EVALUATION OF OPERATIONAL PERFORMANCE AND ENVIRONMENTAL IMPACT OF A COMMERCIAL SCALE ANAEROBIC DIGESTER UTILIZING MULTIPLE FEEDSTOCKS

By

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ABSTRACT

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Food waste and livestock manure become some the of major sources that contribute to greenhouse gas (GHG) emissions in the U.S. Utilizing manure and food wastes as biogas feedstocks through the anaerobic digestion (AD) process can improve renewable energy production while reducing the impact of climate change due to GHG emission from untreated organic wastes. This study evaluated the operational performance of Michigan State University's commercial South Campus Anaerobic Digester (SCAD) as well as the environmental impact during its operation from 2014 to 2020. Evaluation of feedstock supplies quantity and output parameters of SCAD was conducted to understand the operational performance of the digester. A life cycle assessment (LCA) was done to know the environmental impact of SCAD by comparing it to the conventional waste management methods. Technoeconomic analysis was conducted to know the financial feasibility of SCAD as a commercial digester. The result shows that during its operation from 2014 to 2020, SCAD has processed 159,145 metric tons of feedstock from 18 different organic wastes to produce 15,165,156 kWh of electricity for the MSU community. LCA results show that the AD system possesses fewer environmental burdens in both global warming potential (GWP) and water eutrophication potential (WEP) compared to the conventional system. Technoeconomic analysis reveals that SCAD needs 21.5 years to accomplish its payback period, which is considered quite economically competitive. Economic sensitivity analysis shows that electricity becomes the most sensitive parameter to affect the payback period.

This thesis is dedicated to my mother, Mrs. Fatmah, and my father, Mr. Muhammad Ali Ismail.
Thank you for always believing in me.

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KEY TO ABBREVIATIONS

AD	Anaerobic Digester
ANS	Animal Science
ADREC	Anaerobic Digestion Research and Education Center
CapEX	Capital Expenditure
CH_4	Methane
CO_2	Carbon Dioxide
COD	Chemical Oxygen Demand
CSTR	Continuous Stirred Tank Reactor
DQI	Data Quality Inventory
EC	Electrical Conductivity
EPA	Environmental Protection Agency
FOG	Fat, Oil, and Grease
FU	Functional Unit
GWP	Global Warming Potential
H_2S	Hydrogen Sulfide
LCA	Life Cycle Analysis
LCFS	Low Carbon Fuel Standard
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
MLR	Multi Linear Regression
MSU	Michigan State University

N_2O	Nitrous Oxide
NH_3	Ammonia
OLR	Organic Loading Rate
OpEX	Operational Expenditure
REC	Renewable Energy Credit
RIN	Renewable Identification Number
RFS	Renewable Fuel Standard
RPS	Renewable Portfolio Standards
SCAD	South Campus Anaerobic Digester
TA	Total Alkalinity
TN	Total Nitrogen
TP	Total Phosphorus
TS	Total Solids
TSS	Total Suspended Solids
VFA	Volatile Fatty Acids
VS	Volatile Solids
VSS	Volatile Suspended Solids
WEP	Water Eutrophication Potential

CHAPTER 1. INTRODUCTION

1.1 Problem Statement

To address climate change issues and contribute to consuming more renewable energy, Michigan State University launched South Campus Anaerobic Digester (SCAD), a commercial anaerobic digester that produces biogas and renewable electricity from livestock manure and food waste from student's hall to provide energy to south campus buildings. This facility operated starting in 2013 and is still running today.

Throughout the food system, there is a significant loss of food due to spoilage, processing, and damage. The largest source of food waste in American waste occurs at the household level, where approximately 0.5 lb./d/person of food waste is generated (U.S. Environmental Protection Agency, 2018). Manure management is a significant source of methane (CH_4) emissions and a contributor to the carbon footprint of food production. For one of gallon milk, manure management accounts for 24% of the carbon dioxide equivalent (CO_2-e) emissions, which are largely related to CH_4 emissions from long-term manure storage (Thoma et al., 2013). Animal handling sectors such as farms contribute about 18% of GHG emissions when it is not responsibly managed (Esfandiari et al., 2011). Meanwhile in the United States itself, approximately 14% of ammonia emissions come from livestock manure management which is one component of acid rain (Eckert et al., 2018). Environmental impacts associated with food waste and manure management are important contributors to climate change. One of the solutions to address climate change is to produce and utilize more renewable energy sources, especially waste materials. Given the statement, the food system contributes to vast quantities of organic waste materials, such as livestock manure and food waste. These resources can be utilized to produce biogas and further to be renewable electricity (Hosseini & Wahid, 2014).

The SCAD system has not had a comprehensive evaluation of the operational performance or the environmental impact of its existence to date. These operational performances include feedstock supplies (livestock manure and food waste), digester performance, biogas quantity and quality, electricity production, and laboratory analysis of influent and effluent. A life cycle assessment (LCA) needs to be conducted to evaluate SCAD in reducing the negative impact on the environment, such as greenhouse gas (GHG) emissions. Evaluating these parameters will provide valuable information on whether SCAD has been operating in its best condition and provide further recommendations on improving SCAD performance to continue serving the MSU community.

1.2 Goal and objectives

The goal of this study is to evaluate the operational performance of Michigan State University's commercial South Campus Anaerobic Digester (SCAD) as well as the environmental impact during its operation from 2014 to 2020. Additionally, this study aims to achieve these objectives:

1. Evaluate the feedstocks supplies quantity that SCAD received during 2014-2020
2. Evaluate output parameters of SCAD during 2014-2020
3. Determine feedstocks that potentially have the most significant impact on biogas production
4. Compare a life-cycle assessment of SCAD to the conventional waste management method
5. Conduct a technoeconomic analysis to know the financial feasibility of SCAD as a commercial digester
6. Summarize lessons learned and operational experiences

CHAPTER 2. LITERATURE REVIEW

Chapter 2 provides a series of information related to this study. It starts with changes in the global community over several decades, which has eventually led to climate change. Some of these changes have come from the food system, such as food and manure waste from farming. This waste has disrupted the ecosystem balance. To overcome this situation, a series of policies have been implemented to reduce the rate of climate change. This chapter specifically discusses the efforts that the U.S. government has taken to mitigate the impact of climate change, narrowing down to the promotion and utilization of renewable energy sources.

There are various types of renewable energy, including biogas that is produced from the anaerobic digestion (AD) process. The next step of this chapter talks about the AD and several factors that affect its performance. The advantage of this process led Michigan State University (MSU) to launch the South Campus Anaerobic Digester (SCAD), a commercial digester that provides electricity to power buildings on the south campus area. Furthermore, a life cycle assessment (LCA) was conducted to evaluate SCAD's performance in mitigating environmental burdens. The revenue section concludes this chapter to showcase the profits gained by the digester.

2.1 General introduction – global drivers

2.1.1 Societal change

Societal change is an alteration of social structure where social relationships become involved in the process. Relationship in this context refers to interactions, patterns, and processes that involve mutual activities of the various parts of society (Greenwood & Guner, 2008; Sharma, 2007). For example, significant societal change has been experienced by many countries in recent decades as the result of economic restructuring, changes in societal value systems, the spread of media technology, and changes in educational systems or population composition (Weichold & Barber, 2009).

Societal changes are the result of many factors. One of the most significant factors in the recent era technological advancement. Technology exercises its vast influence by changing the environment that demands society to adapt by modifying social norms (Greenwood & Guner, 2008). Endless new technological discoveries have created more machines and methods of communication which alter social interactions. For example, society is experiencing change due to the development and invention of electric, steam, and petrol driven machines for food production. This change cannot be avoided even for institutions like family and marriage. It affects the lives of children, adolescents, and adults throughout the family dynamic, resulting in a risk of emotional development, or less social control around neighborhoods. The obvious effects of technological advancement are labor organizations, specialization, high speed of life, and increase in production (Sharma, 2007; Weichold & Barber, 2009).

Michigan State University Sustainability explains that the advancement of electronic devices such as the latest cell phones and televisions have altered the behavior of students at every corner of campus resulting in the consumption of more energy. During 1965, a student consumed 66 watts of electricity for lighting and playing vinyl records in a student's dorm room. By 1978, the number rose to 255 watts to turn on small fridge, television, light, and radio. Moving forward to 2013, the number significantly increased to 3,671 watts to power computers, television, audio speakers, microwaves, cell phones, and mini fridges. The increasing appetite for power from student in Residence Halls is causing the University to improve energy systems to support campus growth (Michigan State University Sustainability, 2014).

Societal changes in technology have affected change in other related fields, such as agriculture, food, and the environment. Technology advancement has also improved crop production. Moreover, technology helps with food processing, prolonging expiration dates. Nevertheless, agriculture and food processing demand more resources. Agriculture has been correlated with land use changes from forest to farmland, as well as an increase in water demand. The food industry has increased the amount of food waste in landfills, creating new sources of diseases caused by rotten food. Eventually, these issues contribute to climate change which will be discussed in section 2.1.2. Various social movements were conducted to address climate change issues, such as reducing plastic bag use, saving electricity, and providing more mass transportation. Michigan State University enforced several breakthroughs to accomplish this mission, one of them is the establishment of SCAD in 2013 to address the needs of renewable energy sources and food waste management. SCAD will be discussed in section 2.3.

2.1.2 Climate change

Traditional energy sources that mostly consist of fossil fuels such as petroleum, coal, and natural gas consequently contribute to environmental pollution (Zhou et al., 2016). A consequence of fossil fuel use is the significant increase in greenhouse gas (GHG) in the atmosphere which has been observed since the late nineteenth century. GHG effect is a natural phenomenon where sun heat radiation on earth surface gets absorbed by gases in the atmosphere and re-emitted to all directions, increasing earth surface temperature as a result (Quinto et al., 2016). GHG, which includes compounds such as carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and ozone (O_3), have contributed to raising global temperature and potentially became the cause of climate change and global warming (Hosseini & Wahid, 2014).

The United Nations, through The Sustainable Development Goals Reports in 2019 reported that temperature is increasing globally at an average of 0.85 °C from 1880 to 2012. This increase has affected major crop yield, contributed to the melting of snow and ice which has caused an increase in sea level. If this trend continues, global temperature might exceed 1.5 °C causing a sea level rise of 40-63 cm by 2100. Not just causing environmental pollution, but traditional energy sources are also non-renewable. The increase of human activities, particularly in industry and economic sector, requires a larger energy supply. Increasing energy is demanded in industrialized countries while significant populations in developing regions lack reliable energy. Currently, approximately 3 billion people have limited access to clean-cooking solutions and 840 million people have restricted access to electricity. Therefore, increasing clean and renewable energy use is essential to create more resilience communities to face climate change (United Nations, 2019).

2.1.3 Food waste diversion

Food waste has become a global environmental issue over the past decade due to its environmental impact. Additionally, there are approximately 800 million people who suffer from hunger. A third of the food produced for global human consumption is lost or wasted every year, approximately 1.6 billion tons. This loss costs $2.6 trillion, of which $1 trillion is incurred from GHG emissions, water scarcity, biodiversity loss, increased conflicts, and loss of livelihood. Contributing factors are soil erosion, nutrient loss, reduced yields, wind erosion, and pesticides exposures. Moreover, food waste is responsible for 4.4 gigatons of CO_2-e per year. That number represents 8% of the global anthropogenic GHG emissions (World Biogas Association, 2018).

The United States Environmental Protection Agency (U.S. EPA) reported in 2018 that over 35 million tons of food were sent to landfills, which is the equivalent to half a pound per person per day. This waste costs the commercial food service industry about $100 billion annually. The number significantly increased almost a decade later. The country spent $218 billion (about $670 per person in the U.S.) to grow, process, transport, and dispose uneaten food. Each year, the number of foods dumped to the landfill is approximately 52.4 million tons. Meanwhile, there is an additional 10.1 million tons of unharvested food remaining on farms, thus the total of wasted food is roughly 63 million tons annually. From this number, the U.S. restaurant sector itself contributes 11.4 million tons of food waste annually. This number consists of 7.3 million tons from full-service restaurants and 4.1 million tons from limited-services restaurants (ReFED, 2018; U.S. Environmental Protection Agency, 2018).

According to the Michigan Recycling Coalition, of all municipal solid waste disposed in Michigan landfills, 13.6% is food waste. Food waste prevention is the most essential process to reduce the number of organic wastes going through the landfills, which is the top priority from environmental, social, and economic perspectives. The challenge is that the prevention efforts are difficult to quantify considering the diverse waste composition from each household. Therefore, the State of Michigan puts their effort into food surplus diversion by feeding hungry people and then animals. The Food Bank Council of Michigan cooperates with multiple partners such as farmers, individuals, non-profit organizations, corporations, and government to support 7 regional food banks and advance the access to healthy food for people in need in all 83 Michigan counties (O'Brien, 2017).

The U.S EPA explained that food waste diversion should be considered seriously because of the environmental impact of food waste can be damaging. It starts with food waste rooting in landfills that create CH_4, a greenhouse gas (GHG) 25 times stronger than carbon dioxide. Among GHG emissions in the United States, 13% results from the growth, manufacture, sale, transport, and disposal of food. Not only that, wasted foods consumes more than a quarter of the total freshwater in the country (United States Environmental Protection Agency, 2014).

Shifting the management system of food waste from linear to circular can be an option to optimize food waste as a valuable resource. For example, utilizing food waste for biogas production through anaerobic digestion can provide many benefits, such as generating renewable energy, reducing GHG emissions, protection of water bodies, additional revenue streams from sale of electricity and compost, creating more self-sufficient and resilient communities and sustainable industrialization (World Biogas Association, 2018).

2.1.4 Manure management

The existing waste treatment solutions for manure and slurries systems still have several drawbacks regarding soil contamination and negative environmental impacts, such the contamination of water streams and food crops with pathological entities (Goldstein, 2018). Animal handling sectors such as farms contribute about 18% of GHG emissions when not responsibly managed (Esfandiari et al., 2011). Meanwhile in the United States, approximately 14% of the ammonia emissions come from livestock manure management which is one component of acid rain (Eckert et al., 2018).

The perspective of manure as a waste product should be changed, as manure has valuable benefits to save fertilizer cost with proper storage, handling, and application (Courneya, 2010). A critical aspect of sustainable manure management is by constructing housing and manure storage systems thus helping to conserve and maintain high concentrations of nutrients (International Atomic Energy Agency, 2008). To do so, animal manure should not be mixed with human waste to control disease and parasites (Lorimor & Powers, 2018). Moreover, improper manure management can lead to environmental issues such as water pollution and source of odor, flies, and parasites (Bradley, 2019). Lorimor and Powers (2018) classified manure into four different solid contents, as explained in Table 2.1 below.

Table 2.1 Manure treatments based on solid content

Solid content	Treatment
4% or below	Treated as a liquid with irrigation equipment, such as liquids which majority of solids have been removed or diluted manure
4 to 10%	• Handled as a slurry • It may require special pumps, for instance swine pit manure and dairy manure with milking parlor wash water added
10 to 20%	• This is typical of many dairy operations which are too thick to pump but too thin to scoop • Adding water to handle it as liquid and special pumps will be used to agitate and move the manure
20% or more	Treated as a solid which can be stacked and picked up with a fork or bucket loader

Bradley (2019) emphasizes that manure management and utilization plan must include these components: 1) Quantity of manure and bedding generated annually from all livestock on the farm; 2) Manure handling, collection methods, and equipment used. This includes the handling from barns, stalls, paddocks, and pastures; 3) Size and location of storage and/or composting facilities; 4) Methods used to prevent drainage into storage areas, paddocks, and pastures; 5) Nutrient analysis of manure prior to application (if applying to land); 6) Soil analysis for lands in which raw or composted manure will be applied; and 7) Utilization records: land application, compost monitoring, or off-sites uses.

2.1.5 Renewable energy

Renewable energy is energy generated partially or entirely from natural resources which are available on a renewable basis and inexhaustible (naturally replenished), for instance hydropower, wind, solar, geothermal, and bioenergy (plant-based). Renewable energy can be utilized without transforming it into other forms, such as cooking gas. Otherwise, renewable energy would be processed for electricity generation (Gorjian, 2017; The U.S. Environmental Protection Agency (EPA) State and Local Energy and Environment Program, 2018). Renewable energy has received noticeable interest from many countries as a solution to limited energy resources and environmental issues related to fossil fuels consumption (Mohammadrezaei et al., 2018).

According to Abolhosseini et al. (2014), the development of renewable energy technologies was driven by three factors: energy security, economic impacts, and carbon dioxide emissions reduction. The Arab oil embargo in 1973 played a vital role in raising the awareness of energy supply security. This was supported by high oil prices, increasing dependency on oil imports, depletion of fossil fuels, increasing competition from emerging economies, political instability in major oil producers, a high impact due to any disruption in energy supply on developed, and rapidly developing countries. Moreover, energy security issues must address climate change concerns, which demands the diversification of energy sources. That means if energy security is fulfilled only by fossil fuels, it will significantly increase GHG emissions which will worsen climate change. Therefore, energy demand must be fulfilled by renewable energy to embody energy security while lowering GHG emissions. Shifting to economic impacts, renewable energy opens job creation opportunities, industrial innovation, and a balance of payment.

Additionally, renewable energy technologies should reduce CO_2 emissions by substituting fossil fuels in the power generation industry and transportation sector.

Biogas is one of renewable energy sources that has become an alternative fuel for transportation, industrial engines, and residential electricity and heat. Biogas as an alternative fuel has the capacity to reduce the impact of pollution. Additionally, biogas can be utilized further to produce electricity and/or heat through combustion by combining heat and power (CHP) generation systems. The efficiency could reach 34-40% by using large turbines and 25% using small generators (Hosseini and Wahid, 2014). In Chile, electricity generated from biogas could fulfill 50 megawatts (MW) of demand. Moreover, the slurry and residues could be used as fertilizer (Passos et al., 2017; Zhou et al., 2016).

Biogas composition primarily consists of CH_4 and CO_2 with a small amount of hydrogen sulfide (H_2S) and water vapor (H_2O). Biogas typically contains 55-70% of CH_4 that can be used as fuel in a variety of purity levels and efficiencies (Chynoweth et al., 2001; Somers et al., 2018). Biogas which contains high concentration of CO_2 will lower its quality as cooking gas since CO_2 contributes to carbon monoxide (CO) formation which could weaken biogas combustion. Additionally, H_2S reduction level (i.e., via desulphurization processes) must happen before biogas can be used as H_2S is a toxic gas which poses safety concerns for people and may result in additional equipment maintenance (Hosseini & Wahid, 2014). Biogas is produced through anaerobic digestion (AD) which will be discussed further in section 2.2.

2.1.6 Policy drivers – focus in the U.S.

2.1.6.1 Food waste diversion

According to O'Brien (2017), an amendment of the Solid Waste Management Act in 1990 attempted to minimize the hazardous landfill gases yield by banning the disposal of yard clippings. At the same time, this effort promoted the conversion of valuable organics into beneficial resources for municipalities, agriculture, and industry. The Michigan Legislature enacted Public Act 264 in 1990 which define "yard clippings" as "leaves, grass clippings, vegetable or other garden debris, shrubbery, or bush or tree trimmings less than four feet in length and two inches in diameter that possibly to convert into compost humus." Due to this amendment, the Natural Resources and Environmental Protection Act (NREPA) prohibited owners or operators of landfills and municipal solid waste incinerators from accepting solid waste if it was known that the solid waste included yard clippings generated or collected on land owned by a county, municipality, or a state facility.

Granholm and Chester (2007) use the three principles of sustainability – economic vitality, ecological integrity, and improved quality of life – to guide solid waste management decision-making. According to the Policy, Michigan's preference is to first avoid waste generation, then to utilize generated waste for beneficial purposes, and properly dispose of what remains.

According to EPA (2014), much of food waste that reaches landfills is still edible. Wasted food can be divided into three categories as explained in Table 2.2.

Table 2.2 Food waste classification

Category	Description	Example
Avoidable	Food that can be easily prevented from going to waste. Reasons for waste include overpreparation, improper storage, or spoilage. Understanding the cause of this waste is key to preventing it.	an entire tray of lasagna is left over every day at a buffet
Possibly avoidable	Food that may seem inedible but can be used or repurposed	beet tops can be cooked similarly to collard greens or spinach instead of discarded. Also, slightly stale bread can be used for croutons or breadcrumbs
Unavoidable	Food that cannot be consumed by people and should be used for animal feed, compost, or anaerobic digestion	banana peels or peach pits

Moreover, EPA also created the Food Recovery Hierarchy to reduce wasted food. Based on this hierarchy, there are five stages to be considered when utilizing excess food:

a. Source reduction: reduce the volume of food waste generated
b. Feed people: donate extra food to food banks, soup kitchens and shelters
c. Feed animals: provide food to farmers for animal feed
d. Industrial uses: provide fat for rendering, biofuel, and food discards for animal feed production
e. Composting/digesting: convert food scraps into a nutrient rich soil amendment

2.1.6.2 Renewable Portfolio Standard (RPS)

A renewable portfolio standard (RPS) is a policy that demands that electricity providers include a minimum percentage of their electricity supplies from renewable energy sources, such as wind, solar, geothermal, and various forms of biomass and ocean energy. Electricity suppliers have two options to comply with this requirement. First, suppliers can own a renewable energy facility and produce their own electricity. Second, they can purchase renewable electricity from a renewable facility. Furthermore, RPS enables the market to choose any renewable energy resources to fulfill the mandate since renewable energy availability varies depending on the regional climate and geographies (Cory & Swezey, 2007; Rader & Hempling, 2001).

From an environmental perspective, RPS promotes climate change mitigation by reducing air and carbon pollution, waste reduction, and conserving water and other valuable natural resources. Moreover, it can boost local economic development by creating more jobs, taxes, and revenues associated with renewable energy (Environmental Protection Agency, 2015).

According to Lawrence Berkeley National Laboratory and U.S. Department of Energy, 29 States have implemented RPS, including Michigan, California, Nevada, and Minnesota (Figure 2.1). Additionally, Washington DC and 3 territories (Northern Mariana Island, Puerto Rico, and US Virgin Islands) have also had RPS. Meanwhile, 8 states (including Kansas, Oklahoma, and Indiana) and 1 territory (Guam) have established their renewable portfolio goals (Barbose, 2019; U.S. Department of Energy, 2016).

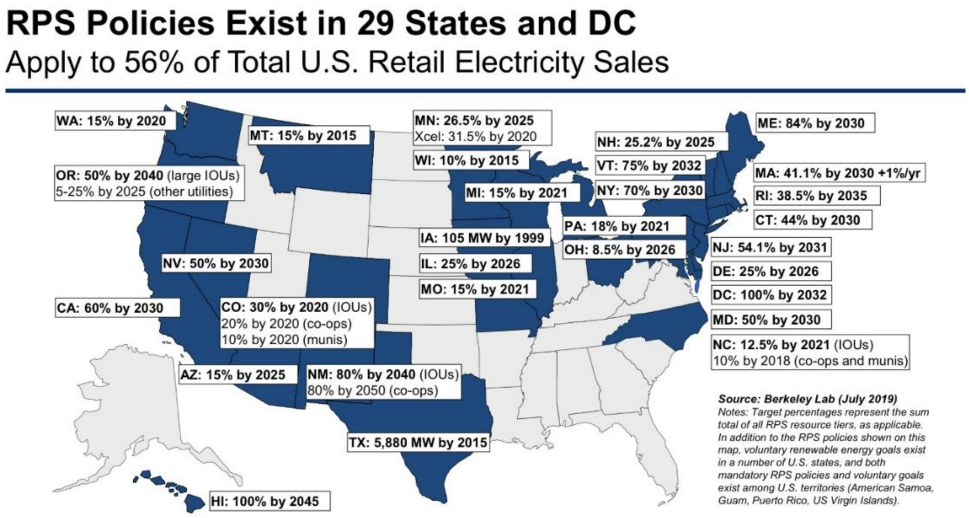

Figure 2.1 RPS Policies Established in the United States (Barbose, 2019)

RPS implementation's most prominent mechanism is renewable energy certificates (RECs). RECs are payments that electricity suppliers offer to renewable energy companies for the renewable electricity they provide to the grid. One REC typically represents 1 megawatt-hour (MWh) of renewable electricity. The implementation of REC provides an accurate, durable record of electricity produced, also a fungible commodity that can be traded among providers to fulfill RPS (Cory & Swezey, 2007).

2.1.6.3 Renewable fuel standard

The United States is the biggest consumer of crude oil in the world. Consequently, the country is facing two major concerns which are low energy security and high greenhouse-gas emissions. Furthermore, the United States imported between 52 to 60% of oil consumed from 2005 to 2009 with roughly 30% of CO_2 emissions resulting from transportation fuels (The National Academy of Sciences, 2011).

Biofuels emerge as an alternative to petroleum-based fuels due to its production from renewable domestic sources which has the potential to improve U.S. energy security. It also provides life-cycle greenhouse-gas benefits when compared to fossil fuel. As a result, the U.S. Congress enacted the Energy Independence and Security Act (EISA) in 2007 to lead the country toward energy independence and security while improving clean renewable fuels production. EISA then resulted in the Renewable Fuel Standard (RFS) program which was created by Congress to address greenhouse gas emissions, broaden renewable fuel sector in the country, and dwindle the demand for imported oil (America's Oil and Natural Gas Industry, 2017).

RFS demands that U.S. transportation fuel contains a minimum volume of renewable fuel. It sets the target for consuming 35 billion gallons of ethanol-equivalent biofuel and 1 billion gallons of biomass-based diesel by 2022. The Environmental Protection Agency (EPA) holds statutory authority on volume amounts after 2022. There are four categories of renewable fuels according to RFS: total renewable, advanced, biomass-based diesel (BBD), and cellulosic. These categories are determined based on the reductions in life-cycle emissions of GHG, relative to petroleum, feedstock, and fuel characteristics (Congressional Research Service, 2020; Stock, 2015).

Nevertheless, many reports and studies are doubtful that the implementation of RFS will be successful and meet the target. First, there is a limit placed on car use of gasoline at 10% ethanol (E10) which is the maximum acceptance under the manufacturer's warranty. This caused an E10 plateau in the US fuel supply in 2013. Second, cellulosic biofuels experience policy uncertainty and high production costs that might hinder investors from supporting this initiative. Eventually, it depends on how biofuels are produced. There are many factors that can affect it that might be unpredictable. These factors include technical expertise, weather conditions, market stability, tax incentives, and trade disputes. These factors could impact the entire industry (Congressional Research Service, 2020; Stock, 2015).

To facilitate RFS compliance, Renewable Identification Number (RIN) systems were created by the U.S. EPA. A RIN is a 38-character numeric code that represents a volume of renewable fuel produced in or imported into the United States. One RIN is equivalent to one gallon of biofuel produced and reported to EPA. A RIN contains information about biofuel sources like~~,~~ production year, biofuel producer, and the type of fuel (Table 2.3). At the end of the calendar year, fuel suppliers must fulfil minimum requirements of RINs to be compliant with RFS. Similar to REC, RIN also can be traded like other commodities. RINs are valid for use during its production year and the following year (Christensen et al., 2014; Cooper, 2018; McPhail et al., 2011; Yacobucci, 2013).

Table 2.3 RIN code definitions (McPhail et al., 2011)

38-character code: KYYYYCCCCFFFFFBBBBBRRDSSSSSSSSEEEEEEEE	
K	RIN assignment code
YYYY	Year batch is produced/imported
CCCC	Company registration ID
FFFFF	Facility registration ID
BBBBB	Producer-assigned bath number
RR	Equivalence value for renewable fuel
D	Renewable type code[1]
SSSSSSSS	RIN block starting number
EEEEEEEE	RIN block ending number

[1]Five separate RIN categories: D=3 for cellulosic biofuel; D=4 for biomass-based diesel; D=5 for advanced biofuel; D=6 for other renewable fuel; D=7 for cellulosic diesel

2.1.6.4 California low carbon fuel standard

The California Low Carbon Fuel Standard (LCFS) is a program created to reduce greenhouse gas emissions (GHG) and other air pollutants from the state’s transportation sector, diversify the State’s fuel mix, and decrease the dependence on petroleum. It is one of the policies in California that comes from the implementation of the Global Warming Act of 2006. LCFS evaluates the full life cycle emissions of transportation fuels and includes all GHG emissions that are the result of production, distribution, and consumption expressed as grams of CO_2e per megajoule (Renewable Fuels Association, 2021; Townsend & Havercroft, 2019). Recently, the transportation sector has contributed 50% of GHG emissions, 80% of nitrogen oxide emissions, and 95% of particulate matter emissions in California (Center for Law, 2019).

LCFS reduces GHG emissions by establishing annual standards to be followed by fuel producers and distributors. It emphasizes the reduction of the average life-cycle carbon intensity (CI) of the fuels supplied to the market. Fuels that gain lower CI values regulated by California Air Resources Board (CARB) will get compliance credits. On the other hand, fuels with CI values higher than the standard will get compliance deficits (Renewable Fuels Association, 2021). Additionally, certain requirements might be needed to fulfill LCFS such as life cycle assessment (LCA) which accounts for the environmental impact of fuel production from feedstock production to end use stage (Congressional Research Service, 2021).

The implementation of LCFS began in 2011. It was amended in 2015 to address fuel CI reduction standard adjustment and extension. Currently, LCFS requires a 10% reduction by 2022 and a 20% reduction by 2030. Since its first implementation, LCFS has achieved more than 77 million credits with each credit referencing a metric ton of GHG emissions reduction contra the annual standard (Renewable Fuels Association, 2021). It has helped to incentivize production of low-carbon fuels and generate additional revenue to encourage investment in statewide low-carbon transportation fuel infrastructure (Center for Law, 2019).

Despite its merits LCFS has some implementation challenges. These challenges include determining the appropriate energy related to GHG target, developing a robust LCA, as well as constructing a transparent compliance system. Moreover, part of Congress opposed LCFS due to concerns about economic effects such as job loss, limited affordable lower carbon fuel options, and increasing fuel price as an effect of fulfilling the certain standards required. Therefore, further improvement of the LCFS is essential (Center for Law, 2019; Congressional Research Service, 2021).

2.1.6.5 Carbon Intensity

Carbon intensity (CI) is the number of GHG emission generated throughout production and use of life cycle energy sources, such as transportation fuel. CI is represented in units of grams of CO_2 per megajoule of energy (gCO_2e/MJ). CI calculation considers extraction, refinement, distribution, storage, and combustion of energy. Therefore, the calculation can be included in life cycle assessments (Ingram, 2015; United Nations Environment Programme, 2019).

CI is calculated using the Greenhouse Gases, Regulated Emissions and Energy Use in Transportation (GREET) model which is developed by U.S. Department of Energy and Argonne National Laboratory. The current model is the CA-GREET 3.0 Model and Tier 1 Simplified Carbon Intensity calculators. The GREET model aims to evaluate and compare energy, environmental impacts of transportation fuels, and vehicle technologies on a life-cycle basis. Over 100 alternative fuel pathways and over 80 vehicle technologies have been evaluated using this model: including aviation fuel, aircraft operation, marine fuels, and vessel operation. Furthermore, GREET evaluates total energy consumption, GHG emissions (CO_2, N_2O, CH_4), air pollutants (SOx, NOx, VOC, CO, PM10, PM2.5), and water consumption (Argonne National Laboratory, 2014; M. Wang, 2007).

2.2 Anaerobic digestion

2.2.1 Introduction

The anaerobic digestion (AD) process is defined as a biological process in which a lack of O_2 causes a degrade in carbon source materials through the help of various microorganism consortiums (Chynoweth et al., 2001). It transforms organic matters into CH_4 gas, thus reducing odor and pathogen risks (R. Chen et al., 2016). AD does not only provide a renewable alternative energy source, but also an alternate pathway to process organic waste, reduce GHG emissions from landfills, and mitigate the demand of fossil fuel and chemical fertilizers (Li et al., 2018; Zou et al., 2018). In terms of efficiency and costs, AD energy could compete with other biomass energy sources, such as heat, synthesis gases, and ethanol (Chynoweth et al., 2001). Moreover, AD could provide electricity storage via upgrading biogas to high purity of methane which might be stored and used for other purposes (Jürgensen et al., 2018). One factor that makes AD attractive is the technology used in AD is scalable (Hosseini & Wahid, 2014). This means AD technology can be applied in various digester capacities; thus, the digesters can be less costly to build, operate, and maintain. This scalability also opens the chance to implement AD technology for small scale farms or communities. For example, the small-scale AD project might be carried out starting from 100 dairy cows or 200 cows or between 200 to 5,000 tons of organic waste per year which is expected to produce 80 kW electricity (Marjolaine, 2019).

AD consists of four main stages: hydrolysis, acidogenesis, acetogenesis, and methanogenesis. The first three stages are maintained by bacterial communities to yield acetate, hydrogen, and carbon dioxide, while the last stage is maintained by methanogenic archaea communities to produce methane from acetate, or from hydrogen and carbon dioxide as alternative sources (Z. Yu et al., 2018; Zhou et al., 2016).

In the hydrolysis process, organic materials such as cellulose and hemicellulose are hydrolyzed, becoming soluble sugars, alcohol, and other organic substances. The hydrolysis products process will be transformed by acid producing bacteria to yield volatile fatty acids that consist of formic, acetic, propionic, and butyric acid. Hydrolysis and acidification are continuous biochemical reactions. When these processes are performed ideally, high yields of organic acids are achieved, degradation or loss of the organic acids is avoided, fermentation inhibitors are minimized, and cellulose and hemicellulose degradation are improved (J. Yu et al., 2017). Methanogens utilize formic and acetic acid directly, whereas propionic and butyric acid need to be converted into acetic acid by acetic acid producing bacteria (Shen et al., 2018).

Temperature and pH play key roles in developing appropriate AD systems. In most studies, AD can be developed in mesophilic and thermophilic temperatures. Mesophilic temperature is preferable if hydrolysis and acidification are done within high solid content condition, while thermophilic temperature is recommended for improving AD efficiency under low solid content in 3 days (J. Yu et al., 2017). An ideal digestion should have a pH range of 6.5-8.0 to provide a convenient environment for anaerobic microbes, especially for archaea in degrading organic compounds and producing methane (Zhong et al., 2015). Appropriate pH for hydrolysis and acidogenesis is 5.5 and 6.5, respectively (Zhou et al., 2016).

2.2.2 Feedstock

2.2.2.1 Manures

Historically, manure has been utilized for many purposes, such as fertilizer, soil amendment, energy source, and even construction material. There are many recyclable components in manure, including solids, organic matter, nutrients, and fiber. The contents in manure can be affected by several key factors such as species, digestibility, protein and fiber content, diet, age, housing, environment, and production stage. Moreover, manure contains nitrogen, phosphorus, and potassium which are critical nutrient sources for crops. In general, manure with higher solids concentrations have higher nutrition content (Kostic et al., 2020; Lorimor & Powers, 2018; U.S. Environmental Protection Agency, 2015).

Nutrients in manure are available in soluble and insoluble forms. Soluble nutrients can be consumed by the crops right away, while insoluble nutrients take up to a year or more to be available. Each nutrient has a different characteristic. For example, phosphorus is typically 80% available in the settled solids of manure storage and insoluble. Meanwhile, potassium is typically 80% found in the liquid and is highly soluble. Nitrogen is split almost evenly between liquid and solids (Lorimor & Powers, 2018).

Among the various methods to utilize manure, anaerobic digestion is a technology that processes manure into biogas as source of heat or electricity. The energy produced can be used on the farm or sold to the local power grid (U.S. Environmental Protection Agency, 2015). Diverse types of manure contribute slightly different percentages of CH_4 in biogas, as shown in Table 2.4.

Table 2.4 Percentage composition of CH_4 from anaerobic digestion of various manures (Anukam et al., 2019)**.**

Manure	CH_4 Composition (%)
Cattle	50-60
Pig	60
Poultry	68
Sheep	65
Horse	66

Manure’s characteristics are critical factors for biogas production and process stability during anaerobic digestion. These characteristics are moisture content, total solids (TS), volatile solids (VS; organic compounds from plant or animal that lost when the dry solids are burnt at 550 °C), biodegradability, particle size, pH, biological oxygen demand (BOD), chemical oxygen demand (COD), also carbon and nitrogen contents (L. Chen & Neibling, 2014).

Additionally, manure contains variative nutrition contents as shown in Table 2.5. These contents are important for the digestate once it is land-applied. The anaerobic digestion process slightly changes the nutritional contents of manure. Most nitrogen is found in the form of organic N and NH_4 in liquid phase of digester sludge. A negligible amount of nitrogen might be emitted as NH_3. Therefore, digester sludge will have higher ammonium content than raw manure. Meanwhile, phosphorus content does not change significantly due to anaerobic digestion process. All the P present in the manure will still be present in the digester sludge. The difference is that the dissolved portion of P will be moved into bacteria bodies that perform anaerobic digestion. Additionally, C in the form of simple sugars, volatile fatty acids, and alcohol is converted to CO_2 and CH_4. As a result, effluent has less C or organic matter compared to raw manure (Manitoba, 2015; Natural Resource Conservation Services, 2007) .

Table 2.5 Nutrition content of Manures (Chandra, 2005)

Manure	Percentage content		
	Nitrogen (N)	Phosphoric acid (P_2O_5)	Potash (K_2O)
Cattle, fresh	0.4-0.5	0.3-0.4	0.3-0.4
Horse, fresh	0.5	0.4-0.6	0.3-1.0
Poultry, fresh	1.0-1.8	1.4-1.8	0.8-0.9

2.2.2.2 Food waste

In this case, material contents are essential as they provide nutrition for the microbial community in the digester. The carbon/nitrogen (C/N) ratio in slurry has a critical contribution in the AD process. If slurry contains high C/N ratio, microbe will consume nitrogen sources rapidly thus decrease biogas productivity. On the other hand, methanogen bacteria reproduction and metabolism will be inhibited as carbon deficit, ammonia accumulation, and pH increase occur in low C/N ratio slurry. Typically, C/N ratio range for AD is 10-90, but 30 is the most common (H. Chen et al., 2016; X. Wang et al., 2012).

To achieve an ideal C/N ratio, previous research combined several resources as AD materials what is known as co-digestion. The co-digestion of various substrates enhances methane yield, improves buffering capacity, and prevents acidification (Li et al., 2018; X. Wang et al., 2018). Compared to animal manure only, applying the AD process to the co-digestion between animal manure and feedstock provides more stable operational performance and produces more methane. This happens because feedstock with a higher C/N ratio balance out with manure which has low C/N ratio achieving an ideal C/N ratio range (X. Wang et al., 2012).

The mixture of food waste and dairy manure also attracts attention as this combination potentially has an ideal C/N achieving productive and efficient AD processes (H. Chen et al., 2016; X. Wang et al., 2012). Li et al. (2018) revealed that methane production could be improved by co-digesting dairy manure and corn stover with tomato residues at 20-40% volatile solid based. However, this process will happen once tomato residue is added beyond 60% since it may trigger pH drop and over produce VFA (Volatile Fatty Acids).

2.2.3 Testing and analysis – Operation data

2.2.3.1 Operational parameters

2.2.3.1.1 pH

pH is a measure of acidity or basicity of a solution. Specifically, pH measures the hydrogen concentration, $[H^+]$ which the value ranges from 0 to 14. Additionally, pH 7 is called "neutral" because it is the center of the measurement scale, where the ratio of $[H^+]$ and $[OH^-]$ (hydroxide ion concentration) is equal. A solution is determined to be acidic if the pH is below 7 because $[H^+]$ is greater than $[OH^-]$, while a solution with pH above 7 is grouped as basic or alkaline which means $[OH^-]$ is greater than $[H^+]$ (Hach, 2018). An anaerobic digester typically has a pH range between 6.4 and 8.2 to maintain methanogens population. This can be achieved by maintaining the balance of acetogens and methanogens. Acetogens are needed to produce acids, while methanogens consume acids to yield methane gas and increase alkalinity. If acetogens surpass methanogens population, it will drop the pH which then inhibit methanogens performance, resulting in a "sour" digester (L. Chen & Neibling, 2014; MSU Anaerobic Digestion and Research Center, 2019).

2.2.3.1.2 VFA

Volatile Fatty Acids (VFAs) are intermediate products of anaerobic digestion process which emerge after polymer hydrolysis and acidogenesis prior to being degraded into acetic acid for methanogenesis stage. VFA belongs to carboxylate which has a low molecular weight consisting of 2 to 6 carbon atoms. VFAs are produced from various feedstocks, for example, agricultural waste, food waste, milk sewage, dairy whey effluent, municipal waste, and cellulose sewage (Mayer et al., 2010; Szacherska et al., 2021; Wainaina et al., 2019). VFA acts in the biopolymers of biofuels production such as methane and hydrogen. Other applications of VFA include carbon sources in biological denitrification, production of biodiesel, and electricity production through microbial fuel cells. Moreover, there are diverse types of microorganisms that contribute to VFA production as shown in Table 2.6 (Lukitawesa et al., 2020; Magdalena et al., 2019). Several factors are crucial for VFA productivity, which are hydraulic retention time (HRT), organic loading rate (OLR), temperature, pH, and pretreatment (Wainaina et al., 2019).

Table 2.6 Production of volatile fatty acids by microorganisms (Szacherska et al., 2021; Wainaina et al., 2019)

Volatile Fatty Acid	Bacteria	Substrate
Acetic Acid	*Acetobacter aceti*	Cheese whey
	Clostridium acetium	Mixed gas (4% H_2:18% Argon:78% CO)
	Clostridium lentocellum SG6	Paddy straw
	Moorela thermoaceatica	Sugarcane straw hydrolysate
	Saccharomyces cerevisiae + Acetobacter pasteurianus	Glucose
Propionic Acid	*Propionibacterium acidipropionici* (ATCC 4965)	Lactate Glycerol Sugarcane molasses
	Propionibacterium acidipropionici (CGMCC 1.223)	Glycerol
	Propionibacterium acidipropionici (ATCC 4875)	Hemicellulose hydrolysate Cheese whey
	Propionibacterium freudenreichii CCTCC M207015	Glucose
	Pripionibacterium freudenreichii spp. shermanii	Glycerol
Butyric Acid	*Clostridium butyricum* S21	Sucrose
	Clostridium butyricum ZJUCB	Glucose
	Clostridium thermobutyricum JW171K	Glucose
	Clostridium tyrobutyricum	Corn husk hydrolysate Sugarcane bagasse hydrolysate

VFA is expressed in equivalent milligrams of acetic acid per liter. VFA is accounted together with total alkalinity (TA), which is expressed in milligrams equivalent of calcium carbonate per liter. VFA/TA ratio will determine the follow up action regarding feedstock supply into the digester, as explained in Table 2.7 (Lossie & Pütz, 2011; MSU Anaerobic Digestion and Research Center, 2019).

Table 2.7 VFA/TA ratio and its correlation to feedstock supply into the digester

VFA/TA Ratio	Background	Corrective Action
>0.6	Highly excessive biomass input	Stop adding biomass
0.5-0.6	Excessive biomass input	Add less biomass
0.4-0.5	Plant is heavily loaded	Monitor plant more closely
0.3-0.4	Biogas production at a maximum	Keep biomass input constant
0.2-0.3	Biomass input is too low	Slowly increase biomass input
<0.2	Biomass input is far too low	Rapidly increase biomass input

There is a correlation between VFA and pH. If VFA level increases, that will decline pH, alkalinity, and biogas production. In a normal operating system, hydrogen and acetic acid formed by acidogenic and acetogenic bacteria is immediately converted into methane by methanogens. However, if VFA is increased, an unbalanced condition between acidogenic and methanogenic activities will reduce methanogens performance. The acceptable range for VFA is between 50 to 300 mg/L as acetic, meanwhile the acceptable range for alkalinity is between 1,500 to 5,000 mg/L as $CaCO_3$ (Krakat et al., 2017; MSU Anaerobic Digestion and Research Center, 2019; Schnaars, 2012).

2.2.3.1.3 Ammonia

Anaerobic degradation of proteins or amino acids produces ammonia through the degradation of nitrogenous matter. Ammonia is present at elevated levels in certain feedstock, such as meat processing by-products, food waste, also swine and poultry manure. Free ammonia (NH_3) form is more toxic to methanogens than the ionized form (NH_4^+). Moreover, anaerobes are more sensitive to ammonia toxicity at higher temperatures. Lowering digester pH will relieve NH_3 toxicity. Additionally, dilution may be needed to measure samples with extreme NH_3 levels. The acceptable range for ammonia content is between 1,500 to 3,000 mg/L. Table 2.8 explains the effect of ammonia concentration on digester. In low concentration (between 50-200 mg), ammonia is beneficial for amino acids, proteins, and nucleic acids synthesis. Furthermore, ammonia maintains neutral pH conditions by neutralizing the organic acids yielded by fermentative bacteria. These conditions are essential for bacterial growth (Y. Jiang et al., 2019; MSU Anaerobic Digestion and Research Center, 2019; Walker et al., 2011).

Table 2.8 Effect of Ammonia-N concentrations on digester

Effects	Ammonia-N (mg/L)
Beneficial	50-100
No adverse effect	200-1,000
Inhibitory effect at higher pH values	1,500-3,000
Toxic	> 3,000

Anaerobes, especially methanogens, are sensitive to ammonia toxicity due to ammonia can freely pass-through methanogens' cell membranes hence cause a proton imbalance. Consequently, the intracellular pH of methanogenic bacteria changes then inhibits specific enzymatic reactions. Moreover, acetate degradation is hindered by high ammonia concentration, leading to acetate accumulation, buffer capacity depletion, methane yield decrease, VFA concentration increase, and pH drop. Digesters with high concentrations of ammonia will experience methanogenesis inhibition and lead to complete failure (H. Chen et al., 2016; Morozova et al., 2020).

2.2.3.1.4 Organic Loading Rate

Organic loading rate (OLR) is defined as the quantity of organics fed to a continuous digester per day (Meegoda et al., 2018). OLR data talks about digester health and space. It is important because OLR indicates the quantity of volatile solids to be fed into the digester each day (Babayee and Shayegan, 2011). OLR can be counted with formula (1) as follows (MSU Anaerobic Digestion and Research Center, 2019):

$$\text{OLR} = \text{mass of Volatile Solids (VS)} / \text{volume of reactor} \qquad (1)$$

Material characteristics and operation conditions are key points to in determining OLR. In general, the biogas yield increase is in line with the OLR increase. If OLR is optimized, the processing efficiency of anaerobic digestion can be improved. Moreover, optimum OLR can reduce the plant capital cost, improve biogas yield, and ensure operation stability (J. Jiang et al., 2020). However, excess OLR can contribute to biogas production inhibition (Musa et al., 2018).

OLR is essential for AD operation since it is related to system stability, waste treatment ability, and biogas production. Ideal OLR is favorable for cell activity, thus contributing to increasing methane production and improving substrate degradation. Nevertheless, increasing OLR has a risk of creating excessive VFA production and lowering the pH that inhibits the entire process (Moguel-Castañeda et al., 2020).

2.2.3.2 Performance indicators

2.2.3.2.1 Mixing

There are many aspects to consider in choosing a reactor type and mixing condition. For example, a conventional AD reactor is working for 20-30 days (about four and a half weeks) of hydraulic retention time, getting minimum once feeding per day with proper mixing at 35 °C (Chynoweth et al., 2001). Mixing in biogas digester aims to achieve balanced nutrient and heat circulation, to minimize precipitation of materials by shaping an adequate mixture of solid particle and liquid suspension and facilitate gas lifting from fermentation substrates. The quality of mixing in AD plant will affect in choosing the mixer type (Eshkaftaki & Ebrahemi, 2019; Kress et al., 2018; Naegele et al., 2014). Mixing also helps create homogenous temperature and bacteria-nutrient composition in the digester. Currently, this process is considered to become an important stage in biomass-methane conversion (Mohammadrezaei et al., 2018).

Nevertheless, mixing has also become a major challenge in AD field application since it consumes approximately 51% of total electricity needs in the complete process. It makes several research focused on analyzing whether mixing time and rate have a significant impact on methane production. A previous study demonstrated that reducing mixing time in a full-scale AD reactor fed with crops did not strongly affect the nutrient distribution that endangers biogas production (Kress et al., 2018). A moderate stirrer rate at 80 rpm is considered as the best condition of stirring process in AD since it provides appropriate mixing pattern. The low-level mixing rate causes high death species near reactor wall. On the other hand, a high mixing rate would affect microorganism structures in the reactor, thus declining biogas production (Mohammadrezaei et al., 2018). Moreover, appropriate mixing for digester with high solid content is beneficial but not to low solid content condition (J. Yu et al., 2017). Therefore, it is essential to determine the type of material that would be digested to choose an ideal reactor and mixing type.

2.2.3.2.2 Economic Analysis

Renewable energy production often faces challenges regarding its economic feasibility. There are several processes in AD that need attention in cost efficiency. First is pretreatment. The type of pretreatment method used, and materials condition are critical for economic feasibility analysis (Fu et al., 2018). According to Passos et al. (2017), the costs that should be anticipated come from extra energy and chemical agent used for pretreatment. These costs might fluctuate depending on the market conditions and negotiation terms between the companies. In addressing this issue, reuse or energy recovery technologies during pretreatment process might be considered to improve the economic performance (Fu et al., 2018). Second, transportation of starting materials to the digester location can be accounted as energy consumption. Therefore, if the digester is placed near the livestock farms, it can eliminate the initial energy used and the cost of biogas production (Mohammadrezaei et al., 2018).

Besides pretreatment and transportation, another method to reduce substantial costs is to improve the efficiency of process steps before feeding biogas, such as harvesting and collection. Simultaneous harvesting and mechanical pretreatment of biomass might become an efficient method to increase energy yield per hectare by selecting an appropriate harvesting machine (Tsapekos et al., 2017).

2.3 Michigan State University South Campus Anaerobic Digester (MSU SCAD)

Michigan State University's South Campus Anaerobic Digester (MSU SCAD) is part of the "Keeping it Green, Recycling Waste to Resource" campus-based projects that concentrate on reducing and reusing waste. It is a single-tank complete mixed anaerobic digester which is projected to utilize approximately 17,000 tons of organic waste per year from MSU and the greater Lansing area to yield biogas than can be converted into more than 2.8 million kWh of electricity per year (Stuever, 2013). Approximately 10% of the energy powers the facility, then the rest offsets energy production in 10 south campus buildings, which is enough energy to power about 250-300 homes (MSU Sustainability). The total cost of the project is about $5 million, and it is expected to pay off itself in less than 15 years (Oswald, 2013).

Figure 2.2 MSU South Campus Anaerobic Digester (personal documentation)

Feedstock materials include dairy manure from MSU Dairy Teaching and Research Center, food waste from campus dining halls, food manufacturing waste from southern Michigan, also fats, oil, and grease (FOG) from local restaurants. The energy produced is used to power several buildings on South Campus (Michigan State University Sustainability, 2014). These feedstocks are received in two reception tanks, one is for manure, and the other one is for other materials. Relying on the delivery schedule and the target blend, feedstock is pumped from each reception tank into a central mix tank to be homogenized. Then, this blended material is pumped through a heat exchanger to raise up the temperature to 37.78 °C before entering the anaerobic digester. The digester is an aboveground steel tank with a liquid capacity of more than 1.7 million liters. Two hydraulically powered submersible mixers are used to keep the digester contents well blended for 25-day hydraulic retention time (Oswald, 2013).

The electricity is generated through powering a 450-kW combined heat and power (CHP) system using biogas yielded from the digester. Hot water produced by the CHP is used to maintain the digester temperature to stay at 37.78 °C and to provide heat to the other buildings at the site. The digestate—remaining mixture of solids and liquid after digestion—is pumped to a solid-liquid separator. Separated solids will be composted while liquid will be transferred to digestate holding tank (DHT) which is an aboveground steel tank with a 7.6-million-liter capacity. An airtight membrane will allow the headspace—the space above the digestate—to be used as biogas storage and minimize odors from the systems. The digestate will be land-applied seasonally as carbon-rich fertilizer. This project provides many benefits, such as renewable energy, emissions reduction, landfill and wastewater diversion, and enhanced fertilizer with few weed seeds and first year-available plant nutrients (Stuever, 2013).

2.4 Life Cycle Assessment (LCA)

2.4.1 What is it?

Life Cycle Assessment (LCA) is a methodology to evaluate environmental loads of processes and products based on their whole life cycles. The assessment includes the extraction and processing of raw materials, manufacturing, transportation, distribution, use, reuse, maintenance, recycling, and final disposal of a product, process, or system. Therefore, LCA has been widely used due to its integrated way of managing the framework, impact assessment, and data quality. LCA is often called as a “cradle-to-grave" method which explains this process by starting with gathering of raw materials from the earth to create product and ends at a stage where all materials are returned to the earth (Khasreen et al., 2009; Odey et al., 2021; Ram & Sharma, 2017).

LCA has gained support from various institutions, including United Nations Environment Programme (UNEP) / Society of Environmental Toxicology and Chemistry (SETAC) Life Cycle

Initiative, the Forum for Sustainability through Life Cycle Assessment (FLSCI), International reference Life Cycle Database System (ILCD), the European reference Life Cycle Database System (ELCD) (Odey et al., 2021). According to DEAT (Department of Environmental Affairs and Tourism) (2004), LCA is currently implemented by large groups of users, such as:

- Industry and other commercial enterprises
- National governments and local, national, and intergovernmental regulatory bodies
- NGOs (consumer organizations and environmental groups)
- Consumers (which includes governments as consumers)

Nevertheless, LCA has several drawbacks to address, which are the absence of a perceived need for LCA, scarcity of LCA expertise, access to high-quality data, and incorrect perception of the application of LCA in relation to other tools (Department of Environmental Affairs and Tourism of South Africa, 2004).

2.4.2 Process

LCA implicates a thorough assessment of environmental aspects of a product system, including all stages of its life cycle, by three major processes: 1) collecting an inventory of relevant inputs and outputs of a system; 2) formulating a thorough evaluation of the potential environmental impacts correlated with those inputs and outputs; and 3) interpreting the results in correlation to objectives of the study (Jensen et al., 1997). LCA is conducted based on ISO 14040 which consists of four analytical stages (Khasreen et al., 2009):

- Defining goal and scope
- Creating the life-cycle inventory
- Assessing the impact

- Interpreting the results

2.4.3 Parameters

2.4.3.1 Water

The amount of freshwater on Earth is only about 2% of all water on the planet. In terms of access to water, approximately one out of six people on Earth lacks access to drinking water. A product's life cycle, either directly or indirectly, has a strong correlation with water consumption. Based on LCA methodologies mentioned in ISO 14040:2006, water is a parameter assessed in water consumption potential (WCP) section, which is described as water that has been removed from the watershed and cannot be returned (Arosemena, 2021).

2.4.3.2 Nutrients

The primary concern about nutrients in the LCA study is the impact of excess nutrients that pollute the environment, such as land, water body, and air. This correlates nutrients with several impacts studied in LCA, which are Water Eutrophication Potential (WEP) and Air Acidification Potential (AAP).

Eutrophication is a situation where a water body contains excessive nutrients that affect the dense growth of plant life and the death of water animals due to a lack of oxygen. It is due to nutrients runoff from the land, such as nitrogen and phosphorus, which then accumulate in the water. As the consequence, it creates a "dead zone" which is an area with low oxygen content that suffocates marine life (Mueller and Helsel, 1996). Water eutrophication potential (WEP) is the impacts resulting from excessive nutrient supplies on terrestrial and aquatic environments, particularly the most important substances such as nitrogen (N) and phosphorus (P). WEP can be presented as either mass of nitrogen equivalents (kg N-eq.) or phosphate equivalents (PO_4-eq.) (Guinee, 2002).

According to the EPA, atmospheric acidification can be defined as: “the result of the oxidation of sulfur, nitrogen, and organic compounds to form their corresponding acids” (Durham & Demerjian, 1985). When absorbed by the atmosphere, these acids can lead to conditions such as acid rain. Air acidification potential (AAP) is an impact category used to convert processes or materials that form acid rain into common units of sulfur dioxide equivalents (SO2-eq.).

2.4.3.3 Greenhouse Gases (GHG)

Greenhouse gases is a parameter in LCA that is assessed into Global Warming Potential (GWP) which is the amount of GHG released during the life cycle of a process. Carbon dioxide is commonly used as a reference gas to compare the impact of various greenhouse (Shine, 2009). Fossil fuel consumption contributes approximately 65% of GHG emissions (Environmental Protection Agency (EPA), 2019). Therefore, renewable energy is expected to address this concern.

2.5 Revenue Value

As an emerging renewable energy source in the United States, anaerobic digestion provides various forms of revenues from renewable electricity, digestate, energy or fuel credits, and feeding fees. Nevertheless, the prices vary depending on location, operating procedures, and state regulations. One example is tipping fees, which are rates that a company should pay for disposing of waste materials as digester input. Tipping fees depend on the water content of materials. Fats, Oils, and Grease (FOG) have a monetary value of $0.10 per gallon due to high water content. However, the price can be about $0.05 per gallon if it has a lower water concentration or as dry material. On the other hand, digestate can be traded to farms or composting facilities for approximately $7.00 per ton (Dr. Dana Kirk, 2020).

Other potential revenues are RINs and RECs as mentioned previously. RIN price ranges between \$0.01 and \$3.50 depending on the biofuel source. RECs prices are various following changes in policy and the availability of RECs within the state. Currently, most RECs are fulfilled through sources such as wind and solar which creates a deviation in the market for prices.

In Michigan itself, RPS increased from 10% in 2015 to 15% in 2021, while it has compliance requirements of 12.5% in 2019 and 2020 (Michigan Public Service Commission, 2021). REC is regulated by The Michigan Renewable Energy Certification System (MIRECS) as a tracking and certification system. According to Consumers Energy, REC price is \$0.014 per kWh or \$14/MWh. Additionally, Michigan's electric providers in total retired 12,812,152 RECs in 2019 (Scripps et al., 2016).

CHAPTER 3. MATERIAL AND METHODS

3.1 Manure Feedstock

The South Campus Anaerobic Digester (SCAD) digester uses various kinds of feedstock, including dairy, beef, waste feed, poultry, and swine manure. Most feedstocks are from the Michigan State University dairy farm which is located adjacent to the SCAD.

3.2 Food Waste Feedstock

Food waste used in the digester included pineapple, pulp, FOG (fat, oil, and grease), and waste feed. A small portion of the food waste comes from Michigan State University dining halls, while the rest comes from off-campus food processors and manufacturers. Most of the food waste comes from southern Michigan, but a small portion of food waste was also gained from the neighboring states such as Indiana and Ohio.

3.3 Real-time (commercial system) sampling methods

The process flow diagram shown in Figure 3.1 provides a better view of the sampling locations.

3.3.1 Gas quantity and quality, and electricity production

Gas quantity was measured by using Endress Hausser Proline t-mass 65 flow meter in real time 24 hours as CHP (Combined Heat and Power) daily total in standard cubic foot (SCF) unit. Gas quality was measured by using AwiFLEX Cool+ gas analyzer every hour. Gas was taken from 2 distinct locations which were before and after the carbon activator scrubber. Three gases were measured which were CH_4 (%), O_2 (%), and H_2S (ppm). Electricity was measured as daily electrical power generated in kilowatts hour (kWh) unit by using SATEC PM172E. The measurement was recorded by the software in the morning until May 2015, then it changed to be in the midnight afterwards.

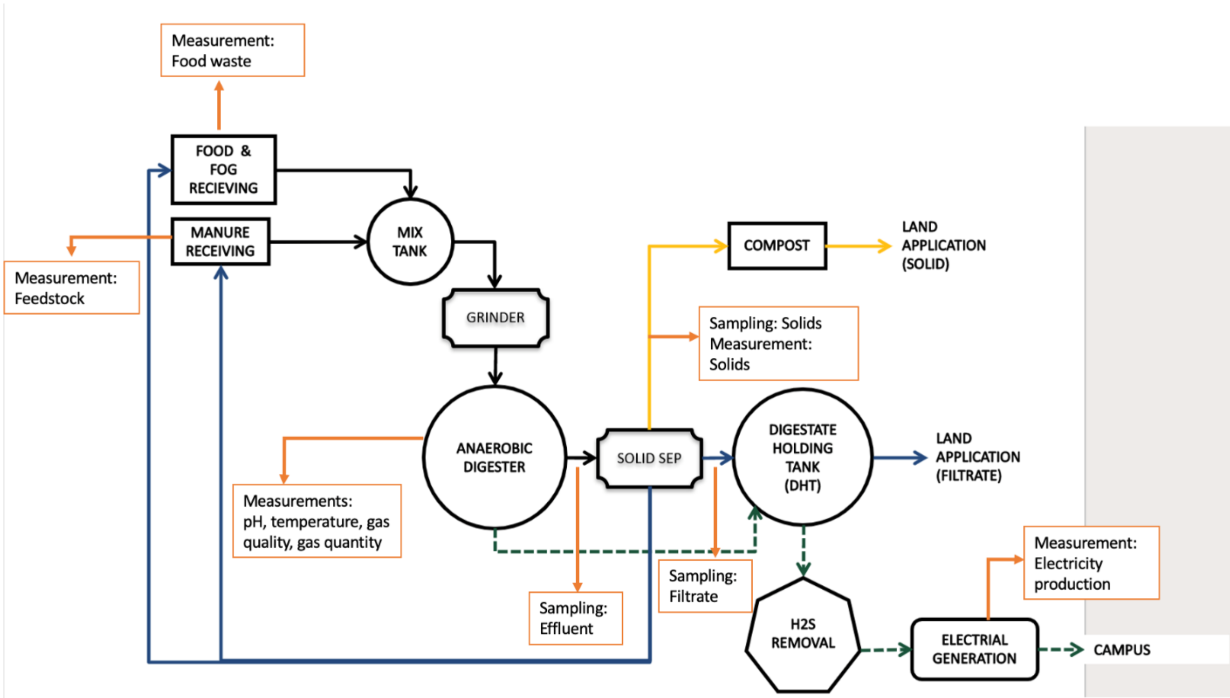

Figure 3.1. Sampling and measurement maps (Source: MSU Anaerobic Research and Education Center)
(Notes: black line: feedstock; yellow line: separated solids; blue line: filtrate; green dashed line: biogas phase; orange line: sample collection and measurement)

3.3.2 Digestate, filtrate, and solids sampling

Digestate or effluent from the digester consists of a mix of cow manure from MSU Dairy Farms and food waste. The effluent was collected from a piping line that connects the digester to the solid separator. The effluent was taken before the slurry went through a solid separator. The ratio between cow manure and food waste changes daily based upon material received. The filtrate was collected after solid liquid separation from a line that connects the solid separator to the digestate holding tank (DHT). Solids were taken at the solid separator station. These samples were regularly sent to ADREC for laboratory analysis. The frequency of sampling varied depending on the workforce availability in the laboratory. However, in general, the sampling was at least once a month.

3.3.3 Temperature sampling

The temperature of digester was measured continuously by using Endress Hausser T13 RTD probe that is located about 3 feet off the floor on the southwest area of the digester. The measurement results were recorded by the Allen Bradley/Rockwell compact logix PLC processor every 10 minutes and put into a CSV file. The measurement results were also recorded by the digester manager twice a day in the morning and at the end of working hours.

3.3.4 pH sampling

The pH of slurry in the digester was measured continuously by using Endress Hauser Liquiline C CM42, which is in the pipe that goes through a heat exchanger. The measurement results were recorded by the Allen Bradley/Rockwell compact logix PLC processor every 10 minutes and put into a CSV file. The measurement results were also recorded by the digester manager twice a day in the morning and at the end of working hours.

3.4 Laboratory Analysis

The laboratory analysis for SCAD samples was done at the MSU Anaerobic Digestion Research and Education Center (ADREC).

3.4.1 Total Solids and Volatile Solids

Total and volatile solids (TS and VS) are the fundamental feedstock and digestate measure for SCAD operational management. In addition to TS and VS, this test also yields information regarding the sample moisture content (MC) and fixed solids (FS). TS and VS analysis were performed following the EPA accepted Hach methods 8271 and 8276, respectively. The procedure for TS was modified from a 6-hour oven holding time to 24 hours to ensure complete drying. The procedure for VS was also adjusted by increasing the time from 1 hour to 6 hours to ensure complete sample combustion.

Materials and equipment needed for the test included the digester's samples (filtrate, effluent, and solids), 50 mL glass beakers (3 per sample), laboratory analytical balances (Scientech SA 120), oven (Precision Scientific, Catalog No. 31578-10), furnace (Lindberg, Model No. CBFM516C), stir plate (Cole-Parmer Instrument Company, Catalog No. 03406-10), magnetic stir bar, desiccator (Boekel 1342), desiccant (Drierite 22001), syringe, spoon, marker, and white board.

3.4.2 Chemical Oxygen Demand

Chemical Oxygen Demand (COD) is used as a measure of pollutant in wastewater or effluent. The results indicate the concentration of pollutants in the sample. The higher COD content, the more polluted the sample. The test was performed following the EPA accepted Hach method 8000. Materials and equipment needed were diluted samples using DI water, HACH heated reactor DRB 200, HACH spectrophotometer DR 5000, HACH COD test vials (Catalog No. 2125915), blank test vial, stir bar and stir plate (Cole-Parmer Instrument Company, Catalog No. 03406-10), micropipette, microtips, and delicate wipes.

3.4.3 Total Suspended Solids / Volatile Suspended Solids

Total Suspended Solids / Volatile Suspended Solids (TSS/VSS) test is a method to determine the amount of total suspended solids and total volatile suspended solids found within a sample. TSS/VSS tests were performed following the EPA accepted Hach methods 8158 and 8164, respectively. Materials and equipment needed were laboratory analytical balances (Scientech SA 120), desiccator, oven (Precision Scientific, Catalog No. 31578-10), furnace (Lindberg, Model No. CBFM516C), stir plate (Cole-Parmer Instrument Company, Catalog No. 03406-10), magnetic stir bar, vacuum filtration system, glass-microfibre discs filter 47 mm (HACH, Catalog No. 253000), tweezers, watch glass, aluminum crucible, DI water, 1 ml syringe, and tongs.

3.4.4 pH and Electrical Conductivity

pH and electrical conductivity (EC) are key measurements to monitor the biological health of a digester hence liquid samples of the digester's filtrate and effluent were evaluated weekly. The recommended range for pH is between 6.4 and 8.2 for a healthy digester (MSU ADREC Operator Training, 2019). Prior to use, the pH probe was calibrated using three calibration solutions at pH 4.01, 7.00, and 10.00. After calibration, pH, and electronic conductivity (EC) probes were rinsed with DI water and wiped using delicate wipes. Sample was stirred on the stir plate using magnetic stirrer; then, the probes were dipped into sample. Both probes were rinsed and wiped after use and the pH probe was stored in a storage solution.

Materials and equipment needed were pH/Conductivity meter (Orion Star A215), pH probe (Orion 8157BNUMD), conductivity probe (Orion 013005MD), double ionized (DI) water, calibration solutions for pH 4.01 (Millipore Sigma BX1634), 7.00 (Millipore Sigma 7BX1635), and 10.00 (Millipore Sigma BX1642), delicate wipes, stir bar, stir plate (Cole-Parmer Instrument Company, Catalog No. 03406-10), magnetic collection stick, and empty beakers.

3.4.5 Alkalinity and Volatile Fatty Acids

Alkalinity and Volatile Fatty Acids (VFA) tests were conducted using the titration method to understand the susceptibility of the digester towards the change within its internal environment. Alkalinity and VFA tests were conducted by referencing O'Brien and Donlan (1977) methods, as follows:

- Samples were centrifuged for 30-40 minutes

- After centrifugation, liquids were filtered using 23 µm then 11 µm filters to gain 50 mL of liquids only
- Filtered samples were then poured into 150 ml and stirred using stir bar on the stir plate
- pH was measured using pH probe prior to titration to know the initial pH
- Samples were gently stirred during titration using 1.0 N H_2SO_4 to a pH of 3.3, then the volume reading is noted. All processes up to this point were part of the alkalinity test
- After the first titration, sample beaker was covered with 65 mm watch glass and then heated on the heated stir plate to a gentle boiling point for 3 minutes
- The sample was then cooled down to room temperature. After that, the watch glass was rinsed into the beaker with DI water
- Sample was then titrated again using 0.05 N NaOH to pH 4.0, then volume reading was noted
- Lastly, sample was titrated again using 0.05 N NaOH to pH 5.1 without refilling the solution from the previous titration, then the volume reading is totaled with the second titration. This entire process was part of the VFA test

Materials and equipment needed were centrifuge (Hermle Labnet Z 206 A), centrifuge vials 50 mL, 150 ml sample beaker, empty beaker, 23 µm (Whatman, Catalog No. 1441-047) and 11 µm filters (Whatman, Catalog No. 1001-047), filter flask (brand), tweezers, pH/Conductivity meter (Orion Star A215), pH probe (Orion 8157BNUMD), delicate wipes, stir bar, heated stir plate (Cole-Parmer Catalog No. EW-03407-36), cone hood, stir plate (Cole-Parmer Catalog No. 03406-10), 65 mm watch glass, double ionized (DI) water, 1.0 N H_2SO_4, and 0.05 N NaOH.

3.4.6 Total Nitrogen

Nitrogen is an important nutrient to both digester performance and fertilizer use of digestate. Total Nitrogen (TN) is a test to determine the total nitrogen by the per sulfate digestion method. The test was performed following the instructions available for the HACH TNT 827 test kit. Materials and equipment used were dilution of samples for range used, HACH heated reactor DRB 200, HACH nitrogen test kit high range (TNT 827), HACH spectrophotometer DR 5000, 20 mm reaction tube, stir bar and stir plate (Cole-Parmer Instrument Company, Catalog No. 03406-10), glass beakers, double ionized (DI water), delicate wipes, micropipette, and microtips.

3.4.7 Ammonia

Ammonia can cause toxicity in digesters if levels exceed 3,000 mg/L (MSU ADREC Operator Training, 2019). An ammonia test was conducted to analyze the ammonia content in the samples. The test was performed following the instructions available for the HACH TNT 832 test kit. Materials and equipment needed were diluted samples using DI water, HACH ammonia test kit high range (TNT 832), HACH spectrophotometer (DR 5000), stir bar and stir plate (Cole-Parmer Instrument Company, Catalog No. 03406-10), micropipette, microtips, and delicate wipes.

3.4.8 Total Phosphorus

Phosphorus is the key limiting nutrient for land application of digestate as a fertilizer. In organic wastes, phosphates are present in organic and condensed inorganic forms. Phosphorus can be obtained from treating the samples with acid and heat providing conditions for hydrolysis of the condensed inorganic forms. Total Phosphorus (TP) test was conducted to measure the phosphorus content in filtrate and effluent samples. The test was performed following the instructions available for the HACH TNT 844 test kit. Materials and equipment needed were diluted samples using DI water, HACH heated reactor DRB 200, HACH phosphorus test kit high range (TNT 844), HACH spectrophotometer DR 5000, stir bar and stir plate (Cole-Parmer Instrument Company, Catalog No. 03406-10), micropipette, microtips, and delicate wipes.

3.4.9 Other laboratory tests

There were several tests conducted outside of ADREC laboratory due to facilities availability. Those tests were conducted by A&L Great Lakes Laboratory (algreatlakes.com) in Fort Wayne, Indiana. The tests included manure nutrition analysis which were moisture, solids, Total Kjeldahl Nitrogen (TKN), phosphorus, potassium, sulfur, calcium, magnesium, sodium, iron, aluminum, manganese, copper, and zinc. All test methods were referred to Recommended Methods of Manure Analysis, UW A3769, summarized in Table 3.1 below.

Table 3.1 List of test methods done by A&L Great Lakes Laboratory

Parameter	Method
Moisture	UW A3769 III.2
Solids	Solids were calculated from moisture
Total Kjeldahl Nitrogen (TKN)	UW A3769 III.3.2
Phosphorus, Potassium, Sulfur, Magnesium, Calcium, Sodium, Aluminum, Copper, Iron, Manganese, Zinc	UW A3769 III.6.3. All minerals ran on Thermo iCAP 6500.

3.5 Statistical Analysis

Three analyses were conducted for this research: mass and energy balance, life cycle impact assessment, and economic analysis. The original data from SCAD manager were reorganized to ease data calculation and further analysis. Data was organized in an Excel spreadsheet and used to calculate the descriptive analysis such as min, max, mean, average, standard deviation, number of samples, and coefficient of variation. Other spreadsheets were created from the reorganized spreadsheet to provide data sources for statistical analysis by using the R Studio programming software.

Multi linear regression (MLR) in R Studio programming software was used to determine the model for gas production from available feedstock combinations. The codes utilized for MLR analysis are provided in Appendix A.

MLR formula is defined as equation below:

$$
\begin{aligned}
&y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_p x_{ip} + \epsilon \\
&\textbf{where, for } i = n \textbf{ observations:} \\
&y_i = \text{dependent variable} \\
&x_i = \text{explanatory variables} \\
&\beta_0 = \text{y-intercept (constant term)} \\
&\beta_p = \text{slope coefficients for each explanatory variable} \\
&\epsilon = \text{the model's error term (also known as the residuals)}
\end{aligned}
\tag{2}
$$

Furthermore, R Studio programming software was also used to create radar and violin charts to check data distribution of each feedstock year to year. A radar chart, also known as a spider plot, is used to visualize the amount of feedstock received by the digester each month and year. Radar chart was created by using fmsb and ggradar packages in R software. The codes utilized for Radar chart are provided in Appendix B.

A violin chart is used to visualize the distribution of individual feedstock amount year to year, also output parameters of the digester. Violin chart is created by using ggplot2 and geom_violin packages in R software. ANOVA (analysis of variance) Tukey multiple comparison was used to determine statistically significant differences between the various operational parameters via the R function TukeyHSD. The codes utilized for Violin chart and ANOVA Tukey multiple comparison are provided in Appendix C.

CHAPTER 4. ANALYSIS OF SCAD OPERATIONAL DATA

4.1 Feedstock Amount

During the operation period January 1, 2014, and ending December 31, 2020, the SCAD utilized 18 different feedstocks. Feedstocks were managed in two reception tanks, one for manure (low energy materials) and another for food waste (high energy materials). Table 4.1 summarizes the feedstocks and reception tank used to manage the inflow. The composition of feedstock received by the digester is variative each year.

Table 4.1 Feedstocks in SCAD Manure Pit and Food Pit

No	Manure Pit	Food Pit
1	Digestate (recycle)	Filtrate (recycle)
2	Filtrate (recycle)	Cart Food
3	ANS Other	Fat, Oil, and Grease (FOG)
4	Beef Manure	Other
5	Dairy Gutter Manure (Dairy G.)	Pineapple (P.A.)
6	Dairy Freestall Manure (Parlor)	Pulp
7	Poultry Manure	SLS Solids
8	SLS Solids	Waste Feed
9	Swine Manure	
10	Waste Feed	

4.1.1 Yearly total

The yearly total of feedstock processed in SCAD is shown in Table 4.2 for manure pit and Table 4.3 for food pit. Digestate is recycled directly from the digester effluent without solid-liquid separation. Filtrate is the liquid generated after coarse solids are separated from digestate. Digestate and filtrate are recycled to thin out pits and to dilute high TS feedstocks. SLS Solids are

Table 4.2 Total Feedstock in Manure Pit Year 2014-2020

Year	Feedstock (metric ton)									
	Digestate	**Filtrate**	**SLS Solids**	**Dairy G.**	**Parlor**	**Beef**	**Waste Feed**	**Poultry**	**Swine**	**ANS Other**
2014		5,643		4,104	4,273	697	17		25	4
2015	311	3,706	192	4,542	4,754	121	3		144	30
2016	1,001	412	56	5,091	4,200	243	34	5		17
2017	656	171	229	4,878	4,787	222	45	13	78	29
2018	296	179	42	4,855	5,110	220			151	5
2019		94	50	4,885	5,877	391	33	20		3
2020	23	45	59	4,664	5,388	7	56	15		75
Max	**1,001**	**5,643**	**229**	**5,091**	**5,877**	**697**	**56**	**20**	**151**	**75**
Min	**23**	**45**	**42**	**4,104**	**4,200**	**7**	**3**	**5**	**25**	**3**
Mean	**268**	**380**	**82**	**4,707**	**4,882**	**160**	**23**	**12**	**81**	**13**
Average	**457**	**1,465**	**105**	**4,717**	**4,913**	**272**	**31**	**13**	**100**	**23**
St. Dev	**378**	**2,266**	**83**	**322**	**599**	**221**	**19**	**6**	**59**	**26**
Coefficient of Variation	**141%**	**597%**	**101%**	**7%**	**12%**	**139%**	**83%**	**54%**	**73%**	**191%**

the coarse fiber separated from digestate via solid-liquid separation. SLS Solids are added solids back into the digester to thicken thin, low TS, feedstocks. ANS stands for animal science, meaning that there were research materials added into the digester in low quantities, for example eggs from research chickens.

There were several years where the digester did not receive certain types of feedstocks. SLS Solids were not used in 2014. Poultry manure did not come to the digester in 2014, 2015, and 2018. Furthermore, there was no swine manure in 2016, 2019, and 2020. Pineapple was only available until 2016. Waste feed was absent in 2018.

Several feedstocks, Dairy Gutter, and Parlor as well as FOG, produced the largest annual mass; meanwhile, the others had significant changes in a certain period. Moreover, each feedstock has a different peak of receiving in the digester. According to manure pit data (Table 4.2), the digester received the highest amount of SLS Solids in 2017; Dairy G in 2016; Parlor in 2019; Beef in 2014; Waste Feed in 2020; Poultry in 2019; and Swine in 2018. The average of each feedstock received by SCAD during 2014-2020 is 105 metric tons for SLS Solids, 4,717 metric tons for Dairy Gutter, 4,913 metric tons for Parlor, 272 metric tons for Beef, 31 metric tons for Waste Feed, 13 metric tons for Poultry, 100 metric tons for Swine, and 23 metric tons for ANS Other.

Regarding the coefficient variation of feedstock, it showed that Dairy Gutter and Parlor had the most consistent amount that the digester received year by year. The coefficient variation for Dairy G and Parlor was 7% and 12% respectively, showing that the number did not significantly change year over year (Figure 4.1). These two feedstocks were also the major feedstocks in manure pit. Based on calculation of Dairy Gutter and Parlor in the total of feedstocks received in manure pit, the percentage of these feedstocks increased every year. Dairy G and Parlor contributed 57% of total feedstock in manure pit in 2014, 67% in 2015, 84% in 2016, 87% in 2017, 92% in 2018, 95% in 2019, and 97% in 2020. It shows that the digester improves the feedstock composition which affects gas production. On the other hand, Filtrate significantly decreased since 2016 due to the conclusion of pineapples waste reception. The primary reason for the addition of filtrate and SLS Solids to the reception pits is to create suitable feedstock for pumping and mixing, TS less than 8%. In 2016 and prior, the digester received a vast amount of pineapples waste that required excessive amount of filtrate to dilute and breakdown the waste before pumped to the mix tank.

Meanwhile, on food pit data (Table 4.3), the digester received the highest amount of SLS Solids in 2019, Pineapple in 2014, Pulp in 2014, FOG in 2020, Waste Feed in 2015, Other Feedstock in 2015, and Cart Food in 2015. The average amount of feedstocks received by the digester in 2014-2020 was 152 metric tons for SLS Solids, 2,098 metric tons for Pineapple, 78 metric tons for Pulp, 8,380 metric tons for FOG, 18 metric tons for Waste Feed, 388 metric tons for Other Feedstocks, and 145 metric tons for Cart Food.

Regarding coefficients of variation, there was no feedstock in the food pit that was as consistent as Dairy G or Parlor in manure pit. FOG was the most consistent followed by Pulp and Pineapple, with coefficients of variation of 31%, 38% and 44%, respectively (Figure 4.2). Pulp feedstock which comes from Brody dining hall experienced a great reduction in 2020 due to COVID-19 pandemic that limited students' activities in the residence halls after March 15, 2020. Moreover, the Pineapple contract with the digester was only until 2016. The supplier proceeded to compost the feedstock afterwards, hence there were no more supplies starting in 2017. Food carts also experienced a significant reduction starting in 2017 due to contamination with “debris.” Overall, FOG dominated feedstock supplies in the food pit.

Table 4.3 Total Feedstock in Food Pit Year 2014-2020

Year	Feedstock (metric ton)							
	Filtrate	SLS Solids	Pineapple	Pulp	FOG	Waste Feed	Other	Cart Food
2014	1,321		2,681	102	4,005	24	117	283
2015	1,804	53	2,493	94	7,792	28	171	366
2016	1,312	271	1,118	80	8,470		154	320
2017	577	85		77	8,330		45	15
2018	201	196		80	8,068	2	44	14
2019	194	275		92	9,875		92	12
2020	256	35		20	12,122		2,094	3
Max	**1,804**	**275**	**2,681**	**102**	**12,122**	**28**	**2,094**	**366**
Min	**194**	**35**	**1,118**	**20**	**4,005**	**2**	**44**	**3**
Mean	**564**	**115**	**1,955**	**71**	**8,016**	**10**	**142**	**43**
Average	**809**	**152**	**2,098**	**78**	**8,380**	**18**	**388**	**145**
St. Dev	**660**	**109**	**853**	**27**	**2,444**	**14**	**754**	**169**
Coefficient of Variation	**117%**	**94%**	**44%**	**38%**	**30%**	**138%**	**530%**	**396%**

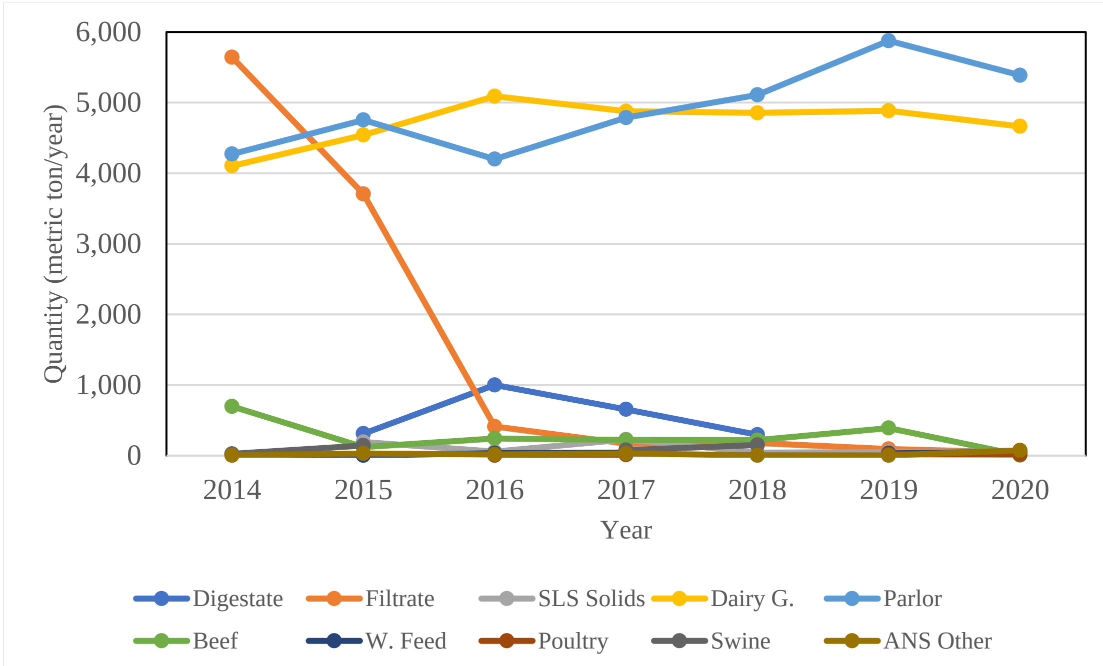

Figure 4.1 Comparison of feedstock received by SCAD in manure pit

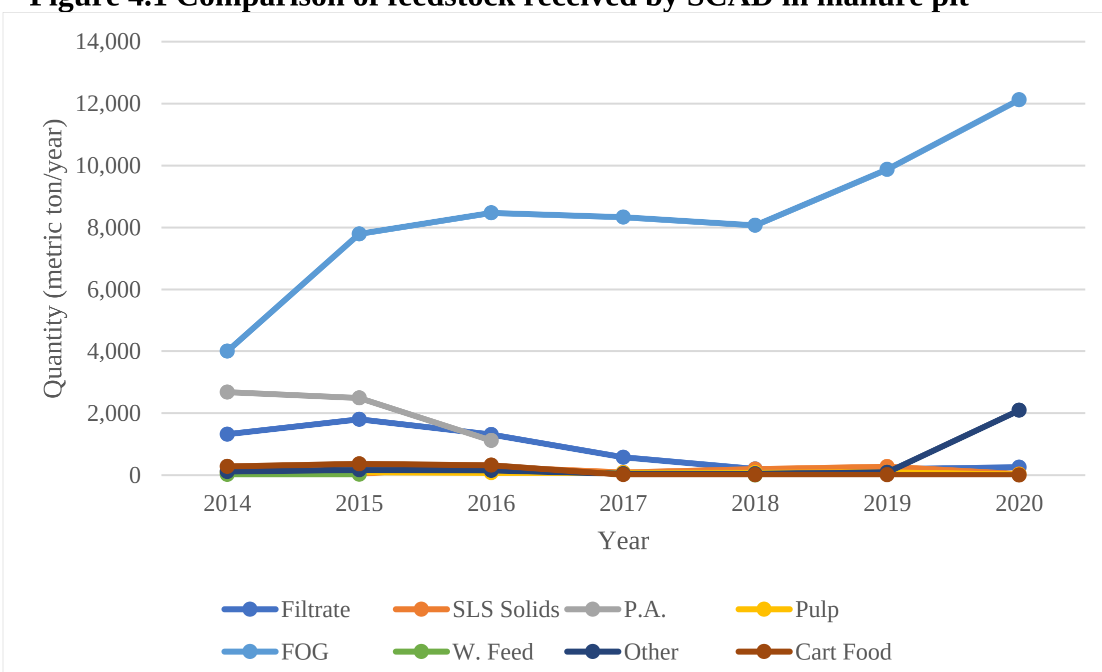

Figure 4.2 Comparison of feedstock received by SCAD in food pit

A ratio of total feedstock between manure pit and food pit was calculated. Based on Table 4.4, the ratio of feedstock from food pit ranged from 37% to 58% with the highest percentage being in 2020. On average, SCAD has received 11,897 metric tons of feedstock in manure pit each year and 10,838 metric ton of feedstock in food pit, for a total of 22,375 metric ton/year with the average ratio of feedstock in food pit was 47%.

Table 4.4 Ratio of Manure Pit and Food Pit

Year	Manure Pit (Metric ton/year)	Food Pit (Metric ton/year)	Total (Metric ton/year)	Food Pit (%)
2014	14,763	8,533	23,297	37%
2015	13,805	12,800	26,605	48%
2016	11,059	11,726	22,785	51%
2017	11,109	9,129	20,238	45%
2018	10,859	8,605	19,464	44%
2019	11,353	10,539	21,893	48%
2020	10,332	14,531	24,863	58%
Max	14,763	14,531	26,605	58%
Min	10,332	8,533	19,464	37%
Mean	11,802	10,637	22,618	47%
Average	11,897	10,838	22,735	47%
St. Dev	1,683	2,294	2,499	7%

4.1.2 Monthly Average

The monthly average of feedstock processed in SCAD is shown in Table 4.5 and 4.6. FOG, Parlor, and Dairy Gutter are three major feedstocks that the digester received each month during the years 2014-2020. Radar charts in Figure 4.3 to 4.9 also give a better picture of feedstock peaks for each month. In 2014 to 2016, Parlor, FOG, and Filtrate consistently had higher peaks compared to the rest of feedstocks. However, from 2017 to 2020, Parlor and FOG remained as the only feedstocks that have consistent peaks of supply. There were several outliers that happened during 2014-2020, which were Digestate (July 2016), Swine (December 2017), Filtrate in manure pit (August 2017 and May 2018), Filtrate in food pit (July 2018), and FOG (October 2019).

Table 4.5 Average Mass Delivered to Digester Each Month (Manure Pit), 2014-2020

Year	Feedstock (kg)									
	Digestate	Filtrate	SLS Solids	Dairy G.	Parlor	Beef	Waste Feed	Poultry	Swine	ANS Other
2014		25,840		11,463	25,466	6,354	4,069		12,645	179
2015	20,592	21,259	2,916	12,647	27,034	4,784	1,069		4,537	741
2016	18,979	12,123	3,263	13,844	21,659	3,914	3,426	568		441
2017	15,338	14,884	3,187	13,307	20,612	2,394	1,451	1,071	25,682	919
2018	16,210	15,258	2,749	13,205	23,907	2,878			17,275	688
2019		10,184	3,159	13,287	21,993	3,432	1,847	1,935		1,562
2020	11,259	12,507	3,637	12,678	21,269	3,053	3,159	1,950		3,022
Max	**20,592**	**25,840**	**3,637**	**13,844**	**27,034**	**6,354**	**4,069**	**1,950**	**25,682**	**3,022**
Min	**11,259**	**10,184**	**2,749**	**11,463**	**20,612**	**2,394**	**1,069**	**568**	**4,537**	**179**
Mean	**16,136**	**15,259**	**3,139**	**12,899**	**23,031**	**3,648**	**2,239**	**1,231**	**12,631**	**779**
Average	**16,475**	**16,008**	**3,152**	**12,919**	**23,134**	**3,830**	**2,503**	**1,381**	**15,035**	**1,079**
St. Dev	**3,218**	**5,173**	**279**	**705**	**2,222**	**1,255**	**1,105**	**589**	**7,653**	**888**
Coefficient of Variation	**20%**	**34%**	**9%**	**5%**	**10%**	**34%**	**49%**	**48%**	**61%**	**114%**

Table 4.6 Average Mass Delivered to Digester Each Month (Food Pit), 2014-2020

Year	Feedstock (kg)							
	Filtrate	SLS Solids	Pineapple	Pulp	FOG	Waste Feed	Other	Cart Food
2014	19,922		11,547	1,112	18,952	2,017	10,870	2,151
2015	18,478	3,032	11,093	1,272	35,270	2,146	2,849	1,845
2016	14,955	3,386	11,345	1,317	35,052		1,341	2,417
2017	18,812	2,844		2,013	32,703		1,067	121
2018	22,917	2,802		1,656	31,780	1,620	1,498	117
2019	14,565	3,228		2,088	34,277		2,857	92
2020	14,102	3,160		1,630	40,428		13,222	67
Max	**22,917**	**3,386**	**11,547**	**2,088**	**40,428**	**2,146**	**13,222**	**2,417**
Min	**14,102**	**2,802**	**11,093**	**1,112**	**18,952**	**1,620**	**1,067**	**67**
Mean	**17,424**	**3,069**	**11,326**	**1,546**	**31,917**	**1,914**	**3,059**	**364**
Average	**17,679**	**3,076**	**11,328**	**1,584**	**32,637**	**1,928**	**4,815**	**973**
St. Dev	**3,031**	**207**	**186**	**346**	**6,143**	**224**	**4,663**	**1,020**
Coefficient of Variation	**17%**	**7%**	**2%**	**22%**	**19%**	**12%**	**152%**	**280%**

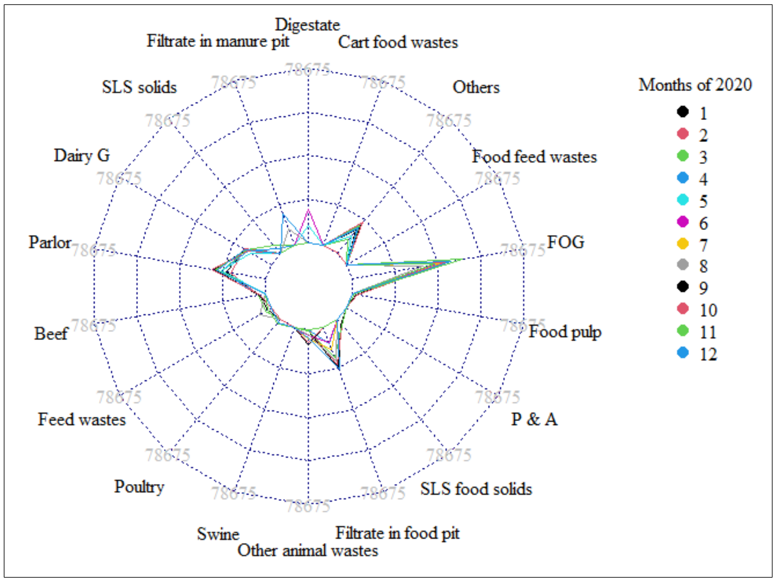

Figure 4.3 Radar chart for feedstock supplies receiveed by SCAD in 2020

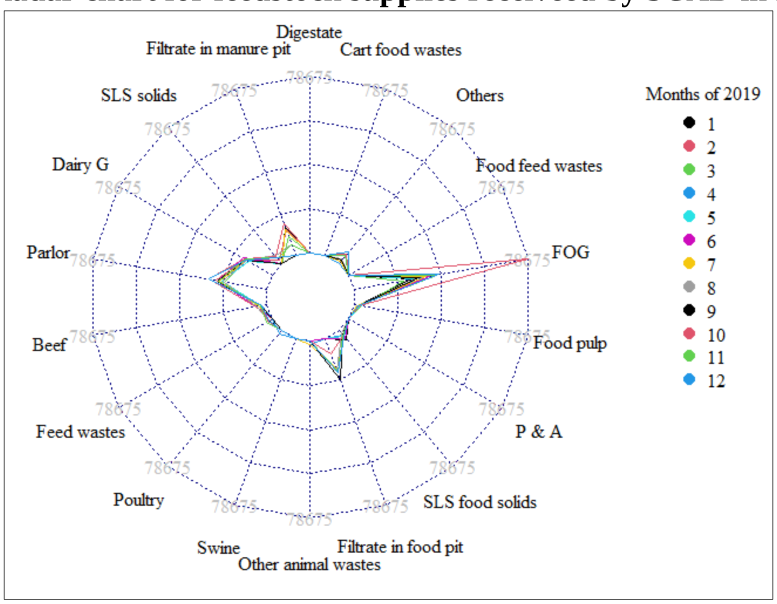

Figure 4.4 Radar chart for feedstock supplies receiveed by SCAD in 2019

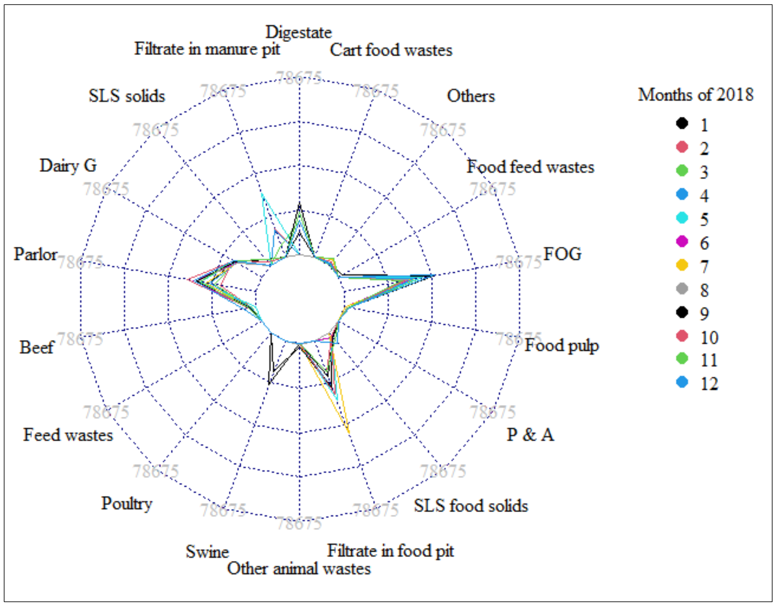

Figure 4.5 Radar chart for feedstock supplies receiveed by SCAD in 2018

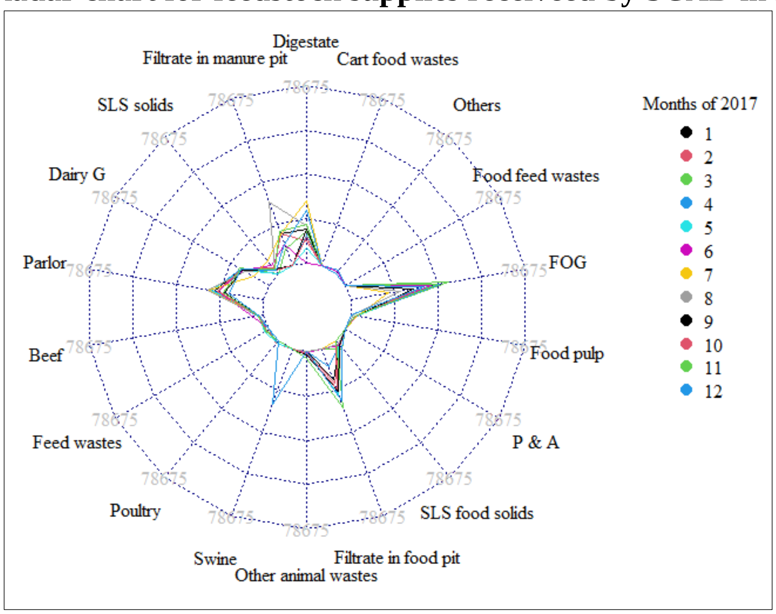

Figure 4.6 Radar chart for feedstock supplies receiveed by SCAD in 2017

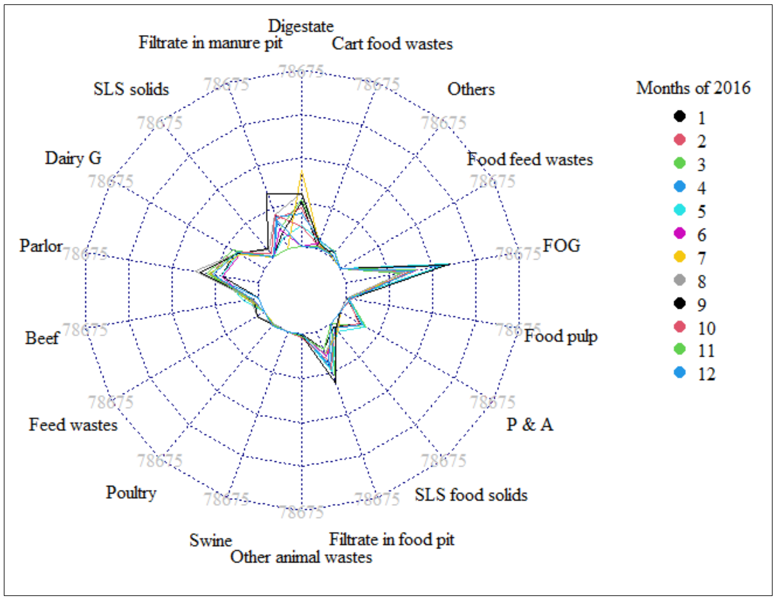

Figure 4.7 Radar chart for feedstock supplies receiveed by SCAD in 2016

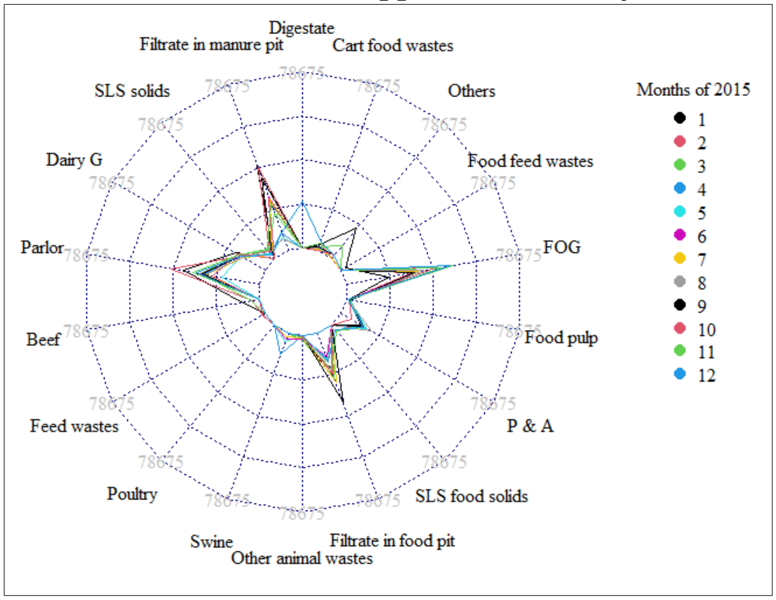

Figure 4.8 Radar chart for feedstock supplies receiveed by SCAD in 2015

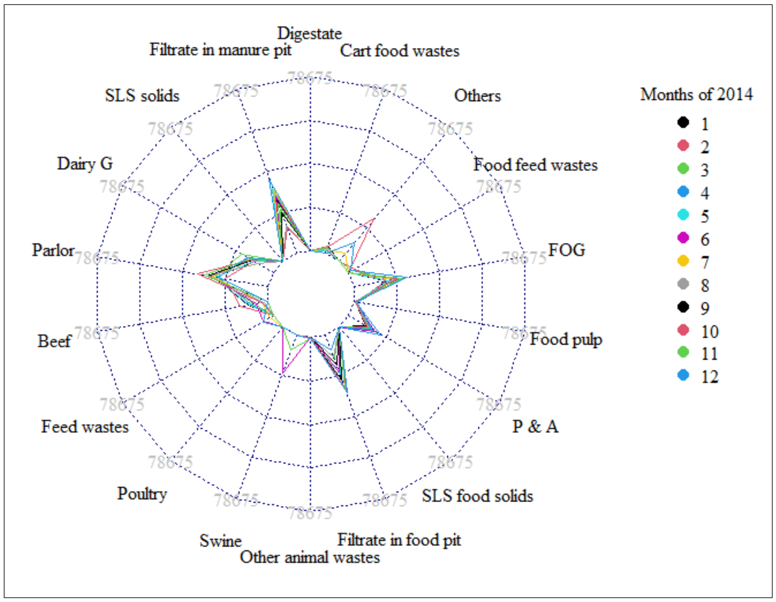

Figure 4.9 Radar chart for feedstock supplies receiveed by SCAD in 2014

4.1.3 Feedstock Distribution

This study also observes the distribution of feedstock received by SCAD for each feedstock from 2014-to 2020. Violin charts were used to check the data distribution of each feedstock year to year. The violin chart consisted of a colored area, a white box, and a straight line with top and bottom points. The colored area represents data points that the parameter has. The more colored the area, the larger the data points. A large part of the colored area shows where most data is located. The white box is in the middle of the colored area. The top part of the box represents the third quartile of data points, a line inside the box represents the median, while the bottom part represents the first quartile. The straight line with top and bottom points represents the range of data with the highest and lowest value, respectively. ANOVA (analysis of variance) Tukey multiple comparisons were used to determine the significance of data compared year to year.

4.1.3.1 Manure Pit

From manure pit, Filtrate manure pit, Dairy Gutter and Parlor are three feedstocks with the largest data points. Figure 4.10 shows the violin chart for Filtrate manure pit. In general, the charts in 2014, 2015, 2019, and 2020 have distinctive shapes which means the data in these years were distributed differently. Meanwhile, the chart shapes in 2016-2018 show were quite similar. There was a significant range of filtrate circulating into manure pit in 2015 with median and highest data point were about 23,000 kg/day and 40,000 kg/day, respectively. The range got smaller and more consistent in 2016-2018 which the medians were roughly 13,000 kg/day. In 2019 and 2020, data distribution for filtrate supplied to manure pit became more consistent with the range of data points was approximately 5,000 kg/day to 15,000. Lower supply of filtrate shows that digester received fewer solid feedstocks; thus, it did not need much dilution using the filtrate.

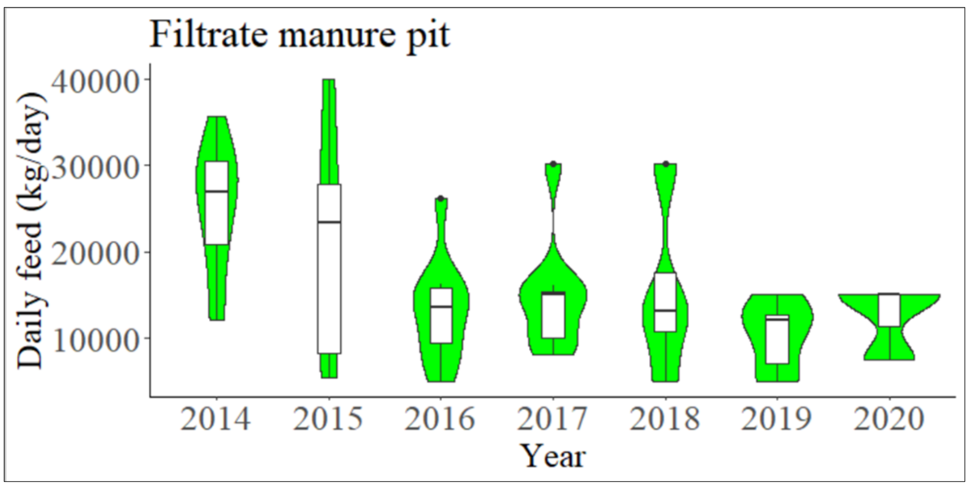

Figure 4.10 Data distribution of Filtrate manure pit

Table 4.7 shows the ANOVA Tukey multiple comparison performed for Filtrate manure pit data distribution. It shows that there was a significant difference in the quantity of Filtrate manure pit received by the digester at the $p<0.05$ level from year to year [$F(6, 49) = 3.729$, $p = 0.00392$).

Table 4.7 ANOVA Tukey Multiple Comparison results for Filtrate manure pit data distribution

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
Year	6	1.533e+09	258,810,814	3.729	0.00392
Residuals	49	3.401e+09	69,412,500		

The violin chart of Dairy Gutter (Figure 4.11) shows different shapes for each year. In 2014, the chart shows an extensive range of data points with most data points located slightly below 12,500 kg/day, while the highest data point was about 16,000 kg/day. There was an outlier in 2017, with data points located around 8,000 kg/day. That means there was a moment where the digester received lower supplies of this feedstock. Meanwhile, feedstock supplies were typically stable in 2018-2020 which the median between 12,500 and 15,000 kg/day.

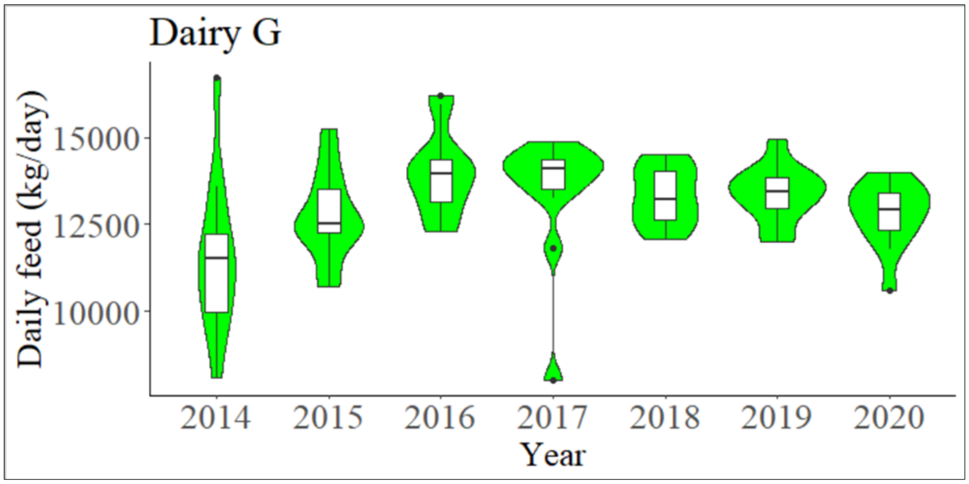

Figure 4.11 Data distribution of Dairy Gutter

Table 4.8 shows the ANOVA Tukey multiple comparison performed for Daily Gutter data distribution. It shows that there was a significant difference in the quantity of Dairy Gutter received by the digester at the $p<0.05$ level from year to year [$F(6, 77) = 3.554$, $p = 0.00368$).

Table 4.8 ANOVA Tukey Multiple Comparison results for Dairy Gutter data distribution

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
Year	6	42,372,311	7,062,052	3.554	0.00368
Residuals	77	152,983,389	1,986,797		

Figure 4.12 shows the data distribution for Parlor. The chart shape was significantly different from year to year. The chart in 2015 shows the most extensive range with the highest peak reaching 40,000 kg/day, becoming the highest data point of all years. Data median also shows

two different trends. Median in 2014, 2015, and 2018 were around 25,000 kg/day, while the rest have median around 20,000 kg/day.

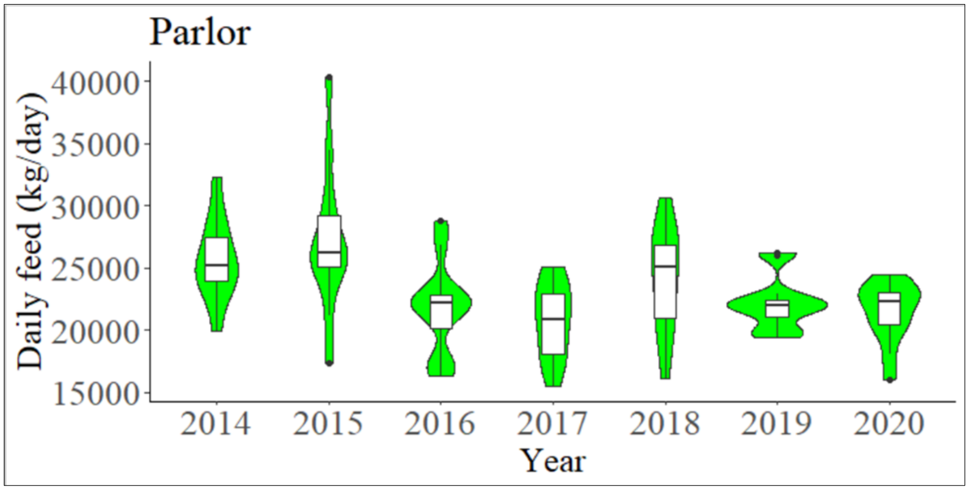

Figure 4.12 Data distribution of Parlor

Table 4.9 shows the ANOVA Tukey multiple comparison performed for Parlor data distribution. It shows that there was a significant difference in the quantity of Parlor received by the digester at the $p<0.05$ level from year to year [$F(6, 77) = 5.017$, $p = 0.000$).

Table 4.9 ANOVA Tukey Multiple Comparison results for Parlor data distribution

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
Year	6	4.214e+08	70,235,648	5.016	0.000
Residuals	77	1.078e+09	14,000,917		

Figure 4.13 shows the data distribution for Total Manure Pit. The chart shows three different trends. Data distribution in 2014 and 2015 share a similar pattern where the curves have clear violin shapes. Data distribution in 2016, 2017, and 2018 share similar shapes where the curves look like a coke bottle. Data distribution in 2019 and 2020 look similar where the curves have shorter shapes, meaning that the data have more consistent ranges. Data median shows a constant slight decrease from 2014 to 2018. There was quite a significant decrease in data median

from 2018 to 2019, then a slight decrease in 2020. Data distribution in 2015 and 2016 shows the most extensive range, from 40,000 to 100,000 kg/day. Data distribution from 2019 to 2020 shows the most consistent data distribution, ranging from roughly 30,000 to 60,000 kg/day.

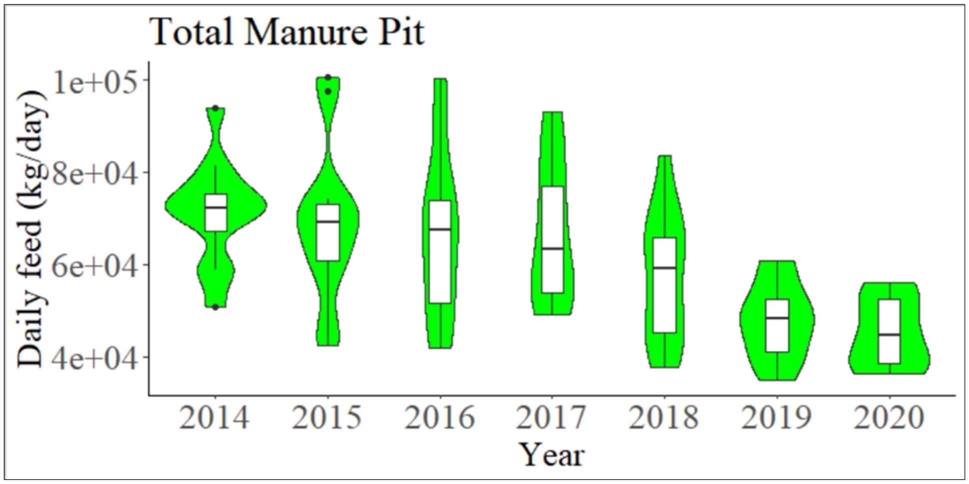

Figure 4.13 Data distribution for total manure pit

Table 4.10 shows the ANOVA Tukey multiple comparison performed for total manure pit data distribution. It shows that there was a significant difference in the quantity of total manure pit received by the digester at the $p<0.05$ level from year to year [$F (6, 77) = 7.098$, $p = 0.000$).

Table 4.10 ANOVA Tukey Multiple Comparison results for Total Manure Pit data distribution

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
Year	6	8.058e+09	1.343e+09	7.098	0.000
Residuals	77	1.457e+10	1.892e+08		

Data for other feedstocks in manure pit are provided in Appendix C.1. In general, some of the feedstocks in the manure pit did not have large enough data points, therefore they show little or no colored area around the white box (SLS Solids, Beef and ANS Other). Meanwhile, other feedstocks did not show a complete chart for each year due to the digester did not receiving them in certain years (Digestate, Waste Feed Manure, Poultry, and Swine).

4.1.3.2 Food Pit

From the manure pit, Pulp and FOG were feedstocks with the largest data points. Figure 4.14 shows data distribution for Pulp. The charts show different shapes each year with 2015 being the year with the most consistent data distribution, ranging from roughly 1,000 to 1,600 kg/day. The peak of pulp received by the digester happened in 2019 exceeding 3,000 kg/day. Data distribution in 2020 was typically consistent although the supply was disrupted by COVID-19 pandemic.

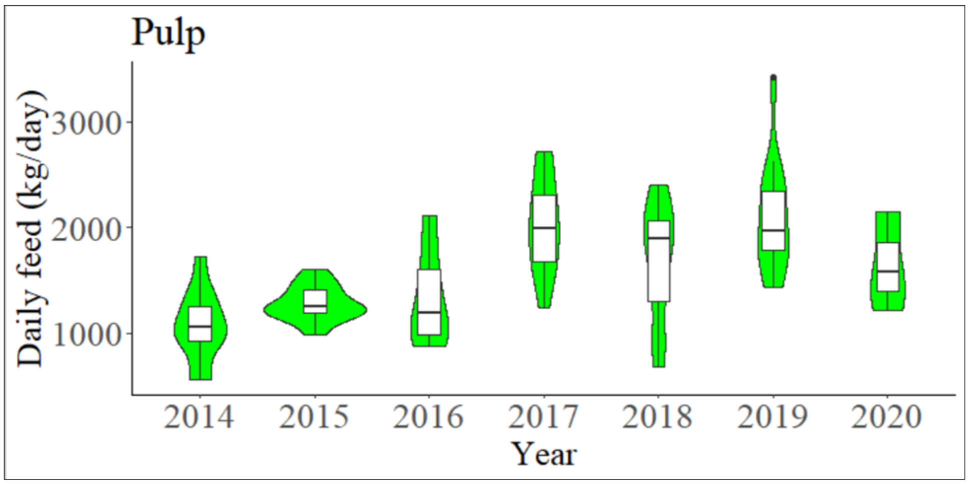

Figure 4.14 Data distribution for Pulp

Table 4.11 shows the ANOVA Tukey multiple comparison performed for Pulp data distribution. It shows that there was a significant difference in the quantity of Pulp received by the digester at the $p<0.05$ level from year to year [$F (6, 67) = 8.78$, $p = 0.000$).

Table 4.11 ANOVA Tukey Multiple Comparison results for Pulp data distribution

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
Year	6	10,479,022	1,746,504	8.78	0.000
Residuals	67	13,326,784	198,907		

Figure 4.15 shows the data distribution for FOG. Data distribution was typically consistent from 2015 to 2019. The data median in 2014 was the lowest at around 20,000 kg/day, while data median for 2020 was the highest which was slightly above 40,000 kg/day. As previously shown in the radar chart, the year 2019 had an outlier for the data peak which was around 80,000 kg/day, and outlier compared to the rest of data points which ranged from about 25,000 kg/day to 40,000 kg/day.

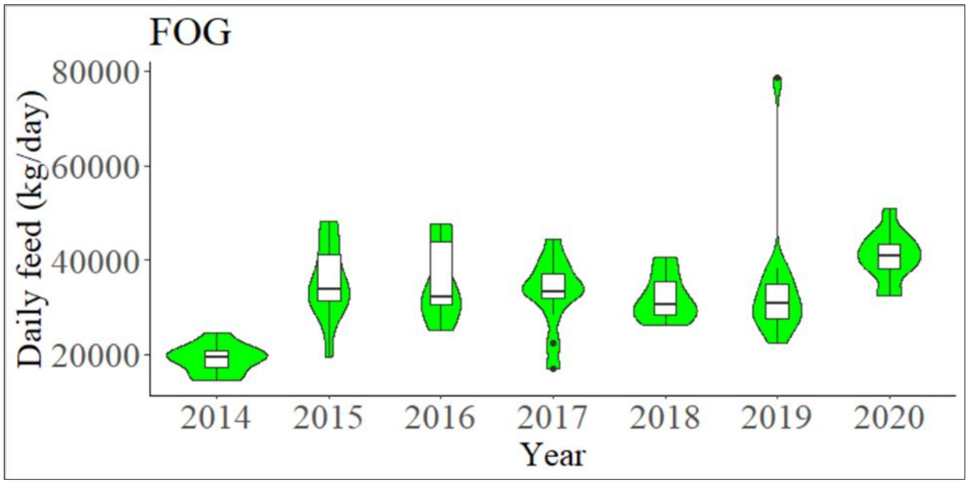

Figure 4.15 Data distribution for FOG

Table 4.12 shows the ANOVA Tukey multiple comparison performed for FOG data distribution. It shows that there was a significant difference in the quantity of FOG received by the digester at the $p<0.05$ level from year to year [$F(6, 77) = 8.095$, $p = 0.000$).

Table 4.12 ANOVA Tukey Multiple Comparison results for FOG data distribution

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
Year	6	3.215e+09	535,833,184	8.095	0.000
Residuals	77	5.097e+09	66,195,896		

Figure 4.16 shows the data distribution for Total Food Pit. The chart in 2020 shows a perfect upside-down violin, while 2014 looks like a violin shape. Data distribution in 2015, 2016, and 2018 share similar chart shapes. The highest data point happened in 2019 which was around

90,000 kg/day, while the lowest data point happened in 2017 which was around 20,000 kg/day, associated with the engine outage. The data range from 2014 to 2016 was typically consistent from slightly above 40,000 kg/day to slightly above 80,000 kg/day, meanwhile the data range from 2018 to 2020 was typically consistent with most data points were approximately between 30,000 kg/day and 80,000 kg/day.

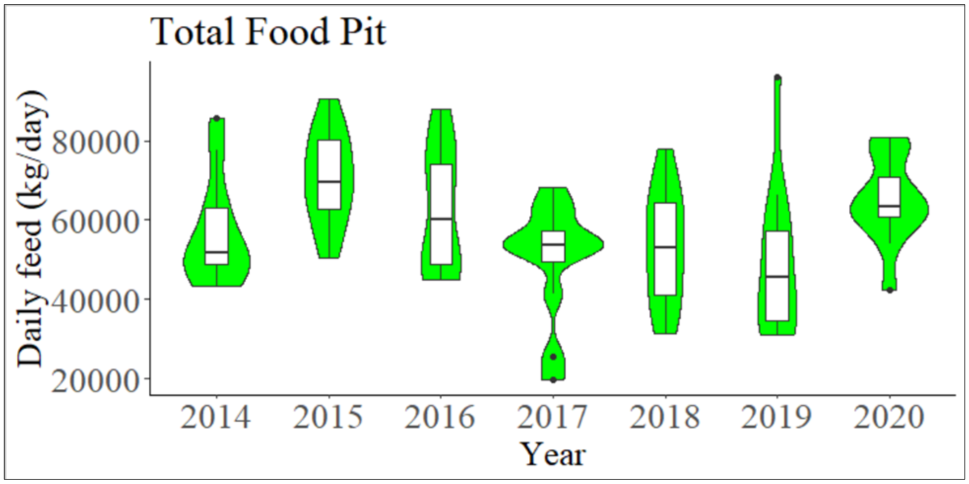

Figure 4.16 Data distribution for Total Food Pit

Table 4.13 shows the ANOVA Tukey multiple comparison performed for Total Food Pit data distribution. It shows that there was a significant difference in the quantity of FOG received by the digester at the $p<0.05$ level from year to year [$F(6, 77) = 3.641$, $p = 0.003$).

Table 4.13 ANOVA Tukey Multiple Comparison results for Total Food Pit data distribution

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
Year	6	4.559e+09	759,802,790	3.641	0.003
Residuals	77	1.607e+10	208,668,601		

Data for other feedstocks in food pit are provided in Appendix C.2. In general, some of the feedstocks in the manure pit did not have large enough data points, therefore they show little or no colored area around the white box (Filtrate Food Pit, SLS Solids Food, Other, and Cart Food).

Meanwhile, other feedstocks did not show a complete curve for each year due to the digester did not receiving them in certain years (Pineapples and Waste Feed).

4.1.3.3 Total Feedstock (Manure Pit and Food Pit)

Figure 4.17 shows the data distribution for Total Feedstock. Data distribution charts in 2015 and 2018 look similar but in a different data range, while the rest of the charts look quite distinctive in shape. Data distribution in 2014 and 2017 were typically similar, ranged approximately from 95,000 kg/day to 155,000 kg/day. The highest data point happened in 2016, while the lowest data point happened in 2019. Data curves in 2016 and 2019 show the most extensive distribution but in a different range. Data distribution in 2018-2020 shows quite a similar range, which means total feedstocks received by the digester were considered consistent in the last three years.

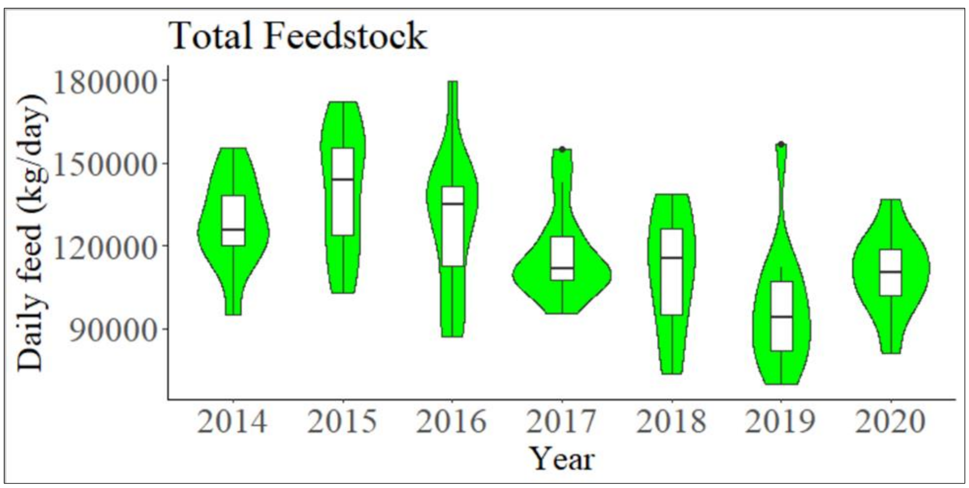

Figure 4.17 Data distribution for Total Feedstock

Table 4.14 shows the ANOVA Tukey multiple comparison performed for Total Feedstock data distribution. It shows that there was a significant difference in the quantity of Total Feedstock received by the digester at the $p<0.05$ level from year to year [$F(6, 77) = 5.736$, $p = 0.000$).

Table 4.14 ANOVA Tukey Multiple Comparison results for Total Feedstock data distribution

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
Year	6	1.47e+10	2.451e+09	5.736	0.000
Residuals	77	3.29e+10	4.273e+08		

4.1.4 Feedstock Characterization

Table 4.15 shows the characterization of feedstocks received by SCAD during 2014-2020. Based on the data available at the digester, there are only seven feedstocks that have laboratory results for characterization: Parlor Manure, Beef, Dairy Gutter, FOG, Food Other, Pineapple, and Pulp. Characteristics measured were total solids (TS), volatile solids (VS), pH, electron conductivity (EC), soluble COD (sCOD), total nitrogen (TN), total phosphorus (TP), and ammonia. The data on table represents average, standard deviation, and number of samples in the brackets.

According to several samples, TS, VS, pH, and EC were the parameters which were measured the most for Parlor Manure, FOG, and Food Other feedstocks. For Parlor Manure, data collected was 11 for TS, VS, and pH, while it had 10 data for EC. They were taken from 2015 to 2018. Characterization data of Parlor Manure were 63,844±20,998 mg/L, 52,742±18,966 mg/L, 7.01±0.30, and 13.72±1.37 mS/cm for TS, VS, pH, and EC, respectively. Data collected for FOG were 28 for TS and VS, 27 for pH, and 23 for EC. They were taken from 2014 to 2019. Characterization data of FOG were 120,191±172,277 mg/L, 105,384±142,739 mg/L, 5.50±1.51, and 12.17±38.04 mS/cm for TS, VS, pH, and EC, respectively. Standard deviation for FOG samples was large due to the wide range of laboratory results. For example, TS ranged from 1,520 to 689,323 mg/L, VS ranged from 532 to 542,778 mg/L, and EC ranged from 0.95 to 189.90

mS/cm. The sample variation is driven largely by the grease interceptor management and the material collection practices.

Meanwhile, data collected for Food Other were 24 for TS and VS, 23 for pH, and 22 for EC. They were taken from 2014 to 2019. Characterization data of Food Other were 219,447±286,460 mg/L, 193,795±265,043 mg/L, 5.41±1.45, and 8.52±6.03 mS/cm for TS, VS, pH, and EC, respectively. Similar to FOG, standard deviation of Food Other feedstock characterizations was large due to significant difference between each data point. For example, TS ranged from 24,072 to 950,355 mg/L, VS ranged from 18,045 to 933,805 mg/L, pH ranged from 3.58 to 7.88, and EC ranged from 0.31 to 18.53 mS/cm.

Other feedstocks and parameters were collected at a minimum data point. For example, the digester only has 1 data point for Dairy Gutter and Pulp, which was taken in 2016 and 2014, respectively. Beef has 3 data points for TS, VS, pH, and EC yet does not have any data for SCOD, TN, TP, and ammonia. These data points were collected in 2014, 2016, and 2018. Characterization data of Beef were 462,152±109,098 mg/L, 393,620±100,761 mg/L, 8.64±0.06, and 1.89±0.76 mS/cm for TS, VS, pH, and EC, respectively. Pineapple has 2 data points for TS, VS, pH, and EC; one data point for TN, TP, and ammonia, while it does not have any data for SCOD. These data points were taken in 2014 and 2016. Characterization data of Pineapple were 127,389±14,312 mg/L, 114,749±5,820 mg/L, 3.91±0.04, and 2.26±0.62 mS/cm for TS, VS, pH, and EC, respectively. The lack of workforce becomes the main reason for minimum characterization analysis for SCAD feedstocks. In general, feedstock received by SCAD has significant differences in terms of characterization results.

Table 4.15 Characterization of SCAD Feedstock [a]

Feedstock	TS (mg/L)	VS (mg/L)	pH	EC (mS/cm)
Parlor Manure	63,844±20,998 (11)	52,742±18,966 (11)	7.01±0.30 (11)	13.72±1.37 (10)
Beef	462,152±109,098 (3)	393,620±100,761 (3)	8.64±0.06 (3)	1.89±0.76 (3)
Dairy Gutter	162,268 (1)	142,940 (1)	8.23 (1)	7.74 (1)
FOG	120,191±172,277 (28)	105,384±142,739 (28)	5.50±1.51 (27)	12.17±38.04 (23)
Food Other	219,447±286,460 (24)	193,795±265,043 (24)	5.41±1.45 (23)	8.52±6.03 (22)
Pineapple	127,389±14,312 (2)	114,749±5,820 (2)	3.91±0.04 (2)	2.26±0.62 (2)
Pulp	275,459 (1)	262,105 (1)	4.36 (1)	1.49 (1)

[a] data including average ± standard deviation, and (number of sample)

Table 4.15

Feedstock	SCOD	TN (mg/L)	TP (mg/L)	NH3 (mg/L)
Parlor Manure	25,900 (1)	2,190±214 (2)	1,210 (1)	932 (1)
Beef	-	-	-	-
Dairy Gutter	-	5,050 (1)	1,386 (1)	1,085 (1)
FOG	109,380±167,383 (4)	15,250 (1)	300 (1)	253.75 (1)
Food Other	-	9,139±10,502 (4)	1,032±1,360 (7)	195±363 (7)
Pineapple	-	595 (1)	109 (1)	62.70 (1)
Pulp	-	-	-	-

4.2 Biogas and Electricity Production

Table 4.16 below shows the total amount of biogas produced by the digester in the year 2014-2020, Methane (CH_4) and Hydrogen Sulfide (H_2S) average. The highest biogas production was in 2016, reaching 1,418,746 Standard Cubic Meter (SCM). In terms of CH_4 percentage, the years 2018 and 2020 had the highest average which was 66%. The lowest H_2S average was in 2014 at 360 ppm.

Table 4.16 Biogas production, methane and H_2S average year 2014-2020

Year	Biogas Total (SCM)	CH_4 Average (%)	H_2S Average (ppm)	Electricity production (kWh)
2014	846,232	63%	360	1,727,073
2015	1,103,695	61%	433	2,118,966
2016	1,418,746	62%	667	1,470,356
2017	1,326,335	65%	421	2,169,693
2018	1,348,024	66%	387	2,680,954
2019	1,280,438	64%	520	2,333,449
2020	1,340,179	66%	652	2,664,665

The digester experienced an outage of the CHP engine twice. The first outage occurred from December 2015 to April 2016, when the engine had a rod bearing failure. Consequently, the engine was rebuilt and back to daily operation from May 2016 to November 2016. Furthermore, the engine experienced a second failure with a similar issue. Therefore, CHP was not operating from December 2016 to January 2017. To overcome this condition, the digester installed a new engine in February 2017; thus, the electricity production is running again on the fourth week of February 2017. Therefore, gas production in 2016, as shown in Figure 4.18, experienced a significant decrease compared to the other years. Additionally, biogas produced during the engine failure solely went to flare to burn the methane and reduce GHG released to the atmosphere; and to the boiler to heat the slurry. Another disturbance happened in 2017 when the feed additive was added to the digester and affected biogas production. July had the lowest production compared to the other months.

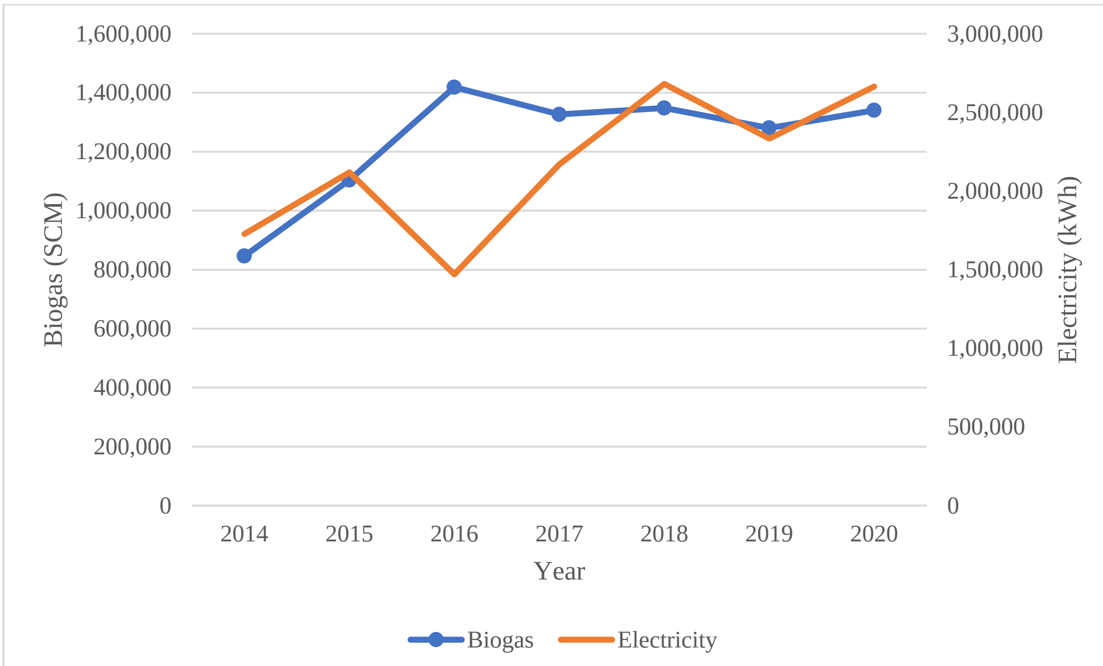

Figure 4.18 Correlation of SCAD biogas and electricity over the year

4.3 SCAD Output Data Distribution

Data distribution analysis for SCAD output, including biogas production, CH4 content, H2S content, electricity production, and laboratory analysis of effluent (total solids, total nitrogen, total phosphorus, pH, and VFA). Like feedstock analysis, the violin chart was also used to check the data distribution of each parameter year to year.

Data distribution for biogas production is shown in Figure 4.19. Among all years, biogas production in 2018 has the most consistent chart with a closed data range between 3,500 to 4,000 m3/day, followed by 2020. Meanwhile, biogas production data distribution in 2015 has the largest range between 700 to 4,700 m3/day. Biogas production in 2017 has an outlier due to feed additive added to the digester during summer. In terms of the median of data, biogas production in 2017, 2018, and 2020 had a similar median of around 3,600 m3/day, while 2019 had a slightly lower median than those three years, which was around 3,400 m3/day.

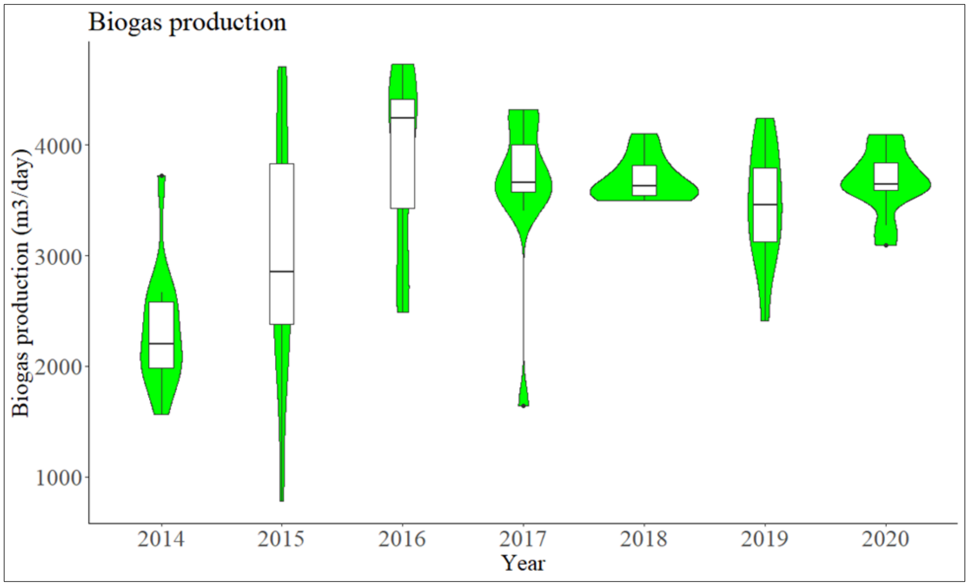

Figure 4.19 Data distribution for biogas production

Table 4.17 shows the ANOVA Tukey multiple comparison performed for biogas production data distribution. It shows that there was a significant difference in the quantity of biogas produced by the digester at the $p<0.05$ level from year to year [$F(6, 77) = 7.678$, $p = 0.000$).

Table 4.17 ANOVA Tukey Multiple Comparison results for biogas production distribution

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
Year	6	20,642,104	3,440,351	7.678	0.000
Residuals	77	34,500,609	448,060		

Data distribution for CH_4 content is shown in Figure 4.20. In general, methane content in biogas produced by SCAD ranged from 58% to 69%. Methane content in 2018 has the most consistent distribution, ranging from 64% to 67%. Meanwhile, methane content in 2014 has the widest distribution, from 60% to 68%. Overall, the methane content is in a good range which biogas typically contains 55-70% of CH_4 (Chynoweth et al., 2001; Somers et al., 2018).

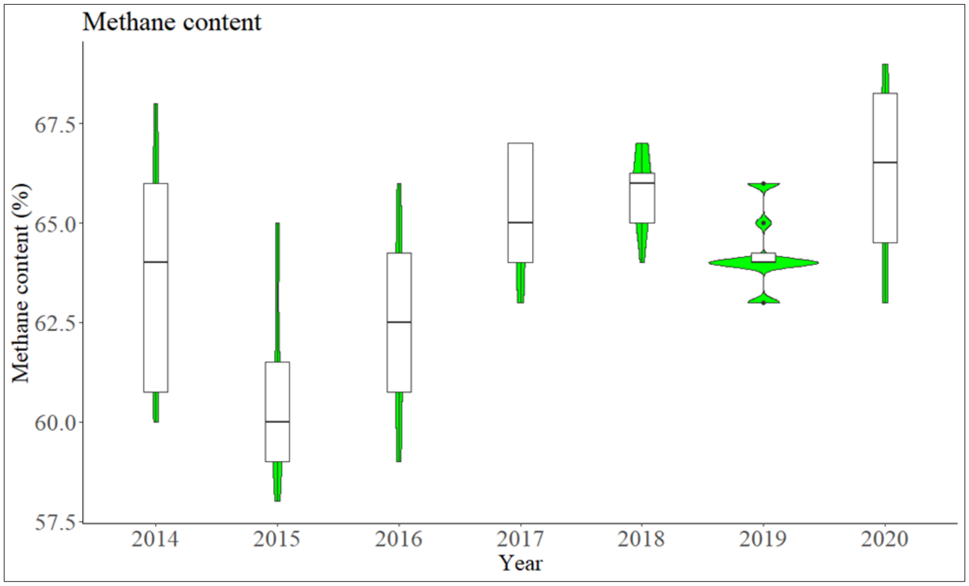

Figure 4.20 Data distribution for CH_4 content

Table 4.18 shows the ANOVA Tukey multiple comparison performed for CH_4 content data distribution. It shows that there was a significant difference in the percentage of CH_4 content at the $p<0.05$ level from year to year [$F(6, 77) = 10.79$, $p = 0.000$).

Table 4.18 ANOVA Tukey Multiple Comparison results for CH_4 content distribution

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
Year	6	268.5	44.75	10.79	0.000
Residuals	77	319.3	4.15		

Figure 4.21 provides the data distribution for H_2S content. H_2S is a toxic gas which poses safety concerns for people and may result in additional equipment maintenance (Hosseini and Wahid, 2014). H_2S can cause corrosion to stainless steel and copper and nickel alloys. It also can produce H_2SO_3 from reaction with water vapor and form sulfur dioxide (SO_2) from its combustion, leading to metal pipe and engine corrosion and gas leaks. H_2S concentration in biogas ranges between 50 and 10,000 parts per million (ppm), depending on the feedstocks (X. Wang et al.,

2018). H_2S content in SCAD biogas ranging from 3 to 2,251 ppm, which is still in an acceptable range. H_2S content in 2016 has the most extensive range, followed by 2020 and 2019. Meanwhile, H_2S content in 2017 shows the most stable data distribution, ranging from 98 to 799 ppm.

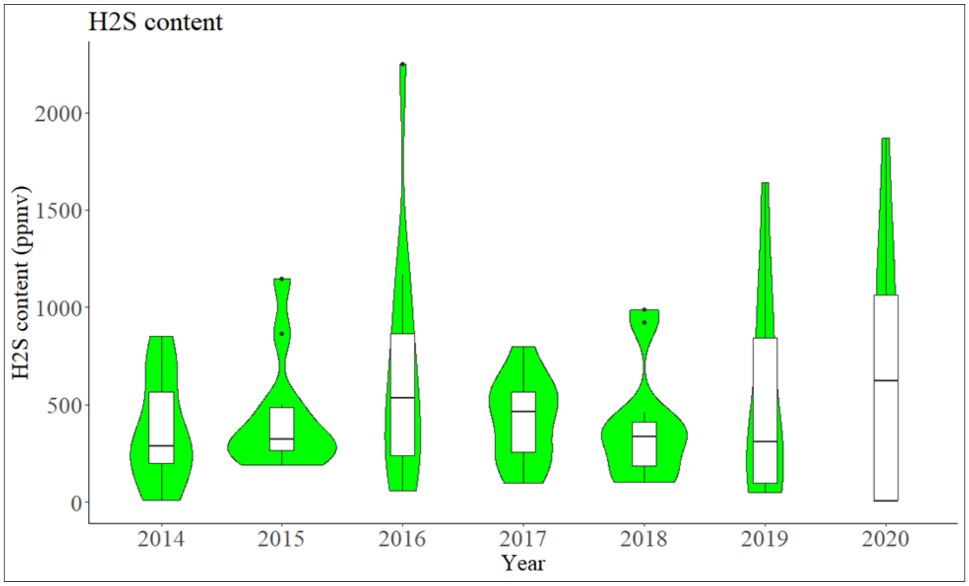

Figure 4.21 Data distribution for H_2S content

Table 4.19 shows the ANOVA Tukey multiple comparison performed for H_2S content data distribution. It shows that there was not any significant difference in H_2S content (p value>0.05) from year to year [F (6, 77) = 0.979, p = 0.445).

Table 4.19 ANOVA Tukey Multiple Comparison results for H_2S content distribution

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
Year	6	1,130,830	188,472	0.979	0.445
Residuals	77	14,823,077	192,507		

Figure 4.22 provides the data distribution for electricity production per day. In terms of chart shape, data in 2014 and 2018 have quite similar shape but in a different data range. Data distribution for electricity was typically consistent in 2016-2020 with data median ranging between 6,500 to 7,600 kWh/day. Electricity production in 2015 had the highest peak but also the widest

range of all years, which the data ranges from 2,200 to 9,700 kWh/day. Meanwhile, violin curves in 2016 and 2017 show the time when SCAD did not produce electricity due to engine issues, showed by outliers happened in 2017.

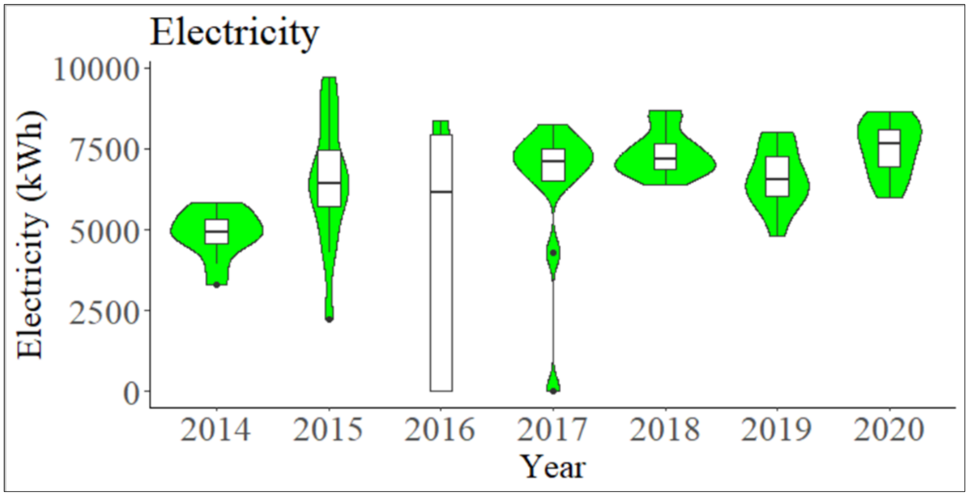

Figure 4.22 Data distribution for electricity production

Table 4.20 shows the ANOVA Tukey multiple comparison performed for electricity production data distribution. It shows that there was a significant difference in electricity production at the $p<0.05$ level from year to year [$F(6, 71) = 7.397$, $p = 0.000$).

Table 4.20 ANOVA Tukey Multiple Comparison results for electricity production distribution

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
Year	6	58,173,817	9,695,636	7.397	0.000
Residuals	71	93,063,092	1,310,748		

Data distribution for effluent TS is shown in Figure 4.23. In general, TS content ranges 40,000 to 85,000 mg/L. Data distribution in 2018 has the most consistent shape, ranging from 53,000 to 65,000 mg/L. Meanwhile, there was an outlier that happened in 2016 where TS content was 85,000 mg/L. TS content in effluent had an increase trend from 2014 to 2017, then became more consistent in 2018-2020 with range from 50,000 to 73,000 mg/L. Data median also increased from 2014 to 2017 from 50,000 to 68,000 mg/L, then became more consistent in 2018 to 2020 which was around 60,000 mg/L.

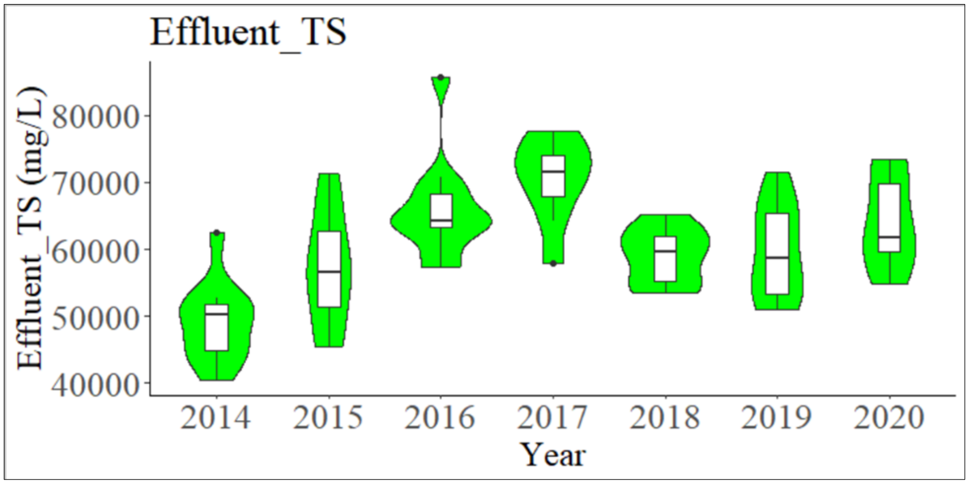

Figure 4.23 Data distribution for effluent TS

Table 4.21 shows the ANOVA Tukey multiple comparison performed for effluent TS data distribution. It shows that there was a significant difference in effluent TS at the $p<0.05$ level from year to year [$F(6, 64) = 10.62$, $p = 0.000$).

Table 4.21 ANOVA Tukey Multiple Comparison results for effluent TS distribution

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
Year	6	2.907e+09	484,541,468	10.62	0.000
Residuals	64	2.919e+09	45,609,925		

Figure 4.24 shows the data distribution for effluent TN. TN data distribution ranges from 1,400 to 5,000 mg/L. Data distribution fluctuated year by year, but it shows a constant decrease from 2016 to 2018. There was an outlier that happened in 2020 where TN was close to 5,000 mg/L. Data median in 2018-2020 were consistent around 3,000 mg/L. TN content in manure was not changed during anaerobic digestion. The process transforms protein and urea nitrogen into inorganic nitrogen such as ammonia gas (NH_3) and ammonium ion (NH_4^+) (Field et al., 1984).

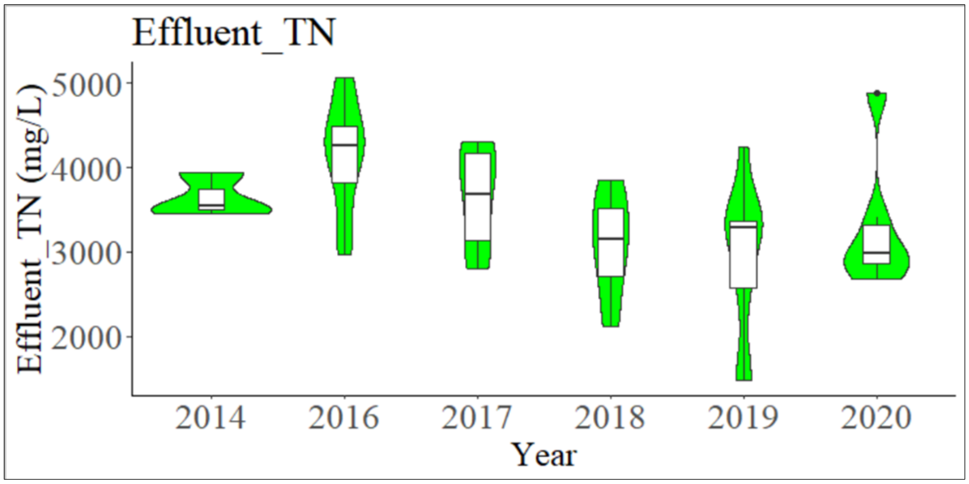

Figure 4.24 Data distribution for effluent TN

Table 4.22 shows the ANOVA Tukey multiple comparison performed for effluent TN data distribution. It shows that there was a significant difference in effluent TN at the p<0.05 level from year to year [F (5, 44) = 4.072, p = 0.004).

Table 4.22 ANOVA Tukey Multiple Comparison results for effluent TN distribution

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
Year	5	9,543,738	1,908,748	4.072	0.004
Residuals	44	20,623,980	468,727		

Figure 4.25 shows the data distribution for effluent TP. Data available for TP content was the least compared to the rest of the parameters. TP effluent content ranges from 200 to 2,100 mg/L. There was a small data point in 2015 thus it did not show any charts. TP content was typically consistent in 2017-2019 with data median around 360 mg/L. TP content in manure was not changed during anaerobic digestion process. This process converts organic phosphorus (Org-P) to phosphate (PO_4^+) phosphorus. Most total P losses in digesters were related to solids accumulation in the reactor (Field et al., 1984).

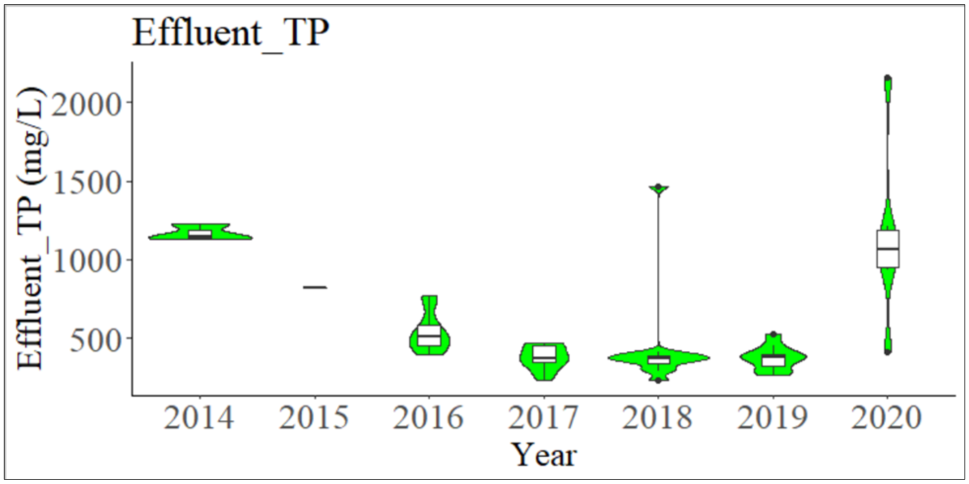

Figure 4.25 Data distribution for effluent TP

Table 4.23 shows the ANOVA Tukey multiple comparison performed for effluent TP data distribution. It shows that there was a significant difference in effluent TP at the $p<0.05$ level from year to year [$F(6, 44) = 9.616$, $p = 0.000$).

Table 4.23 ANOVA Tukey Multiple Comparison results for effluent TP distribution

	Df	**Sum Sq**	**Mean Sq**	**F Value**	**Pr (>F)**
Year	6	4,015,385	669,231	9.616	0.000
Residuals	44	3,062,221	69,596		

Data distribution for effluent pH is shown in Figure 4.26. In general, SCAD effluent pH ranges from 7.4 to 8.1. Effluent pH in 2017 and 2018 are the most consistent in the range of 7.7 to 8, while pH in 2019 and 2020 are consistent in the range of 7.4 to 7.9. These values are in an acceptable range for pH which is between 6.4 and 8.2 for a healthy digester (MSU Anaerobic Digestion and Research Center, 2019).

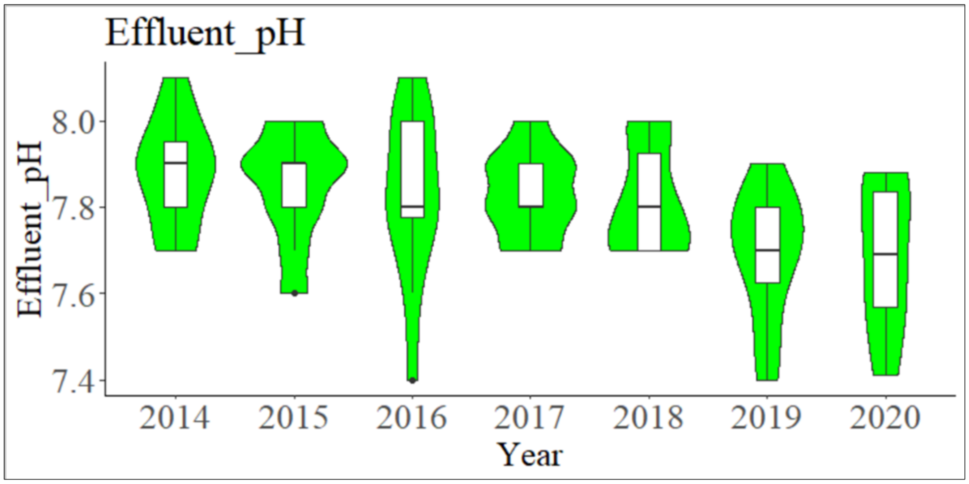

Figure 4.26 Data distribution for effluent pH

Table 4.24 shows the ANOVA Tukey multiple comparison performed for effluent pH data distribution. It shows that there was a significant difference in effluent pH at the $p<0.05$ level from year to year [F (6, 64) = 2.58, p = 0.0266).

Table 4.24 ANOVA Tukey Multiple Comparison results for effluent pH distribution

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
Year	6	0.333	0.05550	2.58	0.0266
Residuals	64	1.377	0.02151		

Data distribution for effluent VFA is shown in Figure 4.27. VFA acts in the biopolymers of biofuels production such as methane and hydrogen (Lukitawesa et al., 2020; Magdalena et al., 2019). Several factors are crucial for VFA productivity, which are hydraulic retention time (HRT), organic loading rate (OLR), temperature, pH, and pretreatment (Wainaina et al., 2019). Data distribution of VFA in 2018-2020 was relatively in a consistent range, while VFA content in 2016 has the widest range and highest peak, ranging from 2,300 to 7,400 mg/L. Some outliers happened in 2014 which the values were around 3,200 and 2,900 mg/L, while majority of the data were around 1,000 mg/L.

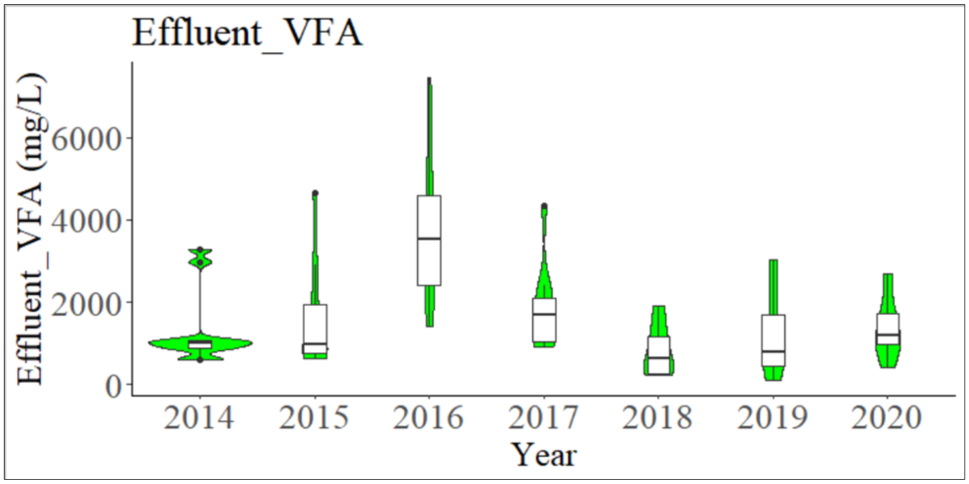

Figure 4.27 Data distribution for effluent VFA

Table 4.25 shows the ANOVA Tukey multiple comparison performed for effluent VFA data distribution. It shows that there was a significant difference in effluent VFA at the $p<0.05$ level from year to year [$F(6, 63) = 7.911$, $p = 0.000$).

Table 4.25 ANOVA Tukey Multiple Comparison results for effluent VFA distribution

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
Year	6	66,702,800	11,117,133	7.911	0.000
Residuals	63	88,531,222	1,405,257		

The acceptable range for VFA is 50-300 mg/L (Schnaars, 2012). Based on the average result of SCAD effluent measurement, VFA content in SCAD effluent ranges from 817 to 3,785 mg/L. These values are higher than the reference. However, VFA/TA ratio is also important to know whether the digester performed at its best ambience. Higher alkalinity values show that the digester has a better capacity to resist pH changes which is associated to the buffering capacity to maintain the digester stability. Alkalinity values in an anaerobic digester range between 1,500 and 5,000 mg/L (Krakat et al., 2017; Schnaars, 2012).

Table 4.26 provides effluent results for VFA and Alkalinity of SCAD during its operation from 2014 to 2020. Alkalinity ranges from 7.583 to 12,779 mg/L, which was higher than the reference value. After calculating the ratio of VFA and Alkalinity, SCAD had VFA/TA ratio between 0.09 and 0.30. The ideal ratio is between 0.3 and 0.4 in the digester and would be 0.2 to 0.3 in the post-digester (Lossie & Pütz, 2011). However, Schnaars (2012) puts a broader range for VFA/TA ratio between 0.1 and 0.35 to maintain a digester in a well-operated condition. Furthermore, it is always better to maintain the ratio to be below 0.35 for a proper digester operation. Therefore, SCAD performance, in general, is well-operated in terms of VFA/TA ratio. The ratio in 2016 was the only year where SCAD performed in its optimum condition based on both references, while the ratio in 2018 was a bit below standard.

Table 4.26 SCAD effluent VFA and Alkalinity

Year	VFA (mg/L)	Alkalinity (mg/L)	VFA/TAC Ratio
2014	1,301	11,007	0.12
2015	1,580	10,477	0.15
2016	3,785	12,779	0.30
2017	1,834	10,413	0.18
2018	817	9,524	0.09
2019	1,187	8,880	0.13
2020	1,378	7,583	0.18

Data distribution for the digester temperature is available in Figure 4.28. Temperature is an important operational parameter as it provides a suitable ambience for microbial growth. Microbial colonies inside the digester are sensitive to temperature changes. Earlier studies found that digesters should not experience any temperature changes more than 2^{o}C within 24 hours, otherwise the microbial colonies will be highly disturbed (Meegoda et al., 2018; Schnaars, 2012). Based on the temperature setting, an anaerobic digester can be divided into three temperature conditions: psychrophilic (15–23°C), mesophilic (35–41°C), and thermophilic (52–58°C).

Based on data from the digester temperature, SCAD is operating in mesophilic temperature. Diverse studies presented in academics revealed that temperature in the mesophilic range is considered as the ideal temperature to promote bacterial activity within the digester (Arosemena, 2021). As shown in the Figure 4.28, the digester temperature ranges from 32.5 to 42.5 °C. The highest temperature recorded was in 2015, while the lowest temperature was in 2020. Moreover, the temperature range in 2015 and 2020 was the most significant, while temperature range in 2019 was the most stable.

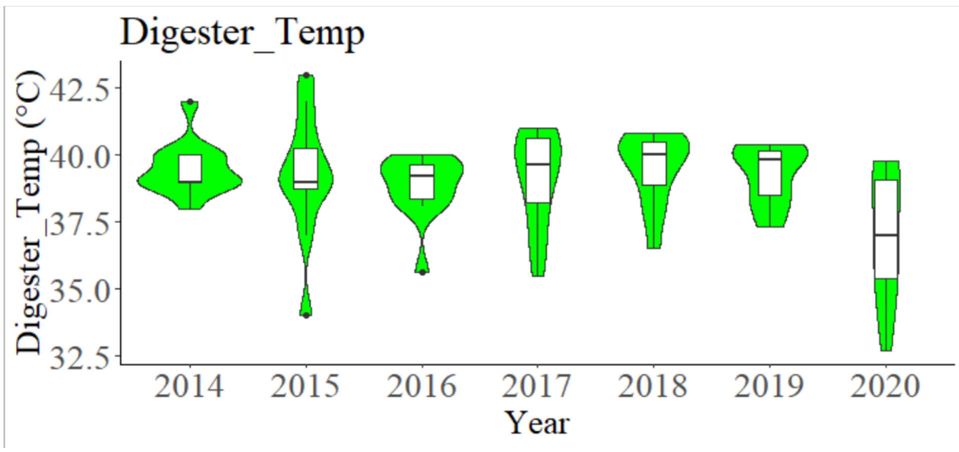

Figure 4.28 Data distribution for digester temperature

Table 4.27 shows the ANOVA Tukey multiple comparison performed for digester temperature data distribution. It shows that there was a significant difference in digester temperature at the $p<0.05$ level from year to year [$F (6, 77) = 3.277$, $p = 0.006$).

Table 4.27 ANOVA Tukey Multiple Comparison results for digester temperature

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
Year	6	55.9	9.317	3.277	0.006
Residuals	77	218.9	2.843		

SCAD experienced a decrease in the digester temperature during winter months each year. Figure 4.29 shows the decrease in digester temperature occurring typically during the November to February timeframe. The digester should be maintained at temperature 35–41°C for mesophilic condition to optimize microbial performance during anaerobic digestion process. However, there were some moments when SCAD temperature went down to be lower than 35 °C, which were in winter 2015, 2019, and 2020. It shows that the digester struggled to maintain the digester temperature in the last two years of this study.

There are two lines added in the figure which represent the highest and lowest temperature in East Lansing to check the gap between air and digester temperatures. It shows that despite the digester experiencing an inconsistent operational temperature lately, it was still above the highest air temperature all the time. Moreover, it emphasizes that more power was needed to heat up the digester during winter since the temperature significantly dropped after September each year. Therefore, heating system is critical for SCAD operational to maintain the mesophilic condition for anaerobic digestion process.

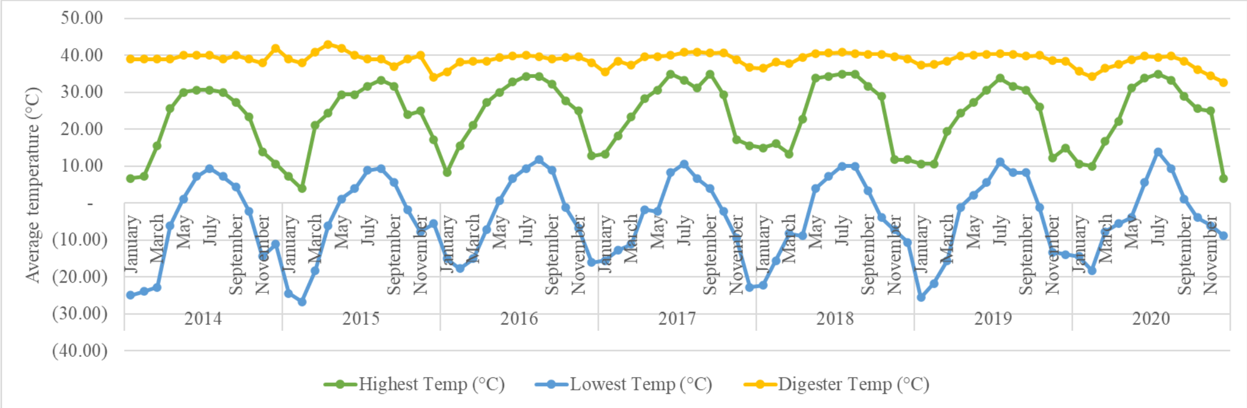

Figure 4.29 Digester temperature average in 2014-2020

4.4 SCAD Laboratory Analysis

This section compares SCAD laboratory analysis for influent and effluent of the digester. Influent samples were obtained from the mix tank before the mixture was pumped inside the digester. Effluent laboratory analysis was done more consistently than influent. Influent analysis was done only until 2018. The main reasons were due to the time and workforce constraints. Therefore, the digester decided to conduct laboratory analysis for filtrate, effluent, and solids only which were done once a month. Another reason to conclude the mix tank sampling was because the digester received feedstocks that had not been changed tremendously from the previous years. Furthermore, other SCAD laboratory results will be provided in Appendix E.

4.4.1 Solids

Table 4.28 shows the comparison between total solids of influent and effluent. TS reduction ranged from 35% to 48%, with the highest reduction being in 2018. In average, SCAD TS for influent and effluent were 105,405 mg/L and 60,744 mg/L, respectively. Moreover, TS destroyed in average was 45,132 mg/L or 43%.

Table 4.28 Comparison of total solids between influent and effluent [a]

Year	TS (mg/L)				TS Destroyed (mg/L)	Reduction %
	Influent	n	Effluent	n		
2014	93,359±12,280	12	49,085±5,709	11	44,274	47
2015	107,615±4,216	4	57,082±8,282	10	50,533	47
2016	104,673±20,115	7	65,928±7,110	12	38,745	37
2017	107,881±17,283	3	70,359±5,929	9	37,522	35
2018	113,498	1	58,913±3,944	12	54,585	48
2019	-		59,702±6,768	10	-	-
2020	-		64,138±6,668	7	-	-
Max	**113,498**		**70,359**		**54,585**	**48**
Min	**93,359**		**49,085**		**37,522**	**35**
Mean	**105,186**		**60,398**		**44,654**	**42**
Average	**105,405**		**60,744**		**45,132**	**43**
St. Dev	**6,666**		**6,377**		**6,603**	**6**

[a] average ± standard deviation

Table 4.29 shows the comparison between volatile solids of influent and effluent. VS reduction ranged from 40% to 54%, with the highest reduction being in 2018. In average, SCAD VS for influent and effluent were 92,803 mg/L and 48,209 mg/L, respectively. Moreover, VS destroyed on average was 44,754 mg/L or 48%.

Table 4.29 Comparison of volatile solids between influent and effluent [a]

Year	VS				VS Destroyed	Reduction
	(mg/L)				(mg/L)	%
	Influent	n	Effluent	n		
2014	80,623±10,397	12	38,018±4,767	11	42,605	53
2015	93,101±3,727	4	43,803±7,684	10	49,298	53
2016	90,718±17,274	7	52,485±6,158	12	37,873	42
2017	96,555±16,237	3	58,056±4,682	9	38,499	40
2018	103,020	1	47,524±3,339	12	55,496	54
2019	-		47,354±6,291	10	-	-
2020	-		51,626±5,843	7	-	-
Max	**103,020**		**58,056**		**55,496**	**54**
Min	**80,623**		**38,018**		**37,873**	**40**
Mean	**92,504**		**48,029**		**44,266**	**48**
Average	**92,803**		**48,209**		**44,754**	**48**
St. Dev	**7,366**		**5,989**		**6,740**	**6**

[a] average ± standard deviation

4.4.2 pH and Electronic Conductivity

Table 4.30 shows the comparison between influent and effluent. Influent had a more acidic pH with a range from 5.18 to 6.44. Anaerobic digestion process increased the mixture pH thus the effluent had pH between 7.70 and 7.90. Table 4.31 shows electron conductivity comparison between influent and effluent. Influent has a range of EC from 13.57 to 19.03, while effluent has a range of EC from 14.00 to 20.40.

Table 4.30 Comparison of pH between influent and effluent [a]

Year	pH				pH Change
	Influent	n	Effluent	n	
2014	6.44±0.32	12	7.90±0.1	11	1.46
2015	5.82±0.84	4	7.86±0.14	10	2.04
2016	5.18±0.67	7	7.80±0.2	12	2.62
2017	5.74±0.51	3	7.80±0.1	9	2.06
2018	5.27	1	7.80±0.1	12	2.53
2019	-	-	7.70±0.1	10	-
2020	-	-	7.70±0.2	7	-
Max	**6.44**		**7.90**		**2.62**
Min	**5.18**		**7.70**		**1.46**
Mean	**5.67**		**7.79**		**2.10**
Average	**5.69**		**7.79**		**2.14**
St. Dev	**0.45**		**0.07**		**0.42**

[a] average ± standard deviation

Table 4.31 Comparison of electronic conductivity between influent and effluent [a]

Year	EC (mS/cm)			
	Influent	n	Effluent	n
2014	13.86±2.07	12	20.00±0.9	6
2015	13.57±3.63	3	17.00±1.74	10
2016	15.55±2.01	7	20.40±3.1	9
2017	19,03±5.86	3	18.00±3.3	9
2018	9.52	1	17.00±0.8	12
2019	-	-	16.80±2.3	10
2020	-	-	14.00±3.3	6
Max	**19.03**		**20.40**	
Min	**9.52**		**14.00**	
Mean	**13.96**		**17.48**	
Average	**14.31**		**17.60**	
St. Dev	**3.45**		**2.00**	

[a] average ± standard deviation

4.4.3 Chemicals

Table 4.32 shows the comparison of soluble COD (sCOD) results between influent and effluent. The digester did not do frequent tests for (sCOD) of influent since the results were relatively consistent in 2014. Based on data in 2014 and 2018 which the only years (sCOD) was conducted for influent, (sCOD) reduction in 2014 and 2018 were 29,556 mg/L and 29,729 ml/L or 79.57% and 76.82%, respectively. It shows that the (sCOD) reduction was consistent.

Table 4.32 Comparison of soluble COD between influent and effluent [a]

Year	sCOD (mg/L)			
	Influent	n	Effluent	n
2014	37,144±7,692	8	7,588±763	2
2015	-	-	-	-
2016	-	-	15,418±3,812	10
2017	-	-	19,075±5,289	4
2018	38,700	1	8,971±5,855	11
2019	-	-	6,816±1,525	7
2020	-	-	-	-
Max	**38,700**		**19,075**	
Min	**37,144**		**6,816**	
Mean	**37,914**		**10,641**	
Average	**37,922**		**11,574**	
St. Dev	**778**		**4,824**	

[a] average ± standard deviation

4.4.4 Fiber Results

Table 4.33 shows the laboratory results for SCAD fiber. In average, total solids and volatile solids are 264,388 and 235,204, respectively with VS content in TS ranging from 87% to 90%.

Table 4.33 Fiber laboratory results

Year	TS (mg/L)	VS (mg/L)	TS %	VS %	VS % of TS	n
2014	238,755	215,338	23.9	21.5	90%	4
2015	264,328	236,833	26.4	23.6	89%	9
2016	249,041	221,187	24.9	22.1	89%	12
2017	277,084	248,754	27.7	24.9	90%	9
2018	268,160	235,912	27.1	23.6	87%	12
2019	268,436	238,752	26.9	23.9	89%	10
2020	284,911	249,653	28.5	25.0	88%	7
Max	**284,911**	**249,653**	**28.5**	**25.0**	**90%**	
Min	**238,755**	**215,338**	**23.9**	**21.5**	**87%**	
Mean	**263,973**	**234,896**	**26.4**	**23.5**	**89%**	
Average	**264,388**	**235,204**	**26.5**	**23.5**	**89%**	
St. Dev	**14,666**	**11,948**	**1.5**	**1.2**	**1%**	

4.4.5 Other laboratory results

Several laboratory analyses for different parameters were done outside of ADREC. The tests were conducted by A&L Great Lakes Laboratory in Fort Wayne, Indiana. The tests included manure nutrition analysis which were moisture, solids, Total Kjeldahl Nitrogen (TKN), phosphorus, potassium, sulfur, calcium, magnesium, sodium, iron, aluminum, manganese, copper, and zinc. Analysis of filtrate was done in 2017 and 2018; effluent was done in 2018; and solids were analyzed in all year except in 2017. The complete results of A&L Great Lakes Laboratory are provided in Appendix F.

4.5 Discussions

4.5.1 Correlation between feedstock and biogas production

As mentioned in the beginning, SCAD was fed with 18 different feedstocks from 2014 to 2020. Figure 4.30 shows a correlation between food waste amount and biogas production. There were different trends occurring years. Using 2014 as the starting point, 2015 and 2020 showed similar trends where the increase in food waste from the previous year is followed by an increase in biogas production. This trend also happened in 2016 but in the opposite direction. A different trend occurred in 2017 and 2018, where the decrease in food waste affected an increase in biogas production. Meanwhile, in 2019, the trend was reversed: an increase in food waste affected by a decrease in biogas production. The correlation between food waste and biogas production is not clear yet. Therefore, further analysis was done.

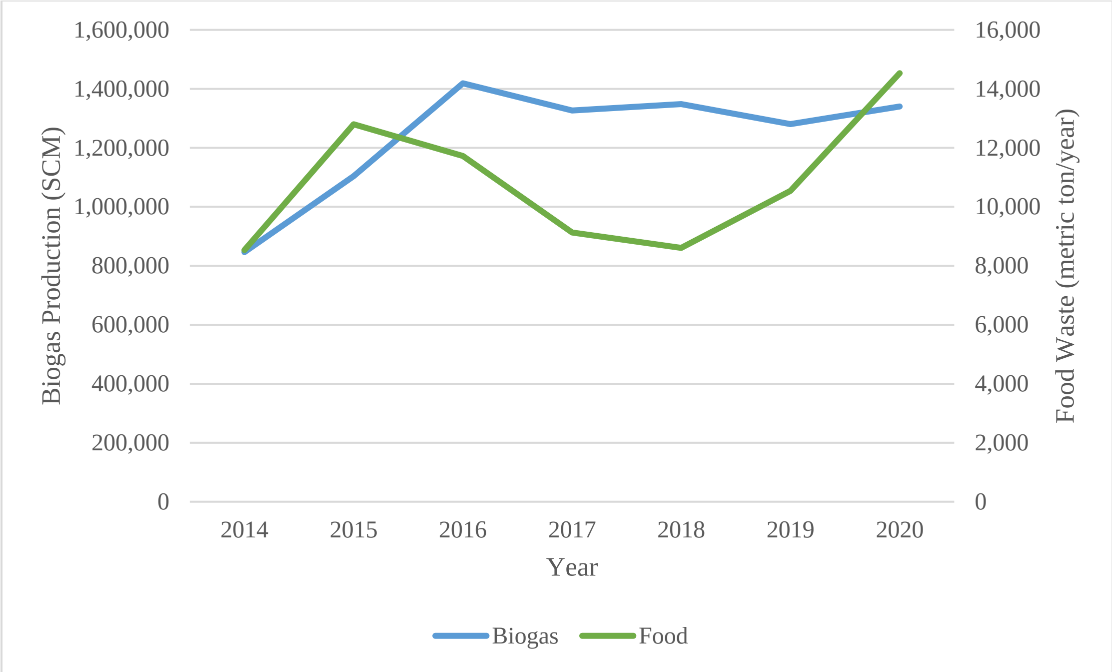

Figure 4.30 Correlation between food waste and biogas production

Multi linear regression (MLR) was done to determine specific feedstock that has significant impact on biogas production. There are two steps in determining the most significant parameter. First is Stepwise Procedure which calculates the top list of feedstocks that significantly affects output among all feedstocks available. Second is the Final Model which calculates the most significant factor among the list of feedstocks from Stepwise Procedure.

Among all feedstock, five feedstocks were included as the result of Stepwise Procedure, which are Filtrate in manure pit, Dairy Gutter, Parlor, ANS Other, and Pineapples (PA). The formula generated was Equation 2, while coefficients for each feedstock are provided in Table 4.34.

Biogas production = Filtrate_manure_pit + Dairy_G + Parlor + ANS_Other + P_A (Equation 2)

Table 4.34 Coefficient of each parameter

Parameter	Coefficient
Intercept	2330.91251
Filtrate_manure_pit	-0.01688
Dairy_G	0.18163
Parlor	-0.04628
ANS_Other	0.08850
P_A	-0.02158

The final model was run to determine the key feedstocks in Equation 2 that influence gas production. As shown in Table 4.35, Filtrate in the manure pit, Dairy Gutter, and Parlor are feedstocks that have the most significant impact on biogas production, with a p-value<0.05. However, this statistical analysis result does not mean that the other feedstocks are not important, for example, FOG and other manures. Those are the baseline in building biogas production due to their vast amount in feedstock composition. However, Filtrate in the manure pit, Dairy Gutter, and Parlor provide a critical role in SCAD feedstock matrices in terms of biogas production variation during the operation years. Therefore, food waste and manure are important baselines for biogas production, and it will significantly change once those three feedstocks are added to the feedstock composition.

This MLR result shows Multiple R-squared as 47.15%, and Adjusted R-squared as 43.75%. It means that the model was able to explain 43% to 47% of the data variance to predict the biogas production.

Table 4.35 MLR results for feedstock impact on the biogas production

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	2.331e+03	7.506e+02	3.105	0.002648**
Filtrate_manure_pit	-1.688e-02	7.464e-03	-2.261	0.026549*
Dairy_G	1.816e-01	4.507e-02	4.030	0.000129***
Parlor	-4.627e-02	1.748e-02	-2.648	0.009804**
ANS_Other	8.850e-02	5.779e-02	1.531	0.129752
P_A	-2.158e-02	1.501e-02	-1.438	0.154510
Residual standard error	611.3 on 78 degrees of freedom			
Multiple R-squared	0.4714			
Adjusted R-squared	0.4375			
F-statistic	13.91 on 5 and 78 DF			
p-value	1.03e-09			

Signif. Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 4.36 presents the result of ANOVA Type II test to support the result of MLR test. Filtrate in manure pit, Dairy Gutter, and Parlor gave a significant impact on biogas production at the level of $p<0.05$.

Table 4.36 ANOVA Type II Results for feedstock correlation with the biogas production

	Sum Sq	Df	F value	Pr(>F)
Filtrate_manure_pit	1,910,236	1	5.1119	0.0265489*
Dairy_G	6,069,859	1	16.2433	0.0001286***
Parlor	2,619,518	1	7.0100	0.0098044**
ANS_Other	876,194	1	2.3488	0.1297516
P_A	772,430	1	2.0671	0.1545103
Residuals	29,147,290	78		

After the first MLR analysis, the data set was treated by using modelDFFITS to take out the data with high leverage or outliers to check whether the R-squared values can be improved. The result shows that Filtrate in manure pit, Dairy Gutter, Parlor, and FOG become four feedstocks that give the most significant impact in biogas production with a p-value<0.05, as shown in Table 4.37. Furthermore, R-squared values improved to be 58.24% and 56.01% for Multiple R-squared and Adjusted R-squared values, respectively. It means that the model was able to explain 56% to 58% of the data variance to predict the biogas production.

This percentage is understandable since SCAD received a wide variety of feedstock with uncertain frequency. Several feedstocks did not come every month; some of them were even only available in certain years. This uncertainty affects the R-squared values. Moreover, feedstock supplies are beyond the digester's control. It depends on whether the supplier still produces the same food waste, for example. However, the study can still draw a conclusion since there are independent variables that are statistically significant to correlate the relationships between the variables.

Table 4.37 MLR results for feedstock impact on the biogas production (after data treatment)

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.804e+03	6.544e+02	2.756	0.007333 **
Filtrate_manure_pit	-2.207e-02	5.581e-03	-3.953	0.000173 ***
Dairy_G	1.915e-01	3.994e-02	4.795	8.05e-06 ***
Parlor	-4.410e-02	1.520e-02	-2.901	0.004880 **
FOG	1.327e-02	6.526e-03	2.034	0.045470 *
Residual standard error	509.4 on 75 degrees of freedom			
Multiple R-squared	0.5824			
Adjusted R-squared	0.5601			
F-statistic	26.15 on 4 and 75 DF			
p-value	1.372e-13			

Signif. Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.5.2 The impact of OLR, HRT, and digester pH and temperature on biogas production and methane percentage

OLR, HRT, and digester pH and temperatures are key parameters in determining optimum biogas production and methane percentage. Regarding OLR and HRT, SCAD data is organized based on daily numbers, an average of 7 days and an average of 30 days. The formula for determining OLR and HRT is provided in Appendix G. This section only includes data from 2018-to 2020, as the digester performance in those years was considered settled.

Table 4.38 shows data related to OLR in 2018-2020. It shows that data on 30 days average have the smallest standard deviation, which means that the data is the most stable, though the difference between daily, 7 days average, and 30 days average are not significantly different. In general, the average OLR increased from 2018 to 2020. OLR average values in 2018 are 3.67, 3.65, and 3.59 g VS/L-d for daily, 7 days average, and 30 days average, respectively. In 2019, the values were 3.75, 3.76, and 3.80 g VS/L-d for daily, 7 days average, and 30 days average, respectively. The values in 2020 are 4.16, 4.14, and 4.16 g VS/L-d for daily, 7 days average, and 30 days average, respectively. Moreover, the table also shows that the standard deviation of OLR in 30 days average in 2018-2020 is very stable, which are 0.50 for 2018 and 2019, and 0.49 for 2020. Therefore, OLR in 30 days average is chosen to represent SCAD OLR. Figure 4.31 shows the OLR in 30 days on average in 2018-2020.

Table 4.38 Comparison of OLR in 2018-2020: daily, 7 days average, and 30 average

Month	OLR								
	g VS/L-d								
	2018			2019			2020		
	Daily	7 Days AVG	30 Days AVG	Daily	7 Days AVG	30 Days AVG	Daily	7 Days AVG	30 Days AVG
January	3.37	3.38	3.28	4.41	4.70	4.89	4.36	4.26	4.01
February	3.40	3.40	3.36	2.69	2.67	3.40	4.56	4.67	4.58
March	3.67	3.69	3.54	4.10	3.88	3.30	3.94	3.89	4.07
April	3.41	3.49	3.62	4.11	4.08	4.06	3.84	3.82	3.98
May	2.85	2.84	3.13	4.33	4.30	4.26	4.09	4.22	4.13
June	3.72	3.61	3.18	3.97	4.03	4.22	3.30	3.23	3.59
July	2.97	3.09	3.49	3.63	3.72	3.69	3.88	3.67	3.34
August	3.23	3.11	2.95	3.44	3.37	3.48	4.40	4.32	4.05
September	3.75	3.76	3.44	4.11	4.05	3.95	5.04	5.06	4.82
October	4.10	3.97	3.99	3.86	3.81	3.96	5.01	5.07	5.14
November	4.53	4.48	4.37	2.86	3.06	3.09	4.12	4.11	4.47
December	5.00	5.00	4.71	3.52	3.40	3.30	3.34	3.43	3.80
Average	3.67	3.65	3.59	3.75	3.76	3.80	4.16	4.14	4.16
St. Dev	0.60	0.58	0.50	0.52	0.53	0.50	0.53	0.56	0.49

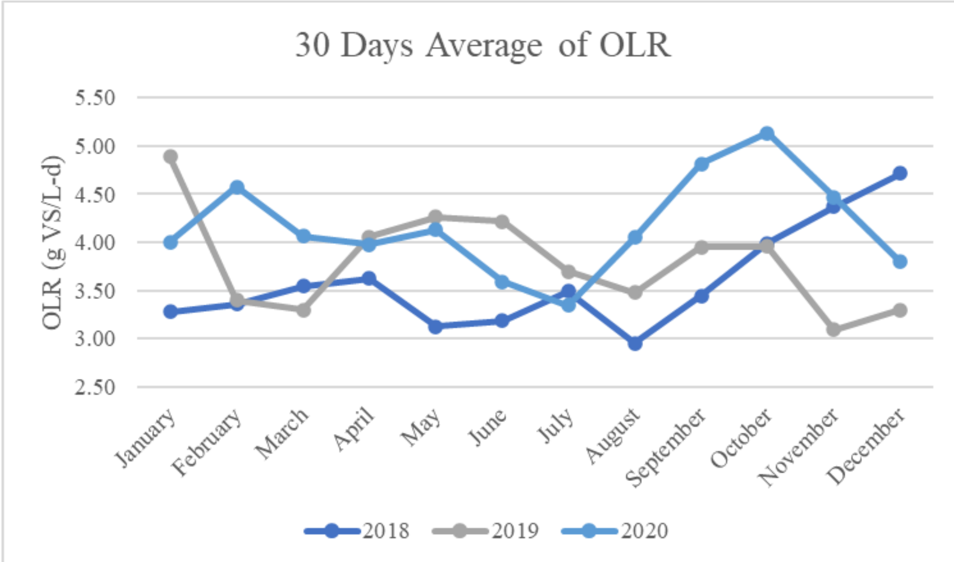

Figure 4.31 OLR in 30 days average 2018-2020

Table 4.39 shows data related to HRT in 2018-2020. It shows that data in 7 days average and 30 days average are relative stable, while daily data has a notable change from 2018 to 2019. HRT in 30 days average has the smallest standard deviation in 2018 and 2019, while HRT in 7 days average has the smallest standard deviation in 2020. HRT average values in 2018 are 21.7, 26.5, and 26.0 days for daily, 7 days average, and 30 days average, respectively. In 2019, the values are 31.2, 25.6, and 23.8 days for daily, 7 days average, and 30 days average, respectively. The values in 2020 are 27.3, 21.8, and 20.3 days for daily, 7 days average, and 30 days average, respectively. Moreover, the table also shows that the standard deviation of OLR in 30 days average in 2018-2020 is slightly more stable than 7 days average, which is 2.7 for 2018, 3.5 for 2019, and 4.8 for 2020. Therefore, OLR in 30 days average is chosen to represent SCAD OLR. Figure 4.32 shows the HRT in 30 days average in 2018-2020.

Table 4.39 Comparison of HRT in 2018-2020: daily, 7 days average, and 30 average

Month	HRT								
	Day								
	2018			2019			2020		
	Daily	7 Days AVG	30 Days AVG	Daily	7 Days AVG	30 Days AVG	Daily	7 Days AVG	30 Days AVG
January	24	24	24	29	21	21	20	20	20
February	28	25	25	71	42	29	19	19	19
March	23	23	23	26	25	30	30	24	22
April	21	26	24	27	26	25	28	24	23
May	20	28	25	18	19	21	20	22	22
June	24	29	28	20	22	19	27	28	25
July	20	28	29	28	25	24	28	21	24
August	25	34	30	35	26	25	18	16	7
September	18	27	31	20	24	20	25	19	19
October	20	28	26	35	21	20	18	16	16
November	21	24	25	40	31	27	27	26	21
December	18	22	22	26	25	25	67	26	26
Average	21.7	26.5	25.9	31.2	25.69	23.8	27.3	21.8	20.3
St. Dev	2.8	3.1	2.7	13.6	5.9	3.5	12.6	3.8	4.8

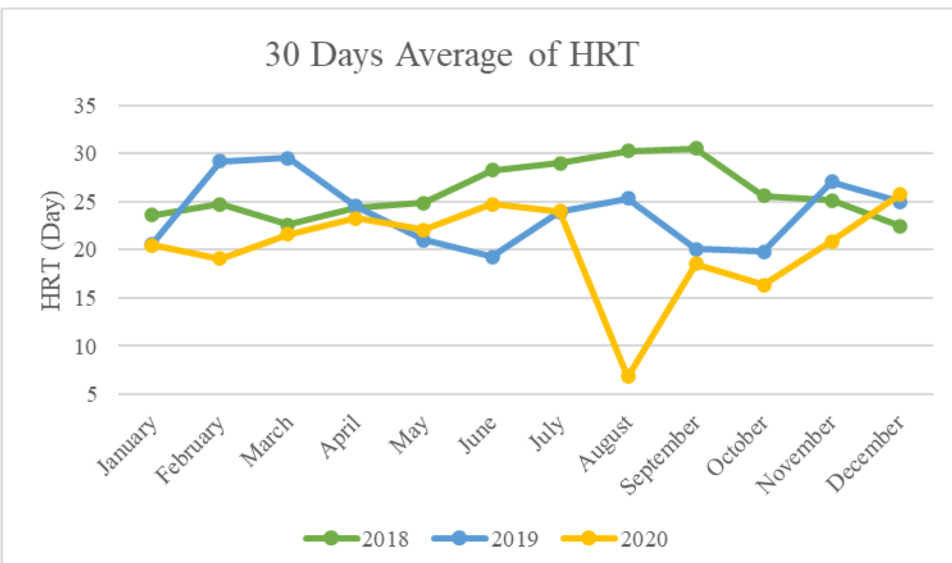

Figure 4.32 HRT in 30 days average 2018-2020

MLR analysis was done to determine the operational parameter that has significant impact on the biogas production (Table 4.40) and the methane percentage (Table 4.41). The results show that none of the parameters tested have a significant impact on both two dependent variables. R-squared values for the biogas production analysis was 6.05% and -6.08% for Multiple R-squared and Adjusted R-squared, respectively. Meanwhile, R-squared values for the methane percentage analysis was 9.93% and -1.69% for Multiple R-squared and Adjusted R-squared, respectively. It means that the model was barely able to explain any of the data variance to predict the biogas production and the methane percentage.

It might show an indication that in the commercial scale, the operational parameters have some impacts on the dependent variables. However, any changes in one parameter will not be significantly impactful since there are many parameters that influence the biogas production and the methane percentage. For example, previous study revealed that any temperature changes more than 2^{o}C within 24 hours in the digester will negatively affect the microbial community in the digester (Meegoda et al., 2018; Schnaars, 2012). It certainly has any impact on the biogas production. Nevertheless, the other operational parameters can still backup the digester performance; therefore, it avoids the digester from a significant disturbance.

A recent study conducted by Rossi et al. (2022) can be a good example on predicting the digester performance based on the operational parameters. The study was performed by considering 55 explanatory variables to predict the specific methane production (SMP) through the MLR model. The study eventually narrowed down the parameters to include only 9 out of 55. These parameters were included as the feedstock characteristics (total solids (TS), total volatile solids (TVS), C/N ratio, and lignin content), the operating parameters (volumetric flow of inlet (Q_{in}), HRT, and OLR), and the inhibitory compounds (N-NH^{+}_{4} and total VFA concentration). Through this process, the study was able to gain R^2 as 0.87 by including TVS, OLR, C/N ratio, and lignin as the predictors. Although this study might not be representative enough as the working volume was only around 28 L capacity (SCAD working volume is roughly 74,000 L), this can be a reference for SCAD to better predict the impact of the operational parameters on the biogas production and the methane percentage for the future study.

Table 4.40 MLR results for operational parameter impact on the biogas production

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	3085.543	1696.503	1.819	0.0786 .
OLR	-31.360	150.304	-0.209	0.8361
HRT	-23.090	19.758	-1.169	0.2515
Temperature	3.676	41.488	0.089	0.9300
pH	135.762	195.569	0.694	0.4927
Residual standard error	365.4 on 31 degrees of freedom			
Multiple R-squared	0.06047			
Adjusted R-squared	-0.06076			
F-statistic	0.4988 on 4 and 31 DF			
p-value	0.7367			

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 4.41 MLR results for operational parameter impact on the methane percentage

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	63.23486	8.17748	7.733	1.01e-08 ***
OLR	1.05067	0.72449	1.450	0.157
HRT	0.10655	0.09524	1.119	0.272
Temperature	0.07043	0.19998	0.352	0.727
pH	-0.91353	0.94268	-0.969	0.340
Residual standard error	1.761 on 31 degrees of freedom			
Multiple R-squared	0.09931			
Adjusted R-squared	-0.01691			
F-statistic	0.8545 on 4 and 31 DF			
p-value	0.5019			

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.5.3 Digester performance from year to year

Table 4.42 provides a summary of SCAD operation in terms of feedstock input and output production. In 2014, SCAD received 14,763 metric tons of manure feedstock and 8,533 metric tons of food feedstock, with a total of feedstock received 23,297 metric tons. This feedstock produced 846,232 SCM of biogas, 1,727,073 kWh of electricity, 11,273 metric tons of effluent, and 3,920 metric tons of wet fiber. In 2015, SCAD received 13,805 metric tons of manure feedstock and 12,800 metric tons of food feedstock, with a total of 26,605 metric tons. This feedstock produced 1,103,695 SCM of biogas, 2,118,966 kWh of electricity, 14,100 metric tons of effluent, and 4,858 metric tons of wet fiber. In 2016, SCAD received 11,059 metric tons of manure feedstock and 11,726 metric tons of food feedstock, with a total of feedstock received was 22,785 metric tons. This feedstock produced 1,418,746 SCM of biogas, 1,470,356 kWh of electricity, 14,007 metric tons of effluent, and 3,583 metric tons of wet fiber. In 2017, SCAD received 11,109 metric tons of manure feedstock and 9,129 metric tons of food feedstock, with a total of feedstock received 20,238 metric tons. This feedstock produced 1,326,335 SCM of biogas, 2,169,693 kWh of electricity, 12,751 metric tons of effluent, and 2,779 metric tons of wet fiber. In 2018, SCAD received 10,859 metric tons of manure feedstock and 8,605 metric tons of food feedstock, with a total of feedstock received was 19,464 metric tons. This feedstock produced 1,348,024 SCM of biogas, 2,680,954 kWh of electricity, 14,857 metric tons of effluent, and 1,884 metric tons of wet fiber. In 2019, SCAD received 11,353 metric tons of manure feedstock and 10,539 metric tons of food feedstock, with the total feedstock receiving 21,893 metric tons. This feedstock produced 1,280,438 SCM of biogas, 2,333,449 kWh of electricity, 15,762 metric tons of effluent, and 2,758 metric tons of wet fiber. In 2020, SCAD received 10,332 metric tons of manure feedstock and 14,531 metric tons of food feedstock, with a total of feedstock received was 24,863 metric tons. This feedstock produced 1,340,180 SCM of biogas, 2,664,665 kWh of electricity, 17,745 metric tons of effluent, and 3,082 tons of wet fiber.

The range of input acquired by SCAD from 2014 to 2020 was 10,332 to 14,763 metric tons for manure feedstock, 8,533 to 14,531 metric tons for food feedstock, and 19,464 to 26,605 metric tons for a total of both manure and food feedstock. The range of output produced by SCAD from 2014 to 2020 was 846,232 to 1,418,746 SCM of biogas, 1,470,356 to 2,680,954 kWh of electricity, 11,273 to 17,745 metric tons of effluent, and 1,884 to 4,858 metric tons of wet fiber. During seven years of operation, SCAD has processed 83,281 metric tons of manure feedstock and 75,864 metric tons of food feedstock with a total of 159,145 metric tons of organic materials to yield 8,663,649 SCM of biogas, 15,165,156 kWh of electricity, 100,495 metric ton of effluent, and 22,864 metric ton of wet fiber.

The range of input acquired by SCAD during 2014 to 2020 was 10,332 to 14,763 metric tons for manure feedstock, 8,533 to 14,531 metric tons for food feedstock, and 19,464 to 26,605 metric tons for total of both manure and food feedstock. The range of output produced by SCAD during 2014 to 2020 was 846,232 to 1,418,746 SCM of biogas, 1,470,356 to 2,680,954 kWh of electricity, 11,273 to 17,745 metric ton of effluent, and 1,884 to 4,858 metric ton of wet fiber. During 7 years of operation, SCAD has processed 83,281 metric ton of manure feedstock and 75,864 metric ton of food feedstock with total of 159,145 metric ton of organic materials to yield 8,663,649 SCM of biogas, 15,165,156 kWh of electricity, 100,495 metric ton of effluent, and 22,864 metric ton of wet fiber.

In general, the operation of SCAD went through several trends. During 2014-2015, SCAD built good trends since its establishment in 2013 due to the output production increased from 2014 to 2015. SCAD operation was disrupted during 2016 and 2017 in terms of electricity production due to the CHP engine outage that happened in those years. Moreover, the SCAD operation in 2018-2020 was more consistent and settled. In summary, the operation of SCAD has been one of the waste management solutions at MSU by processing organic waste from farming and human consumption to provide renewable energy and fertilizer. Moreover, SCAD has provided emissions reduction, such as greenhouse gases and excess nutrients. To better understand the environmental impact resulting by SCAD, a life cycle assessment was conducted, and the result will be provided in the next chapter.

Table 4.42 Summary of SCAD performance

Year	Input			Output			
	Total Manure Pit Metric Ton	Total Food Pit Metric Ton	Total Feedstock Metric Ton	Total Biogas SCM	Total Electricity kWh	Effluent Total Metric Ton	Wet Fiber Total Metric Ton
2014	14,763	8,533	23,297	846,232	1,727,073	11,273	3,920
2015	13,805	12,800	26,605	1,103,695	2,118,966	14,100	4,858
2016	11,059	11,726	22,785	1,418,746	1,470,356	14,007	3,583
2017	11,109	9,129	20,238	1,326,335	2,169,693	12,751	2,779
2018	10,859	8,605	19,464	1,348,024	2,680,954	14,857	1,884
2019	11,353	10,539	21,893	1,280,438	2,333,449	15,762	2,758
2020	10,332	14,531	24,863	1,340,179	2,664,665	17,745	3,082
Total	**83,281**	**75,864**	**159,145**	**8,663,649**	**15,165,156**	**100,495**	**22,864**
Average	**11,897**	**10,838**	**22,735**	**1,237,664**	**2,680,954**	**14,356**	**3,266**
St. Deviation	**1,683**	**2,294**	**2,499**	**198,468**	**1,470,356**	**2,081**	**958**

CHAPTER 5. LIFE CYCLE ASSESSMENT

5.1. Introduction

Life Cycle Assessment (LCA) is a methodology that is developed to evaluate the environmental burdens of processes and products during the overall life cycle, which starts from raw materials handling and processing, manufacturing, transportation and distribution, consumption stage, recycling where needed, and final disposal. ISO 14040 defines this approach as a technique to determine the specific components of a product or process that create high environmental burdens and replace it with more sustainable and environmentally practices. LCA has been used by many institutions due to its integrated way of treating the framework, impact assessment, and data quality. Moreover, it enables the users to identify the potential environmental tradeoffs between stages by systematic analysis of the diverse impacts along the entire life cycle (Azapagic et al., 2006; Khasreen et al., 2009; Odey et al., 2021).

This assessment will compare the commercial MSU South Campus Anaerobic Digester with the conventional approach of organic waste management system: landfilling the food waste and storing the manure in a long-term storage. The comparison will be based on global warming potential (GWP) and water eutrophication potential (WEP). The inputs and outputs represent the major variables that contribute to environmental impacts for both scenarios.

5.2 Goal, Scope, and Functional Unit for Life Cycle Assessment

The LCA study was conducted based on the standard methodology provided by ISO 14040 series, Environmental Management Life-Cycle Assessment. The goal of this assessment was to evaluate the environmental impact of MSU SCAD which is an anaerobic co-digestion system using diverse types of manure and organic waste to produce electricity and agricultural coproducts. The objective was to determine how much the environmental impact of the co-digestion system

(Scenario 1) and to compare these impacts with the conventional reference method (Scenario 0) performance, which stored dairy manure in a long-term storage and landfilled food waste. This LCA only focused on the treatment of raw materials (Figure 5.1). Transportation and logistics of the waste to the treatment facility were not included in the assessment. The geographical scope occurred in the lower peninsula of Michigan. The temporal scope covers waste management for four years of SCAD operations between 2017-2020. The functional unit (FU) of this assessment was 10,913 metric tons of manure wastes and 10,701 metric tons of food wastes per year.

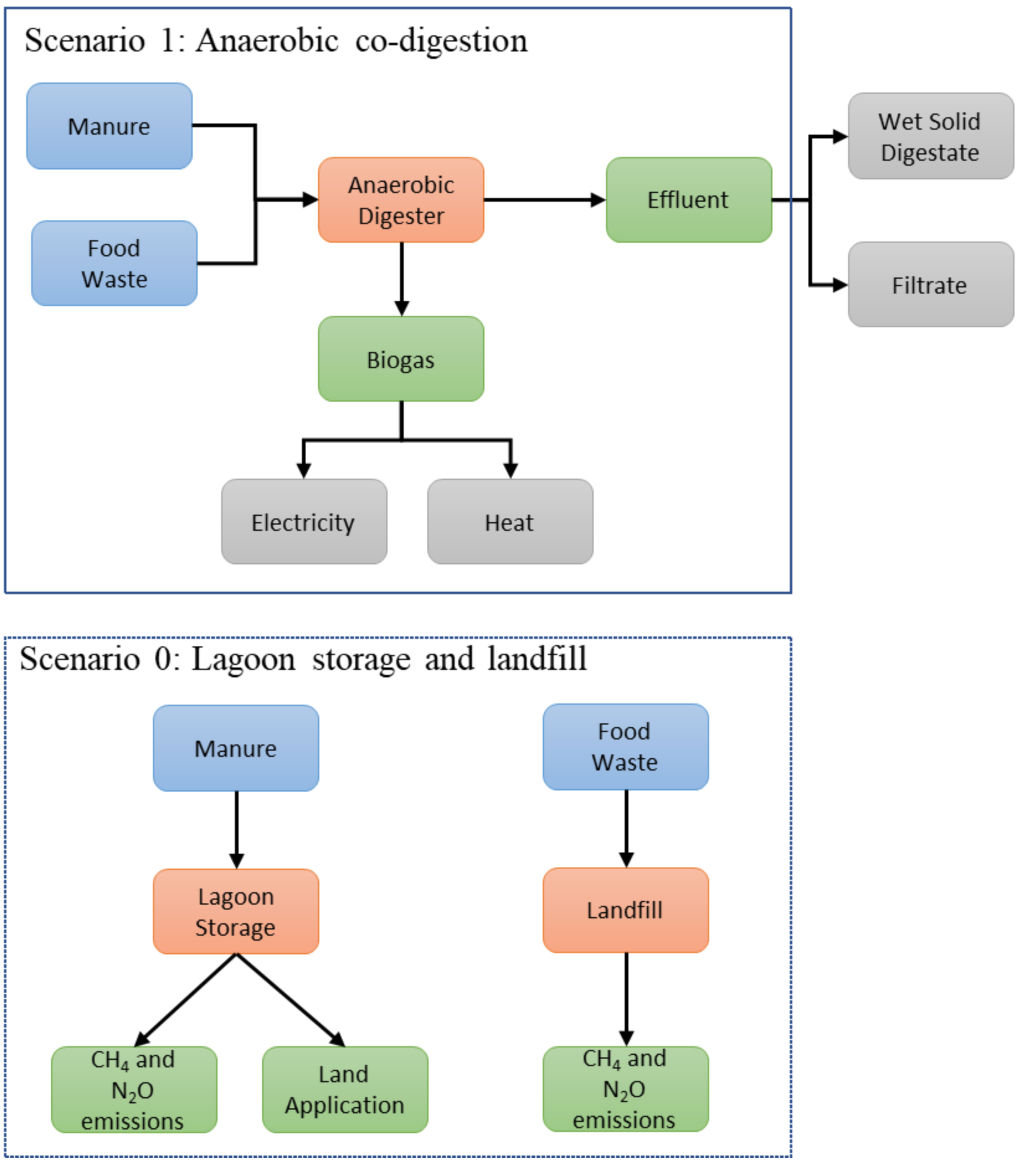

Figure 5.1 System boundaries of Scenario 1 and 0

5.3 Life Cycle Data Inventory

The life cycle inventory (LCI) provides all important information for life cycle impact assessment. In this study, LCI was divided into raw material and handling, anaerobic digestion and energy production, lagoon storage for manure, and food waste landfill. The raw material and handling section holds information regarding the material input into the system and processes before entering the digester. Additionally, this section also includes the emissions associated with manure storage if a digester was not in place. The anaerobic digestion and energy production section provides data regarding the process of anaerobic digestion and energy production from livestock manure and food waste. The third section provides data related to manure long-term storage in lagoon storage. The last section provides data related to the food waste landfill process.

Data quality was evaluated using the Weidema method. It includes six indicators of evaluation: acquisition method, independence of data supplier, representativeness, data age, geographical correlation, and technological correlation. The score ranges from one to five, where one is the best quality and five is the most uncertain. Table 5.1 presents how to apply the indicators based on the pedigree matrix.

Table 5.2 provides information about the inventory for this LCA study. This inventory is divided into raw materials, anaerobic digestion, and energy production, animal wastes lagoon storage and land application, and food wastes landfill inventory with landfill gas (LFG) combustion.

Table 5.1 Data Quality Evaluation Using the Weidema Method (Weidema et al., 2004)

Indicator Score	1	2	3	4	5
Acquisition method	Measured data	Calculated data based on measurements	Calculated data partly based on assumptions	Qualified estimate (by expert)	Nonqualified estimate
Independence of data supplier	Verified data, information from public or other independent source	Verified information from enterprise with interest in the study	Independent source but based on nonverified information from industry	Nonverified information from industry	Nonverified information from the enterprise interested in the study
Representative ness	Representative data form enough samples of sites over an adequate period to even out normal fluctuations	Representative data from smaller number of sites but for adequate periods	Representative data from smaller number of sites, but from shorter periods	Data from adequate number of sites but shorter periods	Representativeness unknown or incomplete data from smaller number of sites and/or from shorter periods
Data Age	Less than 3 years	Less than 5 years	Less than 10 years	Less than 20 years	Age unknown or more than 20 years
Geographical correlation	Data from area under study	Average data from larger area in which the area under study is included	Data from area with similar production conditions	Data from area with slightly similar production conditions	Data from unknown area with very different production conditions
Technological correlation	Data from enterprises, processes, and materials under study	Data from processes and materials under study but from different enterprises	Data on related processes and materials under study but from different technology	Data on related processes or materials but same technology	Data on related processes or materials but from different technology

The first part of the inventory holds information and values related to manure waste, food waste, and its chemical compositions. Manure waste is considered as low energy material, while food waste is high energy material. Therefore, co-digestion of manure with food waste potentially increases biogas production in the anaerobic digestion process (Chen et al., 2015). Data for organic waste quantity were the average of feedstock supplies in 2017-2020, which is considered the stable period of SCAD operation. Based on the data average, SCAD was fed with 10,913 metric tons of manure waste and 10,701 metric tons of food waste per year. One thing to put into consideration is that CO_2 from manure wastes and food wastes is not counted in the calculation of greenhouse gas emissions because the CO_2 is considered of biogenic origin and therefore is assumed to be offset by CO_2 capture by regrowth of the plants.

The second part of the inventory provides information and values related to anaerobic digestion and energy production from this process. Based on SCAD operational data, biogas composition consists of 65% (v/v) of CH_4 and 35% (v/v) of CO_2. The remaining consist of a small percentage of H_2S, NH_3, and H_2. Anaerobic digestion process in SCAD produced 1,323,757 m^3/year of biogas, which further converted biogas into 2,462,190 kWh-e/year of electricity and 5,584,551 kWh-e/year of heat. The remaining material was effluent as much as 19,948 metric tons/year. This part also provides information associated with the chemical contents of the effluent, including TN, TP, and soluble COD. These values will contribute to water eutrophication potential calculation. Meanwhile, biogas combustion and land application of effluent will contribute to global warming potential calculation.

The third part of Table 5.2 provides information and values related to animal waste lagoon storage and land applications. They would include CH_4 and N_2O emissions if animal wastes were only stored in lagoon storage. Furthermore, this section also includes values related to water eutrophication potential from TN, TP, and COD of animal waste land application. The fourth section provides information and values related to food waste landfills with landfill gas combustion (LFG). Like the third section, this section includes CH_4 and N_2O emissions if food wastes were only landfilled, also values related to water eutrophication potential from TN, TP, and COD of food wastes landfill. The moisture content of the typical food waste is about 70% (EPA, 2018).

Table 5.2 Inventory for the life cycle assessment [a]

	Value	Unit	Source	DQI
Raw materials				
Manure wastes	10,913	Metric ton/year	Operational data	1, 1, 2, 2, 1, 1
Total solids of manure wastes	11.4	%	Operational data	1, 1, 2, 2, 1, 1
Volatile solids of manure wastes	10.0	%	Operational data	1, 1, 2, 2, 1, 1
TN of manure wastes	4,143	mg/kg	Operational data	1, 1, 2, 2, 1, 1
TP of manure wastes	413	mg/kg	Operational data	1, 1, 2, 2, 1, 1
sCOD of manure wastes	59,446	mg/kg	Operational data	1, 1, 2, 2, 1, 1
Food wastes	10,701	Metric ton/year	Operational data	1, 1, 2, 2, 1, 1
Total solids of food wastes	10.1	%	Operational data	1, 1, 2, 2, 1, 1
Volatile solids of food wastes	9.3	%	Operational data	1, 1, 2, 2, 1, 1
TN of food wastes	5,318	mg/kg	Operational data	1, 1, 2, 2, 1, 1
TP of food wastes	449	mg/kg	Operational data	1, 1, 2, 2, 1, 1
sCOD of food wastes	17,525	mg/kg	Operational data	1, 1, 2, 2, 1, 1
Anaerobic digestion and energy production inventory				
Biogas production	1,323,757	m^3/year	Operational data	1, 1, 2, 2, 1, 1
CH_4 content in biogas	65	% v/v	Operational data	1, 1, 2, 2, 1, 1
CO_2 content in biogas	34	% v/v	Operational data	1, 1, 2, 2, 1, 1
Electricity production from biogas	2,462,190	kWh-e/year	Operational data	1, 1, 2, 2, 1, 1
Heat production from biogas	5,584,551	kWh-e/year	Operational data	1, 1, 2, 2, 1, 1
Effluent	19,948	Metric ton/year	Operational data	1, 1, 2, 2, 1, 1
TS of effluent	6.3	% (w/w)	Operational data	1, 1, 2, 2, 1, 1
TN of effluent	3,246	mg/kg	Operational data	1, 1, 2, 2, 1, 1
TP of effluent	584	mg/kg	Operational data	1, 1, 2, 2, 1, 1
sCOD of effluent	7,894	mg/kg	Operational data	1, 1, 2, 2, 1, 1

Table 5.2 (cont'd)

N_2O emission from the effluent	0.005	g N_2O/g TN in the effluent	(RTI International, 2010)	2, 1, 1, 4, 1, 2
GWP of N_2O	298	g CO_2-e/g N_2O	(RTI International, 2010)	2, 1, 1, 4, 1, 2
CH_4 emission from effluent	3.08×10^{-4}	Metric ton CO_2-e/metric ton TS in the effluent	(Turnbull & Komthunzi, 2004)	2, 1, 1, 4, 2, 2
Water eutrophication potential (WEP) of TN	0.9864	g N-e/kg TN in the effluent	(RTI International, 2010)	2, 1, 1, 4, 1, 2
Water eutrophication potential (WEP) of TP	7.29	g N-e/kg TP in the effluent	(RTI International, 2010)	2, 1, 1, 4, 1, 2
Water eutrophication potential (WEP) of COD	0.05	G N-e/kg COD in the effluent	(RTI International, 2010)	2, 1, 1, 4, 1, 2
Animal wastes lagoon storage and land application inventory				
CH_4 emission	0.127	Metric ton CH_4/metric ton VS	(Owen & Silver, 2015)	2, 1, 1, 3, 2, 2
N_2O emission	0.005	g N_2O/g TN in the waste	(RTI International, 2010)	2, 1, 1, 4, 1, 2
Water eutrophication potential (WEP) of TN	0.9864	g N-e/kg TN in the waste	(RTI International, 2010)	2, 1, 1, 4, 1, 2
Water eutrophication potential (WEP) of TP	7.29	g N-e/kg TP in the waste	(RTI International, 2010)	2, 1, 1, 4, 1, 2
Water eutrophication potential (WEP) of COD	0.05	g N-e/kg COD in the waste	(RTI International, 2010)	2, 1, 1, 4, 1, 2

Table 5.2 (cont'd)

Food wastes landfill inventory with landfill gas (LFG) combustion				
CH_4 emission, food wastes landfill	2.3	Metric ton CO_2-e/ton TS food waste	(Environmental Protection Agency, 2020)[b]	2, 1, 1, 1, 2, 2
N_2O emission	0.005	g N_2O/g TN in the waste	(RTI International, 2010)	2, 1, 1, 4, 1, 2
Water eutrophication potential (WEP) of TN	0.9864	g N-e/kg TN in the waste	(RTI International, 2010)	2, 1, 1, 4, 1, 2
Water eutrophication potential (WEP) of TP	7.29	g N-e/kg TP in the waste	(RTI International, 2010)	2, 1, 1, 4, 1, 2
Water eutrophication potential (WEP) of COD	0.05	G N-e/kg COD in the waste	(RTI International, 2010)	2, 1, 1, 4, 1, 2

a. CO_2 from manure wastes and food wastes is not counted in the calculation of greenhouse gas emissions because the CO_2 is considered of biogenic origin and therefore is assumed to be offset by CO_2 capture by regrowth of the plants.
b. The moisture content of the typical food wastes in the reference is set at 70%.

5.4 Data Quality Evaluation

This LCA study was supplied by legitimate sources, such as daily operational data from SCAD, research publications, and government annual reports. Table 5.3 provides the data quality evaluation for the life cycle inventory. Acquisition method, independence of data supplier, geographical correlation, and technological correlation were scored 1. Additionally, representativeness and data age were scored 2 and 3, respectively.

Majority of data were from SCAD operational data which are primary data for the study. Furthermore, the study acquired data from verified institutions including EPA and RTI International. For data age, there was one source from RTI International which is less than 20 years old. This data was used because the recent study related to this topic still refers to the data set in this publication. All data included in the study is geographically in the US.

Table 5.3 Data Quality Evaluation Summary for LCI

Indicator	DQI Score	Discussion
Acquisition Method	1	Measured data
Independence of Data Supplier	1	Verified data, information from public or other independent source
Representativeness	2	Representative data from smaller number of sites but for adequate periods
Data Age	3	Less than 10 years
Geographical Correlation	1	Data from area under study
Technological Correlation	1	Data from enterprises, processes, and materials under study

5.5 Mass and Energy Balance of the process at different months and years

Mass and energy balance analysis was carried out based on the operational data from 2017 to 2020. The energy inputs for the digestion operation include heat (W_{heat}, kWh-e/year) to maintain the digestion temperature as well as electricity ($W_{electricity}$, kWh-e/year) to power pumps, mixers, and other accessary equipment. The energy inputs were calculated using the following equations modified from a previous study (Bustamante and Liao, 2017):

$$W_{heat} = m \times C_p \times (T_R - T_O) \times (1 + 20\%) \times 0.0002778 \quad (3)$$

$$W_{electricity} = m \times 0.00788 \quad (4)$$

Where m is the amount of the wet weight of the feedstock per year (kg); C_p is the heat capacity of the wet FM (4.12 kJ/(kg K)); T_R is the reactor temperature (313 K); T_O is the temperature of the wet feedstock based on the average environmental temperature in East Lansing, MI (288 K); 20% is the percentage of the additional heat needed to maintain the digestion temperature; 0.0002778 is the conversion factor of KJ to kWh; and 0.00788 is the average electricity demand unit of the digester operation (kWh/kg wet FM).

Figure 5.2 provides mass balance scheme that happened in SCAD. In general, the input comes from the feedstock then be processed in the digester to produce biogas and effluent. Furthermore, the effluent is divided into wet solid digestate and filtrate. These numbers represent the average values of each parameter in 2017-2020.

From feedstock input, the amount of feedstock processed in the digester was 21,614 metric tons per year, which combined both manure pit and food pit. The amount of feedstock from manure pit and food pit were 10,913 metric ton and 10,701 metric ton per year, respectively. Furthermore, these feedstocks contain 10.6% (w/w) of total solids and 10.0% (w/w) of volatile solids. In terms of the nutrient contents, the amount of total nitrogen, total phosphorus, and soluble COD in the feedstock were 4,690 mg/kg, 633 mg/kg, and 38,700 mg/kg, respectively. These numbers were gained from a single measurement that happened in 2017, as the only measurement for feedstock during this period.

Anaerobic digestion process transformed the raw materials to produce biogas and effluent. Biogas production was 1,323,757 m^3/year with CH_4, CO_2, and H_2S contents were 65% (v/v), 34% (v/v), and 495 ppm, respectively. Effluent yielded from anaerobic digestion process was 19,948 metric ton/year. The effluent contained 6.3% of total solids (w/w) and 5.1% of volatile solids (w/w). In terms of the nutrient contents, the amount of total nitrogen, total phosphorus, and soluble COD in the effluent were 3,246 mg/kg, 584 mg/kg, and 7,894 mg/kg, respectively.

Through the separation process, effluent became wet solid digestate and filtrate for further application. The amount of filtrate produced was 17,081 metric ton/year with total solids and volatile solids contents were 4.5% (w/w) and 3.0% (w/w), respectively. Filtrate also contained 3,293 mg/kg of total nitrogen and 509 mg/kg of total phosphorus. For wet solid digestate, the yield was 2,867 metric ton/year with total solids and volatile solids contents were 27.6% (w/w) and

24.4% (w/w), respectively. Digestate also contained 529 mg/kg of total nitrogen and 171 mg/kg total phosphorus.

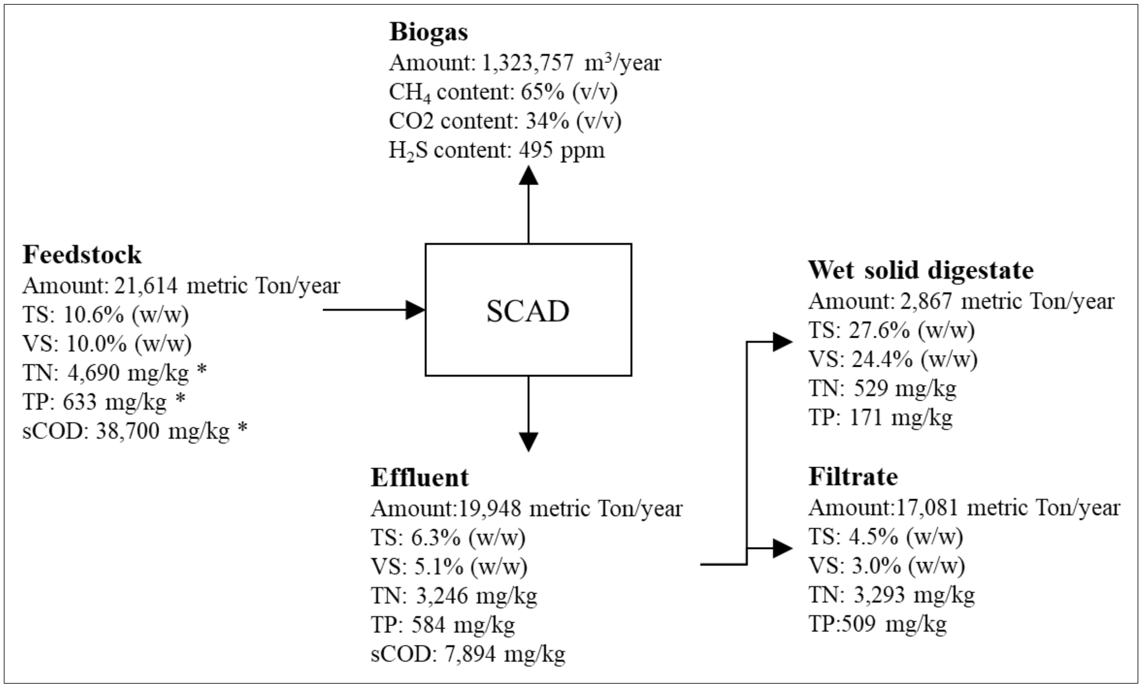

Figure 5.2 Mass balance of the anaerobic digestion process
***: Data are from a single measurement in 2017**

Table 5.4 provides information about energy balance of anaerobic digestion process that happened in SCAD. The energy balance includes energy input, energy output, and net energy output coming from heat and electricity. SCAD consumed 742,090 kWh-e/year of heat to maintain the digester operational temperature and 170,320 kWh-e/year of electricity to power pumps, mixers, and other equipment on the site. Anaerobic digestion process yielded heat and electricity as much as 5,584,551 kWh-e/year and 2,462,190 kWh-e/year, respectively. Net energy output was gained from subtracting energy produced with energy consumed. The net energy output yielded by SCAD in the form of heat and electricity were 4,842,461 kWh-e/year and 2,291,870 kWh-e/year, respectively. Furthermore, from energy output values, the efficiency of electricity generation was calculated which was 29%.

Table 5.4 Energy balance of the anaerobic digestion process [a]

	Anaerobic digester
Energy input	
Heat input (W_{heat}, kWh-e/year) [b]	-742,090
Electricity input ($W_{electricity}$, kWh-e/year) [c]	-170,320
Energy output	
Energy output as heat (E_{heat}, kWh-e/year) [d]	5,584,551
Energy output as electricity ($E_{electricity}$, kWh-e/year) [e]	2,462,190
Net energy output	
Net heat output (kWh-e/year) [f]	4,842,461
Net electricity output (kWh-e/year) [g]	2,291,870

a. Negative numbers mean energy inputs, and positive numbers mean energy outputs.
b. Eq. 1 was used to calculate the heat input.
c. Eq. 2 was used to calculate the electricity input.
d. The annual biogas production of 1,323,757 m^3 with 65% (v/v) of methane was used to calculate the energy content of the biogas. The low heating value of methane is 35.8 MJ/m^3 methane. The thermal conversion efficiency of the CHP unit is 65%.
e. The electricity output is the metered number of the digestion operation.
f. The net heat output = E_{heat} - W_{heat}
g. The net electricity output = $E_{electricity}$ - $W_{electricity}$

5.6 Impact Assessment

Two impact categories were chosen for Life Cycle Impact Assessment: Global Warming Potential (GWP) and Water Eutrophication Potential (WEP). The classification of each category is defined by the US Environmental Protection Agency (EPA). The LCIA provides an analysis of environmental impacts on both scenarios as a comparison to the emissions of waste management methods for animal wastes and food wastes. This could be done by calculating the environmental impacts yielded from processes or products associated with the proposed systems.

5.6.1 Global Warming Potential (GWP)

Global warming is defined as the raising of Earth's temperature due to GHG emissions globally, which mainly coming from human activities. The main GHGs are CO_2, CH_4, and N_2O.

Currently, the main energy supplies are still from fossil fuels such as oil and coal, which contribute roughly 65% of GHG emissions (EPA, 2019). Therefore, renewable energy is expected to address this concern. Anaerobic digestion has been promoted as a renewable energy system that potentially lower the global warming potential by reducing emissions from manure and food waste.

Global Warming Potential (GWP) is the amount of GHG released during the life cycle of a process. Carbon dioxide is commonly used as a reference gas to compare the impact of various greenhouse (Shine, 2009). For this LCA study, data were collected for CH_4, and N_2O emissions. They were normalized to 1 ton of CO_2 equivalent (CO_2-e) based on the following conversions: 1 kg CH_4 = 25 kg CO_2-e; and 1 kg N_2O = 298 kg CO_2-e (RTI International, 2010). CO_2 from manure wastes and food wastes is not counted in the calculation of greenhouse gas emissions because the CO_2 is considered of biogenic origin and therefore is assumed to be offset by CO_2 capture by regrowth of the plants.

Figure 5.3 provides information related to GWP contribution analysis for each scenario. According to the impact assessment, the AD system has an overall GWP of 1,842-ton CO_2-e/year, while the land applications system produces 6,190-ton CO_2-e/year. This result shows that the AD system can reduce GWP up to 70% lower than the landfills system.

Furthermore, biogas and AD effluent were the only parameters to be considered for calculating GWP. Electricity, heat utilization, digestate, and filtrate were not calculated as they are outside of the system boundaries. For the AD scenario, biogas combustion contributed 92% of the total GWP, while land application of effluent only contributed 8%. For the landfill scenario, biogas production was counted as CH_4 and N_2O emissions from manure land application with lagoon storage and food wastes land application with landfill gas combustion. Lagoon storage contributed

58% of the total GWP, followed by landfill gas combustion with 42% of contribution towards the total GWP.

The result of this study was supported by previous result from Chen et al. (2015), where a co-digestion of dairy manure and bakery wastes in the AD system was compared to the AD system with dairy manure only and landfilling the bakery waste. The study revealed that co-digestion of 7,147-ton dairy manure and 2,382-ton food waste had an overall GWP of 1.6×10^4 ton CO_2-e, while another scenario yielded an overall GWP of 2.7×10^4 ton CO_2-e, which means that AD scenario resulted in a 42% reduction in GWP. This could be evidence that the anaerobic co-digestion system has a capability to mitigate the global climate change rather than the conservative methods such as landfilling the food waste or digestion of manure only.

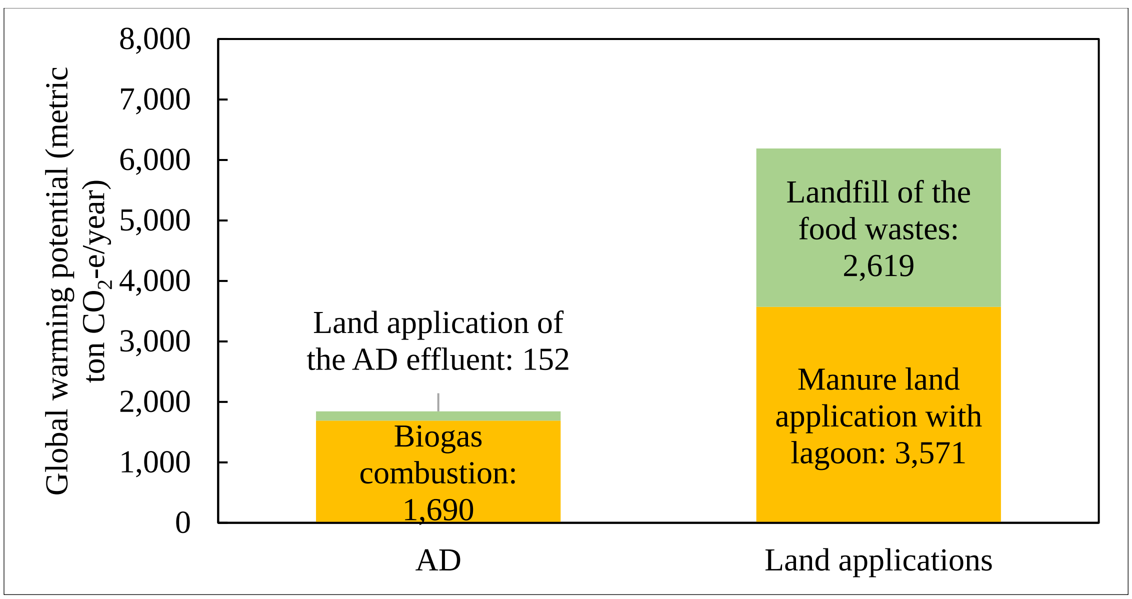

Figure 5.3 GWP contribution analysis of the anaerobic digestion process and land applications

5.6.2 Water Eutrophication Potential (WEP)

Eutrophication is a situation where a water body contains excessive nutrients that affect to a dense growth of plant life and death of water animals due to lack of oxygen. It is due to nutrients runoff from the land, such as nitrogen and phosphorus, which then accumulate in the water. Consequently, it creates a "dead zone," which is an area with low oxygen content that suffocates marine life (Mueller & Helsel, 1996). Water eutrophication potential (WEP) is the impact resulting from excessive nutrient supplies on terrestrial and aquatic environments, particularly the most important substances such as nitrogen (N) and phosphorus (P). WEP can be presented as either nitrogen equivalents (N-eq.) or phosphate equivalents (PO_4-eq.) (Guinee, 2002).

A kilogram of nitrogen equivalents (kg N-eq.) units was used to assess WEP in this study. TN, TP, and COD were the three parameters used for WEP assessment. All values related to TN, TP, and COD contents were measured as SCAD operational data, except for COD concentration of manure which was back calculated. WEP conversion values for TN, TP, and COD are 0.9864 g N-e/kg TN in the waste, 7.29 g N-e/kg TP in the waste, and 0.05 g N-e/kg COD in the waste, respectively (RTI International, 2010).

Figure 5.4 provides information related to WEP contribution analysis for each scenario. According to the impact assessment, the AD system has an overall WEP of 173 kg N-e/year, while the land applications system produces 232 kg N-e/year. This result shows that the AD system can reduce WEP up to 25% lower than the landfills system.

WEP from the AD system came from three parameters, which were TN, TP, and COD of AD effluent. TP became the most significant WEP contributor in the AD system, which was 54% of the total WEP, followed by TN, which contributed 41% of the total WEP. Meanwhile, COD only contributed 9% of the total WEP. In the landfills system, the chemical content was divided into manure waste and food waste. Both wastes have TN as the most significant contributor in WEP. Food waste TN became the highest contributor of WEP in landfills system, which was 27%, followed by Manure TN at 21%. Food waste TP, manure TP, and manure COD were closed together, which were 17%, 16%, and 15% of WEP contribution, respectively. Food waste COD was the least contributor of WEP with 4% of contribution.

AD system does not contribute much to reducing the nutrient content in the organic materials. WEP in AD is more correlated to feedstock quality and the digester's HRT. It barely had any correlation to biogas productivity. Therefore, nutrient content in the feedstock did not significantly alter. Nevertheless, AD transformed the elemental nitrogen and phosphorus to become ammonia and phosphate, respectively. Compared to elemental nitrogen and phosphorus, ammonia and phosphate are more beneficial for soil conversions and plant adsorption (Arosemena, 2021; R. Chen et al., 2015; Field et al., 1984).

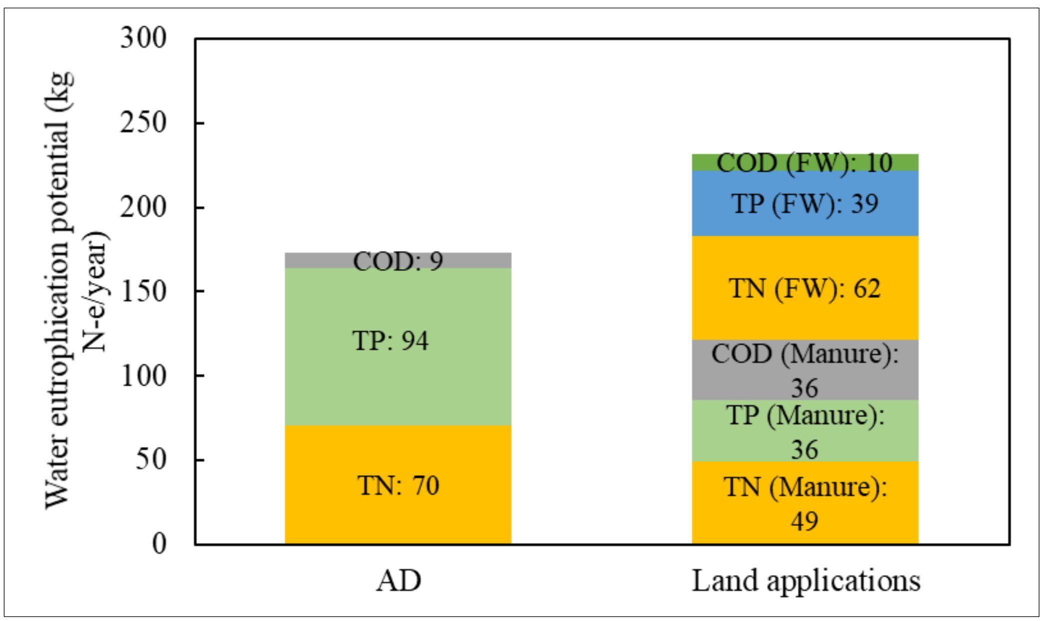

Figure 5.4 WEP contribution analysis of the anaerobic digestion process and land applications

5.7 Interpretation

5.7.1 Sensitivity Analysis

Sensitivity analysis is a method to measure any changes in a certain impact by simulating any changes in key parameters that influence the model. This method can report which parameters greatly affect any changes in each impact category. By doing a sensitivity analysis with LCA, a study can depict further actions to conduct to lower the environmental burdens of a product or a system.

5.7.1.1 Global Warming Potential (GWP)

The sensitivity analysis for the anaerobic digestion and the land applications systems were performed by modifying ±25% of each variable of interest while keeping the other variables constant for the base case. The parameters analyzed for the anaerobic digestion were biogas combustion and AD effluent, while the parameters analyzed for the land applications were NO_2 and CH_4 emissions from manure and food waste. The sensitivity analysis result for the anaerobic digestion system, as presented in Figure 5.5, shows that biogas combustion becomes the most sensitive parameter towards the impact category value, while effluent becomes the least sensitive parameter. The change in biogas combustion (±25%) resulted the highest change in GWP values at 29.44%. It is due to biogas combustion is the main process in converting methane into electricity. Meanwhile, the change in AD effluent only resulted 2.31% change in GWP values.

The sensitivity analysis result for the land application system, as presented in Figure 5.6, shows that CH_4 emission from manure becomes the most sensitive parameter towards the GWP value, followed by CH_4 emission from food waste. The change in CH_4 emissions from manure resulted 14% change in GWP value, while the change in CH_4 emission from food waste resulted 10% change in GWP value. The emissions of NO_2 from food waste and manure become the least sensitive parameters, which only affect 0.54% and 0.43% of change in GWP value, respectively.

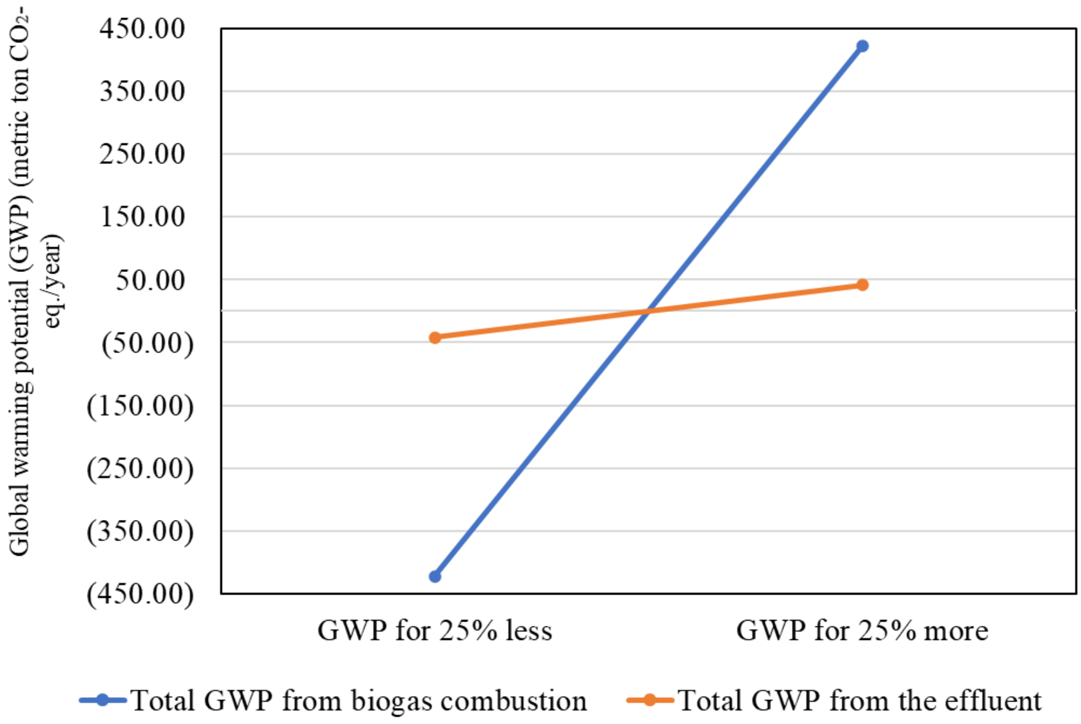

Figure 5.5 Anaerobic digestion sensitivity analysis for GWP

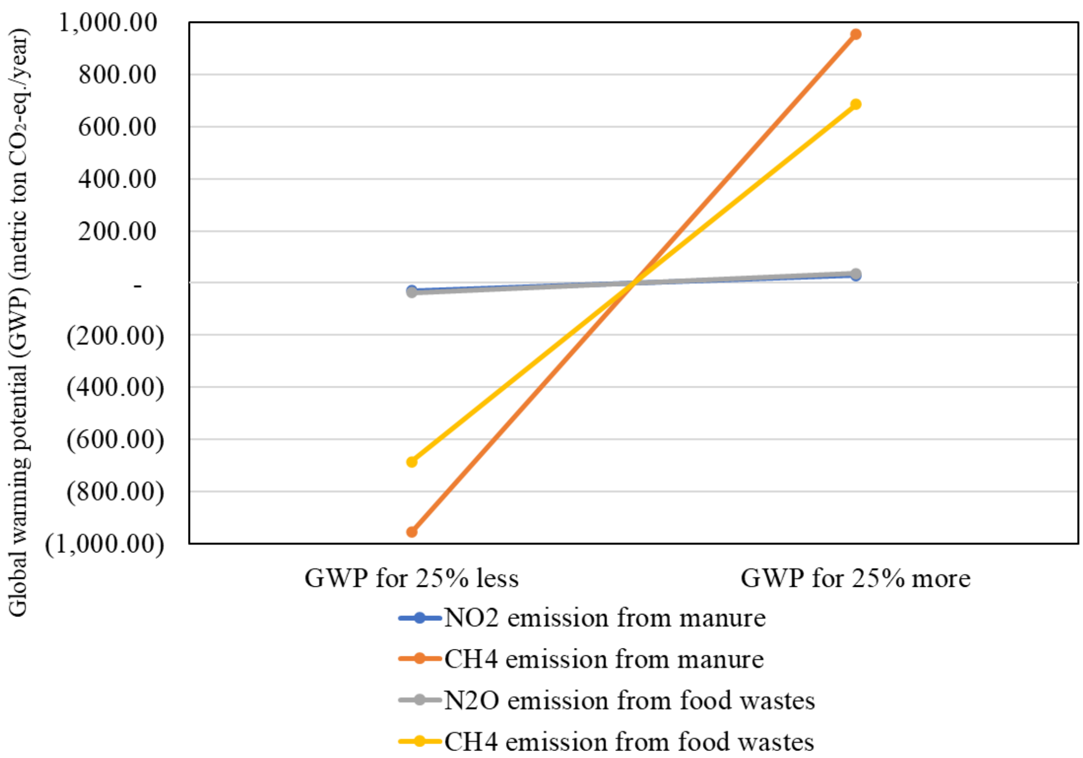

Figure 5.6 Land applications sensitivity analysis for GWP

5.7.1.2 Water Eutrophication Potential (WEP)

The sensitivity analysis for the anaerobic digestion and the land applications systems were performed by modifying ±25% of each variable of interest while keeping the other variables constant for the base case. The parameters analyzed for the anaerobic digestion were TN, TP, and COD of the effluent. Meanwhile, the parameters analyzed for the land applications were TN, TP, and COD of both manure and food waste. The sensitivity analysis result for the anaerobic digestion system, as presented in Figure 5.7, shows that effluent TP becomes the most sensitive parameter towards the impact category value, while effluent COD becomes the least sensitive parameter. The change in effluent TP (±25%) resulted the highest change in GWP values, at 13.5%, followed by effluent TN at 10.2%. Meanwhile, the change in effluent COD only resulted 1.25% change in GWP values.

The sensitivity analysis result for the land application system, as presented in Figure 5.8, does not show significant difference between most of parameters. Food waste TN becomes the most sensitive parameter, followed by manure TN and food waste TP. These three parameters resulted 6.7%, 5.3%, and 4.1% change in WEP value, respectively. On the other hand, food waste COD becomes the least sensitive parameter with only 1.1% change in the WEP value. Manure TP and COD contribute similar impact to WEP value, which are 3.9%.

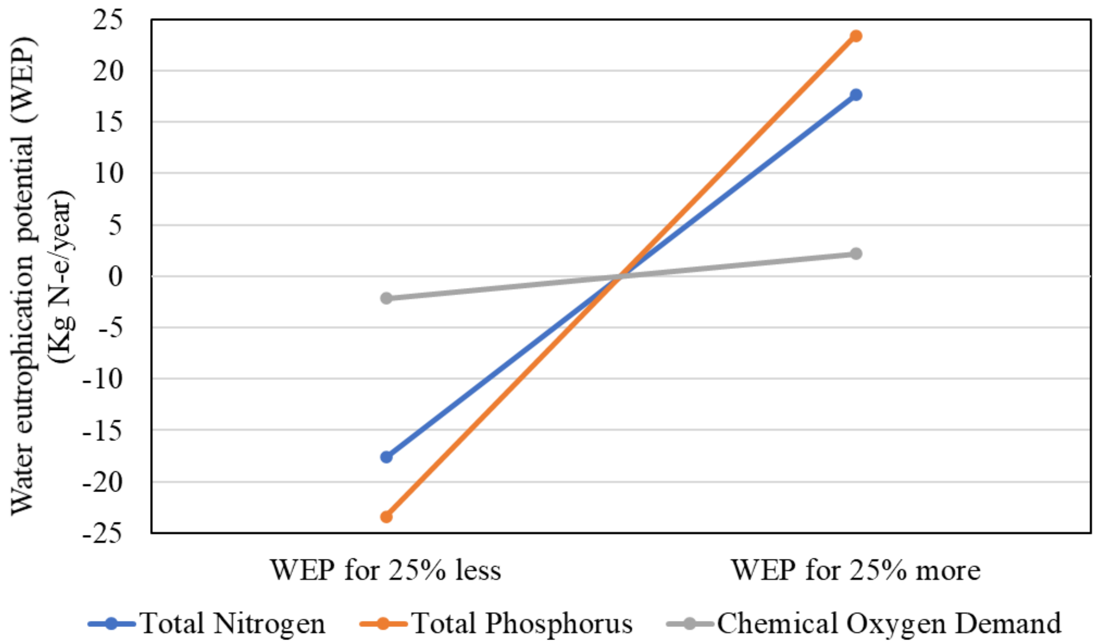

Figure 5.7 Anaerobic digestion sensitivity analysis for WEP

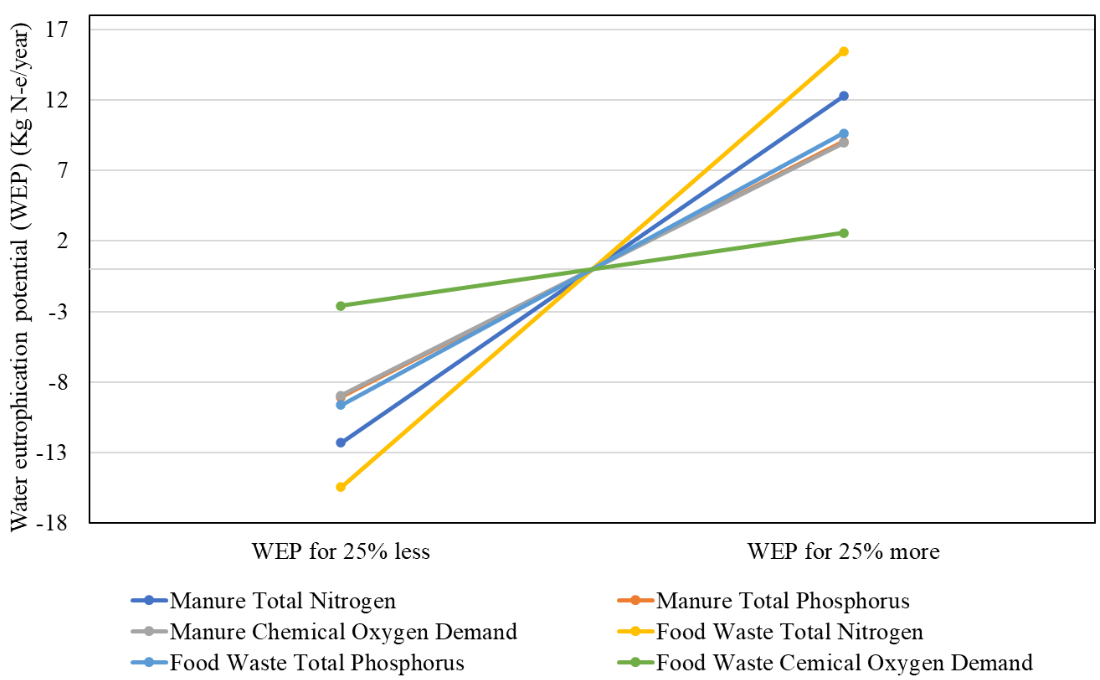

Figure 5.8 Land applications sensitivity analysis for WEP

5.7.2 Consistency and Completeness Check

The consistency check aims to demonstrate that assumptions, methods, and data used throughout the LCA process are aligned with the goal and scope of the study. It can show where the data consistency can be improved to compare systems to one another. The consistency check and explanations of inconsistency are explained within Table 5.5. The overall data adequately shows consistency to support the goal and scope of the study.

Table 5.5 Checklist and Inconsistencies based on Data Quality

Category	Checklist and Inconsistencies
Data Source	Both scenarios have most data based on operational data and legitimate sources
Data Accuracy	Both scenarios are supplied with accurate data from measurement or calculation based on previous studies
Technological Representation	Both scenarios have data available for conducting the study
Temporal Representation	Both technologies are utilized up to date
Geographical Representation	Both technologies include data from the United States
System Boundary, Assumption and Model	Both systems serve as a waste management system

A completeness check ensures that the study has complete available sources for data interpretation. In case there are some gaps in the completeness of the data, it should be verified whether the incompleteness will affect the goal and scope of the study. Table 5.6 provides a completeness check for the AD system, while Table 5.7 provides a completeness check for the landfill system. In general, all data required for the study was completed. SCAD operational data contains most parameters needed for the study, even though there were several parameters that rely on a single measurement and one parameter needed a back-calculation. Manure storage and food waste landfill are two common methods for waste management in the US, therefore providing legitimate sources for the impact assessment. There might be potential data gaps if the system boundary is extended since this study only focused on the waste treatment.

Table 5.6 Completeness check for AD system

Life cycle stage	AD	Complete	Required Actions
Raw materials	X	Yes	-
AD and energy production	X	Yes	-
Output: Effluent	X	Yes	-
X: data available		n.a.: not applicable	

Table 5.7 Completeness check for landfills system

Life cycle stage	Landfill	Complete	Required Actions
Raw materials	X	Yes	-
Manure storage	X	Yes	-
Food waste landfill	X	Yes	-
X: data available		n.a.: not applicable	

5.8 Technoeconomic Analysis

Technoeconomic analysis is conducted to evaluate whether renewable energy production can also attract investors based on its financial benefits of it. One of the significant issues in producing renewable energy on a large scale is the large investment for capital and/or operational costs, which makes renewable energy seems environmentally favorable but less economically competitive (Carneiro and Ferreira, 2012; Fersi et al., 2012). This section will analyze the cost and profit analysis of SCAD as a commercial digester, including capital expenditures (CapEX), operational expenditures (OpEX), and revenues. The payback period was calculated according to capex and total net profit.

Table 5.8 provides information for the whole performance of technoeconomic analysis. The first section holds information about CapEX. Digester construction cost became the highest expense in this section, contributing 40.21% to the total CapEX. Feedstock receiving and combined heating and power (CHP) costs were the other major expenses with relatively similar values, contributing 20.29% and 21.71% to total CapEX, respectively. The total system CapEX was $3,586,861.

The second section of Table 5.8 provides information about the OpEX, which is calculated per year. In this study, OpEX was taken from operational data in 2019-2020 as the recent years of the study. Among 12 items described in OpEX, labor cost became the highest expense which contributed roughly 41.5% to total OpEX. CHP engine service became the second-highest expense, contributing about 25% to total OpEX. DHT transport means that every gallon of food waste brought to the digester has to be exported to maintain nutrient balance on campus. It became the third-largest expense, contributing about 17.75% to total OpEX. The total system OpEX was $298,156.

The third section belongs to revenue. Tipping fees and electricity were the two revenue sources of SCAD. Both commodities had similar values during 2019-2020, which were $237,746 for electricity and $217,854 for tipping fees. The total system revenue was $455,600.

SCAD has experienced volatile revenue from electricity due to some changes in electricity pricing. The model was proposed to the board of trustees at the price of $0.123/kWh. Prior to 2018, the price was between $0.04 and $0.06/kWh due to the standby charge implemented by Consumers Energy. Standby charge is a measurement of energy production in a 15-minute interval and during peak time from 09:00 AM to 06:00 PM. If the digester does not produce power during that 15 minute, the digester gets the lower rate, and it is for the entire month, not only for that 15 minute.

In 2018, SCAD was directly connected to the campus power supply, which resulted in a flat rate of $0.1017/kWh.

Total net revenue was calculated by subtracting total revenue from total OPEX. The net revenue value of SCAD was $157,444. The payback period was then calculated by considering 5-year average local inflation of 3.2% in the U.S. as the inflation rate and 20 years of depreciation period on CapEx. The annual depreciation rates from Modified Accelerated Cost Recovery System (MARCRS) are: 0.100, 0.188, 0.144, 0.115, 0.092, 0.074, 0.066, 0.066, 0.065, 0.065, and 0.033 (after 10 years). Based on cash flow calculation, the payback period will be in 21.5 years; then, the digester will start to gain profit afterward. This can be considered a quite promising payback time and economically competitive. An economic sensitivity analysis would be strongly recommended to be conducted to know which parameter is the most sensitive; thus, it can shorten the length of the payback period.

Table 5.8. Economic performance of the digestion process [a]

Capital expenditure (CapEX)	**Cost**	**Reference**
Feedstock Receiving	$727,927	Data
Digester	$1,442,140	Data
CHP	$778,651	Data
Bond	$38,143	Data
Interconnection	$300,000	Data
Site improvements & excavation	$300,000	Data
Total CapEX	**$3,586,861**	
OpEX (per year)		
AD Repairs	$28,373	Data
ADMIN Fee	$2,948	Data
Bio Analysis	$2,827	Data
CHPS	$74,226	Data
Labor	$123,616	Data
Laundry	$378	Data
Maintenance and Repair	$6,482	Data
MISC	$4,064	Data
Motor Pool / Vehicle	$1,165	Data
Supplies	$396	Data
Telephone	$772	Data

Table 5.8 (cont'd)

Transport (DHT)	$52,910	Data
Total OpEX (per year)	**$298,156**	
Revenue (per year)		
Electricity	$237,746	Data
Tipping	$217,854	Data
Total revenue (per year)	**$455,600**	
Total net revenue (per year) [b]	**$157,444**	
Payback time (Years) [c]	**21.5**	

a. The OpEX and revenue are the operational data from 2019-2020.
b. The net revenue = Total revenue – Total OpEx
c. The 5-year average local inflation of 3.2% in the U.S. is used as the inflation rate. The depreciation period is set at 20 years. The depreciation is just on CapEx. The annual depreciation rates from MARCRS (Modified Accelerated Cost Recovery System) are: 0.100, 0.188, 0.144, 0.115, 0.092, 0.074, 0.066, 0.066, 0.065, 0.065, and 0.033 (after 10 years).

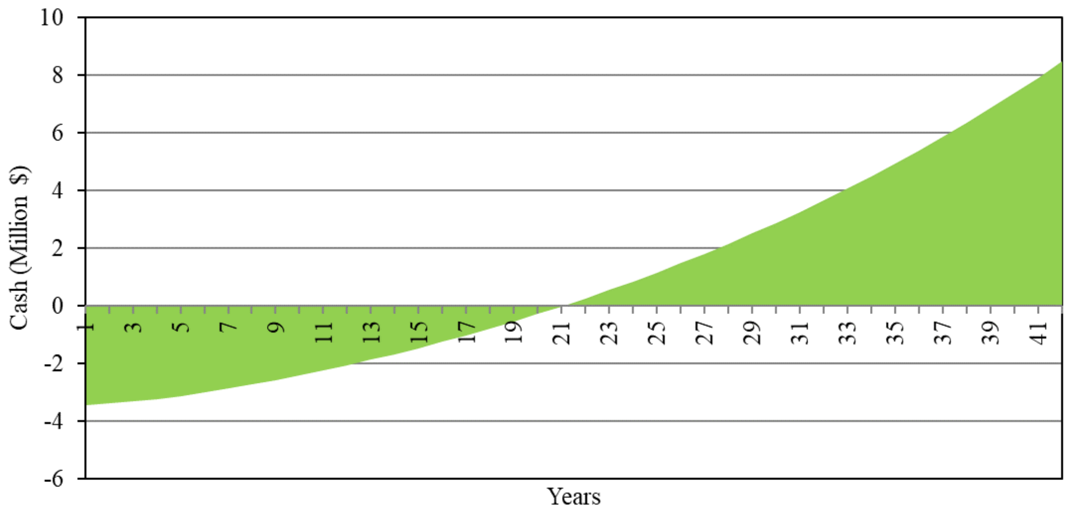

Figure 5.9 Total net cash flow and payback period of SCAD

There are three basic scenarios that can be considered to shorten the payback period. The first scenario would be fixing the electricity price; the second scenario would include digestate as part of revenue, while the third scenario would be the combination of the first and the second scenario.

As mentioned earlier, the proposed electricity price for SCAD to the board of trustees was $0.123/kWh, while the current price for electricity is $0.1017/kWh. That means there is a price gap of as much as $0.0213/kWh. If the proposed price can be achieved, the revenue from electricity would be $307,713. Because of it, the total net revenue will be increased to $227,412, and it will lower the payback period to be in 15 years.

The second scenario would be including digestate as part of the revenue. As per the current study, digestate is still part of OpEX, which is DHT transport. Digestate is a source of nutrients for the soil. If the digester can manage the digestate to be part of the revenue, then the DHT transport cost will be excluded from OpEX. Furthermore, the digestate price is assumed to be $7.00 per metric ton. The average digestate production in 2019-2020 was about 18,471 metric tons. Therefore, the revenue from selling the digestate can be up to $129,297. This additional revenue will increase the total revenue to $584,897 and the total net revenue to $339,652. It will also reduce the total OpEX to $245,246. These changes can reduce the payback period to be in 10.5 years.

The third scenario would be the best scenario that SCAD can afford. With electricity price fixed and digested becoming part of the revenue, the total revenue will become $654,865, total net revenue will be $409,619, and the payback period will be in 9 years. Regardless of which scenario seems to be the most feasible, it shows that SCAD has a competitive economic advantage as a commercial-scale anaerobic digester.

5.8.1 Sensitivity Analysis

Sensitivity analysis was done to check which parameters significantly affect the payback period. Nine variables – feedstock receiving, digester, CHP, interconnections, site improvements, CHP maintenance, labor, electricity, and tipping fees – were taken into consideration for the economic sensitivity analysis of this study. The analysis was done by modifying each variable of interest by ± 25% while keeping the other variables constant for the baseline scenario. The number changed represents how much each variable affects the increasing or decreasing of the payback period compared to the baseline scenario.

The result (Figure 5.6) shows that electricity was the most sensitive among all variables, followed by tipping fees and labor costs as the second and third most sensitive variables. Increasing the revenue from electricity by 25% helps to decrease the payback period by 11.41 years, while the decrease in this parameter by 25% contributes to increasing the payback period by 26.06 years. The increasing of tipping fees by 25% reduces the payback period by 10.69 years while decreasing the tipping fees by 25% increases the payback period by 22.67 years. Meanwhile, the increase of labor cost by 25% increases the payback period by 17.61 years, while reducing the cost by 25% lowers the payback period by 9.44 years. Interconnections, site improvements, and feedstock receiving become the least sensitive among all parameters.

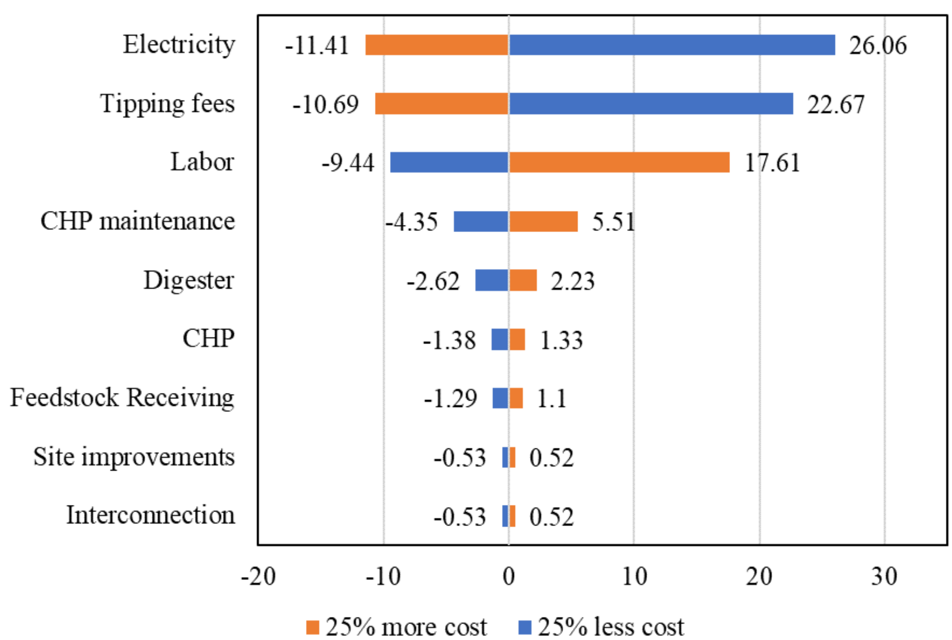

Figure. 5.10 Sensitivity analysis chart for SCAD payback period

CHAPTER 6. OVERALL CONCLUSION AND RECOMMENDATIONS

6.1 SCAD operational performance

The goal of this study is to evaluate the operational performance of Michigan State University's South Campus Anaerobic Digester (SCAD) as a commercial digester, as well as the environmental impact during its operation from 2014-to 2020. This study concluded that SCAD received a total of 18 different feedstocks throughout its operation thus far. Among all feedstocks, Dairy Gutter, Parlor, and FOG become the major feedstocks for the digester. Multilinear regression was conducted to determine feedstocks that have the most significant impact on biogas production. The filtrate in the manure pit, Dairy Gutter, Parlor, and FOG are feedstocks that have the most significant impact on biogas production, with a $p\text{-value}<0.05$. The Multiple R-squared was 58.24%, and the Adjusted R-squared was 56.01%, showing that the model was able to explain 56% to 58% of the data variance to predict the biogas production. It is due to SCAD receiving a wide variety of feedstock with an uncertain frequency which affects the R-squared values. However, the study can still draw a conclusion since there are independent variables that are statistically significant to correlate the relationships between the variables.

In general, the operation of SCAD went through several trends. From 2014 to 2015, SCAD built good trends since its establishment in 2013 due to the output production increased from 2014 to 2015. SCAD operation was disrupted from 2016 to 2017 in terms of electricity production due to the CHP engine outage that happened in those years. Moreover, the SCAD operation from 2018 to 2020 was more consistent and settled.

In summary, the operation of SCAD has been one of the waste management solutions at MSU by processing organic waste from farming and human consumption to provide renewable energy and fertilizer. During its operation years from 2014 to 2020, SCAD has processed 159,145 metric tons of feedstock that consist of 83,281 metric tons of manure wastes and 75,864 metric tons of food waste to produce 8,663,649 SCM of biogas, 15,165,156 kWh of electricity, 100,495 metric tons of effluent, and 22,864 metric tons of wet fiber.

6.2 Life Cycle Assessment and Technoeconomic Analysis

A life cycle assessment was conducted to compare the environmental impact of the AD system with a conventional system that combines lagoon storage for manure wastes and landfills for food wastes. This LCA study was supplied by legitimate sources, such as daily operational data from SCAD, research publications, and annual government reports. Acquisition method, independence of data supplier, geographical correlation, and technological correlation were scored 1. Additionally, representativeness and data age were scored 2 and 3, respectively.

The result showed that the AD system possesses fewer environmental burdens in both GWP and WEP compared to the conventional system. AD system has an overall GWP of 1,842-ton CO_2-e/year, while the land applications system produces 6,190-ton CO_2-e/year. This result shows that the AD system can reduce GWP up to 70% lower than the landfills system. AD system has an overall WEP of 157 kg N-e/year, while the land applications system produces 210 kg N-e/year. This result shows that the AD system has a WEP 26% lower than the landfills system.

Sensitivity analysis was conducted to determine parameters that give the most significant impact on the LCA study. From GWP, biogas combustion became the most sensitive parameter on the AD system. Meanwhile, CH_4 emissions from manure became the most sensitive parameter on the land application system. From WEP, effluent TP became the most sensitive parameter on the AD system. Meanwhile, food waste TN became the most sensitive parameter on the land application system.

Technoeconomic analysis was conducted to understand the financial feasibility of SCAD as a commercial digester. The result showed that SCAD needs 21.5 years to accomplish its payback time, which is considered quite economically competitive. Three basic scenarios can be done to gain a better payback time for up to 9 years. Economic sensitivity analysis shows that the revenue from electricity is the most sensitive parameter to affect the payback period, followed by tipping fees and labor costs. Increasing the revenue from electricity can lower the payback period by 11.41 years. Meanwhile, interconnections, site improvements, and feedstock receiving are the least sensitive parameters.

6.3 Further recommendations

Future work for LCA study can include more impact parameters for the study, such as air acidification potential and smog potential. Since the current study has a system boundary that only includes organic waste treatment at the site, it would be interesting to know the dynamics in the LCA study once the system boundary is extended, such as including digestate land application or transportation to the treatment site.

As for technoeconomic analysis, digestate is not included in the revenue as per the current study. Including digestate as an organic fertilizer can be additional revenue that can shorten the payback time of the digester. Moreover, electricity prices are critical to maintaining SCAD revenue. Getting an ideal price as proposed will be another improvement for SCAD, although it depends on the policy implementation for renewable electricity pricing.

Data availability can be another aspect to improve, especially laboratory chemical analysis. The current study revealed that SCAD has fewer laboratory results for influent chemical analysis and several chemical analyses for effluent due to workforce constraints. If this challenge can be addressed and future work can provide more frequent chemical analysis for the digester influent and effluent, it will help to provide more accurate results for mass balance analysis and life cycle impact assessment.

APPENDIX

A. MLR Codes

```
## Statistical analysis - Multiple regression analysis
## SCAD operation
## Wei Liao, October 23, 2021
## Fahmi Nov 23, 2021
## Fahmi Dec 9, 2021
## Fahmi Dec 14, 2021

# Load libraries -----
library(dplyr)
library(FSA)
library(psych)
library(car)
library(rcompanion)

# Choose data file of "BiogasProduction_v3.txt" -----
con <-file.choose(new = FALSE)
metadata <- read.table(con, header = T, row.names = 1, fill = TRUE)
head(metadata)

##############################
# select data
data.num = select(metadata, Digestate, Filtrate_manure_pit, SLS_Solids, Dairy_G,
            Parlor, Beef, W_Feed_manure, Poultry, Swine, ANS_Other, Filtrate_food_pit,
            SLS_Solids_food, P_A, Pulp,FOG, W_Feed,
            Other, Cart_Food, Biogas_production, CH4_production, H2S_content, Electricity,
Effluent_TS, Effluent_TN, Effluent_TP, Effluent_pH, Effluent_VFA)

data.num

# corr.test(data.num, use = "pairwise", method="pearson", adjust="none", alpha="0.05")

#############################
# Stepwise procedure
model.null = lm(Biogas_production~1, data=data.num)
model.full = lm(Biogas_production ~ Digestate + Filtrate_manure_pit + SLS_Solids+Dairy_G +
            Parlor + Beef + W_Feed_manure + Poultry + Swine + ANS_Other+
            SLS_Solids_food + P_A + Pulp + FOG + W_Feed +
            Other + Cart_Food, data=data.num)

step(model.null, scope = list(upper=model.full), direction="both", data=data.num)


# Define the final model from the results of the stepwise procedure
model.final = lm(Biogas_production ~ Filtrate_manure_pit + Dairy_G + Parlor + ANS_Other +
P_A,
```

```
                data=data.num)
summary(model.final)

# Analysis of variance for individual feed components
Anova(model.final, Type="II")

# Simple plot of predicted values with 1-to-1 line
data.num$predy = predict(model.final)

plot(predy ~ Biogas_production, data=data.num, pch = 16,
     xlab="Actual response value",
     ylab="Predicted response value")

abline(0,1, col="blue", lwd=2)

# Checking assumptions of the model
hist(residuals(model.final), col="darkgray")

plot(fitted(model.final),residuals(model.final))
```

RESULTS

```
Call:
lm(formula = Biogas_production ~ Filtrate_manure_pit + Dairy_G +
    Parlor + ANS_Other + P_A, data = data.num)

Coefficients:
        (Intercept)  Filtrate_manure_pit            Dairy_G
         2330.91251             -0.01688            0.18163
             Parlor            ANS_Other                P_A
           -0.04628              0.08850           -0.02158

> # Define the final model from the results of the stepwise procedure
> model.final = lm(Biogas_production ~ Filtrate_manure_pit + Dairy_G + Parlor + ANS_Other
+ P_A,
+                 data=data.num)
> summary(model.final)

Call:
lm(formula = Biogas_production ~ Filtrate_manure_pit + Dairy_G +
    Parlor + ANS_Other + P_A, data = data.num)



Residuals:
     Min       1Q   Median       3Q      Max
-2064.80  -335.13   -26.08   292.74  1659.95
```

```
Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)         2.331e+03  7.506e+02   3.105 0.002648 **
Filtrate_manure_pit -1.688e-02  7.464e-03  -2.261 0.026549 *
Dairy_G             1.816e-01  4.507e-02   4.030 0.000129 ***
Parlor             -4.627e-02  1.748e-02  -2.648 0.009804 **
ANS_Other           8.850e-02  5.779e-02   1.531 0.129752
P_A                -2.158e-02  1.501e-02  -1.438 0.154510
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 611.3 on 78 degrees of freedom
Multiple R-squared:  0.4714,  Adjusted R-squared:  0.4375
F-statistic: 13.91 on 5 and 78 DF,  p-value: 1.03e-09

> # Analysis of variance for individual feed components
> Anova(model.final, Type="II")
Anova Table (Type II tests)

Response: Biogas_production
                      Sum Sq Df F value    Pr(>F)
Filtrate_manure_pit  1910236  1  5.1119 0.0265489 *
Dairy_G              6069859  1 16.2433 0.0001286 ***
Parlor               2619518  1  7.0100 0.0098044 **
ANS_Other             876194  1  2.3448 0.1297516
P_A                   772430  1  2.0671 0.1545103
Residuals           29147290 78
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

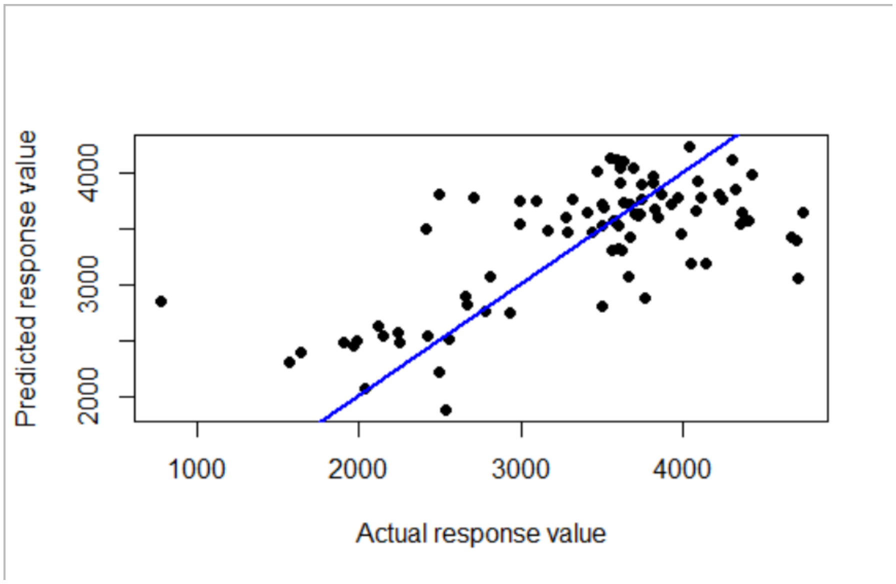

Figure A.1 Final model of MLR for biogas production

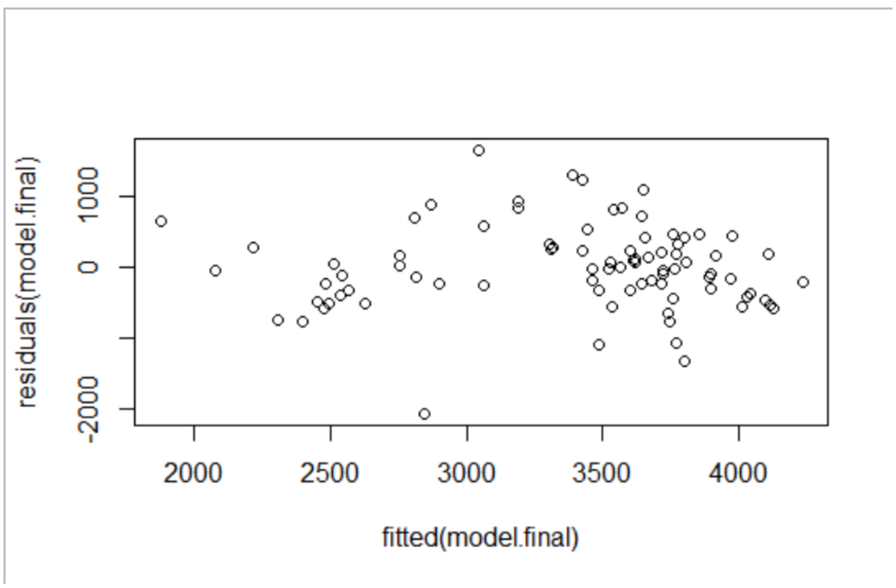

Figure A.2 Residual model of MLR for biogas production

B. Radar Chart Codes

```
## Feed amount - Radar analysis
## SCAD operation
## Wei Liao, October 23, 2021
## Fahmi, Noveberm 5, 2021 updated
## Wei Liao, December 9, 2021 updated

# Load libraries -----
library(fmsb)
```

```
# Choose data file of "FeedAmount_Radar.txt" -----
con <-file.choose(new = FALSE)
metadata <- read.table(con, header = T, row.names = 1, fill = TRUE)
head(metadata)


### Set up the bound for the radargraph
data0<-metadata[,c(3,4,5,6,7,8,9,10,11,12,14,15,16,17,18,19,20,21)]
data0

maxmin <-data.frame(Digestate=c(max(data0), min(data0)),
                    Filtrate_manure_pit=c(max(data0), min(data0)),
                    SLS_Solids=c(max(data0), min(data0)),
                    Dairy_G=c(max(data0), min(data0)),
                    Parlor=c(max(data0), min(data0)),
                    Beef=c(max(data0), min(data0)),
                    W_Feed_manure=c(max(data0), min(data0)),
                    Poultry=c(max(data0), min(data0)),
                    Swine=c(max(data0), min(data0)),
                    ANS_Other=c(max(data0), min(data0)),
                    #Total_manure_pit=c(max(data0), min(data0)),
                    Filtrate_food_pit=c(max(data0), min(data0)),
                    SLS_Solids_food=c(max(data0), min(data0)),
                    P_A=c(max(data0), min(data0)),
                    Pulp=c(max(data0), min(data0)),
                    FOG=c(max(data0), min(data0)),
                    W_Feed=c(max(data0), min(data0)),
                    Other=c(max(data0), min(data0)),
                    Cart_Food=c(max(data0), min(data0))
                    #Total_food_pit=c(max(data0), min(data0))
                   )
maxmin

##############################
## 2020 data
# select data
data1<-
metadata[which(metadata$Year=="2020"),c(3,4,5,6,7,8,9,10,11,12,14,15,16,17,18,19,20,21)]
data1

data1 <- rbind(maxmin, data1)

# Create the radar chart
# Set up the font
windowsFonts(A=windowsFont("Times New Roman")) #Import font
op <- par(family = "A", font =1)
```

```
# Provide the names of columns
colnames(data1) <-c("Digestate", "Filtrate in manure pit", "SLS solids", "Dairy G",
                   "Parlor", "Beef", "Feed wastes", "Poultry", "Swine", "Other animal wastes",
                   "Filtrate in food pit", "SLS food solids", "P & A",
                   "Food pulp", "FOG", "Food feed wastes", "Others", "Cart food wastes")


radarchart(data1, axistype=2, pty=32, plty=1, axislabcol="grey", na.itp=FALSE,
          title="", vlcex=1)

legend(x=1.5, y=1, legend = unique(metadata$Month), title="Months of 2020", bty = "n",
       pch=20, col=unique(metadata$Month), cex=1, pt.cex=2)

##############################
## 2019 data
# select data
data2<-
metadata[which(metadata$Year=="2019"),c(3,4,5,6,7,8,9,10,11,12,14,15,16,17,18,19,20,21)]
data2

data2 <- rbind(maxmin, data2)

# Create the radar chart
# Set up the font
windowsFonts(A=windowsFont("Times New Roman")) #Import font
op <- par(family = "A", font =1)

# Provide the names of columns
colnames(data2) <-c("Digestate", "Filtrate in manure pit", "SLS solids", "Dairy G",
                   "Parlor", "Beef", "Feed wastes", "Poultry", "Swine", "Other animal wastes",
                   "Filtrate in food pit", "SLS food solids", "P & A",
                   "Food pulp", "FOG", "Food feed wastes", "Others", "Cart food wastes")

radarchart(data2, axistype=2, pty=32, plty=1, axislabcol="grey", na.itp=FALSE,
          title="", vlcex=1)

legend(x=1.5, y=1, legend = unique(metadata$Month), title="Months of 2019", bty = "n",
       pch=20, col=unique(metadata$Month), cex=1, pt.cex=2)

##############################
## 2018 data
# select data
data3<-
metadata[which(metadata$Year=="2018"),c(3,4,5,6,7,8,9,10,11,12,14,15,16,17,18,19,20,21)]
data3
```

```
data3 <- rbind(maxmin, data3)

# Create the radar chart
# Set up the font
windowsFonts(A=windowsFont("Times New Roman")) #Import font
op <- par(family = "A", font =1)

# Provide the names of columns
colnames(data3) <-c("Digestate", "Filtrate in manure pit", "SLS solids", "Dairy G",
                  "Parlor", "Beef", "Feed wastes", "Poultry", "Swine", "Other animal wastes",
                  "Filtrate in food pit", "SLS food solids", "P & A",
                  "Food pulp", "FOG", "Food feed wastes", "Others", "Cart food wastes")


radarchart(data3, axistype=2, pty=32, plty=1, axislabcol="grey", na.itp=FALSE,
          title="", vlcex=1)

legend(x=1.5, y=1, legend = unique(metadata$Month), title="Months of 2018", bty = "n",
      pch=20, col=unique(metadata$Month), cex=1, pt.cex=2)

##############################
## 2017 data
# select data
data4<-
metadata[which(metadata$Year=="2017"),c(3,4,5,6,7,8,9,10,11,12,14,15,16,17,18,19,20,21)]
data4

data4 <- rbind(maxmin, data4)

# Create the radar chart
# Set up the font
windowsFonts(A=windowsFont("Times New Roman")) #Import font
op <- par(family = "A", font =1)

# Provide the names of columns
colnames(data4) <-c("Digestate", "Filtrate in manure pit", "SLS solids", "Dairy G",
                  "Parlor", "Beef", "Feed wastes", "Poultry", "Swine", "Other animal wastes",
                  "Filtrate in food pit", "SLS food solids", "P & A",
                  "Food pulp", "FOG", "Food feed wastes", "Others", "Cart food wastes")


radarchart(data4, axistype=2, pty=32, plty=1, axislabcol="grey", na.itp=FALSE,
          title="", vlcex=1)

legend(x=1.5, y=1, legend = unique(metadata$Month), title="Months of 2017", bty = "n",
```

```
      pch=20, col=unique(metadata$Month), cex=1, pt.cex=2)

###############################
## 2016 data
# select data
data5<-
metadata[which(metadata$Year=="2016"),c(3,4,5,6,7,8,9,10,11,12,14,15,16,17,18,19,20,21)]
data5

data5 <- rbind(maxmin, data5)

# Create the radar chart
# Set up the font
windowsFonts(A=windowsFont("Times New Roman")) #Import font
op <- par(family = "A", font =1)

# Provide the names of columns
colnames(data5) <-c("Digestate", "Filtrate in manure pit", "SLS solids", "Dairy G",
                "Parlor", "Beef", "Feed wastes", "Poultry", "Swine", "Other animal wastes",
                "Filtrate in food pit", "SLS food solids", "P & A",
                "Food pulp", "FOG", "Food feed wastes", "Others", "Cart food wastes")

radarchart(data5, axistype=2, pty=32, plty=1, axislabcol="grey", na.itp=FALSE,
        title="", vlcex=1)

legend(x=1.5, y=1, legend = unique(metadata$Month), title="Months of 2016", bty = "n",
      pch=20, col=unique(metadata$Month), cex=1, pt.cex=2)

###############################
## 2015 data
# select data
data6<-
metadata[which(metadata$Year=="2015"),c(3,4,5,6,7,8,9,10,11,12,14,15,16,17,18,19,20,21)]
data6

data6 <- rbind(maxmin, data6)

# Create the radar chart
# Set up the font
windowsFonts(A=windowsFont("Times New Roman")) #Import font
op <- par(family = "A", font =1)

# Provide the names of columns
colnames(data6) <-c("Digestate", "Filtrate in manure pit", "SLS solids", "Dairy G",
                "Parlor", "Beef", "Feed wastes", "Poultry", "Swine", "Other animal wastes",
                "Filtrate in food pit", "SLS food solids", "P & A",
```

```
                "Food pulp", "FOG", "Food feed wastes", "Others", "Cart food wastes")


radarchart(data6, axistype=2, pty=32, plty=1, axislabcol="grey", na.itp=FALSE,
         title="", vlcex=1)

legend(x=1.5, y=1, legend = unique(metadata$Month), title="Months of 2015", bty = "n",
      pch=20, col=unique(metadata$Month), cex=1, pt.cex=2)

##############################
## 2014 data
# select data
data7<-
metadata[which(metadata$Year=="2014"),c(3,4,5,6,7,8,9,10,11,12,14,15,16,17,18,19,20,21)]
data7

data7 <- rbind(maxmin, data7)

# Create the radar chart
# Set up the font
windowsFonts(A=windowsFont("Times New Roman")) #Import font
op <- par(family = "A", font =1)

# Provide the names of columns
colnames(data7) <-c("Digestate", "Filtrate in manure pit", "SLS solids", "Dairy G",
                "Parlor", "Beef", "Feed wastes", "Poultry", "Swine", "Other animal wastes",
                "Filtrate in food pit", "SLS food solids", "P & A",
                "Food pulp", "FOG", "Food feed wastes", "Others", "Cart food wastes")


radarchart(data7, axistype=2, pty=32, plty=1, axislabcol="grey", na.itp=FALSE,
         title="", vlcex=1)

legend(x=1.5, y=1, legend = unique(metadata$Month), title="Months of 2014", bty = "n",
      pch=20, col=unique(metadata$Month), cex=1, pt.cex=2)

#######
```

C. Violin Chart and ANOVA Tukey Multiple Comparison Codes for Feedstock

FULL CODES

```
## Feed amount - Violin analysis
## SCAD operation
## Wei Liao, December 9, 2021
## Fahmi Dwilaksono, December 12, 2021 Updated
## Fahmi, Jan 4,2022
```

```
# Load libraries -----
  library (MASS)
  library(ggplot2)
  library(grid)
  library(gridExtra)
  library(ggpubr)
  library(plyr)
  library(inferr)

# Plot bar chart with standard deviation -----
  #data : a data frame
  #varname : the name of a column containing the variable to be summarized
  #groupnames : vector of column names to be used as
  #grouping variables
  data_summary <- function(data, varname, groupnames){
    require(plyr)
    summary_func <- function(x, col){
      c(mean = mean(x[[col]], na.rm=TRUE),
        sd = sd(x[[col]], na.rm=TRUE))
    }
    data_sum<-ddply(data, groupnames, .fun=summary_func,
                    varname)
    data_sum <- rename(data_sum, c("mean" = varname))
    return(data_sum)
  }

# Choose data file FeedAmount_Violin.txt -----
con <-file.choose(new = FALSE)
metadata <- read.table(con, header = T, row.names = 1, fill = TRUE)
head(metadata)

# Define factors for metadata -----
metadata$Feed_type <- factor(metadata$Feed_type)
metadata$Year<- factor(metadata$Year)
metadata$Month <- factor(metadata$Month)

#Anova

#1. Digstate

##Data selection
data1<-metadata[which(metadata$Feed_type=="Digestate"),]
data1

## Anova
fit1 <- aov(Daily_Feed~Year, data1)
```

```
summary(fit1)
Tukey1 <- TukeyHSD(fit1, conf.level=0.95) #Tukey multiple comparison
Tukey1 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_1 <- ggplot(data1, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "Digestate", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_1
box_1_1 <- box_1 + geom_boxplot(width=0.2) # Add median and quartile
box_1_1

## Mean and standard deviation
box_1_data <- data_summary(data1, varname="Daily_Feed",
                           groupnames=c("Year"))
box_1_data

#2. Filtrate manure pit

##Data selection
data2<-metadata[which(metadata$Feed_type=="Filtrate_manure_pit"),]
data2

## Anova
fit2 <- aov(Daily_Feed~Year, data2)
summary(fit2)
Tukey2 <- TukeyHSD(fit2, conf.level=0.95) #Tukey multiple comparison
Tukey2 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_2 <- ggplot(data2, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "Filtrate manure pit", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
```

```
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_2
box_2_1 <- box_2 + geom_boxplot(width=0.2) # Add median and quartile
box_2_1

## Mean and standard deviation
box_2_data <- data_summary(data2, varname="Daily_Feed",
                    groupnames=c("Year"))
box_2_data
```

#3. SLS Solids

```
##Data selection
data3<-metadata[which(metadata$Feed_type=="SLS_Solids"),]
data3

## Anova
fit3 <- aov(Daily_Feed~Year, data3)
summary(fit3)
Tukey3 <- TukeyHSD(fit3, conf.level=0.95) #Tukey multiple comparison
Tukey3 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_3 <- ggplot(data3, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "SLS Solids", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_3
box_3_1 <- box_3 + geom_boxplot(width=0.2) # Add median and quartile
box_3_1

## Mean and standard deviation
box_3_data <- data_summary(data3, varname="Daily_Feed",
                    groupnames=c("Year"))
box_3_data
```

#4. Dairy G

```
##Data selection
data4<-metadata[which(metadata$Feed_type=="Dairy_G"),]
data4

## Anova
fit4 <- aov(Daily_Feed~Year, data4)
summary(fit4)
Tukey4 <- TukeyHSD(fit4, conf.level=0.95) #Tukey multiple comparison
Tukey4 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_4 <- ggplot(data4, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "Dairy G", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_4
box_4_1 <- box_4 + geom_boxplot(width=0.2) # Add median and quartile
box_4_1

## Mean and standard deviation
box_4_data <- data_summary(data4, varname="Daily_Feed",
                           groupnames=c("Year"))
box_4_data
```

#5. Parlor

```
##Data selection
data5<-metadata[which(metadata$Feed_type=="Parlor"),]
data5

## Anova
fit5 <- aov(Daily_Feed~Year, data5)
summary(fit5)
Tukey5 <- TukeyHSD(fit5, conf.level=0.95) #Tukey multiple comparison
Tukey5 #Output Tukey results

## Plot
```

```
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_5 <- ggplot(data5, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "Parlor", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_5
box_5_1 <- box_5 + geom_boxplot(width=0.2) # Add median and quartile
box_5_1

## Mean and standard deviation
box_5_data <- data_summary(data5, varname="Daily_Feed",
                          groupnames=c("Year"))
box_5_data
```

#6. Beef

```
##Data selection
data6<-metadata[which(metadata$Feed_type=="Beef"),]
data6

## Anova
fit6 <- aov(Daily_Feed~Year, data6)
summary(fit6)
Tukey6 <- TukeyHSD(fit6, conf.level=0.95) #Tukey multiple comparison
Tukey6 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_6 <- ggplot(data6, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "Beef", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_6
box_6_1 <- box_6 + geom_boxplot(width=0.2) # Add median and quartile
```

```
box_6_1

## Mean and standard deviation
box_6_data <- data_summary(data6, varname="Daily_Feed",
                    groupnames=c("Year"))
box_6_data

#7. Waste Feed_Manure

##Data selection
data7<-metadata[which(metadata$Feed_type=="W_Feed_manure"),]
data7

## Anova
fit7 <- aov(Daily_Feed~Year, data7)
summary(fit7)
Tukey7 <- TukeyHSD(fit7, conf.level=0.95) #Tukey multiple comparison
Tukey7 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_7 <- ggplot(data7, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "W Feed Manure", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_7
box_7_1 <- box_7 + geom_boxplot(width=0.2) # Add median and quartile
box_7_1

## Mean and standard deviation
box_7_data <- data_summary(data7, varname="Daily_Feed",
                    groupnames=c("Year"))
box_7_data

#8. Poultry

##Data selection
data8<-metadata[which(metadata$Feed_type=="Poultry"),]
data8
```

```
## Anova
fit8 <- aov(Daily_Feed~Year, data8)
summary(fit8)
Tukey8 <- TukeyHSD(fit8, conf.level=0.95) #Tukey multiple comparison
Tukey8 #Output Tukey results


## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_8 <- ggplot(data8, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "Poultry", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_8
box_8_1 <- box_8 + geom_boxplot(width=0.2) # Add median and quartile
box_8_1

## Mean and standard deviation
box_8_data <- data_summary(data8, varname="Daily_Feed",
                           groupnames=c("Year"))
box_8_data

#9. Swine

##Data selection
data9<-metadata[which(metadata$Feed_type=="Swine"),]
data9

## Anova
fit9 <- aov(Daily_Feed~Year, data9)
summary(fit9)
Tukey9 <- TukeyHSD(fit9, conf.level=0.95) #Tukey multiple comparison
Tukey9 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_9 <- ggplot(data9, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "Swine", subtitle=NULL) +
```

```
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_9
box_9_1 <- box_9 + geom_boxplot(width=0.2) # Add median and quartile
box_9_1

## Mean and standard deviation
box_9_data <- data_summary(data9, varname="Daily_Feed",
                           groupnames=c("Year"))
box_9_data

#10. ANS Other

##Data selection
data10<-metadata[which(metadata$Feed_type=="ANS_Other"),]
data10

## Anova
fit10 <- aov(Daily_Feed~Year, data10)
summary(fit10)
Tukey10 <- TukeyHSD(fit10, conf.level=0.95) #Tukey multiple comparison
Tukey10 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_10 <- ggplot(data10, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "ANS Other", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_10
box_10_1 <- box_10 + geom_boxplot(width=0.2) # Add median and quartile
box_10_1

## Mean and standard deviation
box_10_data <- data_summary(data10, varname="Daily_Feed",
                           groupnames=c("Year"))
```

```
box_10_data

#11. Total Manure Pit

##Data selection
data11<-metadata[which(metadata$Feed_type=="Total_manure_pit"),]
data11

## Anova
fit11 <- aov(Daily_Feed~Year, data11)
summary(fit11)
Tukey11 <- TukeyHSD(fit11, conf.level=0.95) #Tukey multiple comparison
Tukey11 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_11 <- ggplot(data11, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "Total Manure Pit", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_11
box_11_1 <- box_11 + geom_boxplot(width=0.2) # Add median and quartile
box_11_1

## Mean and standard deviation
box_11_data <- data_summary(data11, varname="Daily_Feed",
                            groupnames=c("Year"))
box_11_data

#12. Filtrate Food Pit

##Data selection
data12<-metadata[which(metadata$Feed_type=="Filtrate_food_pit"),]
data12

## Anova
fit12 <- aov(Daily_Feed~Year, data12)
summary(fit12)
Tukey12 <- TukeyHSD(fit12, conf.level=0.95) #Tukey multiple comparison
Tukey12 #Output Tukey results
```

```
## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_12 <- ggplot(data12, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "Filtrate Food Pit", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_12
box_12_1 <- box_12 + geom_boxplot(width=0.2) # Add median and quartile
box_12_1

## Mean and standard deviation
box_12_data <- data_summary(data12, varname="Daily_Feed",
                            groupnames=c("Year"))
box_12_data

#13. SLS Solids Food

##Data selection
data13<-metadata[which(metadata$Feed_type=="SLS_Solids_food"),]
data13

## Anova
fit13 <- aov(Daily_Feed~Year, data13)
summary(fit13)
Tukey13 <- TukeyHSD(fit13, conf.level=0.95) #Tukey multiple comparison
Tukey13 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_13 <- ggplot(data13, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "SLS Solids Food", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
```

```
box_13
box_13_1 <- box_13 + geom_boxplot(width=0.2) # Add median and quartile
box_13_1

## Mean and standard deviation
box_13_data <- data_summary(data13, varname="Daily_Feed",
                            groupnames=c("Year"))
box_13_data
```

#14. P_A

```
##Data selection
data14<-metadata[which(metadata$Feed_type=="P_A"),]
data14

## Anova
fit14 <- aov(Daily_Feed~Year, data14)
summary(fit14)
Tukey14 <- TukeyHSD(fit14, conf.level=0.95) #Tukey multiple comparison
Tukey14 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_14 <- ggplot(data14, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "Pinnapples", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_14
box_14_1 <- box_14 + geom_boxplot(width=0.2) # Add median and quartile
box_14_1

## Mean and standard deviation
box_14_data <- data_summary(data14, varname="Daily_Feed",
                            groupnames=c("Year"))
box_14_data
```

#15. Pulp

```
##Data selection
data15<-metadata[which(metadata$Feed_type=="Pulp"),]
data15

## Anova
fit15 <- aov(Daily_Feed~Year, data15)
summary(fit15)
Tukey15 <- TukeyHSD(fit15, conf.level=0.95) #Tukey multiple comparison
Tukey15 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_15 <- ggplot(data15, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "Pulp", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_15
box_15_1 <- box_15 + geom_boxplot(width=0.2) # Add median and quartile
box_15_1

## Mean and standard deviation
box_15_data <- data_summary(data15, varname="Daily_Feed",
                            groupnames=c("Year"))
box_15_data
```

#16. FOG

```
##Data selection
data16<-metadata[which(metadata$Feed_type=="FOG"),]
data16

## Anova
fit16 <- aov(Daily_Feed~Year, data16)
summary(fit16)
Tukey16 <- TukeyHSD(fit16, conf.level=0.95) #Tukey multiple comparison
Tukey16 #Output Tukey results

## Plot
```

```
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_16 <- ggplot(data16, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "FOG", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_16
box_16_1 <- box_16 + geom_boxplot(width=0.2) # Add median and quartile
box_16_1

## Mean and standard deviation
box_16_data <- data_summary(data16, varname="Daily_Feed",
                            groupnames=c("Year"))
box_16_data
```

#17. Waste Feed

```
##Data selection
data17<-metadata[which(metadata$Feed_type=="W_Feed"),]
data17

## Anova
fit17 <- aov(Daily_Feed~Year, data17)
summary(fit17)
Tukey17 <- TukeyHSD(fit17, conf.level=0.95) #Tukey multiple comparison
Tukey17 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_17 <- ggplot(data17, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "Waste Feed", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_17
box_17_1 <- box_17 + geom_boxplot(width=0.2) # Add median and quartile
```

```
box_17_1

## Mean and standard deviation
box_17_data <- data_summary(data17, varname="Daily_Feed",
                            groupnames=c("Year"))
box_17_data

#18. Other

##Data selection
data18<-metadata[which(metadata$Feed_type=="Other"),]
data18

## Anova
fit18 <- aov(Daily_Feed~Year, data18)
summary(fit18)
Tukey18 <- TukeyHSD(fit18, conf.level=0.95) #Tukey multiple comparison
Tukey18 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_18 <- ggplot(data18, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "Other", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_18
box_18_1 <- box_18 + geom_boxplot(width=0.2) # Add median and quartile
box_18_1

## Mean and standard deviation
box_18_data <- data_summary(data18, varname="Daily_Feed",
                            groupnames=c("Year"))
box_18_data

#19. Cart Food

##Data selection
data19<-metadata[which(metadata$Feed_type=="Cart_Food"),]
data19
```

```
## Anova
fit19 <- aov(Daily_Feed~Year, data19)
summary(fit19)
Tukey19 <- TukeyHSD(fit19, conf.level=0.95) #Tukey multiple comparison
Tukey19 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_19 <- ggplot(data19, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "Cart Food", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_19
box_19_1 <- box_19 + geom_boxplot(width=0.2) # Add median and quartile
box_19_1

## Mean and standard deviation
box_19_data <- data_summary(data19, varname="Daily_Feed",
                            groupnames=c("Year"))
box_19_data

#20. Total Food Pit

##Data selection
data20<-metadata[which(metadata$Feed_type=="Total_food_pit"),]
data20

## Anova
fit20 <- aov(Daily_Feed~Year, data20)
summary(fit20)
Tukey20 <- TukeyHSD(fit20, conf.level=0.95) #Tukey multiple comparison
Tukey20 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_20 <- ggplot(data20, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "Total Food Pit", subtitle=NULL) +
  theme_classic() +
```

```
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_20
box_20_1 <- box_20 + geom_boxplot(width=0.2) # Add median and quartile
box_20_1

## Mean and standard deviation
box_20_data <- data_summary(data20, varname="Daily_Feed",
                            groupnames=c("Year"))
box_20_data

#21. Total Feedstock

##Data selection
data21<-metadata[which(metadata$Feed_type=="Total_feedstock"),]
data21

## Anova
fit21 <- aov(Daily_Feed~Year, data21)
summary(fit21)
Tukey21 <- TukeyHSD(fit21, conf.level=0.95) #Tukey multiple comparison
Tukey21 #Output Tukey results


## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_21 <- ggplot(data21, aes(x=Year, y=Daily_Feed)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Daily feed (kg/day)") + labs(title = "Total Feedstock", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_21
box_21_1 <- box_21 + geom_boxplot(width=0.2) # Add median and quartile
box_21_1

## Mean and standard deviation
box_21_data <- data_summary(data21, varname="Daily_Feed",
                            groupnames=c("Year"))
```

box_21_data

###

RESULTS

C.1 Violin Chart of Feedstock in Manure Pit

C.1.1 Digestate

```
> ## Anova
> fit1 <- aov(Daily_Feed~Year, data1)
> summary(fit1)
            Df    Sum Sq  Mean Sq F value Pr(>F)
Year         4 145459560 36364890   0.906  0.476
Residuals   24 963661949 40152581
> Tukey1 <- TukeyHSD(fit1, conf.level=0.95) #Tukey multiple comparison
> Tukey1 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data1)

$Year
                diff        lwr       upr     p adj
2016-2015 -1625.8753 -21303.490 18051.740 0.9991656
2017-2015 -5303.0678 -24800.975 14194.839 0.9276618
2018-2015 -4567.2934 -24730.849 15596.262 0.9615453
2020-2015 -9407.0445 -32270.367 13456.278 0.7445301
2017-2016 -3677.1925 -12067.756  4713.371 0.6989719
2018-2016 -2941.4181 -12780.226  6897.389 0.9011895
2020-2016 -7781.1692 -22374.479  6812.141 0.5291867
2018-2017   735.7743  -8738.506 10210.054 0.9993463
2020-2017 -4103.9767 -18454.048 10246.094 0.9145118
2020-2018 -4839.7510 -20081.966 10402.464 0.8802393
```

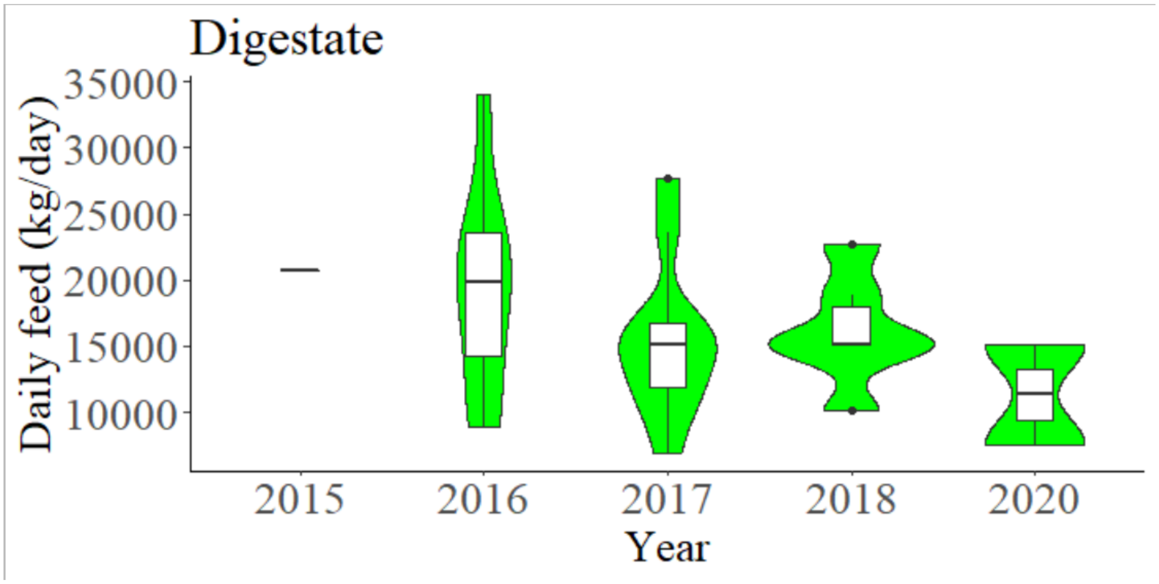

Figure C.1 Feedstock distribution for Digestate

```
Year Daily_Feed       sd
1 2015   20755.92       NA
2 2016   19130.04 7853.040
3 2017   15452.85 5927.523
4 2018   16188.62 4250.253
5 2020   11348.87 5349.909
```

C.1.2 Filtrate Manure Pit

```
> ## Anova
> fit2 <- aov(Daily_Feed~Year, data2)
> summary(fit2)
            Df    Sum Sq   Mean Sq F value  Pr(>F)
Year         6 1.553e+09 258810814   3.729 0.00392 **
Residuals   49 3.401e+09  69412500
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> Tukey2 <- TukeyHSD(fit2, conf.level=0.95) #Tukey multiple comparison
> Tukey2 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data2)

$Year
                diff       lwr        upr     p adj
2015-2014  -3603.9396 -14059.61  6851.7330 0.9367379
2016-2014 -11798.0489 -22764.05  -832.0469 0.0274157
2017-2014 -10023.4382 -21713.24  1666.3592 0.1376290
2018-2014  -9645.7095 -24432.26  5140.8446 0.4245674
2019-2014 -14760.8341 -26941.32 -2580.3440 0.0085485
```

```
2020-2014 -12419.0466 -28950.92  4112.8235 0.2604355
2016-2015  -8194.1092 -19160.11  2771.8928 0.2661668
2017-2015  -6419.4986 -18109.30  5270.2988 0.6269482
2018-2015  -6041.7698 -20828.32  8744.7843 0.8681169
2019-2015 -11156.8944 -23337.38  1023.5956 0.0926584
2020-2015  -8815.1069 -25346.98  7716.7631 0.6582698
2017-2016   1774.6107 -10373.78 13923.0045 0.9993180
2018-2016   2152.3394 -12999.37 17304.0486 0.9994188
2019-2016  -2962.7852 -15584.05  9658.4844 0.9905911
2020-2016   -620.9977 -17480.26 16238.2679 0.9999998
2018-2017    377.7287 -15305.78 16061.2377 1.0000000
2019-2017  -4737.3958 -17992.38  8517.5885 0.9255114
2020-2017  -2395.6084 -19734.38 14943.1632 0.9995043
2019-2018  -5115.1246 -21167.71 10937.4587 0.9561045
2020-2018  -2773.3371 -22334.11 16787.4354 0.9994251
2020-2019   2341.7875 -15331.52 20015.1000 0.9996104
Year Daily_Feed        sd
1 2014   25025.88  7210.635
2 2015   21421.94 12445.617
3 2016   13227.83  5988.434
4 2017   15002.44  6870.595
5 2018   15380.17 10625.096
6 2019   10265.05  3988.524
7 2020   12606.83  4367.135
```

C.1.3 SLS Solids

```
> ## Anova
> fit3 <- aov(Daily_Feed~Year, data3)
> summary(fit3)
            Df   Sum Sq Mean Sq F value Pr(>F)
Year         5  1589309  317862   0.187  0.965
Residuals   27 45912828 1700475
> Tukey3 <- TukeyHSD(fit3, conf.level=0.95) #Tukey multiple comparison
> Tukey3 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data3)

$Year
               diff       lwr      upr     p adj
2016-2015  349.67407 -2280.370 2979.718 0.9983908
2017-2015  274.02501 -1561.700 2109.750 0.9972077
2018-2015 -168.21459 -2531.880 2195.451 0.9999236
2019-2015  244.98504 -1943.344 2433.314 0.9992972
2020-2015  727.06262 -2367.702 3821.827 0.9777973
```

```
2017-2016  -75.64907 -2739.198 2587.900 0.9999992
2018-2016 -517.88867 -3569.368 2533.590 0.9948985
2019-2016 -104.68903 -3022.461 2813.083 0.9999975
2020-2016  377.38854 -3269.827 4024.604 0.9995207
2018-2017 -442.23960 -2843.131 1958.651 0.9925485
2019-2017  -29.03997 -2257.525 2199.445 1.0000000
2020-2017  453.03761 -2670.251 3576.326 0.9975627
2019-2018  413.19963 -2266.945 3093.344 0.9967478
2020-2018  895.27721 -2564.775 4355.329 0.9663717
2020-2019  482.07758 -2860.650 3824.805 0.9976286
```

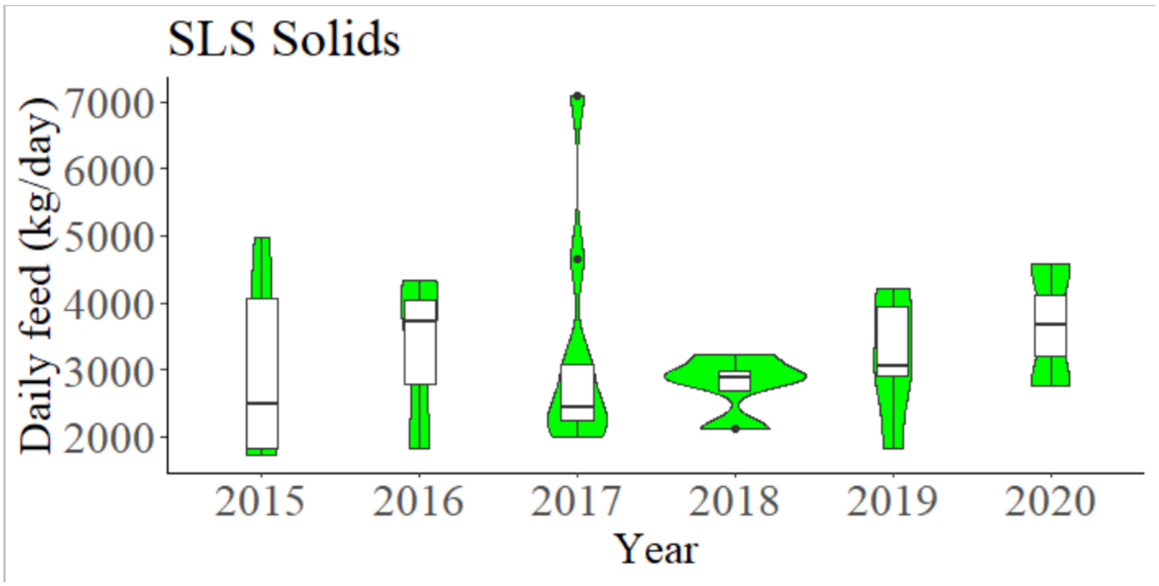

Figure C.2 Feedstock distribution for SLS Solids

```
Year Daily_Feed        sd
1 2015   2938.868 1252.5055
2 2016   3288.542 1312.8727
3 2017   3212.893 1673.5432
4 2018   2770.653  474.1477
5 2019   3183.853  949.3934
6 2020   3665.931 1288.7252
```

C.1.4 Dairy Gutter

```
> ## Anova
> fit4 <- aov(Daily_Feed~Year, data4)
> summary(fit4)
            Df    Sum Sq Mean Sq F value  Pr(>F)
Year         6  42372311 7062052   3.554 0.00368 **
Residuals   77 152983389 1986797
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> Tukey4 <- TukeyHSD(fit4, conf.level=0.95) #Tukey multiple comparison
> Tukey4 #Output Tukey results
```

```
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data4)

$Year
                diff         lwr       upr     p adj
2015-2014  1192.79576  -549.44637 2935.0379 0.3790328
2016-2014  2400.10647   657.86433 4142.3486 0.0014801
2017-2014  1858.36642   116.12429 3600.6086 0.0289095
2018-2014  1755.51444    13.27230 3497.7566 0.0470523
2019-2014  1838.33278    96.09064 3580.5749 0.0318566
2020-2014  1224.58500  -517.65714 2966.8271 0.3470729
2016-2015  1207.31071  -534.93143 2949.5528 0.3642678
2017-2015   665.57066 -1076.67147 2407.8128 0.9078985
2018-2015   562.71868 -1179.52346 2304.9608 0.9573103
2019-2015   645.53702 -1096.70512 2387.7792 0.9194903
2020-2015    31.78924 -1710.45290 1774.0314 1.0000000
2017-2016  -541.74005 -2283.98218 1200.5021 0.9644623
2018-2016  -644.59203 -2386.83417 1097.6501 0.9200129
2019-2016  -561.77369 -2304.01583 1180.4684 0.9576524
2020-2016 -1175.52147 -2917.76361  566.7207 0.3969598
2018-2017  -102.85199 -1845.09412 1639.3901 0.9999971
2019-2017   -20.03365 -1762.27578 1722.2085 1.0000000
2020-2017  -633.78142 -2376.02356 1108.4607 0.9258387
2019-2018    82.81834 -1659.42380 1825.0605 0.9999992
2020-2018  -530.92944 -2273.17157 1211.3127 0.9677964
2020-2019  -613.74778 -2355.98991 1128.4944 0.9358943

Year Daily_Feed        sd
1 2014   11554.80 2239.1947
2 2015   12747.60 1283.0903
3 2016   13954.91 1216.0525
4 2017   13413.17 1876.9954
5 2018   13310.32  837.6477
6 2019   13393.14  809.3594
7 2020   12779.39  942.6853
```

C.1.5 Parlor

```
> ## Anova
> fit5 <- aov(Daily_Feed~Year, data5)
> summary(fit5)
            Df    Sum Sq  Mean Sq F value   Pr(>F)
Year         6 4.214e+08 70235648   5.017 0.000219 ***
Residuals   77 1.078e+09 14000917
```

```
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> Tukey5 <- TukeyHSD(fit5, conf.level=0.95) #Tukey multiple comparison
> Tukey5 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data5)

$Year
               diff        lwr        upr     p adj
2015-2014  1580.2767  -3044.705  6205.2580 0.9443209
2016-2014 -3837.9931  -8462.974   786.9881 0.1693431
2017-2014 -4892.8213  -9517.803  -267.8401 0.0311264
2018-2014 -1571.4695  -6196.451  3053.5118 0.9457526
2019-2014 -3500.9365  -8125.918  1124.0448 0.2613178
2020-2014 -4230.8038  -8855.785   394.1775 0.0953095
2016-2015 -5418.2698 -10043.251  -793.2886 0.0113920
2017-2015 -6473.0980 -11098.079 -1848.1168 0.0011735
2018-2015 -3151.7462  -7776.727  1473.2350 0.3847257
2019-2015 -5081.2132  -9706.194  -456.2319 0.0219480
2020-2015 -5811.0805 -10436.062 -1186.0993 0.0050681
2017-2016 -1054.8282  -5679.809  3570.1530 0.9927745
2018-2016  2266.5236  -2358.458  6891.5049 0.7534924
2019-2016   337.0567  -4287.925  4962.0379 0.9999897
2020-2016  -392.8107  -5017.792  4232.1706 0.9999746
2018-2017  3321.3518  -1303.629  7946.3331 0.3214669
2019-2017  1391.8848  -3233.096  6016.8661 0.9697196
2020-2017   662.0175  -3962.964  5286.9988 0.9994637
2019-2018 -1929.4670  -6554.448  2695.5143 0.8663878
2020-2018 -2659.3343  -7284.316  1965.6469 0.5912253
2020-2019  -729.8673  -5354.849  3895.1139 0.9990631

Year Daily_Feed       sd
1 2014   25669.45 3318.805
2 2015   27249.73 5947.718
3 2016   21831.46 3686.228
4 2017   20776.63 3026.019
5 2018   24097.98 4252.452
6 2019   22168.52 2156.050
7 2020   21438.65 2477.829
```

C.1.6 Beef

```
> ## Anova
> fit6 <- aov(Daily_Feed~Year, data6)
> summary(fit6)
```

```
            Df    Sum Sq  Mean Sq F value   Pr(>F)    
Year         6 100115286 16685881   5.879 8.31e-05 ***
Residuals   56 158938879  2838194                     
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> Tukey6 <- TukeyHSD(fit6, conf.level=0.95) #Tukey multiple comparison
> Tukey6 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data6)
$Year
                diff       lwr         upr     p adj
2015-2014 -1583.1873 -5017.726  1851.35126 0.7943863
2016-2014 -2459.4665 -4826.559   -92.37421 0.0367349
2017-2014 -3991.3828 -6263.117 -1719.64909 0.0000309
2018-2014 -3503.7920 -5819.357 -1188.22661 0.0004279
2019-2014 -2945.2863 -5217.020  -673.55254 0.0037558
2020-2014 -3327.0973 -6042.338  -611.85619 0.0073262
2016-2015  -876.2793 -4267.614  2515.05581 0.9850225
2017-2015 -2408.1955 -5733.673   917.28212 0.3045062
2018-2015 -1920.6047 -5276.178  1434.96833 0.5861362
2019-2015 -1362.0990 -4687.577  1963.37867 0.8700467
2020-2015 -1743.9100 -5386.788  1898.96820 0.7644217
2017-2016 -1531.9163 -3737.789   673.95606 0.3534888
2018-2016 -1044.3255 -3295.312  1206.66137 0.7894796
2019-2016  -485.8197 -2691.692  1720.05261 0.9935552
2020-2016  -867.6308 -3528.013  1792.75134 0.9525220
2018-2017   487.5908 -1662.895  2638.07671 0.9924675
2019-2017  1046.0965 -1057.120  3149.31328 0.7311977
2020-2017   664.2855 -1911.618  3240.18939 0.9851726
2019-2018   558.5058 -1591.980  2708.99170 0.9846223
2020-2018   176.6947 -2437.947  2791.33618 0.9999928
2020-2019  -381.8111 -2957.715  2194.09284 0.9992895
```

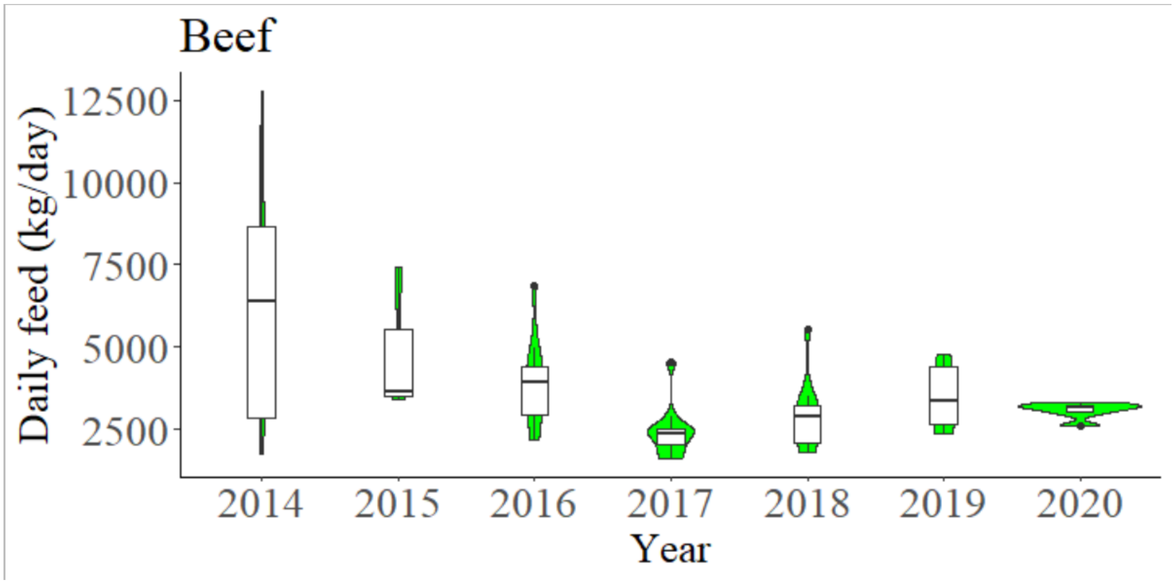

Figure C.3 Feedstock distribution for Beef

```
Year Daily_Feed        sd
1 2014   6404.719 3618.6704
2 2015   4821.532 2269.4265
3 2016   3945.252 1348.7279
4 2017   2413.336  770.9569
5 2018   2900.927 1055.3299
6 2019   3459.433  929.5379
7 2020   3077.622  256.3979
```

C.1.7 Waste Feed Manure

```
> ## Anova
> fit7 <- aov(Daily_Feed~Year, data7)
> summary(fit7)
            Df   Sum Sq Mean Sq F value Pr(>F)
Year         5 23261394 4652279   2.906 0.0472 *
Residuals   16 25618186 1601137
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> Tukey7 <- TukeyHSD(fit7, conf.level=0.95) #Tukey multiple comparison
> Tukey7 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data7)

$Year
               diff        lwr       upr     p adj
2015-2014 -3023.9467 -6745.8869  697.9935 0.1491613
2016-2014  -648.2586 -4370.1988 3073.6816 0.9922582
2017-2014 -2638.3935 -5615.9456  339.1587 0.0985172
```

```
2019-2014 -2239.7768 -5217.3290  737.7753 0.2056048
2020-2014  -916.8304 -3894.3825 2060.7218 0.9138622
2016-2015  2375.6881 -1701.4931 6452.8693 0.4489565
2017-2015   385.5532 -3025.6613 3796.7677 0.9989874
2019-2015   784.1698 -2627.0447 4195.3844 0.9735442
2020-2015  2107.1163 -1304.0983 5518.3308 0.3888309
2017-2016 -1990.1349 -5401.3494 1421.0796 0.4476599
2019-2016 -1591.5183 -5002.7328 1819.6963 0.6671881
2020-2016  -268.5718 -3679.7864 3142.6427 0.9998256
2019-2017   398.6166 -2180.0192 2977.2525 0.9955334
2020-2017  1721.5631  -857.0727 4300.1989 0.3114649
2020-2019  1322.9464 -1255.6894 3901.5822 0.5784162
```

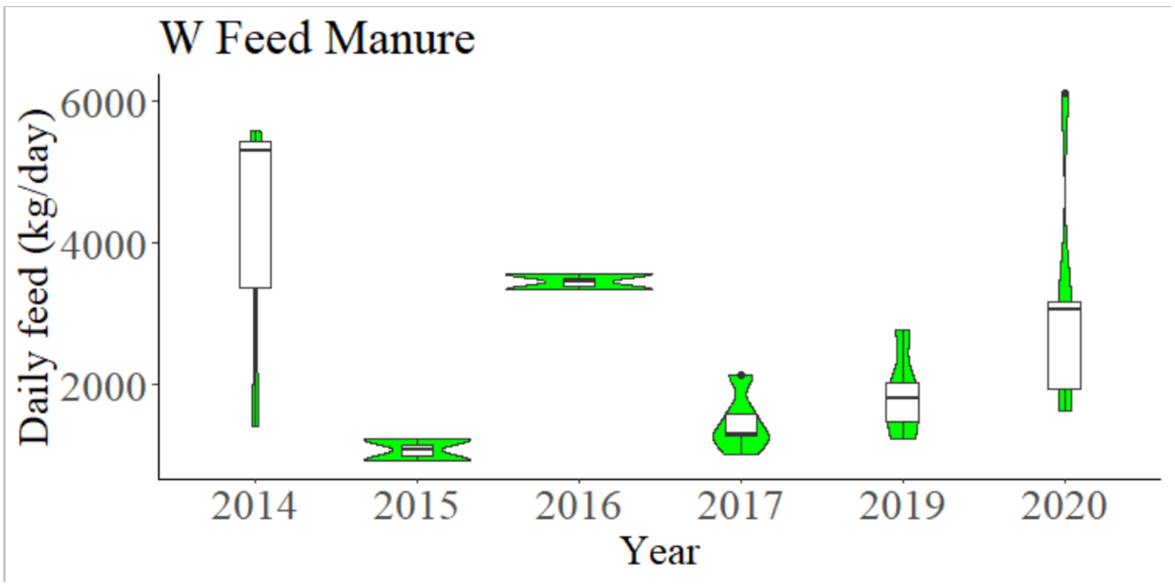

Figure C.4 Feedstock distribution for Waste Feed Manure

```
Year Daily_Feed        sd
1 2014   4101.228 2328.1781
2 2015   1077.281  208.4797
3 2016   3452.969  152.3505
4 2017   1462.834  425.8712
5 2019   1861.451  597.4175
6 2020   3184.397 1771.8344
```

C.1.8 Poultry

```
> ## Anova
> fit8 <- aov(Daily_Feed~Year, data8)
> summary(fit8)
            Df  Sum Sq Mean Sq F value   Pr(>F)
Year         3 4476064 1492021   27.26 3.96e-05 ***
Residuals   10  547330   54733
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
> Tukey8 <- TukeyHSD(fit8, conf.level=0.95) #Tukey multiple comparison
> Tukey8 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data8)

$Year
                diff        lwr       upr     p adj
2017-2016  507.16122   27.02892  987.2935 0.0380139
2019-2016 1377.78570  831.13103 1924.4404 0.0000800
2020-2016 1392.98103  773.13290 2012.8292 0.0002110
2019-2017  870.62448  347.92265 1393.3263 0.0021976
2020-2017  885.81982  286.98963 1484.6500 0.0050653
2020-2019   15.19533 -638.18197  668.5726 0.9998615
```

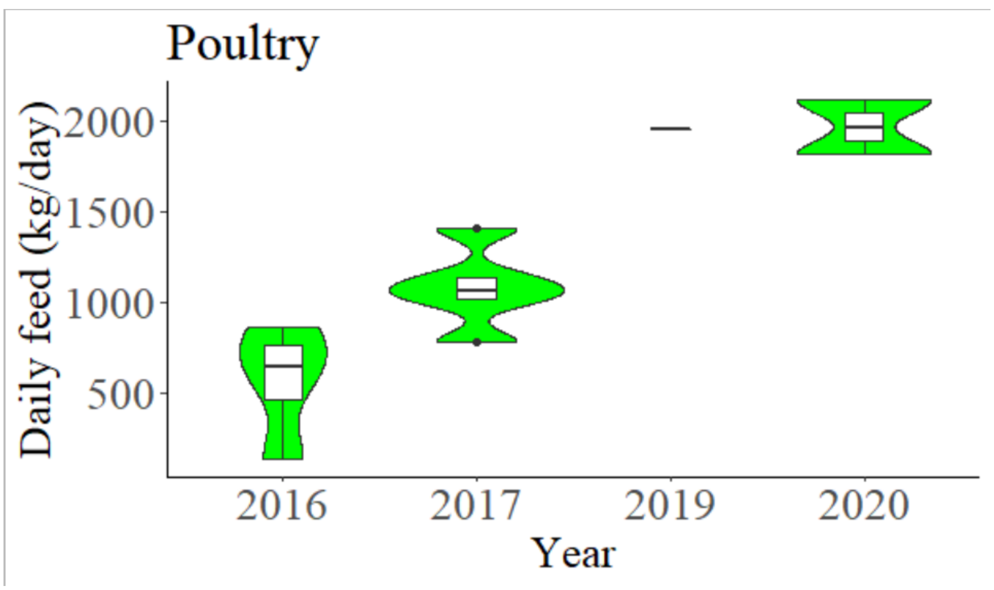

Figure C.5 Feedstock distribution for Poultry

```
Year Daily_Feed       sd
1 2016   572.6599 315.0070
2 2017  1079.8211 225.7625
3 2019  1950.4456   0.0000
4 2020  1965.6409 213.9322
```

C.1.9 Swine

```
## Anova
> fit9 <- aov(Daily_Feed~Year, data9)
> summary(fit9)
            Df    Sum Sq   Mean Sq F value Pr(>F)
Year         3 471835620 157278540   6.639  0.034 *
Residuals    5 118459221  23691844
---
```

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> Tukey9 <- TukeyHSD(fit9, conf.level=0.95) #Tukey multiple comparison
> Tukey9 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data9)

$Year
               diff        lwr       upr     p adj
2015-2014 -8172.480 -23726.627  7381.666 0.3207542
2017-2014 13141.467  -8855.417 35138.352 0.2408659
2018-2014  4667.462 -13292.920 22627.843 0.7773253
2017-2015 21313.948   1233.631 41394.264 0.0400869
2018-2015 12839.942  -2714.204 28394.089 0.0967451
2018-2017 -8474.006 -30470.890 13522.879 0.5388782
```

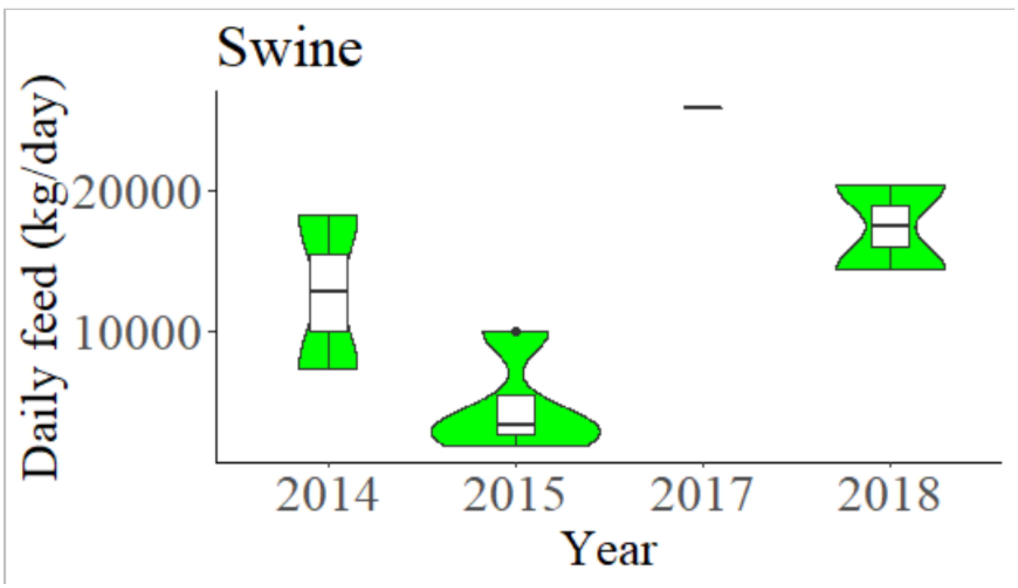

Figure C.6 Feedstock distribution for Swine

```
Year Daily_Feed       sd
1 2014  12745.482 7762.501
2 2015   4573.001 3664.656
3 2017  25886.949       NA
4 2018  17412.943 4232.458
```

C.1.10 ANS Other

```
## Anova
> fit10 <- aov(Daily_Feed~Year, data10)
> summary(fit10)
            Df   Sum Sq Mean Sq F value  Pr(>F)
Year         6 39084480 6514080   4.285 0.00281 **
```

```
Residuals   32 48650416 1520325
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> Tukey10 <- TukeyHSD(fit10, conf.level=0.95) #Tukey multiple comparison
> Tukey10 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data10)

$Year
                diff        lwr      upr     p adj
2015-2014  589.27271 -1784.0243 2962.570 0.9852771
2016-2014  286.21655 -2087.0805 2659.514 0.9997286
2017-2014  768.33625 -1660.8107 3197.483 0.9516286
2018-2014  534.89837 -2821.4505 3891.247 0.9986656
2019-2014 1416.00083 -1940.3480 4772.350 0.8347201
2020-2014 2887.73677   514.4398 5261.034 0.0092548
2016-2015 -303.05615 -2240.8451 1634.733 0.9988001
2017-2015  179.06354 -1826.7385 2184.866 0.9999531
2018-2015  -54.37434 -3118.2876 3009.539 1.0000000
2019-2015  826.72812 -2237.1851 3890.641 0.9775607
2020-2015 2298.46406   360.6752 4236.253 0.0118835
2017-2016  482.11970 -1523.6824 2487.922 0.9875485
2018-2016  248.68181 -2815.2315 3312.595 0.9999732
2019-2016 1129.78427 -1934.1290 4193.698 0.9040714
2020-2016 2601.52022   663.7313 4539.309 0.0032201
2018-2017 -233.43788 -3340.8131 2873.937 0.9999831
2019-2017  647.66458 -2459.7106 3755.040 0.9941396
2020-2017 2119.40052   113.5985 4125.203 0.0328451
2019-2018  881.10246 -2994.4753 4756.680 0.9906926
2020-2018 2352.83840  -711.0749 5416.752 0.2259142
2020-2019 1471.73594 -1592.1773 4535.649 0.7370542
```

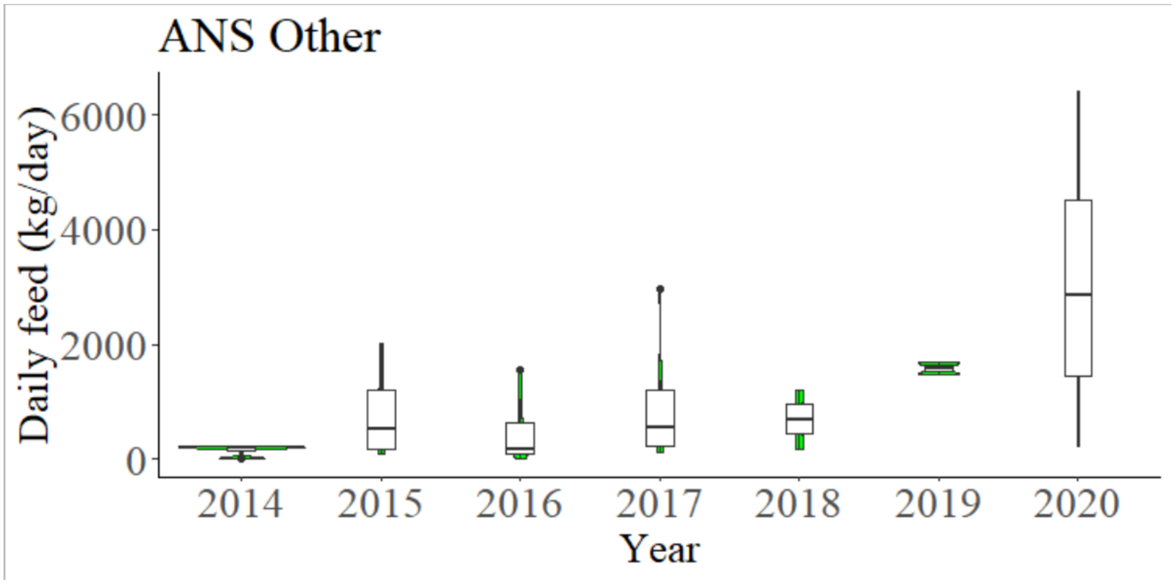

Figure C.7 Feedstock distribution for ANS Other

```
Year Daily_Feed         sd
1 2014   157.9634   99.61785
2 2015   747.2361  709.21161
3 2016   444.1800  562.77269
4 2017   926.2997 1015.13921
5 2018   692.8618  736.09366
6 2019  1573.9642  147.53947
7 2020  3045.7002 2272.07072
```

C.1.11 Total Manure Pit

```
## Anova
> fit11 <- aov(Daily_Feed~Year, data11)
> summary(fit11)
            Df    Sum Sq   Mean Sq F value   Pr(>F)
Year         6 8.058e+09 1.343e+09   7.098 4.84e-06 ***
Residuals   77 1.457e+10 1.892e+08
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> Tukey11 <- TukeyHSD(fit11, conf.level=0.95) #Tukey multiple comparison
> Tukey11 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data11)

$Year
                diff       lwr       upr     p adj
2015-2014  -2271.4375 -19272.71 14729.840 0.9996395
2016-2014  -4954.4342 -21955.71 12046.843 0.9741916
2017-2014  -4340.4218 -21341.70 12660.855 0.9868731
```

```
2018-2014 -13978.4959 -30979.77  3022.781 0.1776912
2019-2014 -23422.4703 -40423.75 -6421.193 0.0014787
2020-2014 -26187.7939 -43189.07 -9186.517 0.0002514
2016-2015  -2682.9967 -19684.27 14318.281 0.9990631
2017-2015  -2068.9843 -19070.26 14932.293 0.9997901
2018-2015 -11707.0583 -28708.34  5294.219 0.3719687
2019-2015 -21151.0328 -38152.31 -4149.756 0.0057191
2020-2015 -23916.3564 -40917.63 -6915.079 0.0010877
2017-2016    614.0124 -16387.26 17615.290 0.9999998
2018-2016  -9024.0616 -26025.34  7977.216 0.6782326
2019-2016 -18468.0361 -35469.31 -1466.759 0.0244380
2020-2016 -21233.3597 -38234.64 -4232.083 0.0054555
2018-2017  -9638.0740 -26639.35  7363.203 0.6073685
2019-2017 -19082.0485 -36083.33 -2080.771 0.0178006
2020-2017 -21847.3721 -38848.65 -4846.095 0.0038195
2019-2018  -9443.9744 -26445.25  7557.303 0.6300296
2020-2018 -12209.2981 -29210.58  4791.979 0.3214553
2020-2019  -2765.3236 -19766.60 14235.954 0.9988876

Year Daily_Feed        sd
1 2014   71283.72 11368.291
2 2015   69012.28 17246.236
3 2016   66329.29 18413.578
4 2017   66943.30 15397.431
5 2018   57305.23 14024.063
6 2019   47861.25  8318.581
7 2020   45095.93  7459.882
```

C.2 Violin Chart of Feedstock in Food Pit

C.2.1 Filtrate Food Pit

```
## Anova
> fit12 <- aov(Daily_Feed~Year, data12)
> summary(fit12)
            Df    Sum Sq  Mean Sq F value Pr(>F)
Year         6 5.047e+08 84113595   2.001 0.0802 .
Residuals   58 2.438e+09 42039631
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> Tukey12 <- TukeyHSD(fit12, conf.level=0.95) #Tukey multiple comparison
> Tukey12 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data12)

$Year
```

	diff	lwr	upr	p adj
2015-2014	-178.2101	-8444.244	8087.824	1.0000000
2016-2014	-3729.6602	-11814.001	4354.680	0.7947930
2017-2014	158.3603	-8880.207	9196.928	1.0000000
2018-2014	4296.0265	-4742.541	13334.594	0.7714169
2019-2014	-4123.0379	-14024.292	5778.217	0.8618493
2020-2014	-4589.5006	-13628.068	4449.067	0.7132479
2016-2015	-3551.4501	-11817.484	4714.584	0.8435061
2017-2015	336.5704	-8864.867	9538.008	0.9999998
2018-2015	4474.2366	-4727.201	13675.674	0.7523395
2019-2015	-3944.8278	-13994.982	6105.326	0.8918034
2020-2015	-4411.2904	-13612.728	4790.147	0.7643244
2017-2016	3888.0205	-5150.547	12926.588	0.8427671
2018-2016	8025.6868	-1012.881	17064.254	0.1135614
2019-2016	-393.3777	-10294.632	9507.877	0.9999997
2020-2016	-859.8403	-9898.408	8178.727	0.9999465
2018-2017	4137.6662	-5763.588	14038.921	0.8598617
2019-2017	-4281.3982	-14975.975	6413.179	0.8824651
2020-2017	-4747.8609	-14649.115	5153.394	0.7641371
2019-2018	-8419.0644	-19113.642	2275.513	0.2154937
2020-2018	-8885.5271	-18786.782	1015.727	0.1063931
2020-2019	-466.4627	-11161.040	10228.115	0.9999995

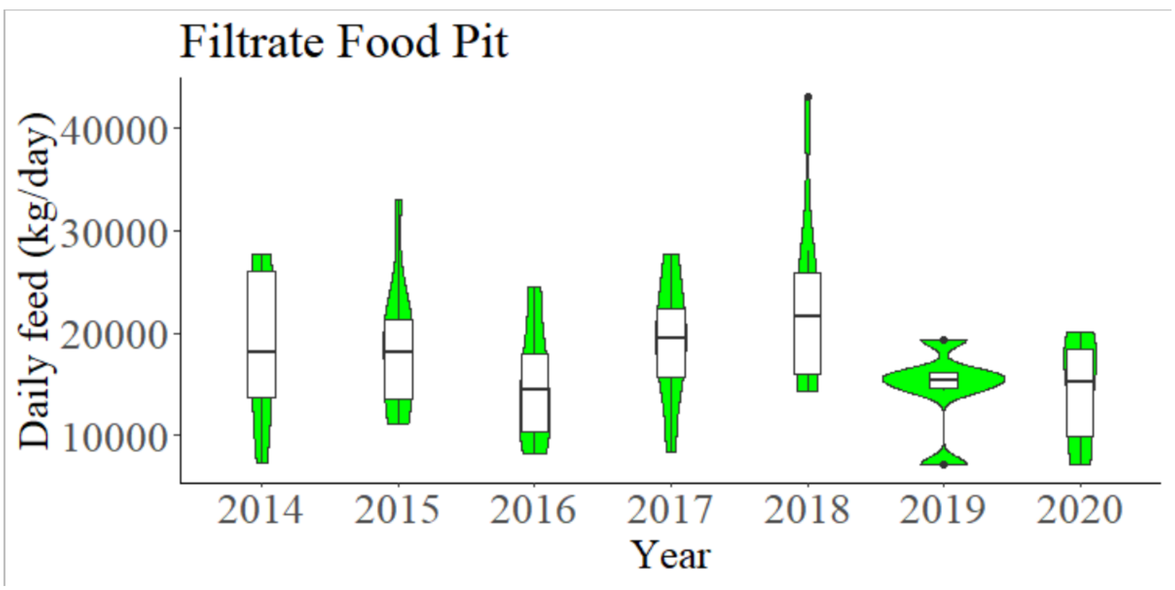

Figure C.8 Feedstock distribution for Filtrate Food Pit

	Year	Daily_Feed	sd
1	2014	18804.22	6936.435
2	2015	18626.01	6325.763
3	2016	15074.56	5643.998
4	2017	18962.58	6082.968
5	2018	23100.25	9488.308
6	2019	14681.19	4057.150

7 2020   14214.72 5168.211

C.2.2 SLS Solids Food

```
> ## Anova
> fit13 <- aov(Daily_Feed~Year, data13)
> summary(fit13)
            Df   Sum Sq Mean Sq F value Pr(>F)
Year         5  2340050  468010   0.472  0.795
Residuals   38 37707433  992301
> Tukey13 <- TukeyHSD(fit13, conf.level=0.95) #Tukey multiple comparison
> Tukey13 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data13)

$Year
                diff        lwr       upr     p adj
2016-2015  357.09030 -2005.4356 2719.6162 0.9974016
2017-2015 -189.04707 -2525.1752 2147.0811 0.9998748
2018-2015 -231.78551 -2546.5787 2083.0077 0.9996439
2019-2015  197.65271 -2084.7641 2480.0696 0.9998253
2020-2015  129.42492 -2598.5850 2857.4348 0.9999911
2017-2016 -546.13737 -1998.2315  905.9568 0.8665252
2018-2016 -588.87581 -2006.3913  828.6397 0.8112956
2019-2016 -159.43759 -1523.4425 1204.5674 0.9992436
2020-2016 -227.66538 -2250.8117 1795.4809 0.9993710
2018-2017  -42.73845 -1415.8067 1330.3298 0.9999989
2019-2017  386.69978  -931.0542 1704.4538 0.9489365
2020-2017  318.47198 -1673.7848 2310.7287 0.9966128
2019-2018  429.43823  -850.1118 1708.9883 0.9127921
2020-2018  361.21043 -1605.9855 2328.4064 0.9935241
2020-2019  -68.22780 -1997.2221 1860.7665 0.9999979
```

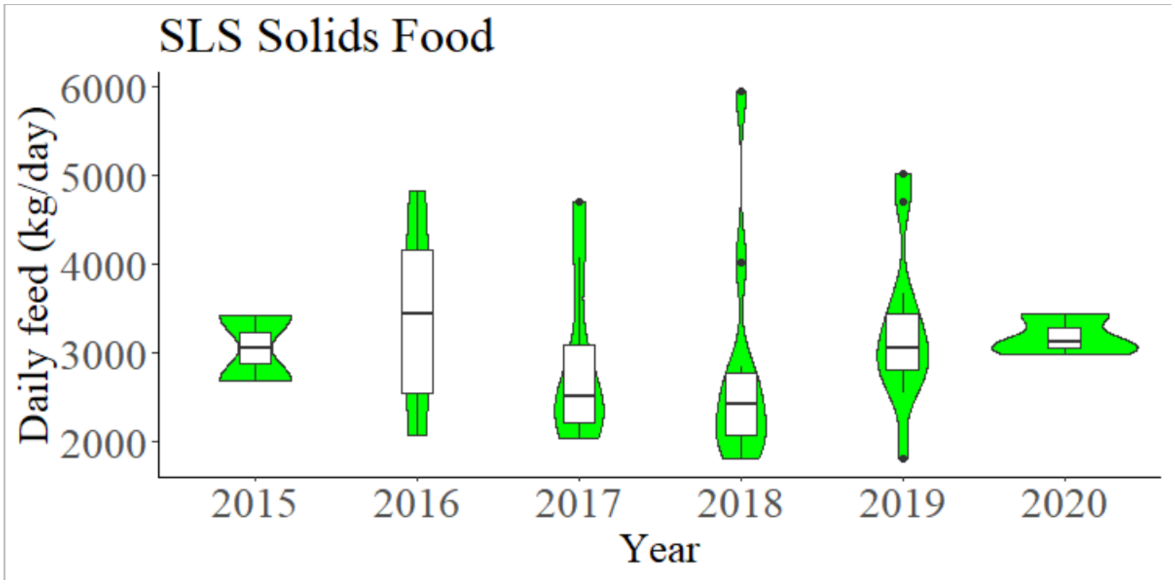

Figure C.9 Feedstock distribution for SLS Solids Food

```
  Year Daily_Feed        sd
1 2015   3056.303  516.3881
2 2016   3413.393 1016.5215
3 2017   2867.256  930.6221
4 2018   2824.517 1268.9409
5 2019   3253.956  888.4573
6 2020   3185.728  228.3480
```

C.2.3 Pineapple (PA)

```
> ## Anova
> fit14 <- aov(Daily_Feed~Year, data14)
> summary(fit14)
            Df    Sum Sq Mean Sq F value Pr(>F)
Year         2   1362345  681173    0.14   0.87
Residuals   26 126273793 4856684
> Tukey14 <- TukeyHSD(fit14, conf.level=0.95) #Tukey multiple comparison
> Tukey14 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data14)

$Year
               diff       lwr      upr     p adj
2015-2014 -476.3094 -2711.951 1759.332 0.8576849
2016-2014 -221.6931 -3136.613 2693.227 0.9805173
2016-2015  254.6163 -2660.303 3169.536 0.9743880
```

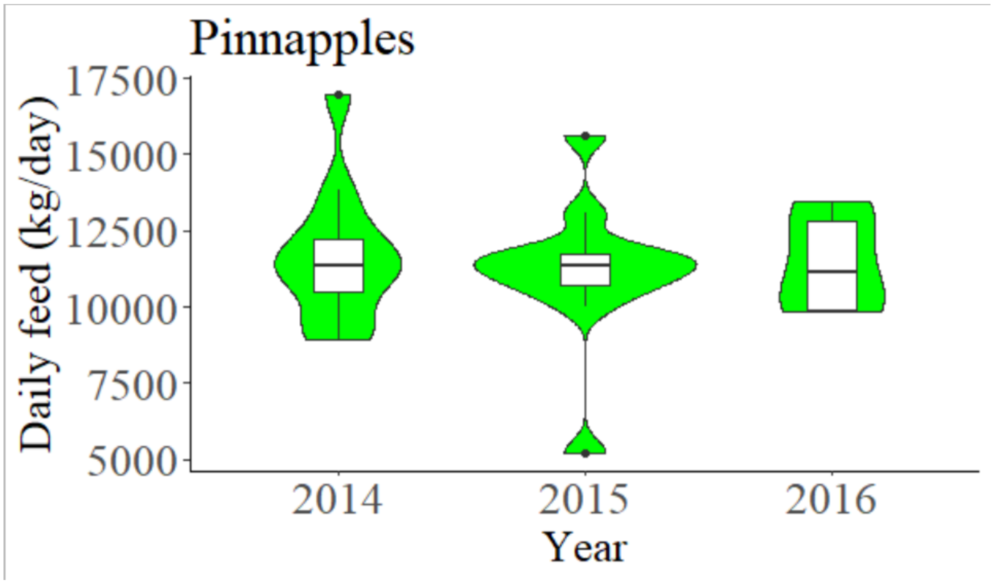

Figure C.10 Feedstock distribution for Pineapple

```
Year Daily_Feed       sd
1 2014   11657.20 2206.999
2 2015   11180.89 2370.419
3 2016   11435.51 1649.753
```

C.2.4 Pulp

```
## Anova
> fit15 <- aov(Daily_Feed~Year, data15)
> summary(fit15)
            Df   Sum Sq Mean Sq F value   Pr(>F)
Year         6 10479022 1746504    8.78 4.63e-07 ***
Residuals   67 13326784  198907
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> Tukey15 <- TukeyHSD(fit15, conf.level=0.95) #Tukey multiple comparison
> Tukey15 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data15)

$Year
                diff        lwr       upr     p adj
2015-2014  203.13362  -350.31903  756.5863 0.9211267
2016-2014  249.21100  -304.24164  802.6637 0.8161929
2017-2014  950.72196   384.83062 1516.6133 0.0000582
2018-2014  590.38779    36.93514 1143.8404 0.0290603
2019-2014 1026.10070   472.64805 1579.5534 0.0000077
2020-2014  564.94884  -310.13664 1440.0343 0.4477754
```

```
2016-2015   46.07739  -507.37526  599.5300 0.9999766
2017-2015  747.58834   181.69700 1313.4797 0.0027771
2018-2015  387.25417  -166.19848  940.7068 0.3493295
2019-2015  822.96709   269.51444 1376.4197 0.0004964
2020-2015  361.81522  -513.27025 1236.9007 0.8687476
2017-2016  701.51095   135.61961 1267.4023 0.0061482
2018-2016  341.17678  -212.27587  894.6294 0.5044607
2019-2016  776.88970   223.43705 1330.3423 0.0011967
2020-2016  315.73783  -559.34764 1190.8233 0.9269321
2018-2017 -360.33417  -926.22551  205.5572 0.4647631
2019-2017   75.37874  -490.51260  641.2701 0.9996339
2020-2017 -385.77312 -1268.77808  497.2318 0.8363818
2019-2018  435.71292  -117.73973  989.1656 0.2177536
2020-2018  -25.43895  -900.52442  849.6465 1.0000000
2020-2019 -461.15187 -1336.23734  413.9336 0.6815731

  Year Daily_Feed       sd
1 2014   1078.566 332.9565
2 2015   1281.700 167.5954
3 2016   1327.777 440.1656
4 2017   2029.288 466.0263
5 2018   1668.954 574.3428
6 2019   2104.667 558.1254
7 2020   1643.515 469.1668
```

C.2.5 FOG

```
## Anova
> fit16 <- aov(Daily_Feed~Year, data16)
> summary(fit16)
            Df    Sum Sq   Mean Sq F value   Pr(>F)
Year         6 3.215e+09 535831329   8.095 8.63e-07 ***
Residuals   77 5.097e+09  66195940
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> Tukey16 <- TukeyHSD(fit16, conf.level=0.95) #Tukey multiple comparison
> Tukey16 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data16)

$Year
                diff        lwr       upr     p adj
2015-2014 16422.8276   6366.315 26479.340 0.0000869
2016-2014 16203.2890   6146.776 26259.802 0.0001120
2017-2014 13835.6144   3779.102 23892.127 0.0015085
```

```
2018-2014 12791.7480   2735.235 22848.261 0.0043489
2019-2014 15421.9768   5365.464 25478.490 0.0002714
2020-2014 21622.0881  11565.575 31678.601 0.0000001
2016-2015  -219.5385 -10276.051  9836.974 1.0000000
2017-2015 -2587.2132 -12643.726  7469.300 0.9863374
2018-2015 -3631.0796 -13687.592  6425.433 0.9282912
2019-2015 -1000.8507 -11057.364  9055.662 0.9999353
2020-2015  5199.2605  -4857.252 15255.773 0.7044122
2017-2016 -2367.6746 -12424.188  7688.838 0.9914359
2018-2016 -3411.5410 -13468.054  6644.972 0.9461552
2019-2016  -781.3122 -10837.825  9275.201 0.9999850
2020-2016  5418.7990  -4637.714 15475.312 0.6626833
2018-2017 -1043.8664 -11100.379  9012.646 0.9999171
2019-2017  1586.3624  -8470.150 11642.875 0.9990653
2020-2017  7786.4737  -2270.039 17842.987 0.2369671
2019-2018  2630.2288  -7426.284 12686.742 0.9851162
2020-2018  8830.3401  -1226.173 18886.853 0.1232539
2020-2019  6200.1113  -3856.402 16256.624 0.5083279

  Year Daily_Feed        sd
1 2014   19128.24  2959.616
2 2015   35551.07  8151.082
3 2016   35331.53  8097.009
4 2017   32963.85  7527.845
5 2018   31919.99  4847.275
6 2019   34550.22 14652.833
7 2020   40750.33  5266.926
```

C.2.6 Waste Feed

```
## Anova
> fit17 <- aov(Daily_Feed~Year, data17)
> summary(fit17)
            Df  Sum Sq Mean Sq F value Pr(>F)
Year         2  162532   81266   0.123  0.891
Residuals    2 1326492  663246
> Tukey17 <- TukeyHSD(fit17, conf.level=0.95) #Tukey multiple comparison
> Tukey17 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data17)

$Year
              diff       lwr      upr     p adj
2015-2014  129.8785 -5409.711 5669.468 0.9895938
2018-2014 -400.3705 -5939.960 5139.219 0.9092011
```

2018-2015 -530.2490 -7314.833 6254.335 0.8954420

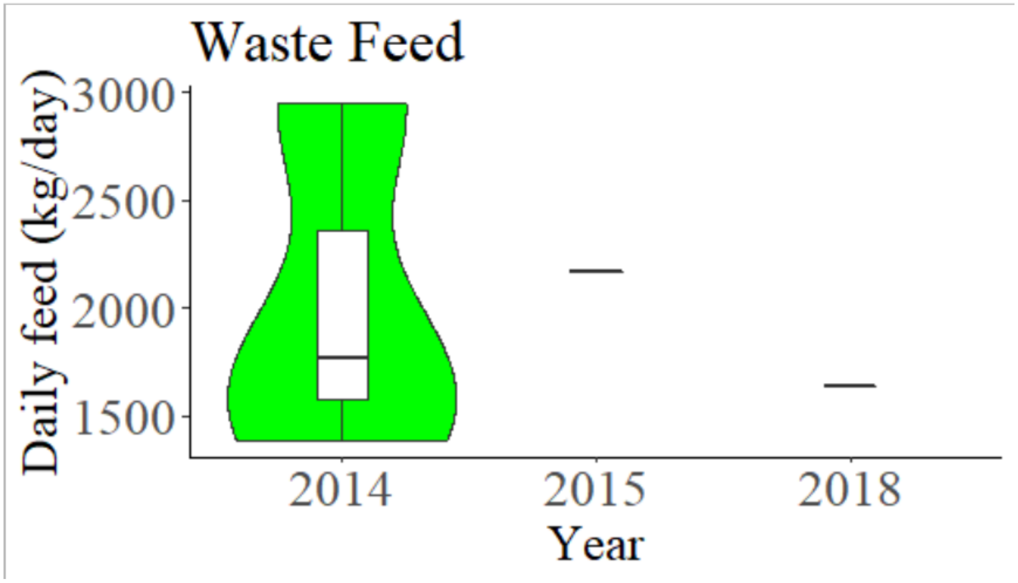

Figure C.11 Feedstock distribution for Waste Feed

```
Year Daily_Feed       sd
1 2014   2033.302 814.3993
2 2015   2163.180       NA
3 2018   1632.931       NA
```

C.2.7 Other

```
## Anova
> fit18 <- aov(Daily_Feed~Year, data18)
> summary(fit18)
            Df    Sum Sq   Mean Sq F value   Pr(>F)
Year         6 1.515e+09 252446057   17.69 1.34e-11 ***
Residuals   59 8.421e+08  14272946
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> Tukey18 <- TukeyHSD(fit18, conf.level=0.95) #Tukey multiple comparison
> Tukey18 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data18)

$Year
                  diff        lwr       upr     p adj
2015-2014 -10337.815271 -17781.398 -2894.233 0.0014831
2016-2014 -11858.180056 -19301.762 -4414.598 0.0001748
2017-2014 -12134.719979 -20288.756 -3980.684 0.0005340
2018-2014 -11700.216642 -19143.799 -4256.634 0.0002197
2019-2014 -10330.305803 -18018.005 -2642.607 0.0023257
```

2020-2014	118.311914	-7325.270	7561.894	1.0000000
2016-2015	-1520.364785	-6228.100	3187.370	0.9551763
2017-2015	-1796.904708	-7562.679	3968.869	0.9622032
2018-2015	-1362.401371	-6070.136	3345.333	0.9737142
2019-2015	7.509468	-5077.425	5092.444	1.0000000
2020-2015	10456.127185	5748.392	15163.862	0.0000001
2017-2016	-276.539923	-6042.314	5489.234	0.9999991
2018-2016	157.963414	-4549.771	4865.698	0.9999999
2019-2016	1527.874253	-3557.060	6612.809	0.9683570
2020-2016	11976.491970	7268.757	16684.227	0.0000000
2018-2017	434.503337	-5331.271	6200.277	0.9999866
2019-2017	1804.414176	-4273.245	7882.074	0.9701660
2020-2017	12253.031893	6487.258	18018.806	0.0000004
2019-2018	1369.910839	-3715.024	6454.846	0.9816758
2020-2018	11818.528556	7110.794	16526.263	0.0000000
2020-2019	10448.617717	5363.683	15533.552	0.0000009

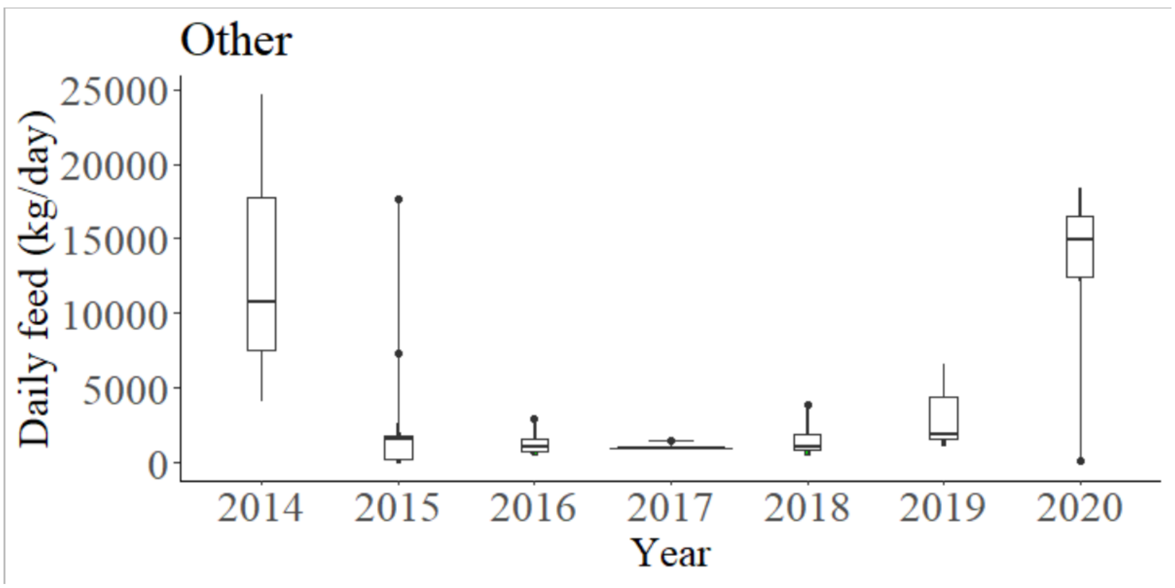

Figure C.12 Feedstock distribution for Other

	Year	Daily_Feed	sd
1	2014	13209.657	10452.4314
2	2015	2871.842	5042.0168
3	2016	1351.477	853.5117
4	2017	1074.937	216.1485
5	2018	1509.441	996.2938
6	2019	2879.352	1944.4467
7	2020	13327.969	5174.6180

C.2.8 Cart Food

```
## Anova
> fit19 <- aov(Daily_Feed~Year, data19)
> summary(fit19)
            Df   Sum Sq  Mean Sq F value Pr(>F)
Year         6 91209454 15201576   29.92 <2e-16 ***
Residuals   77 39124552   508111
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> Tukey19 <- TukeyHSD(fit19, conf.level=0.95) #Tukey multiple comparison
> Tukey19 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data19)
$Year
                 diff        lwr        upr     p adj
2015-2014  -388.577147 -1269.6485   492.4942 0.8331802
2016-2014   187.560292  -693.5110  1068.6316 0.9950230
2017-2014 -2126.439296 -3007.5106 -1245.3680 0.0000000
2018-2014 -2130.332627 -3011.4039 -1249.2613 0.0000000
2019-2014 -2155.620381 -3036.6917 -1274.5491 0.0000000
2020-2014 -2180.945935 -3062.0172 -1299.8746 0.0000000
2016-2015   576.137439  -304.9339  1457.2088 0.4357217
2017-2015 -1737.862149 -2618.9335  -856.7908 0.0000014
2018-2015 -1741.755481 -2622.8268  -860.6842 0.0000013
2019-2015 -1767.043235 -2648.1145  -885.9719 0.0000009
2020-2015 -1792.368788 -2673.4401  -911.2975 0.0000006
2017-2016 -2313.999588 -3195.0709 -1432.9283 0.0000000
2018-2016 -2317.892919 -3198.9642 -1436.8216 0.0000000
2019-2016 -2343.180673 -3224.2520 -1462.1094 0.0000000
2020-2016 -2368.506227 -3249.5775 -1487.4349 0.0000000
2018-2017    -3.893331  -884.9646   877.1780 1.0000000
2019-2017   -29.181085  -910.2524   851.8902 0.9999999
2020-2017   -54.506639  -935.5780   826.5647 0.9999961
2019-2018   -25.287754  -906.3591   855.7836 1.0000000
2020-2018   -50.613307  -931.6846   830.4580 0.9999975
2020-2019   -25.325553  -906.3969   855.7458 1.0000000
```

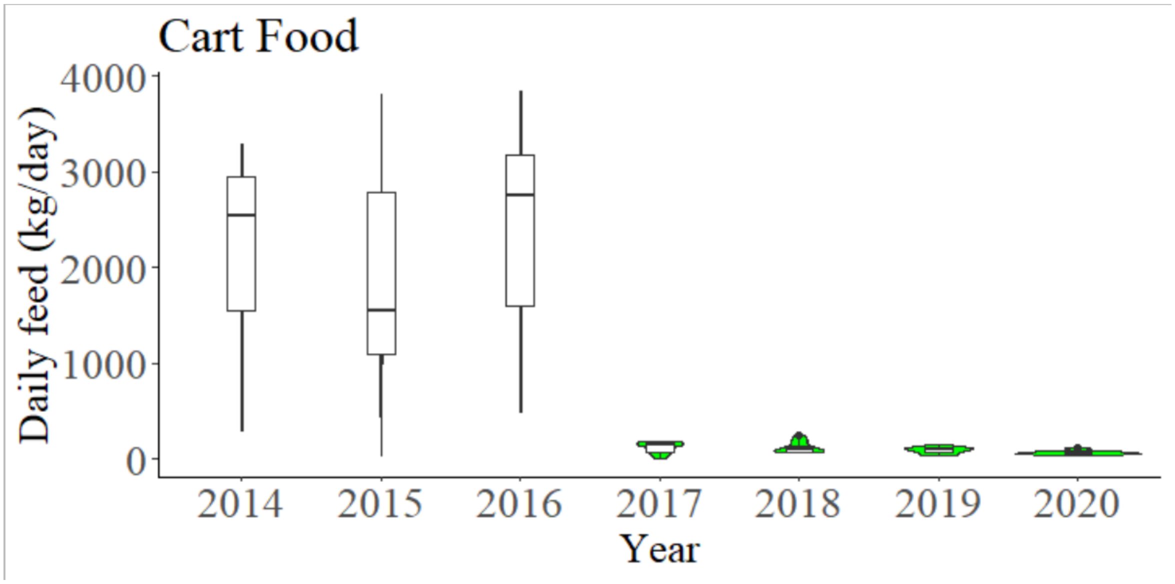

Figure C.13 Feedstock distribution for Cart Food

```
Year Daily_Feed        sd
1 2014 2248.64454  949.06204
2 2015 1860.06739 1201.71795
3 2016 2436.20483 1097.05343
4 2017  122.20524   57.59513
5 2018  118.31191   59.13605
6 2019   93.02416   32.70010
7 2020   67.69861   22.86615
```

C.2.9 Total Food Pit

```
## Anova
> fit20 <- aov(Daily_Feed~Year, data20)
> summary(fit20)
            Df    Sum Sq   Mean Sq F value  Pr(>F)
Year         6 4.559e+09 759802970   3.641 0.00311 **
Residuals   77 1.607e+10 208668601
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> Tukey20 <- TukeyHSD(fit20, conf.level=0.95) #Tukey multiple comparison
> Tukey20 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data20)

$Year
                diff        lwr        upr     p adj
2015-2014  13781.6369  -4073.381 31636.6548 0.2402617
2016-2014   5834.7051 -12020.313 23689.7229 0.9548619
2017-2014  -6451.4390 -24306.457 11403.5788 0.9280614
```

```
2018-2014  -3507.1355 -21362.153 14347.8823 0.9967990
2019-2014  -7225.5316 -25080.549 10629.4863 0.8821913
2020-2014   8102.4005  -9752.617 25957.4184 0.8138326
2016-2015  -7946.9318 -25801.950  9908.0860 0.8271496
2017-2015 -20233.0759 -38088.094 -2378.0581 0.0161612
2018-2015 -17288.7725 -35143.790   566.2454 0.0640479
2019-2015 -21007.1685 -38862.186 -3152.1506 0.0108739
2020-2015  -5679.2364 -23534.254 12175.7814 0.9603379
2017-2016 -12286.1441 -30141.162  5568.8737 0.3728430
2018-2016  -9341.8406 -27196.858  8513.1772 0.6927108
2019-2016 -13060.2367 -30915.255  4794.7812 0.2999843
2020-2016   2267.6954 -15587.322 20122.7133 0.9997311
2018-2017   2944.3035 -14910.714 20799.3213 0.9987976
2019-2017   -774.0925 -18629.110 17080.9253 0.9999995
2020-2017  14553.8395  -3301.178 32408.8574 0.1857086
2019-2018  -3718.3960 -21573.414 14136.6218 0.9955849
2020-2018  11609.5360  -6245.482 29464.5539 0.4427454
2020-2019  15327.9321  -2527.086 33182.9499 0.1406406

  Year Daily_Feed       sd
1 2014   56727.27 13338.33
2 2015   70508.91 11747.97
3 2016   62561.98 15610.50
4 2017   50275.83 14544.59
5 2018   53220.14 14366.86
6 2019   49501.74 19066.94
7 2020   64829.67 10934.65
```

C.2.10 Total Feedstock

```
## Anova
> fit21 <- aov(Daily_Feed~Year, data21)
> summary(fit21)
            Df   Sum Sq   Mean Sq F value   Pr(>F)
Year         6 1.47e+10 2.451e+09   5.736 5.68e-05 ***
Residuals   77 3.29e+10 4.273e+08
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> Tukey21 <- TukeyHSD(fit21, conf.level=0.95) #Tukey multiple comparison
> Tukey21 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Daily_Feed ~ Year, data = data21)

$Year
                diff        lwr         upr      p adj
```

```
2015-2014  11511.2200 -14038.03  37060.475 0.8188421
2016-2014    881.2536 -24668.00  26430.509 0.9999999
2017-2014 -10790.8025 -36340.06  14758.452 0.8595263
2018-2014 -17484.5730 -43033.83   8064.682 0.3795427
2019-2014 -30647.0569 -56196.31  -5097.802 0.0087674
2020-2014 -18084.4862 -43633.74   7464.769 0.3386491
2016-2015 -10629.9663 -36179.22  14919.289 0.8678570
2017-2015 -22302.0224 -47851.28   3247.232 0.1276646
2018-2015 -28995.7930 -54545.05  -3446.538 0.0159145
2019-2015 -42158.2768 -67707.53 -16609.022 0.0000713
2020-2015 -29595.7062 -55144.96  -4046.451 0.0128581
2017-2016 -11672.0561 -37221.31  13877.199 0.8090433
2018-2016 -18365.8267 -43915.08   7183.428 0.3203061
2019-2016 -31528.3105 -57077.57  -5979.056 0.0063055
2020-2016 -18965.7399 -44514.99   6583.515 0.2831181
2018-2017  -6693.7706 -32243.03  18855.484 0.9849832
2019-2017 -19856.2544 -45405.51   5693.000 0.2330349
2020-2017  -7293.6838 -32842.94  18255.571 0.9767234
2019-2018 -13162.4838 -38711.74  12386.771 0.7078275
2020-2018   -599.9132 -26149.17  24949.342 1.0000000
2020-2019  12562.5706 -12986.68  38111.826 0.7505992

  Year Daily_Feed       sd
1 2014  128010.01 16625.39
2 2015  139521.23 22888.56
3 2016  128891.27 25993.66
4 2017  117219.21 16957.01
5 2018  110525.44 21605.39
6 2019   97362.96 23159.83
7 2020  109925.53 14971.79
```

D. Violin Chart and ANOVA Tukey Multiple Comparison Codes for Digester Output Parameters

FULL CODES

```
## Biogas - Violin analysis
## SCAD operation
## Wei Liao, December 9, 2021
## Fahmi Dwilaksono, December 12, 2021
# Load libraries -----
  library (MASS)
  library(ggplot2)
  library(grid)
  library(gridExtra)
  library(ggpubr)
  library(plyr)
  library(inferr)
```

```
# Plot bar chart with standard deviation -----
  #data : a data frame
  #varname : the name of a column containing the variable to be summarized
  #groupnames : vector of column names to be used as
  #grouping variables
  data_summary <- function(data, varname, groupnames){
    require(plyr)
    summary_func <- function(x, col){
      c(mean = mean(x[[col]], na.rm=TRUE),
        sd = sd(x[[col]], na.rm=TRUE))
    }
    data_sum<-ddply(data, groupnames, .fun=summary_func,
                    varname)
    data_sum <- rename(data_sum, c("mean" = varname))
    return(data_sum)
  }

# Choose data file Biogas_Violin.txt -----
con <-file.choose(new = FALSE)
metadata <- read.table(con, header = T, row.names = 1, fill = TRUE)
head(metadata)

# Define factors for metadata -----
metadata$Year<- factor(metadata$Year)
metadata$Month <- factor(metadata$Month)

#Anova
#1. Biogas produciton

## Anova
fit1 <- aov(Biogas_production~Year, metadata)
summary(fit1)
Tukey1 <- TukeyHSD(fit1, conf.level=0.95) #Tukey multiple comparison
Tukey1 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_1 <- ggplot(metadata, aes(x=Year, y=Biogas_production)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Biogas production (m3/day)") + labs(title = "Biogas production", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
```

```
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_1
box_1_1 <- box_1 + geom_boxplot(width=0.2) # Add median and quartile
box_1_1

## Mean and standard deviation
box_1_data <- data_summary(metadata, varname="Biogas_production",
                           groupnames=c("Year"))
box_1_data


#2. Methane content
## Anova
fit2 <- aov(Methane_content~Year, metadata)
summary(fit2)
Tukey2 <- TukeyHSD(fit2, conf.level=0.95) #Tukey multiple comparison
Tukey2 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_2 <- ggplot(metadata, aes(x=Year, y=Methane_content)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Methane content (%)") + labs(title = "Methane content", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_2
box_2_1 <- box_2 + geom_boxplot(width=0.2) # Add median and quartile
box_2_1

## Mean and standard deviation
box_2_data <- data_summary(metadata, varname="Methane_content",
                          groupnames=c("Year"))
box_2_data

#3. H2S

## Anova
fit3 <- aov(H2S_content~Year, metadata)
summary(fit3)
Tukey3 <- TukeyHSD(fit3, conf.level=0.95) #Tukey multiple comparison
```

```
Tukey3 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_3 <- ggplot(metadata, aes(x=Year, y=H2S_content)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("H2S content (ppmv)") + labs(title = "H2S content", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_3
box_3_1 <- box_3 + geom_boxplot(width=0.2) # Add median and quartile
box_3_1

## Mean and standard deviation
box_3_data <- data_summary(metadata, varname="H2S_content",
                           groupnames=c("Year"))
box_3_data

#4. Electricity

## Anova
fit4 <- aov(Electricity~Year, metadata)
summary(fit4)
Tukey4 <- TukeyHSD(fit4, conf.level=0.95) #Tukey multiple comparison
Tukey4 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_4 <- ggplot(metadata, aes(x=Year, y=Electricity)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Electricity (kWh)") + labs(title = "Electricity", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_4
box_4_1 <- box_4 + geom_boxplot(width=0.2) # Add median and quartile
box_4_1
```

```
## Mean and standard deviation
box_4_data <- data_summary(metadata, varname="Electricity",
                    groupnames=c("Year"))
box_4_data

#5. Effluent_TS

## Anova
fit5 <- aov(Effluent_TS~Year, metadata)
summary(fit5)
Tukey5 <- TukeyHSD(fit5, conf.level=0.95) #Tukey multiple comparison
Tukey5 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_5 <- ggplot(metadata, aes(x=Year, y=Effluent_TS)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Effluent_TS (mg/L)") + labs(title = "Effluent_TS", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_5
box_5_1 <- box_5 + geom_boxplot(width=0.2) # Add median and quartile
box_5_1

## Mean and standard deviation
box_5_data <- data_summary(metadata, varname="Effluent_TS",
                    groupnames=c("Year"))
box_5_data

#6. Effluent_TN

## Anova
fit6 <- aov(Effluent_TN~Year, metadata)
summary(fit6)
Tukey6 <- TukeyHSD(fit6, conf.level=0.95) #Tukey multiple comparison
Tukey6 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_6 <- ggplot(metadata, aes(x=Year, y=Effluent_TN)) +
```

```
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Effluent_TN (mg/L)") + labs(title = "Effluent_TN", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_6
box_6_1 <- box_6 + geom_boxplot(width=0.2) # Add median and quartile
box_6_1

## Mean and standard deviation
box_6_data <- data_summary(metadata, varname="Effluent_TN",
                           groupnames=c("Year"))
box_6_data

#7. Effluent_TP

## Anova
fit7 <- aov(Effluent_TP~Year, metadata)
summary(fit7)
Tukey7 <- TukeyHSD(fit7, conf.level=0.95) #Tukey multiple comparison
Tukey7 #Output Tukey results


## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_7 <- ggplot(metadata, aes(x=Year, y=Effluent_TP)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Effluent_TP (mg/L)") + labs(title = "Effluent_TP", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_7
box_7_1 <- box_7 + geom_boxplot(width=0.2) # Add median and quartile
box_7_1

## Mean and standard deviation
box_7_data <- data_summary(metadata, varname="Effluent_TP",
                           groupnames=c("Year"))
```

```
box_7_data

#8. Effluent_pH

## Anova
fit8 <- aov(Effluent_pH~Year, metadata)
summary(fit8)
Tukey8 <- TukeyHSD(fit8, conf.level=0.95) #Tukey multiple comparison
Tukey8 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_8 <- ggplot(metadata, aes(x=Year, y=Effluent_pH)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Effluent_pH") + labs(title = "Effluent_pH", subtitle=NULL) +
  theme_classic() +
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_8
box_8_1 <- box_8 + geom_boxplot(width=0.2) # Add median and quartile
box_8_1

## Mean and standard deviation
box_8_data <- data_summary(metadata, varname="Effluent_TP",
                           groupnames=c("Year"))
box_8_data

#9. Effluent_VFA

## Anova
fit9 <- aov(Effluent_VFA~Year, metadata)
summary(fit9)
Tukey9 <- TukeyHSD(fit9, conf.level=0.95) #Tukey multiple comparison
Tukey9 #Output Tukey results

## Plot
windowsFonts(A=windowsFont("Times New Roman")) #Import font
box_9 <- ggplot(metadata, aes(x=Year, y=Effluent_VFA)) +
  geom_violin(trim=TRUE, fill="green") +
  xlab("Year")+
  ylab("Effluent_VFA (mg/L)") + labs(title = "Effluent_VFA", subtitle=NULL) +
  theme_classic() +
```

```
  theme(title=element_text(size=20, family="A"),
        axis.text.x = element_text(size=20, family="A"),
        axis.text.y=element_text(size=20, family="A"),
        axis.title.y = element_text(size = 20, family="A"),
        axis.title.x=element_text(size=20, family="A"), legend.position = "top")
box_9
box_9_1 <- box_9 + geom_boxplot(width=0.2) # Add median and quartile
box_9_1

## Mean and standard deviation
box_9_data <- data_summary(metadata, varname="Effluent_TP",
                       groupnames=c("Year"))
box_9_data
```

RESULTS

D.1 Biogas Production

```
Year        6 20642104 3440351   7.678 1.76e-06 ***
Residuals   77 34500609  448060
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> Tukey1 <- TukeyHSD(fit1, conf.level=0.95) #Tukey multiple comparison
> Tukey1 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Biogas_production ~ Year, data = metadata)

$Year
               diff         lwr       upr     p adj
2015-2014  694.00000  -133.36997 1521.3700 0.1599213
2016-2014 1541.66667   714.29669 2369.0366 0.0000055
2017-2014 1308.91667   481.54669 2136.2866 0.0001566
2018-2014 1358.50000   531.13003 2185.8700 0.0000784
2019-2014 1128.33333   300.96336 1955.7033 0.0017106
2020-2014 1334.41667   507.04669 2161.7866 0.0001099
2016-2015  847.66667    20.29669 1675.0366 0.0410426
2017-2015  614.91667  -212.45331 1442.2866 0.2817500
2018-2015  664.50000  -162.86997 1491.8700 0.1998249
2019-2015  434.33333  -393.03664 1261.7033 0.6893826
2020-2015  640.41667  -186.95331 1467.7866 0.2372841
2017-2016 -232.75000 -1060.11997  594.6200 0.9783861
2018-2016 -183.16667 -1010.53664  644.2033 0.9938444
2019-2016 -413.33333 -1240.70331  414.0366 0.7365206
2020-2016 -207.25000 -1034.61997  620.1200 0.9881153
2018-2017   49.58333  -777.78664  876.9533 0.9999968
2019-2017 -180.58333 -1007.95331  646.7866 0.9942997
```

```
2020-2017   25.50000  -801.86997  852.8700 0.9999999
2019-2018 -230.16667 -1057.53664  597.2033 0.9795748
2020-2018  -24.08333  -851.45331  803.2866 1.0000000
2020-2019  206.08333  -621.28664 1033.4533 0.9884622

Year Biogas_production        sd
1 2014          2330.500  553.7258
2 2015          3024.500 1143.9877
3 2016          3872.167  794.9921
4 2017          3639.417  702.3386
5 2018          3689.000  199.2326
6 2019          3458.833  523.6508
7 2020          3664.917  286.1870
```

D.2 Methane Content

```
            Df Sum Sq Mean Sq F value   Pr(>F)
Year         6  268.5   44.75   10.79 1.11e-08 ***
Residuals   77  319.3    4.15
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> Tukey2 <- TukeyHSD(fit2, conf.level=0.95) #Tukey multiple comparison
> Tukey2 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Methane_content ~ Year, data = metadata)

$Year
                diff         lwr        upr     p adj
2015-2014 -2.7500000 -5.26714655 -0.2328534 0.0231534
2016-2014 -1.1666667 -3.68381322  1.3504799 0.7984379
2017-2014  1.6666667 -0.85047989  4.1838132 0.4202415
2018-2014  2.2500000 -0.26714655  4.7671466 0.1105162
2019-2014  0.6666667 -1.85047989  3.1838132 0.9841179
2020-2014  2.5833333  0.06618678  5.1004799 0.0404567
2016-2015  1.5833333 -0.93381322  4.1004799 0.4837268
2017-2015  4.4166667  1.89952011  6.9338132 0.0000206
2018-2015  5.0000000  2.48285345  7.5171466 0.0000012
2019-2015  3.4166667  0.89952011  5.9338132 0.0018285
2020-2015  5.3333333  2.81618678  7.8504799 0.0000002
2017-2016  2.8333333  0.31618678  5.3504799 0.0172959
2018-2016  3.4166667  0.89952011  5.9338132 0.0018285
2019-2016  1.8333333 -0.68381322  4.3504799 0.3049407
2020-2016  3.7500000  1.23285345  6.2671466 0.0004418
2018-2017  0.5833333 -1.93381322  3.1004799 0.9921290
2019-2017 -1.0000000 -3.51714655  1.5171466 0.8910075
```

```
2020-2017  0.9166667 -1.60047989  3.4338132 0.9254758
2019-2018 -1.5833333 -4.10047989  0.9338132 0.4837268
2020-2018  0.3333333 -2.18381322  2.8504799 0.9996575
2020-2019  1.9166667 -0.60047989  4.4338132 0.2548637

  Year Methane_content        sd
1 2014        63.58333 2.9374799
2 2015        60.83333 2.3290003
3 2016        62.41667 2.2746961
4 2017        65.25000 1.5447860
5 2018        65.83333 0.9374369
6 2019        64.25000 0.9653073
7 2020        66.16667 2.3677121
```

D.3 H_2S Content

```
          Df   Sum Sq Mean Sq F value Pr(>F)
Year         6  1130830  188472   0.979  0.445
Residuals   77 14823077  192507
> Tukey3 <- TukeyHSD(fit3, conf.level=0.95) #Tukey multiple comparison
> Tukey3 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = H2S_content ~ Year, data = metadata)

$Year
                diff       lwr      upr     p adj
2015-2014   71.83333 -470.4866 614.1532 0.9996570
2016-2014  307.66667 -234.6532 849.9866 0.6065461
2017-2014   61.16667 -481.1532 603.4866 0.9998653
2018-2014   27.66667 -514.6532 569.9866 0.9999988
2019-2014  160.83333 -381.4866 703.1532 0.9718399
2020-2014  292.00000 -250.3199 834.3199 0.6634742
2016-2015  235.83333 -306.4866 778.1532 0.8421465
2017-2015  -10.66667 -552.9866 531.6532 1.0000000
2018-2015  -44.16667 -586.4866 498.1532 0.9999802
2019-2015   89.00000 -453.3199 631.3199 0.9988299
2020-2015  220.16667 -322.1532 762.4866 0.8806089
2017-2016 -246.50000 -788.8199 295.8199 0.8126780
2018-2016 -280.00000 -822.3199 262.3199 0.7057319
2019-2016 -146.83333 -689.1532 395.4866 0.9822128
2020-2016  -15.66667 -557.9866 526.6532 1.0000000
2018-2017  -33.50000 -575.8199 508.8199 0.9999962
2019-2017   99.66667 -442.6532 641.9866 0.9977881
2020-2017  230.83333 -311.4866 773.1532 0.8550638
2019-2018  133.16667 -409.1532 675.4866 0.9892975
```

```
2020-2018  264.33333 -277.9866 806.6532 0.7581408
2020-2019  131.16667 -411.1532 673.4866 0.9901197

  Year H2S_content       sd
1 2014    359.8333 273.7334
2 2015    431.6667 291.7634
3 2016    667.5000 614.5482
4 2017    421.0000 214.4625
5 2018    387.5000 290.1907
6 2019    520.6667 512.9892
7 2020    651.8333 645.3405
```

D.4 Electricity

```
> ## Anova
> fit4 <- aov(Electricity~Year, metadata)
> summary(fit4)
            Df   Sum Sq Mean Sq F value   Pr(>F)
Year         6 58173817 9695636   7.397 3.61e-06 ***
Residuals   71 93063092 1310748
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> Tukey4 <- TukeyHSD(fit4, conf.level=0.95) #Tukey multiple comparison
> Tukey4 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Electricity ~ Year, data = metadata)

$Year
                diff        lwr       upr     p adj
2015-2014 1550.33333   132.0368 2968.6299 0.0231496
2016-2014 2526.72619   874.4607 4178.9917 0.0003011
2017-2014 2114.03788   663.8655 3564.2102 0.0006559
2018-2014 2462.00000  1043.7035 3880.2965 0.0000284
2019-2014 1706.41667   288.1201 3124.7132 0.0085860
2020-2014 2637.08333  1218.7868 4055.3799 0.0000065
2016-2015  976.39286  -675.8726 2628.6583 0.5569849
2017-2015  563.70455  -886.4678 2013.8769 0.8995423
2018-2015  911.66667  -506.6299 2329.9632 0.4547983
2019-2015  156.08333 -1262.2132 1574.3799 0.9998810
2020-2015 1086.75000  -331.5465 2505.0465 0.2467925
2017-2016 -412.68831 -2092.3954 1267.0188 0.9890915
2018-2016  -64.72619 -1716.9917 1587.5393 0.9999997
2019-2016 -820.30952 -2472.5750  831.9559 0.7400160
2020-2016  110.35714 -1541.9083 1762.6226 0.9999938
2018-2017  347.96212 -1102.2102 1798.1345 0.9903727
```

```
2019-2017 -407.62121 -1857.7936 1042.5511 0.9781490
2020-2017  523.04545  -927.1269 1973.2178 0.9277426
2019-2018 -755.58333 -2173.8799  662.7132 0.6722154
2020-2018  175.08333 -1243.2132 1593.3799 0.9997677
2020-2019  930.66667  -487.6299 2348.9632 0.4293029
```

```
Year Electricity        sd
1 2014    4880.417  728.5998
2 2015    6430.750 2041.8703
3 2016    7407.143 1080.8314
4 2017    6994.455 1037.2193
5 2018    7342.417  692.6983
6 2019    6586.833  952.5799
7 2020    7517.500  870.4768
```

D.5 Effluent TS

```
> ## Anova
> fit5 <- aov(Effluent_TS~Year, metadata)
> summary(fit5)
            Df    Sum Sq   Mean Sq F value   Pr(>F)    
Year         6 2.907e+09 484541468   10.62 3.69e-08 ***
Residuals   64 2.919e+09  45609925                     
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> Tukey5 <- TukeyHSD(fit5, conf.level=0.95) #Tukey multiple comparison
> Tukey5 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Effluent_TS ~ Year, data = metadata)

$Year
                diff          lwr       upr     p adj
2015-2014   7997.682   -984.79256 16980.156 0.1122739
2016-2014  16843.182   8261.75241 25424.611 0.0000023
2017-2014  21274.293  12034.12035 30514.466 0.0000000
2018-2014   9827.932   1246.50241 18409.361 0.0147911
2019-2014  10598.882   1616.40744 19581.356 0.0108218
2020-2014  15052.896   5113.18934 24992.603 0.0003813
2016-2015   8845.500     43.05339 17647.947 0.0481143
2017-2015  13276.611   3830.82238 22722.400 0.0012007
2018-2015   1830.250  -6972.19661 10632.697 0.9954403
2019-2015   2601.200  -6592.65563 11795.056 0.9769386
2020-2015   7055.214  -3075.92119 17186.350 0.3538760
2017-2016   4431.111  -4634.15279 13496.375 0.7508227
2018-2016  -7015.250 -15408.05353  1377.554 0.1611800
```

```
2019-2016  -6244.300 -15046.74661  2558.147 0.3318569
2020-2016  -1790.286 -11567.60594  7987.035 0.9977393
2018-2017 -11446.361 -20511.62502 -2381.097 0.0049887
2019-2017 -10675.411 -20121.19984 -1229.622 0.0169013
2020-2017  -6221.397 -16581.69843  4138.905 0.5346432
2019-2018    770.950  -8031.49661  9573.397 0.9999681
2020-2018   5224.964  -4552.35594 15002.285 0.6658345
2020-2019   4454.014  -5677.12119 14585.150 0.8312859

  Year Effluent_TS       sd
1 2014    49084.82 5988.019
2 2015    57082.50 8729.659
3 2016    65928.00 7426.269
4 2017    70359.11 6288.440
5 2018    58912.75 4119.301
6 2019    59683.70 7100.303
7 2020    64137.71 7202.142
```

D.6 Effluent TN

```
> ## Anova
> fit6 <- aov(Effluent_TN~Year, metadata)
> summary(fit6)
            Df   Sum Sq Mean Sq F value Pr(>F)
Year         5  9543738 1908748   4.072  0.004 **
Residuals   44 20623980  468727
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> Tukey6 <- TukeyHSD(fit6, conf.level=0.95) #Tukey multiple comparison
> Tukey6 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Effluent_TN ~ Year, data = metadata)

$Year
                 diff        lwr       upr     p adj
2016-2014   497.666667  -844.8832 1840.2166 0.8769966
2017-2014     9.777778 -1349.8754 1369.4309 1.0000000
2018-2014  -560.000000 -1876.4785  756.4785 0.8008652
2019-2014  -698.033333 -2040.5832  644.5166 0.6354059
2020-2014  -350.333333 -1792.4633 1091.7966 0.9779748
2017-2016  -487.888889 -1424.9651  449.1874 0.6340520
2018-2016 -1057.666667 -1930.9197 -184.4136 0.0095733
2019-2016 -1195.700000 -2107.7830 -283.6170 0.0040739
2020-2016  -848.000000 -1901.1828  205.1828 0.1790566
2018-2017  -569.777778 -1469.1038  329.5482 0.4232430
```

```
2019-2017  -707.811111 -1644.8874  229.2651 0.2364522
2020-2017  -360.111111 -1435.0113  714.7891 0.9161162
2019-2018  -138.033333 -1011.2864  735.2197 0.9969255
2020-2018   209.666667  -810.0732 1229.4065 0.9895575
2020-2019   347.700000  -705.4828 1400.8828 0.9207828

  Year Effluent_TN       sd
1 2014    3645.333 258.6220
2 2016    4143.000 653.1854
3 2017    3655.111 577.1333
4 2018    3085.333 581.5000
5 2019    2947.300 876.2909
6 2020    3295.000 819.1642
```

D.7 Effluent TP

```
> ## Anova
> fit7 <- aov(Effluent_TP~Year, metadata)
> summary(fit7)
            Df  Sum Sq Mean Sq F value   Pr(>F)
Year         6 4015385  669231   9.616 9.39e-07 ***
Residuals   44 3062221   69596
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> Tukey7 <- TukeyHSD(fit7, conf.level=0.95) #Tukey multiple comparison
> Tukey7 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Effluent_TP ~ Year, data = metadata)

$Year
                diff        lwr        upr     p adj
2015-2014 -352.333333 -1293.2144  588.54775 0.9062776
2016-2014 -628.033333 -1164.4181  -91.64859 0.0125302
2017-2014 -792.000000 -1335.2179 -248.78205 0.0009006
2018-2014 -724.250000 -1250.2185 -198.28149 0.0019504
2019-2014 -794.733333 -1331.1181 -258.34859 0.0007161
2020-2014  -27.000000  -603.1696  549.16964 0.9999991
2016-2015 -275.700000 -1130.2977  578.89768 0.9521294
2017-2015 -439.666667 -1298.5697  419.23632 0.6946584
2018-2015 -371.916667 -1220.0154  476.18208 0.8221838
2019-2015 -442.400000 -1296.9977  412.19768 0.6836316
2020-2015  325.333333  -554.7803 1205.44699 0.9113842
2017-2016 -163.966667  -538.3538  210.42047 0.8230582
2018-2016  -96.216667  -445.1047  252.67138 0.9776756
2019-2016 -166.700000  -531.1017  197.70168 0.7919737
```

```
2020-2016  601.033333   180.2585 1021.80814 0.0011970
2018-2017   67.750000  -291.5549  427.05490 0.9970225
2019-2017   -2.733333  -377.1205  371.65380 1.0000000
2020-2017  765.000000   335.5485 1194.45149 0.0000356
2019-2018  -70.483333  -419.3714  278.40471 0.9956522
2020-2018  697.250000   289.8365 1104.66346 0.0000726
2020-2019  767.733333   346.9585 1188.50814 0.0000228

Year Effluent_TP        sd
1 2014   1168.3333  51.98397
2 2015    816.0000        NA
3 2016    540.3000 129.16918
4 2017    376.3333  78.57640
5 2018    444.0833 325.76915
6 2019    373.6000  77.72916
7 2020   1141.3333 571.92715
```

*group with fewer than 2 data points will be deleted. 2015 only has 1 data point so it was removed

D.8 Effluent pH

```
> ## Anova
> fit8 <- aov(Effluent_pH~Year, metadata)
> summary(fit8)
            Df Sum Sq Mean Sq F value Pr(>F)
Year         6  0.333 0.05550    2.58 0.0266 *
Residuals   64  1.377 0.02151
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> Tukey8 <- TukeyHSD(fit8, conf.level=0.95) #Tukey multiple comparison
> Tukey8 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Effluent_pH ~ Year, data = metadata)

$Year
                  diff        lwr         upr     p adj
2015-2014 -0.031818182 -0.2269049 0.163268578 0.9988202
2016-2014 -0.056818182 -0.2431948 0.129558443 0.9666104
2017-2014 -0.048484848 -0.2491685 0.152198755 0.9897882
2018-2014 -0.065151515 -0.2515281 0.121225110 0.9361855
2019-2014 -0.191818182 -0.3869049 0.003268578 0.0569543
2020-2014 -0.197532468 -0.4134090 0.018344039 0.0944586
2016-2015 -0.025000000 -0.2161768 0.166176809 0.9996669
2017-2015 -0.016666667 -0.2218160 0.188482632 0.9999795
```

```
2018-2015 -0.033333333 -0.2245101 0.157843476 0.9982809
2019-2015 -0.160000000 -0.3596777 0.039677665 0.1996821
2020-2015 -0.165714286 -0.3857484 0.054319784 0.2635888
2017-2016  0.008333333 -0.1885515 0.205218166 0.9999996
2018-2016 -0.008333333 -0.1906133 0.173946602 0.9999993
2019-2016 -0.135000000 -0.3261768 0.056176809 0.3372597
2020-2016 -0.140714286 -0.3530640 0.071635413 0.4143088
2018-2017 -0.016666667 -0.2135515 0.180218166 0.9999739
2019-2017 -0.143333333 -0.3484826 0.061815965 0.3499429
2020-2017 -0.149047619 -0.3740589 0.075963618 0.4147777
2019-2018 -0.126666667 -0.3178435 0.064510142 0.4144769
2020-2018 -0.132380952 -0.3447307 0.079968746 0.4893366
2020-2019 -0.005714286 -0.2257484 0.214319784 1.0000000

  Year Effluent_pH        sd
1 2014    7.881818 0.1250454
2 2015    7.850000 0.1269296
3 2016    7.825000 0.1959824
4 2017    7.833333 0.1000000
5 2018    7.816667 0.1267304
6 2019    7.690000 0.1523884
7 2020    7.684286 0.1767161
```

D.9 Effluent VFA

```
> ## Anova
> fit9 <- aov(Effluent_VFA~Year, metadata)
> summary(fit9)
            Df   Sum Sq  Mean Sq F value   Pr(>F)
Year         6 66702800 11117133   7.911 2.26e-06 ***
Residuals   63 88531222  1405257
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> Tukey9 <- TukeyHSD(fit9, conf.level=0.95) #Tukey multiple comparison
> Tukey9 #Output Tukey results
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Effluent_VFA ~ Year, data = metadata)

$Year
                diff        lwr       upr     p adj
2015-2014   278.85455 -1298.6290  1856.3381 0.9981357
2016-2014  2483.37121   976.3183  3990.4241 0.0000896
2017-2014   532.89899 -1089.8410  2155.6390 0.9521232
2018-2014  -484.87879 -1991.9317  1022.1741 0.9565537
2019-2014  -114.54545 -1692.0290  1462.9381 0.9999894
```

```
2020-2014    76.78788 -1755.5436  1909.1193 0.9999996
2016-2015  2204.51667   658.6492  3750.3841 0.0009793
2017-2015   254.04444 -1404.8055  1912.8943 0.9991716
2018-2015  -763.73333 -2309.6008   782.1341 0.7409955
2019-2015  -393.40000 -2008.0059  1221.2059 0.9892838
2020-2015  -202.06667 -2066.4530  1662.3197 0.9998878
2017-2016 -1950.47222 -3542.4951  -358.4493 0.0071468
2018-2016 -2968.25000 -4442.1768 -1494.3232 0.0000013
2019-2016 -2597.91667 -4143.7841 -1052.0492 0.0000621
2020-2016 -2406.58333 -4211.7676  -601.3990 0.0025172
2018-2017 -1017.77778 -2609.8007   574.2451 0.4579787
2019-2017  -647.44444 -2306.2943  1011.4055 0.8958544
2020-2017  -456.11111 -2358.9424  1446.7202 0.9901690
2019-2018   370.33333 -1175.5341  1916.2008 0.9901989
2020-2018   561.66667 -1243.5176  2366.8510 0.9630106
2020-2019   191.33333 -1673.0530  2055.7197 0.9999185

  Year Effluent_VFA        sd
1 2014    1301.5455  918.1749
2 2015    1580.4000 1312.9674
3 2016    3784.9167 1859.0623
4 2017    1834.4444 1103.4844
5 2018     816.6667  597.9409
6 2019    1187.0000 1039.4021
7 2020    1378.3333  796.3772
```

E. Other SCAD laboratory results

E.1 Total Suspended Solids (TSS)

Table E.1 Summary of TSS results

Year	Filtrate (mg/L)	Effluent (mg/L)
2014	22,972	33,604
2015		39,000
2016	23,862	35,556
2017	26,633	33,378
2018	33,172	32,819
2019	26,995	33,328
2020	49,236	48,833
Max	**49,236**	**48,833**
Min	**22,972**	**32,819**
Mean	**29,384**	**36,302**
Average	**30,478**	**36,645**
St. Dev	**9,001**	**5,356**

E.2 Volatile Suspended Solids (VSS)

Table E.2 Summary of VSS results

Year	Filtrate (mg/L)	Effluent (mg/L)
2014	18,556	27,247
2015		33,333
2016	19,795	30,828
2017	20,567	28,311
2018	22,901	27,587
2019	22,858	29,650
2020	34,542	42,389
Max	**34,542**	**42,389**
Min	**18,556**	**27,247**
Mean	**22,694**	**30,995**
Average	**23,203**	**31,335**
St. Dev	**5,306**	**4,916**

E.3 Ammonia

Table E.3 Summary of ammonia results

Year	Filtrate (mg/L)	Effluent (mg/L)
2014	1,942	1,850
2015	1,825	1,566
2016	2,368	2,493
2017	1,917	2,029
2018	1,829	1,845
2019	1,875	1,755
2020	1,609	1,547
Max	**2,368**	**2,493**
Min	**1,609**	**1,547**
Mean	**1,898**	**1,847**
Average	**1,909**	**1,869**
St. Dev	**213**	**299**

E.4 Alkalinity

Table E.4 Summary of alkalinity results

Year	Filtrate (mg/L)	Effluent (mg/L)
2014	1,942	1,850
2015	1,825	1,566
2016	2,368	2,493
2017	1,917	2,029
2018	1,829	1,845
2019	1,875	1,755
2020	1,609	1,547
Max	**2,368**	**2,493**
Min	**1,609**	**1,547**
Mean	**1,898**	**1,847**
Average	**1,909**	**1,869**
St. Dev	**213**	**299**

E.5 Total Dissolved Solids (TDS)

Table E.5 Summary of TDS results

Year	Filtrate (mg/L)	Effluent (mg/L)
2014	17,667	17,653
2015		20,317
2016	17,535	30,988
2017	14,070	34,948
2018	11,299	26,094
2019	13,515	26,374
2020	6,379	16,871
Max	**17,667**	**34,948**
Min	**6,379**	**16,871**
Mean	**12,725**	**23,942**
Average	**13,411**	**24,749**
St. Dev	**3,862**	**6,318**

F. A&L Great Lakes Laboratory Results

F.1 Solids

Table F.1 Summary of Solids results

Year	Filtrate (%)	Effluent (%)	Solids (%)
2014			24.74
2015			39.35
2016			26.23
2017	3.87		
2018	5.24	3.87	27.48
2019			28.25
2020			31.25
Max	5.24	3.87	39.35
Min	3.87	3.87	24.74
Mean	4.50	3.87	29.20
Average	4.56	3.87	29.55
St. Dev	0.69	-	4.81

F.2 Total Kjeldahl Nitrogen (TKN)

Table F.2 Summary of TKN results

Year	Filtrate (%)	Effluent (%)	Solids (%)
2014			0.43
2015			0.72
2016			0.63
2017	0.29		
2018	0.311	0.311	0.45
2019			0.55
2020			0.59
Max	0.31	0.31	0.72
Min	0.29	0.31	0.43
Mean	0.30	0.31	0.55
Average	0.30	0.31	0.56
St. Dev	0.01	-	0.10

F.3 Phosphorus (P)

Table F.3 Summary of Phosphorus results

Year	Filtrate (%)	Effluent (%)	Solids (%)
2014			0.14
2015			0.35
2016			0.23
2017	0.03		
2018	0.037	0.033	0.147
2019			0.19
2020			0.18
Max	0.04	0.03	0.35
Min	0.03	0.03	0.14
Mean	0.03	0.03	0.20
Average	0.03	0.03	0.21
St. Dev	0.00	-	0.07

F.4 Potassium (K)

Table F.4 Summary of Potassium results

Year	Filtrate (%)	Effluent (%)	Solids (%)
2014			0.26
2015			0.65
2016			0.31
2017	0.14		
2018	0.144	0.159	0.143
2019			0.22
2020			0.19
Max	0.14	0.16	0.65
Min	0.14	0.16	0.14
Mean	0.14	0.16	0.26
Average	0.14	0.16	0.30
St. Dev	0.00	-	0.17

F.5 Moisture

Table F.5 Summary of Moisture results

Year	Filtrate (%)	Effluent (%)
2017	96.13	
2018	94.76	0.159
Max	96.13	0.16
Min	94.76	0.16
Mean	95.44	0.16
Average	95.45	0.16
St. Dev	0.68	-

F.6 Sulphur (S)

Table F.6 Summary of Sulphur results

Year	Filtrate (%)	Effluent (%)
2017	0.03	
2018	0.03	0.02
Max	0.03	0.02
Min	0.03	0.02
Mean	0.03	0.02
Average	0.03	0.02
St. Dev	-	-

F.7 Magnesium (Mg)

Table F.7 Summary of Magnesium results

Year	Filtrate (%)	Effluent (%)
2017	0.05	
2018	0.05	0.07
Max	0.05	0.07
Min	0.05	0.07
Mean	0.05	0.07
Average	0.05	0.07
St. Dev	-	-

F.8 Calcium (Ca)

Table F.8 Summary of Calcium results

Year	Filtrate (%)	Effluent (%)
2017	0.11	
2018	0.12	0.13
Max	0.12	0.13
Min	0.11	0.13
Mean	0.11	0.13
Average	0.12	0.13
St. Dev	0.01	-

F.9 Natrium (Na)

Table F.9 Summary of Natrium results

Year	Filtrate (%)	Effluent (%)
2017	0.07	
2018	0.08	0.09
Max	0.08	0.09
Min	0.07	0.09
Mean	0.07	0.09
Average	0.08	0.09
St. Dev	0.01	-

F.10 Aluminum (Al)

Table F.10 Summary of Aluminum results

Year	Filtrate (ppm)	Effluent (ppm)
2017	48.5	
2018	44	67
Max	48.50	67.00
Min	44.00	67.00
Mean	46.20	67.00
Average	46.25	67.00
St. Dev	2.25	-

F.11 Copper (Cu)

Table F.11 Summary of Copper results

Year	Filtrate (ppm)	Effluent (ppm)
2017	4.35	
2018	4.3	4.9
Max	4.35	4.90
Min	4.30	4.90
Mean	4.32	4.90
Average	4.33	4.90
St. Dev	0.02	-

F.12 Iron (Fe)

Table F.12 Summary of Iron results

Year	Filtrate (ppm)	Effluent (ppm)
2017	90.5	
2018	106	162
Max	106.00	162.00
Min	90.50	162.00
Mean	97.94	162.00
Average	98.25	162.00
St. Dev	7.75	-

F.13 Manganese (Mn)

Table F.13 Summary of Manganese results

Year	Filtrate (ppm)	Effluent (ppm)
2017	9.65	
2018	11	12
Max	11.00	12.00
Min	9.65	12.00
Mean	10.30	12.00
Average	10.33	12.00
St. Dev	0.68	-

F.14 Zinc (Zn)

Table F.14 Summary of Zinc results

Year	Filtrate (ppm)	Effluent (ppm)
2017	61	
2018	53	57
Max	61.00	57.00
Min	53.00	57.00
Mean	56.86	57.00
Average	57.00	57.00
St. Dev	4.00	-

F.15 Nitrogen (N)

Table F.15 Summary of Nitrogen results

Year	Solids (%)
2017	0.28
2018	0.45
Max	0.45
Min	0.28
Mean	0.35
Average	0.37
St. Dev	0.09

F.16 Ammonia (NH_3)

Table F.16 Summary of Ammonia results

Year	Solids (%)
2017	0.18
2018	0.14
Max	0.18
Min	0.14
Mean	0.16
Average	0.16
St. Dev	0.02

G. Formula for OLR and HRT Calculation

G.1 OLR Formula

OLR = IF (Total VS g=0, “”, (Total VS g / (Working Volume Liters*Days)))

G.2 HRT Formula

HRT = IF (Volume of Digestate Wasted=0, “”, ((Working Volume Gallons/Volume of Digestate Wasted)) * Days)

H. R-Code of MLR for feedstock impact on biogas production (after data treated)

```
RegressionData1 <- read.table("C:/BIOGAS-AHAY/MLR_ORIGINAL DATA - 
REGRESSION.csv", header = TRUE, sep=',')
validationData <- read.table("C:/BIOGAS-AHAY/MLR_ORIGINAL DATA - 
VALIDATION.csv", header = TRUE, sep=',')
#BL2020a <- read.table("C:/MSU/Biogas data/BiogasProduction_REMOVED.csv", header = 
TRUE, sep=',')
names(RegressionData1) = 
c('row.name','Year','Mon','Digestate','FMP','SLSS','DG','Parlor','Beef','WFM','Poultry','Swine','A
NS','TMP','FFP','SLSSF','PA','Pulp','FOG','WFEED','Other','CartF','TFP','TFS','BiogasP','CH4P','
MethaneC','H2SC','Elec','TS','TN','TP','pH','VFA')
summary(RegressionData1)

RegressionData <- RegressionData1
#BL2020[138,]
RegressionData$Year = as.factor(RegressionData$Year)
RegressionData$Mon = as.factor(RegressionData$Mon)

row.name <- RegressionData[1]
Year <- RegressionData[2]
MoN <- RegressionData[3]
Digestate <- RegressionData[4]
FMP <- RegressionData[5]
SLSS <- RegressionData[6]
DG <- RegressionData[7]
Parlor <- RegressionData[8]
Beef <- RegressionData[9]
WFM <- RegressionData[10]
Poultry <- RegressionData[11]
Swine <- RegressionData[12]
ANS <- RegressionData[13]
```

```
TMP <- RegressionData[14]
FFP <- RegressionData[15]
SLSSF <- RegressionData[16]
PA <- RegressionData[17]
Pulp <- RegressionData[18]
FOG <- RegressionData[19]
WFEED <- RegressionData[20]
Other <- RegressionData[21]
CartF <- RegressionData[22]
TFP <- RegressionData[23]
TFS <- RegressionData[24]
BiogasP <- RegressionData[25]
CH4 <- RegressionData[26]
MethaneC <- RegressionData[27]
H2SC <- RegressionData[28]
Elec <- RegressionData[29]
TS <- RegressionData[30]
TN <- RegressionData[31]
TP <- RegressionData[32]
pH <- RegressionData[33]
VFA <- RegressionData[34]

library(tidyverse)
library(GGally)

# prints first set of rows showing works as a visual check if data were read correctly
head(RegressionData)

#shows the data type and sample of the data
str(RegressionData)

##########################################################################################
##########################
# Standardize variables in a dataset
RegressionData_std <-
data.frame(scale(RegressionData[,c('Digestate','FMP','SLSS','DG','Parlor','Beef','WFM','Poultry','Swine','ANS','TMP','FFP','SLSSF','PA','Pulp','FOG','WFEED','Other','CartF','TFP','TFS','BiogasP','CH4P','MethaneC','H2SC','Elec','TS','TN','TP','pH','VFA')]))
RegressionData_std["Year"] <- RegressionData[,"Year"]
RegressionData_std["Month"] <- RegressionData[,"Mon"]
head(RegressionData_std)
##########################################################################################
##########################
#outliers testing
install.packages("e1071")
install.packages("outliers")
```

```
library(e1071)
library(outliers)

#histograms of weights
hist(RegressionData$FMP, breaks= 12, freq = F, xlab = 'FMP', main="")
hist(sqrt(RegressionData$FMP), breaks= 12, freq = F, xlab = 'SQRT(FMP)', main="")

ggpairs(columns = c('FMP','DG','Parlor','Beef','TMP','Pulp','FOG','Other','CartF'), data =
RegressionData, upper = list(continuous = wrap('cor', size = 8)))
ggpairs(columns = c('FFP','Pulp','FOG','Other','CartF','TFP','TFS'), data = RegressionData, upper
= list(continuous = wrap('cor', size = 8)))

ggpairs(columns = c('BiogasP','CH4P','MethaneC','H2SC','Elec','TS','TN','TP','pH','VFA'), data =
RegressionData, upper = list(continuous = wrap('cor', size = 8)))

ggpairs(columns = c('BiogasP','TMP','TFP','FMP','MethaneC','H2SC','TS','TN','TP','pH','VFA'),
data = RegressionData, upper = list(continuous = wrap('cor', size = 8)))

ggpairs(columns = c('BiogasP', 'sqrtFMP'), data = RegressionData, upper = list(continuous =
wrap('cor', size = 8)))

ggpairs(columns = c('BiogasP', 'TFP'), data = RegressionData, upper = list(continuous =
wrap('cor', size = 8)),aes(color = Mon, alpha = 0.5))

ggpairs(columns = c('BiogasP', 'TMP'), data = RegressionData, upper = list(continuous =
wrap('cor', size = 8)),aes(color = Mon, alpha = 0.5))

ggpairs(columns = c('BiogasP', 'TFS'), data = RegressionData, upper = list(continuous =
wrap('cor', size = 8)),aes(color = Mon, alpha = 0.5))

ggpairs(columns = c('BiogasP', 'TFS'), data = RegressionData, upper = list(continuous =
wrap('cor', size = 8)),aes(color = Year, alpha = 0.5))

ggpairs(columns = c('BiogasP', 'TMP'), data = RegressionData, upper = list(continuous =
wrap('cor', size = 8)),aes(color = Year, alpha = 0.5))

ggpairs(columns = c('BiogasP', 'TFP'), data = RegressionData, upper = list(continuous =
wrap('cor', size = 8)),aes(color = Year, alpha = 0.5))

#Comparisons between the different Months
boxplot(RegressionData$BiogasP ~RegressionData$Mon, ylab ="Biogas Production", xlab
="Mon")
boxplot(RegressionData$BiogasP ~RegressionData$Year, ylab ="Biogas Production", xlab
="Year")
#Analysis of variance
```

```
#Conduct H0 : Mean Biogas production is the same for Months
# Ha: at least one Month is different
aov_Months <- aov(RegressionData$BiogasP~RegressionData$Mon)
summary(aov_Months)
#attributes(aov_species)
aov_Months$coefficients

TukeyHSD(aov_Months)
plot(TukeyHSD(aov_Months), las=1)


################################################################################
###########################
#Specifying the preliminary full model / parameters we wish to investigate
#Full model for original data
#'Year','Mon','Digestate','FMP','SLSS','DG','Parlor','Beef','WFM','Poultry','Swine','ANS','TMP','F
FP','SLSSF','PA','Pulp','FOG','WFEED','Other','CartF','TFP','TFS','BiogasP','CH4P','MethaneC','
H2SC','Elec','TS','TN','TP','pH','VFA'
full_model <- lm(BiogasP ~ FMP + DG + Digestate + SLSS + SLSSF + WFM + Poultry +
                Parlor + Beef + FFP + Swine + ANS + PA + WFEED +
                Pulp + FOG +
                Other + CartF, data=RegressionData)

#Full model for standardized data
full_model_std <- lm(BiogasP ~ FMP + DG + PA + Beef + FFP +
                Pulp + FOG +
                Other + CartF , data=RegressionData_std)

modelDFFITS <- dffits(multiple.regression)

DFITTSThreshold <- sqrt(4*nparameters/ndata) # not a statistical test but to provide a general
judgment

which(abs(modelDFFITS)>DFITTSThreshold)
RegressionData[index(RegressionData)==62,]

RegressionData_noinfluence <- RegressionData[-c(49,50,71,72),]

full_model <- lm(BiogasP ~ FMP + DG + Digestate + SLSS + SLSSF + WFM + Poultry +
                Parlor + Beef + FFP + Swine + ANS + PA + WFEED +
                Pulp + FOG +
                Other + CartF, data=RegressionData_noinfluence)

Bothfit.p <- ols_step_both_p(full_model, pent = .01, prem = .05, details = TRUE)
Bothfit.p
```

```
multiple.regression <- lm(BiogasP ~ FMP + DG + Parlor + FOG,
data=RegressionData_noinfluence)
summary(multiple.regression)
```

RESULT

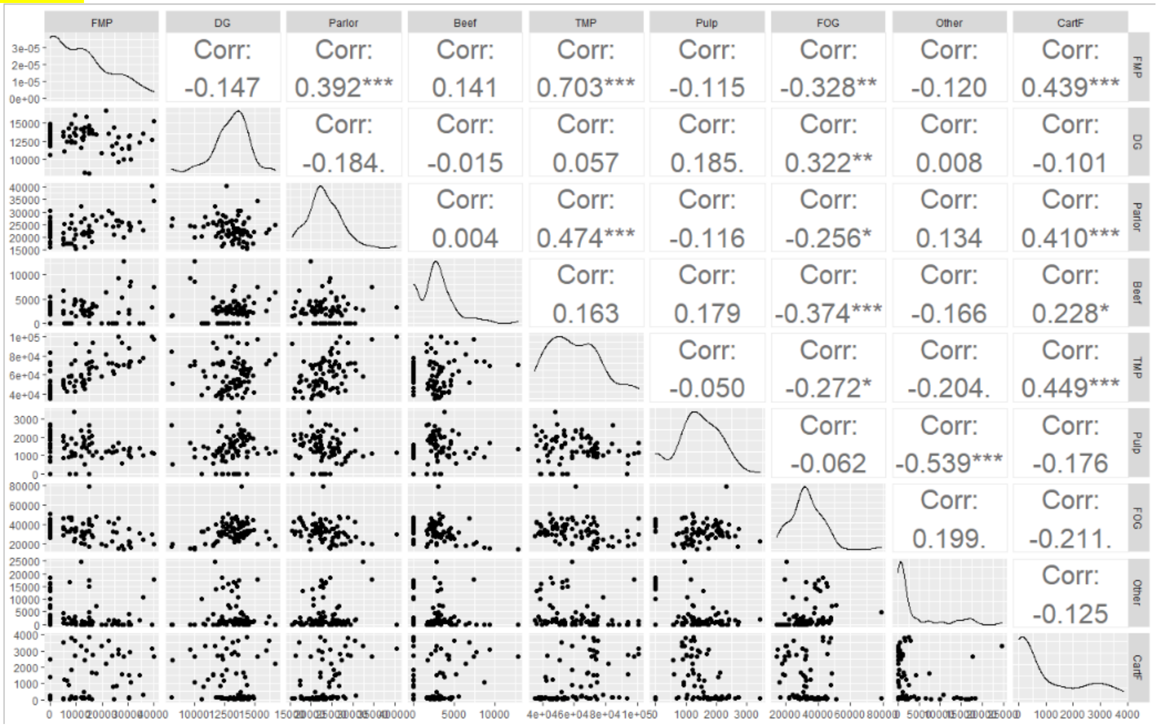

Figure H.1 Correlation plot between the parameters part 1
(Note: FMP = filtrate manure pit, DG = Dairy Gutter, TMP = Total Manure Pit, CartF = Cart Food)

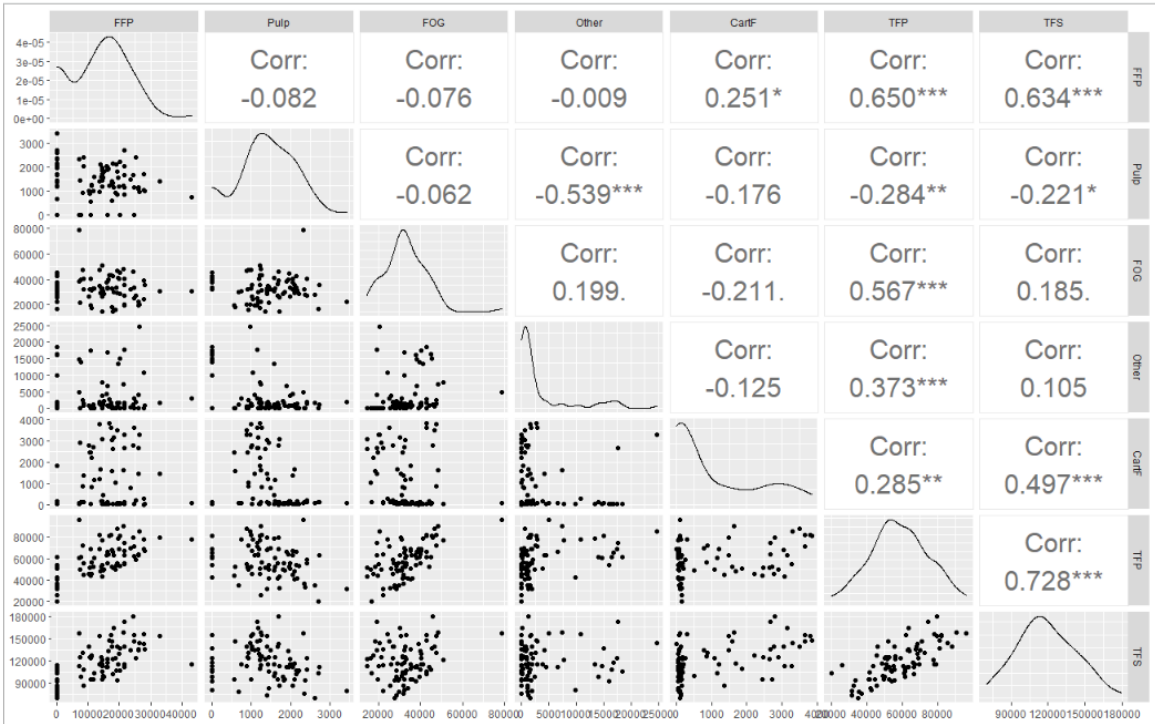

Figure H.2 Correlation plot between the parameters part 2
(Note: FFP = Filtrate Food Pit, TFP = Total Food Pit, TFS = Total Feedstock)

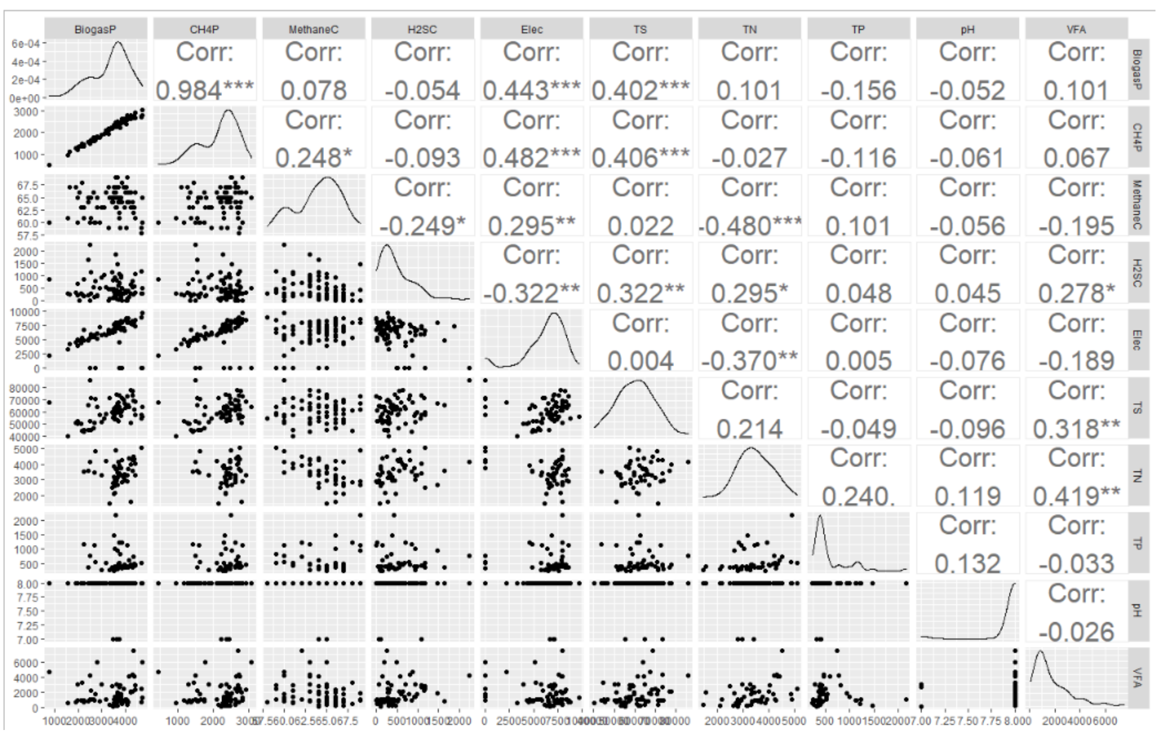

Figure H.3 Correlation plot between the operational parameters
(Note: BiogasP = Biogas Production, CH4P = Methane production, MethaneC = Methane Concentration, H2SC = hydrogen sulfide concentration, Elec = Electricity)

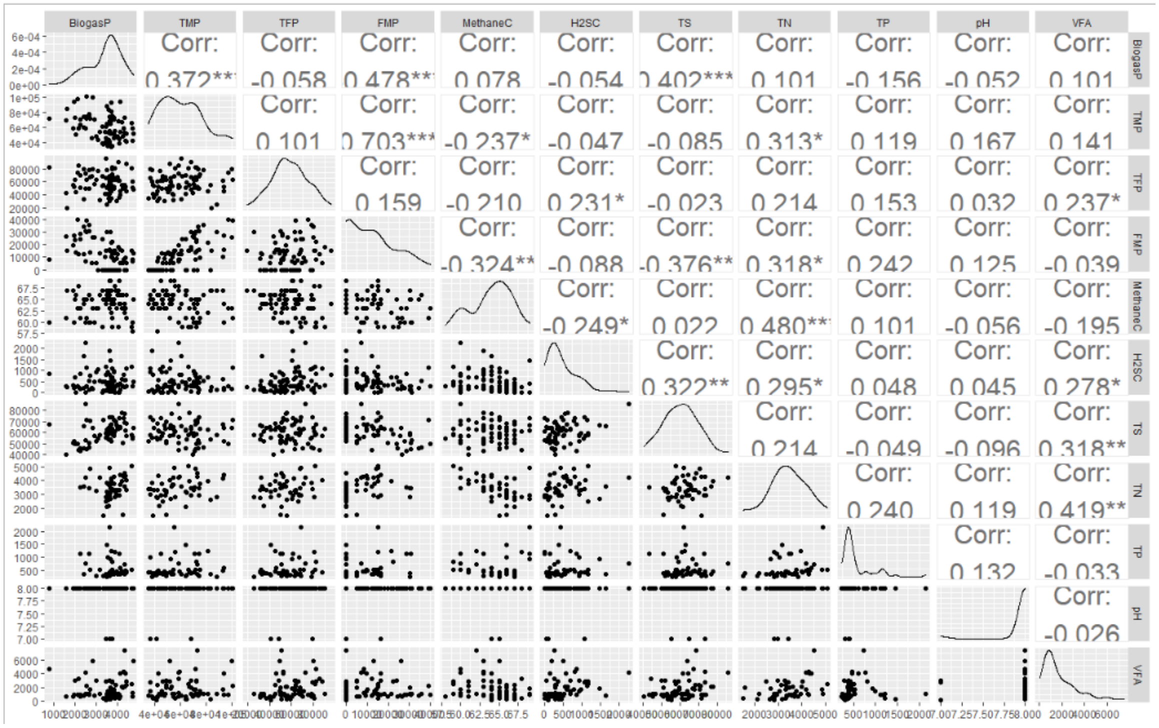

Figure H.4 Correlation plot between the total feedstock and the operational parameters

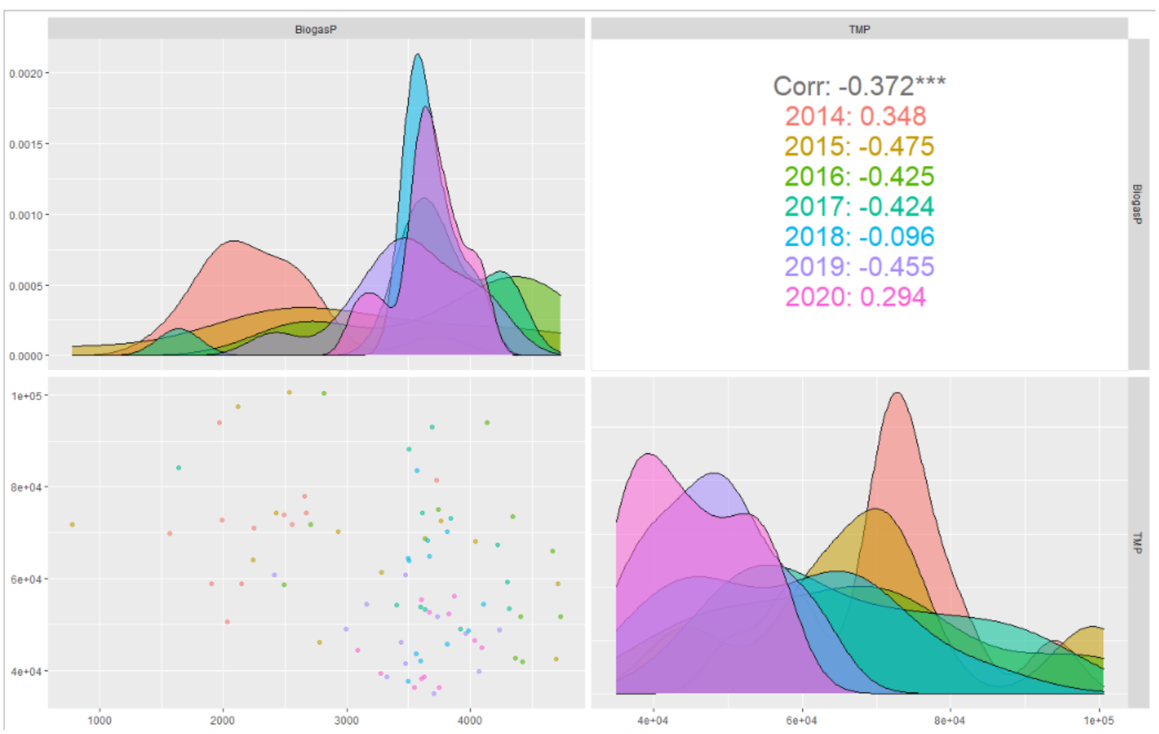

Figure H.5 Correlation plot between the total manure pit and the biogas production

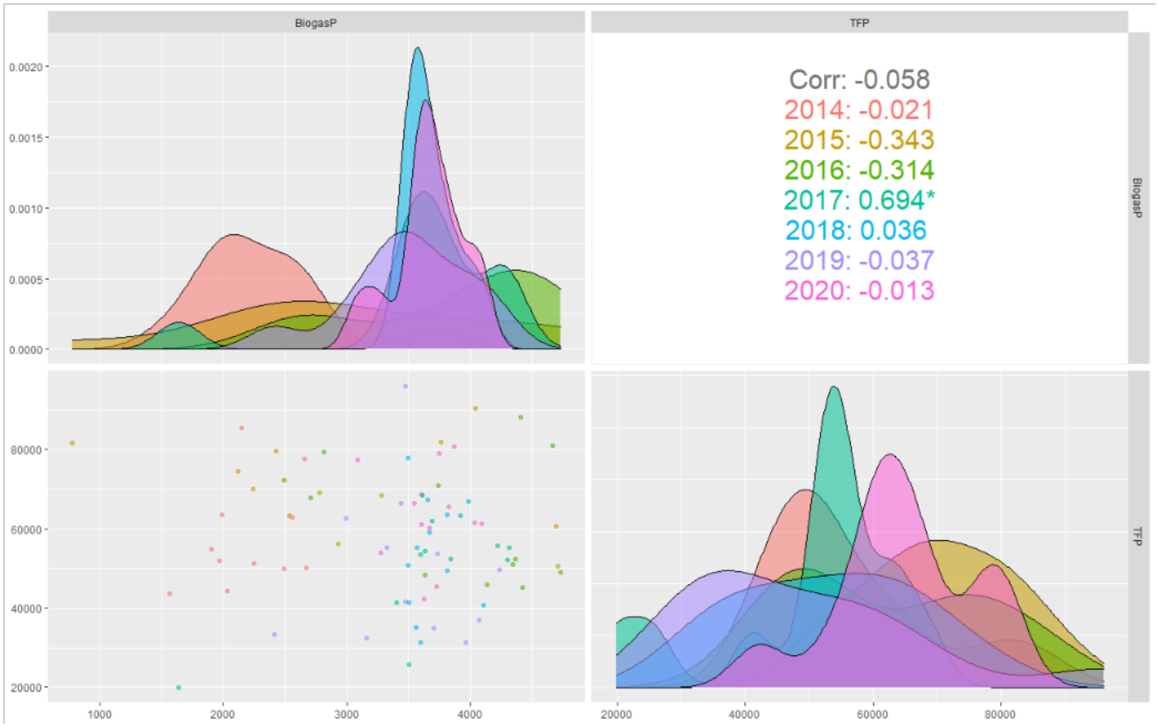

Figure H.6 Correlation plot between the total food pit and the biogas production

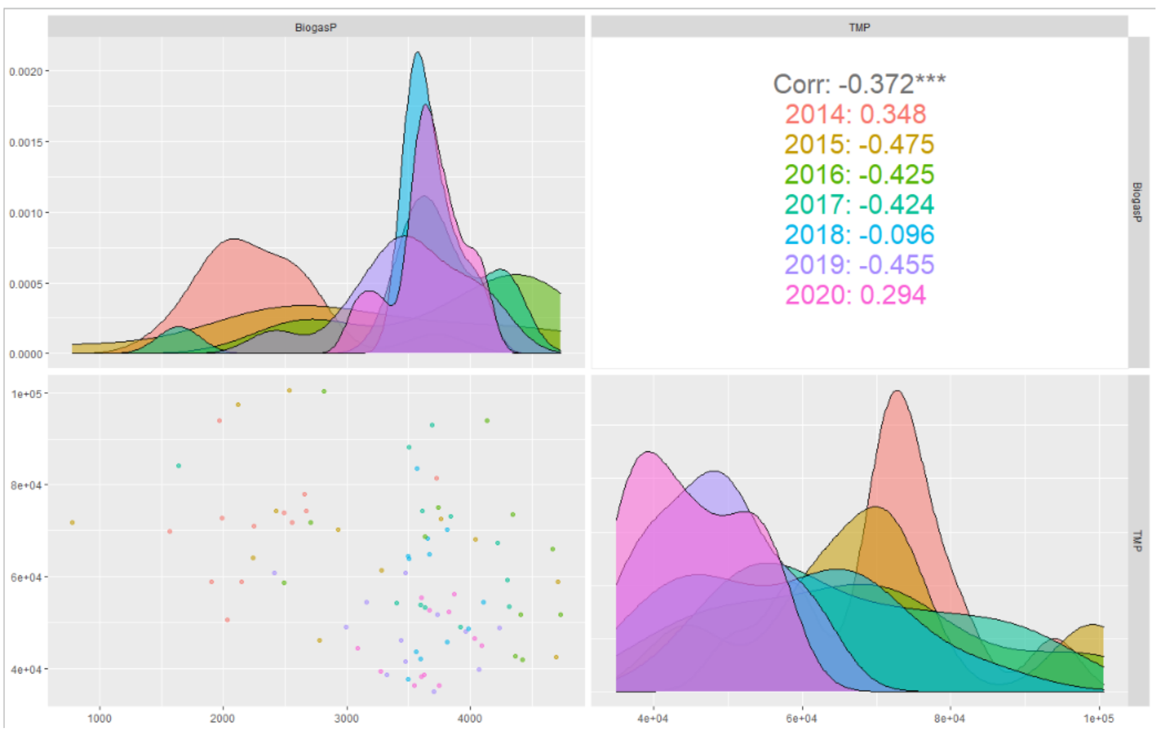

Figure H.7 Correlation plot between the total feedstock and the biogas production

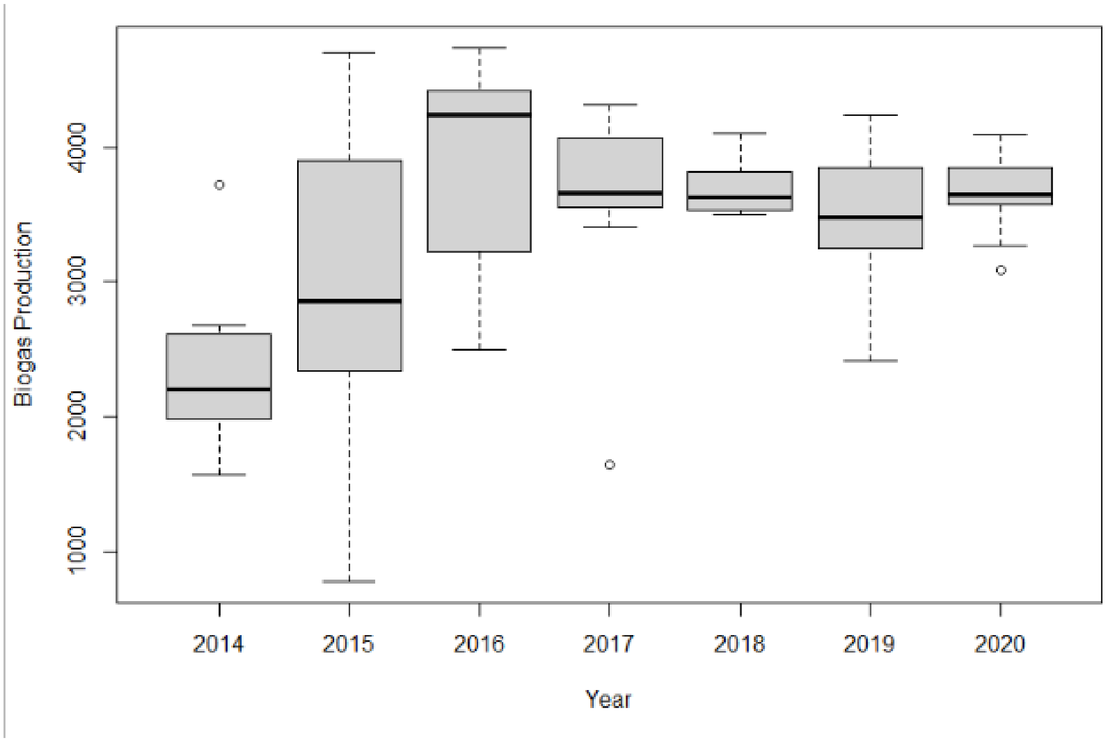

Figure H.8 The data distribution of the biogas production from 2014 to 2020

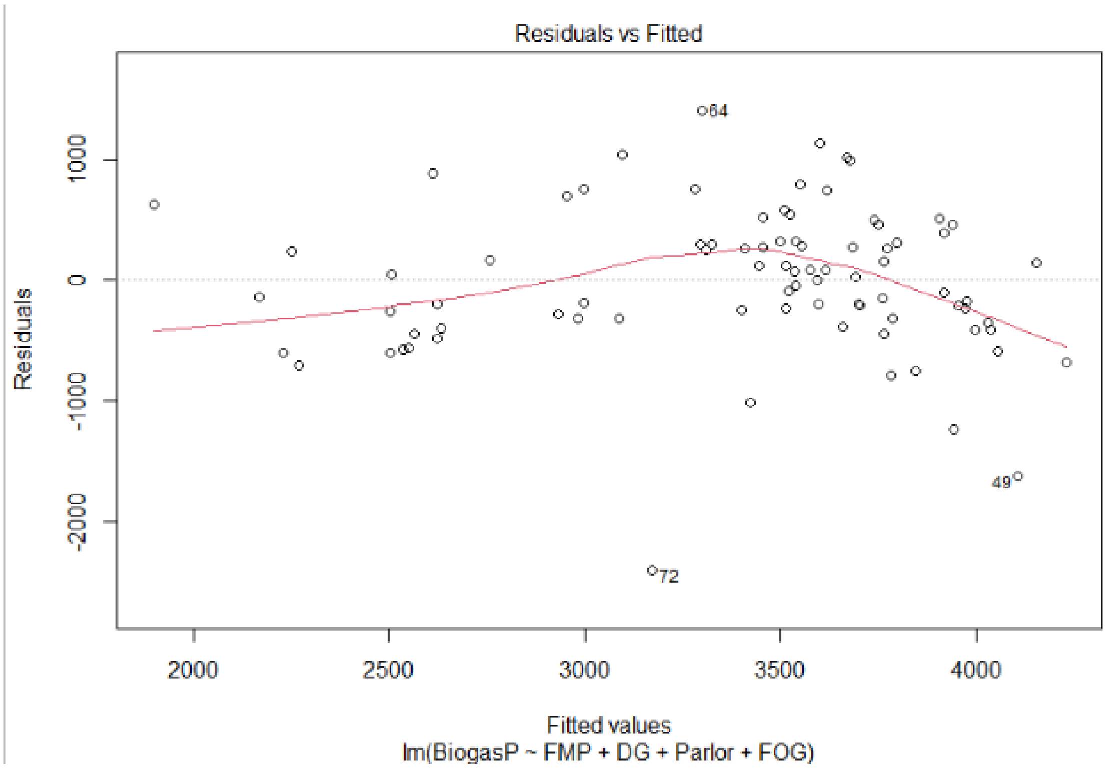

Figure H.9 Linear model plot of biogas production (residuals vs fitted)

I. R-Code of MLR for operational parameters impact on biogas production

```
# Load libraries -----
library(dplyr)
library(FSA)
library(psych)
library(car)
library(rcompanion)

# Choose data file of "MLR_operational_parameters.txt" -----
con <-file.choose(new = FALSE)
metadata <- read.table(con, header = T, row.names = 1, fill = TRUE)
head(metadata)

##############################
# select data
data.num = select(metadata, OLR, HRT, Temperature, pH, Biogas,
               Methane)
head(data.num)

# corr.test(data.num, use = "pairwise", method="pearson", adjust="none", alpha="0.05")


#############################################
#        Correlations                  #
#############################################


library(psych)

pairs.panels(data.num,
          method = "pearson", # correlation method
          hist.col = "#00AFBB",
          density = TRUE,  # show density plots
          ellipses = TRUE # show correlation ellipses
)

summary(data.num$Methane)
plot(data.num$Methane)
hist(data.num$Methane)


model1<-lm(Methane~OLR+HRT+Temperature+pH,data=data.num)
summary(model1)

model2<-lm(Biogas~OLR+HRT+Temperature+pH,data=data.num)
summary(model2)
```

```
# Scatterplots of variables
# regression line : Green
# non-parametric mean : Red
# non-parametric variance: Blue
scatterplotMatrix(data.num,
            diagonal=FALSE,
            regLine = list(col="green",lwd=3),
            smooth=list(col.smooth="red",
                    col.spread="blue")
)
```

RESULTS

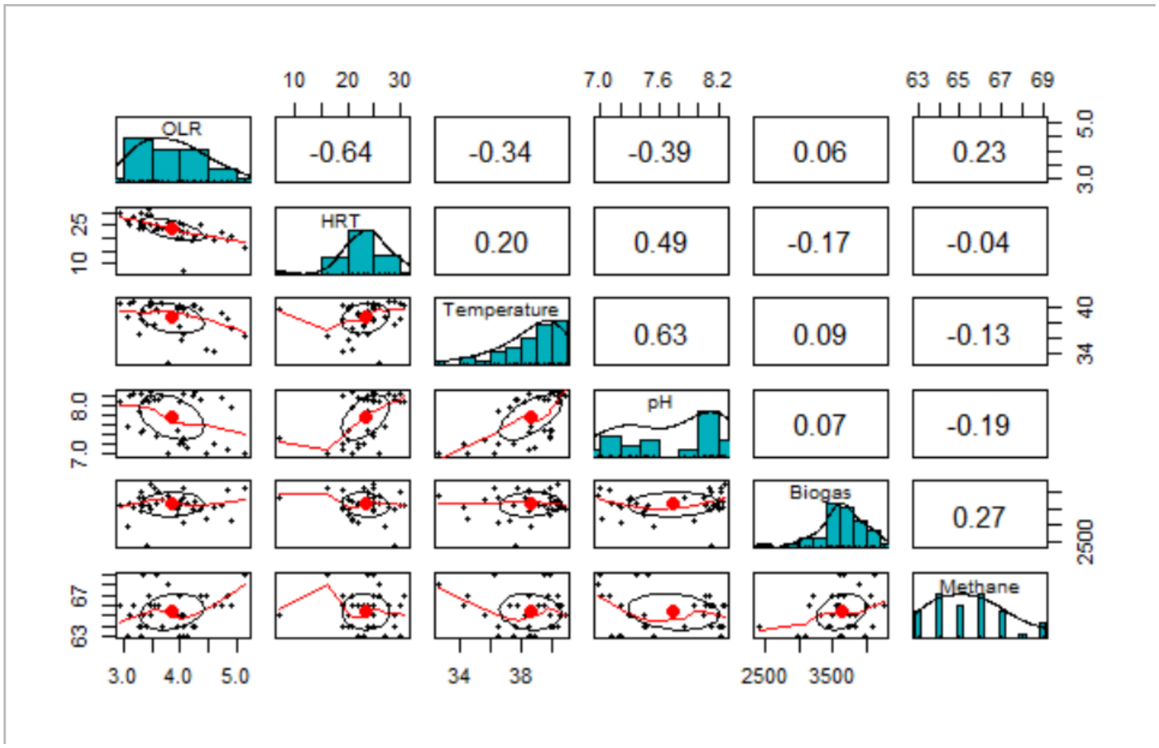

Figure I.1 Correlation plot between the operational parameters and the dependent variables (biogas production and methane concentration)

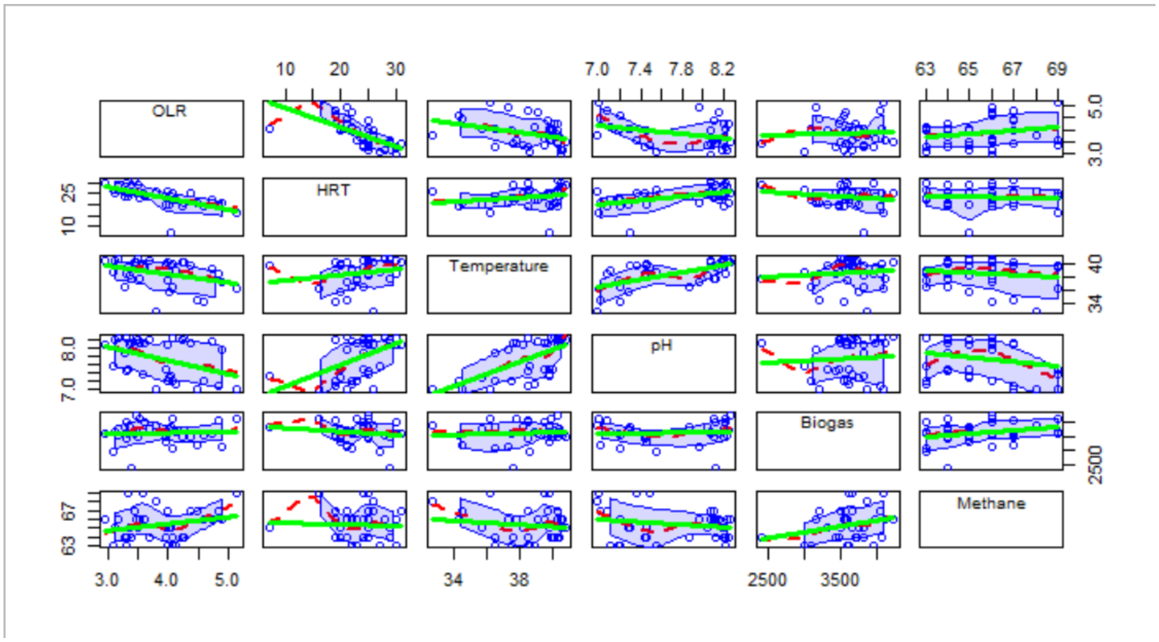

Figure I.2 Scatter plots of variables
(Note: green = regression line, red = non-parametric mean, blue = non-parametric variance)

REFERENCES

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