

# A Comparative Approach for Ranking Contaminated Sites Based on the Risk Assessment Paradigm Using Fuzzy PROMETHEE

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**Abstract** A ranking system for contaminated sites based on comparative risk methodology using fuzzy Preference Ranking Organization METHod for Enrichment Evaluation (PROMETHEE) was developed in this article. It combines the concepts of fuzzy sets to represent uncertain site information with the PROMETHEE, a subgroup of Multi-Criteria Decision Making (MCDM) methods. Criteria are identified based on a combination of the attributes (toxicity, exposure, and receptors) associated with the potential human health and ecological risks posed by contaminated sites, chemical properties, site geology and hydrogeology and contaminant transport phenomena. Original site data are directly used avoiding the subjective assignment of scores to site attributes. When the input data are numeric and crisp the PROMETHEE method can be used. The Fuzzy PROMETHEE method is preferred when substantial uncertainties and subjectivities exist in site information. The PROMETHEE and fuzzy PROMETHEE methods are both used in this research to compare the sites. The case study shows that this methodology provides reasonable results.

**Keywords** Site management · Risk assessment · Ranking system · Comparative risk assessment · Fuzzy PROMETHEE

## Introduction

Management of contaminated sites has become a multi-billion dollar industry worldwide. With increasing numbers

of contaminated sites being identified every year combined with the high cost of remediation and, manpower and budgetary limitations, management of these sites has become increasingly cumbersome. Many companies and municipalities own a number of these sites and as they cannot all be remediated at the same time, a scientifically defensible system to prioritize or rank these sites is needed.

Over the past five decades the risk assessment process has undergone significant changes shifting from a qualitative to a more quantitative direction with the increase in knowledge and understanding of the relationships between adverse effects and exposure to various chemicals. Throughout this period several guidance documents on how risk assessments should be conducted have been developed by the various governing bodies worldwide such as the U.S. Environmental Protection Agency (US EPA), Health Canada and Environment Canada. However, these regulatory bodies also indicate that although the assessment process is standardized, the results obtained contain a high degree of conservatism for the purpose of public safety and over-estimate the true risk associated with the site under investigation. While the absolute number obtained from the standardized assessment process provides a means of comparing and ranking several contaminated sites, the *significance* of the number is lost due to the over-estimation (Burmester and Anderson 1993; Bogen and Spear 1987). A relative score, however, obtained through a Comparative Risk Assessment (CRA) process provides site managers with an indication of the degree of risk associated with one site compared to others under investigation (Shatkin and others 2001) and minimizes the negative connotations generated with absolute risk values.

Scarcity and uncertainty in data, measurement errors, conflicting information, and site variation all contribute to complexities in site characterization. Three types of

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uncertainty exist pertaining to site information (Moller and Beer 2004), i.e., informal uncertainty, caused by a lack of information, such as when the number of observations is too small; lexical uncertainty where words such as “high”, “medium” or “low” are used to represent a range instead of a value; and stochastic uncertainties which are essentially random uncertainties. Of the different uncertainty theories, fuzzy set theory was considered to be more suitable for application for the types of uncertainties that exist at contaminated sites. Hence fuzzy PROMETHEE methods (explained later) were used in this article.

The purpose of this article is to develop a ranking system for contaminated sites utilizing CRA methodology where the *risk* identified is not based on absolute quantitative measures but on comparison of predetermined criteria. This article uses the concepts of fuzzy sets to represent uncertain site information and combines it with PROMETHEE such that the fuzzy PROMETHEE method can be used to obtain results that are more reflective of the uncertainties associated with the site data conditions. It will describe the standard human health risk assessment process, alternative relative ranking methods and introduce the application of Fuzzy PROMETHEE under the confines of the risk assessment paradigm. A case study is used to explain this ranking system.

## Ranking Systems

One of the systems that can be used to rank contaminated sites is to determine and use the human health risk posed by a site. The present day risk assessment paradigm is comprised of four components: hazard identification, dose–response assessment, exposure assessment, and risk characterization. *Hazard Identification* being the first step is the process of determining whether exposure to a particular chemical could cause an increase in the incidence of a health condition in human and/or non-human receptors and the associated strength of evidence. The information is obtained primarily through controlled laboratory experiments involving various animal species or through the limited number of epidemiological studies available. *Dose–response assessments* comprise the second step of estimating toxicity and considers factors such as intensity of exposure, age, lifestyle, sex, etc. of the exposed population (Paustenbach 2002; US EPA 1989). The quantitative method utilizes toxicity values such as reference doses (RfD) for non-carcinogenic substances and slope factors (SF) and weight-of-evidence classification for carcinogenic substances to estimate the potential for adverse effects as a function of exposure. In this, a series of uncertainty factors and a modifying factor to account for intra- and inter-species extrapolations and assumptions are used (Schoeny 2007). The *Exposure*

*Assessment* component of risk assessment involves an estimation of the intensity, frequency, duration and route of potential human or animal exposure to the presence of chemicals in various environmental media (i.e., soil, air, water, food). There are uncertainties associated in all these estimates. In order to quantify exposure estimates, chemical intakes are estimated for each possible exposure pathway associated with each form of contaminated media by combining variables such as chemical concentration, contact rate (amount of contaminated medium contacted per unit time or event), exposure frequency and duration, average body weight over the exposure period and the time period over which the exposure is averaged into a single formula. *Risk characterization* being the final stage involves integrating all the information obtained. Since daily human exposure is believed to be relatively low, the slope in the low-dose portion of the dose–response curve is assumed to be linear and thus risk is directly related to intake. The quantification of carcinogenic and non-carcinogenic effects is thereby achieved through the combination of intakes for all exposure pathways and the respective chemical specific slope factor or RfD. As contaminated sites are never single chemical exposures, multiple chemical exposures are accounted for through the concept of additivity. Similarly, the total non-carcinogenic effect (hazard index, HI) is computed through the summation of pathway and chemical specific hazard quotients. In order to deal with the uncertainty and variability that are intrinsically associated with the assessment process, statistical analysis utilizing Monte Carlo simulation is becoming more widely used and in many jurisdictions, required. A rank based on human health risk can be quite comprehensive requiring substantial amount of site-specific data. It may also require contaminant transport investigations and modeling. Additionally, while human health risk is one criterion, ecological risk may also be a concern at many sites. This will add to the level of analysis and will require a separate ecological risk assessment (ERA) to be conducted. Then a method to combine the two risk values also has to be developed.

A number of simpler methods have been presented to rank contaminated sites such as scoring systems (CCME 1992, 2008), partial ordering (Jensen and others 2003) and fuzzy multi-objective decision making (Garg and others 2004) models. Scoring systems consider an additive method, which assigns subjective scores for different parameters that impact the hazard level, exposure pathways and receptors. The total site score when compared to a preset classification system gives a class and possibly a site rank. The CCME (1992, 2008) National Classification System for contaminated sites and the Waste Minimization Prioritization Tool (WMPT) (US EPA 1997) estimate the relative chemical hazard of a site posed based on the most hazardous contaminant known or suspected to be present in the corresponding site but measures

the mass of contaminants using all the chemicals. The Canadian National Classification system is a simple additive system with categories such as contaminant characterization, exposure pathways and receptors. The total scores on a 100-point scale helps determine whether action is required.

In the partial ordering method, different site parameters are compared. If all the parameter values of site A are greater than those of site B then site A is ranked higher than site B. If not, then the sites are not comparable (Jensen and others 2003). A limitation of the CCME and partial ordering methods is the assignment of subjective scores instead of the use of original data. The fuzzy MODM method identifies key objectives such as magnitude of contamination, potential of groundwater contamination, and potential of contaminant migration from sites to receptor locations, toxicity and persistence of contaminants and then uses a rule-based system to evaluate the objectives (Garg and others 2004). The development of the membership functions for each objective is based on expert opinions or published literatures. Thus, uncertainties will be involved, even though some methods have a theoretical basis (Donald 2003; Masson and Denoeux 2006).

WMPT (US EPA 1997) uses a rule-based methodology to prioritize chemicals based on the chemical attributes for the potential human health risk and ecological risk. These attributes include human toxicity, ecological toxicity, bioaccumulation, persistence, and chemical quantity. For human toxicity, the higher toxic chemical is selected based on available criteria, concentration, and dose–response information. The corresponding non-cancer reference dose or slope factor are compared with the pre-determined criteria and determine the “low”, “medium”, and “high” human toxicity. Increasing scores are assigned to these linguistic variables. The advantage of the WMPT is that this method can be carried out even if insufficient data is available. The disadvantage is that the limited scoring system can not adequately identify the difference between the chemicals.

### Multiple Criteria Decision Analysis

Multiple Criteria Decision Analysis (MCDA) is a class of decision-making methodology based on the premise of assisting a decision-maker through the decision process via explicit formalized models (Figueria and others 2005; Roy 2005; Wang and Triantaphyllou 2006). Kiker and others (2005) present a review of the available literature and provide some recommendations for applying different MCDA techniques. These include the Analytical Hierarchy Process (AHP), ELimination and Choice Expressing the REality (ELECTRE), Multiattribute Utility Theory (MAUT), PROMETHEE, and various combinations of these methods.

A detailed analysis of the theoretical foundations of these methods and their associated strengths and weaknesses has been reported by Belton and Stewart (2002). The basic components in any MCDA method include a finite set of actions or alternatives each of which must be explicitly described in terms of criteria or objects that must be simultaneously assessed. Ideally, the integrity of these criteria should be preserved in their original form without any conversion (i.e., equivalencies, weightings, etc.) to maintain their meaning and accurately evaluate their consequences. The results of the assessment (performance values) are typically placed in a decision matrix along with their associated criteria weights. Pair-wise comparisons are then completed to either find the best alternative or rank the alternatives in order of total preference, known as preference modeling (Figueria and others 2005; Ozturk and Tsoukias 2005; Wang and Triantaphyllou 2006). Since the inception of preference modeling, many methods have been proposed and/or expanded to analyze the data of a decision matrix and provide some measure of alternative comparability. Some methods use additive formulas to compute the final priorities such as the weighted sum model, others use pairwise comparisons such as the AHP method (Millet and Wedley 2002; Triantaphyllou and Mann 1995; Wang and Triantaphyllou 2006), or their later versions the multiplicative AHP and weighted product model (Triantaphyllou 2001). Many studies have reported that the AHP methodology produces inconsistent results and rank reversals have been known to occur with alternatives that are closely similar (Dyer 1990; Millet and Wedley 2002; Perez 1995; Triantaphyllou 2001; Triantaphyllou and Mann 1995).

Other methods that are commonly used are the “out-ranking” methods, primarily ELECTRE and PROMETHEE. These methods make use of binary relations on a set of potential actions to develop a preference relation between and within alternatives (Bouyssou 2005; Wang and Triantaphyllou 2006). Implementation of the ELECTRE methods requires either the direct input of preference parameters from the decision maker or indirectly through inference from answers to a series of questions. In either case, an additional source of arbitrariness is introduced to the problem under investigation (Figueria 2005). Wang and Triantaphyllou (2006) have identified similar ranking irregularities as those seen with the AHP methodology and suggest that acceptance of recommendations obtained through the application of ELECTRE be circumspect.

PROMETHEE methods have also evolved since their initial entry into the realm of MCDA. Their ease of use is based on the premise that all the information requested is clear and easy to define, and the method is easy to apply. Brans and Mareschal (2005) acknowledge that incomparability holds for most pairwise comparisons since when one alternative is better on one criterion the other is often

better on another. The PROMETHEE methods provide a means to account for the amplitude of deviations between alternative comparisons, permit each criterion to be expressed in their own units and allow criteria weight allocation to reflect the decision-makers interpretation of the criterion importance to the final result. The decision maker is also able to select the most appropriate indicator for preference based on six types of preference functions. The preference function selected will indicate the appropriate parameters required (indifference threshold, strict preference threshold, intermediate value). Then based on the pairwise comparisons either a partial ranking (PROMETHEE I) is obtained from the preference values or a complete ranking (PROMETHEE II). A complete ranking ensure that all alternatives are comparable. A graphical profile can also be generated for all the criteria that indicate the degree to which the criterion is preferred over the others and vice versa. This information can be used to finalize the decision (Brans and Mareschal 2005). Because of the relative ease combined with the non-manipulation of original data, PROMETHEE presents a valid method for MCDA and are useful in solving problems with conflicting criteria (Kiker and others 2005).

### Criteria Identification

Criteria identification for the PROMETHEE methods requires very clear information that is easily obtained and understood by both decision makers and analysts (Brans and Mareschal 2005). The criteria do not need to be mathematically linked but need to be contributing factors in the decision making process. Each criterion should be self-contained and should be expressed in its own units. This reduces any scaling effects that could affect the outcome. Weighting assigned to the criteria are at the discretion of the decision makers and generally reflect the relative importance of each criteria in the decision making process. For the purposes of ranking sites, all criteria identified are considered to be of equal importance, and thus of equal weighting.

In order to identify the criteria to be utilized, all site characteristics that impact the site rank were identified and are listed in Table 1.

Conversion of these characteristics into criteria is based on the type and relationship of the information available and how the information can be combined. For the process of ranking sites based on health and ecological risk assessment paradigms, twelve criteria have ultimately been selected as significant contributing factors to the assessment process.

Examination of the contaminant characteristics reveals that the combination of concentration and toxicity has a

**Table 1** Site characteristics impacting rank

Contaminant characteristic
Concentration
In soil
In water
Toxicity
Carcinogenic and weight of evidence
Non-carcinogenic
Chemical properties
Volatilization
Persistence
Bioavailability
Volume of contaminated soil
Volume of contaminated surface and/or groundwater
Types of groundcover
Permeable
Impermeable
Mixed
Receptor
Adult
Child
Adult worker
Exposure
Duration
Frequency
Soil characteristics
Hydraulic conductivity
Porosity
Hydraulic gradient

direct impact on health risk and should be combined into criteria. Further separation is required to account for carcinogenicity or non-carcinogenicity resulting in two essential criteria:

#### Criteria 1: Soil Carcinogenic Risk Index (SCRI)

This criteria accounts for the total carcinogenic potency of the contaminants present at the site as well as their carcinogenic weight-of-evidence. Carcinogenic potency is related to the amount of chemical present at the site (mg/kg soil) and the critical dosage for adverse effects (slope factor,  $(\text{mg}/\text{kg}\cdot\text{day})^{-1}$ ). As each carcinogen identified through laboratory experiments or epidemiological studies has a “Weight-of-Evidence” classification attributed to it weights (Carcinogenic Class Impact, CCI) have been assigned to each classification to represent the degree of impact a compound with that classification would have on the overall health risk assessment. The higher the weight, the higher the impact. The classifications, descriptions and associated weights are presented in Table 2.

**Table 2** Weight-of-evidence classification and associated impact values

Weight of evidence		CCI
Class A	Known human carcinogen	1.0
Class B1	Probable human carcinogen with limited evidence in humans	0.8
Class B2	Probable human carcinogen with sufficient evidence in animals but inadequate or no evidence in humans	0.6
Class C	Possible human carcinogen	0.4
Class D	Not classified as human carcinogen	0.2
Class E	Evidence of non-carcinogenicity in humans	0.0
	Not identified as carcinogen in humans or animals	0.0

As many contaminants may be present at any given site in any combination, the individual contributions are considered to be additive in the derivation of the overall Soil Carcinogenic Risk Index (SCRI):

$$SCRI = \sum_{i=1}^n C_{s,i} \times SF_i \times CCI_i \quad (1)$$

where  $C_{s,i}$  is the  $i$ th chemical concentration in soil and  $SF$  is the slope factor.

#### Criteria 2: Soil Non-Carcinogenic Risk Index (SNCRI)

This criteria accounts for the total non-carcinogenic potency of all the chemicals identified within the site, including those classified as carcinogens. Non-carcinogenic potency reflects the magnitude of the adverse effects and is proportional to the chemical concentrations available (mg/kg) and the critical dosage that is known to result in adverse effects (RfD, mg/kg-day). For multiple chemical exposures the individual contributions are considered to be additive, as in the NCRI:

$$SNCRI = \sum_{i=1}^n \frac{C_{s,i}}{RfD_i} \quad (2)$$

The remaining characteristics identified in Table 1 are independent of dosage and are thereby transformed into separate criteria as follows:

#### Criteria 3: Partition Index (PI)

Contaminant transport through media is dependent upon the hydrophobicity/hydrophilicity of the chemical of concern (COC) and the properties of the media itself (i.e., soil moisture, soil organic content, soil texture, pH). Partition coefficients are generally used to describe the distribution of chemicals between two phases (solid–vapor, solid–liquid, liquid–vapor, two immiscible liquids, two solids, etc.) and the environmental fate of organic compounds (LaGrega and others 2001). In order to account for the concentration of the contaminants detected in water samples the soil–water partition coefficient,  $K_d$ , is selected. This distribution

coefficient describes the tendency of an organic chemical to bind preferentially to soil or sediment versus remaining in aqueous media (pore water, groundwater). The higher the  $K_d$  value, the greater the binding of the chemical to the soil and hence, the lower its mobility and potential for groundwater infiltration. The degree of sorption is dependent on the specific chemical's characteristics and when multiple chemicals are involved, each will sorb differently in the same media. To account for the variation, a site specific  $K_d$  value for each chemical is evaluated and proportioned by the fraction of each chemical contributing to the potential risk ranking of the site ( $F_{s,i}$ ).

$$F_{s,i} = \frac{\text{Concentration of contaminant of concern (mg/kg)}}{\text{Total contaminant concentration detected on site (mg/kg)}} \quad (3)$$

The individual contributions are then considered to be additive in the derivation of the Partition Index (PI):

$$PI = \sum_{i=1}^n F_{s,i} \times (K_d)_i \quad (4)$$

#### Criteria 4 & 5: Volume of Contaminated Soil (VCS) and Volume of Contaminated Groundwater (VCW)

The risk ranking associated with a site is dependent upon the vertical and horizontal extent of the contamination. The zones impacted by the spread of contaminants is based on the amount of chemicals released into the environment, the mode of release and the properties of the COC's. Volume estimates are obtained from results of the sampling protocol utilized for each site. If not explicitly provided, the volume of contaminated soil can be derived from the following equation:

$$VCS = \text{Surface area} \times \text{Deepest detected contamination} \quad (5)$$

where the surface area is determined by the maximum length and width distances between surface samples and

the deepest detected contamination. The deepest detected contamination is selected for this criteria and may extend below the groundwater table. This will account for the sorptive tendency of the COC's to soils at all depths.

The volume of contaminated groundwater is similarly evaluated:

$$\text{VCW} = \text{Surface area} \times \text{Depth of contaminated groundwater} \quad (6)$$

where the surface area is represented by plume size or surface sampling distances (as above) and the depth of contaminated groundwater represents the distance between the depth to groundwater and deepest detected contamination within groundwater.

#### Criteria 6: Percentage of Permeable Groundcover

The amount of permeable groundcover will effectively control the level of exposure of a receptor to a contaminant. When dealing with municipalities, a large portion of the property is generally covered with non-permeable material (asphalt, concrete, buildings) and thus exposure to contaminated soil is restricted. However, a portion of those sites is utilized for landscaping and exposure could occur through that region. Residential zoned areas typically have greater permeable groundcover than commercially zoned areas and industrial zoned areas may vary (typically asphalt or gravel depending on the business activity). The percentage allocated will be at the discretion of the decision maker or may be dictated by municipal bylaws (i.e., % allowable permanent building coverage in respective zoning areas).

#### Criteria 7: Exposure Index (EI)

Under traditional risk assessment methods, the type of receptor is the main factor in assessing exposure. The most sensitive receptor is identified for the site under consideration. If an adult and child are exposed to a site (i.e., residential, parkland, agricultural and commercial zonings) the child is the most sensitive receptor. If subject site exposure is restricted to workers, adults are already implied (i.e., industrial zoning). Once the receptor is identified, there are pre-established statistically identified exposure factors associated with them. Thus an Exposure Index criteria is established based on these exposure values based on adult or child receptor and property zoning:

$$\text{EI} = \frac{\text{ED} \times \text{EF}}{\text{BW}} \quad (7)$$

where ED is exposure duration and EF is frequency, and BW is body weight.

#### Criteria 8: Vapor Pressure Index (VPI)

Volatilization of chemicals has a direct impact on inhalation and dermal absorption exposure pathways and thus the greater number of volatile compounds present, the greater the impact. The tendency of a chemical to move from solid or liquid state to a vapor state is given by its specific equilibrium vapor pressure. The vapor pressure of any chemical increases with increasing temperature and therefore the actual volatilization rate will depend on the environmental conditions at the site. However, in the absence of site-specific volatilization rates the effects caused by site conditions (i.e., temperature) can be considered similar for all COC's and thus standardized vapor pressures (@ 20–25°C) can be used. In order to account for the presence of multiple chemicals in a vapor state a Vapor Pressure Index (VPI) is proposed. The index considers the contribution of each COC as additive and therefore proportions each identified COC's contribution to the final value by combining the mass fraction with the associated vapor pressure.

$$\text{VPI} = \sum_{i=1}^n F_{s,i} \times \text{VP}_i \quad (8)$$

where  $\text{VP}_i$  is the vapour pressure for  $i$ th chemical.

#### Criteria 9: Total Groundwater Ubiquity Score (GUS)

Chemical persistence in soil and groundwater media is reflective of the chemicals resistance to degradation mechanisms and sorptive properties. The more resistive to degradation the longer the chemical persists in its original form and when coupled with a low sorption affinity, the greater the potential for leaching into groundwater. The importance of adsorption and persistence for chemicals in soils has been illustrated by Gustafson (1993) through the use of the Groundwater Ubiquity Score (GUS) index. The GUS is calculated as follows:

$$\text{GUS} = \log(t_{1/2}) \times (4 - \log K_{oc}) \quad (9)$$

where  $t_{1/2}$  is the dissipation half-life of the chemicals (days) and  $K_{oc}$  is the organic carbon partition coefficient. The effects of different chemicals are assumed to be additive and thus the total GUS (TGUS) is given by:

$$\text{TGUS} = \sum_{i=1}^n \text{GUS}_i \quad (10)$$

#### Criteria 10: Hydraulic Conductivity

Hydraulic conductivity is a measure of the ability of fractured or porous media to transmit water (Fetter 1999) and

thus is one of several contributing factors that influence the contaminant fate and transport process. This value is readily available based on the site-specific soil analysis or based on soil charts for the area. If site specific measurements have not been performed, standardized values may be applied for typical soil types (sand, gravel, silt, clay, etc.).

#### Criteria 11: Ecological Toxicity Index (ETI)

In evaluating the ecological impact of contaminants in soil, indicator species associated with the site are typically selected for toxicity analysis. The most frequently selected indicator specie is the earthworm *Eisenia fetida* (Weeks 1998). The selection is based on (1) their high rate of exposure to organics and inorganics via feeding and burrowing activities and (2) contribution to diets of animals higher in the food chain (Efroymson and others 1997). Roberts and Dorough (1983) examined the effects of 90 chemicals on *Eisenia fetida* and were able to identify five categories of ecological toxicity:

- super toxic:  $LC_{50} < 1.0 \mu\text{g}/\text{cm}^2$
- extremelytoxic:  $1 \mu\text{g}/\text{cm}^2 < LC_{50} < 10 \mu\text{g}/\text{cm}^2$
- very toxic:  $10 \mu\text{g}/\text{cm}^2 < LC_{50} < 100 \mu\text{g}/\text{cm}^2$
- moderate toxic:  $100 \mu\text{g}/\text{cm}^2 < LC_{50} < 1000 \mu\text{g}/\text{cm}^2$
- relatively non-toxic:  $1000 \mu\text{g}/\text{cm}^2 < LC_{50}$

To adequately represent the toxicity level associated with multiple contaminants, the Ecological Toxicity Index (ETI) is proposed assuming additivity of fractions:

$$ETI = \sum_{i=1}^n (LC_{50})_i \quad (11)$$

#### Criteria 12: Bioconcentration Index (BCI)

There are several terms which describe the accumulation of organic and/or inorganic chemicals within living biota with the difference being in the process by which this occurs: bioaccumulation occurs through exposure to contaminated media, directly (oral, dermal, inhalation pathways) or indirectly (consumption of food containing the chemical); bioconcentration occurs when the contaminant levels within the organism have increased to levels above the surrounding environment; and, biomagnification involves increased exposure through the food chain. Food chain effects serve as important indicators of ecological stress. The common method of evaluating ecological effects are through the comparative assessment of contaminant concentration in living organisms and in the subject sites water and/or soil.

Several transport models have been developed to account for plant-to-soil and plant-to-air bioaccumulation but their

reliability is reportedly limited (McKone and Maddalena 2007). The majority of the models attempt to correlate uptake with the octanol–water partition coefficient,  $K_{ow}$ . However, the results vary with some models indicating a positive correlation and others a negative correlation (Suter and others 2007). One model that depicts soil-to-plant contaminant transfer was developed by Travis and Arms (1988).

$$\text{Log(BCF)} = 1.588 - 0.578\text{Log}(K_{ow}) \quad (12)$$

This model indicates that contaminant uptake by plants is *inversely* proportional to the square-root of the octanol–water partition coefficient ( $K_{ow}$ ) as transport from the roots to the upper portion of the plant is dependent upon the tendency of the contaminant to partition into water. Translocation and bioconcentration into plant tissue follows root uptake and is dependent on the water and lipid content in the plant tissues. McKone and Maddalena (2007) indicate that this empirical model is valid for compounds at  $1 < \log Kow < 9$  and is selected here.

As the contaminants are located in soil and/or groundwater, the most suitable organism for the assessment of bioconcentration is the earthworm (refer to Criteria 11). Several models have been proposed with for various organisms. Connel and Markwell (1990) developed and calibrated bioconcentration model for earthworms based on organic compounds at  $1 < \log Kow < 6.5$  and is selected here.

$$\text{Log(BCF)} = \text{Log}(K_{ow}) - 0.6 \quad (13)$$

As bioconcentration in biota occur concurrently, the Bioconcentration index will be a combination of the two models and additivity of multiple contaminants is assumed.

$$BCI = \sum_{i=1}^n (\log(\text{BCF})_{\text{plant}} + \log(\text{BCF})_{\text{earthworm}})_i \quad (14)$$

#### PROMETHEE and Fuzzy PROMETHEE

The Preference Ranking Organization METHod for Enrichment Evaluation (PROMETHEE) is a subgroup of Multi-Criteria Decision Making Methods developed in the early 1980s by Brans and others (1984) and Brans and Vincke (1985). By 1994 PROMETHEE had been extended to encompass six ranking formats: PROMETHEE I (partial ranking), PROMETHEE II (complete ranking), PROMETHEE III (ranking based on intervals), PROMETHEE IV (continuous case), PROMETHEE V(MCDA including segmentation constraints) and PROMETHEE VI (representation of the human brain). The success of this methodology in various industry applications is attributed to its flexibility and ease of use (Brans and Mareschal 2005).

PROMETHEE methods promulgated by Brans and others (1986) are based on a set of alternatives,  $A =$

$\{a_1, a_2, \dots, a_n\}$  which will be ordered and a set of criteria,  $F = \{f_1, f_2, \dots, f_m\}$ . A pairwise comparison between two alternatives,  $a_i$  and  $a_j$  is made and the intensity of preference of an action  $a_i$  over action  $a_j$  ( $P_k(d_k)$ ,  $d_k = f_k(a_i) - f_k(a_j)$ ) is determined where  $P_k$  is the preference function for the  $k$ th criterion and  $f_k(a_i)$  is the evaluation of alternative  $a_i$  corresponding to criterion  $f_k$ . Brans and others (1986) defined six different types of preference functions. The value of the preference scales range between 0 (no preference) and 1 (strong preference). The preference of action  $a_i$  over  $a_j$  is evaluated for each criterion and the preference function relation  $\pi$  is determined by,

$$\pi(a_i, a_j) = \sum_{k=1}^m w_k P_k(f_k(a_i) - f_k(a_j)), \quad \forall a_i \in A \tag{15}$$

where  $m$  is the total number of criteria,  $w_k \in W = \{w_1, w_2, \dots, w_m\}$  is a weight which is a measure for the relative importance of each criterion. The leaving flow of  $a_i$  is a measure of the alternative preference over all the other alternatives and is given by

$$\phi^+(a_i) = \frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^n \pi(a_i, a_j) \tag{16}$$

where  $n$  is the total number of alternatives. Similarly, the entering flow of  $a_i$  is determined by,

$$\phi^-(a_i) = \frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^n \pi(a_j, a_i) \tag{17}$$

and represents the preference of all the other alternatives over the alternative being examined. The basic premise associated with the entering and leaving flows is that the higher the leaving flow and the lower the entering flow the better the alternative. PROMETHEE I method leads to a partial pre-order which is obtained by comparing the leaving flow and entering flow. For any two alternatives,  $a_i, a_j \in A$ , the preference relation ( $P^I$ ) is identified when  $\phi^+(a_i) \geq \phi^+(a_j)$  and  $\phi^-(a_i) \leq \phi^-(a_j)$ , the indifference relation ( $I^I$ ) is affirmed when  $\phi^+(a_i) = \phi^+(a_j)$  and  $\phi^-(a_i) = \phi^-(a_j)$ , the two alternatives are incomparability ( $R^I$ ) when  $\phi^+(a_i) > \phi^+(a_j)$  and  $\phi^-(a_i) > \phi^-(a_j)$ , or  $\phi^+(a_i) < \phi^+(a_j)$  and  $\phi^-(a_i) < \phi^-(a_j)$  (Brans and Mareschal 2005).

If a complete pre-order is necessary, PROMETHEE II method will be used. It is a total ranking method based on the evaluation of the net flow obtained by subtracting the entering flow from the leaving flow,

$$\phi(a_i) = \phi^+(a_i) - \phi^-(a_i), \quad \forall a_i \in A \tag{18}$$

The higher the net flow the better the alternative. Brans and others (1986) provided an example of the application of the PROMETHEE methods.

For situations when the input information has non random uncertainty, Goumas and Lygerou (2000) extended the PROMETHEE methods to consider fuzzy inputs along with crisp weights. Geldermann and others (2000) made further enhancements and used fuzzy preference and fuzzy weights to obtain fuzzy scores. They both used trapezoidal fuzzy numbers to represent the uncertainties. The advantage in using a trapezoidal fuzzy number is that a specific value, an interval, and a triangular fuzzy number can all be represented by a specific trapezoidal fuzzy number. The fuzzy PROMETHEE algorithm (Geldermann and others 2000) is briefly given below:

Step 1: Define for each criterion  $f_k$ , a suitable preference function  $p_k(d_k)$ .

Step 2: Define a vector containing the fuzzy weights, each in the form of trapezoidal fuzzy numbers:

$$\tilde{w}^T = (\tilde{w}_1, \tilde{w}_2, \dots, \tilde{w}_m) \text{ with } \tilde{w}_k = (m_l^w, m_u^w, \alpha^w, \beta^w)_{LR} \tag{19}$$

Step 3: Evaluate for all the alternatives  $a_i, a_j \in A$  the fuzzy preference relation  $\tilde{\pi}$ :

$$\tilde{\pi}(a_i, a_j) = \sum_{k=1}^m \tilde{w}_k \langle \times \rangle p_k(\tilde{f}_k(a_i) \langle - \rangle \tilde{f}_k(a_j)) \tag{20}$$

with  $\tilde{f}_k(a_i) = (m_l, m_u, \alpha, \beta)_{LR}$  and  $\tilde{f}_k(a_j) = (n_l, n_u, \gamma, \delta)_{LR}$ . The degree of preference for the comparison of alternatives  $a_i$  and  $a_j$  with regard to criterion  $f_k$  was calculated using fuzzy arithmetic,

$$p_k(\tilde{f}_k(a_i) \langle - \rangle \tilde{f}_k(a_j)) = (m_l^{p_k}, m_u^{p_k}, \alpha^{p_k}, \beta^{p_k})_{LR} \tag{21}$$

where  $m_l^{p_k} = p_k(m_l - n_u)$ ,  $m_u^{p_k} = p_k(m_u - n_l)$ ,  $\alpha^{p_k} = p_k(m_l - n_u) - p_k(m_l - n_u - \alpha - \delta)$ , and  $\beta^{p_k} = p_k(m_u - n_l + \beta + \gamma) - p_k(m_u - n_l)$ . The fuzzy outranking relation  $\tilde{\pi}$  is determined by,

$$\tilde{\pi}(a_i, a_j) = (m_l^\pi, m_u^\pi, \alpha^\pi, \beta^\pi)_{LR} \tag{22}$$

where  $m_l^\pi = \sum_{k=1}^m (m_l^{w_k} \cdot m_l^{p_k})$ ,  $m_u^\pi = \sum_{k=1}^m (m_u^{w_k} \cdot m_u^{p_k})$ ,  $\alpha^\pi = \sum_{k=1}^m (m_l^{w_k} \cdot \alpha^{p_k} + m_l^{p_k} \alpha^{w_k} - \alpha^{w_k} \alpha^{p_k})$ , and  $\beta^\pi = \sum_{k=1}^m (m_u^{w_k} \beta^{p_k} + m_u^{p_k} \beta^{w_k} + \beta^{w_k} \beta^{p_k})$ .

Step 4: Accordingly, for each alternative,  $a_i$ , the fuzzy leaving flow of  $a_i$  is calculated as:

$$\tilde{\phi}^+(a_i) = \frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^n \tilde{\pi}(a_i, a_j) \tag{23}$$

Step 5: As a measure of the weakness of the alternatives,  $a_i \in A$ , the fuzzy entering flow of  $a_i$  is determined by:

$$\tilde{\phi}^-(a_i) = \frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^n \tilde{\pi}(a_j, a_i) \tag{24}$$

Step 6: For PROMETHEE I, the fuzzy scores,  $\phi^+(a_i)$  and  $\phi^-(a_i)$  are defuzzified and compared. For PROMETHEE II, the fuzzy scores are aggregated and then defuzzified and compared/ranked.

### Criteria Optimization

Criteria optimization is an essential step in that provides a means of identifying the impact of a given criterion on the overall risk assessment. A criterion is either maximized or minimized based on the action of a specified attribute and should be established prior to implementing the PROMETHEE or Fuzzy PROMETHEE methods. If the higher the value of an attribute, the higher the potential for environmental risk, then the criterion provided with this attribute should be maximized. Accordingly, if the higher the value of an attribute, the smaller the potential for environmental risk, the criterion for this attribute should be minimized and the formula for calculating the difference between alternatives  $a_i$  and  $a_j$  is defined as:

$$d_k = f_k(a_j) - f_k(a_i) > 0 \quad (25)$$

### Criteria Preference Function Selection

Six types of generalized preference functions have been suggested by Brans and others (1986). The decision makers may also model their preferences using any other specifically shaped preference functions. For ranking purposes, the linear preference function Type III (Brans and others 1986) is considered reasonable and is defined by

$$P_k = \begin{cases} \frac{d_k}{p_k} & \text{if } 0 \leq d_k \leq p_k \\ 1 & \text{if } d_k > p_k \end{cases} \quad (26)$$

where  $d_k = f_k(a_i) - f_k(a_j)$ . The intensity of preference,  $P_k$ , increases linearly with the growth of  $d_k$  up to  $p_k$ . After the threshold,  $p_k$ , has been reached the intensity will be equal to 1. The threshold should be identified by the decision maker and once determined, the preference becomes strict. For ranking purpose the parameter  $p_k$  can be set as:

$$p_k = f_k(\cdot)_{\max} - f_k(\cdot)_{\min} \quad (27)$$

where  $f_k(\cdot)$  is the evaluation of all alternatives for criterion  $k$ .

### The Process of Fuzzy PROMETHEE

The fuzzy PROMETHEE algorithm, steps 1 to step 5 above, are performed for each contaminated site. The leaving flow and entering flow for each contaminated site is

then calculated. This is similar to the addition of risks for multiple pathways suggested by US EPA (1989). Step 6 is based on the defuzzification of the total fuzzy leaving flow and entering flow. The defuzzification method selected is based on the the evaluation of the Centre of Area (COA) allowing for consistent evaluation of trapezoidal fuzzy data as well as crisp data (Geldermann and others 2000).

### Case Study

Promethee and Fuzzy Promethee methodology are each applied to four contaminated dry cleaning sites for the purpose of risk ranking. The data for these sites were obtained from profiles available through the USEPA State Coalition for Remediation of Dry Cleaning Sites ([www.drycleancoalition.org/profiles](http://www.drycleancoalition.org/profiles), accessed in 2007).

### Site Description

All of the subject sites were located in commercial or mixed commercial-residential settings; three in the state of Florida (FL, FO, FD) and one located in Oregon (OG). The contaminants identified in soil and/or groundwater samples included tetrachloroethene(PCE), trichloroethene(TCE), vinyl chloride, cis-1,2-dichloroethene, trans-1,2-dichloroethene and 1,1-dichloroethene. Site geology consisted of combinations of silts, clays, sands and limestones located at varying depths. The subject sites located in Florida had depths to groundwater ranging from 2 to 6 feet below ground surface whereas the Oregon site had groundwater depths at 15–20 feet below ground surface. The site specific data available is summarized Table 3.

### Uncertainty Representation

The PROMETHEE method utilizes a single number to represent each criteria entry and thus cannot couple uncertain site information. Variability is not accounted for in cases where a range of values are provided, and professional judgment is required to determine what value should be used (lower or upper, median, mean). In the case of contaminant concentrations, site soil and groundwater sampling always provides a range of values and generally the highest value detected is selected as representative of the entire site. This practice, while providing a conservative estimate may in fact be exaggerating the risk level of that site.

Fuzzy PROMETHEE allows for the use of data in its available form. That is, any data that is provided as a range may be utilized “as-is” and data that is linguistic in nature (“approximately” and “several”) may be interpreted with a range in values. In this article, the associated

**Table 3** Original site information

	Contaminated site							
	OG		FL		FO		FD	
	Soil (mg/kg)	Water (mg/L)	Soil (mg/kg)	Water (mg/L)	Soil (mg/kg)	Water (mg/L)	Soil (mg/kg)	Water (mg/L)
<b>Contaminants</b>								
Tetrachloroethene (PCE)	>1000	2.60	2.88	0.0052	0.92	0.0372	42	
cis-1,2-Dichloroethene	0.0002	3.00	1.43	0.546	0.0002	0.00122	170	
trans-1,2-Dichloroethene	0.0002	0.39	0.0002	0.0002	0.0002	0.0002	0.260	
Trichloroethene (TCE)	0.0002	0.53	0.0962	0.0045	0.0002	0.0032	12	
Vinyl Chloride	0.0002	0.033	0.0108	1.100	0.0002	0.0002	59	
Property Use/Zoning	Commercial		Residential commercial		Residential commercial		Commercial	
Depth to Groundwater (ft bgs)	15–20		2–4		~5		6	
Deepest groundwater contamination (ft bgs)	~30		16		12		75	
Lithology and Subsurface Geology	Clayey silt and fine sand (0–15 ft); sandy gravel (15–45 ft); basalt (>45 ft)		Fine-grained silty sands with some clay (<48 ft); sandy clay with silt & shell fragments (48–53 ft)		Fine to med sand (<5 ft); weathered limestone (5–8 ft); med-coarse sand and limestone gravel (15–25 ft)		Fine to med quartz sand with limestone stringers (<46 ft); fine to med sand (46–62 ft); coquina (62–68 ft); fine sand and sandstone with limestone stringers (68–84 ft)	
Conductivity (ft/day)	22–491		0.6–2.4		105		92	
Plume size	Several hundred feet long, 100 ft wide, 30 ft deep		125 ft × 35 ft		80ft × 60 ft × 12 ft		1350 ft × 1000 ft	

uncertainties are then incorporated by treating the representative criteria entry as a trapezoidal fuzzy numbers,  $(m_l, m_u, \alpha, \beta)_{LR}$  where  $[m_l, m_u]$  is the certainty interval, i.e. the membership value is equal to 1, with  $m_l$  and  $m_u$  as lower and upper boundaries, respectively.  $\alpha$  and  $\beta$  are the left and right spread of the trapezoidal fuzzy number. When  $m_l = m_u$ , a trapezoidal fuzzy number becomes a triangular fuzzy number. A crisp number can be represented as  $m_l = m_u = n$  and  $\alpha = \beta = 0$  and an interval is represented as  $[m_l, m_u]$  and  $\alpha = \beta = 0$ .

### Evaluation of Criteria Performance

The maximization/minimization of each criterion is determined based on its potential influence on human and ecological risk. Criteria 1–2, Criteria 4–10 and Criteria 12 are all to be maximized as higher values lead to higher potential risk. Criteria 3 and 11 are to be minimized since the highest potential risk associated with these is when the numerical values are small. For example, Criteria 3 (Partition Index) represents the tendency for contaminants to bind to soil rather than enter into water. Thus, the higher the  $K_d$  value the less risk associated with groundwater contamination. Since protection of groundwater is a priority, the lower the  $K_d$  value the higher the risk associated with the site. Thus, Criteria 3 is to be minimized. The data used to evaluate the criteria performance are given in Table 4 (PROMETHEE) and Table 5 (Fuzzy PROMETHEE). The original data provided in Table 3 are a combination of crisp values (singletons) and ranges.

For the conventional PROMETHEE method, crisp values were used as reported whereas the ranges were modified based on professional judgment; the shallowest depth

to ground water was selected due to the greater potential risk for contaminant infiltration, and the average conductivity was used.

For the Fuzzy PROMETHEE evaluation, where crisp values are provided, a triangular fuzzy number is assumed with the most likely range being  $\pm 10\%$  of the crisp value. Wherever ranges are provided,  $\alpha = 0.1m_l$  and  $\beta = 0.1m_u$  were used. This was done assuming that even though single values (or ranges) are reported, the actual field data will vary by  $\pm 10\%$  of the reported values. If all of the data were available, however, the minimum and maximum values obtained from the samples analyzed would be utilized to more accurately represent the conditions at the site under investigation.

### Results and Discussion

Two computer programs in EXCEL<sup>®</sup> were written to implement the PROMETHEE and the Fuzzy PROMETHEE methods.

Using the PROMETHEE program developed and “crisp” data from Table 3, each criteria identified before, are listed in Table 4. The preference of each criteria over the others was then evaluated, summed and weighted to obtain the preference indices for each site. As all the criteria were considered to be of equal importance in the assessment, an equal weighting was assumed for each criteria. While this introduces subjectivity into the overall scheme, in the absence of any definitive influence of one criterion over another the selection of equal weightings would be a standard assumption. These values are placed in a preference index table indicating the preference of one site over the other (Table 6).

**Table 4** PROMETHEE criteria evaluations

Criteria	Max or Min	Contaminated sites (actions)				Preference parameter, $p$
		OG	FL	FO	FD	
1 Soil Carcinogenic Risk Index (SCRI)	Max	324	0.954	0.298	12.45	323.7
2 Soil Non-Carcinogenic Risk Index (SNCRI)	Max	83333.3	495.918	76.667	6994.73	83256.7
3 Partition Index (PI) (l/kg)	Min	384.62	362.42	17.342	0.812	383.8
4 Volume of Contaminated Soil (ft <sup>3</sup> )	Max	2100000	70000	57600	101250000	101192400
5 Volume of Contaminated Water (ft <sup>3</sup> )	Max	1050000	61250	33600	93150000	93116400
6 Percentage of permeable groundcover	Max	18	18	18	90	72
7 Exposure Index, EI	Max	68.18	95.46	95.46	68.18	27.27
8 Vapor Pressure Index (mmHg)	Max	18.35	86.33	18.33	27.42	68.0
9 Total GUS (Groundwater Ubiquity Score Index)	Max	37.09	28.93	28.93	37.09	8.16
10 Hydraulic conductivity	Max	256	1.5	105	92	254.5
11 Ecological Toxicity Index (ETI)	Min	14	179	14	119	165
12 Bioconcentration Index (BCI)	Max	2.25	7.46	2.25	5.90	5.21

**Table 5** Fuzzy PROMETHEE criteria evaluations

Criteria	Max or Min	Contaminated sites (actions)			FD	Preference parameter, <i>p</i>
		OG	FL	FO		
1 Soil Carcinogenic Risk Index (SCRI)	Max	[324, 324, 87.8, 107.2]	[0.94, 0.97, 0.25, 0.32]	[0.3, 0.3, 0.08, 0.1]	[12.05, 12.85, 3.27, 4.25]	431
2 Soil Non-Carcinogenic Risk Index (SNCRI)	Max	[71429, 100000, 13571, 21000]	[418.21, 755.27, 79.46, 158.61]	[65.71, 92 12.49, 19.32]	[5053.12, 14908.67, 960.1, 3130.8]	120988.62
3 Partition Index (PI) (l/kg)	Min	[384.62, 384.62, 132.27, 178.5]	[362.42, 362.42, 124.64, 168.2]	[17.34, 17.34, 5.96, 8.05]	[0.81, 0.81, 0.28, 0.38]	562.59
4 Volume contaminated soil (ft <sup>3</sup> )	Max	[1250000, 3150000, 237500, 661500]	[70000, 70000, 13300, 14700]	[57600, 57600, 10944, 12096]	[101250000, 101250000, 19237500, 21262500]	122465844
5 Volume contaminated water (ft <sup>3</sup> )	Max	[250000, 1800000, 205000, 724500]	[52500, 61250, 12337, 15750]	[28800, 38400, 9792, 13344]	[93150000, 93150000, 19156500, 21343500]	114474492
6 Percentage of permeable groundcover	Max	[1, 35, 0.1, 3.5]	[1, 35, 0.1, 3.5]	[1, 35, 0.1, 3.5]	[90, 90, 9, 9]	98.1
7 Exposure Index (EI)	Max	[68.18, 88.4, 6.82, 8.84]	[68.18, 148.52, 6.82, 14.85]	[68.18, 148.52, 6.82, 14.85]	[68.18, 88.40, 6.82, 8.84]	102.01
8 Vapor Pressure Index (mmHg)	Max	[18.2, 18.5, 4.93, 6.12]	[84.73, 88.3, 22.96, 29.23]	[18.18, 18.48, 4.93, 6.12]	[26.79, 28.48, 7.26, 9.43]	104.28
9 Total GUS	Max	[38.01, 38.01, 3.8, 3.8]	[29.85, 29.85, 2.99, 2.99]	[29.85, 29.85, 2.99, 2.99]	[38.01, 38.01, 3.8, 3.8]	14.95
10 Hydraulic conductivity	Max	[22, 491, 2.2, 49.1]	[0.6, 2.4, 0.06, 0.24]	[105, 105, 10.5, 10.5]	[92, 92, 9.2, 9.2]	539.56
11 Ecological Toxicity Index (ETI)	Min	[11, 17, 1.1, 1.7]	[156, 225, 15.6, 22.5]	[11, 17, 1.1, 1.7]	[102, 139, 10.2, 13.9]	237.6
12 Bioconcentration Index (BCI)	Max	[2.09, 2.42, 0.21, 0.24]	[6.79, 8.00, 0.68, 0.80]	[2.09, 2.42, 0.21, 0.24]	[5.36, 6.32, 0.54, 0.63]	6.92

For example, OG is preferred over FL by 0.419 whereas FL is preferred over OG by 0.255. The total leaving and entering flows provides a measure of outranking and out-ranked characteristics for each contaminated site and are obtained by averaging the sum of the preference index values in the rows and columns, respectively. The net flow ( $\Phi^{net}$ ) provides the overall outranking characteristic of the site and is the resultant difference of  $\Phi^+$  and  $\Phi^-$ . The greater the leaving flow and the lesser the entering flow, the greater the net flow and hence the higher the overall preference of the alternative. A negative net flow can be obtained and is indicative of an alternative that is primarily outranked by all other alternatives for each criterion. Final ranking is then achieved by a numerical sort from highest to lowest net flow. The results for the Traditional PROMETHEE method are also presented in Table 6.

Using the Fuzzy PROMETHEE program developed and trapezoidal/triangular representations of the data provided in Table 3, each of the criteria identified are listed in Table 5. The same procedure was followed as for the traditional method to obtain the fuzzy preference indices, fuzzy leaving and entering flows, and fuzzy net flow. These results are presented in Table 7.

The fuzzy net flow for each contaminated site is illustrated in Fig. 1.

Several approaches have been proposed for ranking fuzzy numbers (Wang and others 2005; Detyniecki and Yager 2001; Dubois and Prade 1999; Lee and others 1994) with the most of them transforming the fuzzy number into a real number. Geldermann and others (2000) suggests that the Center-of-Area (COA) approach provides a more reasonable result than others such as Mean of Maximum or Maxima-Method and allows a consistent evaluation of trapezoidal/triangular fuzzy data as well as of crisp data. The COA method was selected for defuzzification of the resulting fuzzy entering and leaving flows and is determined by (Geldermann and others 2000):

$$x_{defuzzified} = \frac{\int x\mu(x)dx}{\int \mu(x)dx} = \frac{m_u^2 - m_l^2 + \alpha m_l + \beta m_u + (\beta^2 - \alpha^2)/3}{\alpha + \beta + 2m_u - 2m_l} \quad (28)$$

**Table 6** PROMETHEE preference indices

$\pi(S_i, S_j)$	OG	FL	FO	FD	$\phi^+$	$\phi_{net}$	Rank
OG	–	0.419	0.302	0.263	0.328	0.055	2
FL	0.255	–	0.167	0.180	0.201	–0.163	4
FO	0.163	0.192	–	0.141	0.165	–0.130	3
FD	0.400	0.481	0.416	–	0.433	0.238	1
$\phi^-$	0.273	0.364	0.295	0.195			

**Table 7** Fuzzy PROMETHEE preference indices and defuzzified entering, leaving, and net flow

$\pi(S_i, S_j)$	OG	FL	FO	FD	$\phi^+$	Defuzzified $\phi_{net}$	Rank
OG	–	[0.209, 0.376, 0.071, 0.147]	[0.158, 0.292, 0.064, 0.114]	[0.129, 0.249, 0.033, 0.110]	[0.165, 0.306, 0.056, 0.124]	0.039	2
FL	[0.109, 0.225, 0.038, 0.105]	–	[0.106, 0.222, 0.034, 0.094]	[0.051, 0.147, 0.031, 0.067]	[0.088, 0.198, 0.034, 0.089]	–0.132	4
FO	[0.054, 0.168, 0.021, 0.065]	[0.116, 0.237, 0.027, 0.090]	–	[0.032, 0.112, 0.006, 0.030]	[0.067, 0.172, 0.018, 0.062]	–0.114	3
FD	[0.279, 0.355, 0.074, 0.143]	[0.307, 0.397, 0.103, 0.140]	[0.279, 0.349, 0.094, 0.115]	–	[0.289, 0.367, 0.090, 0.133]	0.207	1
$\phi^-$	[0.147, 0.249, 0.044, 0.104]	[0.211, 0.337, 0.067, 0.126]	[0.181, 0.288, 0.064, 0.108]	[0.071, 0.169, 0.024, 0.069]			
$\phi_{net}$	[–0.084, 0.158, 0.161, 0.168]	[–0.248, –0.013, 0.160, 0.156]	[–0.221, –0.008, 0.126, 0.126]	[0.119, 0.296, 0.159, 0.156]			

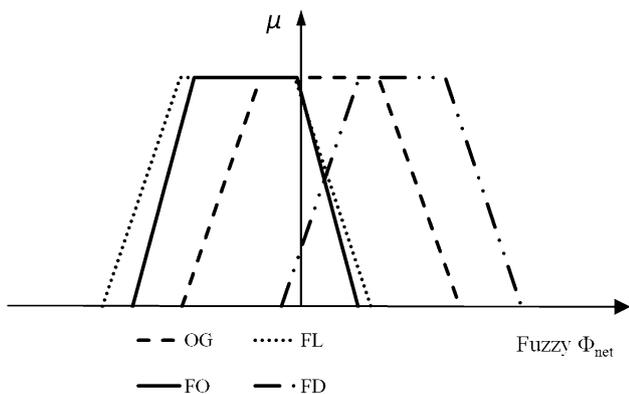


Fig. 1 Fuzzy net flows

where  $\mu$  is the membership function for a trapezoidal fuzzy number. The defuzzified net flows are also provided in Table 7 along with subsequent ranking of the subject sites. The ranking results and the associated uncertain information pertaining to each contaminated site are illustrated in Fig. 2 using box-and-whisker plots.

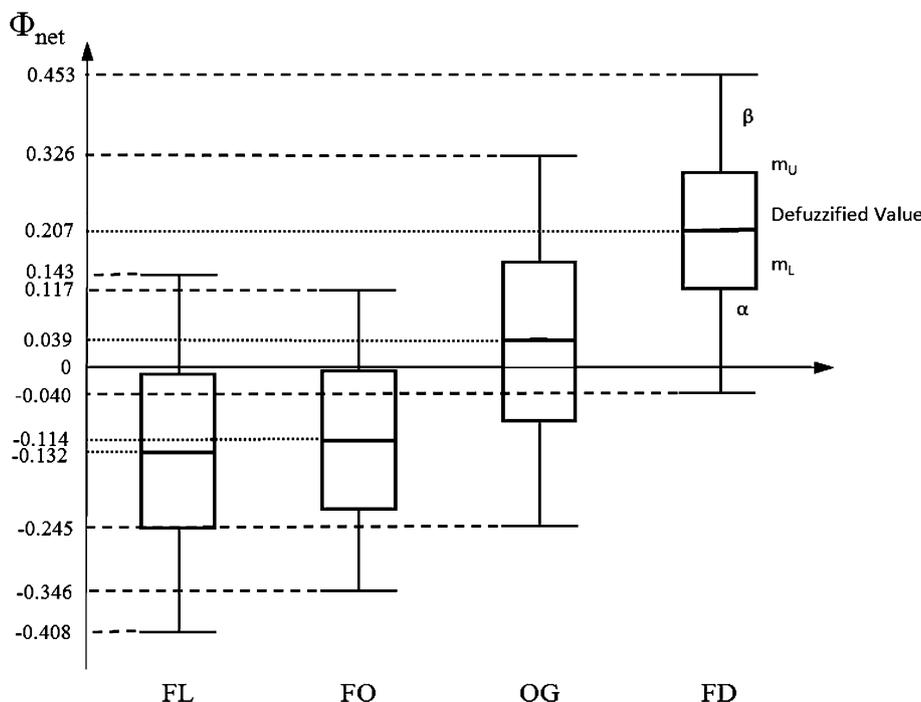
The outrankings obtained for these four sites based on PROMETHEE II and Fuzzy PROMETHEE II based on defuzzified net flows were the same:  $FD \rightarrow OG \rightarrow FO \rightarrow FL$ , where FD was ranked first (highest potential risk) and FL was ranked last (least potential risk). Examination of the original data would intuitively provide the same result as FD has in essence the highest contaminant concentration in soil and groundwater, the highest concentration of a known human carcinogen present in an

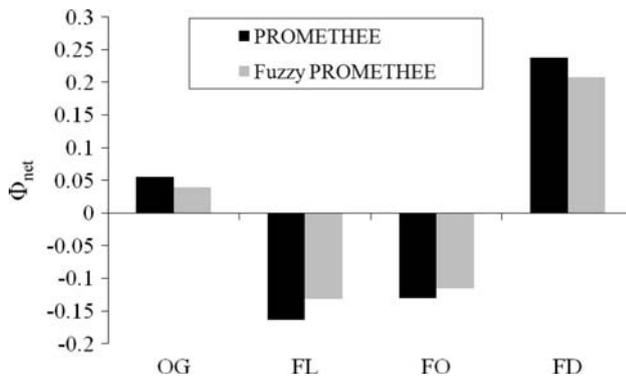
extremely large sized plume that is close to the surface and contamination that reaches to great depths. Information for FD from the State Coalition for Remediation of Dry Cleaning Sites also indicated that the facility had been demolished, so a 90% permeable surface was assumed. OG has the next highest concentration of contaminants present in both soil and groundwater, the next largest plume size, the next largest deepest groundwater contamination but larger depth to groundwater from surface. At first glance the parameter values for FL & FO would tend to indicate FL to be more potentially risky than FO. However, closer examination would reveal that FO could be more potentially risky based on contaminant transport phenomena. Thus, FL and FO are considered close in rank and depending on the interpretation of the data by the decision maker, the final ranking could be either  $FO \rightarrow FL$  or  $FL \rightarrow FO$ .

The final net flow values obtained from the Fuzzy PROMETHEE and the traditional PROMETHEE methods are provided in Fig. 3 for comparison.

Both the PROMETHEE and Fuzzy PROMETHEE methods provide the same final ranking of the contaminated sites, but the  $\Phi^{net}$  values derived by each of the methods are not. This is attributed to more site information being incorporated into the Fuzzy PROMETHEE evaluation. For example, when the sites are compared based only on the upper bounds ( $m_u + \beta$ ) their ranks are different compared to when the COA defuzzified values are used (see Fig. 2). However, in this case, the absolute differences between the traditional methods and fuzzy methods for the different contaminated sites are not that significant (see Fig. 3).

Fig. 2 Box-and-whisker plots of fuzzy net flows





**Fig. 3** Comparison of net flows derived from PROMETHEE and fuzzy PROMETHEE

This may be due to size of the data set and/or the high degree of similarity between the sites examined (e.g., same contaminants, similar data reporting) given that the principle of PROMETHEE is based on comparative differences. The net flow values are much closer when Fuzzy PROMETHEE is utilized for sites FL and FO. This corresponds with the intuitive observations of the initial data where the ranking of FL and FO would be close. While this case may also indicate that the use of average values magnified the difference between the sites it is equally possible that using crisp data may artificially decrease the difference between sites. Thus, when there is substantial uncertainty in the data Fuzzy PROMETHEE should be the preferred methodology. If all criteria have crisp known values, then traditional PROMETHEE methods should be employed.

## Conclusions

A flexible and simple multicriteria ranking system for contaminated sites based on comparative risk methodology is proposed. A number of criteria for risk ranking is developed. The criteria are identified based on the combination of attributes (toxicity, exposure, and receptors) associated with the potential human health and ecological risks of contaminated sites, site- and chemical-specific properties and contaminant transport phenomena. The PROMETHEE and fuzzy PROMETHEE methods are used to compare the sites. The use of the PROMETHEE avoided the assignment of numeric scores to a multi-dimensional problem. When the input data are numeric and crisp the PROMETHEE method can be used. The Fuzzy PROMETHEE method can be used when substantial uncertainties and subjectivities exist in site information.

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