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Integration of AI, Spatial Data, and GIS in Planning: Spatial Application Based on Machine Learning and Deep Learning

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Abstract

The study focuses on the integration of data, deep learning (DL) models, and machine learning (ML) algorithms with geographical information systems (GIS) within the field of spatial planning. An original contribution is provided by addressing the integration of DL and ML into GIS in terms of their advantages, limitations, encountered challenges, and potential directions for development within the context of spatial data and model validation processes. In this context, the objective is to identify the developmental trajectory, challenges, and potentials of spatial studies based on the integration of DL, ML, and GIS. To achieve this aim, 91 research articles published in high-impact journals indexed in the Web of Science (WoS) database were analyzed. The selected studies were evaluated under five main categories: spatial and temporal distribution, applications of DL and ML methods, thematic approaches, employed GIS tools, and data-model validation processes. The findings suggest that artificial intelligence technologies have the potential to serve as significant tools in spatial planning, although the current developmental stage remains in its early phases. While ML algorithms are widely applied across the reviewed studies, the application scope of DL models has expanded in recent years due to the increasing availability of large datasets. Spatial applications predominantly concentrate on land use, natural hazard assessments, environmental issues, and climate-related themes, particularly supported by the extensive use of remote sensing techniques. However, due to the limited accessibility of spatial data in rural areas, the majority of applied studies have been oriented toward urban centers, revealing a noticeable gap in research focusing on rural contexts. Furthermore, studies that implement AI and planning integration in practice demonstrate that the use of spatial data and the necessity of model validation constitute critical requirements. This study may offer guidance for future research by supporting the implementation of applications across diverse thematic domains involving the integration of artificial intelligence, planning, and GIS within spatially oriented processes.

Keywords: *Big data, Deep learning, Geographical information systems, Machine learning, Spatial planning*

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INTRODUCTION

The increasing complexity of urban environments necessitates the advancement of objective decision-making mechanisms. Spatial data plays a crucial role in the development of this necessity. At present, spatial data is widely utilized in urban research and planning. Spatial big data refers to datasets that are collected from diverse sources and characterized by spatial or geographic components, encompassing the dimensions of volume, velocity, variety, and veracity. These datasets incorporate spatial, temporal, thematic, and relational information, all of which are vital for interpreting and understanding space (Zou et al., 2024). However, the diversification of spatial data and the growing demand for data have positioned the use of big data as one of the principal challenges encountered in planning processes (Su et al., 2023).

Throughout history, planning has undergone significant transformations influenced by data, methodological approaches, and technological advancements. In the 1950s, the prevailing planning paradigm emphasized printed documents and maps, with debates centered on the adequacy and consistency of spatial data. During the 1960s, the transition of planning from a design-oriented practice to an applied science was notably shaped by the emergence of computer technologies (Klosterman, 1995). The rapid advancement of computer technologies led to the widespread adoption of computer-based Geographical Information Systems (GIS) in planning practices (Scholten & Stillwell, 2013). The capacity of GIS to provide essential data and techniques across various stages of the planning process—including data storage, data management, monitoring, goal setting, resource inventory, situational analysis, modeling, development of planning alternatives, and feedback—has significantly accelerated its integration into planning studies (Santos et al., 2021; Goodchild, 2009).

In spatial planning, data pertaining to space play a critical role. These data reflect the characteristics of objects analyzed at a specific location, and the results are influenced by changes in location. Therefore, data constitute the core of spatial assessments (Goodchild & Janelle, 2004). With the increasing number of objective and criteria sets in spatial decision-making processes, traditional analytical and evaluative methods have become insufficient to manage large volumes of data (Wan & Ma, 2022). The development of Artificial Intelligence (AI), particularly Machine Learning (ML) and Deep Learning (DL) techniques, has in recent years offered researchers new opportunities to address challenges related to big data and complex urban issues (Peng et al., 2023). Advances in AI technologies have contributed significantly to reducing data collection time, costs, and error rates in spatial applications (Al-Azizi et al., 2020).

The concept of AI and the foundation of the first AI programs date back to 1956 (McCorduck, 2004), during which the focus was on solving non-quantitative, simple-level problems. However, resolving problems characterized by complex processes proved to be a formidable task. In

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spatial disciplines, including geography and earth sciences, the problem-solving capacity of AI began to receive attention in the 1980s (Smith, 1984). More recently, the accessibility of high-quality datasets and advancements in hardware and software have triggered substantial transformations across various fields, particularly spatial sciences (Janowicz et al., 2020).

The progress in data-driven AI has made significant contributions to the analysis, modeling, and assessment of large datasets that are difficult to process using traditional spatial analysis techniques (Li, 2020). Developments in this area are largely driven by the computer-assisted application of ML and DL tools, ensuring the continuity of technological advancement (Zappone et al., 2019). Among AI-driven tools, ML offers important perspectives for decision support systems in spatial planning. First introduced in 1959 (Samuel, 1959), ML represents a data-centered approach that extracts meaningful information from datasets through a learning process (Mitchell, 1997). In general, ML comprises a variety of models and patterns capable of minimizing errors by leveraging processes of data collection, analysis, and monitoring (Hagenauer et al., 2019). ML algorithms are increasingly important in planning due to their ability to outperform traditional modeling techniques, offer accurate predictions, simplify data acquisition, and effectively address urban form modeling challenges (Chaturvedi & De Vries, 2021; Ma et al., 2020). Another AI technique, DL, specializes in classifying data types such as images, text, and audio (Harrington, 2012). With the proliferation of open spatial data sources, DL models—by focusing on perception—have made valuable contributions to spatial data science. While the approach can be applied at various scales, from regional to street level, its dependence on algorithms and limited capacity to incorporate external professional knowledge represent notable drawbacks (Fang et al., 2022). Therefore, there is a growing need for scalable and interpretable DL models capable of effectively processing multimodal spatial data (Zou et al., 2024).

In an era increasingly defined by digitalization, the significance of AI technology has been widely acknowledged across scientific domains and is reflected in applied research. In the field of planning, AI has rapidly emerged as a critical technology for transformation and reconfiguration. Nevertheless, numerous unanswered questions remain regarding the potential impacts of AI on urban and regional planning research and practice, as well as the challenges encountered and appropriate policy responses (Peng et al., 2023). Although the number of studies on ML and DL in spatial planning is on the rise, the field is still considered to be in an early stage compared to other disciplines (Casali et al., 2022). In spatially based research, integrating GIS as an implementation tool for ML and DL algorithms is essential (Jing et al., 2023). The integration of ML and DL with GIS is gaining increasing attention in areas such as land use related to global climate change (Lemonkova, 2024), disaster risk

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assessment (Mishra et al., 2024), waste management (Mondal et al., 2024), biodiversity (Zheng et al., 2024), urban heat islands (Jato-Espino et al., 2022), energy (Ali et al., 2020), ecology (Huettmann et al., 2023), and transportation (Iamtrakulet al., 2023). Despite the growing body of work focused on the application of ML, DL, and GIS, there is a lack of comprehensive discourse regarding the identification of the most suitable learning techniques, the selection of appropriate GIS application tools, the integration of DL and ML into GIS environments, and the validation of spatial big datasets. In particular, the uncertainties in data–model validation processes, the marked variation in the metrics used for data validation within studies addressing similar themes, and the superficial treatment of concepts such as spatial data sources and resolution highlight the need for a critical and guiding discussion. This study distinguishes itself from systematic literature reviews by incorporating a comprehensive discussion not only on spatial data and model validation processes but also on the advantages, limitations, challenges, potentials, and spatial applicability of integrating DL and ML into GIS. In this regard, it aims to provide researchers in spatial sciences with a perspective, grounded in the expectation that the advancement of artificial intelligence will significantly influence spatial planning.

The objective of the study is to examine how ML and DL techniques integrated with GIS have evolved within the context of spatial planning and, based on current literature trends, to propose a conceptual and practical framework for future research that incorporates spatial planning themes within the broader scope of GIS, ML, DL, and big data. To achieve this objective, the study evaluates applied articles published in high-impact journals indexed in the Web of Science (WoS) database, focusing on spatial issues. The analysis reveals the current trajectory of development, existing gaps, emerging potentials, and key challenges. Accordingly, the study focuses on the integration of DL and ML techniques with GIS in spatial planning.

The structure of the study is organized as follows:

Section 2 presents the methodology, including database selection, publication criteria, and the scope of analysis, to reveal prevailing trends in the literature. Section 3 offers findings on the progression of published studies, thematic distributions, the use of ML and DL techniques, GIS implementation tools, data and model validation, and the intended purposes of AI applications. Section 4 discusses the current trends, deficiencies, opportunities, challenges, and data-model validation processes from the perspective of spatial planning. Finally, Section 5 concludes the study with a summary of the main results.

METHODOLOGY

The methodology of the study consists of a two-stage process that addresses spatially applied research based on the integration of ML, DL, and GIS: (i) database and data source, and (ii) scope of analysis. A systematic literature review was conducted to examine the forms of GIS

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integration in ML- and DL-focused studies within spatial planning, to analyze the accumulated scientific knowledge in the field comprehensively, and to identify current research trends. Accordingly, meaningful findings were obtained regarding the dominant themes of the reviewed studies, the most frequently used methods and models, the software employed, the development trajectory of AI technologies in the field of spatial planning, existing challenges and potentials, and the functions through which GIS has been integrated into the planning process.

Database and Data Source

To conduct a comprehensive review of studies based on the integration of DL, ML, and GIS in the context of spatial planning, a method encompassing the entirety of the research field was adopted. In this study, the Web of Science (WoS) database was employed as the data source, being a widely recognized citation and analysis platform at the international level for systematic literature reviews (Yan & Zhiping, 2023; Kar & Wasnik, 2024). WoS was preferred due to its provision of high-quality archival resources (Zhu et al., 2023), comprehensive access to scholarly literature (Junjia et al., 2023), coverage of a broad range of international journals (Wang & Liu, 2014; Birkle et al., 2020; Fang & Zhang, 2024), inclusion of journals with high impact factors and low redundancy rates (Baghini et al., 2024), reliable author identification via ResearcherID (Ohlan et al., 2025), and advanced search functionalities along with an extensive analytical toolset (Avinç & Yıldız, 2025).

In recent years, the growing volume of research on ML and DL, driven by the broad applicability of these techniques across various domains, has increased scholarly interest in the field. However, due to the wide range of applications and the growing number of studies, it has become challenging to conduct evaluations without imposing certain thematic limitations (Casali et al., 2022). For this reason, the present study applies specific constraints focused on DL, ML, spatial data, and GIS integration. Accordingly, the selection of publications from the database was based on the following criteria:

- A search query was constructed using the main keywords DL, ML, GIS, spatial data, and planning. The query applied was: ("GIS" OR "Geographic Information System*" OR "Geographical Information System*") AND ("Deep Learning" OR "Machine Learning") AND ("Urban" OR "City" OR "Planning" OR "Spatial Planning"). To expand the search scope, the wildcard character (*) was included. The review was limited to documents categorized as "articles", and the "Topic" field was used to provide a general overview of each publication (Tang et al., 2023; Guo et al., 2019).
- The article selection was limited to English-language journal articles with high impact factors, indexed in the Social Sciences Citation Index (SSCI), Science Citation Index Expanded (SCI-E), Emerging

Sources Citation Index (ESCI), and Arts & Humanities Citation Index (A&HCI). The database was last updated in March 2025.

Scope of Analysis

This study was conducted through a four-stage process consisting of: (i) identification, (ii) screening, (iii) perspective, and (iv) discussion and suggestion (Figure 1). In the first stage, a total of 135 articles were identified within the database search under the Topic Title (queries) scope. After assessing whether the articles included fieldwork, were based on spatial data, fully addressed the key concepts, and were not duplicates, 91 articles were deemed eligible and included in the review process. According to the research criteria, the earliest of the relevant publication dates to 2017, and to account for the rapidly growing body of recent studies, the time span of 2017–2025 was adopted. To sort, filter, and group the data from the selected studies, a spreadsheet was created in Excel. This table covers a wide range of information, including the author, publication year, topic, use of DL and ML, type and rationale for the GIS application tools, data-model validation methods, scale, and study area. The analysis is structured around five perspectives designed to identify challenges and potentials in the integration of AI technologies and GIS within the field of spatial planning:

- Spatial and temporal distribution on DL & ML: Assesses the spatial and temporal evolution of research through country-level and year-based evaluation, providing insight into the main development trends across nations.
- Distribution of models used in DL and algorithms used in ML: Examines the primary purposes for which DL models and ML algorithms are applied, revealing the underlying rationale for the dominant trends.
- Distribution of themes and topics used in DL and ML: Identifies how the integration of DL, ML, and GIS is reflected in practical applications within spatial planning and evaluates the thematic focus of the research.
- Distribution of software used in DL and ML, and their usage purposes: Investigates the practical tendencies in integrating GIS tools with AI technologies, highlighting the types of software commonly utilized.
- Distribution of accuracy metrics commonly Used in DL and ML: Detects prevailing trends in spatial data and model validation processes in applied studies.

Based on these perspectives, findings are presented and thoroughly discussed in relation to the interrelationship between GIS, AI, and spatial planning, with a particular focus on spatial data and model validation processes.

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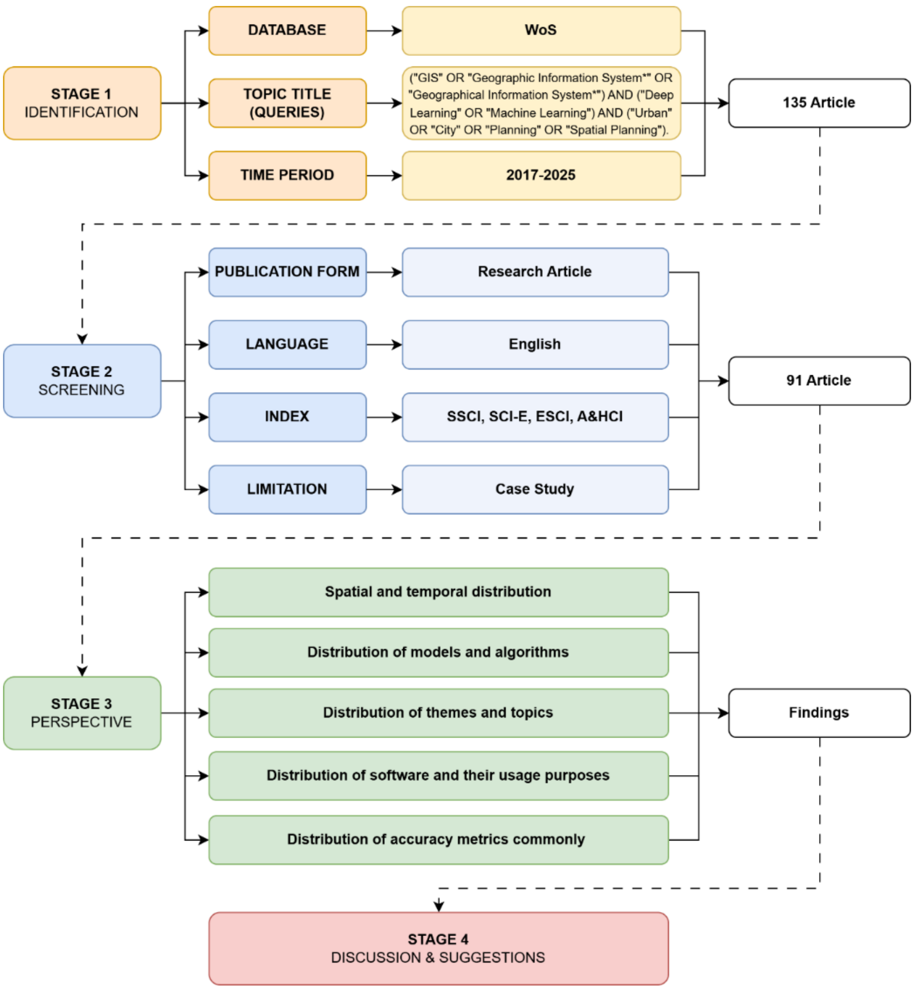

Figure 1. The flowchart of the study

RESULTS

Spatial and Temporal Distribution on DL and ML

This study systematically reviewed 91 research articles integrating DL, ML, spatial data, and GIS. According to the data, a consistent upward trend in publication frequency has been observed since 2019, reaching a peak in 2024 with the publication of 29 articles. As of March 2025, 12 articles had been published, indicating a significant concentration of research activity during the first quarter of the year. The findings reveal that China leads in the application of DL and ML methods in spatial planning, with 24 studies, followed by the United States with 12 studies and India with 10 studies (Figure 2). The rising trend of studies on the integration of DL and ML into GIS indicates that the field is likely to expand further in the coming years. Limited access to spatial data remains a critical factor, and research in this area is concentrated in countries such as China, the United States, and India, where broader access to comprehensive spatial data sources is available. The high data production capacity and urbanization dynamics of these countries support the increasing number of studies in this domain.

Examination of the spatial scales addressed in these studies shows a predominant focus on the ‘city’ scale, represented in 54 publications, followed by 9 studies at the 'regional' level, 7 studies at the 'basin' scale, 7 studies at the 'district' level, 6 studies at the 'neighborhood' scale, 4 studies at the 'street' level, 2 studies at the 'hamlet' scale, and only 1 study at the 'country' level (Figure 2). Due to the increasing number of studies at urban scales, the creation of rural spatial datasets and the expansion of research in this area represent a significant research gap.

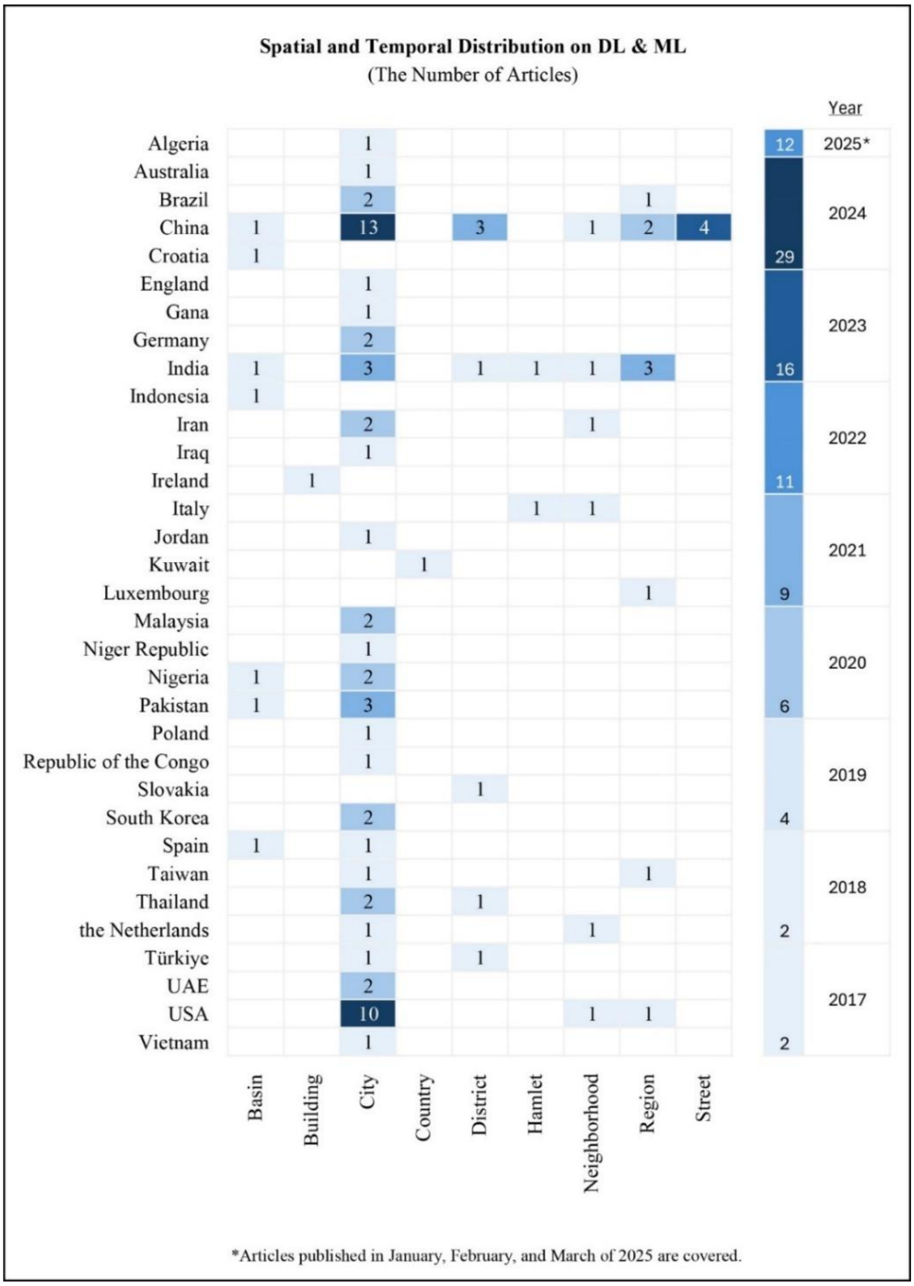

Figure 2. Spatial and temporal distribution on DL and ML

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Distribution of Models Used in DL, and Algorithms Used in ML

A total of 22 publications involving DL have employed 10 distinct models. All of these models are based on deep neural network (DNN) architectures. In several studies, models such as DeepLabV3, FCN, HAU-Net, SegNet, and YOLOv5m have been utilized for the advancement of convolutional neural networks (CNN). Among the DL-related publications, CNN has emerged as the most adopted method, with a usage rate of 45.15% (Figure 3). The prevalence on DNN-based CNNs in DL techniques reveals a limited diversity of models. Therefore, presenting different DL methods in terms of comparative performance and potential for development can make a significant contribution to spatial data analysis and visual-based modeling in the literature.

In the 69 studies applying ML, 34 different algorithms have been documented. The most prevalent algorithms included Random Forest (RF) at 29.09%, Support Vector Machine (SVM) at 18.18%, and Artificial Neural Networks (ANN) at 17.27%, followed by Logistic Regression (LoR) at 7.27%, K-Nearest Neighbor (KNN) and Extreme Gradient Boosting (XGB) each at 5.45%, Decision Tree (DT) at 4.55%, Gradient Boosting Decision Tree (GBDT) and Multilayer Perceptron (MLP) each at 3.64%, and Linear Regression (LiR) and Maximum Likelihood (ML) each at 2.73% (Figure 3). Compared to DL methods, ML techniques stand out due to their greater diversity. The presence of different algorithms offers opportunities for methodological comparisons. However, there is a need to relate these methods to thematic domain, spatial scale, and spatial resolution when selecting appropriate approaches.

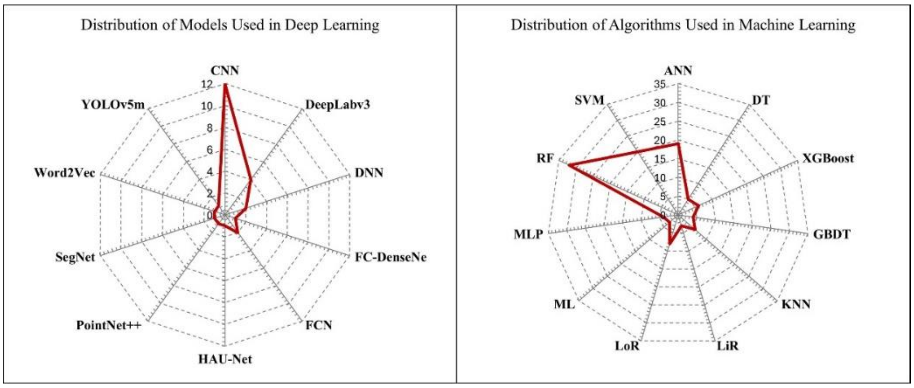

Figure 3. Distribution of models used in DL, and algorithms used in ML

Distribution of Themes and Topics Used in DL and ML

This study categorizes research integrating DL, ML, and GIS in spatial planning into six primary themes, encompassing 54 distinct topics. These themes are Land Use–Land Cover & Urban Growth, Climate, Environment & Energy, Natural Hazards & Risk Assessment, Urban Infrastructure & Planning, Urban Quality & Aesthetic–Perception, and Socio-economic. The most prevalent addressed themes are Land Use–Land Cover & Urban Growth at 25.17% (23 articles), followed by Climate, Environment & Energy at 23.08% (21 articles), and Natural Hazards & Risk Assessment at 21.98% (20 articles). These are followed by Urban Infrastructure & Planning at 14.29% (13 articles), Urban Quality & Aesthetic–Perception at 10.99% (10 articles), and Socio-economic at 4.40% (4 articles). Within these themes, the most frequently addressed topics include Land-Use and Land Cover (LULC) Change Analysis at 20.83% (10 articles), Flood Risk Assessment at 18.75% (9 articles), Landslide Risk Assessment at 14.58% (7 articles), Urban Growth Modeling at 10.42% (5 articles), Land Use Management and Urban Heat Island each at 8.33% (4 articles), Urban Air Quality at 6.25% (3 articles), and LULC Classification, Mapping of Impervious Surfaces, and Wind Environment Analysis each at 4.17% (2 articles) (Figure 4). In the themes where most studies are concentrated, AI methods are shown to be primarily used for monitoring spatial changes and managing environmental risks. This may be linked to the widespread availability of land-use datasets derived from satellite imagery based on advancing remote sensing technologies.

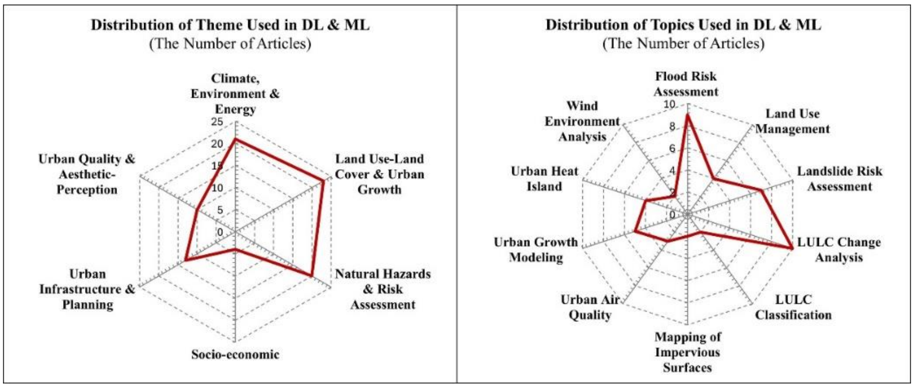

Figure 4. Distribution of theme and topics used in DL and ML

The research articles analyzed within the scope of this study have been classified based on their subjects, identifying 17 distinct subtopics within the Climate, Environment & Energy theme. Among these, Urban Heat Island emerges as a prominent subject, particularly due to its direct relevance to global climate change and its recent treatment through diverse assessment methodologies (Figure 5).

Under the Land Use–Land Cover & Urban Growth theme, six subtopics have been identified. The most extensively studied among these are Land Use Management, LULC Change Analysis, and Urban Growth Modeling, which have primarily been conducted using satellite imagery derived from remote sensing techniques. The Natural Hazards & Risk Assessment theme comprises six subtopics as well. Within this category, Flood Risk Assessment and Landslide Risk Assessment have received the most scholarly attention, typically approached through satellite image–based classification and modeling frameworks.

A total of 12 distinct subtopics have been examined under the Urban Infrastructure & Planning theme. These include: Blue-green infrastructure mapping and assessment, creating building information system, determining spatial risk factors of health inequalities, global terrain and altitude mapping, height-augmented geo-located dataset, identification mapping of buildings, mapping of impervious surfaces, optimizing of outdoor sports facilities, spatial optimization of healthcare facilities, urban parks, urban street pattern analysis, and user experience for greenspace. Compared to other main themes, Urban Quality & Aesthetic–Perception and Socio-economic themes have attracted relatively limited application in spatial research.

While thematic depth and methodological orientations are prominent in certain areas, significant opportunities exist for energy-

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related research, which plays a crucial role in the context of climate change. Although studies on land use are widespread, the integration of multiple data sources, such as social media and mobile data, has not yet received sufficient attention. Incorporating multi-source data could enhance dynamic and real-time planning solutions. In disaster-based risk assessments, planning approaches are predominantly focused on single hazards, and an integrated, multi-hazard risk-based planning approach has not yet matured.

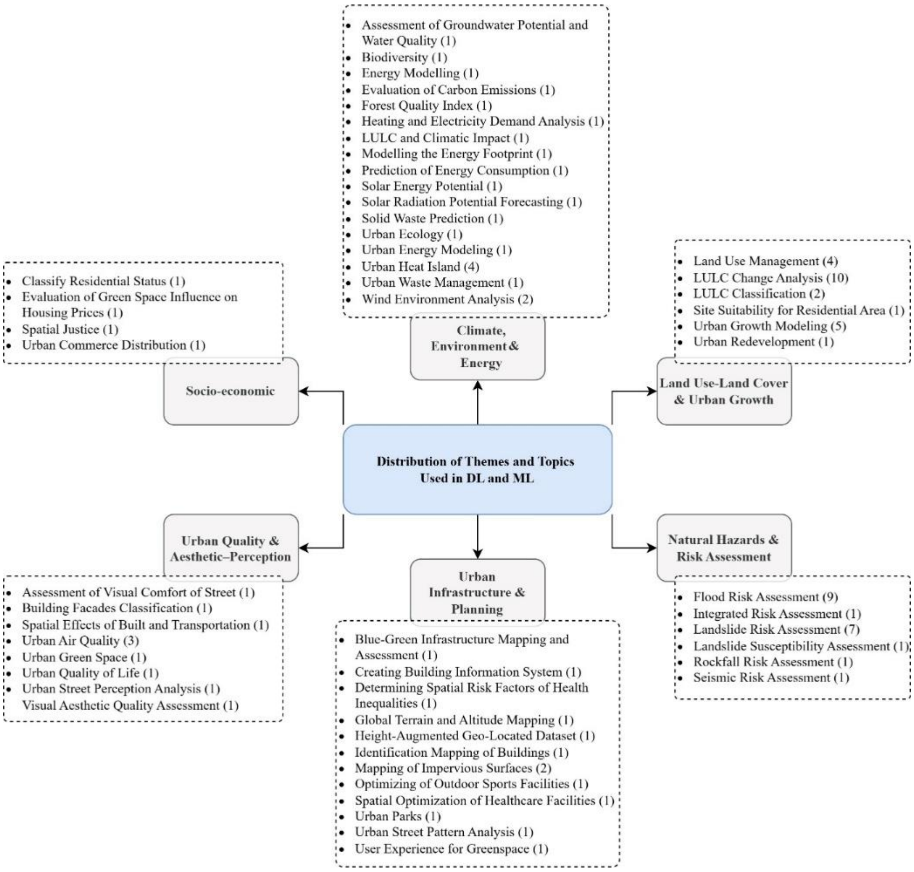

Figure 5. Thematic classification of the articles

Distribution of Software Used in DL and ML, and Their Usage Purposes

An analysis of the reviewed publications reveals that the most frequently utilized software tools are ArcGIS at 35.24% and QGIS at 22.86%. These are followed by Python (4.76%), MATLAB (2.86%), ArcGIS-R Integration (1.90%), GRASS GIS (1.90%), and ENVI (1.90%). Examination of the purposes for which these software tools have been utilized reveals that the most common application is modelling, accounting for 33.04% of use cases. Additionally, the software tools have been employed for data processing (21.74%, 25 studies), classification (18.26%, 21 studies), image analysis (18.26%, 21 studies), and mapping (4.35%, 5 studies). In some publications (4.35%), only the general term "GIS" has been referred without specification of the software used (Figure 6). Studies in this field generally indicate that GIS software (ArcGIS and QGIS) occupies a central role in AI-based research.

Recently, the increasing use of programming-based tools (Python, R, MATLAB, ENVI etc.) has introduced innovation and methodological strengthening in the literature through their integration into AI-driven spatial research.

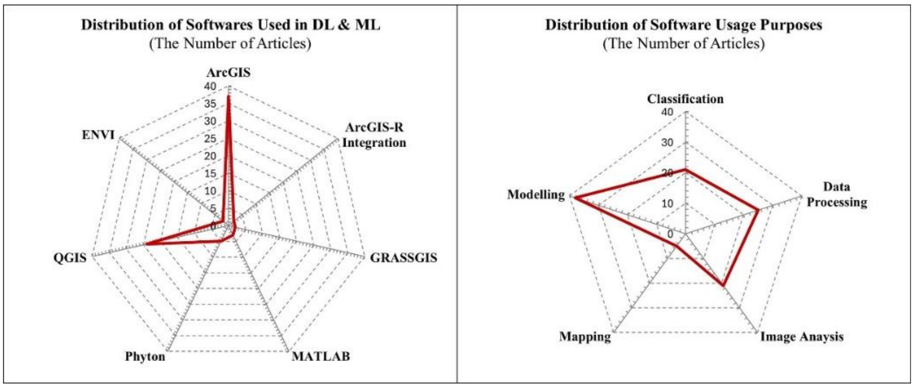

Figure 6. Distribution of software used in DL and ML, and their usage purposes

Distribution of Accuracy Metrics Commonly Used in DL and ML

In studies focusing on the integration of DL, ML, and GIS in spatial planning, the most frequently employed validation metrics include Area Under the Receiver Operating Characteristic Curve (AUC-ROC) at 18.92%, Overall Accuracy at 16.89%, and the Kappa coefficient at 12.16%. These are followed by Root Mean Squared Error (RMSE) at 9.46%, Precision (8.78%), Recall (8.78%), F1 Score (8.78%), Coefficient of Determination (R^2) at 8.11%, Mean Absolute Error (MAE) at 2.70%, Mean Absolute Percentage Error (MAPE) at 1.35%, Mean Squared Error (MSE) at 1.35%, Intersection over Union (IoU) at 1.35%, Cross-validation at 0.68%, and the Kruskal–Wallis test at 0.68% (Table 1).

The focus of existing studies on image processing predominantly emphasizes classification-based accuracy assessments. In spatial data classifications, the reliance on conventional metrics such as Accuracy and Kappa underscores the necessity of incorporating additional measures to generate more objective performance indicators for imbalanced datasets. Accordingly, the dependence of current research on limited and traditional metrics highlights the need for broader adoption of more comprehensive and problem-oriented evaluation measures.

Table 1. Distribution of accuracy metrics commonly used in DL and ML

Author, Year	DL	ML	Accuracy Metrics
Acharya et al., 2024	x	ANN, RF	MAE, RMSE, R^2
Achu et al., 2024	DNN	x	AUC-ROC
Adu et al., 2025	x	RF, LiR, LSTM	MAE, MSE, RMSE, R^2
Ahmadi et al., 2024	CNN	x	AUC-ROC
Al Mazroa et al., 2024	x	ANN, MLP	OA, Kappa
Al-Dousari et al., 2023	x	RF, ANN	RMSE
Ali et. al, 2020	x	SVR, RF, DT, LoR, GBDT, SVM	AUC-ROC
Aliyu et al., 2023	x	SVM	OA, Kappa
Alsumaiti et al., 2024	x	NS	Kappa
AlThuwaynee et al., 2021	x	XGBoost, RF	AUC-ROC
Amirii et al., 2023	x	XGBoost	R^2

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Table 1. (Continued).

Author, Year	DL	ML	Accuracy Metrics
Aslam et al., 2024	x	RF	OA, Kappa
Badshah et al., 2024	x	RF	AUC-ROC, Kappa
Ballesteros et al., 2022	NS	x	x
Blanco et al., 2023	x	RF	x
Boonpook et al., 2021	SegNet	x	Precision, Recall, F1 Score
Bortoloti et al., 2022	CNN	x	OA
Chanpichaigosol et al., 2025	x	RF	x
Chen and Zhang, 2021	x	LoR	AUC-ROC
Chen et al., 2024	x	RF	MAPE, R^2
Darabi et al., 2019	x	GARP, QUEST	AUC-ROC, Kappa
Darabi et al., 2022	x	MLPNN, BRT, RF, MultiB	AUC-ROC
Deb and Smith, 2021	x	KNN, SVM, RF	Precision, Recall, F1 score, AUC-ROC
Di Napoli et al., 2021	x	ANN, GBM, MaxEnt	AUC-ROC
Dogan et al., 2024	x	ANN, SVM	AUC-ROC
Fang et al., 2024	FCN	x	R^2
Fanos et al., 2020	x	RF, ANN, SVM, LoR, KNN	AUC-ROC
Ferreira et al., 2025	x	LoR, RF, SVM	AUC-ROC, F1 Score
Gharaibeh et al., 2020	x	ANN	OA
Gómez et al., 2021	x	SLEUTH CA	x
Hamid et al., 2023	x	LoR	AUC-ROC
He et al., 2018	CNN	x	OA, Kappa
Huettmann et al., 2023	x	SPM	AUC-ROC
Hussain et al., 2025	x	RF, SVM, XGBoost	OA, Kappa, Precision, Recall, F1 Score
Iamtrakul et al., 2023	CNN	x	x
Jato-Espino et al., 2022	x	SVR, MLR, RF	RMSE
Karli and Terzi, 2025	x	RR, KNN, SVM, RF, ANN, XGBoost, GBDT, LGBDM	RMSE, MAE, MAPE, R^2
Leitch and Wei, 2024	x	RF, KNN, GBM2, LASSO	RMSE
Lemankova, 2024	x	ANN, RF, SVM, DT	OA
Li et al., 2022	CNN	x	Over union (IoU), F1 score
Li et al., 2023a	CNN	x	R^2
Li et al., 2023b	CNN	x	composite reliability (C.R.), Cronbach's α
Lin et al., 2024	CNN, DNN	x	OA, Kappa, Precision, Recall, F1 score
Liu et al, 2023	x	ANN	OA, Kappa
Liu et al., 2021	x	LiR, GBDT	RMSE, R^2
Liu et al., 2022	x	SVM	RMSE
Liu et al., 2024	YOLOv5m	x	Precision, Recall
Liu et al., 2025	x	RF, GBM2 DT, LiR, PR	MAE, RMSE, R^2
Lloyd et al., 2020	x	NS	AUC-ROC
Mahendra et al., 2024	CNN	x	NS
Manna et al., 2025	x	ANN, RF, SVM	AUC-ROC
Mansourihanis et al., 2023	x	NS	x
Mishra et al., 2024	x	ANN, SVM	Cross-validation, Kruskal-Wallis, AUC-ROC
Mishra et al., 2025	x	RF, ML	OA
Mondal et al., 2024	x	RF	OA, Kappa
Mustak et al., 2022	x	MLP	OA, Kappa
Mutani et al, 2024	x	RF	MSE, RMSE
Nahid et al., 2025	x	ML, ANN	OA, Kappa
Ni et al., 2024	DeepLab-v3 CNN	x	intersection over union (IoU)
Omrani et al., 2017	x	ANN	Precision, Recall, F1 Score
Park and Yang et al, 2020	x	SVM, ANN	NS
Patil et al., 2024	DNN	x	OA
Pushpalatha et al., 2025	CNN	x	OA
Quan, 2024	x	ANN, KNN, SVM, DT, GBDT	RMSE, R^2
Riaz et al., 2024	x	SVM	AUC-ROC
Rizeii et al, 2019	x	ANN, MLP	RMSE, AUC-ROC
Salale et al., 2023	x	EANN	RMSE, R^2
Sampurno et al., 2023	x	MLR	RMSE

Table 1. (Continued).

Author, Year	DL	ML	Accuracy Metrics
Schrammeijer et al., 2022	x	AIC	AUC-ROC
Segura-Méndez et al, 2023	x	NS	x
Seydou et al., 2024	x	RF, SVM	OA, Kappa
Shao et al., 2023	DeepLabv3	x	x
Sincic et al., 2025	x	SVM, LoR	AUC-ROC
Sobieraj et al., 2023	x	SVM	Kappa
Srivanit et al., 2024	x	RF, DT	Precision, Recall, F1 score, AUC-ROC
Sun et al., 2021	DeepLabv3, PointNet++	x	Precision, Recall, F1 score
Tang et al., 2020	x	LoR	AUC-ROC
Tokarcík et al., 2024	NS	x	OA, Precision, Recall, F1 Score
Trinh et al., 2024	x	SVM, RF, CART, ML, ANN, LoR	OA, Kappa
Wang et al, 2018	x	ANN	AUC-ROC
Wang et al., 2021	x	XGBoost	Precision, Recall, F1 Score
Wang et al., 2024	x	CART	R^2
Wu et al., 2024	x	KNN, MLP, SVM, XGBoost, RF	AUC-ROC, Precision, Recall, F1 Score
Xiao et al., 2019	x	RF	AUC-ROC
Xu et al., 2025	x	RF	OA
Yagoup et al., 2022	x	RF	OA, Kappa
Yao et al., 2017	Word2Vec	x	OA, Kappa
Yao et al., 2022	x	RF	AUC-ROC, R^2
Ye et al., 2019	CNN	x	Precision, Recall
Yu et al., 2022	CNN	x	OA, Recall, Precision, F1 Score
Zheng et al., 2024	x	NS	x

AIC: Artificial Intelligence Companions
ANN: Artificial Neural Networks
BRT: Boosted Regression Tree
CART: Classification and Regression Tree
CNN: Convolutional Neural Network
DNN: Deep Neural Network
DT: Decision Tree
EANN: Emotional Artificial Neural Network
FCN: Fully Convolutional Neural Network
GARP: Genetic Algorithm Rule-Set Production
GBM: Generalized Boosting Model
GBM2: Gradient Boosting Model
GBRT: Gradient Boosting Regression Tree
Google Word2Vec
KNN: K-Nearest Neighbor
LASSO: Least Absolute Shrinkage and Selection Operator
LGBDM: Light Gradient Boosting Decision Model
LiR: Linear Regression
LoR: Logistic Regression
LSTM: Long Short-Term Memory
MaxEnt: Maximum Entropy
ML: Maximum Likelihood
MLP: Multilayer Perceptron
MLPNN: Multilayer Perceptron Neural Network
MLR: Multiple Linear Regression
MultiB: Multi-Boosting
NNLM: Neural Network Language Model
NS: Not Specified
OA: Overall Accuracy
PR: Polynomial Regression
QUEST: Quick Unbiased Efficient Statistical Tree
RF: Random Forest
RR: Ridge Regression
SSN: Semantic Segmentation Network
SVM: Support Vector Machine
SPM: Salford Predictive Modeler
SVR: Support Vector Regression
XGB: Extreme Gradient Boosting

DISCUSSION

This study proposes a research framework that identifies the general trends, challenges, and potentials of integrating ML algorithms and DL models—based on the rise of digital technologies and spatial data—with GIS in planning. Drawing from recent findings, this section provides (i) inferences regarding the impacts, challenges, and future implications of AI–GIS integrated approaches in planning processes, and (ii) evaluations of how spatial data and model validation procedures can be incorporated into multi-criteria decision-making strategies.

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The Correlation Between AI, Spatial Planning, and GIS

The development of AI technologies is driving significant transformations in data-driven spatial planning processes. To capture this general trend, we emphasize the importance of integrating ML algorithms and DL models in spatial data workflows with practical implementation tools. Furthermore, defining the planner's role in decision-making processes shaped by AI technologies is essential. AI technologies have made a substantial contribution to data-driven planning processes (Huang et al., 2025; Kamrowska-Załuska, 2021). Findings show that although AI-based planning studies grounded in spatial data and GIS integration have increased since 2019, the field remains in its infancy and lags behind developments in other disciplines. This trend parallels the historical delay of GIS adoption within planning disciplines (Çelik & Şekeroğlu, 2023). Several factors may contribute to the limited use of AI in planning, such as the early-stage adoption of innovations in planning, the underexplored practical applications of AI technologies, and the relatively low interest in the topic. Nonetheless, many decision-makers in planning practice believe that AI will bring significant innovations to the field (Sanchez et al., 2023). This situation presents promising future research opportunities regarding how AI technologies can be integrated into applied planning practices.

AI technologies are operationalized in planning through the implementation of ML algorithms and DL models. Although these two concepts are interrelated, they differ in technical and practical terms (Batty, 2018). Our findings indicate that ML algorithms are more commonly employed in planning-related applications. In particular, Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN) algorithms are frequently used in environmental risk assessments, land use change analyses, and management and modeling studies. These algorithms, which often rely on remote sensing datasets, prioritize data classification and modeling tasks. Studies demonstrate that RF and SVM algorithms, used for classification, deliver high accuracy in image processing tasks. Similarly, modeling-focused studies show that ANN, SVM, and RF algorithms can generate highly accurate spatial maps (Manna et al., 2025; Lemenkova, 2024; Fanos et al., 2020). However, the optimal algorithm varies depending on the study, influenced by factors such as data volume, study area size, and the validation methods used. Current developments indicate that while SVM and RF are dominant in classification and modeling, ANN is more commonly used for modeling. This suggests a research gap in evaluating the factors influencing the accuracy of these algorithms in detail.

DL models emerge as a powerful method for classifying and recognizing objects in large datasets during the integration of spatial assessments with GIS. These models are generally characterized by deep neural networks (DNNs) with more than two layers, utilizing feature representations learned solely from data (Patil et al., 2024; Achu et al., 2024). Convolutional Neural Networks (CNNs), in particular, have proven successful in areas such as image recognition, object detection, and semantic segmentation (Zhu et al., 2017). Our findings reveal that CNNs—one of the prominent DNN architectures—are frequently used for image recognition, object detection, and classification in spatial studies. Additionally, CNN-based models such as DeepLabV3 (Ni et al., 2024; Shao et al., 2023; Li et al., 2022), FCN (Fang et al., 2024), HAU-Net (Li et al., 2022), SegNet (Boonpook et al., 2021), and YOLO5vm (Liu et al., 2024) have been developed for spatial evaluations. The Word2Vec model, developed by Google, stands out from others by vectorizing words based on their contextual meanings (Yao et al., 2017). The absence of a clear and unified definition of DL in current studies highlights the diversity of models used; however, many of these methods are fundamentally linked to DNNs and their subset, CNNs. Despite being in its early stages, DL is a rapidly growing field. Especially in cases where the data source consists of objects or images and spatial data needs to be produced, DL models demonstrate high applicability in managing large datasets. However, due to their data-driven learning architecture, one major limitation is the inability to easily incorporate new datasets into the system.

The reflections of ML and DL technologies on spatial planning show a clustering around six thematic areas where the assessment of spatial data is essential. This study identifies ML, DL, spatial data, and GIS-based implementation tools as the key concepts. Thematic focuses, primarily including land use, environment, climate, natural hazard assessments, socio-economic evaluation, urban infrastructure, and urban aesthetics, are predominantly driven by spatial data. Land use studies frequently employ ML for land use change analysis, land management, classification, and urban growth modeling using satellite imagery. Recently, DL models are increasingly being utilized in large-scale classification studies. In the domains of climate, environment, and energy, which maintain their topical relevance, ML algorithms and DL models are found to be critical tools for prediction, modeling, and classification in topics such as urban heat islands, biodiversity, energy modeling, energy demand and consumption, and carbon emissions. In the context of natural hazards and risk assessments, ML algorithms are widely used for identifying and predicting risk zones for earthquakes, landslides, floods, and rockfalls. Additionally, DNN models have been employed in flood (Patil et al., 2024) and landslide (Achu et al., 2024) risk assessments to generate sensitivity maps based on existing datasets. For instance, Patil et al. (2024) conducted a comparative analysis using ResNet34, InceptionV3, and VGG16 models, while Achu et al. (2024) relied on the general structure of DNN. As with other thematic areas, satellite image-based land use maps are frequently used in these studies. Moreover, in urban infrastructure and urban quality-aesthetics domains, there has been an increase in the use of ML algorithms and DL models in recent years. In contrast, the application of AI technologies in

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socio-economic studies remains relatively limited. Although ML algorithms have been used in studies on spatial justice (Deb & Smith, 2021), housing classification (Lloyd et al., 2020), and the impact of household income on green space (Xu et al., 2025), the spatial distribution of urban commercial areas has been evaluated using a CNN-based DL model (Ye et al., 2019).

Findings reveal that among GIS-based implementation tools, ArcGIS and QGIS are the most used platforms in spatial studies employing ML and DL approaches. Their capabilities in collecting, storing, managing, mapping, and modeling spatial data contribute to their widespread use as application tools (Anwar & Sakti, 2024). ArcGIS, one of the most widely used GIS software globally, stands out for its integration with AI technologies (Haery et al., 2024). The frequent use of built-in RF and SVM in ArcGIS supports its growing role in planning. Although QGIS does not offer built-in algorithms, it can be integrated with AI applications through Python scripting and plug-ins. Due to the limited number of algorithms available in ArcGIS and QGIS, there is a growing trend toward the development of programming-based tools for various ML and DL models. Among these tools, Python, MATLAB, and R offer significant flexibility in ML and DL studies and are capable of generating spatially explicit results through scripting and plug-in extensions. Additionally, ENVI and GRASS GIS provide map-supported outcomes via various extensions. MATLAB is effective in mathematical modeling and visualization (Xiao et al., 2019), ENVI in satellite image processing and classification (Gharaibeh et al., 2020), GRASS GIS in handling large datasets (Lemenkova, 2024), R Software in statistical ML and analysis (Jato-Espino et al., 2022), and Python in advanced library-based applications (Lin et al., 2024). GIS generally consists of five main components: hardware, software, data, personnel, and methods (Liu & Cheng, 2020). Although GIS is a general concept, its implementation tools may vary depending on the application domain. Nevertheless, it is noteworthy that some studies do not specify which GIS tool is used, treating GIS as the tool itself rather than as a conceptual framework.

Given the trajectory of AI technologies in the existing literature, it becomes increasingly evident that researchers engaged in spatial planning must enhance their ability to understand, interpret, and implement AI-assisted systems. The developmental course of current AI technologies suggests that planning practices will be profoundly influenced, and possessing the experience and competence to engage with and guide these systems will provide a significant advantage. Furthermore, considering that planning cannot be conducted entirely through autonomous systems, the role of AI tools in directing data and information processes, generating scenario-based outcomes for various objectives, and the increasing necessity for GIS in evaluating AI-driven results will become even more prominent. In spatial planning processes, executing models, extracting knowledge, and generating efficient and meaningful decision-making functions from complex and diverse

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datasets will constitute critical components. Our findings indicate that the integration of planning, data, and GIS with ML algorithms and DL models can significantly enhance rationality and expedite decision-making processes by delivering high-performance outcomes. Given that planning heavily relies on spatial data, keeping pace with AI advancements in practice requires a substantial increase in implementation-oriented studies across all planning domains—urban and rural alike—including data collection, processing, transformation, generation of spatial multi-objective decisions, expansion of alternative options, and establishment of dynamic and queryable data optimization mechanisms. Accelerating these practical applications will enable more precise identification of challenges and potential within the field, fostering a broader and more constructive discourse on the future trajectory of planning. Our review of a limited number of studies highlights a critical concern: not all techniques should be assumed equally effective in leveraging the benefits of AI technologies. A notable limitation in the current literature is the superficial use of the terms ML and DL without adequate methodological explanation. Therefore, it is essential to assess and compare the applicability of ML algorithms and DL models in planning processes to determine the most appropriate and effective techniques.

Spatial Data and Model Accuracy

Spatial planning has been significantly influenced by data science. The integration of planning and data science practices expands the diversity of alternatives in decision-making processes. Within this integration, human–AI interaction emerges as a necessity. Given the massive increase in data collection and the growing accessibility and popularity of AI methods, human-AI interaction can be considered a vital component of contemporary decision-making processes. The successful implementation of these new methods requires the acquisition of new skills and knowledge concerning data analysis techniques and information systems (Sanchez et al., 2023).

Our findings reveal that remote sensing techniques and their associated data products are widely utilized in the areas where existing studies are concentrated. In numerous studies involving land use datasets, open-access satellite imagery such as Sentinel and Landsat, along with CORINE maps developed for European countries, are frequently employed. However, biases, uncertainties, and ethical concerns must be considered during the acquisition, analysis, and sharing of spatial data (Zou et al., 2024). The methods of data production, the level of detail, accuracy, and spatial resolution all play crucial roles in this process. For example, CORINE maps (https://land.copernicus.eu/pan-european/highsolution-layers), offered by the European Union at a spatial resolution of 100 meters, represent areas of 25 hectares or larger, which reduces the precision of the resulting outputs (Venter & Sydenham, 2021). While the datasets

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derived from Landsat satellite images with a spatial resolution of 30 meters exhibit higher accuracy compared to CORINE maps (Pflugmacher et al., 2018), the Sentinel datasets produced at a spatial resolution of 10 meters (http://s2glc.cbk.waw.pl/) have been shown to yield more successful results in terms of detail (Immitzer et al., 2016). Given that outcome-oriented approaches are prevalent in current studies, the purpose of the study, the representativeness of the spatial data at the relevant scale, and its processability constitute a critical stage. This stage leads to the conclusion that spatial data must be validated in the initial phase, which is based on data generation.

As spatial data-related systems have developed more extensively in certain regions, studies have become concentrated in countries such as China, India, and the United States. Many of these studies also exhibit a tendency to focus on urban centers, where data collection and access are comparatively easier. This urban-centric focus, fueled by the application of AI technologies primarily in urban contexts, may exacerbate data inaccessibility in rural areas and further intensify the research concentration in urban settings. As a result, planning processes for rural areas risk being overlooked. Therefore, it is essential to map the development trajectory of spatial data in this field and to promote the adoption of innovative approaches. Additionally, the limitations imposed by computational capacity during data storage, analysis, and processing stages remain significant challenges in this field.

Evaluating the performance of ML algorithms and DL models is of paramount importance to ensure the reliability of outcomes (Sierra et al., 2025; Zafar et al., 2024). Model validation is treated as an integral part of the research process. Our findings indicate that commonly used model validation methods in map-based processes include AUC-ROC, RMSE, overall accuracy, R^2, F1 score, recall, Cohen's Kappa, and precision. These metrics are used both individually and in combination to generate more robust and reliable results. However, only a limited number of studies incorporate multiple metrics simultaneously. Among these, multiple evaluation metrics are used, including overall accuracy–kappa (Al Mazroa et al., 2024; Aliyu et al., 2023), precision–recall–F1 score (Sun et al., 2021; Omrani et al., 2017), precision–recall–F1 score–AUC–ROC (Wu et al., 2024; Srivanit et al., 2024), RMSE–AUC–ROC (Rizeii et al., 2019), overall accuracy–kappa–precision–recall–F1 score (Hussain et al., 2025), and overall accuracy–precision–recall–F1 score (Yu et al., 2022). In studies concerning land use, overall accuracy and Kappa statistics should be calculated together (Foody, 2002). Furthermore, in spatial data validation processes, precision, recall, and F1 score are essential indicators of model performance (Belgiu & Drăguţ, 2016). When dealing with binary classification problems, the use of the ROC-AUC metric, which is based on true and false rates, becomes especially important for model evaluation (Fawcett, 2006).

As the complexity and volume of spatial data increase in planning processes, it is foreseeable that traditional methods will be replaced by

AI-driven approaches. The challenges that planners face in acquiring and evaluating data are growing steadily. With increasing digitalization, AI-supported systems can accelerate data access. However, planners are still at an early stage in adapting to advancements in AI technologies, which constrains broader implementation. A lack of clarity regarding the developmental trajectory of AI in spatial planning may result in planning practices falling behind contemporary standards. Therefore, we argue that spatial data and model validation processes must be addressed in greater detail in both current and future studies.

In this context, it is necessary to structure the planning process in stages—from the role of the planner to AI-supported data generation and model validation. We emphasize that the planner or decision-maker should not be excluded from this system. Their direct influence should be evident in key stages such as identifying data types, selecting validation methods for data and models, and determining the most suitable alternative among several options. The fundamental principle is that rather than relying solely on autonomous AI-driven systems, the planner should retain a significant role in managing the process. Moreover, critical elements such as spatial resolution, data types, GIS tools applicable during implementation, and selection of appropriate validation metrics should be treated as core components of the process.

The use of AI systems in spatial planning necessitates adherence to the principles of impartiality and neutrality in decision-making processes. The absence of these principles may foster a framework characterized by subjectivity and heightened ethical concerns (Nizamani et al., 2025). Traditional planning approaches, with their top-down hierarchical scales, risk marginalizing certain groups. Within the scope of human-centered AI in planning, ensuring equality requires the integration of sensitivity and the participation of all community segments in the processes. For an equitable urban future, urban planners should prioritize the inclusion of stakeholders within AI integration stages under a local policy framework, while distancing themselves from biased algorithms.

CONCLUSION

This study evaluates 91 research articles published between 2017 and 2025 that address the trajectory of applied research on the integration of AI technologies and GIS in the field of spatial planning, focusing on their development, challenges, potentials, and research gaps. The assessment suggests that, due to the increasing prominence of AI technologies, evaluation methods in planning are entering a phase of rapid transformation. However, the limited number of studies, along with the lack of clear definitions regarding implementation tools, methods, and the associated problems and potentials of AI technologies, presents fundamental challenges in this area.

Current research trends indicate that ML algorithms are more frequently employed in spatial studies, particularly those involving data

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classification and modeling, with SVM, RF, and ANN being favored for their ease of implementation in existing software environments. More recently, CNN-based DL models have emerged as valuable tools, especially for object detection and classification, producing more successful results when large datasets are available. However, the existing literature provides limited justification for why particular algorithms are preferred over alternative methods. Comparative evaluations regarding thematic domains, spatial scales, and spatial resolutions remain insufficient. As a result, the relationship between AI technologies and spatial planning largely relies on the repetitive application of commonly used algorithms.

Thematic areas where the integration of AI technologies and GIS have found the most application within spatial planning include land use, natural hazard assessments, and environmental and climate-related topics. Many of these studies utilize satellite imagery derived from remote sensing techniques to address the need for detection, classification, and modeling of land use. In contrast, relatively few studies address socio-economic themes and urban infrastructure planning, largely due to limitations in access to spatial data. Research in underexplored areas such as socio-economic dimensions and urban infrastructure should be encouraged to strengthen the societal dimension of spatial planning and its contribution to the Sustainable Development Goals. Such efforts can also make a significant contribution to diversifying thematic studies. Because many studies focus on urban centers, there is a risk of a growing gap between urban and rural spatial studies in the future. Therefore, expanding data production and research with a focus on rural areas can contribute to reducing the urban–rural research imbalance and enhancing inclusiveness in spatial planning.

The implementation of ML and DL methods in spatial planning requires compatible GIS tools. There is a growing trend in the use of ArcGIS and QGIS software in relevant studies. However, due to the limited number of built-in application models and algorithms in these platforms, the use of plugins and custom coding is necessary to broaden the range of algorithms and models available. Additionally, tools such as Python, GRASS GIS, MATLAB, and R provide considerable flexibility for map-based ML and DL evaluations, thereby contributing to the advancement of this field.

One of the key challenges in this domain concerns the verification of spatial data and model accuracy. Validation and model performance should be prioritized in future studies. Concepts such as the source, resolution, and accuracy of spatial data necessitate careful selection of appropriate validation metrics. Similarly, the suitability of each model must be verified using performance metrics, considering its influence on the study's outcomes. Therefore, appropriate validation metrics should be selected by considering data sources, resolution, accuracy, and thematic focus. In spatial data–based studies, these processes should be addressed in detail to ensure that evaluations and modeling objectively reflect the outcomes.

Due to the limited number of existing studies and the relatively low emphasis placed on validation, there is a critical lack of applied research and an evident research gap in the domain of data and model validation. Therefore, planners and decision-makers should not uncritically accept the outputs of fully auto”””nomous AI systems. Rather, they must play a key role in defining and validating data, selecting appropriate validation metrics, and choosing the most suitable alternative among diverse options within the system.

REFERENCES

Acharya, T., Gharekhan, D., & Samal, D. (2024). Harnessing ML and GIS for seismic vulnerability assessment and risk prioritization. *Revue Internationale De Géomatique, 33*(1), 111–134. https://doi.org/10.32604/rig.2024.051788

Achu, A., Thomas, J., Aju, C., Vijith, H., & Gopinath, G. (2024). Redefining landslide susceptibility under extreme rainfall events using deep learning. *Geomorphology, 448*, 109033. https://doi.org/10.1016/j.geomorph.2023.109033

Ahmadi, M., Lonbar, A. G., Nouri, M., Javidi, A. S., Beris, A. T., Sharifi, A., & Salimi-Tarazouj, A. (2024). Supervised multi-regional segmentation machine learning architecture for digital twin applications in coastal regions. *Journal of Coastal Conservation, 28*, 44. https://doi.org/10.1007/s11852-024-01038-1

Al-Azizi, J. I., Shafri, H. Z. M., Hashim, S. J. B., & Mansor, S. B. (2020). Deep auto mapping: low-cost and real-time geospatial map generation method using deep learning and video streams. *Earth Science Informatics, 15*(3), 1481–1494. https://doi.org/10.1007/s12145-020-00529-7

Al-Dousari, A. E., Mishra, A., & Singh, S. (2023). Land use land cover change detection and urban sprawl prediction for Kuwait metropolitan region, using multi-layer perceptron neural networks (MLPNN). *The Egyptian Journal of Remote Sensing and Space Science, 26*(2), 381-392. https://doi.org/10.1016/j.ejrs.2023.05.003

Ali, U., Shamsi, M. H., Bohacek, M., Purcell, K., Hoare, C., Mangina, E., & O'Donnell, J. (2020). A data-driven approach for multi-scale GIS-based building energy modeling for analysis, planning and support decision making. *Applied Energy, 279*, 115834. https://doi.org/10.1016/j.apenergy.2020.115834

Aliyu, A., Isma'il, M., Zubairu, S. M., Gwio-Kura, I. Y., Abdullahi, A., Abubakar, B. A., & Mansur, M. (2023). Analysis of land use and land cover change using machine learning algorithm in Yola North Local Government Area of Adamawa State, Nigeria. *Environmental Monitoring and Assessment, 195*, 1470. https://doi.org/10.1007/s10661-023-12112-w

Alsumaiti, T., Yagoub, M. M., Tesfaldet, Y. T., Alhosani, N., & Pakam, S. (2024). Integration of building age into flood hazard mapping: A case study of Al Ain City, United Arab Emirates. *Water, 16*(17), 2408. https://doi.org/10.3390/w16172408

AlThuwaynee, O. F., Kim, S., Najemaden, M. A., Aydda, A., Balogun, A., Fayyadh, M. M., & Park, H. (2021). Demystifying uncertainty in PM10 susceptibility mapping using variable drop-off in extreme-gradient boosting (XGB) and random forest (RF) algorithms. *Environmental Science and Pollution Research, 28*(32), 43544–43566. https://doi.org/10.1007/s11356-021-13255-4

DOI: 10.15320/ICONARP.2025.337

Amiri, S. S., Mueller, M., & Hoque, S. (2023). Investigating the application of a commercial and residential energy consumption prediction model for urban Planning scenarios with Machine Learning and Shapley Additive explanation methods. *Energy and Buildings, 287*, 112965. https://doi.org/10.1016/j.enbuild.2023.112965

Anwar, M. R., & Sakti, L. D. (2024). Integrating artificial intelligence and environmental science for sustainable urban planning. *IAIC Transactions on Sustainable Digital Innovation (ITSDI), 5*(2), 179–191. https://doi.org/10.34306/itsdi.v5i2.666

Aslam, R. W., Naz, I., Quddoos, A., & Quddusi, M. R. (2024). Assessing climatic impacts on land use and land cover dynamics in Peshawar, Khyber Pakhtunkhwa, Pakistan: A remote sensing and GIS approach. *GeoJournal, 89*, 202. https://doi.org/10.1007/s10708-024-11203-6

Avinç, G. M., & Yıldız, A. (2025). A bibliometric and systematic review of scientific publications on metaverse research in architecture: Web of science (WoS). *International Journal of Technology and Design Education, 35,* 825–849. https://doi.org/10.1007/s10798-024-09918-1

Badshah, M. T., Hussain, K., Rehman, A. U., Mehmood, K., Muhammad, B., Wiarta, R., Silamon, R. F., Khan, M. A., & Meng, J. (2024). The role of random forest and Markov chain models in understanding metropolitan urban growth trajectory. *Frontiers in Forests and Global Change, 7*, 1345047. https://doi.org/10.3389/ffgc.2024.1345047

Baghini, M. S., Mohammadi, M., & Norouzkhani, N. (2024). Usability testing: A bibliometric analysis based on WOS data. *Journal of Scientometric Research, 13*(1), 09–24. https://doi.org/10.5530/jscires.13.1.2

Ballesteros, J. R., Sanchez-Torres, G., & Branch-Bedoya, J. W. (2022). HAGDAVS: Height-augmented geo-located dataset for detection and semantic segmentation of vehicles in Drone aerial orthomosaics. *Data, 7*(4), 50. https://doi.org/10.3390/data7040050

Batty, M. (2018). Artificial intelligence and smart cities. *Environment and Planning B Urban Analytics and City Science, 45*(1), 3–6. https://doi.org/10.1177/2399808317751169

Belgiu, M., & Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing, 114*, 24–31. https://doi.org/10.1016/j.isprsjprs.2016.01.011

Birkle, C., Pendlebury, D. A., Schnell, J., & Adams, J. (2020). Web of Science as a data source for research on scientific and scholarly activity. *Quantitative Science Studies, 1*(1), 363–376. https://doi.org/10.1162/qss_a_00018

Blanco, L., Alhamwi, A., Schiricke, B., & Hoffschmidt, B. (2024). Data-driven classification of urban energy units for district-level heating and electricity demand analysis. *Sustainable Cities and Society, 101*, 105075. https://doi.org/10.1016/j.scs.2023.105075

Boonpook, W., Tan, Y., & Xu, B. (2021). Deep learning-based multi-feature semantic segmentation in building extraction from images of UAV photogrammetry. *International Journal of Remote Sensing, 42*(1), 1–19. https://doi.org/10.1080/01431161.2020.1788742

Bortoloti, F. D., Tavares, J., Rauber, T. W., Ciarelli, P. M., & Botelho, R. C. G. (2022). An annotated image database of building facades categorized into land uses for object detection using deep learning. *Machine Vision and Applications, 33,* 80. https://doi.org/10.1007/s00138-022-01335-5

ICONARP – Volume 13, Issue 2 / Published: 31.12.2025

Casali, Y., Aydin, N. Y., & Comes, T. (2022). Machine learning for spatial analyses in urban areas: A scoping review. Sustainable *Cities and Society, 85*, 104050. https://doi.org/10.1016/j.scs.2022.104050

Celik, K.T. & Sekeroglu, A. (2023). The importance of geographical information systems in urban and landscape planning: A bibliometric analysis. *MEGARON / Yıldız Technical University Faculty of Architecture E-Journal, 18*(4), 499–519. https://doi.org/10.14744/megaron.2023.70962

Chanpichaigosol, N., Chaichana, C., & Rinchumphu, D. (2025). Urban heat island classification through alternative normalized difference vegetation index. *Global Journal of Environmental Science and Management, 11*(1), 57–76. https://doi.org/10.22034/gjesm.2025.01.04

Chaturvedi, V., & De Vries, W. T. (2021). Machine learning algorithms for urban land use planning: A review. *Urban Science, 5*(3), 68. https://doi.org/10.3390/urbansci5030068

Chen, W., & Zhang, S. (2021). GIS-based comparative study of Bayes network, Hoeffding tree and logistic model tree for landslide susceptibility modeling. *CATENA, 203,* 105344. https://doi.org/10.1016/j.catena.2021.105344

Chen, W., Jing, C., Liquan, X., & Haiyun, X. (2022). Spatial potential of recreational services in Western Hubei Region in light of the "all-for-one tourism" development -A machine learning approach based on ensemble model. *Landscape Architecture Frontiers, 10*(5), 8. https://doi.org/10.15302/j-laf-1-020073

Chen, X., Tu, W., Yu, J., Cao, R., Yi, S., & Li, Q. (2024). LCZ-based city-wide solar radiation potential analysis by coupling physical modeling, machine learning, and 3D buildings. *Computers Environment and Urban Systems, 113*, 102176. https://doi.org/10.1016/j.compenvurbsys.2024.102176

Darabi, H., Choubin, B., Rahmati, O., Haghighi, A. T., Pradhan, B., & Kløve, B. (2019). Urban flood risk mapping using the GARP and QUEST models: A comparative study of machine learning techniques. *Journal of Hydrology, 569*, 142–154. https://doi.org/10.1016/j.jhydrol.2018.12.002

Darabi, H., Rahmati, O., Naghibi, S. A., Mohammadi, F., Ahmadisharaf, E., Kalantari, Z., Haghighi, A. T., Soleimanpour, S. M., Tiefenbacher, J. P., & Bui, D. T. (2022). Development of a novel hybrid multi-boosting neural network model for spatial prediction of urban flood. *Geocarto International, 37*(19), 5716–5741. https://doi.org/10.1080/10106049.2021.1920629

Deb, D., & Smith, R. M. (2021). Application of Random Forest and SHAP Tree Explainer in Exploring Spatial (In)Justice to aid Urban Planning. *ISPRS International Journal of Geo-Information, 10*(9), 629. https://doi.org/10.3390/ijgi10090629

Di Napoli, M., Di Martire, D., Bausilio, G., Calcaterra, D., Confuorto, P., Firpo, M., Pepe, G., & Cevasco, A. (2021). Rainfall-Induced shallow landslide detachment, transit and runout susceptibility mapping by integrating machine learning techniques and GIS-Based approaches. *Water, 13*(4), 488. https://doi.org/10.3390/w13040488

Dogan, S., Kilicoglu, C., Akinci, H., Sevik, H., Cetin, M., & Kocan, N. (2024). Comprehensive risk assessment for identifying suitable residential zones in Manavgat, Mediterranean Region. *Evaluation and Program Planning, 106*, 102465. https://doi.org/10.1016/j.evalprogplan.2024.102465

Fang, X., & Zhang, Z. (2024). Hotspots and trends in health-oriented physical literacy research: a visual analysis based on the WOS database. *BMC Public Health, 24*(1). https://doi.org/10.1186/s12889-024-18951-7

DOI: 10.15320/ICONARP.2025.337

Fang, Y., Tian, J., Namaiti, A., Zhang, S., Zeng, J., & Zhu, X. (2024). Visual aesthetic quality assessment of the streetscape from the perspective of landscape-perception coupling. *Environmental Impact Assessment Review, 106*, 107535. https://doi.org/10.1016/j.eiar.2024.107535

Fang, Z., Jin, Y., & Yang, T. (2022). Incorporating Planning Intelligence into Deep Learning: A Planning Support Tool for Street Network Design. *Journal of Urban Technology, 29*(2), 99–114. https://doi.org/10.1080/10630732.2021.2001713

Fanos, A. M., Pradhan, B., Alamri, A., & Lee, C. (2020). Machine Learning-Based and 3D kinematic models for rockfall hazard assessment using LiDAR data and GIS. *Remote Sensing, 12*(11), 1755. https://doi.org/10.3390/rs12111755

Fawcett, T. (2006). An introduction to ROC analysis. *Pattern Recognition Letters, 27*(8), 861–874. https://doi.org/10.1016/j.patrec.2005.10.010

Ferreira, Z., Almeida, B., Costa, A. C., Fernandes, M. D. C., & Cabral, P. (2025). Insights into landslide susceptibility: a comparative evaluation of multi-criteria analysis and machine learning techniques. *Geomatics Natural Hazards and Risk, 16*(1). https://doi.org/10.1080/19475705.2025.2471019

Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment, 80*(1), 185–201. https://doi.org/10.1016/s0034-4257(01)00295-4

Frimpong, A. T., Mensah, L. D., Rockson, M. A. D., & Kemausuor, F. (2025). Forecasting municipal solid waste generation and composition using machine learning and GIS techniques: A case study of Cape Coast, Ghana. *Cleaner Waste Systems, 10,* 100218. https://doi.org/10.1016/j.clwas.2025.100218

Gharaibeh, A., Shaamala, A., Obeidat, R., & Al-Kofahi, S. (2020). Improving land-use change modeling by integrating ANN with Cellular Automata-Markov Chain model. *Heliyon, 6*(9), e05092. https://doi.org/10.1016/j.heliyon.2020.e05092

Gómez, J. A., Guan, C., Tripathy, P., Duque, J. C., Passos, S., Keith, M., & Liu, J. (2021). Analyzing the spatiotemporal uncertainty in urbanization predictions. *Remote Sensing, 13*(3), 512. https://doi.org/10.3390/rs13030512

Goodchild, M. F. (2009). Geographic information systems and science: Today and tomorrow. *Annals of GIS, 15*(1), 3–9. https://doi.org/10.1080/19475680903250715

Goodchild, M. F., & Janelle, D. G. (2004). *Thinking spatially in the social sciences*. In M. F. Goodchild & D. G. Janelle (Eds.), Spatially integrated social science (pp. 3–17). United States: Oxford University Press

Haery, S., Mahpour, A., & Vafaeinejad, A. (2024). Forecasting urban travel demand with geo-AI: A combination of GIS and machine learning techniques utilizing uber data in New York City. *Environmental Earth Sciences, 83,* 594. https://doi.org/10.1007/s12665-024-11900-y

Hagenauer, J., Omrani, H., & Helbich, M. (2019). Assessing the performance of 38 machine learning models: The case of land consumption rates in Bavaria, Germany. *International Journal of Geographical Information Science, 33*(7), 1399–1419. https://doi.org/10.1080/13658816.2019.1579333

Hamid, B., Massinissa, B., & Nabila, G. (2023). Landslide susceptibility mapping using GIS-based statistical and machine learning modeling in the city of Sidi Abdellah, Northern Algeria. *Modeling Earth Systems and Environment, 9*(2), 2477–2500. https://doi.org/10.1007/s40808-022-01633-x

Harrington, P. (2012). *Machine learning in action*. United States: Manning Publications.

He, J., Li, X., Yao, Y., Hong, Y., & Jinbao, Z. (2018). Mining transition rules of cellular automata for simulating urban expansion by using the deep learning techniques. *International Journal of Geographical Information Science, 32*(10), 2076–2097. https://doi.org/10.1080/13658816.2018.1480783

Huang, J., Bibri, S. E., & Keel, P. (2025). Generative Spatial Artificial Intelligence for Sustainable Smart Cities: A pioneering large flow model for urban digital twin. *Environmental Science and Ecotechnology, 24*, 100526. https://doi.org/10.1016/j.ese.2025.100526

Huettmann, F., Kövér, L., Robold, R., Spangler, M., & Steiner, M. (2023). Model-based prediction of a vacant summer niche in a subarctic urbanscape: A multi-year open access data analysis of a 'niche swap' by short-billed Gulls. *Ecological Informatics, 78*, 102364. https://doi.org/10.1016/j.ecoinf.2023.102364

Hussain, K., Badshah, T., Mehmood, K., Rahman, A. U., Shahzad, F., Anees, S. A., Khan, W. R., & Yujun, S. (2025). Comparative analysis of sensors and classification algorithms for land cover classification in Islamabad, Pakistan. *Earth Science Informatics, 18*(2). https://doi.org/10.1007/s12145-025-01720-4

Iamtrakul, P., Chayphong, S., Kantavat, P., Hayashi, Y., Kijsirikul, B., & Iwahori, Y. (2023). Exploring the spatial effects of built environment on quality of life related transportation by integrating GIS and deep learning approaches. *Sustainability, 15*(3), 2785. https://doi.org/10.3390/su15032785

Immitzer, M., Vuolo, F., & Atzberger, C. (2016). First Experience with Sentinel-2 Data for Crop and tree species classifications in Central Europe. Remote Sensing, 8(3), 166. https://doi.org/10.3390/rs8030166

Janowicz, K., Gao, S., McKenzie, G., Hu, Y., & Bhaduri, B. (2020). GeoAI: spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond. *International Journal of Geographical Information Science, 34*(4), 625–636. https://doi.org/10.1080/13658816.2019.1684500

Jato-Espino, D., Manchado, C., Roldán-Valcarce, A., & Moscardó, V. (2022). ArcUHI: A GIS add-in for automated modelling of the Urban Heat Island effect through machine learning. *Urban Climate, 44,* 101203. https://doi.org/10.1016/j.uclim.2022.101203

Jing, Y., Cui, J., Ma, D., & Chen, Y. (2023). Editorial: Towards sustainable urban development: Use of geographic big data for spatial planning. *Frontiers in Environmental Science, 11*. https://doi.org/10.3389/fenvs.2023.1202661

Junjia, Y., Alias, A. H., Haron, N. A., & Bakar, N. A. (2023). A bibliometric review on Safety Risk assessment of construction based on CiteSpace software and WOS database. *Sustainability, 15*(15), 11803. https://doi.org/10.3390/su151511803

Kamrowska-Załuska, D. (2021). Impact of AI-Based tools and urban big data analytics on the design and planning of cities. *Land, 10*(11), 1209. https://doi.org/10.3390/land10111209

Kar, R., & Wasnik, A. (2024). Progress and trends in healthcare marketing strategy (2018–2022): A descriptive and bibliometric analysis of the Web of Science (WOS) dataset. *International Journal of Pharmaceutical and Healthcare Marketing, 18*(2), 325–349. https://doi.org/10.1108/ijphm-12-2022-0106

Karlı, M., & Terzi, F. (2025). Modelling the energy footprint of urban form in Istanbul: A big data and machine learning approach. *Energy and Buildings, 115495.* https://doi.org/10.1016/j.enbuild.2025.115495

DOI: 10.15320/ICONARP.2025.337

Klosterman, R. E. (1995). The appropriateness of geographic information systems for regional planning in the developing world. *Computers Environment and Urban Systems, 19*(1), 1–13. https://doi.org/10.1016/0198-9715(94)00028-x

Leitch, S., & Wei, Z. (2024). Improving spatial access to healthcare facilities: an integrated approach with spatial analysis and optimization modeling. *Annals of Operations Research, 341*(2–3), 1057–1074. https://doi.org/10.1007/s10479-024-06028-y

Lemenkova, P. (2024). Artificial intelligence for computational remote sensing: Quantifying patterns of land cover types around Cheetham wetlands, port Phillip Bay, Australia. J*ournal of Marine Science and Engineering, 12*(8), 1279. https://doi.org/10.3390/jmse12081279

Li, Q., Taubenböck, H., Shi, Y., Auer, S., Roschlaub, R., Glock, C., Kruspe, A., & Zhu, X. X. (2022). Identification of undocumented buildings in cadastral data using remote sensing: Construction period, morphology, and landscape. *International Journal of Applied Earth Observation and Geoinformation, 112*, 102909. https://doi.org/10.1016/j.jag.2022.102909

Li, T., Xu, H., & Sun, H. (2023a). Spatial patterns and multi-dimensional impact analysis of urban street quality perception under multi-source data: A case study of Wuchang district in Wuhan, China. *Applied Sciences, 13*(21), 11740. https://doi.org/10.3390/app132111740

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

Li, X., Zhang, X., & Jia, T. (2023b). Humanization of nature: Testing the influences of urban park characteristics and psychological factors on collegers' perceived restoration. *Urban Forestry & Urban Greening, 79,* 127806. https://doi.org/10.1016/j.ufug.2022.127806

Lin, L., Di, L., Zhang, C., Guo, L., Zhao, H., Islam, D., Li, H., Liu, Z., & Middleton, G. (2024). Modeling urban redevelopment: A novel approach using time-series remote sensing data and machine learning. G*eography and Sustainability, 5*(2), 211–219. https://doi.org/10.1016/j.geosus.2024.02.001

Liu, C., Lin, T., Yuan, K., & Chiueh, P. (2022). Spatio-temporal prediction and factor identification of urban air quality using support vector machine. *Urban Climate, 41,* 101055. https://doi.org/10.1016/j.uclim.2021.101055

Liu, L., Xu, Z., Yao, S., Lv, M., & Liu, C. (2024). Optimizing the spatial accessibility of outdoor sports facilities: a greedy heuristic algorithm based on remote sensing images. *International Journal of Digital Earth, 17*(1). https://doi.org/10.1080/17538947.2024.2390427

Liu, M., Chen, H., Wei, D., Wu, Y., & Li, C. (2021). Nonlinear relationship between urban form and street-level PM2.5 and CO based on mobile measurements and gradient boosting decision tree models. *Building and Environment, 205,* 108265. https://doi.org/10.1016/j.buildenv.2021.108265

Liu, R., Wang, Y., Zhang, Y., Peng, Z., Chen, H., Li, X., Li, H., & Li, W. (2025). Analysis of the city-scale wind environment and detection of ventilation corridors in high-density metropolitan areas based on CFD method. *Urban Climate, 59,* 102274. https://doi.org/10.1016/j.uclim.2024.102274

Liu, R., Xu, Y., Xue, C., Xia, Z., Li, G., Gou, X., & Luo, S. (2023). Simulation of early warning ındicators of urban expansion derived from machine learning. *Journal of Urban Planning and Development, 149*(1). https://doi.org/10.1061/jupddm.upeng-4127

Liu, Z., & Cheng, L. (2020). Review of GIS technology and its applications in different areas. *IOP Conference Series Materials Science and Engineering, 735*(1), 012066. https://doi.org/10.1088/1757-899x/735/1/012066

Lloyd, C., Sturrock, H., Leasure, D., Jochem, W., Lázár, A., & Tatem, A. (2020). Using GIS and machine learning to classify residential status of urban buildings in low and middle income settings. *Remote Sensing, 12*(23), 3847. https://doi.org/10.3390/rs12233847

Mahendra, H., Pushpalatha, V., Mallikarjunaswamy, S., Subramoniam, S. R., Rao, A. S., & Sharmila, N. (2024). LULC change detection analysis of Chamarajanagar district, Karnataka state, India using CNN-based deep learning method. *Advances in Space Research, 75*(12), 6384-6408. https://doi.org/10.1016/j.asr.2024.07.066

Manna, H., Mallick, S. K., Sarkar, S., & Roy, S. K. (2025). Developing decision making framework on built-up site suitability assessment for urban regeneration in the industrial cities of Eastern India. *Scientific Reports, 15*(1). https://doi.org/10.1038/s41598-025-90408-2

Mansourihanis, O., Tilaki, M. J. M., Yousefian, S., & Zaroujtaghi, A. (2023). A computational geospatial approach to assessing land-use compatibility in urban planning. *Land, 12*(11), 2083. https://doi.org/10.3390/land12112083

Mazroa, A. A., Maashi, M., Kouki, F., Othman, K. M., Salih, N., Elfaki, M. A., & S, S. B. (2024). An analysis of urban sprawl growth and prediction using remote sensing and machine learning techniques. *Journal of South American Earth Sciences, 142,* 104988. https://doi.org/10.1016/j.jsames.2024.104988

McCorduck, P. (2004). *Machines who think: A personal inquiry into the history and prospects of artificial intelligence* (2nd ed.). Canada: AK Peters.

Mishra, K., Tiwari, H., & Poonia, V. (2025). An integrated approach of machine learning methods coupled with cellular automation for monitoring and forecasting of land use and land cover. *Journal of Arid Environments, 226*, 105293. https://doi.org/10.1016/j.jaridenv.2024.105293

Mishra, S., Bajpai, A., Mohanta, A., Banerjee, B., Rajput, S., & Kundu, S. (2024). Dynamic flood risk prediction in Houston: A multi-model machine learning approach. *Geocarto International, 39*(1). https://doi.org/10.1080/10106049.2024.2432866

Mitchell, T. M. (1997). *Machine Learning*. New York: McGraw-Hill.

Mondal, S., Parveen, M. T., Alam, A., Rukhsana, N., Islam, N., Calka, B., Bashir, B., & Zhran, M. (2024). Future site suitability for urban waste management in English Bazar and Old Malda municipalities, West Bengal: a geospatial and machine learning approach. *ISPRS International Journal of Geo-Information, 13*(11), 388. https://doi.org/10.3390/ijgi13110388

Mustak, S., Baghmar, N. K., Singh, S. K., & Srivastava, P. K. (2022). Multi-scenario based urban growth modeling and prediction using earth observation datasets towards urban policy improvement. *Geocarto International, 37*(27), 18275–18303. https://doi.org/10.1080/10106049.2022.2138983

Mutani, G., Scalise, A., Sufa, X., & Grasso, S. (2024). Synergising machine learning and remote sensing for Urban heat island dynamics: A Comprehensive Modelling approach. *Atmosphere, 15*(12), 1435. https://doi.org/10.3390/atmos15121435

Nahid, S., Kumar, R. P., Acharya, P., Kumar, K., & Purohit, S. (2025). Forecasting urban expansion in Delhi-NCR: integrating remote sensing, machine learning, and Markov chain simulation for sustainable urban planning. *GeoJournal, 90,* 72. https://doi.org/10.1007/s10708-025-11317-5

DOI: 10.15320/ICONARP.2025.337

Ni, H., Wang, D., Zhao, W., Jiang, W., Mingze, E., Huang, C., & Yao, J. (2024). Enhancing rooftop solar energy potential evaluation in high-density cities: A Deep Learning and GIS based approach. *Energy and Buildings, 309*, 113743. https://doi.org/10.1016/j.enbuild.2023.113743

Nizamani, M. M., Qureshi, S., Tarashkar, M., Zhang, H., Zhou, Q., & Lai, Z. (2025). Ethical AI: Human-centered approaches for adaptive and sustainable urban planning and policy. *Land Use Policy*, *157*, 107650. https://doi.org/10.1016/j.landusepol.2025.107650

Ohlan, R., Ohlan, A., Chhikara, S., & Singh, T. (2025). Bibliometric analysis and review of world trade organization research: Suggesting future avenues using WOS database. *Journal of the Knowledge Economy, 16,* 3741–3771 https://doi.org/10.1007/s13132-024-02134-1

Omrani, H., Tayyebi, A., & Pijanowski, B. (2017). Integrating the multi-label land-use concept and cellular automata with the artificial neural network-based Land Transformation Model: an integrated ML-CA-LTM modeling framework. *GIScience & Remote Sensing, 54*(3), 283–304. https://doi.org/10.1080/15481603.2016.1265706

Park, J., & Yang, B. (2020). GIS-Enabled Digital Twin system for sustainable evaluation of carbon emissions: A case study of Jeonju City, South Korea. *Sustainability, 12*(21), 9186. https://doi.org/10.3390/su12219186

Patil, V., Khadke, Y., Joshi, A., & Sawant, S. (2024). Flood mapping and damage assessment using ensemble model approach. *Sensing and Imaging, 25,* 15. https://doi.org/10.1007/s11220-024-00464-7

Peng, Z., Lu, K., Liu, Y., & Zhai, W. (2023). The pathway of urban planning AI: From planning support to plan-making. *Journal of Planning Education and Research, 44*(4), 2263–2279. https://doi.org/10.1177/0739456x231180568

Pflugmacher, D., Rabe, A., Peters, M., & Hostert, P. (2019). Mapping pan-European land cover using Landsat spectral-temporal metrics and the European LUCAS survey. *Remote Sensing of Environment, 221,* 583–595. https://doi.org/10.1016/j.rse.2018.12.001

Pushpalatha, V., Mallikarjuna, P. B., Mahendra, H. N., Rama Subramoniam, S., & Mallikarjunaswamy, S. (2025). Land use and land cover classification for change detection studies using convolutional neural network. *Advances in Computational and Applied Geosciences, 5*(2), 100227. https://doi.org/10.1016/j.acags.2025.100227

Quan, S. J. (2024). Comparing hyperparameter tuning methods in machine learning based urban building energy modeling: A study in Chicago. *Energy and Buildings, 317*, 114353. https://doi.org/10.1016/j.enbuild.2024.114353

Riaz, M. T., Riaz, M. T., Rehman, A., Bindajam, A. A., Mallick, J., & Abdo, H. G. (2024). An integrated approach of support vector machine (SVM) and weight of evidence (WOE) techniques to map groundwater potential and assess water quality. *Scientific Reports, 14*(1). https://doi.org/10.1038/s41598-024-76607-3

Rizeei, H. M., Pradhan, B., & Saharkhiz, M. A. (2019). Allocation of emergency response centres in response to pluvial flooding-prone demand points using integrated multiple layer perceptron and maximum coverage location problem models. *International Journal of Disaster Risk Reduction, 38,* 101205. https://doi.org/10.1016/j.ijdrr.2019.101205

Salele, B., Dodo, Y. A., Sani, D. A., Abuhussain, M. A., Abdullaeva, B. S., & Brysiewicz, A. (2023). Run-off modelling of pervious and impervious areas using couple SWAT and a novel machine learning model in cross-rivers state

Nigeria. *Water Science & Technology, 88*(7), 1893–1909. https://doi.org/10.2166/wst.2023.304

Sampurno, J., Ardianto, R., & Hanert, E. (2022). Integrated machine learning and GIS-based bathtub models to assess the future flood risk in the Kapuas River Delta, Indonesia. *Journal of Hydroinformatics, 25*(1), 113–125. https://doi.org/10.2166/hydro.2022.106

Samuel, A. L. (1959). Some studies in machine learning using the game of checkers. *IBM Journal of Research and Development, 3*(3), 210–229. https://doi.org/10.1147/rd.33.0210

Sanchez, T. W., Shumway, H., Gordner, T., & Lim, T. (2023). The prospects of artificial intelligence in urban planning. *International Journal of Urban Sciences, 27*(2), 179–194. https://doi.org/10.1080/12265934.2022.2102538

Santos, B., Gonçalves, J., Martins, A. M., Pérez-Cano, M. T., Mosquera-Adell, E., Dimelli, D., Lagarias, A., & Almeida, P. G. (2021). GIS in architectural teaching and research: Planning and heritage. *Education Sciences, 11*(6), 307. https://doi.org/10.3390/educsci11060307

Scholten, H. J., & Stillwell, J. (2013). *Geographical information systems for urban and regional planning*. Germany: Springer Science & Business Media.

Schrammeijer, E. A., Malek, Ž., & Verburg, P. H. (2022). Mapping demand and supply of functional niches of urban green space. *Ecological Indicators, 140,* 109031. https://doi.org/10.1016/j.ecolind.2022.109031

Segura-Méndez, F. J., Pérez-Sánchez, J., & Senent-Aparicio, J. (2023). Evaluating the riparian forest quality index (QBR) in the Luchena River by integrating remote sensing, machine learning and GIS techniques. *Ecohydrology & Hydrobiology, 23*(3), 469–483. https://doi.org/10.1016/j.ecohyd.2023.04.002

Seydou, K. D., Morenikeji, W., Diouf, A., Dicko, K., Erdanaev, E., Loewner, R., & Okhimamhe, A. A. (2024). Dynamics of Zinder's urban landscape: Implications for sustainable land use management and environmental conservation. *Sustainability, 16*(23), 10263. https://doi.org/10.3390/su162310263

Shao, Y., Yin, Y., Xue, Z., & Ma, D. (2023). Assessing and comparing the visual comfort of streets across four Chinese megacities using ai-based image analysis and the perceptive evaluation method. *Land, 12*(4), 834. https://doi.org/10.3390/land12040834

Sierra, S., Ramo, R., Padilla, M., & Cobo, A. (2025). Optimizing deep neural networks for high-resolution land cover classification through data augmentation. *Environmental Monitoring and Assessment, 197*, 423. https://doi.org/10.1007/s10661-025-13870-5

Sinčić, M., Gazibara, S. B., Rossi, M., & Arbanas, S. M. (2025). Comparison of conditioning factor classification criteria in large-scale statistically based landslide susceptibility models. *Natural Hazards and Earth System Sciences, 25*(1), 183–206. https://doi.org/10.5194/nhess-25-183-2025

Smith, T. R. (1984). Artificial intelligence and its applicability to geographical problem solving. *The Professional Geographer, 36*(2), 147–158. https://doi.org/10.1111/j.0033-0124.1984.00147.x

Sobieraj, J., Marín, M. F., & Metelski, D. (2023). Mapping of impervious surfaces with the use of remote sensing imagery: Support Vector Machines classification and GIS-based approach. *Archives of Civil Engineering*, *69*(3), 129-146. https://doi.org/10.24425/ace.2023.146071

Srivanit, M., Pattanasri, S., Phichetkunbodee, N., Manokeaw, S., Sitthikankun, S., & Rinchumphu, D. (2024). Analysis of sensitive urban form indicators of flood susceptible prediction based on machine learning models. *Global Journal of*

DOI: 10.15320/ICONARP.2025.337

Environmental Science and Management, 10(1), 15–28. https://doi.org/10.22034/gjesm.2024.01.02

Su, L., Chen, W., Zhou, Y., & Fan, L. (2023). Exploring city ımage perception in social media big data through deep learning: A Case Study of Zhongshan City. *Sustainability, 15*(4), 3311. https://doi.org/10.3390/su15043311

Sun, C., Zhang, F., Zhao, P., Zhao, X., Huang, Y., & Lu, X. (2021). Automated simulation framework for urban wind environments based on aerial point clouds and deep learning. *Remote Sensing, 13*(12), 2383. https://doi.org/10.3390/rs13122383

Tang, Y., Feng, F., Guo, Z., Feng, W., Li, Z., Wang, J., Sun, Q., Ma, H., & Li, Y. (2020). Integrating principal component analysis with statistically-based models for analysis of causal factors and landslide susceptibility mapping: A comparative study from the loess plateau area in Shanxi (China). *Journal of Cleaner Production, 277,* 124159. https://doi.org/10.1016/j.jclepro.2020.124159

Tokarčík, O., Blišťan, P., Kovanič, Ľ., Peťovský, P., & Topitzer, B. (2024). Assessment of the usability of open data in Slovakia in the context of mapping and evaluating Blue-Green Infrastructure. *Geographia Cassoviensis, 18*(2). https://doi.org/10.33542/gc2024-2-02

Trinh, L. H., Pham, V. T., Tran, X. B., Nguyen, V. T., Vu, X. C., Tong, T. H., & Le, V. P. (2024). Mapping impervious surface change from remote sensing and GIS data: A case study in Hochiminh city, Vietnam. *Ecological Questions, 35*(3), 1–14. https://doi.org/10.12775/eq.2024.030

Venter, Z. S., & Sydenham, M. A. K. (2021). Continental-scale land cover mapping at 10 m resolution over Europe (ELC10). *Remote Sensing, 13*(12), 2301. https://doi.org/10.3390/rs13122301

Wan, T., & Ma, Y. (2022). Urban planning and design layout generation based on artificial intelligence. *Mathematical Problems in Engineering, 2022,* 1–10. https://doi.org/10.1155/2022/8976943

Wang, J., & Liu, Z. (2014). A bibliometric analysis on rural studies in human geography and related disciplines. *Scientometrics, 101*(1), 39–59. https://doi.org/10.1007/s11192-014-1388-2

Wang, L., Pijanowski, B., Yang, W., Zhai, R., Omrani, H., & Li, K. (2018). Predicting multiple land use transitions under rapid urbanization and implications for land management and urban planning: The case of Zhanggong district in central China. *Habitat International, 82*, 48–61. https://doi.org/10.1016/j.habitatint.2018.08.007

Wang, S., Ou, H., Chen, P., & Lin, T. (2024). Implementing policies to mitigate urban heat islands: Analyzing urban development factors with an innovative machine learning approach. *Urban Climate, 55,* 101868. https://doi.org/10.1016/j.uclim.2024.101868

Wang, Z., Zhu, Z., Xu, M., & Qureshi, S. (2021). Fine-grained assessment of greenspace satisfaction at regional scale using content analysis of social media and machine learning. *The Science of the Total Environment, 776,* 145908. https://doi.org/10.1016/j.scitotenv.2021.145908

Wu, C., Wang, Y., Wang, J., Kraak, M., & Wang, M. (2024). Mapping Street Patterns with Network Science and Supervised Machine Learning. *ISPRS International Journal of Geo-Information, 13*(4), 114. https://doi.org/10.3390/ijgi13040114

Xiao, T., Yin, K., Yao, T., & Liu, S. (2019). Spatial prediction of landslide susceptibility using GIS-based statistical and machine learning models in Wanzhou County, Three Gorges Reservoir, China. *Acta Geochimica, 38*(5), 654–669. https://doi.org/10.1007/s11631-019-00341-1

Xu, Y., Chen, R., Du, H., Chen, M., Fu, C., & Li, Y. (2025). Evaluation of green space influence on housing prices using machine learning and urban visual intelligence. *Cities, 158,* 105661. https://doi.org/10.1016/j.cities.2024.105661

Yagoub, M. M., Tesfaldet, Y. T., Elmubarak, M. G., & Hosani, N. A. (2022). Extraction of urban quality of life indicators using remote sensing and machine learning: the case of Al Ain City, United Arab Emirates (UAE). *ISPRS International Journal of Geo-Information, 11*(9), 458. https://doi.org/10.3390/ijgi11090458

Yan, L., & Zhiping, W. (2023). Mapping the literature on academic publishing: A bibliometric analysis on WOS. *SAGE Open, 13*(1). https://doi.org/10.1177/21582440231158562

Yao, Y., Li, X., Liu, X., Liu, P., Liang, Z., Zhang, J., & Mai, K. (2017). Sensing spatial distribution of urban land use by integrating points-of-interest and Google Word2Vec model. *International Journal of Geographical Information Science, 31*(4), 825–848. https://doi.org/10.1080/13658816.2016.1244608

Yao, Y., Yin, H., Xu, C., Chen, D., Shao, L., Guan, Q., & Wang, R. (2022). Assessing myocardial infarction severity from the urban environment perspective in Wuhan, China. *Journal of Environmental Management, 317,* 115438. https://doi.org/10.1016/j.jenvman.2022.115438

Ye, N., Wang, B., Kita, M., Xie, M., & Cai, W. (2019). Urban commerce distribution analysis based on street view and deep learning. *IEEE Access, 7,* 162841–162849. https://doi.org/10.1109/ACCESS.2019.2951294

Yu, J., Zeng, P., Yu, Y., Yu, H., Huang, L., & Zhou, D. (2022). A Combined Convolutional Neural Network for Urban Land-Use Classification with GIS Data. *Remote Sensing, 14*(5), 1128. https://doi.org/10.3390/rs14051128

Zafar, Z., Zubair, M., Zha, Y., Fahd, S., & Nadeem, A. A. (2024). Performance assessment of machine learning algorithms for mapping of land use/land cover using remote sensing data. *The Egyptian Journal of Remote Sensing and Space Science, 27*(2), 216–226. https://doi.org/10.1016/j.ejrs.2024.03.003

Zappone, A., Di Renzo, M., & Debbah, M. (2019). Wireless networks design in the era of deep learning: Model-Based, AI-Based, or both?. *IEEE Transactions on Communications, 67*(10), 7331–7376. https://doi.org/10.1109/tcomm.2019.2924010

Zheng, Y., Wang, Y., Wang, X., Wen, Y., & Guo, S. (2024). Managing landscape urbanization and assessing biodiversity of wildlife habitats: A study of bobcats in San Jose, California. *Land, 13*(2), 152. https://doi.org/10.3390/land13020152

Zhu, X. X., Tuia, D., Mou, L., Xia, G., Zhang, L., Xu, F., & Fraundorfer, F. (2017). Deep Learning in Remote Sensing: A comprehensive review and list of resources. *IEEE Geoscience and Remote Sensing Magazine, 5*(4), 8–36. https://doi.org/10.1109/mgrs.2017.2762307

Zhu, Y., Mao, Y., Yuan, M., Zhang, K., & Lv, C. (2023). Global research productions pertaining to design for safety: A bibliometric analysis based on WOS database. *Buildings, 13*(6), 1515. https://doi.org/10.3390/buildings13061515

Zou, L., Song, Y., & Cervone, G. (2024). Geospatial big data: Theory, methods, and applications. *Annals of GIS, 30*(4), 411–415. https://doi.org/10.1080/19475683.2024.2419749

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Resume

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