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The screening evaluation of environmental odors: a new dispersion modelling-based tool

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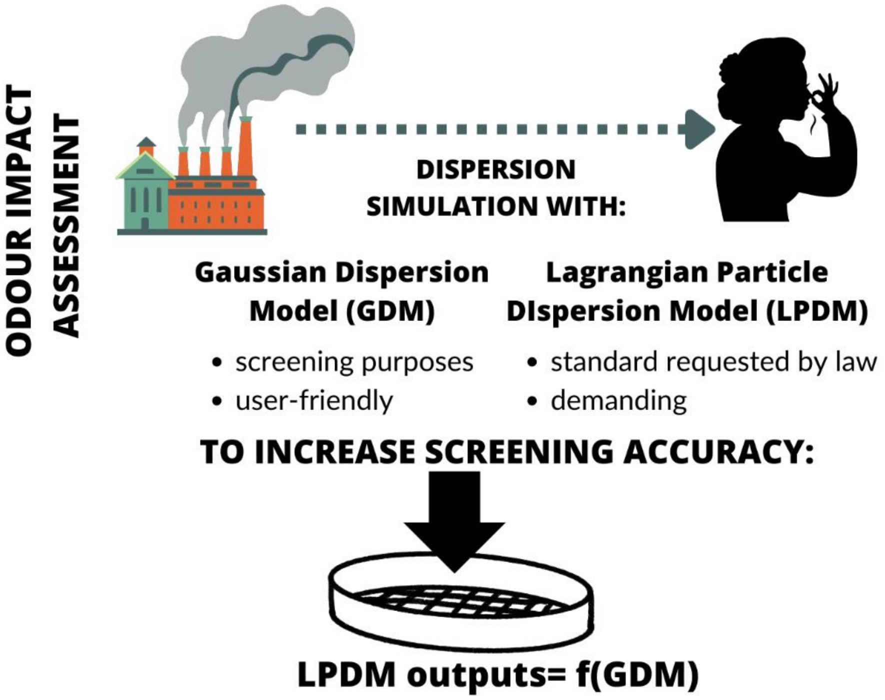
Graphical Abstract:



Abstract:

Odor pollution is the biggest source of complaints from citizens concerning environmental issues after noise. Often, the need for corrective actions is evaluated through simulations performed with atmospheric dispersion models. To save resources, air pollution control institutions perform a first-level odor impact assessment, for screening purposes. This is often based on Gaussian Dispersion Models (GDM), which doesn't need high computational power. However, their outputs tend to be conservative regarding the analyzed situation, rather than representative of the real in-site conditions. Hence, regulations and guidelines adopted at an institutional level for authorization/control purposes are based on Lagrangian Particle Dispersion Models (LPDM). These models grant a more accurate simulation of the pollutants' dispersion even if is more demanding regarding both technical skills and computing power. The present study aims to increase the accuracy of screening odor impact assessment by identifying the correlation function of the outputs derived from the two simulation models. The case-study is placed in northern Italy, where a single-point source, with various stack heights, was considered. The case-study is placed in northern Italy, where a single-point source, with various stack heights, was considered. The obtained correlation functions allow the practitioner to have more accurate first-level odor impact assessment, to save time for training and to reduce the site-specific meteorological data before proceeding with the simulation. The identified functions could allow institutions to estimate the results that would have been forecasted with the application of the more complex LPDM, applying, however, the much simpler GDM. This solution grants an accurate tool which can be used to address citizens' concerns while saving workforce and technical resources. Limitations are related to the specificity of the method regarding type sources, orography and meteorological conditions. Comparison with other screening tools is also presented and discussed.

Keywords:

Odor pollution; Dispersion modelling; Lagrangian Particle Dispersion Modelling; Gaussian Dispersion Modelling; Screening odor impact assessment; First-level odor impact assessment

1. INTRODUCTION

Being second only to noise as the leading cause of environmental complaints from citizens, odor pollution has gained more and more institutional attention in recent years (Bydder and Demetriou, 2019; D-NOSES consortium, 2019). The recent editorials and special issues dedicated to the environmental odor also demonstrate the current importance of the topic and the interest in the subject (Piringer and Schauberger, 2020; Schauberger et al., 2021).

A number of varied anthropogenic sources may lead to odorous emission. These are mainly associated with agricultural, industrial and waste management sectors. Examples vary from wastewater collection and treatment (Zarra et al., 2019), to municipal solid waste management (Sarkar et al., 2003) but also food industries (Brancher and De Melo Lisboa, 2014), and livestock production, alongside many others (Danuso et al., 2015). Despite odors often are not a direct cause of toxicity, as they reach the population in concentration below the toxicity threshold (Piccardo et al., 2022; Blanes-Vidal et al., 2014), several studies correlated exposure to malodorous substances with negative physiological responses (Baldacci et al., 2015; Blanes-Vidal, 2015; Hooiveld et al., 2015). Neurological, respiratory, and gastrointestinal symptoms are related with annoyance (Aatamila et al., 2011; Luginaah et al., 2002; Sucker et al., 2009) and include, among others, irritation of nose and throat, headache, nausea, cough, shortness of breath, stress, drowsiness, and alterations in mood (Schiffman and Williams, 2005). Moreover, malodorous gases have also negative socio-economic effects that must not be forgotten, such as the depreciation of properties near the emitting source (Danthurebandara et al., 2012).

1.1 The fragmented regulatory landscape of odor impact assessment: a global overview

In view of the above, regulatory authorities have responded issuing governmental guidelines and regulations to manage environmental odor. However, assessment of Odor Impact (OI) on the population is not an easy task. In fact, not only chemicals of the odorant mixture interact with each other - through synergism and antagonism, masking and neutralization - which makes it difficult to predict what will be perceived even knowing the emission's composition (Szulczyński et al., 2018; Yan et al., 2015), but there is also a highly variable inter-individual response to the same stimulus (Hayes et al., 2014; Van Harreveld, 2001). Moreover, the complexity is increased by the fact that OI is generated from a combination of five interacting factors: frequency, intensity, duration, offensiveness, and location (Bax et al., 2020). This led to a great variety in the regulatory framework worldwide. As examples, in the US the problem is not assessed at a federal level, and most of the States base their regulation in the nuisance laws. Within the States that have a specific legislation – 10 out of 50 – field olfactometry is the most employed technique to assess odor pollution levels (Bokowa et al., 2021). In Australia and New Zealand, OI assessment is based on the comparison between the State odor guideline values and the odor concentrations from dispersion model outputs, to verify if offensive effects are likely to occur (New Zealand Resource Management Act, 1991; NSW Protection of the Environment Operation Act, 1997). In Europe OI is regulated harmoniously through the Directive 2010/75/EU (European Parliament, 2010), that gives a general framework for odor regulation. Each country has its own legislation on the matter, that stays within the EU guidelines. The framework given by EU establishes odor limits at receptors based on concentration at ground level for many productive activities, which in certain cases can operate only if they have acquired an authorization (European Parliament, 2010). Very different is the Chinese situation, where the legislation (China Environmental Protection Agency, 1993) focuses on emission limits of pollutants, rather than on minimizing odor concentrations at receptors, like it happens in United States, Europe and Australia. Further details are published in review works (Bokowa et al., 2021; Brancher et al., 2017) which summarize the OI management criteria of countries around the world. Therefore, a very fragmented situation is outlined when it comes to the approaches used by jurisdictions to evaluate odor nuisance, both in regard of the regulatory approach and in the applied evaluation tools, which range from measurements of specific odorous chemicals to the use of electronic noses and/or human panelists to the application of atmospheric dispersion models (Laor et al., 2014).

1.2 Dispersion modelling: a powerful tool for OI assessment and regulation

Dispersion modelling is the most common method for conducting OI assessments, particularly under a regulatory context (Capelli et al., 2013; Nicell, 2009). It combines the characteristics of the emission sources with meteorological and topographical data of its surroundings. Then, through mathematical formulas that describe the mechanisms of convection and diffusion of gases and particles, they can estimate the concentration of odorants in ambient air downwind of the emission source (Adami et al., 2022). Therefore, with dispersion models it is possible - in a relatively short time - to estimate the concentrations of the odorous substances for a very high number of receptors (Ranzato et al., 2012). One of the most interesting aspects of dispersion models is that they can be not only descriptive, but also predictive. In fact, they can be used not only to analyze the current state of existing sources and to evaluate their impact on the territory, but also to forecast the emissions of new projects or to estimate the effect of abatement systems, thus, becoming a tool of strategic choice for companies (Cretu et al., 2010). Dispersion modelling is a fundamental step for the estimation of the OI near emission sources, because its output - the odor concentration statistics - can be used to define compliance with the regulatory standards (Mott and Guo, 2022; Uvezzi et al., 2022). The regulatory standards are the so-called Odor Impact Criteria (OIC). The OIC are the jurisdictional limits of emission and are usually determined combining three elements: the odor concentration threshold, its percentile of acceptability and the average time used to calculate the concentrations. Therefore, OIC are based on odor concentrations and the accepted probability of exceeding the threshold concentration in a certain time (Bokowa et al., 2021). Different jurisdictions have established different OIC parameters, which become more or less strict according to the needed level of protection, which is based on the presence of sensitive receptors, the number of populations living nearby the source and the land use, whether urban or rural (Brancher et al., 2017).

1.3 First-level evaluation of odor impact: screening modelling and empirical equations

OI assessment can have purposes of either screening or authorization/control of new or existing facilities. Despite the different aims, dispersion modelling can be used in both cases. Screening procedures – also called ‘first-level odor impact assessment’ – aim to save time and conserve economical resources, identifying sources which need to be further analyzed via refined modeling, and excluding the ones whose impacts are low enough that they will not pose a threat to ambient air quality standards (Maine DEP, 2019a). Screening modeling encompasses conservative analytical modeling techniques for estimating extreme upper bound concentrations (called “worst-case”), which will be compared to OIC. These "worst-case" estimates are based on simplified assumptions/representations of source-receptor geometries. Screening modeling tends to be easy-to-run, quick and conservative, so often results in an overprediction of air contaminant concentrations (US-EPA, 2016). Among the dispersion models listed by US-EPA for screening purposes, there is Screen3 (US-EPA, 1995), which will be used in this study. It is based on a Gaussian Dispersion Model (GDM) and serves as a rapid tool to estimate ground level concentration of contaminants under all atmospheric stability conditions (Cora and Hung, 2003).

In parallel with the screening dispersion models, other simplified tools for the measurement of odor annoyance have been developed. These methods, known as Empirical Equations (EEs), are in use in various jurisdictions and can support first-level evaluations (Brancher et al., 2020). They are reported as a valuable screening asset for countries without specific odor legislation, for a first-instance estimate of the area affected by odor nuisance (Schauberger et al., 2021). Among them, can be listed the Austrian (Schauberger et al., 2012a) and the German (Schauberger et al., 2012b; VDI 3894 Blatt 2, 2012) EEs, both based on exponential functions and derived from dispersion model calculations. Furthermore, there is the Williams and Thompson EE (Williams and Thomson, 1986), which address the distance within which complaints are likely in the worst-case scenario. Along them, others equations parametrized by empirical factors have been developed, like the Belgium one (Nicolas et al., 2008). EEs are also described in published works that summarize them (Guo et al., 2004) or compare them with dispersion models (Wu et al., 2019).

If screening procedures indicate that more in depth analyses are required, ‘second-level odor impact assessments’ are performed. In this case, more refined data (i.e. refined receptor grid, hourly meteorological data, source placement, etc.) and models, such as the Lagrangian Particle Dispersion Model (LPDM) (Johnson, 2022), are used (Maine DEP, 2019b). As for the screening models, the advanced model outputs are compared to the OIC, to verify the compliance of the emitting source with the legislation. In this second case the comparison with OIC is for authorization/control purposes.

1.4 Refining screening procedures for odor impact assessment: a correlation study between dispersion models

In this context, the purpose of the present work is to define the correlation functions between the outputs of a screening dispersion model and a second-level impact assessment dispersion model, considering single-point sources. As first step, the outputs concerning peak odor concentration and its occurring distance obtained from a GDM and a LPDM on analogous emitting sources are compared. Then, correlation functions are sought through a regression operation. Finally, the correlation functions are compared with other already established and published screening tools. Environmental practitioners and authorities could benefit from using these functions by refining GDM outputs to have more accurate screening procedures. The case study is in northern Italy, where dispersion modelling of a fictious single-point-source located in the city of Ravenna is performed with both GDM and LPDM. The height of the stack emitting odorous pollutant is varied through 10 simulation runs according to the following scheme: 10 m, 30 m, 50 m, 80 m, 100 m, 110 m, 140 m, 160 m, 180 m and 200 m. This scheme allows the effects of the emission height on the maximum concentration on the ground to be taken into consideration.

2. METHODS AND MATERIALS

In order to study the correlations between the GDM and the LPDM forecasts regarding the peak odor concentration and its occurring distance, a fictious experimental setting has been considered, and simulations have been carried out with both dispersion models. The predicted values of the GDM have been plotted against values obtained from LPDM. Then, a regression analysis has been performed to find the function that most closely fits them. The good fit of the function to the experimental data has been evaluated through the R-squared parameter.

2.1 Case-study description

The experimental setting includes a single-point source located in the industrial area of Ravenna (north-east Italy, coordinates: WGS84 281880.00 m N, 4927198.00 m E, UTM 33T) at about 7 km north-east of the city center, near an industrial plant whose emissions have been used for the simulation runs. The stack is assumed to be active twenty-four hours a day with a stack gas exit velocity of 1 m/s and an emission rate of 10,000 $UO_E/(m^3s)$. This unit is the European Odor Unit per cubic meter, which measure the number of times that an odorous gas has to be diluted in order to reach the odor threshold of a trained panel of individuals. The odor concentration at the detection threshold is by definition 1 UO_E/m^3. The odor concentration is then expressed in terms of multiples of the detection threshold (EN 13725,2022; Izquierdo et al., 2019).

The area surrounding the case-study source is flat, with a simple orography. The computational grid of the LPDM covers an area of 100 km^2, with dimensions of $(10 \cdot 10 \cdot 4)$ km^3. The computational grid of the GDM covers a downwind distance of 5 km, starting from 100 m from the source.

Ten simulation sets have been conducted with both dispersion models, varying the stack height for each one. Specifically, emissions heights of 10 m, 30 m, 50 m, 80 m, 100 m, 110 m, 140 m, 160 m, 180 m and 200 m have been taken into consideration. These source heights were selected as representative of typical odour sources elevation. Odour sources are generally classified into diffuse and conveyed sources. The first ones do not have a defined waste air flow, the emission of odours occurs by diffusion convection from the surfaces to the atmosphere (landfills, wastewater treatment plants, etc.) and their heights are mostly estimated at 0 – 20 m from the original land level (CPCB, 2019; SWIM-H2020 SM, 2018). The second type of odour sources use canalised ducts (e.g., stacks, vents, etc.), they are typically large-scale animal farms, manure storage, incineration plants, food and beverage industries, etc. In these cases, the stack height is commonly 25 – 100 m (Zanetti et al., 2010; Bokowa et al., 2021).

2.2 Analyzed variables

The considered variables are the peak odor concentration statistics – in compliance with Italian legislation – and their occurring distance from the source.

Italian legislation does not set any regulatory limit regarding odor pollution at a national level. General references can be found in the Italian Environmental Code (D.lgs 152/2006) but the specific regulations and guidelines are of regional competence. The pioneer Italian region to enact odor regulations was Lombardy (north Italy) then followed by various other Italian regions, whose statute was often inspired by the latter.

Whereas other regions directly applied Lombardy's regulation, in the absence of their own specific one. Thus, in this work the odor concentration statistics are calculated in compliance with the legislation of the Lombardy region (DGR Lombardia IX/ 3018, 2012). Lombardy's odor regulation has a maximum impact standard logic. This refers to the frequency of the permitted number of exceedances of a specific odor concentration threshold. This is usually based on a percentile, which is a number that define the percentage of scores within a group of data that fall below it. In Lombardy's jurisdiction this threshold is put at the 98th percentile of annual hourly peak odor concentration values. Then, based on the land use in the surrounding area of the odor source (e.g. industrial or residential area) different concentration thresholds are permitted, and vary between 1, 3 and 5 UO_E/m^3. Note that the concentrations of interest are the ones perceived in 5 seconds, which correspond to one respiratory act. Since the dispersion model output is the hourly average concentration of pollutant, model's output data must be post-processed with an adequate Peak to Mean Ratio, an algorithm that correlates the hourly average value of the concentration with its peak odor value. So, in the present paper, the ground odor concentrations estimated in the worst-case scenario with the screening model is compared to the hourly peak odor concentration values at the 98th percentile, which is the needed value to determine compliance with the limits defined in the Italian legislation. Then, the distance from the source at which these concentrations occur are also compared.

2.3 Gaussian Dispersion Model simulations

First-level OI assessment dispersion simulations were conducted through Lake Environmental Software's Screen View (Lakes Software, 2018), which is a freeware downloadable version. Screen View is an user-friendly interface for the US-EPA screening model, SCREEN3, which is a single source Gaussian plume model. It can estimate the so-called worst meteorological case ground level concentrations for single-point sources, and its occurring distance. Table 1 summarize the input data entered for the simulations. 1 m spatial resolution and a constant value of 2.3 Peak to Mean Ratio have been used, in compliance with Lombardy Region's Guidelines (DGR Lombardia IX/ 3018, 2012).

Table 1. Input of the Screen View software for the GDM simulation. For each simulation run the height of the stack is varied as follows: 10 m, 30 m, 50 m, 80 m, 100 m, 110 m, 140 m, 160 m, 180 m and 200 m.

VARIABILE	INPUT	UNIT OF MEASUREMENT
source type	point	
dispersion coefficient	rural	
emission rate	23000	UO_E/s
stack inside diameter	0.8	m
stack height	variable between 10 and 200	m
stack gas exit velocity	1	m/s
stack gas exit temperature	293.15	K
ambient air temperature	293	K
terrain option	simple terrain	
simple terrain	flat terrain	
simple terrain	automated distances	
meteorology	Full Meteorology	
automated distances min	100	m
automated distances max	5000	m
building downwash	not considered	
fumigation	not considered	

Regarding meteorology, the ‘Full Meteorology’ option was selected. This setting evaluates all combinations of stability classes, and related wind speeds, to find the maximum possible concentration at ground level. These combinations are reported in Table 2, as they are stated in the Screen View’s user guide (Thé et al., 2016). The atmospheric stability classification is based on the one proposed by Pasquill-Gifford, which count six stability classes, from A to F. The A class is the most unstable one, associated with the higher turbulence. This will cause pollutants to disperse more rapidly than with more stable atmospheric conditions, that can be found as you move to classes closer to F.

Table 2. Meteorological combinations of Pasquill-Gifford stability class and wind speed that leads to the maximum ground level concentration.

Pasquill-Gifford stability Class	10-Meter Wind Speed (m/s)												
	1.0	1.5	2.0	2.5	3.0	3.5	4.0	4.5	5.0	8.0	10.0	15.0	20.0
A	*	*	*	*	*								
B	*	*	*	*	*	*	*	*	*				
C	*	*	*	*	*	*	*	*	*	*	*		
D	*	*	*	*	*	*	*	*	*	*	*	*	*
E	*	*	*	*	*	*	*	*	*				
F	*	*	*	*	*	*	*						

2.4 Lagrangian Particle Dispersion Model simulations

More refined air quality modelling simulations are conducted using the LAPMOD modelling system, developed by Enviroware (Enviroware srl, 2022), which is used to estimate the 98th percentile of peak hourly average concentrations on annul basis, in compliance with Italian's OIC. LAPMOD system comprehends both the modelling software, and various pre and post processing data software. Software packages used in this study are LAPMOD and LAPOST. LAPMOD is a tri-dimensional non-stationary Lagrangian particle model that can be used to simulate the atmospheric dispersion over complex terrain and non-homogeneous real time wind flow. Moreover, LAPMOD can also simulate the dispersion of odors. LAPOST is LAPMOD's post-processor. It reads the output files created by LAPMOD and determines several statistics for concentrations and/or for specific temporal intervals. LAPOST has been used to extract the statistics of our interest: the 98th percentile, on an annual basis, of the peak hourly average concentrations perceived over 5 seconds. 100 m spatial resolution has been used.

Regarding meteorological input LAPMOD is fully coupled with the diagnostic meteorological model CALMET that provides all the required information about wind speed and direction, and turbulence parameters. The original meteorological data that we used for the simulations were in AERMOD Ready format (WRF-MMIF), centered at the point named 'Marina di Ravenna' (Latitude: 4927204.82 m N, Longitude: 281863.66 m E, Zone UTM: 33), located in proximity of the emission source and concerning the year 2020. The AERMOD original data have been converted into the CALMET format using the specific developed pre-processor LAPMET. For the Peak to Mean Ratio, Smith's original algorithm (Smith, 1973) was applied, together with Mylne's exponential attenuation function (Mylne, 1992, 1990; Mylne and Mason, 1991), which are already implemented in LAPMOD.

LAPMOD and LAPOST are implemented in FORTRAN language. Input files for both LAPMOD and LAPOST used for the simulations can be found in Annex 1.

2.5 Comparison with other screening tools

After the identification of the functions correlating GDM and LPDM's outputs through regression analysis, a comparison against already established and published screening tools is carried out. Therefore, estimations obtained with the functions proposed in this paper are compared – in terms of annoyance distance or odor concentration – against outputs from previously proposed equations, that comprehend both screening legislative tools and EEs.

The comparison with a screening legislative procedure has been performed against the New South Wales (NSW) screening model (Department of Environment and Conservation (NSW), 2006a, 2006b), while a comparison with EEs has been performed against the Williams and Thompson (W-T) (Williams and Thomson, 1986) EEs and the Belgium EEs (Nicolas et al., 2008).

A tool proposed by Enviroware (https://www.odorimpact.com/en/stackrate.shtml) is used for making the comparison with the NSW framework. This tool bases its calculations precisely on the Level 1 of NSW procedure allowing to estimate the maximum recommended odor emission rate from a stack so that the ground odor level is below annoyance level. In order to make this comparison, a reference level of 1 OU_E – at which 50% of the population perceives the odor – is assumed as the allowed odor concentration at the ground. So, firstly, the recommended odor emission rate from a stack to stay below the 1 OU_E nuisance level is estimated through the Enviroware tool for all the stack heights listed in paragraph 2.1. Then, the outputs from the Enviroware tool are used as emission rate inputs into GDM software. Finally, the odor concentration estimated by the GDM is adjusted with the regression function that allows deriving the concentration that would have been estimated by an LPDM at the 98° percentile (which will be presented in chapter 3.2 as Eq. 3). Because the odor emission rate used in this set of simulations is the one that, according to the NSW legislation, grants to stay below the defined annoyance level of 1 OU_E, it is expected to obtain similar peak concentrations.

The other two performed comparisons are done against EEs. Of them, one will focus on odor concentration as above, while the other will focus on the distance of odor annoyance from the source. Starting from the latter, Williams and Thomson (1986) in their Eq. 7 provide an empirical equation that correlates the distance from an odorous source within which complaints are likely and the odor emission rate. Therefore, the comparison with our case study is performed by entering the case-study emission rate in W-T's EE and comparing their estimated distance with the ones obtained through the combination of the GDM simulation and the regression function that allow to derive the annoyance distance from LPDM (which will be presented in chapter 3.2 as Eq. 1).

The last comparison is performed against the Belgium EEs, and it is based on the distance and the odor emission rate at which it estimates an hourly concentration of 10 UO_E at the 98th percentile. These data are reported by Nicolas and colleagues (2008), and were used as GDM input. Then, as already done for the NSW comparison case, the GDM outputs were corrected with the regression function that allows deriving the concentration that would have been estimated by doing a simulation run with a LPDM (which, as stated above, will be presented in chapter 3.2 as Eq. 3). The odor concentration values are then compared to the 10 UO_E reported in the Belgium's paper (Nicolas et al., 2008).

Lastly, it is significant to note that the GDM simulations in the present paper are performed with the US-EPA screening model, SCREEN3, being the one on which is based the Screen View software. Therefore, all the comparisons above are also performed against this very well-known and established screening tool.

3. RESULTS

3.1 GDM and LPDM outputs

Results of the simulations conducted with Screen View and LAPMOD are shown in Table 3, for each considered emission height. The column 'WMC Cmax' reports the maximum ground concentration of pollutants derived from the GDM simulations in the Worst Meteorological Case. The column '98th percentile' refers to the concentration threshold in compliance with Italian legislation for second-level OI assessment and it is estimated by LPDM model. As expected, for both models the concentration decreases as the height of the stack increases. On the contrary, the distance from the source at which the peak odor concentration occurs increases in accordance with source height.

Table 3. Screen View and LAPMOD simulation of compared concentrations (WMC Cmax and 98th percentile, respectively) and corresponding distance from the source. Last column (C98%/Cmax) is the ratio of 98th percentile predicted by LAPMOD to the WMC Cmax predicted by Screen View.

	Screen View		**LAPMOD**		**C98%/Cmax**
Source height [m]	WMC Cmax [UO$_E$/m^3]	distance [m]	98th percentile [UO$_E$/m^3]	distance [m]	
10	23.94	110	3.68	100	0.154
30	2.94	327	0.94	200	0.320
50	1.14	258	0.53	300	0.465
80	0.51	369	0.358	400	0.702
100	0.357	434	0.288	361	0.807
110	0.307	459	0.245	412	0.798
140	0.212	530	0.177	632	0.835
160	0.175	569	0.145	412	0.829
180	0.151	625	0.115	500	0.762
200	0.139	701	0.117	707	0.842

Concerning the pollutant ground concentration variable, for all the source heights considered in the analysis it is possible to notice that Screen View's simulation outputs are similar, but always higher, compared to LAPMOD ones. Moreover, the higher the emissive source, the closer the estimates of the two models are to each other. The wider difference in the models' estimation noticeable for the 10 meters height can be attributed to the discretization of the LPDM study grid when it estimates average concentrations at distances very close to the emissive source. Therefore, the most critical predictions are for low sources.

These results confirm the effectiveness of screening simulations in identifying those situations in which the concentration is within the regulatory limits. Therefore, a screening ground concentration value below the regulatory limit makes it possible to state that the tested odorous source is below the allowed maximum emission level without further investigation, thus, avoiding aggravating the system with unnecessary more accurate analyses.

3.2 Regression analyses

Firstly, the odorous peaks' distances from the source are compared in a two-dimensional plot to observe a possible correlation between the GDM and LPDM outputs. A linear regression has been applied to the datasets. The independent variables are the odorous peak distances from the source predicted by the GDM, while the dependent variable is the odorous peak distances from the source predicted by the LPDM (Figure 1). The intercept of the trend line is placed at the origin of the axes, to represent those conditions of odorous peak exactly above the emission source.

As reported in sections 2.3 and 2.4 respectively, the distance between the grid's nodes is 1 m for Screen View and 100 m for LAPMOD, therefore, the Screen View output data of odorous peaks are not perfectly congruent with LAPMOD's ones.

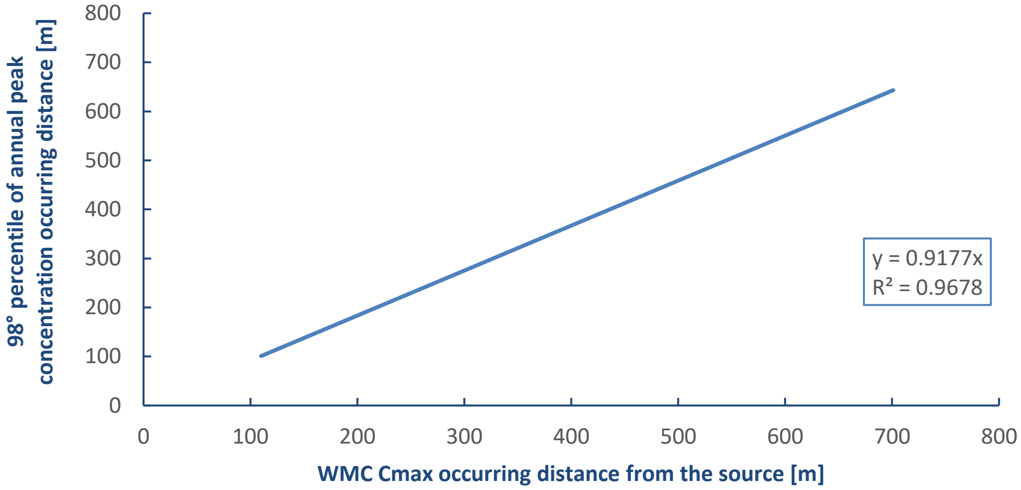


Figure 1: correlation between the distances from the source of the odorous peaks estimated by the two models. The WMC Cmax corresponds to the maximum ground concentration estimated by the GDM in the worst meteorological conditions.

As it is possible to observe from Figure 1, a good correlation between the two models' outputs (R^2=0.9678) was observed. The correlation function obtained is (Equation 1):

$$y = 0.9177\,x \qquad \text{Eq. 1}$$

with:

y =Lagrangian Particle Dispersion Model output;

x = Gaussian Dispersion Model output.

The second correlation operation has initially been carried out by comparing the maximum concentration of odorant substances (Cmax), identified by the simulation carried out with Screen View, and the values at the 98th percentile of the hourly peak concentrations on an annual basis (C98%), identified by the simulation carried out with LAPMOD. Also in this case, the independent variables are data predicted by GDM, while the dependent variables are the ones predicted by LPDM. As it is possible to observe from Figure 2, there is a good correlation between the two models' output estimates (R^2=0.989) especially on low concentrations, which are the ones farthest from the source. To obtain a better vision and correlation of the plotted data regarding low concentrations, the values are reported in a log-log scale.

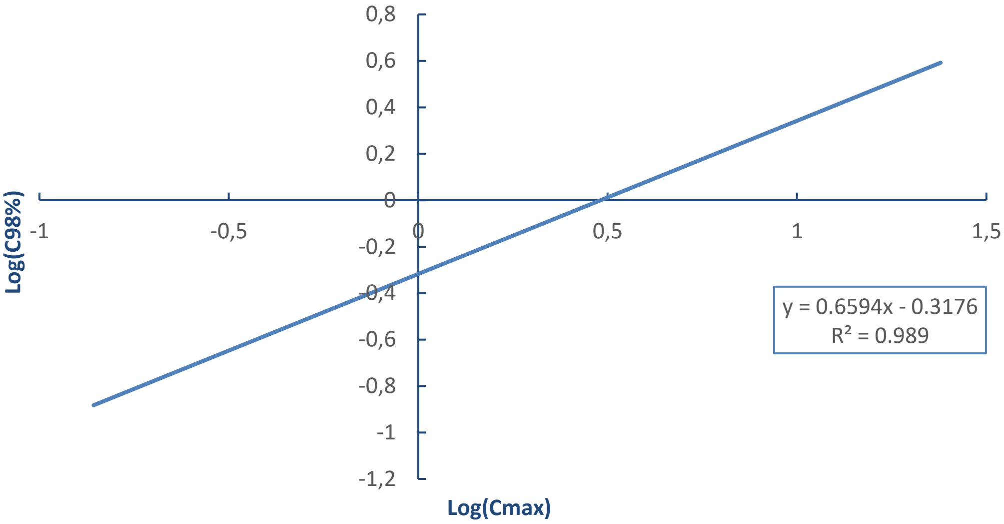


Figure 2: correlation between maximum concentrations predicted by Screen View (Cmax) and LAPMOD (C98%).

The correlation function obtained is (Equation 2):

$$y = 0.6594\, x - 0.3176 \qquad \text{Eq. 2}$$

with:

y =Lagrangian Particle Dispersion Model output;

x = Gaussian Dispersion Model output.

An important limitation of the correlation function indicated above is that it does not account for the fact that the peak concentrations depend both on the emissive source's height and atmospheric stability class. In particular, the peak concentrations of odorous substance occur: 1) in Pasquill-Gifford stability class A-C for a high height source, 2) in Pasquill-Gifford stability class D-F for a low height source.

Therefore, to consider this aspect, it was decided to correlate the C98%/Cmax ratio with the height of the emission source. So, the independent variable x becomes the height, and the dependent variable y is the ratio of concentrations. Knowing the latter, it is possible to extrapolate the desired C98% value simply by multiplying the ratio by Cmax.

Adding the source height variable allows, indirectly, to also consider which stability atmospheric class determines the peak odor concentrations for that specific emission configuration. Therefore, the meteorological conditions associated with these classes of stability, which for a certain area have a certain occurrence probability distribution can also be considered into olfactory impact assessments. Starting from the scatter graph that compares the relationship between concentration ratios and the source's height, the function that best correlated the variables of interest was then sought (Figure 3).

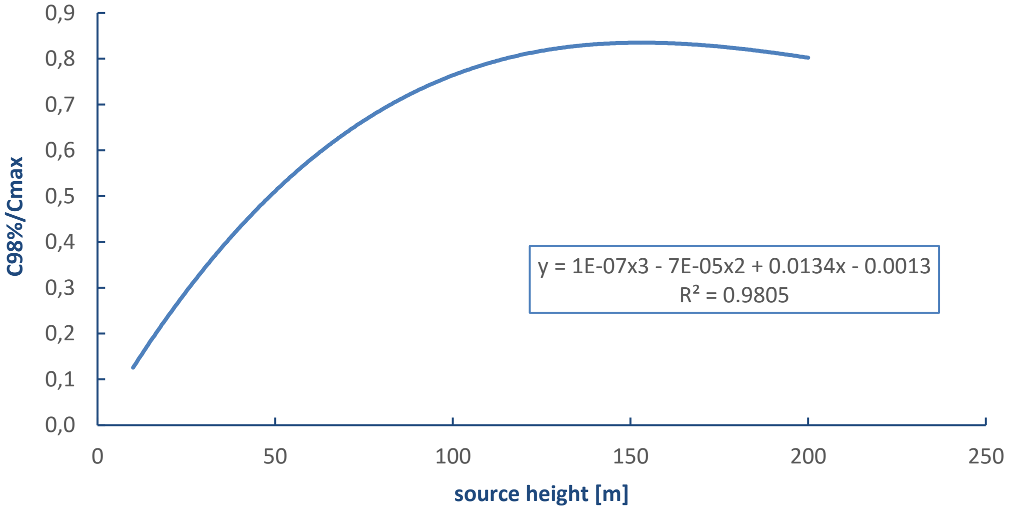


Figure 3: correlation between concentrations ratio (C98%/Cmax) and source height. C98% represents concentrations predicted by LAPMOD and Cmax the ones predicted by Screen View.

The chosen function to represents the experimental data is a third-degree polynomial function (Equation 3):

$$y = 1E - 07\,x^3 - 7E - 05x^2 + 0.0134x - 0.0013 \qquad \text{Eq. 3}$$

with:

x= height of the emission source;

y= C98%/ Cmax.

This function well correlates the two variables (R^2=0.9805) while not requiring high computing power. Moreover, its ease of use facilitates its applicability within first-level olfactory impact studies.

4. DISCUSSION

4.1 Applications, limits, and future developments

As seen above, R^2 parameters show good correlation functions between the estimations done by GDM and those done by LPDM. The advantages of using these functions, which are analytically easy to solve compared to conducting a second-level simulation, are: 1) to obtain more accurate first-level odor impact assessment studies; 2) to reduce the training and learning time necessary for those who have to use the simulation program, since the screening program is much simpler to use; 3) to not need having site-specific meteorological data in order to proceed with the simulation.

In addition, these correlation functions, precisely because of the way they have been constructed, can explain more directly, in terms of percentiles, the effect that less frequent meteorological conditions have on the dispersion of odors in an area of interest, than can be derived from the Empirical Equations (EEs) known from the literature (and cited above). In fact, to date, in the literature, the empirical equations published attempt to define the 98th percentile through ad-hoc coefficients whose values are unclear as they were determined. Moreover, these functions are useful: 1) in all those cases when second-level olfactory impact studies are not mandatory, but in which the impact of the odorous emissions on the territory is still important to be taken into consideration and has to be stated within environmental assessment; 2) to understand how much the outputs of the screening simulations differ from the second level ones. Being aware of the discrepancy, indeed, can give indications and help quantify the extent of the eventually required corrective actions that will have to be implemented so that the production plant's emissions stay within the limits set by law.

An evident limit in the applicability of the aforementioned functions is their close correlation with the emission's condition regarding the source type and the orographic and meteorological characteristics of the study site where the analysis was made. The correlation functions were, inevitably, derived starting from the output data obtained from the simulations carried out with the two dispersion models. If, for similar sites, the approximations made by the simulation models can be considered analogous, and it is, therefore, possible to apply the same correlation functions, the same cannot be said for territories with orography, meteorology or types of emission sources deeply different from those from which the correlation function was derived.

A noteworthy limitation of the proposed method is that it refers to correlations between ‘worst meteorological case’ and ‘98th percentile’ of point sources in the presence of simple or intermediate terrain conditions, i.e. with orographic relief in the study area lower than the physical height of the stack. In addition, the proposed method assumes that the trend of the frequency distributions of airborne malodorous substance concentrations, for values much higher than 50th percentile (such as those on which we focused the study) present a similar log-normal type trend in all cases, as, by the way, also supported by a variety of works in the literature (Lai et al., 2013; Bhandari, 2018; Omar & Hamid, 2022).

As a consequence of these limitations, also considering the growing attention to olfactory pollution, future developments could include the replication of the simulations carried out in other orographic and meteorological conditions and for other types of sources, including areal or volumetric. By using this approach, the accuracy of the screening method will be considerably improved. Moreover, it will thus be possible to examine how and how much the correlation functions vary as the parameters vary input, and it will be possible to have an even wider range of cases to which apply this assessment method.

4.2 Comparison with other Screening tools

Several authors have already compared empirical models and dispersion models applied in odor impact assessment and concluded that empirical models are valuable but must be done with caution. Wu and colleagues (2019) matched empirical models and dispersion models showing that simplified tools can be used for screening applications, but the trade-off between accuracy and simplicity, especially for practical applications, should be carefully considered. Brancher and coauthors (2020) affirm that, although empirical equations are handy to substitute more pricey and time-demanding analysis, they do not grab the inherent complexity of reality as good as dispersion models. As explained in paragraph 2.5, outputs derived from the equations presented in paragraph 3.2 have been matched with those obtained through three previously proposed empirical equations. The empirical tools considered are: 1) the New South Wales (NSW) screening approach (Department of Environment and Conservation, 2006a, 2006b), 2) the empirical equations proposed by Williams and Thompson (W-T) (1986) and 3) the empirical equations proposed by Nicolas and coauthors (2008), called Belgium EEs. Other EEs have been reported both in literature and in countries’ regulatory system, like the German VDI regression model (Schauberger et al, 2012a) or the Ontario MDS II, the

Minnesota OFFSET and the Purdue models (Guo et al.,2004), as well as the Austrian one, for which various versions has been developed over time (Guo et. Al, 2004; Schauberger et al, 2012b). The comparison between all of these other equations and the ones presented in this work wasn’t viable, due to meteorological data or parameter requested by those equations not at our disposal.

In addition to the comparisons with the selected empirical equations, it is also shown, for each of them, the results obtained from the US-EPA SCREEN3 model, which is assumed as “reference model” due to its role as US-EPA screening model and its capability to estimate the so-called worst meteorological case.

The result of the comparison between the correlation proposed in Eq. 3 and NSW’s screening model is shown in Figure 4 and Table 4, along with the US-EPA one. As explained in paragraph 2.5, the three tools have in input the same emission rate (the one which allows to stay below the 1 OU_E according to NSW’s screening model).

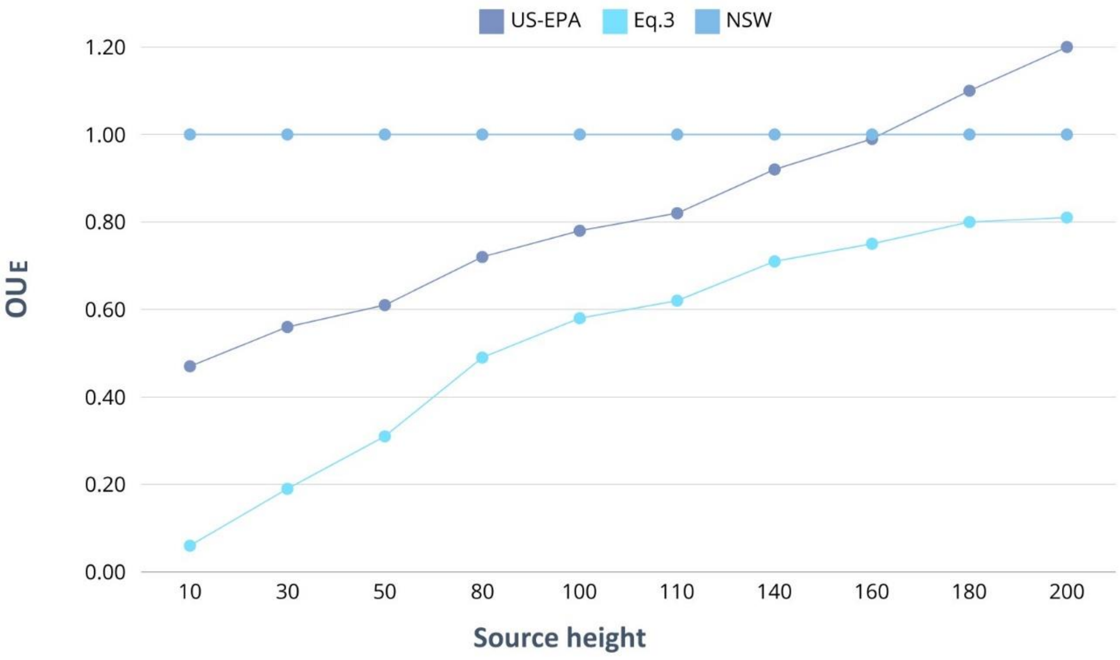


Figure 4: comparison between the estimated ground odor levels of NSW’s screening model, US-EPA procedure and the correlation proposed in Eq. 3 of the present article

Table 4: Comparison between the minimum and the maximum differences of the estimated ground-level odor concentrations based on the odor fluxes calculated by the NSW method. (The reference value for ground concentrations according to the NSW method was taken as 1 OU_E/m^3).

	US-EPA (OU_E/m^3)	Eq. 3 (OU_E/m^3)
Minimum difference	-0.52	-0.92
Maximum difference	+0.2	-0.2

The comparison reveals noteworthy aspects. Firstly, it is possible to notice that our correlation functions, designed to establish the 98th percentile of hourly peak concentrations, produce lower values than NSW formulae for all the emissive source configurations. Interestingly the trend is the same, up to a source height of 160 m, when the NSW estimation is compared against the US-EPA ones (refer to blue and grey lines in Figure 4). Only if source height is more than 160 m, NSW's screening model is more conservative than US-EPA procedure. Therefore, the NSW formulae appear to be overly conservative, even when comparing with the 'worst meteorological case' estimated using US-EPA procedures. So, this comparison suggests considering the NSW formulae as particularly cautious.

Figure 5 and Table 5 show the comparison of the nuisance distances estimated with W-T's EE and US-EPA screening tool against the ones calculated with Eq. 1 of the present paper, for each stack height.

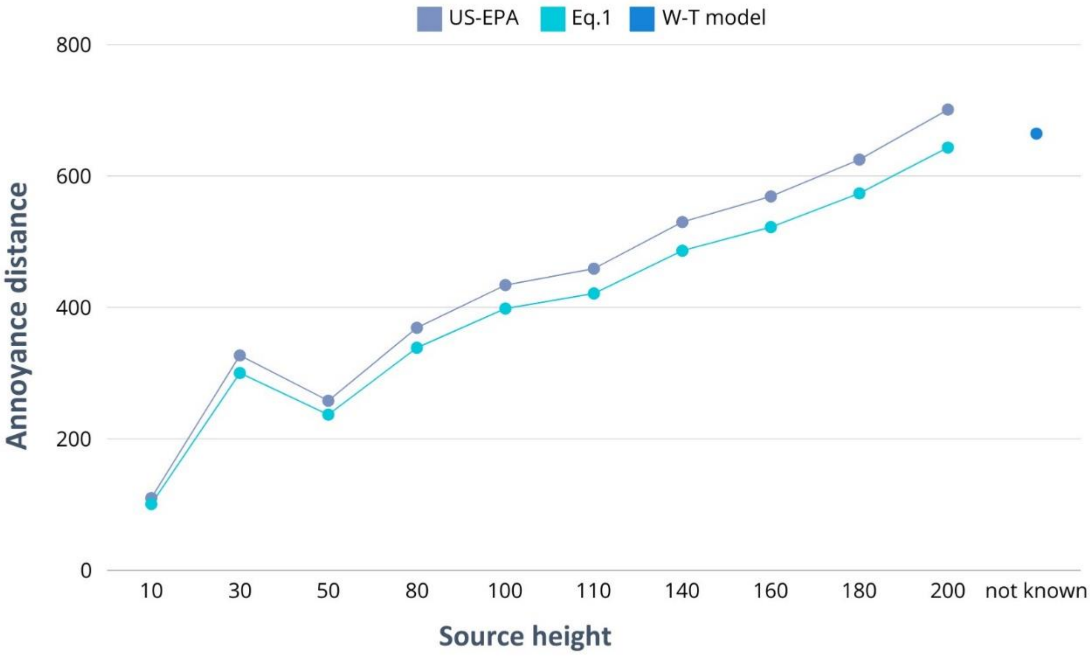


Figure 5: comparison between odor annoyance distance estimated with W-T Empirical Equation, US-EPA procedure and the correlation proposed in Eq. 1 of the present article.

Table 5: Comparison between the minimum and the maximum differences of the odor annoyance distance estimated with W-T Empirical Equation, US-EPA procedure and the correlation proposed in Eq. 1 of the present article

	US-EPA (m)	Eq. 1 (m)
Minimum difference	-36.5	-21.2
Maximum difference	-554	-554

It is possible to notice that the distance estimated by the W-T model is on the higher end of the predicted distances, compared to both US-EPA and our method. However, the model by Williams and Thompson, which is one of the first published, appears overly simplified, as you might expect observing that the resulting distance is independent to the source heigh. The employed formulas are based solely on Gaussian model theory, and they do not account for the effects of different atmospheric stability classes on the perception of the odor peaks, nor does it consider the height of the emissive source. Moreover, there is no established correlation between the highest predicted ground-level concentrations and their percentile values. In contrast, in this study, we introduce correlation functions between the source heights and the distances downwind where the 98th percentile of hourly peak concentrations occur. These equations are presented as a function of source height and provide a valuable contribution to understanding air pollution dispersion.

Lastly, the odor concentration at ground level estimated with Belgium EEs is compared against US-EPA screening procedure and Eq. 3, presented in chapter 3.2. After setting odor emission rate and distance from the source, UO_Es have been calculated and compared. Results of this comparison are presented in Figures 6a and 6b and Table 6.

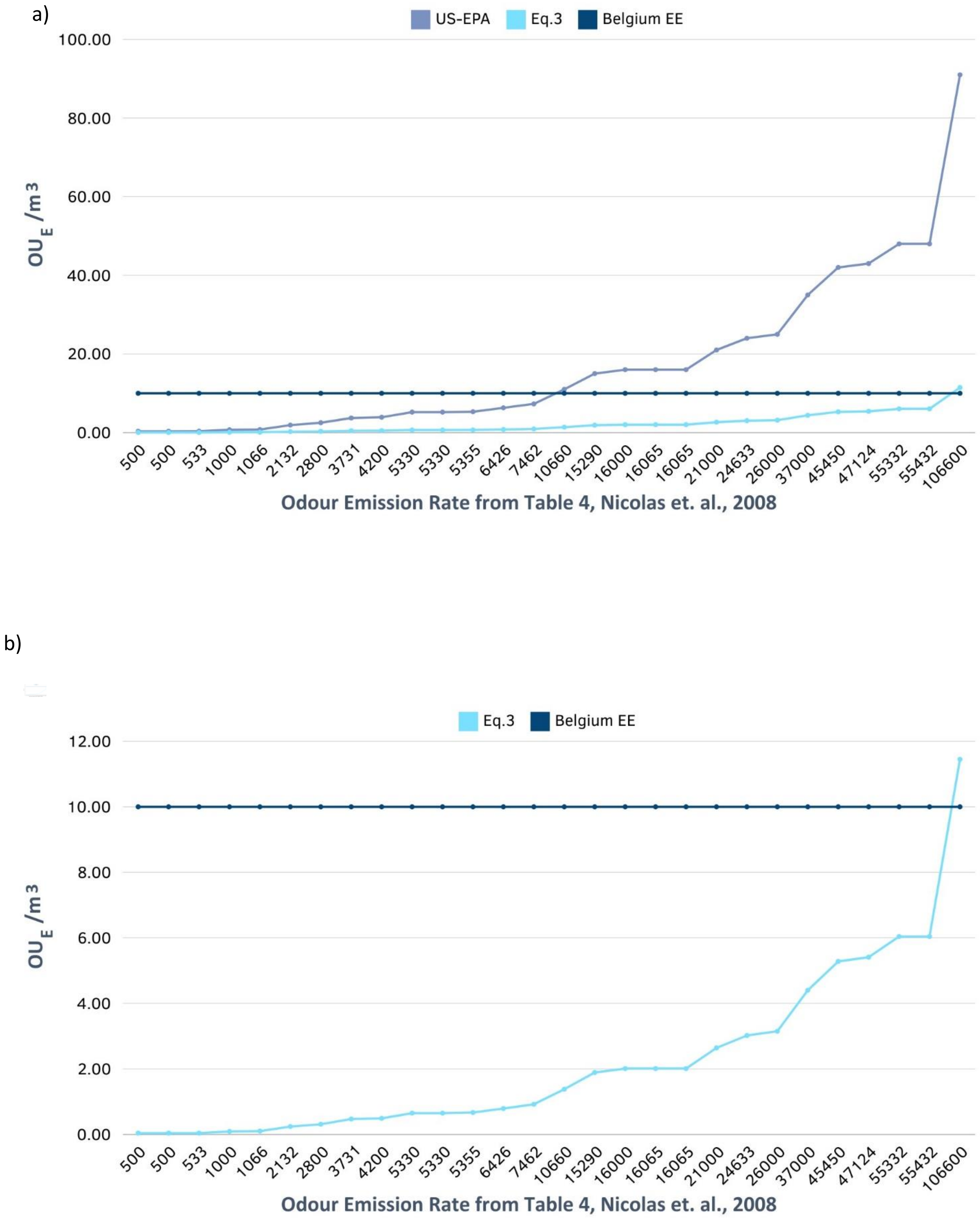


Figure 6a: comparison between the odor concentration estimated with Belgium Empirical Equation, US-EPA procedure and the correlation proposed in Eq. 3 of the present article. Figure 6b: comparison of only Belgium EE and Eq.3, for easier and more precise comparison visualization.

Table 6: Comparison between the minimum and the maximum differences of odor concentration estimated with Belgium Empirical Equation, US-EPA procedure and the correlation proposed in Eq. 3 of the present article.

	US-EPA (OU_E/m^3)	Eq. 3 (OU_E/m^3)
Minimum difference	-10	-10
Maximum difference	+81	+1.8

Again, for almost all the cases analyzed, our proposed method estimates a lower odor concentration than the Belgium EEs. Different is the US-EPA screening estimate, which overshoots the 10 UO_E/m^3 from an emission rate of about 8000 UO_E/s onwards. It should be noted that these high values of emission rates are usually associated not with punctual but with areal sources, and the observed deviation can be explained as an effect of the many assumptions that needs to be made to apply GDMs to areal sources. Therefore, this comparison confirms that, when working with sources other than punctual ones, GDM estimations – such as the US-EPA one- should be used with caution and the correction performed with Eq. 3, based on LPDM, appears useful to bring the data back into a lower range, in accordance with Belgium's EE.

Comparing US-EPA and Eq. 3 estimations only with the cases in which the odor emission rates conform with a punctual emission, it can be observed that the 10 UO_E/m^3 reported in Nicolas et al (2004) seems in many cases overestimated. As previously occurred, also in this case the empirical equations appear more precautionary than both the US-EPA screening model and the Eq. 3 presented in this paper.

5. CONCLUSIONS

Given the growing relevance of OIs on communities, it is foreseeable that there will be an increasing need for assessment for both preventive/authorization and monitoring purposes. For this reason, having user-friendly tools which have both low time and resource requirements is essential for the proper management of production activities and services (such as waste treatment). The use of a screening step in the evaluating process goes in this direction.

In this context, this study proposes a method to increase the accuracy of first-level assessment procedures, by correlating the outputs obtained from the screening GDM Screen View with those obtained from the LPDM

LAPMOD, used for second-level OI assessment and obtain correlation functions. The examined variables are the odorous peaks and their occurring distance from the source. The case study is located in Ravenna (north-east Italy) and the considered regulatory guidelines are from Lombardy region (northern Italy). Simulations' outputs report good correlation functions for both considered variables, evaluated through the R^2 parameter. This method allows to derive the outputs that would have been obtained with the LPDM while using the GDM one. With the first one being demanding but compulsory for legislation compliance if the screening procedure detects a possible risk, it appears relevant to have a robust screening procedure. The proposed correlation function allows to estimate data more closely related to the analyzed territory, while saving both financial and technical resources. Accuracy of the method is related to the possibility of adjusting correlation functions on the basis of site-specific characteristics (like as orography, meteorology, etc.). As a consequence of the method limitations, future developments should be expanded to other areas with different source, orographic and meteorological conditions.

The comparison of this method with already proposed formulae shows that some of them seem overly conservative, even when compared to more cautious procedures such as the one proposed by US-EPA. In general, the method here presented offers an increased accuracy even if it is a screening tool.

This study is only a first step in this direction. The identified correlation functions can be applied in every site with the same OIC as the Italian legislation and similar emitting conditions. However, the accuracy of the method drops varying emission conditions and orography from the case study here considered. Therefore, further studies are needed, to replicate the method in different conditions and expand its applicability.

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Author contribution:

Martina Pelliconi: Data curation; Formal analysis; Methodology; Software analysis; Visualization; Roles/Writing – original draft

Prof.ssa Serena Righi: Project administration; Visualization; Writing – review & editing.

Prof. Massimo Andretta: Conceptualization; Data curation; Formal analysis; Methodology; Software analysis; Supervision; Writing – review & editing.

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