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Posted Date: 26 March 2026

doi: 10.20944/preprints202603.2109.v1

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Artificial Intelligence–Driven Viable First-Mile Food Supply Chains: A Unified Robust Stochastic Programming Approach with Immune-Inspired Adaptation

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Abstract

This study addresses the problem of designing viable first-mile agricultural supply chains under uncertainty, with a focus on small-scale production systems characterized by territorial heterogeneity and logistical constraints. A unified modeling framework is proposed, integrating a data-driven Rural Viability Index (RVI), a Unified Robust Stochastic Programming (URSP) formulation, and adaptive mechanisms inspired by the Human Immune System (HIS). The approach combines territorial assessment, uncertainty management, and endogenous adaptation within a single decision-making structure. The framework is applied to a fresh pea supply chain in Cundinamarca, Colombia, considering multiple uncertainty regimes and adaptive configurations. The results show that system performance is strongly influenced by the interaction between URSP weighting and the activation of adaptive mechanisms. Configurations with HIS activation consistently achieve higher net utility, improved viability indicators, and greater supply capacity, especially under scenarios with a stronger emphasis on disruptive conditions. At the same time, the analysis reveals trade-offs in environmental impact and labor demand, highlighting the multi-dimensional nature of supply chain viability. The findings demonstrate that viability is not achieved through isolated optimization components, but through the coordinated integration of territorial intelligence, uncertainty modeling, and adaptive response capabilities. From a methodological perspective, the study contributes by operationalizing viability within a unified optimization framework, bridging the gap between predictive analytics and prescriptive modeling. From a practical standpoint, the results suggest that first-mile supply chain design should incorporate adaptive mechanisms and spatial information as core elements to ensure sustained performance under uncertainty.

Keywords: supply chain viability; first-mile logistics; agricultural supply chains; Unified Robust Stochastic Programming; adaptive supply chains; Rural Viability Index; facility location under uncertainty

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1. Introduction

The design of agricultural supply chains has been widely addressed as a mechanism to improve efficiency, reduce operational costs, and enhance the connection between producers and markets, particularly in rural contexts characterized by structural limitations and high territorial dispersion [1]. These systems operate under significant uncertainty, where factors such as climate variability, seasonal production patterns, transportation availability, and road infrastructure conditions directly affect the stability of logistics flows and the overall performance of the network [2].

Within these systems, first-mile logistics, associated with the collection of agricultural products from dispersed production units to aggregation or distribution points, represents one of the most critical and least structured stages of the supply chain [3]. In smallholder-based agricultural systems, this stage is often characterized by low coordination, fragmented production, and strong dependence on territorial conditions, leading to increased post-harvest losses, higher transportation costs, and limited market access [4]. These constraints not only affect operational efficiency but also compromise the continuity and functional stability of the supply chain, particularly under disruptive conditions [5].

In this context, the concept of supply chain viability has emerged as an integrative framework that extends beyond traditional efficiency- or resilience-oriented approaches [6]. Viability refers to the ability of a system to maintain its functionality over time under changing and disruptive environments, through the interaction of resilience, agility, and sustainability capabilities [7]. From this perspective, supply chains are not only expected to resist disruptions but to adapt structurally and operationally to preserve performance and continuity [8]. Despite the growing interest in viability-oriented design, existing literature presents an important limitation. Most mathematical optimization models for agricultural supply chains focus on global network decisions, such as facility location, flow allocation, or production planning, while the first-mile stage is typically simplified or aggregated within the modeling structure [9]. As a result, critical aspects such as territorial heterogeneity, connectivity constraints, and localized vulnerabilities are not explicitly captured, limiting the ability of these models to represent the true structural drivers of system. Furthermore, although robust and stochastic optimization approaches have been widely applied to address uncertainty in agricultural supply chains, they mainly focus on exogenous variability in demand, supply, and costs [10]. These approaches rarely incorporate endogenous adaptive mechanisms that allow the system to dynamically respond to disruptions. Consequently, viability is often treated as an ex-post outcome of the model rather than as an intrinsic property embedded in the system design.

To address these limitations, bio-inspired approaches, particularly those based on the Human Immune System (HIS), have been proposed as a conceptual framework for modeling systems capable of detecting anomalies, activating adaptive responses, and generating memory from past events [11]. These systems exhibit properties such as fault tolerance, distributed decision-making, and adaptive learning, which are consistent with the requirements of viable supply chains operating under uncertainty [12,13]. However, their application in mathematical optimization models for agricultural supply chains remains limited, especially in relation to structural decisions such as facility location.

This study proposes an integrated approach for the design of first-mile logistics systems in agricultural supply chains, combining Unified Robust Stochastic Programming (URSP) with adaptive mechanisms inspired by the Human Immune System. The model explicitly incorporates viability as a design criterion, through the integration of a Rural Viability Index (RVI), which captures territorial conditions and regulates the location, activation, and operation of aggregation centers within the network.

The proposed framework is validated through a case study of a fresh pea (*Pisum sativum*) supply chain in Colombia, characterized by small-scale producers, geographic dispersion, and strong dependence on intermediaries. This context provides a relevant setting to analyze how the integration of adaptive mechanisms and viability-based design influences network configuration, economic performance, and system response under uncertainty.

2. Literature Review

2.1. Optimization Models in Agricultural Supply Chains

Mathematical optimization has been widely employed to support decision-making in agricultural supply chains, particularly through Mixed-Integer Linear Programming (MILP) formulations that allow the representation of facility location, flow allocation, and transportation planning under capacity and resource constraints [14]. These models have proven effective in improving operational efficiency and reducing costs in systems characterized by fragmented production and geographical dispersion, especially in developing regions where infrastructure limitations play a critical role [2,15]. Moreover, recent studies have extended these formulations toward multi-objective optimization, incorporating environmental and social dimensions alongside economic performance, which is particularly relevant in rural supply chains involving smallholder farmers [16]. In this context, approaches such as those discussed by Shekarabi et al. [17] and Kalantari Khalil Abad et al. [18] highlight the importance of integrating sustainability criteria into network design decisions.

Despite these advances, a recurrent limitation in the literature is the treatment of the supply chain structure as largely static, where early-stage logistics, particularly first-mile collection, are either simplified or aggregated within broader network representations. This simplification prevents models from capturing the spatial and operational complexity associated with dispersed agricultural production systems [19]. As a result, key structural decisions related to the location and activation of aggregation points are often based on average or homogeneous assumptions, which do not reflect real territorial conditions [20]. This limitation becomes especially critical in systems where logistical inefficiencies at the collection stage propagate through the entire network, affecting both performance and stability. Therefore, while MILP-based models provide a solid foundation for agricultural supply chain design, their ability to represent structurally constrained first-mile systems remains limited.

2.2. Uncertainty Modeling in Agricultural Supply Chains

Uncertainty is an inherent characteristic of agricultural supply chains, driven by factors such as climate variability, yield fluctuations, demand volatility, and disruptions in transportation infrastructure [21]. To address these challenges, stochastic programming and robust optimization approaches have been widely adopted, enabling decision-makers to evaluate multiple scenarios and hedge against adverse conditions [22]. Unified robust stochastic programming (URSP) has emerged as a flexible framework that combines probabilistic and worst-case perspectives, allowing for more balanced and resilient decision-making under uncertainty [23].

These approaches have significantly improved the robustness of supply chain configurations by incorporating uncertainty directly into the modeling process. For example, they allow for the evaluation of trade-offs between expected performance and risk exposure, which is particularly relevant in agricultural contexts where variability is high and margins are often low [24]. However, as noted in recent studies, most of these models treat uncertainty as an external factor affecting parameters such as demand or supply, rather than as a trigger for internal system adaptation [25]. Consequently, while the solutions obtained may be robust in a statistical sense, they do not necessarily reflect the system's capacity to reorganize itself dynamically when disruptions occur. This distinction is critical when moving from robustness toward viability, as the latter requires the explicit modeling of adaptive responses rather than passive resistance to variability.

2.3. Viability and Adaptive Supply Chains

The concept of supply chain viability has been introduced to address the limitations of traditional resilience-focused approaches by emphasizing the system's ability to maintain functionality over time under changing and disruptive conditions. According to Ivanov and Dolgui [7] and Ivanov and Keskin [26], viability integrates resilience, agility, and sustainability into a unified framework that reflects the dynamic behavior of supply chains operating in uncertain environments. Unlike resilience, which is primarily concerned with recovery after disruptions, viability focuses on the continuous adaptation and reconfiguration of the system to preserve its performance and structural integrity [27].

Recent research has explored viability in various contexts, including disruption management, sustainable supply chain design, and multi-objective optimization. For instance, Rezaei Zeynali et al. [28] incorporate resilience and sustainability metrics into network design, while other studies emphasize the importance of balancing economic and environmental objectives. However, a key limitation persists viability is often evaluated as an outcome of the model rather than embedded as a design principle. This means that the structural configuration of the supply chain is not explicitly guided by viability considerations, particularly in relation to localized constraints such as those found in first-mile logistics.

In this regard, bio-inspired approaches, especially those based on the Human Immune System (HIS), offer a promising conceptual framework for modeling adaptive systems [11]. These approaches introduce mechanisms such as anomaly detection, response activation, and memory, which enable systems to learn from past disruptions and improve their behavior over time [29]. While these concepts align closely with the requirements of viable supply chains, their integration into formal mathematical optimization models remains limited, particularly in agricultural contexts where spatial and territorial factors play a dominant role.

2.4. Artificial Intelligence in Supply Chains and Integration with Optimization Models

The incorporation of artificial intelligence (AI) and machine learning (ML) into supply chain management has gained significant attention in recent years, particularly as a means of enhancing decision-making through data-driven insights [30]. A substantial body of literature demonstrates that ML techniques can be used to predict demand, classify risks, estimate operational parameters, and evaluate system performance, thereby improving the accuracy and responsiveness of planning processes. For example, Hu and Monticolo [31] show that ML models can be used to predict supply chain risks in advance, enabling proactive decision-making and reducing system vulnerability. Similarly, Rajendran et al. [32] employ ML techniques to analyze customer behavior in sustainable supply chains, highlighting the ability of these models to capture complex relationships between environmental, social, and operational variables.

Beyond predictive applications, several studies have explored the integration of ML with optimization models, demonstrating that AI can generate parameters or indicators that directly influence decision-making. Ghasemi et al. [33] illustrate how ML can be used to estimate key operational parameters, such as the proportion of usable supply, which are then incorporated into a multi-objective optimization model. In a similar vein, Ghaffari et al. [34] show that ML-derived demand functions can be embedded into optimization formulations, affecting both constraints and objective functions. These approaches confirm that ML can serve not only as a forecasting tool but also as a structural component of mathematical models.

Moreover, hybrid frameworks combining ML with decision-support methods have been proposed to generate composite indicators that guide supply chain decisions. Rezaei Zeynali et al. [28] use ML to evaluate potential partners in a reverse supply chain, while Sarkheil et al. [35] develop a hybrid ML framework to construct ESG-based performance indices that capture multidimensional system characteristics. In addition, Sánchez-Pravos et al. [36] integrate ML-based emission predictions into a multi-objective routing model, demonstrating how data-driven variables can influence optimization outcomes in sustainability-oriented supply chains.

Despite these advances, the current literature reveals an important limitation. Most studies use ML outputs to support operational decisions, such as routing, pricing, or supplier selection, rather than to inform structural decisions related to network design. There is limited evidence of ML-derived indicators being incorporated as territorial or spatial decision drivers within facility location models. This gap is especially relevant in agricultural supply chains, where spatial heterogeneity and local conditions play a critical role in determining system performance and viability.

2.5. Research Gap

The reviewed literature highlights several gaps that motivate this study. First, existing optimization models for agricultural supply chains do not explicitly account for the role of first-mile logistics as a structural determinant of system performance and viability. Second, while robust and stochastic approaches effectively address uncertainty, they lack mechanisms for endogenous adaptation that allow the system to dynamically respond to disruptions. Third, although AI has been successfully integrated into supply chain decision-making, its application has been primarily limited to predictive and operational contexts, with limited use in structural decision-making processes.

In response to these limitations, this study proposes an integrated framework that combines AI-based territorial assessment, robust stochastic optimization, and immune-inspired adaptive mechanisms. By incorporating a Rural Viability Index (RVI) into a MILP-based model for first-mile logistics design, the proposed approach enables the explicit integration of territorial conditions into structural decision-making. This contribution advances the literature by linking AI-driven insights with viability-oriented supply chain design, particularly in the context of agricultural systems characterized by high uncertainty and spatial dispersion.

3. Methodology

This study proposes a hybrid methodological framework for the design of first-mile logistics systems in agricultural supply chains, integrating data-driven analysis, mathematical optimization, and adaptive mechanisms inspired by the Human Immune System (HIS). Unlike traditional approaches that focus solely on optimizing decisions under predefined conditions, the proposed framework explicitly incorporates viability as a structural property of the system.

The methodology is organized into three interconnected layers. At the first level, a Rural Viability Index (RVI) is constructed based on exogenous territorial, productive, and logistical variables through a previously developed artificial intelligence approach. At the second level, the RVI is embedded as a parameter within a Mixed-Integer Linear Programming (MILP) model, which determines the location and operation of collection centers as well as the allocation of flows in the first-mile logistics network. At the third level, the model is extended through a Unified Robust Stochastic Programming (URSP) framework combined with adaptive mechanisms inspired by the Human Immune System, allowing the evaluation of system performance under different uncertainty regimes.

This integrated approach enables the simultaneous representation of territorial heterogeneity, operational uncertainty, and adaptive capacity, overcoming the limitations of static models that treat these elements in isolation. As a result, the framework provides a more realistic basis for analyzing the viability of agricultural supply chains, particularly in contexts characterized by dispersed production and infrastructure constraints.

3.1. RVI Construction

The Rural Viability Index (RVI) was constructed as a normalized composite indicator intended to represent the relative territorial suitability of potential first-mile collection nodes. The index was defined using a set of variables associated with demographic pressure, climatic conditions, logistical accessibility, producer capabilities, and prior delivery performance.

The construction of the RVI is based on a set of variables that characterize each producer's location and its surrounding environment. These variables were selected to represent three main dimensions:

- Territorial and accessibility conditions, including population density, average precipitation, and distance to the collection center. These variables influence both logistical feasibility and operational exposure to environmental constraints.
- Human and productive capacity variables, such as producer education level and machinery availability, which reflect the ability of producers to comply with logistical requirements and sustain regular supply flows.
- Operational reliability variables, including the number of days with impassable roads and the number of previous delivery failures, which directly capture historical disruptions in first-mile logistics.

In addition, two complementary factors were incorporated:

- Topographic factor ($F2$), derived from altitude and slope conditions, representing terrain-related constraints that affect accessibility and transport performance.
- Contextual factor ($F7$), representing an additional variability component integrated into the index to capture latent contextual effects not explicitly modeled by the other variables.

The RVI was initially constructed using a weighted linear combination of the normalized input variables. Each variable was scaled relative to its maximum value to ensure comparability across dimensions. The weighting structure reflects the relative importance of each factor in determining territorial viability, with higher weights assigned to variables directly associated with logistical accessibility and operational reliability. The resulting composite score was subsequently normalized to the $[0, 1]$ interval. Under this formulation, higher RVI values indicate less favorable territorial and operational conditions, whereas lower values correspond to more viable locations for the installation of collection centers.

To support the analytical robustness of the index and evaluate its predictive structure, a supervised learning stage was incorporated. In this stage, the previously computed RVI values were used as target outputs, while the set of explanatory variables described above was used as input features.

Three regression-based machine learning algorithms were considered:

- Random Forest Regressor, to capture non-linear relationships through ensemble decision trees.
- Gradient Boosting Regressor, to model complex interactions using sequential error correction.
- K-Nearest Neighbors (KNN), to provide a distance-based approximation of the index.

Prior to training, the input variables were standardized to ensure compatibility across algorithms, particularly for distance-based methods such as KNN. The dataset was then divided into training and testing subsets using a 75/25 split. Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2).

This stage does not redefine the index but provides a data-driven approximation of the RVI, allowing the identification of learning structures capable of reproducing the composite indicator with high accuracy. Comparing models supports the robustness of the index and validates its internal consistency. This formulation provides a transparent and interpretable baseline representation of territorial viability, while allowing the integration of heterogeneous variables into a single decision-support metric.

Role of the RVI in the Optimization Model

Within the proposed framework, the RVI is incorporated as an exogenous parameter in the MILP formulation. Its primary function is to guide structural decisions related to the location and operation of collection centers in the first-mile network.

Specifically, the RVI is used to:

- impose minimum viability thresholds for candidate locations,
- introduce penalty terms associated with low-viability nodes, and
- prioritize locations with more favorable territorial conditions.

By embedding the RVI into the optimization model, the framework establishes a direct link between territorial assessment and structural decision-making. This integration allows the model to move beyond purely cost-driven configurations, incorporating spatial intelligence into the design of agricultural supply chain networks.

3.2. MILP Formulation Under the URSP Framework

The proposed URSP–MILP framework is developed under a set of assumptions that ensure tractability while preserving the essential characteristics of first-mile agricultural logistics systems. These assumptions reflect both the structure of the available data and the strategic nature of the decisions addressed in this study. The set of candidate collection centers and producers is considered known and fixed throughout the planning horizon. The model therefore focuses on selecting and operating existing alternatives rather than generating new locations. This is consistent with rural supply chains, where infrastructure expansion is typically constrained and decision-making occurs within a predefined spatial configuration.

The planning horizon is discretized into a finite number of periods, and all flows are aggregated at this level. As a result, short-term dynamics such as intra-day routing or temporary storage fluctuations are not explicitly represented. The model instead captures medium-term operational behavior, which aligns with the objective of designing first-mile logistics structures.

Transportation costs between producers and collection centers are assumed to be proportional to distance and remain constant within each period. Variations due to road conditions or weather are not modeled explicitly in the cost structure. Instead, these effects are indirectly captured through the uncertainty scenarios and the Rural Viability Index (RVI), which reflects territorial constraints and accessibility conditions.

RVI is treated as an exogenous parameter derived from a prior data-driven process. It is assumed to remain stable over the planning horizon and to provide a consistent representation of the relative suitability of each location. The model does not update the index dynamically, nor does it attempt to recalibrate it during optimization, as its role is to inform structural decisions rather than evolve within the decision process.

Uncertainty is represented through a combination of stochastic and robust scenarios. The stochastic component captures regular variability in agricultural supply, while the robust component represents severe disruptions that cannot be fully characterized through probabilistic information. The scenario sets are assumed to be sufficiently representative of the range of operating conditions faced by the system.

Adaptive mechanisms inspired by the Human Immune System are incorporated into model detection, response, and memory processes. These mechanisms influence operational behavior through flow adjustments and penalty structures, but do not modify the structural decisions directly. Their purpose is to provide a simplified yet meaningful representation of adaptive capacity within the supply chain.

All model parameters, including costs, capacities, and scenario factors, are assumed to be known at the time of optimization. While this assumption simplifies the representation of real-world uncertainty, it is necessary to ensure solvability and is partially addressed through the URSP formulation, which explicitly accounts for variability and disruption.

These assumptions are not intended to oversimplify the system, but to provide a structured representation that captures the key interactions between territorial conditions, uncertainty, and adaptive behavior in first-mile agricultural logistics.

The proposed optimization model is formulated as a Mixed-Integer Linear Programming (MILP) problem embedded in a Unified Robust Stochastic Programming (URSP) architecture. Using URSP is essential in this study because the first-mile logistics system is exposed to different uncertainty regimes that cannot be adequately represented through a single deterministic, stochastic, or robust formulation alone. Instead of treating uncertainty through isolated models, the proposed framework integrates three interrelated components: a deterministic baseline, a stochastic recourse structure, and a robust protection layer. This allows the model to capture not only average operating conditions, but also demand and supply variability, as well as severe disruptions affecting the viability of the system.

Within this architecture, the deterministic layer defines the strategic backbone of the network, particularly the opening of collection centers, the assignment of capacity levels, and the financial structure associated with these infrastructure decisions. The stochastic layer introduces scenario-dependent adjustments associated with regular operational variability, especially in agricultural supply and first-mile flows. The robust layer, in turn, captures extreme and disruptive conditions that may not be adequately represented through probabilistic expectations, such as severe productivity losses or structural logistical failures. As a result, the model does not simply optimize under uncertainty; it explicitly combines expected performance, adaptability, and protection against adverse conditions within a unified decision framework.

To improve readability and avoid excessively long declarations, the notation is expressed using compact symbols. The main sets of the model are defined as follows:

Symbol	*Description*
$p \in P$	Producers
$a \in A$	Candidate collection centers
$k \in K$	Capacity levels
$t \in T$	Time periods
$s \in S$	Stochastic scenarios
$r \in R$	Robust scenarios

The deterministic model is treated as the baseline regime and therefore does not require a specific scenario index. The stochastic and robust layers are represented explicitly through sets S and R, respectively. The model includes structural, territorial, productive, and economic parameters. Table 1 summarizes the core notation.

Table 1. Main parameters of the URSP-MILP model.

Symbol	Description
ω	URSP weight assigned to the robust component
β	CVaR weight in the objective function
π_s	Probability of stochastic scenario (s)
ρ_r	Weight of robust scenario (r)
cap_k	Capacity associated with level (k)
f_{ak}	Fixed cost of opening center (a) with capacity (k)
ivr_a	Rural Viability Index at location (a)
ivr^{min}	Minimum RVI threshold for opening a center
pen_a^{ivr}	Penalty associated with low-RVI locations
q_{pt}^0	Baseline supply of producer (p) at period (t)
ϕ_{ps}	Stochastic supply factor for producer (p) in scenario (s)
λ_{pr}	Robust disruption factor for producer (p) in scenario (r)
c_{pa}^{tr}	Transport cost from producer (p) to center (a)
c_a^{op}	Operating cost of center (a)
pr_t	Selling price per unit in period (t)
$\bar{u}_{pt}$	Minimum viability yields threshold for producer (p) at period (t)
M	Large positive constant

These parameters allow the model to combine territorial feasibility, logistics costs, and uncertainty-adjusted supply behavior in a single decision framework.

The decision variables are divided into strategic variables, which are scenario-independent and define the network structure, and operational variables, which are scenario-dependent and allow the system to adapt across uncertainty regimes.

doi:10.20944/preprints202603.2109.v1

Table 2. Main decision variables.

Symbol	Description
$z_{ak} \in \{0,1\}$	1 if center (a) is opened with capacity (k)
$y_a \in \{0,1\}$	1 if center (a) is active
$x^D_{pat} \geq 0$	Flow from producer (p) to center (a) in period (t) under the deterministic regime
$x^S_{pat} \geq 0$	Flow from producer (p) to center (a) in period (t) under stochastic scenario (s)
$x^R_{patr} \geq 0$	Flow from producer (p) to center (a) in period (t) under robust scenario (r)
u^D_t	Net utility in period (t) under the deterministic regime
u^S_{ts}	Net utility in period (t) under stochastic scenario (s)
u^R_{tr}	Net utility in period (t) under robust scenario (r)
ζ	VaR-related auxiliary variable
$\varepsilon_r \geq 0$	Positive deviation of robust scenario (r) from (\zeta)
$cvar$	Conditional Value-at-Risk term

This notation keeps the structure compact while preserving the distinction between the three URSP components.

Unified Objective Function

The objective function maximizes a weighted viability-oriented utility that combines deterministic performance, expected stochastic utility, and robust utility penalized through a risk term. In compact form, the URSP objective is expressed as:

$$\max\ Z = (1-\omega)\Big(\sum_{t\in T} u^D_t + \sum_{s\in S} \pi_s \sum_{t\in T} u^S_{ts}\Big) + \omega\Big(\sum_{r\in R} \rho_r \sum_{t\in T} u^R_{tr} - \beta\, cvar\Big)$$

This formulation reflects the core logic of URSP. The first term captures the deterministic baseline and the expected value of the stochastic regime, representing normal operation and uncertainty with known probabilistic structure. The second term captures the contribution of robust scenarios, weighted according to their relevance, while incorporating a CVaR-based penalty that protects the system against extreme utility deterioration. Consequently, the model does not optimize for average efficiency alone; it balances expected performance and protection against severe losses.

The CVaR component is defined as:

$$cvar = \zeta + \frac{1}{1-\alpha}\sum_{r\in R} \rho_r\ \xi_r$$

subject to:

$$\xi_r \geq \zeta - \sum_{t\in T} u^R_{tr}, \forall r \in R$$

$$\xi_r \geq 0, \forall r \in R$$

where α denotes the confidence level. This risk structure allows the model to penalize adverse robust outcomes beyond a chosen threshold, reinforcing the viability-oriented nature of the formulation.

Deterministic Strategic Layer

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The deterministic layer defines the structural configuration of the first-mile network. It determines which candidate collection centers are activated, under which capacity levels, and under what territorial conditions.

The opening of a center is constrained by:

$$\sum_{k \in K} z_{ak} \leq 1, \forall a \in A$$

$$y_a = \sum_{k \in K} z_{ak}, \forall a \in A$$

A collection center can only be opened if its location satisfies the minimum territorial viability requirement:

$$ivr_a\, y_a \geq ivr^{min}\, y_a, \forall a \in A$$

This restriction is central to the framework because it embeds territorial intelligence directly into structural decision-making. In addition, low-RVI locations can generate a penalty in the economic balance, ensuring that opening a center in a weak territorial location is only selected when compensated by other strategic benefits.

Capacity feasibility is enforced through:

$$\sum_{p \in P} x^D_{pat} \leq \sum_{k \in K} cap_k\, z_{ak}, \forall a \in A, \forall t \in T$$

and each producer can only deliver to active centers:

$$x^D_{pat} \leq M y_a, \forall p \in P, a \in A, t \in T$$

This deterministic layer acts as the common structural backbone for the stochastic and robust recourse layers.

Stochastic Recourse Layer

The stochastic layer captures supply variability under known-unknown uncertainty. In this regime, the supply available from each producer is adjusted through scenario-dependent factors:

$$q^S_{pts} = q^0_{pt}\, \phi_{ps}, \forall p \in P, t \in T, s \in S$$

The stochastic flows are then constrained by:

$$\sum_{a \in A} x^S_{pats} \leq q^S_{pts}, \forall p \in P, t \in T, s \in S$$

$$\sum_{p \in P} x^S_{pats} \leq \sum_{k \in K} cap_k\, z_{ak}, \forall a \in A, t \in T, s \in S$$

These constraints allow the system to react operationally to variability in agricultural availability while keeping the strategic structure fixed. This is a key feature of the URSP approach: strategic infrastructure decisions are shared across regimes, while recourse flows adapt to the realization of stochastic conditions.

Robust Protection Layer

The robust layer represents unknown-unknown or highly disruptive conditions, such as severe productivity losses or extreme first-mile bottlenecks. In this regime, producer supply is modified through robust deterioration factors:

$$q^R_{ptr} = q^0_{pt}(1 - \lambda_{pr}), \forall p \in P, t \in T, r \in R$$

The robust recourse constraints are given by:

$$\sum_{a \in A} x^R_{patr} \leq q^R_{ptr}, \forall p \in P, t \in T, r \in R$$

 doi:10.20944/preprints202603.2109.v1

$$\sum_{p \in P} x_{patr}^{R} \leq \sum_{k \in K} cap_k \, z_{ak}, \forall a \in A, t \in T, r \in R$$

The role of this layer is not merely to produce conservative solutions. Rather, it allows the model to test the viability of the network configuration under structurally adverse conditions and to internalize those risks through the objective function. In this sense, the robust component is fully embedded within the URSP architecture, rather than treated as an external stress test.

Utility Balance under the Three Regimes

For each regime, net utility is computed from revenues minus transport, operating, fixed, and penalty costs. In compact notation:

$$u_t^D = rev_t^D - cost_t^D$$
$$u_{ts}^S = rev_{ts}^S - cost_{ts}^S, \forall s \in S$$
$$u_{tr}^R = rev_{tr}^R - cost_{tr}^R, \forall r \in R$$

where revenues depend on the total amount collected and sold, while costs include transport from producers to centers, center operation, fixed opening costs, and penalties associated with low-RVI locations or adaptation requirements. This unified balance makes it possible to compare system performance consistently across normal, variable, and disruptive operating conditions.

The proposed formulation should be understood as a unified viability-oriented optimization architecture rather than as a conventional robust model. The deterministic layer anchors the design, the stochastic layer captures regular variability, and the robust layer represents severe disturbances. Their simultaneous integration through a weighted objective function enables the model to identify configurations that are not only cost-efficient, but also territorially feasible, operationally adaptable, and structurally protected against extreme deterioration.

This distinction is important because the objective is not simply to find a conservative solution. Instead, the model seeks a configuration capable of sustaining logistics functionality across multiple uncertainty regimes, which is consistent with the notion of supply chain viability adopted in this study.

HIS-Based Adaptive Mechanisms

The proposed URSP–MILP formulation is extended through the incorporation of adaptive mechanisms inspired by the Human Immune System (HIS), with the objective of enabling the supply chain to detect, respond to, and learn from disruptions occurring in first-mile logistics. Unlike conventional optimization models that rely solely on pre-defined constraints and recourse decisions, the HIS-based layer introduces endogenous response capabilities that modify system behavior across stochastic and robust regimes.

Conceptual Mapping between HIS and Supply Chain Elements

The integration of HIS principles is based on a functional analogy between biological immune processes and supply chain dynamics. In this mapping, disruptions affecting first-mile logistics—such as supply shortages, road inaccessibility, or delivery failures—are interpreted as antigens, while the system's response mechanisms are modeled as immune reactions activated through detection and adaptation processes.

Within this framework:

- Sentinel nodes act as detection agents, monitoring deviations in supply availability and logistical performance.
- Adaptive responses correspond to operational adjustments, such as reallocating flows, activating alternative centers, or modifying delivery patterns.
- Memory mechanisms store information about previous disruptions, influencing future decisions under similar conditions.

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This analogy allows the model to move beyond static representations of uncertainty and incorporate a dynamic layer of system regulation.

Detection Mechanism (Sentinel Layer)

The first component of the HIS-based extension is the detection of disruptions through a set of sentinel conditions embedded in the model. These conditions identify when the system deviates from expected operational behavior.

For each producer and period, a disruption signal is triggered when the realized supply under a given regime falls below a minimum viability threshold:

$$\delta_{pt\omega} = \begin{cases} 1 & \text{if } q_{pt\omega} < \bar{u}_{pt} \\ 0 & \text{otherwise} \end{cases}$$

where $\omega \in \{S, R\}$ represents stochastic and robust regimes, respectively.

The binary variable $\delta_{pt\omega}$ acts as an indicator of stress in the system. When activated, it signals that the current configuration is insufficient to sustain expected operations, thereby triggering adaptive responses. This detection mechanism is critical because it transforms passive uncertainty representation into an active monitoring process.

Adaptive Response Mechanism

Once a disruption is detected, the model allows for adaptive adjustments in the allocation of flows and the utilization of network resources. These responses are not arbitrary; they are constrained by the existing infrastructure and capacity decisions defined in the deterministic layer.

Adaptive responses are implemented through:

- Flow reallocation across centers, allowing producers to redirect supply to alternative nodes when disruptions occur.
- Activation of underutilized capacity, enabling the system to absorb fluctuations in supply.
- Penalty adjustments reflecting the additional cost associated with operating under stressful conditions.

This behavior is captured through scenario-dependent decision variables and penalty structures in the objective function. For instance, the cost structure under disrupted regimes includes additional terms that penalize deviations from normal operating conditions, ensuring that adaptation is incorporated into the economic evaluation of the system.

Memory Mechanism

A key feature of the HIS-inspired framework is the incorporation of a memory mechanism that allows the system to retain information about past disruptions and adjust future behavior accordingly. This is particularly relevant in agricultural systems where certain disruptions—such as seasonal accessibility issues or recurrent logistical bottlenecks—occur repeatedly over time.

The memory mechanism is represented through a cumulative indicator:

$$m_p = \sum_{t \in T} \sum_{\omega \in \{S,R\}} \delta_{pt\omega}$$

which captures the frequency and intensity of disruptions experienced by each producer. This information is then used to influence decision-making, for example by:

- increasing the effective penalty associated with unreliable nodes,
- prioritizing more stable producers in flow allocation,
- or indirectly affecting the attractiveness of certain collection centers.

Although the memory mechanism does not alter the structural decisions directly, it introduces a temporal dimension to the evaluation of system performance, reinforcing the adaptive capacity of the network.

Integration with the URSP Framework

HIS-based mechanisms are fully integrated into URSP architecture rather than treated as an external layer. Detection variables ($\delta_{pt\omega}$) and memory indicators (m_p) influence both the operational constraints and the objective function across stochastic and robust scenarios.

In particular:

- Detection triggers additional costs and adaptation requirements in disrupted scenarios.
- Memory affects the weighting of penalties and the evaluation of system performance over time.
- Adaptive flows are incorporated into the stochastic and robust recourse decisions.

This integration ensures that the system does not simply react to uncertainty, but actively adjusts its behavior based on both current conditions and past experiences. The incorporation of HIS-inspired mechanisms directly supports the concept of supply chain viability adopted in this study. While the URSP framework ensures robustness and performance under uncertainty, the HIS layer introduces the ability to detect disruptions, respond adaptively, and learn from past events. This combination enables the model to identify configurations that are not only cost-efficient but also capable of sustaining functionality across different uncertainty regimes. In this sense, the HIS-based extension transforms the optimization model into a dynamic decision-support system that captures key properties of viable supply chains, including adaptability, robustness, and learning capacity.

Performance and Viability Metrics

The evaluation of the proposed framework is based on a set of performance and viability metrics that capture the economic, operational, financial, and structural behavior of the supply chain under different uncertainty regimes. Rather than relying on a single indicator, the assessment adopts a multidimensional perspective, consistent with the concept of supply chain viability, which requires the system to sustain functionality, adapt to disruptions, and maintain acceptable performance over time.

The primary economic indicator of the model is the net utility, computed under each regime (deterministic, stochastic, and robust). For each case, utility is defined as total revenue minus operational, transportation, fixed, and penalty costs:

$$
\begin{aligned}
u_t^D &= rev_t^D - cost_t^D \\
u_{ts}^S &= rev_{ts}^S - cost_{ts}^S, \forall s \in S \\
u_{tr}^R &= rev_{tr}^R - cost_{tr}^R, \forall r \in R
\end{aligned}
$$

This structure ensures consistency across regimes and allows direct comparison between expected performance and performance under disruption. The expected utility is obtained through the probabilistic aggregation of stochastic scenarios, while robust utility captures system behavior under adverse conditions. Together, these indicators provide a comprehensive view of economic performance across the URSP framework.

To evaluate the exposure of the system to adverse conditions, the model incorporates a Conditional Value-at-Risk (CVaR) measure derived from the robust component of the objective function. The CVaR captures the expected loss beyond a given confidence level and is computed as:

$$
cvar = \zeta + \frac{1}{1-\alpha}\sum_{r\in R} \rho_r\ \xi_r
$$

 doi:10.20944/preprints202603.2109.v1

This metric reflects the severity of unfavorable outcomes and provides a quantitative measure of the system's vulnerability to extreme disruptions.

In addition, the financial stability of the system is assessed using the Altman Z-score, which is used as a proxy for financial viability. This indicator combines multiple financial ratios into a single score, allowing the evaluation of the system's capacity to remain solvent under different operating conditions. The inclusion of the Z-score complements the CVaR by providing a structural perspective on financial health, beyond short-term performance metrics.

Operational performance is evaluated through indicators that capture the efficiency and reliability of first-mile logistics. These include:

- Total collected volume, representing the amount of product successfully transported from producers to collection centers.
- Unmet supply, reflecting the inability of the system to absorb available production under certain conditions.
- Flow variability across scenarios, indicating the sensitivity of the network to changes in supply and logistics conditions.

These indicators are particularly relevant in agricultural systems, where disruptions in first-mile logistics can lead to significant losses and inefficiencies. By analyzing these metrics across deterministic, stochastic, and robust regimes, the model provides insight into how well the system maintains operational continuity.

The role of territorial conditions in system performance is assessed through the Rural Viability Index (RVI), which directly influences the configuration of the network. The selection of collection centers is evaluated not only in terms of cost efficiency but also in terms of their territorial suitability. In this context, structural viability is interpreted as the alignment between the network configuration and the territorial conditions represented by the RVI. Configurations that rely heavily on low-viability locations are penalized, while those that prioritize high-viability nodes are favored. This approach ensures that the system design is consistent with the spatial constraints of the agricultural environment.

The adaptive capacity of the system is evaluated through the HIS-based mechanisms introduced. Two key indicators are considered:

- Disruption frequency, measured through the activation of sentinel variables, reflecting how often the system experiences stress conditions.
- Adaptation intensity, captured through the magnitude of flow adjustments and penalty costs associated with disrupted scenarios.

In addition, the memory indicator provides information on the persistence of disruptions over time, allowing the identification of structurally vulnerable producers or locations. These metrics provide a dynamic view of system behavior, highlighting its ability to respond to and learn from disruptions.

Integrated Viability Assessment

The combination of economic, risk, operational, territorial, and adaptive indicators enable a comprehensive evaluation of supply chain viability. Rather than focusing on a single dimension, the framework assesses whether the system can:

- maintain acceptable economic performance,
- limit exposure to extreme losses,
- sustain operational flows under variability,
- aligning with territorial conditions, and
- adapt to and learn from disruptions.

This integrated perspective is consistent with the viability framework proposed in the literature and allows the identification of network configurations that are not only efficient, but also resilient, adaptive, and territorially coherent.

 doi:10.20944/preprints202603.2109.v1

4. Case Study

The proposed framework was applied to a real-world case study involving a fresh pea (Pisum sativum) supply chain in the province of Guavio, specifically in the municipalities of Guasca and Guatavita, located in the department of Cundinamarca, Colombia. This region was selected due to its proximity to the main wholesale market of the country, located in Bogotá D.C., which makes it a representative setting for analyzing first-mile logistics and commercial decision-making in small-scale agricultural systems. The production system corresponds to a high-altitude agroecosystem, with elevations above 2000 meters above sea level and a cold climate. The study involves twenty producers operating on small-scale units ranging between two and eight hectares, with up to two productive cycles per year. Although pea cultivation can occur throughout the year, two predominant planting seasons were identified, associated with precipitation patterns, typically between February–March and August–October. The production system is largely rainfed, with limited irrigation infrastructure, which increases exposure to environmental variability.

The product under analysis is fresh peas commercialized in 50 kg bags. The expected yield is approximately 90 bags per hectare, equivalent to 7031 kg/ha, although the actual commercialized volume is affected by post-harvest losses related to quality and handling practices. The predominant varieties include Santa Isabel, Pipa de uva, and San Isidro, each exhibiting differences in yield and market acceptance.

From a logistical perspective, the supply chain follows a conventional structure involving an input supplier, the set of producers, potential collection centers, and a wholesale buyer located in Bogotá. Each producer can be selected as a candidate location for a collection center, subject to capacity and operational constraints. Transportation is modeled based on distance-proportional costs, and the system operates under a unidirectional flow structure from producers to collection centers and from these centers to the wholesale market. The transport process is carried out using a single vehicle with a capacity of three tons, reflecting the access conditions and operational limitations of the region. The planning horizon considers three operational periods, including an initial phase associated with infrastructure preparation. The model assumes that up to two collection centers can be activated simultaneously, each operating with a maximum utilization level of 50% of its capacity. Additionally, technological interventions, such as blockchain-based traceability systems, can be implemented at selected centers, influencing both operational costs and revenue structures.

The model incorporates homogeneous assumptions regarding production costs, selling prices, and post-harvest losses across producers, periods, and scenarios. The cultivated area is expressed in hectares, following the regional standard, and financial consistency is ensured through accounting constraints that prevent negative balances in key financial indicators. These elements allow the model to generate economically consistent results across different uncertainty regimes. HIS-based mechanisms are incorporated through specific operational assumptions. A maximum of 20% of producers can activate sentinel strategies, and memory mechanisms are assumed to generate incremental improvements in productivity over time. Costs and prices associated with adaptive strategies are considered homogeneous across producers, periods, and scenarios. Minimum thresholds for operational viability, yield, and the Rural Viability Index (RVI) are treated as exogenous parameters.

This case study provides a realistic and representative environment for evaluating the interaction between territorial conditions, uncertainty, and adaptive mechanisms in first-mile agricultural logistics. The combination of small-scale production, logistical constraints, and market proximity makes it particularly suitable for assessing the viability-oriented design approach proposed in this study.

4.1. Experimental Design

The performance of the proposed framework was evaluated through a structured experimental design aimed at analyzing the effects of uncertainty modeling (URSP) and adaptive mechanisms

(HIS) on first-mile supply chain viability. The experiments consider a combination of three URSP configurations, defined by different weights assigned to the robust component of the objective function ($\omega = 0.5, 0.3, 0.1$), and two system conditions corresponding to the activation or deactivation of the HIS mechanisms. This results in six experimental scenarios, allowing a controlled comparison between adaptive and non-adaptive system behavior under varying levels of exposure to disruptive conditions.

Uncertainty is represented through two complementary structures. Stochastic scenarios capture variability in agricultural supply, while robust scenarios represent severe disruptions affecting production and logistics. The risk component is incorporated through a CVaR-based formulation, with parameters set to $\alpha = 0.5$and $\beta = 0.1$, ensuring consistency with the URSP framework. All experiments were implemented in GAMS and solved using CPLEX. The analysis focuses on comparing system performance across configurations in terms of economic outcomes, financial stability, operational behavior, and viability indicators. This experimental design enables the identification of the individual and combined effects of URSP weighting and HIS activation, providing a consistent basis for evaluating the contribution of adaptive mechanisms to supply chain viability.

5. Results

The results obtained across the six experimental configurations are synthesized in Table 3, which summarizes the comparative behavior of the system in terms of economic performance, financial stability, operational capacity, and viability. The table consolidates the main patterns observed across scenarios, highlighting the effect of HIS activation and the sensitivity of the system to different URSP weight levels.

Table X provides a consolidated view of system behavior across the six experimental configurations, capturing economic, financial, operational, and viability-related dimensions. The results reveal consistent patterns associated with both the level of URSP weighting and the activation of HIS-based adaptive mechanisms.

A first observation concerns the role of adaptive mechanisms in shaping system performance. Across all URSP levels, the activation of HIS leads to improvements in net utility, total supply, and viability indicators. These improvements are not uniform; they become more pronounced as the model places greater emphasis on robust scenarios. Under higher URSP weights, where disruptive conditions play a more significant role in the objective function, the absence of adaptive mechanisms results in a noticeable deterioration of performance. In contrast, the HIS-enabled configurations maintain stable or improved outcomes, indicating that adaptation is particularly valuable under high-stress conditions.

This behavior directly addresses a key gap identified in the literature, where most optimization models lack endogenous response mechanisms. The results demonstrate that incorporating adaptive capabilities is not only conceptually relevant but also operationally impactful, especially in systems exposed to severe uncertainty.

Table 3. Comparative performance summary across URSP and HIS configurations.

Metric	URSP Level	HIS Inactive	HIS Active	Observed Effect of HIS	Sensitivity to URSP
Net Utility	0.5	Moderate–High	High	Consistent increase in all scenarios; largest gains under robust conditions	Higher URSP → higher utility gains
Net Utility	0.3	Moderate	High	Significant improvement; reduced losses under disruptive scenarios	Moderate sensitivity

doi:10.20944/preprints202603.2109.v1

Net Utility	0.1	Moderate	Moderate–High	Improvement present but less pronounced	Lower sensitivity
Z-Score	0.5	Stable (>3.0)	Improved stability	Strengthening of financial structure under stochastic conditions	Limited variation
Z-Score	0.3	Borderline–Stable	Stable	Transition toward financially stable region	Moderate sensitivity
Z-Score	0.1	Mixed	Slight improvement	Marginal impact compared to higher URSP levels	Low sensitivity
Viability Index	0.5	<1 (stochastic)	≈1 or >1	Strong improvement: system reaches viability threshold	High sensitivity
Viability Index	0.3	Moderate	High	Consistent increase across scenarios	Moderate sensitivity
Viability Index	0.1	Low–Moderate	Moderate	Improvement present but constrained	Low sensitivity
Total Supply	0.5	Lower	Higher (+ significant increase)	Gains up to ~900–1000 units in robust scenarios	High sensitivity
Total Supply	0.3	Moderate	Higher	Noticeable increase due to adaptive mechanisms	Moderate sensitivity
Total Supply	0.1	Stable	Slight increase	Limited effect	Low sensitivity
Environmental Impact	All	Lower	Higher (slightly)	Trade-off: increased production vs resource use	Weak dependence
Labor Demand	All	Baseline	Higher	Increase due to adaptive/agronomic strategies	Moderate dependence

The interaction between URSP weighting and system performance provides insight into how different uncertainty regimes influence decision-making. When the robust component receives a higher weight, the model prioritizes configurations that reduce exposure to extreme losses. This effect is reflected in the CVaR structure and is indirectly observed in the stabilization of net utility under adverse scenarios. However, without adaptive mechanisms, this protective behavior leads to conservative configurations that limit system performance, particularly in terms of supply and revenue generation. The introduction of HIS mechanisms modifies this outcome by allowing the system to maintain higher levels of utility while still managing risk exposure. In this sense, the model does not simply shift from efficiency to conservatism; it enables a balance between performance and protection. This finding contributes to the literature by showing that URSP alone is not sufficient to ensure viability. The combination of robust optimization and adaptive mechanisms is necessary to sustain both economic performance and risk resilience.

The Z-score analysis reveals a clear differentiation between system configurations. Deterministic and stochastic regimes generally remain within financially stable regions, while robust scenarios tend to push the system toward risk zones, particularly when adaptive mechanisms are inactive. This behavior reflects the impact of severe disruptions on financial structure, even when operational decisions remain feasible. The activation of HIS mechanisms leads to a noticeable improvement in financial stability, especially under stochastic conditions. The system moves toward higher Z-score values, indicating a stronger financial position and a reduced likelihood of distress. Although the effect is less pronounced under extreme robust scenarios, the overall trend suggests that adaptive responses contribute to maintaining financial viability. These results reinforce the importance of integrating financial indicators into supply chain evaluation. Viability cannot be assessed solely through operational or economic metrics; financial stability plays a critical role in determining whether the system can sustain its functionality over time.

The inclusion of the Rural Viability Index introduces a structural dimension to the results that is not present in conventional models. The network configurations derived from the model reflect a clear preference for locations with favorable territorial conditions, while still allowing the inclusion of less favorable nodes when supported by adaptive mechanisms. This behavior suggests that territorial constraints are not absolute but can be partially mitigated through system flexibility. In practice, this means that locations with lower RVI values are not necessarily excluded but require additional resources or adaptive strategies to become viable. This finding is particularly relevant for rural supply chains, where spatial heterogeneity is a defining characteristic. By integrating the RVI into the decision-making process, the model addresses a major limitation in literature, where facility location is often treated independently of territorial conditions. The results confirm that incorporating spatial intelligence leads to more realistic and viable network configurations.

The analysis of total supply highlights the system's ability to maintain operational flows under different conditions. The results show that HIS activation leads to a significant increase in collected volume, particularly under robust scenarios. This increase reflects the activation of compensatory mechanisms, such as improved allocation strategies and the use of additional resources.

Without adaptive mechanisms, the system exhibits a reduced capacity to absorb supply variability, leading to lower overall performance. The contrast between adaptive and non-adaptive configurations demonstrates that maintaining supply continuity requires more than robust planning; it requires the ability to respond dynamically to disruptions. This finding directly addresses the gap related to the static nature of traditional models, which often fail to capture the operational adjustments needed to sustain performance under uncertainty.

The results also reveal the presence of trade-offs between economic performance and sustainability-related indicators. Increased supply levels are associated with higher resource use, as reflected in the environmental impact metrics. At the same time, the activation of adaptive mechanisms leads to an increase in labor demand, indicating a greater level of system activity. These trade-offs highlight the importance of evaluating supply chain performance from a multi-dimensional perspective. Improvements in viability and economic performance may involve additional environmental and social costs, which need to be considered in decision-making processes. The framework allows these trade-offs to be explicitly observed and analyzed, providing a more complete understanding of system behavior.

The combined analysis of all metrics confirms that the proposed framework supports the development of viable supply chain configurations. The system demonstrates the ability to maintain economic performance, limit exposure to extreme losses, sustain operational flows, and adapt to changing conditions. These properties align with the definition of supply chain viability as the capacity to operate under uncertainty while preserving functionality over time. The results show that viability is not achieved through a single modeling component, but through the interaction of territorial assessment (RVI), uncertainty management (URSP), and adaptive mechanisms (HIS). This integrated approach provides a more complete representation of real-world supply chain behavior, addressing the gaps identified in the literature and advancing the state of the art in agricultural logistics modeling.

The radar diagrams provide a normalized, multi-dimensional representation of system performance, allowing a simultaneous assessment of economic, operational, financial, and sustainability-related indicators. By projecting all metrics onto a common scale, these figures reveal structural differences between configurations that are not immediately visible in individual plots (Figure 1).

 doi:10.20944/preprints202603.2109.v1

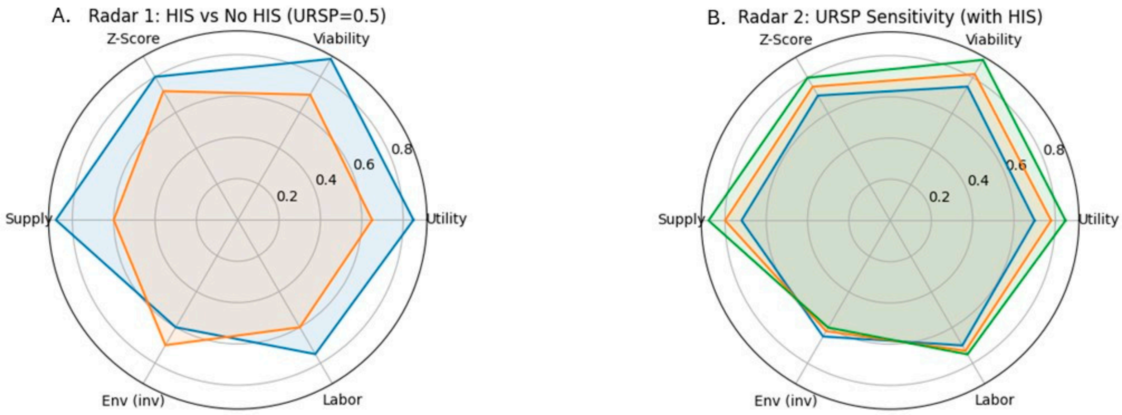

Figure 1. Multi-dimensional performance comparison.

The comparison between systems with and without HIS activation (Radar A) shows a clear expansion of the performance envelope when adaptive mechanisms are enabled. The most pronounced improvements are observed in net utility, total supply, and the viability index, indicating that the system becomes more capable of sustaining operations under uncertainty. At the same time, the radar highlights moderate increases in labor demand and a slight deterioration in environmental performance, reflecting the activation of additional strategies required to maintain system functionality. This pattern confirms that adaptation improves viability, although it introduces measurable trade-offs across sustainability dimensions.

The sensitivity analysis across URSP levels (Radar B) reveals that higher weights assigned to robust scenarios lead to a more balanced and resilient system configuration. As the URSP parameter increases, the system exhibits improvements in viability and supply capacity, while maintaining stable financial performance. Lower URSP levels, in contrast, show reduced adaptability and a more limited ability to respond to disruptions. This result indicates that the consideration of severe uncertainty plays a critical role in shaping viable supply chain configurations. Taken together, the radar diagrams provide strong visual evidence that viability emerges from the interaction of territorial conditions, uncertainty management, and adaptive mechanisms. The HIS-enabled configurations consistently dominate the non-adaptive ones across most dimensions, particularly under higher uncertainty levels, reinforcing the importance of integrating adaptive responses within optimization-based supply chain design. These results confirm that viability is not a single-dimensional outcome, but the result of a coordinated interaction between structure, uncertainty, and adaptive response mechanisms.

6. Discussion

The results obtained in this study suggest that supply chain viability cannot be attributed to a single modeling component but rather emerges from the interaction between territorial assessment (RVI), uncertainty management (URSP), and adaptive mechanisms (HIS). This finding aligns with the conceptualization of viability as a systemic property, where the ability to sustain operations depends on the coordinated behavior of multiple elements rather than isolated optimization decisions. In contrast with traditional models that focus primarily on cost minimization or profit maximization, the proposed framework shows that economically efficient configurations may fail under adverse conditions if they lack adaptive capacity. The results indicate that viability requires not only efficiency under normal conditions but also robustness and responsiveness under disruption. This reinforces the argument that viability should be treated as a design objective rather than as an ex-post performance outcome.

 doi:10.20944/preprints202603.2109.v1

A central contribution of this study is the explicit incorporation of adaptive mechanisms inspired by the Human Immune System. The results show that these mechanisms significantly improve system performance, particularly under conditions where uncertainty plays a dominant role.

This finding addresses a key limitation in literature, where most optimization models treat uncertainty as an external factor and rely on predefined recourse decisions. In the proposed framework, the system actively detects deviations, adjusts its behavior, and incorporates memory effects over time. This introduces a dynamic dimension that is typically absent in static or scenario-based models. The observed improvements in utility, supply, and viability indicators confirm that adaptation is not merely a complementary feature, but a necessary component for sustaining system functionality in uncertain environments. This supports recent calls in the literature for integrating control and adaptation principles into supply chain modeling.

The use of the URSP framework allows the simultaneous consideration of stochastic variability and severe disruptions, overcoming the limitations of models that rely exclusively on one type of uncertainty representation. The results indicate that neither stochastic nor robust modeling alone is sufficient to capture the full spectrum of system behavior. When the model relies primarily on stochastic scenarios, it captures variability but underestimates the impact of extreme events. Conversely, when robust considerations dominate without adaptive mechanisms, the resulting configurations tend to be overly conservative, limiting system performance. The integration of both components within the URSP structure, combined with adaptive responses, enables a more balanced and realistic representation of uncertainty. This finding contributes to the literature by demonstrating that unified uncertainty frameworks are essential for analyzing viability, particularly in agricultural systems where both regular variability and extreme disruptions are present.

The integration of the Rural Viability Index introduces a spatial dimension that is often overlooked in supply chain optimization models. The results show that territorial conditions significantly influence network configuration, but their impact can be partially mitigated through adaptive strategies. This highlights an important insight: territorial constraints are not strictly deterministic barriers but interact with system capabilities. Locations with lower viability can still be incorporated into the network if the system has sufficient adaptive capacity. These finding challenges traditional approaches that treat spatial variables as static constraints and suggest that territorial intelligence should be integrated into decision-making in a more flexible manner. By combining data-driven territorial assessment with optimization, the proposed framework bridges the gap between predictive analytics and prescriptive modeling, providing a more comprehensive approach to supply chain design.

From a practical perspective, the results suggest that supply chain design should move beyond static optimization and incorporate adaptive capabilities as a core component. For first-mile agricultural systems, this implies investing in mechanisms that enhance flexibility, improve monitoring, and enable rapid response to disruptions. The findings also highlight the importance of integrating territorial information into decision-making processes. In rural contexts, where infrastructure and accessibility constraints are significant, ignoring spatial heterogeneity can lead to suboptimal or non-viable configurations.

More broadly, the study suggests that viable supply chains require a combination of structural robustness, operational flexibility, and data-driven decision support. These elements should not be treated independently but as interconnected components of a unified design framework.

7. Conclusions

This study proposed a unified modeling framework for the design and evaluation of first-mile agricultural supply chains, integrating a data-driven territorial indicator (RVI), a Unified Robust Stochastic Programming (URSP) structure, and adaptive mechanisms inspired by the Human Immune System (HIS). The objective was to address the limitations of existing models in capturing the multi-dimensional nature of supply chain viability under uncertainty. The results show that viability is not achieved through isolated modeling components, but through the interaction between

 doi:10.20944/preprints202603.2109.v1

territorial conditions, uncertainty management, and adaptive response capabilities. The integration of the RVI allows the model to incorporate spatial heterogeneity into structural decisions, ensuring that network configurations are consistent with real-world territorial constraints. The URSP formulation provides a balanced representation of uncertainty by combining stochastic variability and severe disruptions, while the HIS-based mechanisms introduce the ability to detect, respond to, and learn from adverse conditions.

The combined effect of these components leads to supply chain configurations that maintain economic performance, improve financial stability, sustain operational flows, and adapt under different uncertainty regimes. The analysis also reveals that these improvements are accompanied by trade-offs, particularly in environmental impact and labor demand, highlighting the importance of evaluating performance from a multi-dimensional perspective. This work contributes to the literature by operating the concept of supply chain viability within a unified optimization framework. It demonstrates that viability can be embedded directly into the decision-making process, rather than evaluated as an ex-post outcome. In addition, the integration of adaptive mechanisms extends traditional optimization approaches by introducing endogenous system responses, addressing a key gap in current research.

The study is subject to several limitations. RVI is treated as a static parameter and does not evolve over time, which may limit its ability to capture dynamic changes in territorial conditions. The uncertainty representation, while comprehensive, relies on predefined scenario sets that may not fully reflect all possible disruptions. In addition, the HIS-based mechanisms are implemented through simplified representations of detection, response, and memory, which could be further refined.

Future research could explore dynamic formulations of territorial indicators, the integration of real-time data into adaptive mechanisms, and the extension of the framework to multi-echelon supply chains. Additional work may also focus on improving the representation of environmental and social dimensions, as well as validating the model in different agricultural contexts.

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