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A multi-attribute methodology for oil contaminated land prioritisation in the Niger Delta

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ABSTRACT:

The Ogoniland region of the Niger Delta contains a vast number of sites contaminated with petroleum hydrocarbons that originated from Nigeria's active oil sector. The United Nations Environment Program (UNEP) reported on this widespread contamination in 2011, however, wide-scale action to clean-up these sites has yet to be initiated. A challenge for decision makers responsible for the clean-up of these sites has been the prioritisation of sites to enable appropriate allocation of scarce resources. In this study, a risk-based multi-criteria decision analysis framework was used to prioritise high-risk sites contaminated with petroleum hydrocarbons in the Ogoniland region of Nigeria. The prioritisation method used a set of attributes relevant to the Niger Delta region that took into account chemical and ecological impacts, as well as socio-economic impacts, which provided a holistic assessment of the risk. Data for the analysis was taken from the UNEP Environmental Assessment of Ogoniland. Over 110 communities were affected by oil-contaminated land, of which eight sites were contaminated with petroleum hydrocarbons in excess of five times the regulatory threshold.

Results from our prioritisation show that the highest-ranking sites were not necessarily the sites with the highest observed level of hydrocarbon contamination. This differentiation was due to our consideration of the likelihood to which a receptor might be exposed to the hazard. Composite measures as such provide a more robust assessment of risk, which can be used to guide decision makers responsible for taking action to allocate resources to manage and clean-up affected sites.

Keywords: Oil contamination, hydrocarbons, Niger Delta, risk-based prioritisation, Ogoniland

1 Introduction

Hydrocarbon contaminated sites in the Niger Delta region of Nigeria are commonplace due to over five decades of oil exploitation activities (UNEP, 2011; Ite et al., 2013; Sam et al., 2015). Attempts to address the problem of hydrocarbon contamination has been constrained by a lack of expertise and capacity (Ajai, 2010; Eneh, 2011), weak regulatory agencies (Ambituuni et al., 2014; Sam et al., 2015), and poor legislative policies and management frameworks (Ajayi and Ikporukpo, 2005; Sam et al., 2016). Immediate attention to clean-up these sites is needed, however, similar to other nations (e.g. UK, France, Netherlands, Australia) (Liedekerke et al., 2014), Nigeria lacks the necessary funds to address all contaminated sites accordingly (Ambituuni et al., 2014; Sam et al., 2016). In order to tackle this problem, decision-makers must prioritise their clean-up activities to maximise the benefit derived from limited funds (Harold et al., 2014; Guo et al., 2016).

Site prioritisation is a complex task that must integrate information about a multitude of socio-economic and physical factors. Prioritisation frameworks are often founded on risk-based principles that assess the likelihood that a hazard will have an adverse impact on a receptor (DEFRA, 2011). By comparing and contrasting these risk scores, decision makers are able to determine priorities. Various countries employ risk-based approaches to prioritise their contaminated sites for remediation (e.g. the UK, Australia, Canada and the USA) (Nathanail et al., 2013; Pizzol et al., 2015, Stewart, 2015).

Problem definition is the first stage of a risk assessment and involves the setting of boundary conditions, the identification of potential receptors, and determination of a link between receptor and exposure (DEFRA, 2011). For contaminated land, a variety of potential receptors must be considered, including controlled water bodies, the public, or an agricultural product, e.g. cassava, fish (Wcisło et al., 2016). A receptor's exposure to a contaminated site hazard (e.g. petroleum hydrocarbon) will be influenced by a number of factors such as ecology (Mayes et al., 2009), population density or proximity to a site (Alvarez-Guerra et al., 2009), or land use (Zabeo et al., 2011). Exposure will also be influenced by the character of the hazard, in particular the contaminant levels, toxicity, and hydrophobicity (Alvarez-Guerra et al., 2009: 2010), we well as soil characteristics such as organic fraction, porosity, and soil make-up (Carter et al., 2006; Brassington et al., 2007; Jiang et al., 2016). Decision makers must also consider broader socio-economic concerns, e.g. economic resources, social acceptance of remediation decisions, availability of expertise (Apitz and White, 2003; Alvarez-Guerra et al., 2009). Which elements to include in a prioritisation framework will depend on the needs of the decision-maker, but more importantly, will be influenced by the availability of data.

When considering multiple sites decision makers need to objectively assess and compare a variety of physical and socio-economic attributes in a single, unified framework. Multi-criteria decision analysis (MCDA) techniques (see Table 1) are a family of frameworks that are commonly used to evaluate decisions that comprise multiple attributes (Zabeo et al. 2011; Rosén et al. 2015; Thokala et al. 2015). In general, these techniques enable decision-makers to evaluate options through a process of ranking alternatives based on a set of defined attributes (Alvarez-Guerra et al. 2010; Pizzol et al. 2011; Lin et al. 2016). Beneficially, MCDA techniques can accommodate different types of data (e.g. qualitative and quantitative) (Rosén et al., 2015), which is useful when considering both the physical and socio-economic aspects of a decision (Linkov et al., 2009, 2015). MCDA techniques provide a structure for organising and integrating data, thus they are flexible and able to accommodate different types of data (Rosén et al., 2015). For example, Bello-Dambatta et al., (2009) used the analytic hierarchy process (AHP) technique to organise contaminated land data for prioritisation decisions; while Sorvari and Seppala (2010) adopted the multi-attribute value theory (MAVT) approach to structure data for risk management options decisions. Alvarez-Guerra et al. (2010) used MCDA to prioritise high risk sites with the aim of allocating limited resources, while Vučijak et al., (2016) used multicriteria optimization and compromise solutions to select the optimum solid waste management scenario. Impetus to prioritise sites in nearly all instances can be attributed to a need to allocate limited resources effectively (Semenzin et al., 2007; Stefanopoulos et al., 2014; Pizzol et al., 2015). For a summary of MCDA techniques applied to environmental management studies see Table 1.

Table 1: Application of MCDA techniques and the unique attributes considered to address complicated environmental decisions

Application area	Method	Attributes considered	Citation
Flood management	Spatial probabilistic multi-criteria decision making (SPMCDM)	Flood depth, velocity, cost and duration	Ahmadisharaf et al., (2016)
Sustainability of contaminated land remediation approaches	Sustainable Choice Of Remediation (SCORE) MCDA	Sediment, cultural heritage, social profitability, health and safety, local acceptance, environmental quality, groundwater, and flora and fauna	Rosén et al., (2015)
Soil function evaluation	MCDA	Non-recyclable waste, non-renewable natural resources, air, surface water and equity	Volchko et al., (2014)
Waste management	VIKOR + AHP	Recovery of raw materials, annual operation cost, employment, maintenance and emissions to environment	Vučijak et al., (2016)
Contaminated land management	AHP	Regulatory obligation, cost effectiveness, technical efficacy, societal considerations and wider environment	Bello-Dambatta et al., (2009)
Contaminated land management	MAVT	Risk reduction, ecological risks, groundwater quality, soil loss, emission to air and energy consumption	Sorvari and Seppala, (2010)
Ground water protection	MAVT	Groundwater, cost, realisation time, measure efficiency and income	Stefanopoulos et al., (2014)
Water protection	PROMETHEE	Investment cost, operating cost, risk to water resources, feasibility	Kuang et al., (2015)
Land management	ELECTRE + GIS	Impacts, air quality, accessibility, noise, climate. landslide, view and technical works	Joerin and Musy, (2000)
Contaminated land management	MAUT	Flood control, wetland habitat, water supply, recreation, hydropower, interior drainage and groundwater	Prato, (2003)

(PROMETHEE: Preference Ranking Organisation Method for Enrichment Evaluations; ELECTRE: ELimination and Choice Expressing Reality; MAUT - Multi-Attribute Utility Theory).

MCDA requires data sets to support each identified attribute. If objective data is not available, subjective data can be used, but this introduces an element of uncertainty to the assessment (Hyde, 2006; Coelho et al., 2016). Data to characterise contaminated sites is often limited, particularly information that links the likelihood of harm to a receptor. One approach to address this data shortcoming is to develop a proxy for likelihood, for example, by determining the proximity of a receptor to a hazard (Kingsley et al., 2015). To this end, geographic information systems (GIS) have been used to assess the distance between a hazard and a receptor to determine the likelihood that a receptor will be exposed to a hazard (definition of risk) (Zabeo et al. 2011; Pizzol et al. 2016).

1.1 Contaminated sites in the Niger Delta

The Niger Delta region is situated in southern Nigeria at the apex of the Gulf of Guinea. The region comprises nine States with a total surface area of 112,110 km^2 and a population of approximately 31 million people (NDDC, 2014; Figure 1). The population is highly reliant on the land and natural resources for their livelihoods, which includes subsistence farming and fishing (Chinweze et al., 2012). Settlements across the region largely consist of small and scattered hamlets. The Niger Delta region contains considerable oil reserves that have made the region the active hub for oil extraction and processing in Nigeria for the past 50 years (OPEC, 2015). Over this period, oil spills caused by engineering failure, oil theft, pipeline vandalism and natural factors have resulted in land contamination (Kadafa, 2012; Anejionu et al., 2015; Onojake et al., 2015), which in turn has impacted human health, groundwater, soil functionality, and ecological systems (UNEP 2011; Pegg and Zabbey 2013; Duke 2016; Obinaju and Martin 2016).

Clean-up costs in the region are estimated to range between US $500 million and US $1 billion, which will be used to treat sediments (watercourses, creeks and tributaries), groundwater (wells and aquifers), and soils (farmlands and residential areas) (UNEP, 2011). Although the current scale of land contamination in the region is difficult to quantify (Duke, 2016), over 2000 sites that require remediation were estimated to exist as of 2008 (Ite et al., 2013). In 2011, at the request of the Nigerian Government, the United Nations Environment Programme (UNEP) confirmed that over 200 locations in Ogoniland were contaminated

(UNEP, 2011). Despite knowledge of crude oil contamination there is no evidence to date to indicate that clean-up has commenced in the region (Könnet, 2014).

Risk based multi-criteria decision analysis frameworks have been used previously to prioritise contaminated sites (Linkov et al., 2005), however, few attempts have been made to prioritise sites in developing regions, particularly in regions with access to limited contaminated land data. We address this gap by developing a multi-attribute value theory (MAVT) framework to prioritise contaminated sites in the Ogoniland region of Nigeria. Our approach is an attempt to overcome the limitation of insufficient data and in doing so, provide decision makers with a pragmatic solution for the determination of priority.

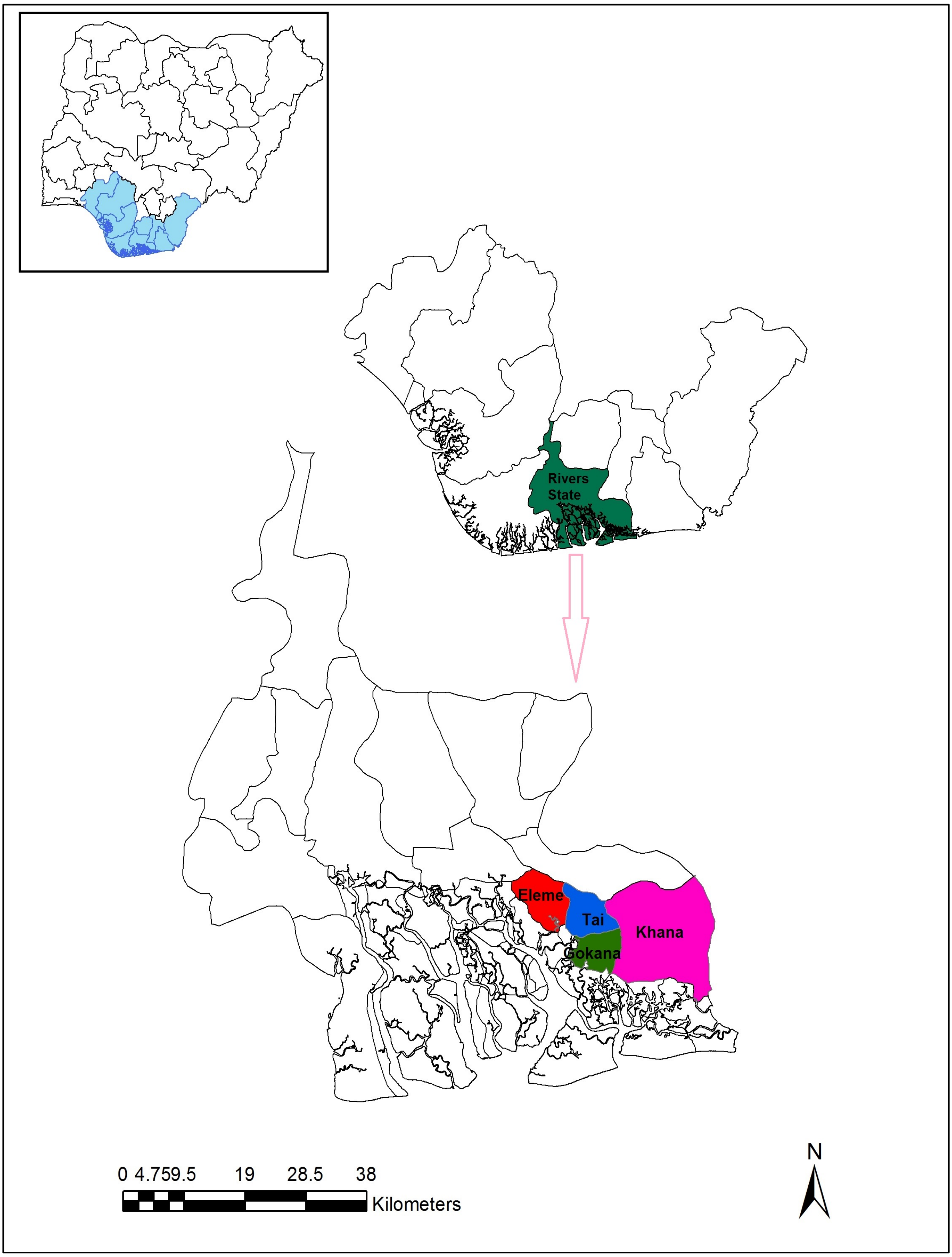

Figure 1: Map describing the region of study. Contaminated sites are located within the Rivers State and spread across the Khana, Gokana, Tai and Eleme regions in Ogoniland.

2 Materials and Methods

A nine-step multi-attributes decision making technique was adopted for the study, as shown in Figure 2. The first step was to define the decision problem **(Step 1)**. Soil and groundwater in Ogoniland are affected to different degrees by oil spills, and have different impacts on environmental and socio-economic values, associated with soil and water quality (e.g. drinking water, fishing and farming). To assess these impacts, the study used the UNEP published data that assessed oil contamination levels in soil and water at 200 locations in the Ogoniland, Niger Delta region (UNEP, 2011). Data included concentrations of total petroleum hydrocarbons (TPH) in soil and groundwater in 66 of the locations that were investigated by UNEP. The data included GIS information for each site location e.g. Eastings (WGS 84, Zone 32N) 294542 and Northings (WGS 84, Zone 32N) 53224 (Ajeokpori-Akpajo), which was used to identify each site. In **Step 2**, risk was characterised. Sites were characterised based on the level of contamination measured in soil and water. Sites were grouped according to their exceedance of Nigerian regulatory standards (Mayes et al., 2009), which were defined by the Environmental Guideline and Standards for Petroleum Industry in Nigeria (EGASPIN). Sites that exceeded regulatory thresholds were considered for prioritisation, those that did not were removed (Table 2). This was because under current Nigerian regulation, no action is needed where there is no exceedance of regulatory thresholds (DPR, 2002).

Table 2: Impact categories for soil and groundwater contamination and their scores

Impact category	TPH in soil (mg/kg)	TPH in groundwater (µg/l)	Level of contamination
< EGASPIN level	< 5000 (25)*	<600 (12)*	Not contaminated
(1× - ≤ 2×)	1-10000 (27)*	1-1200 (3)*	Very low contamination
(2× - ≤ 3×)	10001-15000 (1)*	1201-1800 (2)*	Low contamination
(3× -≤ 4×)	15001-20000 (3)*	1801-2400 (1)*	Medium contamination
(4× - ≤5×)	20001-25000 (2)*	2401-3000 (2)*	High contamination
> 5×	> 25000 (8)*	>3000 (30)*	Very high contamination

(*Numbers in bracket represent number of sites within each category for soil and groundwater contamination)

(EGASPIN - the Environmental Guideline and Standards for Petroleum Industry in Nigeria)

An added benefit of this approach is that it helps decision makers to identify sites that could receive similar treatment interventions when deciding on remediation techniques (Alvarez-Guerra et al., 2009; Mayes et al., 2009).

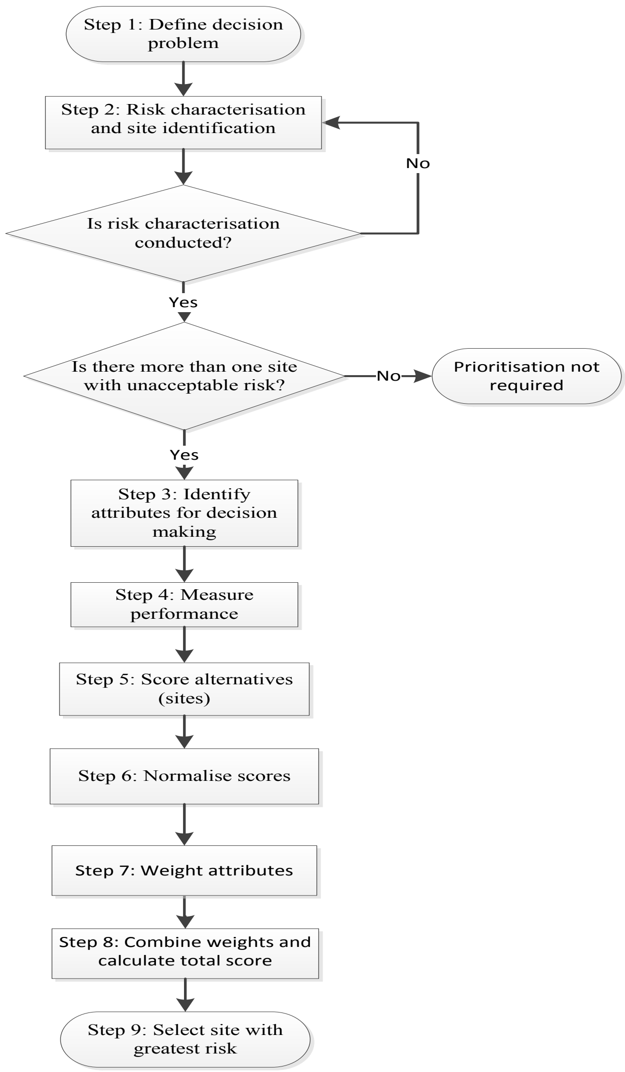

Figure 2: Steps taken to develop the MCDA framework

The next step was to identify the attributes to be used for site evaluation (**Step 3**). Attribute selection can be completed by reviewing previous decisions processes or by speaking with stakeholders (Thokala et al., 2015). Attributes chosen included farmland, residential area, river, surrounding communities and contaminant level. Attributes were chosen for this study based on the availability of data (e.g. contaminant levels, surrounding communities) and the preferences of stakeholders living in the area (e.g. farmland, water, public health) (Table 6). Preferences were determined through a series of engagement studies conducted with stakeholders (21 interviews and 2 workshops attended by 35 persons in August 2015) who lived and worked in the Niger Delta region (Sam et al, 2016 unpublished data). The attributes provided a holistic assessment of risk, encompassing economics (farmlands), environment (rivers), and human health (residential), while contaminant levels provided information about the severity of the risk and surrounding communities inferred scale (taken from UNEP, 2011).

For attributes representing a receptor (i.e. farmlands, rivers, residential area) the likelihood of exposure was determined. Proximity of a receptor (attribute) to a contaminated site was used as a surrogate for likelihood of exposure. The premise of this approximation was that the closer a receptor is to a contaminated site, the more likely that receptor is to be exposed to contamination and thus, is at greater risk (Sorvari et al., 2006; Kuehn et al., 2007; Pizzol et al., 2016). For this approximation to hold valid, it was assumed that the spread of contamination was constant, regardless the type of media (e.g. soil, water, air). The approach proposed in this study is a pragmatic compromise given the availability of the data.

Precedence for the use of proximity exists in the literature. Pizzol et al. (2016) used distance between regional centres and brownfields to demonstrate the likelihood of exposure of receptors to risk i.e. the longer the distance the lesser the likelihood and consequent risk to receptors. Suffo and Nebot (2016) used proximity to determine territorial risk on industrial sites to vulnerable receptors such as human health and the environment. Similarly, Kuehn et al. (2007) and Zabeo et al. (2011) used proximity to indicate the likelihood of exposure of human and environmental receptors to contaminated land risks.

Following the identification of attributes, each site was scored based on contamination levels and proximity data (**Step 4**). Data to describe the maximum concentration of contaminants was available for 66 sites (missing data for one site). A global positioning system (GPS) was used to collect the coordinates for receptors (residential areas, rivers and farmlands) near the contaminated sites similar to the approaches of Keisler and Sundell, (1997) and Sánchez-Lozano et al., (2013). Proximity data was determined by measuring the distance between a receptor and a contaminated site. This was done by inputting the provided contaminated site coordinates, and the estimated receptor coordinates into a GIS software (ArcGIS v. 10.3.1). From this information the distance between hazard and receptor was calculated.

Proximity data was next converted into a derived score to simplify comparison (**Step 5**). This was done by categorising proximity scores into five groups, each of which was assigned a score on a five-point scale (Mayes et al., 2009; Thokala et al., 2015). The scale used to score the attributes is shown in Table 3 and is similar to the approach used by Sorvari et al. (2006).

Table 3: Attributes scoring system and normalisation process

Distance to receptor (m)	Number of surrounding communities	TPH levels	Consequences	Scores	Normalised values
0-100	≥5	>25000	Very High	5	0.33
101-500	4	20001-25000	High	4	0.26
501-1000	3	15001-20000	Medium	3	0.20
1001-3000	2	10001-15000	Low	2	0.13
>3000	1	1-10000	Very Low	1	0.06

Attribute values were normalised to provide a common numerical scale that would enable comparison of attributes (**Step 6**) (Bello-Dambatta et al., 2009; Pizzol et al., 2016; Zabeo et al., 2011).

Weights were assigned to each attribute (**Step 7**). Weight selection was arbitrary, determined primarily based on stakeholder preferences taken from previous stakeholder engagement studies (Sam et al., 2015) and from literature (Thokala et al., 2015). Previous findings have shown that contaminated land stakeholders in the region placed the greatest value on farmlands, and this was due to the economic value that farming provided to the community, as well as its contribution to the local food chain (UNEP, 2011; Pegg and Zabbey, 2013; Fentiman and Zabbey, 2015). However, weightings are subjective and serves the need of the decision makers and thus are adjustable to suit contextual preferences (Adhikary et al., 2013). Based on the context of this study, the needs and values of the public, Table 4 constituted attributes considered for contaminated land prioritisation in the region. Table 4 indicates an example of attributes that could support contaminated land decisions in the region. Contaminant levels were determined to be as important as farmland. These weights reflect the values of the decision maker, and enabled the assessment of the performance of each attribute on an option (site) leading to the calculation of the total score.

Table 4: Attributes and weights

Attributes	Description	Weight
Farmland	Proximity of the nearest farmland to a contaminated site	4
Residential area	Proximity of the nearest residential area to a contaminated site	2
River	Proximity of the nearest of river to a contaminated site	2
Contaminant level	The level of hydrocarbon contamination at each site	4
Surrounding communities	Number of communities that surround a contaminated site	2

A total risk score was calculated for each option (i.e. sites) using Equation 1 (**Step 8**), which aggregated attribute scores to provide a final value for each site. (Zabeo et al., 2011). Preference scores S for option *i* and attribute *j* are multiplied by the weight for each attribute Wj, for *n* attributes, and the overall score for each option, *Si,* is given by:

$$S_i = W_1S_{i1} + W_2S_{i2} + \cdots + W_nS_{in} = \sum_{j=1}^{n} W_1S_{i1} \qquad \text{Equation 1}$$

A final ranking of sites was constructed guided by the total score derived (**Step 9**) and this information was used to support the prioritisation exercise.

A sensitivity analysis was conducted to assess the effect that different attribute weightings might have on the final output. A stochastic approach was used whereby individual attributes weights were varied while the ratios between the weightings of the other attributes remained constant (Sorvari and Seppala, 2010; Brookes et al., 2014). Variability in weights involved reducing and increasing the original weight of attributes, however these weights were restricted between four (highest weight) and one (lowest weight), to provide a limit for the sensitivity analysis. The aim of this analysis was to identify crossover points where the rankings of the contaminated sites might change (Stefanopoulos et al., 2014).

3 Results and Discussion

3.1 Site characterisation

Comprehensive site investigation and characterisation are essential for the prioritisation of contaminated site clean-up (Mayes et al., 2009). For this study, detailed information about site characterisation was provided in the UNEP's report on contamination in the Ogoniland region (2011). This report described sixty-six sites that contained soil and water contaminated with hydrocarbon pollution (Table 5). Despite this data, a complete risk assessment that included receptor identification and assessment of the likelihood of exposure was not conducted. Without a risk-based assessment, priortitisation was not possible, and any subsequent prioritisation activities would have been limited to a ranking based solely on hydrocarbon contaminant levels.

Of the sixty-six hydrocarbon contaminated sites identified in the UNEP report, 62% (or forty-one sites) were contaminated with TPH levels in soil that exceeded the EGASPIN minmum threshold for action (5000 mg/kg). Among these sites, 23% were contaminated to levels that exceeded this minimum threshold by a factor greater than five, thus demonstrating the severity of the contamination. Hydrocarbon contamination in groundwater was reported at fifty sites and 76% of these sites exceeded the EGASPIN threshold for contaminated groundwater. Among these sites, 60% were contaminated with TPH levels that exceeded thresholds by a factor greater than 5, again demonstrating the severity of the problem (Table 2).

If limited to only the data on contaminant levels, a priority ranking for clean-up would identify the following top five sites (in descending order of contaminant level): Debon-Bodo/Mogho, Nweekol-Kegbara Dere, Gior-K.Dere, Barabeedom Dere (009), and Baranyonwa Dere/Gio. Similarly, a priority ranking based on contaminated levels in groundwater would identify the following sites for treatment: Korokoro, Kpite/Biara, Boobanabe-K.Dere (012), Wiikayako-Kpean, and Sivibiragbara-Bodo. Prioritsiation of this manner produced ten different sites that would require clean-up and no single site would be deemed a priority from both the soil and groundwater perspectives. If a decision was made using this information alone, multiple sites would require treatment, which would increase costs, likely generate debate about which attribute, soil or groundwater, is most important, and raise concerns about whether or not the risks to public are actually being reduced.

Of the sites identified in the UNEP report, most are in close proximity to oil extraction facilities, which would increase the likelihood of hydrocarbon contamination (Anejionu et al., 2015). The oil extraction sector in Ogoniland suffers from frequent small volume spills that often result from mechanical errors, engineering failures, or artisanal wells and refining (Onojake et al., 2015). In all instances, these small spills can escalate into larger spills that affect multiple receptors. Spills can originate from any aspect of oil extraction, processing, and transport, which comprises an integrated existence with the local population (Fentiman and Zabbey, 2015) and thus the contaminated sites are distributed across the region. As a result, contamination indiscriminately affects farmlands, residential areas, and waterways (Kadafa, 2012; Anejionu et al., 2015; Elum et al., 2016). Prioritisation must therefore differentiate between the level of risk that is posed to the public given the variable character of each site.

In general, all identified sites were situated within 0.08 km of either farmlands, residential areas or rivers. Nigerian regulation does not stipulate a threshold for distance between receptors and contaminated sites. In the USA, the United States Environmental Protection Agency (USEPA) uses distance to assess whether or not a receptor is at risk. For example, any receptor that is within a distance of 61m of a contaminant site is deemed at risk (USEPA, 2016).

Table 5: Location, soil and water contaminated levels for the sixty-six sites investigated by UNEP (UNEP, 2011)

Local council	Site Name	Soil TPH level (mg/kg)	Groundwater TPH level (µg/l)
Eleme	Ajeokpori-Akpajo	7570	1720
	Nsisioken-Agbi	7310	86100
	Omunwannwan-Sime	36900	133000
	Okuluebu-Ogale (001)	9220	3590
	Oboolo (003)	15300	25100
	Aluejor-Onne	442	10
	Nkeleoken-Alode	4220	16500
	Obaji Oken-Ogale	13200	NA
	Ogale	3740	NA
	Okenta-Alode (006)	11100	NA
	Okponandonwa-Alode	126	11600
	New Elelenwa M/F-Akpajo	629	9540
	Aleto	13400	NA
	Ebubu/Ejama/Agbeta	533	13200
	Ochanni-Ebubu	814	12
	Okenogban-Alode	2950	NA
	Okenta-Alode (007)	5810	NA
	Okenta-Alode (009)	7370	NA
	Nsioken Akpajo	3680	427
	Oboolo (002)	10400	1980
	Okuluebu-Ogale (002)	8580	2740
Gokana	Bera (002)	34500	32000
	Bera (001)	10400	116000
	Boobanabe-K.Dere (046)	NA	NA
	Boobanabe-K.Dere (012)	29600	588000
	Nweekol-Kegbara Dere	63800	3410
	Bera/Kpor	23200	NA
	Sivibiragbara-Bodo	1400	277000
	Kegbara Kpor	3480	10300
	Gbogozor-Bodo	331	NA
	Sibari-Gbe	1220	49
	Vuruvuru Dere	10500	NA
	Nweekol Dere	2640	NA
	Nweekol/Zorbuke K.Dere	7620	NA

	Barabeedom Dere (009)	43600	NA
	Barabeedom Dere (007)	14600	43900
	Saanako-Mogho	9990	109000
	Nweemuu Saanako-Mogho	389	4770
	Gior-K.Dere	52200	29600
	Peeteeh-K.Dere	28300	5650
	Debon-Bodo/Mogho	139000	172000
Khana	Wiibusuu-Kpean	20400	288
	Wiiboora-Kpean	198	519
	Wiieborsi-Kpean	8830	NA
	Wiikaragu-Kpean	157	2140
	Kwawa	8820	77000
	Wiikayako-Kpean	8200	358000
Tai	Aabue Korokoro (001)	14200	769
	Bara-Alue	9200	1760
	Kporghor/Gbam (001)	6210	130000
	Kpite/Biara	34100	1140000
	Bara Akpor-Botem	12300	162000
	Muuborgbara-Kpite/Biara	23100	74700
	Buemene-Korokoro (003)	10800	22600
	Buemene-Korokoro (004)	4860	47
	Buemene-Korokoro (010)	6700	340
	Aabue Ueken-Korokoro	1880	42800
	Guileeh-Korokoro	567	10
	Korokoro	4030	1180000
	Kpite (001)	9030	213000
	Kpite (002)	1040	10900
	Aabue Korokoro (007)	11200	NA
	Kporghor/Gbam (009)	5620	NA
	Baranyonwa Dere/Gio	39200	543
	Gbene-Ue Dor-Um	2930	26900
	Kebara-Kira	645	53

(Numbers in brackets are used to differentiate the same sites with multiple samples; NA: not available)

3.2 Attribute scoring for each site

Risk was defined as the likelihood that a receptor might be exposed to a hazard. The hazard in this instance were petroleum hydrocarbons and the likelihood that a receptor might be exposed to the hazard was defined by the proximity of a receptor to a contaminated site (Thokala et al., 2015). Chosen attributes served two purposes: first, they represented receptors shared by all sites in the region, and second, they represented stakeholder values relevant to the region. Decisions that rely on a single measure of risk (e.g. contaminant levels) might not capture the complexity of a contaminated land issue. For example, contaminant levels do not convey the importance of farmland to a community, particularly a community that relies on agriculture as its primary source of income and nutrition, such as those included in this study (Pegg and Zabbey, 2013; Elum et al., 2016). Selecting holistic attributes that provide economic, environmental, and social perspectives could provide decision makers with information to inform cleanup strategies that are beneficial to communities on multiple levels. Results from the assessment are presented in Table 6.

Table 6: Sites performance based on each attribute

Site Name	Surrounding Communities	Farmland (m)	Residential (m)	River (m)	Soil Contamination (mg/kg)
Kporghor/Gbam (009)	3	300	320	148	620
Okenta-Alode (007)	1	222	335	3784	810
Kporghor/Gbam (001)	2	2990	3159	2097	1210
Buemene-Korokoro (010)	2	541	400	720	1700
Nsisioken-Agbi	9	1245	1081	2516	2310
Okenta-Alode (009)	1	336	147	4002	2370
Ajeokpori-Akpajo	6	6524	6494	5235	2570
Nweekol/Zorbuke K.Dere	1	820	687	1373	2620
Wiikayako-Kpean	3	2460	2518	2889	3200
Okuluebu-Ogale (002)	3	675	375	236	3580
Kwawa	3	1898	1382	1523	3820
Wiieborsi-Kpean	3	555	753	617	3830
Kpite (001)	2	520	618	276	4030
Bara-Alue	2	797	979	1219	4200
Okuluebu-Ogale (001)	3	5270	5608	629	4220
Saanako-Mogho	4	395	322	116	4990
Oboolo (002)	2	260	171	1195	5400
Bera (001)	1	225	423	531	5400
Vuruvuru Dere	1	311	300	234	5500
Buemene-Korokoro (003)	4	518	839	3167	5800
Okenta-Alode (006)	2	320	275	1894	6100
Aabue Korokoro (007)	1	176	120	1165	6200
Bara Akpor-Botem	3	99	954	574	7300
Obaji Oken-Ogale	3	310	167	1316	8200
Aleto	2	178	156	135	8400
Aabue Korokoro (001)	3	80	668	3825	9200
Barabeedom Dere (007)	2	352	696	1916	9600
Oboolo (003)	2	3275	3062	3268	10300
Wiibusuu-Kpean	4	757	1079	213	15400
Muuborgbara-Kpite/Biara	2	3498	3289	2652	18100
Bera/Kpor	1	499	1151	2182	18200
Peeteeh-K.Dere	4	451	354	116	23300
Boobanabe-K.Dere (012)	2	400	277	198	24600
Kpite/Biara	3	3985	3551	4453	29100
Bera (002)	1	3339	3611	1523	29500
Omunwannwan-Sime	2	3825	2614	5082	31900
Baranyonwa Dere/Gio	2	932	1218	849	34200
Barabeedom Dere (009)	3	329	1356	1747	38600
Gior-K.Dere	6	3489	3233	770	47200
Nweekol-Kegbara Dere	5	2038	833	2165	58800
Debon-Bodo/Mogho	1	1447	590	1035	134000

(Numbers in brackets next to site names are used to differentiate the same sites with multiple samples). m – meters.

3.3 Ranking the sites using MCDA

A prioritised list of contaminated sites is presented in Table 7. The results show a wide distribution of scores, suggesting the heterogeneity of contamination in the region. The top ranked site was Peeteeh K-Dere, which is located within the Gokana local council, covers 16.44 ha of land, and is located less than 0.5 km from four communities (UNEP, 2011). Evidence that describes the scale and severity of oil contamination in the region exists. Fentiman and Zabbey (2015) have shown that oil contamination has reduced soil functionality in the region, which has reduced agricultural production. The authors point to diminish cassava production, a staple food, to illustrate this impact. They also report on fish kills and the destruction of fish breeding mangrove swamps, attributed to oil contamination, as contributing factors to the reduction of fish yields. These effects are not observed in isolation. Unable to produce their own food, individuals have been forced to seek alternative nutritional options (Elum et al., 2016), which has proven difficult given the economic circumstances of individuals reliant on agricultural production (Okoli and Orinya, 2013; Oyebamiji and Mba, 2013).

Peeteeh K-Dere would not have been the highest ranked site if prioritisation was based on contaminant levels alone. Peeteeh K-Dere is a priority site because of the impact that contamination has had on the socio-economic foundation of the local communities. Current cleanup practices in the Niger Delta prioritise sites based solely on contaminant levels (UNEP, 2011). This finding represents a significant shift in how sites could be prioritised and managed in the Niger Delta. The implications are clear; future clean-up actions in the Niger Delta, specifically Ogoniland, should include consideration of the socio-economic factors that define the livelihoods and well being of all stakeholders in the region. In addition, this finding should inform policy development in the region to ensure that decision-making on site prioritisation is based on risk-based approaches, rather than on contaminant levels alone. Such policy will foster effective collaboration among decision-makers as the selection of attributes will be dependent on the interest of all stakeholder groups. In general, the integration of a composite of factors provides a holistic determination of risk that single value assessments are unable to provide (Prpich et al., 2011).

The density of oil extraction activities and their proximity to communities had an affect on the ranking. Tai and Gokana councils own the highest number of contaminated sites in the region, but they also have the greatest density of oil wells and pipelines (e.g. Trans Niger crude oil pipeline) (Akinbami and Abiona, 2014; Onojake et al., 2015). Leaking pipelines in the region, due to corrosion, fatigue, and aging, have been a major contributor to hydrocarbon contamination (Lindén and Pålsson, 2013; Ukpaka, 2013; Onojake et al., 2015). Gokana council is also located along the coastline and therefore closer to the gulf with its numerous oil extraction facilities (UNEP, 2011; Fentiman and Zabbey, 2015). These unique features of the local councils make them vulnerable to substantial spills from oil exploration and extraction activities.

The goal of the MCDA framework was to use the available data to provide a holistic and systematic assessment of contaminated sites in the Niger Delta region and to provide a defensible approach to support decisions about the allocation of limited resources for remediation action. The results are supported by studies done by other researchers who have identified notoriously contaminated sites such as Peeteeh-K.Dere and Boobanabe-K.Dere (Tanee and Albert, 2011; UNEP, 2011).

Table 7: Performance matrix showing attribute weighted score for each site (TPH in soil)

Site Name	Surrounding communities	Farmland	Residential	River	Soil contamination	Total score
Peeteeh-K.Dere	0.52	1.04	0.52	0.52	1.04	3.64
Boobanabe-K.Dere (012)	0.26	1.04	0.52	0.52	1.04	3.38
Barabeedom Dere (009)	0.40	1.04	0.26	0.26	1.32	3.28
Nweekol-Kegbara Dere	0.66	0.52	0.40	0.26	1.32	3.16
Baranyonwa Dere/Gio	0.26	0.80	0.26	0.40	1.32	3.04
Wiibusuu-Kpean	0.52	0.80	0.26	0.52	0.80	2.90
Saanako-Mogho	0.52	1.04	0.52	0.52	0.24	2.84
Bara Akpor-Botem	0.40	1.32	0.40	0.40	0.24	2.76
Gior-K.Dere	0.66	0.24	0.12	0.40	1.32	2.74
Kporghor/Gbam (009)	0.40	1.04	0.52	0.52	0.24	2.72
Debon-Bodo/Mogho	0.12	0.52	0.40	0.26	1.32	2.62
Aleto	0.26	1.04	0.52	0.52	0.24	2.58
Okuluebu-Ogale (002)	0.40	0.80	0.52	0.52	0.24	2.48
Aabue Korokoro (001)	0.40	1.32	0.40	0.12	0.24	2.48
Bera/Kpor	0.12	1.04	0.26	0.26	0.80	2.48
Obaji Oken-Ogale	0.40	1.04	0.52	0.26	0.24	2.46
Vuruvuru Dere	0.12	1.04	0.52	0.52	0.24	2.44
Oboolo (002)	0.26	1.04	0.52	0.26	0.24	2.32
Bera (001)	0.12	1.04	0.52	0.40	0.24	2.32
Okenta-Alode (006)	0.26	1.04	0.52	0.26	0.24	2.32
Wiieborsi-Kpean	0.40	0.80	0.40	0.40	0.24	2.24
Buemene-Korokoro (010)	0.26	0.80	0.52	0.40	0.24	2.22
Kpite (001)	0.26	0.80	0.40	0.52	0.24	2.22
Barabeedom Dere (007)	0.26	1.04	0.40	0.26	0.24	2.20
Kpite/Biara	0.40	0.24	0.12	0.12	1.32	2.20
Omunwannwan-Sime	0.26	0.24	0.26	0.12	1.32	2.20
Aabue Korokoro (007)	0.12	1.04	0.52	0.26	0.24	2.18
Buemene-Korokoro (003)	0.52	0.80	0.40	0.12	0.24	2.08
Bera (002)	0.12	0.24	0.12	0.26	1.32	2.06
Okenta-Alode (007)	0.12	1.04	0.52	0.12	0.24	2.04
Okenta-Alode (009)	0.12	1.04	0.52	0.12	0.24	2.04
Bara-Alue	0.26	0.80	0.40	0.26	0.24	1.96
Nsisioken-Agbi	0.66	0.52	0.26	0.26	0.24	1.94
Nweekol/Zorbuke K.Dere	0.12	0.80	0.40	0.26	0.24	1.82
Wiikayako-Kpean	0.40	0.52	0.26	0.26	0.24	1.68
Kwawa	0.40	0.52	0.26	0.26	0.24	1.68
Muuborgbara-Kpite/Biara	0.26	0.24	0.12	0.26	0.80	1.68
Kporghor/Gbam (001)	0.26	0.52	0.12	0.26	0.24	1.40
Okuluebu-Ogale (001)	0.40	0.24	0.12	0.40	0.24	1.40
Ajeokpori-Akpajo	0.66	0.24	0.12	0.12	0.24	1.38
Oboolo (003)	0.26	0.24	0.12	0.12	0.52	1.26

(Numbers in brackets are used to differentiate the same sites with multiple samples; NA: not available)

3.4 Sensitivity analysis

Uncertainty is most likely to be introduced in data that involves the use of subjective judgment (Hyde, 2006). A sensitivity analysis was conducted to ascertain the impact that uncertainty associated with the attribute weightings might have on the final decision outcomes. Results from the sensitivity analysis were limited to the top five ranked sites and are presented in Table 8. Modifying the weightings for farmland, surrounding communities, residential area and river attributes changed the ranking outcomes. Reducing the weighting for the farmland attribute from 4 to 2 and 1 caused a crossover between the originally ranked second (Boobanabe-K.Dere 012) and fourth (Nweekol-Kegbara Dere) sites. A crossover was also observed when the weighting for surrounding communities was increased from 2 to 4, which resulted in the second (Boobanabe-K.Dere 012) and fourth (Nweekol-Kegbara Dere) ranked sites being changed (Table 8). It was also observed that a change in the weight of river and residential area from 2 to 1 resulted in Boobeedom Dere 009 and Boobanabe-K.Dere 012 swapping ranks. Based on these results, the sensitivity analysis shows that farmland, surrounding communities, and rivers and residential area (slightly) changed the ranking, but did not reveal a scenario whereby the highest priority site (Peeteeh-K. Dere), and the lowest priority site (Baranyonwa Dere/Gio) changed rankings. The lack of variability in the results suggests that the prioritisation method is robust, but that it is also sufficiently sensitive to reflect subtle changes in how decision makers might value (i.e. assign weights to) different attributes. Sensitivity analysis is one approach used to validate MCDA models. MCDAs incorporate subjective weightings that will vary dependent on the different viewpoints of stakeholders, and therefore outputs (i.e. priorities) are not static. Uncertainty, in the form of differing viewpoints, cannot be reduced and this represents both a strength and a weakeness of MCDA methods. On one hand, MDCAs provide decision makers with a multitude of outlooks that can be used to inform a decision, but on the other hand, myriad of perspectives introduces uncertainty that might encumber the decision process.

Table 8: Sensitivity analysis illustrating changes in the ranking of the top five sites.

Attribute	Weight	Site ranking 1	2	3	4	5
Farmland	4	PKD	BKD	BBD	NKD	BDG
	3	PKD	BKD	BBD	NKD	BDG
	2	PKD	NKD	BKD	BBD	BDG
	1	PKD	NKD	BKD	BBD	BDG
Surrounding communities	4	PKD	NKD	BBD	BKD	BDG
	3	PKD	BKD	NKD	BBD	BDG
	2	PKD	BKD	BBD	NKD	BDG
	1	PKD	BKD	BBD	BDG	NKD
River	4	PKD	BKD	BBD	NKD	BDG
	3	PKD	BKD	BBD	NKD	BDG
	2	PKD	BKD	BBD	NKD	BDG
	1	PKD	BBD	BKD	NKD	BDG
Residential area	4	PKD	BKD	BBD	NKD	BDG
	3	PKD	BKD	BBD	NKD	BDG
	2	PKD	BKD	BBD	NKD	BDG
	1	PKD	BBD	BKD	NKD	BDG
Contaminant level	4	PKD	BKD	BBD	NKD	BDG
	3	PKD	BKD	BBD	NKD	BDG
	2	PKD	BKD	BBD	NKD	BDG
	1	PKD	BKD	BBD	NKD	BDG

Ranking key PKD – Peeteeh-K.Dere (red); BKD – Boobanabe-K.Dere 012 (amber); BBD – Boobeedom Dere 009 (yellow); NKD – Nweekol-Kegbara Dere (light green); BDG – Baranyonwa Dere/Gio (Green). Broken lines represent weights used for decision making.

3.5 Implications for decision makers

The MCDA approach proposed in this study provides decision makers with the holistic and objective perspectives necessary to make multi-dimensional decisions about contaminated sites. The approach is flexible, able to accommodate different types of data inputs and decision outcomes, and could be used to support decisions about other contamination issues. Care must be taken to control for bias that might be introduced through the inclusion of attributes or the subjective assessement of weightings. For example, decision makers in Nigeria's Zamfara state need to clean-up artisanal gold mining sites contaminated with lead, which have been linked to the death of over 400 children (Bello et al., 2016; Tirima et al., 2016). Risks that involve children are highly emotive, which is likely to bias clean-up decisions by leading assessors to overestimate risk (Alemayehu, 2015; Kim et al., 2015). A transparent MCDA can mitigate this bias by using a suite of risk attributes that includes risk posed to children (e.g. proximity of contamination to schools, play areas, or residences). In this instance, a broader assessment of risk can be provided, but stakeholders can still reflect their preferences (i.e. risks to children) through the weightings. This approach does not eliminate uncertainty, nor bias, but it does improve the quality of discussions about risk and contaminated land.

Ranking sites solely on the presence or level of hydrocarbon contaminants in the soil assumes that the exposure of a receptor to different contaminated sites is equivalent, but is there a risk to a receptor if that receptor is not exposed to a contaminated site? By using proximity as a surrogate for exposure, this study was able to overcome this issue and provide decision makers with a method to prioritise contaminated sites based on risk levels, rather than contaminant levels.

Despite this benefit, the results should not be taken as the final decision for clean-up, but rather as an additional piece of information that can support decisions about contaminated land clean-up. For decision makers seeking to optimise their expenditure, additional considerations might be necessary to identify correlated benefits (Cox, 2008). This information might include the consideration of an area's socio-economic status, or its environmental sensitivity. By enriching the decision context, decision makers could identify sites for which clean-up might generate knock-on effects that improve the economy or environment. In this manner, decision makers could optimise risk reduction expenditure, while providing broader societal benefit.

Site investigation data for the area is now over five years old, and during this time it would be reasonable to expect that new contamination events have occurred and for sites that have not experienced additional contamination, it is reasonable to expect TPH levels to be reduced due to natural attenuation or weathering processes (Brassington et al., 2007; Jiang et al., 2016). Site investigations should be conducted routinely to validate conditions, but these activites are expensive. Prioritisation rankings can be used to facilitate this activity by targeting analysis to those sites that are deemed the most risky, which would avoid the costs associated with full-scale re-assessment of all contaminated sites.

4 Conclusion

In sum, this research is the first attempt to compare and prioritise the disparate contaminated sites of Ogoniland, as identified in the UNEP report. In this study we presented an MCDA framework that was used to assess the risk that oil contaminated sites posed, despite the lack of available data. The framework considered multiple receptors (e.g. farmlands, rivers, communities) and used the proximity of a receptor to oil contaminated site as a surrogate for exposure. The top sites identified for clean-up were Peeteeh-K.Dere, Boobanabe-K.Dere, Barabeedom Dere, Nweekol-Kegbara Dere, Baranyonwa Dere/Gio. Nigeria currently uses contaminant levels to determine priority, which would have provided a different list of priorities. Our approach provides an objective, holistic perspective of risk that could be used by decision makers to initiate cleanup activities, specifically the allocation of resource.

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