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Review article

From tradition to smart: A comprehensive review of the evolution and prospects of land use planning tools

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ABSTRACT

Land use planning tools are essential for effective land management. However, existing research has not thoroughly explored the evolution and future potential of these tools. This study addresses this gap through comprehensive literature review and data collection, mapping the progression of land use planning tools from their inception to their future trajectories. Our findings indicate that land use planning tools have evolved through four distinct epochs: 1.0 to 4.0. These epochs are defined as follows: Foundational Surveying Tools (1900s–1950s), Computerized Tools (1960s–1980s), Internet Technology Tools (1990s–2000s), and Smart Tools (2010s to Present). Presently, these tools face several limitations, including complex and redundant planning systems, poor adaptability, insufficient public engagement, and a lack of emphasis on sustainable development. Looking ahead, the emergence of the 5.0 era around the 2040s is anticipated, marked by advancements such as blockchain, VR/AR, quantum computing, and digital twins. This study provides valuable insights for scholars in the field and informs future development of land use planning tools.

1. Introduction

Land use planning is a multifaceted process that necessitates the use of suitable tools to ensure both efficiency and effectiveness [1]. The choice and application of these tools are crucial in shaping the success of land use planning initiatives [2]. Consequently, researching land use planning tools is essential for enhancing planning processes, refining land use methodologies, and maximizing the benefits derived from land use strategies [3].

Examining the evolution of land use planning tools is essential for gaining insights into their historical development. A thorough overview of this evolution elucidates the history of these tools and enhances our understanding of their progression [4]. This paper begins with a detailed review of the historical development of land use planning tools, laying the groundwork for an exploration of their future prospects.

Exploring the prospects of land use planning tools is crucial for advancing their development, enhancing their functionality, and driving necessary changes [5]. Such advancements can significantly improve the efficiency and effectiveness of land use planning [6]. Therefore, this paper aims to investigate the future potential of land use planning tools.

Current research on the evolution and future prospects of land use planning tools provides valuable insights and references for this study. For instance, Riveira and Maseda [7] conducted a historical review of tools utilized in rural land use planning, highlighting that

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GIS has become an essential component in this field. However, their study, which dates back over a decade, may not reflect the latest advancements in smart land use planning tools driven by emerging technologies such as Big Data, "Internet+", and AI. Additionally, their analysis was limited to tools for rural land use planning and did not encompass tools relevant to urban land use planning.

While recent studies have examined the evolution of emerging smart land use planning tools, they often focus on a single land type. For instance, one study specifically reviewed tools for urban underground space planning [8]. In contrast, there is a lack of comprehensive discussions on tools applicable to multiple land types.

Several studies have also investigated the future prospects of land use planning tools. For instance, Li et al. [9] identified that Cellular Automata (CA) falls short in integrating dynamic simulation models with socio-economic factors. They proposed enhancing land use planning by combining CA with Artificial Neural Networks (ANN) to address this limitation.

Other studies have highlighted the challenges posed by rapidly evolving environmental, social, and technological factors, noting that Land Change Models (LCM) are limited as standalone tools. Consequently, future land use planning tools may need to integrate multiple methods and utilize a range of modeling techniques to enhance predictive performance [10]. However, these studies often focus on individual tools (e.g., only Cellular Automata) or specific land use contexts (e.g., urban land use). Thus, there is a notable gap in research regarding the prospects of diverse land use planning tools across various land types.

This study offers several significant contributions compared to previous research. Firstly, it delineates the evolution of land use planning tools into four distinct stages. Secondly, it examines four potential future trajectories for these tools. Lastly, it emphasizes the latest advancements in smart land use planning, particularly those incorporating AI, big data, and intelligent monitoring, thus providing a timely and insightful perspective.

This paper is organized as follows: The introduction is presented in the first section, followed by the methodology in the second section and the results in the third. The fourth and fifth sections are dedicated to the discussion and conclusions, respectively.

2. Methodology

This study employs a generalized literature search method, utilizing the Web of Science (WoS) database for literature retrieval. The references and primary sources for this paper are derived from peer-reviewed research articles.

First, we utilized the "Advanced Search" function of Web of Science, selecting the "Web of Science Core Collection" database for retrieval, with the citation index set to "All".

Next, we selected "Topic" as the primary search criterion. Given that the focus of this paper is to investigate the evolution of land use planning tools and provide future perspectives, we used the search keywords "land use planning tools" and set the publication date range to "2004–2023," covering a span of 20 years. This search yielded 6257 documents. We then refined the search by language to "English" and by document type to "Article" or "Review," resulting in a total of 6043 documents.

We then performed a preliminary review of the titles and abstracts displayed in the database. Given the primary objective of this paper is to investigate the evolution of land use planning tools and provide future perspectives, we focused on identifying documents that were closely related to "land use planning," particularly "land use planning tools." Based on this focus, we conducted a rigorous evaluation of each article, ensuring it was highly relevant to the topic and reflected the evolution of tools. We excluded irrelevant or duplicate articles according to these criteria and, considering journal quality, research timing, and citation frequency, identified 149 peer-reviewed relevant papers for in-depth reading and note-taking.

However, during the review of these seminal documents, we found that the 149 classic papers alone were insufficient to fully highlight certain groundbreaking achievements in land use planning tools. Therefore, we also utilized our institution's library resources to obtain some essential electronic books and relevant materials, which were included as additional references.

Additionally, we gathered relevant materials and case studies from official websites of organizations such as the Food and Agriculture Organization (FAO) and the United Nations Economic and Social Commission for Asia and the Pacific (ESCAP). After careful selection, these were also included as references. Although these sources and electronic books are not peer-reviewed, they provide significant insights into the development, future prospects, and challenges of land use planning tools. Since these are publicly published materials, their use helps reduce bias and error. We included 26 non-peer-reviewed sources as references, ensuring the reliability and authenticity of the information.

Finally, we listed a total of 175 references as the primary sources for this study. Based on these references, we provided a theoretical discussion and case evidence on the evolution, development prospects, and future challenges of land use planning tools, leading to the conclusions presented in this paper.

3. Results

3.1. Evolution of land use planning tools

The history of human land use planning extends back to antiquity. Different regions and civilizations have developed distinct land use planning tools, shaped by variations in their political institutional contexts and socio-economic conditions. Ancient Egyptians used ropes for land measurement, while the Romans employed a groma for surveying. Additionally, ancient Chinese civilizations utilized the sinan (a precursor to the compass) for orientation in land planning and measurement [11]. In these early stages, such tools were essential and laid the groundwork for modern land use planning instruments. However, due to the technological constraints of their eras, the evolution of these tools in early agricultural societies was gradual, with limited planning capabilities that hindered substantial technological advancements [12].

Maps, crucial tools for modern land use planning, have a complex and extensive evolutionary history. One of the oldest known maps, dating back approximately 2500 years to ancient Babylonia, depicted the locations of hills, rivers, and land features. Later, Greco-Roman civilizations, drawing on Egyptian geometry, advanced cartography by emphasizing the measurement of latitude and longitude [13]. However, during the European Middle Ages, the dominance of religion in the political and cultural spheres led to maps often serving symbolic roles within religious and theological contexts. The T-O maps constructed on this basis are particularly representative, they typically lacked the precision and scientific rigor of contemporary maps, including scale and latitude and longitude information [14].

By the Renaissance and the Age of Geographic Discoveries, driven by the demands of humanism and scientific literacy, maps began to emphasize scientific rigor and precision. Modern cartography, which emerged in the 19th century, introduced standardized methodologies and symbol systems for map production [15]. The early 20th century saw significant advancements with the advent of aerial photography, which greatly improved map accuracy and detail. With the rise of computer technology, digital mapping and GIS revolutionized map production, analysis, and application in the late 20th and early 21st centuries. Today, cartography is advancing into an era of big data and intelligence, where maps have evolved from static images to dynamic, interactive tools capable of real-time updates [16].

The analysis above indicates that early agricultural societies utilized only basic land use planning tools due to constraints imposed by economic development conditions. Significant technological advancements in planning tools, particularly maps, emerged in the 20th century, driven by improvements in national governance capacity, shifts in social and cultural contexts, and enhancements in the overall quality of the population. This study aims to outline the evolutionary trajectory of land use planning tools and project future directions for their development. Given that the evolution of early planning tools offers limited insights into future technological advancements, this study will focus on the development and evolution of land use planning tools from the 20th century onward.

The evolution of land use planning tools since the 20th century can be divided into three distinct periods. The first period, the 1960s, was marked by the rapid advancement of computer technologies, particularly GIS and remote sensing (RS). The second period, the 1990s, saw the global proliferation of IT products, including the advent of internet-based tools such as the "3S" system (RS + GPS + GIS). The third period, the 2010s, was characterized by the emergence of "Internet+," Cloud Computing, and Big Data Analysis, which facilitated the transition of smart land use planning tools, like AI and Machine Learning, from theoretical concepts to practical applications.

This study categorizes the evolution of land use planning tools into four distinct stages.

1. Land Use Planning Tools 1.0 (1900s–1950s) – Characterized by foundational surveying tools.
2. Land Use Planning Tools 2.0 (1960s–1980s) – Marked by the advent of computerized tools.
3. Land Use Planning Tools 3.0 (1990s–2000s) – Defined by the integration of IT tools.
4. Land Use Planning Tools 4.0 (2010s to present) – Represented by the emergence of smart tools.

Fig. 1 offers a broad overview of representative tools across various stages, with a detailed evolution discussed in the subsequent sections.

It is important to note that the evolution of land use planning tools is influenced by multiple factors, including policy, governance, cultural contexts, and socio-economic dynamics, all of which collectively drive technological advancements. However, due to space constraints, this study primarily focuses on the specific evolutionary characteristics of the tools themselves, with technological progress as the main subject of analysis. Therefore, the subsequent sections will emphasize technological advancements in the tools while also considering certain aspects of policy, governance, culture, and socio-economic dynamics.

3.1.1. Foundational surveying tools (1900s–1950s)

The early 20th century (1900s–1920s) marked a breakthrough in land use planning tools with the advent of aerial photography technology, which allowed for more precise mapping [17]. Despite this advancement, the process remained largely dependent on foundational land surveys and manual cartographic techniques for initial classification and assessment of land resources.

In the 1930s, the "Land Utilization Survey of Great Britain (LUSGB)" utilized cutting-edge tools of the era, such as high-resolution color scanning, to meticulously document land use across Great Britain [18]. Simultaneously, in the United States, R. Earl Storie

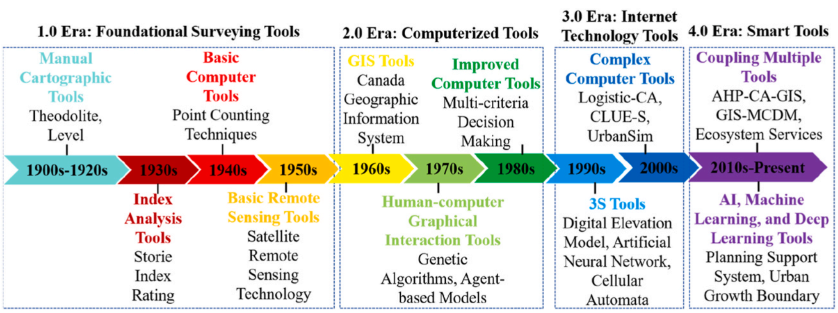

Fig. 1. Representative land use planning tools in different stages.

developed the Storie Index Rating (SIR), an efficient index analysis tool [19]. The SIR quantitatively assessed land's production potential and suitability through a series of indicators and scoring systems, thereby enhancing the capacity of land use planning [20].

Since 1936, California has consistently utilized the Storie Index Rating (SIR) as a guiding principle for agricultural land suitability planning, integrating it into every soil survey report issued in the state. Similarly, Saskatchewan, a major grain-producing province in Canada, has adapted and applied SIR to its unique conditions, leading to significant successes in land suitability planning.

However, land use planning tools of this period were relatively rudimentary, with slow and limited capabilities for calculating parametric indexes. This underscored the need for advancements to enhance their planning effectiveness.

The advent of electronic computers in the 1940s significantly enhanced calculation speed and computational power, leading to greater accuracy in land use planning [21]. As computers evolved, their performance improved, making them indispensable tools for land use planning, including techniques such as point counting [22]. Initially, in the 1940s, computers had limited performance and were primarily used in military applications. Their software and hardware were still in nascent stages, which meant their potential for land use planning was not fully realized at that time [23].

As knowledge of land use planning advanced, the 1950s saw experts and scholars begin to investigate non-soil factors in the planning process. This shift marked a transition from purely qualitative to increasingly quantitative analysis, enriching the toolkit for land use planning [24]. The concept of "Artificial Intelligence (AI)" was first introduced at the Dartmouth Conference in 1956, driven by advancements in computer technology. The advent of AI profoundly influenced the development of future land use planning tools, leading to the creation of numerous tools still in use today, such as expert systems [25]. However, during this period, AI development remained largely theoretical and conceptual.

In the 1950s, satellite remote sensing technology began its initial development, eventually becoming a crucial tool for land use planning. The launch of Sputnik-1 by the Soviet Union in 1957 marked the advent of artificial satellites, establishing the foundation for remote sensing technology. Soon after, the United States launched TIROS-1, the first satellite dedicated to meteorological observation, which facilitated the long-term monitoring of Earth's atmosphere and set the stage for the subsequent application of remote sensing technology in land use planning.

Furthermore, it is important to recognize that the impact of the two World Wars during this period objectively facilitated the development of land use planning tools. For instance, maps created by various countries based on geopolitical strategies saw significant advancements during this phase [17]. Additionally, military technologies that evolved alongside the wars played a notable role in the development of land use planning tools both during and after the conflicts.

As previously discussed, the period from the 1900s to the 1950s saw the emergence of computer technology, remote sensing techniques, and theoretical concepts of artificial intelligence, which enriched the specific forms of land use planning tools. This study posits that this period represents the foundational stage of land use planning tools, characterized primarily by Manual Cartographic Tools such as Theodolite and Index Analysis Tools like Storie Index Rating (SIR), with supplementary use of Basic Computer Tools such as Point Counting Techniques and Basic Remote Sensing Tools like Satellite Remote Sensing Technology. Building on this analysis, this study designates this period as the Land Use Planning Tools 1.0 era, charactered primarily by foundational surveying tools.

3.1.2. Computerized tools (1960s–1980s)

In the 1960s, land use planning tools transitioned into the 2.0 era, characterized by the rapid advancement of computerized technologies [26]. Although computers had been introduced in the 1940s and initial map measurement, analysis, and production techniques were developed in the 1950s, the limitations of early computer hardware constrained software development [27]. It was not until the 1960s that significant improvements in computer hardware and software, coupled with advancements in GIS technology, propelled land use planning tools into a new and transformative era.

The ongoing development of land use planning tools and the growing expertise of scholars in the 1960s led to the introduction of innovative tools that significantly impacted the field. Notable examples include the Land Capability Classification System, developed by Klingebiel and Montgomery [28], and the revised United States Bureau of Reclamation (USBR) Classification System for Irrigated Land, which followed shortly thereafter [29]. These systems unified and standardized previously disparate tools and methods, greatly enhancing the land use planning process [30].

In practical applications, the Land Capability Classification System became a cornerstone of official documents, with the United States Department of Agriculture (USDA) extensively adopting it for agricultural land use planning across the nation. This system emerged as the most widely used land capability classification framework of its time. Additionally, the USBR Classification System for Irrigated Land, a key tool for irrigation land planning and evaluation during that period, remains widely utilized in the United States today.

Additionally, two pivotal land use planning tools emerged in the 1960s. First, the Canada Geographic Information System (CGIS), the world's first truly operational GIS, was successfully developed in the mid-1960s. This system integrated computer technology with geographic information to assess land suitability for various uses in land use planning [31]. Second, the creation of ARPAnet in the United States in 1969 marked the inception of the Internet, heralding a new era for land use planning tools. The subsequent evolution of the Internet has driven advancements in big data analysis and smart planning [32].

With the rapid advancements in computer software and hardware after the 1970s, land use planners increasingly demanded sophisticated GIS and other computational tools, driving further development in GIS software [33]. A key advancement of the 1970s was the emergence of human-computer graphical interaction technology, alongside the introduction of scanning input systems. For instance, some researchers assessed the suitability of proposed flood-control reservoirs and parkways in the USA for recreational and other land uses [34]. Despite these innovations, computer software at the time had limited graphical capabilities and relatively weak data management functions [35].

The 1970s witnessed the emergence of numerous tools that remain integral to land use planning today, driven by rapid advancements in computer software and hardware [36]. Technologies such as Genetic Algorithms (GA) [37], Agent-based Models (ABM) [38], and the Analytic Hierarchy Process (AHP) [39]. However, during this period, these tools were predominantly in the conceptual and theoretical stages of development.

Despite the advancements in computerized land use planning tools, qualitative assessment methods continue to play a dominant role in this period. Approach such as the land suitability evaluation [40] and the comprehensive balance method, which focuses on balancing land supply and demand [41], remain central to the field.

These methods were primarily rooted in the experiences and subjective judgments of professional planners and decision-makers, aiming to guide the future development of land use and allocate land for agriculture, forestry, animal husbandry, and fisheries [42]. However, a lack of unified standards for land use planning tools persisted at that time [43]. Consequently, there is a pressing need for the academic community to address the enduring issue of standardization in land use planning tools.

In this context, there is a need to establish a unified policy assessment framework to standardize land use planning tools. In 1976, the Food and Agriculture Organization of the United Nations (FAO) tackled these issues by publishing *A Framework for Land Evaluation* [44]. This framework sought to standardize existing land use planning tools, marking a shift from qualitative analyses of land use types to quantitative assessments of land planning horizons [45].

In practical applications, the Portuguese government, building on the FAO framework, developed a tailored evaluation system using land use survey data. They meticulously crafted an intensive land use plan for the Lezíria Grande, a 13,000-ha island in the Tagus River estuary. This implementation demonstrated the feasibility and high applicability of the FAO framework in project selection, planning, and evaluation.

The FAO established land evaluation as the foundation of land use planning, integrating the differences in policies, governance, culture, and socio-economic dynamics across various countries and regions to develop guidelines for land use planning suitable for diverse locales. In the 1980s, it published *Land Evaluation for Rainfed Agriculture* [46] and *Land Evaluation for Irrigation* [47], creating a comprehensive land use planning evaluation system. This system was further refined with the release of *The Guidelines for Land-use Planning* [48], enhancing the completeness and effectiveness of land use planning evaluations.

In the 1980s, rapid advancements in computer technologies enabled the resolution of complex mathematical models, facilitating the application of these models to address challenging land use planning issues [49]. For instance, scholars combined two weighted function methods to identify optimal locations for power plants in western Maryland, USA [50]. Additionally, Multi-Criteria Decision Making (MCDM) was employed to determine site selections for primary healthcare centers in Zambia [51], new fire stations in North York, Ontario in Canada [52], and highway placements in France [53].

In practical applications, the Régie Autonome des Transports Parisiens (RATP) partnered with the Laboratoire d'Analyze et Modélisation de Systèmes pour l'Aide à la Décision (LAMSADE) at the University Paris-Dauphine. They employed the MCDM ELECTRE model to evaluate land use planning for 224 metro stations under RATP's jurisdiction during the Paris Metro renovation. This collaboration effectively addressed the land use planning challenges associated with the redevelopment of the Paris Metro.

This stage marked the widespread adoption of remote sensing, computer, and mathematical methods in land use planning, significantly enhancing the scientific rigor, efficiency, and accuracy of the process [54].

Meanwhile, advancements in computer software and hardware technologies have led to the maturation of Geographic Information Systems (GIS) [55]. In 1982, the Environmental Systems Research Institute, Inc. (ESRI) introduced ARC/INFO 1.0, the world's first commercial GIS software, representing a major advancement in GIS capabilities [56]. GIS has since achieved significant breakthroughs in raster scan data processing, data storage, data manipulation, and data output [57]. Moreover, spatial database management systems tailored for GIS spatial relationship analysis have been developed, and numerous microcomputer GIS software systems have been created to support geographic information management [58].

With advancements in computer technology and a deeper understanding of the complexity of land use planning, scholars now recognize that this field must consider not only technological advancements but also dynamic factors such as policy, governance, culture, and socio-economic conditions [59]. In response, the United States Department of Agriculture (USDA) introduced the Land Evaluation and Site Assessment (LESA) system in the 1980s. This system integrates multiple factors to assess land conservation needs, and a manual was developed to support its application in land use planning [60].

As previously discussed, the period from the 1960s to the 1980s witnessed significant technological breakthroughs, including iterative upgrades in computer software and hardware, the adoption of GIS technology, and the emergence of the Internet. This study characterizes this period as the "Computerized Tools" stage in land use planning, marked primarily by GIS tools such as the Canada Geographic Information System, Human-computer Graphical Interaction Tools including Genetic Algorithms and Agent-based Models, and Improved Computer Tools like Multi-criteria Decision Making. Building on this analysis, this study designates this period as the Land Use Planning Tools 2.0 era, charactered mainly by computerized tools.

3.1.3. Internet technology tools (1990s–2000s)

The primary technological breakthrough of the 1990s was the widespread proliferation of the Internet [61], which enabled the integrated development of various tools. This extensive adoption of the Internet significantly enhanced computer algorithms and performance, driving continuous improvements in land use planning [62]. As a result, since the 1990s, land use planning tools have entered a new era defined by the application of Internet Technology (IT) tools.

During this era, the rise of geographic information industries and the global proliferation of digital information products facilitated the integration of GIS into various sectors and even households, making it an essential tool for production, daily life, education, and work [63]. Concurrently, societal awareness of GIS grew, leading to a substantial increase in demand [64]. In this context, GIS, along with Remote Sensing (RS) and the Global Positioning System (GPS), which was fully developed by the mid-1990s, collectively became known as the “3S” technologies [65]. For instance, scholars utilized 3S technologies and socio-economic data to assess land use/cover changes and urban expansion in Greater Dhaka, Bangladesh from 1975 to 2003 [66].

In practical applications, under the unified direction of the State Council, the State Land Administration of the People’s Republic of China utilized 3S technology—primarily remote sensing—in the late 1980s and early 1990s to conduct a nationwide county-level land survey. In eastern regions, aerial remote sensing was the primary method for conducting a 1:10,000 scale land use survey and mapping. In contrast, western regions employed a combination of satellite and aerial remote sensing to carry out land use surveys at scales of 1:15,000 and 1:100,000. This effort provided extensive reference data for economic development and land use planning at all levels of the Chinese government and offered valuable information for specialized departments, including agriculture, industry, water resources, energy, and transportation, in their land use planning processes.

Additionally, 3S technology integrates systems for collecting and processing spatial information and creating maps. For instance, scholars have utilized the Digital Elevation Model (DEM)—a land use planning tool derived from 3S technology—to support urban and regional planning in the coastal areas of New South Wales (NSW), Australia [67].

Furthermore, significant advancements in computer performance and the widespread adoption of the Internet have led to the extensive use of AI-based tools in land use planning, including Artificial Neural Networks (ANN) [68], Cellular Automata (CA) [69], Support Vector Machines (SVM) [70], and Expert Systems (ES) [71]. Among these, Cellular Automata (CA) has experienced the most rapid development. For example, in the United States, scholars have applied CA-derived tools such as SLEUTH [72], CA-GIS [73], and Logistic-CA [74] to analyze urban growth in regions such as the San Francisco Bay Area, the Washington/Baltimore Corridor, and the Atlanta metropolitan area.

Meanwhile, Rossiter [75] introduced the Automated Land Evaluation System (ALES) as a land use planning tool leveraging rapidly advancing technologies such as computers and the Internet. Hall et al. [76] developed the first fuzzy logic algorithm, building on earlier land use planning, and later applied it to assess land quality suitability for rubber cultivation in Thailand [77]. Goodchild [78] proposed “Geographic Information Science (GIS)” as a research paradigm for land use planning and identified key planning tools, including ArcGIS, MapGIS, SuperMap, ConverseEarth, Erdas, Envi, and AutoCAD.

Land use planning tools have been tailored to address different types of land use. For urban land use planning, the Land Change Model (LCM) enables planners to transform uncertain future land changes into more predictable conditions, thereby facilitating the visualization of potential future land use scenarios through scenario planning [10]. For instance, scholars have utilized LCM-based tools such as the Land Use Scanner [79], What IF [80], CLUE-S [81], and UrbanSim [82] to generate spatial predictions of land use in regions including the Netherlands, Ohio, the Philippines, and Salt Lake City.

In practice, the Netherlands Environmental Assessment Agency tailored the Land Use Scanner tool to local conditions. This tool, comprising approximately 200,000 grid cells, utilized comprehensive data covering the entire Netherlands to generate spatial prediction models for various land use types, including residential, industrial, agricultural, natural areas, and water bodies. The Land Use Scanner has been extensively applied across the Netherlands, yielding positive results and demonstrating its effectiveness in land use planning.

Additionally, for agricultural land planning, the FAO introduced the concept of “Agro-Ecological Zoning (AEZ)” [83] to assess the agricultural potential of land resources. Moreover, emerging landscape planning tools, such as ecological land use models, are becoming increasingly prevalent [84]. One such tool, Multi-Criteria Evaluation Geographic Information Systems (MCE-GIS), is employed to simulate land suitability maps. For instance, researchers have utilized MCE-GIS to investigate renewable resource management and landscape conservation in Palermo, Sicily, Italy [85].

It is important to note that during this phase of rapid internet technology development, the use of internet technologies in various countries and regions has been regulated to some extent within legal and institutional frameworks to prevent misuse and safeguard personal information. However, due to differences in political systems, cultural backgrounds, and social customs, there are notable discrepancies and delays in the formulation of regulations that promote the normative use of the internet. This has resulted in significant disparities in the development of internet-based land use planning tools across different regions.

As previously highlighted, the most significant technological advancement between the 1990s and 2000s was the widespread proliferation and application of Internet technology. The Internet improved the accuracy and suitability of land use planning by integrating and coordinating various planning tools. Consequently, this study designates this period as the “Internet Technology Tools” stage of land use planning, represented by 3S tools such as Digital Elevation Models, Artificial Neural Networks, and Cellular Automata, as well as complex computer tools like Logistic-CA, CLUE-S, and UrbanSim. Building on this analysis, this study designates this period as the Land Use Planning Tools 3.0 era, charactered mainly by internet technology tools.

3.1.4. Smart tools (2010s to the present)

In the 2010s, the world transitioned into the smart era, driven by the rapid advancements of the fourth technological revolution. This era is marked by breakthroughs in AI, the Internet of Things (IoT), Big Data Analysis (BDA), Information and Communications Technology (ICT), Augmented Reality (AR), Virtual Reality (VR), and Cloud Computing (CC) [16]. During this period, land use planning tools have undergone continuous evolution, leading to significant enhancements in their performance. In this context, land use planning has entered the 4.0 era, characterized by the extensive application of smart technologies, including AI, machine learning, and deep learning [86].

In practice, the Bavarian Survey Authority in Germany employs laser scanning measurements for land use planning, moving beyond the use of stereoscopic images. They utilize an in-house BIM-integrated GIS system to achieve greater detail in their digital maps and data storage. Additionally, machine learning algorithms are applied to detect newly constructed houses and buildings by comparing consecutive images of the same area.

Recent years have seen growing focus on the role of digital technologies in urban planning [87]. This trend is exemplified by the emergence of the “Smart City” concept and the adoption of various digital initiatives by governments. Currently, 26 cities in ASEAN have been designated as pilot locations for smart city development, with the goal of creating an extensive network of interconnected smart cities.

In practical contexts, Kuopio and Helsinki have emerged as leading centers of smart city planning in Finland, playing a pivotal role in the national digitization of urban planning. Their smart city initiatives focus on developing collaborative operational frameworks and integrated data solutions, aiming to create a people-centric and adaptive service network. These efforts have proven highly effective, inspiring other Finnish municipalities, such as Turku, to adopt similar smart city planning strategies.

The “Smart City” concept prioritizes people-centered, sustainable urban development, with a particular emphasis on land use planning tools. Planning Support Systems (PSS), which are based on geographic information technology, aid planners in executing specific tasks [88] and play a crucial role in achieving “Smart City” objectives. PSS typically integrate spatial data, models, and geovisualization to enable dynamic modeling, testing, and evaluation of urban development [89]. For instance, scholars have employed PSS tools such as Envision Scenario Planner [90], OWI [91], and RAISE [1] to model scenarios in cities like Canning, Sydney, and Parramatta in Australia.

In practical applications, Australia utilizes the Walkability Planning Support System to enhance land use planning for pedestrian pathways in three suburbs within Victoria. Additionally, this Planning Support System has been instrumental in guiding land use planning initiatives for the development of subway stations in Perth, the capital city of Western Australia.

As the emphasis on the development of “smart cities” continues to grow, along with shifts in policy governance and cultural values across various regions, increasing attention is being directed toward “Urban Growth Boundaries (UGB)”. This strategy aims to mitigate urban sprawl, optimize the layout of urban life service industries, and guide the sustainable development of smart cities [92]. Currently, the rapid and uncontrolled urban expansion has led to irreversible land cover changes due to urban sprawl [93], and the UGB has emerged as one of the most effective tools for managing this phenomenon [94]. Various research tools are employed for UGB analysis. For instance, Zhao et al. [95] examined UGB delineation in mountainous cities in Chongqing, China, and found that land use simulations using the Markov-FLUS tool were particularly effective. Additionally, other studies have utilized a combination of three tools, Logistic-MC-CA, to analyze UGB in Kolkata, India, achieving promising simulation results [96].

In practical application, the United States extensively employs Urban Growth Boundaries (UGB) in urban land use planning. This strategy promotes compact and connected development by restricting land use within designated boundaries to urban purposes. Additionally, China has established urban growth boundaries through institutional and legal measures, enacting the “*Urban and Rural Planning Law of the People's Republic of China*”. This law delineates Urban Construction Boundaries (UCB) to separate urban and rural land and, in 2014, initiated pilot projects in 14 cities to define urban growth boundaries.

The concept of the “Smart City” has underscored the significance of effective traffic planning in urban areas [97], making the integration of urban planning and traffic management particularly essential [98]. With advancements in artificial intelligence (AI), Intelligent Decision Support Systems (IDSS) that merge AI with traditional decision support systems (DSS) have emerged as valuable tools for urban transportation planning. For example, Zhao et al. [99] employed an IDSS based on OpenStreetMap (OSM) to analyze the planning utilization of Drivable Street Networks (DSN) and Walkable Street Networks (WSN) in ASEAN, facilitating insights into urban land use planning. Building on this approach, Ogryzek et al. [100], using Poland as a case study, applied Support Vector Machine (SVM) and Analytic Hierarchy Process (AHP) methodologies. They proposed a comprehensive model solution that integrates public participation for planning smart city and smart village road infrastructure within a sustainable transportation framework.

Cellular Automata (CA) is arguably the most advanced derivative tool in artificial intelligence [101], known for its robust capability to simulate complex spatio-temporal processes. Its integration with other tools can significantly enhance land use planning across various domains. CA-based tools are versatile and can be applied to nearly any type of land use planning [9]. For instance, researchers have utilized tools such as ANN-CA [102], ACO-CA [103], and UV-CAGA [104] to analyze the urban growth boundary in Tehran, Iran; the urban land configuration in the Changsha-Zhuzhou-Xiangtan agglomeration in China; and the urban form simulation in Wuhan, China.

With the development of socio-economic conditions and the enhancement of government governance capabilities, people's values have gradually evolved, influencing the evolution of land use planning tools. As emphasis on “Smart Planning” and “Sustainable Development” grows, numerous tools based on “Ecological Planning” have been developed [105]. Some scholars assessed the value of Ecosystem Services (ES) in planning by creating multidimensional indicators for measuring and evaluating urban development [106, 107]. Additionally, researchers have employed tools and concepts such as the Ecosystem Portfolio Model (EPM) [31], the Green View Index (GVI) [108], and the Green Infrastructure Suitability Map (GISM) [109] to investigate land use and cover changes in Florida, street greening trends in New York City, and green infrastructure planning in the Monza-Brianza province of Italy.

Beyond urban planning, land use planning tools have also significantly influenced the management of various land types. For instance, researchers have utilized tools such as AHP-CA-GIS to simulate the suitability of irrigated farmland in the Macintyre River Basin in southern Queensland, Australia [110], to guide coastal land use planning in Quebec, Canada [111], and to incorporate flood risk considerations into land use planning in Rostock, Germany [112].

Furthermore, the integration of Geographic Information Systems (GIS) with Multi-Criteria Decision Making (MCDM) methods, referred to as GIS-MCDM, has become increasingly prevalent in land use planning. For example, scholars have employed GIS-MCDM to assess the spatial suitability for large-scale solar power plants in Tanzania [113], optimize site selection for wind farm development in South Korea [114], and conduct land use planning in Iran with consideration of forest fire scenarios [115]. Additionally, tools derived from GIS-MCDM, such as TOPSIS [116], Grey Cumulative Prospect Theory [101], and PALM [117], have been utilized to evaluate the siting of thermal power plants in India, photovoltaic power plants in northwest China, and landscape planning in Switzerland.

With the rapid advancement of digital technologies, the demand for 3D city modeling has increased significantly. CityGML is commonly used in conjunction with Geographic Information System (GIS) software for 3D city modeling and analysis. Currently, CityGML has emerged as the globally recognized standard for 3D city digital modeling exchange formats and languages, and it has been adopted as a standard by the Open Geospatial Consortium (OGC) [118]. Furthermore, the Application Domain Extensions (ADEs) of CityGML provide significant flexibility and extensibility.

Liamis and Mimis [119] utilized the ADE of CityGML—GRextADE, to develop a 3D city model for Athens, Greece, tailored to meet the cadastral development needs of Greece and to support digital modeling for future urban planning in the country. Seto et al. [120] examined the case of Japan and found that Japan has developed software using CityGML for land use planning. They have accurately converted approximately 18 million building data points from 150 Japanese cities into CityGML format, creating open data that complements the OpenStreetMap (OSM) data for urban areas. This significant enhancement has greatly improved land use planning capabilities.

In practical applications, the cases of the Netherlands, Germany, Turkey, and Sweden illustrate this. In Netherlands, the CityGML-IMGeo ADE has been used to supplement models in the national geographic database, enhancing its land planning capabilities for large-scale terrains. In Germany, AvD-CityGM has been employed to establish a national standard for 3D city models, significantly improving land planning capabilities for urban buildings. Turkey has utilized CityGML extensions to create 3D city models conforming to Turkish standards and integrated them with large-scale terrain databases to enhance land planning capabilities. In Sweden, CityGML 3.0 has been used to develop CityGML Sve-Test, addressing the country's land use planning needs.

However, it is important to note that the most significant characteristic of this stage is the advancement of tools derived from applications such as machine learning (ML) and deep learning (DL). In recent years, the applications of tools such as the patch-generating land use simulation model (PLUS), convolutional neural networks (CNN), random forests (RF), support vector machines (SVM), generative adversarial networks (GANs), spatial analysis models, multi-objective optimization algorithms, agent-based models (ABM), and hybrid algorithms have matured considerably, greatly enhancing the efficiency and effectiveness of land use planning.

The PLUS model is a land use change simulation framework based on patch data, designed to integrate land expansion analysis strategies with a cellular automata model utilizing multiple types of random patch seeds. This integration aims to reveal the potential driving factors behind land use changes and to better simulate the temporal and spatial evolution of multiple land use patches [121].

In practical applications, Gao et al. [122] employed the PLUS model to simulate four different types of land use scenarios for Nanjing, China, in 2025. Li et al. [123], using Ningbo, China, as a case study, optimized the quantity structure and spatial layout of Production-Living-Ecological Land (PLEL) by integrating genetic algorithms (GA) and the PLUS model, finding that the GA-PLUS model exhibits strong robustness. Furthermore, scholars have utilized COCKPIT-PLUS [124], Markov-PLUS [125], and MOP-PLUS [126] models for land use planning in the Gunungsewu karst region of Java, Indonesia, scenarios for Foshan City, China in 2030, and small-scale mountainous areas in Chongqing, China, respectively, demonstrating that the PLUS model offers higher simulation accuracy compared to traditional models such as CLUE-S, ANN-CA, and Logistic-CA.

Currently, algorithms such as Random Forest (RF), Convolutional Neural Networks (CNN), and Support Vector Machines (SVM) are most suitable for classifying and analyzing patterns in Earth observation data. Generative Adversarial Networks (GANs) have been employed to simulate urban patterns. Additionally, algorithms like cellular automata, spatial logistic regression, and agent-based modeling have been used to study urban growth, land use change, and settlement pattern analysis [127].

Random Forest is an ensemble learning algorithm based on decision tree classifiers, bagging, and bootstrapping, serving as a beneficial tool for land use planning [127]. In practical applications, Kamusoko and Gamba [128] employed a hybrid approach combining Random Forest and cellular automata (CA) to study urban land changes in the Harare metropolitan area of Zimbabwe. Reis et al. [129] utilized maximum likelihood and Random Forest (RF) classification algorithms, leveraging Light Detection and Ranging (LiDAR) data and multispectral images from unmanned aerial vehicle (UAV) cameras to inform forest land planning in Brazil. Goodspeed et al. [130] illustrated a model for predicting land use changes within the Huron River watershed in Michigan, employing a calibrated Random Forest model. Additionally, researchers have applied the Random Forest model to guide land use planning in Ciudad Juárez, Mexico [131], and Kumamoto City, Japan [132].

Convolutional Neural Networks (CNN) are a typical deep learning model that has been widely applied in image recognition, providing a promising solution due to their ability to utilize convolutional kernels to extract high-level features from the raw neighborhood information of each pixel [86]. In practical applications, Yu et al. [133] generated a well-labeled high-resolution urban land use image dataset using GIS data, based on which they proposed a composite convolutional neural network, DUA-Net, for the complex and diverse classification of urban land use. Similarly, Zhai et al. [134] developed a hybrid model, CNN-Vector Cellular Automata (VCA), using Shenzhen City, China, as a case study. This model employs CNN to extract high-level features of driving factors within irregularly shaped neighborhoods, uncovering relationships between various land use changes and their driving factors at the neighborhood level.

Support Vector Machines (SVM) are a set of non-parametric maximum likelihood algorithms, with the core operation involving the construction of a separating hyperplane (i.e., decision boundary) based on the attributes of training samples, particularly their distribution in feature space. SVM has been applied in various fields, including land use change modeling [135]. In practical applications, Yousef et al. [136] utilized SVM to generate land use/cover maps from Sentinel-2 satellite images in selected humid and arid climate zones in Iran. Additionally, research employing SVM-based land use modeling techniques investigated changes in land use categories over a decade in Zemun, Serbia [137]. Furthermore, Kesikoglu et al. [138] examined the effectiveness of various classification algorithms (SVM, ANN, and MLH) for detecting land cover changes in Turkey, finding that the SVM method provided the highest overall accuracy in image classification.

Moreover, Generative Adversarial Networks (GAN) and Agent-Based Models (ABM) have become popular tools for land use planning [127]. In practical applications, Gite and Gupta [139] proposed an effective mechanism for change detection utilizing Fuzzy Neural Networks (FNN), which combines fuzzy concepts with Neural Networks (NN) and employs Taylor Shuffled Shepherd Optimization (TSSO) based GAN for segmentation to optimize satellite images. Zhao et al. [140] used an Agent-Based Model (ABM) to develop a spatial planning optimization model in Anyue County, China, finding that the optimal allocation derived from the ABM was more applicable than that obtained from non-agent-based models.

As indicated above, since the 2010s, the most significant technological advancements in land use planning have been the widespread application of artificial intelligence (AI), machine learning (ML), and deep learning (DL). These applications have led to a transformative leap in computer performance and Internet technologies, shortening the iteration cycles of model computational power and giving rise to advanced models such as GPT. This has greatly enhanced the efficiency and precision of land use planning.

Therefore, this study designates this period as the "Smart Tools" stage of land use planning, characterized by Coupling Multiple Tools such as AHP-CA-GIS, GIS-MCDM, and Logistic-MC-CA, as well as AI, Machine Learning, and Deep Learning Tools like Planning Support Systems (PSS), Intelligence Decision Supporting System (IDSS), PLUS model, Random Forest (RF), Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Generative Adversarial Networks (GAN), and Agent-Based Models (ABM). Building on this analysis, this study designates this period as the Land Use Planning Tools 4.0 era, charactered mainly by smart tools.

3.1.5. Summary of evolution

As previously discussed, the iteration cycles of land use planning tools have progressively shortened. Furthermore, these tools are increasingly dependent on advanced technologies such as AI, big models, IoT, and cloud computing, which signals the future trajectory of land use planning tools. Table 1 provides the evolution of land use planning tools.

3.2. Prospects of land use planning tools

As detailed in Section 3.1.4, the widespread adoption of geospatial technologies is evident. Geographic Information Systems (GIS), Global Navigation Satellite Systems (GNSS), and remote sensing technologies are increasingly employed to enhance the accuracy and efficiency of land surveying and mapping. These technologies offer high-precision data, facilitate real-time data collection and analysis, and drive the demand for more advanced land use planning tools.

Additionally, the integration of artificial intelligence (AI), machine learning (ML), and spatiotemporal Big Data algorithms into land use planning tools has revolutionized data processing, accuracy, and decision-making capabilities. AI-driven functionalities such as object recognition, image classification, and predictive analysis enhance the value of land use planning, significantly advancing both the precision and sophistication of the planning process.

What are the future directions for the development of land use planning tools, and what changes can be anticipated? This section will address these questions as its central focus.

Building on the current development status of land use planning tools and considering the momentum of emerging technologies,

Table 1
Evolution of land use planning tools.

Developmental Stages	Characteristics	Representative Tools	Literature
Land Use Planning Tools 1.0 Era (From the 1900s to the 1950s)	Foundational Surveying Tools Such as Index Analysis Tools	Storie Index Rating (SIR)	[19]
		Satellite Remote Sensing	[54]
Land Use Planning Tools 2.0 Era (From the 1960s to the 1980s)	Computerized Tools Such as GIS	Land Capability Classification System	[28]
		Canada Geographic Information System (CGIS)	[31]
		Multi-Criteria Decision Making (MCDM)	[51]
Land Use Planning Tools 3.0 Era (From the 1990s to the 2000s)	IT Tools Such as 3S (RS + GPS + GIS)	Automated Land Evaluation System (ALES)	[75]
		Artificial Neural Network (ANN)	[68]
		Digital Elevation Model (DEM)	[67]
		Expert System (ES)	[71]
		Cellular Automata (CA)	[72]
Land Use Planning Tools 4.0 Era (From the 2010s to the Present)	Smart Tools Such as PLUS	Planning Support Systems (PSS)	[88]
		Envision Scenario Planner	[90]
		Markov-FLUS	[94]
		Logistic-MC-CA	[95]
		UV-CAGA	[103]
		AHP-CA-GIS	[109]
		TOPSIS	[115]
		PALM	[116]
		Random Forest (RF)	[129]
		Agent-Based Models (ABM)	[38]
		Generative Adversarial Networks (GANs)	[139]
		Support Vector Machines (SVM)	[70]
		Convolutional Neural Networks (CNN)	[133]
		Patch-generating Land Use Simulation Model (PLUS)	[123]
		ANN-CA	[101]

this study identifies the following key prospects for the future of these tools.

3.2.1. The widespread application of blockchain technology

Blockchain technology, an emerging distributed database innovation, allows multiple participants to collaboratively manage an ever-expanding ledger of records, or blocks, characterized by decentralization, transparency, and immutability [141]. Its significant potential across various domains positions it as a crucial tool for the future of land use planning.

Currently, blockchain technology has seen preliminary application in land use planning, including the development of systems for land use approval, natural resource management, property rights protection, and data sharing. Nevertheless, its application within land use planning tools remains largely exploratory, and widespread adoption has yet to be achieved.

Presently, the application of blockchain in land use planning is beginning to take shape. For instance, Georgia has adopted blockchain as the foundation for land registration to achieve more effective land planning and cadastral management [142]. Additionally, countries such as India, Japan, China, South Korea, Indonesia, and Malaysia are developing country-specific Land Administration Domain Model (LADM) profiles and exploring the integration of blockchain with LADM and CityGML 3D data modeling methods. This integration aims to further enhance land management data prediction through blockchain technology, building upon 3D cadastral systems [143].

In the future, blockchain technology is expected to significantly impact land use planning in the following ways: (1) Land Registration and Titling: Blockchain can provide a secure and transparent system for recording land ownership, minimizing fraud and errors by accurately tracking ownership transfers, thus enhancing the precision and efficiency of land registration. (2) Data Sharing and Collaboration: Blockchain can function as a unified platform for government agencies, landowners, and planners to share land use data, fostering greater transparency and collaboration.

(3) Decision Support for Land Planning: Blockchain data analysis can yield deeper insights into land use patterns and trends, thereby improving decision-making processes in land planning. (4) Community Engagement: Blockchain can serve as a platform for community involvement in land planning decisions, enhancing public participation and satisfaction. (5) Predictive Analysis: When integrated with big data analytics, blockchain data can be leveraged for predictive analysis, forecasting land demand and supply, and providing proactive guidance for land planning.

Furthermore, blockchain technology can enhance land use planning in several key areas: First, smart contracts facilitate the automatic enforcement of land use agreements, triggering penalties or other stipulated actions if planning regulations are violated. Second, blockchain supports environmental monitoring and conservation by recording data on land conditions, such as soil quality and vegetation coverage, thus improving the management and protection of land resources.

Thirdly, blockchain technology enhances fund tracking in land development and planning projects by providing a transparent and compliant system for tracing financial flows. Additionally, blockchain's immutability ensures the permanent storage and traceability of historical land use records, which is crucial for resolving land disputes. Finally, blockchain facilitates cross-border land transactions by offering a secure and reliable system for recording transactions, thus streamlining the process.

With technological advancements and supportive policies, the application of blockchain technology in land use planning tools is anticipated to become more prevalent. This integration will enhance transparency in land management and significantly improve the efficiency of land use planning.

However, integrating blockchain into land use planning also presents several challenges and obstacles. Firstly, from a technical perspective, incorporating blockchain into the land use planning process requires robust hardware and software support. It also necessitates official registration systems to record and verify land ownership, which may pose significant challenges in some countries, especially in developing nations. These countries often face infrastructural deficiencies and limited short-term technological advancements, and many official registration systems may only include leasehold rather than freehold information. This complicates the integration of blockchain technology.

Secondly, from a socio-cultural perspective, integrating blockchain technology into land use planning requires careful consideration of the social and cultural factors specific to different countries. For example, in Ghana, data on land ownership, land use, and land value remain fragmented and unstandardized, with automation and accessibility of information services being inefficient. This has led to social issues such as double selling of land, unauthorized alterations of land documents, corruption, and bribery [144]. Therefore, integrating blockchain technology within varying socio-cultural contexts will be a significant challenge for future land use planning.

Thirdly, data privacy and security issues present a challenge. While blockchain technology's decentralization, transparency, and immutability offer numerous benefits, they also raise concerns about privacy and security. Balancing the protection of personal privacy and ensuring data security while leveraging the potential advantages of blockchain technology will be a key obstacle in future land use planning.

3.2.2. The extensive application of VR and AR technologies

Virtual Reality (VR) and Augmented Reality (AR) are immersive technologies that enhance or transform real-life experiences through computer-generated imagery and sound [145]. As technology evolves, VR and AR are increasingly converging to create Mixed Reality (MR) experiences, which blend elements of both VR and AR to offer users more dynamic and versatile interactions [146]. These advancements in VR and AR open up new possibilities for land use planning tools by providing immersive and interactive environments.

Currently, VR and AR technologies have made significant contributions to land use planning, including precise simulation and visualization for urban development, the preservation and interpretation of historical and cultural heritage, the optimization of intelligent transportation and infrastructure systems, and the efficient utilization and planning of urban spatial resources. However, the adoption of VR and AR in land use planning remains limited, with considerable potential for further development and enhancement of these applications.

Recent studies have begun to explore the use of VR/AR technologies in land use planning. For example, Suhari and Owa propose integrating Building Information Modeling (BIM) with Augmented Reality (AR) and Virtual Reality (VR) technologies to address 3D cadastral information management, land issues, and sustainable development in Indonesia [147]. Their research indicates that when BIM is appropriately complemented with VR/AR, the synergistic effect of these different tools can significantly support the advancement of 3D cadastral information, benefiting land use planning [143].

In the future, the application of VR and AR technologies in land use planning will primarily manifest in several key areas: (1) Three-dimensional Visualization: VR and AR can provide immersive 3D visualizations of land and structures, facilitating a more intuitive understanding of planning schemes for both planners and stakeholders. (2) Interactive Planning: VR environments will allow planners to simulate and adjust land use scenarios, observing real-time changes and their effects on overall planning. (3) Public Participation: AR technology will enable the public to view and interact with planning schemes in the real world via mobile devices, thereby enhancing engagement and feedback efficiency.

(4) Environmental Impact Assessment: VR and AR technologies can simulate potential environmental impacts of various planning schemes, including ecological, hydrological, and visual effects. (5) Collaboration Tools: VR and AR can facilitate collaboration within multidisciplinary teams by allowing members to work and discuss within a shared virtual environment. (6) Risk Assessment: By simulating extreme weather events or natural disasters, VR and AR can aid planners in evaluating the resilience of land use strategies against potential risks.

Moreover, VR and AR technologies can further enhance land use planning in the following ways: (1) Education and Training: VR can be leveraged for educational and training purposes, allowing learners to explore the principles and practices of land planning within immersive, simulated environments. (2) Historical and Future Scenario Simulation: AR technology can illustrate historical land use changes and project future developments, providing planners and the public with insights into the temporal impacts on land use.

Additionally, VR and AR technologies can advance land use planning in several critical areas: (1) Resource Optimization: These technologies can help planners identify and utilize underutilized resources, such as green spaces and water bodies, more effectively. (2) Real-time Data Integration: VR and AR can incorporate real-time data—such as traffic flow and population density—providing dynamic and actionable information for planning decisions. (3) Compliance Checks: By facilitating on-site inspections, VR and AR can assist in verifying that planning schemes adhere to regulatory requirements, thereby minimizing compliance issues.

As technology progresses and costs decrease, the integration of VR and AR technologies in land use planning is expected to become increasingly widespread. This adoption will significantly enhance the cost-effectiveness and efficiency of the planning process.

However, there are several impediments and challenges in integrating VR/AR technology into land use planning. One major issue is the legal and regulatory framework. The adoption of VR/AR technology requires support from legal and regulatory structures. Currently, in many countries, existing legal systems may not accommodate the application of these technologies, or significant reforms may be necessary to adapt to this new technology.

Secondly, privacy and ethical issues are a concern. While the transparency and immutability of VR/AR technology offer numerous benefits, they also raise concerns regarding privacy and security. Moreover, ethical considerations related to VR/AR technology warrant attention, as cultural norms and practices vary across countries and may lead to disputes over the ethical use of these technologies. This presents a significant challenge for the future integration of VR/AR technology into land use planning.

Thirdly, issues related to data quality and system compatibility pose challenges. Existing land management systems may suffer from data inconsistencies and incompleteness, which could hinder the integration of VR/AR technology. Additionally, compatibility between new and existing systems is a critical consideration when implementing VR/AR technology.

3.2.3. *The extensive application of quantum computing*

Quantum computing represents a computational paradigm grounded in the principles of quantum mechanics, distinguishing it fundamentally from classical computing [148]. Unlike traditional computers that use classical bits, quantum computing employs quantum bits (qubits) [149]. While still in the research and development phase, quantum computing promises transformative applications across various fields, including machine learning [150]. As technology progresses, quantum computers are expected to tackle problems that are virtually insurmountable for classical systems, potentially offering substantial benefits in land use planning as well.

At present, quantum computing technology is not widely applied in land use planning. While quantum computing is still in the early stages of research and development, it offers promising new possibilities for the field. Despite this potential, practical applications remain relatively limited. As quantum computing technology matures and costs decrease, it is anticipated that its application in land use planning will expand, leading to more innovative and effective solutions in the future.

Currently, the application of quantum computing in land use planning is still relatively rare, but exploratory practices are beginning to emerge. For example, Gowri et al. [151] integrated quantum computing with artificial intelligence (AI) to design a plant watering robot capable of measuring the relative moisture of agricultural or planting soils. This research provides an AI controller for effective irrigation planning and develops an automated quantum computing irrigation system. The system can delineate irrigation areas based on measurement results, facilitating site-specific land use planning for irrigation zones.

In the future, quantum computing technology is expected to significantly impact land use planning in several key areas. Firstly, it will enhance complex system simulation, allowing for efficient modeling of intricate natural and social systems to better understand and predict land use changes and their environmental and societal effects. Secondly, quantum computing will advance optimization algorithms, accelerating the resolution of complex optimization problems, such as determining optimal land allocation schemes to meet various objectives and constraints. Lastly, it will improve big data analysis, utilizing quantum computers' rapid processing capabilities to manage and analyze extensive datasets from sources like remote sensing and GIS.

Fourthly, quantum computing will advance machine learning and pattern recognition, enhancing the accuracy of land use pattern detection, such as identifying land cover types or predicting urban expansion trends. Fifthly, it will improve resource management, enabling more precise assessment and management of land, water, and other natural resources to support sustainable land use planning. Sixthly, quantum computing will enhance risk assessment by simulating various planning scenarios to evaluate potential environmental and societal risks, including floods, droughts, or ecological degradation. Lastly, it will revolutionize interactive planning tools: by integrating quantum computing with VR or AR technologies, it will provide complex, dynamic tools that allow planners and the public to explore and assess different planning scenarios in real-time.

Furthermore, quantum computing technology has the potential to impact land use planning in several additional ways: (1) Real-time decision support: The rapid processing power of quantum computing can enable real-time adjustments to planning strategies in response to dynamically changing conditions. (2) Multidisciplinary integration: Quantum computing can facilitate the integration of knowledge and models from diverse fields, such as ecology, economics, sociology, and geography, leading to more holistic and effective land use planning.

(3) Long-term planning and forecasting: Quantum computers can perform extensive simulations and forecasts, aiding planners in assessing the potential impacts of various strategies over extended timeframes, spanning decades or more. (4) Smart contracts and blockchain: By integrating quantum computing with blockchain technology, more secure and efficient solutions can be developed for land registration, transactions, and smart contracts. (5) Education and training: Quantum computing can facilitate the creation of advanced educational and training tools, enhancing the ability of planners and decision-makers to grasp the complexities of land use planning.

Currently, integrating quantum computing into land use planning faces significant challenges. Firstly, in terms of technology, quantum computing is still in its developmental phase, and its application in land use planning may require addressing issues related to technological maturity, including challenges in qubit coherence manipulation and quantum error correction.

Secondly, in terms of cost, the complexity of quantum computing technology may pose implementation challenges for some regions. Although these technologies may reduce costs in the long term, the initial implementation costs can be quite high, presenting a significant challenge for resource-constrained areas.

Thirdly, in terms of environmental impact, the energy consumption and environmental effects of quantum computing devices are also considerations for future land use planning, particularly when using consensus mechanisms such as Proof-of-Work.

Despite encountering various technical and practical challenges, the application of quantum computing in land use planning offers tremendous potential and could herald transformative changes in the future. As quantum computing technology continues to advance, it is expected to unlock innovative applications that could revolutionize land use planning.

3.2.4. The widespread application of digital twinning technology

Digital twinning technology is an advanced information technology that simulates, analyzes, and optimizes the performance of a physical entity or system through the creation of a virtual digital replica (i.e., a digital twin model) [152]. Its application in land use planning is progressively emerging, introducing enhanced innovation and efficiency to the planning process. As the technology continues to evolve and mature, digital twinning is anticipated to assume a central role in shaping future land use planning strategies.

The application of digital twinning technology in land use planning is progressively emerging, with notable implementations in areas such as the digital transformation of parks, 3D GIS technology, IoT and big data, immersive technologies, and land use monitoring. However, widespread adoption in land use planning remains limited. As the technology continues to advance and mature, it is expected that digital twinning will increasingly influence and enhance the land use planning process.

Currently, digital twins have seen some practical application in land use planning. For instance, the city of Seoul in South Korea has developed a digital twin tool named S-Map to replicate a 3-square-kilometer area of the city. The South Korean government aims to utilize S-Map for simulating smart city models to improve land use planning [153]. Additionally, Malaysia and Indonesia have also undertaken various initiatives to cultivate digital twins through building models integrated with GIS. The goal is to develop interactive and interconnected 3D cadasters through the integration of different tools to enhance land use planning [143].

In the future, the application of digital twinning technology in land use planning is expected to focus on the following key aspects.

(1) Precise Modeling: Digital twinning technology will enable the creation of detailed three-dimensional models of land, buildings, and infrastructure, providing planners with comprehensive and accurate land use information.
(2) Real-time Monitoring: By integrating sensor data, digital twinning will facilitate the real-time monitoring of land use, encompassing the status of buildings, traffic flow, and environmental conditions.
(3) Simulation and Prediction: Digital twinning technology will allow for the simulation of various land use scenarios, enabling the prediction of their impacts on transportation, the environment, the economy, and other critical factors.
(4) Planning Scheme Evaluation: Digital twinning can be used to assess the feasibility and effectiveness of planning schemes, optimizing decisions through advanced simulations.
(5) Multi-stakeholder Collaboration: It offers a shared virtual environment that facilitates collaboration among planners, architects, engineers, and the public on a unified platform.
(6) Risk Management: By simulating extreme weather events or natural disasters, digital twinning aids in evaluating the resilience of land use plans against various risks.

(7) Historical Data Analysis: Digital twinning can integrate historical data to analyze land use trends over time, providing valuable insights for future planning efforts.

Additionally, digital twinning technology in land use planning manifests in several impactful ways.

(1) Interactive Display: Digital twinning facilitates the creation of interactive platforms that offer the public a more intuitive understanding of land planning objectives and outcomes.
(2) Resource Optimization: By leveraging digital twinning, planners can identify and optimize the use of land resources, thereby enhancing overall land use efficiency.
(3) Compliance Checks: Digital twinning technology can automatically verify whether planning schemes adhere to relevant regulations and standards, thereby mitigating compliance issues.
(4) Continuous Updates: As land use conditions evolve, digital twin models can be perpetually updated to ensure that planning tools accurately reflect the most current land status.
(5) Education and Training: Digital twinning can serve as a valuable resource in education and training, helping students and emerging planners grasp the complexities of land use planning.

Digital twinning technology, through its provision of a highly integrated and interactive virtual environment, enhances efficiency, accuracy, and engagement in land use planning. With ongoing technological advancements, the adoption of digital twinning in land use planning tools is anticipated to become increasingly prevalent.

However, integrating digital twin technology into land use planning also faces certain challenges. One major challenge is technological in nature, varying data collection capabilities across different countries and regions result in inconsistent data acquisition, and critical data may not be effectively sensed. Issues such as information silos and application service silos can lead to incomplete data and application chains within digital service systems. Additionally, the uneven distribution of digital sensing and application infrastructure further complicates the integration of digital twin technology.

The second challenge pertains to legal and regulatory issues, integrating digital twin technology into land use planning requires supportive legal and regulatory frameworks. Existing legal systems may need to be reformed to accommodate this new technology, particularly in areas such as technical standards and norms, intellectual property protection, liability and accountability mechanisms, licensing and approval processes, the role of regulatory bodies, public engagement, and transparency.

The third challenge is related to privacy leakage. Digital twin models under collaborative learning paradigms pose potential risks of privacy breaches during the aggregation process. Specifically, semi-honest cloud/edge servers may collect information such as plaintext gradients and use advanced techniques, such as Generative Adversarial Networks (GANs), to reconstruct original training samples, thereby leading to data leakage.

3.2.5. *Summary of prospects*

This study thoroughly explores the potential of land use planning tools and reveals the challenges they may face. Additionally, the study identifies that technologies such as blockchain, VR/AR, quantum computing, and digital twins can interact synergistically with each other and with additional technologies. These advancements significantly enhance the practice of land use planning (see Fig. 2.).

We are currently in the era of Land Use Planning Tools 4.0, marked by the use of advanced smart tools. As the prospects outlined in this study come to fruition, we anticipate entering a new era. It is important to note that while these technologies may currently be in the initial application or early stages, significant disparities in institutional contexts, socio-cultural factors, and funding and technological resources across different countries and regions may pose considerable barriers and challenges to their practical implementation. Nevertheless, given the rapid pace of technological evolution and the robust trends in technological advancement, we

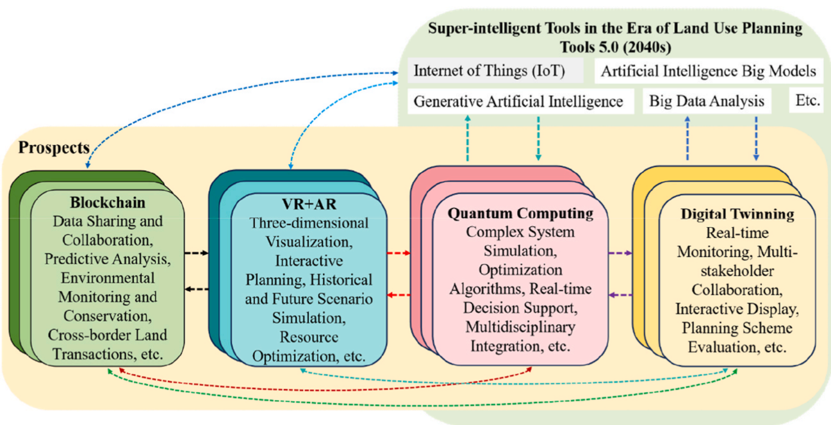

Fig. 2. The integration of multi-tools in the era of land use planning tools 5.0.

maintain that the future applications of these tools hold substantial potential. We anticipate that this transformation could occur within the next two decades, leading to revolutionary changes in land use planning.

This study forecasts that by the 2040s, we will transition into the era of Land Use Planning Tools 5.0, characterized by super-intelligent tools. By then, the advancements and prospects outlined in this study for land use planning tools are expected to have materialized.

4. Discussion

After reviewing the evolution of land use planning tools and outlining their future prospects, several key issues warrant further discussion. These are categorized as follows:

First, the evolution of land use planning tools encompasses not only technological aspects but also factors such as policies, governance, culture, and socio-economic dynamics. Second, our research reveals variations in the primary research subjects across different stages of the evolution of these tools. Third, we emphasize specific issues currently present in land use planning tools. Fourth, we categorize these tools into three distinct types.

(1) The evolution of land use planning tools in non-technological dimensions. Firstly, in terms of policy, there is an increasing emphasis on environmental protection, sustainable resource use, and social equity in land use planning policies, driven by growing concerns about sustainable development and climate change. The policy-making process increasingly prioritizes scientific evidence, public participation, and the balance of multiple interests. Secondly, in terms of governance, the governance of land use planning extends beyond the planning system to encompass broader initiatives, such as fiscal policies and tax systems. The concept of governance is expanding to include multi-scale governance that spans from international to local levels, as well as the involvement of public, private, and civil actors. Governance practices increasingly emphasize coordination across regions and scales, as well as the mediation of diverse interests and objectives.

Thirdly, at the cultural level, different cultures and societies profoundly influence the values and usage of land. The evolution of land use planning tools must take these cultural differences into account, as well as the unique perspectives and rights of indigenous peoples regarding land. For instance, indigenous worldviews are often not incorporated into formal land use planning systems. However, understanding the cultural and social significance of land is crucial in the planning process. Fourthly, at the level of socio-economic dynamics, changes such as population growth, shifts in economic structure, technological development, and household formation all impact land use planning. Planning tools must adapt to these changes while also seeking to guide and shape these dynamics through planning to achieve social and economic development goals.

In summary, the evolution of land use planning tools reflects a pursuit of more integrated, flexible, and sustainable land management approaches. These developments are evident not only in the updating of policies and governance models but also in the responsiveness to socio-cultural values and economic dynamics. Furthermore, the evolution of land use planning tools underscores the importance of interdisciplinary research and practice, as well as the mediation of objectives among diverse stakeholder groups.

(2) Distinct variations in the main research subjects of land use planning tools can be observed across different eras. During the Land Use Planning Tools 1.0 era, the focus was predominantly on agricultural land planning, as many countries had not yet undergone rapid urbanization [154]. Agricultural production land played a pivotal role in national economic development, highlighting the period's emphasis on agricultural planning. In contrast, the Land Use Planning Tools 2.0 era, marked by the post-World War II population boom and accelerated urbanization, especially in developed countries [155], saw a shift towards urban planning. Despite this, agricultural land planning remained significant, as evidenced by the initial development of GIS technology for agricultural applications. This period thus reflected a dual focus on both agricultural and urban land planning.

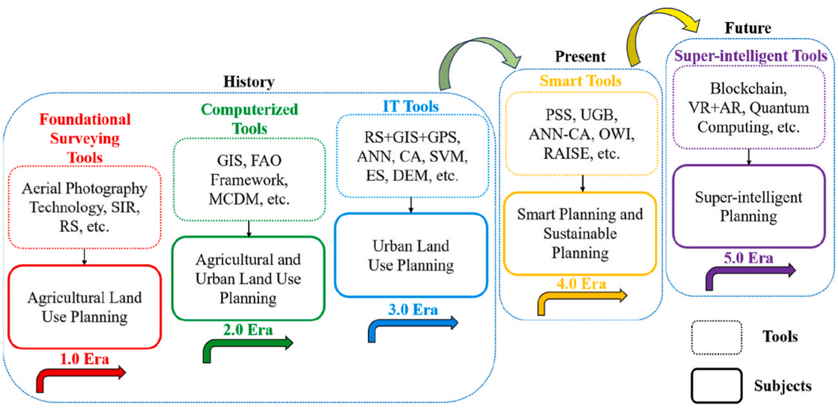

Fig. 3. Main research subjects of land use planning tools in different eras.

In the Land Use Planning Tools 3.0 era, global urbanization surged, although developed countries began to experience counter-urbanization [156]. This global trend shifted the core focus of land use planning to urban land management. By the Land Use Planning Tools 4.0 era, urbanization in key developed nations had reached a point of saturation [157]. This saturation led to the emergence of concepts such as smart city planning and sustainable development, thereby prioritizing smart and sustainable planning approaches during this period.

Looking ahead to the Land Use Planning Tools 5.0 era, advancements in technology, policy implementation, and increased societal awareness are expected to usher in a period characterized by super-intelligent tools. In this era, the primary focus is likely to shift towards super-intelligent planning, emphasizing sophisticated models and fostering a harmonious coexistence between humans and nature. Fig. 3 visually depicts the evolution of research subjects in land use planning tools across different eras.

(3) Current challenges in land use planning tools include several key issues. Firstly, the complexity and redundancy of planning systems—encompassing national, regional, and urban planning, among others—lead to difficulties in coordination and result in overall inefficiencies. Magidi et al. [29], studying the Mpumalanga Province in South Africa, found that current land use planning tools must manage increasingly large volumes of remote sensing data and products. Many of these tools involve cumbersome and slow preprocessing, processing, and post-processing workflows, reflecting the complexity and redundancy inherent in some current planning systems.

Secondly, these tools often exhibit inadequate adaptability, lacking the flexibility necessary to address rapidly evolving land use scenarios. For example, Mustafa et al. [158], focusing on the Wallonia in Belgium, found that current land use planning tools such as logistic regression and cellular automata are based on an implicit assumption that human behavior remains unchanged within the considered time frame. This assumption limits the tools' ability to simulate long-term predictions, highlighting a deficiency in adaptability. Additionally, the study noted that another land use planning tool, the agent-based model, often requires extensive data, which restricts its capacity to simulate large research areas, demonstrating a lack of flexibility in current tools.

Thirdly, public participation in land use planning remains inadequate. The limited involvement of the public hampers the comprehensive consideration of all stakeholder interests, thereby complicating the implementation of planning initiatives. Rönkkö and Herneoja [159], studying Helsinki and Kuopio in Finland, found that current land use planning faces certain challenges regarding public participation. In some areas, land use planning inadequately involves and coordinates urban management departments, policymakers, frontline staff, and citizens, resulting in insufficient public engagement. In certain regions, the perspectives on public services have been overshadowed by competing interests.

Therefore, in addition to enhancing the technical performance of planning tools, it is crucial to strengthen the legal and regulatory framework for public participation. Legislation should clearly define the rights and responsibilities of the public, ensuring their rights to information, participation, and oversight in land use planning. On this basis, effective mechanisms for public participation must be established, allowing for direct involvement in discussions and decision-making processes through announcements, hearings, and consultations, thereby increasing the transparency of public engagement. Additionally, feedback and oversight mechanisms should be implemented to ensure that public opinions and suggestions receive effective responses and that the planning implementation process is monitored, thereby guaranteeing the rationality and fairness of the planning outcomes.

Fourthly, there is a notable deficiency in the emphasis on sustainable development. This shortfall is particularly evident in areas such as farmland protection, industrial land transformation and upgrading, land pollution control, and ecological restoration. Sejati et al. [160], analyzing the city of Balikpapan in Indonesia, discovered that many GIS-based land use planning tools exhibit insufficient attention to sustainability. These tools often fail to adequately address long-term planning for areas such as industrial land transformation and ecological restoration. Additionally, paid software provided by web GIS service providers is extremely expensive and requires annual license renewals, imposing significant costs for long-term sustainable land use planning and thereby affecting the overall sustainability of land use planning efforts.

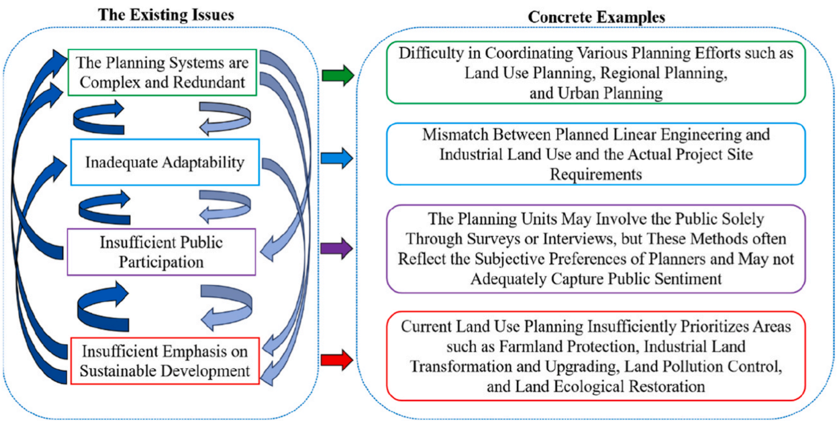

Fig. 4. The current challenges within the process of land use planning.

Moreover, these issues are interconnected, hindering improvements in land use planning efficiency. Fig. 4 visually illustrates these challenges.

(4) Specific Types of Current Land Use Planning Tools. Based on the evolution of land use planning tools, they can be classified into three main categories. The first category encompasses tools for land use quantity structure planning. This category primarily includes optimization tools grounded in mathematical analysis [161,162], predictive tools based on statistical inference [163, 164], and bio-inspired algorithmic tools [165].

The second category comprises tools for land use spatial layout planning. This includes tools based on systemic spatial causal relationships [166,167], spatial optimization and configuration tools informed by suitability assessments and bio-inspired optimization techniques [168,169], and spatial optimization zoning tools designed to address uncertainties in spatial management [170, 171].

The third category includes tools for the coordinated coupling of land use quantity structure and spatial layout planning. These tools primarily employ dual coupled "Top-down" and "Bottom-up" approaches, encompassing both loosely-coupled tools [172,173] and tightly-coupled tools [174,175].

Table 2 provides a detailed illustration of the specific types of current land use planning tools.

5. Conclusions

This study employs a comprehensive literature review and data collection methods to systematically elucidate the evolution of land use planning tools. Building on this foundation, it provides a prospective analysis of future developments in these tools. The study not only clarifies the historical progression of land use planning tools but also offers guidance for advancing sustainable and efficient land use practices. Specifically, the research findings of this paper are as follows.

(1) Since the 20th century, the evolution of land use planning tools has progressed through four distinct stages: 1.0 to 4.0. Each stage is marked by its representative tools: Foundational Surveying Tools (1900s–1950s), Computerized Tools (1960s–1980s), Internet Technology Tools (1990s–2000s), and Smart Tools (2010s to the Present).
(2) Current land use planning tools face several limitations, including complex and redundant planning systems, inadequate adaptability, insufficient public participation, and a lack of emphasis on sustainable development. These issues necessitate urgent optimization.
(3) By the 2040s, land use planning tools are anticipated to evolve into the 5.0 era, characterized by super-intelligent tools. Emerging technologies such as blockchain, VR + AR, quantum computing, and digital twins are expected to be more widely integrated.

CRediT authorship contribution statement

Yong Liu: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Conceptualization. **Walter Timo de Vries:** Writing – review & editing. **Guanghong Zhang:** Writing – review & editing, Supervision. **Xufeng Cui:** Writing – review & editing, Conceptualization, Project administration.

Table 2
Specific types of current land use planning tools.

Types	Characteristics	Tools	Literature
Tools for Land Use Quantity Structure Planning	Optimization Tools Based on Mathematical Analysis	General Linear Programming Tools; Fuzzy Linear Programming Tools	[161, 162]
	Prediction Tools Based on Statistical Inference	Markov Prediction Tools; Neural Network Prediction Tools	[163, 164]
	Bio-inspired Algorithm Tools	Genetic Algorithms	[165]
Tools for Land Use Spatial Layout Planning	Tools Based on Systemic Spatial Causal Relationships	Land Use Change Spatial Simulation Tools; CLUE-S Analysis Tools	[166, 167]
	Spatial Optimization and Configuration Tools Grounded in Suitability Assessment and Bio-inspired Optimization	Particle Swarm Optimization; Ant Colony Optimization Spatial Configuration Tools	[168, 169]
	Spatial Optimization Zoning Tools Addressing Uncertainties in Spatial Management	Target Planning-Simulated Annealing Zoning Tools; Multi-objective Particle Swarm Zoning Tools	[170, 171]
Tools for the Coordinated Coupling of Land Use Quantity Structure and Spatial Layout Planning	Loosely-coupled Tools	Markov-CA; Logistic-Markov	[172, 173]
	Tightly-coupled Tools	Multi-objective Ant Colony Optimization; Multi-agent Tools	[174, 175]

Data availability statement

Data will be made available on request.

Ethics declaration

Informed consent was not required for this study because it does not involve detailed privacy information of each person, nor does it involve biomedical research on them.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:Dr. Xufeng Cui is currently serving as an Associate Editor for Heliyon. While the editorial process for this manuscript is handled independently and without his involvement in the review or decision-making, his editorial role at the journal is disclosed for transparency.

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