood prone area of Khyber Paktunkhwa	Khyber Pakhtunkhwa, Pakistan	2024	AHP & GIS(MCA & GIS)	[247]
2	MCA applied to ranking rehabilitation strategies of WDNs	(Simulated)	2023	TOPSIS (MCA)	[81]
3	The Failure Risk Analysis of the Water Supply Network	Rzeszow, Poland	2023	Vulnerability Identifying Method (VIM) – (MCA)	[269]
4	Using MCAD in a geographical information system framework to assess drought risk	Thailand	2023	MCDA & GIS (MCA & GIS)	[270]
5	VA of water supply infrastructures through multiple indicator methodology	Italy	2023	MCA	[271]
6	Assessment of Flooding Impact on WSSs: A Comprehensive Approach Based on DSS	Italy	2022	WASPP–DSS Custom Tool	[49]
7	Comparative MCA of Hydrological Vulnerability	Romania	2022	AHP & TOPSIS (MCA)	[272]
8	Integrated strategic planning & MCA framework to agricultural water management	Iran	2022	AHP & Fuzzy TOPSIS (MCA)	[82]
9	Assessing the Vulnerability of Water Resources System	Zhongshan, Guangdong, China	2022	System Dynamics (SD)	[273]
10	*Urban Water Security: A Comparative Assessment and Policy Analysis	5 Asian Cities	2022	WSM (MCA)	[19]
11	Hierarchical Bayesian Approach for Assessing WDS	Shelby County, Tennessee, USA	2021	BN (Probabilistic)	[55]
12	Development of Multi-Hazard Risk Assessment Model for Agricultural WSS	Zayandeh-Rud, Isfahan, Iran	2021	FFTA & HBN (Probabilistic)	[57]

13	Simulation and VA of WDNs Under Deliberate Contamination Attacks	(Simulated)	2021	EPANET-MSX	[64]
14	Water Vulnerabilities Mapping	6 Provinces In Central Chile	2021	(Multiple MCAs)	[274]
15	Application Technic Based VA of Aquifers to Pollution	Tehran, Iran	2021	Integrated AHP-PROMETHEE (MCA)	[5]
16	Nodal VA of WDNs	Apulia, Italy	2021	Integrated Fuzzy AHP-TOPSIS (MCA)	[6]
17	VA of WDN with Real-Life Pipe Failure Statistics & VA of WDNs to Accidental Pipe Burst	27 WDNs In Hungary	2021	Statistical Estimates & EPANET	[78] & [79]
18	Evaluation of Different Natural Wastewater Treatment Alternatives	(Unspecified)	2020	Fuzzy PROMETHEE II (MCA)	[83]
19	Vulnerability of Urban Water Infrastructures to Climate Change at City Level	22 Provincial Capital Cities of China	2020	(MCA)	[264]
20	*Assessing Water Security in Water-Scarce Cities	Madaba, Jordan	2020	AHP (MCA)	[48]
21	Fuzzy Reliability-Vulnerability for Evaluation of WSS Performance	(Simulated)	2020	Fuzzy Reliability Index (FR)	[275]
22	Risk Management of Drinking Water Supply in Critical Conditions	Tehran, Iran	2020	Fuzzy AHP & PROMETHEE V (MCA)	[9]
23	Systemic VA of Urban WDNs Considering Failure Scenario Uncertainty	Eastern Chinese City	2019	Network Entropy (Probabilistic)	[74]
24	Flood-Hazard Assessment Modelling	Ras Gharib, Egypt	2019	GIS & AHP (GIS & MCA)	[66]

25	Ranking Approach to Scheduling Repairs of a WDS for the Post-Disaster Response	Unnamed Real City	2019	GIS, EPANET 2 & PROMETHEE (GIS, EPANET & MCA)	[276]
26	Urban WSS Management in Critical Conditions	Tehran, Iran	2019	Fuzzy PROMETHEE V (MCA)	[277]
27	Reliability Assessment Model for WDNs	Canadian City	2019	FTA & PROMETHEE (Probabilistic & MCA)	[80]
28	An Approach to Estimating Water Quality Changes in WDS	(Unspecified)	2019	FFTA (Probabilistic)	[56]
29	Machine Learning, Urban Water Resources Management and Operating Policy	Athens, Greece	2019	FFN (Probabilistic)	[278]
30	*Urban Water Security: Definition and Assessment Framework	(Unspecified)	2019	WSM (MCA)	[84]
31	VA of WSN Against Seismic Hazards	Vancouver, British Columbia, Canada	2018	GIS & Seismic Vulnerability Index	[279]
32	Integrated Evaluation of Hybrid WSS	Melbourne, Australia	2018	PROMETHEE–GAIA (MCA)	[280]
33	VA of Water Resources	Ogallala, Kansas, USA	2018	STA	[281]
34	Infrastructure Vulnerability Index of WSS to Terrorist Attacks	Crotone, Calabria, Italy	2018	AHP (MCA)	[282]
35	A MCA of Water Supply in Ugandan Refugee Settlements	Uganda	2018	NPV (MCA &Economics)	[61]
36	A New Vulnerability Measure for WDN	(Simulated)	2018	AHP (MCA)	[283]
37	GIS MCA for Flood Risk-Vulnerability Mapping of Ikom Cross River State	Nigeria	2018	MCA & GIS	[284]
38	Risk Assessment of Water Distribution Service	Matera, Basilicata, Italy	2017	FAHP (MCA)	[285]

39	WDN Segmentation Based on Group MCA	Pernambuco, Brazil	2017	PROMETHEE (MCA)	[286]
40	MCA for Sub-Watsheds Ranking	Belgrade, Serbia	2017	AHP & PROMETHEE II (MCA)	[287]
41	The measurement of water scarcity: Defining a meaningful indicator	Africa - Multiple	2017	WSM (MCA)	[288]
42	Topological Robustness and VA of WDNs	Nicosia, Cyprus	2017	connectivity MATLAB Matrix & GIS	[75]
43	VA in the WSS with uncertainties	Shanghai, China	2016	Stochastic ANP-GCE (MCA)	[289]
44	New Resilience Index for Urban WDNs	Calascibetta, Sicily, Italy	2016	New Resilience Index 'R' & EPANET 2.0	[76]
45	MCA for the monitoring of aquifer vulnerability: A scientific tool in environmental policy	Portugal	2015	DRASTIC AHP, WSM & GIS(MCA & GIS)	[290]
46	Sustainable Urban Solid Waste Management Planning	Attiki, Greece	2015	PROMETHEE II (MCA)	[291]
47	Water Resources VA	Zhangjiakou, China	2015	AHP & BN(MCA & Probabilistic)	[54]
48	Urban Flood Vulnerability and Risk Mapping	Eldoret, Kenya	2014	AHP & GIS (MCA & GIS)	[4]
49	Assessing Mechanical Vulnerability In WDNs Under Multiple Failures	Oslo, Norway	2014	Genetic Algorithms & OPTIMOGA	[292]
50	VA of WDSs Using Directed and Undirected Graph Theory	Unnamed Real City	2014	MBC & CA	[293]
51	Graph-Based Hydraulic VA of WDNs	Limassol, Cyprus	2014	EPANET	[294]
52	BN VA Tool for WDS Under Extreme Events	Ofanto River, Italy	2014	BN, GIS & EPANET (Probabilistic, GIS & EPANET)	[67]

53	Node Vulnerability of WDNs Under Cascading Failures	(Simulated)	2014	Nodes Cascading Failures Ranking	[295]
54	Selecting Alternatives to Rehabilitate WSN with Detected Leaks	(Simulated)	2013	PROMETHEE V (MCA)	[296]
55	VA of WSN	Blida, Algeria	2012	GIS	[73]
56	WDS VA Using Weighted and Directed Network Models	Richmond, UK & Colorado Springs, USA	2012	Network Models (Probabilistic)	[77]
57	Sustainability Assessment of Urban WSS: A Case Study	Tehran, Iran	2011	FAHP (MCA)	[297]
58	Developing a PEA Model of an Urban WSS	Australia	2010	PEA (Economics)	[60]
59	Fuzzy TOPSIS MCDA Applied to Karun Reservoirs System	Iran	2010	TOPSIS (MCA)	[248]
60	VA and Risk Reduction of WSS	(Unspecified)	2010	WSM (MCA)	[298]
61	Quantifying Water Vulnerability	87 Municipalities In South Africa	2010	Supply-Demand (Economics)	[299]
62	VA of Regional WDS	Tianjin, China	2009	EPANET	[300]
63	Hierarchical Risk Assessment of WSS	(Unspecified)	2007	EPANET, FTA & FAHP (MCA, EPANET & Probabilistic)	[22]
64	VA of a Drinking WDS	(Simulated)	2007	EPANET	[65]
65	VA of WSS For Insufficient Fire Flows	Micropolis (Virtual City)	2006	GIS & EPANET	[72]
66	WSS decision making using MCA	Brazil	2006	ELECTRE I (MCA)	[301]
67	Assessing the Vulnerabilities of U.S. Drinking Water Systems	USA	2004	RAM-W™ Risk Assessment	[302]
68	Software for Specific Aquifer VA	North Arcot, Tamil Nadu, India	2003	DRASTIC AHP & GIS (MCA & GIS)	[3]

MCA Solvers from the Literature

2003 Analytical Hierarchy Process (AHP)

This is an example of a 2003 AHP solver software from the literature [3]. Here are criticisms of it:

- It is not web-based as it was not scripted in HTML and JS, despite being such a simple app. This would have been easy to implement, and it would have increased accessibility, as it would have been possible to run on a website. This applies to all the other MCA Solvers from the Literature, so this will not be repeated.

- There are too many buttons: 'Exit' and 'X', 'Create File', 'Previous', 'Next', 'Remove', 'Finish', and most notably 'Run'. These functions should all be automatic. There are other buttons on the other hand, which are actually useful but do not exist, see Buttons' Red Highlights & Comments below.

- Multiple pages. Need to go 'Back' to rename criteria, as opposed to having an editable textarea wherever criteria names are displayed, such as the pair-wise preference matrix, see GUI 5 in section 3.4.

- Inconveniently, arbitrarily only allows entering preference values from the upper side of the square matrix diagonal. See how GUI S6 in sub-section 2020 AHP & WPM in Appendix B – Software has integrative fraction number input fields whereby inputting numbers synchronises automatically on the mirror side of the diagonal.

- Only includes the AHP weighting method, as the name suggests, not an all-inclusive MCA calculator with other weighting methods, correlation matrix analysis, and other features.

2023 MCDA-KIT

Another example of an existing MCA software from the literature is the 2023 'Multi Criteria Decision Analysis at Karlsruhe Institute of Technology' or 'MCDA-KIT', so short [70]. It is *"In general free to use for non-commercial purposes, provided that the MCDA project of KIT is referenced. Commercial usage would be subject to negotiation."* This is an excerpt from the User Guide PDF file of MCDA-KIT.

As shown in GUI S1 below, the more recent and modern MCDA-KIT is more sophisticated in functionality than the above 2003 Analytical Hierarchy Process (AHP) solver. Beyond increasing the number of methods and charts available, it even allows for more preference options. In the bottom-left of GUI S1, intervals of 1 and their reciprocals in the range of 1 – 9 and ½ – 1/9. In comparison, the 2003 AHP solver above only provides intervals 2 in odd numbers [3], despite some AHP in the literature specifically using even numbers, as shown in GUI S6 for 'Screen Size' – 'RAM' and 'Processor', and 'Brand' – 'Hard Disk Capacity' in sub-section 2020 AHP & WPM below.
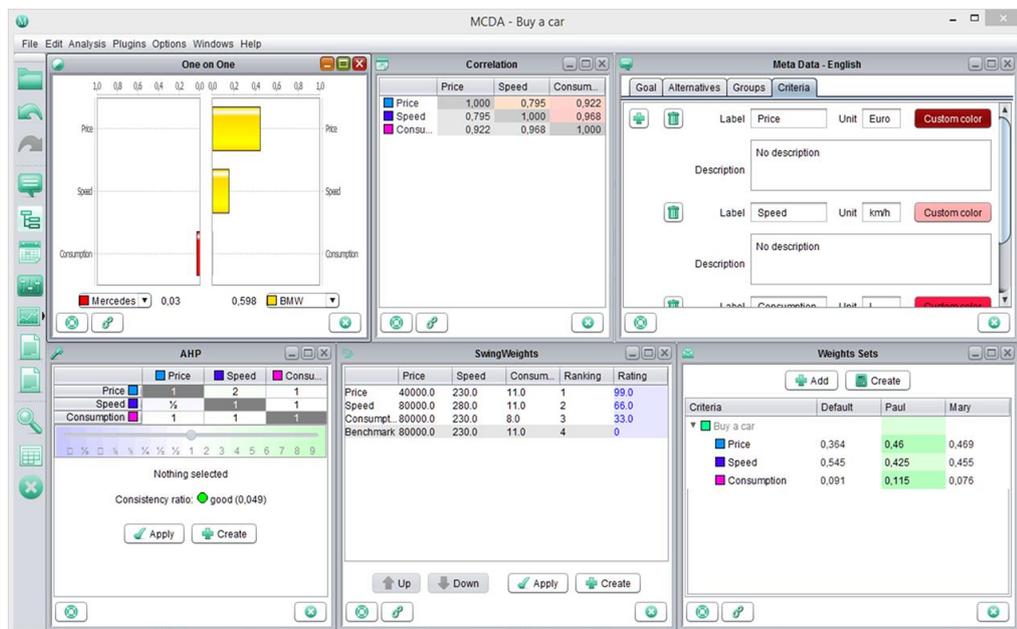
GUI S1 – MCDA-KIT common tools [70], Open Source

However, there are some criticisms here as well. The range of reciprocal preferences uses inconsistent symbols that are difficult to read, and in the case of 1/7 and 1/9, they are unreadable as '☐'. Similarly to the 2003 Analytical Hierarchy Process (AHP), MCDA-KIT also has too many unnecessary input fields such as units and descriptions, which in comparison the MCA solver of this research allows units which do not affect the math to be part of the label of each criterion and provides a single large textarea for all descriptions in one place as shown in GUI S8 in the Supplementary GUIs sub-section in Appendix B – Software.

Furthermore, GUI S2 below shows the *"less common tools"* of the MCDA-KIT, which received this name due to being completely unnecessary, such as the 'GrathView – Tree', 'Normalization' graph, Pie Chart of final ranks, 'Weights cobweb chart', generic automated report, and range sliders for individual weights. These are all fairly simple to program and do not involve complicated algorithms.
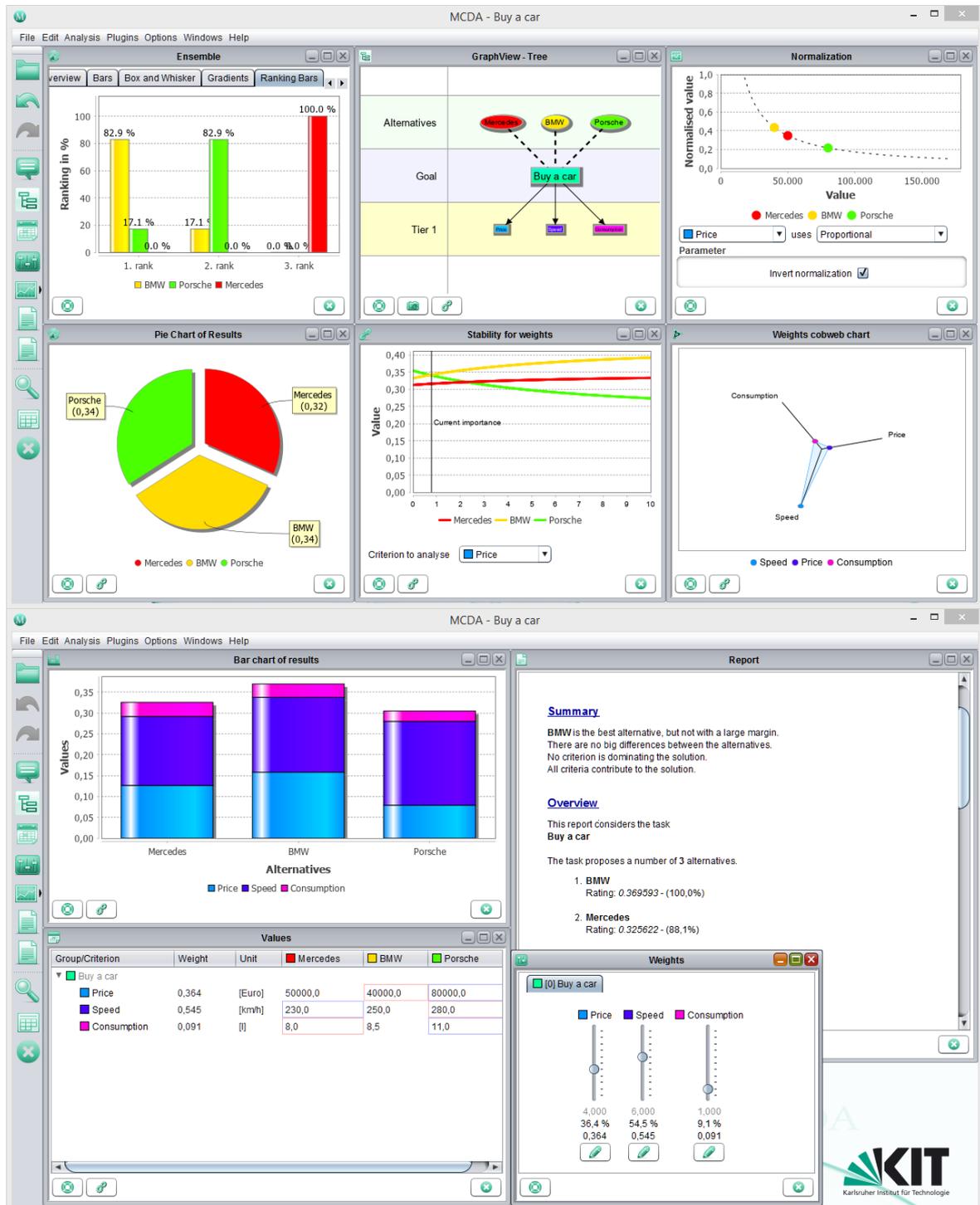
GUI S2 – MCDA-KIT, less common tools [70], Open Source

2024 Decerns MCDA

The following is a list of the inadequacies of the 2024 Decerns MCDA software and, by extension a need for improvement:

Decerns MCDA requires opening a Command Prompt, and closing it would also close the application without saving, see GUI S3 below. So while the custom MCA solver of this research only requires a single tab in a browser, Decerns MCDA inconveniently requires two at the taskbar.
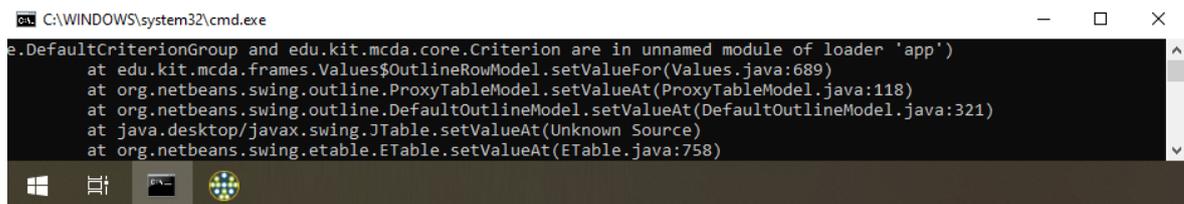
GUI S3 – Decerns MCDA Opened Terminal Example

Secondly, Decerns' automatic commentator at the top-right makes an error when claiming that one alternative ranks better than another in a comparison where all have the same scores exactly.

Thirdly, Decerns MCDA shows again the unnecessary complications of having a 'help' button which opens a window on the side instead of automatically floating a help window when hovering the caret on an element, as is the case with this research's MCA solver, see GUI S16 in the Buttons' Red Highlights & Comments sub-section in Appendix B – Software for illustrations.

Fourthly, the windows are also unneeded, because they lack the logical flow of starting with title and description, import button, criteria weighting, followed by alternatives scoring, correlation matrix analysis, and ultimately final ranks, as shown in GUI S8 in the Supplementary GUIs sub-section in Appendix B – Software. At the centre-left, there is a button for sorting the windows out, but it always returns them to the same location, even if they are moved to different corners, hence the button's description blocks the 'Alternative 1' text.

Moreover, Decerns MCDA plots a correlation between two criteria, but no correlation is actually calculated. There is no zoom-in and out feature in the Decerns software. This makes using the program uncomfortable.

Zooming in and out is a basic feature of HTML by holding either 'Ctrl' button and scrolling up and down, or pressing the minus – or plus + buttons. There are also inconsistencies in the size and alignment of different texts in the Decerns MCDA app.

Lastly, ranks are not broken down into the contributions by each criterion in the bar charts.

Appendix B – Software

Validated MCA exercises from the literature

The following papers in Table S3 below are from MCA literature. Each of these performed extensive MCA calculations and has shown their inputs, methods, working, and output results. These are used for verifying the MCA Solver Software Tool. Table S3 is sorted by publication years.

Table S3 – Validated MCA exercises from literature

#	Name of paper	Number and type of Alternatives	Number and type of Criteria	Weighting & Ranking Methods	Published Year & Reference
1	Application Of WSM In Determining Special Allocation Funds Recipients User Inputs	8 Schools	9 Features	Manual Assignment & WSM	2017 [11]
2	A Comprehensive Study of Weighted Product Model for Selecting the Best Product in Our Daily Life	6 Laptop Models	7 Features & Specifications	AHP & WPM	2020 [10]
3	Outranking methods: PROMETHEE I and PROMETHEE II	6 Laptop Models	7 Features & Specifications	AHP & PROMETHEE I & II	2020 [95]

In these examples, scores are normalised using Script S4 under Supplementary Scripts from Appendix B – Software. These examples are all included in the MCA solver as well for the user to launch to better understand how to use the MCA solver software tool, under 'Load Up Example Demos & Case Studies', see GUI S4 below:

Load Up Example Demos & Case Studies:

Water Supply Vulnerability Index
2017 Manual Weights & WSM
2020 AHP & WPM
2020 AHP & PROMETHEE

GUI S4 – Demo Examples Dropdown List

2017 Manual Weights & WSM

GUI S5 below summarises the 2017 paper 'Application Of WSM In Determining Special Allocation Funds Recipients User Inputs' [11] from Table S3 above, verify that the MCA Solver Software Tool calculates correct outputs using this paper.

Criteria Weighting

Number of Criteria = 9

User Inputs: Criteria Preferences

Weighting Method: -Manual-

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
Raw Weights	2	1	1	1	1	1	1	1	1
Normalised Weights	0.20	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10

Reset Criteria Names   Reset Weights

Alternatives Ranking

Number of Alternatives = 8

User Inputs: Alternatives Scores

Use ±Uncertainties? ☐   Reset Uncertainties

Reset Alternatives Names   Reset Scores   Auto Generate Uncertainties

Auto Generate Best & Worst Scores

\Criteria Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9
A1	1	2	1	3	2	3	2	1	1
A2	2	2	3	3	3	3	3	2	2
A3	2	2	2	1	3	2	3	1	2
A4	2	2	3	1	2	1	2	2	1
A5	1	1	2	3	3	1	3	2	1
A6	2	2	2	2	3	3	1	1	2
A7	1	2	3	2	1	3	3	2	2
A8	1	1	3	3	3	3	2	1	2
Best Possible Score	10	10	10	10	10	10	10	10	10
Worst Possible Score	0	0	0	0	0	0	0	0	0

Show Working? ☑

Criteria Correlation Analysis

These are the Pearson's 'R' correlations between the scores of each criterion.
If the scores between any two criteria correlate too strongly,
it raises the concern that they both measure a very similar or even the same indicator.

|R| < 0.3 : Low Correlation |R| < 0.5 : Moderate Correlation |R| ≥ 0.5 : High Correlation

\Criteria Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	1	0.58	0.18	-0.60	0.35	-0.15	-0.18	0.00	0.26
C2	0.58	1	-0.10	-0.52	-0.41	0.25	-0.10	0.00	0.15
C3	0.18	-0.10	1	-0.16	-0.13	-0.03	0.23	0.54	0.42
C4	-0.60	-0.52	-0.16	1	0.21	0.40	0.05	0.00	-0.08
C5	0.35	-0.41	-0.13	0.21	1	-0.10	-0.13	-0.35	0.18
C6	-0.15	0.25	-0.03	0.40	-0.10	1	-0.24	-0.44	0.64
C7	-0.18	-0.10	0.23	0.05	-0.13	-0.24	1	0.54	0.05
C8	0.00	0.00	0.54	0.00	-0.35	-0.44	0.54	1	-0.26
C9	0.26	0.15	0.42	-0.08	0.18	0.64	0.05	-0.26	1

Normalised Scores

\Criteria Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9
A1	0.1	0.2	0.1	0.3	0.2	0.3	0.2	0.1	0.1
A2	0.2	0.2	0.3	0.3	0.3	0.3	0.3	0.2	0.2
A3	0.2	0.2	0.2	0.1	0.3	0.2	0.3	0.1	0.2
A4	0.2	0.2	0.3	0.1	0.2	0.1	0.2	0.2	0.1
A5	0.1	0.1	0.2	0.3	0.3	0.1	0.3	0.2	0.1
A6	0.2	0.2	0.2	0.2	0.3	0.3	0.1	0.1	0.2
A7	0.1	0.2	0.3	0.2	0.1	0.3	0.3	0.2	0.2
A8	0.1	0.1	0.3	0.3	0.3	0.3	0.2	0.1	0.2

Alternatives Ranks

Ranking Method: WSM

Alternatives	Final Scores (Out Of 1)	Absolute Ranks (1 Is Best)
A1	0.17	8
A2	0.25	1
A3	0.20	2
A4	0.18	6
A5	0.18	6
A6	0.20	2
A7	0.20	2
A8	0.20	2
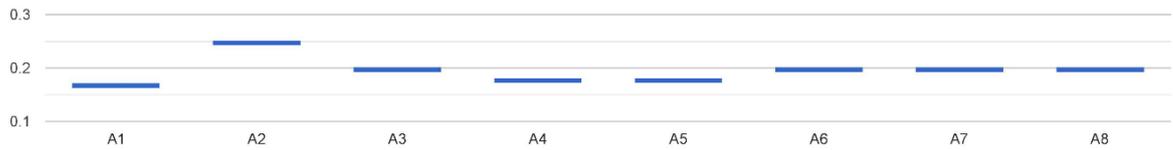
GUI S5 – Manual Weights & WSM weights, scores, and ranks

2020 AHP & WPM

GUI S6 below summarises the 2020 paper 'A Comprehensive Study of Weighted Product Model for Selecting the Best Product in Our Daily Life' [10] from Table S3 and verifies that the MCA Solver Software Tool calculates correct outputs using this paper.

Criteria Weighting

Number of Criteria = 7

User Inputs: Criteria Preferences

Weighting Method: AHP

Criteria	Processor	Hard Disk Capacity	Operating System	RAM	Screen Size	Brand	Color
Processor	1 / 1	5 / 1	7 / 1	3 / 1	2 / 1	7 / 1	9 / 1
Hard Disk Capacity	1 / 5	1 / 1	3 / 1	1 / 3	1 / 3	2 / 1	5 / 1
Operating System	1 / 7	1 / 3	1 / 1	1 / 5	1 / 3	1 / 3	3 / 1
RAM	1 / 3	3 / 1	5 / 1	1 / 1	2 / 1	3 / 1	9 / 1
Screen Size	1 / 2	3 / 1	3 / 1	1 / 2	1 / 1	3 / 1	7 / 1
Brand	1 / 7	1 / 2	3 / 1	1 / 3	1 / 3	1 / 1	5 / 1
Color	1 / 9	1 / 5	1 / 3	1 / 9	1 / 7	1 / 5	1 / 1
Relative Weights	2.64	0.66	0.32	1.51	1.19	0.54	0.16
Normalised Weights	0.38	0.09	0.05	0.22	0.17	0.08	0.02

Reset Criteria Names   Reset Weights

Alternatives Ranking

Number of Alternatives = 6

User Inputs: Alternatives Scores

Use ±Uncertainties? ☐   Reset Uncertainties

Reset Alternatives Names   Reset Scores   Auto Generate Uncertainties

Auto Generate Best & Worst Scores

\Criteria Alternatives	Processor	Hard Disk Capacity	Operating System	RAM	Screen Size	Brand	Color
Model 1	5	3	3	5	5	9	3
Model 2	7	9	5	5	7	3	3
Model 3	7	5	9	7	7	7	5
Model 4	3	5	9	3	3	2	9
Model 5	7	9	9	7	7	9	9
Model 6	5	3	5	5	7	5	3
Best Possible Score	7	9	9	7	7	9	9
Worst Possible Score	0	0	0	0	0	0	0

Show Working? ☑

Criteria Correlation Analysis

These are the Pearson's 'R' correlations between the scores of each criterion.
If the scores between any two criteria correlate too strongly,
it raises the concern that they both measure a very similar or even the same indicator.

| |R| < 0.3 : Low Correlation | | |R| < 0.5 : Moderate Correlation | | |R| ≥ 0.5 : High Correlation |

\Criteria Criteria	Processor	Hard Disk Capacity	Operating System	RAM	Screen Size	Brand	Color
Processor	1	0.60	0.06	0.87	0.88	0.44	-0.22
Hard Disk Capacity	0.60	1	0.37	0.32	0.35	-0.08	0.36
Operating System	0.06	0.37	1	0.23	-0.09	-0.11	0.83
RAM	0.87	0.32	0.23	1	0.79	0.72	-0.03
Screen Size	0.88	0.35	-0.09	0.79	1	0.36	-0.41
Brand	0.44	-0.08	-0.11	0.72	0.36	1	-0.04
Color	-0.22	0.36	0.83	-0.03	-0.41	-0.04	1

Normalised Scores

\Criteria Alternatives	Processor	Hard Disk Capacity	Operating System	RAM	Screen Size	Brand	Color
Model 1	0.71	0.33	0.33	0.71	0.71	1	0.33
Model 2	1	1	0.56	0.71	1	0.33	0.33
Model 3	1	0.56	1	1	1	0.78	0.56
Model 4	0.43	0.56	1	0.43	0.43	0.22	1
Model 5	1	1	1	1	1	1	1
Model 6	0.71	0.33	0.56	0.71	1	0.56	0.33

Alternatives Ranks

Ranking Method: (WPM)

Alternatives	Final Scores (Out Of 7)	Absolute Ranks (1 Is Best)
Model 1	0.64	5
Model 2	0.81	3
Model 3	0.92	2
Model 4	0.44	6
Model 5	1.00	1
Model 6	0.67	4
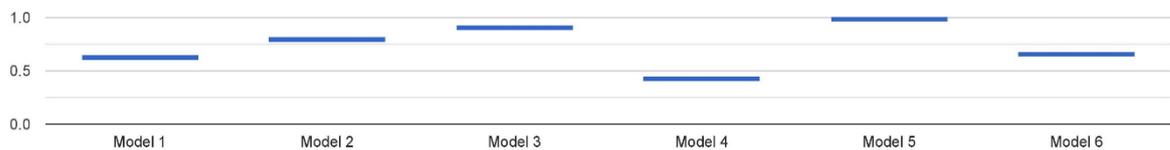
GUI S6 – AHP & WPM weights, scores, and ranks

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2020 AHP & PROMETHEE I & II

GUI S7 below summarises the 2020 paper 'Outranking methods: PROMETHEE I and PROMETHEE II' [95] from Table S3 and verifies that the MCA Solver Software Tool calculates correct outputs using this paper. The weights themselves were calculated using AHP identically as in the 2020 AHP & WPM in GUI S6 above.

Alternatives Ranking

Number of Alternatives = 6

User Inputs: Alternatives Scores

Use ±Uncertainties? ☐   Reset Uncertainties

Reset Alternatives Names   Reset Scores   Auto Generate Uncertainties

Auto Generate Best & Worst Scores

\Criteria Alternatives	Processor	Hard Disk Capacity	Operating System	RAM	Screen Size	Brand	Color
Model 1	3	5	3	5	3	9	3
Model 2	5	7	5	5	7	3	3
Model 3	5	9	9	7	7	7	5
Model 4	7	9	9	9	9	2	9
Model 5	5	7	9	7	7	9	9
Model 6	3	5	5	5	7	5	3
Best Possible Score	7	9	9	9	9	9	9
Worst Possible Score	3	5	3	5	3	2	3

Show Working? ☑

Criteria Correlation Analysis

These are the Pearson's 'R' correlations between the scores of each criterion.
If the scores between any two criteria correlate too strongly,
it raises the concern that they both measure a very similar or even the same indicator.

| |R| < 0.3 : Low Correlation | |R| < 0.5 : Moderate Correlation | |R| ≥ 0.5 : High Correlation |

\Criteria Criteria	Processor	Hard Disk Capacity	Operating System	RAM	Screen Size	Brand	Color
Processor	1	0.89	0.77	0.87	0.77	-0.55	0.75
Hard Disk Capacity	0.89	1	0.84	0.82	0.68	-0.37	0.61
Operating System	0.77	0.84	1	0.86	0.74	-0.11	0.83
RAM	0.87	0.82	0.86	1	0.66	-0.27	0.89
Screen Size	0.77	0.68	0.74	0.66	1	-0.69	0.58
Brand	-0.55	-0.37	-0.11	-0.27	-0.69	1	-0.04
Color	0.75	0.61	0.83	0.89	0.58	-0.04	1

Normalised Scores

\Criteria Alternatives	Processor	Hard Disk Capacity	Operating System	RAM	Screen Size	Brand	Color
Model 1	0	0	0	0	0	1	0
Model 2	0.5	0.5	0.33	0	0.67	0.14	0
Model 3	0.5	1	1	0.5	0.67	0.71	0.33
Model 4	1	1	1	1	1	0	1
Model 5	0.5	0.5	1	0.5	0.67	1	1
Model 6	0	0	0.33	0	0.67	0.43	0

Alternatives Ranks

Ranking Method: PROMETHEE I

Alternatives	Leaving Flow φ⁻	Entering Flow φ⁻	Sum Flows Σφ	Relative Ranks (1 Is Best)
Model 1	0.22	2.52	-2.3	6
Model 2	0.61	1.13	-0.52	4
Model 3	1.36	0.43	0.93	2
Model 4	3.06	0.26	2.8	1
Model 5	1.32	0.45	0.87	3
Model 6	0.19	1.98	-1.79	5

Export Graph As .svg   Export Graph As .jpg

Model 4
2.8 - 2.8, 2.8 - 2.8

Alternatives Ranks

Ranking Method: PROMETHEE II

Alternatives	Leaving Flow φ⁻	Entering Flow φ⁻	Sum Flows Σφ	Relative Ranks (1 Is Best)
Model 1	0.04	0.5	-0.46	6
Model 2	0.12	0.23	-0.11	4
Model 3	0.27	0.09	0.18	2
Model 4	0.61	0.05	0.56	1
Model 5	0.26	0.09	0.17	3
Model 6	0.04	0.4	-0.36	5

Export Graph As .svg   Export Graph As .jpg

Model 4
0.56 - 0.56, 0.56 - 0.56

GUI S7 – 2020 AHP & PROMETHEE I & II scores and ranks

CSV & JSON Data Storage Files

Table S4 – Downloaded CSV opened in a spreadsheet app

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1	Criteria	Affordability (10⁴ m³/Capita·Year)	±	Flood Risk (1-5)	±	Water Stress (1-5)	±	Soil Moisture Content (%)	±	Source Water Quality (0-10)	±	Tap Water Quality (%)	±	Water Loss (%)	±		Final Scores (Out Of 1)	±	Absolute Ranks (1 Is Best)
2	\Weight Alternative	0.07		0.21		0.14		0.07		0.07		0.21		0.21					
3	Amsterdam, Holland	1700	850	4	0	1	0	37	1	3.06	0.01	74	1	4	1		0.65	0.02	6
4	Bahrain	7.8	3.9	3	0	5	0	13	1	2.92	0.01	25	1	24	1		0.27	0.01	19
5	Berlin, Germany	1600	800	4	0	4	0	21	1	4.09	0.01	100	0	5	1		0.59	0.02	8
6	Brussels, Belgium	3000	1500	2	0	5	0	13	1	1.9	0.01	100	0	26	1		0.53	0.03	9
7	Copenhagen, Denmark	2100	1050	1	0	3	0	42	1	5.32	0.01	100	0	7.22	0.01		0.83	0.02	1
8	Dallas, Texas	2700	1350	5	0	2	0	27	1	5.48	0.01	4	1	8.8	0.1		0.44	0.03	14
9	Doha, Qatar	23	11.5	4	0	5	0	11	1	2.72	0.01	91	1	26	1		0.34	0.01	18
10	Dubai, UAE	17	8.5	5	0	5	0	10	1	6.09	0.01	0	0	5.3	0.1		0.27	0	20
11	Hong Kong	7.5	3.75	5	0	3	0	36	1	5.22	0.01	99	1	32.5	0.1		0.41	0	16
12	Houston, Texas	2700	1350	4	0	3	0	34	1	6.7	0.01	24	1	16.87	0.01		0.47	0.03	11
13	Kuwait City, Kuwait	7.7	3.85	4	0	5	0	12	1	3.91	0.01	0	0	10	1		0.26	0.01	21
14	London, England	2400	1200	4	0	4	0	31	1	2.31	0.01	100	0	26.7	0.1		0.47	0.03	13
15	Los Angeles, California	2900	1450	4	0	5	0	15	1	6.12	0.01	50	1	9.9	0.1		0.47	0.03	12
16	Manchester, England	1600	800	2	0	2	0	32	1	4.38	0.01	100	0	24.4	0.1		0.67	0.02	5
17	Melbourne, Australia	2000	1000	4	0	4	0	13	1	6.74	0.01	51	1	10	1		0.49	0.02	10
18	Mexico City, Mexico	640	320	4	0	5	0	8	1	2.59	0.01	0	0	40	1		0.08	0.01	24
19	Paris, France	1300	650	4	0	3	0	30	1	4.56	0.01	1	1	6	1		0.42	0.02	15
20	Riyadh, Saudi Arabia	8.4	4.2	2	0	5	0	6	1	3.58	0.01	0	0	30	1		0.24	0.01	23
21	Rome, Italy	1400	700	3	0	5	0	15	1	4.02	0.01	68	1	27.8	0.1		0.39	0.02	17
22	Shanghai, China	2100	1050	5	0	5	0	46	1	3.9	0.01	0	0	17.6	0.1		0.26	0.02	22
23	Singapore	23	11.5	4	0	1	0	29	1	5.71	0.01	100	0	5	1		0.69	0.01	3
24	Taipei, Taiwan	2000	1000	4	0	2	0	57	1	6.21	0.01	100	0	17.73	0.01		0.67	0.02	4
25	Toronto, Canada	1800	900	2	0	1	0	36	1	4.08	0.01	100	0	10	1		0.79	0.02	2
26	Washington DC	3200	1600	2	0	2	0	34	1	5.97	0.01	48	1	25	1		0.62	0.04	7
27	Best Possible Score	3200		1		1		57		6.74		100		4					
28	Worst Possible Score	7.5		5		5		6		1.9		0		40					
29																			
30	Weighting Method	Ranking Method																	
31	-Manual-	WSM																	

Table S5 – 'EditCSV' Extension in Visual Studio Code

Script S1 below presents an efficient way of saving bytes: city names that do not include a comma `,`, for example, Singapore compared to "Shanghai, China" do not include quotation marks ` " " `.

```
Criteria,"Affordability (10⁴ m³/Capita·Year)",±,"Flood Risk (1-5)",±,"Water Stress (1-5)",±,"Soil Moisture Content (%)",±,"Source Water Quality (0-10)",±,"Tap Water Quality (%)",±,"Water Loss (%)",±,,"Final Scores (Out Of 1)",±,"Absolute Ranks (1 Is Best)"
"\Weight
Alternative","0.07",,"0.21",,"0.14",,"0.07",,"0.07",,"0.21",,"0.21",
"Amsterdam, Holland","1700","850","4","0","1","0","37","1","3.06","0.01","74","1","4","1",,"0.65","0.02","6"
"Bahrain","7.8","3.9","3","0","5","0","13","1","2.92","0.01","25","1","24","1",,"0.27","0.01","19"
"Berlin, Germany","1600","800","4","0","4","0","21","1","4.09","0.01","100","0","5","1",,"0.59","0.02","8"
"Brussels, Belgium","3000","1500","2","0","5","0","13","1","1.90","0.01","100","0","26","1",,"0.53","0.03","9"
"Copenhagen,
Denmark","2100","1050","1","0","3","0","42","1","5.32","0.01","100","0","7.22","0.01",,"0.83","0.02","1"
"Dallas, Texas","2700","1350","5","0","2","0","27","1","5.48","0.01","4","1","8.8","0.1",,"0.44","0.03","14"
"Doha, Qatar","23","11.5","4","0","5","0","11","1","2.72","0.01","91","1","26","1",,"0.34","0.01","18"
"Dubai, UAE","17","8.5","5","0","5","0","10","1","6.09","0.01","0","0","5.3","0.1",,"0.27","0.00","20"
"Hong Kong","7.5","3.75","5","0","3","0","36","1","5.22","0.01","99","1","32.5","0.1",,"0.41","0.00","16"
"Houston, Texas","2700","1350","4","0","3","0","34","1","6.70","0.01","24","1","16.87","0.01",,"0.47","0.03","11"
"Kuwait City, Kuwait","7.7","3.85","4","0","5","0","12","1","3.91","0.01","0","0","10","1",,"0.26","0.01","21"
"London, England","2400","1200","4","0","4","0","31","1","2.31","0.01","100","0","26.7","0.1",,"0.47","0.03","13"
"Los                                                                                                                  Angeles,
California","2900","1450","4","0","5","0","15","1","6.12","0.01","50","1","9.9","0.1",,"0.47","0.03","12"
"Manchester,
England","1600","800","2","0","2","0","32","1","4.38","0.01","100","0","24.4","0.1",,"0.67","0.02","5"
"Melbourne, Australia","2000","1000","4","0","4","0","13","1","6.74","0.01","51","1","10","1",,"0.49","0.02","10"
"Mexico City, Mexico","640","320","4","0","5","0","8","1","2.59","0.01","0","0","40","1",,"0.08","0.01","24"
"Paris, France","1300","650","4","0","3","0","30","1","4.56","0.01","1","1","6","1",,"0.42","0.02","15"
"Riyadh, Saudi Arabia","8.4","4.2","2","0","5","0","6","1","3.58","0.01","0","0","30","1",,"0.24","0.01","23"
"Rome, Italy","1400","700","3","0","5","0","15","1","4.02","0.01","68","1","27.8","0.1",,"0.39","0.02","17"
"Shanghai, China","2100","1050","5","0","5","0","46","1","3.90","0.01","0","0","17.6","0.1",,"0.26","0.02","22"
"Singapore","23","11.5","4","0","1","0","29","1","5.71","0.01","100","0","5","1",,"0.69","0.01","3"
"Taipei, Taiwan","2000","1000","4","0","2","0","57","1","6.21","0.01","100","0","17.73","0.01",,"0.67","0.02","4"
"Toronto, Canada","1800","900","2","0","1","0","36","1","4.08","0.01","100","0","10","1",,"0.79","0.02","2"
"Washington DC","3200","1600","2","0","2","0","34","1","5.97","0.01","48","1","25","1",,"0.62","0.04","7"
"Best Possible Score","3200",,"1",,"1",,"57",,"6.74",,"100",,"4",
"Worst Possible Score","7.5",,"5",,"5",,"6",,"1.90",,"0",,"40",
,
Weighting Method,Ranking Method
-Manual-,WSM
```

Script S1 – CSV text file downloaded user inputs data

Script S2 below illustrates the differences between JSON and CSV text files regarding storing user data:

```
{"A_24":"Washington DC","A_23":"Toronto, Canada","A_22":"Taipei,
Taiwan","A_21":"Singapore","A_20":"Shanghai, China","A_19":"Rome,
Italy","A_18":"Riyadh, Saudi Arabia","A_17":"Paris, France","A_16":"Mexico City,
Mexico","A_15":"Melbourne, Australia","A_14":"Manchester, England","A_13":"Los
Angeles, California","A_12":"London, England","A_11":"Kuwait City,
Kuwait","A_10":"Houston, Texas","A_9":"Hong Kong","A_8":"Dubai, UAE","A_7":"Doha,
Qatar","A_6":"Dallas, Texas","A_5":"Copenhagen, Denmark","A_4":"Brussels,
Belgium","A_3":"Berlin, Germany","A_2":"Bahrain","A_1":"Amsterdam, Holland","Ranking
Method Selector":"WSM","C_7":"Water Loss (%)","C_6":"Tap Water Quality
(%)","C_5":"Source Water Quality (0-10)","C_4":"Soil Moisture Content
(%)","C_3":"Water Stress (1-5)","C_2":"Flood Risk (1-5)","C_1":"Affordability (10⁴
m³/Capita·Year)","F_A1C7":"40","F_A1C6":"0","F_A1C5":"1.90","F_A1C4":"6","F_A1C3":"5
","F_A1C2":"5","F_A1C1":"7.5","F_A0C7":"4","F_A0C6":"100","F_A0C5":"6.74","F_A0C4":"
57","F_A0C3":"1","F_A0C2":"1","F_A0C1":"3200","U_A24C7":"1","S_A24C7":"25","U_A24C6"
:"1","S_A24C6":"48","U_A24C5":"0.01","S_A24C5":"5.97","U_A24C4":"1","S_A24C4":"34","
U_A24C3":"0","S_A24C3":"2","U_A24C2":"0","S_A24C2":"2","U_A24C1":"1600","S_A24C1":"3
200","U_A23C7":"1","S_A23C7":"10","U_A23C6":"0","S_A23C6":"100","U_A23C5":"0.01","S_
A23C5":"4.08","U_A23C4":"1","S_A23C4":"36","U_A23C3":"0","S_A23C3":"1","U_A23C2":"0"
,"S_A23C2":"2","U_A23C1":"900","S_A23C1":"1800","U_A22C7":"0.01","S_A22C7":"17.73","
U_A22C6":"0","S_A22C6":"100","U_A22C5":"0.01","S_A22C5":"6.21","U_A22C4":"1","S_A22C
4":"57","U_A22C3":"0","S_A22C3":"2","U_A22C2":"0","S_A22C2":"4","U_A22C1":"1000","S_
A22C1":"2000","U_A21C7":"1","S_A21C7":"5","U_A21C6":"0","S_A21C6":"100","U_A21C5":"0
.01","S_A21C5":"5.71","U_A21C4":"1","S_A21C4":"29","U_A21C3":"0","S_A21C3":"1","U_A2
1C2":"0","S_A21C2":"4","U_A21C1":"11.5","S_A21C1":"23","U_A20C7":"0.1","S_A20C7":"17
.6","U_A20C6":"0","S_A20C6":"0","U_A20C5":"0.01","S_A20C5":"3.90","U_A20C4":"1","S_A
20C4":"46","U_A20C3":"0","S_A20C3":"5","U_A20C2":"0","S_A20C2":"5","U_A20C1":"1050",
"S_A20C1":"2100","U_A19C7":"0.1","S_A19C7":"27.8","U_A19C6":"1","S_A19C6":"68","U_A1
9C5":"0.01","S_A19C5":"4.02","U_A19C4":"1","S_A19C4":"15","U_A19C3":"0","S_A19C3":"5
","U_A19C2":"0","S_A19C2":"3","U_A19C1":"700","S_A19C1":"1400","U_A18C7":"1","S_A18C
7":"30","U_A18C6":"0","S_A18C6":"0","U_A18C5":"0.01","S_A18C5":"3.58","U_A18C4":"1",
"S_A18C4":"6","U_A18C3":"0","S_A18C3":"5","U_A18C2":"0","S_A18C2":"2","U_A18C1":"4.2
","S_A18C1":"8.4","U_A17C7":"1","S_A17C7":"6","U_A17C6":"1","S_A17C6":"1","U_A17C5":
"0.01","S_A17C5":"4.56","U_A17C4":"1","S_A17C4":"30","U_A17C3":"0","S_A17C3":"3","U_
A17C2":"0","S_A17C2":"4","U_A17C1":"650","S_A17C1":"1300","U_A16C7":"1","S_A16C7":"4
0","U_A16C6":"0","S_A16C6":"0","U_A16C5":"0.01","S_A16C5":"2.59","U_A16C4":"1","S_A1
6C4":"8","U_A16C3":"0","S_A16C3":"5","U_A16C2":"0","S_A16C2":"4","U_A16C1":"320","S_
A16C1":"640","U_A15C7":"1","S_A15C7":"10","U_A15C6":"1","S_A15C6":"51","U_A15C5":"0.
01","S_A15C5":"6.74","U_A15C4":"1","S_A15C4":"13","U_A15C3":"0","S_A15C3":"4","U_A15
C2":"0","S_A15C2":"4","U_A15C1":"1000","S_A15C1":"2000","U_A14C7":"0.1","S_A14C7":"2
4.4","U_A14C6":"0","S_A14C6":"100","U_A14C5":"0.01","S_A14C5":"4.38","U_A14C4":"1","
S_A14C4":"32","U_A14C3":"0","S_A14C3":"2","U_A14C2":"0","S_A14C2":"2","U_A14C1":"800
","S_A14C1":"1600","U_A13C7":"0.1","S_A13C7":"9.9","U_A13C6":"1","S_A13C6":"50","U_A
13C5":"0.01","S_A13C5":"6.12","U_A13C4":"1","S_A13C4":"15","U_A13C3":"0","S_A13C3":"
5","U_A13C2":"0","S_A13C2":"4","U_A13C1":"1450","S_A13C1":"2900","U_A12C7":"0.1","S_
```

A12C7":"26.7","U_A12C6":"0","S_A12C6":"100","U_A12C5":"0.01","S_A12C5":"2.31","U_A12C4":"1","S_A12C4":"31","U_A12C3":"0","S_A12C3":"4","U_A12C2":"0","S_A12C2":"4","U_A12C1":"1200","S_A12C1":"2400","U_A11C7":"1","S_A11C7":"10","U_A11C6":"0","S_A11C6":"0","U_A11C5":"0.01","S_A11C5":"3.91","U_A11C4":"1","S_A11C4":"12","U_A11C3":"0","S_A11C3":"5","U_A11C2":"0","S_A11C2":"4","U_A11C1":"3.85","S_A11C1":"7.7","U_A10C7":"0.01","S_A10C7":"16.87","U_A10C6":"1","S_A10C6":"24","U_A10C5":"0.01","S_A10C5":"6.70","U_A10C4":"1","S_A10C4":"34","U_A10C3":"0","S_A10C3":"3","U_A10C2":"0","S_A10C2":"4","U_A10C1":"1350","S_A10C1":"2700","U_A9C7":"0.1","S_A9C7":"32.5","U_A9C6":"1","S_A9C6":"99","U_A9C5":"0.01","S_A9C5":"5.22","U_A9C4":"1","S_A9C4":"36","U_A9C3":"0","S_A9C3":"3","U_A9C2":"0","S_A9C2":"5","U_A9C1":"3.75","S_A9C1":"7.5","U_A8C7":"0.1","S_A8C7":"5.3","U_A8C6":"0","S_A8C6":"0","U_A8C5":"0.01","S_A8C5":"6.09","U_A8C4":"1","S_A8C4":"10","U_A8C3":"0","S_A8C3":"5","U_A8C2":"0","S_A8C2":"5","U_A8C1":"8.5","S_A8C1":"17","U_A7C7":"1","S_A7C7":"26","U_A7C6":"1","S_A7C6":"91","U_A7C5":"0.01","S_A7C5":"2.72","U_A7C4":"1","S_A7C4":"11","U_A7C3":"0","S_A7C3":"5","U_A7C2":"0","S_A7C2":"4","U_A7C1":"11.5","S_A7C1":"23","U_A6C7":"0.1","S_A6C7":"8.8","U_A6C6":"1","S_A6C6":"4","U_A6C5":"0.01","S_A6C5":"5.48","U_A6C4":"1","S_A6C4":"27","U_A6C3":"0","S_A6C3":"2","U_A6C2":"0","S_A6C2":"5","U_A6C1":"1350","S_A6C1":"2700","U_A5C7":"0.01","S_A5C7":"7.22","U_A5C6":"0","S_A5C6":"100","U_A5C5":"0.01","S_A5C5":"5.32","U_A5C4":"1","S_A5C4":"42","U_A5C3":"0","S_A5C3":"3","U_A5C2":"0","S_A5C2":"1","U_A5C1":"1050","S_A5C1":"2100","U_A4C7":"1","S_A4C7":"26","U_A4C6":"0","S_A4C6":"100","U_A4C5":"0.01","S_A4C5":"1.90","U_A4C4":"1","S_A4C4":"13","U_A4C3":"0","S_A4C3":"5","U_A4C2":"0","S_A4C2":"2","U_A4C1":"1500","S_A4C1":"3000","U_A3C7":"1","S_A3C7":"5","U_A3C6":"0","S_A3C6":"100","U_A3C5":"0.01","S_A3C5":"4.09","U_A3C4":"1","S_A3C4":"21","U_A3C3":"0","S_A3C3":"4","U_A3C2":"0","S_A3C2":"4","U_A3C1":"800","S_A3C1":"1600","U_A2C7":"1","S_A2C7":"24","U_A2C6":"1","S_A2C6":"25","U_A2C5":"0.01","S_A2C5":"2.92","U_A2C4":"1","S_A2C4":"13","U_A2C3":"0","S_A2C3":"5","U_A2C2":"0","S_A2C2":"3","U_A2C1":"3.9","S_A2C1":"7.8","U_A1C7":"1","S_A1C7":"4","U_A1C6":"1","S_A1C6":"74","U_A1C5":"0.01","S_A1C5":"3.06","U_A1C4":"1","S_A1C4":"37","U_A1C3":"0","S_A1C3":"1","U_A1C2":"0","S_A1C2":"4","U_A1C1":"850","S_A1C1":"1700","AlternativesNum":"24","N_7":"3","N_6":"3","N_5":"1","N_4":"1","N_3":"2","N_2":"3","N_1":"1","Weighting Method Selector":"-Manual-","CriteriaNum":"7","Description":"Assesses The Vulnerabilities Of Drinking Water Distribution Systems Which Could Specifically Cause Water Shortages\n\nSources:\n\n•\tSoil Moisture: Climate Data Store - Satellite soil moisture explorer\n\n•\tWater Loss (Leakage) Rates: IB-Net primarily, supplemented by regional sources of data such as city council websites.\n\n•\tWater Stress & Floods: Resource Watch & Think Hazard.\n\n•\tWater Source Quality: Custom Index Of BOD, Dissolved Oxygen, Phosphates & Nitrates. Sources are WWF Risk Filter Suite 3.1.1 & Quality Unknown - World Bank Water Data\n\n•\tTap Water Quality: Mixed Absolute & Relative compliance. Based on CDC's NIOSH IDLH\n\n•\tTreatment Cost Affordibility Is Nominal GDP Per Capita/Cost Of Water Production (m3/Capita·Year). Its Sources Are Faithful+Gould Location Factors, IMF Nominal GDP Per Capita and Several Papers and Books On Estimated Water Purification Costs By Conventional and Desalination Technologies","Title":"Water Supply Vulnerability Index","ShowWorkingBox":1,"UncertaintiesBox":1}

Script S2 – JSON text file downloaded user inputs data

Although both are efficient, it is clear from Script S1 and Script S2 above that JSON uses up a larger byte size because it names each cell in the software, whereas CSV only uses single-byte commas as delimiters. It is more convenient to use CSV to download user data for the sake of displaying it as a spreadsheet table, as shown above in Table S4 and Table S5.

Currently, in the MCA Solver, only JSON is used for uploading user data, as shown below in GUI S8, because it is more convenient to save localStorage and then upload it as it is natively in a JSON format. As part of future work, it may be possible to only use CSV (or TSV) as the storage solution file format to both save on byte size and be able to view the data as a spreadsheet table, but it would also be advantageous to slightly decrease the byte size. By picking only one single file format for downloading and uploading user data, it is possible to eliminate the need for one of the three top buttons in GUI S8 below that downloads or uploads data.

One small advantage of JSON over other storage file formats, such as XML and CSV, is that JSON's format can more easily be written directly into a JS file using the curly brackets { : } object notation which is useful for storing examples in-built into the software as shown in GUI S4 – Demo Examples Dropdown List in the Validated MCA exercises from the literature above. Because HTML applications can be minified into a single file for low byte size and fast and convenient launching in a browser, this software tool includes these demo examples in a JS file using JSON and localStorage format.

This advantage however is only small because technically both XML and CSV can be written directly in an HTML file, with XML having a dedicated <script type="application/xml"></script> tag while CSV can use a custom tag such as <pre id="csvData"></pre> or simply be the string text value of a variable in JS. This latter option might actually save on bytes because CSV text does not use as many quotation marks ` " " ` as JSON does.

The main reason for exporting and importing using JSON is the ease and quickness of programming its two buttons in the GUI S8 below. The export button merely downloads localStorage as text, and the upload button merely sets the new localStorage as the uploaded JSON file and reloads the page. The latter is not the most efficient practice in terms of having to relaunch the whole page and having to compromise on the slightly extra byte size, but for this project, it delivers perfect functionality at minimal development time, albeit at a minimal expense to performance.

Supplementary GUIs

GUI S8 below shows what the MCA solver looks like with JS turned off and only HTML and CSS kept on. This is interesting to see for any HTML application. It shows which parts of the front end most likely do not change with JS. Specifically with this software tool, the only changes that are made are the addition of cells in the 'tBodies' of the HTML tables, adding text, selecting options in drop-down menus, unticking checkboxes, and plotting a bar chart. Besides the changes to the page, hovering over elements shows comments and temporarily changes colours. Pressing buttons allows downloading and uploading user data.

GUI S8 – MCA solver's HTML & CSS when JS is turned off

There are two so-called 'range' type inputs, also known as sliders, in the MCA solver shown in several GUIs in this thesis, including in GUI S9 below. These are for selecting the number of criteria and alternatives. Any time their value is changed by the user, the 'number' type input field next to them changes accordingly and vice versa.

Technically, any 'number' type input field may be synchronised with a 'range' type input slider, but this would be potentially too much. For example, imagine if all the scores and uncertainty inputs in GUI S9 would have their own slider. This would be overwhelming and waste a lot of space on the page. The use of sliders in a minimalist fashion allows highlighting to the user which few 'number' type input fields are the most important.

As an aside, the default values for both criteria and alternatives are 4, see Script S3 below. This is due to it being a small and not overwhelmingly large number of rows and columns for a new user to see. It is also a number that is often used in MCA tutorials, see Appendix B – Software under the section Validated MCA exercises from the literature. 4 is also a power of 2, and some believe that arbitrary default values should be powers of 2 unless there is a good reason otherwise, for luck.

As for a maximum number of each, due to limited processing power and high standards set for quick calculations, it was decided that 32 should be sufficient for each. Script S3 below contains the only lines in the whole program that specify these 32 limit numbers; hence changing them here would be all that is required for the user, should their preferences vary.

Similarly, this is the case with the minimum and default numbers. For the record, the Custom Index in this research only studies 24 Case Study Cities (alternative scenarios) and 7 vulnerability indicators (criteria), and all the Validated MCA exercises from the literature also suffice with 32 maximum of each. As for minimum values, recall that Absolute Ranking Methods (section 3.3.1) may assess a single alternative, hence alternatives have a minimum number of 1.

```
<article id='Weights'><h2>Criteria Weighting</h2>
Number of Criteria = <input id='CriteriaNum' type='number' min=2 max=32 value=4>
<br> <input type='range' id='CriteriaSlider' min=2 max=32 value=4>

<article id='Ranks'><h2>Alternatives Ranking</h2>
Number of Alternatives = <input id='AlternativesNum' type='number' min=1 max=32 value=4>
<br> <input type='range' id='AlternativesSlider' min=1 max=32 value=4>
```

Script S3 – HTML criteria and alternative range sliders

Buttons' Red Highlights & Comments

GUI S9 and GUI S10 below show how the two reset weighting buttons highlight in red the criteria names and weights as the mouse cursor hovers over these buttons to warn the user and to point out which input fields are subject to having their data reset.

GUI S9 – Hovering over 'Reset Criteria Names' button red highlights

GUI S10 – Hovering over 'Reset Weights' button red highlights

GUI S11, GUI S12, GUI S13, and GUI S14 below show how the four reset scores buttons highlight in red the names of the alternatives, the scores, and the uncertainties as the mouse cursor hovers over these buttons to warn the user and to indicate which input fields are subject to having their data reset. GUI S14 stands out as removing input fields but can also toggle to re-introduce them, as it is a tick box.

GUI S11 – Hovering over 'Reset Alternatives Names' button red highlights

GUI S12 – Hovering over 'Reset Scores' button red highlights

GUI S13 – Hovering over 'Reset Uncertainties' button red highlights

GUI S14 – Hovering over the 'Use ±Uncertainties?' button red highlights

GUI S15 and GUI S16 above show how two additional buttons automatically generate inputs into empty input fields as opposed to resetting data. Similar to the reset buttons, hovering the mouse cursor over these auto-gen buttons highlights which input fields are subject to being filled if the buttons are clicked.

GUI S15 – Hovering over 'Auto Generate Uncertainties' button red highlights & comment

GUI S16 – Hovering over 'Auto Gen Best & Worst Scores' button red highlights & comment

Both of these buttons make assumptions to automatically generate inputs.

GUI S15 assumes the best possible score is equal to the largest score of that criterion, and it likewise assumes the worst possible score is equal to the smallest score of that criterion.

GUI S16 gives a ±1 adjusted to the number of decimal places of any given score, as scripted in Script 11 in sub-section 5.2.2.

GUI S17 below shows which tables and columns will be hidden, not deleted, should a user wish for a simpler visual without seeing much of the working and focusing on the inputs and results instead.

It is the only example of red highlights when hovering the mouse cursor over a button without the threat of deleting or adding any data.

Show Working? ☑

Scores Correlations
These are the Pearson's 'R' correlations between the scores of each criterion.
If the scores between any two criteria correlate too strongly,
it raises the concern that they both measure a very similar or even the same indicator.

| |R| < 0.3 : Low Correlation | |R| < 0.5 : Moderate Correlation | |R| ≥ 0.5 : High Correlation |

\Criteria Criteria	Price ($)	Storage (GB)	Camera (MP)	Looks
Price ($)	1	0.87	0.32	0.55
Storage (GB)	0.87	1	0.00	0.32
Camera (MP)	0.32	0.00	1	-0.22
Looks	0.55	0.32	-0.22	1

Normalised Scores

\Criteria Alternatives	Price ($)	Storage (GB)	Camera (MP)	Looks
Mobile 1	0.5	0	0	1
Mobile 2	0	0	1	0.33
Mobile 3	1	1	1	0.67
Mobile 4	0.75	1	1	0.67
Mobile 5	0.25	0	1	0

Alternatives Ranks
Ranking Method: (WSM)

Alternatives	Final Scores (Out Of 1)	Absolute Ranks (1 Is Best)
Mobile 1	0.30	5
Mobile 2	0.38	3
Mobile 3	0.91	1
Mobile 4	0.90	2

GUI S17 – Hovering over 'Show Working?' button red highlights

Supplementary Scripts

Script S4 below demonstrates the differences and similarities between the normalisation functions of weights and scores. The key similarity is that the normalisation of either weights or scores aims at converting each of them into fractions between zero and one inclusive.

Note that, unlike normalising scores, normalising weights is not necessary for generating accurate final ranks of alternatives and is only done for simplicity and convenience. Normalising both also allows setting clear highest and lowest final rank scores of one and zero, respectively, for absolute ranking methods, as shown in Table 7 – Absolute Ranking Methods in sub-section 3.3.1 for increased clarity.

In fact, for outranking methods such as PROMETHEE, because they generate relative outranks, their final calculations would arrive at the same ratios of final scores relative to each other, regardless. This can be easily proven by multiplying the weights in the example in Script 8 – JS PROMETHEE I & II function in sub-section 3.3.2 by a factor of 10 and then 100 each.

For this reason, the function for normalising weights is simpler and thus shorter in terms of lines of script, as can be seen by the fact that the only input is the array of weights, compared to also requiring the best and worst possible values, as is the case with normalising scores. Normalising weights is merely dividing each by their sum total, resulting in the new sum total of normalised weights being equal to 1.00 exactly [83].

Normalising scores requires inputting the best and worst possible values of any given criterion, not only to determine the range but also to determine whether a higher score is good or bad. Best and Worst scores are not necessarily the largest and smallest values in the array, but they tend to be. Hence, in GUI S16 above, auto-generating best and worst values fills them in as the largest and smallest value scores, respectively, for each criterion.

If a user would like to auto-generate the opposite way around, they can input all scores as negative numbers, which would achieve the same result. On the same note, Script S4 below also demonstrates how input scores are always normalised between 0 and 1, regardless of whether all scores are positive, negative, or a mixture of both, including some equal to zero.

Script S4 also automatically fixes a potential issue of the user inputting scores out of bounds of the best and worst values. It does so by normalising such scores to equal either 0 or 1, depending on each of either bound they breach.

```
,NormaliseWeights=Weights=>{
    // This function inputs an array of numbers and divides each by their
total, so the returned array will have a sum of 1.00

    let L=Weights.length,l=L,S=0;do{S+=Weights[--L]}while(L>0)
    while(--l>=0)Weights[l]/=S
    return Weights
}// e.g. NormaliseWeights([3,3,1,1,1,1,2]) //➜
[0.25,0.25,0.08,0.08,0.08,0.08,0.17]

,NormaliseScores=(Scores,Best,Worst)=>{
    // For a given single criterion, 'Scores' is an array where each value
corresponds to an alternative

    /*---------------------Checks---------------------*/
    if(isNaN(Best))return'Best Score Must Be A Number!'
    if(isNaN(Worst))return'Worst Score Must Be A Number!'
    if(Best===Worst)return'Best and Worst Scores Must Be Different Numbers!'

    /*---------------------Calculations---------------------*/
    for(let L=Scores.length;--L>=0;){
        const Score=(Scores[L]-Worst)/(Best-Worst)
        // Normalise the score between 1 and 0

        Scores[L]=Score<=0?0:Score>1?1:Score-0/*
If a score is out of bounds, make it equal to its nearest bound,
    i.e. 1 OR 0.

'<=0' is used to avoid a score of '-0'.

Score-0 is to return NaN instead of scripting isNaN(Score) to minify.
    */
    }
    return Scores
}//e.g. NormaliseScores([3,7,8,2,5,6,'Str'],7,3) //➜ [0,1,1,0,0.5,0.75,NaN]
```

Script S4 – JS Normalisation functions

```
/*-------------Cloner functions()-------------*/
,InputsColors=Input=>{
    Input.addEventListener('mouseenter',ev=>Arr.from(gEBCN(ev.target.className))
        .forEach(Box=>Box.classList.add('Aqua')),{passive:1})
    Input.addEventListener('mouseleave',ev=>Arr.from(gEBCN(ev.target.className))
        .forEach(Box=>Box.classList.remove('Aqua')),{passive:1})
    Input.addEventListener('focusin',ev=>Arr.from(gEBCN(ev.target.className))
        .forEach(Box=>Box.classList.add('YellowGreen')),{passive:1})
    Input.addEventListener('focusout',ev=>Arr.from(gEBCN(ev.target.className))
        .forEach(Box=>Box.classList.remove('YellowGreen')),{passive:1})
}
,NumCloner=()=>{
    const NumClone=Create('input');NumClone.type='number'
    InputsColors(NumClone);NumClone.addEventListener('wheel',WheelStep,{passive
:false})
    NumClone.addEventListener('click',ClickSelect,{passive:1})
    return NumClone
}
,RatioNumCloner=ClassName=>{
    const NumClone=NumCloner();NumClone.min=0;NumClone.max=9
    NumClone.addEventListener('keydown',SingleNumKeyDown)
    NumClone.addEventListener('input',SingleNumInput,{passive:1})
    NumClone.addEventListener('keydown',EnterTable,{passive:1})
    NumClone.classList.add(ClassName);NumClone.value=lS.getItem(ClassName)??''
    return NumClone
}
,TextAreaCloner=(Index,Type)=>{
    const TextAreaClone=Create('textarea'),Class=Type+Index
    TextAreaClone.classList.add(Class);InputsColors(TextAreaClone)
    TextAreaClone.addEventListener('input',ClassInput,{passive:1})
    if(Type=='C_'){Type='Criteria'}else{Type='Alternative'
    TextAreaClone.addEventListener('input',Plot,{passive:1})}
    TextAreaClone.placeholder=`${Type}${Index}Name`
    TextAreaClone.value=lS.getItem(TextAreaClone.classList[0])??''
    return TextAreaClone
}
,ScoreCloner=(Type,AlternativeIndex,CriteriaIndex)=>{
    //Note: NumClone is re-done here to avoid using InputsColors(NumClone)
which would highlight all scores in a col unnecessarily
    const NumClone=Create('input');NumClone.type='number'
    NumClone.addEventListener('wheel',WheelStep,{passive:false})
    NumClone.addEventListener('click',ClickSelect,{passive:1})
    NumClone.addEventListener('input',ScoresInput,{passive:1})
    NumClone.addEventListener('keydown',EnterTable,{passive:1})
    NumClone.id=Type+'_A'+AlternativeIndex+'C'+CriteriaIndex
    Type=='S'&&NumClone.classList.add('Criteria'+CriteriaIndex+'Scores')
    Type=='U'&&(NumClone.min=0);NumClone.value=lS.getItem(NumClone.id)??''
    return NumClone
}
```

Script S5 – JS MCA Cloner functions

Appendix C – Index

Types of water pipe materials

This is the discussion for improving the resiliency of Tap Water Quality from sub-section 4.3.3.4. Table S6 below compares the advantages and disadvantages of the main groups of materials for the composition of water pipes.

Table S6 – Water Pipes Materials Comparison

Criteria	Concrete	Plastic (Polymers)	Metal (Alloys)	Glass
g/cm³ Density (of the material itself, excluding hollow internal) [303]	• Light: 0.5 – 1.0 • Medium: 1.3 – 1.7 • Dense: 2.0 – 2.4	• PEH: 0.96 • PVC: 1.4 • CPVC: 1.6	• Steel: 7.8 • Copper & Brasses: 8.5 – 8.8	2.4 – 2.8
Thermal Conductivity (W/mK @ 25°C) [304]	• Light: 0.1 – 0.3 • Medium: 0.4 – 0.7 • Dense: 1.0 – 1.8	• PVC: 0.19 • PEH: 0.42 – 0.51	• Steel: 16.3 • Copper & Brasses: 28 – 390	0.96 – 1.05
Not Brittle	✔/✖	✔	✔	✖
Can be detected by a metal detector	✖	✖	✔ (Steel-Only)	✖
Non-porous, easy-to-clean	✖	✔	✔	✔
Can realistically be both small and large diameter	✖ (Only large. Cannot melt and cast into shape. Requires a large minimum thickness for strength due to porosity)	✔	✔	✖ (Only small, it is too brittle to risk)
Can be flexible	✖	✔	✔	✖
Can be transparent	✖	✔	✖	✔

Withstands high temperature and pressure	✔/✘	✔/✘	✔	✘
Resistant to corrosion	✔	✔	✘	✔
Does not Leach	✔/✘ (May release small amounts of minerals)	✘ (Up to 163 substances, including microplastics [262], [263])	✘ (Corrosion, and constant release of the metal regardless)	✔
Not noisy due to vibrations	✘	✔	✘	✘
Can Be Welded	✘	✘	✔	✘

Glass is good for laboratory and liquid cooling, where pipes can be small in both length and diameter and where transparency and lack of leaching can be important. But it is too brittle for water distribution.

The figures below are meant to illustrate some of the items involved in the journey of potable water from the treatment plant to residential homes and inside homes. It is simple to get overly focused on the properties of materials in Table S6 above and to forget how the items that are made out of these materials are shaped for water delivery in real life. Picture S1 [193] and Picture S2 [305] below demonstrate how both plastic polymers and metal alloys make up flexible water hoses:

Picture S1 – Flexible Braided Transparent PVC Hose [193], generated using ChatGPT

Picture S2 – Flexible Metal Hose [305], by ds_30 via Pixabay's license

The global valve in Picture S3 [184] below is based on valves in real life whose body is cast of a different alloy than its handle. Its handle is verifiably steel, as can be easily proved by hand with a strong magnet. Steel is strong, inexpensive, and reliable; hence, the handle is made of steel. Yet, to limit corrosion, the valve's body itself, including the two ends, is composed of another non-magnetic alloy, presumably one that is less prone to corrosion.

Similar to Picture S3, Picture S4 [193] also functions as a connection of pipes. Unlike Picture S3, which is a valve and may regular flow rate, Picture S4, which is a water meter, can only measure the flow rate and the amount of flow over a period of time. Such connections are found and labelled in CPE P&IDs [306]. Both must connect to pipes that are made out of the same metal as them, or non-metallic pipes like PVC, or else they would corrode faster, as happens when different metals connect and touch water.

Picture S5 [307] below demonstrates an advantage of metal pipes, which is that they are able to connect via bolts, which allows them to withstand high temperatures:

Picture S3 – Metal 3-Way Valve [184], generated using DeepAI

Picture S4 – Water Meter [193], generated using ChatGPT
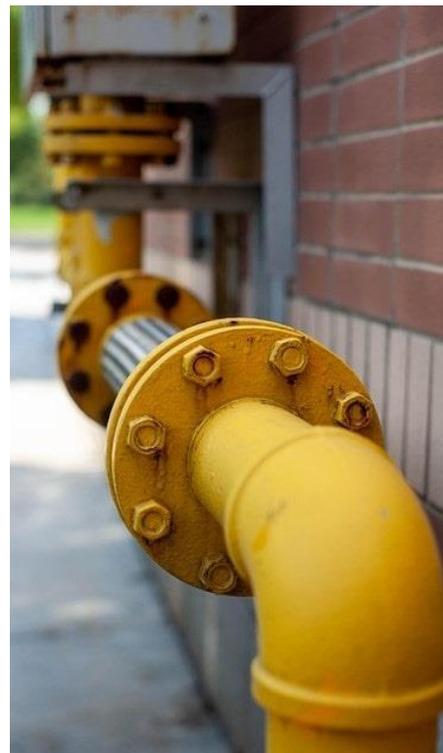
Picture S5 – Metal pipes connected via bolts [305], by marvinsikanyika via Pixabay's license

Water Supplier Sources

Case Studies Basic Statistics

The statistics below in Table S7 are of the Case Study Cities, which were selected in sub-section 4.2. The boundaries of the case studies are for water supply systems and exclude wastewater management for simplicity, but include populations outside of the city that are served by the supplier. Several water systems are difficult to determine their exact boundaries; therefore, it was decided to estimate their total area and population only in their city centres to calculate roughly accurate population densities and to give the benefit of the doubt that a city is indeed 'large'.

Whenever a source reference provides multiple values, it is placed at the heading of the column, while references for single values are placed in a specific cell. Several of these source references are as recent as 2024, and all others are within a decade old.

Total Water Consumption is the sum of potable blue water used in industry, agriculture, and domestically/residentially/municipality. It excludes green and grey water uses, as well as seawater, which has not been desalinated and is not potable, such as Hong Kong's seawater for toilet flushing.

Equation S1 below presents how the units of area and volumetric flow rates are converted from various sources, particularly American cities, to standard units of km^2 and MCM/year:

Area:

$$1 \text{ mile}^2 = \cancel{\text{mile}^2} \times \left(\frac{1.61 \text{ km}}{\cancel{\text{mile}}}\right)^2 = 2.59 \text{ km}^2$$

Volumetric Flow Rates:

$$\text{MCM} = 10^6 \text{ m}^3 \quad , \quad \text{MGD} = \frac{10^6 \text{ Gallon}}{\text{Day}}$$

$$1\frac{\text{US Gallon}}{\text{Day}} = \frac{\cancel{\text{US Gallon}}}{\cancel{\text{Day}}} \times \frac{365 \cancel{\text{Days}}}{\text{Year}} \times \frac{\text{m}^3}{264 \cancel{\text{US Gallon}}} = 1.38 \frac{\text{m}^3}{\text{Year}}$$

$$1\frac{\text{Imperial Gallon}}{\text{Day}} = \frac{\cancel{\text{Imperial Gallon}}}{\cancel{\text{Day}}} \times \frac{365 \cancel{\text{Days}}}{\text{Year}} \times \frac{\text{m}^3}{220 \cancel{\text{Imperial Gallon}}} = 1.66 \frac{\text{m}^3}{\text{Year}}$$

$$1\frac{\text{L}}{\text{Day}} = \frac{\cancel{\text{L}}}{\cancel{\text{Day}}} \times \frac{365 \cancel{\text{Days}}}{\text{Year}} \times \frac{\text{m}^3}{10^3 \cancel{\text{L}}} = 0.365 \frac{\text{m}^3}{\text{Year}}$$

Equation S1 – Area and Volumetric Flow Rate units conversions

Statistic / Case Study City	Population [308], [309]	Area (km^2) [119], [308], [309]	Population Density (People/km^2) [308], [309]	Total Water Consumption (MCM/Year) [119]	Total Water Consumption Per Capita (m^3/ Year·Capita)
Amsterdam, Holland	1 200 000	220 [107]	5 450	61	51 [310] (141 L/Day)
Bahrain	1 600 000	760	2 100	355 [311]	222
Berlin, Germany	3 700 000 [107]	900 [107]	4 100	199 [147] (546 × 10^3 m^3/Day)	54
Brussels, Belgium	1 200 000	161	7 450	60 [312]	50
Copenhagen, Denmark	600 000 [107]	88 [107]	6 820	50 [313]	83
Dallas, Texas [254], [255]	1 300 000	1 810 (700 mile^2)	718	583 (154 10^9 US gallons/year)	448
Doha, Qatar	2 200 000 (2 600 000 × 85% [314])	589 [315]	3 740	403	183 [314] (500 L/Day)
Dubai, UAE [316]	3 100 000	4 110	763	605 [317] (133 10^9 Imp gallons/year)	195
Hong Kong	7 400 000	1 050	7 100	990 [Figure 6 in section 1.3]	134
Houston, Texas [152]	2 200 000	1 550 (600 mile^2)	1 420	651 (472 US MGD)	296
Kuwait City, Kuwait	3 400 000	491 [315]	6 920	554	163 [314] (447 L/Day)

London, England	9 700 000	1 600	6 060	514	53 [318] (144 L/Day)
Los Angeles, California [119]	18 000 000	10 500	1 710	3 660	203
Manchester, England	580 000 [315]	116 [315]	5 000	30	51 [319] (141 L/Day)
Melbourne, Australia [122], [320]	4 500 000 [107]	10 000 [107]	450	387	86 (162/0.69 L/Day)
Mexico City, Mexico	8 800 000 [321]	1 500 [321]	5 870	1 030	117 [322] (320 L/Day)
Paris, France	12 000 000	2 500	4 800	1 700	142
Riyadh, Saudi Arabia	7 800 000	1 800	4 330	1 100 [323]	141
Rome, Italy	4 300 000	1 930	2 230	581	135 [324] (370 L/Day)
Shanghai, China	30 000 000	6 340	4 730	7 300 [325]	243
Singapore	5 800 000	720 [107]	8 060	714 (430 Imp MGD) [Figure 5 in section 1.3]	123
Taipei, Taiwan	6 600 000	232	28 500	804 (2.2 MCM /day [326])	121 (330 L/Day)
Toronto, Canada	6 400 000	3 080 [327]	2 080	435 [32]	68
Washington DC [328]	1 800 000	1 880 (725 mile^2)	957	131 (95 US MGD)	73

Water Supplier emails

Along with the discolouration photos of Picture 2 and Picture 3 in sub-section 4.3.3.3: Analytical Observations, Figure S1 below presents two accompanying emails from the United Utilities local water supplier. The first email was sent on 24/10/2023 in advance of the expectation of the inconvenient maintenance event, and the second email was sent on 26/01/2024, confirming and reassuring after it happened.

Project number: 80065275
Hello
We're carrying out some night time work on the water pipes in your area between Wednesday 15 November and Saturday 23 December, from 11pm until 5.30am
We wanted to let you know about work we're carrying out to clean the water pipes in your area. It's part of a programme taking place across the North West region to help remove historical sediments, keep the pipes in tip-top condition and make sure we continue to provide high quality water to your home or business.

You can find further information at **unitedutilities.com/pipe-cleaning**

What does the work involve?

We'll be using the water in the pipes to flush out and remove any historical sediments that may have settled at the bottom. We won't need to turn off your water and we'll be moving through the area in stages. We carry out the work during the night to cause as little disruption as possible. In most instances you may not even notice we're there, but of course our team will do all they can to minimise any noise and make sure your water supply is unaffected.

You may notice a temporary change to the colour of your tap water

When we're cleaning your local pipes you may find that your tap water temporarily reduces in pressure or, after the work takes place may appear a little discoloured. We do understand discoloured water can look unpleasant and want to reassure you that our work would only impact your property for a short amount of time as our team progresses through the area. This is nothing to worry about and any discolouration will quickly return to normal. We're sorry if you do experience any changes to the colour of your water and information and advice so you can help to clear discoloured water quickly.

Thanks for your patience as we carry out this important work. We're here to help you with any queries or if your water doesn't clear after following the simple guidance, so please don't hesitate to get in touch. You can do this via our social media channels or if you prefer give us a call on 0345 6723 723 and select option 1.

Need additional support?

We can all benefit from a bit of extra help at some stage in our lives. This could be due to age, ill health, disability, mental health problems, financial worries or language barriers. Registering for our FREE Priority Services means you, your family or your friends could benefit from additional services or support.

Don't forget it's easy to save water at home, which could save you money on your water and energy bills. Sign up to getwaterfit.co.uk for great tips and FREE goodies too.

Thank you

Customer Services Team

We've recently fixed an issue affecting water supplies in your area. If your water's not flowing yet, it soon will be. It can take a while to fill up the network in the surrounding area and return water pressure to normal. We do our best to turn the water on gradually to prevent creating further problems, such as bursts, leaks or discoloured water.

Occasionally after an interruption, water can be a different colour for a couple of reasons:
1. It may look milky or cloudy. This is just tiny air bubbles in the water, there's nothing to worry about, you don't need to do anything to clear this, it's safe to use, and will clear naturally in time.
2. It could look discoloured. Sometimes historically occurring deposits in the pipe can be disturbed as the water is turned back on, making it look light yellow to dark brown.
You can clear the problem, by running the cold water tap that's closest to your internal stop tap, just above a trickle. This may take anywhere from a few minutes to an hour, why not collect this water and use it to water your plants? If you're on a meter, don't worry, that's less than 5 pence.

While water is discoloured, we advise not to run the hot water tap, use dishwashers, washing machines, or any other appliances which uses your hot water supply.
Get more information on discoloured water and how to clear it at www.unitedutilities.com/watercolour. We're sorry for any inconvenience caused.

Figure S1 – emails from the United Utilities water supplier

Interactive Maps

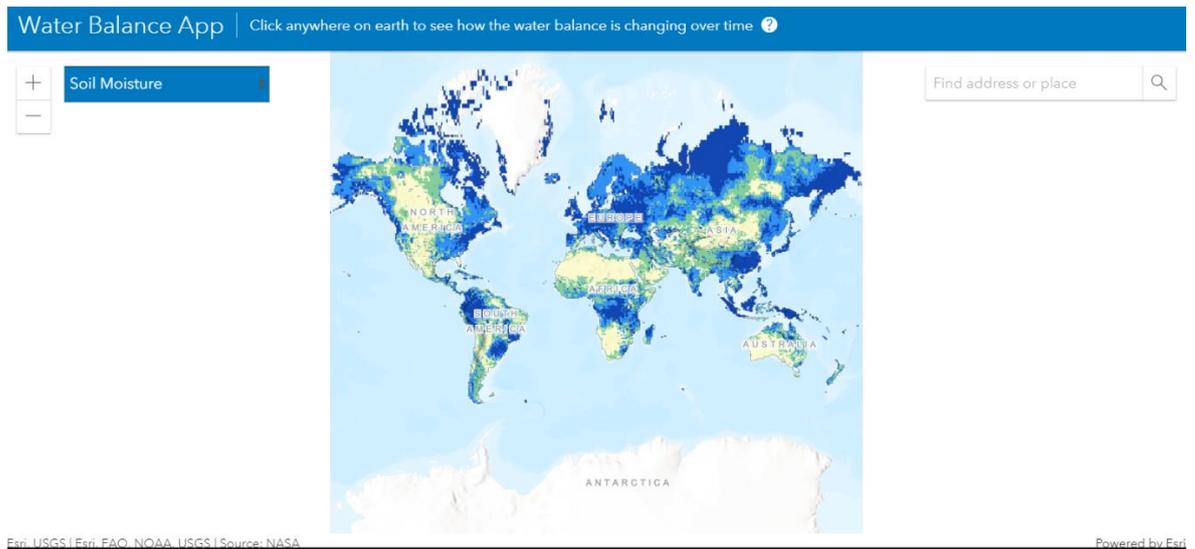## Soil Moisture Content Interactive Map

Map S1 below shows how cities globally may be examined for Soil Moisture Content generated by ECMWF's satellite data [199]. In this example, 0.32 v/v is the lowest soil moisture for Manchester, England, which occurs in the month of August. The collected Soil Moisture Content values for the case studies are available in Table 12 in sub-section 4.3.7.
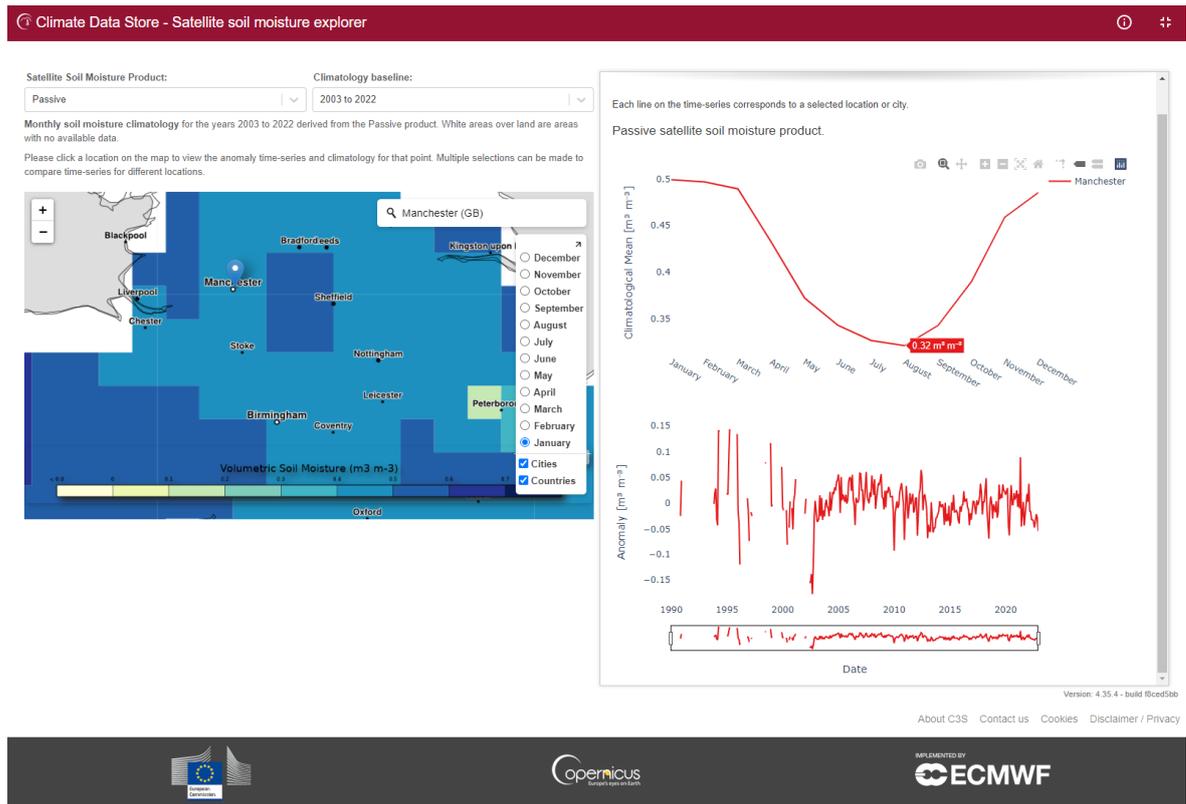

Map S1 – Manchester Soil Moisture Content [199], ©Copernicus free, full, and open policy

Water Balance Change in Storage Interactive Map

The 'Water Balance App' [329] is an interactive map with data available globally, as shown below in Map S2. It features six metrics, as shown below in Map S3. Of greatest interest, 'Change in Storage', was initially considered as an indicator as discussed in 4.3.5: Water Stress, until it was replaced with the Water Stress Interactive Maps below.

Map S2 – World Soil Moisture by the Water Balance App [329], under ©Esri's fair use
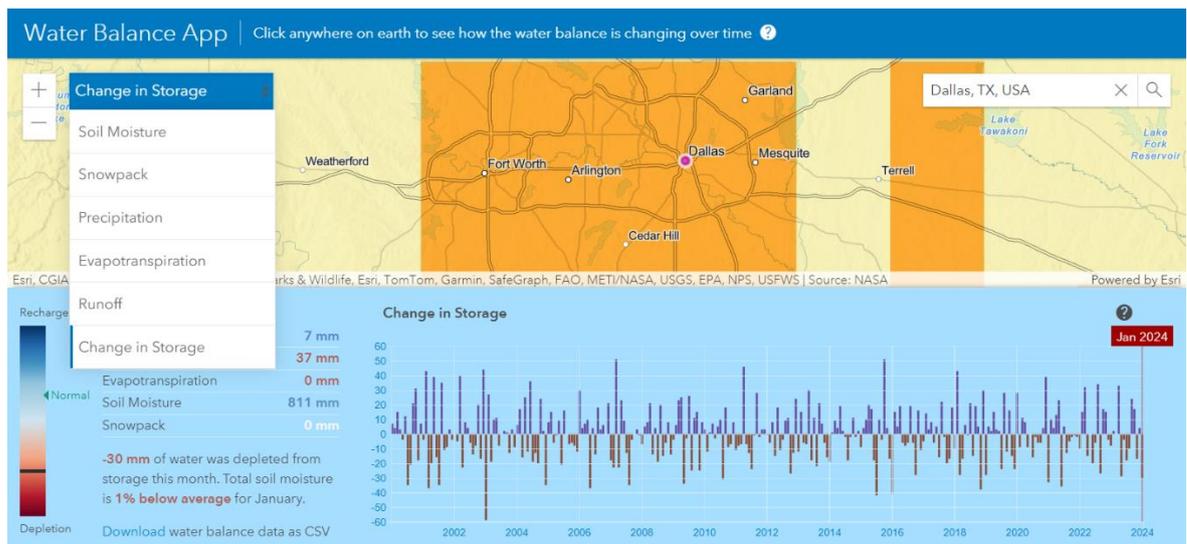
Map S3 – Dallas Change in Storage by the Water Balance App [329], under ©Esri's fair use

Water Stress Interactive Maps

Map S4 [110] and Map S5 [249] below present the online interactive maps for Water Stress and Scarcity discussed in sub-section 4.3.5: Water Stress. In this example, Shanghai has water stress at the second-highest rating out of a possible four from either of these sources.
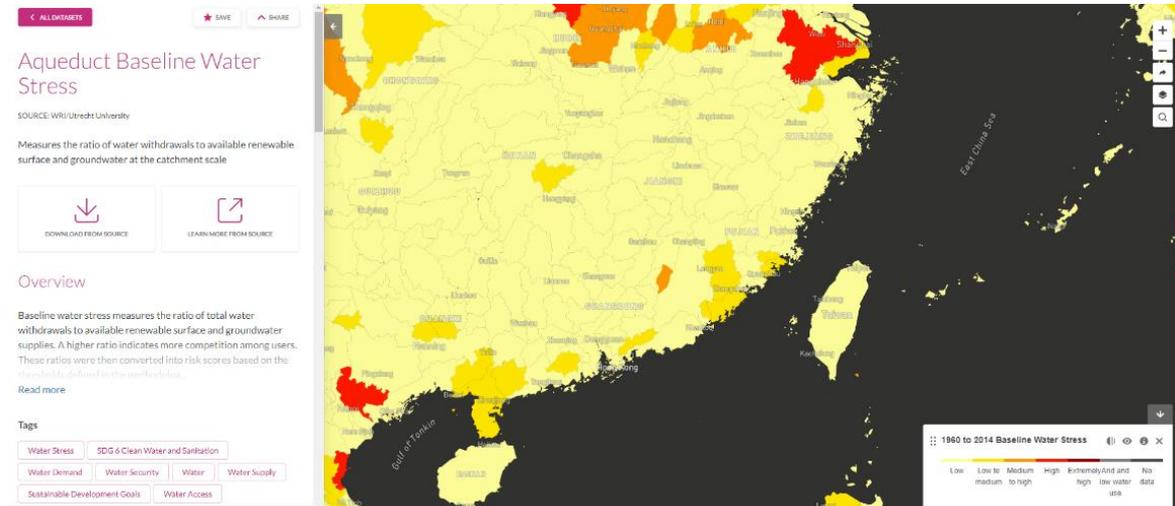
*Map S4 – South East Asia Water Stress by ResourceWatch [110],* CC BY 4.0
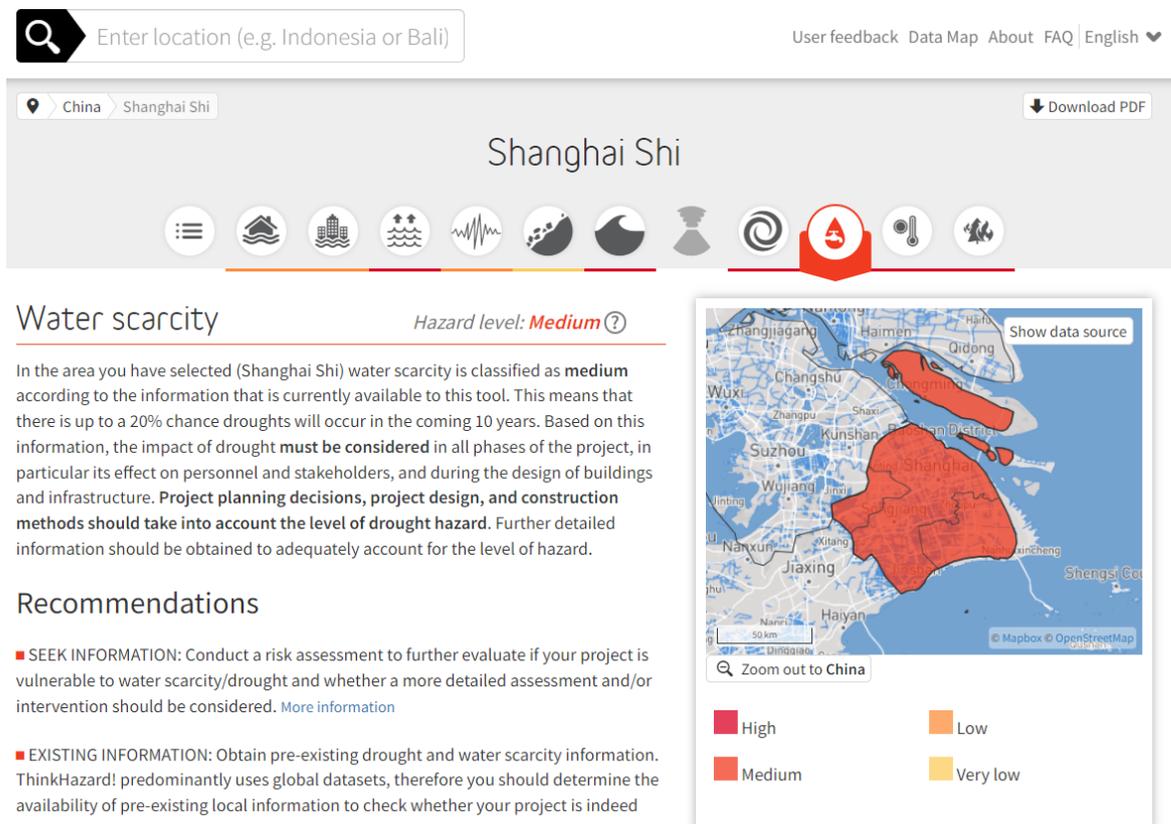
Map S5 – Shanghai Water Scarcity by ThinkHazard [249], GNU GPLv3

Flood Risk Interactive Maps

Map S6 [250], Map S7 [251], Map S8 [252], and Map S9 [253] below present by example the online interactive maps for the Riverine, Urban, and Coastal Flood Risk discussed in sub-section 4.3.5: Water Stress. In this example, Hong Kong has a flood risk at the highest rating out of four possible scores from three of the four maps.
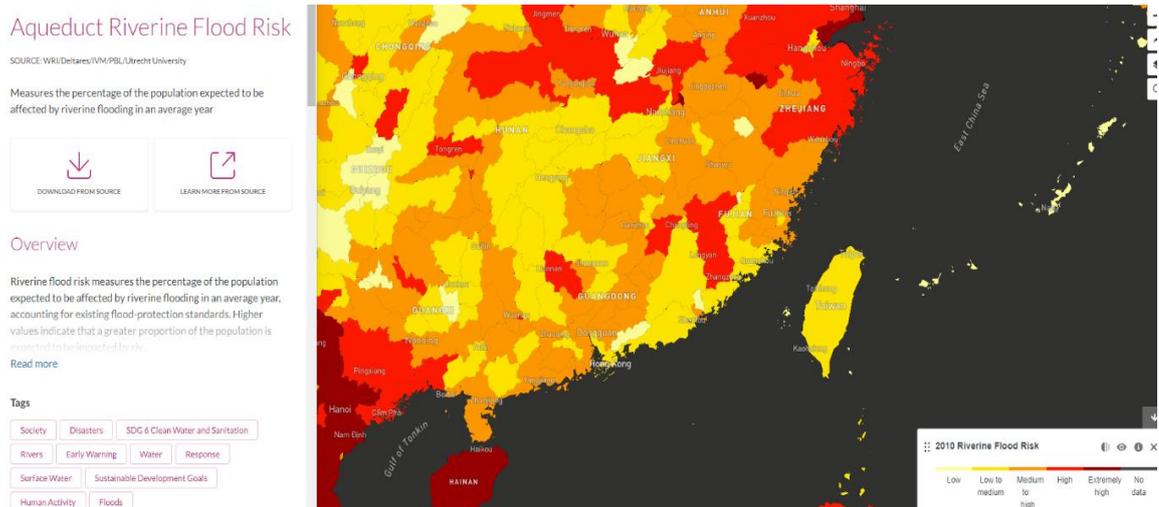
Map S6 – South East Asia Riverine Flood Risk by ResourceWatch [250], CC BY 4.0
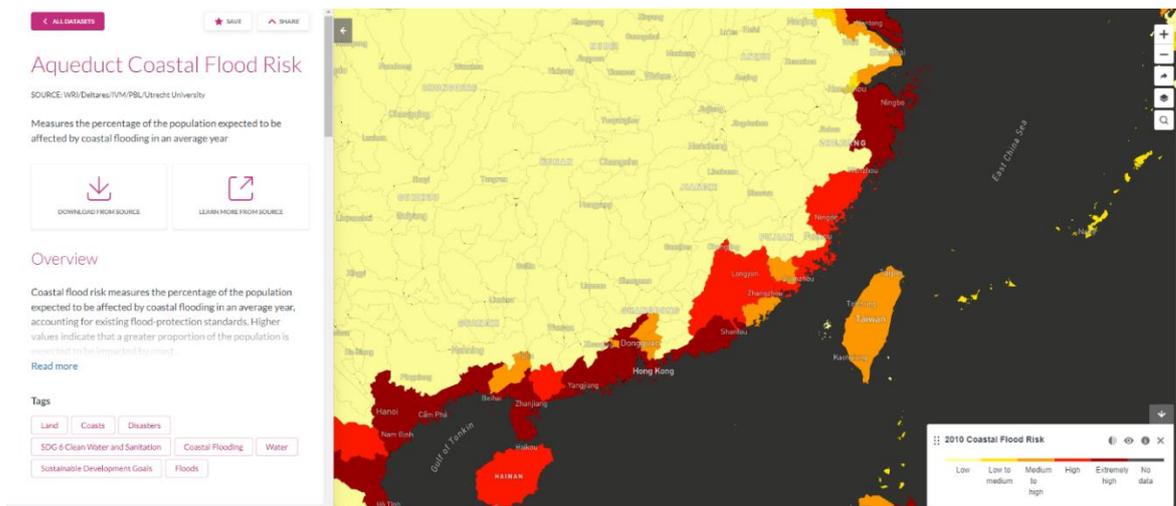
Map S7 – South East Asia Coastal Flood Risk by ResourceWatch [251], CC BY 4.0

Hong Kong, SAR   ⬇ Download PDF

Hong Kong, SAR

Urban flood

Hazard level: **High** ⑦

In the area you have selected (Hong Kong, SAR) urban flood hazard is classified as **high** based on modeled flood information currently available to this tool. This means that potentially damaging and life-threatening urban floods are expected to occur at least once in the next 10 years. **Project planning decisions, project design, and construction methods must take into account the level of urban flood hazard.** The following is a list of recommendations that could be followed in different phases of the project to help reduce the risk to your project. Please note that these recommendations are generic and not project-specific.

Climate change impacts: Medium confidence in an increase in heavy precipitation. The present hazard level may increase in the future due to the effects of climate change. It would be prudent to design projects in this area to be robust to river flood hazard in the long-term.

Recommendations

▪ EXISTING INFORMATION: Obtain pre-existing flood hazard information. The high-level information available in this tool may indicate the presence of flood hazard in your project area. However, because flood hazard can change dramatically over short

Show data source

■ High   ■ Low

■ Medium   ■ Very low
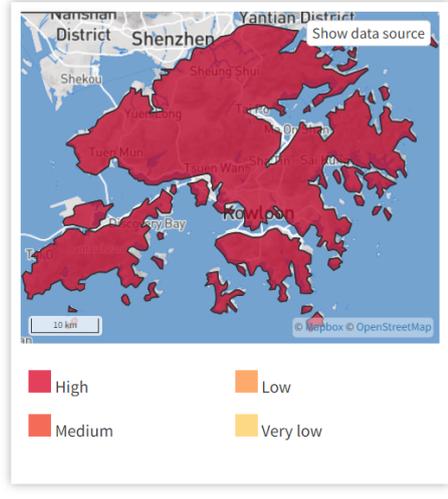
Map S8 – Hong Kong Urban Flood Risk by ThinkHazard [252], [GNU GPLv3](#)
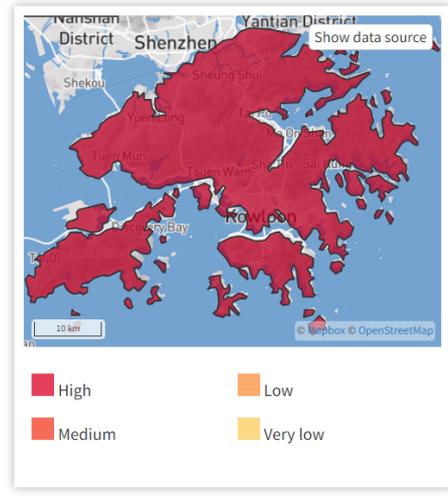
Coastal flood

Hazard level: **High** ⑦

In the area you have selected (Hong Kong, SAR) coastal flood hazard is classified as **high** according to the information that is currently available. This means that potentially-damaging waves are expected to flood the coast at least once in the next 10 years. Based on this information, the impact of coastal flood **must be** considered in different phases of the project for any activities located near the coast. **Project planning decisions, project design, and construction methods must take into account the level of coastal flood hazard.** Further detailed information should be obtained to adequately account for the level of hazard.

Climate change impact: According to the IPCC (2013), there is high confidence that extremes in sea level will increase with mean sea level rise yet there is low confidence in region-specific projections in storm surges. Projects in low-lying coastal areas such as deltas, or in island states should be designed to be robust to projected increases in global sea level.

Recommendations

▪ INTERACTING HAZARDS: Project planning, design, and construction practices should account for coastal flood and storm surge from cyclones and other weather events

Show data source

■ High   ■ Low

■ Medium   ■ Very low

Map S9 – Hong Kong Coastal Flood Risk by ThinkHazard [253], [GNU GPLv3](#)

Source Water Quality Interactive Maps

Map S10 [172], Map S11, and Map S12 [12] below present the online interactive maps for the Source Water Quality discussed in sub-section 4.3.4. The six selected Source Water Quality sub-index criteria are BOD, Total Nitrogen, Electrical Conductivity, Dissolved Oxygen, Nitrates, and Total Phosphorus. The latter three are taken from QualityUnknown as opposed to WWF, because, despite QualityUnknown being older data, at least it is provided, unlike with WWF for these three.
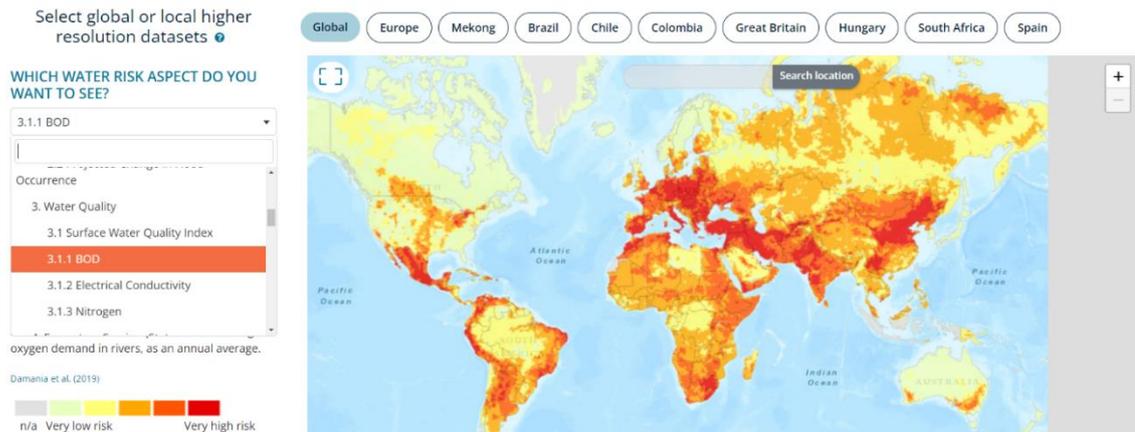
Map S10 – World BOD, Source - WWF Risk Filter Suite: riskfilter.org [172], CC BY-SA 4.0
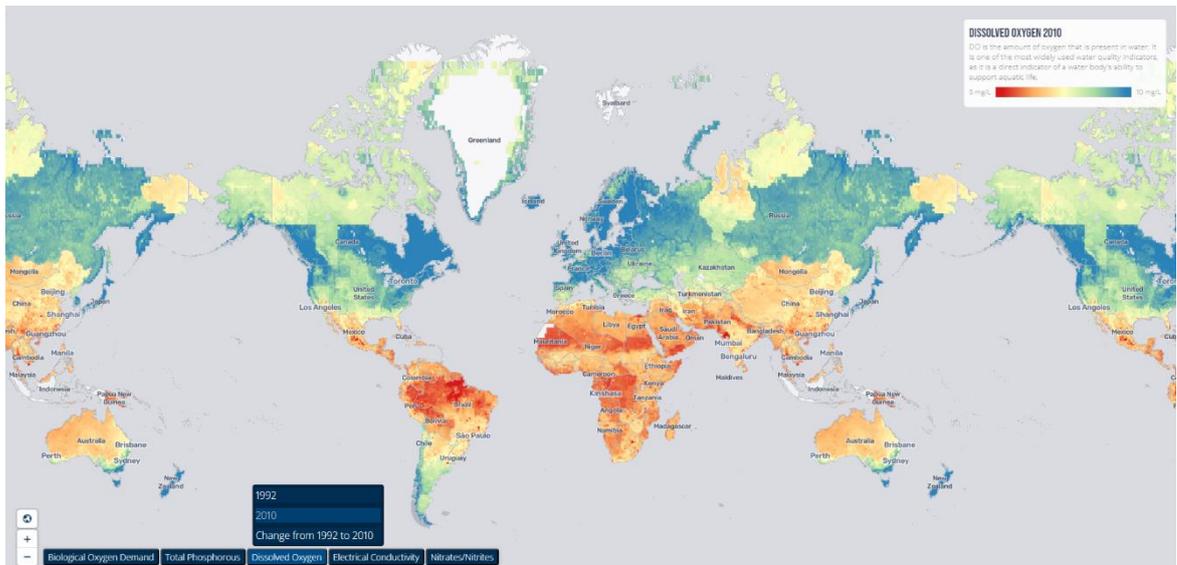
Map S11 – World Dissolved Oxygen by QualityUnknown [12], CC BY-SA 4.0
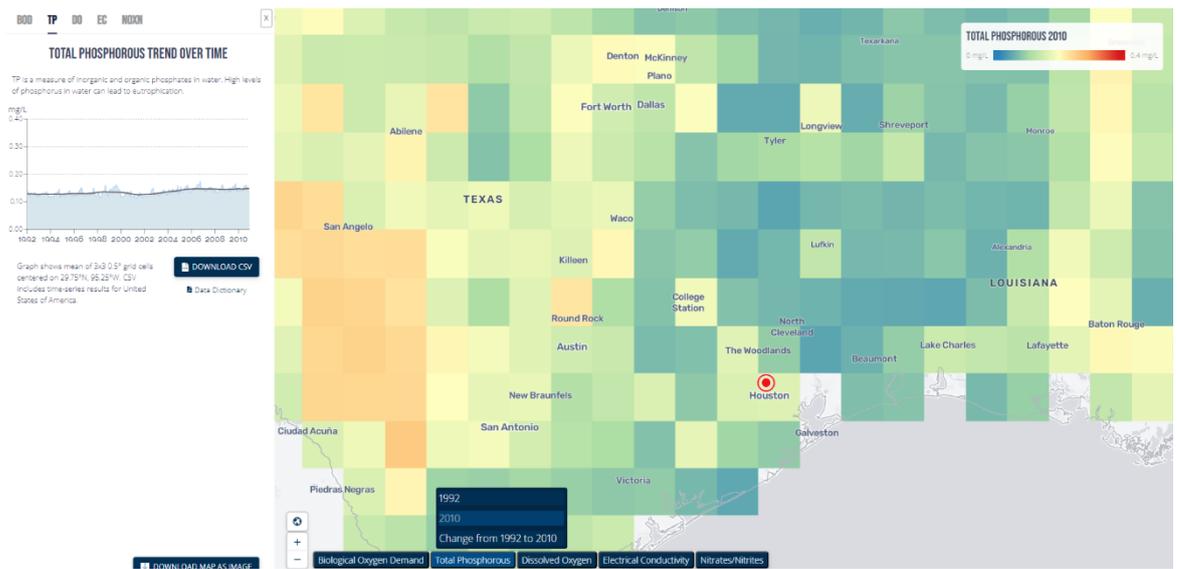
Map S12 – Houston Total Phosphorus by QualityUnknown [12], CC BY-SA 4.0