

Urban air pollution by odor sources: short time prediction

Nicola Pettarin^{b,c}, Marina Campolo¹ and^a, Alfredo Soldati^{b,c}

^a*Dept. Chemistry, Physics & Environment,
University of Udine, 33100 Udine, Italy*

^b*Dept. Management, Electric & Mechanical Engineering,
University of Udine, 33100 Udine, Italy
^cLOD srl, 33100 Udine, Italy*

Abstract

A numerical approach is proposed to predict the short time dispersion of odors in the urban environment. The model is based on (i) a three dimensional computational domain describing the urban topography at fine spatial scale (one meter) and on (ii) highly time resolved (one minute frequency) meteorological data used as inflow conditions. The time dependent, three dimensional wind velocity field is reconstructed in the Eulerian framework using a fast response finite volume solver of Navier-Stokes equations. Odor dispersion is calculated using a Lagrangian approach. An application of the model to the historic city of Verona (Italy) is presented. Results confirm that this type of odor dispersion simulations can be used (i) to assess the impact of odor emissions in urban areas and (ii) to evaluate the potential mitigation produced by odor abatement systems.

Keywords: Dispersion modelling, short averaging time, odor pollution,

¹Corresponding author. Address via Cotonificio 108, 33100 Udine (UD), Italy; e-mail marina.campolo@uniud.it; phone: +39 432 558822; fax: +39 432 558803

1. Introduction

Exposure to unpleasant odors is one of the most frequent causes of air quality complaints in both industrial and urban areas. The chemical compounds responsible for odor generation are volatile species (Olafsdottir and Gardarsson, 2013): once emitted from a source, their transport, dispersion and fate in the environment is controlled by the complex interaction among strength of emission (Campolo et al., 2005), meteorological conditions and site topography. Odors become perceptible whenever the instantaneous and local concentration of these chemicals transpasses very low concentration values corresponding to the odor detection threshold. This may occur nearby a source but also some distance away from it.

Odor perception is synchronous with breathing and involuntary, but the subsequent reaction to a given odor stimulus is to some degree subjective: it depends on odor intensity and offensiveness, duration and frequency of exposure but also on pleasantness/unpleasantness of the sensation evoked by the odor (Blanes-Vidal et al., 2012). Annoyance may be produced from acute exposure to few, high odor intensity events or to chronic exposure to repeated, low odor intensity events (Griffiths, 2014). Whichever the exposure mode, odors generating a negative appraisal induce changes in people behavior and may trigger a stress-mediated response which may develop into a public health concern. Bad smells which occasionally cause annoyance, are proactively reported to the Health Services: when the source of the odor can be clearly identified and associated to a specific emission either by the

24 analysis of resident nuisance odor reports (Nicolas et al., 2011), by the use
25 of chemical sensors (Sohn et al., 2009; Seo et al., 2011) or by other sensory
26 methods (Brattoli et al., 2011, Capelli et al., 2011), corrective actions can be
27 devised as needed to contain/reduce the odor impact.

28 Odor impact in urban areas can be very difficult to assess and control
29 due to the inherent complexity of the urban environment, the large num-
30 ber of potential sources and the local small scale variability of the dispers-
31 ing wind. Odor nuisance is most frequently associated with discontinuous
32 emissions generated by restaurants, fast food and bar which may occur for
33 short/prolonged times (from a few seconds to minutes), occasionally or on
34 a repetitive basis depending on the actual operating hours of the facility.

35 The odor impact potentially arising from these commercial activities should
36 be taken into account when planning new installations: best practices for
37 design and operation of commercial kitchen ventilation systems have been
38 developed (see DEFRA, 2005) and yet more accurate modelling tools could
39 be profitably used for odour pollution assessment, prevention and mitiga-
40 tion. Odor emissions in a high populated urban area could be confidently
41 authorized if the potential impact of each source could be estimated *a priori*
42 by modelling; moreover, the precise evaluation of the odour impact of an ex-
43 isting source might be required for the detailed analysis of resident nuisance
44 odor reports in support of litigations for odor impact problems.

45 Odor impact assessment based on chemical sensors would require the ac-
46 quisition of highly time resolved, compound specific, qualified low-concentration
47 data which are very difficult to obtain experimentally. Furthermore, most
48 odors are generated by mixtures of compounds and the relationship between

49 species concentration and odor nuisance is not straightforward. A more prac-
50 tical and effective approach may be the numerical prediction of odor disper-
51 sion.

52 Numerical models have been successfully used to predict odor dispersion
53 and to assess odor impact in industrial areas (see Nicell, 2009, Sironi et al.,
54 2010). The common approach is to model the odor as a passive chemical,
55 equivalent to the mixture of chemicals present, whose concentration is con-
56 veniently represented by the number of odor units, a multiple of the mixture
57 detection threshold. Most of the models in use has been adapted from ear-
58 lier studies on air pollution: steady state Gaussian plume models (Latos et
59 al., 2011), fluctuating plume models (Mussio et al., 2001; Dourado et al.,
60 2014) and Lagrangian stochastic dispersion models (Franzese, 2003) have
61 been used. The main challenge when using these models to predict odor
62 dispersion is related with the different time and space resolution at which
63 the prediction is required. The time scale of few seconds (corresponding to a
64 single human breath) required to evaluate odor impact is much smaller than
65 the hourly time scale typically used to evaluate the dispersion of pollutant
66 species. If a hourly time scale is maintained for odor dispersion modelling,
67 the peak odor concentration at the time scale relevant for odor impact as-
68 sessment should be estimated using a peak to mean ratio, which can be
69 either assumed to be constant (Sironi et al., 2010) or calculated based on
70 wind speed, atmospheric stability, distance from and geometry of the source
71 (Piringer et al., 2012; Schuberger et al., 2012).

72 Very different regulation limits and guidelines have been used worldwide
73 to fix benchmark concentration for odors: Nicell (2009) reports values of off-

74 site odor limits ranging from 0.5 to 50 odor units, averaging time ranging
75 from 1 s to 1 hr and compliance frequency ranging from 98% to 100%. In
76 Australia odor criteria (based on 3 minute average and 99.9% frequency) are
77 population density dependent (see EPA 373/07). The large variability in
78 odor exposure criteria indicates that there is still little consensus on what
79 odor concentration and/or averaging time represent the most effective and
80 fair odor limits for off-site impact. Recently, odor criteria have been clas-
81 sified into two groups (Sommer-Quabach et al., 2014): those based on low
82 odor concentration threshold and high exceedance frequency, relevant to as-
83 sess chronic exposure, and those based on high concentration threshold and
84 low exceedance frequency, relevant to assess acute exposure. At now, the rec-
85 ommended approach for odor regulation in Europe belongs to the first type
86 (chronic exposure oriented) and consists in predicting by numerical models
87 the hourly mean of odor concentration for at least one year period (up to 3 or
88 5 years) and to check odor exposure considering the 98th percentile of those
89 data (see Environment Agency, 2011). The choice of the 98th percentile
90 is supported by the strong correlation found with annoyance measured by
91 community surveys (see Pullen and Vawda, 2007). Yet, different assessment
92 tools and regulatory responses may be required to effectively manage acute
93 exposure scenario (Griffiths, 2014).

94 A possibility is to use a smaller time scale for the odor dispersion mod-
95 elling by which the peaks in odor concentration which result in annoyance
96 for the population can be directly captured: Drew et al. (2007) demon-
97 strated that dispersion modelling based on short averaging time was more
98 successful than the current regulatory method at capturing odor peak con-

99 concentrations from a landfill site. Peak odor intensity is often associated with
100 relatively weak meteorological dynamics (light winds) for which short term
101 and short range effects may be important: wind directions can be highly vari-
102 able (Huiling-cui et al., 2011), turbulent motions may be of the same order
103 as wind speed and the shear production term may dominate in the turbulent
104 kinetic energy budget equation (Manor, 2014) making the turbulent trans-
105 port of species more sensitive to the presence of boundaries (complex terrain
106 and presence of buildings) and highly anisotropic (Pitton et al., 2012).

107 Eulerian-Eulerian models based on Reynolds Averaged Navier Stokes
108 (RANS) equations and Large Eddy Simulation (LES) have proven to be
109 accurate to simulate the dispersion of chemical species (pollutants) in com-
110 plex three dimensional domains (Hanna et al., 2006). Gailis et al. (2007)
111 investigated tracer dispersion in a boundary layer sheared by a large array of
112 obstacles using a Lagrangian stochastic plume model. They found that inter-
113 nal plume fluctuations can have a greater effect on tracer dispersion than the
114 meander motion of the plume, which may be significantly damped in a rough-
115 walled boundary layer. Michioka et al. (2013) implemented a short term,
116 highly resolved (10 s) microscale large-eddy simulation (LES) model coupled
117 to a mesoscale LES model to estimate the concentration of a tracer gas in
118 an urban district considering both the influence of meteorological variability
119 and topographic effects. Their results underlined the key role of coupling
120 between mesoscale and local atmospheric dynamics in driving the dispersion
121 of tracer gas.

122 The same type of short term, fine scale models can be used to simulate
123 odor dispersion in the urban environment. Odor dispersion under steady

wind and constant emission in the presence of few buildings has been evaluated using Eulerian-Eulerian Re-Normalisation Group (RNG) $k - \epsilon$ model by Maizi et al. (2010), using Large Eddy Simulation (LES) by Dourado et al. (2012) and using a fluctuating plume model by Dourado et al. (2014). Despite the increasing number of applications based on local, short averaging time dispersion models, this modelling approach has not yet been adequately validated to be confidently used for odor impact assessment (Pullen and Vawda, 2007). Moreover, we are not aware of applications of odor dispersion models to more complex urban environments. One of the reason is most likely the high cost associated with the time-dependent, fine resolved calculations needed to characterize the flow field of the carrier fluid and the transport of dispersed species into a complex domain. A fine spatial grid resolution (order of 1-2 meters) is required to model faithfully the complex urban domain and a fine time resolution is required to model concentration fluctuations and to capture the peak values responsible of the impact (see Pullen and Vawda, 2007). The simulation of local atmospheric dynamics highly resolved in space and time may become cheaper if representative scenarios rather than full year periods can be identified and considered. Moreover, cost/time of computation can be reduced adopting fast response models of Eulerian-Lagrangian type developed and used successfully to calculate dispersion of species in urban environments (Gowardhan et al., 2011).

In this work we propose the use of one of these models (QUIC – Quic Urban & Industrial Complex model, Los Alamos Laboratories) (Gowardhan et al., 2011) to evaluate the impact of odor emissions in urban environments. The work is based on the assumption that the local wind field and turbulence

controlling dispersion is triggered by the urban geometry more than by the microscale wind and atmospheric turbulence. Our objective is to demonstrate how different can be the odor impact evaluated in the short term when the dynamic interaction between wind field and complex urban topography is accounted for. We will use highly resolved (one minute frequency) microscale wind velocity data to reconstruct the flow field around buildings; this flow field will then be used to simulate the transport of odor, to evaluate odor exposure in terms of frequency of exceedance and intensity and to assess the potential odor impact. To demonstrate our idea, two different meteorological scenarios will be considered. Increasing the number of simulated scenarios enough to cover all the meteorological conditions that may influence the impact, the model could become a powerful tool to help Public Authorities in their planning and control activities.

First, we will demonstrate that the proposed model can be used to evaluate comparatively the odor impact of a given emission source when located in alternative positions inside the urban micro-environment; second, we will prove that the model can be used to check if the odor impact can be sufficiently abated by the installation of odor control systems. The potential of the model will be demonstrated comparing the effect of untreated/treated emission associated to the planned installation of fast food activities in two different urban zones in the historical city of Verona (Italy).

170 **2. Methods, site and data**

171 *2.1. Numerical model*

172 The model proposed (QUIC) is a 3D finite volume solver of Reynolds-
173 Averaged Navier-Stokes (RANS) equations for incompressible flow. The
174 model is implemented and runs in the Matlab environment. The compu-
175 tational domain, corresponding to an urban area including a large number
176 of buildings, is defined using a structured grid in which solid/fluid cells are
177 identified using numerical coding (zero and one identify solid and fluid cells,
178 respectively). The grid is generated from Environmental Systems Research
179 Institute (ESRI) shape files using the code built-in pre-processor.

180 RANS equations are solved explicitly in time on a staggered mesh using
181 a projection method. The discretization scheme is second order accurate
182 in space and time (see Gowardhan et al., 2011 for further details). A zero
183 equation (algebraic) turbulence model is used. Free slip conditions are used
184 at the top and side boundaries of the computational domain; a prescribed,
185 time dependent velocity profile derived from an urban meteorological station
186 can be imposed at the upwind side while an outflow boundary condition is
187 imposed at the downwind side.

188 A Lagrangian particle approach is used to model odor dispersion: thou-
189 sands of "particles" released from the emission point are tracked as they
190 are randomly advected and dispersed over the domain (Zwack et al., 2011).
191 Particles are modeled as infinitesimally small, neutrally buoyant gas parcels.
192 For the present application, a steady state emission is considered for the odor
193 plume: each particle is associated with a fraction of the odor emission rate
194 and is tracked using a small time step (0.1 seconds). Overall, about half

195 a million QUIC particles were released over the simulation time period (15
196 minutes).

197 Odor concentrations are determined in the Eulerian reference frame by
198 counting how many particles pass through a given computational volume
199 during the time averaging period of interest (30 seconds in our demo).

200 *2.2. Urban district*

201 Figure 1 (a) shows an aerial view of Verona downtown (near to the Arena).
202 Two different zones were selected for modelling odor dispersion to check
203 whether the specific localization of the source could significantly affect odor
204 impact: the first area (230×290 m wide), identified as Area 1, is characterized
205 by street canyons; the second area (495×250 m wide), identified as Area
206 2, faces the open square of the Arena. Figures 1 (b) and (c) show the two
207 computational models which extend 50 m above the ground.

208 The potential positions of the odor emission source in Area 1 and Area
209 2 are shown as red (light gray) dots S_1 and S_2 . The emission height was
210 fixed as one meter above the roof level. In the local coordinates system,
211 with the grid origin at the lower left corner of each area, source positions
212 are identified by (x, y, z) triples equal to (138.5, 176.5, 18.5) for Area 1 and
213 (161.5, 238.5, 17.5) for Area 2. The blue (dark gray) circles indicate control
214 points P_1 and P_2 located 50 m downstream the source in the prevailing wind
215 blowing direction. The elevation of control points is 1.5 m above the ground.

216 *2.3. Meteorological data*

217 Data used in this work are taken from the urban station of Verona Golo-
218 sine (latitude $45^{\circ}28'51''$, longitude $10^{\circ}52'35''$, 61 m above sea level). One-

219 minute time resolved records of wind speed and direction collected during
220 February 2012 were made available from MeteoVerona. One week of data was
221 statistically analysed. Statistics suggest that the prevailing wind blowing di-
222 rection is from Nord, North-East (N-E) and the average wind speed is about
223 0.89 m/s at the wind monitoring station (10 m elevation above the ground).
224 To demonstrate how different can be the odor impact evaluated in the short
225 term when time dependent winds interact with a complex urban topography,
226 two 15 minute long periods were extracted for modelling odor dispersion: the
227 first, event 1, is characterized by wind intensity of 3.12 ± 0.67 m/s (average
228 plus standard deviation) and wind blowing from direction $48 \pm 44^\circ$ degrees
229 N (average plus standard deviation); the second, event 2, is characterized
230 by wind intensity of 3.3 ± 1.2 m/s and wind blowing from direction $2 \pm 20^\circ$
231 degrees N. Even if average wind intensity is similar, variability of wind in-
232 tensity is larger for event 2, whereas wind directions differ both in average
233 value and variability. The two events selected are examples of “similar” and
234 yet substantially different scenarios which need to be simulated to obtain
235 a consistent evaluation of odor impact. Considering the size of computa-
236 tional domain and average wind intensity, each 15 minute long period is long
237 enough to track the dispersion of the odor plume up to the boundaries of the
238 computational domain. More/longer periods could be routinely simulated
239 once extended meteorological data are made available.

240 Figure 2 shows the wind variation of the two selected events using a
241 polar representation (Figure 2 (a)) and time series plots of wind speed and
242 direction (Figure 2 (b) and (c)). At each time step, the direction from which
243 the wind is blowing identifies the upstream side of the computational domain;

²⁴⁴ the vertical profile of wind velocity used as inflow condition is defined by the
²⁴⁵ wind speed recording at the anemometer (red arrow in Figure 1 (b)) using a
²⁴⁶ power law.

²⁴⁷ *2.4. Emission data*

²⁴⁸ To characterize the strength of the emission, we considered a restaurant
²⁴⁹ using the same cooking methods (deep frying and stewing) of the planned
²⁵⁰ fast food installation. Samples used to quantify the odor emission rate were
²⁵¹ collected from the chimney of the restaurant when a frying food system was
²⁵² active. The mean cooking time for lunch (or dinner) period was 109 minutes.
²⁵³ The stack diameter was 1 m. The mean values of stack outlet velocity and
²⁵⁴ exhaust flow rate were 4.12 m/s and 350 Nm³/min. The mean stack inlet
²⁵⁵ and outlet temperatures were 44°C and 31°C. The variability of the source
²⁵⁶ was checked during sampling according to EN ISO 16911:2013. We collected
²⁵⁷ three samples according to EN 13725:2003 using a vacuum pump to suck air
²⁵⁸ from the emitting stack into Nalophan bags (8 L volume); sampling required
²⁵⁹ about 1.5 minutes for each sample, with 10 minute stop between samples
²⁶⁰ to check emission variability over time; odor samples were then transferred
²⁶¹ to the lab for the sensory evaluation of odors off site by a group of trained
²⁶² panels. Mixtures of sampled air and neutral air at decreasing dilution ratio
²⁶³ were sequentially prepared by the olfactometer and smelt by the panels. The
²⁶⁴ test started from an odor sample which was very diluted. The dilution ratio
²⁶⁵ was gradually reduced up to the identification of the odor threshold, i.e. the
²⁶⁶ point at which the odor is only just detectable to 50% of the test panel. The
²⁶⁷ numerical value of the dilution ratio necessary to reach the odor threshold
²⁶⁸ was taken as the measure of the odor concentration at the source expressed

269 in European odor units per cubic meter ($o.u_E/m^3$, ou/m^3 in brief).

270 Sampling was performed in two different working conditions, correspond-
271 ing to off/on operation for the activated carbon filter installed for odor con-
272 trol. Data collected during sampling are summarized in Table 1. Data vari-
273 ability during sampling and among samples was found to be not significant
274 and odor emission rates used to set up the model are values averaged over
275 the three samples.

276 3. Results

277 3.1. Flow field

278 The QUIC code calculates the flow field in the three dimensional do-
279 main every one minute. Figure 3 shows the comparison between the wind
280 speed/direction measured at the meteorological station (10 m height, line
281 with circles) and used as inflow condition, and those calculated in differ-
282 ent points of the computational domain: at the source (1 m above roof level,
283 empty triangles) and at the reference control point (solid triangles) for Area 1
284 (triangles pointing upward) and Area 2 (triangles pointing downward) (1.5 m
285 above ground). The effect of urban topography is to produce local differences
286 in wind intensity and direction calculated at different points.

287 Wind speed and direction calculated at the emission point (i.e. above
288 the buildings) are similar to the values recorded at the meteorological sta-
289 tion: the wind speed is a bit larger at the emission point since it is more
290 elevated than the anemometric sensor. At control points, the wind speed
291 is generally smaller than the sensor due to the different elevation above the
292 ground (1.5 m); the wind direction may be significantly different. For control

293 points located in a street canyon, the effect of the urban topography is to
294 smooth out the variability of wind direction. For wind event 1, the local wind
295 direction is about $50^{\circ}N$ whichever the value recorded at the meteorological
296 station for both control points P1 and P2; for event 2, the wind direction
297 is similar at the meteorological station and point P2, whereas it is always
298 about $50^{\circ}N$ for point P1.

299 *3.2. Odor dispersion*

300 Animations of the odor plume dispersing from sources S1 and S2 during
301 the two simulated wind events are available as supplementary material. The
302 position of the emission point is indicated by the black circle; isocontours
303 represent the odor concentration (in ou/m^3) calculated in the plane 1.5 m
304 above the ground (reference height of human noses potentially smelling in
305 the area). Figures 4-5 shows snapshots (one every 240 seconds) taken from
306 the animations. The color scale for odor concentration shown in the plots
307 in limited to the sub-range $[2 \div 12 \text{ } ou/m^3]$. To relate odor concentration to
308 perceived odor intensity in the field we refer to the following scale (Sommer-
309 Quabach et al., 2014): non detectable ($C < 2 \text{ } ou/m^3$), acceptable ($2 <$
310 $C < 5 \text{ } ou/m^3$), annoyance ($5 < C < 15 \text{ } ou/m^3$) and severe annoyance
311 ($C > 15 \text{ } ou/m^3$). The lower and upper values of the color scale represent
312 an odor concentration threshold at which the odor is clearly detected and a
313 value at which the odor perceived is strong enough to cause annoyance.

314 Isocontours calculated during wind event 1 in Area 1 (Figure 4 upper
315 row) show the odor plume extending in different directions depending on
316 the leading wind. Yet, the urban topography determines a preferential path
317 for odor dispersion which spreads along the main street canyons near to the

source. Due to the changing wind direction, some of the odor puffs may reach regions not directly exposed to the emitting source, producing diffuse odor impact even at significant distances. During wind event 2, isocontours (Figure 4 bottom row) show odor puffs moving along three main street canyons (aligned with the wind blowing directions) with odor concentration mainly controlled by wind speed. Odor dispersion produced in Area 2 (open area facing the Arena) for wind event 1 (Figure 5 top row) indicates that odor puffs remain confined along the prevailing wind direction (from N-E to S-W) despite the wind direction variability, and may penetrate into the urban topography when the blowing wind direction is from S-E. For wind event 2 (Figure 5 bottom row) the odor plume oscillates back and forth in the open square facing the Arena.

The dynamic evolution of odor isocontours gives a qualitative idea of the odor impact expected from the emission, given the position and the meteorological scenario. Yet, for a quantitative comparison we need more synthetic descriptors which can be obtained from the statistical analysis of the time series of odor concentration calculated for each grid point of the computational domain.

Figure 6 shows the time series of odor concentration calculated during wind event 1 for the grid point closest to the emission source S1 and for point P1. According to the FIDOL methodology (see Environment Agency, 2011) the intensity and frequency of odor exposure are two of the main characteristics necessary to assess the offensiveness of odors. Due to the short averaging time and brief simulation period used in this work we can not use the recommended regulation approach to assess odor impact. We propose to

343 use two odor impact criteria similar to those discussed by Griffiths (2014),
344 based on either intensity or frequency of odor impact events evaluated over
345 the time interval of interest (the 15 minute long period in our case). Specific-
346 ically, for the first odor criteria, we fix the frequency of exceedance (10%)
347 and derive odor concentration isocontours which can be compared against
348 threshold values; for the second odor criteria, we fix an odor concentration
349 threshold ($C_{ref} = 5 \text{ ou}/\text{m}^3$) and derive maps of frequency of exceedance. Any
350 specific value of frequency of exceedance and odor concentration threshold
351 could be adopted to perform the kind of analysis we propose.

352 Figure 6 shows that near to the source (S1) the odor concentration is
353 quite large ($653 \pm 100 \text{ ou}/\text{m}^3$ average value \pm standard deviation, coefficient
354 of variation equal to 0.15) and only slightly changing over time; at point
355 P1, the odor intensity is significantly lower ($11 \pm 8.7 \text{ ou}/\text{m}^3$ average value \pm
356 standard deviation, coefficient of variation equal to 0.79) but the variability
357 in time is larger. The 90th percentiles are equal to 24.4 (indicated as dashed
358 thin line in the graph) and $802.6 \text{ ou}/\text{m}^3$ (not shown) for P1 and S1; the
359 reference threshold concentration C_{ref} (dashed thick line in the graph) is
360 exceeded 80% of time at P1 and 100% of time at S1.

361 Figure 7 shows the results of this analysis replicated for each point of
362 the computational grid: this can be used to compare and rank, according
363 to the two proposed assessment criteria, the odor impacts for Area 1 and
364 Area 2 for simulated wind events. Isocontours of 90th percentile of odor
365 concentration are shown in the top row and isocontours of the exceedance
366 frequency ($C > C_{ref}$) are shown in the bottom row. These maps show
367 the area in which any plotted concentration of odor is exceeded 10% of the

368 time at maximum, or the area in which detectable odor may be perceived
369 persistently (i.e. most frequently) in time.

370 Comparison between isocontours of 90th percentile calculated for Area 1
371 and Area 2 for wind event 1 (Figure 7, left half) indicates that the emission
372 will produce annoyance/severe annoyance at least 10% of the time along the
373 main street canyon in Area 1 and in front of the buildings facing the Arena
374 in Area 2. Detectable odor will be perceived for more than 50% of the time
375 in these areas.

376 The odor impact becomes even more significant for wind event 2 (Fig-
377 ure 7, right half). In this case, the emission will produce annoyance/severe
378 annoyance at least 10% of the time along the three street canyons for Area
379 1 and in a wide area close to the Arena in Area 2. Detectable odor will be
380 perceived for more than 50% of the time in even wider areas.

381 Figure 8 shows a final synthetic picture of odor impact given in the form
382 of odor roses, i.e. polar plots in which (i) the 90th percentile of odor concen-
383 tration (top half) or (ii) the percent frequency of exceedance of C_{ref} (bot-
384 tom half) are plotted at reference distances (5, 25 and 45 m away from the
385 emission point) for each angular direction. Top and bottom rows in each half
386 represent the impact of the emission as is (untreated) or when the odor abate-
387 ment system is on. The radial scale of each plot is shown in the bottom right
388 corner. Consider first the impact of untreated source, S1 and S2, for wind
389 event 1 (first row, left half). The peak of odor concentration is found in the
390 south-west (S-W) direction, with odor concentrations as large as 20 ou/m^3
391 25 and 45 m away from emission point S1 and as large as 40 ou/m^3 25 and
392 45 m away from emission point S2. Minor peaks are also found along those

393 directions in which the wind and the local topography are “in phase”. The
394 frequency of exceedance of C_{ref} (third row, left half) is up to 60% both 25
395 and 45 m away from emission point S1 in the S-W direction, and up to 55%
396 and 75% respectively 25 and 45 m away from emission point S2 in the same
397 direction. When the abatement system is on (second and fourth rows), the
398 odor impact becomes lower than $10 \text{ ou}/\text{m}^3$ whichever the distance and an-
399 gular direction and C_{ref} is exceeded 50% of the time at most. The right half
400 of Figure 8 shows the odor impact for wind event 2. In this case, the peak of
401 odor concentration is in the south-south-west (S-S-W) direction, with odor
402 concentrations as large as 40 and $76 \text{ ou}/\text{m}^3$ respectively 5 m and 25 m away
403 from emission point S2. The frequency of exceedance is about 100% 25 m
404 and 45 m away from S2 in the S-W direction. These data indicate a more
405 intense and persistent odor impact for wind event 2. The odor impact can
406 be reduced in Area 1 treating the emission (second and fourth rows), with
407 annoying odor perceived less than 40% of the time 25 m away from the source
408 in the S-W direction. Annoying odor can be still perceived up to 60% of the
409 time 45 m away from the source in the W-S-W direction. The situation is
410 more critical for the source located in Area 2: even if the abatement system
411 reduces the odor impact, annoying odor will still be perceived 80% of the
412 time in the S-W direction 25 and 45 m away from the source.

413 4. Conclusions

414 In this work we propose the use of a fast response Eulerian-Lagrangian
415 type model to calculate the short term, short time average dispersion of odor
416 in urban areas. The model is based on a three dimensional computational

417 domain describing the urban topography at fine (one meter) spatial scale and
418 on highly time resolved (one minute frequency) meteorological data used as
419 inflow conditions.

420 We propose two odor impact criteria similar to those discussed by Griffiths
421 (2014) to assess odor impact: for the first odor criteria we fix the frequency
422 of exceedance (10%) to derive odor concentration isocontours which can be
423 compared against threshold values; for the second odor criteria we fix an
424 odor concentration threshold ($C_{ref} = 5 \text{ ou}/\text{m}^3$) to derive maps of frequency
425 of exceedance. Simulations performed for the historical city of Verona for
426 two 15 minute long time periods show that the model can be used (i) to
427 comparatively evaluate and rank the odor impact of a given emission source
428 when located in alternative positions of the urban area; (ii) to check if end of
429 pipe technologies devised for odor control are effective or not to reduce the
430 impact.

431 We propose the odor rose plot of model output statistics (90th percentile
432 and exceedance frequency) as a simple graphical tool to compare odor impact
433 for different source locations and in different meteorological scenarios and to
434 evaluate the effectiveness of solutions proposed for odor impact mitigation.

435 Acknowledgements

436 The authors would like to thank Comune di Verona for geographical data
437 and R. Snidar and S. Rivilli for fruitful discussions. M.C. gratefully acknowl-
438 edges Michael Brown and R&D staff of Los Alamos National Laboratory for
439 the use of QUIC code and technical support, and MeteoVerona for the acqui-
440 sition of highly resolved wind data. N.P. gratefully acknowledges Laboratorio

- 441 di Olfattometria Dinamica, Udine, Italy for funding his PhD fellowship.
- 442 [1] Blanes-Vidal, V., Suh, H., Nadimi, E.S., Løfstrøm, P., Ellermann, T.,
443 Andersen, E.V., Schwartz, J., 2012, Residential exposure to outdoor
444 air pollution from livestock operations and perceived annoyance among
445 citizens, Environment International, 40: 44-50.
- 446 [2] Brattoli, M., de Gennaro, G., de Pinto, V., Loiotile, A.D., Lovascio, S.,
447 Penza, M., 2011, Odour Detection Methods: Olfactometry and Chemical
448 Sensors, Sensors, 11(5): 5290-5322.
- 449 [3] Campolo, M., Salvetti, M.V., Soldati, A., 2005, Mechanisms for mi-
450 croparticle dispersion in a jet in crossflow, AIChE J., 51(1): 28-43.
- 451 [4] Capelli, L., Sironi, S., Del Rosso, R., Centola, P., Rossi, A., Austeri, C.,
452 2011, Olfactometric approach for the evaluation of citizens' exposure
453 to industrial emissions in the city of Terni, Italy, Science of the Total
454 Environment, 409: 595-603.
- 455 [5] DEFRA, Department for Environment, Food and Rural Affairs 2005,
456 Guidance on the Control of Odour and Noise from Commercial Kitchen
457 Exhaust Systems, Nobel House, 17 Smith Square, London SW1P 3JR.
- 458 [6] Dourado, H., Santos, J.M., Reis, N.C., Mavroidis, I., 2012, Numerical
459 modelling of odour dispersion around a cubical obstacle using large eddy
460 simulation, Water Science and Technology, 66(7): 1549-1557.
- 461 [7] Dourado, H., Santos, J.M., Reis, N.C., Mavroidis, I., 2014, Development
462 of a fluctuating plume model for odour dispersion around buildings,
463 Atmospheric Environment, 89: 148-157.

- 464 [8] Drew, G.H., Smith, R., Gerard, V., Burge, C., Lowe, M., Kinnersley, R.,
465 Sneath, R., Longhurst, P.J., 2007, Appropriateness of selecting different
466 averaging times for modelling chronic and acute exposure to environ-
467 mental odours, Atmospheric Environment, 41(13): 2870-2880.
- 468 [9] EN 13725:2003, Air quality – Determination of odour concentration by
469 dynamic olfactometry.
- 470 [10] EN ISO 16911:2013, Stationary source emissions – Manual and auto-
471 matic determination of velocity and volume flow rate in ducts – Part 1:
472 Manual reference method.
- 473 [11] Environment Agency, 2011, Additional guidance for H4 Odor Manage-
474 ment: How to comply with your environmental permit, Environment
475 Agency Horizon House, Deanery Road Bristol, BS1 5AH.
- 476 [12] EPA 373/07 guidelines: Odour assessment using odour source modelling,
477 2007, www.epa.sa.gov.au/files/477172_guide_odour.pdf
- 478 [13] Franzese, P., 2003, Lagrangian stochastic modeling of a fluctuating
479 plume in the convective boundary layer, Atmospheric Environment,
480 37(12): 1691-1701.
- 481 [14] Gailis, R.M., Hill, A., Yee, E., Hilderman, T., 2007, Extension of a
482 fluctuating plume model of tracer dispersion to a sheared boundary layer
483 and to a large array of obstacles, Boundary-Layer Meteorol., 122: 577-
484 607.
- 485 [15] Gowardhan, A.A., Pardyjak, E. R., Senocak, I., Brown, M.J., 2011, A

- 486 CFD-based wind solver for an urban fast response transport and disper-
487 sion model, Environmental Fluid Mechanics, 11(5): 439-464.
- 488 [16] Griffiths, K.D., 2014, Disentangling the frequency and intensity dimen-
489 sions of nuisance odour, and implications for jurisdictional odour impact
490 criteria, Atmospheric Environment, 90: 125-132.
- 491 [17] Hanna, S.R., Brown, M.J., Camell, F.E.; Chan, S.T., Coirier, W.J.,
492 Hansen, O.R., Huber, A.H., Kim, S., Reynolds, R.M., 2006, Detailed
493 simulations of atmospheric flow and dispersion in downtown Manhattan:
494 An application of five computational fluid dynamics models, Bulletin of
495 the American Meteorological Society, 87(12): 1713-1726.
- 496 [18] Huiling cui, Yao, R., Xu, X., Xin, C., Yang, J., 2011, A tracer experiment
497 study to evaluate the CALPUFF real time application in a near-field
498 complex terrain setting, Atmospheric Environment, 45: 7525-7532.
- 499 [19] Latos, M., Karageorgos, P., Kalogerakis, N., Lazaridis, M., 2011, Disper-
500 sion of Odorous Gaseous Compounds Emitted from Wastewater Treat-
501 ment Plants, Water Air Soil Pollut., 215: 667-677.
- 502 [20] Maizi, A., Dhaouadi, H., Bournot, P., Mhiri, H., 2010, CFD prediction of
503 odorous compound dispersion: Case study examining a full scale waste
504 water treatment plant, Biosystems Engineering, 106: 68-78.
- 505 [21] Manor, A., 2014, A Stochastic Single-Particle Lagrangian Model for
506 the Concentration Fluctuations in a Plume Dispersing Inside an Urban
507 Canopy, Boundary-Layer Meteorology, 150(2): 327-340.

- 508 [22] Michioka, T., Sato, A., Sada, K., 2013, Large-eddy simulation coupled to
509 mesoscale meteorological model for gas dispersion in an urban district,
510 Atmospheric Environment, 75: 153-162.
- 511 [23] Mussio, P., Gnyp, A.W., Hensha, P.F., 2001, A fluctuating plume dis-
512 perssion model for the prediction of odour-impact frequencies from con-
513 tinuous stationary sources, Atmospheric Environment, 35: 2955-2962.
- 514 [24] Nicell, J.A., 2009, Assessment and regulation of odour impacts, Atmo-
515 spheric Environment, 43 (1): 196-206.
- 516 [25] Nicolas, J., Cors, M., Romain, A.C., Delva, J., 2011, Identification of
517 odour sources in an industrial park from resident diaries statistics, At-
518 mospheric Environment, 44(13): 1623-1631.
- 519 [26] Olafsdottir, S., Gardarsson, S.M., 2013, Impacts of meteorological fac-
520 tors on hydrogen sulfide concentration downwind of geothermal power
521 plants, Atmospheric Environment, 77: 185-192.
- 522 [27] Piringer, M., Schaubberger, G., Petz, E., Knauder, W., 2012, Comparison
523 of two peak-to-mean approaches for use in odour dispersion models,
524 Water Science and Technology, 66(7): 1498-1501.
- 525 [28] Pitton, E., Marchioli, C., Lavezzo, V., Soldati, A., Toschi, F., 2012,
526 Anisotropy in pair dispersion of inertial particles in turbulent channel
527 flow, Phys. Fluids, 24(7): 073305.
- 528 [29] Pullen, J., Vawda, Y., 2007, Review of Dispersion Modelling for Odour
529 Predictions, Science Report: SC030170/SR3 Environment Agency, Rio
530 House, Waterside Drive, Aztec West, Almondsbury, Bristol, BS32 4UD

- 531 [30] Schauberger, G., Piringer, M., Schmitzer, R., Kamp, M., Sowa, A.,
532 Koch, R., Eckhof, W., Grimm, E., Kypke, J., Hartung, E., 2012, Con-
533 cept to assess the human perception of odour by estimating short-time
534 peak concentrations from one-hour mean values. Reply to a comment
535 by Janicke et al., Atmospheric Environment, 54: 624-628.
- 536 [31] Sironi, S., Capelli, L., Centola, P., Del Rosso, R., Pierucci, S., 2010,
537 Odour impact assessment by means of dynamic olfactometry, dispersion
538 modelling and social participation, Atmospheric Environment, 44(3):
539 354-360.
- 540 [32] Sohn, J.H., Pioggia, G., Craig, I.P., Stuetz, R.M., Atzeni, M.G., 2009,
541 Identifying major contributing sources to odour annoyance using a non-
542 specific gas sensor array, Biosystems Engineering, 102(3): 305-312.
- 543 [33] Sommer-Quabach, E., Piringer, M., Petz, E., Schauberger, G., 2014,
544 Comparability of separation distances between odour sources and resi-
545 dential areas determined by various national odour impact criteria, At-
546 mospheric Environment, 95: 20-28.
- 547 [34] Zwack, L.M., Hanna, S.R., Spengler, J.D., Levy, J.I., 2011, Using ad-
548 vanced dispersion models and mobile monitoring to characterize spatial
549 patterns of ultrafine particles in an urban area, Atmospheric Environ-
550 ment, 45(28): 4822-4829.

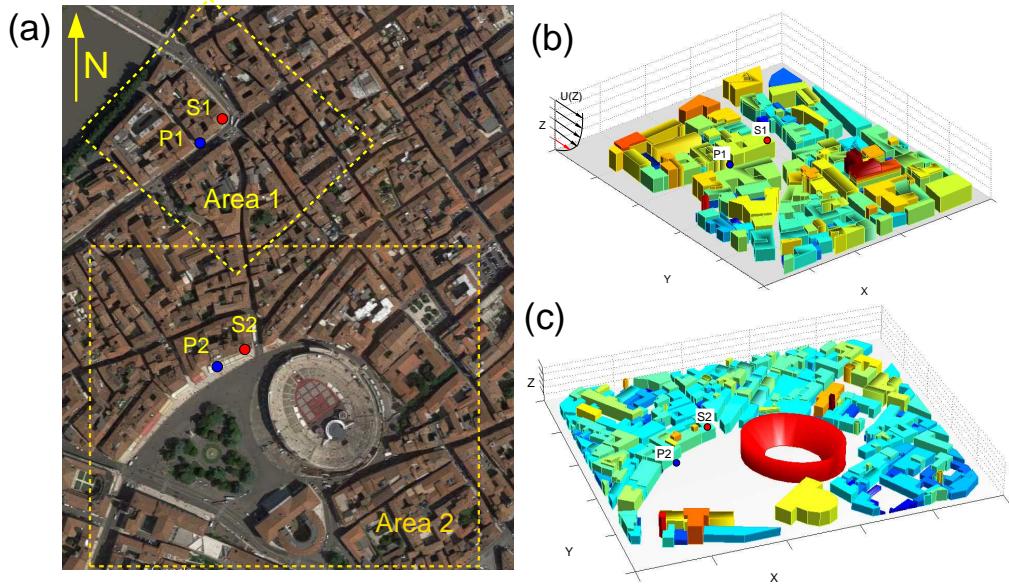


Figure 1: Aerial view of Verona (a) and areas selected for odor dispersion demo: (b) street canyons (Area 1) and (c) open square nearby the Arena (Area 2); potential positions of odor emission source are shown as (light gray) red circles (S1 and S2); points 50 m away from the source downstream the prevailing blowing wind direction (N-E) are shown as (dark gray) blue circles (P1 and P2).

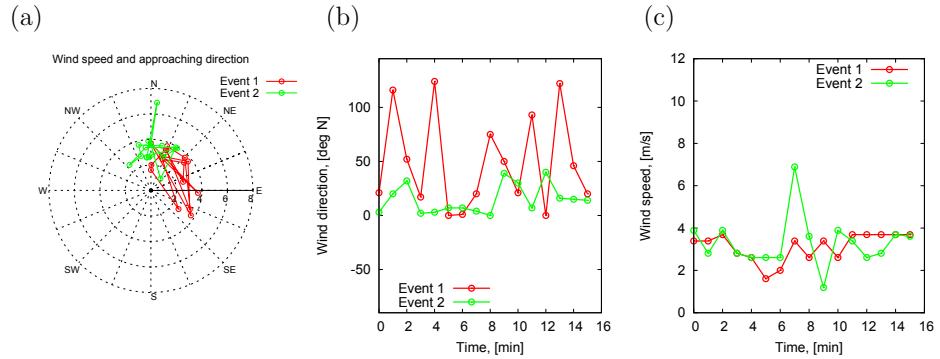


Figure 2: Polar representation (a) and time series plots of wind direction (b) and wind speed (c) of wind data extracted for simulating odor dispersion: data are taken from meteorological station of Verona Golosine.

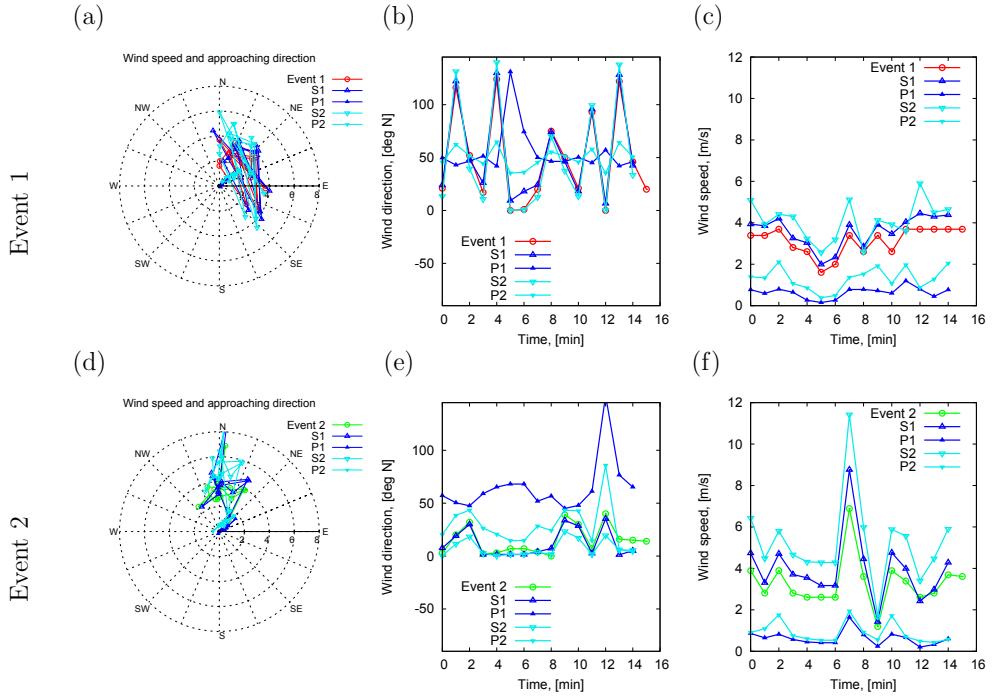


Figure 3: Polar representation (a, d) and time series plots of wind direction (b, e) and wind speed (c, f) calculated in different points of the computational domain for wind events 1 (top row) and 2 (bottom row): lines with symbols correspond to (i) anemometric data used as inflow condition (10 m above ground) (red/green, solid), (ii) emission point position (1 m above roof level) (solid symbol, S1 blue/dark gray, S2 pale blue/light gray), (iii) control point position (1.5 m above ground) (empty symbol, P1 blue/dark gray, P2 pale blue/light gray).

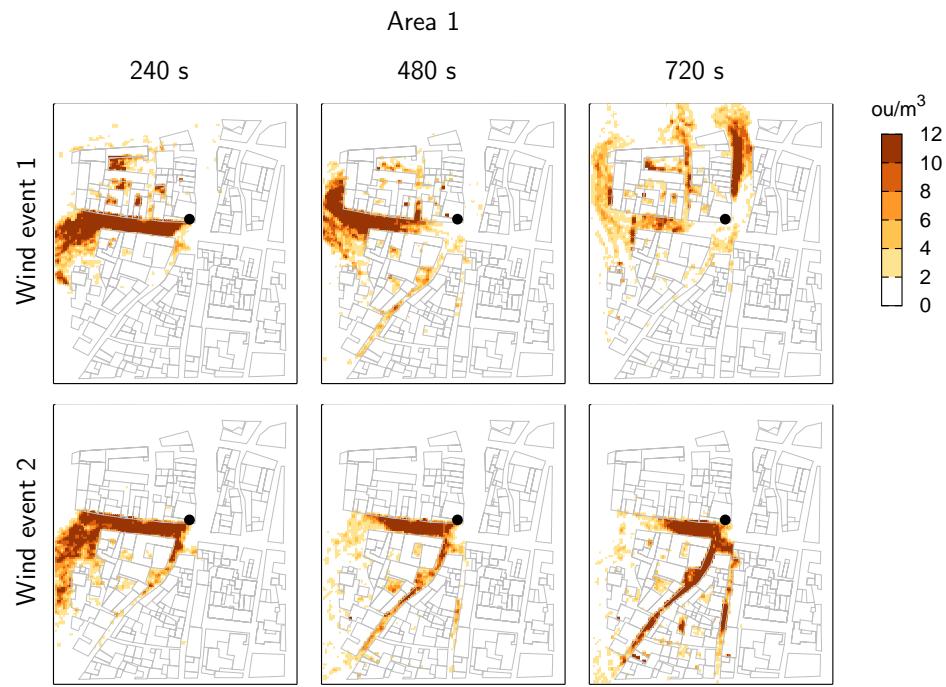


Figure 4: Isocontours of odor concentration calculated for Area 1 and wind event 1 and 2. Values are shown for a plane $z = 1.5 \text{ m}$ above the ground: snapshots are taken at every 240 s.

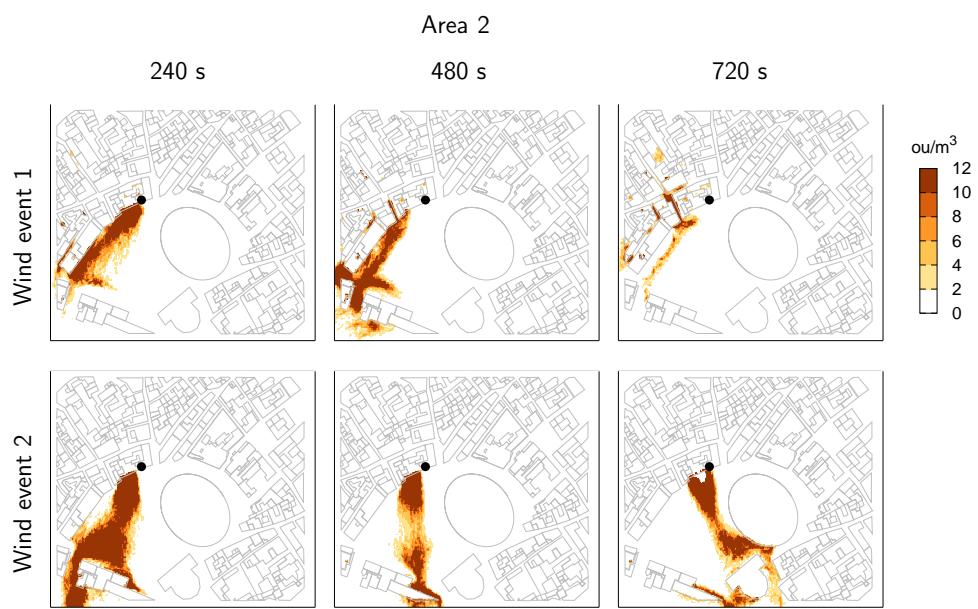


Figure 5: Isocontours of odor concentration calculated for Area 2 and wind event 1 and 2. Values are shown for a plane $z = 1.5 \text{ m}$ above the ground: snapshots are taken at every 240 s.

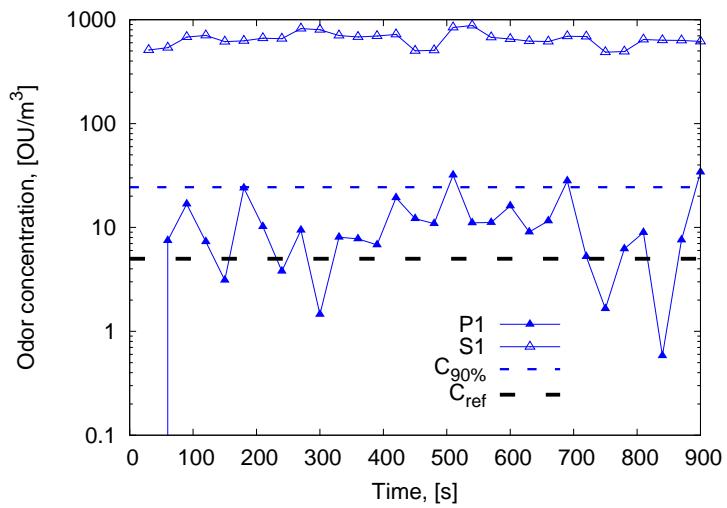


Figure 6: Time series of 30 seconds average odor concentration calculated at point P1 (closed symbol) and S1 (open symbol) for wind event 1: dashed lines represent 90th percentile of odor concentration for point P1 (thin dashed line) and a reference odor concentration threshold (5 ou/m^3 , thick dashed line) sufficient to cause nuisance.

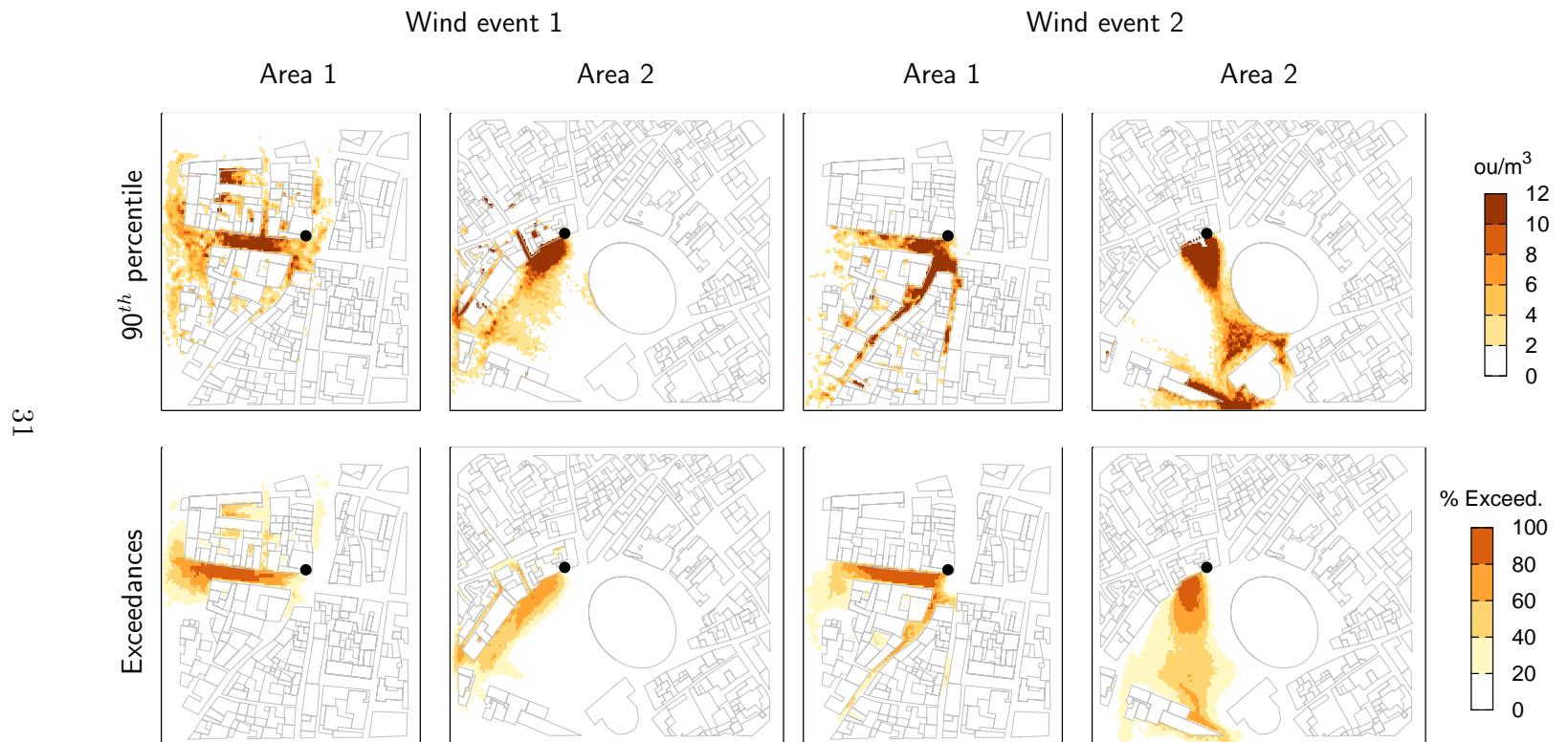


Figure 7: Statistics for odor impact assessment: (a) 90th percentile of odor concentration and (b) percent of exceedances ($C > 5 \text{ ou}/\text{m}^3$) during wind event 1 and 2 in Area 1 and 2.

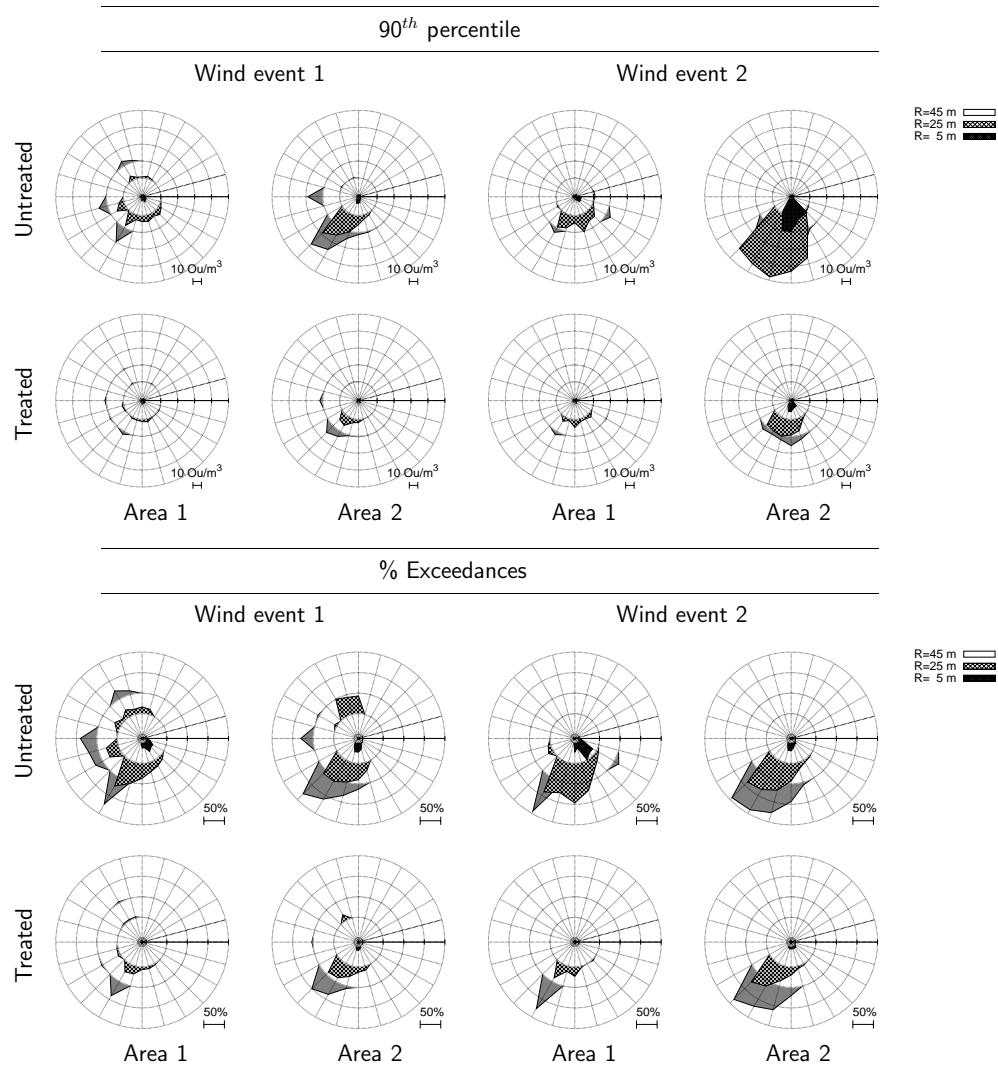


Figure 8: Odor rose of $90^{\text{th}} \text{ percentile}$ of odor concentration and % Exceedances for untreated and treated emission S1 and S2 and wind event 1 and 2.

Sample N.	$T, [^{\circ}C]$	RH, [%]	Q, [Nm^3/s]	$C, [ou/m^3]$
U-1	31.3	24.1	5.4	5,000
U-2	29.5	22.4	6.2	3,800
U-3	32.2	28.7	5.9	5,000
Average	31.0	25.07	5.83	4,600
T-1	30.8	24.6	6.0	1,300
T-2	30.3	22.7	4.3	1,300
T-3	30.9	23.5	4.5	2,000
Average	30.7	23.6	4.93	1,533

Table 1: Results of odor source sampling: U (untreated) identifies odor emission with abatement system turned off, T (treated) identifies odor emission with abatement system turned on.