Agentic Large Language Model Workflows for Earth Observation: Tool Orchestration, Foundation-Model Adaptation, and the Evaluation Gap

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Abstract

Large language model (LLM) agents have moved rapidly from general-purpose assistants to domain systems that orchestrate specialised remote-sensing models. Within roughly two years, geospatial agents have demonstrated reliable task planning across dozens of Earth Observation (EO) tasks, benchmark environments containing hundreds of tools, and fine-tuned open-weight controllers that outperform far larger proprietary models at generating geospatial tool-use chains. This review synthesises that literature and argues that it has converged on a common architecture with a common limit. Every system surveyed orchestrates models that human researchers built, over data that human analysts prepared; none designs a model, and none constructs its own analysis-ready data. We identify three gaps that follow from this. First, a reliability wall: reported agent success falls from above 95% on single-tool tasks to below 70% beyond eight tool calls, and scaling benchmark volume tenfold does not expose or improve this, so the binding variable is composition depth rather than data quantity. Second, a preprocessing gap: benchmark datasets arrive co-registered, temporally aligned and quality-flagged, so agents are never evaluated on the multi-source data-cube construction that dominates real EO practice. Third, an evaluation gap: automated LLM-as-judge scoring is widely reported as ground truth without calibration against human experts. We survey the open geospatial foundation models that now form the practical substrate for EO modelling, argue that adaptation strategy rather than architecture is the under-searched design variable, and set out a research agenda in which domain constraint — verified templates, physically grounded data contracts, explicit compute budgets and the capacity to refuse — is treated as the mechanism by which agentic autonomy becomes verifiable rather than merely fluent.

Keywords: Earth Observation; large language model agents; remote sensing; geospatial foundation models; multi-sensor data fusion; agent evaluation; trustworthy AI.

1. Introduction

Earth Observation is not short of data. Sentinel-1 and Sentinel-2, Landsat, and a growing commercial constellation fleet deliver petabyte-scale multi-sensor archives with global coverage and increasingly short revisit intervals, and open benchmark datasets now span continents with curated labels. What has not scaled at the same rate is the process by which those archives become validated scientific findings. That process remains largely manual: a researcher reads the literature, identifies a methodological gap, assembles and aligns data from several sensors, designs an architecture, implements it, debugs it, trains it, validates it, and iterates. Each turn of the loop costs weeks, and the loop must be repeated for every new sensor configuration, geographic region, label schema and downstream task.

Two developments make it reasonable to ask whether parts of that loop can be automated. The first is the emergence of LLM agents capable of multi-step reasoning, tool invocation and self-correction. The second is the arrival of open geospatial foundation models, which have shifted competent EO modelling away from training from scratch and towards selecting and adapting a pre-trained encoder. Taken together, these suggest a system that could, in principle, read the literature, prepare data, propose an architecture, train it and evaluate it with limited human intervention.

This review examines how far the field has actually travelled towards that, and identifies where it has stopped. Our argument is that the geospatial agent literature has converged on a productive but bounded architecture, and that three specific gaps — reliability at composition depth, multi-source data construction, and evaluation validity — are the obstacles that must be addressed before further progress. Section 2 reviews the agentic components. Section 3 surveys geospatial agents. Section 4 covers foundation models as the modelling substrate. Sections 5 to 7 set out the three gaps. Section 8 proposes a research agenda.

Scope and method. We surveyed peer-reviewed papers and archival preprints published between 2020 and 2026 concerning LLM agents applied to remote sensing and Earth Observation, together with the foundation-model and agent-evaluation literature these depend on. Systems were included where they either (i) apply an LLM controller to remote-sensing tasks, or (ii) provide pre-trained backbones or benchmarks intended for EO model development. Purely end-to-end multimodal models without tool orchestration are discussed for context but are not the focus. This is a narrative rather than a systematic review; we make no claim to exhaustive coverage, and the field is moving quickly enough that any snapshot dates rapidly.

2. Background: from language models to agents

The components now assembled into geospatial agents were developed separately over roughly four years. Chain-of-thought prompting demonstrated that intermediate reasoning could be elicited and externalised rather than left implicit [1]. ReAct interleaved reasoning with acting, allowing an agent to revise its plan against environmental feedback rather than committing to a single trajectory [2]. Tree-of-Thoughts introduced deliberate search over reasoning states [3], and Reflexion added verbal self-improvement from execution traces without weight updates [4]. Anticipatory reflection subsequently moved error handling ahead of execution, having the agent challenge its own proposed step and pre-compute remedies before committing resources [5].

In parallel, tool augmentation extended agents beyond their parametric knowledge, first by teaching models to call APIs [6] and then by scaling to thousands of real-world tools [7]. Retrieval-augmented generation supplied external knowledge at inference time [8], with graph-structured variants improving recall where entities and constraints are distributed across a corpus [9]. A recent synthesis organises these components into the conventional perception–reasoning–memory–action decomposition, and, more usefully for the present argument, catalogues the failure modes that persist across implementations: repetitive action loops, tool misuse, hallucinated grounding, and drift from the original goal over long trajectories [10].

That failure catalogue matters because it is not incidental. The behaviours it lists are all functions of trajectory length, and they therefore set the practical ceiling on what an agent can be asked to do in one episode. We return to this in Section 5.

3. Agentic systems in Earth Observation

3.1 From single-task tools to orchestration

Early domain agents targeted narrow applications. TreeGPT assembled an expert system for forestry image understanding, and Change-Agent provided interactive change detection with captioning [11,12]. These demonstrated feasibility but did not generalise across the heterogeneous task space that EO analysis actually spans.

RS-ChatGPT introduced tool chaining, linking a general LLM to a collection of pre-trained discriminative remote-sensing models so that a natural-language request could be decomposed into a sequence of model invocations [13]. This established the pattern the field subsequently refined: an LLM controller, a fixed toolkit, and a planning step that maps intent to tool sequence.

3.2 Structured orchestration and domain retrieval

RS-Agent represents the most developed version of that pattern [14]. It introduces a central controller with task-aware retrieval over an expert-curated solution space, and a dual-path retrieval mechanism for domain knowledge, reporting task-planning accuracy above 95% across 18 remote-sensing tasks and outperforming end-to-end multimodal models on scene classification, object counting and visual question answering.

Its ablation is more informative than its headline result. Multi-tool task-planning accuracy is reported at 9.42% without the orchestration structure and 90.62% with it, on an identical underlying toolset [14]. The entire gain is attributable to orchestration rather than to model capability. This is the strongest available evidence that structure, not scale, is the operative variable in domain agents — an observation we build on throughout this review.

3.3 Environments, benchmarks, and open-weight controllers

GeoLLM-Engine approached the problem from the environment side, providing a realistic web interface with over 175 tools and a benchmark of more than half a million tasks across 1.1 million satellite images, generated through a self-consistency sampling scheme that removes most human curation from the loop [15]. Its central empirical finding is discussed in Section 5. More recent work has extended benchmarking further: ThinkGeo and EarthAgent establish broader evaluation suites for tool-augmented agents in remote sensing [16,17].

GTChain established that open-weight models are viable controllers rather than a compromise. A LLaMA-2-7B model fine-tuned with low-rank adaptation [18] on a synthetically generated tool-use corpus outperformed both GPT-4 and Gemini 1.5 Pro at generating geospatial tool-use chains, and transferred to tool counts and tool identities unseen during training [19]. Alongside these, end-to-end multimodal models such as GeoChat and the RSVQA line made EO imagery conversationally accessible without orchestration, at the cost of hallucination on quantitative tasks and an inability to produce pixel-level outputs [20,21].

3.4 The common architecture, and its boundary

Abstracting across these systems yields a consistent picture: an LLM controller performs task inference and planning; a retrieval mechanism supplies domain procedures or knowledge; a fixed toolkit of pre-trained models executes; and results are aggregated into a response. The differences lie in how retrieval is conditioned and how the toolkit is organised.

The boundary is equally consistent. Every system surveyed invokes models that human researchers designed and trained, operating on data that human analysts prepared. The tools in these toolkits are the products of exactly the research cycle that remains unautomated. Figure 2 positions the field along two axes: grounding in the EO domain, and autonomy over the research loop itself. Systems cluster in the lower right; the upper right is unoccupied.

4. Geospatial foundation models as the modelling substrate

A parallel development has changed what an EO modelling system should be searching over. Since 2023 the field has acquired open, high-quality pre-trained backbones. Prithvi-EO is a masked-autoencoder vision transformer pre-trained on Harmonized Landsat–Sentinel-2 imagery, with the 2.0 release extending substantially in scale and geographic coverage [22]. Clay provides multi-modal embeddings for arbitrary Earth coordinates and timestamps across Sentinel-1, Sentinel-2, Landsat and elevation data [23]. Presto is a lightweight transformer for multi-spectral pixel time series, unusually efficient in dual-sensor settings [24]. The SSL4EO-S12 backbones are trained self-supervised on approximately 250,000 co-located Sentinel-1 and Sentinel-2 patch pairs across four seasons, using several distinct self-supervised objectives [25]. SatMAE and Scale-MAE address variable ground sample distance directly, handling 10, 20 and 60 metre bands without resampling artefacts [26,27]. GEO-Bench provides a common evaluation surface across this family [28].

The practical consequence is that competent EO modelling rarely begins from random initialisation. It begins by selecting a backbone and choosing an adaptation strategy. Any system claiming to automate EO model development must therefore operate over that decision rather than around it.

Adaptation strategy is the under-searched variable. The choice among frozen encoder, linear probe, low-rank adaptation at a given rank, partial unfreezing and full fine-tuning determines most of the compute–accuracy trade-off in practice, and it is rarely searched systematically in published EO work; practitioners default to full fine-tuning or a linear probe by convention. We are not aware of a study that reports, across task types and sensor modalities, which adaptation strategy is preferable at what compute cost. This is a straightforward empirical gap and an obvious target for automation.

Pre-training geography is a neglected confound. Prithvi-EO-1.0 was pre-trained over the contiguous United States. Even geographically broader releases carry a distributional signature that may not transfer cleanly to, for example, Baltic land cover, boreal peatland or inland water. Backbone selection made by convention or popularity will inherit that bias silently. We suggest that pre-training geography should be recorded as first-class metadata and treated as an experimental variable rather than an assumption.

5. The reliability wall

The most consequential empirical result in this literature is not a headline accuracy figure but a degradation curve. GeoLLM-Engine reports task success above 95% for prompts requiring a single tool call, falling below 70% beyond eight tool calls, and to 27% for some agent configurations [15]. The same study scales its benchmark tenfold, from 10,000 to 100,000 queries covering over half a million tool calls, and finds the aggregate success rate essentially unchanged.

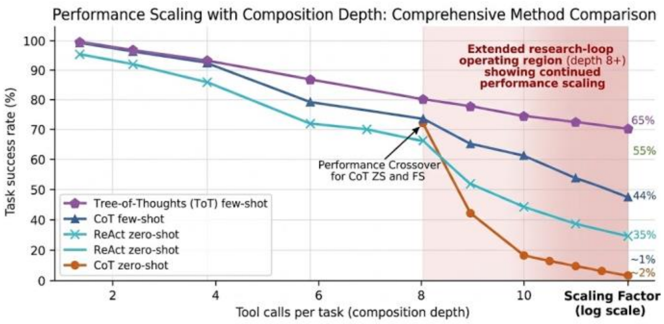

Figure 1. Reported agent success rate against composition depth, redrawn from results in [15] for GPT-4-Turbo under three prompting strategies. Performance is near-ceiling for single-tool tasks and degrades sharply beyond roughly six to eight tool calls. The shaded region indicates the depth at which a full research loop — literature synthesis, data preparation, implementation, training, evaluation, revision — would necessarily operate.

Two conclusions follow. First, it is task complexity rather than benchmark volume that exposes the limits of current agents; expanding a benchmark with more tasks of uniform difficulty yields little additional information. Second, the failure is not method-specific: the same study finds that missed function calls account for more than half of all correctness errors, consistently across prompting strategies, which points to a limitation of the underlying model rather than of any particular scaffold.

This matters for the automation ambition in a direct way. A research loop is, by construction, a long-horizon multi-tool task. If data preparation is included — as it must be for any realistic EO problem — composition depth increases further. Such a system would operate permanently in the region of Figure 1 where current agents fail.

The prevailing response has been to pursue scale: larger models, longer context windows, more benchmark data. The RS-Agent ablation cited in Section 3.2 suggests a different reading. If structure alone moves multi-tool planning from 9.42% to 90.62% on a fixed toolset, then the binding constraint may be the size of the space the agent is permitted to search rather than the capability of the model searching it. On this view, constraint is not a limitation imposed on an agent but the mechanism by which its output becomes verifiable. We regard this as the central open question in the area, and note that it is empirically testable: constrained and unconstrained agentic search can be compared directly on the same tasks, under the same compute budget, with novelty and validity measured separately.

6. The preprocessing gap

A second gap is less discussed and, in our view, more consequential for real deployment. Public EO benchmarks arrive analysis-ready: co-registered, temporally aligned, quality-flagged and packaged. An agent evaluated only on such benchmarks never encounters the problem that dominates operational multi-source remote sensing.

Real multi-sensor practice — combining, for example, Sentinel-1 C-band SAR with high-resolution X-band SAR, hyperspectral imagery and meteorological series — is dominated by temporal asynchrony between acquisitions, differing ground sample distances, incompatible coordinate reference systems, inconsistent quality flags and missing observations. Recent work on peatland moisture retrieval illustrates the difficulty concretely: asynchronous observation gaps are the binding constraint on retrieval accuracy, and addressing them requires explicit temporal weighting rather than naive stacking [29].

A finding that rests on a badly constructed data cube is not recoverable by any downstream architecture, however well designed. Yet no agentic system we surveyed treats cube construction as a first-class capability with its own verifiable constraints. We suggest the following as a minimum set of machine-checkable contracts that an EO data-preparation agent would need to satisfy, each of which is independently testable:

Contract	What must be verified	Failure if absent
Geometry and CRS	Reprojection correctness; co-registration verified rather than assumed; pixel-grid alignment	Sub-pixel misregistration silently degrades fusion and is later attributed to the architecture
Resolution harmonisation	GSD reconciliation across bands and sensors; declared resampling policy; no illegal upsampling	Interpolation artefacts read as signal; effective resolution overstated
Temporal alignment	Revisit asynchrony; declared compositing window; no future information leaking into training windows	Temporal leakage inflates validation scores, particularly in continuous regression
Quality and missingness	Cloud and quality flags honoured; gap-filling policy explicit and logged; missingness pattern reported	Gap-filled values treated as observations; contamination enters the target variable
Sensor physics	Valid band arithmetic; backscatter units and calibration; incidence-angle and terrain correction for SAR	Physically meaningless indices; SAR fused as though it were optical

Table 1. Proposed machine-checkable contracts for agentic multi-source data-cube construction. Each is independently ablatable, which converts "careful preprocessing" from a claim about researcher diligence into a measurable system property.

We note that this gap also has an evaluation consequence: because benchmarks supply prepared data, current agent benchmarks systematically under-estimate the difficulty of real EO tasks, and comparative results between agents may say more about tool-selection accuracy than about end-to-end research capability.

7. The evaluation gap

The third gap concerns how these systems are assessed. As agentic outputs become less tractable to exact matching — a generated architecture or an analysis plan has no single correct form — evaluation has increasingly relied on LLM-as-judge scoring. This is understandable and often unavoidable, but it is frequently reported as though it were ground truth.

An automated judge is an instrument, and instruments require calibration. Where judge scores are used to assess qualities such as novelty or plausibility, we would expect to see agreement with human expert assessment reported using standard inter-rater statistics, variance across judge models and seeds, and a stated threshold below which the instrument is not considered usable. This is rare in the current literature. Without it, a reported improvement in "novelty" cannot be distinguished from a change in judge preference.

We suggest a hierarchical evaluation structure in which deterministic and objective measures are primary, and judged qualities are secondary and explicitly anchored to them:

- **Primary, deterministic:** does the generated pipeline execute end-to-end without error, satisfy declared data contracts, and exceed a stated baseline?
- **Primary, objective:** downstream held-out performance on the target task, using the standard metric for that task.
- **Secondary, calibrated:** novelty and plausibility via multi-run judge panels, reported with agreement against a human expert panel.
- **Secondary, instrumented:** composition depth, compute consumed, and success rate as a joint function of both — the axis of Figure 1, which is currently reported only rarely.

Compute reporting deserves separate mention. Agentic systems consume compute in a manner that is difficult to compare across papers, and token counts are reported inconsistently where they are reported at all. GeoLLM-Engine notes that token consumption does not correlate cleanly with success rate [15], which suggests that efficiency is a genuine and under-examined dimension of agent design rather than an accounting detail.

8. A research agenda

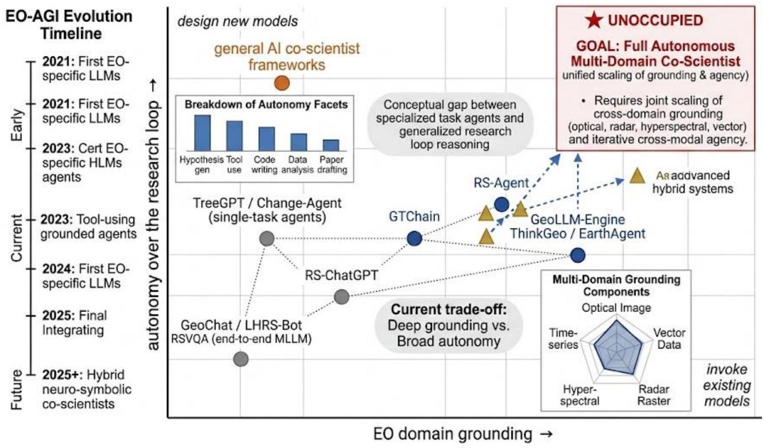

Figure 2. Positioning of surveyed systems along two axes: grounding in EO domain practice, and autonomy over the research loop. Geospatial agents achieve strong domain grounding while orchestrating pre-existing models over prepared data; general-purpose scientific-discovery frameworks pursue loop autonomy without domain constraint or physically grounded validation. The upper-right region is unoccupied.

The gaps identified above suggest five directions, stated as testable propositions rather than aspirations.

- **1. Constraint as a mechanism, not a limitation.** The hypothesis that domain-specific constraint improves the novelty–validity frontier of agentic search, at reduced compute, is directly falsifiable. It fails if constrained search proves more valid but demonstrably less novel, or if the compute advantage does not materialise. Either outcome would be informative.
- **2. Data-cube construction as a first-class agentic capability.** The contracts in Table 1 are implementable and individually ablatable. Establishing which contracts matter, and by how much, would be a concrete contribution independent of any wider automation claim.

- **3. Systematic search over adaptation strategy.** An empirical map of which (task type, sensor modality, label volume, backbone, adaptation strategy) combinations perform well, and at what cost, would be useful to practitioners whether or not it is produced by an agent.
- **4. Calibrated evaluation instruments.** Judge–human agreement studies, pre-registered with stated thresholds and a commitment to publish negative results, would put agentic evaluation on a firmer footing than it currently rests on.
- **5. Refusal as a measured capability.** A system whose outputs are scientific claims must be able to decline when evidence, data or budget is insufficient. We suggest that failure to refuse — producing confident output under insufficient evidence — is the most consequential failure mode for scientific agents, and that it should be measured explicitly rather than assumed absent.

A note on task-type asymmetry. We observe, tentatively, that the binding constraint may differ by task type. For classification, where a strong pre-trained encoder resolves most of the representational problem, performance appears backbone- and adaptation-limited. For continuous biophysical regression — canopy height, biomass, moisture, chlorophyll concentration — the constraint appears to shift towards multi-source feature construction, which a classification-pre-trained encoder does not supply. If this holds, an automated system would need to detect which regime it is operating in and allocate effort accordingly. We are not aware of a study that tests this directly.

9. Conclusion

Geospatial LLM agents have progressed rapidly, and the architecture the field has converged on — an LLM controller with domain-conditioned retrieval over a curated toolkit — works well within its boundary. That boundary is the point of this review. These systems orchestrate models that humans built, over data that humans prepared, and the evidence suggests they degrade sharply as the number of composed steps rises.

We have argued that three gaps follow: a reliability wall at composition depth, an unaddressed preprocessing problem in multi-source data construction, and an evaluation practice that treats automated novelty judgement as ground truth without calibration. None of these is a reason for pessimism about the direction. All three are tractable, and all three are more likely to yield to explicit domain constraint — verified templates, physically grounded data contracts, hard compute budgets and a capacity to refuse — than to further increases in model scale. The most useful near-term contribution may not be a more autonomous agent but a more honest instrument for telling whether an autonomous agent is producing science.

Competing interests

The author declares no competing interests.

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