DOI: 10.1111/tgis.12830

REVIEW ARTICLE

Transactions in GIS WILEY

GeoAI in the US Geological Survey for topographic mapping

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Abstract

Geospatial artificial intelligence (GeoAI) can be defined broadly as the application of artificial intelligence methods and techniques to geospatial data, processes, models, and applications. The application of these methods to topographic data and phenomena is a focus of research in the US Geological Survey (USGS). Specifically, the USGS has researched and developed applications in terrain feature extraction, hydrographic network extraction, and semantic modeling. This article is a documentation of the recent work and current state of research and development. The article helps define the accomplishments and directions of research and applications in fields of GeoAI for topographic mapping within the USGS and more broadly.

1 | INTRODUCTION

The acquisition of nationwide data sets of high-resolution elevation, hydrography and associated data including transportation, trails, geographic names, structures, boundaries, land cover, and orthographic images is a current effort of the National Geospatial Program (NGP) of the USGS. The goal of this acquisition is to better record the USA's natural and built structures in support of science and decision applications for the US Geological Survey (USGS) and Department of Interior, as well as other federal and state agencies and the public. The frameworks and structure of these data sets, which are all core parts of the National Map, are provided in the 3D Elevation Program (3DEP) and National Hydrography Dataset (NHD) websites. Ongoing research in the field of spatial artificial intelligence applications known as geospatial artificial intelligence (GeoAI) aims to supplement the acquisition, processing, and use of these national data sets for mapping, modeling, and decision-making applications. This article will present current (2021) USGS work in feature extraction, multiscale processing, hydrography, terrain feature extraction and representation, geospatial knowledge, and semantic representation for logical and inference processing. The focus is on the use of GeoAI methods and techniques in topographic mapping and digital geospatial databases for this work.

The research and design of an intelligent National Map require the use of GeoAI research and implementation to be capable of feature extraction, representation, knowledge construction and automated logic and inference from the geospatial data. The specific problem addressed in this research is how to use GeoAI methods and techniques to meet the needs of an intelligent National Map. Those needs include feature detection, extraction, representation, visualization, and parameterization for modeling, logic, and inference. This article addresses initial research to achieve an intelligent National Map. The article is organized as an initial review of GeoAI and some application areas with literature citations. The following sections detail the application of GeoAI to topographic mapping applications and the development of these in support of an intelligent National Map (USGS, 2020).

1.1 | Definition of GeoAI

For this research, GeoAI is defined broadly as the application of artificial intelligence (AI) methods and techniques to geospatial data, processes, models, and applications. GeoAI includes AI methods, geospatial big data, and high-performance computing (HPC) to provide technology solutions for data and computationally intensive geospatial problems. The focus within the NGP is on topographic mapping applications of the USGS. Included in this work are applications in hydrographic, terrain, and geographic names feature extraction, semantic logical processing, and HPC implementation of the developed techniques, methods, and solutions for topographic mapping.

1.2 | Current research work in GeoAI

GeoAI has emerged as a new approach to the development, modeling, storage, retrieval, and analysis of geospatial data. It incorporates methods from AI and GIScience, usually combined with HPC and geospatial big data (Li, 2020). Simultaneous development of geospatial applications, big data resources, the Semantic Web (W3C, 2021a) and related technologies with linkages from AI methods and HPC are fueling the advance of geographic information for new types of spatial analysis and applications (Janowicz, Gao, McKenzie, Hu, & Bhaduri, 2020). Specific review of some research and development of GeoAI applicable to topographic mapping follows.

1.2.1 | Hydrographic feature extraction and modeling

The application of AI to hydrology has largely focused on atmospheric modeling and image segmentation (Ball, Anderson, & Chan, 2017). However, there is a growing body of research using AI for modeling hydrologic variables (Nourani, Baghanam, Adamowski, & Kisi, 2014) such as flow (Alquraish, Abuhasel, Alqahtani, & Khadr, 2021), runoff (Han, Choi, Jung, & Kim, 2021; Kratzert et al., 2019), sediment, and flooding (Dazzi, Vacondio, & Mignosa, 2021; Han et al., 2021; Jiang, Xie, & Sainju, 2019; Schmidt, Heße, Attinger, & Kumar, 2020). Surface water modeling is informed by atmospheric modeling, yet hydrologic feature extraction often employs traditional image segmentation methods using reflectance and elevation data. The AI work on surface water feature extraction generally focuses on open water body identification and boundary delineation (Chen, Tang, Kan, Bilal, & Li, 2020; Duan & Hu, 2019; Feng, Sui, Huang, Xu, & An, 2018; Zhang et al., 2020). Although some research addresses fuzzy boundaries in relation to waterbody edges (Chen et al., 2020) and variable feature geometry (Duan & Hu, 2019; Feng et al., 2018), most published AI research on surface water feature extraction primarily focuses on tailoring general image segmentation algorithms for extraction of the water features. These studies do not adequately address feature connectivity, headwater feature extraction, and variable landscape conditions that continue to confound surface water modeling and feature extraction (Fritz et al., 2013; Wohl, 2018). Flood extent mapping (Jiang et al., 2019; Schmidt et al., 2020) and runoff modeling (Kratzert et al., 2019) are other applications of AI, and specifically machine learning (ML), that have received some attention.

1.2.2 | Terrain feature extraction and modeling

LiDAR and other high-resolution elevation data are being acquired as a part of the USGS 3DEP and have sufficient resolution to capture many and varied aspects of terrain features. Terrain features are constituents of the planetary surface, landforms and other natural features which include valleys, canyons, ridges, mountains, lakes, and streams. The Terrain Analysis and Natural Feature Extraction project is creating national products derived from elevation data and decision support systems with the 3DEP and geospatial semantics. The modeling, recognition, and mining methods for terrain features such as mountains, hills, and valleys are grounded in their geomorphological formation, morphometric characteristics such as shape and size, and human interpretation. Hence, the employment of geographic data as a source to extract terrain features hinges upon comprehensive knowledge of both their formation processes and ordinary conceptions of the natural world. Resulting features support topographic science, spatial reasoning, and natural language processing.

Delineating terrain features enhances gazetteers (Goodchild & Hill, 2008), terrain navigation (Biesiadecki, Leger, & Maimone, 2007), emergency response to natural events such as dust storms, floods, and avalanches (Bejiga, Zeggada, Nouffidj, & Melgani, 2017; Kok, 2010; Kömüşçü, Erkan, & Çelik, 1998), and advances our knowledge of land-surface and land-atmosphere processes (Regalia, Janowicz, Mai, Varanka, & Usery, 2018). A better comprehension of the complexities of natural features, such as their extents and geomorphological characteristics and origins, expands our spatial understanding of the Earth.

1.2.3 | Geospatial semantics and ontology

The Semantic Web set of World Wide Web Consortium (W3C) data handling standards is primarily based on the Resource Development Framework (RDF) platform. The basic data model of the RDF, the triple, consists of two nodes that typically represent individual or sets of objects and an edge that represents the relations between them. Nodes connected by lines form a federated graph of related data. Triples improve semantic representation of graph databases by supporting dereferenceable namespaces, a formal logic data schema called an ontology, and a query language, SPARQL Protocol and RDF Query Language (SPARQL) that supports semantic search, inference, and data management. Technologies supporting the Semantic Web have inspired parallel graph model approaches that integrate to create knowledge graphs (KGs). A KG system architecture includes modules to capture and align semantics inherent in particular domains of expertise and infer new data using reasoning engines. As artifacts of knowledge representation and reasoning, ontology fits within the area of AI called neural-symbolic AI (d'Avila Garces et al., 2015).

Geospatial data concepts have made ontology designs more complex and this subject remains an important and rich area for research. Primary technologies of geographic and geospatial information such as geographic information systems (GIS), topological spatial relations, big geospatial data on the internet, and natural language texts can lack specificity because their semantics are largely defined by geospatial coordinate representation and because place names can lack context. Initially, geospatial data triples defined basic vocabularies for latitude, longitude, and their supporting detail that benefited data users in applications such as gazetteer interfaces and place name disambiguation, as demonstrated by some news organizations, for example geonames.org.

The establishment of the GeoSPARQL standard (Perry & Herring, 2012) advanced topological spatial relations between geometric features of the type commonly found in topographic data. GeoSPARQL may eventually offer the possibility of enabling geospatial relation reasoning. However, the storage, retrieval, and processing of geospatial feature coordinate geometries present a challenge (Regalia, Janowicz, & McKenzie, 2017). Geospatial semantic topics are increasingly included in advanced ontology research such as ontology alignment and spatially enriched knowledge graphs (Amini, Zhou, & Hitzler, 2020; Janowicz et al., 2020; Pour et al., 2020). Perhaps the earliest leader in national topographic data delivery following Semantic Web standards was the United Kingdom Ordnance Survey (OS; Goodwin, Dolbear, & Hart, 2008). Currently (2021), OS has integrated linked identifiers to a range of digital geospatial entities and data products to advance workflows (Ordnance Survey, n.d.).

A particular area of AI research is symbolic reasoning algorithms hybridized with neural networks. Such systems can be called "neural-symbolic" or "machine reasoning" systems. Symbolic AI is powerful at manipulating and modeling abstractions but deals poorly with massive empirical data streams, which lack attribution and knowledge needed for logic and reasoning. A long-term goal for GeoAI is the design of computational models that combine ML and reasoning to benefit from statistics and logic (Besold et al., 2017).

1.2.4 | High-performance computing and CyberGIS for GeoAI support

CyberGIS (Wang, 2010, 2016) has established a standard in HPC and GIScience through the use of parallel supercomputing, distributed processing, and cloud support. The impact on geospatial information processing and AI is significant for applications in hydrography, terrain, and other topographic data including scalability to big data and national data sets (Wang, 2010, 2013, 2016).

The following sections of this article provide some details and examples of USGS applications of GeoAI to topographic mapping. The sections are organized as terrain, hydrography, geospatial semantics, HPC and a concluding section on how these lead to an intelligent National Map.

2 | APPLICATIONS IN TOPOGRAPHIC MAPPING

The development of an intelligent National Map for the USGS is the goal of this GeoAI research. The components of an intelligent National Map require feature extraction, feature matching, generalization, multiscale representation, semantic data development, logical inference processing, and graphical user interfaces with query and visualization capability for results of direct queries and connections to the plethora of data and information on the World Wide Web (USGS, 2020).

The USGS is using AI methods, such as deep learning (DL), for geographic feature extraction of terrain, hydrography, geographic feature extents and names from lidar, imagery, historic topographic maps, and other sources. The methods and some examples of real data results are presented below in the detailed discussion of the application of AI methods and feature extraction processes (Arundel, Li, & Wang, 2020; Arundel, Li, et al., 2020). The use of AI in spatial query and search uses a variety of methods including DL and semantic logical processing using semantic data models such as the RDF and logical processing with the Web Ontology Language (OWL; Schreiber & Raimund, 2014; W3C OWL Working Group, 2012). Inference in semantic data models results in the capability to generate new features. To support this logical inference processing and development of new features, the USGS developed and implemented the concept of the map as a knowledge base (MapKB; Varanka & Usery, 2018). Example system design and results of this approach are presented below, and this approach is now being extended from prototype applications to National datasets.

2.1 | Hydrographic feature extraction and modeling

Increased availability of precise topographic data has led to improved hydrologic modeling that can extract more detailed and accurate watershed boundaries and stream networks from elevation data than earlier methods (Clubb, Mudd, Milodowski, Hurst, & Slater, 2014; Metz, Mitasova, & Harmon, 2011; Passalacqua, Do Trung, Foufoula-Georgiou, Sapiro, & Dietrich, 2010; Shavers & Stanislawski, 2020; Shin & Paik, 2017; Tarboton, Schreuders, Watson, & Baker, 2009; Wilson, Lam, & Deng, 2007; Woodrow, Lindsay, & Berg, 2016). However, methods that use flow-accumulation modeling with high-resolution elevation data involve several challenges that are tedious and require expert knowledge and techniques such as parameterizing extraction thresholds, eliminating flow obstructions, identifying headwater locations, and validating and editing features through interactive image interpretation. These methods that ensure the accuracy of collected features make update and maintenance of hydrography data a costly process.

Advances in ML, GeoAI, and HPC have opened new possibilities for improving feature extraction and modeling. Recent research in ML shows promise for extraction of hydrography and other features from LiDAR point cloud and other remotely sensed data (Bernhardt et al., 2020; Chen, Fan, Yang, Wang, & Latif, 2018; Chen et al., 2020; Lin, Pan, Wood, Yamazaki, & Allen, 2021; Shaker, Yan, & LaRocque, 2019; Stanislawski, Brockmeyer, & Shavers, 2018, 2019; Xu, Jiang, Shavers, Stanislawski, & Wang, 2019). New geomorphological tools, such as Whitebox GAT (Lindsay, 2016), and relief visualization tools (Kokalj & Somrak, 2019; Zakšek, Oštir, & Kokalj, 2011), and the full realm of computational tools for working with geospatial data enable testing of new geomorphic and hydrologic analysis techniques (Shavers & Stanislawski, 2018). Resulting geomorphological feature layers and characterizations—such as curvature, topographic position, and geomorphons (Deumlich, Schmidt, & Sommer, 2010; Newman, Lindsay, & Cockburn, 2018; Passalacqua et al., 2010; Stepinski & Jasiewicz, 2011)—are ideal input layers for GeoAI models. Freely available modeling tools that apply ML—such as Tensorflow (Abadi et al., 2016), Pytorch (Paszke et al., 2019), Google Earth Engine (Gorelick et al., 2017)—enable rapid development and testing of new AI modeling techniques such as recursive convolutional neural networks, U-Net, and genetic algorithms. These advanced tools and data in conjunction with HPC enable rapid development and testing for modeling techniques such as extracting hydrographic features for a large area such as the entire United States (Stanislawski, Falgout, & Buttenfield, 2015; Stanislawski, Survila, Wendel, Liu, & Buttenfield, 2018), or features associated with hydrologic modeling, such as roads, bridges, and culverts. Stanislawski, Brockmeyer, and Shavers (2018) employ elevation derivatives and a convolutional neural network for identifying road and stream channel intersections with the aim of automated hydro-conditioning of digital elevation models.

Advances in GeoAI show potential for identifying complex spatial, spectral, and temporal patterns for automated extraction and characterization of hydrographic features. Complex themes represented as layers have been employed for surface water mapping ranging from multispectral optical data to elevation and LiDAR point-cloud derivatives (Stanislawski et al., 2018; 2021; Xu et al., 2021). An example of extending reference hydrographic data to extract additional features for the surrounding area using DL is shown in Figure 1. Methods are also being tested for fully automated extraction of hydrography from elevation by controlling flow accumulation models through DL (Stanislawski et al., 2021). HPC systems provide the computing power to rapidly generate or derive input data layers and test diverse strategies at speeds that make such testing viable.

Complex and varied surface representations of hydrographic features make identification and classification challenging. The task is made more complicated by the rates of land cover change and global ecologic conditions (Donchyts et al., 2016). Researchers at the Center of Excellence for Geospatial Information Science (CEGIS) are also developing methods for stream channel characterization (Shavers & Stanislawski, 2020; Stanislawski, Buttenfield, Kronenfeld, & Shavers, 2020) and multiscale representation (Kronenfeld, Stanislawski, Buttenfield, & Brockmeyer, 2020; Stanislawski, Finn, & Buttenfield, 2020) to advance informed scaling necessary for an intelligent National Map.

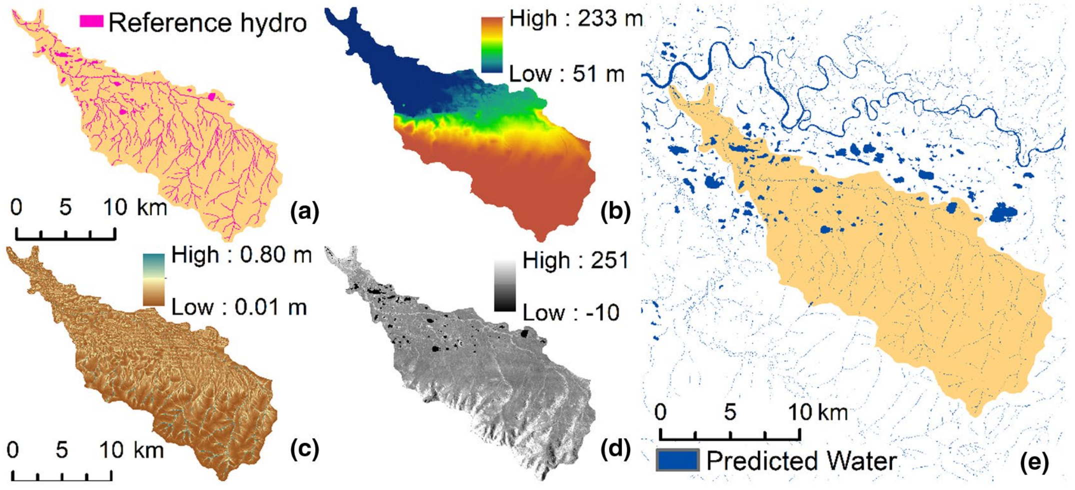

FIGURE 1 Extending elevation-derived hydrography with deep learning. At left is (a) reference elevation-derived hydrography, and three input layers derived from interferometric aperture radar (ifsar) data for a watershed in Alaska used to train a neural network to predict hydrography: (b) digital surface model in meters, (c) shallow water channel depth model in meters, and (d) orthorectified ifsar intensity. At right (e) is predicted hydrography for area surrounding the reference data

Applications of GeoAI for hydrographic feature extraction address long-standing questions in hydrology, ecology, and landscape engineering, among others. Identification of stream bank lines informs discharge estimates, and lake extent measurement supports various climate studies.

2.2 | Terrain feature extraction and modeling

The manual discrimination of land surface features is costly and time prohibitive (Adediran, Parcharidis, IPoscolieri, & Pavlopoulos, 2004). Most methods, whether manual or automated, rely on morphological discontinuities in simple elevation derivatives such as slope and curvature, or more complex terrain characteristics such as the topographic position index or surface roughness (Savigear, 1965). These discontinuities can define the boundaries between objects on a continuous field (Minár & Evans, 2008). Whereas approaching feature extraction by maximizing internal and minimizing external heterogeneity is a valid baseline approach, it may not apply well to composite landforms, or even simple ones such as craters and glacial cirques.

Automated methods segment the land surface based on discontinuities in elevation-related characteristics using raster-based pixelwise modeling (Arundel & Sinha, 2020; Li, Arundel, Zhou, Li, & Arundel, 2018), object-based spatial analysis (Arundel & Sinha, 2018), and either graph-based or supervised or unsupervised classification approaches (Zhou, Li, & Arundel, 2018). The majority of methodologies rely on pixelwise supervised classification. For example, new research combines cell-level classification with object-level classification in a supervised scenario (Zhou, 2018). ML approaches, such as support vector machines and random forest, may be incorporated into the classification process (Bhaduri, Gao, Hu, Janowicz, & McKenzie, 2020).

Although most methods of automated terrain feature extraction require the input of an elevation surface (field) or its derivatives, remotely sensed imagery may also be useful depending on the feature type, the environment, and the compelling application.

Modern prevalent methods of terrain feature delineation involve the use of segmentation and classification based on low- to mid-level features and properties such as shape, color, and texture. Whereas these practices are successful at identifying simple and definitive features from small data sets comprising less uncertainty and fewer outliers, their performance decreases as data set size and detection task complexity increase (Li, 2020). Using these methods, there is a requirement to manually engineer the classification of feature attributes to set them as selection criteria.

Recently, deep learning, as an evolution in ML and even AI universally, has pioneered growth in image processing and many GeoAI operations embracing big geospatial data. In comparison to conventional ML techniques, DL models, specifically deep convolutional neural networks, exploit deep (many-layered) neural net structures. These techniques can determine low-level features from raw data and organize those features into mid- to high-level semantics through information propagation and composition. The resulting knowledge reinforces effectual analysis (Li & Hsu, 2020).

Although DL has increasingly been successful in object detection for scene recognition, resources have focused on identifying features such as buildings, roads, people, and airplanes. Several key challenges remain that inhibit progress in automated natural feature detection (is there an object there?), recognition, (what is the object?) and delineation (what is the spatial extent of the object?). First, and most significantly, natural features, as fiat objects, rarely present the clearly discernible edges of bona fide features. Detection tasks are confounded by these vague boundaries, by intrinsically complex composition, and by similarities between classes. A second challenge is the lack of copious, quality training data essential to successful DL applications (Goodfellow, Bengio, & Courville, 2016). A third dilemma is DL algorithm reliance on single-source, non-georeferenced data, such as optical camera images, that fail to exploit the potential of georeferenced, multiresolution data. Because most GeoAI applications are direct imports of tools from computer science, they fail to integrate the geospatial principles that GIS has toiled decades to optimize for the treatment of digital spatial data. Examples include the explicit teaching of patterns related to spatial relationships such as nearby, within, and adjacent, automated handling of changes in scale, and easy overlap of multiple data sources. Finally, as a data-driven methodology, DL success or failure often remains a "black box" to scientists, missing expert knowledge powering theories as to how and why effective ML develops. This problem is exacerbated by limited understanding of how human and ML processes relate.

The general goals of continuing research at the USGS are to pioneer methods to automatically map terrain features for national mapping and blaze a trail for analogous work in other subject-matter domains (Figure 2). This work has focused not only on GeoAI but also on semantics-based extraction rules in the development of the landform reference ontology (Sinha et al., 2018), currently being cultivated for Semantic Web for Earth and Environmental Terminology harmonization. However, as mentioned above, feature engineering using set criteria often fails to accurately delineate natural features, although it can provide a generalized classification to extract more precise locations. To address this problem, recent research has advanced the creation of DL data sets and tools specifically designed for application to natural features. GeoNat v.1, for example, is a natural feature data set that supports AI-based mapping and automated detection of natural features under a supervised learning paradigm (Arundel, Li, & Wang, 2020; Arundel, Li, Wang, et al., 2020). TerrainAI is a National Science Foundation funded framework in progress that tests the dataset in object detection via a popular DL model, Faster-RCNN (Arundel, Li, & Wang, 2020; Arundel, Li, Wang, et al., 2020). In other current research, automated DL data sets and procedures for optical character recognition detect natural feature labels on historical topographic maps, including natural feature names and summit spot elevations. This work will continue with DL solutions to natural feature detection and recognition for national mapping and address challenges in developing training data in the geospatial domain, such as scale and geographical representativeness.

2.3 | Semantic representation and knowledge bases for topographic data

The initial objective toward applying formal semantics and inference reasoning for data from the National Map was to create sets of linked open data (LOD) using RDF. LOD consist of core specifications converted from GIS to triples in relatively simple forms to enable reuse with other data in accordance with the "base" character of

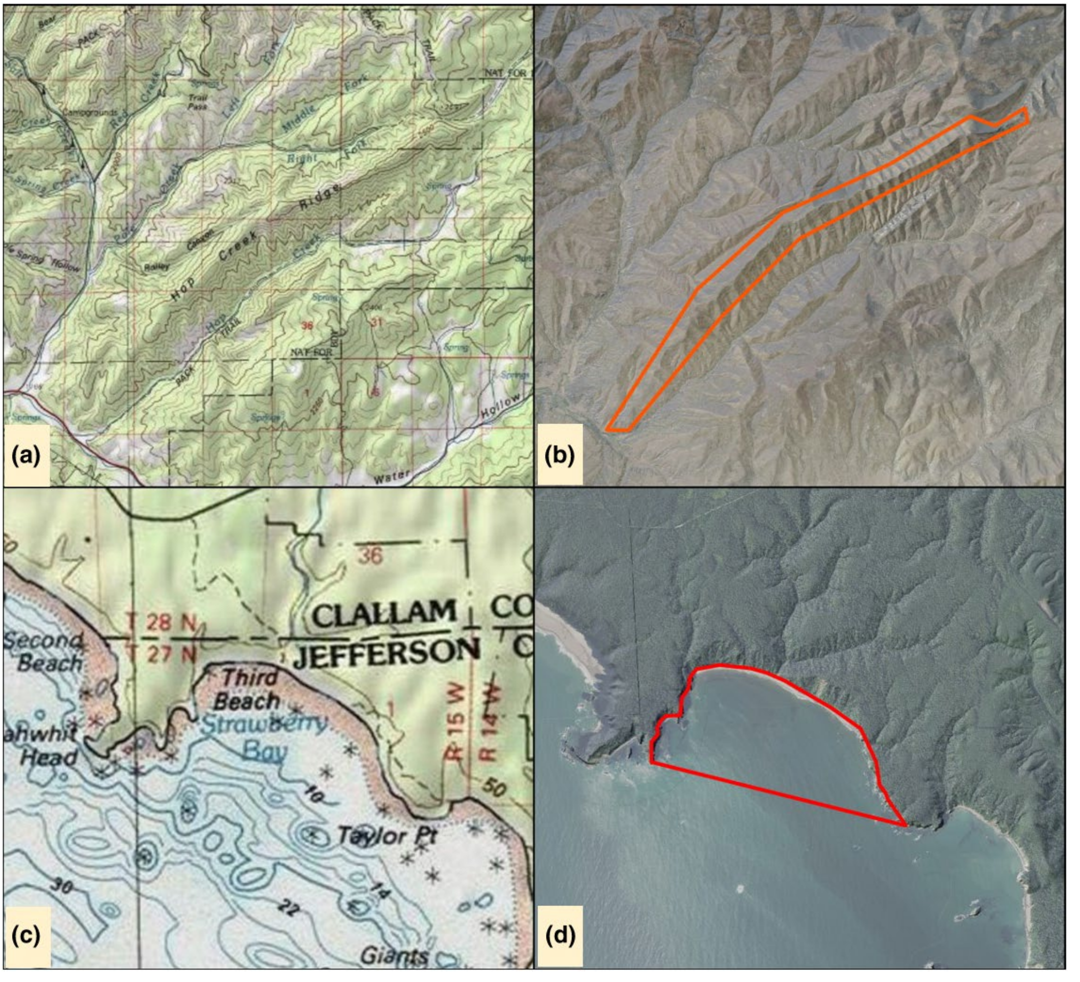

FIGURE 2 Extraction of two terrain features types, ridges and bays. (a) Hop Creek Ridge, UT, labeled in the historical topographic map collection (HTMC) and (b) extent extracted from elevation and imagery data. (c) Strawberry Bay, WA, labeled in the HTMC and (d) its extent

national topographic maps. Ontology models using the logic vocabulary of OWL were designed for cross-thematic entity interoperability. To test these data using queries and reasoning, a semantic technology system architecture was needed to support the graph triplestore, SPARQL endpoint, and reasoning software. The system was designed and built using primarily free and open-source software and custom software scripts to execute and test the ontology models. Data sets transformed from the National Map were organized as schemas of feature semantics based on data themes collected nationwide and standardized for over 125 years. Individual feature instances have spatial and non-spatial properties, including metadata that are normally stored outside the GIS layer, and basic taxonomy. The primary challenge of this work is establishing a system for linked universal resource identifiers (URIs) using connections to major vocabularies such as those published by the Open Geospatial Consortium (OGC, 2021) and the World Wide Web Consortium (W3C, 2021b). An approach for the specification of complex topographic features as subgraphs was described by Varanka (2011).

Ontology engineering directly from GIS databases is an efficient beginning for capturing explicit or implicit semantics of source data. Post-processing is required to improve semantic relations among entities through the inclusion of logic properties and to promote ontology alignment. The limited vocabularies for spatial relations are still in development for many geospatial data concepts. A study of topographic properties and relations based on natural language definitions helped clarify the formal semantics for their representation as graphs (Varanka & Caro, 2013; Varanka, Carter, Usery, & Shoberg, 2011). Database semantics are more intuitive when integrated with upper-level science ontologies. Such integration was demonstrated using the NHD (Varanka & Usery, 2015). That work was applied toward automated geospatial ontology alignment with semantics of significantly different conceptual bases (Cheatham, Varanka, Arauz, & Zhou, 2020).

An overall system was developed exploring various data handling stages, including data conversion, data model transformation, storage and processing, information retrieval, reasoning, and interactive visualization. The theoretical and conceptual bases of the implementation were tested using different iterative approaches and modules. Investigations focused on feature-based information retrieval, to test GeoSPARQL for processing feature relation queries, and the implementation of browseable graph search functionality using the map interface (Baumer, Powell, & Varanka, 2018; Powell & Varanka, 2017) (Figure 3). The map interface was integrated with other open-source software components for data storage and a SPARQL service endpoint (Wagner, Varanka, & Usery, 2020). Annotation property research and use are limited in the current Semantic Web literature; however, the creation of annotation properties from separate metadata files by Wagner and Varanka (2020) improved automated ontology alignment. The system (MapKB) was documented and shared in 2020 with a parallel USGS project for large-scale operational implementation in 2020. The proof-of-concept and technical details are available on GitHub (Bourquin, n.d.).

The MapKB implementation demonstrates that an "intelligent" map for topographic data can be developed and extended for scientific and social information and applications. A base of spatial data semantic models has been clarified and initial interoperability aspects are understood as the basis for a knowledge graph.

2.4 | Implementation of GeoAI for topographic mapping with HPC and distributed computing

The USGS uses HPC clusters and AI software and methods to support our topographic feature extraction and implementation of DL and semantics and analysis. The HPC clusters consist of multiple compute nodes each containing a large amount of memory and CPUs. The high-speed, low-latency connections between the nodes provide speed between nodes on par with local memory. In our HPC environments, resources are requested and allocated explicitly on a per-job basis, with jobs defined as the programs that will run on the cluster. Once a job begins, separate instances of user programs are concurrently executed on each allocated compute node as tasks. Information is provided by the execution environment about the nodes and tasks in the allocation. While some low-level networking constructs are set up, the programs are responsible for organizing inter-task communication on the high-speed connections with either TCP/IP or lower-latency remote direct memory access facilities.

AI software operates within these parameters. The AI frameworks must support setting up this inter-task communication and support spreading their computations across the nodes. Without these supports, individual jobs are limited to running on a single compute node. Even when limited in such a way, it can be possible to make more use of cluster resources when there are enough independent jobs to fill more nodes. For example, one may need to execute multiple trainings in order to compare different training sets and parameters. In this case, one's own software must directly orchestrate the distribution of work and determine which tasks will run. This can be done with a modest Python script in concert with the job scheduler. CEGIS has made more use of multiple single-node training runs, but preliminary training runs using multiple nodes have been completed.

The resources that support our GeoAI efforts include a CEGIS internal hardware cluster-based system named Unity, consisting of 12 nodes interconnected with an Infiniband network. Other USGS supercomputing resources accessed for the AI work include a supercomputer cluster, Yeti, in Denver, Colorado, and additional clusters, Tallgrass and Denali, located at Earth Resources and Science Observation Center in Sioux Falls, South Dakota. All are accessible

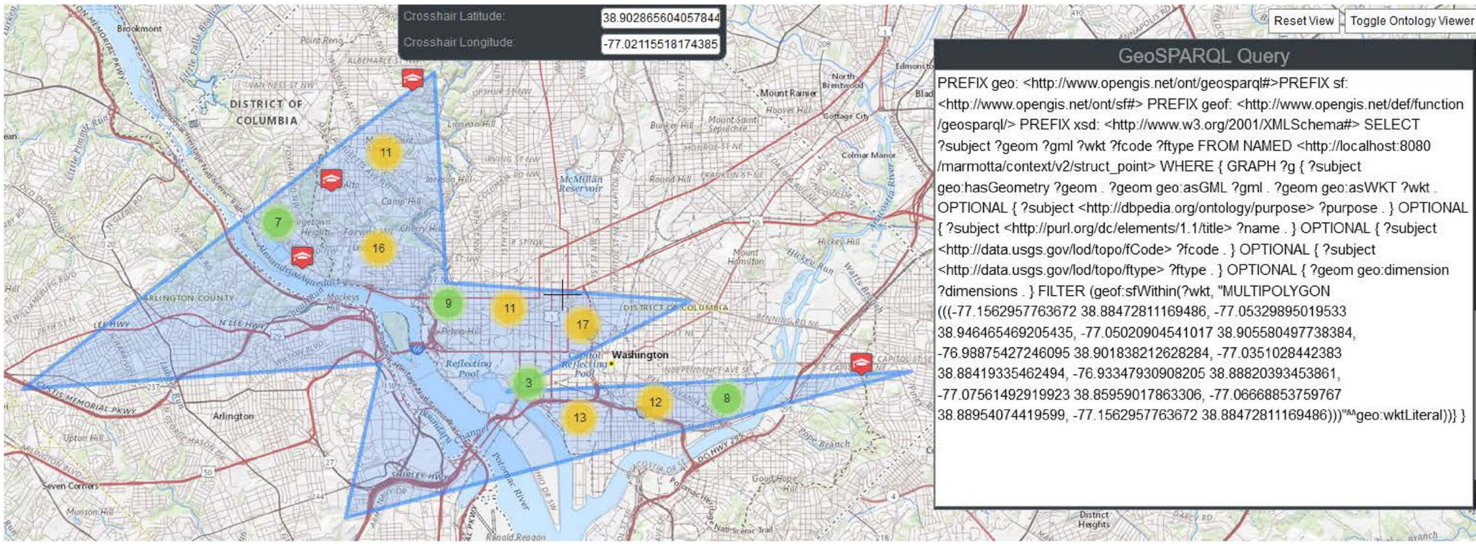

FIGURE 3 The user interface showing generated output of a custom GeoSPARQL query from the query builder. Here, the query searched a graph, relating to structure points, using the GeoSPARQL function sfWithin coupled with the latitude and longitude of each point from the user-created geometry (area in blue)

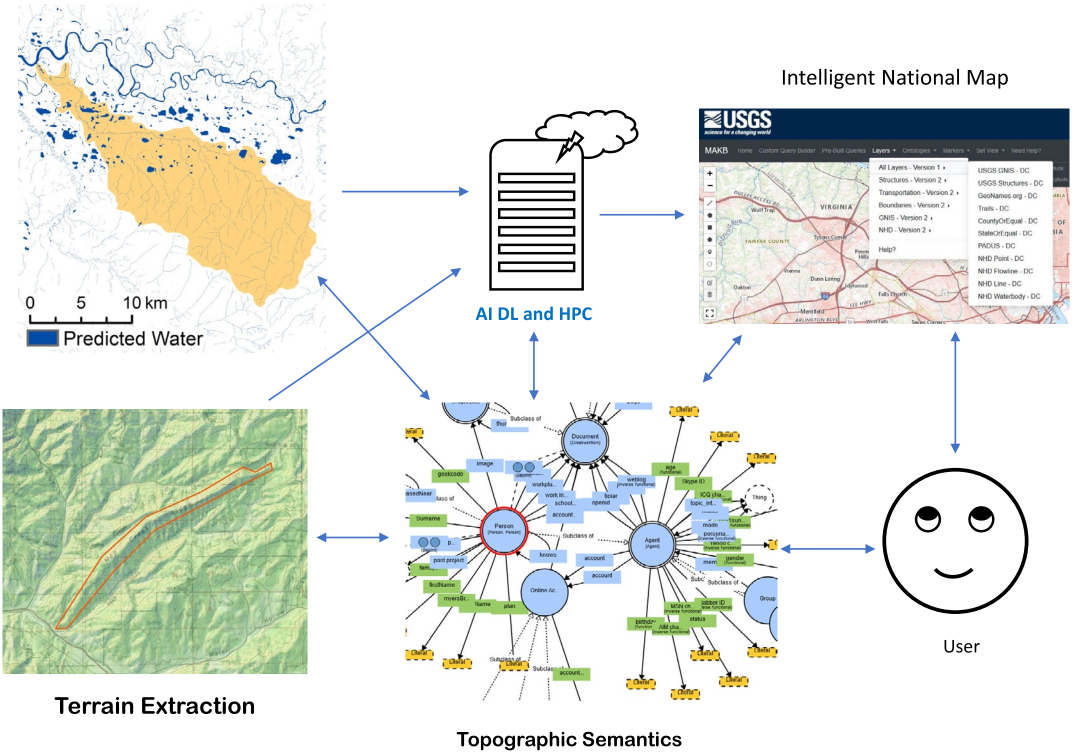

FIGURE 4 Intelligent National Map concept built from terrain, hydrography, and semantic components linked though high-performance computing

in a similar way. The AI research also uses a graphical processing unit (GPU) node named Serenity permitting a high degree of parallelism. Common AI frameworks have core features implemented in this fashion, so when configured, AI software will take advantage of the GPUs and any traditional processors in the HPC environment.

3 | BUILDING AN INTELLIGENT NATIONAL MAP

The design and development of an intelligent National Map is dependent on GeoAI techniques and methods implemented with national data sets. These data, such as the LiDAR and elevation from the 3DEP; hydrography from the NHD and other sources; imagery; historical topographic maps; and geographic names and features from the Geographic Names Information System provide the basis for feature extraction using DL and traditional ML including remote sensing classification methods. The extracted features contribute to the data sets for the National Map and results are being developed to support automated characterization, generalization, semantic feature representation, and building intelligence into the features. The intelligent National Map includes a semantic representation component in which the features are extracted, then built as GIS data sets within the current National Map data structures, then used through a MapKB interface to build logic and inference with the newly extracted features (Figure 4).

Intelligent data are represented semantically as RDF, which supports logic and inferencing using OWL. Data elements are individually represented with URIs, ontology (metadata), and connection to geometric representations that use image, map, network, topology, and coordinate geometry. Reasoning and inference are supported allowing creation of new features and applications based on the connections. The intelligent National Map provides links to other USGS data, models, and processes, for example, a link from the intelligent National Map to the EarthMap (Jenni et al., 2017) model catalog. The initial MapKB development is a prototype example of an intelligent map that is now being implemented on national data sets. These models connect to data from the National Map, but also have connections to the wealth of data on the World-Wide Web, specifically to RDF data sets, such as DBpedia, Geonames, and other data sets and triplestores. These connections enhance the capabilities and provide the basis for an intelligent National Map.

4 | CONCLUSIONS

GeoAI has emerged as a new paradigm for geospatial data processing and forms a new subfield of GIScience. The USGS is adapting GeoAI to help establish an intelligent National Map. The adoption of these GeoAI techniques and approaches for feature extraction, representation, generalization, visualization, and semantic processing for logic and inference contributes to intelligence in geospatial data. GeoAI methods are being used with basic USGS national data sets of elevation, hydrography, land cover, imagery, historical topographic maps, and other data sets. GeoAI processes are establishing an intelligent National Map and are being interfaced with traditional GIS capabilities, ontologies and semantic representation of geospatial data, and logical and inference processing with OWL and the Semantic Web.

Disclaimer: Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the US government.

DATA AVAILABILITY STATEMENT

All data are publicly available.

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How to cite this article: Usery, E. L., Arundel, S. T., Shavers, E., Stanislawski, L., Thiem, P., & Varanka, D. (2021). GeoAI in the US Geological Survey for topographic mapping. *Transactions in GIS*, 00, 1–16. https://doi.org/10.1111/tgis.12830