INTELLIGENT NATIONAL MAP: A VISION FOR DISTRIBUTED AND AGENTIC GEOSPATIAL INTELLIGENCE

Samantha T. Arundel
U.S. Geological Survey

Wenwen Li
Arizona State University

Kevin G. McKeehan
HNTB Corporation

Bryan B. Campbell
U.S. Geological Survey

Jung-Kuan Liu
U.S. Geological Survey

Lawrence V. Stanislawski
U.S. Geological Survey

Ethan J. Shavers
U.S. Geological Survey

Greg D. Matthews
U.S. Geological Survey

Philip T. Thiem
U.S. Geological Survey

Dalia E. Varanka
U.S. Geological Survey

E. Lynn Usery
U.S. Geological Survey

ABSTRACT

An Intelligent National Map (INM) can change how worldwide mapping agencies, such as the U.S. Geological Survey, deliver the geospatial foundation of the Nation, as well as the capacity for the public to engage and use the data. It is envisioned as an innovative system that can coordinate analysis for spatial questions using structured reasoning grounded in semantic relationships, domain rules, and validated workflows. It is designed to coordinate analytic workflows autonomously and deliver validated, relevant geospatial answers and data quickly. This paper presents the technical and conceptual foundations of an INM, centered on multi-agent orchestration, natural language interfaces, retrieval-augmented generation, and access to trusted public data. Unlike static systems, an INM initiates from user input, which it analyzes and then activates task-specific agents to locate, analyze, and explain results in a transparent and accountable system. The platform represents a paradigm shift toward autonomous geospatial systems that could be capable of internal review, self-correction, and continuous learning. An INM can open new possibilities for changing access to geospatial intelligence, improving scientific rigor and decision-making, and building adaptive infrastructure aligned with federal science integrity principles.

Keywords GeoAI · Agentic AI · Autonomous Geospatial Analysis · Spatial Intelligence

1 Introduction

Artificial intelligence (AI) is beginning to reshape geospatial science by enabling a transition from simple and discrete representations of the environment to platforms that synthesize diverse data inputs and support real-time spatial analysis. Integrating AI with cloud-based processing and streaming datasets offers new capabilities for modeling and mapping that evolve with the data. Applications that once relied on periodically updated base layers can now be extended to support monitoring, forecasting, hazard mapping, and resource management that adapts to changing inputs. These capabilities align with broader paradigm shifts in the science community toward scalable, automated processing and reproducible workflows [50, 56].

The development of GIS technology provides important context for the emergence of next-generation geospatial systems. Early systems were built for desktop use [20], followed by browser-based WebGIS platforms [29] and, later, cloud-based systems that supported more scalable access and processing [78]. Each stage expanded the reach and function of GIS.

Current platforms support on-demand GIS tools that help users explore, analyze, and present information more effectively [12]. ArcGIS Online, for example, provides cloud services that support spatial analysis, visualization, and collaborative work, allowing users to apply spatial thinking to a wide range of problems [26]. Still, the gap between data availability and usable insights remains wide. Traditional analysis methods, even automated GIS workflows, are often unable to process the scale and complexity of data produced by modern sources, such as satellites, sensors, and uncrewed aerial systems (UAS) (Table 1) [54].

Data silos and incompatible systems can make it difficult for organizations to share information and coordinate efforts. The Geospatial Data Act of 2018 (43 U.S.C. § 2801 et seq.) mandates that data silos disappear altogether. A platform that combines varied geospatial sources, applies AI methods to extract meaning, and supports joint analysis could help overcome these barriers [32].

These trends point to the need for a new class of geospatial infrastructure: the *Intelligent National Map* (INM). An INM is a system that redefines user interaction with spatial data, not by replacing traditional "clip-and-ship" services, but by enabling semantic interfaces that interpret natural language questions and return synthesized, validated answers. Rather than serving as a static interface, an INM operates as a geospatial analyst, capable of executing complex spatial workflows with limited guidance [1, 74]. Users interact through natural language while the system manages data discovery, analysis, and interpretation in the background.

Table 1: *Motivation and Context for an Intelligent National Map.*

Traditional GIS	**Intelligent National Map**
Manual layer selection and pre-processing	Structured queries with automated data retrieval
Static maps and delayed updates	Current inputs drawn directly from authoritative sources
Limited model transparency	Explainable models with traceable diagnostics
Fragmented workflows	Coordinated agents with defined task roles
Difficult to produce results	Versioned logs with full provenance

An INM differs from traditional GIS in that spatial analysis begins with a natural language query and proceeds through predefined (or automated, chained) workflows to generate structured outputs. These workflows produce interpretable results without requiring the user to configure data layers or processing steps manually. An INM assigns fixed processing steps to each input type based on intelligent workflows. It determines the layers and processing steps needed to answer the query. After input ingestion, data are clipped to the spatial extent of the query, aligned to the target coordinate system, and evaluated using parameters specific to the data source and analysis type. These steps are applied automatically and in sequence, without requiring manual selection of layers or file formats. Redundant operations, such as clipping of layers, reprojecting datasets, or applying the same transformation steps, are eliminated by restricting each input to a single transformation path.

The revised integration sequence bypasses the earlier staging step by spatially and temporally aligning each input file at the point of entry. Datasets are reprojected, clipped, and sorted according to the spatial and temporal constraints defined by the query. Output rasters and vectors retain their source schema, including classification values and resolution. As a result, comparisons across layers can be made directly, without reprocessing or reformatting. Users do not need to reconstruct the workflow to interpret the result.

Many national and regional mapping systems still depend on separate data sources and manual workflows. These systems may not scale well and often require expert intervention at multiple stages, limiting their ability to support real-time analysis or responsive applications. Systems that can synthesize intent, connect information across sources, and produce results without manual oversight are becoming essential for decision-making in a data-rich world [60, 49, 56, 36].

An INM can support queries about recent changes in terrain, infrastructure risk under current environmental conditions, or projected impacts under forecasted climate scenarios. Such systems integrate expert rules, spatial logic, and domain ontologies to deliver actionable insights. Their development draws on progress in machine learning, remote sensing, and scalable data infrastructure.

Efforts to develop authoritative national geospatial platforms are underway in several countries. Organizations such as the United States Geological Survey (USGS) [22], Ordnance Survey in the United Kingdom [48], Natural Resources Canada [10], and Geoscience Australia [76] have each developed national mapping initiatives. These platforms typically include foundational datasets, such as orthoimagery, elevation, hydrography, and geographic names, that support a broad range of applications in mapping, modeling, and environmental decision-making [34].

To meet rising demands for timeliness, scalability, and insight extraction, many of these national mapping initiatives must now embed artificial intelligence into their core systems—enhancing efficiency, improving automation, and enabling new forms of geospatial analysis.

This paper outlines the essential features, development approach, and potential applications of an Intelligent National Map (INM), using the USGS initiative as a concrete example of how this vision is being pursued in practice.

2 The USGS Intelligent National Map Initiative

The U.S. Geological Survey's (USGS) National Geospatial Program is positioned to help guide the development of intelligent mapping infrastructure in the United States. As part of a broader push to accelerate federal use of AI through innovation, governance, and public trust (Executive Office of the President 2025), the USGS has articulated a vision for an Intelligent National Map grounded in scientific transparency, adaptability, and openness [71, 34]. This vision builds upon prior work establishing scalable frameworks for high-volume spatial data management [5].

Research supporting this initiative has progressed quickly, with machine learning and deep learning methods applied across a range of spatial analysis tasks [4, 33]. Deep learning models have performed especially well in remote sensing for land cover classification and object recognition. For example, Zhou et al. [83] used multispectral satellite imagery to classify land cover with high accuracy. Wang et al. (2020) developed a convolutional neural network (CNN) model to identify features in aerial imagery, with strong results for detecting roads and buildings.

Geospatial artificial intelligence has also been used to support national mapping. Arundel et al. [4] compiled a labeled dataset to train deep learning models for identifying natural features. This work was later extended to a new multi-source dataset, GeoImageNet [37], which combines satellite imagery and elevation products to enhance intelligent mapping. Stanislawski et al. [61] applied a U-net architecture to extract hydrographic features from elevation data, a method directly applicable to floodplain analysis. These workflows recur in later sections where the INM is applied to scenario-based queries. More recently, Liu et al. [41] used transformer-based models to classify 3DEP lidar point clouds into feature classes suitable for analysis.

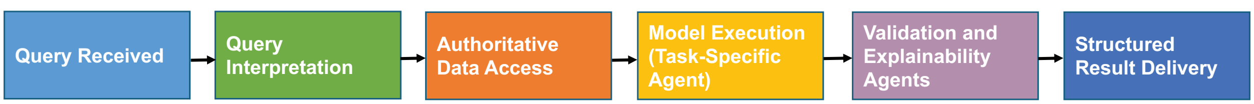

Figure 1: Simplified workflow of an INM. An INM is not a new dataset, geospatial tool, or model. It is a reasoning engine built on top of existing federal data holdings. Instead of requiring users to prepare layers and configure models, it assigns those steps to modular agents. Each agent performs a specific task, retrieving data, running a model, checking results,and all steps are linked to the original query. The result is a structured, traceable workflow from question to answer, with all intermediate operations documented.

An Intelligent National Map requires natural language interfaces that can interpret the full structure and context of a spatial query before any modeling step can occur. Recent work has demonstrated that pretrained language models fine-tuned on geospatial corpora can extract user intent and route queries to appropriate workflows based on task type, spatial scope, and temporal context [43, 38]. To achieve this, the system must map input text to structured representations using ontologies and spatially enriched knowledge graphs that reflect the semantics of geographic entities, topological relations, and physical processes [28, 67, 39]. These representations enable disambiguation, query reformulation, and task classification prior to computation. In this front-end layer, natural language inputs are matched to pre-indexed methods, data themes, and spatial domains to ensure that each analytic step follows from a clearly defined conceptual model. Rather than treating language parsing as an auxiliary function, the INM elevates it to the first stage of reasoning, using geospatially grounded NLP to reduce ambiguity and align questions with authoritative content. This approach supports transparency, reproducibility, and system interoperability from the outset (Figure 1).

3 Key Features and Capabilities of an Intelligent National Map

3.1 Advanced Geospatial Analysis

An Intelligent National Map relies on geospatial analysis to support its core functions. Artificial intelligence is key in improving how spatial patterns are detected and interpreted. When applied to imagery, sensor data, and other sources, AI methods can help highlight changes over time, detect anomalies, and extract features that would be difficult to identify using traditional techniques. With these tools in place, an INM becomes a resource for generating spatial insight across domains. It functions as an analytical system that can construct and carry out geoprocessing workflows based on user input, without requiring manual design of each step. Rather than asking users to build GIS processes, the platform interprets a question and assembles the data, models, and code required to answer it [6, 1].

Recent work in Geospatial Artificial Intelligence (GeoAI) [28, 33] demonstrates that large language models can interpret natural language prompts and coordinate GIS operations in response [1]. An INM applies these capabilities by selecting relevant data, identifying appropriate methods, such as classification, clustering, or prediction, and performing the analysis from these types of prompts. Neural networks for image interpretation and transformer models for temporal patterns operate together on inputs ranging from satellite imagery to time-series sensor data. This approach can reduce the need for specialized technical knowledge while speeding up the production of results. When integrated into broader geospatial systems, machine learning models also support forecasting. For example, models that estimate projections of future land cover, urban growth, or resource availability, such as transitions in flood-prone or fire-exposed regions, can be used to define monitoring intervals and select areas for early intervention by decision makers. These same models can be triggered in INM workflows involving infrastructure impact assessments, flood corridor evaluations, or wetland loss analysis, reinforcing consistent application across scenarios. Anticipating these changes can help decision-makers to determine solutions to land cover and demographic changes before conditions deteriorate, rather than responding after the fact [45].

3.2 Continuous Data Ingestion and Integration

An Intelligent National Map draws on government GIS sources, structured text records, satellite imagery, sensors, and ground-based instruments. As new information becomes available, the system makes it available to answer queries in real-time. Users interact with current data rather than relying on static map layers. This continuous integration can support analysis in situations where assumed conditions may shift quickly and updated inputs are essential.

As an autonomous system, an Intelligent National Map can identify and retrieve data needed to answer a specific question. It responds to a question by identifying the data required, comparing it to the data available, and retrieving it without manual input. For example, a query about flood risk would prompt the system to obtain recent precipitation records, stream gauge data, and current satellite imagery depicting flood extent. The system relies on Application Programming Interfaces (APIs) and cloud-based infrastructure to manage incoming data streams and large volumes of input [53, 80]. These components support the continuous integration of varied sources without manual coordination.

An Intelligent National Map retrieves the required data without requiring users to select sources or prepare files. For example, it might obtain recent streamflow measurements, satellite flood maps, or sensor readings as soon as they are validated and accessible [58]. The resulting analysis would integrate terrain and land cover data, as discussed in Section 3.1, and be rendered in 3D as described in Section 3.3. These inputs can then be organized for analysis without additional user direction [19]. Flood conditions, fire perimeters, and vegetation change may not be accurately assessed using static inputs alone [84]. These applications depend on data that reflect recent or near-real-time measurements or observations. When an INM draws from current data sources, it can improve the quality of analysis in situations where conditions do not remain constant.

3.3 3D Visualization and Mapping

Three-dimensional (3D) visualization improves spatial analysis by providing a more complete representation of the landscape than traditional, two-dimensional or 2.5-dimensional methods. The Intelligent National Map includes tools that support 3D exploration and analysis, allowing users to examine terrain, infrastructure, and hydrologic features in more realistic detail and with clearer spatial relationships.

The 3D National Topographic Model (3DNTM) is the U.S. Geological Survey's framework for integrating elevation, hydrography, and associated surface features into a single, spatially aligned reference system [70]. It replaces earlier approaches that treated elevation and hydrography as separate data products by establishing a standard geometry, consistent schema, and version-controlled dataset structure across topographic domains. The model incorporates inputs from the 3D Elevation Program (3DEP) [68] and the 3D Hydrography Program (3DHP) [69], ensuring that all derivative layers are built from validated, high-resolution source data. These core datasets support analytic consistency across domains such as flood modeling, sediment transport, infrastructure planning, and ecological analysis.

The 3DNTM serves as the structural basis for simulation and predictive analysis in an Intelligent National Map. It supports the development of digital representations that can incorporate change over time and simulate physical processes. Within this environment, an intelligent system can estimate outcomes under specific conditions. For example, the model might be used to evaluate the effect of a proposed development on surface runoff or to project wildfire spread under a defined wind pattern.

By combining AI methods with 3D data, an INM can perform spatial analyses that extend beyond traditional classification and rendering routines. The system might identify visible corridors for communication towers, calculate solar exposure on roof surfaces, or compare elevation surfaces over time to detect topographic change in areas prone to landslide or flood risk. These capabilities complement earlier examples of floodplain modeling and infrastructure siting, ensuring that spatial queries remain analytically consistent across dimensions. These analyses depend on structured geometry and vertical differentiation that are unavailable from two-dimensional representations.

Unlike conventional computer vision routines, which infer structure from imagery using brightness gradients, textures, or shadows, AI-enabled 3D methods operate directly on georeferenced elevation and structural data. This distinction is essential for modeling hydrologic connectivity, surface exposure, or barrier propagation across terrain. Recent advances in neural radiance fields and deep learning-based scientific visualization have demonstrated that AI methods can reconstruct and render complex 3D scenes from sparse or multi-modal inputs, allowing spatial structure to be inferred at resolutions and accuracies not achievable with pixel-based methods alone [79, 72].

In addition to analytic use, 3D outputs improve interpretability. Users can assess results from multiple viewpoints, trace feature extent across vertical surfaces, and compare simulations against familiar landscape geometry [52]. These representations support scenario analysis and allow an INM to test conditional outcomes under variable constraints. Typical applications include hazard zone delineation, infrastructure alignment, and landscape change evaluation, all of which require consistent spatial reasoning over elevation, slope, and adjacency in three-dimensional space.

3.4 Collaborative Partnerships

The development of an INM benefits from collaboration. National-scale geospatial systems are bolstered by a range of expertise, including scientific, technical, and institutional knowledge. An INM platform can support contributions from federal agencies, academic researchers, private industry, and the public. It allows multiple groups to work with shared data and tools. Agencies, researchers, and other contributors can examine the same inputs, apply their own methods, and compare results without the need to build separate systems. This structure can support efforts that span jurisdictions or rely on diverse sources of expertise, including hazard mapping, land use analysis, environmental monitoring, and natural resource management.

Contributors can connect new datasets or methods without rebuilding the platform. A regional classification model, for instance, can be inserted into an existing land cover workflow without changing how elevation or hydrology are processed. Updates are applied where needed and do not alter unrelated components. Eventually, through AI methods, the system could self-validate and self-regulate data updates.

The system assigns tasks to separate components based on function. One module might collect data, another might run a segmentation model, and another might generate summary statistics or graphics. Each module operates independently but passes its output to the next, forming a complete process that no single part manages alone.

This internal division of labor allows users to focus on questions and interpretation rather than data processing or system configuration. Users interact with the system through query construction and output review rather than managing the underlying workflow. Scientists, planners, and regional stakeholders define objectives, examine results, and revise inputs as needed, without modifying the processing steps directly.

When combined with external partnerships, this design can sustain an open and extensible platform that draws on both human and machine contributions to address geospatial challenges that can exceed the scope of any single organization.

3.5 Public and Government Data Utilization

An INM uses publicly available, authoritative datasets produced and maintained by agencies that understand and apply established data quality standards. Core inputs can include elevation, hydrography, and land cover from the USGS, satellite observations from USGS and the National Aeronautics and Space Administration (NASA), and environmental measurements from the National Oceanic and Atmospheric Administration (NOAA) and other federal sources. These datasets form the foundation for analysis and visualization across the platform.

Using authoritative and vetted sources can reduce the risk of introducing errors from unverified or biased data. Analyses can then be grounded in records that reflect known standards for accuracy and documentation. When answering a question, the system directly refers to these sources, helping to ensure that inputs reflect the most reliable information available at the national scale.

An INM also incorporates structured reference materials, including domain ontologies and published scientific literature. For example, if the system receives a question about a species' habitat, it checks official wildlife records and relevant regulations that are publicly available before producing a response. The system uses published sources to confirm location, status, and policies tied to land or species classification. When possible, it compares the result to known values drawn from government databases or scientific literature. If the answer conflicts with those sources, the system flags the output and may withhold a conclusion until it can reconcile a solution. These checks can help reduce the risk of producing an answer that may misrepresent legal boundaries, scientific interpretation, or established data.

As an INM becomes more autonomous, its reliance on transparent, high-quality inputs and documented verification steps becomes even more important to the model. For each task, or requested solution, the system will generate a report detailing data used, associated metadata, methods applied, a summary of the quality of results, along with a list of references of applied techniques, and a description of alternative methods with logistics justifying the selected method. Users must be able to trace outputs back to source data and confirm that results reflect established knowledge. The use of public and government data, alongside structured reference materials, can reinforce the credibility of the system and help support its role in scientific and policy contexts. Furthermore, the system will classify and log completed tasks and generate data to form a system of learning to become more efficient and eliminate duplicate tasks, or portions of tasks, when possible.

4 Action Plans for an INM

Building an INM requires a flexible development approach that combines natural language interfaces, domain-specific AI models, and methods for verification. A text-based query interface serves as the primary point of interaction for users. Figure 2 illustrates a prototype for the INM. Through this interface, users can submit questions in plain language and receive structured responses, including maps, tables, and explanatory graphics.

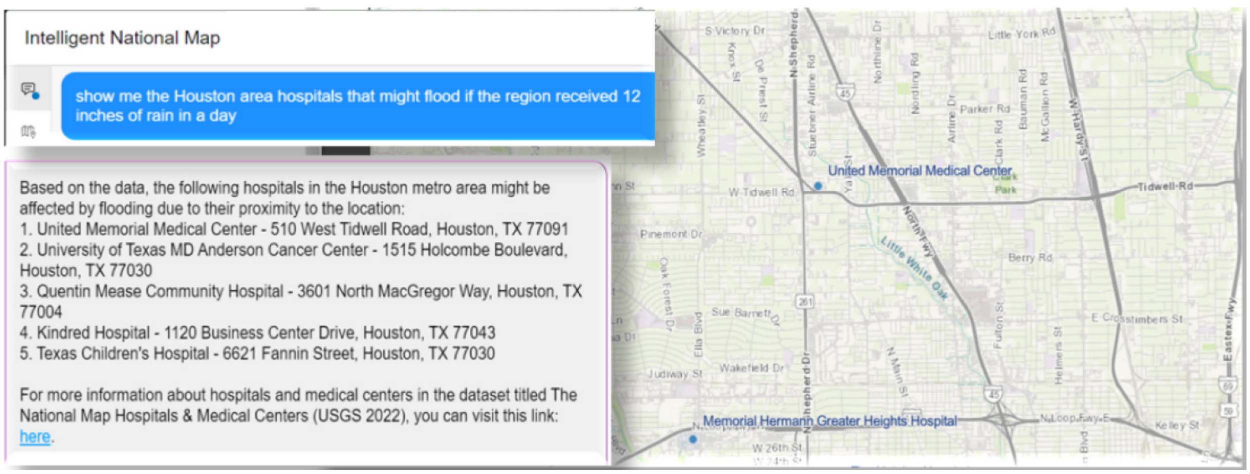

Figure 2: An illustration of an Intelligent National Map based on Esri's Hub technology. [13].

When a query is submitted, large language models adapted for geospatial tasks will interpret the request. These models can be trained on geospatial data and tuned using examples from Intelligent National Map applications. Their output will depend not only on general language patterns but also on the structure and content of the underlying INM databases.

To interpret queries, the system can draw on structured vocabularies, reference ontologies, and retrieval methods that link user terms to indexed content. Each query is matched against stored relationships derived from curated datasets, allowing the response to reflect documented sources and preserve consistency across variables and spatial units. Rather than producing results from a standalone model, the system will draw from Intelligent National Map sources and reference materials to generate responses that reflect current data and operational context.

As large language models become more closely integrated into geospatial systems, new areas of research are beginning to shape advanced initiatives such as an INM. Several developments now underway may define the next phase of technical progress, including multimodal AI, neuro-symbolic reasoning, and foundation models trained on geospatial data.

Multimodal AI combines different forms of input, including imagery, text, sensor feeds, and spatial layers, to support analysis across data types [35]. A model with this capacity could synthesize a disaster report, satellite observations, and sensor readings, producing more complete situational assessments than one limited to text alone.

Neuro-symbolic models use both statistical learning and rule-based reasoning. A system structured in this manner can apply defined constraints during analysis by linking pattern-based methods to formal representations of domain knowledge. In the context of an INM, this includes comparing outputs to established environmental thresholds and verifying that spatial results conform to administrative or regulatory boundaries. These methods also make it possible to trace how a conclusion was reached, using logic drawn from ontologies or scientific documentation [17].

Foundation models trained on Earth observation data are also under development. These models provide a broad geospatial context, which can be adapted to specific tasks, reducing the need for training from the beginning of each workflow [77, 16, 64]. A system with access to this kind of embedded knowledge, including climate ranges, terrain forms, and urban structure, can reason more efficiently across locations and applications.

New capabilities may be added to an INM gradually. As models become able to handle more input types and apply more structure to their reasoning, the system can begin to manage complex geospatial tasks without close supervision. A future version of an INM might run an entire analysis pipeline based on a single user question, selecting the data, choosing appropriate models, testing outputs, and summarizing results. This approach parallels structured automation in other domains, where systems progress through defined levels of independence [25].

The Intelligent National Map evaluates each analytical result against authoritative datasets, scientific literature, and applicable regulations. Suppose a result differs from a known, authoritative source, such as a federal land cover assessment or a peer-reviewed estimate of change. In that case, the system flags the conflict and either reprocesses the analysis or prompts for expert review.

These steps are part of the standard workflow. When inconsistencies arise, the platform identifies them for further examination, which may include reviewing the inputs, rerunning specific models, or documenting uncertainty. For example, suppose an INM finds that its estimate of land cover change does not match a recent government report. In that case, it can isolate the difference and either adjust the output or recommend additional review.

The platform also adapts over time. Language models used within the system are constrained to draw from verified public sources and refined through repeated interaction. Over time, the system adjusts how it interprets queries based on prior responses and outcomes, similar to how a technical analyst modifies a method based on prior evaluations.

An INM uses internal validation steps alongside repeated exposure to new queries to refine how it produces and checks results. These methods can support consistency across analyses and help ensure the system remains trusted in applications requiring clear, verifiable outputs.

To illustrate the capabilities of the INM, a user could ask, **"Where are the most populated wetland areas under flood risk this season in Houston, Texas, USA?"** The system would initiate a structured workflow across its configured agents (as shown in Figure 3). The Data Access and RAG agent retrieves the relevant elevation surfaces from 3DEP, current flood hazard zones from FEMA, and recent streamflow observations from USGS monitoring stations. A Task-specific AI Agent aligns these datasets spatially and temporally, filtering wetland features from the National Wetlands Inventory (NWI) database and overlaying them with census-derived population estimates. Hydrologic connectivity and flow accumulation are derived from elevation derivatives, and areas within defined thresholds are flagged as high exposure. The system returns spatial results along with a ranked list of affected wetland units, accompanied by versioned references to each data source and indicators of analytical confidence.

The Validation and Delivery Agent evaluates the flood risk result by comparing the output to existing FEMA flood zones and historical flood events in the Houston region. If the extent of high-risk wetland areas deviates from known patterns, the system may repeat the analysis using alternative classification thresholds or hydrologic models. Once consistency is confirmed, the system returns a map highlighting wetlands with elevated flood exposure and a summary of the estimated population within those boundaries. The response may indicate, for example, that densely populated wetlands adjacent to Buffalo Bayou show high flood potential based on current streamflow and rainfall accumulation. Accompanying the map is a report detailing the source data, version history, and a confidence indicator for each contributing variable, with suggested follow-up actions such as prioritizing gauge monitoring near critical locations.

Throughout this process, an INM acts as an autonomous geospatial analyst. It selects data, runs models, validates outputs, and communicates results without user intervention at each step. Although users are not required to direct the workflow, they remain informed throughout and retain control over how the query proceeds.

4.1 Key Technologies

An INM depends on a set of core technologies that together support its analytic, interactive, and adaptive capabilities. These include machine learning methods for geospatial modeling, natural language processing for user interaction, and automated approaches for model selection and workflow design. Figure 4 illustrates the key components of the INM for automated processing and handling of geospatial queries. Each component makes the system more responsive, interpretable, and scalable.

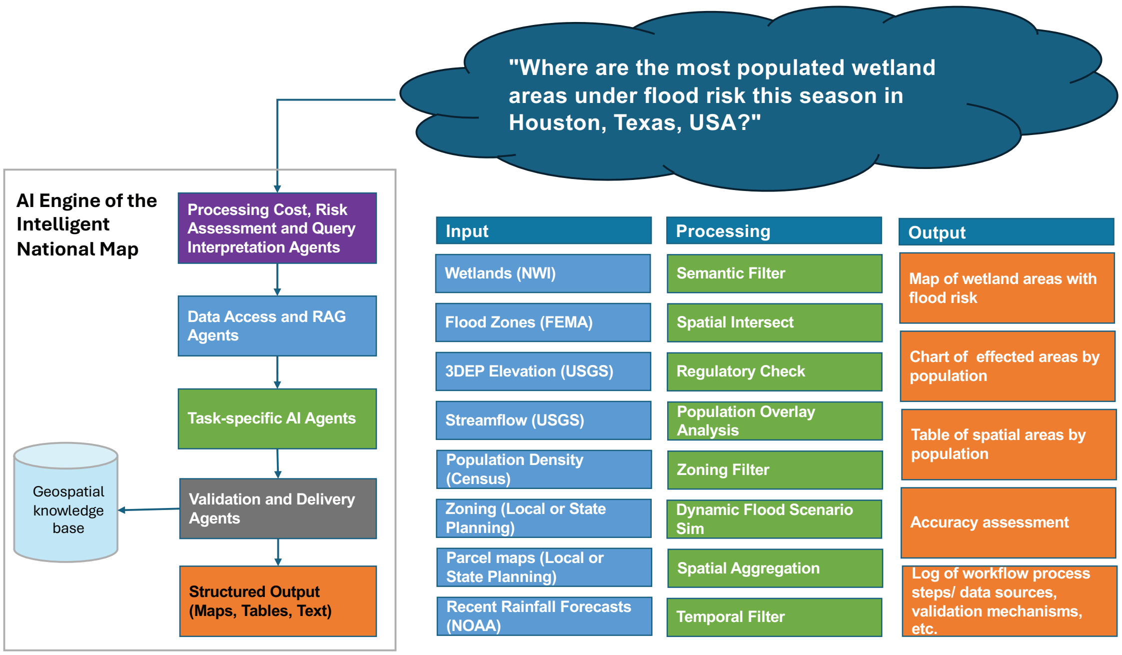

Figure 3: A modular workflow illustrating optional AI agents that might be used in answering a query. Each agent may be created on the fly as required and is replaceable.

4.1.1 AI-Driven Geospatial Workflows

Advanced geospatial workflows in an INM rely on methods drawn from current research in spatial modeling and machine learning. Convolutional neural networks are used to identify objects, extract features, and classify land use from satellite or aerial imagery [42]. Models designed to work with sequences, including Long Short-Term memory models (LSTMs) and transformer-based architectures, are used to analyze time series data. These approaches allow the system to track patterns such as vegetation change, flood extent, or land development over time [59].

An INM will also include automated approaches for model selection and tuning. These methods, sometimes referred to as AutoML, reduce the need for manual configuration by evaluating multiple modeling options and selecting those that perform best for the task at hand [51, 57]. These selections are based on known properties of the data and the performance of candidate models under test.

Recent prototypes have demonstrated that large language models can generate functional GIS workflows from plain language prompts [81, 74, 40]. Within an INM, this functionality allows users to describe a task in ordinary language and receive a structured analytical response. The system translates the question into a sequence of geospatial operations, drawing on both natural language processing and established modeling libraries.

Together, these technologies support a framework in which advanced spatial analysis is available through direct interaction. Users do not need to write code or specify technical parameters. Instead, the system interprets the request, selects appropriate methods, and delivers results as maps, reports, graphs, charts, structured data, or whatever means required to impart the information.

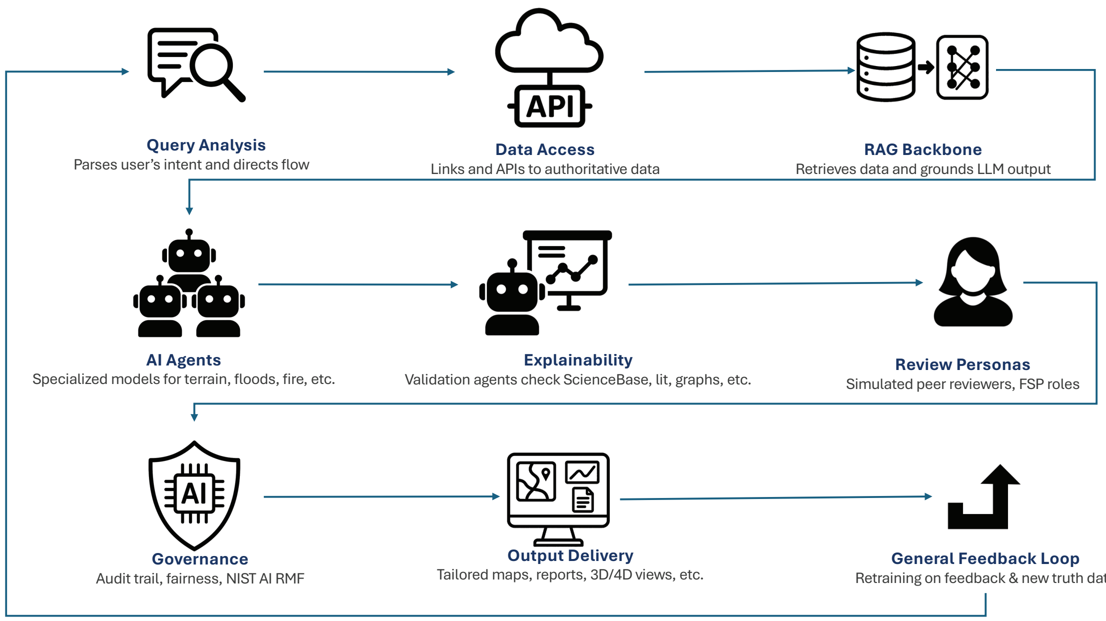

Figure 4: A detailed visualization of the proposed INM workflow. API – application programming interface, RAG – retrieval-augmented generation, LLM – large language model, lit – scientific literature, FSP – USGS Fundamental Science Practices, NIST AI RMF – National Institute of Standards and Technology Artificial Intelligence Risk Management Framework.

4.1.2 Predictive Analytics and Simulation

An INM incorporates predictive modeling methods that connect historical trends to future outcomes. Machine learning models embedded in geospatial workflows allow the system to estimate where change is likely to occur based on past conditions and current observations. These methods can support forecasting for various applications, including land cover change, wildfire probability, and groundwater decline. For example, models that combine climate records with spatial dependencies can be used to estimate where wildfires are most likely to emerge under current drought and wind conditions.

Simulation within an INM builds on this predictive capacity. The platform uses digital representations of the landscape to test hypothetical scenarios. For example, the system can estimate how adding a reservoir will influence downstream flood conditions by adjusting flow inputs across a modeled terrain surface. These simulations rely on the 3D National Topographic Model, which provides the structural framework for virtual testing across elevation, hydrology, and infrastructure.

The system can also repeat simulations under varying conditions to evaluate the sensitivity of each outcome. Parameters are adjusted automatically, and outputs are compared to identify thresholds or points of failure. This design can allow an INM to conduct structured experimentation, such as evaluation of options for building more resilient infrastructure systems, generating results that can guide project selection or resource allocation before any intervention occurs on the ground.

4.1.3 Semantic Integration and Knowledge Graphs

Semantic technologies help an INM interpret geospatial questions and organize results in ways that reflect context, scale, and meaning. Knowledge graphs play a central role in this process by representing formal relationships among spatial features, administrative units, physical systems, and domain concepts [27, 7]. These structures support interoperability across datasets and scales and allow the system to resolve ambiguity in language. For example, when a user refers to "Washington," an INM uses spatial and linguistic cues to determine whether the term refers to a city, a state, a river, or a person.

Knowledge graphs also provide access to spatial hierarchies, constraints, and domain-specific facts [23]. These references allow the system to reason about spatial relationships using explicit structure. When paired with machine learning models, knowledge graphs complement pattern-based inference with logical consistency. The system uses the semantic layer to represent spatial categories and their relationships, such as containment, adjacency, or function. The learning models contribute through data-driven classification and predictive mapping. Together, these components allow an INM to address questions that require both contextual understanding and spatial modeling [73].

A knowledge graph can serve as an effective conceptual model for managing established prior knowledge, supporting the validation of both the processing and results of the INM. With the aid of large language models (LLMs), key findings and guidelines from government reports and peer-reviewed publications can be efficiently summarized. Before integration into the knowledge graph, expert reviewers validate the extracted information to eliminate potential errors introduced by the LLMs and to ensure the accuracy and authenticity of the incorporated reference knowledge.

To support traceability, an INM uses retrieval-based methods that link outputs to specific source content. If a user asks about changes in floodplain boundaries, the system can return the current response along with the relevant Federal Emergency Management Agency (FEMA) maps, the associated topographic layer, and the regulatory boundary file used in the analysis. These records are returned alongside the output so that users can check where the information came from and determine whether the source is appropriate for their use [31].

An INM combines datasets from federal sources, scientific publications, Earth observation platforms, and sensor networks. These sources are incorporated as they become available. The system checks each input for format, coverage, and alignment with existing content before using it in analysis (Figure 3).

Data flow into the platform through a series of pipelines that assign each input to a specific task. During an active flood event, for example, an INM retrieves satellite imagery, precipitation totals, and gauge data from external feeds. As soon as new readings arrive, the system updates its estimates of flood extent using terrain models and hydrologic thresholds. These updates are reflected in current outputs without waiting for a scheduled batch or manual trigger.

To manage this process at a national scale, an INM uses cloud infrastructure that adjusts the amount of computing power based on the number and size of incoming tasks. If additional models are activated during a high-impact event, or if an increase in sensor activity adds more input, the system provisions the necessary resources to continue processing without delay.

External datasets are incorporated into an INM only if they meet defined quality criteria. Before any new source is used, the system checks its spatial reference, temporal resolution, and field structure to confirm consistency with existing inputs. These checks prevent the inclusion of incompatible or incomplete records.

An INM also establishes agreements with external data providers. As described in Section 3.4, these agreements cover information from state and local agencies, private entities where appropriate, and contributors of volunteered or user-submitted content. These partnerships allow the platform to include recent observations without requiring users to supply the data themselves.

The system operates within a cloud environment that provides both long-term storage and scalable processing. National datasets can be retrieved, filtered, and analyzed without delay, even when multiple users submit queries at the same time. This structure supports the platform's ability to serve diverse analytical tasks using a shared technical foundation [53, 24].

For example, an INM can use FEMA's Flood Insurance Rate Maps [14] to evaluate flood risk within the context of official hazard zones. When new hydrologic data are received, the system compares observed conditions to the FEMA-defined boundaries. If recent gauge data or satellite observations indicate that water levels have exceeded those limits, an INM can flag the discrepancy and trigger a review. These comparisons require both datasets to be aligned in the same spatial reference system. Because FEMA flood zones and TNM elevation surfaces follow shared standards for projection and vertical datum, an INM can compare them directly without additional adjustments. The same flood evaluation pipeline may also incorporate additional evidence not represented in FEMA rate zones. For example, an analyst might compare historical elevation surfaces with newer 3DEP derivatives to detect landform change, or reference NLCD-classified land cover to evaluate the expansion of impervious surfaces. Surface water records and wetland extent data can be added to this configuration to refine exposure estimates under localized rainfall conditions. This composite analysis can return spatial outputs alongside change history, source references, and version indicators for each contributing layer.

4.1.4 Immersive 3D and Visualization Tools

An INM uses elevation data and structural models to render terrain and built environments in three-dimensional space. These scenes are generated from source datasets that are already spatially referenced and stored within the system. A user can move from a national overview to a specific location without changing tools or importing separate files.

The platform also supports time-based visualization. Sequences of imagery or classification results can be displayed frame by frame, showing changes in land cover, water extent, or development.

Three-dimensional scenes also support scenario testing. A planner can place a proposed structure into an existing city model and examine its effect on skyline views or solar exposure. An emergency manager can model fire spread using terrain slope, vegetation type, and wind direction. These visualizations are tied directly to the underlying analysis, so changes in inputs or model assumptions are reflected in the display without additional formatting [7, 21].

Visualization also helps identify data problems. A point that appears valid in a table may show as misaligned or inconsistent when mapped across a surface. Errors in elevation, duplicate features, or misclassified segments often become visible when viewed in context. For this reason, visualization in an INM is not treated as an optional output. It supports quality control, guides interpretation, and communicates results in applied settings.

4.1.5 Collaboration and Governance Framework

The partnerships outlined in Section 3.4 form the foundation for both the development and sustained operation of an INM. Agencies, research groups, and technical collaborators contribute at different data lifecycle stages, including collection, processing, distribution, and applied use. Their roles are defined through formal agreements and aligned to specific functions within the broader system framework.

Structures for governance are designed to address data licensing, privacy, and security. For example, suppose a dataset includes household income or educational attainment by block group, the system must apply masking or aggregation rules before the data are displayed or used in analysis. Access to those attributes may also be limited to summary outputs, preventing retrieval at the individual feature level.

Safeguards will also be applied to the analytical components of the platform. The system is designed to track how AI-generated outputs are produced and can confirm that responses remain consistent with public documentation or established rules [11, 9]. If a result is produced using a model drawn from multiple sources, the system must record those references and flag conditions that might lead to inaccurate or inappropriate conclusions.

The governance framework also includes mechanisms for public involvement. A reporting function may allow individuals to correct location names, flag outdated imagery, or suggest missing features. The system can review these reports and, when validated, incorporate them into the data stream. This kind of input provides local knowledge that may not be available from national datasets and helps the platform remain responsive to the communities it serves. Well-defined agreements and long-term partnerships can help ensure that an INM is not only technically functional but also publicly trusted and institutionally supported over time.

4.1.6 Reliability, Validation, and Ethics

An INM uses public government data sources described in Section 3.5. These sources can provide a foundation for reliability, but the system also includes additional validation steps as part of its development plan. Subject matter experts can help contribute during the training and refinement of AI models. For example, hydrologists may define how inputs are handled in flood modeling, including methods for interpreting flow direction, identifying low-lying terrain, or classifying inundation areas from satellite imagery.

Each output produced by an INM is traceable to its source through automatically generating provenance about the data, intermediate results, as well as the entire workflow [3]. The platform records which datasets were used and how they were processed. Users can examine these records through audit trails that document the steps leading to each result, including any model used in classification, prediction, or transformation (Figure 5).

Semantic structures can also contribute to validation. The system references ontologies and rule sets that describe basic spatial and environmental principles. If a model returns a value that violates known relationships—for example, placing

Validation Dashboard

Citations Checked	Variable Weights	Source Metadata
Li et al. 2023 - GeoImageNet	Wetland Extent: 0.35	Wetlands: NWI (USFWS)
Zhou et al. 2023 - Flood Simulation	Flood Risk: 0.30	Flood Zones: FEMA NFHL 2023
Zhao and Deng 2024 - Road Risk AI	Population Density: 0.25	3DEP Elevation: USGS 2022
	Zoning Status: 0.10	Population: ACS 2020
		Zoning: City of Houston

Figure 5: An example validation dashboard. Every result is paired with an explanation layer. You can see which features influenced the model, how confidence was determined, and what rules or thresholds were applied. This is critical for expert responses: answers need to be interpretable and backed by traceable logic.

a water body at a location higher than surrounding ridges—the reasoning layer can flag the result for review [27]. These semantic checks can serve as a form of internal error detection.

Ethical considerations are also incorporated into the development process. The team applies standards for fairness and representation by monitoring the distribution of training data, checking for skew in the results, and reviewing outputs across geographic and demographic categories. Guidelines for responsible data science are applied during testing and review, with references to frameworks that emphasize transparency and user oversight [85].

The platform includes functions that can allow users to submit corrections or challenge unexpected results, so that concerns can be addressed and incorporated back into future runs. Together, these measures can link data quality, subject matter expertise, and transparency into a single process. Each element is designed to help ensure that outputs can be both technically consistent and accountable to users.

Before executing any query, a review process is conducted to evaluate its potential costs, benefits, and risks. Particular attention is given to national security risks, including AI hallucinations, data privacy concerns, and vulnerabilities to adversarial manipulation [8]. Additional risks may involve health and safety issues, such as the mishandling of hazardous substances, insufficient safety measures in devices or systems, or the injection of malicious data into the learning process [62].

Given that planning decisions may rely on the query results, the INM enforces strict safeguards to ensure accuracy and reliability. Each incoming query is evaluated to estimate its computational cost against predefined expense thresholds. Furthermore, the trustworthiness of the platform is assessed to promote user confidence in the system and its outputs [30].

4.2 Intelligent National Map: End-to-End AI Workflow

An Intelligent National Map can re-imagine the Department of the Interior's (DOI) geospatial platforms as an autonomous "digital geospatial analyst" that can ingest trusted data, reason about complex spatial problems, and deliver validated, tailored outputs, often in minutes rather than months. This system uses a novel, agent-driven workflow that begins with a natural language query or geospatial task expressed in common terms, rather than raw data ingestion. From here, the system orchestrates the appropriate agents to fulfill the task, whether retrieving data, performing analyses, validating results, or producing outputs. The steps outlined below form a pipeline where AI agents collaborate autonomously to deliver trustworthy, explainable, and relevant geospatial intelligence (Table 2). Each response is grounded in authoritative data, aligned with scientific standards, and designed for transparency and continuous improvement [2, 15, 65].

Table 2: Steps in an INM workflow.

Step	Component	Summary
4.2.1	Processing cost estimation agent	Estimates a range of costs for the analysis from a initial approximating to a more robust solution with sensitivity analysis and uncertainty estimates.
4.2.2	Risk assessment agent	Identifies national security risk level of performing task and assigns a security clearance level requirement if necessary. Also probably need a security authorization agent validate user credentials and clearance levels and control access to specific tasks or data.
4.2.3	Query Analysis	Parses user's intent using large language models (LLMs), classifies tasks, and decides next steps, including required data and baseline analysis workflow. Also evaluates security risks of performing the request and estimates a range of costs for the analysis from an initial approximating to a more robust solution with sensitivity analysis and uncertainty estimates.
4.2.4	Authoritative Data Access	Accesses authoritative geospatial datasets (including 3DHP, 3DEP, TNM, NOAA, NASA) via APIs. Automated Extract, Transform, Load (ETL) harmonizes schemas, spatial references, and metadata to ensure ingestion-ready data.
4.2.5	Retrieval-augmented generation (RAG) Backbone	A lightweight vector store indexes vetted documents, maps, and code. LLM identifies and retrieves relevant information and data (examples: research articles, methods options, rainfall grids, slope rasters) to generate evidentiary supported, traceable answers.
4.2.6	Task-Specific AI Agents	Domain-specialized agents: HydroAgent (floods), TopoAgent (lidar/terrain), WildfireAgent (risk forecasts). Orchestrated via LangChain-style framework for multi-agent cooperation.
4.2.7	Explainability & Trust	explainable AI (XAI) Panel with validation agents: ScienceBaseAgent (catalog validation), ScholarlyAgent (literature), KnowledgeGraphAgent (semantic checks). Transparent workflows support interpretability and traceability.
4.2.8	Fundamental Science Practices (FSP)-Inspired Review Personas	Synthetic reviewers, including InternalPeerReviewer, CenterDirector, and BureauApprover, validate completeness, reference integrity, and policy compliance in a sandboxed review step.
4.2.9	Governance, Risk & Compliance	Model runs logged in immutable audit trail. Nightly fairness/drift tests feed a National Institute of Standards and Technology (NIST) AI Risk Management Framework (RMF)-aligned dashboard to monitor and manage responsible AI practices.
4.2.10	Output & Delivery	Workflow agent selects report subagents (examples, WebMapAgent, CartographyAgent, PublicReportAgent, DecisionMakerAgent) to generate outputs in formats such as Open source, standardized formats (including hypertext markup language (HTML), SpatioTemporal Asset Catalog [STAC], and GeoPackage).
4.2.11	Feedback & Continuous Learning	User feedback and performance data loop back to the training pipeline. Agents are continuously retrained or fine-tuned to improve accuracy and adaptability over time.

In this new paradigm, an INM does not simply respond to static inputs; it can engage in focused reasoning from the inception, inferring what information is needed, where to access it, how to analyze it, and how best to communicate the results. This consumer-centric, agent-facilitated architecture represents a transformation from traditional GIS workflows and aligns with current trends toward multi-agent systems, retrieval-augmented reasoning, and explainable geospatial AI [63, 73].

The core production workflow defines the operational sequence of an INM, beginning with data ingestion and continuing through transformation, analysis, and output generation. Each stage is linked by predefined procedures that determine how inputs are handled and how results are produced.

4.2.1 Processing cost estimation agent

This agent operates as a planning function rather than a computational step. It parses the user's request, identifies the intended scope, and compares the task to prior workflows indexed by theme, region, and method [75]. The agent then returns several processing options, each defined by its expected input size, computational intensity, and storage load. Each option lists parameter requirements, expected runtime, and memory use. Prior workflows with similar configurations are noted. This allows the analyst to determine whether the task fits within current constraints and reject configurations that are infeasible. The evaluation step reduces unnecessary job submissions and avoids processing that cannot be completed under defined limits.

4.2.2 Risk assessment agent

This agent reviews incoming queries to identify potential risks to critical infrastructure, national security, human health and safety, information integrity, or other high-impact concerns [66]. It ensures that proposed query solutions do not inadvertently facilitate threats, such as identifying tactical advantages for foreign adversaries, or introduce false information (for example, hallucinations, [8]) that could compromise infrastructure, environmental resources, or information systems. By analyzing the query's intent and geospatial context using rule-based logic and language models, and referencing a predefined risk library, the agent flags high-risk requests. If a query is deemed sensitive or high-risk, it is escalated to the Security Authorization Agent for to verify the user's credentials, roles, and clearance levels before granting access to associated workflows or data. This process ensures the INM framework complies with federal AI implementation guidelines to advance innovation and share data and AI assets in a manner that fosters public trust [66].

4.2.3 Query Interpretation Agent

Upon receiving the prompt, this agent is activated. It parses the user's intent using fine-tuned large language models (LLMs) trained on geospatial tasks and terminology [81]. It classifies the type of task being asked (For example, "Where is...", "What is the risk of...", "Show changes in..."), identifies the spatial and temporal context, and determines the data and analytic elements required to fulfill the request. This step functions as a cognitive triage, ensuring the system understands the question's words and the analytical implications [44].

4.2.4 Authoritative Data Access

An INM accesses data from authoritative sources via the web and public APIs, ensuring it uses current information, including the latest geospatial data, such as 3DHP, 3DEP, TNM vector layers, NOAA weather feeds, NASA Earth observation imagery, and other trusted government datasets. This direct, API-based access to vetted data eliminates the need for duplicative storage. Ingested datasets undergo schema harmonization as they arrive. For example, automated ETL pipelines align spatial references, metadata, and provenance information so that every dataset is analysis-ready upon ingestion.[5]

4.2.5 RAG Backbone

A lightweight vector store indexes all vetted documents, code snippets, and map layers that an INM might need to answer queries. When a user poses a question, the system's LLM first retrieves the most relevant data chunks (for example, slope rasters, recent rainfall grids, land-cover change reports) before drafting an answer, ensuring the response is grounded in factual data rather than the model's memory file. This RAG approach guarantees that AI-generated answers remain traceable to real data sources.

4.2.6 Task-Specific AI Agents

An INM employs multiple specialized AI modules that handle domain-specific tasks. For example:

HydroAgent: employs U-Net and other CNN models for hydrologic analyses such as stream delineation and flood-extent mapping, producing outputs like dynamic flood polygons and hydro-conditioning masks.

TopoAgent: uses transformer-based classifiers on 3DEP lidar data for topographic feature extraction, yielding classified point clouds and high-resolution digital elevation model (DEM) edits.

WildfireAgent: utilizes spatiotemporal LSTM models for wildfire risk forecasting, generating burn probability rasters at various time intervals, such as 6-hour, 12-hour, and 24-hour forecasts.

These agents cooperate through an orchestration layer using frameworks such as LangChain, so that complex queries can automatically chain their specialized skills. In practice, a single user query might invoke multiple agents in sequence or parallel, with an INM autonomously coordinating their outputs to form a cohesive answer.

4.2.7 Explainability & Trust

Each agent within an INM ecosystem produces outputs accompanied by diagnostic information that supports interpretation and review. Beyond logging feature-importance maps or attention scores, INM agents operate within a broader framework of explainable AI (XAI), supported by specialized validation agents that simulate expert reasoning and source cross-verification. For example:

ScienceBaseAgent: validates agent queries and retrieves relevant, authoritative geospatial records from the USGS ScienceBase catalog, anchoring AI-generated outputs in curated scientific products (https://github.com/DOI-USGS/sciencebasepy).

Scholarly literature agent: leverages access to indexed scientific publications (via APIs such as Semantic Scholar or CrossRef) to validate the interpretive chain against peer-reviewed sources and track provenance through citation networks [16, 18].

Domain-specific knowledge graph agent: interacts with structured geospatial ontologies, such as the GeoLink knowledge graph or environmental vocabularies such as Semantic Web for Earth and Environment Technology Ontology (SWEET) [55], to validate semantic consistency, reason about geospatial relationships, and detect potential conflicts or contradictions in interpretation.

Collectively, these agents form a multi-faceted XAI panel integrated into the user interface. This panel enables analysts to explore layered diagnostic views that trace how conclusions were reached, such as identifying which hydrological, ecological, or elevation attributes were most influential in determining a wildfire hazard score. Each result can be reviewed in relation to external datasets selected for the same spatial or temporal extent. Analysts may compare feature boundaries, classifications, or values across sources to identify conflicts or confirm agreement. When inconsistencies are found, the system allows revision of query parameters or replacement of individual inputs before advancing to the next stage of analysis. Such layered explainability aligns with recent best practices in XAI design, which emphasize combining model interpretability with traceability to external knowledge systems [47, 2]. It also reflects emerging research on RAG frameworks that strengthen trust by grounding model outputs in authoritative corpora [16]. It enables transparent agent-based workflows to be audited, adapted, and improved.

4.2.8 Fundamental Science Practices (FSP)-Inspired Review Personas

To mirror USGS FSP, an INM incorporates synthetic reviewer agents (personas) that critique and review the AI's outputs before finalizing them. For example, InternalPeerReviewer, ExternalPeerReviewer, Supervisor, CenterDirector, and BureauApprovingOfficer personas automatically check the draft answers for completeness, verify that cited data and references are correctly used, and flag any policy or communication issues. This internal review step, happening in a sandbox environment, can help ensure that INM's products meet the standards of scientific rigor and policy compliance prior to user delivery.

4.2.9 Governance, Risk & Compliance

All model runs within an INM are recorded in a permanent audit log that captures the full configuration of each execution, including parameter values, selected inputs, and resulting data layers. Each entry is time-stamped and associated with a unique query or processing task. The record allows analysts to trace each step in the analytical process, including how inputs were selected, how parameters were applied, and how results were generated. When discrepancies are found or additional review is required, the full sequence can be examined to determine whether the procedures followed align with documented methods. Maintaining this level of detail is necessary for reproducibility and required in applications subject to formal oversight.

In alignment with modern AI governance practices, an INM system conducts automated fairness and drift detection tests on its AI models at regular intervals (for example, nightly). Fairness tests evaluate potential demographic or spatial biases in predictions, whereas drift detection identifies shifts in data distributions or model behavior over time. The results are visualized in a governance dashboard that can enable near-real-time monitoring by technical and management stakeholders.

Critically, the dashboard is designed to support the National Institute of Standards and Technology (NIST) AI Risk Management Framework (AI RMF), a standardized methodology developed by NIST for managing risks associated with AI systems [65]. The AI RMF emphasizes four key functions: map, measure, manage, and govern. These functions can collectively guide the lifecycle of responsible AI. Integrating automated monitoring and structured decision support into these functions can help ensure alignment with ethical AI principles and national-level best practices for transparency, safety, and accountability [46, 82].

INM's design further limits the risk of misuse by operating within a closed ecosystem of preauthorized data sources, validated analytical tools, and predefined workflows. These constraints help prevent the application of AI in unintended or inappropriate contexts. While there remains a possibility that an agent selects suboptimal inputs or parameters, such issues are traceable through detailed metadata and audit trails, allowing users or reviewers to validate outcomes and flag anomalies. This balance between automation and accountability ensures that INM can deliver scalable AI capabilities without compromising scientific integrity or public trust.

4.2.10 Output & Delivery

An INM delivers its answers in multiple formats tailored to stakeholders, using various "report" agents. These agents are managed by a workflow agent, which decides which subagents to instantiate based on the user input, the query, and the desired results. For example, a web map report agent allows direct access to data, particularly spatial data, used to create the results. A cartography agent ensures that the web map is grounded in basic cartographic principles. A multi-dimensional display generation report agent creates 3- and 4-D visualizations for advanced users, whereas a public report agent provides easily understood information, allowing ease of use by the public. For interagency partners and advanced users, results can be provided in standardized open geospatial formats (such as GeoPackage files or STAC items) to facilitate data exchange and further analysis. Additionally, a decision-maker report agent can generate narrative briefs (in Portable Document Format (PDF) or HTML format) with inline citations and maps for decision-makers, summarizing the findings and providing context, much like a report generated by a human analyst.

4.2.11 Feedback & Continuous Learning

An INM is designed to continuously learn from its interactions and outputs. User feedback mechanisms such as user ratings, error reports, suggestions, and performance metrics are looped back into the training pipeline. The system can retrain or fine-tune its AI agents on the latest ground truth data and corrections provided by users, improving over time without extensive human retraining effort. New data are added to an INM through defined ingestion routines tied to each dataset type. When a query is rerun with updated inputs or revised parameters, the system stores the new configuration alongside the earlier record. Analysts reviewing the results may adjust spatial extent, reclassify features, or replace individual layers based on updated guidance or observed error. The system records these revisions so that subsequent analyses can contribute to system refinement over time. Over time, this process can improve the agreement between system behavior and evolving user requirements while refining the accuracy of derived results.

In addition to the general user feedback loop described above, an INM incorporates a set of internal validation loops at each major step in the workflow (as shown in Figure 6). These loops evaluate the performance and consistency of outputs generated at each stage. When a result fails to meet the validation threshold, the workflow returns not to the immediately preceding step but to the one before it. That earlier output is re-evaluated over a defined number of iterations, chosen during configuration. This approach allows the system to isolate errors that originate earlier in the sequence rather than attributing failure to the most recent operation. The process continues in reverse through the workflow until the result satisfies the required criteria. Each step is assessed based on its influence on subsequent outputs, allowing errors to be traced and corrected within the pipeline.

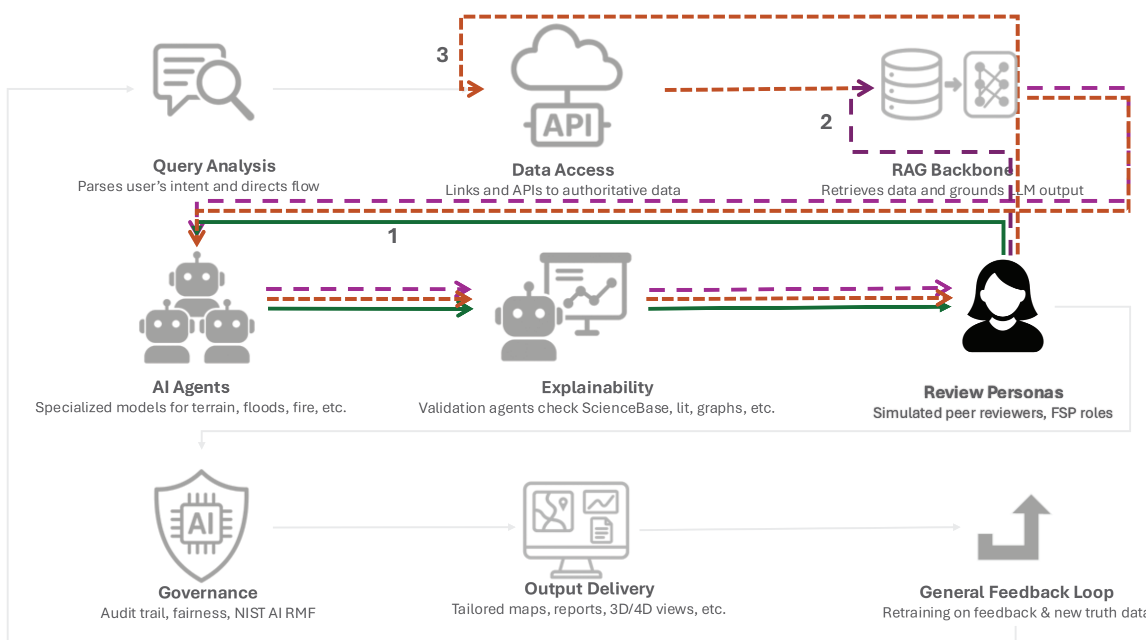

Figure 6: Visualization of internal validation loops. Assuming output from Review Personas is insufficient or incorrect in some way, such as the answer is too short, too long, or fails to pass review, the workflow returns to the Artificial Intelligence (AI) agents, two steps before, and its new output is passed to Explainability and then Review Personas. This can iterate *n* steps before the results from Review Personas are sent back to a step earlier in the process, which iterates similarly, and so on. API – application programming interface, RAG – retrieval-augmented generation, LLM – large language model, lit – scientific literature, FSP – USGS Fundamental Science Practices, NIST AI RMF – National Institute of Standards and Technology Artificial Intelligence Risk Management Framework

The review continues stepwise through the workflow until the results fall within acceptable limits. Each component is evaluated in relation to its downstream impact, allowing errors to be traced to their source and corrected without restarting the full sequence. Such recursive refinement and fault-tolerant processing align with current best practices in agentic AI design, especially in multi-agent coordination and retrieval-augmented generation systems [63, 15, 2].

5 Next Steps and Potential Challenges

Moving from concept to operational implementation, several near-term priorities can accelerate the development of an Intelligent National Map. Pilot deployments with agency partners can demonstrate real-world utility in domains such as flood monitoring, urban expansion analysis, and seasonal vegetation tracking. These use cases provide a foundation for refining data workflows, model retraining strategies, and event-based update mechanisms.

Parallel technical efforts might include standardizing public APIs, configuring natural language parsing to reflect domain-specific vocabularies, and formalizing rule sets to ensure alignment with regulatory datasets. Ontology integration and semantic typing will allow models to detect boundary conflicts or classification mismatches and flag these during review.

Initial training pipelines could focus on task-specific applications where ground truth exists, such as hydrographic change detection or infrastructure overlay analysis, to validate accuracy and model responsiveness. Language models can be evaluated for their ability to identify incomplete queries, segment compound tasks, and match spatial terms to defined extents.

Despite these opportunities, several challenges might influence the system's stability and reliability. Interoperability remains uneven across agencies, with discrepancies in schema documentation, coordinate reference systems, and update cadence. Knowledge graph integration has not yet resolved all semantic alignment conflicts, particularly when feature classification differs between sources. Contradictory results produced by distinct agencies using the same base inputs may raise questions about interpretability and acceptance. Flagging these instances is an important step, but the review pipeline must also trace how differences emerge and indicate when results cannot be reconciled without manual intervention. Consistency across asynchronous updates remains a documented limitation. Inputs acquired or refreshed on divergent schedules may often reflect mismatched reference dates. When queries rely on multiple datasets with misaligned temporal resolution, the returned results incorporate inconsistencies that are not flagged by the system unless explicitly configured. In cases where one source has been updated while others retain earlier values, spatial comparisons and derived classifications produce conflicting or unstable interpretations. These discrepancies can be difficult to detect without audit trails or metadata validation steps embedded in the workflow.

For example, the reclassification of land cover in a wildfire region based on newer imagery may be applied in isolation, with no concurrent update to slope, vegetation index, or infrastructure layers. These errors can propagate unless all dependencies are versioned and linked within the workflow.

Long-term success of the INM will depend on transitioning from technical experimentation to sustained institutional coordination. Platform governance can be improved with training model bias, unresolved input conflict, and variable precision across regions. Designating review agents that apply domain-specific thresholds and compare modeled results to observed behavior can also improve the model, in addition to continuous retraining, version control of model configurations, and documented audit logs in the system architecture.

As the INM evolves into a trusted, AI-powered geospatial platform, its authoritative status introduces unique vulnerabilities related to well-recognized challenges in AI deployment—such as model hallucination, misuse of tools, or inappropriate extrapolation in decision-making contexts. These risks are especially critical when digital agents act autonomously or when outputs are interpreted without human oversight. To mitigate such issues, the INM must implement safeguards including the validation of AI outputs against authoritative datasets, continuous monitoring of model behavior in edge cases, and reinforcement learning pipelines that incorporate domain expert feedback. Mechanisms for auditability—such as explainable inference paths and version-controlled model configurations—will be critical to tracing how results are produced. Responsibility for addressing unintended consequences must be shared across system architects, data stewards, and agency partners, with clearly defined governance structures for adjudicating discrepancies and refining AI behavior in unanticipated applications.

6 Conclusion

The Intelligent National Map (INM) offers a transformative vision for geospatial data infrastructure, one that is automated, adaptive, and analytically transparent. By continuously ingesting and validating diverse data streams from authoritative and external sources, the INM can deliver timely, domain-relevant insights without manual intervention. Its architecture leverages structured workflows, event-based processing, and distributed computation to ensure scalability, reliability, and responsiveness.

What sets the INM apart is not just technical innovation, but its emphasis on traceability, quality assurance, and institutional integration. The ability to update analyses in real time, flag anomalies, and provide interpretable outputs grounded in validated observations makes it a powerful foundation for evidence-based governance and environmental resilience. Achieving this vision requires sustained investment in interoperability, model transparency, and interagency collaboration—but the payoff is a national-scale platform capable of supporting robust spatial decision-making for the future.

Artificial intelligence will be a core enabler of the INM, deeply embedded across the entire reasoning system—from automated data ingestion and quality filtering to dynamic analytics and knowledge-based interpretation. AI techniques, including large language models, machine learning pipelines, and geospatial knowledge graphs, will not only enhance automation and scalability but also support explainable, context-aware decision support. As AI becomes an integral part of the INM's cognitive infrastructure, it will drive the system's ability to reason across heterogeneous inputs, adapt to emerging conditions, and deliver trustworthy, actionable insights to users across scientific, operational, and policy domains.

Acknowledgment

Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

References

[1] T. Akinboyewa, Z. Li, H. Ning, and M. N. Lessani. Gis copilot: Towards an autonomous gis agent for spatial analysis. *arXiv*, 2024.

[2] S. Ali, T. Abuhmed, S. El-Sappagh, K. Muhammad, J. M. Alonso-Moral, R. Confalonieri, R. Guidotti, J. Del Ser, N. Díaz-Rodríguez, and F. Herrera. Explainable artificial intelligence (xai): What we know and what is left to attain trustworthy artificial intelligence. *Information Fusion*, 99:101805, november 2023.

[3] L. Anselin, S. J. Rey, and W. Li. Metadata and provenance for spatial analysis: the case of spatial weights. *International Journal of Geographical Information Science*, 28(11):2261–2280, 2014.

[4] S. T. Arundel, W. Li, and S. Wang. Geonat v1.0: A dataset for natural feature mapping with artificial intelligence and supervised learning. *Transactions in GIS*, 24(3):556–72, 2020.

[5] S. T. Arundel, K. G. McKeehan, B. B. Campbell, A. N. Bulen, and P. T. Thiem. A guide to creating an effective big data management framework. *Journal of Big Data*, 10(1):146, 2023.

[6] S. Barke, M. B. James, and N. Polikarpova. Grounded copilot: How programmers interact with code-generating models. *Proceedings of the ACM on Programming Languages*, 7(OOPSLA1):85–111, 2023.

[7] F. Biljecki, J. Stoter, H. Ledoux, S. Zlatanova, and A. Çöltekin. Applications of 3d city models: State of the art review. *ISPRS International Journal of Geo-Information*, 4(4):2842–89, 2015.

[8] W. N. Caballero and P. R. Jenkins. On large language models in national security applications. *Stat*, 14(2):e70057, 2025.

[9] J. Cinnamon, S. K. Jones, and W. N. Adger. Evidence and future potential of mobile phone data for disease disaster management. *Geoforum*, 75:253–64, october 2016.

[10] P. Daly. Mapping artificial intelligence use in the government of canada. *Revue Gouvernance*, 20(1):74–95, 2023.

[11] A. Degbelo, B. Schmidt, C. Henzen, S. Lechler, B. Lubahn, and F. Zander. Desiderata for intelligent maps: A multiperspective compilation. *KN - Journal of Cartography and Geographic Information*, 73(3):183–98, 2023.

[12] J. Döllner. Geospatial artificial intelligence: Potentials of machine learning for 3d point clouds and geospatial digital twins. *PFG – Journal of Photogrammetry, Remote Sensing and Geoinformation Science*, 88(1):15–24, 2020.

[13] Esri. Graphic generated using arcgis hub, 2025. Available from: https://hub-sandbox-compass.arcgis.com/embed.html?id=2b82e6e4fe5b4a8e8012e44da9b2d486&header=true.

[14] FEMA (Federal Emergency Management Agency). FEMA map service center, may 2025. Available from: https://msc.fema.gov/portal/home.

[15] S. Gao, Y. Hu, and W. Li. Introduction to geospatial artificial intelligence (geoai). In *Handbook of Geospatial Artificial Intelligence*, pages 3–16. CRC Press, Boca Raton, 1st edition, 2023.

[16] Y. Gao, Y. Xiong, X. Gao, K. Jia, J. Pan, Y. Bi, Y. Dai, J. Sun, M. Wang, and H. Wang. Retrieval-augmented generation for large language models: A survey. *arXiv*, 2024.

[17] A. d. Garcez and L. C. Lamb. Neurosymbolic ai: The 3rd wave. *arXiv*, 2020.

[18] J. Genesis. Retrieval-augmented text generation: Methods, challenges, and applications. 2025.

[19] Z. Gharineiat, F. T. Kurdi, and G. Campbell. Review of automatic processing of topography and surface feature identification lidar data using machine learning techniques. *Remote Sensing*, 14(19):4685, 2022.

[20] M. F. Goodchild. Geographical information science. *International journal of geographical information systems*, 6(1):31–45, 1992.

[21] M. Grieves and J. Vickers. Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In F.-J. Kahlen, S. Flumerfelt, and A. Alves, editors, *Transdisciplinary Perspectives on Complex Systems*, pages 85–113. Springer International Publishing, Cham, 2017.

[22] C. G. Groat. The national map-a continuing, critical need for the nation. *Photogrammetric Engineering and Remote Sensing*, 69(10):1087–1108, 2003.

[23] L. Hu, W. Li, J. Xu, and Y. Zhu. Geoentity-type constrained knowledge graph embedding for predicting natural-language spatial relations. *International Journal of Geographical Information Science*, 39(2):376–99, Feb. 2025.

[24] X. Huang, C. Wang, and Z. Li. A near real-time flood-mapping approach by integrating social media and post-event satellite imagery. *Annals of GIS*, 24(2):113–23, 2018.

[25] Y. Huang. Levels of ai agents: From rules to large language models. *arXiv*, 2024.

[26] M. Ivić. Artificial intelligence and geospatial analysis in disaster management. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLII-3/W8:161–66, august 2019.

[27] K. Janowicz, K. Currier, C. Shimizu, R. Zhu, M. Shi, C. K. Fisher, D. Rehberger, P. Hitzler, Z. Liu, and S. Stephen. Fast forward from data to insight: (geographic) knowledge graphs and their applications. In *Handbook of Geospatial Artificial Intelligence*, pages 411–26. CRC Press, Boca Raton, 1st edition, 2023.

[28] K. Janowicz, S. Gao, G. McKenzie, Y. Hu, and B. Bhaduri. GeoAI: spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond. *International Journal of Geographical Information Science*, 34(4):625–636, Apr. 2020.

[29] F. R. Kearns, M. Kelly, and K. A. Tuxen. Everything happens somewhere: using webgis as a tool for sustainable natural resource management. *Frontiers in Ecology and the Environment*, 1(10):541–548, 2003.

[30] S. Kelly, S.-A. Kaye, and O. Oviedo-Trespalacios. What factors contribute to the acceptance of artificial intelligence? a systematic review. *Telematics and Informatics*, 77:101925, 2023.

[31] P. Lewis, E. Perez, A. Piktus, F. Petroni, V. Karpukhin, N. Goyal, H. Küttler, et al. Retrieval-augmented generation for knowledge-intensive nlp tasks. *arXiv*, 2020.

[32] W. Li. Lowering the barriers for accessing distributed geospatial big data to advance spatial data science: The polarhub solution. *Annals of the American Association of Geographers*, 108(3):773–793, 2018.

[33] W. Li. Geoai: Where machine learning and big data converge in giscience. *Journal of Spatial Information Science*, 20:71–77, 2020.

[34] W. Li, S. Arundel, S. Gao, M. Goodchild, Y. Hu, S. Wang, and A. Zipf. Geoai for science and the science of geoai. *Journal of Spatial Information Science*, (29):1–17, Sept. 2024.

[35] W. Li, C.-Y. Hsu, S. Wang, Z. Gu, Y. Yang, B. M. Rogers, and A. Liljedahl. A multi-scale vision transformer-based multimodal geoai model for mapping arctic permafrost thaw. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2025.

[36] W. Li, M. Song, and Y. Tian. An ontology-driven cyberinfrastructure for intelligent spatiotemporal question answering and open knowledge discovery. *ISPRS International Journal of Geo-Information*, 8(11):496, 2019.

[37] W. Li, S. Wang, S. T. Arundel, and C.-Y. Hsu. Geoimagenet: a multi-source natural feature benchmark dataset for geoai and supervised machine learning. *GeoInformatica*, 27(3):619–640, 2023.

[38] W. Li, S. Wang, S. T. Arundel, and C.-Y. Hsu. GeoImageNet: a multi-source natural feature benchmark dataset for GeoAI and supervised machine learning. *GeoInformatica*, 27(3):619–640, July 2023.

[39] W. Li, S. Wang, S. Wu, Z. Gu, and Y. Tian. Performance benchmark on semantic web repositories for spatially explicit knowledge graph applications. *Computers, environment and urban systems*, 98:101884, 2022.

[40] Z. Li, H. Ning, S. Gao, K. Janowicz, W. Li, S. T. Arundel, C. Yang, B. Bhaduri, S. Wang, A. Zhu, et al. Giscience in the era of artificial intelligence: A research agenda towards autonomous gis. *arXiv preprint arXiv:2503.23633*, 2025.

[41] J. K. Liu, R. Qin, and S. Song. Automated deep learning-based point cloud classification on usgs 3dep lidar data using a transformer. In *IGARSS 2024-2024 IEEE International Geoscience and Remote Sensing Symposium*, pages 8518–8521. IEEE, 2024.

[42] L. Ma, Y. Liu, X. Zhang, Y. Ye, G. Yin, and B. A. Johnson. Deep learning in remote sensing applications: A meta-analysis and review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 152:166–77, june 2019.

[43] A. Mansourian and R. Oucheikh. ChatGeoAI: Enabling Geospatial Analysis for Public through Natural Language, with Large Language Models. *ISPRS International Journal of Geo-Information*, 13(10):348, Oct. 2024.

[44] A. Mansourian and R. Oucheikh. Chatgeoai: Enabling geospatial analysis for public through natural language, with large language models. *ISPRS International Journal of Geo-Information*, 13(10):348, 2024.

[45] A. E. Maxwell, T. A. Warner, and F. Fang. Implementation of machine-learning classification in remote sensing: An applied review. *International Journal of Remote Sensing*, 39(9):2784–2817, 2018.

[46] G. McKenzie, K. Janowicz, and D. Seidl. Geo-privacy beyond coordinates. In *Geospatial data in a changing world: Selected papers of the 19th AGILE Conference on Geographic Information Science*, pages 157–175. Springer, 2016.

[47] T. Miller. Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence*, 267:1–38, Feb. 2019.

[48] J. Murray, I. Sargent, D. Holland, A. Gardiner, K. Dionysopoulou, S. Coupland, J. Hare, C. Zhang, and P. M. Atkinson. Opportunities for machine learning and artificial intelligence in national mapping agencies: enhancing ordnance survey workflow. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 43:185–189, 2020.

[49] S. Newsam. Forward thinking on geoai. In *Handbook of Geospatial Artificial Intelligence*, pages 427–34. CRC Press, Boca Raton, 1st edition, 2023.

[50] R. Ngo, L. Chan, and S. Mindermann. The alignment problem from a deep learning perspective. *arXiv*, 2025.

[51] R. S. Olson, R. J. Urbanowicz, P. C. Andrews, N. A. Lavender, L. C. Kidd, and J. H. Moore. Automating biomedical data science through tree-based pipeline optimization. *arXiv*, 2016.

[52] G. Poli, S. Cuntò, E. Muccio, and M. Cerreta. A spatial decision support system for multi-dimensional sustainability assessment of river basin districts: the case study of sarno river, italy. *Land Use Policy*, 141:107123, 2024.

[53] V. Ponce-López and C. Spataru. Social media data analysis framework for disaster response. *Discover Artificial Intelligence*, 2(1):10, 2022.

[54] E. Psomiadis, N. Charizopoulos, N. Efthimiou, K. X. Soulis, and I. Charalampopoulos. Earth observation and gis-based analysis for landslide susceptibility and risk assessment. *ISPRS International Journal of Geo-Information*, 9(9):552, 2020.

[55] R. G. Raskin and M. J. Pan. Knowledge representation in the semantic web for earth and environmental terminology (sweet). *Computers & geosciences*, 31(9):1119–1125, 2005.

[56] M. Reichstein, G. Camps-Valls, B. Stevens, M. Jung, J. Denzler, N. Carvalhais, and Prabhat. Deep learning and process understanding for data-driven earth system science. *Nature*, 566(7743):195–204, 2019.

[57] I. Salehin, M. S. Islam, P. Saha, S. Noman, A. Tuni, M. M. Hasan, and M. A. Baten. Automl: A systematic review on automated machine learning with neural architecture search. *Journal of Information and Intelligence*, 2(1):52–81, 2024.

[58] A. Shaamala, T. Yigitcanlar, A. Nili, and D. Nyandega. State-of-the-art machine learning models for geospatial analysis: A systematic review of urban and environmental studies. *SSRN*, 2023.

[59] X. Shi, Z. Chen, H. Wang, D.-Y. Yeung, W.-k. Wong, and W.-c. Woo. Convolutional lstm network: A machine learning approach for precipitation nowcasting. *arXiv*, 2015.

[60] Y. Song, M. Kalacska, M. Gašparović, J. Yao, and N. Najibi. Advances in geocomputation and geospatial artificial intelligence (geoai) for mapping. *International Journal of Applied Earth Observation and Geoinformation*, 120:103300, june 2023.

[61] L. V. Stanislawski, E. J. Shavers, S. Wang, Z. Jiang, E. L. Usery, E. Moak, A. Duffy, and J. Schott. Extensibility of u-net neural network model for hydrographic feature extraction and implications for hydrologic modeling. *Remote Sensing*, 13(12):2368, 2021.

[62] A. Steimers and M. Schneider. Sources of risk of ai systems. *International Journal of Environmental Research and Public Health*, 19(6):3641, 2022.

[63] H. Su, R. Chen, S. Tang, Z. Yin, X. Zheng, J. Li, B. Qi, et al. Many heads are better than one: Improved scientific idea generation by a llm-based multi-agent system. *arXiv*, 2024.

[64] D. Szwarcman, S. Roy, P. Fraccaro, Þ. E. Gíslason, B. Blumenstiel, R. Ghosal, P. H. de Oliveira, et al. Prithvi-eo-2.0: A versatile multi-temporal foundation model for earth observation applications. *arXiv preprint arXiv:2412.02732*, 2024.

[65] E. Tabassi. Artificial intelligence risk management framework (ai rmf 1.0). *NIST AI 100-1*, 2023.

[66] The White House. Removing barriers to american leadership in artificial intelligence, jan 2025. Available from: https://www.whitehouse.gov/presidential-actions/2025/01/removing-barriers-to-american-leadership-in-artificial-intelligence/.

[67] H. T. Uitermark, P. J. Van Oosterom, N. J. Mars, and M. Molenaar. Ontology-based integration of topographic data sets. *International Journal of Applied Earth Observation and Geoinformation*, 7(2):97–106, Aug. 2005.

[68] U.S. Geological Survey. 3d elevation program, 2025. Available from: https://www.usgs.gov/3d-elevation-program.

[69] U.S. Geological Survey. 3d hydrography program, 2025. Available from: https://www.usgs.gov/index.php/3DHP.

[70] U.S. Geological Survey. 3d national topography model, 2025. Available from: https://www.usgs.gov/3d-national-topography-model.

[71] E. L. Usery. Geoai for topographic mapping and the intelligent national map. *Abstracts of the ICA*, 3:1–1, 2021.

[72] C. Wang and J. Han. Dl4scivis: A state-of-the-art survey on deep learning for scientific visualization. *arXiv*, 2022.

[73] S. Wang, P. Qiu, Y. Zhu, J. Yang, P. Peng, Y. Bai, G. Li, X. Dai, and Y. Qi. Review, framework, and future perspectives of geographic knowledge graph (geokg) quality assessment. *Geo-Spatial Information Science*, pages 1–21, Sept. 2024.

[74] C. Wei, Y. Zhang, X. Zhao, Z. Zeng, Z. Wang, J. Lin, Q. Guan, and W. Yu. Geotool-gpt: a trainable method for facilitating large language models to master gis tools. *International Journal of Geographical Information Science*, 39(4):707–731, 2025.

[75] N. Wiegand and C. García. A task-based ontology approach to automate geospatial data retrieval. *Transactions in GIS*, 11(3):355–376, 2007.

[76] P. Woodgate, I. Coppa, S. Choy, S. Phinn, L. Arnold, and M. Duckham. The australian approach to geospatial capabilities; positioning, earth observation, infrastructure and analytics: issues, trends and perspectives. *Geo-spatial information science*, 20(2):109–125, 2017.

[77] A. Xiao, W. Xuan, J. Wang, J. Huang, D. Tao, S. Lu, and N. Yokoya. Foundation models for remote sensing and earth observation: A survey. *arXiv*, 2024.

[78] C. Yang, M. Goodchild, Q. Huang, D. Nebert, R. Raskin, Y. Xu, M. Bambacus, and D. Fay. Spatial cloud computing: How can the geospatial sciences use and help shape cloud computing? *International Journal of Digital Earth*, 4(4):305–29, 2011.

[79] S. Yao, Y. Lu, and C. Wang. Visnerf: Efficient multidimensional neural radiance field representation for visualization synthesis of dynamic volumetric scenes. *arXiv*, 2025.

[80] J. Zhang, P. Atkinson, and M. F. Goodchild. *Scale in Spatial Information and Analysis*. CRC Press, 0 edition, 2014.

[81] Y. Zhang, Z. He, J. Li, J. Lin, Q. Guan, and W. Yu. Mapgpt: An autonomous framework for mapping by integrating large language model and cartographic tools. *Cartography and Geographic Information Science*, 51(6):717–43, 2024.

[82] B. Zhao and J. Feng. A humanistic future of geoai. In *Handbook of Geospatial Artificial Intelligence*, pages 406–410. CRC Press, 2023.

[83] X. Zhou and W. Li. A geographic object-based approach for land classification using lidar elevation and intensity. *IEEE Geoscience and Remote Sensing Letters*, 14(5):669–673, 2017.

[84] X. X. Zhu, D. Tuia, L. Mou, G. S. Xia, L. Zhang, F. Xu, and F. Fraundorfer. Deep learning in remote sensing: A comprehensive review and list of resources. *IEEE Geoscience and Remote Sensing Magazine*, 5(4):8–36, 2017.

[85] M. Zook, S. Barocas, D. Boyd, K. Crawford, E. Keller, S. P. Gangadharan, A. Goodman, et al. Ten simple rules for responsible big data research. *PLOS Computational Biology*, 13(3):e1005399, 2017.