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Vibrational Spectroscopy for Qualitative and Quantitative Analysis of Fatty Acids in Edible Fats and Oils

Nina Marit Øyunn Knobel

Organic analytical chemistry

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Nina Knobel

Abstract

Fats and oils are an important part of the diet for many organisms, and fatty acids (FA) are important structural components within organisms. Vibrational spectroscopy are rapid and non-destructive analytical tools, and in this study FTIR and Raman spectroscopy were applied for qualitative and quantitative analysis of fats and oils. Gas chromatography mass spectrometry (GC-MS) served as reference method. The goal was to develop calibration models that enable the prediction of FA content of single FAs, by creating a sample design with low correlation between the FAs. Multivariate methods were used to make the calibration models.

The first step concerned the classification of marine oils based on analysis with FTIR and Raman spectroscopy. Principal component analysis was used to differentiate oils based on their chemical composition. Next, the FA profiles of a set of reference oils was determined with GC-MS, by transforming the samples to fatty acid methyl esters prior to analysis. Based on these FA profiles a sample design with low correlation between the FAs was made, which gave rise to 80 calibration samples. The calibration set was analysed with FTIR and Raman spectroscopy. The obtained spectral data were used in combination with the reference analyses and partial least squares regression to establish calibration models. Lastly, the obtained calibration models were validated through analysis of independent oil samples.

Classification of marine oils showed that FTIR was a suitable method for differentiating various types of oils, while Raman spectroscopy could not be used for this purpose due to a strong fluorescence background. The calibration set was shown to have little correlation between the main FAs, and calibration models were achieved for the FAs C14:0, C16:0, C18:0, C18:1n-9, C18:2n-6, C18:3n-3, C20:5n-3 and C22:6n-3. All models had an $R^2 \geq 0.93$, some as high as 0.99. The models based on FTIR spectroscopy had lower RMSECV values than the models for Raman spectroscopy, and generally seemed to be more accurate and robust. Validation of the calibration models showed that both FTIR and Raman spectroscopy gave good predictions of FA content that clearly reflected the FA profiles in the analysed samples. In conclusion, both FTIR and Raman spectroscopy were shown to be promising methods for qualitative and quantitative FA determination in samples of edible oils.

Sammendrag

Fett og oljer er en viktig bestanddel av kostholdet til mange organismer, og både fett og fettsyrer har viktige funksjoner i organismer. Vibrasjonsspektroskopiske metoder brukes til rask og ikke-destruktive analyser, og i denne studien ble FTIR og Ramanspektroskopi anvendt til kvalitativ og kvantitativ analyse av oljer. Gasskromatografi massespektrometri (GC-MS) ble brukt som referansem metode. Målet med denne studien var å lage modeller for å bestemme innholdet av enkeltfettsyrer i fett og oljer. Dette skulle gjøres ved å lage et kalibreringssett med prøver basert på et prøvedesign med lav korrelasjon mellom de ulike fettsyrene. Analyse av kalibreringssettet i kombinasjon med multivariate metoder skulle gi kalibreringsmodeller for fettsyreprediksjon i fett og oljer.

Det første steget var å bruke FTIR og Ramanspektroskopi til klassifisering av marine oljer. Prinsipal komponent analyse ble anvendt for å skille oljene basert på kjemiske ulikheter. Neste steg var å bestemme fettsyreprofilene til et sett med referanseoljer, hvilket ble gjort ved å omestrem oljene til fettsyremetylestere før analyse med GC-MS. På bakgrunn av disse fettsyreprofilene ble det laget et prøvedesign med lav korrelasjon mellom de ulike fettsyrene. Prøvedesignet ble brukt for å lage et kalibreringssett, som så ble analysert med FTIR og Ramanspektroskopi. PLS regresjon basert på spektrale data fra analysene og referansedata ble brukt for å lage modeller for fettsyreprediksjon. Det siste steget var å validere modellene som ble laget ved å analysere uavhengige oljeprøver.

Klassifiseringen av marine oljer viste at FTIR var en egnet metode for å skille mellom ulike typer olje. Raman spektroskopi var derimot lite egnet til analyse av marine oljer, da signalet i for stor grad ble påvirket av fluorescens. Kalibreringssettet hadde lav korrelasjon mellom hovedfettsyrene, og kalibreringsmodeller ble opprettet for fettsyrene C14:0, C16:0, C18:0, C18:1n-9, C18:2n-6, C18:3n-3, C20:5n-3 og C22:6n-3. Alle modellene hadde $R^2 \geq 0.93$, for noen modeller var $R^2 = 0.99$. Modellene basert på FTIR spektroskopi hadde generelt lavere RMSECV verdier enn modellene for Raman spektroskopi, og de så også ut til å være mer nøyaktige og robuste. Validering av modellene viste at både FTIR og Raman spektroskopi ga gode verdier for fettsyreinhold som gjenspeilet den faktiske fettsyreprofilen i de analyserte oljene. Det kan altså konkluderes med at både FTIR og Ramanspektroskopi er lovende metoder for kvalitative og kvantitative analyser av fettsyrer i oljeprøver.

Abbreviations

ALA	Alpha-linolenic acid
ATR	Attenuated total reflectance
DHA	Docosahexaenoic acid
EMSC	Extended multiplicative signal correction
EPA	Eicosapentaenoic acid
ES	External standard
FA	Fatty acids
FAME	Fatty acid methyl ester
FT	Fourier transform
FTIR	Fourier transform infrared spectroscopy
GC	Gas chromatography
IR	Infrared
IS	Internal standard
LA	Linoleic acid
MF	Match factor
MIR	Mid-infrared
MP	Mobile phase
MS	Mass spectrometer
MUFA	Monounsaturated fatty acid
NIR	Near-infrared spectroscopy
PC	Principal component
PCA	Principal component analysis
PLS-DA	Partial least squares discriminant analysis
PLSR	Partial least squares regression
PUFA	Polyunsaturated fatty acid
RMSECV	Root mean square error of cross validation
RRF	Relative response factor
RT	Retention time
SFA	Saturated fatty acid
SIMCA	Soft independent modelling of class analogies
SP	Stationary phase
TAG	Triacylglycerol

UI

Unsaturation index

Contents

Acknowledgments	I
Abstract	II
Sammendrag	III
Abbreviations	IV
Contents	VI
1. Introduction	1
1.1 Background	1
1.1.1 Human consumption of fats and oils in relation to health	1
1.1.2 Quality control of fats and oils	2
1.1.3 Previous research	2
1.2 Aims of thesis	4
2. Theory	5
2.1 Fatty acids	5
2.1.1 Nomenclature	5
2.1.2 Triacylglycerol	6
2.1.3 Unsaturation index	7
2.2 Sources of edible fats and oils	7
2.3 Analytical methods	7
2.3.1 Transesterification of fatty acids	7
2.3.2 GC-MS	8
2.3.3 Qualitative and quantitative analysis	9
2.3.4 Vibrational spectroscopic methods	10
2.3.5 FTIR	10
2.3.6 Interpretation of FTIR spectra	11
2.3.7 Raman spectroscopy	13
2.3.8 Interpretation of Raman spectra	14
2.4 Multivariate data analysis	16
2.4.1 Preprocessing of data	17
2.4.2 Principal component analysis	18
2.4.3 Partial least squares regression	19
2.5 Classification of oils	20
2.6 Correlation coefficient	21

3.	Experimental	22
3.1	Project description	22
3.2	Materials and chemicals	23
3.3	Sample storage.....	25
3.4	Part I – Classification of marine oils	25
3.4.1	Analysis of oils with FTIR spectroscopy	26
3.4.2	Analysis of oils with Raman spectroscopy	26
3.4.3	Multivariate data analysis.....	27
3.5	Part II – Method development	27
3.5.1	Prepared solutions	27
3.5.2	Reference oils	28
3.5.3	Transesterification of neutral lipids.....	29
3.5.4	Analysis using GC-MS.....	29
3.5.5	Identification and quantification of FAs	30
3.5.6	Calibration set	31
3.5.7	Analysis of the calibration set	32
3.5.8	Calibration models based on FTIR.....	32
3.5.9	Calibration models based on Raman	32
3.6	Part III – Model validation	32
3.6.7	Validation of calculated FA profiles in calibration set	32
3.6.8	Validation of calibration models	33
3.6.9	FTIR	33
3.6.10	Raman spectroscopy.....	33
4.	Results and discussion.....	35
4.1	Part I – Classification	35
4.1.1	Raman spectra of marine oils	35
4.1.2	FTIR spectra of marine oils.....	36
4.1.3	Classification using FTIR spectra and PCA.....	37
4.2	Part II – Method development	41
4.2.1	FA composition in reference oils – determined with GC-MS	41
4.2.2	Calculated FA composition in the calibration set	45
4.2.3	Calibration models based on FTIR spectroscopy.....	49
4.2.4	Calibration models based on Raman spectroscopy	56
4.3	Part III – Method validation	62
4.3.1	Validation of calculated FA profiles in calibration samples	62

4.3.2	Validation of calibration models for FTIR spectroscopy	63
4.3.3	Validation of calibration models for Raman spectroscopy	65
4.4	General discussion and future work	68
5.	Conclusion.....	72
	References	73
	Appendix A – Fatty acids.....	i
	Appendix B – Internal standard	ii
	Appendix C – Relative response factors	iii
	Appendix D – Calibration set.....	v
	Appendix E – Fatty acid profiles of the reference oils.....	vii
	Appendix F – Reference oils	x
	Appendix G – Calibration set.....	xii
	Appendix H – Validation of calculated FA profiles of calibration set.....	xv
	Appendix I – Data from GC-MS analyses of reference oils	xvi
	Appendix J - Data from GC-MS analyses of validation oils.....	xxxi
	Appendix K – PLSR based on FTIR	xxxvii
	Appendix L – PLSR based on Raman.....	xlii

1. Introduction

1.1 Background

1.1.1 Human consumption of fats and oils in relation to health

Fats and oils are an important part of the nutrition for many animals, including humans. Compared to carbohydrates and proteins, fats are the macronutrients with the highest energy content, and certain fatty acids (FA) are essential for life and must be provided through the diet. However, the type of FAs as well as the consumed amounts do impact human health in different ways. According to the World Health Organization (WHO) dietary fats should not contribute more than 30% of the daily energy intake, and the energy uptake from saturated fatty acids (SFA) should ideally be less than 10%. Trans FAs are generally considered to be unhealthy, and less than 1% of the energy uptake should be from trans FAs (WHO, 2020).

High consumption of SFA has been associated with adverse health effects such as cardiovascular diseases (Nettleton et al., 2018; Sacks et al., 2017), and a diet low in SFAs is often recommended. The topic of SFA-consumption in relation to human health is however quite complex, and there are arguments for and against this recommendation (Krauss & Kris-Etherton, 2020b; Kris-Etherton & Krauss, 2020). Further research is clearly needed to better understand the chronic effects of SFA-consumption (Krauss & Kris-Etherton, 2020a). On the other hand, monounsaturated FAs (MUFA) and especially polyunsaturated FAs (PUFA) are considered healthy in certain amounts. Among the unsaturated FAs the n-3 FAs have shown many positive health benefits. The n-3 FAs alpha-linolenic acid (ALA), eicosapentaenoic acid (EPA) and docosahexaenoic acid (DHA) have been found to reduce the risk of coronary heart disease, and EPA and DHA also have other positive health benefits such as lowering blood pressure (Wijendran & Hayes, 2004). For healthy adults the daily recommended intake of EPA and DHA is in the range of 250 – 1000 mg per day, while the daily intake of DHA should be somewhat higher for pregnant and lactating women (Hamilton et al., 2020).

There are two FAs which are characterized as essential fatty acids (EFA) because they cannot be synthesised by the human body and therefore must be included in the diet (Punia et al., 2019). These two fatty acids are linoleic acid (LA); C18:2n-6, and ALA; C18:3n-3. ALA can further be converted to EPA and DHA; all three are n-3 FAs with important biological activities in the human body (Punia et al., 2019). The ratio between essential n-6 and n-3 FAs is considered to be important for maintaining good health and to evade chronic diseases, with an optimal ratio of 1:1 – 2:1 (Saini & Keum, 2018). A high ratio of dietary n-6/n-3 fatty acids

is often considered to be problematic because n-6 FAs are precursors for pro-inflammatory signalling molecules in the body called eicosanoids, while n-3 FAs are precursors for anti-inflammatory eicosanoids (Balić et al., 2020). Nevertheless, the absolute mass of consumed fats might be more important than the ratio of n-6/n-3 (Wijendran & Hayes, 2004).

1.1.2 Quality control of fats and oils

Quality control of fats and oils is important for different reasons, one of them being human health. As mentioned above, the total amount of daily consumed fat as well as the type of FAs that are consumed have an impact on our physical wellbeing. Thus, it is essential to know the fat content of foods and the FA composition of edible fats and oils.

Today, FA composition is often determined using GC; a time-consuming and laborious method, which is not suitable for continuous monitoring of quality parameters directly in the food and supplement production line (Tao & Ngadi, 2018). Controlling the quality and safety of fats and oils is, however, very important. The quality is affected by factors throughout the production process, such as raw material, processing method, refining, bottling and storage (Pereira et al., 2008). The quality is controlled by measuring different parameters such as iodine value, saponification value, peroxide value, acidity and colour (Pereira et al., 2008). The largest safety-concern for oils is oxidation, as toxic compounds are formed in this process, leading to rancidity (Guillén & Goicoechea, 2007; Li et al., 2018). Very often the peroxide value is the parameter monitored to assess the oxidation state (Li et al., 2018). Quality control of fats and oils is also important to ensure the authenticity of a product and to detect any adulteration. This is first and foremost done by monitoring the FA composition (Didham et al., 2020; Rohman & Irnawati, 2020).

1.1.3 Previous research

In the last decades, research has been conducted on the use of vibrational spectroscopy in food analysis, both for the determination of fat content and FA composition in foods and fish oil supplements. Mid-infrared spectroscopy (MIR) became interesting as an analytical method after the introduction of Fourier-transform IR (FTIR) spectrometers (Li-Chan et al., 2006), and instrumental improvements made Raman spectroscopy a suitable detection technique (Tao & Ngadi, 2018). Both methods are frequently used in combination with chemometrics and multivariate data analysis.

In a study from 1997, edible oils and lard were characterized by FTIR, and relationships between the composition of the fats and oils and specific bands in the fingerprint region were

studied (Guillén & Cabo, 1997). In a different publication, FTIR was applied to determine the relative amounts of n-3 and n-6 PUFAs in vegetable oils (Yoshida & Yoshida, 2003).

Vibrational spectroscopic methods, including both FTIR and Raman, have been applied for the determination of n-3 FAs in fish oil supplements. The results showed that these methods in combination with PLSR could be applied for the quantification of EPA, DHA and sum of total n-3 FAs (Bekhit et al., 2014). In 2020 Rohman and Irnawati published a study concerning the determination of three oils in ternary mixtures by using FTIR and multivariate data analysis. The conclusion of this study was that certain wavenumbers can be used for accurate determination of the different oils in the mixtures (Rohman & Irnawati, 2020). Today, a commercial analysis service called QTA (Quality Trait Analysis) is provided by Eurofins. QTA is based on FTIR technology and can for instance provide information on FA contents in edible oil samples (Eurofins, 2020).

Raman spectroscopy has been used for the classification of fats and oils, where the results showed that intensities at different Raman shift values were highly correlated with the FA profile of the analysed fats and oils (Baeten et al., 1998). In another study Raman spectroscopy was applied to a complex food model system with the goal of quantifying the fat fraction of the samples. Raman gave promising results for the prediction of total unsaturation in the samples, and different FA classes could also be predicted quantitatively, with good correlations and low estimation errors (Afseth et al., 2005). Raman spectroscopy has also been applied to salmon samples: on intact salmon muscle, ground muscle and fat extracts, with the goal of characterizing the fatty acid unsaturation. Here it was found that the oil extracts gave the best results (Afseth et al., 2006).

Despite the high number of publications related to vibrational spectroscopy and quantification of FA features, there is still a lack of knowledge related to how suitable these techniques are for quantification of single FAs. The possibility for rapid analysis of FA features comes with a “cost”, and there are several limitations in using vibrational spectroscopy for this purpose. The limitations include:

1. FTIR and Raman have far lower chemical resolution than GC. Whereas the latter technique can provide individual signals from most FA features in an oil, the peaks in Raman and FTIR spectra will always be the sum of multiple FA features.
2. Quantification of FAs can only be done after multivariate calibration of FTIR or Raman spectra. For calibration, larger samples sets are needed. In samples sets, unfortunately, one will always find higher or lower correlation patterns between

different FAs (Eskildsen et al., 2014). If two FAs are highly correlated in a sample set, the sample set cannot be used for predicting these two FAs independently in new samples.

1.2 Aims of thesis

The main objective of this thesis was to study and develop a rapid and robust method for the determination of the FA composition in fats and oils using vibrational spectroscopy. The objective was divided into three sub-objectives:

1. Study the use of FTIR and Raman spectroscopy for the classification of closely related marine oils.
2. Develop a FA calibration system based on an experimental design of fat and oil mixtures containing uncorrelated FA features. All measurements included FTIR and Raman spectroscopy, with GC-MS as the reference method.
3. Validate the obtained FTIR and Raman calibrations using marine oils from objective 1 and independent oil samples.

2. Theory

2.1 Fatty acids

FAs are hydrocarbon chains with a methyl-group in one end and a carboxyl-group in the other end. Naturally occurring FAs are usually unbranched with an even number of carbon atoms, ranging from four to 28 carbon atoms per FA (Moss et al., 1995). However, branched FAs and FAs with odd numbered carbon chains do exist (Christie, 1997; Hart, 2012). Figure 1 shows the general structure of a straight chain SFA.

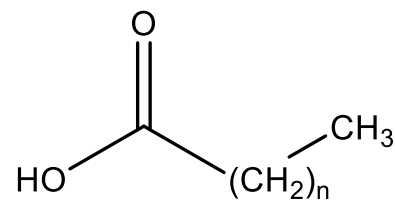


Figure 1 – General structure of a SFA, where n can be any number from 2 to 26.

The hydrocarbon chain of a FA can contain one or more double bonds, most commonly in *cis* configuration. The opposite configuration of *cis* is called *trans* (Hart, 2012). The melting point of a FA is partly dependent on the number of double bonds in the FA, called the degree of unsaturation, because double bonds in *cis* configuration make the FAs bend at an angle. This leads to less interaction with other FAs through van der Waals forces, thus giving rise to a lower melting point (Hart, 2012). Increased chain length will increase the melting point.

2.1.1 Nomenclature

FAs are named after the number of carbon atoms in the carbon chain and the number of double bonds present in the chain. All FAs have a systematic name, and the common ones also have trivial names. For example, oleic acid is a common FA in olive oil, with 18 carbon atoms and one double bond in the carbon chain. The systematic name is (Z)-octadec-9-enoic acid, and the shortened form is C18:1n-9 (U.S. National Library of Medicine). The first number in the shorthand notation indicates the number of carbon atoms in a FA, the second number states the number of double bonds present, and the number after n states the position of the first double bond counted from the methyl terminal carbon. The abbreviated form used here is called the n - x notation, which is equivalent to the omega notation. The n indicates that the position of a double bond is counted from the methyl terminal carbon and x indicates the

position of the first double (or triple) bond (Davidson & Cantrill, 1985). The table in appendix A lists all the FAs relevant in this thesis.

Classification of FAs is based on the position of the first double bond counted from the methyl terminal carbon, and the total number of double bonds in the hydrocarbon chain. FAs with the first double bond in n-3 position are called n-3 FAs, n-6 FAs are one group and so on. If there is no double bond present, the FA is classified as a SFA. MUFAs contain one double bond, PUFAs contain two or more double bonds (Orsavova et al., 2015).

If a double bond is in *cis*- configuration, this is indicated with a Z in the name of the FA. For a *trans*-double bond, the letter E is used in the name. The shorthand notation used here will include *trans* if it is a *trans*-FA, and if nothing is indicated the FA is a *cis*-FA.

2.1.2 Triacylglycerol

FAs in the free form are rarely found in large amounts in nature. They are usually part of more complex lipids, one example being triacylglycerol (TAG), more commonly called a triglyceride. TAGs consist of three FAs that are esterified to one molecule of glycerol, which is a trivalent alcohol. The three FAs bound to glycerol can be identical, this is called a simple TAG. In contrast, mixed TAGs contain two or three different FAs, which can be placed in any of the three possible positions (Hart, 2012). Mixed TAGs are much more common than simple TAGs. The three carbon atoms in the glycerol backbone allow for stereochemically different FA bond positions. These positions are called sn-1, sn-2 and sn-3 (Lichtenstein, 2013). Both the type of FAs and the position they occupy determines the physical properties of a TAG.

Figure 2 shows the general structure of a TAG, where R₁, R₂ and R₃ are the hydrocarbon chains of identical or different FAs (Matthews et al., 2013).

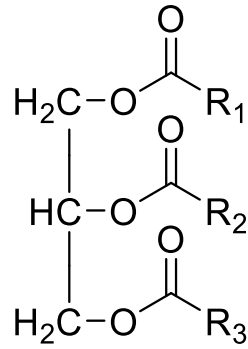


Figure 1 - General structure of a triacylglycerol, where R1, R2 and R3 are the hydrocarbon chains of identical or diverse FAs. The three fatty acids can be identical or different.

2.1.3 Unsaturation index

For oils of a known FA composition, a value for the total degree of unsaturation can be calculated. This is called the unsaturation index (UI), and it is presented in equation 1 (Suutari, 1995). A value of one in the unsaturation index indicates that the average number of unsaturations is one for each FA in an oil.

$$\text{Eq. 1:} \quad \textit{Unsaturation index} = \frac{(\sum(\% \textit{monoene} + 2 \times \% \textit{diene} + 3 \times \% \textit{triene} + \dots))}{100}$$

2.2 Sources of edible fats and oils

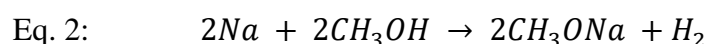
TAGs are the preferred form of energy storage in most organisms (Matthews et al., 2013), and thus TAGs can be extracted from both animal and plant sources. Depending on the FA composition in the TAGs, the extracted fat will be more solid or liquid at room temperature. Animal fats from mammals tend to be solid at room temperature; examples are butter, tallow and lard, while fats from plants are often liquid; such as olive oil and sunflower oil. Fish oil is often rich in PUFAs and is thus liquid at room temperature. There also exist plant oils with a higher melting point such as coconut oil and shea butter.

2.3 Analytical methods

2.3.1 Transesterification of fatty acids

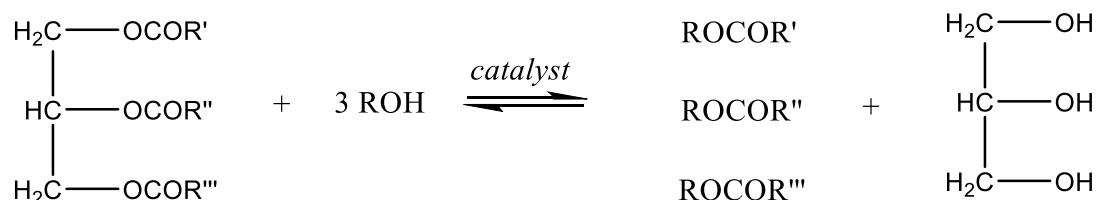
GC is a method used to analyse volatile substances; however, edible oils are not volatile enough for this analysis. Thus, the TAGs in oils and fats must be derivatized into volatile fatty

acid methyl esters (FAME) prior to analysis. This process is called transesterification; where an ester is transformed into a different ester by exchange of the alkoxy moiety (Schuchardt et al., 1998). Typically, the TAGs will react with methanol in the presence of a catalyst, which can be either a base or an acid. Sodium methoxide is a common base catalyst that gives high yields of FAMEs in short reaction times (Schuchardt et al., 1998). Equation 2 shows the net reaction for the formation of sodium methoxide.



Equation 3 displays the net reaction for one mole of a TAG (an ester) that is transesterified into FAMEs (Schuchardt et al., 1998). A catalyst is added to speed up the reaction, and once all three esters of a TAG have reacted, the final products are FAMEs and glycerol. The FAMEs are extracted into a non-polar organic solvent, and can then be analysed using GC-MS.

Eq. 3:



2.3.2 GC-MS

The conventional way of quantifying FAs is using gas chromatography (GC) (Coltro et al., 2005; Tao & Ngadi, 2018). This is a proven method for the separation of different components in a sample, and GC can perform highly accurate quantitative and qualitative analyses when the instrument is equipped with a suitable detector, such as a mass spectrometer (MS) (Miller, 2005). Chromatography uses two different phases for the separation of different components in a sample, where one phase is held stationary on a GC column, while the other phase is passed over it. The different components in the sample that is introduced to the GC system will ideally equilibrate or differently partition between the stationary phase (SP) on the column and the mobile phase (MP), here a carrier gas (Miller,

2005). Depending on the strength of the interaction with either the SP or the MP, the different components in the mixture will be separated from each other. In GC the MP is an inert gas such as nitrogen, helium or hydrogen. Thus, there is no chemical interaction between the analyte and the MP, and it is the interaction between the SP and the analyte which is of interest (Miller, 2005). Open tubular columns are often used with GC-MS instruments. These columns have a small diameter, and a thin layer of SP is coated on the inside of the column (Miller, 2005).

A variety of detectors can be used with a GC, here the detector was a MS. This detector first ionizes and/or fragments the incoming molecules from the GC, before they are separated by a mass filter. The MS instrument used in this research was equipped with a single quadrupole as mass filter, which separates the incoming ions based on their mass-to-charge ratio. These fragments are then detected, and a mass spectrum is produced. This spectrum is characteristic for the original analyte and can be used for structural identification. Nowadays it is quite common to use a database such as the mass spectral library by the National Institute of Standards and Technology (NIST), where obtained mass spectra are compared to spectra in the database for identification of the original analyte (Miller, 2005).

2.3.3 Qualitative and quantitative analysis

Qualitative analysis based solely on chromatography is not ideal. Different retention parameters can be used for qualitative analysis, such as retention time (RT), when compared to the RT of standards. This can give a first indication on what compounds a sample consists of. However, spectral measurements are required for positive identification of the analytes in a sample (Miller, 2005). Thus, GC systems are often coupled to a MS when the goal is to perform qualitative analysis (Miller, 2005). A MS will enable identification of a compound based on its unique mass spectrum, and often a database such as NIST 2017 is used as reference. With GC-MS it is thus possible to identify analytes in a sample based on their mass spectra followed by comparison of their RTs to the RTs of standards that have been analysed with the same GC-MS instrument.

In order to quantify analytes in a sample, one can use an external standard (ES) or internal standard (IS) (Wang et al., 2017). An ES is usually identical to the analyte of interest, and a pure form of it is used to establish a calibration curve. Nevertheless, it is essential to maintain identical experimental conditions when analysing both the sample and the standard, which cannot be guaranteed when applying an ES (Wang et al., 2017). Thus, an IS is often the more accurate choice. The IS should ideally be a compound which is not naturally present in the

sample, but with similar chemical characteristics as the analyte of interest. It should be added to the sample as early as possible during sample preparation, and due to simultaneous analysis of the analyte and IS, any variations in preparation and/or experimental conditions will be compensated for (Wang et al., 2017).

After analysis of a sample containing FAMES and IS with GC-MS, followed by identification of the peaks in the chromatogram, the amount of a FA in the sample can be determined using equation 3. In this equation the mass of a FA in the sample is determined by comparing the peak area of a chosen FAME with the peak area of the IS in the same chromatogram. The amount of IS is known, and by dividing with a relative response factor (RRF) it is possible to correct for the mass differences between the IS and the chosen FA. Lastly, multiplication with the molecular mass of the chosen FA will result in the total mass of the FA in the sample. In equation 3 A_{FAME} denotes the area of the chosen FAME in a chromatogram, A_{IS} is the area of the IS in the same chromatogram, n_{IS} is the number of moles IS added to the sample and RRF is the relative response factor for the chosen FAME.

$$\text{Eq. 3: } \quad Mass_{FA} = \frac{A_{FAME} \cdot n_{IS}}{A_{IS} \cdot RRF} \cdot \text{Molecular mass}_{FA}$$

2.3.4 Vibrational spectroscopic methods

Over the course of the last few decades, vibrational spectroscopic methods have increased in popularity (Berghian-Grosan & Magdas, 2020; Li-Chan, 2010; Matsakidou et al., 2020). These methods include Raman spectroscopy and infrared (IR) spectroscopy; both mid-IR (MIR) and near-IR (NIR). In contrast to the classical method for analysis of FAs, which is GC, IR and Raman spectroscopy are optical-based methods which rarely require any sample preparation. They are quick and easy to apply, require no use of hazardous solvents, and are ideal for application directly at the production line. Spectra obtained with vibrational spectroscopy give structural information and can be used for quantitative analysis when combined with regression models (Li et al., 2018).

2.3.5 FTIR

IR spectroscopy is an analytical method used to obtain an absorption or emission spectrum of a sample by irradiation with light in the IR region (Hart, 2012). In FTIR spectroscopy, high resolution spectra are collected over a wide spectral range simultaneously as opposed to the

way of measuring with dispersive IR instruments in the early days of IR spectroscopy. Nowadays most IR instruments are Fourier transform (FT) instruments, which require a conversion by applying a FT to the raw data in order to obtain transmission or absorbance spectra.

In a MIR instrument such as the one used in this study, the IR region includes the frequencies from 4000 cm^{-1} to 400 cm^{-1} (Li et al., 2018). The different chemical bonds present in the analyte will emit or absorb different wavelengths of light based on changes in dipole moment (Tao & Ngadi, 2018). This means that polar groups such as C=O, O-H and N-H give a strong signal in IR spectroscopy (Li-Chan, 2010; Tao & Ngadi, 2018).

The FTIR instrument utilized here was an instrument of attenuated total reflectance (ATR). This method is based on the total reflection of an IR-beam through a refractive crystal, and in this case the ATR sampling unit is equipped with a diamond. As the light is reflected internally in the crystal, an evanescent wave is formed which extends beyond the surface of the crystal, and into the sample that is applied directly on top of the crystal. The evanescent wave will then be attenuated in the infrared regions where the sample absorbs the light (PerkinElmer, 2005). The light that has passed through the sample is detected, and based on the observed changes in frequencies, the system will generate an IR spectrum for the analysed sample (PerkinElmer, 2005).

2.3.6 Interpretation of FTIR spectra

The presence of certain functional groups give characteristic absorption bands at specific frequencies in an IR spectrum. These localised vibrations of individual bonds can mostly be found in the higher-frequency area from 4000 cm^{-1} to 1500 cm^{-1} in a MIR instrument. Two factors that influence the vibrational frequency of a given bond are the bond strength and the mass of the atoms involved. Strong bonds will vibrate at a higher frequency, meaning that $\text{C}\equiv\text{C} > \text{C}=\text{C} > \text{C}-\text{C}$, and if all else is equal, C – H stretching vibrations will be higher than those of C – C, which in turn are higher than the frequency of C – Halogen (Williams & Fleming, 2008). The area below 1500 cm^{-1} is often called the fingerprint region because the absorptions in this area are characteristic for each compound (Williams & Fleming, 2008).

When working with analysis of oils, the functional groups of interest are those that can be found in the TAG structure. The most prominent peak in the IR spectrum of oils can often be found around 1743 cm^{-1} and is caused by the carbonyl group (C=O) in the ester linkage of the TAG. Any peak around 3007 cm^{-1} is due to the =C–H stretch in *cis* configuration, and

absorptions in the area of 2980 – 2800 cm^{-1} are from the asymmetric stretching of C–H in -CH(CH₃) and -CH(CH₂)-, and the symmetric stretch of -CH(CH₃). The stretch of an alkene group, -C=C-, can be found around 1654 cm^{-1} in TAGs with unsaturated FAs, but this signal is usually quite weak. A strong signal at 1460 cm^{-1} and a medium signal at 1376 cm^{-1} are due to the scissoring vibrations of -CH₂- and -CH₃. Stretching vibrations from the hydrocarbon skeletal can be found at approximately 1237 cm^{-1} , and a band caused by -C–O stretching vibration will be in the area from 1159 cm^{-1} to 1096 cm^{-1} . Presence of a weak peak at 970 cm^{-1} can indicate trans-FAs because of the =C–H *trans* stretching vibrations (Guillén & Cabo, 1997; Li-Chan et al., 2006; Li et al., 2018; Rohman & Irnawati, 2020). Table 1 shows a summary of the relevant absorption bands for analysis of edible fats and oil.

Table 1 – Frequencies of absorption bands (b) and shoulders (sh) of different chemical vibrations, for MIR spectrum of soybean oil. The table is adapted from Guillén & Cabo, 1997, and assignments are based on various articles (Guillén & Cabo, 1997; Li-Chan et al., 2006; Li et al., 2018; Rohman & Irnawati, 2020).

Frequency (cm^{-1})	Functional group	Mode of vibration	Intensity*
3008 (b)	=C–H (<i>cis</i>)	Stretching	w
2953 (sh)	-C–H (CH ₃)	Stretching (asym)	vw
2922 (b)	-C–H (CH ₂)	Stretching (asym)	vs
2853 (b)	-C–H (CH ₃)	Stretching (sym)	vs
1743 (b)	-C=O (ester)	Stretching	vs
1655 (b)	-C=C- (<i>cis</i>)	Stretching	vw
1461 (b)	-C–H (CH ₂ , CH ₃)	Bending (scissoring)	m
1377 (b)	-C–H (CH ₃)	Bending (sym)	w
1239 (b)	-C–O, -CH ₂ -	Stretching, bending	w
1161 (b)	-C–O, -CH ₂ -	Stretching, bending	s
1120 (b)	-C–O	Stretching	vw
1098 (b)	-C–O	Stretching	w
1037 (s)	-C–O	Stretching	vw
966 (b)	-HC=CH- (<i>trans</i>)	Bending out of plane	vw
909 (b)	-HC=CH- (<i>cis</i>)	Bending out of plane	vw
722 (b)	-(CH ₂) _n -, -HC=CH-	Bending (rocking)	m

* vw, very weak; w, weak; m, medium; vs, very strong; s, strong

Figure 3 provides the FTIR absorbance spectra of three replicates of soybean oil with marked frequencies for each band/shoulder. The peak of medium intensity at 3008 cm^{-1} is attributed to a *cis* =C–H stretching vibration while the shoulder at 2953 cm^{-1} and the intense peaks at 2922 and 2853 cm^{-1} come from the asymmetrical stretching of -C–H in CH₃ and CH₂ and the symmetrical stretching of -C–H in CH₂. At 1743 cm^{-1} the most intense peak can be observed, it arises from the ester groups (C=O) in the TAGs. The very weak peak at 1655 cm^{-1} is caused

by the *cis* $\text{C}=\text{C}$ stretching vibration, and the remaining peaks are part of the fingerprint region. The $\text{C}-\text{H}$ bending vibration of CH_2 and CH_3 give rise to the peak at 1461 cm^{-1} and symmetrical bending vibrations of $\text{C}-\text{H}$ in CH_3 cause the medium peak at 1377 cm^{-1} . The peak at 1239 cm^{-1} is caused by the $\text{C}-\text{O}$ and CH_2 stretching and bending vibrations of the hydrocarbon skeleton, and the strong peak at 1161 cm^{-1} arises from the same vibrations. At 1120 , 1098 and 1037 cm^{-1} one can find peaks due to the $\text{C}-\text{O}$ stretching vibration in the TAGs, while the peaks at 966 and 909 cm^{-1} are associated with the *trans* and *cis* out of plane bending of $\text{HC}=\text{CH}$ -, respectively. The last peak that can be assigned to any vibrations in TAGs is the peak at 722 cm^{-1} , which can be associated with the bending vibrations of *cis* $\text{HC}=\text{CH}$ - and $\text{-(CH}_2\text{)}_n\text{-}$ (Guillén & Cabo, 1997; Li-Chan et al., 2006; Li et al., 2018; Rohman & Irnawati, 2020). A summary of the mentioned bands and shoulders can be found in table 1.

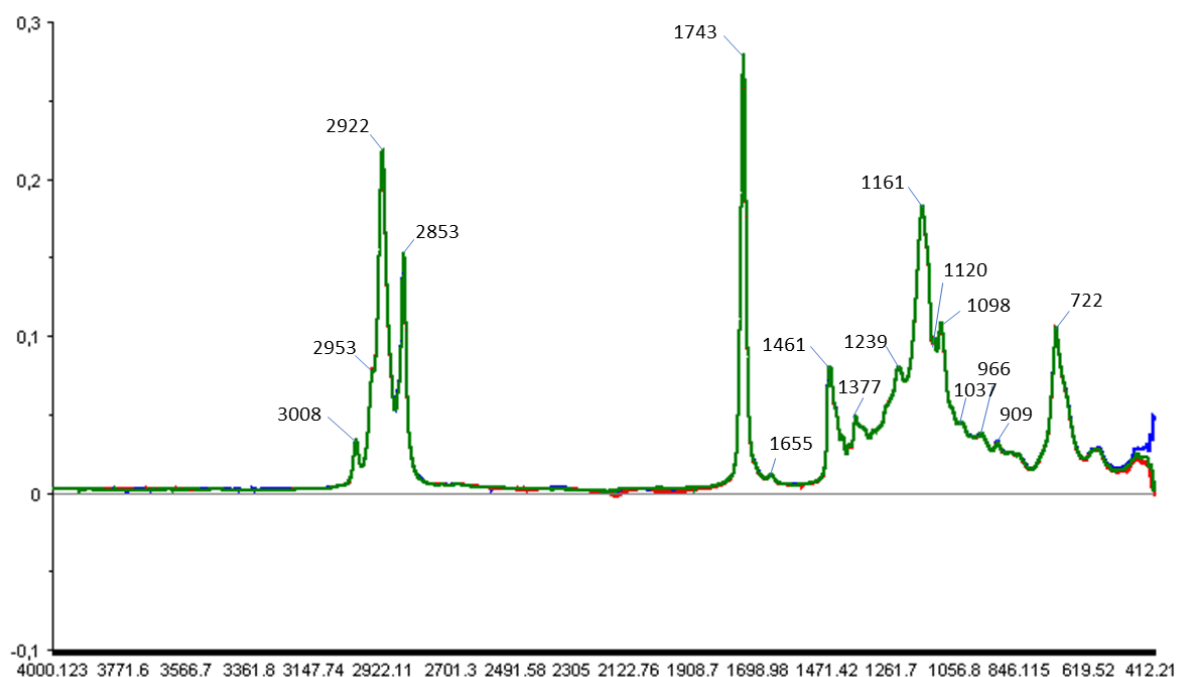


Figure 3 – FTIR spectrum for three replicates of soybean oil in the MIR region, including the wavenumbers $4000\text{-}400\text{ cm}^{-1}$. The numbers above the peaks indicate the wavenumbers in cm^{-1} .

2.3.7 Raman spectroscopy

While FTIR measures elastic scattering of photons, called Rayleigh scattering, Raman spectroscopy is based on inelastic scattering of light, named Raman scattering. In other words: FTIR deals with the photons of the same energy as the incident light, while Raman measures the photons with a shifted frequency (Tao & Ngadi, 2018). A source of monochromatic light

is used to excite the molecules in the sample, and a small fraction of this light will be Raman scattering (Li-Chan, 2010). These photons are detected and give information about the change in polarizability of the molecule. A Raman spectrum will thus show intense bands for nonpolar groups such as C=C, C–C and S–S (Li-Chan, 2010; Tao & Ngadi, 2018). FTIR and Raman spectroscopy are complementary methods, because they give intense bands for polar and nonpolar groups, respectively. In recent years instrumental improvements have made Raman spectroscopy more accessible than before. Instrumental improvements regarding sensitivity, stability and sampling technique have been introduced, as well as better filters and lasers (Tao & Ngadi, 2018).

2.3.8 Interpretation of Raman spectra

Raman spectra provide structural information about the sample in the same way as FTIR spectra do, but these results are based on Raman scattering. Stretching and deformation of chemical bonds in the sample give rise to distinct spectral bands. However, the intensity of Raman spectra may vary a lot. Factors such as laser intensity and wavelength, acquisition time, physical properties of the chosen matrix and in this case also the set-up of the ball-probe can impact the intensity of the spectra (Afseth et al., 2006). Fluorescence in the samples can result in large variations in the spectral offset between different measurements (Afseth et al., 2005) and the biological matrix will influence the peak intensities. Nonpolar groups generally result in high intensity stretching vibrations and stretching vibrations result in more intense bands than deformation vibrations. Symmetrical vibrations result in scattering bands with higher intensities than asymmetric vibrations, and multiple bonds such as a C=C can give intense bands (Baeten et al., 1998). It is essential to use the right type of preprocessing methods to correct for these differences in baseline and spectral intensities prior to interpretation of the spectra. The chapters 2.4 and 2.4.1 will deal with the topic of data preprocessing.

Raman spectra are based on Raman shift values (cm^{-1}), and the important bands can be found in the same region as in IR spectra. The specific values for the bands have been reported with some variations. The asymmetric stretch of *cis* =C–H will give a band at approximately 3012 cm^{-1} , while for –C–H the symmetric and asymmetric stretches are found at 2930 cm^{-1} and 2900 cm^{-1} , respectively. The symmetric stretch of –C–H gives a signal at 2855 cm^{-1} . A carbonyl stretch can be seen around 1745 cm^{-1} and the very strong peak of the C=C stretch is positioned around 1656 cm^{-1} . For CH_2 the scissoring and twisting vibrations can be found at 1445 cm^{-1} and 1300 cm^{-1} , and 1263 cm^{-1} shows the =C–H symmetric rocking (Afseth et al.,

2005). The bands below 1200 cm^{-1} are in the fingerprint region of the Raman spectrum. MUFAs and PUFAs in *cis*-configuration will have a band in the area $1670 - 1680\text{ cm}^{-1}$, while the band for the *trans*-configuration will be around $1650 - 1665\text{ cm}^{-1}$ (Afseth et al., 2005; Baeten et al., 1998; Li-Chan et al., 2006; Tao & Ngadi, 2018). Table 2 shows a summary of the most relevant values for Raman bands in TG analysis.

Table 2 – Raman shift values for absorption bands of different chemical vibrations, based on Raman spectrum of soybean oil. The table is adapted from Guillen & Cabo, 1997, and assignments are based on various articles (Afseth et al., 2005; Baeten et al., 1998; Li-Chan et al., 2006; Tao & Ngadi, 2018).

Raman shift (cm^{-1})	Functional group	Mode of vibration	Intensity*
3012 ^a	=C–H	Stretching (asym)	
2930 ^a	C–H	Stretching (asym)	
2900 ^a	C–H	Stretching (sym)	
2855 ^a	–C–H	Stretching	
1747	C=O (ester)	Stretching	m
1658	–C=C– (<i>cis</i>)	Stretching	s
1440	CH ₂	Scissoring	s
1302	CH ₂	Twisting	s
1265	=C–H	Bending (rocking, sym)	s
1079	–C–C–, –C–O–	Stretching	m
1066	–C–C–, –C–O–	Stretching	vw
972	–C–C–, –C–O– / =C–H	Stretching/ out of plane deformation	w
870	–C–C–, –C–O–	Stretching	w
843	–C–C–, –C–O–	Stretching	w

^a = Values outside the spectral area recorded by the Raman instrument used in this study. The values are based on an article by Afseth *et al.* from 2006.

A typical Raman spectrum of soybean oil for the frequencies of 500 cm^{-1} to 1890 cm^{-1} is provided in figure 4. The peaks below 1200 cm^{-1} are mostly caused by skeletal stretching vibrations such as C–C and C–O, while the peak at 1265 cm^{-1} is caused by the symmetric rocking of =C–H. Twisting and rocking of CH₂ creates the band at 1302 cm^{-1} , while the intense peak at 1440 cm^{-1} is caused by CH₂ scissoring vibrations. The peak at 1658 cm^{-1} comes from *cis* –C=C– stretching vibrations, and the final peak at 1747 cm^{-1} is caused by the –C=O stretch found in the ester linkage of the TAGs.

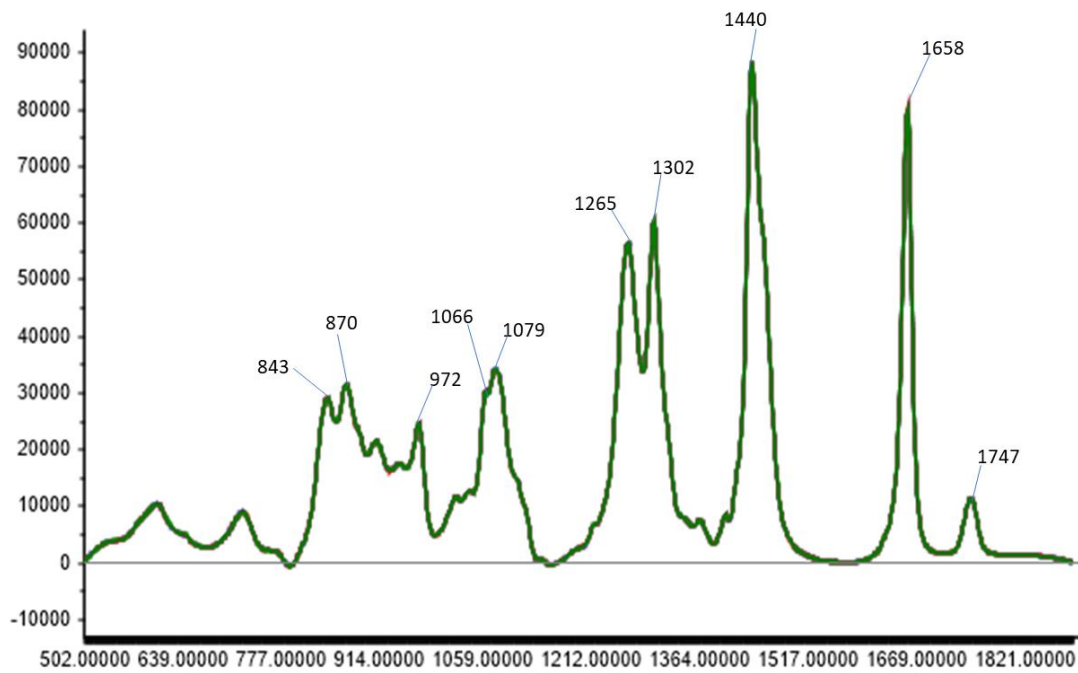


Figure 4 – Raman spectrum for three replicates of soybean oil in the Raman shift region of 500-1890 cm^{-1} . The numbers above the peaks indicate the Raman shift values in cm^{-1} .

2.4 Multivariate data analysis

Multivariate data analysis is a necessary tool whenever there are multiple variables measured per sample (Esbensen, 2002). Spectroscopic data is such a case. Usually an entire spectrum of wavelengths is measured for every sample that is analysed, which creates an extensive data set. Multivariate data analysis often seeks to determine a desired parameter based on indirect observations (Esbensen, 2002). In spectroscopy this would equal the prediction of one or more components present in a sample based on the absorption of light at specific wavelengths. However, multivariate observations will always consist of both relevant data and irrelevant information, called noise. This principle is illustrated in figure 5, which is adapted from Esbenesen (2002).

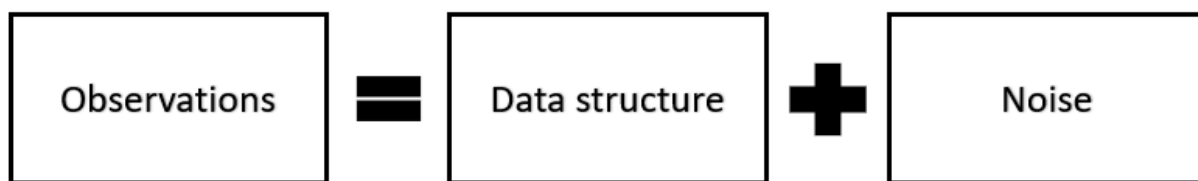


Figure 5 – Illustration of the principle behind multivariate data analysis, which is to separate the data structure in the observations from the noise (Esbensen, 2002).

Multivariate data analysis aims to extract the relevant information while reducing the irrelevant information (Reich, 2005). In this thesis principal component analysis (PCA) and partial least squares regression are the multivariate methods of interest, however the spectral data needs preprocessing prior to multivariate analysis.

2.4.1 Preprocessing of data

Preprocessing of data is important before applying any multivariate methods. This way many unwanted effects of physical nature such as light scattering, path length variations and random noise as well as instrumental effects can be removed, reduced or standardized (Reich, 2005). Thus, such effects will not impact further transformation or analysis of the data set. Preprocessing methods can be divided into filtering methods and model-based methods. Filtering methods only improve or “smooth” the data by removing some undesired types of variation (Afseth & Kohler, 2012), while model-based methods can be applied to quantify and separate different types of chemical and physical variations in the obtained spectra (Afseth & Kohler, 2012).

Derivation is a common filtering method, which is often used for baseline corrections, and can remove additive and multiplicative effects (Rinnan et al., 2009). The first derivative will only remove the baseline of a spectrum, while the second derivative removes the baseline and the linear trend in the data (Rinnan et al., 2009). Derivation can often amplify spectral noise, which is why a smoothing algorithm such as the Savitzky-Golay is applied prior to derivation (Reich, 2005).

One of the common model-based methods is the multiplicative scatter correction (MSC), which is a method used to correct for physical variability between samples due to scattering (Rinnan et al., 2009). The basic idea of MSC can be applied to signal processing in general and has been extended in what is called extended multiplicative signal correction (EMSC).

EMSC is more selective regarding scattering and other unwanted variation effects, and can correct for baseline effects, interference effects and multiplicative scaling effects (Afseth & Kohler, 2012). Transformation through EMSC requires a reference spectrum, and often the average spectrum of the calibration set is used (Rinnan et al., 2009). In many cases the main effect of EMSC is a normalisation of each spectrum of the data set. Once the baseline of the obtained spectra has been corrected and unwanted scattering effects have been removed, multivariate methods can be applied to the preprocessed data.

2.4.2 Principal component analysis

Principal component analysis (PCA) is a common multivariate method used to extract relevant information from large datasets (Jolliffe & Cadima, 2016). It can be used in an early step to check for outliers and sample variation, to detect trends or groupings in the data, and to find and evaluate relevant structures in the data set (Bekhit et al., 2014). The main principle of PCA is to reduce the dimensionality of the dataset while keeping as much as possible of the statistical information (Jolliffe & Cadima, 2016). When relating this to figure 5, the goal of PCA is to separate the data structure from the noise.

The starting point for PCA is a dataset consisting of n objects (samples) and p variables (measurements) (Esbensen, 2002). These points are plotted in a coordinate system with p dimensions, and the goal is to model the phenomena (data structure) which differentiates the data. This phenomenon is defined as the axis which maximizes the longitudinal variance and at the same time minimizes the squared projection distance (Esbensen, 2002). This axis is called the first principal component (PC) and explains the largest amount of variation. Per definition, PC-2 will be orthogonal to PC-1 and will be directed to model the second largest variation. PC-3 (and all following PC's) will be orthogonal to previous PC's while modelling the largest remaining variance (Esbensen, 2002). This method will generate many PC's; however, the first ones often contain the useful information while higher order PC's explain the noise part. The number of dimensions is thus reduced dramatically. A new coordinate system is formed by the PC's, and the variables in this new system do not co-vary. Figure 6 visualizes how PC-1 and PC-2 create a new coordinate system (Esbensen, 2002).

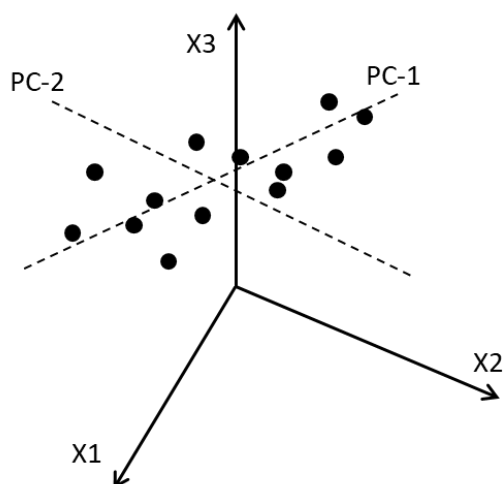


Figure 6 – Illustration of observations (dots) in a coordinate system. PCA seeks to find the pattern in these observations and creates a new coordinate system by placing the different principal components orthogonal to each other. This illustration is adapted from Esbensen (2002).

When using a data program to perform PCA on a data matrix, there are two plots which are of special interest. First there is the score plot, which visualizes the score vectors of two chosen PC's. This plot is useful for the detection of outliers, groupings and trends in the data by studying the pattern of the samples. Similar samples will be located close to each other. Secondly, the loading plot shows how the different variables contribute to each PC. These two plots are interesting because the score plot indicates *how* the objects of two PC's are related, while the complementary loading plot can be used for explaining *why* the objects are related (Esbensen, 2002).

In spectroscopy it is especially useful to always study the score plot and the associated 1-D loading plot. By studying the position of the individual samples in the score plot, one may get an idea of what the hidden phenomena is. The 1-D loading plot will supply information regarding which spectral bands vary the most, and this information can be used to determine which functional groups differentiate the samples.

2.4.3 Partial least squares regression

Partial least squares regression (PLSR) is a multivariate method used to make calibration models (Viscarra Rossel et al., 2006). It is an extension of PCA, however, instead of considering only the predictor variables X when reducing the information to a few important PC's, PLSR also takes a response variable Y into account (Boulesteix & Strimmer, 2006; Viscarra Rossel et al., 2006). These Y variables will guide the decomposition of the X matrix,

which is performed much the same way as for PCA (Esbensen, 2002). Here the spectral data will equal the predictor variables X and the different parameters which might explain the variation in X will be the response variables Y . PLSR searches for the model with maximum covariance between X and Y , and reduction of dimensions is performed simultaneously to regression (Boulesteix & Strimmer, 2006). A fitted model should ideally consist of a few factors that explain most of the variation in both the response and predictor variables (Viscarra Rossel et al., 2006). The result of PLSR will thus be an optimal regression for the prediction of the chosen parameter Y based on spectral information X (Esbensen, 2002).

The PLSR models are evaluated based on the number of factors that explain most of the variation, the root mean square error of cross validation (RMSECV) and the coefficient of determination (R^2). Cross-validation is used to determine the optimal number of PLSR factors (Afseth et al., 2010). RMSECV is calculated by comparing the actual chemical values to the ones predicted by the linear model, and the prediction error of this cross-validated calibration model is calculated by use of equation 4 (Afseth et al., 2010).

$$\text{Eq. 4:} \quad RMSECV = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}$$

Here i is the number of samples from 1 to N , y_i is the observed value and \hat{y}_i is the predicted value for Y (Afseth et al., 2010). The value of RMSECV is generally wanted to be as small as possible (Esbensen, 2002), and has the same unit as predictor variables. The coefficient of determination, R^2 , does explain how much of the variation in the predictor variables is explained by the response variable. R^2 will always have a value between zero and one, where a value of zero would mean that no variation in the predictor variables is explained by the chosen response variable, and one would mean that all variation is explained (Ross, 2010).

2.5 Classification of oils

The goal in classification is to distinguish two groups based on collected data, or to assign a new sample to one of the groups (Esbensen, 2002; Olkin & Sampson, 2001). Classification can be performed based solely on the collected data without any *a priori* information about class membership; this is called unsupervised classification (Rajalahti & Kvalheim, 2011). A common method used for unsupervised classification is PCA. Other methods such as soft

independent modelling of class analogies (SIMCA) and partial least squares discriminant analysis (PLS-DA) are supervised methods that incorporate *a priori* information about class membership (Rajalahti & Kvalheim, 2011). Classification results based on supervised methods will generally be more optimistic regarding class affiliation than results from unsupervised methods. Before classification, it is important to preprocess the spectral data in order to remove any physical effects that may differentiate the samples. A classification method can then discriminate the samples based on the chemical differences.

2.6 Correlation coefficient

The correlation coefficient is a measurement for the relationship between two variables. It indicates both the strength and direction of this relationship. Pearson's correlation coefficient (r) is calculated as described in equation 5.

Eq. 5:
$$r_{x,y} = \frac{\Sigma(x-\bar{x})(y-\bar{y})}{\sqrt{\Sigma(x-\bar{x})^2\Sigma(y-\bar{y})^2}}$$

Here \bar{x} and \bar{y} are the mean values for array 1 and array 2. The coefficient is always between 1 and -1, where 1 indicates a perfect correlation and -1 is a perfect inverse correlation. A value of 0 means there is no correlation between the chosen variables (Akoglu, 2018).

3. Experimental

3.1 Project description

As mentioned in the introduction, the main objective of this thesis was the classification and quantification of FAs in edible oils using vibrational spectroscopy. Figure 7 illustrates how the main objective is divided into three sub-objectives. The first sub-objective dealt with the classification, where 72 samples of marine oils from Orivo (table 6) were analysed with FTIR and Raman spectroscopy and the results were studied using PCA. In sub-objective two, the reference method was used to determine the FA composition in 18 reference oils (table 7) and based on these results a sample design with low correlation between the FAs was created. Based on the sample design a calibration set of 80 samples was made (appendix D). These calibration samples were analysed with FTIR and Raman, and the obtained information was used in the development of calibration models using PLSR. In sub-objective three the calibration models were validated by analysing independent oil samples.

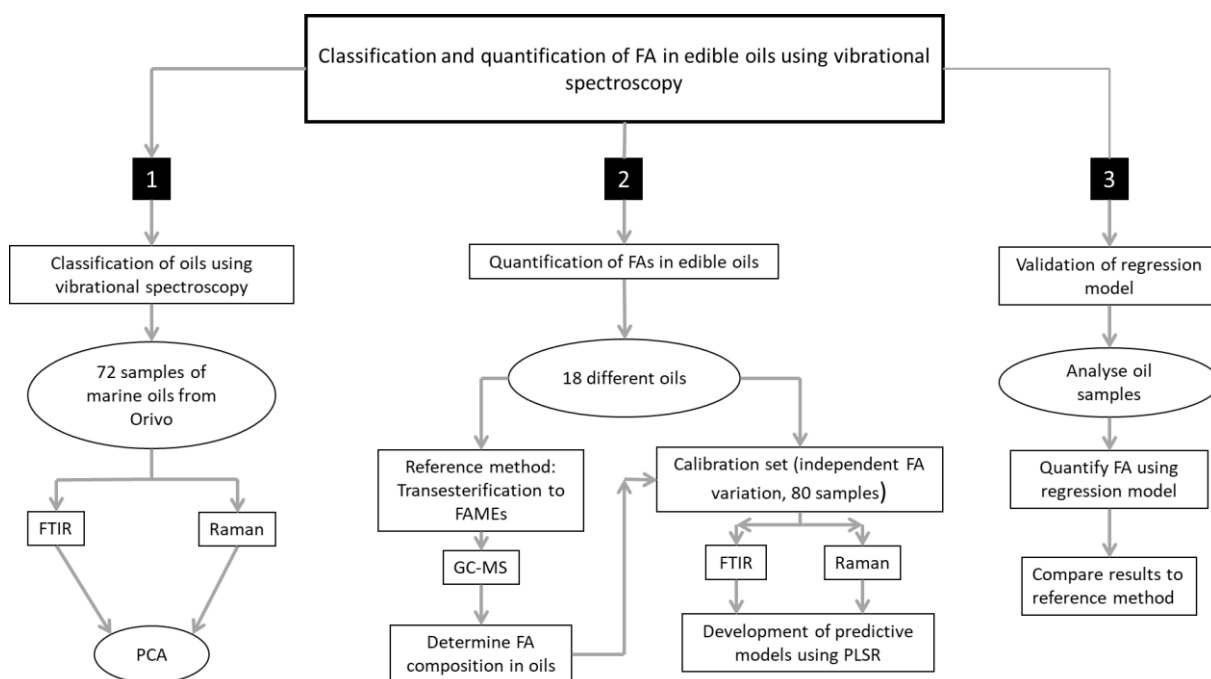


Figure 7 – Illustration of the main objective of this research and how it is divided into three sub-objectives.

3.2 Materials and chemicals

Table 3 presents all the chemicals used for this research, while table 4 lists the equipment and instrumentations. Applied software systems are provided in table 5 and all the oils that were analysed can be found in tables 6 and 7.

Table 3 – All chemicals used in this research, with manufacturer, purity grade and CAS-number.

Product	Manufacturer	Purity [%]	CAS-nr.
n-Heptane	VWR Chemicals, Poland	≥ 99	142-82-5
Methanol	VWR Chemicals, Netherlands	≥ 99.9	67-56-1
Sodium	Merck, Germany		
Chloroform	VWR Chemicals, France	100	67-66-3
Trinonadecanoin	Larodan AB, Sweden		26536-13-0
Food industry fame mix (37 components)	RESTEK, USA		
Isopropanol prima	Kemetyl Norge AS		

Table 4 – Equipment and instruments used in this research with name, manufacturer and other specifications.

Instrumentation/ Equipment	Name	Manufacturer	Specifications
Centrifuge	EBA 20	Hettich®	
Orbital shaker	PSU-10i	Biosan	
Vortex mixer	Yellowline TTS2	IKA-Werke	
Heater	Dri-Block®	Techne®	
Mass spectrometer	ISQ™ QD	Thermo Scientific™	Single quadrupole
Gas Chromatograph	Trace™ 1310	Thermo Scientific™	
GC column	Rtx-2330	Restek	60 m, 0,25 mm ID, 0,2 µm df
Manual pipette	Acura 826	Socorex	10-100 µL
Manual pipette	M10	BioHit	0.5-10 µL
Evaporator	Reacti-Vap™	Thermo Scientific™	27 ports
Micro balance	CP2P Sartorius	VWR International	
Culture tubes	Culture tubes with screw cap	Duran®	
Pasteur pipettes	Disposable glass Pasteur pipettes	VWR International	150 mm
GC vials	Crimp neck vials	VWR International	32 x 11,6 mm
Aluminium cap	Aluminium crimp seal	VWR International	
Aluminium micro weighing dishes	Oval Weighing dishes	VWR International	0.04 mL
Plastic tubes with cap	Tube 25ml 90x25PP + Cap NAT	SARSTEDT	25 mL
FTIR spectrometer	Nicolet™ iS™5 Spectrometer	Thermo Scientific™	
ATR accessory for FTIR spectrometer	iD7 ATR	Thermo Scientific™	With monolithic diamond ATR crystal
Laboratory drying oven	Series TS8000	Termaks	Used at 40 °C
Raman spectrometer	RamanRxn2™ Hybrid	Kaiser Optical Systems, Inc.	Used with MR-probe
MR-probe	RamanRxn™Probe	Kaiser Optical Systems, Inc.	Connected to MultiRxn Probe – 785
Polypropylene tube	CELLSTAR®	Greiner Bio-One International	15 mL
Blue cap bottle	Duran® Laboratory glass bottle	SCHOTT DURAN®	200 mL

Table 5 – Software used in this research, listed with name and manufacturer.

Software	Name	Manufacturer
Chromatography data system software	Chromeleon™ 7	Thermo Scientific™
Spectroscopy data system software	OMNIC™ Series Software	Thermo Scientific™
Raman Software	iC Raman™ Software	Kaiser Optical Systems, Inc.
Multivariate analysis software	The Unscrambler X 10.3	Camo Analytics
Spreadsheet program	Excel	Microsoft

3.3 Sample storage

All the oil samples were stored at -20 °C to prevent oxidation. Before analysis with spectroscopy they were put in a fridge at 4 °C over night, and an hour before analysis the samples were put in room temperature so they could be analysed at approximately the same temperature (22–23 °C). The samples were homogenised through manual shaking or use of a vortex mixer. Some of the samples from Orivo contained particles, which had to sediment as much as possible before the oils could be analysed. Some samples containing coconut oil were not fully melted at 23 °C and were heated to 38 °C in a laboratory drying oven for approximately 20 minutes. Once they were cooled down to room temperature again, they were analysed before any precipitation could form. This was the standard procedure for preparation of all samples before analysis with spectroscopy.

Prior to preparation of FAME samples for analysis with GC-MS, the oil samples were put in room temperature until fully melted. They were thoroughly shaken to ensure homogeneity. The fats were used in their solid state.

3.4 Part I – Classification of marine oils

The company Orivo supplied samples of seven different types of marine oils for the use in this research. The types of oil and number of different samples received for each type are listed in table 6.

Table 6 – The seven types of marine oils from Orivo, listed with number of samples per type of oil.

Type of oil	Nr. of samples
Wild salmon	10
Farmed salmon	12
Krill	10
Anchovy	10
Sardine	10
Norwegian cod liver	10
Islandic cod liver	10

3.4.1 Analysis of oils with FTIR spectroscopy

For the FTIR analyses the Thermo Scientific™ Nicolet™ iS™5 spectrometer with the iD7 ATR accessory was used. The instrument was equipped with a monolithic diamond. For the analyses the absorbance was measured, and the instrument was set to take 40 scans with a resolution of 4 cm⁻¹ for each measurement. First a background spectrum was obtained with the clean crystal, before a drop of sample was applied over the entire surface of the crystal with a disposable Pasteur pipette. A new spectrum was obtained and corrected relative to the background spectrum. The crystal was then cleaned using tissue paper and 70% isopropanol (Kemetyl Norge AS), before analysing the next sample. One sample was used as a reference and was measured once a day over the period of sample analysis in order to monitor changes in the instrument. Three replicates were taken for each sample. The software used with the instrument was the Thermo Scientific™ OMNIC™.

3.4.2 Analysis of oils with Raman spectroscopy

These analyses were conducted using the Raman spectrometer RamanRxn2™ Hybrid by Kaiser Optical Systems, Inc. A ball-probe was connected to the system and mounted every morning before analysis of the fish oil samples from Orivo. The laser was set to 400 mW. Once the system was ready, the samples were transferred into plastic tubes (SARSTEDT) that were wide enough for the ball-probe. The head of the probe was immersed in the oil sample until it was fully covered. All the lights in the room were turned off to avoid pollution of the measurement, and the sample was analysed with 6 scans of 5 seconds. Once the measurement was done, the probe was lightly swirled inside the sample, and the next replicate was measured. A total of three replicate measurements for each sample were recorded. Between the different samples the probe was cleaned using dish soap, water and tissue paper. The probe was dried thoroughly before analysing the next sample to avoid contamination by

water. A reference oil was analysed regularly to monitor any changes in the measurements which could be due to changes in the instrument or instrumental set up.

3.4.3 Multivariate data analysis

The software The Unscrambler X 10.3 (Camo Analytics) was used to determine whether the different fish oils from Orivo (table 6) could be classified based on analysis by vibrational spectroscopy. All spectra were plotted in Unscrambler to check if the overall picture looked normal, and PCA was performed on the raw data to check for any outliers.

Preprocessing of all spectra was performed prior to data analysis. The FTIR spectra were preprocessed by applying Savitzky Golay second derivatives (with second order polynomial and 27 smoothing points). Subsequently, EMSC was applied to the spectral area with information of interest, in this case the area of $4000 - 2700 \text{ cm}^{-1}$ and $1800 - 500 \text{ cm}^{-1}$. The last step was calculating the average of the three replicates for each sample. For the classification PCA was performed with random cross-validation, and only on the areas with relevant spectral information.

A custom-made routine (Matlab) for baseline correction was used in order to remove the fluctuating baselines of the Raman spectra. In the routine, a sixth-ordered polynomial was fitted and then subtracted from the Raman spectra (Lieber & Mahadevan-Jansen, 2003). Subsequently, normalization using EMSC was performed in the region of $500 - 1890 \text{ cm}^{-1}$. The last step was calculating the average of the three replicates for each sample.

3.5 Part II – Method development

3.5.1 Prepared solutions

Sodium methoxide

A sodium methoxide solution was prepared using 200 mL methanol (VWR Chemicals, Netherlands) which were transferred to a blue cap bottle (SCHOTT DURAN®).

Approximately 1.0 gram of metallic sodium (Merck, Germany) was added to the methanol while the bottle was standing in a fume hood, to attain a concentration of 5 mg/mL of sodium methoxide in methanol. After ended reaction the bottle was closed, and the sodium methoxide was stored at room temperature until use.

Internal standard – Trinonadecanoin

It was decided to use one IS for the quantification of all FAs in the reference oils.

Trinonadecanoin, a simple TAG with three C19:0 FAs, was chosen because this FA should not occur naturally in edible oils. A stock solution with a concentration of 10 mg/mL was prepared by dissolving 80 mg of trinonadecanoin (Larodan AB) in 8.0 mL chloroform (VWR Chemicals, France). The solution was prepared in a plastic tube (Greiner Bio-One International) and homogenized using a vortex mixer (IKA-Werke) before it was stored at 4 °C until use. The stock solution was vortexed again before it was added to any samples. In total two IS stock solutions had to be prepared, see appendix B for exact amounts.

3.5.2 Reference oils

For the reference analysis different edible oils were bought. 18 different oils were chosen, the types of oil and manufacturers are presented in table 7.

Table 7 – 18 reference oils, listed with manufacturer.

Type of oil	Manufacturer
Rapeseed	Eldorado
Peanut	International collection
Sesame	Apotek 1
Olive	Eldorado
Flaxseed	Helios
Soybean	Eldorado
Sunflower	Eldorado
Vita hjertego' OPTIMAL	Mills
Frying oil	Eldorado
Möller's tran	Peter Möller (Orkla)
Rice bran oil	Emmy's choice
Salmon	Nofima
Herring	Nofima
Coconut, extra virgin	Helios
0370 ^a	GC Rieber
4030 ^a	GC Rieber
3040 ^a	GC Rieber
Camelina oil	Nofima

^a = oils enriched in EPA and DHA

3.5.3 Transesterification of neutral lipids

The method applied here is based on the master thesis by Katarina Breivik Halvorsen (Halvorsen, 2019). Two series of FAMEs with different IS concentration were made from the reference oils in table 7, in order to be able to quantify both the major fatty acids as well as the ones present in smaller amounts. Series one had a low IS concentration, while series two had a high IS concentration. Three replicates of FAMEs were prepared for each oil in both series.

In the first series (low IS concentration), approximately 50 mg of each reference oil were weighed into separate culture tubes (Duran®). 100 µL of IS solution (trinonadecanoin, 10 mg/mL) was added to each culture tube. The samples were dried for approximately 30 minutes using low heat and a flow of N₂-gas. The triglycerides were then solvated in 2.0 mL of n-heptane (VWR Chemicals, Poland), before 1.5 mL of sodium methoxide solution (5 mg/ml methoxide in methanol) was added. For 30 minutes the samples were shaken at 385 g in room temperature and then centrifuged at 381 rcf for five minutes to properly separate the two phases in the samples. Approximately 1.5 mL of the heptane phase (upper phase) was transferred to GC-vials. These solutions were then diluted 1:5 with n-heptane in order to achieve a suitable concentration for the analysis with GC-MS. The samples were stored at -20 °C before and after analysis.

For the second series (high IS concentration), the steps above were repeated using approximately 5 mg of oil, which were weighed into small aluminium micro weighing dishes (VWR®). These FAME samples were not diluted before analysis with GC-MS.

3.5.4 Analysis using GC-MS

The FAME samples made from the oils of table 7 were analysed with GC-MS. A Trace™ 1310 gas chromatograph was coupled to an ISQ™ QD mass spectrometer, both were from Thermo Scientific™. The GC was run in split operating mode with a split ratio of 10. It was equipped with a 60 m fused silica column from Restek with an inner diameter of 0.250 mm and a film thickness of 0.20 µm. Figure 8 shows the temperature run of the GC oven. At sample injection, the oven temperature was at 50 °C and by the end of the run it had risen to 245 °C. The MS had a single quadrupole mass filter with a selected mass range of 50-700 amu. The software used with the GC-MS was Chromeleon 7 (Thermo Scientific™).

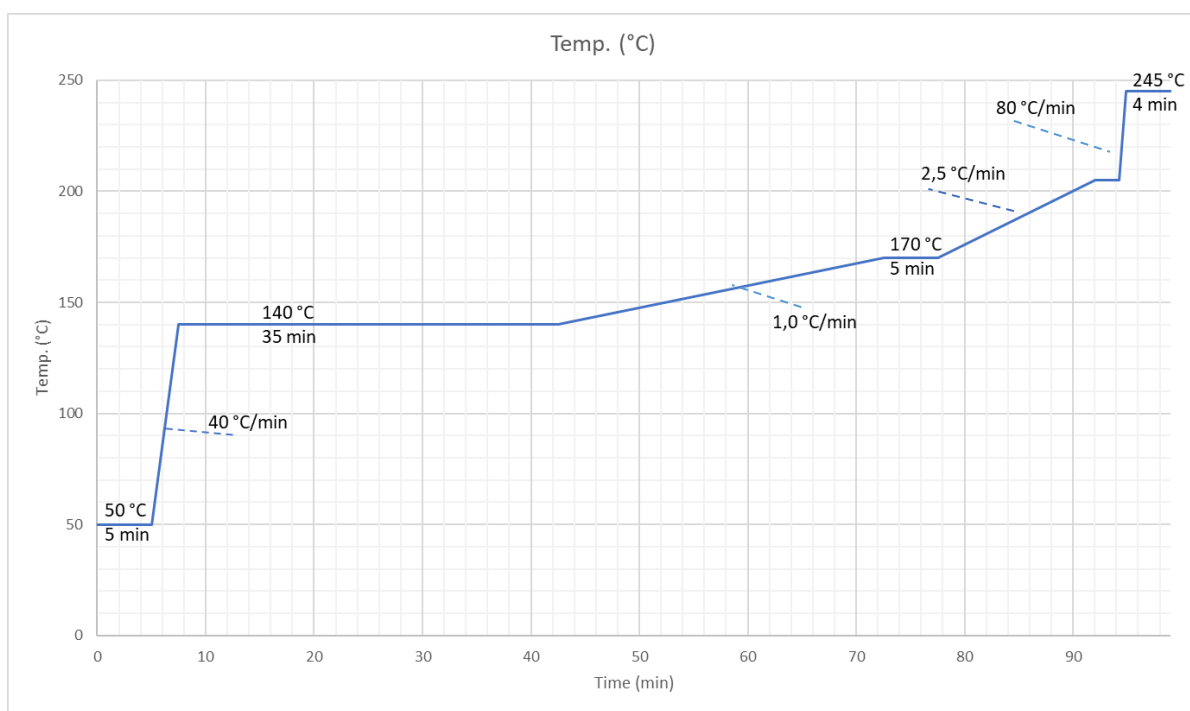


Figure 8 – Temperature run of the GC oven. Total run-time was 99 minutes, with a starting temperature of 50 °C and a final temperature of 245 °C.

3.5.5 Identification and quantification of FAs

The FAMES were identified by comparing the RT of the peaks in the sample chromatograms to the peaks of the reference mix containing 38 different FAMES (Food Industry FAME mix, Restek, with added 19:0). In addition, NIST 2017 database was used to identify the FAs based on the obtained mass spectra. Once the peaks were assigned to FAMES from the reference mix, the masses of the different FAs were calculated based on equation 3, as described in section 2.3.3. The RRF-values (Molversmyr, 2020) and molecular masses for the various FAs can be found in appendix C.

The reference oils from marine sources contained FAs that could not be identified with a standard in the Food industry FAME mix (RESTEK). In order to be able to quantify as many of the FAs present as possible, some of these FAs were identified only by spectral searches in a database (NIST 2017). The exact isomers were not determined. The table presented in appendix C lists all the unidentified isomers that were found, with RRF-values based on the values that were found for equivalent isomers in the Food industry FAME mix. Three of the unidentified isomers did not have an equivalent isomer in the Food industry FAME mix and thus were assigned RRF-values of one.

The series of FAME samples with a high IS concentration (series two) was used to quantify the largest peaks in the chromatograms, while the other series (series one) was used for the remaining peaks. The ratio of the peak areas of FA/IS were used to determine which series was best suited for the individual peaks, and the series with the smallest ratio of FA/IS was used.

3.5.6 Calibration set

Based on one replicate of each of the 18 oils with known FA composition, a sample design for the calibration models was made by a chemometrician at Nofima. Eight different FAs were chosen based on their concentration in the oils. All these FAs are important FAs commonly found in foods and biological samples. A mixture design was used to make “theoretical” mixtures of all the 18 reference oils. This included:

1. All Combinations of two oils in ratios 25 / 75 and 50 / 50
2. All combinations of three oils in the ratios 25 / 25 / 50 and 33 / 33 / 33
3. Pure oils

In total, this resulted in 3741 oil mixtures and candidates for our calibration design.

Subsequently, the Kennard-Stone algorithm was used to choose the set of 80 mixtures that spanned the variation of all eight chosen FAs, and at the same time provided the lowest correlation between these FAs in the 80 samples (Daszykowski et al., 2002).

The samples were prepared by mixing the respective oils of a sample in 25 mL plastic tubes with cap (SARSTEDT) in the given ratios and homogenising them using a vortex mixer. A 100 % of a sample was chosen to equal 15 g, and the exact masses were recorded so that the actual mixing ratios of the samples could be calculated. This data was used together with the data for the FA content in the reference oils to calculate the theoretical amount of each FA in these 80 samples, as is demonstrated in equation 6.

$$\text{Eq. 6: } \quad \text{Mass}_{FA1} = \left(\frac{w1}{tw} \cdot FA1_{ref1}\right) + \left(\frac{w2}{tw} \cdot FA1_{ref2}\right) + \left(\frac{w3}{tw} \cdot FA1_{ref3}\right)$$

FA1 denotes a chosen FA, w1, w2 and w3 are the recorded masses of the reference oils which were mixed in each sample. tw is the total weight of the sample, and FA1_{ref1}, FA1_{ref2} and FA1_{ref3} equal the FA content (% FA of total FA content) of the one, two or three reference oils in each sample. Lastly, Σ SFA, Σ MUFA, Σ PUFA and the UI for all calibration samples

was calculated based on the FA composition of the samples. UI was calculated as described in section 2.1.3.

3.5.7 Analysis of the calibration set

All the samples of the calibration set were analysed with FTIR and Raman as described in sections 3.4.1 and 3.4.2, with the same settings and three replicates per sample.

3.5.8 Calibration models based on FTIR

The obtained spectral data from the samples of the calibration set were preprocessed prior to performing PLSR, as described in section 3.4.3. The data was transformed using EMSC on the area containing important spectral information, which here was the area of 3100-2750 cm^{-1} and 1800-500 cm^{-1} . PLSR (15 maximum components) with random cross-validation (20 segments, four samples per segment) was performed on the spectral area of 3100 – 2750 cm^{-1} and 1700 – 500 cm^{-1} . The spectral data served as the predictor variables (X), and the calculated FA content in the calibration samples for the FAs 14:0, 16:0, 18:1(n-9), 18:2(n-6), 18:3(n-3), 20:5(n-3), 22:6(n-3) in addition to ΣSFA , ΣMUFA , ΣPUFA and the calculated UI were response variables.

3.5.9 Calibration models based on Raman

Again, the same preprocessing methods as in section 3.4.3 were applied to the obtained Raman spectral data prior to performing PLSR analysis. The average of the three replicates for each sample was calculated, and PLSR (15 maximum components) with random cross-validation (20 segments, four samples per segment) was performed on the spectral area of 500 cm^{-1} to 1800 cm^{-1} . The spectral data from Raman analyses of the calibration samples served as predictor variables (X), and the FAs 14:0, 16:0, 18:1(n-9), 18:2(n-6), 18:3(n-3), 20:5(n-3), 22:6(n-3) in addition to ΣSFA , ΣMUFA , ΣPUFA and the calculated UI were response variables.

3.6 Part III – Model validation

3.6.7 Validation of calculated FA profiles in calibration set

Prior to validation of the calibration models, a validation was performed to check how accurate the calculated FA profiles of the calibration set were. The samples with numbers 32, 54, 58 and 77 were chosen randomly from the calibration set, and their FA profiles were

determined according to the procedure described in sections 3.5.3, 3.5.4 and 3.5.5. The results were compared to the previously calculated FA profiles of these samples.

3.6.8 Validation of calibration models

Validation of the established calibration models was done by comparing predicted FA content in independent oil samples with their reference values. For this step four new oils were purchased and analysed with GC-MS. These oils are listed in table 8. The FA profiles were determined as described in sections 3.5.3, 3.5.4 and 3.5.5.

Table 8 – Oils for validation of the calibration models. Listed with manufacturer.

Type of oil:	Manufacturer:
Grapeseed oil	Pietro Coricelli
Frying oil	Helios /Alma Norge AS
Walnut oil	International collection
Cooking oil	Coop

3.6.9 FTIR

The independent oils were analysed with FTIR as described in section 3.4.1. All spectral data (raw data) from FTIR analysis of the 80 samples of the calibration set, the 10 samples of norwegian cod liver oil (Orivo) and from the four validation samples were put into one Unscrambler file. The data was preprocessed as described in section 3.4.3. All the data was preprocessed in the same Unscrambler file because EMSC had to be performed on the data of all samples at the same time. This way all data sets were treated the same way, which was necessary in order to predict the FA content in the independent samples.

A PCA was run on the preprocessed data to check for deviations in spectral values of the validation samples compared to the calibration set. PLSR for the different response parameters was performed as described in section 3.5.8 and based on these models the FA content of the eight main FAs in the validation samples was predicted. The predicted values were compared to the reference values found with GC-MS.

3.6.10 Raman spectroscopy

Samples of the validation oils were analysed with Raman spectroscopy as described in section 3.4.2. All spectral data from Raman analysis of the 80 samples of the calibration set and the four validation samples were preprocessed as described in section 3.4.3. All spectral data was preprocessed in the same Unscrambler file. PCA was run on the preprocessed data, and PLSR

was performed for the response variables as described in section 3.5.9. Based on these models the FA content of the eight main FAs in the validation samples was predicted. The values were compared to the reference values found with GC-MS.

4. Results and discussion

4.1 Part I – Classification

Marine oil samples were analysed with FTIR and Raman spectroscopy, and PCA was the classification method used to check if the samples of different groups could be separated from each other. The marine oils (Orivo) that analysed were quite diverse in colour. Krill oil had a deep red colour, while anchovy and sardine had a brown to yellow tone. Samples from both types of salmon oil were orange with a tone of pink, and the two types of cod liver oil were transparent and colourless. Some of the samples from anchovy, sardine and krill oil also had particles in them, and the consistency of these three types of oil was quite thick. Figure 9 shows a photo of samples of farmed salmon oil, sardine oil and norwegian cod liver oil.



Figure 9 – From left to right: one samples of farmed salmon oil, two samples of sardine oil and three samples of norwegian cod liver oil. The samples were from Orivo.

4.1.1 Raman spectra of marine oils

The average Raman spectra of the three replicates for each marine oil are presented in figure 10. Quite a few of these samples showed a spectrum that was not possible to interpret due to a saturated signal. A reduction of the scanning time from five to one second gave no significant change in the recorded spectra. This saturation is most likely caused by fluorescence (Bekhit et al., 2014). A strong fluorescence background is a common problem in Raman spectroscopy, because the probability for fluorescence is much higher than for Raman scattering (Kostamovaara et al., 2013). The samples with a saturated spectrum were all of the types krill, sardine and anchovies. Thus, these three types of marine oils could not be used for

classification. Although the remaining four types of marine oils were possible to analyse, it was decided not to pursue the classification of marine oils with Raman, since the remaining dataset was very limited. The classification was thus only based on the results from FTIR analysis.

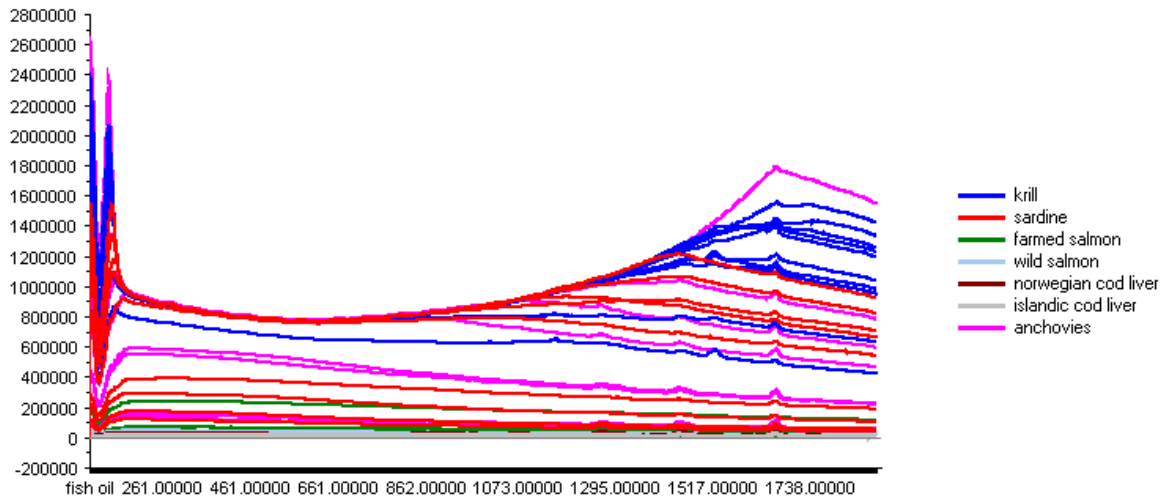


Figure 10 – Average ($n=3$) Raman spectra for the 72 samples marine oils from Orivo. The spectra are colour-coded based on type of oil.

4.1.2 FTIR spectra of marine oils

The average FTIR spectra for each sample of the marine oils are provided in figure 11.

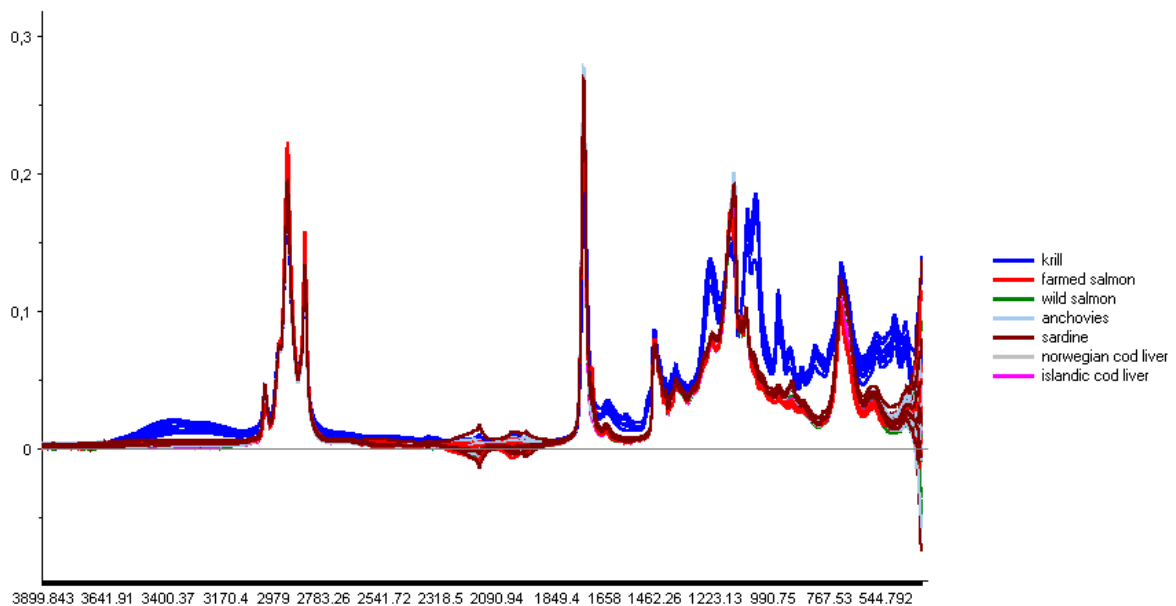


Figure 11 – Average ($n=3$) FTIR spectra for the 72 samples of marine oils from Orivo. The spectra are colour-coded based on type of oil.

The area between 2700 – 1800 cm^{-1} and $< 450 \text{ cm}^{-1}$ did not contain any relevant information for fats and oils. However, as can be seen in figure 11, these two areas showed a lot of variation for the different oils. As this was no relevant chemical information, it was decided to remove these areas before performing further data analysis.

4.1.3 Classification using FTIR spectra and PCA

After preprocessing the data, a PCA was run and the score plot for PC-1 and PC-2 can be seen in figure 12. The samples within each group were clustered together, which means they contain the same spectral information. However, the group of krill was clearly distinguished from all other groups. One significant difference between krill and other fish is that the lipid fraction of fish mainly consists of TAGs, while a large portion of this fraction in krill consists of phospholipids. Typically, about 43 g/100 g of krill oil are phospholipids (Burri & Johnsen, 2015). Such a difference in chemical composition is not ideal for this type of classification, as the goal here was to differentiate marine oils based on FA composition.

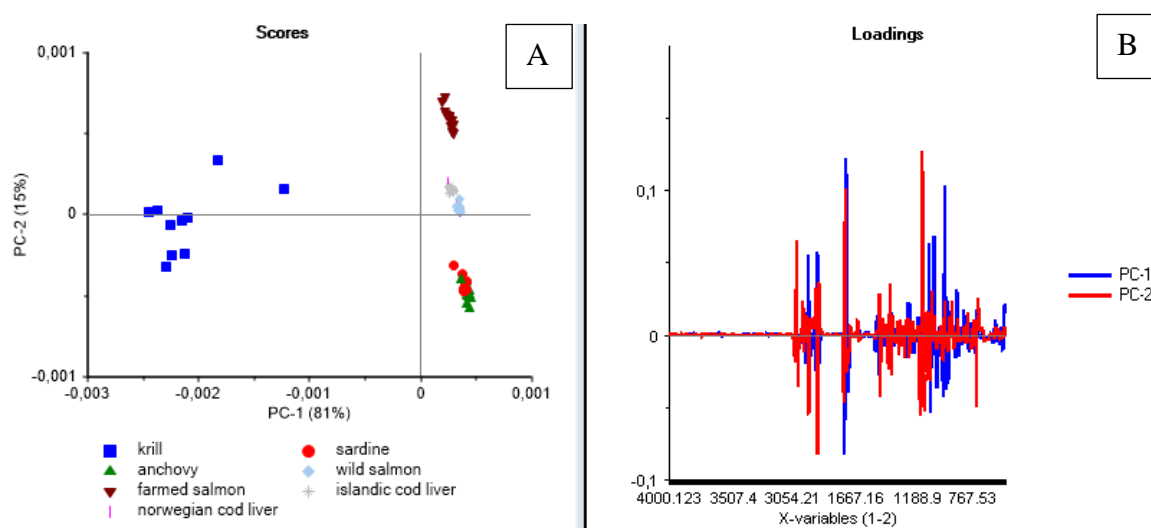


Figure 12 – Principal component analysis for all samples of marine oils from Orivo. Figure 12A shows the score plot for PC-1 and PC-2, and figure 12B shows the loading plot for PC-1 and PC-2. The oil samples were analysed with FTIR spectroscopy.

The associated loading plot for PC-1 and PC-2 is provided in figure 12B. Based on PC-1 the main absorption frequencies that distinguished the groups were 2923 cm^{-1} , 2852 cm^{-1} , 1730 cm^{-1} , 1090 cm^{-1} , 1050 cm^{-1} and 968 cm^{-1} . For PC-2 the main bands in the loading plot were found at wavenumbers 3012 cm^{-1} , 2850 cm^{-1} , 1737 cm^{-1} and 1142 cm^{-1} . The characteristic absorption areas for FA in FTIR are mentioned in section 2.3.6. Phospholipids do have

characteristic stretches at $\sim 1230\text{ cm}^{-1}$, $\sim 1085\text{ cm}^{-1}$, $\sim 1045\text{ cm}^{-1}$ and $\sim 820\text{ cm}^{-1}$ due to the asymmetric and symmetric stretches of PO_2^- , the stretch of C–O–P and the P–O asymmetric stretch, respectively (Socrates, 2004). Nevertheless, a lack of reference values for the marine oils made proper interpretation of the loading plot for the PCAs difficult and was not attempted.

Since the difference between krill and the other oils dominated the initial PCA, a new PCA was performed leaving out the krill samples. Removal of the krill oil samples resulted in the score plot for PC-1 and PC-2 that is provided in figure 13A. Here the samples of farmed salmon were separated from all other oil types, while the groups of wild salmon, norwegian cod liver and islandic cod liver were located close together. The clusters of sardine and anchovy were positioned away from the other groups, but they did somewhat overlap. According to this score plot the six fish oils could be classified into three different groups based on the associated loading plot in figure 13B. For PC-1 the main absorption frequencies that differentiated these three groups were at 3012 cm^{-1} , 2853 cm^{-1} , 1739 cm^{-1} and 1141 cm^{-1} . Based on PC-2 the main differences were found at wavenumbers 3010 cm^{-1} , 2930 cm^{-1} , 2847 cm^{-1} , 1709 cm^{-1} , 1145 cm^{-1} and 1136 cm^{-1} .

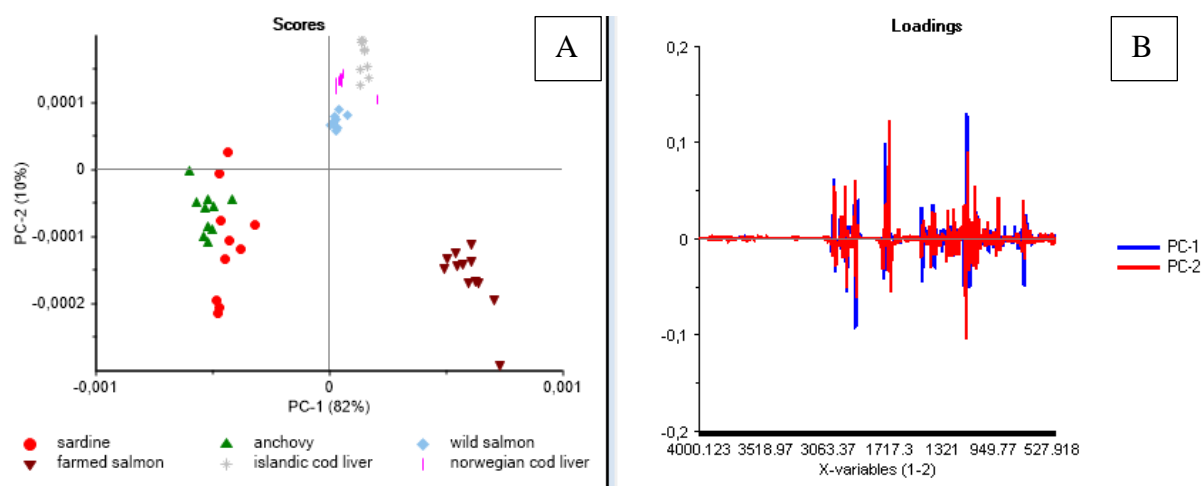


Figure 13 - Principal component analysis for all samples from Orivo, except krill. Figure 13A shows the score plot for PC-1 and PC-2 and figure 13B shows the loading plot for PC-1 and PC-2. The oil samples were analysed with FTIR spectroscopy.

PC-4, presented in figure 14, seemed to add some information on how to separate the group of wild salmon a bit better from norwegian and islandic cod liver. The most important bands in the loading plot for PC-4, which can be seen in figure 14B, were at wavenumbers 3014 cm^{-1} ,

1746 cm^{-1} , 1091 cm^{-1} and 723 cm^{-1} . Based on PC-1 and PC-4 the fish oils could be divided into four different classes.

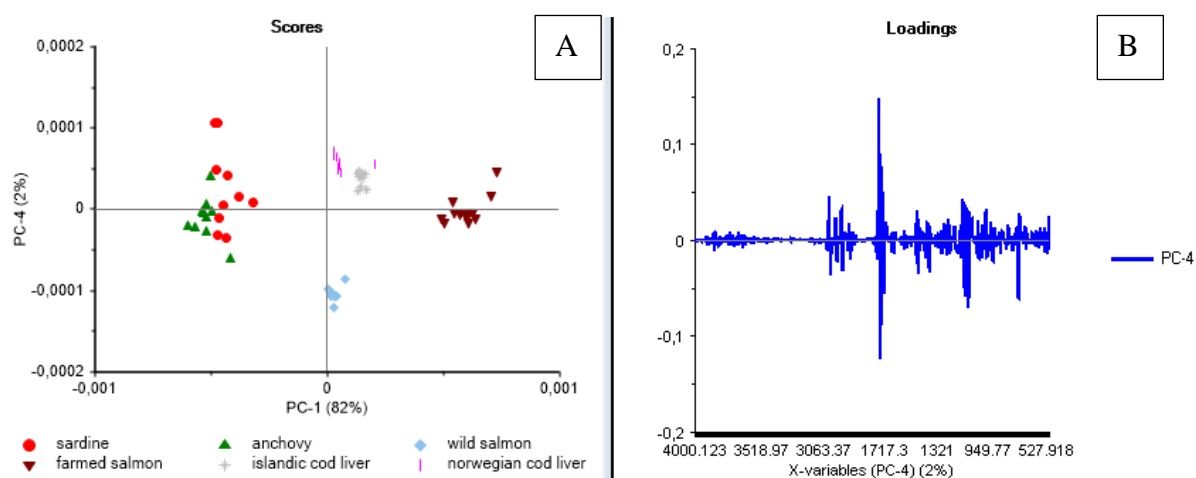


Figure 14 - Principal component analysis for all samples from Orivo, except krill. Figure 14A shows the score plot for PC-1 and PC-4 and figure 14B shows the loading plot for PC-4. The oil samples were analysed with FTIR spectroscopy.

Based on PCA with all six groups of marine oils it was not possible to distinguish the fish oil samples any further. Thus, a PCA was run based only on the groups that were hard to separate. Figure 15 displays a score and loading plot for sardine and anchovy, and here the samples could only be partly separated based on PC-1. The most prominent bands in the loading plot of PC-1 were at wavenumbers 2921 cm^{-1} , 2853 cm^{-1} , 1738 cm^{-1} , 1710 cm^{-1} , 1472 and 1144 cm^{-1} . The samples of sardine were quite scattered while the samples of anchovy were more clustered. Although the separation of these two groups was not perfect, the PCA in figure 15A still shows some separation.

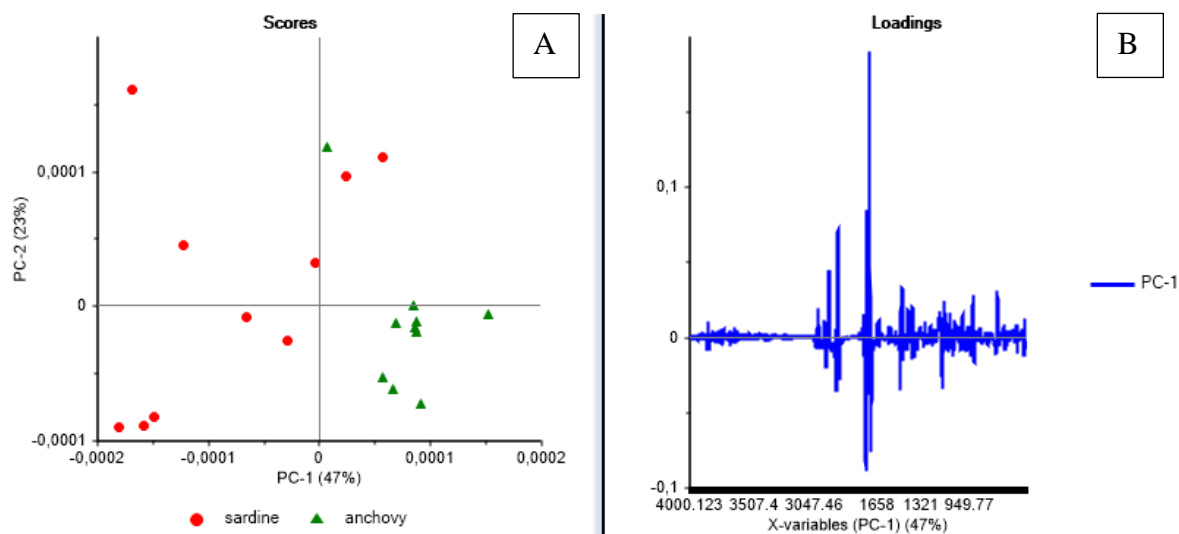


Figure 15 - Principal component analysis for the samples of sardine and anchovy. Figure 15A shows the score plot for PC-1 and PC-2, and figure 15B shows the loading plot for PC-1. The oil samples were analysed with FTIR spectroscopy.

A PCA of the samples of wild salmon, norwegian cod liver and islandic cod liver gave better results, as can be seen in figure 16. All samples of the same type of marine oil were clustered and placed apart from the other groups, except for one sample of norwegian cod liver oil that seemed to be an outlier. The most prominent bands in the loading plot for PC-1 were at 3012 cm^{-1} , 1746 cm^{-1} , 1137 cm^{-1} , 1119 cm^{-1} , 1090 cm^{-1} and 722 cm^{-1} . For PC-2 the main peaks in the loading plot were at wavenumbers 2922 cm^{-1} , 2850 cm^{-1} and 1740 cm^{-1} .

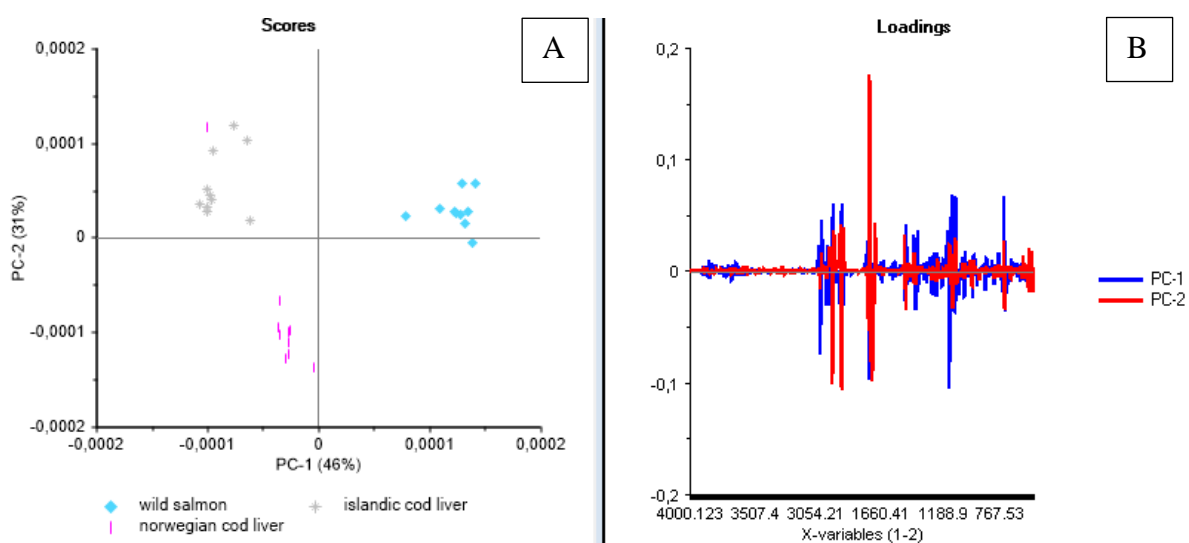


Figure 16 - Principal component analysis for all oil samples of the types of wild salmon, islandic cod liver and norwegian cod liver. Figure 16A shows the score plot for PC-1 and PC-2 and figure 16B shows the loading plot for PC-1 and PC-2.

Overall, PCA showed that each of the seven different marine oils could be separated from the other groups. Interpretation of the spectral bands was not attempted because no reference values were at hand, but the results seemed promising, and further classification with other classification methods should be pursued.

4.2 Part II – Method development

4.2.1 FA composition in reference oils – determined with GC-MS

In order to make a sample design with low correlation between the different FAs, the FA profiles of 18 reference oils were determined. A test run of FAME samples made from the reference oils and fats without added IS showed that there appeared to be some C19:0 present in three of the fish oils. The amounts present were however low and should not have any noteworthy impact on the results. Using C19:0 as IS will give quite accurate results for the FAs of similar chain length, but somewhat less accurate results for the shorter chain FAs such as C8:0 and C10:0. Out of the selected oils only coconut oil had significant amounts of shorter chain FAs.

Two series of samples with different IS concentration had to be prepared in order to accurately quantify both the large peaks and the smaller ones. In the 18 reference oils (table 7) 32 different FAs could be identified based on a comparison with the reference mix and the NIST 2017 database. Furthermore 12 unknown isomers of unsaturated FA were determined by using the NIST database. All FAs are listed in appendix C.

However, due to an unidentified mistake or problem, the quantification of FAs in the reference oils using the method with IS and calculations (Eq. 3) for the mass of each FA in the samples was not successful. In theory the sum of all identified FAs should have been close to 90g/100g of oil, but this was not the case. Thus, the FA profiles were used instead. The FA profiles for each oil were found by looking at the area in percent for the peaks of identified FAs in the chromatogram for each oil. By comparison with reference values for the FA composition of edible oils (matportalen.no, 2019), it could be seen that these values gave an accurate representation of the expected FA composition. All six sample replicates (from series one and two) were used for each reference oil, but some minor FAs were only identified in one of the two series of samples. This was mostly the case for the FAs present in small amounts, which could only be identified in the series with higher FAME concentration. The more unusual FAs were also only identified in the series with high FAME concentration.

The FA profile for the different reference oils (appendix E) showed that the FAs C16:0, C18:1n-9 and C18:2n-6 were generally present in large amounts in many of the oils. The FAs C20:5n-3 and C22:6n-3, which represent EPA and DHA respectively, were only found in the fish oils, as expected. The content of these valuable n-3 FAs was especially high in the oils 0370, 3040 and 4030, which are all fish oils enriched in EPA and DHA. C14:0, C18:0 and C18:3n-3 were also detected in larger amounts in most of the oils. These 8 FAs are the main FAs in the reference oils. Table 9 is an excerpt of appendix E and shows the FA profile for the reference oils including only the main FA, given in % FA of the total FA content.

Table 9 – Fatty acid content in % (based on area in % of the assigned peaks in the chromatograms) for the 18 reference oils. This table is an excerpt from the table on appendix E. Numbers marked in red are only based on three replicates (n=3), for all other values n=6.

	14:0 [%]	16:0 [%]	18:0 [%]	18:1n-9 [%]	18:2n-6 [%]	18:3n-3 [%]	20:5n-3 [%]	22:6n-3 [%]
Rapeseed oil	0.06 ±0.03	4.97 ±0.14	1.73 ±0.08	61.64 ±1.00	19.06 ±0.33	6.72 ±0.07	n.d.	n.d.
Peanut oil	0.02 ±0.00	6.90 ±0.11	2.12 ±0.13	67.59 ±1.48	15.36 ±0.35	0.47 ±0.05	n.d.	n.d.
Sesame oil	0.02 ±0.00	9.72 ±0.16	6.10 ±0.31	41.09 ±0.16	40.97 ±0.55	0.20 ±0.02	n.d.	n.d.
Olive oil	0.01 ±0.00	12.51 ±0.11	3.30 ±0.13	71.29 ±0.61	8.33 ±0.19	0.53 ±0.06	n.d.	n.d.
Linseed oil	0.04 ±0.00	6.73 ±0.07	4.32 ±0.14	20.50 ±0.31	15.31 ±0.39	51.92 ±0.92	n.d.	n.d.
Soybean oil	0.07 ±0.01	11.17 ±0.11	4.85 ±0.14	23.09 ±0.42	52.02 ±1.26	5.93 ±0.20	n.d.	n.d.
Sunflower oil	0.06 ±0.00	6.61 ±0.044	3.46 ±0.14	31.99 ±0.66	56.04 ±0.91	0.12 ±0.03	n.d.	n.d.
Vita hjertegó	0.04 ±0.00	6.24 ±0.09	2.31 ±0.07	56.39 ±0.79	25.75 ±0.44	5.24 ±0.13	n.d.	n.d.
Frying oil	0.05 ±0.00	5.70 ±0.06	2.48 ±0.08	45.47 ±0.15	38.23 ±0.35	4.52 ±0.13	n.d.	n.d.
Møllers tran	3.77 ±0.09	10.21 ±0.30	2.14 ±0.06	15.20 ±0.15	2.39 ±0.21	0.72 0.05	7.74 ±0.08	9.68 ±0.58
Rice bran oil	0.41 ±0.01	20.45 ±0.35	2.04 ±0.07	40.72 ±0.13	32.51 ±0.16	1.05 ±0.07	n.d.	n.d.
Salmon oil	2.19 ±0.06	9.96 ±0.34	2.68 ±0.09	42.58 ±0.41	13.78 ±0.19	4.91 ±0.08	1.99 ±0.34	2.80 ±0.17
Herring oil	8.91 ±0.19	14.25 ±0.35	1.09 ±0.04	6.99 ±0.11	1.52 ±0.09	1.12 ±0.07	7.00 ±0.08	6.14 ±0.18
Coconut oil	25.71 ±0.93	11.62 ±0.82	4.96 ±0.67	7.23 ±0.77	1.15 ±0.16	n.d.	n.d.	n.d.
0370	0.36 ±0.18	0.63 ±0.08	0.29 ±0.02	0.55 ±0.06	0.16 ±0.02	n.d.	12.89 ±1.50	62.32 ±3.55
4030	0.37 ±0.03	0.51 ±0.06	2.03 ±0.23	2.60 ±0.34	n.d.	0.19 ±0.04	44.08 ±0.94	28.21 ±2.67
3040	0.16 ±0.02	0.38 ±0.02	1.30 ±0.15	1.70 ±0.18	0.24 ±0.02	0.09 ±0.01	40.30 ±0.27	34.52 ±2.94
Camelina oil	0.04 ±0.01	6.12 ±0.13	2.93 ±0.09	16.79 ±0.11	19.32 ±0.33	37.97 ±0.48	n.d.	n.d.

Although a few of the FAs are dominating these profiles, important variations in FA composition can be found in the reference oils. As can be seen in figure 17 coconut oil is unique in regard to chain length because it contains many of the shorter chain FAs, the shortest being C6:0. The content of 12:0 in coconut oil is especially high compared to the other oils, with $35,82 \pm 2,91$ % FA as opposed to a content of $<0,2$ % in the other samples. The longest FAs detected were C24:0 and C24:1n-9. C24:0 was mainly found in the plant oils and C24:1n-9 in the fish oils. Nevertheless, the amounts detected of these two long chain FAs were $<1,2$ % in all reference oils. C22:6n-3 was the long chain FA present in largest amounts, ranging from $2,80 \pm 0,17$ % in salmon oil to $64,32 \pm 3,55$ % in 0370. By dividing all the FA found in the reference oils into three categories based on chain length (C6 to C13, C14 to C19 and C20 to C24), one could see that the plant oils consisted of mainly FAs in the medium fraction, while the fish oils also contained large amounts of the longest chain fraction. Coconut oil was the only oil with significant amounts of FAs in the shortest chain fraction. Chain length of the reference oils is visualized in figure 17.

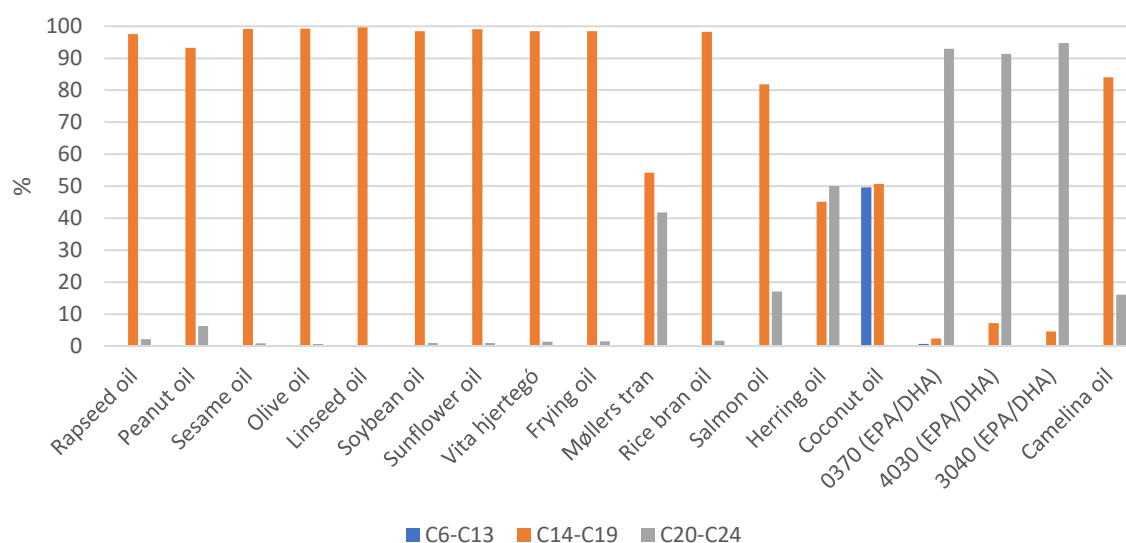


Figure 17 – Illustration of fatty acid composition in the 18 reference oils. The fatty acids are summarized into the categories of fatty acids with 6-13 carbon atoms, 14-19 carbon atoms and 20-24 carbon atoms. The figure is based on table F2 in appendix F.

The degree of unsaturation in the reference oils is shown in figure 18, where the sum of SFAs, MUFAs and PUFAs are presented for each oil. Coconut oil has the highest content of SFAs, followed by rice bran oil and herring oil. Olive, peanut and rapeseed oil have the highest

content of MUFAs, while the largest quantity of PUFAs can be found in 0730, 3040, and 4030.

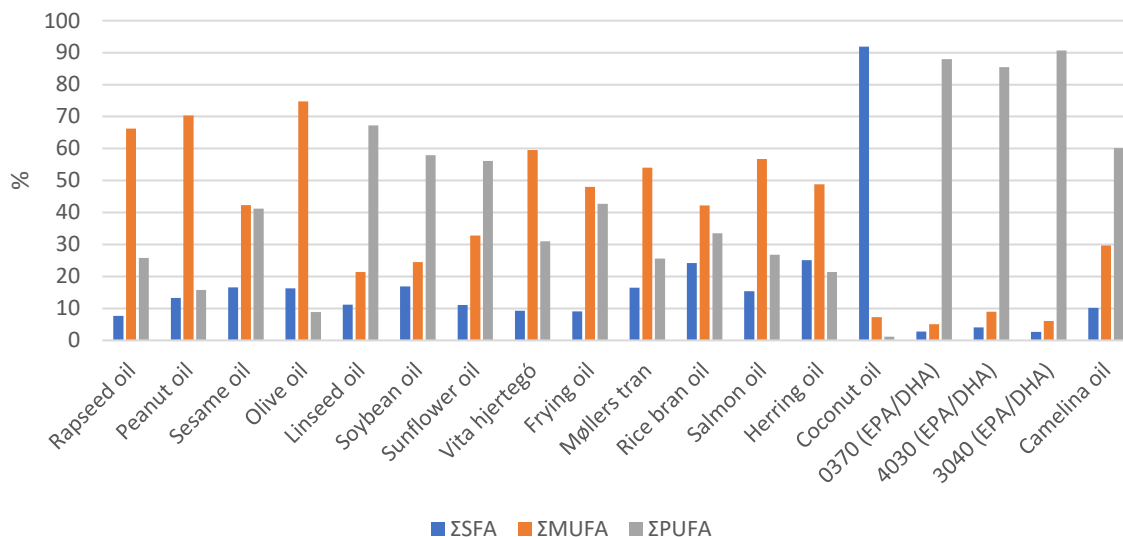


Figure 18 – Illustration of the FA composition in the 18 reference oils. The FAs are displayed as ΣSFA, ΣMUFA and ΣPUFA. The figure is based on table F1 in appendix F.

4.2.2 Calculated FA composition in the calibration set

The analyses of the reference oils showed that there were eight FAs that dominated the FA profiles. They included the SFAs C14:0, C16:0 and C18:0, the common FAs C18:1n-9, C18:2n-6 and C18:3n-3 as well as the valuable n-3 FAs C20:5n-3 and C22:6n-3. The set of mixtures that was chosen for the calibration set contained 80 mixtures of reference oils in different ratios. The details for these 80 mixtures can be found in appendix D.

The upper right part of figure 19 shows all possible mixtures (blue dots) of the sample design and the 80 samples that were chosen for the calibration set (red dots). Here one can see that the chosen mixtures do span the whole area of variation between two and two FAs quite well. The correlation between the different FAs in this set of samples should ideally be as low as possible. As can be seen in the lower left part of figure 19, correlations for the theoretical set were in the region between 0.03 – 0.65 (absolute values), which was acceptable for the purpose of the present study. C18:2n-6 and C18:3n-3 were the two FAs that were the least correlated, as could be seen from the correlation coefficient of -0.03. Many of the other FA combinations had correlation coefficients between ± 0.1– 0.3, while a few were above ± 0.5. This indicated that some of the FAs were correlated to some extent. However, as the samples

of the calibration set were made by mixing natural oils, some degree of correlation between different FAs in the samples was expected.

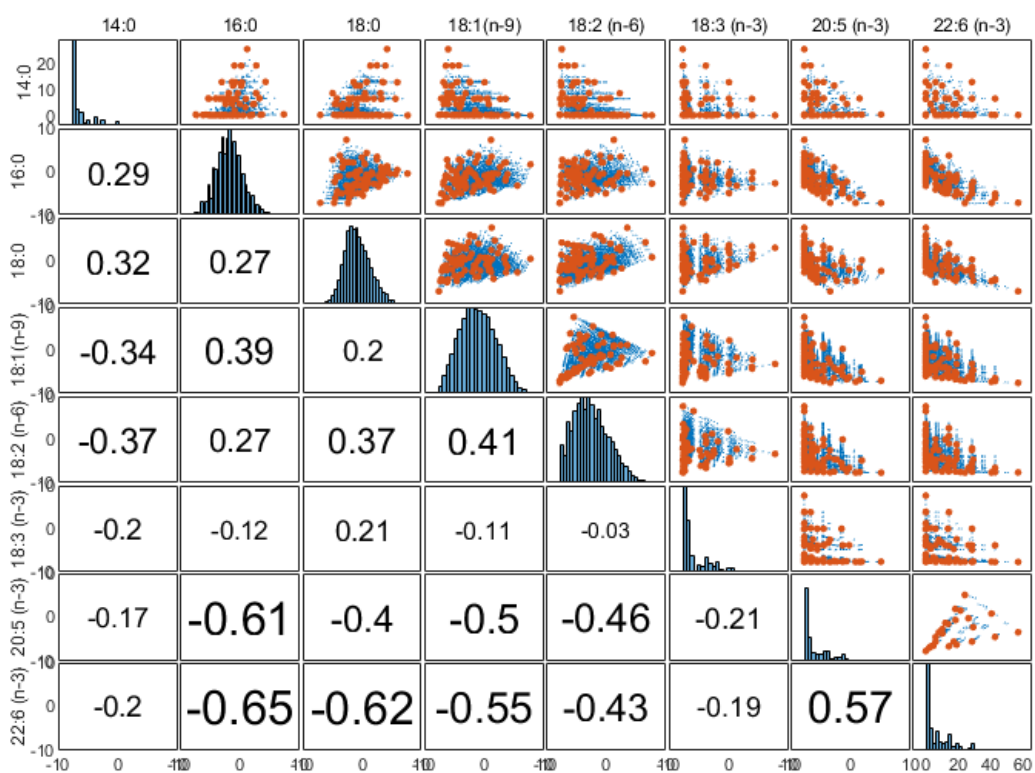


Figure 19 – The numbers in the lower left part of the figure express the correlation between two and two FAs of the theoretical calibration set. The blue dots in the upper right part of the figure represent the possible mixtures, while the red dots represent the 80 samples that were chosen for the calibration set.

The correlation values for the main FAs in the prepared samples of the calibration set are presented in table 10. By comparing these values with the theoretical values above, one could see that some of the calculated values deviated with ± 0.02 while most values deviated with ± 0.01 or were identical to the theoretical value. The small changes that could be seen for some of the correlation coefficients were likely since these calculated values were based on FA profiles from multiple replicates of each sample, and because the actual mixing ratios were slightly differing from the theoretical values. In table 10 the FA features are also included (i.e. Σ SFA, Σ MUFA, Σ PUFA and UI). The correlation coefficients for these features could be described as logic: Σ SFA was highly correlated C14:0, Σ MUFA was highly correlated to C18:1n-9 and the UI was highly correlated to C22:6n-3 (DHA) and Σ PUFA. One could also see that Σ SFA had low correlations with the unsaturated FAs and Σ MUFA had correlation

coefficients $\leq (\pm 0.55)$ for all other FAs than C18:1n-9. For Σ PUFA and the UI no further trends in the correlation coefficients could be observed.

Table 10 – Correlation between the parameters of the prepared samples of the calibration set, expressed as Pearson's correlation coefficients.

	C4:0	C16:0	C18:0	C18:1 n-9	C18:2 n-6	C18:3 n-3	C20:5 n-3	C22:6 n-3	Σ SFA	Σ MUFA	Σ PUFA	UI
C14:0												
C16:0	0.27											
C18:0	0.34	0.27										
C18:1n-9	-0.35	0.38	0.18									
C18:2n-6	-0.37	0.27	0.36	0.40								
C18:3n-3	-0.20	-0.11	0.20	-0.11	-0.04							
C20:5n-3	-0.17	-0.58	-0.39	-0.48	-0.45	-0.20						
C22:6n-3	-0.20	-0.66	-0.61	-0.55	-0.43	-0.19	0.55					
Σ SFA	0.97	0.43	0.48	-0.18	-0.21	-0.19	-0.32	-0.35				
Σ MUFA	-0.35	0.45	-0.03	0.89	0.27	-0.14	-0.41	-0.55	-0.25			
Σ PUFA	-0.57	-0.71	-0.36	-0.51	0.00	0.28	0.58	0.69	-0.67	-0.55		
UI	-0.45	-0.76	-0.60	-0.54	-0.35	0.02	0.74	0.90	-0.60	-0.51	0.89	

The calculated FA profiles for the calibration set including the eight main FAs and the parameters Σ SFA, Σ MUFA, Σ PUFA as well as the UI are presented in appendix G. The variation in FA composition in these samples is illustrated in figure 20, where the FAs are shown as Σ SFA, Σ MUFA, Σ PUFA. This figure clearly illustrated the sample variation in terms of types FAs they contained.

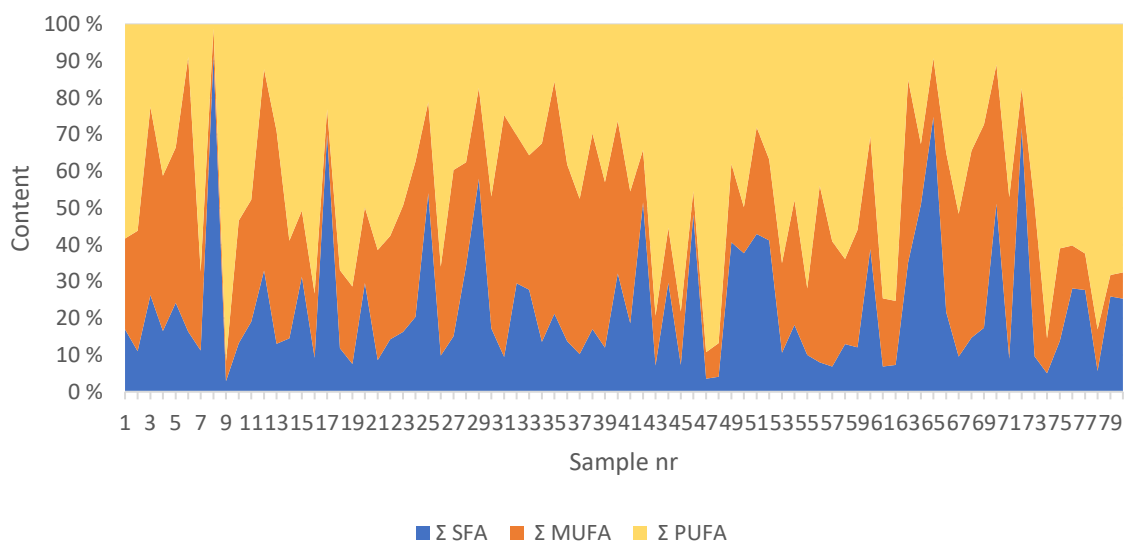


Figure 20 – Illustration of the FA composition in the 80 samples of the calibration set. The FAs are displayed as Σ SFA, Σ MUFA and Σ PUFA.

Based on the unsaturation index for each sample, the total degree of unsaturation is visualized in figure 21. Since the FA profiles were used to calculate the unsaturation values for each sample, a value of 1 will mean that each FA has one double bond on average. Sample nr eight was found to be the sample with the lowest degree of unsaturation, with a value of 0.10. This sample consisted of pure coconut oil. The highest unsaturation value was found for sample nr nine, which consisted of only 0370. All other samples had values spanning the area between these two values.

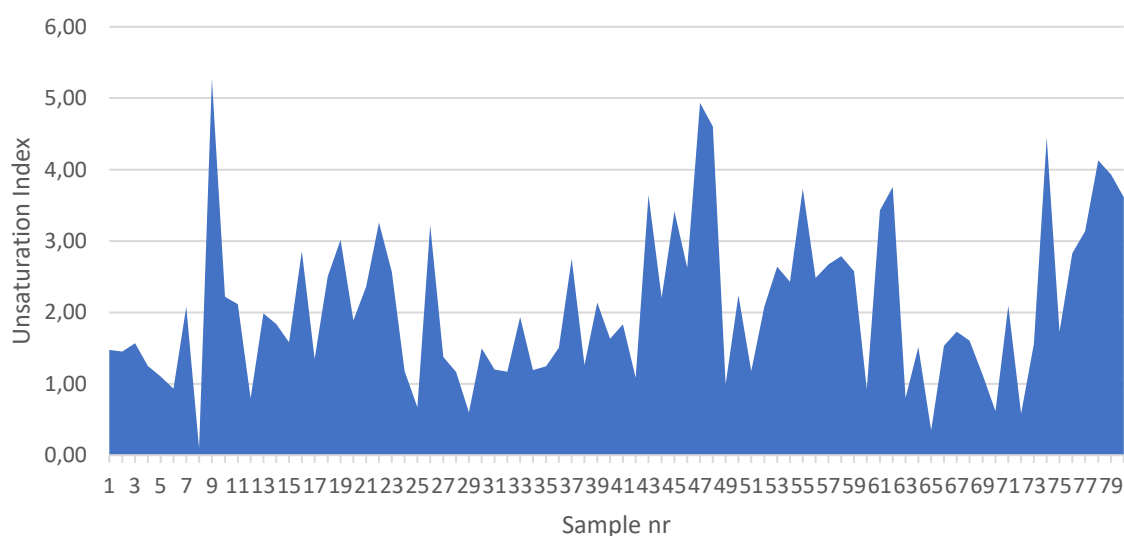


Figure 21 – Illustration of the variation in total degree of unsaturation in the 80 samples of the calibration set, expressed as values of the unsaturation index.

The goal of this thesis was to find calibration models that enable the use of vibrational spectroscopy to predict the FA composition in oils. The main FAs as well as Σ SFA, Σ MUFA, Σ PUFA and the UI were the parameters of interest for these models. Table 11 sums up the range (min. and max. values) for these 12 parameters in the 80 calibration samples that were prepared, in addition to the mean values of all samples and the standard deviations. Together with the low internal correlations between FAs that were seen in table 10, this showed that the chosen calibration set of 80 samples provided a high variation of each of the eight FAs, and low correlations between them.

Table 11 – Range, mean and standard deviation (SD) for the 12 parameters of interest in the samples of the calibration set.

Parameter	Min [%]	Max [%]	Mean [%]	SD [%]
C14:0 [%]	0.01	25.71	4.23	5.69
C16:0 [%]	0.51	20.45	8.17	3.92
C18:0 [%]	0.29	6.10	3.02	1.19
C18:1(n-9) [%]	0.55	71.29	24.25	16.01
C18:2(n-6) [%]	0.00	56.04	15.65	12.40
C18:3(n-3) [%]	0.00	51.92	8.78	11.61
C20:5(n-3) [%]	0.00	44.08	6.97	9.32
C22:6(n-3) [%]	0.00	62.32	11.33	13.61
Σ SFA [%]	2.78	91.92	23.18	18.24
Σ MUFA [%]	5.11	74.73	29.59	16.05
Σ PUFA [%]	1.15	88.01	46.27	20.66
UI	0.10	5.27	2.09	1.11

4.2.3 Calibration models based on FTIR spectroscopy

A line plot of the preprocessed FTIR spectra for the 80 calibration samples is presented in figure 22. Here one can see the main absorption bands for the samples, these are found in the area of $3100 - 2750 \text{ cm}^{-1}$ and $1800 - 500 \text{ cm}^{-1}$. The bands are generally the same in all oils, but with small variations in intensity.

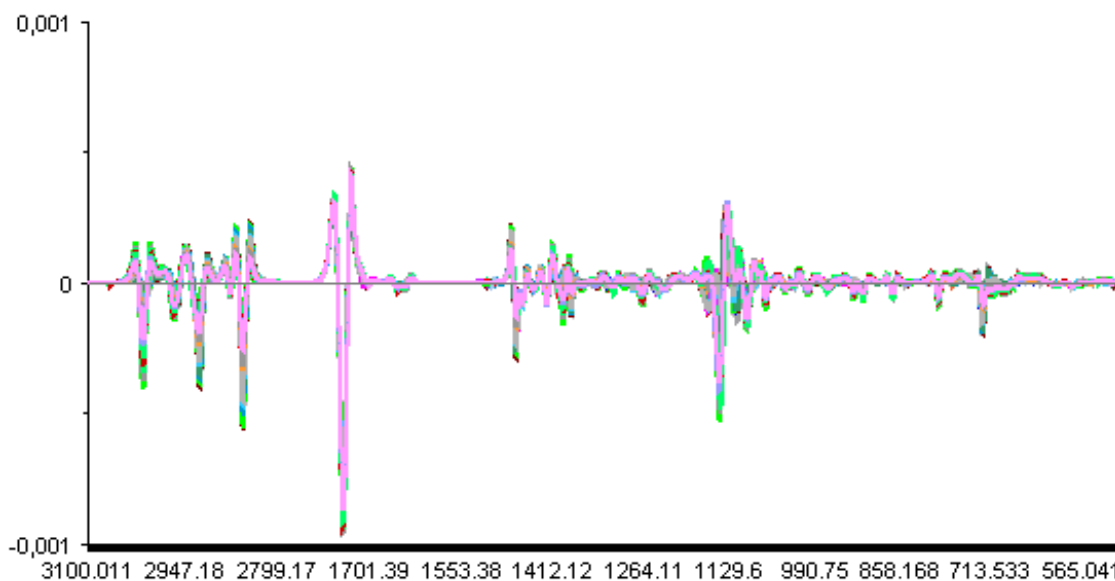


Figure 22 - Line plot of the preprocessed FTIR spectra for the 80 calibration samples. The spectra have been preprocessed with Savitzky-Golay second derivatives and EMSC. The spectral area included is $3100 - 2750 \text{ cm}^{-1}$ and $1800 - 500 \text{ cm}^{-1}$.

When making the PLSR models based on FTIR spectral data, the area of $1800 - 1700 \text{ cm}^{-1}$ was not included. In FTIR spectra of oils, as can be seen in figure 22, the carbonyl peak at around 1743 cm^{-1} is quite dominant. As can be seen in the subsequent discussion, the C–O information in the FTIR spectrum can be indirectly related to FA composition. However, since different oils might have different glyceride composition, the band might in the worst case be indirectly correlated to the oils in the calibration set. In order to avoid any indirect link between the oils in the data set and the FA features, the carbonyl peak was not included when making the subsequent calibration models for the FTIR spectra.

PLSR with cross-validation was performed on the data from the 80 samples of the calibration set. The spectral data from FTIR analysis, which were preprocessed as described in section 3.4.3, served as predictor variables, and the different parameters listed in table 11 were response variables. All regression coefficients and predicted vs. reference plots for the calibration models with the 12 parameters of interest can be found in appendix K. A summary of the main information including the main bands of the regression coefficients for these analyses are presented in table 12.

The results of PLSR performed with 14:0 as response variable are provided in figure 23. Here the optimal number of factors was found to be four, and the correlation between the predictor

and response variables was good, as can be seen from the R^2 -value of 0.98. RMSECV was found to be 0.8 %, which compared to the average C14:0 content in the calibration set (4.23 %) was an acceptable value. Thus, the overall fit of the model was good. The spectral bands for this regression can be seen in the regression coefficient plot of figure 23B, where the most prominent peaks were found at wavenumbers 1147 cm^{-1} , 1138 cm^{-1} , 1108 cm^{-1} and 1083 cm^{-1} . An interpretation of these important wavelengths based on section 2.3.6 would suggest that the calibration model for C14:0 is largely based on the stretching of C–O in the ester part of the TAG structure. The vibration of C–O is based on two asymmetric coupled vibrations; primarily the vibration of C–C(=O)–O in addition to the vibration of O–C–C (Guillén & Cabo, 1997; Silverstein et al., 2015). FAs can thus be differentiated based on the vibration of C–O as this vibration is influenced by the length of the carbon chain that is bound to the glycerol part of the TAG by an ester linkage.

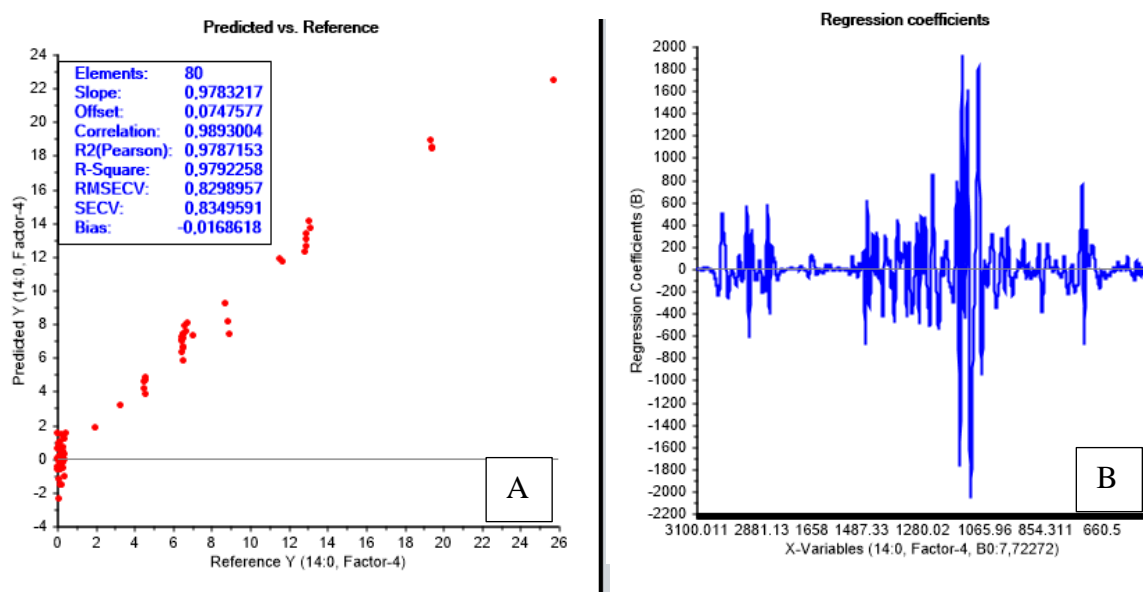


Figure 2 – Predicted vs. Reference response values (A) and regression coefficients (B) for the calibration model obtained with 14:0 as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with FTIR spectroscopy.

Unfortunately, not all plots for the regression coefficients showed only few important spectral bands, as was seen in the model for C14:0. Especially the regression with C16:0 as response variable resulted in a PLSR plot where many of the spectral bands were of similar intensity, this can be seen in figure 24. The reason for this can partly be found by looking at the number of factors of this model, which was nine. Thus, the model for C16:0 was substantially more complex than the model for C14:0, which was based on only four factors. In the worst case,

an increase in model complexity might indicate more noise, which makes interpretation of the spectrum more difficult.

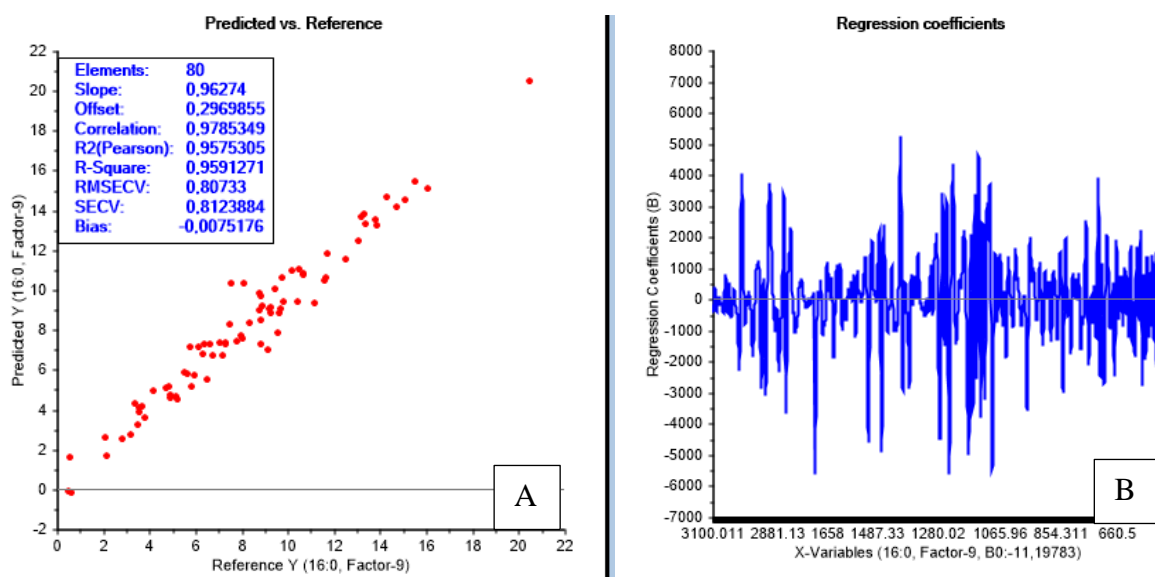


Figure 3 – Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with 16:0 as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with FTIR spectroscopy.

For the calibration model of C16:0 the most prominent spectral bands were found at 1698 cm^{-1} , 1237 cm^{-1} , 1089 cm^{-1} , 510 cm^{-1} and 503 cm^{-1} , but there were many other spectral bands of importance for this PLSR model. Interpretation of the bands of the regression coefficients was difficult due to the high model complexity and was thus not performed here.

For all the remaining parameters, the PLSR-plots can be found in appendix K. Table 12 summarizes the main information that was gathered from these analyses: R^2 , RMSECV, number of factors and the main regression coefficients.

Table 12 – Summary of RMSECV, R^2 , number of factors and main spectral bands in the regression coefficient plots for the calibration models based on analysis with FTIR spectroscopy.

Parameter	RMSECV	R^2	Factors	Main spectral bands (cm^{-1})
C14:0	0.8	0.98	4	1147, 1138, 1108*, 1083
C16:0	0.8	0.96	9	1698, 1237, 1089, 510, 503*
C18:0	0.3	0.93	7	1504*, 1497, 1490, 1040*
C18:1(n-9)	2.2	0.98	5	2924, 1102, 1082*, 725
C18:2(n-6)	1.4	0.99	5	2954, 1397, 1111*, 1101*, 1067
C18:3(n-3)	1.3	0.99	5	2954, 1141*, 1131, 1067
C20:5(n-3)	1.4	0.98	5	1312, 1153*, 1137, 1110
C22:6(n-3)	1.6	0.99	4	3013, 1151, 1133*, 1120, 1109
Σ SFA	2.3	0.98	4	2926, 1145, 1138, 1120, 1108*, 1085
Σ MUFA	2.1	0.98	5	1468, 1403, 1396, 1118, 1103*
Σ PUFA	2.5	0.99	4	2928, 2917, 2858, 2849*, 1112
UI	0.1	0.99	4	3015, 2926*, 2916, 2849, 713

* = strongest band in regression coefficient plot

In terms of model complexity, the simplest models were based on four factors. These were the models for C14:0, C22:6n-3, Σ SFA, Σ PUFA and UI. The models for C18:1n-9, C18:2n-6, C18:3n-3, C20:5n-3 and Σ MUFA were based on five factors and thus somewhat more complex. For C16:0 and C18:0 the models were more complex, with an optimal number of factors of nine and seven, respectively.

Based on R^2 alone, all models seemed to have high correlations. Depending on the model, 93 % to almost 100 % of the variation in the response variables could be explained from the spectral data. The regression model for C18:0 had the lowest fit with an R^2 -value of 0.93, while the model for UI explained the largest amount of variation, close to 1.00. Regression analysis using C16:0 as response variable resulted in the second lowest R^2 , with a value of 0.96. For the remaining models the R^2 value was 0.98 to 0.99.

The error of prediction for the PLSR models was here expressed as RMSECV. It estimates the deviations between the actual parameter-values in the samples that were left out during cross validation and the values predicted by the model based on the remaining samples. Although RMSECV has the same unit as the values for mean and range, direct comparison of the prediction error for the different models was not possible. The reason for this was that UI had a different unit than the other parameters, and the range and mean values for the parameters were quite diverse. Thus, RMSECV in percent of the mean value for each parameter in the 80 calibration samples was calculated to create better grounds for comparison, see table 13. UI clearly had the lowest prediction error, while C14:0 and C20:5n-3 had the largest with almost

20 % of the mean value. A relative prediction error >10 % of the mean value was also found for C18:0, C18:3n-3 and C22:6n-3. For C16:0, C18:1n-9, C18:2n-6, Σ SFA, Σ MUFA and Σ PUFA the prediction error was between 5 % and 10 %. The lowest prediction errors were found for the models based on the predictor variables Σ MUFA, Σ PUFA and UI.

Table 13 – RMSECV for the calibration models based on FTIR spectroscopy, expressed in percent of the mean content for all samples of the calibration set. The mean values are based on the calculated FA content in the calibration samples.

Parameter	Mean	RMSECV	RMSECV [%]
C14:0 [%]	4.23	0.8	19.6
C16:0 [%]	8.17	0.8	9.9
C18:0 [%]	3.02	0.3	10.6
C18:1(n-9) [%]	24.25	2.2	8.9
C18:2(n-6) [%]	15.65	1.4	9.0
C18:3(n-3) [%]	8.78	1.3	15.3
C20:5(n-3) [%]	6.97	1.4	19.5
C22:6(n-3) [%]	11.33	1.6	13.9
Σ SFA [%]	23.18	2.3	10.0
Σ MUFA [%]	29.59	2.1	6.9
Σ PUFA [%]	46.27	2.5	5.5
UI	2.09	0.1	2.4

Based on both RMSECV and R^2 , the calibration model created using UI as response variable was the best model, followed by the models for Σ MUFA and Σ PUFA. These results indicated that the degree of unsaturation, Σ MUFA and Σ PUFA in edible oils could be predicted quite accurately using FTIR spectroscopy, while content of individual FAs and Σ SFA could be predicted with a somewhat larger error of prediction. Nevertheless, the calibration models for the single FAs did look promising. Considering the chemical structure of SFAs vs MUFAs or PUFAs, it seems logical that prediction of unsaturated FAs is easier than prediction of SFAs. Introduction of a double bond will give rise to a weak peak in the spectral area of 3010 cm^{-1} , while introduction of another C–C bond will only influence the intensity of the peaks that are already present in the region of $2800 - 3000\text{ cm}^{-1}$. When a sample consists solely of SFAs, one way to distinguish them will be based on the relation between the different absorption bands for C–H stretching, or between C–H and C=O stretches, because this relation will vary with chain length (Socrates, 2004).

As mentioned before, the regression coefficient plots give information regarding what wavelengths are important when establishing a calibration model. More intense bands indicate larger spectral differences between the samples of the calibration set and show that the absorption at the given wavelength can be used for predictive purposes. Evaluation of the important bands a model is based on is a way to verify the model, by checking that the interpretation of the bands is meaningful. The PLSR models in appendix K show that for most of the models there was not one but a few bands that were intense. These main bands for all calibration models are summarized in table 12.

Many of the most important spectral bands were found in the area of $1040 - 1153 \text{ cm}^{-1}$, and for multiple models the main peak was also found in this area. Absorptions at wavenumbers in the area of $1037 - 1239 \text{ cm}^{-1}$ are caused by -C-O stretching in the TG and bending of $\text{-CH}_2\text{-}$ in the case of vibrations around 1163 cm^{-1} . The vibration of C-O can be used to separate FAs based on their chain length, because this vibration consists of the two asymmetric coupled vibrations of C-C(=O)-O and O-C-C (Guillén & Cabo, 1997; Silverstein et al., 2015). Smaller variations in wavenumbers can generally be explained by differences in chemical surroundings.

For the models of Σ PUFA and UI the main peaks were found at 2849 cm^{-1} and 2926 cm^{-1} , respectively, which means the symmetrical and asymmetrical stretching vibrations of -C-H in CH_2 were the most important absorptions. The spectral area of approximately 2800 cm^{-1} to 3000 cm^{-1} is important because it shows absorptions related to saturation of the FAs. Long chain FAs without any double bonds will show a strong absorption in this area, while FAs with one or more double bonds will have a less intense band in this area. It is expected, however, that the presence of C=C double bonds will also indirectly affect the symmetrical and asymmetrical stretches in this region, which is clearly visible from the interpretation of the regression models for UI and Σ PUFA.

For PUFAs the intensity of the peaks in area of $2800 - 3000 \text{ cm}^{-1}$ will be lower than for SFAs, so the total degree of unsaturation, here expressed as the UI, can be predicted based on the intensity of the peaks in this area. The same applies for prediction of Σ PUFA. The calibration set included samples of varying UI, ranging from 0.1 – 5.27, and with a Σ PUFA content ranging from 1.15 % – 88.01 %. Due to these large variations in UI and Σ PUFA for the samples of the calibration set, it makes sense that the main bands for this model were found in the spectral area of 2800 cm^{-1} to 3000 cm^{-1} .

The models based on C18:1n-9, C18:2n-6, C18:3n-3, Σ SFA and Σ PUFA had a strong band in the spectral area of 2800 cm^{-1} to 3000 cm^{-1} , which was to be expected, as they all deal with separating unsaturated FAs from SFAs. One would expect the models for C20:5n-3, C22:6n-3 and Σ MUFA to also have a main peak in this area, but this was not the case. However, the PLSR models for these three parameters (appendix K) did have less intense bands in this area. This means that the models are, to a smaller extent, built on the differences in absorption intensity at wavelengths in this area, but other bands were found to be more important.

One of the main bands for C22:6n-3 was found at 3013 cm^{-1} . Absorptions in the area of $\sim 3008 \text{ cm}^{-1}$ are important in relation to the degree of unsaturation, because they are caused by the stretching vibration of =C–H in *cis* configuration. Besides the model for C22:6n-3 only the model for UI had one of the main bands in this area. Although the spectral band $\sim 3008 \text{ cm}^{-1}$ is important in relation to distinguishing the SFAs from the unsaturated FAs, other spectral areas such as 2800 cm^{-1} to 3000 cm^{-1} seemed to be more important overall for the models based on the other parameters.

The main peak at 1504 cm^{-1} in the model for C18:0 was somewhat difficult to interpret. Scissoring of –C–H in CH_2 and CH_3 found at 1465 cm^{-1} was the closest value for interpretation, however such a large deviation means the observed band might be caused by some other vibration. As mentioned earlier, the large peak at 503 cm^{-1} in the model for C16:0 cannot be explained based on the knowledge about interpretation of FTIR spectra. See section 2.3.6 for interpretation of the remaining bands listed in table 12.

4.2.4 Calibration models based on Raman spectroscopy

In figure 25 the preprocessed Raman spectra of the calibration set are presented. The shift values included were in the range of 500 – 1800 cm^{-1} , and various absorption peaks could be found in this area.

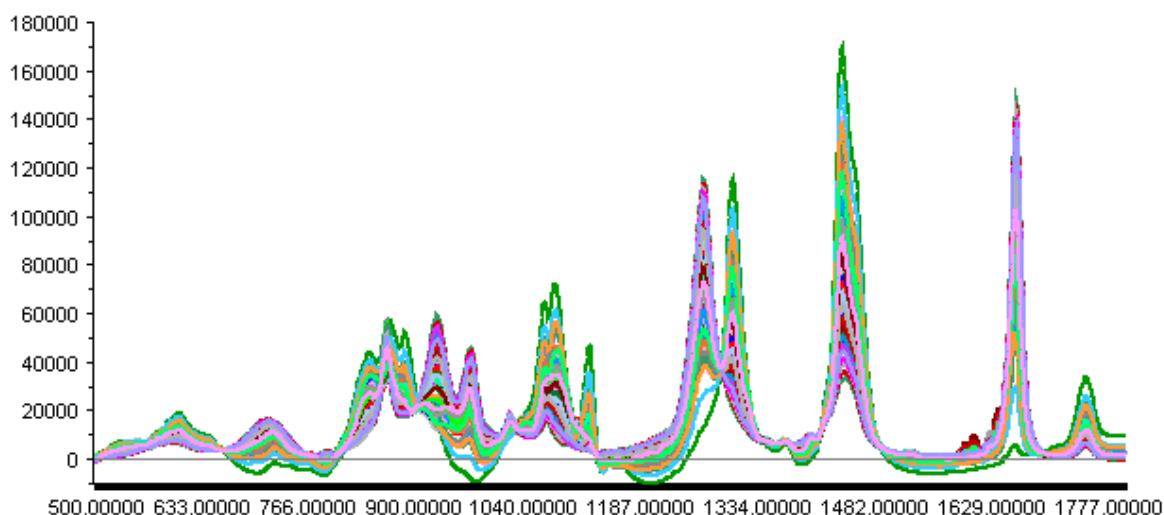


Figure 25 - Line plot of the preprocessed Raman spectra for the 80 calibration samples. The spectra were baseline-corrected in Matlab and transformed with EMSC in Unscrambler. The spectral area included is 500 – 1800 cm^{-1} .

PLSR with cross-validation was performed on the spectral data from the 80 samples of the calibration set. Details for the Raman analysis can be found in chapter 3.4.2. Prior to PLSR analysis the obtained Raman spectra were preprocessed as described in section 3.4.3. For PLSR analysis the spectral data served as predictor variable, while the same parameters as previously were used as response variables. All obtained regression plots can be found in appendix L, and a summary of R^2 , RMSECV, number of factors and main spectral bands can be found in table 14.

PLSR plots for the regression performed with C14:0 as response variable are provided in figure 26. The regression model was built on five factors, which means that the model complexity is relatively low. R^2 was found to be 0.96, which means that 96 % of the variation in C14:0 content could be explained by the Raman spectral data. RMSECV is 1.10 %, which is an acceptable value compared to the range of C14:0 content in the calibration samples (0.01 – 25.71 %). Compared to the mean content of C14:0, 4.23 %, the prediction error was somewhat high. When taking both R^2 and RMSECV into consideration, the model for C14:0 seemed to be good, with a slightly high prediction error.

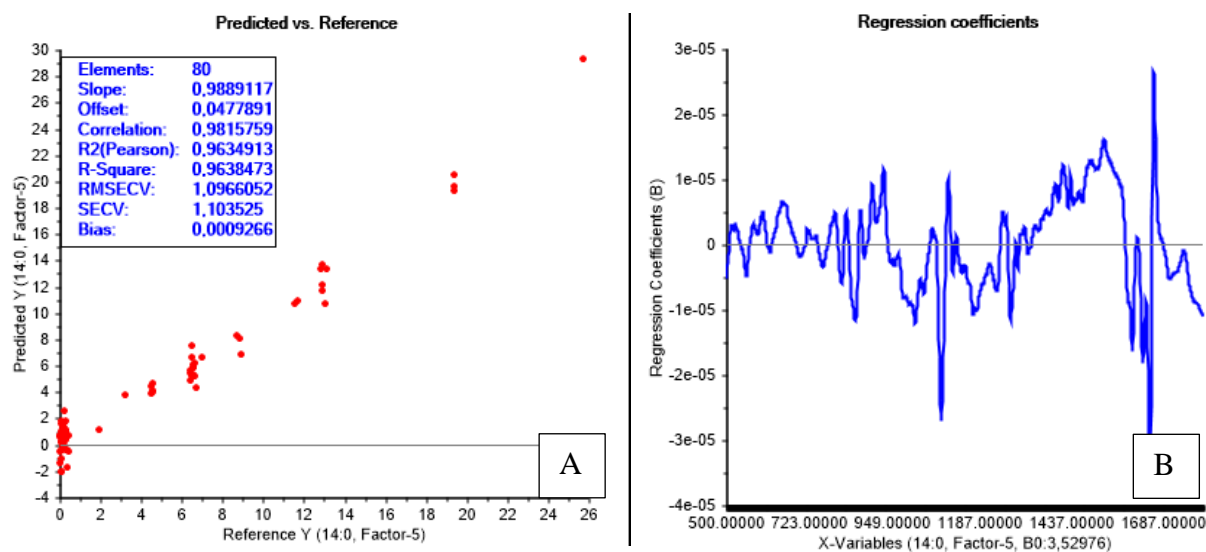


Figure 4 – Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with C14:0 as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with Raman spectroscopy.

As can be seen from the regression coefficient plot in figure 26B, three of the bands are more intense than the others. These main bands are located at the Raman shifts of 1085 cm^{-1} , 1654 cm^{-1} and 1665 cm^{-1} . The band at 1085 cm^{-1} is most likely caused by a skeletal vibration such as a C–C or C–O stretch. The bands at 1654 cm^{-1} and 1665 cm^{-1} are both related to the C=C stretch. For an increase in degree of unsaturation, for example when going from MUFAs to PUFAs, the band for the C=C stretch will shift to a higher wavenumber. Figure 26B also shows how the regression coefficients shift from positive to negative in the area of $1400\text{ – }1650\text{ cm}^{-1}$, which indicates a shift in the degree of unsaturation (Afseth et al., 2005).

The model with C18:2n-6 as response variable, which is presented in figure 27, shows different main bands in the regression coefficient plot than the model for C14:0. Here the main bands are located at the wavenumbers of 837 cm^{-1} , 866 cm^{-1} , 959 cm^{-1} and 1109 cm^{-1} . Based on the section about interpretation of Raman shifts, section 2.3.8, all these bands can be assigned to the skeletal vibrations of the C–C and C–O stretch that can be found in the $(\text{CH}_2)_n$ - part of the FAs and in the C–O part of the TG structure. The band at 959 cm^{-1} can potentially be assigned to the out of plane deformation of =C–H in the unsaturated part of C18:2n-6 (Afseth et al., 2006).

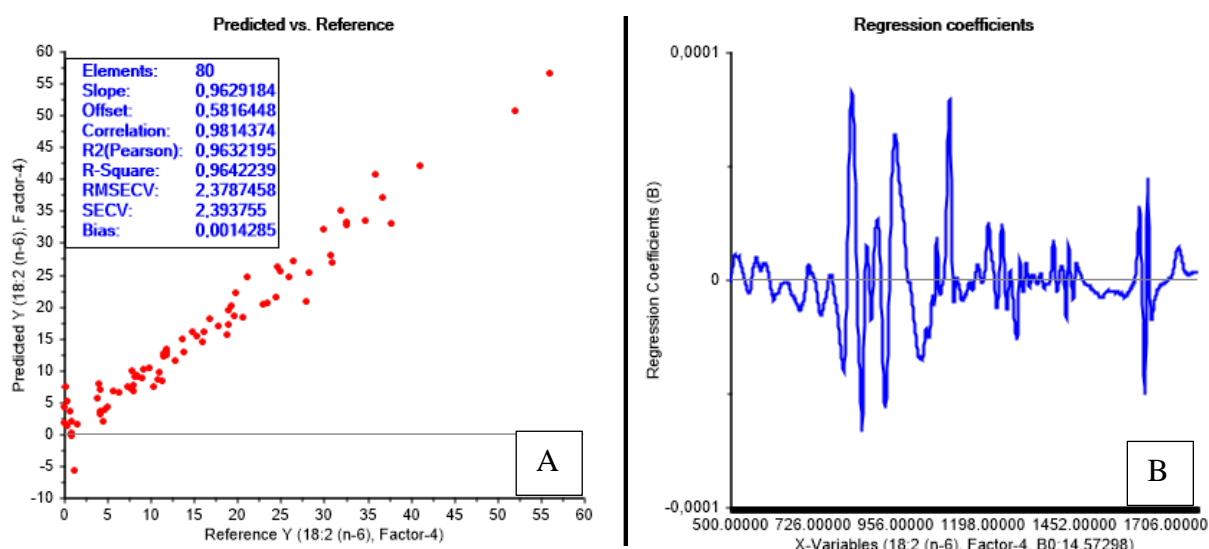


Figure 5 – Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with C18:2n-6 as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with Raman spectroscopy.

As can be seen from the PLSR plots in figure 27, the model for C18:2n-6 is based on four factors, with an R^2 value of 0.96 and RMSECV of 2.3 %. Accordingly, the model complexity is low as the model is built on only four factors, and the overall fit is good, as can be seen from the correlation coefficient. 96 % of the variation in the spectral data could be explained by the response variable C18:2n-6. Considering the range of C18:2n-6 in the samples, 0.00 – 56.04 % with a mean content of 15.56 %, a prediction error of 2.3 % is low. Overall this seems like a good model for the prediction of C18:2n-6 content in oils.

The PLSR plots for the remaining parameters can be found in appendix L, and table 14 shows a summary of the main information that was gathered from these analyses, including number of factors the different models were based on, R^2 and RMSECV.

Table 14 - Summary of RMSECV, R^2 , number of factors and main spectral bands in the regression coefficient plots for the calibration models based on analysis with Raman spectroscopy.

Fatty acid	RMSECV	R^2	Factors	Significant wavelengths/spectral bands (cm^{-1})
C14:0	1.1	0.96	5	1085, 1654*, 1665
C16:0	0.8	0.96	8	1096, 1117*, 1654
C18:0	0.3	0.94	14	1625, 1638*, 1653
C18:1n-9	3.3	0.96	6	1084*, 1103, 1660
C18:2n-6	2.4	0.96	4	837*, 866, 959, 1109
C18:3n-3	2.6	0.95	5	867*, 954, 1040
C20:5n-3	1.9	0.96	7	857, 903, 928, 1038*
C22:6n-3	2.2	0.97	7	859, 929*, 990, 1035
Σ SFA	2.8	0.98	5	1654*, 1665
Σ MUFA	3.6	0.95	3	835, 868, 955, 1652*, 1661
Σ PUFA	2.6	0.98	5	955, 1658*, 1667
UI	0.2	0.97	4	931, 1438, 1655*, 1665

* = strongest band in regression coefficient plot

As shown in table 14, the complexity of the models based on Raman spectroscopy was quite diverse, ranging from three to 14 factors. The most complex model was the one for prediction of C18:0, with an optimal number of factors of 14. Eight factors were found to be optimal for C16:0, seven factors were optimal for C20:5n-3 and C22:6n-3 and six factors were optimal for C18:1n-9. For the models based on the parameters C14:0, C18:3n-3, Σ SFA and Σ PUFA five factors were found to be optimal, while the models for C18:2n-6 and UI were based on four factors. The simplest model was found for Σ MUFA, which was based on only three factors

The individual models had R^2 values in the range of 0.94 to 0.98. Thus, the overall fit of the models was good. Nevertheless, the model for C18:0 had the lowest fit with an R^2 value of 0.94, and the models for Σ SFA and Σ PUFA had the best fit with an R^2 value of 0.98. Calibration models for C18:3n-3 and Σ MUFA had R^2 values of 0.95, and the models for C14:0, C16:0, C18:1n-9, C18:2n-6 and C20:5n-3 had R^2 -values of 0.96. Among the better models were C22:6n-3 and UI with R^2 of 0.97.

Again, RMSECV for the different models was calculated in percent of the mean value for the different parameters to achieve better grounds for comparison of the prediction errors. Table 15 summarizes the mean value for the parameters in the calibration samples, RMSECV for the calibration models and RMSECV in percent of the mean value.

Table 15 - RMSECV for the calibration models based on Raman spectroscopy, expressed in percent of the mean value for all samples of the calibration set. The mean values are based on the calculated FA content in the calibration samples.

Parameter	Mean	RMSECV	RMSECV [%]
C14:0 [%]	4,23	1,1	26,0
C16:0 [%]	8,17	0,8	10,3
C18:0 [%]	3,02	0,3	9,6
C18:1(n-9) [%]	24,25	3,3	13,4
C18:2(n-6) [%]	15,65	2,4	15,2
C18:3(n-3) [%]	8,78	2,6	29,3
C20:5(n-3) [%]	6,97	1,9	27,3
C22:6(n-3) [%]	11,33	2,2	19,5
Σ SFA [%]	23,18	2,8	12,2
Σ MUFA [%]	29,59	3,6	12,3
Σ PUFA [%]	46,27	2,6	5,6
UI	2,09	0,2	8,6

These calculations reveal that RMSECV had values equivalent to 5.6 – 29.3 % of the mean values for the respective parameters in the calibration samples. Σ PUFA had the lowest RMSECV with a relative value of 8.6 %, while C18:3n-3 had the highest RMSECV with a relative value of 29.3 %. Other parameters with a relative RMSECV of >20% were found for C14:0 and C20:5n-3, values between 10 – 20 % were found for the models of C16:0, C18:1n-9, C18:2n-6, C22:6n-3, Σ SFA and Σ MUFA. Only the models for C18:0, Σ PUFA and UI had a relative RMSECV <10 %.

Based on both R^2 and RMSECV it looks like the PLSR model for Σ PUFA was the best, because it had an R^2 value of 0.98 and the lowest relative RMSECV. The model for UI was also quite promising, with an R^2 of 0.97 and relative RMSECV of 8.6 %. The remaining models either had a lower fit, as the model for C18:0 with R^2 of 0.94, or an RMSECV that was >10 % of the mean value. Especially the models for C14:0, C18:3n-3 and C20:5n-3 had high RMSECV values relative to the mean values, which means that the prediction error was quite large.

For all calibration models, except the ones for single PUFAs (C18:2n-6, C18:3n-3, C20:5n-3, C22:6n-3), one of the main bands in the regression coefficient plots was found in the area of 1638 – 1667 cm^{-1} . As can be seen in section 2.3.8, this area corresponds to the $-\text{C}=\text{C}-$ *cis* stretch, and the higher shifts in this area indicate a higher degree of unsaturation. A prominent band in this area is logical for the models of Σ SFA, Σ MUFA, Σ PUFA and the UI, as these

models all deal with unsaturation. For the single FAs a strong peak in this area was only found for the SFAs and C18:1n-9. One explanation for this might be that an absorption in the area of 1638 – 1667 cm^{-1} indirectly gives information whether a FA is saturated or not.

The calibration models for C14:0, C16:0, C18:1n-9, C18:3n-3, C20:5n-3 and C22:6n-6 had a main band in the spectral range of 1035 – 1096 cm^{-1} . A main band in the area of 929 – 990 cm^{-1} was found for the calibration models for C18:2n-6, C18:3n-3, C20:5n-3, C22:6n-3, Σ MUFA, Σ PUFA and UI. Lastly, the calibration models for C18:2n-6, C18:3n-3, C20:5n-3, C22:6n-3 and Σ MUFA had a main band in the area of 835 – 867 cm^{-1} . Spectral bands in all three of these regions arise from skeletal stretching vibrations such as –C–C– and –C–O–. Differences in chain length and the number of C–C single bonds (as opposed to C=C double bonds) might give small differences in these bands, and it is thus reasonable to find main bands in this area for all calibration models.

Only the calibration model for UI showed a main peak in the area of 1438 cm^{-1} . Such a band arises from the scissoring vibration of CH_2 . Considering that the number of CH_2 groups present in PUFAs < MUFAs < SFAs (if the number of carbon atoms in the FAs is the same), an absorption in this area for the UI is reasonable.

Three of the calibration models also had a main absorption band in the area of 1103 – 1117 cm^{-1} , these were the models for C16:0, C18:1n-9 and C18:2n-6. Raman shift values in this area could not be assigned to any FA stretching vibrations.

4.3 Part III – Method validation

4.3.1 Validation of calculated FA profiles in calibration samples

The last objective concerned the validation of the established calibration models. Prior to this, the calculated FA profiles of the calibration set were validated. Analysis of four samples from the calibration set with GC-MS showed that the calculated FA profiles were acceptable.

Appendix H presents the calculated vs reference values of the eight main FAs in the calibration samples with numbers 32, 54, 58 and 77. The deviations of the calculated values from the reference values are also presented. Generally, the calculated FA profiles were good, however the calculated values for C14:0 and C20:5n-3 showed larger deviations from the reference values than the other FAs. One reason for the observed deviations was that the standard deviations for the FAs in the reference oils were not considered when the FA profiles

of the calibration set were calculated. Nevertheless, this can only explain a small part of the observed deviations.

4.3.2 Validation of calibration models for FTIR spectroscopy

PCA of the preprocessed data from the 80 samples of the calibration set, the 10 samples of norwegian cod liver oil and the four validation samples resulted in the score plot that is provided in figure 28. All points for the validation oils and norwegian cod liver samples (red and green dots) could be found within the area spanned by the calibration samples (blue dots). Thus, the spectral composition of the validation samples and the samples of norwegian cod liver oil did not differ from the calibration set. This is good, as all the predictions are based solely on the spectral signatures of the validation samples.

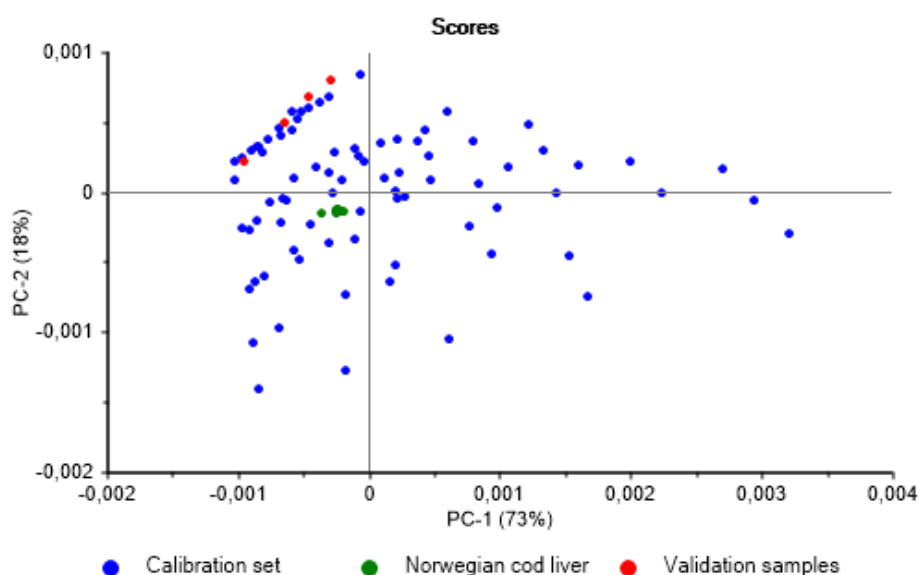


Figure 28 – Score plot for PCA of the preprocessed samples of the calibration set, validation set and samples of norwegian cod liver oil. The score plot consists of PC-1 and PC-2.

Table 16 provides the results for the predicted FA content and the equivalent reference values for the validation samples in addition to samples of norwegian cod liver oil. Reference values for the Norwegian cod liver oil were taken from matvaretabellen.no (matportalen.no, 2019). Deviations of the predicted values from the reference values are presented in percentage.

Table 16 – Predicted and reference values for the 12 parameters in the validation samples and the sample of norwegian cod liver oil. The predicted values were found by using the calibration models that were established for FTIR spectroscopy, while the reference values were determined using GC-MS. The deviation in percent expresses the difference in predicted value compared to the reference value.

Type of oil		C14:0	C16:0	C18:0	C18:1n-9	C18:2n-6	C18:3n-3	C20:5n-3	C22:6n-3	Σ SFA	Σ MUFA	Σ PUFA	UI
Grapeseed oil	Predicted	-2.7	5.7	3.9	23.1	64.9	1.1	2.9	3.2	10.1	20.0	68.12	1.66
	Reference	0.0	7.3	4.3	20.9	65.2	0.3	0.0	0.0	12.0	22.0	65.52	1.54
	Deviation [%]	-	-21.7	-9.4	10.5	-0.6	304.6	-	-	-15.8	-9.2	4.0	7.9
Frying oil	Predicted	-0.7	6.4	2.7	76.2	11.2	1.3	1.9	0.0	12.2	76.3	19.0	1.0
	Reference	0.0	4.0	2.9	80.5	10.0	0.1	0.0	0.0	8.2	81.7	10.1	1.0
	Deviation [%]	-	59.6	-6.9	-5.3	13.0	782.0	-	-	48.8	-6.6	87.9	2.1
Walnut oil	Predicted	-2.7	6.1	4.3	17.8	60.6	12.9	2.9	2.5	9.0	13.8	75.3	1.9
	Reference	0.0	7.4	2.9	15.4	60.0	12.5	0.0	0.0	10.5	16.5	72.4	1.8
	Deviation [%]	-	-17.2	46.2	15.7	1.1	3.4	-	-	-14.1	-16.4	4.0	6.4
Cooking oil	Predicted	-1.5	5.2	3.4	44.9	38.1	4.8	2.7	1.4	10.9	44.1	47.4	1.5
	Reference	0.1	5.7	2.8	45.3	38.2	3.5	0.0	0.0	9.5	48.4	41.7	1.4
	Deviation [%]	-	-8.0	19.4	-0.9	-0.3	35.7	-	-	14.2	-8.8	13.5	6.6
Norwegian	Predicted	5.2	10.5	1.3	24.7	3.4	0.3	9.0	8.1	20.8	49.1	26.9	1.9
Cod liver oil	Reference	4.0	10.4	2.5	20.8	1.7	1.0	8.7	13.0	-	-	-	-

The predicted values for 14:0 were negative for all samples except for the norwegian cod liver oil. Such a prediction makes no sense, and future models should include a factor that excludes predictions below zero. The models for 16:0 and 18:0 are promising, with deviations ranging from $\pm 0.7 - 59.0\%$ and $\pm 6.9 - 46.6\%$, respectively. Predictions for C18:1n-9 were good, with predicted values differing $\pm 0.9 - 18.3\%$ of the reference values. C18:2n-3 showed very good predictions for three out of four oils, with deviations of $\pm 0.3 - 13.0\%$. For the sample of norwegian cod liver the deviation was 93.8%. The model for C18:3n-3 showed the largest deviations, up to 782% for frying oil. Predicted values for C20:5n-3 and C22:6n-3 resulted in positive predictions for the four validation oils, although none of them contained any of these two FAs. In norwegian cod liver oil C20:5n-3 content seemed to be predicted quite accurately, while C22:6n-3 content was predicted less accurately. Content of Σ SFAs was predicted with acceptable deviations for all samples, ranging from $\pm 14.1 - 48.8\%$. The models for the remaining parameters, Σ MUFA, Σ PUFA and UI were good, with prediction deviations ranging from $\pm 4.0 - 16.4\%$, except for frying oil prediction where Σ PUFA was predicted to be 87.9% higher than the actual content. For norwegian cod liver oil the predictions for the last four parameters were not evaluated, since the FA composition of these oils were only obtained online from Matvaretabellen.no.

Out of all the calibration models for FTIR spectroscopy, UI had the smallest differences between predicted and reference values for all five samples. UI is a parameter that considers the FA composition of the complete samples, which means it is indirectly based on all models. Thus, good predictions for UI as well as Σ MUFA and Σ PUFA were as expected. The calibration models for the single FAs did overall look promising. The prediction accuracy for the FAs C18:1n-9 and C18:2n-6 was found to be good, while the other FAs were predicted with a lower accuracy. The model for C18:3n-3 gave the least accurate predictions. The overall trend in the predictions does indicate that FTIR and the design approach used in the present thesis may be a suitable method for prediction of individual FAs.

4.3.3 Validation of calibration models for Raman spectroscopy

The score plot for PCA of the preprocessed spectral data for the calibration samples, the validation samples and the norwegian cod liver oil is presented in figure 29. The reference values for cod liver oil were taken from matvaretabellen.no, since no reference analyses were done for these samples. Here one can see that the samples of norwegian cod liver oil (green dots) are placed far away from the calibration samples (blue dots). The spectral information in these samples is thus different from the calibration set and will not be included for the

prediction. Most likely, this is related to the sample background and noise levels, which were difficult to completely remove with the preprocessing techniques used. The validation samples (red dots) are within the area spanned by the calibration set, meaning that the calibration models can be applied for these samples.

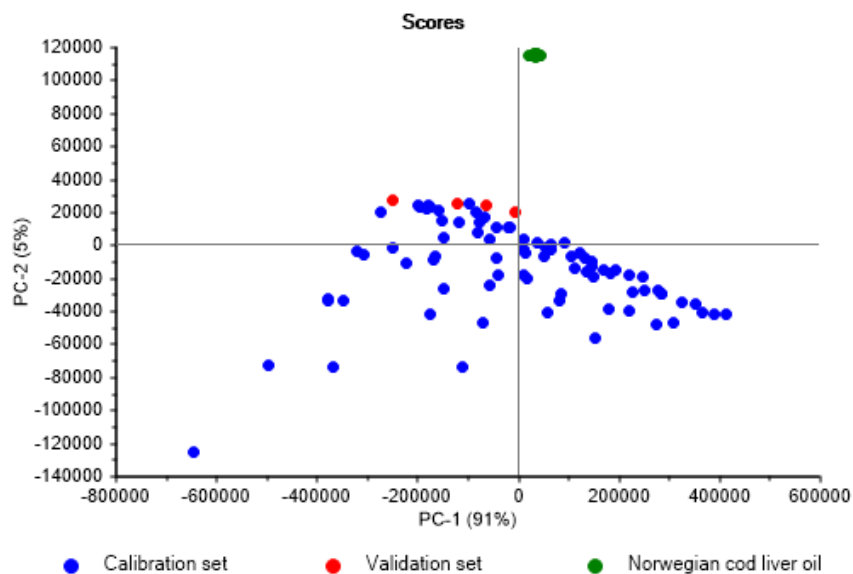


Figure 29 - Score plot for PCA of the preprocessed data from the samples of the calibration set, validation set and samples of norwegian cod liver oil. The score plot consists of PC-1 and PC-2.

The predicted and reference values for the FAs in the validation oils are presented in table 17. The deviations of the predicted values from the reference values are presented in percentage.

Table 17 - Predicted and reference values for the 12 parameters in the validation samples. The predicted values were found by using the calibration models that were established for Raman spectroscopy, while the reference values were determined using GC-MS. The deviation in percent expresses the difference in predicted value compared to the reference value.

Sample nr.		C14:0	C16:0	C18:0	C18:1n-9	C18:2n-6	C18:3n-3	C20:5n-3	C22:6n-3	Σ SFA	Σ MUFA	Σ PUFA	UI
Grapeseed oil	Predicted	-3.6	9.2	5.1	25.7	66.1	1.2	1.8	1.3	11.5	21.2	62.1	1.7
	Reference	0.0	7.3	4.3	20.9	65.2	0.3	0.0	0.0	12.0	22.0	65.5	1.5
	Deviation [%]	-	25.8	17.5	23.2	1.4	352.8	-	-	-4.0	-3.5	-5.2	8.2
Frying oil	Predicted	0.2	2.5	0.6	78.6	11.8	-0.3	1.6	1.6	9.2	78.7	16.1	1.0
	Reference	0.0	4.0	2.9	80.5	10.0	0.1	0.0	0.0	8.2	81.7	10.1	1.0
	Deviation [%]	296.1	-39.2	-78.4	-2.3	18.3	-	-	-	12.2	-3.7	59.9	-1.2
Walnut oil	Predicted	-4.0	5.5	4.8	22.3	58.9	13.5	3.8	-0.4	7.1	18.3	69.7	1.9
	Reference	0.0	7.4	2.9	15.4	60.0	12.5	0.0	0.0	10.5	16.5	72.4	1.8
	Deviation [%]	-	-25.5	64.6	44.9	-1.7	7.8	-	-	-32.1	11.2	-3.9	9.3
Cooking oil	Predicted	-2.0	5.9	3.8	48.3	40.7	4.0	2.2	-0.7	9.3	46.9	42.9	1.4
	Reference	0.1	5.7	2.8	45.3	38.2	3.5	0.0	0.0	9.5	48.4	41.8	1.4
	Deviation [%]	-	3.8	32.6	6.6	6.3	12.6	-	-	-2.2	-3.1	2.6	1.3

As can be seen in table 17, some of the predicted FA values were negative. These were predicted values mainly for C14:0, but C18:3n-3 and C22:6n-3 did also have one negative prediction value. The model for C16:0 showed variations between predicted and reference values of ± 3.8 -39.2 %, and for prediction of 18:0 the deviations were in the range of ± 17.5 – 78,4 %. Content of C18:1n-3 was predicted to be ± 2.3 – 44.9 % smaller/larger than the reference values, and prediction of C18:2n-6 resulted in good predictions with deviations in the range of ± 1.4 – 18.3 %. Predicted content of C18:3n-3 in grapeseed oil was 352.8 % larger than the reference value, while the two remaining positive prediction values were 7.8 – 12.6 % larger than the respective reference values. All predictions for C20:5n-3 were positive, although this FA was not present in any samples. For C22:6n-3 two of the predicted values were negative, and two were positive, but this FA was also not present in any of the validation samples. The predicted values for Σ SFA and Σ MUFA had deviations from the reference values in the ranges of ± 2.2 – 32.1 % and ± 3.1 – 11.2 %, respectively. For Σ PUFA and UI the predicted values showed differences ranging from ± 2.6 – 59.9 % and ± 1.2 – 9.3 % of predicted vs reference values.

Overall the model for UI gave the most accurate predictions, closely followed by the model for prediction of Σ MUFA. The models for Σ SFA and Σ PUFA gave somewhat less accurate predictions. Good predictive abilities for the models of the FA parameters were expected, as these parameters are indirectly based on the models for the individual FAs. The model for C18:2n-6 gave the most accurate predictions of the models for single FAs, while the models for C16:0 and C18:1n-9 also gave good predictions. The predictive abilities of the models for C18:0 and C18:3n-3 were less accurate, and the predictive abilities for C20:5n-3 and C22:6n-3 could not be evaluated as none of the validation samples contained any of these n-3 FAs.

4.4 General discussion and future work

The first objective of this study was to classify marine oils using vibrational spectroscopy. The results showed that FTIR was a suitable method for separating all seven types of oils from each other, while the spectral data obtained with Raman spectroscopy could not be used due to fluorescence background. PCA was used to perform classification, and this is an unsupervised method. This means that there is no *a priori* information about class membership included in the model and thus PCA will give the least optimistic results, compared to supervised classification methods. Supervised classification methods generally

are better suited for classifying samples, and in future work such methods should be applied. Examples of supervised classification methods are partial least squares discriminant analysis (PLS-DA) and soft independent modelling of class analogies (SIMCA). For future classification of oils based on FTIR spectroscopy, the sample set should ideally also be larger than the sample set that was used here.

Raman spectroscopy was shown to be an unsuitable method for use in classification. There was a lot of background information in the spectra which might have influenced the classification despite preprocessing of the data. The background noise will however not add any information regarding chemical differences in the samples, but rather make it harder to achieve robust classification. Fluorescence background was also a recurring problem.

For the classification performed with FTIR spectroscopy, the spectral area of $4000 - 2700 \text{ cm}^{-1}$ and $1800 - 500 \text{ cm}^{-1}$ was used. These two areas include all spectral information regarding FA composition, TG structure and phospholipid structure that can be obtained using FTIR. When looking for class membership in oil samples, the type of lipids as well as FA composition can give relevant information, which is why a wide range of spectral information was included.

The second objective was to make calibration models for the prediction of FA composition based on analysis of a calibration set. 18 reference oils were analysed with GC-MS, and their FA composition was determined. Originally the idea was to quantify the FAs in the reference oils by using an IS and RRF-values in addition to the information obtained from the GC-MS analyses. However, due to an unidentified problem or miscalculation the total amount of FAs that were quantified in each oil was much lower than expected. Fats and oils generally contain about 90 % FAs, the remaining 10 % being the glycerol backbone (Lichtenstein, 2013). The amounts of FAs that were quantified in the reference oils were in the range of 40 – 80 g/100 g of oil. Thus, it was decided to use the FA profiles based on the peak areas in the chromatograms in percentage instead. A quick comparison with previously determined FA profiles for these oils (Matvaretabellen.no) showed that the obtained results seemed realistic. These FA profiles were then used to make 80 calibration samples.

Calibration models were established based on analysis of a set of 80 calibration samples. The samples were created based on reference analysis of 18 oils and contained one to three different oils in various ratios. The calibration set showed little correlation between the main FAs in the samples; the highest correlation was found to be -0.66. When working with

biological samples as basis for sample mixtures it is impossible to avoid correlation altogether. The created samples were also shown to span out the area of varying FA composition, with differing FA chain lengths and varying degrees of unsaturation.

For the calibration models based on FTIR, the spectral ranges of 3100 – 2750 cm^{-1} and 1700 – 500 cm^{-1} were the areas included. Thus, a narrower range of the spectral information was used for PLSR than for PCA. The reason for this was that the purpose of the calibration models was to predict single FAs and some FA features, so the information $>3100 \text{ cm}^{-1}$ and 2750 – 1800 cm^{-1} did not contain any relevant information. Spectral information of the carbonyl group was also excluded when making the calibration models. The reason for this was that the carbonyl-signal was quite strong in all spectra, and it influenced in the calibration models when the area of 1800 – 1700 cm^{-1} was included for PLSR analysis. Since the carbonyl-band might be indirectly correlated to the oils in the calibration set, it was decided to exclude the area of 1800 – 1700 cm^{-1} when establishing the calibration models.

The calibration models based on FTIR spectroscopy were found to be slightly better than the models based on Raman spectroscopy. R^2 values for FTIR models were in the range of 0.96 – 0.99, only one model had $R^2 = 0.93$. For Raman spectroscopy the range included 0.94 – 0.98. RMSECV values were overall lower for FTIR models than for Raman. For both FTIR and Raman the highest number of factors were found for the models of C16:0 and C18:0, they were nine and seven for FTIR and eight and 14 for Raman. It is generally accepted that the signal-to-noise ratio provided by FTIR is higher than for Raman for samples that are easily analysed using FTIR spectroscopy (for instance edible oils). It is thus to be expected that the FTIR models are slightly better than the models obtained for Raman (Larkin, 2011).

Evaluation of the established calibration models is important. The main steps are interpretation of the regression coefficients and their charge, as was shown in section 4.2.3 and 4.2.4. Such interpretation might indicate whether the models are built on relevant chemical information in the data or not. Nevertheless, there are also limitations to such interpretations. Firstly, one should always keep in mind that the observed regression coefficients might not be caused by actual differences in the data but are caused by the modelling. Thus, it is important not to read too much into the regression coefficients and their corresponding intensities. Secondly, rising complexity of the models, observable as the number of optimal factors, will make interpretation of the regression coefficients more difficult.

The third objective of the thesis dealt with validation of the established calibration models. Overall the deviations between predicted and reference values for FTIR spectroscopy were in the range of $\pm 0.3 - 782.0$ % and for Raman spectroscopy they were in the range of $\pm 1.2 - 367.8$ %. Many of the models showed very good predictions, with deviation of < 10 %. Few predictions had deviations > 100 %, but these were all for FAs that were present in small amounts in the respective oils. Some of the predicted values might seem very inaccurate based on the percentwise deviations from the reference values, but the values obtained with the calibration models clearly reflect the actual FA profiles. Through the eyes of a chromatographer the predictions might not seem very accurate, but from the view of a spectroscopist the results are very good and promising. A specific challenge with Raman spectroscopy is the fluctuating baseline features caused by e. g. fluorescence, which is clearly visible from the raw Raman spectra. When existing mathematical correction methods fail in removing these features completely, this will also affect prediction accuracies.

Regarding future work, the classification of marine oils should be repeated with a larger sample set for more representative results, and a supervised classification method such as SIMCA or PLS-DA should be used. It would also be interesting to have reference values for the FA profiles and different lipid fractions in the marine oil samples, so that the classification results can be better understood. In relation to the calibration models, the FAs in the reference oils should be quantified so that the FA profiles can be based on masses. A larger calibration set would also make the models more accurate and robust. Ideally the FA profiles for all samples of the calibration would also be determined using GC-MS. The size of the validation set should also be increased to further test the accuracy and robustness of the established calibration models. Anyhow, an intriguing aspect with the presented calibration design is to explore the use of this calibration to predict individual FAs in new samples, from oils to fat-containing tissues and microorganisms. If this works, this low-cost design approach could find many new applications in the future.

5. Conclusion

The objective of this work was to study and develop a robust method for the determination of single FAs in edible oils using vibrational spectroscopy, by creating a sample design with low correlation between the FAs. In the first sub-objective it was shown that FTIR is a suitable method for the classification of oils, while Raman spectroscopy could not be applied for this purpose due to a strong fluorescence background in the samples. Next, the calibration set that was made based on the sample design was shown to have low correlations between the different FAs. The calibration models that were established after analysis of the calibration set with FTIR and Raman spectroscopy seemed to be good. All models had R^2 -values ≥ 0.93 . The models for FA features such as Σ MUFA and UI showed good results, as expected, but the models for single FAs did also look very promising. Overall FTIR spectroscopy was better suited for the prediction of FAs than Raman spectroscopy, in part due to the background noise that was present in Raman spectra. Validation with a small set of independent samples showed that good predictions were achieved for the calibration models of both FTIR and Raman spectroscopy.

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Appendix A – Fatty acids

Summary of the IUPAC names, trivial names and shorthand notation for all the FA relevant to this study. The IUPAC nomenclature is based on the entries in the online database PubChem (U.S. National Library of Medicine).

IUPAC Nomenclature	Trivial Nomenclature	Shorthand Notation
Hexanoic acid	Caproic acid	C6:0
Octanoic acid	Caprylic acid	C8:0
Decanoic acid	Capric acid	C10:0
Undecanoic acid		C11:0
Dodecanoic acid	Lauric acid	C12:0
Tridecanoic acid		C13:0
Tetradecanoic acid	Myristic acid	C14:0
(Z)-tetradec-9-enoic acid	Myristoleic acid	C14:1n-5
Pentadecanoic acid		C15:0
Hexadecanoic acid	Palmitic acid	C16:0
(Z)-hexadec-9-enoic acid	Palmitoleic acid	C16:1n-7
Heptadecanoic acid	Margaric acid	C17:0
Octadecanoic acid	Stearic acid	C18:0
(Z)-octadec-9-enoic acid	Oleic acid	C18:1n-9
Nonadecanoic acid		C19:0
(9Z,12Z)-octadeca-9,12-dienoic acid	Linoleic acid	C18:2n-6
Eicosanoic acid	Arachidic acid	C20:0
(9Z,12Z,15Z)-octadeca-9,12,15-trienoic acid	Linolenic acid	C18:3n-3
(Z)-icos-11-enoic acid	Gondoic acid	C20:1n-9
Heneicosanoic acid		C21:0
(11Z,14Z)-icosa-11,14-dienoic acid		C20:2n-6
(8Z,11Z,14Z)-icosa-8,11,14-trienoic acid	Dihomo-gamma-linolenic acid	C20:3n-6
Docosanoic acid	Behenic acid	C22:0
(11Z,14Z,17Z)-icosa-11,14,17-trienoic acid		C20:3n-3
(5Z,8Z,11Z,14Z)-icosa-5,8,11,14-tetraenoic acid	Arachidonic acid	C20:4n-6
(Z)-docos-13-enoic acid	Erucic acid	C22:1n-9
Tricosanoic acid		C23:0
(5Z,8Z,11Z,14Z,17Z)-icosa-5,8,11,14,17-pentaenoic acid	EPA	C20:5n-3
(13Z,16Z)-docosa-13,16-dienoic acid		C22:2n-6
Tetracosanoic acid	Lignoceric acid	C24:0
(Z)-tetracos-15-enoic acid	Nervonic acid	C24:1n-9
(4Z,7Z,10Z,13Z,16Z,19Z)-docosa-4,7,10,13,16,19-hexaenoic acid	DHA	C22:6n-3

Appendix B – Internal standard

Exact amounts of trinonadecanoin and chloroform used to make stock solutions of the internal standard.

	Trinonadecanoin	Chloroform	Concentration	Mole IS (TG)	Mole IS (FA)
IS 1	80.7 mg	8.0 mL	10.1 mg/mL	$1.08 \cdot 10^{-6}$	$3.24 \cdot 10^{-6}$
IS 2	81.3 mg	8.0 mL	10.2 mg/mL	$1.09 \cdot 10^{-6}$	$3.26 \cdot 10^{-6}$

Appendix C – Relative response factors

Relative response factors and molecular weight for all fatty acids in this study, including the unidentified isomers (u.i.).

Fatty acid	Molecular weight [g/mol]	RRF
C6:0	116.16	0.62
C8:0	144.21	0.88
C10:0	172.26	1.00
C11:0	186.29	0.94
C12:0	200.32	1.08
C13:0	214.34	1.01
C14:0	228.37	1.11
C14:1n-5	226.35	0.97
C15:0	242.20	1.01
C16:0	256.42	1.10
C16:1n-7	254.41	0.86
C17:0	270.50	0.92
C18:0	284.50	1.00
C18:1n-9	282.50	1.04
C19:0	298.50	1.00
C18:2n-6	280.40	1.15
C20:0	312.50	1.15
C18:3n-3	278.40	1.15
C20:1n-9	310.50	1.00
C21:0	326.60	0.97
C20:2n-6	308.50	1.02
C22:0	340.60	1.04
C20:3n-6	306.50	0.96
C20:4n-6	304.50	1.26
C20:3n-3	306.50	1.15
C22:1n-9	338.60	1.03
C23:0	354.60	1.08
C20:5n-3	302.50	1.32
C22:2n-6	336.60	1.41
C24:0	368.60	1.38
C24:1n-9	366.60	1.24
C22:6n-3	328.50	1.24
C16:1 u.i.	254.41	0.86
C17:1 u.i.	268.40	0.88
C18:1 u.i.	282.50	1.04
C18:2 u.i.	280.40	1.15
C18:3 u.i.	278.40	1.15
C18:4 u.i.	276.40	1.00*
C20:1 u.i.	310.50	1.00
C20:2 u.i.	308.50	1.02
C20:4 u.i.	304.50	1.26

C21:5 u.i.	316.50	1.00*
C22:1 u.i.	338.60	1.03
C22:5 u.i.	330.50	1.00*

* = RRF value set to one for the unidentified FAs with no standard of equivalent isomer.

Appendix D – Calibration set

Samples of the calibration set with composition and mixing ratios of reference oils.

Sample nr.	Contents
1	100 % Soybean
2	100 % Sunflower
3	100 % Herring
4	100 % Sesame
5	100 % Rice bran
6	100 % Olive
7	100 % Flaxseed
8	100 % Coconut
9	100 % 0370 (EPA/DHA)
10	75 % Sesame + 25 % 0370 (EPA/DHA)
11	75 % Rice bran + 25 % 0370 (EPA/DHA)
12	75 % Peanut + 25 % Coconut
13	75 % Olive + 25 % 0370 (EPA/DHA)
14	75 % Flaxseed + 25 % Rice bran
15	75 % Flaxseed + 25 % Coconut
16	75 % Flaxseed + 25 % 0370 (EPA/DHA)
17	75 % Coconut + 25 % 0370 (EPA/DHA)
18	50 % Soybean + 25 % 0370 (EPA/DHA) + 25 % Camelina
19	50 % Sunflower + 50 % 4030 (EPA/DHA)
20	50 % Sunflower + 25 % Coconut + 25 % 4030 (EPA/DHA)
21	50 % Sunflower + 25 % Frying oil + 25 % 0370 (EPA/DHA)
22	50 % Herring + 50 % 3040 (EPA/DHA)
23	50 % Herring + 25 % 0370 (EPA/DHA) + 25 % Camelina
24	50 % Sesame + 50 % Rice bran
25	50 % Sesame + 50 % Coconut
26	50 % Sesame + 50 % 0370 (EPA/DHA)
27	50 % Sesame + 25 % Olive + 25 % Flaxseed
28	50 % Sesame + 25 % Flaxseed + 25 % Coconut
29	50 % Rice bran + 50 % Coconut
30	50 % Rice bran + 50 % Camelina
31	50 % Rapeseed +25 % Peanut + 25 % Vita hjertgó
32	50 % Rapeseed +25 % Flaxseed + 25 % Coconut
33	50 % Rapeseed +25 % Coconut + 25 % 0370 (EPA/DHA)
34	50 % Peanut +25 % Sesame + 25 % Sunflower
35	50 % Olive +50 % Herring
36	50 % Olive +50 % Flaxseed
37	50 % Olive +50 % 4030 (EPA/DHA)
38	50 % Olive +25 % Flaxseed + 25 % Rice bran
39	50 % Olive +25 % Flaxseed + 25 % 4030 (EPA/DHA)
40	50 % Olive +25 % Coconut + 25 % 4030 (EPA/DHA)
41	50 % Flaxseed + 50 % Herring

42	50 % Flaxseed + 50 % Coconut
43	50 % Flaxseed + 50 % 0370 (EPA/DHA)
44	50 % Flaxseed + 25 % Coconut + 25 % 4030 (EPA/DHA)
45	50 % Flaxseed + 25 % 4030 (EPA/DHA) + 25 % 3040 (EPA/DHA)
46	50 % Coconut + 50 % 0370 (EPA/DHA)
47	50 % 0370 (EPA/DHA) + 50 % 4030 (EPA/DHA)
48	100 % 4030 (EPA/DHA)
49	33 % Soybean + 33 % Sunflower + 33 % Coconut
50	33 % Soybean + 33 % Coconut + 33 % 0370 (EPA/DHA)
51	33 % Herring + 33 % Coconut + 33 % Camelina
52	33 % Herring + 33 % Coconut + 33 % 4030 (EPA/DHA)
53	33 % Sesame + 33 % Flaxseed + 33 % 4030 (EPA/DHA)
54	33 % Rice bran + 33 % Herring + 33 % 4030 (EPA/DHA)
55	33 % Rice bran + 33 % 0370 (EPA/DHA) + 33 % 3040 (EPA/DHA)
56	33 % Rapeseed + 33 % Peanut + 33 % 0370 (EPA/DHA)
57	33 % Rapeseed + 33 % 3040 (EPA/DHA) + 33 % Camelina
58	33 % Flaxseed + 33 % Rice bran + 33 % 0370 (EPA/DHA)
59	33 % Frying oil + 33 % Rice bran + 33 % 0370 (EPA/DHA)
60	25 % Sunflower + 50 % Rice bran + 25 % Coconut
61	25 % Sunflower + 50 % 0370 (EPA/DHA) + 25 % Camelina
62	25 % Sesame + 75 % 4030 (EPA/DHA)
63	25 % Sesame + 50 % Olive + 25 % Coconut
64	25 % Sesame + 50 % Coconut + 25 % 4030 (EPA/DHA)
65	25 % Rice bran + 75 % Coconut
66	25 % Rice bran + 50 % Herring + 25 % Camelina
67	25 % Rapeseed + 75 % Camelina
68	25 % Rapeseed + 25 % Soybean + 50 % Møllers tran
69	25 % Rapeseed + 25 % Peanut + 50 % Rice bran
70	25 % Rapeseed + 25 % Peanut + 50 % Coconut
71	25 % Peanut + 50 % Frying oil + 25 % 4030 (EPA/DHA)
72	25 % Flaxseed + 75 % Coconut
73	25 % Flaxseed + 75 % Frying oil
74	25 % Flaxseed + 75 % 0370 (EPA/DHA)
75	25 % Flaxseed + 50 % Soybean + 25 % Camelina
76	25 % Flaxseed + 25 % Coconut + 50 % 4030 (EPA/DHA)
77	25 % Flaxseed + 25 % Coconut + 50 % 0370 (EPA/DHA)
78	25 % Flaxseed + 25 % 0370 (EPA/DHA) + 50 % 4030 (EPA/DHA)
79	25 % Coconut + 75 % 0370 (EPA/DHA)
80	25 % Coconut + 25 % 4030 (EPA/DHA) + 50 % 3040 (EPA/DHA)

Appendix E – Fatty acid profiles of the reference oils

Fatty acid profiles in % of total area in the chromatogram, with standard deviations based on six replicate measurements. Numbers marked in red are only based on three replicates. n.d. = not detected. For numbers in red n=3, for all remaining values n=6.

Fatty acid	Rapeseed oil	Peanut oil	Sesame oil	Olive oil	Linseed oil	Soybean oil	Sunflower oil	Vita hjertego	Frying oil	Møllers tran	Rice bran oil	Salmon oil	Herring oil	Coconut oil	0370 (EPA/DHA)	4030 (EPA/DHA)	3040 (EPA/DHA)	Camelina oil
C6:0	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.47 ±0.05	n.d.	n.d.	n.d.	n.d.
C8:0	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	6.77 ±0.37	0.07 ±0.05	n.d.	n.d.	n.d.
C10:0	0.01 ±0.0	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.01 ±0.0	6.43 ±0.13	0.05 ±0.05	n.d.	n.d.	n.d.
C11:0	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.03 ±0.0	n.d.	n.d.	n.d.	n.d.
C12:0	0.01 ±0.01	n.d.	0.01 ±0.0	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.02 ±0.01	0.01 ±0.0	0.03 ±0.01	0.12 ±0.02	35.82 ±2.91	0.50 ±0.46	0.04 ±0.05	0.05 ±0.07	0.01 ±0.01
C13:0	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.01 ±0.0	n.d.	0.03 ±0.03	0.04 ±0.0	0.05 ±0.01	n.d.	n.d.	n.d.	n.d.
C14:0	0.06 ±0.03	0.02 ±0.00	0.02 ±0.01	0.01 ±0.00	0.04 ±0.00	0.07 ±0.01	0.06 ±0.00	0.04 ±0.00	0.05 ±0.00	3.77 ±0.09	0.41 ±0.01	2.19 ±0.06	8.91 ±0.19	25.71 ±0.93	0.36 ±0.18	0.37 ±0.03	0.16 ±0.02	0.04 ±0.01
C14:1n-5	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.12 ±0.01	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.
C15:0	0.02 ±0.01	0.01 ±0.00	n.d.	n.d.	0.02 ±0.01	0.01 ±0.00	0.01 ±0.00	0.01 ±0.00	0.01 ±0.00	0.31 ±0.01	0.02 ±0.01	0.14 ±0.04	0.45 ±0.01	n.d.	n.d.	n.d.	n.d.	0.01 ±0.00
C16:0	4.97 ±0.14	6.90 ±0.11	9.72 ±0.16	12.51 ±0.11	6.73 ±0.07	11.17 ±0.11	6.61 ±0.04	6.24 ±0.09	5.70 ±0.06	10.21 ±0.30	20.45 ±0.35	9.96 ±0.34	14.25 ±0.35	11.62 ±0.82	0.63 ±0.08	0.51 ±0.06	0.38 ±0.02	6.12 ±0.13
C16:1n-7	0.20 ±0.02	0.06 ±0.01	0.13 ±0.01	0.93 ±0.05	0.06 ±0.02	0.06 ±0.01	0.08 ±0.01	0.21 ±0.01	0.11 ±0.01	9.89 ±0.18	0.16 ±0.01	2.30 ±0.20	4.98 ±0.06	n.d.	0.20 ±0.03	0.24 ±0.03	0.13 ±0.01	n.d.
C17:0	0.05 ±0.01	0.07 ±0.01	0.03 ±0.01	0.07 ±0.01	0.05 ±0.01	0.08 ±0.02	0.03 ±0.01	0.04 ±0.01	0.04 ±0.01	n.d.	0.04 ±0.01	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.04 ±0.0
C18:0	1.73 ±0.08	2.12 ±0.13	6.10 ±0.31	3.30 ±0.13	4.32 ±0.14	4.85 ±0.14	3.46 ±0.14	2.31 ±0.07	2.48 ±0.08	2.14 ±0.06	2.04 ±0.07	2.68 ±0.09	1.09 ±0.04	4.96 ±0.67	0.29 ±0.02	2.03 ±0.23	1.30 ±0.15	2.93 ±0.09
C18:1n-9	61.64 ±1.00	67.59 ±1.48	41.09 ±0.16	71.29 ±0.61	20.50 ±0.31	23.09 ±0.42	31.99 ±0.66	56.39 ±0.79	45.47 ±0.15	15.20 ±0.15	40.72 ±0.13	42.58 ±0.41	6.99 ±0.11	7.23 ±0.77	0.55 ±0.06	2.60 ±0.34	1.70 ±0.18	16.79 ±0.11

C18:2n-6	19.06 ±0.33	15.36 ±0.35	40.97 ±0.55	8.33 ±0.19	15.31 ±0.39	52.02 ±1.26	56.04 ±0.91	25.75 ±0.44	38.23 ±0.35	2.39 ±0.21	32.51 ±0.16	13.78 ±0.19	1.52 ±0.09	1.15 ±0.16	0.16 ±0.02	n.d.	0.24 ±0.02	19.32 ±0.33
C20:0	0.52 ±0.05	0.92 ±0.09	0.58 ±0.06	0.37 ±0.03	n.d.	0.38 ±0.02	0.21 ±0.02	0.37 ±0.02	0.34 ±0.03	n.d.	0.80 ±0.05	0.29 ±0.04	0.16 ±0.01	0.08 ±0.01	0.34 ±0.06	0.81 ±0.11	0.55 ±0.08	0.89 ±0.01
C18:3n-3	6.72 ±0.07	0.47 ±0.05	0.20 ±0.02	0.53 ±0.06	51.92 ±0.92	5.93 ±0.20	0.12 ±0.03	5.24 ±0.13	4.52 ±0.13	0.72 0.05	1.05 ±0.07	4.91 ±0.08	1.12 ±0.07	n.d.	n.d.	0.19 ±0.04	0.09 ±0.01	37.97 ±0.48
C20:1n-9	1.12 ±0.09	1.90 ±0.13	0.12 ±0.01	0.18 ±0.02	0.09 ±0.01	0.14 ±0.01	0.11 ±0.01	0.66 ±0.04	0.57 ±0.05	13.13 ±0.07	0.43 ±0.02	4.47 ±0.05	12.15 ±0.15	n.d.	0.73 ±0.13	2.89 ±0.41	1.77 ±0.22	10.79 ±0.14
C21:0	n.d.	n.d.	n.d.	n.d.	n.d.	0.03 ±0.02	n.d.	n.d.	0.02 ±0.01	n.d.	0.04 ±0.01	n.d.	0.05 ±0.01	n.d.	0.14 ±0.03	0.10 ±0.02	0.08 ±0.02	n.d.
C20:2n-6	0.04 ±0.00	n.d.	n.d.	n.d.	n.d.	0.02 ±0.00	n.d.	n.d.	n.d.	0.27 ±0.02	n.d.	1.05 ±0.05	0.18 ±0.01	n.d.	0.14 ±0.04	0.48 ±0.09	0.28 ±0.07	1.66 ±0.11
C22:0	0.21 ±0.03	2.13 ±0.18	0.07 ±0.01	0.05 ±0.01	0.05 ±0.01	0.27 ±0.02	0.55 ±0.04	0.26 ±0.02	0.37 ±0.03	n.d.	0.18 ±0.02	0.09 ±0.01	n.d.	n.d.	0.41 ±0.01	0.19 ±0.01	0.16 ±0.02	0.13 ±0.02
C20:3n-6	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.04 ±0.01	n.d.	0.23 ±0.02	0.05 ±0.00	n.d.	0.11 ±0.01	0.36 ±0.06	0.34 ±0.06	n.d.
C20:4n-6	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.24 ±0.04	n.d.	0.10 ±0.02	0.31 ±0.03	n.d.	0.72 ±0.33	2.30 ±0.47	2.06 ±0.40	n.d.
C20:3n-3	n.d.	n.d.	n.d.	n.d.	0.02 ±0.01	n.d.	n.d.	n.d.	n.d.	0.07 ±0.01	n.d.	0.37 ±0.03	0.12 ±0.03	n.d.	n.d.	0.23 ±0.02	0.13 ±0.04	1.16 ±0.10
C22:1n-11	0.11 ±0.01	0.14 ±0.01	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.02 ±0.01	6.32 ±0.16	n.d.	0.44 ±0.08	21.32 ±0.47	n.d.	1.09 ±0.56	0.78 ±0.03	0.82 ±0.02	1.04 ±0.10
C23:0	n.d.	0.01 ±0.00	n.d.	n.d.	n.d.	0.01 ±0.00	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.
C20:5n-3	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	7.74 ±0.08	n.d.	1.99 ±0.34	7.00 ±0.08	n.d.	12.89 ±1.50	44.08 ±0.94	40.30 ±0.27	n.d.
C22:2n-6	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.06 ±0.01	n.d.	n.d.	n.d.	n.d.	n.d.	0.04 ±0.01
C24:0	0.06 ±0.01	1.11 ±0.14	0.02 ±0.01	0.01 ±0.01	0.02 ±0.01	0.05 ±0.01	0.11 ±0.02	0.05 ±0.01	0.07 ±0.01	n.d.	0.24 ±0.03	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.04 ±0.01
C24:1n-9	0.05 ±0.01	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.03 ±0.01	0.02 ±0.01	0.19 ±0.01	n.d.	0.26 ±0.03	0.39 ±0.17	n.d.	1.00 ±0.16	0.27 ±0.08	0.30 ±0.07	0.28 ±0.03
C22:6n-3	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	9.68 ±0.58	n.d.	2.80 ±0.17	6.14 ±0.18	n.d.	62.32 ±3.55	28.21 ±2.67	34.52 ±2.94	n.d.
C16:1. u.i.	0.03 ±0.01	0.04 ±0.00	0.02 ±0.01	0.09 ±0.01	0.02 ±0.00	n.d.	0.01 ±0.00	0.03 ±0.01	0.02 ±0.00	0.62 ±0.26	0.04 ±0.01	0.19 ±0.01	0.40 ±0.26	n.d.	n.d.	n.d.	n.d.	n.d.
C17:1 u.i.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.22 ±0.01	n.d.	n.d.	0.19 ±0.00	n.d.	n.d.	n.d.	n.d.	n.d.

C18:1 u.i.	3.14 ±0.13	0.68 ±0.09	0.93 ±0.07	2.25 ±0.13	0.75 ±0.05	1.26 ±0.09	0.63 ±0.06	2.25 ±0.14	1.85 ±0.11	6.08 ±1.21	0.84 ±0.06	3.13 ±0.15	1.48 ±0.41	0.05 ±0.01	0.15 ±0.00	0.86 ±0.15	0.54 ±0.07	0.82 ±0.07
C18:2 u.i.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.14 ±0.01	n.d.	n.d.	0.08 ±0.01	n.d.	n.d.	0.33 ±0.01	n.d.	n.d.
C18:3 u.i.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.11 ±0.00	n.d.	n.d.	0.08 ±0.01	n.d.	n.d.	n.d.	n.d.	n.d.
C18:4 u.i.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	2.29 ±0.03	n.d.	n.d.	3.59 ±0.02	n.d.	n.d.	n.d.	n.d.	n.d.
C20:1 u.i.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	1.46 ±0.07	n.d.	0.42 ±0.03	0.90 ±0.01	n.d.	n.d.	1.17 ±0.01	0.59 ±0.01	n.d.
C20:2 u.i.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.65 ±0.02	0.55 ±0.01	n.d.
C20:4 u.i.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.56 ±0.01	n.d.	0.78 ±0.01	0.52 ±0.03	n.d.	n.d.	2.88 ±0.05	2.49 ±0.05	n.d.
C21:5 u.i.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.33 ±0.00	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	3.32 ±0.09	n.d.
C22:1 u.i.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	0.77 ±0.02	n.d.	2.92 ±0.06	n.d.	n.d.	1.39 ±0.09	0.18 ±0.01	0.19 ±0.01	n.d.
C22:5 u.i.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	1.01 ±0.01	n.d.	0.77 ±0.02	0.68 ±0.05	n.d.	11.67 ±0.12	5.73 ±0.58	6.35 ±0.15	n.d.

Appendix F – Reference oils

Table F1 - Sum of SFA, MUFA and PUFA in the reference oils (% based on total area in the chromatograms).

	Σ SFA	Σ MUFA	Σ PUFA
Rapeseed oil	7.63	66.28	25.82
Peanut oil	13.28	70.40	15.83
Sesame oil	16.55	42.29	41.17
Olive oil	16.32	74.73	8.86
Linseed oil	11.23	21.41	67.25
Soybean oil	16.90	24.54	57.97
Sunflower oil	11.03	32.81	56.16
Vita hjertegó	9.31	59.57	30.98
Frying oil	9.08	48.06	42.75
Møllers tran	16.47	54.00	25.58
Rice bran oil	24.23	42.19	33.55
Salmon oil	15.39	56.71	26.84
Herring oil	25.07	48.80	21.38
Coconut oil	91.92	7.28	1.15
0370 (EPA/DHA)	2.78	5.11	88.01
4030 (EPA/DHA)	4.05	8.98	85.43
3040 (EPA/DHA)	2.68	6.03	90.66
Camelina oil	10.21	29.71	60.15

Table F2 - Sum of the FAs of different chain lengths in the reference oils (% based on total area in the chromatograms).

	C6-C13	C14-C19	C20-C24
Rapeseed oil	0.02	97.61	2.10
Peanut oil	0.00	93.30	6.20
Sesame oil	0.01	99.19	0.80
Olive oil	0.00	99.30	0.61
Linseed oil	0.00	99.71	0.18
Soybean oil	0.00	98.51	0.90
Sunflower oil	0.00	99.03	0.97
Vita hjertegó	0.00	98.51	1.36
Frying oil	0.00	98.48	1.41
Møllers tran	0.03	54.20	41.81
Rice bran oil	0.01	98.27	1.69
Salmon oil	0.06	81.85	17.03
Herring oil	0.17	45.12	49.96
Coconut oil	49.56	50.71	0.08
0370 (EPA/DHA)	0.62	2.32	92.95
4030 (EPA/DHA)	0.04	7.11	91.31
3040 (EPA/DHA)	0.05	4.53	94.80
Camelina oil	0.01	84.04	16.02

Appendix G – Calibration set

Calculated fatty acid profiles of the calibration set. Only the eight main fatty acids are included, in addition to the parameters Σ SFA, Σ MUFA, Σ PUFA and UI.

Sample nr.	C14:0	C16:0	C18:0	C18:1n-9	C18:2n-6	C18:3n-3	C20:5n-3	C22:6n-3	Σ SFA	Σ MUFA	Σ PUFA	UI
1	0.07	11.17	4.85	23.09	52.02	5.93	0.00	0.00	16.90	24.54	57.97	1.47
2	0.06	6.61	3.46	31.99	56.04	0.12	0.00	0.00	11.03	32.81	56.16	1.45
3	8.91	14.25	1.09	6.99	1.52	1.12	7.00	6.14	25.07	48.80	21.38	1.57
4	0.02	9.72	6.10	41.09	40.97	0.20	0.00	0.00	16.55	42.29	41.17	1.25
5	0.41	20.45	2.04	40.72	32.51	1.05	0.00	0.00	24.23	42.19	33.55	1.10
6	0.01	12.51	3.30	71.29	8.33	0.53	0.00	0.00	16.32	74.73	8.86	0.93
7	0.04	6.73	4.32	20.50	15.31	51.92	0.00	0.00	11.23	21.41	67.25	2.08
8	25.71	11.62	4.96	7.23	1.15	0.00	0.00	0.00	91.92	7.28	1.15	0.10
9	0.36	0.63	0.29	0.55	0.16	0.00	12.89	62.32	2.78	5.11	88.01	5.27
10	0.10	7.45	4.65	31.00	30.81	0.15	3.21	15.52	13.12	33.03	52.83	2.22
11	0.40	15.48	1.60	30.64	24.40	0.78	3.23	15.63	18.85	32.89	47.21	2.12
12	6.45	8.08	2.83	52.49	11.81	0.35	0.00	0.00	32.95	54.61	12.15	0.79
13	0.10	9.54	2.55	53.59	6.29	0.40	3.22	15.59	12.93	57.32	28.66	1.98
14	0.13	10.17	3.75	25.57	19.62	39.17	0.00	0.00	14.48	26.62	58.80	1.84
15	6.45	7.95	4.48	17.19	11.77	38.95	0.00	0.00	31.38	17.88	50.73	1.58
16	0.12	5.20	3.31	15.50	11.51	38.90	3.23	15.63	9.11	17.32	72.45	2.86
17	19.36	8.87	3.79	5.55	0.90	0.00	3.23	15.61	69.59	6.73	22.90	1.35
18	0.13	7.26	3.22	15.86	30.84	12.46	3.23	15.62	11.68	20.97	66.04	2.50
19	0.21	3.56	2.74	17.29	28.00	0.15	22.05	14.11	7.54	20.89	70.80	3.02
20	6.55	6.34	3.48	18.46	28.32	0.11	11.01	7.05	29.51	20.47	49.72	1.89
21	0.13	4.89	2.42	27.49	37.65	1.19	3.22	15.57	8.48	29.69	60.77	2.36
22	4.54	7.32	1.19	4.35	0.88	0.61	23.64	20.32	13.88	27.42	56.00	3.26

23	4.54	8.80	1.36	7.87	5.69	10.18	6.69	18.55	15.76	33.10	47.77	2.57
24	0.21	15.08	4.07	40.90	36.74	0.62	0.00	0.00	20.39	42.24	37.36	1.18
25	12.85	10.67	5.53	24.18	21.08	0.10	0.00	0.00	54.19	24.80	21.18	0.67
26	0.19	5.17	3.19	20.80	20.54	0.10	6.45	31.19	9.65	23.68	64.61	3.22
27	0.02	9.67	4.96	43.51	26.40	13.19	0.00	0.00	15.16	45.20	39.59	1.38
28	6.50	9.45	5.37	27.42	24.53	13.06	0.00	0.00	34.21	28.25	37.60	1.16
29	13.07	16.03	3.50	23.95	16.81	0.52	0.00	0.00	58.11	24.71	17.33	0.60
30	0.23	13.28	2.49	28.75	25.91	19.51	0.00	0.00	17.22	35.95	46.85	1.50
31	0.05	5.77	1.97	61.81	19.81	4.79	0.00	0.00	9.46	65.63	24.62	1.20
32	6.45	7.07	3.18	37.76	13.65	16.40	0.00	0.00	29.53	40.32	30.07	1.17
33	6.54	5.54	2.17	32.72	9.84	3.36	3.24	15.65	27.45	36.19	35.28	1.94
34	0.03	7.54	3.46	52.02	31.98	0.31	0.00	0.00	13.54	53.93	32.29	1.19
35	4.48	13.39	2.19	38.98	4.91	0.83	3.52	3.08	20.72	61.70	15.15	1.24
36	0.03	9.62	3.81	45.86	11.82	26.26	0.00	0.00	13.77	48.03	38.09	1.51
37	0.19	6.52	2.67	36.97	4.17	0.36	22.02	14.09	10.19	41.88	47.11	2.75
38	0.12	13.05	3.24	50.94	16.11	13.52	0.00	0.00	17.02	53.26	29.64	1.26
39	0.11	8.04	3.23	41.26	7.96	13.25	11.14	7.13	11.95	44.82	42.77	2.14
40	6.52	9.28	3.40	38.07	4.45	0.31	11.05	7.07	32.12	41.40	26.14	1.63
41	4.47	10.49	2.71	13.75	8.42	26.54	3.50	3.06	18.14	35.09	44.33	1.83
42	12.89	9.18	4.64	13.86	8.22	25.93	0.00	0.00	51.62	14.34	34.16	1.08
43	0.20	3.68	2.30	10.53	7.73	25.96	6.45	31.16	7.00	13.26	77.63	3.64
44	6.55	6.40	3.91	12.70	7.94	25.99	11.02	7.05	29.63	14.77	55.25	2.20
45	0.15	3.56	2.99	11.25	7.65	25.82	21.28	15.79	7.27	14.41	77.71	3.41
46	13.04	6.13	2.62	3.89	0.65	0.00	6.44	31.15	47.37	6.19	44.56	2.62
47	0.36	0.57	1.16	1.58	0.08	0.09	28.49	45.26	3.41	7.05	86.72	4.93
48	0.37	0.51	2.03	2.60	0.00	0.19	44.08	28.21	4.05	8.98	85.43	4.60
49	8.84	9.82	4.43	20.59	35.93	1.99	0.00	0.00	40.65	21.35	37.92	0.99
50	8.70	7.80	3.36	10.29	17.77	1.98	4.30	20.79	37.17	12.31	49.06	2.24
51	11.54	10.66	2.99	10.34	7.34	13.06	2.33	2.05	42.34	28.61	27.61	1.18

52	11.67	8.78	2.70	5.60	0.89	0.43	17.04	11.46	40.39	21.63	36.00	2.08
53	0.14	5.64	4.14	21.34	18.70	17.41	14.76	9.45	10.59	24.18	64.68	2.64
54	3.24	11.73	1.72	16.74	11.32	0.78	17.03	11.45	17.78	33.32	46.78	2.43
55	0.31	7.14	1.21	14.30	10.95	0.38	17.75	32.30	9.88	17.76	70.77	3.73
56	0.15	4.16	1.38	43.25	11.52	2.39	4.30	20.79	7.90	47.25	43.23	2.48
57	0.09	3.82	1.99	26.68	12.86	14.92	13.45	11.52	6.84	33.98	58.91	2.67
58	0.27	9.27	2.22	20.59	15.99	17.67	4.30	20.77	12.74	22.90	62.94	2.79
59	0.27	8.84	1.59	28.60	23.38	1.83	4.39	21.23	11.93	31.49	55.13	2.58
60	7.01	14.72	3.16	29.73	30.00	0.54	0.00	0.00	38.87	30.67	30.54	0.92
61	0.20	3.51	1.75	12.52	19.00	9.54	6.43	31.06	6.71	18.23	73.03	3.43
62	0.28	2.81	3.05	12.22	10.24	0.19	33.07	21.16	7.17	17.30	74.37	3.75
63	6.41	11.59	4.42	47.75	14.74	0.31	0.00	0.00	35.20	49.79	15.05	0.80
64	12.89	8.32	4.50	14.45	10.74	0.10	11.21	7.18	50.87	16.40	32.52	1.51
65	19.39	13.83	4.23	15.60	8.99	0.26	0.00	0.00	75.00	16.00	9.25	0.35
66	4.57	13.76	1.79	17.87	13.72	10.33	3.50	3.07	21.14	42.37	34.13	1.53
67	0.05	5.83	2.63	28.00	19.25	30.16	0.00	0.00	9.56	38.86	51.57	1.73
68	1.93	9.14	2.71	28.72	18.87	3.51	3.89	4.87	14.37	49.73	33.69	1.61
69	0.23	13.18	1.98	52.68	24.85	2.32	0.00	0.00	17.33	55.28	27.18	1.12
70	12.88	8.78	3.44	35.91	9.17	1.80	0.00	0.00	51.21	37.79	10.98	0.62
71	0.12	4.70	2.28	40.24	22.94	2.42	11.05	7.07	8.87	43.83	46.74	2.09
72	19.38	10.41	4.80	10.50	4.64	12.80	0.00	0.00	72.03	10.76	17.44	0.58
73	0.05	5.96	2.94	39.23	32.50	16.36	0.00	0.00	9.61	41.40	48.87	1.56
74	0.28	2.16	1.30	5.55	3.95	13.00	9.66	46.72	4.89	9.19	82.81	4.45
75	0.05	8.79	4.24	20.86	34.66	25.44	0.00	0.00	13.81	25.06	60.83	1.73
76	6.64	4.85	3.34	8.23	4.11	13.06	22.01	14.09	27.89	11.66	59.75	2.83
77	6.61	4.90	2.46	7.19	4.18	12.95	6.46	31.20	27.16	9.72	61.12	3.14
78	0.28	2.09	2.16	6.55	3.86	13.05	25.21	29.78	5.52	11.11	81.54	4.13
79	6.72	3.39	1.46	2.22	0.41	0.00	9.66	46.69	25.14	5.65	66.22	3.93
80	6.55	3.20	2.39	3.30	0.40	0.09	31.26	24.35	25.18	7.09	67.12	3.61

Appendix H – Validation of calculated FA profiles of calibration set

Calculated vs reference values for the FA profiles of four randomly picked samples from the calibration set. The deviations of the calculated values from the reference values in percent are included.

Sample nr.		C14:0	C16:0	C18:0	C18:1 n-9	C18:2 n-6	C18:3 n- 3	C20:5 n- 3	C22:6 n- 3	ΣSFA	ΣMUFA	ΣPUFA	UI
32	Predicted	6,45	7,07	3,18	37,76	13,65	16,40	0	0	29,53	40,32	30,07	1,17
	Reference	4,52	6,11	2,89	40,34	14,07	16,53	0	0	25,72	43,28	30,60	1,21
	Deviation [%]	42,5	15,7	10,3	-6,4	-3,0	-0,8	-	-	14,8	-6,8	-1,7	-3,7
54	Predicted	3,24	11,73	1,72	16,74	11,32	0,78	17,03	11,45	17,78	33,32	46,78	2,43
	Reference	3,02	11,69	1,65	17,92	11,95	0,80	15,10	11,51	17,31	35,60	43,07	2,31
	Deviation [%]	7,0	0,3	4,3	-6,5	-5,2	-2,4	12,8	-0,5	2,7	-6,4	8,6	5,1
58	Predicted	0,27	9,27	2,22	20,59	15,99	17,67	4,30	20,77	12,74	22,90	62,94	2,79
	Reference	0,18	9,78	2,43	22,71	16,97	18,55	2,60	19,81	13,35	24,85	60,29	2,61
	Deviation [%]	46,3	-5,2	-8,7	-9,3	-5,8	-4,8	65,1	4,8	-4,6	-7,8	4,4	6,5
77	Predicted	6,61	4,90	2,46	7,19	4,18	12,95	6,46	31,20	27,16	9,72	61,12	3,14
	Reference	5,43	4,48	2,35	7,97	4,90	15,24	4,43	32,33	26,70	10,21	60,80	3,08
	Deviation [%]	21,8	9,4	4,7	-9,7	-14,6	-15,1	45,8	-3,5	1,8	-4,8	0,5	1,9

Appendix I – Data from GC-MS analyses of reference oils

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
18:1(n-9)	59.60	941	59.48	941	59.63	940
18:2(n-6)	65.52	898	65.38	904	65.47	903
10:0	12.60	834	12.55	882	12.56	830
12:0	15.68	847	15.63	809	15.63	837
14:0	21.65	869	21.55	885	21.55	871
15:0	26.61	838	26.49	787	26.50	785
.16:0	34.01	905	33.84	923	33.88	902
16:1(n-7)	38.68	883	38.48	875	38.50	891
17:0	43.96	807	43.72	770	43.75	783
18:0	55.03	924	54.88	920	55.03	924
20:0	71.81	889	71.69	889	71.73	887
18:3(n-3)	72.41	935	72.24	939	72.32	936
20:1(n-9)	75.03	863	74.86	882	74.93	884
20:2(n-6)	80.98	799	80.84	783	80.88	775
22:0	85.78	880	85.70	875	85.71	887
22:1(n-11)	87.72	801	87.63	844	87.65	844
24:0	93.88	843	93.81	848	93.82	844
24:1(n-9)	94.99	809	94.06	805	94.96	816
18:1 u.i.	59.88	907	59.74	919	59.87	920

Figure I.1: Data for the various FAs identified in rapeseed oil by analysis with GC-MS. Information for the first three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
18:1(n-9)	59.68	942	59.63	941	59.54	944
18:2(n-6)	65.46	897	65.36	901	65.63	902
14:0	21.64	850	21.54	844	21.56	829
16:0	34.06	913	33.92	908	33.95	901
16:1(n-7)	38.65	813	38.46	863	38.50	845
17:0	43.94	804	43.74	805	43.77	829
18:0	55.08	907	55.01	916	55.00	918
20:0	71.82	902	71.72	893	71.73	890
18:3(n-3)	72.20	935	72.06	936	72.09	926
20:1(n-9)	75.09	862	74.96	888	74.96	881
22:0	85.95	909	85.87	889	85.86	903
22:1(n-11)	87.74	851	87.65	831	87.66	852
23:0	90.10	722	90.03	756	90.04	687
24:0	94.00	863	93.93	871	93.93	875
18:1 u.i.	59.85	869	59.79	836	59.79	894

Figure I.2: Data for the various FAs identified in peanut oil by analysis with GC-MS. Information for the first three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
16:0	34.12	911	34.00	902	34.00	908
18:1(n-9)	59.36	948	59.25	942	59.22	948
18:2(n-6)	65.36	896	65.66	905	65.63	901
12:0	15.68	799	15.63	850	15.63	820
14:0	21.63	794	21.55	828	21.55	817
16:1(n-7)	38.66	857	38.49	872	38.49	881
17:0	43.93	749	43.73	772	43.76	739
18:0	55.16	934	55.08	925	55.03	930
20:0	71.77	899	71.67	904	71.66	881
18:3(n-3)	72.19	934	72.07	930	72.06	925
20:1(n-9)	74.91	816	74.79	837	74.80	818
22:0	85.75	860	85.68	869	85.68	872
24:0	93.85	778	93.79	759	93.81	806
18:1 u.i.	59.63	899	59.51	886	59.50	899

Figure I.3: Data for the various FAs identified in sesame oil by analysis with GC-MS. Information for the first three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

RT (min)	Replicate 1		Replicate 2		Replicate 3	
	MF	RT (min)	MF	RT (min)	MF	RT (min)
16:0	34.19	908	34.07	904	34.05	912
18:1(n-9)	59.61	944	59.65	944	59.54	941
18:2(n-2)	65.32	904	65.21	891	65.17	897
14:0	21.64	769	21.55	834	21.56	760
16:1(n-7)	38.72	891	38.54	890	38.56	886
17:0	43.93	840	43.76	824	43.76	829
18:0	55.13	922	55.12	919	54.97	917
20:0	71.74	888	71.63	892	71.63	882
18:3(n-3)	72.21	931	72.09	939	72.07	933
20:1(n-9)	74.92	843	74.79	826	74.80	830
22:0	85.75	871	85.68	860	85.69	858
24:0	93.84	763	93.79	759	93.80	721
18:1 u.i.	59.91	916	59.87	924	59.74	916

Figure I.4: Data for the various FAs identified in olive oil by analysis with GC-MS. Information for the first three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
18:1(n-9)	59.05	941	58.90	944	58.88	944
18:2(n-6)	65.41	895	65.28	896	65.28	896
18:3(n-3)	72.92	934	72.83	934	72.83	934
14:0	21.64	868	21.56	863	21.56	852
15:0	26.60	778	26.50	791	26.49	792
16:0	34.03	915	33.90	904	33.88	913
16:1(n-5)	38.66	849	38.49	853	38.49	828
17:0	43.92	777	43.74	801	43.77	780
18:0	54.96	909	54.81	935	54.77	925
20:1(n-9)	74.91	805	74.79	812	74.78	792
22:0	85.75	838	85.67	829	85.69	879
20:3(n-3)	86.17	753	86.09	812	86.09	813
24:0	93.86	782	93.80	782	93.80	780
18:1 u.i.	59.43	882	59.28	888	59.27	883

Figure I.5: Data for the various FAs identified in flaxseed oil by analysis with GC-MS. Information for the first three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
16:0	34.17	905	33.95	910	34.07	906
18:1(n-9)	59.10	940	58.85	942	59.00	942
18:2(n-6)	65.89	901	65.62	895	65.78	895
14:0	21.64	846	21.54	870	21.56	892
15:0	26.60	742	26.47	694	26.50	737
16:1(n-7)	38.67	868	38.47	823	38.53	827
17:0	43.94	838	43.71	847	43.79	837
18:0	55.03	930	54.77	927	54.97	932
20:0	71.77	883	71.60	845	71.70	861
18:3(n-3)	72.39	857	72.17	863	72.27	860
20:1(n-9)	74.93	825	74.74	814	74.81	836
21:0	79.81	764	79.65	719	79.69	790
20:2(n-6)	80.97	760	80.93	718	80.87	740
22:0	85.79	874	85.67	901	85.72	887
23:0	90.09	735	90.01	681	90.04	727
24:0	93.86	796	93.78	727	93.82	819
18:1 u.i.	59.50	889	59.26	907	59.39	902

Figure I.6: Data for the various FAs identified in soybean oil by analysis with GC-MS. Information for the first three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
18:1(n-9)	59.20	946	59.14	941	59.10	945
18:2(n-6)	65.89	899	65.80	906	65.80	897
14:0	21.63	866	21.54	814	21.56	847
15:0	26.59	734	26.50	728	26.52	693
16:0	34.02	901	33.89	898	33.91	908
16:1(n-7)	38.66	763	38.46	822	38.49	836
17:0	43.92	752	43.74	748	43.77	752
18:0	55.00	927	59.94	922	54.92	925
20:0	71.71	885	71.62	874	71.62	891
18:3(n-3)	72.21	853	72.06	879	72.08	910
20:1(n-9)	74.90	811	74.78	808	74.78	817
22:0	85.81	886	85.73	898	85.73	885
24:0	93.87	826	93.81	835	93.82	830
18:1 u.i.	59.50	886	59.41	876	59.40	883

Figure I.7: Data for the various FAs identified in sunflower oil by analysis with GC-MS. Information for the first three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
18:1(n-9)	59.49	947	59.37	947	59.37	942
18:2(n-6)	65.56	905	65.45	901	65.45	896
12:0	15.67	786	15.62	740	15.63	748
14:0	21.62	843	21.53	871	21.56	873
15:0	26.59	741	26.47	786	26.51	762
16:0	33.99	912	33.85	907	33.91	908
16:1(n-7)	38.62	875	38.47	895	38.51	876
17:0	43.88	743	43.71	778	43.77	755
18:0	54.98	906	54.88	920	54.92	928
20:0	71.74	865	71.64	911	71.69	893
18:3(n-3)	72.32	864	72.18	892	72.24	865
20:1(n-9)	74.93	861	74.82	862	74.85	856
22:0	85.75	884	85.69	866	85.72	876
23:0	90.07	665	90.03	647	90.04	670
24:0	93.84	810	93.79	812	93.82	793
24:1(n-9)	94.98	758	94.95	777	94.96	791
18:1 u.i.	59.76	897	59.64	912	59.70	907

Figure I.8: Data for the various FAs identified in Vita Hjertegó by analysis with GC-MS. Information for the first three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
18:1(n-9)	59.37	946	59.34	939	59.42	943
18:2(n-6)	65.74	900	65.64	901	65.73	895
14:0	21.60	888	21.55	838	21.56	867
15:0	26.55	770	26.50	760	26.53	772
16:0	33.97	912	33.88	918	33.93	906
16:1(n-7)	38.60	860	38.46	869	38.51	859
17:0	43.85	794	43.71	789	43.77	782
18:0	55.03	910	54.96	911	55.01	922
20:0	71.74	902	71.66	888	71.70	897
18:3(n-3)	72.31	860	72.21	868	72.26	866
20:1(n-9)	74.92	856	74.83	866	74.88	861
21:0	79.76	638	79.67	662	79.70	633
22:0	85.77	881	85.73	877	85.75	858
22:1(n-11)	87.68	782	87.73	757	87.65	751
24:0	93.85	825	93.81	842	93.83	819
24:1(n-9)	94.98	739	94.96	770	94.96	783
18:1 u.i.	59.69	906	59.63	911	59.67	912

Figure I.9: Data for the various FAs identified in frying oil by analysis with GC-MS. Information for the first three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
16:0	34.06	913	34.01	901	33.98	904
16:1(n-7)	38.95	903	38.86	905	38.85	905
18:1(n-9)	58.83	945	58.81	940	58.73	938
20:1(n-9)	75.40	900	75.36	901	75.31	894
22:6(n-3)	96.96	917	96.96	921	96.95	925
12:0	15.66	862	15.62	840	15.64	837
13:0	18.13	748	18.07	766	18.09	792
14:0	21.67	913	21.62	905	21.63	908
14:1(n-5)	24.79	777	24.72	798	24.74	770
15:0	26.57	894	26.50	894	26.51	886
18:0	54.50	916	54.58	929	54.53	921
18:2(n-6)	64.98	879	64.94	886	64.93	880
18:3(n-3)	72.10	848	72.04	857	72.03	860
20:2(n-6)	80.93	863	80.87	860	80.88	848
20:3(n-6)	84.03	647	83.98	635	83.99	572
20:4(n-6)	86.00	844	85.95	865	85.95	870
20:3(n-3)	86.12	827	86.08	864	86.08	835
22:1(n-11)	87.60	900	87.60	912	87.57	906
20:5(n-3)	90.39	918	90.37	923	90.34	919
24:1(n-9)	95.00	844	95.00	858	94.99	845
16:1 u.i.	36.16	786	36.06	811	36.08	791
16:1 u.i.	36.73	809	36.63	833	36.67	821
16:1 u.i.	37.72	884	37.61	857	37.61	867
16:1 u.i.	40.03	862	39.92	860	39.93	868
17:1 u.i.	48.88	870	48.77	824	48.81	817
18:1 u.i.	57.96	905	57.95	898	57.89	890
18:1 u.i.	59.46	915	59.42	914	59.36	903
18:1 u.i.	60.53	887	60.45	866	60.45	846
18:2 u.i.	66.69	825	66.62	832	66.62	808
18:3 u.i.	69.11	825	69.04	802	69.05	803
20:1 u.i.	74.55	865	74.52	827	74.50	832
20:1 u.i.	75.89	831	75.84	818	75.83	812
18:4 u.i.	76.65	901	76.59	899	76.58	899
22:1 u.i.	87.82	818	87.82	810	87.80	822
20:4 u.i.	88.63	897	88.60	900	88.60	893
21:5 u.i.	94.66	896	94.65	896	94.65	892
22:5 u.i.	96.30	912	96.29	901	96.29	911

Figure I.10: Data for the various FAs identified in Möller's Tran by analysis with GC-MS. Information for the first three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
16:0	34.24	906	34.27	898	34.18	901
18:1(n-9)	59.23	947	59.26	945	59.18	941
18:2(n-6)	65.57	900	65.58	925	65.51	901
12:0	15.65	815	15.63	839	15.63	845
14:0	21.59	890	21.56	892	21.55	904
15:0	26.52	824	26.52	807	26.49	783
16:1(n-7)	38.59	874	38.55	884	38.51	882
17:0	43.80	766	43.76	789	43.72	784
18:0	54.83	917	54.84	927	54.76	919
20:0	71.70	897	71.71	891	71.66	901
18:3(n-3)	72.11	858	72.10	862	72.08	850
20:1(n-9)	74.84	828	74.84	861	74.81	855
21:0	79.68	609	79.69	604	79.67	571
22:0	85.70	888	85.70	868	85.70	875
24:0	93.83	852	93.85	859	93.85	855
18:1 u.i.	59.50	901	59.52	902	59.44	898

Figure I.11: Data for the various FAs identified in rice bran oil by analysis with GC-MS. Information for the first three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
16:0	34.03	899	34.02	910	33.97	900
18:1(n-9)	59.24	945	59.27	942	59.16	945
18:2(n-6)	65.28	896	65.30	896	65.23	896
12:0	15.64	742	15.63	807	15.63	859
13:0	18.09	750	18.08	771	18.08	751
14:0	21.63	897	21.60	891	21.60	896
15:0	26.53	894	26.51	878	26.50	884
16:1(n-7)	38.65	896	38.64	893	38.62	900
18:0	54.81	905	54.84	908	54.77	907
20:0	71.68	769	71.70	876	71.68	847
18:3(n-3)	72.23	871	72.20	862	72.18	870
20:1(n-9)	75.10	859	75.10	859	75.04	848
20:2(n-6)	80.95	886	80.94	893	80.90	894
20:3(n-6)	84.02	831	84.00	826	83.99	837
22:0	85.78	824	85.78	838	85.78	825
20:4(n-6)	85.96	776	85.95	744	85.95	750
20:3(n-3)	86.12	894	86.10	835	86.10	885
22:1(n-11)	87.73	874	87.73	867	87.72	858
20:5(n-3)	90.30	894	90.27	899	90.26	896
22:2(n-6)	90.84	777	90.83	697	90.83	668
24:1(n-9)	94.99	854	94.98	863	94.98	858
22:6(n-3)	96.92	874	96.91	876	96.91	920
18:1 u.i.	59.60	901	59.63	917	59.54	911
18:1 u.i.	60.57	733	60.57	712	60.51	718
20:1 u.i.	74.41	832	74.41	781	74.36	793
20:1 u.i.	75.75	706	75.75	693	75.73	688
22:1 u.i.	87.46	850	87.46	844	87.45	848
20:4 u.i.	88.62	890	88.62	854	88.58	889
22:5 u.i.	96.30	895	96.30	921	96.28	916

Figure I.12: Data for the various FAs identified in salmon oil by analysis with GC-MS. Information for the first three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
14:0	21.72	907	21.71	908	21.71	908
16:0	34.12	913	34.09	906	34.13	905
20:1(n-9)	75.38	904	75.35	896	75.39	901
22:1(n-11)	87.87	914	87.85	907	87.90	908
10:0	12.57	730	12.56	734	12.56	848
12:0	15.65	886	15.63	884	15.64	890
13:0	18.10	869	18.09	844	18.08	891
15:0	26.55	912	26.51	894	26.52	913
16:1(n-7)	38.79	899	38.74	902	38.75	903
18:0	54.43	912	54.40	925	54.42	915
18:1(n-9)	58.58	942	58.56	937	58.59	943
18:2(n-6)	64.90	871	64.88	877	64.89	884
18:3(n-3)	72.08	926	72.04	938	72.05	938
20:2(n-6)	80.89	837	80.87	855	80.88	845
20:3(n-6)	84.00	739	83.97	699	83.99	758
20:3(n-3)	86.11	847	86.09	841	86.11	861
20:5(n-3)	90.39	922	90.37	924	90.38	923
24:1(n-9)	95.01	868	95.00	868	94.65	871
22:6(n-3)	96.95	924	96.93	923	96.94	924
16:1 u.i.	36.70	877	36.65	876	36.66	882
16:1 u.i.	37.66	843	37.62	840	37.63	821
16:1 u.i.	39.96	870	39.92	871	39.93	874
17:1 u.i.	48.88	823	48.81	816	48.80	836
18:1 u.i.	59.20	873	59.16	901	59.19	888
18:1 u.i.	57.80	871	57.77	875	57.77	874
18:1 u.i.	60.42	853	60.39	853	60.40	859
18:2 u.i.	66.65	769	66.61	799	66.60	768
18:3 u.i.	69.06	807	69.05	808	69.05	806
20:1 u.i.	74.53	864	74.47	843	74.46	827
18:4 u.i.	76.67	902	76.61	905	76.64	904
20:4 u.i.	88.63	877	88.61	885	88.61	882
22:5 u.i.	96.30	909	96.28	910	96.29	916

Figure I.13: Data for the various FAs identified in herring oil by analysis with GC-MS. Information for the first three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
12:0	15.81	923	15.82	922	15.81	923
14:0	21.82	906	21.82	909	21.81	912
16:0	33.96	918	33.97	910	33.95	902
6:0	9.06	932	9.05	941	9.05	936
8:0	10.71	917	10.71	924	10.72	922
10:0	12.58	934	12.57	938	12.58	937
11:0	13.87	918	13.86	869	13.87	838
13:0	18.10	901	18.09	886	18.12	854
18:0	54.55	920	54.56	933	54.57	930
18:1(n-9)	58.48	942	58.50	943	58.48	933
18:2(n-6)	64.85	872	64.84	881	64.86	863
20:0	71.54	843	71.53	866	71.55	808
18:1 u.i.	59.08	874	59.07	810	59.07	651

Figure I.14: Data for the various FAs identified in coconut oil by analysis with GC-MS. Information for the first three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
20:5(n-3)	90.36	922	90.35	914	90.37	917
22:6(n-3)	97.11	929	97.11	933	97.11	931
8:0	10.70	778	10.70	901	10.70	909
10:0	12.56	643	12.55	884	12.56	882
12:0	15.64	856	15.63	907	15.65	896
14:0	21.56	883	21.55	888	21.58	880
16:0	33.62	893	33.58	889	33.64	917
16:1(n-7)	38.47	853	38.44	841	38.53	842
18:0	54.27	873	54.24	861	54.30	858
18:1(n-9)	58.21	858	58.19	890	58.28	888
18:2(n-6)	64.79	794	64.76	806	64.81	819
20:0	71.57	877	71.56	846	71.61	833
20:1(n-9)	74.77	848	74.76	836	74.80	840
21:0	79.74	777	79.74	803	79.79	830
20:2(n-6)	80.84	795	80.82	788	80.87	806
20:3(n-6)	83.98	766	83.95	750	84.00	743
20:4(n-6)	85.93	775	85.92	748	85.96	753
22:1(n-11)	87.43	877	87.44	852	87.46	874
24:1(n-9)	95.14	854	95.14	867	95.16	859
18:1 u.i.	59.00	766	58.97	770	59.02	774
22:1 u.i.	87.78	757	87.77	732	87.79	719
22:1 u.i.	88.30	845	88.29	802	88.33	831
22:5 u.i.	96.34	900	96.34	926	96.36	932

Figure I.15: Data for the various FAs identified in 0370 (cod liver oil enriched in EPA/DHA) by analysis with GC-MS. Information for the first three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
20:5(n-3)	90.59	917	90.59	916	90.62	921
22:6(n-3)	97.03	921	97.02	921	97.04	927
12:0	15.63	746	15.63	760	15.65	741
14:0	21.56	875	21.55	866	21.58	872
16:0	33.60	894	33.60	890	33.65	891
16:1(n-7)	38.48	802	38.44	813	38.52	802
18:0	54.40	915	54.43	905	54.48	918
18:1(n-9)	58.33	919	58.33	897	58.40	919
20:0	71.71	878	71.71	876	71.78	901
18:3(n-3)	71.97	721	71.98	771	72.05	797
20:1(n-9)	74.93	855	74.96	866	75.01	863
21:0	79.81	787	79.83	768	79.90	746
20:2(n-6)	80.87	831	80.90	819	80.95	826
20:3(n-6)	84.00	819	84.00	801	84.05	805
20:4(n-6)	85.98	850	85.98	881	86.03	886
20:3(n-3)	86.11	866	86.12	858	86.16	857
22:1(n-11)	87.54	842	87.55	845	87.58	840
24:1(n-9)	95.05	826	95.06	831	95.07	835
18:1 u.i.	59.07	853	59.05	843	59.13	864
18:2 u.i.	64.79	847	64.77	834	64.85	830
20:1 u.i.	74.35	704	74.35	664	74.38	708
20:1 u.i.	75.74	832	75.77	802	75.83	802
20:2 u.i.	79.29	901	79.29	774	79.36	797
22:1 u.i.	88.41	796	88.43	768	88.44	767
20:4 u.i.	88.63	896	88.64	894	88.68	900
22:5 u.i.	96.32	924	96.31	920	96.33	928

Figure I.16: Data for the various FAs identified in 4030 (cod liver oil enriched in EPA/DHA) by analysis with GC-MS. Information for the first three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
20:5(n-3)	90.54	921	90.54	925	90.62	918
22:6(n-3)	97.03	922	97.04	922	97.07	926
12:0	15.69	815	15.63	722	15.65	679
14:0	21.65	870	21.54	883	21.59	842
16:0	33.81	885	33.57	868	33.67	892
16:1(n-7)	38.66	720	38.44	744	38.54	743
18:0	54.51	902	54.35	900	54.47	904
18:1(n-9)	58.39	891	58.25	906	58.37	906
18:2(n-6)	65.04	807	64.76	802	64.85	772
20:0	71.74	868	71.64	870	71.76	867
20:1(n-9)	74.96	837	74.85	850	74.97	847
21:0	79.41	703	79.80	744	79.91	752
20:2(n-6)	81.00	797	80.85	791	80.95	778
20:3(n-6)	84.11	820	83.98	758	84.06	807
20:4(n-6)	86.08	881	85.97	886	86.03	881
20:3(n-3)	86.22	807	86.09	829	86.14	807
22:1(n-11)	87.87	836	87.49	848	87.59	851
24:1(n-9)	94.93	796	95.06	839	95.11	829
18:1 u.i.	59.00	825	59.02	821	59.14	812
20:1 u.i.	75.68	833	75.70	775	75.82	787
20:2 u.i.	79.25	890	79.26	794	79.39	803
22:1 u.i.	88.35	789	88.37	755	88.46	766
20:4 u.i.	88.61	900	88.62	888	88.68	903
21:5 u.i.	94.66	921	94.66	918	94.69	920
22:5 u.i.	96.31	928	96.32	846	96.35	929

Figure I.17: Data for the various FAs identified in 3040 (cod liver oil enriched in EPA/DHA) by analysis with GC-MS. Information for the first three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
18:1(n-9)	58.81	943	58.81	941	58.93	942
18:2(n-6)	65.34	900	65.33	928	65.43	899
18:3(n-3)	72.68	937	72.67	939	72.79	935
20:1(n-9)	75.29	895	75.30	900	75.41	901
12:0	15.62	793	15.64	611	15.65	651
14:0	21.54	863	21.55	878	21.60	874
15:0	26.48	719	26.49	703	26.56	705
16:0	33.88	900	33.89	908	33.96	899
17:0	43.71	724	43.72	728	43.85	753
18:0	54.68	911	54.70	905	54.83	920
20:2(n-6)	80.95	904	80.95	901	81.06	904
22:0	85.69	880	85.69	819	85.79	839
20:3(n-3)	86.12	932	86.11	923	86.20	930
22:1(n-11)	87.70	889	87.69	887	87.77	894
24:0	93.80	713	93.80	767	93.87	793
24:1(n-9)	94.96	864	94.97	865	95.00	869
18:1 u.i.	59.23	888	59.23	893	59.34	876

Figure I.18: Data for the various FAs identified in camelina oil by analysis with GC-MS. Information for the first three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer

Appendix J - Data from GC-MS analyses of validation oils

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
14:0	20.13	864	20.09	862	20.09	889
16:0	30.64	951	30.56	947	30.61	953
16:1(n-7)	34.71	883	34.61	856	34.61	870
17:0	39.10	802	38.98	758	39.02	784
18:0	50.32	959	50.23	964	50.32	953
18:1(n-9)	54.51	943	54.40	946	54.48	945
18:2(n-6)	61.55	946	61.47	945	61.58	949
20:0	67.66	903	67.56	882	67.57	903
18:3(n-3)	68.13	901	68.01	900	68.03	912
20:1(n-9)	70.64	888	70.53	883	70.54	891
20:2(n-6)	76.49	724	76.37	656	76.36	730
22:0	82.54	846	82.49	826	82.48	856
24:0	91.35	684	91.35	672	91.35	683
18:1 u.i.	55.01	935	54.89	934	54.95	942

Figure J.1: Data for the various FAs identified in grapeseed oil by analysis with GC-MS. Information for all three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
14:0	20.10	873	20.10	798	20.08	846
15:0	24.35	695	24.34	549	24.33	618
16:0	30.53	948	30.46	949	30.48	948
16:1(n-7)	34.64	867	34.61	790	34.59	829
17:0	39.01	722	39.00	598	38.96	698
18:0	50.36	953	50.12	957	50.24	962
18:1(n-9)	55.12	949	54.80	935	54.98	949
18:2(n-6)	60.99	947	60.86	947	60.90	948
20:0	67.59	932	67.54	886	67.55	924
18:3(n-3)	68.05	900	68.00	857	68.00	852
20:1(n-9)	70.58	906	70.52	871	70.52	882
22:0	82.52	928	82.47	922	82.46	936
23:0	87.42	619	87.42	713	87.41	683
24:0	91.31	900	91.31	889	91.30	889
18:1 u.i.	55.32	946	55.07	925	55.21	939

Figure J.2: Data for the various FAs identified in frying oil (Coop) by analysis with GC-MS. Information for all three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
14:0	20.08	812	20.08	912	20.08	803
15:0	24.33	684	24.32	668	24.30	647
16:0	30.57	944	30.58	947	30.55	950
16:1(n-7)	34.62	811	34.60	836	34.59	795
17:0	39.01	772	39.00	747	38.94	748
18:0	50.13	958	50.15	958	50.11	959
18:1(n-9)	54.28	946	54.32	943	54.27	941
18:2(n-6)	61.35	952	61.44	951	61.36	948
20:0	67.65	849	67.66	852	67.62	852
18:3(n-3)	68.25	941	68.25	943	68.21	944
20:1(n-9)	70.55	882	70.54	883	70.51	876
22:0	82.50	684	82.50	697	82.48	665
18:1 u.i.	54.87	931	54.88	937	54.84	933

Figure J.3: Data for the various FAs identified in walnut oil by analysis with GC-MS. Information for all three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
14:0	20.09	871	20.08	871	20.09	877
15:0	24.33	654	24.32	680	24.32	664
16:0	30.50	961	30.51	950	30.49	950
16:1(n-7)	34.61	858	34.59	849	34.59	852
17:0	38.97	663	38.99	661	38.98	668
18:0	50.09	962	50.10	946	50.06	945
18:1(n-9)	54.56	946	54.59	950	54.56	944
18:2(n-6)	61.15	950	61.16	946	61.13	950
20:0	67.56	911	67.55	906	67.54	920
18:3(n-3)	68.06	943	68.05	947	68.03	939
20:1(n-9)	70.55	928	70.52	922	70.52	926
22:0	82.47	909	82.46	909	82.45	914
22:1(n-9)	84.58	791	84.58	796	84.56	818
23:0	87.42	603	87.42	630	87.42	622
24:0	91.31	803	91.30	841	91.30	825
24:1(n-9)	92.80	699	92.80	722	92.79	719
18:1 u.i.	54.97	955	54.99	951	54.95	944

Figure J.4: Data for the various FAs identified in cooking oil by analysis with GC-MS. Information for all three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
6:0	8.93	857	8.92	896	8.93	905
8:0	10.54	931	10.54	936	10.54	930
10:0	12.24	952	12.23	944	12.23	948
12:0	14.97	958	14.97	953	14.96	950
14:0	20.11	951	20.11	953	20.11	953
16:0	30.52	945	30.51	947	30.54	949
16:1(n-7)	34.62	843	34.59	859	34.59	851
17:0	38.99	688	38.97	700	38.98	719
18:0	50.08	961	50.05	951	50.11	953
18:1(n-9)	54.55	949	54.54	947	54.61	944
18:2(n-6)	60.92	945	60.89	948	60.93	955
20:0	67.66	930	67.65	926	67.65	929
18:3(n-3)	68.25	942	68.23	949	68.24	946
20:1(n-9)	70.54	925	70.53	923	70.52	921
22:0	82.45	882	82.45	887	82.44	894
22:1(n-9)	84.60	788	84.58	811	84.56	814
24:0	91.31	794	91.32	786	91.31	793
24:1(n-9)	92.81	699	92.81	721	92.79	731

Figure J.5: Data for the various FAs identified in sample nr. 32 of the calibration set by analysis with GC-MS. Information for all three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
12:0	14.96	870	14.95	848	14.95	869
14:0	20.10	954	20.09	949	20.10	955
15:0	24.33	913	24.32	900	24.31	923
16:0	30.63	950	30.60	951	30.61	941
16:1(n-7)	34.67	916	34.65	940	34.64	941
18:0	49.96	950	49.93	953	49.93	945
18:1(n-9)	54.30	946	54.25	944	54.27	947
18:2(n-6)	60.89	946	60.94	797	60.87	945
20:0	67.59	929	67.58	920	67.57	936
18:3(n-3)	67.99	932	67.98	932	67.97	931
20:1(n-9)	70.69	944	70.65	944	70.66	941
20:2(n-6)	76.34	858	76.31	856	76.29	882
20:3(n-6)	80.27	821	80.24	833	80.25	841
20:4(n-6)	82.63	906	82.60	907	82.60	894
20:3(n-3)	82.73	825	82.72	817	82.73	822
22:1(n-9)	84.43	949	84.38	949	84.40	942
20:5(n-3)	87.65	962	87.62	953	87.63	954
24:0	91.30	669	91.29	655	91.29	661
24:1(n-9)	92.81	879	92.79	875	92.79	886
22:6(n-3)	95.75	961	95.74	956	95.75	957

Figure J.6: Data for the various FAs identified in sample nr. 54 of the calibration set by analysis with GC-MS. Information for all three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
14:0	20.09	932	20.08	938	20.08	921
15:0	24.33	672	24.32	681	24.32	679
16:0	30.62	948	30.59	950	30.57	950
16:1(n-7)	34.62	863	34.61	858	34.60	876
17:0	38.99	714	38.98	692	38.97	682
18:0	50.06	948	50.02	956	49.99	958
18:1(n-9)	54.43	944	54.35	947	54.33	947
18:2(n-6)	60.98	947	60.95	946	60.94	948
20:0	67.70	928	67.67	929	67.66	938
18:3(n-3)	68.29	946	68.25	946	68.25	943
20:1(n-9)	70.50	922	70.50	916	70.50	905
21:0	75.11	655	75.10	687	75.09	657
20:2(n-6)	76.32	756	76.32	753	76.31	733
20:3(n-6)	80.26	704	80.27	701	80.25	699
22:0	82.49	902	82.47	896	82.48	900
20:4(n-6)	82.58	844	82.57	758	82.58	789
20:3(n-3)	82.73	729	82.69	709	82.69	684
22:1(n-9)	84.61	866	84.59	856	84.70	837
20:5(n-3)	87.54	955	87.52	949	87.52	956
24:0	91.32	760	91.31	728	91.31	741
24:1(n-9)	92.82	878	92.82	882	92.81	882
22:6(n-3)	95.79	917	95.77	953	95.77	957

Figure J.7: Data for the various FAs identified in sample nr. 58 of the calibration set by analysis with GC-MS. Information for all three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

FA	Replicate 1		Replicate 2		Replicate 3	
	RT (min)	MF	RT (min)	MF	RT (min)	MF
6:0	8.93	913	8.93	882	8.92	880
8:0	10.54	934	10.54	938	10.54	931
10:0	12.23	943	12.23	947	12.23	952
12:0	14.97	956	14.96	947	14.96	952
13:0	17.07	618	17.07	619	17.06	616
14:0	20:12	946	20.11	951	20.11	950
16:0	30.47	953	30.44	952	30.46	945
16:1(n-7)	34.61	807	34.61	786	34.58	818
18:0	49.92	951	49.89	956	49.89	956
18:1(n-9)	54.07	940	54.02	940	54.03	939
18:2(n-6)	60.72	944	60.68	945	60.70	945
20:0	67.59	882	67.57	911	67.58	906
18:3(n-3)	68.21	947	68.16	946	68.16	946
20:1(n-9)	70.48	892	70.48	887	70.46	920
21:0	75.10	678	75.10	681	75.10	705
20:2(n-6)	76.29	757	76.30	736	76.28	766
20:3(n-6)	80.24	725	80.24	717	.. ^a	.. ^a
22:0	82.50	892	82.48	866	.. ^a	.. ^a
20:4	82.56	832	82.59	838	.. ^a	.. ^a
22:1(n-9)	84.62	828	84.60	856	84.62	819
20:5(n-3)	87.53	963	87.52	953	87.52	958
24:1(n-9)	92.83	904	92.83	888	92.82	896
22:6(n-3)	95.80	887	95.79	956	95.79	955

^a = Replicate could not be used due to poor separation of the peaks in the chromatogram.

Figure J.8: Data for the various FAs identified in sample nr. 77 of the calibration set by analysis with GC-MS. Information for all three replicates is included. RT = Retention time, MF = Match factor, u.i. = Unidentified isomer.

Appendix K – PLSR based on FTIR

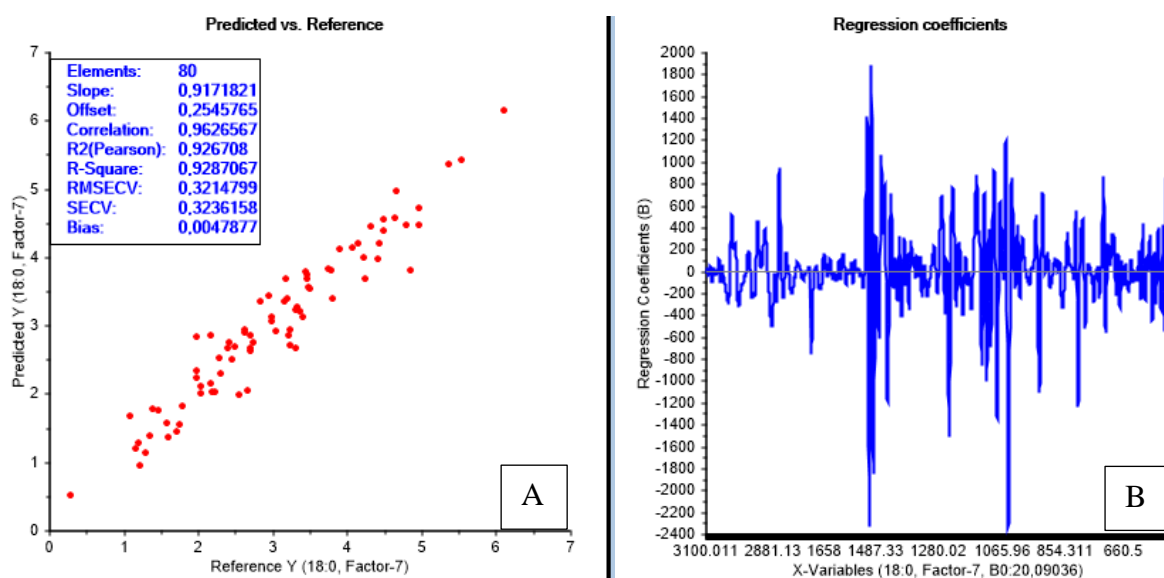


Figure K.1: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with C18:0 as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with FTIR spectroscopy.

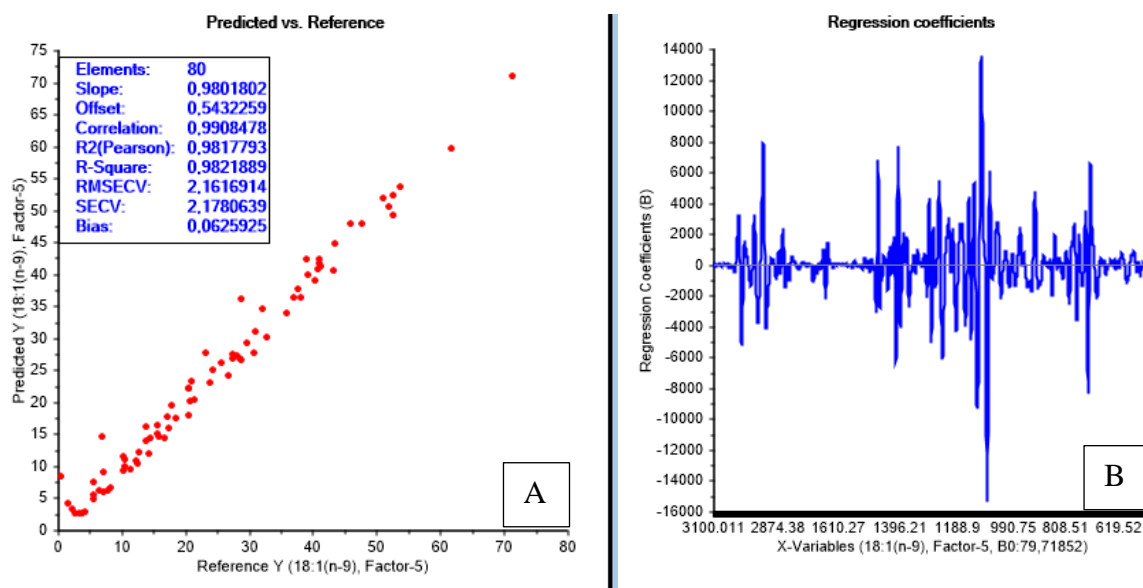


Figure K.2: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with C18:1n-9 as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with FTIR spectroscopy.

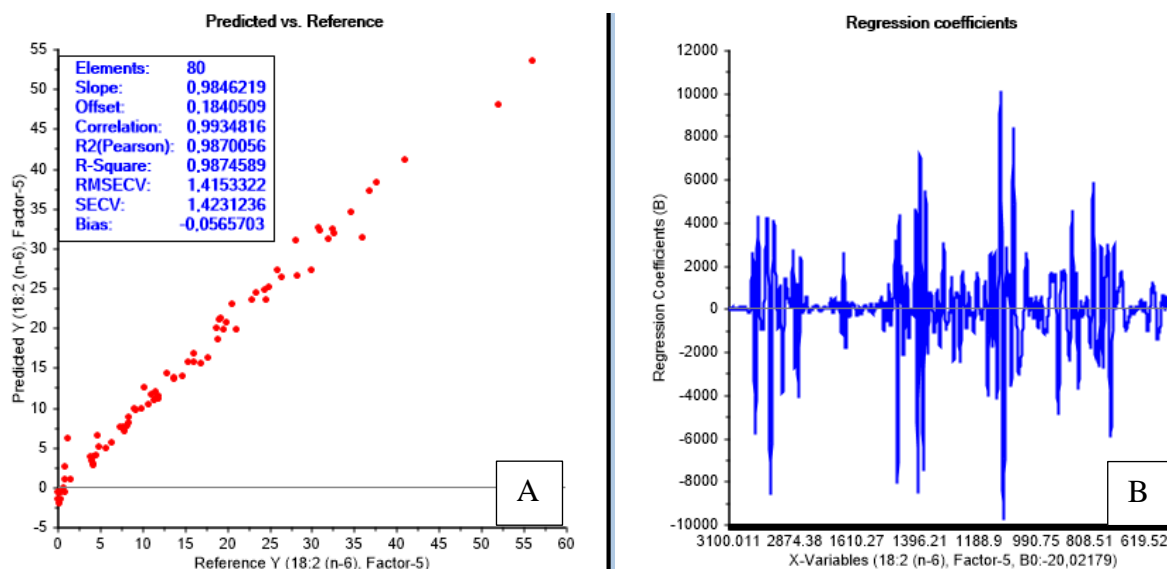


Figure K.3: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with C18:2n-6 as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with FTIR spectroscopy.

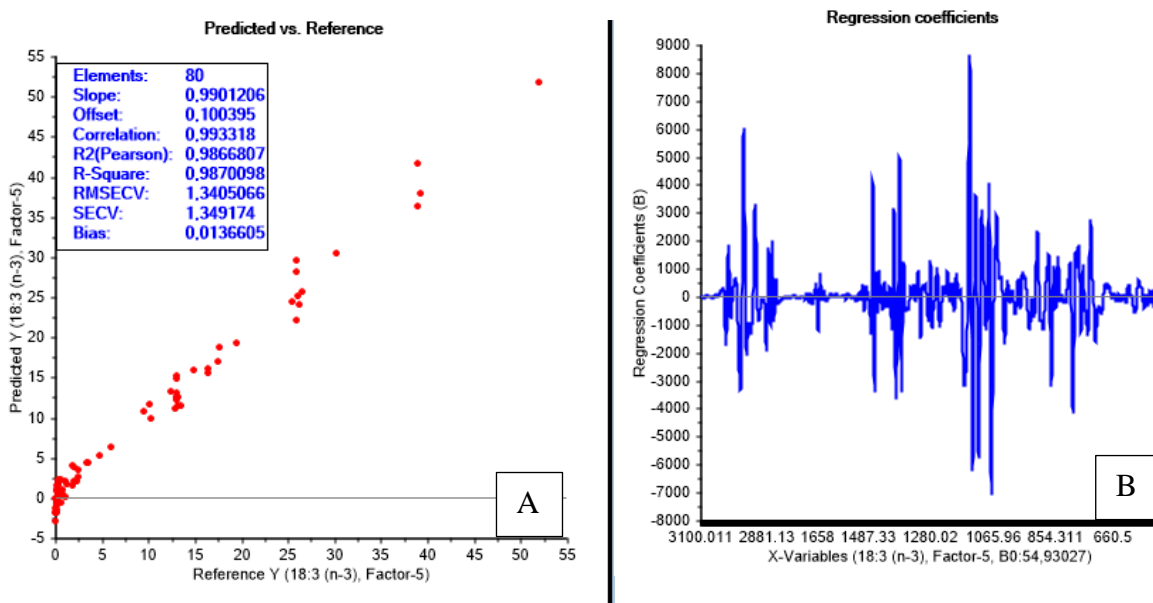


Figure K.4: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with C18:3n-3 as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with FTIR spectroscopy.

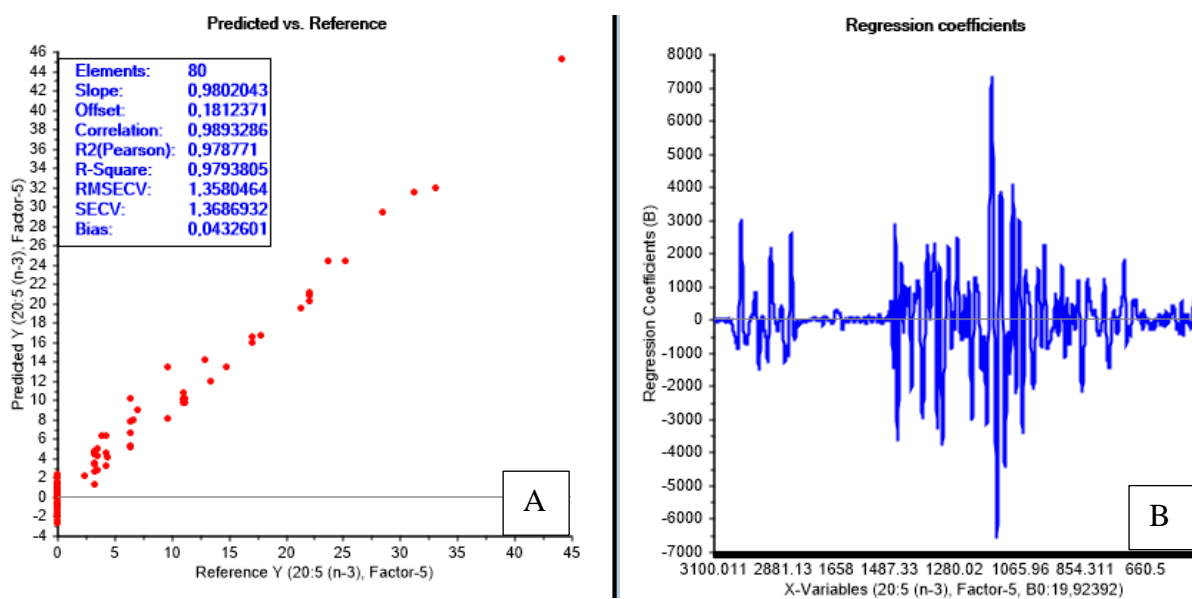


Figure K.5: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with C20:5n-3 as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with FTIR spectroscopy.

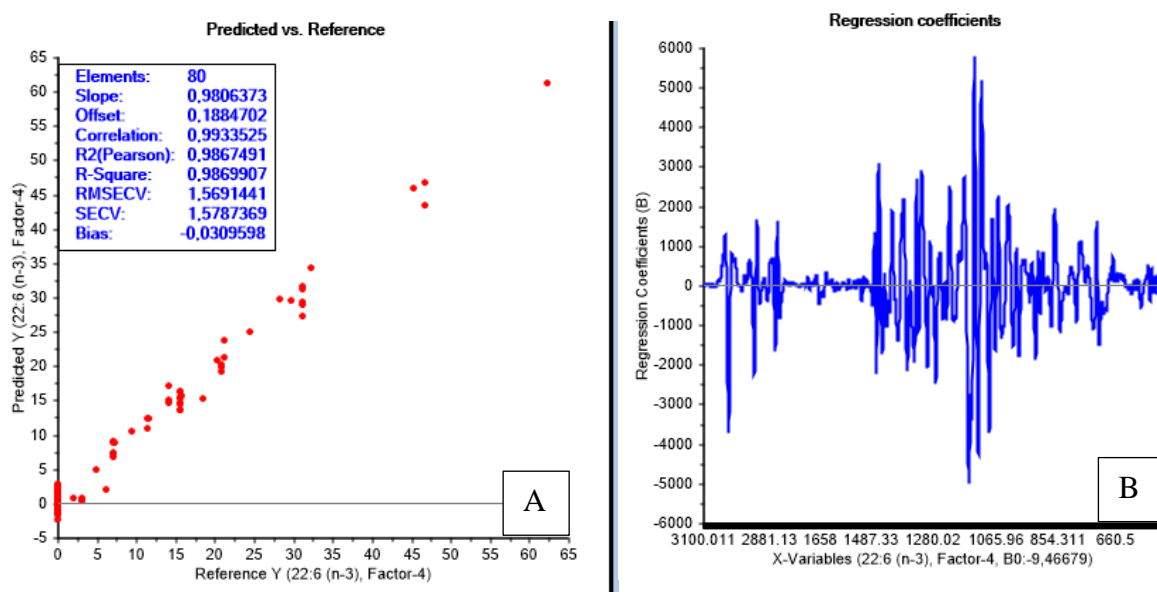


Figure K.6: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with C22:6n-3 as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with FTIR spectroscopy.

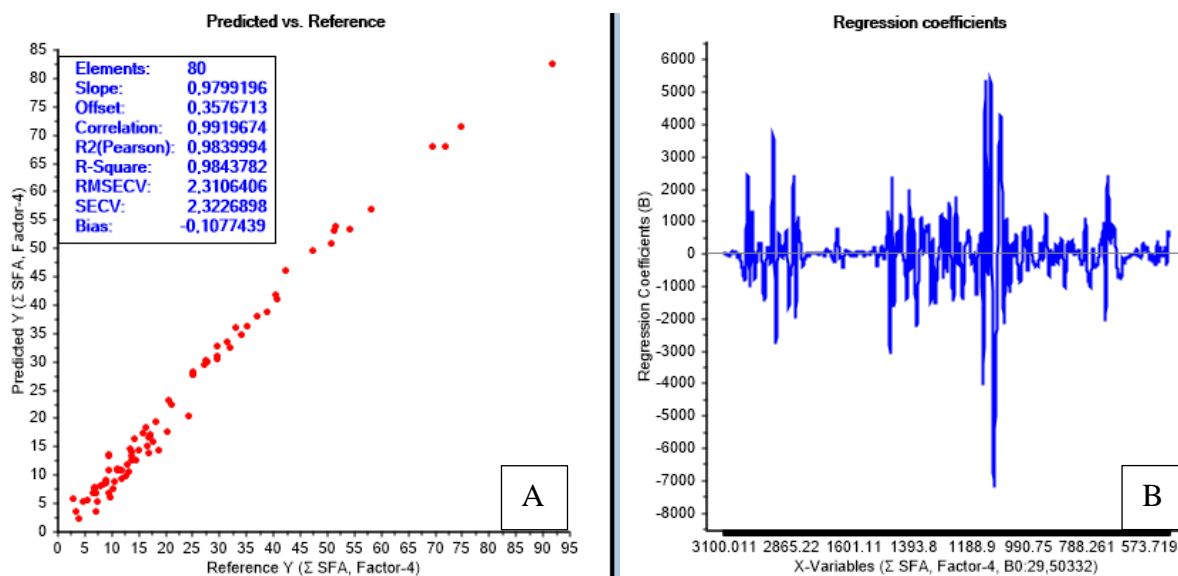


Figure K.7: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with Σ SFA as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with Raman spectroscopy.

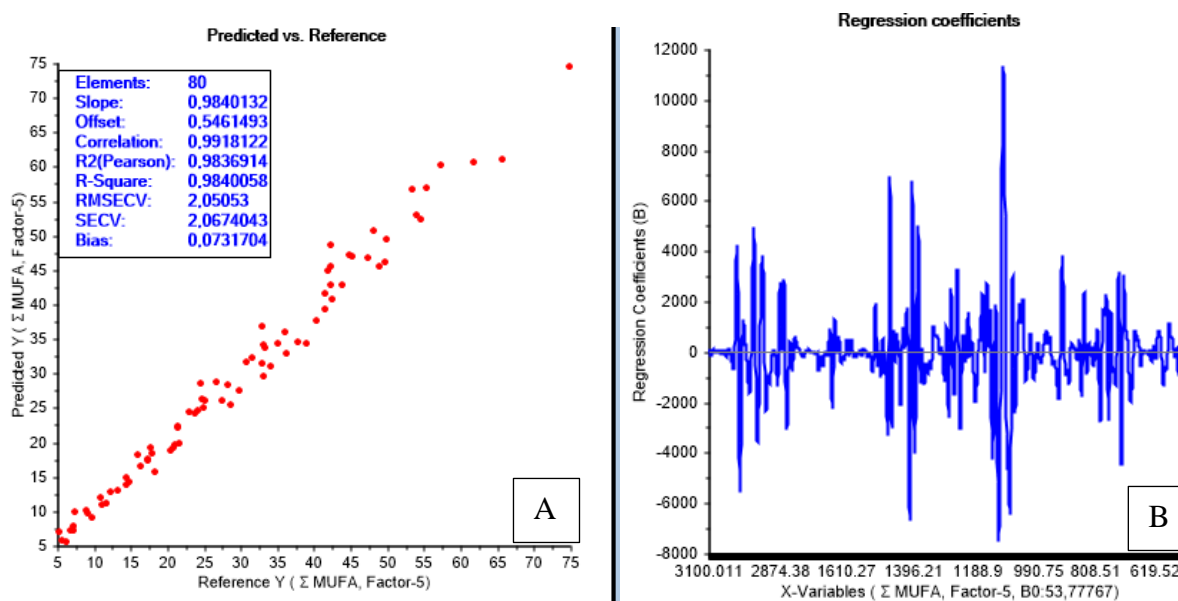


Figure K.8: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with Σ MUFA as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with FTIR spectroscopy.

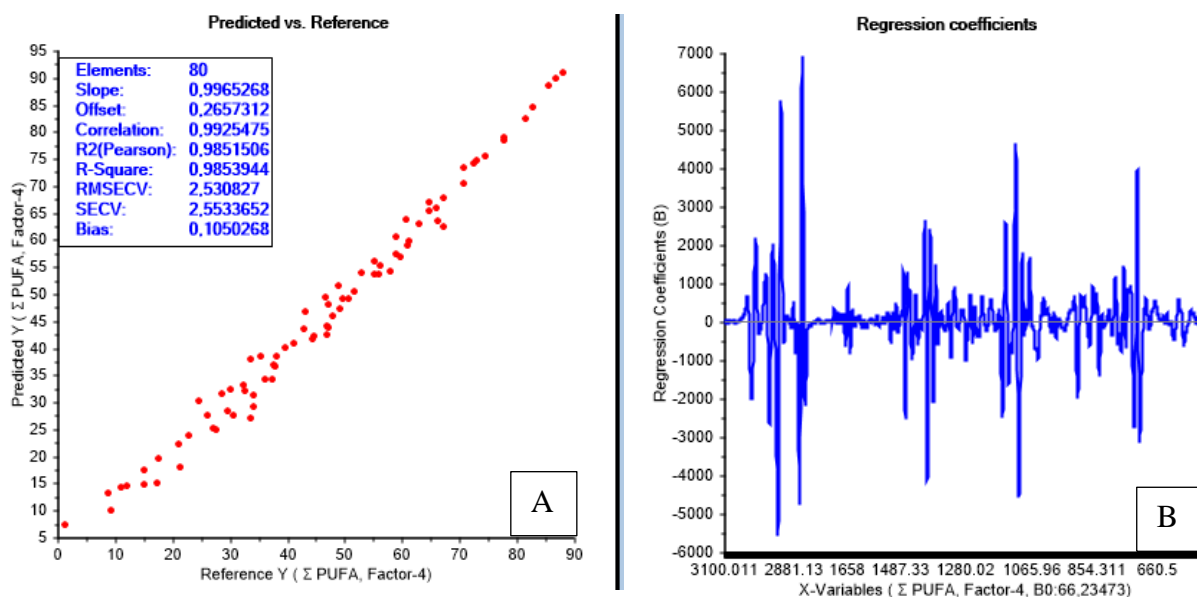


Figure K.9: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with Σ PUFA as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with FTIR spectroscopy.

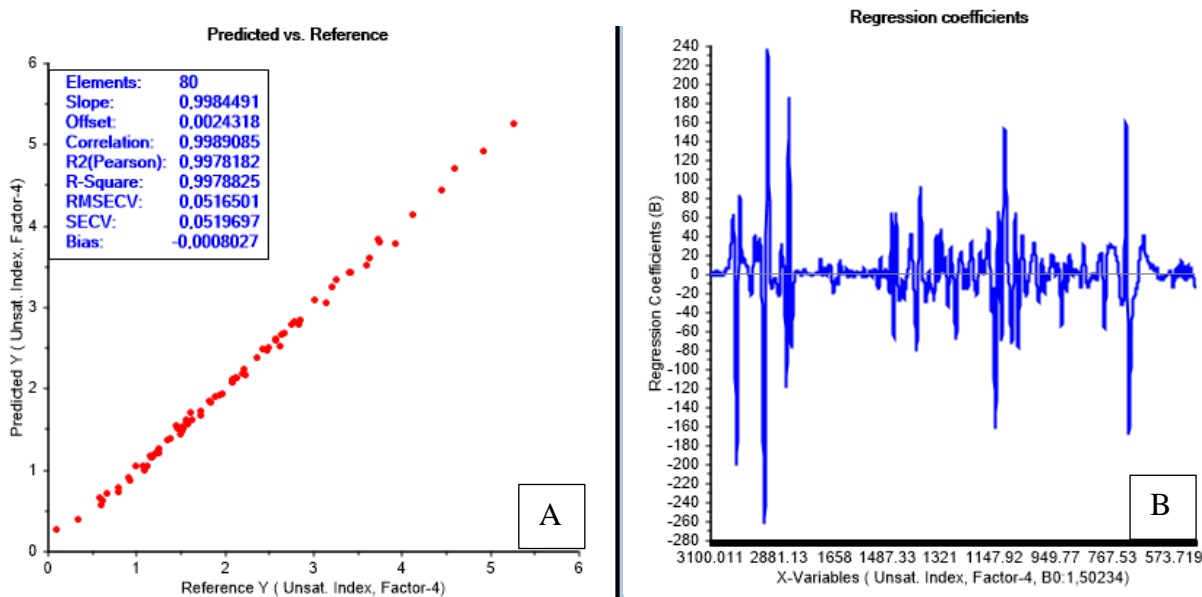


Figure K.10: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with UI 1 as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with FTIR spectroscopy.

Appendix L – PLSR based on Raman

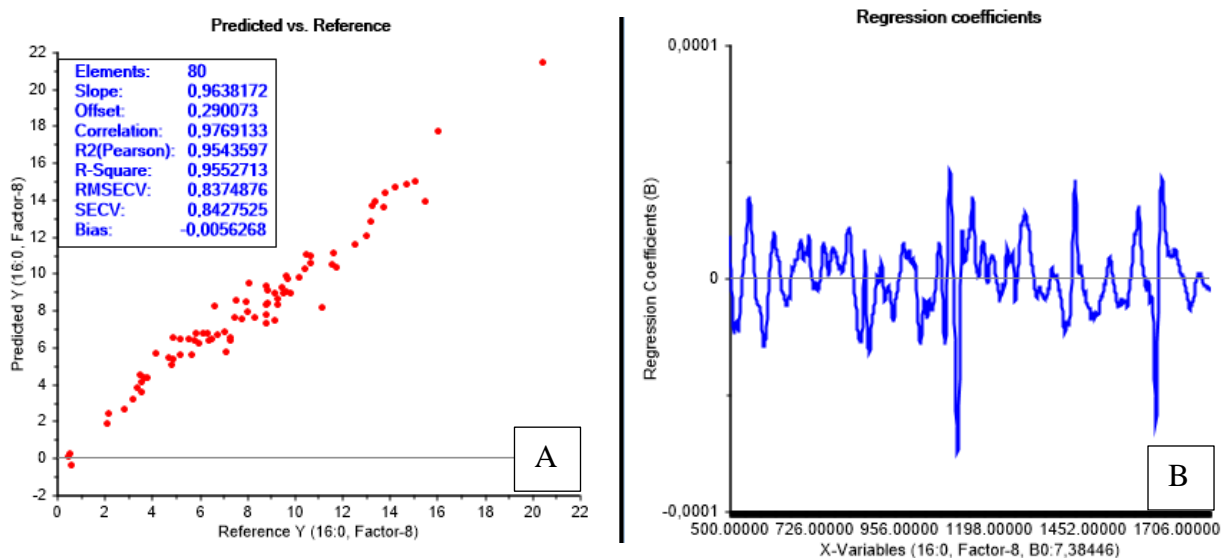


Figure L.1: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with C16:0 as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with Raman spectroscopy

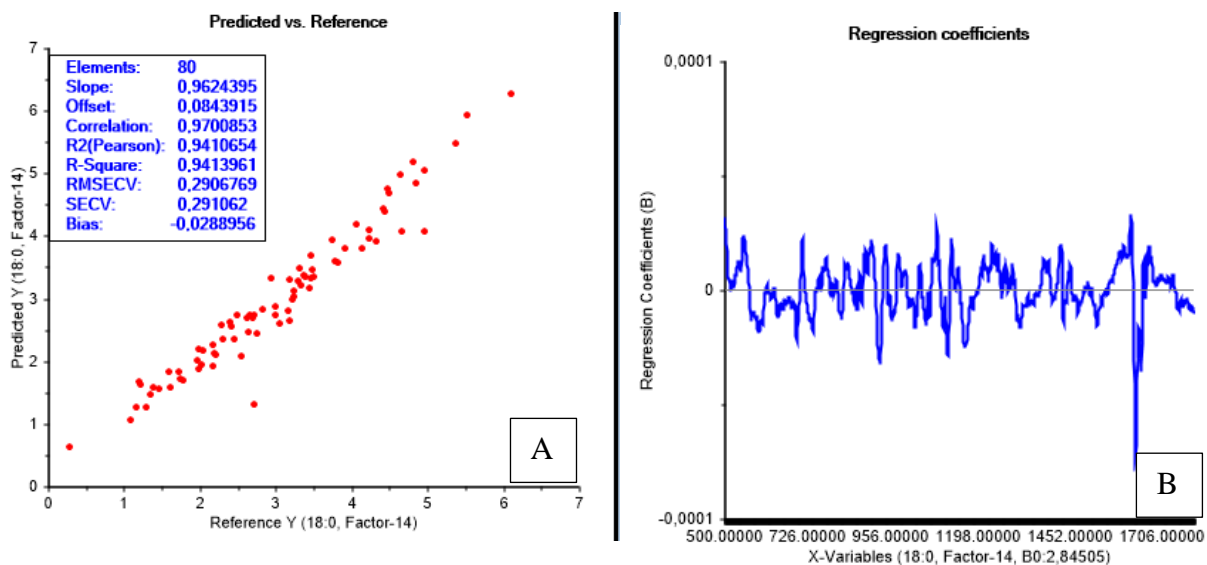


Figure L.2: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with C18:0 as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with Raman spectroscopy.

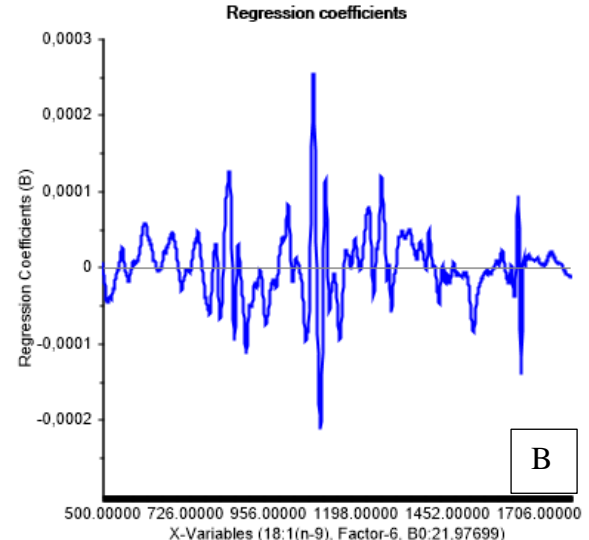
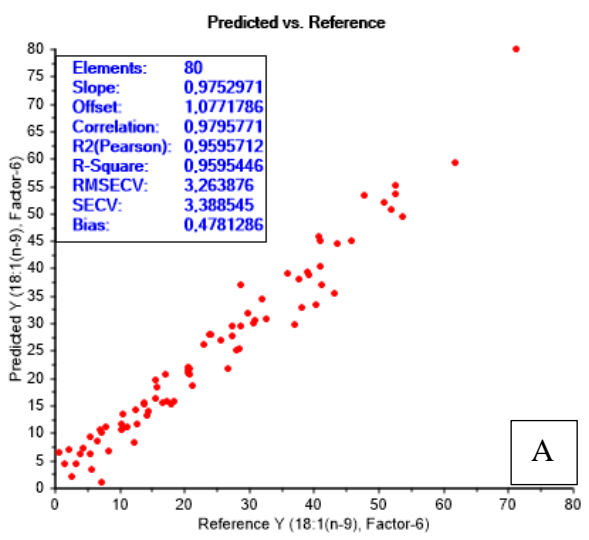


Figure L.3: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with C18:1n-9 as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with Raman spectroscopy.

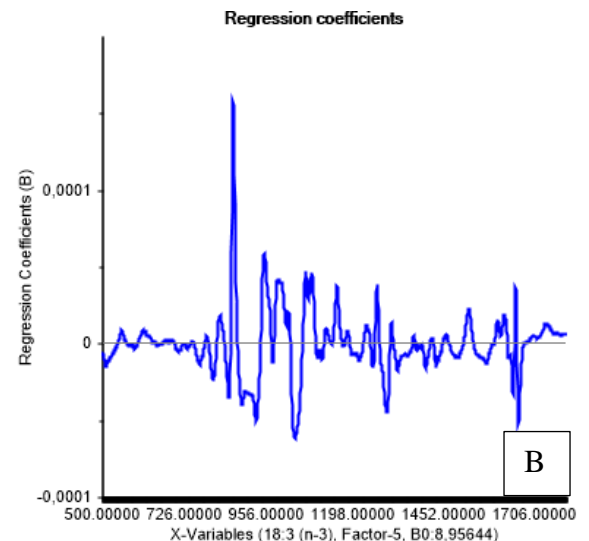
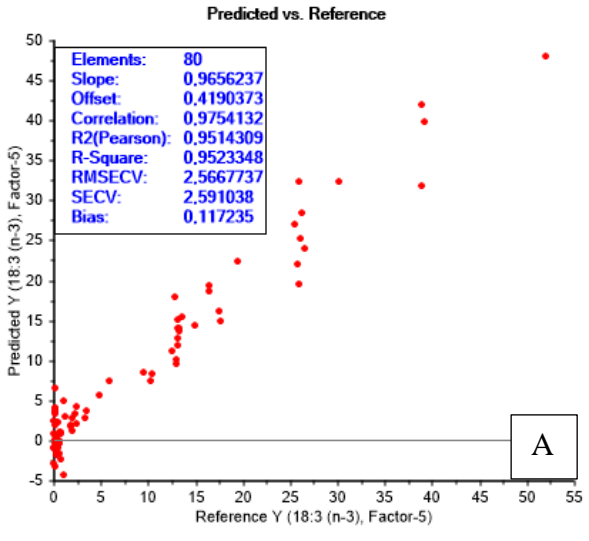


Figure L.4: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with C18:3n-3 as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with Raman spectroscopy.

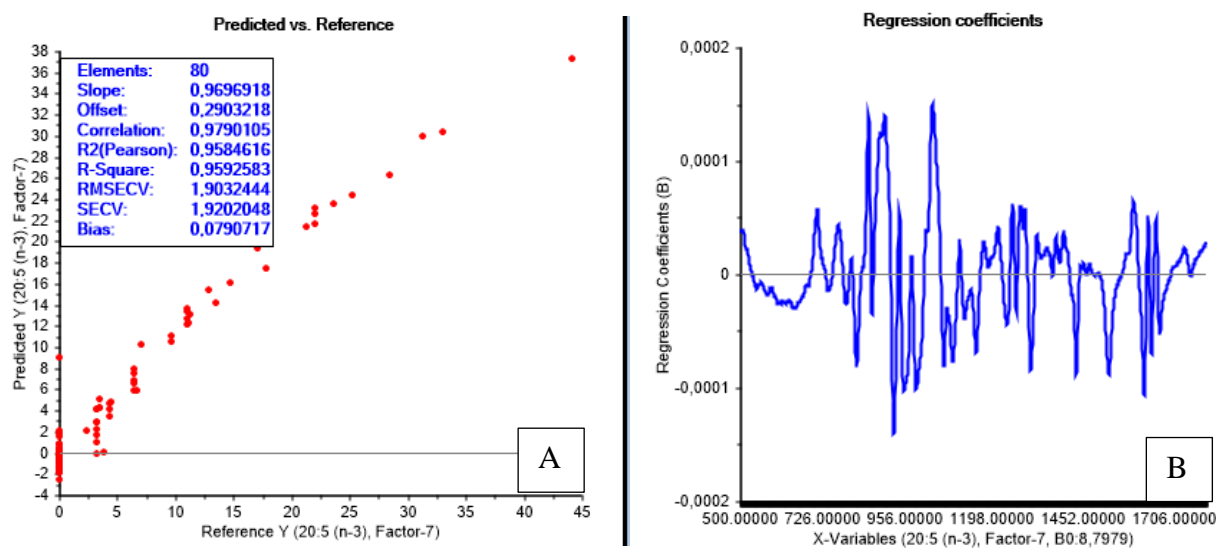


Figure L.5: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with C20:5n-3 as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with Raman spectroscopy.

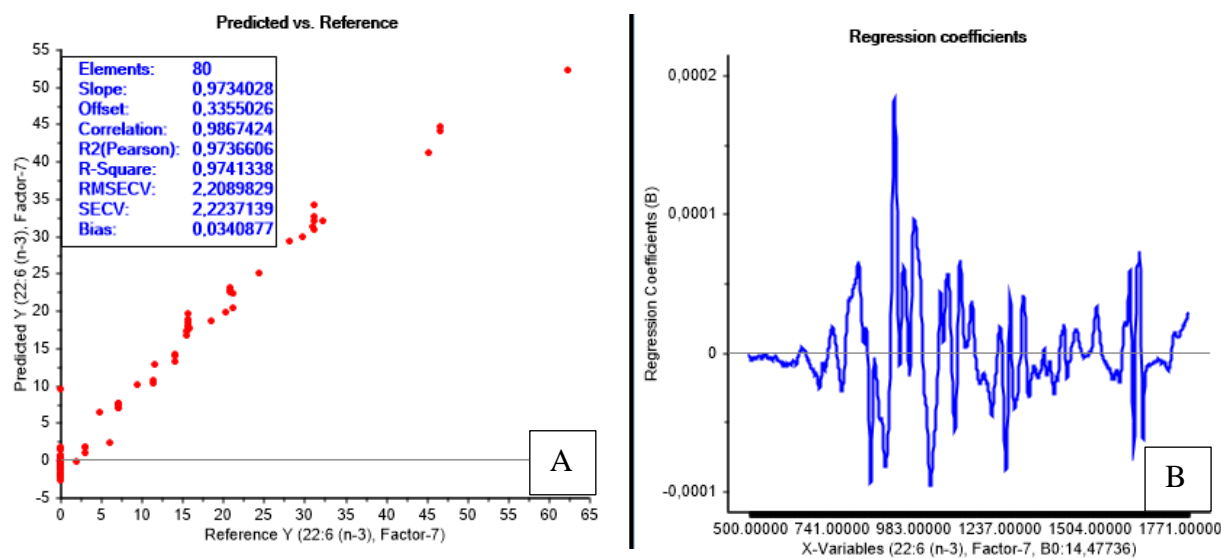


Figure L.6: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with C22:6n-3 as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with Raman spectroscopy.

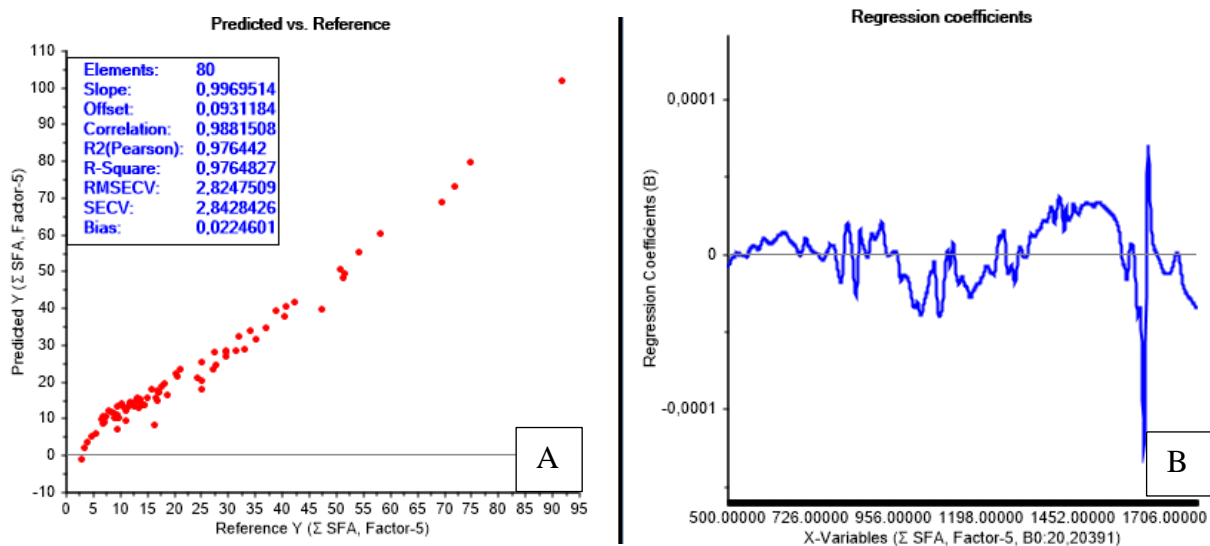


Figure L.7: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with Σ SFA as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with Raman spectroscopy.

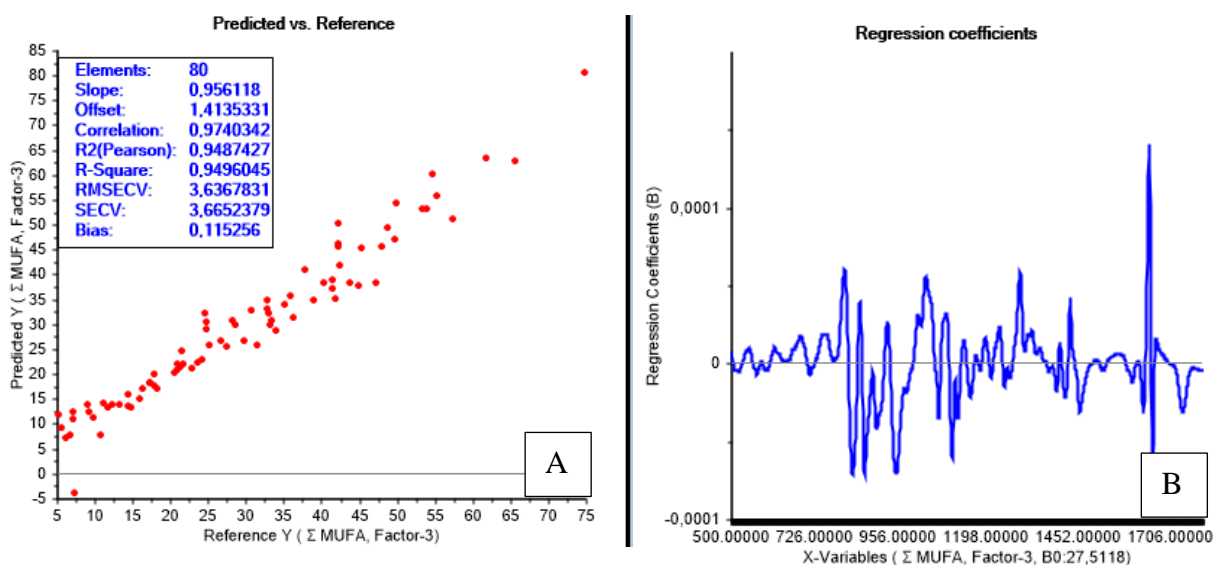


Figure L.8: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with Σ MUFA as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with Raman spectroscopy.

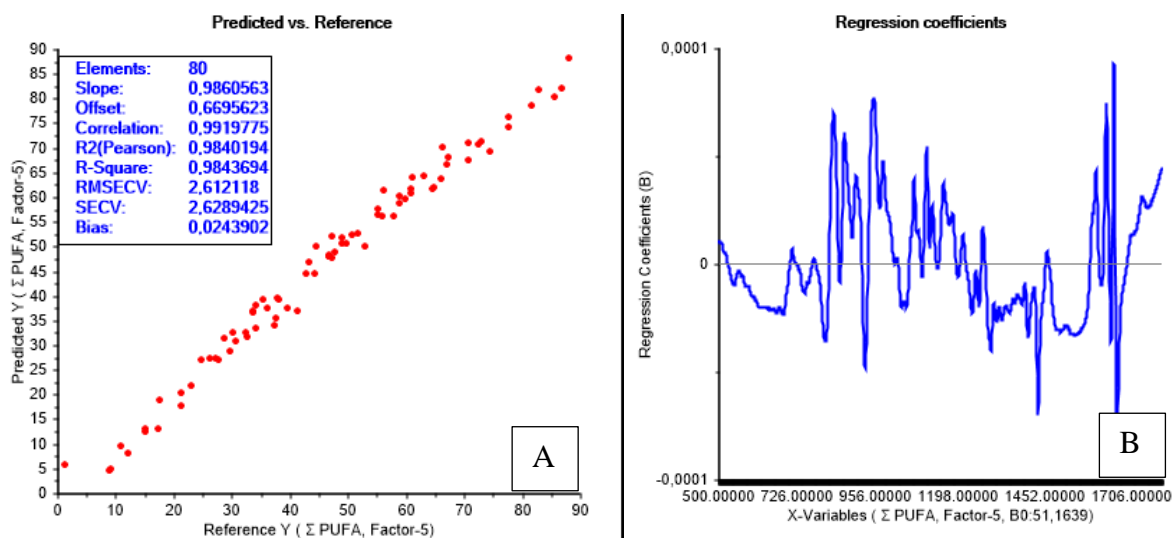


Figure L.9: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with Σ PUFA as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with Raman spectroscopy.

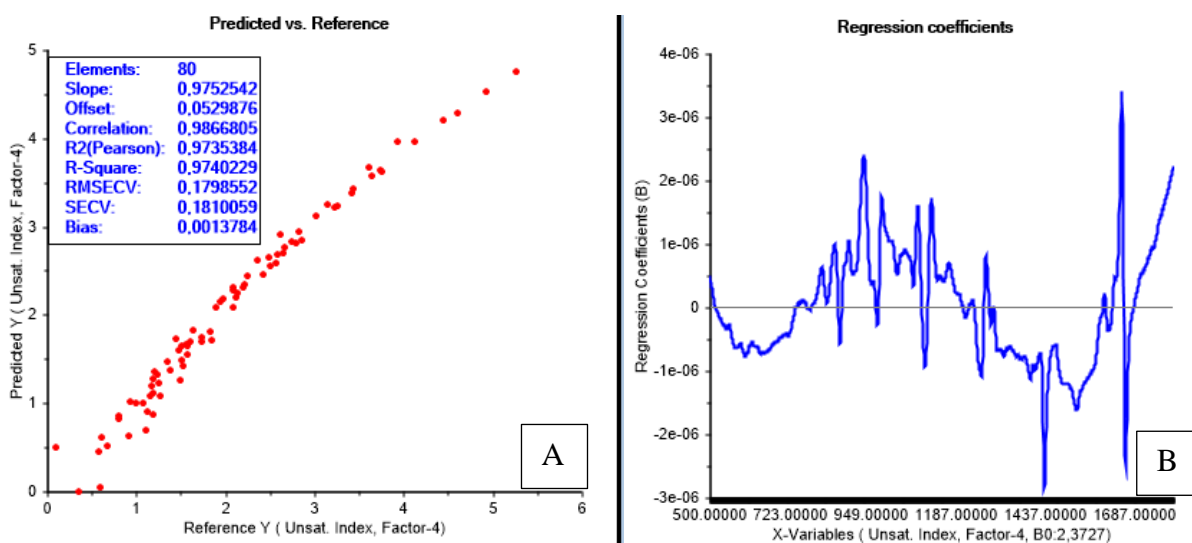


Figure L.10: Predicted vs. reference values (A) and regression coefficients (B) for the calibration model obtained with UI as response variable. The model was made using PLSR and was based on data from analysis of the calibration set with Raman spectroscopy.



Norges miljø- og biovitenskapelige universitet
Noregs miljø- og biovitenskapelige universitet
Norwegian University of Life Sciences

Postboks 5003
NO-1432 Ås
Norway