Beyond Boundary Lines: Emerging Innovative Trends in Geospatial Data for Decision-Making

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Abstract

As technology and the use of data innovates and iterates by the second, so does the use and implementation of geospatial data into decision-making processes across the globe. The use of geospatial data is intertwined in every part of life with technology, from accessing bank transactions to adaptive navigational systems. This literature review identifies new and evolving trends in the use of geospatial data by analyzing 83 publications between January 2023 and December 2024. Top trends included the use of machine learning and artificial intelligence, natural language model usage, and object detection studies; with all trends focusing on analysis of large data sets. Use cases are initially reviewed for the private commercial sector, such as technological integration and open-data initiatives, before discussing emerging areas, such as the pervasive utilization of deep learning algorithms and neural networks. The Sustainable Development Goals (SDGs) were kept in mind for this study, especially when attempting to identify emerging areas that may aid in the assessment and solution paths of each goal.

Keywords: geospatial data, artificial intelligence, deep learning, Sustainable Development Goals (SDGs), disaster response, urban development, decision-making processes

1. Introduction

Decision-making processes worldwide have become increasingly reliant on information that includes geospatial data, which encompasses any information with location or spatial components. This data can describe events, objects, or features and has become indispensable across a wide range of sectors, including agriculture, urban planning, and national security. The convergence of artificial intelligence, big data analytics, and advanced sensing technologies has ushered in a new era of geospatial capabilities, offering unprecedented insights into complex spatial phenomena.

The use of geospatial data in governance dates back to the late 18th century with initiatives like the planning of Washington, D.C., as the U.S. capital. Since then, the importance and application of geospatial data have grown significantly, both in the United States and globally. Countries such as Canada, with its GeoConnections program, and the European Union, through the INSPIRE Directive, have established frameworks to promote geospatial data sharing and integration. In Asia, nations like China and India are advancing satellite imaging and geospatial technologies to support large-scale urban development and disaster management. Today, nearly every federal agency in the U.S. and many governments worldwide maintain dedicated departments for geospatial data collection and analysis.

The private sector has also been instrumental in driving innovation globally. Companies like Airbus and Maxar have led advancements in satellite imaging, while organizations such as Google and Esri have developed transformative tools for geospatial analysis and visualization. Within the U.S., the Geospatial Data Act of 2018 has established robust frameworks for data governance and interagency collaboration, with the Federal Geographic Data Committee (FGDC) overseeing geospatial data management. The FGDC's National Spatial Data Infrastructure (NSDI) Strategic Plan for 2025–2035 emphasizes commercial applications, recognizing that cutting-edge innovations often remain classified or outside the scope of public discourse. Globally, these advancements demonstrate a shared commitment to harnessing geospatial data for societal and economic progress.

To understand how geospatial data is being used, we must first answer how geospatial data is created. Geospatial data can be created through multiple avenues, broken down into categories such as terrestrial, air-borne, and space-borne platforms for collection. Fig. 1 below shows different examples of platforms that collect geospatial data and where they may be found.

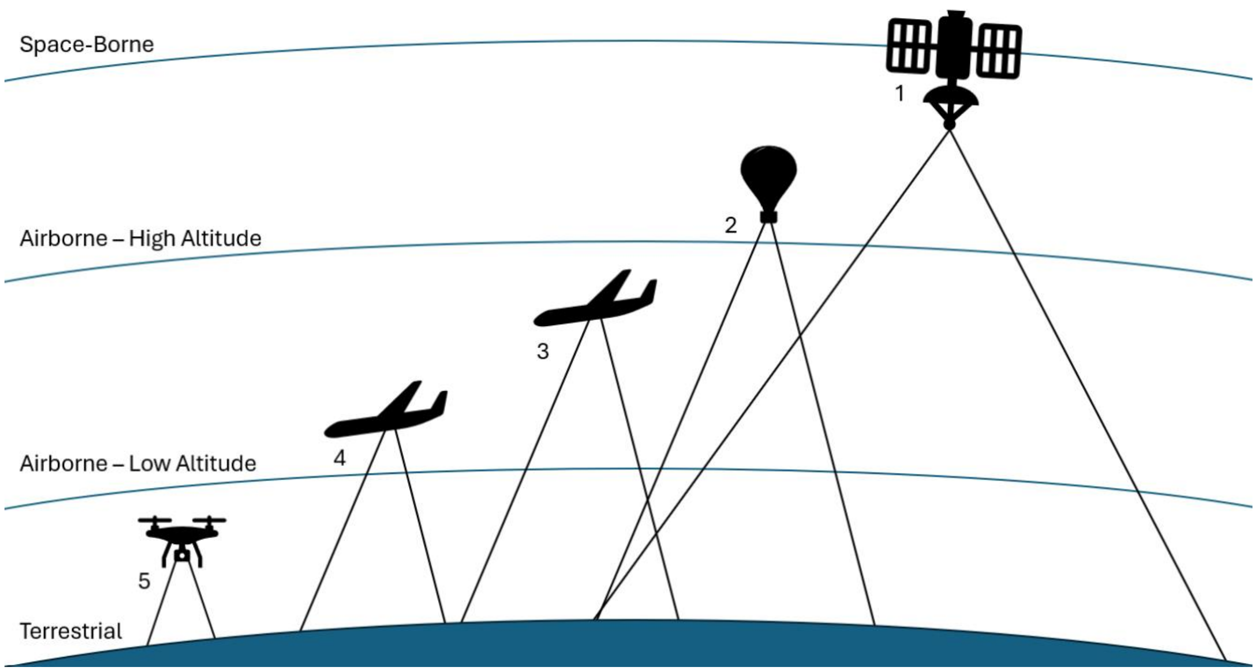

Fig. 1. Levels at which geospatial sensors may be found.

Fig. 1 represents different altitudes and different sensor types, noted with numbers. The satellite (1) exists in the space-borne level of sensors, and records geospatial data in the forms of types of collections within the electromagnetic spectrum of the Earth's surface. These sensors are typically expensive and time-consuming in both production and tasking of collection. High-altitude crafts, such as balloons (2) or high-endurance Unmanned Aerial Vehicles (UAV) (3). These can carry a multitude of different sensors but are not as large as those carried on the satellites. They are also quicker to launch and task for collection, with a farther reach at longer endurance. Aircraft that are human piloted (4) are often used in aerial surveys or disaster response and normally fly at altitudes above smaller, commercially produced personal drone aircraft (5). These smaller aircraft are available to the populace to purchase and use in creating geospatial data. Not depicted in this figure are the terrestrial or online creators of data, such as radio towers or surveyors.

This paper aims to explore the cutting-edge developments in geospatial technologies, their applications across private and public sectors, how they influence decision making, and the emerging challenges that accompany these advancements. We address the following research questions:

1. What are the key emerging technologies shaping the future of geospatial data and the use within decision-making processes?
2. How are these technologies being applied across different sectors within commercial space, and what are their potential impacts on sustainable development?
3. What are the major policy and ethical challenges associated with the rapid advancement of geospatial technologies?

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2. Methodology

This review comprehensively analyzes and discusses recent advancements in the use of geospatial data from January 2019 to December of 2024. We have gathered and selected over 83 papers from reputable journals and various grey literature publications. To gather these sources, we utilized IEEE Xplorer, Google Scholar, ResearchGate, Nature.com, Science.com, European Space Agency (ESA) Copernicus Programme, National Geospatial-Intelligence Agency resources, Geo-spatial Information Science by Taylor & Francis, and arXiv. A secondary search was performed in order to capture news articles related to innovations in the geospatial industry that may not have been peer-reviewed and published. The primary keywords consisted of geospatial data, geospatial industry, spatial data, machine learning, environmental monitoring, and sustainable development goals. These keywords were combined along with others in order to refine search results while still capturing relevant publications.

The search strategy consisted of the identification of reputable sources, including journals and various news or government-aligned sources. We focused on a specified timeline with strict inclusion criteria focused on geospatial technologies, applications, and innovations. Our systematic review followed the PRISMA protocol, including comprehensive database searches, inclusion of peer-reviewed articles, conference proceedings, government reports, and news articles, and rigorous quality assessment of the selected sources.

To extract data from the sources selected, we developed a framework that targeted technological advancements in use of geospatial data, applications of said data, any policy changes, and ethical considerations in the use of geospatial data. Each author collected sources independently and added them to a database to be reviewed and analyzed by the others. Data for this review was collected to answer the research questions, following a timeframe to analyze recent trends, certain keywords to find breadth of publications that still pertain to the topic, and to reduce risk of bias.

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3. Private Industry

Geospatial data has transformed the way decisions are made across industries, from agriculture to logistics. The private sector, known for its adaptability and innovation, has been pivotal in expanding the use of geospatial technologies by harnessing advancements in satellite systems, machine learning, and data analytics. While initially dominated by government and military uses, the commercial landscape for geospatial data has grown significantly over the past two decades, driving significant technological progress [3][5][8][9].

Collaborations like public-private partnerships, open data initiatives, and venture capital investments have collectively increased the accessibility of geospatial data now more so than ever. Take, for example, the European Space Agency's Copernicus programme and platforms like OpenStreetMap that have allowed startups and established firms to leverage high-quality datasets without incurring high costs [4][7][12]. However, the private-sector's heavy reliance on geospatial data brings its own challenges. Issues of interoperability, privacy concerns, and regulatory compliance often complicate the process.

The following sections examine trends and challenges in private industry, provide insights into funding mechanisms, and conclude with how these findings link to emerging issues in geospatial technologies.

3.1 Private Industry: Trends and Applications

3.1.1 Private-Sector Contributions

The private sector has played a transformative role in geospatial technology, driving innovations like high-resolution satellite imaging, 3D mapping, and geospatial predictive models [3][5][9]. Companies like Maxar Technologies and Planet Labs are pushing boundaries with near-daily Earth observation capabilities, enabling applications in environmental monitoring, urban planning, and natural resource management [11][14][20]. For example, startups specializing in Unmanned Aerial Vehicles (UAVs) have revolutionized agricultural monitoring by delivering cost-effective, high-resolution insights for farm management [23][26].

Building on its innovative capabilities, the private sector continues to drive advancements in geospatial technologies that align with the United Nations Sustainable Development Goals (SDGs) [68]. Through solutions like AI-driven analytics and GIS platforms, companies such as Esri have enhanced real-time data collection essential for goals like SDG 13 (Climate Action) and SDG 11 (Sustainable Cities and Communities). Initiatives like SDGs Today integrate private expertise with public policy to optimize data usage [22][25]. Open data platforms like OpenStreetMap foster collaboration in humanitarian aid and urban planning [10][24][69][78]. Furthermore, private entities use satellite imagery and modeling to monitor environmental changes, contributing to SDGs focused on climate resilience and ecosystem conservation [19][30][33]. Geospatial data enables informed decision-making and resource allocation, solidifying its role in achieving global sustainability targets.

Additionally, private firms are tailoring niche solutions to meet industry-specific challenges. In the energy sector, geospatial technologies monitor pipeline integrity and optimize renewable energy placement [15][29]. Financial technology companies leverage geospatial intelligence to analyze regional economic data, informing investment strategies and insurance risk assessments [18][35]. Such advancements reflect how private-sector innovation addresses global challenges while stimulating market growth.

3.1.2 Technological Integration

The integration of artificial intelligence (AI), machine learning (ML), and cloud computing has enhanced the utility and processing of geospatial data. AI-driven models enable real-time detection of urban sprawl, environmental changes, and infrastructure needs [1][13][19]. For example, Google Earth Engine combines vast geospatial datasets with machine learning for tasks such as forest monitoring, flood prediction, and urban expansion analysis [43][44].

Cloud-based platforms like AWS, Azure Maps, and Esri's ArcGIS Online facilitate scalable data storage and analysis, providing solutions for disaster resilience, pandemic control, and global supply chain optimization [8][11][28]. Integration of digital twins—virtual replicas of physical environments—further supports real-time simulation and planning in industries like transportation, real estate, and urban management [18][25][40].

3.1.3 Open Data Initiatives

Open data initiatives have been critical to expanding geospatial accessibility. Programs like Copernicus and OpenStreetMap offer high-resolution datasets at minimal or no cost, empowering both startups and established firms to innovate [4][7][10]. Open-source tools such as QGIS and R-based spatial packages allow researchers and practitioners to analyze spatial data effectively [15][32]. A notable success is the use of Copernicus imagery for climate monitoring. Data from the Sentinel satellites helps track deforestation, ice melt, and atmospheric changes, informing global climate policies and local interventions [10][27][35]. Similarly, OpenStreetMap has proven indispensable during humanitarian crises, enabling rapid mapping of flood-prone regions or disaster-affected zones [12][24][33].

Governments and international agencies increasingly collaborate with the private sector to enhance data quality and availability. For instance, initiatives like the Open Data Cube integrate diverse datasets, supporting research in sustainable development, food security, and resource management [14][30][38].

3.1.4 Emerging Applications

The private sector's use of geospatial data is rapidly expanding across industries. Below is a curated list gathered from the literature of notable and emerging applications:

1. <u>Precision Agriculture</u>: UAVs, IoT sensors, and geospatial platforms enable farmers to monitor soil health, optimize irrigation, and improve crop yields [5][23][26]. AI-driven models provide actionable insights for resource efficiency and environmental sustainability.

2. Infrastructure and Planning: Digital twins are increasingly being adopted across various types of infrastructure to simulate systems, optimize traffic flow, enhance utilities management, and integrate renewable energy grids [18][24][42]. These tools facilitate the design and management of resilient, smart infrastructure, addressing challenges in housing, transportation, and resource distribution across urban, suburban, and rural areas.
3. Energy Management: Geospatial analytics optimize solar and wind energy site selection, track pipeline networks, and ensure compliance with environmental regulations [15][35].
4. Disaster Response: Near real-time geospatial data assists in disaster preparedness, response, and recovery. AI algorithms analyze satellite imagery to identify flood zones, damaged infrastructure, and vulnerable communities, facilitating rapid resource allocation [2][18][44].
5. Autonomous Vehicles: Geospatial data underpins autonomous vehicle navigation systems, enabling precise mapping, obstacle detection, and route optimization. Companies like Tesla and Waymo use LiDAR, satellite imagery, and high-definition maps to enhance safety and efficiency [19][25][32].
6. Health Industry Planning: Geospatial technologies are used to map healthcare access, identify underserved regions, and optimize resource allocation during health crises. For example, during the COVID-19 pandemic, geospatial tools helped track infection hotspots and plan vaccine distribution [22][28][37].
7. Environmental Justice: Geospatial tools play a crucial role in identifying and addressing environmental inequalities. By mapping pollution levels, socio-economic conditions, and public health data, stakeholders can develop targeted interventions for vulnerable communities [20][30][39].

3.2 Private Industry: Challenges

3.2.1 Data Quality and Bias

Private-sector datasets often prioritize speed and scale over accuracy, leading to issues of quality and reliability. Inconsistencies in sensor calibration, data granularity, and collection methods can introduce errors that affect decision-making processes [5][13][22]. For instance, geospatial data collected via UAVs in developing regions may lack the rigor of government-validated datasets [18][30].

Bias in data collection is another significant issue. Areas with limited technological infrastructure, such as remote or rural regions, often remain underrepresented in geospatial datasets, exacerbating socio-economic inequalities [21][32][36]. Addressing these biases requires standardized protocols, equitable access to technology, and validation through multi-source data integration.

3.2.2 Privacy and Ethical Consideration

As private firms expand their use of location-based services and predictive analytics, concerns over privacy and ethics have intensified. Geospatial data derived from social media geotags, mobile apps, and IoT devices raise questions about surveillance, data ownership, and user confidentiality [9][22][32]. For instance, mobile data tracking for pandemic monitoring sparked debates around individual privacy versus public safety [13][30].

To navigate these challenges, companies are increasingly implementing anonymization techniques, encryption standards, and compliance frameworks that align with global regulations. For example, partnerships with data protection agencies help companies adhere to regional laws such as the GDPR while maintaining operational flexibility [20][31][34]. Collaboration across stakeholders can also address ethical dilemmas by setting clear boundaries for data collection and usage [15][41].

3.2.3 Interoperability Challenges

The diversity of data formats and proprietary standards used by private firms poses challenges to interoperability. This hinders the smooth integration of datasets from multiple providers, particularly in multinational projects requiring consistent data sharing [4][11][28]. Efforts by organizations like OGC and FGDC to develop standardized protocols are ongoing, but widespread adoption remains limited [24][37]. Additionally, the rapid development of new technologies often outpaces the creation of common frameworks. Emerging tools, such as digital twins and geospatial AI platforms, introduce complexities as they rely on multiple data sources with varying standards and levels of granularity [18][29][40]. For example, integrating 3D mapping data from LiDAR sensors with satellite imagery can be resource-intensive without common standards, limiting the scalability of solutions.

To address these challenges, private companies are collaborating with international organizations to develop open-source frameworks and APIs that enable data interoperability. Platforms like GeoNode and MapServer facilitate standardized data sharing, while initiatives like OGC SensorThings API ensure real-time integration across IoT devices and geospatial systems [32][41][44]. By fostering global alignment, these efforts improve data accessibility and utility for cross-industry applications.

Moreover, emerging technologies such as cloud-based GIS platforms and data lakes are helping bridge interoperability gaps. These systems aggregate and harmonize data from disparate sources, making it easier for private firms to integrate geospatial intelligence into broader workflows [18][36]. Industry coalitions, such as the Geospatial Interoperability Reference Architecture (GIRA), are also working to align frameworks across sectors, fostering greater compatibility [25][38].

3.2.4 Regulatory and Legal Barriers

Geospatial operations conducted by global private firms often face conflicts with national sovereignty laws and security regulations. Policies restricting data sharing across borders can limit the scalability of geospatial solutions [8][27][40]. For example, restrictions on high-resolution imagery exports hinder international collaboration on environmental monitoring [14][30]. Some companies are addressing these challenges by forming region-specific partnerships that comply with local data laws while ensuring operational continuity. For instance, Maxar Technologies works with national agencies to provide customized solutions that balance data security with innovation [35][40]. Developing compliance frameworks that align with international standards, such as the UN’s Global Geospatial Information Management (GGIM) initiative, can help overcome these barriers [27][41].

An emerging strategy involves the use of blockchain-based data-sharing systems. These technologies allow for decentralized, secure, and auditable transfers of geospatial data while adhering to regional regulations. For example, blockchain solutions have been piloted to streamline data access for cross-border environmental monitoring projects while maintaining transparency and compliance [33][39].

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4. Funding Mechanisms Supporting Innovation

4.1 Public-Private Partnerships

PPPs provide critical support for private-sector innovation. Programs like NASA's partnerships and the Copernicus Programme offer access to datasets that drive solutions for disaster resilience, climate adaptation, and infrastructure development [4][10][35].

One notable example is the Landsat Program, a long-standing collaboration between NASA and the US Geological Survey (USGS). By providing free access to satellite imagery, Landsat has enabled private companies to develop tools for precision agriculture, urban analysis, and forest monitoring [20][25][38]. Similarly, PPPs like the Sentinel Asia Initiative integrate regional partnerships to address disaster monitoring and response in Asia-Pacific regions [12][30].

4.2 Venture Capital Investments

Venture capital plays a vital role in supporting private-sector innovation, particularly in emerging areas such as AI-driven analytics, high-resolution satellite systems, and UAV technologies. Startups like Planet Labs and ICEYE have benefited from substantial venture funding, enabling them to scale operations and deliver near-real-time geospatial insights to global markets [1][14][23].

In addition to traditional investment firms, impact investors are increasingly funding geospatial startups that address societal and environmental challenges, such as climate resilience, renewable energy mapping, and food security [18][35]. For example, venture-backed platforms are being developed to monitor carbon emissions, optimize deforestation prevention strategies, and support disaster relief efforts [22][26]. Furthermore, corporate venture arms are playing a growing role in funding geospatial innovation. Technology giants such as Google, Amazon, and Microsoft are investing in geospatial analytics startups to integrate advanced spatial intelligence into their ecosystems, driving efficiencies in logistics, urban planning, and resource management [28][36][40].

Venture funding trends also highlight an increased interest in space-based geospatial solutions, including small satellite constellations and AI-enhanced Earth observation systems. Investments in companies such as Capella Space and Spire Global have accelerated breakthroughs in radar imaging, maritime tracking, and climate monitoring [32][38].

4.3 Alternative Funding Models

New approaches like blockchain-based financing and community-driven crowdsourcing are opening exciting possibilities for funding geospatial projects [9][24][39]. Blockchain technology ensures secure and transparent data sharing, while initiatives like OpenStreetMap empower local communities to contribute to mapping efforts, especially in regions that are often underserved [25][33][45]. Broadband connectivity is also becoming increasingly important, as it enhances decentralized platforms by enabling real-time data sharing and supporting cloud-based analytics. These advancements are making geospatial tools more affordable and easier to use, helping to expand the reach of blockchain applications and driving forward projects that align with the Sustainable Development Goals (SDGs) [68].

In addition, global organizations like the United Nations Development Programme (UNDP) and the World Bank contribute significantly to alternative funding models for geospatial projects. Initiatives such as the World Bank's Geo-Enabling Initiative for Monitoring and Supervision (GEMS) enhance transparency and efficiency in development projects using geospatial tools [26][38]. Similarly, the Group on Earth Observations (GEO) pools resources from member nations to support open data initiatives and climate resilience [19][33].

Successful examples of alternative funding models include the Humanitarian OpenStreetMap Team (HOT) which uses crowdsourcing to map disaster-affected areas in real-time, providing vital data for relief operations [10][24]. Blockchain platforms such as FOAM further enable decentralized mapping by allowing secure data contributions while rewarding participants [14][39]. These approaches are reshaping geospatial funding, especially in regions with limited access to traditional resources.

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5. Emerging Issues

Using artificial intelligence (AI) in geospatial data analysis has changed the playing field and has proved itself as one of the largest emerging trends within the field of study. Now able to address complex challenges across various domains such as environmental monitoring, urban planning, and business decision-making, these AI-powered tools can leverage any number of datasets available. Remotely sensed imagery, geospatial data, along with processed spatial content are used to derive meaningful insights and actionable strategies.

5.1 What role does AI play in environmental geospatial data?

AI has proved itself as an important player when it comes to addressing environmental issues through data analysis for things like water resource management, land use classification, among many others. Many machine learning techniques exist and are tailored towards specific tasks. For example, gradient boosted decision trees (GBDT), a land classification model, has shown impressive accuracy in water level predictions and land-cover classification [64]. Similarly, AI-integrated models enable precision agriculture by accurately mapping soil nutrients, promoting sustainable farming practices. It should be mentioned that similar machine learning frameworks are vital for mineral exploration and water resource management. These methods can offer higher accuracy and utility in resource management, especially in more fragile ecosystems like semi-arid regions.

5.2 What role does AI play in urban development?

On the urban development side, AI has been instrumental in analyzing infrastructure during the development phases. The introduction of quantitative models to assess community quality combines AI-powered semantic analysis with multiple data sources to highlight criteria such as convenience, comfort, and safety. AI also facilitates urban and regional planning by analyzing economic, social, and spatial data by enabling planners to forecast urban trends thus enhancing the effectiveness of the planning systems. Explainable AI methods (XAI) like the fuzzy analytic hierarchy process ensure that there are transparent and actionable insights for choosing optimal infrastructure sites, whether that be in urban or rural settings. Explainable Ai is a multi-criteria decision-making tool that has served to construct sustainability models. It is incredibly useful for these kinds of complex problems because Fuzzy handles uncertainty and subjective judgments well [63].

5.3 What is the role of AI in risk assessment and disaster management?

Tools have been developed that can enhance flood mapping capabilities to analyze what types of infrastructure are more at risk for specific flood events. They have enabled authorities to quickly respond to these disasters by mapping the best routes possible for administering aid or evacuating casualties. Specific systems like Desk-AId have helped humanitarian and military forces to navigate landmine fields during demining operations. It used a type of novel data processing called “hard-negative” sampling, where negative samples are incorporated near hazardous (positive) zones. For the sake of that study, negative samples refer to non-hazardous zones and positive points are in hazardous zones. By using this type of sampling, the model is less prone to misclassification by creating more robust decision boundaries. One can imagine why this is so important in higher-stakes applications like landmine detection [55].

5.4 What are the limitations of AI in geospatial applications, such as change detection or object recognition?

AI models can struggle with projects that have a high-resolution requirement. This means that small objects or edges that were classified can be unreliable due to insufficient pixel resolution. Currently, there is often a tradeoff when it comes to resolution and spatial coverage. Typically, what will work on the smaller scale will not perform the same at the larger. Models can also struggle with understanding broader geographic contexts that human analysts are better at considering. Despite research making solid progress in object detection using multispectral sensors, the actual science behind how to blend these data streams is forever evolving. It is critical for improving model accuracy that the streams are integrated effectively and are flexible across a wide spectral and spatial scale [53][65][66][67].

5.5 Natural Language Processing

Natural Language Processing or NLP is a field of digital linguistics that concentrates on how to bridge the gap between human language and computational data. By using a blend of linguistic rules and machine learning algorithms NLP is able to interpret and, as we have seen with the surge of AI language models, create human-like responses. NLP has shown itself to be an invaluable tool in the advancement in how we can communicate with machines and leverage them for advancing geospatial data exploration and analysis [51][52][54].

5.6 Challenges to Natural Language Processing

Integrating natural language processing has enhanced analysis and interpretation of spatial data significantly although there have been prevalent challenges that have come to light in recent years. The core challenges to NLP in geospatial data analytics lie in multiple areas including tokenization, part of speech tagging, disambiguation, and coreference resolutions.

The common theme here is that the challenge lies in how the model handles both traditional language processing tasks and spatial relationships at the same time. Many times, the issue is as simple as confusing context. The same word could have different spatial implications depending on the training data or structure. For example, the word “bank” could refer to a financial institution or a riverbank. Furthermore, terms like nearby and walking distance are solely dependent on context and are inherently subjective. In many use cases, social media is used for NLP studies and can prove quite challenging at times. NLP functions based on how concisely and clearly the user presents terminology. This means that any deviation from clearly defined terms, like using slang or vernacular, can distort analysis outcomes. Another prime example of verbiage that NLP struggles with is sarcasm; as the actual meaning of the term or sentence depends on inflection and context, both things that NLP is not great at considering [54].

Geospatial textual information usually falls into three separate categories that become increasingly complex. The first category is explicit coordinates which admittedly are somewhat rare in natural language. The second category is where the text has the proper place names and addresses. This requires geocoding which tends to be a straightforward process. The most challenging of the categories involves “relative” spatial references. Examples of these could be when someone says, “just around the corner”, “between the park and the bank” and “two blocks down from the library.” It can easily be discerned that understanding of both local context and spatial relationships is crucial for achieving accurate data.

The real-world impacts of geospatial NLPs are significant and impactful. Benefits have manifested in first responder agencies, where NLP frameworks analyzed the text in police reports and were able to create crime hotspot maps. Most often, the implementation of these frameworks requires a multi-layered approach. To handle text analytics and entity extraction, cloud services are used like Azure Cognitive Services, an AI API distribution service developed by Microsoft, and NetOwl, a leading provider of text identification analysis currently partnered with ESRI. They are then combined with GIS platforms to provide spatial analysis [57][58][59] [62].

Another more innovative approach to handling more ambiguous location references involves the use of Bayesian probability frameworks. These systems can overlay multi-scale grids on top of geographic AOIs while updating the probability of the appropriate location classification by using addresses, local points of interest, and directional references. This approach is useful in projects where real-time visualization of probable locations is needed. This is also useful in certain emergency response scenarios where the caller is unable to provide a precise description of their location [61] [57].

5.7 Object Detection

Object detection is the identification of different objects within an image, such as vehicles, animals, or ships on open waters [83]. The ability to parse through large image sets to identify and verify objects is trending as an in-demand function of the geospatial field.

A more niche part of object detection that has been gaining popularity lately has been with work in more complex mediums, such as multi- and hyperspectral or SAR data types. The evolution of multispectral object detection allows for analysis, automation, and identification in the non-visible spectrum [67]. Within the past two years, multiple studies have been published focused on using deep learning algorithms for object detection within SAR imagery, be it for real time analysis or for a longer study period. Most of the object detection studies are also a study on neural learning or deep networks, so have overlap with the above discussion points. As for trends, the SAR studies gathered focused on You Only Look Once (YOLO) versions, Convolutional Neural Networks (CNN), and Histogram of Oriented Gradient (HOG) methods. At present, the SAR image target detection method based on traditional algorithms is principally classified into three categories: detection algorithm based on structural feature (SF), detection algorithm based on gray feature (GF), and detection algorithm based on image texture feature (ITF) [79].

5.8 Predicting on-the-ground conditions from satellite imagery

The ability to predict on the ground conditions has only become more streamlined since the recent advancements in geospatial analytical methodologies. One of these compelling applications is the way that one could predict cell phone adoption rates in certain regions. This is useful when attempting to address critical issues such as bridging the digital divide in more undeveloped areas. This digital divide, in short, can be defined by unequal access to digital infrastructure and their services. As of 2021, approximately half of the world still lacks internet access, which in turn impedes the socioeconomic development of many.

A study conducted by Edward J. Oughton and Jatin Mathur details the methodologies of how the integration of publicly available imagery paired with ML tools can predict metrics such as telecom demand and cell phone adoption. Along with using satellite imagery from PlanetScope and combining it with socioeconomic survey data, they employeds CNNs to derive predictions for cell phone penetration on telecommunication services.

After the data was compiled from both methodologies. The results showed that the CNN methodology outperformed other traditional models that used other indexes like population density and nightlight luminosity data. The CNN models measured up to 41 percent data variance and provided a 40 percent improvement over the other models.

The predictive capability shown by these types of methodologies has significant implications for stakeholders such as policymakers, the telecommunication industry, and humanitarian organizations. By identifying those areas that are underserved, these groups can make better decisions when discussing infrastructure investments. These findings could help humanitarian agencies or organizations to allocate resources in a manner that would align with their SDGs to ensure universal access to digital connectivity [72].

6. Discussion

6.1 Collaboration and Funding

Public-Private Partnerships (PPPs) such as NASA's Landsat Program and the European Space Agency's Copernicus Programme have democratized access to critical datasets, enabling private firms to develop commercial applications while advancing public research goals [4][10][35]. Governments play a key role through funding and regulatory frameworks, supporting large-scale projects and ensuring ethical data usage. Programs like Sentinel Asia and GEOSS demonstrate how global cooperation fosters solutions for climate challenges and disaster resilience [12][27][40].

Emerging funding models, such as blockchain-based financing and community-driven initiatives, are addressing gaps in regions with limited access to traditional capital. These models also enable SDG-aligned projects, such as decentralized geospatial data sharing for sustainable development in underserved regions, as previously highlighted in the private sector contributions. Platforms like the Humanitarian OpenStreetMap Team (HOT) exemplify the power of crowdsourcing for disaster response and infrastructure mapping [10][24]. Simultaneously, blockchain solutions like FOAM enable decentralized and secure geospatial data verification, creating new opportunities for collaborative projects [14][39].

6.2 Future Trends

The geospatial industry is rapidly evolving, driven by advancements in satellite technologies, artificial intelligence (AI), and data integration methods. Hyperspectral and nanosatellite constellations are expanding observational capabilities, providing unprecedented detail for environmental monitoring, resource management, and disaster preparedness [19][38]. Small, agile satellites launched by private firms allow for more frequent revisits and cost-efficient data acquisition compared to traditional platforms.

AI and machine learning are enhancing geospatial analytics by automating data processing and generating actionable insights. Applications include real-time land-use classification, deforestation monitoring, and predictive modeling for urban expansion [13][19][43]. Additionally, edge computing—processing data closer to the source—reduces latency and enables faster decision-making in applications such as autonomous navigation and IoT-connected smart cities [29][36].

IoT (Internet of Things) advancements are increasingly integrating with geospatial platforms. Sensors deployed across urban and rural environments generate vast spatial datasets for climate monitoring, smart infrastructure planning, and agricultural optimization [5][18][40]. This convergence of IoT, AI, and geospatial data is critical for addressing global challenges, such as climate change adaptation and food security.

6.3 Key Findings

The private sector's contributions to geospatial technology have transformed industries ranging from agriculture and energy to urban planning and disaster response. Innovations such as high-resolution satellite imaging, AI-driven analytics, and open data platforms have lowered entry barriers, fostering a more competitive and diverse geospatial market [3][9][11].

Key findings from this review include:

1. Public-Private Partnerships (PPPs) are foundational to geospatial innovation, providing critical datasets and infrastructure for private-sector solutions [4][10][35].

2. Government Funding and Policy Support play a crucial role in enabling large-scale projects, ethical data usage, and equitable access to geospatial resources [12][22][40].

3. Venture Capital and Corporate Investments drive commercialization, particularly in AI-enabled platforms, small satellites, and Earth observation services [18][23][42].

4. Emerging Technologies such as hyperspectral satellites, edge computing, and IoT-integrated systems will continue to reshape the geospatial landscape [19][29][38].

5. Challenges include interoperability, regulatory restrictions, and data quality biases, which require multi-stakeholder efforts to address [13][28][40].

6.4 Research Roadmap

Future research must address emerging challenges and opportunities in the geospatial industry to ensure scalability, inclusivity, and sustainability. Key areas for investigation include:

1. Standardization and Interoperability: Developing global standards for data formats, APIs, and sharing protocols to streamline integration across platforms and providers [4][28][37].

2. Privacy and Ethics: Exploring frameworks to balance data utility with user confidentiality, particularly in cross-border applications involving sensitive location data [22][32][34].

3. Sustainability of Open Data Initiatives: Evaluating long-term funding mechanisms for open platforms like Copernicus and OpenStreetMap, ensuring equitable access to geospatial data worldwide [10][24][30].

4. AI and Automation in Geospatial Analytics: Advancing AI-driven tools for automated data processing, predictive modeling, and real-time decision-making across industries [13][19][36].

5. Climate Resilience and Environmental Justice: Leveraging geospatial technologies to monitor climate impacts, identify vulnerable communities, and inform equitable policy interventions [20][30][39][70][71][80][81].

6. Government-Led Research and Policy Integration: Aligning private-sector innovations with government-driven priorities, such as climate monitoring, disaster management, and national security initiatives. Government agencies play a key role in funding fundamental research, implementing data-sharing policies, and ensuring equitable geospatial infrastructure development across regions [8][27][35].

7. There were a few limitations to current research that should be corrected in future studies. All search terms were in English and only sources written in English were analyzed. This study aims to collect trends and advances worldwide but is currently limited at this time. Secondly, private sector advances were analyzed over governmental advances due to ease of access

of information. This does not account for all advances within the field, but instead those that are easy to access.

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7. Conclusion

This review identified multiple trends for use of geospatial data, to include use of artificial intelligence in analyzing data, natural language models, and impacts to assessment of the SDGs. The overall trend is a movement towards efficiency in data analysis, with the goal of quick results for decision-making at every level. All sources included in this review showed a positive roadmap towards the future with ever evolving processes and ideas. The constant through all is the heavy reliance on technology and computing power, opening the door to dilemmas in energy sourcing and ethics surrounding collection.

This review aimed to build awareness of the current state of the field of geospatial information and the path forward. The community must come together to decide on ethical boundaries for data use and continue to build depth in methods for analysis. The Sustainable Development Goals will be assessed in 2030 and will use geospatial data to conduct said assessment into each of the 17 goals.

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