International Cartographic Association
Association Cartographique Internationale

Development of AI geo-agents for retrieval, analysis, and visualization of spatial data

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Keywords: autonomous GIS, generative AI, large language models, Geo-agent, AI assistant

Abstract:

In recent years, the increasing availability of large language models (LLMs) - such as Claude 3 or GPT 4 - combined with the need to process ever larger volumes of spatial data, has opened new perspectives for Geographic Information Systems (GIS) and cartography. At the same time, many research communities wonder whether, in the coming years, we will achieve the state of so-called Artificial General Intelligence (AGI), also referred to as the singularity point, beyond which it is difficult to predict further directions of development. In the context of geoinformatics, the question is whether we can construct a fully autonomous GIS solution in which an intelligent agent would be capable of passing a “GIS Turing test” (Janowicz, 2020). In other words, a user formulates a query (e.g., for selecting the best location for solar installations), and the agent independently acquires the appropriate data layers from spatial data infrastructures (SDI), performs advanced analyses (e.g., solar irradiance analysis), and returns a map indistinguishable from work done by a human expert. The concept of a “GIS artificial analyst,” proposed by Janowicz (2020), aims to develop by 2030 software capable of independently solving complex geoinformation problems.

Similarly to Li & Ning (2023), the term Autonomous GIS was introduced to highlight the potential of integrating LLMs as the central “reasoning engine.” According to this approach, an autonomous GIS should meet five key assumptions: self-generation (the ability to initiate processes), self-organization (prioritization and task management), self-verification (monitoring the correctness of results), self-execution (carrying out planned stages), and self-extension (the ability to develop its own competencies). Ning et al. (2024) emphasize the necessity of creating prototypes of geoinformation agents capable of retrieving and selecting relevant data from various sources, such as OpenStreetMap, administrative databases, or meteorological datasets, as well as automatically debugging the code used in analyses. Further contributions in this area include the development of AI assistants like GeoGPT, designed for understanding and processing geospatial tasks (Zhang et al., 2024). This idea aligns with the broader trend of defining an “agent” by various entities, including Anthropic (2024), where a distinction is made between a workflow (a predefined sequence of actions) and an agent (a system capable of autonomously deciding on processes).

The present work aims to examine the extent to which multi-agent GeoAI systems based on large language models (LLMs) can independently solve complex geoinformatics problems and what barriers exist to achieving full autonomy in GIS systems. By a GeoAI agent, we understand a specialized, autonomous entity operating in a geoinformatics environment, which utilizes advanced tools (GIS libraries, spatial data analysis models, natural language processing algorithms) and an LLM as its “reasoning engine.” As a result, it can understand the context of tasks, formulate hypotheses and recommendations, and generate or modify source code to process spatial information.

In the experiments, a set of geo-agents was developed, each assigned a specific role, such as retrieving raster data from the national spatial data infrastructure, performing vector data analyses, or generating software for data visualization. A key aspect here is that the definition of the tasks and the agents’ scope of work was not coded in the traditional way (i.e., by calling specific functions with parameters), but rather was included as part of the prompts provided to the LLM. Based on its “knowledge state,” the agent evaluated which steps to take, which of its assigned tools to use, and how to coordinate its actions with the other agents.

https://doi.org/10.5194/ica-abs-10-124-2025

Two case studies were carried out to illustrate the practical applications of multi-agent GeoAI systems. The first focused on a typical GIS problem: the semantic search and retrieval of specific information regarding a given location, data analysis, and the visualization of the processed data.

A second case study involved analyzing correlations between the sentiment of newspaper articles and selected economic indicators in a given region. The geo-agent was responsible for retrieving a corpus of texts (e.g., from local news services), analyzing their tone (positive, neutral, or negative), and comparing the results obtained with specific economic data (e.g., unemployment rates or the PMI index). A key challenge here was ensuring the quality control of the Python code being generated and validating the correctness of the computational process itself.

Instead of focusing on potential improvements through fine-tuning and reinforcement learning, the study adopted a different strategy. The improvement in results was achieved by providing selected agents with domain-specific knowledge bases via the Retrieval Augmented Generation (RAG) mechanism. This knowledge, provided in text form, included both methods of acquiring data and metadata, and ways of conducting analyses aimed at specific problems.

The results indicate that multi-agent GeoAI systems can significantly facilitate advanced geospatial analysis and spatial data processing - even for individuals with limited GIS experience. Agents controlled by LLMs often succeed in effectively retrieving the necessary data, processing it, and presenting it as cartographic visualizations. An undeniable advantage is the ability to communicate with the system in natural language, in many languages. At the same time, the study highlights well-known limitations of LLM technology, such as susceptibility to so-called “hallucinations” (necessitating self-verification), the lack of any guarantee of reliability in real-time generated code, and the non-deterministic nature of responses. Non-determinism means that identical queries can lead to different outcomes depending on the model’s state, context, or subtle changes in prompts, posing challenges for stability and reproducibility in GIS environments. Tasks of a repetitive nature that can be described using a well-defined workflow lead to more predictable results; however, this comes at the cost of limiting the autonomy of the agents. From the perspective of GeoAI development, introducing mechanisms that enhance the reliability and stability of multi-agent systems appears crucial. This requires, among other things, expanding validation protocols and optimizing the structure of prompts for specific applications. Further integration with local spatial databases and standardization of input and output formats would also be advisable so that geo-agents could more effectively “learn” and “collaborate” with other tools. As LLMs and agent methods evolve, geo-agents will gain flexibility and precision, which may revolutionize many industries that utilize spatial data - ranging from urban planning and precision agriculture to environmental monitoring.

Acknowledgments

This research was conducted as part of the European Union’s Horizon 2020 research and innovation program under the Marie Skłodowska-Curie grant agreement No. 101007638 (EYE – Economy bY spacE) and within the framework of an international project under the Ministry of Science and Higher Education program “PMW” for the years 2022–2025; agreement no. 5239/H2020/2022/2.

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https://doi.org/10.5194/ica-abs-10-124-2025