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Review

The Application of Genetic Algorithm in Land Use Optimization Research: A Review

Xiaoe Ding [1], Minrui Zheng [2,*] and Xinqi Zheng [1,3]

[1] School of Information Engineering, China University of Geosciences (Beijing), Beijing 100083, China; dingxiaoe@cugb.edu.cn (X.D.); zhengxq@cugb.edu.cn (X.Z.)
[2] School of Public Administration and Policy, Renmin University of China, Beijing 100872, China
[3] Technology Innovation Center for Territory Spatial Big-Data, MNR of China, Beijing 100036, China
* Correspondence: minruizheng@ruc.edu.cn

Abstract: Land use optimization (LUO) first considers which types of land use should exist in a certain area, and secondly, how to allocate these land use types to specific land grid units. As an intelligent global optimization search algorithm, the Genetic Algorithm (GA) has been widely used in this field. However, there are no comprehensive reviews concerning the development process for the application of the Genetic Algorithm in land use optimization (GA-LUO). This article used a bibliometric analysis method to explore current state and development trends for GA-LUO from 1154 relevant documents published over the past 25 years from Web of Science. We also displayed a visualization network from the aspects of core authors, research institutions, and highly cited literature. The results show the following: (1) The countries that published the most articles are the United States and China, and the Chinese Academy of Sciences is the research institution that publishes the most articles. (2) The top 10 cited articles focused on describing how to build GA models for multi-objective LUO. (3) According to the number of keywords that appear for the first time in each time period, we divided the process of GA-LUO into four stages: the presentation and improvement of methods stage (1995–2004), the optimization stage (2005–2008), the hybrid application of multiple models stage (2009–2016), and the introduction of the latest method stage (after 2017). Furthermore, future research trends are mainly manifested in integrating together algorithms with GA and deepening existing research results. This review could help researchers know this research domain well and provide effective solutions for land use problems to ensure the sustainable use of land resources.

Keywords: genetic algorithm; land use optimization; bibliometric analysis; evolutionary process

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1. Introduction

Land resources are the foundation for human living and survival and provide critical materials and space for human development [1,2]. Since the 20th century, the world's land use patterns have rapidly changed due to the rapid increase in the population, urbanization, and industrialization [3,4]. Therefore, various land use planning projects have been implemented in different countries. To reasonably plan land use and allocate the limited land resources effectively, while meeting the requirements of human production and life, has become a critical issue [5,6]. In the process of land use planning, in order to resolve multiple conflicting interests as reasonably as possible, decision makers must not only consider which land use types to choose, but also think about which land units are appropriate to allocate these types of land use [7]. While optimizing the allocation of land use, depending on the nature of the region, there are both win–win and conflicts in the optimization goals. How to improve the benefits of social services and the ecological environment in the process of pursuing economic growth is the key to promoting the efficient and sustainable use of land resources. Therefore, the optimal allocation of land use is also a typical multi-objective optimization problem [8]. The Genetic Algorithm (GA), as one of global optimization algorithms, can be used to handle multi-objective optimization problems. GA was proposed and developed by Professor John Holland from the University of Michigan in the late 1950s and early 1960s [9–11]. With high versatility and strong robustness [12], GA shows its ability to achieve better performance than other algorithms in solving highly complex spatial problems [13–16].

Using the global optimization search ability of GA, it is possible to build the optimal allocation model of land use to improve the effective method for land use planning [17]. Scholars have obtained illuminating results in the research of GA for land use optimization (GA-LUO). Some focus on improving the algorithm principle to generate a variety of high-quality multi-objective optimization schemes. For example, Cao [18] proposed a boundary-based fast GA for solving multi-objective LUO problems under the idea of sustainable development, and achieved good results. Yuan [19] integrated a multi agent system (MAS) that simulates the behaviors of land use stakeholders with regard to their choices of specific locations with GA that simultaneously evaluates and optimizes land use configurations to meet various regional development objectives. The results showed that the performance of the coupled model is superior to a pure GA model. The optimal configuration promoted sustainable regional land use development from the local scale to the regional scale. J. Porta [20] used a high performance GA to make land use plans in consideration of land suitability and shape rules. This work focused on implementing and analyzing different parallel paradigms: multi-core parallelism, cluster parallelism, and the combination of both. Some tests were performed that show the suitability of GA to land use planning problems. Some studies combine GA with other intelligent algorithms to compensate for drawbacks, as GA is easy to integrate into local optimal solutions. For example, Julian [21] integrated artificial neural networks (ANN) and GA to investigate urban land use patterns from voluntary geographic information. Zhou [22] and Javadi [23] proposed a hybrid optimization algorithm combining neural network and GA, in which neural network was used to improve the convergence performance of GA when searching for global optimality. These valuable research results show the ability of GA in handling the multi-objective land use optimization issue. However, there are little studies that comprehensively analyze the research history of GA-LUO, which can provide a powerful reference for subsequent scientific research.

Bibliometrics is an integrated method for quantitatively and objectively analyzing large amounts of previous studies in a research field using mathematical and statistical methods [24,25]. In recent years, the bibliometric analysis has been widely used in many fields, such as global research on climate change, remoting sensing, and artificial intelligence, etc. [26–28]. However, the use of bibliometric analysis in reviewing previous studies in the field of GA-LUO is not enough.

In fact, a comprehensive literature review on the issue of GA-LUO will contribute to a better understanding of current research status, research characteristics, and evolution of the field; therefore, it is essential to explore the issues of GA or LUO further. Compared with conventional literature reviews, bibliometric analysis can avoid the influence of the analyst's subjectivity on the research conclusions, then enhancing the objectivity and credibility of the research conclusions. Thus, a bibliometric-based literature review conduct in this study to review the field of GA-LUO, retrieved from 1995 to 2020. Our objectives are: (1) to focus on the research hotspots in various academic groups and active study regions; (2) to identify the progress of research evolution in different stages; and (3) to give the future recommendations over the last 25 years by reading literature more carefully.

2. Data Sources

Web of Science (WoS) is one of the most comprehensive databases, providing a good basis for the reliability of the literature data. In the core dataset of WoS, we selected "genetic algorithm" and "land use" as key words, "All document types" as document type, and "1995–2020" as the time span; then we obtained 1154 articles including the author, title, abstract, keywords, and citations. Figure 1 shows the annual statistical results of the literature.

Before 2000, the annual volume of articles was less than 10, and it showed a slow upward trend in 2000–2009. The number of articles in 2010–2012 increased rapidly, reaching 74 in 2012. Although the number in 2016 reduced slightly, the overall trend is rising. In 2017, more than 90 articles were published. In general, the GA-LUO research showed an overall upward trend.

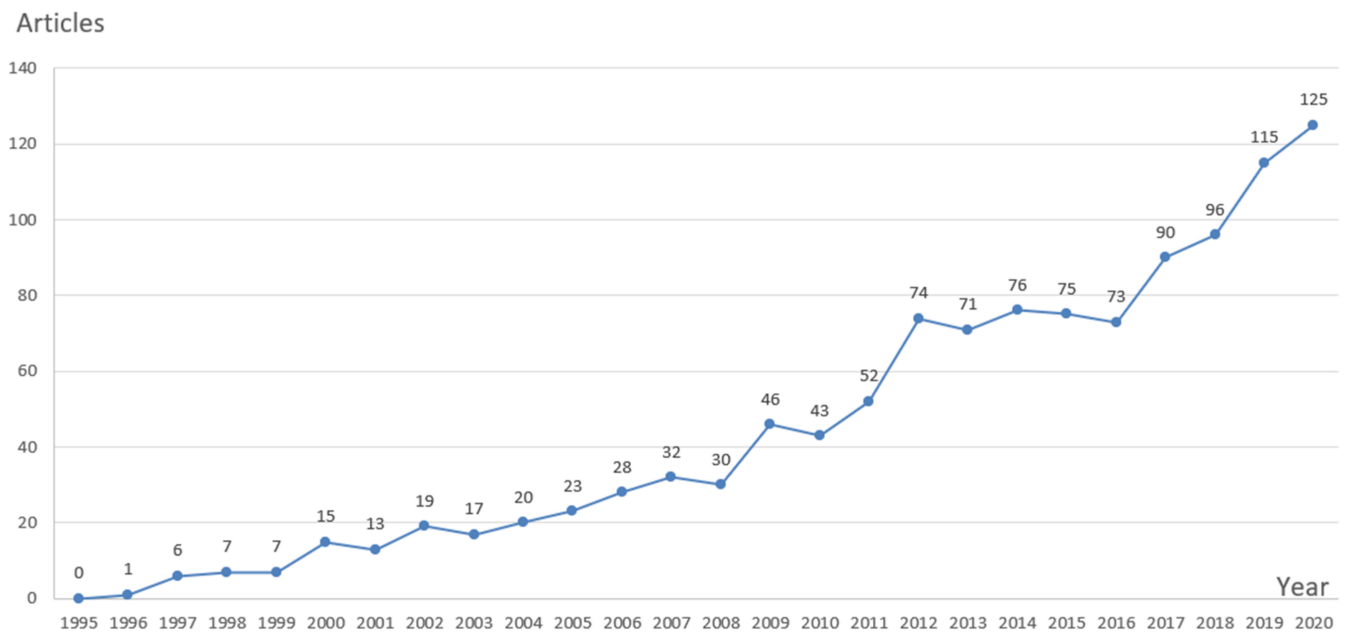

Figure 1. Distribution of the literature in the timeline.

3. Methods

3.1. Bibliometric Analysis

The bibliometric analysis is a comprehensive literature review method. It uses mathematical, statistical, and visual methods to summarize research trends in scientific publications to support the quantitative analysis of scientific knowledge. On the basis of traditional bibliometrics, more and more researchers use visualization tools to study the development in a certain domain [29]. This study framework is shown in Figure 2. CiteSpace [30] is one of the most commonly used software in bibliometric analysis. It is a knowledge mapping tool with powerful co-citation analysis capabilities. It can draw a multi-dimensional, time-sharing map based on citations, and present the evolution process of a knowledge domain on a citation network map [31]. In this study, we use CiteSpace to analyze the knowledge maps of cooperative features, and conducted corresponding data mining on the cited literature and citations with the themes of "land use" and "GA" over a 25-year period.

Besides CiteSpace, HistCite, which means citation history, is a software for analyzing citation graphs. The co-occurrence relationship of CiteSpace references is de-clustered to obtain different research topics. Histcite directly uses the relationship between citing documents and references to draw the map, which is time-sensitive. It can also perform detailed analysis of highly cited documents in the research field. It can graphically show the relationship between different documents in a certain field. So, we could quickly illustrate a field's development history and locate its most important literature using HistCite. In this paper, HistCite was used to locate the top 10 most cited articles on GA-LUO.

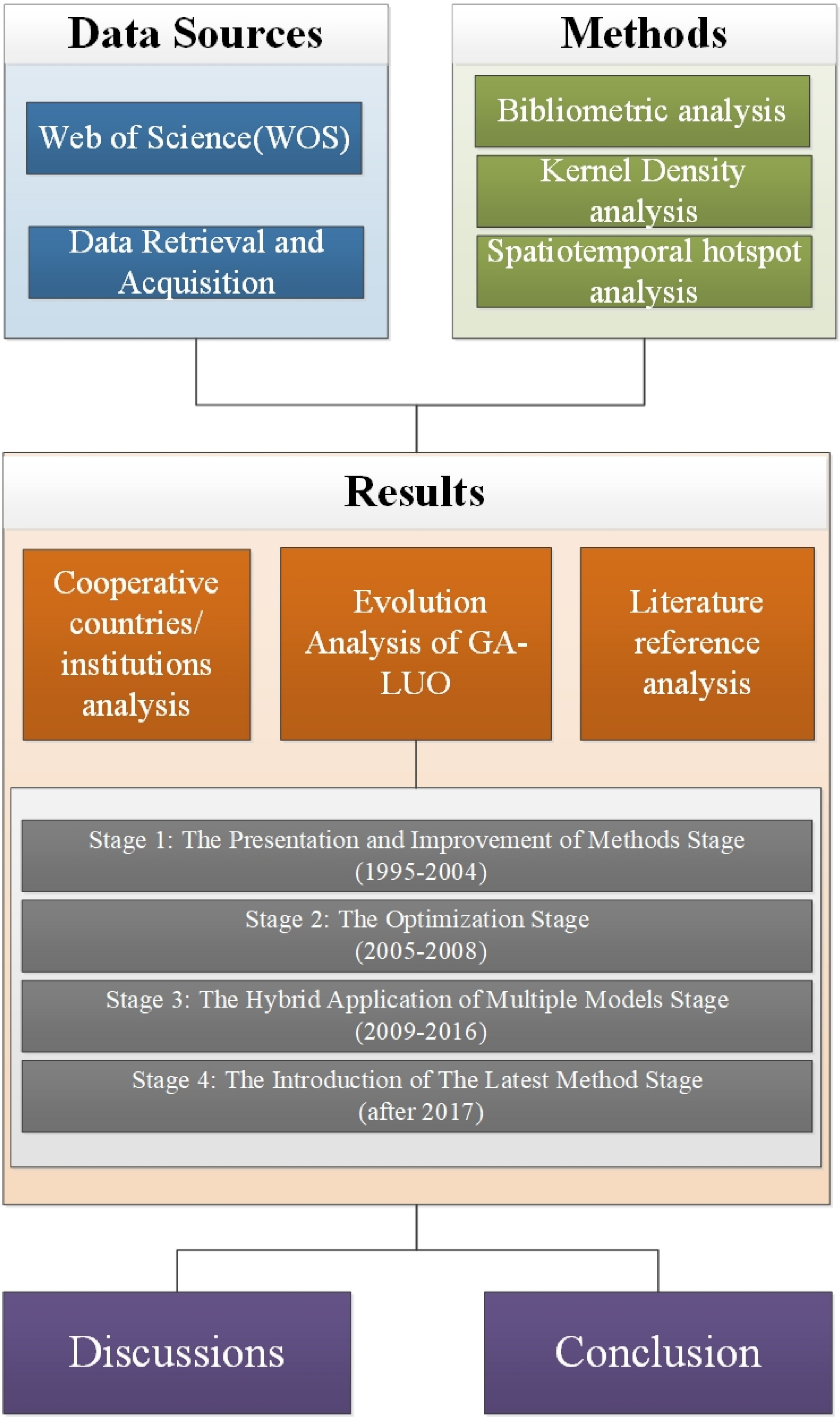

Figure 2. The framework of this research.

Among the commonly used literature information analysis software, Citespace has an advantage in visual effect display. Histcite can easily add documents that are missed in search process, thereby making the database completer and more credible, but it is relatively weak in terms of visualization. Therefore, this article used a combination of Citespace and Histcite software. Nevertheless, traditional literature reading methods are still indispensable. Reading and collating hot literature was also an important method in this article.

3.2. Kernel Density Analysis

Kernel density analysis is a typical spatial hotspot analysis method. It assumes that there is a density value at any point in the study area; a smooth surface is constructed by calculating the density around the element in order to generate the transition from a discrete object model to a continuous field model. Roughly speaking, the purpose of kernel density analysis is to obtain an estimated value of each point of the density function that can approximate the data distribution, so as to show the distribution of data. Therefore, this method was used to visualize the global geographic distribution of the authors. In this article, BibExcel was used to geo-decode the authors' locations in order to obtain the latitude and longitude of publication cities. Then, ArcMap 10.6 was used to perform kernel density analysis and display the geographic distribution of the authors.

Let $(x_1, x_2, \ldots, x_n)$ be the spatial coordinates of the city where authors published the literature. The kernel density estimate can be calculated as follows:

$$\hat{f}_h(x) = \frac{1}{n}\sum_{i=1}^{n} K_h(x - x_i) = \frac{1}{nh}\sum_{i=1}^{n} K(\frac{x - x_i}{h}) \tag{1}$$

where $K(x)$ is the kernel function represented by the Gaussian normal distribution, and h is the smoothing parameter of the kernel function, usually called bandwidth.

The literature from WoS was sequentially formatted by BibExcel, according to the steps of extracting geographic information, standardization processing, data selection and geographic visualization. Using the data of the authors' cities as the point data, we used kernel density analysis to obtain authors' global geographical distribution.

3.3. Spatiotemporal Hotspot Analysis

We further used spatiotemporal hotspot analysis to detect the cold and hot spots, and to evaluate their changing trends over time. Getis-Ord Gi* statistical model is used to obtain the intensity of feature clustering. Then, the trend of time series changes of cold and hot spots can be analyzed based on the Mann-Kendall trend analysis method. Using the spatiotemporal cube model to incorporate spatiotemporal relationships into spatial hotspot analysis, we could evaluate trends of cold and hotspots over time. By identifying hot or cold spots with new, enhanced, reduced, continuous, oscillating, or dispersed trends, we could mine spatiotemporal hotspot distribution patterns and rules about GA-LUO. Based on the geographic visualization [32] of author distribution, we further explored the spatiotemporal pattern of the published literature. From the perspective of spatiotemporal cognition and mathematical statistics theory, we quantitatively analyzed and classified the spatiotemporal trends of the literature and visualized the results.

In scientific exploration, scholars are most concerned about discovering the topics and scientific documents that they are most interested in from the massive literature in their research fields. From these literatures, we can find the most active research hotspots, frontiers, and future development trends, and have a clear understanding of the development process of the research field. Considering that the use of a single quantization method may cause errors, thus, we involve multiple methods to reduce experimental bias and improve the references of the research [33–35].

4. Results

4.1. The Results of Cooperative Features

4.1.1. Cooperative Countries Analysis

In CiteSpace, we use centrality (0–1) to measure the importance of a research object [36], and its measurement is related to the number of occurrences of two countries or institutions in the same article. The higher the centrality, the more active the country or institution is, indicating that they play a more important role in cooperative relationships. Among the top 15 cooperative countries in centrality (Figure 3, Table 1), China has the highest frequency with 274 articles, followed by the USA with 228 articles, which was the first country to conduct relevant research. There were 63 articles in Iran and 62 articles in India, ranking third and fourth, respectively. The number of articles published in England was 34, ranking seventh, but the centrality was 0.21, following China and USA, indicating that England is an active country in this research field and has great communication with other countries. China's centrality was 0.28, indicating that China also plays a very important role in cooperative research.

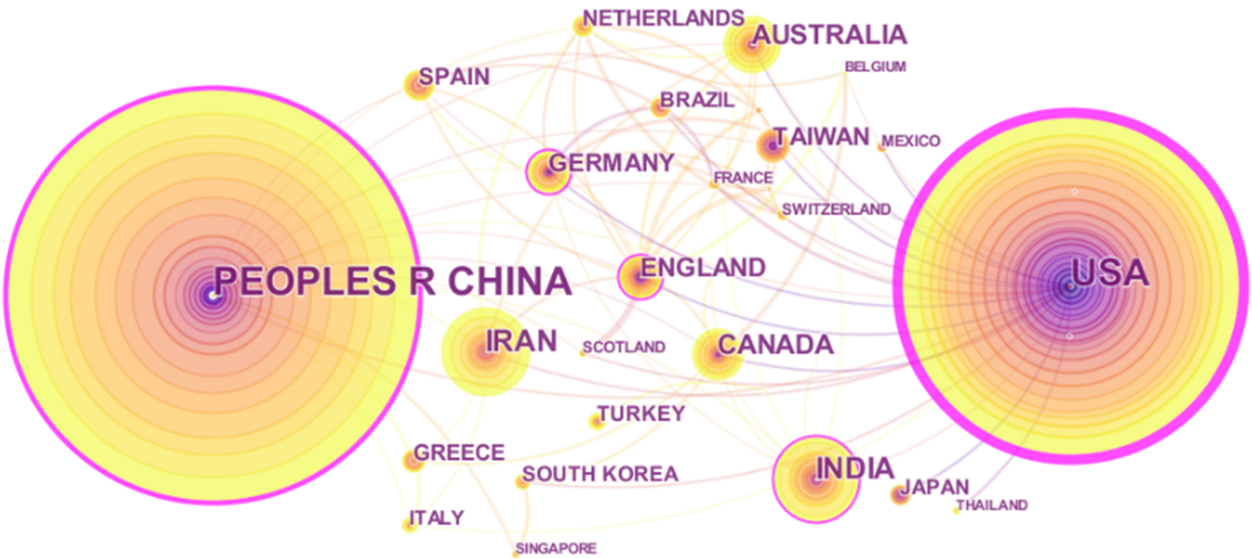

Figure 3. The knowledge map of cooperative countries.

As shown in Figures 4 and 5, the main spatial clusters of authors are in the USA, Europe, and East Asia. In the USA and China, most of the authors are from the east and coastal areas instead of west. In East Asia, the authors are mainly concentrated in China, Japan, and South Korea. The clusters of European authors are mainly located in England, Spain, Germany, Italy, Greece, and Netherlands. In West Asia, there are clusters in Iran and Turkey. There are also spatial clusters of authors distributed in India and Australia. Brazil is an exception: the distribution of authors does not form a cluster, although there are many authors with productive output. Figure 5 shows the spatiotemporal hotspot analysis results. Emerging hot spots are concentrated in Europe, India, Southeast Asia and Australia. There are continuous hotspots in the northeastern USA, eastern China, and western Europe, indicating that these areas have played an important role in this research over a long period of time; Central America, Central China, and Southeast Asia are fluctuating hot spots, indicating that although there are many related studies, they have not become long-term hot spots.

Table 1. The frequency and centrality of cooperative countries.

Frequency	Centrality	Country
274	0.28	China
228	0.64	USA
63	0.09	Iran
62	0.16	India
42	0.12	Canada
41	0.11	Australia
34	0.21	England
32	0.20	Germany
27	0.03	Spain
21	0.02	Greece
19	0.07	Netherlands
18	0.00	Japan
18	0.01	Brazil
16	0.00	Turkey
15	0.03	Korea

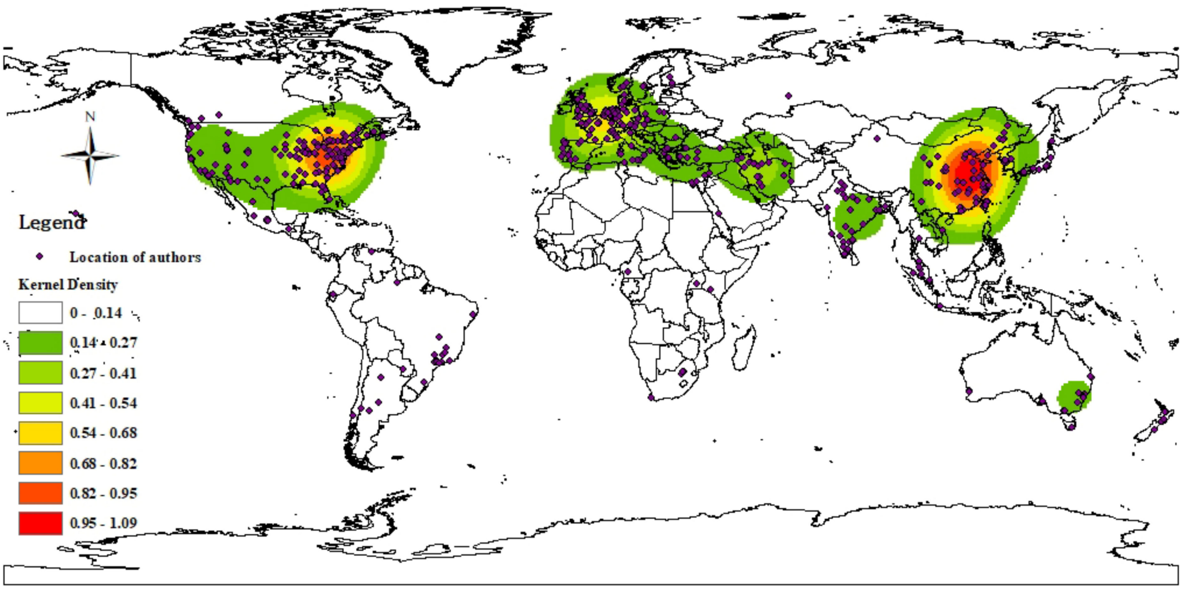

Figure 4. Authors' geographical distribution by kernel density estimation.

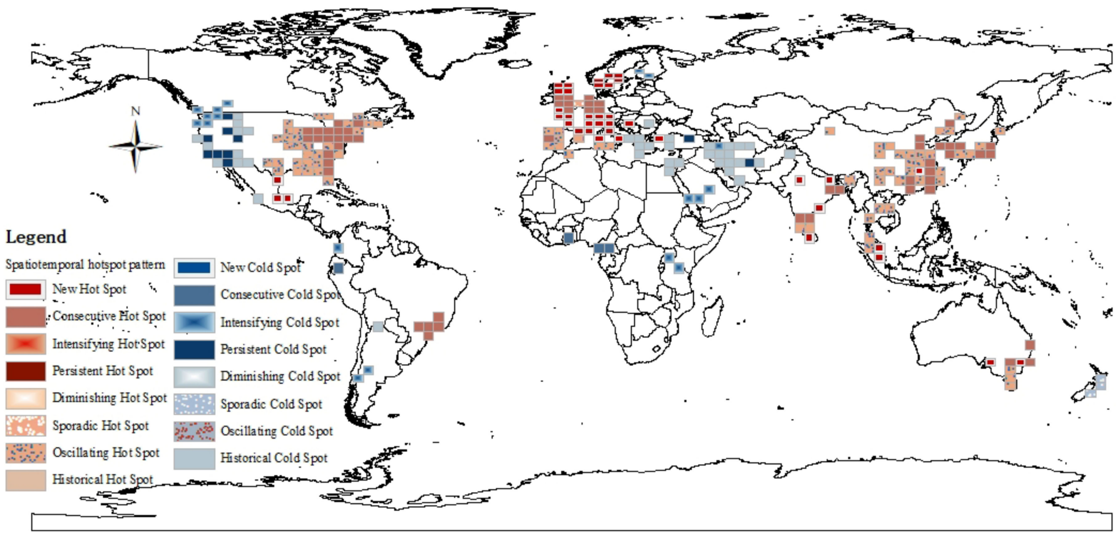

Figure 5. Distribution pattern of spatiotemporal hotspot trends.

4.1.2. Institution Analysis

Table 2 shows the centrality of the cooperative institutions. The Chinese Academy of Sciences has the highest level of activity, with the largest number of documents and the highest centrality of 0.39. Wuhan University published 20 articles, but its centrality is 0.08, indicating that this research institution pays more attention to internal communication and lacks communication with other institutions. Following Wuhan University, Tehran University, Aristotle University, the Chinese Academy of Sciences, and Purdue University have all issued more than 10 articles, but their centrality is still low at less than 0.1, indicating that they have little influence on other related institutions around the world. In general, in order to strengthen research in this field, it is necessary for institutions to emphasize communication and cooperation.

Table 2. The frequency and centrality of cooperative institutions.

Frequency	Centrality	Institution
43	0.39	Chinese Academy of Sciences University
20	0.08	Wuhan University
18	0.05	University of Tehran
12	0.00	Aristotle University of Thessaloniki
11	0.10	Purdue University
10	0.03	K.N.Toosi University of Technology
9	0.05	Texas A & M University
9	0.02	University of Toronto
9	0.06	Chinese University of Hong Kong
8	0.02	Seoul National University
7	0.07	Indian Institute of Technology

Figure 6 shows the top 15 research institutions in the last 5 years (2015–2020). Considering the publications within these 5 years deeply, we find that among the 456 articles retrieved, 21 were published by the Chinese Academy of Sciences, ranking first. Among the secondary institutions of the Chinese Academy of Sciences, the number of papers published by the Institute of Geographic Sciences and Natural Resources Research is the largest. The researchers of this institution focus on using a variety of different intelligent algorithm models to optimize land use allocation. Pan et al. [37] developed a land use intensity-restricted multi-objective spatial optimization model using GA with more realistic patch size initialization, novel mutation, elite strategies, and objectives balanced via nominalizations and weightings. Huang et al. [38] coupled a spatial layout evaluation module, system dynamics models, and the multi-agent system to establish the rural settlement consolidation model. The outcomes indicate that the model can improve land use suitability and solve the village hollowing-out issue. In addition, Huang et al. [39] coupled the multi-agent system (MAS) that contains land use planning knowledge with the search iteration mechanism in the shuffled frog leaping algorithm (SFLA) and rebuilt the local optimization behavior of the SFLA. The results showed that the model could relieve land use conflicts between different decision-making agents and realize the optimum allocation of regional land use in terms of both spatial structure and quantity under multiple optimization goals and restrictions. Yang et al. [40] built a knowledge-informed and pareto-based artificial bee colony optimization algorithm for multi-objective land use allocation. We believe that these authors and institutions contribute the most in the study of social commerce.

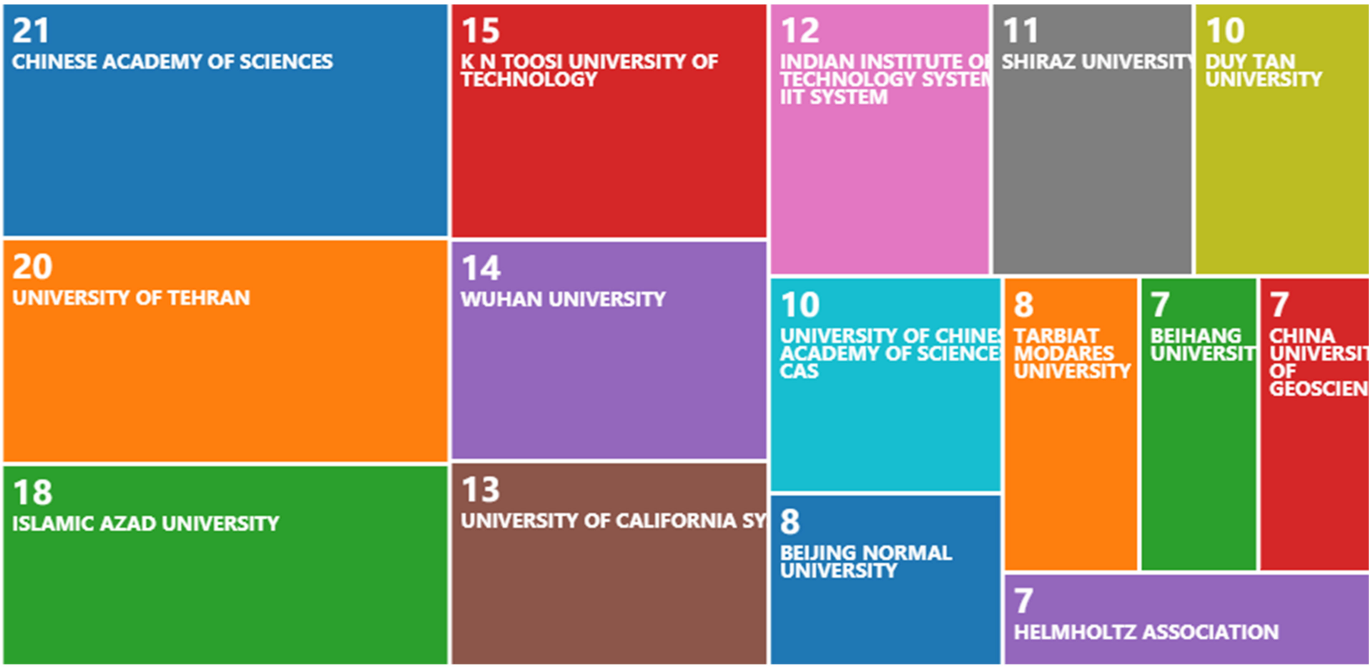

Figure 6. Top 15 research institutions in the last 5 years (2015–2020).

4.2. Literature Reference Analysis

In HistCite, the number of local citations (Local citation score, LCS) reflects the extent to which the literature is focused on the field. To analyze more specific research directions, highly cited articles were ranked and analyzed. Co-citation analysis is an important method in bibliometrics to identify articles that are regularly cited and to investigate any internal relationships they have. The top 10 LCS in GA-LUO research over the last 25 years are listed in Table 3. These highly cited articles were varied in type, but what they had in common was that were widely cited because of their great academic value.

Table 3. The top 10 literature of LCS and their related attributes.

No.	Year	Author	Title	Source	LCS
1	2004	Stewart, T.J.	A genetic algorithm approach to multi-objective land use planning	Computers & Operations Research	66
2	1999	Balling, R.J.	Multi-objective urban planning using genetic algorithm	Journal of Urban Planning and Development-Asce	34
3	2011	Cao, K.	Spatial multi-objective land use optimization: extensions to the non-dominated sorting genetic algorithm-II	International Journal of geographical information science	32
4	2012	Cao, K.	Sustainable land use optimization using Boundary-based Fast Genetic Algorithm	Computers, Environment and Urban Systems	30
5	2012	Liu, X.P.	A multi-type ant colony optimization (MACO) method for optimal land use allocation in large areas	International Journal of Geographical Information Science	24
6	2007	Duh, J.D.	Knowledge-informed Pareto simulated annealing for multi-objective spatial allocation	Computers, Environment and Urban Systems	22
7	2013	Porta, J.	High performance genetic algorithm for land use planning	Computers, Environment and Urban Systems	22

Table 3. *Cont.*

No.	Year	Author	Title	Source	LCS
8	2013	Liu, X.P.	Combining system dynamics and hybrid particle swarm optimization for land use allocation	Ecological Modelling	20
9	2013	Liu, X.P.	An improved artificial immune system for seeking the Pareto front of land-use allocation problem in large areas	International Journal of Geographical Information Science	19
10	2002	Xiao, N.C.	Using evolutionary algorithms to generate alternatives for multi-objective site-search problem	Environment and Planning	18

At a global scale, the hotspots of the mainstream literature concentrate on multi-objective land use planning, land use optimization, and hybrid model research. These three aspects cover most of the research directions of the GA-LUO study, which deserve to be valued. Among the articles in the top 10 most cited, ranked first in LCS is Stewart's method of GA for multi-purpose land use planning in 2004 [41]. The second highest cited is multi-objective urban planning based on GA, proposed by Balling in 1999. The two authors described the same spatial planning problem. Optimizing land use allocation is a challenging task, as it involves multiple stakeholders with conflicting objectives. Due to the constraints of various conflicting management objectives, it is a complex nonlinear and multi-objective problem. In total, 5 of the 10 articles mentioned multi-objective optimization. To solve this problem more efficiently, more research studies concentrated on improving the performance of GA itself, such as the improvement of non-dominated sorting GA [20]. As GA itself also has certain limitations, more and more scholars have constructed hybrid models to improve computing efficiency. For example, No. 5 [42] presents a new ant colony optimization algorithm by incorporating multiple types of ants for solving complex multiple land use allocation problems. The experiments results have demonstrated that the proposed model was an efficient and effective optimization technique for generating optimal land use patterns. No. 8 [43] proposes a novel model that integrates system dynamics (SD) and hybrid particle swarm optimization (HPSO) for solving land use allocation problems in a large area. The experiments demonstrated the proposed model had the ability to reflect the complex behavior of land use system at different scales, and can be used to generate alternative land use patterns based on various scenarios.

4.3. Evolution Analysis of GA-LUO

Through the results of the above three sections, a preliminary understanding of the current research situation in the GA-LUO domain was described. Keywords, as the label of research literature, can highlight the content of research, and if the same keywords appear, it shows that there is a correlation between literature [44]. Furthermore, over a period of time, the change in the number of co-occurring keywords can explain the degree of research activity and the number of research hotspots around this domain [45].

In CiteSpace [46], setting the time period to "1995–2020", selecting "keyword" as the node type and "TOP50" as the threshold, we obtained a co-occurrence map of keywords, including 712 nodes and 2383 links. We then generated the time-zone map (Figure 7). In the keyword time-zone map obtained by running the software, each point represents a keyword; the keywords shown in the figure were the first high-frequency words used, which was a new hot spot in the research direction during each period. Therefore, according to the number of keywords that appear for the first time in each time period, we divided the development process of GA-LUO into four stages in this article.

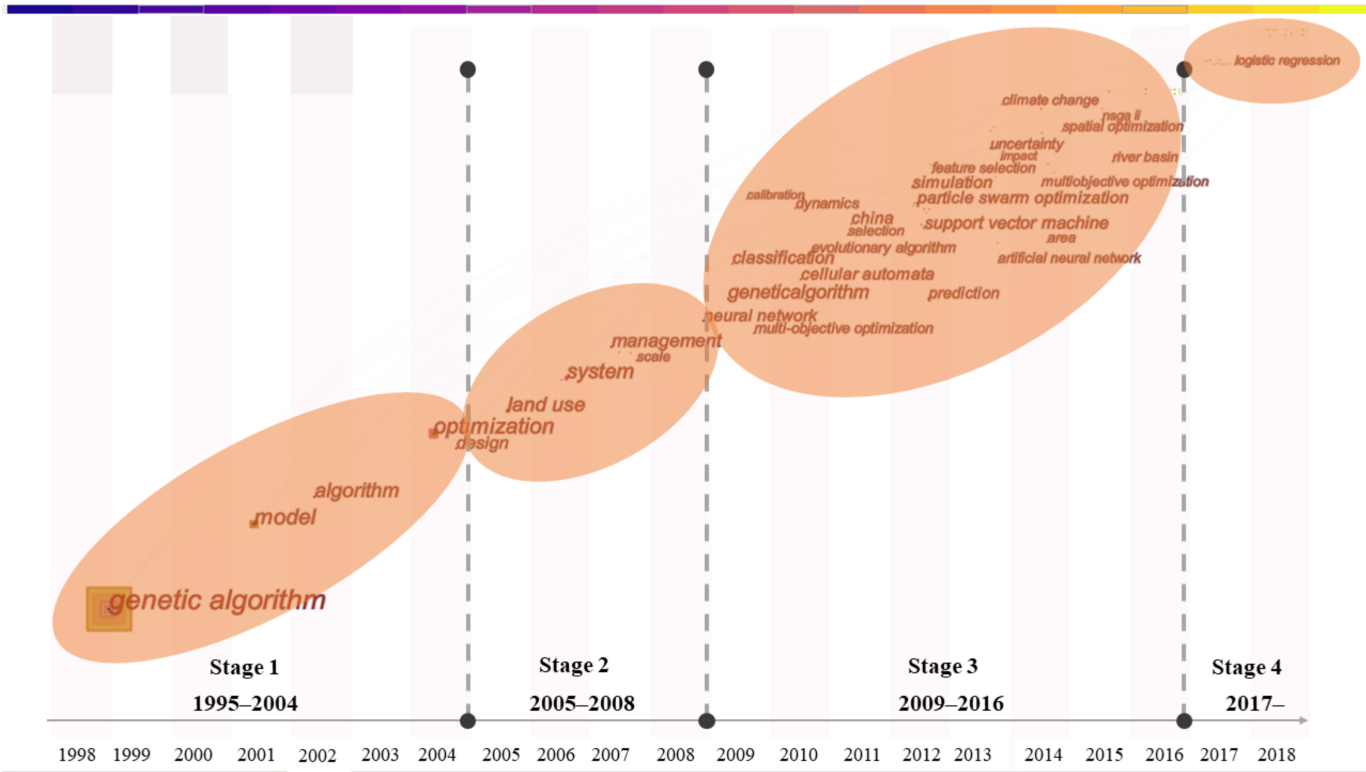

Figure 7. The time-zone map of keywords from 1995 to 2020. The time corresponding to each keyword is the time when the keyword appears in document for the first time; the size of the node represents the frequency of occurrence of the keyword, and the larger the node, the higher the frequency of occurrence of the keyword.

From 1995 to 2004, a new keyword appeared every 2 to 3 years on average, indicating that GA-LUO research progress in this period was relatively slow and still in its infancy. From 2005 to 2008, new keywords appeared almost every year, indicating that this research area has gradually attracted attention. From 2009 to 2016, new keywords showed explosive growth, and there was not much difference in the number of related documents. In this period, research enthusiasm reached its highest level. After 2017, few new keywords appeared, indicating that research has entered a stage of stable development, and scholars mostly conduct deeper knowledge mining.

Stage 1: The Presentation and Improvement of Methods Stage (1995–2004)

This is the preliminary research stage in which GA was applied to land use and attempted to use modeling methods. The keywords at this stage are mainly related to land use [47,48]. In earlier years, there was no major improvement in GA. Since 2003, traditional intelligent algorithms such as probabilistic neural networks combined with GIS [49] technology and expert systems have been introduced into GA in land use. Dong [50] proposed a method for optimal allocation of land use spatial structure based on multi-objective GA in 2003. By using the inherent parallel mechanism of GA and its global optimization characteristics, this method effectively solved the problem of arranging land use quantity structure to specific land units. Balling [51] used an elitist GA to find a diverse non-dominated set of optimal future zoning and street plans for two high-growth cities in the USA. The result shows that the algorithm is general enough to be applied to other cities and metropolitan regions.

Stage 2: The Optimization Stage (2005–2008)

More research directions emerged in the Optimization Stage. After nearly a decade in the Presentation and Improvement of Methods Stage, GA-LUO research was no longer limited to single algorithm. At this stage, GA was mainly used for land optimization and management. The keywords are “optimization”, “design”, “land use”, and “system”. Researchers provided efficient management patterns through establishing different systems. However, there is no major change in the application mechanism of GA. Guo [52] used the global optimization search ability of GA to adopt two-dimensional matrix coding corresponding to a land use status map. In 2005, Liu [53] constructed a land use structure optimization model with multi-objective linear programming that takes social, economic, and ecological benefits into account, providing a useful reference for later land use planning. As the development of computer technology has not yet reached the period of vigorous development, intelligent algorithms have not been widely used. The research during this period is mainly the application of some traditional algorithms. Since large amounts of studies on land use planning have not been carried out worldwide, there are few studies on the optimization of land use in this period. GA was mainly used in basic works such as land-cover classification [54,55], remote sensing image classification [56,57], satellite image segmentation [58]. The research on land use mainly provides convenience for management departments to carry out land management. Affected by computer performance, researchers generally lack the scientific research enthusiasm for technological innovation.

Stage 3: The Hybrid Application of Multiple Models Stage (2009–2016)

The Hybrid Application of Multiple Models Stage was the continuation and deepening of the previous stage. The research foci at this stage focused on coupling GA and other algorithms to build a hybrid algorithm model to solve the problem of multi-objective LUO allocation. Firstly, the research scale at this stage extended from global to regional with 'United States' and 'China' as the research hotspots on the regional scale. The USA had completed urbanization, but China was experiencing rapid urbanization after 1990, leading to dramatic changes in land use and land cover, so they were both worthy of study [8]. As the level of urbanization increases, problems such as ecological destruction and environmental pollution have emerged one after another, seriously affecting the quality of human life [59]. A good LUO configuration plan is conducive to alleviating the contradiction between land supply and demand, promoting rapid economic growth, promoting healthy social development, building a good ecological environment, and realizing sustainable development of the region. Therefore, the optimal allocation of land use has gradually become a focus.

With the continuous expansion of people's understanding of various fields, traditional optimization methods can no longer deal with such non-linear and highly difficult optimization problems. Intelligent stochastic optimization algorithms have become a hot spot for researchers. At the same time, the rapid development of Internet technology also provides a good environment for the in-depth expansion of intelligent optimization algorithms. As each algorithm has its own unique advantages, but also has its shortcomings, scholars are no longer limited to studying only one algorithm; they have tried to combine research content of multiple algorithms [60]. In 2009–2016, a variety of hybrid GA models were applied to land use research. Algorithms which can be coupled with GA are ant colony algorithms [61–63], simulated annealing algorithms [64], artificial neural networks [65,66], particle swarm optimization [67–69]. The standard GA has poor local search ability, and its convergence is prone to obtaining underdeveloped results at low speed. Due to the combination of GA with strong global search ability [70] and the traditional heuristic search method with strong local search ability, the hybrid models are able to avoid redundancy or falling into local optima, and improve efficiency and convergence speed.

In order to solve the problem of parameter optimization effectively, Yi et al. [71] analysis the fundamental theory of Support Vector Machine (SVM) and finally accomplish the combination of GA and SVM. Meanwhile this model was used to analyze the construction land use. The results showed that the new model is far superior to recent models in terms of predicting accuracy, algorithm complexity, and computational efficiency. A niche hybrid GA is proposed by Wei [72] to solve continuous multimodal optimization problems more efficiently, accurately, and reliably. The proposed method not only makes the exploration capabilities of GA stronger through niche techniques, but also has more powerful exploitation capabilities by using simplex search. So, it effectively alleviates premature convergence and improves weak exploitation capacities of GA. The Pareto front can provide valuable information on land use planning decision by revealing the possible trade-offs among multiple, conflicting objectives. However, seeking the Pareto front of land use allocation is much more difficult than finding a unique optimal solution, especially when dealing with large-area regions. Huang et al. [73] proposes an improved artificial immune system for multi-objective land use allocation to tackle this challenging task. Experimental results indicate that this algorithm, even dealing with large-area LUO problems, is capable of generating optimal alternative solutions approximate to the true Pareto front. Yan et al. [74] presents a method to optimize the calibration of parameters and land use transition rules of a cellular automata (CA) urban growth model using a self-adaptive GA (SAGA). Optimal calibration is achieved through an algorithm that minimizes the difference between the simulated and observed urban growth [75,76].

The simulated annealing algorithm (SA) is a random search algorithm that traverses the entire space and emerges out of the local optimal solution. The hybrid GA model (SAGA) can be constructed to overcome the shortcomings of traditional GA (premature convergence) and SA (insufficient global search ability). Artificial neural networks (ANN) simulate an interconnected neuron system that enables computers to mimic brain detection patterns [77]. Its performance depends on the choice of attributes. Although there are complex nonlinear relationships between a variety of attributes, GA can effectively obtain the approximate optimal attribute set constructed by ANN [78]. Fuzzy logic has strong knowledge expression ability, and fuzzy control can simulate people's decision behavior to make correct outputs. Therefore, the idea of fuzzy control can be used to guide the operation of GA. The population size, crossover probability, mutation probability, and fitness function of GA can be adaptively changed to improve performance. Inspired by the principles of biological immune systems, the artificial immune algorithm can make full use of information to artificially remedy problematic features. The global search ability of GA and the local optimization function of the immune algorithm can be combined to greatly improve overall search efficiency. Mahmoud et al. [79] aim at developing novel algorithms through hybridizing Tabu search (TS), GA, and SA and examining their quality and efficiency in practice. Firstly, these algorithms were applied for solving small and large-size single-row facility layout problems to evaluate their performance and functionality and to select the satisfactory algorithm in comparison with the other developed hybrids. Secondly, the selected algorithm was performed on a study area to solve a LUO problem with two constraints and seven nonlinear objective functions. The outputs showed that the quality and efficiency of the hybrid algorithm were slightly better than single algorithm and it can be considered as a favorable tool for land-use planning process.

Through other keywords at this stage—"dynamics" and "multi-objective optimization"—it can be concluded that the hybrid GA is mainly used for dynamic monitoring and multi-objective optimization in the field of LUO. In the optimization process, more attention is paid to the spatial relationship—that is, the optimization of land use spatial structure [80,81]. Cao [82] proposed a coarse-grained parallel GA to search for the approximate optimal solution of LUO under multi-objective constraints. In 2014, Liu et al. [83] constructed a LUO allocation model based on multi-agent GA to promote the development of land use quantity structure and spatial layout in a sustainable direction. A proxy-based spatial GA framework was also proposed for simulating land development [84].

Stage 4: The Introduction of The Latest Method Stage (After 2017)

Entering the Stage 4, there were few emerging keywords for GA-LUO study. On one hand, previous studies had proposed much research, and many issues had not been well clarified. On the other hand, the time entering this stage was short, and research in this field also required further generalization. With the rapid development of object-oriented smart technologies, the current research hotspots and future development trends are the formation of new integrated technologies, namely, the Hybrid Intellectual System [85–87]. Advanced algorithms represented by Logical Regression, Internet of Things, cloud computing, and big data have emerged one after another, making artificial intelligence a breaking point in recent years [88]. Chen [89] proposed Broad Learning System (BLS) that aims to offer an alternative way of learning in deep structures in 2007. This method is fully applicable to the era of big data, and is a breakthrough in the field of artificial intelligence. This pushes the research of GA into a new stage of absorbing the latest methods. The combination of machine learning [90] and spatial GA [18,91] is applied to unearth a new model of LUO research. For example, Zhang [92] proposed a multi-population niche GA, which effectively improved optimization ability by enhancing the selection, crossover and mutation steps.

5. Discussion

In this research, we aimed to reveal the research models and trends of GA in LUO from the perspective of bibliometrics. For future research, we will focus on the improvement of the bibliometric analysis model. First, more bibliometric indicators will be used to enhance the bibliometric analysis function, such as trying to obtain the regional information of the literature research. Second, more spatial analysis and geographic visualization methods will be introduced into the bibliometric analysis under an explicit spatial background. This study mainly chooses the CiteSpace software. However, the software also has shortcomings [93]. For example, it can only display the analysis results in two-dimensional flattened graphics, and cannot express more content in combination with spatial information such as latitude and longitude coordinates. For a better overview, we have introduced spatial analysis methods [94]. We mapped the results of CiteSpace analysis to geographic space to discover the hidden relationship between the publication hotspot institutions/authors and geographical coordinates. Such improved research methods can obtain more explicit results and provide readers with more intuitive information.

It would not be surprising if many people on reading these results had a healthy level of skepticism regarding the facets of this output. One merely needs to revisit Figure 7 to understand that the knowledge domain for GA-LUO is dense and highly complex. Further, there are many more key terms derived in this analysis that are not mentioned due to space constraints. Again, knowledge domains are large, dynamic entities that are constantly evolving. If this analysis was undertaken 2 years from now, it is unlikely that an identical set of key terms would emerge. Dynamism is the hallmark of science [95].

From this research, it also appears that the researchers studying the problem mainly come from developed countries. China is one of the few developing countries that have made major contributions to this issue, especially over the past decade. Presently, it ranks first in the number of papers in this field. With the expansion of urbanization in China, land use coverage has undergone tremendous changes in the past three decades [96]. The reduction of cultivated land, the degradation of forest and the reclamation of grassland have not only caused enormous ecological problems, but also caused a certain degree of impact on the regional climate [97]. Therefore, the research on the optimal allocation of land use has gradually become a hot spot [98]. The number of publications from China has grown rapidly, but in terms of the importance of research results, we found that the USA ranked first, followed by China, England, Germany, and other countries. The main reason may be that these countries have carried out this research for a long time and have accumulated a large amount of research foundation. This also indicated that the importance of the research results is closely related to the time of conducting the research.

Although some pivotal studies have been carried out, including the spatial optimization for land use allocation accounting for sustainability concerns [99], the regional land use allocation from local simulation to global optimization using a coupled MAS and GA model [19], the spatial optimization for sustainable multi-objective land use allocation [100], the improved knowledge-informed NSGA-II for multi-objective land allocation [101], the improved GA for spatial optimization of multi-objective and multi-site land use allocation [5]. More countries need to pay attention to these issues, especially developing countries, to unite the global scientific research forces to jointly solve the problem of land use planning.

From the four-stage division results we obtained, the keywords and software calculation results are reasonable. By reading the relevant review literature, we find that some studies divide the historical development process of research goals into three stages [102–104], and some divide them into five stages [105], but they are mainly determined based on the method and the literature. The stage division results of this article may deviate from expert experience, but it is also a result that can be referred to. Our future recommendations are also based on the results of visual analysis and are summarized by careful reading of the literature on the key nodes in the result graph. The research on GA-LUO will follow the trend of time with the deepening of GA. However, what is certain is that its integration with cutting-edge technologies such as artificial intelligence and big data should be the main development direction in the future [106,107].

By reading the literature in detail, we can conclude that it can be inferred from the existing research that the future research may be conducted in the following three directions.

(1) The improvement of GA

Currently, land use and land cover change (LUCC) is of utmost concern for research on global environmental change and sustainability. Among the portfolio of techniques, modelling is considered as the best approach to explore LUCC dynamics. GA provides a universal template for solving complex optimization problems, and is one of the hotspots of evolutionary algorithm research in recent years. A very critical issue in artificial intelligence is finding an approximate optimal solution in a very large and complex solution space. GA can quickly search out the whole solutions with its strong global search ability, which overcomes the trap of the other algorithms' rapid decline. In addition to classical intelligent algorithms, GA will be more integrated with emerging hotspot technologies such as artificial intelligence, machine learning, and embedded technology in the future. At the same time, the statistical data show that these intelligent hybrid GAs have gradually been applied to actual cases, and are especially widely used in data mining [108]. At present, there are still insufficient theoretical studies on deception issues and parameter settings, which limit the deeper development of GA [109]. Therefore, future research will focus more on theory, with the expectation of establishing a more stable mathematical foundation. An innovative simulated evolutionary algorithm was even proposed as a stochastic search method to handle optimization problems [110]. This evolved from one of the most important books in the world's literature, I-Ching [111], which is the philosophy of China and ancient science. Consequently, the new algorithm is an attempt to find and apply the profound wisdom of this ancient culture.

(2) Future expansion of LUO research

Multi-objective LUO will be a hot research topic for a long time in the future. In research on land use with endless problems, complex conditions such as nonlinearity and changing parameters also place higher requirements on the application of GA. The optimal allocation of land use spatial structure is an important means to promote effective intensive use of land resources and achieve sustainable development goals. Most of the existing research studies lack discussion on the optimal allocation of land use spatial patterns. Heuristic algorithms are one of the most effective methods for solving this problem. Therefore, we can combine land use planning knowledge and GA to construct a spatial explicit GA (SEGA) model. SEGA may have the potential to improve the effectiveness of regional land use allocation and obtain more vivid visualization effects. The SEGA transforms the spatially implicit computation mode of the GA into a spatially explicit optimization style, which helps to promote the effectiveness of regional land use allocation [74,112]. Land use research is a spatial issue, but future research will also focus on the study of spatiotemporal models. Dynamic monitoring and comparison from the two dimensions of time and space will yield more unique findings.

(3) The extension of the methodological application

By further improving methods of how to apply GA in LUO, researchers can consolidate a structural model with high applicability and versatility, and extend the research area to transportation and climate, etc. At present, the world is experiencing rapid population growth and urbanization. According to forecasts from the United Nations (2018), another 2.5 billion people will be added to the world population during 2018–2050, and

68% of all people will live in cities and towns. Cities are home to most of the world's population, contributing 75% of global gross domestic product (GDP) as well as 75% of carbon emissions [113]. During urban expansion, conflicts in land resource utilization have become increasingly prominent. These conflicts are mainly associated with the occupation of cropland, and ecological security should also receive more attention [114]. Scenario simulation is a good method to cope with the problem of urban sprawl, for it is based on historical land use data which can predict land use status under different development scenarios, and thereby propose how to optimize the quantity and spatial allocation of land resources under specific scenarios [115]. Therefore, GA-LUO can be extended to the field of urbanization research. The sustainable development of land use affects biodiversity, food security, carbon storage, and other issues. Taking these influencing factors as variables in the application of GA will be a research focus in the future [116,117].

Both WoS and SCOPUS are world-renowned authoritative search databases. WoS appeared earlier, and this database is more focused on journal articles. SCOPUS is currently the world's largest search database, with more comprehensive types of searched documents [118,119]. Therefore, we will use SCOPUS as a key data source for in-depth research in the future.

6. Conclusions

By using bibliometric analysis and geographic visualization methods on the GIS platform, we summarized the development process for GA-LUO from 1995 to 2020, and predicted future research trends in this research. The number of documents related to GA-LUO has increased rapidly in the past 25 years, which indicates that the research has entered a new upsurge in recent years. The results of the geographic visualization show the global geographic distribution of authors and research hotspot patterns. From the macro perspective understanding of the development of GA-LUO, we noted the main research group and the country, and the correlation between the distribution of research authors. We aimed to understand the research focus and evolution path of GA-LUO, and analyze the main articles and the research results of the main authors. It is expected that this paper will provide relevant researchers with a comprehensive reference and help scholars to understand the latest content on GA-LUO and to conduct more in-depth research based on the existing studies and future research trends. The main conclusions are as follows:

(1) The results show that the global research on GA-LUO is mainly concentrated in Asia (China and India), North America (USA and Canada), Europe (Germany, Britain, Greece and Netherlands), and Oceania (Australia), among which Asia and North America are the most active. Different research institutions in various countries should strengthen cooperation to better deal with the contradiction between supply and demand of land resources. To extract important GA-LUO research directions, highly cited references were explored. Through the analysis of 10 highly cited publications, specific targeted research directions were discovered.

(2) According to an identified quantitative trend in emerging keywords, GA-LUO research has experienced four stages of The Presentation and Improvement of Methods Stage, The Optimization Stage, The Hybrid Application of Multiple Models Stage, and is now entering The Introduction of The Latest Method Stage. The introduction of scientific problems to the establishment of the theoretical basis, related research around the theoretical basis, the blooming of research fields, and finally the in-depth discussion of this issue, reflect these stages of the process.

With the rapid development of global computer technology, in order to better meet the arrival of the 5G network era, the improvement of combining GA with artificial intelligence methods need to be explored. Multi-model coupling for spatial explicit analysis appears to be an effective method to realize the spatial improvement of the algorithms in the actual LUO problem, although multi-data integration is a challenge. The methodological application could extend to the management of urbanization issues, which may be a way forward for human beings and land resources toward. By using a variety of bibliometric analysis tools and methods, GA-LUO was analyzed and summarized comprehensively, delineating the development context and predicting the development direction. This should provide valuable reference directions for future research and strengthen the tackling of difficult problems.

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