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Measurements techniques and models to assess odor annoyance: A review

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ABSTRACT

Odors have received increasing attention among atmospheric pollutants. Indeed, odor emissions are a common source of complaints, affecting the quality of life of humans and animals. The odor is a property of a mixture of different volatile chemical species (sulfur, nitrogen, and volatile organic compounds) capable of stimulating the olfaction sense sufficiently to trigger a sensation of odor. The impact of odors on the surrounding areas depends on different factors, such as the amount of odors emitted from the site, the distance from the site, weather conditions, topography, other than odors sensitivity and tolerance of the neighborhood. Due to the complexity of the odor issue, the aim of this review was to give an overview of: (i) techniques (sensorial and analytical) that can be used to determine a quantitative and qualitative characterization; (ii) air dispersion models applied for the evaluation of the spatial and temporal distribution of atmospheric pollutants in terms of concentration in air and/or deposition in the studied domain; (iii) major sources of odor nuisance (waste and livestock); (iv) mitigation actions against odor impact. Among sensorial techniques dynamic olfactometry, field inspection, and recording from residents were considered; whereas, for analytical methodologies: gas chromatography-mass spectrometry, identification of specific compounds, and electronic nose. Both kinds of techniques evaluate the odor concentration. Instead, to account for the effective impact of odors on the population, air dispersion models are used. They can provide estimates of odor levels in both current and future emission scenarios. Moreover, they can be useful to estimate the efficiency of mitigation strategies. Most of the odor control strategies involve measures oriented to prevent, control dispersion, minimize the nuisance or remove the odorants from emissions, such as adequate process design, buffer zones, odor covers, and treatment technologies.

1. Introduction

The growing interest of people towards the environment and the greater attention to the quality of life have led to defining odors as harmful atmospheric pollutants (Capelli et al., 2013b; Henshaw et al., 2006), since malodorous conditions are mostly associated with unhealthy air situations (Aatamila et al., 2011). Because of accelerated urbanization and the lack of suitable sites, urban areas are sometimes built directly within or close to existing waste treatment plants and farms (Peters et al., 2014). Nuisance due to odor generation by waste treatment plants (e.g. landfill and composting plants) (Blanco-Rodríguez et al., 2018; Rincón et al., 2019), and animal production operations is one of the major sources of complaints of people living near these facilities (Keck et al., 2018), and has triggered increased emphasis on controlling the impact of atmospheric pollutants on neighboring areas (Bibbiani and Russo, 2012; Hayes et al., 2014). Unpleasant odors may cause a variety of emotional and undesirable reactions in people, ranging from annoyance to documented health effects, leading to a reduced quality of life (Blanes-Vidal, 2015; Domingo and Nadal, 2009; Palmiotto et al., 2014).

The odor is defined by ISO 5492:2008 as an organoleptic attribute perceptible by the olfactory organ (including nerves) on sniffing certain volatile substances (International Organisation for Standardization, 2008). Thus, the odor can be defined as “perception of smell” or “a sensation resulting from the reception of stimulus by the olfactory sensory system”. Whereas odorant is a substance which stimulates a human olfactory system so that an odor is perceived (Blanco-Rodríguez et al., 2018). The odor is given by the interaction of different volatile chemical species, including sulfur compounds (e.g. sulfides, mercaptans), nitrogen compounds (e.g. ammonia, amines) and volatile organic compounds (e.g. esters, acids, aldehydes, ketones, alcohols) (Barth et al., 1984). Odorous compounds include both organic odorants and inorganic molecules that contribute to odor level (Zhu et al., 2016). Volatile organic compounds (VOCs) are a large group of organic chemicals, formed by molecules with different functional groups, having different physical and chemical behaviors, but characterized by certain volatility (Komilis et al., 2004), such as volatile fatty acids, alcohols, aldehydes, amines, carbonates, esters, sulfides, disulfides, mercaptans, and heterocyclic nitrogen compounds (Fang et al., 2012). On the other hand, inorganic compounds (H_2S, NH_3, Cl_2) due to their low molecular

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weights can bind olfactory receptors and affect odor level (Heaney et al., 2011; Huang et al., 2014; Pagans et al., 2006).

Different approaches and techniques have been used for measuring odors, both physical and chemical measurements (Capelli et al., 2013b; Munoz et al., 2010), and for simulating their dispersion in the atmosphere to plan setback distances, aimed at maintaining adequate buffer zones between livestock units and residents (Guo et al., 2004; Jacobson et al., 2005; Jacobson et al., 2000; Nimmermark et al., 2005; Schauberger et al., 2012).

Odors have always represented a social problem, but recently public concerns about their potential impact on health and wellbeing have been raised. This has led public opinion to concern on air quality issues and to complain to local Authorities (Brancher et al., 2019), with waste treatment plants and livestock farms representing the major sources of complaints (Keck et al., 2018; Sironi et al., 2005) to local Authorities (Brancher et al., 2019).

Thus, the aim of this review was to present, through the analysis of the published literature, an overview of techniques and models for measuring odors and simulating their dispersion, other than of odor emissions from waste management plants and livestock farms.

With this review we wanted to answer the following questions:

- Which techniques can be adopted for measuring odors in the field or in the laboratory?
- How can odor annoyance be assessed?
- Where do the biggest odors come from?
- How to protect people from odor nuisance?

According to these questions, the review has been organized as follows: Section 2 will be focused on odor measurements, Section 3 on dispersion models, Section 4 will be on the major sources of odor, waste and livestock, respectively, and, finally, Section 5 will be about strategies to protect people from odor nuisance.

2. Technical approaches to odor measurement

Quantitative and qualitative characterization of odors can be carried out by direct or indirect methods. In 2018, the European Union published a BREF (Bat REFerence document) on emissions monitoring “JRC Reference Report on Monitoring of Emissions to Air and Water from IED Installations” (Brinkmann et al., 2018). Regarding odor emissions, the following approaches are mentioned: dynamic olfactometry, dispersion models, field inspection, electronic noses, and odor surveys. Overall, in order to quantify the effective odor discomfort, sensorial techniques or analytical methodologies, based on human examiners, and on instruments, respectively, can be used (Munoz et al., 2010). According to this criterion, in sensorial techniques are included: dynamic olfactometry (Section 2.1.1), field inspection (2.1.2), and recording from residents (2.1.3); whereas, in analytical methodologies are mentioned: gas chromatography-mass spectrometry (2.2.1), identification of specific compounds (2.2.2), and electronic nose (2.2.3).

2.1. Sensorial techniques

2.1.1. Dynamic olfactometry

Olfactometry analysis is a standardized methodology (CEN EN 13725) used for determining the concentration of odors, combining an olfactometer with human panelists. The EN 13725:2003 standardized the procedures and methods of analysis, making the dynamic olfactometry a reliable and consolidated measurement method (EN 13725 2003).

The olfactometer submits the odor sample, diluted with neutral air at precise ratios, to a panel of human assessors (Munoz et al., 2010). The samples are presented to the panel at increasing concentrations until the panel members start perceiving an odor different from the neutral reference air. The result is the odor concentration (Cod), expressed in European odor units per cubic meter (ouE m^{-3}), which corresponds to the dilution factor necessary to reach the odor threshold, that is the minimum concentration perceived by 50% of the population (Blanco-Rodríguez et al., 2018). The odor concentration is calculated as a geometric mean of at least 12 odor detection threshold values of each member of the panel. The advantage of using a human nose is its higher sensitivity, even if it suffers from a lack of specificity for individual odorants (Barth et al., 1984). During the analysis of the air samples it is necessary to monitor the following parameters: temperature, spare parts/hour, soundproofing and code of behavior of the panel (not smoking or using perfume, be cold, be stressed, etc. before performing the analysis to avoid jeopardizing the results) (Brinkmann et al., 2018; Hayes et al., 2014). During the evaluation, panelists should be located in a dedicated and comfortable laboratory with temperature control and they must not be influenced by the response of other panelists or by the panel operator (Capelli et al., 2010; Dravnieks and Jarke, 1980).

Although all the panelists are selected according to their individual sensitivity and repeatability regarding the reference gas, n-butanol, they must be continuously screened and trained (Brattoli et al., 2011). For this latter purpose, samples of n-butanol at different concentration shall be used so that the panel members will not be able to guess the right answer (Capelli et al., 2010).

On the market, there are different types of olfactometers, but two are the most common. The first can be called “yes/no”; from the sniffing port, odorless air or air with odor comes out alternatively and the panelist shall indicate on the evaluation card if he/she detects the odor or not. The second olfactometer, called “forced choice” presents two or three different sniffing ports and each panelist shall indicate from which sniffing port the odor comes from (Guffanti et al., 2018; Munoz et al., 2010).

Actually, the EN 13725 edited in 2003 is under revision with respect to storage and materials for olfactometry, sampling techniques, reference material for panel selection, panel size and panel management procedures (EN 13725 2003). The reviewed EN 13725:2003 should be available by the end of 2019.

2.1.2. Field inspection

Field inspection methodology is standardized by EN 16841:2016, it is a field analysis that uses a panel of people (from 2 to 8) who assess the presence or absence of an odor directly in the ambient air. EN 16841 (starting from pre-existing VDI Guideline 3940-Part 1 and Part 2) establishes two different methods: Grid and Plume method (EN 16841-1 2016; EN 16841-2:2016 2016). The application of the grid method is odor exposure, whereas of the plume method is odor extent from a specific source (Capelli et al., 2013b).

Grid method consists in designing a grid around the odor source to cover all the sensitive receptors and areas where complaints were recorded (Dentoni et al., 2013). Each panelist has a specific path that covers different intersection points (which correspond to evaluation points) of this grid and walks inside and outside the mapped area to prevent odors habituation. Prior to the field inspection, odor bags shall be collected in order to train the panelists for the specific odor/odors they need to recognize (Dentoni et al., 2013; Guillot et al., 2012). The duration of a single evaluation is 10 min, during which every 10 s the panelist shall indicate on his/her card if he/she perceives no odor (e.g. 0 = no odor), one of the training odors (e.g. 1 = landfill, 2 = livestock, etc.), the mixture of the training odors (e.g. 3 = 1 + 2) or a different odor that is no under evaluation (e.g. 4 = barbecue) (Dentoni et al., 2013; Diallo et al., 2018). Each measurement is defined as “odor hour” if 10% of the measurements is attributable to that/those specific odor/odors considered (Diallo et al., 2018; Guillot et al., 2012). For each area, the EN 16841 establish 104 evaluations (or 52 for 6 months) given by the sum of the four intersection points considering that in each point the panel goes 26 times a year. At the end of the field inspection, the result will be a map with different squares where will be reported the odor frequency, expressed as a percentage, derived from the sum of "odor hours" (EN 16841-1 2016). The minimum period for this evaluation is at least 6 months; however, the evaluation of one year is recommended to take into account the seasonality.

The Plume method is used to determine the extent of detectable and recognizable odor from a specific source using direct observation in the field by panelists under specific meteorological conditions (Guillot et al., 2012). The extent of the plume is assessed as the transition from zones in which odor is not perceived to zones in which is perceived. It is used to verify the outputs of odor dispersion modeling (Capelli and Sironi, 2018). The plume method includes two approaches: the stationary and the dynamic method (Dentoni et al., 2013; Van Elst and Delva, 2016).

According to the stationary method, five panelists move in the field upwind, approaching the odor source and along parallel lines, that are perpendicular to the plume extent (Van Elst and Delva, 2016). Panelists follow the same procedure illustrated for the grid method, except for the fact that their path will consist of parallel lines and they do not have to identify odors but only the presence or absence of recognizable odors (Capelli et al., 2013b). A measurement cycle shall consist of at least 20 single measurements (four intersection lines each consisting of five single measurement points), and eight transition points. Transition points are those between points with absence and presence of odor. The distance between the line without odor presence and the nearest line with odor presence shall be less than 20% of the maximum odor plume, otherwise, the odor plume remains too undefined.

According to the dynamic method, two panelists follow exactly the same indications of the stationary method with the only difference that they will move zigzag inside and outside from the plume, to identify the presence or absence of recognizable odors (Brinkmann et al., 2018; EN 16841-2:2016 2016; Guillot et al., 2012; Van Elst and Delva, 2016).

Regardless of the method adopted, field inspections must occur on different days, with different weather conditions and prior to the analyses, an inspection should be planned to decide the optimum location and distribution of sampling points, accordingly to the topography and also to the different kind of odor sources (Sówka, 2010). To define the inspection area, information on the prevailing wind direction and wind speed have to be taken into account. Moreover, the panel should be composed of qualified assessors, selected using the criteria proposed for the dynamic olfactometry procedure (Guillot et al., 2012).

In conclusion, the grid method uses panelists to characterize odor exposure in a defined assessment area over a sufficiently long period (typically one year) to include all different meteorological conditions of that location. Instead, the plume method uses panelists to determine the extent of the odor impact, under specified emission situation (based on the source characteristics) and meteorological conditions (including specific wind direction, wind speed, and boundary layer turbulence).

2.1.3. Recordings from residents

This method is based on reporting cards filled out by the population living near the odor source, engaged as regular odor monitors (Capelli et al., 2013b). It can be useful to identify the origin of the odor episodes when the odor episode is geolocalized or when a new plant is built (Aatamila et al., 2011). The database can be built using the reporting cards, where residents have to sign their name, their position when they perceive the odor, the date and duration (start and end time) of the odor episode, and a description of both quality and intensity of the odor (Blanes-Vidal et al., 2012; Gallego et al., 2008). Data obtained from social participation can subsequently be associated with the meteorological parameters recorded during the episodes detected (Sironi et al., 2010).

Usually, this method takes a long time, but it is not expensive. However, the limit is the weak scientific stability of the data due to the psychological effect of the population involved that need to be formed to have similar recordings (Brinkmann et al., 2018; Capelli et al., 2013b; Sironi et al., 2010). Even if they are trained, they cannot be considered experts like panelists used in the above-mentioned sensorial techniques. Moreover, data variability based on people's characteristics must be considered. Indeed, for example, people living in rural place probably will not associate livestock activities to malodor, instead, people living in big cities will consider them a source of odor nuisance. Finally, since participants are recruited on a voluntary basis, it is necessary making them actively involved in the odor impact assessment, for example, asking them to regularly complete the reporting cards. Social participation can be useful to identify odor episodes or record odor incidents (Capelli et al., 2013b) and allows to build sensory databases (based on completed questionnaires) (Gallego et al., 2008). Data obtained from residents need to be associated with meteorological parameters recorded during the perceived odor episodes, thus allowing the comparison to dispersion models (Sironi et al., 2010).

2.2. Analytical techniques

2.2.1. Gas chromatography-mass spectrometry, GC–MS

In the chemical analysis, the use of gas-chromatographic techniques coupled with mass spectrometry allows to identify and quantify odorous compounds, even if the source cannot be characterized and it is not possible to know if the olfactory sensation is due to an individual constituent or to the whole mixture (Blanco-Rodríguez et al., 2018; Cadena et al., 2018).

The principle of the gas chromatographic method is the separation of the components from the odor mixture according to their affinity with the stationary phase in the column (Munoz et al., 2010). Since each type of molecule has a different rate of progression, the various components of the analyte mixture are separated as they progress along the column and reach the end of the column at different times (retention time). According to the retention time, components are qualitatively identified. Then they are quantitative identified thanks to mass spectrometry (Dincer et al.,et al., 2006). The association of these two techniques amplifies their potential and enables to lower the detection limits, allowing to identify analytes in very low concentrations (Guffanti et al., 2018).

A problem that can arise during GC is the elution problem due to poor chromatographic separation. It occurs when two (or more) compounds due to widely differing retention properties do not chromatographically separate because the late ones remain in the column too long. Changing the chemistry of the mobile phase, stationary phase, temperature, and column or plane length are good methods to increase the separation (Brattoli et al., 2013; Delahunty et al., 2006).

An alternative approach to GC–MS is gas chromatography-mass spectrometry coupled with olfactory analysis (GC–MS/O). The process is equal to classical GC–MS with the only difference that at the end of GC, the sample is split between an MS detector and the trained human panelists (Munoz et al., 2010). Panelists shall press a button and record what they are sniffing. In the end, the olfactogram and the chromatogram are combined. This represents an improvement compared to GC–MS because the human nose is more sensitive, but there is subjective components and panelists shall be really concentrated during the analysis (Brattoli et al., 2013; Guffanti et al., 2018; Hayes et al., 2014) because peaks are eluted very quickly and the panelist at the same time has to both recognize odors and provide a description (Brattoli et al., 2013). Since the odor detection is linked to the human perception, as for dynamic olfactometry, the panel must be periodically screened and trained, and observe a simple behavior code (Capelli et al., 2010). Moreover, in order to obtain reproducible data, panel members are selected according to their sensitivity, and the ability to recall and recognize odor qualities (Brattoli et al., 2013).

Finally, being the GC–MS/O sessions quite long, the position of the sniffing-port must be comfortable (long transfer line) and the panelist should be seated far from the hot chromatograph components during detection to avoid the smell of hot metal (Delahunty et al., 2006).

Table 1
Advantages and disadvantages of sensorial techniques.

Sensorial techniques	Advantages	Disadvantages	Reference
Dynamic olfactometry	• Recognized and standardized technique • Endpoint assessment • High sensitivity • Possible implementation to atmospheric dispersion models • Sensitivity of human nose is higher than electronic instruments	• Only quantitative characterization • Impossibility of continuous measurements and monitoring • High measurement uncertainty • Not applicable for low odor concentrations • Time consuming • Lower repeatability compared to chemical analysis • Subjectivity of human perception • Psychological factors could affect the evaluation	Blanco-Rodríguez et al. (2018), Cadena et al. (2018), Capelli et al. (2014a), Guffanti et al. (2018), Hayes et al. (2014), and Van Elst and Delva (2016)
Field inspection	• Direct determination of the odor impact in terms of frequency (Grid method) or area of impact of the odor at the receptor (Plume method) • Possibility of comparing the results with other methods • Possibility to validate air dispersion method • Sensitivity of human nose is higher than electronic instruments	• High cost • Many data to be processed • Logistical difficulties related to the planning of the evaluation card and to the identification of paths (Plume method) • Difficulty of finding an adequate panel, available and not directly involved (Grid method) • Lack of reference acceptability values • Time consuming • Subjectivity of human perception • Psychological factors could affect the evaluation	Both (2001), Hayes et al. (2014), and Van Elst and Delva (2016)
Recordings from residents	• Low or no cost • Useful for involving and sensitizing citizenship (psychological effect) • Sensitivity of human nose is higher than electronic instruments	• Management difficulties in collecting similar data • Poor scientific stability of the data (due to psychological effect) • Lack of reference acceptability values • Possibility of bias • Long response times • Subjectivity of human perception	Di Francesco et al. (2001), Hayes et al. (2014) andSironi et al. (2010)

2.2.2. Identification of specific compounds

Analysis of a single gas, for example, NH_3 or H_2S, can be useful when these gases are tracer and representative of a specific source, such as livestock farming and landfill, respectively. However, it is not possible to identify tracer compounds for all situations and or sources, nor to relate analytical concentrations to odor properties, thus considering a single compound may not be enough to determine the effective odor perception (Capelli et al., 2013b). On the other hand, alternative approaches have been established for analysis of VOCs. One approach is to use real-time detection devices, such as PID (photo ionization detectors). PID is a broadband detector that detects ionized species with a UV lamp. The output of this kind of sensors is a non-specific total concentration of organic compounds, expressed in ppm (or ppb) equivalent (Biasioli et al., 2011; Chen et al., 2013). Alternatively, colorimetric sensors can be used, which are easy to use and cost effective. Thanks to the interactions between the analyte and the responsive colorants VOCs are identified (Lin et al., 2011).

2.2.3. Electronic nose

The electronic nose allows a qualitative classification of the analyzed air, attributing the air sample to a specific olfactory class. It is composed of an array of sensors that simulate the receptors of the human olfactory system and a computer that simulates the response of the human brain. The output is a pattern, which is typical of the gas mixture (Blanco-Rodríguez et al., 2018; Capelli et al., 2014a). The electronic nose includes three major parts: a matrix of sensors, a data processing system, and a pattern recognition system. They simulate three components of the human olfactory system: nose receptors, olfactory bulb, and brain. Odor interacts with the surface of the sensor and causes a change in certain chemical and/or physical properties, these variations are converted to an electronic signal which is sent to the data processing unit. Here feature extraction is performed, followed by an explorative analysis which converts features in results and representations that can be easily interpreted, thanks to statistical analysis. Finally, odor samples thanks to a series of algorithms are classified into clusters (Guffanti et al., 2018). Prior to the measurements, the electronic nose needs to be trained with qualified samples to build a database of reference. For the training, odor bags near the odor source need to be collected to train the nose for odor or odors it has to identify (Brinkmann et al., 2018). For this reason, training is always site-specific. In case of long monitoring times (> 1 year) the nose needs to be controlled to verify if the training is still valid and if sensors have been damaged by adverse weather conditions. Indeed, during analysis, it is important to always keep temperatures and humidity monitored to avoid damaging the sensors (Hayes et al., 2014). Thanks to this method, since the instrument is used in injection, the air is monitored continuously (if installed at the borders of the installation) and at the receptor (sensitive even a few kilometers away). Unfortunately, there is no standard that provides minimum requirements for this type of analysis (Capelli et al., 2014a).

2.3. Conclusions on technical approaches to odor measurement

Regardless of the measurement technique adopted (sensorial or analytical techniques), the quality of the results obtained is heavily dependent on appropriate sampling, which is one of the main issues relating to odor characterization and measurement (Capelli et al., 2013a). The purpose of sampling is to obtain representative information on the typical characteristics of odor sources by collecting a volumetric fraction of the effluent (Lucernoni et al., 2016). Unfortunately, these techniques alone are not sufficient to assess odor impact within a community. Indeed, both sensorial (dynamic olfactometry) and analytical techniques are used for the evaluation of odor concentration. In the first case, the concentration is given by a panel of experts based on

Table 2
Advantages and disadvantages of analytical techniques.

Analytical techniques	Advantages	Disadvantages	Reference
Gas chromatography-mass spectrometry (GC–MS)	• Recognized and repeatable technique • Possibility to identify and quantify single components • Possibility to perform the analysis at the emission and at the receptor • Possible implementation to atmospheric dispersion models • Objectivity of the evaluation	• No information on the odor impact provided • Non-reliable in case of mixture of many odorants at very low odor concentration • High technical requirements • Detection limits below the odor detection threshold of the compounds • Precise calibration required • Interaction between odorants not detected • Possible masking effects with complex odor mixtures	Blanco-Rodríguez et al. (2018), Cadena et al. (2018), Capelli et al. (2014a), Guffanti et al. (2018), Hayes et al. (2014) and Mielcarek and Rzeznik (2015)
Identification of specific compounds	• Possibility to make measurements at the receptor • Possibility to control accidental emissions • Objectivity of the evaluation • User-friendly (PID)	• Non-reliable in case of mixture of many odorants at very low odor concentration • Possible only with a source with a particular type of emission • Results depend on the type of instrument and sensor • High costs • Impossible correlation with odor concentration (different response factors, different OTV) • Inability to recognize source (many interferers, no speciation)	Capelli et al. (2013b) and Hayes et al. (2014)
Electronic nose	• Continuous analysis of the ambient air at the receptor • Direct determination of the presence/absence of odors where odor annoyance is lamented • Determination of odor provenience in case of multiple sources • Odor recognition/classification (at the source) • Possibility of comparing the results with other methods • Objectivity of the evaluation • Positive effect on population which is comforted by the presence of an instrument that perform a continuous analysis of the ambient air	• Absence of a specific regulation that standardize the method • Instrument complexity: precise procedures for its use (training and data processing) • Odor impact assessment based only on the quantification of the frequency of odor episodes and not on their intensity • Interaction between odorants not detected	Blanco-Rodríguez et al. (2018), Cadena et al. (2018), Capelli et al. (2014a), Di Francesco et al. (2001), Guffanti et al. (2018) and Hayes et al. (2014)

samples of air, in the second one, it is assessed by means of complex physical and chemical analyses (Mielcarek and Rzeznik, 2015).

Odor concentration is necessary to find the Odor Activity Value (OAV), which is defined as the concentration of a single compound divided by the odor threshold for that compound. Knowing the OAV of an odorous compound allows to understand which is the contribute of that specific odorant to the overall odor (Brattoli et al., 2013). However, an approach based just on OAVs is imprecise due to the different values of the odor threshold reported in the literature (Capelli et al., 2013b).

In odor measurement, the evaluation of odor concentration alone is not sufficient. Also, the air flow associated with the monitored odor source have to be taken into account, being these parameters interrelated in most cases. Thus, Odor Emission Rate (OER) has to be evaluated, which is the quantity of odor emitted per unit of time and it is expressed in ouE s^{-1} (Capelli et al., 2013a) (OER will be better described in Section 3 – Air dispersion models).

In Tables 1 and 2 are reported the main advantages and disadvantages of sensorial techniques and analytical methodologies, respectively. Odor dispersion models, combined with odor measurements, allow a better understanding of odor nuisance and odor characterization.

3. Air dispersion models

Different types of models, that take into account meteorological, topographic and emission data, can be used to determine odors dispersion into the atmosphere (Yu et al., 2010). They offer the possibility of mathematically simulating the spatial and temporal variation of odor concentrations (Zhou et al., 2005) and can provide estimates of odor levels in both current and future emission scenarios, predicting the atmospheric impact of a facility before being realized (Sheridan et al., 2004). Therefore, these models are useful to determine appropriate setback distances between production facilities (farms, industries, and waste treatment plants) and neighboring areas (Capelli et al., 2013b; Danuso et al., 2015; Guo et al., 2004).

Most dispersion models are Gaussian models, which assume the concentration profile across the plume to follow a Gaussian probability curve (Daly and Zannetti, 2007). The other models follow the Lagrangian or Eulerian approaches (Danuso et al., 2015). They are mathematical models used to estimate (in case of existing facilities) or to predict (when planning new operations or evaluating the efficacy of mitigation strategies) the downwind concentration of air pollutants emitted from sources, such as farms (Zhou et al., 2005).

Gaussian models assume "steady-state" conditions. The meteorological conditions are assumed to remain constant during the dispersion from source to the receptor, which is effectively instantaneous. Also, emissions are considered time-invariant and, for this reason, calculations refer to periods of one hour or less (Danuso et al., 2015). However, emissions and meteorological conditions can vary from hour to hour thus the model simulate hourly-average concentrations, so that calculations in each hour are independent of those in other hours. The plume formula has the uniform wind speed in the denominator and hence breaks down in calm conditions (Danuso et al., 2015). It is usual

Table 3
Principal air dispersion models with related characteristics, advantages, and limitations.

Model name	Type of model	Characteristics	Consider:		Advantages	Limitations	Reference
			Topographic data	Meteorological data			
AERMOD (U.S.)	Gaussian plume model	It enables comparison of predicted and measured data and among different kind of source (point, volume, and area sources).T	✓ (includes simple and complex terrain because it is an advanced plume model)	✓	• It follows the default regulatory options consistent with the Guideline on Air Quality Models (U.S. EPA). • Topographic features and meteorological conditions: considered. • Suited for near-field dispersion.	• Under-predict odor concentrations when configured as an area source.	Schulte et al. (2007) and Baawain et al. (2017)
LODM (Canada)		Designed for livestock facilities for predicting hourly odor frequency with input hourly meteorological data.	✓	✓	• Adequate in predicting both odor concentration and frequency.	• Surface parameters (roughness, albedo, and Bowen ratio) essential input required to predict odor concentration and frequency. • Stack height, stack diameter, and exit velocity affect concentration values.	Yu et al. (2013a) and Yu et al. (2013b)
STINK (Australia)		It calculates odor emission rates from ground level area sources. It predicts the dispersion of odors downwind of area sources of finite size and any orientation with respect to the wind direction.	X	✓ (averaged over a period of 1 h or less)	• Applicable to sources of irregular shape or of limited lateral extent. • Any location can be used for the measurements providing the location, the size of the source and the wind direction.	• An accurate description of the source geometry is requested. • Not applicable to wind directions perpendicular to the source.	Galvin et al. (2004) and Smith (1995)
OdiGauss software (Italy)		Free multilingual software application for estimating odor dispersion from multiple point sources and to generate the related maps.	X (also parameters of odor emission sources required)	X (for all the odor sources, the weather conditions are considered to be the same)	• User-friendly. • Available in several languages. • Little training required. • Fast in performing simulations. • It can simulate the dispersion of particles (e.g. PM10)	• It allows only short-term simulations. • It does not consider inversion processes of the plume. • It considers only the mean hourly odor concentration. • Not suitable for complex orographic conditions.	Danuso et al. (2015)
INPUFF-2 (U.S.)	Gaussian puff model	This model can simulate airborne pollutants dispersion of from semi-instantaneous or continuous point sources	✓	✓ (actual, not empirical formula)	• It can handle single and multiple odor sources. • It can deal with multiple receptors at the same time. • It uses actual odor emissions.	• It correlates best with the field data at 100 m distance and worst at 400-m and 500-m distances. • The scaling factors used are only valid for this model.	Zhu et al. (2000) and Asadollahfardi et al. (2015)
CALPUFF (U.S.)	Lagrangian model	It is a multi-layer, multi-species non-steady-state dispersion model that simulates the effects of time- and space-varying meteorological conditions on pollution transport, transformation and removal	✓	✓	• It contains modules for complex terrain effects, over-water transport, coastal interaction effects, building downwash, wet and dry removal and simple chemical transformation. • It keeps track of recent past pollution information (e.g. over a few hours); as a result, pollutant concentrations that occurred during these previous hours have an impact on current and future pollutant dispersion. • It can predict actual and potential effects of odor emissions at any point in space with a high temporal resolution. • It can identify the odor nuisance generated by single emission sources.	• Applied best only to long term modeling. • It tends to underestimate peak intensities close to the source. • It needs realistic emissions rates, that are difficult to estimate. • It requires a great number of inputs.	de Melo et al. (2012) and Ranzato et al. (2012)

(*continued on next page*)

Table 3 (*continued*)

Model name	Type of model	Characteristics	Consider:		Advantages	Limitations	Reference
			Topographic data	Meteorological data			
CALGRID (U.S.)	Eulerian model	It is a photochemical transport and dispersion model that requires three-dimensional fields of air temperature and vertical velocity.	✓	✓ (Precipitation rate not considered)	● It includes modules for: horizontal and vertical advection/diffusion, dry deposition, photochemical mechanism ● Transport dispersion is more realistic ● It can simulate multi-day scenarios ● More accurate compared to the other models	● It requires a great number of inputs. ● It needs high computing power	Scire et al. (2000) and Yamartino et al. (1992)

to specify a minimum allowable wind speed for the model.

Assumptions in plume Gaussian modeling: (i) continuous emission, (ii) conservation of mass, (iii) steady-state conditions, (iv) absence of wind in calm conditions. Gaussian dispersion models are the most widely used (Yu et al., 2010) since they are quite easy to be applied, indeed assuming "steady-state" conditions they do not require significant computer resources (Zhou et al., 2005). However, compared to other models, they do not consider topography, so they give a precise evaluation only in flat terrain (Danuso et al., 2015).

Puff models (no steady-state) are an evolution of classical Gaussian models; the plume is presented by a series of independent elements (puff) that evolve over time according to spatial and meteorological characteristics (Zhou et al., 2005). These models are based on sets of equations describing the three-dimensional space concentration generated from a point source and are able to encounter with changing wind and emission data (Jung et al., 2003; Yu et al., 2010).

Lagrangian models (also known as particle models) describe the motion in space of individual, non-interacting elementary odor particles (Danuso et al., 2015). Lagrangian models are based on the idea that pollutant particles in the atmosphere move along trajectories determined by the wind field, the buoyancy, and the turbulence effects (Wilson and Sawford, 1996). The final distribution of randomly moving particles gives a stochastic estimation of the concentration field; this means that these models require high computing power as they simulate several trajectories of elementary particles to achieve an adequate accuracy level (Flesch et al., 1995). Lagrangian models are exceptionally efficient close to the source and are particularly suited for elevated point sources. Puff models are far less computationally expensive than particle models but are not as realistic in their description of the pollutant distribution.

In Eulerian models (grid models), the area under investigation is divided into grid cells, both in vertical and horizontal directions and in each grid is calculated the average concentration of pollutant particles. Their limit is the high computing power required, due to the fact they allow a more correct spatio-temporal representation (Danuso et al., 2015). The main difference between Lagrangian and Eulerian models is related to the perspective of atmospheric motion (Nguyen et al., 1997). The first ones take the perspective of an air particle, whereas the second ones define specific reference points in a gridded system and treat the particle phase as a continuum.

Dispersion models usually calculate the hourly mean odor concentrations for every receptor for every hour of the simulation domain. However, the sensation of the odor depends on the momentary ("peak") odor concentration. For the assessment of peak values, a so-called "peak-to-mean" factor is used in order to account for these fluctuations (Piringer and Schauberger, 2013). The goal of the use of peak-to-mean factors is to simulate the rapid response of the human nose. The pick-to-mean factor is calculated by dividing the peak concentration by the 1-h averaged (mean) concentration (Schauberger and Piringer, 2012). The applied peak-to-mean factors differ from country to country (Piringer and Schauberger, 2013). For example, in Italy, DGR n. IX/3018 15/02/2012 suggests a constant peak-to-mean factor of 2.3. Results are represented as a map of the 98th percentile of the peak odor concentration values (D.G.R. 15 febbraio 2012 e n. IX/3018 Regione Lombardia, 2012). Austria suggests variable peak-to-mean factors in function of the atmospheric stability and of the distance from the source (Schauberger and Piringer, 2012). The United Kingdom establishes peak odor concentration values at 1.5 ouE m^{-3}, 3.0 ouE m^{-3} and 6.0 ouE m^{-3} (at the 98th percentile), for high, medium and low "offensiveness" industry types, respectively (UK-Environmental-Agency, 2002).

Models modified in this way are then able to calculate separation distances for so-called odor impact criteria, a combination of odor concentration (mostly an odor threshold) and a pre-selected exceedance probability according to land use. An overview of various national odor impact criteria can be found in Sommer-Quabach et al. (2014) and Piringer et al. (2016).

A summary of principal dispersion models with their characteristics, advantages, and limitations that have been applied to simulate odor dispersion from waste and agricultural sources are reported in Table 3.

Regardless of the type of model, necessary input data are: (i) topographic and orographic data; (ii) meteorological data (e.g. air temperature, relative humidity, air pressure, solar radiation, precipitations, wind speed, and wind direction); (iii) emission data (identification and characterization of the odor source, quantification/estimation of the amount of pollutant emitted in unit of time) (Schauberger et al., 2012; Schulte et al., 2007; Sironi et al., 2010). The quality of the input data affects the goodness of the results other than the choice of the model (Capelli et al., 2013b).

Topographic and orographic data shall include the characteristics of the terrain roughness, heights of potential receptors near the emitting source, the planimetry of the plant and of the surrounding impact area (Schauberger et al., 2012; Sheridan et al., 2002).

Regarding meteorological input data, besides wind data (speed and direction), the main weather variables involved are temperature, solar radiation, atmospheric pressure, humidity and precipitations (Danuso et al., 2015; Piringer and Schauberger, 2013). Furthermore, information on the stability of the atmosphere and the planetary boundary layer (the portion of the atmosphere where the generation, decay, transformation, and diffusion of most pollutants take place) is important, usually expressed as time series over at least one year (Piringer and Schauberger, 2013). The classifications proposed by Pasquill (1961) and Gifford (1959) for atmospheric stability classes are usually adopted (ranging from class F "very stable", to class A "very unstable", according to the meteorological conditions). Meteorological data can be obtained from one or more near surface meteorological stations to define a representative station for the emission source considered (Capelli et al., 2013b; Wu et al., 2019).

In addition to topographic and meteorological data, emission data are necessary for the simulation of odor dispersion, since the evaluation of odor concentration alone is not sufficient, also the air flow associated with the monitored odor source has to be taken into account. OER (ouE s^{-1}) is calculated by taking the product of the odor concentration and flow rate from a source. So, the method adopted for OER estimation is strictly related to the characteristics of odor source (point or area). In case of point sources, OER is the product between the odor concentration and the emitted air flow. For active area sources, the average emitted odor concentration needs to be used (Capelli et al., 2013a). Finally, in case of passive area sources, the procedure is quite complex. Firstly, it is necessary to calculate the Specific Odor Emission Rate (SOER), which is the odor emitted from the area source per unit of time and surface (ouE m^2 s^{-1}), then OER is calculated by multiplying the SOER and the emitting surface of the considered source (Lucernoni et al., 2016).

To predict the odor impact, when data for a specific source are not available, odor emission factors (OEFs) are fundamental for estimating emissions since they enable the estimation of the OER. OEFs correlate the quantity of odor emitted with the activity associated with the emission of that odor. OEFs can be derived from experimental data or found in the literature (Capelli et al., 2014b). OEFs are usually expressed as OER divided by a specific activity index, expressed in terms of unit, such as animal, animal body weight, gross weight production, area, production place, the site surface or a time unit (Mielcarek and Rzeznik, 2015).

3.1. Conclusions on air dispersion models

Different types of air dispersion models are available and can be applied to simulate odor dispersion into the atmosphere. They are considered a useful tool in assessing the odor impacts associated with existing and future or modified (with abatement systems) emission sources.

Regarding Gaussian models, they assume that dispersion in cross-wind direction and in the vertical direction has a Gaussian distribution, with the maximum concentration in the center of the plume. Their main advantage is that they require little computing power. However, they are less accurate due to their assumptions (no three-dimensional space characteristics; no memory of past conditions; no calm wind conditions).

Conversely, Lagrangian and Eulerian models need high computing power because, to achieve an adequate accuracy level, they simulate several trajectories of elementary particles and consider more inputs. However, having a more correct spatial-temporal representation, they are more accurate and represent a more advanced tool. Their limit is that turbulence is difficult to represent (Capelli et al., 2013b), indeed turbulence that characterizes the planetary boundary layer has mainly two origins: movement of air masses with viscosity effects on a rough surface (mechanical turbulence) and soil heating/cooling effects caused by daily solar radiation and nightly radiative cooling effects (Schiffman et al., 2005).

4. Major sources of odor nuisance

4.1. Waste from treatment plants

Landfill, compost and anaerobic digestion plants are among the main disposal technologies to treat municipal solid waste (MSW) (Cadena et al., 2018). During waste handling and biological decomposition steps, several gaseous compounds are emitted from the organic matrix (Sarkar and Hobbs, 2002). VOCs, NH_3, and H_2S are responsible for the unpleasant odors (Rincón et al., 2019), contributing to the odor impact (Moreno et al., 2014). Among the organic compounds, it is possible to find: terpenes, alkanes, oxygenated compounds, aromatics, ketones, and other compounds such as sulfur compounds (Cheng et al., 2019; Fang et al., 2012). Sulfur compounds or VSCs consist of VOCs that contain sulfur, they are toxic and easily perceived at extremely low concentrations, they are produced by organic matter degradation during waste treatment and composting conditions (Rincón et al., 2019; Zhang et al., 2013).

The organic fraction of MSW (OFMSW) is usually treated with anaerobic digestion and composting (Font et al., 2011, Bacenetti and Fiala, 2015). Although the objective of these technologies, as well as other waste treatment technologies, is to enable sanitization of the waste by the elimination of pathogenic microorganisms and transforms the organic fraction in soil amendment (Renaud et al., 2017), they emit potential toxic compounds, such as VOCs, VSCs, NH_3 and nuisance odors (Moreno et al., 2014; Nie et al., 2019; Rincón et al., 2019). Degradation of the organic fraction by microorganisms is the main cause of odor production (Pierucci et al., 2005). Ammonia emissions depend almost on the C/N ratio of the waste, temperature, moisture content and pH (Moreno et al., 2014; Pagans et al., 2006), whereas VSCs emissions are correlated to temperature and O_2 concentration (Higgins et al., 2006; Moreno et al., 2014). Moreover, offensive odors generated by waste treatment depend on the type of raw material, the stage of the decomposition and the operating conditions at the site (Bruno et al., 2007; Toledo et al., 2018). As an example, Toledo et al. (2019) found that fresh organic waste such as sewage sludge and OFMSW were the most influential odorous substrates, due to their high concentration in biodegradable organic matter.

The presence of odors associated with VOC emissions has been investigated by a wide number of researchers (Bruno et al., 2007; Defoer et al., 2002; Fang et al., 2012; Mao et al., 2006; Pierucci et al., 2005), that focused on how the odors mixture change according to the type of waste, treatment technology and the sites within the treatment plant, as reported in Table 4.

According to the literature reported in Table 4, in landfill the main emissions sources can be identified in the MSW-related area, the leachate-related area, and the sludge-related area, in particular gas extraction wells, sludge discharge area, sludge disposal work place,

Table 4
Odor compounds from different sources of waste.

Waste	Technology	Source	Odor compounds	Reference
Solid wastes and digestate	Composting reactor[a]	Agricultural wastes	Nitrogen compounds (NH_3 and trimethylamine), sulfide compounds, terpenes, benzene, toluene, and methyl thiocyanate	Rincón et al. (2019)[1,2]
		Biowastes	Terpenes, and oxygenated compounds (ethanol, methanol, ethyl acetate, methyl acetate, and 2-butanone)	
		Green wastes	Terpenes (limonene and α-pinene), ketones (acetone and 2-butanone), and alcohols (methanol)	
		Sewage sludge	Nitrogen compounds (NH_3), terpenes (limonene), sulfide compounds (methanethiol and dimethyl sulfide), and acetic acid	
		Municipal solid waste	Terpenes (limonene and α-pinene), nitrogen compounds (NH_3), sulfide compounds (methanethiol), ketones, and alcohols (methanol)	
		Digestates	Nitrogen compounds (NH_3), terpenes (limonene, α-pinene, and myrcene), sulfide compounds, alcohols, aldehyde and ketones, acids, esters, and alkenes	
Solid waste	Landfilling[b]	Landfill at the moment the material was discharged and during a period of inactivity at the landfill	2-butanone, α-pinene, tetrachloroethylene, dimethyldisulfide, β-pinene, limonene, phenol, and benzoic acid	Bruno et al. (2007)[1]
MSW	Landfilling[b]	Wharf, dumping pool, lane, active working face and gas vent	Sulfides (H_2S and ethyl sulfide), aromatics, alkanes (heptane)	Cheng et al. (2019)[1,2]
MSW	Landfilling[b]	Landfill	Styrene, toluene, xylene, acetone, methanol, n-butanone, n-butylaldehyde, acetic acid, dimethyl sulfide, and ammonia	Fang et al. (2012)[1]
		Gas extraction wells	Acetaldehyde, ethyl benzene, xylene, methylamine, and dimethyl formamide	
		Sludge discharge area	Methyl mercaptan, valeric acid, and isovaleric acid	
		Sludge disposal work place	Carbon disulfide, acetone, 3-pentanone, methanol and trimethylamine	
		Leachate storage pool	Hydrogen sulfide, n-butylaldehyde, and acetic acid	
MSW	Landfilling[b]	Inside and away from the dumping area	Benzene, alkylbenzenes, terpenes (α-pinene, β-pinene, camphene, methyl-isopropylbenzene, and limonene), aromatic hydrocarbons (BTEX), chlorinated aromatics and hydrocarbons	Zou et al. (2003)[1]
MSW	Anaerobic digestion[b]	Working face	Ethyl alcohol, α-pinene, hydrogen sulfide, dimethyl sulfide, limonene, methyl mercaptan, dimethyl disulfide, and diethyl sulfide	Wenjing et al. (2015)[1,2]
		Mixed paper	Alkylated benzenes, alcohols and alkanes	
		Yard wastes	Terpenes (α-pinene and D-limonene), aromatic hydrocarbons, ketones, and alkanes	
		Food wastes	Sulfides, acids, alcohols, and terpenes	
MSW	Anaerobic digester and composting[b]	Fresh compost fraction	Limonene, p-cymene, pinene	Moreno et al. (2014)[1]
		Rejected compost fraction	Limonene, ketones, pinene	
		Leachate pond	Limonene, hydrocarbons, cyclohexane, pinene, ketones	
		Landfill leaks	p-cymene, pinene, C4-C5 hydrocarbons, BTEX	
MSW	Composting[b]	Belt conveyor area, pile-turning workshop, and stacking workshop	NH_3, oxygenated compounds (ethyl acetate and 1-butanol), alkanes (n-hexane and heptane)	Cheng et al. (2019)[1,2]
MSW	Composting[a]	MSW Kitchen waste Kitchen waste mixed with dry cornstalks	Hydrogen sulfide, methyl mercaptan, dimethyl sulfide, carbon bisulfide, and dimethyl disulfide	Zhang et al. (2013)[1]
OFMSW	Composting[a]	All waste	Aromatic VOCs: toluene, ethylbenzene, 1,4-dichlorobenzene, p-isopropyl toluene, and naphthalene	Komilis et al. (2004)[1]
Green waste	Natural decay[b] and composting[a]	Feedstock	Terpenes: α-pinene, β-pinene, 3-carene, camphene, β-myrcene, and D-limonene	Büyüksönmez and Evans (2007)[1]

(*continued on next page*)

Table 4 (*continued*)

Waste	Technology	Source	Odor compounds	Reference
MSW	Lab-scale reactor[a]	MSW headspace before processing	Alkanes, terpenes, benzene, and halogen-containing compounds	Pierucci et al. (2005)[1,2]
		Airflow stream exit from the reactor	Terpenes (α-pinene, β-myrcene, and D-limonene), monocyclic arenes (C2, C3, C4 benzenes), alkane, halogenated compounds and esters	
		Before and after the biofilter	Terpenes, toluene, monocyclic arenes (C2, C3, and C4 benzenes), halogen-containing compounds, alkane, and bicyclic arenes	
		Condensate and leachate of the reactor	Alkane, alcohols, ketones, aldehyde, acid, ester, terpenes, benzenes, phenols, heterocyclic, chlorinated, sulfurated, nitrogenated, and phosphorated	
		Airflow stream exit from the reactor	Terpenes (α-pinene, β-myrcene, and D-limonene), monocyclic arenes (C2, C3, C4 benzenes), alkane, halogenated compounds and esters	
MSW	Mechanical–biological waste treatment[b]	All emitting areas	Alkanes, aromatic hydrocarbons, terpenoids, esters, alcohols, ketones, halocarbons, aldehydes, acids, ethere, and furans	Gallego et al. (2012)[1]
		Rotating biostabilizers	Esters, acids, and aldehydes	
		Shipping warehouse	Esters, acids, and aldehydes	
		Composting tunnels	Ketones (methyl ethyl ketone), aromatic hydrocarbons (BTEX and styrene), esters, and acids	
		Digest centrifugal	Esters, aldehydes, acids, organosulfurs, and alcohols	
		Humid pre-treatment	Esters, aldehydes, acids, and organosulfur	

[a] Laboratory experiment.
[b] Common disposal methods.
[1] GC-MS or GC-FID.
[2] Dynamic olfactometry.

leachate storage pool, wharf, dumping pool, lane, active working face, and gas vent (Cheng et al., 2019; Fang et al., 2012). Instead in composting plants, odorants are released by belt conveyor area, pile-turning workshop, stacking workshop other than by the different substrates (agricultural wastes, biowastes, green wastes, and kitchen waste) (Cheng et al., 2019; Rincón et al., 2019; Zhang et al., 2013).

In general, to characterize the odor and chemical emissions released from the different sources of waste, GC–MS and dynamic olfactometry have been used. In particular, GC–MS to determine the chemical composition and dynamic olfactometry the odor concentration.

As it is possible to see from Table 4, among VOCs, terpenes, hydrocarbons, and oxygenated compounds were the most emitted chemical families. While, among nitrogen and sulfide compounds, NH_3 and H_2S were the most abundant compounds emitted, respectively. Not in all studies results of the chemical analyses showed a correlation with odor concentration measured by dynamic olfactometry.

4.2. Livestock farms

Intensive livestock farming, especially swine operations (Trabue et al., 2011), extensively contributes to NH_3, VOCs and particulate matter (PM_{10} and $PM_{2.5}$) emissions (Bibbiani and Russo, 2012). The agricultural sector is currently responsible for the vast majority of NH_3 emissions in the European Union (EEA, 2018). NH_3 is an atmospheric pollutant causing soil acidification, nutrient-N enrichment of ecosystems, and eutrophication of terrestrial and aquatic ecosystems (Erisman et al., 2007). Moreover, in the atmosphere it reacts with other compounds to form ammonium sulfate and ammonium nitrate aerosols, leading to the formation of secondary inorganic aerosol ($PM_{2.5}$), a potential hazard (Kiesewetter and Amann, 2014). Therefore, NH_3 affects human and animal health both as a gas and as particulate matter (Wagner et al., 2015). The particulate form of NH_3 has broader implications for the population, while the gaseous form is a localized issue for the health of animals and agricultural workers (Kafle and Chen, 2014). Emissions of NH_3 mainly occur from feces and urine in housing and manure storage systems, from excreta of grazing animals voided on pastures and from agricultural land following application of manure and mineral N fertilizers (Velthof et al., 2014). The principal key categories for NH_3 emissions considered in EU are: i) animal manure applied to soils; ii) inorganic N-fertilizers; iii) non-dairy manure management; iv) dairy cattle manure management; v) swine manure management; they jointly make up 52% of total NH_3 emissions (EEA, 2018).

As for NH_3 emissions, manure and urine are the main constituents of odor from livestock operations (Barth et al., 1984; Kreis, 1978; Lemay, 1999). Particularly, storage, handling and land application of livestock manure are the main causes of odor annoyance (Hansen et al., 2006; Sheridan et al., 2002). Offensive odor is related to the incomplete anaerobic decomposition of animal wastes (slurry or manure) (Wheeler et al., 2011). However, odor emissions from animal production facilities are a function of many variables including species, housing types, feeding methods, management factors, manure storage, and handling methods (Guo et al., 2004; Jacobson et al., 2005). Instead, their impact on nearby communities depends on the amount of odor emitted from the site, the distance from the site, weather conditions, topography, other than odor sensitivity and tolerance of the neighborhood (Danuso et al., 2015). Finally, the extent of emissions depends on: the size of the settlement, phase of the rearing cycle, feeding operations, type of building, conditioning and ventilation, type of paving and manure removing and collection systems (Guo et al., 2006; Mielcarek and Rzeznik, 2015).

Regarding species, for example in the north of Italy, intensive poultry and pig farming are the major contributors to ammonia, odor and particulate matter emissions (Bibbiani and Russo, 2012). Similarly, in Denmark, odor annoyance is strictly related to pig farming, being Denmark a country with an intense production of pork meat (Cantuaria et al., 2017). For swine facilities, Ni et al. (2012) identified six major sources of VOCs: confined spaces, wastewater, air above wastewater surfaces, ambient air nearby, manure, dust inside and outside pig barns.

For swine facilities, different authors have investigated the relation between animal buildings and odors (Akdeniz et al., 2012; Blanes-Vidal et al., 2009; Miller et al., 2004; Ye et al., 2008). Akdeniz et al. (2012) reported that OER for pig finishing rooms were lower than OER for sow gestation barns although management characteristics of swine building were similar (slatted floor type, mechanical tunnel ventilation, deep pit manure storage removed twice a year) and they differed only for the average body weight of animals and for the feeding method. Miller et al. (2004) examined the OER differences between deep pit buildings and shallow pit systems, taking into account building characteristics and farming management (air cleanliness, barn cleanliness, manure depth, and pig density). In the end, deep pit was found to have lower OERs than shallow pit systems. Ye et al. (2008) focused only on NH_3. From the results of their study, NH_3 emission rate resulted to be influenced by ventilation rate, floor slat opening and the air headspace height in the slurry pit. Differently Schauberger et al. (2014a) focused on constant emission factors vs time-resolved emission models. Usually to calculate setback distance between livestock building and nearby residents OER is estimated as an annual constant value, obtained by multiplying live mass of the animals and OEF. However, this approach is inappropriate since the live mass increases and also the odor release is influenced by the indoor temperature, ventilation rate, animal activity and so on. Taking into account these variables using time-resolved OER allows to obtain reliable separation distances, avoiding bias due to the assumption of an annual mean value of OER.

In poultry production, Dunlop et al. (2016) identified litter as the primary source of odor caused by anaerobic and aerobic microbial activity. Also, Hayes et al. (2006) reported that litter is an important factor in the production of odor and NH_3 emissions for broiler units.

Regarding dairy farms, buildings and manure management (flooring system, removal system, and land application) are a relevant source of NH_3 and odors (Baldini et al., 2016; O'Neill and Phillips, 1991). Odor is a result of the incomplete anaerobic degradation of manure (Barth et al., 1984). Baldini et al. (2016) identified higher NH_3 emission in dairy farms equipped with scrapers, and lower with perforated floor or flushing system for manure removal.

Approximately 330 different odorous compounds have been identified in swine production facilities (Schiffman et al., 2001), 110 in dairy facilities (Filipy et al., 2006), and more than 75 in animal manure (Barth et al., 1984). Regardless of livestock facilities, relevant odorants included many acids, alcohols, aldehydes, ketones, esters, ethers, aromatic hydrocarbons, halogenated hydrocarbons, terpenes, other hydrocarbons, amines, amides, nitriles, phenols, steroids, other nitrogen-containing compounds, and sulfur-containing compounds, and other compounds (Barth et al., 1984; Filipy et al., 2006; Schiffman et al., 2001).

5. Mitigation strategies and odor impact assessment

5.1. Mitigation strategies against odor nuisance

The relevance of the odors on public health and the increasing interest of national and international authorities have led Authorities and Governments to tackle the problem. In Europe, according to the Directive 2008/98/CE, "Member States shall take the necessary measures to ensure that waste management is carried out without endangering human health, without harming the environment and, in particular: (b) without causing a nuisance through noise or odors". Moreover, Commission Implementing Decision (EU) 2018/1147 establishes best available techniques (BAT) conclusions for waste treatment and Commission Implementing Decision (EU) 2017/302 establishes BAT for the intensive rearing of poultry or pigs.

In the U.S. the Environmental Protection Agency (EPA) does not regulate odor, even if it is in force the Clean Air Act, a federal law designed to control air pollution on a national level. Nevertheless, EPA allows states to regulate odor directly. States that try to regulate odor, follow the principles of the Nuisance Laws, that means that they identified odor as a nuisance and established limits for odorous emissions as a nuisance phenomenon (Brancher et al., 2017; Nicell, 2009).

In Japan, the Offensive Odor Control Law regulates offensive odors emitted from business activities in order to preserve the living environment and to protect people's health (Government of Japan - Ministry of the Environment, 2019).

Moreover, some countries (e.g. Germany, The Netherlands, Switzerland, Austria, and Canada) have established guidelines based on minimum separation distances between livestock units and residential areas, for determination of odor-annoyance-free level (Ubeda et al., 2013). Setback distances can be determined by either by empirical models or by a combination of experience and calculations by dispersion models. Using this last technique, separation distances are calculated in a direction-dependent manner (Piringer et al., 2016). Dispersion models are able to predict time series of ambient odor concentrations with suitable meteorological data and source information (Capelli et al., 2013b). Combinations of tolerated exceedance probabilities and threshold odor concentrations are referred to as odor impact criteria (OIC) (Piringer et al., 2016). In the study of Sommer-Quabach et al. (2014) a wide variety of OIC used to determine separation distances is reported, thus avoiding odor nuisance and complaints by the residents. To establish appropriate OIC it is necessary to consider odor concentration, intensity and hedonic tone and their relationship (Huang and Guo, 2018). These impact criteria are selected by the responsible authorities and vary by a quite extend (Sommer-Quabach et al., 2014). In this regard, for example, in Austria a peak-to-mean approach is used to assess the odor perception (Piringer et al., 2016). In particular, in Germany and Austria the separation distances are established with two empirical models based on dispersion model AUSTAL2000 (also included in German VDI guidelines) and AODM (Austrian Odor Dispersion Model), respectively. These empirical models are based on equations that include one or more factors, such as type of the animal, indoor air temperature and meteorology (Wu et al., 2019).

Overall, in empirical models (experience-based) setback distances are established according to different scaling factors, determined by animal number and species, weather parameters, housing characteristics (e.g. ventilation, manure collection system, etc.) and abating technologies used. Subsequently, these factors have been used to adjust dispersion models to determine odor-annoyance-free intensity (Lim et al., 2000; Yu et al., 2010). For example, the OFFSET (Odor From Feedlots – Setback Estimation Tool) model was developed in Minnesota, taking in consideration numerous emission measurement, an air dispersion model (INPUFF-2) and historical weather data (Jacobson et al., 2005). In Canada Minimum Distance Separation guidelines (MDS-I and II) were developed by the Ontario Ministry of Agriculture, Food, and Rural Affairs in the 1990s (OMAFRA, 1995a,b), with separate procedures for buildings and manure storage units (Guo et al., 2004). Instead, AODM estimates the odor emission by considering animal number and species, housing and ventilation systems, handling of manure inside the building, the feeding methods, land use, and topography (Guo et al., 2004; Schauberger et al., 2001). In conclusion, since the setback distance models consider different scaling factors, they generate different odor-annoyance-free level, ranging from 99% to 91% (Guo et al., 2004). However, these models, used to determine separation distance, need the same input data previously described in Section 3, namely topographic, meteorological and emissions data. Regarding this last input, OERs are usually estimated as an annual constant value (Hayes et al., 2006) obtained by multiplying the mean live mass of the animals by a constant OEF. This means that the increasing of the live mass of the animals, as well as variation in indoor air temperature and ventilation rate are usually not considered (Schauberger et al., 2013). Therefore, assuming an annual mean and a constant OEF to calculate OER is inappropriate, as pointed out by Schauberger et al. (2014a) and

Schauberger et al. (2014b). In their studies, they suggest using an emission model which considers a time series of the OER, to obtain a more realistic description of the odor emission characteristics and to avoid overestimation (in winter) or underestimation (in summer).

In addition to separation distance, other strategies against odor nuisance can be applied. Generally, the odor control strategies involve different measures oriented to prevent, control dispersion, minimize the nuisance or remove the odorants from emission. Prevention of odorant formation at the source can be obtained by adequate process design and good operational practices. Establishing buffer zones or installation of odor covers are useful for the control of dispersion of the emissions (Guo et al., 2004; Hörnig et al., 1999). To minimize/remove the nuisance an alternative to the traditional treatment technologies (e.g. scrubber, incineration, and biofilter) is the use of chemical additives designed to mask, neutralize or minimize the perception of odorous emission (McCrory and Hobbs, 2001). However, as reported by Bortone et al. (2012), these technologies are not suitable to treat extensive areas such as waste landfills.

Also composting can be applied to reduce odorous emissions (Hurst et al., 2005). The odor reduction efficacy of composting is strictly linked to well functioning composting plants, where the conditions (pH, temperature, and aeration rates) are maintained optimal throughout the whole process (Sundberg et al., 2013). The odor emission reduction can be furtherly enhanced by increasing compost bulk density, Hurst et al. (2005) obtained a reduction by up to 97% of odors, and sulfurous compounds by up to 100% from landfill sites.

To reduce VOCs emissions from composting facilities, composting process need to be conducted at neutral or alkaline pH values (Sundberg et al., 2013), alternatively biofilter can be used to remove VOCs and NH_3 from the exhaust gases during organic waste composting process (Li et al., 2013; Pagans et al., 2007).

Instead, regarding odor control strategies to reduce odors from concentrated animal feeding operations, livestock housing, manure storage facilities, and during land application, they have been studied since the end of the 1900s (Kreis, 1978; Powers, 1999). Indeed, a wide range of mitigation techniques is available, such as nutritional strategies, manure additives, building design, air filtration, manure covers, and treatment systems (Bibbiani and Russo, 2012; Ubeda et al., 2013).

Modified animal feeding can decrease odors. Since proteins and fermentable carbohydrates are the main precursors of odor formation, it has been demonstrated that altering their level can affect odor emissions (Le et al., 2005). In their study, Hayes et al. (2004) found a 30% reduction of odor emissions in case of 160 and 130 g/kg crude protein diets. Moreover, reducing crude protein can effectively reduce excreted nitrogen, which is associated with lower NH_3 emissions (Ubeda et al., 2013). Similar results can also be obtained increasing the fermentable carbohydrates in diets. Indeed, they affect bacterial proliferation in both the gastrointestinal tract and in the manure modifying N excretion mechanism thus reducing NH_3 and odor emissions (Le et al., 2005).

As regards manure additives, the most common are: digestive additives, disinfecting additives, oxidizing agents, adsorbents, and masking agents (McCrory and Hobbs, 2001). However, at the moment, the main disadvantages of using additives are that they provide a short-term efficacy and they require frequent reapplication (McCrory and Hobbs, 2001; Wheeler et al., 2011). Alternatively, covering stored manure provides a physical barrier to reduce both NH_3 and odors emissions, by constructing rooftops or covering the surface with different materials to reduce the free surface of the slurry (Hörnig et al., 1999). Other manure treatments are based on solid-liquid separation alone (Zhang and Westerman, 1997) or coupled with anaerobic digestion (Hansen et al., 2006; Hjorth et al., 2009). By reducing the dry matter content, anaerobic digestion degrades also some VOCs, particularly volatile fatty acids, which can be reduced by between 79% and 97% (Hansen et al., 2006).

Regarding air filtration, bioscrubbers and biofilters can be used for reducing the emission of odors and VOCs to the atmosphere, thanks to the action of microorganisms that degrade gaseous contaminants (Sheridan et al., 2002). In short, the exhaust air is injected in these devices, pass through a biologically enriched layer where microorganisms use the organic matter as feed, thus letting clean air out (Pagans et al., 2005). Another straightforward way to reduce emissions is to install air scrubbers at the ventilation outlets of livestock buildings. Scrubbers consist mainly of three parts, at the bottom is located the buffer tank, in the middle the packing material and on the top, there are spray nozzles and air outlet nozzle.·NH_3, odorous compounds, and dust are trapped by the packing material (Van der Heyden et al., 2015).

In conclusion, odor emission reduction can be obtained thanks to the application of one or more of the strategies reported above. Although these strategies have been longer investigated and are well known, further research is needed to explore efficient and cost-effective management systems other than to ensure effective implementation at the farm level.

5.2. Odor impact in life cycle assessment

The Life Cycle Assessment (LCA) is holistic approach to evaluate the potential environmental impact of production processes. Although originally developed for industrial processes, in the last years, it is more and more applied also to agricultural systems. Nowadays, LCA is internationally recognized as a viable and consistent approach for the environmental impact assessment. Nevertheless, among the different environmental impacts that can be quantify with LCA the odor impact is missing. Recently some preliminary approaches to include odor impact in the LCA framework were proposed (Cadena et al., 2018; Peters et al., 2014).

In particular, Cadena et al. (2018) presented an indicator for odor impact potential (named Odor Impact Potential, OIP) that can be applied to different activities and processes. In the study, OIP is applied to an anaerobic digestion plant considering that anaerobic digestion has been recognized as an effective solution to reduced odor impact from animal slurry storage (Lim et al., 2003; Fusi et al., 2016). OIP aims to include odor-derived impact in LCA studies by combining (and not replacing) parameters such as odor emission rates, odor concentration, or odor emission factors. OIP expresses the amount of air needed to dilute the odor emission below a concentration not detectable by human panelists in olfactometry. According to the LCA approach, OIP should be referred to the functional unit (i.e., the reference to which the inputs and outputs and the potential environmental impact can be related).

Based on the previous experience of OIP proposed by Cadena et al (2018), odor could be introduced in the LCA framework with an additional impact category able to quantify the potential odor impact. More in details, using olfactometry the different odor sources could be quantified and, at the end, summed up to calculate the potential olfactometryc unit (OU) related to a specific production process. Even if OU is quantified in laboratory and doesn't account the dispersion models, the developed odor impact category could be useful to compare different production processes that provide the same function and are responsible of odor annoyance. As for other impact categories such as Climate Change, Ozone depletion, Human toxicity, the odor impact category will consider (and sum up) emissions geographically located in different areas; this issue should be considered in the last step of LCA "Results interpretation". From a practical point of view, the first step to set up the odor impact category is the building, using olfactometry, of a database with the different odor emission sources.

6. Conclusions

The release of odorous components, from waste treatment plant and husbandry practices, is a concern for the people living near these facilities, other than for the health of workers and animals. A literature review of odor measurements and of a major source of complaints was carried out to point out the state of the art of this concern with regard to the odor from waste management and from livestock activity.

The literature reviewed highlighted that, over the last century, wide attention has been paid to "odor issue" in different countries. If in Asia, and in China in particular, it is mainly focused on odor from waste management plants in other countries some researchers investigated the issue from a livestock point of view. Considering that the impact of odors on the surrounding communities depends on several factors (from climatic conditions to technological aspects), some general conclusion can be drawn regarding the evaluation of odors as well as about possible mitigation solutions and future research activities.

Sensorial or analytical techniques can be used, in alternative or in combination, for quantitative and qualitative characterization of odors. The main advantage of sensorial techniques is the higher sensitivity of human nose compared to electronic instruments, while the main disadvantage is that the panel should be composed of qualified assessors to ensure reliable and repeatable results. Instead, analytical methodologies are not subjected to human errors, but are less sensitive, non-reliable in case of mixture of many odorants at very low odor concentration and they are not able to detect the interaction between odorants. The goal of both techniques is the evaluation of odor concentration.

However, to simulate odor dispersion, the evaluation of odor concentration alone is not sufficient, as also the air flow associated with the monitored odor source have to be taken into account. For determining odor plume extents, and therefore evaluating odor exposure at receptors, different air dispersion models, that applied different simulation procedures, can be used. Models follow the Gaussian, Lagrangian or Eulerian approaches. To be performed they require topographic/orographic, meteorological and emission data, which goodness affect the quality of the results. Air dispersion models are a useful tool when evaluating technologies to reduce the odor re-lease at existing operations or when planning new operations, thus having not only a descriptive nature but also predictive. Based on the model applied an underestimation or an overestimation can be obtained. So, it could be useful combining with sensorial and analytical techniques. Concerning the livestock sector, specific odor dispersion models should be developed to include all the specific features of livestock odor dispersion (e.g. short distance of transportation, multiple sources, animal mass, and number). OERs are usually estimated as a yearly constant value obtained by multiplying the average live mass of the animals by a constant OEF. However, in this way, some factors (e.g. live mass, variation of indoor air temperature, ventilation rate) that influence the odor release are not considered. So, using a model that takes into account a time series of OERs allows obtaining a better description of OEF and consequently a more realistic emission scenario. This scenario will be useful to improve the reliability of the calculation of setback distances.

Separation distances are just one possibility to protect people from odor annoyance, but a wide range of mitigation techniques are available and applied. Some solutions have been longer investigated and are well known (e.g. scrubber, additives, manure covers, etc.), while for others (e.g. activated carbon adsorption and activated sludge diffusion) further research is needed to explore efficient and cost-effective management systems other than to ensure effective implementation. To minimize the nuisance of waste treatment plants a strategy is represented by composting which need to be conducted at neutral or alkaline pH values. Regarding intensive livestock farming, the common mitigation techniques adopted are: nutritional strategies, manure additives, building design, air filtration, manure covers, and treatment systems, whose efficacy increases by combining them.

In conclusion, since odors have such a big impact on the surrounding environment, it would be useful to quantify the nuisance also from an environmental point of view. Thus, it is reasonable to integrate odors as an indicator to be used in a Life Cycle Assessment framework, and consequently, to develop a specific impact category quantifying the odorous impact related to the life cycle of a product or a process. In fact, up to now, although the different compounds responsible of the odor (e.g·NH_3, VOCs) affect some impact categories (e.g. eutrophication, acidification, and particular matter formation) an impact category specifically referred to the odor is missing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Aatamila, M., Verkasalo, P.K., Korhonen, M.J., Suominen, A.L., Hirvonen, M.R., Viluksela, M.K., Nevalainen, A., 2011. Odour annoyance and physical symptoms among residents living near waste treatment centres. Environ. Res. 111, 164–170. https://doi.org/10.1016/j.envres.2010.11.008.

Akdeniz, N., Jacobson, L.D., Hetchler, B.P., Bereznicki, S.D., Heber, A.J., Koziel, J.A., Cai, L., Zhang, S., Parker, D.B., 2012. Odor and odorous chemical emissions from animal buildings: Part 2. Odor emissions. Trans. ASABE 55, 2335–2345.

Asadollahfardi, G., Asadi, M., Youssefi, M., Elyasi, S., Mirmohammadi, M., 2015. Experimental and mathematical study on ammonia emission from Kahrizak landfill and composting plants, Tehran, Iran. J. Mater. Cycles Waste Manage. 17, 350–358. https://doi.org/10.1007/s10163-014-0242-1.

Baawain, M., Al-Mamun, A., Omidvarborna, H., Al-Jabri, A., 2017. Assessment of hydrogen sulfide emission from a sewage treatment plant using AERMOD. Environ. Monit. Assess. 189, 263. https://doi.org/10.1007/s10661-017-5983-6.

Bacenetti, J., Fiala, M., 2015. Carbon footprint of electricity from anaerobic digestion plants in Italy. Environ. Eng. Manage. J. 14 (7), 1495–1502.

Baldini, C., Borgonovo, F., Gardoni, D., Guarino, M., 2016. Comparison among NH3 and GHGs emissive patterns from different housing solutions of dairy farms. Atmos. Environ. 141, 60–66. https://doi.org/10.1016/j.atmosenv.2016.06.047.

Barth, C.L., Elliott, L.F., Melvin, S.W., 1984. Using odor control technology to support animal agriculture. Trans. ASAE 27, 859–864. https://doi.org/10.13031/2013.32885.

Biasioli, F., Yeretzian, C., Mark, T.D., Dewulf, J., Van Langenhove, H., 2011. Direct-injection mass spectrometry adds the time dimension to (B)VOC analysis. Trac-Trends Anal. Chem. 30, 1003–1017. https://doi.org/10.1016/j.trac.2011.04.005.

Bibbiani, C., Russo, C., 2012. Odour emission from intensive livestock production system: approaches for emission abatement and evaluation of their effectiveness. Large Animal Rev. 18, 135–138.

Blanco-Rodríguez, A., Camara, V.F., Campo, F., Becherán, L., Durán, A., Vieira, V.D., de Melo, H., Garcia-Ramirez, A.R., 2018. Development of an electronic nose to characterize odours emitted from different stages in a wastewater treatment plant. Water Res. 134, 92–100. https://doi.org/10.1016/j.watres.2018.01.067.

Blanes-Vidal, V., 2015. Air pollution from biodegradable wastes and non-specific health symptoms among residents: Direct or annoyance-mediated associations? Chemosphere 120, 371–377. https://doi.org/10.1016/j.chemosphere.2014.07.089.

Blanes-Vidal, V., Hansen, M.N., Adamsen, A.P.S., Feilberg, A., Petersen, S.O., Jensen, B.B., 2009. Characterization of odor released during handling of swine slurry: Part II. Effect of production type, storage and physicochemical characteristics of the slurry. Atmos. Environ. 43, 3006–3014. https://doi.org/10.1016/j.atmosenv.2009.01.046.

Blanes-Vidal, V., Suh, H., Nadimi, E.S., Løfstrøm, P., Ellermann, T., Andersen, H.V., Schwartz, J., 2012. Residential exposure to outdoor air pollution from livestock operations and perceived annoyance among citizens. Environ. Int. 40, 44–50. https://doi.org/10.1016/j.envint.2011.11.010.

Bortone, I., Carrillo, S., Di Nardo, A., Di Natale, M., Musmarra, D., 2012. Mitigation of the odorous impact of a waste landfill located in a highly urbanized area. Chem. Eng. Trans. 28, 229–234. https://doi.org/10.3303/Cet1228039.

Both, R., 2001. Directive on odour in ambient air: an established system of odour measurement and odour regulation in Germany. Water Sci. Technol. 44, 119–126. https://doi.org/10.2166/wst.2001.0521.

Brancher, M., Griffiths, K.D., Franco, D., de Melo Lisboa, H., 2017. A review of odour impact criteria in selected countries around the world. Chemosphere 168, 1531–1570. https://doi.org/10.1016/j.chemosphere.2016.11.160.

Brancher, M., Piringer, M., Franco, D., Belli Filho, P., Lisboa, H.D.M., Schauberger, G., 2019. Assessing the inter-annual variability of separation distances around odour sources to protect the residents from odour annoyance. J. Environ. Sci. 79, 11–24. https://doi.org/10.1016/j.jes.2018.09.018.

Brattoli, M., et al., 2011. Odour Detection Methods: Olfactometry and Chemical Sensors. Sensors 11, 5290–5322. https://doi.org/10.3390/s110505290.

Brattoli, M., Cisternino, E., Dambruoso, P., De Gennaro, G., Giungato, P., Mazzone, A., Palmisani, J., Tutino, M., 2013. Gas chromatography analysis with olfactometric detection (GC-O) as a useful methodology for chemical characterization of odorous compounds. Sensors 13, 16759–16800. https://doi.org/10.3390/S131216759.

Brinkmann, T., Both, R., Scalet, B.M., Roudier, S., Sancho, L.D., 2018. JRC reference report on monitoring of emissions to air and water from IED installations. European IPPC Bureau, European Commission, Joint Research Centre. Seville, Spain.

Bruno, P., Caselli, M., De Gennaro, G., Solito, M., Tutino, M., 2007. Monitoring of odor compounds produced by solid waste treatment plants with diffusive samplers. Waste Manage. 27, 539–544. https://doi.org/10.1016/j.wasman.2006.03.006.

Büyüksönmez, F., Evans, J., 2007. Biogenic emissions from green waste and comparison to the emissions resulting from composting part II: Volatile Organic Compounds (VOCs). Compost. Sci. Util. 15, 191–199. https://doi.org/10.1080/1065657x.2007.10702332.

Cadena, E., Adani, F., Font, X., Artola, A., 2018. Including an Odor Impact Potential in Life Cycle Assessment of waste treatment plants. Int. J. Environ. Sci. Technol. 15, 2193–2202. https://doi.org/10.1007/s13762-017-1613-7.

Cantuaria, M.L., Brandt, J., Løfstrøm, P., Blanes-Vidal, V., 2017. Public perception of rural environmental quality: Moving towards a multi-pollutant approach. Atmos. Environ. 170, 234–244. https://doi.org/10.1016/j.atmosenv.2017.09.051.

Capelli, L., Sironi, S., 2018. Combination of field inspection and dispersion modelling to estimate odour emissions from an Italian landfill. Atmos. Environ. 191, 273–290. https://doi.org/10.1016/j.atmosenv.2018.08.007.

Capelli, L., Sironi, S., Del Rosso, R., 2013a. Odor sampling: techniques and strategies for the estimation of odor emission rates from different source types. Sensors 13, 938–955. https://doi.org/10.3390/s130100938.

Capelli, L., Sironi, S., Del Rosso, R., 2014a. Electronic noses for environmental monitoring applications. Sensors 14, 19979–20007. https://doi.org/10.3390/s141119979.

Capelli, L., Sironi, S., Del Rosso, R., 2014b. Odour emission factors: Fundamental tools for air quality management. Chem. Eng. Trans. 40, 193–198. https://doi.org/10.3303/Cet1440033.

Capelli, L., Sironi, S., Del Rosso, R., Centola, P., Bonati, S., 2010. Improvement of olfactometric measurement accuracy and repeatability by optimization of panel selection procedures. Water Sci. Technol. 61, 1267–1278. https://doi.org/10.2166/wst.2010.023.

Capelli, L., Sironi, S., Del Rosso, R., Guillot, J.M., 2013b. Measuring odours in the environment vs. dispersion modelling: A review. Atmos. Environ. 79, 731–743. https://doi.org/10.1016/j.atmosenv.2013.07.029.

Chen, C., Tsow, F., Campbell, K.D., Iglesias, R., Forzani, E., Tao, N., 2013. A wireless hybrid chemical sensor for detection of environmental volatile organic compounds. IEEE Sens. J. 13, 1748–1755. https://doi.org/10.1109/JSEN.2013.2239472.

Cheng, Z., Sun, Z., Zhu, S., Lou, Z., Zhu, N., Feng, L., 2019. The identification and health risk assessment of odor emissions from waste landfilling and composting. Sci. Total Environ. 649, 1038–1044. https://doi.org/10.1016/j.scitotenv.2018.08.230.

D.G.R. 15 febbraio 2012 e n. IX/3018 Regione Lombardia, 2012. Determinazioni generali in merito alla caratterizzazione delle emissioni gassose in atmosfera derivanti da attività a forte impatto odorigeno. Bollettino Ufficiale 20 febbraio 2012.

Daly, A., Zannetti, P., 2007. Air pollution modeling–An overview. Ambient air pollution, pp. 15–28.

Danuso, F., Rocca, A., Ceccon, P., Ginaldi, F., 2015. A software application for mapping livestock waste odour dispersion. Environ. Modell. Software 69, 175–186. https://doi.org/10.1016/j.envsoft.2015.03.016.

de Melo, A.M.V., Santos, J.M., Mavroidis, I., Junior, N.C.R., 2012. Modelling of odour dispersion around a pig farm building complex using AERMOD and CALPUFF. Comparison with wind tunnel results. Build. Environ. 56, 8–20. https://doi.org/10.1016/j.buildenv.2012.02.017.

Defoer, N., De Bo, I., Van Langenhove, H., Dewulf, J., Van Elst, T., 2002. Gas chromatography–mass spectrometry as a tool for estimating odour concentrations of biofilter effluents at aerobic composting and rendering plants. J Chromatogr. A 970, 259–273 Pii S0021-9673(02)00654-4 Doi 10.1016/S0021-9673(02)00654-4.

Delahunty, C.M., Eyres, G., Dufour, J.P., 2006. Gas chromatography-olfactometry. J. Sep. Sci. 29, 2107–2125. https://doi.org/10.1002/jssc.200500509.

Dentoni, L., Capelli, L., Sironi, S., Guillot, J.-M., Rossi, N.A., 2013. Comparison of different approaches for odour impact assessment: Dispersion modelling (CALPUFF) vs field inspection (CEN/TC 264). Water Sci. Technol. 68, 1731–1738. https://doi.org/10.2166/wst.2013.387.

Di Francesco, F., Lazzerini, B., Marcelloni, F., Pioggia, G., 2001. An electronic nose for odour annoyance assessment. Atmos. Environ. 35, 1225–1234. https://doi.org/10.1016/S1352-2310(00)00392-7.

Diallo, M., Maalem, F., Piet-Sarnet, H., 2018. Implementation of a new protocol of odour field investigations for the Paris wastewater treatment plants. Chem. Eng. Trans. 68, 145–150. https://doi.org/10.3303/cet1868025.

Dincer, F., Odabasi, M., Muezzinoglu, A., 2006. Chemical characterization of odorous gases at a landfill site by gas chromatography–mass spectrometry. J. Chromatogr. A 1122, 222–229. https://doi.org/10.1016/j.chroma.2006.04.075.

Domingo, J.L., Nadal, M., 2009. Domestic waste composting facilities: a review of human health risks. Environ. Int. 35, 382–389. https://doi.org/10.1016/j.envint.2008.07.004.

Dravnieks, A., Jarke, F., 1980. Odor threshold measurement by dynamic olfactometry: Significant operational variables. J. Air Pollut. Control Assoc. 30, 1284–1289.

Dunlop, M.W., Blackall, P.J., Stuetz, R.M., 2016. Odour emissions from poultry litter–A review litter properties, odour formation and odorant emissions from porous materials. J. Enviro.n Manage. 177, 306–319. https://doi.org/10.1016/j.jenvman.2016.04.009.

EEA, 2018. Report No 6/2018. European Union emission inventory report 1990-2016 under the UNECE Convention on Long-range Transboundary Air Pollution (LRTAP).

EN 13725, 2003. CEN EN 13725:2003. Air Quality—Determination of Odour Concentration by Dynamic Olfactometry. Brussels, Belgium: CEN European Committee for Standardization.

EN 16841-1, 2016. Ambient Air - Determination of Odour in Ambient Air by Using Field Inspection - Part 1: Grid Method. European Committee for Standardization CEN, Brussels.

EN 16841-2:2016, 2016. Ambient Air - Determination of Odour in Ambient Air by Using Field Inspection - Part 2: Plume Method. Brussels, Belgium.

Erisman, J., Bleeker, A., Galloway, J., Sutton, M., 2007. Reduced nitrogen in ecology and the environment. Environ. Pollut. 150, 140–149. https://doi.org/10.1016/j.envpol.2007.06.033.

Fang, J.-J., Yang, N., Cen, D.-Y., Shao, L.-M., He, P.-J., 2012. Odor compounds from different sources of landfill: Characterization and source identification. Waste Manage. 32, 1401–1410. https://doi.org/10.1016/j.wasman.2012.02.013.

Filipy, J., Rumburg, B., Mount, G., Westberg, H., Lamb, B., 2006. Identification and quantification of volatile organic compounds from a dairy. Atmos. Environ. 40, 1480–1494. https://doi.org/10.1016/j.atmosenv.2005.10.048.

Flesch, T.K., Wilson, J.D., Yee, E., 1995. Backward-time lagrangian stochastic dispersion models and their application to estimate gaseous emissions. J. Appl. Meteorol. 34, 1320–1332. https://doi.org/10.1175/1520-0450(1995) 034<1320:Btlsdm>2.0.Co;2.

Font, X., Artola, A., Sánchez, A., 2011. Detection, composition and treatment of volatile organic compounds from waste treatment plants. Sensors 11, 4043–4059. https://doi.org/10.3390/s110404043.

Fusi, A., Bacenetti, J., Fiala, M., Azapagic, A., 2016. Life cycle environmental impacts of electricity from biogas produced by anaerobic digestion. Front. Bioeng. Biotechnol. 4, 26. https://doi.org/10.3389/fbioe.2016.00026.

Gallego, E., Roca, F.J., Perales, J.F., Sánchez, G., Esplugas, P., 2012. Characterization and determination of the odorous charge in the indoor air of a waste treatment facility through the evaluation of volatile organic compounds (VOCs) using TD–GC/MS. Waste Manage. 32, 2469–2481. https://doi.org/10.1016/j.wasman.2012.07.010.

Gallego, E., Soriano, C., Roca, F., Perales, J., Alarcón, M., Guardino, X., 2008. Identification of the origin of odour episodes through social participation, chemical control and numerical modelling. Atmos. Environ. 42, 8150–8160. https://doi.org/10.1016/j.atmosenv.2008.08.004.

Galvin, G., Lowe, S., Smith, R., 2004. The validation of a simple Gaussian dispersion model for determining odour emission rates from area sources. Dev. Chem. Eng. Min. Process. 12, 545–558. https://doi.org/10.1002/apj.5500120509.

Gifford, F.A., 1959. Statistical properties of a fluctuating plume dispersion model. Adv. Geophys. 6, 117–137.

Government of Japan - Ministry of the Environment, 2019. Offensive Odor Control Law. http://www.env.go.jp/en/laws/air/odor/ch.html#ch2.

Guffanti, P., Pifferi, V., Falciola, L., Ferrante, V., 2018. Analyses of odours from concentrated animal feeding operations: A review. Atmos. Environ. 175, 100–108.

Guillot, J.M., Bilsen, I., Both, R., Hangartner, M., Kost, W.J., Kunz, W., Nicolas, J., Oxbol, A., Secanella, J., Van Belois, H., Van Elst, T., Van Harreveld, T., Milan, B., 2012. The future European standard to determine odour in ambient air by using field inspection. Water Sci. Technol. 66, 1691–1698. https://doi.org/10.2166/wst.2012.375.

Guo, H., Dehod, W., Agnew, J., Laguë, C., Feddes, J., Pang, S., 2006. Annual odor emission rate from different types of swine production buildings. Trans. ASABE 49, 517–525.

Guo, H., Jacobson, L., Schmidt, D., Nicolai, R., Janni, K., 2004. Comparison of five models for setback distance determination from livestock sites. Can. Biosyst. Eng. 46, 17–25. https://doi.org/10.13031/2013.5534.

Hansen, M.N., Kai, P., Møller, H.B., 2006. Effects of anaerobic digestion and separation of pig slurry on odor emission. Appl. Eng. Agric. 22, 135–139.

Hayes, E.T., Curran, T.P., Dodd, V.A., 2006. A dispersion modelling approach to determine the odour impact of intensive poultry production units in Ireland. Bioresour. Technol. 97, 1773–1779. https://doi.org/10.1016/j.biortech.2005.09.019.

Hayes, E.T., Leek, A.B., Curran, T.P., Dodd, V.A., Carton, O.T., Beattie, V.E., O'Doherty, J.V., 2004. The influence of diet crude protein level on odour and ammonia emissions from finishing pig houses. Bioresour. Technol. 91, 309–315.

Hayes, J.E., Stevenson, R.J., Stuetz, R.M., 2014. The impact of malodour on communities: a review of assessment techniques. Sci. Total Environ. 500–501, 395–407. https://doi.org/10.1016/j.scitotenv.2014.09.003.

Heaney, C.D., Wing, S., Campbell, R.L., Caldwell, D., Hopkins, B., Richardson, D., Yeatts, K., 2011. Relation between malodor, ambient hydrogen sulfide, and health in a community bordering a landfill. Environ. Res. 111, 847–852. https://doi.org/10.1016/j.envres.2011.05.021.

Henshaw, P., Nicell, J., Sikdar, A., 2006. Parameters for the assessment of odour impacts on communities. Atmos. Environ. 40, 1016–1029. https://doi.org/10.1016/j.atmosenv.2005.11.014.

Higgins, M.J., Chen, Y.-C., Yarosz, D.P., Murthy, S.N., Maas, N.A., Glindemann, D., Novak, J.T., 2006. Cycling of volatile organic sulfur compounds in anaerobically digested biosolids and its implications for odors. Water Environ. Res. 78, 243–252. https://doi.org/10.2175/106143005X90065.

Hjorth, M., Nielsen, A.M., Nyord, T., Hansen, M., Nissen, P., Sommer, S., 2009. Nutrient value, odour emission and energy production of manure as influenced by anaerobic digestion and separation. Agron Sustain Dev 29, 329–338. https://doi.org/10.1051/agro:2008047.

Hörnig, G., Türk, M., Wanka, U., 1999. Slurry covers to reduce ammonia emission and odour nuisance. J. Agric. Eng. Res. 73, 151–157. https://doi.org/10.1006/jaer.1998.0402.

Huang, B., Lei, C., Wei, C., Zeng, G., 2014. Chlorinated volatile organic compounds (Cl-VOCs) in environment—sources, potential human health impacts, and current remediation technologies. Environ. Int. 71, 118–138. https://doi.org/10.1016/j.envint.2014.06.013.

Huang, D.D., Guo, H.Q., 2018. Relationships between odor properties and determination of odor concentration limits in odor impact criteria for poultry and dairy barns. Sci. Total Environ. 630, 1484–1491. https://doi.org/10.1016/j.scitotenv.2018.02.318.

Hurst, C., Longhurst, P., Pollard, S., Smith, R., Jefferson, B., Gronow, J., 2005. Assessment of municipal waste compost as a daily cover material for odour control at landfill sites. Environ. Pollut. 135, 171–177. https://doi.org/10.1016/j.envpol.2004.09.004.

International Organisation for Standardization, 2008. ISO 5492: 2008. Sensory analysis–vocabulary.

Jacobson, L.D., Guo, H., Schmidt, D., Nicolai, R., Zhu, J., Janni, K., 2005. Development of the OFFSET model for determination of odor-annoyance-free setback distances from

animal production sites: Part I. Review and experiment. Trans. ASAE 48, 2259–2268. https://doi.org/10.13031/2013.20089.
Jacobson, L.D., Guo, H., Schmidt, D.R., Nicolai, R.E., Zhu, J., Janni, K.A., 2000. Development of an Odor Rating System to Estimate Setback Distances from Animal Feedlots: Odor from Feedlots-Setback Estimation Tool (offset). St Joseph: American Society of Agricultural Engineers.
Jung, Y.-R., Park, W.-G., Park, O.-H., 2003. Pollution dispersion analysis using the puff model with numerical flow field data. Mech. Res. Commun. 30, 277–286. https://doi.org/10.1016/S0093-6413(03)00024-7.
Kafle, G.K., Chen, L., 2014. Emissions of odor, ammonia, hydrogen sulfide, and volatile organic compounds from shallow-pit pig nursery rooms. J. Biosyst. Eng. 39, 76–86. https://doi.org/10.5307/JBE.2014.39.2.076.
Keck, M., Mager, K., Weber, K., Keller, M., Frei, M., Steiner, B., Schrade, S., 2018. Odour impact from farms with animal husbandry and biogas facilities. Sci. Total Environ. 645, 1432–1443. https://doi.org/10.1016/j.scitotenv.2018.07.182.
Kiesewetter, G., Amann, M., 2014. Urban PM2. 5 levels under the EU Clean Air Policy Package. http://pure.iiasa.ac.at/11152.
Komilis, D.P., Ham, R.K., Park, J.K., 2004. Emission of volatile organic compounds during composting of municipal solid wastes. Water Res. 38, 1707–1714. https://doi.org/10.1016/j.watres.2003.12.039.
Kreis, R.D., 1978. Limiting the environmental impact of animal production odors. Environ. Int. 1, 247–275.
Le, P.D., Aarnink, A.J., Ogink, N.W., Becker, P.M., Verstegen, M.W., 2005. Odour from animal production facilities: its relationship to diet. Nutr. Res. Rev. 18, 3–30. https://doi.org/10.1079/NRR200592.
Lemay, S.P., 1999. Barn management and control of odours. Adv. Pork Prod. 10, 81–91.
Li, Z., Lu, H., Ren, L., He, L., 2013. Experimental and modeling approaches for food waste composting: A review. Chemosphere 93, 1247–1257. https://doi.org/10.1016/j.chemosphere.2013.06.064.
Lim, T., Heber, A., Ni, J.-Q., Grant, R., Sutton, A., 2000. Odor impact distance guideline for swine production systems.
Lim, T.-T., et al., 2003. Odor and gas release from anaerobic treatment lagoons for swine manure. J. Environ. Qual. 32 (2), 406–416. https://doi.org/10.2134/jeq2003.4060.
Lin, H., Jang, M., Suslick, K.S., 2011. Preoxidation for colorimetric sensor array detection of VOCs. J. Am. Chem. Soc. 133, 16786–16789. https://doi.org/10.1021/ja207718t.
Lucernoni, F., Capelli, L., Sironi, S., 2016. Odour sampling on passive area sources: principles and methods. Chem. Eng. Trans. 54, 55–60. https://doi.org/10.3303/CET1654010.
Mao, I.-F., Tsai, C.-J., Shen, S.-H., Lin, T.-F., Chen, W.-K., Chen, M.-L., 2006. Critical components of odors in evaluating the performance of food waste composting plants. Sci. Total Environ. 370, 323–329. https://doi.org/10.1016/j.scitotenv.2006.06.016.
McCrory, D.F., Hobbs, P.J., 2001. Additives to reduce ammonia and odor emissions from livestock wastes. J. Environ. Qual. 30, 345–355. https://doi.org/10.2134/jeq2001.302345x.
Mielcarek, P., Rzeznik, W., 2015. Odor emission factors from livestock production. Pol. J. Environ. Stud. 24, 27–35. https://doi.org/10.15244/pjoes/29944.
Miller, G.Y., Maghirang, R.G., Riskowski, G.L., Heber, A.J., Robert, M.J., Muyot, M.E., 2004. Influences on air quality and odor from mechanically ventilated swine finishing buildings in Illinois. J. Food Agric. Environ. 2, 353–360.
Moreno, A.I., Arnáiz, N., Font, R., Carratalá, A., 2014. Chemical characterization of emissions from a municipal solid waste treatment plant. Waste Manage. 34, 2393–2399. https://doi.org/10.1016/j.wasman.2014.07.008.
Munoz, R., Sivret, E.C., Parcsi, G., Lebrero, R., Wang, X., Suffet, I.M., Stuetz, R.M., 2010. Monitoring techniques for odour abatement assessment. Water Res. 44, 5129–5149. https://doi.org/10.1016/j.watres.2010.06.013.
Nguyen, K.C., Noonan, J.A., Galbally, I.E., Physick, W.L., 1997. Predictions of plume dispersion in complex terrain: Eulerian versus Lagrangian models. Atmos. Environ. 31, 947–958. https://doi.org/10.1016/S1352-2310(96)00292-0.
Ni, J.-Q., Robarge, W.P., Xiao, C., Heber, A.J., 2012. Volatile organic compounds at swine facilities: A critical review. Chemosphere 89, 769–788. https://doi.org/10.1016/j.chemosphere.2012.04.061.
Nicell, J.A., 2009. Assessment and regulation of odour impacts. Atmos. Environ. 43, 196–206. https://doi.org/10.1016/j.atmosenv.2008.09.033.
Nie, E.Q., Zheng, G.D., Gao, D., Chen, T.B., Yang, J.X., Wang, Y.W., Wang, X.K., 2019. Emission characteristics of VOCs and potential ozone formation from a full-scale sewage sludge composting plant. Sci. Total Environ. 659, 664–672. https://doi.org/10.1016/j.scitotenv.2018.12.404.
Nimmermark, S.A., Jacobson, L.D., Schmidt, D.R., Gay, S.W., 2005. Predictions by the odor from feedlots, setback estimation tool (OFFSET) compared with observations by neighborhood monitors. J. Air Waste Manage. Assoc. 55, 1306–1314. https://doi.org/10.1080/10473289.2005.10464730.
O'Neill, D., Phillips, V., 1991. A review of the control of odour nuisancefrom livestock buildings: Part 1, influence of the techniques for managing waste within the building. J. Agric. Eng. Res. 50, 1–10.
OMAFRA, 1995a. Minimum Distance Separation I (MDS I). Queen's Printer, Toronto.
OMAFRA, 1995b. Minimum Distance Separation II (MDS II). Queen's Printer, Toronto.
Pagans, E., Barrena, R., Font, X., Sánchez, A., 2006. Ammonia emissions from the composting of different organic wastes. Dependency on process temperature. Chemosphere 62, 1534–1542. https://doi.org/10.1016/j.chemosphere.2005.06.044.
Pagans, E., Font, X., Sánchez, A., 2007. Coupling composting and biofiltration for ammonia and volatile organic compound removal. Biosyst. Eng. 97, 491–500. https://doi.org/10.1016/j.biosystemseng.2007.03.03S.
Pagans, E.l., Font, X., Sánchez, A., 2005. Biofiltration for ammonia removal from composting exhaust gases. Chem. Eng. J. 113, 105–110. https://doi.org/10.1016/j.cej.2005.03.004.
Palmiotto, M., Fattore, E., Paiano, V., Celeste, G., Colombo, A., Davoli, E., 2014. Influence of a municipal solid waste landfill in the surrounding environment: Toxicological risk and odor nuisance effects. Environ. Int. 68, 16–24. https://doi.org/10.1016/j.envint.2014.03.004.
Pasquill, F., 1961. The estimation of the dispersion of windborne material. Met. Mag. 90, 33.
Peters, G.M., Murphy, K.R., Adamsen, A.P.S., Bruun, S., Svanström, M., ten Hoeve, M., 2014. Improving odour assessment in LCA—the odour footprint. Int. J. Life Cycle Assess. 19, 1891–1900. https://doi.org/10.1007/s11367-014-0782-6.
Pierucci, P., Porazzi, E., Martinez, M.P., Adani, F., Carati, C., Rubino, F.M., Colombi, A., Calcaterra, E., Benfenati, E., 2005. Volatile organic compounds produced during the aerobic biological processing of municipal solid waste in a pilot plant. Chemosphere 59, 423–430. https://doi.org/10.1016/j.chemosphere.2004.10.040.
Piringer, M., Knauder, W., Petz, E., Schauberger, G., 2016. Factors influencing separation distances against odour annoyance calculated by Gaussian and Lagrangian dispersion models. Atmos. Environ. 140, 69–83. https://doi.org/10.1016/j.atmosenv.2016.05.056.
Piringer, M., Schauberger, G., 2013. Dispersion modelling for odour exposure assessment. Odour Impact Assessment Handbook 125–174.
Powers, W., 1999. Odor control for livestock systems. J. Anim. Sci. 77, 169–176.
Ranzato, L., Barausse, A., Mantovani, A., Pittarello, A., Benzo, M., Palmeri, L., 2012. A comparison of methods for the assessment of odor impacts on air quality: Field inspection (VDI 3940) and the air dispersion model CALPUFF. Atmos. Environ. 61, 570–579. https://doi.org/10.1016/j.atmosenv.2012.08.009.
Renaud, M., Chelinho, S., Alvarenga, P., Mourinha, C., Palma, P., Sousa, J.P., Natal-da-Luz, T., 2017. Organic wastes as soil amendments–Effects assessment towards soil invertebrates. J. Hazard. Mater. 330, 149–156. https://doi.org/10.1016/j.jhazmat.2017.01.052.
Rincón, C.A., De Guardia, A., Couvert, A., Le Roux, S., Soutrel, I., Daumoin, M., Benoist, J.C., 2019. Chemical and odor characterization of gas emissions released during composting of solid wastes and digestates. J. Environ. Manage. 233, 39–53. https://doi.org/10.1016/j.jenvman.2018.12.009.
Sarkar, U., Hobbs, S.E., 2002. Odour from municipal solid waste (MSW) landfills: A study on the analysis of perception. Environ. Int. 27, 655–662. https://doi.org/10.1016/S0160-4120(01)00125-8.
Schauberger, G., Lim, T.-T., Ni, J.-Q., Bundy, D.S., Haymore, B.L., Diehl, C.A., Duggirala, R.K., Heber, A.J., 2013. Empirical model of odor emission from deep-pit swine finishing barns to derive a standardized odor emission factor. Atmos. Environ. 66, 84–90. https://doi.org/10.1016/j.atmosenv.2012.05.046.
Schauberger, G., Piringer, M., 2012. Assessment of separation distances to avoid odour annoyance: interaction between odour impact criteria and peak-to-mean factors. Chem. Eng. Trans. 30, 13–18. https://doi.org/10.3303/CET1230003.
Schauberger, G., Piringer, M., Heber, A., 2014a. Modelling of odour emission rates for fattening pigs as time-resolved input for dispersion models. Chem. Eng. Trans. 40, 49–54. https://doi.org/10.3303/Cet1440009.
Schauberger, G., Piringer, M., Heber, A.J., 2014b. Odour emission scenarios for fattening pigs as input for dispersion models: A step from an annual mean value to time series. Agric. Ecosyst. Environ. 193, 108–116. https://doi.org/10.1016/j.agee.2014.04.030.
Schauberger, G., Piringer, M., Petz, E., 2001. Separation distance to avoid odour nuisance due to livestock calculated by the Austrian odour dispersion model (AODM). Agric. Ecosyst. Environ. 87, 13–28. https://doi.org/10.1016/S0167-8809(00)00299-1.
Schauberger, G., Schmitzer, R., Kamp, M., Sowa, A., Koch, R., Eckhof, W., Eichler, F., Grimm, E., Kypke, J., Hartung, E., 2012. Empirical model derived from dispersion calculations to determine separation distances between livestock buildings and residential areas to avoid odour nuisance. Atmos. Environ. 46, 508–515. https://doi.org/10.1016/j.atmosenv.2011.08.025.
Schiffman, S.S., Bennett, J.L., Raymer, J.H., 2001. Quantification of odors and odorants from swine operations in North Carolina. Agric. For. Meteorol. 108, 213–240. https://doi.org/10.1016/S0168-1923(01)00239-8.
Schiffman, S.S., McLaughlin, B., Katul, G.G., Nagle, H.T., 2005. Eulerian-Lagrangian model for predicting odor dispersion using instrumental and human measurements. Sens. Actuators B-Chem. 106, 122–127. https://doi.org/10.1016/j.snb.2004.05.067.
Schulte, D.D., Modi, M.R., Henry, C.G., Billesbach, D.P., Stowell, R.R., Hoff, S.J., Jacobson, L.D., 2007. Modeling odor dispersion from a swine facility using AERMOD. International Symposium on Air Quality and Waste Management for Agriculture, 16-19 September 2007, Broomfield, Colorado: American Society of Agricultural and Biological Engineers.
Scire, J.S., Strimaitis, D.G., Yamartino, R.J., 2000. A user's guide for the CALPUFF dispersion model. Earth Tech, Inc Concord, MA; 10.
Sheridan, B., Curran, T., Dodd, V., Colligan, J., 2002. Biofiltration of odour and ammonia from a pig unit-a pilot-scale study. Biosyst. Eng. 82, 441–454. https://doi.org/10.1006/bioe.2002.0083.
Sheridan, B., Hayes, E., Curran, T., Dodd, V., 2004. A dispersion modelling approach to determining the odour impact of intensive pig production units in Ireland. Bioresour. Technol. 91, 145–152. https://doi.org/10.1016/S0960-8524(03)00179-2.
Sironi, S., Capelli, L., Céntola, P., Del Rosso, R., Grande, M.I., 2005. Odour emission factors for assessment and prediction of Italian MSW landfills odour impact. Atmos. Environ. 39, 5387–5394. https://doi.org/10.1016/j.atmosenv.2005.05.023.
Sironi, S., Capelli, L., Centola, P., Del Rosso, R., Pierucci, S., 2010. Odour impact assessment by means of dynamic olfactometry, dispersion modelling and social participation. Atmos. Environ. 44, 354–360. https://doi.org/10.1016/j.atmosenv.2009.10.029.
Smith, R.J., 1995. A Gaussian model for estimating odour emissions from area sources. Math. Comput. Modell. 21, 23–29. https://doi.org/10.1016/0895-7177(95)00048-7.
Sommer-Quabach, E., Piringer, M., Petz, E., Schauberger, G., 2014. Comparability of separation distances between odour sources and residential areas determined by various national odour impact criteria. Atmos. Environ. 95, 20–28. https://doi.org/

10.1016/j.atmosenv.2014.05.068.
Sówka, I., 2010. Assessment of air quality in terms of odor according to selected European guidelines: grid and plume measurements. Environ. Prot. Eng. 36, 133–141.
Sundberg, C., Yu, D., Franke-Whittle, I., Kauppi, S., Smårs, S., Insam, H., Romantschuk, M., Jönsson, H., 2013. Effects of pH and microbial composition on odour in food waste composting. Waste Manage. 33, 204–211. https://doi.org/10.1016/j.wasman.2012.09.017.
Toledo, M., Gutierrez, M.C., Siles, J.A., Martin, M.A., 2018. Full-scale composting of sewage sludge and market waste: Stability monitoring and odor dispersion modeling. Environ. Res. 167, 739–750. https://doi.org/10.1016/j.envres.2018.09.001.
Toledo, M., Gutierrez, M.C., Siles, J.A., Martin, M.A., 2019. Odor mapping of an urban waste management plant: Chemometric approach and correlation between physico-chemical, respirometric and olfactometric variables. J. Clean Prod. 210, 1098–1108. https://doi.org/10.1016/j.jclepro.2018.11.109.
Trabue, S., Kerr, B., Bearson, B., Ziemer, C., 2011. Swine odor analyzed by odor panels and chemical techniques. J. Environ. Qual. 40, 1510–1520. https://doi.org/10.2134/jeq2010.0522.
Ubeda, Y., Lopez-Jimenez, P.A., Nicolas, J., Calvet, S., 2013. Strategies to control odours in livestock facilities: a critical review. Span J. Agric. Res. 11, 1004–1015. https://doi.org/10.5424/sjar/2013114-4180.
UK-Environmental-Agency, 2002. Horizontal Guidance for Odour Part 1 e Regulation and Permitting. Integrated Pollution Prevention and Control (IPPC).
Van der Heyden, C., Demeyer, P., Volcke, E.I., 2015. Mitigating emissions from pig and poultry housing facilities through air scrubbers and biofilters: State-of-the-art and perspectives. Biosyst. Eng. 134, 74–93. https://doi.org/10.1016/j.biosystemseng.2015.04.002.
Van Elst, T., Delva, J., 2016. The European Standard prEN 16841–2 (Determination of Odour in Ambient Air by Using Field Inspection: Plume Method): a Review of 20 Years Experience With the Method in Belgium. Chem. Eng. Trans. 54, 175–180. https://doi.org/10.3303/CET1654030.
Velthof, G.L., Lesschen, J.P., Webb, J., Pietrzak, S., Miatkowski, Z., Pinto, M., Kros, J., Oenema, O., 2014. The impact of the Nitrates Directive on nitrogen emissions from agriculture in the EU-27 during 2000–2008. Sci. Total Environ. 468–469, 1225–1233. https://doi.org/10.1016/j.scitotenv.2013.04.058.
Wagner, S., Angenendt, E., Beletskaya, O., Zeddies, J., 2015. Costs and benefits of ammonia and particulate matter abatement in German agriculture including interactions with greenhouse gas emissions. Agric. Syst. 141, 58–68. https://doi.org/10.1016/j.agsy.2015.09.003.
Wenjing, L., Zhenhan, D., Dong, L., Jimenez, L.M.C., Yanjun, L., Hanwen, G., Hongtao, W., 2015. Characterization of odor emission on the working face of landfill and establishing of odorous compounds index. Waste Manage. 42, 74–81. https://doi.org/10.1016/j.wasman.2015.04.030.
Wheeler, E.F., Adviento-Borbe, M.A.A., Brandt, R.C., Topper, P.A., Topper, D.A., Elliott, H.A., Graves, R.E., Hristov, A.N., Ishler, V.A., Bruns, M.A.V., 2011. Evaluation of odor emissions from amended dairy manure: preliminary screening. Agric. Eng. Int.: CIGR J. 13.
Wilson, J.D., Sawford, B.L., 1996. Review of Lagrangian Stochastic Models for Trajectories in the Turbulent Atmosphere. Springer.
Wu, C., Brancher, M., Yang, F., Liu, J., Qu, C., Schauberger, G., Piringer, M., 2019. A comparative analysis of methods for determining odour-related separation distances around a dairy farm in Beijing, China. Atmosphere 10, 231. https://doi.org/10.3390/atmos10050231.
Yamartino, R., Scire, J., Carmichael, G., Chang, Y., 1992. The CALGRID mesoscale photochemical grid model—I. Model formulation. Atmos. Environ. Part A 26, 1493–1512.
Ye, Z., Zhang, G., Li, B., Strøm, J., Dahl, P., 2008. Ammonia emissions affected by airflow in a model pig house: effects of ventilation rate, floor slat opening, and headspace height in a manure storage pit. Trans. ASABE 51, 2113–2122.
Yu, Z., Guo, H., Laguë, C., 2010. Livestock odor dispersion modeling: a review. Trans. ASABE 53, 1231–1244 10.13031/2013.22109.
Yu, Z., Guo, H., Laguë, C., 2013a. Sensitivity analysis of a livestock odour dispersion model (LODM) to input parameters, Part 1: Source parameters and surface parameters. Can. Biosyst. Eng. 55, 6.1-6.11. https://doi.org/10.7451/cbe.2013.55.6.1.
Yu, Z., Guo, H., Laguë, C., 2013b. Sensitivity analysis of a livestock odour dispersion model (LODM) to input parameters, Part 2: Meteorological parameters. Can. Biosyst. Eng. 55, 6.13–16.23. https://doi.org/10.7451/cbe.2013.55.6.13.
Zhang, H., Schuchardt, F., Li, G., Yang, J., Yang, Q., 2013. Emission of volatile sulfur compounds during composting of municipal solid waste (MSW). Waste Manage. 33, 957–963. https://doi.org/10.1016/j.wasman.2012.11.008.
Zhang, R., Westerman, P., 1997. Solid-liquid separation of annual manure for odor control and nutrient management. Appl. Eng. Agric. 13, 385–393.
Zhou, X., Zhang, Q., Guo, H., Li, Y., 2005. Evaluation of air dispersion models for livestock odour application. CSAE/SCGR 2005 Meeting Winnipeg, Manitoba.
Zhu, J., Jacobson, L.D., Schmidt, D.R., Nicolai, R., 2000. Evaluation of INPUFF-2 model for predicting downwind odors from animal production facilities. Appl. Eng. Agric. 16, 159–164. https://doi.org/10.13031/2013.5068.
Zhu, Y.-L., Zheng, G.-D., Gao, D., Chen, T.-B., Wu, F.-K., Niu, M.-J., Zou, K.-H., 2016. Odor composition analysis and odor indicator selection during sewage sludge composting. J. Air Waste Manage. Assoc. 66, 930–940. https://doi.org/10.1080/10962247.2016.1188865. (1995).
Zou, S., Lee, S., Chan, C., Ho, K., Wang, X., Chan, L., Zhang, Z., 2003. Characterization of ambient volatile organic compounds at a landfill site in Guangzhou, South China. Chemosphere 51, 1015–1022. https://doi.org/10.1016/S0045-6535(03)00004-3.