The Use of Geospatial Artificial Intelligence Technologies (GeoAI) within National Mapping Agencies: A Review

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Abstract

The field of geospatial artificial intelligence (GeoAI) has brought transformative opportunities to the geospatial domain. Technological advances in machine learning and deep learning, the proliferation of big geospatial data of different sources, computing power capabilities, and the expansion of geographic information systems (GIS) have all contributed to the impact of GeoAI technological trends. National mapping agencies (NMAs) represent a promising and ongoing area for the implementation of GeoAI, enabling them to fully leverage its advantages given the nationwide data infrastructures managed, the missions accomplished, and the challenges faced. However, the implementation of the GeoAI solution also involves technical and ethical constraints that must be taken into account. This paper reviews the integration of GeoAI within NMAs, focusing on practical applications, technical challenges, and ethical considerations. Based on recent scientific literature and institutional reports, the study defines four main application domains: geospatial data extraction, change detection, 3D point cloud classification and standardization of geographical names. The study present how NMAs are leveraging GeoAI to improve efficiency, data quality, and the automation of mapping workflows, while addressing challenges related to data availability, AI infrastructure, and human expertise. The article also discusses key aspects of trustworthy GeoAI, such as explainability, bias and geoprivacy. By bridging applied scientific research and the practical applications, this paper provides a structured overview of a transformative emerging technology, GeoAI, within the context of organizations as specific as NMAs and presents the future trends, such as the development of geofoundational models and agentic AI.

1. Introduction

National mapping agencies (NMAs) provide authoritative and reference geospatial data for their respective countries. All geospatial agencies operate within a dynamic landscape shaped by rapid technological advancements, financial constraints, national obligations, and competition from alternative providers of tools and services (Cantat et al., 2024).

National mapping agencies have undergone significant transformations over the past four decades, particularly with the development of geographic information systems (GIS), remote sensing technologies, and increased computing power. The processes of acquiring, processing, storing, and use of maps have been revolutionized to provide comprehensive, up-to-date, and accurate geospatial information (Geospatial World, 2024).

One of the major trends for geospatial information management in the next years is artificial intelligence (AI) (UN-GGIM, 2025). The field of AI involves not just understanding but also building intelligent entities or machines that can compute how to act effectively and safely in a wide variety of unseen situations (Russell & Norvig, 2022).

Artificial intelligence is offering tremendous opportunities and raises new challenges for geospatial research. Geospatial artificial intelligence (GeoAI) can be considered as a field that integrates geospatial studies and AI to develop intelligent computer programs to mimic the processes of human perception, spatial reasoning, and discovery about geographical phenomena and dynamics and to solve problems related to human and environmental systems and their interactions, with a focus on spatial contexts and roots in geography or GIS (Gao, 2021).

While AI aims to develop intelligent systems capable of reasoning like humans, GeoAI, is the intersection of AI and Geography, aiming to develop next-generation machines that possess the ability to conduct spatial reasoning and location-based analytics, as do humans, with the aid of geospatial big data. This convergence requires extending current AI capabilities towards spatially-explicit GeoAI methods and solutions so that AI can be properly adapted to the geospatial domain by integrating geospatial knowledge and spatial thinking (W. Li & Hsu, 2022).

The application of GeoAI to topographic mapping offers significant opportunities for NMAs worldwide. These agencies are particularly well-positioned to leverage GeoAI and improve their efficiency, data quality, and deliver faster, smarter, and more cost-effective services in the face of various challenges (Kausika & Van Altena, 2025). The adoption of AI technologies is one of the core components of the strategies of NMAs for the next years (Bandrova et al., 2025; IGN, 2022a ; Ordnance Survey, 2025a ; U.S.DOI & USGS, 2021).

The exploitation of GeoAI offer possibilities for optimizing and automating workflows as well as reducing the manual workload. While GeoAI presents considerable advantages, its adoption may also raise significant technical and ethical challenges.

This paper presents the results of a review related to the applications of GeoAI concerning the activities of NMAs, along with the main challenges and ethical considerations.

2. Methodology

This paper is based on scientific literature research performed on GeoAI, exploring its methodological foundations, and

applications and undertaking in-depth investigations on its practical implementations in several NMAs. The purpose was to identify and collect the documented, relevant, and most recent case studies from the past five years. This research was intended to include not only success stories but also experiences reflecting different approaches to AI adoption within NMAs. These experiences combined scientific research activities or collaborations with academic institutions or industry partners, as well as internal initiatives. Diversity in applications and uses was sought to create as broad a map as possible of the practical uses of GeoAI within NMAs across different continents, representing varying levels of maturity and operationally use cases depending on their stage of development or production, as well as the specific needs. For this research, Scopus and Google Scholar databases were used for scientific articles, focusing on the most recent and frequently cited studies. Technical and institutional reports of NMAs and other organizations including United Nations Committee of Experts on Global Geospatial Information Management (UN-GGIM), United Nations Group of Experts on Geographical Names (UNGEGN), the International Cartographic Association (ICA), EuroGeographics, European Spatial Data Research (EuroSDR) and Geospatial World were also studied. The collection of documents was based on keywords, including "GeoAI", "deep learning", "geospatial", "remote sensing", "earth observation", "mapping", "national mapping agencies" and "review", were used for this investigation.
Given the vast and promising range of applications, the intersection of the academic research’s areas and the analysis of results from academic literature and practical approaches has permitted to categorize and classify the most used, popular and known applications into four categories : geospatial data extraction, change detection, point cloud data classification, and standardization of geographical names.
The second research component focused on the technical and ethical challenges of implementing GeoAI in NMAs to complement the practical applications. Investigations were conducted to understand the technical implications and ethical considerations, highlighting both common and specific aspects inspired by national concerns and challenges. Analysis and comparison of the different experiences revealed the technical aspects involved in developing digital capacity in terms of data, computing infrastructure, and human expertise, as well as the ethical considerations addressed within the framework of trustworthy GeoAI.
A summary of this study was compiled to synthesize the aspects addressing the different points discussed, the applications and methods used, the data employed, as well as the opportunities identified and the constraints encountered.

3. The GeoAI applications and National Mapping Agencies

Geospatial information provides a basic infrastructure for sustainable development and smart public services. The global geospatial industry is experiencing continuous evolution influenced by accelerated technological innovations and increased user demand. Economic projections confirm this trend, with growth estimated from US $530 billion in 2023 to US $655 billion by 2025, representing an annual growth rate of 11% to 12% (Geospatial World, 2024).
Investment flows into AI have increased by a factor close to eight. Experts in the field of AI predict that its impact will be greater than any other technological revolution in human history (Russell & Norvig, 2022; World Economic Forum, 2025).
Deep learning (DL) methods are particularly promising for the field of remote sensing, given the success of deep neural networks in similar computer vision tasks and the availability of large image datasets (Stewart et al., 2022). AI offers several opportunities and perspectives for analyzing geospatial data and extracting information from diverse data sources, including imagery, point clouds, and radar data, collected from various platforms such as satellites, aircraft, drones, and ground systems (EuroSDR, 2025).
The results of a survey published by EuroGeographics and EuroSDR (Figure 1) show that the primary motivations for implementing GeoAI techniques for European NMAs are cost and time optimization, as well as more efficient business processes (EuroGeographics, 2024; EuroSDR, 2022).
The next section presents the applications of using GeoAI in relation to the activities of NMAs, illustrating them with concrete use cases.

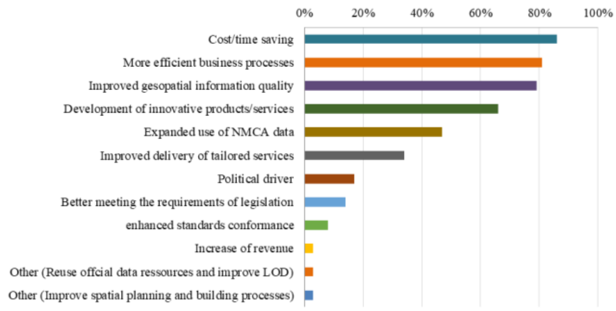

Figure 1. EuroSDR Survey on the purposes for adopting machine and deep learning by 32 projects from European National Mapping Agencies (EuroSDR, 2022).

3.1 Geospatial data extraction

Recent methods based on neural networks have revolutionized geospatial data extraction. They assign a class to each pixel, which is a more complex and time-consuming task than simple image classification (W. Li & Hsu, 2022).
The architectures of DL based segmentation works, are categorized into three types, namely convolutional neural networks (CNN)-based, transformer-based, and hybrid structure-based models, taking advantages of the capabilities for information extraction by CNN-based models and the powerful global information modeling by transformer-based methods (J. Li et al., 2024). Recently, the use of large language models (LLMs) has transformed geospatial data processing (Hao et al., 2025).
In a practical use context within NMAs, the Ordnance Survey (OS) of Great Britain seeks to leverage computer vision and machine learning (ML) techniques for object extraction from images to optimize its efficiency and productivity (Ordnance Survey, 2024b). Automatic data extraction from imagery uses semantic segmentation and object detection models. The process automatically identifies details in the imagery to optimize manual object capture (Bowden, 2024).
With the participation of British universities, the OS developed TopoNet, a convolutional deep learning architecture for extracting buildings from aerial imagery (Murray et al., 2020).
The training data consisted of a labeled dataset of 1.2 million examples using the national topographic data. ResNet-50 was used as the object extractor. Transfer learning was used to reduce the computation time required to train the weights. More advanced model architectures have been developed, such as object-oriented convolutional neural networks (OCNNs) for the classification of land use in urban areas. OCNNs uses convolutional neural networks coupled with object-oriented image analysis (OBIA) to take into account the spatial context

at the object level. The OCNN approach achieves a classification accuracy of 90% and paved the way for the subsequently developed concept of joint deep learning (JDL) for the simultaneous classification of land cover and land use using Markov iteration as an update process (Murray et al., 2020).

In 2025, the OS published new data on over 40 million roofs in Great Britain in its national geographic database, providing valuable information on buildings (Ordnance Survey, 2025b). The new attribute data on roofs provides information on their shapes, orientations, materials, and the presence of green roofs and solar panels. This data was generated using ML methods. The newly collected roof data can be used in several sectors, including insurance, real estate, energy, and emergency services (Ordnance Survey, 2025a).

Moreover, the Advanced Technology for topographic Map Updating (ATMU) project was implemented by the National Land Survey (NLS) of Finland in order to develop GeoAI methods for object extraction, specifically buildings, roads, and water bodies. The manual work involved in updating topographic maps on aerial stereoscopic models, the availability of large volumes of image and light detection and ranging (LiDAR) data nationwide, and the need to leverage technological innovations to improve efficiency motivated the launch of the ATMU project within the NLS map production. The goal of the project is to develop DL methods for geospatial object extraction to reduce manual work, optimize data updating and accuracy, and provide the geospatial community with a high-quality training dataset. The training data used are true orthophotos with a resolution of 30 cm, vector layers, digital elevation model (DEM), and digital surface model (DSM). Different DL architectures including U-Net, MaskR-CNN, DenseUNet, RoadVecNet, DSAMNet and MDESNet, were experienced (Zhu et al., 2023).

Several transfer learning techniques and their combinations with U-Net have been tested. The results obtained for buildings showed a gain in accuracy of at least 5% when transfer learning techniques are used compared to a model trained from scratch (Hattula et al., 2023).

For building, U-Net has reached an accuracy of up to 97.9% when compared to different reference data. The U-Net model for buildings is available for practical implementation in map production. For roads, RoadVecNet showed the best results while the U-Net model performs better for watercourse (Zhu et al., 2023). The use of LiDAR data to improve building extraction was also investigated. The results show that using a LiDAR DSM combined with a high-resolution DEM improves the extracted building shapes (Hattula et al., 2024a). Future research should focus on exploring the integration of 3D data for enhancing building extraction in areas with dense vegetation or complex built structures (Hattula et al., 2024b).

In France, the National Institute of Geographic and Forest Information (IGN) has launched in 2022, the national large-scale land cover maps project (OCS GE) to monitor land artificialization throughout the country. The use of AI in production lines has had a positive impact on the processing and updating of OCS GE data (IGN, 2025b). The OCS GE is a reference vector database for describing land use, designed to monitor changes and support land-use planning (IGN, 2022b, 2025a).

The reference data used are aerial orthophotos and DEMs. The role of GeoAI is to predict the class to which each pixel belongs through semantic segmentation. The creation of national annotated datasets categorized by land cover type was conducted. The training is performed using U-Net and DeepLab V3+ architectures. A cross-validation methods were performed, yielding overall results of approximately 83.2% correctly classified pixels for DeepLab V3 and 86.2% for U-Net. A post-processing including vectorization from other existing databases is performed followed by a photo interpretation to ensure the quality control of the final product (Porte, 2022).

Furthermore, the United States Geological Survey (USGS) launched the 3D Hydrography Program (3DHP) to renew and modernize hydrographic data nationwide. The water data theme provides a new systematic map of hydrography including hydrographic data derived from LiDAR and Interferometric Synthetic Aperture Radar (IFSAR) data which is produced by the 3D Elevation Program (3DEP), enriched with additional attributes to facilitate hydrographic analysis and queries. With regional-scale hydrological data updates planned every 4-5 years, the planning of the 3DHP project has raised different scientific research questions (Anderson et al., 2024).

Advances in ML and the power of computing resources have paved the way for exploiting their potential for object extraction and modeling. The USGS is working on the extraction and representation of hydrographic and topographic features, geospatial knowledge, and semantic representation for logical and inferential processing (Usery et al., 2021). U-Net architecture was used for the automatic extraction of hydrographic features from 5-m resolution IFSAR data in Alaska in order to update and validate hydrographic databases. The training and test data used were the National Hydrography Dataset (NHD) 24k reference hydrographic data. Hydrographic predictions with approximately 80% accuracy were obtained (Stanislawski et al., 2021).

Further work has been carried out, in collaboration with academia, to develop an attention-based U-Net model for extracting fine hydrographic details from high-precision LiDAR data. Evaluation of the results obtained shows that the attention-based U-Net model confirms promising results and achieves significantly improved fluidity and connectivity between classified hydrological details (Xu et al., 2021).

The USGS is adapting GeoAI to help building an intelligent national map. To integrate intelligence into geospatial data, the intelligent map involves several needs in terms of object extraction, generalization, semantic data development, logical inference processing, visualization and geospatial queries (Usery et al., 2021).

3.2 Change Detection

Change detection is the identification of differences in an object or phenomenon by observing it at different dates (Guo et al., 2025). DL techniques are widely used for successful change detection to enable several practical applications (Shafique et al., 2022). The success of the results remains closely dependent on the image data preprocessing phases (W. Li & Hsu, 2022; Shafique et al., 2022).

The most popular DL architectures used for change detection are CNNs such as ResNet, AlexNet, and DenseNet, recurrent neural networks (RNNs), particularly long- and short-memory networks (LSTMs) and more recent models, such as transformers and hybrid CNN-Transformer networks, have also demonstrated their effectiveness in handling complex scenes and multi-scale changes (Bai et al., 2023; Guo et al., 2025; Papadomanolaki et al., 2019; Shafique et al., 2022).

Change detection applications face additional challenges. While segmentation and classification tasks process images taken on a single date, change detection analyzes images acquired on multiple dates simultaneously. This multiplies the limitations associated with extracting information from a single image. Furthermore, multi-temporal images can exhibit radiometric or

geometric inconsistencies, differences in spatial resolution, or variations in sensor technology, further complicating change detection processing. Additionally, the fact that changes are often minimal in images makes it difficult to identify minority pixels that have undergone modification (Bai et al., 2023).
At the level of NMAs, The work of the Cartographic and Geological Institute of Catalonia (ICGC) on GeoAI generally aims to detect changes in order to explore new opportunities for optimizing geospatial production and monitoring processes (Harmsen et al., 2025). The experiment conducted on change detection relies on the use of CNN to identify significant urban changes on a multi-date dataset (2019 and 2023). The training data used are high-resolution RGB and infrared orthophotos at 25 cm and DSM at 1 m resolution supplemented by the calculation of the normalized difference vegetation index (NDVI). The automatic extraction of urban classes from the LCLU (Land Cover Land Use) database in Oracle is carried out to produce binary masks with a resolution of 1 m per 64*64m tile by applying an urban cover threshold rule to assign the binary classes (urban/non-urban). The training of Esri's pre-trained CNN model is performed on historical reference tiles from 2019, followed by inference to apply the trained model to tiles dated 2023 in order to generate probability masks of urbanized areas. A differential analysis is then used to subtract the generated two-times masks (2019 vs. 2023) to isolate urban gains. A validation using photo-interpretation for evaluating the results was conducted, revealing successful detections of major changes and also highlighting prioritized false positives and false negatives in the context of illegal urban planning surveillance (Gómez & Pérez, 2024). Through this project, the difficulties raised concern the radiometric discrepancies observed between multi-date series, the significant processing delays, and the lack of annotated data for change detection (Gómez & Pérez, 2024; Harmsen et al., 2025). These issues raise questions related to computing infrastructure, the availability of training dataset, and the pre-processing process.
The OS of Great Britain uses GeoAI for change detection to assist the work of update operators and inform editing, given satellite and aerial imagery (Bowden, 2024).
The OS is also exploring the development of a geofoundational model which would support various data and applications such as image classification, object detection, semantic segmentation, and change detection (Bowden, 2024; Ordnance Survey, 2025a). Moreover, among the recommended future research topics in EuroSDR is the development of an European foundational model (Harmsen et al., 2025).

3.3 3D point clouds classification and analysis

3D LiDAR point clouds are among the most broadly used data formats produced by actives sensors. Various research studies have been established on using DL methods on point clouds and remote sensing tasks (Diab et al., 2022). Point cloud classification is the basis of point cloud analysis, and several deep learning-based methods have been widely used in this task (Zhang et al., 2023).
The USGS and the French IGN are working on creating nationwide high-density LiDAR point cloud coverage of their respective territories. The data processing workflow incorporates deep learning solutions to automate the classification of the acquired LiDAR data (IGN, 2024; Liu et al., 2024).
The 3DEP is a program to cover the territory of the United States of America by acquiring altimetric data using LiDAR technology across the entire territory and IFSAR, in Alaska, in order to produce the national database of homogeneous, high-resolution and standardized reference terrain for the digital terrain model and 3D point clouds (Lukasi et al., 2025). The first generation of 3DEP enabled the production of 3D LiDAR DEMs and point clouds with a quality level of 2 or higher, signifying an altimetric accuracy of 10 cm and a resolution of 1 m (a quality level of 5 in Alaska provides a resolution of 5 m and an altimetric accuracy of 1.85 m). The project is led by the USGS National Geospatial Program in collaboration with several public and private partners (NGAC, 2023). By the end of 2024, the 3DEP program had achieved 98.3% national coverage and is expected to be completed in 2026. The USGS is already planning the next generation of the program to achieve a 5-year update cycle, improve the quality of the data produced, and build a 3DEP ecosystem to create a single portal for managing altimetry data with various agencies and stakeholders (Lukasi et al., 2025).
The USGS was asked to direct its research towards optimizing LiDAR workflows using AI and ML techniques for processing and validating quality control, as well as change detection to guide data collection priorities (NGAC, 2023).
A research has been conducted to use a trained point transformer architecture to improve the classification of 3DEP point clouds (Liu et al., 2024). The results show more promising performance for the bare ground, built-up, and vegetation classes than for the water and bridge classes. The scalability of this method involves adopting a tiling approach to optimize distributed computing resources. An open-source automatic classification toolkit was developed to enhance and enrich the results of current and future 3DEP data and facilitate its sharing with partners and the wider LiDAR community (Liu et al., 2024). For the next generation of 3DEP, the USGS is expected to use API services for data processing in a cloud environment (NGAC, 2023).
On the other side of the European continent, the coverage of French territory by the high-density (HD) LiDAR program will enable the creation of a 3D map of the terrain. The data from the flights and LiDAR processing, released as open data, meets the various demands and needs of public policies. A territorial coverage of 80% is planned by the end of 2025, utilizing internal resources and relying on the assistance of subcontractors. The IGN leverages the role of AI in its production chains for the processing and classification of LiDAR data. The classification automation process developed by IGN incorporates AI algorithms to extract 12 terrain classes (vegetation, soil, buildings, water, bridge deck, etc.) from LiDAR data with a density of 10 pulses/m² (IGN, 2025b).
Data classification combines the use of the TerraScan tool from the TerraSolid suite to classify the point cloud using explicit rules and the Myria3D deep learning library (Roche, 2024).
This PyTorch-based library is developed by IGN for multi-class semantic segmentation of aerial LiDAR point clouds and predicting the probability of each point in a 3D cloud belonging to predefined classes. It uses 3D segmentation neural networks such as RandLA-Net or, in the past PointNet++, with optimized data processing and evaluation logic during the fitting process (IGN, 2026).
Indeed, AI is used in production for the building and soil classes. For the building class, AI is used to validate the results of the automatic classification generated by TerraScan by leveraging vector data from the national topographic database (BD TOPO). Continuous improvement of the AI model has enabled the automation of decisions for 96% of the classified points, thus reducing the time required for visual verification to address uncertainties. For the soil class, AI is used to classify ground points at rocky ridges. Experiments are underway to

deploy AI models for processing data related to other classes, such as hydrography and vegetation (Roche, 2024).
Moreover, the Singapore Land Authority (SLA) has in charge the Singapore's national 3D mapping program, which provides the basic data required for applications such as climate change monitoring and coastal protection. The program requires the post-processing of LiDAR and aerial imagery data to update the DEM and provide other 2D and 3D datasets. This data infrastructure enables the development of Singapore's 3D digital twin providing essential geospatial intelligence for land-use planning and management, as well as coastal resilience strategies (The Singapore Land Authority, 2026).

3.4 Standardization of Geographical names

The standardization of geographical names is fundamental to any spatial data infrastructure. Conventional approaches to the standardization of geographical names face several constraints, including the processing of large volumes of data, the management of multilingual considerations, and the romanization of non-Latin scripts. AI offers an innovative technique that provides solutions to the various constraints associated with standardizing place names (Gammeltoft, 2025).
In a practical level, the Indonesian Ministry of Public Works has implemented a workflow based on a GeoAI solution to automate the standardization of geographical names. This GeoAI solution uses a YOLOv8 (You Only Look Once) as an object detection architecture from images. LSTM architecture was employed to extract place names from road signs. This process combines these technologies to improve the speed, accuracy, and efficiency of geographical data management (Hartini et al., 2025).
The Czech State Administration of Cadastre and Surveying (ČUZK) used GeoAI techniques to automate the generation of audio files to ensure the correct pronunciation of Czech exonyms. The generated audio files are integrated into its web application (UNGEGN, 2025).
New Zealand's national naming authority, Ngā Pou Taunaha o Aotearoa New Zealand Geographic Board, is required to publicly notify geographical name suggestions and invite submissions with reasons for supporting or objecting in the context to facilitate the communication of information about name features and places, and to preserve New Zealand heritage and culture. The Board has decided to explore the use of AI in the processes of standardizing geographical names in order to ensure consistent and objective analysis, better accuracy and to reduce delays and costs. AI tools such as Claude have been tested for the compilation, processing and analysis of the data collected relating to the different submissions anonymized to protect the privacy of submitters. Based on the results and information obtained, the Board will decide on the suitability of permanently adopting a refined AI process for assisting with processing and analyzing large volumes of submissions in the future while taking into account the legal, privacy, security and ethical considerations (New Zealand, 2025; UNGEGN, 2025).

4. Technical and ethical challenges

4.1 Development of AI infrastructure and human expertise

Data management and computing resources present major challenges for the implementation of DL models. These models require a large volume of training data, which is often very expensive. Using transfer learning and data augmentation can provide practical solutions that optimize the performance of the models used (Kamusoko, 2025).
In the context of NMAs, the French IGN has developed the dataset FLAIR (French Land cover from Aerospace ImageRy), for training GeoAI models (Garioud et al., 2023). It is a high-resolution land cover dataset consisting of over 2,800 km² of high resolution aerial imagery annotated by photo-interpreters, covering diverse landscapes acquired at different dates to train a semantic segmentation AI model applicable at a national scale. This dataset has been updated by integrating multimodal data to include SPOT satellite imagery and Sentinel-1 and 2 data, as well as historical aerial images (EuroSDR, 2025). The IGN has also developed the FRench ALS Clouds from TArgeted Landscapes (FRACTAL) dataset, based on 100,000 dense airborne LiDAR point clouds with high-quality labels for seven semantic classes, covering 250 km², to support research and development of 3D DL methods (Gaydon et al., 2024).
Furthermore, managing large geospatial datasets requires significant computing resources to improve the efficiency of GeoAI applications (Wang et al., 2024). Access to high-performance computing resources for deploying AI systems is essential and requires substantial financial support to back pilot projects and scientific research initiatives in GeoAI (U.S.DOI OIG, 2025).
The widespread use of AI and ML, coupled with cloud computing, presents a remarkable opportunity to leverage technological advancements in scientific fields. The USGS has significant opportunities, both internally and in collaboration with its partners, to utilize cloud computing and high-performance computing (HPC) solutions. Establishing a long-term cloud computing and HPC strategy within the USGS is paramount (U.S.DOI & USGS, 2021).
Furthermore, developing AI expertise through skills training, institutional collaboration, and knowledge sharing is essential for the informed and responsible use of AI at all levels. This includes upgrading human resources through job-specific training, identifying AI experts, and recruiting suitable profiles in data science, ethics, and systems engineering (U.S.DOI, 2025).
Indeed, the optimization of the processing and analysis of geodata is supported by the use of AI-assisted cartographic systems but the final interpretation and validation remain the tasks of human experts. Developing new skills among cartography professionals is critically important by training in areas such as AI cartography and ML (Bandrova et al., 2025).

4.2 Trustworthy GeoAI

A reliable and trustworthy AI system should meet criteria including: validity and reliability, safety, security and resilience, accountability and transparency, explainability and interpretability, respect for privacy, and fairness through the management of harmful biases. Designing trustworthy AI requires a balance between these criteria depending on its context of use (NIST, 2023).
Certain distinctive ethical principles remain specific to GeoAI, such as geoprivacy, spatial fairness and bias, data provenance and quality and the misuse prevention (Yoo, 2026).
Geolocation of data offers diverse applications but it can produce vulnerabilities that can be exploited to infringe on users' privacy. Several privacy-preserving techniques exists such as privacy policy–based mechanisms and obfuscation-based mechanisms by distorting the user's information through some designed algorithms like anonymization and cryptography-based mechanisms (Jiang et al., 2022).
Biases in GeoAI refer to errors and inaccuracies that can affect the data, models, or interpretations of GeoAI applications (Kang et al., 2023). In the context of DL, preprocessing and the choice

of training data are important to reduce bias (Janiesch et al., 2021). Deploying GeoAI solutions requires integrating human intervention to examine and correct biases (Kang et al., 2023).

DL models are often referred to as "black boxes". For applications requiring clear and responsible decision-making, explainability and transparency are necessary (Kamusoko, 2025). Explainability and interpretability of AI are closely related concepts. Explainability concerns the ability to describe and understand the mechanisms involved by an AI model, while interpretability concerns the extent to which the model's predictions can be aligned with understandable and concrete concepts (Mai et al., 2025).

Security in GeoAI involves preventing and mitigating damage to data, models, and operations by responding effectively to malicious behaviors and recovering from incidents (Yoo, 2026). The deployment of security requires an operational framework integrating safety, security, reliability, and resilience by ensuring governance, documentation, testing, verification, and continuous monitoring (NIST, 2023).

GeoAI safety involves integrated governance ensuring security, robustness, and integrity, combined with risk assessment, verification, monitoring, and auditing. The ethics of GeoAI should not be perceived as an obstacle to innovation, but rather as an infrastructure that guarantees the trustworthy GeoAI (Yoo, 2026). Through scrutiny, auditing, and legal mechanisms, AI technologies can be used and developed trustworthy (Oluoch, 2024).

Within NMAs, the British OS signed, in 2021, the Locus Charter, an international guideline for the ethical and responsible use of location data (EthicalGeo, 2021; Ordnance Survey, 2022). The United Kingdom Geospatial Commission addressed ethical issues by publishing a policy paper in 2022 outlining guidelines ethical use for public confidence in location data (Geospatial Commission, 2022).

The need to document and audit AI systems is one of eight principles of the AI charter established by the OS to ensure their explainability. The OS has implemented its own internal charter, the Responsible AI Charter, in 2024, outlining practical rules for the use of AI for geospatial data. The eight principles underpinning this charter are first responsibility and good governance by ensuring the monitoring, improvement, and documentation of any AI system to guarantee explainability, non-discrimination, fairness, technical robustness, confidentiality, and security. The OS ensures compliance with all governance frameworks, standards, and regulations related to responsible AI, while prioritizing accountability over technical capabilities (Ordnance Survey, 2024a).

Furthermore, Ethical considerations cover the entire lifecycle of an AI system, from design to deployment. The principles of clarity, documentation, critical review, and governance apply to the entire AI ecosystem. Therefore, the impact on stakeholders is also taken into account by the analysis of the risks and social consequences of the use of AI (Ordnance Survey, 2024a).

5. Results and Discussion

With regard to the topics presented and summarized in figure 2 and through reviewing those various experiences and given the common and specific needs arising from each organization's unique context, it emerges that the NMAs’ position as providers of national-level, reference geospatial data allows them to access a wide range of vast data sources for training and implementing GeoAI solutions. Restructuring, harmonization, and labeling are necessary to build ready-to-use training datasets.

Depending on the levels of research and development activities implemented and the collaboration with academia, the model and architectures used are either existing, pre-trained, or developed in-house, in order to bring AI developments closer to practical production needs. Those AI developments are associated with appropriate production workflows. While the models used, especially for applications such as geospatial data extraction or change detection, are sensitive to the morphology and type of terrain even within a single territory, sharing experiments, methodologies employed, adapting pipelines and workflows implemented, remain inspiring and adaptive.

There is growing interest in more advanced and broader adoption to meet specific needs, with projects at different levels of maturity and development phases, ranging from "proof of concept" to production deployment, while aligning with scientific advances in the field.

Nevertheless, successful deployment of GeoAI requires the establishment of the necessary computing resources, either autonomously or shared with other institutions, on site or in the cloud, for the implementation of AI-driven projects.

Furthermore, human validation and oversight throughout the entire lifecycle of projects managed by GeoAI is crucial. Developing human expertise is necessary to strengthen human capacity through training, recruitment, and the establishment of teams with complementary profiles.

As for AI applications, they stem from the specific needs of each organization and from the public good, addressing various challenges and structuring projects. The motivations remain common and concern the optimization of workflows, the reduction of manual workload and ensuring the availability and accuracy of geospatial data. Specific objectives arise from the local context.

The technological evolution cycle in AI is very short and rapid, which further accentuates the challenges that organizations face in deploying this technology. Common ethical challenges are raised, such as bias and transparency, but also specific challenges inspired by local concerns.

The adoption of DL techniques within NMAs, compared to other organizations, may present common characteristics and similarities regarding the technical challenges and issues related to the methods used, innovative architectures, data, digital capacity, human expertise to be developed, and ethical considerations of trustworthy and responsible AI. Given the specific nature of the missions of NMAs, the differences lie in the pursuit of accuracy, scalability across the national territories, and consistency with applicable standards and specifications.

Finally, the development of geofoundational models is an emerging area of research that offers transformative potential in the field of GeoAI (Janowicz et al., 2025; Mai et al., 2024). Trained on heterogeneous spatio-temporal data, geofoundational models are specifically designed to perform advanced spatio-temporal processing and are capable of integrating spatial, temporal and other contextual factors to ensure a wide range of downstream tasks (Janowicz et al., 2025). Given their ability to be trained on different data types and to perform several geospatial tasks, they represent a growing interest for NMAs (Harmsen et al., 2025; Ordnance Survey, 2025b).

Furthermore, the combination of agentic AI and spatial intelligence offers promising prospects in several fields (Felicia et al., 2026). Future trends are also moving towards the integration of GeoAI into the development of next-generation spatial data infrastructure, paving the way for growing possibilities given the AI-powered geospatial analytics (Sofianopoulos et al., 2025; Yue et al., 2026).

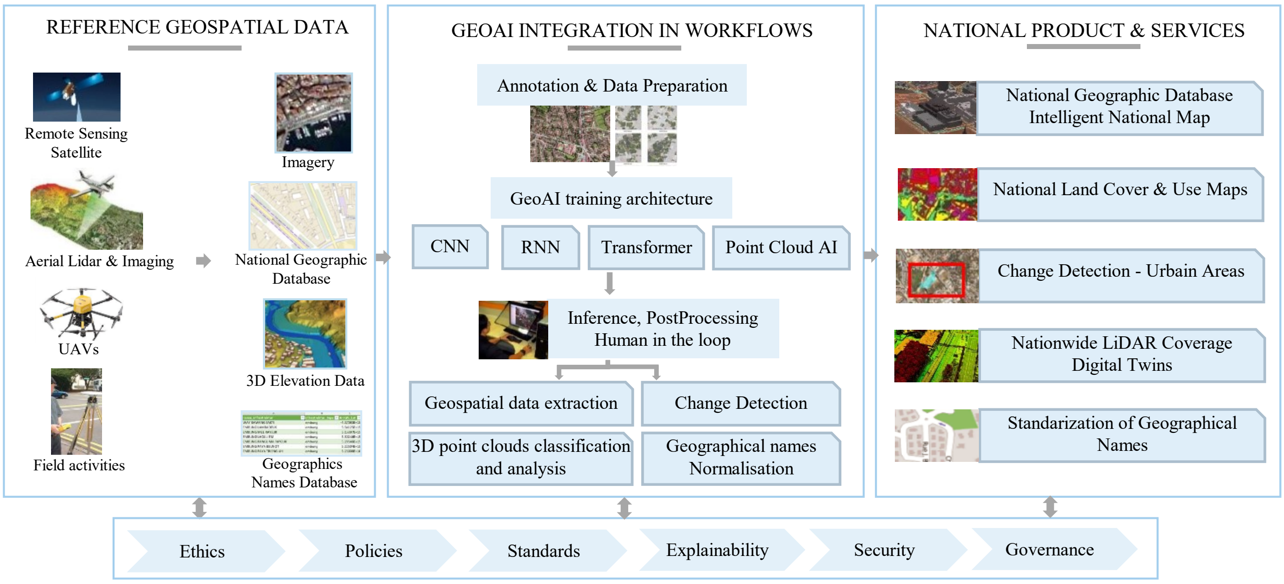

Figure 2. The GeoAI ecosystem for NMAs.

6. Conclusion

With the strength to be integrated with multiple workflows and by offering highly diversified applications, the potential of GeoAI for NMAs remains very promising. The results of this research indicate that the specific context and needs dictate the approach developed by each agency. The implementation of this technology to meet the specific needs of each context and to serve structuring projects and local challenges is paramount. Sharing experiences through collaboration and cooperation is essential to leverage and pool efforts.
Academia and industry also play a significant role in bringing these technologies to market for the benefit of NMAs. This collaboration NMAs, academia and industry would stimulate convergence between scientific research, the development of industrialized cutting-edge technological solutions, and practical production needs for the benefit of the geospatial sector and community. The synergy with all the stackholders would pool to develop geofoundational models, shared AI solutions and safe infrastructure in order to construct a powerful GeoAI ecosystem.
For national mapping agencies, the implementation of GeoAI is not limited to the separate technological, regulatory, ethical or development of digital capacity aspects, but involves the establishment of a global and integrated vision combining these different aspects to strengthen a sustainable and thoughtful digital sovereignty.
Finally, the theme of GeoAI governance, encompassing the frameworks, policies and practices that ensure the ethical, transparent and responsible use of AI technologies, as well as the development of geofoundational models and agentic AI, are areas of scientific research that are generating considerable interest, particularly among the public sector and NMAs.

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