Applying Air Pollution Modelling within a Multi-Criteria Decision Analysis Framework to Evaluate UK Air Quality Policies

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Abstract

A decision support system for evaluating UK air quality policies is presented. It combines the output from a chemistry transport model, a health impact model and other impact models within a multi-criteria decision analysis (MCDA) framework. As a proof-of-concept, the MCDA framework is used to evaluate and compare idealised emission reduction policies in four sectors (combustion in energy and transformation industries, non-industrial combustion plants, road transport and agriculture) and across six outcomes or criteria (mortality, health inequality, greenhouse gas emissions, biodiversity, crop yield and air quality legal compliance). To illustrate a realistic use of the MCDA framework, the relative importance of the criteria were elicited from a number of stakeholders acting as proxy policy makers. In the prototype decision problem, we show that reducing emissions from industrial combustion (followed very closely by road transport and agriculture) is more advantageous than equivalent reductions from the other sectors when all the criteria are taken into account. Extensions of the MCDA framework to support policy makers in practice are discussed.

Key words

Air quality policies; Air pollution modelling; Decision analysis; Health impacts

Highlights

- A modelling framework for evaluating UK air quality policies has been developed
- The framework combines decision analysis, air pollution and impact modelling
- Multi-criteria decision analysis is used for comparative evaluation of policies
- The framework is used to evaluate idealized UK air quality policies

1. Introduction

Atmospheric chemistry-transport models have been used in various ways to evaluate air quality policies. They have been used mainly as either stand-alone simulation models (Chemel et al 2014) or embedded within comprehensive integrated assessment tools (Lim et al 2005, Amann et al 2011, Thunis et al 2012, Carnevale et al 2012a, Carnevale et al 2012b, Oxley et al 2013). However, if air pollution modelling is to be used in practice to help policy makers choose amongst potentially competing policies, appropriate methods for comparative evaluation of such policies are needed (Browne and Ryan 2011). Such methods include cost-effectiveness analysis (CEA), cost-benefit analysis (CBA) and multi-criteria decision analysis (MCDA).

CEA is mainly used when the policies are assessed against two criteria: monetary (e.g. cost of the policy) and non-monetary (e.g. effectiveness or benefit of the policy such as health gain). A cost-effectiveness ratio (cost per unit gain) is calculated for each policy and is used as the metric for comparative evaluation; the policy with the lowest ratio is deemed to be the most cost-effective. CBA is similar to CEA except that the non-monetary criterion is monetised and the ratio of cost to benefit becomes dimensionless, which eases comparison. CBA can cater for more than two criteria because all the non-monetary criteria are monetised. MCDA is different from CEA and CBA in one important aspect: the comparative evaluation between policies is carried out across several criteria without the need to monetise the criteria i.e., the criteria are maintained in their natural units. Browne and Ryan (2011) and Scrieciu et al (2014) discuss the advantages and disadvantages of the different methods.

The use of MCDA to support environmental decision making has solid foundation (Kiker et al 2005, Zhou et al 2006). It has been recommended for this purpose by some UK Government Departments (DCLG, 2009). Huang et al (2011) provide a review of the applications of MCDA in environmental sciences. The applications of MCDA of relevance to this study include evaluation of flood risk management policy options in Scotland (Kenyon 2007), air quality policies in the UK (Philips and Stock 2003, Fisher 2006), and climate change mitigation and adaptation policies (Konidari and Mavrakis 2007, Scrieciu et al 2014, Chalabi and Kovats 2014). Apart from the flood risk management MCDA study, the abovementioned studies describe MCDA frameworks rather than evaluate specific polices.

The aim of this study is to demonstrate the use of an air pollution model alongside impact models within a MCDA framework to evaluate and compare relatively simple UK air quality policies across several criteria which include health and health inequality. We used the EMEP4UK chemical transport model (Vieno et al 2010, Vieno et al 2014) to simulate air pollution over the UK for 2010. Results from an earlier version of the model have been used for health impact estimation (Doherty et al 2009, Vardoulakis and Heaviside 2012, Heal et al 2013).

The paper is structured as follows. Section 2 describes the methods used in this study. Section 3 gives the results of the MCDA analysis. Section 4 highlights the main findings and discusses the merits and challenges of this approach in theory and practice, and the final section concludes. The paper is supported by five technical appendices.

2. Methods

2.1 Multi-Criteria Decision Analysis (MCDA)

Several MCDA methods with varying degrees of complexity could be used to carry out comparative evaluation of air quality policies. Exposition of MCDA methods are given by Belton et al (2002) and Figueira et al (2005). The method we used in this study belongs to the family of Simple Multi-Attribute Rating Techniques (SMART) and is also known as the weighted-sum method (Cunich et al 2011, Dowie et al 2013). We used the SMART software tool *Annalisa* (©Maldaba Ltd, http://maldaba.co.uk/products/annalisa) for implementing the MCDA. *Annalisa* has been used as a decision support framework for risk prioritisation of environmental health hazards (Woods et al 2016).

The elements of this MCDA method are: (i) a set of policies, (ii) a set of criteria against which the policies are evaluated and compared, (iii) a set of preference weights which give the relative importance of each criterion (the weights add up to 1), (iv) a set of models to determine the impact of each policy on each criterion (each impact is normalised between 0 and 1), and (v) a method for integrating the impacts and the weights to give a total impact for each policy across all the criteria. The total impacts of all the policies are the metrics which are used to compare the policies. If the impacts are burdens then the policy with the lowest total impact is deemed to be the "optimal policy". Conversely, if the impacts are benefits then the policy with the highest total impact is the "optimal policy".

The theoretical details of the MCDA method are provided in Supplementary Material A to E. In summary, Supplementary Material A describes the stakeholder survey used to rank the criteria (described in Section 2.4: mortality, health inequality, greenhouse gas emissions, air quality legal compliance, biodiversity, crop yield) in order of their importance.

Supplementary Material B describes the method of converting the ranks obtained from the stakeholders to a set of aggregated weights for the criteria. Supplementary Material C shows the method of normalising the impacts across the criteria to make them dimensionless. Supplementary Material D provides details on the measurement of pollution exceedance. Finally, Supplementary Material E describes the MCDA calculation.

2.2 Air pollution modelling

For the purposes of this study, pollutant concentrations of nitrogen dioxide (NO_2), ozone (O_3) and particulate matter with aerodynamic diameter of less than 2.5 µm ($PM_{2.5}$) were simulated by the EMEP4UK atmospheric chemistry transport model. EMEP4UK is a nested regional application of the main European Monitoring and Evaluation Programme (EMEP) MSC-W chemical transport model (Simpson et al, 2012) targeted specifically at air quality in the UK. EMEP4UK uses one way nesting to scale down from 50 x 50 km horizontal resolution in the EMEP greater European domain to 5 x 5 km resolution in a nested inner domain located over the British Isles. Model outputs include surface concentrations of gaseous pollutants and particulate matter (both primary and secondary) along with their rates of wet and dry deposition. The driving meteorology for EMEP4UK was taken from the Weather Research and Forecasting (WRF) model including data assimilation of 6-hourly meteorological reanalyses from the US National Center for Environmental Prediction (NCEP) global forecast system. Continuously constraining the WRF fields to observations ensures that the meteorology supplied to the chemistry-transport model is closely representative of the real weather conditions prevailing throughout the simulations. Full details of the WRF-EMEP4UK coupled model are described elsewhere (Vieno et al 2010, Vieno et al 2014).

2.3 Policies

In this study we assess relatively simple policies that would reduce UK emissions from specific sectors by fixed fractions. We use the Selected Nomenclature for Air Pollution (SNAP) emission sectors, as defined by the EMEP CEIP (Centre on Emissions Inventories and Projections: www.ceip.at). In particular, we evaluate policies that control emissions from the following sectors: SNAP 1. 'Combustion in energy and transformation industries'; SNAP 2. 'Non-industrial combustion plants'; SNAP 7. 'Road Transport'; and SNAP 10. 'Agriculture'.

2.3.1 Base simulation

The base simulation was for 2010. It used anthropogenic emissions of primary pollutants and pollutant precursors as reported in official inventories for that year. Annual gridded emissions of nitrogen oxides ($NOx = NO + NO_2$), sulphur dioxide (SO_2), ammonia (NH_3), Volatile Organic Compounds (VOCs), carbon monoxide, and particulate matter (PM_{10} and $PM_{2.5}$) were taken from the National Atmospheric Emissions Inventory (NAEI, http://naei.defra.gov.uk) for the UK and from CEIP for the rest of Europe. The provided anthropogenic emissions for each species are apportioned across a standard set of ten SNAP source sectors as defined by EMEP CEIP. Emissions are distributed vertically within the model according to SNAP sector. Natural emissions (mainly biogenic isoprene) were calculated interactively by the model. Model outputs of pollutant concentration and deposition fluxes were utilised for impacts calculations. A detailed evaluation of the base EMEP4UK simulation against measured pollutant concentrations is given by Lin et al (2016) (here we use only the year 2010 from the decade long simulation examined in that paper).

2.3.2 Variant simulations

Variant simulations were performed for 2010 to examine the response of atmospheric concentrations and deposition rates to a change in UK emissions from several individual SNAP sectors. Emission from specific SNAP sectors were switched off (i.e. 100% reductions) to assess the maximum influence of reductions in emissions in a given sector on pollutant concentrations:

1. 100% reduction in UK emissions from the 'Combustion in energy and transformation industries sector' (SNAP 1)

2. 100% reduction in UK emissions from 'Non-industrial combustion plants' (SNAP 2)

3. 100% reduction in UK emissions from 'Road Transport' (SNAP 7)

4. 100% reduction in UK emissions from 'Agriculture' (SNAP 10)

In these integrations, the UK anthropogenic emissions of all species in the relevant SNAP sector were set to zero (in both the outer and inner EMEP4UK domains), while UK emissions in the other SNAP sectors and all anthropogenic emissions outside the UK were left unchanged. Natural emissions and meteorology were also unchanged. The differences between these variant simulations or perturbations and the base simulation therefore arise solely from the removal of UK anthropogenic emissions in that particular SNAP sector.

2.4 Criteria

There is no one ideal or perfect set of criteria to use as basis for comparing the expected performance of the above air quality policies. The selection of the criteria is a subjective matter. Ideally from a decision-analytical perspective, the criteria should be independent of each other. However in practice this independence can rarely be achieved. Informed by a stakeholder workshop, the following six criteria were chosen: mortality, health inequality, greenhouse gas emissions, air quality legal compliance, biodiversity and crop yield. The workshop participants came from academia, government departments and environmental consultancies. The selected criteria represent a spectrum of higher level criteria which span a range of environmental policy concerns: human health (mortality), social (health inequality), climate (greenhouse gas emissions), legal compliance (pollution exceedance), natural ecosystem health (biodiversity) and agricultural ecosystem health (crop yield). The impacts on all the criteria are presented as burdens. We provide below a brief description of each criterion and the quantitative metric that is used to model the impact of each policy on the criterion.

Mortality: We calculated the mortality impact of long-term $PM_{2.5}$ exposure for the base simulation and each SNAP sector variant simulation using a life table model (Miller and Hurley 2003) and following the health impact assessment method of COMEAP (2010). The main output of the life table model used as a metric in the MCDA analysis is the Years of Life Lost (YLL).

Health inequality: We reconstructed a socioeconomic deprivation index based on the Income and Employment domains of the English Index of Multiple Deprivation (IMD) 2010. IMD is the composite measure of deprivation constructed from a number of deprivation indicators (such as income, employment, education skills and training) using appropriate weights to produce a single overall index of multiple deprivation for small geographical areas known as Lower Super Output Areas (LSOAs). Each LSOA has about 1,500 inhabitants. The IMD is grouped into 10 deciles with 1 representing the least deprived 10% of the population and 10 the most deprived 10%. Based on separate life tables created for each decile of IMD (to reflect differences in underlying mortality risk), we used the change in years of life gained per 5th to 9th decile of IMD as the measure of health inequality.

Greenhouse gas emissions: We calculated the CO_2-equivalent emissions reductions associated with each policy, based on the impacts on the Kyoto protocol gases (UNFCCC, 2008). Other species that influence climate, such as ozone (O_3) and aerosols are not included.

Pollution exceedance: We used the European Commission's air quality standards to define the standards for the relevant air pollutants: $PM_{2.5}$ and O_3 (Table 1)

Table 1. EC air quality standards for $PM_{2.5}$ and O_3 (EC, 2015)

Pollutant	Concentration	Averaging period	Legal time entered into force	Permitted exceedance each year
$PM_{2.5}$	25 µg m^{-3}	1 year	1 Jan 2015	N/A
O_3	120 µg m^{-3}	Max daily 8 h mean	1 Jan 2010	25 day averaged over 3 years

NO_2 is also an important pollutant in terms of legal compliance, but due to its short lifetime, its concentrations show steep gradients away from its sources such as major roads. As the monitoring sites for which NO_2 exceedances are typically reported (e.g. in 2010 in the UK) are situated at roadside locations, simulating NO_2 levels comparable with these reported occurrences, would require road emissions to be modelled explicitly, which is not possible in the gridded chemistry transport model despite its fairly high horizontal resolution of 5 km by 5 km. Hence for the purpose of legal compliance only $PM_{2.5}$ and O_3, which have lifetimes sufficiently long to undergo regional transport, and are hence suitable to be simulated in a 5 km by 5km model, are considered.

There is no unique way of quantifying multi-level pollutant exceedance over the whole of the UK. Supplementary Material D gives the details of the quantitative measures we used. In summary we used as a proxy for legal compliance the total number of surface level 5×5 km^2 model grids cells in which each pollutant standard is exceeded.

Biodiversity: Nitrogen-deposition flux (kg-N m^{-2} y^{-1}) is a quantitative measure of the degree of loss of biodiversity (e.g., Stevens et al., 2004). Many ecosystems are sensitive to inputs of reactive nitrogen (i.e. oxidised and reduced forms of nitrogen, such as nitrogen dioxide (NO_2), nitric acid (HNO_3), nitrate (NO_3^-) aerosol, ammonia (NH_3) and ammonium (NH_4^+) aerosol) by dry and wet deposition. There is a background level of nitrogen deposition from natural sources that is enhanced by anthropogenic emissions of NOx (e.g. from combustion processes) and ammonia (e.g. from intensive agriculture). Enhanced nitrogen deposition tends to increase the exposure of ecosystems to acidity (depending upon the local neutralising capacity of the soil) and also tends to reduce biodiversity (fertilisation favours generalist species at the expense of specialists). Low levels of reactive nitrogen input are seen as a measure of a pristine natural environment. Nitrogen deposition was chosen as an indicator of loss of biodiversity although it is noted that sulphur deposition can also be used to give a fuller indication of acidity or pH levels.

Crop yield: Ozone deposition flux (kg-O_3 m^{-2} y^{-1}) is used to measure the impact of a policy on crop yield. A major route of ozone removal from the atmosphere is dry deposition to vegetation. About half of this flux is into plants' stomata, from where ozone directly enters the plant's vascular system. Because ozone is a strong oxidant, it can cause significant damage to some plants, including major UK crops such as wheat, and reduce yields. Irrigated crops are particularly susceptible, as they are more likely to have open stomata. Current baseline ozone levels in air entering the UK can reduce yields of staples crop such as wheat and potato by up to 15% (Pleijel et al., 2007; Mills et al., 2011; RoTAP, 2012). This has significant economic and food security implications. Locally produced ozone from precursor emissions from within the UK itself can further affect crop yields.

2.5 Subjective weights

There are various ways of eliciting preference weights on attributes or criteria from stakeholders. Weernink et al (2014) reviewed preference elicitation methods used in healthcare decision-making. These methods can be time-consuming because a stakeholder must follow strict procedures in order to satisfy certain axioms of decision making. We opted instead for a less time consuming method which has been used in in environmental health policy (e.g. Kenyon 2007). In this method each stakeholder is asked to rank (independently from other stakeholders) the criteria in order of their importance as they perceive it. Supplementary Material A gives the survey questionnaire which we asked the stakeholders to complete. In this case of six criteria, rank 1 means that the associated criterion is the most important and rank 6 means that it is the least important. The ranks should be converted to weights between 0 and 1 such that (i) the weights add up to unity and (ii) the weights are positioned numerically in the same order as the ranks i.e., for the six criteria the weight corresponding to rank 1 has the highest numerical value and the weight corresponding to rank 6 has the lowest numerical value. There are several methods of achieving transformation between ranks and weights. These methods differ in how steeply the weights vary with the ranks. We used a method which gives a mildly steep pattern so that the weights are moderately sensitive to the ranks. Details of the method are given in Supplementary Material B. In the MCDA calculation the set of weights of each stakeholder can be used separately, or alternatively, the set of weights aggregated over all stakeholders can be used. Supplementary Material B also explains the aggregation procedure.

3. Results

In this section, the results of the survey questionnaires of ranks and the associated aggregated weights are presented, followed by the calculated impacts of the air quality policies on the selected criteria and the MCDA outputs.

3.1 Survey questionnaire

There were 15 respondents overall, the majority of whom attended the MCDA stakeholder workshop (approximately 65% response rate). Figure 1 shows the distribution of the rankings for each criterion. To reiterate, rank 1 means that the criterion was deemed to be the most important and rank 6 means that the criterion to be the least important. Taking mortality as an example, fourteen respondents gave it rank 1 and one respondent gave it rank 2. For Biodiversity, two respondents gave it rank 2, one gave it rank 3, six gave it rank 4, three gave it rank 5, and 3 gave it rank 6.

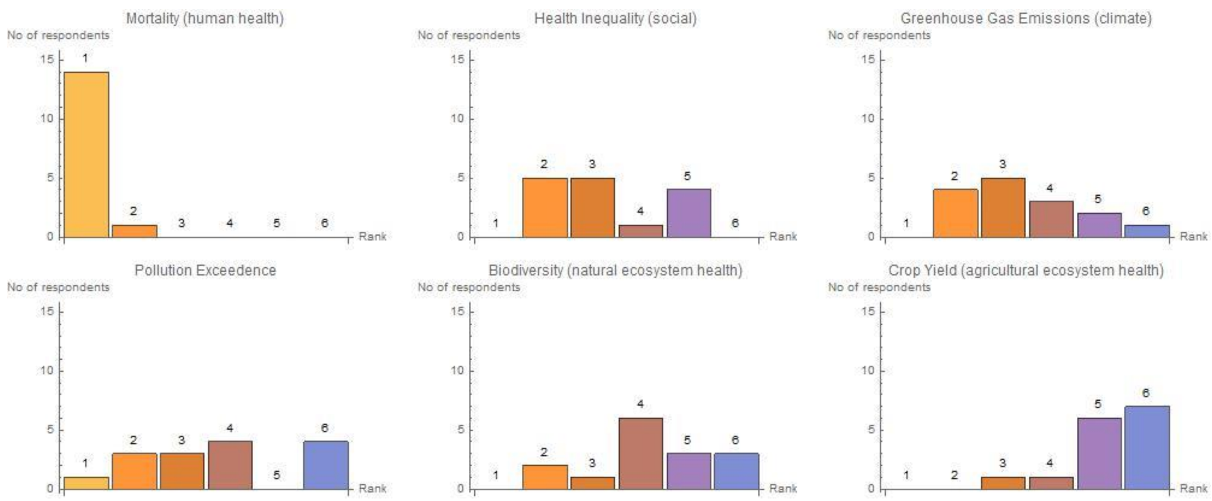

Figure 1. Distribution of ranks for each criterion, as selected by survey correspondents.

Supplementary Material B describes the method for mapping ranks to weights. As explained previously, the map is a mathematical transformation which converts the ranks to weights such that the weights are positive, add up to unity and are in the same numerical order as the ranks. Applying this transformation gives the following weights: 0.2857 (rank 1), 0.2381 (rank 2), 0.1905 (rank 3), 0.1429 (rank 4), 0.0985 (rank 5) and 0.0476 (rank 6). The ratio of two weights represents the relative importance between the associated ranks. For example, rank 1 is deemed to be 1.2 (=0.2857/0.2381) times more important that rank 2, and 6.0 (=0.2857/0.0476) times more important than rank 6. Individual weights are then aggregated proportionally to the number of respondents who selected the associated ranks so that the aggregated weights also add up to unity (Supplementary Material B).

Figure 2 shows the aggregated weights for the 6 criteria across all 15 respondents.. The weights can be interpreted as follows. Overall the respondents judged that mortality is the most important criterion and crop yield is the least important. The ratio of two weights represents how important one criterion is judged to be relative to the other. For example, mortality was considered to be 1.6 times more important than health inequality and 3.4 times more important than crop yield. Biodiversity was considered to be 1.6 times more important than crop yield.

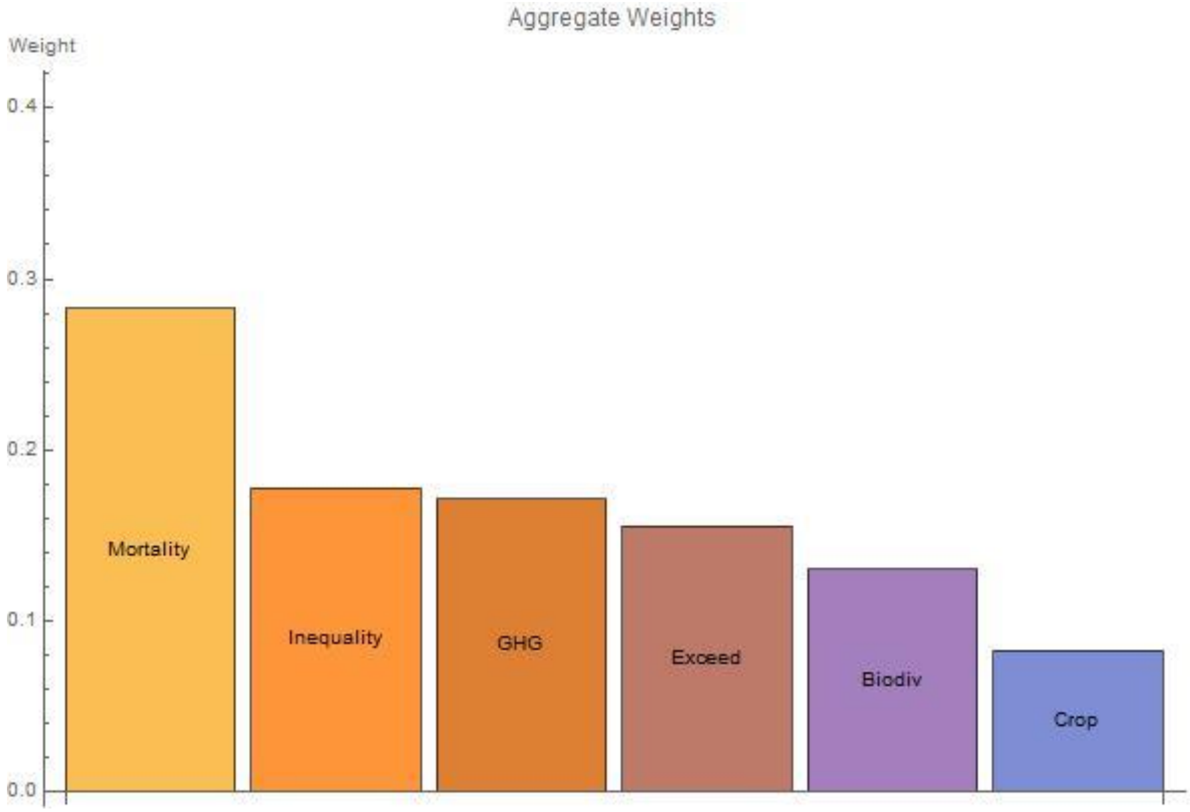

Figure 2. Aggregated weight of each criterion.

Having established the relative weights to be assigned to each criteria, we now apply the air pollution modelling simulation results to calculate the impact of each policy on each of the criteria in the sections below.

3.2 Mortality

We calculated mortality impacts applying the life table model to the simulated air pollution levels for 2010. Table 2 gives the population-weighted annual mean $PM_{2.5}$ concentration (µg m^{-3}) per socio-economic (SE) deprivation decile group along with the YLL (years) associated with long-term $PM_{2.5}$ exposure summed over the whole population in England.

Table 2. Annual mean PM2.5 concentrations on (μg m^{-3}) and associated mortality per decile group for the baseline and for 100% SNAP emission reduction (perturbation) in each of the four SNAP sectors.

SE-deprivation decile groups	Baseline		SNAP 1		SNAP 2		SNAP 7		SNAP 10	
	$PM_{2.5}$	YLL	$PM_{2.5}$	YLL	$PM_{2.5}$	YLL	$PM_{2.5}$	YLL	$PM_{2.5}$	YLL
1 (the least)	9.175	20,667	8.341	18,789	8.690	19,575	8.421	18,969	7.901	17,797
2	9.180	24,373	8.352	22,175	8.706	23,115	8.462	22,467	7.877	20,914
3	9.186	26,261	8.364	23,912	8.721	24,932	8.475	24,229	7.881	22,532
4	9.208	27,492	8.393	25,060	8.752	26,131	8.492	25,356	7.921	23,652
5	9.202	28,691	8.393	26,171	8.749	27,280	8.482	26,449	7.929	24,726
6	9.228	29,621	8.420	27,030	8.772	28,159	8.499	27,283	7.966	25,574
7	9.272	29,671	8.462	27,082	8.816	28,214	8.524	27,280	8.023	25,679
8	9.316	30,697	8.502	28,019	8.857	29,187	8.547	28,167	8.081	26,634
9	9.366	31,554	8.548	28,803	8.907	30,011	8.575	28,894	8.140	27,431
10 (the most)	9.450	34,057	8.634	31,121	8.996	32,423	8.631	31,110	8.244	29,717
Total	N/A	283,084	N/A	258,162	N/A	249,452	N/A	260,204	N/A	244,656
Total relative to baseline		0		-24,922		-33,632		-22,880		-38,426

Table 2 shows that the burden of $PM_{2.5}$ pollution in 2010 is about 283,000 YLL with SNAP 1 (Industrial combustion plants) contributing about 25,000 YLL, SNAP 2 (non-industrial combustion plants) 34,000 YLL, SNAP 7 (road transport) 23,000 YLL and SNAP 10 (Agriculture) 38,000 YLL. Hence changes in $PM_{2.5}$ concentrations due to removing UK emissions in the agriculture sector have the largest impact on mortality due to the large geographical area it covers compared to other sectors. This finding is in agreement with that of Vieno et al (2016) who compared the impacts of reductions in individual pollutants and reported that reductions in ammonia (NH_3) – whose emissions occur primarily from agriculture – had the greatest effect in area-weighted $PM_{2.5}$ concentrations.

3.3 Health inequality

As outlined, above health inequality is defined as the change in YLL (associated with long-term PM2.5 exposure) per 5th to 9th decile of socioeconomic deprivation index in England. Table 2 shows that both overall, and for each SNAP sector, the most deprived parts of the population are exposed to higher levels of $PM_{2.5}$, and that there is an (almost monotonic) increase in exposure for each sector as deprivation rises. Table 3 gives the change in YLL (ΔYLL) calculated by subtracting YLL at the 5th decile group from that at the 9th decile group:

Table 3. Change in YLL per 5th to 9th decile deprivation score for baseline and each SNAP perturbation

	Baseline	SNAP 1	SNAP 2	SNAP 7	SNAP 10
Change in $PM_{2.5}$, μg/m^3	0.164	0.155	0.158	0.093	0.211
Change in YLL in years	2,863	2,632	2,731	2,445	2,705
Relative to baseline	0	-231	-132	-418	-158

Table 3 shows that the reductions in road transport emissions (SNAP 7) have the biggest impact in reducing health inequalities (≈ 420 YLLs), followed by industrial combustion plants emissions (≈ 230 YLLs), agricultural emissions (≈160 YLLs) and then non-industrial combustion plants (≈130 YLLs).

3.4 Greenhouse gas emissions, biodiversity and crop yield

Table 4 gives CO_2-equivalent emissions (measure of greenhouse gas emissions), the N-deposition flux (measure of impact on biodiversity), O_3-stomatal conductance flux (measure of impact on crop yield) for the baseline and SNAP perturbations for the UK.

Table 4. CO_2-eq emissions, N-deposition flux and ozone stomatal deposition flux for baseline and each SNAP perturbation

	Baseline	SNAP 1	SNAP 2	SNAP 7	SNAP 10
CO_2-eq (Gg/yr)	563,341	369,711	457,148	452,612	526,048
Relative to baseline	0	-193,630	-106,193	-110,729	-37,293
N deposition (Gg/yr)	278.925	268.943	277.096	265.646	219.76
Relative to baseline	0	-10.0	-1.8	-13.3	-59.2
O_3 deposition (Gg/yr)	1838	1850.58	1844.98	1872.52	1840.54
Relative to baseline	0	12.6	7.0	34.5	2.5

It is shown that for CO_2-eq emissions, SNAP 1 (industrial combustion plants) contributes around 34%, followed by SNAP 7 (road transport) 20%, SNAP 2 (non-industrial combustion plants) 19%, and SNAP 10 (agriculture) 7%. For N-deposition, agriculture is most important, again due to the larger geographical area for emissions in this sector. Reducing UK emissions leads to an increase in O_3 deposition – this is because the ozone titration reaction (O_3 + NO →NO_2 +O_2) is reduced as emissions of NO fall, and hence ozone concentrations are higher. Transport emissions (SNAP 7) have the largest effect on ozone deposition change owing to their high NOx content.

3.5 Pollutant exceedance

Table 5 gives the number of 5km grids for which O_3 and $PM_{2.5}$ exceeded the permitted levels in 2010 according to the definitions in Table 1. As explained above NO_2 was not considered due to insufficient model resolution.

Table 5. Pollutant exceedance for O_3 and $PM_{2.5}$.

Country	Baseline	SNAP 1	SNAP 2	SNAP 7	SNAP 10
England					
O_3	0	0	0	0	0
$PM_{2.5}$	0	0	0	0	0

The above table shows that the EU permitted levels of O_3 and $PM_{2.5}$ are never exceeded in the simulations. Although non-legislative thresholds could be used (e.g. 95th or 97.5th centile for each pollutant), these levels would be arbitrary and would not represent "legal compliance". This means that the pollutant exceedance criterion ends up playing no part in the MCDA analysis. Although pollution exceedance did not impact the MCDA calculation we cannot remove it because it was selected by the stakeholders. The stakeholders also ranked it in terms of its importance in relation to other criteria. We only found in the impact modelling afterwards that it does not affect the MCDA calculation. It would not be appropriate to remove it and re-rank the remaining criteria without going back to the stakeholders.

3.6 Normalised impacts

Because the impacts on the criteria are in different units, the impacts should be normalised so that they become dimensionless. Supplementary Material C describes a method for normalisation for each criterion which is to divide by the maximum impact across all policy options. Other methods could also be used and the Discussion section comments on the sensitivity of the results to the normalisation method chosen.

Table 6 gives the normalised impacts across all criteria.

Table 6. Normalised impacts

	Baseline	SNAP 1	SNAP 2	SNAP 7	SNAP 10
Mortality	1.0000	0.9120	0.8812	0.9192	0.8643
Health Ineq.	1.0000	0.9193	0.9539	0.8540	0.9448
GHG emissions	1.0000	0.6563	0.8115	0.8034	0.9338
Exceedance	1.0000	1.0000	1.0000	1.0000	1.0000
Biodiversity	1.0000	0.9642	0.9934	0.9524	0.7879
Crop yield	0.9816	0.9883	0.9853	1.0000	0.9829

The entries in Table 6 are obtained as follows. The highest mortality impact is 283084 YLLs which corresponds to the baseline (Table 2). All other mortality impacts are normalised by this value: 258262/283085 (SNAP 1), 249452/283084 (SNAP 2), 260204/283084 (SNAP 7) and 244656/283084 (SNAP 10). For health inequality, the largest change in YLL per 5^{th}-9^{th} decile is 2863 YLLs which also corresponds to the baseline. All other health inequality impacts are normalised by this value: 2632/2863 (SNAP 1), 2731/2863 (SNAP 2), 2445/2863 (SNAP 7) and 2705/2863 (SNAP 10). The other entries are derived in the same manner.

For all criteria, the highest impacts were for the baseline case except for the impact on crop yield where it is highest for SNAP 7 (road transport) reductions (section 3.4). This explains why the crop yield entry for the baseline is below unity and that of SNAP 7 is unity. All the entries for exceedance are 1 because there are no exceedances and all the impacts are equal.

3.7 MCDA results

The total impacts (burdens in this case) for each policy option are obtained by integrating the impacts and the criteria using the calculation method described in Supplementary Material E. The results are shown in Figure 3 using the *Annalisa* MCDA template:

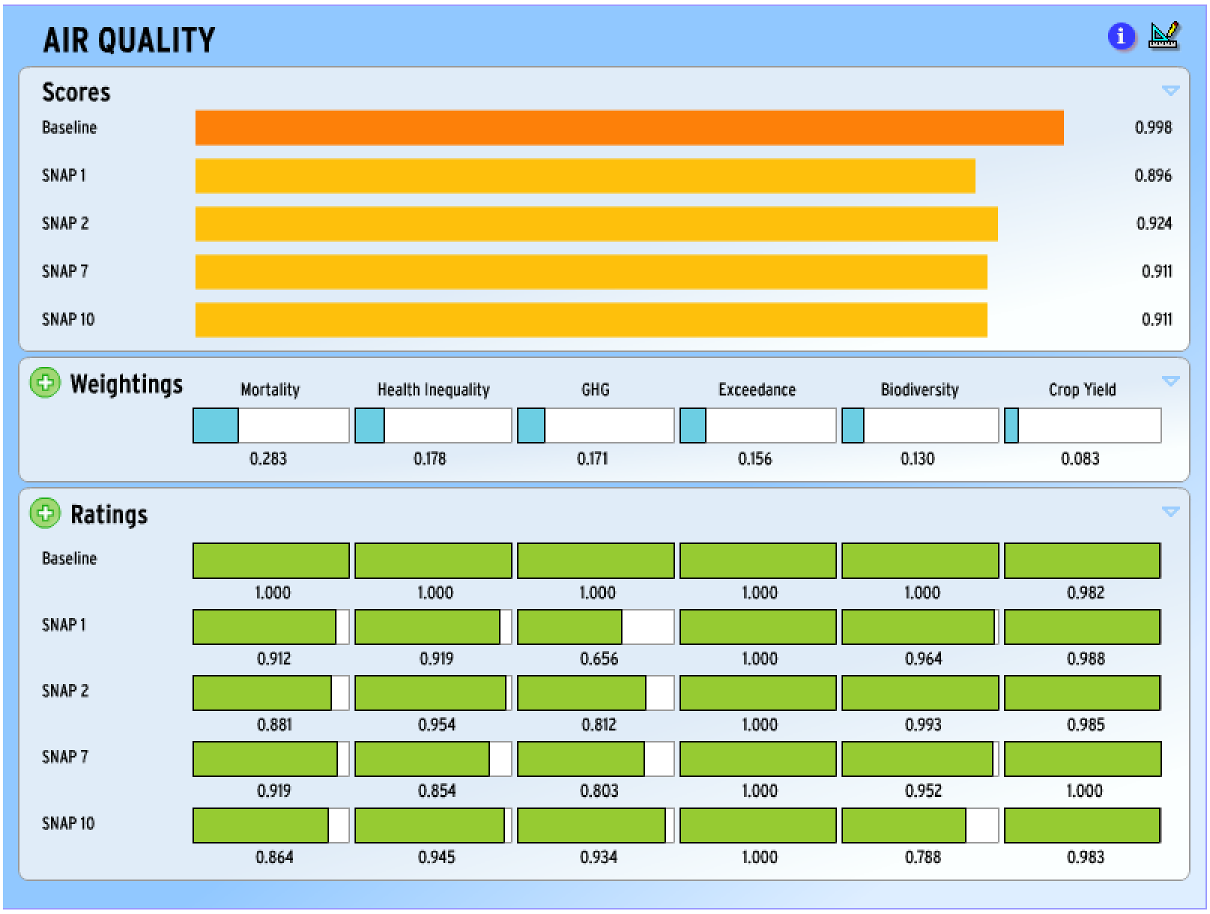

Figure 3. MCDA results.

The template is divided into three rectangular windows. The middle window ("Weightings") gives the group's aggregated relative weight (importance) of each criterion (Figure 3). The lower window ("Ratings") is a 5 by 6 matrix which gives the burden of each option on each criterion (e.g. column 1 gives the normalised mortality burdens for the four policy options and the base case, column 3 gives the normalised greenhouse gas emissions burdens for the four policy options and the base case). The top window ("Scores") gives the overall burden of each option across all the criteria. The higher the score the higher is the integrated burden. The option with the lowest score i.e. SNAP 1 (industrial combustion) represents the policy with the smallest integrated burden. This is followed very closely by SNAPs 7 (road transport) and 10 (agriculture). The "scores" are dimensionless numbers and their ratios can be interpreted as their relative strength; for example 100% perturbation in SNAP 1 yields 0.896 times less burden than the base case. Naturally this outcome depends on the relative weights and the normalisation constants chosen. Figure 4 shows the counterpart results if all the criteria were weighted equally.

Figure 4. MCDA results with equal weightings.

This shows that reduction in industrial combustion emissions is still the best single policy even if equal weights are assigned to all the criteria.

4. Discussion

From a scientific perspective, atmospheric chemistry transport models are very useful in contributing to the understanding of the spatio-temporal dynamics of air quality, while impact models provide a link to relevant outcomes from a policy perspective. These models are also useful because they can be used to evaluate how policies based on reduction of emissions in various sectors impact air quality. However in practice policy makers take into account multiple criteria when assessing polices in addition to their impact on pollutant exposures. To enable policy makers to make effective use of the pollutant outputs from air pollution models, we suggest that pollution and impact models are embedded within decision analytical frameworks which support decision making. The use of an MCDA framework allows a more transparent assessment of policies where the evidence base for the impacts of the policies on the criteria (“Ratings”) is shown alongside the importance assigned to the criteria (“Weightings”) and the overall impacts of the policies (“Scores”). The main contribution of this paper is to demonstrate as a proof-of-concept the use of a MCDA framework that employs both air pollution and health and non-health impact models to evaluate UK air quality policies.

For this approach to move forward from a proof-of-concept to a practical decision support tool further development is required. Firstly, the set of policies and criteria selected for this study emerged from “informal discussions” in a workshop. There are however formal facilitator-led procedures such as “decision conferencing” which guide stakeholders (or policy makers) as a group to reach some consensus on the appropriate policies and criteria (e.g. Quaddus and Siddique 2001, Mustajoki et al 2007, Phillips and e Costa 2007). These procedures are however very time-consuming but nevertheless they are necessary in practice.

Secondly, the axioms of MCDA require that all the criteria are independent. If some of the criteria are dependent, then they are best embedded in a hierarchical decision tree structure and appropriate methods for eliciting the weights of hierarchical criteria should be used (Scrieciu et al 2014). It can be argued that the criteria used here are nearly independent although it is debatable whether the criteria of mortality and health inequality are truly independent.

Thirdly, no sensitivity or uncertainty analyses were carried out in the MCDA because the decision problem was illustrative rather than real. In practice sensitivity and uncertainty analyses should be performed. However what is important in decision analysis is not the quantification of uncertainty per se but whether the uncertainty in the evidence base (“ratings”) or variability in the importance of weights attached to the criteria (“weightings”) will change the rankings of the integrated impacts (”scores”). Simple sensitivity analysis can be performed using the above interactive decision tool by changing the numbers to reflect the uncertainty in the “ratings” and variability in the “weightings”. The uncertainties in the evidence matrix require either carrying out extensive probabilistic simulations of the models or using experts to define the uncertainty in the central estimates (e.g. Tuomisto et al 2008). Sensitivity analysis should also be performed to determine sensitivity of the “scores” to the chosen normalisation method. We have normalised the impact of each policy option by the maximum impact across all options. Other approaches would normalise by the highest possible impact (e.g. normalising by worst case scenario) or by presenting the impacts as percentage changes from the baseline. There is not a preferred method. It depends on the exact application and the choice of the normalisation method can influence the outcome.

Fourthly, legal compliance was not an issue in this MCDA but could be in the future. More thought may be required to differentiate between modelling different types of compliance for air quality in the MCDA, e.g. in relation to soft law ‘target values’ for some pollutants and mandatory law ‘limit values’ for others (EC, 2008).

Finally, the policy analyses were carried out by perturbing via model simulations the emissions of some of the SNAP sectors by -100%. Clearly this large reduction in emission in any SNAP sector does not represent a realistic policy option and the question then is whether more realistic reductions in emissions can be deduced from the -100% perturbation result via linear scaling. Linearity simulation experiments performed with the air pollution model (not shown here) suggest that the results are scalable for at least three of the impacts (CO_2-eq emissions, N and O_3 deposition fluxes), but further analysis is required to ascertain the scalability of the results for all outcomes.

5. Conclusion

This study demonstrates a proof-of-concept MCDA method which uses an atmospheric chemistry transport model (WRF-EMEP4UK) for the purpose of evaluating and comparing country-wide air pollution related policy options. The policy options were formulated in terms of reductions of 100% in emissions in four sectors: energy and industrial combustion, non-industrial combustion, road transport and agriculture. Six criteria were used for the comparative evaluation of the policy options: mortality, health inequality, greenhouse gas emissions, pollution exceedance, biodiversity and crop yield. The selection of the policy options and the criteria were informed by a workshop of interested stakeholders. The MCDA analysis consisted of three main steps: (i) eliciting the relative weights (importance) of the criteria from the stakeholders (acting as proxy policy makers), (ii) calculating the impacts of each policy option on each criterion, and (iii) combining the weights with the modelled impacts to rank the options in terms of their overall impact scores. This ranking can be used to guide policy makers on how the different policy options compare relatively in terms of their overall impact across all the criteria. Using the six criteria, it is found that reductions in industrial combustion has the largest overall impacts, followed very closely by reductions in road transport and agricultural emissions. Reductions in agricultural emissions are important for mortality and N-deposition.

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