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GeoAI in Topographic Mapping: Navigating the Future of Opportunities and Risks

Bala Bhavya Kausika * and Vincent van Altena

Het Kadaster, Hofstraat 110, 7311 KZ Apeldoorn, The Netherlands; vincent.altenavan@kadaster.nl
* Correspondence: bhavya.kausika@kadaster.nl

Abstract

Geospatial Artificial Intelligence (GeoAI) has been advancing and altering geographic information systems and Earth observation by enhancing the computation and understanding capabilities of these systems. In this context, the application of GeoAI in topographic mapping presents a transformative opportunity for national mapping agencies worldwide. While GeoAI offers significant advantages, its adoption can also introduce new challenges, necessitating organization-wide transformations for sustainable implementation. Opportunities in the future of topographic mapping include improved data processing and real-time mapping capabilities. However, the adoption of GeoAI also brings forth various risks, including data privacy concerns, algorithmic biases, and the need for robust cybersecurity measures, which are pivotal to the national mapping organizations. Given the rapid technological advancements in AI and computing, and the challenges that national mapping agencies currently face, we discuss the potential opportunities and risks of GeoAI from a multi-perspective view. By examining global examples and trends, and synthesizing insights from current applications and theoretical frameworks, this paper aims to provide a comprehensive overview of GeoAI's impact on topographic mapping within the context of national mapping, offering strategic recommendations for stakeholders to leverage opportunities while mitigating risks.

Keywords: GeoAI; topographic mapping; multi-dimension analysis; national mapping and cadastral agency

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1. Introduction

1.1. GeoAI

Geospatial Artificial Intelligence (GeoAI) represents a subfield of spatial data science and artificial intelligence (AI), focusing on methods, systems, and services that leverage geographic knowledge. Being an interdisciplinary field, it integrates machine learning, deep learning, and knowledge graph technologies with high-performance computing and big data mining, enhancing our understanding of geographic phenomena and human–environment interactions [1–3]. It also helps solve geographic problems. Recently, a new perspective has emerged that GeoAI is more than a mere application in the geosciences field. It not only leverages AI to derive insights from geographic data but also provides the spatio-temporal perspective to AI, especially when knowledge, behavior, and intelligence are concerned [4]. In other words, it is about creating AI models that explicitly integrate spatial thinking and reasoning [5,6]. These models consider unique geospatial characteristics, such as spatial autocorrelation, heterogeneity, and dependency, which are often overlooked in traditional AI approaches. GeoAI is gradually changing how topographic data is collected, processed, interpreted, and used [7,8]. National Mapping and Agencies (NMAs) are uniquely positioned to benefit from GeoAI to enhance efficiency, improve data quality, and respond more flexibly to increasing pressure to deliver faster, smarter, and more cost-efficient services amid resource constraints, as well as global, societal, and environmental challenges [9].

1.2. Global Trends in Topographic Mapping

Topographic mapping is evolving due to the convergence of technological advancements, user demands, and global pressures on government institutions. According to the future trends report published by the United Nations Committee of experts on Global Geospatial Information Management, the next five to ten years will see five major driving forces shaping the geospatial information management landscape [10]:

- Technological advancements: Innovations like machine learning, deep learning, and high-resolution imagery are transforming data collection, processing, and interpretation. Big data processing and digital infrastructure will further empower geospatial workflows that are pivotal in topographic mapping.
- Digital Transformation and Real-Time Information: The push toward real-time data integration and digital platforms enables dynamic map updates and on-demand analytics, moving away from static datasets toward continuously refreshed information systems requiring mapping agencies to transform and rethink strategies.
- Rise of New Data Sources and Analytical Methods: New opportunities for data gathering, like drones and sensors, enrich the topographic mapping process. The proliferation of data cubes and integration platforms enhances analytical depth and interoperability.
- Legislative Pressures and Governance Needs: Increasing emphasis on digital ethics, privacy, and responsible AI frameworks guides how GeoAI can be safely implemented. Pressures on public institutions to be transparent and efficient will add urgency to AI governance.
- Changing User Expectations: There is a growing demand for user-centric services, personalized and interactive visualizations, and responsive infrastructure. This shift requires agencies to rethink map production and delivery as a two-way engagement rather than one-way provision.

1.3. Topographic Mapping at the Dutch Kadaster

Topographic mapping involves data collection on the elevation, shape, and features of the land, as well as documenting the locations of natural and man-made objects such as mountains, rivers, roads, and buildings. Cartography, the art of map making, focuses on designing, creating, and interpreting both analog and digital maps to visually and comprehensibly represent topographical and geographical information. At Kadaster, basisregistratie topography (key register topography) is produced annually. It is a collection of topographic maps produced at different scales, the most important being the TOP10NL, which is produced at a 1:10,000 scale [11]. Rather than starting from scratch each year, essential changes are captured, and the maps are revised and updated based on these changes. The production process involves collecting new features or triggers for change detection, updating the map based on these triggers, followed by map design, which includes generalization and quality checks. Current workflows are producer-centric, but a paradigm shift is underway where users take center stage. There is a growing demand for real-time data, user-friendly data/map visualizations, and interactive products.

Within Kadaster, GeoAI applications are being developed and deployed not only for use in topographic mapping but also for supporting questions from different internal and external stakeholders. Use of object detection models for identifying storage tanks, solar panels [12], forest trails, building and road detections for helping operators with data collection for the Multi-national Geospatial Co-production Program, detection of parking garages from streetview images, change detection and quality analysis of existing registers have been explored, and a few are already in production (see Figure 1). National Mapping Agencies (NMAs) within Europe are also actively piloting and operationalizing use cases such as automated roof and building detection, land cover classification, and road feature extraction using deep learning models trained on satellite imagery, LiDAR point clouds, and aerial data [13]. However, the adoption of AI within NMAs is not without challenges.

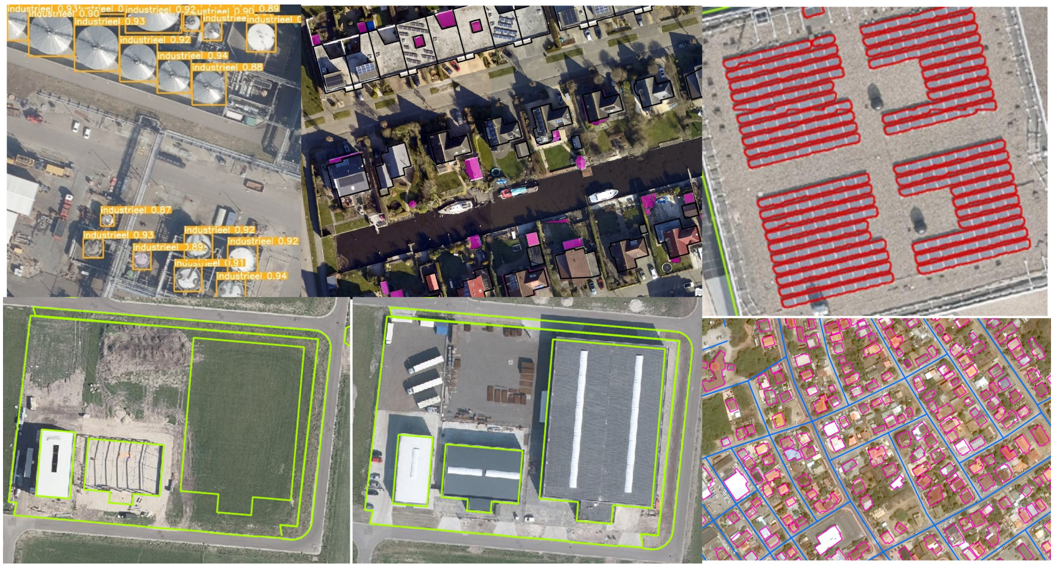

Figure 1. Examples of current GeoAI applications within Kadaster. Various applications require different approaches, which in turn have different system and infrastructure requirements. A few of the examples shown above are the detection and extraction of storage tanks (**top left**), quality checks of existing registers (**top centre**), solar panel installations (**top right**), buildings and roads (**bottom right**), and change detection (**bottom left and centre**).

1.4. Charting the Path: The Future of Topographic Mapping

Despite the growing body of research on GeoAI applications in general geospatial analysis, there remains a notable gap in the literature regarding the systematic integration of GeoAI into national topographic mapping practices. Prior studies have largely focused on technical advancements such as automated feature extraction, terrain classification, and the use of deep learning for generalization demonstrating how AI can improve map production workflows and accuracy [14–18] . With the advent of generative AI, large language-vision models are also being employed for data collection and interpretation purposes [19–21]. These contributions have been invaluable in advancing technical capabilities and proving feasibility through pilot projects and case studies.

At its core, GeoAI enables automation in feature detection [3,22], change intelligence [23], 3D data processing [24–26], and map generalization [27,28]. These are processes traditionally reliant on human interpretation and manual updates. Advancements in the above-mentioned areas promise considerable gains in the speed, consistency, and scalability of map production [29].

However, what remains less explored are the organizational, governance, and strategic dimensions required to move from proof-of-concept to sustainable, production-level adoption of GeoAI within NMAs. Questions about how to structure institutional processes, manage data governance, align AI use with public mandates, and bridge the cultural gap between domain experts and data scientists have received comparatively little attention.

This article aims to address these gaps by mapping the broader dimensions that shape GeoAI adoption within NMAs. By doing so, we seek to complement existing technical research with strategic insights that can guide national mapping agencies and policy makers in effectively integrating GeoAI into their workflows.

For NMAs such as Kadaster, it is essential to understand not only the benefits but also the risks of implementing these technologies. Moreover, the use of this technology should be able to tackle real operational challenges created by global trends like fewer subject matter experts and the competitive labor market, austerity measures, and legacy systems. At the same time, GeoAI comes with its own challenges calling for significant upfront investments, the need for specialized expertise to manage and interpret complex models, legal issues, and the difficulties in the operationalization of pilot projects. Furthermore, establishing the necessary infrastructure while ensuring compliance with policy, governance, and the unique responsibilities of NMAs remains a critical concern.

2. Analytical Framework and Methodological Approach

To structure the exploration of opportunities and risks associated with GeoAI adoption in national topographic mapping, this study develops and applies a five-dimensional analytical framework. The framework comprises the following thematic dimensions: Technology & Process, Data, People, Governance, and Policy & Compliance. Together, these dimensions offer a holistic perspective that connects technical considerations with organizational factors.

This five-dimensional framework was derived through an iterative process involving literature review, followed by expert interviews. Peer-reviewed articles, national mapping agency reports, and AI governance guidelines were analyzed to identify recurrent themes in GeoAI adoption. The study builds on the research agenda on the future of topographic mapping within Kadaster [30]. Institutional insights were gathered from dialogues and expert interviews with peers from other NMAs and research organizations. These discussions helped validate the relevance and practicality of each dimension, and brought to light issues that go beyond purely technical innovation.

While the importance of ethics in GeoAI has been recognized in broader geospatial AI research [14,31–33], this study does not address ethical considerations in detail. The focus here remains on organizational dimensions relevant to topographic mapping, rather than evaluating ethical frameworks.

This paper is conceptual and exploratory rather than empirical: it does not propose new algorithms or present experimental results, but instead maps the landscape of opportunities and risks to help stakeholders see connections and anticipate challenges. The approach is qualitative and stakeholder-oriented, aiming to complement existing technical literature by highlighting the real-world conditions under which GeoAI is being introduced, evaluated, or scaled.

3. Interdependencies in GeoAI Implementation

Kadaster strives for responsible innovation, transparency and accountability, and upholding trust towards citizens. Therefore, the interaction between technical, organizational and societal factors is central to ensure no crucial dimension is overlooked. Five dimensions that reflect these factors have been chosen to define and analyze the opportunities and risks: technology and process, data, governance, people, and policy. These parameters do not operate in isolation (see Figure 2), instead they are interdependent and therefore valuable to study for a balanced assessment that aligns with the organization's strategic goals and principles. These factors are often used to measure an organization's ability to deliver in a technological era [34]. In addition, the challenges mentioned earlier are driven by these dimensions. Therefore, evaluations based on these parameters prepares the organization to adapt to the complexity and inter-dependencies of real-world implementation of GeoAI. Successful adoption of GeoAI lies in the understanding of how these domains influence each other and how well it can be integrated into the existing frameworks. Discussed below is a synthesis of how these domains connect, why they are important, and where the critical points lie.

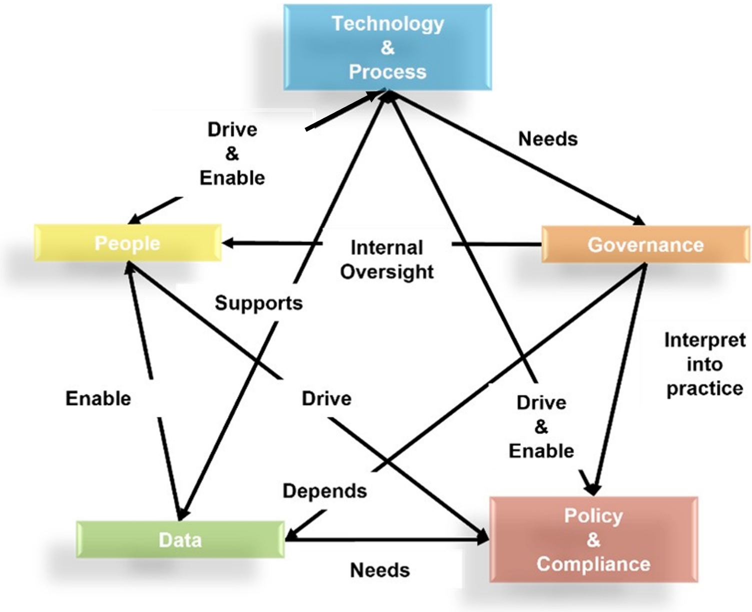

Figure 2. Research perspectives and their inter-dependencies. The relationships are mutually influential, with no single dimension driving the others. These domains interact as a part of a complex, interconnected system that must evolve together.

The **technology and process** perspective examines the core AI methods, tools, and production flows involved in map making. Infrastructure, automation, and optimization are the key pillars. The **data** perspective addresses the input quality, structure, and integrity of geospatial data that fuels the AI systems, in short, the accuracy, access and risk. The **governance** perspective explores internal oversight, accountability, trustworthiness, ethical implementation, and cross-institutional coordination. The **people** perspective focuses on the changing roles, expertise needs, and organizational culture impacted by GeoAI adoption. Finally, the **policy and compliance** perspective situates GeoAI within current and emerging regulatory frameworks, privacy laws, and institutional mandates. Each perspective highlights both opportunities and potential risks, helping to shape a strategic and sustainable path forward. We can also observe the relationship and inter-dependencies of these perspectives from the opportunities and challenges that Geo-AI applications bring, as presented in Table 1. Although most of the opportunities have been analyzed from Kadaster's perspective, they are generically applicable to most NMAs.

Table 1. Opportunities and risks of AI adoption in the geospatial domain.

Opportunities	Risks
Technology and Process	
Automated feature extraction/Map production	High computing and storage costs
Accelerated map updates	Continuous updates and tech debt
Process optimization with AI workflows	Pilots to production gap

Table 1. *Cont.*

Opportunities	Risks
Data	
Assisted and inclusive cartography Operational efficiency and cost savings Real-time data ingestion and delivery Enhanced accuracy with data fusion of high resolution imagery Automated data classification Big data integration across systems AI-ready data	Innovation without impact Security and system compatibility Data provenance (quality) and lineage Risk of geofencing misuse Data leaks or bias in training sets Ambiguity in data responsibility between organizations
People	
Collaboration between domain experts and data scientists Opportunities for upskilling in AI and spatial analytics AI to assist rather than replace human expertise	Reskilling or replacement anxiety Loss of domain knowledge Disparity in digital literacy and communication gaps Ethics of automation in critical public services
Governance	
Control and overview of AI activities Policy aligned innovation Transparency and accountability frameworks to manage AI lifecycle Strategic investment prioritization	Siloed/distributed knowledge of AI capabilities Innovation without direction ("Innovation in name only") Fragmented strategy between innovation and operations
Policy and Compliance	
AI policies can boost trust and ethical use Compliance accelerates responsible innovation GeoAI can support open data initiatives and SDGs	Ambiguity in legal accountability of AI outputs Delay in policy catching up with fast-paced tech Risk of overregulation slowing down experimentation Difficulty applying GDPR and AI Act in geospatial contexts

4. Synthesis of the Inter-Dependencies

The following elaborations help understand the intricate yet strong interconnections between the dimensions and support the opportunities and risks that have been described.

1. **Technology and Process–People**: AI capabilities are only as effective as the people who design, deploy, and monitor them. While GeoAI enables assisted cartography, feature detection, and process optimization, it still relies heavily on domain-specific context for accurate interpretation. Loss of domain knowledge, due to over-reliance on automation or staff attrition, leads to the "black box problem", where AI makes decisions no one can fully explain or validate. Use of generative AI for mapping purposes can pose various risks, especially when the outputs are not evaluated. The accuracy of the outputs is questioned, or outputs are completely rejected, leading to loss of trust. The missing link points to this particular relation, and human-in-the-loop systems with explainability could be a future-proofing strategy.
2. **Data–Governance**: AI models thrive on large, high-quality datasets, but who owns, curates, and governs these datasets becomes critical. In the absence of governance, poor data quality or synthetic data misuse can damage both performance and public trust. When this link is overlooked, one risk scenario could be a model failing during production, creating an impact on costs for rework and reputation damage.
3. **Governance–Policy**: Governance ensures internal oversight, but without alignment with external regulatory frameworks, it is ineffective. Compliance needs governance mechanisms to translate laws into operational practice. If a tool violates regulation,

there might be legal actions, and operations might be halted. Early involvement of legal and compliance teams, and processes where policy is translated to internal regulations helps overcome risks associated with this inter-dependency.

4. **Technology and Process–Data**: Even the most sophisticated AI model is only as good as the data feeding it. GeoAI-based map updates, real-time change detection, and inclusive visualizations require clean, current, and context-rich datasets. Mismatches between data, technology and process could lead to inconsistencies between model expectations and data structures. This in turn leads to errors, and the high cost of processing large datasets limits experimentation. Since NMAs deal with privacy sensitive data, decisions over open source vs proprietary models and infrastructure solutions is largely discussed and is a major source for stalled innovations. Focusing on scalable infrastructure planning and cloud optimization (private, public or hybrid) strategies can help overcome this risk scenario.
5. **People–Governance–Policy**: People drive ethical behavior. Even with laws in place, without organizational culture and staff understanding of compliance, policies are just checklists. This could be problematic for several reasons. Policies are designed to manage risks, but if employees don't understand why they exist, compliance becomes mechanical. A checklist mindset often discourages proactive and adaptable behavior. For example, if new AI tools are introduced, but because they aren't yet reflected in formal policy, staff may avoid using them or could misuse them without proper controls. Another example of ethical decision making beyond policy compliance is if an employee sees a privacy breach that technically is not covered by existing policy, they might ignore it instead of reporting it. This could be because they're not empowered by a culture that values responsible data stewardship. Similarly, staff concerns about AI replacing jobs can lead to resistance. Lack of transparency in how AI affects employment, or failure to communicate safeguards, may erode employee trust and result in low adoption.

In practice, several pilots in the topographic mapping domain illustrate how these inter-dependencies unfold. For instance, an aerial-imagery-based feature extraction tool, though technically successful, failed to scale due to a lack of training and model oversight capabilities in production teams. GeoAI-driven models also encountered resistance when their outputs conflicted with cartographic norms or existing data models. Although such pushback is often framed as concerns over quality or consistency, it seems to reflect deeper issues such as limited AI literacy, uncertainty around model behavior, and anxiety about the impact of automation on existing roles. In other cases, legal uncertainty or established laws around the reuse of third-party data for training or data fusion led to stalled implementations, despite their technical promise. Additionally, several well-functioning pilots failed to operationalize due to fragmented governance and unclear ownership. Infrastructure limitations, such as the absence of GPU environments, prohibition of certain cloud environments have either delayed or hindered the deployment of computationally intensive models or in scaling. These examples underscore that without coordinated progress across organizational, technical, and governance domains, GeoAI innovations risk remaining isolated proofs of concept.

The risks associated with GeoAI adoption across the five thematic dimensions are often interdependent and shaped by institutional context. Table 2 outlines a set of mitigation strategies tailored to the nature of these risks. These are not one-size-fits-all solutions but ideas that can support national mapping agencies and similar institutions in designing context-specific responses.

Table 2. Strategies to reduce risks across key dimensions of GeoAI adoption in topographic mapping.

Dimension	Example Risk	Mitigation Strategy
Technique & Process	Pilot models remain siloed due to lack of production readiness	Develop end-to-end pipelines early; Use scalable infrastructure; engage operations teams from the start.
Data	Limited training data	Use synthetic or open training data; co-create or share data among organizations; develop AI ready data and standards.
People	Production teams lack skills to evaluate and monitor AI models	Cross-train GIS specialists and data scientists; co-design workflows; embed explainable AI tools.
Governance	Model responsibility unclear post-deployment	Assign ownership through MLOps roles; define lifecycle stages; establish internal AI oversight groups.
Policy and Compliance	Regulatory uncertainty around AI-generated outputs	Engage compliance teams early; create internal policies and regulations and brief the employees; align projects with national AI strategies.

5. Towards Strategic GeoAI

While the previous section outlined individual opportunities and risks across five key perspectives—technology and process, data, people, governance, and policy and compliance—it is at the intersection of these dimensions where the most critical challenges often emerge. For example: Loss of domain knowledge or experts has internal and external drivers (think about organizational culture, austerity measures, technological developments, competitive labor market). Failures are rarely due to a single weak point but instead result from misaligned dependencies or gaps in coordination. Considering and evaluating the interconnected dimensions carefully, can lead to successful implementation or scaling of GeoAI. This section also draws inspiration from NMAs with best practices.

5.1. Integrated Strategic Vision

For successful GeoAI adoption in topographic mapping, a clear and organized strategy is key. With evolving technology, its impact and changing user needs, how to keep up and stay relevant? Serving trustworthy data is one side, but how can this be carried out efficiently and promptly? In an era dominated by Google Maps and instant geospatial content, topographic maps, an essential information source for navigational and spatial understanding, are often overlooked or misunderstood by this generation. Many users are unaware of the accuracy, purpose and value that topographic mapping represents. To remain relevant and future-oriented, transforming public perception of mapping institutions is as important as investing in technological capabilities. SwissTopo sets a good example of this with their SwissTopo mobile app, catering to the needs of the younger generation, engaging a digitally native audience with interactive and useful products [35]. Long-term vision considering influencing factors helps integrate the changing landscapes into existing workflows. Ordnance Survey Great Britain's vision and work towards a MasterMap is worth acknowledging [36]. A strategic vision balances top-down implementation with feedback and innovations from bottom-up initiatives.

5.2. Principles for GeoAI Adoption

The success or failure of technology depends on organizational principles that vary across organizational cultures and governance contexts. This is particularly true of disruptive technologies such as AI, where reliance on technology alone does not guarantee success. To ensure transparency and explainability towards both customers and internal stakeholders, frameworks for the sustainable and responsible deployment of AI are recommended. Within the context of Kadaster, we identified a few key organizational principles that play a key role in integrating GeoAI. These go beyond purely technological innovations, ensuring that trust in mapping organizations is retained. The provided framework is intended to guide organizations in developing their own evaluation tools, aligned with their organizational principles and institutional capacities.

- Purpose over technology: GeoAI adoption must begin with clarity of purpose, not merely because it is cutting edge and an appealing innovation. Rather than use deep learning because it is state of the art, NMAs should ask the following: how does this enhance data quality, accessibility, or public trust? Is it about speeding up processes and technical efficiency or does it serve a broader purpose?
- Human-centric by design: AI should be incorporated to assist and not to replace humans. At least in the topographic domain, it is hard to replicate the domain expertise completely and automatically without human intervention. Using AI to support cartographers in repetitive tasks helps retain human judgment in ambiguous or high-risk contexts. Co-designing and implementation with experts from various backgrounds ensures data relevance and usability. Human-in-the-loop also accounts for oversight and maintaining documentation to preserve institutional knowledge and avoid overreliance on models to overcome fake geography or inaccurate representations [37,38] as not all art and science can be fully automated.
- Open and transparent systems: Trustworthy AI systems depend on transparency and explainability, especially in public-sector institutes like the NMAs. Prioritizing open data standards and clear documentation of process steps and model logic, making the outputs interpretable to technical and non-technical stakeholders, and building feedback loops or traceability in decision making supports sustainable adoption. The users should be aware of which outputs were generated using AI, the quality of these outputs and the extent of autonomy of the models. Algorithm registers are a way of accomplishing this and in the Netherlands, public-sector organizations are obliged to register impactful and high-risk algorithms used within the organizations [39] and soon this could be a norm in many countries [40].
- Ethical foundations: Ethics is widely recognized as a foundational concern in the development and deployment of AI. While we cannot explore the topic here in depth, we acknowledge its importance and aim to offer some insights into the complexities involved. Given recent developments in AI, society at large, as well as collectives and individuals, are calling for ethical reflection and consideration of legal and moral aspects that encompass societal and environmental concerns. A more in-depth treatment of ethical frameworks, particularly in the context of national mapping, remains an important area for future research [41].

The temptation here is to approach ethics in isolation: One could start with fundamental ethical questions of what constitutes "good" or "bad" use of AI. While important, such discussions could quickly become abstract, arguing about fairness, justice and truth, all of which vary across cultural, societal and legal contexts. In the geospatial domain, data ethics that concerns bias in training data, misuse of sensitive geospatial information, and informed consent can be examined [14]. Environmental ethics has emerged as another area of concern, especially regarding sustainability and resource demands.

The institutionalization of ethical principles within NMAs, is complex due to diverse roles and responsibilities of these institutions. It requires not only policies but also monitoring mechanisms and leadership commitment [42,43].

In the end, the definition of ethics itself remains questionable. Philosophers offer various approaches from various perspectives. These approaches are either outcomes-based (teleological), rule-based (deontological), or character-based (aretaic) perspectives [44]. Each offers valuable insights but also limitations. Navigating ethical concerns in practice may require combining these approaches in a context-based and balanced manner [45].

5.3. Leveraging Strengths

GeoAI adoption does not require starting from scratch. The success of it lies in amplifying what already works well. Most of the organizations already have robust mapping workflows and the necessary domain expertise. The critical point is the AI transformational journey. Instead of scrapping existing processes, the focus should be to embed AI where it enhances value, not where it introduces unnecessary complexity and risk. Initiatives should focus on identifying quick wins and tipping points for the biggest impact, that is, focusing on low-risk, high-impact opportunities, especially when faced with monetary constraints. Areas where there is already a clear business case, good quality data for training and where domain experts can guide the outputs effectively are low-hanging fruits for quick wins, for example, automated feature extraction in well-known or small areas of interest. Embedding AI tools into existing operational workflows minimizes disruption or the need to redesign the whole process around AI. Change detection or feature updates can be integrated within current map maintenance or update cycles. The cartographic department of Cantabria, Spain is an example of how one could leverage strengths despite of being a small team to create space for innovation without compromising what already delivers public value [46].

5.4. Governance Models

For successful GeoAI adoption governance is vital. Important questions to consider are where should innovations related to GeoAI be organized? Who should steer these? How can successful innovations be operationalized? When there is a problem, who is the point of contact? How can experimentation be encouraged while managing risks? In the context of topographic mapping, data sources span multiple administrative levels and policies are set nationally or internationally. Alignment across various domains is needed to produce topographic information that is reliable. Governance determines where innovation is housed, how it is monitored and how risks are managed. Many organizations including Kadaster are now focusing on this aspect to take GeoAI from being a hopeful experiment to a sustainable operation. Another important aspect of governance is the room for co-creation and collaboration. When key strengths are missing in-house, reliance on other organizations, peers, research or industry to learn and co-create could really boost Geo-AI adoption. Recently, a Nordic initiative for research and innovation on responsible and ethical use of AI has been started [47]. Such initiatives help in sharing and learning from the experiences of other organizations, co-creation or reusing models, which is not only efficient but also tackles the issue of energy consumption while training models.

5.5. Organizational Readiness

Even with a compelling vision, cutting-edge technologies, guiding principles, and sound governance, the adoption of GeoAI will fall short without institutional readiness. GeoAI introduces new ways of working that require continuous learning and upskilling. GIS experts would need AI skills to interpret model outcomes or retrain models to obtain the required outputs. Topographic data operators would have to understand how to effectively integrate outputs from GeoAI to assist them in their work. Thus, AI literacy across roles, from operators to management, can lead to the required pragmatic outlook for AI deployments. In addition, technical expertise in siloed units must be distributed across the organization. Cross-functional teams break these isolated units and foster collaborative innovation that is easier to put in production. As part of this shift, institutions may require new roles that reflect governance strategies and ethical principles. AI ethics officers, data stewards or AI strategy leads can help in aligning innovation with production thereby reducing the current gap. Practical steps towards shift may include internal training programs, peer learning sessions across teams and organizations or mandatory basic AI courses tailored for GIS professionals or data operators. These initiatives can bridge knowledge gaps and improve skill development and equip staff with the necessary critical thinking needed to adopt GeoAI effectively.

6. Outlook

Adoption of AI in the topographic domain is complex and requires organization-wide transformation. From a change in our perspective towards technological advancements to process, organizational, and behavioral change. These changes do not occur overnight but might take years or even decades. GeoAI presents a transformative opportunity for national mapping and cadastral agencies. Its potential depends on how well we integrate it into our work processes. Successful implementation of GeoAI requires a holistic approach; balancing innovation with governance, and automation with accountability. In addition to technology and data, people, governance and policy play a central role in the successful adoption of GeoAI. To harness GeoAI in topographic mapping processes and contribute effectively to society with regard to the sustainable development goals, it is recommended that NMAs embrace collaboration, transparency, and adaptability. The authors foresee a strong focus on developing AI data standards and frameworks, ensuring data lineage and quality. Collaboration across public, private and academic sectors will also be at the forefront as NMAs strive for digital sovereignty.

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