Odor, air quality, and well-being: understanding the urban smellscape using crowd-sourced science

Abstract

It is challenging to study odors and their effects on health and well-being due to variability in individual sensitivity and perception, atmospheric physico-chemical processes, and emissions of mixtures of odorous contaminants. Here, we conduct quantitative and qualitative analyses of a 12-month data set from a web application collecting crowd-sourced odor reports, including spatiotemporal information, odor and self-reported impacts description (OSAC: odors, symptoms, actions in response, and suspected causes), and demographics, in Vancouver, Canada. Users report diverse OSAC with strong seasonality and spatial variability. Reported symptoms, ranging from neurological to emotion- and mood-related, highlight the complexity of odor-related well-being impacts. Odors can trigger maladaptive actions, where individuals are exposed to other environmental stressors (e.g., heat stress) or curtail healthy behaviors (e.g., exercising outside) to cope with odor impacts. Clustering analysis of OSAC suggests that odor exposures may be linked to well-being impacts through complex mechanisms, related not only to the odor experienced but perceived causes. Spatiotemporal patterns highlight the influence of persistent sources (e.g., waste management) and transient events (e.g., accidents). Exploratory multiple linear regression models suggest that monitoring of air quality and meteorology may be insufficient to capture odor issues. Overall, these results suggest that crowd-sourced science incorporating self-reported health effects and behavioral responses can enrich understanding of the impacts of odorous emissions at large spatiotemporal scales, complementing traditional air pollution monitoring.

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1 Introduction

Odors are complex mixtures of volatile compounds that are emitted from a wide variety of anthropogenic and natural sources[1]. Though some of these odorous compounds are inorganic (e.g., H_2S, NH_3), many are volatile organic compounds (VOCs). VOCs have been studied extensively in atmospheric science[2–4], given their direct impacts on air quality and their contributions to the formation of secondary pollutants, such as particulate matter (PM) and ground-level ozone (O_3)[5]. The health effects of these secondary pollutants are considered one of the greatest environmental health threats to humanity[6–8]. More broadly, air pollutants can cause climate forcing, and environmental damages to ecosystems and biodiversity[9, 10]. They are also associated with negative economic, social, and psychological effects[11], often mediated through annoyance. However, odors themselves are typically seen as only a nuisance issue [1]. This limited focus has restricted odor exposure research to a mostly local regulatory context, in contrast to other dimensions of air quality[4, 12, 13]. However, odor experiences are increasingly recognized to be an important component of cumulative environmental stressors, linked to community health and well-being, and in some cases, indicators of other environmental pollutant exposures[14]. Here, we define the term “odor mediation" as the phenomenon of odors mediating the influence of air pollution sources on community health.

As far back as the 1st century BCE, people believed there were links between odor and health through the miasma theory of disease transmission: “the poisonous breath of creatures...to be wafted into the bodies of the inhabitants...will make the site unhealthy"[15]. In *ca* CE 63–65, Seneca wrote of “awful odor of reeking kitchens" linked to “ruinous...soot" and causing “languor" and “sluggishness in ... brain"[16]. Today, odorous compounds have been recognized to impact human health through several mechanisms, including via direct activation of chemosensory targets through inhalation (e.g., volatile compounds), ingestion (e.g., retronasal delivery of diet-based compounds), or dermal exposure (e.g., hydrophobic compounds penetrating skin), or biotransformation in the body[17, 18]. Odorous compounds often stimulate the trigeminal nerve generating feelings such as pain or irritation, even during sleep[19–22]. Self-reported data suggest that odors can contribute to the incidence of nose itching, dryness, and irritation[23], and cough, headaches, and nausea[24]. Odors also have broader influences on human well-being[25], which goes beyond the absence of disease. Both consciously and subconsciously, odors can affect cognition[26] and emotions and mood[27], including by tapping into human memory, which in turn can have secondary behavioural and physiological effects[18, 28]. Odors can curtail healthy behaviors, and odor annoyance is linked to stress, poor mental health, and well-being, including strong associations with neurological, respiratory, and gastrointestinal symptoms [29]. Odorous compounds have been associated with cancer and non-cancer health effects, especially in the neighborhood of polluting sources[29]. Further, these compounds may not affect health in isolation; instead, people are often co-exposed to multiple compounds in chemical mixtures that can result in enhanced toxicity, which requires more study[30]. Thus, instead of individual chemical measurements, odors could serve as air pollution markers for complex exposures, which have been identified as particularly important for environmental injustice[31, 32]. While studies have linked odorous compounds to air quality and health impacts, further work is needed to establish strong associations, particularly concerning the role of odor mediation. [18, 23, 29, 30, 33].

Challenges associated with odor monitoring highlight some spatial and temporal limits of the traditional regulatory approach. Regulatory monitors are stationary and often have a time resolution of 15 min–1 hour. Additionally, the current legal and legislative frameworks typically monitor or model the odor impacts of individual sources and use site-specific judgments for odors[12]. However, odors are often associated with a "chronic presence of unpredictable spikes in toxic chemicals"[34], and odor episodes can occur from events as short as a few seconds[34–37]. Thus, extensive odor monitoring is needed to understand very short-term exposures that get averaged in regulatory monitoring. However, no instruments or technologies exist to measure odors on substantial spatial and temporal scales quantitatively and affordably[38]. In light of these challenges, one approach for odor monitoring is crowd-sourced science which engages volunteers in the generation of scientific data[39]. Odor perception is inherently subjective[40], and so are odor reporting and odor impacts. By collecting data from many human noses, crowd-sourcing incorporates a diversity of odor experiences and offers a low-cost solution to effectively estimate odor impacts at large spatiotemporal scales[38]. Research linking air quality and crowd-sourced science has grown over the past decade[41] and several studies such as the Smell Pittsburgh project [42] have documented the smellscape[43] of the urban environment.

Here, we introduce a crowd-sourced project called Smell Vancouver (SmellVan), which provides long-term characterization of the evolving smellscape of a major city and its self-reported impact on human well-being[44]. The crowd-sourced project uses a web app to engage the community around their subjective odor experiences. In addition to reporting on the characteristics of the odors themselves, SmellVan extends previous odor crowd-sourcing projects by allowing users to report their demographics, perceived physiological and psychological impacts of odor, actions taken in response to odor, and their perception of odor sources. We call this novel odor monitoring approach that accounts for behavioral response—STOSAC (Spatio Temporal Odors Symptoms Actions Causes). Here, we report on the qualitative and quantitative analyses conducted over 12 months of STOSAC data in SmellVan odor reports. We also connect the odor report counts to external data sources related to air quality and meteorology to explore potential linkages and drivers. This study not only offers insights into urban odor experiences but also demonstrates the value of crowd-sourced science for identifying well-being impacts of odor-related air pollution at the local level.

In this study, we use the convergent mixed methods approach[45] to study odor experiences (qualitative analysis of odor report data, e.g., OSAC) and the underlying spatiotemporal characteristics related to those experiences (quantitative analysis of odor report counts, ORC, and OSAC). We focus on three research questions/objectives:

1. Descriptive: What are the patterns of odor reporting (spatial and temporal ORC and OSAC)? What does this crowd-mapped dataset suggest about the smellscape and odor impacts in a major city?

2. Explanatory: Odors have similar origins to many regulated air pollutants and are expected

to be influenced by meteorology. What are the links between ORC, air quality, and meteorology? What are the potential drivers or influences of odor reporting?

3. Methodological: What are the strengths and limitations of a crowd-sourced science approach for characterizing a region's smellscape and better understanding odor pollution?

2 Methods

2.1 *Study Site*

Metro Vancouver (MetroVan), Canada, is a federation of 14 cities, 4 district municipalities, 3 villages, one Electoral Area and one Treaty First Nation with a total population of 3 million people[46]. MetroVan is bound by the Strait of Georgia on the west and south sides, the Coast Mountains to the North, and Fraser River Valley to the east. It lies in the Pacific Maritime ecozone and experiences a moderate oceanic climate (Köppen climate classification Cfb)[47, 48]. The population of MetroVan is distributed in compact urban areas spread across the region, with the largest population center being the City of Vancouver. Seven cities and district municipalities with more than 100,000 residents account for 80% of the regional population (Supplementary Table S1). Land use in MetroVan is primarily conservation and recreation (about 50%), general urban (25%), and agriculture (20%), with some concentrated industrial centers[49]. Detailed descriptions of the region's atmospheric conditions, land use, and demographics are provided in the Supplementary data file (Section S1).

2.2 *Odor and MetroVan*

MetroVan has a long history of odor concerns, and odor complaints account for the largest group of complaints about air emissions [50, 51]. In particular, three source types have perennially affected residents, yielding thousands of complaints over multiple years: composting, landfills, and other waste disposal; animal processing facilities (storage and handling of animal waste from slaughterhouses, rendering, etc.); and wastewater treatment plants[52–57]. MetroVan regulates odorous air contaminants by targeting specific sources through industrial permits[51]. At the same time, in recent years, odor complaints associated with cannabis have increased substantially following the legalization of recreational cannabis in Canada[58] and the development of industrial-scale cultivation facilities in and around MetroVan [59]. Here, we explore the evolving smellscape of MetroVan, with its mix of perennial and new odor sources, as a test bed to implement a crowd-sourced science-based odor monitoring approach.

2.3 *The SmellVan App*

We launched a web application in December 2020 called Smell Vancouver or SmellVan for short[44]. Inspired by the Smell Pittsburgh app[60], SmellVan is designed to track and map crowd-sourced reports of odors throughout the MetroVan area using the STOSAC reporting framework. Users can submit odor reports that describe the smell (qualitative selection of odor description from 9 choices, including free text), the physical and mental health symptoms they experience (12 choices, including free text), and their behavioural changes in response to odor (6 choices, including free text). Additionally, participants report the time and location of their odor experience, odor strength (two choices of low and moderate or higher), odor offensiveness ratings on an ordinal scale from 1 (mild) to 5 (extreme), and suspected odor sources as free text. Finally, users can disclose their demographic information (age, race, gender, financial situation, and health condition). The user interface is shown in Supplementary Figures S2a–b. The free text options provide respondents flexibility to use subjective descriptions (100 character word limit) for odors, symptoms, actions, and suspected causes (OSAC). We do not collect the IP addresses of the app users and thus cannot track unique users. For this work, we assume that each report is independent. All data (except descriptive text) have been made publicly available on an interactive map that allows users to see the reports. We publicized the app using Twitter and Instagram posts using the handle @SmellVancouver, as well as through the press[61]. Despite a small base, we observe a high engagement rate from followers (Supplementary Table S4).

2.4 *Data collection, processing, and analysis*

We collected the odor data used in this paper from Dec 2020–Dec 2021. The raw data set containing odor reports was downloaded at the end of one year of data collection. An R[62] package was developed to partially automate the processing and analysis of SmellVan data. As part of data cleaning, we applied temporal (Dec 8, 2020–Dec 7, 2021) and spatial (MetroVan region) filters on the data set. We retrieved the spatial boundaries of MetroVan using the Vancouver census metropolitan area boundaries[63]. We removed inappropriate reports from the analysis, and a summary of the problematic components of such reports is available in the Supplementary data file (Section S2).

2.4.1 *Descriptive patterns of odor experience*

We conducted exploratory data analysis of values/categories of each variable and the demographics within the odor reports (Section S3). To quantify the spatial patterns of odor reporting, we aggregated odor counts in MetroVan at the Canadian census tract (CT) level[64]. We used these odor data to calculate spatial metrics such as Global Moran's I, Local Moran's I, Getis Ord I, and Getis Ord Gi*[65–67]. These metrics allow us to map hotspots and coldspots and spatial clusters and outliers based on the Local Moran's I (and the Getis Ord Gi*) metric. As a robustness check, we also analysed area-normalized and population-normalized odor counts, to account for area-based bias (larger areas are expected to have more odor sources) and population-based bias (larger populations are expected to report more odors). Due to consistency in the key findings and for brevity, we only present spatial analysis results based on the Local Moran's I metric for population-normalized odor-counts in the main manuscript. Additional details on the methods and results of spatial analysis are available in the Supplementary data file (Section S4, Supplementary Figures S3a–j).

2.4.2 *OSAC free text analysis*

We conducted thematic (free text) analysis[68, 69] on the free text associated with OSAC. Briefly, we coded descriptive text for odors reported, inductively generating high-level odor categories. These high-level categories account simultaneously for the drop-down fields and the free text descriptions of OSAC. This practice of characterising odor perception using reference vocabulary has been widely employed for drinking water, wastewater and compost, urban odors, and even wines[70–73]. The categories for symptoms and actions were refined based on a review of the public health literature on odor[29]. Odors and causes were categorised based on local knowledge of important odors and odor sources in the region[51, 74]. A detailed list of the categories and the related descriptors is available in the Supplementary data file (Supplementary Table S5). For this categorical data (e.g., odor categories), we conducted textual pairwise correlation analysis, presented in terms of the correlation coefficient, *phi*[75, 76] and hierarchical (divisive) clustering analysis for trinary and quarternary associations[77, 78]. We also conducted bootstrap analysis to quantify 95% confidence intervals for this coefficient *phi*, which are reported in brackets with its observed value. To better understand the large symptom category of emotional and mood disturbance, we conducted sentiment and emotion analysis using three sentiment scales: the Finn Årup Nielsen (AFINN), the National Research Council Canada (NRC) Emotion lexicon, and the NRC Valence, Arousal, and Dominance (VAD) lexicons[79–81]. Finally, to better understand the relationships of OSAC categories, we represent them visually as a 2-D network of vertices (OSAC categories) and linear edges (binary relationships) based on the Kamada-Kawai algorithm[82]. Details of the bootstrapping, sentiment analysis, and textual associations and visualizations conducted for OSAC are in the Supplementary data file (Section S5).

2.4.3 *Explanatory analysis of SmellVan odor reports*

To investigate the possible relationship between odor report counts (ORC, dependent) and meteorology, air quality, and odor-related and app-related counts of news stories (independent), we conducted exploratory multiple linear regression (MLR) modeling of daily-averaged odor counts at the regional scale. This analysis was carried out for separate months within the study period. Several quality assurance (QA) and quality control (QC) steps were employed to identify key variables for conducting MLR. Finally, we estimated the relative importance of the independent variables based on the fraction of variance explained in the linear model[83]. Similar to the textual correlation coefficient *phi*, we conducted bootstrap analysis to quantify 95% confidence intervals for variance explained, which are reported in brackets with its observed value. Additional details on the meteorological variables, air quality monitoring indicators, news reports, QA/QC, and uncertainty analysis are included in the Supplementary data file (Section S6, Tables S6–S9).

2.4.4 *Sensitivity Test*

To test the assumption of independence of individual odor reports, we checked the spatiotemporal variability of reported odors in our dataset. Specifically, we generated a sensitivity test data subset by only keeping the first report with a reported odor in a particular census tract within a particular hour and excluding subsequent reports. Then, we compared the number of reported odors in the original dataset and the sensitivity test dataset to assess the impact of this assumption on our analysis. Our analysis revealed that the original dataset contained 760 combinations of tract, hour, and reported odor, while the sensitivity test dataset had 733 combinations. This difference of less than 5% of reported odors indicates that the impact of the assumption of independence of odor reporting in the app is mostly limited. To further validate our findings, we replicated the main figures in the manuscript using the sensitivity test dataset (Section S7, Supplementary Figures S4–S7). We found that the figures and the underlying results and conclusions were consistent with those obtained from the original dataset, suggesting that the assumption of independence of odor reporting does not significantly affect our analysis. However, we acknowledge that the assumption of independence of reports may not hold true in certain situations [39], such as when there are multiple reports of an odor from the same individual across multiple hours/locations or when there is a systematic bias in the reporting behavior of participants.

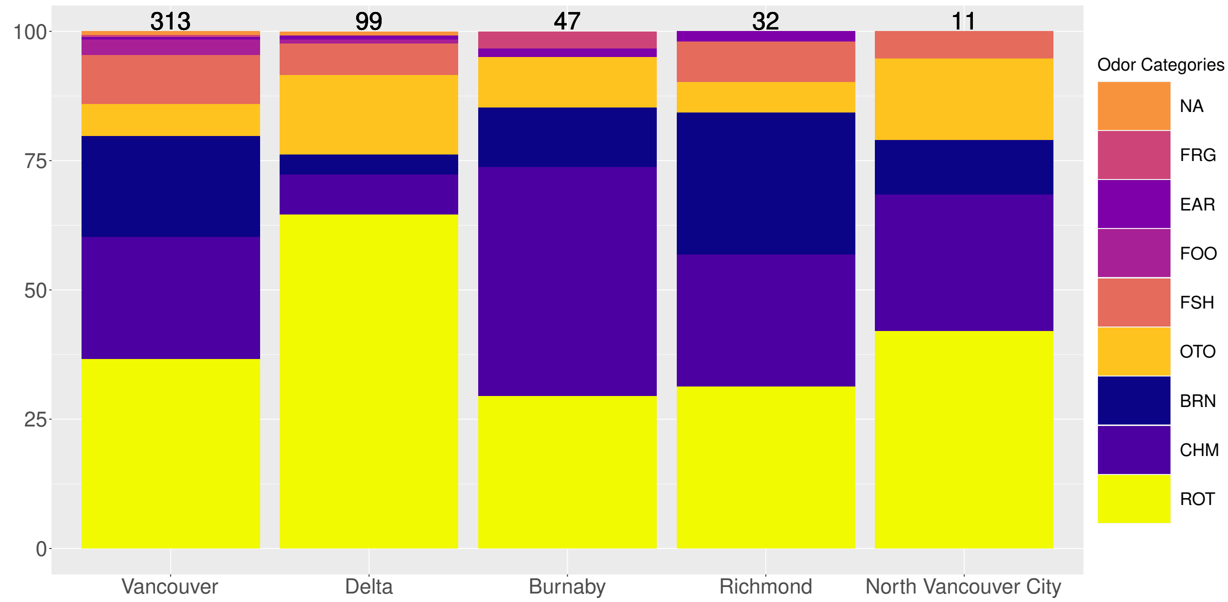
3 Results

Over the 12-month period of the study (8 Dec 2020–7 Dec 2021), we received 549 legitimate odor reports from MetroVan, summarized in Figure 1. Figure 1a shows the distribution of odor categories (e.g., fishy, burning) reported in SmellVan across the five most important subdivisions. Figure 1b shows the distribution of odor categories by month. Note that not all reports have a reported odor characteristic; in the discussion below, we discuss prevalence of an odor characteristic only after removing these reports (N/A odor characteristic). In Section 3.1, we focus on the characteristics of the crowd-sourced science process of SmellVan and the subjective odor experience of the participants. To do this, we discuss the patterns and clusters of qualitative data from the app and categories of OSAC. In Section 3.2, we discuss the temporal and spatial patterns of regional ORC and OSAC. In Section 3.3, we use the collected odor data to characterize odor hotspots, coldspots, and spatial clusters and outliers in the MetroVan region. We also examine temporal patterns of regional ORC in the context of odor news, air quality, and meteorology. Finally, in Section 3.4, we compare the demographics of the app data relative to the MetroVan region.

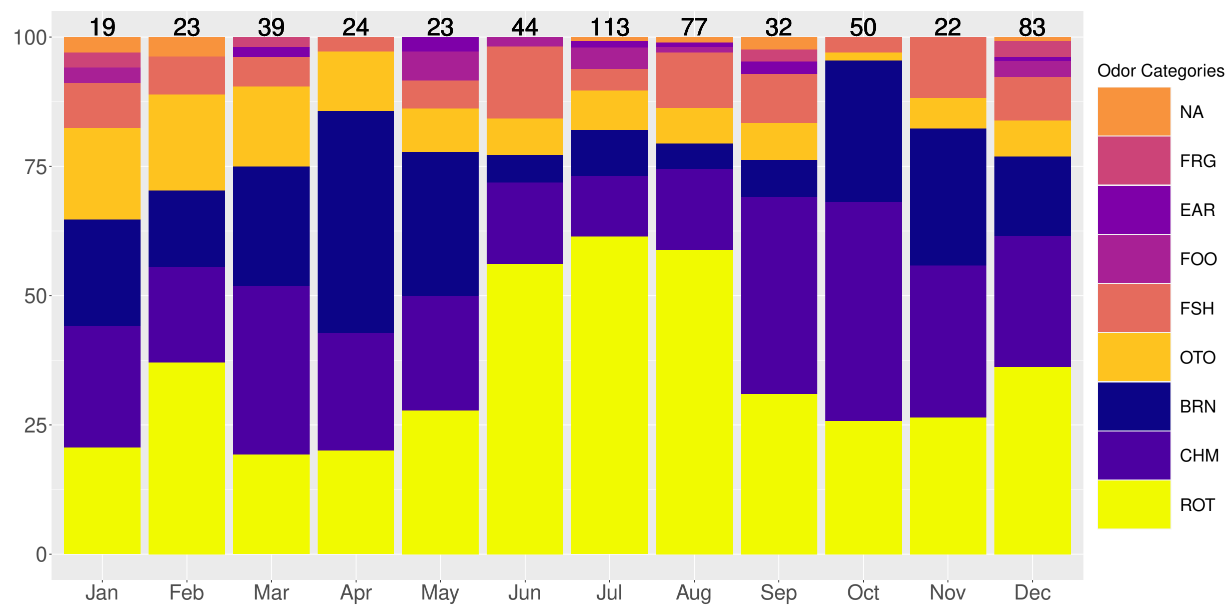
3.1 *Characteristics of the MetroVan smellscape*

3.1.1 *Odors and possible causes*

The descriptions of smells experienced demonstrate the different types and perceptions of odors encountered (Supplementary Table S10). Users often use rich and evocative language to describe their odor experiences in free text responses. For instance, one user writes, “rotting waste, garbage cheese, pungent vinegar death, fresh vomit." “Rotten" and “chemical" account for about 65% of submissions with a reported odor (Supplementary Table S11). Burning is the third most important odor category, accounting for 16% of the reports. While odors can co-occur (Supplementary Figure S8a), the binary associations of such co-occurrences are weak ($phi < 0.25$). In fact, some odors statistically significantly do not co-occur (e.g., ROT and CHM; $phi = -0.47[-0.54, -0.40]$, ROT and BRN; $phi = -0.38[-0.45, -0.30]$).



(a)



(b)

Figure 1: (a) Spatial and (b) temporal distribution of odors reported in SmellVan (Dec 2020–Dec 2021). The y-axis shows the %-distribution of odors reported in a MetroVan subdivision/month. The numbers on top indicate the total count of reports in that subdivision/month. Specific odors are presented as three-letter shorthands summarized here: ROT = “Rotten", CHM = “Chemical", BRN = “Burning", OTO = “Other Odors", FSH = “Fishy", FOO = “Food", EAR = “Earthy", FRG = “Fragrance", NA = “No odor reported".

Users identify many potential odor sources, including: garbage and compost (29%); chemicals (16%); fire, smoke, and burning (14%); sewage and wastewater treatment (9%); and animal processing (9%) (Supplementary Table S12). Users mostly report single causes, accounting for about 80% of all reports (Supplementary Figure S8b). Only two pairs of cannabis facilities and smoking ($phi = 0.44[0.24, 0.61]$) and cannabis facilities and farming ($phi = 0.25[0.14, 0.50]$) shows relatively strong binary associations.

3.1.2 *Symptoms*

App users report experiencing several classes of symptoms, such as neurological (e.g., dizziness, headache), respiratory irritation (e.g., cough, difficulty breathing), emotional and mood disturbance (e.g., anxiety, frustration, anger), ophthalmological (e.g., irritated eyes), and dermatological (e.g., hives). Neurological, respiratory symptoms, and emotional and mood disturbance occur most frequently, accounting for 87% of the symptoms reported (Supplementary Table S13). We observe that while prominent symptoms often co-occur (Supplementary Figure S8c); only two co-occurrence of symptoms is statistically significant —respiratory irritation with ophthalmological symptoms ($phi = 0.30[0.21, 0.38]$) and respiratory irritation with emotional and mood disturbance ($phi = 0.29[0.20, 0.38]$).

Emotional and mood disturbance accounts for a substantial fraction (23%) of reported symptoms, pointing to the negative moods induced by unpleasant odors[33]. Analysis of semantic descriptors of symptoms shows the expression of a wide range of emotions, but particularly a large number of negative sentiments and usage of words expressing displeasure (NRC VAD lexicon; “difficulty", n=132; "sore", n=80) and arousal (NRC VAD lexicon; “disturbed", n = 132;“irritated", n=79) as well as more specific emotions such as anger, sadness, disgust, and fear, all of which occur at least 250 times (Supplementary Figure S9). Likewise, using the AFINN lexicon, we observe sentiment scores ranging from about +1 to as low as -10, suggesting a strong bias towards negative sentiments (Supplementary Figure S10). We document quotes from odor reports rated with an AFINN sentiment score of -7.5 and lower in Supplementary Table S14. Users employ evocative phrases about symptoms (“Disgust, annoyance, anger, concern about carcinogens and family health"), causes (“uncontrolled – not monitored – disregard to permit"), and broader societal effects (“Listened to my wife scream about ongoing problem as home values go down") as they express their negative sentiments, often identifying details of the odor issues (e.g., going on for “over 12 years"). Finally, users also employed the free text to express non-verbal cues such as emotional accentuation[84, 85] through the use of capital letters [86–88], and we observe multiple such descriptions (“CLOSE WINDOWS - VERY MAD - TIME FOR ACTION – GOVERNMENTS NEED TO COME SEE THIS ON GOING PROBLEM"). We also find that the reported odor strength and offensiveness are positively associated, consistent with literature (Section S8, Supplementary Figure S11).

3.1.3 *Actions*

Users report a range of actions in response to odors (Supplementary Table S15). Ventilation and air cleaning (43%), gone inside (26%), making a complaint (15%), and stopped exercising outdoors (10%) are the most reported actions, with other actions, such as smell-masking (e.g., adding a pleasant fragrance) accounting for less than 5% each. Users also report long-term avoidance of odorous areas (1% of the reported actions), such as “moved away" or going “to a distant part of the city to go for a walk”—significant life changes to avoid odors. Similar observations of the desire to relocate due to the impacts of malodor have been reported elsewhere as well[89]. We observe gone inside co-occurring repeatedly with other actions (Supplementary Figure S8d); likewise, we observe strong associations (Gone inside with Stopped exercising outdoors: $phi = 0.35[0.28, 0.42]$). Analysis of semantic descriptors for actions also shows the expression of a wide range of emotions. The sentiments are largely negative, dominated by anger (Supplementary Figure S12).

In a few reports, we also observe instances of maladaptation, where actions taken by users to avoid odors also negatively affect their well-being due to exposure to other environmental stressors or curtailment of healthy behaviors (Supplementary Table S16). Users report temporarily stopping or changing breathing patterns (e.g., “breathe through mouth", “removed my mask temporarily to air it out"), using smell masking (e.g., “put Vick’s in my nose", “deoderize the house"), as well as changing local ventilation (“turned off car ventilation", “have to close all windows on summer’s evening"), speeding (“ran home"), and inability to exercise or enjoy outdoors (“Very disturbing to to family ANGER and unable to enjoy outdoors"). Smell masking agents can themselves have substantial health effects[90, 91], hence our inclusion of it as a maladaptive behavior.

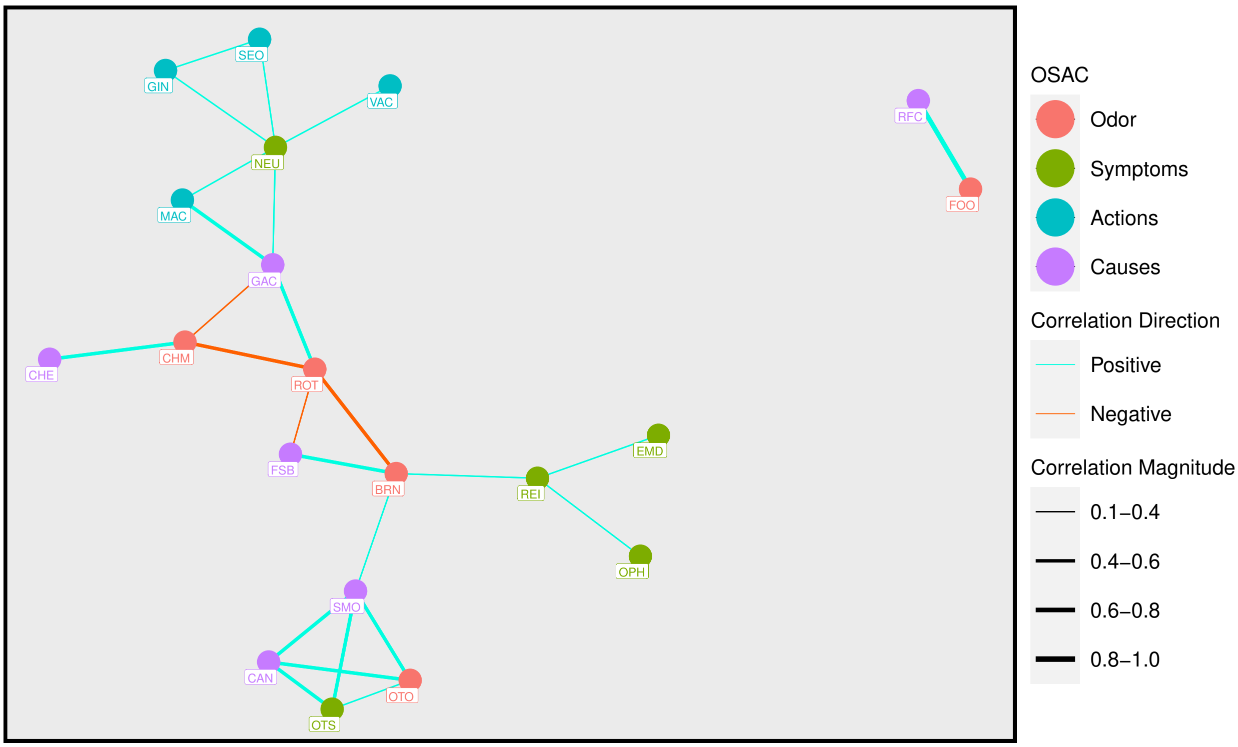


Figure 2: OSAC associations based on the descriptions reported in SmellVan (Dec 2020–Dec 2021). Specific values of OSAC are presented as three-letter shorthands summarized here: Odors: CHM = “Chemical", ROT = “Rotten", FOO = “Food", BRN = “Burning", OTO = “Other odors". Symptoms: EMD = “Emotional disturbance", REI = “Respiratory irritation", NEU = “Neurological", OPH = “Ophthalmological", OTS = “Other symptoms". Actions: VAC = “Ventilation and air cleaning", GIN = “Gone inside", SEO = “Stopped exercising outdoors", MAC = “Made a complaint". Causes: RFC = “Restaurants and food cooking", FSB = “Fires, smoke, and burning", CHE = “Chemicals", GAC = “Garbage and compost", SMO = “Smoking", CAN = “Cannabis facilities".

3.1.4 *OSAC clusters*

We observe hundreds of groupings of odors, symptoms, actions, and possible causes, even when only three of the four parameters are analysed at a time (Supplementary Table S17). Our clustering analysis reveals OSAC associations that show odor- and cause- connections to actions and symptoms (Figure 2). In figure 2, OSAC categories in a higher number of combinations are placed closer together and the strength of binary associations are represented by the thickness of the edge connecting them with other OSAC categories[82] (Section S5). For example, we find that suspected causes (fires, smoke, and burning) are often linked to specific symptoms (respiratory irritation) through the experience of specific odors (burning) (Figure 2). However, suspected causes (garbage and compost) are also directly linked to symptoms (neurological) and actions (making a complaint) without odor mediation.

3.2 *Spatial and temporal patterns of ORC and OSAC*

3.2.1 *Spatial patterns of ORC and OSAC*

Four municipalities (City of Vancouver, Delta, Burnaby, and Richmond) account for 90% of ORC (Supplementary Table S18). These municipalities show substantial differences in reported OSAC (Figure 1a, Supplementary Tables S18–S22) and OSAC associations (Supplementary Figures S13a–e).

The City of Vancouver, the region's urban center, reports the highest fraction of ORC (57%) among all subdivisions, and contributes over half of all rotten (52%) and chemical (59%) odors received in the region (Supplementary Table S19). Within the City, rotten (n = 161), chemical (n = 104), and burning odors (n = 86) account for about 80% of the odors reported (Figure 1a). But, the City also reports a disproportionately large number of reports with the suspected cause of animal processing (95%) (Supplementary Table S20). In contrast, the reported possible causes of farming (0% from Vancouver), garbage and compost (22% from Vancouver), and cannabis facilities (27% from Vancouver) are predominantly found outside of the urban center. Majority ($\geq$ 50%) of the other less-frequent odors and nearly all possible causes occur in the City of Vancouver (Tables S19–S20). The City also leads in reporting of most symptoms and actions ($\geq$ 50%) as well, though interestingly, the action of making a complaint (28%) is a major exception and is more common from a suburban area, Delta (52%) (Supplementary Tables S21–S22). Within the City, common odor–cause connections include food odors and restaurant and food cooking (Supplementary Figure S13a). But, the most complex connections in the City are with regards to burning odors, which are related to the causes of smoking and fires, smoke, and burning, and also the symptoms of respiratory irritation. The symptom of respiratory irritation itself is related to neurological symptoms and emotional and mood disturbance. The City also shows cannabis facilities being related to other symptoms and other odors, suggesting that odor characteristics and effects of this source need to be studied further.

When contrasted with the City of Vancouver, reports from Delta—another municipality in the region—illustrate the spatial variability in smellscape based on OSAC and OSAC relationships. While reports from Delta represent 18% of ORC, Delta accounts for a large fraction of reports suspecting garbage and compost (58%), cannabis (73%), and farming (60%) causes (Tables S18–S20). Within Delta, rotten odors (n = 84) account for 65% of odors reported, and the next two frequently reported categories are other odors (n = 20) and chemical odors (n = 10) (Figure 1a). Users from Delta more commonly report symptoms associated with odor, compared to other jurisdictions in the region (Supplementary Table S21). The same is true for the actions of making a complaint (52%), stopped exercising outdoors (41%), gone inside (30%), and ventilation and air cleaning (22%) as well (Supplementary Table S22). Delta shows the connections of rotten odor and the possible cause of garbage and compost linked to multiple symptoms and actions (Supplementary Figure S13b). Like the City of Vancouver, Delta also shows cannabis facilities being related to an other category (other odors) (Supplementary Figures S13a–b).

Other jurisdictions combined account for the remaining 25% of ORC (Supplementary Table S18). Of note, Burnaby, a municipality with a dense industrial presence, contributes 15% of reports with chemical odors, and 26% and 16% of the reported possible causes of fire, smoke, and burning and chemicals respectively (Supplementary Tables S19–S20). Within Burnaby, chemical (n = 27), rotten (n = 18), and burning (n = 7) odors account for 85% of odors reported (Figure 1a). With regards to OSAC connections, Burnaby reports connections of the cause of fires, smoke, and burning to chemical odors, emotional and mood disturbance and the action of ventilation and air cleaning; additionally, the cause of fires, smoke, and burning is connected to respiratory irritation through mediation by the chemical odor (Supplementary Figure S13c). Finally, Richmond is marked by similar reporting of rotten (n = 16), burning (n = 14), and chemical (n = 13) odors, that account for 84% of its reported odors (Figure 1a). Like Delta, rotten odors in Richmond are linked to the cause of garbage and compost, and both are linked to neurological symptoms and emotional and mood disturbance (Supplementary Figure S13d). Like Burnaby, Richmond reports connections of chemical odors with respiratory irritation (Supplementary Figures S13c–d).

3.2.2 *Temporal patterns of ORC and OSAC*

Temporal patterns of regional ORC exhibit variability within days and between months (Figures 1, 3, Supplementary Figures S14a–c). We see spikes in reporting during Dec 8–11 (35), June 28–July 4 (41), July 7–15 (48), July 20–Aug 1 (40), Aug 4–Aug 7 (33), and October 3 (22). These spikes together account for about 40% of the reports (Supplementary Figure S14a) and are likely related to specific events such as the launch of the app and related news coverage, odor accidents, and extreme weather conditions. These drivers are discussed in Section 3.3 and Section 4.2. We also find that three months (July, August, and December) together account for about 50% ORC (Supplementary Figure S14b). At an hourly scale, time-of-day ORC patterns are marked by three distinct transitions, one in the morning (0900 hours), one in the evening (1600 hours), and one at night (0300 hours) (Supplementary Figure S14c). Early morning hours of the day (0300–0900 hours) account for about 50% ORC, and on average, there are 4 times more reports during this peak time compared to the diurnal minima, which occurs during daytime (0900–1600 hours).

While we find variation in reported OSAC categories across months, this variation in different OSAC are broadly similar to the temporal patterns of all reports (Figure 3, Supplementary Figures S15a–d). Rotten odors are mostly reported in the warm months of June–Aug and the cold month of Dec, whereas chemical odors show higher prevalence in the cold months (Supplementary Figure S15a), and we see similar patterns in relative contributions (Figure 1b). The suspected causes, symptoms, and actions show much larger variations by month of the year compared to all reports

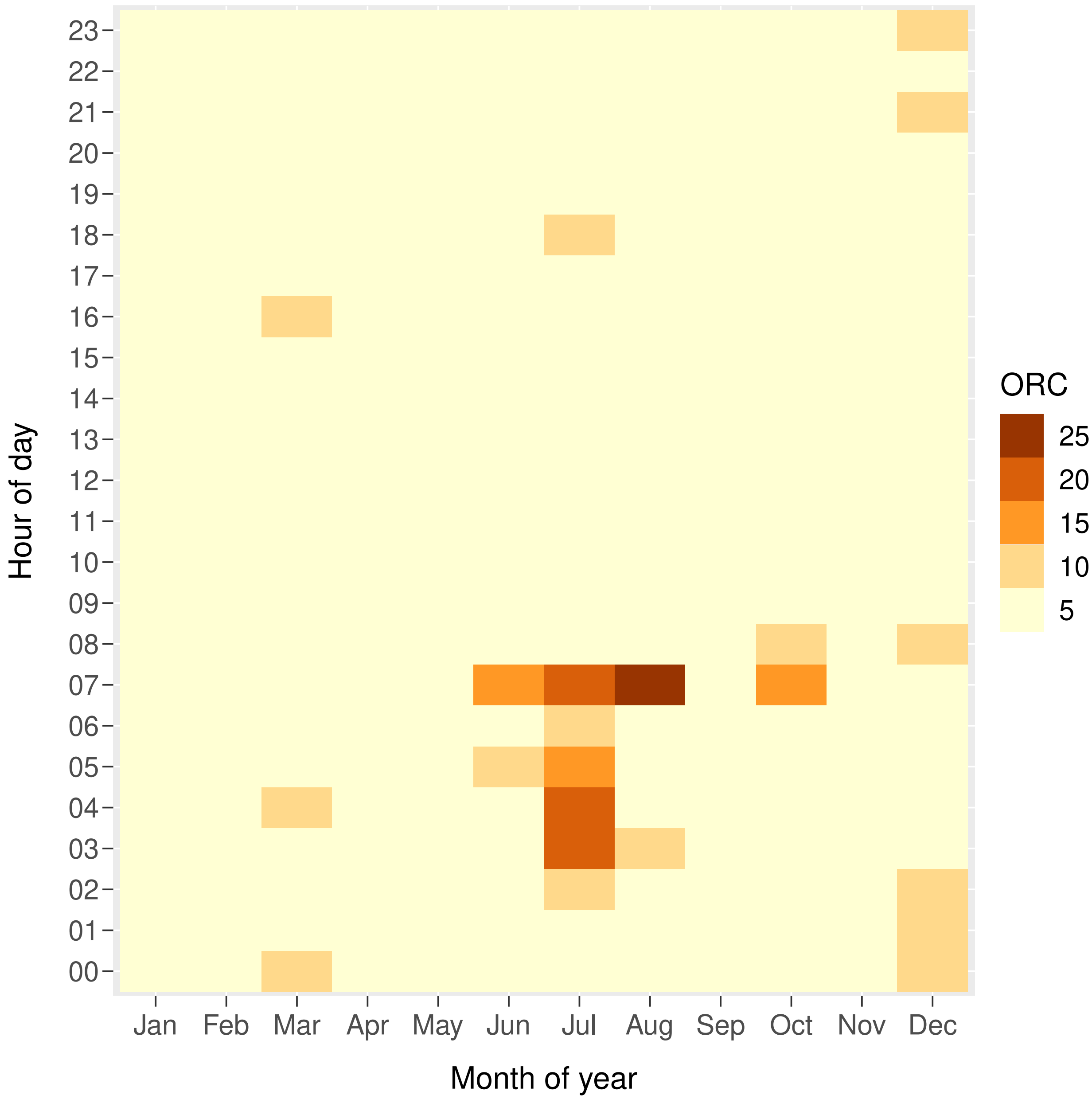


Figure 3: SmellVan ORC by hour of day and month of year

(Figure 3, Supplementary Figures S15b–d). We note that more than 30% of reports corresponding to several odor causes and actions are associated with specific months. For example, 45% of all reports with the cause of garbage and compost were reported in July and 50% of reports with the cause of cannabis facilities are in March; similarly, 43% of reports with the action of making a complaint were reported in July. We also find different OSAC associations across months and seasons (Supplementary Figures S16a–l): in February, rotten odor is associated with neurological symptoms and the suspected cause of animal processing, and in September, it is associated with respiratory irritation and the suspected cause of garbage and compost, suggesting different types of rotten odors that might be varying seasonally (Supplementary Figures S16b, S16i).

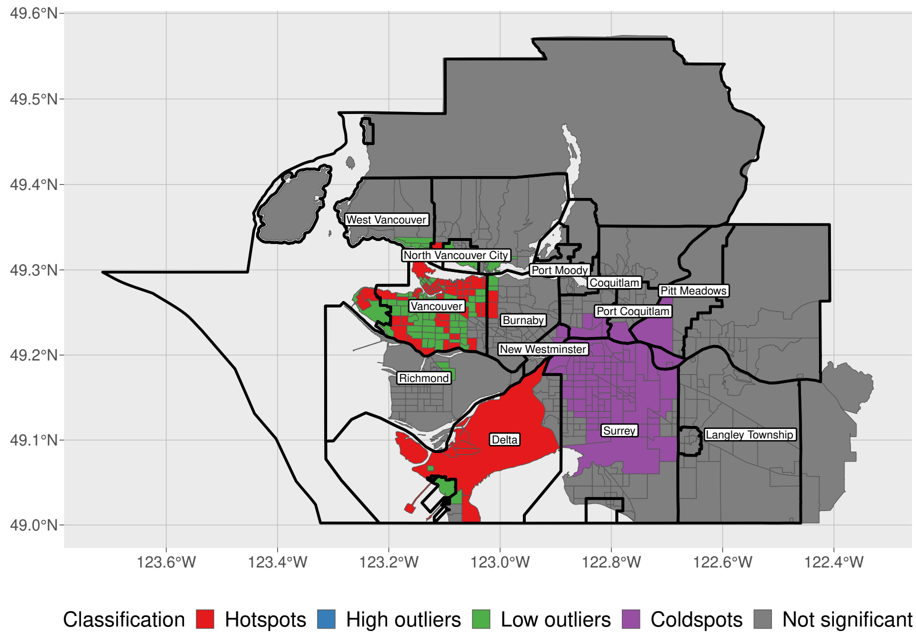
3.3 *Results from hotspot analysis and MLR*

3.3.1 *Odor report clusters and outliers*

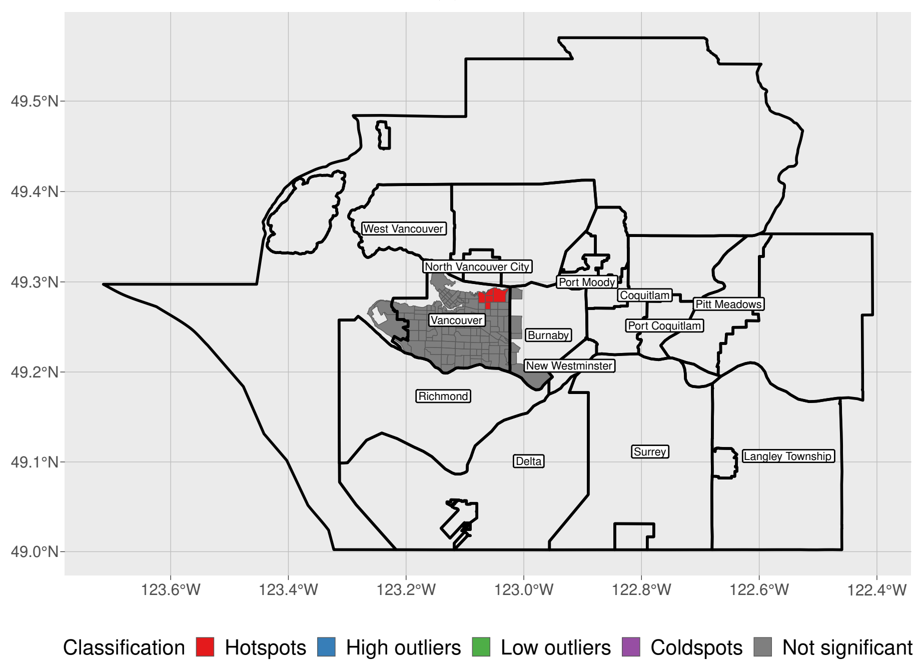
Through Local Moran's I analysis of population-normalized ORC, we find the presence of statistically significant spatial clusters of reports. Figures 4a–b show four types of spatial distributions of ORC in the region—hotspots: areas with high ORC surrounded by areas with high ORC, high outliers: areas with high ORC surrounded by areas with low ORC, low outliers: areas with low ORC surrounded by areas with high ORC, coldspots: areas with low ORC surrounded by areas with low ORC. We observe that the City of Vancouver and Delta account for a large number of tracts in regional odor hotspots (Figure 4a).

Hotspots dominate large parts of the City of Vancouver (Supplementary Table S23, Hotspots and Vancouver: $phi = 0.65[0.56, 0.73]$); however, not all parts of the city are reported to be equally odorous, and there are also low outlier neighbourhoods (Figure 4a; Supplementary Table S23, Low outliers and Vancouver: $phi = 0.51[0.40, 0.60]$). Further, neighborhoods bordering the inlet in the northeast have a dense mix of industrial and residential zoning, and are hot spots, within the region and within the city (Figures 4a–b).

In contrast to the City of Vancouver, we find more homogeneity in neighboring jurisdictions (Figure 4a). Most census tracts in Delta emerge as regional odor hotspots. Large parts



(a)



(b)

Figure 4: Spatial clusters of population-normalized ORC in SmellVan based on the Local Moran's I metric for (a) MetroVan and (b) Vancouver (Dec 2020–Dec 2021).

of the Surrey township are odor coldspots (Supplementary Table S23, Coldspots and Surrey: $phi = 0.82[0.63, 1.0]$). Future work can test these preliminary spatial connections by conducting proximity and dispersion modeling analysis for odor report locations.

3.3.2 *MLR analysis of temporal patterns of ORC*

Exploratory MLR modelling suggests that criteria air pollutants and meteorology fail to capture most of the variance in daily ORC (Tables 1, S6, S9). The most important air pollutants associated with ORC are PM (3%[1–4%]), NO and NO_2 (2%[1–4%]). But, other factors such as accidents (11%[2–14%]) and prominent events (Launch of SmellVan app, national network coverage, (6%[3–8%]) and solar radiation and heat fluxes (8%[3–15%]) may have a stronger influence. However, the relative importance of different variables varies substantially across different months. For example, the contributions of wind speed to explained variance in linear models for ORC ranges from 2–55% in different months, and we observe mixed behaviors with regards to the association (positive and negative correlation slopes).

Table 1: Key MLR variables explaining variance in daily ORC. Arrows show directionality of relationships—up (blue) is positive, up-down (yellow) refers to split (positive and negative), and down (red) indicates negative. Values inside brackets under absolute variance explained show 95% confidence intervals.

Model month	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Avg.	Wt. Avg.	Variance explained
Variance explained: Absolute (A)/Relative (R)?	R	R	R	R	R	R	R	R	R	R	R	R	R	R	A
Odor-related incidents			98 ↑	18 ↑					65 ↑				15	15	11 (2, 14)
Solar radiation and heat fluxes	4 ↓	39 ↓				51 ↑	47 ↕	33 ↓		47 ↑		31 ↓	21	19	8 (3, 15)
SmellVan news	58 ↑												5	9	6 (3, 8)
Rainfall								67 ↑					6	14	5 (2, 12)
Wind speed	8 ↓		2 ↑				30 ↕		12 ↓	33 ↑	55 ↓		12	12	5 (2, 8)
Pressure	5 ↑			28 ↓			22 ↓		6 ↓			69 ↑	11	8	4 (2, 6)
Temperature, Humidity, DPT	25 ↑			22 ↓		49 ↑							8	7	4 (2, 6)
PM		61 ↑		17 ↑					15 ↑				8	5	3 (1, 4)
NO and NO2				16 ↓	41 ↓				2 ↓	20 ↑	45 ↓		10	8	2 (1, 4)
CO					59 ↑								5	3	1 (0, 1)
Adjusted R^2	0.63	0.28	0.86	0.48	0.14	0.23	0.58	0.35	0.66	0.26	0.08	0.16	0.39	0.43	
Total variance explained	0.70	0.32	0.87	0.57	0.20	0.28	0.70	0.39	0.75	0.33	0.14	0.22	0.46	0.50	
Number of reports	83	19	23	39	24	23	44	113	77	32	50	22			

3.4 *Participant demographics underlying SmellVan*

SmellVan app user demographics show biases in age and gender and do not represent the diverse racialized and/or minority communities of MetroVan (Tables S1–S3, S24–S28). Not all app users report demographics: about 20%-25% of users do not report their age, financial status, health condition, or racial/minority status. The age group 30-49 is over-represented in the data set; 52% of SmellVan users identified as being aged 30–49, in comparison to MetroVan's 29% (Tables S3, S24). Only 16% of app users report belonging to a racialized/ethnic minority group; however, about 54.5% of MetroVan's population belongs to a visible minority community (Tables S2, S25). There is a large gender difference as well, with women reporting 64% and men reporting 36% of the reports, in contrast to the 51-49% split in the general population (Tables S2, S26). We also assess the financial status and chronic disease incidence of the user population compared with that of the whole region, and find similarities. The bottom three groups by income reporting to SmellVan (representing those self-reporting "never" to "sometimes" having the financial resources necessary to meet their needs) contribute about 17% reports whereas census-based low-income households account for about 7%–11% of MetroVan's population, with about 19% population reporting income in the lowest quintile (Tables S2, S27). Most app users (78%) do not report a chronic health condition (Supplementary Table S28), similar to regional population reporting very good or excellent mental health (about 70%) and absence of a chronic disease ($\leq$25%, e.g., hypertension, asthma, etc.) to the healthcare administrative data collected by the BC Chronic Disease Registry [92, 93]. However, we note that the measures used above to assess financial status and chronic condition are not equivalent. Finally, cluster analysis on demographic data identifies two major clusters of reporting groups: white women aged 30-49 with no health conditions (103 reports, or about 19% of data) and men belonging to the highest financial status category (73 reports, or about 13% of data) (Supplementary Figure S17). Overall, this data set is consistent with other findings that participation in crowd-sourced science often does not reflect the population demographics [39].

4 Discussion

In this work, we use odor experiences from the public in a major city to provide insights into the patterns of odor reporting and the underlying spatiotemporal characteristics and behavioral responses related to those experiences. Here, we utilize findings from the Smell Vancouver project to shed light on (1) the smellscape of and odor impacts in Metro Vancouver, (2) key environmental and human factors that influence odor patterns, and (3) the strengths and limitations of crowd-sourced science for odor monitoring.

4.1 *Descriptive patterns of odor reporting*

Our results highlight the range of odors and possible causes as well as potential odor-related health and well-being impacts (e.g., health-related symptoms, maladaptive actions) and their spatiotemporal variability, and point to the complex mechanisms through which odor-related impacts occur (Sections 3.1–3.2). While spatiotemporal patterns of odor and symptom reporting have been the subject of previous work[60], the patterns of actions and perceived causes as well as the OSAC associations (linkages across odors, symptoms, actions, and perceived causes) presented in this study are novel (Sections 3.1, 3.1.4; Figure 2).

Odor experiences are often linked to persistent sources, which have specific spatiotemporal patterns as observed in this study (Figure 1, Section 3.3). We find distinct smellscapes across cities, and find that reporting of possible causes is consistent with documented local controversies around odor sources such as waste management (composts, landfills, incinerators) and industrial processes (chemicals) and odor-relevant accidents (e.g., sewage spills) (Tables S7–S8). In contrast, only one residential cause, wood smoke from open burning and wood-fired appliances, has a history of air pollution issues in Vancouver and is also frequently reported in SmellVan[94]. It is important to note here that current odor management approaches typically do not manage wood smoke or smoke from wildfires. However, as reporting in SmellVan shows, people still experience odors from these sources, and such impacts should be considered in decision making from a public health perspective.

Urban residents also report a range of physiological (e.g., neurological symptoms such as headaches and nausea, respiratory irritation), and emotional and mood-related impacts (e.g., generating negative feelings such as anger and frustration) as well as maladaptive actions (e.g., reducing air exchange indoors at high temperatures) in response to adverse odors (Section 3.1). Maladaptive actions such as changed breathing patterns (e.g., breathing through the mouth, removing masks) and reducing ventilation inside vehicles and homes can give a false sense of safety due to lower odor. However, they can also increase heat-stress, disease transmission, and reduce indoor air quality due to pollutants that cannot be detected by smell (e.g., radon gas). In each case, maladaptive behaviors put individuals in situations where they must choose amongst environmental stressors (impacts of heat and indoor air pollutants or risks of speeding or exposure to particle pollution versus odor exposure), or tradeoff between increased odor exposure and reduced healthy behaviors (e.g., outdoor exercise). This finding of complex health impacts of odor stands in contrast to odor regulation primarily for nuisance reduction[1].

We find statistically significant clusters in reported OSAC (Figure 2, Supplementary Figures S13a–e), and there are several possible explanations for these observed OSAC associations. It is possible that odors and suspected causes could be connected in a 1:1 relationship so that they share all symptoms and actions. However, we find that a given odor can be associated with multiple causes, and depending on the cause from which the odor was reported, it mediates different symptoms (Section 3.2.2). Additionally, it is possible that since the connections of odors and causes are intuitive, people may report only one of them. Nevertheless, for often-reported odors such as rotten odor, we observe non-intuitive connections; for example, in January, rotten odors are linked to the cause of smoking (Supplementary Figure S16a). Finally, these OSAC patterns could also indicate that observation of cause–symptom–action linkages correspond to impacts of the cause itself, while odor–symptom–action linkages correspond to impacts of exposure to certain odorous contaminants. For instance, past research has indicated that stress-mediated impact pathways for odors could be linked to whether suspected odor producers are perceived as being socially responsible and law-adhering [29]. These patterns and associations point to potential causal mechanisms by which odors influence health, both physiologically and psychologically. Although these OSAC associations vary across months (Section 3.2.2) and in space (Section 3.2.1), they still follow similar structures of odor experience. The identification of location-specific odor-related impacts (symptoms and actions) that are associated with specific odors and perceived causes reported in those municipalities underscore the need for place-based and tailored approaches to odors. These findings could be used as starting points to better understand possible interventions for reducing odor impacts.

Traditionally, odor complaints have been perceived as a mere annoyance issue, reflected in the current regulatory framework that mandates impact assessments of facilities at an individual level[95]. However, our analysis based on crowd-sourced data reveals that odors can significantly impact determinants of health and well-being such as the physical environment, social support, coping skills, and healthy behaviors[96]. In light of these findings, incorporating smellscapes into urban planning could play a vital role in promoting healthier communities[42]. Given the effectiveness of crowd-sourcing on capturing the wide range of STOSAC characteristics displayed in this study, it may be prudent to prioritize community inputs as a key driver in decision-making processes related to social justice and odors.

4.2 *Explanatory drivers of odor reporting*

We also use crowd-sourced data to connect the dots from odor impacts to pollution sources, air quality, and meteorology. Our findings suggest that the presence of statistically significant spatial clusters of odor reports and the variance in temporal patterns of odor reports are related to a mix of environmental and human factors (Section 3.3). Here, we discuss plausible explanations for the different spatiotemporal patterns.

Odor reporting in the region's municipalities captures land use patterns of odor sources in those areas. The City of Vancouver, Delta, and Richmond accounted for a large number of tracts in regional odor hotspots. Urban areas such as the City of Vancouver are expected to have odor issues, given the wide variety of odorous sources encountered in the city, such as municipal waste management and wastewater treatment, fires, smoking, and vehicle exhaust, the port, the rail yard, and restaurants. We also find that reporting in neighborhoods in the northeast is consistent with the presence of an animal rendering facility and slaughterhouses in this area (within the City, Hotspots and animal processing, $phi = 0.36[0.19, 0.50]$), and the history of odor nuisance reports from nearby residents (Supplementary Table S8). Odor reporting in the Delta region is also consistent with the presence of odorous sources such as waste management facilities (a regional landfill, a composting anaerobic digester), which have been odor sources of concern for residents' groups (Supplementary Table S8, Supplementary Table S28; the cause of garbage and compost and Delta: $phi = 0.56[0.47, 0.64]$). The recent shift to cannabis cultivation has further exacerbated the reports from farming[58]. Thus, the distinct smellscapes identified across cities in SmellVan have land use-related origins, and the links of land use to smellscapes should be investigated further.

Our exploratory MLR modeling suggests that associations between the different air quality and meteorological variables and ORC vary across different months due to changing sources and meteorology (Table 1), and this variability and the underlying causal links are discussed in the Supplementary data file (Section S9). However, despite incorporating a comprehensive set of air quality and meteorology variables (Supplementary Table S6, 75 variables in total), the models capture approximately 50% [17–80%] of the variance in ORC (Table 1). This limited performance could be attributed to the temporal scale (daily) and sample size (monthly total ORC ranging from 19 to 113) of the modelled data. Nonetheless, the model itself is adequately representative, as evidenced by its ability to capture lead/lag relationships with news events and the association with the app's publicity upon its launch (Section S6). Considering that odor reports can occur on short time scales (e.g., 3 minutes), it is unlikely for air quality and meteorological monitoring alone, even at higher time resolutions, to sufficiently capture the significant spatiotemporal variability in ORC. Thus, traditional monitoring approaches fail to predict a substantial portion of odor experiences, highlighting the importance of community science in bridging this gap.

In summary, our study identifies potential environmental (e.g., wind speed) and human factors (e.g., land use) associated with spatial and temporal patterns of odor reports in the Metro Vancouver region. Future work investigating the relationships between residential demographics and the distribution of spatial odor report clusters could advance the understanding of odors as an environmental justice issue.

4.3 *Strengths and limitations of crowd-sourced science*

The STOSAC framework-based crowd-sourced science deployed in this study draws out important insights into the odor experience. The use of free text in STOSAC allows app users to communicate their odor experiences and provide information (such as sentiments and emotions) that complements quantitative data collected in the odor reports. We observe the interlinking of OSAC patterns and report multiple complete cases of OSAC associations (Supplementary Table S29). This interlinking suggests a substantial drawback of traditional odor documentation approaches such as FIDOL (Frequency, Intensity, Duration, Offensiveness, and Location) and CICOP (Concentration, Intensity, Character, Offensiveness, and Persistence) as well as odor nuisance indices based on these approaches[97], which do not account for such subjective experiences (e.g., relationships between odor and symptoms). The large spatiotemporal coverage of the approach are in much contrast compared to traditional odor monitoring approaches such as dynamic olfactometry [73, 97, 98] that can only measure odor concentrations at a specific location and time. Thus, STOSAC makes it easier to obtain a comprehensive understanding of the spatial and temporal variability of odors and their behavioral response compared to traditional approaches. Additionally, given that regulatory monitoring with its hourly or coarser measurements often does not capture concentration peaks or odor exposure that occur at shorter time scales, STOSAC-based odor reporting could serve as a marker of such pollution exposures and their health impacts. Future work could utilize the STOSAC approach to build policy-relevant tools and metrics.

Despite the strengths, the crowd-sourced science approach has its limitations, particularly with regards to biases from self-selection in reporting (Section 3.4). The negative (“offensive") hedonic tone on the app could bias the users to report more health symptoms[40]. This could be addressed in the future by also inviting positive odor experiences to SmellVan. Additionally, in the current iteration of the project, community engagement was restricted to awareness of the app via social media. Future iterations of the project could involve community scientists at the design stage of the project, and give communities “multiple ways to participate at different levels of commitment"[39, 99]. The project could also initiate active community support groups to provide an avenue for users to share odor concerns and solutions to address odors. The aggregation of odor report counts across time (e.g., by day, by month) and space (e.g., by city, by census tract, region-wide) assumes limited variation within the daily timescale (temporal basis of analysis) and within the census tract (spatial basis of analysis). These are strong assumptions—odor reports can occur on short time scales (e.g., 3 minutes) and odor concentrations can depend on wind direction and meteorology, resulting in changes in ORC not dependent on the spatial basis of analysis. Nevertheless, these assumptions are also the basis for most filter-based studies of air pollution, and have been broadly accepted by the community. Finally, the temporal MLR methods link variables collected in the study with external datasets, and OSAC associations link OSAC categories with each other. However, these associations may not be representative of causation and should be treated as preliminary evidence to investigate causality.

In summary, the range of odor experiences, and complex links between odor and well-being impacts, documented in SmellVan indicate that more nuanced approaches to odor management may be required to support community health than fixed separation distances from odorous sources [100]. Community feedback in the OSAC framework could be used as a starting point to design policy actions that prioritize specific odor sources (e.g., facility-specific improvements) and address their co-occurring symptoms (e.g., targeted resident health monitoring and care), and this process of OSAC-based data collection can be conducted on a recurring basis at low cost and at large spatiotemporal scales. The STOSAC approach, which incorporates behavioral response of humans to environmental exposures, points to new opportunities for community science to inform policy and planning decisions.

5 Conclusion

This study emphasizes the importance and potential of community science projects, such as SmellVan, in characterizing the odorous environment and its impacts on human health and well-being. Crowd-sourced science also allows for a comprehensive understanding of the spatial and temporal variability of the odor experience compared to traditional approaches. The STOSAC framework-based crowd-sourced science approach used in this study provides important insights into the odor experience, including complex linkages between environmental exposures and well-being, which are mediated through human perception and adaptive responses. The findings suggest that odors can significantly impact determinants of health and well-being, such as the physical environment, social support, coping skills, and healthy behaviors. While the study identifies potential environmental and human factors associated with spatial and temporal patterns of odor reports in the Metro Vancouver region, it also highlights the limitations of a purely quantitative approach to odor monitoring and the importance of citizen and community science to fill such gaps. However, citizen and community science data collection often has biases such as those seen in the SmellVan app data, including the under-representation of racialized and/or minority communities and the over-representation of certain age and gender groups. Overall, this study suggests that crowd-sourced science–based odor reporting could serve as a marker of pollution exposures and their health impacts at large spatiotemporal scales, complementing traditional air pollution monitoring.

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