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Analysis of the Specialization Patterns of an Agricultural Innovation System: A Case Study on the Banana Production Chain (Colombia)

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Abstract: The learning approach, understood as the process through which agribusiness creates knowledge and develops capabilities, is key to understanding the voluntary effort made by the firm to acquire the capabilities necessary to compete in an agricultural innovation system (AIS) and improve their transition to sustainability. In this framework, learning is understood as a complex phenomenon emerging alongside specialization. Agent-based modelling (ABM) has proven to be an appropriate method of analysis for such phenomena; however, existing models have limitations related to the bounded rationality of agents, their relational proximity, and market forces. In order to help overcome these limitations, we propose this model representing the local dynamics of competing and collaborating innovation agents, and the complementarity of their capabilities. The model makes it possible to study the dynamics of local learning and how patterns of specialization emerge, and to improve the transfer and adoption of technologies (smart farming), increasing their productivity and sustainability, and reducing their environmental impact in an agricultural innovation system. It also provides a point of reference to guide policies, programs, and strategies aiming to improve the system’s economic and innovative performance. To achieve this objective, we use a case study of the banana production chain to build an agent-based model.

Keywords: learning; specialization; sustainability; local interactions; capabilities

1. Introduction

The term “learning patterns” is currently being used in agent-based models (ABM) [1,2] as a methodology for studying distinct phenomena within organizational and social contexts [3]. This makes it possible to analyze the emergence of behavioral patterns from a local system at the macro level, such as specialization based on the local interactions of semi-intelligent agents at the micro level. From this perspective, refs. [4,5] are of the opinion that the current approach to addressing problems in innovation and localized systems displays a top-down bias, which is more typical of national innovation systems. The characterization of these systems should include a bottom-up perspective that includes: communication patterns, invention, localized learning, localized knowledge sharing, localized search and exploration procedures, and localized network integration, as well as the alignment of governance methods and dependence on historical paths of innovation processes, such as agricultural innovation systems (hereinafter AIS). AIS comprises the networking and interactive learning between agents involved in agricultural chains to develop innovation and institutional change [6].

The concept of local learning patterns helps to analyze specialization in innovation systems and their influence on Global Value Chains (GVC) [7]. According to [8], a pattern describes a problem that occurs repeatedly in the environment, exhibiting the core of the problem’s solution, so that the user can use the solution multiple times. The literature
defines “learning” as the dynamics in which a company builds up its capabilities, which, if recognized by the market, generates what are called core capabilities. From this perspective, capabilities are the core that describes local behavior dynamics, which aim to integrate, construct, and reshape both internal and external capabilities in any firm to adapt to rapidly changing environments, fostering what is known as “common practices and local learning patterns.” Such practices could lead to the specialization of company(ies) [9], and therefore the system(s), through interactions between agents immersed in the GVC.

The functions of generation, dissemination, and use of knowledge in an Agricultural Innovation System (AIS) play a primary role in defining the specialization patterns based on the accumulation of capabilities in the context of learning, according to [10,11]. From this perspective, the pattern of local capability specialization obeys the learning rate. The interaction between agents follows the learning rate adopted by the local system. The learning patterns characterized by the accumulation of innovation capabilities influence the manner in which the agents participate in the cycles of exploration and exploitation posed by [12], and mediation proposed by [13].

Thus, despite representing the dynamics of the processes involved in local innovation and stressing the importance of learning, some current innovation models reported in the literature [14] do not provide an understanding of the mechanisms responsible for making up these agricultural innovation systems due to the difficulty generated by the heterogeneity of the agents involved and the complexity of such dynamic processes [7]. In particular, these models do not represent the different ways in which the agricultural innovation system’s agents learn and specialize. This has led to AIS being considered as complex adaptive systems (CAS), a concept developed by [2] as an arrangement of agents interacting through rules that adjust as agents gain more experience and become more specialized.

Agent-based modeling provides a novel framework to analyze the local interaction of autonomous agents in the environment [15] and is used to examine complex social phenomena such as local technology adoption dynamics, local technology transfer, local social networks, and local segregation [16]. It overcomes the static gaze of mathematical models through the development of scenarios that facilitate the understanding of the phenomenon. A second topic is the changing role of actors in the food supply chain and its impact on innovation systems and public or private partnerships. In this sense, the ABM framework considers agent characteristics and their heterogeneity over time [17], which allows macro behaviors to be studied through micro-level agent interactions in the system [15,18]. This case allows the emergence of innovation to be identified based on the interaction of agents, explorers, intermediaries, and exploiters affected by how they make decisions in the environment [19].

Smart farming comprises the use of technology (e.g., IoT, big data, and drones) to improve agricultural systems’ efficiency, sustainability, and productivity. These kinds of emerging technologies can help farmers cope with climate change by improving crop adaptation, reducing energy and water use, and eliminating waste [20]. In this sense, the proposed framework allows emerging patterns to be identified as a product of the local interactions between agents in a competitive environment, and how they develop capabilities to adopt and use knowledge and technology (i.e., technological capabilities). In this sense, ABM is considered a stream of thought of artificial intelligence that allows complex systems to be modeled and simulated, such as the transfer process of agricultural technology. The use of smart farming technologies allows agribusiness from the banana chain in Antioquia, Colombia to monitor cultivation (i.e., climate, soil, agrochemical, and diseases) and use the information to make smart decisions.

The banana chain in Colombia is a promising productive chain that generates a large amount of employment in regions with high levels of armed conflict. In addition, it is a very important production chain that supplies fruit to Europe and the United States. It is a rapidly growing chain, and therefore technological advancements are a means to improve productivity, including the use of Fourth Industrial Revolution (4IR) technologies.
Clarification is needed on the degree of specialization, what capacities the chain must employ, and how said technologies are applied.

In 2019 in Colombia, a total of 51,227 ha of bananas were planted—542 more than in 2018. This growth was especially noticeable in the northern region towards the areas of La Guajira and Cesar. Banana exports in 2019 totaled US $852.8 million, exporting a total of 100.2 million boxes. The main destinations were countries such as Belgium (22.7 million boxes), followed by the United Kingdom (17.7 million boxes), Italy (13.6 million boxes), and the USA (12.3 million boxes). In 2019, banana production reached 2.1 million tons, of which 1.8 million tons were allocated for export and 300,000 tons for national consumption [21,22].

The specialization patterns identified using AMB help create theories for policymakers. The capability accumulation patterns allow researchers to identify how the AIS of the banana chain and agribusiness coevolve, and how to increase the capabilities to use the knowledge and technology to improve productivity and sustainability.

The ABM methodology is based on research by [23] and starts with an assumption to develop the conceptual model and its logic of simulation. A parameterization is then conducted, as well as the implementation of the model based on the simulation of scenarios that make it possible to experiment with the different agents and analyze specialization patterns and their effect on system performance. A survey of 210 agents (e.g., explorers, intermediaries, and exploiters) from the banana chain AIS in Antioquia, Colombia measured the capabilities of the banana agricultural chain from a longitudinal perspective. The survey was used to validate and calibrate the model, which was then used to determine policy strategies to improve the learning process and capability accumulation.

The survey used for the evaluation of technological capabilities was developed by [24] and was based on the congruence model of [25], in which the authors propose that organizational management be carried out through corporate guidelines and people, and is composed of four dimensions: formal organization, informal organization, technology, and human resources. The survey relates technological capabilities with the systemic organizational congruence model of [25] and its four dimensions through a Likert scale to better understand the evolution and level of each capacity of the actors in the production chains. This survey has been used in other studies to analyze productive chain capacities, such as those reported in the specialized literature by [26–28].

This work introduces a model based on agents whose competitive environment represents the demands generated by the system as innovation opportunities. In addition, it introduces many competing agents that meet the demand through interacting and building formulas for success. Local interactions between agents is described by decision rules, making it possible to observe the system’s learning and specialization patterns, which result from the use and accumulation of the agents’ capabilities. This work is structured as follows: initially, a group of major assumptions is proposed to develop the conceptual model and its logic of simulation. A parameterization is then conducted, as well as the model implementation, based on the simulation of scenarios that have made it possible to experiment with the different agents, in order to analyze local specialization patterns based on the learning dynamics and their effect on system performance.

### 2. Conceptual Model

#### 2.1. Model Assumptions

In order to better understand the effects of learning and specialization patterns regarding innovation in an AIS, the three main agent-based models reported in the literature were identified. These models were recognized as useful sources for formulating a new proposal to analyze learning in AIS: the simulating knowledge dynamics in innovation networks model (SKIN) [29], the chemistry-inspired economic production model or hypercycle model [30,31], and the Self-Sustaining Regional Innovation System model (SSRIS) [32]. To analyze an AIS’s learning and the specialization patterns through a simulation model, the concept of learning must be addressed. The literature defines learning as the dynamics in which a company accumulates and generates capabilities. However, ref. [33] adds that
an innovation system emerges from the interaction of heterogeneous agents that can be characterized as competing agents, and may have the characteristics of explorers, exploiters, and intermediaries, as Ponsiglione, Quinto, and Zollo point out [14]. Ref. before [34] suggests that proximity and relationship are key to the production, transmission, and sharing of knowledge in interactive learning. Modeling and simulating learning in an AIS based on the accumulation of capabilities make it possible to perform experiments with different heterogeneous agents to analyze interactive learning and observe agents’ different specialization patterns. This makes it possible to analyze appropriate policies and strategies for the system’s better economic, environmental, and innovative performance.

Representing the competing agents of an AIS through a vector of technological innovation capabilities makes it possible to explore the specialization patterns of the agents’ capabilities in one or more functions: “a set of possibilities an agent has to explore, exploit, and mediate in the system.” This is how a competing agent is considered competent, provided the capabilities of its vector are accepted by the competitive environment or market where it operates. This allows us to represent the competitive environment agent, describing the needs that must be satisfied by the system’s competing agents through innovation opportunities (IO) that may be related to the market or technology. Competing agents must have the minimum capacity to fill the attributes required by the environment, giving the model a systemic and driving behavior, as emphasized by [35].

These assumptions make it possible to analyze the local learning dynamics of the doing-interacting type and their local specialization patterns through a learning rate defined for the system. According to [10], some factors promote or inhibit interactive learning in an innovation system. These factors are related to promoting or restricting the development of new products and their economic performance in the market. The distinction of agents’ heterogeneity is significant in comparison with other models, since heterogeneous agents are represented through a vector of capabilities for the competing agents and a vector of attributes for the competitive environment agent. The vector offers the possibility of agents interacting through decision-making rules, such as relational proximity (Rp) and the complementarity of capabilities (Cc). In this work [7], relational proximity is key for the competing agents when it comes to making interaction decisions in GVCs due to their bounded rationality [36]. In the model, agents have the capabilities to integrate, build, and reconfigure goods and services, as well as capabilities to address rapidly changing environments. Capabilities, then, are represented in learning through their accumulation and subsequent specialization for technological innovation. This learning, according to Teece (1988), is located in the vicinity of activities prior to knowledge, due to restrictions imposed by routines.

2.2. Model Logic

The proposed model is based on the research carried out by [37,38] regarding the representation of learning in innovation systems. The model portrays five procedures: (1) competitive environments, which is the market demand generated by the agent; (2) the success for formula (SF), which is the construction of offers by competing agents; (3) decision-making rules defining agents’ behavior; (4) the reward and benefit function; and (5) the doing-interacting local learning procedure, observed through the dynamics of accumulation in the capabilities of the competing agents through the interactions. Such dynamics will depend on a learning rate adopted by the system and intend to represent the market forces. The procedures of the model and how it is made are described below.

The competitive environment demands innovative goods and services (e.g., technologies) with their own attributes; in the model, this demand is represented as an innovative opportunity. In turn, the environment identifies the innovative opportunity located randomly during a period. The innovative opportunity is defined by a vector of \( n \) attributes and volatility (\( v \)), as well as a life cycle time (lct). If the system manages to satisfy the innovative opportunity, then it receives a return in the same period. The innovative opportunity is created through the competing agents (Ajs) in the environment. A competing
agent can respond to one or several innovative opportunities and satisfy them through a vector of capabilities of length \( n = 5 \). This agent response can be individual or collective to complement their capabilities.

The first two positions to the left of the vector represent exploration capabilities (i.e., research and development). The central position represents intermediation capabilities, and the positions on the left represent exploitation capabilities (i.e., production and marketing). In both vectors, the magnitude is between 0 and 9, where 0 is low capacity, and 9 is high or developed capacity. According to the innovative opportunity, the agent complements the attribute with the magnitude of the required position (see Figure 1).

![Figure 1. AIS learning model.](image)

Rules of interaction for decision making between agents are operated through two mechanisms mentioned in the model assumptions. The first of them is the complementarity of capabilities (Cc) distance between agents, and the second is the relational proximity (Rp) distance.

Based on the above rules, the innovative opportunities are built by the agents as follows: when the competing agents of the environment identify the demand through the location mechanism, the magnitude comparison of the vectors of capabilities and attributes from right to left (RtL) can be carried out. If the capabilities vector in position five is greater than or equal to the innovative opportunity, the process is repeated for the following positions in the vector. If the competing agent has magnitudes greater than or equal to all the evaluated positions, a (SF) is configured, and it will be able to construct an offer on its own.

Now, if the magnitude of position five’s vector of capabilities is less than the magnitude of the vector of attributes, the competing agent will not identify the innovative opportunity no matter how small its relational proximity or geographical distance. This method of operation is demonstrated through the market-pull dynamics, meaning that those agents are better able to visualize and evaluate a demand. If the agent identifies the innovative opportunity through the mechanism of locating and comparing position five of the vector but is not capable of configuring a (SF), it can search the environment through the (Cc) mechanism by agents that collaboratively configure a (SF) and are able to leverage the innovative opportunity.

Competing agents are equipped with a monetary resource called surplus stock (SSt), which is assigned randomly (monetary units per year). The agents identifying and exploiting the innovative opportunities obtain a benefit (Bt) in monetary units, given
by the magnitudes of the vector of attributes (reward procedure) and calculated in each period (hereinafter tick in years). Returns are defined as the income or reward per attribute delivering the demand (IA). This benefit will depend on the magnitudes at each position of the attribute vector and the (randomly assigned) innovative opportunity, and (lct) according to Gaussian behavior (given in years). The agents also incur a cost to remain in the system (Ct) in monetary units, which allows them to maintain their capacities over time and participate in the interactions to identify and exploit innovative opportunities. This is calculated as the sum of the magnitudes of the vector of capacities in a tick. SSt + 1 in monetary units per year is calculated using Equation (1).

Equation (1):

\[ SSt + 1 = SSt + Bt - Ct \]

From this perspective, the learning dynamics are oriented from the competing agents’ resources and capacities. Considering the fact that learning is expressed based on routines, the model understands the use of skills as a way to reinforce them as a result of the accumulation of experience and rewards derived from identifying and exploiting innovative opportunities in the environment (learning by doing) (LBD) [39]. Otherwise, unused capacities will be weakened, demonstrating unlearning by not doing (UBND), until their resources are exhausted (SSt) in monetary units per year, and they disappear from the environment. This dynamic corresponds to sigmoid or S-shaped trajectories calculated using Equation (2).

Equation (2):

\[ \frac{X}{1 + e^{-\gamma t}} \]

where X represents the maximum value that the vector magnitude can take between 0 and 9, \( \gamma \) or \( \delta \) denotes the learning or unlearning rate, and t is the time in which the capacity is used or not (in years). The greater a capacity is used in time (t), the greater the accumulation of capacities as a result of doing-interactive learning. Under this logic, the basic and advanced abilities (high and low values) when used exhibit slower and longer learning dynamics than the intermediate abilities that show faster learning dynamics. The model focuses not only the unlearning dynamics [40,41], but also the interactive learning dynamics and the deaccumulation of innovative capacity due to the lack of use of some capabilities or vector positions, which, in some cases, results in poorly generated competencies in the system. In this sense, these dynamics are a crucial factor when understanding the intentional effort made by firms to discard non-essential capabilities in order to compete in an innovation system.

3. Model Parameterization and Implementation

The data used in the research was collected through the software “measurement of technological capabilities for innovation in the agricultural productive chain” as a structured survey of the companies in the banana productive chain in the department of Antioquia, Colombia. The initial parameters of the model and the logic to define them can be seen in Table 1. For scenario election, the fact that AIS are CAS with several leverage points where “small additions produce large, directed changes” [2] was considered. Therefore, learning is discussed as a possible leverage point for understanding these systems’ performance based on the specialization patterns resulting from the change in the vector magnitudes of the competing agents of the system’s innovation.

A simulation will be conducted in three distinct scenarios. Scenario 1, or the attractive AIS, is based on interactive learning with agents’ competitive potential and uses learning and unlearning rates (\( \gamma \) and \( \delta = 0.3 \)), agents’ birth rates greater than 6%, accumulation of capabilities, high economic and innovative performance, and emerging patterns of the functional specialization of the agent’s capabilities vector. Scenario 2, high potential AIS with high potential for agents’ interactive and competitive learning, uses learning rate (\( \gamma \) and \( \delta = 0.9 \)), agents’ birth rates above 6%, accumulation of capabilities, plausible economic performance, and emerging patterns of the integral specialization of the agent’s
capabilities vector. Scenario 3, restrictive AIS, uses the potential restriction of interactive learning as well as the development of the system, learning rate ($\gamma$ and $\delta = 0.1$), agents’ birth rates below 6%, deaccumulation of capabilities due to agents’ non-interaction, and the system’s poor innovative and economic performance (see Figure 2).

### Table 1. Model parameter values and description.

| Variables     | Description                                                                                                                                 |
|---------------|---------------------------------------------------------------------------------------------------------------------------------------------|
| Vectors $l = 5$ | Chain length of attributes or capabilities vectors. Each position is related to an attribute for the functions of generation (research and development), diffusion (intermediation), and use (production and marketing). |
| Magnitudes    | Represent the degree of development of each vector position and includes values between 0–9.                                               |
| Birth rate    | Represents the percentage of agents and innovative opportunities that are created in the system at each tick for the SESRA model, of 6% and 12%, respectively, according to data from the World Bank [42]. |
| Learning rate ($\gamma$) | Represents the speed with which capacities are accumulated in each position of the vector of attributes in time $t$ (years). For the model, it will take values between 0.1–0.9. |
| $l_{ct}$      | It refers to the time in which an innovative opportunity remains in the environment, delivering benefits to the agents identifying and exploiting it. For the model, it will take a random value with Gaussian behavior. |
| Reward income (IA) | Refers to the income or reward (monetary units) that the innovative opportunity provides to the agent identifying and exploiting it in one or more vector positions. |
| Cost ($C_t$)  | The cost (monetary units) that the agent incurs to stay in the environment. This depends proportionally on each magnitude of the capabilities vector. |
| Surplus stock SS | Economic resources (monetary units) with which agents are born in the environment. This allows them to interact dynamically with other agents to identify and exploit opportunities, and also addresses the accumulation or deaccumulation of capabilities. For the model, this takes a random value between 0 and 255 units. |

Figure 2. Model Scenarios.
Results

A completely randomized design of experiments was carried out with the statistical tool and software R (version 4.0.0, Ross Ihaka and Robert Gentleman, Auckland, NZ, USA). The objective was to establish the existence of significant differences in the twenty (20) experiments carried out for each of the scenarios in order to obtain valid and objective conclusions about the simulation process. Randomization allows for a more compliant analysis, thus preventing the introduction of systematic biases in the experiments. If this analysis is not used, it is not possible to say whether an observed significant difference is caused by the differences between the treatments in the design or by the method used.

Experiment design was based on a response variable (the accumulated capacity) in the different positions of the vector of capacities in the agents using formulas for success. The covariates or fixed effects, called factors, corresponded to the surplus stock, the proposed scenarios, and capacity. The covariates were found to be significant on the response variable of the model. The experiments that were analyzed are presented below and correspond to the three scenarios: attractive, high potential, and restrictive. Table 2 shows the factors and their respective levels for model implementation.

Table 2. Analyzed factors and levels.

| Factors | Scenario | Capabilities | Learning | Unlearning | Inventory |
|---------|----------|--------------|----------|------------|-----------|
| 1       | Attractive AIS | R&D | 0.3 | 0.3 | 1, 2, 3, … 2600 |
| 2       | High potential AIS | Resources Management | 0.9 | 0.9 | |
| 3       | Restrictive AIS | Intermediation | 0.1 | 0.1 | |
| 4       |           | Production | | | |
| 5       |           | Marketing | | | |

Studies by [43,44] were the basis for simulating the different periods, spanning 37 years. To identify trends in the behavior of each of the scenarios, 50 years were considered for the three scenarios; however, the scenario of a restrictive AIS only reached 30 years, as shown in Figure 3.

![Success Formulas](image1.png) ![SS Accumulated of System](image2.png)

**Figure 3.** (a) Agents using formulas for success (SF); (b) Surplus stock accumulated in the local system.

The understanding of the learning and unlearning dynamics of the different competing agents emerges through the interaction and accumulation of the agents’ capabilities. The competitive environment requirements facilitate a better understanding of the economic
and innovative performance addressed by [45] through the number of agents creating formulas of success and the cumulative surplus stock, respectively (see Figure 3).

4. Discussion of Results

Local learning can be analyzed through the accumulation of capabilities, which makes it possible to analyze and observe the local specialization. Scenarios 1 and 2, as seen in Figure 4, were the most suited to analyze learning and the capability specialization patterns pertaining to exploitation and exploration. Scenario 3 presented a dynamic of unlearning, and therefore a deaccumulation of capabilities. When analyzing the variation of capabilities in different positions, it is apparent that the agents overlapping in formulas for success learn and unlearn their capabilities. However, this average variation makes it possible to visualize how patterns of accumulation emerge and how system specialization can be determined based on capability accumulation.

Figure 4. Comparative analysis of the accumulation and variation of capabilities in the three scenarios.
The analysis of simulations makes it possible to observe variations of the agents’ capabilities vector. When a variation is negative, as shown in Scenario 1 of Figure 3 where agents’ specialization patterns are functional, the agent(s) interacting and making formulas for success acquires advanced capabilities in some vector positions. By contrast, when a variation is positive, as shown in Scenario 2 of Figure 4, agents’ specialization patterns are comprehensive, which means that agent(s) acquire advanced capabilities in all vector positions, and therefore more capabilities.

One of the most important advantages of the model is the ability to simulate and analyze different scenarios as a way to provide support to regional policymakers, as mentioned by [46]. It is of great importance to better our understanding of the different dynamics of interactive learning proposed by [11] and the learning patterns cited by [47] in order to determine the performance of any AIS, as suggested by [45]. Therefore, further studies and analyses are needed that make it possible to recognize specialization patterns of the capabilities of different AIS available in developing countries. Agents actively taking part in the construction of formulas for success will most likely learn and survive in time; this is due to the ability to generate benefits, which is reflected in surplus stock and, consequently, the system’s greater economic performance. The systems or regions that have accumulated and learned their capabilities have a broad range of heterogeneous agents capable of responding quickly to any demand no matter how challenging its attributes. Similarly, these are regions with greater resilience, and therefore, their adaptation and response in times of crisis is more proactive as a result of past learning.

5. Conclusions and Future Works

Even though the concept of AIS has been addressed extensively in theoretical and empirical spheres over the past 20 years, the simulation of these systems and their bottom-up innovation processes is a topic that is yet to be developed. The greatest value of the model is not the realization of forecasts, but rather, the possibility of scenario analysis for decision-making. The model’s strength lies in the possibility it offers to integrate knowledge, concepts, and relationships of innovation processes from a bottom-up perspective, and develop theories [48] from the perspective of ABM.

The model helps understand the interactive learning dynamics of any AIS and serves to develop the policy and, in some cases, the strategy of AIS in order to improve the agents’ productivity, and economic and innovation performance in agricultural innovation system. Having more detailed modeling that encompasses the dynamics, in addition to learning and skill specialization patterns, such as the one outlined above, can add value not only to the theory and concepts of agricultural innovation systems and how they transfer and adopt technology to help improve sustainability, but also to inform the policies of any AIS. Furthermore, the construction of an empirical and comprehensive database that includes indicators related to distinct capability types and their evolution over time in developing countries could be very useful in the future for replicating the analysis of specialization capability and the validation process of these systems’ behavior (local, sectoral, and regional). The model integrates and implements the concepts of the agents’ “functional and comprehensive specialization” patterns in the context of the AIS, which may become a prosperous path for the theoretical and empirical exploration of the economic and innovative performance of these systems based on interactive local learning dynamics, particularly from a resources and capabilities perspective. The results of the study are important to better understand and compare other agricultural innovation systems (such as the banana chain), and thus develop programs and projects to improve the transfer and adoption of smart farming technologies and how they help reduce the environmental impact of the producers in the banana chain in Antioquia, Colombia.

As future work, the model’s structure and behavior in the regional sectoral systems (e.g., regional agricultural systems of innovation for coffee and avocado) of high, medium, and low economic and innovative performance must be replicated in order to identify the local specialization patterns. Similarly, the model has been improved and used to
measure performance through the transaction costs of the system’s mediation agents. Finally, delving deeper into the capability specialization patterns will provide greater rapprochement regarding the change and distribution of the characteristics of an AIS agent population through interaction mechanisms such as selection, variation, and inheritance. This last mechanism is not examined in the model; however, it may be considered under the cellular automation paradigm to conduct prospecting through collective intelligence.

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