International Journal of Science and Research Archive

eISSN: 2582-8185

Cross Ref DOI: 10.30574/ijsra

Journal homepage: https://ijsra.net/

(Review Article)

Check for updates

Ethical and technical challenges of AI-driven geospatial applications in civil, environmental, and geomatics engineering

John Adeyemi Eyinade *

Department of Surveying and Geoinformatics, Faculty of Environmental Design and Management, Obafemi Awolowo University, Ile-Ife, Nigeria.

International Journal of Science and Research Archive, 2025, 16(01), 1188-1199

Publication history: Received on 07 June 2025; revised on 13 July 2025; accepted on 16 July 2025

Article DOI: https://doi.org/10.30574/ijsra.2025.16.1.2130

Abstract

The field of civil, environmental, and geomatics engineering (CEGE) is changing as a result of the combination of artificial intelligence (AI) and geospatial technologies, or GeoAI. Advanced predictive modeling, spatial automation, and data-driven infrastructure planning at previously unheard-of scales are made possible by this convergence. However, despite these advancements, there are still a number of technical difficulties and unexamined ethical issues with using AI in geospatial contexts. In order to assess how GeoAI is operationalized within CEGE and how ethical and technical aspects intersect throughout its development lifecycle, this study provides a critical synthesis of 30 peer-reviewed publications (2013–2025). From conceptual ambiguity in defining GeoAI to application trends in hydrological modeling, urban planning, and environmental surveillance, five main themes emerge: persistent technical limitations like data heterogeneity, poor model transferability, and high computational demands; ethical risks like algorithmic bias, surveillance-driven privacy erosion, model opacity, and accountability gaps; and the lack of strong governance frameworks, especially in underrepresented global regions. The review shows a disjointed body of knowledge where engineering optimization and ethical foresight are often separated. In response, this study presents an ethics-by-design-based research agenda with a focus on sustainability-centered evaluation metrics, contextualized model development, and participatory co-design. To incorporate ethical protections into the GeoAI pipeline, a conceptual roadmap is put forth. A Critical GeoAI paradigm one that promotes social justice, openness, and ecological responsibility in built environment systems in addition to technical sophistication is advocated in the study's conclusion.

Keywords: GeoAI. Civil and Environmental Engineering; Geomatics; AI Ethics; Spatial Data Governance; Ethics-by-Design; AI Governance

1. Introduction

Traditional workflows are being significantly altered by the growing integration of Artificial Intelligence (AI) across spatially intensive disciplines, especially in the field of Civil, Environmental, and Geomatics Engineering (CEGE) [1, 2, 3]. A significant methodological change is taking place in these data-rich domains, which include the planning, design, analysis, and management of environmental and infrastructure systems [4]. CEGE, which has historically relied on empirical and deterministic models, is increasingly embracing AI-driven methodologies that improve predictive capacity [5, 6], optimize intricate systems, and derive useful insights from large, diverse spatial datasets [7, 8, 9]. There has never been a more pressing need for CEGE professionals to utilize and critically evaluate AI's potential, from intelligent transportation networks and hydrological forecasting to pollution monitoring and land-use classification [10, 11, 12].

* Corresponding author: John Adeyemi Eyinade

The fundamental function of geomatics engineering, the field that supports the collection, processing, and analysis of spatial data, is essential to this change. The spatial scaffolding necessary for CEGE decision-making has long been supplied by tools like Geographic Information Systems (GIS), remote sensing technologies (such as satellite and UAV imagery), and spatial data infrastructures (SDIs) [13, 14]. These tools are now engines for AI integration, enabling dynamic, predictive, and scalable insights, rather than just being repositories of geographic data in the AI era. In order to perform tasks like accurate land use and land cover (LULC) classification and sophisticated urban growth simulations [15], machine learning models have demonstrated remarkable efficacy in analyzing high-dimensional geospatial data [16, 17, 18]. In contrast, GIS offers the analytical framework and spatial logic required to model and visualize these results, enabling a sophisticated interpretation of socio-environmental phenomena [18]. However, there are also complicated ethical risks associated with this AI-geomatics synergy, such as the possibility of surveillance, spatial discrimination, and unanswered issues regarding data ownership and governance [19, 20, 21].

It is becoming more and more necessary to examine the technical viability and morality of AI-enabled geospatial tools as their use spreads throughout CEGE. Unchecked AI implementation could have unintended consequences because of the sectors' direct influence on environmental stewardship, resource distribution, and public safety. Uncertain accountability for engineering failures informed by AI outputs [22, 23], opacity in “black-box” models used in structural or environmental risk decisions [24], privacy erosion from unconsented satellite and drone surveillance [25, 26], and algorithmic bias in zoning and flood-risk assessments [27, 28, 18] are among the risks that have been documented. These difficulties are made worse by technical constraints like poor robustness, limited model generalizability, fragmented data interoperability, and the high environmental cost of computation [28].

Even though normative discussions on AI ethics are gaining traction and research on AI applications in the civil and environmental domains is growing, these two threads are still mainly disconnected. Few studies look at the ways that important ethical issues like fairness, environmental justice, or procedural accountability interact with GeoAI’s technical limitations, such as data sparsity, algorithmic opacity, or spatial autocorrelation. In addition to creating governance blind spots, this conceptual and disciplinary fragmentation has hindered the creation of ethical safeguards that are context-sensitive and specific to CEGE practice.

By offering a methodical synthesis of the ethical and technical issues raised by the growing use of AI in geospatial applications in the fields of civil, environmental, and geomatics engineering, this review seeks to close that gap. It specifically lays out the new terrain of GeoAI applications, classifies the most common technical limitations, and examines important moral conundrums throughout the whole AI lifecycle, from data collection and model training to deployment and post-deployment monitoring. Additionally, the study critically assesses the limitations and suitability of existing AI ethics frameworks in the context of geospatial engineering. In light of this synthesis, it suggests professional best practices and concrete research avenues to encourage the adoption of transparent, ethical, and context-aware AI in the built and natural environment sectors.

The focus of the review is on AI applications in core CEGE subdomains that heavily utilize geospatial technologies, such as GIS, remote sensing, and SDIs. These consist of land-use optimization, hydrological modeling, structural evaluation, environmental hazard forecasting, infrastructure condition monitoring, and sustainable urban planning. Algorithmic bias, explainability and transparency (XAI), accountability, spatial surveillance and privacy, and wider socio-ecological justice implications are among the ethical aspects examined. At the same time, the impact of technical issues like model generalization, computational scalability, resolution mismatches, and data availability on fair and trustworthy AI use in CEGE practice is critically evaluated.

2. Methodology

The intersection of artificial intelligence (AI), geospatial data applications, and the technical and ethical ramifications of such integration within Civil, Environmental, and Geomatics Engineering (CEGE) is critically examined in this review using a methodical literature mapping approach. This study's methodological framework is based on well-established evidence synthesis protocols, especially those described by [29, 30], which place a strong emphasis on conceptual rigor, reproducibility, and methodological transparency.

2.1. Review Protocol

This review was designed using a structured five-phase protocol that allowed for thematically grounded insights while guaranteeing thorough coverage of the body of existing literature. The scope and main research questions were established, pertinent databases were found, a targeted set of search terms was created, studies were screened according to inclusion and exclusion criteria, quality improvement and thematic coding were carried out, and the results were synthesized into key analytical categories.

The central question of this protocol is: How do ethical issues and technical difficulties interact when using AI-driven geospatial applications in the fields of geomatics, environmental, and civil engineering? The review's dual goals are reflected in this framing: first, to document and assess AI applications that use geospatial technologies in CEGE; and second, to examine the ethical frameworks or lack thereof that support these implementations.

2.2. Search Strategy

Four significant academic databases Scopus, Web of Science, IEEE Xplore, and Science Direct known for their thorough coverage in computer science, engineering, and spatial science were the focus of a methodical search. Boolean keyword combinations were used in the search strategy to capture both ethical and technical aspects. Domain-specific terms like "civil engineering," "environmental engineering," "geomatics," "urban planning," and "infrastructure" intersected with core search terms like variations of "GeoAI," "geospatial artificial intelligence," "AI in GIS," and "AI in remote sensing." The ethical dimensions of "bias," "privacy," "transparency," "explainability," "accountability," and "ethical challenges" further refined these.

In order to reflect the period of rapid development and diversification in AI applications for geospatial engineering, the publication time window was set between 2013 and 2025. To guarantee academic quality and accessibility, only high-impact conference papers and peer-reviewed journal articles published in English were taken into consideration.

2.3. Inclusion and Exclusion Criteria

Studies that (i) used AI methods to solve geospatial issues in CEGE contexts and (ii) specifically addressed at least one aspect of the implications for ethics, society, or governance were accepted. Only papers from prestigious conferences or peer-reviewed journals were kept. Papers that were not geospatial or engineeringly relevant, that only addressed algorithm performance without addressing ethical or societal issues, or that came from grey literature (such as theses, blog posts, and non-peer-reviewed sources) were not included. Publications written in languages other than English were also not included. The study's selection criteria are compiled in Table 1.

Table 1 Inclusion and Exclusion Criteria

Inclusion Criteria	**Exclusion Criteria**
Studies applying AI to geospatial problems in civil/environmental/geomatics domain	Articles without clear geospatial or engineering relevance
Articles discussing ethical, governance, or social implications	Purely technical studies without ethical framing
Peer-reviewed journal or top-tier conference publications	Grey literature, preprints, theses, blog posts
Publications between 2013 and 2025 in English	Non-English or non-peer-reviewed sources

2.4. The Selection Process for Studies

812 articles were found in the first database search. 112 articles were chosen for full-text review after titles and abstracts were filtered based on inclusion and exclusion criteria and duplicates were eliminated. A final sample of 30 studies was chosen for in-depth thematic analysis after a secondary evaluation that focused on methodological soundness, ethical relevance, and domain specificity. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines were adhered to during the process. The PRISMA flow diagram for the identification, screening, and inclusion phases is shown in Figure 1.

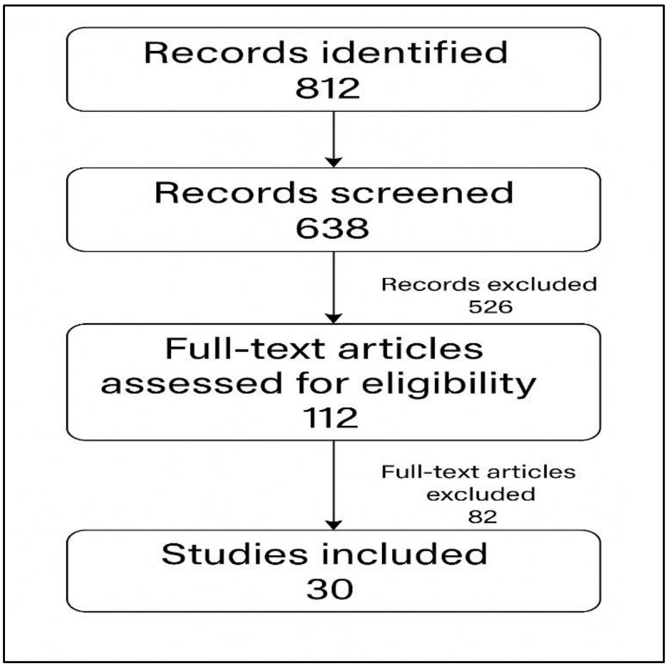

Figure 1 PRISMA-style flow diagram for study selection

2.5. Thematic Coding and Data Extraction

To methodically record important characteristics from every study, a standardized data extraction sheet was created. The following variables were extracted: the year of publication, the author, the application domains (e.g., flood prediction, infrastructure health, pollution detection, land-use modeling), the geospatial technologies (e.g., GIS, remote sensing, UAV imagery), and the AI methodologies (e.g., convolutional neural networks, random forests, support vector machines, LSTMs).

Every paper was assessed based on how well it addressed ethical issues like data colonialism, explainability, model opacity, algorithmic bias, privacy violations, and accountability. When governance mechanisms or frameworks were suggested, they were also recorded.

Thematic analysis used a hybrid methodology that combined qualitative pattern recognition in NVivo with manual coding in Excel. Five thematic clusters emerged as a result of this iterative process, and these clusters organize the core synthesis that is shown in the following section:

- GeoAI’s conceptual and definitional bounds
- AI's application domains in CEGE
- Challenges with technical design and implementation
- Institutional, governance, and regulatory gaps
- Ethical issues throughout the AI lifecycle

These themes offer a critical lens through which the developing field of AI-integrated geospatial systems in CEGE can be examined, exposing both areas of technological and ethical vulnerability as well as innovative potential.

3. Results and Literature Synthesis

The technical accomplishments, methodological flaws, and ethical conflicts that define current work on AI-driven geospatial applications in civil, environmental, and geomatics engineering (CEGE) are outlined by five interlocking themes that emerged from a careful reading of the thirty articles that were kept for analysis. The sequence progresses from fundamental definitional questions to applied domains, followed by cross-cutting technical and ethical challenges, and ultimately ends with structural governance gaps. Each theme is summarized below.

3.1. Definitions and Conceptual Limitations of GeoAI

Even though the term "GeoAI" is now commonly used, its definition is still open-ended. The majority of authors define it as the combination of data-driven algorithms derived from machine learning, deep learning, or knowledge graph reasoning with geospatial technologies, including remote sensing, Geographic Information Systems (GIS), and spatial data infrastructures (SDIs) [31, 32]. However, a number of studies note that the term fluctuates between subfield, methodological toolkit, and even paradigm shift [33, 32], creating uncertainty in the design and assessment of research. Notably, geomatics engineering, which has its roots in surveying, geoinformation science, and spatial measurement, is becoming more and more integrated with geoAI as a field that advances algorithmic spatial analytics and as a source of fundamental geospatial data.

There are two recurring technical blind spots. First, a lot of GeoAI pipelines inflate accuracy estimates by downplaying spatial autocorrelation, which goes against the independence assumptions of classical machine learning. Second, there is still a significant label scarcity problem in remote sensing applications, which frequently lead to inadequate supervision that increases uncertainty. The epistemological conflict that arises when deterministic physical phenomena, like structural loads or hydrological flows, are mapped onto probabilistic models is rarely discussed in literature. To put it briefly, there is currently no rigorous, domain-specific ontology of GeoAI, which makes methodological comparability and ethical decision-making difficult.

3.2. AI Application Domains in CEGE

Table 2 summarizes the corpus's five main application areas. Over 80% of the reviewed studies are related to flood forecasting, urban growth modeling, pollution surveillance, structural health assessment, and infrastructure optimization. The methodological landscape is dominated by random forests, convolutional neural networks, and long short-term memory architectures, which are often combined with multi-sensor imagery, digital elevation models, or BIM integrated sensor feeds.

Table 2 AI techniques, representative application domains, and recurrent ethical concerns

Application domain	Predominant AI methods	Core geospatial inputs	Salient ethical risk
Flood prediction / hydrology	RF, LSTM, SVM	RS imagery, DEMs, hydrological GIS layers	False-positive alarms; liability
Urban growth & planning	CNN, decision-tree ensembles	Multi-temporal RS, crowdsourced VGI	Zoning bias, gentrification
Pollution & hazard monitoring	Deep CNN, k-NN	Hyperspectral RS, in-situ sensors	Surveillance, data fairness
Structural health monitoring	Sensor-fusion ML	BIM + IoT, GIS layers	Model opacity, safety verification
Infrastructure optimisation	GA, RL hybrids	UAV photogrammetry, SDIs	Energy cost, explainability

While performance metrics are routinely reported, fewer than one-third of the studies interrogate distributive impacts, stakeholder participation or long-term governance revealing a persistent technocentric bias.

3.3. Technical Challenges in Model Design and Implementation

Four bottlenecks recur across domains. Data heterogeneity disparities in spatial resolution, spectral range and temporal cadence complicates data fusion and undermines replicability [34]. Interoperability remains weak: proprietary model pipelines often cannot be ported across software ecosystems, fragmenting cumulative progress. Generalization is another fault line: models tuned to data rich metropolitan regions of the Global North deteriorate sharply when applied to informal or data scarce settings [35]. Finally, the computational footprint of large convolutional networks, particularly in very high-resolution imagery, raises both economic and environmental concerns [36]. Each technical limitation has an ethical shadow whether exclusions of low resource regions, opacity for cross platform auditing, or carbon costs borne by communities that derive minimal benefit.

3.4. Ethical Issues Throughout the AI Lifecycle

Ethics is often not a design driver, but rather emerges only after model validation. There are five main risk categories (Table 3). Unfair mapping of disasters and distorted land use classifications are examples of algorithmic bias [37, 38]. Unauthorized high frequency satellite and drone surveillance compromises privacy [39]. Professional accountability in infrastructure decisions is hampered by opacity, or the lack of strong XAI tools [40]. When engineering decisions are informed by AI outputs but there is no obvious chain of responsibility for the failures that result, responsibility gaps arise [41]. Last but not least, data colonialism emerges when actors in the Global North gain the most from training datasets taken from the Global South [42]. A governance gap is confirmed by the low number of papers that use formal frameworks like IEEE EAD or EU Trustworthy AI. Figure 2 shows the Lifecycle of Ethical Risks in GeoAI for CEGE.

Table 3 Dominant ethical concerns and illustrative manifestations

Ethical concern	Typical manifestation in CEGE	Illustrative reference
Algorithmic bias	Unequal flood-risk zoning	[37, 38]
Privacy loss	Unregulated aerial monitoring	[39]
Model opacity	Uninterpretable structural-risk scores	[40]
Accountability gaps	Ambiguous liability for AI errors	[41]
Data colonialism	External exploitation of local imagery	[42]

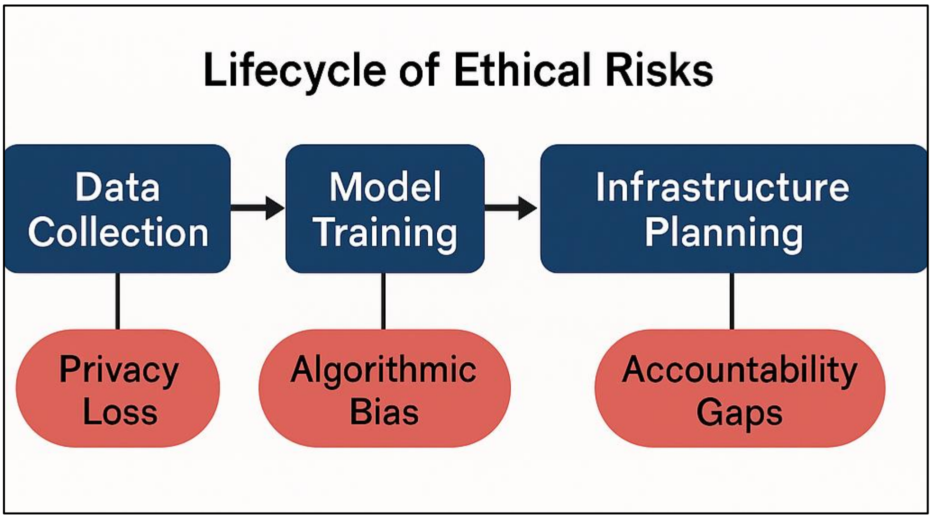

Figure 2 Lifecycle of Ethical Risks in GeoAI for CEGE.

This conceptual diagram shows how various ethical issues, like algorithmic bias, privacy loss, and accountability gaps, correspond to different phases of AI development and application. As AI becomes more integrated into civil and environmental engineering workflows, it emphasizes how crucial it is to address ethical vulnerabilities early in the lifecycle rather than after the fact.

3.5. Governance Shortfalls and Prospects

Three deficiencies at the system level become apparent. First, there is a governance blind spot: there is no single oversight framework for GeoAI in engineering professional associations, especially in fields like geomatics where the ethics of geospatial data are still not well-established. Second, only three papers in the corpus reported community feedback loops or stakeholder co-creation, indicating the rarity of participatory design. Third, evidence is skewed by geographic asymmetry: over 80% of studies come from the US, Europe, or China, under examining contexts in the Global South. Table 4 provides a summary of the thematic findings.

Governance tools that emphasize indigenous and local knowledge systems, incorporate participatory co-design into GeoAI projects, and require geographically contextual benchmarking prior to deployment will be necessary to address these deficiencies.

Table 4 Summary of thematic findings

Theme	Analytical focus	Principal gap or risk
1 Conceptual foundations	Definition of GeoAI	Ontological ambiguity
2 CEGE applications	Domain coverage	Technocentric bias; limited equity analysis
3 Technical challenges	Data, interoperability, energy	Weak generalisation & sustainability
4 Ethical challenges	Bias, privacy, opacity, liability	Minimal integration of formal frameworks
5 Governance & equity	Oversight, participation, geography	Poor Global South representation

When taken as a whole, these themes demonstrate that although GeoAI is technically superior, its governance and ethical framework is not up to par. This discrepancy serves as the impetus for the ethics by design roadmap and discussion that follow.

4. Discussion

4.1. Understanding the Intersections: The Dual Potential and Danger of GeoAI

The data gathered for this review demonstrates GeoAI's conflicted status in modern civil, environmental, and geomatics engineering (CEGE). On the one hand, the combination of geospatial analytics and artificial intelligence techniques allows for previously unheard-of improvements in environmental stewardship, infrastructure responsiveness, and predictive accuracy. These days, engineers can simulate structural vulnerability under compound climate stressors, trace pollution dynamics through real-time sensor networks, and model flood risk with sub-hour temporal granularity all of which collectively reshape the analytical toolkit of the built environment professions.

However, vulnerabilities that are still poorly understood cast a shadow over these technological advancements. Algorithmic bias, spatial injustice, widespread surveillance, and systemic opacity are ethical issues that are usually addressed after model deployment, if at all, according to the literature. Because design and ethics are no longer linked, there is an ethics lag in which standards, safeguards, and interpretive frameworks are constantly surpassed by technological innovation. Therefore, high-stakes applications like pollution monitoring, zoning automation, and disaster early warning are still vulnerable to unsafe or unfair outcomes, especially in areas with weak institutions or limited data. Epistemic justice, participatory governance, and local agency are further marginalized by a persistent technocentric orientation; the majority of empirical demonstrations come from the Global North, where computational infrastructure and data abundance offer advantages that are rarely found in the Global South. GeoAI thus risks reinforcing existing asymmetries in infrastructure investment, risk exposure, and policy responsiveness.

4.2. A Prospective Research Agenda for Ethical GeoAI

A research agenda that combines technical advancement with ethical reflection is necessary to reposition GeoAI as a tool for innovation and equity. Model architectures need to be trained and validated in a variety of geographical, cultural, and sociopolitical contexts. Instead of defaulting to sensor-rich metropolitan areas, data pipelines should prioritize the realities of informal settlements and urban–rural discontinuities. Fairness-aware sampling, interpretable machine learning diagnostics, and scenario-based impact simulations during data curation and model calibration must all be incorporated into ethical auditing, which should become standard practice throughout the AI lifecycle. These requirements suggest a cultural shift toward preventive ethics as standard engineering practice, in addition to technical changes.

The institutionalization of inclusive and participatory design is equally important. Even though vulnerable populations are disproportionately impacted by the socio-technical systems being modeled such as flood exposure, air quality gradients, and transportation accessibility community engagement is still uncommon in contemporary GeoAI workflows. In order to change impacted communities from passive data subjects into active epistemic partners, participatory mapping, co-design workshops, and easily accessible visualization dashboards are crucial. Lastly, it is necessary to make clear the environmental cost of computation, which is frequently invisible. There are significant energy overheads associated with large-scale model training on very high-resolution imagery, which are rarely documented in the literature. Transparent carbon accounting, edge-based inference, and energy-efficient architectures should be the main focus of future research.

4.3. CEGE's Ethics-by-Design Roadmap for GeoAI

An Ethics by Design roadmap is shown in Figure 3, which links specific governance checkpoints to each stage of the AI pipeline, including data collection, model development, validation, and deployment. These checkpoints are translated into suggested practices in Table 5, which covers everything from socio-spatial error analysis and public redress mechanisms to participatory VGI collection and stratified sampling. Along with accuracy, scalability, and cost effectiveness, the roadmap treats normative alignment as a constitutive design criterion, emphasizing preventive rather than reactive ethics.

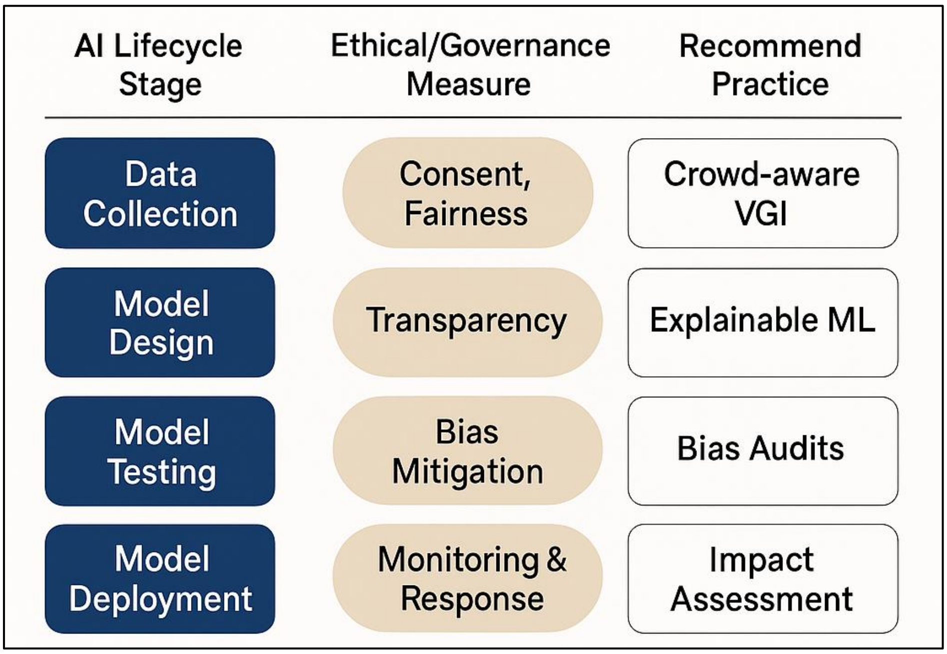

Figure 3 Ethics-by-Design Roadmap for GeoAI in CEGE

Table 5 Mapping Ethical Principles to AI Lifecycle Stages in CEGE

AI Lifecycle Stage	Ethical Checkpoint	Recommended Practices
Data Acquisition	Informed consent, spatial representativeness	Participatory VGI collection, drone regulations, stratified data sampling
Model Development	Bias detection, contextual relevance, explainability	Interpretable ML, spatial fairness testing, culturally appropriate feature engineering
Validation	Simulated impact audits, accountability metrics	Socio-spatial error analysis, stakeholder trialing, differential performance checks
Deployment	Governance infrastructure, public redress mechanisms	Open dashboards, audit logs, community monitoring feedback systems

Embedding such safeguards during design, rather than retrofitting them post-deployment, provides a pragmatic pathway toward socially and environmentally responsible GeoAI.

4.4. Moving Toward an Important GeoAI Framework

The review's thematic patterns highlight the need for a Critical GeoAI paradigm that prioritizes reflexivity, equity, and plural knowledge systems over instrumental optimization. The critical approach asks what infrastructure conditions are necessary for AI to function justly, rather than what AI can do for infrastructure. Deep interdisciplinary cooperation between geomaticians, computer scientists, ethicists, civil and environmental engineers, and urban scholars is necessary to realize this paradigm. Equally important is institutional reform: funding organizations should support governance frameworks that elevate indigenous epistemologies and Global South leadership; professional standards should be updated to include algorithmic accountability; and engineering curricula must incorporate ethical literacy.

In the absence of such changes, GeoAI might, in the name of technological neutrality, reproduce and even exacerbate already-existing spatial injustices. On the other hand, a critically minded, ethically conscious GeoAI has the potential to support environmental and infrastructure systems that are not only more intelligent but also observably more equitable, transparent, and sustainable. CEGE's future legitimacy and societal relevance are at stake.

5. Conclusion

The field of civil, environmental, and geomatics engineering (CEGE) is changing as a result of the convergence of artificial intelligence (AI) and geospatial technologies, or GeoAI as it is commonly known. AI-driven geospatial tools have greatly increased the analytical and operational capacity of infrastructure systems, from flood forecasting and structural diagnostics to environmental surveillance and predictive urban planning. However, this review shows that these developments are taking place in the midst of unresolved technical vulnerabilities, ethical blind spots, and insufficient governance. The unrestrained growth of GeoAI could jeopardize the very social and environmental goals it claims to support in the absence of critical examination and interdisciplinary reform.

The robustness, scalability, and equity of GeoAI deployments are still threatened by ongoing technical issues. Data heterogeneity, including differences in sensors, formats, spatial resolutions, and temporal cadences, makes integration more difficult and jeopardizes the generalizability of models in a variety of geographical contexts. When used in areas with informality, disjointed infrastructure, or few records conditions common in much of the Global South models trained in high-density, data-rich environments usually fall short. Platform-level incompatibilities and proprietary standards that limit interoperability and impede cumulative innovation exacerbate these disparities. The environmental cost of AI computation, especially when deep learning models are trained on high-resolution remote sensing data, raises additional concerns because it introduces carbon-intensive workflows that are not sufficiently acknowledged in discussions of "smart" or "green" infrastructure.

The moral ramifications are just as urgent. Socio-spatial disparities can be replicated or exacerbated by algorithmic bias in spatial models used for zoning, risk mapping, or land-use classification. Pervasive, frequently unregulated aerial and satellite surveillance carried out without consent frameworks or redress mechanisms gives rise to privacy violations. Numerous AI models operate as opaque black boxes, making them difficult to understand and hiding the lines of accountability in the event of a failure. Remarkably, not many systems incorporate morality into the design process. Rarely does the community participate, particularly in marginalized or vulnerable areas where lived experiences, cultural contexts, and local knowledge are not included in model validation and training. These omissions raise serious concerns about data colonialism and epistemic injustice in addition to decreasing the accuracy and fairness of AI systems.

The results of this review show that a fundamental change in perspective is required, one that acknowledges GeoAI as a socio-technical system with material, political, and ethical implications rather than as a neutral tool of optimization. The entire AI pipeline needs to be imbued with ethical foresight in order to promote a more responsible paradigm. Context-sensitive model development should take sociospatial complexity and geographically varied data into account. Fairness, explainability, and community impact must be included in evaluation metrics in addition to predictive accuracy. Participatory design needs to become a fundamental practice; it cannot stay on the periphery. GeoAI systems should be actively co-produced and examined by engineers, planners, and impacted communities.

At the same time, computational issues related to AI sustainability need to be addressed. Aligning GeoAI with environmental responsibility requires the use of transparent carbon accounting, edge computing for field deployment, and energy-efficient architectures. There is also a severe lack of governance frameworks tailored to the physical and infrastructure realities of CEGE. Funding agencies, academic publishers, and professional associations must set up auditing procedures, ethical standards, and oversight systems that take into account local sensitivities as well as international standards. Equitable collaborations that prioritize Global South leadership and context-specific risk and resilience strategies are necessary to offset the dominance of Global North institutions in influencing the development of GeoAI.

The future of GeoAI in CEGE ultimately rests on how it is governed, whose knowledge it privileges, and what kinds of ecological and infrastructure futures it makes possible, in addition to what AI allows us to model, predict, or automate. GeoAI has the potential to worsen environmental damage, infrastructure damage, and spatial injustice if it is not controlled. However, GeoAI has the potential to support more robust, transparent, and just systems if it is guided by the principles of reflexivity, inclusivity, and ethics-by-design. This review urges the geospatial and engineering communities to take an interdisciplinary, critical approach that views AI as a potent force for social and environmental change rather than as an end in and of itself.

Limitations

In order to contextualize its findings and guide future research directions, it is important to acknowledge the limitations of this review, even though it offers an organized and multidisciplinary synthesis of the ethical and technical aspects of AI-driven geospatial applications in civil, environmental, and geomatics engineering (CEGE).

First, the review's scope was limited by the publication type and language. The study misses out on a potentially useful body of knowledge found in grey literature, technical reports, local policy documents, and non-English academic sources because it only looks at peer-reviewed English-language literature published between 2013 and 2025. The adoption of AI in geospatial systems frequently develops under unique infrastructure, cultural, and regulatory circumstances that are not sufficiently represented in mainstream academic publishing, making this exclusion particularly significant for contexts in the Global South. In the GeoAI discourse, the lack of locally based innovations and indigenous knowledge systems runs the risk of reiterating epistemic hierarchies.

Second, it is difficult to fully capture the range of new approaches due to the quick speed of technological advancement. The review covers sophisticated techniques like deep learning and hybrid models, but it might not adequately represent the latest developments, such as foundation models, multimodal GeoAI architectures, federated learning, or the increasing integration of satellite data with large language models (sat-LLMs). The new ethical and technical issues raised by these frontier techniques from increased surveillance capabilities and interpretability gaps to data sovereignty issues remain understudied in the literature today and are therefore underrepresented in this review.

Third, publication bias has an impact on the review. Research that shows ethically positive stories or successful AI implementations is more likely to be published than studies that show contested deployments, failures, or contentious results. Because of this dynamic, there is a chance that the impact of GeoAI in CEGE will be overestimated, hiding important cases that could shed light on governance issues and ethical weaknesses. Furthermore, knowledge integration is still hampered by the disciplinary silos that exist between engineering, computer science, geography, and applied ethics. This leads to fragmented perspectives and unaddressed blind spots.

The interpretive character of the thematic coding procedure is another drawback. Although methodical procedures were adhered to, the categorization of themes entails subjective assessment, especially in a quickly developing, multidisciplinary field such as GeoAI ethics. Using the same dataset, different reviewers may highlight different thematic categories or theoretical frameworks. This indicates the need for methodological transparency and pluralism in future synthesis efforts, but it does not negate the insights offered.

Finally, empirical validation through stakeholder engagement, field-based experimentation, or original data collection is not included in this review. Because of this, although theoretical links between ethical issues and technical constraints are made, they have not been put to the test in practical situations. The findings' generalizability and practical applicability are limited by their lack of empirical support, particularly for practitioners looking for practical advice.

These restrictions are not insignificant. However, they also highlight important directions for future study, such as incorporating grey and multilingual literature; assessing ethical frameworks in working GeoAI systems empirically; and implementing intersectional, participatory, and internationally inclusive research designs. Achieving more responsible, equitable, and context-sensitive GeoAI development will require tackling these constraints as AI becomes more integrated into the built environment's spatial governance and infrastructure systems.

References

[1] Lu, P., Chen, S., & Zheng, Y.-J. (2012). Artificial Intelligence in Civil Engineering. *Mathematical Problems in Engineering*, *2012*, 1–22. https://doi.org/10.1155/2012/145974

[2] Dudhee, V., & Vuković, V. (2023). How large language models and artificial intelligence are transforming civil engineering. *ProCEGEdings of the Institution of Civil Engineers*, *176*(4), 150. https://doi.org/10.1680/jcien.2023.176.4.150

[3] Akhmedov, J., Jurayev, U., Kosimova, S., Rakhimova, G., Tursunov, Q., & Kosimov, L. (2024). *The Significant Technical Mantle of AI in the Field of Secular Engineering: an Innovative Design*. 601–606. https://doi.org/10.1109/icacite60783.2024.10616399

[4] Sargiotis, D. (2025). *Transforming Civil Engineering with AI and Machine Learning: Innovations, Applications, and Future Directions*. https://doi.org/10.2139/ssrn.5021723

[5] Abdel-Kader, M. Y., Ebid, A. M., Onyelowe, K. C., Mahdi, I. M., & Abdel-Rasheed, I. (2022). (AI) in Infrastructure ProjectsGap Study. *Infrastructures*, *7*(10), 137. https://doi.org/10.3390/infrastructures7100137

[6] Narkarunai, J., Malaiyappan, A., Karamthulla, M. J., & Tadimarri, A. (2023). Towards Autonomous Infrastructure Management: A Survey of AI-driven Approaches in Platform Engineering. *Online*. https://doi.org/10.60087/jklst.vol2.n2.p314

[7] Dabous, S. A., Rashidi, M., Zhu, Z., Alzraiee, H. S., Mantha, B. R. K., & Alsharqawi, M. (2023). Editorial: Automation and artificial intelligence in construction and management of civil infrastructure. *Frontiers in Built Environment*, *9*. https://doi.org/10.3389/fbuil.2023.1155240

[8] Azanaw, G. M. (2024). Revolutionizing Structural Engineering: A Review of Digital Twins, BIM, and AI Applications. *Indian Journal of Structure Engineering (IJSE)*, *4*(2), 1–8. https://doi.org/10.54105/ijse.b1321.04021124

[9] Jain, R., Singh, S. K., Palaniappan, D., Parmar, K., & Premavathi, T. (2025). Data-Driven Civil Engineering: Applications of Artificial Intelligence, Machine Learning, and Deep Learning. *Turkish Journal of Engineering*, *9*(2), 354–377. https://doi.org/10.31127/tuje.1581564

[10] Abid, S. K., Sulaiman, N., Chan, S. W., Nazir, U., Abid, M., Han, H., Ariza-Montes, A., & Vega-Muñoz, A. (2021). Toward an Integrated Disaster Management Approach: How Artificial Intelligence Can Boost Disaster Management. *Sustainability*, *13*(22), 12560. https://doi.org/10.3390/SU132212560

[11] Jeyalakshmi, J., Kandasamy, V., Berna, I. E., & Manohar, E. (2024). *Smart Cities and Urban Sustainability With AI* (pp. 330–350). IGI Global. https://doi.org/10.4018/979-8-3693-1702-0.ch017

[12] Kumar, D., & Bassill, N. P. (2024). *Artificial intelligence for sustainable urban climate studies* (pp. 291–307). Elsevier BV. https://doi.org/10.1016/b978-0-323-99164-3.00017-3

[13] Taktak, F. (2024). AI-Enhanced Geomatics Engineering: Innovative Solutions and Applications Using ChatGPT, an Advanced AI Language Model. *International Journal of Engineering and Geosciences*. https://doi.org/10.26833/ijeg.1510209

[14] Alshiha, A. (2024). A Review of the Integration Between Geospatial Artificial Intelligence and Remote Sensing. *Iraqi Journal for Computer Science and Mathematics*. https://doi.org/10.52866/ijcsm.2024.05.03.013

[15] Waghela, H., Patel, S., Sudesan, P., Raorane, S., & Borgalli, R. A. (2022). *Land Use Land Cover Classification using Machine Learning*. 708–711. https://doi.org/10.1109/ICACRS55517.2022.10029176

[16] *Land Use Land Cover Classification in Remote Sensing Using Machine Learning Techniques*. (2023). https://doi.org/10.1109/ihcsp56702.2023.10127126

[17] Rane, J., Kaya, Ö., Mallick, S. K., & Rane, N. (2024). *Artificial intelligence-powered spatial analysis and ChatGPT-driven interpretation of remote sensing and GIS data*. https://doi.org/10.70593/978-81-981271-7-4_5

[18] Rana, R., & Bhambri, P. (2024). Harnessing AI and Machine Learning for Enhanced Geospatial Analysis. *Advances in Geospatial Technologies Book Series*, 27–72. https://doi.org/10.4018/979-8-3693-8054-3.ch002

[19] Micheli, M., Gevaert, C. M., Carman, M. E., Craglia, M., Daemen, E., Ibrahim, R., Kotsev, A., Mohamed-Ghouse, Z. S., Schade, S., Schneider, I., Shanley, L., Tartaro, A., & Vespe, M. (2022). AI ethics and data governance in the geospatial domain of Digital Earth. Big Data & Society, 9(2), 205395172211387. https://doi.org/10.1177/20539517221138767

[20] Janowicz, K. (2023). Philosophical Foundations of GeoAI: Exploring Sustainability, Diversity, and Bias in GeoAI and Spatial Data Science (pp. 26–42). Informa. https://doi.org/10.1201/9781003308423-3

[21] Waykar, Y. A., & Yambal, S. (2024). AI and Geospatial Intelligence. Advances in Geospatial Technologies Book Series, 1–28. https://doi.org/10.4018/979-8-3693-8104-5.ch001

[22] Micheli, M., Gevaert, C. M., Carman, M. E., Craglia, M., Daemen, E., Ibrahim, R., Kotsev, A., Mohamed-Ghouse, Z. S., Schade, S., Schneider, I., Shanley, L., Tartaro, A., & Vespe, M. (2022). AI ethics and data governance in the

geospatial domain of Digital Earth. *Big Data & Society*, *9*(2), 205395172211387. https://doi.org/10.1177/20539517221138767

[23] Jena, M. C., Mishra, S. K., & Moharana, H. S. (2024). The way forward to overcome challenges and drawbacks of AI. *Computing and Artificial Intelligence.*, 1581. https://doi.org/10.59400/cai1581

[24] Shenson, J., Hasan, M. R., Ahmad, M., & Jain, N. (2024). Ethical Geospatial Analytics Balancing Business Interests and Social Responsibility. *Advances in Marketing, Customer Relationship Management, and e-Services Book Series*, 191–212. https://doi.org/10.4018/979-8-3693-3478-2.ch010

[25] Afolabi, A. I., Hussain, N. Y., Austin-Gabriel, B., Ige, A. B., & Adepoju, P. A. (2023). Geospatial AI and data analytics for satellite-based disaster prediction and risk assessment. *Open Access Research Journal of Engineering and Technology*, *4*(2), 058–066. https://doi.org/10.53022/oarjet.2023.4.2.0058

[26] Oluoch, I. (2024). Crossing Boundaries: The Ethics of AI and Geographic Information Technologies. *ISPRS International Journal of Geo-Information*, *13*(3), 87. https://doi.org/10.3390/ijgi13030087

[27] Chen, X., Hui, T., Yan-lin, L., & Yang, H. (2025). Discussion on Artificial Intelligence Safety and Ethical Issues. *ITM Web of Conferences*, *70*, 04031. https://doi.org/10.1051/itmconf/20257004031

[28] Shawky, S., Quach, S., Quach, S., & Ferm, L. C. (2023). *Ethical Issues of Artificial Intelligence (AI)* (pp. 283–300). IGI Global. https://doi.org/10.4018/978-1-6684-9591-9.ch013

[29] Moher, D., et al. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Medicine*, *6*(7), e1000097.

[30] Kitchenham, B. (2009). Systematic literature reviews in software engineering: Guidelines and summary. *Software Engineering Group, Department of Computer Science, Keele University*

[31] Li, W. (2020). GeoAI: Where machine learning and big data converge in GIScience. *Journal of Spatial Information Science*, *2020*(20), 71–77. https://doi.org/10.5311/JOSIS.2020.20.658

[32] Choi, Y. (2023). GeoAI: Integration of Artificial Intelligence, Machine Learning, and Deep Learning with GIS. *Applied Sciences*, *13*(6), 3895. https://doi.org/10.3390/app13063895

[33] Bordogna, G., & Fugazza, C. (2022). *Artificial Intelligence for Multisource Geospatial Information*. *12*(1), 10. https://doi.org/10.3390/ijgi12010010

[34] Mandreoli, F., & Montangero, M. (2019). *Dealing With Data Heterogeneity in a Data Fusion Perspective: Models, Methodologies, and Algorithms* (Vol. 31, pp. 235–270). Elsevier. https://doi.org/10.1016/B978-0-444-63984-4.00009-0

[35] Misra-Hebert, A. D. (2023). *The Impact of the "AI Divide" between the Global North and South*. https://doi.org/10.31219/osf.io/2yjtz

[36] Yan, E., Luo, L., & Ceze, L. (2021). Characterizing and Taming Resolution in Convolutional Neural Networks. *arXiv: Computer Vision and Pattern Recognition*. https://dblp.uni-trier.de/db/journals/corr/corr2110.html#abs-2110-14819

[37] Gevaert, C. M., Carman, M., Rosman, B., Georgiadou, Y., & Soden, R. (2021). *Fairness and accountability of AI in disaster risk management: Opportunities and challenges*. *2*(11), 100363. https://doi.org/10.1016/J.PATTER.2021.100363

[38] Gevaert, C., Buunk, T., & van den Homberg, M. (2024). Auditing geospatial datasets for biases: using global building datasets for disaster risk management. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 1–12. https://doi.org/10.1109/jstars.2024.3422503

[39] Crews, K. A. (2013). *Public/Private: The Ethics, Legalities, and Practice of Airborne and Satellite Surveillance Technologies* (Vol. 9, pp. 330–336). https://doi.org/10.1016/B978-0-12-409548-9.10422-1

[40] Rane, N., Choudhary, S., & Rane, J. (2023). Explainable Artificial Intelligence (XAI) Approaches for Transparency and Accountability in Financial Decision-Making. *Social Science Research Network*. https://doi.org/10.2139/ssrn.4640316

[41] Königs, P. (2022). Artificial intelligence and responsibility gaps: what is the problem? *Ethics and Information Technology*, *24*(3). https://doi.org/10.1007/s10676-022-09643-0

[42] Kshetri, N. (2024). *Diffusion and impact in the Global South*. 214–234. https://doi.org/10.4337/9781035346745.00020