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Aquaponics and the crossroads of profitability and sustainability viewed through sensitivity and risk modeling

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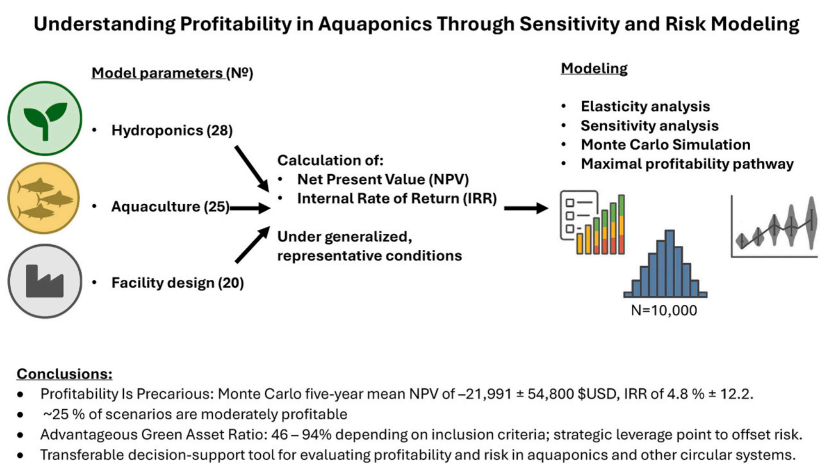
GRAPHICAL ABSTRACT



ABSTRACT

Aquaponics integrates aquaculture effluent with hydroponic crop production, offering a resource- and water-efficient alternative to conventional agriculture. However, its economic viability remains contested, with many commercial operations having short lifespans. This study develops a financial modelling framework to evaluate aquaponics profitability and sustainability by analyzing the sensitivity of Net Present Value (NPV) and Internal Rate of Return (IRR) to variations in aquaculture, hydroponics, and facility operational parameters. A 73-parameter financial model was built. Sensitivity and elasticity analyses ranked parameters by their influence on NPV and IRR over realistic ranges. Monte Carlo simulations estimated the likelihood of positive returns, while Latin Hypercube Sampling of truncated normal distributions identified parameter combinations yielding optimal outcomes. Life Cycle Analysis (LCA) and Green Asset Ratio (GAR) were applied to assess environmental impacts and eligibility for sustainable financing.

Labor, managerial efficiency, production yield and market price were dominant profitability drivers; plant revenues influenced profitability more than fish. The mean five-year NPV was −21,991 ± 54,800 $USD; IRR was 4.8 ± 12.2 %, with only ~25 % of simulations yielding positive values. The high variability suggests persistent operational vulnerability. LCA showed electricity as the largest contributor to GWP (~20,000 kg CO_2-eq y^{-1} median) followed by infrastructure

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maintenance. Moreover, the profile of profitable scenarios diverged from non-profitable ones. GAR scores ranged from 46 to 94 %, indicating suitability for EU green-finance instruments to buffer risk. This stochastic modelling approach enables researchers to target parameters for optimization, operators to address process constraints, and investors to assess risk–return trade-offs. Applied here to aquaponics, the methodology is transferable to other circular systems as a risk assessment tool.

1. Introduction

Aquaponics is the co-culture of fish and plants in a closed loop, controlled environment agriculture (CEA) system. Aquaponics is often promoted as an ideal sustainable food production system that promises circularity through nutrient cycling between its two main constituent products, fish and plants (Forchino et al., 2017; Goddek et al., 2019). Aquaponic cultivation has expanded markedly in recent years, as evidenced by the growing cohort of start-up enterprises that have progressed beyond backyard or educational installations toward fully integrated, commercial-scale production (Pattillo et al., 2022; Raulier et al., 2023). The novelty of this cultivation platform combined with the variety of fish species and crops that can be grown has attracted people from a variety of domains. Aquaculturalists for instance, have shown interest in the hydroponics component as a water purification step to reduce discharge from facilities, while also generating a side income from plants alongside fish sales. Similarly, people from the hydroponics industry may view fish production as a means of generating bioavailable fertilizer for their crops, and to generate a niche product with higher market value based on 'green' production. Finally, there are people attracted by the sustainability of aquaponics who may focus on its use as a platform for community engagement and education, or backyard or community supported agriculture (CSA) enthusiasts interested in growing food locally. Thus, the scale and industrialization of aquaponics operations varies considerably, ranging from small, manually managed community systems to highly automated, vertically integrated facilities supplying regional markets (Raulier et al., 2023).

This diversity of operational models not only affects production efficiency but also shapes the relative economic emphasis on either the aquaculture or hydroponic components. Despite the wide variety of fish and plant combinations possible in aquaponics, the determinants of economic viability—such as production scale, system design, and market positioning—remain poorly quantified in the literature. Existing models often overlook the interdependencies between aquaculture and horticulture subsystems such as how production volume dictates infrastructure needs, or how changes in stocking or planting density affect water exchange, oxygenation, nutrient availability, and ultimately profitability in both compartments (Al Tawaha et al., 2021; Komal et al., 2024; Liu et al., 2015; Ni et al., 2016; North et al., 2006). This lack of robust, integrated modelling contributes to the high failure rate among start-ups (Raulier et al., 2023; Turnsek et al., 2020; Greenfeld et al., 2019). In this paper, we aim to address these gaps by developing and testing a framework that explicitly links technical production parameters to economic outcomes, enabling more accurate assessment of profitability across different operational scales.

1.1. The need for economic modeling in aquaponics

While resource utilization models are well-established in aquaculture and aquaponics, few studies have applied stochastic economic modelling to these systems (Danish et al., 2021; Zhang et al., 2022a; Stalport et al., 2022; Francisco et al., 2024; Baganz et al., 2020; Lobillo-Eguíbar et al., 2020). Economic models serve two important functions. First, they predict which factors most strongly influence investment returns. The novelty of circular food production systems brings additional financial burdens from internalizing waste treatment costs, leading to greater reluctance among investors to engage in riskier, novel business models that diversify target outcomes. Such outcomes my include environmental or social well-being, instead of exclusively focusing on monetary profit. In such cases, profitability often depends on clear product differentiation in the marketplace.

To illustrate the need for robust modelling, this study establishes a baseline for a "typical" aquaponics farm in a highly industrialized country and uses it to explore profitability scenarios. Our framework evaluates vulnerabilities that could substantially increase financial risk. For example, electricity prices in the European Union range from €0.08/kWh to €0.26/kWh for industrial consumers (Eurostat, 2025) while in the USA they range from 8.15¢/kWh (€0.08/kWh) to 39.85¢/kWh (€0.37/kWh) (EIA. Table 5.6.A, 2025). Electricity in particular can have a significant impact on the profitability of energy-intensive CEA systems (Eurostat, 2024).

System diversity further complicates economic assessment. Aquaculture units generally follow recirculating aquaculture system (RAS) designs (Colt et al., 2022), however the choice in fish species cultivated may range from omnivores such as Nile tilapia (*Oreochromis niloticus*) to carnivores such as salmon (*Salmo salar*) (Tennøy, 2022; Skar et al., 2022; Al-Hafedh et al., 2008). While tilapia have a relatively short lifespan and are typically harvested within a year in most facilities (Hussain and Brown, 2024), other species such as sturgeon may remain in the farm for many years (Lobanov et al., 2024). In hydroponic units, leafy greens can be harvested within weeks whereas vine crops like cucumbers may require several months (Eck et al., 2019a; Yang and Kim, 2020a; Yep and Zheng, 2019). Cultivation strategies influence water usage, lighting, and spatial requirements (Sharma et al., 2018; Wootton-Beard, 2019). The extent to which aquaculture wastes are remineralized into plant-available compounds is a burgeoning topic of research (Goddek et al., 2016; Lobanov et al., 2021), and a critical factor in determining the amount of nitrogen and phosphorus that can be taken up by plants. Finally, the ideal production scale for aquaponics systems is a highly debated topic with notably divergences in recommended sizes (Lobanov et al., 2025; Zheng et al., 2024; Channa et al., 2024). Some articles claim that small operations of around 100 m^2 often run at a loss and that only much larger facilities— above 1000 m^2 —can achieve profitability through economies of scale (Baganz et al., 2020; Karimanzira et al., 2017; Tetreault et al., 2023; Turnšek et al., 2019; Love et al., 2015). Yet, the lack of large aquaponics facilities in the EU and North America suggests this trend may not be valid. Unsurprisingly, many studies have advocated for the opposite trend – that small <500 m^2 facilities are more profitable (Channa et al., 2024; Gosh and Chowdhury, 2019; Tokunaga et al., 2015). To address how these divergences influence total system profitability, a generalized model encompassing the full spectrum of diversity is required.

Economic modelling furthermore allows sustainability to be more thoroughly assessed under different economic conditions. Life-cycle assessments (LCA) track resource and emission flows from "cradle to grave" based on impact categories such as global-warming potential, water and land use, and eutrophication pressure (Chomkhamsri et al., 2011). Several LCAs have been carried out on aquaponic systems (Hognes et al., 2014; Jaeger et al., 2019; Henriksson et al., 2025; Elnour et al., 2023; Ianchenko and Proksch, 2019), however these are always focused on existing farms. Broadly speaking, these studies show that redirecting nitrogen and phosphorus wastes to crops can cut fertiliser-related greenhouse-gas emissions by up to half compared with stand-alone recirculating aquaculture or hydroponic facilities. However, an association between generalized profitability metrics and LCA-derived sustainability assessments is lacking. The GAR, in turn, operationalises these environmental gains for capital markets by expressing the proportion of taxonomy-aligned capital expenditure in a single metric under the EU Sustainable Finance framework (Brühl, 2023). Because aquaponic facilities combine high resource-use efficiency with potential classification of both operational and (in many cases) construction costs as taxonomy-aligned, they are well positioned to achieve high values, unlocking preferential debt terms and sustainability-linked funding. Framing aquaponics through the dual lenses of LCA and GAR therefore not only quantifies its environmental benefits but also demonstrates clear pathways for de-risking investment and accelerating its adoption as a circular, climate-smart food-production system.

1.2. Scope of the model

For the purposes of this model, we begin with assumptions about greenhouse size, defined as the annual crop production (kg plants/year). In this way, nitrogen use efficiency is prioritized as a key variable. Fish production is scaled such that it entirely satisfies plant needs for nitrogen, thereby necessitating minimal additional nutrient supplementation. From this starting point, a total of 73 aquaculture, hydroponics, and facility parameters are defined to calculate all relevant production inputs and outputs with the goal of establishing a base case and realistic ranges for future aquaponics studies. This enables an exploration into different efficiencies (e.g., feed conversion ratios from 0.8 to 1.5 kg feed/kg fish) and as well a consideration for different crops. For example, parameters such as yield (kg/plant) or nitrogen assimilation rate (g N/kg plant) will vary across cultivars. Similarly, the range for fish selling price ($/kg) reflects both low- and high-value species.

Starting from the list of assumptions, we calculate the Net Present Value (NPV) and Internal Rate of Return (IRR) for a theoretical aquaponics farm. NPV represents the present value of all future cash flows—both incoming and outgoing—discounted back to today (time value of money), thereby reflecting the overall profitability of the investment. IRR, by contrast, is the discount rate at which the NPV equals zero; it serves as the project's financial break-even point in terms of rate of return accounting for the time value of money. The parameters were then assessed in a sensitivity analysis and elasticity test to identify the parameters which most strongly influence NPV and IRR. This refined list of parameters was used to simulate NPV and IRR changes across each parameter's range using Monte Carlo simulations and Latin hypercube sampling (Helton and Davis, 2003). Finally, integrating taxonomies such as the Green Asset Ratio (GAR) defined by the EU Taxonomy Disclosures Delegated Act provide an additional tool for aquaponics facility to reduce their risk profile for investors (Brühl, 2023; Commission, 2023). Moreover, it can help identify key areas for further research, as parameters with the greatest influence on profitability are likely to offer the most leverage for cost optimization. With the pressing need for industrial circularity in the face of climate change, this multi-faceted approach will aid decision-makers in understanding the variability of potential outcomes and support more informed strategic planning in aquaponics and other emerging circular industries (Kaya and Monsù

Table 1
Aquaculture assumptions included in the model. All prices are in USD. FTE = Full-Time Equivalent.

Class	Model Assumptions	Unit	Base Case	Lower Bound	Upper Bound	References
Aquaculture	Aquaculture Energy Productivity	kWh/kg fish * y	2	1	10	(Bujas et al., 2022; Zoli and Bacenetti, 2025; Nistad, 2020)
Aquaculture	Aquaculture Water Productivity	L/kg fish	1000	333	2000	(Vielma et al., 2022; Gallego-Alarcón et al., 2019)
Aquaculture/ Fertilizer	Calcium Carbonate	$/kg	0.5	0.25	3	Nindarwi et al. (2019)
Aquaculture	Feed	$/kg	2.2	1	4.4	Pate (2025)
Aquaculture	Feed Conversion Ratio (FCR)	kg feed/kg fish	1.1	0.8	1.5	Fry et al. (2018)
Aquaculture	Feed phosphorus content	%	1.2	0.8	1.5	(Chatvijitkul et al., 2018; Glencross et al., 2007; Schumann and Brinker, 2020)
Aquaculture	Feed protein content	%	32	28	45	Ullah-Khan et al. (2019)
Aquaculture	Fingerlings	$/fingerling	0.55	0.1	2.5	(Pate, 2025; Nations FaAOotU, 2025)
Aquaculture	Fish selling price	$/kg	10	2.2	50	(Pate, 2025; Nations FaAOotU, 2025; Bostock et al., 2010)
Aquaculture	Harvest size	kg	1	0.5	2.2	(Seginer and Ben-Asher, 2011; Yu and Leung, 2006) (Suhl et al., 2016; Quagrainie et al., 2018)
Aquaculture	Investment capital fish	$ inv.cap/kg fish	2	1.5	3.98	Landazuri-Tveteraas et al. (2023)
Aquaculture	Labor efficiency, fish	kg fish/FTE * y	37510	31883.5	474000	Engle et al. (2021)
Aquaculture	Liquid oxygen	$/m3	1.5	0.5	5	(Ebeling and Timmons, 2012; Whangchai et al., 2022)
Aquaculture	Management efficiency, fish	kg Fish/FTE * y	88000	74800	1505000	Engle et al. (2021)
Aquaculture	Nitrogen assimilation of fish	g N/kg/fish	28.8	27	31	(Sun et al., 2016; Conceição et al., 2012; Pucher and Focken, 2017)
Aquaculture	Nutrient remineralization	%	0.5	0.05	0.95	(Lobanov et al., 2021, 2023)
Aquaculture	Oxygen consumption	m3/kg feed	0.3757	0	0.4	(Colt and Watten, 1988; McLean et al., 1993)
Aquaculture	Package size	kg/unit	0.5	0.25	1	(Engle, 2010; Coale et al., 1993)
Aquaculture	Packaging, fish	$/unit	0.05	0.001	1	Engle (2010)
Aquaculture	Phosphorus assimilation of fish	g P/kg/fish	4.1	2	6	(Luo, 2023; Benstead et al., 2014)
Aquaculture	Processing efficiency, filleted	kg yield fish filleted/kg whole fish	0.4	0.3	0.6	(Rørå et al., 2001; Fu et al., 2024)
Aquaculture	Processing efficiency, gutted	kg yield gutted/kg whole fish	0.15	0.1	0.6	(Rørå et al., 2001; Fu et al., 2024)
Aquaculture	Solid nitrogen waste	%	0.1	0.05	0.3	Schumann and Brinker (2020)
Aquaculture	Space utilization efficiency, fish	m2 cultivatable space/m2 uncultivatable space	0.75	0.5	0.9	(Engle et al., 2021; Zhang et al., 2022b; Terjesen et al., 2013)
Aquaculture	Surface area productivity	kg fish/m2	20	10	30	(Engle et al., 2021; Zhang et al., 2022b; Terjesen et al., 2013)
Aquaculture	Survival rate, fish	%	0.95	0.8	0.98	(Brown et al., 2024; Li et al., 2023)

Scolaro, 2023; Velasco-Muñoz et al., 2021).

2. Materials and methods

2.1. Input parameters

The model begins with a set of assumptions (Tables 1–4). These are grouped into aquaculture, hydroponic, facility, and fertilizer classes; each parameter has a base case value as well as lower and upper bounds. Values are drawn from peer-reviewed literature and complemented with farm-level measurements collected by Regen Aquaculture (Pate, 2025) with the purpose of describing a typical aquaponics facility, but in a generalized format.

Aquaculture assumptions are included in Table 1. Here, a RAS is assumed for fish cultivation. The aquaculture energy productivity (kWh kg^{-1} fish yr^{-1}) describes the amount of electricity consumed in operation (pumping, aeration, filtration) used to produce 1 kg of market-size fish in a year. This is mirrored by the aquaculture water productivity (L kg^{-1} fish) which describes the water consumed per kilogram of fish harvested. Carbonate is almost universally added to stabilize the pH and alkalinity (Boyd et al., 2016). Here it is subsumed as an aquaculture cost (\$ kg^{-1}) despite Ca^{2+} also being an essential plant nutrient.

Feed consumption is a calculated parameter, however the base cost for feed (\$ kg^{-1}) is assumed. Likewise, the feed conversion ratio (kg feed kg^{-1} fish) is assumed and used to calculate the conversion of feed to biomass waste generated by the fish. The nitrogen assimilation of fish (g N kg^{-1} fish) and phosphorus assimilation of fish (g P kg^{-1} fish) represent the fractions of dietary N and P retained in biomass. Solid nitrogen-waste fraction (%) represents the excreted N by fish bound as settleable solids, determining how much N is captured in sludge versus dissolved effluent. Alongside the feed phosphorus content (%) and feed protein content (%), these values are used to calculate the phosphorus and nitrogen budgets, respectively. The nutrient remineralization efficiency (%) represents the percentage of settled solids converted into plant-available nutrients through microbial activity, a process described in detail elsewhere (Lobanov et al., 2021; Gichana et al., 2018; López-Mosquera et al., 2011; van Rijn, 2013).

Oxygen consumption (m^3 kg^{-1} feed) represents the cubic meters of O_2 metabolized by fish per kilogram of feed. As oxygen is often supplemented, a liquid oxygen cost (\$ $m^{3\text{-}1}$) is assumed.

New fish are purchased as (\$ $fingerling^{-1}$) under the assumption that the facility is continuously harvesting and stocking fish. The fraction of stocked fingerlings that reach harvest size is represented as the survival rate (%). Harvest economic metrics are the fish selling price (\$ kg^{-1}) and the target weight at harvest (harvest size, kg). The investment capital (fish) (\$ inv.cap kg^{-1} fish) represents the up-front tank and equipment expenditure allocated per kilogram of steady-state annual capacity. Labor efficiency (fish) (kg fish FTE^{-1} yr^{-1}) and management efficiency (fish) (kg fish FTE^{-1} yr^{-1}) consider the quantity of fish each technician or manager can oversee annually. Package size (kg $unit^{-1}$) and packaging cost (fish) (\$ $unit^{-1}$) define the retail unit mass and the associated materials/labor cost for fish products. The processing efficiency, filleted (kg yield kg^{-1} whole fish) and processing efficiency, gutted (kg yield kg^{-1} whole fish) describe the loss in product during final processing. The space-utilization efficiency (fish) (m^2 cultivatable m^{-2} uncultivatable) and surface-area productivity (kg fish m^{-2}) are used to translate biomass output into building-footprint requirements and land cost.

The hydroponic assumptions are shown in Table 2. Here, a soilless hydroponic greenhouse cultivation model is assumed; the specific growing system (e.g., nutrient film technique, deep well cultivation) is not specified. Hydroponic parameters use annual crop energy productivity (kWh kg^{-1} plant yr^{-1}) to describe the electricity consumed per kilogram of plant biomass for pumps and lighting. Annual crop production (kg plant yr^{-1}) describes the total plant mass harvested each year. With the goal of using the aquaponics system in a maximally resource-sustainable way, this parameter is used to calculate the plant nitrogen demand, and from that the amount of fish that should be cultivated to provide that amount of nitrogen. Annual crop water productivity (L kg^{-1} plant yr^{-1}) describes the amount of aquaculture and aquifer water consumed annually. The canopy-area productivity (kg

Table 2
Hydroponic assumptions included in the model. All prices are in USD. FTE = Full-Time Equivalent.

Class	Model Assumptions	Unit	Base Case	Lower Bound	Upper Bound	References
Hydroponics	Annual crop energy productivity	kWh/kg plant * y	10	1	200	(Engler and Krarti, 2021; Pomoni et al., 2023; Lages Barbosa et al., 2015)
Hydroponics	Annual crop production	kg plants/y	10000	5000	15000	(Suhl et al., 2016; Quagrainie et al., 2018; Bodiroga and Sredojević, 2018; Goh et al., 2023)
Hydroponics	Annual crop water productivity	L/kg plants * y	25	0	250	(Pomoni et al., 2023; Lages Barbosa et al., 2015)
Hydroponics	Canopy area productivity	kg plants/m2 *y	100	50	150	(Fernández-Cabanás et al., 2020; Modarelli et al., 2023)
Hydroponics	Grow medium	\$/plant	0.06	0.01	0.1	Pate (2025)
Hydroponics	Investment capital plants	\$ inv.cap/kg plants	2	0.5	50	Pate (2025)
Hydroponics	Labor Efficiency, Plants	kg plants/FTE	10000	5000	25000	Pate (2025)
Hydroponics	Management efficiency, plants	kg plants/FTE	25000	5000	75000	Pate (2025)
Hydroponics	Nitrogen assimilation plants	N g/kg	4	2.9	5.5	(Tan et al., 2000; Wongkiew et al., 2017)
Hydroponics	Packaging weight	kg/package	0.5	0.25	12	(Pate, 2025; Iqbal et al., 2024)
Hydroponics	Packaging, plants	\$/unit	0.05	0.001	0.75	Pate (2025)
Hydroponics	Phosphorus assimilation plants	P g/kg	0.6	0.3	1.2	(Yang and Kim, 2020a; Cerozi and Fitzsimmons, 2017)
Hydroponics	Plant selling price	\$/kg	17.5	3	22.05	Pate (2025)
Hydroponics	Processing efficiency plants	%	0.95	0.8	0.99	Pate (2025)
Hydroponics	Seeds	\$/seed	0.001	0.0001	0.06	Pate (2025)
Hydroponics	Space utilization efficiency, plants	m2 cultivatable space/m2 uncultivatable space	0.6	0.15	0.9	(Hydroponics, 2025; Solutions, 2024; Evans)
Hydroponics	Survival rate, plants	%	0.95	0.8	0.99	(Treftz and Omaye, 2016; Atherton and Li, 2023; Joshi et al., 2022)
Hydroponics	Yield/plant	kg/plant	10	0.1	30	(Goh et al., 2023; Pantanella et al., 2010; Cardoso et al., 2018; Sardare and Admane, 2013)

Table 3
Fertilizers assumed to supplement aquaculture-derived nutrients. The ratio of fertilizers additions is provided in Supplementary Table 1.

Class	Model Assumptions	Unit	Base Case	Lower Bound	Upper Bound	References
Fertilizer	Copper Sulfate (Pentahydrate) (25 % Cu)	$/kg	6	8	10	Icis (2025a)
Fertilizer	Iron DTPA (10 % Fe)	$/kg	15	20	25	International Fertilizer A (2024a)
Fertilizer	Magnesium Sulfate (9.8 % Mg, 12.9 % S)	$/kg	1.5	3	5	IndexMundi (2025a)
Fertilizer	Manganese sulfate (32 % Mn)	$/kg	4	6	8	IndexMundi (2025b)
Fertilizer	Monopotassium Phosphate (22.7 % P or 52 % P2O5)	$/kg	5	7	10	Service UAM (2025)
Fertilizer	Potassium Sulfate (44.74 % K or 53 % K20)	$/kg	4	6	8	Icis (2025b)
Fertilizer	Sodium Molybdate (39.65 % Mo)	$/kg	20	25	30	IndexMundi (2025c)
Fertilizer	Solubor (Disodium Octaborate Tetrahydrate), 20.5 % B)	$/kg	5	7	10	International Fertilizer A (2024b)
Fertilizer	Zinc Sulfate (Monohydrate) (35.5 % Zn)	$/kg	4	6	8	IndexMundi (2025d)

Table 4
Business assumptions included in the model. All prices are in USD. FTE = Full-Time Equivalent.

Class	Model Assumptions	Unit	Base Case	Lower Bound	Upper Bound	References
Facility	Building Cost	$/m2	25	10	200	(Pate, 2025; Engle, 2016)
Facility	Building Depreciation Timespan	Years	25	10	30	(Pate, 2025; Nicholson et al., 2020)
Facility	Construction Cost	$/m2	50	10	200	(Pate, 2025; Nicholson et al., 2020)
Facility	Energy	$/kWh	0.1	0.01	0.3	
Facility	Equipment Depreciation Timespan	Years	15	5	20	(Pate, 2025; Nicholson et al., 2020)
Facility	General & Administrative	% Revenue	0.05	0	0.6	(Pate, 2025; Nicholson et al., 2020)
Facility	Interest Rate on Building and Equipment	%	0.08	0.06	0.22	(Pate, 2025; Fernández-Cabanás et al., 2020; Nicholson et al., 2020)
Facility	Interest Rate on Land Capital	%	0.06	0.04	0.22	(Pate, 2025; Fernández-Cabanás et al., 2020; Nicholson et al., 2020)
Facility	Interest Rate on Operating Capital	%	0.06	0.04	0.22	(Pate, 2025; Nicholson et al., 2020)
Facility	Labor Cost	$/FTE	45000	30000	60000	Pate (2025)
Facility	Land Cost	$/m2	20	0.5	50	Fernández-Cabanás et al. (2020)
Facility	Manager Cost	$/FTE	60000	45000	120000	Pate (2025)
Facility	Misc Fixed Expenses	% Revenue	0.01	0	0.05	Pate (2025)
Facility	Operating Capital Reserve	months	12	6	60	Pate (2025)
Facility	Present Value Discount Rate	%	0.1	0.07	0.48	Pate (2025)
Facility	Sales & Marketing	% Revenue	0.05	0	0.35	Pate (2025)
Facility	Salvage Value as a % of Original Value, Building	%	0.1	0.05	0.5	Pate (2025)
Facility	Salvage Value as a % of Original Value, Equipment	%	0.05	0.01	0.5	Pate (2025)
Facility	Time Horizon	Year	5	4	10	Reilly et al. (2016)
Facility	Water	$/L	0.005	0.0005	0.03	(Fernández-Cabanás et al., 2020; Rubin, 2018)

plant m^{-2} yr^{-1}) describes the biomass yield per square meter of greenhouse floor annually. Space utilization efficiency (plants) (m^2 cultivatable m^{-2} uncultivatable) connects the canopy area to total warehouse footprint. The nitrogen assimilation plants (g N kg^{-1} plant) and phosphorus assimilation plants (g P kg^{-1} plant) complement the aquaculture N and P supply budgets from the consumption perspective. Labor efficiency (plants) (kg plants FTE^{-1}) and management efficiency (plants) (kg plants FTE^{-1}) describe the amount of harvest a full-time employee can manage per year.

Economic metrics include the cost of grow medium ($ $plant^{-1}$), the investment capital (plants) ($ inv.cap kg^{-1} plants) for the greenhouse per kg plant harvested, seed cost ($ $seed^{-1}$), packaging weight (kg $package^{-1}$), packaging cost (plants) ($ $unit^{-1}$), plant selling price ($ kg^{-1}). The percentage of seedlings that reach harvest is the survival rate (plants) (%). The quantity of harvested plants is determined by the yield per plant (kg $plant^{-1}$), representing the edible portion of a plant, while the processing efficiency (plants) (%) describes the product loss after removal of roots and trimming.

In addition to the base hydroponic assumptions, the following fertilizer additions were considered (Table 3), describing the cost ($ kg^{-1}) of mineral nutrients used to compliment the aquaculture-derived wastewater.

Finally, several parameters were used to create the facility business model (Table 4). Building and construction cost ($ m^{-2}) were used to calculate the total construction cost for an area determined by the production metrics. Building and equipment depreciation timespan (yr) accounts for the lifetimes over which capital is recovered. Energy price ($ kWh^{-1}) is used to translate the electrical consumption into a monetary amount. General & administrative (% revenue), sales & marketing (% revenue), and miscellaneous fixed expenses (% revenue) are assumed as percentages applied to the total sales to account for overheads such as office staff, insurance, and advertising. Interest rate on building & equipment (%), interest rate on land capital (%), and interest rate on operating capital (%) were used to simulate long-term loans and short-term working-capital lines which are significant cumulative expenses for small businesses such as aquaponics facilities (Pattillo et al., 2022; Raulier et al., 2023). Additionally, the salvage value for the building (% original) and equipment (% original) represents the residual values at the end of the analysis horizon, required for the net present value calculation alongside the present value discount rate (%) and time horizon (y). The labor cost ($ FTE^{-1}) and manager cost ($ FTE^{-1}) describe annual wages, land cost ($ m^{-2}) is the amount required per meter for site acquisition, operating-capital reserve (months) represents the number of months of cash that should be set aside up-front to cover inventory build-up and payment terms, likewise water cost ($ L^{-1}) is cost of water usage.

These assumptions were fed into an R script to calculate the efficiency and economic viability of an aquaponics farm.

2.2. Model design

First, the nitrogen demand (g/y) was calculated from crop production (kg/y) and the plant nitrogen assimilation rate (g N/kg fresh weight plant biomass).

$$N\ demand = Crop\ production \times Plant\ assimilation\ rate$$

The total N waste available (%) in the feed is derived from the feed protein fraction (%) and the standard nitrogen-to-protein conversion factor of 6.25.

$$Feed\ N = \frac{Feed\ Protein}{6.25}$$

Fish assimilated nitrogen (g N/kg fish) from the feed is then calculated based on the FCR (kg feed/kg fish) and fish assimilation rate (g N/kg fish biomass).

$$N\ Assimilated_{Fish} = Feed\ N \times FCR \times Fish\ assimilation\ rate$$

And the total nitrogen waste produced by fish (g N/kg fish) is calculated from the feed nitrogen and assimilation rate.

$$N\ Waste_{Fish} = Feed\ N \times FCR - N\ Assimilated_{Fish}$$

The amount of solid nitrogen in the fish excreta produced per amount of feed input (g N/kg feed) was calculated by multiplying the feed protein content (%) by the FCR, then dividing by the nitrogen-to-protein conversion factor, and finally multiplying by the percentage of nitrogen in the feces:

$$Solid\ N\ Waste = \frac{Feed\ Protein\ (\%) \times FCR}{6.25} \times Fecal\ N\ Fraction\ (\%)$$

Of this, the dissolved nitrogenous waste produced by fish (g N/kg feed) is calculated from the *Solid N Waste* subtracted from the above $N\ Waste_{Fish}$ divided by the FCR.

$$Soluble\ N\ Waste = \frac{N\ Waste_{Fish}}{FCR} - Solid\ N\ Waste$$

And finally, the fraction of the feed nitrogen converted to waste and available for plant uptake (g N/kg feed) is calculated as the *Soluble N Waste* minus *Solid N Waste* and multiplied by the remineralization efficiency (%) of nutrients from the sludge into the water column, accounting for both aqueous nitrogenous species carried downstream and the degradation of fecal matter:

$$Plant\ available\ N = N\ waste_{soluble} - (Solid\ N\ Waste * Remineralization\ Efficiency)$$

To determine phosphorus availability, the content in the feed (%) is multiplied by the amount of phosphorus not assimilated by fish (g P/kg feed):

$$P\ waste_{total} = Feed\ P \times (1 - P_{Fish\ assimilated})$$

Total nitrogen was converted to nitrate (the end point of the redox reaction for most nitrogenous waste in aquaponics) which was subsequently used to calculate nutrient requirements for plants with other nutrients calculated as per target ratios (Table S2).

$$NO_3^-\ Equivalent = Plant\ available\ N \times molar\ mass\ ratio\ \frac{NO_3^-}{N}$$

As the second most prominent nutrient, annual P supplementation (g P/y) based on the annual plant P requirement (g P/y) was adjusted to compensate for waste-derived P (g P/kg feed):

$$P\ Supplementation = Plant\ P\ Requirement - P\ Waste$$

Calcium was likewise assumed to be used as a buffer in the aquaculture system and thus the concentration was multiplied by the amount of fish feed as a proxy for the pH correction. Micronutrients were not considered to be present in fish waste nor water source, meaning the calculations overestimate actual concentrations. However, given the minute requirements for these compounds, the contribution to the facility NPV and IRR was considered negligible.

Next, aquaculture parameters were calculated for one year of production, starting with annual feed requirements based on the plant available N calculated above and the plant N demand (g/y):

$$Feed\ (kg) = Plant\ available\ N \times N\ demand$$

The total fish biomass (kg) at harvest was calculated from the required feed (kg/y) and FCR (kg feed/kg biomass):

$$Fish\ biomass = \frac{FCR}{Annual\ feed}$$

Dividing fish biomass by the harvest size (kg) gave the number of fish produced per year:

$$N^{\underline{o}}\ Fish_{harvest} = \frac{Fish\ biomass}{Harvest\ size}$$

Dividing this value over the survival rate (%) gives the starting number of fish in the system:

$$N^{\underline{o}}\ Fish_{start} = \frac{N^{\underline{o}}\ Fish_{harvest}}{Survival\ rate}$$

Total fish yield (kg) was calculated by multiplying the harvest size (kg) by the number of fish and either the mass loss percentage from filleting (% loss) or gutting (% loss):

$$Product\ Yield, fish = N^{\underline{o}}\ fish \times Harvest\ Size \times \left(Processing\ Effiency_{fillet}\ OR\ Processing\ Effiency_{gutted}\right)$$

This is analogous to the processing efficiency for plants, which accounts for the loss of product during harvest (% loss) multiplied by the harvest weight (kg):

$$Product\ Yield, plants = Plant\ Harvested\ Weight \times Processing\ Effiency_{plants}$$

This model assumed oxygenation is entirely delivered with liquid oxygen supplementation based on the amount of suspended matter, proxied by the feed (kg) and a standard oxygenation requirement metric used in aquaculture for m^3 O_2 required per kg feed:

$$O_2\ addition = Feed \times O_2\ Requirement$$

To generalize the model to diverse fish or crop species, the area requirement was calculated by dividing the fish or plant biomass (kg) over a specific productivity (kg biomass/m^2 grow area) for either fish or plants.

$$Area\ required = \frac{Biomass}{Productivity}$$

However, the minimal facility space for plants additionally assumed additional room to allow for pathways between plants as the plant area (m^2) divided by the space utilization efficiency (%):

$$Facility\ Space = \frac{Plant\ Area}{Space\ Utilization\ Efficiency}$$

The aquaculture or hydroponics energy productivity (kWh/kg biomass) or water productivity (L water/kg biomass) was used to link specific productivity to electrical or water consumption:

$$Energy\ Use = Biomass \times Energy\ Productivity$$

$$Water\ Use = Biomass \times Water\ Productivity$$

Estimations for the labor and management full time equivalent (FTE) requirements were determined based on the number of fish or plants in the system multiplied by an FTE productivity per amount of fish or plant biomass harvested (kg biomass/FTE * y).

Assumptions for the number of packaging units required were determined based on the fillet weight (kg fish) or sellable plant weight (kg plant) divided by the target packaging weight (kg unit weight).

An income statement was drafted based on the above results. Revenue from fish fillet sales ($USD) was calculated as the fillet weight (kg) multiplied by the fish price ($USD/kg fish); an identical calculation was done to determine plant revenue.

$$Revenue = \left(Fish\ Fillet\ (kg) \times Fish\ Price\ \frac{\$}{kg}\right) + \left(Plant\ Yield\ (kg) \times Plant\ Price\ \frac{\$}{kg}\right)$$

Investment cost for land was determined based on the area required for fish and plants (m^2) multiplied by the land price ($USD/$m^2$). The same area calculation was multiplied by the construction cost ($USD/$m^2$ building area) to provide an estimate for the building cost. The equipment cost is calculated from the total fish and plant biomass (kg) produced multiplied by a CapEx estimation for the general cost of fish or plant related equipment ($USD/kg).

$$Land\ Cost = Land\ Area \times Land\ Price$$

$$Building\ Cost = Building\ Area \times Construction\ Cost$$

$$Equipment\ Cost = Fish, Plant\ Production \times Fish, Plant\ Equipment\ CapEx$$

The Cost of Goods Sold (COGS) for both fish and plants were estimated based on inputs for aquaculture (feed, fingerlings, energy fish, buffer, liquid oxygen, water fish, labor, packaging) and hydroponics production (seeds, packaging, energy, water, labor, grow medium, fertilizer costs).

$$COGS = \sum Feed + Seeds + Energy + Water + Packaging + Labor + Inputs$$

Management costs were derived from the earlier FTE estimates, multiplied by an annual FTE wage for laborers or management. Sales & marketing, administration, and miscellaneous fixed expenses were estimated as a percentage of the total revenue. The sum of these expenses was considered the total fixed expenses.

$$Fixed\ Expenses = Revenue \times (Sales\ \&\ Marketing + Administration + Miscellaneous)$$

Three loans are assumed for land, buildings, and equipment costs, and operational costs with different interest rates based on typical effective annual rates (EAR) provided by agriculture banks.

$$Monthly\ Payment = Loan\ Amount \times (1 + EAR)^{1/12} - 1$$

From this, the monthly rate was calculated on an annual basis, as well as the interest payment per month.

$$Monthly\ Payment = Loan\ Amount \times Monthly\ Rate$$

The earnings before interest, taxes, depreciation, and amortization (EBITDA) are the difference between the gross profit and total fixed expenses. Then, Earnings Before Interest and Taxes (EBIT) is calculated as the difference between the EBITDA and the depreciation cost of building and equipment as defined in the initial parameter list. Subtracting further the interest on buildings & equipment and operating capital gives the earnings before taxes (EBT), with interest values defined in the initial parameter list.

$$EBITDA = Revenue - COGS - Fixed\ Expenses$$

$$EBIT = EBITDA - Depreciation_{building,equipment}$$

$$EBT = EBIT - Loan\ Interest$$

The present value for year zero was considered the investment cost, and then for year one onwards the EBT multiplied by a present value discount rate. The net present value was then calculated as:

$$NPV = -I_0 + \sum_{t=1}^{T} \frac{EBT_t}{(1+r)^t}$$

where:

I_0 is the initial investment, r is the discount rate, and T is the project horizon. Taxes were not taken into consideration in this model due to the diversity of taxing and subsidy regimes. From this, the internal rate of return was calculated as:

$$0 = -I_0 + \sum_{t=1}^{T} \frac{EBT_t}{(1+IRR)^t}$$

2.3. Model evaluation

To assess model robustness, a sensitivity analysis was performed by varying each input parameter individually between its defined lower (best-case) and upper (worst-case) bounds, while keeping all other parameters constant. The IRR is recalculated for each variation, and the resulting IRR range quantifies each variable's impact. The elasticity of each parameter, defined as the percentage change in IRR relative to the percentage change in the parameter itself, was then calculated to determine the subset for the Monte Carlo simulation. Each parameter's IRR sensitivity was determined by averaging the model's IRR at its lower and upper bound values and then applying cut-offs of 10 % IRR for High sensitivity, 5 % IRR for Medium, and <5 % for Low. NPV sensitivity was measured using the same cut-off percentages for "high", "medium", and "low" categories. Parameters contributing less than 1 % to the IRR variability were excluded from further simulations.

To visualize the absolute influence of each parameter, the change in IRR or NPV between the upper and base case values were plotted against the corresponding elasticity. These plots identified variables that both significantly influenced model outcomes and risked crossing critical financial thresholds (NPV <0 or IRR <0). This approach supported the identification of parameters with both high leverage and high downside risk.

Monte Carlo simulations were run for 10,000 iterations to assess how parameter uncertainty influences model outcomes. For each iteration, high- and medium-priority parameters from the sensitivity analysis were randomly sampled, both within ±10 % of their base-case values and across their full defined ranges. The frequency of each IRR and NPV outcomes were plotted in histograms to visualize the range of potential economic outcomes possible across the ranges of high and medium priority parameters.

In addition, Latin hypercube sampling was used to identify the optimal combinations of high-sensitivity parameters associated with positive NPV outcomes. A truncated normal distribution bounded by the parameter's best- and worst-case values was used to generate 1000 stratified parameter sets. Each set was evaluated for its resulting NPV, and the high-sensitivity parameters were analyzed to extract parameter means and standard deviations for the top 5 outcomes. These were visualized in a scaled parallel-coordinates plot to identify the combinations of parameter values most associated with profitability. This two-step probabilistic sampling approach (Monte Carlo for overall risk quantification and LHS for optimal pathway identification) enabled a comprehensive assessment of aquaponics system viability under realistic parameter uncertainty.

Two sustainability assessments were conducted on the modelled data set. Firstly, to assess the aquaponics facility from the perspective of sustainable investment, the Green Asset Ratio (GAR) was calculated under four scenarios: 1) Conservative; only equipment costs included as taxonomy-aligned) 2) Moderate; an additional 50 % of building and construction costs are included as taxonomy-aligned 3) High Sustainability; full inclusion of building and construction as taxonomy-aligned alongside equipment costs, 4) Ecosystem Service; 50 % of land costs are additionally included as taxonomy-aligned in addition to the High Sustainability criteria. All GAR values were computed as the ratio of taxonomy-aligned capital expenditure to total capital investment, based on EU Taxonomy alignment logic (Brühl, 2023). The resulting percentage values were plotted as violin plots to visualize their distribution, central tendency, and variability. Secondly, environmental impacts were assessed by integrating inventory outputs with life cycle assessment (LCA) emission factors for electricity (Raimi et al., 2024; Electricity, 2025), feed (Henriksson et al., 2025; Skretting, 2022; Wang et al., 2022), fertilizers (Ravani et al., 2023; Greenfeld et al., 2021), infrastructure (Song et al., 2019), and packaging (Henriksson et al., 2025; Downie and Stubbs, 2012). Output variables included total global warming potential (GWP), land use, water use, and eutrophication potential (kg excess phosphorus) as per ISO 14044 methodology (Chomkhamsri et al., 2011). Positive IRR simulations were compared to unrestricted (all) simulations (n = 1000). All computations were conducted in R (v4.4.1).

3. Results

To assess the relevance of model inputs, we first classified each parameter by its elasticity-based sensitivity for both NPV and IRR (Fig. 1A and B). Variables which contributed less than 0.05 % to the

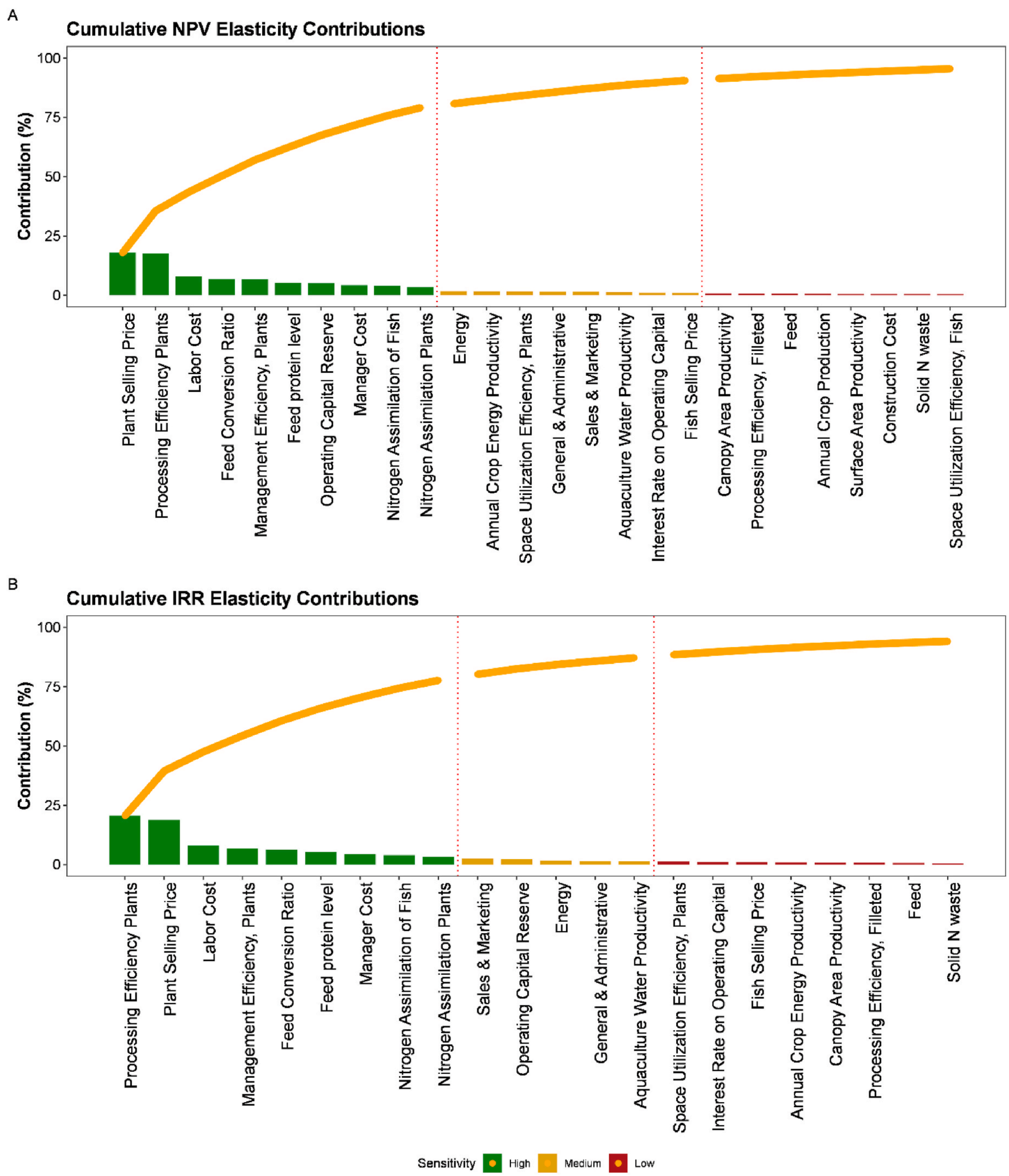

Fig. 1. Individual and cumulative contributions to total (A) NPV and (B) IRR elasticity. Bars show each parameter's share of the sum of all NPV elasticities color-coded by sensitivity class (High/Medium/Low). Orange line and points trace the cumulative contribution; dashed red vertical lines mark the boundaries between elasticity groups.

cumulative NPV or IRR were removed. In both cases, an even spread across high, medium, and low impact variables was observed. The subset of highly elastic inputs accounts for >75 % of the variability in both economic metrics, as evidenced by the steep initial rise in the cumulative curves.

The sensitivity and elasticity contributions were further evaluated by plotting the absolute impact on IRR and NPV (Fig. S1). This shows the impact of an individual parameter varied between its upper and lower bound on the IRR or NPV in absolute terms.

Then, in Fig. 2, the forward difference IRR (A) or NPV (B) contribution was plotted against the parameter's elasticity between the base case and either upper or lower bound. Forward difference refers to the change in model outputs when a parameter is perturbed from its base case to its upper (forward) bound, capturing the directional impact of parameter uncertainty. As the IRR measures the break-even discount rate of the cash flow, a parameter shock can more easily drive the computed rate below zero (sign reversal point) even while the NPV remains positive.

Tornado plots list which parameters were responsible for the greatest shift in elasticity and in which direction (Fig. 3).

The parameters with "high" or "medium" elasticity classification were then fed into a Monte Carlo simulation (n = 10,000 simulations) to assess the likelihood of profitability for values within ±10 % of the baseline for each parameter (Fig. 4), with panel A depicting the distribution of simulated NPV and panel B showing the corresponding IRR outcomes. Monte Carlo simulations for the full parameter range are shown in Fig. S2.

Fig. 5 shows a parallel-coordinates plot displaying each run with NPV >0 as a line across the five key inputs. The high and medium elasticity categories were identified fed into 1000 Latin-hypercube simulations (Supplementary Fig. 3) were used to calculate the Spearman rank-correlation between each of the high/medium parameters and the resulting NPV. The highest-value pathway represents the most profitable set of conditions when each variable is pushed to its extreme (either maximized or minimized) and is shown here as a parallel coordinate plot (Fig. 5). Behind each axis, violin plots show the full probabilistic distribution of that parameter across all high-medium scenarios. The wider the bulge, the more common a particular value is. The break-even distribution by parameter is shown in Supplementary Fig. 4.

The green asset ratio was calculated from the Monte Carlo simulation results (Fig. 4) under different taxonomy alignment inclusion scenarios (Fig. 6).

Life cycle analyses were conducted on 1000 scenarios with positive internal rates of return (IRR) to evaluate the contribution of different production components to greenhouse warming potential (GWP) (Fig. 7a). These results were then compared to those from 1000 unrestricted IRR scenarios, regardless of profitability (Fig. 7b).

Alongside GWP, the impact of excess water usage, land use, and eutrophication potential was evaluated between the positive-IRR and unrestricted scenarios as pairwise relationships.

Lastly, the ideal fish-plant ratio was predicted for profitable scenarios compared to all scenarios (Fig. 9).

4. Discussion

The objective of this study was to establish a comprehensive economic model to assess the viability of aquaponics systems by evaluating the sensitivity of net present value (NPV) and internal rate of return (IRR) to variations in key parameters. The parameters were chosen to reflect real-world efficiencies in aquaculture and hydroponics production, as well as financial parameters related to investment and operational variables.

Both NPV and IRR are common investment appraisal metrics, but emphasize different aspects of profitability. The NPV emphasizes parameters directly affecting cash flow magnitude, creating more sensitivity to absolute monetary variations. In contrast, the IRR assesses cash flow timing and margins, leading to an emphasis on efficiency metrics. This provides insight into parameters influencing the scale of investment rather than absolute returns. In this study, we prioritize parameters that strongly shape the NPV output following the logic that 1) the IRR often aligns directionally with NPV and 2) there often exist multiple IRR solutions in complex cash-flow scenarios (Pantaleo et al., 2009; Lin, 2023; Robison et al., 2015).

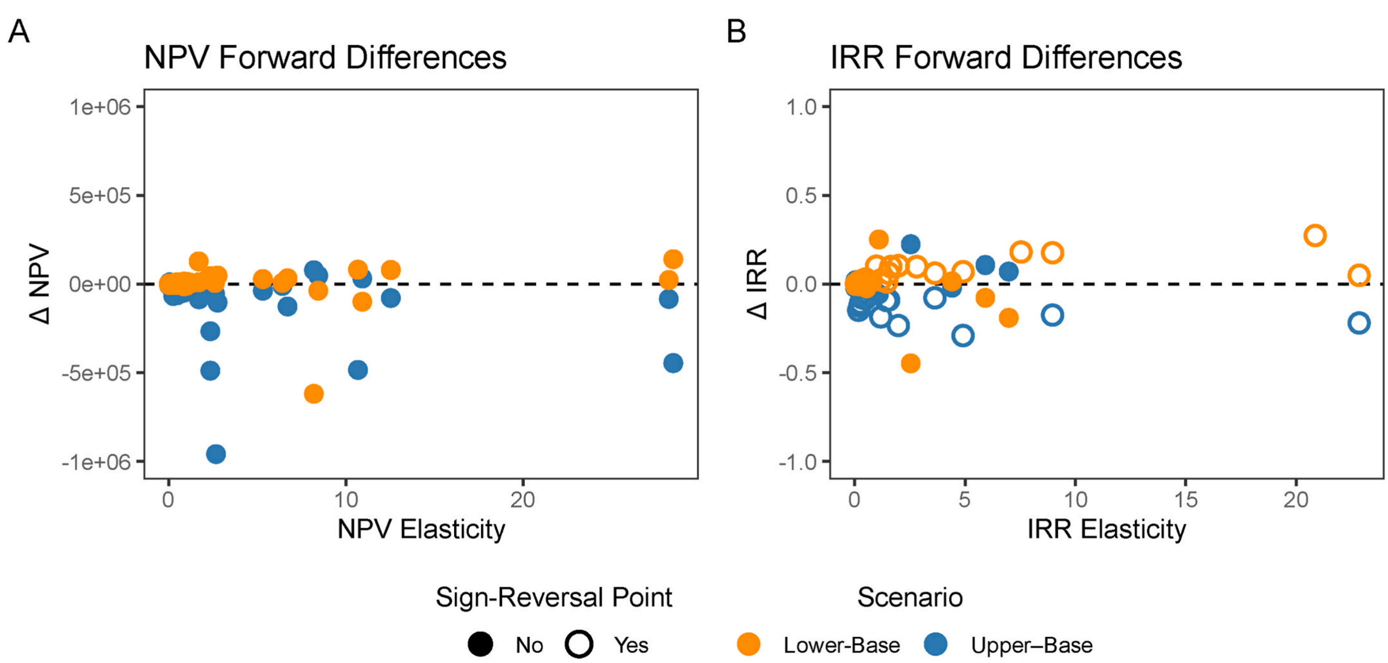

Fig. 2. Forward difference (delta) plots for NPV (A) and IRR (B). Orange dots ("Base − Lower") show parameter movement from the base case to the lower bound; blue dots ("Upper − Base") shows movement from the base case to the upper bound. Sign-reversal indicates when movement to the extremes results in negative profitability for the given parameter.

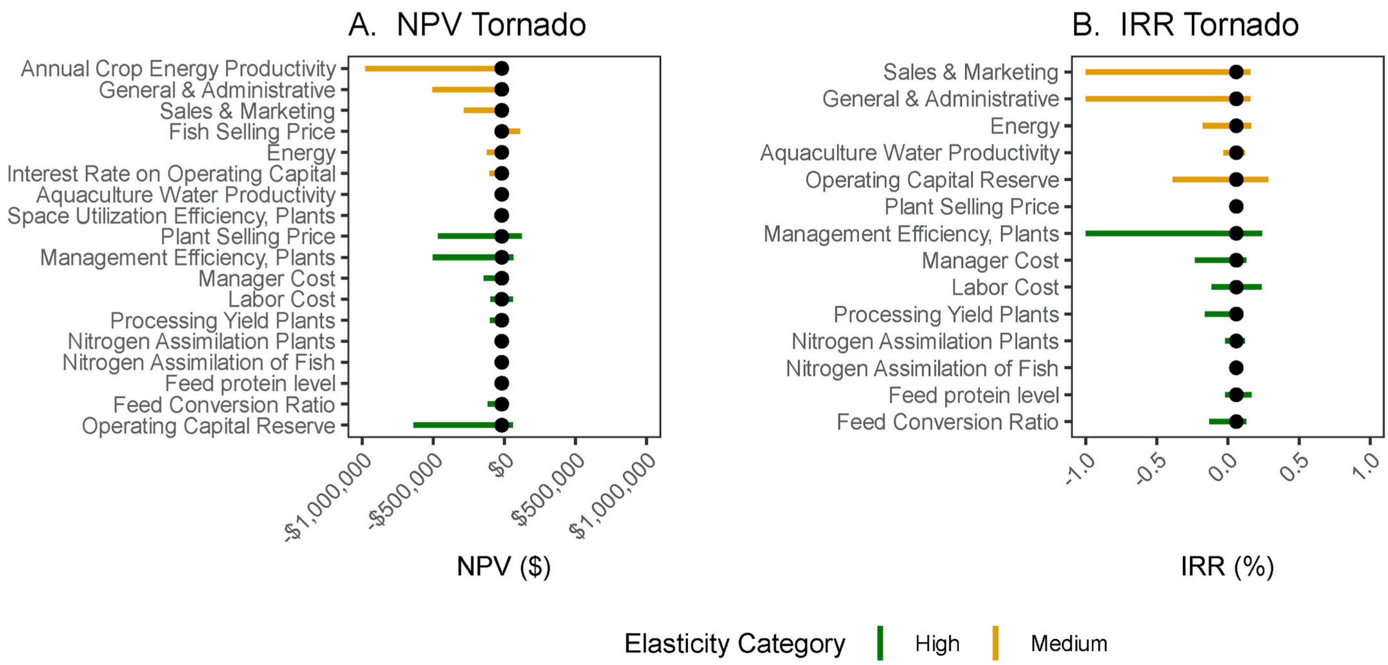

Fig. 3. Tornado plots of the NPV and IRR forward differences for each high and medium classified parameter. The total delta of NPV and IRR sensitivity is provided in Supplementary Fig. 1.

4.1. Revenue and efficiency parameters shape elasticity ranking

The sensitivity and elasticity analyses underscore that disproportionate influence that a subset of parameters exert over economic viability (Fig. 1A and B). Variables that were ranked as having a high impact in both NPV and IRR elasticity include revenue streams (plant selling price, labor and management cost), efficiency parameters (feed conversion ratio, processing efficiency plants, plant management efficiency), and certain input variables (feed protein level, fish and plant nitrogen assimilation efficiency). One variable was included only in the NPV list – "Operating capital reserve". This parameter directly influences cash liquidity and capital reserves and thus present value but not the efficiency of the operation. As such, operating capital reserve has limited influence on the IRR. The ranking list was consistent with our prediction for which parameters would influence either parameter. Plant selling price and processing efficiency were the two highest ranking NPV variables that directly related to revenue, while labor cost and management efficiency – proxies for worker efficiency - were more important in the IRR ranking.

The forward difference and tornado graphs (Figs. 2 and 3) plot elasticity values against the absolute change in upper and lower bound estimates for each parameter. This highlights parameter sensitivity and outcome variability as a strategy to prioritize risk management. Here, parameters were assessed based on a tightening flag to identify variables which cross a financial viability threshold (sign reversal point at NPV <0 or IRR <0). In this model, the IRR calculation (Fig. 2B) was found to be more sensitive to fluctuation than the NPV calculation (Fig. 2A) and correspondingly highlighted several variables with large ranges.

4.2. Monte Carlo simulations highlight profitability precarity

The forward difference plots may underestimate risk due to the hard cut-off value at which the NPV or IRR become negative. Thus, to investigate the NPV and IRR outcomes with more granularity, the data were passed into Monte Carlo simulations which ultimately reinforced in the initial findings (Fig. 4). Modeling base-case assumptions in the range of ±10 % resulted in a negative mean for the NPV in the 5-year range (−21,991 $ ± 54,800). Considering the mean IRR of 4.8 % ± 12.2 suggests that a well-managed facility can be moderately profitable in 25 % of the scenarios. This contrasts sharply with the Monte Carlo simulations over the entire range (Fig. S2), which shifts the NPV and IRR means far into the negative (−2,376,714 $ ± 1,248,595) and (−99.3 % ± 7.29). A similar trend can be seen in the Latin hypercube sampling distribution (Fig. S3).

The Monte Carlo simulations emphasize the precarity of profitability – while possible, a sustained drop in efficiency can quickly shift the NPV and IRR to negative territory. Targeted optimizations—such as selecting high-value fish and plant species, improving feed formulations to release nitrogen more efficiently, or adopting cultivars with superior biomass yield—offer the greatest immediate leverage to reducing financial risk. This is a trend that is widely assumed to be true within the aquaponics industry, with several studies focusing on improving yield efficiencies (Suhl et al., 2016; Goddek and Keesman, 2020; Ayipio et al., 2019).

These results may explain the observed trend in the private sector of aquaponic facilities being highly susceptible to external economic pressures. Aquaponics boomed during the COVID-19 pandemic when many food distributors turned to local suppliers as international trade slowed, however this trend reversed in Europe during the Russian invasion of Ukraine in early 2022 which greatly stressed energy markets especially in the European Union, significantly driving up prices for EU producers. Climate change is another major risk for individual aquaponics facilities, as in addition to natural disasters damaging facilities, blackouts in the local electrical grid resulting in RAS failure may rapidly kill off the entire fish stock. If the goal of promoting aquaponics is to create sustainability in food production, then these risks must be addressed to avoid the possibility that extreme pressures bankrupt a facility, similarly to RAS facilities (Badiola et al., 2012). This Achilles' heel of localized food production stands in contrast to the current global food supply model, where multinational companies source products internationally, resulting in significantly higher greenhouse gas emissions due to extensive transportation, refrigeration, and distribution networks (Weber and Matthews, 2008; Schmitz et al., 2012).

4.3. Identifying the best-case scenarios for profitability

The previous sections outline the methodology to assess the

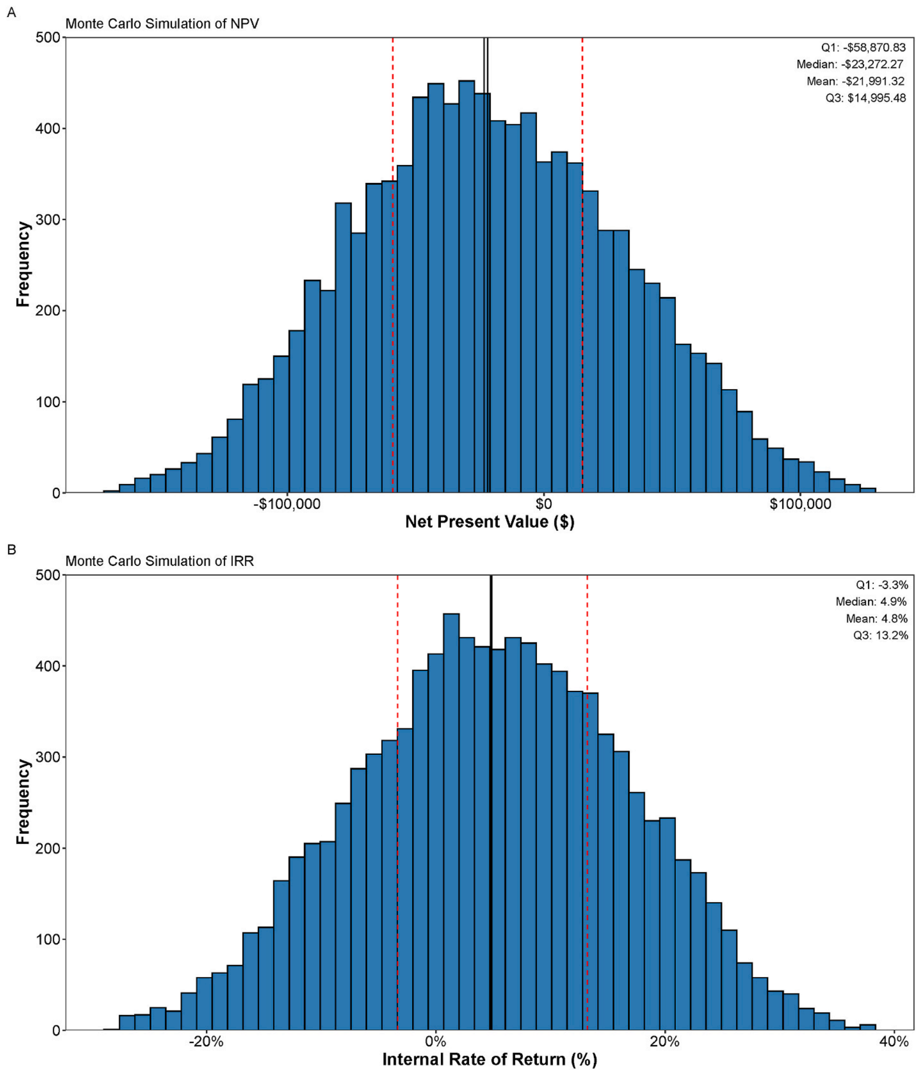

Fig. 4. Result from the Monte Carlo simulations to predict the most likely NPV (A) and IRR (B) across all simulations within ±10 % of the baseline. Histograms are annotated with dashed red lines marking the first and third quartiles, solid lines for the mean and median. Histograms for the full parameter range are provided in Supplementary Fig. 2.

individual and net effect of parameters on the NPV and IRR for a simulated aquaponics facility. However, the most practical outcome from this research is the identification of the optimal path through each of the most influential variables (those identified as "high" impact in the elasticity test). This is shown by the parallel-coordinates visualization of positive-NPV runs (Fig. 5).

Compared to the original assumptions, the ideal FCR (1.17 ± 0.03 kg feed/kg fish) was calculated to be near the base case (1.1 kg feed/kg fish). A higher FCR indicates that more nitrogen is available for plants, yet the lower cost of synthetic fertilizer discourages using aquaculture feed as a nutrient source for plants (Colt and Schuur, 2021). Similarly, our model gravitated towards a slightly higher feed protein level (33.16 % ± 2.60 % vs. 32 %), likely for the same reason. Although individual plants generate less revenue than fish, their higher production turnover compensates for this difference.

As expected, the model penalized wages, in this case achieving profitability at 42,754 ± 4987 $ annually for labor and 57,106 ± 10516 $ for management cost compared to 45,000 $ and 60,000 $ in the base case, respectively. Facilities may easily fall into a catch-22 around labor use. On the one hand, automation helps reduce the required labor, however on the other hand it adds additional investment, operational, and depreciation costs. Efficient facility design to streamline physical operations is a strong requirement. For example, while the base case assumption of plant management efficiency was 25,000 kg plants/FTE, the model predicted the ideal figure to be 29,570 kg plants/FTE ±11,140. This again signals a requirement for higher operational efficiencies. Likewise, the predicted processing efficiency was projected to be higher (96 % ± 2 vs. 95 %). Fortunately, the predicted cash reserve period was estimated to only require 10.89 ± 3.46 months, which is slightly shorter than the 12-month base case, suggesting that in this aspect, the base case overcompensated for risk.

Nutrient assimilation values for both fish and plants were closely aligned with base case values, indicating minimal deviation in biological assumptions. However, the plant selling price showed a substantial positive deviation (20.70 ± 2.05 $/kg vs. 17.50 $). This has a couple of important implications. Firstly, profitable aquaponics must find a niche in higher-value products. The goal of applying aquaponics as a food solution for lower income areas is probably not realistic without other income streams unless significant changes are made to the system design (i.e., low-tech aquaponics in a favorable environment to the target fish and plant species). Secondly, profitability incentivizes transforming products into higher value processed goods (e.g., selling pesto instead of bulk basil) (Engle, 2010). When all parameters are considered, it can be seen the margins for aquaponics are tight, albeit still potentially profitable.

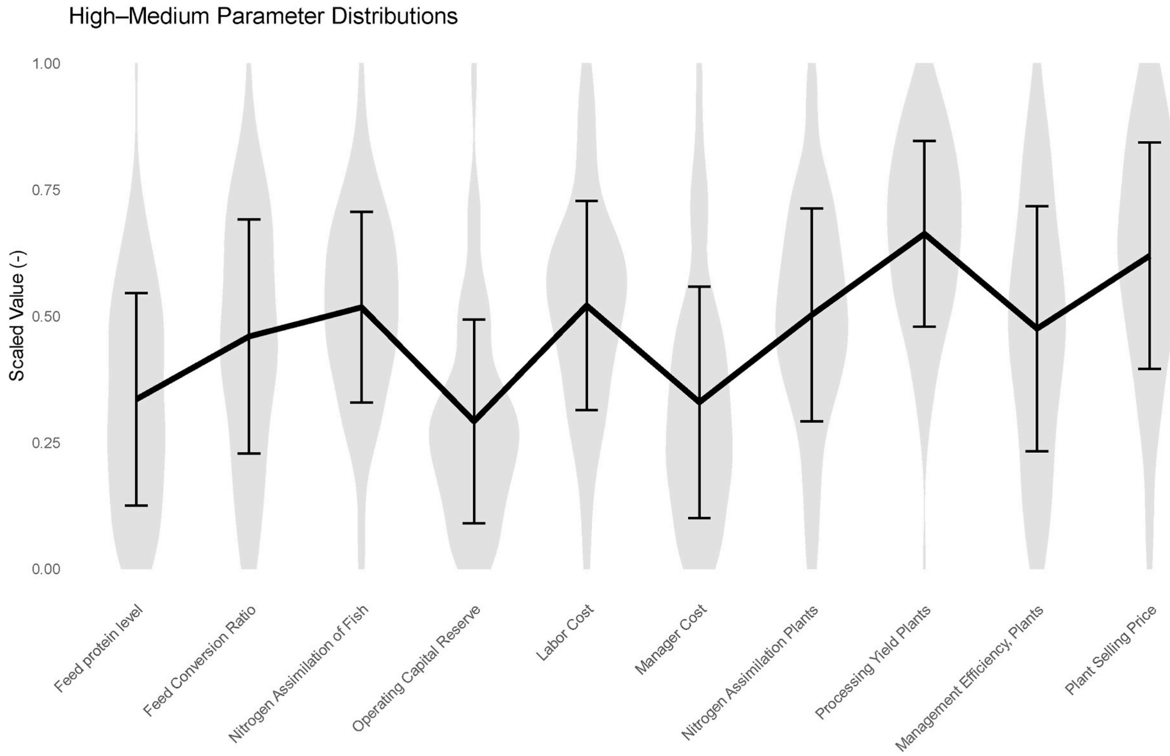

Fig. 5. Parallel coordinates plot of scaled parameter values for Monte Carlo simulations yielding positive net present value. The average and standard deviation of all runs are plotted over violin plots of the distribution to indicate both the most likely values and the total spread of values, respectively.

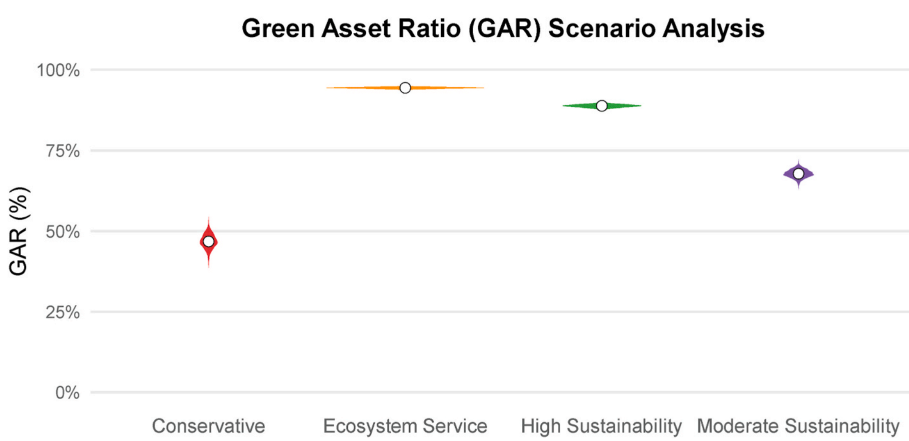

Fig. 6. Distribution of Green Asset Ratios (GAR) across four taxonomy-alignment scenarios in a Monte Carlo simulation of an aquaponics system (n = 1000).

4.4. Sustainability assessment through LCA

The simulations were assessed in a life cycle assessment with the goal of identifying the main contributors to greenhouse warming potential and evaluating how water and land use, as well as eutrophication potential changes as a function of profitability. From Fig. 7a, electricity is the main GWP contributor both due to the potentially high greenhouse gas contributions from electricity generation as well as the facility's high electricity demand. The hydroponics unit is sized such that aquaculture-derived nitrogen waste is sufficient to meet plant needs, hence external nitrogen fertilizer inputs are effectively eliminated. As a result, the greenhouse gas emissions associated with fertilizer use are substantially reduced from an estimated 2.4–3.0 kg CO_2-eq per kg of product to approximately 0.5–1.0 kg CO_2-eq per kg (Brentrup et al., 2016). Comparing positive IRR scenarios to all scenarios, a few trends emerge: feed and fertilizer usage remains similar, however electricity and infrastructure were reduced and packaging doubled (Fig. 7b). This suggests a shift towards scenarios where a high fish stocking density and quicker plant turnover are preferred, corroborating the preference in the commercial sector for high-turnover leafy green crops such as lettuce (Pattillo et al., 2022; Raulier et al., 2023). Water, land, and eutrophication potential were not correlated with increasing profitability, as measured by the change in IRR (Fig. 8), however the IRR was found to be negatively correlated with total GWP ($r = -0.38$, $p < 0.01$).

4.5. Green asset ratio as a tool for investors

The EU taxonomy for Green Asset Ratio (GAR) identifies and prioritizes activities and investments that significantly contribute to environmental objectives (Santos, 2024; Saeed et al., 2020). Generally corresponding to the UN Sustainable Development Goals (SDGs), these activities may involve climate change mitigation, sustainable use of

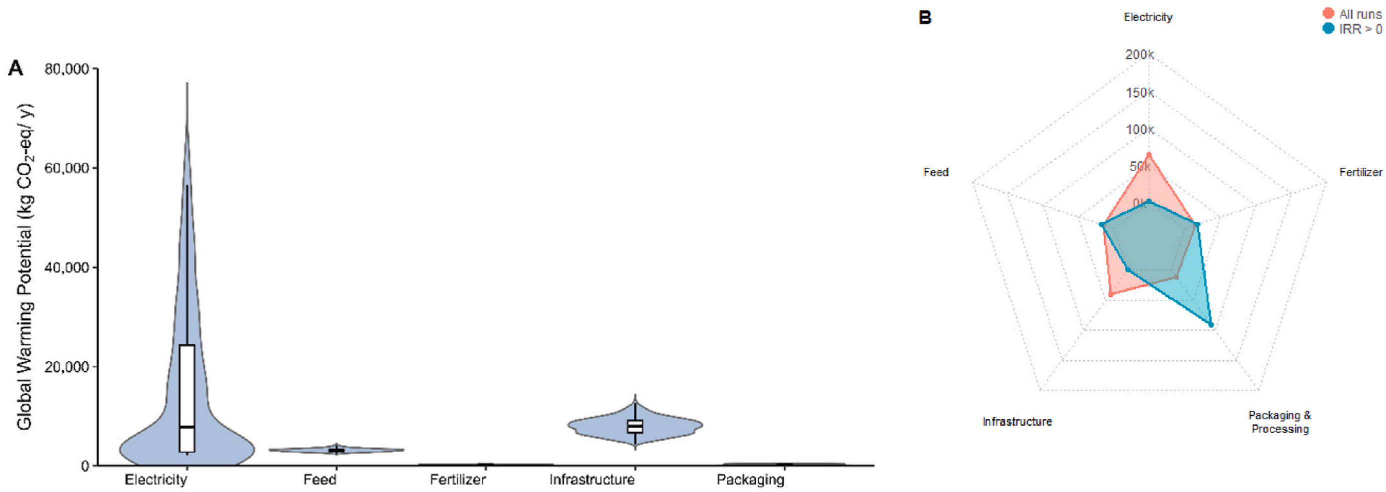

Fig. 7. A) Violin plots of Global Warming Potential (GWP, in kg CO_2-equivalents) for each major sub-category. Distributions are derived from positive-IRR scenarios (n = 1000). B) Radar plot comparing the median contribution of five GWP sub-categories between all Monte Carlo runs (red) and profitable simulations (IRR >0; blue). Values are plotted in raw units (kg CO_2-eq), not normalized.

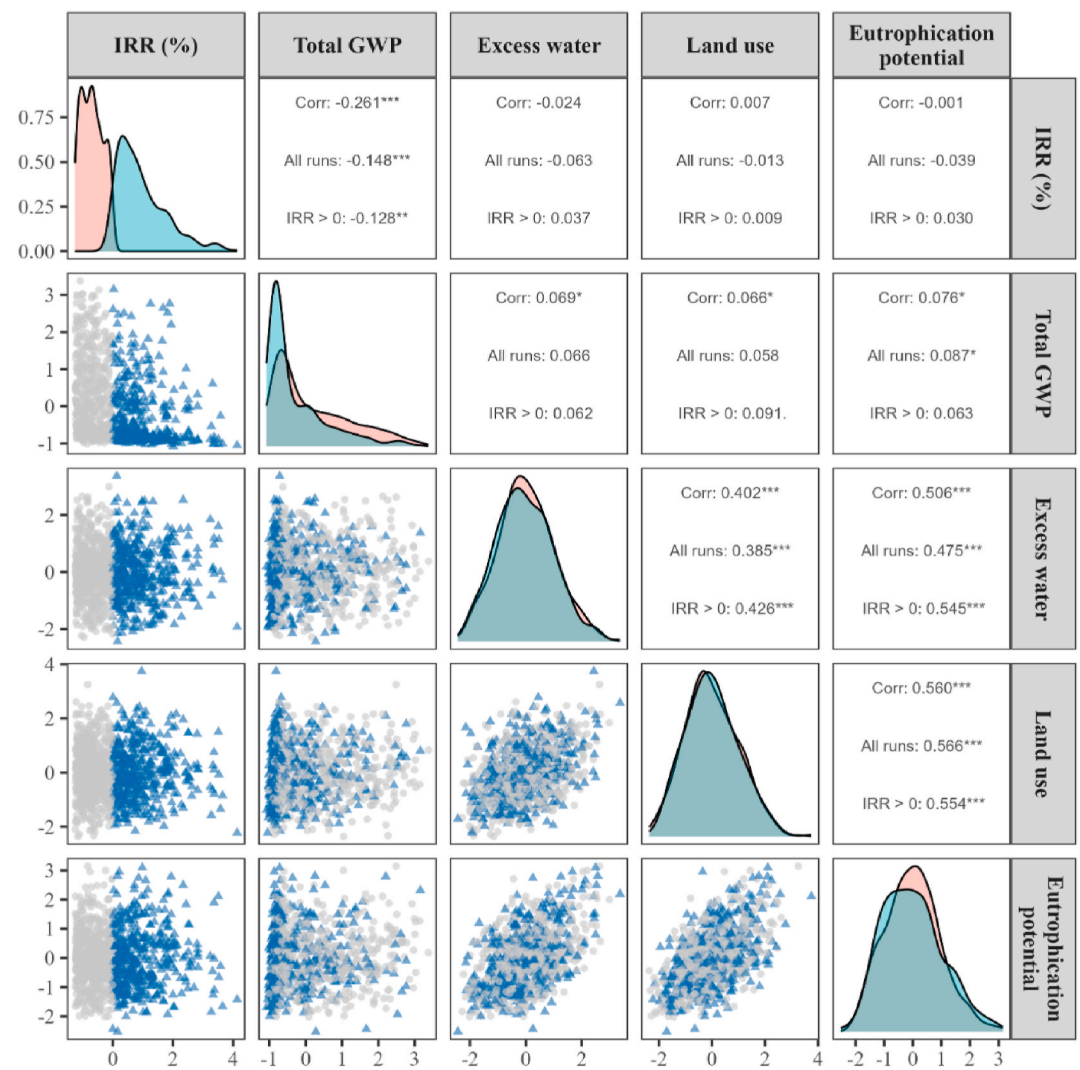

Fig. 8. Correlation matrix of z-score standardized LCA variables. Upper-right panels show Pearson correlation coefficients and significance levels across all simulations and IRR >0 scenarios. Lower-left panels display bivariate scatterplots between across all simulations (grey triangles) and IRR >0 scenarios (blue triangles), while diagonal panels show kernel density estimates of each variable's distribution by group.

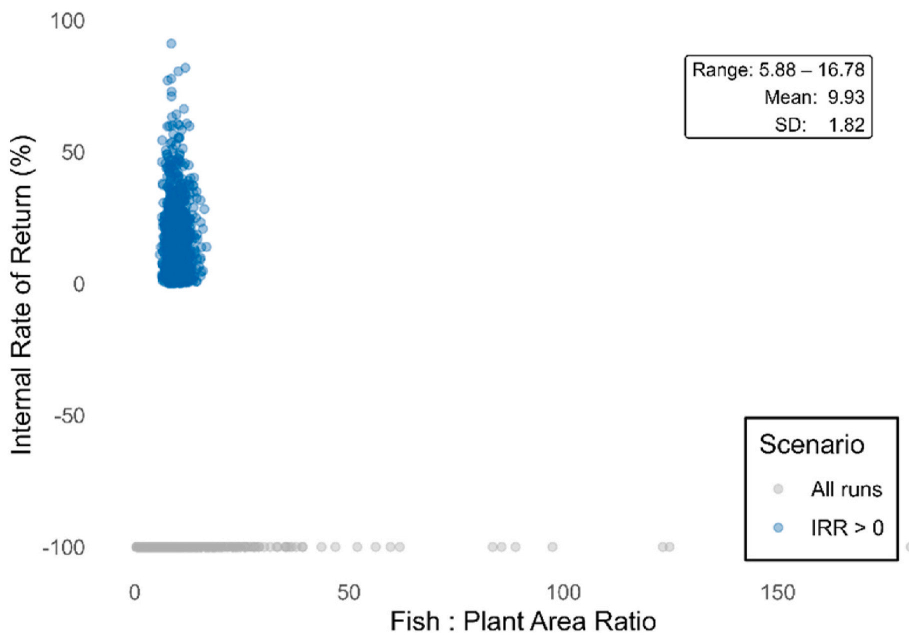

Fig. 9. Fish-plant ratio plotted as a function of internal rate of return (IRR) from 1000 sorted IRR >0 simulations and 1000 unprofitable simulations.

water resources, pollution prevention, and ecosystem services such as biodiversity enhancement, water purification, and sustainable nutrient cycling (La Française Asset, 2024; CS, 2024). Regarding building costs, the taxonomy specifically emphasizes construction and infrastructure that demonstrate high energy efficiency, sustainable materials use, and minimal environmental impact. Operational costs prioritized under the taxonomy include renewable energy use, efficient water management, waste minimization, and reduced greenhouse gas emissions.

Aquaponics facilities are inherently well positioned to meet these EU taxonomy requirements. Operationally, RAS and nutrient remineralization are resource-efficient processes. When only operational factors are considered (conservative scenario), the GAR score is close to 50 % (Fig. 6). In our moderate and high sustainability scenarios, we consider the potential of classifying 50 % or 100 % of the building and construction costs as fulfilling GAR criteria, resulting in scores of 67.8 ± 1.2 % and 88.8 ± 0.5 %, respectively. Another way the GAR could be increased is through ecosystem services. Combining the high sustainability and assuming 50 % of the land costs may be classified as performing an ecosystem service, we achieve a GAR score of 94.4 ± 0.2 %. A high GAR score may offset some of the previously identified risks associated with aquaponic facilities, providing valuable leverage when addressing investor concerns.

4.6. Limitations of the current methodology

All modeling efforts carry the risk of over- or underfitting, often influenced by parameter selection. In this study, 28 hydroponic, 25 aquaculture, and 20 facility parameters were used to describe the system. Although the facility was sized according to plant nitrogen demand, the reverse approach—basing sizing on aquaculture targets—is equally valid. The diversity and balanced spread of hydroponic and aquaculture parameters prevents the starting point from biasing the elasticity and sensitivity outcomes. Furthermore, the model incorporated variables such as total fish count instead of stocking density when estimating labor and management needs, accommodating differences between low-density species like sturgeon and high-density species like tilapia. While species-specific models might yield different outputs, parameter ranges were selected to reflect both extremes.

Certain trade-offs were excluded from the model. Nutrient supplementation values were approximate, based on literature and assuming partial contribution from the water source (Lobanov et al., 2021; Keesman et al., 2019; Yang and Kim, 2020b; Eck et al., 2019b; Marschner, 2012; Somerville et al., 2014). Fertilizer costs were minor in the model, and factors like remineralization or water source composition were not explored. Production cycles were also omitted but may affect turnover and outcomes.

This model focused on a generalizable approach. For example, in the calculation for labor and management FTE requirements, we used the final number of fish instead of stocking density in the calculation to generalize for the higher post-processing work in low density fish species (e.g., sturgeon) compared to high density fish (e.g., tilapia). While it is possible that species-specific models would result in different outcomes, the ranges defined in the input parameters were chosen to accommodate for both extremes. Nonetheless, higher-resolution models would benefit specific use cases, accounting for operational trade-offs such as labor needs, oxygen demand, or species responses to stocking density. Future models should consider process-level dynamics (e.g., canopy effects in vine crops) and incorporate stochastic variables such as energy price volatility, disease outbreaks, or market fluctuations to improve risk prediction (Körner et al., 2021; Ramírez et al., 2023). As a promising, but emerging industry, aquaponics is especially vulnerable to limitations in risk prediction, where high-profile failures or repeated media attention on bankruptcies may signal to investors that the industry itself is unviable.

4.7. The path to wider adoption of circular food production systems

Circular systems must deal with two unique burdens compared to their linear counterparts. Firstly, they cannot, by definition, externalize the cost of waste treatment. For example, a flow-through aquaculture system flushes waste products downstream with little or no treatment whereas a RAS must include active waste removal in the operational costs (Ebeling and Timmons, 2010). Our model reflects these higher costs through the assumed values for aquaculture and crop energy productivity as well as associated parameters. Secondly, there is a significant difference between farming crops in the ground and farming in CEA facilities with respect to operational costs and depreciation. By virtue of incorporating high-tech automation and biofeedback systems, CEA facilities face both higher overhead costs alongside building and equipment depreciation, as accounted for in this model. Depreciation represents a significant portion of the operational costs (3.28 ± 0.1 % on average for the five years in our base case). Acknowledging these weaknesses are crucial for investors, facility operators, and policy makers as a tool to evaluate the true cost of circularity.

A key barrier to clarity is the limited transparency around commercial funding, hindering efforts to distinguish self-sustaining from externally supported ventures. Likely, scaling is more a question of available markets and supply logistics, which will exert an increasing influence over profitability as a facility increases in size. A recent investigation into external factors in an aquaponics context was done by Zaniboni et al. (2024) in a study where geographic parameters influencing the suitability of an aquaponics operation were identified including water availability and quality, climatic and topographic conditions, available infrastructure & facilities (energy, roads, sewage, hatcheries), as well as access to market (consumer demand and willingness to spend extra for sustainable products) (Zaniboni et al., 2024). Furthermore, region-specific electricity prices and technical-assistance coverage have been shown to exhibit spatial spill-over effects that can magnify or dampen profitability across neighbouring markets (Wang et al., 2023). While these factors were outside the scope of the current model, future work in this direction should encompass the role of socioeconomic factors in consumer preferences, for instance factors that determine which fish and plant species are marketable in particular regions, local labor conditions, and the reliability of transportation and other types of infrastructure that are required for successful business operations (Greenfeld et al., 2019; Short et al., 2018; Davis et al., 2025; David et al., 2022).

The model suggests that a more important metric than scale is the fish-plant ratio, which determines the amount of nitrogenous waste delivered to plants. From a sustainability perspective, this resulted in a low greenhouse warming potential attributed to fertilizer production and as well eutrophication potential. Our model predicted a base-case productivity of 8.43 kg fish·m^{-2}·y^{-1}, slightly below the FAO target range (10–15 kg m^{-2} yr^{-1} (Somerville et al., 2014)). However, this rose to 9.93 ± 1.82 kg m^{-2} yr^{-1} among the profitable scenarios (Fig. 9). Here, the model predicts profitability at any scale so long as the three pillars of aquaculture, hydroponics, and facility operational costs are scaled proportionally.

5. Conclusion

There is significant public and academic interest in developing more circular production systems, yet currently major challenges limit widespread adoption. To identify these issues, we attempted to provide a comprehensive economic framework to evaluate the financial viability of aquaponics systems by integrating production efficiencies with investment and operational variables.

In this study, we were able to identify and analyze the most influential parameters affecting the economic performance of an aquaponics facility, drawing from both published sources and practitioner experience. By combining sensitivity analysis, elasticity assessment, and Monte Carlo simulations, we identified a core set of parameters—particularly those related to labor, processing efficiency, and product pricing—that disproportionately influence profitability. Our analysis shows that while aquaponics can be financially viable under certain conditions, facilities operate within narrow economic margins and are especially sensitive to external market and infrastructure constraints. These findings highlight the need for strategic optimization, such as selecting high-value crops and fish species, streamlining labor through efficient facility design, and minimizing OPEX without compromising system performance.

Our approach reveals the conditions under which aquaponics operations can be viable and offers a foundation for more data-driven decision-making across the sector. Analyses such as presented here can serve as powerful tools for researchers seeking to identify opportunities for efficiency improvements with significant impact on the underlying NPV or IRR, for industrial stakeholders aiming to optimize operations, for investors evaluating the feasibility of prospective ventures, and for policy makers attempting to promote circularity. As the field matures, expanding this framework to incorporate more finely tuned models for RAS and greenhouse dynamics, as well as regionally tailored socioeconomic and climate variables, will be essential to advancing aquaponics as a resilient, circular food production system.

CRediT authorship contribution statement

Victor Lobanov: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Joe Pate:** Writing – review & editing, Methodology, Investigation, Formal analysis, Conceptualization. **François Latrille:** Writing – review & editing, Investigation. **Alyssa Joyce:** Writing – review & editing, Validation, Supervision, Investigation, Funding acquisition, Conceptualization.

Ethical approval

Not applicable. No primary data on humans or animals were collected.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author Victor Lobanov used the service ChatGPT (OpenAI, USA) in order screen for spelling and grammar mistakes as well as suggest improvements for sentence fluidity as a complement to the spell-check function native to Microsoft Word (Microsoft, USA). After using this tool, the author reviewed and evaluated the suggestions, integrating them into the manuscript on a case-by-case basis. The author takes full responsibility for the content of the publication.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Regen Aquaculture is an aquaponics consultancy group. While they did not provide funding for this project, they were consulted during the development of the initial parameter set (data collection). The co-author Joe Pate is the CEO of Regen Aquaculture, a commercial aquaponics consultancy that provides design and advisory services for facilities. The co-author François Latrille is employed by SENECT GmbH & Co. KG, a company that manufactures monitoring and control equipment that can be used in aquaculture and aquaponics. Neither Regen Aquaculture nor SENECT GmbH & Co. KG provided financial support for this study and neither organization had any involvement in the study design, analysis, or the decision to submit the work for publication. Victor Lobanov and Alyssa Joyce declare that they have no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2025.146674.

Data availability

Data will be made available on request.

References

Al Tawaha, A.R., Wahab, P.E.M., Jaafar, H.B., Zuan, A.T.K., Hassan, M.Z., 2021. Effects of fish stocking density on water quality, growth performance of tilapia and yield of butterhead lettuce grown in decoupled recirculation aquaponic systems. J. Ecol. Eng. 22 (1), 8–19.

Al-Hafedh, Y.S., Alam, A., Beltagi, M.S., 2008. Food production and water conservation in a recirculating aquaponic system in Saudi Arabia at different ratios of fish feed to plants. J. World Aquacult. Soc. 39 (4), 510–520.

Atherton, H.R., Li, P., 2023. Hydroponic cultivation of medicinal Plants—Plant organs and hydroponic systems: techniques and trends. Horticulturae 9 (3), 349.

Ayipio, E., Wells, D.E., McQuilling, A., Wilson, A.E., 2019. Comparisons between aquaponic and conventional hydroponic crop yields: a meta-analysis. Sustainability 11 (22), 6511.

Badiola, M., Mendiola, D., Bostock, J., 2012. Recirculating aquaculture systems (RAS) analysis: main issues on management and future challenges. Aquac. Eng. 51, 26–35.

Baganz, G., Baganz, D., Staaks, G., Monsees, H., Kloas, W., 2020. Profitability of multi-loop aquaponics: year-long production data, economic scenarios and a comprehensive model case. Aquac. Res. 51 (7), 2711–2724.

Benstead, J.P., Hood, J.M., Whelan, N.V., Kendrick, M.R., Nelson, D., Hanninen, A.F., et al., 2014. Coupling of dietary phosphorus and growth across diverse fish taxa: a meta-analysis of experimental aquaculture studies. Ecology 95 (10), 2768–2777.

Bodiroga, R., Sredojević, Z., 2018. Economic and financial feasibility of investments in the greenhouse production. Economic Insights-Trends Challenges 70 (1).

Bostock, J., McAndrew, B., Richards, R., Jauncey, K., Telfer, T., Lorenzen, K., et al., 2010. Aquaculture: global status and trends. Phil. Trans. Biol. Sci. 365 (1554), 2897–2912.

Boyd, C.E., Tucker, C.S., Somridhivej, B., 2016. Alkalinity and hardness: critical but elusive concepts in aquaculture. J. World Aquacult. Soc. 47 (1), 6–41.

Carbon footprint analysis of mineral fertilizer production in Europe and other world regions. In: Brentrup, F., Hoxha, A., Christensen, B. (Eds.), 2016. Conference Paper, the 10th International Conference on Life Cycle Assessment of Food (LCA Food 2016).

Brown, A.R., Wilson, R.W., Tyler, C.R., 2024. Assessing the benefits and challenges of recirculating aquaculture systems (RAS) for Atlantic salmon production. Reviews in Fisheries Sci. Aquaculture 1–22.

Brühl, V., 2023. The green asset ratio (GAR): a new key performance indicator for credit institutions. Eurasian Econ. Rev. 13 (1), 57–83.

Bujas, T., Koričan, M., Vukić, M., Soldo, V., Vladimir, N., Fan, A., 2022. Review of energy consumption by the fish farming and processing industry in Croatia and the potential for zero-emissions aquaculture. Energies 15 (21), 8197.

Cardoso, F.B., Martinez, H.E.P., Silva, DJHd, Milagres, CdC., Barbosa, J.G., 2018. Yield and quality of tomato grown in a hydroponic system, with different planting densities and number of bunches per plant. Pesqui. Agropecuária Trop. 48 (4), 340–349.

Cerozi, BdS., Fitzsimmons, K., 2017. Phosphorus dynamics modeling and mass balance in an aquaponics system. Agric. Syst. 153, 94–100.

Channa, A.A., Munir, K., Hansen, M., Tariq, M.F., 2024. Optimisation of small-scale aquaponics systems using artificial intelligence and the IoT: current status, challenges, and opportunities. Encyclopedia 4 (1), 313–336.

Chatvijitkul, S., Boyd, C.E., Davis, D.A., 2018. Nitrogen, phosphorus, and carbon concentrations in some common aquaculture feeds. J. World Aquacult. Soc. 49 (3), 477–483.

Chomkhamsri, K., Wolf, M.-A., Pant, R., 2011. International reference life cycle data system (ILCD) handbook: review schemes for life cycle assessment. Towards Life Cycle Sustainability Management, pp. 107–117.

Coale, Jr CW., Anthony, J.P., Flick, Jr GJ., Libey, G.S., Hong, G.-P., Spittle, G., et al., 1993. Marketing Aquaculture Products: a Retail Market Case Study for Sunshine Bass.

Colt, J., Schuur, A.M., 2021. Comparison of nutrient costs from fish feeds and inorganic fertilizers for aquaponics systems. Aquac. Eng. 95, 102205.

Colt, J., Watten, B., 1988. Applications of pure oxygen in fish culture. Aquac. Eng. 7 (6), 397–441.

Colt, J., Schuur, A.M., Weaver, D., Semmens, K., 2022. Engineering design of aquaponics systems. Reviews in Fisheries Sci. Aquaculture 30 (1), 33–80.

Commission, E., 2023. Taxonomy regulation: delegated and implementing acts. European commission directorate-general for financial stability, financial services and capital markets union. In: Directorate-General for Financial Stability FSaCMU.

Conceição, L.E., Aragão, C., Dias, J., Costas, B., Terova, G., Martins, C., et al., 2012. Dietary nitrogen and fish welfare. Fish Physiol. Biochem. 38, 119–141.

Cs, p.A., 2024. An Overview of European Banks' Green Asset Ratio Disclosure for 2024, 2024/02/07.

Danish, M.S.S., Senjyu, T., Sabory, N.R., Khosravy, M., Grilli, M.L., Mikhaylov, A., et al., 2021. A forefront framework for sustainable aquaponics modeling and design. Sustainability 13 (16), 9313.

David, L.H., Pinho, S.M., Agostinho, F., Costa, J.I., Portella, M.C., Keesman, K.J., et al., 2022. Sustainability of urban aquaponics farms: an emergy point of view. J. Clean. Prod. 331, 129896.

Davis, J., Murray, R.R., Crichton, R., Starkey, F., Cammies, C., 2025. Bridging the gap: exploring consumer knowledge, perceptions, and willingness to pay for aquaponics products across the UK. Aquac. Int. 33 (1), 30.

Downie, J., Stubbs, W., 2012. Corporate carbon strategies and greenhouse gas emission assessments: the implications of scope 3 emission factor selection. Bus. Strat. Environ. 21 (6), 412–422.

Ebeling, J.M., Timmons, M.B., 2010. Recirculating Aquaculture. Cayuga Aqua Ventures, Ithaca, NY, USA.

Ebeling, J.M., Timmons, M.B., 2012. Recirculating aquaculture systems. Aquaculture Production Syst. 245–277.

Eck, M., Körner, O., Jijakli, M.H., 2019a. Nutrient cycling in aquaponics systems. Aquaponics Food Production Systems: Combined Aquaculture and Hydroponic Production Technologies for the Future. Springer International Publishing, Cham, pp. 231–246.

Eck, M., Körner, O., Jijakli, M.H., 2019b. Nutrient cycling in aquaponics systems. Aquaponics Food Production Systems: Combined Aquaculture and Hydroponic Production Technologies for the Future, pp. 231–246.

EIA. Table 5.6.A, 2025. Electric power monthly. Average Price of Electricity to Ultimate Customers by End-Use Sector.

Electricity, M., 2025. Electricity Maps Datasets Portal.

Elnour, M., Haller, H., Martin, M., 2023. Life cycle assessment of a retail Store aquaponic system in a cold-weather region. Front. Sustain. 3, 1051091.

Engle, C.R., 2010. Aquaculture Economics and Financing: Management and Analysis. John Wiley & Sons.

Engle, C.R., 2016. Economics of Aquaponics.

Engle, C., Kumar, G., van Senten, J., 2021. Resource-use efficiency in US aquaculture: farm-level comparisons across fish species and production systems. Aquaculture Environ. Interactions 13, 259–275.

Engler, N., Krarti, M., 2021. Review of energy efficiency in controlled environment agriculture. Renew. Sustain. Energy Rev. 141, 110786.

Eurostat, 2024. Electricity Prices for Household Consumers (Nrg_Pc_204).

Eurostat, S.E., 2025. Electricity Price Statistics.

Evans, M.R.. Greenhouse management university of Arkansas2014. https://greenhouse.hosted.uark.edu/Unit02/Section05.html.

Fernández-Cabanás, V.M., Pérez-Urrestarazu, L., Juárez, A., Kaufman, N.T., Gross, J.A., 2020. Comparative analysis of horizontal and vertical decoupled aquaponic systems for basil production and effect of light supplementation by LED. Agronomy 10 (9), 1414.

Forchino, A.A., Lourguioui, H., Brigolin, D., Pastres, R., 2017. Aquaponics and sustainability: the comparison of two different aquaponic techniques using the life cycle assessment (LCA). Aquac. Eng. 77, 80–88.

Francisco, E.C., Freato, T.A., Piolli, A.L., Poz, M.E.S.D., 2024. Analysis of the aquaponic system sustainability via system dynamics Modelling–FEW nexus approach. Circ. Econ. Sustain. 1–16.

Fry, J.P., Mailloux, N.A., Love, D.C., Milli, M.C., Cao, L., 2018. Feed conversion efficiency in aquaculture: do we measure it correctly? Environ. Res. Lett. 13 (2), 024017.

Fu, J., He, Y., Cheng, F., 2024. Intelligent cutting in fish processing: efficient, high-quality, and safe production of fish products. Food Bioprocess Technol. 17 (4), 828–849.

Gallego-Alarcón, I., Fonseca, C.R., García-Pulido, D., Díaz-Delgado, C., 2019. Proposal and assessment of an aquaculture recirculation system for trout fed with harvested rainwater. Aquac. Eng. 87, 102021.

Gichana, Z.M., Liti, D., Waidbacher, H., Zollitsch, W., Drexler, S., Waikibia, J., 2018. Waste management in recirculating aquaculture system through bacteria dissimilation and plant assimilation. Aquac. Int. 26 (6), 1541–1572.

Glencross, B.D., Booth, M., Allan, G.L., 2007. A feed is only as good as its ingredients–a review of ingredient evaluation strategies for aquaculture feeds. Aquac. Nutr. 13 (1), 17–34.

Goddek, S., Keesman, K.J., 2020. Improving nutrient and water use efficiencies in multi-loop aquaponics systems. Aquac. Int. 28 (6), 2481–2490.

Goddek, S., Schmautz, Z., Scott, B., Delaide, B., Keesman, K.J., Wuertz, S., et al., 2016. The effect of anaerobic and aerobic fish sludge supernatant on hydroponic lettuce. Agronomy-Basel. 6 (2), 37.

Goddek, S., Joyce, A., Kotzen, B., Dos-Santos, M., 2019. Aquaponics and global food challenges. Aquaponics Food Production Systems: Combined Aquaculture and Hydroponic Production Technologies for the Future. Springer International Publishing, Cham, pp. 3–17.

Goh, Y.S., Hum, Y.C., Lee, Y.L., Lai, K.W., Yap, W.-S., Tee, Y.K., 2023. A meta-analysis: food production and vegetable crop yields of hydroponics. Sci. Hortic. 321, 112339.

Gosh, K., Chowdhury, S., 2019. Review of aquaponics system: searching for a technically feasible and economically profitable aquaponics system. J. Agricultural Environment. Consumer Sci. 19, 5–13.

Greenfeld, A., Becker, N., McIlwain, J., Fotedar, R., Bornman, J.F., 2019. Economically viable aquaponics? Identifying the gap between potential and current uncertainties. Rev. Aquacult. 11 (3), 848–862.

Greenfeld, A., Becker, N., Bornman, J.F., Spatari, S., Angel, D.L., 2021. Monetizing environmental impact of integrated aquaponic farming compared to separate systems. Sci. Total Environ. 792, 148459.

Helton, J.C., Davis, F.J., 2003. Latin hypercube sampling and the propagation of uncertainty in analyses of complex systems. Reliab. Eng. Syst. Saf. 81 (1), 23–69.

Henriksson, E.F., Elnour, M., Martin, M., 2025. Environmental life cycle assessment of a commercial aquaponic system. Cleaner Environ. Syst. 17, 100282.

Hognes, E.S., Nilsson, K., Sund, V., Ziegler, F., 2014. LCA of Norwegian Salmon Production 2012.
Hussain, A.S., Brown, P.B., 2024. A literature review of tilapia/lettuce aquaponics—production status, varieties, and research gaps. Aquac. Res. 2024 (1), 2642434.
Hydroponics, H., 2025. Advantages of rolling benches. https://www.hydrotekhydroponics.com/blog/advantages-of-rolling-benches.
Ianchenko, A., Proksch, G., 2019. Urban food systems: applying life cycle assessment in built environments and aquaponics. Building Technol. Educator's Soc. 2019 (1), 29.
Icis, 2025a. Sulphates Price Assessment (Bulk Copper Sulfate Pentahydrate).
Icis, 2025b. Potassium Price Assessment (Bulk Potassium Sulfate).
IndexMundi, 2025a. Magnesium Sulfate Bulk Price Data.
IndexMundi, 2025b. Manganese Sulfate Bulk Price Data.
IndexMundi, 2025c. Sodium Molybdate Bulk Price Data.
IndexMundi, 2025d. Zinc Sulfate Bulk Price Data.
International Fertilizer A, 2024a. World Fertilizer Trends & Outlook Report 2024 (Micronutrient Fertilizers).
International Fertilizer A, 2024b. World Fertilizer Trends & Outlook Report 2024 (Boron Fertilizers).
Iqbal, A., Butt, S.J., Haq, Z., Naseem, I., Khan, Q.A., Sajid, M., 2024. Efficacy of various packaging materials on the postharvest life of hydroponically grown tomatoes (Lycopersicon esculentum, mill). Sarhad J. Agric. 40 (4), 1260–1268.
Jaeger, C., Foucard, P., Tocqueville, A., Nahon, S., Aubin, J., 2019. Mass balanced based LCA of a common carp-lettuce aquaponics system. Aquac. Eng. 84, 29–41.
Joshi, D., Nainabasti, A., Awasthi, R.B.P., Banjade, D., Malla, S., Subedi, B., 2022. A review on soilless cultivation: the hope of urban agriculture. Archives Agriculture Environ. Sci. 7 (3), 473–481.
Karimanzira, D., Keesman, K., Kloas, W., Baganz, D., Rauschenbach, T., 2017. Efficient and economical way of operating a recirculation aquaculture system in an aquaponics farm. Aquacult. Econ. Manag. 21 (4), 470–486.
Kaya, F.E., Monsù Scolaro, A., 2023. Circularity as a climate change mitigation strategy in the building sector: the stakeholder's involvement in the interconnected life cycle phases. Sustainability 15 (9), 7554.
Keesman, K.J., Körner, O., Wagner, K., Urban, J., Karimanzira, D., Rauschenbach, T., et al., 2019. Aquaponics systems modelling. Aquaponics Food Production Systems. Springer, pp. 267–299.
Komal, W., Fatima, S., Minahal, Q., Liaqat, R., 2024. Investigating the optimum stocking density of tilapia (Oreochromis niloticus) for intensive production focused to in-pond raceway system. Sci. Prog. 107 (2), 00368504241257128.
Körner, O., Fanourakis, D., Hwang, M.C.-R., Hyldgaard, B., Tsaniklidis, G., Nikoloudakis, N., et al., 2021. Incorporating cultivar-specific stomatal traits into stomatal conductance models improves the estimation of evapotranspiration enhancing greenhouse climate management. Biosyst. Eng. 208, 131–151.
La Française Asset, M., 2024. Green Asset Ratio – is the Crash Test Really a Complete Failure?, 2024/05/03.
Lages Barbosa, G., Almeida Gadelha, F.D., Kublik, N., Proctor, A., Reichelm, L., Weissinger, E., et al., 2015. Comparison of land, water, and energy requirements of lettuce grown using hydroponic vs. conventional agricultural methods. Int. J. Environ. Res. Publ. Health 12 (6), 6879–6891.
Landazuri-Tveteraas, U., Misund, B., Tveterås, R., Zhang, D., 2023. Determinants of investment behavior in Norwegian salmon aquaculture. Aquacult. Econ. Manag. 27 (4), 790–808.
Li, H., Cui, Z., Cui, H., Bai, Y., Yin, Z., Qu, K., 2023. A review of influencing factors on a recirculating aquaculture system: environmental conditions, feeding strategies, and disinfection methods. J. World Aquacult. Soc. 54 (3), 566–602.
Lin, J., 2023. A comparative study on the application of NPV and IRR in financial market investment decision. Academic J.Business Management 5 (4), 51–54.
Liu, B., Liu, Y., Wang, X., 2015. The effect of stocking density on growth and seven physiological parameters with assessment of their potential as stress response indicators for the Atlantic salmon (Salmo Salar). Mar. Freshw. Behav. Physiol. 48 (3), 177–192.
Lobanov, V.P., Combot, D., Pelissier, P., Labbé, L., Joyce, A., 2021. Improving plant health through nutrient remineralization in aquaponic systems. Front. Plant Sci. 12, 683690.
Lobanov, V., De Vrieze, J., Joyce, A., 2023. Simultaneous biomethane production and nutrient remineralization from aquaculture solids. Aquac. Eng. 101, 102328.
Lobanov, V.P., Pate, J., Joyce, A., 2024. Sturgeon and paddlefish: review of research on broodstock and early life stage management. Aquaculture and Fisheries 9 (6), 871–882.
Lobanov, V.P.L.F., Pate, J., Savidov, N., Monsees, H., Derksen, J., Padeniya, U., Joyce, A., 2025. Leveraging microbial ecological insights to bridge and classify differences between coupled and decoupled aquaponic systems. Rev. Aquacult. Publication in review.
Lobillo-Eguíbar, J., Fernández-Cabanás, V.M., Bermejo, L.A., Pérez-Urrestarazu, L., 2020. Economic sustainability of small-scale aquaponic systems for food self-production. Agronomy 10 (10), 1468.
López-Mosquera, M.E., Fernández-Lema, E., Villares, R., Corral, R., Alonso, B., Blanco, C., 2011. Composting fish waste and seaweed to produce a fertilizer for use in organic agriculture. Procedia Environ. Sci. 9, 113–117.
Love, D.C., Fry, J.P., Li, X., Hill, E.S., Genello, L., Semmens, K., et al., 2015. Commercial aquaponics production and profitability: findings from an international survey. Aquaculture 435, 67–74.
Luo, G., 2023. Review of waste phosphorus from aquaculture: source, removal and recovery. Rev. Aquacult. 15 (3), 1058–1082.
Marschner, H., 2012. Marschner's Mineral Nutrition of Higher Plants. Academic press.
McLean, W.E., Jensen, J.O., Alderdice, D.F., 1993. Oxygen consumption rates and water flow requirements of Pacific salmon (oncorhynchus spp.) in the fish culture environment. Aquaculture 109 (3–4), 281–313.
Modarelli, G.C., Vanacore, L., Rouphael, Y., Langellotti, A.L., Masi, P., De, Pascale S., et al., 2023. Hydroponic and aquaponic floating raft systems elicit differential growth and quality responses to consecutive cuts of basil crop. Plants 12 (6), 1355.
Nations FaAOotU, 2025. Globefish – prices. https://www.fao.org/in-action/globefish/prices/en/.
Ni, M., Wen, H., Li, J., Chi, M., Bu, Y., Ren, Y., et al., 2016. Effects of stocking density on mortality, growth and physiology of juvenile Amur sturgeon (Acipenser schrenckii). Aquac. Res. 47 (5), 1596–1604.
Nicholson, C.F., Harbick, K., Gómez, M.I., Mattson, N.S., 2020. An Economic and Environmental Comparison of Conventional and Controlled Environment Agriculture (CEA) Supply Chains for Leaf Lettuce to US Cities. Springer.
Nindarwi, D.D., Rochman, A.N., Tsany, M.R.N., Rachmawati, V., Masithah, E.D., 2019. Study of calcium hydroxide (Ca (OH) 2) and sodium bicarbonate (NaHCO3) treatment on the dynamics of pH, COD N/P ratio and plankton abundance. J. Aquaculture and Fish Health 8 (2), 72–79.
Nistad, A.A., 2020. Current and Future Energy Use for Atlantic Salmon Farming in Recirculating Aquaculture Systems in Norway. NTNU.
North, B., Turnbull, J., Ellis, T., Porter, M., Migaud, H., Bron, J., et al., 2006. The impact of stocking density on the welfare of rainbow trout (Oncorhynchus mykiss). Aquaculture 255 (1–4), 466–479.
Pantaleo, A., Pellerano, A., Carone, M., 2009. Potentials and feasibility assessment of small scale CHP plants fired by energy crops in puglia region (italy). Biosyst. Eng. 102 (3), 345–359.
Pantanella, E., Cardarelli, M., Colla, G., Rea, E., Marcucci, A. (Eds.), 2010. Aquaponics Vs. Hydroponics: Production and Quality of Lettuce Crop. XXVIII International Horticultural Congress on Science and Horticulture for People (IHC2010), vol 927. International Symposium on.
Pate, J., 2025. Analysis of customer profiles. Regen Aquaculture.
Pattillo, D.A., Hager, J.V., Cline, D.J., Roy, L.A., Hanson, T.R., 2022. System design and production practices of aquaponic stakeholders. PLoS One 17 (4), e0266475.
Pomoni, D.I., Koukou, M.K., Vrachopoulos, M.G., Vasiliadis, L., 2023. A review of hydroponics and conventional agriculture based on energy and water consumption, environmental impact, and land use. Energies 16 (4), 1690.
Pucher, J., Focken, U., 2017. Uptake of nitrogen from natural food into fish in differently managed polyculture ponds using 15N as tracer. Aquac. Int. 25 (1), 87–105.
Quagrainie, K.K., Flores, R.M.V., Kim, H.-J., McClain, V., 2018. Economic analysis of aquaponics and hydroponics production in the US midwest. J. Appl. Aquacult. 30 (1), 1–14.
Raimi, D., Zhu, Y., Newell, R.G., Prest, B.C., 2024. Global energy outlook 2024: peaks or plateaus. Resources for the Future: Washington, DC, USA.
Evapotranspiration prediction for suitable combinations of Cascade hydroponic systems. In: Ramírez, T., Elvanidi, A., Katsoulas, N., Körner, O. (Eds.), 2023. International Symposium on New Technologies for Sustainable Greenhouse Systems: Greensys2023 1426.
Raulier, P., Latrille, F., Ancion, N., Kaddouri, M., Crutzen, N., Jijakli, M.H., 2023. Technical and business evaluation of professional aquaponics in Europe. Water 15 (6), 1198.
Ravani, M., Georgiou, K., Tselempi, S., Monokrousos, N., Ntinas, G.K., 2023. Carbon footprint of greenhouse production in EU—How close are we to green deal goals? Sustainability 16 (1), 191.
Reilly, G., Souder, D., Ranucci, R., 2016. Time horizon of investments in the resource allocation process: review and framework for next steps. J. Manag. 42 (5), 1169–1194.
Robison, L.J., Barry, P.J., Myers, R.J., 2015. Consistent IRR and NPV rankings. Agric. Finance Rev. 75 (4), 499–513.
Rørå, A.B., Mørkøre, T., Einen, O., 2001. Primary processing (evisceration and filleting). Farmed fish quality 249–260.
Rubin, S.J., 2018. Water costs and affordability in the United States: 1990 to 2015. J. Am. Water Works Assoc. 110 (4), 48–52.
Saeed, T., Bouri, E., Tran, D.K., 2020. Hedging strategies of green assets against dirty energy assets. Energies 13 (12), 3141.
Santos, S., 2024. The importance of practicality: the role of a transition green asset ratio for banks. Sustainable Finances and the Law: Between Public and Private Solutions. Springer, pp. 63–76.
Sardare, M.D., Admane, S.V., 2013. A review on plant without soil-hydroponics. Int. J. Renew. Energy Technol. 2 (3), 299–304.
Schmitz, C., Biewald, A., Lotze-Campen, H., Popp, A., Dietrich, J.P., Bodirsky, B., et al., 2012. Trading more food: implications for land use, greenhouse gas emissions, and the food system. Glob. Environ. Change 22 (1), 189–209.
Schumann, M., Brinker, A., 2020. Understanding and managing suspended solids in intensive salmonid aquaculture: a review. Rev. Aquacult. 12 (4), 2109–2139.
Seginer, I., Ben-Asher, R., 2011. Optimal harvest size in aquaculture, with RAS cultured sea bream (Sparus aurata) as an example. Aquac. Eng. 44 (3), 55–64.
Service UAM, 2025. Weekly Fertilizer Summary (Monopotassium Phosphate).
Sharma, N., Acharya, S., Kumar, K., Singh, N., Chaurasia, O., 2018. Hydroponics as an advanced technique for vegetable production: an overview. J. Soil Water Conserv. 17 (4), 364–371.
Short, G., Yue, C., Abbey, M., Anderson, N., Phelps, N., Venturelli, P., et al., 2018. Consumer preferences for aquaponic produce: implications from an experimental auction. Agribusiness 34 (4), 742–755.
Commercial aquaponic system developed for Atlantic salmon (Salmo salar) production in RAS together with vegetable production a CO2 zero concept. In: Skar, S., Birkeland, M., Nordal, O., Thorarinsdottir, R. (Eds.), 2022. XXXI International

Horticultural Congress (IHC2022): International Symposium on Urban Horticulture for Sustainable Food 1356.
Skretting, 2022. The Carbon Footprint of Our Products.
Solutions, L.G., 2024. How to optimize your greenhouse benching design. https://llk-solutions.com/how-to-optimize-your-greenhouse-benching-design/.
Somerville, C., Cohen, M., Pantanella, E., Stankus, A., Lovatelli, A., 2014. Small-Scale Aquaponic Food Production: Integrated Fish and Plant Farming, vol. 589. FAO Fisheries and aquaculture technical paper, p. I.
Song, X., Liu, Y., Pettersen, J.B., Brandão, M., Ma, X., Røberg, S., et al., 2019. Life cycle assessment of recirculating aquaculture systems: a case of Atlantic salmon farming in China. J. Ind. Ecol. 23 (5), 1077–1086.
Stalport, B., Raulier, P., Jijakli, H., Lebeau, F., 2022. Modeling aquaponics: a review on available models and simulation tools. Biotechnologie, Agronomie, Société Et Environnement.
Suhl, J., Dannehl, D., Kloas, W., Baganz, D., Jobs, S., Scheibe, G., et al., 2016. Advanced aquaponics: evaluation of intensive tomato production in aquaponics vs. conventional hydroponics. Agric. Water Manag. 178, 335–344.
Sun, M., Hassan, S.G., Li, D., 2016. Models for estimating feed intake in aquaculture: a review. Comput. Electron. Agric. 127, 425–438.
Tan, X.W., Ikeda, H., Oda, M., 2000. The absorption, translocation, and assimilation of urea, nitrate or ammonium in tomato plants at different plant growth stages in hydroponic culture. Sci. Hortic. 84 (3–4), 275–283.
Tennøy, A.K., 2022. Exploring the Potential for Hydroponic Plant Growth in Water from Atlantic Salmon Recirculating Aquaculture Systems (Aquaponics). NTNU.
Terjesen, B.F., Summerfelt, S.T., Nerland, S., Ulgenes, Y., Fjæra, S.O., Reiten, B.K.M., et al., 2013. Design, dimensioning, and performance of a research facility for studies on the requirements of fish in RAS environments. Aquac. Eng. 54, 49–63.
Tetreault, J., Fogle, R.L., Guerdat, T., 2023. Scalable coupled aquaponics design: lettuce and tilapia production using a parallel unit process approach. Front. Sustain. Food Syst. 7, 1059066.
Tokunaga, K., Tamaru, C., Ako, H., Leung, P., 2015. Economics of small-scale commercial aquaponics in hawai ‘i. J. World Aquacult. Soc. 46 (1), 20–32.
Treftz, C., Omaye, S.T., 2016. Comparision between hydroponic and soil systems for growing strawberries in a greenhouse. Int. J. Agricultural Extension 3 (3), 195–200.
Turnšek, M., Morgenstern, R., Schröter, I., Mergenthaler, M., Hüttel, S., Leyer, M., 2019. Commercial aquaponics: a long road ahead. Aquaponics food production systems 18, 453–485.
Turnsek, M., Joly, A., Thorarinsdottir, R., Junge, R., 2020. Challenges of commercial aquaponics in Europe: beyond the hype. Water 12 (1), 306.
Ullah-Khan, K., Tellechea-Rodrigues, A., Menegasso-Mansano, C.F., Queiroz, DMdA., Kazue-Sakomura, N., Romaneli, RdS., et al., 2019. Dietary protein quality and proper protein to energy ratios: a bioeconomic approach in aquaculture feeding practices. Latin American J. Quatic Res. 47 (2), 232–239.
van Rijn, J., 2013. Waste treatment in recirculating aquaculture systems. Aquac. Eng. 53, 49–56.
Velasco-Muñoz, J.F., Mendoza, J.M.F., Aznar-Sánchez, J.A., Gallego-Schmid, A., 2021. Circular economy implementation in the agricultural sector: definition, strategies and indicators. Resour. Conserv. Recycl. 170, 105618.
Vielma, J., Kankainen, M., Setälä, J., 2022. Current Status of Recirculation Aquaculture Systems (RAS) and Their Profitability and Competitiveness in the Baltic Sea Area.
Wang, S., Cheng, L., Liu, X., 2022. Comparative study on the carbon footprints of extruded and pelleted feed and their potential for carbon reduction: a case study of grass carp feed. J. Clean. Prod. 381, 135192.
Wang, Q., Guo, J., Li, R., Mikhaylov, A., Moiseev, N., 2023. Does technical assistance alleviate energy poverty in sub-saharan African countries? A new perspective on spatial spillover effects of technical assistance. Energy Strategy Rev. 45, 101047.
Weber, C.L., Matthews, H.S., 2008. Food-Miles and the Relative Climate Impacts of Food Choices in the United States. ACS Publications.
Whangchai, N., Klahan, R., Balakrishnan, D., Unpaprom, Y., Ramaraj, R., Pimpimol, T., 2022. Development of aeration devices and feeding frequencies for oxygen concentration improvement in 60-tones freshwater recirculating aquaculture and biofloc ponds of Asian seabass (Lates calcarifer) rearing. Chemosphere 307, 135761.
Wongkiew, S., Hu, Z., Chandran, K., Lee, J.W., Khanal, S.K., 2017. Nitrogen transformations in aquaponic systems: a review. Aquac. Eng. 76, 9–19.
Wootton-Beard, P., 2019. Growing Without Soil: an Overview of Hydroponics.
Yang, T., Kim, H.-J., 2020a. Comparisons of nitrogen and phosphorus mass balance for tomato-, basil-, and lettuce-based aquaponic and hydroponic systems. J. Clean. Prod. 274, 122619.
Yang, T., Kim, H.-J., 2020b. Characterizing nutrient composition and concentration in tomato-, basil-, and lettuce-based aquaponic and hydroponic systems. Water 12 (5), 1259.
Yep, B., Zheng, Y.B., 2019. Aquaponic trends and challenges - a review. J. Clean. Prod. 228, 1586–1599.
Yu, R., Leung, P., 2006. Optimal partial harvesting schedule for aquaculture operations. Mar. Resour. Econ. 21 (3), 301–315.
Zaniboni, A., Tassinari, P., Torreggiani, D., 2024. GIS-based land suitability analysis for the optimal location of integrated multi-trophic aquaponic systems. Sci. Total Environ. 913, 169790.
Zhang, Y., Zhang, Y-k, Li, Z., 2022a. A new and improved aquaponics system model for food production patterns for urban architecture. J. Clean. Prod. 342, 130867.
Zhang, J., Jia, G., Wang, M., Cao, S., Mkumbuzi, S.G., 2022b. Hydrodynamics of recirculating aquaculture tanks with different spatial utilization. Aquac. Eng. 96, 102217.
Zheng, Y., Zhao, W., Varga, M., Li, D., 2024. Stochastic energy management of large industrial-scale aquaponics considering robust optimization-based demand response program. Appl. Energy 374, 123982.
Zoli, M., Bacenetti, J., 2025. Energy analysis in fish aquaculture: cumulative energy demand of different farming systems. Aquac. Eng. 110, 102525.