**Word Count: 9,038 (Without References)**

An Integrative Framework for Comprehensive Eco-efficiency Assessment in Plant-Protein Extraction Processes*: Techno-eco-environmental Hotspot Characterization, Multi-step Protein Loss Quantification, and Advanced Uncertainty Analysis*

**Abstract**

Over the past few years, there has been an increasing demand of plant-based proteins. Towards the adoption of existing methods, modified extraction methods as well as emerging technologies, at the industrial/commercial scale to meet this increasing demand, there is the need to assess and ascertain the overall sustainability performance of the methods, integrating both economic, product value and environmental perspectives. Although eco-efficiency assessment is the best avenue for assessing the environmental impact of process and product systems, this concept has not yet been applied to assess the sustainability of plant-based protein extraction methods. This study presents a novel eco-efficiency assessment framework for evaluating plant-protein extraction methods, focusing on their industrial commercialization potential. The framework integrates eco-efficiency analysis, hotspot identification of product system values and environmental impacts, and includes uncertainty and global sensitivity analyses to highlight key production variables that affect economic and environmental outcomes. The framework was then applied to perform an eco-efficiency assessment on a case study of pea protein extraction by the alkaline-isoelectric precipitation (ALK-IEP) method with different trials using different yellow pea varieties. Results highlighted the major contribution of the spray drying, pasteurization and extraction-decantation sections to eco-environmental outcomes and protein content loss. The findings offer insights for optimizing the extraction process and improving eco-efficiency, contributing to more sustainable, scalable commercial pea protein production.

**Keywords:** plant-protein extraction; eco-efficiency; hotspot analysis; techno-eco-environmental analysis; uncertainty analysis

**List of Abbreviations**

ALK-IEP – Alkaline-Isoelectric Precipitation

EE – Eco-efficiency

FCI – Fixed Capital Investment

FRS – Fossil Resource Scarcity

GSA – Global Sensitivity Analysis

GWP – Global Warming Potential

HCT – Human Carcinogenic Toxicity

LCI – Life Cycle Inventory

MSP – Minimum Selling Price

NPV – Net Present Value

OPEX – Operating Expenses

ROI – Return on Investment

TEA – Techno-economic Assessment

# Introduction

Plant-based proteins are steadily gaining popularity over the past few years and this trend is expected to rise in the next decades (Balandrán-Quintana et al., 2019; Langyan et al., 2021). This is primarily due to the significantly lower environmental impact associated with their production compared to animal-based protein sources, hence considered a sustainable option. Plant-based proteins are produced by either dry or wet fractionation methods, with a recent emerging technology known as the hybrid fractionation method. Even though plant-based proteins have been identified as a sustainable option, there is the need to assess and establish the technical, economic, and environmental impacts of processing methods for hotspot analysis towards maximizing resource use efficiency, increasing protein recovery, minimizing environmental impacts, while achieving a high financial sustainability at industrial application levels. Eco-efficiency is a sustainability assessment concept that aims to reduce the consumption of resources and raw materials, as well as the environmental impact while maintaining or enhancing the value of the manufactured product (Gumus et al., 2017). It is a very suitable tool for industrial companies and economists as it provides an integrated outlook to environmental impacts and economic benefits (ISO, 2012; Maxime et al., 2006)

Uncertainty analysis has also become very imperative in sustainability assessment due to the inherent uncertainty of parameters and models used for these assessments (Adeyi et al., 2021). Moreover, global sensitivity analysis (GSA) used to quantify the relative measure of parameter contribution to the output variance, in other words, how sensitive is the output results to the entire input space, has also gained popularity in the last few years (Groen et al., 2016; Heijungs, 2010). This is different from the Local Sensitivity Analysis (LCA), which deals with varying one parameter at a time to evaluate how it influences the output (economic or environmental indicator) GSA as used in sustainability assessments, allows practitioners to understand the main uncertainty drivers in LCA/TEA models, helps in prioritizing data collection, and also supports improved modeling of most important processes (Corona et al., 2018; Gaffey et al., 2024). Moreover, in GSA when the correlation and covariance analyses are ignored, this can result in false discernibility and threshold analysis of the parameters with consequences of underestimating important parameters and vice versa (Groen and Heijungs, 2017).

Although, eco-efficiency has been used as an assessment tool to evaluate the sustainability performance of food production processes (Benoit et al., 2019; Izuchukwu, 2020), there has not been a comprehensive evaluation of plant-protein extraction processes that holistically assesses the economic performance, environmental impacts, stochastic tendencies (uncertainty and global sensitivity), eco-efficiency performance as well a protein recovery tracking to identify hotspots for the overall process sustainability optimization. Assessing this from a system-based and holistic perspectives allows to identify all the major contributing factors to each sustainability dimension as well as reveal the synergetic effects and trade-offs among process variables and sustainability performance indicators.

To address this challenge, this present study seeks to develop an eco-efficiency assessment framework that holistically assesses the overall sustainability performance of plant-based protein extraction methods. For purposes of optimization and commercial scale-up, the framework encompasses performing a comprehensive hotspot analysis to identify the process stages that contribute to the economic, environmental as well as protein content losses, which also includes an uncertainty and global sensitivity analysis to identify which production variables are the economic and environmental indicators most sensitive to. The framework also describes various eco-efficiency indicators that integrate the different sustainability dimensions based on both economic (monetary) values and product-quality (functional) value. The framework is then applied to assess a pilot-scale pea protein extraction by the wet fractionation (alkaline-isoelectric precipitation) method to identify the critical nodes for overall eco-efficiency improvement.

To this end, this manuscript is presented under 6 sections including the Introduction. The methodological approaches that detail the novel eco-efficiency framework developed in aspects of TEA-LCA methods, hotspot analysis, uncertainty and sensitivity analysis, and eco-efficiency performance indicators, as well as the case study with pea protein extraction, are described in Section 2. Section 3 presents and discusses the findings from the application of the framework to assess the holistic eco-efficiency of the pea protein extraction process under study. Section 5 highlights the final concluding remarks and indicates the direction for prospective studies in eco-efficiency of plant-based protein extraction. This study would contribute to a deeper understanding regarding the application of a holistic techno-eco-environmental approach that can be adopted to accurately assess the sustainability of pea protein extraction processes.

# Materials and methods

This section describes the new eco-efficiency assessment framework for plant-based protein extraction as well as presents the application of the model to a case study of upscaling a protein extraction process. The main aim of this methodological framework is to be adopted to perform holistic techno-eco-environmental hotspot analyses of protein extraction methods to identify areas for improvement towards industrial or commercial scale applications. The framework seeks to track the protein loss along the processing line, evaluate economic and environmental impacts hotspots using Techno-economic Assessment (TEA) and Life Cycle Assessment (LCA) methods after which uncertainty analysis, global sensitivity analysis (GSA) as well as the eco-efficiency performance is also performed. This framework is then applied to a case study of protein extraction from yellow peas. The detailed methodologies are presented in the subsequent sections.

## Development of novel quality-based eco-efficiency assessment framework

This section details the approaches in the ***novel methodological framework*** that has been developed to investigate the comprehensive techno-eco-environmental efficiency of plant protein production method as illustrated in Fig. 1. The framework follows the guidelines of the which entails product system description (case study), methods to account for the product system values: functional value (protein purity and recovery analysis) and monetary value (techno-economic assessment). The novelty of this framework lies in the adoption of a holistic perspective to perform a hotspot analysis on the environmental impacts of the extraction process as well as the profitability indicators and protein purity. In addition it details the methods for the environmental impact assessment as well as eco-efficiency indicators, uncertainty analysis and sensitivity analysis (ISO, 2012).

**A diagram of a system

Description automatically generated**

**Figure 1: Proposed Methodological Framework for Comprehensive Eco-efficiency Assessment of Pea Protein Extraction**

### Protein Content Tracking (recovery analysis)

From the pilot scale extraction process, a hotspot analysis is conducted to track the protein content in the initial legume flour (assuming there is from extraction till spray drying to identify processing stages or separation nodes that contributed to highest protein losses. The initial protein content of the flour after the dry pre-milling steps is determined (Ref) and protein content of in-process samplings at different separation nodes measured. Mass balances are then carried at the different stages through to the dried product.

The mass flow analysis is conducted for the processes step at which separation occurs using the formula below:

where and represents total protein entering and leaving a process step, respectively, , , and , represents protein content (%) in entering stream, mainstream (stream that enters the next separation step) and side stream (the “unwanted phase”), respectively.

With this assumption, only protein content from the unwanted phase (losses) is measured and used to estimate the protein content in the “mainstream”, for a more accurate protein tracking along the process line. Therefore , which is percentage of protein in the mainstream leaving a process step is estimated as:

Where , is the initial protein content (kg) in the flour, and is estimated by:

At the first process, is 100% and reduces along the processing line till the spray drying step. At this point, becomes protein recovery, which represents the percentage of initial protein in flour in the final protein isolate (Annoh-Quarshie, 2018). This data is now plotted in a Sankey Diagram for protein content tracking.

### Techno-economic Assessment (TEA)

Mass and energy balances

Mass flows and energy requirements that would be used to estimate subsequent equipment costs and operating expenses are calculated based on the process performance data in terms of material and energy usage of the pilot-scale extraction conducted. This would also include the yield, assuming the same yield would be recorded at the industrial scale. The next step is to estimate the capital and operating costs, as presented in the subsequent sections.

Capital Investment (CAPEX) and Operating Costs (OPEX)

The capital costs evaluation follows methods as outlined by (Peters et al., 2003). The Fixed Capital Investment (FCI) is estimated from plant equipment costs and indirect costs related to equipment installation, piping, engineering design, storage, etc. The Working Capital is also estimated where the sum of these values and the FCI becomes the Total Capital Investment (TCI) (Peters et al., 2003). The total annual operating costs are estimated as a sum of direct manufacturing costs and indirect production costs, which include raw materials, utilities, labour costs, taxes, as well as plant overheads and general expenses. . Estimating these values, in terms of the percentage of the capital investment and direct production costs, are shown in the Supplementary document.

Profitability Analysis

To assess the profitability of the process plants, economic indicators such as Net Present Value (NPV), Return on Investment (ROI), Payback Period, Turn-Over Ratio (TOR), and Minimum Selling Price (MSP). The MSP is evaluated to determine the least price that would make the investment profitable at the capital, operating, and financial costs, as well as the protein production rate (the yield) recorded. However, the ROI and NPV can also be evaluated to determine the profitability levels of the process when at a specific price of the protein isolate, fibres, and starch slurry.

The ROI is estimated according to the equation:

The MSP was estimated as the minimum selling price of the protein isolate that would yield an NPV of 0 (below which a negative NPV would be achieved), as calculated below:

Economic Hotspot Analysis

Presenting the different hotspot analyses is a specificity of this framework. The economic hotspot analysis focuses on the equipment costs and operating costs. For easier hotspot analysis, in addition to presenting capital costs of all the equipment, a potential user of this framework can also categorize the different costs into appropriate sections as protein extraction methods could have more than 10-12 process units. Preferably, for the economic hotspot of the extraction process, the equipment are grouped under three sections: “Pre-treatment and Milling”, which constitutes all pre-treatment and milling equipment (could be one, two or three-staged milling), “Protein Extraction and Recovery”, which constitutes all process units for extracting the protein, separation of phases, precipitation and recovery of proteins, and “Post-Extraction and Drying”, which focuses on the conditioning of the protein slurry, pasteurization and spray drying to produce protein isolates. This suggested categorization principle is based on the fact that the first section produces the flour, second section produces the protein curd, and the final section produces the final protein isolate product.

Since this framework is developed towards assessing the scalability of an extraction method to the commercial/industrial scale, further hotspot analysis is conducted where the framework explores the influence of different plant production capacities on the profitability indicators selected, to identify the peak(s), or decline(s) in performance for a range of annual production capacities.

### Environmental Impact Assessment

The environmental impact assessment follows the life cycle assessment guidelines described in the ISO 14044 which includes the goal and scope definition, functional unit specification, system boundary selection, life cycle inventory, impact assessment method, and data presentation and interpretation (ISO, 2006).

Scope, functional unit, system boundary, and geographical location

The scope of the LCA studies would be focused on identifying the critical points of environmental impact along the processing steps of a pulse protein extraction line. In terms of functional unit, 1 kg of protein isolate (or concentrate) would be used. For the purpose of this framework, it is also suggested that the system boundary be specified as gate-to-gate excluding the production phases of the pulses and the end-use phase of protein isolates, to perform a focused hotspot analysis on the processing technique. In addition, the geographical scope at which this assessment is conducted should be specified, to guide the selection of the appropriate life cycle inventories from the databases as well as the impact assessment method.

Impact Assessment

Life Cycle Impact Assessment methods are used to characterize the input and output elementary flows around a defined system boundary into impact categories using foreground data provided by the practitioner. To account for the environmental impacts, both midpoint and endpoint categories are measured. The impact assessment method used for this study is the Recipe 2016 Midpoint (H) and Endpoint (H) method. The allocation method used is the economic allocation method as shown to be the most appropriate method due to the wide difference in prices of the fibre, protein isolates, and starch slurry.

Environmental hotspot analysis

The environmental impact results are presented in terms of the relative contribution of all various process steps to each impact category. However, for easier hotspot analysis, the framework categorizes the fractionation processes into five sections, with some sections comprising multiple process steps while other sections are represented by a major process step. The sections namely “Pretreatment & Milling” (pretreatment, dehulling and milling step (s)), “Extraction & Decantation” (alkaline extraction and decantation steps), “Precipitation & Recovery” (isoelectric precipitation, protein curd separation, centrifugation) post-recovery (process steps that conditions the curd such as homogenization, neutralization, and solids adjustment), and “Pasteurisation” and “Spray Drying”.

Uncertainty and global sensitivity analysis

The goals of uncertainty analyses are numerous which include testing the robustness of a model, provides insights into changes in input due to variation of inputs and determine the key drivers of uncertainty using their probabilities (Strunge et al., 2023). The first stage of uncertainty analysis usually deals with the uncertainty characterization of the assumptions (input variables), also termed as specifying the probability distribution function best fit for specific parameter (Bhat and Kumar, 2008). This involves characterizing the probability distribution of a particular variable as uniform, normal, lognormal, triangular, etc. (McNulty et al., 2021). Based on the distribution function assumed, required values that fit a particular function such as mean, standard deviation for normal distribution, highest, least, and likeliest values for triangular distribution or geometric mean and deviation for lognormal distribution, are specified (Oke et al., 2022). However, for uncertainty analysis of the environmental impact forecast variables, it is suggested that a lognormal distribution be specified for all parameters (inventory flows) (Sala and Bieda, 2021).

### Eco-efficiency Assessment

As a core component of this framework, eco-efficiency assessment is employed to integratively quantify the value of a product or process system per environmental impact incurred. Economic profitability, production costs, revenue generation, product quality, product functionality social impact, socio-economic improvement amongst others are value-addition variables that could be considered in eco-efficiency assessment (Houssard et al., 2022; Simboli et al., 2014; Sproedt et al., 2015). The selection of a specific product system value highly depends on the sustainability perspectives considered by the stakeholder (ISO, 2012).

Where represents the economic value indicator, represents the economic-based eco-efficiency, represents the Midpoint Impact categories which include GWP, HCT, WC, etc.

Similarly for the product quality-based value indicator, for this framework, this could be the protein purity, techno-functional properties, nutritional composition, and/or physicochemical properties. This represents the amount of protein per 1 kg of protein isolate and also indicates the increase of the protein content from the flour to the isolate. This is expressed as the equation below.

where is the product quality-based eco-efficiency, represents the protein purity.

## Case Study: Alkaline extraction of pea proteins from yellow peas.

The novel framework was applied to conduct a first-time comprehensive eco-efficiency evaluation of pea protein extraction by the wet (alkaline) fractionation method. For the pilot scale extraction, four trials were performed with each trial using different Western Canada yellow pea varieties, thus, CDC Lewochko, CDC Spectrum, CDC Meadow, and AAC Profit, all sourced from Saskatoon, SK, Canada, in 2021 harvest year. Trials were conducted by the National Research Council Canada research group using pilot facilities at Cereals Canada (Winnipeg, MB, Canada) and the Manitoba Food Development Centre (FDC) (Portage, MB, Canada). The pilot scale extraction process constituted dehulling of seeds, two-stage milling to prepare flours, protein extraction, protein recovery, post-extraction processing, pasteurization and spray drying. Protein extraction process

Pre-treatment and milling

The pretreatment and milling process steps to produce pea flour was conducted at the Cereals Canada (Winnipeg, MB, Canada). The yellow pea seeds were first tempered for 3 hours to have 12% moisture, dehulled using a stone mill (Buhler Stone Mill MJSG), and the hulls were separated and collected with the help of an aspirator. Prior to milling into fine flour for extraction, the dehulled seeds were coarsely milled into grits for easier and more efficient milling. This process was carried out using a hammer mill (Jacobson Model 120-B) with a screen size of 3/64″ after which a fine milling was carried out using a roller mill (Bühler Laboratory Mill MLU 202, Bühler Company, Uzwil, Switzerland)**.** Mass balances were recorded throughout the process. The fine flour obtained was then sent into the protein extraction and recovery line.

Protein extraction and recovery

The protein extraction process conducted at the Manitoba Food Development Centre (FDC) (Portage, MB, Canada) included following steps: protein solubilization/extraction under alkali conditions, decanting, centrifuging to recover soluble proteins, clarification to remove fines, acid precipitation followed by centrifugation to recover protein curd. Approximately 25 kg of pea flour was dispersed into the water at a 1:10 (w/w) ratio of solid to liquid. The pH of the slurry was adjusted to 9.0 using 2M sodium hydroxide solution to solubilize the protein for 1h. The protein-rich liquid stream (light phase) was separated from the spent meal (heavy phase, insoluble starch, and fiber) using a decanter centrifuge (Model: SCE 205-01-32, Clarifier Decanter). The light phase obtained from the decanter centrifuge (Clarifier Decanter, Model: SCE 205-01-32) was passed through a disc stack centrifuge (Westfalia Separator, Model: SB7-02-076) to further clarify and remove any insoluble non-proteinaceous particles before the protein precipitation step. The centrate was precipitated at pH of 4.5 using 3M hydrochloric acid solution with continuous agitation for 0.5h. The precipitated protein slurry was passed through the disc stack centrifuge (Westfalia Separator, Model: SB7-02-076) to separate the protein curd. Samples were taken throughout the process from different fractions to record protein and moisture contents (mass balances). Moisture content was measured using a rapid moisture analyzer (Model IR-30, Denver Instrument) and protein content was measured using a LECO FP828 nitrogen analyzer (Nx6.25).

Post-extraction, drying and analysis.

This section includes homogenization of protein curd, solid content adjustment, neutralization, pasteurization, and spray drying at the Manitoba Food Development Centre (FDC) (Portage, MB, Canada). The resulting protein curd was homogenized (single pass) using a colloid mill (Rheinfeldon, Model: CH4310). The solids content of the homogenized protein curd was adjusted to 8-10%, neutralized to pH 7.0, pasteurized at 74±2°C for 30 seconds using lab pasteurizer (Micro Thermic UHT/HTST Lab 25, EHV Hybrid), and spray-dried (Dryer Model: Carlisle, CPS 600) using 190°C and 85°C inlet and outlet temperature respectively. The spray-dried protein powder was collected every 30 minutes from the product collection vessel. A composite sample of the spray-dried protein powder was taken for analysis.

### Techno-economic Assessment (TEA)

For the techno-economic Assessment, the pilot scale process was scaled up to 40,000 tonnes per annum processing capacity (of yellow peas). This value is based on the processing capacity of a pea protein plant in Alberta, Canada, currently in its construction phase (Guide, 2022). Using the pilot scale process data in terms of yield, residence time, material and energy consumption of the different units, the processes were scaled up with the sixth-tenth rule to estimate the proportional cost at the industrial scale capacity assumed (Peters et al., 2003). The plant is scheduled to operate for 8,000 hours per year with the remaining time allocated for downtime and maintenance. The project period is assumed to be 20 years, and the straight-line depreciation method was selected to estimate the depreciation value at a salvage value of 10% of fixed capital investment.

Total Operating Costs (OPEX)

The total annual operating costs are estimated as a sum of direct manufacturing costs and indirect production costs. The direct production costs include variable operating costs (raw materials, utilities), and fixed operating costs (maintenance, labour, cost of supervision, plant overheads, insurance, taxes, royalties). The indirect manufacturing costs, also known as the general expenses, include sales, research, development, and administrative expenses. Estimating these values, in terms of the percentage of the capital investment and direct production costs, are shown in the Supplementary document.

Profitability Analysis

To assess the profitability of the process plants, economic indicators such as Net Present Value (NPV), Return on Investment (ROI), Payback Period, Turn-Over Ratio (TOR) and Minimum Selling Price (MSP) that produces an NPV of 0. For the analysis MSP, ROI and were used as the main economic indicators. The MSP is evaluated to determine the least price that would make the investment profitable at the capital, operating and financial costs, as well as protein production rate (the yield) recorded. However, the ROI and NPV are also evaluated to determine the profitability levels of the process when protein isolate is sold at the normal market price (@ $5.00 per kg).

Scope and functional unit

The present LCA study is based on assessing the environmental impacts associated with the production of protein isolate from yellow peas by the wet fractionation method (ALK-IEP). The functional unit selected for the analysis is based on 1 kg of protein isolate. The geographical scope considered for the analysis is Saskatoon, Canada.

System boundary

The system boundary excludes the environmental impacts associated with the production of the pea seeds and the end use of the products rendering the assessment a gate-to-gate approach. This is to help critically understand the processing aspect for a better process-based hotspot analysis. Therefore, the system boundary includes dehulling, hammer milling, roller milling, alkaline extraction, decantation, polishing (clarification), isoelectric precipitation, centrifugation, homogenization, solids adjustment and neutralization, pasteurization and spray drying (**Figure 2**).

Diagram

Description automatically generated

**Figure 2: System boundary for Wet Fractionation Process**

Life Cycle Inventory

Life Cycle Inventory (LCI) is a very important step in LCA studies as it determines the accuracy, quality, comprehensiveness, and reliability of the results obtained. For this assessment, the foreground data is based on technical operation results obtained from a pilot scale wet fractionation process, including the electricity, steam, and water consumption and chemical (NaOH and HCL) activities selected are presented in Table 1. Background data that quantifies the emissions and resource usage that are used to estimate the characterized impacts were sourced from the Ecoinvent database v 3.9 The specific process

Table 1: Process Flows used for Impact Assessment

|  |  |
| --- | --- |
| Process Flow | Data source (from Ecoinvent) |
| Sodium Hydroxide    Hydrochloric Acid  Electricity  Steam  Process Water | Market for sodium hydroxide, without water, in 50% solution state | sodium hydroxide, without water, in 50% solution state | APOS, S  hydrochloric acid production, from the reaction of hydrogen with chlorine | hydrochloric acid, without water, in 30% solution state | APOS, S - CA  market for electricity, medium voltage | electricity, medium voltage | APOS, S - CA-SK  steam production, as energy carrier, in chemical industry | heat, from steam, in chemical industry | APOS, S – RoW  water production, deionised | water, deionised | APOS, S - RoW |

Impact assessment

The impact assessment followed the steps as outlined in the framework. The impact assessment was carried out in the open-source life cycle assessment software, Open-LCA V1.11.0. using was Recipe 2016 Midpoint (H) and Endpoint (H) as the LCIA methods. The characterized impacts (midpoint) are estimated for all 12 process steps (results are presented in the Supplementary Sheet). However, for easier hotspot analysis, the processes were categorised into five sections namely Dehulling & Milling, Extraction & Decantation (centrifugal decantation, clarification), Precipitation & Recovery (centrifugation) post-recovery (homogenization, solids adjustment and neutralization), and Pasteurisation and Spray Drying. The relative contributions of these sections to the impact categories (10) were illustrated for hotspot identification, as well as potential impacts recorded for all 16 impact categories were also presented.

Uncertainty and global sensitivity analysis

For this study, uncertainty analysis and GSA were performed for both economic and environmental impact indicators. For the economic performance, the NPV and ROI were used as the forecast variables (output variables). The choice of probability distributions for the variables is of prime importance for uncertainty analysis and GSA. For this study, parameters relating to the process performance such as protein yield, were selected based on the standard error obtained from the four fractionation extraction trials. Table 2 presents the probability distribution function specified for the different parameters that were selected for the uncertainty analysis with their associated distribution functions and values (mean, base case, uncertainty, etc.). The equipment cost, utility costs, labour costs, and cost of yellow peas, are the same for all trials (same process configuration), therefore does not depend on the experiment. For these parameters, their uncertainties are based on market and costing dynamics, with references presented in Table 2. However, for the yield, since each trial with a different variety produced varying results, there exists an uncertainty based on the pilot scale experiment.

To perform using Monte Carlo Simulation (MCS) with 10,000 trials was carried out using in Oracle Crystal Ball software with Microsoft Excel 2016) to quantify the uncertainty propagation and distribution of the indicators. For each indicator, the 90% certainty range is identified. The GSA was performed alongside as the simulation results also outputs the proportional contribution to the variance of the indicators by the assumptions (Igos et al., 2018).

Table 2: The probability distributions specified for the economic parameter assumption to quantify the uncertainty in NPV and ROI

|  |  |  |
| --- | --- | --- |
| Assumption | Distribution | References |
| Equipment costsa | Normal (base caseb ± 15% relative uncertainty) | (FasterCapital, 2024) |
| Utility costsa | Lognormal (base caseb± 15% relative uncertainty) | (FasterCapital, 2024) |
| Cost of yellow peas | Triangular (±5% base case [$0.47/kg]) | (Fairchild et al., 2016) |
| Labour cost | Lognormal ((±5% base case [$18.25/operator]) | (Canada, 2024) |
| Yield | Normal (mean: TBDb; standard deviation: TBDb) | Present study |
| Tax rate | Triangular (±10% base case [25%]) | (Charles Lammam, 2018) |
| Interest rate | Triangular (±10% base case [10%]) | (Charles Lammam, 2018) |

aBase case equipment costs and utility costs are taken from the results obtained from the previous deterministic cost evaluation performed for hotspot analysis.

b- Value would be determined based on the yield obtained from the four trial experimental studies

With regards to environmental forecasting, uncertainty in LCI arises from both foreground and background data. In LCA a high level of uncertainty stems from how representative a chosen LCI source is, compared to the scope of the study. To this end, uncertainty values for the background data are determined from the Pedigree matrix (Fernandez-Rios et al., 2024). Since the uncertainty analysis was performed outside OpenLCA, the geometric mean and standard deviation of the characterization factors were sourced from the total estimated uncertainty values ascribed to the process provider after selecting the data completeness levels (temporal, geographical and technological) in the Pedigree Matrix. This step is known as the Data Quality Indexing (DQI), a very critical step in LCA uncertainty analysis (Igos et al., 2018). Regarding the foreground data, similarly, lognormal distribution was assumed for all parameters (process flows). For instance, the uncertainty of electrical and steam energy consumption has been identified to follow a lognormal distribution (Wang et al., 2012)

### Eco-efficiency Assessment

Eco-efficiency assessment is employed to integratively quantify the increase in the value of a product or process system per environmental impact incurred The selection of a specific product system value highly depends on the sustainability perspectives considered by the stakeholder (ISO, 2012) .

Where represents the economic value indicators which are the Net Profit and NPV, represents the economic-based eco-efficiency, represents the Midpoint Impact categories. For this study, the selected environmental indicators are Global Warming Potential (GWP), Terrestrial Ecotoxicity (TE), and Fossil Resource Scarcity (FRS).

For the product quality-based value indicator, the protein purity was selected which represents the amount of protein per 1 kg of protein isolate and indicates the increase of the protein content from the flour to the isolate.

# Results and discussion

## Process Performance Analysis

### Protein yield and purity (product-quality value)

The technical performance indicators of the extraction process are presented in Table 3 showing the protein yield, protein purity (functional value) and protein recovery. The dehulling yield which represents the percentage of cotyledon produced form the process and the milling yield (yield of flour) were recorded as 72.2±1.3% and 98.0±0.1%, respectively. The total protein yield which quantifies the percentage of the total flour that forms the final product (protein isolate), was recorded as 15.66±0.75% (Table 3). Protein purity levels, described as the total amount of protein present in the protein isolate was reported as 83.73 ± 0.86% also occurring the acceptable range of purity levels by the AE-IEP method (Annoh-Quarshie, 2018). The protein recovery describing the percentage of protein in the starting flour which ends up in the protein isolate (final product), was also estimated as 41.23 ±1.48% indicating that more than 50% protein was lost along the extraction line. This was expected since this work was conducted at a pilot scale and higher losses during each unit operation such as decantation, clarification, homogenization, and pasteurization can be expected compared to most of the lab-scale studies reported in the literature. Nonetheless, for this study, a stagewise tracking of protein losses along the extraction line to identify the hotspots for protein material loss is comprehensively reported and discussed in the next section.

Table 3: Process performance analysis in terms of yield purity and recovery based on four trials

|  |  |
| --- | --- |
| Performance indicator | Value |
| Dehulling yield | 72.2 ± 1.32% |
| Milling yield | 98.0± 0.01% |
| Protein yield | 15.66 ± 0.75% |
| Protein purity (dry basis) | 83.73 ± 0.86% |
| Protein recovery | 41.23 ±1.48% |

### Protein recovery hotspot analysis

Figure 3 presents a Sankey Diagram that describes the tracking protein material from the starting slurry along the extraction process line to the final protein recovery (percentage of flour protein in isolate, final product). From the figure, not all the individual process steps were captured since this analysis focused only on the process steps where separation (into two phases, or streams) occurred.

It could be observed that the extraction-decantation step recorded the highest protein loss as 80.8±2.8% of the proteins in the flour, ended up in the supernatant phase (solubilized proteins), subject to further losses along the fractionation line, making that section a hotspot for protein recovery maximization. The remaining 19.2±2.7% ended up in the heavy phase (starch-fiber slurry) after the decantation. Although the extraction step might not yield 100% protein solubilization, the decanting, and clarifying steps could also contribute to the loss of protein material based on the operating configuration and conditions used in this study.(Schmidt et al., 2022). Further investigation is needed to optimize the combined extraction-decantation-clarification step through a multi-stage optimization to achieve a high protein recovery at the pilot scale (optimization using both extraction and decantation/clarification processing conditions). Optimizing protein recovery during commercial-scale processes is usually done by adjusting equipment and processing parameters.

Since this is a hotpot for protein loss, an experimental-based comparative techno-eco-environmental analysis could be performed to assess the sustainability implications of integrating a starch purification line also aimed at further extracting the proteins from the starch slurry to increase overall protein recovery, with the associated economic and environmental impact trade-offs. The precipitate separation represents the centrifugation after the isoelectric precipitation step to produce the protein curd. At this stage, there was about 8.2±1.7% protein loss recorded. This protein loss could be attributed to the loss of albumins which are mostly still soluble across a wide pH range including the isoelectric point (pH 4-5), as compared to the globulins (Möller et al., 2022; Philips and Williams, 2011). Also, some of the loss is attributed to the centrifugation stage during the light phase and protein curd separation where some precipitated proteins could be removed with the light phase if disc stack centrifugation conditions are not optimized. Despite this, from a processing perspective, results from this study suggest that there is a higher protein loss in the solubilizing-decantation-clarification (extracting) stage than the precipitation-centrifugation (recovering) stage. This can be however different from standard commercial processing recovery results.

A diagram of a precipitate separation

Description automatically generated

**Figure 3: Protein content loss tracking from the flour (in the alkaline slurry) through to the final drying to obtain the protein isolates, also referred to as the protein recovery hotspot analysis.**

The losses at the post-recovery section which includes homogenizing, solids adjustment, neutralization, and pasteurization, were also accounted for, recording a loss level of 10.2±0.3%. These losses were highly attributed to the forming of some curd layers on the inner walls of the colloid mill and foam formation during homogenization prior to pasteurization. The unpasteurized foam and some curd left in the tank contained some proteins and this could be attributed to possible losses. Although not classically accounted for in typical lab-scale protein extraction studies, these process steps are crucial and therefore studies could be carried out to focus on, identify, and mitigate the causes of protein loss at these intermediate stages during pilot scale and commercial scale protein production. The spray drying stage also recorded a significant loss of proteins of 14.1±1.9%. Losses at the spray drying stage were quantified from the protein content in the dryer wall sweeps and the residual powder from the bag house. This is indicative of the spray drying stage also posed a significant influence on the yield of the final protein isolate product and protein recovery, thus optimization towards increasing the overall recovery of pea proteins should be targeted at identifying the optimum operating conditions for the spray drying process. Finally, the percentage of protein recovered from the flour and retained in the final product was 42.1±1.5%, revealing a protein loss of more than half (57.9±1.5%, %) of the initial protein along the processing line during this pilot scale work.

## Baseline economic and environmental impacts analysis

### Economic impacts

To perform a techno-economic assessment of a production process, the first step is to estimate the capital and operating costs. Equipment costs for all 12-unit operations are detailed in Table S4 in the Supplementary Sheet. The equipment were categorized under three sections as seen in **Fig. 4A**. The process steps in each section have been highlighted in the figure caption. From the figure, the post-extraction and drying section recorded the highest percentage of 46.6%. The spray dryer contributed highest which formed about 42% of the total equipment costs. The second highest equipment costs was recorded by the protein extraction and recovery section (29.1%). The pre-treatment and milling section recorded the least percentage of 24.3%. With regards to the production costs, which constitute raw materials, labour, utilities, financial costs other manufacturing expenses, is presented in **Fig 4B** with the respective distributions. From the figure, raw materials recorded the highest percentage of 45.1%. Although price of peas are low (0.3-0.5$/kg), the total costs of the material (40,000,000 tonnes) considered for this evaluation surpass the additional costs related to utility, labour and others, as evidenced in a techno-economic assessment of pea protein extraction by the alkaline extraction method (Annoh-Quarshie, 2018). This is followed by general or secondary manufacturing expenses (sales, administrative and research expenses) contributing to 21.8%. Labour costs and financial costs (insurance, interests, taxes) constituted 12.4 and 10.8%, respectively. Typically for pea protein extraction plants, feedstock cost is usually the highest contributor to the production costs (Annoh-Quarshie, 2018), with utilities recording the least contribution (9.9% in this case). It is however worth noting that, these economic costs may vary at different industrial scale applications.

Profitability analysis is required to assess the economic viability of the wet fractionation plant at the industrial scale. As shown in Table 4, the profitability indicators recorded 68.29 M$ for Net Present Value (NPV), 9.63 M$ for Net Annual Profit, 2.1 $/kg for Profit per kg isolate, 33.1% for Return on Investment (ROI), 3 years for payback time and 3.35 for Profitability Index.

Also, from **Fig. 4 C&D**, the annual profit (at a fixed selling price) and minimum selling price (**Fig. 4D**) were used to assess the profitability, respectively. Overall, the profitability of a processing plant is also dependent on processing capacity. While the annual profit depicts the viability of the processing plant, it is limited at ascertaining the continual profitability of the plant in the long term. The MSP, however, remains the “best” economic indicator as it cumulatively considers the project period, depreciation value, and discounted cash flow. Results are also reflected in Fig. 2D, thus the MSP at different processing capacities. However, for the MSP, it decreases steeply between 20kt to 80 kt plant capacities and remains steady thereafter. These results reveal that, for this processing pathway, at higher processing capacities, the proportional increase in the production rate of the protein isolates, starch slurry, and hulls as the feedstock increases, can largely offset the associated increase in equipment and operating costs for a better economic performance, leveraging on the economies of scale.

Table 4: Summary of economic performance indicators (monetary values) for the wet fractionation process

|  |  |
| --- | --- |
| Economic Indicator | Value |
| Net Present Value (@ $5.00 selling price) | 68.29 M$ |
| Total Annualised Production costs | 50.13 M$ |
| Net Annual Profit | 9.63 M$ |
| Net profit per kg of protein isolate | 2.01 $/kg isolate |
| Return on Investment | 33.1 % |
| Payback time | 3 years |
| Profitability index | 3.35 |

A pie chart with numbers and text

Description automatically generated A pie chart with numbers and text

Description automatically generated

**A B**

A graph of growth of plants

Description automatically generated with medium confidence A graph with numbers and dots

Description automatically generated

**C D**

**Figure 4: Summary of Techno-economic Performance. Cost Analysis: A) Equipment Costs B) Production Costs,**

**Profitability Analysis: C) Annual Net Profit D) Minimum Selling Price at different plant capacities. Purple data points represents the baseline capacity**

**Sections are categorised as the following- Pre-treatmenet and milling: Dehulling, Hammer milling, Roller milling; Protein Extraction and Recovery: Alkaline extraction, Decanatation, Isoelectric precipitation, Centrifugation and Clarification; Post-treatmenmt and Drying: Homogenization, Solids Adjustment and Neutralization, Pasteurization and Spray Drying0**

### Environmental impact hotspot analysis

This section discusses the environmental impact of the baseline process. contribution of the process steps to the different impact categories. For easier hotspot analysis, thus identifying sections in the fractionation processing line that contribute most to the environmental impacts, the 12 process steps were categorized under 5 process sections **(Figure 5)**.

From Figure 5, the spray drying and pasteurization section recorded the largest contribution in most of the impact categories, thus 44.9%, 49.9%, 37.7%, 34.3%, and 32% for GWP, FRS, TA, OFH, and FPM. This is primarily attributed to the high consumption of energy for steam production and electricity for heating and drying the protein slurry into powder. The WC recorded its highest proportion (52%) from the extraction and decantation steps due to the high consumption of water (1:10 ratio). Although water was ejected from the system at the decanting step, since this water is treated as wastewater which moves from the system boundary as untreated, it does not positively contribute to the WC potential of the process. Therefore integrating a waste treatment section in the typical processing plant can lower the WC, however, the cost and environmental impacts associated with this additional treatment line. The extraction step also contributed significantly to the LU (28.8%), OFH (24.7%), and FPM (28.6%), which primarily stems from the use of sodium hydroxide in the extraction step. The dehulling and milling section also contributed significantly to the environmental impact owing to the two-stage milling (hammer and roller milling) carried out, requiring more electricity. The section that contributed least to the overall impacts (less than 10%) was the post-treatment, comprising the neutralization, solid adjustment, and homogenization.

A graph of multiple colored bars

Description automatically generated**Figure 5: Midpoint Environmental impacts (relative contributions) based on the different processing sections.**

From these findings, it could be deduced that the spray drying step and pasteurization are the major hotspots of environmental impacts hence as well as the presence of chemicals used, thus alkaline and acid for extraction and precipitation, respectively, also contribute significantly to the environmental impacts relating to toxicity potentials. These factors can inform the configuration/modifications towards optimizing the alkaline extraction process targeted at significantly reducing the environmental impacts. The total values recorded for 10 midpoint impact categories and 3 endpoint categories are presented in **Table 5.** All other impact categories are presented in the Supplementary Material (Table S8).

Table 5: Total environmental impact of the wet extraction process, per kg of protein isolate for 10 midpoint impact categories and 3 endpoint categories.

|  |  |  |  |
| --- | --- | --- | --- |
| Impact category | Abbreviation | Reference unit | Value |
| *Midpoint impacts categories* | | | |
| Fossil resource scarcity | FRS | kg oil eq | 1.75E+00 |
| Fine particulate matter formation | FPM | kg PM2.5 eq | 7.11E-03 |
| Global warming | GW | kg CO2 eq | 6.15E+00 |
| Human carcinogenic toxicity | HCT | kg 1,4-DCB | 5.97E+00 |
| Land use | LU | m2a crop eq | 7.55E-02 |
| Ozone formation, Human health | OFH | kg NOx eq | 1.01E-02 |
| Stratospheric ozone depletion | SOD | kg CFC11 eq | 3.30E-06 |
| Terrestrial acidification | TA | kg SO2 eq | 1.33E-01 |
| Terrestrial ecotoxicity | TE | kg 1,4-DCB | 8.12E-0 |
| Water consumption | WC | m3 | 1.33E-01 |
| *Endpoint impact categories* | | | |
| Damage to Human Health | HH | DALYs | 1.31E-05 |
| Damage to Ecosystem Quality | ED | species.year | 2.87E-08 |
| Damage to Resource Availability | RA | USD 2013 | 4.00E-01 |

## Uncertainty and global sensitivity analysis

In this section, we estimate the stochastic tendency of selected economic and environmental indicators subject to their underlying uncertainty as well as explore the overall variance contribution degree of the different techno-eco-environmental parameters to these indicators using global sensitivity analysis.

### Techno-eco-environmental uncertainty

The profitability certainty is the risk marker (as anchored on the distribution graphs) that assures an industrial stakeholder of the economic performance at a specified probability highlighted in **Figure 6,** at an estimated confidence interval of 90%, for Annual Profit, NPV, and ROI. For the Annual Net Profit, the value fell between 5.72 M$ (lower bound) and 12.05 M$ (upper bound) with a mean profit of 8.88 M$ (base case: 9.63 M$), as presented in Table 6. between 26.74 MM$ (lower bound) and 94.4 M$ (upper bound) centered around a mean of 60.91 M$ (base case: 68.3 M$). Similarly, for the ROI. The base case estimates are the results obtained from the deterministic models without considering their stochastic tendencies.

The MCS also provided the associated statistics parameters including the standard deviation, coefficient of variation, skewness, and kurtosis as presented in Table 6. From the Table, we can perform a first-hand financial risk analysis. The certainty of an NPV greater than the mean was recorded as 50.34% which implies that the probability of attaining an NPV higher than the mean is above average (50%). This is also known as the risk marker that ascertains the financial performance of the process at the industrial scale (Perez-Lopez et al., 2018). However, for the Annual Profit and ROI, this value is a little below the average, thus 49.70% and 46.91%, respectively. This is also explained by the values for the skewness and kurtosis recorded for the Annual Net Profit and ROI as positive skewness indicating a higher weight distribution below the mean (shorter left tail), with smaller percentage of values falling below hence the lower probability of obtaining an ROI higher than the mean and also the base case (38.06%). With respect to the goodness of fit (Fig.6), the Beta frequency distribution was best fit for the Annual Net profit and NPV with associated chi-square value of 141.286 and the highest Anderson-Darling (A-D) value of 0.2364 for Annual Profit and NPV, while the Lognormal Distribution was the best fit for ROI with A-D value of 0.4803. This information can be used to approximate the uncertainty model when making financial decisions in a typical pea protein fractionation plant that would depend on the NPV or ROI.

### GSA for economic indicators

Towards addressing the individual contribution of the different parameters to the process output (economic performance) variance, a quantitative GSA based on the rank correlation indices was adopted to ascertain the most influential techno-economic variables (Iooss and Lemaître, 2015). Among the input variable assumptions, it was observed that isolate selling price was the major contributing variable to the annual net profit (38.6%) while the equipment cost had the highest contribution to the variance economic for both NPV (-40.6%) and ROI (-60.3%), indicating the significant effect of these variables on the profitability. The high contribution could mainly be attributed to the fact that from the techno-economic model, the equipment cost is used to estimate most of the costs including the direct costs and fixed capital investment as well as some operating costs including maintenance, financing, etc., which are all used in determining the overall economic indicator performance. Other contributing variables include the cost of yellow peas, interest rate, tax rate, and cost of utilities.

Table 6: Statistical Outputs of the Monte Carlo Simulation (Economic & Environmental indicators)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Statistical parameters | Economic and Environmental Indicators | | | | |
| Economic | **Annual Profit** | | **NPV** | **ROI** | |
| Mean | 8.89M$(9.63)c | | 60.91M$ (68.2)c | 31.29% (33.1%)c | |
| Pvalue>meana | 49.7% | | 50.34 % | 46.91% | |
| Pvalue>base caseb | 39.1% | | 35.81% | 38.00% | |
| Standard deviation | 1.91 M$ | | 20.76 M$ | 8.93% | |
| Co-efficient of Variation | 0.2149 | | 0.3356 | 0.2858 | |
| Skewness | 0.0012 | | 0.0077 | 0.4527 | |
| Kurtosis | 2.85 | | 2.92 | 3.31 | |
| Goodness of fit | Beta (141.286)d | | Beta (0.2364)e | Lognormal (0.4803)e | |
| Environmental | **GWP** | | **TE** | **FRS** | |
| Mean | 5.83E+00 (6.15E+00)c | 5.98E-04 (8.12E-04)c | | 1.64E-00(1.75E-00)c |
| Pvalue<meana | 49.7% | 48.3% | | 49.97% |
| Pvalue<base caseb | 52.11% | 53.50% | | 53.27% |
| Standard deviation | 0.49 | 0.47 | | 0.14 |
| Co-efficient of Variation | 0.0833 | 0.0780 | | 0.0839 |
| Skewness | 0.2867 | 0.234 | | 0.3074 |
| Kurtosis | 3.12 | 3.10 | | 3.14 |
| Goodness of fit | Gamma (0.4986)e | Lognormal (0.4397)e | | Gamma (0.5815)e |

a Probability of obtaining an NPV or ROI that is greater (or less) than the mean of the distribution.

b Probability of obtaining an NPV or ROI that is greater (or less) than the base case (the deterministic value)

c Value for base case

d Ranking by chi-square

e Ranking by A-D (Anderson-Darling) value that describes goodness of fit for distribution

NPV: Net Present Value, ROI: Return on Investment, GWP: Global Warming Potential (kgCO2 eq) TE: Terrestrial Ecotoxicity (kg 1,4 DCB), FRS: kg oil eq

BNV FG MFBJ,

A screenshot of a graph

Description automatically generated A screenshot of a graph

Description automatically generated

**A B**

A screenshot of a graph

Description automatically generated A screenshot of a graph

Description automatically generated

**C D**

A screenshot of a graph

Description automatically generated A screenshot of a graph

Description automatically generated

**E F**

**Figure 6: Uncertainty quantification of the economic indicators (at 90% confidence interval) and their global sensitivity analysis showing the relative contribution to the variance. A&B: Annual Profit, C&D: Return on Investment, E&F: Net Present Value**

### Environmental uncertainty & GSA

Similar to the economic uncertainty, we can also perform a first-hand environmental risk analysis, using statistical outputs of the MCS for the environmental indicators Table 6. From the MCS, the means recorded for the selected environmental indicators were 5.82 kg CO2, 1.64 kg oil eq and 5.98 kg 1,4-DCB for GWP, FRS, and TE, respectively. For the environmental impact, since lower values are desired, the probability for obtaining an impact level below the mean or base case is presented as shown in Table 6. Probability levels for which a value is lower than the mean of 49.6%, 48.3%, and 49.97% for GWP, TE, and FRS, respectively. Although these values are below average (50%), they are very close to 50% which highlights a stochastically positive or safe performance of the environmental performance of the extraction process. Finally, the best-fitted distributions for the environmental indicators were the Gamma distribution for GWP and FRS, with TE fitting best with a Lognormal distribution. For stakeholders who are interested in identifying the leading contributors to a specific environmental impact relevant to the geographical or study scope, these results provide a basis for understanding not only the hotspots but the proportional contribution of the input variables to the environmental performance indicator considering their uncertainty characteristics*.*

A screenshot of a graph

Description automatically generated A graph of a heat wave

Description automatically generated with medium confidence

**A B**

A graph of a graph showing a graph of a function

Description automatically generated with medium confidence A graph of a graph

Description automatically generated with medium confidence

**C D**

A graph of a graph showing a number of numbers

Description automatically generated with medium confidence A screenshot of a graph

Description automatically generated

**E F**

**Figure 7: Uncertainty quantification of the midpoint environmental impacts (at 90% confidence interval) and their global sensitivity analysis showing the relative contribution to the variance. A&B: Global Warming Potential, C&D: Fossil Resource Scarcity, E&F: Terrestrial Ecotoxicity**

## Ecoefficiency performance

It has become imperative to integrate economic and environmental impacts of a process system in order to assess the environmental consequences incurred while improving upon the value of the product system, in terms of profitability, lower costs, product quality, functionality, etc. Hence in this section, the principle of eco-efficiency (EE) is adopted to understand the techno-eco-environmental performance of the wet fractionation system using different system value (economic/product quality) and environmental performance measures to estimate EE indicators where two monetary-based and one functional value (product-quality based) EE indicators were used to evaluate the eco-efficiency performance of the system with three environmental midpoint impact indicators including GWP, FRS and TE. The alkaline fractionation process recorded 0.327$/kg CO2 eq., 11.1 M$/ kg CO2 eq., and 0.135 kg protein/kg CO2 eq. for the net profit per kg isolate, NPV, and protein purity using GWP as the midpoint impact indicator. For FRS, the process recorded 1.15 $/kg oil eq., 39.0 M$/kg oil eq., and 0.473 kg protein/kg oil eq., also for net profit per kg isolate, NPV, and protein purity value indicators, respectively. EE indicators relating to the TE impact category are also presented accordingly. Although the NPV is the most suitable indicator to measure the economic viability of a product system, the unit-based economic indicators such as the Net Profit per kg isolate ($/kg of isolate*)* and the protein purity (kg protein/kg isolate) do have the same reference (denominator) as the environmental impact, kgCO2/*kg of isolate*, and therefore make these indicators easily relatable, comparable (in terms of other different process scenarios) and easily scalable.

In addition, EE indicators based on the Endpoint impacts are presented in Table 9, in terms of the economic and product quality value indicators expressed in terms of DALY, species.year, and USD 2013.

Table 8: Eco-efficiency indicators matrix for economic *and product quality based on three* environmental *(midpoint)* indicators

|  |  |  |  |
| --- | --- | --- | --- |
| Economic and Product  Value Indicators | Environmental Indicators | | |
| GWP | FRS | TE |
| Net profit per kg of isolate | **0.327 $/kg CO2 eq.** | 1.15 $/kg oil eq. | 0.248 $/kg 1,4 DCB |
| Net Present Value | 11.1 M$/ kg CO2 eq. | 39.0 M$/ kg oil eq. | 8.41 M$/kg 1,4 DCB |
| Protein purity (kg protein) | **0.135 kg/kg CO2 eq**. | 0.473 kg/kg oil eq. | 0.102 kg/kg 1,4 DCB |

Table 9: Eco-efficiency indicators matrix for economic and product quality based on environmental (endpoint) indicators.

|  |  |  |  |
| --- | --- | --- | --- |
| Product system value | Human Health | Ecosystem Quality | Resource Scarcity |
| Net profit per kg of isolate | 1.95E+05  $/DALY | 6.99E+07  $/species. year | 5.025  $/USD 2013 |
| Net Present Value | 6.63E+06,  M$/DALY | 2.38E+09  M$/species.year | 170.7  M$/USD 2013 |
| Protein purity (kg protein) | 8.03E+04  kg protein/DALY | 2.88E+07  kg protein/species.year | 2.07  kg protein/USD 2013 |

As seen in the table each indicator is expressed in a different unit which has been derived from the economic and environmental parameters used to estimate the EE indicator. It is also salient to note that, the results in Tables 8 and 9 are not comparable with one another since each data is evaluated in different measurement units. Notwithstanding, these results establish the first eco-efficiency assessment in pea protein extraction and therefore future studies can leverage the data for informative and comparative purposes where the eco-efficiency of different (or modified) wet extraction processes could be computed and compared both absolutely (difference) or relatively (ratio) to assess the eco-efficiency improvement.

# Conclusion

This study presents the development of an innovative, comprehensive eco-efficiency assessment framework designed to facilitate a holistic techno-eco-environmental analysis of plant-protein extraction pathways, with a particular focus on their potential for industrial commercialization. Beyond merely assessing eco-efficiency, the framework offers an in-depth hotspot analysis that examines both product system values and environmental impacts (midpoint impacts), incorporating uncertainty and global sensitivity analyses to identify key production variables that exert the greatest influence on economic and environmental outcomes. Additionally, a protein loss tracking methodology is introduced, enabling the identification of critical points during the extraction process where protein losses occur. The framework categorizes the different unit operations under into three sections: extraction section, recovery section, and post-recovery & drying.

To demonstrate the applicability of the framework, a case study on pea protein extraction using the alkaline extraction method was conducted, with an emphasis on different yellow pea varieties. The findings revealed that the spray drying stage was the primary contributor to eco-efficiency challenges. Global sensitivity analysis further highlighted that economic performance is most sensitive to variables such as the selling price of the isolate and equipment costs, whereas environmental impacts are primarily influenced by flows of electricity, steam, and sodium hydroxide. The protein content tracking analysis pinpointed the extraction-decantation and spray drying stages as key "hotspots" or nodes for protein loss in this study. This can be different for each pilot scale or commercial scale protein extraction process depending on the equipment and process conditions used. However, in-depth hotspot analysis framework developed using pilot scale data in this study can be easily adapted and applied to other pilot scale and commercial processes. Eco-efficiency metrics, incorporating both monetary value (annual profits and net present value) and functional value (product quality, measured by protein purity), were also estimated in this study and can serve as a baseline for comparing future performance improvements in pea protein extraction.

The insights derived from the technical, economic, and environmental hotspot and sensitivity analyses are expected to inform industrial stakeholders and guide efforts to optimize process steps and identify the most influential factors affecting the overall eco-efficiency of pea protein extraction. Furthermore, the study contributes to a broader understanding of how uncertainty propagation may affect sustainability assessments in the pea protein processing sector. Since techno-functionality is a core product quality indicator for protein concentrates and isolates, prospective studies can incorporate the different techno-functional properties to assess the overall eco-efficiency. Ultimately, the findings of this research are intended to stimulate further exploration into the optimization of techno-eco-efficiency within the pea protein extraction industry, geared towards enhancing its commercial viability and scaling up production processes in a sustainable manner.

# Acknowledgement

The funding for this research was provided by the Sustainable Protein Production Program of the National Research Council Canada (SPP 119 - DAF# 58544).

**References**

Adeyi, A.J., Adeyi, O., Oke, E.O., Okonkwo, C.E., Ogunsola, A.D., 2021. Effective moisture diffusivity of Sierrathrissaleonensis cracker: optimization, sensitivity and uncertainty analyses. Scientific African 12.

Allotey, D.K., Kwofie, E.M., Adewale, P., Lam, E., Ngadi, M., 2023. Life cycle sustainability assessment outlook of plant-based protein processing and product formulations. Sustainable Production and Consumption 36, 108-125.

Annoh-Quarshie, J., 2018. Development and comparison of processes for the extraction of dietary protein from yellow peas, Chemical Engineering. Stellenbosch University, Stellenbosch.

Assatory, A., Vitelli, M., Rajabzadeh, A.R., Legge, R.L., 2019. Dry fractionation methods for plant protein, starch and fiber enrichment: A review. Trends in Food Science & Technology 86, 340-351.

Balandrán-Quintana, R.R., Mendoza-Wilson, A.M., Ramos-Clamont Montfort, G., Huerta-Ocampo, J.Á., 2019. Plant-Based Proteins, Proteins: Sustainable Source, Processing and Applications. pp. 97-130.

Benoit, S., Margni, M., Bouchard, C., Pouliot, Y., 2019. A workable tool for assessing eco-efficiency in dairy processing using process simulation. Journal of Cleaner Production 236.

Bhat, A., Kumar, A., 2008. Application of the Crystal Ball® software for uncertainty and sensitivity analyses for predicted concentration and risk levels. Environmental Progress 27(3), 289-294.

Canada, S., 2024. Production Labourer - Food Processing in Canada, in: Information, L.M. (Ed.).

Charles Lammam, H.M., Milagros Palacios, 2018. Measuring the Distribution of Taxes in Canada: Do the Rich Pay Their “Fair Share”?, Towards a Better Understanding of Income Inequality in Canada. Fraser Institute, pp. 187-197.

Corona, A., Ambye-Jensen, M., Vega, G.C., Hauschild, M.Z., Birkved, M., 2018. Techno-environmental assessment of the green biorefinery concept: Combining process simulation and life cycle assessment at an early design stage. Sci Total Environ 635, 100-111.

Fairchild, K.W., Misra, L., Shi, Y., 2016. Using Triangular Distribution for Business and Finance Simulations in Excel. Journal of Financial Education 42(3-4), 313-336.

FasterCapital, 2024. How To Choose The Right Probability Distribution For Your Cost Data. <https://fastercapital.com/topics/how-to-choose-the-right-probability-distribution-for-your-cost-data.html/1>.

Ferdous, J., Bensebaa, F., Pelletier, N., 2023. Integration of LCA, TEA, Process Simulation and Optimization: A systematic review of current practices and scope to propose a framework for pulse processing pathways. Journal of Cleaner Production 402.

Fernandez-Rios, A., Laso, J., Aldaco, R., Margallo, M., 2024. Life cycle assessment and energy return of investment of nutritionally-enhanced snacks supplemented with Spanish quinoa. Sci Total Environ 954, 176542.

Fernando, S., 2022. Pulse protein ingredient modification. J Sci Food Agric 102(3), 892-897.

Gaffey, J., Matinez, A.A., Andrade, T.A., Ambye-Jensen, M., Bishop, G., Collins, M.N., Styles, D., 2024. Assessing the environmental footprint of alternative green biorefinery protein extraction techniques from grasses and legumes. Sci Total Environ 949, 175035.

Ghani, H.U., Mahmood, A., Finkbeiner, M., Kaltschmitt, M., Gheewala, S.H., 2023. Evaluating the absolute eco-efficiency of food products: A case study of rice in Pakistan. Environmental Impact Assessment Review 101.

Grassauer, F., Herndl, M., Nemecek, T., Fritz, C., Guggenberger, T., Steinwidder, A., Zollitsch, W., 2022. Assessing and improving eco-efficiency of multifunctional dairy farming: The need to address farms' diversity. Journal of Cleaner Production 338.

Groen, E.A., Bokkers, E.A.M., Heijungs, R., de Boer, I.J.M., 2016. Methods for global sensitivity analysis in life cycle assessment. The International Journal of Life Cycle Assessment 22(7), 1125-1137.

Groen, E.A., Heijungs, R., 2017. Ignoring correlation in uncertainty and sensitivity analysis in life cycle assessment: what is the risk? Environmental Impact Assessment Review 62, 98-109.

Guide, S., 2022. Pea Processing Facility to be Built in Strathmore. <https://www.seed.ab.ca/pea-processing-facility-to-be-built-in-strathmore/>.

Gumus, S., Egilmez, G., Kucukvar, M., Shin Park, Y., 2017. Integrating expert weighting and multi-criteria decision making into eco-efficiency analysis: the case of US manufacturing. Journal of the Operational Research Society 67(4), 616-628.

Hansen, L., 2020. The Optimization and Scale-Up of Pea Protein Extractions and Impact on Structural and Functional Properties. University of Minnesota, United States -- Minnesota, p. 170.

Hartini, S., Azzahra, F., Purwaningsih, R., Ramadan, B.S., Sari, D.P., 2023. Framework for Increasing Eco-efficiency in the Tofu Production Process: Circular Economy Approach. Production Engineering Archives 29(4), 452-460.

Heijungs, R., 2010. Sensitivity coefficients for matrix-based LCA. The International Journal of Life Cycle Assessment 15(5), 511-520.

Houssard, C., Revéret, J.-P., Maxime, D., Pouliot, Y., Margni, M., 2022. Measuring shared value creation with eco-efficiency: Development of a multidimensional value framework for the dairy industry. Journal of Cleaner Production 374.

Huang, Y., Zhen, Y., Liu, L., Ning, X., Wang, C., Li, K., Zhao, L., Lu, Q., 2023. Comprehensive competitiveness assessment of four typical municipal sludge treatment routes in China based on environmental and techno-economic analysis. Sci Total Environ 895, 165123.

Igos, E., Benetto, E., Meyer, R., Baustert, P., Othoniel, B., 2018. How to treat uncertainties in life cycle assessment studies? The International Journal of Life Cycle Assessment 24(4), 794-807.

Iooss, B., Lemaître, P., 2015. A Review on Global Sensitivity Analysis Methods, in: Dellino, G., Meloni, C. (Eds.), Uncertainty Management in Simulation-Optimization of Complex Systems: Algorithms and Applications. Springer US, Boston, MA, pp. 101-122.

ISO, 2006. Environmental Management—Life Cycle Assessment—Requirements and Guidelines. Geneve.

ISO, 2012. ISO 14045:2012(en) Environmental management — Eco-efficiency assessment of product systems — Principles, requirements and guidelines. Technical Committee ISO/TC 207.

Iten, M., Fernandes, U., Oliveira, M.C., 2021. Framework to assess eco-efficiency improvement: Case study of a meat production industry. Energy Reports 7, 7134-7148.

Izuchukwu, J., 2020. Development of a food process sustainability metric based on eco-efficiency, Department of Bioresource Engineering. McGill University.

Konstantas, A., Stamford, L., Azapagic, A., 2020. A framework for evaluating life cycle eco-efficiency and an application in the confectionary and frozen-desserts sectors. Sustainable Production and Consumption 21, 192-203.

Krentz, A., Garcia-Cano, I., Ortega-Anaya, J., Jimenez-Flores, R., 2022. Use of casein micelles to improve the solubility of hydrophobic pea proteins in aqueous solutions via low-temperature homogenization. J Dairy Sci 105(1), 22-31.

Langyan, S., Yadava, P., Khan, F.N., Dar, Z.A., Singh, R., Kumar, A., 2021. Sustaining Protein Nutrition Through Plant-Based Foods. Front Nutr 8, 772573.

Maxime, D., Marcotte, M., Arcand, Y., 2006. Development of eco-efficiency indicators for the Canadian food and beverage industry. Journal of Cleaner Production 14(6-7), 636-648.

McNulty, M.J., Kelada, K., Paul, D., Nandi, S., McDonald, K.A., 2021. Introducing uncertainty quantification to techno-economic models of manufacturing field-grown plant-made products. Food and Bioproducts Processing 128, 153-165.

Moll, P., Salminen, H., Seitz, O., Schmitt, C., Weiss, J., 2022. Characterization of soluble and insoluble fractions obtained from a commercial pea protein isolate. Journal of Dispersion Science and Technology 44(13), 2417-2428.

Möller, A.C., van der Padt, A., van der Goot, A.J., 2022. Influence of the fractionation method on the protein composition and functional properties. Innovative Food Science & Emerging Technologies 81.

Oke, E.O., Okolo, B.I., Adeyi, O., Adeyi, J.A., Otolorin, J.A., Nnabodo, D., Ude, C.J., Okhale, S.E., Adeyanju, J.A., Adeniyi, A.G., Eleanyan, E., Agbai, S.O., 2022. Bioactive Extract Production from Citrullus Clocynthis Fruit via Microwave-Assisted Extraction: Experimental Optimization, Process Design and Economics with Uncertainty Quantification. Journal of Pharmaceutical Innovation 18(2), 687-703.

Owusu‐Ansah, Y.J., McCurdy, S.M., 2009. Pea proteins: A review of chemistry, technology of production, and utilization. Food Reviews International 7(1), 103-134.

Park, Y.S., Egilmez, G., Kucukvar, M., 2015. A Novel Life Cycle-based Principal Component Analysis Framework for Eco-efficiency Analysis: Case of the United States Manufacturing and Transportation Nexus. Journal of Cleaner Production 92, 327-342.

Pelgrom, P.J.M., Boom, R.M., Schutyser, M.A.I., 2015. Functional analysis of mildly refined fractions from yellow pea. Food Hydrocolloids 44, 12-22.

Perez-Lopez, P., Montazeri, M., Feijoo, G., Moreira, M.T., Eckelman, M.J., 2018. Integrating uncertainties to the combined environmental and economic assessment of algal biorefineries: A Monte Carlo approach. Sci Total Environ 626, 762-775.

Peters, M.S., Timmerhaus, K.D., West, R.E., 2003. Plant Design and Economics for Chemical Engineers, Fifth ed. McGraw Hill, New York.

Petersen, A.M., Annoh-Quarshie, J., van Rensburg, E., Görgens, J.F., 2020. Optimizing the processes of extracting proteins from yellow peas and ethanol production from spent pea residues. Biomass Conversion and Biorefinery 12(7), 2913-2924.

Philips, G.O., Williams, P.A., 2011. Handbook of Food Proteins. Woodhead Publishing.

Pulivarthi, M.K., Buenavista, R.M., Bangar, S.P., Li, Y., Pordesimo, L.O., Bean, S.R., Siliveru, K., 2023. Dry fractionation process operations in the production of protein concentrates: A review. Compr Rev Food Sci Food Saf 22(6), 4670-4697.

Rajpurohit, B., Li, Y., 2023. Overview on pulse proteins for future foods: ingredient development and novel applications. Journal of Future Foods 3(4), 340-356.

Rivera, J., Siliveru, K., Li, Y., 2022. A comprehensive review on pulse protein fractionation and extraction: processes, functionality, and food applications. Critical Reviews in Food Science and Nutrition, 1-23.

Sala, D., Bieda, B., 2021. Life Cycle Inventory (LCI) Stochastic Approach Used for Rare Earth Elements (REEs), Considering Uncertainty. Inżynieria Mineralna 1(2).

Schmidt, F., Blankart, M., Wanger, J., Scharfe, M., Scheuerer, T., Hinrichs, J., 2022. Upscaling of alkaline pea protein extraction from dry milled and pre-treated peas from laboratory to pilot scale: Optimization of process parameters for higher protein yields. Journal of Food Measurement and Characterization 16(6), 4904-4913.

Shanmugam, K., Bryngelsson, S., Östergren, K., Hallström, E., 2023. Climate Impact of Plant-based Meat Analogues: A Review of Life Cycle Assessments. Sustainable Production and Consumption 36, 328-337.

Simboli, A., Taddeo, R., Morgante, A., 2014. Value and Wastes in Manufacturing. An Overview and a New Perspective Based on Eco-Efficiency. Administrative Sciences 4(3), 173-191.

Simona, C., Nicola, F., Micol, M., Rodríguez Carmen, M., Raffaella, M., Daniele, P., Andrea, V., Roberto, Z., 2024. A multi-indicator approach to compare the sustainability of organic vs. integrated management of grape production. Ecological Indicators 158.

Sproedt, A., Plehn, J., Schönsleben, P., Herrmann, C., 2015. A simulation-based decision support for eco-efficiency improvements in production systems. Journal of Cleaner Production 105, 389-405.

Strunge, T., Renforth, P., Van der Spek, M., 2023. Uncertainty quantification in the techno-economic analysis of emission reduction technologies: a tutorial case study on CO2 mineralization. Frontiers in Energy Research 11.

Wang, L., Mathew, P., Pang, X., 2012. Uncertainties in energy consumption introduced by building operations and weather for a medium-size office building. Energy and Buildings 53, 152-158.