

Article

GC-IMS Assessment of Odor Fingerprints and Scrubber Efficiency in a Multi-Floor Swine Building

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Abstract

Intensive swine production has elevated concerns regarding malodorous emissions, whose high complexity poses substantial challenges for deodorization assessment. This study conducted a multidimensional evaluation of a dual-stage scrubbing system in a multi-floor swine facility using gas chromatography–ion mobility spectrometry (GC-IMS). By establishing volatile compound fingerprints, we quantified the shifts in 29 individual constituents before and after treatment. The GC-IMS results were further validated through comparative analysis with infrared photoacoustic spectroscopy (PAS) and sensory olfactometry. Results from multivariate statistical analysis (PCA) successfully differentiated the removal efficiencies of various components. Notably, GC-IMS revealed an apparent increase in the signal intensities of certain compounds, which might be overlooked by traditional analytical methods. While NH₃ removal efficiency measured by GC-IMS (79.86% with semi-quantitative analysis) was in high agreement with PAS results (77.89%), sensory olfactometry showed a non-significant reduction ($p = 0.1571$). Although GC-IMS provides a rapid platform for screening volatile compounds and tracking dynamic shifts during the deodorization process, detecting certain key swine malodor components requires further optimization. Ultimately, future methodological integration of GC-IMS, GC-MS, and olfactometry is essential to establish a field-validated evaluation framework for swine odor monitoring and deodorization efficiency assessment.

Keywords: multi-floor swine building; volatile compounds; GC-IMS; dual-stage scrubbing; air purification



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1. Introduction

Over the past decade, the swine industry has undergone rapid intensification and scaling, characterized significantly by the emergence and widespread adoption of multi-floor swine production facilities. Compared to conventional single-floor systems, multi-floor swine buildings significantly increase the livestock stocking density per unit of land area. As a result, odor emissions are highly concentrated and typically discharged from centralized exhaust systems on the rooftop. This high concentration of emissions means that

any inefficiency or failure in the deodorization systems can rapidly lead to severe localized odor pollution incidents and subsequent environmental complaints from surrounding communities. Furthermore, the increased height of these structures substantially extends the dispersion range of airborne contaminants. For instance, Xin et al. (2023) demonstrated through dispersion modeling that under specific meteorological conditions (wind direction of 67.5° and speed of 2 m/s), NH₃ emissions with a source concentration of 20 ppm from a multi-floor facility could reach a dispersion distance of 1380 m [1]. This rapid expansion of intensive swine production, coupled with the extended footprint of its emissions, has brought the critical issue of odor pollution into sharp focus. Ineffective odor mitigation often leads to public complaints and environmental non-compliance, making efficient odor management a critical factor for the sustainable development of the swine industry. Extensive research has demonstrated that malodorous gases emitted from livestock farms exert adverse effects on human health. Malodors generated during swine production have been associated with acute increases in blood pressure, potentially contributing to the development of chronic hypertension [2]. The cancer risks associated with ethylbenzene, benzene, and p-cresol emissions from swine barns exceeded the EPA's benchmark of one per million [3]. Air pollution from livestock farms is associated with lung function deficits even among residents living in the vicinity who are not involved in farming [4]. Nie et al. (2020) analyzed gas emissions from swine farms and found that cumulative carcinogenic risks in certain areas exceeded the acceptable thresholds [5]. Establishing a reliable, high-resolution monitoring framework is therefore imperative to balance industrial growth with environmental stewardship.

To achieve effective monitoring, various analytical approaches have been developed. Swine house emissions contain a wide variety of odorous compounds with concentrations spanning several orders of magnitude [5,6], which poses a significant challenge for their comprehensive analysis. Common methods for assessing swine farm odors include sensory olfactometry, chemical analysis, portable detectors, electronic noses (E-noses), and spectroscopic techniques. Sensory olfactometry directly reflects human subjective perception and serves as the benchmark for regulatory enforcement and standard-setting. However, it requires a panel of trained assessors, making it labor-intensive, costly, and susceptible to the physiological and psychological states of the individuals. Among chemical analysis methods, gas chromatography–mass spectrometry (GC-MS) is widely employed for the precise identification of complex volatile compounds (VCs). More recently, advanced proton transfer reaction–mass spectrometry (PTR-MS) has enabled online measurements with high temporal resolution [7]. Nevertheless, its widespread application is constrained by high instrumental costs and the requirement for specialized operational expertise. Portable instruments, primarily based on gas sensors, offer low cost and ease of operation but suffer from limited precision and an inability to resolve complex odor mixtures [8]. E-nose technology utilizes non-selective sensor arrays combined with pattern recognition algorithms to distinguish odors [9], yet it requires frequent calibration and lacks quantitative accuracy. While spectroscopic techniques provide high selectivity and rapid response, they are often limited to a narrow suite of detectable gas species, failing to capture the full odor fingerprint of intensive farming.

Gas chromatography–ion mobility spectrometry (GC-IMS), an emerging technique for gas component analysis, has been widely adopted for the flavor profiling of food products. It integrates the high separation efficiency of gas chromatography with the high sensitivity of ion mobility spectrometry, enabling rapid analysis of VCs. The technique exhibits exceptional analytical sensitivity, enabling the quantification of trace-level VCs at parts-per-billion (ppb) concentrations with high precision and accuracy [10]. Gas samples can be analyzed directly without any special pre-treatment, and the resulting spectra provide

intuitive visualization of the data, allowing rapid characterization of odor profiles [11]. However, compared to standard GC-MS, GC-IMS possesses certain limitations. It is predominantly effective for highly volatile, low-molecular-weight gases and exhibits lower efficiency for larger, high-boiling-point molecules. Furthermore, because GC-IMS relies on retention and drift times rather than mass spectral fragmentation patterns, its identification confidence for unknown compounds is relatively lower. It also carries more stringent calibration requirements and a narrower linear range, as high analyte concentrations can easily lead to ion source saturation. Reports on the application of GC-IMS for the detection and assessment of swine house odors remain scarce. Given that swine emissions are characterized by volatile fatty acids and reduced sulfur compounds [12–14], GC-IMS holds great promise as a highly sensitive and efficient tool for odor monitoring and evaluation.

To mitigate swine house odor emissions, various odor reduction technologies have been developed, primarily categorized into physical methods (e.g., activated carbon and dilution diffusion), biological systems (e.g., biofiltration, biotrickling, and bioscrubbing), and chemical or physicochemical processes (e.g., plant extract spraying, wet scrubbing, combustion, non-thermal plasma, and photocatalytic oxidation) [15]. While physical adsorption suffers from high replacement costs and biofilters have a large footprint and intensive maintenance requirements, chemical scrubbing offers an efficient and compact alternative for high-volume exhaust treatment. Recently, multi-stage or dual-stage chemical scrubbing processes have emerged as highly promising configurations [12,16]. By combining sequential washing stages with different scrubbing agents (such as acid-alkali or oxidant combinations), dual-stage systems can simultaneously capture diverse chemical classes of VCs [16], overcoming the limitations of single-stage systems that target only specific odorants. However, a comprehensive, molecular-level evaluation of dynamic VC profiles across such dual-stage processes remains limited.

The primary objective of this study lies in an exploratory evaluation of using GC-IMS for the rapid profiling of volatile compounds emitted from multi-floor swine buildings and tracking their short-term removal efficiencies by a dual-stage scrubbing system. Crucially, to cross-validate the feasibility and reliability of this analytical approach, the GC-IMS findings were systematically compared against conventional photoacoustic spectroscopy (PAS) and sensory olfactometry. Finally, by analyzing the removal trends of specific odor components, this work aims to provide preliminary directional insights for optimizing deodorization equipment. Overall, this study serves as a methodological exploration to establish a highly responsive and accessible tool for volatile odor screening and abatement performance tracking.

2. Materials and Methods

2.1. Experimental Swine House and Deodorizing Device

The experiment was conducted in a multi-floor swine building located in the suburban area of Zhengzhou, Henan Province, China (34°30' N, 114°04' E), on 29 May 2025. The swine building selected for the study was a six-story, fully enclosed building with an annual output of 200,000 finishing pigs, maintaining a live inventory of approximately 80,000 heads during the experimental period. The dimensions of the building were 240 m in length, 93.58 m in width, and 24 m in height. Each floor was partitioned into distinct independent units to accommodate piglets, sows, growers, and finishers, with stocking densities ranging from 0.67 to 4.0 heads/m² depending on the specific growth stage. The manure management utilized a deep-pit system with concrete slats. The slurry depth within the pits was strictly maintained at approximately 0.1 m and automatically discharged once exceeding this threshold, ensuring a maximum manure residence time of less than two weeks. For environmental control, a ducted mechanical ventilation system was implemented on each

floor, with the ventilation rate dynamically regulated based on indoor temperatures to maintain optimal temperature and humidity. The exhaust air from all floors was collected and directed by rooftop fans into the centralized deodorization scrubbing system. Additionally, animal nutrition was managed via an automated feeding regime throughout the study. The gases emitted from the building were treated by a water-scrubbing system. Figure 1 shows the deodorization process. The scrubbing system consisted of two sequential stages, both utilizing porous plastic spheres as packing media with continuous water irrigation. Sulfuric acid and sodium hypochlorite were metered into the recirculating liquids of Stage 1 and Stage 2, respectively. Specifically, Stage 1 was designed to capture particulate matter and neutralize NH_3 , while Stage 2 functioned as an oxidative stage, employing sodium hypochlorite to degrade organic odorous components. The circulating reservoirs were integrated with online sensors for real-time monitoring of pH and active chlorine concentration. An automated feedback dosing system was employed to precisely supplement concentrated sulfuric acid or sodium hypochlorite whenever the parameters deviated from the preset thresholds. This control mechanism ensured that the scrubbing solutions maintained a consistent chemical composition throughout the experimental period. During the first stage, the pH of the sulfuric acid scrubbing solution was maintained within the range of 3.0–4.0, with an actual average pH of 3.8 recorded during sampling. In the subsequent second stage, the active chlorine concentration in the circulation tank was regulated between 3.0 and 10.0 mg/L to ensure consistent oxidative performance, maintaining an actual mean concentration of 8.0 mg/L throughout the sampling process. The ventilation rate through the filter media fluctuated with the changes in the barn environment, and the average air velocity through the filter media was approximately 1 m/s. The residence time of the gas in the filter media was less than 1 s.

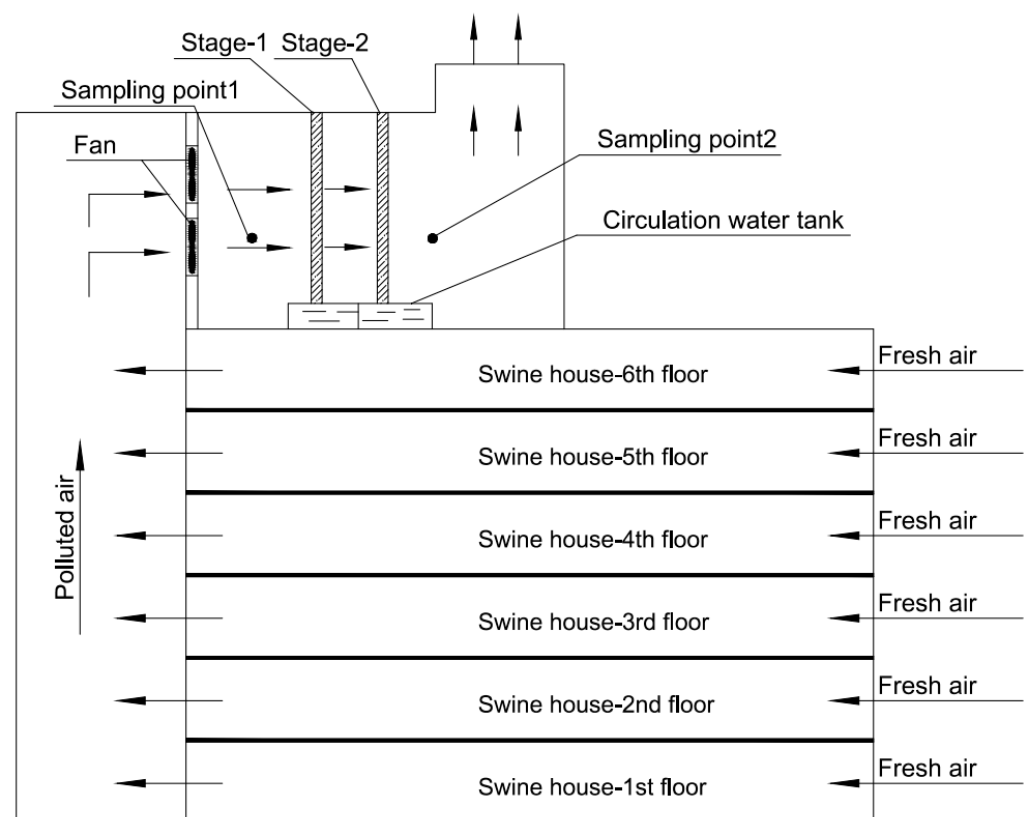


Figure 1. Schematic diagram of the deodorization process.

2.2. Sample Collection and Analytical Method

2.2.1. Sampling Strategy and Site Description

Gas sampling before and after the deodorization treatment was strictly synchronized using vacuum sampling boxes with dimensions of 0.50 m × 0.37 m × 0.29 m (L × W × H), which were connected to vacuum pumps (Model LGZ1-5G; flow rate: 5 L/min; Beijing Jinjian Xinhua Biotechnology Co., Ltd., Beijing, China). At each sampling interval, two researchers collected the pre- and post-treatment gas samples simultaneously, completing a total of 6 paired sampling rounds (6 pre-treatment and 6 post-treatment samples). The samples were stored in 10 L odorless polyester gas bags. Gas sampling for sensory olfactometry was strictly conducted in accordance with the Technical Specifications for Environmental Monitoring of Odor Pollution (HJ 905-2017) [17]. For organized emission sources (the dual-stage scrubber outlet and swine building exhaust), the protocol mandates a minimum of three replicate samples to capture representative malodorous profiles. Sampling points are illustrated in Figure 1. Each sample was collected in at least six replicates from 1 m above the floor. All sampling components were made of inert materials to minimize VC adsorption. The sampling campaign was conducted from 10:00 to 20:00. Samples were collected at discrete intervals to ensure temporal representativeness and to capture potential diurnal fluctuations in gas emissions during the operational cycle. During the sampling period, the mean ambient temperature and relative humidity were 23.8 ± 2.5 °C and $80.3 \pm 0.9\%$, respectively. These meteorological parameters were monitored using a portable temperature and humidity meter (Model MJ-1360A, Juchuang Group Co., Ltd., Qingdao, China) positioned adjacent to the scrubbing system. Following collection, the gas samples were immediately transported to the laboratory and analyzed within 24 h to ensure the integrity of the VCs and minimize potential degradation.

2.2.2. Odor and NH₃ Analysis

The odor concentration was determined according to the Chinese National Standard HJ 1262-2022 [18], utilizing the static triangle odor bag method (ambient air and waste gas—determination of odor). Sensory olfactometry was performed by a panel of four trained assessors (aged 19–21 years) with no history of olfactory dysfunction. Panel selection and calibration were conducted using five standard reference odorants: methyl cyclopentenolone, β -phenylethyl alcohol, γ -undecalactone, β -methylindole, and isovairic acid. Prior to formal evaluation, preliminary dilution screening established an initial dilution range of 100 to 5000-fold. Samples were then systematically evaluated using a step-by-step ascending dilution series. At each step, the diluted sample gas was randomly injected via a borosilicate glass syringe into one of three odor bags (labeled A, B, and C) filled with odorless air, while the other two bags served as blanks (the triangular odor bag method). This procedure was repeated four times, and the sets were randomly assigned to the four assessors to record correct identifications and determine individual odor thresholds. Robust quality control was maintained through independent duplicate sessions for each sample. A *t*-test at a 95% confidence interval was applied to compare the individual threshold datasets between the two duplicate runs. If no significant difference was detected ($p > 0.05$), the session concluded, and the two datasets were utilized to calculate the final odor concentration. If a significant difference was observed ($p \leq 0.05$), a third supplementary session was conducted. Additionally, an experimental termination criterion was enforced: a testing session was terminated when all four assessors had recorded a false identification at a given dilution level. Assuming the mean individual odor threshold for a sample is X , the final odor concentration was calculated and expressed as 10^X . NH₃ concentration was measured via PAS using a gas monitor (Table 1). Prior to the experiments, the sensor was calibrated using a certified standard gas (15.5 ppm NH₃,

N₂ balance) and ultra-high-purity nitrogen (99.9999%) supplied by Taineng Gas Co., Ltd., Taiyuan, China. The monitor system demonstrated a measurement repeatability of 1% and a zero-point stability of $\pm 0.25\%$. Notably, the limit of detection was established at 0.2 ppm, providing the necessary sensitivity to accurately evaluate the removal efficiency of the dual-stage scrubbing system.

Table 1. Specifications of the primary monitoring instruments.

Instrument	Target Analytes	Detection Limits	Accuracy	Sensitivity	Manufacturer
Innova 1512	NH ₃	0.2 ppm	Zero drift: $\pm 0.25\%$	Acoustic sensitivity: not influenced by external sound Vibration sensitivity: strong vibrations @ 20 Hz can affect the detection limit	LumaSense Technologies, Inc., Ballerup, Denmark
GC-IMS	Volatile compounds	Low ppb to ppt range	Relative error is controlled within $\pm 20\%$	The absolute sensitivity depends heavily on the chemical class and the specific proton affinity of each volatile compound.	G.A.S., Dortmund, Germany

2.2.3. VC Analysis

The detection of VCs was performed using a GC-IMS instrument (Table 1). During the fieldwork, real-time monitoring via photoacoustic spectroscopy (PAS) indicated that the post-treatment gas concentration profiles remained highly stable and uniform. Therefore, to optimize instrument runtime while ensuring statistical validity, 3 post-treatment samples (A1, A2 and A3) were randomly selected from the 6 collected rounds for subsequent laboratory GC-IMS injection and compared against the 6 pre-treatment counterparts (B1–B6). Specifically, these 3 post-treatment replicates were selected via a rigorous drawing-lots system, wherein all sample bags were first assigned anonymous codes, and three individual codes were blindly drawn from a sealed container prior to the GC-IMS analysis. The sampling bag containing the collected gas was connected to the sample inlet of the GC-IMS for analysis. For the chromatographic separation, a column was operated isothermally at 80 °C using ultra-high-purity helium ($\geq 99.999\%$) as the carrier gas. The carrier gas flow was programmed with a ramped profile: an initial flow of 5.00 mL/min (held for 2 min), followed by a linear increase to 100.00 mL/min over 10 min, and finally maintained for 8 min, resulting in a total run time of 20 min. Regarding the IMS settings, a tritium source was utilized for ionization in positive ion mode. The drift tube, with a length of 53 mm and an electric field strength of 500 V/cm, was maintained at 45 °C. High-purity nitrogen ($\geq 99.999\%$) served as the drift gas at a constant flow rate of 75.0 mL/min. The shutter grid opening time was set at 100 μ s, with a blocking voltage of 90 V (digital units). A series of ketone standards (C4–C9) was utilized to establish a calibration curve correlating retention time with the retention index (RI). The RI of each target compound was calculated based on its specific retention time recorded during the analysis. Qualitative identification was then performed using VOCal software 2.0.0 (G.A.S., Dortmund, Germany), which enabled dual-verification by cross-referencing the calculated RI and ion migration times against the integrated GC retention index database (NIST 2020) and the IMS drift time database. This multidimensional approach ensured the reliable identification of the target volatile components. Given the marked consistency of the purified gas, three representative samples were deemed sufficient to yield a statistically robust characterization. In contrast, six samples were prioritized for the highly variable raw gas to ensure the accurate capture of peak fluctuations and inherent emissions variability. To demonstrate the stability of the samples and the robustness of our deodorization process, we evaluated the data using

Pearson correlation analysis based on the peak heights of the 29 volatile substances across 9 samples. The statistical analysis and matrix visualizations were performed using Python (version 3.10), leveraging the *scipy.stats* and *seaborn* packages.

2.3. Statistical Analyses

Statistical analyses of NH_3 and odor concentrations were performed using SAS (version 9.4; SAS Institute Inc., Cary, NC, USA). Data normality was assessed using the Shapiro–Wilk test. Differences between groups were analyzed using paired *t*-tests. A *p*-value < 0.05 was considered statistically significant. However, for the VC profiling, due to shared instrument access and budgetary constraints during the joint GC-IMS analysis phase, a modified exploratory design was adopted. While six pre-treatment samples were initially profiled, only three post-treatment samples were tracked and analyzed. Crucially, these three post-treatment samples directly correspond to three specific pre-treatment profiles, establishing three fully intact, synchronized chronological pairs for direct within-round comparison: Pair 1 (pre-treatment sample B4 vs. post-treatment sample A1), Pair 2 (B5 vs. A2), and Pair 3 (B6 vs. A3). Due to the limited sample size of this GC-IMS convenience subset ($n = 3$ pairs), a formal statistical assessment of normality (such as the Shapiro–Wilk test) cannot be reliably performed, and compliance with the normality assumption cannot be mathematically guaranteed. Furthermore, multi-test corrections across parallel compound screenings under such a small cohort lack sufficient statistical power to yield valid significance. To maintain strict scientific integrity and prevent statistical overinterpretation, no formal inferential hypothesis testing (such as *t*-tests or Wilcoxon rank-sum tests) was conducted for the VC dataset. Instead, the VC dynamics are characterized descriptively based on the average removal efficiencies or concentration change rates derived strictly from the synchronized chronological pairs. Although a sample size of $n = 3$ biological replicates is an accepted practice in volatile profiling within agricultural silage [19] and food processing domains [11,20,21], due to instrument constraints, future larger-scale studies with fully balanced paired designs are strictly required to validate these temporal dynamics. Therefore, the VC profiles should be interpreted as preliminary pilot observations rather than a definitive statistical characterization. Principal component analysis (PCA) was performed using SIMCA-P software (Umetrics, version 18.0, Malmö, Sweden) to evaluate the differences in the volatile profiles of swine house emissions before and after the scrubbing system. For the PCA model, auto-scaling (Z-score normalization) was applied to standardize the data by setting the mean to 0 and the standard deviation to 1. The scaling type in the settings was selected as unit variance scaling, corresponding to the parameter type = UV. The block settings were configured with block = 1 and a block weight of 1/square root. The corrector was set to a default value of 1.

The removal efficiency (RE, %) or concentration change rate (CR, %) of the targeted odorants was calculated according to Equation (1).

$$\text{RE or CR} = \frac{X_{pre} - X_{post}}{X_{pre}} \times 100\% \quad (1)$$

where X_{pre} and X_{post} represent the mean concentrations or the mean peak heights (for VCs identified by GC-IMS) of the gas samples obtained before and after the scrubbing treatment, respectively.

The stability and consistency of concentration dynamics during the treatment were evaluated using the coefficient of variation calculated from either the average removal efficiency or the concentration change rate.

3. Results and Discussion

3.1. GC-IMS Profiling of VCs Before and After a Dual-Stage Scrubbing Process

2D topographies of GC-IMS profiling of VCs in swine house emissions during gas treatment are shown in Figure 2. The six panels on the left in Figure 2 represent the GC-IMS profiles of samplings from the raw swine house exhaust, while the three panels on the right represent those after treatment. The horizontal and vertical axes represent the drift time and the gas chromatographic retention time (RT), respectively. The color scale represents the concentration of VCs, ranging from blue (background) to red (high intensity). The vertical red line located at 1.0 on the horizontal axis represents the reaction ion peak (RIP), which has been normalized. By comparing the 2D topographic plots across different samples, a high degree of visual similarity was observed within the six pre-treatment replicates, as well as within the three post-treatment counterparts. Concurrently, a stark contrast in the 2D topographies was evident before and after the deodorization treatment. To rigorously quantify these similarities, a Pearson correlation matrix analysis was performed across all sample profiles. As shown in Figure 3, the correlation coefficients among the six pre-treatment samples were consistently above 0.91, while those among the three post-treatment samples exceeded 0.98. This demonstrates good reproducibility within each group and a mathematically distinct shift in the odor profile following the scrubbing process.

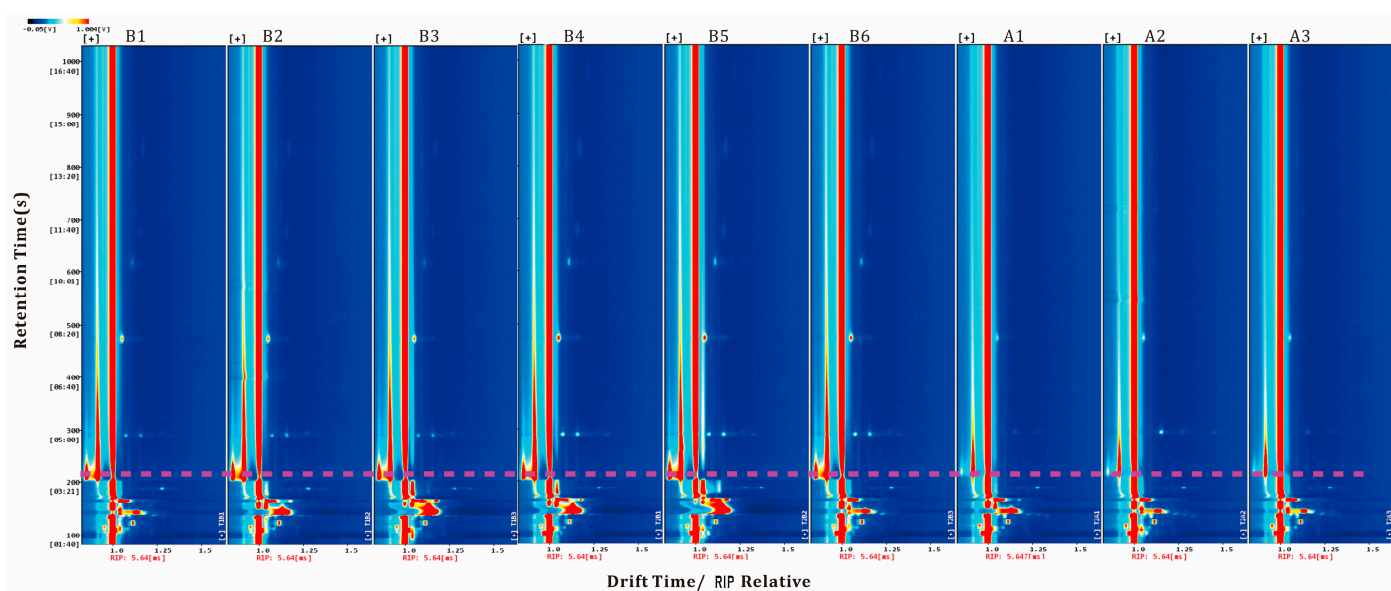


Figure 2. 2D topographies of GC-IMS profiling of VCs in swine house emissions during the dual-stage scrubbing process. Note: B1–B6, samples collected before scrubbing (pre-treatment); A1–A3, samples collected after scrubbing (post-treatment). The pink dashed line in the figure represents the retention time of ammonia (retention time = 213.583 s).

To comprehensively characterize the dynamic variations in individual chemical components, VCs were extracted from the 2D topographic plots to construct a detailed fingerprint (Figure 4). As shown in Figure 4, each column depicts the peak intensities of the same VCs across all samples. The color scale ranges from dark blue to red, indicating an increase in the concentration of VCs. Some compounds exhibited two signal spots, identified as the monomer (M) and dimer (D), due to the high concentration of the analyte or its high proton affinity. A total of 29 VCs were identified in the samples, and the detailed profiles are summarized in Table 2. The retention times listed in Table 2 directly correspond to the chromatographic coordinates in Figure 2, serving as a reliable reference to index the specific chemical identities of the corresponding signal peaks in the 2D topographies. For instance, the signal peak corresponding to NH_3 at a drift time (DT) of 0.85705 and a RT of

213.583 s exhibited a pronounced decrease in intensity following the treatment (indicated by the pink dashed frame in Figure 2).

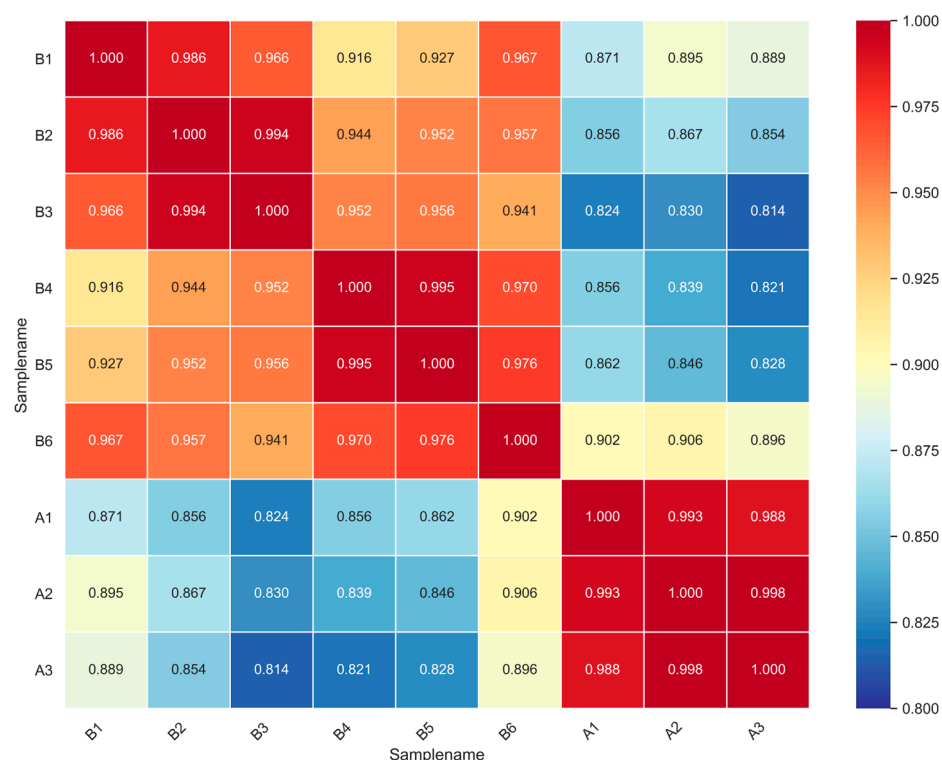


Figure 3. Pearson correlation matrix of GC-IMS samples.

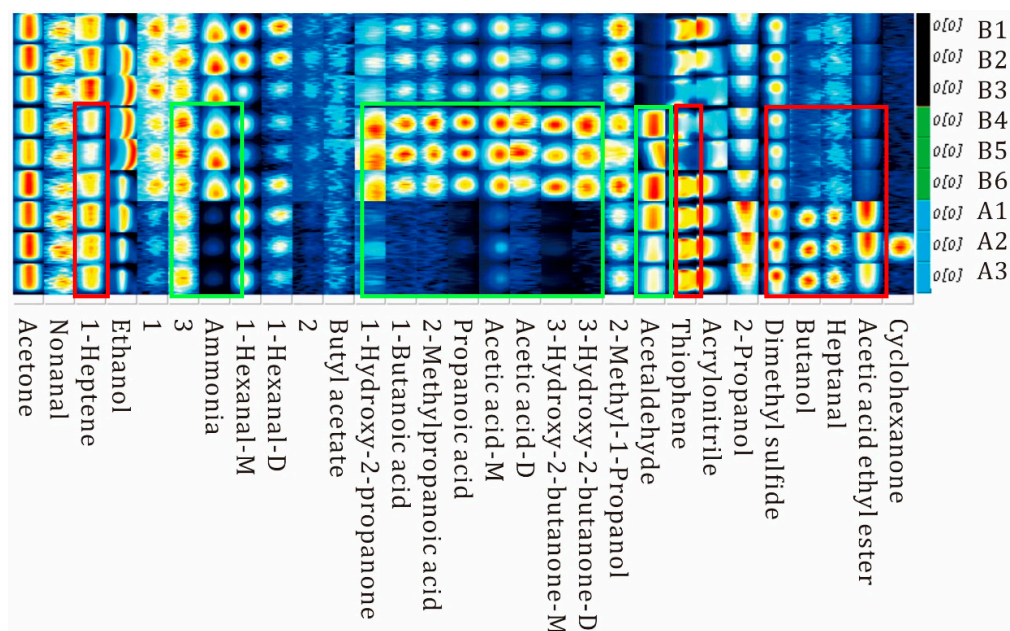


Figure 4. Fingerprints of VCs in swine house emissions during the dual-stage scrubbing system. Note: Several VCs were detected but remained unidentified, which are denoted by numbers in the fingerprint profile; the green and red frames highlight volatile compounds with a coefficient of variation of removal efficiencies or concentration change rates below 0.6, denoting post-treatment concentration decreases and increases, respectively.

Table 2. Volatile compounds detected in this study.

Count	Compound	CAS#	Formula	MW	Henry's Law Constant (mol/m ³ Pa) ^a	RI	Mean $\pm$ SD ^b	CV for RE or CR	RT [sec]	DT [a.u.]
1	Acetone	C67641	C ₃ H ₆ O	58.1	2.7×10^{-1}	822.44446	-8.60 ± 7.81	0.91	122.542	1.11512
2	Acetic acid-M	C64197	C ₂ H ₄ O ₂	60.1	4.0×10^1	1478.5	61.90 ± 4.22	0.07	472.504	1.05281
3	Acetic acid-D	C64197	C ₂ H ₄ O ₂	60.1	NA	1478	64.80 ± 5.63	0.09	471.861	1.16266
4	NH ₃	C7664417	NH ₃	17	5.9×10^{-1}	1146.4	79.86 ± 1.26	0.02	213.583	0.85705
5	Acetaldehyde	C75070	C ₂ H ₄ O	44.1	1.3×10^{-1}	677.5	23.03 ± 12.84	0.56	101.28	0.96929
6	Dimethyl sulfide	C75183	C ₂ H ₆ S	62.1	5.3×10^{-3}	781.8	-31.39 ± 10.45	0.33	116.167	0.95574
7	Acetic acid ethyl ester	C141786	C ₄ H ₈ O ₂	88.1	6.5×10^{-2}	891	-169.56 ± 11.36	0.07	134.093	1.09906
8	2-Propanol	C67630	C ₃ H ₈ O	60.1	1.2	910.8	-25.89 ± 17.49	0.68	137.634	1.09376
9	1-Heptene	C592767	C ₇ H ₁₄	98.2	2.0×10^{-5}	757.3	-17.90 ± 6.52	0.36	112.478	1.08901
10	Acrylonitrile	C107131	C ₃ H ₃ N	53.1	1.0×10^{-1}	1014.6	-41.53 ± 31.46	0.76	165.559	1.08627
11	Thiophene	C110021	C ₄ H ₄ S	84.1	4.1×10^{-3}	1014.2	-17.46 ± 9.71	0.56	165.426	1.04344
12	1-Hexanal-M	C66251	C ₆ H ₁₂ O	100.2	4.5×10^{-2}	1082.5	-32.42 ± 55.85	1.72	187.203	1.2845
13	1-Hexanal-D	C66251	C ₆ H ₁₂ O	100.2	NA	1084.2	-2.86 ± 38.64	13.50	187.796	1.55272
14	2-Methyl-1-propanol	C78831	C ₄ H ₁₀ O	74.1	8.3×10^{-1}	1079	-0.42 ± 30.35	71.96	186.016	1.17288
15	Butanol	C71363	C ₄ H ₁₀ O	74.1	1.2	1132	-224.64 ± 2.51	0.01	207.285	1.18528
16	Butyl acetate	C123864	C ₆ H ₁₂ O ₂	116.2	3.8×10^{-2}	1069.3	8.42 ± 21.68	2.57	182.784	1.23329
17	1	unidentified	u	0	21.14	1147.8	9.86 ± 13.27	1.35	214.204	1.35195
18	2	unidentified	u	0	NA	1166.3	11.19 ± 14.39	1.29	222.663	1.38291
19	Heptanal	C111717	C ₇ H ₁₄ O	114.2	3.4×10^{-2}	1179.2	-113.33 ± 10.41	0.09	228.702	1.34968
20	3-Hydroxy-2-butanone-M	C513860	C ₄ H ₈ O ₂	88.1	3.1	1298.7	89.60 ± 2.82	0.03	292.567	1.07677
21	3-Hydroxy-2-butanone -D	C513860	C ₄ H ₈ O ₂	88.1	NA	1297.7	80.51 ± 3.20	0.04	291.793	1.32439
22	Cyclohexanone	C108941	C ₆ H ₁₀ O	98.1	1.5	1300.8	-142.86 ± 201.05	1.41	294.251	1.45076
23	Nonanal	C124196	C ₉ H ₁₈ O	142.2	1.1×10^{-2}	1396.7	-12.93 ± 13.66	1.06	379.913	1.48419
24	Propanoic acid	C79094	C ₃ H ₆ O ₂	74.1	3.9×10^4	1578.1	83.53 ± 1.07	0.01	616.059	1.10935
25	2-Methylpropanoic acid	C79312	C ₄ H ₈ O ₂	88.1	4.6×10^1	1615.6	65.15 ± 0.93	0.01	680.968	1.16
26	1-Butanoic acid	C107926	C ₄ H ₈ O ₂	88.1	4.3×10^1	1693	64.72 ± 3.39	0.05	836.872	1.1698
27	3	unidentified	u	0	NA	1679.4	9.98 ± 5.52	0.55	807.138	1.09587
28	1-Hydroxy-2-propanone	C116096	C ₃ H ₆ O ₂	74.1	7.7×10^1	1309.9	50.36 ± 6.97	0.14	301.484	1.0785
29	Ethanol	C64175	C ₂ H ₆ O	46.1	1.9	923.9	8.78 ± 9.65	1.10	140.516	1.06886

Note: RI, retention index; MW, molecular weight; RT, retention time; DT, relative drift time; RE, removal efficiency; CV, coefficients of variation; ^a, the values were cited from (Sander, 2023) [22]; ^b average removal efficiencies or concentration change rates $\pm$ standard deviation; u, some compounds were detected but remained unidentified; NA, not applicable for dimers or not available for unidentified compounds.

3.2. Assessment of VC Removal Efficiencies or Concentration Change Rates in Swine Farm Air Purification Systems via GC-IMS

The simultaneous determination of multiple components provides a robust dataset for multivariate statistical analysis, such as PCA. This approach facilitates a holistic evaluation of deodorization performance and the identification of key volatile markers. The results of the PCA are illustrated in Figure 5. This approach performs dimensionality reduction on the multi-component dataset, effectively condensing the complex chemical information into a few principal variables. This simplification facilitates a clearer understanding of the compositional evolution of odorous compounds throughout the treatment process. The classification of compounds across different processing stages was effectively characterized by the first two principal components, with PC1 and PC2 accounting for 57.4% and 17.9% of the variance, respectively. Their cumulative variance contribution reached 75.3%, providing a robust representation of the dataset. The PCA score plot revealed a distinct separation between pre- and post-treatment samples, indicating a pronounced transformation in the chemical composition of the swine house exhaust. Specifically, the pre-treatment samples exhibited a dispersed distribution, reflecting the high variability of the raw gas matrix. In contrast, the post-treatment samples formed a tighter, more compact cluster. This transition demonstrates that the scrubbing process not only altered the gas profile but also effectively homogenized the fluctuating emissions into a more stabilized and consistent output.

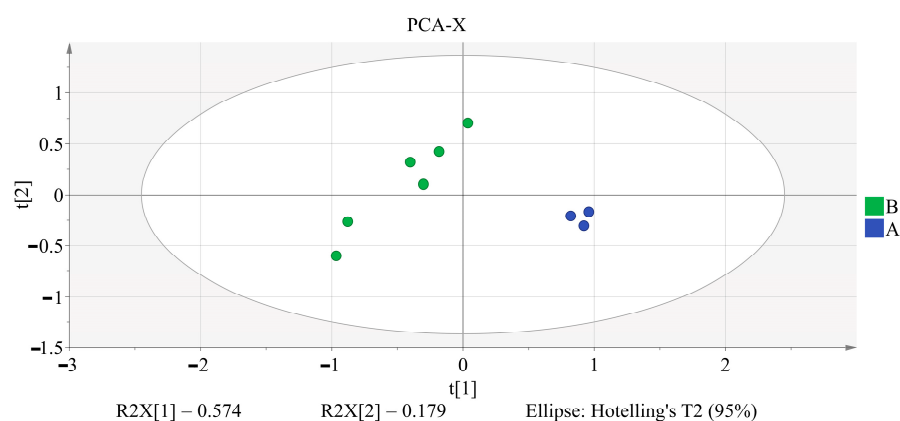


Figure 5. Principal component analysis of VCs in swine house emissions during the dual-stage scrubbing system.

Due to the absence of absolute quantification in this study, the exact OAVs could not be directly calculated based on our experimental data. Nevertheless, to bridge the gap between chemical profiles and sensory odor relevance, we cross-referenced our findings with literature-reported OAVs and odor thresholds specific to swine buildings, which have been compiled in Table S1. According to the literature data, several key malodor components identified in our study, such as acetic acid, 2-methylpropanoic acid, acetaldehyde, NH_3 , 1-butanoic acid, nonanal, and dimethyl sulfide, were estimated to be major contributors to the sensory odor profile due to their high OAVs (greater than 2) in some swine facilities. Furthermore, certain compounds detected in our screening, including thiophene, 1-heptene, and acetic acid ethyl ester, possess relatively low odor thresholds, rendering them highly potent odor contributors even at trace levels. Although their absolute concentrations require further quantitative validation in future studies, their presence suggests a non-negligible sensory risk.

Based on the coefficient of variation of the removal efficiencies or concentration change rates (Table 2), we confirmed that the signal intensities of certain compounds—especially 1-heptene, dimethyl sulfide, acetic acid ethyl ester, butanol, thiophene, and heptanal—not only exhibited a sharp and reliable post-treatment accumulation (with a coefficient

of variation of concentration change rates below 0.6) but also maintained a high degree of stability across all samples, as visually supported by the chromatic variations in the GC-IMS fingerprints (Figure 4). Among these, dimethyl sulfide was identified as a key odor-contributing gas [23], offering clear targets for the optimization of the scrubbing system.

In alignment with previous studies utilizing GC-MS [24,25], several common VCs were also identified in the present work, including acetic acid, dimethyl sulfide, hexanal, butanol, heptanal, 2-butanone-3-hydroxy, nonanal, propanoic acid, 2-methylpropanoic acid, and 1-butanoic acid. However, other compounds (1-heptene, acrylonitrile, 2-methyl-1-propanol, and 1-hydroxy-2-propanone) observed in this study were not reported in previous GC-MS-based investigations [13,26,27]. This is likely due to the superior sensitivity and distinct selectivity of the IMS detector toward specific chemical classes. These results indicate that the method applied in this study can complement other analytical techniques by addressing their limitations in odor evaluation studies.

3.3. Comparison of Deodorization Efficacy Measured by GC-IMS, PAS, and Olfactometry

In the absence of standard gases, a semi-quantitative analysis was conducted by comparing peak heights under identical experimental conditions. The removal efficiency for each gas component was determined by comparing peak heights, as summarized in Table 2. It is worth noting that the comparison of removal efficiency or concentration change rate was restricted to the same gas component before and after treatment under identical parameters, without cross-compound comparison. The RIP, set at 1.0 on the horizontal axis, served as an internal operational baseline to normalize all drift times. Under identical analytical conditions, this benchmark minimizes instrumental fluctuations, thereby ensuring that the peak-height variations in the same compound before and after treatment reliably reflect comparative estimation of relative changes, despite the semi-quantitative nature of the non-calibrated absolute concentrations. According to the removal efficiency and concentration change rate, the detected odorants can be explicitly classified into three distinct categories: (1) target components that exhibited robust positive removal efficiencies, including acetic acid, NH_3 , 3-hydroxy-2-butanone, propanoic acid, 2-methylpropanoic acid, 1-butanoic acid, acetaldehyde, and 1-hydroxy-2-propanone, with the coefficient of variation of their removal efficiencies remaining below 0.6; (2) species that displayed a clear accumulation in post-treatment signal intensities, notably 1-heptene, dimethyl sulfide, acetic acid ethyl ester, butanol, heptanal, and thiophene, with the coefficient of variation of their concentration change rates remaining below 0.6; and (3) odorants showing negligible variations during the scrubbing process, including nonanal, acetone, ethanol, 1-hexanal, 2-methyl-1-propanol, butyl acetate, cyclohexanone, as well as acrylonitrile (a Group 1 carcinogen [28]). The removal efficiencies or concentration change rates of different gas components are primarily driven by two intertwined physicochemical factors: water solubility and chemical reactivity toward the scrubbing agents. Specifically, NH_3 possesses an exceptionally high Henry's law constant (highly water-soluble) and undergoes instantaneous acid–base neutralization within the acidic stage of the dual-stage scrubbing matrix, yielding a high removal efficiency. Conversely, volatile compounds like acetic acid ethyl ester exhibit much lower water solubility, while molecules like butanol possess structural stabilities that make them more chemically inert or less reactive toward acidic or hypochlorite ions under standard operational contact times. The relative enrichments or fluctuations at the outlet can thus be explained by these massive variations in mass-transfer and reaction kinetics between different gas species.

The apparent increase in the signal intensities of these components after scrubbing suggests a potential accumulation of these species in the effluent gas. While this could be hypothetically linked to incomplete mineralization, recombination, or partial oxidation

during the advanced oxidation process—such as the oxidative cleavage of high-molecular-weight organic matters into smaller, more volatile fragments (e.g., heptanal and alcohols) or the chlorination pathway of nitrile formation as suggested by How et al. (2018) [29]—alternative underlying mechanisms cannot be dismissed. These include the desorption of previously trapped volatile compounds from the scrubber packing material, variations in matrix effects after treatment that alter the competitive ionization in GC-IMS, or sampling artifacts. To explore the chemical hypotheses, a plausible formation pathway can be proposed. In the context of swine house exhaust, amino acids likely originate from airborne feed particles and organic dust. During the scrubbing process, the reaction between hypochlorite and protons could theoretically generate active chlorine species or molecular chlorine, which might subsequently trigger the oxidative deamination and decarboxylation of these nitrogenous precursors. Similarly, the increase in thiophene and dimethyl sulfide might be linked to the fragmentation and subsequent recombination of sulfur-bearing proteins. If chemically generated, this trend would underscore a critical trade-off between primary purification efficiency and the inadvertent generation of high-risk byproducts. Nevertheless, as noted above, further investigations involving scrubber-liquid monitoring or controlled reaction tests are required to definitively map these chemical transformations.

PAS is an established technique for the detection of NH_3 and greenhouse gases in animal husbandry [30–34], valued for its robustness and high analytical accuracy. The variations in NH_3 concentrations before and after the deodorization unit, as determined by this method, are illustrated in Figure 6. The average concentration of NH_3 emitted from the multi-floor swine building was $16.468 \pm 7.265 \text{ mg/m}^3$, with a fluctuating range of 4.192–22.596 mg/m^3 . Following the scrubbing process, the NH_3 levels exhibited a significant reduction ($p < 0.05$), reaching a mean concentration of $3.641 \pm 2.530 \text{ mg/m}^3$. Consequently, the system achieved an average NH_3 removal efficiency of 77.89%, which is in good agreement with the value obtained by GC-IMS (79.86%). The remarkable consistency validates the robustness of utilizing ion mobility peak intensities for assessing the performance of air purification systems. The pronounced fluctuations in pre-treatment NH_3 levels shown in Figure 6 parallel the results obtained from GC-IMS analysis for the same sampling points. These comparable results further confirm the feasibility and accuracy of utilizing GC-IMS for monitoring odor mitigation.

The results of the odor concentration measurements determined by the olfactometry method are presented in Figure 7. The initial odor concentration emitted from the swine building exhibited substantial fluctuations, ranging from 657 to 2077, with a mean value of 1204 ± 601 . Following the dual-stage scrubbing process, the average odor concentration decreased to 656 ± 302 , corresponding to a mean removal efficiency of 45.5%. However, the reduction was not statistically significant ($p = 0.1571$). This lack of statistical significance can be attributed to the high inherent variability of the raw emissions and the limited sample size of the olfactometric evaluation, which restricts the confirmation of a definitive olfactory mitigation. Consequently, these sensory results should be interpreted as tentative, underscoring the necessity for future large-scale, long-term monitoring campaigns with expanded sample cohorts to rigorously validate the sensory deodorization stability. The odor levels observed in this study are comparable to those reported by Conti et al. (2021) during early September [35]. Such alignment indicates that the odor emissions from our experimental facility are typical of commercial swine operations. In evaluating the odor mitigation performance for swine barn exhaust, Conti et al. (2021) also found the odor concentration in swine houses fluctuated dramatically and reported that a two-stage wet acidic scrubber—comprising one water tank and one 15% citric acid tank (50 L each)—achieved an average odor removal efficiency of only 16%. To achieve higher odor removal efficiencies, further optimization and refinement of the current two-stage

scrubbing configuration are required [35]. This critical divergence precisely highlights the distinct technological benefits of the newly introduced GC-IMS method. While olfactometry showed non-significant variations in odor levels after treatment, GC-IMS demonstrated the capability to detect precise changes in the composition of individual odorants. Although olfactometry is effective for assessing overall odor intensity, it remains constrained by inherent human subjectivity and an inability to discriminate between specific odorants. Consequently, sensory evaluation alone provides insufficient diagnostic guidance for the targeted optimization of deodorization systems. Despite its practical importance, the insights offered by olfactometry are ultimately hampered by a lack of molecular-level specificity, a gap that is effectively bridged by the high-resolution chemical profiling of GC-IMS.

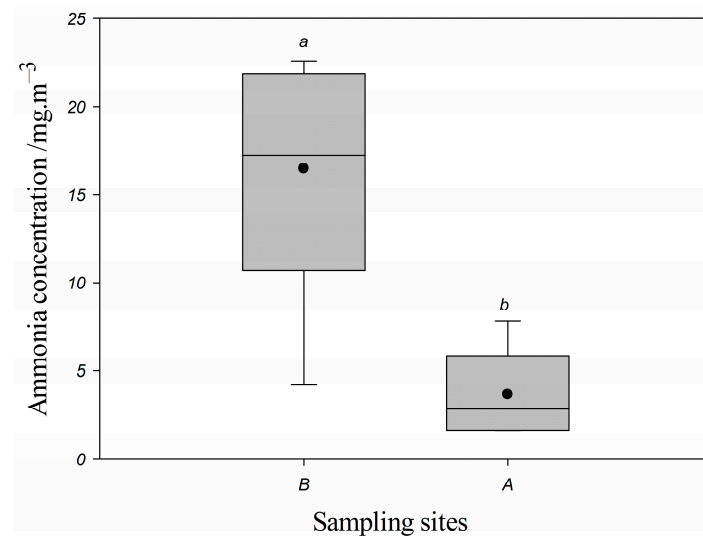


Figure 6. Comparison of NH_3 concentrations in the exhaust air of a multi-floor swine building before and after a dual-stage scrubbing process. Note: B, before treatment; A, after treatment. Box plots illustrate the median and IQR, with whiskers extending to the most extreme data points within 1.5 times the IQR. The dark dots indicate the mean concentrations; different letters above the boxes indicate significant differences at the $p < 0.05$ level.

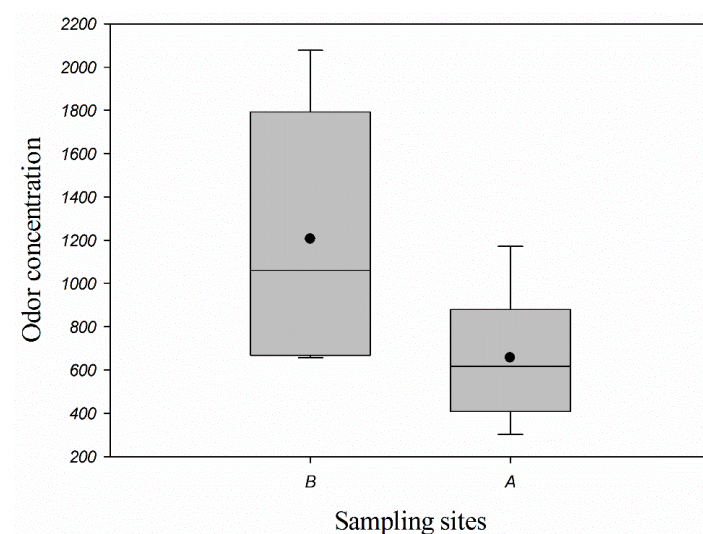


Figure 7. Comparison of odor concentrations in the exhaust air of a multi-floor swine building before and after a dual-stage scrubbing process. Note: B, before treatment; A, after treatment. Box plots illustrate the median and IQR, with whiskers extending to the most extreme data points within 1.5 times the IQR. The dark dots indicate the mean concentrations.

3.4. Limitations and Future Works

Despite the high sensitivity of GC-IMS in identifying volatile fingerprints, several characteristic malodorous compounds typically found in swine house emissions—including hydrogen sulfide, dimethyl disulfide, phenol, indole, and skatole [14,26,36]—were not detected in the present study. This absence can be attributed to several technical constraints. First, sampling methodologies can significantly influence the adsorption of VCs. In this study, odorless bags were employed for sample collection, whereas previous works utilized SUMMA canisters or sorbent tubes [12,13]. Although this sampling approach was selected for gas sampling in this study due to logistical constraints, it is important to note that GC-IMS is intrinsically capable of on-site detection. Because sample transport under ambient conditions may compromise chemical integrity, future research could leverage the portability of this technique for in situ analysis, thereby eliminating potential artifacts or biases introduced by sampling and storage procedures. Second, chemical profiling was performed without absolute on-site calibration and quantification, relying instead on relative abundance and cross-referenced literature-reported odor thresholds to infer sensory relevance. Consequently, the volatile profile characterized in this work represents a selective chemical screening rather than an exhaustive sensory representation. Third, certain compounds like phenol may exhibit enhanced sensitivity in negative-mode ionization, which was not the primary configuration of this analysis. Finally, instrumental operational parameters, specifically analysis duration and column and drift tube temperatures, require systematic optimization. This is particularly crucial given that key malodorous compounds, such as indole and skatole, possess high boiling points exceeding 250 °C, which may hinder their elution and detection under standard settings.

These identified analytical boundaries provide a structured roadmap for our future validation studies. While these preliminary findings provide a baseline reference for evaluating livestock air treatment systems, future research should incorporate multi-modal analytical configurations, such as integrating negative-mode IMS alongside rigorous absolute quantification. Furthermore, to establish a more comprehensive evaluation matrix for livestock odor profiles, future investigations ought to conduct comparative and correlation studies by pairing GC-IMS with traditional dynamic olfactometry (sensory panelists) and conventional GC-MS. Bridging the gap between instrumental relative abundance, absolute mass concentration, and human sensory perception will be essential for developing more convenient, reliable, and field-validated methodologies for agricultural odor assessment and deodorization equipment optimization.

4. Conclusions

In this study, GC-IMS was applied to preliminarily explore a detection methodology for swine farm odor emissions and to evaluate the corresponding deodorization efficiency. The results demonstrate that GC-IMS provides a rapid and user-friendly platform for screening VCs in a multi-floor swine building. By generating intuitive topographic visualizations, a total of 29 distinct gas components were successfully detected. Crucially, the dual-stage chemical scrubbing system was found to mitigate the emissions of key odorants, including acetic acid, NH₃, 2-methylpropanoic acid, acetaldehyde, and butanoic acid. Among these, the average removal efficiency of NH₃ reached 79.86% based on semi-quantitative analysis, which was highly consistent with the parallel PAS results of 77.89%. Consequently, GC-IMS serves as a valuable diagnostic complement to traditional olfactometry, particularly for tracking short-term, episodic odor pollution events. However, several inherent limitations of this study must be acknowledged. The detection and sensitivity for certain key swine malodor components—such as hydrogen sulfide, dimethyl disulfide, phenol, indole, and skatole—require further optimization regarding sampling

conditions, ion mobility separation modes, and operational parameters, including column temperature, drift tube temperature, and analysis duration. Furthermore, as our sampling campaign was restricted to a single-day window, the current approach is best positioned for the rapid screening of abnormal emission incidents and the preliminary evaluation of specific odorant removal. A more comprehensive understanding of the diurnal and seasonal odor emission characteristics from multi-floor swine buildings, as well as the long-term removal efficiency and operational stability of the deodorization system, necessitates extensive, longitudinal and well-balanced sampling campaigns. Ultimately, future methodological explorations coupling GC-IMS with traditional dynamic olfactometry and absolute quantitative techniques (such as GC-MS) will be essential to establish a more convenient, robust, and industry-validated framework for swine odor monitoring and deodorization equipment assessment.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/agriculture16182019/s1>, Table S1: Odor thresholds and description of the detected compounds. References [37–41] are cited in the Supplementary Materials.

Author Contributions: T.L.: conceptualization, methodology, writing—original draft; L.X.: resources, methodology, validation; S.L.: conceptualization, methodology, data curation, funding acquisition; B.L.: data curation, validation, visualization, investigation; G.Z.: writing—review and editing, methodology, supervision, validation; L.D.: investigation, data curation, software, formal analysis. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

GC-IMS	Gas chromatography–ion mobility spectrometry
VCs	Volatile compounds
PTR-MS	Proton transfer reaction–mass spectrometry
PAS	Photoacoustic spectroscopy
PCA	Principal component analysis
OPLS-DA	Orthogonal partial least squares discriminant analysis

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