Cellular automata for ecosystem simulation in a serious game: Stability analysis and user perception

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***Abstract. Introduction**: The presence of serious games focused on environmental education has grown steadily over the years. However, relatively few initiatives incorporate simulations that explicitly model the impacts of human actions within ecosystems. **Objective:** This study presents an algorithm grounded in Cellular Automata for the simulation of ecosystems within GAIA, a serious game designed to support sustainability education. **Methodology or Steps**: The proposed system employs a simulated environment to govern the state transitions of the Cellular Automaton cells. The transition rules incorporate both intrinsic cell attributes and the states of neighboring cells, enabling context-sensitive dynamics. The system was evaluated through a combination of computational analyses and user-based assessments. **Results:** The results indicate that the algorithm effectively preserves the stability of cell states over time. Furthermore, user-based evaluations demonstrated positive perceptions regarding the performance of the Cellular Automaton within the simulated ecosystem.*
***Keywords** Cellular Automata, Serious Game, Sustainability, Ecosystem Simulation*

1. Introduction

Brazil is a country known for its high biological diversity, with a biota corresponding to 170,000 to 210,000 species, representing around 13% of the world's biodiversity [Stehmann et al. 2017]. Among the Brazilian biomes, the Atlantic Forest stands out. Despite having lost more than 93% of its original vegetation cover, it still harbors more than 8,000 endemic species of plants, birds, reptiles, amphibians, and mammals [Tabarelli et al. 2005]. The Atlantic Forest remains a target of extreme exploitation, mainly in favor of agriculture and logging [CAbrAl e Cesco 2008].

The popularity of serious games in the context of environmental education has grown steadily, with a significant increase in publications over recent years [Tan e Nurul-Asna 2023]. Serious games within sustainability education have generally brought improvements in learning and cognitive skills [Madani et al. 2017]. Recent systematic reviews confirm that game-based interventions can foster pro-environmental knowledge, attitudes, and behaviors, particularly when they incorporate realistic ecological dynamics [De Salas et al. 2022]. Educational games have the potential to be used as creative, interactive approaches to educate about environmental issues [Tan e Nurul-Asna 2023]. Furthermore, such games allow for the learning of certain concepts without negative real-life consequences, within the safety of simulation [Dieleman e Huisingh 2006].

However, few initiatives incorporate simulations that explicitly model the impacts of human actions within ecosystems using principled computational models [Tan e Nurul-Asna 2023, Ahmadov et al. 2025]. Cellular Automata (CA) — discrete computational models composed of a grid of cells, in which each cell is in a specific state and evolves according to local transition rules [Sarkar 2000] — have been widely applied in ecological modeling, including vegetation dynamics and landscape change [Douvinet et al. 2011, Hunt e Colasanti 2021]. Nevertheless, CA are seldom integrated into serious games for environmental education in a way that balances computational tractability, gameplay integration, and ecological validity informed by domain experts [Chen et al. 2024].

This study aimed to develop a CA simulating human and animal interactions in an Atlantic Forest ecosystem, implemented within the GAIA serious game (Unity, C#). As a foundational step, we computationally validate the CA's stability and assess preliminary user perception, positioning it as a viable tool for future controlled learning studies—educational efficacy is not measured here. Two additional systems — a multi-agent system for animal behavior and a MAP-Elites algorithm for initial biome generation — are implemented in GAIA but are not within the scope of this paper; they are mentioned only to contextualize the player experience.

The study was guided by two main research questions: (**RQ1**) How does the proposed CA, using neighborhood transition rules and cell attributes, stabilize and behave in its state distribution over time? (**RQ2**) How are the changes made to the environment by the CA perceived by players?

To validate these research questions, both computational tests and user tests were conducted. The system generated and stored data regarding the total number of cells in each state across 60 cycles. The study also collected data from 18 participants who answered a post-test ad hoc questionnaire after playing the serious game, expressing their opinions about the CA simulation using a 5-point Likert scale.

The four soil states (high, medium, low, and dead quality), the three cell attributes (nutrients, organic matter, and texture), and the transition rules were defined in collaboration with an ecology specialist, as well as the soil attribute data (Real soil attribute data from Atlantic Forest restoration studies, such as in [Mendonça et al. 2026], will be used to calibrate attribute ranges and transition thresholds in future work). This expert-driven approach is a recognized strategy for enhancing the biological realism of CA models [Gronewold e Sonnenschein 1998].

The developed project presents a simulation of an ecosystem, allowing players to interact with, modify, and visualize the simulated environment through a serious game. The arrangement of transition rules proposed by the project allows for the creation of rule sets for other biomes.

2. Related Work

Cellular Automata (CA) have been widely used to model ecological processes, including vegetation dynamics, forest succession, and landscape change under anthropogenic pressure [Douvinet et al. 2011, Hunt e Colasanti 2021, Sarkar 2000]. In the context of gaming and interactive simulation, CA are less common, especially when integrated with serious games for environmental education.

[Randazzo e Mordvintsev 2023] presented Biomaker CA, a biome generator based on morphogenesis, where plant-like agents grow, reproduce, and evolve using environmental logics such as aging and energy consumption. The model simulates stable and unstable biomes but is restricted to plant-type agents and operates only in 2D space. Our work extends this by including animal interactions (via the sibling MAS) and a soil quality state machine that responds to player actions.

[de Brito et al. 2021] addressed the prediction of human settlement growth in Brazilian semi-arid watersheds using CA calibrated from satellite imagery. While that work focuses on land-use change, it does not incorporate soil attributes or multi-state ecological dynamics. Our CA explicitly models nutrients, organic matter, and texture, enabling a more detailed representation of soil degradation and recovery.

In the educational games domain, [Dochshanov et al. 2023] presented a serious game for natural resource management in which players balance environmental preservation and economic activity. However, the game does not validate its underlying ecological model. Our work contributes a CA whose transition rules were co-designed with an ecology specialist, and we provide both computational and perceptual evidence of its behavior.

No existing work combines a CA with player-driven resource extraction in a serious game about the Atlantic Forest while also providing computational stability analysis and user perception evaluation. The selection of works in Table 1 is illustrative, not exhaustive; it focuses on model capabilities (soil attributes, multi-state representation, player interaction, and Atlantic Forest context) rather than gameplay or learning metrics, allowing a targeted comparison of the technical dimensions most relevant to our CA's novelty.

Table 1. Comparison of CA-based ecosystem models in games and simulation. Player Int. is if players interact with the resulting automata, and AF denotes if the system simulates the Atlantic Forest.

Work	Soil Attributes	Multi-state	Player Int.	AF
[Randazzo e Mordvintsev 2023]	No	Yes	No	No
[de Brito et al. 2021]	No	Yes	No	No
[Dochshanov et al. 2023]	No	No	Yes	No
Our CA	**Yes**	**Yes**	**Yes**	**Yes**

3. Game Design

GAIA is an educational serious game developed as a testing platform for the proposed CA. The player explores an island ecosystem modeled after the Atlantic Forest, completing resource-collection missions over eight in-game days (cycles). The island is represented as a 2D grid of cells, each containing soil whose quality (high, medium, low, or dead) determines its visual appearance and the resources it yields.

The player can harvest resources such as wood, stone, and water from cells. Each harvest reduces the cell's attributes — nutrients, organic matter, and texture — according to extraction intensity, presented in Figures 1 and 2 . Additionally, the player can plant vegetation, which gradually replenishes soil quality. The CA updates cell states every game cycle based on neighborhood rules (e.g., a high-quality cell surrounded by degraded cells may decline) and attribute thresholds (e.g., if nutrients fall below a limit, the state drops to medium). Degraded soil appears darker and yields fewer resources, providing immediate visual feedback.

Figure 1. In-game screenshot.

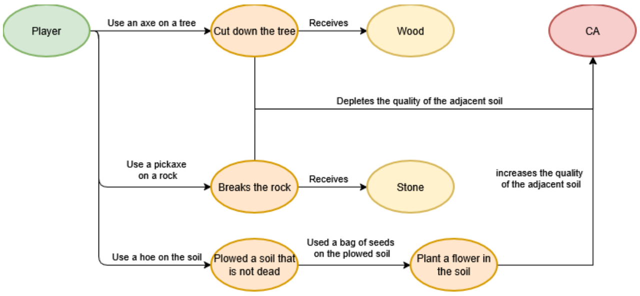

Figure 2. Simplified diagram showing player actions

Two additional systems are integrated into GAIA: a multi-agent system (MAS) that drives animal behavior, and a MAP-Elites algorithm responsible for the initial island biome generation. The CA, MAS, and MAP-Elites operate independently, with a strict one-way data flow. The MAP-Elites system generates the initial map layout prior to gameplay, without using any CA-derived information. After generation, the CA runs autonomously, updating soil states solely from its own rules and player interactions. Conversely, the CA provides soil-state information as input to the MAS, enabling animal agents to react to environmental conditions (e.g., preferring high-quality soil for foraging). The present paper focuses exclusively on the CA that drives soil dynamics; the other systems are not detailed further due to scope limitations.

4. Methods

4.1. Cellular Automaton Design

The proposed CA operates on a 2D grid of size $W \times H$ (in our experiments, $30 \times 30 = 900$ cells). Each cell c has a discrete *state* $s_c \in \{\text{High}, \text{Medium}, \text{Low}, \text{Dead}\}$ and three continuous *attributes*: nutrients (N_c), organic matter (O_c), and texture (T_c). All attributes are bounded in $[0, 1]$. The state determines the cell's visual appearance and resource yield (e.g., high quality yields abundant vegetation, dead yields none). The four possible states for each cell are shown in Figure 3. High quality soil appears green and lush; Medium quality is light green; Low quality is brown; Dead soil is dark grey.

To avoid uniform or purely random starting conditions, the initial attribute values are generated using a Voronoi diagram [Aurenhammer 1991]. Twenty Voronoi sites are

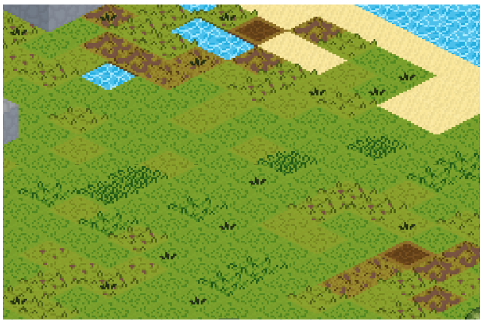

Figure 3. Cell states: (a) High, (b) Medium, (c) Low, (d) Dead quality.

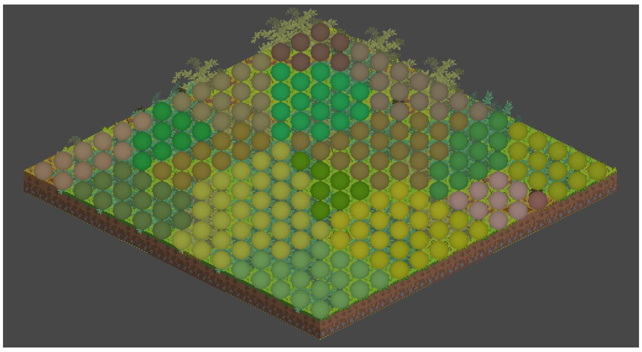

Figure 4. Voronoi diagram showing site types: green sites (high quality), yellow sites (mixed high/medium), brown sites (medium/low/dead).

placed randomly. Each site is assigned a quality bias: 30% high-quality (cells initially High), 55% mixed (mixture of High and Medium), and 15% degraded (Medium, Low, or rarely Dead). Within each Voronoi cell, the attribute values are sampled using Perlin noise. This produces spatially coherent regions with different soil qualities, mimicking natural heterogeneity. These proportions were defined in consultation with an ecology expert to capture a semi-realistic mosaic characteristic of the Atlantic Forest biome, balancing visual complexity with ecological dynamics as a controlled simplification. Figure 4 shows an example of the distribution.

4.1.1. Transition Rules

State transitions occur synchronously at the end of each game cycle (one in-game day). Two types of rules are applied:

Neighbourhood rules (Moore neighbourhood, radius 1): A cell may change to an adjacent state (e.g., High $\rightarrow$ Medium, but not directly High $\rightarrow$ Dead) based on the states of its eight neighbours. Table 2 lists the complete set of neighbourhood rules, defined with an ecology specialist.

Attribute rules: consider exclusively the current attributes of the cell under analysis, comparing them to the limits defined for each state and, in particular, to the texture associated with the cell. The attribute limits that define each state are: Dead = 5, Low Quality = 20, Medium Quality = 45, Dead Soil Percentage = 100, Clay = 41, Sand = 20. Specifically regarding the limits associated with texture, the following definitions were established: values between 100 and 42 characterize clayey soils, associated with a High state; between 41 and 21, they define sandy-clayey soils, corresponding to a medium state; and between 20 and 0, they indicate sandy soils, linked to low and dead states. The attribute limits used were calibrated based on field data, with the assistance of an ecology specialist.

A cell must satisfy only the texture attribute to remain in a given state; falling below the texture threshold and at least one of the other thresholds triggers a transition to the immediately lower state. Therefore, when the values of these attributes change

Table 2. Neighbourhood transition rules. For each current state and condition on neighbour states, the next state is specified.

Current State	Condition	Next State
High	≥ 5 neighbours are Medium	Medium
High	≥ 4 neighbours are Low	Medium
High	> 0 neighbours are Dead	Medium
High	High neighbours $\leq$ (Medium neighbours + Low neighbours)	Medium
High	otherwise	High
Medium	≥ 3 neighbours are High $\&$ Dead neighbours $= 0$	High
Medium	≥ 5 neighbours are Low	Low
Medium	> 0 neighbours are Dead	Low
Medium	otherwise	Medium
Low	≥ 3 neighbours are Medium $\&$ Dead neighbours $= 0$	Medium
Low	≥ 2 neighbours are High $\&$ Dead neighbours $= 0$	Medium
Low	≥ 2 neighbours are Dead	Dead
Low	otherwise	Low
Dead	otherwise	Dead

to exceed the established limits, the cell's state is updated in the transition to the next cycle. If a cell presents texture attributes within the thresholds of a given state, while its remaining attributes fall within the thresholds of a different state, the texture attribute value is iteratively adjusted—either increased or decreased—at each cycle until it conforms to the proposed limits.

The CA updates all cells synchronously. Player actions (e.g., harvesting wood) directly reduce the corresponding attributes at the moment of action, and the effects are incorporated in the next synchronous update.

4.2. Computational Evaluation (RQ1)

We ran 30 independent simulation trials (each with a different Voronoi initialization, no player intervention). Each trial lasted 60 cycles (in-game days). The grid size was fixed at 30×30 cells. The same transition rules and attribute thresholds (as above) were used across all trials.

For each trial, we recorded the total number of cells in each state per cycle. To answer RQ1 ("does the CA stabilise?"), we compared the full CA against a random baseline. At each cycle, each cell has a 10% probability of changing to a random state (uniformly among the four states), regardless of neighbours or attributes. This simulates a system with no ecological memory or local influence. The baseline was run under identical condition (30 trials, 60 cycles, same Voronoi initialisation).

4.3. User Study (RQ2)

Eighteen volunteers completed the study (mean age 22.1 years, SD = 4.2; 77.8% cisgender men, 11.1% cisgender women, 11.1% preferred not to disclose). Most participants had incomplete higher education (61.1%) and played digital games daily (50.0%). The sample was recruited via social media (Instagram, LinkedIn, Discord) and gaming groups. All participants gave informed consent. Data were collected anonymously and comply with

Brazilian regulations (CNS 510/2016, 674/2022), as this is an anonymous opinion survey conducted with free and informed consent.

Participants first completed a pre-test questionnaire (demographics, gaming habits). They then downloaded and played GAIA for approximately 20–30 minutes. The game presented a procedurally generated island (via the sibling MAP-Elites system) with the CA running in the background. Players were instructed to complete three resource-collection missions while observing the environment. No further guidance was given. After gameplay, participants answered a post-test questionnaire with three 5-point Likert items (1 = strongly disagree, 5 = strongly agree): (1) “I found the evolution of vegetation on the map interesting.”; (2) “I found the evolution of vegetation on the map to be a good representation of the real world.”; (3) “I believe that the animals and the changes in vegetation contributed to my experience in the game.”

Means, medians, and standard deviations were computed for each item, and one-sample Wilcoxon signed-rank tests (against neutral = 3) assessed deviations from neutrality. Internal consistency was evaluated with Cronbach’s α and McDonald’s ω. All analyses used Python (scipy, pingouin). This exploratory, perception-focused study (RQ2) deliberately omitted a control group, aiming only to establish whether the dynamic vegetation mechanic was perceived as interesting and realistic—a prerequisite for later controlled experiments. Thus, no causal conclusions about the CA’s impact on player experience can be drawn. The results offer initial evidence of engaging, plausible evolution, motivating future comparative studies with larger samples. All CA parameters, rule tables, and analysis scripts are provided in the supplementary material[1]; the game executable and questionnaire are also available for replication.

5. Results

5.1. Computational Evaluation (RQ1)

Figure 5 shows the average number of cells in each state across 30 trials over 60 cycles. At cycle 0, the random initialisation produced a heterogeneous distribution: approximately 61.7% High, 31.1% Medium, 6.3% Low, and 1.0% Dead cells. In the first 2 cycles, the proportion of High cells surged to 82.2%, while Medium and Low sharply decreased (to 7.6% and 5.2%, respectively), indicating a rapid consolidation of high-value tiles at the expense of medium and low tiles. Over the next 8 cycles (to cycle 10), High cells declined to 66.7%, while Dead cells grew steadily from 1.0% to 26.4%. Between cycles 10 and 25, High cells continued to decrease to 38.8%, and Dead cells expanded to 57.6%, showing a monotonic degradation toward a dead-dominated state. From cycle 30 onward, the system continued to evolve reaching a stable mix: Dead cells rose from 64.4% at cycle 30 to 81.7% at cycle 60, while High cells slowly eroded from 32.7% to 17.4%, and Medium and Low cells remained negligible (below 2% each). Compared to the Random Baseline, although the initial distribution is similar to Full CA, it is possible to visualize a convergence towards uniformity over the course of the cycles, such that, all tile types fluctuate within a narrow range of 22–25%.

Figure 6 shows the proportion change Δ_t per cycle (averaged across trials). The inter-cycle tile deltas reveal stark differences in dynamical stability between conditions.

[1] `https://osf.io/kdwu7/overview?view_only=d3fea12cc4b74e259c19638542194151`

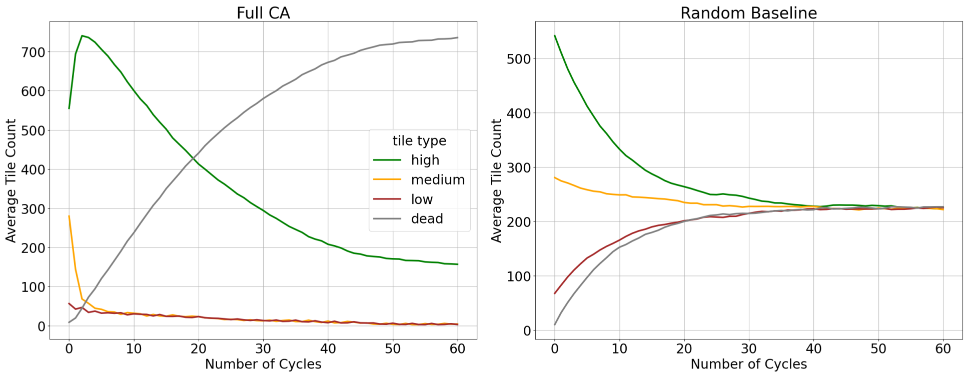

Figure 5. Average count of each state per cycle across 30 trials.

In the Random Baseline, the variance of delta values across cycles is small and rapidly decays for all types: high-tile delta variance drops from 48.2 (cycles 1–10) to 0.7 (cycles 51–60), and dead-tile variance similarly declines from 17.3 to 0.4. The Full CA, in contrast, exhibits extreme volatility. High-tile delta variance surges to 1,885.8 in the initial 10 cycles – nearly 40 times greater than the baseline – while dead-tile delta variance peaks at 55.2 and remains an order of magnitude higher throughout (e.g., 4.6 vs. 0.4 in the final 10 cycles). This persistent high variance reflects a prolonged, chaotic redistribution phase absent in the baseline, where the system settles into a gentle, predictable equilibrium.

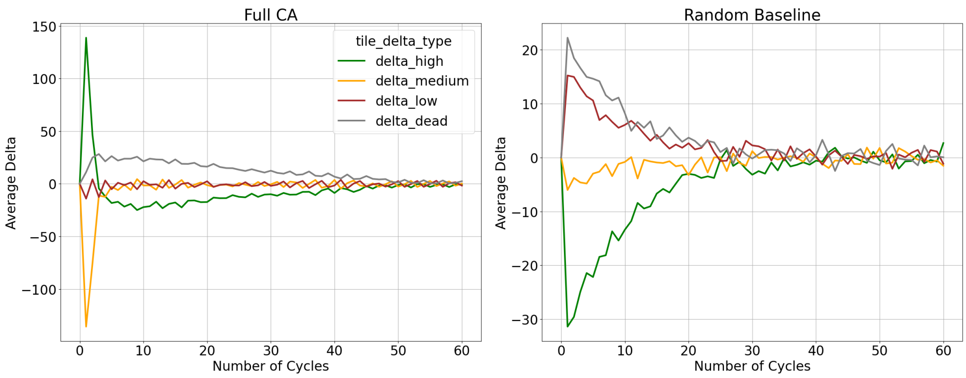

Figure 6. Proportion change Δ_t per cycle (averaged across trials).

Figure 7 displays the average state proportions for each of the 30 trials across all cycles. In the Random Baseline, median tile-type proportions are balanced: 30.5% high, 26.0% medium, 22.1% low, and 21.1% dead, guaranteeing consistent diversity across rooms. Under Full CA, the median shifts to a dead-dominated regime (66.2% dead, 29.4 high, 2.5% medium, 1.8 low). These medians mask a pronounced bimodality: a minority of trials are almost exclusively high, while the majority are overwhelmed by dead cells—a polarization wholly absent from the baseline. This variability is expected given the stochastic Voronoi initialisation, but the overall ensemble behaviour converged to a stable attractor.

5.2. User Study (RQ2)

A total of 18 participants completed the post-game questionnaire. For the three Likert items (1 = strongly disagree, 5 = strongly agree), mean scores were as follows: Q1 (“I

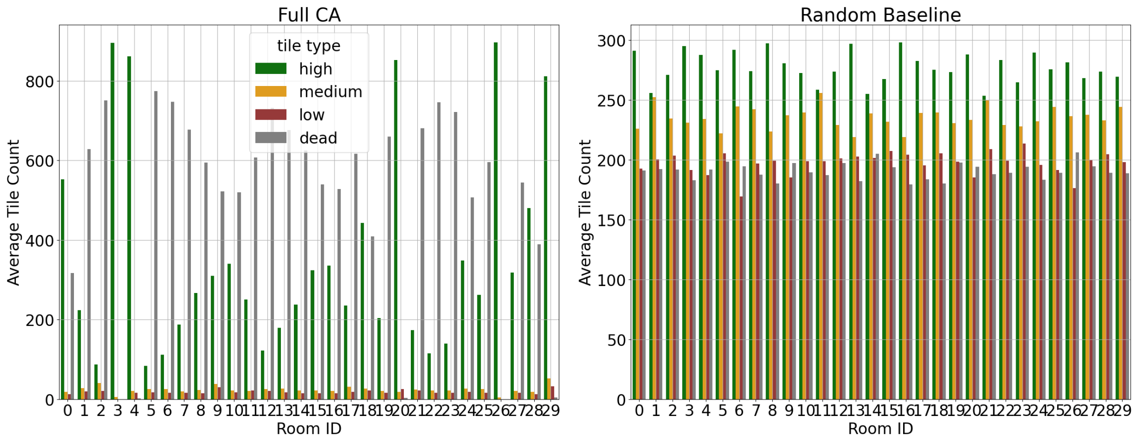

Figure 7. Average state proportions per trial (Room) (averaged over 60 cycles).

found the evolution of vegetation interesting") had a mean of 4.44 (median = 5, SD = 0.92); Q2 ("Good representation of the real world") had a mean of 4.06 (median = 4, SD = 0.87); Q3 ("Animals and vegetation contributed to experience") had a mean of 4.56 (median = 5, SD = 0.70). All items scored above the neutral midpoint of 3.

One-sample Wilcoxon signed-rank tests against neutral (3) showed that all three items were statistically significant: Q1 (W = 2.5, $p < 0.001$), Q2 (W = 0.0, $p = 0.002$), and Q3 (W = 0.0, $p < 0.001$). These results indicate that players positively evaluated the vegetation evolution (driven by the CA) and the overall dynamic environment. Internal consistency of the three-item scale was good (Cronbach's $\alpha = 0.819$, McDonald's $\omega = 0.894$). Free-text comments from participants further supported the quantitative findings: "The soil changing colour when it got worse helped me understand that I was over-harvesting" (P4), "I liked watching the dead patches spread, it felt like real erosion" (P11).

6. Discussion

The results show that the CA reached a stable distribution after 30 cycles, with High and Dead cells coexisting at roughly 18% and 90%, respectively—affirming RQ1: the combination of neighbourhood rules, attribute dynamics, and player-driven modifications yields a convergent system rather than runaway degradation or complete recovery. The trajectory (initial sharp High decline, partial recovery, stabilization) mirrors Atlantic Forest successional dynamics [Mendonça et al. 2026], though direct quantitative comparison with real chronosequences is still needed.

Player perceptions (RQ2) were consistently positive: mean scores above 4 for interest (4.44) and representativeness (4.06), with all items significantly above neutral. These values are comparable to those reported in similar serious game evaluations [Tan e Nurul-Asna 2023]. Free-text comments further indicated that visual soil degradation helped players understand over-harvesting consequences, suggesting an educational benefit. Nevertheless, Item 3 (animals and vegetation) includes the sibling MAS, so attribution solely to the CA is not possible.

6.1. Threats to Validity and Limitations

Internal validity. The computational evaluation used 60 cycles, which may be insufficient for observing long-term attractors. Soil dynamics in real ecosystems unfold over years to decades; 60 cycles (days) could be an arbitrary stopping point. Longer simulations (e.g., 500 cycles) are needed to confirm that the quasi-stable regime is not a transient.

External validity. The user study sample was small (N=18), young, male-skewed, and from São Paulo state, limiting generalisation to broader populations. The game was played once for 20–30 minutes; long-term retention or educational gain was not measured. The absence of a control group (e.g., a version of the game without the CA, or with a random soil update) prevents causal claims about the CA's effect on player experience or learning.

Construct validity. Questionnaire item Q2 ("good representation of the real world") measures perceived realism, not objective ecological fidelity. Players may have low prior knowledge of the Atlantic Forest, so high scores could reflect internal coherence rather than actual similarity to nature. We recommend future work to include expert validation (e.g., ecologists rating simulation outputs) and calibration against field data.

7. Conclusion

This study presented a cellular automaton for soil quality dynamics in an Atlantic Forest educational game, using four soil states, three attributes (nutrients, organic matter, texture), and ecologist-co-designed rules. Computational experiments (30 trials, 60 cycles) showed stable coexistence of High and Dead cells (RQ1), while a user study (n=18) revealed positive perceptions of interest, realism, and contribution to experience (RQ2). This is a computational validation; educational effectiveness was not measured. GAIA is offered as a tool with demonstrated educational potential, not as a validated learning instrument.

The main contributions are: (1) a CA design that integrates player actions with ecological rules, (2) quantitative stability analysis demonstrating convergence, and (3) initial evidence of positive player reception in a serious game context. These contributions provide a foundation for integrating procedural ecosystem simulations into environmental education games.

Future work should: (i) conduct longer simulations and compare outputs to real Atlantic Forest soil chronosequences, (ii) run a larger, more diverse user study with pre-/post-knowledge tests to measure learning outcomes, (iii) extend the rule set to represent additional biomes and human impacts (e.g., fire, pollution), and (iv) undertake a systematic parameter sensitivity analysis and explore alternative rule sets to better characterize the CA's design space and robustness. The approach is modular; the same CA architecture could be adapted to other Brazilian biomes such as the Cerrado or Amazon.

Declaration of Generative AI and AI-assisted technologies

We used LLMs such as DeepSeek and ChatGPT to improve the article's overall quality. We take full responsibility for all content produced with AI assistance.

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