

Ranking of Greenhouse Vegetable Suppliers across Three Canadian Provinces Using Data Envelopment Analysis with Multiple Inputs and Outputs

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Abstract

This study explores the application of Data Envelopment Analysis (DEA) as a tool for evaluating the operational efficiency of agricultural operations in Canada under varying conditions. While traditional DEA models are designed for precise input-output data, they may not adequately address uncertainties present in real-world scenarios. This research extends the conventional DEA framework to accommodate multiple scenarios, specifically assessing greenhouse, sod, and nursery operations in British Columbia, Ontario, and Quebec from 2019 to 2023. Utilizing a modified DEA model that remains linear and computationally efficient, this study evaluates efficiency based on various input and output metrics, including operational expenses and product value. Findings indicate that Quebec achieved full operational efficiency consistently, whereas Ontario and British Columbia showed improvement over time but did not match Quebec's performance. Introducing a multi-scenario approach enhances the robustness of efficiency analysis in agricultural contexts. However, the study notes certain limitations, such as the static nature of the analysis and the exclusion of qualitative factors.

Keywords

Data Envelopment Analysis (DEA), Efficiency, Ranking, Multiple Scenario, Supplier Selection, Green House Production, Decision Making Unit (DMU)

1. Introduction

The selection of efficient suppliers is considered critical in the modern concept of supply chain management to gain competitiveness and sustainability. Numerous

traditional methods of supplier selection depend on subjective judgment or simple metrics, resulting in less-than-optimal decisions. DEA is a more sophisticated approach in which the relative efficiency of DMUs will be analyzed using multiple inputs and outputs. This approach has particular value within complex supply chain environments where other methods might miss vital nuance.

DEA benchmarks the input-output ratio of each DMU against that of the best-performing homogeneous ones, considering several factors that may include costs, quality, delivery time, customer satisfaction, and product innovation. One of the critical strengths of DEA lies in its capability to handle different scenarios and variations in inputs and outputs, which is quite apt for dynamic supply chain contexts wherein the fluctuation in market demand, availability of resources, or changes in the regulatory environment can result in radical shifts in the performance of suppliers.

The present research has focused on applying DEA within a supplier selection context, considering various scenarios for inputs and outputs. This study retools DEA models to overcome the specific challenges presented by the dynamics of supply chains and enhance decision-making processes for organizations to make more informed and resilient choices for suppliers.

2. Literature Review

2.1. Advancements in Supply Chain Management and the Role of Data Envelopment Analysis

The concept of SCM has altered over the years due to changes in business practices, information technology, and globalization. According to CSCMP, supply chain management may be defined as managing all sourcing, production, and logistics activities, seamlessly integrating core business functions with other operational aspects for various stakeholders. This would involve integration among suppliers and through intermediaries to customers, where efforts are coordinated in several functional areas, including sales, marketing, finance, production, procurement, and logistics.

Historically, supply chain management has roots in logistics literature from the mid-20th century, emphasizing internal operations. Early contributions by Joseph Juran and W. Edwards Deming focused on optimizing internal business processes but did not extend to the network of suppliers, manufacturers, distributors, and customers. The 1980s marked a significant shift toward an integrated SCM approach, driven by the Just-In-Time (JIT) concepts developed by Japanese manufacturers, particularly Toyota. These concepts emphasized synchronization with customer demand to reduce inventory costs, laying the groundwork for modern supply chain partnerships [Tang \(2006\)](#).

With increasing globalization, the structure of supply chains has gradually become complex, involving many players across various industries and geographies. This has ushered in its own set of problems related to more significant risks from fluctuations in demand, uncertainties within firms, and other disruptions to

supply. Indeed, there have been recent disastrous events from terrorist attacks, pandemics, and natural calamities that eventually accentuated the Achilles heel of global supply chains as contributing factors. These changes have encouraged, if not coerced, businesses—huge multinationals—to adopt continuous improvement and become more flexible if they want to remain competitive in a market that is becoming increasingly volatile.

Advances in information technology have also modified supply chains. The wide diffusion of enterprise resource planning (ERP) systems during the 1990s further integrated internal processes, allowing for much better supply chain coordination. Out of this era came concepts such as Vendor-Managed Inventory (VMI) and Collaborative Planning, Forecasting, and Replenishment (CPFR) that increased supply chain visibility and responsiveness (Davenport, 1998). Recent trends in SCM are sustainability, digitalization, and omnichannel retailing, given increased consumer awareness and regulatory demands for corporate social responsibility.

DEA is a powerful tool that should be used for benchmarking and improving supply chain performance across different dimensions, including efficiency, sustainability, and supplier selection. Initially proposed by Charnes, Cooper, and Rhodes (1978), DEA calculates the efficiency scores of a set of DMUs from multiple inputs and outputs using linear programming. Other DEA models, such as constant and variable returns to scale, have been applied in many sectors, such as banking, education, and health care.

Over the years, DEA has evolved to address the complexities of real-world supply chain management, incorporating various models and methodologies to handle uncertain data. Traditional DEA models often assume precise data, but uncertainty is prevalent in real-world datasets. Researchers have developed fuzzy DEA models and robust optimization approaches to account for this uncertainty, enhancing the accuracy and applicability of DEA in diverse decision-making contexts (Zahedi-Seresht, et al., 2016).

DEA has proven particularly useful in assessing supply chain efficiency, where traditional production function data is often scarce or difficult to obtain. For example, Li et al. (2012) used DEA to measure the efficiency of the Chinese manufacturing industry's supply chain, identifying areas for improvement to achieve leaner and more cost-effective operations.

Advanced applications of DEA in supply chain management include two-stage models that evaluate the performance of multi-tier supply chains, incorporating suppliers, manufacturers, and distributors. Such models provide a more comprehensive analysis by measuring efficiency across the entire supply chain and its components (Tavana, 2015). Another innovative approach integrates undesirable outputs, such as emissions or waste generation, alongside traditional metrics to evaluate supply chain performance holistically (Liu et al., 2012).

In a nutshell, DEA is a precious tool for supply chain management, as it offers a sound ground for performance assessment and improvement in many dimensions. Its flexibility in treating multiple inputs and outputs, combined with the

adaptability of the approach to various contexts, makes this asset all-important for researchers and practitioners interested in optimizing supply chain operations. As supply chains continue to grow ever larger and more complex, the contribution of DEA to enhancing efficiency, sustainability, and resilience in supply chains will most likely become even more relevant.

2.2. Advanced Techniques in Supplier Selection Using Data Envelopment Analysis (DEA)

Supplier evaluation has been a significant component of supply chain management and a subject of widespread research, given its impact on the competitiveness and sustainability of organizations. Various methods have emerged for supplier evaluation, ranging from theoretical and empirical studies to modeling approaches. The present paper discusses quantitative models for supplier evaluation with particular emphasis on Data Envelopment Analysis.

Empirical research on supplier evaluation dates back to the 1960s when [Dickson \(1966\)](#) conducted a seminal study to identify the top three criteria for industrial purchasing managers: cost, quality, and delivery performance. Successive work by [Monczka et al. \(1981\)](#), [Moriarty \(1983\)](#), [Woodside and Vyas \(1987\)](#), [Chapman and Carter \(1990\)](#), [Tullous and Munson \(1991\)](#), and [Weber et al. \(1991\)](#) developed these criteria further to recommend the use of multiple factors in selecting suppliers beyond that of cost.

[Weber et al. \(1991\)](#) reviewed 74 articles on supplier selection, revealing that quality, delivery performance, and cost were the most frequently used criteria, reflecting a trend toward multi-criteria approaches in supplier evaluation. These studies collectively highlight the importance of considering multiple attributes rather than focusing solely on cost, although they often lack specific decision models for supplier evaluation.

Despite their wide usage in practice, traditional supplier evaluation techniques using multi-criteria approaches have several limitations including, but not limited to, the absence of objective methods for the assignment of factor weights, the lack of relative comparisons of alternative suppliers for benchmarking and SDI; insufficient emphasis on strategic-level capabilities or practices; and not addressing the issues and reasons behind ineffective supplier performance.

In this regard, DEA has been argued to be a tool that could help overcome some of these limitations, especially in strategic sourcing. DEA is a non-parametric method that evaluates the relative efficiency of DMUs based on their input-output relationship. However, the application of DEA in supplier evaluation has been limited. For instance, [Kleinsorge et al. \(1992\)](#) used DEA for performance monitoring of a single supplier over time, but their research did not address strategic supplier selection or benchmarking issues. Similarly, [Weber and Desai \(1996\)](#) and [Weber et al. \(1991\)](#) focused solely on operational metrics, relying on traditional DEA models with certain limitations.

More recent studies have explored advanced DEA models for supplier evaluation.

Narasimhan et al. (2001) applied DEA to evaluate suppliers by considering various strategic and operational factors, although traditional DEA model evaluations also constrained their approach. Talluri and Narasimhan (2004) demonstrated the practical applicability of DEA in supplier selection processes by assessing the performance of suppliers using multiple input and output criteria. Their study revealed that DEA could effectively identify efficient suppliers and provide insights into improving the performance of inefficient ones.

Recent advancements in DEA for supplier selection include the work of Zahedi-Seresht et al. (2017) proposed using the area's magnitude under the efficient curve to estimate supplier performance, utilizing Monte Carlo simulation for the complete ranking of initially efficient DMUs. This approach offers a computationally simple method for generating random weights for inputs and outputs in the feasible region, ultimately deriving the probability that DMUs are efficient. Another study by Jahanshahloo and Zahedi-Seresht (2015) also utilized the Monte Carlo method for ranking extremely efficient units in DEA, highlighting the various attempts in the literature to rank efficient units and presenting a method free from the problems typically associated with such rankings.

2.3. Multi-Scenario Data Envelopment Analysis in Supplier Selection

Traditional supplier selection methods face severe challenges from the complexity of modern supply chains and the multidimensionality of supplier performance. Often, there are multiple scenarios concerning inputs and outputs within the DMUs themselves, reflecting variability inherent in the dynamics of supply chains. A supplier may have different products or services with different characteristics and attributes or operate in multiple geographic locations, resulting in differences in performance on various markets or product lines.

Thus, DEA can handle multiple inputs and various outputs of DMUs efficiently since it can consider those diverse dimensions all at once and provide a comprehensive ranking of the suppliers for their performance. For instance, a manufacturing firm willing to select a critical component supplier must base its selection on various criteria such as cost, delivery time, quality, and flexibility. Each supplier's performance might differ concerning various product lines or regions, requiring more critical analysis.

Since this is a multi-scenario context, DEA can be applied to evaluate each supplier individually for each scenario to bring out their relative strengths and weaknesses under different conditions. This will enable firms to develop better strategies for supplier selection, procurement, inventory management, and production planning. Companies can gain valuable insights into which suppliers perform well under different eventualities by understanding how each supplier performs under different circumstances; this could provide a better basis for informed decisions.

Several scholars have proposed models incorporating fuzzy data, interval data, probabilistic data, and other forms of uncertainty to address the uncertainty in

supplier performance data. Zahedi-Seresht et al. (2021) developed a model for scenarios where multiple alternative scenarios represent uncertainty in the dataset. Based on the traditional CCR framework, their model considers an aggregated DMU defined as the weighted sum of all possible alternative scenarios, providing a method for assessing efficiency under uncertainty.

Furthermore, the two-stage DEA model is a unique version designed to assess the efficiency of DMUs with a two-step internal process. In this model, initial inputs are first converted into intermediate outputs, which are then transformed into final outputs in the subsequent stage. Alimohammadi Ardekani et al. (2016) emphasized that traditional DEA models often fail to consider the internal structure of DMUs, necessitating models that can handle variations and provide more detailed efficiency analyses. Robust optimization (RO) has emerged as a popular method for addressing data uncertainty, offering an alternative to stochastic programming (SP) for sensitivity analysis and uncertainty management.

In conclusion, advanced DEA models offer significant potential for improving supplier selection processes by addressing the multidimensionality and uncertainty inherent in supplier performance data. By incorporating multiple scenarios and robust optimization techniques, DEA can provide a more comprehensive and accurate supplier efficiency assessment, enabling firms to make more informed decisions and enhance their supply chain performance.

3. Methodology

3.1. Data Envelopment Analysis

DEA is a non-parametric (linear programming) frontier-based method that is used to assess the relative efficiency of a set of decision-making units (DMUs).

By calculating the efficiency of each DMU, each input and output variable for each DMU is allocated a weighted ratio. Using these weight ratios, the efficiency rate for each DMU can be computed under optimal conditions to realize maximum efficiency. The efficiency rate of a DMU can be expressed as the weighted sum of outputs divided by the weighted sum of inputs.

Maximize

$$\theta_q = \sum_{k=1}^r u_k y_{kq} \quad (1)$$

Subject to;

$$\begin{aligned} \sum_{k=1}^r u_k y_{kj} - \sum_{i=1}^m v_i x_{ij} &\leq 0, \quad j = 1, 2, \dots, n, \\ \sum_{i=1}^m v_i x_{iq} &= 1, \\ u_k &\geq \varepsilon, \quad v_i \geq \varepsilon. \end{aligned} \quad (2)$$

v_i —Input weight of the i -th input.

u_k —Output weight of the k -th output.

Non-Archimedean element $\varepsilon > 0$,

v_i and u_k represent input and output weights for the i -th input and k -th output. On the other hand, $\varepsilon > 0$ is a non-Archimedean element, smaller than any positive real number.

The optimal objective function value $qq^* = 1$ demonstrates the efficiency of the evaluated unit. Units with values less than one are considered inefficient. Reducing the number of inputs can help achieve the efficiency threshold.

3.2. Multi Scenario Data Envelopment Analysis

There are multiple scenarios concerning inputs and outputs within the DMUs themselves, reflecting variability inherent in the dynamics of supply chains. Consider a situation where there are n Decision Making Units (DMUs), each using s inputs to produce r outputs. However, instead of having precise or clear-cut data for these inputs and outputs, the decision-maker is faced with several different possible scenarios for the values of the inputs and outputs. **Table 1** shows the dataset, with n DMUs and S scenarios.

Table 1. A set of n DMUs with s inputs, r outputs, and S scenarios.

| Scenario | | Inputs | | | Outputs | | |
|----------|-----|------------|-----|------------|------------|-----|------------|
| | | I_1 | ... | I_s | O_1 | ... | O_r |
| DMU 1 | 1 | x_{i1}^1 | | x_{s1}^1 | y_{11}^1 | | y_{r1}^1 |
| | ... | | | | | | |
| | s | x_{1s}^1 | | x_{ss}^1 | y_{1s}^1 | | y_{rs}^1 |
| DMU 2 | 1 | x_{i1}^2 | | x_{s1}^2 | y_{11}^2 | | y_{r1}^2 |
| | ... | | | | | | |
| | s | x_{1s}^2 | | x_{ss}^2 | y_{1s}^2 | | y_{rs}^2 |
| ... | | | | | | | |
| DMU n | 1 | x_{i1}^n | | x_{s1}^n | y_{11}^n | | y_{r1}^n |
| | ... | | | | | | |
| | s | x_{1s}^n | | x_{ss}^n | y_{1s}^n | | y_{rs}^n |

The efficiency of the decision-making unit is calculated by aggregating the individual efficiency of each scenario, which is graphically represented below in **Figure 1** and **Figure 2**.

4. Analysis

4.1. Overview of the Data

Indoor agriculture in Canada, especially within the greenhouse vegetable and mushroom industries, is recognized as one of the most modern and innovative in the world. These are significant agricultural sectors in Canada and significant

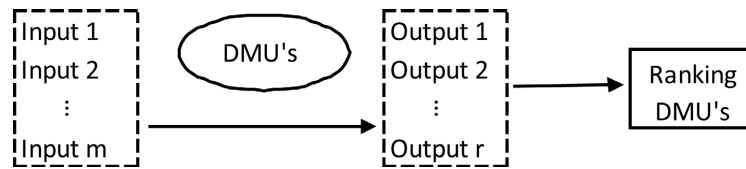


Figure 1. Single scenario DEA with multiple inputs and outputs.

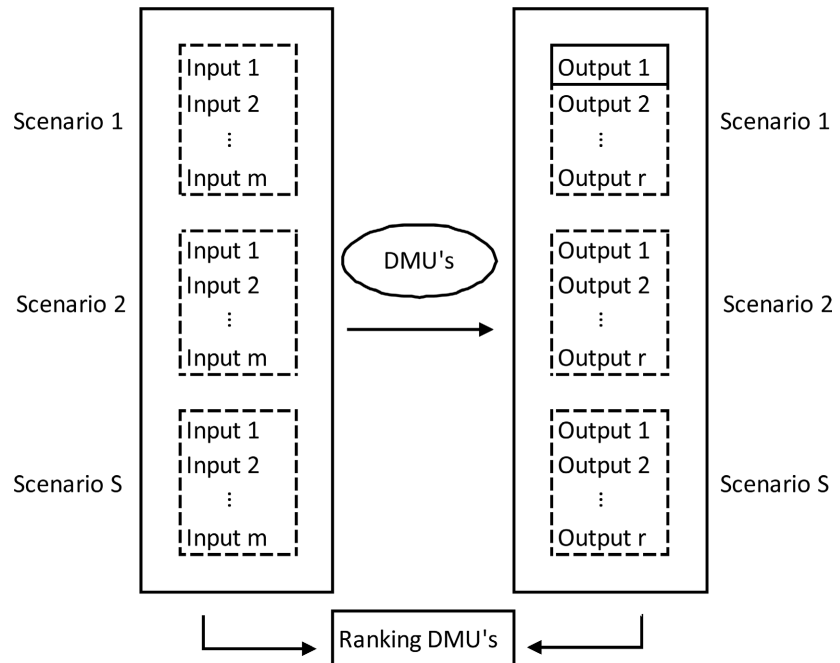


Figure 2. Multi scenario DEA with multiple inputs and outputs.

economic drivers for the country. Based on the statistics from the “Statistical Overview of the Canadian Greenhouse Vegetable and Mushroom Industry” of 2023, they attained a farm-gate sales value of \$2.2 billion in the year 2022, thus depicting their contribution to the nation’s economy. The export value attained approximately \$1.9 billion, which, in fact, brought out the prominence of Canada’s position in the international market. In this respect, tomato, pepper, and cucumber production is the most important, the three crops alone accounting for 2022 for about 96% of the country’s total greenhouse vegetable production. This type of concentration shows how specialized the sector has become, with the primary objective being producing high-quality crops to satisfy internal and international demand. The growth and success are proof of commitment to both the development of advanced technology and agricultural innovation.

The Canadian greenhouse operators have invested heavily in modern greenhouses, thus enabling high production volumes to meet fresh vegetable demands throughout the year. Currently, a majority of the greenhouse facilities within Canada are fully equipped with highly advanced automation technologies. The presence of the most advanced technologies in almost all production units across Canada shows that growers are committed to raising efficiency in production, lowering labor and input costs, and ensuring higher-quality products. By exploiting

these technologically advanced opportunities, the natural harvest seasons have been extended, thereby increasing the efficiency of Canadian farmers. The improvements named above have considerably increased Canadian greenhouse producers' competitiveness with notable product quality advances.

The greenhouse vegetable industry in Canada is strategically located near the US border, with significant production nodes in places like the Fraser Valley in British Columbia, Southern Ontario, and Quebec. Some of the diverse strategic advantages include proximity to large consumer markets, efficient transportation networks, and excellent growing conditions. This positioning solely has the fresh produce reaching the distribution points in record time while allowing the farms to reach a point most conducive to the growing conditions, significantly contributing to the success and sustainability of the industry.

4.2. Recent Statistics

There were 934 commercial greenhouse vegetable operations in Canada in 2022 combined to produce 752,685 metric tons of vegetables. This represents a 5% increase in operations from 2021 and a 7% increase in production. Ontario remains the largest producer of greenhouse vegetables in Canada, accounting for about 71% of national production. British Columbia accounted for 14.5%, while Quebec contributed 8%. The remaining 6.5% of the greenhouse vegetable production has been divided among the other provinces. The same table, therefore, shows not only growth but also the regional shift that, to this point in time, has characterized the development of Canada's greenhouse vegetable industry.

Tomatoes, cucumbers, lettuce, bell peppers, beans, eggplants, strawberries, a wide assortment of herbs, and microgreens are just some of the crops grown by Canadian greenhouse producers. However, the three primary crops most producers produce are tomatoes, cucumbers, and sweet peppers, which form the base of the greenhouse vegetable market in Canada. By sales, tomatoes have the largest share of 36% within the greenhouse vegetable sector, while it is 33% for cucumbers and bell peppers; the percentage of sales is 25%, respectively. Taken together, these three crops represent the foundation of the greenhouse vegetable market in Canada and reflect their comparative importance to the agricultural economy.

Greenhouse fruit and vegetable production brings substantial economic rewards to Canada. This industry's total sales increased 11% in 2022 over the previous year, reaching a record value of \$2.2 billion. This extends the multiyear upward trajectory that began in 2013, reflecting the increased contribution of greenhouse agriculture to the economy. That is a steady rise indicative of growing demand for greenhouse-grown produce, together with improvements in continuous technology and farming practices, which have brought significant gains in productivity and efficiency to the sector.

In 2022, the value of Canada's greenhouse vegetable exports was up 7.5% over 2021 and topped \$1.4 billion. This makes greenhouse vegetables the most valuable category among all fresh produce exports in the country, including fruits,

mushrooms, field vegetables, and potatoes, accounting for 39% of the total value of all fresh produce exports. Cucumbers, peppers, and tomatoes dominate the greenhouse vegetable market, with a substantial share of export value: cucumbers and peppers account for 34%, and tomatoes represent 32% of the share.

Like greenhouse vegetables, mushroom production in Canada occurs in highly controlled environments year-round. In these dark, specially climatized homes, growers further optimize conditions through temperature and humidity regulation. Mushroom cultivation is a continuous process, with harvesting occurring every day of the year around the clock, seven days a week. During 2022, Canadian mushroom growers harvested 139,090 metric tons of mushrooms, a 0.9% increase over the previous year. This growth was supported by a 1.8% increase in cultivated area and a 7.2% increase in harvested area.

In 2022, financial performance in the mushroom industry expanded as the overall value of mushrooms sold rose 6.3% to \$694.5 million on higher fresh and processed prices. Ontario and British Columbia continue to be Canada's two leading mushroom-producing provinces, accounting for approximately 93% of the total value of Canadian mushrooms. More than half of the country's volume comes from just Ontario.

On the export side, the U.S. remained the most important market for Canadian mushrooms, similar to the case for greenhouse vegetable exports. The U.S. received more than 97% of the value of fresh mushroom exports. Over the last five years, mushroom exports have grown, with a value increase of 66%, reaching USD 446.0 million in 2022, showing deep demand and value for Canadian mushrooms within the global market, mainly the United States.

4.3. COVID-19 Impact on Greenhouse Revenue

Food safety has become one of the most critical concerns recently, as the world is projected to have about 9.6 billion people by the year 2050. On the other hand, the arable lands are regularly shrinking. The COVID-19 pandemic has disrupted international trade in such a context, making a country's self-dependence on food production even more important.

Although Canada is practically self-sufficient in most foods, including meat and dairy products, it relies heavily on imports of fresh vegetables. Such heavy reliance on international supply chains puts Canada at a high risk resulting from disruptions in international trade. The solution to this would be to expand the greenhouse vegetable industry. Greenhouses can grow fresh vegetables year-round, regardless of external weather conditions. Greenhouses employ cutting-edge agricultural technologies that can supply fresh produce consistently and throughout the year. Building local food production will help Canada become more self-sufficient and less vulnerable to risk brought about by the country's dependence on international imports.

It would also create numerous employment opportunities along the value chain, thereby contributing to the economy's growth and, simultaneously,

reducing environmental decay by lowering the carbon footprint for long-distance transportation of supplies. In this manner, Canada could enhance its resistance to future global disruption by reinvesting and developing its greenhouse vegetable production. The COVID-19 pandemic highlighted the need to adapt the selection criteria for its suppliers to ensure supply chain resiliency. When consumer behaviors changed and supply chains became disrupted, there was a real need for pace in adaptation among greenhouse operators in Canada. This meant prioritizing suppliers who could deliver reliably and on time against a global transport backdrop replete with challenges. So, the outcome was to move decisively toward local suppliers to minimize risks from international delays in shipping and border restrictions. This move also enhanced the efficiency indexes whereby there was less dependency on suppliers in far-flung global geographies, reducing lead times and transportation costs, which means much better efficiency for the whole supply chain.

As it looks ahead, the question for the Canadian greenhouse sector is whether growth experienced in the year 2020 will continue into 2021, a year declared by the United Nations as the International Year of Fruits and Vegetables. Greenhouse sales for 2020 were up 9.4% compared to the previous year, supported by a robust crop of fruit and vegetables. Growing operational costs and a stronger Canadian dollar quickly become significant obstacles in attempting to continue the growth mark at the start of 2021.

In a year dominated by the COVID-19 pandemic, greenhouse-grown fresh vegetables had their most significant growth in receipts since 2012, moving an impressive 12.3% higher to \$1.8 billion in 2020, as seen in **Figure 1**. This incredible growth follows from a solid performance in 2019 when sales rose by 5.0% to \$1.6 billion.

As the pandemic got underway, greenhouse operators moved quickly to accommodate new consumer behaviors, curbside pickup, and online shopping in the astonishing 19.8% year-over-year increase in farm cash receipts in the first quarter of 2020. This trend continued well into the second and third quarters, showing that rapid adaptation was essential for sustaining growth in this sector through the pandemic. These changes underlined the dynamism of the sector and the need for a flexible supply chain, backed by effective selection of suppliers.

In the period 2015-2020, the total area of greenhouses for the production of fruits and vegetables increased considerably by 23.9%, up to 1809 hectares in the last year. The result of this situation was the increase in the production of peppers and cucumbers, two of the three main varieties of fresh vegetables produced in large quantities. Contrasting with this, despite tomato sales continuing to be the most valuable and voluminous, they decreased by 3.2%. However, tomatoes ranked first regarding value sales growth, showing a gain of 12.1%, against a 9.4% increase in cucumbers and a 7.3% gain in peppers in value terms. In all, these three vegetables reached a value share of 92.5% and reconfirmed their leading position within this commodity group.

This suggests that the COVID-19 pandemic accelerated the need for an efficient and resilient supply chain in agriculture, especially in greenhouse vegetable production. Such investment in local suppliers and improvements in their supply chain practices will make the food security of Canada strong by reducing dependence on international imports and developing a formidable food supply chain that would stand resilient against future global shocks.

4.4. Inputs and Outputs of DEA

To demonstrate the proposed mathematical model for multi-scenario Data Envelopment Analysis (DEA), we use data from [Statistics Canada \(2024\)](#) covering greenhouse, sod, and nursery operations across Canada. This model is designed to evaluate the efficiency of these operations over a span of multiple years. The analysis uses the total value of greenhouse products as the output variable. As for input variables, the model considers various operating expenses of specialized greenhouse producers, which are categorized into expenses for specialized greenhouse vegetables and specialized greenhouse flowers and plants.

The multi-scenario approach involves analyzing data over five years, from 2019 to 2023. This longitudinal dataset allows for an assessment of efficiency trends and changes over time. The data plays a critical role for federal and provincial agricultural departments and producer associations, aiding in market trend analysis and the examination of domestic production, particularly with regard to import dynamics. Additionally, the survey data contributes to Statistics Canada's agricultural receipts program, which is a component of the System of National Accounts.

Agriculture and Agri-Food Canada and other federal departments use this information to formulate and manage agricultural policies. Similarly, provincial departments use the data for production and price analysis and economic research. The survey is part of the Integrated Business Statistics Program (IBSP), which consolidates around 200 individual business surveys into a single, comprehensive survey program. The IBSP aims to collect detailed industry and product information at the provincial level, reducing redundancy across different survey questionnaires.

For the purpose of this DEA analysis, we focus on three key provinces: British Columbia, Ontario, and Quebec. These provinces are treated as the decision-making units (DMUs) in the model. Within each province, farms are categorized based on their involvement in greenhouse, sod, and nursery activities, as well as their primary North American Industry Classification System (NAICS) code. The four categories used are:

- 1) Greenhouse—Floriculture.
- 2) Greenhouse—Other.
- 3) Sod.
- 4) Nursery.

Farms producing multiple commodities are classified according to the primary contribution of each commodity at the provincial level. These categories and the

provincial divisions form the sampling cells for this analysis.

The target population for this study includes all greenhouse, sod, or nursery operations that meet Statistics Canada's definition of a farm. A farm is an operation that produces at least one agricultural product and reports related revenue and expenses to the Canada Revenue Agency. However, specific small populations are excluded from the survey, including farms in Canada's three territories, institutional farms, community farms, greenhouses producing marijuana, and greenhouses or nurseries producing tree seedlings for reforestation.

4.4.1. Input—Specialized Greenhouse Producers' Operating Expenses

In general, the categories in Canada include greenhouse vegetable producers and greenhouse flower and plant producers. These exclude the operations that involve a combination of vegetables and flowers/plants and those that grow cannabis. The total expenses for each type of operation are calculated by summing several specific types of costs.

For greenhouse vegetable producers, the total expenses include:

- **Plant Material Purchases for Growing On:** This involves the cost of buying flowers, plants, cuttings, seedlings, seeds, and bulbs that are to be cultivated on-site. These costs are calculated before any sales tax is applied.
- **Plant Material Purchases for Resale:** This covers the expenses of acquiring flowers, plants, cuttings, seedlings, seeds, and bulbs for resale purposes, also before sales tax.
- **Gross Yearly Payroll:** This includes all wages paid to seasonal and permanent greenhouse employees.
- **Electricity Costs:** These are the expenses incurred for electricity used for various greenhouse operations, such as lighting, running airflow fans, and heating.
- **Fuel Costs:** This includes all fuel-related expenses required for the greenhouse operations.
- **Other Crop Expenses:** This category encompasses various costs associated with crop production, including fertilizers, pesticides, pollination services, irrigation, containers, packaging, bioprograms, and different growing mediums such as soil, peat moss, vermiculite, perlite, sand, Styrofoam, and sawdust.
- **Other Operating Expenses:** These are additional costs necessary for maintaining greenhouse operations. They include interest payments, land taxes, insurance premiums, advertising expenses, repairs to farm buildings, machinery, agricultural equipment, vehicles, contract work costs, and telephone and telecommunications services.

Similarly, the total expenses are calculated using the same categories for greenhouse flower and plant producers.

4.4.2. Output—Total Value of Greenhouse Products

The output evaluated in this study is the total sales value of greenhouse products, divided into two primary categories: fruit and vegetable sales and flower and plant sales and resales.

1) Fruit and Vegetable Sales: This category captures the revenue from the direct sale of produce grown on farms before tax. It includes various items, such as greenhouse vegetables, herbs, and sprouts.

2) Flower and Plant Sales and Resales:

- Flower and Plant Sales: This represents the revenue from directly selling flowers and plants grown on farms, excluding sales tax. This category does not encompass sales related to cannabis.
- Flower and Plant Resales: This includes the revenue from reselling flowers and plants, reflecting transactions where previously sold items are sold again.

The study focuses on the total revenue generated from these greenhouse sectors, distinguishing between the direct sales of fruits, vegetables, flowers, and plants and the resales within the flower and plant market.

Table 2 consists of the summarized data, including inputs and outputs for each scenario and each DMU collectively.

Table 2. Input data for all the DMUs.

| DMU | Input 1 | | | | | Input 2 | | | | | Output | | | | |
|---------|-------------|-------------|---------------|---------------|---------------|-------------|-------------|-------------|-------------|-------------|---------------|---------------|---------------|---------------|---------------|
| | Scenarios | | | | | | | | | | | | | | |
| | 2019 | 2020 | 2021 | 2022 | 2023 | 2019 | 2020 | 2021 | 2022 | 2023 | 2019 | 2020 | 2021 | 2022 | 2023 |
| Quebec | 89,891,228 | 103,156,388 | 137,123,650 | 141,540,012 | 132,752,229 | 123,630,623 | 123,095,007 | 119,654,567 | 129,356,875 | 138,175,442 | 362,006,150 | 414,794,857 | 478,589,953 | 520,026,432 | 542,733,817 |
| Ontario | 854,689,431 | 966,548,414 | 1,104,545,402 | 1,208,202,267 | 1,299,518,856 | 608,010,480 | 608,487,946 | 603,136,222 | 649,617,004 | 711,591,369 | 1,884,974,133 | 2,030,124,141 | 2,214,253,122 | 2,517,240,579 | 2,715,343,184 |
| BC | 230,175,833 | 248,689,687 | 252,363,903 | 264,232,035 | 262,680,674 | 181,242,917 | 202,960,631 | 226,567,822 | 233,007,324 | 240,665,144 | 649,068,393 | 730,189,718 | 775,299,181 | 837,340,045 | 883,540,756 |

The mathematical models for each DMU for each scenario are developed, and the mathematical models are included in the Appendix. Those mathematical equations were solved using Python’s Pyomo Library, and the results are reported in **Table 3**.

Table 3 presents the efficiency scores for each Decision-Making Unit (DMU) over the years 2019 to 2023, along with their average efficiency across this period. An efficiency score of 1 signifies that the DMU is operating at peak efficiency compared to the others assessed. Scores below 1 indicate varying degrees of inefficiency, with the value representing the proportion of the maximum efficiency

achieved.

Table 3. Efficiency score of each DMU for different scenarios.

| | | DMU | | |
|--------------------|------|-------------|-------------|--------|
| | | BC | Ontario | Quebec |
| Scenario | 2019 | 1 | 1 | 1 |
| | 2020 | 1 | 0.927356472 | 1 |
| | 2021 | 0.880219281 | 0.917862352 | 1 |
| | 2022 | 0.893915332 | 0.963898794 | 1 |
| | 2023 | 0.934667996 | 0.971489329 | 1 |
| Average Efficiency | | 0.941760522 | 0.956121389 | 1 |

In 2019, all three DMUs—British Columbia (BC), Ontario, and Quebec—achieved a perfect efficiency score of 1, indicating optimal performance for that year. By 2020, Quebec and BC maintained this level of efficiency. However, Ontario's efficiency slightly decreased to 0.927, suggesting it operated at about 92.7% of its potential efficiency.

In 2021, Quebec remained fully efficient with a score of 1. In contrast, both BC and Ontario saw reductions in their efficiency scores, with BC's score falling to 0.880 and Ontario's to 0.918. This reflects a decline in efficiency for these provinces relative to Quebec.

By 2022, Quebec continued to perform at full efficiency with a score of 1. BC and Ontario showed improvement, with their efficiency scores rising to 0.894 and 0.964, respectively. This increase indicates a positive trend in efficiency for these provinces.

In 2023, Quebec again scored 1, indicating sustained full efficiency. BC and Ontario continued their upward trajectory, with efficiency scores reaching 0.935 and 0.971, respectively. These scores reflect a consistent improvement in efficiency for BC and Ontario over the years. **Table 4** displays the three provinces' average efficiency scores and rankings across the observed period.

Table 4. Ranking of DMUs according to the efficiency measure.

| DMU | Average Efficiency | Rank |
|---------|--------------------|------|
| Quebec | 1 | 1 |
| Ontario | 0.956121389 | 2 |
| BC | 0.941760522 | 3 |

Quebec achieved the highest average efficiency score of 1.0, securing the first position. Ontario ranked 2nd with an average efficiency score of 0.956. British Columbia ranked third with the lowest average efficiency score of 0.942. These results indicate that Quebec consistently operated at full efficiency, while Ontario

and British Columbia, despite showing improvements, still had some efficiency gaps to address.

5. Conclusion

5.1. Results and Discussion

In conclusion, this paper explores the application of data envelope analysis (DEA) to evaluate supplier efficiency in the supply chain industry across multiple scenarios. Utilizing data from Statistics Canada, the study focuses on greenhouse, sod, and nursery operations in British Columbia, Ontario, and Quebec from 2019 to 2023. The DEA model assesses the efficiency based on the total value of greenhouse products and various operating expenses. Findings show that Quebec has consistently been the most efficient province, achieving full efficiency yearly. At the same time, Ontario and British Columbia have improved over time but still have room for enhancement. This study introduces a multi-scenario DEA approach to better capture variations and uncertainties in agricultural operations, enhancing the efficiency analysis in this sector.

5.2. Limitations and Future Directions

In this study, the DEA application on supplier efficiency evaluation in greenhouse, sod, and nursery operations has various limitations. Firstly, the analyses have been done on only the mentioned agricultural sectors and therefore the findings may not easily be applied to any other agricultural or even industrial sectors. Its application on a broader scale could make its results useful.

Second, it focuses on three Canadian provinces, namely British Columbia, Ontario, and Quebec. Such focus might be too constricting to pick out a general trend or regional variation across these three provinces and, as such, restricts the level of generalization of results. Moreover, the data in the study is only up to 2023, which may be less than adequate to effectively scan the latest and freshest trends and disruptions occurring within the industry and therefore tend to reduce the relevance of findings to the current and future context.

Third, the DEA model requires convexity and similar operating conditions among DMUs, which may practically not be validated in many cases due to regional variations in market conditions, policies, or operational environments. Thus, this may further lead to the assumption of convexity, causing distorted results and less accuracy.

The second level of analysis also adopts a static perspective, whereby each individual year reflects a different scenario. This does not consider the dynamism in the performance of suppliers over time. Such a dynamic or longitudinal analysis may bring in further insights into the trends in performance and adaptability across successive years.

Moreover, the study does not take qualitative aspects into consideration, like the relationships with suppliers, their capabilities for innovation, and the general economic conditions surrounding them. These could drastically alter the strength

of efficiency analyses. These factors are paramount in agriculture and may prove pivotal to supplier success.

Future research work on this subject should, therefore, cover these limitations by the inclusion of real-time data and extension to more agricultural and industrial sectors. Increasing the sample size beyond three provinces and integrating qualitative aspects, such as supplier relationships and innovation capabilities, with quantitative indicators would further enhance the results. The refinement of results can be obtained by using methodologies of stochastic DEA models or hybrid models that include both. Continuous updating of data and consideration of exogenous factors, namely, economic conditions and changes in policy, will enhance the pertinence and accuracy of this study to make the best resilient supplier selection decisions for organizations.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix

Developing the Mathematical Model for each DMU

DEA model for BC 2019

$$\text{Max } \theta = 649068393u_1$$

Subject to

$$649068393u_1 - 230175833v_1 - 181242917v_2 \leq 0$$

$$1884974133u_1 - 854689431v_1 - 608010480v_2 \leq 0$$

$$362006150u_1 - 89891228v_1 - 123630623v_2 \leq 0$$

$$230175833v_1 + 181242917v_2 = 1$$

$$u_1, v_1, v_2 \geq \varepsilon$$

DEA model for BC 2020

$$\text{Max } \theta = 730189718u_1$$

Subject to

$$730189718u_1 - 248689687v_1 - 202960631v_2 \leq 0$$

$$203012414u_1 - 966548414v_1 - 608487946v_2 \leq 0$$

$$414794857u_1 - 103156388v_1 - 123095007v_2 \leq 0$$

$$248689687v_1 + 202960631v_2 = 1$$

$$u_1, v_1, v_2 \geq \varepsilon$$

DEA model for BC 2021

$$\text{Max } \theta = 775299181u_1$$

Subject to

$$775299181u_1 - 252363903v_1 - 226567822v_2 \leq 0$$

$$2214253122u_1 - 1104545402v_1 - 603136222v_2 \leq 0$$

$$478589953u_1 - 137123650v_1 - 119654567v_2 \leq 0$$

$$252363903v_1 + 226567822v_2 = 1$$

$$u_1, v_1, v_2 \geq \varepsilon$$

DEA model for BC 2022

$$\text{Max } \theta = 837340045u_1$$

Subject to

$$837340045u_1 - 264232035v_1 - 233007324v_2 \leq 0$$

$$2517240579u_1 - 1208202267v_1 - 649617004v_2 \leq 0$$

$$520026432u_1 - 141540012v_1 - 129356875v_2 \leq 0$$

$$264232035v_1 + 233007324v_2 = 1$$

$$u_1, v_1, v_2 \geq \varepsilon$$

DEA model for BC 2023

$$\text{Max } \theta = 883540756u_1$$

Subject to

$$\begin{aligned} 883540756u_1 - 262680674v_1 - 240665144v_2 &\leq 0 \\ 2715343184u_1 - 1299518856v_1 - 711591369v_2 &\leq 0 \\ 542733817u_1 - 132752229v_1 - 138175442v_2 &\leq 0 \\ 262680674v_1 + 240665144v_2 &= 1 \\ u_1, v_1, v_2 &\geq \varepsilon \end{aligned}$$

DEA model for Ontario 2019

$$\text{Max } \theta = 1884974133u_1$$

Subject to

$$\begin{aligned} 649068393u_1 - 230175833v_1 - 181242917v_2 &\leq 0 \\ 1884974133u_1 - 854689431v_1 - 608010480v_2 &\leq 0 \\ 362006150u_1 - 89891228v_1 - 123630623v_2 &\leq 0 \\ 854689431v_1 + 608010480v_2 &= 1 \\ u_1, v_1, v_2 &\geq \varepsilon \end{aligned}$$

DEA model for Ontario 2020

$$\text{Max } \theta = 203012414u_1$$

Subject to

$$\begin{aligned} 730189718u_1 - 248689687v_1 - 202960631v_2 &\leq 0 \\ 203012414u_1 - 966548414v_1 - 608487946v_2 &\leq 0 \\ 414794857u_1 - 103156388v_1 - 123095007v_2 &\leq 0 \\ 966548414v_1 + 608487946v_2 &= 1 \\ u_1, v_1, v_2 &\geq \varepsilon \end{aligned}$$

DEA model for Ontario 2021

$$\text{Max } \theta = 2214253122u_1$$

Subject to

$$\begin{aligned} 775299181u_1 - 252363903v_1 - 226567822v_2 &\leq 0 \\ 2214253122u_1 - 1104545402v_1 - 603136222v_2 &\leq 0 \\ 478589953u_1 - 137123650v_1 - 119654567v_2 &\leq 0 \\ 1104545402v_1 + 603136222v_2 &= 1 \\ u_1, v_1, v_2 &\geq \varepsilon \end{aligned}$$

DEA model for Ontario 2022

$$\text{Max } \theta = 2517240579u_1$$

Subject to

$$837340045u_1 - 264232035v_1 - 233007324v_2 \leq 0$$

$$2517240579u_1 - 1208202267v_1 - 649617004v_2 \leq 0$$

$$520026432u_1 - 141540012v_1 - 129356875v_2 \leq 0$$

$$1208202267v_1 + 649617004v_2 = 1$$

$$u_1, v_1, v_2 \geq \varepsilon$$

DEA model for Ontario 2023

$$\text{Max } \theta = 2715343184u_1$$

Subject to

$$883540756u_1 - 262680674v_1 - 240665144v_2 \leq 0$$

$$2715343184u_1 - 1299518856v_1 - 711591369v_2 \leq 0$$

$$542733817u_1 - 132752229v_1 - 138175442v_2 \leq 0$$

$$1299518856v_1 + 711591369v_2 = 1$$

$$u_1, v_1, v_2 \geq \varepsilon$$

DEA model for Quebec 2019

$$\text{Max } \theta = 362006150u_1$$

Subject to

$$649068393u_1 - 230175833v_1 - 181242917v_2 \leq 0$$

$$1884974133u_1 - 854689431v_1 - 608010480v_2 \leq 0$$

$$362006150u_1 - 89891228v_1 - 123630623v_2 \leq 0$$

$$89891228v_1 + 123630623v_2 = 1$$

$$u_1, v_1, v_2 \geq \varepsilon$$

DEA model for Quebec 2020

$$\text{Max } \theta = 414794857u_1$$

Subject to

$$730189718u_1 - 248689687v_1 - 202960631v_2 \leq 0$$

$$2030124141u_1 - 966548414v_1 - 608487946v_2 \leq 0$$

$$414794857u_1 - 103156388v_1 - 123095007v_2 \leq 0$$

$$103156388v_1 + 123095007v_2 = 1$$

$$u_1, v_1, v_2 \geq \varepsilon$$

DEA model for Quebec 2021

$$\text{Max } \theta = 478589953u_1$$

Subject to

$$775299181u_1 - 252363903v_1 - 226567822v_2 \leq 0$$

$$2214253122u_1 - 1104545402v_1 - 603136222v_2 \leq 0$$

$$478589953u_1 - 137123650v_1 - 119654567v_2 \leq 0$$

$$137123650v_1 + 119654567v_2 = 1$$

$$u_1, v_1, v_2 \geq \varepsilon$$

DEA model for Quebec 2022

$$\text{Max } \theta = 520026432u_1$$

Subject to

$$837340045u_1 - 264232035v_1 - 233007324v_2 \leq 0$$

$$2517240579u_1 - 1208202267v_1 - 649617004v_2 \leq 0$$

$$520026432u_1 - 141540012v_1 - 129356875v_2 \leq 0$$

$$141540012v_1 + 129356875v_2 = 1$$

$$u_1, v_1, v_2 \geq \varepsilon$$

DEA model for Quebec 2023

$$\text{Max } \theta = 542733817u_1$$

Subject to

$$883540756u_1 - 262680674v_1 - 240665144v_2 \leq 0$$

$$2715343184u_1 - 1299518856v_1 - 711591369v_2 \leq 0$$

$$542733817u_1 - 132752229v_1 - 138175442v_2 \leq 0$$

$$132752229v_1 + 138175442v_2 = 1$$

$$u_1, v_1, v_2 \geq \varepsilon$$