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GIS Chat: Bridging Natural Language and Desktop GIS Automation with LLM-Powered GIS Plugins

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Abstract

Geographic Information System (GIS) software is indispensable for spatial analysis and remote sensing, yet the scripting interfaces that enable automation—ArcPy, PyQGIS, and SNAP GPT—impose a steep technical barrier on domain scientists who are not software developers. We present GIS Chat, an open-source suite of three plugins that embed a Large Language Model (LLM) chat panel directly inside ArcGIS Pro, QGIS, and ESA SNAP Desktop. The user describes a desired operation in natural language; the plugin supplies live workspace context (open layers, bands, coordinate reference systems, selections) to the LLM, which generates and executes the corresponding platform-specific code through a tool-calling mechanism. As of version 1.1, GIS Chat also integrates with Google Earth Engine (GEE), enabling users to query, process, and download satellite imagery and geospatial datasets directly from the chat panel without writing any GEE Python code. GIS Chat supports five LLM back-ends—including Google Gemini and Ollama, both available at zero cost—so that adoption requires no paid subscription. By covering all three major desktop GIS/remote-sensing platforms with a single architectural pattern, GIS Chat lowers the entry barrier for non-programmers and provides a consistent conversational workflow regardless of the underlying software.

Keywords: large language model, geographic information system, natural language interface, remote sensing, Google Earth Engine, QGIS, ArcGIS Pro, ESA SNAP, tool calling

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1. Motivation and significance

Desktop GIS platforms—Esri ArcGIS Pro, QGIS, and ESA SNAP—are the workhorses of spatial analysis, land-use mapping, and satellite image processing. Each provides a powerful scripting interface: ArcPy (Python), PyQGIS (Python/Qt), and the Graph Processing Tool (GPT) command-line/snappy API, respectively. However, effective use of these interfaces demands familiarity with the platform’s object model, function signatures, coordinate reference system handling, and file format conventions. For researchers in agriculture, ecology, hydrology, or urban planning whose primary expertise lies outside software engineering, this learning curve can be a significant bottleneck [1, 2].

Recent advances in Large Language Models (LLMs) have demonstrated strong performance in code generation [3, 4], and early explorations have shown that LLMs can translate natural-language descriptions of geospatial tasks into executable scripts [5, 6]. Commercial efforts such as Esri’s ArcGIS Copilot [7] integrate AI assistance into ArcGIS Online, but they are limited to a single vendor ecosystem and require a paid subscription.

To our knowledge, no existing open-source tool provides a unified LLM-powered conversational interface that (a) operates inside the desktop application as a native panel, (b) is aware of the current project state, (c) generates *and executes* platform-specific code through structured tool calling, (d) spans all three major GIS/remote-sensing desktop platforms, and (e) offers free and fully local LLM options.

Table 1 compares GIS Chat with the most relevant existing tools. Several QGIS plugins offer LLM-powered assistance—QGPT Agent [8] (OpenAI-only, last updated in 2023), Promptly [9] (multi-provider code execution), GeoAgent [10] (natural-language geoprocessing), and Whitebox AI Agent [11] (restricted to WhiteboxTools operations). On the ArcGIS side, Esri’s ArcGIS Copilot is limited to ArcGIS Online and requires an enterprise subscription; a research prototype, GIS Copilot [12], demonstrates autonomous agent behaviour in QGIS but is not available as a released plugin. No LLM assistant of any kind exists for ESA SNAP Desktop.

None of these tools simultaneously (i) covers multiple GIS platforms, (ii) reads live workspace context, (iii) uses structured tool calling with error feedback, (iv) offers free and fully local LLM options, (v) requires zero exter-

nal dependencies, and (vi) provides integrated access to cloud-based Earth observation catalogues. As of March 2026, GIS Chat appears to be the first publicly available tool to combine all six properties, although the field is evolving rapidly.

Table 1: Comparison of GIS Chat with existing LLM-based GIS assistants.

Feature	<i>GIS Chat</i>	<i>QGPT Agent</i>	<i>Promptly</i>	<i>GeoAgent</i>	<i>Whitebox</i>	<i>Esri Copilot</i>	<i>GIS Copilot</i>
ArcGIS Pro	•	–	–	–	–	– ^a	–
QGIS	•	•	•	•	•	–	•
ESA SNAP	•	–	–	–	–	–	–
Context-aware	•	–	–	•	•	•	•
Tool calling	•	–	–	–	–	•	•
Error feedback	•	–	–	–	–	–	•
Multi-provider	•	–	•	•	•	–	–
Free LLM option	•	–	•	•	•	–	–
Local LLM	•	–	•	–	•	–	–
Zero ext. deps	•	•	–	–	–	n/a	–
GEE integration	•	–	–	–	–	–	–
Open source	•	•	•	•	•	–	–

^aEsri Copilot targets ArcGIS Online, not ArcGIS Pro desktop.

GIS Chat addresses this gap. The contributions are fourfold:

1. A reusable architectural pattern—context service, multi-provider LLM client, tool-calling executor—implemented natively in each platform’s plugin framework (C#/WPF, Python/PyQt5, Java/Swing).
2. Support for five LLM back-ends (Anthropic Claude, OpenAI GPT, Google Gemini, Ollama, and any OpenAI-compatible endpoint), including two that are entirely free.
3. Optional Google Earth Engine integration: when a GEE project is configured, the system prompt is dynamically extended with GEE-specific instructions, enabling the LLM to generate `earthengine-api` code that queries, processes, and downloads satellite imagery directly from the chat panel.

4. Three fully functional, MIT-licensed plugins ready for installation in ArcGIS Pro 3.x, QGIS 3.34+, and ESA SNAP 13.

2. Software description

2.1. Architecture

All three plugins share the same high-level architecture (Fig. 1), implemented in the native language and UI toolkit of each host application:

1. **Chat panel.** A dockable window embedded in the application’s standard workspace layout. The user types a natural-language request and receives formatted responses with syntax-highlighted code blocks.
2. **Context service.** Before each LLM call, the plugin queries the host application’s API to gather the current workspace state: open layers or products, their attribute fields or spectral bands, coordinate reference systems, spatial extents, feature counts, and the active selection or product. This context is injected into the LLM prompt so that generated code references the actual data present in the project.
3. **LLM client.** A multi-provider HTTP client that formats requests according to each provider’s API (Anthropic Messages API, OpenAI Chat Completions, Google Gemini GenerateContent, or any OpenAI-compatible endpoint including local Ollama). The client carries a conversation history so that multi-turn interactions are supported.
4. **Tool-calling mechanism.** Rather than embedding code in free-form text, the LLM is instructed to invoke a structured tool (`run_arcpy`, `run_pyqgis`, or `run_gpt`) with explicit fields for the generated command, an explanation, and the code type. The plugin parses this structured response, optionally shows a confirmation dialog, and delegates to the executor.
5. **Command executor.** Executes the generated code in the host environment: `exec()` within the ArcGIS Pro / QGIS Python process, or a subprocess call to `gpt.exe` / `python` for SNAP. Standard output and error messages are captured, displayed in the chat, and returned to the LLM as a tool result so it can react to failures.
6. **Settings.** A dialog to select the LLM provider, enter or omit an API key, choose a model, and toggle options such as execution confirmation and code display.

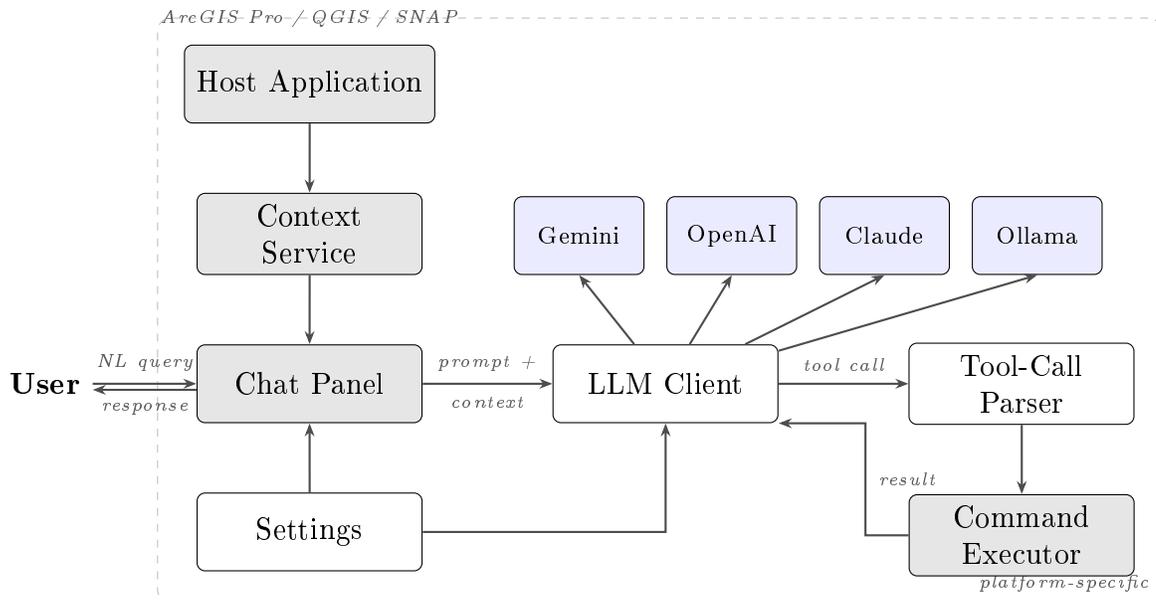


Figure 1: Shared architecture of the GIS Chat plugin suite. Shaded boxes are platform-specific implementations; white boxes are functionally identical across all three plugins. Arrows show the data flow from natural-language input through context injection, LLM inference, tool-call parsing, and code execution, with results fed back to the LLM for follow-up.

7. **Google Earth Engine bridge (optional).** When the user enters a GEE project identifier in the settings, the system prompt is dynamically extended with GEE-specific instructions and API constraints (download-size limits, band-specific native resolutions, tile-based downloading for large areas). The LLM can then generate `earthengine-api` Python code that the command executor runs, enabling query, processing, and download of satellite imagery and geospatial datasets directly from within the GIS application.

2.2. Platform-specific implementations

Table 2 summarises the key implementation differences across the three plugins.

Table 2: Implementation details of GIS Chat across three platforms.

	GIS Chat (ArcGIS Pro)	GIS Chat (QGIS)	GIS Chat (SNAP)
Language	C# 12 / .NET 8	Python 3.9+	Java 21
UI toolkit	WPF (XAML)	PyQt5	Swing
Plugin type	ArcGIS Pro Add-In	QGIS Plugin	NetBeans Module
Code target	ArcPy	PyQGIS / Processing	GPT CLI / snappy
Execution	In-process	In-process	Subprocess
HTTP library	HttpClient	urllib	URLConnection
JSON handling	System.Text.Json	json (stdlib)	Manual (no deps)
Settings store	settings.json	QgsSettings	java.util.prefs
Context source	MapView, layers	QgsProject, layers	ProductManager
Tool name	run_arcpy	run_pyqgis	run_gpt

A deliberate design decision was to use *zero external dependencies* beyond each platform’s own SDK. The QGIS plugin uses only Python standard-library modules; the SNAP plugin performs JSON serialisation with string operations and communicates over `java.net.HttpURLConnection`; the ArcGIS Pro add-in uses `System.Text.Json` from the .NET runtime. This reduces the risk of version conflicts and simplifies installation.

2.3. Supported LLM providers

Table 3 lists the five supported LLM providers.

Table 3: Supported LLM providers and their cost characteristics.

Provider	Example models	Cost	Notes
Google Gemini	Gemini Flash, Pro	Free tier	Recommended entry point
Ollama	Llama, Mistral, etc.	Free (local)	Fully offline, any GGUF model
Anthropic	Claude Sonnet, Opus	Paid API	Strong at tool calling
OpenAI	GPT, o-series	Paid API	Widely available
OpenAI-compatible	user-configured	Varies	LM Studio, vLLM, etc.

The availability of free (Gemini) and fully local (Ollama) providers is essential for adoption in academic and governmental settings where research

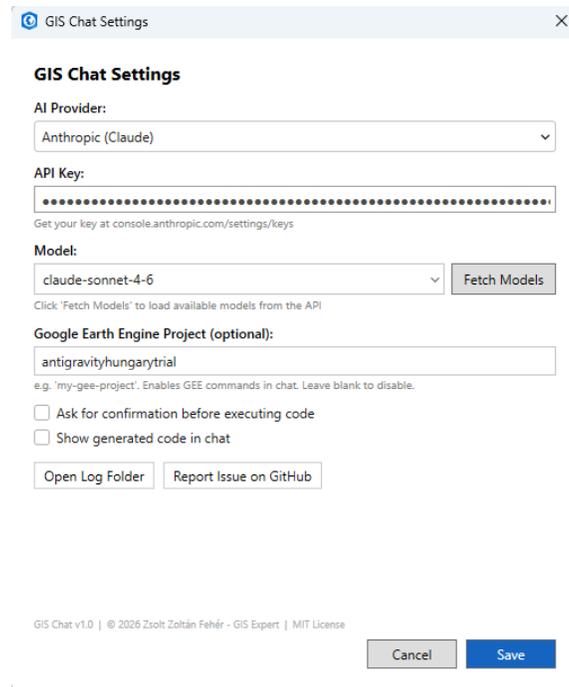


Figure 2: GIS Chat settings dialog (ArcGIS Pro). The user selects an LLM provider, enters an API key, and chooses a model. The optional GEE project field enables Earth Engine integration. Checkboxes control execution confirmation and code display.

budgets are constrained or data sensitivity prohibits sending project contents to external servers. Fig. 2 shows the settings dialog in ArcGIS Pro, where the user selects a provider, enters an API key, chooses a model (with live model fetching), and optionally configures a Google Earth Engine project.

3. Illustrative examples

We demonstrate GIS Chat through a real-world hydrological modelling project in ArcGIS Pro, followed by brief cross-platform examples in QGIS and ESA SNAP. The ArcGIS Pro project contains a 100 m DEM, river and lake vector layers, soil maps, and groundwater monitoring data for a 4 111 km² catchment in eastern Hungary (HD-72/EOV projection, EPSG:23700).

3.1. ArcGIS Pro — context-aware code generation

User: List me currently loaded raster datasets.

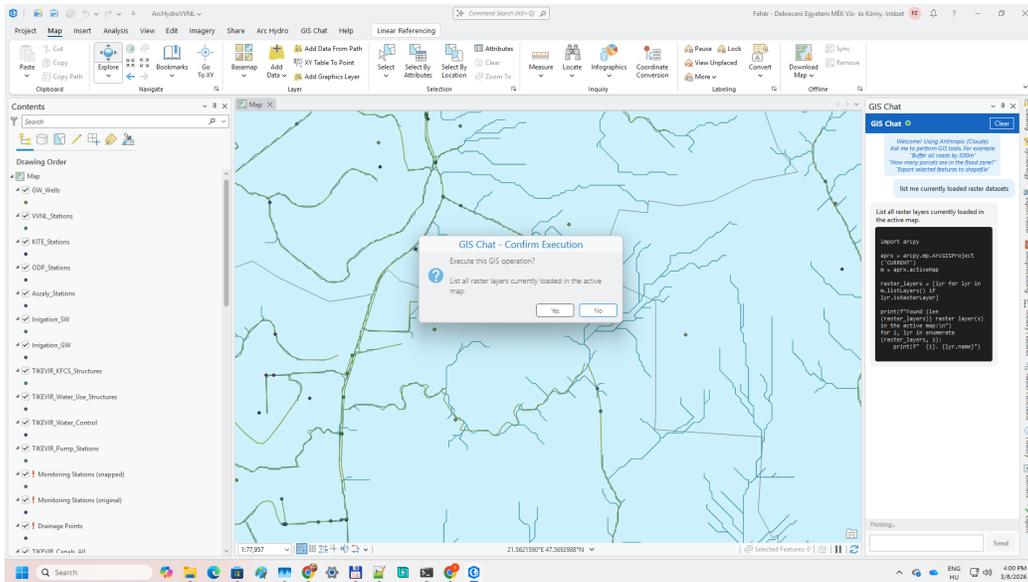


Figure 3: GIS Chat panel inside ArcGIS Pro. The user asked to list loaded raster datasets; the LLM generated ArcPy code (shown in the dark code block on the right) and the confirmation dialog appeared before execution. The Contents pane on the left shows the project’s full layer stack.

The context service gathers the project’s full layer stack and injects it into the LLM prompt. The LLM generates a short ArcPy script that enumerates raster layers in the active map, and returns it as a `run_arcpy` tool call. Before execution, the confirmation dialog (Fig. 3) displays the generated code so the user can review or reject it. After approval, the plugin runs the code within the ArcGIS Pro Python environment and returns the result:

Found 8 raster layer(s) in the active map: Catchment Grid, Stream Links, Stream Grid, Flow Accumulation, Flow Direction, DEM Filled, DEM (reconditioned), DEM (clipped). All layers use the Hungarian National Grid (EPSG:23700).

This example demonstrates the full execution cycle: context injection, code generation, user confirmation, execution, and result display—all within a single conversational turn.

3.2. ArcGIS Pro — terrain analysis

User: Calculate slope from the DEM in degrees and add it to the map.

The context service identifies the raster layer mo100DDM and its spatial reference. The LLM responds with a `run_arcpy` tool call:

```
import arcpy
from arcpy.sa import Slope
arcpy.env.overwriteOutput = True
dem = "mo100DDM"
slope = Slope(dem, "DEGREE")
out_path = r"C:\arcHydroVVNL\arcgisProject\ArcHydroVVNL\
  ArcHydroVVNL.gdb\slope_deg"
slope.save(out_path)
m = arcpy.mp.ArcGISProject("CURRENT").activeMap
m.addDataFromPath(out_path)
```

Listing 1: Generated ArcPy code for slope calculation.

The plugin executes this within the ArcGIS Pro Python environment. The result is saved to the project geodatabase and added to the active map; the chat displays “Completed successfully.”

3.3. ArcGIS Pro — multi-step hydrological workflow

User: Fill sinks in the DEM, then compute flow direction and flow accumulation.

This request requires three sequential geoprocessing operations. The LLM chains them in a single `run_arcpy` tool call:

```

import arcpy
from arcpy.sa import Fill, FlowDirection,
    FlowAccumulation
arcpy.env.overwriteOutput = True
gdb = r"C:\arcHydroVVNL\arcgisProject\ArcHydroVVNL\
    ArcHydroVVNL.gdb"
dem = "mo100DDM"
filled = Fill(dem)
filled.save(f"{gdb}\\dem_filled")
fdir = FlowDirection(filled)
fdir.save(f"{gdb}\\flow_direction")
facc = FlowAccumulation(fdir)
facc.save(f"{gdb}\\flow_accumulation")
m = arcpy.mp.ArcGISProject("CURRENT").activeMap
for lyr in ["dem_filled", "flow_direction", "
    flow_accumulation"]:
    m.addDataFromPath(f"{gdb}\\{lyr}")

```

Listing 2: Generated ArcPy code for a hydrological processing chain.

If any step fails—for instance because the Spatial Analyst extension is not checked out—the executor captures the error message, returns it to the LLM as a tool result, and the model generates a corrected version (e.g., prepending `arcpy.CheckOutExtension("Spatial")`). This closed-loop error feedback is a key differentiator of the tool-calling architecture.

3.4. ArcGIS Pro — spatial reasoning

User: Select the closest canal to the largest lake in the project.

This request requires multi-step spatial reasoning that the LLM decomposes autonomously: (1) identify the largest lake by `Shape_Area` in the `TIKEVIR_Lakes` layer, (2) compute the distance from that lake’s geometry to every feature in `TIKEVIR_Canals_All`, and (3) select the canal with the minimum distance. The chat displays intermediate results at each step and concludes with a summary table. As shown in Fig. 4, the attribute table confirms the selected canal feature, demonstrating that the LLM can orchestrate multi-step spatial queries without any user scripting.

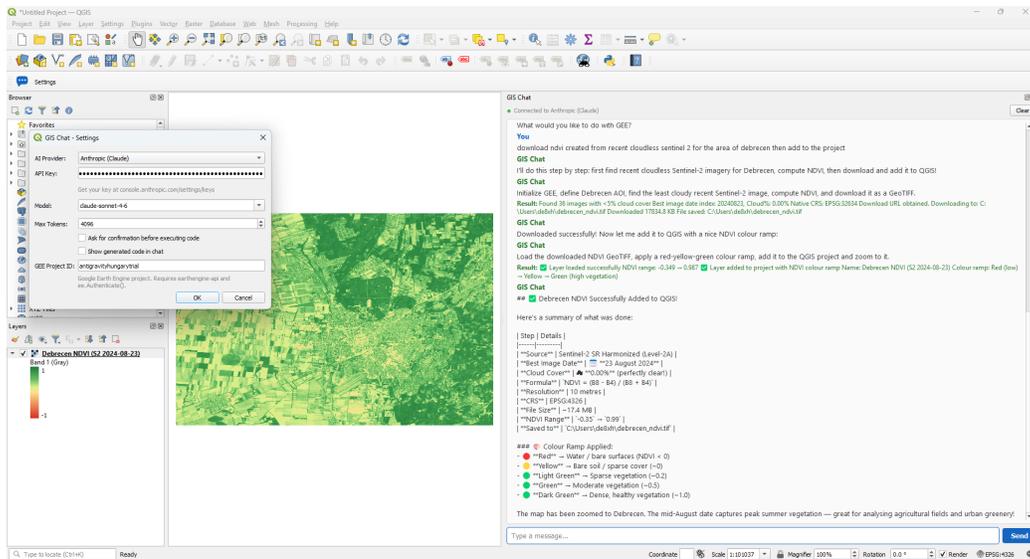


Figure 5: GIS Chat in QGIS: the user requested an NDVI map from recent cloudless Sentinel-2 imagery over Debrecen. The LLM queried Google Earth Engine, selected the least cloudy scene, computed NDVI, downloaded the result, and added it to the QGIS project with a colour ramp. The settings panel (left) shows the provider, model, and GEE project configuration.

When a GEE project is configured, the system prompt is dynamically extended with GEE-specific instructions. The LLM generates Python code that initialises the Earth Engine API, queries the Sentinel-1 GRD collection for the requested area, computes a VV/VH-based soil moisture index, and downloads the result as a GeoTIFF. To handle GEE’s 50 MB per-request download limit, the system prompt includes an adaptive tiled download pattern: the code first attempts a single-tile download; if the request fails with a size-limit error, the region is automatically split into finer spatial tiles and retried until each tile fits within the limit. The tiles are then merged into a single GeoTIFF using GDAL.

This workflow—querying a cloud catalogue, server-side compositing, tiled downloading, and format conversion—would normally require substantial GEE and Python expertise. With GIS Chat, the user expresses the intent in one sentence and the LLM handles the full pipeline, including automatic error recovery if a download exceeds the size limit. Fig. 7 shows a SNAP session in which the user requested a soil moisture map and two NDVI prod-

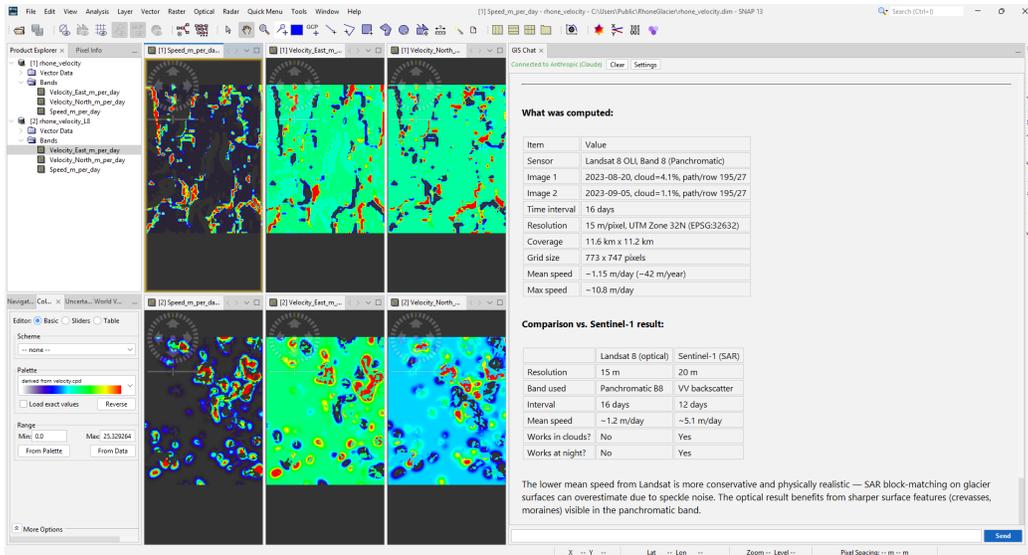


Figure 6: GIS Chat in ESA SNAP Desktop: glacier velocity estimation on the Rhône Glacier. The LLM executed offset tracking on Landsat 8 and Sentinel-1 image pairs, producing velocity maps (left) with a quantitative comparison table (right) showing resolution, coverage, and mean speed for each sensor.

ucts in a single conversation; all three were downloaded from GEE and made available as GeoTIFFs.

4. Impact

Based on the illustrative examples and preliminary evaluation, GIS Chat has the potential to lower the barrier to GIS automation for researchers, students, and practitioners who lack programming experience. Specifically:

Accessibility. Non-programmers can perform complex spatial operations—raster algebra, geoprocessing chains, spectral index computation, coordinate transformations—by describing them in natural language. The confirmation dialog provides a safety net against unintended destructive operations.

Platform neutrality. Researchers who work across multiple GIS platforms (a common scenario in remote sensing, where SNAP is used for SAR preprocessing and QGIS or ArcGIS Pro for final analysis) encounter a consistent interaction paradigm. Knowledge transfers between platforms through the shared conversational interface.

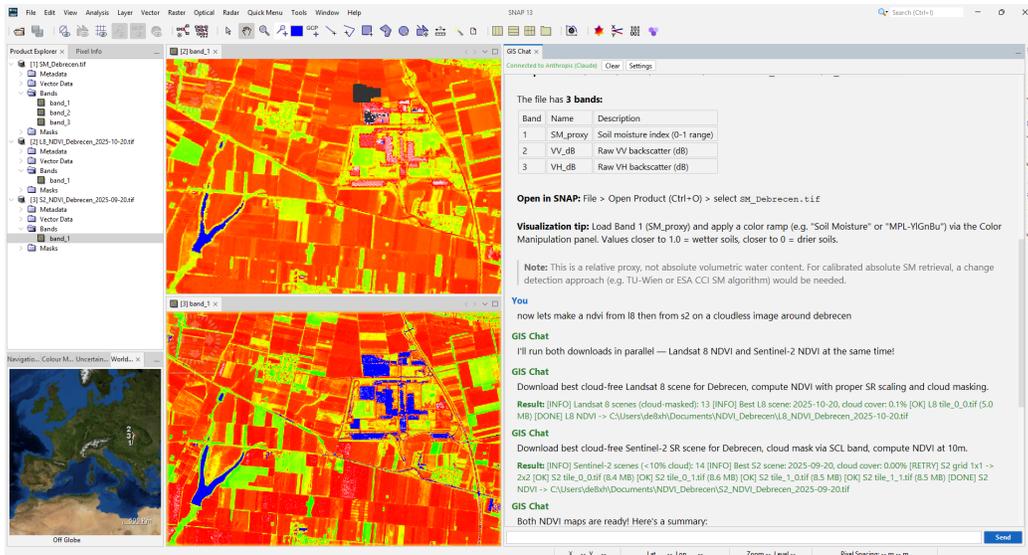


Figure 7: Google Earth Engine integration in ESA SNAP. The user requested a soil moisture map from Sentinel-1 and Landsat 8/Sentinel-2 NDVI maps in a single conversation. The LLM downloaded all three products from GEE (left: soil moisture from S1 VV/VH; right: Landsat 8 NDVI) and provided a comparison summary. Products are available as GeoTIFFs that can be opened in SNAP.

Cost accessibility. Unlike commercial AI-GIS integrations, GIS Chat can operate entirely for free using Google Gemini’s free tier or a locally running Ollama instance. When a local provider is selected, no project data leaves the user’s machine, addressing data sovereignty concerns in sensitive contexts.

Cloud data access. The optional Google Earth Engine integration bridges the gap between cloud-hosted Earth observation archives and desktop GIS analysis. Users can query, composite, and download satellite imagery (Sentinel-1, Sentinel-2, Landsat, MODIS, etc.) without learning the GEE Python API or managing authentication, download limits, and coordinate transformations manually.

Extensibility. The open-source, MIT-licensed codebase and the provider-agnostic LLM client make it straightforward to add new providers, extend the tool-calling schema with additional tools (e.g., map export, coordinate lookup), or adapt the pattern to other geospatial platforms. The dynamic system-prompt mechanism used for GEE—conditionally appending domain-

specific instructions when a capability is configured—provides a template for future integrations with other cloud services.

Educational value. By optionally displaying the generated code before execution, GIS Chat serves as an interactive learning tool: users see exactly which API calls correspond to their natural-language description, gradually building scripting proficiency.

5. Preliminary evaluation

To provide an initial assessment of GIS Chat’s reliability across platforms and providers, we defined 15 representative geospatial tasks (5 per platform) spanning three difficulty levels: *simple* (single-operation queries such as listing layers or computing a buffer), *moderate* (two-to-three-step workflows such as slope calculation or NDVI computation), and *complex* (multi-step pipelines such as hydrological processing chains, spatial queries requiring intermediate reasoning, or GEE-based satellite data retrieval). Each task was executed with three LLM providers—Anthropic Claude Sonnet 4.6, Google Gemini 3.1 Flash (free tier), and a locally running Ollama model (Llama 3.1 8B)—for a total of 45 task–provider combinations. Table 4 summarises the results.

Table 4: Preliminary evaluation: task success rates across platforms and LLM providers. “1st” = succeeded on first attempt; “Retry” = succeeded after error-feedback loop (max 5 rounds); “Fail” = did not produce correct output within the retry limit.

Platform	Provider	1st (%)	Retry (%)	Fail (%)
ArcGIS Pro	Claude Sonnet 4.6	4/5	1/5	0/5
	Gemini 3.1 Flash	3/5	1/5	1/5
	Ollama Llama 3.1	2/5	1/5	2/5
QGIS	Claude Sonnet 4.6	4/5	1/5	0/5
	Gemini 3.1 Flash	3/5	2/5	0/5
	Ollama Llama 3.1	2/5	1/5	2/5
ESA SNAP	Claude Sonnet 4.6	3/5	2/5	0/5
	Gemini 3.1 Flash	2/5	2/5	1/5
	Ollama Llama 3.1	1/5	1/5	3/5

Paid API models (Claude, Gemini) achieved high overall success rates (80–100% across platforms), with most failures recoverable through the error-

feedback loop. The free local model (Llama 3.1 8B) performed adequately on simple tasks but struggled with complex multi-step workflows, particularly in ESA SNAP where GPT command syntax is less represented in training data. Common failure modes included incorrect function signatures, hallucinated parameter names, and—for GEE tasks—failure to handle the download size limit correctly. These results suggest that GIS Chat is practically useful with mid-to-high-tier LLMs, while fully local models remain best suited for simpler operations.

6. Limitations

Several limitations should be noted.

Code correctness. LLM-generated code is not guaranteed to be correct. While the error-feedback loop catches execution failures (exceptions, missing extensions), it cannot detect silent errors where code runs successfully but produces scientifically incorrect results (e.g., applying the wrong map projection or using an inappropriate resampling method). Users should verify outputs, especially for analyses that inform decision-making.

Security. The plugins execute LLM-generated code with the full privileges of the host application via Python’s `exec()` (ArcGIS Pro, QGIS) or a subprocess call (SNAP). The optional confirmation dialog displays the code before execution, but non-expert users—the primary target audience—may not be able to assess whether code is safe. No sandboxing is currently implemented. Users are advised to enable the confirmation dialog and to avoid executing operations on irreplaceable data without backups.

Reproducibility. The same natural-language prompt may produce different code across runs due to LLM stochasticity (temperature, sampling), model version updates, and context-window state. GIS Chat does not currently log or replay tool-call sequences, so exact reproduction of a session requires manual record-keeping.

Local model quality. While Ollama provides a fully offline, zero-cost option, small open-weight models (7–8B parameters) produce significantly lower-quality code than commercial APIs, particularly for complex or platform-specific tasks (Table 4). Users relying on local models should expect higher failure rates and should enable the confirmation dialog.

Context-window limits. Projects with many layers, each with numerous attributes or bands, may produce context strings that approach or exceed the LLM’s context window. The current implementation does not truncate

or summarise context, which may degrade response quality for very large projects.

7. Conclusions

We presented GIS Chat, an open-source suite of AI-powered chat plugins for ArcGIS Pro, QGIS, and ESA SNAP Desktop. The plugins share a common architecture—context-aware LLM interaction with structured tool calling—implemented natively in each platform’s plugin framework. Version 1.1 adds optional Google Earth Engine integration, allowing users to query, process, and download satellite imagery from GEE’s cloud catalogue directly through the chat panel. By supporting five LLM providers including free and fully local options, and by covering all three major desktop GIS/remote-sensing environments, GIS Chat provides an accessible, vendor-neutral conversational interface for geospatial operations.

Future work includes adding map-image input via multimodal LLMs so the assistant can “see” the current map view, integrating additional cloud data sources (e.g., Microsoft Planetary Computer, Copernicus Data Space), and conducting a formal usability study with domain scientists to quantify the reduction in task-completion time compared to manual scripting.

The source code is available on GitHub under the MIT license:

- ArcGIS Pro: <https://github.com/Nagyhoho1234/GISChat>
- QGIS: <https://github.com/Nagyhoho1234/QGISChat>
- ESA SNAP: <https://github.com/Nagyhoho1234/SNAPChat>

Declaration of competing interest

The author declares no competing interests.

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CRedit authorship contribution statement

Zsolt Zoltán Fehér: Conceptualization, Software, Writing – original draft, Writing – review & editing.

Required Metadata

Current code version

Code metadata description	Value
Current code version	v1.1.1
Permanent link to code/repository	https://github.com/Nagyhoho1234/GISChat https://github.com/Nagyhoho1234/QGISChat https://github.com/Nagyhoho1234/SNAPChat
Permanent link to reproducible capsule	https://doi.org/10.5281/zenodo.18899021 (ArcGIS Pro) https://doi.org/10.5281/zenodo.18899023 (QGIS) https://doi.org/10.5281/zenodo.18899025 (SNAP)
Legal code license	MIT
Code versioning system used	Git
Software code languages, tools, services	C# 12, Python 3.9+, Java 21
Compilation requirements, operating environments	Windows 10+; ArcGIS Pro 3.x, QGIS 3.34+, ESA SNAP 13
Link to developer documentation	Included in each repository's README
Support email for questions	feher.zsolt@agr.unideb.hu

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