Evaluating Crop Planning Decisions in Family Farming Systems under Resource Constraints: A Dynamic Modeling Approach

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Abstract:
Agricultural systems face increasing pressure to improve productivity while ensuring sustainable resource use, particularly in family farming contexts. This study develops a system dynamics model to evaluate crop allocation and rotation strategies in a municipality in Colombia. The model integrates environmental, productive, economic, and social variables through a stock-and-flow structure, capturing feedback mechanisms over time. Five production scenarios, derived from a multi-objective crop planning model, were simulated over a 96-month horizon using Vensim DSS.
Results reveal significant trade-offs between economic performance, environmental sustainability, and employment. Profit-oriented scenarios increase soil degradation and water footprint, especially the grey component, while more conservative strategies reduce environmental impacts but lower economic returns. Key crops such as potato and onion drive profitability and labor demand, whereas permanent crops provide greater stability. These findings highlight the value of system dynamics for supporting sustainable decision-making in family farming systems.

Keywords: Family farming, dynamic simulation, sustainability, agricultural crops.

Introduction

Globally, farmers determine land use and diversification based on a range of factors, including socioeconomic conditions, climate, topography, and public policies. These decisions are also influenced by production costs of agricultural goods, changes in labor allocation within productive units, labor availability, access to road infrastructure, and the distance to distribution centers such as local markets or collection hubs, among others [1]. In Colombia, the agricultural frontier covers 39,600,143 hectares (ha), of which approximately 14,173,004 ha are estimated to correspond to family farming systems [2].

According to the 2014 National Agricultural Census, more than 70.4% of productive units are smaller than 5 ha, occupying a relatively small proportion of the total agricultural area. This reflects a fragmented, small-scale production structure[3], where peasant-based economies predominate. The production from these units is primarily oriented toward self-consumption as well as local, regional, and even international markets [4].

However, significant limitations persist, including low coverage of technical assistance, limited production planning, and inadequate land use. These constraints result in low productivity, high production costs, and degradation of natural resources such as soil and water [5] [6].

Although farmers possess empirical knowledge of their local conditions and make adaptive decisions based on available resources [7], [8], there is currently a lack of integrated tools to support decision-making regarding crop allocation and rotation while simultaneously considering economic, social, and environmental variables.

In this context, the problem addressed in this study is the absence of integrated models capable of dynamically evaluating efficient crop allocation in family farming systems, while considering resource sustainability and the economic stability of producers.

To address this gap, a system dynamics-based simulation model was developed to evaluate different crop allocation and rotation strategies in family farming units, integrating environmental, economic, and social variables within a Colombian municipality.

This study contributes to the system dynamics literature by developing an integrated model for analyzing agricultural production systems in the context of family farming. The model is structured into five interdependent subsystems (soil, water, social, production, and economic), capturing complex feedback mechanisms through reinforcing and balancing loops. Unlike conventional approaches, it explicitly represents dynamic interactions between biophysical and productive variables, enabling the identification of emergent system behaviors over time. The model is formalized using a Forrester structure and implemented in Vensim DSS, allowing simulation over medium-term horizons. Its structural and behavioral validation, supported by consistency checks and comparison with empirical data, enhances its reliability as a decision-support tool. Additionally, the model reveals non-linear dynamics and trade-offs driven by feedback interactions, particularly those associated with resource use and production intensification. Overall, this work advances the application of system dynamics by providing a robust, adaptable, and analytically rich framework for studying complex agricultural systems.

State of the art

System dynamics has become a relevant methodological approach for analyzing complex agricultural systems, due to its ability to model non-linear interactions, feedback mechanisms, and temporal dynamics. To characterize its application in the agricultural sector, a literature review was conducted using the Web of Science and Scopus databases, identifying a total of 185 documents published between 2006 and 2024. The scientific output consists mainly of research articles (97.8%), with a marginal presence of review and conference papers, indicating a predominantly applied field.

The review revealed significant growth over the past decade, with 89% of publications concentrated in this period. This increase reflects a growing interest in using system dynamics to address issues related to land use, natural resource management, and the sustainability of agricultural production systems. Geographically, scientific production is highly concentrated, with China leading (62.7%), followed by the United States and Iran. A moderate level of international collaboration (34.6%) was also identified, suggesting opportunities to strengthen global research networks.

From an applied perspective, system dynamics has been widely used to simulate policy scenarios and assess their impact on key variables such as water availability, land-use change, agricultural productivity, and socioeconomic indicators. These applications enable the analysis of system evolution over time, facilitating scenario comparison and the identification of more sustainable management strategies [9]. Tools such as Vensim [10], Stella [11], and AnyLogic [12], are the most commonly used for model development.

The main research lines identified are concentrated in three areas. First, water resource management, where dynamics of supply and demand, irrigation methods, and climate variability are modeled, along with their impact on agricultural productivity [9], [13], [14]. Second, the optimization of production systems, including the efficient use of inputs such as fertilizers, pesticides, and energy [15], as well as adaptation to water stress and drought conditions [16] Third, the analysis of socioeconomic impacts, particularly in rural communities, where effects on income, food security, and well-being are evaluated [17], [18].

The reviewed studies demonstrate the versatility of system dynamics across different geographic and production contexts. Applications have been developed in Latin America, Africa, Asia, and Europe, addressing issues such as shade-grown coffee production, irrigation system management, emission mitigation in rice cultivation, and drought adaptation [19][20], [21], [13], [22], [14], [9], [23], [17], [24], [25], [16]. Additionally, innovative approaches such as the integration of text mining for the analysis of sustainable agricultural systems have been incorporated [18].

A relevant aspect identified in the literature is the integration of system dynamics with mathematical models [26], enabling a more precise approach to resource allocation problems under multiple objectives and uncertainty conditions [27]. Common approaches include linear programming [20], [28], [29], stochastic programming [11], [26], [30] and finite element-based models such as HYDRUS [31], which simulate complex physical processes like soil water flow and solute transport. These integrations enhance the analytical capacity of models, particularly at local scales and in contexts of high climate variability.

In terms of modeling, variables are typically grouped into five interrelated systems: economic, productive, technological, social, and environmental. The economic system includes variables such as costs, revenues, investment, and demand [32], [33], [34], [35], [36], [37]; the productive system includes yield, input use, and labor [38], [39], [37], [36], [40], [41], [33], [35]; the technological system incorporates mechanization and innovation levels [38], [35]; the social system considers factors such as population, poverty, and migration [40], [32], [33], [35], [38], [34], [37], [39] and the environmental system focuses on land use [32], [38], [35], [39], [12], [11], [30], [38] [34], [42], [37] water availability [36], [11], [41], [40], [12] and emissions [33], [37]. This structure highlights the multidimensional nature of agricultural systems and the need for integrated approaches in their analysis.

Additionally, system dynamics has been applied to land-use planning beyond agriculture, including urban contexts [43], where variables such as population growth, GDP, and urbanization influence land transformation. Specific applications have also been developed to model biophysical processes such as water infiltration, water and salinity stress, and soil–water–plant interactions [31].

Finally, the review highlights a wide diversity of production systems analyzed, including cereals (rice, maize, wheat) [30], [44], [16], [17], [22], industrial crops (sugarcane, coffee) [45], [46], [30], fruit crops (mango, nuts) [10] and mixed systems integrating agriculture, livestock, and natural ecosystems [26], [20], [28], [29]. This diversity confirms the flexibility of system dynamics to adapt to different production contexts.

In conclusion, system dynamics represents a robust and expanding tool for analyzing and managing complex agricultural systems. Its ability to integrate multiple dimensions and simulate dynamic scenarios makes it a key approach for supporting decision-making in the context of sustainability and climate change. However, challenges remain, including the geographic concentration of scientific production and the need to strengthen interdisciplinary and integrated approaches to better address the complexity of the agricultural sector.

Methodology

A dynamic simulation model is proposed based on the system dynamics methodology developed by Sterman [47], following the steps outlined in Figure 1. The model integrates variables related to natural resources (soil and water), economic factors, social components, and characteristics of family farming production units.

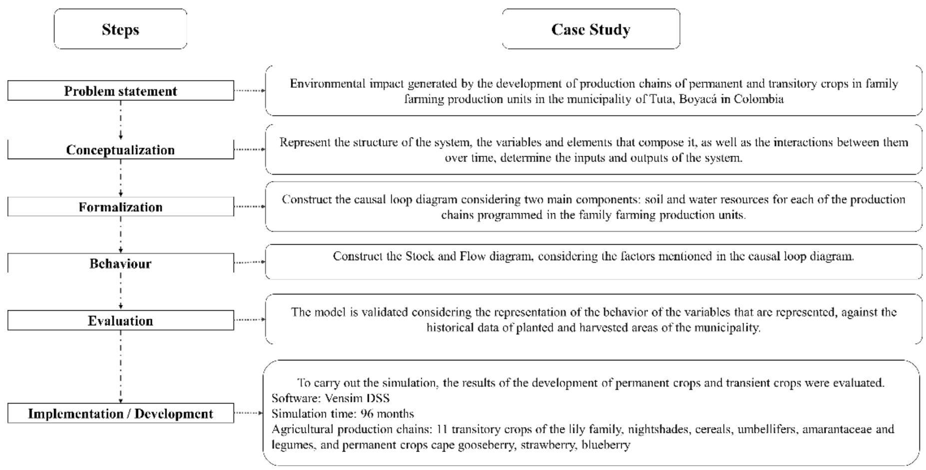


Figure 1: Methodological approach, adapted from [48], [49]

Conceptualization:

The system is structured into six main subsystems: soil resources, water resources, production units, production chains, agricultural production, and economic and social factors. A stock-and-flow modeling approach is employed, enabling the representation of the temporal evolution of key variables such as resource availability, productivity, and yield.

Formalization:

The causal loop diagrams represent the agricultural production system in family farming units, based on the literature review and structured into interconnected subsystems: soil, water, production, social, and economic components.

The soil subsystem (Figure 2) captures the dynamics between land use, agricultural expansion, soil degradation, and fertility, incorporating seven balancing loops and five reinforcing loops. These feedback structures explain processes such as resource depletion, the effects of crop rotation, and the role of practices like compost use in mitigating soil degradation.

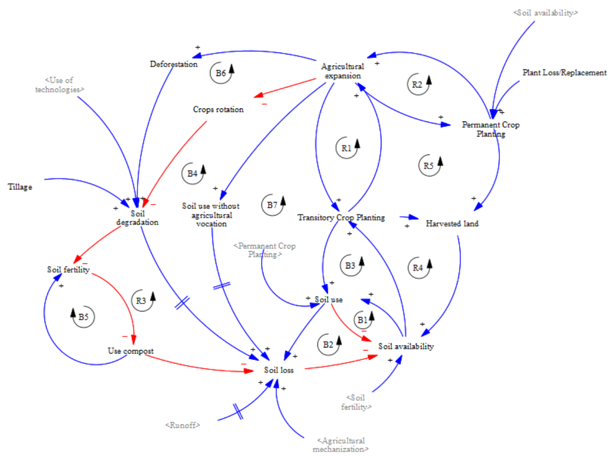


Figure 2. Causal loop diagram for the soil resource. Source: [49]

The water subsystem (Figure 3) describes the interactions between water availability, irrigation practices, crop production, and environmental factors such as climate variability. It includes three balancing loops and four reinforcing loops, highlighting feedbacks related to water demand, efficiency of irrigation systems, and water quality degradation due to agricultural inputs.

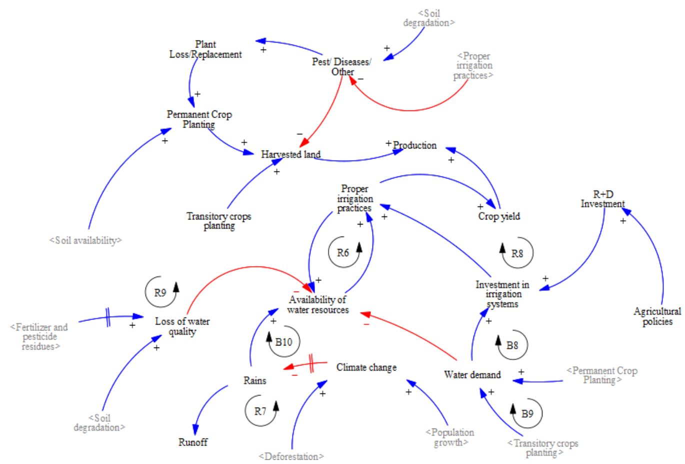


Figure 3. Causal loop diagram for the water resource. Source: [49]

Additionally, the model integrates production, social, and economic subsystems (Figure 4), linking crop yield, technological investment, labor demand, and profitability. These interactions capture how increases in production and income can reinforce investment and expansion, while also generating pressures on natural resources.

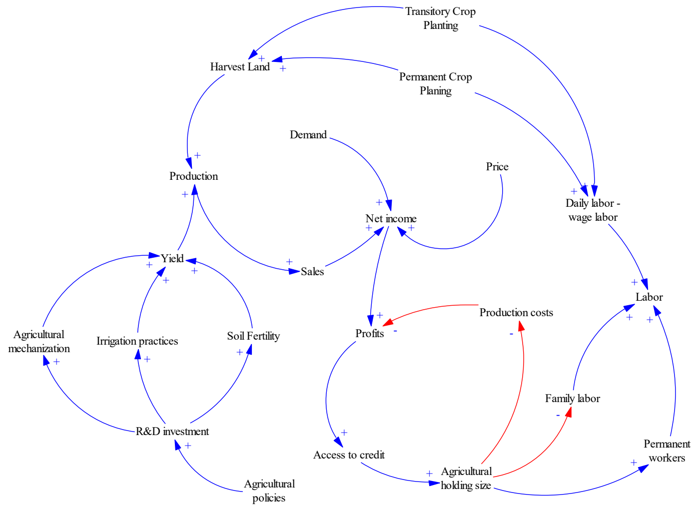


Figure 4. Causal loop diagram for the production, social and economic subsystems.

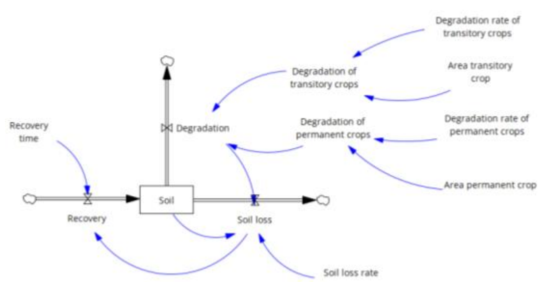
Overall, the integrated structure of the model allows the representation of key feedback mechanisms driving trade-offs between productivity, resource use, and socio-economic outcomes in agricultural systems.

Behaviour:

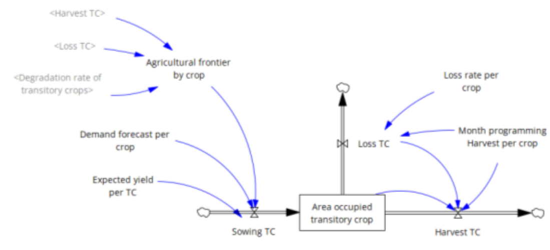
Following the conceptualization, the causal loop diagrams were translated into a stock-and-flow model implemented in Vensim DSS. The model distinguishes between state variables (levels), which represent system accumulations over time, and flow variables, which define the rates of change. Additionally, auxiliary variables and parameters are included to represent system relationships and improve model transparency.

The model is structured into five interconnected subsystems:

Soil subsystem: The soil stock represents the total available land for agricultural activities (Figure 5). It is affected by soil loss (Figure 5.a degradation) and recovery processes, driven by the intensity of land use and crop type (transitory and permanent). Degradation rates vary by crop, while recovery depends on management practices and time, capturing the dynamic balance between use and restoration.

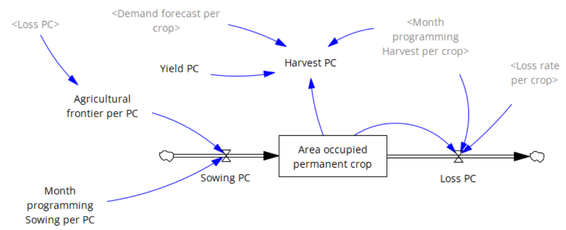


a)



b)

Figure 5. a) Stock and flow diagram for soil resource Level 1. b) Stock and flow diagram for soil resource Level 2. Source: [49].



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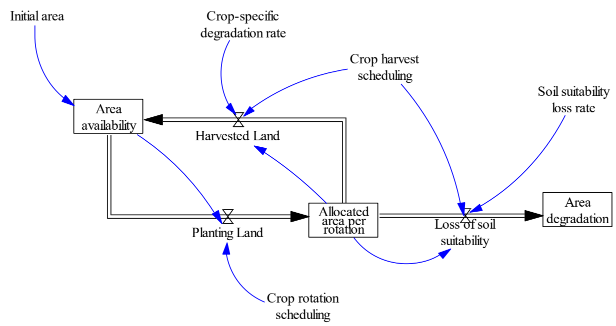
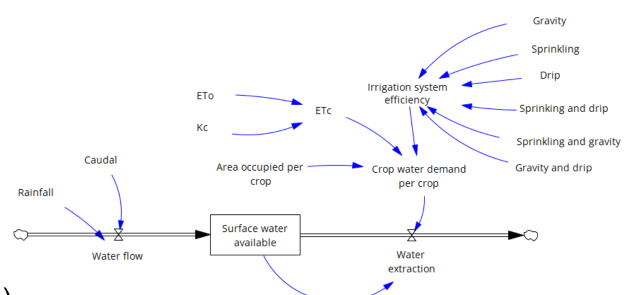


d)

Figure 5. c) Stock and flow diagram for soil resource Level 3. d) Stock and flow diagram for soil resource Level 4. Source: [49].

Water subsystem: The water subsystem models surface water availability and its extraction based on crop water demand (Figure 6). Water demand depends on evapotranspiration (ETc), crop area, and irrigation efficiency. Additionally, the model incorporates blue, green, and grey water footprints, linking water use with environmental impacts such as contamination from agricultural inputs.



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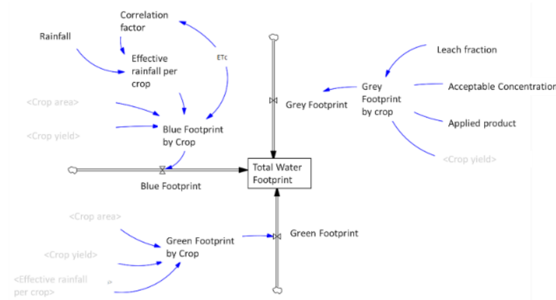


Figure 6. a) Stock and flow diagram for water resource Level 1. b) Stock and flow diagram for water resource Level 2.
Source: [49].

Production subsystem: The production subsystem represents the dynamics of cultivated area, sowing, harvesting, and yield for both transitory and permanent crops (Figure 7). Crop production is determined by scheduled rotations, expected yields, and demand conditions, allowing the simulation of temporal production patterns.

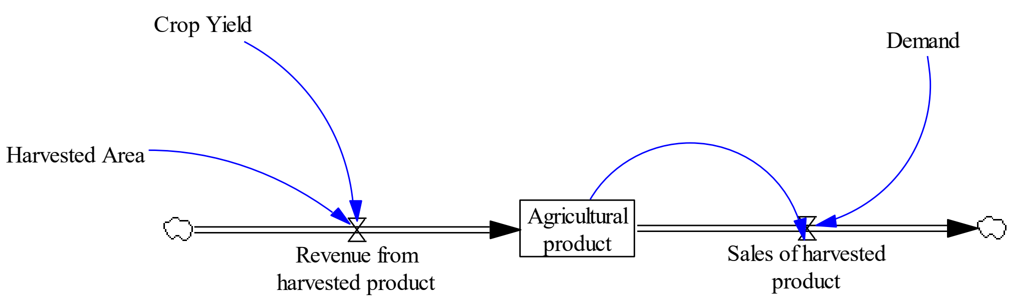


Figure 7. Stock and flow diagram for production subsystem Level 1.

Economic subsystem: The economic component estimates revenues, costs, and profits based on production levels, crop prices, and harvested volumes (Figure 8). This structure enables the evaluation of the economic performance of different crop configurations over time.

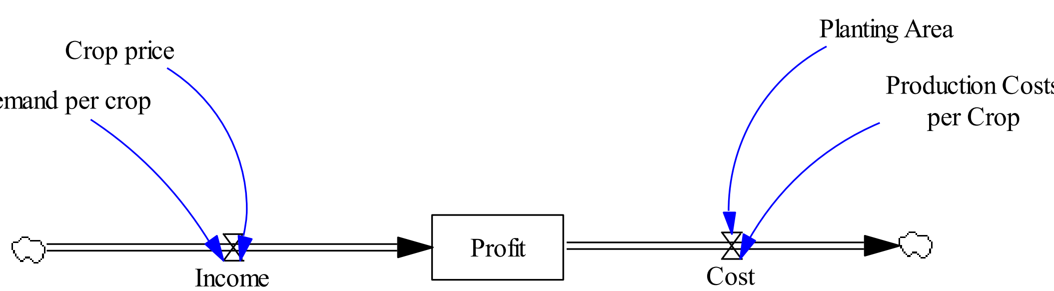


Figure 8. Stock and flow diagram for economic subsystem Level 1.

Social subsystem: The social subsystem captures labor demand as a function of crop area and agricultural activities, particularly during sowing and harvesting periods (Figure 9). This allows the assessment of employment generation and its variability across production scenarios.

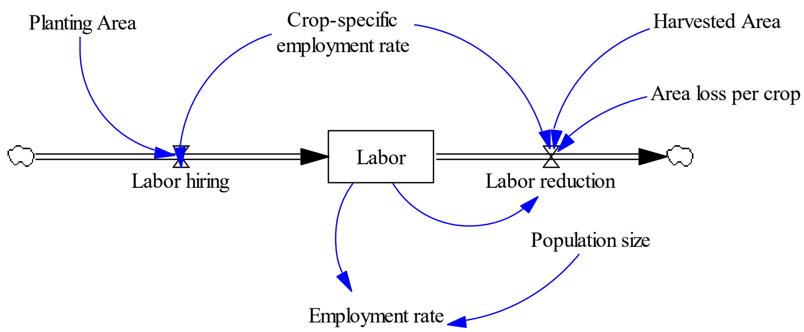


Figure 9. Stock and flow diagram for social subsystem Level 1.

Model validation

The model was validated through both structural and behavioral validation approaches. Structural validation was ensured by grounding the model formulation on an extensive literature review and by verifying the consistency between the causal loop diagrams, stock-and-flow structure, and governing equations.

Behavioral validation was performed by comparing the simulated dynamics of key variables with historical data on sown and harvested areas at the municipal level. Additionally, a sensitivity analysis was conducted to assess the robustness of the model under variations in key input parameters.

The analysis considered changes in the allocation of agricultural area, using minimum, base, and maximum values expressed in hectares and as percentages of total available land. The results show consistent system responses, preserving expected trends in land use distribution (Figure 10).

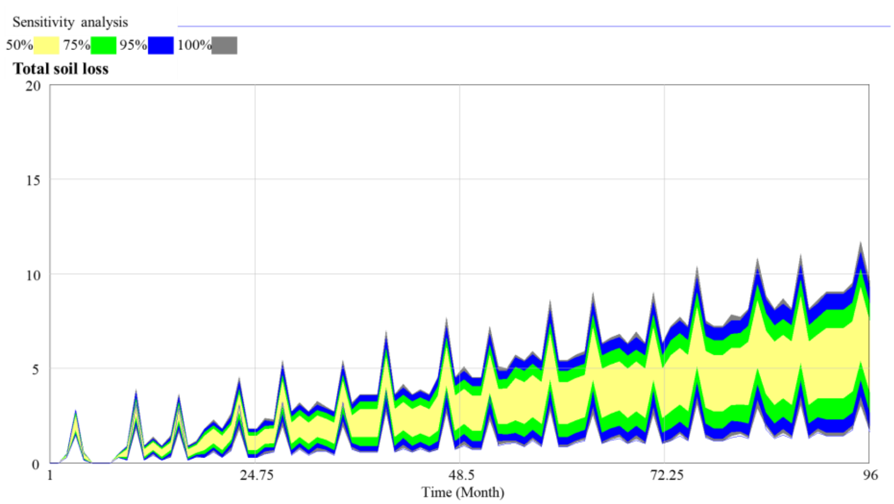


Figure 10. Sensitivity analysis of total soil loss

Sensitivity tests were also extended to key outputs such as labor demand and total water footprint, showing stable dynamic patterns across scenarios, with variations in magnitude but no structural instability (Figure 11).

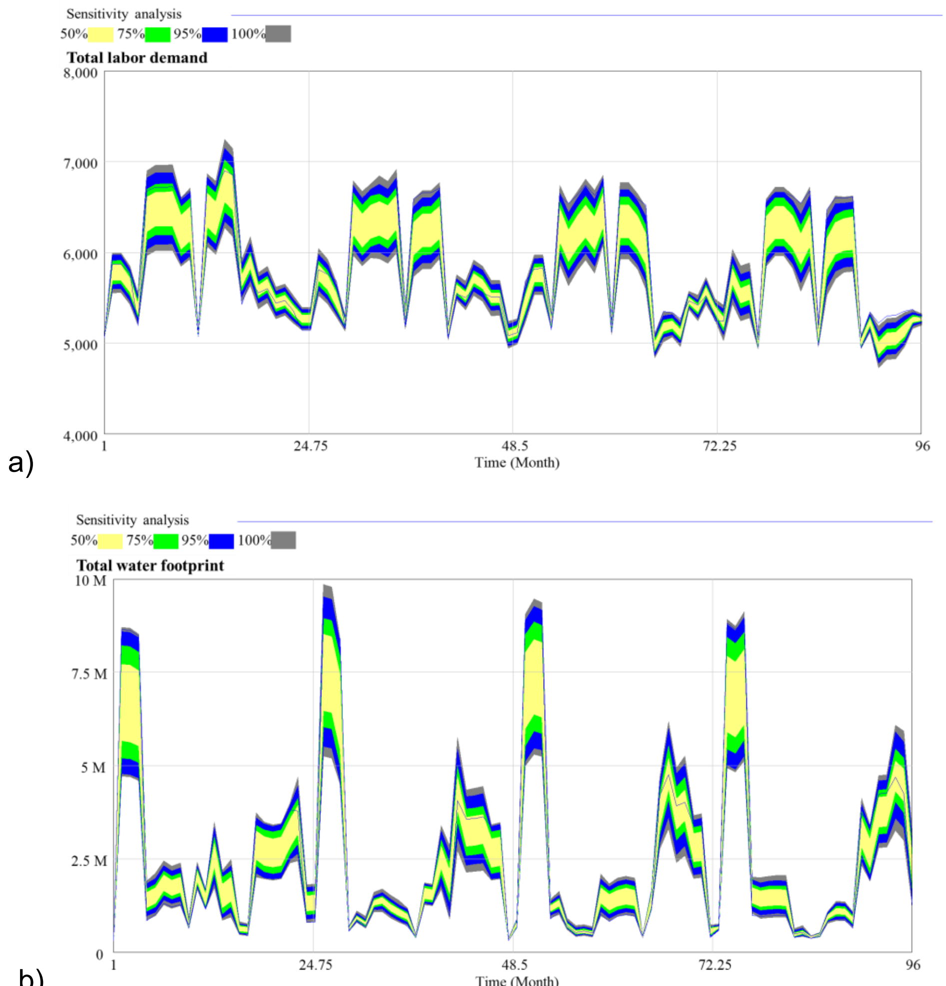


Figure 11. Sensitivity analysis of total labor demand and total water footprint

Overall, the model demonstrates structural consistency, behavioral realism, and robustness, supporting its applicability as a decision-support tool for sustainable agricultural planning.

Simulation

Five production scenarios were developed based on a prior crop scheduling model and simulated over a 96-month horizon using Vensim DSS. These scenarios include five rotations of transitory crops and three permanent crops, defined as model inputs derived from a compromise programming approach applied to family farming production units.

The analysis was structured around key system variables, including land use by production chain, occupation of production units, water resource use, agricultural production, profits, and labor demand.

For the simulation, an agricultural frontier of 3,986 hectares allocated to transitory crops was considered, classified according to soil quality (good, medium, and regular) [50]. For permanent crops, the initial cultivated area in the municipality was used as a reference, with a maximum capacity of 714 hectares for perennial crops and 544 hectares for other fruit crops [51], according to irrigation system conditions.

The allocation of crop rotations corresponds to the efficient scenario, aimed at maximizing benefits while reducing income variability among production units according to their size. For permanent crops, planting schedules were determined based on interannual percentage variations observed in historical data from the municipality of Tuta [52] (Figure 12)

Transitional Crop Rotation

<table>
<tr><th></th><th colspan="28">Month</th><th></th><th></th></tr>
<tr><th>Rotation</th><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th><th>6</th><th>7</th><th>8</th><th>9</th><th>10</th><th>11</th><th>12</th><th>13</th><th>14</th><th>15</th><th>16</th><th>17</th><th>18</th><th>19</th><th>20</th><th>21</th><th>22</th><th>23</th><th>24</th><th>25</th><th>26</th><th>27</th><th>28</th><th>APUF</th><th>Land</th></tr>
<tr><td>1</td><td colspan="5"></td><td colspan="7">Potato</td><td colspan="6">Quinoa</td><td colspan="10"></td><td>10%</td><td>5%</td></tr>
<tr><td>2</td><td colspan="4">Pea</td><td colspan="7">Potato</td><td colspan="5">Bulb onion</td><td colspan="7">Wheat</td><td colspan="5"></td><td>60%</td><td>76%</td></tr>
<tr><td>3</td><td colspan="4">Pea</td><td colspan="7">Potato</td><td colspan="4"></td><td colspan="6">Maize</td><td colspan="5">Barley</td><td colspan="2"></td><td>10%</td><td>4%</td></tr>
<tr><td>4</td><td colspan="3">Coriander</td><td colspan="6"></td><td colspan="4">Pea</td><td colspan="7">Potato</td><td colspan="7">Wheat</td><td colspan="1"></td><td>10%</td><td>8%</td></tr>
<tr><td>5</td><td colspan="5">Oat</td><td colspan="6">Bean</td><td colspan="7">Potato</td><td colspan="4">Carrot</td><td colspan="6"></td><td>10%</td><td>7%</td></tr>
</table>

Anual fluctuation land area sowing per permanent crops

	Year 1	2	3	4	5	6	7	8	Initial Area (ha)
Strawberry	17,2%	2,9%	5,1%	5,5%	17,2%	2,9%	5,1%	5,5%	70
Gooseberry	4,8%	25,0%	50,0%	4,8%	4,8%	25,0%	50,0%	4,8%	3
Blueberry	83,5%	11,6%	14,8%	200,0%	83,5%	11,6%	14,8%	200,0%	15

Figure 12. Transitory crop rotation scheduling and variation in planted area per permanente crops

The prioritized transitory and permanent crops, as well as the rotations derived from the crop scheduling model, are incorporated into the simulation. The analysis is structured around key system variables, including land use by production chain, occupation of production units, water resource use, production levels, generated profits, and labor requirements.

Additionally, variables such as soil degradation, water resource use, and water footprint (green, blue, and grey) are incorporated, allowing for the evaluation of the environmental impact of each scenario over time.

Results

Based on the simulation, transitory crop rotations and the scheduling of permanent crops were analyzed according to key variables such as land use, water footprint, production, sales, and profits by crop type. Results are presented in an aggregated form by scenario, allowing for the comparison of performance across different configurations.

Transitory crop rotations were distributed across areas with agricultural suitability, while permanent crops show variations in their occupied area according to the scheduling, respecting maximum land-use constraints.

The evaluated scenarios correspond to different rotation configurations aimed at identifying alternatives that improve economic benefits and reduce income variability among production units, while simultaneously considering the use of natural resources.

Soil resource: Soil loss was estimated by comparing the occupied area at the end of the simulation with the initial area assigned to each rotation, allowing the identification of differences in the impact of each production sequence (Figure 13).

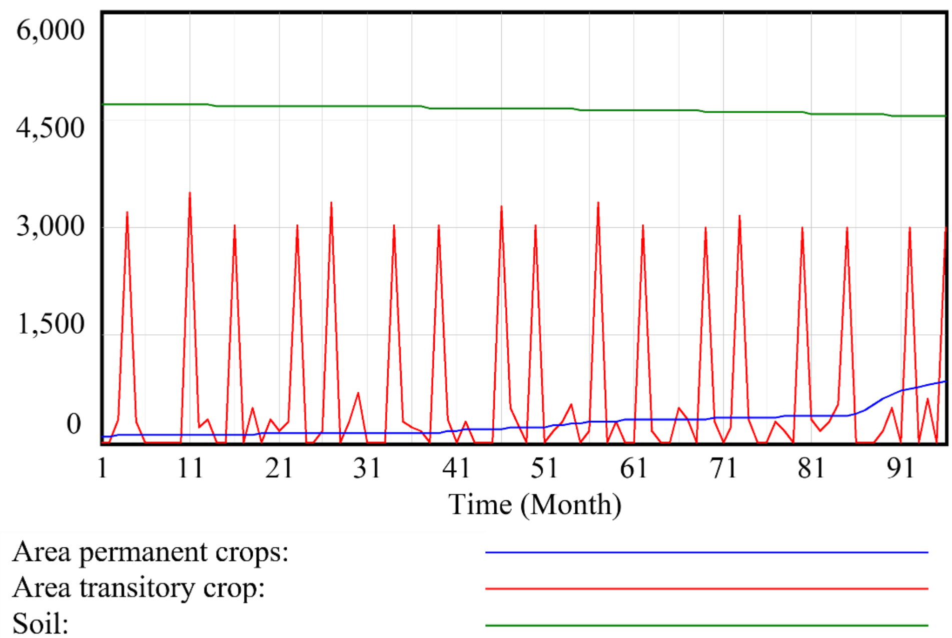
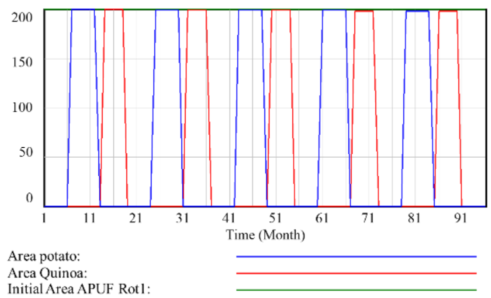


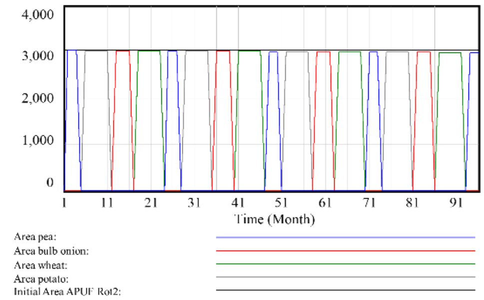
Figure 13. Land use by crop type

The results (figure 12) show that Rotation 2, which concentrates the largest share of land (76%) and production units (60%), presents a soil loss of 1.44%, highlighting the effect of large-scale production intensification (Figure 86). Similarly, Rotations 3 (1.46%) and 4 (1.17%) exhibit relatively high levels of degradation, associated with the sequencing of high-demand crops.

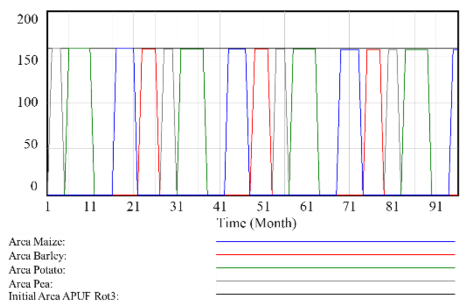
In contrast, Rotations 1 (0.67%) and 5 (0.96%) show a lower impact on soil resources, suggesting that certain crop combinations can contribute to reduced system degradation.



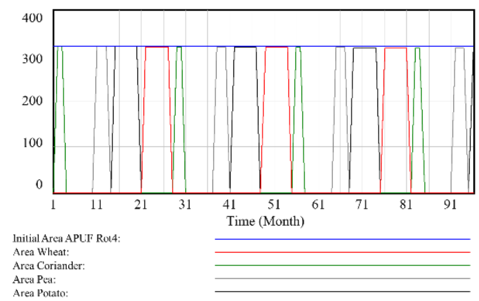
a) Rotation 1 Occupation Land



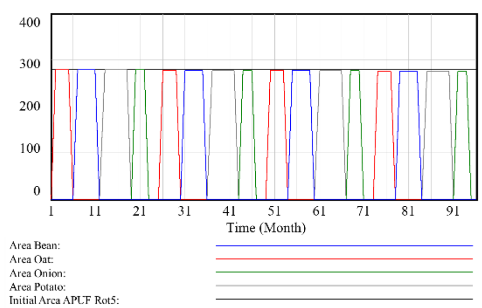
b) Rotation 2 Occupation Land



c) Rotation 3 Occupation Land



d) Rotation 4 Occupation Land



e) Rotation 5 Occupation Land

Figure 14. Occupation land per rotation

Regarding permanent crops, a progressive expansion of blueberry cultivation is observed. From the third year onward, its share increases and surpasses the cultivated area of strawberry by the fourth year (Figure 15), indicating structural changes in land use over time.

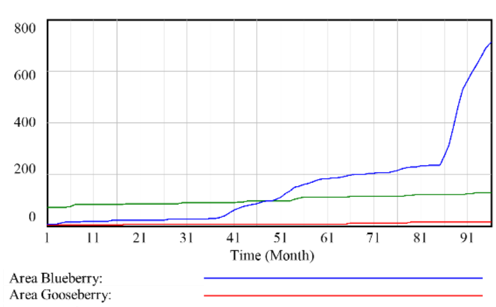


Figure 15. Occupation land by permanente crop

Water resource: The results show that the grey water footprint is the main component of total water consumption, followed by the green water footprint and, to a lesser extent, the blue water footprint (Figure 16). This pattern indicates that the greatest water-related impact is associated with the use of agricultural inputs and the generation of pollutants, rather than with the natural availability of the resource.

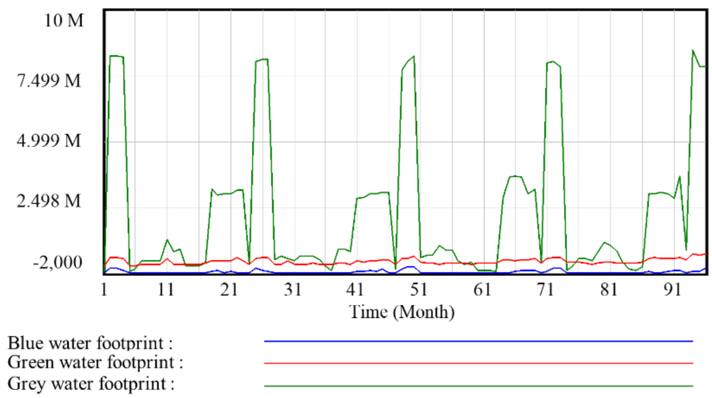


Figure 16. Water footprint

At the temporal level, the total water footprint reaches its highest values in January and between October and December, coinciding with periods of higher agricultural demand. On average, water consumption per hectare exhibits seasonal variations, reflecting the dynamics of production cycles (Tables 1 and 2).

Table 1. *Monthly water footprint of the total cultivated area*

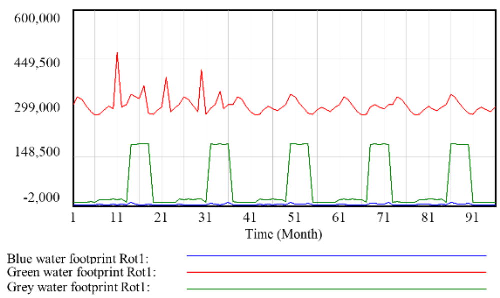
Consumption	**Month**	**1**	**2**	**3**	**4**	**5**	**6**
Average	m^3/ha	3660379	3835303	3182920	2577977	1912394	2329154
Maximum	m^3/ha	8801133	9133664	9013313	8857877	4187382	4220654
Minimum	m^3/ha	314228	530070	438941	636268	387053	447884
Consumption	Month	**7**	**8**	**9**	**10**	**11**	**12**
Average	m^3/ha	2361149	2472099	2078245	2633171	3197581	3684036
Maximum	m^3/ha	4269063	4409558	3843059	9247366	8626875	8842532
Minimum	m^3/ha	768356	799522	802702	691811	503765	471142

Table 2. *Monthly water footprint per hectare of cultivated area*

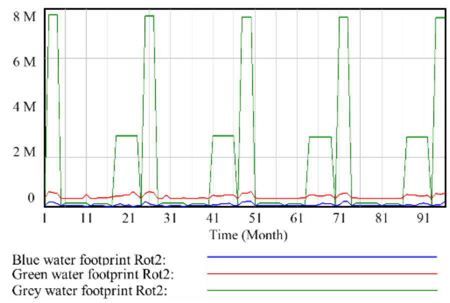
Consumption	**Month**	**1**	**2**	**3**	**4**	**5**	**6**
Average	m^3/ha	1467	1075	935	957	672	586
Maximum	m^3/ha	4029	2336	2331	2495	1067	1029
Minimum	m^3/ha	122	136	164	162	226	137
Consumption	Month	**7**	**8**	**9**	**10**	**11**	**12**
Average	m^3/ha	637	614	706	791	982	1274
Maximum	m^3/ha	1175	1023	1133	2116	2164	2475
Minimum	m^3/ha	213	213	213	215	199	127

The analysis by rotation reveals differentiated patterns. Rotations that include crops such as pea, potato, and wheat exhibit higher grey water footprint values, particularly during phases with greater input use. In contrast, rotations including crops such as quinoa, oat, or bean tend to show a higher contribution of the green water footprint and a lower relative impact.

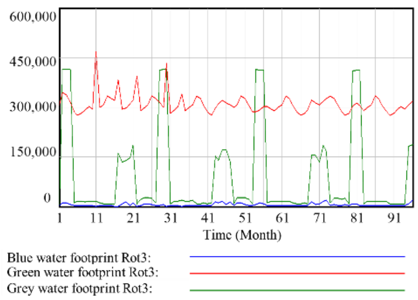
In particular, Rotation 3 presents the highest water consumption per hectare, suggesting greater pressure on the resource compared to the other configurations (Figure 17).



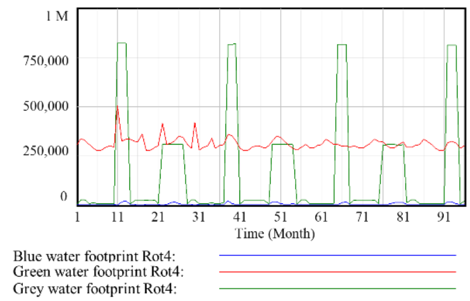
a) Rotation 1 Water footprint



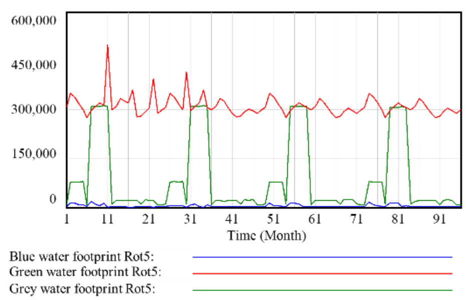
b) Rotation 2 Water footprint



c) Rotation 3 Water footprint



d) Rotation 4 Water footprint



e) Rotation 5 Water footprint

Figure 17. Water footprint per rotation

Permanent crops, in turn, exhibit lower water footprint values per hectare, with a shift from grey to green water footprint dominance starting around month 38, associated with the expansion of crops such as blueberry and strawberry (Figure 18). This pattern suggests greater water use efficiency, possibly linked to the implementation of more advanced irrigation systems.

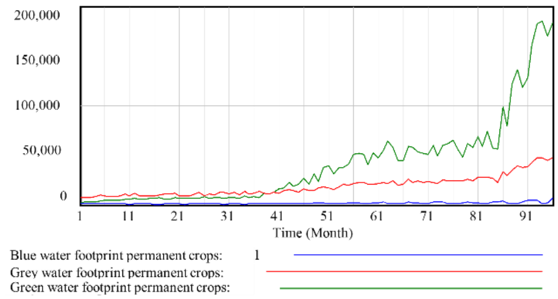
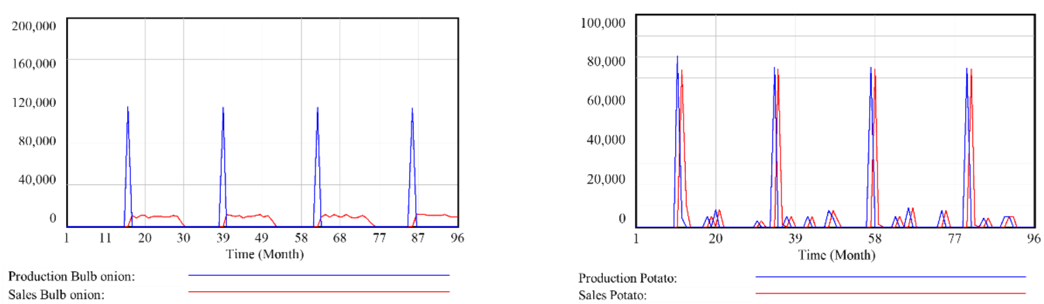


Figure 18. Water footprint per permanent crop

Production: The results show the relationship between production (blue line) and sales (red line) for different crops, expressed in tons. In general, production exhibits a cyclical pattern associated with harvest periods, while demand tends to remain relatively stable over time.

For the prioritized transitory crops, bulb onion and potato, distinct dynamics are observed. Onion production shows peaks concentrated in specific periods, generating surpluses relative to a relatively constant demand. In contrast, potato exhibits a more balanced pattern, where production is almost immediately absorbed by demand, indicating a high product turnover (Figure 19).

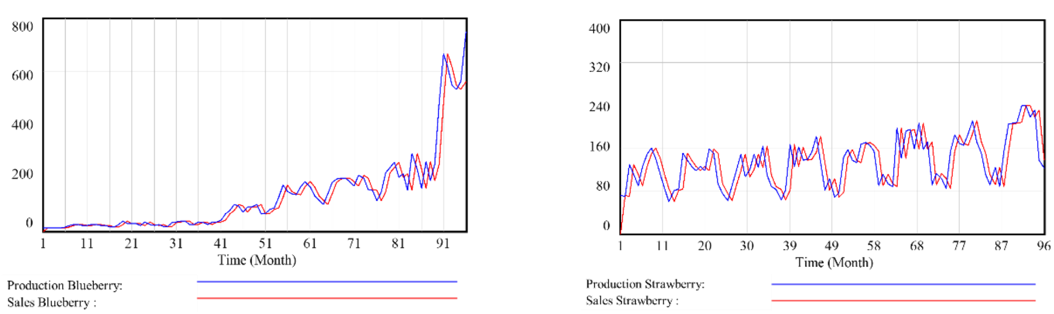


a) Production Vs sales bulb onion

b) Production Vs sales potato

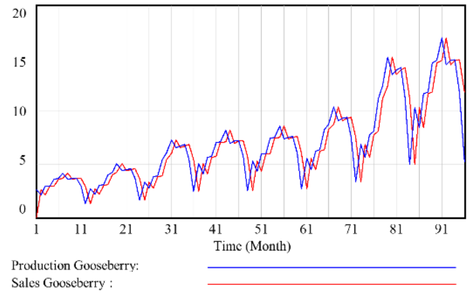
Figure 19. Production and sales of prioritized transitory crops

For permanent crops, production is more stable and shows a growing trend over time, particularly for blueberry, whose increase becomes notable from the fifth year onward. Under the model assumptions, total production is fully absorbed by demand, suggesting a balance between supply and consumption (Figure 20).



a) Production and sales of blueberry

b) Production and sales of strawberry



c) Production and sales of Gooseberry

Figure 20. Production and sales of permanent crops

Profits: The results reveal significant differences in profit generation across crop families (Figure 21). The Solanaceae family shows the highest returns throughout the simulation horizon, standing out as the main source of profitability, particularly associated with potato cultivation. The Liliaceae family (bulb onion) ranks second, exhibiting variable behavior but with high profit peaks during specific periods.

In turn, permanent crops display a progressive increase in profits, associated with the sustained expansion of cultivated area, which reaches approximately 851 hectares by the end of the period. Although their profitability is lower compared to transitory crops, they show greater stability over time.

In contrast, other crop families exhibit marginal contributions or even negative values in some periods, highlighting differences in economic efficiency among production chains.

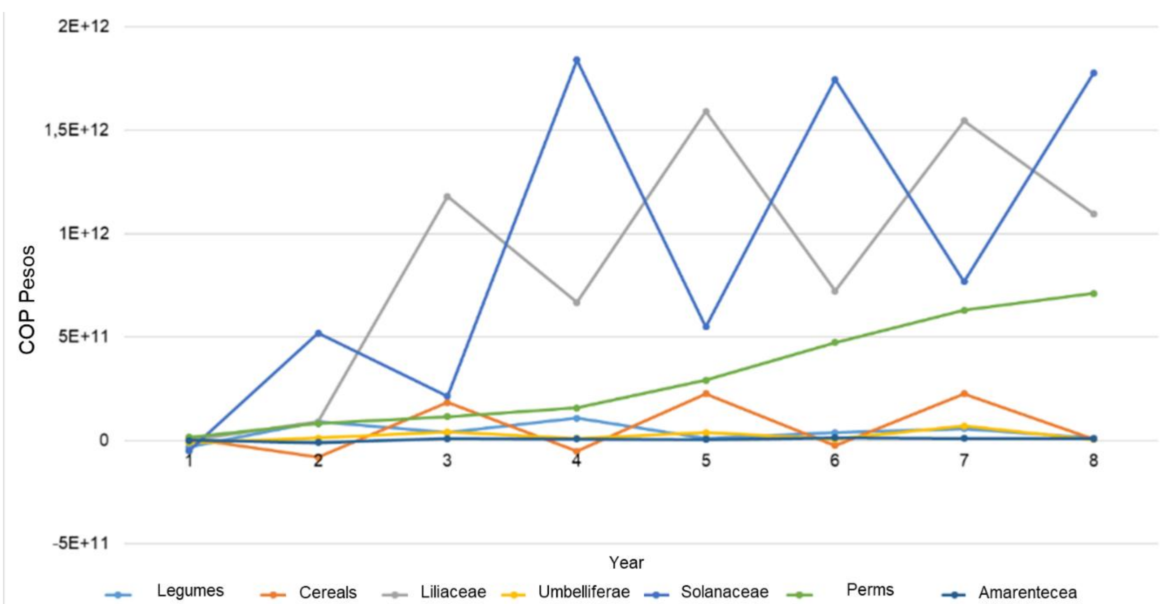


Figure 21. Profits by crop family (COP)

Social dimensión: The results show that employment generation is primarily concentrated in the most production-intensive crop families. In particular, the Solanaceae family (potato) exhibits the highest levels of labor demand, followed by the Apiaceae family (bulb onion), reflecting their high labor requirements during production cycles (Figure 22).

From a temporal perspective, both families display fluctuating patterns associated with planting and harvesting periods. However, a slight decrease in employment is observed toward the end of the simulation horizon (1.12% for potato and 1.06% for bulb onion in 2030 compared to 2024), suggesting adjustments in labor intensity within the system.

In contrast, permanent crops show a sustained increase in employment, reaching an approximate growth of 670% by the end of the period. This trend is associated with the expansion of cultivated area and their consolidation as a stable production alternative.

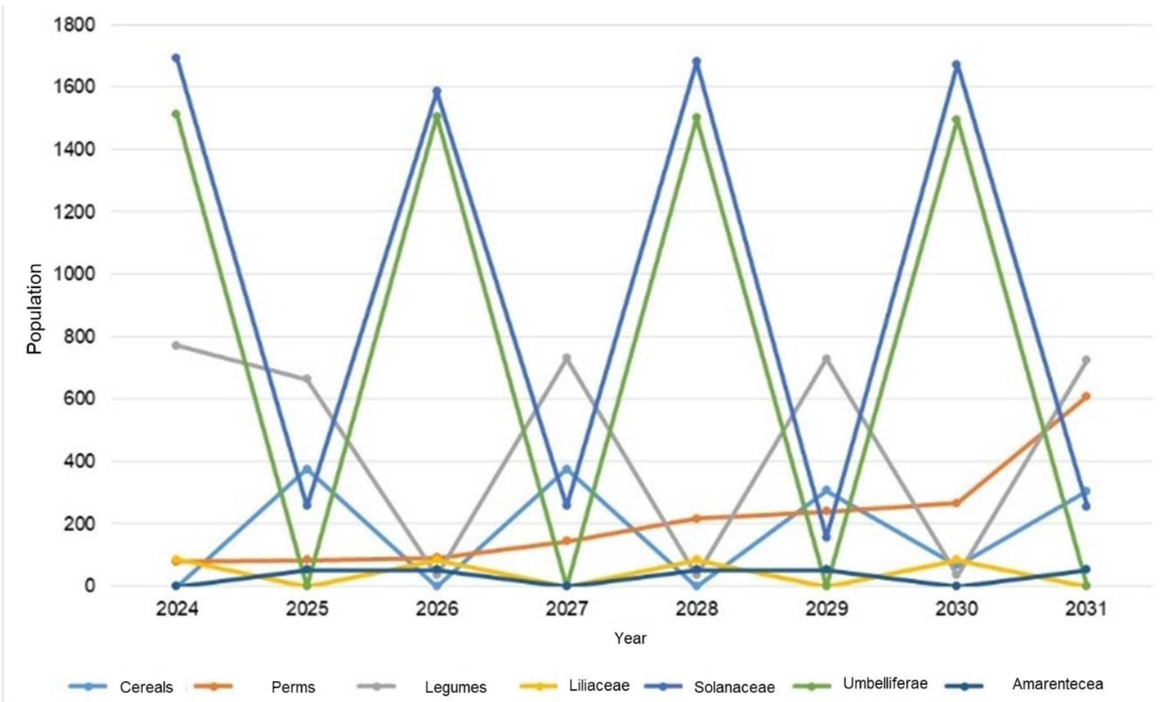


Figure 21. Labor demand by crop family

Conclusions

The system dynamics model developed in this study enabled an integrated evaluation of crop planning decisions in family farming systems by explicitly representing the interactions among environmental, productive, economic, and social subsystems over time. Unlike static planning approaches, the model captures the cumulative effects of feedback mechanisms, revealing how decisions that maximize short-term economic performance may progressively increase pressure on soil and water resources while simultaneously affecting employment dynamics.

The comparison of the five crop rotation strategies revealed important differences in their long-term performance. Rotations 1 and 5 exhibited the most balanced behavior, generating lower levels of soil degradation (0.67% and 0.96%, respectively) while maintaining acceptable productive performance, making them suitable alternatives when environmental conservation is prioritized. In contrast, Rotations 2 and 3, characterized by a higher concentration of intensive crops such as potato and bulb onion, produced the greatest economic returns but also generated the highest levels of soil degradation and water footprint, particularly the grey water footprint. Rotation 4 presented an intermediate performance, suggesting that moderate intensification can partially balance productivity and environmental impacts. These results demonstrate that no single rotation simultaneously optimizes all sustainability dimensions, highlighting the importance of explicitly analyzing trade-offs among economic, environmental, and social objectives.

The simulations also revealed differentiated crop behaviors. Potato and bulb onion consistently generated the highest profits and labor demand, making them economically attractive but environmentally demanding due to their intensive use of soil and agricultural inputs. Conversely, permanent crops such as blueberry and strawberry showed lower short-term profitability but greater production stability, increasing employment generation over time while exhibiting a relatively more favorable environmental performance. These findings suggest that combining transitory and permanent crops may contribute to improving the long-term resilience of family farming systems.

From a methodological perspective, this study demonstrates the added value of integrating multi-objective crop planning with System Dynamics. While optimization models identify efficient land allocation alternatives at a specific decision point, they cannot fully represent how these decisions evolve under dynamic feedback processes. The proposed System Dynamics model complements optimization by revealing delayed effects, cumulative resource degradation, seasonal production patterns, and interactions among environmental, productive, economic, and social variables that remain hidden in static optimization approaches. This integration therefore provides a more comprehensive framework for supporting strategic agricultural planning.

These findings also contribute to the broader literature on agricultural planning. Most previous studies addressing crop allocation and rotation rely primarily on mathematical optimization, stochastic programming, or simulation models that focus on maximizing economic performance or resource efficiency under fixed assumptions. In contrast, the proposed approach explicitly captures the dynamic evolution of agricultural systems and the feedback processes driving long-term sustainability. This capability makes the model particularly valuable for evaluating agricultural policies, land-use strategies, and production planning under changing environmental and socioeconomic conditions.

Finally, although the proposed framework proved robust for evaluating alternative production scenarios, future research should incorporate additional sources of uncertainty, including climate variability, price fluctuations, farmers' adaptive decision-making, public policy interventions, and technological adoption. Expanding the representation of fertilizer and pesticide management, irrigation technologies, and technical assistance services would further improve the model's ability to support sustainable agricultural planning in family farming systems across different regional contexts.

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