Exploring Role of GeoAI in Urban Governance Towards Supporting Sustainable Development

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Abstract

Governance refers to the structures and processes that are designed to ensure accountability, transparency, responsiveness, rule of law, stability, equity and inclusiveness, empowerment, and broad-based participation. Urban governance is the procedure through which stakeholders, including local, regional, and national governments, choose how to plan, fund, and manage urban regions in many countries. Urban governance systems are currently unfit for proper governance purposes and need critical reforms to enable sustainable and inclusive urban development. Urbanization is a global phenomenon, although it develops even more rapidly in developing nations like Egypt. Unplanned growth, rising immigration, and a quickly growing population are the key drivers of urbanization. One of the most significant issues confronting developing countries is the problem of urban sprawl in agricultural areas, which has an environmental impact on several levels. This paper introduces an innovative approach to manage, monitor, and control urban sprawl on agricultural lands using spatial artificial intelligence GeoAI. Tasa village was selected as study area, which is located in Sahel Selim city, Assiut governorate, Egypt. Three satellite images were employed for the study area to monitor change detection from 1998 to 2020.

Keywords: Sustainable development; Governance; Artificial Intelligence (AI); GeoAI.

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1. Introduction

Nowadays, the world is increasingly encountering environmental challenges because of industrialization, urbanization, and globalization. These challenges include climate change, freshwater shortage, desertification, contamination of land, air, and water from hazardous waste, biodiversity loss, and several more issues that impede sustainable development (Jianping et al., 2014). As a result, environmental analyses are becoming more important in urban planning procedures around the world. Rapid urbanization, accompanied by enormous population growth and construction projects, leads to significant losses in urban green spaces and an expansion of impervious areas (Dou et al., 2020). One of the primary factors contributing to environmental deterioration that results in encroachments on fertile lands is unplanned urbanization. According to Brind'amour's research in 2016, between 1.8 and 2.4 percent of agricultural areas worldwide will be lost to urban sprawl by 2030.

In 2000, 3 to 4% of the world's total agricultural production was produced in these regions. They are also 1.77 times more productive than normal agricultural fields throughout the world. In addition, 80 percent of these land losses are concentrated in Asia and Africa, where productivity is thought to be more than twice that of their national averages. Cropland sprawl often poses a danger to livelihood and is associated with other sustainability problems. Along with urban development follows the rapid expansion of informal settlements, where numerous residents wastefully squander the resources that are available and cannot access basic requirements and services (Bren d'Amour et al., 2017). Urban governance is generally acknowledged for its strategic value towards a more sustainable future since urban development constructs a potential for more sustainable development (De Guimarães et al., 2020). Egypt 2030 agenda for sustainable development emphasized the local level for meeting sustainability challenges, by calling for the embracing of an institutionalized participatory approach to sustainable urban development and the establishment of the capacity of local governing frames to cope with sustainability challenges (Lewis et al., 2021). Urban planning has continuously shifted towards urban governance procedures over time. Analyzing various types of sustainability strategies is crucial to enhancing our understanding of urban governance and its consequences (Zhang et al., 2020).

Hence, the preservation of the environment is a key component of sustainable development, and urbanization may pose an imminent threat to both food security and the ecosystem in general. Additionally, the unexpected growth in informal settlements promotes a demographic transition, leading to a lack of basic services.

Monitoring the growth of urban sprawl on agricultural areas is one of the most important urban governance tools, as it provides an accurate and comprehensive depiction of the rate of decreasing agricultural land and population growth in the study area.

Spatial data has long been used to manage urban expansion on agricultural lands. Satellite images have been employed in previous studies to track changes in land use over time (Hepinstall et al., 2013); (Dupras & Alam, 2015); (Huang et al., 2019); (Salem et al., 2020); (Shao et al., 2021).

This paper introduces an innovative approach integrating spatial data with artificial intelligence GeoAI for monitoring and management of growth of urban sprawl on agricultural land in Tasa village, Assiut, Egypt, with a total area 6.38 km^2. Three satellites were deployed to monitor the encroachment of urbanization on agricultural areas between 1998 and 2020. For each image, the number of buildings was assessed using artificial intelligence algorithms to determine the percentage of agricultural land lost over time.

2. GeoAI Overview

Geospatial studies have been integrated with AI since 1963, Significant advances in AI were made due to theoretical speculations in the 1950s and 1960s (Natale & Ballatore, 2020). As a result of artificial intelligence, geospatial science is currently experiencing both enormous new potential and challenges. Theoretical advancement, large data sets, computer hardware, and high-performance computing platforms are enabling its major development, as they make it possible to design, train, and deploy AI models more efficiently (Xu et al., 2021).

In recent years, significant advancements have been made in both academia and business in the field of geospatial artificial intelligence (GeoAI), which blends geospatial research with AI, including deep learning and machine learning techniques. GeoAI is capable of creating intelligent computer programmes that mimic human perception, spatial reasoning, and discovery of geographic phenomena and dynamics. It can also be used to address problems in human environmental systems and their interactions with a focus on spatial contexts and roots in geography or geographic information science (Nguyen et al., 2023).

GeoAI research, therefore, involves an understanding of AI theory, programming, and computing techniques, as well as geographic domain expertise integrating remote sensing, physical environment, and human civilization, with expanding incorporation between different data analysis techniques (Li, & Hsu, 2022). Given the interdisciplinary nature of the field and the overlap between artificial intelligence and other scientific disciplines, it is essential to establish a few key terms related to geospatial and artificial intelligence, as shown in figure 1.

Artificial Intelligence refers to the development of computational techniques and tools capable of performing tasks that typically require human intelligence, such as reasoning, learning, and anticipation, which allow it to act appropriately in its context (Pramanik et al., 2018). Machine Learning is a branch of AI that leverages mathematics or statistical optimization approaches to model data without explicitly scripting each model parameter or computation step (Angermueller et al.,2016). Deep Learning is A specific approach to machine learning where artificial neural networks, and algorithms inspired by the human brain, identify the patterns and the guidelines for prediction from a large volume of data (Janiesch et al.,2021).

GeoAI is a developing scientific discipline that integrates innovations in spatial science with AI/ML methods (e.g., deep learning), data mining, and powerful analysis to acquire information from spatial big data (Alastal & Shaqfa., 2022).

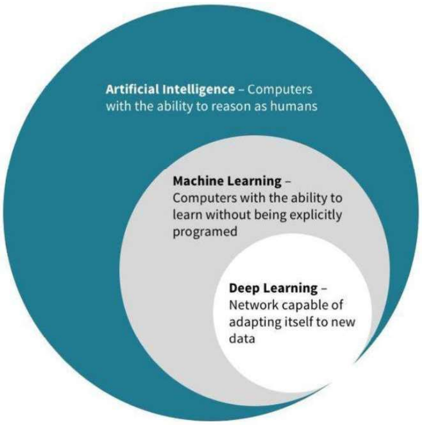


Figure (1): Relation inside AI. (Ryan, 2020)

Artificial intelligence (AI) and machine learning (ML), presents additional approaches for efficient monitoring, interpretation and predicting the development of urban areas. ML approaches are data-driven as relevant information extracted from data processing. The term 'learning' refers to how well an algorithm performs in a certain task (Gonzales et al.,2022). There are two categories of machine learning algorithms: supervised and unsupervised learning. Supervised learning employs a training set of examples with appropriate responses. On the other hand, in unsupervised learning, there are no appropriate responses provided. Instead, the algorithms attempt to discover and categorize similarities between inputs and group them (Nasteski, 2017), as shown in figure 2.

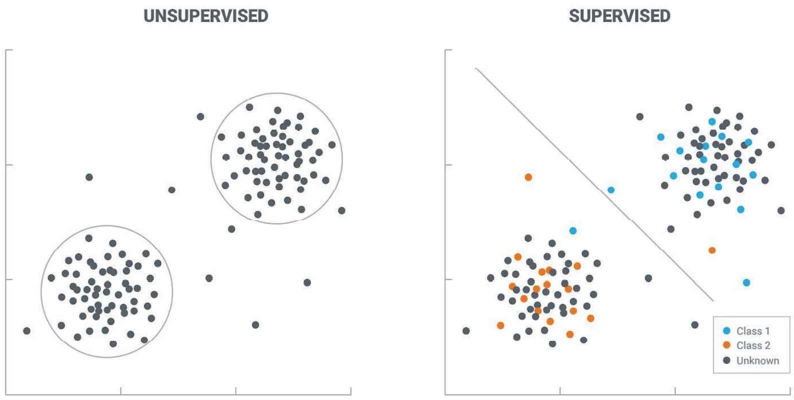


Figure (2): Supervised Vs Unsupervised learning. (Alloghani et al, 2020)

3. History of GeoAI

Although there is no institutional start timeline for GeoAI, the initial GeoAI instances were estimated by detecting significant events in GIS utilising statistics. Danie Krige created the first spatial predictive model in 1951, which was later modified and implemented by Matheron in 1963. This technique is known as 'kriging,' and it is one of the most significant approaches in geostatistics. Anglo-Canadian Roger Tomlinson developed the concept of GIS in the same year (1963) (Li et al., 2014). Afterwards, Howard Fisher at Northwestern University developed the first GIS operational software in 1946 (Carlsson, 2013). With the advancement of spatial prediction technologies and the GIS paradigm. Therefore, GeoAI originated in the mid-1960s, merely decades after Alan Turing developed his famous AI Test (Taulli, 2019). With the basics of GeoAI constructed, the following question is how GeoAI has developed over time. To address this question, a timeline involving four generations of GeoAI developments is explored, defined by changes in eight major key dependent drivers. Each of these drivers is briefly elaborated within each generation. as shown in figure 3.

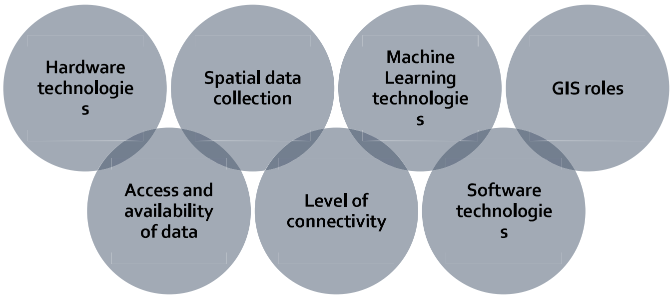


Figure (3): Key dependent driver of GeoAI. (Janowicz et al, 2020)

3.1.1 Generation of GeoAI (mid-1960s to late-1990s): Limited Local Intelligence

Most of the components that composed the first generation (1G) of GeoAI were confined to a single computer, and insufficiently integrated. As a result, the term “limited local intelligence.” This generation was characterized by computational limited bandwidth and data availability and accessibility limitations, which limited the full application of machine learning techniques. Furthermore, AI "winters," or periods of neglect, appeared during the 1970s and 1990s because earlier developers exaggerated claims, and unexpectedly high demands from end users. As a result, the first generation of GeoAI remained stable for three decades. (resources.esri.ca).

3.2.2 Generation of GeoAI (2000 to late-2000s): Early Enterprise & Web Era

The extensive use of the Internet and personal computers (PCs) characterizes 2G GeoAI. Compared to 1G, enhanced data accessibility and availability, upgraded GIS applications, and the utilization of enterprise geodatabases. Thus, compared to 1G, 2G GeoAI has a longer lifespan and is identified by the beginning of the Web era and the early adoption of enterprise solutions. (resources.esri.ca).

3.3.3 Generation of GeoAI (2010 – 2019): The “Big” Leap

3G GeoAI was evolved in accordance with the increasing adoption of the Internet and personal network devices (i.e. smartphones), key advancements in GIS, ML, techniques for computing and storage, and flexible data accessibility and availability. In addition to AI, 3G GeoAI has observed an enormous growth in adoption by government organizations, corporations, NGOs, and academics to address spatial problems in the real world. These significant milestones, achieved in a short time frame, have changed the perspective of GeoAI into a new generation (3G), which is defined as the “big” leap in GIS, with “big” here referring to the growth of big data. (resources.esri.ca)

3.4.4 Generation of GeoAI (2020 -): The Frontier of Intelligence

Since 3G GeoAI impacted the GIS ecosystem, there are upcoming new technologies and applications that could lead to more massive improvements in GeoAI. Drones and Internet of Things (IoT) technology, for instance, are the latest frontiers in "big" data collection. Deep learning and data science approaches will be augmented with real-time data, which will also lead to new use cases and analytics, such as interpretation and smart cities. With these components, GeoAI has been transited from a time span of collecting and analyzing "big" data to procedures for automated, informed decision-making that are guided by "intelligent" technologies and involve little to no human interference. This is what would be considered as a more "intelligent" ML platform (resources.esri.ca).

4. Application of deep learning for mapping

A significant application of deep learning is the generation of digital maps through automatic road network extraction from satellite imagery and building footprints. Deep learning (DL) has the ability to apply a trained model to an extended geographic area and produce a map containing all local roads. Furthermore, it has the capacity to generate driving directions using the detected road network. This can be particularly helpful for developing countries that do not have high quality digital maps or in areas where newer development has taken place (Campbell et al., 2019).

It's evident that merging AI and GIS has proved to be quite promising for a more profitable and efficient environment. AI made a significant contribution to GIS that has been appearing independently. During the last decade, there has been a significant convergence between the fields of GIS and AI.

Figure (4): Roads detected using deep learning and converted to geographical features (Nassar et al, 2023)

GIS has tools to help with every step of the data science workflow starting from data preparation and exploratory data analysis, to training the model and to performing spatial analysis and finally disseminating results using web layers and maps and driving field activity.

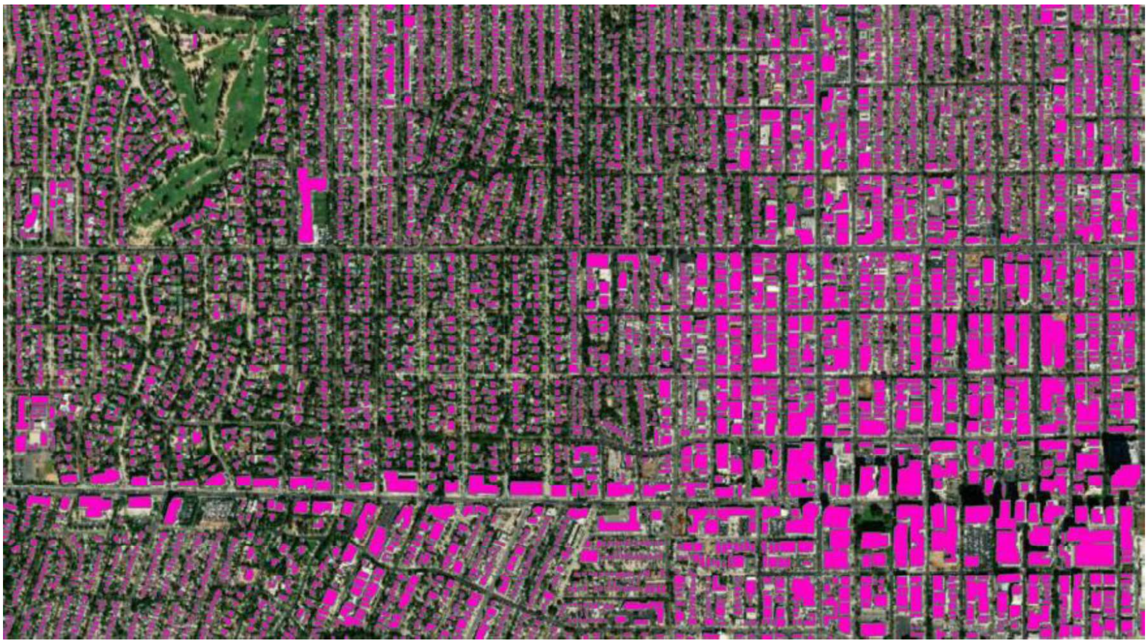
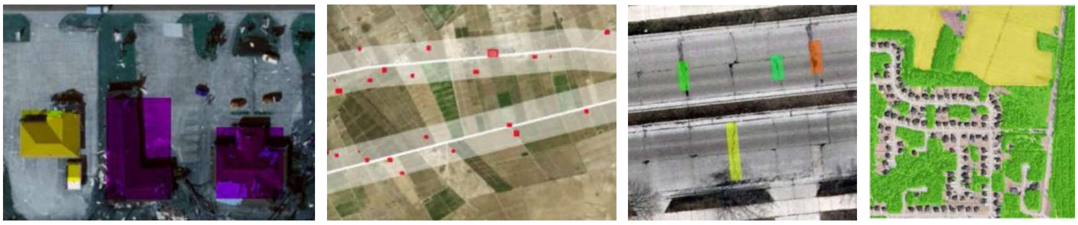


Figure (5): Building footprints extracted out of satellite imagery(Nassar et al, 2023)

While the examples above; figures 4,5; have focused on imagery and computer vision, deep learning can also be used equally well for processing large volumes of structured data such as observations from sensors, or attributes from a feature layer.

Figure (6): large volumes of structured data mapping (Nassar et al, 2023)

Applications of such techniques to structured data include predicting the probability of accidents to sales forecasting, natural language routing and geocoding and different other applications; figures 6,7.



Damaged Structures Pipeline Encroachment Road Cracks Land Cover

Figure (7): Large volumes of structured data mapping (Nassar et al, 2023)

5. Case study: Tasa village, Assiut, Egypt

Assiut Governorate is one of the Egyptian governorates. It stretches across a section of the Nile River. The rate of poverty in Assiut is more than 60%. The governorate is divided into municipal divisions, with a total estimated population of 4,407,335, as of July 2017 according to the Central Agency for Public Mobilization and Statistics (CAPMAS). Tasa Village is One of the settlements in Sahel Selim city - Assiut Governorate -Egypt with total area 6.38 km^2; figure 8.

In 2017, Sahel Selim had a population of 180,996 inhabitants (CAPMAS). Sahel Salim is located on the East coast of the Nile at a 24 km distance south from the city of Assiut.

It is characterized by its fruit gardens; some of its fruit production is exported abroad. The village of Tasa was chosen as the study area for monitoring the development of urban expansion on agricultural lands.

Creating digital maps for villages and small communities has historically required a significant amount of time and effort, especially when determining the locations of buildings and roads, which often required field surveys. This process demands considerable time and effort from stakeholders and decision-makers, in addition to incurring extra costs. Decision-makers can automate much of the mapping process by building a deep learning model and training a dataset with GIS, leading to immediate benefits in terms of time and cost savings, as well as improved data accuracy. A GeoAI machine learning model allows decision-makers to automatically update base maps for Tasa village with streets and buildings, producing results that are increasingly accurate.

Figure (8): Tasa village, Assiut governorate (google earth)

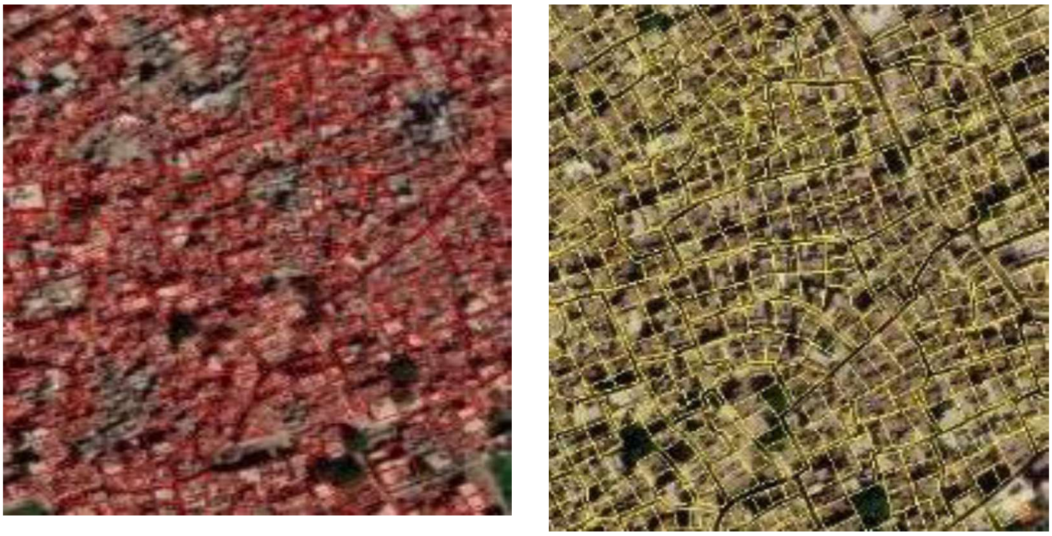


Figure (9): Building footprints digitized manually on the left compared to the deep learning algorithm outputs on the right

Three satellite images were used to detect urban expansion changes from 1998 to 2020 using GeoAI for building detection. It was found that in 1998, the total number of buildings was 458, while there were 1,146 buildings in 2014 and 1,648 buildings in 2020. Additionally, agricultural land in Tasa village has been reduced by 88.4% of the total area, as shown in table 1

Table 1: Change detected from 1998 to 2020 utilizing GeoAI

Observation year	Total No of Buildings	Population	Agriculture land area (%)	Urban area (%)
1998	458	3664	96.8%	3.2%
2014	1146	9168	91.9%	8.1%
2020	1648	13184	88.4%	11.6%

Traditionally, GIS projects require several years to finish projects using traditional techniques for creating and analyzing spatial data, as well as a considerable number of work and quality control teams to complete projects in the appropriate form and time. it is anticipated that GeoAI will provide a breakthrough in the field of Spatial projects, where the process of automatic detection of the necessary data takes several hours to produce data, and the quality control process takes a few days to complete. In 1998 it took 6 months of field survey and quality control to directly survey and mapping buildings on the study area, while in 2014 it took about one month of on-screen digitizing and field quality control on mapping data due to advanced approaches of mapping and GIS software as well as the availability of high-resolution satellite imageries as shown in figures 9, 10

1998 2014 2020

Figure (10): Change Detection From 1998 to 2020, Tasa village, Assiut, Egypt

While it took 40 hours of manual digitization and quality control in 2020 to perform the task as required with less quality and more effort, the area under study was processed using GeoAI in 30 minutes. The task was a bit more complex as it required the computer to tell it about anything new across the entire study area. It was necessary to establish a common geospatial framework that would encompass the existing database. GeoAI platform was able to train using 30 objects of data to provide input for the model to scan 1684 objects in the satellite imagery, so, the algorithm performs efficiently and successfully, even identifying changes that human intuition would miss. Additionally, the model provided a more accurate representation of the roads in the study area.

Although more effective GeoAI applications are being introduced, AI is still in the early stages of development. It's still unclear how interoperable and dependable machine learning algorithms are. Due to a lack of understanding in the algorithms used and the scope of the finding's generalization, the level of overall confidence in machine learning outcomes across the geospatial community remains moderate. The continued reliance on cloud storage raises additional questions about data integrity. Within the next five to ten years, it's expected that change detection and pattern identification will be completely automated in geospatial production.

6. Conclusion

Over the next ten years, artificial intelligence, particularly image analysis and information extraction, will present some of the biggest opportunities for geospatial information management. Machine learning, a branch of artificial intelligence known as geospatial artificial intelligence (GeoAI), is used to extract knowledge from spatial data. Automation is essential for enabling the efficient processing of an exponentially growing amount of sensed data from the Internet of Things and remote sources. This is necessary to realize the objective of real-time data. Machine learning will be crucial in the long run to handle the increasing demands of a connected world. One of the initial steps in putting artificial intelligence (AI) solutions into practice is automation.

Three factors can be used to summarize the technological developments enabling advances in geospatial artificial intelligence (GeoAI): the increase in low-cost cloud computing, the accessibility of inexpensive sensor technology, the ongoing expansion of geospatial information, and the development of new algorithms that can leverage multiple data sources. To achieve the goals of sustainable development and Egypt's Vision 2030, a deep learning algorithm was employed in this study to detect buildings and streets in the village of Tasa, Sahel Selim city, Assiut Governorate. The results demonstrated a promising model for automating the production of maps.

Comparing the use of conventional methods for producing spatial maps, which required 40 working hours, with leveraging GeoAI, which produced spatial maps for the same area in 30 minutes with higher precision and with less working and quality control time, of Tasa village with an area of 6.38 square kilometers, it was found that GeoAI introduces innovative and promising technique for automatic objects detection and mapping for the determination of development priorities.

The potential use of the technology will eventually benefit a larger range of geospatial applications, even though the current implementations of machine learning for geospatial data concentrate on object extraction and change detection. Digital twins, driverless vehicles, sustainable smart city management, enhanced structures, and energy management are some examples of application areas.

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