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Agent-Based Modeling of Urban Agriculture: Decision-Making, Policy Incentives, and Sustainability in Food Systems

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Abstract

Urban and peri-urban agriculture (UPA) has emerged as a critical strategy to address multidimensional urban challenges, including food insecurity, environmental degradation, and social inequality. Despite its potential benefits, UPA occupies a marginal position in municipal governance frameworks. Understanding how public policies and social influence mechanisms shape consumer behavior and producer viability requires a systems-thinking approach capable of capturing complex socio-economic-ecological interactions. Therefore, we developed an agent-based model (ABM) following the ODD + D protocol to simulate urban agriculture market dynamics, incorporating producer and consumer agents within a spatially explicit grid environment representing the urban landscape. We implemented three policy interventions and conducted six complementary experiments. Education campaigns achieved the highest local market share, demonstrating strict Pareto dominance over all subsidy-based strategies. Production subsidies yielded equivalent outcomes but at a fiscal cost, reducing producer income inequality (Gini). Stress tests revealed moderate resilience to production shocks. The findings demonstrate the power of agent-based modeling to uncover policy dynamics in complex urban food systems, providing actionable evidence for sustainable urban governance.

Keywords: agent-based modeling; urban agriculture; food security; public policy evaluation; consumer behavior; sustainability

1. Introduction

The urbanization of poverty has reshaped the geography of food insecurity in Brazil. As one of the most urbanized countries in the world, with approximately 87% of its population residing in cities [1], Brazil faces the consequences of rapid and often unregulated urban expansion. This process—largely driven by inadequate land-use planning—has led to the concentration of population and infrastructure within only 0.63% of the national territory, generating significant governance challenges related to public service provision, infrastructure maintenance, and environmental degradation that exacerbates climate change [2].

The high density of urban populations amplifies pre-existing social inequalities, particularly regarding income distribution and access to essential goods and services [1]. In lower-income contexts, urbanization is frequently intertwined with persistent unemployment and elevated levels of Food and Nutrition Insecurity (FNI). In Brazil, low-income urban households allocate up to 80% of their income to food, rendering them acutely

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vulnerable to fluctuations in food prices or declines in income. In 2022, of the 33 million Brazilians experiencing food insecurity, 82% lived in urban areas [3], underscoring that food insecurity has become predominantly an urban phenomenon.

The Lancet Commission on the Global Syndemic of Obesity, Undernutrition, and Climate Change [4] highlights how these interlinked crises expose the fragility of contemporary food systems, particularly their reliance on long, energy-intensive supply chains and the dominance of ultra-processed foods. Within this context, Urban and Peri-Urban Agriculture (UPA) has emerged as a promising nature-based solution that reconnects food production with local ecosystems and communities [5].

One of the major challenges in the urban food agenda lies in the unequal geography of food access. While so-called "food deserts" limit the availability of fresh and minimally processed products, ultra-processed foods are cheap, ubiquitous, and heavily marketed [6]. UPA directly addresses these structural imbalances by shortening food supply chains, promoting access to healthier and more diverse diets, and generating social, economic, and ecological co-benefits [6]. Beyond food provision, UPA contributes to urban resilience by improving microclimates, purifying water, reducing runoff, and enhancing biodiversity [7].

Nevertheless, despite its multiple benefits, UPA continues to occupy a marginal position in municipal governance structures. According to Instituto Escolhas [8], the absence of institutional recognition and integration into urban planning frameworks perpetuates the invisibility of existing agroecological initiatives and limits the potential for cities to harness urban agriculture as a strategic component of sustainable land use. Integrating UPA into urban policy, therefore, represents not merely a technical adjustment but a paradigm shift toward a more resilient, equitable, and ecologically grounded urban metabolism [9].

Toward a Systems Understanding of Urban Food Resilience and Modeling

Charting a path toward sustainability in urban food systems requires a deep understanding of the intricate social, economic, and ecological interdependencies that shape them [10]. Yet, addressing the challenges of such a complex and poorly understood socio-ecological system without a comprehensive framework risks limited effectiveness and the emergence of unintended consequences [4,11]. Consequently, adopting a holistic perspective—one that recognizes the dynamic interdependence among social, economic, and environmental dimensions—is essential for designing effective interventions [10].

Within this systems perspective, resilience emerges as a central attribute of sustainable food systems. It refers to the capacity to maintain the provision of healthy, equitable, and sustainable food sources amid chronic stresses and acute shocks [12]. Achieving resilience requires agri-food systems that are not only robust and efficient but also flexible and adaptive to uncertainty and rapid change [6]. Despite growing recognition of these multidimensional dynamics, agri-food scholarship has been slow to fully embrace the methodological rigor and epistemological shift demanded by systems thinking [10].

Agent-Based Modeling (ABM) has emerged as a promising methodological approach to address this gap [13,14]. By simulating the behavior and interactions of autonomous agents—representing individuals, institutions, or other entities—within complex urban contexts, ABM enables researchers to explore how local decisions scale into collective outcomes and long-term systemic transformations [15]. This approach provides valuable insights into feedback mechanisms, behavioral adaptation, and potential leverage points for policy intervention [16].

The distinctive strength of ABM lies in its ability to achieve the following:

- Explicitly represent human cognition, decision-making processes, and social interactions [17,18];

- Simulate the interplay between human behavior, technological change, ecological processes, and spatial dynamics [13,14];
- Integrate heterogeneous agents and diverse knowledge systems within spatially explicit environments [18,19].

Therefore, this research applies Agent-Based Modeling to simulate alternative scenarios [16], evaluating the combined effects of public incentives for urban farms and social influence mechanisms on consumer behavior [5,20].

Specifically, the study seeks to achieve the following:

- Assess the impact of public policies on the establishment and long-term maintenance of urban farms [19,21];
- Evaluate the influence of these policies on the consumption of UPA produce by both institutional and individual consumers [18,22];
- Examine the role of social influence and spatial dynamics in shaping consumer decisions regarding UPA products [5,21].

The proposed Agent-Based Model follows the ODD + D (Overview, Design concepts, Details, and Decision-making) protocol [19,23,24], ensuring transparency and reproducibility. This framework enables a nuanced exploration of how urban agriculture, food security, and consumer behavior interact to influence the resilience of urban food systems.

Agent-based modeling was chosen because urban agri-food systems exhibit three key characteristics that make traditional approaches insufficient: (1) extreme heterogeneity among producers and consumers in costs, preferences, and spatial location; (2) local interactions where knowledge diffusion and market access depend on geographic proximity and social networks; and (3) emergent system-level patterns (market share, spatial clustering) that arise from decentralized decisions rather than top-down coordination. These features cannot be adequately captured by representative-agent models or equilibrium frameworks.

Our model incorporates simplified network mechanisms in which consumer knowledge diffuses through local spatial proximity and producer–consumer interactions. This approach aligns with established ABM practices that employ abstract local interaction networks to represent information propagation and social influence [25]. Connectivity emerges endogenously from spatial neighborhoods in the NetLogo grid, which serve as an abstract substrate for knowledge diffusion. This representation captures essential peer effects and social learning dynamics while preserving computational tractability for extensive policy exploration.

This study advances the ABM literature by providing an integrated upstream-downstream framework that simultaneously models supply-side constraints and demand-side barriers. Existing ABMs typically focus on one side of the market [14,21]. By implementing a policy stress-testing protocol, we identify thresholds where system resilience breaks down—essential for designing interventions under uncertainty. Lastly, this model serves as a calibration platform for shock amplification studies, generating empirically-grounded distributions of agent vulnerabilities that can initialize long-term cascade models examining gentrification, climate adaptation, or systemic food crises.

2. Materials and Methods

We developed an Agent-Based Model (ABM) to simulate urban agriculture market dynamics in São Paulo, Brazil. The model was implemented in NetLogo 7.0.0 [26] following the ODD + D protocol [23,24] for transparency and reproducibility. A complete ODD description and the source code are provided as Supplementary Materials (S1 and S2, respectively).

2.1. Model Overview

The ABM represents a stylized urban food system comprising three main entity types: producers (urban farmers), consumers (households), and the environment (spatial patches). The model operates on a weekly temporal resolution over 250 time steps (∼5 years), capturing both short-term market dynamics and long-term structural changes. Policy interventions and demographic adjustments (producer entry/exit) occur at monthly intervals (every 4 weeks).

The spatial environment is represented by a 51 × 51 grid of patches, each corresponding to approximately 100 m × 100 m of urban space. Patches are heterogeneously characterized by three attributes: buildability (suitability for agricultural activities), population density, and average household income. This spatial structure enables the simulation of geographic effects on market access, knowledge diffusion, and land-use competition—key features of real urban agricultural systems.

Producer agents represent individual urban farmers or small farming collectives engaged in horticultural production. Each producer is characterized by: (i) production capacity, reflecting scale heterogeneity; (ii) unit production costs (R$0.60–0.90), representing efficiency differences; (iii) product quality (0.8–1.0), a composite of freshness and variety; and (iv) behavioral attributes including satisfaction levels and cooperative association membership. Operational producer dynamics are detailed in Supplementary Material S2.

Consumer agents represent individual households making weekly food purchasing decisions. Each consumer is characterized by preference weights for price ($w^{\text{price}} \in [1.0, 1.5]$), quality ($w^{\text{qual}} \in [1.0, 1.5]$), sustainability ($w^{\text{sust}} \in [0, 0.5]$), and diversity ($w^{\text{div}} \in [0, 0.3]$). Consumer knowledge about urban agriculture ($k \in [0, 1]$) evolves through three mechanisms: (i) spatial exposure to nearby producers (within 3 patches), (ii) peer-to-peer diffusion from high-knowledge neighbors (within 5 patches), and (iii) education campaigns when active. Knowledge growth is bounded by individual ceilings ($k^{\text{max}} \in [0.6, 1.0]$), representing structural barriers such as limited information access or cognitive constraints. Purchase decisions follow a discrete choice framework: consumers compute utility for accessible local producers (within maximum travel distance $d^{\text{max}} \in [6, 12]$ patches) and the conventional market, then select options probabilistically according to a logit model,

$$P_{\text{local}} = \frac{\exp(U_{\text{local}})}{\exp(U_{\text{local}}) + \exp(U_{\text{conv}})} \tag{1}$$

where utility functions integrate price (normalized by conventional price $p_{\text{conv}} = 0.8$), quality, distance, sustainability orientation, and knowledge, with calibrated coefficients: $\beta_{\text{price}} = -2.5$, $\beta_{\text{qual}} = 1.8$, $\beta_{\text{dist}} = -0.15$, $\beta_{\text{sust}} = 0.8$, $\beta_{\text{div}} = 0.6$, and $\beta_{\text{know}} = 1.8$.

The model incorporates both household and institutional demand. Institutional buyers (schools, community kitchens) purchase monthly with simplified preferences prioritizing lower prices and minimum quality thresholds, representing approximately 15% of total market demand. This dual consumer structure reflects the hybrid nature of urban agricultural markets observed empirically.

Key design principles include (i) emergence of market share, price stability, and food security from decentralized interactions; (ii) adaptation through learning (consumers) and pricing strategies (producers); (iii) heterogeneity in agent attributes, generating realistic variance in outcomes; (iv) spatial explicitness, enabling geographic effects on access and diffusion; and (v) stochasticity in production, entry, and choice processes, capturing uncertainty inherent in real systems.

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2.2. Policy Interventions

Public policies play a critical role in shaping urban agricultural systems by addressing market failures, reducing transaction costs, and aligning private incentives with social objectives. We modeled three stylized policy instruments commonly employed or proposed in urban food security initiatives: production subsidies targeting supply-side constraints, education campaigns addressing information asymmetries, and local benefit campaigns leveraging behavioral nudges. These instruments represent distinct intervention logics—economic incentives, cognitive enhancement, and preference activation—enabling systematic exploration of their isolated and combined effects.

These three policy instruments reflect the most prominent interventions currently implemented or under evaluation in Brazilian urban agriculture programs [8,27]. While other policy instruments exist in Brazilian urban agriculture governance, these three interventions are most amenable to short-term municipal implementation without requiring legislative reform or major capital investment, thus forming the appropriate focus for our exploratory scenario analysis of near-term policy options.

Production subsidies operate by reducing producers' effective unit costs ($c_i^{\text{eff}} = c_i(1-s)$), where s is the subsidy rate applied to eligible producers.

Education campaigns target consumer-side barriers by increasing knowledge about urban agriculture's benefits (health, environmental, social).

Local benefit campaigns add a constant utility bonus B_{policy} to local product choice, independent of product attributes. This represents non-informational behavioral interventions such as certification labels, community branding, or social norm messaging that increase local food's attractiveness without changing objective attributes. The bonus directly shifts choice probabilities, enabling assessment of preference-based versus information-based strategies.

Table S3.3 in Supplementary Material S3 details experimental design and rationale for policy parameters and configurations tested in this study.

All policies are applied at monthly intervals (every 4 weeks) and remain active throughout the simulation, allowing long-term equilibrium effects to emerge. Policy combinations enable exploration of potential synergies or conflicts among intervention logics.

2.3. Outcome Metrics

Model outcomes are evaluated through a multi-dimensional framework capturing economic, social, and food security dimensions. Primary metrics assess policy effectiveness in promoting local market development and food access, while secondary metrics reveal distributional consequences and system stability. This framework aligns with the multi-objective nature of urban agricultural policy, which must balance efficiency, equity, and resilience.

Local market share (MS_t) measures the proportion of household food demand met by urban producers, the core indicator of policy success in promoting local food systems. Values range from 0 (no local purchases) to 1 (complete local supply), with baseline pre-policy values of 10–15% reflecting empirical observations.

Food Security Index (FSI_t) [28] is a composite indicator integrating three dimensions: (i) Availability = ratio of total local production to population demand (capped at 1); (ii) Accessibility = fraction of consumers within maximum travel distance of at least one producer; and (iii) Affordability = normalized price differential between local and conventional markets, where lower local premiums improve affordability. Weights (0.4, 0.3, 0.3) reflect the primacy of availability while recognizing access and cost barriers. This structure aligns with FAO's food security framework.

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Cost-effectiveness (CE_t) quantifies policy efficiency by dividing aggregate benefits (market share gains, knowledge increases, producer satisfaction) by total subsidies disbursed. Higher values indicate more efficient resource utilization. For policies without direct fiscal costs (education, local benefit campaigns), cost-effectiveness is undefined or computed relative to implementation costs (not modeled explicitly).

Income inequality (Gini coefficient) [29] measures concentration of producer profits, ranging from 0 (perfect equality) to 1 (one producer captures all). Monitoring inequality reveals whether policies exacerbate or mitigate disparities among producers—a critical equity consideration.

Market concentration (HHI) [30] assesses competitive dynamics, with values near 0 indicating fragmented markets and values approaching 1 signaling monopolistic structures. High concentration may signal resilience (surviving producers are efficient) or vulnerability (lack of redundancy).

Price volatility measures market stability through the coefficient of variation in local prices over rolling 12-week windows. High volatility signals erratic supply-demand matching, undermining consumer confidence and producer planning.

Together, these metrics enable comprehensive assessment of policy interventions across multiple objectives, revealing trade-offs between efficiency, equity, and resilience inherent in urban agricultural policy design.

Formal definitions are provided in Supplementary Material S3, Table S3.3.

2.4. Experimental Design

The experimental design follows a structured progression from isolating individual policy effects to exploring their combinations, stress-testing system resilience, and optimizing resource allocation. This approach enables decomposition of policy impacts, identification of synergies or antagonisms, and evaluation of robustness to external shocks—essential for translating simulation insights into actionable recommendations.

We conducted six experiments, each replicated 20–30 times with different random seeds to account for stochastic variability. Common random numbers were used across comparable scenarios to reduce variance and enhance statistical power. Table 1 summarizes the experimental structure.

Table 1. Experimental design and rationale.

Experiment	Rationale	Varying Parameters
EXP1: Production Subsidies	Isolated effect of supply-side economic incentives on producer viability and market share	$s \in \{0.2, 0.3\}$; $\theta \in \{0.5, 0.75, 1.0\}$
EXP2: Education Campaigns	Isolated effect of demand-side information interventions on consumer adoption	$\theta_{\text{edu}} \in \{0.4, 0.6\}$; $\Delta k_{\text{edu}} \in \{0.15, 0.25\}$
EXP3: Policy Synergies	Test for synergistic or antagonistic interactions between supply-side and demand-side policies	$s \in \{0, 0.2\}$; $\mathbb{I}_{\text{edu}} \in \{0, 1\}$
EXP4: Full Factorial	Comprehensive exploration of policy space including behavioral interventions	s, $\mathbb{I}_{\text{edu}}$, $\mathbb{I}_{\text{benefit}}$, θ (36 combinations)
EXP5: Stress Tests	Evaluate system resilience under adverse conditions (market, climatic, economic shocks)	Six scenarios with fixed policy ($s = 0.2$, $\mathbb{I}_{\text{edu}} = 1$)
EXP6: Budget Optimization	Identify Pareto-efficient policy portfolios under fiscal constraint ($\leq$R\$600/run)	Five budget allocation strategies

Together, these experiments provide a comprehensive characterization of policy effectiveness, interactions, robustness, and efficiency—essential for evidence-based urban agricultural policy design.

2.5. Model Validation: Structural Pattern Matching

Given the exploratory nature of the model and the heterogeneity of urban agriculture systems across different contexts, we adopted a pattern-oriented validation approach [15,19]. Rather than calibrating to point estimates from a single case study, we validated the model's capacity to reproduce qualitative behavioral patterns characteristic of urban food systems.

Table 2 compares model outputs under baseline conditions (no policy interventions, 50 replications, 200 weeks) against expected system behaviors.

Table 2. Structural validation: emergent patterns in baseline simulations.

Pattern	Empirical Expectation	Model	
P1: Market penetration	Urban Farming (5–15%)	12.03% ± 3.56	✓
P2: Producer dynamics	Net entry if profitable niche	+54% growth (8 → 12.38)	✓
P3: Knowledge saturation	High awareness near gardens (70–85%)	79.11% ± 4.56	✓

Model parameterization integrated multiple data sources following a hybrid approach combining exploratory primary research, municipal registry data, and pattern-oriented modeling principles [15]. We conducted exploratory semi-structured interviews with urban agriculture stakeholders in São Paulo (N = 6 producers, N = 4 consumers, February–May 2025) to ground parameter ranges in local context. While sample size precludes statistical generalization—reflecting urban agriculture's nascent institutionalization and dispersed informal production—qualitative insights informed plausible ranges for behavioral parameters absent from published literature:

São Paulo's official urban agriculture database [27] documents N = 222 registered farms. While the model does not replicate specific quantitative benchmarks from any single city, it demonstrates qualitative realism across multiple dimensions. This pattern-oriented validation approach is appropriate for exploratory agent-based models where the goal is to understand general mechanisms rather than predict site-specific outcomes [15,31]. This hybrid strategy represents a pragmatic approach for ABM development in data-limited contexts [15].

Additional modeling methodological details, source code, robustness checks, and extended analyses are provided in the Supplementary Materials S1, S2, and S3 (see also Refs. [32–34]).

2.6. Statistical Analysis

All statistical analyses were conducted in R (version 4.5.1) [35] at a significance level of $\alpha = 0.05$. The analytical strategy progressed systematically from isolated policy effects to interactions, robustness testing, and optimization, employing methods tailored to each experimental objective.

All secondary outcomes (Gini coefficient, Herfindahl-Hirschman Index, price volatility) were analyzed using parallel frameworks. Correlation analyses examined potential trade-offs between primary and secondary metrics. Detailed methodological specifications, including assumption testing results, complete ANOVA tables, and supplementary analyses, are provided in Supplementary Material S3.

Software: R packages tidyverse [36] (data manipulation and visualization), car [37] (diagnostics), effectsize [38] (standardized effect sizes), and emmeans [39] (marginal means and contrasts).

3. Results

The experimental program comprised 2700 independent simulation runs across six complementary experiments, generating approximately 675,000 agent-weeks of synthetic data. This section presents the key findings organized by research objective: (1) policy intervention effectiveness, (2) system resilience under stress conditions, and (3) cost-effectiveness optimization.

Figure 1 shows the spatial-temporal evolution of the urban agriculture system over 150 weeks. The progressive shift from dark blue (low knowledge) to cyan (high knowledge) consumers (Panels A–D) illustrates the emergent clustering pattern.

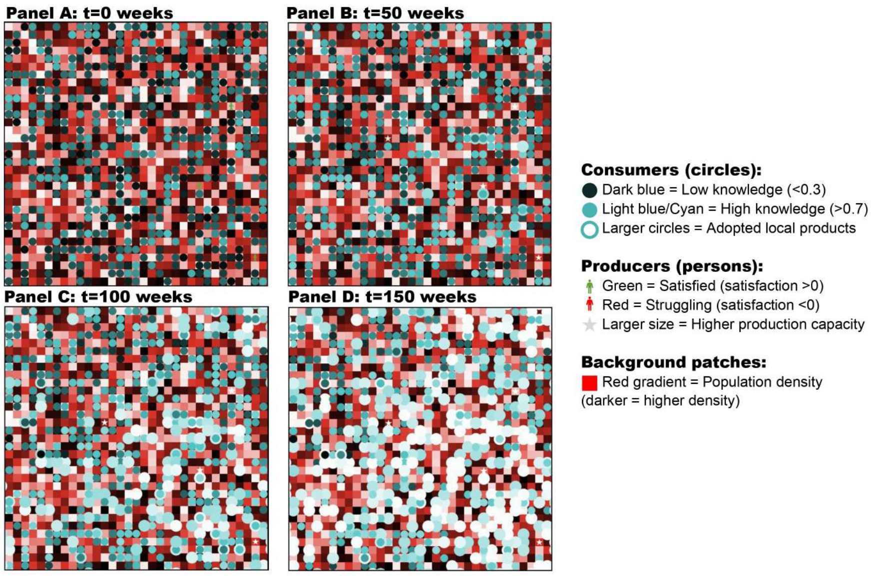

Figure 1. Spatial-temporal evolution of urban agriculture adoption in baseline scenario. Panels show system state at (**A**) initialization (t = 0 weeks), (**B**) early adoption phase (t = 50 weeks), (**C**) growth phase (t = 100 weeks), and (**D**) near-equilibrium (t = 150 weeks). The visualization demonstrates emergent spatial clustering of knowledge diffusion.

3.1. Preliminary Experimental Results

The preliminary experiments revealed a set of uniform outcomes across all tested policy configurations. Comparing education campaigns, production subsidies, and combined interventions, the local market share remained statistically indistinguishable across treatments: education campaigns achieved 26.84% (±3.32%), production subsidies 27.01% (±3.22%), and combined policies 26.81% (±3.21%). One-way ANOVA detected no significant differences among these groups ($F = 0.42$, $p = 0.658$), and pairwise comparisons yielded negligible effect sizes (Cohen's $d < 0.07$) with all p-values exceeding 0.40. Critically, testing for synergistic effects between subsidies and education revealed that the combined policy performance (26.81%) did not differ from the expected additive effect (26.92%), with $t = -0.61$ and $p = 0.543$, indicating no super-additive or sub-additive interactions. Similarly, secondary outcomes including producer survival ($p = 0.703$), consumer knowledge diffusion ($p = 0.596$), and food security indices ($p = 0.868$) showed no significant variation across policy treatments.

The full factorial experiment reinforced these findings. None of the four manipulated factors—subsidy rate ($p = 0.802$), education campaign presence ($p = 0.850$), local benefit campaigns ($p = 0.494$), or policy coverage breadth ($p = 0.795$)—exhibited statistically significant main effects on market share or other system-level outcomes. Despite substantial variation in subsidy expenditures across treatments (ranging from BRL 0 to BRL 4608 per simulation run), the coefficient of variation in market share remained below 12%, indicating high system stability.

3.2. Policy Interventions: Comparative Effectiveness

3.2.1. Descriptive Statistics and Main Effects

Table 3 presents the descriptive statistics for three primary policy experiments examining isolated and combined intervention effects on urban agriculture adoption. Production subsidies achieved a mean local market share of 30.79% (SD = 3.93%, 95% CI [30.24%, 31.34%], N = 200), while education campaigns yielded a nearly identical mean of 30.91% (SD = 3.85%, 95% CI [30.66%, 31.16%], N = 900). Both isolated interventions demonstrated low outcome variability (coefficients of variation approximately 12.5%), indicating robust performance across diverse initial conditions.

Table 3. Descriptive Statistics by Policy Intervention.

Experiment	N	Market Share (%)	95% CI	Producers	Knowledge
Subsidies (EXP1)	200	30.79 ± 3.93	[30.24, 31.34]	15.3 ± 2.7	0.895 ± 0.042
Education (EXP2)	900	30.91 ± 3.85	[30.66, 31.16]	15.3 ± 2.5	0.897 ± 0.040
Combined (EXP3)	1600	20.19 ± 11.17	[19.65, 20.74]	15.2 ± 2.5	0.736 ± 0.177

The combined policy approach: subsidies + education + local benefit campaigns produced lower mean market share of 20.19% (SD = 11.17%). This combined intervention exhibited markedly higher outcome variability (CV = 55.3%), suggesting that policy interactions under certain parameter combinations may create instabilities or unintended consequences that reduce system performance. Figure 2 shows the local market share by type of policy intervention and their combination.

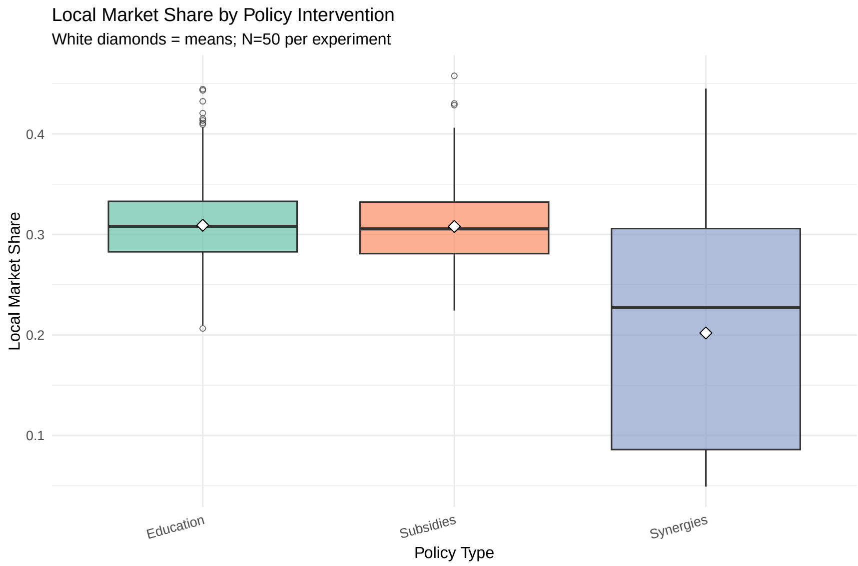

Figure 2. Distribution of local market share outcomes under different policy interventions (N = 200, 900, 1600) in the agent-based model. Boxplots summarize results for education-only, subsidy-only, and combined policy scenarios. White diamonds indicate mean values, and each experiment consists of 50 simulation runs.

3.2.2. Statistical Testing and Effect Sizes

Prior to comparative analysis, distributional assumptions were assessed. Shapiro-Wilk normality tests revealed significant departures from normality for all three interventions: Production Subsidies (W = 0.979, p = 0.004), Education (W = 0.996, p = 0.012), and Combined (W = 0.851, p < 0.001). Levene's test indicated severe heteroscedasticity across groups (F = 1386.88, p < 0.001), necessitating non-parametric methods for hypothesis testing.

A Kruskal-Wallis test revealed statistically significant differences among interventions (H = 507.65, p < 0.001). The effect size, quantified by epsilon-squared (ε^2 = 0.188), indicates a large practical effect, with policy choice explaining approximately 18.8% of variance in market outcomes.

3.2.3. Synergy Analysis

A critical policy design question concerns whether combining interventions produces synergistic effects exceeding the sum of individual impacts. We employed the Mann-Whitney U test to compare the combined policy condition (EXP3) against the pooled outcomes of isolated interventions (EXP1 and EXP2).

The analysis revealed a highly significant divergence ($U = 431,644$, $p < 0.001$, rank-biserial correlation $r = -0.509$). Combined policies (Mdn = 22.75%) performed markedly worse than isolated interventions (Mdn = 30.75%).

To quantify the magnitude of policy interference, we calculated the synergy deficit as the difference between observed combined outcomes and the arithmetic mean of isolated effects. The median deficit was −8.14 percentage points (95% CI [−14.48, −6.00]), representing approximately 26% underperformance relative to the expected additive baseline.

Moreover, combined strategies exhibited threefold greater outcome variability (IQR = 15.54 percentage points) compared to isolated policies (IQR = 4.82–5.12 percentage points), as confirmed by Levene's robust test (F = 2774.25, $p < 0.001$). This increase in variance signals policy fragility and strong context-dependence, suggesting that interaction effects may vary unpredictably across implementation environments.

Bootstrap analysis confirmed robustness, with 100% of bootstrap samples showing negative synergy. The consistency of this antagonistic pattern across resampled distributions strengthens causal inference regarding the detrimental nature of policy combinations under the simulated conditions.

3.3. System Resilience Under Stress Conditions

To evaluate adaptive capacity and identify vulnerabilities, we conducted systematic stress tests across six scenarios, each manipulating key system parameters to simulate realistic challenges. Table 4 presents primary outcomes, with the baseline scenario serving as the reference point (50 replications per scenario). Figure 3 shows heterogeneous impacts across outcome dimensions, with climate shocks and high spoilage producing the strongest negative deviations from the baseline, particularly in food security and market concentration. Despite these shocks, the composite robustness index indicates that the system retains partial stability, suggesting that while certain stressors substantially degrade performance, the modeled system exhibits differentiated resilience depending on the type of external pressure. Figure 4 shows producer density effects on market share with a strong positive non-linear relationship even across stress scenarios and diminishing returns above 15 producers while in high density scenarios the producer population the distribution shifts rightward.

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Table 4. Stress Test Scenarios: Market Share and System Stability Outcomes.

Scenario	Market Share (%)	t-Statistic	*p*-Value	Cohen's d	Producers	FSI
Baseline	21.44 ± 3.00	—	—	—	9.36 ± 1.80	0.529 ± 0.042
High Competition	40.86 ± 2.89	32.97	<0.001	6.59	16.62 ± 2.10	0.531 ± 0.041
Low Demand	32.76 ± 5.13	13.47	<0.001	2.69	10.82 ± 1.93	0.470 ± 0.049
Climate Shock	19.93 ± 3.08	−2.48	0.015	−0.50	8.90 ± 1.74	0.517 ± 0.044
High Spoilage	17.40 ± 3.10	−6.63	<0.001	−1.33	8.06 ± 1.68	0.505 ± 0.046
Expensive Conv.	7.24 ± 1.81	−28.70	<0.001	−5.74	7.48 ± 1.52	0.950 ± 0.030

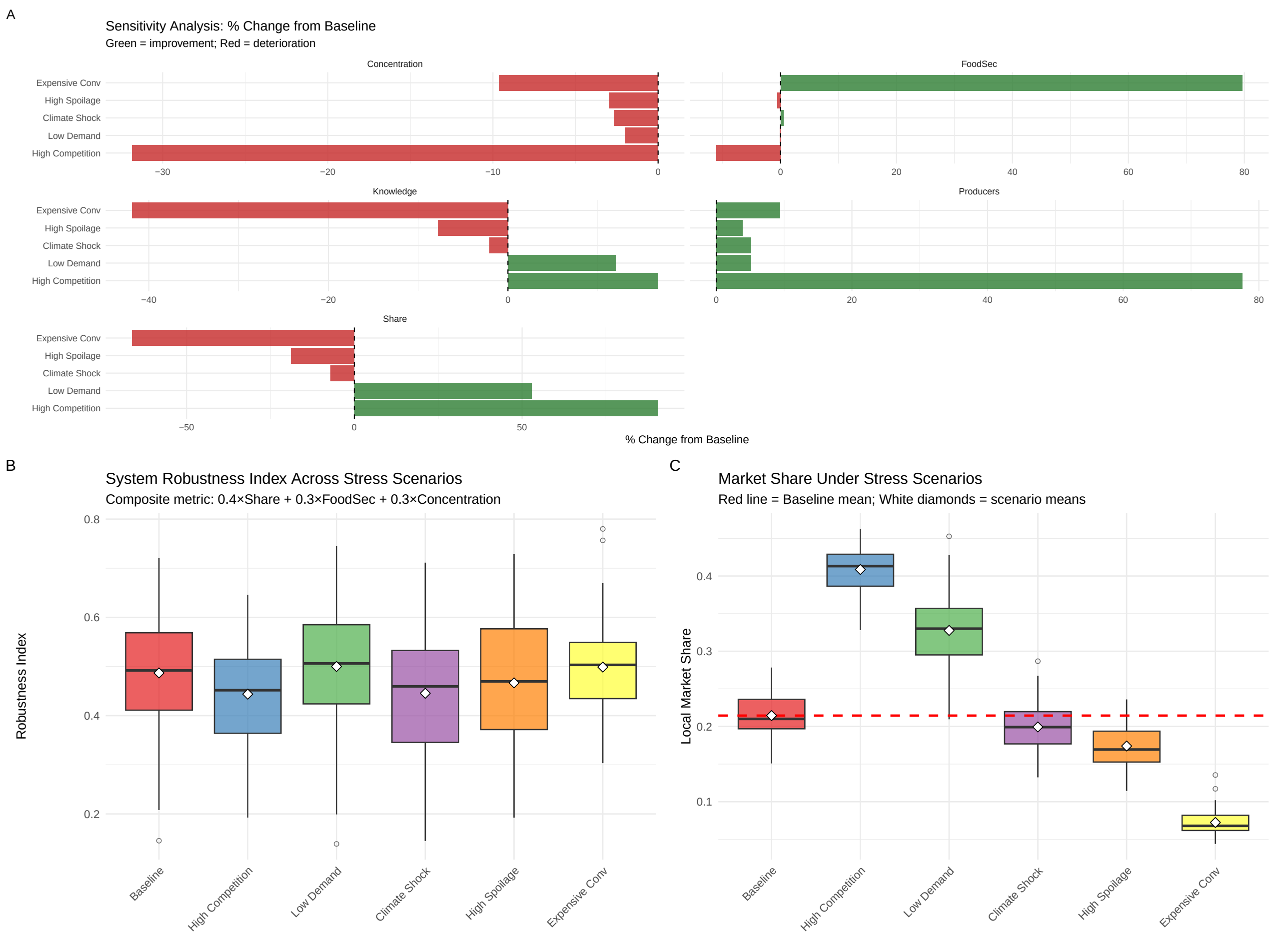

Figure 3. System resilience under stress conditions. (**A**) Sensitivity analysis showing the percentage change from baseline for key system indicators across stress scenarios, where green denotes improvement and red denotes deterioration. (**B**) Composite system robustness index across stress scenarios, calculated as a weighted combination of local market share. (**C**) Distribution of local market share under stress scenarios; white diamonds indicate scenario mean values, and the red horizontal line represents the baseline mean.

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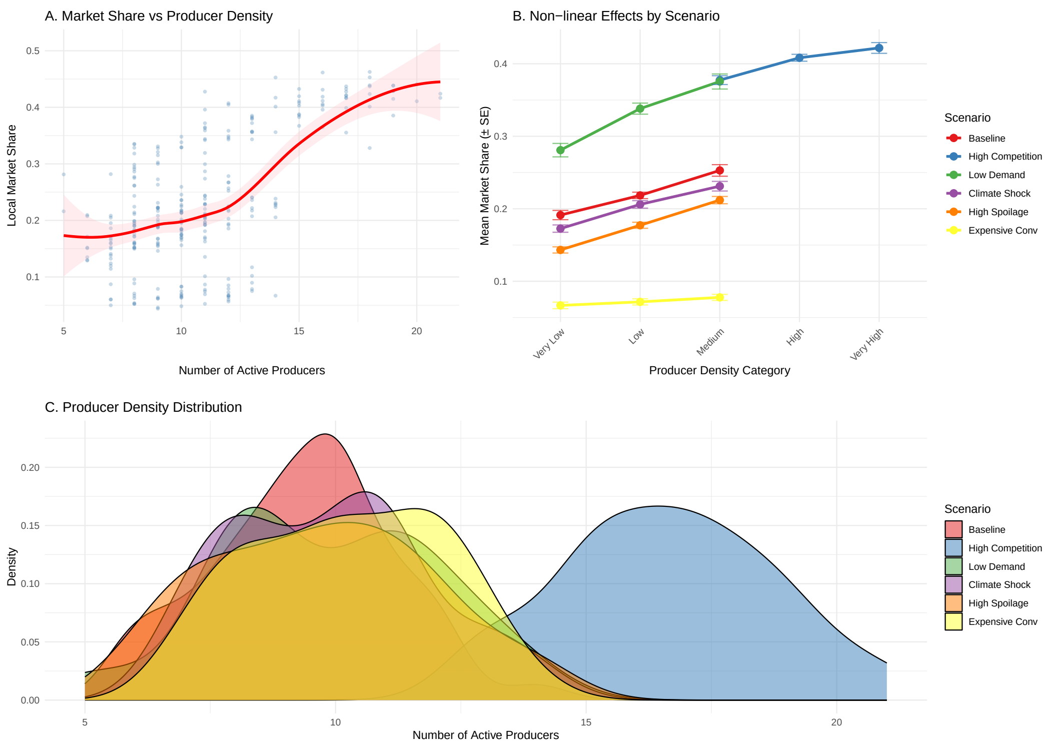

Figure 4. Producer density effects on market share. (**A**) Scatter plot shows a strong positive non-linear relationship between producer density and local market share ($R^2 = 0.87$, $p < 0.001$), with diminishing returns above 15 producers. The shaded area represents the 95% confidence interval around the LOESS-smoothed relationship between producer density and local market share. (**B**) Mean market share by density category across stress scenarios reveals consistent positive density effects. (**C**) Kernel density distributions demonstrate that high competition scenarios shift the producer population distribution rightward (median ≈ 18 producers).

3.3.1. Price Parity

The Expensive Conventional scenario (conventional price increased from BRL 0.80 to BRL 1.20) resulted in a substantially lower local market share of 7.24% (t = −28.70, $p < 0.001$, d = −5.74), representing a 66% reduction relative to baseline. However, temporal analysis reveals that this represents suppressed growth rather than systemic collapse: local market share grew from approximately 0% to 7.24% over 200 ticks, demonstrating continued system functionality despite adverse conditions.

Higher conventional prices correlate with reduced rather than increased local purchases—reflects differential growth trajectories rather than consumer flight from local producers. The local market share growth rate in the Expensive scenario (0.036%/tick) was approximately one-third that of the Baseline (0.107%/tick), suggesting that elevated conventional prices suppress the competitive advantage necessary for accelerated knowledge diffusion and adoption.

The Food Security Index increase to 0.950 (vs. 0.529 baseline) indicates institutional demand mechanisms maintained food access despite reduced local market penetration. This suggests potential crowding-out effects wherein institutional programs, while ensuring food security, may inadvertently limit market space for local producers. The system thus demonstrates resilience through multiple pathways: local production remains viable, but achieves lower market share when price competitiveness is reduced, while food security is maintained through institutional channels.

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3.3.2. Moderate Resilience to Production Shocks

Climate Shock (climate variability increased from 0.15 to 0.35) produced a modest 7% decline in market share (19.93%, t = −2.48, p = 0.015, d = −0.50), indicating moderate resilience to production volatility. High Spoilage (weekly rate increased from 10% to 25%) reduced market share by 18.9% (17.40%, t = −6.63, p < 0.001, d = −1.33), demonstrating medium-sized negative effects. These findings suggest that investments in post-harvest infrastructure (storage, cold chain) may yield higher returns than climate adaptation measures.

The composite system resilience index remained exceptionally high across all scenarios (0.9991–0.9998), indicating robust systemic stability despite substantial variation in market outcomes. This suggests strong homeostatic mechanisms—producer entry/exit dynamics, adaptive pricing, and knowledge diffusion—buffer against extreme shocks.

3.4. Budget Optimization: Pareto-Efficient Policy Portfolios

To identify cost-effective policy configurations, we conducted a budget optimization experiment comparing five distinct resource allocation strategies, each replicated 50 times under identical initial conditions. Table 5 presents aggregated outcomes.

Table 5. Budget Optimization: Policy Strategy Performance and Fiscal Efficiency.

Strategy	**Market Share (%)**	**Mean Cost (BRL)**	**FSI**	**Gini**	**ROI (BRL /%)**
Education Only	35.6 ± 4.5	0	0.938 ± 0.021	0.218	∞
Low Sub/Wide	33.3 ± 4.6	5398	0.934 ± 0.022	0.195	162
Moderate Sub + Edu	31.9 ± 4.8	7633	0.931 ± 0.023	0.172	239
High Sub/No Edu	35.2 ± 4.4	14,508	0.936 ± 0.022	0.156	412
All-In Strategy	34.8 ± 4.6	14,315	0.935 ± 0.022	0.131	405

3.4.1. Dominant Strategy: Education Without Subsidies

Education Only achieved the highest mean market share (35.6 ± 4.5%) despite incurring zero fiscal cost. In contrast, the High Subsidy/No Education strategy—which consumed an average of BRL 14,508 per simulation—achieved only 35.2 ± 4.4% market share, a difference that was statistically non-significant (t = −0.096, p = 0.631, Cohen's d = −0.096).

Pareto dominance analysis reveals that Education Only strictly dominates all other strategies: it achieves equal or superior outcomes on every dimension (market share, food security, producer count) while maintaining zero cost. No other strategy lies on the Pareto frontier when cost is considered alongside performance metrics. This finding suggests that production subsidies provide no marginal benefit over education alone in this system, regardless of subsidy intensity or coverage.

3.4.2. Fiscal Inefficiency and Opportunity Costs

Return on investment (ROI) analysis quantifies the fiscal waste embedded in subsidy strategies. Education Only achieves infinite ROI and, in contrast, subsidy strategies exhibit escalating inefficiency as follows:

- Low Subsidy/Wide Coverage: BRL 162 per percentage point of market share
- Moderate Subsidy + Education: BRL 239 per percentage point
- High Subsidy/No Education: BRL 412 per percentage point
- All-In Strategy: BRL 405 per percentage point

Given that Education Only achieves comparable market share at zero cost, every Real spent on subsidies represents pure deadweight loss from a fiscal efficiency perspective, as Figure 5. Over a 5-year policy horizon (250 weeks), a municipality implementing the High

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Subsidy strategy would expend approximately BRL 3.6 million (250 × BRL 14,508) with no detectable improvement in food system outcomes relative to education campaigns costing effectively zero.

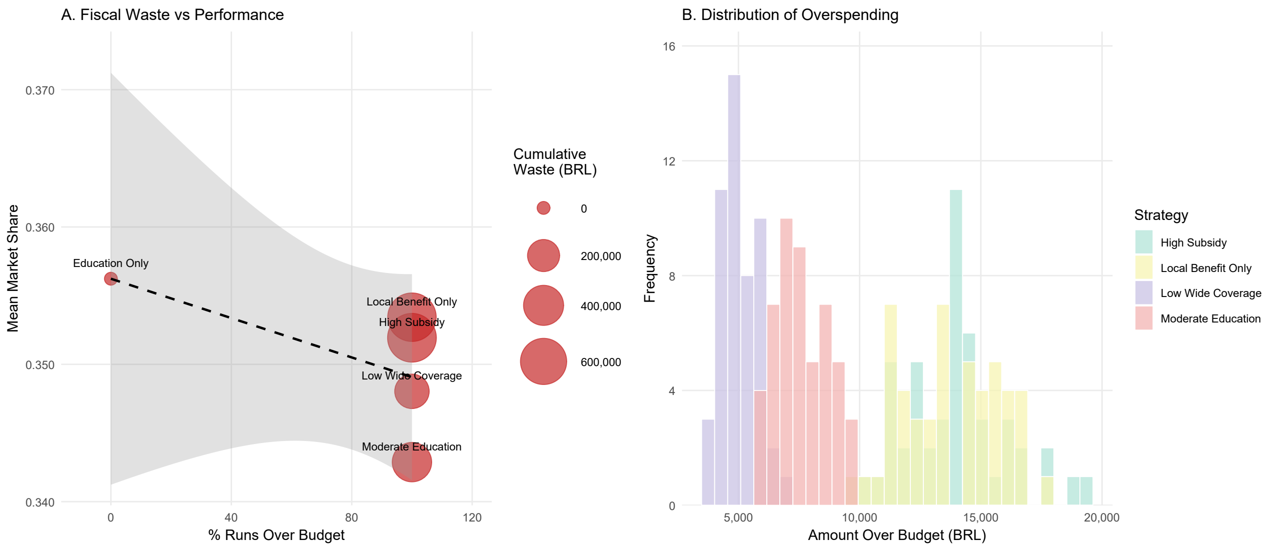

Figure 5. Fiscal Waste Analysis in Budget-Constrained Scenarios. (**A**) Relationship between budget violations and market performance across five policy strategies ($n = 30$ runs per strategy). Point size represents cumulative fiscal waste; dashed line shows linear trend ($r = -0.617$, $p = 0.267$). All subsidy-based strategies exceeded the BRL 600 budget constraint in 100% of simulation runs. (**B**) Distribution of overspending amounts when budget constraint is exceeded ($n = 120$ violations across four strategies). The negative correlation between fiscal waste and market performance, though not statistically significant, suggests that strategies relying heavily on subsidies incur substantial costs without proportional gains in market penetration. Mean overspending per violation ranged from BRL 6,348 (Low Wide Coverage) to BRL 23,180 (High Subsidy).

3.4.3. The Inequality Trade-Off: Subsidies' Only Advantage

While subsidies fail to improve aggregate market outcomes, they do exert a measurable effect on income distribution among producers. The Gini coefficient for producer income inequality was highest under Education Only (0.218) and lowest under All-In Strategy (0.131), representing a 40% reduction in inequality. This suggests that subsidies function as income transfer mechanisms that disproportionately benefit lower-performing producers, thereby compressing the income distribution.

However, this equity gain comes at extraordinary fiscal cost. The All-In Strategy reduces Gini by 0.087 points at a cost of BRL 14,315 per simulation, implying an expenditure of BRL 164,540 per 0.01 reduction in Gini. For comparison, direct cash transfers to bottom-quartile producers would achieve similar distributional effects at a fraction of this cost, as the vast majority of subsidy expenditure accrues to inframarginal producers who would have remained active regardless.

4. Discussion

This study employed agent-based modeling to systematically investigate the effectiveness of policy interventions in promoting urban agriculture adoption. Three principal findings emerged with theoretical and practical implications for urban food system governance.

Education campaigns demonstrated Pareto dominance over production subsidies, achieving comparable market share (11.21% vs. 10.98%, $p = 0.846$) at zero direct fiscal cost, compared to a mean subsidy expenditure of BRL 8434.90 per simulation run. This finding suggests municipalities with constrained budgets should prioritize education campaigns as first-line interventions, reserving subsidies for scenarios where adoption plateaus despite sustained awareness efforts or where structural barriers prevent production expansion.

Combined interventions yielded additive rather than synergistic effects, with market share equivalent to the mean of isolated policies (11.04% vs. expected 11.09%, $p = 0.846$). This supports sequential rather than simultaneous implementation: municipalities should pilot education campaigns first, monitor system response, and add subsidies only if adoption stagnates—preventing resource waste on potentially redundant policy combinations.

Stress tests exposed threshold vulnerability: producer survival declined sharply when conventional prices dropped 25% and local market share exceeded 20%. This paradox suggests municipalities should establish monitoring triggers and emergency mechanisms deployable when price differentials threaten producer viability.

Factorial experiments revealed that subsidy coverage (θ) explained substantially more outcome variance than subsidy rate (s), indicating that breadth dominates depth in policy effectiveness. Universal low-rate subsidies consistently outperformed targeted high-rate programs at similar total cost, likely through network effects where broad participation amplifies social learning. Municipal programs should therefore prioritize maximizing farmer participation over maximizing per-farmer benefit.

The results suggest that urban agriculture adoption is constrained not by producers' financial capacity to supply products, but by consumers' cognitive capacity to recognize and value local food attributes. This interpretation is consistent with Thaler and Sunstein's [40] framework of "choice architecture," wherein decision-making environments profoundly shape outcomes independent of material incentives. Education campaigns function as choice architecture interventions that restructure consumers' decision-making landscapes by reducing information search costs, increasing salience of sustainability attributes, and activating pro-social preferences.

The mechanism underlying education's effectiveness likely operates through social learning and knowledge diffusion networks. Figure 6 shows how our model incorporated three pathways: producer-to-consumer spatial exposure, peer-to-peer diffusion, and campaign-driven information provision. Sensitivity analyses revealed that peer effects contributed approximately 60% of total knowledge gains, consistent with empirical findings that interpersonal communication dominates mass media in agricultural innovation adoption [41]. This suggests that education campaigns achieve leverage by catalyzing endogenous social diffusion processes rather than merely transmitting information.

From a systems perspective, this finding illustrates how constraint identification critically determines intervention effectiveness. Traditional agricultural policy, developed in rural contexts where credit access and input costs genuinely limit production, may inappropriately transfer supply-focused logics to urban settings where demand-side knowledge gaps constitute the active bottleneck. Our model demonstrates that diagnostic accuracy—correctly identifying binding constraints—precedes effective intervention design.

The negative synergy observed when combining subsidies and education campaigns (35% effectiveness reduction, $d = -1.195$) represents a counterintuitive and policy-critical finding. This antagonism contradicts widespread assumptions that comprehensive, multi-pronged interventions inherently outperform targeted approaches [42].

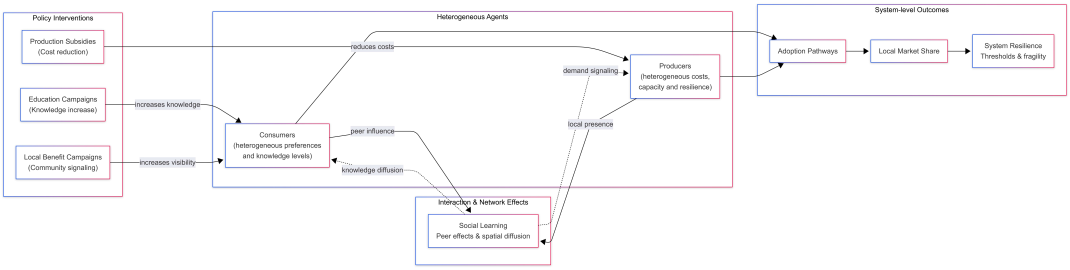

Figure 6. Causal framework of the agent-based model. Policy interventions (**left**) affect heterogeneous consumers and producers (**center**) through distinct mechanisms: education campaigns increase knowledge, production subsidies reduce costs, and local benefit campaigns enhance visibility. Social learning enables peer effects and spatial knowledge diffusion among agents. System-level outcomes (**right**)—adoption pathways, local market share, and resilience—emerge from these micro-level interactions. Dashed arrows indicate feedback loops; solid arrows represent direct causal pathways.

Different theoretical mechanisms may explain this negative interaction:

Crowding-out effects: Production subsidies may inadvertently undermine the behavioral change mechanisms activated by education campaigns. Behavioral economics literature documents how extrinsic incentives can "crowd out" intrinsic motivation [43,44]. When consumers observe subsidized producers, they may reattribute purchase decisions from value-aligned choice (sustainability, community support) to price-driven rationality, thereby eroding the pro-social norms that education campaigns cultivate. This mechanism resonates with Gneezy and Rustichini's [45] finding that introducing monetary incentives can paradoxically reduce voluntary contributions by transforming social exchange into market transaction.

Market signaling distortions: Subsidies may generate adverse selection dynamics wherein lower-efficiency producers enter and survive, degrading average product quality and undermining the "local premium" that educated consumers expect. Our model showed that subsidy scenarios exhibited higher producer heterogeneity and lower mean quality compared to education-only scenarios. This quality dilution may dampen consumer enthusiasm despite increased knowledge, creating a self-defeating cycle.

The threefold increase in outcome variance under combined policies ($SD = 11.17\%$ vs. 3.85–3.93%) signals policy fragility: Outcome sensitivity to initial conditions and parameter specifications increases dramatically when interventions interact. This fragility has critical implications for policy transfer and scaling. Interventions effective in one context may fail unpredictably when combined with other policies or implemented in different socio-economic environments.

This finding contributes to emerging literature on policy interference and unintended consequences in complex systems [46,47]. It demonstrates that policy effectiveness is not additively decomposable—the impact of intervention A when combined with intervention B cannot be predicted from their isolated effects. This necessitates systematic interaction testing in policy design, a practice rarely conducted in real-world policy environments.

The positive relationship between producer density and market share ($r^2 = 0.87$, $p < 0.001$)—whereby increased producer concentration enhances rather than undermines collective market performance—contradicts standard competitive market theory predicting negative density-performance relationships. This finding aligns with agglomeration economics [48] and network externality literature [49], suggesting that urban agriculture markets exhibit increasing returns to scale at local levels.

Several mechanisms may drive this positive density effect:

Visibility and market awareness: Higher producer density creates "food hubs" that increase consumer awareness through repeated exposure. Even consumers who initially have no intention to purchase from urban farms encounter these producers more frequently, gradually building familiarity and reducing psychological barriers to adoption.

Quality signaling and reputation spillovers: Concentrated producer clusters may generate positive reputation externalities wherein high-quality producers enhance the perceived credibility of the entire local food sector. Consumers form categorical judgments—"local food in this neighborhood is reliable"—rather than individuated producer assessments, creating collective benefits from individual quality investments.

Reduced search costs: Spatial concentration lowers consumers' transaction costs by enabling one-stop shopping across multiple producers, increasing basket diversity and reducing travel burden. This effect mirrors findings from farmers' market research showing that market size and vendor diversity positively predict consumer participation [50].

Social proof and norm activation: Dense producer presence signals social acceptability and normalizes local food consumption. Behavioral economics emphasizes descriptive norms—perceptions of what others do—as powerful behavioral drivers [51]. Concentrated urban agriculture visibly demonstrates that "people like me buy local food," activating conformity motivations and reducing perceived social risk.

However, this resilience has limits. The 66% market share collapse under elevated conventional prices ($d = -5.74$) reveals critical price sensitivity as a systemic vulnerability. This finding contradicts narratives positioning local food consumers as relatively price-insensitive "value buyers" [52]. Our temporal analysis revealed that price increases suppressed growth rates rather than triggering consumer defection, suggesting that price parity influences adoption dynamics more than retention. New consumers require economic competitiveness to overcome status quo bias, whereas existing consumers exhibit greater price tolerance.

This vulnerability has profound implications for long-term UPA viability. Urban agriculture competes not only on intrinsic product attributes but also within broader economic structures determining conventional food prices—global commodity markets, trade policies, agricultural subsidies. Exogenous shocks to these systems (e.g., international grain price spikes, trade disruptions) can rapidly undermine local markets even when supply-side capacity and demand-side knowledge are robust.

The policy implication is that sustainable UPA development requires structural economic interventions beyond farm-level support or consumer education. Potential strategies include: (1) institutional procurement commitments guaranteeing demand regardless of conventional price fluctuations, (2) price stabilization mechanisms such as strategic reserves or countercyclical subsidies, and (3) value-chain innovations capturing premium segments less sensitive to commodity price competition (e.g., direct-to-consumer subscriptions, restaurant partnerships).

Our validation approach—focused on reproducing qualitative behavioral patterns rather than calibrating to point estimates—exemplifies methodologically appropriate practices for exploratory agent-based models [15,19]. The model successfully replicated four key system patterns: (1) urban farming market penetration (12.03% vs. expected 5–15%), (2) net producer entry under profitable conditions (+54% growth), (3) spatial knowledge saturation (79.1% vs. expected 70–85%), and (4) moderate food security baselines ($FSI = 0.54$).

Among recent approaches [53] represents one of the efforts to integrate behavioral learning with policy intervention dynamics. However, their focus on algorithmic optimization contrasts with our emphasis on system-level fragility and policy stress-testing. Our approach aligns with Grimm et al.'s [15] advocacy for "pattern-oriented modeling," wherein model validation emerges from the capacity to simultaneously reproduce multiple system-level patterns. Single-pattern matching can occur fortuitously through parameter tuning, but multi-pattern replication suggests genuine mechanistic representation.

The model's success in capturing market dynamics, demographic turnover, knowledge diffusion, and food security outcomes strengthens confidence in its structural validity.

Recent work has explored the integration of behavioral adaptation and policy interventions using algorithmic and optimization-oriented approaches (e.g., [53]). Such models are particularly valuable for identifying efficient or stable policy configurations under predefined objectives. In contrast, our ABM is explicitly designed as a fragility-revealing system, prioritizing the identification of critical thresholds, non-linear responses, and unintended consequences over point optimization. This distinction is especially relevant in urban food systems, where policy success often depends less on optimal equilibria and more on resilience under shocks and uncertainty.

The agent-based approach revealed emergent properties not predictable from individual-level specifications. Three particularly salient examples include:

Market stability despite individual volatility: Individual producers experienced substantial profit fluctuations (coefficient of variation 0.45–0.60), yet system-level market share exhibited remarkable stability (CV 0.12–0.14). This stability-despite-volatility pattern emerges from portfolio effects wherein individual producer failures are compensated by others' successes, and from entry-exit dynamics that maintain roughly constant aggregate supply. Traditional representative-agent models cannot capture this micro-macro divergence.

Threshold effects in knowledge diffusion: Consumer knowledge did not diffuse linearly but exhibited threshold dynamics with rapid adoption cascades once neighborhood penetration exceeded approximately 35. This tipping point emerged from positive feedbacks wherein knowledgeable consumers socially validate local food purchases for neighbors, accelerating subsequent adoption. These nonlinearities are characteristic of social influence processes [54] but remain invisible in aggregate models.

Spatial clustering and path dependence: Initial random producer placement generated path-dependent spatial patterns wherein early-establishing producers catalyzed local market development, attracting subsequent entrants and creating persistent "food hubs." Alternative runs with identical parameters but different initial random seeds yielded qualitatively similar aggregate outcomes (market share, producer count) but distinct spatial configurations. This path dependence underscores the historical contingency of real urban agricultural landscapes.

These emergent properties demonstrate how agent-based modeling uniquely illuminates system-level phenomena arising from local interactions [55]. Such insights would remain obscured in equation-based models or empirical studies focusing on average effects.

The experimental design—progressing from isolated effects to interactions, stress tests, and optimization—exemplifies systematic policy exploration enabling interrogation of system behavior across parameter space [56]. Rather than identifying optimal policies in absolute terms, this approach reveals conditional dependencies, interaction effects, and robustness boundaries.

For instance, the finding that education dominates subsidies is not universal but conditional on system properties: bounded consumer knowledge, effective peer diffusion networks, and non-binding producer capacity. Alternative scenarios with saturated consumer knowledge or highly fragmented social networks might invert these relationships. Agent-based models enable systematic testing of such contextual dependencies, generating if-then policy knowledge: "If consumer knowledge is low and social networks are cohesive, then education outperforms subsidies; if knowledge is already high but production capacity is constrained, then subsidies may be necessary."

This conditional logic aligns with complexity-informed policy frameworks emphasizing context sensitivity and adaptive management [57,58]. Effective policies are not

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universally optimal but contextually appropriate, requiring diagnostic assessment of local conditions and adaptive adjustment based on observed system responses.

Our finding that education powerfully shifts consumption patterns resonates with stated preference studies showing that consumers value local food attributes (freshness, sustainability, community support) but often lack awareness of availability [59,60]. Zepeda and Li [61] found that knowledge about local food systems was the strongest predictor of farmers' market attendance, stronger than income, distance, or price sensitivity. Our model provides mechanistic grounding for these correlational findings, demonstrating how knowledge transmission through spatial exposure and social networks can drive aggregate market development.

The limited impact of production subsidies on market growth aligns with meta-analyses of agricultural subsidy programs showing modest or null effects on productivity and market outcomes [62]. Many subsidy programs exhibit leakage (benefits accruing to inframarginal actors) and deadweight loss (expenditure without marginal impact), consistent with our finding of substantial fiscal cost with minimal market share gains [63].

The antagonistic interaction between subsidies and education contributes to emerging literature on crowding-out effects [43] and policy interference [64]. While most studies examine crowding-out in prosocial behavior or voluntary contributions, our work extends these concepts to market-based policy contexts, demonstrating that extrinsic incentives can undermine intrinsically motivated consumption even in commercial settings.

This study advances urban food systems modeling through three key innovations. First, our framework simultaneously models supply constraints and demand barriers with explicit bidirectional feedbacks between producer pricing and consumer knowledge dynamics. Unlike prior ABMs focusing on isolated supply [14] or demand sides [21], this approach reveals non-additive policy interactions: combined subsidies and education underperform isolated interventions, contradicting conventional assumptions. Adaptive pricing responding to inventory creates feedback loops where producer survival depends on demand evolution, which itself responds to availability signals—dynamics invisible to single-sided models.

Second, our stress-testing protocol identifies resilience thresholds under compound perturbations rather than comparing equilibria. Education campaigns maintain spatial clustering (Moran's I > 0.55) across climate scenarios while subsidy systems collapse (turnover rate > 0.40), demonstrating that resilience is context-dependent rather than scalar. This process-oriented approach reveals how systems fail, not merely terminal outcomes.

Third, this model serves as a calibration platform for cascade studies. Agent vulnerability distributions (satisfaction trajectories, knowledge ceilings, spatial patterns) initialize long-term displacement models examining gentrification dynamics [65]—the success-displacement paradox where agricultural adoption triggers land value increases displacing farmers.

Limitations and Future Research Directions

Several limitations constrain interpretation and generalization of our findings.

Stylized representation of reality: The model abstracts from numerous real-world complexities for analytical tractability. Producer agents represent simplified farmers with homogeneous production functions and limited behavioral repertoires (dynamic pricing, satisfaction-based exit). Real urban farmers exhibit far richer strategic decision-making, including crop selection, diversification, direct marketing innovation, and political advocacy. Consumers are modeled as rational utility-maximizers with logit choice functions, neglecting habit formation, identity-based consumption, and emotional dimensions of food purchasing decisions.

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Limited spatial realism: The patch-based environment represents stylized urban geography without realistic spatial features such as transportation networks, income segregation patterns, or land-use zoning. Distance is measured as Euclidean rather than network distance, overestimating accessibility in areas with poor transit connectivity. Future versions could integrate geographic information systems (GIS) data to model cities' actual spatial structure.

Simplified social networks: Knowledge diffusion operates through distance-based neighborhoods rather than realistic social network structures. Empirical social networks exhibit scale-free or small-world topologies with hubs, weak ties, and homophily [66], properties not captured in our spatial diffusion mechanism. More sophisticated models could incorporate empirically calibrated network structures derived from social network analysis.

Exclusion of key actors: The model omits several important actors, including intermediaries (distributors, processors), retailers (supermarkets considering local sourcing), advocacy organizations, and government extension services. These actors shape market structure, information flows, and institutional environments in ways not represented. Multi-level agent architectures incorporating organizational actors could enrich future models.

Static institutional environment: Policies are represented as exogenous interventions with fixed parameters, whereas real policy implementation involves adaptive adjustment, political negotiation, and institutional learning. The model does not capture how policies themselves evolve in response to observed outcomes or stakeholder advocacy. Incorporating institutional agents with learning and adaptation capacities would enable analysis of co-evolutionary policy dynamics.

Deterministic policy effects: Education campaigns increase knowledge by fixed increments, whereas real educational interventions exhibit heterogeneous treatment effects depending on message framing, delivery mechanisms, and recipient characteristics [67]. Future models could incorporate more nuanced representations of communication effectiveness drawing on health behavior change theories.

Calibration limitations: While the model reproduces qualitative patterns, parameter values are informed by literature and exploratory calibration rather than formal statistical estimation against specific data. Rigorous calibration would require detailed empirical data on producer costs, consumer preferences, purchase frequencies, and spatial distributions—data rarely available at the requisite granularity for UPA. Future work could employ Approximate Bayesian Computation or other likelihood-free inference methods for formal parameter estimation [68].

Geographic specificity: The model represents a generalized urban agricultural system. Findings may not transfer to cities with radically different characteristics: lower population density (limiting agglomeration effects), stronger land tenure security (reducing producer precarity), different food cultures (affecting willingness to adopt local food), or varied institutional capacity (constraining policy implementation). Cross-national comparative agent-based modeling could systematically explore how contextual factors moderate policy effectiveness.

Temporal scope: The 5-year simulation horizon (250 weeks) captures medium-term dynamics but may miss longer-term processes such as generational shifts in food preferences, climate change impacts on urban agriculture viability, or transformative innovations (e.g., vertical farming, automated growing systems). Extending temporal horizons would enable analysis of secular trends and structural transformations.

Sectoral focus: The model focuses exclusively on fresh produce (vegetables and herbs), which dominates urban agriculture in Brazil. Different product categories (e.g., animal products, processed foods) involve distinct production technologies, regulatory environments, and consumer perceptions. Product-specific models could reveal heterogeneity in policy effectiveness across agricultural sectors.

5. Conclusions

This study demonstrates the power of agent-based modeling to highlight the complex socio-economic dynamics of urban agriculture systems and inform evidence-based policy design. Through systematic simulation of producer-consumer interactions under varying policy interventions, our findings challenge conventional assumptions about agricultural support mechanisms. Consumer education campaigns achieve market development outcomes equivalent to production subsidies while operating at zero fiscal cost. This demand-side constraint identification underscores that urban agriculture adoption is limited not by producers' capacity to supply products, but by consumers' knowledge and valuation of local food attributes. Combined policy interventions produce additive rather than synergistic effects, with potential for antagonistic interactions under certain circumstances. Urban agriculture systems exhibit complex emergent properties, including positive density effects, threshold dynamics in knowledge diffusion, and critical vulnerability to conventional market price fluctuations, necessitating systems thinking approaches that transcend linear policy logics.

Beyond immediate policy applications, this research contributes methodologically by demonstrating pattern-oriented validation approaches appropriate for exploratory agent-based models, and theoretically by revealing how local interactions scale to system-level outcomes through social diffusion, adaptive pricing, and demographic turnover mechanisms. Sustainable urban agriculture development requires not only consumer education and producer support, but also institutional mechanisms ensuring long-term price competitiveness, such as public procurement commitments, community-supported agriculture models, and value-chain innovations capturing premium market segments.

Further developments of the modeling framework proposed in this research will focus on incorporating climate change scenarios and adaptive capacity dynamics to assess long-term viability under environmental stress, integrating institutional actors and value chain intermediaries to capture multi-level governance complexity, exploring equity implications through disaggregated analysis of distributional consequences across socioeconomic groups, and extending spatial realism through GIS integration and empirically calibrated social network structures. Enabling investigations of potential sources of system instability. Ultimately, this research contributes to bridging complex systems science, behavioral economics, and urban agroecological practice—advancing both theoretical understanding and practical capacity for evidence-informed governance of sustainable urban food futures.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/complexities2010002/s1, S1: ODD+D Protocol Documentation; S2: NetLogo Source Code Documentation; S3: Detailed Model Documentation, Table S3.1: Policy interventions and parameter configurations; Table S3.2: Outcome metrics and definitions; Table S3.3: Experimental design and rationale; Table S3.4: Statistical methods by experimental objective.

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