Using Multi-Criteria Decision Analysis to Investigate Drinking Water Regulatory

Stringency and Quality Outcomes in Canada

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Abstract

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The relationship between drinking water regulatory stringency, water quality and health outcomes are not well understood. Systemic gaps in water quality data, underreporting of waterborne outbreaks, treatment processes and variations in water quality between regions make it difficult to determine whether regulatory levels play a causal role or not in improving water quality outcomes. This is particularly interesting in a water rich country like Canada.

Canadian drinking water regulation is unique among developed nations in that it is nonbinding at the Federal level. Provinces and territories have autonomy in determining which contaminants (if any) to regulate, and to what level, giving rise to heterogeneous levels of water regulation. This diversity in regulation allows us to explore the relationship between water regulation, quality outcome and effects of both short term exposure to biological contaminants and long term exposures to chemical contaminants. This thesis serves as a first approximation of the relationships between drinking water standards, health and water quality outcomes. We use Data Envelopment Analysis (DEA), a multi-criteria decision analysis method to evaluate the efficiency of provinces and territories.

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Acronyms	Meaning
AB	Alberta
AHP	Analytic Hierarchy Process
ANN	Artificial Neural Network
BC	British Columbia
CCR	Charnes, Cooper & Rhodes
DEA	Data Envelopment Analysis
MACBETH	Measuring Attractiveness by Categorical
	Based Evaluation Technique
MB	Manitoba
MCDA	Multi-Criteria Decision Analysis
NB	New Brunswick
NL	Newfoundland and Labrador
NS	Nova Scotia
NWT	Northwest Territories
ON	Ontario
PEI	Prince Edward Island
QC	Quebec
SK	Saskatchewan
YT	Yukon

List of Acronyms

Chapter 1

Introduction

1.1 Background

Science and engineering can be applied to virtually all areas of life with the aim of improving the quality of life. This is particularly true of technology to improve drinking water quality.

A number of illnesses and diseases are caused by contaminated drinking water. The occurrence of drinking water related diseases occurs across the globe. The most widespread and preventable cases occur in developing countries while these illnesses are generally well managed in developed regions with notable exceptions.

The most common type of drinking water diseases caused by bacterial contamination are gastrointestinal disorders which could occur from fecal contamination of the water source. Other types of illnesses can be related to bacterial contamination. This type of infection can be noticeable within days or weeks, however, other types of drinking water related infections caused by chemical contaminants are not noticeable upon contamination. It can take years of continuous exposure before the illness is diagnosable, an example is cancer. There are significant methodological difficulties in determining the causal factors which lead to a specific instance of cancer; however, some estimates are made of attributable cancers.

1.2 Problem definition

Taking a close look at Canada, drinking water regulations vary across provinces and territories. Differences in drinking water regulatory regulations, source water quality and industries which contribute to pollution result in varied drinking water quality across the country. There are a number of research questions that need to be addressed. Three questions are stated here:

- 1. What factors affect drinking water quality?
- 2. How do provincial and territorial regulatory stringency affect drinking water quality?
- 3. Does drinking water testing reduce the occurrence of a disease outbreak?

We present a number of analyses to support these three research question. The aim of this thesis is to provide a multi-criteria decision analysis framework for drinking water regulatory stringency.

1.3 Thesis Outline

This thesis is organized as follows:

Chapter 2 is a review of academic and industrial practices related to drinking water quality, diseases and outbreaks in Canada; drinking water standards and ways in which multi-criteria decision analysis techniques have been applied to drinking water and its treatments.

Chapter 3 presents a multi-criteria analysis methodology used to provide answers to the defined problems. Chapter 4 enumerates data acquisition and how the data is been fed into model. Chapter 5 shows the data analysis and results. Chapter 6 briefly shows other

works carried out in the course of this thesis. Finally, Chapter 7 presents our conclusions, further discussions and future work.

Chapter 2

Literature Review

By nature, this research topic is broad as it spans both geographically across all provinces and territories in Canada, and by discipline since the problem combines issues of policy and regulation, biology, chemistry and environmental engineering as well as decision sector. While introducing the important issues associated with drinking water, we also discuss entrenched issues that make water quality improvements difficult.

2.1 Scope of the Literature review

Canada is famous for its abundance of water, and water in Canada is generally perceived to be of high quality. The relatively high quality of Canada's abundant natural resource coupled with a unique regulatory system makes drinking water regulation in Canada a particularly interesting issue.

Treatment of source water is required to render water suitable for drinking. This is as a result of and not limited to environmental activities, pollution, mining and other human activities which have made the water sources unsafe to drink. Additionally, climate change adversely modifies water quality parameter values (biological, micro pollutants and physio-chemical parameters) Delpla *et al* (2009).

Drinking water regulatory standards in Canada are unique in that they vary between provinces and territories. This is as a result of the autonomy given to the province and territories by the federal government to set their drinking water quality standard. The federal government in Canada made available drinking water regulatory guidelines to indicate the maximum acceptable concentrations (MAC) of contaminants found in drinking water (Health Canada, 2012). The provinces and territories are not mandated to use these guidelines; therefore they are sets of guidelines not regulations. While the variability in regulatory standards have been established in the literature (Hill, Furlong, Bakker, & Cohen, 2008) and (Boyd, 2006) that precise variability between provinces has not been quantified. Understanding the potential impact of regulatory stringency first requires a compilation of regulatory values and a comparison of those values.

Nova Scotia is one of the provinces that adopted the federal drinking water guidelines as legally binding (Snook, 2003) while others like Alberta, Manitoba, Ontario and Quebec adopted part of the federal drinking water guidelines by setting some drinking water regulatory standards that surpass the federal guidelines (Hill, Furlong, Bakker, & Cohen, 2006).

In this thesis, we gathered data and make comparisons on the level of regulatory stringency within provinces and territories

2.2 Disease outbreaks and drinking water

There have been a number of reported cases of disease outbreaks associated with drinking water in most of the provinces in Canada (S. E. Hrudey & Hrudey, 2007). The most commonly reported cases of outbreaks are as a result of biological contaminants with *Escherichia coli 0157:H7, Cryptosporidium* or other pathogens found in test samples. Hrudey *et al* (2003) and Charron *et al* (2004) pointed out that weather played a substantial role in the number of reported cases of water borne diseases in Canada.

Schuster *et al* (2001) did a study on infectious disease outbreaks associated with drinking water in Canada from 1974 to 2001 and was able to identify the contributing factors linked to these diseases. They defined an *outbreak* as an incident with more than two cases of illness but an accurate number of occurrences could not be ascertain due to variations in reporting, detection methods and diagnostic specificity and sensitivity. They observed that while outbreaks caused by biological contaminants were easily detected, chemical contaminants are not. This is essentially a truncation problem; we do not know whether (or to what extent) chemical contaminants are present. In addition, determining attributable cancer levels is fraught with difficulty.

Canada has had its own share of water problems which led to disease outbreaks caused by contaminants in drinking water. Though wide-spread underreporting is always an issue when evaluating waterborne illnesses (Moffatt & Struck, 2011); we will briefly mention some of the occurrences that were recorded. In 2005, eighty two (82) wells tested positive to E. coli bacteria in Yukon and boil water advisory was issued (Government of Yukon). In British Columbia, between 1980 and 2000, there have been some numbers of reports on several cases of waterborne disease outbreaks both laboratory confirmed and clinical cases in some communities and municipals. It was also noted that a large portion of these outbreak were caused by biological contamination. An example of one of these cases was that which occurred in Kelowna caused by *Cryptosporidium* with one hundred and seventy seven (177) lab cases, however there is still uncertainty about the original source of contamination (British Columbia Provincial Health Report, 2001). Alberta had some reported cases of outbreaks over a decade ago, an example is that which occurred in Edmonton in 1983 with 895 cases (S. E. Hrudey & Hrudey, 2007; King-Collier & Macdonald, 1983), also in Drumheller, Alberta, of the same year, there were confirmed cases of 2 deaths and an estimated number of 3000 cases (S. E. Hrudey & Hrudey, 2007; O Neil *et al.*, 1985). Though these outbreaks were long recorded, care has to be taken so that these incidents are not repeated. In May 2000, Ontario experienced a severe outbreak in the town of Walkerton where about 2,300 people were ill as a result of exposure to contaminated drinking water and about 7 deaths were recorded. It was then observed that the pathogens responsible for this contamination were primarily *Escherichia coli 0157:H7* and *Campylobacter jejuni* (S. Hrudey, Payment, Huck, Gillham, & Hrudey, 2003). Also in North Battleford, Saskatchewan, there were reported cases of waterborne outbreak caused by Cryptosporidiosis. This occurred in April 2001 with 1,907 estimated cases reported out of which 3% were hospitalized and 31% visited a physician; however no deaths were recorded (Stirling *et al.*, 2001).

2.3 Drinking water quality and standards

Not having a universal drinking water regulatory standard in Canada affords some jurisdictions the opportunity to have better drinking water quality than others. For example, drinking water systems in some First Nations communities are commonly reported to be poor (O'Connor, 2002; Mascarenhas, 2007). This could be as a result of some jurisdictions being financially buoyant than others.

To correctly associate drinking water regulation, drinking water quality and drinking water related illnesses; there is a need to identify how they influence one another. In the

United States, (Reynolds, Mena, & Gerba, 2008) noted that disease caused by drinking water are a result of technological failure or treatment failure. It was also revealed that out of the drinking water outbreaks that occurred in the United States from 1971 to 2002, eight percent (8%) were caused by viruses, fourteen percent (14%) by bacteria, nineteen percent (19%) by protozoa, twelve percent (12%) were chemical related and forty seven percent (47%) resulted in unknown acute gastrointestinal illnesses. While these unknown cases are most likely the result of biological contaminants, this cannot be demonstrated.

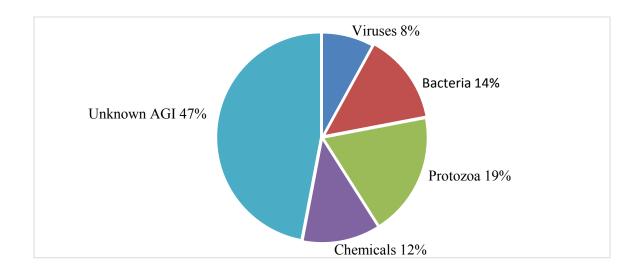


Figure 2.1 United States drinking water outbreaks 1971- 2002 caused by etiological agents (Blackburn et al. 2004; Reynolds et al 2008)

The United States Environmental Protection Agency (U.S. EPA) defines water contaminants as biological, chemical or radioactive elements or substances in water. The lower the number contaminants present below the recommended maximum acceptable concentrations, the better the water quality. Exposure to drinking water contaminants over a period of time (short term or long term exposure) can consequently result in a disease outbreak.

In Taiwan, high rates of liver cancer deaths were found in a population with elevated concentration of arsenic, a carcinogenic drinking water contaminant (A. H. Smith et al., 1992; Wu, Kuo, Hwang, & Chen, 1989). A number of short term effects are biologically related, an example is fecal contamination which could lead to a gastrointestinal disorder like diarrhea. This is a short term illness; the effect can be seen almost immediately after contamination. Chemical and radioactive contaminants can be categorized as having long term effect on humans as they require prolong exposure to these contaminants. As example of this type of illness could be cancer. The health effect of arsenic, a chemical contaminant, and other known carcinogens as enumerated by (Hogue, 2001; Smith & Steinmaus, 2009) is the risk of cancer.

A number of factors inhibit the availability of potable drinking water. Potable drinking water in the context means good quality drinking water. The water source first has to be free of contaminants or pollutants to help reduce the risk of infection, these sources could be surface water or groundwater.

In countries like Canada and the United States, there are set standards whereby the water quality is been assessed. This assessment involves the overall evaluation of the water makeup, that is, the biological, chemical and physical component. Apart from this assessment, there are monitoring methods in place to ensure that these standards are maintained. Water quality monitoring only has to do with collection of significant information. The World Health Organization (WHO) uses a guide that involves various sampling progammes to monitor water quality (Chapman, 1996). Though the Federal government has set guidelines for drinking water quality in Canada, it is not enforced at the provincial or municipal level (Boyd, 2006). Each province has its regulatory body

that works to ensure good quality drinking water; some meet or surpass the federal guidelines.

Since drinking water quality standard varies across the provinces and territories in Canada, we need to understand how these standards vary as well as illnesses caused by drinking water.

2.4 MCDA and water problem

Multi-criteria decision analysis (MCDA) takes into account all the criteria involved in making decision. In decision making, there are a number of factors to be considered and the resulting decision is based on which of the outcomes best fits the purpose or objective for which the decision is to be made. Multi-criteria decision analysis is a decision making tool used in solving problems characterized as a choice among alternatives. This tool has been used in several areas that require making complex decisions and the choice of the method used is based on the type of problem or situation. A number of steps or conditions are required to be able to successfully apply one of the available multi-criteria decision analysis methods. These steps are summarized as follows:

- The goal must be clearly stated.
- Preference based on decision maker opinion. This further means that in line with the goal, what are the important factors that must also be satisfied.
- What are the available options in achieving this goal?
- Evaluate the alternatives in line with the goal.
- Having chosen from the available alternatives, which outcome best meet the goal.

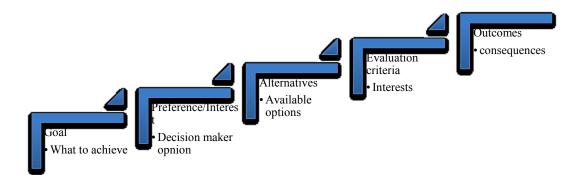


Figure 2.2 Steps involved in a Multi-Criteria Decision Analysis

Multi-criteria decision analysis (MCDA) has also been used to solve a number of water problems. One of its applications is in the selection of a drinking water treatment system (Bouchard, et al., 2010). In this case, three water treatment systems were identified as alternatives and based on the interests of stakeholders with respect to the goal to be achieved, the best alternative was chosen using ELECTRE II, a multi-criteria decision making analysis tool. Another application of multi-criteria decision analysis (MCDA) was to assess the vulnerability of drinking water utilities. The multi-criteria decision making analysis (MCDA) tool used was MACBETH; the approach was to consider different kinds of information simultaneously with the goal of ranking twenty-eight drinking water systems supplied by ground water in Quebec based on their vulnerabilities to microbiological contamination (Joerin, Cool, Rodriguez, Gignac, & Bouchard, 2010). While there are a number of multi-criteria decision making analysis techniques, in this thesis, we consider Analytical Hierarchical Process (AHP) and Data Envelopment Analysis (DEA) methods.

2.4.1 Analytical Hierarchy Process (AHP)

The analytical hierarchy process (AHP) was developed in the 1970s by Thomas L. Saaty (1980) as a mathematical based technique for analyzing and organizing complex decisions. It uses a pairwise comparison approach on the criteria or alternatives. The structure of an AHP hierarchy is to consider the decision problem as a goal to be achieved that have several alternatives to attain this goal. But before these goals can be reached, there are criteria these alternatives have to fulfill. These criteria can divided into sub-criteria depending on the complexity of the decision problem, this hierarchy is described in Figure 2.3.

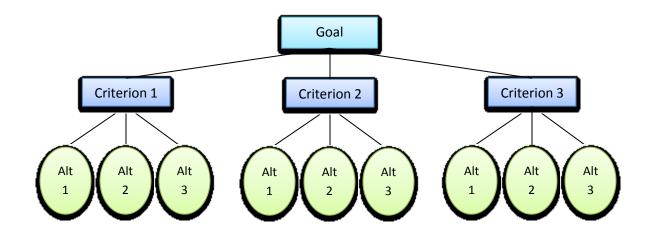


Figure 2.3 An AHP hierarchy model

A preference scale, ranging from 1 to 9, is used for pair-wise comparison and to form a comparison matrix. The AHP ends by computing the eigenvector.

There are limitations in AHP that makes it not a suitable MCDA in solving drinking water problems. In Saaty's scale of preference, Dodd and Donegan (1995) criticized the absence of zero, while another limitation is in the pairwise comparison where the

reciprocal cannot always be used, that is not reciprocally symmetric, in cases like in currencies exchanges (Hovanov, 2008), which could be the case in water regulation.

Intensity of Importance	Definition
9	Extreme importance
7	Very Strong
5	Strong importance
3	Moderate Strong
1	Equal importance
2,4,6,8	For compromise between the above values

Table 2.1 Scale of relative importance or preference¹

2.4.2. Data Envelopment Analysis

Data envelopment analysis (DEA) was developed by (Charnes, Cooper, & Rhodes, 1978) to measure the efficiencies of decision making units and was described as a mathematical programming model. Decision making units are groups of individual or team who participate in a decision process. DEA has been used to give more insight into entities that were previously evaluated by other methods (Cooper & Seiford, 2000).

Definition 2.1 (Efficiency): A 100% (full) efficiency is said to be achieved by any decision making unit (DMU) if and only if no other input or output can be improved without worsening one or more of the other inputs or outputs 2 .

¹ Wind, Y., & Saaty, T. L. (1980). *Marketing applications of the analytic hierarchy process*. *Management Science*, *26*(7), 641-658.

² Cooper, W. W., Seiford, L. M., & Zhu, J. (2011). *Data envelopment analysis: History, models, and interpretations* Springer.

2.4.2.1 CCR Model

A number of models have been developed and used in data envelopment analysis, however the basic model will be discussed.

The CCR (Charnes, Cooper, Rhodes) model

Assuming there are n DMUs to be evaluated and each DMU consumes m different inputs to give s different outputs. This can be expressed as:

 DMU_i consumes x_{ij} of input *i* to produce y_{rj} of output *r*

We assume $x_{ij \ge 0}$ and $y_{rj \ge 0}$; also that each *DMU* has at least one positive input and output. The concept of relative efficiency as introduced by Charnes, Cooper and Rhodes is the ratio of outputs to inputs. This reduced the multi-output/multi-input state of each DMU to a single 'virtual' output to 'virtual' input ratio which gives a measure of efficiency for each DMU referred to as the objective function (mathematically) of the DMU being evaluated.

$$\max h_o(u, v) = \sum_r u_r y_{ro} / \sum_i v_i x_{io}$$

In this thesis we use DEA to observe how regulatory stringency affects drinking water quality. We attempt to describe the relationship between disease outbreaks related to drinking water and the available drinking water regulatory standard using, data Envelopment Analysis (DEA). Data envelopment analysis has been used in a number of performance and efficiency assessment studies. (Ntantos & Karpouzos; Yılmaz & Yurdusev, 2011) used data envelopment analysis to evaluate the technical efficiencies of

irrigation systems. The idea is that with known inputs such as irrigation area and volume of water supplied and given output(s), data envelopment analysis (DEA) can, with its linear programming, evaluate the technical efficiency of irrigation systems by defining the production function and efficiency frontier of the decision making units (DMUs). (Farrell, 1957) introduced this concept; in this case, the irrigation systems are the decision making units (DMUs).

Data envelopment analysis (DEA) has also been used in the regulatory context. (Thanassoulis, 2000) enumerated how DEA was used to estimate potential cost saving by water companies in England and Wales. Identifying the input and output parameters of a decision making unit can be difficult and is one of the most important areas of data envelopment analysis. Having the wrong selection of input and output directly affects the performance evaluation of DMUs; some of the ways these variables are selected include expert knowledge, known theory or accepted practice (Morita & Avkiran, 2009).

2.5 Artificial Neural Network and drinking water decision quality evaluation

Another area we looked into is using artificial neural network (ANN) to predict the number of illnesses caused by drinking water. Artificial neural network (ANN) consists of multi-connected elements called neurons. These neurons are arranged in layers and information is transfers from one layer to another in serial operations (Haykin, 1994). In simple terms, ANN consist of three distinct layers; input layer, hidden layer(s) and output layer where each functions respectively as the area where data is loaded to the neural network, another layer where the input data is processed then passed on to the third layer

which produces the result (Haykin, 1994). ANN works by generating output based on applied weight(s) and a transfer function is used which determines the "input-output" behavior. As ANN is modeled after the human brain, it also performs learning just as we learn from experience. The learning capability of ANN is achieved through iteration and this allows the weights to be adjusted accordingly.

Artificial neural network has been applied in quite a number of water related studies. (Diamantopoulou, Papamichail, & Antonopoulos, 2005) used ANN to predict water quality parameters in Greece. ANN was used to predict monthly values of three parameters that at the Sidirokastro station of Strymon River, Greece. Monthly data for some of the water quality parameters from 1980-1990 and the discharge from the station were used for the study; for the training of the network, 90% of the data was used with an hyperbolic-tangent transfer function while the remaining 10% served as testing data. This data set was randomly selected for training and testing. The result of the analysis showed that artificial neural networks can predict successfully water quality and also helps with filling missing data in the input data. Another important area where artificial neural network has been used is in drinking water quality treatment (Baxter et al., 2001). This was applied in two water treatment plants in Edmonton, Alberta. It provided the treatment plant operators feasible ways for determining optimal result.

For the purpose of this thesis, in making decisions, we will dwell more on data envelopment analysis which can be used to make meaningful decisions while artificial neural networks can be used for prediction. These tools can then be used to observe the relation that exists between drinking water guidelines, water quality and associated illnesses as we take Canada as a case study.

Chapter 3

Methodology

Amongst various multi-criteria decision analysis methods, in this thesis, we have decided to explore the use of data envelopment analysis (DEA). However, because of the type of data gathered and the need to make graphical representation of the information gathered, other methods were used to enhance the decision making process. Data gathering for analysis has a peculiar nature as it took a very huge portion of the research period. This is owing to the fact that a huge percentage of the required data were not readily available on the provinces and territories official websites. Emails and phone calls had to be made to authorities in these province and territories. Though some responded quite fast, others took a number of reminder mails, so as to get the needed data. The reason we had to go through all these was to make sure that the results obtained from the analysis is reasonable and realistic.

3.1 MCDA method

We used an input oriented data envelopment analysis (DEA), a multi-criteria decision analysis method. The reason for using an input oriented DEA is because of what we intend to derive from the analysis. Our aim is to investigate if same or improved outputs can be achieved using fewer resources.

According to the workings of DEA we need to define input and output variables, choose the decision making units, assign weights and using the linear programming capability of DEA evaluate the objective functions and efficiencies. This system takes into account each decision making unit and evaluates it based on the given inputs and applied weights. Depending of the evaluated efficiency, DEA creates a virtual decision making unit that will produce the same output using fewer resources than the decision making unit being evaluated.

3.2 Input and output variables

In choosing the right input and output for this model, it is imperative to consider what the results should be. Meaning that, the result of the analysis should give answers to questions raised in the first chapter.

Inputs variables should consist of resources used to perform the task of providing quality drinking water. These should include cost, drinking water regulations and monitoring. The output variables should what we intend to achieve from the analysis, that is drinking water quality. But this alone cannot be used as output as other factors contribute to the drinking water quality. The most common factor across the provinces and territories is the boil water advisory. This is based on the data we gathered showing that monitoring and testing of biological contaminants is common among observed provinces and territories.

Though the number of boil water advisories issued varies and is affected by factors like population, it is also seen as an undesirable output, that is, assuming the lower the number of boil water advisories issued, the less the contamination and the better the water quality. All these factors were taken into consideration and we used to normalize this data thereby making it appear desirable for use in DEA model analysis.

Chapter 4

Data

4.1 Data Acquisition

In this chapter, we briefly discussed how we obtained data. Data acquisition was the most time consuming part of this thesis and is clearly the most important. We began by searching for information made available by individual province and territories as this data varied by territory and province. In some cases, the available data had other drawbacks including the rate at which changes and updates where been made while in others. A happy finding from our review of provincial regulation is that provinces and territories are actively trying to improve their drinking water quality. Using the report obtain from (Boyd, 2006) as a starting point, we reviewed and updated existing data and augmented it with new normality. For example, between 2006 and 2011, Prince Edward Island developed a drinking water treatment program having been the only jurisdiction without a mandatory drinking water treatment (Christensen, 2011).

The problem of under-reporting also created a huge challenge as some of the provinces and territories provide limited information about the data associated with drinking water, some provinces and territories give an overview of what is expected of them according to the federal drinking water guidelines. An alternative way out of this problem was to observe drinking water related data at the municipalities, which was quite productive. We contacted drinking water authorities in all other territories except for Nunavut due unavailability of drinking water related data. While responses varied, we were able to develop the following insight. This approach gave us an understanding that though some provinces do not mention how often they test and treat their drinking water, they still do all that was to be done to provide better quality drinking water. An example of this case is Yukon. From data obtained, we noticed that regular drinking water testing is been carried out both on their raw (water source) and treated water.

4.2 Data Normalization

After gathering data across twelve (12) provinces and territories, it was observed that there were variations in testing, monitoring and drinking water regulations. If these variations were not guided against, it will greatly affect the result of the analysis. Therefore we used normalization to ensure consistency of data.

Based on the responses we received and what we obtained from all sources, we then created a scale to normalize the available datasets. We began the normalization process by first putting together all the drinking water parameters in the most recent federal drinking water guidelines (Health Canada, 2012), which was used as a reference for the provincial and territorial drinking water regulated parameters. The data was categorized into:

1. Provinces and territories with drinking water regulations that are less than, meet or surpass the federal guidelines: Under this category, we assigned the following:

Nominal representation	Contaminant's MAC w.r.t. federal guidelines
0	No MAC set for contaminant
1	MAC < federal guidelines
2	MAC = federal guidelines
3	MAC > federal guidelines

Table 4.1 Maximum acceptable concentration with respect to federal guidelines

2. Contaminants being monitored by the provinces and territories: These are guidelines that are in the provincial or municipal set drinking water standard and are also being monitored or checked. We assign the following for this category:

Nominal representation	Contaminant monitoring
0	No monitoring
1	Monitoring

Table 4.2 Contaminant monitoring and nominal representation

 Contaminants tested for with respect to provincial or territorial detection limit: Similar to the monitored category, we also assign the following:

Nominal representation	Test result w.r.t. detection limit
0	> detection limit
1	< detection limit

 Table 4.3 Contaminant tested for with respect to detection limit

 The test result is compared with the provincial or territorial's detection limit.

4. Boil water advisory with respect to population: This is another data type that needs to be normalized. It was observed that some provinces had more boil water advisory issues that others. We assume that population is an important factor to be considered, so we normalize the number of boil water advisories with the provincial or territorial population.

5. Total Operational and maintenance cost: This is the estimated total amount of money each province or territory spend in maintaining their drinking water plants. The costs include labour, material, energy and other costs in millions of dollars (Statistics Canada, 2011).

4.3 Stringency and Biological Contamination

Having considered the necessary inputs and outputs, we need to be able to select the appropriate ones for individual analysis. The first part of this analysis is to observe how regulatory stringency affects biological contamination. The question to be considered

here is does having more stringent drinking water regulation makes the province or territory to have less water borne outbreaks?

To address this issue, we will use data envelopment analysis (DEA) in the decision making process.

First of all, we need to identify the inputs, outputs and decision making units (DMUs). Inputs in this case are the resources that are being consumed to produce or give a result. The following assumed inputs are considered:

- *Drinking water monitoring*: This input is derived for each of the provinces and territories by observing the drinking water parameters that were monitored and adding them up for each of the provinces and territories.
- *Drinking water regulation*: This is derived by comparing each province or territory's drinking water regulation with the federal drinking water guidelines using the nominal scale of three to one (3 to 1) as mentioned earlier, then total sum of individual province and territory is used.
- Total operational and maintenance cost: This is one input that drives other inputs.
 It provides an avenue for other inputs to be carried out to produce a desirable output.

The assumed outputs are results or consequence of using a particular level or amount of inputs. The following are the considered outputs:

Number of boil water advisories: It was observed that boil water advisories were commonly issued as a result of a biological contamination (Eggertson, 2008).
 This parameter is not evenly distributed across provinces as some provinces or

territories had more boil water advisories than others with the assumption that population has a high influence on this. To this end, we will normalize the number of boil water advisories issued with the population of the province or territory.

Drinking water quality score: This is a measure of performance of the provinces and territories based on their drinking water quality and water programme as complied by (Christensen, 2011). The drinking water score compiled in 2011 was an update of that which was evaluated in 2006, which showed that more provinces have drinking water quality treatments that are now legally binding (Christensen & Parfitt, 2006). The provinces and territories serves as the decision making units (DMUs)

Chapter 5

Analysis

We verified results using off the shelf DEA packages such as Microsoft Excel Solver add-in. The main reason for choosing this approach is to demystify the thought of DEA as a black box. We employed the linear programming capability of MS excel solver to reveal the internal workings of data envelopment analysis. The results obtained from this analysis are later compared with an industry standard DEA application developed by Joe Zhu.

We need to specify the three major parameters of a DEA model:

- 1. DMUs
- 2. Inputs
- 3. Outputs

We define decision making units (DMUs) as the provinces and territories. The inputs are resources consumed; the outputs are therefore the benefits. In a case were the outputs are not considered benefits, for example, issuance of boil water advisory, an inverse of it is used (1/undesirable effect).

The inputs used are:

- 1. The normalized provincial or territorial drinking water guidelines
- 2. Number of drinking water contaminants being monitored
- 3. Total operational and maintenance cost

The outputs considered are:

- 1. Number of boil water advisories with respect to population
- 2. Numeric value of the provincial / territorial drinking water score

Provinces and Territories DMUs	Total op & maintenance cost per population (Input 1)	Drinking water guidelines (Input 2)	Drinking water monitoring <i>(input 3)</i>	Normalized boil water advisories (10 ²) (Output 1)	Drinking water quality score (Output 2)
Alberta	32.53	142	41	0.34	61
British Columbia	16.69	52	33	11.58	68
Manitoba	32.28	145	30	4.71	78
New Brunswick	17.87	69	32	0.26	78
Newfoundland and Labrador	32.56	48	34	44.45	78
Northwest Territories	24.35	52	29	2.26	65
Nova Scotia	158.37	187	33	7.06	82
Ontario	23.62	207	73	5.08	87
Prince Edward Island	21.28	23	12	0.01	71
Quebec	25.87	170	59	0.76	71
Saskatchewan	49.35	114	21	11.91	71
Yukon	59.32	61	30	0.03	57

Table 5.1 Inputs and Outputs of the DEA Model

** In Table 5.1, Nunavut, was not in the list because the territory's data were not available when the analysis was carried out. We tried to make contact like we did with other jurisdictions but came to no avail.

The objective " θ " is to find out if higher stringency implies better drinking water quality.

5.1 DEA Model

We use an input oriented data envelopment analysis model. This is to be able to minimize the number of inputs used to "produce" the outputs. This is mathematically represented as follows:

Minimize θ_o

Subject to:

$$\sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{io} \quad i = 1, \dots, m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro} \quad r = 1, \dots, s$$
$$\lambda_j \ge 0 \qquad \qquad j = 1, \dots, n.$$

5.2 DEA Model Using Excel Solver and Visual Basic Program

We implemented an input oriented CCR model with emphasis on reduction of inputs to improve efficiency using the linear programming capability of Microsoft Excel Solver add-in and used visual basic program to automate the process. We used an input oriented model because we assumed that decision makers have more control over the inputs than the outputs.

No. of boil water Advisories	Drinking water Score		Total Op and maintenance cost	Drinking Water Regulation	Drinking Water Monitoring
with respect to population (10^2)	(Output 2)		wrt to population	(Input 2)	(Input 3)
0.34	61		32.53	142	41
11.58	68		16.69	52	33
4.71	78		32.28	145	30
0.26	78		17.87	69	32
44.45	78		32.56	48	34
7.06	82		24.35	187	33
2.26	65		158.37	52	29
5.08	87		23.62	207	73
0.01	71		21.28	23	12
0.76	71		25.87	170	59
11.91	71		49.35	114	21
0.03	57		59.32	61	30
					DMU under evaluation
		Efficiency		Unit under	2
	Constraints	Reference Set		Evaluation	
	Total Op & Maintenance cost	16.69	<	16.69	
	Drinking water regulation	52.00	≤	52.00	
	Drinking water monitoring	33.00	≤	33.00	
	BWA per population	11.58	2	11.58	
	Drinking water score	68.00	2	68.00	
				RUN DEA	
				NON DEA	

Figure 5.1 DEA spreadsheet Model

The figure above is a representation of the DEA model. The cells F3-F14 and G3-G14 represents the inputs, cells B3-B14 and C3-C14 represents the outputs, cells A3-A14 are the decision making units (DMUs) and cells I3 – I14 represents λ_j , which represent the decision variables with *j* have values from 1 to 12 representing the number of decision making units. Nunavut, one of the territories in Canada was not used in the calculation due to lack of data availability, making the total number if DMUs equal to 12. Cell I20 represents the efficiency score θ , also called the objective function, while cell G19 is to identify the DMU being evaluated.

Our objective is to obtain values for λ_j and efficiency score θ . Also in the spreadsheet model in Figure 5.1, we have three columns, *constraints*, *efficiency reference set* and *unit under evaluation*. The constraints are the input and output variables, the efficiency reference set is calculated as the weighted sums of all inputs and outputs variables. This

part of the model is for benchmarking purpose. This is one of the advantages of DEA. Apart from identifying efficient decision making units, it also shows the improvements needed to make inefficient DMUs more efficient. The following cells in the Figure 5.1 representing the *efficiency reference set* were calculated as follows:

D21 = SUMPRODUCT (E3:E14,\$I\$3:\$I\$14) D22 = SUMPRODUCT (F3:F14,\$I\$3:\$I\$14) D23 = SUMPRODUCT (G3:G14,\$I\$3:\$I\$14) D24 = SUMPRODUCT (B3:B14,\$I\$3:\$I\$14) D25 = SUMPRODUCT (C3:C14,\$I\$3:\$I\$14)

Using the value of cell D21 as an example the DMU 9 under evaluation, we have:

$$D21 = (122.9)(0) + (76.4)(0) + (40.4)(0) + (13.5)(0) + (16.7)(1) + (23.1)(0) + (7)(0) + (315)(0) + (3.1)(1) + (206.4)(0) + (52.2)(0) + (2.1)(1)$$

D21 = 5.2

As for the *unit under evaluation* column, the INDEX function was used as follows:

F21 = \$I\$20*INDEX (E3:G14,G19,1) F22 = \$I\$20*INDEX (E3:G14,G19,2) F23 = \$I\$20*INDEX (E3:G14,G19,3) F24 = INDEX (B3:C14,G19,1) F25 = INDEX (B3:C14,G19,2) The INDEX function used here basically places the actual values of the inputs and outputs of the DMU being evaluated. As seen in Table 5.2, the ninth DMU is under evaluation, therefore, the INDEX function returns the input and output values of the ninth DMU.

5.3 DEA model result interpretation

The DEA model shows the basic workings of DEA as it tries to make every decision making unit efficient. When a decision making unit is said to be inefficient, DEA creates a virtual DMU that utilizes equal or fewer inputs to produce better output. From the model, we observed that three (3) out of the observed twelve (12) provinces and territories were considered efficient with a score of 1 while others scored less than 1. The efficient DMUs are: Newfoundland and Labrador, Prince Edward Island and Yukon.

5.3.1 Inefficiency and benchmarking

Alberta: The first DMU to be analyzed is Alberta with an efficiency score of 26%. This means that based on the data, Alberta spends about \$123 million on operating and maintaining drinking water plants, sets drinking water standards for 142 contaminants and strictly monitors 41 contaminants; at the end the drinking water quality score is 61%. The DEA model suggested that Alberta can still achieve the same water quality score without using as much inputs.

DMUs	Efficiency (Input-Oriented CCR)
Alberta	0.480
British Columbia	1.000
Manitoba	0.692
New Brunswick	1.000
Nova Scotia	0.888
Newfoundland and Labrador	1.000
Northwest Territories	0.424
Ontario	0.864
Prince Edward Island	1.000
Quebec	0.631
Saskatchewan	0.837
Yukon	0.321

Table 5.2 Input oriented CCR model efficiency result

Table 5.2 shows that with Alberta's efficiency of about 0.480 (48%), a virtual DMU using 48% of Alberta's input can produce output greater or equal to Alberta's output. The input slack shows that of all the inputs, all are binding, meaning used to produce the outputs except the input, drinking water regulation with a slack value of 26.97. This 'slack value' represents the amount of an input a virtual decision making unit (DMU) will not use to produce its output.

DMUs	AB	BC	MB	NB	NL	NS	NWT	ON	PEI	QC	SK	YT
Weights λ	0	0.019	0	0.475	0	0	0	0	0.319	0	0	0

Table 5.3	Alberta ⁷	s	efficiency	reference	set
			5		

The reference DMUs for improvement are *British Columbia, New Brunswick and Prince Edward Island*. Alberta can achieve efficiency by using about 1.9% of British Columbia's inputs, 47.5% of New Brunswick inputs and 31.9% Prince Edward Island's inputs.

	Efficiency		Unit under
Constraints	Reference Set		Evaluation
Total Op & Maintenance cost	15.60	5	15.60
Drinking water regulation	41.11	5	68.08
Drinking water monitoring	19.66	5	19.66
BWA per population	0.34	2	0.34
Drinking water score	61.00	2	61.00

Constraints

Cell	Name	Cell Value	Formula	Status	Slack
\$D\$21	Total Op & Maintenance cost Reference Set	15.60	\$D\$21<=\$F\$21	Binding	0
\$D\$22	Drinking water regulation Reference Set	41.11	\$D\$22<=\$F\$22	Not Binding	26.96948357
\$D\$23	Drinking water monitoring Reference Set	19.66	\$D\$23<=\$F\$23	Binding	0
\$D\$24	BWA per population Reference Set	0.34	\$D\$24>=\$F\$24	Binding	0.00
\$D\$25	Drinking water score Reference Set	61.00	\$D\$25>=\$F\$25	Binding	0.00

Figure 5.2 Alberta's efficiency data

British Columbia: British Columbia (BC) has an efficiency score 100%, which means no other virtual decision making unit can utilize the same number of inputs con produce an output greater than or equal to that which BC already produces. British Columbia is therefore said to be efficient. Figure 5.3 shows that there are no slacks in inputs, this confirms BC's efficiency.

	Efficiency		Unit under
Constraints	Reference Set		Evaluation
Total Op & Maintenance cost	16.69	5	16.69
Drinking water regulation	52.00	≤	52.00
Drinking water monitoring	33.00	≤	33.00
BWA per population	11.58	2	11.58
Drinking water score	68.00	2	68.00

Constraints

Cell	Name	Cell Value	Formula	Status	Slack
\$D\$21	Total Op & Maintenance cost Reference Set	16.69	\$D\$21<=\$F\$21	Binding	0
\$D\$22	Drinking water regulation Reference Set	52.00	\$D\$22<=\$F\$22	Binding	0
\$D\$23	Drinking water monitoring Reference Set	33.00	\$D\$23<=\$F\$23	Binding	0
\$D\$24	BWA per population Reference Set	11.58	\$D\$24>=\$F\$24	Binding	0.00
\$D\$25	Drinking water score Reference Set	68.00	\$D\$25>=\$F\$25	Binding	0.00

Figure 5.3 British Columbia's efficiency data

Manitoba: having an efficiency of about 70%, Manitoba is considered inefficient. Though with a water quality score of 78%, this analysis implies that based on the inputs used in this model, Manitoba can still have this same water quality score without having that much number of contaminants been regulated. A virtual DMU utilizing 70% of Manitoba's input can produce the same output.

Constraints

Cell	Name	Cell Value	Formula	Status	Slack
\$D\$21	Total Op & Maintenance cost Reference Set	22.32	\$D\$21<=\$F\$21	Binding	0
\$D\$22	Drinking water regulation Reference Set	35.69	\$D\$22<=\$F\$22	Not Binding	64.59176067
\$D\$23	Drinking water monitoring Reference Set	20.75	\$D\$23<=\$F\$23	Binding	0
\$D\$24	BWA per population Reference Set	4.71	\$D\$24>=\$F\$24	Binding	0.00
\$D\$25	Drinking water score Reference Set	78.00	\$D\$25>=\$F\$25	Binding	0.00

	Efficiency		Unit under
Constraints	Reference Set		Evaluation
Total Op & Maintenance cost	22.32	5	22.32
Drinking water regulation	35.69	≤	100.28
Drinking water monitoring	20.75	≤	20.75
BWA per population	4.71	≥	4.71
Drinking water score	78.00	2	78.00

Figure 5.4 Manitoba's efficiency data

Figure 5.4 shows a slack value of 64.59 meaning that this amount of its regulation was not used to produce the output while other inputs are used up in the model.

Manitoba's efficiency can be improved by using 33.3% of British Columbia's (BC) inputs, 1.91% of New Brunswick's (NB) inputs and 75.8% of Prince Edward Island's (PEI) inputs.

DMUs	AB	BC	MB	NB	NL	NS	NWT	ON	PEI	QC	SK	ΥT
Weights λ	0	0.333	0	0.019	0	0	0	0	0.758	0	0	0

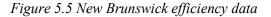
Table 5.4 Manitoba's efficiency reference set

New Brunswick: New Brunswick has an efficiency of about 100% which is considered efficient. New Brunswick also serves as a reference decision making unit improving other inefficient ones. The model shows that with a drinking water score of 78%, NB utilises all its input to attain this water quality score with a slack value of zero meaning that no virtual decision making can produce the same outputs using the same number of inputs.

Constraints

Cell	Name	Cell Value	Formula	Status	Slack
\$D\$21	Total Op & Maintenance cost Reference Set	17.87	\$D\$21<=\$F\$21	Binding	0
\$D\$22	Drinking water regulation Reference Set	69.00	\$D\$22<=\$F\$22	Binding	0
\$D\$23	Drinking water monitoring Reference Set	32.00	\$D\$23<=\$F\$23	Binding	0
\$D\$24	BWA per population Reference Set	0.26	\$D\$24>=\$F\$24	Binding	0.00
\$D\$25	Drinking water score Reference Set	78.00	\$D\$25>=\$F\$25	Binding	0.00

	Efficiency		Unit under
Constraints	Reference Set		Evaluation
Total Op & Maintenance cost	17.87	5	17.87
Drinking water regulation	69.00	≤	69.00
Drinking water monitoring	32.00	≤	32.00
BWA per population	0.26	2	0.26
Drinking water score	78.00	2	78.00



Newfoundland and Labrador: With an efficiency score of 100%, Newfoundland and Labrador (NL) are considered to be efficient with input slack value of zero. This means that there is no virtual DMU can that produce the same outputs as Newfoundland and Labrador using the same number of inputs.

Constrair	nts				
Cell	Name	Cell Value	Formula	Status	Slack
\$D\$21	Total Op & Maintenance cost Reference Set	32.56	\$D\$21<=\$F\$21	Binding	0
\$D\$22	Drinking water regulation Reference Set	48.00	\$D\$22<=\$F\$22	Binding	0
\$D\$23	Drinking water monitoring Reference Set	34.00	\$D\$23<=\$F\$23	Binding	0
\$D\$24	BWA per population Reference Set	44.45	\$D\$24>=\$F\$24	Binding	0.00
\$D\$25	Drinking water score Reference Set	78.00	\$D\$25>=\$F\$25	Binding	0.00

	Efficiency		Unit under
Constraints	Reference Set		Evaluation
Total Op & Maintenance cost	32.56	5	32.56
Drinking water regulation	48.00	<u> </u>	48.00
Drinking water monitoring	34.00	≤	34.00
BWA per population	44.45	2	44.45
Drinking water score	78.00	2	78.00

Figure 5.6 Newfoundland and Labrador's efficiency data

Nova Scotia: Having an efficiency score of about 89%, Nova Scotia is considered inefficient. This is because a virtual DMU can produce similar outputs using Nova Scotia's inputs. Though Nova Scotia's water quality score is 82%, which is a good score, the model shows that 115.77 of the number drinking water regulations was not used to produce the outputs.

Constraints

Cell	Name	Cell Value	Formula	Status	Slack
\$D\$21	. Total Op & Maintenance cost Reference Set	21.63	\$D\$21<=\$F\$21	Binding	0
\$D\$22	Drinking water regulation Reference Set	50.34	\$D\$22<=\$F\$22	Not Binding	115.7763348
\$D\$23	Drinking water monitoring Reference Set	29.31	\$D\$23<=\$F\$23	Binding	0
\$D\$24	BWA per population Reference Set	7.06	\$D\$24>=\$F\$24	Binding	0.00
\$D\$25	Drinking water score Reference Set	82.00	\$D\$25>=\$F\$25	Binding	0.00

	Efficiency		Unit under
Constraints	Reference Set		Evaluation
Total Op & Maintenance cost	21.63	N	21.63
Drinking water regulation	50.34	≤	166.12
Drinking water monitoring	29.31	≤	29.31
BWA per population	7.06	2	7.06
Drinking water score	82.00	2	82.00

Figure 5.7 Nova Scotia's efficiency data

Nova Scotia's efficiency can be improved by using 15.9% of Newfoundland's inputs and about 98% of Prince Edward Island's inputs.

DMUs	AB	BC	MB	NB	NL	NS	NWT	ON	PEI	QC	SK	ΥT
Weights λ	0	0.607	0	0.128	0	0	0	0	0.433	0	0	0

Table 5.5 Nova Scotia's efficiency reference set

Northwest Territories: Having an efficiency score of 42.4%, this decision making unit is considered inefficient as there exist a virtual decision making unit that can produce

same output with 42.4% of Northwest Territories' number of inputs. In this case we have two input slack values for Total operation and maintenance cost and Drinking water monitoring. These values are the amount of theses inputs not used by the model to produce this outputs.

Constraints

Cell	Name	Cell Value	Formula	Status	Slack
\$D\$21	Total Op & Maintenance cost Reference Set	19.80	\$D\$21<=\$F\$21	Not Binding	47.35532244
\$D\$22	Drinking water regulation Reference Set	22.05	\$D\$22<=\$F\$22	Binding	0
\$D\$23	Drinking water monitoring Reference Set	11.96	\$D\$23<=\$F\$23	Not Binding	0.33804435
\$D\$24	BWA per population Reference Set	2.26	\$D\$24>=\$F\$24	Binding	0.00
\$D\$25	Drinking water score Reference Set	64.50	\$D\$25>=\$F\$25	Binding	0.00

	Efficiency		Unit under
Constraints	Reference Set		Evaluation
Total Op & Maintenance cost	19.80	5	67.15
Drinking water regulation	22.05	≤	22.05
Drinking water monitoring	11.96	≤	12.30
BWA per population	2.26	2	2.26
Drinking water score	64.50	2	64.50

Figure 5.8 Northwest Territories' efficiency data

The only binding input is the number of drinking water regulation. This DMU can be improved by using 5.1% of Newfoundland and Labrador's inputs and 85.3% of Prince Edward Island's inputs.

DMUs	AB	BC	MB	NB	NL	NS	NWT	ON	PEI	QC	SK	ΥT
Weights λ	0	0	0	0	0.051	0	0	0	0.853	0	0	0

Table 5.6 Northwest Territories efficiency reference set

Ontario: This DMU has an efficiency score of 86%. This means that there exist a virtual DMU that can produce the same outputs as Ontario and not use up to the number of inputs used by Ontario.

	Efficiency		Unit under
Constraints	Reference Set		Evaluation
Total Op & Maintenance cost	20.40	≤	20.40
Drinking water regulation	73.52	≤	178.83
Drinking water monitoring	37.84	≤	63.06
BWA per population	5.08	2	5.08
Drinking water score	87.00	2	87.00

Constraints

Cell	Name	Cell Value	Formula	Status	Slack
\$D\$21	Total Op & Maintenance cost Reference Set	20.40	\$D\$21<=\$F\$21	Binding	0
\$D\$22	Drinking water regulation Reference Set	73.52	\$D\$22<=\$F\$22	Not Binding	105.3033162
\$D\$23	Drinking water monitoring Reference Set	37.84	\$D\$23<=\$F\$23	Not Binding	25.22145483
\$D\$24	BWA per population Reference Set	5.08	\$D\$24>=\$F\$24	Binding	0.00
\$D\$25	Drinking water score Reference Set	87.00	\$D\$25>=\$F\$25	Binding	0.00
	Eigene 5 0 Outani	1	1		

Figure 5.9 Ontario's efficiency data

Using 86% of Ontario inputs, a virtual decision making unit can use fewer numbers of drinking water regulations and drinking water monitoring to produce the same amount of outputs.

DMUs	AB	BC	MB	NB	NL	NS	NWT	ON	PEI	QC	SK	ΥT
Weights λ	0	0.422	0	0.748	0	0	0	0	0	0	0	0

Table 5.7 Ontario's efficiency reference set

Ontario's efficiency can be improved by using 42.2% of British Columbia's inputs and 74.8% of New Brunswick inputs.

Prince Edward Island: This decision making unit is considered efficient and it serves and an efficiency improvement reference for other inefficient decision making units. Being efficient means that no other virtual DMU can produce similar or better outputs having the same number of inputs.

	Efficiency		Unit under
Constraints	Reference Set		Evaluation
Total Op & Maintenance cost	21.28	5	21.28
Drinking water regulation	23.00	5	23.00
Drinking water monitoring	12.00	5	12.00
BWA per population	0.01	2	0.01
Drinking water score	71.00	2	71.00

Constraints

Cell	Name	Cell Value	Formula	Status	Slack
\$D\$21	Total Op & Maintenance cost Reference Set	21.28	\$D\$21<=\$F\$21	Binding	0
\$D\$22	Drinking water regulation Reference Set	23.00	\$D\$22<=\$F\$22	Binding	0
\$D\$23	Drinking water monitoring Reference Set	12.00	\$D\$23<=\$F\$23	Binding	0
\$D\$24	BWA per population Reference Set	0.01	\$D\$24>=\$F\$24	Binding	0.00
\$D\$25	Drinking water score Reference Set	71.00	\$D\$25>=\$F\$25	Binding	0.00

Figure 5.10 Prince Edward Island's efficiency data

Quebec: This DMU has an efficiency of about 63%, which implies that it is inefficient. Meaning that there exist a virtual DMU that can utilize fewer resources to produce same output.

Cell	Name	Cell Value	Formula	Status	Slack
\$D\$21	Total Op & Maintenance cost Reference Set	16.32	\$D\$21<=\$F\$21	Binding	0
\$D\$22	Drinking water regulation Reference Set	62.43	\$D\$22<=\$F\$22	Not Binding	44.81361377
\$D\$23	Drinking water monitoring Reference Set	29.36	\$D\$23<=\$F\$23	Not Binding	7.856792656
\$D\$24	BWA per population Reference Set	0.76	\$D\$24>=\$F\$24	Binding	0.00
\$D\$25	Drinking water score Reference Set	71.00	\$D\$25>=\$F\$25	Binding	0.00

	Efficiency		Unit under
Constraints	Reference Set		Evaluation
Total Op & Maintenance cost	16.32	5	16.32
Drinking water regulation	62.43	≤	107.25
Drinking water monitoring	29.36	≤	37.22
BWA per population	0.76	2	0.76
Drinking water score	71.00	2	71.00

Figure 5.11 Quebec's efficiency data

Quebec can be made efficient by using 4.6% of British Columbia's inputs and 87% of New Brunswick inputs.

DMUs	AB	BC	MB	NB	NL	NS	NWT	ON	PEI	QC	SK	ΥT
Weights λ	0	0.046	0	0.870	0	0	0	0	0	0	0	0

Table 5.8 Quebec efficiency reference set

Saskatchewan: With an efficiency of 83.7%, Saskatchewan is not efficient because a virtual decision making unit can still produce same of better outputs without using as much inputs.

Cor	stra	ain	ts
001	15010		ιJ

Cell	Name	Cell Value	Formula	Status	Slack
\$D\$21	Total Op & Maintenance cost Reference Set	23.74	\$D\$21<=\$F\$21	Not Binding	17.56416307
\$D\$22	Drinking water regulation Reference Set	29.09	\$D\$22<=\$F\$22	Not Binding	66.32245958
\$D\$23	Drinking water monitoring Reference Set	17.58	\$D\$23<=\$F\$23	Binding	0
\$D\$24	BWA per population Reference Set	11.91	\$D\$24>=\$F\$24	Binding	0.00
\$D\$25	Drinking water score Reference Set	71.00	\$D\$25>=\$F\$25	Binding	0.00

	Efficiency		Unit under
Constraints	Reference Set		Evaluation
Total Op & Maintenance cost	23.74	5	41.30
Drinking water regulation	29.09	≤	95.41
Drinking water monitoring	17.58	5	17.58
BWA per population	11.91	2	11.91
Drinking water score	71.00	2	71.00

Figure 5.12 Saskatchewan's efficiency data

The efficiency of Saskatchewan can be improved by using 26.8% of Newfoundland and Labrador's inputs and 70.6% of Prince Edward Island's inputs.

DMUs	AB	BC	MB	NB	NL	NS	NWT	ON	PEI	QC	SK	YT
Weights λ	0	0	0	0	0.268	0	0	0	0.706	0	0	0

Table 5.9 Saskatchewan efficiency reference set

Yukon: This decision making unit has an efficiency of 32.1 % and thereby considered inefficient. This implies that a virtual decision making unit can produce same outputs using fewer inputs.

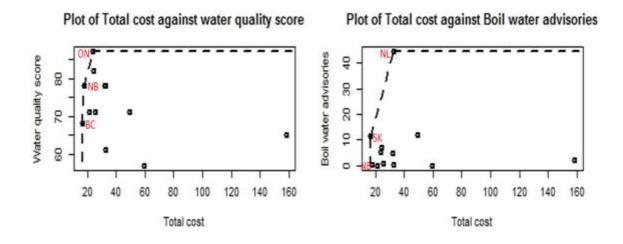
Constraints

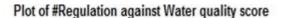
Jonistian	115				
Cell	Name	Cell Value	Formula	Status	Slack
\$D\$21	Total Op & Maintenance cost Reference Set	17.09	\$D\$21<=\$F\$21	Not Binding	1.985041818
\$D\$22	Drinking water regulation Reference Set	18.48	\$D\$22<=\$F\$22	Not Binding	1.133968693
\$D\$23	Drinking water monitoring Reference Set	9.64	\$D\$23<=\$F\$23	Binding	0
\$D\$24	BWA per population Reference Set	0.03	\$D\$24>=\$F\$24	Binding	0.00
\$D\$25	Drinking water score Reference Set	57.00	\$D\$25>=\$F\$25	Binding	0.00

	Efficiency		Unit under
Constraints	Reference Set		Evaluation
Total Op & Maintenance cost	17.09	<u> </u>	19.07
Drinking water regulation	18.48	≤	19.61
Drinking water monitoring	9.64	≤	9.64
BWA per population	0.03	2	0.03
Drinking water score	57.00	2	57.00

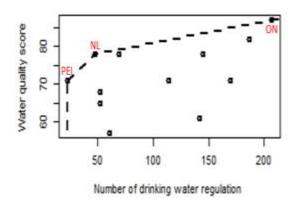
Figure 5.13 Yukon's efficiency data

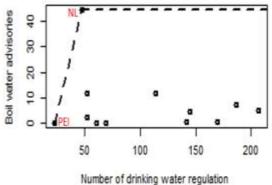
Yukon's efficiency can be improved by using 0.05% of Newfoundland and Labrador's inputs and 80.2% of Prince Edward Island's inputs.











Plot of #Monitored against Water quality score



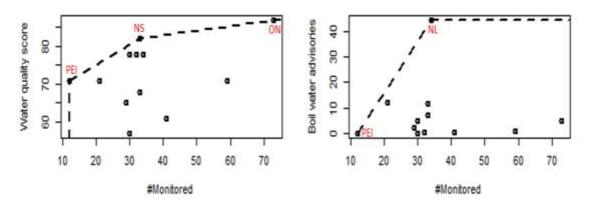


Figure 5.14 Input-output efficient frontiers

5.4 Discussion

From the results obtained from the analysis, we noticed that the input with more slack value, that is, the input which is most non-binding is the number of drinking water regulation, though there were cases were other inputs had slack values. Figure 5.14 shows the efficient frontier for a single input in each column and a single output in each row. The first row shows the single output of total cost (adjusted by population), the middle row shows the single outputs of number of regulated contaminants, and the lowest row shows the number of monitored contaminants.

The efficient frontier in each of these plots varies in shape, but what we consistently see is that having a higher number of regulations does not imply a great water quality. For example, in figure 5.14 in the middle row, we can see that PEI, a decision making unit, is on the efficient frontier having the lowest number of drinking water regulations.

The results for boil water advisories are more consistent, as for both number of regulated contaminants and number of monitored contaminants, the efficient frontier was described by the provinces with the highest and lowest number of boil water advisories, signifying that this input does not affect the outputs.

This does not nullify the variability of the DEA model; it only shows that some factors not common to all provinces and territories play a role in the efficiency scores obtained. Some of these factors are:

- Underreporting: a good number of missing data affects the efficiency score when actual data of work done to improve drinking water quality cannot be captured.

- Variability in source water

- Variability in industries: Some jurisdictions have industries that produces wastes that affects the quality of their and also makes them to utilize more resources to get rid of these pollutant which might not be the case in other provinces and territories thereby not using too many resources to improve their water quality.

We compared short-term outcomes which are biological in the DEA analysis because their effects are easily observed and the source of infection can be confirmed. However, in the case of chemical contaminants which could result in excess cancer, the source of infection cannot easily be ascertained as other factors could also cause cancer having calculated a lower risk exposure rate for excess arsenic in drinking water.

Chapter 6

Other works implemented

6.1 Occurrence of excess cancer from drinking water contaminants

This chapter provides a methodological framework for a more complete treatment of the regulatory stringency-quality problem. A fundamental issue is that the easily observable data are related to short term, biological exposures while the bulk (numerically) of possible regulations involve chemical contaminant. This is in part due to the limited number of regularly tested biological indicators compared to the less frequently tested but more numerous chemical contaminants.

Contaminants in drinking water have been indicated as carcinogenic, a famous example is arsenic.

We examine how likely a population, exposed to a particular level of arsenic in drinking water, will be susceptible to cancer. We assume that exposure to arsenic and its possible effect of causing cancer is independent of other carcinogens found in drinking water. We demonstrate a population level cancer assessment for arsenic. A complete analysis would require additional contaminants including arsenic, benzene, bromate, cadmium etc.

6.1.1 Arsenic – A carcinogen in drinking water

Arsenic, a known contaminant found in drinking water has been identified to be carcinogenic if exposure reaches the threshold. The International Agency of Research on Cancer (IARC, 2004) classified arsenic as a human carcinogen (Group 1) confirming its carcinogenicity in humans. A. H. Smith et al., (1992) presented evidence that aside from

skin cancer that can result from arsenic exposure, lung and liver cancer can also result from arsenic ingestion. Other studies pointed out that other internal cancer like bladder, kidney, prostate and the above mentioned types can be associated with the intake of arsenic (Martinez, Vucic, Becker-Santos, Gil, & Lam, 2011; Morales, Ryan, Kuo, Wu, & Chen, 2000; A. H. Smith et al., 1992)

In Taiwan, high rates of liver cancer deaths were found in populations with high level of arsenic in well water sources. In one of these studies, the population was classified into three groups based on the level of arsenic in their drinking water; some had $300\mu g/L$, $300-600\mu g/L$ and the last group were greater than $600\mu g/L$ (A. H. Smith et al., 1992; Wu, Kuo, Hwang, & Chen, 1989). Individuals in the highest level had elevated mortality rate of liver cancer.

6.1.1.1 Exposure Assessment

The United States environmental protection agency (U.S. EPA), estimated that the lifetime risk of dying from cancer related to arsenic from taking 1L/day of drinking water with about 50 μ g/L of arsenic concentration could be as high as 13 per 1000 persons (A. H. Smith et al., 1992). About 350,000 people in the United States are supplied with water with arsenic level above 50 μ g/L while over 2.5 million people may have water with levels above 25 μ g/L; this then brings the average risk estimate to about 1 per 1000 (Morales, Ryan, Kuo, Wu, & Chen, 2000; A. H. Smith et al., 1992).

In Canada, the Federal Drinking Water Guidelines stipulates that the maximum acceptable concentration (MAC) of arsenic in drinking water be 10µg/L. While the MAC

is not legally enforceable at the federal level, some provinces and municipalities monitor or enforce the MAC for arsenic (McGuigan et al, 2010).

Though this is not mandated at the provincial, territorial or municipal level, our conversations with regulators indicate that they try to maintain this concentration limit. There are some areas in Canada which are referred to as hotspots because of the presence of elevated concentration of arsenic, that is, concentration greater than $10\mu g/L$ (McGuigan, Hamula, Huang, Gabos, & Le, 2010).

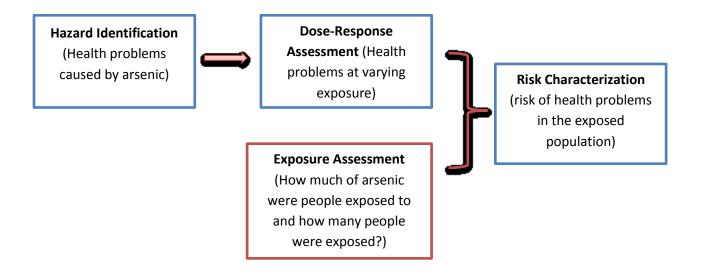


Figure 6.1 Step Risk Assessment Process (U.S. EPA)

6.1.1.2 Dose Response Analysis

In this section, we estimate the likely risk of exposure at different levels of interest. We will assume a daily intake of 2L/day of drinking water. The federal drinking water guideline for arsenic in Canada is 0.010 mg/L, with the assumption it makes it 0.020 mg/L/day or $20 \mu \text{g/L/day}$.

The United States Environmental Protection Agency, U.S. EPA., published guidelines for carcinogenic risk assessment which defines "mode of action" as the 'sequence of key events and processes, starting with interaction of an agent with a cell, proceeding through operational and anatomical changes, and resulting in the effect' (U.S. EPA, 2005). The mode of action can be modeled either as linear or non-linear. Non-linear mode of action is based on the threshold theory which means that some range of exposure can be tolerated without having any adverse effect and the point where the effect starts to occur is the threshold. While the linear mode assumes that there is no threshold, that is, any quantity carries some risk. According to the United States environmental protection agency, radiation and some known carcinogens use a linear approach, this means that the risk of concern increases at exposures greater than zero. We then assume the same linear approach for arsenic.

Theoretically, in linear mode of action or linear dose-response assessment, there is no level of exposure without the risk of carcinogenicity although the factor of time differs. Consequently the extrapolation will result in a straight line that starts from the origin, having zero doses and zero response, to the points of the observed data; this is known as the slope factor (cancer slope factor). The slope factor is then used to estimate the risk at the observed levels that fall on the line.

Though there exist a reference dose (RfD) for chronic exposure as it is assumed that there is a degree of exposure that can actually cause cancer such as skin cancer and other site related cancer. The reference dose (RfD) is measured in mg/kg-day (U.S. EPA, 1988).

In cases where the linear model is assumed, non-zero regulatory values are the result of cost-benefit analysis or the minimum detection limit (Calder & Schmitt, 2010). The EPA drinking water standard of 50 micro grams of arsenic per liter water, 50μ g/L, which is equivalent to 50 parts per billion, has now been lowered to 10μ g/L (U.S. EPA, 2002).

Kurttio et al (1999) estimated two latency period of exposure, short latency which is between 3 and 9 years and long latency, which starts from 10yrs prior to cancer diagnosis. We will consider the long latency period which is closer to a lifetime exposure.

The National Academy of Sciences used a linear dose- response to estimate cancer risk at different exposure levels to arsenic in tap water in the United States (U.S. EPA, 2002). We will use this to derive our slope factor in other to calculate the risk of excess cancer. The slope factor of inorganic arsenic as reviewed by the U.S. Environmental Protection Agency in a draft released in February 2010 is 3.0E-4 (0.0003).

Approximate Total Cancer risk per 1000				
(assuming 2 liters of water is consumed/day)				
0.1				
0.2				
0.6				
0.8				
1.0				
2.0				
4.0				
5.0				
10.0				
-				

Table 6.1 Lifetime risk of dying of cancer in from tap water consumption (Natural RecoursesDefense Council, 2000)

6.1.1.3 Calculation of cancer risk

This involves age intervals in its calculation. The U.S. EPA guidelines shows that exposure assessment involving age groups require the addition of ADAF (Age Dependent Adjustment Factor) to estimate age group specific risk.

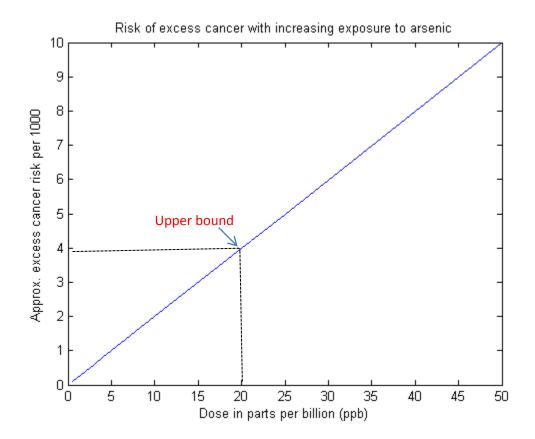


Figure 6.2 : Risk of excess cancer with increasing exposure to arsenic in drinking water

$$Risk_{i} = C \cdot \frac{IR_{i} \cdot EF_{i} \cdot ED_{i}}{BW_{i} \cdot AT} \cdot SF \cdot ADAF$$

Where:

C = Concentration of the chemical in the contaminated environmental medium (soil or water) to which the person is exposed. mg/l for water.

- IR_i = Intake rate of the contaminated environmental medium for age bin "i". The units are mg/day for soil and l/day for water.
- $BW_i = Body$ weight of the exposed person for age bin "i".
- $EF_i = Exposure$ frequency for age bin "i" (days/year). This describes how often a person is exposed to the contaminated medium over the course of a typical year.
- $ED_i = Exposure$ duration for age bin "i" (years). This describes how long a person is exposed to the contaminated medium over the course of their lifetime.
- AT = Average days. This term specifies the length of time over which the average dose is calculated. For quantifying cancer risk a "lifetime" of 70 years is used (i.e., 70 years times 365 days/year).
- $SF = Cancer slope factor (mg/kg-day)^{-1}$
- ADAF = Age-dependent adjustment factor for age bin "i" (unitless)

Steps for calculating cancer risk³

Scenario: We want to calculate the lifetime risk of excess cancer from arsenic concentration in drinking water.

Age	С	IR	EF	ED	BW	AT	SF	ADAF
0-<2	0.010	1.5	350	2	12	25550	3.0E-04	10
2 - < 6	0.020	1.5	350	4	18	25550	3.0E-04	3
6 - < 16	0.020	1.5	350	10	45	25550	3.0E-04	3
16 < 30	0.020	2.0	350	14	65	25550	3.0E-04	3
30 - <46	0.020	2.0	350	16	70	25550	3.0E-04	1
46 - < 60	0.020	2.0	350	14	75	25550	3.0E-04	1
60 - < 70	0.020	2.0	350	10	80	25550	3.0E-04	1

Wa	00000000	<i>a</i> a a	1101000	fucin	hinth	to	70.	Noana
we	assume	uge	runge	jrom	Dirin	ιo	70	years.

Table 6.2 Cancer risk calculation

³

USEPA 1991. Standard Default Exposure Factors. OSWER Directive 9285.6-03

Cancer Risk Calculations:

Risk (0 - < 2) = [0.010 * (1.5/12) * (350/365) * (2/70) * 3.0E-04 * 10] = 1.0E-07Risk (2 - < 6) = [0.020 * (1.5/18) * (350/365) * (4/70) * 3.0E-04 * 3] = 8.2E-08Risk (6 - < 16) = [0.020 * (1.5/45) * (350/365) * (10/70) * 3.0E-04 * 3] = 8.2E-08Risk (16 - < 30) = [0.020 * (2.0/65) * (350/365) * (14/70) * 3.0E-04 * 3] = 1.1E-07Risk (30 - < 46) = [0.020 * (2.0/70) * (350/365) * (16/70) * 3.0E-04 * 1] = 3.8E-08Risk (46 - < 60) = [0.020 * (2.0/75) * (350/365) * (14/70) * 3.0E-04 * 1] = 3.1E-08Risk (60 - < 70) = [0.020 * (2.0/80) * (350/365) * (10/70) * 3.0E-04 * 1] = 2.1E-08Total Risk (0 - < 70) = 1.0E-07 + 8.2E-08 + 8.2E-08 + 1.1E-07 + 3.8E-08 + 3.1E-08 + 2.1E-08 = 4.6E-07

Summary of Results:

Age Interval	Estimated Risk
0-<2	1.0E-07
2 - < 6	8.2E-08
6 - < 16	8.2E-08
16 < 30	1.1E-07
30 - <46	3.8E-08
46 - < 60	3.1E-08
60 - < 70	2.1E-08
Total Risk	4.6E-07

Table 6.3 Estimated cancer risk at different age interval

The means that the life time risk of excess cancer from arsenic found in drinking water is 4.6E-07.

Chapter 7

Conclusion and Future Work

7.1 Conclusion

The aim of this thesis was to investigate how drinking water regulatory stringencies affect drinking water quality. We were able to reach a conclusion based on the input and output variables used in the model. The model used was a multi-criteria decision making tool known as data envelopment analysis. We used a CCR data envelopment analysis model with the aim of minimizing inputs because our goal is to observe whether or not more inputs used is synonymous to better output. We used the number of drinking water contaminants being regulated by each of the provinces and territories, the number of contaminants that are closely monitored and the cost involved in the operation and maintenance of drinking water plants across provinces and territories. All these were used as inputs in the model.

On the other hand, we used the historical data of both the number of boil water advisories that have been issued and the drinking water quality score of each of the provinces and territories as outputs. In order not to go against the goal of minimizing inputs to maximize outputs, we made the outputs desirable by using its inverse in the model. We also had to normalize the number of boil water advisories issued with the population of each province and territory.

After all inputs and outputs were used in the model, we were able to conclude that based on our set of inputs and output data, drinking water regulatory stringency has a relationship with the quality of drinking water, however, this relationship shows that more stringent water regulation does not necessarily imply better water quality. Moreover, the leaders in efficiency were not the provinces with the highest water quality. While this constitutes an important research result, it is important to keep in mind the limitations of this work. Most important among these is that we use long term indicators to model short term consequences. Methods to address this limitation are discussed in Chapter 5.4 and 6.

7.2 Future works

Future research on drinking water quality could be expanded into using Bayesian network or artificial neural networks to forecast drinking water quality outcomes. This could be achieved by understanding the patterns in which historical data changes and using this information as a base for data training and testing all the aim of improving the water quality.

Also the use of precision tree could be expanded to help decision makers to have a clearer view of the decision problem and helps to navigate the most cost-effective path in the tree. It suggests possible outcomes with the aim of getting the best path also to improve drinking water quality and possibly reduce the occurrence of illnesses associated with drinking water. An example could be to use the tree to decide whether or not to test drinking water samples. The answer to the question is either a yes or no. However, if the answer is "yes", then more questions are asked unlike if "no" then no further questions can be asked.

To make the tree more effective, historical data will help in the decision making process. What kind of historical data is needed? If any testing had been done in the past, the cost associated with testing and drinking water related diseases. These and more could help decision makers to improve drinking water quality.

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Appendices

Guidelines for Canadian Drinking Water Quality (Health Canada, 2012) (biological, chemical and physical parameters)

Parameter in federal guidelines	Туре	Federal Guidelines (mg/L)
Bacterial waterborne pathogens		No guideline
Enteric viruses		No guideline
Escherichia coli (E. coli)		0 per 100 mL
Heterotrophic plate count		No guideline
Protozoa: Giardia and Cryptosporidium		No guideline
Total coliforms		0 per 100 mL
Turbidity		0.3/1.0/0.1 NTU
Alachlor		No guideline
Aldicarb		No guideline
Aldrin + Dieldrin		No guideline
Alkalinity		No guideline
Aluminium	Т	0.1-0.2
Ammonia	Ι	No guideline
Antimony	Ι	0.006
Arsenic	Ι	0.01
Asbestos	Ι	No guideline
Atrazine	Р	0.005
Azinphos-methyl	Р	0.02
Barium	Ι	1

Bendiocarb		No guideline
Benzene	0	0.005
Benzo[a]pyrene	0	0.00001
Boron	Ι	5
Bromide		No guideline
Bromate	DBP	0.01
Bromoxynil	Р	0.005
Bromo-dichloromethane		No guideline
Cadmium	Ι	0.005
Calcium	Ι	No guideline
Carbaryl	Р	0.09
Carbofuran	Р	0.09
Carbon tetrachloride	0	0.002
Chloramines	D	3
Chlordane (Total)		No guideline
Chlorate	DBP	1
Chloride	Ι	AO: ≤ 250
Chlorine	D	No guideline
Chlorine residue		No guideline
Chlorine dioxide	D	No guideline
Chlorite	DBP	1
Chlorpyrifos	Р	0.09
Chlorophenols		No guideline
Chromium	Ι	0.05
Colour	Т	AO: <= 15

CopperIAO: ≤ 1.0 CyanazineNo guidelineCyanideIO0.2Cyanobacterial toxinsODiazinonPDicambaP1,2-DichlorobenzeneOO0.005DichlorodiphenytrichloroethaneO1,2-DichloroethaneO00.005	
CyanideI0.2Cyanobacterial toxinsO0.0015DiazinonP0.02DicambaP0.121,2-DichlorobenzeneO0.21,4-DichlorobenzeneO0.005Dichlorodiphenytrichloroethane(DDT) +No guidelinemetabolites	
Cyanobacterial toxinsO0.0015DiazinonP0.02DicambaP0.121,2-DichlorobenzeneO0.21,4-DichlorobenzeneO0.005Dichlorodiphenytrichloroethane (DDT) +No guidelinemetabolites	
DiazinonP0.02DicambaP0.121,2-DichlorobenzeneO0.21,4-DichlorobenzeneO0.005Dichlorodiphenytrichloroethane (DDT) +No guidelinemetabolites	
DicambaP0.121,2-DichlorobenzeneO0.21,4-DichlorobenzeneO0.005Dichlorodiphenytrichloroethane (DDT) +No guidelinemetabolites	
1,2-DichlorobenzeneO0.21,4-DichlorobenzeneO0.005Dichlorodiphenytrichloroethane (DDT) +No guidelinemetabolites	
1,4-Dichlorobenzene O 0.005 Dichlorodiphenytrichloroethane (DDT) + No guideline metabolites	
Dichlorodiphenytrichloroethane (DDT) + No guideline metabolites	
metabolites	
1,2-Dichloroethane O 0.005	
1,1-Dichloroethylene O 0.014	
Dichloromethane O 0.05	
2,4-Dichlorophenol, O 0.9	
2,4-Dichlorophenoxyacetic acid (2,4 -D) P 0.1	
Diclofop-methyl P 0.009	
Dimethoate P 0.02	
Dinoseb No guideline	
Dioxin and Furan No guideline	
Dissolved Organic Carbon No guideline	
Diquat P 0.07	
Diuron P 0.15	
EthylbenzeneO $AO: \leq 0.0024$	
Fluoride I 1.5	

	DBP	No guideline
Gasoline and its organic constituents	0	No guideline
Glyphosate	Р	0.28
Haloacetic acids (HAAs)	DBP	0.08
Heptachlor + Heptachlor Epoxide		No guideline
Hardness	Т	80 and 100 mg/L (as CaCO ₃)
Iron	I	AO: ≤ 0.3
Lead	I	0.01
Lindane (Total)		No guideline
Magnesium	I	No guideline
Malathion	Р	0.19
Manganese	I	AO: ≤ 0.05
Mercury	I	0.001
2-Methyl-4-chlorophenoxyacetic acid	Р	0.1
Methyl-tert-butyl-ether (MTBE)	0	AO: ≤ 0.015
Methoxychlor		No guideline
Metolachlor I	Р	0.05
Metribuzin I	Р	0.08
Microcystin-LR		No guideline
Monochlorobenzene	0	0.08
Nickel		No guideline
Nitrate/nitrite I	I	Nitrate: 45 as nitrate; 10 as nitrate-
		nitrogen
Nitrilotriacetic acid (NTA)	I	0.4
N-Nitrosodimethylamine (NDMA)	DBP	0.00004

Odor	А	Inoffensive
Paraquat	Р	0.01 as paraquat dichloride; 0.007 as
		paraquat ion
Parathion		No guideline
Pentachlorophenol	0	0.06
Polychlorinated Biphenyls (PCB)		No guideline
Prometryne		No guideline
рН	Т	6.5-8.5
Phorate	Р	0.002
Phosphorus		No guideline
Potassium		No guideline
Picloram	Р	0.19
Selenium	Ι	0.01
Silver	Ι	No guideline
Simazine	Р	0.01
Sodium	Ι	AO: ≤ 200
Sulphate	Ι	AO: ≤ 500
Sulphide	Ι	AO: ≤ 0.05
Taste	А	Inoffensive
Temperature	Т	AO: ≤ 15°C
Temephos		No guideline
Terbufos	Р	0.001
Tetrachloroethylene	0	0.03
2,3,4,6-Tetrachlorophenol	0	0.1
Triallate		

Toluene	0	AO: ≤ 0.024
Total dissolved solids	А	AO: ≤ 500
Total organic carbon		No guideline
Total Phosphorus		No guideline
Trichloroethylene	0	0.005
2,4,6-Trichlorophenol	0	0.005
Trichlorophenoxy acetic acid (2,4,5-T)		No guideline
Trifluralin	Р	0.045
Trihalomethanes (THMs)	DBP	0.1
Uranium	Ι	0.02
Vinyl chloride	0	0.002
Xylene	0	AO: ≤ 0.3
	Ι	AO: ≤ 5.0

A – Acceptability	D – Disinfectant
P – Pesticide	I – Inorganic chemical
1	•

DBP –Disinfection by-product **O** – Organic chemical

T – Treatment related

Province	BWAs
Alberta	13
British Columbia	530
Manitoba	59
New Brunswick	2
Newfoundland and	
Labrador	228
Nova Scotia	67
Northwest Territories	1
Nunavut	0.01
Ontario	679
Prince Edward Island	0.01
Quebec	61
Saskatchewan	126
Yukon	0.01

*BWAs = Boil Water Advisories

R-CODES

x<-matrix(c(32.53,16.70,32.28,17.87,32.56,24.35,158.37,23.62,21.27,25.87,49.35,59.32), ncol=1,dimnames=list(c("AB","BC","MB","NB","NL","NS","NWT","ON","PEI","QC", "SK","YT"), "Total cost"))

x<-matrix(c(32.53,16.70,32.28,17.87,32.56,24.35,158.37,23.62,21.27,25.87,49.35,59.32), ncol=1,dimnames=list(c("AB","BC","MB","NB","NL","NS","NWT","ON","PEI","QC", "SK","YT"), "Total cost"))

x2<matrix(c(32.53,16.70,32.28,17.87,32.56,24.35,158.37,23.62,21.27,25.87,49.35,59.32) ,ncol=1,dimnames=list(c("AB","BC","MB","NB","NL","NS","NWT","ON","PEI","QC", "SK","YT"), "Total cost"))

y2<matrix(c(0.344,11.581,4.714,0.265,44.453,7.064,2.262,5.080,0.007,0.764,11.912,0.0 28), ncol=1,

dimnames=list(c("AB","BC","MB","NB","NL","NS","NWT","ON","PEI","QC","SK"," YT"), "BWA"))

> plot(x2,y2)

> plot(x2,y2, xlab="Total cost", main = "Plot of Total cost against Boil water advisories", ylab="Boil water advisories", RTS="vrs", ORIENTATION="in-

```
out",add=TRUE,lty="dashed",lwd=2
```

+))

Error: unexpected ')' in:

```
"plot(x2,y2, xlab="Total cost", main = "Plot of Total cost against Boil water advisories",
ylab="Boil water advisories", RTS="vrs",ORIENTATION="in-
out",add=TRUE,lty="dashed",lwd=2
```

```
))"
```

> plot(x2,y2, xlab="Total cost", main = "Plot of Total cost against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> dea.plot(x2,y2, xlab="Total cost", main = "Plot of Total cost against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> x3 <- matrix(c(142,52,145,69,48,187,52,207,23,170,114,61), ncol=1, dimnames=list(c("AB","BC","MB","NB","NL","NS","NWT","ON","PEI","QC","SK"," YT"), "DWR"))

> y3 <- matrix(c(61,68,78,78,78,82,65,87,71,71,71,57), ncol=1, dimnames=list(c("AB","BC","MB","NB","NL","NS","NWT","ON","PEI","QC","SK"," YT"), "WQS"))

> plot(x3,y3)

> plot(x3,y3, xlab="#Regulation", main = "Plot of #Regulation against Water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> dea.plot(x3,y3, xlab="#Regulation", main = "Plot of #Regulation against Water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> plot(x3,y3, xlab="Number of regulation", main = "Plot of #Regulation against Water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> plot(x3,y3, xlab="Number of drinking water regulation ", main = "Plot of #Regulation against Water quality score", ylab="Water quality score",

RTS="vrs",ORIENTATION="in-out",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> dea.plot(x3,y3, xlab="Number of drinking water regulation ", main = "Plot of")

#Regulation against Water quality score", ylab="Water quality score",

RTS="vrs",ORIENTATION="in-out",add=TRUE,lty="dashed",lwd=2)

> x4 <- matrix(c(142,52,145,69,48,187,52,207,23,170,114,61), ncol=1, dimnames=list(c("AB","BC","MB","NB","NL","NS","NWT","ON","PEI","QC","SK"," YT"), "DWR"))

> y4 <-

matrix(c(0.344,11.581,4.714,0.265,44.453,7.064,2.262,5.080,0.007,0.764,11.911,0.028), ncol=1,

dimnames=list(c("AB","BC","MB","NB","NL","NS","NWT","ON","PEI","QC","SK"," YT"), "BWA"))

> plot(x4,y4, xlab="Number of drinking water regulation ", main = "Plot of #Regulation against Boil water advisories", ylab="Boil water advisories",

RTS="vrs",ORIENTATION="in-out",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> dea.plot(x4,y4, xlab="Number of drinking water regulation ", main = "Plot of

#Regulation against Boil water advisories", ylab="Boil water advisories",

RTS="vrs",ORIENTATION="in-out",add=TRUE,lty="dashed",lwd=2)

> x5 <- matrix(c(41,33,30,32,34,33,29,73,12,59,21,30), ncol=1, dimnames=list(c("AB","BC","MB","NB","NL","NS","NWT","ON","PEI","QC","SK"," YT"), "#monitored"))

> y5 <- matrix(c(61,68,78,78,78,82,65,87,71,71,71,57), ncol=1, dimnames=list(c("AB","BC","MB","NB","NL","NS","NWT","ON","PEI","QC","SK"," YT"), "WQS"))

> plot(x5,y5, xlab="#Monitored ", main = "Plot of #Monitored against Water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> dea.plot(x5,y5, xlab="#Monitored ", main = "Plot of #Monitored against Water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> x6 <- matrix(c(41,33,30,32,34,33,29,73,12,59,21,30), ncol=1,

dimnames=list(c("AB","BC","MB","NB","NL","NS","NWT","ON","PEI","QC","SK"," YT"), "#monitored"))

> y6 <-

matrix(c(0.344,11.581,4.714,0.265,44.453,7.064,2.262,5.080,0.007,0.764,11.911,0.028), ncol=1,

dimnames=list(c("AB","BC","MB","NB","NL","NS","NWT","ON","PEI","QC","SK"," YT"), "BWA"))

> plot(x5,y5, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> dea.plot(x5,y5, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> plot(x5,y5, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> plot(x5,y5, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> dea.plot(x5,y5, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> utils:::menuInstallPkgs()

trying URL 'http://cran.skazkaforyou.com/bin/windows/contrib/2.14/calibrate_1.7.1.zip' Content type 'application/zip' length 311621 bytes (304 Kb)

opened URL

downloaded 304 Kb

package 'calibrate' successfully unpacked and MD5 sums checked

The downloaded packages are in

 $C: \label{eq:constraint} C: \label{eq:constraint} C: \label{eq:constraint} Users \label{eq:constraint} Adedotun \label{eq:constraint} C: \label{eq:constraint} Users \label{eq:constraint} Adedotun \label{eq:constraint} Addotun \label{$

There were 50 or more warnings (use warnings() to see the first 50)

> local({pkg <- select.list(sort(.packages(all.available = TRUE)),graphics=TRUE)</pre>

+ if(nchar(pkg)) library(pkg, character.only=TRUE)})

Loading required package: MASS

Attaching package: 'calibrate'

The following object(s) are masked from 'package:rms':

calibrate

Warning message:

package 'calibrate' was built under R version 2.14.2

> library(calibrate)

> textxy(x,y)

Error in as.graphicsAnnot(labels) :

argument "labs" is missing, with no default

> textxy(x,y,dmu)

Error in as.graphicsAnnot(labels) : object 'dmu' not found

> par(mfrow=c(3,2))

> dea.plot(x,y, xlab="Total cost", main = "Plot of Total cost against water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> dea.plot(x2,y2, xlab="Total cost", main = "Plot of Total cost against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> dea.plot(x3,y3, xlab="Number of drinking water regulation ", main = "Plot of #Regulation against Water quality score", ylab="Water quality score",

RTS="vrs",ORIENTATION="in-out",add=TRUE,lty="dashed",lwd=2)

> dea.plot(x4,y4, xlab="Number of drinking water regulation ", main = "Plot of #Regulation against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="in-out",add=TRUE,lty="dashed",lwd=2)

> dea.plot(x5,y5, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> dea.plot(x6,y6, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2) Error in plot.xy(xy.coords(x, y), type = type, ...) :

plot.new has not been called yet

> plot(x6,y6, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> dea.plot(x6,y6, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> plot(x5,y6, xlab="#Monitored ", main = "Plot of #Monitored against Water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> dea.plot(x5,y6, xlab="#Monitored ", main = "Plot of #Monitored against Water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> dea.plot(x6,y6, xlab="#Monitored ", main = "Plot of #Monitored against Water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

```
> dea.plot(x5,y5, xlab="#Monitored ", main = "Plot of #Monitored against Water quality
score", ylab="Water quality score", RTS="vrs",ORIENTATION="in-
out",add=TRUE,lty="dashed",lwd=2)
```

```
Error in plot.xy(xy.coords(x, y), type = type, ...) :
```

plot.new has not been called yet

> plot(x5,y5, xlab="#Monitored ", main = "Plot of #Monitored against Water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="in-

out",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> dea.plot(x5,y5, xlab="#Monitored ", main = "Plot of #Monitored against Water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> par(mfrow = c(3,2))

> dea.plot(x,y, xlab="Total cost", main = "Plot of Total cost against water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> dea.plot(x,y, xlab="Total cost", main = "Plot of Total cost against water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

Error in plot.xy(xy.coords(x, y), type = type, ...) :

plot.new has not been called yet

> plot(x,y, xlab="Total cost", main = "Plot of Total cost against water quality score",

ylab="Water quality score", RTS="vrs", ORIENTATION="in-

out",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> dea.plot(x,y, xlab="Total cost", main = "Plot of Total cost against water quality score",

ylab="Water quality score", RTS="vrs", ORIENTATION="in-

out",add=TRUE,lty="dashed",lwd=2)

> dea.plot(x2,y2, xlab="Total cost", main = "Plot of Total cost against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> plot(x2,y2, xlab="Total cost", main = "Plot of Total cost against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> dea.plot(x2,y2, xlab="Total cost", main = "Plot of Total cost against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> plot(x3,y3, xlab="Number of drinking water regulation ", main = "Plot of #Regulation against Water quality score", ylab="Water quality score",

RTS="vrs",ORIENTATION="in-out",add=TRUE,lty="dashed",lwd=2)

> dea.plot(x3,y3, xlab="Number of drinking water regulation ", main = "Plot of #Regulation against Water quality score", ylab="Water quality score",

```
RTS="vrs", ORIENTATION="in-out", add=TRUE, lty="dashed", lwd=2)
```

> plot(x4,y4, xlab="Number of drinking water regulation ", main = "Plot of #Regulation against Boil water advisories", ylab="Boil water advisories",

RTS="vrs",ORIENTATION="in-out",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> dea.plot(x4,y4, xlab="Number of drinking water regulation ", main = "Plot of #Regulation against Boil water advisories", ylab="Boil water advisories",

RTS="vrs",ORIENTATION="in-out",add=TRUE,lty="dashed",lwd=2)

> plot(x5,y5, xlab="#Monitored ", main = "Plot of #Monitored against Water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> dea.plot(x5,y5, xlab="#Monitored ", main = "Plot of #Monitored against Water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> plot(x6,y6, xlab="#Monitored ", main = "Plot of #Monitored against Water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> dea.plot(x6,y6, xlab="#Monitored ", main = "Plot of #Monitored against Water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> y6 <-

matrix(c(0.344,11.581,4.714,0.265,44.453,7.064,2.262,5.080,0.007,0.764,11.911,0.028), ncol=1,

dimnames=list(c("AB","BC","MB","NB","NL","NS","NWT","ON","PEI","QC","SK"," YT"), "BWA"))

There were 50 or more warnings (use warnings() to see the first 50)

> plot(x6,y6, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> plot(x6,y6, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> plot(x6,y6, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> dea.plot(x6,y6, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> par(mfrow=c(3,2))

> dea.plot(x6,y6, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> dea.plot(x6,y6, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> dea.plot(x6,y6, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> dea.plot(x6,y6, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> dea.plot(x6,y6, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> par(mfrow=c(3,2))

```
> plot(x,y, xlab="Total cost", main = "Plot of Total cost against water quality score",
ylab="Water quality score", RTS="vrs",ORIENTATION="in-
out",add=TRUE,lty="dashed",lwd=2)
```

> dea.plot(x,y, xlab="Total cost", main = "Plot of Total cost against water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> plot(x2,y2, xlab="Total cost", main = "Plot of Total cost against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> dea.plot(x2,y2, xlab="Total cost", main = "Plot of Total cost against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> plot(x3,y3, xlab="Number of drinking water regulation ", main = "Plot of #Regulation against Water quality score", ylab="Water quality score",

RTS="vrs",ORIENTATION="in-out",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> dea.plot(x3,y3, xlab="Number of drinking water regulation ", main = "Plot of

#Regulation against Water quality score", ylab="Water quality score",

RTS="vrs",ORIENTATION="in-out",add=TRUE,lty="dashed",lwd=2)

> plot(x4,y4, xlab="Number of drinking water regulation ", main = "Plot of #Regulation against Boil water advisories", ylab="Boil water advisories",

RTS="vrs",ORIENTATION="in-out",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> dea.plot(x4,y4, xlab="Number of drinking water regulation ", main = "Plot of #Regulation against Boil water advisories", ylab="Boil water advisories",

RTS="vrs",ORIENTATION="in-out",add=TRUE,lty="dashed",lwd=2)

> plot(x5,y5, xlab="#Monitored ", main = "Plot of #Monitored against Water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> dea.plot(x5,y5, xlab="#Monitored ", main = "Plot of #Monitored against Water quality score", ylab="Water quality score", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

> plot(x6,y6, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)

There were 18 warnings (use warnings() to see them)

> dea.plot(x6,y6, xlab="#Monitored ", main = "Plot of #Monitored against Boil water advisories", ylab="Boil water advisories", RTS="vrs",ORIENTATION="inout",add=TRUE,lty="dashed",lwd=2)