Received: 7 August 2025 | Revised: 8 February 2026 | Accepted: 10 February 2026

DOI: 10.1002/ppp3.70191

Plants People Planet PPP Open Access

RESEARCH ARTICLE

A walk in the park—Identifying healthy greenspaces using scents

William T. Kay[1] | Anya Lindström Battle[1] | Mahal Humberstone[1] | Molly Tucker[1] | Kieran E. Storer[1] | Geoffrey Kite[2] | Katherine Willis[1]

[1]Department of Biology, University of Oxford, Oxford, UK

[2]Jodrell Laboratory, Royal Botanic Gardens, Kew, Richmond, UK

Correspondence
William T. Kay, Department of Biology, University of Oxford, South Parks Road, Oxford OX1 3RB, UK.
Email: william.kay@biology.ox.ac.uk

Funding information
Leverhulme Trust, Grant Number: RC-2021-76.

Societal Impact Statement

As urbanisation accelerates globally, access to nature is increasingly recognised as vital for public health and wellbeing. We captured and analysed plant-emitted airborne 'scent signatures' across Oxford's urban greenspaces to assess their potential health relevance. We found that sites differ in levels of health-promoting volatiles and harmful pollutants and that these compounds vary with environmental conditions such as temperature and humidity. Our findings provide a novel framework for evaluating urban greenspaces, informing planning, air-quality management and public health strategies to create greener, healthier cities.

Summary

- Biogenic volatile organic compounds (bVOCs) emitted by plants can promote stress reduction and cognitive benefits, whereas anthropogenic VOCs (aVOCs) common in urban air, such as BTEX compounds, pose health risks. We aimed to characterise and compare these airborne chemicals across urban greenspaces and develop a novel, health-oriented metric for site evaluation.
- Air samples were collected across six Oxford greenspaces on a single date using Tenax™ filters and analysed by GC-MS. Data were processed using metabolomics-style workflows, identifying 245 biologically relevant compounds. Multivariate analyses compared site profiles, and one site was monitored over 12 months to assess environmental influences.
- Greenspaces exhibited significantly different volatile signatures, including variation in both health-promoting bVOCs and harmful aVOCs. Temperature, humidity, wind speed and rainfall significantly influenced the presence and abundance of beneficial compounds.
- These results highlight the importance of considering airborne chemistry in urban planning and public health decision-making. Integrating VOC profiling into planning and public health strategies could support delivery of higher-quality, health-

promoting urban environments and inform guidance on optimal timing for outdoor activity.

KEYWORDS
biogenic volatile organic compounds, gas chromatography–mass spectrometry, greenspace chemical ecology, health, terpenes, volatile analysis, volatile organic compounds

1 | INTRODUCTION

Biogenic volatile organic compounds (bVOCs) are a chemically diverse group of carbon-based secondary metabolites produced across all kingdoms of life (Wang et al., 2024). They function in stress protection, signalling and communication within and between species (Weisskopf et al., 2021), and many are released into the air via passive diffusion from different tissues. In plants, bVOCs such as isoprene, monoterpenes and sesquiterpenes account for almost all biogenic emissions (Guenther et al., 2012). Among these, monoterpenes such as alpha-pinene, beta-pinene and limonene are key contributors to both atmospheric chemistry and human well-being. Numerous studies link exposure to plant-emitted terpenes with lowered cortisol, blood pressure and heart rate, as well as improved mood, cognition and immune function (Bratman et al., 2015; Li, 2010; Park et al., 2010; Zeng et al., 2022). By contrast, anthropogenic VOCs (aVOCs) derived from transport, plastics and industrial sources—particularly benzene, toluene, ethylbenzene and xylene (collectively known as the BTEX compounds) are well-known urban pollutants associated with respiratory and cardiovascular diseases and cancer (Gao et al., 2023).

Because of their location, the 'scentscapes' (the total volatile profile in a specific time and place) of urban greenspaces are likely to comprise both bVOCs and aVOCs. Understanding the balance between these 'healthy' and 'unhealthy' volatiles is therefore essential for assessing how urban greenspaces influence well-being and for driving policy for positive changes in urban development.

Here, we present a new analytical pipeline for characterising ambient air VOCs in situ, integrating field sampling and thermal desorption gas chromatography mass spectrometry (TD-GC-MS) analysis. Although similar methods have been developed for headspace sampling (de Carvalho Couto et al., 2024; Reyrolle et al., 2024; Yin et al., 2022), none have yet been published for the analysis of ambient air. We apply this approach to six Oxford greenspaces to test whether site location determines the distribution of biogenic versus anthropogenic volatiles—and to identify those environments most likely to promote human health.

Additionally, it is well known that the release of bVOCs varies in time. For instance, plants coordinate their volatile production with the availability of substrates from photosynthesis, which varies considerably over the course of a day. Indeed, the production of most plant volatiles is under diurnal and/or circadian control; on a longer timescale, the effects of factors such as seasonality, phenology and other environmental effects including temperature and humidity on the emission of volatiles have been well established (Joo et al., 2018; Li et al., 2023; Mu et al., 2022; Yang et al., 2024).

First, we analysed volatiles on a single date as a snapshot across six outdoor greenspace sites. Second, we sampled a single site—the Botanical Garden outdoors—over a full year, linking differences in volatile fingerprints to seasonal environmental changes and transient weather events. Our work aimed to assess three main hypotheses: (i) that a site's location is a significant driver of volatile difference enabling the separation of greenspaces by their scentscape, (ii) that urban greenspace volatile profiles change over time dependent on environmental variables and (iii) there is sufficient distinction between the presence and abundance of both bVOCs and aVOCs between urban green spaces that it is possible to determine which may be more healthy/unhealthy for human recreation.

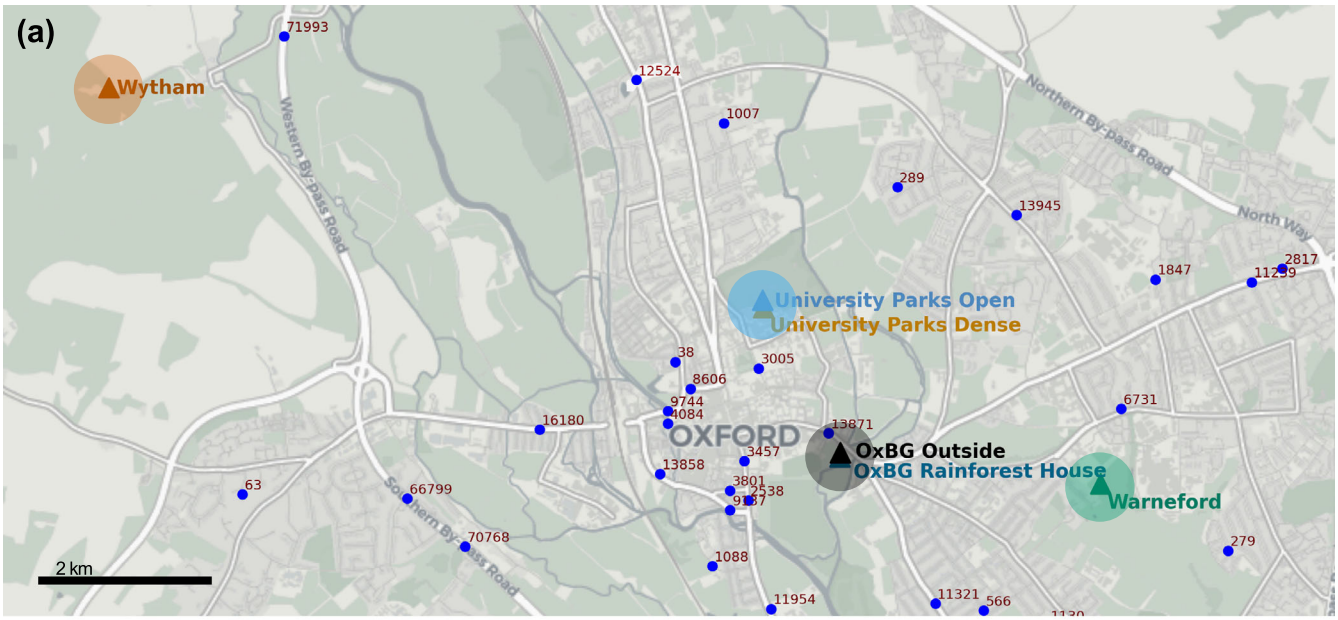
2 | MATERIALS AND METHODS

2.1 | Site locations and sampling strategy

Six urban greenspace sites around Oxford were chosen as sampling sites due to their (i) public accessibility, (ii) different ecologies and (iii) contrasting distance from the city centre. We selected five outdoor greenspaces (Botanic Garden Outdoors, University Parks Dense, University Parks Open, Warneford Meadow and Wytham Woods) and one indoor site (the Rainforest Glasshouse at the Oxford Botanical Gardens) (Figure 1A).

To investigate the characteristic VOC profiles of the selected sites, we employed a collection protocol adapted from Walker et al. (2023) with the addition of housing the pump and apparatus within a bespoke metal box (VOKSBOX, B). Ambient air was captured using a GilAir pump (Sensidyne, LP, St. Petersburg, FL, United States) connected simultaneously to four replicate Markes (Markes international Ltd. Bridgend, United Kingdom) Tenax® TA tubes using a flow rate of 400 ml/min for 2 h (12 L of air per tube). Samples were collected at a height of 1.5 m—based on the approximate level of the adult human nose while walking—between the hours of 11:00 and 13:00 (±1 h) GMT. Tubes were capped immediately after collection and stored at −20°C for up to 14 days before GC-MS analysis.

A pilot dataset was collected on 27 November 2024 and used to assess the hypothesis that sampling sites have distinct volatile profiles (Figure 2). As well as looking at a snapshot of the scentscapes across



(b) SAMPLING

(c) DATA ACQUISITION

Desorbtion: TD100-xr
Column: J&W DB-5ms (30m×0.25mm×0.25µm)
GCMS: Agilent 8890/5977C

Agilent
MARKES international

(d) COMPOUND ID

LIBRARY: Modified vesion of NIST20 based on Chebi database. Semi-standard RI only.
3027 unique CAS remain.

NIST ChEBI

AMDIS v2.73 for ID
Match threshold ≥70
Component width = 25.
Adjacent peak subtraction = 2.
Shape requirements = medium.
Sensitivity = high.
333 unique compounds found

(e) POST PROCESSING

Best spectral matches retained only (Net match mode) - **245 unique compounds remain**

Technical replicates normalised
Rel. ethylbenzene peak area differences

Background subtraction
Removal of compounds detected in blank control tubes

Abundance normalisation
Normalised to total ion current (TIC) to calculate relative **compound abundance**

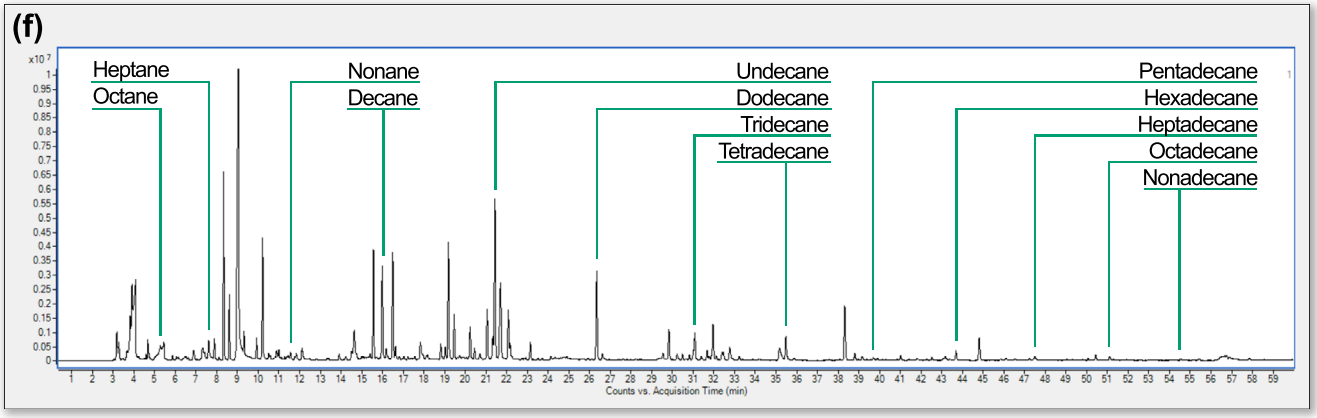


FIGURE 1 Legend on next page.

FIGURE 1 (A) Map of the sampling locations used in this study (botanic garden outdoors; botanic garden rainforest glasshouse; university parks dense; university parks open; Warneford meadow; Wytham woods). Numbers on roads indicate annual average daily traffic (AADF) for 2023 as representative data for each site (GOV.UK, 2023). (B) Sampling box (VOKSBOX) developed for this work on a tripod at 1.5-m height. Air from the GilAir® sample pump is split up to six ways using brass splitters with silicone tubing. (C–E) A flow chart of the methods used in this paper for acquisition, identification and processing of compounds. Red text shows number of compounds identified after each processing step. (F) Example chromatogram resulting from sample collection in botanical gardens outdoors sampling site and GC-MS (gas chromatography–mass spectrometry) protocol—annotated with positions of alkanes used to build Kovats retention index.

the six urban greenspaces, we also wanted to explore how these scentscapes change across time and in the face of environmental variation (Figure 3). Because of the known impacts of seasonality on bVOC emissions, we focused only on biogenic volatiles. Due to the higher numbers of biogenic volatiles present in the Botanical Outdoors location, and as this was likely to be the site with the highest footfall, we also sampled this site on 20 January 2025, 4 March 2025, 30 April 2025, 30 June 2025, 24 July 2025 and 4 September 2025. This allowed us to capture a range of temperature, humidity, precipitation and wind conditions (Figure 3A). All botanical outdoors' samples during the year were taken from 11:00 to 13:00 in exactly the same GPS location and height.

Site-specific temperature and relative humidity at the time of sampling were recorded using a Kestrel Drop D2 data logger (Nielsen-Kellerman Company, Boothwyn, PA, United States). Historical meteorological data were obtained from multiple sources: Air temperature data were retrieved from the Oxford Radcliffe Weather Station, and mean values recorded between 11:00 and 13:00 were used to coincide with the sampling window. Precipitation, humidity, wind speed and wind direction data were obtained from the Kidlington weather station via Weather Underground (www.wunderground.com).

2.2 | Identification and analysis of VOC profiles

2.2.1 | GC-MS protocol

For identification of VOC profiles (Figure 1C–E), we employed gas chromatography mass spectrometry (GC-MS) analysis at the Jodrell laboratory, Royal Botanic Gardens, Kew. Samples were stored at room temperature for at least 2 h before desorption using a TD100-xr automated thermal desorption (TD) unit from Markes (Markes international Ltd. Bridgend, UK). Samples were desorbed on to a Tenax® TA packed cold trap (set to 4°C) by heating the sampling tubes for 10 min at 230°C using a flow rate of 50 ml/min helium. Samples were purged from the cold trap onto a J&W DB-5 ms GC column (30 m × 0.25 mm × 0.25 μm) within an Agilent 8890 GC System (Agilent Technologies, Santa Clara, CA, United States) by heating from 4°C to 300°C over 5 min at a purge flow rate of 1 ml/min helium. Chromatography was achieved by heating the column at an initial temperature of 40°C at a rate of 3°C/min to 220°C at a flow rate of 1 ml/min helium. Data were collected in electron ionisation (EI) mode using an Agilent 5977C GC/MSD over a mass range of 50–400 amu.

2.2.2 | Library development

The GC-MS library used for identification of compounds was a modified version of the NIST20 Wiley Registry 12th edition mass spectral library minimised to compounds existing in the Chemical Entities of Biological Interest (ChEBI) database (Degtyarenko et al., 2007). Only compounds with entries for retention indexes (RI) on semi-standard non-polar columns (to match the J&W DB-5 ms column used) were selected. To avoid mismatches, isomers with the same RI were combined (e.g., (−)-alpha-pinene/ (+)-alpha-pinene became alpha-pinene). The final library used (W12N20MAIN_chebi_WK_edit.MSP) contained 3027 unique compounds.

2.2.3 | Pre-analysis

To aid in the correct identification of compounds, a non-isothermal Kovats index (Kovats, 1958) was built using retention times from C8 to C20 alkane standards (Merck KGaA, Darmstadt, Germany, 04070-1ML; Figure 1F). This index uses known compounds to produce accurate estimations of where all compounds will elute from the GC column (retention times), thus allowing precise identification. We validated this index using 60 pure terpene standards (Restek Corporation, Bellefonte, PA, United States, 34142 and 34143).

2.2.4 | Compound identification

Sample analysis was performed using the Automated Mass Spectral Deconvolution and Identification System (AMDIS) Version 2.73. Compound identification relied on spectral and RI matching, with a minimum match factor threshold of 70 (Net), a RI window of ±10 and a very strong match factor penalty. Deconvolution settings were component width: 25; adjacent peak subtraction: two; shape requirements: medium; sensitivity: high; and resolution: medium. The analysis was restricted to a single identification per library compound. A full list of compounds identified can be found in Table S1.

2.2.5 | Post-processing

The relative amount (%) of each compound within a sample was used for all analysis in this paper. This was calculated as based on the Total Ion Count (TIC) of the sample/peak area of each compound. No absolute quantification was carried out in this work due to not having

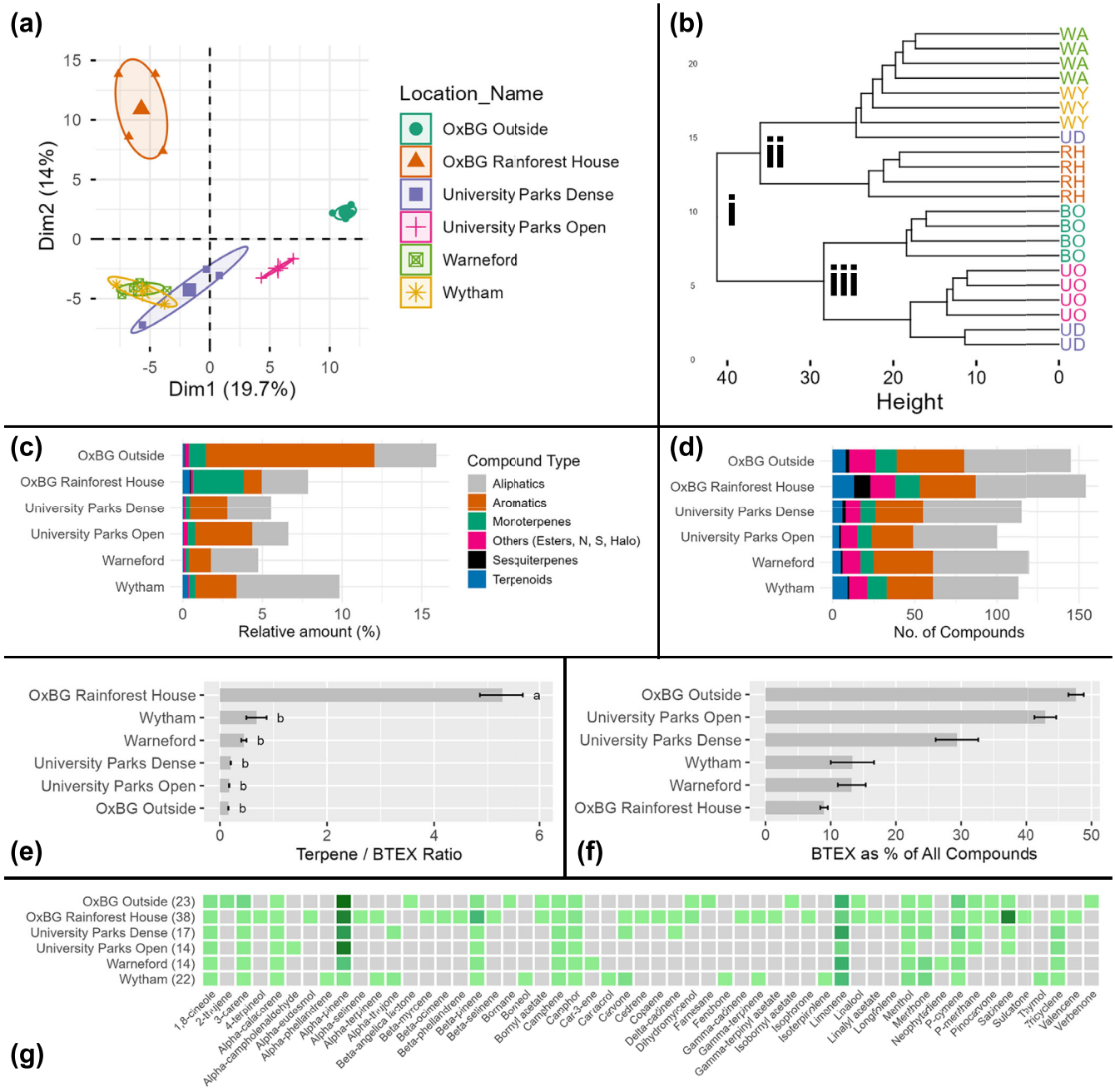


FIGURE 2 (A) PCA (partial least squares discriminant analysis), which used all 245 identified compounds as predictor variables revealed significant variation between sites, each showing distinctive site-specific clustering (PERMANOVA, F5, 16 = 6.557, $p = 0.001$). (B) HCA (hierarchical cluster analysis) conducted using Ward's linkage and Euclidean distances using all technical replicate samples over six urban greenspaces. (C) Relative abundance (means) of detected volatile compounds split by classes across sites, expressed as a percentage of the total sample. (D) Total number of detected volatile compounds per site, categorised by compound class. Results show that the number of all compounds groups differed between sites. (E) Terpene: BTEX ratio of sampling sites (∑terpenes/∑BTEX). Relative amounts of all terpenes/terpenoids as a ratio to the anthropogenic BTEX compound. (F) ∑BTEX as % of all identified compounds between sampling sites. Error bars represent standard error (SE). (G) terpenes/terpenoid compounds identified across sampling locations. Heatmap showing the scaled relative amount (light green > dark green) or absence (grey) of any terpenes/terpenoid VOCs detected across six sampling locations. Scaling was carried out within single locations. (C, D, F) Bars represent the mean ($n = 4$ technical replicate sampling tubes per site). Letters indicate statistically distinct sampling locations within chemical classes based on one-way ANOVA followed by Tukey's HSD post hoc test ($p < 0.05$).

concentration curves for all compounds identified. Best-match compounds for each retention time and replicate tube were then chosen based on net match score. Peak areas of any compounds identified in blank control tubes were removed from the peak areas of all samples within a GC-MS run. Missing values for compounds (i.e., those compounds found only in some technical replicate tubes) were zero-filled.

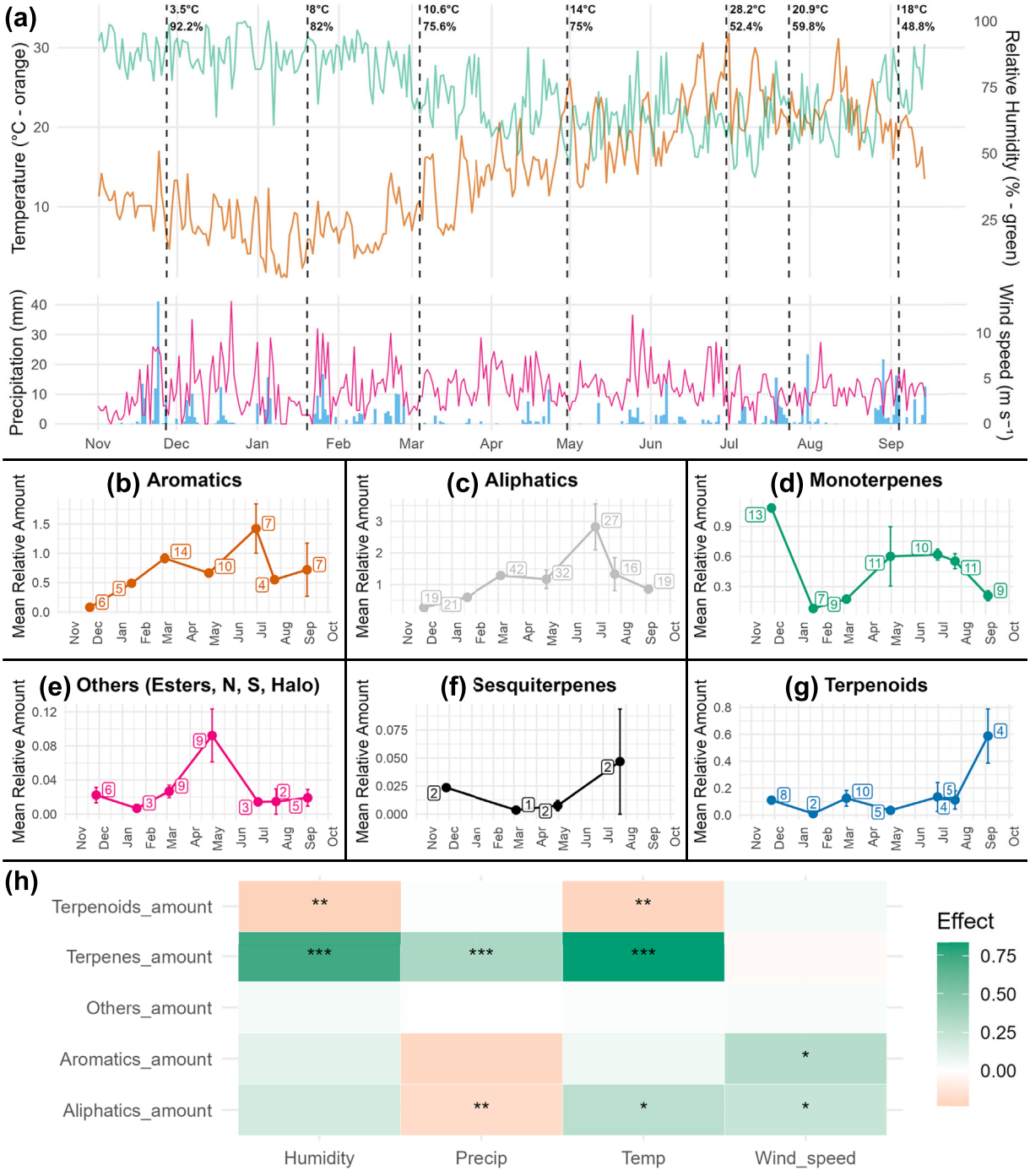


FIGURE 3 Seasonal dynamics and environmental drivers of biogenic volatile organic compounds (bVOCs) at the botanical garden outdoor site. (A) Daily temperature (orange) and relative humidity (green) and daily precipitation (bars) with wind speed (line), derived from local and regional meteorological datasets. Vertical dashed lines indicate sampling dates; values above denote site-specific temperature and relative humidity measured during sampling. (B–G) Monthly mean relative abundances (±SE) of compound classes (aliphatics, aromatics, monoterpenes, sesquiterpenes, terpenoids, and 'others' including esters and N-, S- and halogen-containing compounds) from November 2024 to September 2025. Numbers beside points indicate the number of detected compounds contributing to each class per sampling event. (H) Mixed-effects model coefficients linking standardised environmental predictors (temperature, precipitation, humidity, and wind speed) to log-transformed relative abundances of each compound class. Tile colour represents effect size (positive = green; negative = brown), and symbols denote statistical significance (*p < 0.05; **p < 0.01; ***p < 0.001). Models were fitted with sampling date as a random effect to account for temporal structure.

2.3 | Statistics and data visualisation for volatile analysis

For all VOC data (Figures 2 and 3), TIC (total ion count) data for all compounds were converted to relative amount (%) using the formula ion count/total ion count of sample.

For the single (November 2024) snapshot, multivariate analyses were performed using all 245 retained compounds following post-processing and filtering. Compound abundance data were square-root transformed to reduce the influence of highly abundant compounds and to mitigate zero inflation, following established ecological recommendations (Chang & Lin, 2011; Legendre & Legendre, 2012).

For principal component analysis (PCA, Figure 2A), transformed data were mean-centred and scaled to unit variance to ensure comparability among compounds with differing absolute abundances. PCA was conducted using the FactoMineR package with visualisation provided by factoextra in R (Kassambara & Mundt, 2017; Lê et al., 2008). To assess compositional differences in VOC profiles among sampling locations, a permutational multivariate analysis of variance (PERMANOVA) was performed using the adonis2 function from the vegan R package, based on Euclidean distances and 9999 permutations (Oksanen, 2015).

Hierarchical cluster analysis (HCA, Figure 2B) was conducted using Ward's minimum variance linkage method with Euclidean distance, a combination that favours the formation of compact and internally coherent clusters. Cluster structure identified by HCA was subsequently used to define groups for downstream exploratory analyses. Partial least squares discriminant analysis (PLS-DA) was applied as a supervised exploratory method to characterise compounds contributing most strongly to differences among the three major clusters identified by HCA. PLS-DA was implemented using the pls and mixOmics R packages (Rohart et al., 2017). To minimise over-interpretation, PLS-DA results were not used for hypothesis testing but to identify patterns in variable contributions. The top 10 compounds with the highest Variable Importance in Projection (VIP) scores for each cluster are reported in Table 1.

To examine differences in VOC composition using ecologically interpretable groupings, compounds were classified into six functional classes: aliphatics, aromatics, monoterpenes, sesquiterpenes, terpenoids and others (including esters and nitrogen- and sulphur-containing compounds) (Figure 2C,D). For each class, compound richness (number of compounds) and summed relative abundance were calculated per location. One-way ANOVAs were used to test for differences among locations, with post hoc Tukey's HSD tests applied to identify pairwise differences in both summed abundance (Tables S2 and S3) and compound richness (Tables S4 and S5).

Spatial variation in terpene abundance was visualised using a hierarchical heatmap (Figure 2E) in which colour intensity represents compound abundance scaled within individual locations.

To contextualise VOC profiles in relation to anthropogenic influence, the relative abundance of all terpenes and terpenoids was expressed as a ratio to the summed relative abundance of anthropogenic BTEX compounds (Figure 2F, benzene, toluene, ethylbenzene and p-xylene; ∑terpenes/∑BTEX), following established approaches for assessing biogenic versus anthropogenic dominance (Malik et al., 2025).

TABLE 1 Top 10 compounds from PLS-DA VIP analysis (partial least squares discriminant analysis using variable importance in projection) of the first three clusters of the HCA (hierarchical cluster analysis) analysis in Figure 2B.

Cluster i	**P-xylene (aromatics), ethylbenzene (aromatics), isooctane (aliphatics), 2,3,4-trimethylpentane (aliphatics), toluene (aromatics), 3-methylhexane (aliphatics), methylcyclohexane (aliphatics), 2-dodecene (aliphatics), 1-ethyl-2-methylbenzene (aromatics), 3-methylheptane (aliphatics)**
Cluster ii	**Beta-ocimene (monoterpenes), dihydromyrcenol (terpenoids), sabinene (monoterpenes), beta-pinene (monoterpenes), pinocarvone (terpenoids),** hydrindane (aliphatics), **alpha-pinene (monoterpenes), copaene (sesquiterpenes), 4-terpineol (terpenoids), beta-phellandrene (monoterpenes)**
Cluster iii	**2-thujene (monoterpenes),** prehnitene (aromatics), **farnesane (sesquiterpenes),** P-isopropenylmethylbenzene (aromatics), bromodichloromethane (others [esters, N, S, halo]), 1,4-diethylbenzene (aromatics), **tricyclene (monoterpenes),** 2,2,4,6,6-pentamethylheptane (Aliphatics), **bornyl acetate (terpenoids),** propylbenzene (aromatics)

Note: Bold compounds highlight terpenes/terpenoids.

For analysis of VOC profiles over time in the single sampling site (Figure 3), relative amount data were used. The average relative amounts of all identified biogenic volatiles were summed within six compound classes and compared across the seven time-points.

All statistics were run using R version 4.4.1 (2024-06-14 ucrt) within RStudio 2024.09.0 + 375 'Cranberry Hibiscus' release for windows. All graphs were generated using the ggplot2 (Wickham, 2011) package.

2.4 | Statistical modelling of meteorological drivers of bVOC emissions

To investigate environmental drivers of bVOC emissions within a single greenspace (Botanical Gardens Outdoors) across the calendar year, linear mixed-effects models were fitted to compound class-level emission data from the Oxford Botanic Garden Outdoor site (BO) using R (v.4.x). Peak areas were averaged across technical replicates for each sampling date prior to analysis. Compounds were grouped into five functional classes: monoterpenes, sesquiterpenes, terpenoids, aromatics, aliphatics and others (esters, nitrogen-, sulphur- and halogen-containing compounds), and summed abundances were calculated for each class per sampling date. Response variables were log-transformed using $\log(1 + x)$ to stabilise variance and reduce right skew. Predictor variables included mean daily temperature (°C), relative humidity (%), daily precipitation (mm) and wind speed (m s^{-1}). All predictors were centred and scaled (z-score transformation) prior to modelling to facilitate comparison of effect sizes. For each compound

class, a linear mixed-effects model was fitted using the lme4 package, with sampling date included as a random intercept to account for repeated measurements over time:

$$log(1+yi) = \beta 0 + k\sum \beta kXk,i + bi + \varepsilon i,$$

where y_i is the summed abundance of a given compound class on sampling date i, X_k is scaled meteorological predictors, b_i is the random effect of sampling date and ε_i is the residual error.

Statistical significance of fixed effects was assessed using Wald tests implemented via the lmerTest package. Model coefficients and standard errors were extracted for visualisation as coefficient plots and heatmaps, with colour intensity representing the direction and magnitude of standardised effects. Model structure was defined a priori based on hypothesised meteorological drivers, and model fit was assessed to ensure consistency across compound classes.

3 | RESULTS

3.1 | A snapshot in time: Distinctive fingerprints of six urban greenspaces

Our analysis pipeline resulted in 245 unique compounds being identified within our 6 Oxford sampling sites (Table S1). A PCA (Figure 2A) using all identified compounds as predictor variables revealed significant site-specific clustering (PERMANOVA, F5, 16 = 8.889, $p = 0.001$) with pair-wise separation of all sites ($p < 0.05$) except Wytham Woods (WY) in the Warneford Meadow (WA, PERMANOVA, $p = 0.846$). Further HCA analysis revealed site-level structuring of most VOC profiles (Figure 2B). Primarily, University Parks Open (UO) and Botanical Gardens Outdoors (BO) separate from all other sites (Figure 2B, Cluster i). PLS-DA VIP analysis (Tables 1 and S6) was due to higher amounts of many anthropogenic emission-related compounds such as 2,3,3-trimethylpentane, p-xylene, 2-ethylhexan-1-ol, indane and ethylbenzene. Plant-related compounds (beta-ocimene, dihydromyrcenol, sabinene, beta-pinene and pinocarvone) were chiefly responsible for the secondary clustering (Figure 2B, Cluster ii) due to presence (or higher proportions) in the Rainforest Glasshouse (RH) compared with University Parks Dense (UD), Wytham Woods (WY) and Warneford Meadow (WA). The third most significant cluster (Figure 2B, Cluster iii) splits University Parks Open (UO) and Botanical Gardens Outdoors (BO), again due to the higher proportion/presence of terpenes/terpenoids such as 2-thujene, farnesane and bornyl acetate found in Botanical Gardens Outdoors. Full results of PLS-DA analysis can be found in Table S6.

3.1.1 | Urban greenspaces show distinctive mix of compound classes

The number of identified terpenoids, monoterpenes and sesquiterpenes was found to be highest in the Rainforest Glasshouse (13, 15 and 10, respectively). These compound numbers were significantly higher than the other five sites (one-way ANOVAs followed by Tukey's HSD post hoc test $p < 0.05$, Figure 2D—full statistics in Tables S4 and S5). Numerically, the Botanical Gardens Outdoors was the outdoor location with the highest counts of terpenoids, monoterpenes and sesquiterpenes (8, 13 and 2, respectively), closely followed by Wytham (9, 12 and 1). In terms of relative abundance (Figure 2C—full statistics in Tables S2 and S3), botanic garden outdoors contained a significantly higher proportion of aromatic compounds compared to other sites suggesting a strong influence from anthropogenic sources. The rainforest glasshouse showed a significantly higher proportion of monoterpenes, whereas sesquiterpenes were shared by the rainforest glasshouse and botanical gardens outdoors (one-way ANOVAs followed by Tukey's HSD post hoc test $p < 0.05$).

3.1.2 | Presence/absence of plant-based terpenes and terpenoids

A total of 54 terpenes/terpenoids were identified in this work (Figure 2G). Ten compounds—1-8 cineole (eucalyptol), 3-carene, alpha-calacorene, alpha-pinene, beta-pinene, camphene, camphor, limonene, menthol and p-cymene—were detected at every site, with a further two—menthone and tricyclene—detected in five of the six sampling sites. Again, the rainforest glasshouse exhibited the largest number of identified terpenes/terpenoid compounds overall (38 compounds), of which 16 were not detected at other sites. Of the outdoor sites, botanical gardens outdoors contained the highest number of identified terpenes/terpenoid (23), of which six were uniquely present at this site. University Parks Dense (17), University Parks Open (14), Warneford Meadow (14) and Wytham Forest (22) all showed an overlapping but distinctive terpene mix. A full breakdown of compounds unique to individual sites is shown in Table S7.

3.1.3 | BTEX compounds as predictors of pollution

The ratio of biogenic terpenes/terpenoids to anthropogenic BTEX compounds was significantly higher in the rainforest glasshouse compared to the other sites (Figure 2E, one-way ANOVA followed by Tukey's HSD post hoc test $p < 0.001$). This is in part due to the increased prevalence of terpenes/terpenoids and in part to the lower proportion of BTEX compounds (Figure 2F) in this indoor space. The outdoor sites all had significantly lower ratios but were not significantly different from each other.

3.2 | How do urban greenspace bVOC profiles vary through time under real-world conditions?

Using the same classification system for our identified compounds, we counted both compound numbers and summed abundances to visualise each class over time. In terms of the relative abundances, all

compound classes peaked during late spring to summer (May to August 2025) with two notable outliers—monoterpenes had an early peak on 27 November 2024, and terpenoids had a late peak on 29 October 2025. Interestingly, in terms of the absolute number of compounds identified, it was early spring (4 March 2025) that showed peaks for aliphatics (42), aromatics (14), terpenoids (10) and others (9), with monoterpene counts being more stable over the year.

Mixed-effects modelling revealed that different components of the biogenic scentscape responded in contrasting ways to short-term environmental variation (Figure 3C). Temperature emerged as the most consistent positive driver of terpene emissions, with higher temperatures associated with increased relative abundances of both monoterpenes and sesquiterpenes. Humidity also showed compound-class-specific effects, with terpenes exhibiting a significant positive association with increased levels of relative humidity, whereas aromatic and aliphatic compounds were weaker or neutral. Increased wind speed contributed to increases in both aromatic and aliphatic fractions.

4 | DISCUSSION

4.1 | bVOCs and aVOCs shape urban greenspace scentscapes

An initial PCA of our six sampling sites on a single date (27 November 2024) revealed significant site-specific clustering. Further HCA revealed site structuring was due to both bVOCs and aVOCs (Table 1 and Figure 2B). We chose to interrogate the first three clusters, which appeared. The first cluster separated two outdoor sites—botanical gardens outdoors and university parks open—from all other sampling sites. PLS-DA VIP analysis showed that this was due to many emission-related aVOCs (Table 1) including the traffic-related BTEX compounds (Figure 2F). These two sites are very close to busy city centre roads (Figure 1A), suggesting that traffic is the likely main contributor. This is supported by BTEX presence measurements where over 40% of identified volatiles were BTEX compounds in the Botanical Gardens Outdoors and University Parks Open, but just 13% in Wytham Woods and Warneford Meadow, which are more isolated from traffic. The relationship between proximity to traffic and BTEX prevalence has not been assessed in this paper but has been previously reported (Hoque et al., 2008).

Interestingly, despite its proximity to university parks open (~80 m), university parks dense showed markedly lower BTEX levels (43% to 29%). Localised differences in BTEX presence within urban greenspaces have been demonstrated before; for example, Upmanis et al. (2001) reported that concentrations of benzene and toluene were up to one third lower just 40 m into urban parkland within two large Scandinavian cities. A second study also showed decreases in particulate matter (PM10 and PM2.5) of up to 50% at 200 m (Gómez-Moreno et al., 2019). Additionally, the presence of exposed soil and leaf litter layer around trees in university parks dense compared to the grassy university parks open site may contribute to increased degradation of BTEX compounds through microbial metabolism. A 2012 study, for example, showed that by adding a mixed bacterial consortium to soil, BTEX compounds were more rapidly degraded (Mukherjee & Bordoloi, 2012).

Biogenic volatiles, particularly terpenes (Table 1 and Figure 2G), were chiefly responsible for the secondary clustering of samples from rainforest house and those of Wytham Woods and Warneford Meadow. In total across all sampling sites, we identified 54 unique terpenes/terpenoids. The rainforest glasshouse contained the highest number of terpenes (38) with considerable spread across the outdoor sampling sites (14 to 23). The presence of these compounds is highly suggestive of multiple and specific health benefits within each location. For example, 10 terpenes/terpenoids were ubiquitous across all sampling sites—compounds that have also been found in air samples elsewhere using similar methods (Bryant et al., 2022; Detournay et al., 2011; Gu et al., 2024; Hakola et al., 2003; Hellén et al., 2024; Jones et al., 2011; Walker et al., 2023). These compounds alone are cited to have anti-inflammatory, anxiolytic, antimicrobial, immune-boosting, antidepressant, anaesthetic, gastroprotective, antioxidant, anti-cancer (in vitro), immune-modulatory, sedative, hypolipidemic, analgesic, decongestant, bronchodilatory, mucolytic and cognitive enhancing effects (Jo et al., 2021; Lee et al., 2022; Oliveira et al., 2024; Salehi et al., 2019; Sun, 2007; Vallianou & Hadzopoulou-Cladaras, 2016; Woo et al., 2019). It could be argued, therefore, that spending time in any of these sites could impart significant health gains. However, the relationships between these compounds and their benefits are likely concentration dependent; therefore, further methodological work is needed to quantify and make precise recommendations such as when, and for how long, to visit specific greenspaces. Previously, it was found that just 20 min is adequate to derive physiological and psychological benefits from time in woodland (Haluza et al., 2025; Park et al., 2010).

Another useful metric to separate our sites is a ratio of biogenic to anthropogenic compounds. An example of this can be found in a study that assessed air over Covid lockdown in 2020 at an urban site in India (Malik et al., 2025) in which a sharp increase in the $\sum\alpha + \text{beta-pinene}/\sum\text{BTEX}$ ratios during the strict lockdown phase was hypothesised to be due to a reduction in traffic-related activity. We mirrored this study and found that, on a particular day, the rainforest house had a significantly higher terpene/BTEX ratio than all the other sites (Figure 2F). This result is likely due to the interplay of two different factors known to affect the volatile makeup of indoor spaces. On the one hand, this glasshouse is plant rich and enclosed and as such likely acts as an enclosure for those bVOCs produced within, and conversely, aVOC ingression may be limited. These results suggest that plant-rich greenhouses may be the most beneficial place to spend time; however, in a 2006–2007 study, aVOCs were found to be significantly higher in indoor sites than outdoor sites in the vicinity of an industrial park (Chang et al., 2019), showing that simply being inside is little protection from external sources of pollution.

4.2 | The impacts of seasonality on bVOC emissions in the botanical gardens

As well as looking at a snapshot of the scentscapes across the six urban greenspaces, we also explored how bVOC change across time and in the face of environmental variation in the Botanical Outdoors location. Using the same classification system for our identified compounds, we counted both compound numbers and summed abundances to visualise each class over time. In terms of the relative abundances, all compound classes peaked during late spring to summer (May to August 2025) with two notable outliers: monoterpenes had an early peak on 27 November 2024, and terpenoids had a late peak on 29 October 2025. Interestingly, in terms of the absolute number of compounds identified, it was early spring (4 March) which showed peaks for aliphatics (42), aromatics (14), terpenoids (10) and others (9), with monoterpene counts being more stable over the year.

Higher temperature and relative humidity were the most consistent positive predictors of biogenic emissions, particularly for terpenes. For temperature, this is likely linked to the well-established positive relationship between emission rates and leaf temperatures via both biosynthesis through increased enzymatic activity and volatilisation vapour pressure (Guenther et al., 1993; Luo et al., 2025). Aliphatics also showed a positive temperature response, likely driven by enhanced volatilisation at higher temperatures but also resistance to biodegradation (Abbasian et al., 2015). In contrast, terpenoids, which are oxygenated terpenes and much more reactive, declined with increasing temperature. This is consistent with their greater susceptibility to photochemical degradation at higher temperatures (Atkinson & Arey, 2003; Hallquist et al., 2009). The role of humidity in terpene/terpenoid presence may be linked to an increase in stomatal opening and subsequent environmental release when relative humidity is higher (Arve & Torre, 2015).

Precipitation effects also differed among VOC classes. Terpene abundances showed a positive association with precipitation. Wetting is known to give a short-term pulse release through mechanical displacement from soil air spaces after rain (Pugliese et al., 2023), and this was likely the reason for the high amount recorded on 27 November 2024, where 8.10 mm of rain was recorded. In contrast, aromatics and aliphatics showed a negative association with precipitation on the day of sampling, consistent with atmospheric dilution, wet deposition or reduced resuspension of background hydrocarbons rather than changes in emission strength (Casas et al., 2021). There was a second rainfall event on 4 September 2025 (9.4 mm); however, this followed 16.3 mm of rain on the previous day, which is likely to have negatively affected soil-based terpene release on the day of sampling. Notably, only two sampling events coincided with measurable rainfall so these patterns need further exploration in urban greenspaces.

Wind speed effects showed significant positive associations for aromatic and aliphatic compounds. Given their relatively long atmospheric lifetimes compared to terpenes and terpenoids (Hellén et al., 2018; Luo et al., 2025), these increases are more likely to reflect regional background concentrations than increases in local emissions. In contrast, terpene emissions showed little sensitivity to wind speed, consistent with their predominantly local, vegetation-derived sources and rapid atmospheric reactivity leading to degradation if produced distantly.

Overall, these results indicate that temperature, precipitation, wind speed and humidity all impact on the detection of different bVOC chemical classes. The absence of a single dominant predictor across all VOC classes highlights the importance of considering scentscapes as multidimensional chemical systems, shaped by interacting biological and meteorological processes. However, this class-specific sensitivity to environmental drivers adds to understanding of when and where urban greenspaces may be most chemically beneficial for human exposure. These results are suggestive that warm, humid and (unfortunately) rainy conditions increase the levels of health-promoting terpene/terpenoid compounds in the air and as such are likely the most beneficial conditions for humans to spend time in urban greenspaces.

4.3 | Methodological advancements, limitations and future work

As well as providing an understanding of urban greenspace scentscapes over time, this study aimed to develop a robust and repeatable protocol for measuring the presence and relative amounts of a wide range of volatiles of interest. Although similar methods have been developed for headspace sampling (de Carvalho Couto et al., 2024; Reyrolle et al., 2024; Yin et al., 2022), air sampling studies have historically employed targeted approaches that significantly limit the number of compounds identified. For instance, previous studies have used between 15 and 66 VOCs across various forest and urban environments (Mula et al., 2024; Pripdeevech et al., 2025; Walker et al., 2023). In contrast, our study adopted an untargeted metabolomics-style approach commonly used in biological matrices to enhance the depth and resolution of VOC profiling (Fernie et al., 2011; Rosenthal et al., 2024; Van den Berg et al., 2006) to identify 245 unique compounds, of which 54 were unique terpenes/terpenoids. This is significantly higher than any studies on ambient air so far published (Mula et al., 2024; Sanaei et al., 2023; Walker et al., 2023). This improved identification capacity is likely attributable to several key enhancements in our analytical pipeline: greater technical replication, the use of a Kováts retention index, a more focused compound library, a slow GC temperature ramp and the use of deconvolution for resolving co-eluting peaks. Furthermore, the tight clustering of technical replicates observed in the PCA (Figure 2A) confirms that our collection methods and downstream processing are sufficiently controlled to ensure analytical reproducibility and minimise technical variability.

Despite these improvements, our analyses capture only a fraction of the chemical complexity present. In most samples, we detect far more chromatographic features than we can confidently identify, and the ~245 compounds reported here represent ~10% (or less) of the total compounds present. This limitation is expected in untargeted

ambient-air GC-MS, where a large proportion of peaks correspond to (i) compounds absent from reference libraries, (ii) compounds lacking retention index (RI) values on comparable stationary phases, (iii) low-abundance or highly reactive species near the detection limit and (iv) co-eluting mixtures that remain partially unresolved even after deconvolution. As a result, our interpretation focuses on the 'identifiable fraction' of the scentscape rather than the full atmospheric mixture. One major benefit of TD work is the ability for the 'recollection' of the split portion of the GC-MS analysis. Future work intends to use this feature to analyse the same samples on multiple GC column types (polar/non-polar)—this will help to resolve significantly more atmospheric compounds.

Identification confidence is a further constraint. We used a minimum net match threshold of 70, which is permissive and may increase the risk of imperfect annotations, particularly for isomeric compounds and low-intensity peaks. Although 99 compounds had a match factor >90, the mean match factor for retained identifications was 86. Therefore, a subset of compounds should be regarded as putative with future work concentrating on targeted confirmation of key marker compounds using standards. Our identifications are strengthened by combining spectral matching with RI matching; however, expanding the RI coverage of our library on DB-5-type phases and continuing to develop an in-house 'Oxford greenspace' standard set would improve annotation rates. Additionally, we did not employ chiral separation in this work, meaning stereoisomers of compounds such as Alpha-pinene (+/−) were not resolved. These may be important for understanding biological source and ecological function and, as such, could be included in future. Finally, to truly overcome co-elution, two-dimensional gas chromatography (GC x GC) could be used to separate overlapping peaks without the need for software-based deconvolution.

Our sampling design also imposes important constraints. First, sampling was conducted within a narrow daytime window (11:00–13:00). As our models show, many bVOCs are affected by environmental changes; therefore, abundance and composition likely differ through the day. Second, we used a fixed sampling duration (2 h) and flow rate (100 ml/min). This equates to just 2 min of human breathing. Longer sampling times or higher sampled volumes would likely increase detection of low-abundance compounds, but at the risk of sorbent saturation, breakthrough of other volatile species and increased influence of meteorology during the sampling window. Third, although technical replication was employed, biological/environmental replication was limited: The 'snapshot' comparison is based on a single calendar date, and the year-long analysis focuses on one site. In both cases, sampling was carried out at a precise location within each site. As such, our site-level inferences should not be interpreted as definitive rankings of whole sites across seasons and years.

Quantification is another limitation. Relative measures are useful for compositional comparisons, but absolute quantification will be essential to translate scentscape metrics into health-relevant exposure estimates. The quantification of compounds such as terpenes will help to support policy-facing recommendations.

Finally, the environmental predictors included here (temperature, humidity, precipitation and wind speed) are only a subset of the drivers that shape ambient VOC fingerprints. A more holistic predictive framework will need to incorporate additional covariates such as (i) local vegetation composition and phenology (biodiversity and functional traits), (ii) microclimate at the sampling point (solar radiation, canopy cover, boundary-layer stability and VPD), (iii) soil moisture and microbial activity, (iv) episodic disturbances (mowing, leaf litter pulses and pest/pathogen outbreaks) and (v) urban pollution context (traffic intensity, background NOx/O and atmospheric oxidation capacity). Incorporating these variables—alongside expanded temporal coverage, multi-year replication and partial targeted quantification—will be necessary to move from descriptive classification of scentscapes to robust prediction of when and where greenspaces maximise health-relevant exposures.

AUTHOR CONTRIBUTIONS

William Kay was responsible for methods development, data collection and all data analyses. William Kay and Anya Lindstrom Battle were both involved in the writing and editing of the manuscript. Kathy Willis conceived of the initial ideas and methodologies and was also involved in the writing and editing of the manuscript. Mahal Humberstone, Molly Tucker and Kieran Storer all contributed to in-field sample collection. Geoffrey Kite was involved in the GC-MS data collection, as well as providing useful guidance. All authors contributed critically to the drafts and gave final approval for publication.

ACKNOWLEDGEMENTS

We would first like to thank the University of Oxford Botanic Garden and Wytham Woods for permission to sample on their sites. We would also like to thank Dr. Ben Martin who provided helpful advice for sampling and analysis as well as the development of early sampling methodologies and Dr. Luciana Carvalho who always had time to share thoughts and ideas relating to the project. In addition, we thank Dr. Pedro Bota for his generosity of time, availability and equipment. Finally, we thank all members of the Oxford long-term ecology lab for their ongoing feedback.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Raw AGILENT files are available online (https://doi.org/10.5281/zenodo.18493789).

ORCID

William T. Kay https://orcid.org/0000-0002-2561-4856

REFERENCES

Abbasian, F., Lockington, R., Mallavarapu, M., & Naidu, R. (2015). A comprehensive review of aliphatic hydrocarbon biodegradation by bacteria. *Applied Biochemistry and Biotechnology*, *176*, 670–699. https://doi.org/10.1007/s12010-015-1603-5

Arve, L. E., & Torre, S. (2015). Ethylene is involved in high air humidity promoted stomatal opening of tomato (*Lycopersicon esculentum*) leaves. *Functional Plant Biology*, *42*, 376–386. https://doi.org/10.1071/fp14247

Atkinson, R., & Arey, J. (2003). Atmospheric degradation of volatile organic compounds. *Chemical Reviews*, *103*, 4605–4638. https://doi.org/10.1021/cr0206420

Bratman, G. N., Daily, G. C., Levy, B. J., & Gross, J. J. (2015). The benefits of nature experience: Improved affect and cognition. *Landscape and Urban Planning*, *138*, 41–50. https://doi.org/10.1016/j.landurbplan.2015.02.005

Bryant, D. J., Nelson, B. S., Swift, S. J., Budisulistiorini, S. H., Drysdale, W. S., Vaughan, A. R., Newland, M. J., Hopkins, J. R., Cash, J. M., & Langford, B. (2022). Biogenic and anthropogenic sources of isoprene and monoterpenes and their secondary organic aerosol in Delhi, India. *Atmospheric Chemistry and Physics Discussions*, *2022*, 1–35. https://doi.org/10.1016/j.apr.2019.07.004

Casas, G., Martinez-Varela, A., Vila-Costa, M., Jiménez, B., & Dachs, J. (2021). Rain amplification of persistent organic pollutants. *Environmental Science & Technology*, *55*, 12961–12972. https://doi.org/10.1021/acs.est.1c03295

Chang, C.-C., & Lin, C.-J. (2011). LIBSVM: A library for support vector machines. *ACM Transactions on Intelligent Systems and Technology*, *2*, 1–27. https://doi.org/10.1145/1961189.1961199

Chang, T.-Y., Liu, C.-L., Huang, K.-H., & Kuo, H.-W. (2019). Indoor and outdoor exposure to volatile organic compounds and health risk assessment in residents living near an optoelectronics industrial park. *Atmosphere*, *10*, 380. https://doi.org/10.3390/atmos10070380

de Carvalho Couto, C., Chávez, D. W. H., Oliveira, E. M. M., Freitas-Silva, O., & Casal, S. (2024). SPME-GC-MS untargeted metabolomics approach to identify potential volatile compounds as markers for fraud detection in roasted and ground coffee. *Food Chemistry*, *446*, 138862. https://doi.org/10.1016/j.foodchem.2024.138862

Degtyarenko, K., de Matos, P., Ennis, M., Hastings, J., Zbinden, M., McNaught, A., Alcántara, R., Darsow, M., Guedj, M., & Ashburner, M. (2007). ChEBI: A database and ontology for chemical entities of biological interest. *Nucleic Acids Research*, *36*, D344–D350. https://doi.org/10.1093/nar/gkm791

Detournay, A., Sauvage, S., Locoge, N., Gaudion, V., Leonardis, T., Fronval, I., Kaluzny, P., & Galloo, J.-C. (2011). Development of a sampling method for the simultaneous monitoring of straight-chain alkanes, straight-chain saturated carbonyl compounds and monoterpenes in remote areas. *Journal of Environmental Monitoring*, *13*, 983–990. https://doi.org/10.1039/c0em00354a

Fernie, A. R., Aharoni, A., Willmitzer, L., Stitt, M., Tohge, T., Kopka, J., Carroll, A. J., Saito, K., Fraser, P. D., & DeLuca, V. (2011). Recommendations for reporting metabolite data. *The Plant Cell*, *23*, 2477–2482. https://doi.org/10.1105/tpc.111.086272

Gao, X., Wang, Y., Wu, L., Zheng, F., Sun, N., Liu, G., Liu, Y., Meng, P., Sun, L., & Jing, B. (2023). The impact of anthropogenic VOC emissions on atmospheric pollution: A case study of a typical industrialized area in China. *Atmosphere*, *14*, 1586. https://doi.org/10.3390/atmos14101586

Gómez-Moreno, F. J., Artíñano, B., Ramiro, E. D., Barreiro, M., Núñez, L., Coz, E., Dimitroulopoulou, C., Vardoulakis, S., Yagüe, C., Maqueda, G., Sastre, M., Román-Cascón, C., Santamaría, J. M., & Borge, R. (2019). Urban vegetation and particle air pollution: Experimental campaigns in a traffic hotspot. *Environmental Pollution*, *247*, 195–205. https://doi.org/10.1016/j.envpol.2019.01.016

GOV.UK. (2023). Road traffic statistics—Local authority Oxfordshire. Edited by Department for Transport. roadtraffic.dft.gov.uk: GOV.UK. Retrieved 2025-04-01, from, https://roadtraffic.dft.gov.uk/local-authorities

Gu, S., Luo, W., Charmchi, A., McWhirter, K. J., Rosenstiel, T., Pankow, J., & Faiola, C. L. (2024). Limonene enantiomeric ratios from anthropogenic and biogenic emission sources. *Environmental Science & Technology Letters*, *11*, 130–135. https://doi.org/10.1021/acs.estlett.3c00794

Guenther, A. B., Zimmerman, P. R., Harley, P. C., Monson, R. K., & Fall, R. (1993). Isoprene and monoterpene emission rate variability: Model evaluations and sensitivity analyses. *Journal of Geophysical Research: Atmospheres*, *98*, 12609–12617. https://doi.org/10.1029/93JD00527

Guenther, A., Jiang, X., Heald, C. L., Sakulyanontvittaya, T., Duhl, T. a., Emmons, L., & Wang, X. (2012). The model of emissions of gases and aerosols from nature version 2.1 (MEGAN2. 1): An extended and updated framework for modeling biogenic emissions. *Geoscientific Model Development*, *5*, 1471–1492. https://doi.org/10.5194/gmd-5-1471-2012

Hakola, H., Tarvainen, V., Laurila, T., Hiltunen, V., Hellén, H., & Keronen, P. (2003). Seasonal variation of VOC concentrations above a boreal coniferous forest. *Atmospheric Environment*, *37*, 1623–1634. https://doi.org/10.1016/S1352-2310(03)00014-1

Hallquist, M., Wenger, J. C., Baltensperger, U., Rudich, Y., Simpson, D., Claeys, M., Dommen, J., Donahue, N. M., George, C., Goldstein, A. H., Hamilton, J. F., Herrmann, H., Hoffmann, T., Iinuma, Y., Jang, M., Jenkin, M. E., Jimenez, J. L., Kiendler-Scharr, A., Maenhaut, W., … Wildt, J. (2009). The formation, properties and impact of secondary organic aerosol: Current and emerging issues. *Atmospheric Chemistry and Physics*, *9*, 5155–5236. https://doi.org/10.5194/acp-9-5155-2009

Haluza, D., Kersten, P., Lazic, T., Steinparzer, M., & Godbold, D. (2025). Unlocking the power of nature: Insights from a 20-minute forest visit on well-being. *Forests*, *16*, 792. https://doi.org/10.3390/f16050792

Hellén, H., Praplan, A. P., Tykkä, T., Ylivinkka, I., Vakkari, V., Bäck, J., Petäjä, T., Kulmala, M., & Hakola, H. (2018). Long-term measurements of volatile organic compounds highlight the importance of sesquiterpenes for the atmospheric chemistry of a boreal forest. *Atmospheric Chemistry and Physics*, *18*, 13839–13863. https://doi.org/10.5194/acp-18-13839-2018

Hellén, H., Tykkä, T., Schallhart, S., Stratigou, E., Salameh, T., & Iturrate-Garcia, M. (2024). Measurements of atmospheric C 10–C 15 biogenic volatile organic compounds (BVOCs) with sorbent tubes. *Atmospheric Measurement Techniques*, *17*, 315–333. https://doi.org/10.5194/amt-17-315-2024

Hoque, R. R., Khillare, P., Agarwal, T., Shridhar, V., & Balachandran, S. (2008). Spatial and temporal variation of BTEX in the urban atmosphere of Delhi, India. *Science of the Total Environment*, *392*, 30–40. https://doi.org/10.1016/j.scitotenv.2007.08.036

Jo, H., Cha, B., Kim, H., Brito, S., Kwak, B. M., Kim, S. T., Bin, B.-H., & Lee, M.-G. (2021). A-pinene enhances the anticancer activity of natural killer cells via ERK/AKT pathway. *International Journal of Molecular Sciences*, *22*, 656. https://doi.org/10.3390/ijms22020656

Jones, C. E., Hopkins, J., & Lewis, A. (2011). In situ measurements of isoprene and monoterpenes within a south-east Asian tropical rainforest. *Atmospheric Chemistry and Physics*, *11*, 6971–6984. https://doi.org/10.5194/acp-11-6971-2011

Joo, Y., Schuman, M. C., Goldberg, J. K., Kim, S. G., Yon, F., Brütting, C., & Baldwin, I. T. (2018). Herbivore-induced volatile blends with both "fast" and "slow" components provide robust indirect defence in nature. *Functional Ecology*, *32*, 136–149. https://doi.org/10.1111/1365-2435.12947

Kassambara, A., & Mundt, F. (2017). Package 'factoextra'. In Extract and visualize the results of multivariate data analyses, 10.18637. Retrieved 2025-04-01, from https://rpkgs.datanovia.com/factoextra/

Kovats, v. E. (1958). Gas-chromatographische charakterisierung organischer verbindungen. Teil 1: Retentionsindices aliphatischer halogenide, alkohole, aldehyde und ketone. *Helvetica Chimica Acta*, *41*, 1915–1932. https://doi.org/10.1002/hlca.19580410703

Lê, S., Josse, J., & Husson, F. (2008). Factominer: An R package for multivariate analysis. *Journal of Statistical Software*, *25*, 1–18. https://doi.org/10.18637/jss.v025.i01

Lee, S. H., Kim, D. S., Park, S. H., & Park, H. (2022). Phytochemistry and applications of *Cinnamomum camphora* essential oils. *Molecules*, *27*, 2695. https://doi.org/10.3390/molecules27092695

Legendre, P., & Legendre, L. (2012). *Numerical ecology*. Elsevier.

Li, Q. (2010). Effect of forest bathing trips on human immune function. *Environmental Health and Preventive Medicine*, *15*, 9–17. https://doi.org/10.1007/s12199-008-0068-3

Li, T., Baggesen, N., Seco, R., & Rinnan, R. (2023). Seasonal and diel patterns of biogenic volatile organic compound fluxes in a subarctic tundra. *Atmospheric Environment*, *292*, 119430. https://doi.org/10.1016/j.atmosenv.2022.119430

Luo, R., Lun, X., Gao, R., Wang, L., Yang, Y., Su, X., Habibullah-Al-Mamun, M., Xu, X., Li, H., & Li, J. (2025). A review of biogenic volatile organic compounds from plants: Research progress and future prospects. *Toxics*, *13*, 364. https://doi.org/10.3390/toxics13050364

Malik, T. G., Gupta, M., Tripathi, N., & Sahu, L. K. (2025). Change in monoterpene concentrations during winter-to-summer transition period and impact of COVID-19 lockdown at an urban site in India. *Atmospheric Environment*, *350*, 121141. https://doi.org/10.1016/j.atmosenv.2025.121141

Mu, Z., Asensio, D., Llusia, J., Filella, I., Ogaya, R., Yi, Z., & Penuelas, J. (2022). Annual and seasonal variations in soil volatile organic compound concentrations in a Mediterranean shrubland and holm oak forest. *Geoderma*, *405*, 115401. https://doi.org/10.1016/j.geoderma.2021.115401

Mukherjee, A. K., & Bordoloi, N. K. (2012). Biodegradation of benzene, toluene, and xylene (BTX) in liquid culture and in soil by *Bacillus subtilis* and *Pseudomonas aeruginosa* strains and a formulated bacterial consortium. *Environmental Science and Pollution Research*, *19*, 3380–3388. https://doi.org/10.1007/s11356-012-0862-8

Mula, V., Bogdanov, J., Stanoeva, J. P., Zeneli, L., & Zdravkovski, Z. (2024). Monitoring volatile organic compounds in air using passive sampling: Regional cross-border study between N. Macedonia and Kosovo. *Aerosol and Air Quality Research*, *24*, 230170. https://doi.org/10.4209/aaqr.230170

Oksanen, J. (2015). Vegan: Community ecology package. In *R package version*, 3. Retrieved 2025-04-01, from https://www.researchgate.net/publication/313502495_Vegan_Community_Ecology_Package

Oliveira, C. D., Cardoso, M. d. G., Batista, L. R., Alves, E., Rosa, M. B. P., Ferreira, V. R. F., de Souza, L., Pineda, M., Fernandes, A. I., & Nelson, D. L. (2024). The antibacterial, antioxidant, and insecticidal activities of essential oils from *Thymus vulgaris* L., *Salvia officinalis* L., and *Ocimum basilicum* L. *Journal of Food Safety*, *44*, e13145. https://doi.org/10.1111/jfs.13145

Park, B. J., Tsunetsugu, Y., Kasetani, T., Kagawa, T., & Miyazaki, Y. (2010). The physiological effects of Shinrin-yoku (taking in the forest atmosphere or forest bathing): Evidence from field experiments in 24 forests across Japan. *Environmental Health and Preventive Medicine*, *15*, 18–26. https://doi.org/10.1007/s12199-009-0086-9

Pripdeevech, P., Janta, R., Sripahco, T., Meesang, W., Aiyathiti, C., Prabamroong, T., Mahatheeranont, S., Poshyachinda, S., Pongpiachan, S., & Khruengsai, S. (2025). Seasonal volatile organic compound dynamics in urban and forest environments in Thailand: Implications for air quality and secondary pollutants. *Environmental Pollution*, *367*, 125565. https://doi.org/10.1016/j.envpol.2024.125565

Pugliese, G., Ingrisch, J., Meredith, L. K., Pfannerstill, E. Y., Klüpfel, T., Meeran, K., Byron, J., Purser, G., Gil-Loaiza, J., & van Haren, J. (2023). Effects of drought and recovery on soil volatile organic compound fluxes in an experimental rainforest. *Nature Communications*, *14*, 5064. https://doi.org/10.1038/s41467-023-40661-8

Reyrolle, M., Desauziers, V., Pigot, T., Gautier, L., & le Bechec, M. (2024). Comparison of untargeted and markers analysis of volatile organic compounds with SIFT-MS and SPME-GC-MS to assess tea traceability. *Food*, *13*, 3996. https://doi.org/10.3390/foods13243996

Rohart, F., Gautier, B., Singh, A., & Lê Cao, K.-A. (2017). mixOmics: An R package for 'omics feature selection and multiple data integration. *PLoS Computational Biology*, *13*, e1005752. https://doi.org/10.1371/journal.pcbi.1005752

Rosenthal, K., Lindley, M., Turner, M., Ratcliffe, E., & Hunsicker, E. (2024). Current data processing methods and reporting standards for untargeted analysis of volatile organic compounds using direct mass spectrometry: A systematic review. *Metabolomics*, *20*, 42. https://doi.org/10.1007/s11306-024-02104-3

Salehi, B., Upadhyay, S., Erdogan Orhan, I., Kumar Jugran, A., Jayaweera, S. L. D., Dias, D. A., Sharopov, F., Taheri, Y., Martins, N., & Baghalpour, N. (2019). Therapeutic potential of α-and β-pinene: A miracle gift of nature. *Biomolecules*, *9*, 738. https://doi.org/10.3390/biom9110738

Sanaei, A., Herrmann, H., Alshaabi, L., Beck, J., Ferlian, O., Fomba, K. W., Haferkorn, S., van Pinxteren, M., Quaas, J., & Quosh, J. (2023). Changes in biodiversity impact atmospheric chemistry and climate through plant volatiles and particles. *Communications Earth & Environment*, *4*, 445. https://doi.org/10.1038/s43247-023-01113-9

Sun, J. (2007). D-limonene: Safety and clinical applications. In Alternative Medicine Review, 259. Retrieved 2025-04-01, from https://scispace.com/pdf/d-limonene-safety-and-clinical-applications-h7olkx6n2e.pdf

Upmanis, H., Eliasson, I., & Andersson-Sköld, Y. (2001). Case studies of the spatial variation of benzene and toluene concentrations in parks and adjacent built-up areas. *Water, Air, and Soil Pollution*, *129*, 61–81. https://doi.org/10.1023/A:1010357914047

Vallianou, I., & Hadzopoulou-Cladaras, M. (2016). Camphene, a plant derived monoterpene, exerts its hypolipidemic action by affecting SREBP-1 and MTP expression. *PLoS ONE*, *11*, e0147117. https://doi.org/10.1371/journal.pone.0147117

Van den Berg, R. A., Hoefsloot, H. C., Westerhuis, J. A., Smilde, A. K., & Van der Werf, M. J. (2006). Centering, scaling, and transformations: Improving the biological information content of metabolomics data. *BMC Genomics*, *7*, 1–15. https://doi.org/10.1186/1471-2164-7-142

Walker, H., Jena, A., McEwan, K., Evans, G., & Campbell, S. (2023). Natural volatile organic compounds (NVOCs) are greater and more diverse in UK forests compared with a public garden. *Forests*, *14*, 92. https://doi.org/10.3390/f14010092

Wang, L., Lun, X., Wang, Q., & Wu, J. (2024). Biogenic volatile organic compounds emissions, atmospheric chemistry, and environmental implications: A review. *Environmental Chemistry Letters*, *22*, 3033–3058. https://doi.org/10.1007/s10311-024-01785-5

Weisskopf, L., Schulz, S., & Garbeva, P. (2021). Microbial volatile organic compounds in intra-kingdom and inter-kingdom interactions. *Nature Reviews Microbiology*, *19*, 391–404. https://doi.org/10.1038/s41579-020-00508-1

Wickham, H. (2011). ggplot2. *Wiley Interdisciplinary Reviews: Computational Statistics*, *3*, 180–185. https://doi.org/10.1002/wics.147

Woo, J., Yang, H., Yoon, M., Gadhe, C. G., Pae, A. N., Cho, S., & Lee, C. J. (2019). 3-Carene, a Phytoncide from pine tree has a sleep-enhancing effect by targeting the GABA (A-)benzodiazepine receptors. *Experimental Neurobiology*, *28*, 593–601. https://doi.org/10.5607/en.2019.28.5.593

Yang, K., Llusià, J., Preece, C., Ogaya, R., Tur, L. M., Mu, Z., You, C., Xu, Z., Tan, Y., & Peñuelas, J. (2024). Impacts of seasonality, drought, nitrogen fertilization, and litter on soil fluxes of biogenic volatile organic compounds in a Mediterranean forest. *Science of the Total Environment*, *906*, 167354. https://doi.org/10.1016/j.scitotenv.2023.167354

Yin, X.-L., Fu, W.-J., Chen, Y., Zhou, R.-F., Sun, W., Ding, B., Peng, X.-T., & Gu, H.-W. (2022). GC-MS-based untargeted metabolomics reveals the key volatile organic compounds for discriminating grades of Yichang big-leaf green tea. *LWT*, *171*, 114148. https://doi.org/10.1016/j.lwt.2022.114148

Zeng, W., Liu, H., Hou, S., Qiu, X., Chen, X., Liu, M., Wu, D., & Liu, L. (2022). Explore the benefits of natural air: New insights from field and chamber tests on cognitive performance. *Atmosphere*, *13*, 1006. https://doi.org/10.3390/atmos13071006

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Kay, W. T., Battle, A. L., Humberstone, M., Tucker, M., Storer, K. E., Kite, G., & Willis, K. (2026). A walk in the park—Identifying healthy greenspaces using scents. *Plants, People, Planet*, 1–14. https://doi.org/10.1002/ppp3.70191