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**Lipidomic and metabolomic profiles of *Coffea canephora* L. beans cultivated in South-western Nigeria**

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## 33 **Abstract**

34

35 Coffee (*Coffea* spp.) is one of the most popular refreshments globally. Coffee lipid diversity has

36 untapped potential for improving coffee marketability because lipids contribute significantly to both the

37 health benefits and cup quality of coffee. However, there have not been extensive studies of lipids of *C.*

38 *canephora* genotypes. In this study, Ultra-performance liquid chromatography coupled with mass

39 spectrometry (UPLC–MS) profiling of lipid molecules was performed for 30 genotypes consisting of 15

40 cultivated and 15 conserved genotypes of *C. canephora* in Southwestern Nigeria. We identified nine

41 classes of lipids in the 30 genotypes which belong to the ‘Niaouli’, ‘Kouillou’ and ‘Java Robusta’ group:

42 among these, the most abundant lipid class was the triacylglycerols, followed by the fatty acyls group.

43 Although ‘Niaouli’ diverged from the ‘Kouillou’ and ‘Java Robusta’ genotypes when their lipid profiles

44 were compared, there was greater similarity in their lipid composition by multivariate analysis,

45 compared to that observed when their primary metabolites and especially their secondary metabolite

46 profiles were examined. However, distinctions could be made among genotypes. Members of the fatty

47 acyls group had the greatest power to discriminate among genotypes, however, lipids that were low in

48 abundance e.g. a cholesterol ester (20:3), and phosphatidylethanolamine (34:0) were also helpful to

49 understand the relationships among *C. canephora* genotypes. The lipid diversity identified among the *C.*

50 *canephora* genotypes examined correlated with their overall Single Nucleotide Polymorphism diversity

51 assessed by genotype-by-sequencing, supporting the relevance of this study to coffee cup quality

52 improvement.

53

54 **Keywords:** *Coffea canephora*; bean lipidomics; UPLC-MS; metabolites; SNP

55

## 56 Introduction

57 “Lipids” are any organic compounds that are insoluble in water, but soluble in organic solvents  
58 [1]. Represented in this group are a broad range of molecules such as fatty acids, triacylglycerols, and  
59 phospholipids. Lipids serve diverse and critical biological roles in plants such as maintaining cellular  
60 membrane integrity and homeostasis, acting as key components in cell signaling pathways and being  
61 used as an energy store [2]. In coffee beans, lipids are important reserve compounds and can make up  
62 to 10-17% of fresh weight [2,3].

63 The lipids accumulated in coffee beans are important contributors to beverage organoleptic  
64 properties [4-6], and are excellent discriminators of coffee quality [7-11]. Lipids determine beverage  
65 foam and emulsion formation and stabilization, which in turn influences flavour and aroma  
66 enhancement, especially in espresso brewing [4,12]. Coffee foam and emulsions are responsible for the  
67 characteristic pleasant aroma of coffee by trapping and retaining the volatile compounds [13]. Further,  
68 the foam created during coffee brewing also influences beverage creaminess and texture [14,15], which  
69 further enhances coffee sensory perception.

70 Coffee bean lipid composition is influenced by the environment but is largely genotype-  
71 dependent [11,16]. Differences are apparent in *C. arabica* and *C. canephora*, the two most consumed  
72 types of coffee [11]. Arabica coffees generally have lipid contents of 15% which is higher than that in  
73 Robusta which averages 10% [2,3]. Arabica also has higher palmitic (16:0), arachidic (20:0), stearic (18:0)  
74 and linolenic acids (18:3), but is lower in oleic acid (18:1) compared to *C. canephora* [17,18]. A recent  
75 genome wide association study of 107 *C. arabica* accessions found single nucleotide polymorphisms  
76 positioned within or near genomic regions coding for proteins involved in lipid and diterpenes metabolic  
77 pathways [19], indicating the potential genetic diversity of these key metabolites. In addition to  
78 genotype, coffee growth environment e.g. altitude, shade and temperature can also influence lipid  
79 composition [8,9,14,20].

80 Lipidomics in plants is still in its infancy compared to the broader metabolomic profiling, and the  
81 data for *C. canephora* is comparatively less than that available for *C. arabica*. *C. arabica* is known to  
82 have a high lipid content compared to *C. canephora* [2,3]. However, there have not been extensive  
83 studies of lipids of *C. canephora* genotypes, so the variability relative to *C. arabica* still remains largely  
84 undiscovered. This is important because although *C. canephora* is not as popular as *C. arabica*, its  
85 production and consumption is increasing, making it important to understand its organoleptic properties  
86 [21]. Further, genetic diversity among tetraploid *C. arabica* is not as high as diploid *C. canephora* [22] and  
87 this may be reflected in the metabolomic and lipid species diversity within these species.

88 The aim of this study was to determine the lipid and metabolomics profiles of *C. canephora*  
89 genotypes conserved in the Cocoa Research Institute of Nigeria (CRIN) coffee repository, and those used  
90 as a source of subsistence by farmers in the southwestern region of Nigeria. Because of the multifaceted  
91 role lipids play in determining coffee sensory quality, we wished to identify potential lipid markers  
92 differentiating among these *C. canephora* genotypes. These markers would be critical for future coffee  
93 improvement programs in Nigeria. We also wished to broaden the current understanding of lipid  
94 profiles in diverse coffee species for which there is relatively scarce data. An ultraperformance liquid  
95 chromatography method that incorporated a charged surface hybrid (CSH) solid phase was used to  
96 separate the different lipid molecules, followed by electrospray ionization (ESI) quadrupole time of flight  
97 (QTOF) tandem mass spectrometry (MS/MS) i.e. CSH-ESI QTOF MS/MS. These compounds were  
98 subjected to univariate and multivariate analyses to understand their relative abundance. They were  
99 also compared to the primary and secondary metabolites profiled in these same coffees, and their  
100 relatedness based on lipidomics was compared to that based on Genotyping-by-Sequencing data. We  
101 therefore were able to build a comprehensive, multidimensional overview of bean lipids in  
102 Southwestern Nigerian coffees.

103

## 104 **Materials and methods**

### 105 **Plant material**

106 Coffee beans (*Coffea canephora*) were harvested from coffee germplasm repository of Cocoa  
107 Research Institute of Nigeria (CRIN) and coffee farmers' field. Similar genotypes were used for  
108 metabolomics [23] consisting of 'Niaouli', 'Kouillou' and 'Java Robusta' varieties. They were classified  
109 into six groups based on the result from Single Nucleotide Polymorphism-Genotype by Sequencing  
110 analysis [23]. 'Niaouli' is comprised of three genotypes: Nia\_1, Nia\_2 and Nia\_3, (respectively, classified  
111 as Groups 1, 2 and 3), 'Kouillou' is comprised of two genotypes: C111 and C36, (respectively, classified as  
112 Groups 4, and 5) and, 'Java Robusta' is comprised of one genotype: T1049, and was classified as Group  
113 6. There were five replicates for each group (genotypes) giving a total of 30 samples (Table 1).

114

115 **Table 1:** Coffee genotypes used in this study and their symbols

Variety	'Niaouli'			'Kouillou'		'Java Robusta'
Group/ Genotype	Group1 (Nia_1)	Group 2 (Nia_2)	Group 3 (Nia_3)	Group 4 (C111)	Group 5 (C36)	Group 6 (T1049)
Samples' Symbols	Nia_11	Nia_21	Nia_31	C111_1	C36_1	T1049_1
	Nia_12	Nia_22	Nia_32	C111_2	C36_2	T1049_2
	Nia_13	Nia_23	Nia_33	C111_3	C36_3	T1049_3
	Nia_14	Nia_24	Nia_34	C111_4	C36_4	T1049_4
	Nia_15	Nia_25	Nia_35	C111_5	C36_5	T1049_5

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117

### 118 **Sample Preparation**

119 Reddish mature (ripened), coffee beans of these genotypes were collected in ice bags and  
120 immediately transferred to -80°C. The endosperms of the coffee bean were excised using sterile blade  
121 and re-transferred to -80°C. These endosperms were lyophilized, ground into powder with Udy mill (Udy

122 Corporation) and sealed prior to lipidomic analysis. The lipid was extracted following the protocols  
123 according to Matyash *et al.*, [24]. Dried extracts were resuspended using a mixture of methanol/toluene  
124 (9:1, v/v) (60  $\mu$ L) containing an internal standard [12-[(cyclohexylamino)carbonyl] amino]-dodecanoic  
125 acid (CUDA)] used as a quality control.

126

## 127 **Data Acquisition**

128         Extracted lipids were separated on an Acquity UPLC CSH C18 column (100  $\times$  2.1 mm; 1.7  $\mu$ m)  
129 maintained at 65  $^{\circ}$ C. The mobile phases for positive mode consisted of 60:40 ACN:H<sub>2</sub>O with 10 mM  
130 ammonium formate and 0.1% (v/v) formic acid (A) and 90:10 IPA:ACN with 10 mM ammonium formate  
131 and 0.1% (v/v) formic acid (B). For negative mode, the mobile phase modifier was 10 mM ammonium  
132 acetate instead. The gradient was as follows: 0 min 85% (A); 0–2 min 70% (A); 2–2.5 min 52% (A); 2.5–11  
133 min 18% (A); 11–11.5 min 1% (A); 11.5–12 min 1% (A); 12–12.1 min 85% (A); and 12.1–15 min 85% (A).  
134 Sample temperature was maintained at 4  $^{\circ}$ C in the autosampler. 2  $\mu$ L of sample was injected. Vanquish  
135 UHPLC system (ThermoFisher Scientific) was used. Thermo Q-Exactive HF Orbitrap MS instrument was  
136 operated in both positive and negative ESI modes respectively with the following parameters: mass  
137 range 120–1700  $m/z$ ; spray voltage 3.6kV (ESI+) and –3kV (ESI–), sheath gas (nitrogen) flow rate 60  
138 units; auxiliary gas (nitrogen) flow rate 25 units, capillary temperature 320  $^{\circ}$ C, full scan MS1 mass  
139 resolving power 60,000, data-dependent MS/MS (dd-MS/MS) 4 scans per cycle, normalized collision  
140 energy at 20%, 30%, and 40%, dd-MS/MS mass resolving power 15,000. Thermo Xcalibur 4.0.27.19 was  
141 used for data acquisition and analysis. The instrument was tuned and calibrated according to the  
142 manufacturer’s recommendations.

143

## 144 **Data Processing**

145           Raw data files were converted to the mzML format using the ProteoWizard MSConvert utility.  
146 For each  $m/z$  values ion chromatogram was extracted with  $m/z$  thresholds of 0.005 Da and retention  
147 time threshold of 0.10 min. Apex of the extracted ion chromatograph was used as peak height value and  
148 exported to a .txt file. Peak height files for all the samples were merged together to generate a data  
149 matrix. Targeted peak height signal extraction was performed using an R script that is available  
150 at <https://github.com/barupal>. Extracted ion chromatograms for each peak were saved as pictures. CSH-  
151 POS and CSH-NEG data matrices were generated. No normalization was applied as minimum signal drift  
152 was observed during analysis.

## 153 **Statistical analysis**

154           Chroma TOF 4.3X software of LECO Corporation and LECO-Fiehn Rtx5 database were used for  
155 raw peaks exacting, the data baselines filtering and calibration of the baseline, peak alignment,  
156 deconvolution analysis, peak identification and integration of the peak area [25]. The RI (retention time  
157 index) method was used in the peak identification, and the RI tolerance was 5000. Metabolite data were  
158 normalized by dividing each peak area value by the area of internal standard (Ribitol). Data were  $\log_{10}$   
159 transformed, mean-centered and divided by the standard deviation of each variable before performing  
160 statistical analysis. The statistical analyses, such as ANOVA, PCA, PLS-DA were performed by using  
161 MetaboAnalyst 3.0 [26]. Univariate and multivariate statistical approaches were performed with  
162 MetaboAnalystR [26]. One-way Analysis of Variance (ANOVA) test was performed to ascertain the  
163 significant variables, and they were expressed as  $f$  - and  $p$ -values. The level of statistical significance  
164 ( $\log_{10}(p)$ ) was determined, followed by post-hoc analyses to correct the  $p$ -value and thus generate the  
165 False Discovery Rate (FDR). Fisher's least significant difference method (LSD) was used to identify groups  
166 that differ in their lipid profiles [26]. The Hierarchical Clustering Analysis (HCA) plots for SNPs and lipids

167 were generated under the R environment. Pearson correlative analysis was performed using lipid and  
168 metabolism parameters. Two packages in R were used: “psych” [27] and “reshape2” [28] for calculating  
169 Pearson’s correlation coefficient (PCC), *p*-value and *q*FDR. The correlation network was drawn using  
170 MetScape 3.1.3 [29] in the Cytoscape environment [30].

## 171 **Results and discussion**

172 The primary aim of this work was to determine the lipid profile and potential lipid markers  
173 differentiating *C. canephora* conserved and cultivated in southwestern Nigeria. The main classes of  
174 lipids, their relative abundance among the genotypes and their ability to discriminate among the  
175 genotypes were determined. Next, how the genotypes associated with each other based on their  
176 primary, secondary and lipid profiles. Finally, the relationship among genotypes based on lipidomics was  
177 compared to genotyping-by-sequencing SNP data, to determine if there was good accordance between  
178 genotypic and functional data i.e. lipids.

### 179 **Identification of lipids**

180 A total of 1824 lipid species consisted of identified (96) and unidentified (1728) lipids were  
181 detected with CSH-ESI QTOF MS/MS. The positive and negative ESI operating modes separated the lipids  
182 into 1171 positive and 653 negative lipids. Six lipid subclasses are typically recognized in living systems  
183 [31], five were found in the *C. canephora* genotypes studied (Fig 1A).

184 Each class of lipid contains multiple molecules of varying lengths and degree of saturation.  
185 Although these lipid classes are diverse, we constructed a simplistic figure of how they may be related to  
186 each other in a metabolic network (Fig 1B). We identified a cholesterol ester (20:3) in this work but  
187 these compounds have not been well studied in plants.

188



189 **Fig 1. Lipid classes and their interrelationship. A)** Lipid classes and subclasses detected in *C. canephora* beans.  
190 Classification is based on the LIPID MAPS (Metabolites and Pathways Strategy) system, which separates lipids  
191 based on their two fundamental “building blocks” - the ketoacyl group and the isoprene group [31]. Abbreviations:  
192 FA- Fatty acyls; DG - Diacylglycerol; TG- Triacylglycerols; PE - Phosphatidylethanolamine; PC -Phosphatidylcholine;  
193 LPC Lysophosphatidylcholine; SM-Sphingomyelins; CE- Cholesterol esters. **B)** A simplified view of a proposed  
194 biochemical interrelationship among the lipid classes according to data in [32,33], as well as in the MetaCyc  
195 database [34] derived from plants. The red dashed arrow indicates data obtained from human cells [35].  
196

## 197 **Relative amount of lipids variability among genotypes studied**

198 Each lipid group i.e. FA, TG, DG, PC, LPC, is made up of multiple chemicals of varying molecular  
199 mass, degree of unsaturation etc. The triacylglycerol (TG) group contained the most chemicals, with 45  
200 different species identified (Figure S1A-S1F). We also identified 13 different fatty acyls (FA), nine  
201 phosphatidylcholines (PC), four lysophosphatidylcholine (LPC), three diacylglycerol (DG) species and one  
202 each of a cholesterol ether, sphingomyelin and phosphotidylethanolamine.

203 The relative abundance of the chemicals within each lipid class was examined across genotypes.  
204 The ratio of the compounds with the maximum and minimum concentration was determined and was  
205 highest for the TG, FA and DG classes i.e. 2145-, 2923- and 20-fold respectively and lowest for PC, LPC,  
206 CE, SM, and PE (Fig 2). Triacylglycerol (52:2) and was the most abundant lipid molecule, while  
207 Sphingomyelin (SM) was the lowest (Fig 2). the TG and FA were the most abundant lipids in these  
208 genotypes consistent with previous reports [2,3]. Genotype C36\_1 (‘Kouillou’) had the highest amount  
209 of TG while Nia\_11 (‘Niaouli’) had the highest amount of FA. The ‘Niaouli’ (Nia) genotypes are cultivated  
210 by farmers, while ‘Kouillou’ (C111 and C36) and ‘Java Robusta’ (T1049) are conserved in the CRIN  
211 germplasm. To better understand the lipid composition in coffee beans, we examined the specific lipids  
212 identified within eight of the nine classes (the unknown compounds were not discussed) and compared  
213 them across genotypes. Each class was considered in turn, and all data referenced from 3.2.1 to 3.2.3 is  
214 contained in S1 Figure.

215 **Fig 2. Relative lipid abundance in the *C. canephora* species studied.** We identified nine subclasses of lipids within  
216 the five broader lipid classes described in LIPIDS MAPS. For each subclass, the relative abundance of compounds

217 among each genotype was assessed. Values shown are the maximum and minimum values within each compound  
218 class, and the label indicates the genotype in which the highest value was found.  
219

## 220 **Fatty-acyl group (FA).**

221 The predominant fatty acyls among our *C. canephora* germplasm were linoleic acid (18:2) followed by  
222 palmitic acid (16:0) (S1A Figure), which together encompassed 50% of the total fatty acids. Linoleic and  
223 palmitic were also the predominant FAs in a range of *C. arabica* and *C. canephora* genotypes studied by  
224 Speer and Kölling-Speer [2]. The number of carbons in the fatty acyls in this study ranged from C15 to  
225 C28, also similar to the range i.e. C14 to C24, found by Speer and Kölling-Speer [2].

226 The proportion of the major FA among genotypes was also examined, because of their influence  
227 on coffee quality. These FAs are also members of highly related biosynthetic pathways (Fig 3). FA (16:0)  
228 i.e. palmitic acid, was higher in ‘Kouillou’ and ‘Java Robusta’ compared to ‘Niaouli’ (S1A Figure). This is of  
229 interest because palmitic acid was positively associated with the high hedonistic values in some specialty  
230 Brazilian *C. arabica* coffees [9]. Oleic, linoleic, and linolenic acid levels have also been identified as good  
231 markers for Brazilian *C. arabica* coffees which had lower acidity, fragrance, body and flavor [9]. Oleic  
232 acid (18:1) was 3-fold lower than linoleic acid (18:2) especially in Nia\_11 (S1A Figure). Further, linolenic  
233 acid (18:3) was low (10-fold) relative to linoleic acid (18:2). It is tempting to speculate that there is  
234 differential regulation of the enzymes that catalyze these steps (Fig 3). In Arabidopsis these two fatty  
235 acid desaturases (FAD2 and FAD3) operate independently [36].

236

237 **Fig 3. Desaturation of C18 fatty acids.** This pathway is found in plastids (catalyzed by fatty acid desaturases - FAD6  
238 and FAD7/8) and in the endoplasmic reticulum (catalyzed by FAD2 and FAD3). Arrows indicate the relative amount  
239 of each compound based on data derived from this study.

240

241

## 242 **Triacylglycerol (TG).**

243 This group can comprise up to 75% of the lipids in coffee beans [37], and during coffee roasting, they  
244 become the carriers of the emerging flavor volatiles [4,12]. There were 45 classes of TGs identified,  
245 varying in acyl carbons from C48 to C60 in this study. The farmer cultivated accessions i.e. the ‘Niaouli’  
246 genotypes had a greater proportion of high-carbon triacylglycerols i.e. C56, C58 lipids compared to  
247 ‘Kouillou’ which had more C48-C52 compounds (S1B Figure). The C52 triacylglycerols showed great  
248 structural diversity containing up to six double chain triacylglycerols i.e. (52:1) to (52:6).

249

### 250 **Cholesterol ester (CE).**

251 Cholesterol esters are cholesterol molecules with a long-chain fatty acid linked to the hydroxyl group  
252 [38]. Cholesterol was thought to only be important in animal metabolism with low amounts found in  
253 plants, however, this molecule has now been identified as a key precursor for thousands of bioactive  
254 plant metabolites [39]. Cholesterol ester (20:3) was very low in abundance in *C. canephora* relative to  
255 the other lipid classes (Fig 2), however, levels were notably higher in ‘Niaouli’ when compared to  
256 ‘Kouillou’ and ‘Java Robusta’ (S1B Figure).

257

### 258 **Lysophosphatidylcholine (LPC), Phosphatidylcholine (PC) and** 259 **Phosphatidylethanolamine (PE).**

260 Phospholipids are potentially important to food sensory perception [37,40]. PCs accumulated to higher  
261 levels than LPCs which makes sense given their relative position the lipid biosynthetic pathway (Fig 1B).  
262 Generally, the relative levels of these lipids did not vary among genotypes. PEs are usually found in plant  
263 membranes [41]. Their levels were low among the genotypes studied, but there was a significant  
264 difference found between ‘Java Robusta’ which did not accumulate as much PE as the other genotypes.

265

## 266 Discriminatory lipid markers

### 267 Univariate analysis.

268 Several studies indicate that lipids can be used as a marker to discriminate among coffee types  
269 [13,15,19,42]. One-way analysis of variance ( $p < 0.05$ ; Table 3), was used to identify lipid species that  
270 could broadly discriminate among coffees genotypes. Twenty-four lipids separated metabolites in the  
271 farmer's genotypes from those conserved at CRIN, since the data for 'Kouillou' and 'Java Robusta' were  
272 identical. 'Kouillou' and 'Java Robusta' were treated as a single group i.e. 'Kouillou/Java Robusta'  
273 because of the similarities detected. Fourteen of these lipid species were higher in 'Niaouli' and ten  
274 were higher in 'Kouillou/Java Robusta' (Table 3).

275  
276 **Table 3. One-way Analysis of Variance and Fisher's Least Square Difference (LSD) for discriminating genotypes**  
277 **based on lipid content.** The Farmer's cultivated accessions ('Niaouli' i.e. Nia\_1, Nia\_2, Nia\_3) and those from the  
278 conserved genotypes ('Kouillou' i.e. C111, C36 and 'Java Robusta' i.e. T1049) were compared. The *f*-value is derived  
279 from the *F*. statistic test for significance, the *p*-value tests variability between two groups,  $-\text{LOG}_{10}(p)$  determines  
280 the significant levels, and FDR means False Discovery Rate.

Lipid species more abundant in 'Niaouli'	<i>f.value</i>	<i>p.value</i>	$-\text{LOG}_{10}(p)$	FDR
TG (56:2)	15.454	7.86E-07	6.1044	3.20E-05
TG (58:4)A	15.260	8.79E-07	6.0562	3.20E-05
PE (34:2)	15.037	1.00E-06	6.0000	3.20E-05
CSH_negESI (19:2)	11.988	6.84E-06	5.1650	0.000131
TG (58:3)	11.987	6.84E-06	5.1648	0.000131
CE (20:3)	11.212	1.18E-05	4.9299	0.000188
CSH_posESI (11:6)	9.9478	3.00E-05	4.5229	0.000411
FA (28:0)	9.0851	5.94E-05	4.2263	0.000713
TG (58:2)	6.4147	0.000645	3.1901	0.006197
TG (56:3)	5.2852	0.002060	2.6862	0.014124
TG (56:1)	5.1318	0.002431	2.6142	0.014586
FA (22:0)	5.0736	0.002590	2.5867	0.014627
FA (20:1)	4.4342	0.005305	2.2754	0.025462
TG (56:4)	3.9802	0.009030	2.0443	0.037692

Lipid species more abundant in 'Kouillou' /'Java Robusta'	<i>f.value</i>	<i>p.value</i>	$-\text{LOG}_{10}(p)$	FDR
FA (16:0)	7.3943	0.000255	3.5933	0.002721
FA (20:0)	6.2489	0.000760	3.1189	0.006637
TG (50:1)_1	5.9483	0.001029	2.9874	0.008235

CSH_posESI (17:6)	5.7749	0.00123	2.9102	0.009082
CSH_posESI (29:8)	5.1657	0.002343	2.6302	0.014586
CSH_posESI (04:1)	4.6549	0.004124	2.3847	0.021996
CSH_posESI (28:2)	4.5120	0.004852	2.3141	0.024513
TG (52:2)	4.2978	0.006211	2.2069	0.028392
TG (48:1)	4.1161	0.007685	2.1144	0.033535
CSH_posESI (14:1)	3.8540	0.010507	1.9785	0.042028

281  
 282 The lipid with the highest discriminatory power between the two groups of genotypes were TG (56:2),  
 283 TG (58:4)A, and PE (34:2) which accumulated to high levels in ‘Niaouli’ relative to other genotypes. The  
 284 lipid species which differentiates ‘Kouillou/Java Robusta’ from ‘Niaouli’ were two saturated fatty acids,  
 285 palmitic (16:0) arachidic acids (20:0) and TG (50:1). Based on our data analysis we show in Table 4, the  
 286 lipids that have a high discriminatory power in the coffees in our study, were compared with  
 287 information from data that was published by others. Fatty acids were the most discriminatory of all  
 288 lipids, although the types varied with respect to the species examined (Table 4).

289  
 290 **Table 4. Fatty acids with high discriminatory power among coffee genotypes.** Included are the two main  
 291 varieties of *C. canephora* (‘Niaouli’ and ‘Kouillou’) used in this study, two cultivated *Coffea* species (*C. arabica*  
 292 and *C. canephora*) and specialty or high-quality coffee. Citations to the referenced data are included.  
 293

‘Niaouli’	‘Kouillou’	<i>C. arabica</i>	<i>C. canephora</i>	Specialty coffees
▪ FA (22:0) Behenic acid.	▪FA (16:0) Palmitic acid	▪ FA (18:2) Linoleic acid [17]	▪ FA (18:1) Oleic acid [17]	▪ FA (14:0) Myristic acid [6] <sup>1</sup>
▪ FA (20:1) Arachidic acid.	▪ FA (20:0) Arachidic acid	▪ Polyunsaturated Fatty acids [16]	▪ Monounsaturated fatty acids [17]	▪ FA (20:0) Arachidic acid.
▪ FA (28:0) Montanic acid				▪ FA (18:0) Stearic acid ▪ FA (16:0) Palmitic acid [9] <sup>2</sup>

294 <sup>1</sup> *C. canephora*; <sup>2</sup> *C. arabica*

295  
 296 **Multivariate analysis – Partial Least Square Projections**

297 Variable influence (or importance) of projection (VIP) scores were used as another tool to  
 298 identify the lipids that contribute most to differences among genotypes (Fig 4). This analysis predicted

299 that PE 34:2, a negative unknown lipid, CSH\_negESI (19:2), and FA (28:0) i.e. dodecanoic acid could  
300 distinguish 'Niaouli' from the conserved genotypes. The ANOVA data in Table 3, also indicated that these  
301 three compounds accumulated to higher levels in the 'Niaouli' genotype.

302

303 **Fig 4. Potential lipidomic markers differentiating 'Niaouli' (genotypes groups 1–3) from 'Kouillou' (groups 4–5)**  
304 **and 'Java' (group 6).** The variable importance in projection (VIP) scores on the x-axis provide an estimate of the  
305 contribution of a given predictor (lipid species shown on the y-axis) to the Partial Least Square (PLS) regression  
306 above. The higher the VIP score, the better the lipid species is as a predictor of the discrimination among the  
307 genotypes.  
308

## 309 **Understanding the lipid networks in *C. canephora* coffee beans**

310 We examined the lipid-to-lipid correlations among *C. canephora* beans. Many compounds in  
311 related pathways tend to occur within defined stoichiometries and kinetics parameters [43,44].  
312 Neighbouring compounds may be correlated with each other. This is also true of metabolites that are in  
313 chemical equilibrium, show mass conservation, or are highly sensitive to a common parameter [43,45].  
314 Using Pearson's correlation coefficient at a cut-off of  $\geq |\pm 0.75|$ , we identified those lipids that co-  
315 occurred at similar relative levels across the *C. canephora* genotypes studied. Highly specific interactions  
316 between lipids are essential for regulation of cell physiology [46,47] (Fig 5 and detailed in S2 Table).

317 The most notable observation was the very strong negative correlations between CE (20:3) and  
318 other lipids, many of which were uncharacterized (Fig 5). Negative correlations were also found with CE  
319 (20.3) and TG (54.1), TG (52.1), but most notably with TG (50.1). Based on the number of carbons in  
320 their acyl chains, it seems likely that these three TGs are closely connected in the TG biosynthetic  
321 pathway. Negative correlations among metabolites are sometimes due to regulatory mechanisms  
322 controlling metabolites that have conserved moieties, or metabolites connected by enzymes with high  
323 variance which can cause negative correlations between its substrate and product metabolites [43,48].  
324 Based on the simplified pathway in Figure 1B, a relationship between the CE and TGs can be envisaged.

325 Not all of the relationships between CE (20:3) and other lipids were negative. There was a positive  
326 correlation between CE (20:3) and TG (58.2), TG (58.4), and FA (22.0) respectively. Most triacylglycerols  
327 were positively associated with other lipids except, TG (52:0) and TG (50:1), which showed a negative  
328 correlation (Fig 5).

329

330 **Fig 5. Pearson's correlation network illustrating correlation patterns among lipids.** Correlations found among lipid  
331 data are shown as attribute circular layout. The blue lines indicate lipids whose occurrence negatively correlate,  
332 while the pink lines denote lipids that show a positive correlation. Line thickness indicates the strength of  
333 correlation. A permissive threshold level of  $\geq |\pm 0.75|$  was set for the Pearson's correlation coefficient and a  $qFDR$   
334 of  $<0.05$  was chosen for the identification of significant correlations within the lipid data.  
335

## 336 **Comparing the primary, secondary metabolites and lipid**

### 337 **profiles among *C. canephora***

338 Metabolomics and lipidomics are powerful strategies to qualitatively and quantitatively analyze  
339 a wide range of small molecules in a biological sample, which represent endpoints of genome expression  
340 [49]. The metabolomics data from our recent work [21] was subjected to PLS-DA analysis for both  
341 primary and secondary metabolites and compared to the lipidomics profile of these coffees. Our aim  
342 was to determine the diversity of metabolism across genotypes. We expected greater similarity in  
343 primary metabolism across genotypes, and that specialized metabolites would be more divergent [50].  
344 Lipids are primary metabolites but in coffee beans, it is not known the extent to which they are part of  
345 the fundamental or specialized metabolic machinery.

346 We found that there was clearer differentiation between 'Niaouli' genotypes which clustered  
347 together and away from the 'Kouillou' and 'Java Robusta' when secondary metabolites were examined  
348 (Fig 6B) compared to primary metabolites (Fig 6A). No clear difference was observed among the groups  
349 with PLS-DA on lipid (Fig 6C) but SPLS-DA - (Fig 6D) was able to reveal more similarity between 'Java' and  
350 the 'Niaouli' types, while the 'Kouillou' genotypes were separate from the rest. This is noteworthy

351 because of the many studies that show 1) that lipids are valuable components of the sensory attributes  
352 of coffee and 2) that they are excellent at discriminating genotypes and growing environment [8,9,14].

353

354 **Fig 6. Differentiating among the *C. canephora* genotypes using multivariate analyses. A)** Primary metabolites  
355 analyzed by PLS-DA, **B)** Secondary metabolites analyzed by PLS-DA, **C)** lipids analyzed by PLS and **D)** lipids analyzed  
356 by Sparse-PLS. (PCA = Principal Component Analysis, PLS-DA = Partial Least Square –discriminate analysis.  
357 Genotypes 1-3 belong to the ‘Niaouli’ group i.e. Nia\_1, Nia\_2 and Nia\_3, Genotypes 4-5 are members of the  
358 ‘Kouillou’ group i.e. C111 and C36, and Genotype 6 is ‘Java Robusta’ i.e. T1049. The primary and secondary  
359 metabolite data were derived from Anagbogu *et al.*, 2019b [21].

360

361

## 362 **Comparing the lipid variability among accessions with their**

## 363 **Single Nucleotide Polymorphism diversity**

364 In spite of the importance of lipids in coffee cup quality improvement, as far as we know, it has  
365 not been fully integrated into coffee breeding strategies. The DNA of coffees extracted in this study was  
366 analyzed using Genotype-by-Sequencing and their relatedness compared using hierarchical clustering.  
367 The lipidomics data was also analyzed similarly. Overall, there was good agreement between the DNA-  
368 and metabolite-based clustering (Fig 7A). From the genetic perspective, we observed three clusters I, II  
369 and III representing ‘Niaouli’, ‘Kouillou’, and ‘Java’ respectively (Fig 7A). The lipidomic analysis of the  
370 genotypes based on the mean values (Fig 7B) revealed two main clusters, separating the ‘Niaouli’ from  
371 ‘Kouillou’/‘Java Robusta’ respectively (Fig 7B). However there were notable exceptions: SNP analysis  
372 indicated that C36 and C111 (‘Kouillou’) were highly related, while T1049 (‘Java Robusta’) was divergent,  
373 in contrast, lipidomics indicated that T1049 and C111 formed a distinguishable subgroup (cluster IIa)  
374 while C36 was more distant. (Fig 7C).

375 All lipid analyses (Figs 7B and C) revealed a clear disparity between the ‘Niaouli’ and ‘Kouillou’/  
376 Java Robusta’ genotypes. We suggest that there are two lipid diversity structures within the population



377 studied which can be used for future coffee improvement in Nigeria. From this study, FA(16:0) and  
378 FA(20:0) were higher ( $p < 0.05$ ) in the 'Kouillou' genotypes (Table 3), and these fatty acids are among the  
379 precursors of good quality coffee (Table 3). Incorporating these important traits into the genome of  
380 cultivated variety ('Niaouli') will be of great help towards its improvement. Also, further study on the  
381 SNP data to detect sources or causes of this great difference between 'Kouillou' and 'Niaouli' is needed.

382

383 **Fig 7. Comparative analysis of the genomics and lipidomic analysis based on their hierarchical structure. A)**  
384 genetic analysis based on ~100,000 SNP, **B)** lipidomic analysis indicating the mean value of each genotype from five  
385 biological replicates and **C)** lipidomic analysis including all replicates. The genotypes and replicates names were  
386 described in Table 1 as follows: Nia\_11- Nia\_15 were Genotype 1, Nia\_21-Nia\_25 were genotype 2, Nia\_31-Nia35  
387 were Genotype 3 and belong to the 'Niaouli' group; Members of the 'Kouillou' group have been referred to as  
388 Genotypes 4 and 5 in this study and included C111\_1-C111\_5 and C36\_1 to C36\_5. 'Java Robusta' coffee has been  
389 described as Genotype 6 included T1049\_1-T1049\_5.

390

## 391 Conclusion

392

393 There is much interest in using lipid profiles to identify biomarkers for coffee cup quality  
394 improvement. In this study, we used various data mining tools to better understand variations in lipid  
395 profiles of South western Nigerian coffee genotypes, and how these lipids relate to other metabolites,  
396 and to other studies done on coffee. Our findings can be summarized as following: 1) Lipids that could  
397 discriminate among the genotypes studied were identified, even though there was less variability for  
398 lipids among genotypes compared with other types of metabolites. 2) 'Java Robusta' and 'Kouillou'  
399 especially 'Kouillou' genotype C36, contained more saturated fatty acyls species such as FA(26:0),  
400 FA(16:0), FA(20:0), while 'Niaouli' contained more unsaturated FAs such as FA(16:1), FA(20:1). It should  
401 be interesting to study the SNPs of gene such as FADs which are responsible for desaturation in coffee  
402 bean. 3) Unexpected observations were made with respect to Cholesterol ester (20:3) which was one of

403 the least abundant lipids in our analysis. The levels of CE(20:3) and some TG compounds, showed some  
404 of the strongest negative correlations. Further, CE(20:3) can discriminate between ‘Niaouli’ and  
405 “Kouillou’ and Java Robusta’ indicating its value as a genotypic marker. 4) Lipids as a class of compounds  
406 in this analysis did not discriminate among the genotype studied, as well as secondary metabolites but  
407 grouped genotypes into two lipid diversity structures. 5) There was a good correlation between  
408 classification of genotypes based on SNP variability and lipidomic profile.

409

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416

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569

## 570 **Supporting information**

571 **S1 Fig.** The relative amounts of the different groups of lipids in the coffee.

572 **S1 Table.** The lipid species identified with corresponding charge mode

573 **S2 Table.** Pearson's Correlation Coefficient Values, P-values and Adjusted P-values for Lipid-to-  
574 Lipid Associations.

575 **S3 Table.** Pearson's Correlation Coefficient Values, P-values and Adjusted P-values for  
576 Metabolite-to-Lipid Associations.

577 **S4 Table.** Pearson's Correlation Coefficient Values, P-values and Adjusted P-values for all  
578 Metabolites vs. All Metabolites Associations.

579

580

581



## FIGURES

### Lipidomic and metabolomic profiles of *Coffea canephora* L. beans cultivated and harvested from South-western Nigeria

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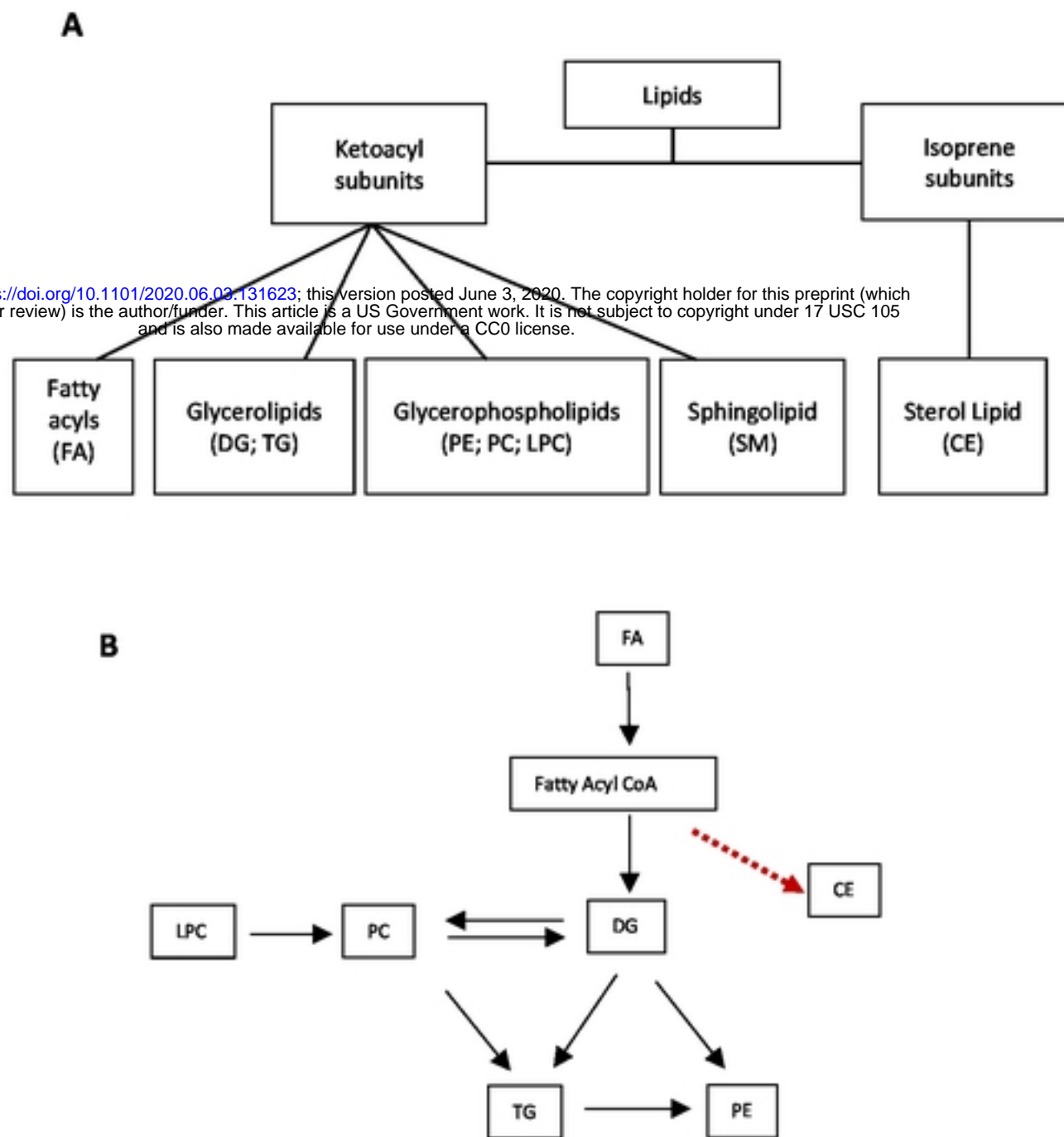
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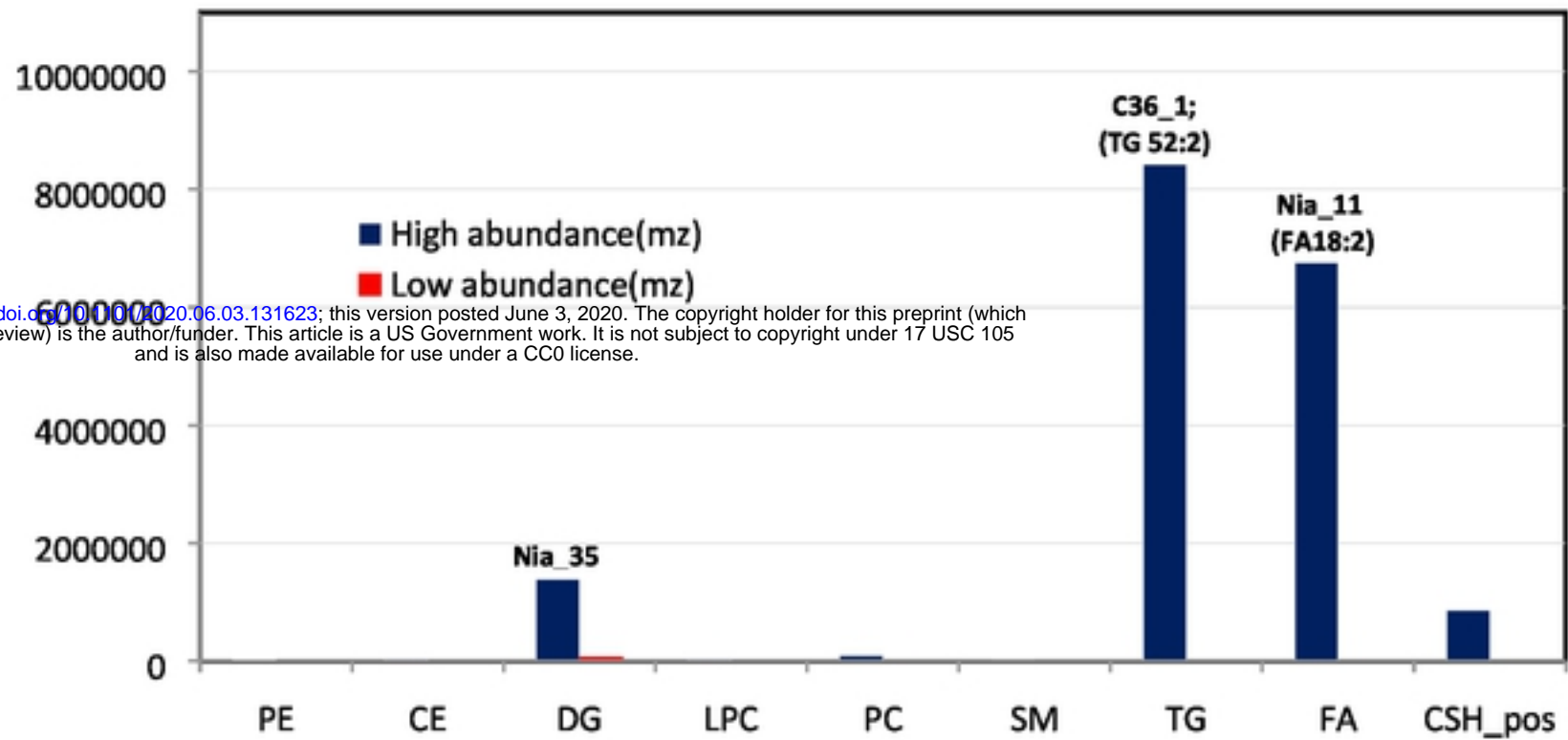


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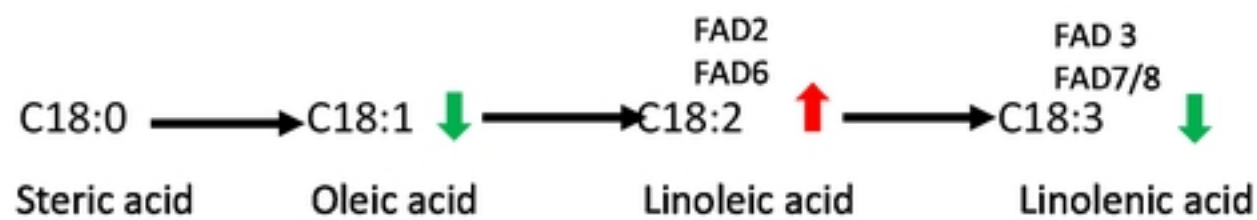


**Fig 1. Lipid classes and their interrelationship. A)** Lipid classes and subclasses detected in *C. canephora* beans. Classification is based on the LIPID MAPS (Metabolites and Pathways Strategy) system, which separates lipids based on their two fundamental “building blocks” - the ketoacyl group and the isoprene group [31]. Abbreviations: FA- Fatty acyls; DG - Diacylglycerol; TG- Triacylglycerols; PE - Phosphatidylethanolamine; PC -Phosphatidylcholine; LPC Lysophosphatidylcholine; SM-Sphingomyelins; CE- Cholesterol esters. **B)** A simplified view of a proposed biochemical interrelationship among the lipid classes according to data in [32,33], as well as in the MetaCyc database [34] derived from plants. The red dashed arrow indicates data obtained from human cells [35].

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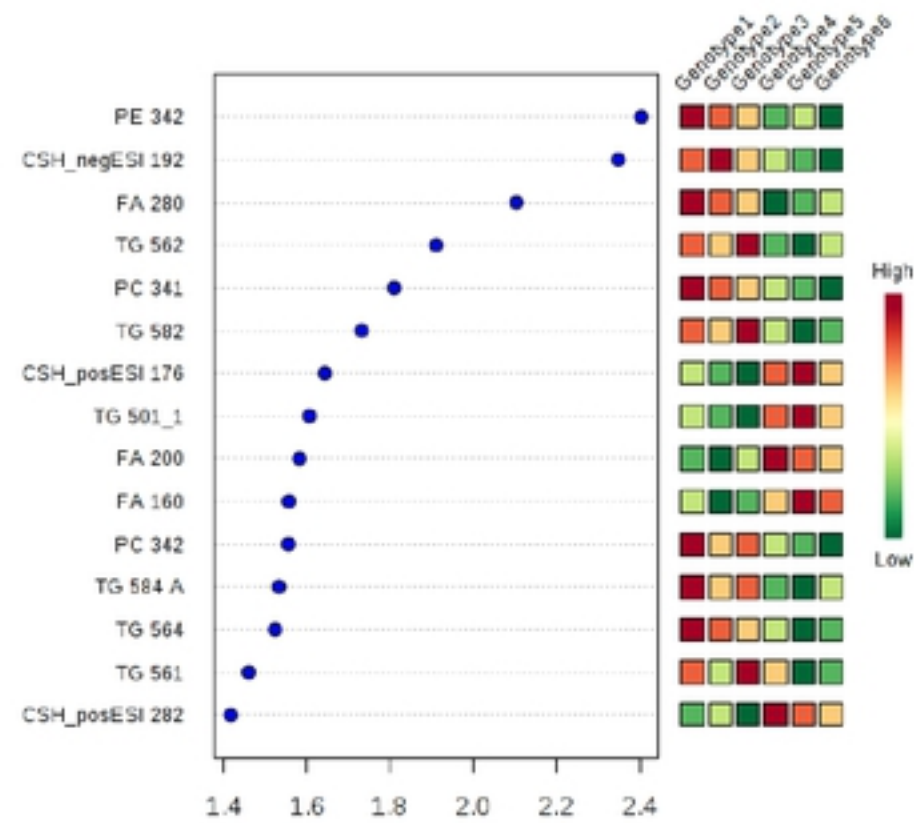


**Fig 2. Relative lipid abundance in the *C. canephora* species studied.** We identified nine subclasses of lipids within the five broader lipid classes described in LIPIDS MAPS. For each subclass, the relative abundance of compounds among each genotype was assessed. Values shown are the maximum and minimum values within each compound class, and the label indicates the genotype in which the highest value was found



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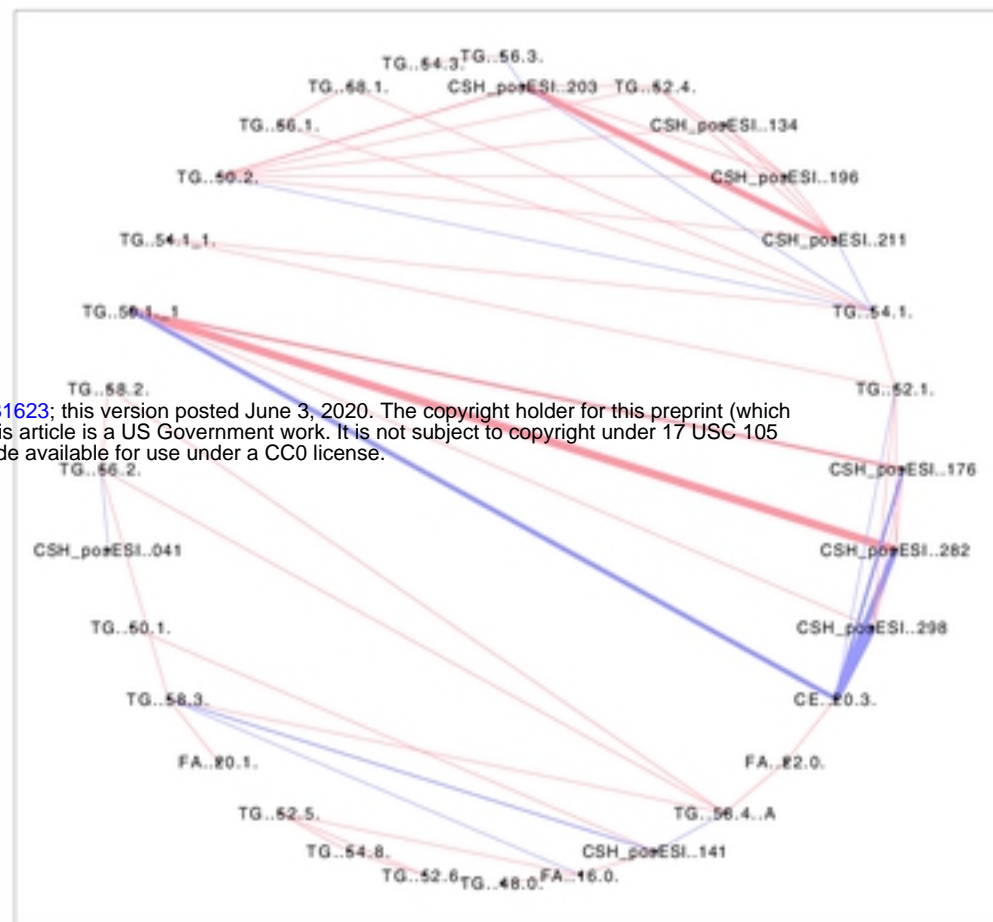
**Fig 3. Desaturation of C18 fatty acids.** This pathway is found in plastids (catalyzed by fatty acid desaturases - FAD6 and FAD7/8) and in the endoplasmic reticulum (catalyzed by FAD2 and FAD3). Arrows indicate the relative amount of each compound based on data derived from this study.



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**Fig 4. Potential lipidomic markers differentiating ‘Niaouli’ (genotypes groups 1–3) from ‘Kouillou’ (groups 4–5) and ‘Java’ (group 6).** The variable importance in projection (VIP) scores on the x-axis provide an estimate of the contribution of a given predictor (lipid species shown on the y-axis) to the Partial Least Square (PLS) regression above. The higher the VIP score, the better the lipid species is as a predictor of the discrimination among the genotypes.

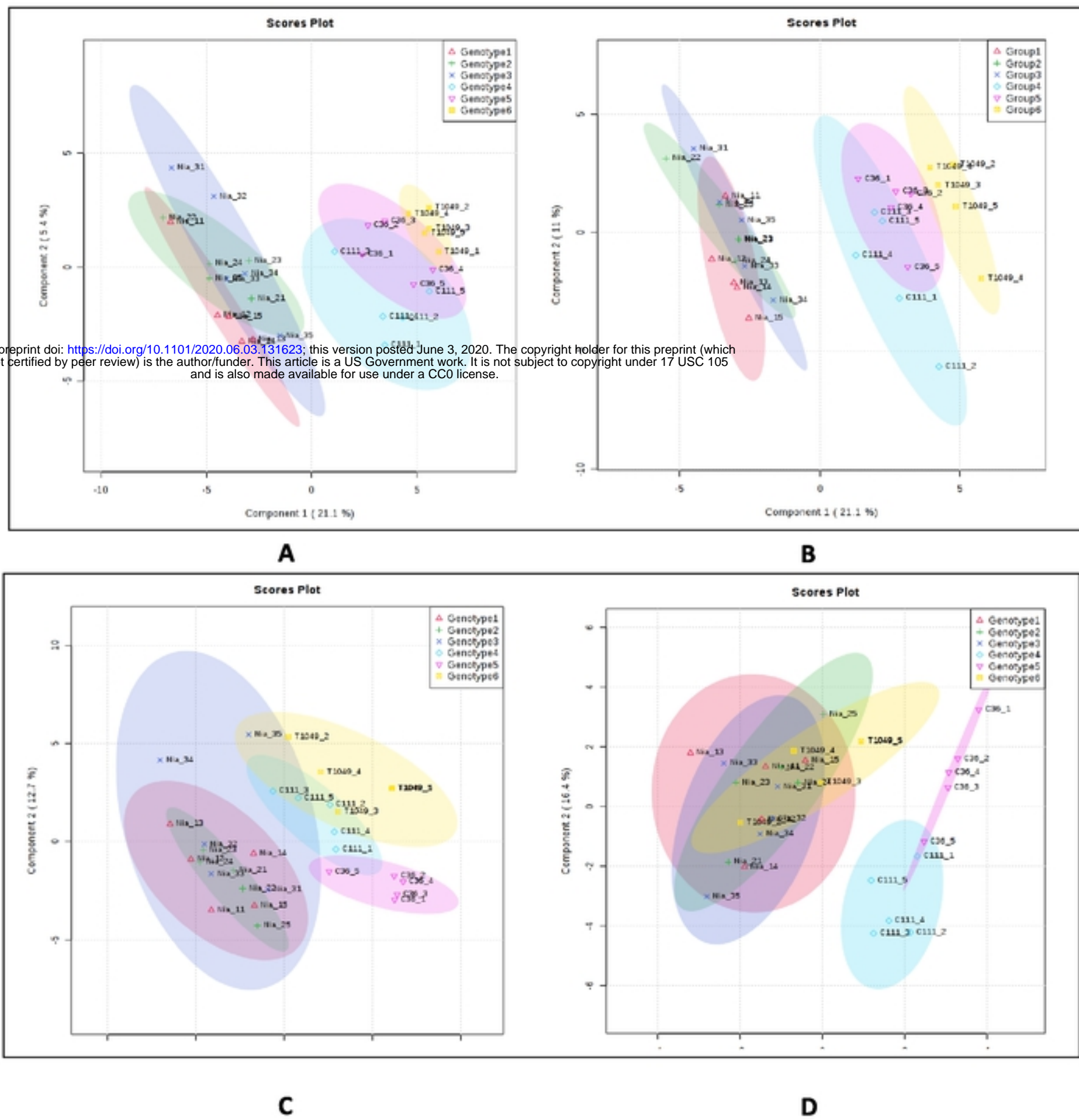
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**Fig 5. Pearson's correlation network illustrating correlation patterns among lipids.** Correlations found among lipid data are shown as attribute circular layout. The blue lines indicate lipids whose occurrence negatively correlate, while the pink lines denote lipids that show a positive correlation. Line thickness indicates the strength of correlation. A permissive threshold level of  $\geq |\pm 0.75|$  was set for the Pearson's correlation coefficient and a  $qFDR$  of  $<0.05$  was chosen for the identification of significant correlations within the lipid data.



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**Fig 6. Differentiating among the *C. canephora* genotypes using multivariate analyses.** A) Primary metabolites analyzed by PLS-DA, B) Secondary metabolites analyzed by PLS-DA, C) lipids analyzed by PLS and D) lipids analyzed by Sparse-PLS. (PCA = Principal Component Analysis, PLS-DA = Partial Least Square –discriminate analysis. Genotypes 1-3 belong to the ‘Niaouli’ group i.e. Nia\_1, Nia\_2 and Nia\_3, Genotypes 4-5 are members of the ‘Kouillou’ group i.e. C111 and C36, and Genotype 6 is ‘Java Robusta’ i.e. T1049. The primary and secondary metabolite data were derived from Anagbogu *et al.*, 2019b [21].

