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*Review*

# GeoAI-Driven Intelligent Governance: Leveraging Large Language Models and Geospatial Analytics for Public-Sector Decision Support

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**Abstract:** Public institutions increasingly rely on diverse geospatial, administrative, environmental, sensor, and citizen-generated data, but turning these assets into trustworthy and usable governance intelligence is challenging. GeoAI integrates and leverages the power of GIS, remote sensing, machine learning and deep learning, spatial analysis, and LLM (large language models) for natural-language interaction and knowledge extraction. This PRISMA 2020-informed systematic review collates 51 studies, covering the development, use, enablers, benefits and barriers to using GeoAI and LLM in public-sector governance. Evidence ranges from urban and regional planning, disaster-risk management, infrastructure, environmental governance, agriculture and natural-resource management, public-service delivery, to monitoring of Sustainable Development Goals. Although the technologies support predictive and conversational decision-making, the literature remains weighted toward technical feasibility, with limited evidence concerning policy effectiveness, service quality, equity, accountability, citizen trust, and long-term public value. Drawing on the Resource-Based View, Dynamic Capability Theory, the Technology–Organization–Environment framework, and Public Value Theory, the study proposes a six-layer GeoAI-Driven Intelligent Governance Framework linking data resources, technological capabilities, analytics, governance functions, decision support, and public-value outcomes. It also develops testable propositions and a future research agenda emphasizing institutional capability, explainability, human oversight, and context-sensitive adoption.

**Keywords:** GeoAI; large language models; intelligent governance; geospatial analytics; decision support systems; conversational governance; public value

## 1. Introduction

Public-sector organizations are working in an era of rapid urbanisation, climate risks, infrastructure limitations, social inequity, fiscal stress and the growing expectations of citizens. Such challenges are geographically interrelated, and governments are increasingly turning to the use of artificial intelligence (AI), big-data analytics, Internet of Things (IoT), remote sensing and geographic information systems (GIS) to bolster planning, allocation of resources, accountability measures and public-service delivery [1,2]. But the complexity of administrative data, the variety of satellite images, sensors and citizen-generated data is too great for traditional analytical systems [2,3].

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Most governance decisions have a geographical dimension, including infrastructure provision, disaster preparedness, environmental protection, transport, healthcare, agriculture, and regional development. Conventional GIS supports spatial data management and analysis but often requires specialist expertise and predefined analytical workflows [4,5]. GeoAI extends these capabilities by combining spatial data with machine learning, deep learning, computer vision, and pattern-recognition techniques to support forecasting, anomaly detection, and governance-related prediction [6–8].

LLMs can extract knowledge from administrative documents, summarize complex information, generate explanatory narratives, and support natural-language interaction with geospatial databases [3,9,10]. Their integration with GeoAI, spatial ontologies, knowledge graphs, retrieval-augmented generation, and multimodal data creates opportunities for conversational GIS and accessible, context-aware public-sector decision support. However, general-purpose LLMs have limited spatial-reasoning capability and may produce geographically inaccurate outputs [11]. GeoAI adoption also raises concerns about data quality, interoperability, privacy, bias, cybersecurity, accountability, institutional capacity, and public trust [12–22]. Public-sector systems must therefore be accurate, explainable, accountable, context-sensitive, and subject to meaningful human oversight.

### *1.1. Evolution from GIS to GeoAI-Enabled Governance*

Geospatial technology in governance has progressed from conventional GIS for collecting, visualizing, and analysing spatial data [4] to Spatial Decision Support Systems that integrate analytical models, scenario evaluation, and policy alternatives [5]. Satellite data, sensor networks, mobile devices, Internet of Things systems, and citizen-generated information now enable more timely monitoring but also increase data volume and complexity. GeoAI addresses this complexity through spatial pattern recognition, prediction, and prescriptive analysis [6–8]. This trend toward intelligent geospatial decision support will enhance problem identification, policy appraisal, resource allocation and public engagement, as long as public institutions can comprehend and respond to the evidence.

### *1.2. LLMs and Conversational Geospatial Intelligence*

LLMs are transformer-based foundation models pretrained on large text corpora to capture linguistic patterns, semantic relationships, and context [9,10]. However, general-purpose models do not explicitly encode spatial knowledge and may generate incorrect geographical relationships or locations. GeoLLMs address this limitation by integrating maps, spatial ontologies, location knowledge, and geospatial data to support geographic question answering, information retrieval, routing, disaster assessment, and environmental monitoring. When combined with imagery, maps, and sensor observations, these models can support multimodal analysis and context-aware geospatial governance.

### *1.3. Research Gap*

Research on GeoAI and LLMs is dispersed across geography, computer science, information systems, public administration, urban planning, and decision science. Existing studies often examine individual technologies or applications rather than their integration across the governance process. Consequently, limited knowledge explains how GeoAI and LLM capabilities connect data acquisition and knowledge extraction with decision support, policy implementation, and public-value creation. support and public value.

### *1.4. Research Objectives and Questions*

This systematic literature review aimed to address these gaps with the following objectives:

**RO1:** To explore the shift from traditional GIS and spatial decision-support to GeoAI- and LLM-based governance.

**RO2:** To systematically categorize the included studies in terms of the research methods, geographical context, application domain, technological aspect, and the main findings.

**RO3:** To analyze, synthesize, and critique both the applications and the ways in which these are enabled, and the outcomes, limitations, and strength of evidence related to GeoAI and LLMs in public-sector governance.

**RO4:** To detect the technical, organizational, institutional, ethical and societal obstacles related to adoption and implementation.

**RO5:** To communicate the significance of the key themes identified in the literature reviewed to the development of an Intelligent Governance Framework through the use of GeoAI.

Thus, this study aims at answering the following research questions:

**RQ1:** How has public-sector geospatial decision support evolved from conventional GIS to GeoAI- and LLM-enabled governance?

**RQ2:** What are the methodological, geographical, technological and application aspects that characterize the available literature?

**RQ3:** What governance applications, enabling mechanisms, outcomes and limitations are documented in literature?

**RQ4:** What technical, organisational, institutional, ethical and societal factors affect the uptake of governance with GeoAI and LLMs?

**RQ5:** How can the reviewed evidence be integrated into a theoretically informed governance framework and future research agenda?

### *1.5. Contributions of the Study*

This study makes four contributions. First, it consolidates fragmented research on GeoAI, LLMs, geospatial analytics, and public-sector governance. Second, it systematically characterizes and critically evaluates the current evidence. Third, it develops a six-layer GeoAI-Driven Intelligent Governance Framework linking data inputs, GeoAI capabilities, analytics, governance functions, decision support, and public-value outcomes. Fourth, it synthesizes the Resource Based View, Dynamic Capability Theory, the Technology–Organization–Environment framework and Public Value Theory to develop testable propositions and future research directions. Collectively, these contributions explain GeoAI-enabled governance as a socio-technical transformation shaped by technological capabilities, organizational readiness, institutional accountability, responsible decision-making, and public-value creation.

## 2. Review Methodology

This study used a systematic literature review to identify, review, and synthesize multi-disciplinary evidence regarding GeoAI, LLMs, geospatial analytics, and public-sector governance. The process of selecting studies was conducted in accordance with the reporting framework of PRISMA 2020 [23] and systematic-review principles were used to identify and synthesize the evidence [24–27].

### *2.1. Information Sources and Search Period*

The relevant studies were identified using Scopus, Web of Science, IEEE Xplore, ScienceDirect, and SpringerLink, with the aid of Google Scholar for additional research, backward citation tracking, and forward citation tracking. The review includes the publications between January 2018 and December 2025 in English that address public-sector governance enabled by GeoAI and LLM technologies.

All database searches were conducted on 30 January 2026.

### *2.2. Search Strategy*

The search combined terms representing geospatial technologies, artificial intelligence, and public-sector governance. The principal Boolean expression was:

(“GeoAI” OR “geospatial artificial intelligence” OR “geospatial analytics” OR “spatial decision support” OR “conversational GIS” OR “GeoLLM*” OR “large language model*”) AND (“governance” OR “public administration” OR “public sector” OR “smart cit*” OR “policy” OR “government decision support”)

The expression was adapted to each database’s syntax and field restrictions. Scopus searches used title, abstract, and keyword fields; Web of Science used the Topic field; and IEEE Xplore, ScienceDirect, and SpringerLink used the available title, abstract, keyword, or metadata fields. Searches were limited to English-language, peer-reviewed publications issued between January 2018 and December 2025. The database-specific syntax and field adaptations were recorded in the review search log to support replication.

The database search was supplemented by backward reference-list screening and forward citation tracking of eligible studies through Google Scholar. Records retrieved were then consolidated prior to deduplication and eligibility screening. This process underpinned coverage in the geospatial science and artificial intelligence, the information systems, the decision science and the public administration domains.

### *2.3. Eligibility Criteria*

The studies were included in the study if they were peer-reviewed, published between 2018–2025 in English, available in full text, and they contained (conceptual, empirical, technical, methodological, or review-based) evidence relevant to GeoAI or AI-enabled GIS, geospatial analytics, spatial decision-support systems, GeoLLMs, or LLM-enabled public-sector governance applications. Relevant contexts encompassed public administration, smart city, disaster-risk management, environmental governance and management, infrastructure, agriculture, natural resources management, public service delivery and policy decision support. Studies were not included if they only focused on conventional GIS but not on an AI-based analytical component, only on AI but not on the geospatial or governance aspects, were not peer-reviewed and/or did not include the necessary information to assess eligibility, duplicated records, substantially overlapping with or outside other included studies, or lacked the required information for the necessary assessment.

### *2.4. Study Selection*

The search identified 312 records. After 47 duplicates were removed by comparing titles, authorship, publication information, and digital identifiers, 265 records underwent title-and-abstract screening, resulting in 183 exclusions. As mentioned in Table 1, The full texts of 82 studies were assessed against the eligibility criteria, with uncertain cases reassessed for consistency. Thirty-one studies were excluded because they were unrelated to governance (n = 12), unrelated to GeoAI or geospatial analytics (n = 8), lacked an AI-enabled component (n = 5), had unavailable full texts (n = 3), were not peer-reviewed (n = 2), or contained overlapping content (n = 1). Consequently, 51 studies were included in the qualitative synthesis.

**Table 1.** PRISMA study-selection summary.

| Review Stage | Number of Records |
|---|---|
| Records identified through database searching | 312 |
| Duplicate records removed | 47 |
| Records screened by title and abstract | 265 |
| Records excluded during title-and-abstract screening | 183 |
| Full-text articles assessed for eligibility | 82 |
| Full-text articles excluded | 31 |
| Studies included in the qualitative synthesis | 51 |

The study-selection process is illustrated in Figure 1.

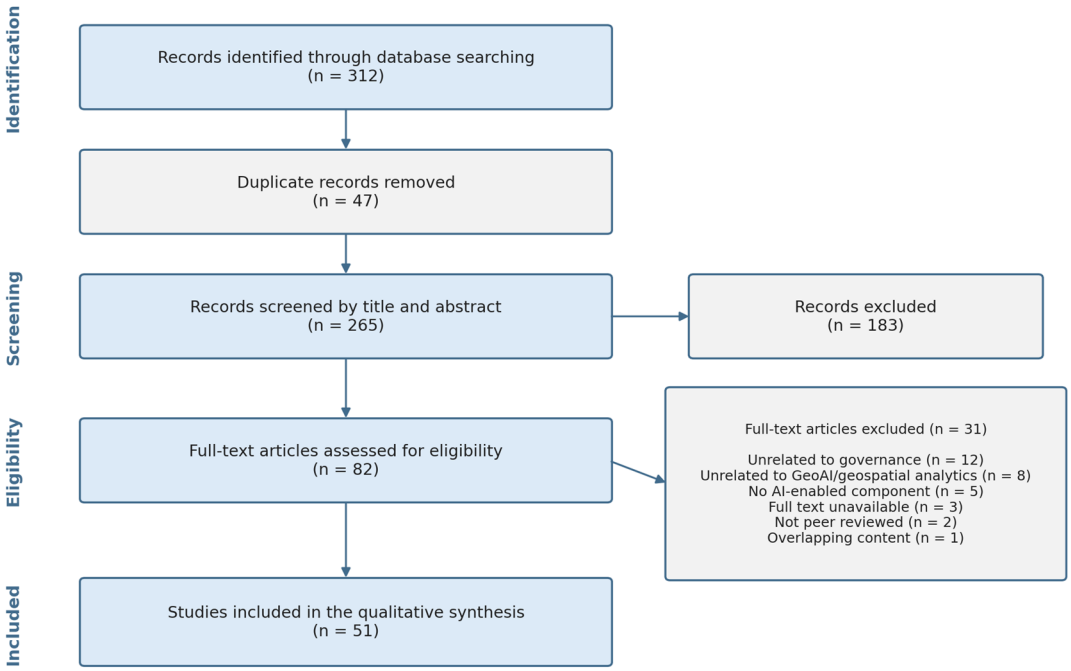



**Figure 1.** PRISMA 2020 study-selection flow Diagram (Reprinted with permission from Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; et al. [23], 2021).

### *2.5. Data Extraction and Study Characterisation*

A structured data-extraction framework was used to characterize and systematically compare the 51 included studies by publication year, geographical setting, research design, governance domain, geospatial data source, GeoAI or LLM technology, principal application, reported outcomes, implementation barriers, theoretical perspective, and research and policy implications. After consistency checks, the study-level dataset was used to analyze publication trends, methodological patterns, geographical coverage, technological applications, governance outcomes and research gaps.

### *2.6. Quality Assessment*

The methodological quality and relevance of the 51 studies was evaluated by considering the clarity of the purpose, the research design, the transparency of the data and analytical procedures, the quality of supporting evidence, the relevance to public-sector governance, the use of ethical and methodological considerations, and the contribution to theory or practice. The assessment process confirmed that the contributions were: solid empirical evidence contributions; preliminary contributions; conceptual contributions; and technique oriented contributions; and that studies with methodologically diverse approaches and relevant to the decision support of the public sector on GeoAI and LLM were kept.

### *2.7. Data Analysis and Evidence Synthesis*

The analysis method used a descriptive profiling, a thematic synthesis and also a comparative analysis across the publication year, geographical setting, research methods, governance domains, technologies and application areas. A hybrid coding approach combined themes from the review goals with recurring themes related to geospatial data resources, the capabilities of GeoAI and LLM, analytical and decision-support processes, governance functions, public value outcomes, institutional conditions, ethical, regulatory, and societal challenges. Studies were grouped into conceptual, proof of concept, simulation-based, case-based, or empirical evaluations. This classification helped identify governance outcomes that were demonstrated in practice and prospective applications, and revealed methodological gaps, spatial variation, conflicting evidence, and gaps in the research literature.

### *2.8. Framework and Proposition Development*

The GeoAI-Driven Intelligent Governance Framework is based on thematic linkages between geospatial data resources, GeoAI and LLM capabilities, analytical processes, governance functions, decision support and public-value outcomes. The six layers were explained using the Resource Based View, Dynamic Capability Theory, the Technology-Organization-Environment and Public Value Theory. The reviewed evidence was correlated with these theoretical mechanisms to inform the research propositions and to provide a foundation for future empirical research in GeoAI-enabled public-sector decision support.

### *2.9. Methodological Limitations*

The literature search only included English language, peer-reviewed sources from 2018 to 2025 and may not have captured relevant multilingual and grey literature. There may be coverage changes due to variations in terminology and database indexing between GeoAI, LLMs, and public governance. Only as a secondary information source was Google Scholar consulted, as its coverage and ranking process was not as transparent as that of structured bibliographic databases. The limitations were taken into account in interpreting the findings and formulating the research agenda.

## 3. Evidence Profile of the Included Studies

The 51 included studies formed a methodologically and geographically heterogeneous evidence base. The literature comprised conceptual and framework papers, technical and proof-of-concept studies, simulation-based evaluations, public-sector case studies, and empirical assessments of governance outcomes. Technical demonstrations and predictive-performance evaluations were more developed than longitudinal, comparative, or causal assessments of policy effectiveness and public value. Consequently, evidence for analytical feasibility was generally stronger than evidence for sustained institutional or societal outcomes.

Geographically, the literature covered cross-national research and country-, regional-, and city-level applications, but developed-country and urban or smart-city settings received greater attention than developing-country, rural, and resource-constrained contexts. Application domains included urban and regional planning,

disaster-risk management, infrastructure, environmental governance, agriculture and natural-resource management, public-service delivery, and SDG monitoring. The studies used satellite imagery, GIS layers, sensors, administrative records, and citizen-generated data, with machine learning, deep learning, remote sensing, and spatial modelling representing established approaches and LLMs, GeoLLMs, conversational GIS, and knowledge graphs representing an emerging evidence stream. Table 2 discussed qualitative evidence profiling of included studies.

**Table 2.** Qualitative evidence profile of the 51 included studies.

| Dimension | Characterization of the Evidence Base | Implication for Evidence Strength |
|---|---|---|
| Research design | Conceptual and framework studies; technical or proof-of-concept demonstrations; simulations; public-sector cases; empirical outcome evaluations | Technical feasibility is better established than longitudinal or causal governance effects. |
| Geographical coverage | Cross-national, national, regional, and city-level settings; stronger representation of developed and urban contexts | Transferability to developing, rural, and resource-constrained settings remains uncertain. |
| Governance domains | Urban planning; disaster risk; infrastructure; environmental governance; agriculture and resources; public services; SDG monitoring | Applications are broad, but outcome measures differ across domains and limit direct comparison. |
| Data resources | Satellite imagery; GIS layers; sensors; administrative records; citizen-generated information | Data quality, interoperability, completeness, and representativeness remain recurring constraints. |
| Technological focus | Machine learning, deep learning, remote sensing, spatial modelling, LLMs, GeoLLMs, conversational GIS, and knowledge graphs | LLM-enabled and conversational applications are promising but have limited field validation. |
| Principal findings | Improved prediction, monitoring, optimization, knowledge access, and decision support | Few studies directly measure policy effectiveness, equity, accountability, citizen trust, or long-term public value. |
| Methodological quality | Variation in data transparency, validation, uncertainty reporting, and discussion of ethical limitations | Stronger studies specify data, models, validation, limitations, and governance context; preliminary studies mainly demonstrate possibility. |

## 4. Evolution of Geospatial Intelligence for Governance

Geospatial intelligence has advanced from descriptive mapping to predictive and conversational decision support [4–8]. While GeoAI and LLMs can enhance public-sector problem identification, policy evaluation, resource allocation, and service delivery [9,10,28,29], their governance value relies on evidence of enhanced institutional decisions and public outcomes.

### *4.1. From Conventional GIS to Spatial Decision Support*

Conventional GIS can be used to analyze spatial information on infrastructure, environment, disparities and service gaps, and citizen generated information can augment the evidence base for public sector. SDSS expands these capabilities to include planning, location, resource allocation, and intervention options [5]. Despite this, its success relies on the quality of the information, the clarity of the model assumptions, the interpretation of an expert and the evaluation of institutional capacity, distributional effects and public acceptability.

### *4.2. Smart Governance and the Transition to GeoAI*

GeoAI empowers smart governance by leveraging machine learning and spatial analysis of satellite, sensor, administrative and citizen-provided data to support infrastructure planning, monitoring of environmental parameters, disaster preparedness and allocation of the public services [6–8,28,29]. But data alone cannot guarantee good and fair governance. Public institutions need to be able to incorporate data, interpret model outcomes, and move to accountably actionable outcomes. Therefore, the effectiveness of the policy, the equitable allocation of resources, the usability of the institutions and the welfare of the citizens should all be considered together with the technical accuracy of GeoAI [3,28,29].

### *4.3. LLM Integration and Conversational Geospatial Decision Support*

The combination of LLM and GIS and GeoAI can help users formulate spatial queries naturally using language, interpret the analytical results, and communicate the evidence of policies to decision makers who are not GIS specialists [9,10]. However, to ensure reliability in conversational decision support, the queries and spatial analyses

must be validated, traceable sources must be identified, uncertainty must be communicated explicitly, and human oversight must be in place to uphold transparency, accountability, and responsible use of AI [3,14,15,20].

### *4.4. Implications for Intelligent Public-Sector Governance*

Figure 2 shows how these technologies are used in combination, not as alternatives. GIS is used for managing spatial data, SDSS is used for comparing alternatives, GeoAI for automated and predictive analysis, and LLMs for conversational access or explanation. They can be integrated with public-sector decision support where there is a reliable data, an organization ready, there are institutional coordination, analytical capacity, and accountable implementation [3,6,28,29]. GeoAI-enabled governance should therefore be assessed as a socio-technical capability through both technical performance and improvements in decision quality, service delivery, equity, and public value.




**Figure 2.** Evolution of geospatial intelligence for public-sector governance.

Figure 2 distinguishes five phases in the evolution of geospatial technologies for governance. Descriptive GIS focuses on mapping and visualization while diagnostic GIS is for spatial analysis and monitoring. Predictive GeoAI supports machine learning–based risk and demand forecasting, and prescriptive GeoAI includes prediction, optimization, and multicriteria analysis to provide recommendations for interventions. The emerging phase combines conversational GIS and AI, real-time learning, and human-AI collaboration. These phases increase governance value from transparency and efficiency, to resilience, citizen-centred decision-making, accountability and public trust.

## 5. Large Language Models in Geospatial Analytics

The combination of LLM, GIS, remote sensing, and GeoAI enables natural-language queries to be used to search for geospatial data, extract knowledge from geo-referenced remote sensing imagery, generate reports, and provide conversational support for decision making. The potential of these capabilities is to increase access to spatial evidence for public governance, but their trustworthiness is contingent upon the validation of spatial analysis, high quality data, traceable evidence and meaningful human oversight.

### *5.1. Foundations and GeoLLMs*

LLMs are transformer-based foundation models pretrained on large text corpora to capture linguistic patterns, semantic relationships, and context [9,10].

General-purpose models, however, do not include any explicit knowledge of spatial relations and can produce false geographic relationships or locations. GeoLLMs address this limitation by integrating maps, spatial ontologies, location knowledge, and geospatial data to support geographic question answering, information retrieval, routing,

disaster assessment, and environmental monitoring. These models can be used in conjunction with imagery and maps, and with sensor observations, to enable multimodal analysis and context-aware geospatial governance.

### *5.2. Natural-Language Querying and Knowledge Extraction*

LLMs can translate natural-language policy questions into executable spatial queries and extract knowledge from large geospatial repositories [6]. Although these functions reduce technical barriers and analytical effort, governance applications require query verification, evidence traceability, spatial validation, and human oversight. Table 3 summarizes the main LLM-enabled technologies and their governance applications in geospatial analytics.

**Table 3.** LLM-enabled technologies and governance applications in geospatial analytics.

| Technology | Primary Function | Governance Application | Key Sources |
|---|---|---|---|
| Large Language Models | Natural-language understanding and generation | Policy support, information retrieval, citizen engagement | [9,10] |
| GeoLLMs | Spatial reasoning and geospatial knowledge processing | Location-based decision support, planning, resource allocation | [11] |
| Natural-language GIS interfaces | Conversion of natural language into spatial queries | Accessible geospatial analytics for policymakers | [6] |
| Retrieval-augmented generation | Context-aware information retrieval and synthesis | Automated governance reports and decision support | [3] |
| Knowledge graphs | Structured representation of spatial knowledge | Infrastructure planning and governance intelligence | [6] |
| Multimodal GeoAI systems | Integration of text, maps, imagery, and sensor data | Disaster management, environmental monitoring | [7] |
| Foundation models | General-purpose AI adaptable to geospatial tasks | Strategic planning and predictive governance | [9] |
| Conversational GIS platforms | Interactive geospatial decision support | Citizen-centric and participatory governance | [3] |

## 6. Applications of GeoAI in Governance

### *6.1. Urban Planning and Disaster-Risk Governance*

GeoAI facilitates evidence-based urban planning and disaster-risk governance by mapping land, modelling urban growth, assessing urban vulnerability, providing early warnings, and allocating resources. By combining satellite imagery, sensor observations, meteorological data, and socioeconomic indicators, it can help governments anticipate floods, landslides, wildfires, and other hazards, assess potential impacts, and plan mitigation and emergency resources [6,8]. Automated imagery analysis can facilitate post-disaster damage assessment, and conversational interfaces can provide timely access to spatial evidence to the responders. However, effective governance is still reliant on trustworthy data, models that have been well tested, institutional capacity and the implementation of forecasts in planning and crisis response.

### *6.2. Infrastructure and Environmental Governance*

GeoAI is used for infrastructure governance to evaluate the suitability of sites, predict demand, optimize networks, and monitor infrastructure in real time in water, energy, and transport. When used in conjunction with remote sensing and LLMs, it also helps in monitoring land-use change, deforestation, water resources, pollution, environmental hazards, and ecosystem degradation [6,7]. In agriculture, GeoAI is used for predicting crop yields, identifying pests, planning irrigation, assessing land suitability, and tracking droughts, and natural-language interfaces provide better access to location-specific evidence [6,7]. These capabilities are able to improve infrastructure investments, environmental compliance, sustainable resource management, food security and rural development, especially in developing nations [30–32]. Their governance value still requires valid and reliable prediction and data and institutional capacity and responsible implementation.

### *6.3. Public-Service Delivery and SDG Monitoring*

GeoAI integrates administrative, remote-sensing, sensor and citizen-generated data to detect gaps in services, predict service needs, optimize service locations, track interruptions and allocate resources within the healthcare, education, transport and utilities sectors [4,6,33]. Interfaces that are capable of providing natural language analysis, reporting, citizen access and issue reporting are further enhanced by LLM capabilities [3]. Additionally, GeoAI also helps to further spatial monitoring and predictive evaluation of SDGs such as food security, water, sustainable

cities, climate action and ecosystems [6,33,34]. Its governance value is in making its services more accessible, reliable, equitable, engaging, and anticipatory of a sustainable future. The key applications, capabilities and governance outcomes are summarized in Table 4.

**Table 4.** GeoAI applications and public-sector governance outcomes.

| Application Area | Core GeoAI Capability | Governance Outcome | Sources |
|---|---|---|---|
| Urban and infrastructure planning | Growth modelling, site suitability, demand forecasting, and network optimization | Sustainable planning and efficient resource allocation | [6,33] |
| Disaster-risk management | Hazard prediction, vulnerability assessment, and early warning | Improved preparedness, resilience, and emergency response | [8] |
| Environmental and agricultural governance | Ecosystem and crop monitoring, climate-risk modelling, and water optimization | Environmental protection, food security, and sustainable resource use | [4,7,30–32] |
| Public-service delivery | Accessibility analysis, demand forecasting, and service optimization | Improved service quality, spatial equity, and citizen satisfaction | [3,6] |
| SDG monitoring | Indicator mapping and predictive sustainability analytics | Evidence-based policy and support for evidence-based SDG planning | [33,34] |

## 7. GeoAI-Driven Intelligent Governance Framework

Figure 3 displays a six-layer conceptual framework that connects geospatial data, GeoAI capabilities, analytical processes, governance functions, decision support, and public-value outcomes, which is derived from the hybrid thematic synthesis. The layers are directly mapped to the higher-order coding categories reported in Section 2.7 and evidence profile in Section 3. From the reviewed studies, recurrent relationships showed that data and technological capacity only generate governance value when it is translated via institutional functions and processes of accountability in decision-support. The framework thus elucidates the path on which public institutions can move from reactive, institution-centred governance to proactive, evidence based and citizen focused decision making.




**Figure 3.** Proposed six-layer GeoAI-driven intelligent governance framework.

- Data-input layer: Represents governance conditions as assembled from satellite imagery, GIS layers, administrative databases, sensor observations and citizen-generated data.
- GeoAI-capability layer: Use machine learning, deep learning, LLMs, and knowledge graphs to discover spatial patterns, derive knowledge from it, merge heterogeneous data, and provide natural-language interaction [6].

- Analytics Layer: Spatial analysis, predictive modelling and scenario assessment to provide analytics layer for identifying service gaps, predicting risks and demand, and assessing policy options [33].
- Governance-function layer: Carries out the translation of analytical evidence to policymaking, allocation of resources, service delivery and targeted public interventions [3].
- Decision-support layer: Transforms governance intelligence into alerts, recommendations, dashboards, conversational queries and human-in-the-loop decisions.
- Public-value layer: Links decisions that use GeoAI with transparency, efficiency, sustainability, equity and citizen satisfaction [1,35].

The model represents the six layers as a socio-technical system and not as individual technical elements. Knowledge graphs, explainable analytics, human oversight, and citizen participation enhance interpretability, accountability, legitimacy, and geospatial evidence to support action in the public arena. The framework also offers a foundation to empirically test the effect of GeoAI capabilities on the performance of the public sector.

The six layers are interconnected and form a feedback mechanism. Multi-source data is translated and transformed into GeoAI driven intelligence, used as part of Governance functions and then translated by a combination of Humans and AI in decision-support functions to achieve public-value outcomes. All layers are supported by cross-cutting enablers such as standards, data governance, ethics, skills, infrastructure, explainability, and human oversight, which facilitate the entire process, and outcome feedback for institutional learning and continuous improvement.

## 8. Theoretical Foundations and Research Propositions

The framework brings together four theoretical perspectives to illustrate how the capabilities and tools of geospatial data and GeoAI are transformed into governance functions and public-value outcomes, as shown in Figure 4. The Resource-Based View highlights the strategic resources needed for GeoAI governance, the Dynamic Capability Theory captures the manner in which institutions bring these resources to light and transform them, the Technology–Organization–Environment framework delineates the conditions that influence adoption, and Public Value Theory evaluates whether adoption creates public value.

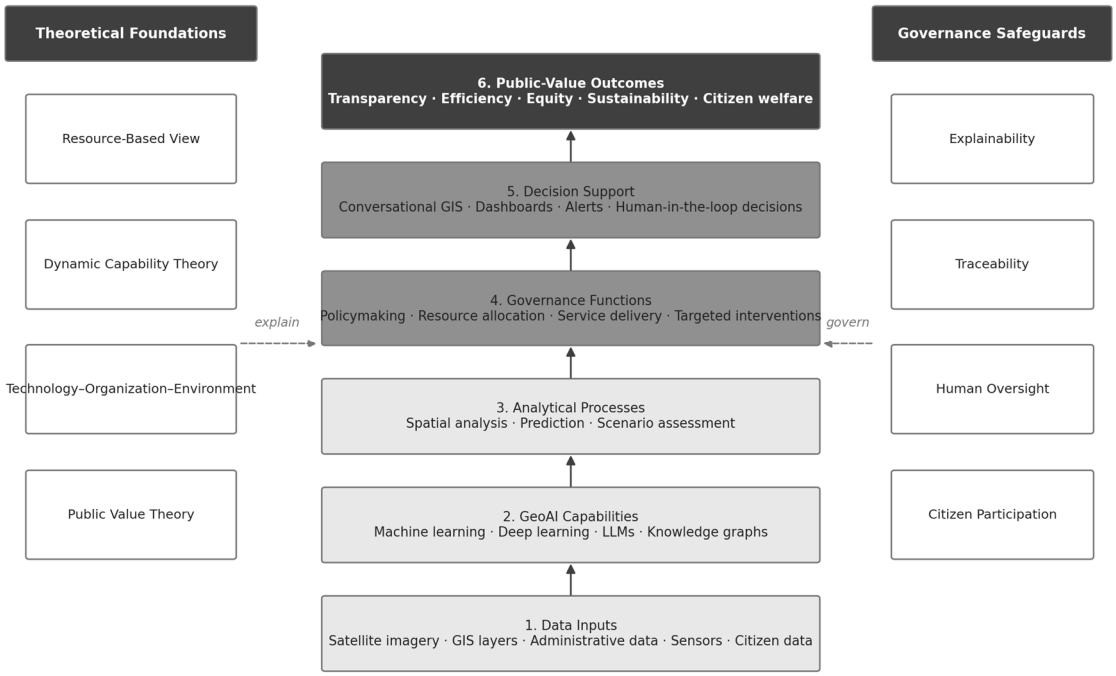



**Figure 4.** GeoAI-driven intelligent governance framework.

### *8.1. Resource-Based View*

The Resource-Based View (RBV) centered around geospatial data, digital infrastructure, analytical skills, institutional knowledge, and inter-organizational networks as strategic public sector resources [36]. The availability of these resources does not ensure good governance, but value is added through their effective integration and synthesis to create credible spatial intelligence for policy-making, resource allocation and service delivery. Data quality, interoperability, technical competence and institutional knowledge are thus essential to public-sector GeoAI capability.

### *8.2. Dynamic Capability Theory*

Dynamic Capability Theory bridges the gap between public institutions, governance demands, and the opportunities for technology and the need to reconfigure structures and processes when conditions change [37]. While GeoAI and LLMs can aid in risk forecasting, monitoring, scenario assessment, and conversational access to evidence [6,9,10], institutional learning, interagency coordination, workforce capability, and the integration of analytical outputs into operational decision-making is also essential to their effective use.

### *8.3. Technology–Organization–Environment Framework*

The T-O-E framework offers insights into the factors that influence the adoption of GeoAI, categorizing them into three areas: technological, organizational, and environmental [38]. The technical performance, however, is not the only condition for the effective adoption.

### *8.4. Public Value Theory*

Public Value Theory extends the assessment of GeoAI beyond technical efficiency to societal outcomes [39]. GeoAI can create public value through transparency, accountability, service quality, equity, sustainability, citizen engagement, and welfare [1,3,35]. However, flawed data and models, privacy risks, opaque decision-making, and inequitable access can undermine trust and deepen spatial inequalities. Human oversight and responsible governance are therefore essential to legitimate public-value creation.

### *8.5. Research Propositions*

The following propositions translate the framework into testable relationships. P1 follows the Resource-Based View by linking resource orchestration to GeoAI capability; P2 links that capability to governance functions; P3 introduces dynamic capabilities as an institutional translation mechanism; P4 applies the Technology-Organization-Environment framework to adoption and effective use; and P5 applies Public Value Theory by connecting governance functions with societal outcomes under responsible-governance conditions.

**P1:** The effective orchestration of high-quality geospatial data, digital infrastructure, analytical skills, and institutional knowledge positively influences public-sector GeoAI capability.

**P2:** GeoAI capability positively influences predictive, adaptive, and evidence-based governance functions through spatial analysis, risk forecasting, and decision support.

**P3:** Institutional dynamic capabilities strengthen the translation of GeoAI capability into policymaking, resource allocation, and public-service delivery.

**P4:** Technological readiness, organizational capacity, and supportive environmental conditions positively influence the adoption and effective use of GeoAI in public institutions.

**P5:** GeoAI-enabled governance functions positively influence public-value outcomes when supported by explainability, accountability, human oversight, equity, and citizen participation.

## 9. Challenges and Barriers

There are multiple and interrelated technical, organizational, institutional, ethical and societal barriers to GeoAI adoption in public governance [1,15]. Public-sector data are frequently incomplete, inconsistent, and siloed, and the quality of the analysis is poor; general-purpose LLMs can generate inaccurate information and lack proper spatial reasoning skills [7,11–13,16]. Technical weaknesses are governance risks when they constrain policy, resource allocation or critical services.

The issues of privacy, surveillance, bias, misuse of data, and lack of human control are ethical and institutional issues [14,15]. In addition, the development of regulation has fallen behind innovation, with questions remaining regarding the ownership of the data, the accountability of algorithms, compliance and liability [35,40]. Explainability and legitimacy are restricted in opaque models [20,21] and public acceptance relies on perceive fairness and transparency [22]. The failure of cybersecurity can cause issues with services, sensitive information leakage, and loss of trust [40].

Organizational readiness is equally important. Adoption and effective use can be constrained due to limited funding, skills shortage, risk aversion, hierarchical structures and bureaucratic procedures [1,17,18,28]. All of these barriers are interdependent: weak data erode models and trust, lack of explainability erode accountability,

lack of skills erode interpretation, and lack of regulation erodes legitimacy. Table 5 presents the key constraints and proposed framework responses, which have been summarised. Much of the evidence reviewed indicates that what is technically feasible is not necessarily what yields sustainable governance outcomes, so these responses are provided as design criteria to be tested in the field.

**Table 5.** Challenges, governance constraints, and proposed framework.

| Challenge | Governance Constraint | Proposed Framework Response | Sources |
|---|---|---|---|
| Data quality and availability | Unreliable analysis and decisions | Multi-source integration, data validation, and provenance | [12,13] |
| Interoperability and data silos | Fragmented coordination and information sharing | Common standards, knowledge graphs, and integrated architecture | [13,16] |
| Limited LLM spatial reasoning | Inaccurate or fabricated spatial recommendations | Validated integration of LLMs with GIS and GeoAI | [7,11] |
| Privacy, bias, and surveillance | Legal, ethical, and public-trust risks | Privacy safeguards, fairness assessment, and human oversight | [14,15] |
| Regulatory gaps | Unclear ownership, accountability, and liability | Rules for data governance, auditing, compliance, and responsibility | [35,40] |
| Legacy-system integration | Operational inefficiency and implementation failure | Modular and interoperable GeoAI architecture | [16,28] |
| Organizational resistance | Slow adoption and weak institutional use | Leadership support, change management, and user participation | [17,28] |
| Skills and financial constraints | Underused systems and limited scalability | Capacity building, accessible interfaces, and phased implementation | [1,18] |
| Cybersecurity risks | Service disruption, data loss, and declining trust | Secure and resilient data and system architecture | [40] |
| Limited explainability | Weak accountability and decision legitimacy | Explainable analytics, traceable evidence, and knowledge graphs | [20,21] |
| Digital divide | Unequal access and social exclusion | Inclusive design, natural-language access, and alternative service channels | [18] |

The alignment of GeoAI capabilities and organizational processes, institutional capacity, regulation and societal expectations are the key challenges. Public agencies can bring in new technologies without investments in data governance, staff capacity, organizational transformation, citizen participation, and regulatory readiness. Therefore, a socio-technical approach is needed to address the need to keep GeoAI initiatives governance-driven, accountable, inclusive and able to generate public value.

## 10. Research Gaps and Future Research Agenda

The review shows the gap between technological development and evaluation of the governance. Many papers evaluate the predictive performance, computational costs, or technical feasibility, but there is less research examining policy impacts, service quality, transparency, equity, citizen satisfaction, and public value in the long term [3,35]. Studies are therefore required to confirm the governance impact of GeoAI adoption over time, across various organizations, and as an outcome.

Five main gaps are identified. First, there is little empirical evidence that links the adoption of GeoAI with measurable governance and public-value outcomes [3,35]. Second, there is a limited number of validated maturity models for institutional readiness, data capability and governance integration [1,28]. Third, there is little existing research on conversational geospatial governance beyond the simple use of chatbots, especially on the topics of spatial accuracy, explainability, accountability, and trust [21]. Fourth, the literature is concentrated in developed-country contexts, limiting its transferability to settings characterized by constrained resources, infrastructure, institutional capacity, and digital access [2]. Fifth, existing performance measures rarely integrate technical, organizational, institutional, and societal dimensions [16].

Future research should prioritize comparative field studies, longitudinal evaluations, institutional case studies, and citizen-centred designs. Conversational and explainable GeoAI should be evaluated through validated spatial queries, traceable evidence, human oversight, and user-trust measures [3,20,21]. Smart-city research should test how real-time spatial intelligence affects services and infrastructure, while climate-resilience studies should examine adaptation and disaster preparedness across diverse institutional and geographic contexts [40–43]. More focus is required on developing countries and marginalised communities. Human-AI collaboration should also be explored as a governance model in which AI supplements, not replaces, ethical, contextual and politically accountable human judgement [40–43]. This agenda is summarized in Table 6.

**Table 6.** Future research agenda for GeoAI-driven intelligent governance.

| Research Theme | Unresolved Research Problem | Methodological Priority | Expected Contribution | Sources |
|---|---|---|---|---|
| Governance impact and maturity | Limited evidence linking GeoAI adoption with sustained governance outcomes and institutional readiness | Longitudinal studies, maturity-model development, and cross-agency comparisons | Validated relationships among readiness, adoption, performance, and public value | [1,3,28,35] |
| Conversational and explainable GeoAI | Uncertain spatial accuracy, explainability, accountability, and trust in LLM-enabled systems | User experiments, query-validation studies, algorithmic audits, and field trials | Accessible and accountable geospatial decision support | [3,20,21] |
| Smart-city and public-service governance | Limited evidence that real-time GeoAI improves services, mobility, and infrastructure decisions | Comparative city studies and service-performance evaluations | Improved urban efficiency, accessibility, and sustainability | [3,16,33] |
| Climate resilience and developing-country contexts | Geographical bias and inadequate consideration of institutional and resource constraints | Multi-country studies, local case research, and participatory methods | Context-sensitive climate adaptation and disaster governance | [2,41] |
| Human–AI governance and public value | Limited understanding of how human judgement, AI recommendations, and accountability interact | Mixed-method research, stakeholder studies, and public-value assessment | Legitimate, equitable, and citizen-centred governance | [39–41] |

## 11. Managerial and Policy Implications

GeoAI should be viewed as a strategic governance capability, and not just a technology. Interoperable administrative databases, satellite observations, GIS layers and sensor data, citizen-generated information, workforce development, data-governance mechanisms, and organizational change should be the top priority for public agencies. Governance issues must be identified and public outcomes measured first, before investment decisions are made on technology procurement.

Urban-intelligence platforms and digital twins can support smart-city administrations in traffic control management, urban infrastructure maintenance, urban growth assessment, and emergency response management [42]. While the conversational interface can make it easier for the non-specialist officials and citizens to access the content, the results it produces have to be checked, explained, and monitored by humans. Spatial targeting and predictive analysis can also be useful to decentralise provisioning of resources, disaster preparedness and development planning in district administrations, especially when resources and information is scarce.

Data-governance frameworks need to include data quality, interoperability, privacy, algorithmic auditing, accountability, human responsibility and cybersecurity. Agencies should start with pilots and only expand if they are evaluated and verified separately. Technical feasibility is not enough to ensure governance impact over time: consider decision quality, service accessibility, spatial equity, efficiency, citizen trust, and public value.

Table 7 discussed the managerial and policy implications of GeoAI-driven governance.

**Table 7.** Managerial and policy implications of GeoAI-driven governance.

| Stakeholder | Principal Implication | Priority Actions |
|---|---|---|
| Government agencies | Build GeoAI as an institutional capability | Incorporate GIS data, build GIS skills, create governance processes, and assess public benefits |
| Smart-city administrations | Use GeoAI for coordinated urban management | Build intelligence platforms, digital twins, real-time monitoring and validated conversational access that are interoperable. |
| District administrations | Strengthen decentralized and context-sensitive decision-making | Use GeoAI for resource allocation, disaster preparation, infrastructure planning, and service-gap assessment. |
| Policymakers and regulators | Establish an environment that has accountability within its institutional structure. | Implement interoperability, privacy, auditing, cybersecurity, liability and human oversight standards |
| Technology providers | Create reliable and scalable systems | Focus on explainability, spatial validation, interoperability, security, accessibility and citizen-centred design. |

The implications suggest that GeoAI-led governance is a socio-technical transition that involves coordinated investments in data, institutions, people, regulation and public trust.

## 12. Conclusions and Prospects

This systematic review focused on the application of GeoAI, LLMs, and geospatial analytics in public-sector governance, such as urban planning, disaster management, infrastructure, environmental management, agriculture, public-service delivery and SDG monitoring. Findings reveal a shift from descriptive GIS to predictive and prescriptive, and even conversational, decision support systems. The evidence, however, is mostly technical, and limited in empirical evaluation of the effectiveness of the policies, quality of the services, equity, accountability, trust of citizens and public value in the long term.

The study suggests a six-layer GeoAI-Driven Intelligent Governance Framework that connects geospatial data, GeoAI capabilities, analytical processes, governance functions, decision support and public-value outcomes. It builds on Resource Based View, Dynamic Capability Theory, the Technology-Organization-Environment model and Public Value Theory and outlines how the elements of technological resources, institutional capabilities, adoption conditions and governance protective measures affect outcomes. The propositions below are a starting point for empirical testing at administrative and geographic level.

The review also highlights the interdependent barriers related to data quality, data interoperability, spatial reasoning, privacy, bias, regulations, readiness, skills, cybersecurity, explainability and digital inclusion. Further research is needed using longitudinal designs and measures of governance performance that have been validated, as well as using evidence from developing country settings. Conversational AI, explainable GeoAI, digital twins, and knowledge graphs have significant potential, but rely on spatial validation, institutional capacity, human oversight, regulatory accountability, and citizen involvement to be public.

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## Conflicts of Interest

The authors declare no conflict of interest.

## Use of AI and AI-Assisted Technologies

During preparation of this manuscript, the authors used an AI-assisted tool for language editing and structural organization. The authors subsequently reviewed and revised the content and take full responsibility for the published work.

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