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A protocol for leveraging AI in GEE for land use and land cover transition mapping: the Case of São Paulo (1985-2024)

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ABSTRACT

This paper explores the application of generative artificial intelligence as a coding assistant to produce land use and land cover transition maps within the Google Earth Engine (GEE) platform. Focusing on urban expansion in the State of São Paulo from 1985 to 2024, we propose a protocol that enables researchers—particularly those with limited programming expertise—to harness the power of AI to utilize GEE's extensive geoprocessing capabilities. The protocol concurrently implements quality assurance layers to guarantee the accuracy of the final map product. The successful results of the mapping demonstrate the viability and effectiveness of this approach.

Keywords: Geoprocessing; Artificial Intelligence; Google Earth Engine; Urban Expansion.

Um protocolo para aproveitamento de IA no GEE para mapeamento de transição de uso e cobertura da terra: o caso de São Paulo (1985-2024)

RESUMO

Este artigo explora a aplicação de inteligência artificial generativa como um assistente de codificação para produzir mapas de transição de uso e cobertura da terra dentro da plataforma Google Earth Engine (GEE). Focando na expansão urbana no Estado de São Paulo de 1985 a 2024, propõe-se um protocolo que permite aos pesquisadores — particularmente aqueles com limitada expertise em programação — aproveitar o poder da IA para utilizar as extensas capacidades de geoprocessamento do GEE. O protocolo implementa concorrentemente camadas de garantia de qualidade para assegurar a acurácia do mapa final. Os resultados bem-sucedidos do mapeamento demonstram a viabilidade e a eficácia desta abordagem.

Palavras-chave: Geoprocessamento; Inteligência artificial; Google Earth Engine; Expansão Urbana.

Un protocolo para el aprovechamiento de la IA en GEE para el mapeo de la transición de uso y cobertura del suelo: el caso de São Paulo (1985-2024)

RESUMEN

Este artículo explora la aplicación de la inteligencia artificial generativa como asistente de codificación para producir mapas de transición de uso y cobertura del suelo dentro de la plataforma Google Earth Engine (GEE). Centrándose en la expansión urbana en el Estado de São Paulo de 1985 a 2024, se propone un protocolo que permite a los investigadores —particularmente a aquellos con experiencia limitada en programación— aprovechar el poder de la IA para utilizar las extensas capacidades de geoprocesamiento de GEE. El protocolo implementa simultáneamente capas de garantía de calidad para asegurar la precisión del mapa final. Los exitosos resultados de la cartografía demuestran la viabilidad y eficacia de este enfoque.

Palabras clave: Geoprocesamiento; Inteligencia artificial; Google Earth Engine; Expansión Urbana.

1. Introduction

The ongoing advancement of technology has reached a new stage where human intelligence and reasoning—central elements in solving complex problems—are now being simulated or similarly executed by machines. Like any technological innovation, but to a greater extent, Artificial Intelligence (AI), particularly Large Language Models (LLMs), has elicited a spectrum of reactions, from pessimistic to optimistic. Indeed, its application can have both beneficial and detrimental implications (Ludermir, 2021), a fact that has prompted considerable discussion. Within the scientific community, the conservative view is that generative AI is paradigmatically equivalent to the creation of the first scientific journal in

1665. However, its impact could be far greater, potentially promoting the complete transformation of scientific culture and practices (Vasconcelos; Marušić, 2025).

In the academic fields of geoprocessing and spatial analysis, the implications of AI are particularly promising. Researchers have contended that the development of models such as LLMs can yield significant benefits. The standout capabilities of this technology relate to crucial factors: natural language understanding, sophisticated reasoning, and, notably, code generation. These capabilities can be leveraged to automate geoprocessing tasks, albeit partially. This foreshadows an era of autonomous Geographic Information Systems (GIS), capable of performing highly complex activities (Akinboyewa et al., 2025; Li et al., 2025).

These expectations, however, should not overlook the challenges associated with the tool. Concerns related to the reliability of processes, the accuracy of generated outputs, and ethical implications must also be addressed to maintain scientific integrity, which "is linked to the adherence to ethical, transparent, and rigorous scientific practices" (Vasconcelos; Marušić, 2025, author's translation).

In this context, the present study aims to contribute to the formulation of protocols that allow researchers, even those with limited coding knowledge, to utilize cloud-based geoprocessing through the Google Earth Engine (GEE), leveraging its vast computational power. To this end, the code-generation capabilities of generative AI are employed, using natural language instructions to make GEE more accessible. The safety protocol proposed herein, however, is intended to ensure that the resulting output meets the level of confidence required by scientific integrity.

To validate the protocol, it was applied to a case study: the production of a land use and land cover transition map focused on the urban expansion of the State of São Paulo between 1985 and 2024. It is important to note that the proposed protocol is specific in nature, being, at this initial stage, designed for generating transition maps from reliable, pre-existing raster data sources, such as the MapBiomas collections.

By doing so, this study aims to contribute to the debate on the opportunities and challenges that the use of generative AI, in conjunction with geotechnologies, can introduce into any activity involving geographic information and reasoning. It is hoped, therefore, to contribute to the technical and methodological analysis of the reliable production of geographic information in the era of generative AI.

2. Theoretical Foundations and Challenges

Two major transformations have enabled significant advances in contemporary geographical research. On one hand, the evolution of theories and methodologies has allowed a multitude of topics to be approached systemically, rather than merely encyclopedically. On the other hand, the advancement of geotechnologies has reinforced a synthetic approach through techniques that facilitate more complex representation and modeling of spatial phenomena, with greater volume and velocity in data processing. Geotechnologies comprise all instruments that allow for the collection and processing of geographically referenced information (Rosa, 2011).

The growing symbiosis between Geography and technological apparatuses has led to the emergence of additional concepts such as Technological Geography and Automated Geography (Fitz, 2008). Meanwhile, the revolution represented by Web 2.0 also introduced new possibilities for interaction between users and cloud-based systems. Another concept then emerged: Geography 2.0, which occurs through Web 2.0 and represents the potential for interactivity between users of geographic information and cloud-based systems. This is Interactive Geography, accessed and produced via the cloud (Morgato, 2011).

The socioeconomic relevance of Geography 2.0 is evidenced by the fact that so-called Big Tech companies invest significant sums in creating infrastructures, products, and services directly related to geoinformation. Many of these, such as Google Maps, Google Earth, and Bing Maps, are user-friendly and easily accessible, making them popular. For more specialized users with sophisticated geoinformation demands, there is the Google Earth Engine (GEE). It is: "[...] a cloud-based platform for planetary-scale geospatial analysis that brings Google's massive computational capabilities to bear on a variety of high-impact societal issues [...]" (Gorelick et al., 2017, p. 18). According to Yang et al. (2022, p. 1), "GEE also provides access to the vast majority of freely available, public, multi-temporal RS data".

Working with large-area raster data—such as for a state, a country, or even continents and the entire globe—would be a challenge for the average researcher without access to expensive information systems, due to the high computational capacity required. However, while GEE can be a solution for processing power needs on one hand, it can, on the other, inhibit its use by those with little to no familiarity with programming languages like JavaScript and Python (the platform's designated languages).

The accessibility solution that emerges is precisely generative AI, with its capacity for reasoning, coding, and understanding natural language. It is a technology that allows users who are laypersons in information technology and programming to interact with general-purpose intelligent tools and even those specialized in coding and software development (Krakowski, 2025). This stems from the rapidly increasing accuracy of LLMs. Some benchmarks show that Gemini significantly increased its programming capabilities from version 1.5 Pro to 2.5 Pro (from 30.5% to 74.2% on LiveCodeBench and from 16.9% to 82.2% on Aider Polyglot) (Gemini Team, 2025).

According to Russell and Norvig (2013), there is no single, unequivocal definition of AI. In the context of current LLM-based chatbots, it is logical to characterize them as tools that perform functions that would require the use of intelligence or reasoning in humans. This is a definition that is sufficiently informative from a cognitive standpoint and neutral from an ontological one, making it suitable for the purposes of this paper. A dispute exists between the theses of weak AI and strong AI: the former merely assumes a similarity between AI's actions and human intelligence, while the latter admits the possibility of a truly thinking and, eventually, conscious AI. The aforementioned definition aligns, for the moment, with the more conservative weak AI thesis.

Although the first work on AI emerged in 1943, the landscape shifted radically from 2020 onward with the development of LLMs to power chatbots. This was due to accumulated research and the unprecedented availability of vast datasets for model training. Through natural language, the average user gained the ability to set tasks for autonomous execution by AI. The horizons for application became vast, spanning education, research, healthcare, business, software engineering, and more (Dam et al., 2024).

Ironically, despite its great and continuous improvements, generative AI also resembles humans in its production of flaws. The main ones stem from outdated training data and hallucinations: when it provides responses that are verifiably false, cannot be confirmed, or are inconsistent with the inputs (Dam et al., 2024; Zhang et al., 2025). There is also the issue of correctly apprehending user intentions, which can be affected by the quality of the input prompts themselves. This means its use cannot be considered completely risk-free regarding the production of errors.

The dual situation that arises, therefore, is that generative AI is potentially capable of mediating the programming of activities with GEE by converting a researcher's intentions into JavaScript code, while at the same time not being completely free from the possibility of errors—either in the code itself or in the correct understanding of the user's intentions. Thus, the need to reconcile the accessibility benefits for GEE that AI can provide with the imperative to preserve scientific integrity becomes clear.

2.1. The Safety Protocol

The fact that AI is not immune to hallucinations is not a sufficient argument to completely reject its use for producing GEE scripts. Even in the context of Software Engineering, numerous techniques have been developed to detect potential errors arising from human coding. Pfleeger (2004) considered the scenario in which developed programs always work upon execution to be merely ideal, arguing that testing must therefore occur after coding. Through testing, software becomes reliable (Peters & Pedrycz, 2001). Thus, if neither the use of AI nor purely human programming can, by itself, guarantee the absence of potential errors, the most appropriate approach in either case is to adopt risk minimization procedures.

Given this context, it is worth mentioning an inspirational example: in the domain of cybersecurity, the "defense in depth" technique is employed to minimize the risk of failure. This involves creating a series of protective or security layers that, as a whole, aim to make such risks increasingly improbable. It is an adaptation of military strategies (Silva, 2022). The protocol proposed herein utilizes this very principle of layered defense against potential coding errors from generative AI. It should be emphasized that, at this initial stage, it is designed to ensure the reliable generation of land use and land cover transition maps, and is described below.

The first layer of security, after obtaining the script from the interaction with the AI, is to simply run it in GEE itself. This is because errors that prevent the code from executing will be flagged by the console, decisively aiding in the debugging process. In the case study presented later, it was necessary to debug the code several times due to errors made by the AI. The error message from the console was then fed back to the AI, which would then attempt to correct it. At times, this debugging process had to be repeated sequentially until the code could finally generate an output. This, then, is a first-level process that can be overcome through a trial-and-error strategy.

Although an error that prevents the code from executing completely is frustrating, it is less dangerous than an error that does not impede execution but generates an incorrect output. Such errors can vary in severity, from the most blatant—which can be identified by a simple visual inspection of the output—to those that are more subtle and risky. In any case, the source of these errors will be either flawed logic in the AI-generated script or the incorrect use of GEE functions.

In this context, the second layer of protection is the visual and qualitative inspection of the final output, in order to check for potential blatant errors based on the researcher's domain knowledge of the study area's expected characteristics, either as a whole or in specific zones. Thus, for example, if a researcher knows that a zone should be vegetated cover and the output generated an urban area, then the presence of a script error is certain. For a study of an unfamiliar area, the researcher can conduct a brief survey using historical imagery, such as from Google Earth, to check the expected content for certain zones against what was obtained from the GEE-generated output. This is an adaptation of a code verification methodology that can be classified as what is known in Software Engineering as black-box testing. According to Pfleeger (2004), in this type of test, the contents of the box (the code) remain unknown. The test focuses on providing the input (in this case, the raster with land cover data) and observing whether the produced outputs are as expected (i.e., whether certain transition zones are indeed of the expected class).

The third layer of security seeks to quantify the output's accuracy, still within a black-box testing model, but a more rigorous one capable of catching subtler errors that an initial visual analysis might miss. This is an adaptation of the technique known in Remote Sensing as "Ground Truth," in which the researcher selects samples from the field or from a reliable source and compares them with the pixels and their respective classes on a land cover map generated from supervised or unsupervised classification. The procedure aims to build a confusion matrix in which the diagonal shows how many sample points were classified correctly, allowing for the generation of accuracy indices (Souza, 2020).

Thus, the protocol establishes a validation method, termed "Reference Truth," focused on ensuring the accuracy of the transition map relative to the combination of input images—not on certifying the quality of these images, as Ground Truth would. To achieve this, in designing the audit script, the AI is instructed to implement a stratified sampling logic on the original images. The script must collect sample pixels, apply conditional logic to predict the correct classification in the transition map, and finally, compare these expected values with the results generated by the main script. Based on this comparison, a confusion matrix is constructed to extract accuracy statistics.

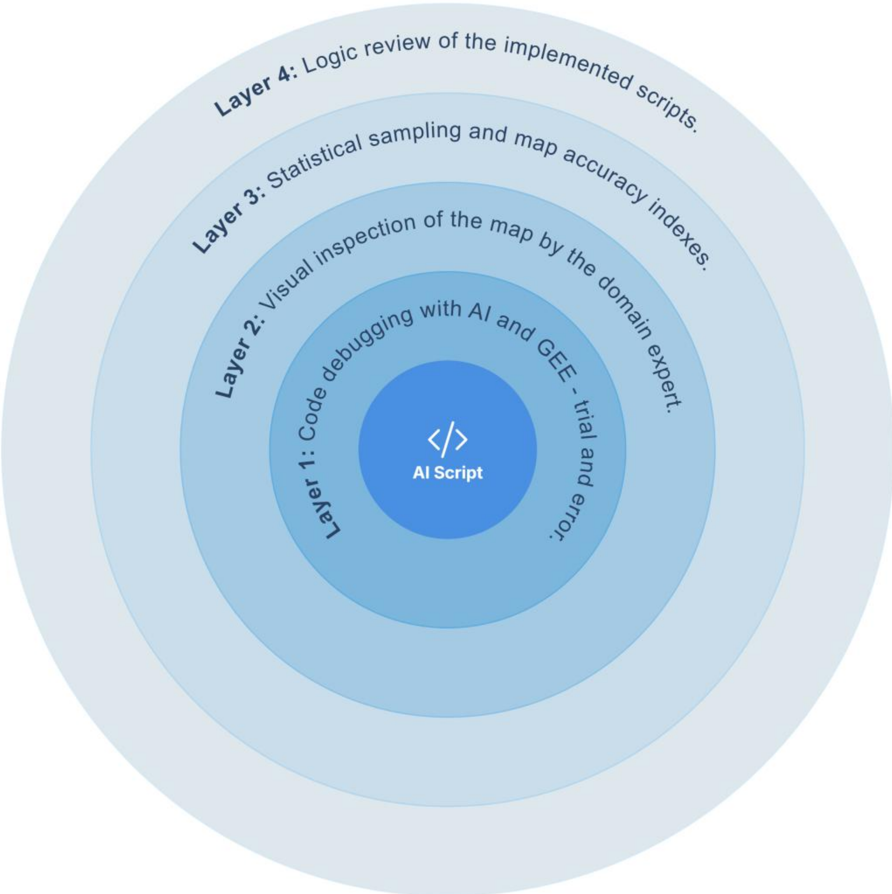
The sub-protocol for verifying and validating the main script via Reference Truth is implemented by an auxiliary audit script, also generated with AI assistance. It is noted that automated testing processes are not foreign to practices used in Software Engineering, as seen in automated static analysis (Sommerville, 2007). However, to ensure genuine independence and mitigate the risk of common-cause or systemic failures (where model biases could lead to identical errors), the approach separates the conceptual design of the algorithm's logic from its implementation in code. Thus, the researcher designs the logical flow and procedural steps of the verification, delegating to the AI only the task of translating this design into functional code.

This creates two computational paths to the same intended result, whose origin logics are cognitively distinct: one is autonomous from the AI (main script), and the other is human-designed (audit script). Although the AI, as the implementer, can still introduce coding errors into the audit script, it is improbable that a logical error in the main script would coincidentally converge on the same result as a separate implementation error in the audit script. Therefore, agreement between the results produced by the two scripts offers a strong indication that the AI's autonomous logic is correct and that both implementations are functionally reliable.

The fourth layer of protection constitutes what can be termed "Soft White-Box Testing." In Software Engineering, white-box testing focuses on the code and its internal logic (Oliveira, 2015). The limiting factor, however, is the potential lack of coding knowledge of the user for whom this protocol is specifically designed. Although users may not be able to attest to the quality of the code's syntax, they can ask the AI to explain each line and/or step in detail, making it possible for them to audit at least the implemented logic. It is a procedure that also establishes a learning curve for the coding process. Again, there is a risk of AI hallucinations, but the probability of complete errors in advanced models is low, and any more specific errors can be minimized by the joint action of the four developed layers of protection.

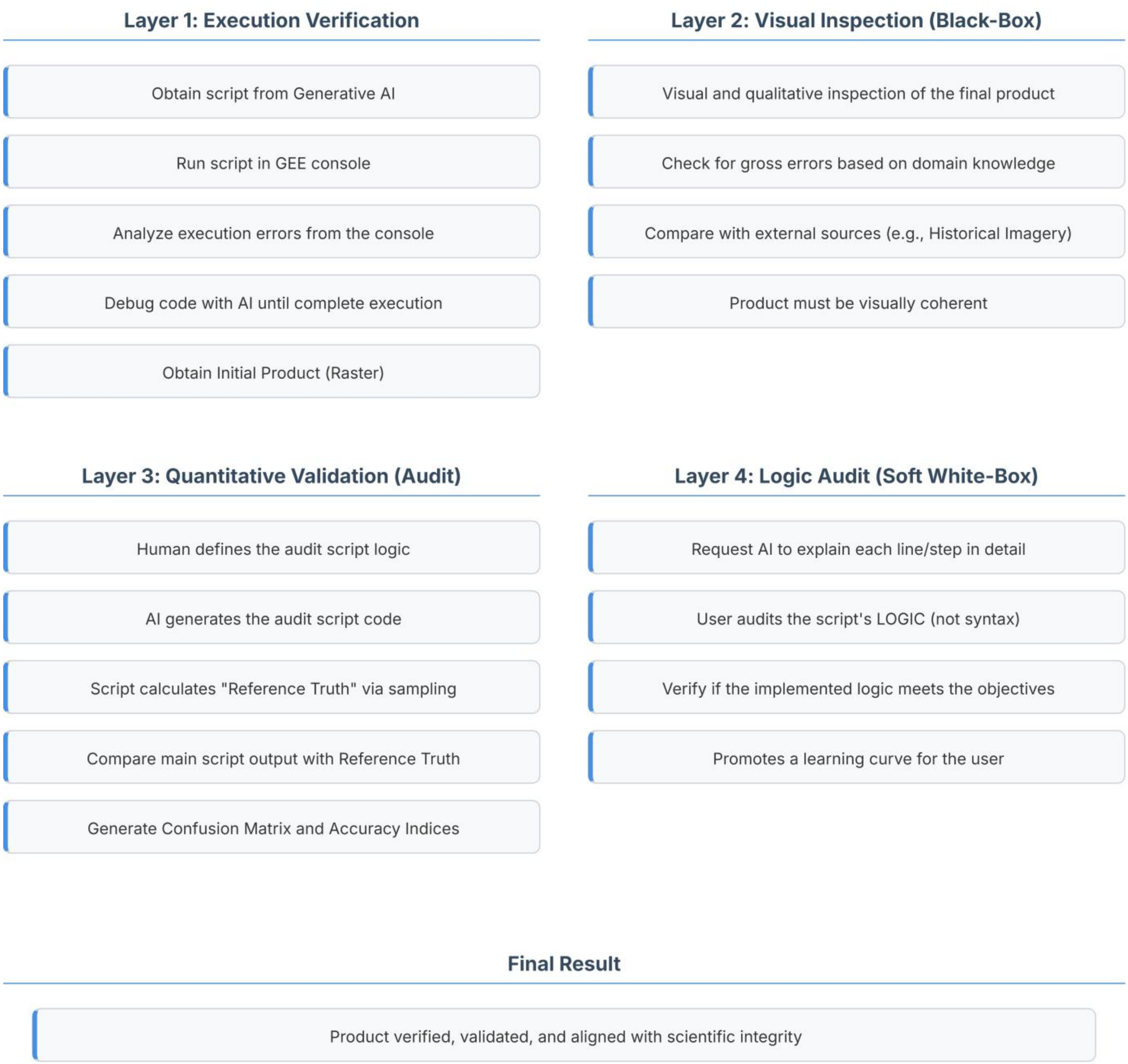
Figure 1 illustrates the security layers of the defense-in-depth system. The detection of insoluble failures (which did not occur in the case study) may require the process to be restarted.

Figure 1. Layers of the defense-in-depth system.



The proposed protocol allows the researcher to verify and validate the codes generated with AI assistance. In Software Engineering, verification seeks to demonstrate that a program aligns with its specifications (what it is supposed to do), while validation seeks to confirm that the program meets the user's needs (Sommerville, 2007). Ultimately, the obtained output will be aligned with the requirements of scientific integrity, with significantly reduced quality risks. Figure 2 presents a diagram outlining the main points and a synthesis of the protocol.

Figure 2. Main features of the defense-in-depth protocol.



3. Materials and Methods

This section details the most relevant materials and methodological procedures of the research, which implement the verification and validation protocol for the AI-generated code for GEE.

3.1. Materials and Software

To apply the protocol, the following data and platforms were used:

3.1.1. Vector Data:

3.1.1.1. A shapefile of the federative units of Brazil, obtained from the Brazilian Institute of Geography and Statistics (IBGE, 2025a).

3.1.1.2. A shapefile of the highways of the State of São Paulo (São Paulo, 2025).

3.1.2. Original Raster Data:

3.1.2.1. Annual maps from Collection 10 of MapBiomas (2025a), with a 30-meter spatial resolution, covering the period from 1985 to 2024.

3.1.3. Platforms and Software:

3.1.3.1. Google Earth Engine (GEE): A cloud-based geoprocessing platform used to generate the land use and land cover transition raster file.

3.1.3.2. Gemini Pro 2.5: Used to create the JavaScript script for generating the transition raster and statistics in GEE, and also to assist in the code's verification and validation process.

3.1.3.3. QGIS 3.34.11: A free and open-source Geographic Information System (GIS) software employed for handling the GEE output raster, conducting visual analyses, and creating the final cartographic product.

3.2. Methodological Procedures

The workflow was executed in 8 main steps, seven of which belonging to and synthesized in the defense-in-depth diagram (Figure 2).

3.2.1. Phase 1: Initially, the land use and land cover codes from MapBiomas Collection 10 were provided to Gemini. The asset paths (internal GEE addresses) for the State of São Paulo boundary and for Collection 10 itself were also supplied.

3.2.2. Phase 2: The AI was then asked to create a land use and land cover transition map using the 1985 and 2024 raster files, with the State of São Paulo as the area of interest. From the numerous land cover classes in MapBiomas, it was specified that the transition map should have only three classes: stable urban area, urbanization, and other (for all other situations). It was made clear that the main objective was to map the growth of the urban footprint during the period. The AI was also tasked with calculating statistics on the area occupied by each new class in km², hectares, and as a percentage of the state's total area. The methodology for creating the transition map was not specified; thus, it was up to the AI to implement a solution. As the initial script did not run completely due to errors, the errors reported in the GEE console were fed back to Gemini to be resolved (Layer 1 of the safety protocol), until an output raster was finally generated. To identify the urbanization dynamics, the AI applied a map algebra technique to the original raster files, generating binary maps with the following possible pixel values: 1, representing the "Urban Infrastructure" class (code 24 in the MapBiomas legend), and 0 for all other classes. The mathematical expression used then multiplied the 1985 binary values by ten and added them to the 2024 binary values [(Binary_Map_1985 * 10) + Binary_Map_2024]. This operation resulted in a transition map with four possible values:

3.2.2.1. 11: The pixel was urban in 1985 and remained urban in 2024.

3.2.2.2. 1: The pixel was not urban in 1985 and became urban in 2024.

3.2.2.3. 10: The pixel was urban in 1985 and ceased to be by 2024.

3.2.2.4. 0: The pixel was not urban in 1985 and remained so in 2024.

This map was then reclassified into three final classes of interest: 1 for Stable Urban Area (from the original value 11), 2 for Urbanization/Urban Expansion (from the original value 1), and 3 for Other Classes (from the original values 0 and 10). Additionally, a mask was applied to remove all pixels classified as "Not Observed" in either year, ensuring the integrity of the analysis.

3.2.3. Phase 3: With the transition map finalized, the absolute areas (in km²) and relative areas (as a % of the state) for each of the three classes were automatically calculated. The statistics were exported in spreadsheet format (.CSV), and the transition map was exported in raster format (.GeoTIFF).

3.2.4. Phase 4: When running the main script, the audit script was also run (Layer 3), which produced 500 sample points for each class to obtain the Reference Truth. The audit script was designed by the researcher, and the AI only coded its implementation, seeking to ensure the independence of the methodological path for producing the results relative to the main script. The conditional logic adopted applied the rules below:

3.2.4.1. If it was urban in 1985 and remained urban in 2024, then the expected value is 1.

3.2.4.2. If it was not urban in 1985 and became urban in 2024, then the expected value is 2.

3.2.4.3. In all other cases, the value is 3.

With all the comparison values, a confusion matrix was generated, contrasting the classification of the final transition map with the Reference Truth, which allowed for the calculation of accuracy indices and the Kappa coefficient. It is important to distinguish the computational execution order from the methodological validation order. Although automation allows the Layer 3 audit script to be executed simultaneously with the generation of the transition map—an approach that optimizes processing time—the researcher's analysis strictly followed the defense-in-depth sequence. Thus, the quantitative results of the audit (the confusion matrix and accuracy indices) were only analyzed to validate the map after the satisfactory completion of the previous steps: code debugging (Layer 1) and qualitative visual inspection (Layer 2). This approach combines computational efficiency with the rigor of sequential validation.

3.2.5. Phase 5: Layer two of the safety protocol was then applied, involving a visual inspection of zones on the generated map, checked against prior knowledge of the areas, thereby also qualitatively assessing its quality.

3.2.6. Phase 6: The confusion matrix and the accuracy and Kappa indices were analyzed and approved, in accordance with layer three of the safety protocol.

3.2.7. Phase 7: Layer four of the safety protocol was implemented by requesting the AI to produce a detailed explanation of each part and function of the codes, in order to permit the "Soft White-Box" audit of the logics used.

3.2.8. Phase 8: The GeoTIFF file resulting from Phase 3 was imported into the QGIS environment. In this step, symbology and a color palette were applied to represent the classes, and other information layers (such as the highway network) were added to enrich the visual analysis. Finally, the final map layout was composed, including essential cartographic elements such as a legend, scale bar, coordinate grid, and title.

3.3. Other Uses of Artificial Intelligence

In accordance with good practices for research integrity (Sampaio; Sabbatini; Limongi, 2024) and to ensure methodological transparency, it is disclosed that the generative artificial intelligence tool Gemini 2.5 Pro was used as an auxiliary resource in the preparation and writing of this manuscript. The specific applications included:

3.3.1. Writing and Revision: Assistance with proofreading and improving the scientific writing style, aiming for greater clarity and grammatical correctness.

3.3.2. Creation of Visual Elements: Generation of the illustration of the security layers and the diagram of the safety protocol (Figures 1 and 2). Both elements were created through an iterative process of prompts provided by the researcher, who guided and refined the results to their final version.

3.3.3. Translation: Assistance in translating into other languages.

3.3.4. Exploratory Use: Conducting initial dialogues to explore concepts and structure ideas, the results of which served as a starting point for subsequent, deeper investigation into established academic literature.

It should be emphasized that, in all stages, the content and elements generated by the tool were treated as raw data and were subjected to critical analysis, validation, and editing by the author. The researcher holds full responsibility for the final content, assertions, and data presented in this work.

4. Results and Discussion

Figure 3 shows the final transition map obtained. Its analysis provides the expert with an initial mechanism for validating the entire process; after all, if the mapping script and its logic contained blatant errors, the effects would be noticeable in the final product. In the present case, it is easy to see that the central area of the large urban footprint of the São Paulo Metropolitan Region should be classified as a stable urban area (no change during the period), which is indeed the case in the produced map, as expected. The area of the Serra do Mar State Park, created for environmental protection in 1977 (Fundação Florestal, 2025), should, in turn, appear in the "Other" class, as it was natural and remains natural—which is again well-indicated on the map. Finally, it is logical to assume that on the edges of stable urban footprints in cities that have undergone population growth, such as São Paulo, there should be areas of urban fabric expansion, which is also observable on the map. This qualitative analysis provides strong indications of success in the mapping process.

Figure 3. Urban area transition map of the State of São Paulo (1985-2024).

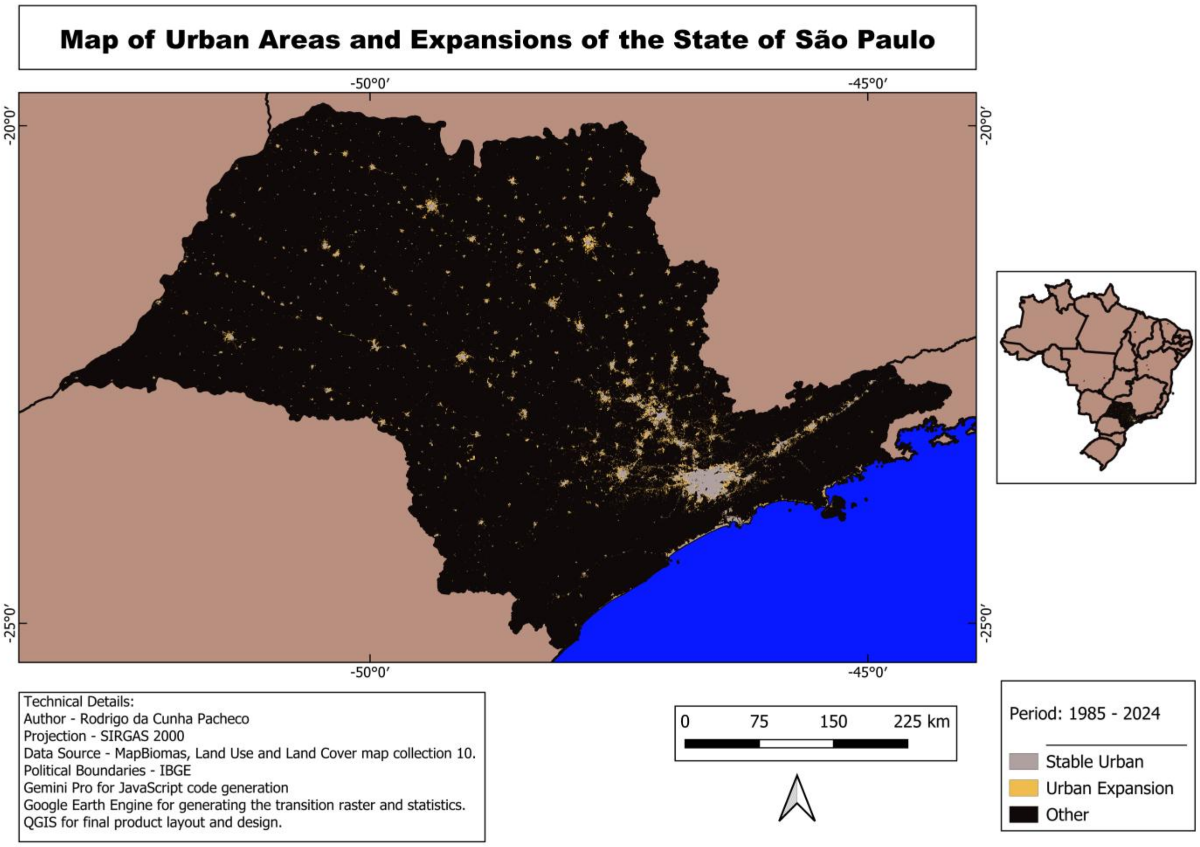


Table 1 shows the result of the confusion matrix. The diagonal presents the number of correctly classified samples. All sample points from the transition map matched the expected Reference Truth. This resulted in an overall accuracy index of 1 and a Kappa coefficient of 1. It is further compelling evidence of the mapping's success under the applied protocol.

Table 1. Confusion matrix for the transition map.

Classes	1	2	3
1	500	0	0
2	0	500	0
3	0	0	500

Table 2, in turn, presents the data obtained regarding the areal extent of each class.

Table 2. Land use and land cover transition classes for the State of São Paulo (1985-2024).

Land Use Classes	Area in Ha	Area in Km²	Values in %
Stable Urban Area	389,585.55	3,895.9	1.57
Urban Expansion	469,025.49	4,690.3	1.89
Other	23,963,518.50	239,635.2	96.54
Total	24,822,129.53	248,221.3	100.00

Notably, the total area in km², calculated from the pixels of the land use transition raster, achieved 99.9% accuracy relative to the state's size as reported by IBGE (2025b)—248,219.485 km²—which once again reinforces the robustness of the generated code.

The "Other" class is by far the largest category in terms of area (96.54%), which is understandable given the reclassification methods applied, focused on mapping urban expansion during the period. In a relatively large state like São Paulo, it would be expected that rural and environmental preservation areas would occupy the majority of the state. Nonetheless, there was an increase in urban areas during the study period, estimated at 120.39%, making them correspond to approximately 3.46% of São Paulo's territory in 2024. The total value of 8,586.2 km² for total urban areas in 2024 is slightly lower than the IBGE's estimate for 2019 (8,614.62 km²). Certainly, there was no reduction in these areas during the period; the difference should be attributed to the different mapping techniques used by IBGE and MapBiomas (e.g., the use of heterogeneous classification algorithms). On the other hand, the proximity of the values also indicates that any potential errors in the mapping script, if they existed, would not be very large.

Table 3 shows the population data for the State of São Paulo, produced by IBGE and compiled by Ipeadata (2025), except for the year 2025, which corresponds to a direct projection by IBGE (2025b). Equation 1, in turn, shows a method for estimating and obtaining the population for the years 1985 and 2024 (the start and end years of this study) by means of linear interpolation, assuming linear population growth. Thus, the population estimates for 1985 and 2024 are 28,017,915 and 45,524,947 inhabitants, respectively. Therefore, the estimated population growth for the period was 62.49%.

Table 3. Population evolution of the State of São Paulo (IPEA and IBGE).

	1980	1991	1996	2000	2007	2010	2022	2025
Population	25,042,074	31,588,925	34,119,110	37,035,456	39,827,570	41,262,199	44,411,238	46,081,801

Equation 1. Formula for population estimation via linear interpolation.

$$Y = \left[\frac{y_2 - y_1}{x_2 - x_1} \times (x - x_1)\right] + y_1$$

Where:

Y = The estimated population to be found.
x = The year for which the population is to be estimated (1985 or 2024).
x1 and x2 = The known years bracketing the year to be estimated.
y1 and y2 = The known populations corresponding to years x1 and x2.

Applying the demographic density formula (absolute population / area), the estimated demographic densities for 1985 and 2024 are 7,192 and 5,302 inhabitants per square kilometer, respectively, a decrease of 26.28%. This occurred because, although the state's population grew by approximately 62.49% during the period, its urban area grew by approximately 120.39%. Thus, the state experienced lower-density urban growth—in other words, greater urban sprawl—and consequently, a greater demand for infrastructure construction to support the expanding urban fabric. Such a process can be conceptualized as urban rarefaction, a consequence of sprawl. Nadalin and Igliori indicated the occurrence of this process between 1960 and 2000 in the São Paulo Metropolitan Region, relating it to the occupation of suburbs by low-income families. They defined the process as “the urbanized area becoming less and less concentrated, less dense, and with more urban voids” (Nadalin; Igliori, 2015, p. 109, author's translation). In this study, however, a distinction is made between the process of sprawl (the growth) and the loss of population density, which will be termed the process of urban rarefaction, a consequence of sprawl.

In the map in Figure 4, the highway network of the State of São Paulo has been added, allowing for the perception of the physical articulation of flow paths within the statewide urban network. Figure 5, in turn, focuses on the expansion of urban areas in the approximate region of the São Paulo Macrometropolis, in the easternmost sector of the state, making it easier to perceive the phenomenon of expansion on the urban fringes around more established urban fabrics.

Figure 4. Urban area transition map of the State of São Paulo (1985-2024) with the highway network.

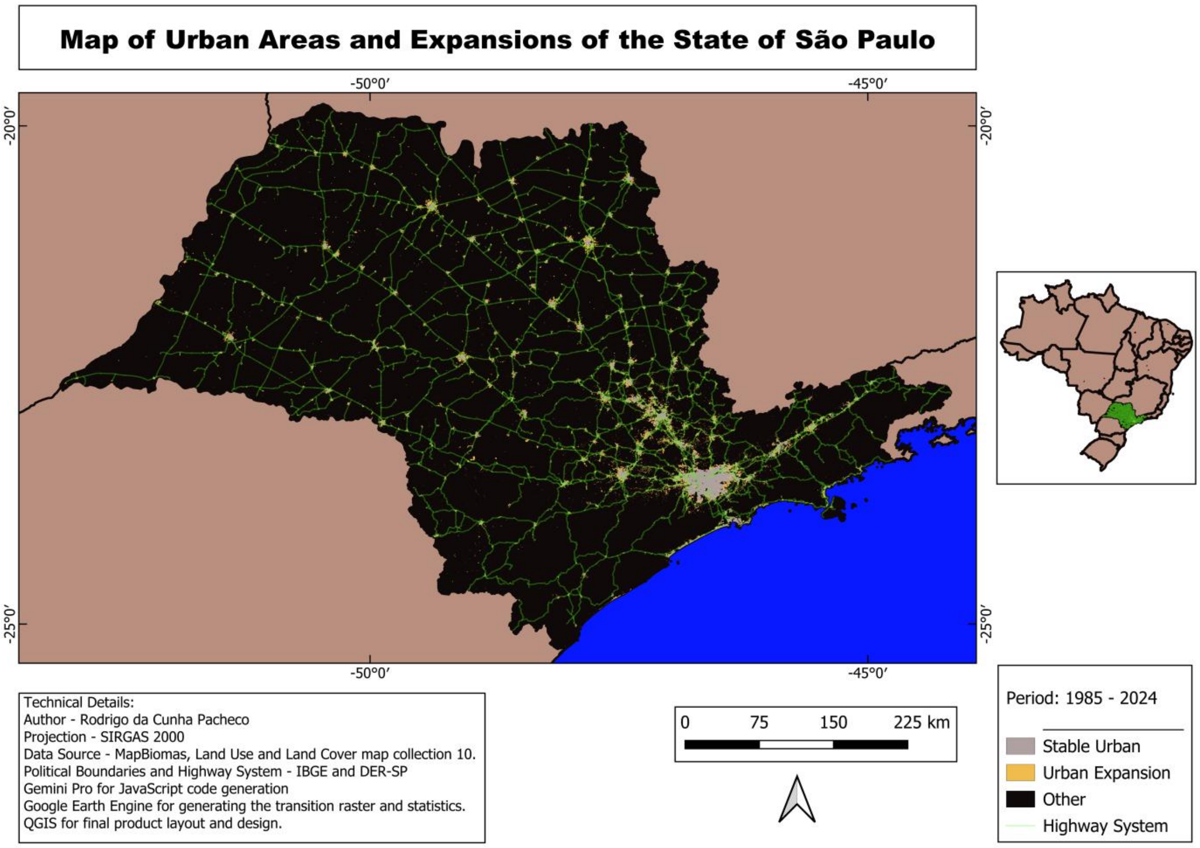
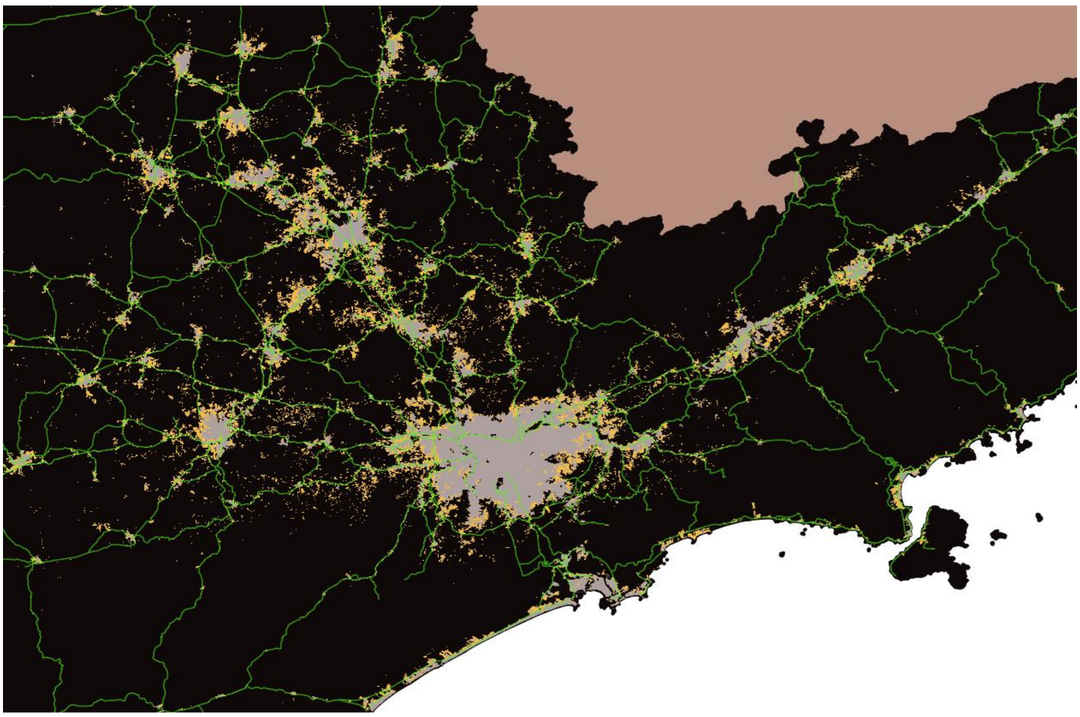


Figure 5. Screenshot focusing on the urban area transition (1985-2024) in the São Paulo Macrometropolis region, with the highway network.



Finally, this analysis could not conclude without addressing the reliability of the source land use maps, which enabled the creation of the transition map focused on urban expansion. After all, the protocol proposed herein is based on the assumption that the source data is reliable. In the case of the land cover collection used, it was produced by a team of experts: "MapBiomas is a global, multi-institutional network of universities, NGOs, and technology companies that monitors changes in land cover and use and their impacts" (MapBiomas, 2025b). Although accuracy information for the utilized Collection 10 was not found (likely because it has not yet been made available), the previous Collection 9 reported an accuracy index of 86.53% for the Atlantic Forest biome region at mapping level 2, and 91.67% at level 1.

5. Conclusion

This research proposed a protocol that allows researchers with limited programming knowledge to use GEE for producing land use transition maps by leveraging generative AI, without sacrificing scientific integrity. The protocol's application to the study of urban transition in the State of São Paulo between 1985 and 2024, using raster maps produced by MapBiomas, was successful, suggesting its effectiveness.

The layered defense approach, notably the quantitative validation via an independent audit script, proved to be fundamental in ensuring the reliability of the generated code. The importance of this finding stems from the potential to promote greater accessibility to GEE for researchers through the responsible use of generative AI.

The data obtained revealed considerable growth of the state's urban fabric during the analysis period (120.39%), as well as a decrease in demographic density. This indicates a character of this process conceptualized here as urban rarefaction, with the consequence of requiring public authorities to invest in the expansion of urban infrastructure at the expense of better utilizing the existing infrastructure.

It is acknowledged, however, that the protocol was validated for a specific transition mapping task. Future research could, therefore, explore its applicability to other geospatial analyses in GEE, as well as test its effectiveness with different generative AI models or in regions with different land use dynamics.

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Declaração de conflito de interesse

O autor declara que não há conflito de interesse.

Declaração de disponibilidade de dados da pesquisa

Todo o conjunto de dados de apoio aos resultados deste estudo foi publicado no próprio artigo e anexado ao processo de submissão na plataforma Scielo.