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Research article

Sensitivity of predicted bioaerosol exposure from open windrow composting facilities to ADMS dispersion model parameters

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ABSTRACT

Bioaerosols are released in elevated quantities from composting facilities and are associated with negative health effects, although dose-response relationships are not well understood, and require improved exposure classification. Dispersion modelling has great potential to improve exposure classification, but has not yet been extensively used or validated in this context. We present a sensitivity analysis of the ADMS dispersion model specific to input parameter ranges relevant to bioaerosol emissions from open windrow composting. This analysis provides an aid for model calibration by prioritising parameter adjustment and targeting independent parameter estimation. Results showed that predicted exposure was most sensitive to the wet and dry deposition modules and the majority of parameters relating to emission source characteristics, including pollutant emission velocity, source geometry and source height. This research improves understanding of the accuracy of model input data required to provide more reliable exposure predictions.

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1. Introduction

Composting of organic waste is now a common practice in many parts of the world and generates a useful product from waste which might otherwise go to landfill. However, one potential issue with composting is the emission of bioaerosols; aerosolised material containing a range of fungal and bacterial species and constituents of microbial cells, some of which can be pathogenic (Douwes et al., 2003; Viegas et al., 2014). Bioaerosol emissions from composting facilities have become an increasing concern for regulators as the potential health effects associated with bioaerosols have become known (Douwes et al., 2003; Pearson et al., 2015; Swan et al., 2003; Walser et al., 2015; Wheeler et al., 2001). However, the dose-response relationship remains unknown and, therefore, regulators have adopted a precautionary approach to the planning, permitting and compliance monitoring of composting facilities (Environment Agency, 2010).

An understanding of the magnitude and frequency of bioaerosol emissions and resulting temporal and spatial patterns of exposure is required in order to assess the potential health risks. However, this is difficult as the nature, scale and frequency of composting processes and, therefore, emissions at open windrow sites (which represent the greatest proportion of facilities in the UK) are complex and not well understood (see Supplementary Materials [SM] 1) and vary by individual site. Additionally, established sampling methods are expensive, time consuming and provide relatively limited "snapshots" of the behaviour of bioaerosols (Douglas, 2013). The nature of emissions also makes monitoring difficult and potentially dangerous. Sampling data from composting facilities with high spatial and temporal resolution are, therefore, rare.

These uncertainties have limited progress on numerical modelling to date, which has the potential to overcome some of the

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shortfalls of intermittent low frequency sampling methods. In principle, if the spatial and temporal patterns of emissions can be characterised and transport processes well described, a continuous prediction of exposure in and around a composting facility can be constructed. A recent review of atmospheric dispersion modelling of bioaerosols highlighted the importance of well-quantified emissions (Van Leuken et al., 2016). The small number of studies that have compared dispersion model predictions with monitoring data, comparisons have been made at very few sampling points and the monitored data are typically limited to a few measurements collected over a short period of time (Pearson et al., 2015). Unfortunately, the few studies that have attempted to model bioaerosol emissions often lack justification for the selection of several input values or simply fail to state the input values used. In addition, due to the varied nature of bioaerosols, information on particle properties (such as size, density and aggregation) is limited (Tamer Vestlund et al., 2014). Model default options are, consequently, often adopted to define bioaerosol particles in modelling studies. It is unsurprising, therefore, that comparisons between modelled and monitored data are often poor.

Sensitivity Analysis (SA) has many valuable uses including: giving insight into the relationships between input and output variables; identifying important parameters or critical values in the model; determining which parameters need further quantification for model validation; providing insightful information where data is partial or missing and increasing the understanding of how a model works (Hamby, 2004; Ireland et al., 2004; Pannell, 1997). Although a number of sensitivity analyses on dispersion models have previously been reported (e.g. Futter, 2000; Harsham and Bennett, 2008; Mensink and Maes, 1997; Tamer Vestlund, 2009) these typically test parameter spaces which are not relevant to the composting context.

The results from this study will (i) aid future model calibration by identifying the priority parameters that should be adjusted in the first instance during model calibration or those which should be estimated independently (e.g. via direct measurements); and (ii) provide recommendations for additional monitoring, such as characterising particle properties, which will provide quantified and justified model input values, where there is currently little or no data or knowledge. This has the potential to lead to improved model predictions that would also be useful for interpolating sparse monitoring data, optimising future monitoring designs and predicting long term patterns of exposure. Good quality exposure assessment is imperative for epidemiological studies, which are needed in this field to help quantify dose-response relationships and public health risk from bioaerosols. Dispersion modelling is an established and practical method of predicting exposure in epidemiological studies. Work which improves confidence in dispersion model outputs in this field is, therefore, of great importance to epidemiologists. Moreover, since modelling is likely to become a key tool in the planning, permitting and quantitative risk assessment process, improved confidence in modelled outputs will also have positive regulatory and permitting implications for site operators by reducing the frequency of routine monitoring and associated costs.

The aim of this study was to determine which model inputs most significantly affect predicted exposure in the context of simulating bioaerosol emissions from open windrow composting facilities, using a widely-used standard dispersion model.

2. Material and methods

2.1. Software description

The atmospheric dispersion model ADMS [Atmospheric Dispersion Modelling System] (version 4.2 CERC, Cambridge, UK) (CERC, 2010a) was used. ADMS is an advanced steady state 'new generation' Gaussian-based dispersion model (CERC, 2010a). It uses current knowledge of the structure of the atmospheric boundary layer, incorporating the Monin-Obukhov length and boundary layer depth (CERC, 2010a). It is widely used to model the dispersion of airborne pollutants and nuisances in the UK, and has been extensively calibrated and tested by the model developers (Carruthers et al., 1993, 1998; 2001; CERC, 2010b). Since ADMS is a commercial product, the code behind the model is unavailable, although technical specifications are available online (CERC, 2016). Model input parameters can be entered into ADMS by manipulating input files (.apl files) or via a user-friendly model interface.

2.2. Approach

A global SA method was adopted, whereby all parameters are altered within specified ranges simultaneously, so that any potential parameter interactions are not overlooked (Homma and Saltelli, 1996). Global SA methods involve generating random values within a plausible parameter space defined by a probability distribution for each model input parameter (Saltelli et al., 2000; Tomlin, 2013). Random input values were generated using Monte Carlo simulation, which has been the method of choice for many SA studies, including environmental modelling (Branger et al., 2015; Post et al., 2008).

Input parameters and ranges relevant to bioaerosol emissions from open windrow composting were determined based literature and occasionally supplemented with data from analogous scenarios and the experience of the research team (which increased the degree of uncertainty). Details and justification of the parameters and ranges included within the SA are provided in Table 1. Parameters not relevant to the composting scenario, but requiring an input value to allow the model to run, were held at constant values. Other parameters and switches including the Dry Deposition Module (DDM), Wet Deposition Module (WDM), Puff Module (PUF), Terminal Velocity Known (TVK), Deposition Velocity Known for a Gas (DVKG) and Deposition Velocity Known for a Particle (DVKP) input parameters were included in the SA, but are not included in Table 1 as they are categorical parameters ("on/off" or "yes/no").

The emission rate was not included, as the sensitivity of exposure to this parameter is already known to be linear and directly proportional (Johnson, 2011). The buildings and complex terrain input parameters were not included as this would have significantly increased computational and analysis time. Moreover, these modules would be of limited relevance to most windrow composting operations because they tend to be located in open areas with relatively flat terrain. Information is limited on bioaerosol properties such as size, density and aggregation (Tamer Vestlund et al., 2014), and it is uncertain whether they are best represented as a gas or a particle in dispersion models. For completeness, options for both gas and particulates were included.

Continuously variable meteorological data were not included in the study, as predicted exposures have also been reported to be sensitive to meteorological data in previous studies (e.g. Futter, 2000; Harsham and Bennett, 2008; Tamer Vestlund, 2009). Instead, four meteorological scenarios representative of UK weather conditions were considered (Table 2), based on a screening sensitivity analysis, which tested meteorological input values relevant to UK weather (SM 2).

Precipitation data were not included in the meteorological scenarios, as this was accounted for in the SA using the washout coefficient. The washout coefficient can be used in two ways; i) as a function of pollutant species and rainfall rate or ii) specified as a constant value which implies that wet deposition is independent of

Table 1
Input parameters and ranges included within the sensitivity analysis, with justification.

Parameter (units)	Abbreviation	Range allowed in ADMS	Range included in SA	Justification
Pollutant specific heat capacity (J/°C/kg)	SHC	1–10^5	800–2100	Based on the specific heat capacities of common airborne gases, particles and pollutants (Kaye and Laby, 1995).
Pollutant molecular mass (g/mol)	PMM	1–300	15–45	Based on the molecular masses of common airborne gases, particles and pollutants (Kaye and Laby, 1995).
Source type	SOT	Point, Line, Area, Volume and Jet	Point, Line, and Area only	Represent various activities taking place on site (Fig. 1). Jet and volume sources were not included - A jet source is a release where the exit velocity has horizontal and vertical components. Volume sources are assumed not to have any plume rise (CERC, 2010b). Bioaerosol emissions are assumed to have vertical plume rise so these options are omitted from this study.
Source height (m)	SOH	0–15,000	0–5	Composting activities can take place from ground-level to the maximum height of any machinery used on site, which can range up to approximately 5 m.
Source diameter, L1 or geometry (m)	GEO	0–100	0.5–15.0	Agitation activities are known to result in elevated bioaerosol concentrations (Taha et al., 2006). The range is based on the areas of compost that can be agitated at any one time, estimated using the technical specifications of typical machinery (Volvo, 2009; Doppstadt, 2015a; 2015b).
Pollutant exit velocity (m/s)	PEV	0–1000	0–25	There are limited data and knowledge on this parameter in the bioaerosols and composting context. Therefore this range was based on observations of dust and steam emissions at the source of agitation activities.
Pollutant temperature (°C)	PTE	−100–5000	0–60	Based on the core temperatures of a composting windrow and the temperature at which the majority of bioaerosols released from composting facilities can survive (Strom, 1985; Sidhu et al., 2001; Swan et al., 2003).
Deposition velocity (m/s)	DVE	0–10	0–10	There is no prior art on deposition velocities of bioaerosols, and therefore the maximum range possible within ADMS was included.
Terminal velocity (m/s)	TVE	0–10	0–10	There is no prior art on the terminal velocity of bioaerosols and, therefore, the maximum range possible within ADMS was included.
Particle diameter (m)	PDI	1×10^{-9} -1×10^{-2}	5×10^{-7} -3×10^{-6}	Based on measurements completed by Tamer-Vestlund et al. (2014).
Particle density (kg/m^3)	PDE	1–1,000,000	1–1100	There is no bioaerosol density information and, therefore, the range included was based on the densities of common air pollutants, particles and gases (Green and Perry, 2008).
Washout coefficient (/s)	WCO	0–1	0–1	There is no prior art on the washout coefficients of bioaerosols and, therefore, the maximum range possible within ADMS was included.
Duration (s)	DUR	0–86,400	0–36,000	This parameter is associated with the PUF. The range covers the approximate length of the working hours of a typical operational composting facility (36,000 s equates to 10 h, a typical working day).
Latitude (°)	LAT	−90–90	49.5–58.4	This range covers the latitudes for the British Isles.
Surface roughness (m)	SRO	$10^{-7} - 10$	0.005–1.500	The range correlates to the surface roughness of short grass close to urban areas (CERC, 2010b).

Table 2
The four meteorological scenarios, with input values, used in the sensitivity analysis (Oke, 1987; Willett et al., 2008; Meteorological Office, 2011).

Meteorological scenario	Inputs			
	Wind speed (m/s)	Temperature (°C)	Sensible heat flux (W/m^2)	Boundary layer depth (m)
1	1.00	−5	120	1400
2	5.25	30	0	90
3	3.00	9	0	1000
4	18.00	9	0	1000

precipitation (CERC, 2012). The second option was adopted here, as the first option added complexity to the SA that was deemed unnecessary in this study.

There is little information regarding the probability distributions of most input parameter values for bioaerosol releases from composting. Therefore, all input distributions were assumed to be uniform (Tomlin, 2013), i.e. all values in a specified range have an equal likelihood of occurrence. Palisade's @Risk© add-in for Microsoft® Excel was used to generate 500 randomised values for each input parameter (Palisade, 2016). This value was chosen on the basis of preliminary trials as a compromise between acceptable output convergence and reasonable computational and analysis times, as recommended by the software developers (Palisade, 2016). Discrete uniform distributions were assigned in @Risk© if the model input parameter was categorical (for example, on or off). Three source types were included within the analysis: point, area and line. These were all considered to be most appropriate for the different sources of bioaerosol emissions from the various composting processes (SM 1). As some of the input options differ depending on the source type used, the SA was performed three times, once for each source type.

Predicted output concentrations were generated at 10, 100, 250, 500, 1000, 5000 and 10,000 m downwind of the simulated emission source, at a height of 1.7 m, chosen to correspond to breathing height level and the Association for Organics Recycling (AfOR) standard sampling height (AfOR, 2009). A constant wind direction was used to allow direct comparisons at these distances between the model runs. The downwind distances were chosen to include, and extend beyond, the downwind locations where the sampling equipment has been positioned in previous studies, and to comply with current sampling recommendations (AfOR, 2009; Pankhurst et al., 2011; Pearson et al., 2015; Reinthaler et al., 1997; Williams et al., 2013). Overall 500 sets of inputs were generated for each of the three source types and four meteorological scenarios (Table 2).

2.3. Data analysis methods

To determine the level of sensitivity of the modelled outputs to the model parameters, we employed a fixed analysis of covariance (ANCOVA). This was performed within a General Linear Model (GLM) using Statistica version 11 (Statsoft, 2012) following methods outlined in Makler-Pick et al. (2011). We fitted 84 GLMs (one for each of the four meteorological scenarios, *m*, at each of the seven downwind locations, *L* and for each of the three source type, *s*,

(Table 2). The GLM's take the general form:

$$Y_{m,L} = b_0 + \sum_{i=1}^{N} (b_i \cdot X_i) + e \quad (1)$$

where Y is the predicted bioaerosol concentration (dispersion model output) at downwind location L for meteorological scenario m and for source type s, X_i is the value of parameter i (of N parameters), b_0 is the predicted Y value when all parameter values are zero, b_i is a coefficient for predictor i, and e is an error term (due to combined systematic and random errors).

A GLM assumes data are normally distributed and therefore natural log transformations were performed. Normality was checked via Q plots (Crawley, 2007). As per Griensven et al. (2006) absolute t-values for each source type, including and excluding the WDM, for each case were summed and ranked from highest to lowest (i.e. from most to least sensitive) using standard competition ranking (Winkler, 2012).

The dry deposition situation represents a "worst case" with respect to bioaerosol concentration downwind as it is assumed that there is no removal from the plume due to wet deposition, resulting in higher concentrations, and has been of primary interest with respect to short-term modelling. However, in order to gauge the impact that wet deposition might have on the longer term mean and variance of downwind concentration, this analysis was carried out twice, with and without the WDM.

3. Results

The cumulative absolute t-values produced by the GLM for each parameter (summed for each meteorological scenario and downwind distance) are displayed graphically in Fig. 1, for each source type, with and without the WDM. The t-values represent the magnitude of the GLM coefficient for that parameter (b_i) relative to its standard error. The higher the value of t, the more significant the parameter in terms of its control over the predicted exposure. Absolute t-values were ranked similarly to Vanuytrecht et al. (2014).

Fig. 1 shows that predicted exposure is most sensitive to PEV, WDM, DDM, GEO, pollutant molecular mass (PMM) and SOH and least sensitive to deposition velocity for a particle and a gas (DVP and DVG respectively), particle diameter (PDI), PUF and LAT.

The pollutant exit velocity (PEV) has the highest absolute t-value when excluding the WDM from the analysis. When the WDM is included, the WDM has the highest absolute t-value except when modelling as a point source where it ranks second. Inclusion of the WDM alters the rankings of the majority of the input parameters. The largest and most consistent of these changes are observed with (i) GEO, particularly with a line source, where the ranking tends to decrease with the WDM included; (ii) surface roughness (SRO) where the ranking decreases by 10, except with a line source where it decreases by 3; (iii) latitude (LAT) where inclusion of the WDM causes a decrease in ranking by 6 for point and area sources and 13 for a line source; and (iv) pollutant specific heat capacity (SHC) where inclusion of the WDM causes a decrease in ranking by 10 for point and area sources and 4 for a line source. Rankings for the DDM and DVKG all decrease for every source type when the WDM is included, whereas the rankings for pollutant type (PTY), source height (SOH), terminal velocity (TVE) and TVK all increase. Rankings for all other parameters do not vary consistently when the WDM is included.

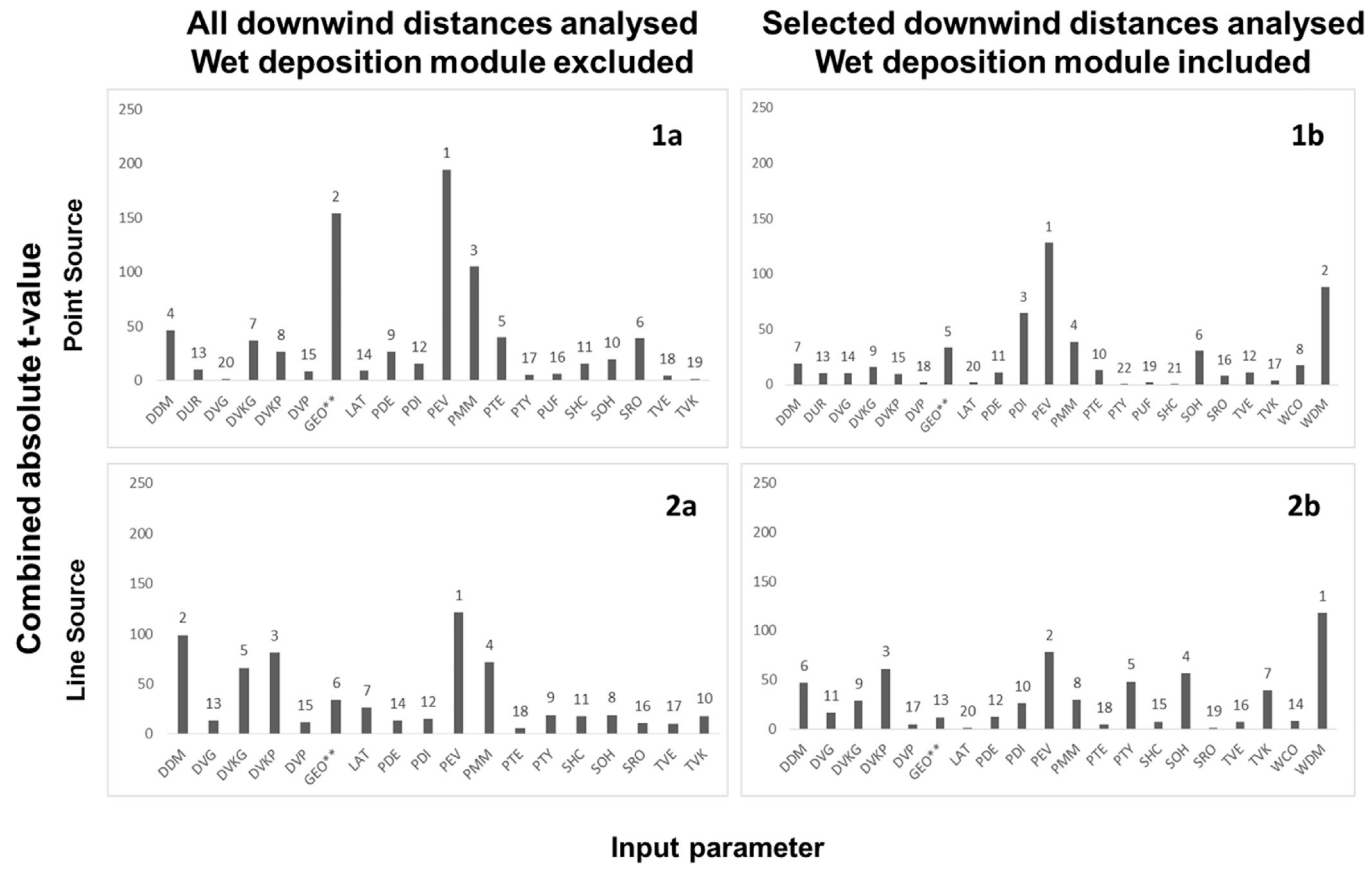
4. Discussion

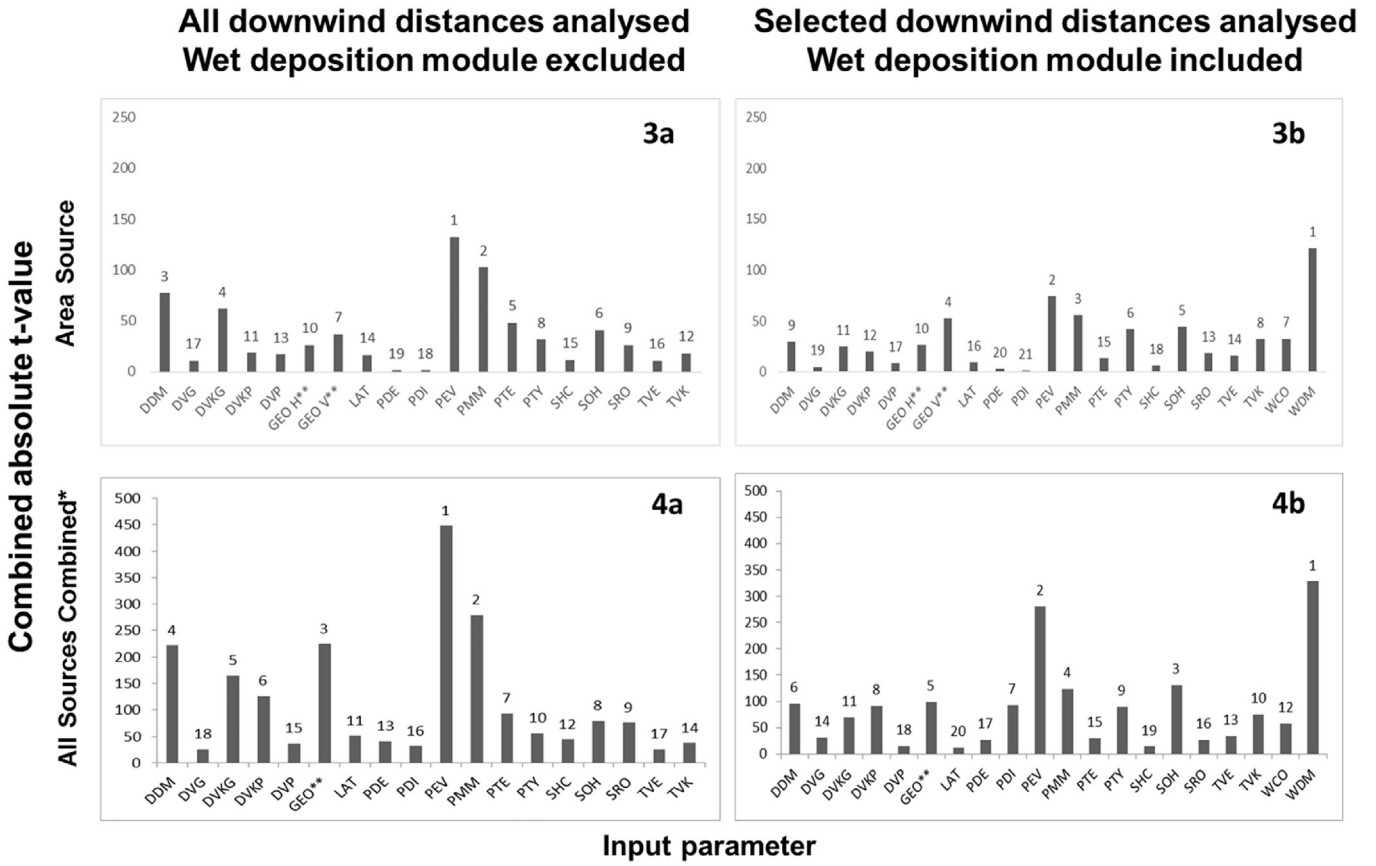
Results are consistent with the SA performed by Mensink and Maes (1997) and Tamer Vestlund (2009) who also found that predicted exposure was sensitive to model inputs associated with the source, such as source height and pollutant temperature. When comparing the source types, the ranking of the parameters generally follows similar trends. However, modelled exposure is more sensitive to GEO when a point source is assumed, but less sensitive to TVK and PTY. Predicted exposure is not particularly sensitive to pollutant temperature (PTE) and SRO when a line source is assumed, but is more sensitive to these parameters when an area or point source is assumed, particularly when the WDM is not included. Predicted exposure is more sensitive to LAT when a line source is assumed.

Details about the nature of the bioaerosol source type, e.g. point, line, or area, are difficult to define for composting facilities using dispersion models because the magnitude and location of emissions are complex and can change rapidly. Bioaerosols are released in different quantities from static windrows as well as from a range of agitation activities including shredding, turning and screening (Taha et al., 2006). Agitation activities can be performed at the same time in various locations around any one site, and may be performed over very different time scales (from a few minutes to several hours). Agitation activities are also performed on the compost material at different stages of the process, which influences the type and amount of microorganisms present in the material (Swan et al., 2003), and hence the nature of the bioaerosol emission. These activities often have no fixed pattern, altering hourly and daily, with emission dispersal also affected by changing ambient conditions which may affect the condition of the compost (e.g. moisture content) and, in turn, impact aerosolisation. Furthermore, emissions are seldom controlled or contained. This can present challenges for dispersion modelling as it is difficult to quantify meaningful and justified dispersion model input parameters.

Fig. 1 shows that outputs were also sensitive to the nature of aerosol deposition assumed (WDM and DDM). This was expected as these modules simulate pollutant fate and transport in the air due to turbulent diffusion, gravitational settling or 'wash out' caused by precipitation (CERC, 2010a) which will all affect the remaining airborne concentration. Predicted exposure had varying levels of sensitivity to parameters related to the DDM and WDM. It was initially thought that predicted exposure would show some sensitivity to particle diameter, particle density, deposition velocity and terminal velocity, which can control simulated pollutant fallout rates within the plume. However, the results of this study show that exposure appears to be relatively insensitive to these parameters (Fig. 1). This partially agrees with the results of Tamer Vestlund (2009) who also found that predicted exposure was not sensitive to particle density but, conversely, found that predicted exposure was sensitive to particle diameter, terminal velocity and deposition velocity (for a particle and a gas). Tamer Vestlund (2009) used a "one-at-a-time" (OAT) SA method. This discrepancy in results may be a consequence of the fact that OAT SA methods can overlook parameter interactions (Haaker and Verheijen, 2004).

When using the WDM and DDM, model users are required to define pollutant parameters including the pollutant deposition velocity, terminal velocity, and particle diameter and density, depending on the options used. It is likely that these properties will vary with the nature of the material being composted, the age of the compost and the activities being carried out on the site, just as the microbiological composition of bioaerosols has been shown to vary (Swan et al., 2003). This widens the probability distributions from which values must be selected. Given this inherent uncertainty there is a case for not using the WDM and DDM under some circumstances, such as screening-level risk assessments, since the


All downwind distances analysed
Wet deposition module excluded
Selected downwind distances analysed
Wet deposition module included
Combined absolute t-value
Point Source
Line Source
1a
1b
2a
2b
DDM DUR DVG DVKG DVKP DVP GEO** LAT PDE PDI PEV PMM PTE PTY PUF SHC SOH SRO TVE TVK
DDM DUR DVG DVKG DVKP DVP GEO** LAT PDE PDI PEV PMM PTE PTY PUF SHC SOH SRO TVE TVK WCO WDM
DDM DVG DVKG DVKP DVP GEO** LAT PDE PDI PEV PMM PTE PTY SHC SOH SRO TVE TVK
DDM DVG DVKG DVKP DVP GEO** LAT PDE PDI PEV PMM PTE PTY SHC SOH SRO TVE TVK WCO WDM
Input parameter


All downwind distances analysed
Wet deposition module excluded
Selected downwind distances analysed
Wet deposition module included
Combined absolute t-value
Area Source
All Sources Combined*
3a
3b
4a
4b
DDM DVG DVKG DVKP DVP GEO H** GEO V** LAT PDE PDI PEV PMM PTE PTY SHC SOH SRO TVE TVK
DDM DVG DVKG DVKP DVP GEO H** GEO V** LAT PDE PDI PEV PMM PTE PTY SHC SOH SRO TVE TVK WCO WDM
DDM DVG DVKG DVKP DVP GEO** LAT PDE PDI PEV PMM PTE PTY SHC SOH SRO TVE TVK
DDM DVG DVKG DVKP DVP GEO** LAT PDE PDI PEV PMM PTE PTY SHC SOH SRO TVE TVK WCO WDM
Input parameter

"no-deposition" case gives the most conservative (and hence precautionary) estimate of bioaerosol concentration downwind. Higher tier risk assessments would, however, require more accurate predictions of exposure. Since this SA indicates that the impact of deposition (wet and dry) can be significant across the realistic parameter ranges tested, this would require the inclusion of deposition which would necessitate better information about the aerodynamic properties (size, shape, density, agglomeration, hygroscopicity etc.) of bioaerosol particles (Tamer Vestlund et al., 2014; Galès, 2015).

4.1. Implications of research

The results presented provide a focus for further research into the quantification of dispersion model input parameters with respect to bioaerosol emissions from an open windrow composting environment. In particular, better estimates are required for the pollutant exit velocity, source height and geometry, pollutant particle mass, pollutant temperature and inputs relating to the DDM and WDM in order to improve dispersion model performance in such a scenario. Improved confidence in modelled outputs would subsequently lead to a better knowledge of bioaerosol emissions both spatially and temporally. This would lead to improved exposure estimates, which are essential in epidemiological studies for assessing the probable impact of existing or proposed composting facilities on health risks. If there is improved confidence in model outputs, dispersion models have the potential to become key tools in the site planning and permitting processes for both site operators and regulators, by reducing the frequency of routine monitoring that is currently required (which will, in turn, reduce costs). Furthermore, routine monitoring relies on infrequent snapshot samples that cannot be representative of the emissions variability of the site. Improved modelling of time-varying emissions will potentially improve simulations of a range of plausible emission-dispersion scenarios. This will ultimately provide an improved prediction of exposure risk than monitoring can with currently available methods.

The findings on sensitivity ranking presented here indicate the parameters for which further investigation would provide the greatest return with respect to improved model performance. However, it may be more efficient to refine several parameters of lower sensitivity than a single, highly sensitive parameter which is costly-to-resolve.

4.2. Limitations

Although we attempted to justify the basis of the probability distributions adopted for the SA presented here using existing evidence where possible (Table 1), a significant limitation of the study was the uncertainty which exists in distribution shape and parameters for open windrow composting, for most of the model input parameters examined. Uniform probability distributions were assumed for the Monte Carlo Simulation, in the absence of better information on appropriate alternatives. This may have resulted in a broader distribution of predicted exposures at each location due to the fact that extreme parameter values are just as likely as those occupying the centre of the distributions. At the same time, the predicted probability of the most realistic combinations of parameters will have been reduced.

Processes occurring in complex terrain and the effects of buildings on the dispersion of bioaerosols have not been considered in this study for a number of reasons. First, many different possible scenarios exist which would need to be considered systematically. In each scenario, the number of additional highly uncertain parameter values is likely to be large. Secondly, in practice a large proportion of open windrow composting sites, at least in the UK, are located in open and relatively flat terrain where use of building and complex terrain modules would not be required. Finally, including additional complexity and input parameters may result in parameter interaction and affect the general conclusions about the importance of different parameters in controlling exposure. Similarly, the number of meteorological scenarios was limited to four and the influence of more extensive meteorological parameters was not investigated. Future modelling studies could consider all of the above options, particularly if the model performance is compared with detailed observations in a formal validation process. Poor parameterisation of those inputs which significantly affect predicted bioaerosol exposure may result in disagreements with measured data. It is likely that a review of the effects of these modules on the dispersion of other air pollutants might provide some pertinent information.

5. Conclusions

This paper presents the most comprehensive sensitivity analysis of bioaerosol dispersion modelling designed and undertaken specifically for emissions from composting facilities. A Monte-Carlo simulation approach was used with the steady state ADMS model. Results were analysed using a GLM, which explained the variability in the model output concentrations in terms of the contribution of the model input parameters.

The results showed that:

- The majority of the model input parameters to which predicted emission was most sensitive were associated with the emission source. These include the pollutant exit velocity, source height and geometry, pollutant particle mass and pollutant temperature.
- Outputs were also sensitive to the presence or absence of the DDM and WDM over the range of input values tested.

This analysis improves our understanding of how the ADMS dispersion model responds to different combinations of input parameters from plausible ranges for open windrow composting. The results can be used to:

i) Identify which model input parameters should be adjusted initially when calibrating this dispersion model for "bioaerosol emissions from composting" scenarios. Initially, the pollutant exit velocity, source geometry, pollutant particle mass and source height should be altered as these are inputs to which the model outs are sensitive and are easily adjusted.
ii) Guide future model input parameterisation. Specifically, an initial focus on quantifying the pollutant emission velocity is

Fig. 1. Bar charts of the ranked cumulative absolute *t*-values for each source type: 1) point, 2) line, 3) area and 4) all sources combined, excluding (a) and including (b) the wet deposition module. The numbers above the bars represent the ranking of the input parameters based on total absolute *t*-value from most sensitive to least sensitive. The abbreviation of the input parameters correspond to those provided in Table 1. * DUR and PUF have been excluded as they are only associated with point sources (graph 1) **'GEO' refers to the geometry, which differs for each source type (diameter for graphs 1a and 1b, length for graphs 2a and 2b, and vertical and horizontal length for graphs 3a and 3b). In graphs 4a and 4b, the 'GEO' values for each source were combined (GEO in graphs 1a and 1b, GEO in graphs 2a and 2b, and GEO V or GEO H in graphs 3a and 3 - the highest t-value of GEO V or GEO H was used).

likely to yield the single greatest return in terms of model performance.

Author contributions

P.D., S.F.T., M.W., R.P.K., P.J.L., K.W., and G.H.D designed the research and wrote the paper, P.D performed the research and analysed the data, S.J.T.P, research conception.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jenvman.2016.10.003.

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