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A Multi-Objective Multi-Item Vendor Optimization Framework for Sustainable Supply Chain Management: Evidence from the Ganye–Tougo Agro-Allied Sector, Adamawa State, Nigeria

Shehu Ahmed[1,*], Umar Muhammad Modibbo[2], and Ikeme John Dike[3]

[1,2,3] Department of Operations Research, Faculty of Computing, Modibbo Adama University Yola, Nigeria

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ABSTRACT

Procurement in many developing-economy agro-allied supply chains is still driven mainly by unit price, which can hide environmental waste and unreliable delivery. This study develops a Multi-Objective Multi-Item Vendor Optimization Framework for Sustainable Supply Chain Management (SSCM) and demonstrates it for the agro-allied sector of Ganye and Tougo Local Government Areas, Adamawa State, Nigeria. Guided by the Triple Bottom Line, a Multi-Objective Linear Programming (MOLP) model minimizes total purchasing cost (economic), rejected units (environmental proxy) and late deliveries (social proxy) subject to demand, vendor capacity, budget and quality constraints. The model is solved with the Weighted Sum Method after linear min–max normalization, using exact linear programming in Python (SciPy/HiGHS). In a numerical case study of a processor buying 10,000 tons of maize, 8,000 tons of beans and 12,000 tons of rice from three vendors over seven months, a balanced weighting (0.4, 0.3, 0.3) raises total cost from ₦9.522 million to ₦9.669 million (+1.5%) while cutting rejected units by 19.9% and late deliveries by 34.8% relative to a cost-only strategy. Sensitivity analysis shows that these gains hold over a wide range of weights and that the plan is affordable once the budget exceeds the minimum feasible cost. The framework gives procurement managers in North-Eastern Nigeria a transparent quantitative tool for aligning sourcing decisions with Sustainable Development Goal 12.

1. Introduction

Research on supplier selection has a long tradition dating back to the 1960s, and the criteria used to select and rate vendors remain a central topic in supply chain management (SCM). Mathematical programming models are used extensively to solve the Vendor Selection Problem (VSP). More recently, sustainability has become a critical aspect of SCM as firms try to limit their environmental impact, act responsibly towards society and remain economically viable (Seuring & Müller, 2008). The United Nations Sustainable Development Goals (SDGs) give organizations a framework for prioritizing sustainability, with SDG 12 addressing responsible consumption and production (Lee *et al.*, 2016).

* *Corresponding author.*
E-mail address: ahmedshehu1145@gmail.com

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The drivers of sustainability include environmental degradation, social inequality and economic instability. Climate change is among the most pressing of these, and companies face growing pressure to cut their carbon footprint through renewable energy, improved energy efficiency and sustainable land-use practices. In the agrarian hubs of Ganye and Tougo in Adamawa State, the supply chain is vital to the regional economy. However, high wastage, reflected in the rejection of poor-quality raw materials, and unreliable delivery schedules hamper growth. Prioritizing sustainability in such a setting can reduce costs, improve reputation and increase competitiveness.

Supply chain management requires a balance among economic, environmental and social objectives. Nevertheless, procurement in Nigerian industries has tended to prioritize cost minimization. This mono-objective focus produces suboptimal outcomes in which cheap vendors are chosen even though they generate high waste (environmental impact) or fail to deliver on time (social impact) (Seuring & Müller, 2008). Local agro-processors in Ganye and Tougo face particular difficulty with vendor reliability and raw-material quality. High rejection rates cause physical waste and financial loss, while late deliveries disrupt production schedules and affect the livelihoods of downstream workers. No comprehensive mathematical framework integrates these conflicting objectives, so decision-makers rely largely on intuition.

Practically, the framework supports procurement managers in the North-East of Nigeria by giving a mathematical justification for paying slightly higher prices to cleaner and more reliable vendors. Theoretically, it extends the classical VSP with constraints typical of developing economies, namely strict vendor capacity limits and budget rigidity, alongside sustainability metrics. In terms of policy, it supports Nigeria's SDG commitments, particularly waste reduction.

The study is limited geographically to the Ganye and Tougo Local Government Areas and to the agro-allied sector. It concentrates on the upstream sourcing and procurement stage and uses deterministic linear programming, assuming that demand, cost and performance parameters are known with certainty over the planning period.

2. Literature Review

This section review related works under the triple bottom line concept, vendor selection and sustainable supply chain models applications.

2.1 Theoretical framework: the Triple Bottom Line

The theoretical basis of this study is the Triple Bottom Line (TBL) framework of Elkington (1997). Unlike conventional SCM, which emphasizes financial efficiency and cost reduction, TBL calls for balanced integration of economic prosperity, environmental stewardship and social equity, often summarized as Profit, Planet and People. Carter and Rogers (2008) moved the field from isolated "green" initiatives towards holistic strategic integration, arguing that sustainability is a source of long-term competitive advantage rather than a trade-off. Pagell and Wu (2009) found that leading sustainable supply chains often outperform conventional ones by reducing waste and improving resource efficiency.

Green supply chain management was the first major offshoot of TBL; studies such as Srivastava (2007) and Sarkis *et al.* (2011) examined carbon footprints, waste management and renewable energy. The social pillar has historically been neglected in quantitative models. Seuring and Müller (2008) stressed the importance of supplier social audits, and Mani et al. (2016) developed and validated measures of social sustainability in supply chains. Seuring and Müller (2008) supplied the conceptual lens but not the granular variables needed for local implementation. In the present work, the late delivery rate is used as a concrete mathematical proxy for the social impact on downstream workers' livelihoods.

Disruptions such as COVID-19 have fused sustainability with resilience. Tundys and Wiśniewski (2023) argue that TBL-oriented supply chains tend to be more resilient because of stakeholder transparency and decentralized resource networks. Moving from linear to circular supply chains is regarded as the fullest realization of the environmental pillar, and Govindan and Hasanagic (2018) identified the drivers and barriers to this transition, including reverse logistics and remanufacturing. The literature shows a trajectory from TBL as a moral obligation to TBL as a strategic imperative. For vendor selection, the implication is that a supplier should be chosen not on price alone but also on environmental compliance (waste or rejection rates) and social reliability.

2.2 The Vendor Selection Problem

The VSP, also called the Supplier Selection Problem, is a strategic decision that affects a firm's ability to reduce cost, improve quality and stay competitive. Its formal study began with Dickson (1966), who identified 23 criteria used by purchasing managers, with quality, delivery and performance history ranked highest. Weber *et al*. (1991) reviewed 74 articles published between 1966 and 1990 and found that price, although the most frequent criterion (appearing in about 80% of papers), was rarely the only one. This established the VSP as a Multi-Criteria Decision-Making (MCDM) problem.

A wide range of techniques has been applied. The Analytic Hierarchy Process (AHP) is popular for handling qualitative data through pairwise comparison; Ghodsypour and O'Brien (1998) integrated AHP with linear programming to cover tangible and intangible factors under resource constraints, and Sarkis and Talluri (2002) used the Analytic Network Process to capture interdependence among criteria. Recent work continues to combine AHP with fuzzy sets to reduce subjectivity (Ali *et al.,* 2021). Data Envelopment Analysis (DEA) evaluates relative supplier efficiency and gives inefficient suppliers a benchmark (Weber, 1996). Linear and mixed-integer linear programming are central to order allocation; Basnet and Leung (2005) solved a multi-period lot-sizing problem with supplier selection using mixed-integer programming, and recent models balance cost, resilience and sustainability through multi-objective programming (Shao et al., 2023). Where data are imprecise, fuzzy approaches such as the fuzzy TOPSIS of Chen *et al*. (2006) let decision-makers use linguistic ratings, and later work employs Pythagorean and interval-valued fuzzy numbers (Celik & Gul, 2024).

Environmental concern has made green criteria prominent (Govindan et al., 2015), and resilience thinking has shifted sourcing from just-in-time towards just-in-case, with resilience defined as the ability to resist and recover from disruption (Hosseini et al., 2019). Industry 4.0 has added criteria such as digital maturity; Büyüközkan and Göçer (2018) explored the digital supply chain, Schmidt *et al*. (2023) examined IoT and big-data analytics in buyer–supplier relationships, and Resende *et al*. (2020) reviewed decision-making models in supplier selection. Ghobakhloo *et al*. (2025) discuss digital transformation as an enabler of supply chain resilience. A digitalization–sustainability gap remains in emerging economies, where advanced tools such as block chain are discussed conceptually but rarely applied in local agro-logistics. The present work is a pragmatic step: it provides a normative model that tells managers what they should do, rather than merely describing the problem.

Most classical VSP models are single-objective (minimizing total cost subject to demand), which fails when objectives such as cost and quality conflict; a vendor with the lowest unit price may also have the highest late delivery rate. This motivates multi-objective techniques such as Goal Programming and the Weighted Sum Method.

2.3 Sustainable SCM models: empirical and modelling studies

Zimmer et al. (2016) reviewed supplier selection models and found that environmental criteria are increasingly included while social criteria remain under-represented in mathematical models. Recent scholarship integrates TBL with technological and circular principles. Studies of the digitalization–sustainability nexus show that AI, big-data analytics and IoT enable real-time monitoring and reduce operational waste, while Industry 4.0 is

identified as a driver of closed-loop systems (Ghobakhloo *et al.*, 2025). Asante-Darko *et al.* (2025) suggest that supply chain integration may be costly in the short term but yields win–win outcomes for firm performance over the long term. Sector-specific work includes a hybrid MCDM approach for perishable aquatic products (Vijay & Raju, 2024) and multi-objective approaches for resilient agri-food chains under mixed uncertainty (Tsoulfas, 2025). Collectively, this literature indicates a research bias towards environmental over social factors and a need for models that connect theory with practice.

Several operations research contributions are directly relevant to the present formulation. Govindan and Sivakumar (2016) integrated MCDM with multi-objective linear programming for green supplier selection and order allocation in a low-carbon paper industry. Ali *et al.* (2020) formulated an LR-type fuzzy multi-objective vendor selection problem using fuzzy goal programming to balance lead time, ordering cost and quality. Ahmadini *et al.* (2021) proposed multi-objective models for sustainable green supply chains in which green investment is a decision variable that reduces carbon emissions without harming operational efficiency. Modibbo *et al.* (2021) studied reliability allocation, showing that inventory flows cannot be separated from the reliability of the production systems that feed them. Modibbo *et al.* (2022) applied fuzzy TOPSIS to pharmaceutical supplier selection and showed that, in high-stakes settings, resilience and geographical reliability should outweigh price. Modibbo *et al.* (2024) developed an integrated multi-objective, multi-product inventory-managed production planning model under uncertainty using interval type-2 fuzzy sets and stochastic programming, achieving near-total delivery-time reliability while minimizing production and transshipment cost. Malik *et al.* (2024) extended this line to decaying items with inflation, trade credit and preservation technology to reduce waste in perishable inventories.

In the Nigerian context, to the authors' knowledge, applied multi-objective optimization models for multi-item vendor allocation in the agricultural supply chains of Adamawa State and the wider North-East are scarce. Local studies of logistics and procurement have tended to be survey-based and descriptive rather than quantitative and prescriptive.

Although the global literature on sustainable vendor selection is growing, applied mathematical frameworks for North-Eastern Nigeria are scarce, and procurement decisions there still rely largely on intuition. This study addresses the gap by applying the Weighted Sum Method to a multi-item vendor allocation problem representative of the Ganye–Tougo agro-axis. The resulting model is normative: it tells managers what they should order from each vendor, subject to limited vendor capacity and strict budgets, rather than only describing current practice.

3. Methodology

This section outline the research design, data used, model assumptions, variable definitions, model formulation, and implementation.

3.1 Research design and data

The problem is modelled as a Multi-Objective Linear Programming (MOLP) problem, and the Weighted Sum Method is adopted as the solution technique because of its computational efficiency and ease of interpretation for decision-makers. The case-study parameters are representative values informed by secondary data from an agro-allied company; expert opinions gathered through interviews were used to judge the structure of the model and its applicability to real SSCM settings. Because the objectives and constraints are linear, every weighted-sum problem is itself a linear program and is solved exactly.

3.2 Assumptions

i. **Determinism:** demand, costs, capacities and vendor performance ratings are known and constant over the planning horizon.
ii. **Linearity:** relationships between variables and objectives are linear (no economies of scale or quantity discounts).
iii. **Non-negativity:** order quantities cannot be negative.
iv. **Multi-sourcing:** the buyer may split orders for one item among several vendors to mitigate risk.

3.3 Notation

Indices. $i = 1, \dots, m$ Indexes vendors; $j = 1, \dots, n$ indexes items.

Parameters.

D_j: Aggregate demand for item j over the planning period.

CAP_{ij}: Maximum quantity of item j that vendor i can supply.

C_{ij}: Unit purchasing cost of item j from vendor i (Naira).

Q_{ij}: Proportion of rejected units of item j from vendor i ($0 \leq Q_{ij} \leq 1$); environmental proxy.

L_{ij}: Proportion of late deliveries of item j from vendor i ($0 \leq L_{ij} \leq 1$); social proxy.

B: Total procurement budget (Naira).

S_j: Maximum allowable rejection rate for item j.

Decision variable

X_{ij}: Quantity of item j ordered from vendor i.

3.4 Objective functions

1. Economic objective: minimize total purchasing cost (Z_1).

$$min \quad Z_1 = \sum_i \sum_j \boldsymbol{C_{ij} X_{ij}} \qquad (\mathbf{1})$$

This is the traditional financial "Profit" pillar.

2. Environmental objective: This objective minimize total rejected units (Z_2) as shown in Eq. (2)

$$min \quad Z_2 = \sum_i \sum_j \boldsymbol{Q_{ij} X_{ij}} \qquad (\mathbf{2})$$

Rejected units represent physical waste, return-logistics emissions and resource inefficiency, so reducing them addresses the "Planet" pillar.

3. Social objective: This objective is to minimize late deliveries **(Z_3)** as shown in Eq. (3)

$$min \quad Z_3 = \sum_i \sum_j \boldsymbol{L_{ij} X_{ij}} \qquad (\mathbf{3})$$

Late deliveries disrupt production schedules and weaken the reliability on which downstream employees and customers depend, so reducing them addresses the "People" pillar.

3.5 Constraints

Five groups of constraints cover demand, vendor capacity, budget, quality and non-negativity.

1. **Demand Constraint:** Total orders from all vendors exactly meet the demand for each item. The statement is given in Eq. (4) mathematically.

$$\sum_{i} \boldsymbol{X_{ij}} = D_j, \quad \forall j \tag{4}$$

2. **Vendor capacity constraint:**. An order cannot exceed what the vendor can supply, see Eq. (5).

$$X_{ij} \leq CAP_{ij}, \quad \forall i,j \tag{5}$$

3. **Budget constraint:** Total spent cannot exceed the available budget, which is important for small and medium enterprises facing budget rigidity. The constraint is mathematically represented in Eq. (6).

$$\sum_{i}\sum_{j} C_{ij}X_{ij} \leq B \tag{6}$$

4. **Quality constraint:** The rejected quantity of each item cannot exceed the permitted share of its demand, the relation is given in Eq. (7).

$$\sum_{i} Q_{ij}X_{ij} \leq S_j D_j, \quad \forall j \tag{7}$$

5. **Non-negativity restriction:** That is no negative quantity is allowed. This is reflected in Eq. (8).

$$X_{ij} \geq 0, \quad \forall i,j \tag{8}$$

The Complete Model is given in Eq.

$$\left.\begin{aligned} &\min \quad Z_1 = \textstyle\sum_i \sum_j \boldsymbol{C_{ij}X_{ij}} \\ &\min \quad Z_2 = \textstyle\sum_i \sum_j \boldsymbol{Q_{ij}X_{ij}} \\ &\min \quad Z_3 = \textstyle\sum_i \sum_j \boldsymbol{L_{ij}X_{ij}} \\ &\boldsymbol{Subject\ \ to}: \\ &\textstyle\sum_i \boldsymbol{X_{ij}} = D_j, \quad \forall j \\ &X_{ij} \leq CAP_{ij}, \quad \forall i,j \\ &\textstyle\sum_i \sum_j C_{ij}X_{ij} \leq B \\ &\textstyle\sum_i Q_{ij}X_{ij} \leq S_j D_j, \quad \forall j \\ &X_{ij} \geq 0, \quad \forall i,j \end{aligned}\right\} \tag{9}$$

3.6 Weighted Sum Method and normalization

The three objectives are converted into a single scalar objective by assigning weights $w_1, w_2\ and\ w_3$ to be minimize, which is shown in Eq. (10)-Eq. (12);

$$min \quad Z_{combined} = \sum_{k} w_k Z_k^* \tag{10}$$

Subject to:

$$\textstyle\sum_k w_k = 1, \tag{11}$$ and

$$w_k \geq 0 \tag{12}$$

Where Z_*^* is the normalized value of objective k. because cost (in Naira) cannot be added directly to units of waste or lateness, and because an objective with large numerical values would otherwise dominate irrespective of its weight, normalization is essential in this case. Several approaches exist (linear, utopia-point, vector and goal-attainment normalization); the study adopts linear min–max normalization, which scales each objective to the interval $[0, 1]$. For a minimization objective, the model is given in Eq. (13);

$$f_{k,norm}(x) = \frac{\left(f_k(x) - f_{k,min}\right)}{\left(f_{k,max} - f_{k,min}\right)} \qquad (13)$$

For a maximization objective, the normalization is given by Eq. (14);

$$f_{k,norm}(x) = \frac{\left(f_{k,max} - f_k(x)\right)}{\left(f_{k,max} - f_{k,min}\right)} \qquad (14)$$

Where $f_{k,min}$is the value of an objective at its own single-objective optimum and $f_{k,max}$ is the worst value of that objective among the single-objective optima (the payoff table). Normalised objectives therefore lie between 0 (best) and 1 (worst).

3.7 Implementation and experimental design

Each weighted-sum problem is a linear program solved with the HiGHS solver through SciPy's linprog routine (Huangfu & Hall, 2018; Virtanen et al., 2020). The experiments comprise (i) a traditional scenario A with weights (1, 0, 0) and a balanced sustainable scenario B with weights (0.4, 0.3, 0.3); (ii) a sensitivity analysis over twelve weight vectors; and (iii) a sensitivity analysis over the procurement budget. The complete Python script is reproduced in Appendix A.

4. Results and Discussion

4.1 Case study data

The framework is applied to a processing company, "Adamawa Agro-Processors", that sources three items (maize, beans and rice) from three vendors (Vendor A, B and C; V1, V2 and V3) over a seven-month planning period (June–December 2025). Demand over the period is 10,000 tons of maize, 8,000 tons of beans and 12,000 tons of rice (see Table 1). The procurement budget is B = ₦10,500,000, about 10% above the minimum feasible cost (₦9,522,000), and the maximum allowable rejection rate is $S_j = 5\%$ of demand for every item. Vendor capacities are the monthly capacities in Table 2 multiplied by seven, so combined capacity exceeds demand by 26% for maize, 49% for beans and 11% for rice.

Table 1. Demand and unit purchasing cost (Naira per ton)

Item	Demand (tons)	Vendor A (V1)	Vendor B (V2)	Vendor C (V3)
Maize	10,000	200	190	210
Beans	8,000	350	340	360
Rice	12,000	400	380	410

Table 2. Vendor capacity: monthly (planning-period) tons

Vendor	Maize	Beans	Rice
Vendor A (V1)	600 (4,200)	700 (4,900)	500 (3,500)
Vendor B (V2)	500 (3,500)	400 (2,800)	600 (4,200)
Vendor C (V3)	700 (4,900)	600 (4,200)	800 (5,600)

Table 3. Rejection rate Q and late-delivery rate L

Vendor	Q maize	Q beans	Q rice	L maize	L beans	L rice
Vendor A (V1)	0.02	0.03	0.01	0.05	0.04	0.02
Vendor B (V2)	0.05	0.06	0.04	0.08	0.07	0.06
Vendor C (V3)	0.01	0.05	0.01	0.01	0.01	0.00

The vendors have distinct profiles. Vendor B is the cheapest (maize at ₦190 against ₦210 from Vendor C) but the weakest on sustainability: summed across the three items its rejection rates total 0.15 and its late-delivery rates 0.21. Vendor C is the most expensive but the most reliable (late-delivery rates summing to 0.02), and Vendor A is intermediate. See Table 3.

4.2 Normalization ranges

Solving each objective on its own with the script in Appendix A gives the payoff Table 4, from which the normalization ranges follow: ₦158,000 for cost, 171 tons for rejections and 461 tons for late deliveries. Across the whole set of single-objective optima, total cost varies by only 1.7%, whereas rejections and lateness vary far more.

Table 4. Payoff table (single-objective optima)

Objective minimized	Cost (₦)	Rejected (tons)	Late (tons)
Cost	9,522,000	858	1,230
Rejections	9,669,000	687	802
Late deliveries	9,680,000	709	769

4.3 Scenario results

Scenario A (traditional) uses weights (1, 0, 0) and scenario B (sustainable) uses (0.4, 0.3, 0.3). Moving from A to B increases total cost by ₦147,000 (1.5%) but reduces rejected units by 19.9% and late deliveries by 34.8%, as shown in Table 5.

Table 5. Optimization results by scenario

Metric	A: Cost focus	B: Balanced	Change
Total cost (₦)	9,522,000	9,669,000	+147,000 (+1.5%)
Rejected units (tons)	858	687	−171 (−19.9%)
Late deliveries (tons)	1,230	802	−428 (−34.8%)

In scenario A the cheapest vendor, V2, is used to its capacity for every item, then V1 is filled to capacity, and V3 supplies the remainder; V2 therefore provides 35% of total volume. In scenario B, V1 is again fully used, but V2's share falls to 12.7% (3,800 tons) and V3's rises from 23.0% to 45.3% (13,600 tons). The quality constraint is not binding in either scenario: rejected quantities (at most 330 tons of beans) stay below the permitted 500, 400 and 600 tons as shown in Table 6.

Table 6. Optimal allocation (tons) by item and vendor

Item	A: V1	A: V2	A: V3	B: V1	B: V2	B: V3
Maize	4,200	3,500	2,300	4,200	900	4,900
Beans	4,900	2,800	300	4,900	0	3,100
Rice	3,500	4,200	4,300	3,500	2,900	5,600

4.4 Sensitivity analysis

Weights. Twelve weight vectors were tested at a budget of ₦10.5 million. They produce only four distinct plans (Table 7), because the weighted-sum solution changes only when a weight shift makes a different vertex of the feasible region optimal. The balanced plan reaches the minimum possible rejections (687 tons) and is within 33 tons (4.3%) of the minimum possible lateness (769 tons). Putting most weight on reliability reduces lateness to 769 tons at an extra ₦11,000 but raises rejections to 709 tons.

Table 7. Effect of objective weights (w_1, w_2, w_3)

Weight vectors tested	Cost (₦)	Rejected (tons)	Late (tons)	V2 share
(1, 0, 0) to (0.7, 0.15, 0.15)	9,522,000	858	1,230	35.0%
(0.6, 0.2, 0.2), (0.5, 0.25, 0.25)	9,574,000	754	1,048	26.3%
(0.4, 0.3, 0.3), (0.2, 0.4, 0.4), (0, 1, 0)	9,669,000	687	802	12.7%
(0.2, 0.2, 0.6), (0.1, 0.1, 0.8), (0, 0, 1)	9,680,000	709	769	12.7%

Budget. With weights (0.4, 0.3, 0.3), a budget of ₦9.5 million is infeasible because the cheapest feasible plan costs ₦9,522,000. At ₦9.6 million the model can afford only a partial improvement; from ₦10.0 million the balanced plan is reached and further budget has no effect (Table 8). The sustainable plan therefore needs only a small budget margin above the minimum feasible spend.

Table 8. Effect of the procurement budget

Budget (₦)	Cost (₦)	Rejected (tons)	Late (tons)
9,500,000	Infeasible	–	–
9,600,000	9,574,000	754	1,048
10,000,000 to 12,000,000	9,669,000	687	802

4.5 Discussion

The results illustrate the trade-off at the heart of SSCM and show that it can be cheap to resolve. Scenario B shifts 6,700 tons from Vendor 2 to Vendor 3 at an average premium of about ₦22 per ton, which adds ₦147,000 to total spend (1.5%) and removes about one fifth of rejected units and over a third of late deliveries. The lowest unit price is therefore often a false economy: a small price premium buys a large improvement in quality and reliability. The saving that scenario A offers is real but small relative to the waste and disruption it leaves in place, and the premium can plausibly be recovered through lower reverse-logistics costs and fewer production stoppages, although the model does not quantify these.

Two features of the results are useful for managers. First, the allocation is multi-sourced in both scenarios, as vendor capacity prevents any one vendor from supplying everything; sustainability weights change the mix rather than forcing a single supplier. Second, the weight sensitivity shows stable plans over wide weight ranges, so a manager does not need precise weights: the choice among four plans is a policy choice between cost, waste and punctuality. The budget analysis adds that the sustainable plan needs only a modest margin over minimum feasible spend.

The findings are consistent with the literature reviewed above. Single-objective cost minimization neglects the environmental and social dimensions stressed by Seuring and Müller (2008) and Zimmer et al. (2016), and multi-objective formulations such as those of Govindan and Sivakumar (2016) and Ahmadini et al. (2021) can reconcile them. The contribution here is a simple, transparent formulation that small and medium agro-

processors in North-Eastern Nigeria can implement in a spreadsheet or a short script. Vendor B's prices remain competitive, so a buying firm might work with that vendor to improve quality and delivery rather than simply dropping it.

4.6 Limitations and future research

The case-study parameters are representative rather than observed values and should be validated with firm-level data. The model is deterministic and linear; future work should use stochastic or fuzzy programming to capture uncertainty in crop yields and transport times caused by weather and security conditions. Rejection and lateness are proxies for environmental and social performance, and explicit carbon-emission coefficients and richer social indicators would refine the model. The weighted sum method finds only supported Pareto-optimal solutions, so goal programming or other multi-objective techniques could be compared, and the offsetting savings from reduced reverse logistics should be modelled explicitly.

Author Contributions

Conceptualization, S. A. and U.M.M.; methodology, S.A.; software, S.A.; validation, S. A.; U.M.M. and I.J.D.; formal analysis, S.A.; investigation, S.A.; resources, S.A.; data curation, S.A.; writing—original draft preparation, S.A.; writing—review and editing, S. A.; U.M.M. and I.J.D.; visualization, S.A.; supervision, U.M.M.; project administration, U.M.M.; funding acquisition, S.A. All authors have read and agreed to the published version of the manuscript."

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Data Availability Statement

The data used in this study are provided in the manuscript.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Python implementation

The script below implements the model of Equations (1) to (13) and reproduces Tables 4 to 8. It requires Python with NumPy and SciPy; each weighted-sum problem is solved with the HiGHS linear programming solver.

```
import numpy as np
from scipy.optimize import linprog

ITEMS, VENDORS = ["Maize", "Beans", "Rice"], ["V1", "V2", "V3"]
D = np.array([10000, 8000, 12000.0])          # demand, tons (item)
C = np.array([[200, 190, 210],
              [350, 340, 360],
              [400, 380, 410]], float)        # Naira per ton (item x vendor)
Q = np.array([[.02, .05, .01],
              [.03, .06, .05],
              [.01, .04, .01]])               # rejection rates
L = np.array([[.05, .08, .01],
              [.04, .07, .01],
              [.02, .06, .00]])               # late-delivery rates
CAP_MONTHLY = np.array([[600, 700, 500],
                        [500, 400, 600],
                        [700, 600, 800]], float)   # vendor x item, tons per month
CAP = CAP_MONTHLY.T * 7                       # 7-month planning period (item x vendor)
S = np.array([.05, .05, .05])                 # maximum rejection share per item
B_DEFAULT = 10_500_000                        # budget, Naira


def solve(c, B):
    """Minimise c.x subject to demand, budget, quality and capacity constraints."""
    n = 9
    A_eq = np.zeros((3, n))
    for j in range(3):
        A_eq[j, 3*j:3*j+3] = 1                # demand: sum over vendors = D_j
    A_ub, b_ub = [C.flatten()], [B]           # budget
    for j in range(3):                        # quality: sum Q*X <= S_j * D_j
        r = np.zeros(n)
        r[3*j:3*j+3] = Q[j]
        A_ub.append(r)
        b_ub.append(S[j] * D[j])
    bounds = [(0, u) for u in CAP.flatten()]  # capacity and non-negativity
    return linprog(c, A_ub=np.array(A_ub), b_ub=b_ub, A_eq=A_eq,
                   b_eq=D, bounds=bounds, method="highs")


def objectives(x):
    return np.array([C.flatten() @ x, Q.flatten() @ x, L.flatten() @ x])


def weighted_sum(B, w):
    """Weighted Sum Method with min-max normalisation from the payoff table."""
    payoff = []
    for M in (C, Q, L):
        r = solve(M.flatten(), B)
        if not r.success:
            return None
        payoff.append(objectives(r.x))
    payoff = np.array(payoff)
    f_min, f_max = np.diag(payoff), payoff.max(axis=0)
    c = sum(w[k] * M.flatten() / (f_max[k] - f_min[k])
```

```
            for k, M in enumerate((C, Q, L)))
    r = solve(c, B)
    return None if not r.success else (r.x.reshape(3, 3), objectives(r.x), payoff)


if __name__ == "__main__":
    for name, w in [("A: cost focus", (1, 0, 0)), ("B: balanced", (.4, .3, .3))]:
        x, o, payoff = weighted_sum(B_DEFAULT, w)
        print(name, "cost=%.0f rejected=%.0f late=%.0f" % tuple(o))
        print(x.round(0))
    print("Payoff table:\n", payoff.round(0))
    for w in [(1, 0, 0), (.9, .05, .05), (.8, .1, .1), (.7, .15, .15),
              (.6, .2, .2), (.5, .25, .25), (.4, .3, .3), (.2, .4, .4),
              (0, 1, 0), (.2, .2, .6), (.1, .1, .8), (0, 0, 1)]:
        print("weights", w, "->", "cost=%.0f rej=%.0f late=%.0f"
              % tuple(weighted_sum(B_DEFAULT, w)[1]))
    for B in (9.5e6, 9.6e6, 10e6, 10.5e6, 11e6, 12e6):
        r = weighted_sum(B, (.4, .3, .3))
        print("budget", B, "INFEASIBLE" if r is None
              else "cost=%.0f rej=%.0f late=%.0f" % tuple(r[1]))
```