

**Process Modeling and Life Cycle Assessment of a Large Pilot-Scale Aquaponics Facility at
Auburn University**

by

Rohit Kalvakaalva

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Approved by

Brendan Higgins, Chair, Assistant Professor Biosystems Engineering
David Blersch, Associate Professor Biosystems Engineering
Terry Hanson, Professor School of Fisheries, Aquaculture and Aquatic Sciences
Daniel Wells, Associate Professor Horticulture

Abstract

Aquaponics has often been hailed as a more sustainable approach to fish and crop production when compared to traditional aquaculture and hydroponics. However, there have been insufficient data to support claim in addition to a general lack of studies seeking to model the biological and chemical interactions within system operation. In an effort to address this knowledge gap, an internally consistent life cycle assessment (LCA) was conducted on a decoupled, semi-commercial aquaponics facility which produced tilapia and cucumbers. The LCA was able to quantify environmental impacts such as global warming potential (GWP), Marine Eutrophication (MEP), Freshwater Eutrophication (FWP), water depletion (WD), cumulative energy demand (CED) and land usage (LU) for one calendar year. In order to further understand the water and nutrient flows through the system, a process engineering model was constructed and calibrated based on elemental composition data of biological materials, soluble nutrient concentration, greenhouse gas emissions, water flows and feed inputs. The resultant model was utilized to understand how changes in upstream inputs affected downstream impacts. The assessment found that seasonal differences of environmental impacts existed within normal system operation stemming from operational changes as well as changes in system demands such as heating requirements in the winter and increased ventilation during the summer months. Utilizing the process model for scenario analyses found that sufficient nutrients exist for further plant production which could lower eutrophication environmental impacts.

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Table of Contents

Acknowledgments.....	iii
List of Tables	vi
List of Figures	vii
List of Abbreviations	ix
1. Introduction	1
2. Chapter 1: Direct Greenhouse Gas Emissions	4
2.1 Introduction	4
2.2 Materials and Methods	6
2.2.1 Aquaponics Facility Description.....	6
2.2.2 <i>Gas Sampling Across Seasons and Experiments</i>	7
2.2.3 Gas Sampling in Fish Tank.....	8
2.2.4 Gas Sampling in Clarifiers	10
2.2.5 Gas Sampling in Plant Greenhouse.....	10
2.2.6. Gas Concentration Measurements by Gas Chromatography	11
2.2.7 Measurement of Operational Parameters	11
2.2.8 Statistical Analysis	12
2.3 Results	13
2.3.1 Fish Tank Emissions	13
2.3.2 Clarifier Emissions.....	14
2.3.3. Plant Production Emissions	16
2.4 Discussion.....	20
2.4.1 System Emissions	20
2.4.2 Practical Implications.....	23
3.0 Chapter 2: Construction of a Mass-Balance Process Engineering Model	25
3.1 Introduction	25
3.2 Methods	27
3.2.1 System Description	27
3.2.2 Biological Material Collection and Compositional Analysis.....	28
3.2.3 Water Sampling.....	29
3.2.4 Greenhouse Gas Emissions	29
3.2.5 Other Data Collection	30
3.2.6 Model Construction and Calibration.....	30
3.2.7 Model Assumptions	33

3.3 Results and Discussion	35
3.3.1 System Production	35
3.3.2 Nitrogen	36
3.3.2.1 Denitrification.....	38
3.3.3 Phosphorus	39
3.3.4 Water Partition	41
3.4 Limitations and Conclusions	43
4.0 Chapter 3: Life Cycle Assessment.....	45
4.1 Introduction	45
4.2 Methods	47
4.2.1 Goal and Scope	47
4.2.2 System Description	48
4.2.3 Data Collection.....	49
4.2.3.1 Water Quantity and Quality.....	50
4.2.3.2 Greenhouse Gas and Nutrient Emissions	50
4.2.4 Life Cycle Inventory	51
4.2.5 Co-product Allocation.....	51
4.2.6 Life Cycle Impact Assessment.....	53
4.2.7 Scenario Analysis.....	53
4.3 Results and Discussion	55
4.3.1 Inventory and System Yields	55
4.3.2 System Impacts	55
4.3.2.1 Greenhouse Gas Emissions.....	55
4.3.2.2 Eutrophication Potential	58
4.3.2.3 Energy Demand	60
4.3.2.4 Water depletion.....	61
4.3.2.5 Land Usage	62
4.3.3 Scenario Analyses	62
5.0 Conclusions.....	65
5.1 Future Work.....	66
6.0 References.....	67
7.0 Appendix.....	76
7.1 Appendix Figure 1	77
7.2 Appendix Figure 2.....	75

List of Tables

Table 1 Model Parameters from the 3-stage Clarifier	16
Table 2 Model Parameters from the pH Study	18
Table 3 Model Parameters from the Substrate Study	19
Table 4 Empirical Formulas.....	32
Table 5 Stoichiometric Constants	33
Table 6 Extent of Reactions	34
Table 7 Life Cycle Inventory	51
Table 8 Description of Scenarios	54
Table 9 Scenario 1 Results.....	59
Table 10 Overall Scenario Results.....	60

List of Figures

Figure 1: Scheme of the pilot-scale aquaponics system at Auburn University.	7
Figure 2: A general schematic of flow through the aquaponics facility (upper left). Water from the fish tank recirculates through a 3-stage clarifier (blue), which removes a portion of the suspended solids. From there, clarified water either returns to the fish tank or is pumped to the plant house for irrigation use. Values (g L^{-1}) are total suspended solids. Photographs showing GHG collection equipment: the inflatable bag used in the fish tank (upper right); the floating fixed-headspace rafts used in the clarifiers (lower left); and the fixed-headspace gas flux chamber placed on the plant growth substrate in 11 L Dutch buckets (lower right).	8
Figure 3: Efflux of GHGs (CO_2 , CH_4 , N_2O) from the fish tank. Measurement of the aerated regions (blue lines) using inflatable bags were conducted throughout the study. Measurement of the non-aerated regions (red lines) using the fixed-headspace rafts began in the fall of 2019.	14
Figure 4: Efflux of GHGs (CO_2 , CH_4 , N_2O) from the clarifier system. Clarifiers 1, 2, and 3 refer to the three stages of the clarifier system which were connected in series. Stage 1 receives influent water from the fish tank.	15
Figure 5: Efflux of GHGs (CO_2 , CH_4 , N_2O) from the plant production system during the pH study conducted in the summer of 2019. Data for pH 7.0 from the fourth sampling date were unavailable due to sampling error.	17

Figure 6: Efflux of GHGs (CO ₂ , CH ₄ , N ₂ O) from the plant production system during the substrate study conducted in the fall of 2019 and the winter of 2020.	18
Figure 8: Flow of nitrogen through the aquaponics facility based on outputs from the model parametrized with spring season data.	37
Figure 9: Nitrate concentrations in the three main unit processes of the aquaponics system: fish tank (top), clarifier (middle), and plant production (bottom).	38
Figure 10: Flow of phosphorus through the aquaponics facility based on outputs from the model parametrized with spring season data.	40
Figure 11: Soluble phosphate concentrations in the three main unit processes of the aquaponics system: fish tank (top), clarifier (middle), and plant production (bottom).	41
Figure 12: Distribution of water flows through the aquaponics system across season.	42
Figure 13: Comparison of modeled and actual irrigation water flows over time.	43
Figure 14: System boundary of the semi-commercial aquaponics facility.....	49
Figure 15: Global warming potential of direct and upstream processes (top) and direct system emissions (bottom). All values are represented per kilogram of tilapia.	57
Figure 16: Marine eutrophication potential (top) and freshwater eutrophication (bottom) represented in terms of kilograms of tilapia produced.....	59
Figure 17: Cumulative energy demand of system operations per kilogram of tilapia produced..	61
Figure 18: System water depletion per kilogram of tilapia produced.....	62

List of Abbreviations

LCA	Life Cycle Assessment
GWP	Global Warming Potential
MEP	Marine Eutrophication Potential
FWP	Freshwater Eutrophication Potential
CED	Cumulative Energy Demand
WD	Water Depletion
LU	Land Usage
FU	Functional Unit

1. Introduction

As the world's population continues to grow, the need for clean water and sustainable food sources is becoming increasingly important. Currently, over 60 percent of the world's fish supply comes from traditional inland aquaculture systems (FAO and UNICEF 2018). These systems present various environmental problems, specifically the production of nutrient-rich waste water. Traditionally, nutrient-rich water as a byproduct of aquaculture production has been treated as a waste product contributing to runoff and eutrophication leading to wide variety of environmental problems. Aquaponics, which is the practice of combining traditional aquaculture and hydroponics, addresses these problems by making use of the aquaculture waste nutrients and utilizing them for hydroponic crop production. It is also known to reduce water use (Jaeger et al. 2019), naturally clean waste water from aquaculture production, increase food production capacity, and potentially increase profitability to producers (Love et al. 2015). The crops produced affectively treat the water allowing for simultaneous water treatment and food production while solid waste produced in the aquaculture system, also rich in nitrogen-based compounds, can be repurposed as fertilizer for traditional field crops initially allowing for a more environmentally friendly approach to fish and crop production (Mirzoyan, Tal, and Gross 2010).

Thus far, aquaponics has been assumed to be a sustainable means of fish and crop production especially when compared to traditional aquaculture and hydroponic practices. However, there is currently insufficient data to fully support this claim; therefore, a robust study on the environmental impacts of large pilot-scale aquaponics systems is necessary in order to support the hypothesis that aquaponics is more sustainable than a stand-alone recirculating aquaculture systems. Life cycle assessments (LCA) are a "cradle-to-grave" methodological approach to

quantitatively assess sustainability of a system (Bohnes et al., 2019). LCA's have been used to analyze aquaponics systems (Forchino et al. 2017; Gennotte et al. 2017; Jaeger et al. 2019; Xie and Rosentrater 2015) but most of these studies are internally inconsistent as they often draw upon data from multiple literature sources and studies of systems that are not comparable. Through this project, we aim to remedy this deficiency by leveraging our access to a semi-commercial scale aquaponics facility at Auburn University. Here we seek to utilize data collected in this pilot facility to develop and calibrate engineering process models and use these to create an internally consistent life cycle assessment. By first engaging in process modeling, it allows us to more fully understand the impact of different management practices and scenarios on environmental performance.

Conducting a life cycle assessment will help to further increase the sustainability of aquaponics and reduce environmental impacts by providing decision support to producers. Our analyses pinpoint key processes that contribute most to environmental impacts, allowing for development of new technologies and best management practices to mitigate these impacts. Because life cycle assessment looks at a wide range of sustainability metrics (e.g. energy, water, nutrients), any tradeoffs associated with different management practices will be quantifiable which allows for the design of a system that simultaneously meets multiple sustainability goals.

The main goal of this project was to (1) Construct an internally-consistent LCA model to quantify the environmental impacts of the aquaponics facility at Auburn University. Additionally, there are very few models which include the greenhouse gas emissions from different operations from aquaponics systems. Therefore, we sought to (2) collect greenhouse gas data from multiple stages within the system including from the main tilapia tank, greenhouse Dutch buckets, and clarifiers to further understand environmental impacts of the system.

Additionally, the constructed LCA should be able to explain which operations within the system contribute the most to environmental impacts. Due to data being collected for a full calendar year, this study will also be able to (3) answer whether seasonal variations in operating parameters strongly influence environmental impacts as well. The resultant modeling will (4) be able to direct future decisions regarding operation of the system in order to decrease environmental impact, increase productivity and profit as well as increase the overall sustainability.

2. Chapter 1: Direct Greenhouse Gas Emissions

2.1 Introduction

Increased anthropogenic emissions of CO₂ and other greenhouse gases (GHG) have been cited as the main driving force for climate change (Florides and Christodoulides, 2009) with CO₂, CH₄, and N₂O levels increasing by approximately 42, 154, and 21%, respectively, since 1750 (Blasing and Smith, 2016). According to the IPCC, agriculture accounts for ~24% of the world's GHG emissions, dwarfed only by electricity and heat production (25%; IPCC, 2014). This presents the need to understand and create effective ways to mitigate GHG emissions from agricultural systems.

Previous studies have quantified direct trace gas emissions from agriculture production systems and have suggested mitigation techniques based on their findings (Erda et al., 1994; Smith et al., 1997; Kroeze and Mosier, 2000; Paustian et al., 2000). Such techniques include no-till agriculture and more efficient use of N fertilization in an effort to mitigate direct emissions (Prior et al., 2004; Torbert et al., 2004). Various studies have also examined non-traditional agriculture methods such as container based production (Marble et al., 2012a, b) and greenhouse plant production (Pishgar-Komleh et al., 2013). Other studies have attempted to quantify emissions from aquaculture in open-pond production (Wu et al., 2018); some of these studies did not measure direct emissions, instead focusing on upstream emissions for inputs such as electricity and feed (Robb et al., 2017).

Aquaponics, the practice of combining aquaculture and hydroponics, has the potential to reduce environmental impacts of food production by repurposing aquaculture wastewater for hydroponic crop production (Rakocy et al. 2003). The crops produced can effectively treat this water allowing for simultaneous water treatment and food production. The solid waste produced

in aquaculture systems (rich in nitrogen-based compounds) could be repurposed as fertilizer for traditional field crops, allowing for sustainable crop production.

Many studies have attempted to quantify and qualify the environmental impacts of aquaponics (Genotte et al., 2019; Jaeger et al., 2019), and in many cases have shown aquaponics to have lower overall environmental impacts than traditional aquaculture. Even with such promise of environmental benefit, there are still questions concerning the fate and flow of key elements such as carbon, nitrogen, and phosphorus (Cerozi and Fitzsimmons, 2017), as well as the overall sustainability of aquaponics systems (Konig et al., 2016).

While most studies on aquaponics focus on nutrients and aquatic pollutants, there is little information regarding direct GHG emissions from aquaponic facilities. Previous studies have examined GHG emissions from more traditional hydroponic and greenhouse production systems (Hashida et al., 2014; Monsees et al., 2019), but aquaponic systems have significantly different water quality and microbial communities compared to hydroponic production systems (Schmautz et al., 2017). Even within aquaponic systems, there are vast differences in unit operations that could impact both water quality and microbial populations that are major drivers of direct GHG emissions. To our knowledge, there are no studies that have measured direct GHG emissions from a commercial-scale aquaponic system. The objective of this research was to quantify direct GHG emissions (i.e., CO₂, CH₄, and N₂O) from a pilot-scale, decoupled biofloc aquaponic system. Emissions were measured across all major unit operations in this system (i.e., fish production, solids separation, and plant production). Within these unit operations, we also sought to understand which environmental, operational, and water quality parameters influenced GHG emissions. These data will support environmental assessments of aquaponics including life cycle assessments (LCAs) that, to-date, have only focused on upstream GHG emissions (e.g.,

electricity and feed production) while ignoring direct facility emissions (Love et al., 2015; Xie and Rosentrater, 2015; Ghamkhar et al., 2020).

2.2 Materials and Methods

2.2.1 Aquaponics Facility Description

Auburn University operates a commercial-scale aquaponics facility located at the E.W. Shell Fisheries Center. This aquaponics facility consists of two separate 279 m² environmentally-controlled greenhouses; one for fish production and one for vegetable/plant production. The facility has been in operation as an integrated production system for Nile tilapia (*Oreochromis niloticus*) and Beit Alpha seedless cucumbers (*Cucumis sativus*) since November 2015 (Figure 1). This facility currently produces an average of 23 kg of tilapia and 45 kg of cucumbers weekly for Auburn University campus dining facilities. Tilapia were produced in happa nets within a 150 m³ biofloc tank and fed using a combination of 3606 and 4010 soy based feed (Cargill, Franklinton, LA, USA). 3606 indicates a combination of 36% protein and 6% fat content while 4010 indicates 40% protein and 10% fat. The average feeding rate (kg/h) was determined on a weekly basis by summing the total amount of feed used in a given week and dividing by the number of hours in a week. Water from the fish tank was recirculated through a 3-stage clarifier, which removes a portion of the suspended solids. From there, clarified water either returns to the biofloc fish tank or is pumped to the plant house for irrigation use. Plants were grown in 11-L

Dutch buckets (Crop King Inc., Lodi, OH, USA), which feature a water perch and drain and were filled with a solid substrate (either perlite or pine bark in the studies conducted).

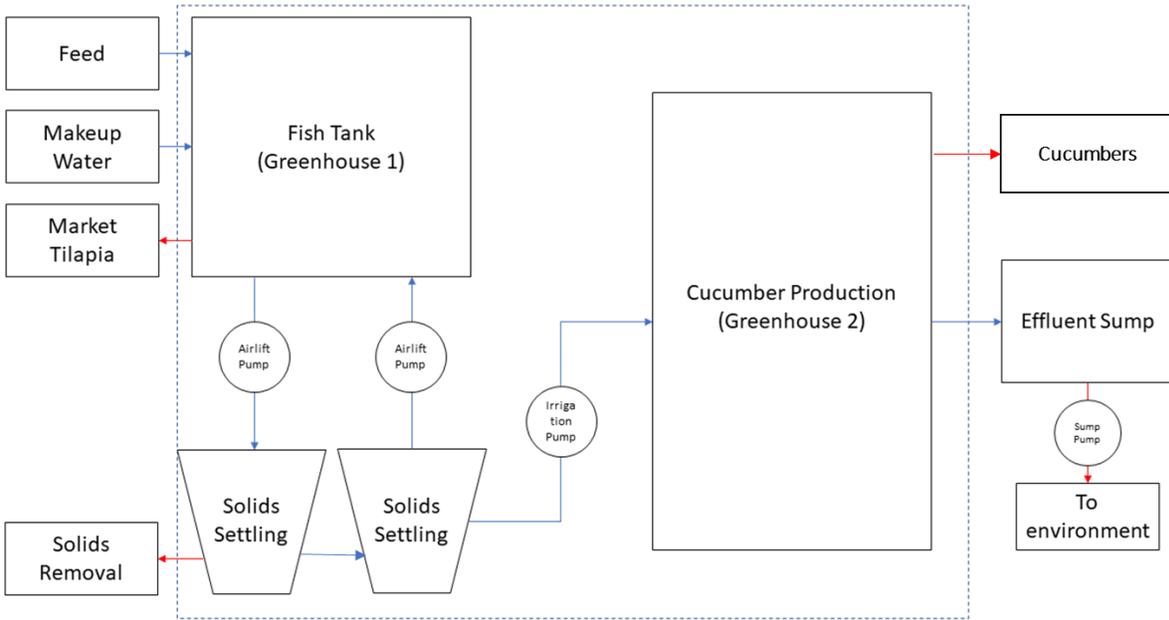


Figure 1: Scheme of the pilot-scale aquaponics system at Auburn University.

2.2.2 Gas Sampling Across Seasons and Experiments

Gas sampling occurred at the aquaponics facility from May 2019 to March 2020 in concurrence with three plant production studies. Gas samples were taken from the fish tank, the 3-stage clarifier, and the plant production greenhouse (Figure 2).

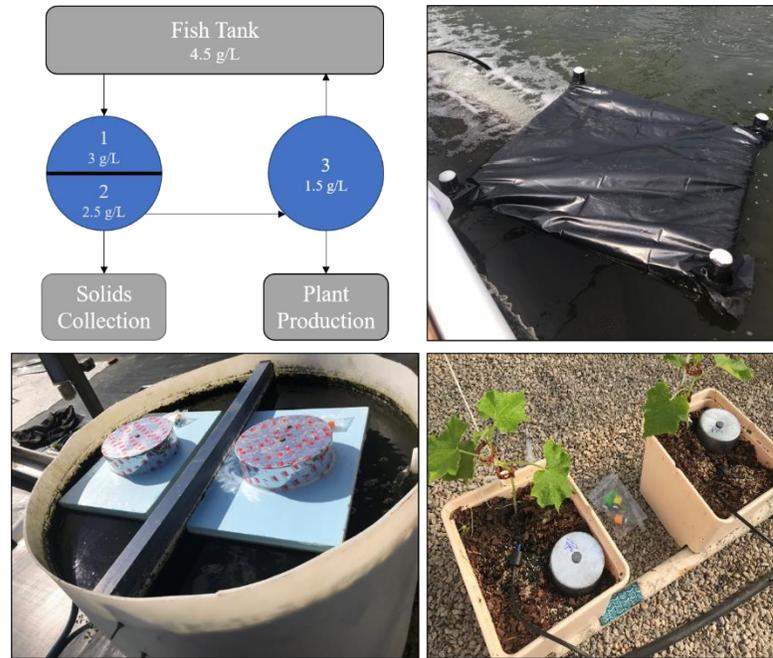


Figure 2: A general schematic of flow through the aquaponics facility (upper left). Water from the fish tank recirculates through a 3-stage clarifier (blue), which removes a portion of the suspended solids. From there, clarified water either returns to the fish tank or is pumped to the plant house for irrigation use. Values (g L^{-1}) are total suspended solids. Photographs showing GHG collection equipment: the inflatable bag used in the fish tank (upper right); the floating fixed-headspace rafts used in the clarifiers (lower left); and the fixed-headspace gas flux chamber placed on the plant growth substrate in 11 L Dutch buckets (lower right).

2.2.3 Gas Sampling in Fish Tank

The fish tank was constantly aerated to maintain appropriate dissolved oxygen (DO) levels in the bulk liquid ($>7 \text{ mg/L}$). Three 1 m^2 inflatable floating rafts were constructed and supported an inflatable plastic bag. The rafts were placed at three separate locations in the fish tank with bags completely deflated of air. Gas samples were collected from bags (once fully inflated by rising aeration bubbles) using a polypropylene syringe and injected into previously evacuated 10 ml glass vials. A similar approach has been used to measure direct GHG emissions from aerated wastewater treatment tanks (Czepiel et al., 1995; Law et al., 2012). Assuming that the fish tank was constantly and uniformly aerated, airflow rate and aerator depth were used to calculate trace

gas flux (Eq. 1). Airflow in the blower line was determined by measuring air velocity in the line (1 m s^{-1}) using a pitot tube probe (Velocicalc Air Velocity Meter 9535, TSI Inc., USA) and multiplying by the pipe cross sectional area. Air pressure was obtained based on the pressure head at the diffuser exit, which was placed at a depth $\sim 1 \text{ m}$ below the water line.

$$Flux \left(\frac{mg}{m^2 \cdot day} \right) = MW_{Gas} * \dot{n} * C * \frac{86400}{SA_{FishTank}} \quad \text{Eq. 1}$$

$$\dot{n} = \frac{P * Q}{R * T} \quad \text{Eq. 2}$$

In the above equation, MW_{Gas} is the molecular weight of a given GHG, \dot{n} is the molar flow rate of air including GHGs (mol/sec) into the entire fish tank (Eq. 2), C is the concentration of a particular GHG on a molar percent basis as measured by gas chromatography, SA is the surface area of the fish tank, P is the air pressure at the diffuser exit (Pa), Q is the gas flow rate (m^3/sec), R is the ideal gas constant, and T is the temperature (K).

In reality, aeration bubbles were not distributed uniformly across the surface of the fish tank. Since some areas received less aeration than others, we also employed fixed-headspace rafts for measurement of GHG emissions from these areas of low aeration. Polystyrene rafts ($0.61 \text{ m} \times 0.41 \text{ m}$) holding fixed-headspace gas chambers (0.28 m diameter $\times 0.11 \text{ m}$ height above the waterline), were sampled using the methods described in Hutchinson and Mosier (1981); chambers were sampled at three time points ($t_0=0 \text{ min}$, $t_1=20 \text{ min}$, $t_2=40 \text{ min}$). At each time collection interval, gas samples were collected using a polypropylene syringe and injected into previously-evacuated 10 ml glass vials.

Concurrent measurement of well-aerated (via inflatable raft) and poorly-aerated (fixed headspace) allowed us to obtain a range of GHG fluxes in different regions of the tank. Ambient air samples were collected inside the fish greenhouse to capture background concentrations of GHGs. These background levels were subtracted from the concentrations measured in the rafts.

2.2.4 Gas Sampling in Clarifiers

The clarification system consisted of two 3,690 L cone-bottom settling tanks with the first unit divided into two partitions. Greenhouse gas emissions from each section of the clarifier were measured separately (Figure 2) where “Clarifier 1” is the first partition of the first settling tank into which fish tank water enters and “Clarifier 2” is the second partition where additional solids are removed. Water exiting “Clarifier 2” then enters “Clarifier 3” where the liquid effluent is either recirculated to the fish tank or used for irrigation. Floating rafts (as described above) were placed in each section of the clarifiers and sampled as described for the fish tank.

2.2.5 Gas Sampling in Plant Greenhouse

Greenhouse gas emission measurements in the greenhouse took place during three seasons, encompassing the summer and fall of 2019 and the early winter of 2020. During this time period, three separate plant studies were conducted in the greenhouse facility. In all three studies, cucumbers were grown in 11-L Dutch buckets and were irrigated with aquaculture effluent via drip irrigation. An irrigation timer provided 6 to 8 L of fresh aquaculture effluent per day during daylight hours with timing varying based on growing season (Blanchard et al., 2020).

The summer study examined cucumbers grown using aquaculture effluent adjusted to four pH levels (5.0, 6.0, 6.5, and 7.0), where plants grown in pH 7.0 were the control. Fish tank pH was maintained at 7.0 by addition of hydrated lime, with downward adjustments of pH achieved by dosing with sulfuric acid. Further description of this study is outlined in Blanchard et al. (2020). All plants in this study were grown in perlite substrate. Out of the 125 cucumber plants grown in the greenhouse during the summer study, 12 plants (three plants grown in each pH treatment) were selected and monitored for GHG emissions biweekly from planting (week 1) until final harvest (week 9) for a total of 5 samplings.

During the fall and winter studies, plants were grown under two substrate conditions and irrigated with aquaculture effluent in which pH was left unaltered (pH = 7.0). Five plants grown in pine bark and five grown in perlite were selected and monitored approximately once per week from one week after planting (week 2) to final harvest (week 9) for a total of 6 time sampling points per study. Plants in all studies were randomly spaced throughout the greenhouse in order to eliminate the possibility of unintentional bias. Using the static closed chamber method (Rochette et al., 1992), measurements were taken *in situ* by placing a custom built gas flux chamber with a headspace of 0.206 L on the top of the substrate (Figure 2).

2.2.6. Gas Concentration Measurements by Gas Chromatography

Gas samples were analyzed to quantify three trace gases (CO₂, CH₄, and N₂O) using a gas chromatograph (Shimadzu GC-2014, USA) equipped with three detectors: thermal conductivity detector for CO₂, electrical conductivity detector for N₂O, and flame ionization detector for CH₄ and closely followed the procedures described by Marble et al. (2012b). Gas concentrations were determined by comparison with standard curves developed using gas standards (Air Liquide America Specialty Gases, LLC, USA). Trace gas fluxes (mg m⁻² d⁻¹) were calculated from the rate of change in gas concentration in the chamber headspace across the sampling time interval (0, 20, 40 min).

2.2.7 Measurement of Operational Parameters

Water samples were collected from each of the three aquaponics system components (i.e., fish tank, clarifier, and plant greenhouse) approximately weekly for one year. Samples were

collected, filtered (0.2 μm), and stored at $-80\text{ }^{\circ}\text{C}$ until analysis. At the conclusion of the sampling period, all samples were analyzed for soluble ion concentrations via high pressure liquid chromatography (HPLC; Shimadzu Prominence System, Kyoto, Japan) using an anion exchange column (Dionex AS22, ThermoFisher Scientific, USA) and ion suppressor (Dionex AERS 500, ThermoFisher Scientific, USA). The HPLC methods followed the procedures previously described by Chaump et al. (2019). Compounds detected included nitrate (NO_3^-), nitrite (NO_2^-), and phosphate (PO_4^{3-}).

In addition to feeding rates, water flows were metered and recorded daily and included fish tank makeup water and irrigation. Total suspended solids were also measured throughout the study in the fish tank and in each stage of the clarifiers using a 1000 ml Imhoff cone (Sojka, Carter, and Brown 1992). Outdoor air temperature data were imported from the National Centers for Environmental Information (NCEI) climate database for Auburn, AL and were averaged for each sampling day.

2.2.8 Statistical Analysis

Results were analyzed with SAS/STAT[®] software using multiple regression with a forward stepwise selection process in order to determine possible correlations between various parameters and each trace gas. Parameters for the plant house study included pH for the pH study and substrate type for the substrate study, weeks after planting (as a proxy for plant growth stage), temperature, irrigation rate, and NO_3^- concentration in the water. Clarifier parameters included temperature, irrigation rate (as a proxy for water flowrate), NO_3^- concentration, total suspended solids (TSS), and fish feeding rate. The same parameters were also evaluated for the fish tank. In all cases, correlations were considered significant at $p \leq 0.05$. After significant

variables were determined, modeled and actual values were compared, and the accuracy of the statistical models were quantified through the root mean square error (RMSE) for each model.

2.3 Results

2.3.1 Fish Tank Emissions

Carbon dioxide, methane, and nitrous oxide emissions from the fish tank averaged 8178, 4.68, and 16.7 mg m⁻² d⁻¹, respectively, based on collection from actively aerated regions of the fish tank (Figure 3). Flux measurements using the static headspace method in poorly-aerated regions of the tank were 1240, 0.10, and 3.54 mg m⁻² d⁻¹ for the respective trace gases. These values were roughly an order of magnitude lower than emissions from active aeration. The fish tank was an aerobic system (DO never dropped below 7 mg L⁻¹ in the bulk fluid) and was temperature-controlled using a propane air heater and fan ventilation (water temperatures ranged from 16.5 to 32.5°C over the course of the year). Trace gas emissions from the fish tank showed no significant relationships with any of the operational parameters (e.g. temperature, NO₃⁻, average weekly feed rate).

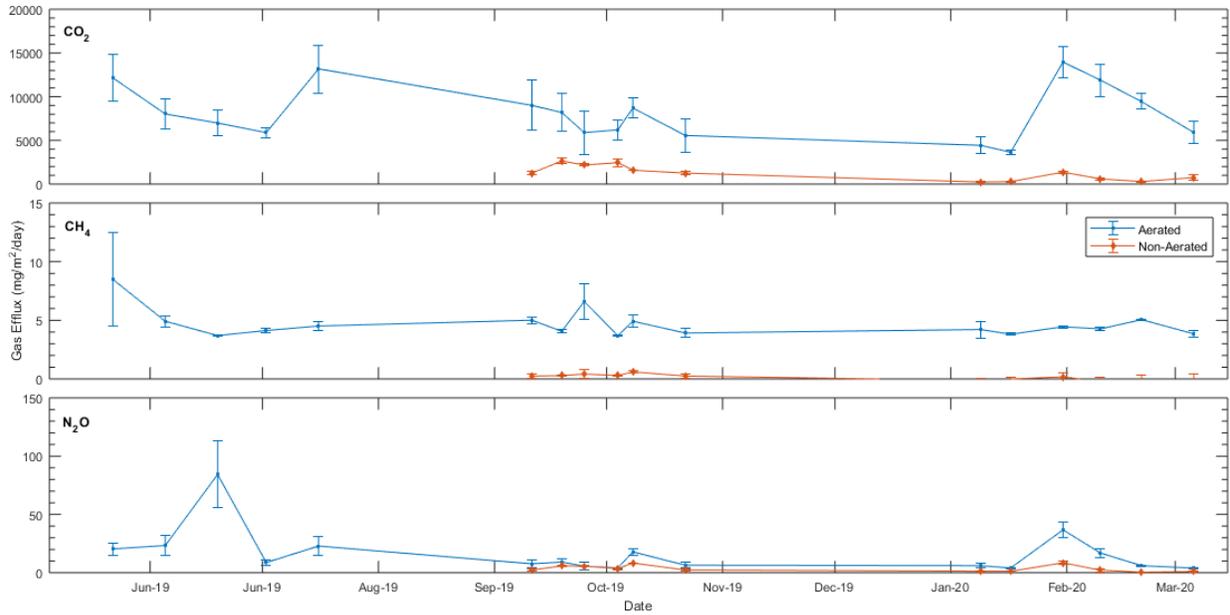


Figure 3: Efflux of GHGs (CO_2 , CH_4 , N_2O) from the fish tank. Measurement of the aerated regions (blue lines) using inflatable bags were conducted throughout the study. Measurement of the non-aerated regions (red lines) using the fixed-headspace rafts began in the fall of 2019.

2.3.2 Clarifier Emissions

Carbon dioxide, methane and nitrous oxide efflux from the 3-stage clarification system averaged 1070.4, 4831.9, 18.7 $mg\ m^{-2}\ d^{-1}$, respectively. The system had a maximum measured efflux for CO_2 on 7/16/19, CH_4 on 9/25/19, and N_2O on 10/8/19 at 5575, 44870, and 52.8 $mg\ m^{-2}\ d^{-1}$, respectively (Figure 4).

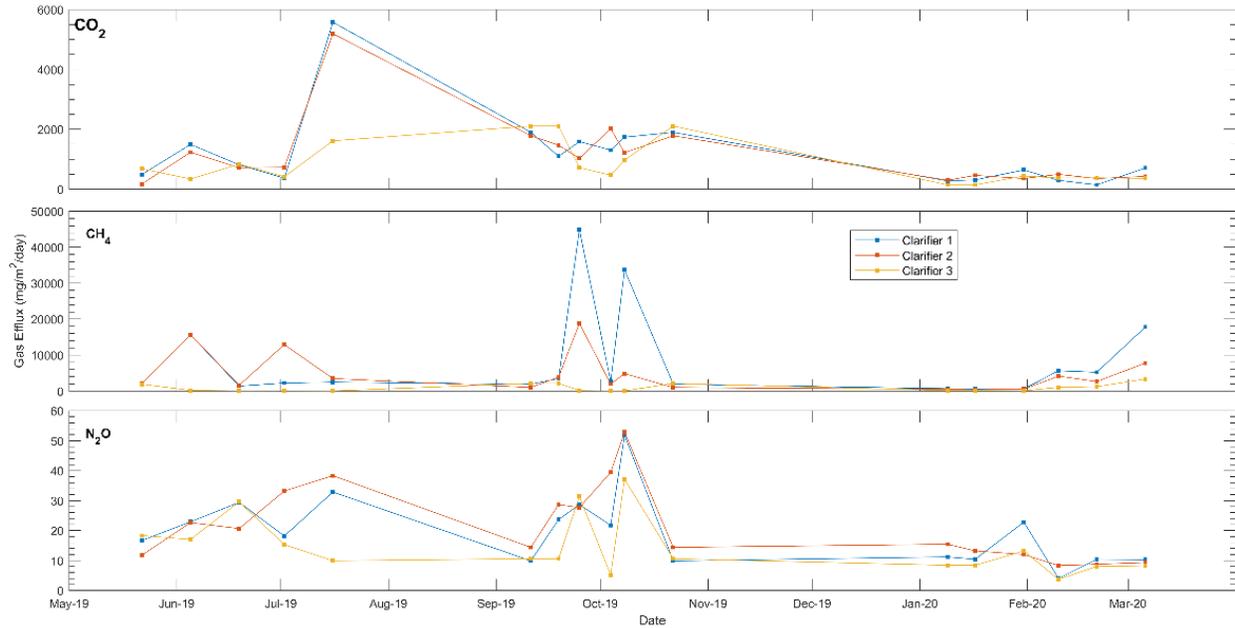


Figure 4: Efflux of GHGs (CO_2 , CH_4 , N_2O) from the clarifier system. Clarifiers 1, 2, and 3 refer to the three stages of the clarifier system which were connected in series. Stage 1 receives influent water from the fish tank.

The average ratio of CH_4 to CO_2 was 10^4 fold higher than in aerated portions of the fish tank. The clarifier had the highest levels of CH_4 emissions out of the three unit components with effluxes at four orders of magnitude higher than the fish tank and six orders of magnitude higher than in plant production. In general, the clarification process had lower gas effluxes as solids and water moved through each partition. Trace gas emissions from the clarification system also showed significance toward multiple operational parameters (Table 1). Carbon dioxide had a positive relationship with irrigation rate and NO_3^- concentration ($F_{2,48}=15.67$, $p<0.0001$, $RMSE=830.16$). Methane had a positive relationship with TSS ($F_{1,48}=7.73$, $p=0.0077$, $RMSE=7814.41$) while N_2O had a positive relationship with temperature ($F_{1,48}=14.98$, $p=0.0003$, $RMSE=19.54$).

Table 1.: Model parameters for CO₂, CH₄, and N₂O efflux from the 3-stage clarifier. Values were significant at a 95% confidence level.

Compound	Parameter	Parameter Estimate	F Value	P-Value
CO ₂	Intercept	-2000	15.67	<0.0001
	Irrigation	30.5		
	Nitrate	3.53		
CH ₄	Intercept	-7050	7.73	0.0077
	TSS	5090		
N ₂ O	Intercept	-4.86	14.98	0.0003
	Temperature	0.354		

2.3.3. Plant Production Emissions

Carbon dioxide, methane and nitrous oxide efflux from the pH cucumber study averaged 732.091, 0.105, and 4.60 mg m⁻² d⁻¹, respectively. The maximum efflux for CO₂ and CH₄ were recorded within week nine of the study and N₂O at week three at 1398.67, 0.295, and 11.06 mg m⁻² d⁻¹, respectively (Figure 5).

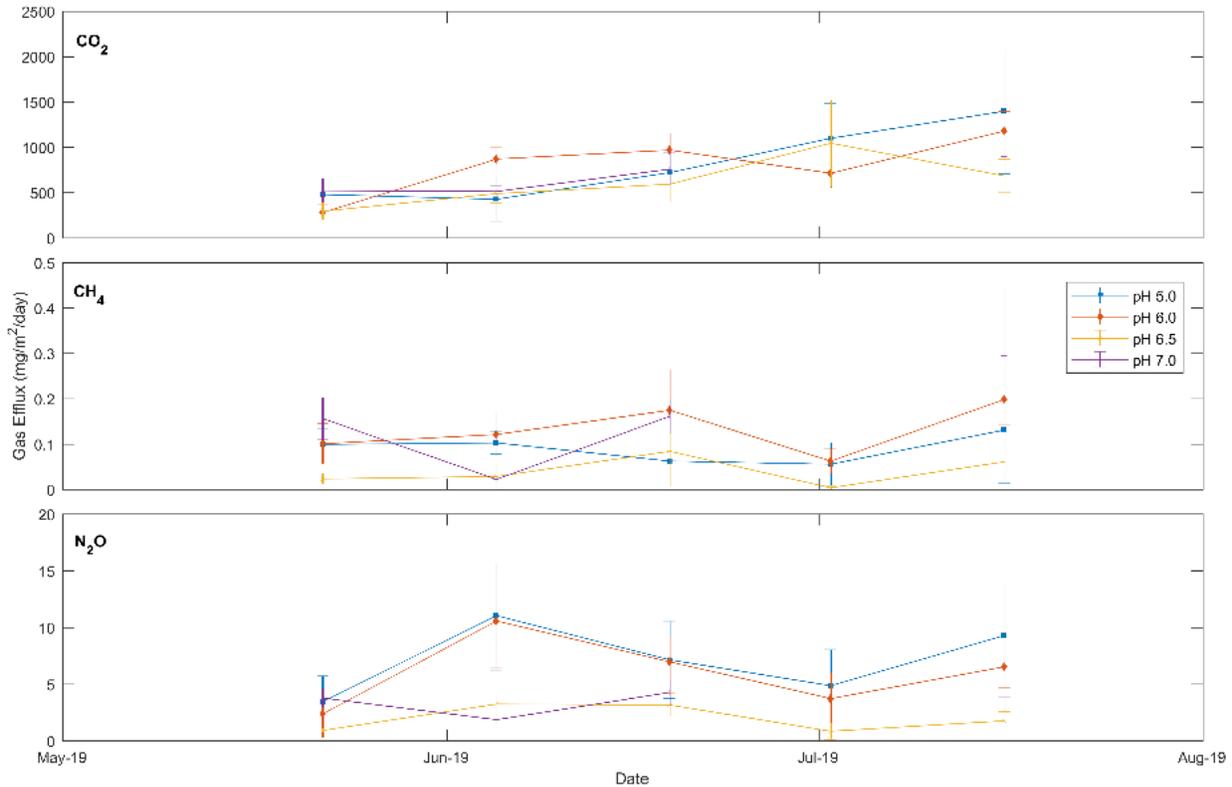


Figure 5: Efflux of GHGs (CO_2 , CH_4 , N_2O) from the plant production system during the pH study conducted in the summer of 2019. Data for pH 7.0 from the fourth sampling date were unavailable due to sampling error.

The CH_4 to CO_2 ratio averaged $\sim 1 \times 10^{-4}$ indicating aerobic conditions. Trace gas emissions from the pH study showed significance toward multiple operational parameters (Table 2). Carbon dioxide had a positive relationship with growth stage only ($F_{1,55}=18.01$, $p<0.0001$, $RMSE=414.57$), while CH_4 had a positive relationship with irrigation rate only ($F_{1,55}=10.19$, $p=0.0023$, $RMSE=0.10$). Nitrous oxide had a positive relationship with growth stage and a negative relationship with pH, temperature, and irrigation, ($\beta = -2.742$), ($F_{4,55}=5.65$, $p=.00075$, $RMSE=3.79$). The negative coefficient reported indicates that N_2O efflux is increased as pH decreases.

Table 2.: Model parameters for CO₂, CH₄, and N₂O efflux from the cucumber pH study undertaken in summer of 2019. Values were significant at a 95% confidence level.

Compound	Parameter	Parameter Estimate	F Value	P-Value
CO ₂	Intercept	330	18.01	<0.0001
	Week	82.8		
CH ₄	Intercept	-0.122	10.19	0.0023
	Irrigation	0.00458		
N ₂ O	Intercept	213	5.65	0.0008
	Temperature	-2.28		
	Week	2.24		
	Irrigation	-0.463		
	pH	-2.74		

Averaged across both the fall and winter substrate studies, CO₂, CH₄, and N₂O efflux from the perlite substrate were 665, 0.13, and 1.48 mg m⁻² d⁻¹, respectively. From the pine bark substrate, efflux for the three trace gases averaged 1096, 0.16, and 1.91 mg m⁻² d⁻¹, respectively. Maximum efflux of CO₂, CH₄ and N₂O were recorded on 10/4/19, 10/8/19, and 10/8/19 at 4005, 0.879, and 11.49 mg m⁻² d⁻¹, respectively (Figure 6).

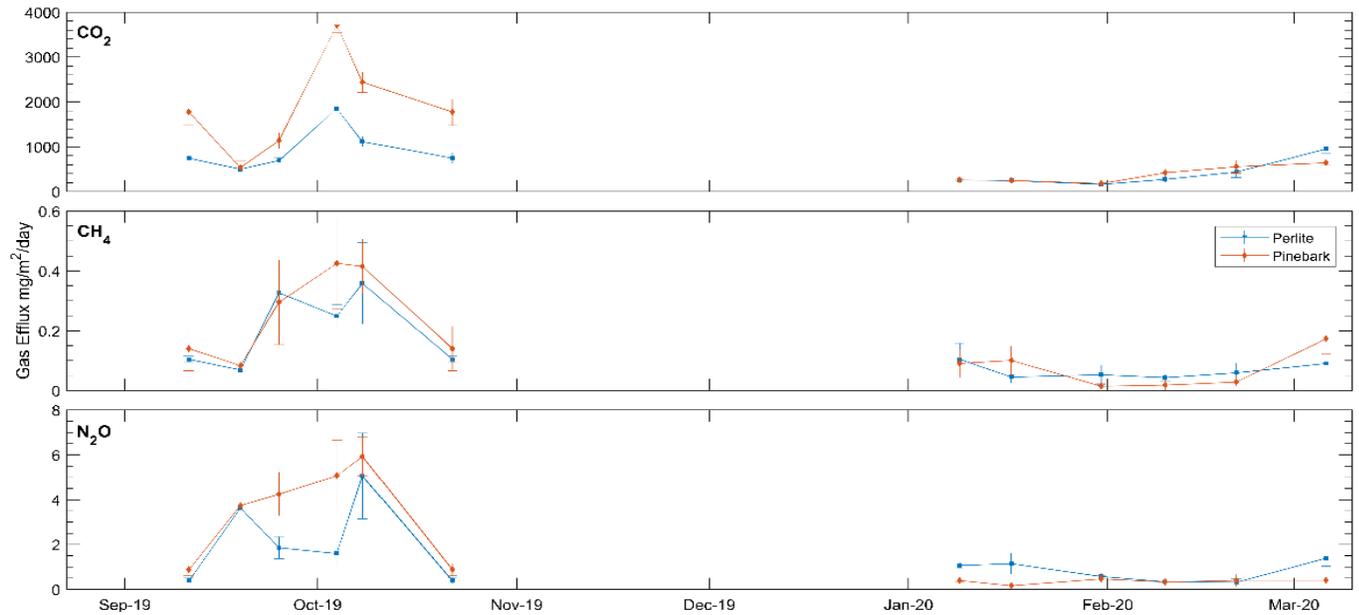


Figure 6: Efflux of GHGs (CO₂, CH₄, N₂O) from the plant production system during the substrate study conducted in the fall of 2019 and the winter of 2020.

The CH₄ to CO₂ ratio averaged 0.0002 which is indicative of aerobic conditions. Trace gas emissions from the substrate study showed significance toward multiple operational parameters (Table 3). Carbon dioxide had a positive relationship with growth stage, substrate, and temperature and a negative relationship with feeding rate ($F_{4,183}=36.59$, $p<0.0001$, $RMSE=591.5$). The significant positive relation with substrate indicates that pine bark had CO₂ levels approximately 58% higher than perlite. Methane had a positive relationship with temperature and irrigation rate and a negative relationship with NO₃⁻ ($F_{2,186}=10.48$, $p<0.0001$, $RMSE=0.1604$). Nitrous oxide showed a positive relationship with temperature and feeding rate ($F_{2,186}=22.56$, $p<0.0001$, $RMSE=2.01$).

Table 3.: Model parameters for CO₂, CH₄, and N₂O efflux from the cucumber substrate study undertaken in the fall and winter of 2019/2020. Values were significant at a 95% confidence level.

Compound	Parameter	Parameter Estimate	F Value	P-Value
CO ₂	Intercept	-2320	36.59	<0.0001
	Week	120		
	Substrate	428		
	Temperature	37.6		
	Feed	-1250		
CH ₄	Intercept	-0.271	10.48	<0.0001
	Temperature	0.00555		
	Irrigation	0.00197		
	Nitrate	-0.000260		
N ₂ O	Intercept	-2.85	22.56	<0.0001
	Temperature	0.0624		
	Feed	2.97		

2.4 Discussion

2.4.1 System Emissions

Trace gas samples were collected over the course of a year during system operation in which multiple plant studies were undertaken by researchers in Auburn University's Department of Horticulture. The measurements in this study aimed to capture the range of direct GHG (CO₂, CH₄, and N₂O) emissions from an aquaponics facility over multiple growing seasons.

While fish tank GHG efflux showed some variation over time, there was no significance found between operational parameters and trace gas emissions. This could be the product of constant aeration and partial temperature control, which may have created a relatively uniform environment thereby limiting the ability to detect interactions between GHG emissions and environmental or operational variables. We initially hypothesized that CO₂ efflux would be correlated with average fish feeding rates but no correlation was found in this study. This could be due in part to the “snapshot” method used to measure GHGs; it is possible that more frequent sampling would have detected differences.

Despite highly aerobic conditions, the fish tank was a source of N₂O emissions. Nitrous oxide is an intermediate in the denitrification process which occurs under anaerobic conditions (Winkler and Straka, 2019). However, N₂O is also formed during ammonia oxidation (Law et al., 2012), which occurs at a rapid rate in biofloc systems (Robles-Porchas et al., 2020). Our finding that N₂O emissions from the fish tank varied from <10 to 150 mg m⁻² d⁻¹ align well with the results of others who have studied N₂O emissions from activated sludge wastewater treatment systems (Czepiel et al., 1995). We also found that GHG emissions from aeration likely dwarfed emissions via diffusion at the water surface. This was similar to the findings of Kimochi et al. (1998) who reported that continuous aeration of a wastewater treatment basin led to much more

rapid N₂O flux into the atmosphere compared to an intermittently-aerated system. Kimochi et al. (1998) also found that intermittent aeration generated greater dissolved N₂O concentrations suggesting that aeration was responsible for stripping N₂O out of the water column. Nitrous oxide efflux had a positive correlation with temperature, which is consistent with previous studies showing increases in N₂O efflux with temperature during anaerobic conditions (Willén et al., 2016).

High CH₄ emissions are evidence that the clarifier system was operating under anaerobic conditions. That CH₄ had a positive correlation with total suspended solids (TSS) was no surprise. As TSS decreased through the clarification process, so did CH₄ efflux which can be used as a proxy for the amount of sludge and is consistent with findings from previous studies of anaerobic digestion (Chen et al., 1997; Mirzoyan et al., 2010). Lack of aeration, other than water flow through the system, likely allowed anaerobic conditions to develop.

Cucumbers grown under varying pH conditions showed significant correlation between pH and N₂O. Carbon dioxide also had a positive relationship with growth stage. Carbon dioxide is generated from root (autotrophic) and microbial (heterotrophic) respiration. Thus, a larger root mass along with a larger microbial rhizosphere population can explain the positive relationship between plant growth stage and CO₂ emissions (Brito et al., 2009; Runion et al. 2012). The same phenomenon was observed in the substrate study. Methane had a positive relationship with irrigation rate which was also observed in the substrate study. This could be explained by entrained CH₄ in the irrigation water that was pumped from the clarifiers being released during drip irrigation of plants. Similar CH₄ emissions have been observed during release of effluent from anaerobic digesters (De Mes et al., 2003).

The increase in N₂O efflux as pH decreased has been previously observed in other studies which studied N₂O efflux from acidic soils (Hénault et al. 2019; Smith et al. 1997; Wang et al. 2018). These studies have found that low soil pH has prevented the reduction of N₂O by inhibiting N₂O reductase (Liu, Frostegård, and Bakken 2014). Another possible explanation is that lower pH supports denitrifying bacteria, but the published literature does not support this explanation (Šimek et al., 2002; Saleh-Lakha et al., 2009).

For the substrate study, average values for all three trace gases were found to be higher during the fall study compared to observations made during the winter study. This was most likely due to differences in upstream parameters such as feeding and irrigation rate between the two study seasons. Substrate type was found to be significant for CO₂ efflux but not for CH₄ or N₂O. Perlite is an inorganic, porous volcanic rock which has the potential to remove heavy metals (Mathialagan and Viraraghavan, 2002; Trois et al., 2010) and has been known to foster microbial growth (Carlile and Wilson, 1990). Pine bark is an organic substrate that allows for a bacteria-rich environment as well as fungal build up (Kokalis-Burelle and Rodriguez-Kabana, 1994). Biological degradation of pine bark is the most likely explanation for elevated CO₂ emissions compared to perlite (Jackson et al., 2009). Carbon dioxide efflux has also been shown to increase with temperature (Fang and Moncrieff, 2001), which is in line with our findings.

Positive correlations between temperature, irrigation, and CH₄ are in accordance with previous studies which found that increases in temperature and moisture can lead to higher CH₄ efflux (Mariko et al., 1991; Dijkstra et al., 2012). Although average CH₄ efflux rates were nominally higher for plants grown in pine bark, there was no significant correlation between CH₄ and substrate type. This could indicate that anaerobic conditions did not develop in our pine bark substrate, in comparison to that observed by others (Syed et al., 2016). This is likely due to

Dutch buckets being well-drained (Robertson et al., 2000). Thus, it is imperative that outflow orifices remain unclogged to insure free water flow. Finally, high NO_3^- levels in the irrigation water appeared to suppress CH_4 emissions in the plant study and this is likely explained by microbial use of NO_3^- as an electron acceptor (Percheron et al., 1999). Nitrate is known to suppress CH_4 production in a range of anaerobic microbial systems (Van Zijderveld et al., 2010; Patra and Yu, 2014). Unexpectedly, N_2O efflux was not correlated with growth stage in contrast to the findings of Marble et al. (2012b), who studied nursery container production. However, this may have also been confounded by high variability in NO_3^- levels. Like CH_4 , N_2O efflux was found to be significantly correlated with temperature, which is similar to the findings of Kamp et al. (1998) who studied N_2O emissions from open field wheat production.

The large RMSE values observed for the different unit procedures statistical models could be the result of fitting a linear model to a highly variable system. The GENMOD function in SAS was used to verify our initial assumption that using a linear model was the appropriate choice. It is likely that a larger sample size with more frequent data collection (at least weekly) would lead to a reduction in overall model error. Therefore, we recommend further investigation into direct emissions from similar systems based on the framework outlined in this study. The direct GHG emissions measured in this study will be used in a subsequent life cycle assessment, providing a more complete picture of the overall upstream, direct, and downstream emissions from the system.

2.4.2 Practical Implications

The findings from this study shed light on how operational variables can affect direct GHG emissions from an aquaponics facility. Based on our results, we recommend the use of non-organic substrates for plant growth in order to reduce CO_2 emissions. Likewise, we also

recommend the management substrate pH and avoidance of the addition of sulfuric acid to prevent additional N₂O production and denitrification. Within clarifiers, we suggest implementing a faster separation process with frequent solid removals to avoid anaerobic conditions. Additionally, the data from this study will further aid the calibration of a mass-balance process model in order to track nutrient flows under changing operating conditions. Most importantly, this study will allow for a basic framework to quantify direct GHG emissions from other types of aquaponics systems.

3.0 Chapter 2: Construction of a Mass-Balance Process Engineering Model

3.1 Introduction

To cope with global population growth, methods of providing sufficient, nutritious food and clean water must be developed. At the same time, there is an urgent need to mitigate the negative environmental impacts of agricultural production systems. Currently, over 50 percent of the world's fish supply comes from aquaculture production (FAO and UNICEF 2018). Aquaculture creates environmental emissions, particularly the production of nutrient-rich wastewater. This wastewater, which is often rich in ammonium, nitrate, and phosphate, can enter the environment through incidental runoff or routine draining (Guong and Hoa 2012). This can result in severe cases of eutrophication, affecting preexisting ecosystems or surrounding aquaculture facilities (Cao et al. 2007).

Aquaponics presents a solution to the problems associated with traditional aquaculture by repurposing the nutrients from aquaculture effluent for hydroponic plant production (Love et al. 2014; Wongkiew et al. 2017). This reduces nutrient emissions while promoting sustainable food production. Aquaponics has recently grown in popularity due to its intensive production of fish and plant crops in a relatively small space and its perception of sustainability (Love et al. 2014; Palma Lampreia Dos Santos 2018). In some cases, it has also shown promise as an economically competitive approach (Xie and Rosentrater 2015b). However, to maximize both economic and environmental performance of aquaponics, it is important to understand the fate and flow of nutrients in these systems in order to ensure their efficient use. For example, nitrogen can be lost to the atmosphere via denitrification while phosphorus can be lost through precipitation and other conversion processes that reduce its availability to plants (Cerozi and Fitzsimmons 2016;

Eck, Körner, and Jijakli 2019; Yang and Kim 2019). Additionally, imbalance between plant crop and fish production can lead to excess nutrients in post-plant effluent water from decoupled aquaponics systems, leading to negative downstream environmental impacts such as eutrophication (Calone et al. 2019; Maucieri, Nicoletto, et al. 2018).

Few studies have attempted to construct detailed mass-balance models of aquaponics systems. Cerozi and Fitzsimmons (2017) created an empirical phosphorus mass balance model of a recirculating coupled aquaponics system to predict how various management practice can affect downstream nutrient fate. Karimanzira et al. (2016) created a sophisticated dynamic mass balance simulation model for an aquaponics system, however, their model was not calibrated using real system data (Karimanzira et al. 2016). Rather, parameters were inserted from the literature for simulation purposes. Other researchers have created mass balance models for recirculating aquaculture systems (RAS) but these did not include aquaponics (Klas et al., 2006; Wik et al., 2009). Others have examined the production of non-usable compounds (Wright 2018) or how changes in operational environments such as sizing can influence the nutrient flows and environmental impacts of proposed systems (Dijkgraaf, Goddek, and Keesman 2019; Goddek and Körner 2019). However, none of these studies have created a comprehensive mass balance model for water, nitrogen, and phosphorus nutrients in an aquaponics system based on comprehensive data collected from a large-scale system.

Here we present a mass-balance process engineering model based on a large pilot-scale, decoupled biofloc aquaponics system located at Auburn University. This system produces Nile tilapia and cucumbers. The goal of this study was to utilize data from the facility, collected over the course of one year, to construct a mass-balance model which is able to predict nutrient transformations based solely on upstream inputs (water, feed, and season). Experimentally-

validated stoichiometric equations and empirical formulas of each major output of the system (e.g. tilapia, sludge, and cucumber plant components) were developed. Ultimately, we seek to utilize this model to aid in management and operational decisions as well as to carry out scenario analyses in future life-cycle assessments.

3.2 Methods

3.2.1 System Description

The system of study is operated by Auburn University and is located approximately 5 miles north of the main campus at the E.W. Shell Fisheries station. The system was operated in a decoupled fashion meaning water from post-plant production was not recirculated back into the fish tank (Figure 7). The pilot system includes two 279 m² climate-controlled greenhouses. The first greenhouse houses a 150,000 L fish tank, outfitted with hoppa nets for the production of Nile tilapia (*Oreochromis niloticus*). The fish tank was constantly aerated using a submerged aeration system (Wagner and Pöpel 1998) and tilapia were fed using a combination of 3606 and 4010 feed (Cargill, Franklinton, LA, USA). The fish tank was operated as a biofloc system to regulate ammonia concentrations and water was circulated through an airlift pump to a 3-stage clarifier where solids were removed and remaining water was used for plant irrigation or recirculated back into the fish tank. The second greenhouse is used for the production of Beit Alpha seedless cucumbers (*Cucumis sativus*) grown in Perlite-filled 11 L “Dutch” buckets (Crop King Inc., Lodi, OH, USA). Cucumbers were irrigated using drip irrigation (He et al. 2018) and unused drained water was fed to underground sumps before being released to a drainage ditch.

3.2.2 Biological Material Collection and Compositional Analysis

Solid biological materials associated with the system were collected in April of 2019 and included fish feed, tilapia, sludge from the clarifiers, and cucumber roots, stems/leaves, and fruit. Both juvenile and adult fish were collected to account for any compositional variations between age groups. Cucumber stems and leaves were first dried using an industrial drier and then homogenized using a plant grinder (Thomas Scientific USA). Fish feed, tilapia, and cucumber fruit were homogenized using a kitchen blender (Ninja) and stored in 10 ml vials. Homogenized material was transferred to vials (n = 6 for fish feed and tilapia, n = 10 for cucumber materials) and then freeze dried at -45 °C (Labconco). Cucumber roots were removed from the perlite root balls by hand and then homogenized using a kitchen knife before freeze drying. Sludge was collected from the clarifier effluent and centrifuged (4696 x g, 15min) to concentrate solid material. The remaining material was stored in 10 ml vials and freeze dried to remove the remaining moisture (n = 3).

Following the methods described in Wang et al., 2020, samples were analyzed using a vario MICRO cube Elemental Analyzer (Elementar, Langensfeld, Germany) for carbon (C), hydrogen (H), nitrogen (N), and sulfur (S) content. Samples were also analyzed for other elements such as phosphorus (P), iron (Fe) and potassium (K), using inductively coupled plasma with optical emission spectrometry (ICP-OES) analysis following the methods described in Chaump et al. 2019. Ash content was determined using standard gravimetric methods. Oxygen content was estimated by subtraction of C, H, N, S, and ash from the total dry mass.

3.2.3 Water Sampling

Water samples were collected on an approximately weekly basis for one year and at four locations within the aquaponics system: system influent, fish tank, clarifier effluent, and the post-plant sumps. The water was filtered (0.2 μm) and then stored at -80°C prior to analysis. At the conclusion of the sampling period, each sample was analyzed for soluble ion concentrations via high pressure liquid chromatography (HPLC; Shimadzu Prominence System, Kyoto, Japan) using an anion exchange column (Dionex AS22, ThermoFisher Scientific, USA) and ion suppressor (Dionex AERS 500, ThermoFisher Scientific, USA) per a previously-published method (Chaump et al. 2019). Compounds detected included nitrate (NO_3^-), nitrite (NO_2^-) and soluble phosphate (PO_4^{3-}). Cation chromatography was also performed (Dionex CS12, ThermoFisher Scientific, USA) using an ion suppressor (Dionex CERS500, ThermoFisher Scientific, USA). Compounds detected included potassium (K^+) and ammonium (NH_4^+) ions. Along with the compositional analysis of the solid materials, these data were used in the development of empirical formulas and construction of the mass-balance process model.

3.2.4 Greenhouse Gas Emissions

Direct greenhouse gas emissions were measured in the system from the summer of 2019 through the winter of 2020 as detailed in our previous work (Kalvakaalva, Prior, et al. 2021). During each growing period, samples were taken on an approximate weekly basis. Gas samples were collected from the fish tank, clarifiers, and the greenhouse Dutch buckets and closely followed the sampling protocol as described in Marble et al. (2012). Using a gas chromatograph (Shimadzu GC-2014, Columbia, MD), samples were analyzed for three trace gases: carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). Readings were then converted and

presented as gas flux ($\text{kg}/\text{m}^2/\text{day}$). These data assisted with the stoichiometry of carbon and nitrogen transformations.

3.2.5 Other Data Collection

Water flows were metered and recorded daily and included fish tank makeup water and irrigation. Water recirculation rate from the clarifiers to the fish tank, and sludge removal were recorded during a one month period and were used to generate water partitioning parameters. Based on this information, water losses due to evaporation and leakages were calculated. Fish feed type and rates were also recorded on a daily basis. Additionally, parameters such as fish tank aeration were assumed to be constant throughout the sampling period. Aeration rate for the fish tank was based on a one-time measurement of air flow through aeration manifolds with the use of an anemometer as described in (Kalvakaalva, Prior, et al. 2021).

3.2.6 Model Construction and Calibration

The mass balance process model was constructed in SuperPro Designer[®] v.8.5 (Appendix 1). Due to the seasonal variation of certain parameters, such as denitrification and plant growth rate, a separate model was parametrized for each season. Within each seasonal model, only three model inputs drove downstream mass flows, partitioning, and transformations: feeding rate, input water to the fish tank, and influent nitrate. All model input and outputs were presented as an average kg/h calculated on a weekly basis (the approximate rate of water quality sampling) over the course of a year. The model inputs were based on the average values for the seven days prior to the water sampling date. The model was structured as a semi-steady-state system in which the system is assumed to operate at steady state based on average inputs for a given week.

Then the steady state operation is allowed to adjust based on the inputs for the subsequent week. The system in reality is constantly in flux but modeling such a dynamic system would require a continuous stream of real-time data for all mass flows within the system. This was not practical and unlikely to add significant value when using the model for decision-making and simulation purposes over long timeframes.

Using the methods described in Tattershall (1979), mass based macro-element quantities, derived from CHN and ICP analysis, were used to create empirical formulas (Table 4) for the different materials associated with the aquaponics system. The empirical formulas were then used to generate stoichiometric relationships among constituents in the system (Table 5). Several of these reactions (e.g. feed conversion) are actually the sum of dozens of reaction steps but were combined for simplicity and because intermediates were not measured. Although fish secrete ammonia-N, this form of nitrogen was nearly undetectable in the fish tank due to the high DO levels (>7 mg/L) leading to rapid nitrification by biofloc bacteria. While the reaction stoichiometry did not vary in the different seasonal models, the reaction extent was adjusted by season for various processes based on measured data (Table 5). This included denitrification, gas production from sludge clarification, and plant growth rate. Fish tank evaporation rates were set to not exceed total calculated water losses for the season but to also achieve a targeted, average concentration of PO_4 for each season. Following this, denitrification rates for the fish tank were set to achieve the average concentration of NO_3 within the fish tank during a given season. The stoichiometry of trace gas production (CH_4 , N_2O) in the fish tank was based on the feeding rate and trace gas measurements during the summer period. This stoichiometry was built into the feed conversion stoichiometry and therefore was retained for the other seasons as well. The stoichiometry of gases emitted from the clarifiers was modeled as an anaerobic digestion

process. This was done because the methane emissions from the clarifier exceeded the measured CO₂ emissions. The production of CO₂ and CH₄ was set as a constant molar ratio of 35:65 in order to account for soluble forms of CO₂ which were not measured by trace gas analysis. This ratio represents a typical balance of CH₄ and CO₂ in an anaerobic digester (Moestedt, Malmberg, and Nordell 2015). N₂O emissions from the clarifier were integrated into the stoichiometry of sludge mineralization to balance the N mineralization. Typically digesters produce reduced forms of nitrogen as either ammonia-N or nitrogen gas (Percheron et al. 1999). No ammonia-N was detected in the clarifier during preliminary tests so denitrification was assumed to be the predominant reductive pathway. The extents of sludge mineralization and denitrification reactions were adjusted by season to target the average measured CH₄ and N₂O emissions from the clarifier. These emissions were found to vary considerably among seasons (Kalvakaalva, Prior, et al. 2021).

Predicted values were compared with measured weekly data for phosphate and nitrate from the fish tank, clarifier and post greenhouse sumps. Root mean squared error and percent error was calculated at each time point and averaged for each unit operation across all seasons to assess the accuracy of the model.

Table 4.: Empirical formulas for each biological material within the system determined by elemental composition analysis

Material	Empirical Formula
Root	C _{28.2} H _{43.4} N _{4.4} O _{23.8} P _{0.1}
Plant	C ₃₃ H _{48.4} N _{2.3} O ₁₆ P _{.07}
Cucumber	C _{27.4} H _{52.9} N _{1.4} O _{18.1} P _{0.1}
Mixed Feed	C _{32.9} H ₅₄ N _{3.45} O _{9.35} P _{0.28}
Tilapia	C _{35.15} H _{57.68} N _{4.86} O _{1.7} P _{0.58}
Sludge	C _{27.8} H _{53.67} N _{3.62} O _{14.16} P _{0.66}

3.2.7 Model Assumptions

The model was constructed and run based on the following assumptions. (1) Inputs of feed and water drive all downstream mass flows. (2) A constant feed conversion ratio (FCR) of 1.6 was used throughout the year based on an FCR study carried out in the spring/ summer of 2019.

Table 5.: Stoichiometric constants for each reaction within the process engineering model

Component →	Feed	Tilapia	Sludge	O₂	Fruit	Stem/Leaves	Root	NO₃	NO₂	PO₄	CO₂	CH₄	N₂O	N₂	H₂O
Process ↓															
Fish Tank															
Feed Conversion	-0.1523	0.0268	0.0385	-4.11				0.252	0.0014	0.0047	2.99868	0.0003	0.0007		2.3002
Denitrification				1.5				-1						0.5	
Clarification															
Mineralization			-1	-4.2543						0.6811	9.7337	18.1213	0.4788	1.3328	
Denitrification				0.5									-1	1.0000	
Plant House															
Plant Production				0.0403	0.0012	0.0002	2.71E-05	-0.0023		-0.0002	-0.0401				-0.0555
NO ₂ Oxidation				-0.5				1	-1						
NO ₃ Denitrification				1.5				-1						0.5	

(3) A constant elemental formula was assumed for fish, sludge, cucumber fruit, and plant stems/roots/leaves based on the elemental analyses for macro-elements carried out in the spring of 2019. (4) The system operates at quasi steady-state, assuming that the fish tank volume is constant and that each week is treated as a steady-state operating period based on feed/water inputs for that week. (5) The fish tank is well mixed through intensive aeration. (6) The following parameters vary by season (Spring, Summer, Fall, Winter): Growth rate of cucumber plants, water evaporation & evapotranspiration, denitrification extent, and irrigation and recirculation rate (Table 6).

Table 6. Extent of reactions set in each seasonal variation of the process engineering model

Season →	Spring	Summer	Fall	Winter
Process ↓				
Fish Tank				
Feed Conversion	100	100	100	100
Denitrification*	36.0	73.1	36.0	80.0
Clarification				
Mineralization	0.875	1.000	2.800	0.750
Denitrification	91.25	92.00	95.00	90.50
Plant House				
Plant Production	41	28	37	40
NO ₂ Oxidation	89.6	89.6	89.6	89.6
NO ₃ Denitrification	30.5	12.5	20.5	28.5

3.3 Results and Discussion

3.3.1 System Production

The system model yielded approximately 455 kg of dry weight tilapia and 175 kg of dry weight cucumbers within the calendar year based on recorded upstream inputs of feed and water. This compared favorably to a recorded 460 kg of dry weight tilapia and 218 kg of dry weight cucumbers produced within the study period. Greater magnitude of error is expected in downstream processes (e.g. cucumber fruit production) given the potential for error propagation through the model.

3.3.2 Nitrogen

Measured data showed large fluctuations in soluble forms of nitrogen throughout the study period. Nitrate concentrations in the fish tank reached a high concentration of 863.53 mg/L on the first collection date of 3/22/2019 and achieved a low of 81.303 mg/L on 10/30/2019. This trend was reflective of an increased water flow rate through the system in the fall and winter periods. According to the model, 34% of nitrogen entering the system from feed was converted into nitrate while approximately 21.5% each was converted to sludge and tilapia (Figure 8). Major losses of nitrogen in the system occurred in the form of N₂ gas (19.5%) while 34.3% and 25.2% of available nitrate in the system escaped via water leakage or was unused after plant production, respectively. Overall, the model had 2.72% of nitrogen unaccounted for within the entire system.

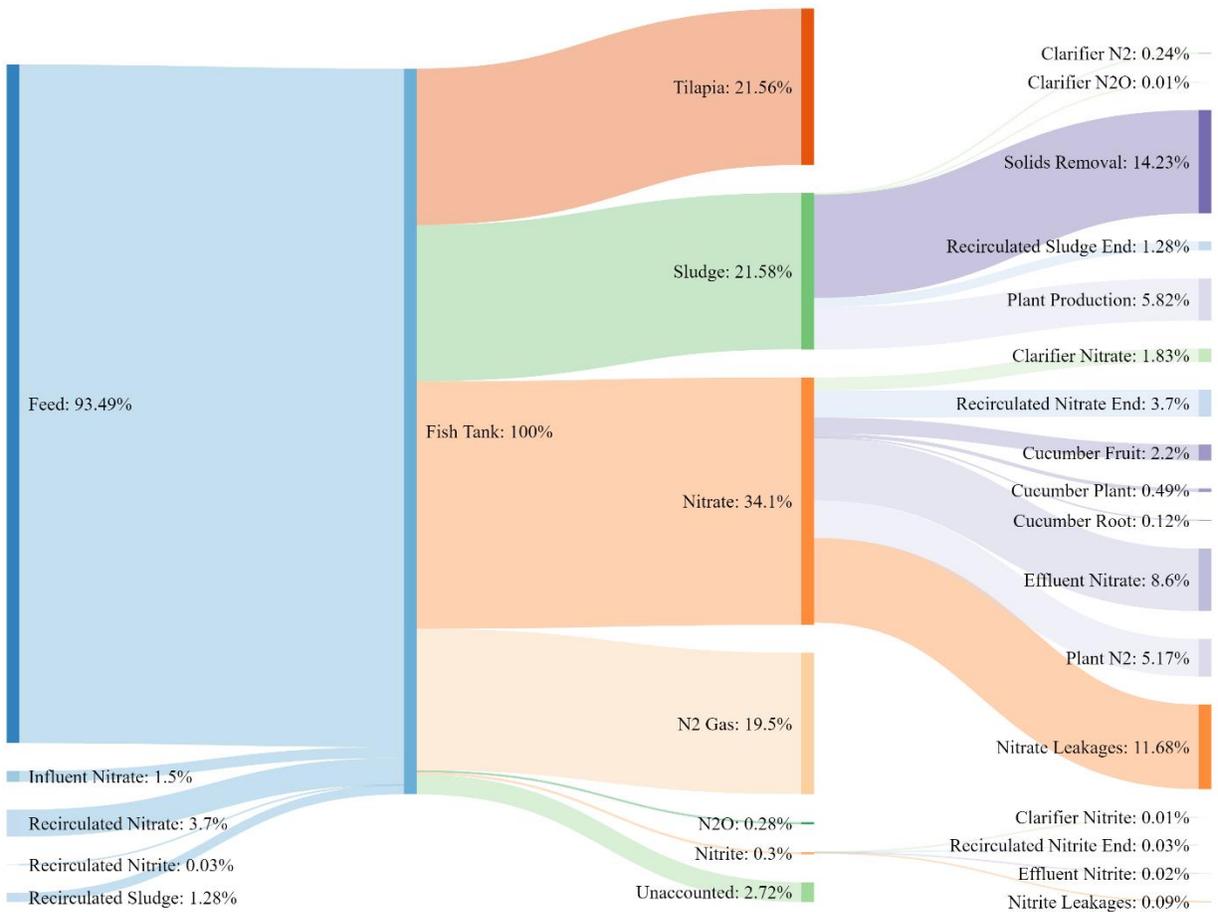


Figure 7: Flow of nitrogen through the aquaponics facility based on outputs from the model parametrized with spring season data.

Modeled values for nitrate followed general trends observed in the measured values over time but with some deviation during certain seasons (Figure 9). The largest differences occurred within the spring season and the smallest within the winter season. This could be explained by the highly variable system operation during the spring period when water flow rates and feeding rates were rapidly being ramped up. This rapid ramp-up briefly destabilized the biofloc system's nitrifying bacteria, leading to a sharp spike in nitrite formation (Appendix 2). The weekly steady-state assumption was likely violated during this period due to the rapid pace of operational change. Over the entire modeled period, the modeled nitrate concentration had a root-mean

square error (and percent error) of 275.27 (49.33%), 289.19 (67.36%), and 167.79 (154.33%) for the fish tank, clarifier and post-plant production, respectively. The percent error was calculated per Eq. 3.

$$Error \% = (modeled - measured) / measured \quad \text{Eq. 3}$$

The increased percent error in each unit procedure is likely the product of hydraulic residence time creating a lag effect (Meals, Dressing, and Davenport 2010) as well as error propagation within the modeled system.

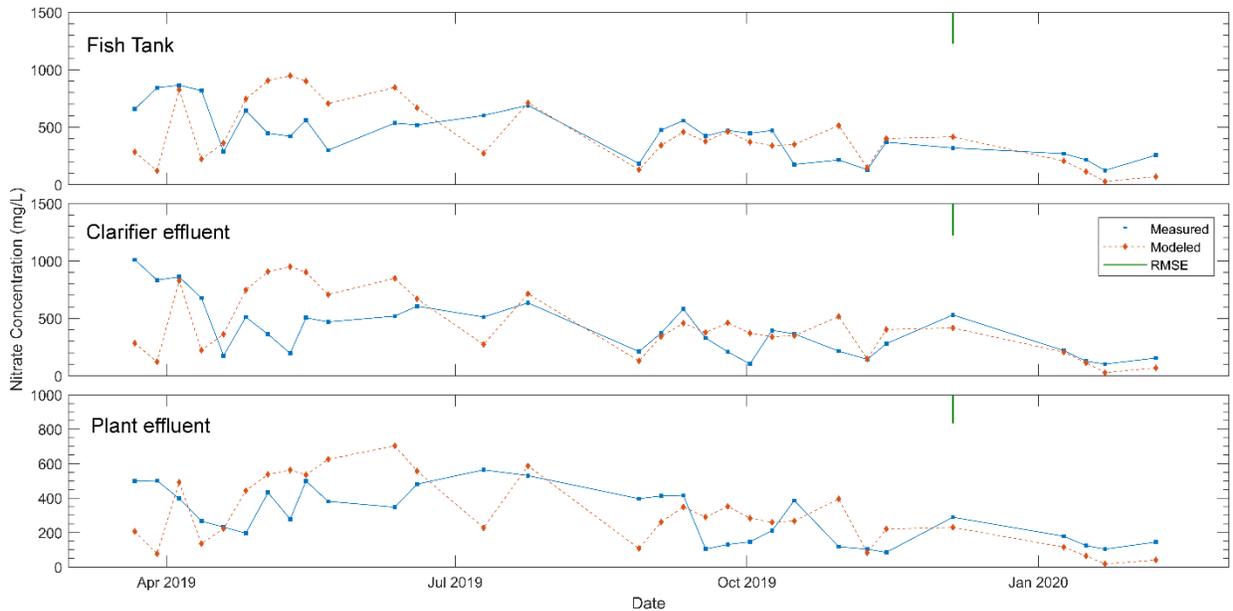


Figure 8: Nitrate concentrations in the three main unit processes of the aquaponics system: fish tank (top), clarifier (middle), and plant production (bottom).

3.3.2.1 Denitrification

After determining evaporative rates for each unit procedure, denitrification extent was set to hit target nitrate concentrations averaged for each season. The fish tank was the largest source of N_2 gas emissions with an average emission rate of 6.11, 0.08, 0.75 g/h from the fish tank, clarifier, and plant greenhouse respectively. The largest modeled denitrification rates came

during the summer months which aligns with previous studies which observed a relationship between increased temperature and denitrifying microbial activity (Dawson and Murphy 1972; Elefsiniotis and Li 2006). This also aligns with the increased feed and water input during this time period.

3.3.3 Phosphorus

Phosphate concentrations in the fish tank reached a high concentration of 52.18 mg/L on 9/11/2019 and achieved a low concentration of 13.68 mg/L on 10/30/2019. Only 13.53% of phosphate in the feed entering the system was converted into soluble phosphate while 33% and 50.2% of feed was integrated into tilapia and sludge, respectively (Figure 10). This is similar to previous studies which modeled phosphorus mass balance flows within an aquaponics system (Cerozi and Fitzsimmons 2017). The majority of phosphorus exited the system with tilapia and

sludge but additional losses occurred in the form of water leakages (4.51%) and post-plant production effluent (4.17%). 3.74% of phosphorus was unaccounted for in the model.

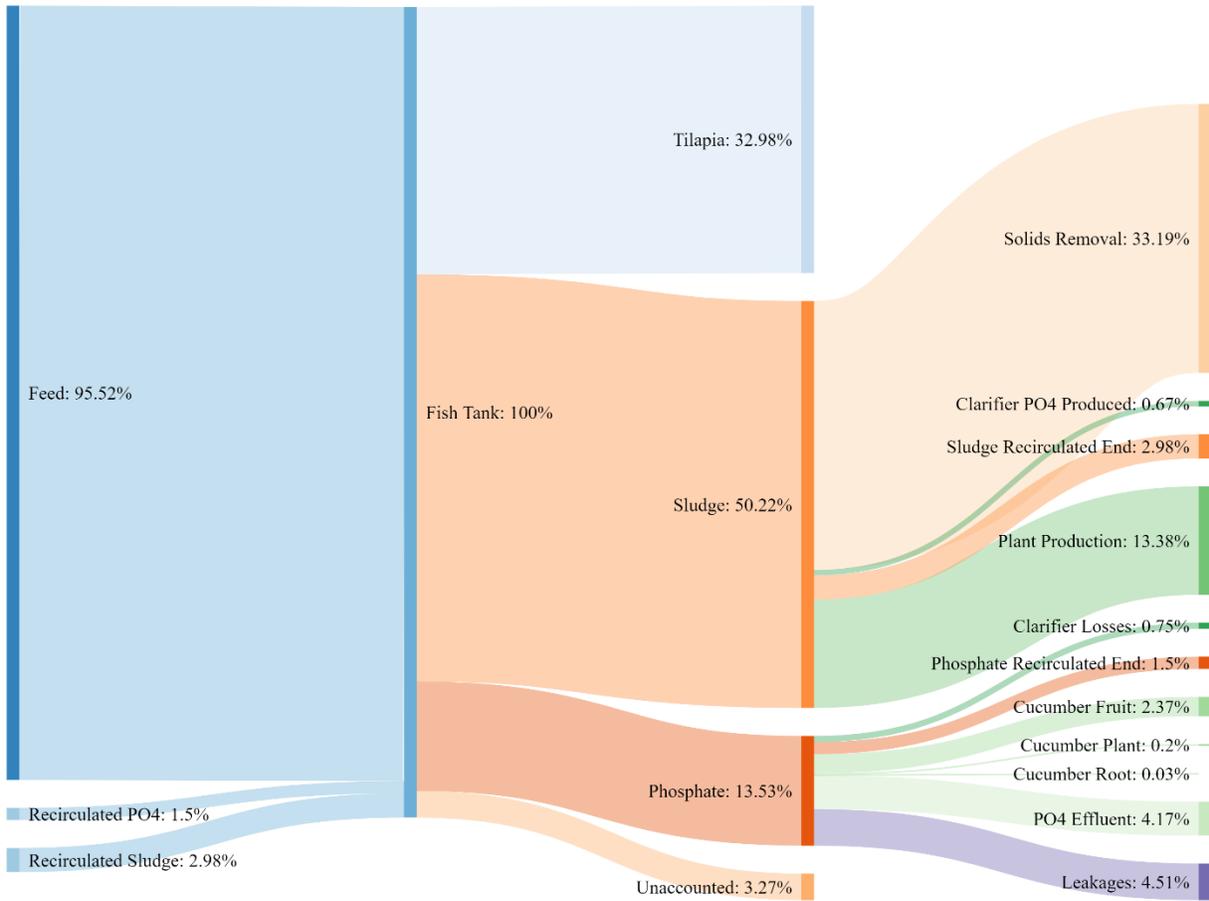


Figure 9: Flow of phosphorus through the aquaponics facility based on outputs from the model parametrized with spring season data.

Measured phosphate concentrations followed similar trends as measured nitrate concentrations with generally lower concentrations in the winter months when feeding rate slowed and water input increased. Modeled values for phosphate followed general trends observed from measured values but with noticeable deviation in the Fall season (Figure 11). Over the entire modeled period, modeled phosphate exhibited root-mean square and percent errors of 16.85 (51.66%), 16.64 (50.81%), and 15.59 (54.74%) for the fish tank, clarifier, and

post-plant production, respectively. The largest differences came within the fall season as the model was not able to achieve target phosphate concentrations without violating the assumption of constant tank volume. This could be the product of a change in base elemental composition of biological materials (e.g. sludge), a change in the forms of phosphorus within the system, or the absorption of phosphate by the increased presence of algae (Guillen-Jimenez et al. 2000; Mesplé et al. 1995, 1996). Moreover, tank volume was not constant throughout the study period despite efforts to maintain a set volume. Changes in relative humidity (and therefore evaporation) and occasional operational challenges likely impacted our ability to sustain a constant tank volume.

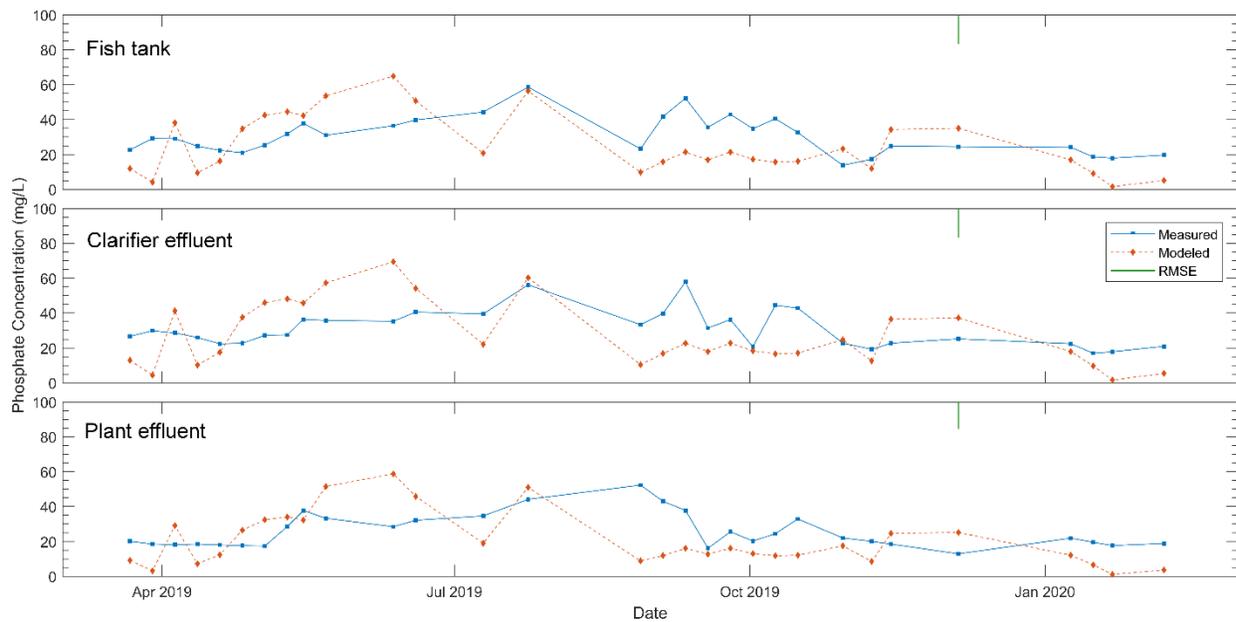


Figure 10: Soluble phosphate concentrations in the three main unit processes of the aquaponics system: fish tank (top), clarifier (middle), and plant production (bottom).

3.3.4 Water Partition

Water flow rates through the system were based on initial makeup water inputs which drove preset portioning into evaporation, evapotranspiration, leakage, released sludge, recirculation, and irrigation rates for each season (Figure 12). Evaporation rates accounted for the greatest water losses in all seasons except for the spring and were highest during the summer and fall

months. This is consistent with management practices during hotter months where greenhouse temperature is often regulated by ventilation fans. Moreover, fall is the driest season in Auburn, AL (Beck et al. 2018) with lower relative humidity driving additional water losses from the system.

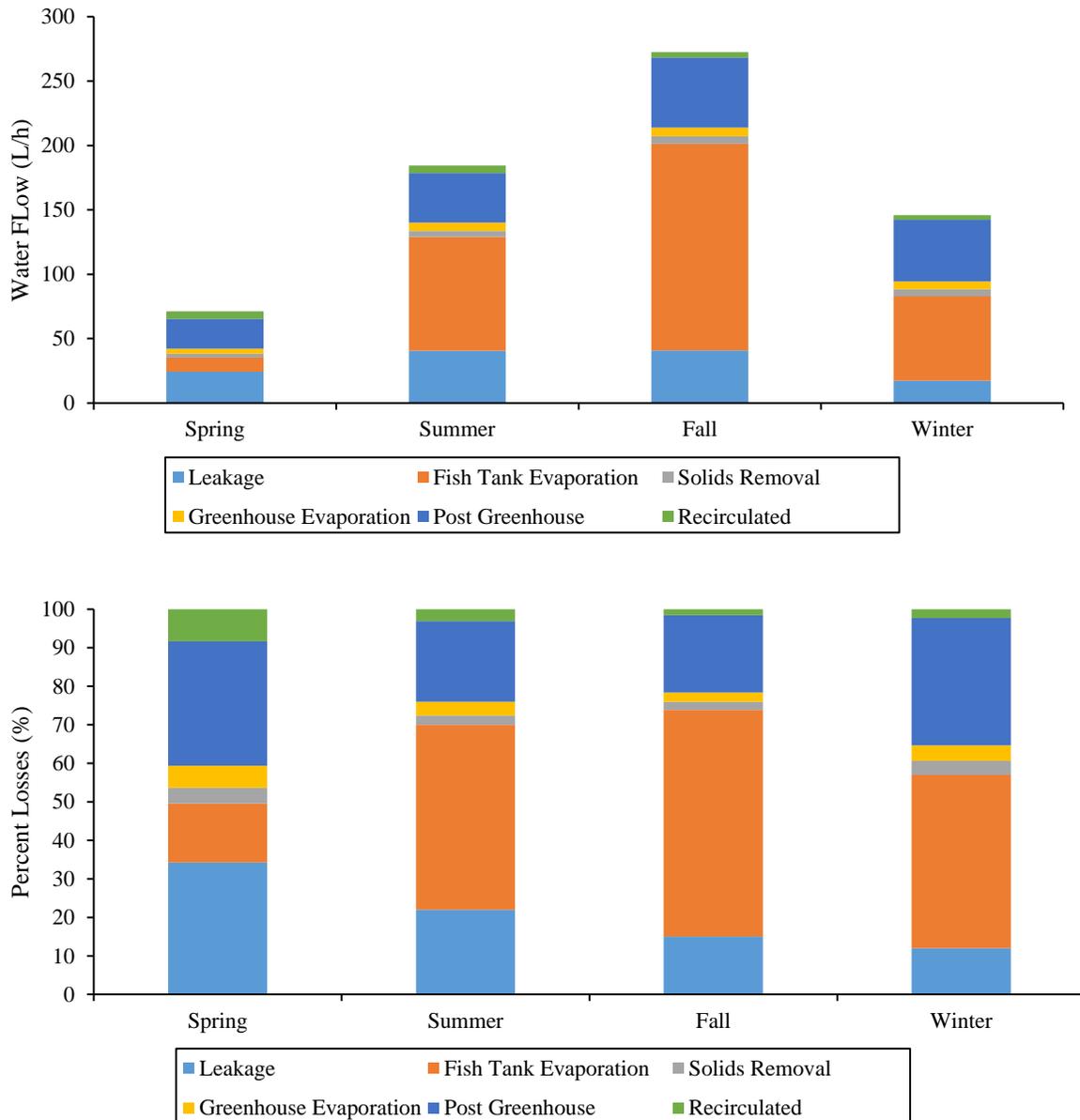


Figure 11: Distribution of water flows through the aquaponics system across season.

Modeled irrigation rates closely followed measured values based on water partitioning coefficients set for each season (Figure 13). Over the entire modeled period, the model showed root-mean square and percent errors of 18.02 (33.38%). The increased irrigation rates in the late summer and fall reflect an intensive campaign of cucumber production during that period.

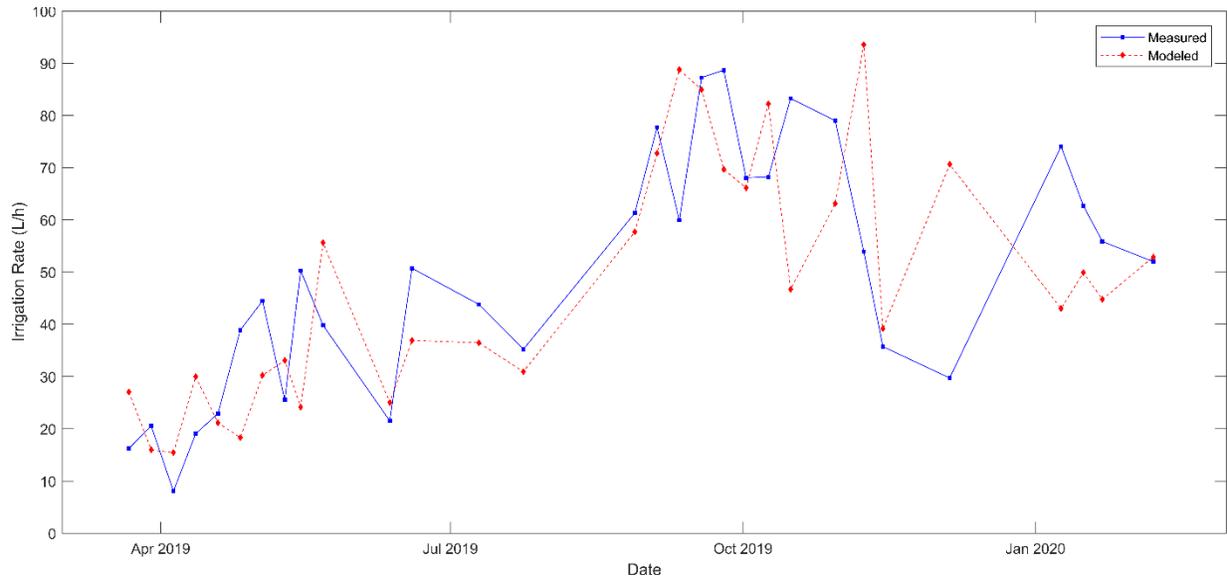


Figure 12: Comparison of modeled and actual irrigation water flows over time.

3.4 Limitations and Conclusions

Based on the results of the model, there are some limitations in its use. As seen in the increased errors in the modeled nutrient concentrations in each unit procedure, error propagation occurred. This is expected of mass balance models that are driven entirely by system inputs. An example of this is the discrepancy between modeled and actual cucumber production which resulted in part due to the discrepancy in available phosphate in the fall months. Under-estimation of phosphate by the model led lower predicted cucumber growth and yield than what likely occurred.

The quasi-steady state operation assumption on a weekly basis also led to significant error during periods of rapid system change (as happened during production ramp-up in the spring season). The model fails to capture the “memory” of the system beyond a 1-week timeframe and therefore works best when week-to-week changes are gradual. This model does not include detailed reaction kinetics based on rate-limiting nutrients similar to the Activated Sludge Model (Gujer et al. 1999). Calibration of kinetic parameters would require significant additional experimental work in the field to understand the impact of rate-limiting nutrients in each reaction step. Because of these limitations we recommend the use of this model only for predictions of broader system trends rather than short term effects of sudden operational changes.

The model is also unable to accurately predict greenhouse gas emissions from the system in relation to measured greenhouse gas data due to the multitude of parameters which affect emission rates (Czepiel et al. 1995; Dijkstra et al. 2012; Kalvakaalva, Prior, et al. 2021; S. Christopher Marble et al. 2012). Thus the model in this case was only used to predict an average release of CH₄ and N₂O emissions by season. Additionally, the analysis in variations of possible algal growth or changes in the forms of phosphate within the system may aid in accounting for modeled variations of phosphate within the system (e.g. an increase in insoluble phosphate in the sludge). Despite its limitations, the model was able to capture the macro-level trends in system mass flow across four seasons and with significant operational changes within seasons. The latter included large changes in the scale of fish production and multiple cucumber production campaigns. Thus the model is likely to be useful in making operational decisions. This model will also be used to predict changes in environmental impacts based on operational and system alterations as part of a future life cycle assessment.

4.0 Chapter 3: Life Cycle Assessment

4.1 Introduction

Due to recent trends in global population growth, advancements in methods of providing sufficient, nutritious food and clean water while reducing the negative environmental impacts of agricultural production systems are becoming increasingly important. Aquaculture, with its high feed conversion efficiency (Fry et al. 2018), has great potential to meet growing global demand for animal protein. Currently, over 50 percent of the world's fish supply comes from aquaculture systems (FAO and UNICEF 2018). However, aquaculture systems also produce large amounts of nutrient pollutants that can degrade environmental quality (Cao et al. 2007; Eng, Paw, and Guarin 1989). Aquaponics, a system that utilizes waste water from the fish production for the hydroponic production of plant crops (Rakocy, Masser, and Losordo 2016), is a viable solution to environmental shortcomings set forth by traditional aquaculture systems. Crops grown using fish production effluent provide a natural biofilter and remove dissolved nitrogen and phosphorus from system effluent (Graber and Junge 2009). In addition, the nutrients from the aquaculture wastewater greatly reduce or eliminate the need for freshwater resources and fertilizer in hydroponic plant production. The solid waste produced in the system, also rich in nitrogen-based compounds, can be repurposed as fertilizer for field crops allowing for a more environmentally friendly approach to fish and crop production.

Thus far, aquaponics has been assumed to be a sustainable means of fish and crop production especially when compared to traditional aquaculture practices. Aquaponics has been found in previous studies to have lower eutrophication impacts when compared to aquaculture systems (Enduta et al. 2011; Wahyuningsih, Effendi, and Wardiatno 2015) but has also been found to

often have higher impacts associated with energy demand (Love, Uhl, et al. 2015; Maucieri, Forchino, et al. 2018). Other studies have examined impacts of aquaponics and hydroponics systems and found that aquaponics largely avoids the impacts associated with artificial fertilizer use (Chen et al. 2020).

Life cycle assessments (LCA) are powerful tools and present a “cradle-to-grave” methodological approach to quantitatively assess environmental impacts of a system (Bohnes et al., 2019). Previous studies have utilized LCA’s in order to quantify the environmental impacts of aquaponics systems (Cohen et al. 2018; Forchino et al. 2017; Xie and Rosentrater 2015b) but these studies have relied on data from very small-scale pilot systems, or in some cases, data from the literature only. Moreover, few studies have examined performance across multiple growing seasons over the course of a production year.

Auburn University operates a decoupled, large pilot-scale aquaponics system that currently produces tilapia and cucumbers. The tilapia are currently being sold and distributed to local markets while the cucumbers are sold to Auburn University dining services. Here we seek to conduct a robust life cycle assessment based on data collected from this large-scale system to quantify its environmental impacts. Data was collected over a 1-year duration in order to analyze possible variations in environmental impacts of unit operations based on seasonal differences. This study utilizes a process engineering model described in Kalvakaalva et al., (2021b) in order to aid in scenario analyses. This mass-balance model allows for tracking of water, carbon, and nutrient flows through the system. This study also includes direct greenhouse gas emissions from unit operations (Kalvakaalva, Prior, et al. 2021), something that no other aquaponics LCA has included. This allows for the comparison of direct facility emissions versus emissions from upstream inputs such as electricity and fish feed.

4.2 Methods

4.2.1 Goal and Scope

The goal of this study was to perform a cradle-to-gate life cycle assessment of aquaponics, primarily using data from a large-scale pilot aquaponics facility operated year-round at Auburn University. LCA midpoint methodology (Huijbregts et al. 2017) was used to determine the key sources of environmental impacts within the system and how seasonal variations can affect these impacts. Five impact categories were used including global warming potential (GWP, kg CO₂ eq), marine eutrophication (MEP, kg NO₃⁻eq), freshwater eutrophication (FWP, kg PO₄³⁻ eq), cumulative energy demand (CED, kWh), water depletion (WD, L), and land use (LU, m²). A mass-balance process model (Kalvakaalva, Smith, et al. 2021) was used to perform scenario analyses and to aid recommendations for better management practices. A function unit (FU) of 1 kilogram of dry-weight tilapia was used because tilapia is the main economic product of the system (Blidariu and Grozea 2011; Bosma et al. 2017; Love, Fry, et al. 2015). Cucumbers were treated as a co-product and were handled using the method of system expansion. Dry weight of tilapia and cucumbers was used in order to be consistent with the outputs of the mass-balance model described in Kalvakaalva et al. (2021). However, such values can be converted to fresh-weight basis based on a determined moisture content of ~75% for tilapia and ~96% for cucumbers.

The system boundary (Figure 14) was determined using a cradle-to-gate methodology which accounted for upstream impacts of feed, lime, propane, and electricity production. The boundary does not include any of the impacts incurred after the product leaves the system such as packaging, transportation, and post-consumer waste due to a lack of reliable data and high variability among end-consumers. Pesticides and fertilizers were not used in this system and

therefore were not included. Fish hatchery impacts were not considered in this study due to its relatively low environmental impacts based on a previous LCA (Ayer and Tyedmers 2009). This selected boundary is similar to previous studies (Chen et al. 2020; Cohen et al. 2018; Ghamkhar et al. 2020) which also used cradle-to-gate approaches for aquaponic systems.

4.2.2 System Description

The data used in this study was primarily obtained from a commercial-pilot scale aquaponics facility located at the E.W. Shell Fisheries Station in Auburn, AL which has a humid-subtropical climate (Beck et al. 2018). It is a decoupled aquaponics systems which means that the water effluent from plant production is not recycled back into the fish tank. The facility currently produces an average of 23 kg of tilapia and 45 kg of cucumbers per week for Auburn University campus dining facilities. The system consists of one 150,000 L fish tank which produces Nile tilapia (*Oreochromis niloticus*) and is housed in a 279 m² greenhouse (Figure 13). Fish were fed with a combination of 3606 and 4010 feed (Cargill, Franklinton, LA, USA) and the fish tank was operated as a biofloc system in order to biologically oxidize ammonia. Tilapia were grown in happa nets paced within the fish tank and were sorted biweekly based on maturity with an average of 6,000 tilapia in the tank at any given time over the one year operation period. Market size tilapia were harvested on-demand based on customer needs. Water was circulated via an airlift pump to a 3-stage clarifier where solids were partially removed and dried in geotextile bags. The remaining water fraction was recirculated back to the fish tank or to a separate 279 m² greenhouse which housed Beit Alpha seedless cucumbers (*Cucumis sativus*) grown in 11 L Dutch buckets (Crop King Inc., Lodi, OH, USA) filled with Perlite substrate. Cucumbers were irrigated using drip irrigation (Goldberg, Gornat, and Rimon 1976) and effluent water was collect in underground sumps until discharge into a drainage ditch (endpoint water

emissions). The greenhouses included humidity-controlled fans which provided ventilation. The fish house utilized a submerged aeration system powered by 1.5 hp blowers to ensure sufficient dissolved oxygen levels (Wagner and Pöpel 1998). Space heaters were utilized in cold weather months in both greenhouses and utilized propane as a fuel source. No artificial lighting was used in either greenhouse.

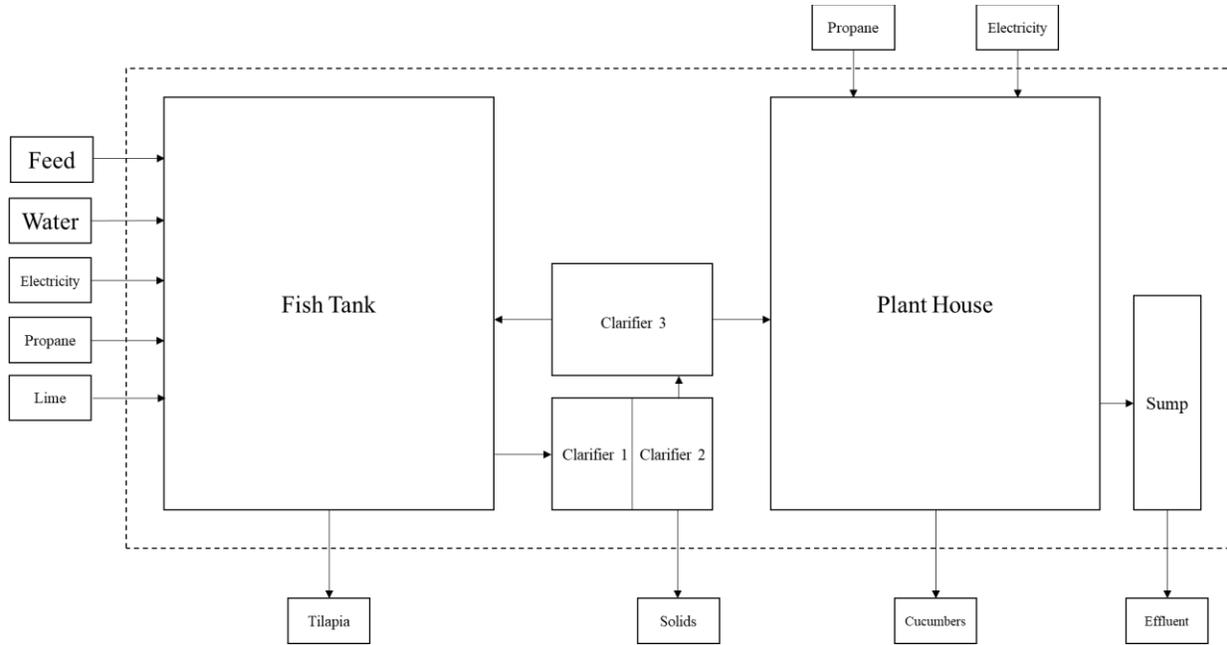


Figure 13: System boundary of the semi-commercial aquaponics facility

4.2.3 Data Collection

Data was collected on a daily basis from 3/15/2019 to 2/26/2020 and included the metering of input, irrigation, and post-greenhouse water flows, propane for heating both greenhouses, and electricity usage for each greenhouse. Additionally, the amount of feed and lime used each day was recorded as well as the amount of sludge discharged daily.

4.2.3.1 Water Quantity and Quality

A breakdown of water flows within the system has been described in a previous publication (Kalvakaalva, Smith, et al. 2021) but roughly breaks down to fish tank leakage, fish tank evaporation, plant evapotranspiration, and effluent water. All but the effluent water are considered consumptive (non-recoverable) water use. Ammonium, dissolved oxygen, temperature and pH were all measured daily. The biofloc system within the fish tank allowed for ammonium levels to be regulated while pH was regulated by the addition of hydrated lime ($\text{Ca}(\text{OH})_2$). Makeup water to the system was drawn from a rainwater retention pond in the North Auburn Fisheries Unit watershed which was upstream from the location of the aquaponics facility. Therefore no pumping energy was used. Water temperature averaged 27 °C over the course of the year and dissolved oxygen levels were maintained at an average of 7 mg/L.

4.2.3.2 Greenhouse Gas and Nutrient Emissions

Direct greenhouse gas emissions (CO_2 , CH_4 , N_2O) from each of the three unit procedures (fish tank, clarifiers, plant production) were measured from the system during the summer, fall and winter seasons (Kalvakaalva, Prior, et al. 2021) and were included in this study. Average GHG efflux rates were utilized in estimating the direct emissions for each season.

Water samples were collected on an approximately weekly basis from influent water, the fish tank, clarifiers, and plant-greenhouse sumps and were analyzed for nitrate (NO_3^-), nitrite (NO_2^-), and soluble phosphate (PO_4^{3-}) via anion chromatography using methods described previously in Chaump et al., (2019) and Kalvakaalva et al., (2021b).

4.2.4 Life Cycle Inventory

Table 7 shows an inventory of the system inputs and outputs for each season based on the system boundary. All inventory data was obtained from direct facility measurements. Heating was only used during the cold-weather months while electricity was used for fish tank aeration and humidity-controlled fans throughout the year. Propane combustion emissions were calculated on a stoichiometric basis and upstream emissions were accounted for using the GREET model (2018). The total amounts of soluble nutrients released were determined by the average concentration for each season and the total amount of water discharge after plant production for that season. Leakages from the fish tank and water lost with sludge solids were also accounted for. Fish produced was based on the calculated FCR of 1.6.

4.2.5 Co-product Allocation

Coproduct allocation of cucumbers was avoided via system expansion using LCA data from Khoshnevisan et al., (2014) who studied conventional greenhouse production of cucumbers. Sludge production was handled similarly and assumed to displace upstream impacts of chemical fertilizer production based on its nitrogen and phosphorus content (Corbala-Robles et al. 2018).

Table 7. Life Cycle Inventory of the aquaponics facility at Auburn University

	Spring	Summer	Fall	Winter	Total	Data Source
Water (L)						
Input	93726	440508	341557	355256	1.231E6	Measured
Output	48389	123509	120543	168245	4.6E5	Measured
Evaporation	27504	61530	97309	99661	2.86E5	Kalvakaalva et al (2021b)
Leakages	16870	96911	51233	42630	2.1E5	Measured
Sequestered	962	1840	934	1664	5400	Kalvakaalva et al, (2021b)
Fish Tank						
Tilapia (kg DW)	69,67	248,29	73,39	110,43	501.78	Measured
Sludge (kg DW)	115,70	412,31	121,87	183,37	833.25	Measured
Feed (kg DW) ^a	437,72	1559,9	461,08	693,77	3152.47	Measured
Lime (kg DW) ^b	8,17	57,61	32,66	44,45	142.89	Measured
Electricity (kwh)	5172	9975	5271	10106	30524	Measured
Propane (m ³)	0,55	0	0,17	3,78	4.5	Measured
Planthouse						
Cucumbers (kg DW)	35,90	68,68	34,85	62,12	201.55	Measured
Plant Mass (kg DW)	7,94	15,19	7,72	13,71	44.56	Kalvakaalva et al, (2021b)
Electricity (kwh)	842,51	4223	1974	2947	9986.51	Measured
Propane (m ³)	0,2	0,02	0,08	1,88	2.18	Measured
Direct System Emissions (kg)						
CO ₂	76,43	138,63	57,71	138,54	401.31	Measured
CH ₄	1,65	1,69	1,47	0,74	5.55	Measured
N ₂ O	3,36	4,14	0,42	0,33	8.25	Measured
NO ₃ ⁻	29,92	100,71	45,78	30,72	207.13	Measured
PO ₄ ³⁻	1,53	8,54	4,96	4,16	19.19	Measured

4.2.6 Life Cycle Impact Assessment

The environmental impacts of the system were determined using ReCiPe Midpoint hierarchical (H) assessment method (Dong and Ng 2014; Huijbregts et al. 2017). Impacts were calculated for each season in order to better understand how seasonal differences may affect the environmental impacts of the system: Spring (3/15/19-5/15/19), summer (5/16/19-9/4/19), fall (9/5/2020 - 10/31/2020), and winter (11/1/19-2/26/20). The impact assessment was carried out using a combination of Microsoft Excel and OpenLCA software (Microsoft 2018; OpenLCA v 1.10; Appendix 2). Life cycle inventory data was based entirely on measured emissions/inputs in the field whereas previously-published life cycle assessments and databases were used for upstream and downstream impacts. These included upstream impacts for lime (Yang et al. 2017), feed (Avadí et al. 2015), and propane (GREET 2020). The results of another life cycle assessment were used to estimate the downstream impacts of the released sludge, assuming the sludge was used for field application (Corbala-Robles et al. 2018). Emissions were estimated based on the nitrogen and phosphorus content of the sludge (Kalvakaalva, Smith, et al. 2021)

The published LCA's used for feed, released sludge, and lime production included additional impact categories which we did not include in our study. Data for electricity production was retrieved from the EPA Power Profiler database (EPA 2018) which provided specific emissions from electricity generation supplied to Auburn, AL (SRSO Region).

4.2.7 Scenario Analysis

Five alternative scenarios were selected and analyzed to understand how changes in system operation would impact environmental performance (Table 8). We specifically focused on scenarios that are realistic to implement and likely to have a significant impact on environmental

performance. Values for the current (baseline) system were based on average data for the entire period of operation (1 year) and compared to the four alternative scenarios. The first scenario (Scenario 1) analyzed was the substitution of wind energy for the current Alabama grid mix which is mostly sourced from fossil-fuels (natural gas and coal). This scenario accounts for the upstream environmental impacts associated with construction of a wind farm (GREET 2018). Scenario 2 involves the reduction of fish tank leakages which led to large impacts on eutrophication potential and water depletion. This scenario assumes that evaporation and irrigation rate remains the same as the baseline scenario and makeup water input is decreased in order to maintain a constant fish tank volume. Scenario 3 analyzes the utilization of the entirety of the plant greenhouse space. As this is both a research and production facility, the full floor space of the greenhouse was not used for cucumber production during the 1-year period. We estimate that production levels 2.45 times higher than baseline production could be achieved if the full greenhouse area were utilized. To accomplish this, the mass-balance process model described in Kalvakaalva et al., (2021b) was used to expand plant production using existing stoichiometric relationships within the model to predict changes in water nutrient status. Scenario 4 expands the system to two fully-utilized plant greenhouses in order to better match the nutrient flows from the fish tank. Additional greenhouse space was not added because the final effluent nitrate level would drop below 100 mg/L which is likely to begin negatively impacting plant growth. Scenario 5 combines all three previously mentioned scenarios in order to represent semi-ideal system operation.

Table 8. List of scenarios analyzed and utilized data for each.

Scenario	Description	Data Utilized
Scenario 1	Electricity generation was replaced from the conventional non-renewable fuel mix to a proposed wind farm	GREET
Scenario 2	Elimination of fish tank leakages	-
Scenario 3	Full utilization of existing plant greenhouse space	Kalvakaalva (2021b)
Scenario 4	Expansion to 2 full-utilized plant greenhouses	Kalvakaalva (2021b)
Scenario 5	Ideal facility operation without the use of non-renewable energy sources, elimination of system leakages, and full utilization of greenhouse space,	GREET (2018), Kalvakaalva (2021b)

4.3 Results and Discussion

4.3.1 Inventory and System Yields

Across the 1-year study period, the system produced 502 kilograms of tilapia (dry weight) and 202 kilograms of cucumbers (dry weight). The highest level of production was achieved during the summer season mainly due to a combination of a longer selected time period as well as increased feeding rates (Table 7).

4.3.2 System Impacts

4.3.2.1 Greenhouse Gas Emissions

The system exhibited variation in GHG emissions across each season and among unit operations (Figure 15) Emissions associated with electricity consumption and heating dominated this impact category, accounting for 37.4% and 35.1% of emissions, respectively. GHG

emissions were highest in the winter season, mainly due to the use of propane heating in the fish and plant houses, combined with relatively low yields of tilapia and cucumbers. Together, direct emissions from the system only contributed 1.2% of total global warming potential. This is the first LCA of aquaponics, to our knowledge, that included direct facility emissions. Past LCAs all assumed direct emissions were negligible in comparison to electricity and heating. Our results now provide data to support the assumption made in those studies (e.g. Chen et al., 2020; Forchino et al., 2017; Ghamkhar et al., 2020), however, we caution that although heating and feed still dominate, direct emissions rise to 2.3% of total GHG emissions if renewable energy sources are used. Fish production contributed to the highest global warming potential from direct system emissions due to large amounts of N₂O production, aeration, and a large surface area (Figure 15). The clarifiers also contributed significantly to global warming potential relative to its surface area due to anaerobic conditions that resulted in large amounts of methane production (Kalvakaalva, Prior, et al. 2021). Greenhouse cucumbers sequestered 0.122 kilograms of CO₂-eq per kilogram of tilapia produced. The release of N₂O from the fish tank is largely unavoidable due to the biofloc system within the fish tank that converts ammonium to nitrate (Robles-Porchas et al., 2020), releasing N₂O as a bi-product (Law et al., 2012). However, operational changes could be made to the clarification system in order to reduce anaerobic conditions and methane production. The biofloc within the fish tank and solids settling systems eliminates the need for more energy intensive treatment systems such as a fluidized bed system (Barak et al. 2003; Matsumoto 2012). These results are similar to previous studies such as Chen et al., (2020) which determined that electricity and heating accounted for 90% of GWP impacts. This is also similar to the findings of Ghamkhar et al., (2020) which studied a system located in a colder climate and

found that electricity and heating accounted for 36% and 55% respectively while calculated direct emissions only accounted for 0.24% of GWP.

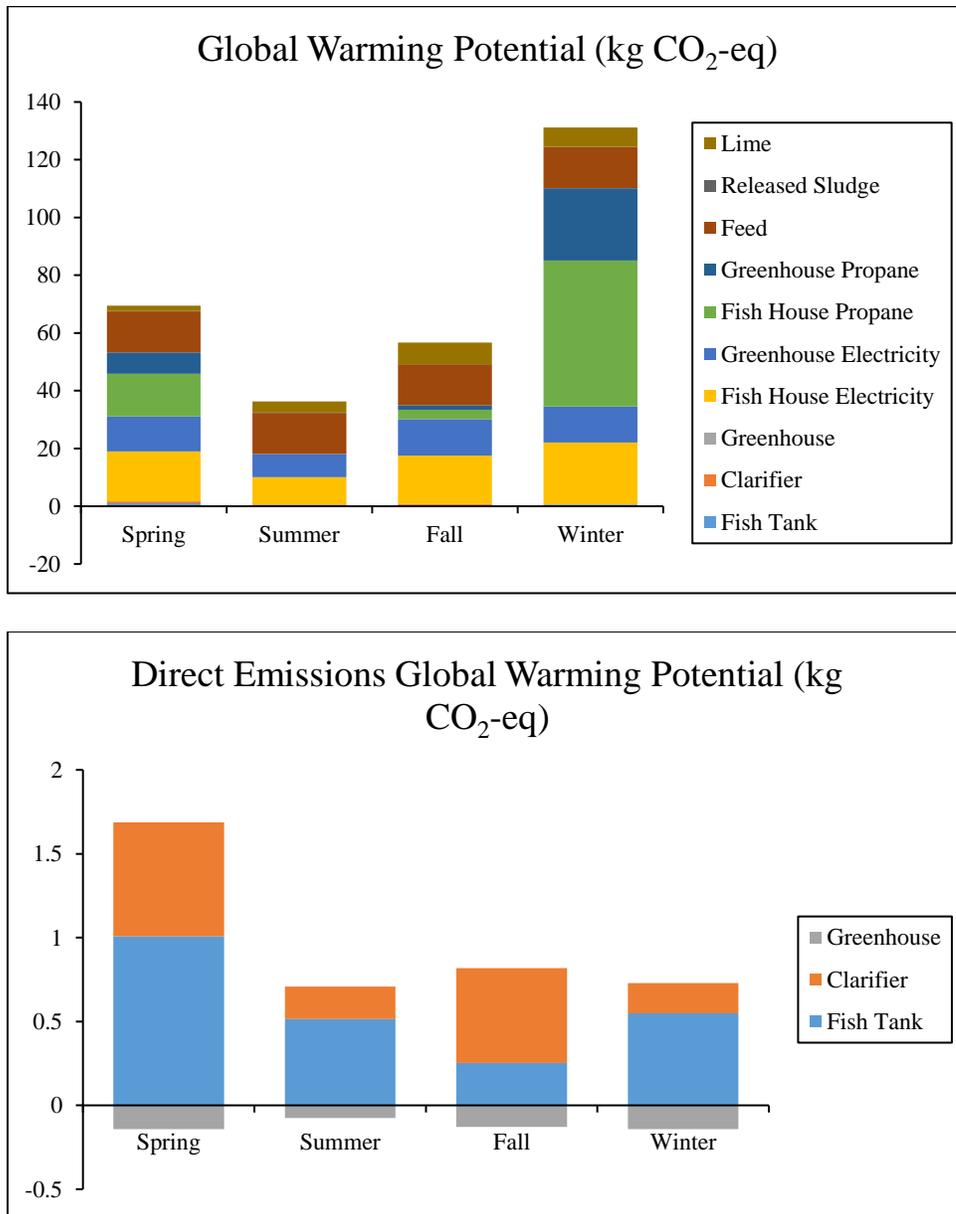


Figure 14: Global warming potential of direct and upstream processes (top) and direct system emissions (bottom). All values are represented per kilogram of tilapia.

4.3.2.2 Eutrophication Potential

Marine eutrophication (kg NO₃-eq) was dominated by leakages from the fish tank and final system effluent, accounting for 41.9% and 47.4% respectively (Figure 16a). Fish feed production was the next highest contributor followed by sludge filtrate at 5.7% and 4.6%, respectively. Lime inputs and field-applied sludge solids contributed minimally to total marine eutrophication impacts. Freshwater eutrophication (kg PO₄-eq) showed similar results as marine eutrophication with fish tank leakages and final effluent contributing 36.9% and 57.2%, respectively (Figure 16b). Sludge filtrate only contributed 3.9% of impacts and the solid fraction was only marginal. Other upstream system inputs such as feed and lime were not included in freshwater eutrophication due to external data availability and to avoid double counting impacts. Land-application of the sludge had a minimal impact on freshwater eutrophication, similar to the

marine eutrophication results found in Ghamkhar et al., (2020) which found that sludge accounted for 10% of eutrophication potential.

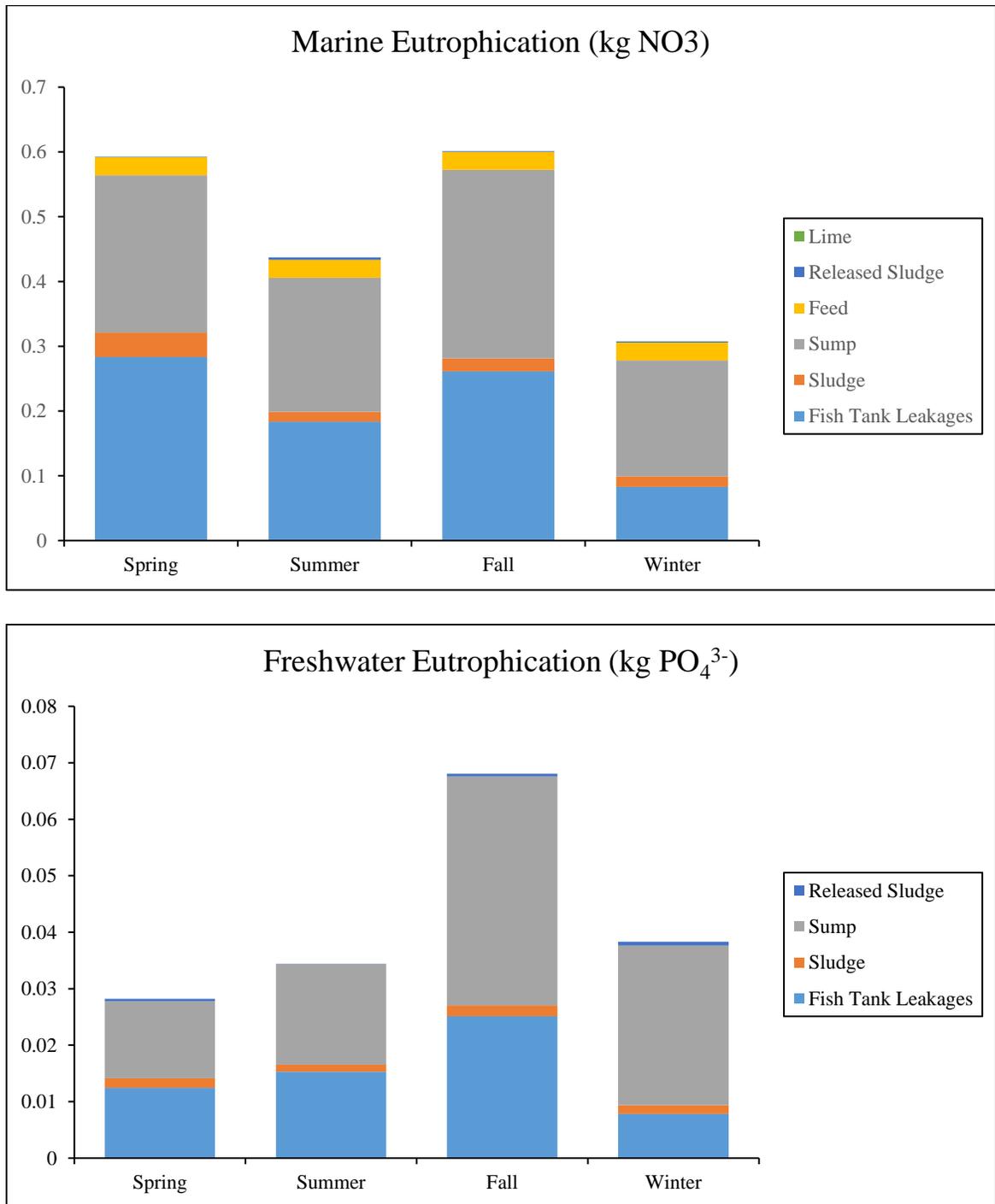


Figure 15: Marine eutrophication potential (left) and freshwater eutrophication (right) represented in terms of kilograms of tilapia produced

4.3.2.3 Energy Demand

Energy demand per kilogram of tilapia was highest in the spring (101 kwh/kg tilapia) and winter seasons (118 kwh/kg tilapia). The high CED during these periods was driven by low levels of fish and cucumber production coupled to high heating demand. Production during the spring was undergoing a period of ramp-up in terms of both fish and cucumber production. By summer, the system was operating at a high tempo, putting out 15.7 and 4.3 kg/week of tilapia and cucumbers, respectively. This is compared to a return to low tempo in the winter with the system outputting 6.5 and 3.9 kg/week of tilapia and cucumbers. The CED across all seasons was driven by aeration for the fish tank, humidity controlled fans, and irrigation pumps. On average, electricity for the fish house operations including aeration accounted for 73.6% of cumulative energy demand. Aeration accounted for 20.7% of fish house energy consumption (Figure 17).

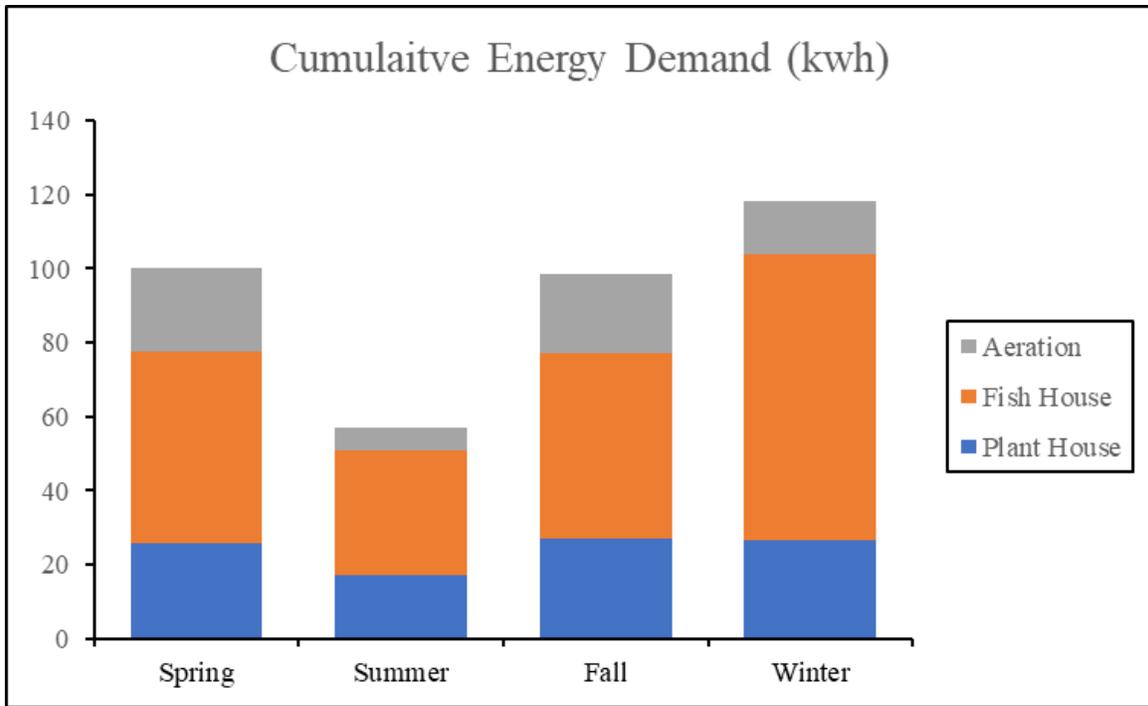


Figure 16: Cumulative energy demand of system operations per kilogram of tilapia produced

4.3.2.4 Water depletion

Water depletion also varied across seasons and was highest during the fall seasons due to high evaporative rates, leakage, and planthouse effluent. Fall in Auburn AL is a relatively warm, dry period (Beck et al. 2018) which likely explains the high rate of evaporation. In addition, a significant new leak in the fish tank emerged during October of 2019 which could explain the higher loss due to leakage during that period. Fish tank leakages accounted for 38.3% of all water depletion while evaporation accounted for 57.3%. Water released with solids removal only accounted for 2.5% of water depletion (Figure 18). Plant production effluent accounted for 43.6% of makeup water entering the system but was not included in water depletion as we assume that this water is still usable.

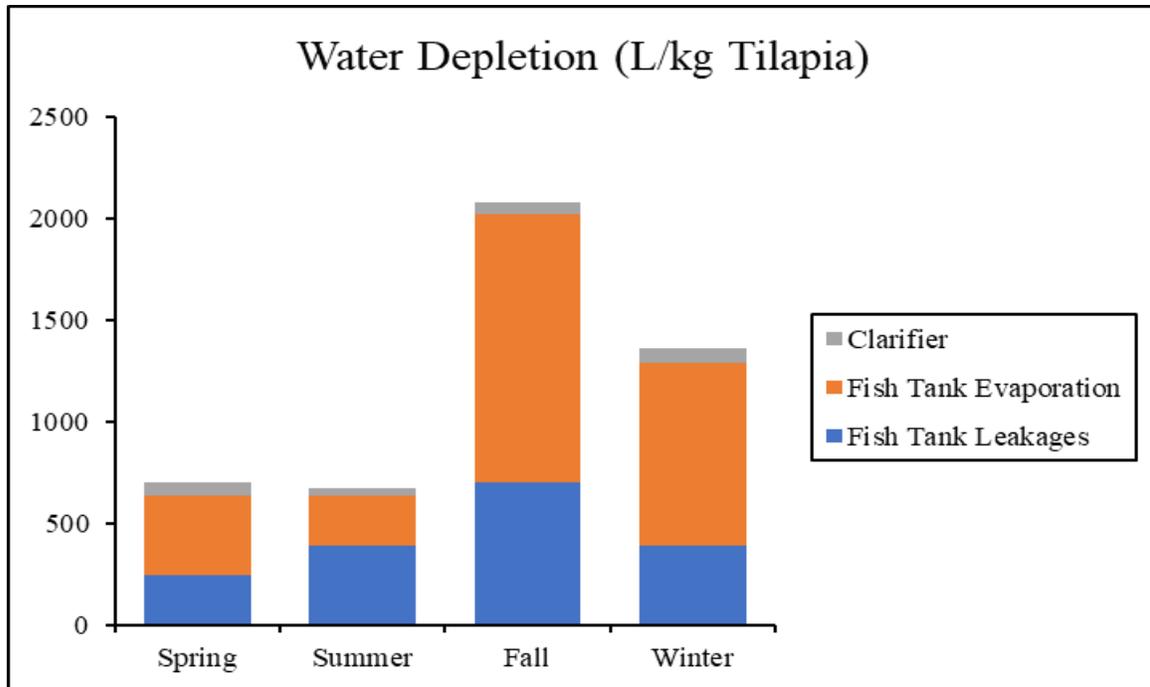


Figure 17: System water depletion per kilogram of tilapia produced.

4.3.2.5 Land Usage

Land usage was calculated based on the assumption that the system’s lifespan is approximately 10 years. We assume that the system will continue to produce the functional unit of tilapia at the same rate throughout system operation. The system occupied 0.06 ha of land and would produce approximately 5017 kg of tilapia in a 10 year period. The result is a direct land use impact of 0.12 m² per kilogram of tilapia.

4.3.3 Scenario Analyses

Scenario 1, by substituting grid electricity with wind energy, greatly reduces the environmental impacts of electricity usage from the fish house and planthouse which previously dominated impacts (Table 9). During the colder months, impacts associated with propane heating contributed the most to global warming potential but feed production attributed the most

(87.03%) to GWP during the summer months when heating was not required. Feed substitution or management practices to induce a more efficient feed conversion ratio could reduce this impact (Omasaki et al. 2017; Papatryphon et al. 2004; Siddiqui, Howlader, and Adam 1988).

Table 9. Changes in system global warming potential per season based on scenario 1.

Season	Original	Scenario 1
Spring	69.36	33.76
Summer	36.19	11.91
Fall	56.54	17.38
Winter	130.99	87.94

Scenario 2 reduced the amount of water lost through leakages (Table 10) from the fish tank which accounted for 41.2% and 36.9% of marine and freshwater eutrophication respectively as well as 21.6% of water depletion in the baseline case. The result was a corresponding decline in these impact categories when the leaks were eliminated. Meanwhile, the evaporation rates and plant production rate were assumed to be unaffected by the elimination of leakage. As a result, plant production effluent dominated impacts for both marine and freshwater eutrophication (50.4% & 90%) while evaporative losses accounted for 92.8% of water depletion. These results indicate that if leakage losses were largely eliminated from the system, better utilization of irrigated water would be necessary to further reduce environmental impacts. Scenarios 3 and 4 addresses this issue since they include better utilization of greenhouse space for increased plant production, as well as the addition of a second greenhouse. Plant production in the second greenhouse was set not to exceed amounts which utilized nitrate concentrations below 100 mg/L where applicable (Table 10). Consumptive water use is marginally improved in these scenarios but marine and freshwater eutrophication are improved to such an extent that fish tank leakages

become the most dominant source of eutrophication impacts. The addition of a second greenhouse further improves eutrophication impacts but increases impacts of GWP and CED.

Table 10.: Changes in environmental impact categories through each scenario studies.

	Global Warming Potential (kg CO ₂ -eq)	Marine Eutrophication (kg NO ₃ -eq)	Freshwater Eutrophication (kg PO ₄ -eq)	Cumulative Energy Demand (kwh)	Water Depletion (L)
Current Production	77.19	0.68	0.054	80.52	1482
Scenario 1	52.82	0.68	0.054	80.52	1482
Scenario 2	77.19	0.30	0.026	80.52	588
Single Greenhouse Scaled	77.19	0.60	0.038	77.42	1482
Two Greenhouses Scaled	87.37	0.56	0.034	97.98	1482
Idealistic	52.84	0.19	0.007	97.98	588

Scenario 5 combines scenarios 1, 2, and 4 to represent an idealized system (Table 10). The result is a 31.6% reduction in GWP compared to the baseline case even though CED increased by 26.4%. Marine and freshwater eutrophication also decreased on average by a factor of 2. Water depletion is also largely reduced as less makeup water is needed to replace water loss through leakages.

5.0 Conclusions

Overall, heating (35.1%) and electricity (37.5%) are the dominant impacts of aquaponics global warming potential followed by feed production (19.4%). Direct emissions from the system only accounted for <2% of system impacts. By switching to renewable electricity sources, global warming potential is reduced by a factor of 2.5. Leakages and post-plant effluent of the decoupled aquaponics system were the main sources of eutrophication potential. By eliminating leakage losses and increasing plant production, marine and freshwater eutrophication potential could be reduced by 46% and 90% respectively. Fish tank evaporation and leakages were the largest water consumers with 32.3% and 21.6% of impacts coming from these two areas, respectively. Low yields of system products can also lead to higher impacts as seen in the winter where system production of tilapia and cucumbers decreased.

It was originally hypothesized that seasonality would lead to differences in environmental impacts. We found that seasonality largely affects global warming potential and energy demand. Changes in system operation confounded this to an extent as a reduction in system outputs exacerbated impacts in the winter months. The process modeling proved to be a useful tool in scenario analyses by predicting how upstream changes affect downstream nutrient flows to a certain degree of accuracy.

Greenhouse gas emission data provided much needed insight on direct system impacts. By now understanding the high methane efflux from the clarifiers, future decision making of current system changes or future proposed systems can now be influenced by this knowledge.

5.1 Future Work

The identification of the underutilization of available nutrients within the system leaves room for easily achievable system improvement. It would be interesting to make such improvements to the system and compare the results to the results predicted by the process engineering model. Additionally, system construction impacts were not currently included in the impact assessment. It would prove to be beneficial to include these impacts to understand the impacts of future systems. Finally, further greenhouse gas studies would prove to make more definitive claims on direct emissions of aquaponics systems. The inclusion of greenhouse gas efflux from effluent sludge would also be useful as well as the possibility of field application.

6.0 References

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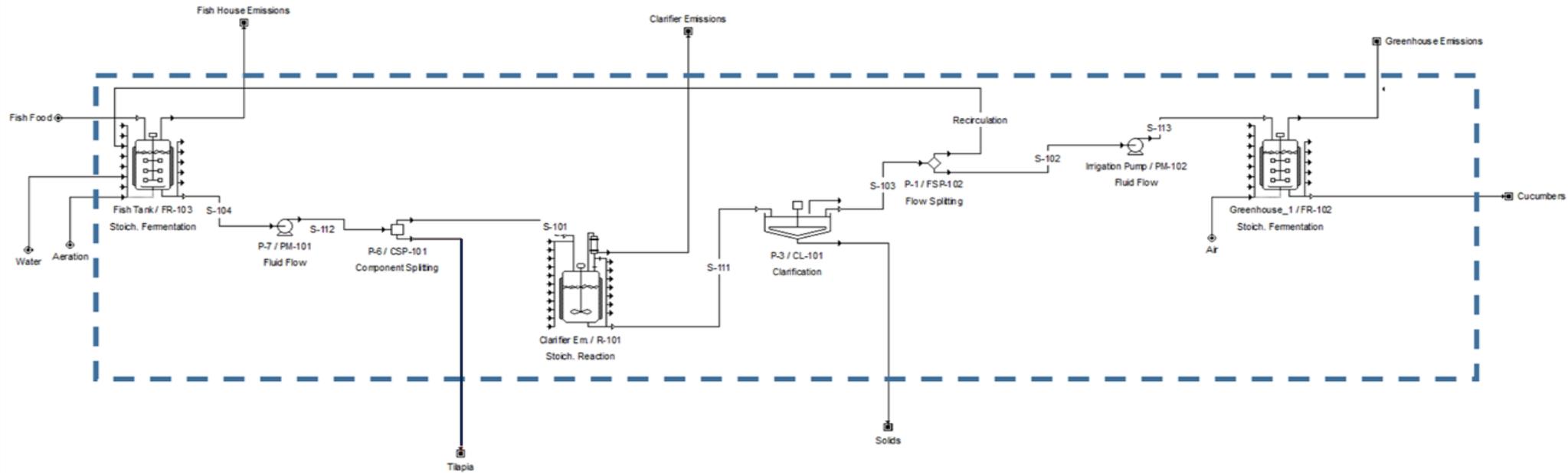
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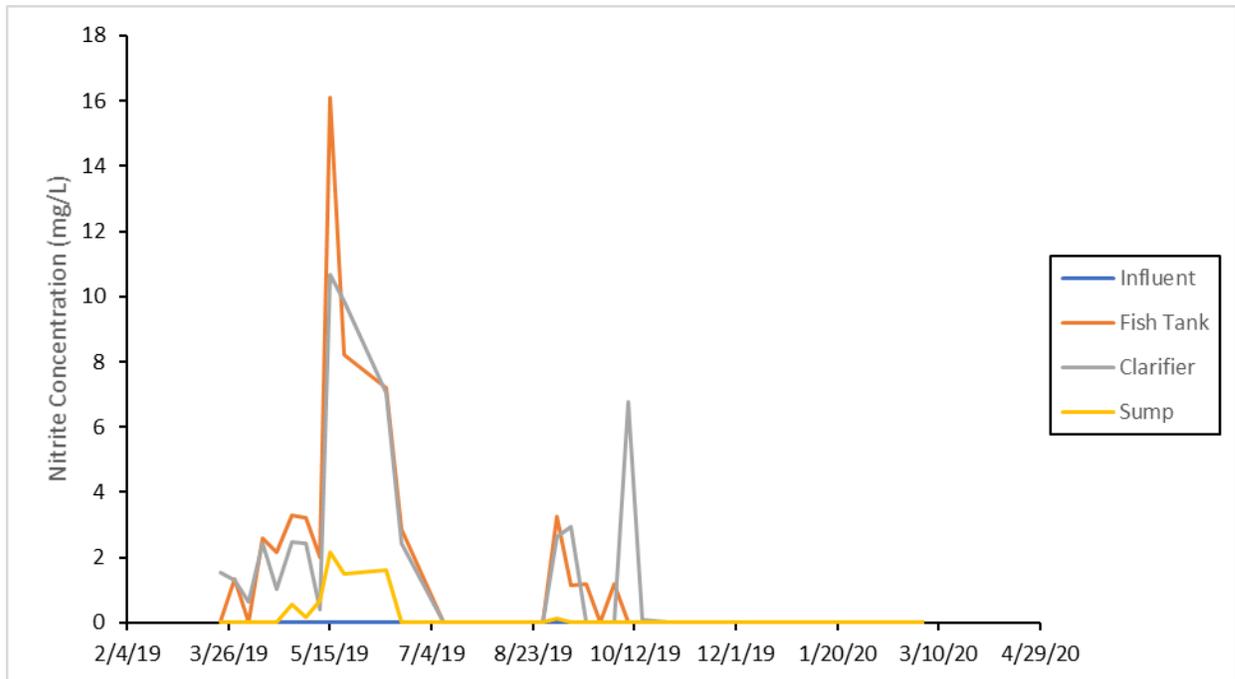
7.0 Appendix

7.1 Appendix Figure 1



Appendix Figure 1: Visualization of the constructed process engineering model in SuperPro Designer

7.2 Appendix Figure 2



Appendix Figure 2: Nitrite concentration within four locations throughout the study period. The spike in nitrite concentrations throughout the system occurred in the late spring/early summer of 2019 and was most likely due to a sudden increase in system feeding rate.