Biochemical composition and methane production correlations

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Abstract
Substrates for anaerobic digestion are composed of heterogeneous and complex organic matter. General parameters of the organic matter can be used to describe its composition such as sugar, protein and lipid contents, Chemical Oxygen Demand (COD), Biochemical Methane Potential (BMP) and kinetic of methane production. These parameters are required for the monitoring of digesters but their characterization are time consuming and expensive; thus, these parameters are rarely assessed all together. We investigated the existing correlations between COD, methane yield, biodegradability, kinetic of methane production and sugar, protein and lipid contents on 222 samples using principal component analysis and Pearson's correlation coefficient. Our work aims at providing a support to operators when only a partial characterization of the substrates is available. Positive correlation between methane yield and methane production kinetic but also unexpected independence of COD and BMP are shown. Sugars, proteins and lipids modulated differently the anaerobic digestion performances. Sugars are correlated with readily biodegradable organic matter while proteins are slightly anti-correlated with biodegradability. Lipids were correlated with high methane yield but slow methane productions. Finally, partial least square regression points towards more descriptive organic matter characterization that could be used to predict the kinetic of methane production.

Keywords
Solid waste characterization; biochemical composition; kinetic of methane production, biochemical methane potential, chemical oxygen demand, principal component analysis.

INTRODUCTION

The development of Anaerobic digestion (AD) for the production of energy from biomass, the growing number of installations and the diversity of substrates used for AD lead to the need of increasing robustness, performance and monitoring of the plants. AD technology has been successfully monitored for many years, see for example (Jimenez et al., 2015), and has been reported as mature technology for organic solid wastes (Mata-Alvarez et al., 2000). Nonetheless, its application remains challenging because of the heterogeneity in compositions of the substrate (Charnier et al., 2016). Thus co-digestion development for the production of methane from a large diversity of wastes occurs simultaneously with the need for advanced dynamic anaerobic digestion models like Anaerobic Digestion Model 1 (ADM1) (Batstone et al., 2015). The use of such models required a detailled biochemical characterization of the substrates (Jimenez et al., 2014). Chemical Oxygen Demand (COD), Biochemical Methane Potential (BMP), kinetic of methane production as well as sugar, protein and lipid contents of the substrate are the minimal parameters describing the substrate required to implement ADM1 (Batstone et al., 2002)(García-Gen et al., 2014). The understanding and characterization of these parameters are essential issues for optimal plant monitoring.

COD measurement gives the theoretical production of methane if all the organic matter is converted into biogas. COD analysis is often reported as a convenient, low cost and time-efficient analysis, which is traditionally used to evaluate AD performances (Jimenez et al., 2015). For solid substrate, an adaptation of the international standard method ISO15705:2002 is recommanded which consists

in a freeze drying and grinding of the solid substrates before COD analysis (Buffiere et al., 2008). Biochemical composition in lipid, protein and sugar content is more difficult to obtain. Lipid content can be obtained by hexane extraction (Girault et al., 2012). Protein content can be measured by the Kjeldahl procedure (Madsen et al., 2011). Ugwuanyi et al., (2005) recommended to assess sugar content by colorimetric measurements described in DuBois et al., (1956). Eventually, BMP assessment is obtained anaerobically by digesting a substrate in batch under optimal condition over 50 days (Hansen et al., 2004). Lesteur et al., (2011) and Jacobi et al., (2012) proved that Near InfraRed Spectroscopy (NIRS) can be used to analyze rapidly BMP. BMP analyses are labor-intensive and time-consuming. The use of NIRS to predict gas yields cut the analysis time to a matter of minutes (Ward, 2016). Nonetheless, NIR spectrometer remains expensive, which makes it affordable only for very few units. Eventually, estimation of the kinetic of methane production has been reported as inaccurate on single batch analysis and requires 6-8 successive feeding of the same reactor, to adapt the biomass to the substrate, before estimating the kinetic of methane production (García-Gen et al., 2015). As a result, kinetic estimation is rather labor intensive and longer than traditional BMP assessment.

Hence, the estimation of total sugar, protein or lipid contents, COD, BMP and kinetic of methane production in solid samples is feasible but remains challenging, expensive and time-consuming (Jimenez et al., 2015). Thus, a detailed characterization of the substrate providing the required parameters for plant monitoring is rarely available and only few of these parameters are assessed in real plant monitoring conditions. A better understanding of their relationships could encourage the use of advanced dynamic models such as ADM1 and help the developpement of anaerobic digestion industries (Lauwers et al., 2013).

The aim of this study is to understand the existing correlations between sugar, protein or lipid contents, COD, BMP and the kinetic of methane production to facilitate plant monitoring with partial characterization of the substrates. For that purpose, Principal Component Analysis (PCA) and Pearson's correlation were carried out on these parameters measured for 222 fully characterized samples. Finally, PLS regression was carried out to evaluate the feasibility of methane production kinetics prediction from the biochemical composition.

MATERIALS AND METHODS

Sugar content analyses

An adaptation of the protocol described by Dubois et al., (1956) was used. An hydrolysis of 0.050 g of freeze-dried and grinded samples was done in a shaker for 6h in 5 mL sulfuric acid (98% mass). Then, Dubois et al, (1956) protocol was used. Phenol and sulfuric acid were added to the solution. Absorbance of the samples was measured at 490 nm with a spectrophotometer. Sugar content is expressed in COD equivalents in $mgO_2.g^{-1}$.

Protein content analyses

Total Kjeldahl Nitrogen (TKN) standard method was used to analyze the nitrogen content of the samples. Freeze-dried and grinded samples were suspended in 5mL of distilled water and 10 mL of sulfuric acid solution (98% in mass) with 0.366 $g.L^{-1}$ copper selenite as a catalyzer. The sample was heated to 420°C until the hydrolysis was completed. TKN was finally measured using TKN Buchi AutoKjeldahl Unit K-370 (Buchi®, Flawil, Switzerland), Kjeldhal method. TKN was expressed in grams of nitrogen per gram of dry matter. The TKN content is then converted into protein content using a ratio of 6.25 (Girault et al., 2012).

Lipid content analyses

Freeze-dried and grinded sample was extracted with hot and pressurized heptane using an extra-accelerated solvent extractor ASE 200 (Thermo Fisher Scientific®, Sunnyvale, California 94085 USA). The extracted solution was collected and heptane was evaporated under a N_2 flow. The remaining quantity of extracted fatty matter was considered to be the lipid content of the sample. Results were expressed in grams of lipids per gram of dry matter ($g.TSg^{-1}$).

Chemical oxygen demand and biodegradability analyses

The COD of samples and extracts were measured according to the ISO15705:2002 international standard using a COD Vario Tube Test MR (Tintometer GmbH, Division Aqualytic, Dortmund, Germany). An hydrolysis of 0.050g of freeze-dried and grinded sample were done in a shaker for 6 h in 5 mL sulfuric acid (98% mass). The traditional procedure was then applied, vials were heated to 150 °C for 2 h and the resulting oxygen consumption was determined by spectrophotometry (Muller and Jimenez, 2014). Results were expressed in milligrams of O_2 per gram of dry matter ($mgO_2.TSg^{-1}$). According to Jimenez et al, (2014), biodegradability was calcultate as a ratio of BMP to COD (Equation 1).

$$Biodegradability = \frac{\mathrm{BMP}_{(\mathrm{NmlCH_4.TSg^{-1}})}}{0.35 * \mathrm{COD}_{(\mathrm{mgO_2.gTS^{-1}})}} \quad (1)$$

Methane yield and methane production time

According to (García-Gen et al., 2015), biological degradations of the substrates were carried out under mesophilic conditions in 8.5 L batch reactors with 6L of sludge and a loading rate of 1 $gVS.l^{-1}$. Eight successive batches were run with the same substrate in order to adapt the micro-organism to the substrate. The biogas produced was recorded online using a milligas counter fitted with a digital output (MGC-1 gas flow meters, DR.-ING.RITTER APPARTEBAU GMBH & CO.KG, Bochum, Germany). Methane yield and methane production time were assessed on the eighth batch. Methane yield of the substrate corresponded to the methane produced from one gram of total solid. Methane production times were selected based on the methane production rate as the times required reaching a certain percentage of the methane yield from 5 to 95 % with a regular increment of 5 %.

Samples analyzed

222 samples representing a wide range of AD substrates were used in this study. In details, analyses were carried out on Fat, Oil and Grease (FOG), fruits, vegetables, farm wastes, cereal, meat or fish extracts, micro-algae and mixed organic wastes. The mean content was about 0.032 $g.gTS^{-1}$, 0.034 $g.gTS^{-1}$, 710 $mgO_2.gTS^{-1}$, 1205 $mgO_2.gTS^{-1}$, 0.70 and 0.297 $L.gTS^{-1}$ for proteins, lipids, sugars, COD, biodegradability and methane yield respectively. From 5 to 95 percent of the methane yield, the methane production mean times were respectively 0.07 d^{-1}, 0.12 d^{-1}, 0.16 d^{-1}, 0.22 d^{-1}, 0.28 d^{-1}, 0.35 d^{-1}, 0.44 d^{-1}, 0.54 d^{-1}, 0.68 d^{-1}, 0.86 d^{-1}, 1.10 d^{-1}, 1.43 d^{-1} 1.88 d^{-1}, 2.53 d^{-1}, 3.43 d^{-1}, 4.55 d^{-1}, 5.80 d^{-1}, 7.13 d^{-1}, 8.54 d^{-1}. The standard deviations were about 0.029 $g.gTS^{-1}$, 0.094 $g.gTS^{-1}$, 246$mgO_2.gTS^{-1}$, 148$mgO_2.gTS^{-1}$, 0.15 and 0.063 $L.gTS^{-1}$ for proteins, lipids, sugars, COD, biodegradability and methane yield respectively. From 5 to 95 percent of the methane yield, the methane production mean time were respectively 0.05 d^{-1}, 0.10 d^{-1}, 0.14 d^{-1}, 0.19 d^{-1}, 0.25 d^{-1}, 0.31 d^{-1}, 0.38 d^{-1}, 0.45 d^{-1}, 0.52 d^{-1}, 0.59 d^{-1}, 0.67 d^{-1}, 0.75 d^{-1} 0.81 d^{-1}, 0.82 d^{-1}, 0.77 d^{-1}, 0.65 d^{-1}, 0.51 d^{-1}, 0.35 d^{-1}, 0.18 d^{-1}. Figure 1A summarizes the data set characteristics for proteins, lipids, sugars, COD, biodegradability and methane yield using boxplot. Data were scaled and centered in order to represent the different data on the same figure. Figure 1B summarizes the data set characteristics of methane production time expressed in days needed to reach a percent of the methane yield from 5 to 95 %.

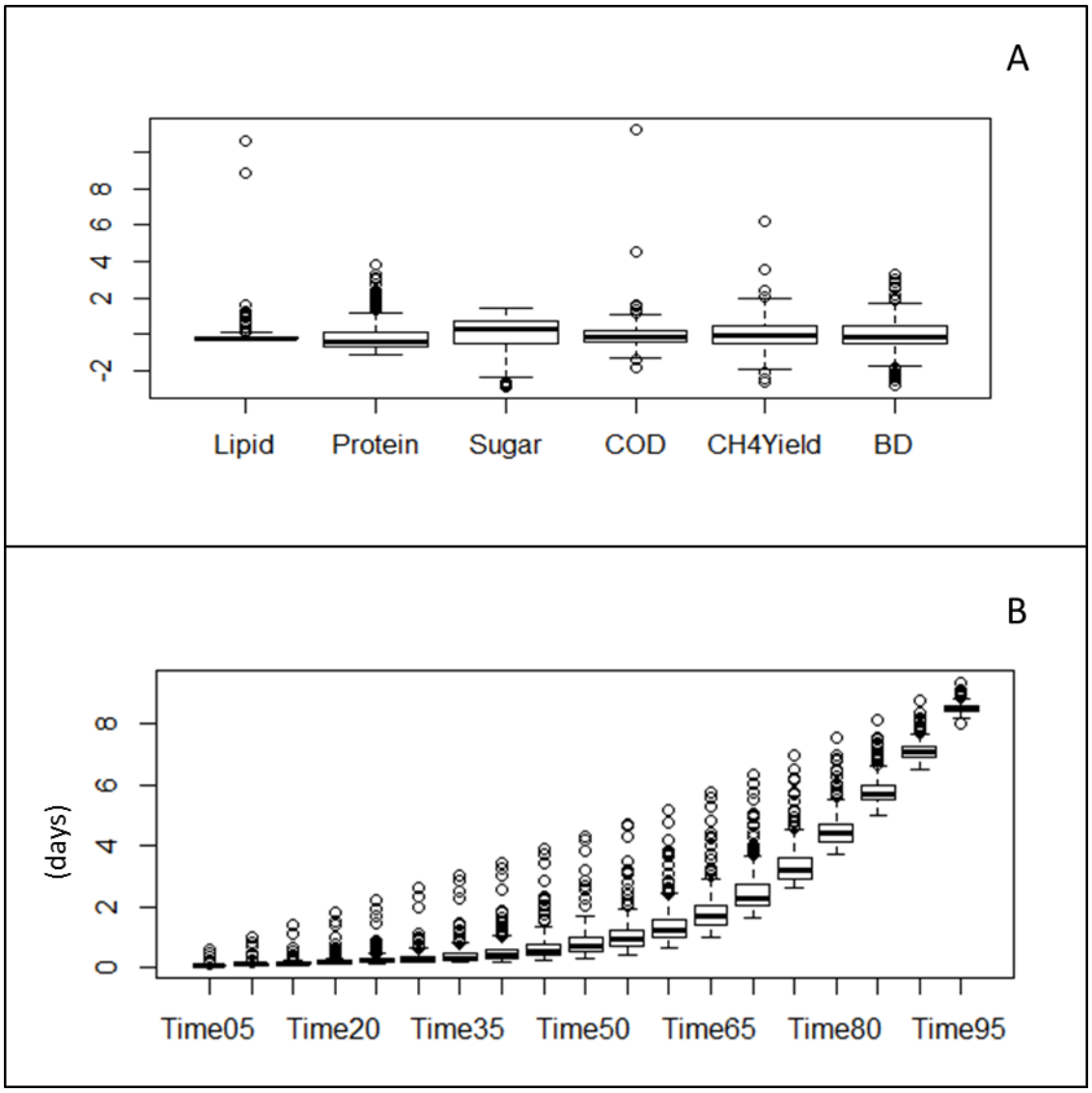

Figure 1: Boxplot of data set characteristics. Figure 1A represents the lipid, protein and sugar contents, COD, methane yield (CH4YIELD) and biodegradability (BD) on centered and scaled data. Figure 1B represents the methane production time expressed in days needed to reach a percent of the methane yield from 5 to 95%.

Principal component analysis

Principal Component Analysis (PCA) reduces the dimensionality of the data while retaining as much variance as possible (Al-Kandari and Jolliffe, 2005). PCA projects the data into the space spanned by orthogonal axis named principal components, which are a linear combination of the original variables. In this study, the original variables are lipid, protein and sugar contents, COD, methane yield, biodegradability and methane production time expressed in days needed to reach a percent of the methane yield from 5 to 95%. For the PCA analysis, data were centered and scaled. The number of principal components has been chosen to represent 90% of the total variance. PCA was used as an exploratory tool to identify the variables that explain most of the variance within the data set and to assess the existing correlations between variables. In order to verify the accuracy of the PCA, projections of the samples on the principal components were also observed.

Pearson's correlation and neural network

The correlations highlighted with the PCA were validated using Pearson's correlation. Pearson's correlation sets the correlations between the variables two by two by dividing their covariance with

the product of their standard deviation. It provides a coefficient which varies in a range from 1 to -1, indicating respectively a correlation to an anti-correlation . Permutation test with 9999 permutation were performed on the Pearson Correlation Coefficient (PCC) indicating if the coefficient were significantly different (alpha=0.05) from 0. One heatmap and one network were drawn using the package corrplot from R 3.2.2 which takes in consideration either PCC and p-values. The non-significant correlations were represented as non-existing correlation.

Partial least square regression

PLS regression model was performed using the FACT toolbox with Scilab® 5.5.0. To select the number of latent variables, cross-validation was performed. The Jackknife method, splitting the dataset into 15 blocks of equivalent sizes, was used. Each block was alternatively removed from the calibration dataset used for the cross-validation in order to estimate the accuracy of the prediction. Thanks to these results, the number of latent variables was chosen to maximize the accuracy and robustness of prediction. The Standard Error of Calibration (SEC), Standard Error of Cross Validation (SECV), determination coefficients between predicted and reference values (R^2) were assessed.

RESULTS AND DISCUSSION

Dataset exploration using a principal component analysis

A principal component analysis has been carried out on the dataset to explore the existing correlation between sugar, protein and lipid contents, COD, methane yield, biodegradability and methane production time. It was decided to focus on the three first principal components (PC) which take into account more than 90% of the total variance. Figure 2 shows the samples of the dataset represented on the three PC of the PCA. Spheres has been colored depending on their biochemical composition, turqoise spheres have a lipid content above 50%, yellow spheres have a protein content above 50% and red spheres have sugar content above 50%, grey spheres represent the remaining data. No overlapping on the conditions were found. Four differents groups of samples can be observed. The majority of the samples are rich in sugar and represented in the Elipse Hoteling's T2 (95%). Another group is composed by two samples with a high score on PC1 and PC2. It corresponds to the FOG samples, characterized with a high content of lipids. Seven samples composed a third group, with high score on PC1 and PC3 but low on PC2, it matches the farm waste samples rich in sugars and proteins. Eventually, samples present a low score on PC1 and PC2 but a high score on PC3, corresponding to protein rich substrate like meat and fish extracts and micro-algae. The three first components differentiate farm waste, FOG and meat and fish exctrat or micro-algae from cereal, fruits and vegetables. Samples are fairly represented on the three PCs and samples seem to be classified depending on their protein, sugar and lipid contents, with farm waste rich in proteins and sugars, meat, fish or micro-algae rich in proteins, and FOG rich in lipids.

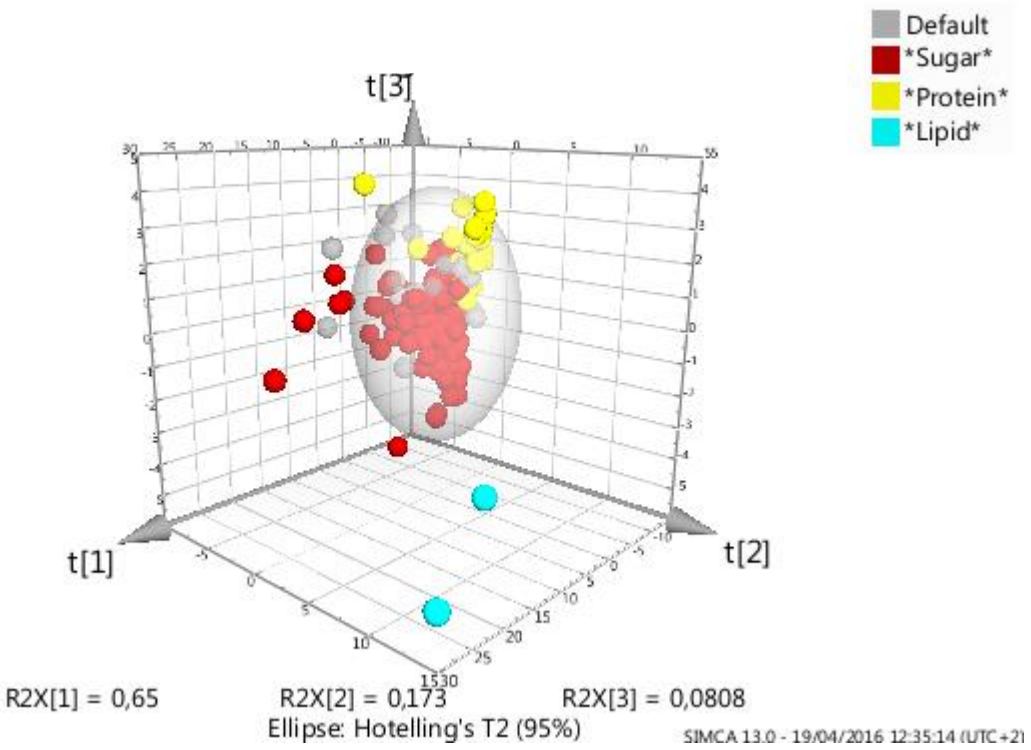

Figure 2: 3D representation of the dataset on the three first principal components of the PCA. Spheres are colored depending on their biochemical composition, turquoise spheres: lipid content up to 50%, yellow spheres: protein content up to 50%, red spheres: sugar content up to 50%, grey spheres represent the remaining data.

Variables correlation exploration using a principal component analysis

To go further on the analysis, PCA variables have been plotted on the PC1/ PC2 and PC1/PC3 (Figure 3). PC1, accounting for 65 % of the variance is mainly supported by the methane production time. It shows correlations between the methane production times. These correlations make sense since the production of one point depends of the previous points. Lipids and COD in a smaller manner also participate to PC1 and seem correlated with methane production times while sugar concentration and biodegradability are in opposition with the methane production times in PC1. In PC2, methane yield, COD and lipid content are opposed to sugar content but also early and late kinetic of methane production. PC3 is supported by protein content which is in opposition to biodegradability, sugar content and methane yield. To sum up the variable analysis on PCA, methane production times are represented as correlated to each other and represent, with lipid content, most of the variance. PC2 represents a smaller part of the variance and opposes proteins and sugars. PC3 opposes biodegradability and sugar content to protein content. Biodegradability is opposed to sugar content on PC2. Their correlation on PC3 indicates that PC3 does not contain any discriminante information between sugar and biodegradability. Biodegradability is shown as anti-correlated with lipid content and COD but correlated with methane yield on PC1-2-3.

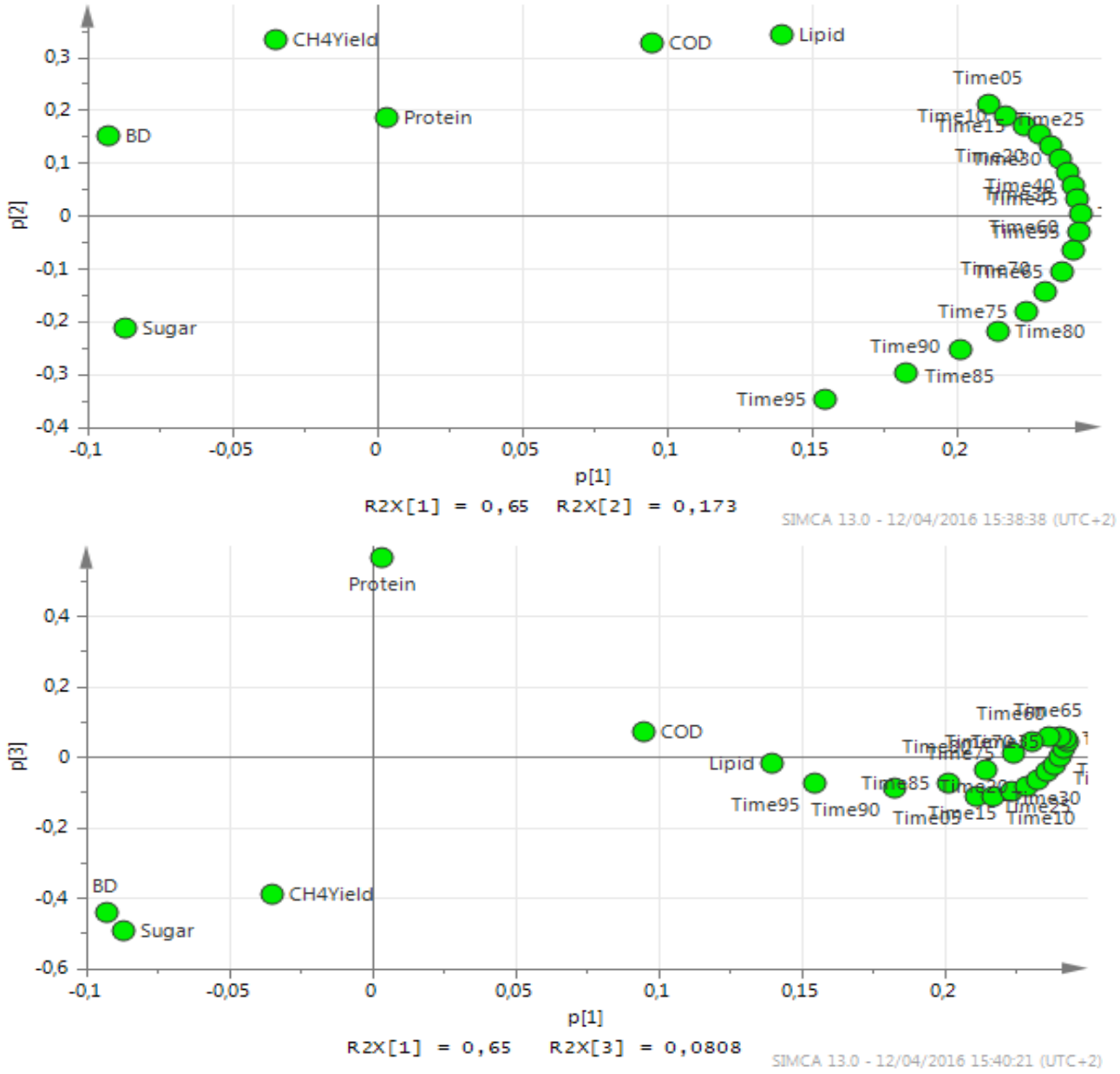

Figure 3: PCA variables representation on PC1/PC2 (up part) and PC1/PC3 (down part). BD and CH4Yield stand respectively for biodegradability and methane yield. Time 05 to 95 represent the time needed to reach a percent of the methane yield from 5 to 95%.

Variables correlation analysis using Pearson correlation coefficients

PCA has been used as an exploratory tool to assess potential correlations between lipid, protein and sugar contents, COD, methane yield, biodegradability and methane production time expressed in days needed to reach a percent of the methane yield from 5 to 95 %. As pointed out, PCC must be used to validate these correlations (see MATERIALS AND METHODS section). This led to a correlation matrix which has been plotted as a heatmap (Figure 4). From the p-values analysis, correlations revealed non-significant are shown as non-existing correlation, PCC=0. Thus, every correlation shown in figure 4, even low, is significant. As it can be seen in Figure 4 and PCA analysis, methane production times are correlated to each other. Nonetheless, weak correlations, around 0.2, are found between early and late methane production times. This indicates that the methane production is represented by at least two distinct kinetics as validated on sludge or fruit and vegetables AD by Jimenez et al., (2014) and García-Gen et al., (2015).

Relationship between biochemical composition and methane production time can be observed in Figure 4. Lipid content is correlated with methane production time from 5 to70% of the methane yield with decreasing PCC respectively from 0.81 to 0.21. Sugar content is anti-correlated with methane production time from 5 to 75 % of the methane yield with PCC from -0.20 to -0.38. Protein content is anti-correlated with methane production time from 80 to 95 % of the methane yield with PCC of respectively -0.24, -0.28, -0.29. COD is correlated with methane production times, with decreasing PCC from 5 to 70 % of the methane yield in a range from 0.61 to 0.19, and anti-correlated with methane production time of 95 % of the methane yield (PCC: -0.23). Methane yield is weakly correlated with methane production time, with decreasing PCC from 5 to 15 % of the methane yield in a range from 0.21 to 0.13, and anti-correlated with methane production time, with decreasing PCC from 50 to 95 % of the methane yield in a range from -0.15 to -0.47. Biodegradability is anti-correlated with methane production times, with decreasing PCC from 5 to 95% of the methane yield in a range from -0.14 to -0.44.

Correlation and anti-correlation between the indicators of the biochemical composition of the organic matter are shown in Figure 4. Lipid content is correlated with the methane yield, weakly with protein content and anti-correlated with the sugar contents with PCC of respectively 0.44, 0.16, -0.49. Sugar content is anti-correlated with lipid and protein content and COD with PCC of respectively -0.49, -0.85, -0.40. Protein content is weakly correlated with lipid content and COD with PCC of respectively 0.16, 0.19. Biodegradability is anti-correlated with COD with a PCC of -0.23. Eventually, methane yield is correlated with COD with a PCC of 0.35.

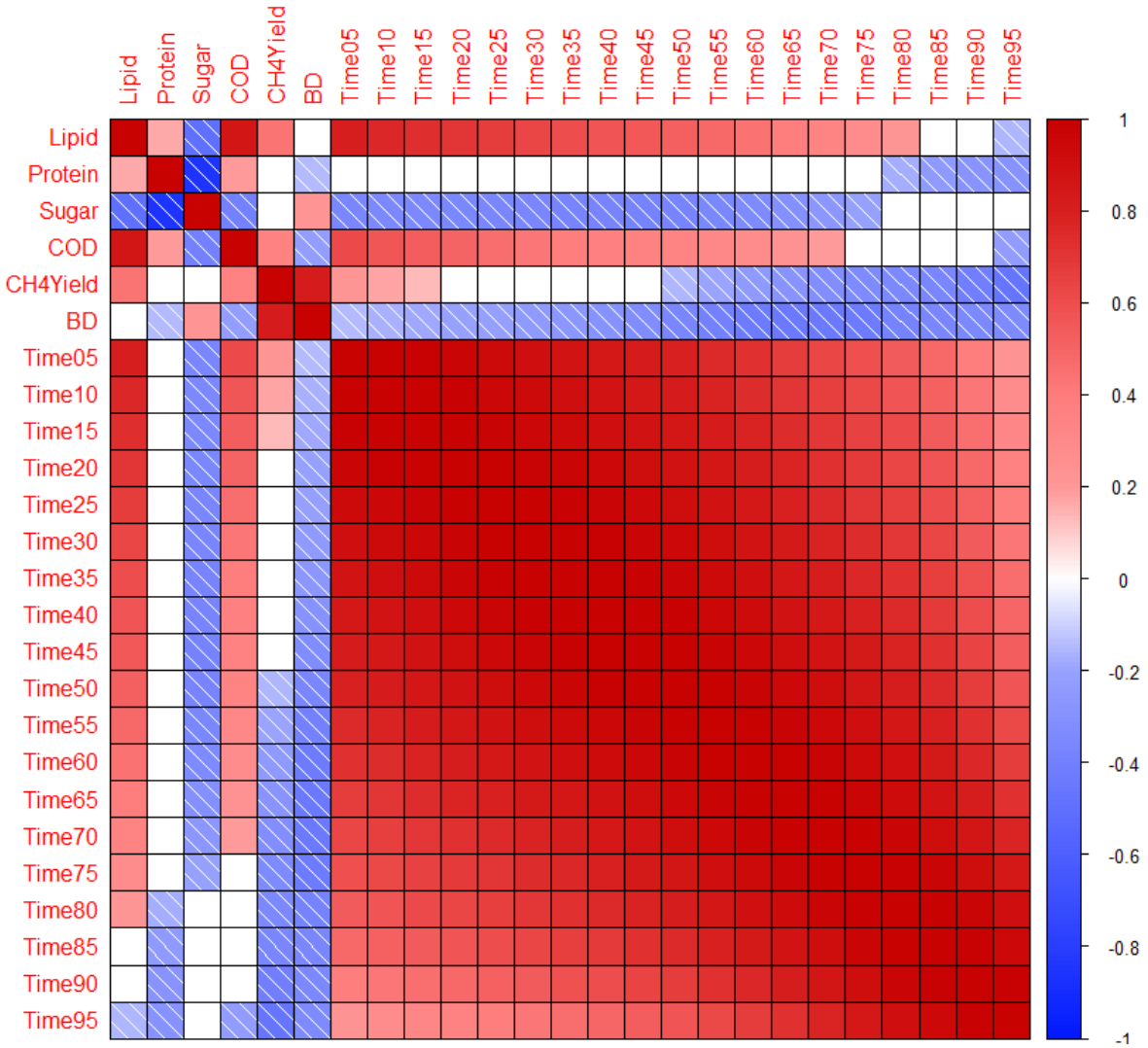

Figure 4: Matrix of Pearson's correlation coefficients between lipid, protein and sugar contents, COD, methane yield (CH4YIELD) and biodegradability (BD), methane production time expressed in days needed to reach a percent of the methane yield from 5 to 95%.

Discussion about variables correlation analysis

From PCA and Pearson's correlation coefficients, a first conclusion can be drawn about the existing correlations between lipid, protein and sugar contents. Part of the organic matter such as lignin is not analyzed as protein, lipid or sugar. Thus one hypothesis could be that, biodegradable organic matter represented by sugars, lipids and proteins are correlated between each other and anti-correlated with non biodegradable organic matter such as lignin. However, protein and lipid contents were correlated indicating that high-protein content in a sample is often correlated with an important lipid content. Meat or micro-algae are good examples of the correlation between protein and lipid content. But lipid and protein contents were both anti-correlated with sugar content, which can be explained by the difference between animal cells with high protein content and vegetal cells with high sugar content.

From PCA and PCC analyses, COD is strongly correlated with biochemical composition in sugar, protein and lipid content. Sugars are shown highly biodegradable but with a lower COD than proteins which has a lower COD than lipids. COD and methane yield are both indicators of the energy contained in the organic matter and their ratio represents the biodegradability. Nonetheless,

correlations found on COD cannot be extended to methane yield. The low correlation between COD and methane yield and the anti-correlation between COD and biodegradability observed indicate that methane yield and COD are quite independent parameters. Indeed, supposing a constant methane yield, the higher the COD, the lower the biodegradability. Hence, COD cannot be used to estimate the methane yield.

Correlations between methane production time and biochemical composition are complex. From Figure 1, it can be observed that the higher standard deviation between methane production time is observed at 70% of the methane yield. This means that most of the methane production time differences between the samples can be found at 70% of the methane yield. Thus the time needed to reach 70% of the methane is the most informative point about methane production kinetics. In order to simplify correlation analyses, a correlation network between methane production time at 70% of the methane yield and protein, sugar, lipid contents and COD, methane yield and biodegradability has been plotted in Figure 5. It reveals that methane production time at 70% of the methane yield is mainly correlated with lipid and COD and anti-correlated with sugar, biodegradability and methane yield. It indicates that readily degradable organic matter is highly biodegradable and rich in sugar and *vice versa*. Lipids and high COD compounds, which are strongly correlated, are found to be mainly slowly degradable. This conclusion was also drawn on the PCA. Nonetheless, Figure 2 shows that correlations with lipid content are mainly supported by only two substrates. Therefore it has to be considered carefully.

Figure 4 provides detailed information about kinetic of methane production. Methane yield, lipid content and COD have a negative impact on early methane production kinetic but a positive one on the time needed to reach the methane yield. Sugar content affects positively the early methane production kinetic. Protein content is correlated with the time needed to reach the methane yield. Only biodegradability impacts positively the whole kinetic of methane production. In conclusion, substrates with a high content of sugar were composed of readily degradable organic matter, such as glucose or starch that account for approximately 70% of the methane yield, and slowly degradable organic matter that account for the last 30% of the methane yield. The readily degradable organic matter of substrate with high sugar content could be sugar reserve of plant and slowly degradable, structuring sugar such as cellulose. The impact of lipids on the methane production time could be explained by a first phase in which the anaerobic digestion process is inhibited by volatile fatty acids and long chain fatty acids, followed by a quick methane production once the inhibitions is overcome.

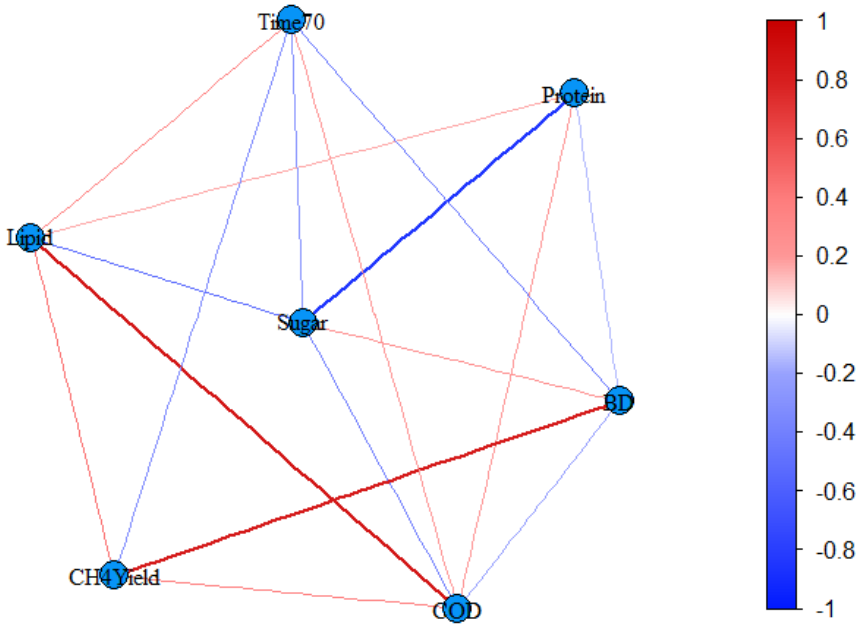

Figure 5: Correlation network between lipid, protein and sugar contents, COD, methane yield (CH4YIELD) and biodegradability (BD), methane production time expressed in days needed to reach 70 percent of the methane yield. The level correlation is represented by the intensity and thickness of the link.

Predictability of degradation time from biochemical composition

An important question arises from the correlation observed between the biochemical composition and methane production time: could methane production kinetics be anticipated from the biochemical composition? In the introduction, kinetics estimation has been reported as labor-intensive and time-consuming, whereas biochemical composition is simpler to assess. Thus prediction of the kinetic from the biochemical analysis is of great interest. A PLS regression has been carried out in order to predict the time required to reach 70% of the methane yield that was demonstrated to be the most informative methane production time. Sugar, protein, lipid contents and COD, methane yield and biodegradability were used as input variables of the PLS regression model. The Standard Error of Calibration (SECV) reaches a minimal plateau from 4 to 6 latent variables. Thus 4 latent variables were selected for the PLS regression model. The PLS regression provides a SECV of 0.65 days and a Standard Error of Calibration (SEC) of 0.62. The results between estimated and reference production time can be observed in Figure 6. The coefficient of determination R^2 was about 0.38. These results show that even if correlations exist between methane production time and biochemical composition of the organic matter, no prediction can be made of the methane production time or kinetic from the biochemical composition indicator that are currently used. Indeed, it can be expected that macro-indicators of the biochemical composition such as lipid, protein, sugar contents or COD, methane yield and biodegradability are not precise enough. From the variables correlation analysis, the study already revealed that, depending on the types of sugars, sugars can be slowly or readily biodegradable. It can be assumed that, with more detailed organic matter methods of characterization, the methane production time could be predicted from the biochemical composition analysis.

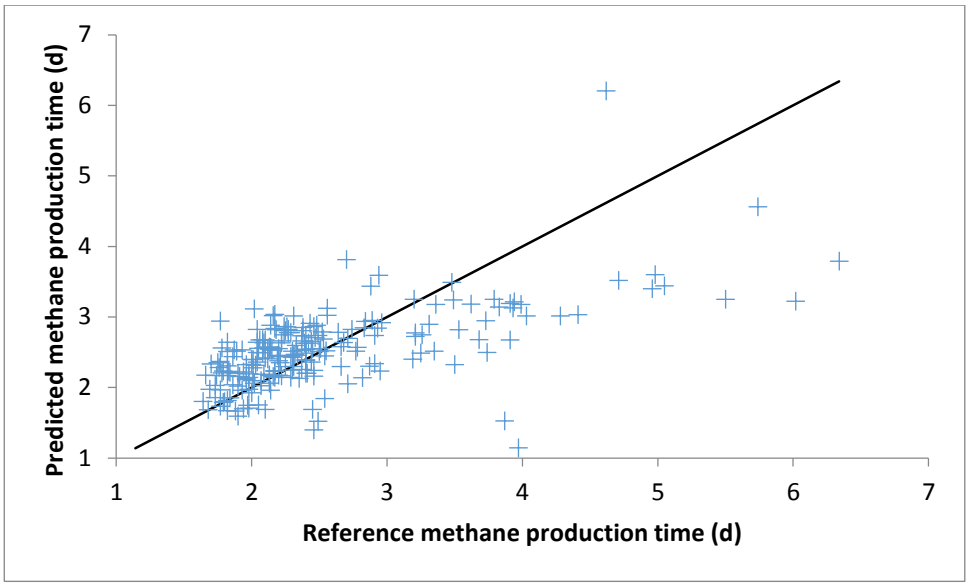

Figure 6: Prediction of methane production time needed to reach 70% of the methane yield using sugar, lipid, nitrogen content, COD, biodegradability and methane yield as variables of PLS regression model.

Near InfraRed (NIR) spectroscopy is known to give insights about the organic matter composition and the quantitative prediction of the organic matter biochemical composition in lipids, proteins and sugars (Núñez-Sánchez et al., 2016). NIR absorption bands are composed of overtones and combinations of the molecular vibrations of C–H, N–H, and O–H bonds which are correlated with molecules such as phenol, acids, alkane, amines, amides and celluloses content (Ward, 2016; Williams and Norris, 2001). Moreover, NIR spectroscopy is widely used for methane yield prediction (Lesteur et al., 2011). It is a powerful tool for anaerobic digestion process monitoring (Jacobi et al., 2012; Krapf et al., 2013). Thus, it can be assumed that NIR spectroscopy could provide an aditionnal and accurate description of the organic matter and this should be assessed in future studies trying to correlate NIR spectra with methane production kinetics.

Conclusion

Correlations between methane production time, methane yield, COD, biodegradability, sugar, protein and lipid contents have been assessed using PCA and Pearson correlation coefficients analysis. It revealed that sugars are mainly readily biodegradable while lipids are correlated with high methane yields but also with slow methane production kinetics which could be related to process inhibition in the early methane production time. A negative correlation between COD and biodegradability indicates that COD cannot replace methane yield analysis. Eventually, correlations between sugar, protein and lipid contents, COD, methane yield, biodegradability and kinetic of methane production were highlighted leading to the idea that kinetic of methane production could be predicted from the biochemical composition. However, the indicators currently used to assess biochemical composition provide a vague description of the organic matter which are not sufficient to accurately predict kinetic of methane production using PLS regression. Nonetheless, it points towards more descriptive organic matter characterizations such as NIR spectroscopy that could be used to predict kinetic of methane production.

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