Procedural generation of biomes using a MAP-Elites algorithm applied to the context of a serious game

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***Abstract. Introduction**: The Atlantic Forest is one of the most biodiverse and threatened biomes in the world, requiring new approaches to promote awareness and understanding of its ecological dynamics. Procedural Content Generation (PCG), combined with evolutionary algorithms, offers a promising way to simulate and represent such complex environments in interactive systems. **Objective:** This work aims to develop a MAP-Elites evolutionary algorithm capable of procedurally generating terrains that resemble Atlantic Forest biomes, and to evaluate its effectiveness within an educational game context. **Methodology or Steps**: The proposed algorithm generates biomes based on six physical attributes, using a Dirichlet distribution and mutation strategies to guide evolution toward predefined input values. The system was integrated into an educational game (GAIA), enabling both computational evaluation and user-based assessment. **Results:** The algorithm satisfactorily converges to desired attributes. Pilot study (N=18) shows positive perceptions of generated environments. Given small exploratory sample, this is a computational proof-of-concept for terrain generation, not a validated educational intervention. Positive findings suggest potential, but educational efficacy needs future controlled studies.*

***Keywords** Procedural Generation, Sustainability, MAP-Elites, Educational Game.*

1. Introduction

The Atlantic Forest encompasses various forest types forming biomes along the Brazilian coast from Rio Grande do Norte to Rio Grande do Sul, with inland extensions in the south, northeast, and southeast [Belanha 2023]. Brazil has the greatest biodiversity on Earth and several highly relevant biomes [Brasil. Ministério do Meio Ambiente e Mudança do Clima nd], among which the Atlantic Forest notably stands out. However, this ecosystem has been intensely deforested and lost vegetation cover, making it one of the most threatened and devastated biomes on the planet [Cardoso 2016], with only a small portion of its native forest remaining.

With this in mind, our work adapts the MAP-Elites dungeon generator from [Pereira et al. 2024] to generate semi-realistic replicas of Atlantic Forest biomes instead of dungeons, which can then be used in an educational game to convey sustainability and environmental preservation concepts. We adapt the original algorithm's genotype to incorporate biome-related data (e.g., percentage of water, uncovered soil, rocks, and different vegetation heights per room), its phenotype (rooms are assembled into a free-roaming island, not a dungeon divided into rooms), and its fitness (to match specific desired levels of biome attributes). Other elements are preserved: enemy placement turns into animal placement, and key-items become key-tools for the player to interact with the environment (e.g., an axe).

Finally, the biome-generator is integrated into an educational game to generate its map. The player completes quests (gather resources), talks to NPCs to learn about the Atlantic Forest, and interacts with the biome's fauna, providing a new gameplay experience at each playthrough while preserving the biome's main characteristics.

We assess convergence of the adapted algorithm across generations and the proximity of biome attributes to desired values after convergence. We also conducted a pilot player-study on the generated biome. Our study addresses two research questions: How accurately can a procedural dungeon generator reproduce a biome's attributes and animal/resource distribution (**RQ1**)? How do players perceive the terrains of Atlantic Forest-based biomes procedurally generated by MAP-Elites (**RQ2**)?

The evolutionary approach is capable of generating a biome whose attributes generally fall within very satisfactory ranges compared to the desired input values. Depending on the tolerance adopted for what is considered satisfactory, the algorithm achieved at least 57% of satisfactory values, reaching between 80% and 90% depending on input values. In an ad hoc questionnaire about the biomes in the game, 18 users gave overall positive responses and perceived the biomes as a positive aspect of the game.

Thus, our algorithm may help develop an educational game where players acquire relevant notions about the Atlantic Forest, contributing to combating deforestation and predatory exploitation of such environments. Nonetheless, the algorithm can reproduce biomes that may also be used for other semi-realistic simulation purposes.

2. Related Work

This section reviews prior research on procedural content generation (PCG) for biomes and levels, focusing on evolutionary algorithms and MAP-Elites. Three strands are examined: (i) dungeon generation with MAP-Elites (our direct foundation), (ii) biome generation tools for 3D environments, and (iii) large-scale terrain generation with climate simulation.

The most influential work is the Overlord system [Pereira et al. 2024], which employs a MAP-Elites algorithm for dungeon level generation, itself an adaptation of [Pereira et al. 2021]. Overlord generates diverse dungeon rooms with enemies, keys, locks, and traps, but rooms are not physically connected—movement occurs only through discrete doors. This suits compartmentalized dungeons but not continuous open environments.

In contrast, our work requires a single cohesive biome where cells are adjacent without doors. While retaining the MAP-Elites archive and selection, we modified connectivity from graph-based adjacency to contiguous tile-based placement, adapting genotype representation and mutation operators accordingly (Figures 1 and 2). Dungeon elements were replaced by ecological resources (soil, water, vegetation, animals, tools) aligned with the Atlantic Forest.

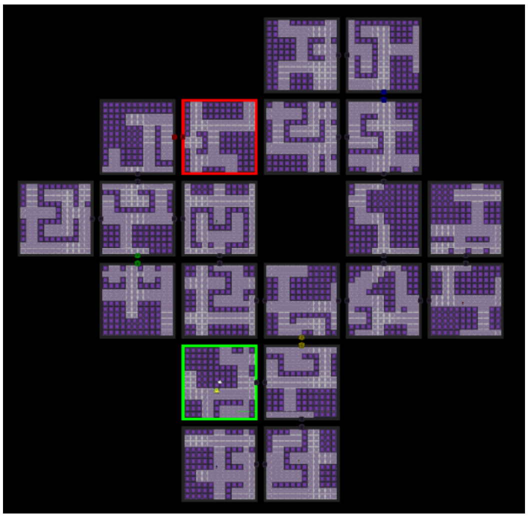

Figure 1. Dungeon generated by Overlord with door-based room transitions.

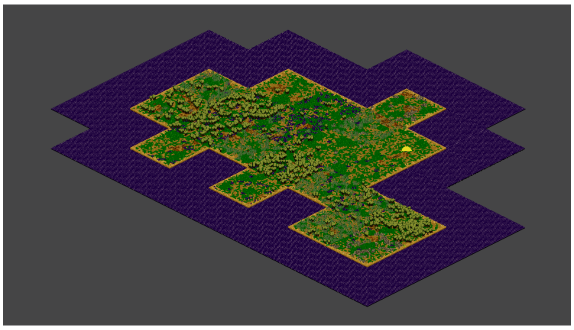

Figure 2. Our contiguous biome without door separation.

Thus, we contribute four adaptations: (i) continuous biome layout, (ii) ecological feature space, (iii) fitness function with environmental fidelity, and (iv) isometric perspective.

Two other studies informed our resource modeling. [Sepúlveda et al. 2023] presented BGT, a Unity plugin using evolutionary mixed-initiative biome design on 2D heightmaps with four element categories (trees, plants, animals, minerals) and stat dependencies (e.g., trees provide shade required by animals). This dependency model ensures ecological plausibility, but BGT prioritizes visual fidelity over real-world ecological data. Our work grounds attribute targets in domain specialist values and models gameplay impact within a serious game.

[Fischer et al. 2020] introduced AutoBiomes, generating large terrains via noise and simplified climate simulation, representing biome layers as 2D matrices. Evaluation focused on computational performance, with visual similarity assessed subjectively. Nonetheless, it inspired our layered attribute representation and resource distribution evaluation. Our work embeds generation in an evolutionary MAP-Elites loop, enabling explicit convergence to target distributions.

Collectively, prior research demonstrates PCG feasibility for biomes and levels, but none address a continuous, ecologically grounded Atlantic Forest biome in a 2D serious game. MAP-Elites from [Pereira et al. 2024] provides the algorithmic backbone, while BGT and AutoBiomes inform attribute design—yet neither targets ecological fidelity as a primary objective. This work bridges PCG for serious games and domain-specific ecological modeling, contributing a MAP-Elites variant for biodiversity education.

3. Game Design

GAIA is an educational serious game developed alongside the MAP-Elites algorithm to serve both as a testing environment and as a vehicle for ecological awareness. While the primary contribution of this paper is the procedural biome generation algorithm, the game provides the context in which generated terrains are evaluated by users and where the ecological attributes (soil, water, vegetation, etc.) gain functional meaning. Two additional systems, a cellular automaton for soil impact simulation and intelligent agents for animal behavior, are also part of GAIA but are not within the scope of this paper; they are mentioned here only to clarify the complete player experience and to note that the player experience reported in Section 5 reflects the full game, while our analysis isolates the contribution of the MAP-Elites biome generator.

The player assumes the role of an explorer on an island whose terrain is procedurally generated by the MAP-Elites algorithm to resemble the Atlantic Forest biome. The island is represented as a 2D grid of cells, which the player navigates while interacts with natural resources and receives missions that require collecting specific resources (e.g., harvesting vegetation, extracting water, or obtaining tools). Each mission rewards the player with progress, but indiscriminate resource extraction degrades the environment. The player must decide how much to extract from each cell, balancing short-term mission goals against long-term sustainability.

Each cell in the generated biome contains six physical attributes defined by the MAP-Elites output: soil, water, rock, tall vegetation, medium vegetation, and low vegetation. These attributes determine both the visual appearance of the cell and the resources available for extraction. For example: - **Medium vegetation** provides harvestable plants. - **Tall vegetation** yields wood. - **Water** can be collected. - **Soil** quality affects regrowth rates. The player uses tools (axes, pickaxes, and water containers) to extract resources. Tools themselves are found within the biome and replace the keys and locks from the original Overlord system. Figure 3 shows a gameplay screenshot.

Figure 3. Gaia screenshot.The player (blue robot) wields a tool. There are tall, medium and low vegetations, some rocks, water, and uncovered soil. The menu is in Brazilian Portuguese as the study was conducted in Brazil.

If extraction makes an attribute fall below a critical threshold, the cell becomes depleted. Moreover, the soil quality evolves over time via a cellular automaton (outside this paper's scope) that simulates erosion, compaction, and regeneration. Animal agents move across the biome, seek food and water, and react to player activity; their behavior influences resource availability and provides feedback on ecosystem disturbance.

The MAP-Elites algorithm generates a different island layout at each execution, before the game starts, based on the target attribute set (e.g., Soil=0.4, Water=0.1, Rock=0.05, Tall Veg=0.3, Medium Veg=0.1, Low Veg=0.05), ensuring replayability and diverse testing conditions. Attribute distributions directly govern resource abundance, impacting difficulty and strategy. For instance, an island with higher rock content may provide fewer harvestable plants, forcing the player to explore more cells. Thus, GAIA serves as a realistic evaluation environment for the algorithm: user perceptions of "realism" and "pleasantness" (measured in the post-game questionnaire) are grounded in actual gameplay interactions, not merely visual inspection.

4. Methods

The algorithm builds upon the MAP-Elites implementation from [Pereira et al. 2024] but introduces three major adaptations: (i) continuous spatial arrangement of cells (rooms) without doors, (ii) a new set of six ecological attributes representing the Atlantic Forest, and (iii) a reformulated fitness function that includes an environmental penalty term.

Each individual in the population represents a complete biome (island) composed of a fixed number of cells arranged in a 2D grid. Every cell c is described by a 6-dimensional vector $\mathbf{a}_c = (a_{c,1}, \ldots, a_{c,6})$ where the dimensions correspond to: (1) Soil, (2) Water, (3) Rock, (4) Tall vegetation, (5) Medium vegetation, (6) Low vegetation. For each cell, the six values are sampled from a Dirichlet distribution and therefore satisfy $a_{c,i} \geq 0$ and $\sum_{i=1}^{6} a_{c,i} = 1$.

The initial population of N_{pop} individuals is generated by sampling each cell's attribute vector from a Dirichlet distribution with concentration parameters $\alpha_1 = \cdots = \alpha_6 = 0.3$ (generates sparse vectors). The MAP-Elites archive maintains the best individual found for each combination of behavioral characteristics. In our implementation, the archive is a 2D grid discretizing two selected phenotype features (e.g., average soil percentage and average tall vegetation percentage). The resolution of each dimension is set to $k = 20$ bins, following [Pereira et al. 2024].

For each cell, attribute proportions are drawn from Dirichlet($\boldsymbol{\alpha}$) with $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_6)$. During initialisation, all $\alpha_i = 0.3$. During evolution, offspring cells may inherit proportions from parents or be mutated (see below). The Dirichlet distribution guarantees that the six values sum to one, preserving the compositional nature of ecological data [Ng et al. 2011].

Two mutation operators are applied to the attribute vectors of offspring individuals, with a mutation probability of p_m (set to 0.15).

Swap mutation: The six attribute values are cyclically permuted: $(a_1, a_2, a_3, a_4, a_5, a_6) \rightarrow (a_2, a_3, a_4, a_5, a_6, a_1)$. This preserves the sum but alters the mapping between attributes and ecological roles.

Bounce-back mutation (adapted from [Nordmoen et al. 2021]): Three distinct attributes are randomly selected to be incremented by $\delta \sim \text{Uniform}(0, 0.05)$; the other three are decremented by the same total amount, ensuring $\sum a_i$ remains 1. If any attribute would become negative, the decrement is redistributed among the other two attributes in the decrement set.

The fitness of an individual (biome) is computed as Equation 1 where base_fitness corresponds to the original Overlord fitness (evaluating tool and animal placement, mission feasibility, etc.).

$$fitness = base\_fitness + environmentalPenalty \tag{1}$$

The environmentalPenalty is defined as Equation 2, where $\overline{a}_i$ is the average of attribute i over all cells in the biome, and target_i is the desired global proportion (e.g., Soil = 0.4, Water = 0.1, ...). This penalty is detrimental to fitness (i.e., it is added to fitness and makes it worse) and encourages the evolutionary algorithm to produce biomes whose global attribute averages approach the target values.

$$environmentalPenalty = \sum_{i=1}^{6} |target_i - \overline{a}_i| \tag{2}$$

At each generation, the algorithm:

1. Selects parents uniformly at random from the current archive (if non-empty) or from the population.
2. Produces offspring via crossover (uniform crossover of cell attribute vectors) followed by mutation.
3. Evaluates offspring fitness.
4. Updates the archive: for each offspring, its behavior characteristics (two selected phenotype dimensions) determine an archive cell; the offspring replaces the existing solution in that cell if its fitness is higher.
5. Forms the next population by selecting the N_{pop} highest-fitness individuals from the combined pool of parents, offspring, and archive elites.

The algorithm runs for dozens of generations until it meets the stopping criteria, after which the best individual (highest fitness) is returned as the generated biome.

4.1. Computational Evaluation (RQ1)

To assess whether the algorithm can converge to target attribute values (RQ1), we performed 30 independent runs for two different input sets.

- **Set 1 (baseline Atlantic Forest):** Soil = 0.4, Water = 0.1, Rock = 0.05, Tall Veg = 0.3, Medium Veg = 0.1, Low Veg = 0.05.
- **Set 2 (alternative distribution):** Soil = 0.2, Water = 0.1, Rock = 0.1, Tall Veg = 0.2, Medium Veg = 0.3, Low Veg = 0.1.

Both sets were defined with the support of the project's ecology specialist.

For each run, we recorded the best individual's attribute averages and computed the absolute error $|\text{target}_i - \overline{a}_i|$ per attribute. An attribute was considered "satisfactory" if its error was within a tolerance t. Two tolerance values were examined: $t = 0.10$

and $t = 0.15$. We report the percentage of satisfactory attributes across the 30 runs (aggregated). Additionally, we recorded the fitness values and monitored the evolution of maximum, mean, and minimum population fitness over generations for a representative run.

4.2. User Study (RQ2)

To evaluate player perceptions of the generated biomes (RQ2), we conducted a user study integrated with the gameplay of GAIA.

Participants were recruited through game development study groups, social media (Instagram, LinkedIn), and university mailing lists. Inclusion criteria were: age ≥ 18 years and the ability to install and run the game on a personal computer. No prior knowledge of the Atlantic Forest or procedural generation was required. The final sample comprised 18 participants (detailed demographics in Section 5).

The study consisted of three phases: **(1) Pre-game questionnaire**: Participants answered demographic questions (age, gender, education, income) and self-assessed their familiarity with educational games and ecology. (2) **Gameplay session**: Participants installed GAIA and played for approximately 20–30 minutes. They explored the procedurally generated island, completed three missions (e.g., collect 10 units of medium vegetation, obtain an ax, restore water to a depleted cell), and were free to experiment with extraction and observe environmental consequences. The NPCs provided dialogues about sustainability and the Atlantic Forest's biome. (3) **Post-game questionnaire**: Immediately after gameplay, participants responded to three statements using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree): **(Q1)** "I found the map's resource distribution to be pleasant." **(Q2)** "I found the map's resource distribution to be similar to what I would expect from the Atlantic Forest." **(Q3)** "I believe that the animals and changes in vegetation contributed to my experience in the game."

All responses were collected anonymously via Google Forms. The study protocol was reviewed for ethical compliance (no personally identifying information was stored; participants could withdraw at any time).

4.3. Data Analysis

For RQ1, we computed descriptive statistics (mean, median, standard deviation) of attribute errors across 30 runs and derived the satisfactory percentages per tolerance. For RQ2, we calculated mean and median Likert scores for each item, along with internal consistency measures (Cronbach's α and McDonald's ω). All analyses were performed using Python (pandas, scipy, pingouin).

5. Results

5.1. Computational Evaluation (RQ1)

For each of the two input sets, we executed the MAP-Elites algorithm 30 times. For each run, we recorded the attribute averages $\overline{a}_i$ of the best individual (biome) and computed the absolute error $e_i = |\text{target}_i - \overline{a}_i|$. This data, along with other important information for the work, was organized into tables and made available in a project created on the *Open Science Framework* (OSF) online platform. [1]

[1] `https://osf.io/tyh2e/overview?view_only=7f3c9b8bb3e24eaeb7d6707f000e4527`

Figure 4 shows the distribution of generated attribute values for Input Set 2 (the Atlantic Forest baseline). Attributes with higher target values (Soil, Tall Veg, Medium Veg) present higher medians, though there is some dispersion. Water, Rock, and Low Veg (targets ≤ 0.1) have lower and more compact distributions.

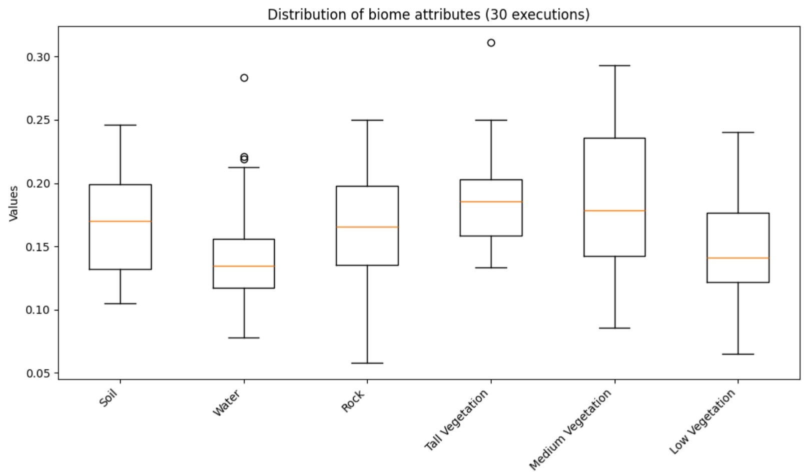

Figure 4. Distribution of generated attribute values for Input Set 2 across 30 runs.

There is a table available in OSF that reports the mean absolute error (MAE) and standard deviation per attribute for both input sets. For Input Set 2, the MAE ranges from 0.0403 (Soil) to 0.1300 (Medium Veg), indicating satisfactory convergence.

Using tolerance thresholds ($t = 0.10$ and $t = 0.15$), we computed the percentage of attributes considered satisfactory ($e_i \leq t$). For Input Set 2, 82% of attributes are within ± 0.10 and 94% within ± 0.15 (Table with complete values in OSF).

To assess whether the evolutionary approach provides measurable benefit, we compared MAP-Elites against a baseline that generates biomes by sampling each cell from the Dirichlet distribution, but we run only two generations of the algorithm (enough to produce a non-random initial population, yet too few to allow any meaningful archive accumulation or selective pressure to take effect). For Input Set 2, 30 independent runs were generated. The baseline achieved only 73% of attributes within $t = 0.10$. This only reinforces that the evolutionary pressure is essential for convergence.

Figure 5 shows the evolution of population fitness over 70 generations for a representative execution (Input Set 2). Fitness improves rapidly in the first 20 generations and continues to increase slowly, indicating successful optimization.

MAP-Elites converges to the desired attribute distributions with MAE < 0.1 for most attributes and significantly outperforms random generation. Thus, RQ1 is answered affirmatively; the algorithm can accurately reproduce the biome's attributes. The animal and resource distribution were preserved from the original algorithm and were also successfully achieved.

5.2. User Study (RQ2)

A total of 18 participants completed the pre-game questionnaire. Data cleaning was required to remove incomplete responses and data from participants who failed attention

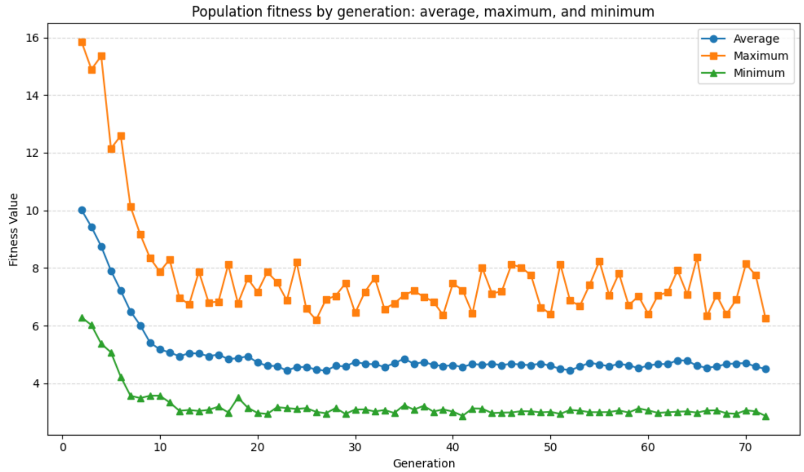

Figure 5. Evolution of population fitness (max, mean, min) over generations (Input Set 2).

checks (N = 2, from an original set of 20 answers), developed following established recommendations [Pei et al. 2020, Kung et al. 2018, Silber et al. 2022]. The sample was predominantly male (77.8% cisgender men, n=14), aged 19–22 years (77.8%, n=14), with incomplete higher education (61.1%, n=11), residing in São Paulo state (83.3%, n=15). Monthly household income varied, with the most common ranges being 3–5 and 5–10 minimum wages (22.2%, n=4 and 27.8%, n=5, respectively). Half of the participants played digital games daily (50.0%, n=10).

After playing GAIA, they rated three statements on a 5-point Likert scale. The first statement obtained a mean of 4.22 (median 4, SD = 0.81). The second statement yielded a mean of 3.72 (median 4, SD = 1.32). The third statement produced a mean of 4.56 (median 5, SD = 0.70).

A one-sample Wilcoxon signed-rank test against the neutral value of 3 was performed. Due to the presence of zero differences (responses equal to 3), the normal approximation was used as recommended by SciPy. All three items showed statistically significant deviations from neutrality: Q1 (W = 5.5, p = 0.001), Q2 (W = 23.5, p = 0.033), and Q3 (W = 0.0, p = 0.000). These results indicate that players positively evaluated the resource distribution, perceived the biome as reasonably similar to the Atlantic Forest, and found that the changes in animals and vegetation enhanced their gameplay experience.

Internal consistency of the three-item scale was assessed using both Cronbach's α and McDonald's ω. Cronbach's α was 0.584 (95% CI: 0.086–0.832), while McDonald's ω was 0.802. The discrepancy is expected given the small number of items and the distinct facets measured (pleasantness, realism, engagement); ω is considered the more appropriate reliability estimate for scales with unequal loadings.

Nevertheless, the Cronbach's α value of 0.584 is relatively low, which, combined with the small number of items, suggests that the current scale has limited internal consistency. We acknowledge this as a limitation, and future work should employ validated psychometric scales to obtain more reliable and comparable assessments.

Post-hoc power analysis via bootstrap (1000 resamples) indicated that the

Wilcoxon test had high power for Q1 and Q3 (power = 1.000) and moderate power for Q2 (power = 0.605). The slightly lower power for Q2 is consistent with its larger standard deviation and the presence of some neutral/disagree responses. Overall, the user study answers RQ2 affirmatively: players perceive the procedurally generated biomes positively, with mean scores above the neutral point for all three dimensions.

6. Discussion

Analysis of Figure 4 confirms that attributes with higher target values predominate in the generated biome, despite some difficulty in converging toward the highest inputs. Overall, the algorithm demonstrates solid performance in evolving the six attributes. Figure 5 shows that the best biome achieves good final fitness values rapidly, exceeding those reported in [Pereira et al. 2024]—as expected given the increased complexity of the modified evolutionary algorithm. Thus, the algorithm converges satisfactorily, preserving the target input properties and producing biomes aligned with its intended purpose.

This work offers a strategy for developers creating realistic terrain with multiple ecological attributes. The algorithm provides a foundation for GAIA, extendable with advanced techniques. A key contribution is the combination of procedural generation with a serious game to teach ecology and ecosystem formation, adaptable to other biomes beyond the Atlantic Forest. The main limitation is the lack of robust educational evaluation; time constraints prevented deeper assessment of knowledge conveyance about sustainability. The user study (N=18) had a demographically homogeneous sample—young (19–22 years), mostly male (77.8%), and from São Paulo (83.3%)—which limits the generalizability of perceived pleasantness and realism. A larger, more diverse sample would provide stronger validation, and a control group was considered but not implemented.

7. Conclusion

In this study, a MAP-Elites evolutionary algorithm was developed for the procedural generation of terrains representing biomes inspired by the Atlantic Forest, applied within an educational game focused on ecology. With each execution, the algorithm is capable of generating a different environment while maintaining the core characteristics of the biome, aiming to converge toward desired values for six physical attributes.

The computational analysis showed that the algorithm converges satisfactorily, producing visually plausible ecosystems. User testing indicated that overall impressions of the evolutionary system were largely positive, but we emphasize that this was a small-scale pilot (N=18) with a demographically skewed sample. Consequently, this work should be viewed as a computational framework proof-of-concept rather than a validated educational tool. Future work should investigate the algorithm's behavior with more extreme target values, support additional biomes, and, crucially, conduct larger-scale, controlled studies with validated psychometric instruments to measure actual knowledge retention and educational impact.

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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