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Mapping Tomorrow's Cities: GeoAI Strategies for Sustainable Urban Planning and Land Use Optimization

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ABSTRACT

As urbanization continues to shape the world's landscape, concerns have intensified over environmental degradation and depletion of natural resources. Accordingly, international agendas emphasize managing urban sprawl for inclusive, resilient, and sustainable cities. On this basis, this study consists of exploring the nexus of urbanization and advanced technologies following a methodological approach based on a bibliometric analysis using the Dimensions Database to analyse research related to urban sprawl and LULC Changes from 1994 to the recent years; and a systematic review to synthesize existing literature on different methodologies integrating GeoAI technologies and LULC Analytics in the process of monitoring landscape, which optimizes Urban Planning and empowers predictive modelling to monitor environmental changes, therefore, promoting intelligent decision-making and inclusive growth via enabling the creation of targeted policies that address socio-economic disparities, environmental sustainability and infrastructure enhancement. By improving comprehension of scientific concepts, this article aims to fill the knowledge gap between urban studies and remote sensing using machine learning.

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Highlights:	Contribution to the field statement:
- Introducing the integration of GeoAI with remote sensing (RS) and geographic information system (GIS) technologies to enhance urban planning and land use optimization. - Using a unique combination of bibliometric and systematic reviews to synthesize diverse methodologies, bridging urban studies with remote sensing and machine learning. - Implementing advanced machine learning techniques to improve predictive modelling and forecast urban growth trends more accurately.	This paper advances academia by integrating GeoAI with sustainable urban planning, enhancing predictive modelling for environmental monitoring, and informing data-driven policy-making. It bridges urban studies and remote sensing, offering novel applications for optimizing urban growth, and fosters interdisciplinary collaboration through bibliometric and systematic reviews of diverse methodologies.

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1. Introduction

1.1. Background and Context

By 2030, eighty percent of the world's population is expected to live in cities, surpassing the fifty percent average (Kirati et al., 2023). The population in rural areas is becoming more urbanized, as seen by the rise, which further strains housing and job prospects. Global urbanization is a critical social and economic phenomenon (Dasgupta, 2001) that shows no signs of abating. It is a subject that has generated much discussion over the last 30 years and evolved into a serious policy concern. It is among the most apparent factors that have altered the physical dimensions and patterns of the terrain in cities worldwide (Abebe, 2013). Understanding its dynamics and patterns has proven beneficial for formulating efficient strategies and arriving at better-informed planning decisions (Hembram & Jana, 2022).

The benefits and advancements that accompany urbanization also give rise to several environmental issues and risks, including floods, encroachment into wetlands and agricultural areas, contamination of the environment, population growth, substandard housing, inadequate sanitation and water supply, transportation issues, growing living expenses, and income disparity (Halingali et al., 2012).

Urban expansion is typically described as changes to the physical and functional aspects of the urban environment brought about by social, economic, and political changes (Kivell, 2002). The interactions of many biophysical and socioeconomic factors cause rural landscapes' land use and land covers (LULCs) to change into urban structures (Rahman et al., 2023). While sprawl is a result of emerging nations' faster urbanization (Ghosh, 2019), it poses significant challenges to the delivery of services and quality of life, as well as economic, environmental, cultural, and aesthetic effects on natural resources (Krishnaveni & Anilkumar, 2022). Thus, many urban planning strategies that limited urban sprawl were first supported because accomplishing so would protect the surrounding rural area and the natural environment, providing necessary amenities for city citizens (Beattie & Haarhoff, 2018).

Currently, resource managers and city planners need to understand the dynamics of urban expansion in rapidly evolving cities (Cengiz et al., 2022) and fulfil Sustainable Development Goal (SDG) 11 (Nations, 2018); future-focused urban development and sustainable city planning will depend on how well this urban physical expansion is understood and assessed (Mithun et al., 2022), A comprehensive and well-rounded approach is required to tackle the related issues.

1.2. Problem Statement and Research Gap

Controlling suburban land-use change (LULC) is a significant challenge in emerging nations due to its negative environmental impacts and loss of productive and natural areas. These changes pose an important issue for sustainable development (Degife et al., 2018) and the management of natural resources, and they have been crucial in shaping global environmental settings (Hossein et al., 2023). According to Hamad et al. (2018), LULC change significantly contributes to environmental deterioration and is mainly caused by human activity. Reducing land-use conflicts and implementing sustainable development techniques (Ruben et al., 2020) depend on land-use planning, which aims to resolve and prevent conflicts by balancing diverse land uses and implementing strategies like urban decentralized growth (Zou et al., 2019). One effective method for examining the geographic pattern of LULC dynamics is to use their models (Motlagh et al., 2020).

Development initiatives highlight the importance of land-use planning, as its neglect causes environmental issues. This decision-making technique allocates land-use types across zones using spatial statistical models and LULC change detection (Xia et al., 2018). Advancements in Geographical Information Systems and remote sensing technologies enable the mapping and monitoring of LULC changes, providing academics with advanced data and spatial analysis (Islam et al., 2018). The key benefit of Geographic Information Systems (GIS) is their modelling capabilities (Murray, 2010) Because they offer a fundamental source of data and strategic land-use planning. Techniques like artificial neural networks, LULC change, and multi-criteria models automate this process, aiding policymakers and legislators (Motlagh et al., 2020). Their most advantageous applications include morphological spatial analysis and land-use appropriateness mapping planning and management (Agboola et al., 2018).

Based on these studies, can GIS and Remote Sensing combined with Artificial Intelligence approaches be as effective in land use management and urban planning to mitigate the predicted effects of urban growth on agriculture and other LULC classes?

1.3. Objectives and Hypotheses

Since urbanization is becoming increasingly prevalent, GIS and remote sensing are essential, not optional. Scientific inquiry indicates that this data precisely maps urban environments, aiding in urban planning and sustainability policies (Hembram & Jana, 2022). Recent advances in deep learning and machine learning, or more broadly, artificial intelligence, have made it possible for a new paradigm of data-driven science to analyse and visualize massive Spatial Big Data, i.e., large volumes, high velocity, and a wide range of geotagged data which is beyond the capabilities of the widely nowadays' used spatial computing platforms (P. Liu & Biljecki, 2022). Furthermore, the synergy between AI and GIS allows for more accurate predictions and comprehensive insights into urban dynamics (Alastal & Shaqfa, 2022), aiding in proactive planning and mitigation strategies. By also combining geographical data with socioeconomic data, initiatives that encourage equity in development and eliminate gaps may be promoted by analysing the link between urbanization and employment, income distribution, and service accessibility.

1.4. Significance and Structure of the Paper

This study conducts a systematic literature review and bibliometric analysis of three decades of research on urban growth dynamics. It integrates management systems, remote sensing, GIS, and artificial intelligence to enhance landscape analysis, resource management, infrastructure access, and management strategies, demonstrating AI's effectiveness in these areas.

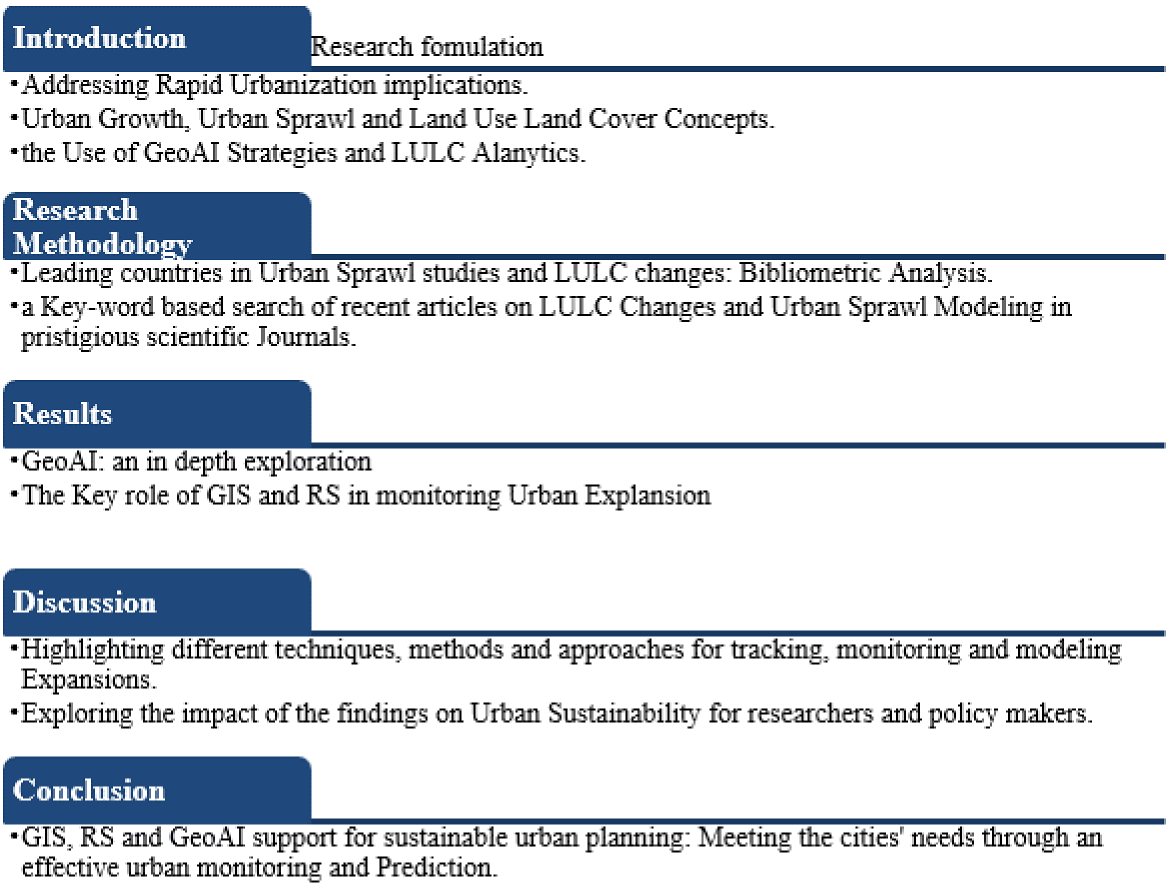

Figure 1. Structure of the Study (Developed by the Authors).

2. Materials and Methods

The review concentrates on the application of GeoAI models in urban socio-geographical research. It delves into utilizing these advanced models for detecting and predicting changes in land use and land cover (LULC); illustrating the potential of these models to provide insights into urban dynamics, including urbanization patterns, environmental impacts, and the socioeconomic variables influencing land-use alterations, by analysing how traditional and new spatial mapping techniques can analyse spatial data. The focus is on how GeoAI can enhance the understanding and management of urban growth and transformation. It is divided into two sections:

2.1. Bibliometric Analysis of Urban Sprawl Modelling and LULC Changes using DIMENSIONS Database:

The study extensively used the Dimensions database, a widely recognized academic data source, to evaluate information. The VOSviewer software was employed to create a bibliometric map, a tool known for its ability to visualize and analyse bibliometric data. We conducted data mining on March 11, 2024, focusing on 'Urban Sprawl Modelling' and 'LULC Changes' in titles, abstracts, and keywords. We primarily sourced academic papers due to the database's widespread use in the scientific community. Our data collection process was thorough and meticulous, ensuring the validity and reliability of our findings.

The outcome of the initial search, which used the search string query TITLE-ABS-KEY (urban AND sprawl AND modelling), yielded old to recent year articles from 1994 to 2024. The previous search string query generated 81759 documents in the search results, adding the option to limit the number of articles obtained to 39180 documents. TITLE-ABS-KEY (urban AND sprawl AND modelling) AND (LIMIT-TO (OA, "all") was the second search string query that produced 19300 items. The main focus of this study will be the distribution of the top 30 papers, chosen based on publication quality, among various nations between 1994 and 2024. In addition, it will examine the bibliometric map of co-authorship, the year-by-year published papers since 1994, and the co-authorship nations about the core topic of “urban sprawl modelling”.

Applying the same proceeds to the second search revealed 25737 items following the choice to limit to Article. The string query used for this search was TITLE-ABS-KEY (LULC AND Changes). The second search string query produced 14972 items: TITLE-ABS-KEY (LULC AND Changes) AND (LIMIT-TO 5OA, "all").

2.2. Systematic Review

For this review, we followed the field's commonly used systematic review process to select relevant publications. We began by creating a set of relevant keywords (Urban Planning, GeoAI, LULC Changes, GIS, Remote Sensing, Change Detection, Landscape Metrics, Shannon's Entropy) to use in our search. These keywords were chosen because they are commonly used in GeoAI and urban socio-geographical research, and they represent key concepts and methods in the study of urban dynamics and land-use alterations. We then used the ELSEVIER and DIMENSIONS databases to identify the first set of prestigious articles from which we pulled data. Given the relatively new nature of GeoAI and LULC Changes, we ensured our review was sufficiently diverse. To gather state-of-the-art, we divided the review into two workflows: one focused on papers based on technological models developed or used with vector data (i.e., points, polylines, polygons, graphs, or networks) that are spatially organized in more irregular formats, and another focused on papers published in the last four years (2021, 2022, 2023, and 2024), where we encountered no limitations due to the abundance of papers on the topic, tackling up-to-date ones that use new methods and GeoAI techniques, to see how these methods may be used to create practical tools for tracking land changes throughout time.

3. Results

3.1 Results of the Bibliometric Analysis

The comprehensive set of published publications for the search term "urban sprawl modelling" from 1994 to March 11, 2024, is graphically depicted in Figure 2. This data, which we have observed to follow a unique trend, provides valuable insights into the evolution of urban sprawl modelling over the years. The peak in 2022, with 2741 published papers, and the subsequent drop in 2023 to 2551, are particularly noteworthy.

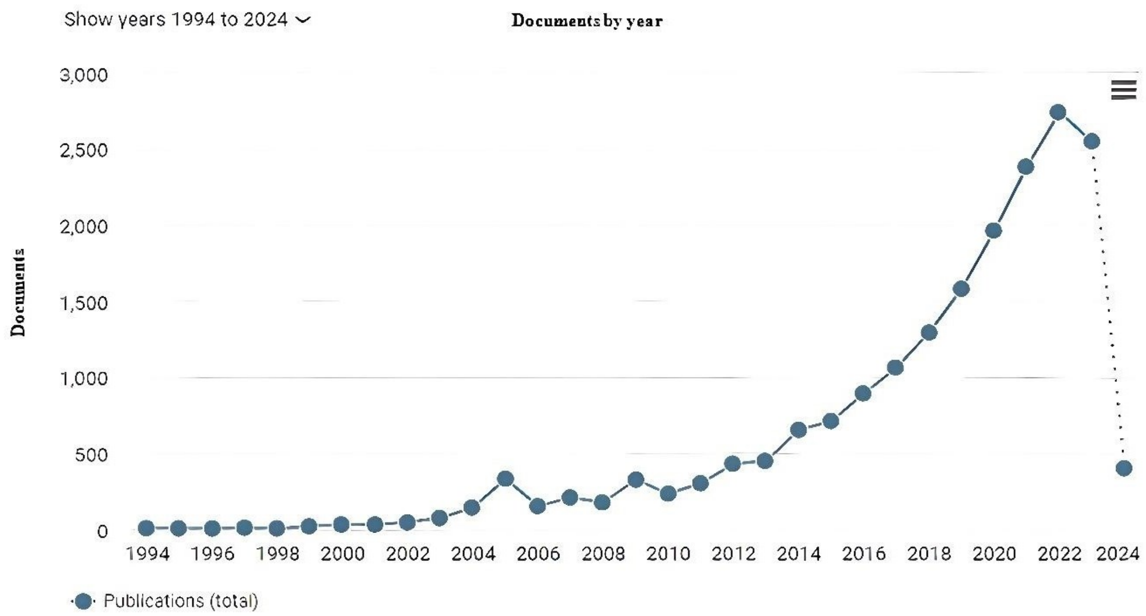

Figure 2. Urban sprawl modelling documents covering the years 1994 through March 11, 2024. Source Dimensions Database: (https://www.dimensions.ai).

Using a network diagram, the map (Figure 3) displayed co-authorship. In total, there were 9672 co-authors, of whom 190 met the criteria. The software played a crucial role in determining the final author selection number, 50, after applying all the filters. Notably, Chen, Y., published the most papers of any author, with 13 and 572 citations and total strength links, respectively.

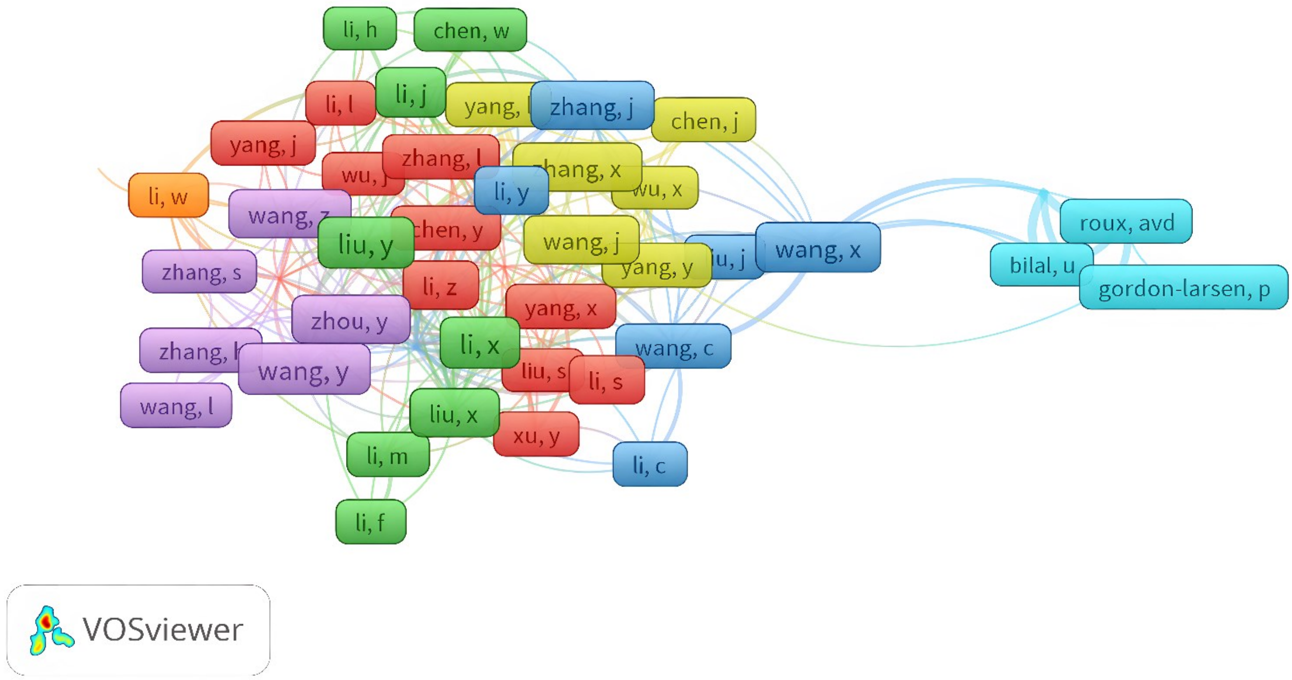

Figure 3. Network visualization mode and co-authorship-based bibliometric map.

The distribution of previous authors' published works throughout various nations from 1994 to March 11, 2024, is shown in the map (Figure 4) below. A total of 19300 published articles have the United States of America contributing 899 articles, with the United Kingdom (288), Australia (178), Canada (157), Germany (124), Spain (115), Italy (112), France (105), India (80), Netherlands (77), Switzerland (63), Brazil (61), Sweden (56), Japan (52), Portugal, South Africa (42), Belgium (39), Austria (33), Iran (33), Mexico (31), Norway (29), South Korea (28), and so forth. Other nations include Ghana, Uganda, and Lithuania. A few articles were published by countries such as Hungary, Estonia, Ecuador, etc. The availability of papers served as the basis for generating the bibliometric map. Apart from a country's minimal quantity of documents, 110 nations satisfied the 62 thresholds. After all the limitations had been applied, 50 nations were chosen. The program determined which 50 countries had the highest overall strength links among the 2711 co-authorship relationships with other nations.

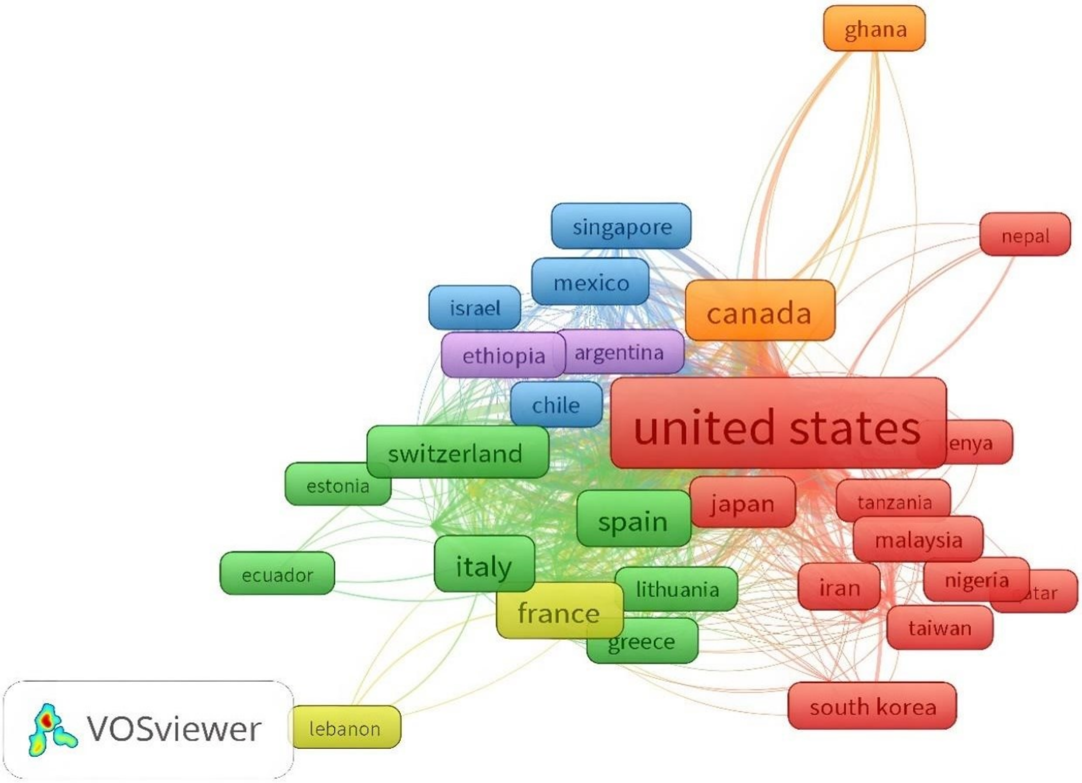

Figure 4. A network visualization mode bibliometric map based on co-authorship nations.

The total number of published papers from the "LULC Changes" search from 1994 to April 2024 is illustrated in the graph (Figure 5) presented downward. It has been seen that there have been notably fewer published documents since the first few years. However, this trend altered in an increasing and decreasing way after 2006. Out of 14972 papers, the maximum number published in 2022 was 3134.

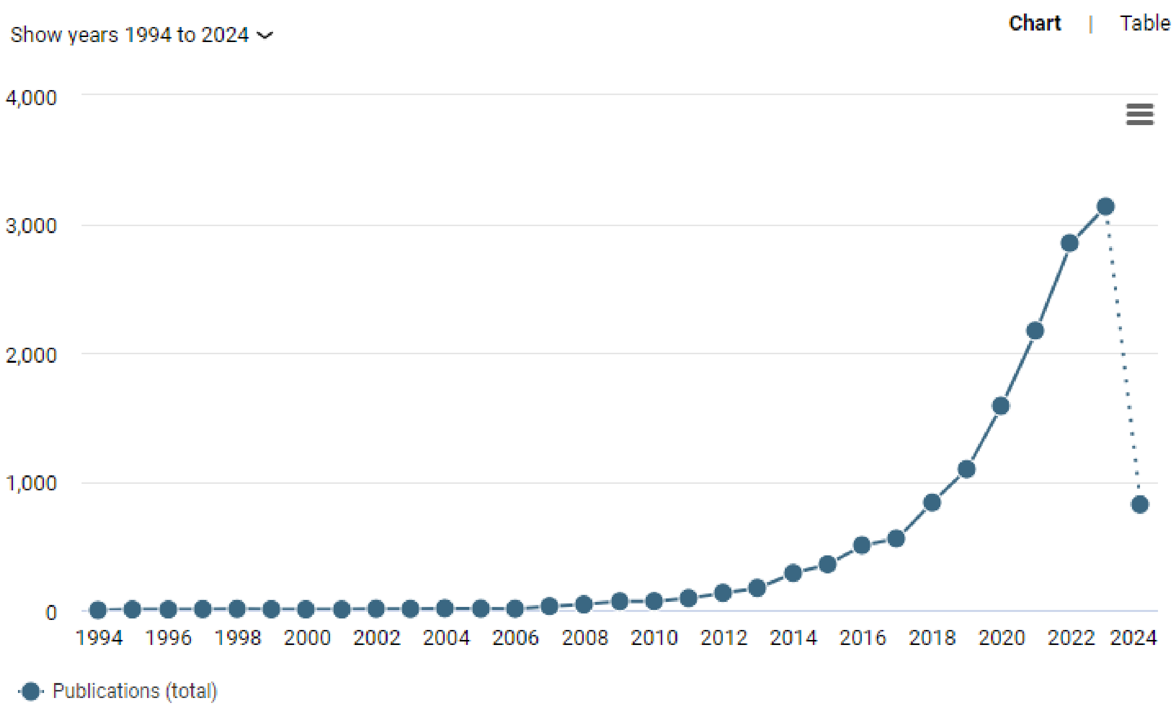

Figure 5. LULC Changes graph from 1994 to 2024. Source Dimensions Database: (https://www.dimensions.ai).

Using a network layout, the map (Figure 6) demonstrated co-authorship. In total, there were 11382 co-authors, of whom 67 met the criteria. The software played a crucial role in determining the ultimate author selection number, 67, after applying all the filters. Notably, Pradhan Biswajeet published the most documents of all the writers, with a total of 13 and 1 strong link. Another author, Kumar Pankaj, has eight total strength connections despite only ten published papers.
Other recognizable authors were Xiao X., Li Xia, Li Li, Furst Christine, Tariq Aqil, and Almirew T. Distinct colors, varying line thicknesses, and proximity indicate several clusters and authors with shared interests.

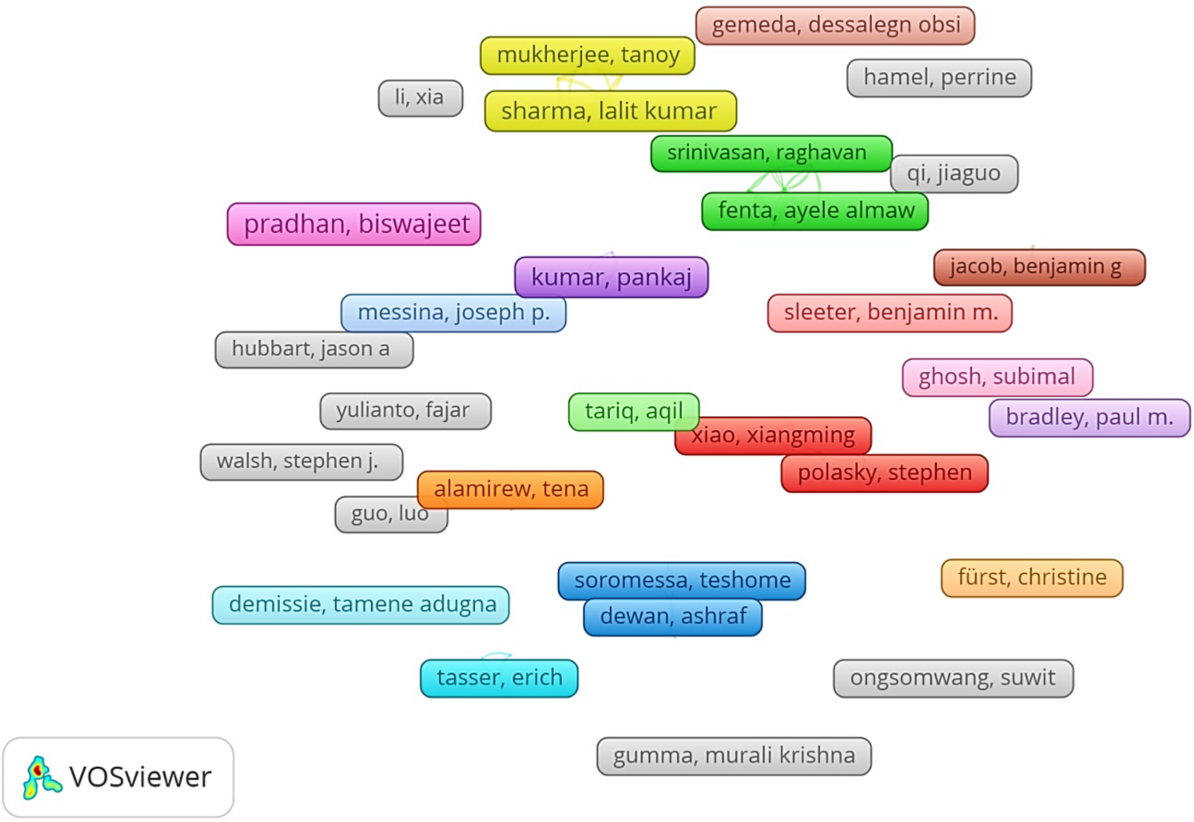

Figure 6. Network visualization mode and co-authorship-based bibliometric map.

The distribution of previous authors' published works throughout various nations from 1994 to 2024 is shown in the map (Fig. 7) below. China contributed by 599 articles out of the total 14972 published articles, with the United States (581), India (314), Ethiopia (201), the United Kingdom (161), Germany (155), Australia (90), Japan (85), Spain (81), Netherlands (79), Canada (66), Brazil (66), Italy (65), South Africa (60), Bangladesh (60), France (55), Pakistan (52), Indonesia (49), Ghana (48), Iran (47), Switzerland (46), South Korea (42), Austria (41), Nigeria (40), and so on. Other nations, including Cameroon and the United Arab Emirates, published a minimum number of articles. The availability of papers served as the basis for creating the bibliometric map. One hundred nineteen nations satisfied 69 threshold levels in addition to the minimum number of a country's documents. Sixty-nine nations were ultimately chosen after all constraints were applied. These nations determined which co-authorship ties with other nations had the most substantial total link strength out of 2484, and all of the above choices were made using the software.

Figure 7. A network visualization mode bibliometric map based on co-authorship nations.

3.2 Results of the Systematic Review

3.2.1. Studies in Urban Growth and Urban Sprawl

In contemporary urban research, assessing urban expansion and growth alongside their temporal dynamics is a critical focus (Schneider, 2012). It is a standard practice to identify and measure patterns and manifestations of urban physical growth (Tv et al., 2012). Dechaicha et al. (2021) emphasized the use of remote sensing satellite images in monitoring and understanding the uncontrolled and fast-growing expansion of urban and peri-urban regions and evaluating the effects this has on nearby ecosystems. Wilson and Chakraborty (2013) highlight that urban sprawl is characterized by examining physical growth patterns. Urban built-up areas effectively measure this growth. Traditional surveying is costly and time-consuming, leading to integrating statistical methods with GIS and remote sensing in studies of expanding cities (Punia & Singh, 2011).

In recent years, remote sensing has emerged as a practical, and widely used method for analysing urban expansion (Yeh & Li, 2001). As a result, the use of remote sensing and GIS techniques for mapping and monitoring urban sprawl has increasingly attracted the attention of researchers (Epsteln et al., 2002), Implementing a specific process (fig. 8) that shares some steps but differs in its approaches.

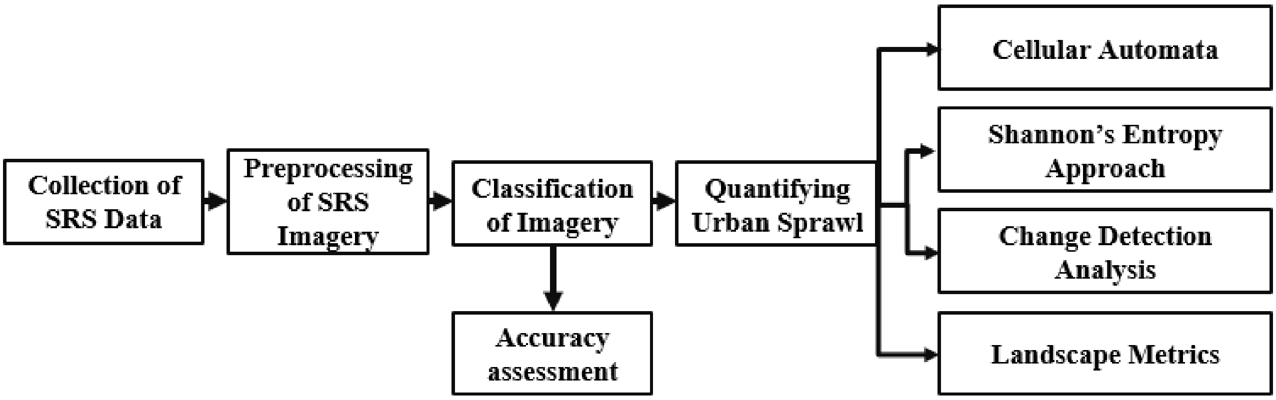

Figure 8. Framework for integrating GIS, Remote Sensing and AI in Urban Studies (Developed by the authors).

3.2.1.1. Collection and Pre-processing of Satellite Remote Sensing Data:

Analysing satellite data allows easy identification of temporal and geographical changes in the urban landscape. The collected remote sensing data preprocessing entails topography correction, geometric rectification or picture registration, radiometric calibration, atmospheric correction, and poor line restoration (*Lillesand et al*,2015). Image preprocessing, extensively covered in textbooks and papers, requires precise geometric rectification and atmospheric calibration, especially when combining multi-temporal or multi-sensor data for classification. Several techniques are developed for atmospheric normalization, correction, and radiometric calibration, including relative calibration, dark object removal, and other complex calibration methods (Lu & Weng, 2007). According to Nazeer et al. (2014), some of the advanced techniques that are often used include quick atmospheric correction (QUAC), fast line-of-sight atmospheric analysis of hypercubes (FLAASH), second simulation of the satellite signal in the solar spectrum (6S), and atmospheric correction (ATCOR). One of the most advanced and widely used atmospheric correction programs, FLAASH, is implemented by many researchers to calibrate multi- and hyper-spectral images, such as those from Landsat (Wang et al., 2019), Hyperion (Perkins et al., 2005), AVIRIS (Perkins, 2012). Several studies find that, in terms of consistency, the FLAASH radiometric calibration performs better than many other techniques (Jinguo Yuan & Zheng Niu, 2008). Furthermore, ENVI is an established software for FLAASH correction (Rahman et al., 2023).

3.2.1.2. Classification of imagery and accuracy assessment

Preprocessing of RS data should ideally be followed by picture classification, which examines image pixels using various guidelines and methods (*Lillesand et al*, 2015) that generate the predetermined land cover classes (Araya & Cabral, 2010).

Image Classification is a main focus. The information that may be extracted from satellite imagery through the thereby produced LULC maps depends on how well the categorization is done. Many variables affect the accuracy of this classification, including (a) the type of image to be used, including its sensor, resolution, and quality (e.g., haze, clouds, and shadows); (b) the area coverage and type of landscape being examined (e.g., local, regional, or global; homogeneous or heterogeneous); (c) the number of classes to be extracted; (d) the individual's own local or expert knowledge of the area of interest, as well as the availability of relevant ground truth information; and (e) the classification technique to be used (Estoque et al., 2015). Although many effective remote sensing applications, such as LULC mapping, still rely on pixel-based image processing, this method has limitations regarding context, relative size, and smooth or fuzzy transitions (Blaschke et al., 2000). The advent of high-resolution satellite sensors has spurred the development of GEOBIA methods (Blaschke et al., 2014), replacing old pixel-based techniques. Object-based approaches offer advantages like incorporating expert knowledge and optimizing feature space

during classification (Platt & Rapoza, 2008). Also, object-based techniques are known for their advantage in reducing the 'salt-and-pepper effect' (Blaschke et al., 2000). It has been noted that GEOBIA has gained more incredible notoriety than conventional pixel-based analysis (Estoque et al., 2015).
Researchers have used various methods to categorize satellite images (Lu & Weng, 2007). The per-pixel supervised classification based on the parametric maximum likelihood classifier (MLC) is one of the most used techniques (Aburas et al., 2017). Additionally, nonparametric classifiers—such as neural networks, decision trees, and knowledge-based classifiers—are being utilized increasingly in categorizing images (Rahman et al., 2023). However, because mixed pixels are often included in this sort of data, per-pixel LULC classification may not be helpful for moderate-resolution satellite imagery, such as that collected by the Landsat thematic mapper (TM) and Landsat operational land imager (OLI) (30 m) (Lu & Weng, 2006). Machine learning techniques have advanced so that medium-resolution satellite images, such as Landsat TM and OLI, can be identified more precisely at the per-pixel, sub-pixel, and object basis (Estoque et al., 2015). The support vector machine (SVM), an AI classifier, is an effective non-linear, non-parametric, supervised classification technique with good classification accuracy (Rimal et al., 2018). When Schneider (2012) used Landsat data to analyse LULC change over urban and peri-urban regions, the results showed that SVM and decision tree (DT) were better classifiers than MLC. SVM is superior because it is less sensitive to noise, correlated bands, and an uneven distribution of training sites within each class (ESRI, 2018).
An evaluation of their accuracy follows the procedure of classifying images. "Accuracy assessment" refers to conveying the degree of "correctness" in picture categorization. According to Congalton (2001) and Congalton and Green (1993), accuracy assessment research can be divided into four main stages. The fourth type uses ground truth verification to evaluate how well-classified images match real-world observations, using a confusion matrix to show class allocation patterns compared to reference data. This era is characterized by error matrices, which may also be used to calculate the producer's accuracy (PA), user's accuracy (UA), and overall accuracy (OA). The most often reported accuracy assessment method is the measure of OA; however, individual class accuracies are represented by PA and UA (Yang et al., 2017). Another crucial factor in determining the accuracy of categorized photos is sample size. Researchers Congalton & Kass Green (1993) advise obtaining at least fifty samples of each classified image for images smaller than one million acres and include less than twelve groups or categories. For multi-spectral and temporal Landsat imagery, studies (e.g., Belal & Moghanm, 2011; Zaki et al., 2011) have attained accuracy levels of 3-7 land-cover classes ranging between 85 and 95%. The sampling technique chosen for site selection is essential to assessing accuracy. The Kappa discrete multivariate approach is utilized in accuracy evaluation to statistically determine whether there is a significant difference between two error matrices (Congalton, 1991).

3.2.1.3. Quantifying Urban Sprawl
Researchers have developed numerous indices and models linked with RS-GIS to evaluate urban growth patterns. These include the relative entropy index, sprawl dimensions, landscape metrics, and Shannon's. These metrics can be absolute or relative, allowing us to distinguish between sprawling and non-sprawled cities (Rahman et al., 2023). So many approaches have been developed, mentioning:
a. **Change Detection Analysis,** pertains to using co-registered multi-temporal Satellite Remote Sensing data to determine an aerial change in land coverings. Various perspectives led to a summary and categorization of change detection methodologies. In general, there are two kinds of approaches for detecting changes in land cover: (1) utilizing different image-enhancing techniques to identify the change and (2) extracting specific categories of land cover change by employing classification algorithms (Jensen & Im, 2007). Various studies employ distinct methods for detecting changes, including principal component analysis (PCA), differences in vegetation index, image rationing, post-classification comparison (PCC), and image differencing. The PCC is arguably the most extensive and well-liked change detection method (Abd El-Kawy et al., 2011). In post-classification comparison, each corrected imagery date is independently classified and aligned with a shared land type schema, then categorized and

contrasted pixel-by-pixel (Punia & Singh, 2011). With remote sensing and GIS, statistical methods are used to quantify, estimate, map, and monitor urban expansion (Jat et al., 2008).

b. **Shannon's Entropy Approach** is the haphazardly occurring mathematical calculation of urban expansion. Entropy may also be used to assess how scattered or compact a city's land development is, which might reveal information about the extent of urban expansion or sprawl (Lata et al., 2001). According to Bhatta (2010), this metric is robust because it can categorize sprawl in black and white.

c. **The Cellular Automata model** has also been applied to research on urban expansion. CAs are described as elementary dynamic spatial systems in which each array cell's state is determined by its neighbours' past states and a collection of transition principles (White et al., 1999).

d. **Landscape Metrics** are a frequently applied method in landscape ecology (H. Liu & Weng, 2013). They are widely used in studies on landscape variability over time (Mcalpine & Eyre, 2002) and have been defined as quantifiable biotic or abiotic environmental characteristics that allow for the collection of quantitative information on ecological resources and the functioning of the landscape. The metrics are applied to evaluate the functioning, status, and features of the spatial structure of different types of landscapes, such as degraded, urban, rural, and forest landscapes (Barwicka & Milecka, 2021). According to Herold et al. (2005), landscape metrics may quantify spatial variability at patch, class, and landscape metrics at three levels. As per McGarrigal and Marks (1995), A class is an assembly of all the patches in a specific category, a landscape is the collection of all the patches in all patches within a landscape, and a patch is a homogenous unit of a class or category being investigated. Measurements capture spatial properties even in the absence of spatial explicitness. On the other hand, pixel- or patch-based indices might represent spatially explicit measurements (Herold et al., 2005). Similarly, Dechaicha et al. (2021) claim that measures based on remote sensing and landscape metrics are essential to controlling the unbridled urbanization occurring in oasis cities and lessening its adverse consequences on palm groves. Herold (2005) also advocated connecting RS and geographical metrics to give more comprehensive and consistent data on urban structure, analysis, and dynamics. To demonstrate the importance of the metrics and argue for further research into urban analysis, some specific metrics have been used and proposed by the RS-GIS integrated studies that deal with the application of spatial metrics, including James, 2012, H. Liu & Weng, 2013, Motlagh et al., 2020. Nevertheless, there is not a set of metrics universally applicable to urban studies, and because the significance of metrics varies depending on the research goal, selecting independent measures for a given study has proven to be challenging for researchers (Parker et al., 2001). Because of this, it is critical to evaluate and examine metrics' ability to gather pertinent data while using them (Mithun et al., 2023). These metrics might include, for example, point density, edge density, the edge effect, most extensive point index, and landscape index (Elmi et al., 2022).

The methods mentioned happen to take place thanks to different software such as FRAGSTATS, ArcGIS, QGIS, ERDAS IMAGINE, and Google Earth Engine.

3.2.2. Artificial Intelligence in Urban Sprawl Prediction and Modelling

Resource managers and city planners should be aware of the dynamics of urban expansion (Herold et al., 2005). particularly in rapidly changing cities. Urban expansion has been modelled using various analytical and static techniques since the 1950s. These methods were based on assumptions about social dynamics, economic activity, and urban geometry (Berling-Wolff & Wu, 2004). Hybrid models, such as neural network CA (Yeh & Li, 2001), fuzzy-CA (Y. Liu, 2012), logistic-CA, and CA-Markov (Mithun et al., 2022), have been used to improve performance. Other sophisticated models, such as artificial neural network (ANN) (Shafizadeh-Moghadam et al., 2021), agent-based model (Jokar Arsanjani et al., 2013), genetic algorithm (Tang et al., 2007), geographically weighted regression (Mondal et al., 2015), bivariate or step-wise multiple regression (Al-sharif & Pradhan, 2013), SLEUTH model (Serasinghe Pathiranage et al., 2018), analytic hierarchy process (Devendran & Lakshmanan, 2019), logistic regression, Markov chain (Jokar Arsanjani et al., 2013), and fuzzy logic (Y. Liu, 2012), have also been created to forecast LULCs in metropolitan areas in the future (Rahman et al., 2023).

One popular Artificial Neural Network (ANN) for modelling and predicting urban expansion is the multi-layer perceptron (MLP) (Sahana et al., 2018). In comparison to other methods, its transition potential is the best. MC is helpful for simulating changes in LULC in intricate regions. When paired with MC, ANN modelling may accurately represent urban dynamics by fitting intricate non-linear relationships between urban land use dynamics and the forces propelling population expansion. This method works exceptionally well for intricate changes in land cover (Eastman et al., 2005).

Urban growth may be effectively detected, mapped, monitored, and analysed using satellite images and GIS technologies. Satellite imaging may obtain a synoptic picture of a landscape, revealing trends in land cover and usage. RS-GIS technology is robust and affordable and simulates and tracks urban sprawl dynamics. Since 1972, Landsat data has identified spatiotemporal urban expansion, with advanced models integrated into RS-GIS for trend assessment and simulation (Mithun et al., 2023).

4. Discussion

The perception of urban expansion as a looming threat to sustainable development underscores the necessity for infrastructure projects, effective resource allocation, and urban planning. The bibliometric study, a crucial tool in this field, has revealed that China leads research on LULC change, while the USA is at the forefront of urban sprawl research. This study, which selected papers aimed at providing a clearer overview, guides future research and underscores the importance of understanding the leaders in this field, thereby keeping the audience informed and knowledgeable. Researchers have concluded that remote sensing and geographic information system tools are optimal for mapping, measuring, evaluating, and modelling the spatiotemporal dynamics of urban expansion, as they have been employed in most studies on urban sprawl over the past few decades. One common, easy-to-use criterion for evaluating urban expansion and sprawl is the urban built-up cover, and the primary way that urban sprawl is researched is as an urban expansion pattern and process about the cause and effect of that indicator.

Urban sprawl studies extensively use open-source satellite remote sensing data from IRS LISS III, TM, ETM+, and Landsat 5-7-8, and they also preprocess that data, which is very important.

Moreover, FLAASH atmospheric correction is a widely used method for radiometric calibration and atmospheric correction of satellite images. This is followed by a classification of the data, and the MLC approach is the most commonly used classifier for identifying the different types of land cover using RS data. However, there has been a significant rise in the use of some machine learning methods, including SVM, decision trees, and random forest classifiers. Urban sprawl and expansion may be measured using various metrics and indices. Nevertheless, Shannon's entropy approach and landscape metrics are now widely used to quantify urban sprawl and are very efficient and reliable approaches; they can be used to evaluate and improve city management decisions. These tools provide the chance to formalize the most appropriate choices and solutions that fulfil the requirements for promoting and protecting ecosystems.

MC, CA, SLEUTH, and LR are the most common modelling approaches used with RS-GIS. Moreover, specific machine learning methods (such as MLP) have been utilized for this purpose very recently. However, parameterization and model calibration remain important and challenging processes.

The study on GeoAI strategies and LULC analytics reveals significant patterns in urban development, underscoring their role in sustainable urban planning and policymaking. By leveraging advanced GeoAI techniques, the research provides insights into LULC changes and can be vital in helping decision-makers make informed choices. Yet, more research should focus on the inclusion of real-time data, improving prediction models, and taking socioeconomic consequences into account to further improve urban planning methods and guarantee thorough policy formulation for sustainable cities.

5. Conclusion

Urban expansion is perceived as a significant threat to sustainable development, necessitating robust infrastructure projects, effective resource allocation, and comprehensive urban planning. Remote Sensing (RS) and Geographic Information System (GIS) tools are optimal for mapping, measuring, and modelling the spatio-temporal dynamics of urban expansion due to their use over the past decades. Studies heavily

employ open-source Satellite Remote Sensing data, with preprocessing and FLAASH atmospheric correction being crucial steps. Preprocessing is usually followed by the classification of the collected and assessed data, and the Maximum Likelihood Classifier (MLC) is the most commonly used. However, there has been a notable rise in the use of machine learning methods like support vector machines (SVM), decision trees, and random forest classifiers. This shift towards machine learning methods is significant, as it not only enhances the accuracy and efficiency of urban expansion studies but also opens up new avenues for future research and development in this field. As for the quantification of sprawl, several measures are employed; Shannon's entropy and landscape measures are frequently used. While machine learning techniques like multi-layer perceptron MLP have recently gained popularity, RS-GIS modelling approaches like Markov Chain, Cellular Automata, and SLEUTH remain popular despite difficulties with parameterization and model calibration.
GeoAI strategies and LULC analytics reveal essential patterns in urban development, underscoring their role in sustainable planning for providing insights into urban space (infrastructure maintenance needs, reducing costs…), such as population density, traffic flow, and environmental impact, supporting evidence-based decision-making. When AI is integrated into RS-GIS technology, it becomes more effective in predicting future evolutions, foreseeing problems, and making implicit decisions that lead to successful land planning and more sustainable, resilient, and liveable cities. These technologies have proven reliable, affordable, and technically sound, allowing the simulation and tracking of urban expansion dynamics. To further improve urban planning and policy development, future research should concentrate on integrating real-time data for more timely and accurate analysis; improving predictive models to better anticipate urban growth patterns; investigating sophisticated machine learning techniques for data classification and modelling; and carrying out socio-economic impact assessments.

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CRediT author statement
-Dr. Assoule Dechaicha performed Supervision.
-Pr. Djamel Alkama performed Conceptualization; Methodology; Supervision.
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