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PROMPT ENGINEERING AND PROMPT CHAINING IN ARTIFICIAL INTELLIGENCE: TOOLS FOR MAPPING FUTURE CLIMATE SCENARIOS AS MECHANISMS OF ADAPTATION AND CLIMATE JUSTICE AND JUST TRANSITION PROMOTION

ENGENHARIA DE PROMPT E ENCADEAMENTO DE COMANDOS EM INTELIGÊNCIA ARTIFICIAL: FERRAMENTAS PARA MAPEAMENTO DE CENÁRIOS CLIMÁTICOS FUTUROS E PROMOÇÃO DE JUSTIÇA CLIMÁTICA E TRANSIÇÃO JUSTA

INGENIERÍA DE COMANDOS RÁPIDOS Y ENCADENAMIENTO DE COMANDOS EN INTELIGENCIA ARTIFICIAL: HERRAMIENTAS PARA MAPEAR ESCENARIOS CLIMÁTICOS FUTUROS Y PROMOVER LA JUSTICIA CLIMÁTICA Y UNA TRANSICIÓN JUSTA

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ABSTRACT

The climate emergency demands innovative methodological approaches to reach socioeconomically and environmentally vulnerable populations and areas as quickly as possible. This article proposes the use of Open Science, Prompt Engineering, and Prompt Chaining as tools for mapping future climate scenarios using automated methods produced with the aid of Generative Artificial Intelligence (AI – LLMs models). Based on an applied study, it demonstrates how these techniques can be integrated into climate mapping models focused on family farming, in line with IPCC frameworks on climate justice and just transition, significantly increasing productivity, scalability and reducing time and potential errors. The results indicate that AI, when guided by well-structured prompts and chained logical flows, can democratize access to complex analyses, support public policies, and strengthen the resilience of vulnerable communities. The workflow proposed here can be replicated for other areas, models, climate scenarios, and agricultural crops. The deposit of all Python scripts generated on the Zenodo open access platform is in line with the FAIR principles of open science.

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Keywords: Climate Change. Climate Emergency. Sustainable Development Goals. 1988 Brazilian Federal Constitution. Automated GIS. AIGIS.

RESUMO

A emergência climática exige abordagens metodológicas inovadoras para alcançar populações e áreas socioeconomicamente e ambientalmente vulneráveis o mais rápido possível. Este artigo propõe o uso de ciência aberta, engenharia rápida e encadeamento rápido como ferramentas para mapear cenários climáticos futuros usando métodos automatizados produzidos com a ajuda de inteligência artificial generativa (IA - modelos LLM). Com base num estudo aplicado, demonstra como essas técnicas podem ser integradas em modelos de mapeamento climático focados na agricultura familiar, em linha com as estruturas do IPCC sobre justiça climática e transição justa, aumentando significativamente a produtividade e a escalabilidade e reduzindo o tempo e os erros potenciais. Os resultados indicam que a IA, quando orientada por instruções bem estruturadas e fluxos lógicos encadeados, pode democratizar o acesso a análises complexas, apoiar políticas públicas e fortalecer a resiliência de comunidades vulneráveis. O fluxo de trabalho aqui proposto pode ser replicado para outras áreas, modelos, cenários climáticos e culturas agrícolas. O repositório de todos os scripts Python gerados na plataforma de acesso aberto Zenodo está em conformidade com os princípios FAIR da ciência aberta.

Palavras-chave: Mudanças Climáticas. Emergência Climática. Objetivos de Desenvolvimento Sustentável. Constituição Federal Brasileira de 1988. SIG Automatizado. AIGIS.

RESUMEN

La emergencia climática exige enfoques metodológicos innovadores para llegar lo más rápido posible a las poblaciones y zonas socioeconómicamente y medioambientalmente vulnerables. Este artículo propone el uso de la ciencia abierta, la ingeniería de prompts y el encadenamiento de prompts como herramientas para cartografiar escenarios climáticos futuros utilizando métodos automatizados producidos con la ayuda de la inteligencia artificial generativa (IA - modelos LLM). Basándose en un estudio aplicado, demuestra cómo estas técnicas pueden integrarse en modelos de cartografía climática centrados en la agricultura familiar, en línea con los marcos del IPCC sobre justicia climática y transición justa, aumentando significativamente la productividad y la escalabilidad y reduciendo el tiempo y los posibles errores. Los resultados indican que la IA, cuando se guía por indicaciones bien estructuradas y flujos lógicos encadenados, puede democratizar el acceso a análisis complejos, apoyar las políticas públicas y reforzar la resiliencia de las comunidades vulnerables. El flujo de trabajo aquí propuesto puede replicarse para otras áreas, modelos, escenarios climáticos y cultivos agrícolas. El depósito de todos los scripts de Python generados en la plataforma de acceso abierto Zenodo se ajusta a los principios FAIR de la ciencia abierta.

Palabras clave: Cambio Climático. Emergencia Climática. Objetivos de Desarrollo Sostenible. Constitución Federal Brasileña de 1988. SIG Automatizado. AIGIS.

INTRODUCTION

Global Climate Change (GCC), or as it has recently been agreed to call it, climate emergency, represents one of the greatest challenges of our time, capable of causing immeasurable negative impacts on society. It transcends geographical, social, and economic boundaries. However, they do not affect different peoples equally, with those who are socioeconomically vulnerable or live in more vulnerable areas possibly being more affected due to their lower resilience (IPCC, 2021; IPCC, 2023).

The Intergovernmental Panel on Climate Change (IPCC) attributes unequivocal causes of warming of the atmosphere, oceans, and land to human activities. Furthermore, the scale of recent changes observed in the climate system is unprecedented in thousands of years. There is virtual certainty that heat waves have become more frequent and cold waves less frequent. There is also high confidence that the frequency and intensity of extreme precipitation events have increased. Human actions have increased the occurrence of agricultural and ecological droughts in some regions due to increased processes such as evapotranspiration (medium confidence) (IPCC, 2021).

This whole scenario can compromise food and nutrition security, public health, and the stability of ecosystems, especially in already vulnerable regions such as the Brazilian northeastern semi-arid region and for populations with less potential to adopt strategies aimed at increasing resilience and climate adaptation, which often depend on climate predictability to maintain their agricultural production that is, sometimes, their only source of subsistence and income (Mirzabaev et al., 2023; Hultgren et al., 2025). These issues may even lead to the migration of populations living in these regions to others where the impacts of climate change are less severe, leading to modern challenges such as an increased risk of non-endemic infectious diseases, mental disorders, food and nutritional insecurity, difficulties in accessing healthcare, and social exclusion (Makharia et al., 2024). Hutgren et al. (2025) highlights that technological innovations are an essential tool for adapting production systems and vulnerable populations to GCC.

Climate intelligence tools are a set of technological innovations usually designed to adapt to GCC. The use of digital technologies such as Artificial Intelligence (AI) Large Language Models (LLMs), when used with due care and employing concepts such as Prompt Engineering and Prompt Chaining, can streamline the development and use of such tools by increasing productivity, not only helping to generate climate data but also promoting democratization of access to climate information. Another important point is the use of already modeled data openly available on digital platforms such as WorlClim (Fick & Hijmans, 2017), Chelsea (Cui et al., 2021), and the Brazilian INPE's Climate Projections Portal (Chou et al., 2014). The use of open-source geoprocessing software such as QGIS also facilitates the spatialization of climate scenarios (Grinspan & Worker, 2021). The combined use of such technologies leads to less dependence on expensive infrastructure (Amnuaylojaroen et al., 2025) often making it possible to use home computing structures to generate relevant information.

Prompt engineering and Prompt Chaining are emerging fundamental techniques capable of expanding the applicability and control of AI models in generating climate scenarios more efficiently. The use of these tools allows, for example, the development of scripts capable of automating geoprocessing, significantly reducing the time required to generate maps of future climate scenarios. These processes allow researchers and technicians to formulate precise commands, optimizing the way LLMs process multiple stages of analysis, enabling everything from direct questions to the establishment of interactive workflows for complex tasks and the incremental refinement of spatial projections. Additionally, Prompt Chaining promotes the structuring of Prompt Engineering steps into logical sequences, ensuring process continuity and facilitating both the detailing and traceability of analytical flows, potentially reducing errors and improving the contextualization of results. This mechanism allows the analysis of complex problems to be subdivided into modular steps, improving the results of AI responses (Bommasini et al., 2021).

For all the above reasons, this paper aims to present a methodological proposal based on Prompt Engineering and Prompt Chaining for the automation of mapping future climate scenarios using generative AI, collaborative platforms, and open science, using the PyQGIS environment for geoprocessing. The work was the result of a case study conducted for the Lower São Francisco region between Sergipe and Alagoas (LSF/SE-AL) with a focus on family farming, promoting the IPCC frameworks for climate justice and just transition, through support for environmental and agricultural planning, as well as a tool to assist in the development of public policies.

METHODOLOGICAL FRAMEWORK

Methodological Workflow

The methodological workflow was structured in four main stages:

1. **Data collection and organization** (from WorldClim v.2.1).
2. **Prompt engineering and Prompt Chaining** to structure interactions with generative AI.
3. **Spatial structuring, automation, and mapping using AI to generate Python scripts** that were run in a PyQGIS environment (QGIS 3.42.3). The automation process was conducted in batches of 12 monthly maps, increasing productivity and reducing processing time.
4. **Operational validation** by comparing individually and manually generated maps and the automated flow.

Prompt Chaining

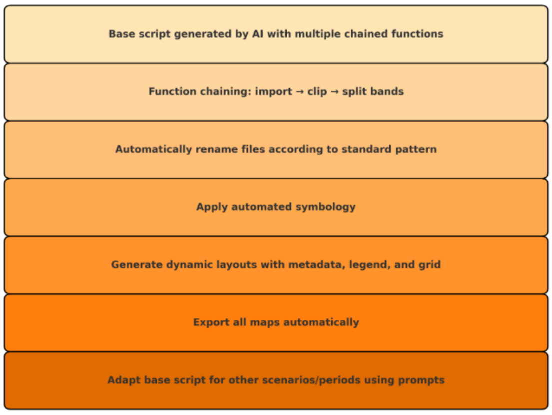
Prompt Chaining refers to the technique of dividing complex tasks into smaller subtasks using specific and sequential prompts. This sequential flow allows for the construction of processing pipelines, which facilitates control, traceability, and modularization of steps, in addition to reducing ambiguity and achieving greater precision in the result. This approach is fundamental in advanced workflows and applications that require logical decomposition of problems for LLMs (Kirskovka, 2024).

The logical sequence used for Prompt Chaining to generate Python scripts developed with the aid of generative AI in this study is shown in Figure 1.

Prompt Engineering

Prompt engineering is a modern strategy for maximizing the results of using LLMs as generative AIs. It can be defined as the art and science of designing, structuring, and optimizing instructions (prompt layers) to guide AIs to provide the desired responses, maximizing accuracy, robustness, relevance, and results. In short, it involves creating clear, specific, and contextualized commands to improve interaction and the quality of results from model outputs, encompassing iterative practices for refining and evaluating the responses generated (Kirskovka, 2024).

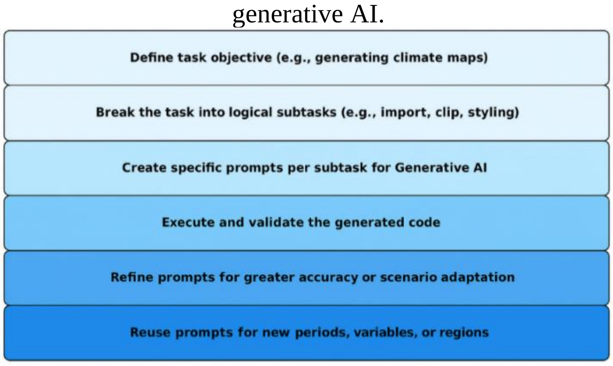
Figure 1 - Workflow used to define the Prompt Chaining used to generate Python scripts for automating the generation of climate scenario maps from ACCESS-CM2 raster images from WorldClim v.2.1 with support of generative AI.



Source: The authors with support of AI tools

The structure used to prepare the developed Prompt Engineering in this work considered the sequence of commands and tasks necessary for mapping climate scenarios. At this point, it is important to mention that for the Prompt Engineering development stage to be performed correctly, the user of the applied AI must have full knowledge of the geoprocessing steps necessary to carry out the work to be performed. This structure can be seen in Figure 2.

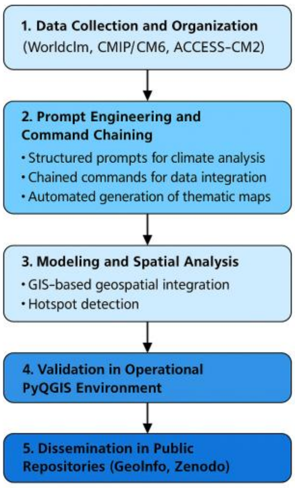
Figure 2 - Workflow used to define the Prompt Engineering used to generate Python scripts for automating the generation of climate scenario maps from ACCESS-CM2 raster images from WorldClim v.2.1 with support of generative AI.



Source: The authors with support of AI tools

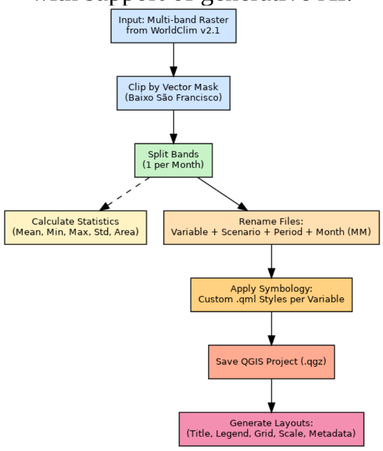
Basically, we started with layers referring to raster images of climate modeling using the ACCESS-CM2 model with 1 km^2 spatial resolution obtained via download on the WorldClim v.2.1 platform (https://worldclim.org/data/cmip6/cmip6_clim30s.html), loaded in the QGIS 3.42.3 environment, as well as a vector shapefile layer containing the boundaries of the study area, also loaded into the GIS. Figure 3 summarizes all processes used to make this methodological study, which will be detailed below. Figure 4, in turn, shows the steps (Prompt Chaining) followed to perform the mapping.

Figure 3 – Summarize of workflow used to mapping future climate scenarios using Prompt Chaining, Prompt Engineering and Artificial Intelligence from open science database, software and repositories.



Source: The authors with support of AI tools

Figure 4 – Example of summarized workflow used to apply Prompt Engineering used to generate Python scripts for automating the generation of climate scenario maps from ACCESS-CM2 raster images from WorldClim v.2.1 with support of generative AI.



Source: The authors with support of AI tools

To generate the Python scripts that enabled the automation of future climate scenario map generation, the following steps were followed.

1. Importing multi-band raster datasets, with 12 bands representing the months of the year.
2. Spatial clipping of the raster, using a vector mask
3. Separating monthly bands into individual single-band raster files.

4. Standardized file naming, based on variable, scenario, period, and month.
5. Apply statistical data extraction
6. Applying customized symbology, using predefined QGIS style files manually adjusted per variable.
7. Generating monthly map layouts, including title, legend, scale bar, coordinates, grid frame, and footer with metadata.
8. Exporting maps in PNG format, at publication-quality resolution.

Note: all steps were conducted as batch of 12 layers in QGIS, except the 1, 2 and 3.

All procedures were conducted using Python scripts to automate the geoprocessing steps, increasing productivity and reducing work time. For this purpose, the PyQGIS environment was used. The following steps were taken to generate the scripts:

1. Development of the initial version of the Python script using ChatGPT.
2. Improvement of the initial version of the Python script using generative AI focused on the generation of computer codes (GitHub Copilot).
3. Preliminary tests using a collaborative environment (Google Colab) and specific programming software (Visual Studio Code).

Note: necessary corrections were made at all stages.

It is also important to mention that the methodology proposed in this study can be applied to the production of monthly and seasonal climate scenario maps under GCC conditions from multiband raster images for various regions and climate models, which is of paramount importance for activities such as agricultural planning, risk and vulnerability analysis, and the development of strategies to increase resilience and climate adaptation.

The integration of AI into geoprocessing workflows has opened new opportunities for research and innovation in studies involving climate impacts (Akter et al., 2024). The combination of data from open science and open-source software, as well as its storage in public repositories, associated with prompt-driven automation, enables replicability, scalability, and increased efficiency (Mai et al., 2025). Furthermore, it complies with the principles of findability, accessibility, interoperability, and reuse (FAIR) (Go Fair, 2016), the gold standard for open science. In the sequence Prompt Engineering and Prompt Chaining developed in this work can be seen.

PROMPT ENGINEERING AND CHAINING DEVELOPED TO OBTAIN SCRIPTS PYTHON TO AUTOMATE MAPPING OF CLIMATE SCENARIOS FROM GEOTIFF RASTER IMAGES USING AI

General Prompts for ChatGPT

First Prompt: Prepare a Python script to execute in the PyQGIS environment that clip a multiband raster image using the mask vector layer corresponding to the study area. Ensure that the output raster preserves the original band structure.

Second Prompt: Prepare a Python script to be run in the PyQGIS environment that separates a multiband raster (GeoTiff) into 12 single spectral bands raster layers, each corresponding to one month. Save each output raster using the first three letters of the corresponding month.

Third Prompt: Rename each of 12 single-band monthly raster layers following the standardized structure:

Period_SSP_climate variable (Unity)_MonthAbbrev

Where:

Period: corresponds to the time interval (Historical, 2021-2040, 2041-2060, 2061-2080 or 2081-2100).

SSP: corresponds to the IPCC scenario (Historical, SSP1 2.6, SSP2 4.5, SSP3 7.0 or SSP5 8.5).

Climate variable: corresponds to the climate variable analyzed (minimum temperature, maximum temperature or precipitation).

MonthAbbrev: corresponds to the three-letter abbreviation of the corresponding month (e.g, Jan, Feb, Mar).

Fourth Prompt: Choose a suitable color palette for each of the three climate variables analyzed (minimum temperature, maximum temperature, and precipitation). Then, prepare a Python script to be executed in the PyQGIS environment that applies the chosen color palette to each raster layer according to the climate variable. Ensure that the symbology is consistent across all months, scales and variables.

Fifth Prompt: Save QGIS project files: Prepare a Python script to be run in the PyQGIS environment that saves the current workspace as a QGIS project file (.qgz). The file must be a standardized name (**climate variable_period_SSP.qgz**). For example: precipitation_2021_2040_SSP126.qgz.

Sixth Prompt: Prepare a Python script to be executed in the PyQGIS that calculates basic statistics for each layer opened in QGIS, including mean, median, standard deviation, 95% confidence interval and area occupied by pre-defined value classes. Export the results as a .txt file. Use the following model of standardized name: ***Period_SSP_climate variable (Unity)_MonthAbbrev.txt***

Seventh Prompt: Prepare a Python script to be used in the PyQGIS environment that create dynamic layouts for each month with full cartographic elements for all raster images opened in QGIS changing the IPCC scenario, period and name of month according to the name of the opened raster layers. Each layout title must automatically update to reflect the IPCC scenario, period, climate variable and month name, according to the opened raster layers. All layouts must contain north star, scale bar, grids and geographic coordinates, legends, climate model used, and database used as a footnote.

Eighth Prompt: Prepare a Python script to be executed in the PyQGIS that exports all layout as a PNG image. The exported files must follow a standardized naming as follow: ***Period_SSP_climate variable (Unity)_MonthAbbrev.png***

General Prompts for GitHub Copilot

First Prompt: Analyze the attached script and identify any error.

Second Prompt: Correct the errors and improve the structure of the prompt so that it can be run in the PyQGIS environment.

Note: The first tests are run on Google Colab or Visual Studio Code. If any remaining errors are detected, they are corrected manually.

Table 1 presents a summary of the Prompts' functions, the chaining of subtasks, and the expected inputs and outputs. In the end, approximately 300 Python scripts, 720 raster images with monthly projections of minimum temperature, maximum temperature, and precipitation, 60 QGIS project files (.qgz), 720 text files with statistical information (.txt), and 720 dynamic layouts are obtained. This is a very robust and extensive set of products that, for better evaluation, will undergo future tests of interpretation of the results using AI.

Table 1 - Summarizes the function of each prompt and the expected result for the application of each one.

Prompt	Objective	Expected Input	Expected Output
ChatGPT			
1. Clipping	Clip a multiband raster using a vector mask	Multiband raster (GeoTIFF) + region shapefile	Clipped raster preserving original band structure
2. Band Separation	Split the multiband raster into 12 monthly layers	Clipped raster (12 bands)	12 single-band rasters (one per month)
3. Standardized Naming	Apply a standardized naming convention	Generated monthly layers	Renamed files: ***Period_SSP_climate variable (Unity)_MonthAbbrev***
4. Color Scheme	Apply appropriate symbology for each variable	Assigned style file (qml)	Rasters with standardized symbology (colors and ranges)
5. Save Project	Save the QGIS project with standardized naming	Active QGIS workspace	.qgz file saved as: **climate variable_period_SSP.qgz**
6. Statistics	Calculate basic statistics (mean, median, standard deviation, 95% CI, area by predefined classes)	Raster layers opened in QGIS	.txt files saved as: ***Period_SSP_climate variable (Unity)_MonthAbbrev.txt***
7. Dynamic Layouts	Create dynamic layouts with full cartographic elements	Raster layers + metadata	Monthly layouts with title, legend, grid, scale, metadata
8. Export Layouts	Export layouts as images	Generated layouts in QGIS	.png files exported as: ***Period_SSP_climate variable (Unity)_MonthAbbrev.png***
GitHub Copilot			
1. Error analyser	Analyze scripts and identify errors	Python script	Error and inconsistency repor
2. Error corrector	Correct errors and improve script structure	Script with identified errors	Corrected, modular script ready for tests in Google Colab and Visual Studio Code

Source: The authors with support of AI tools

Applicability: summarizing a case of study of LSF/SE-AL

Below is an example of a developed script (Table 2). It is a Python script that aims to crop the raster image (GeoTiff) using a vector mask layer (shapefile). The complete set of developed scripts can be found in public repositories (Lima et al., 2025a-c). The application of the workflow presented here allows the development of 720 maps, beyond the scripts and data analysis, in approximately eight days, guaranteed high quality information for climate planning.

Table 2 – An example of developed script that aim to clip a raster image based on a mask vector shapefile mask.

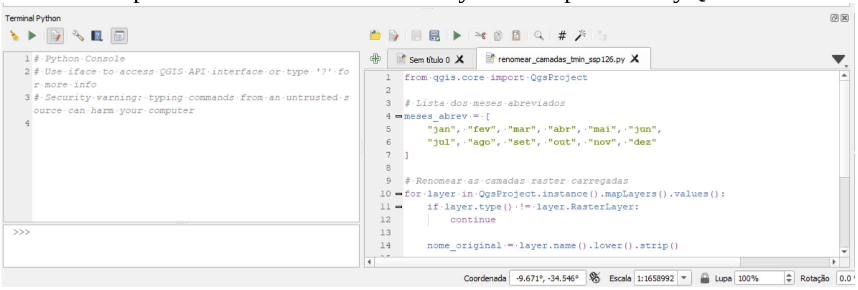
import os
from qgis.core import (
QgsProject,
QgsProcessingFeedback,
QgsRasterLayer,
QgsVectorLayer
)
import processing
Obtém todas as camadas carregadas no QGIS
project = QgsProject.instance()

layers = list(project.mapLayers().values())
Identifica a primeira camada raster no projeto
raster_layer = next((layer for layer in layers if isinstance(layer, QgsRasterLayer)), None)
Identifica a primeira camada vetor (shapefile) no projeto
vector_layer = next((layer for layer in layers if isinstance(layer, QgsVectorLayer)), None)
Verifica se encontrou as camadas necessárias
if not raster_layer:
print("Erro: Nenhuma camada raster encontrada no projeto.")
elif not vector_layer:
print("Erro: Nenhuma camada shapefile encontrada no projeto.")
else:
print(f"Raster encontrado: {raster_layer.name()}")
print(f"Shapefile encontrado: {vector_layer.name()}")
Define caminho de saída para o arquivo recortado
output_path = "E:/Mudanças Climáticas/Nova geografia da produção de hortaliças/Imagens Raster BR/raster_recortado.tif"
Configuração dos parâmetros do processamento
params = {
'INPUT': raster_layer, # Camada raster de entrada
'MASK': vector_layer, # Camada de máscara (limites do Brasil)
'TARGET_EXTENT': vector_layer.extent(), # Usa a extensão do shapefile como referência
'NODATA': 10000000, # Define valor NoData
'DATA_TYPE': 0, # Mantém o mesmo tipo de dados da entrada
'ALPHA_BAND': False, # Sem banda alfa
'CROP_TO_CUTLINE': True, # Recorta pela máscara
'KEEP_RESOLUTION': True, # Mantém a resolução original
'OUTPUT': output_path # Caminho do arquivo de saída
}
Execução do processamento no QGIS
try:
feedback = QgsProcessingFeedback()
result = processing.runAndLoadResults("gdal:cliprasterbymasklayer", params, feedback=feedback)
print("Processo concluído com sucesso! O raster recortado foi salvo e carregado no QGIS.")
except Exception as e:
print(f"Erro no processamento: {str(e)}")

Source: The authors with support of AI tools

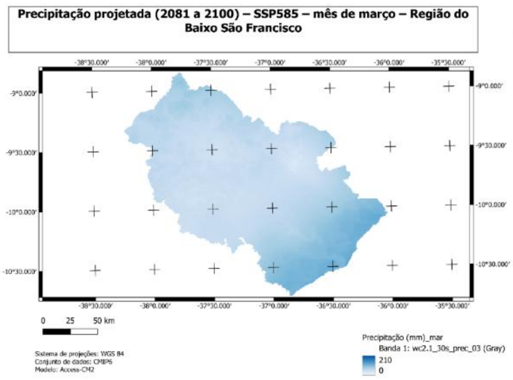
Figure 5 shows an example of running a Python script in the PyQGIS environment, while Figure 6 shows an example of a map generated using the automated procedure for the LSF/SE-AL region.

Figure 5 - Example of execution of a rename Python script in the PyQGIS environment.



Source: The authors with support of AI tools

Figure 6 – Example of a precipitation map generated for LSF/SE-AL, 2081-2100 period, march and SSP5 8.5 scenario through automated workflow showed before.



Source: The authors with support of AI tools

The LSF/SE-AL region is characterized by a humid tropical climate on the coast and surrounding areas and, for the most part, a semi-arid climate. It is therefore characterized by quantitative water scarcity in the semi-arid region and qualitative water scarcity at the mouth of the São Francisco River, due to saline intrusion caused by the constant rise in sea level. Its main economic activities are agriculture, livestock, and aquaculture.

According to the Brazilian Institute of Geography and Statistics (IBGE), around 70% of agricultural enterprises are linked to family farming. These establishments have less access to credit and technologies capable of promoting increased resilience and climate adaptation and are therefore highly dependent on public policies to remain sustainable (Silva et al., 2022).

Investing in climate intelligence is therefore essential to mitigate the impacts of GCC, enabling the anticipation of adaptation strategies, environmental planning, territorial planning, and the development and implementation of public policies. In this regard, increasing the speed and efficiency of generating future climate scenarios is essential (Wang et al., 2023), constituting not only an aspect of technical relevance, but also a strategy for providing climate justice and a just transition (Cairney et al., 2023). Therefore, this methodological study is also a necessary condition for ensuring the achievement of targets related to Sustainable Development Goals (SDGs) number 1 (poverty eradication), 2 (zero hunger and sustainable agriculture), 6 (clean water and sanitation), 8 (decent work and economic growth), 10 (reduced inequalities), and 13 (climate action). Finally, it is also a matter of complying, at a minimum, with Articles 1, 5, 6, 7, 170, and 225 of the 1988 Federal Constitution of Brazil.

The constitutional alignment shows that the proposed method not only responds to technical challenges, but also contributes to the fulfillment of constitutional rights such as human dignity (Art. 1), equality (Art. 5), social rights (Art. 6 and 7), an economic order oriented toward social justice (Art. 170), and the right to a balanced environment for current and future generations (Art. 225). The democratization of access to climate scenarios and climate intelligence tools promotes transparency through open science, strengthening social participation and improving state decision-making. However, the inclusion of AI in the formulation, implementation, and execution of public policies requires attention to ethical, legal, and technical limits, especially the prevention of digital exclusion and the mitigation of technological dependence. At this point, it is necessary to emphasize that AIs should be considered as tools to streamline and improve decision-making, without, however, replacing human discernment and reasoning.

The average time saved when using the automated workflow compared to the manual workflow can be seen in Table 3. It is important to note that the estimate of the time spent when using the manual process was provided by an analysis performed by AI. The average time spent when using the automated workflow was measured when the mapping work was performed. It is possible to see that the time savings are around 50 to 75%, with additional advantages of reproducibility, replicability, reduction of human error, and standardization of the format of the products obtained. Considering the maximum mapping generation times shown in the table using the automated workflow, all the material would be produced in approximately eight days, while using the conventional workflow, the time taken would be approximately 25 days.

Table 3 – Summary of the comparison between the estimated time spent mapping future climate scenarios using the conventional (manual) method and the proposed automated workflow.

Workflow Step	Automated (Batch Processing)	Manual (Per Map)	Estimated Total Time (Manual)	Estimated Total Time (Automated)	Time Saved (%)	Additional Advantages of Automation
Script Generation	4–8 hours (prompting + testing)	Not applicable	—	4–8 hours	—	Reusable templates; scalable to new scenarios
Mapping (clipping, splitting, renaming, styling, layouts, export)	1–2 hours per batch of 12 maps	25–40 minutes per map	300–480 hours	60–120 hours	60–75%	Consistency in naming and symbology; reduced human error; reproducibility across datasets
Statistical Analysis (.txt export)	0.5–1 hour per batch of 12 maps	5–10 minutes per map	60–120 hours	30–60 hours	50–60%	Standardized file formats; easier integration with other analyses; minimizes transcription errors

Source: The authors with support of AI tools

CONCLUSION

This methodological proposal has proven to be feasible, robust, and capable of increasing productivity and reducing the time required to map climate scenarios from GeoTiff raster images downloaded from open access platforms such as WorldClim v.2.1. The integrated use of Prompt Engineering and Prompt Chaining techniques in the automation of workflows via the generation of Python scripts for mapping future climate scenarios can accelerate the adaptation process and guide the formulation of public policies to serve vulnerable populations and regions, meeting the IPCC's climate justice and just transition frameworks. The use of the proposed workflow has reduced working time by between 50% and 75%, with low operating costs and the ability to be conducted in home digital environments. It also allows for scalability, replicability, standardization, and reduction of human error. The advances achieved strengthen the role of open science and the use of Artificial Intelligence tools as climate intelligence and adaptation strategies. However, structural advances are still needed in the scripts generated, tests for other regions and scenarios, as well as for the use of AI to evaluate the large volume of results obtained from work such as this.

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