Research Square

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Ohmic Fermentation Differentiates Volatile Fingerprints of Roasted Arabica and Robusta Coffees from Four Indonesian Origins

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Abstract

This study evaluated whether ohmic fermentation differentiates the volatile fingerprints of roasted Arabica and Robusta coffees from four Indonesian origins. Arabica beans from Enrekang and Gowa/Malakaji and Robusta beans from Bulukumba and Bantaeng were fermented under origin-specific time–temperature conditions, roasted, and analyzed by headspace solid-phase microextraction coupled with gas chromatography–mass spectrometry. Detected compounds were organized into aroma-relevant classes and interpreted using principal component analysis. The analysis detected 477 compounds in Enrekang Arabica, 469 in Gowa/Malakaji Arabica, 316 in Bulukumba Robusta, and 425 in Bantaeng Robusta. Furans, pyrazines, pyridines, ketones, pyrroles, phenols, aldehydes, acids, thiophenes, thiazoles, alcohols, and lactones constituted the dominant interpretable chemical space. Treatment-level PCA explained 71.84% of variance in Enrekang, 73.16% in Gowa/Malakaji, 68.33% in Bulukumba, and 70.53% in Bantaeng, indicating structured treatment responses within each origin. Class-level PCA further separated Arabica and Robusta origins, with Enrekang and Gowa/Malakaji characterized mainly by furan–ketone profiles and Bantaeng Robusta by the strongest pyrazine representation. The results support ohmic fermentation as a promising pre-roasting process for origin-specific volatile modulation. Because the current dataset is based on detected-compound classes and PCA associations, future work should include peak-area normalization, retention-index confirmation, odor-activity analysis, and sensory validation.

1 Introduction

Coffee flavour is generated through a sequence of pre-harvest, post-harvest, thermal, and extraction events rather than by roasting alone. Species, genotype, altitude, fermentation, drying, roasting, grinding, storage, and brewing can all affect the composition and release of volatile and non-volatile compounds. Recent mapping of coffee-quality research shows increasing attention to biochemical composition, cup quality, post-harvest intervention, and analytical chemistry, but the links between controlled processing and aroma-forming chemistry remain incompletely resolved [1]

Fermentation is now understood as an active route for coffee quality modulation. Studies on wet, spontaneous, semi-carbonic, yeast-assisted, probiotic, anaerobic, and biomimetic fermentation have shown that post-harvest processes can alter organic acids, sugars, free amino acids, esters, alcohols, aldehydes, pyrazines, and related volatile or non-volatile precursors [2, 3, 4, 5, 6, 7, 8, 9, 10, 11]. Additional studies on acetic-acid immersion, organic-acid soaking, enzymatic germination, combined microbial-enzymatic processing, and probiotic fermentation further demonstrate that targeted pre-roasting treatments can modify coffee taste, aroma, and volatile composition [12, 13, 14, 15, 16].

Roasting then converts this modified matrix into volatile products through Maillard reaction, Strecker degradation, caramelization, pyrolysis, and secondary oxidation. Heat and mass transfer during roasting regulate the kinetic window within which furans, pyrazines, pyridines, pyrroles, aldehydes, ketones, phenols, and sulfur-containing compounds are formed [17, 18, 19, 20, 21, 22, 23]

Ohmic fermentation is relevant to this processing continuum because electrical resistance heating can deliver heat internally through the material matrix. This may provide better thermal control during fermentation than purely ambient processes. However, the specific relationship between ohmic fermentation and the volatile fingerprint of roasted coffee remains insufficiently characterized, especially for Indonesian Arabica and Robusta origins. The key research gap addressed here is therefore not whether fermentation changes all coffee chemistry, but whether roasted coffee volatile fingerprints differ after ohmic fermentation across species, origins, and time–temperature treatments.

The Indonesian context strengthens the relevance of this question. Origin-specific studies have shown that altitude, fertilization, processing method, and terroir affect coffee precursors, volatile markers, antioxidant compounds, and sensory expression. Indonesian coffee studies have also demonstrated that Gayo, Solok, Kalosi-Enrekang, and Robusta samples can be differentiated by volatile chemistry and sensory attributes [24, 25, 26, 27, 28, 29]

Analytically, HS-SPME-GC-MS and chemometric methods are suitable for volatile fingerprinting because roasted coffee contains many overlapping compounds distributed across multiple chemical families. Recent coffee studies have used GC-MS, GC-MS-O, GC-TOF/MS, electronic nose systems, PCA, LDA, PLS-DA, OPLS-DA, and self-organizing maps to classify origins, processing histories, roasting levels, and sensory-related markers [30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41]

This study aimed to determine whether ohmic fermentation differentiates the volatile fingerprints of roasted Arabica and Robusta coffees from Enrekang, Gowa/Malakaji, Bulukumba, and Bantaeng. The study tested the hypothesis that time–temperature conditions during ohmic fermentation produce origin-specific and species-specific shifts in aroma-relevant volatile families after roasting. The analysis focused on detected compound classes and PCA structures, while deliberately separating chemical fingerprinting from unvalidated sensory impact.

2 Materials and methods

2.1 Coffee material and experimental design

The experimental material consisted of roasted coffee beans obtained after ohmic fermentation. Four Indonesian origins were evaluated: Enrekang and Gowa/Malakaji Arabica, and Bulukumba and Bantaeng Robusta. In this manuscript, Gowa/Malakaji is treated as one regional origin label following the supplied dataset. The design allowed comparison of species-level and origin-level responses to ohmic fermentation.

Treatment codes preserved the original duration–temperature structure: EH2T30, EH12T30, EH12T35, and EH12T40 for Enrekang; MH12T30, MH12T35, MH18T35, and MH12T40 for Gowa/Malakaji; BLH12T30, BLH18T30, BLH12T35, and BLH12T40 for Bulukumba; and BTH12T30, BTH12T35, BTH12T40, and BTH18T40 for Bantaeng. The codes are retained to maintain traceability and avoid unsupported assumptions about conditions not explicitly documented in the dataset.

Table 1
Treatment codes used for roasted Arabica and Robusta coffees after ohmic fermentation

Origin/species	Treatment codes	Interpretation retained in manuscript
Enrekang Arabica	EH2T30; EH12T30; EH12T35; EH12T40	Ohmic fermentation treatments differing in time and temperature
Gowa/Malakaji Arabica	MH12T30; MH12T35; MH18T35; MH12T40	Ohmic fermentation treatments differing in time and temperature
Bulukumba Robusta	BLH12T30; BLH18T30; BLH12T35; BLH12T40	Ohmic fermentation treatments differing in time and temperature
Bantaeng Robusta	BTH12T30; BTH12T35; BTH12T40; BTH18T40	Ohmic fermentation treatments differing in time and temperature
Note. Treatment labels were retained from the supplied dataset to preserve traceability.		

2.2 Sample preparation and HS-SPME-GC-MS analysis

Roasted beans from each treatment were ground using a standardized procedure. A 5 g portion of roasted ground coffee was transferred into a 20 mL Supelco vial for headspace analysis. Volatile release from roasted coffee is sensitive to grinding, time after grinding, temperature, oxygen exposure, and storage; therefore, the protocol was interpreted as a comparative volatile-fingerprinting workflow rather than an absolute odor-active quantification procedure [42, 43]

Volatile compounds were extracted using headspace solid-phase microextraction with a DVB/CAR/PDMS fiber (2 cm, 50/30 µm). GC-MS analysis was conducted using an Agilent 7890A gas chromatograph equipped with a DB-Wax column (30 m × 250 µm × 0.25 µm) and mass spectrometric detection at 70 eV. Helium was used as the carrier gas. The oven program started at 40°C and increased to 220°C at 4°C min − 1, followed by a final hold. Injector and interface temperatures were maintained at 250°C. Compounds were identified by comparison with the NIST mass spectral database.

Table 2
HS-SPME-GC-MS analytical conditions used for roasted coffee volatile profiling

Parameter	Condition
Sample mass	5 g roasted ground coffee
Extraction mode	Headspace solid-phase microextraction
SPME fiber	DVB/CAR/PDMS, 2 cm, 50/30 µm
GC system	Agilent 7890A GC
Column	DB-Wax, 30 m × 250 µm × 0.25 µm
Detector	Mass spectrometry, 70 eV
Carrier gas	Helium, linear velocity 32.434 cm s − 1
Oven program	40°C initial; 4°C min − 1 to 220°C; 10 min final hold
Injector/interface	250°C / 250°C
Identification	Mass spectral matching against NIST database
Note. The analytical workflow was used for descriptive volatile fingerprinting and treatment differentiation.	

2.3 Data matrix construction and validation status

Identified compounds were grouped into pyrazines, pyrroles, pyridines, phenols, furans, aldehydes, alcohols, ketones, thiophenes, thiazoles, lactones, acids, and other/unclassified compounds. Class assignment was performed to provide chemically interpretable families rather than to infer sensory intensity from single compounds. Duplicate names and isomeric entries were retained as reported in the source dataset when they represented distinct GC-MS identifications.

The data matrix used in this manuscript consisted of detected compound counts by class and PCA structures reported in the source dataset. Complete normalized peak-area matrices, internal-standard quantification, replicate-level variance estimates, retention indices, and authentic-standard confirmation were not available for all compounds. Consequently, compound identities based only on mass spectral matching should be regarded as tentative, and all results are interpreted as descriptive volatile fingerprints. This qualification follows the journal requirement that compound identifications based on one method should be labelled tentative unless confirmed by independent methods.

No human participants or animals were involved in the experimental work.

2.4 Statistical analysis

Principal component analysis was used to describe multivariate relationships among treatments and volatile variables. The first two components were interpreted because they explained 71.84% of variation for Enrekang Arabica, 73.16% for Gowa/Malakaji Arabica, 68.33% for Bulukumba Robusta, and 70.53% for Bantaeng Robusta. Combined class-level PCA explained 56.05% of variation for Arabica and 58.10% for Robusta. Because replicate-level information was not available, PCA was interpreted descriptively and not as inferential proof of clustering.

Shannon and Simpson indices were calculated from compound-class counts to describe class evenness. These metrics were not used as sensory-complexity indices because odor impact depends on abundance, odor threshold, release dynamics, and matrix interactions rather than on detection count alone.

3 Results

3.1 Number of detected compounds and dominant classes

HS-SPME-GC-MS revealed complex volatile profiles in all roasted coffees produced after ohmic fermentation. Enrekang Arabica had 477 detected compounds, Gowa/Malakaji Arabica had 469, Bantaeng Robusta had 425, and Bulukumba Robusta had 316. The pattern indicates that the number of detected volatile compounds was not determined by species alone. Bantaeng Robusta approached the Arabica range, whereas Bulukumba Robusta had a substantially lower detected-compound count.

Table 3
Number of volatile compounds identified in roasted coffee after ohmic fermentation by origin and compound class

Origin/species	Total	Pyrazines	Pyrroles	Pyridines	Phenols	Furans	Aldehydes	Alcohols	Ketones	Thiophenes	Thiazoles	La
Enrekang Arabica	477	38	26	30	19	56	16	11	45	8	2	2
Gowa/Malakaji Arabica	469	27	29	35	27	54	12	10	51	2	11	2
Bulukumba Robusta	316	28	18	27	13	38	10	6	29	2	11	2
Bantaeng Robusta	425	40	23	31	13	31	14	7	37	3	3	2

Note. The grouped class counts are presented as supplied. The large 'Other' category indicates the need for further compound curation.

Furans were the most represented interpretable class in both Arabica origins, whereas Bantaeng Robusta showed the highest pyrazine count. Ketones were especially prominent in Gowa/Malakaji Arabica. Pyridines and pyrroles were widely represented across origins. These classes are consistent with common roasted-coffee volatile families and with previous studies linking furans, pyrazines, aldehydes, ketones, pyrroles, pyridines, phenols, and sulfur compounds to processing and quality differentiation [20, 22, 30, 31, 36, 37, 38, 39, 40, 41]

3.2 Class-level balance

Class-level composition showed origin-specific differences. Enrekang and Gowa/Malakaji Arabica were characterized by furan–ketone profiles. Bulukumba Robusta had fewer total detected compounds but a relatively high acid count, whereas Bantaeng Robusta was distinguished by pyrazine representation and a large unclassified fraction. These patterns suggest that ohmic fermentation produced distinct roasted volatile fingerprints across origin–species combinations.

Table 4
Exploratory class-level diversity descriptors derived from volatile compound counts

Origin/species	Total detected compounds	Interpretable class sum	Other/unclassified	Shannon index	Simpson index	Dominant interpretable class	Dominant-class count
Enrekang Arabica	477	272	205	1.94	0.77	furans	56
Gowa/Malakaji Arabica	469	283	186	2.01	0.8	furans	54
Bulukumba Robusta	316	215	103	2.14	0.84	furans	38
Bantaeng Robusta	425	225	200	1.86	0.74	pyrazines	40

Note. Diversity values were calculated from compound-class counts and are intended as descriptive indices rather than sensory-intensity metrics.

3.3 Treatment-dependent PCA structuring

Treatment-level PCA showed clear structuring within each origin. For Enrekang Arabica, F1 and F2 explained 38.77% and 33.07%, respectively, for a cumulative variance of 71.84%. EH12T30 and EH2T30 were associated with distinct nitrogen heterocycles, oxygenated volatiles, furanic compounds, and caffeine-related variables. For Gowa/Malakaji Arabica, the first two components explained 73.16%, and each treatment occupied a different region of PCA space, indicating treatment-dependent volatile differentiation.

Robusta samples also showed treatment structure. Bulukumba Robusta had 68.33% of variance explained by the first two components, whereas Bantaeng Robusta had 70.53%. Bantaeng treatments were associated with several sulfur- and nitrogen-containing compounds, pyrazines, pyrroles, carbonyls, and furan derivatives. The combined Robusta PCA separated Bantaeng from Bulukumba, consistent with their class-count differences.

4 Discussion

4.1 Evidence for volatile fingerprint differentiation

The revised manuscript makes a narrower and more defensible claim than the initial version: ohmic fermentation was associated with treatment-, species-, and origin-dependent volatile fingerprints after roasting. The data support this claim through class-count differences and PCA separation. They do not, by themselves, prove that ohmic fermentation quantified precursor pools or directly caused specific sensory attributes. This distinction is important because detected-compound counts are not equivalent to concentration or odor activity.

The observed class distributions are nevertheless chemically plausible. Furans, pyrazines, pyrroles, pyridines, ketones, aldehydes, phenols, thiophenes, and thiazoles are consistent with volatile families expected from roasting-related reactions. Experimental and model-system studies indicate that sugars, amino acids, acid conditions, and thermal processing influence furan and pyrazine formation. Thus, the present findings are consistent with the hypothesis that fermentation time and temperature can influence the chemical matrix entering roasting, but this mechanism should be tested directly through precursor analysis [7, 23, 44, 45]

4.2 Species and origin should be interpreted together

The dataset does not support a simple Arabica-versus-Robusta hierarchy. The two Arabica origins had the highest detected-compound counts, yet Bantaeng Robusta showed a strong pyrazine signature and a total count closer to Arabica than to Bulukumba Robusta. This indicates that species identity interacts with origin and fermentation regime. Similar conclusions are supported by studies showing that coffee volatile composition can discriminate species, origin, altitude, processing, and roasting level, but that quality-relevant markers depend on the specific chemical family and sensory context [24, 25, 26, 35, 36, 37, 38, 41]

For Arabica, Enrekang and Gowa/Malakaji shared a furan-rich profile but differed in ketones, pyrazines, pyridines, phenols, and thiazoles. For Robusta, Bantaeng and Bulukumba differed more strongly, with Bantaeng showing greater pyrazine representation and Bulukumba showing relatively higher acids. These differences suggest that a single ohmic fermentation condition is unlikely to be optimal across origins.

4.3 Chemical families and sensory implications

The dominant chemical families provide hypotheses about sensory direction but do not substitute for sensory evaluation. Pyrazines may be associated with roasted and nutty attributes, furans with sweet or caramelized impressions, aldehydes and ketones with malty or fruity notes, and sulfur-containing compounds with high-impact roasted or sulfury notes. However, the sensory value of each class depends on compound identity, abundance, odor threshold, release behavior, and matrix effects. Previous studies show that consumer liking and descriptive sensory outcomes are linked to specific compounds and compound balances rather than to total volatile counts [33, 34, 36, 37, 42, 46, 47, 48, 49, 50]. Recent work also shows that sulfury/roasty fading indicators contribute to coffee freshness perception [51], while yeast-associated processing can generate characteristic flavor-forming volatile pathways [52].

Accordingly, Bantaeng Robusta's pyrazine-rich signature should be interpreted as a promising chemical target rather than proof of stronger nutty aroma. The furan-rich Arabica profiles similarly suggest caramelization-related potential, but they require odor-activity and sensory confirmation. Future GC-olfactometry, trained cupping, quantitative descriptive analysis, and odor activity value calculations would allow the volatile fingerprints reported here to be translated into sensory relevance.

4.4 Analytical limitations and future validation

The main analytical limitation is the reliance on detected-compound counts and PCA associations. HS-SPME-GC-MS is appropriate for screening and class differentiation, but high-impact publication would require stronger validation, including retention indices, match-factor thresholds, authentic standards for key compounds, internal-standard normalization, and replicate-level statistics. The journal guidelines also require that compound identifications based on a single method be labelled tentative, which has been incorporated into the revised methods and interpretation.

The large other/unclassified category is another limitation. It indicates that the detected chemical space is broader than the current class taxonomy. A supplementary table listing all compounds, retention times, tentative identities, mass spectral match quality, class assignment, and relative abundance should be prepared before submission. If raw peak-area data are available, PERMANOVA or MANOVA, loadings tables, confidence ellipses, and hierarchical clustering should be added to strengthen the statistical evidence.

4.5 Practical significance

Despite these limitations, the study provides a useful process-oriented framework for Indonesian coffee. Enrekang and Gowa/Malakaji Arabica may be suitable matrices for developing furan–ketone aroma profiles, whereas Bantaeng Robusta appears promising for pyrazine-associated roasted complexity. Bulukumba Robusta may require re-optimization of ohmic time–temperature conditions to increase desirable heterocyclic and carbonyl representation. More broadly, the results suggest that ohmic fermentation should be optimized by origin rather than applied as a universal protocol.

5 Conclusion

Ohmic fermentation followed by roasting produced distinct volatile fingerprints in Arabica and Robusta coffees from four Indonesian origins. HS-SPME-GC-MS detected 477 compounds in Enrekang Arabica, 469 in Gowa/Malakaji Arabica, 316 in Bulukumba Robusta, and 425 in Bantaeng Robusta. Furans, pyrazines, pyridines, ketones, pyrroles, phenols, aldehydes, acids, thiophenes, thiazoles, alcohols, and lactones formed the main interpretable volatile classes.

PCA showed treatment-dependent structuring within all origins, with the first two components explaining 71.84% of variation for Enrekang, 73.16% for Gowa/Malakaji, 68.33% for Bulukumba, and 70.53% for Bantaeng. Class-level PCA further separated Arabica and Robusta origins. The findings support the conclusion that ohmic fermentation is a promising pre-roasting strategy for origin-specific volatile modulation. The interpretation remains fingerprint-based rather than fully mechanistic; future work should add normalized peak areas, retention-index confirmation, replicate statistics, odor-activity analysis, and sensory validation.

Declarations

Competing interests

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

Ethics approval

This study did not involve human participants or animals.

Clinical trial number

not applicable.

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Author Contribution

Reta: Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. A Ita Juwita: Investigation. Arnida Mustafa: Methodology. Zaimar: Writing – review & editing, Writing – original draft, , Funding acquisition, Conceptualization.Henny Poerwanty: Supervision, Methodology

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Data availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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Figures

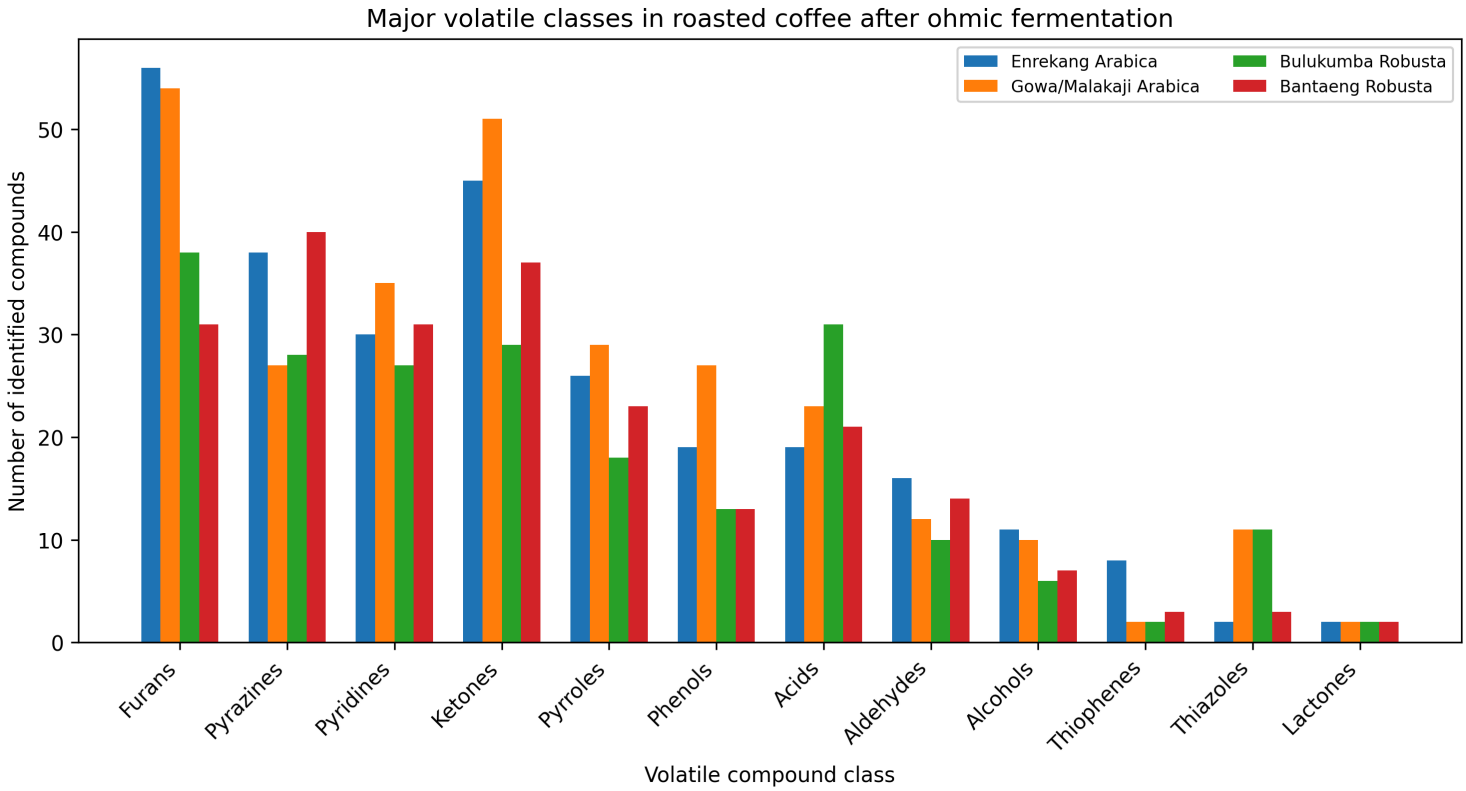


Figure 1

Distribution of major volatile compound classes identified by HS-SPME-GC-MS in roasted coffee from four Indonesian origins after ohmic fermentation. Bars represent detected compound counts by class

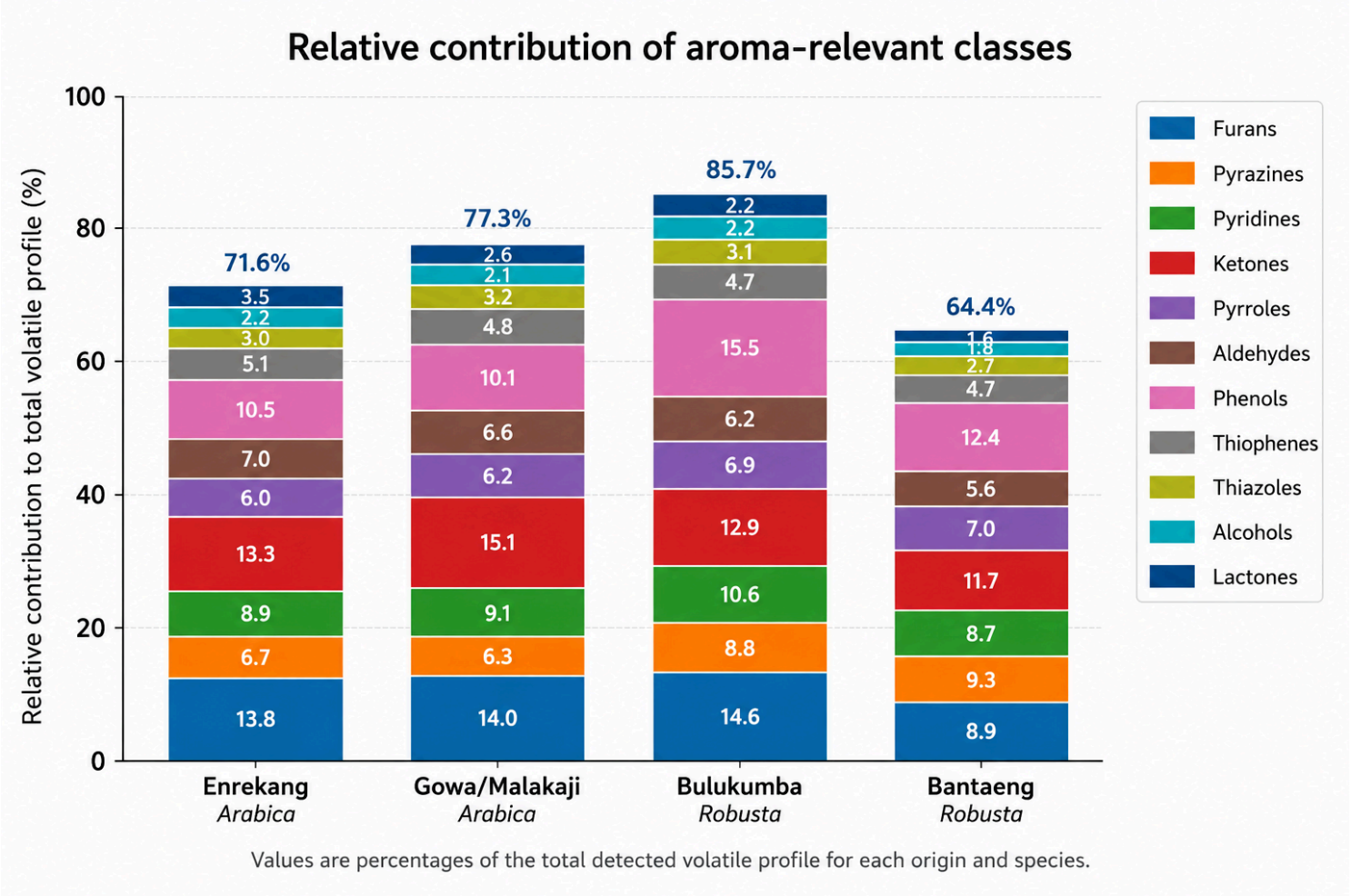


Figure 2

Relative contribution of aroma-relevant volatile classes to the class-count profile of roasted Arabica and Robusta coffees after ohmic fermentation. Values are based on detected compound counts, not normalized peak areas

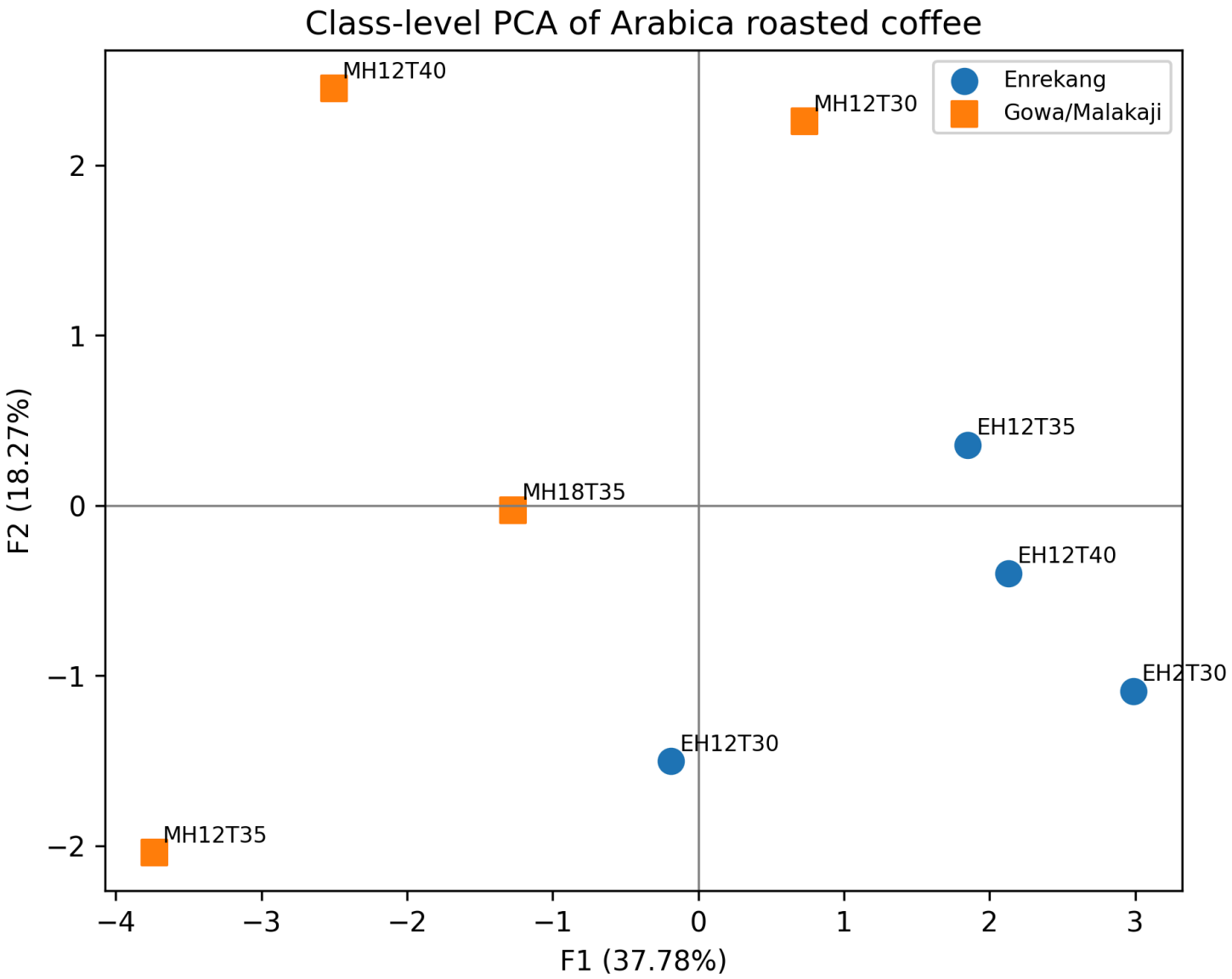


Figure 3

PCA score plot for combined class-level Arabica samples from Enrekang and Gowa/Malakaji. The first two components explain 56.05% of class-level variation

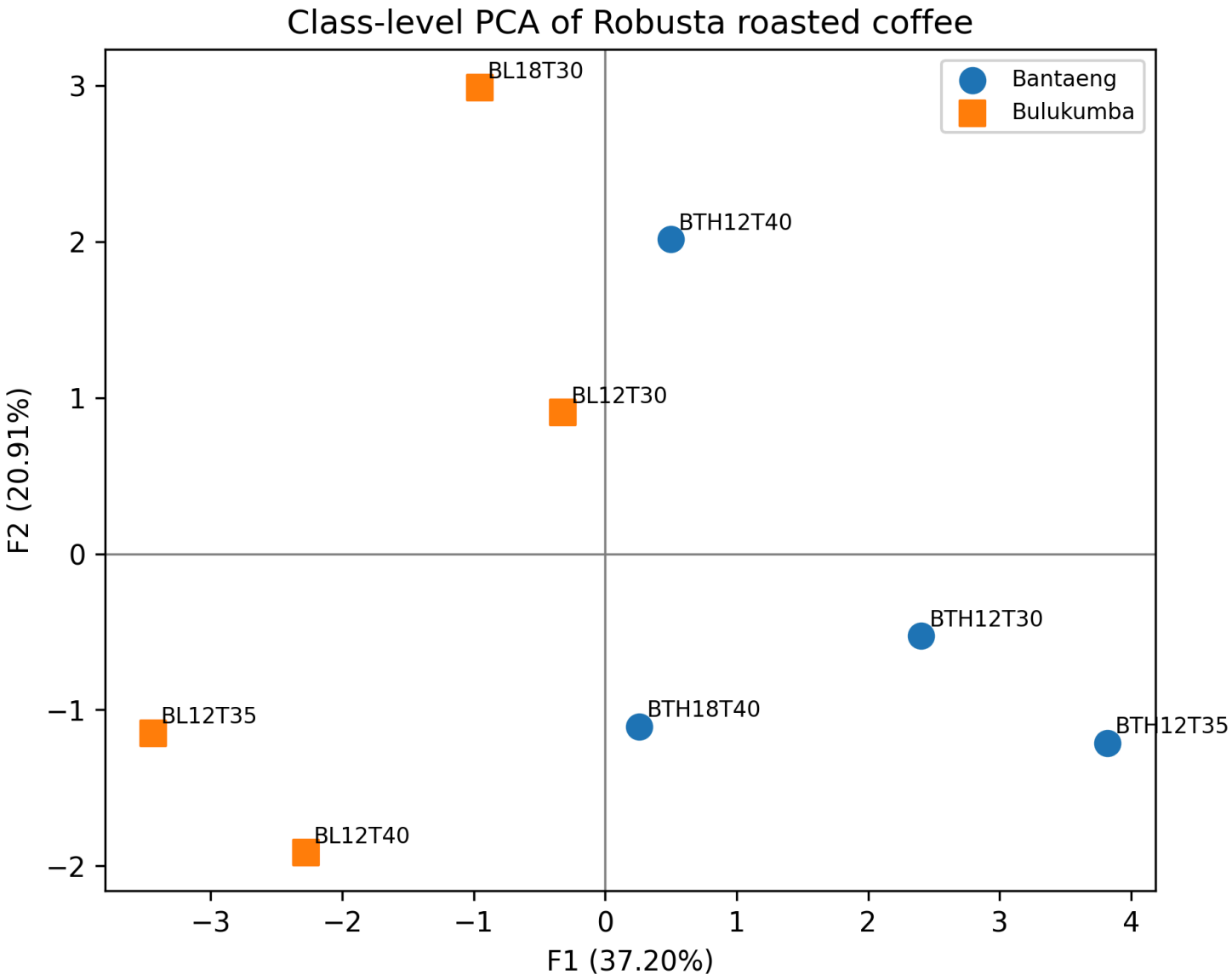


Figure 4

PCA score plot for combined class-level Robusta samples from Bantaeng and Bulukumba. The first two components explain 58.10% of class-level variation