

# Land Use Thematic Maps Recommendation Based on Pan-Map Visualization Dimension Theory

Yebin Chen <sup>1</sup>, Zhicheng Shi <sup>2</sup>, Yaxing Li <sup>1</sup>, Dezhi Han <sup>1</sup>, Minmin Li <sup>3,4,\*</sup> and Zhigang Zhao <sup>1</sup>

<sup>1</sup> Research Institute of Smart City, School of Architecture and Urban Planning, Shenzhen University, Shenzhen 518060, China; chenyebin@szu.edu.cn (Y.C.); yaxing\_li@u.nus.edu (Y.L.); 2100325009@email.szu.edu.cn (D.H.); zhaozgrisc@szu.edu.cn (Z.Z.)

<sup>2</sup> School of Computer Science and Technology, Wuhan University of Science and Technology, Wuhan 430081, China; shizhicheng@wust.edu.cn

<sup>3</sup> Guangdong Laboratory of Artificial Intelligence and Digital Economy (SZ), Shenzhen 518123, China

<sup>4</sup> Key Laboratory of Urban Land Resources Monitoring and Simulation, Ministry of Natural Resources, Shenzhen 518034, China

\* Correspondence: liminmin@gml.ac.cn

**Abstract:** In the era of information and communication technology (ICT), the advancement of science and technology has led to a trend of diversification in map representation. However, the lack of professional knowledge means that there is still a challenge in determining the appropriate type of thematic map for land use expression. To address this issue, this paper proposes a knowledge recommendation method for land use thematic maps based on the theory of visualization dimensions. Firstly, we establish a knowledge ontology of land use thematic maps centered on spatial data, data characteristics, visualization dimensions, thematic map forms, and application scenarios. A land use thematic map knowledge graph is constructed through knowledge extraction and storage operations. Secondly, knowledge embedding is performed on the knowledge graph to enable the knowledge-based expression of map visualization elements. Finally, based on the knowledge elements of land use thematic expression, a similarity calculation model is established to calculate the similarity between input data and the spatial data characteristics, visualization dimensions, and application scenarios within the knowledge graph, deriving a comprehensive similarity result to achieve precise recommendation for land use thematic map forms. The results show that the method can provide a more accurate visualization reference for the selection of land use themes, meeting the diversified needs of land use thematic expression to a certain extent.

**Keywords:** land use thematic map; knowledge graph; knowledge representation; knowledge recommendation; similarity calculation



**Citation:** Chen, Y.; Shi, Z.; Li, Y.; Han, D.; Li, M.; Zhao, Z. Land Use Thematic Maps Recommendation Based on Pan-Map Visualization Dimension Theory. *Land* **2024**, *13*, 1389. <https://doi.org/10.3390/land13091389>

Academic Editor: Antonio Miguel Martínez-Graña

Received: 6 July 2024

Revised: 11 August 2024

Accepted: 26 August 2024

Published: 29 August 2024



**Copyright:** © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

## 1. Introduction

Land resources are irreplaceable for human survival, production, and development. During the 21st century, the total volume of basic data, including land use data, land use planning data, and basic farmland data, has reached the petabyte (PB) level [1–3]. A timely understanding of the distribution of land resources, the spatiotemporal changes in land use, and the quantity of land resources is crucial for the rational utilization of land resources, optimization of industrial structures, and formulation of development plans [4,5].

Land use thematic maps are specialized cartographic representations that depict the spatial distribution and categorization of various land use patterns across a geographical area [6]. They reflect the spatio-temporal trends in land use and land cover change (LUCC), facilitating macro decision-making in land use planning, management, and monitoring at regional and national levels [7]. The compilation and application of land use thematic maps involve multiple disciplines such as geography, ecology, and environmental science;

it provides data support for assessing the rational use of land resources and investigating the relationship between LUCC and environmental changes [8].

In recent years, with the rapid development of information and communication technology (ICT), maps have transitioned from manual cartography to digital, automated, and intelligent cartography [9,10]. Map products exhibit great flexibility in both data and form of expression, presenting personalized and diversified characteristics [11]. Thematic maps have evolved from adhering to the core theoretical bases composed of mathematical rules, cartographic generalization, and symbol systems to the emergence of various map-like forms that break through the existing theoretical bases [12]. These map-like forms, along with standard maps, adapt to the personalized thematic expression needs of the ICT era, meeting the diverse map-reading needs of map users. Guo collectively referred to standard maps and map-like forms as “pan-maps” [13–15]. Pan-maps extend standard maps, offering a comprehensive expression of geography, social, and cyberspace, including both standard maps composed of traditional cartographic theory and various map-like forms that break through traditional artistic forms [16–19], such as land use distribution maps, Dorling cartogram maps, area cartogram maps, and kriskogram maps. Compared to traditional land use distribution maps, pan-maps are richer in form and diverse in style, more vivid and intuitive in expressing statistical information, spatiotemporal relationships, and spatiotemporal trend distributions, which helps land managers quickly obtain necessary information and make informed decisions.

In traditional digital cartography, producing land use thematic maps requires professional prior knowledge or assistance from a cartographic expert to meet the expression needs of the thematic content [20]. The constraints of this prior knowledge have limited the popularization and development of maps. Cartographers who lack professional cartographic theoretical knowledge are prone to falling into the “cartographic traps” that violate common sense in map expression, leading to the use of inappropriate map types for the expression of land use themes. Moreover, in the Internet environment, land use themes demand higher timeliness in map information transmission and richer information interaction [10,11]. However, most existing cartographic technologies are aimed at one or a few specific map forms, such as the rule-based cartographic representation method [21,22]; template-based cartographic pattern and display style transfer applications [23]; and the use of existing software packages (such as ArcEngine 10.3) to achieve the automation of specific types of thematic maps [24,25]. Facing the personalized, diversified, and intelligent needs of the ICT era’s “pan-maps”, an important issue in the development of cartography is how to internalize the basic rules, visual characteristics, and knowledge of pan-map cartography into the cartographic process, using knowledge as the driving force for the production of pan-maps, thereby forming constraints and guidance for the cartographic behavior of cartographers, and promoting the intelligent expression process of land use thematic maps. To address Pan-map expression, Guo has proposed the “pan-map visualization dimension theory” [13], which deconstructs the expression of pan-maps into 10 first-level dimensions—time, geometry, dimensionality, form, format, status, scale, carrier, reference plane, and reader viewpoint—as well as 26 s-level dimensions, clarifying the diverse characteristics of pan-maps in different dimensions. This provides an important opportunity and theoretical support for the intelligent research of land use thematic maps.

A knowledge graph is a structured semantic knowledge base that describes concepts in the physical world and their inter-relationships in symbolic form [26]. In recent years, this field has gradually attracted attention from scholars in cartographic research. In expressing land resource knowledge, Zhang divided public land cover datasets into gridded units using hierarchical administrative divisions and structured the datasets at the semantic level for storage, constructing a knowledge graph of land resources [27]. Based on the semantic relationship expression capability of the knowledge graph, Meng has solidified the experts’ knowledge of big data mining models, proposing a knowledge graph-driven natural resource big data mining model framework that expresses the logical relationships between natural resource data and processing, enhancing the reusability

of the mining model [28]. Accurately describing the elements of natural resources and their interactions is key to achieving integrated and systematic management of natural resources. Ding proposed an integrated “data-model-knowledge” conceptual model. An integrated knowledge graph visually describes the time and space of natural resource entities and the interactions between entities, achieving visualization of the detail level and semantic relationships of natural resource entities [29]. Facing urban soil pollution issues, Han constructed a pollution site knowledge graph with sites, chemicals, pollutants, and cities as entities, achieving efficient information queries of pollution sites, and rapid discovery of characteristic pollutant and main pollutant regional distribution [30]. In terms of map expression, Li [31] proposed a visualization recommendation method based on the knowledge graph, which helps users obtain suitable visualization recommendations according to their needs from the effective rules between datasets and visualization forms. Li [32] took the data, data characteristics, visualization methods, and data sources of marine maps as core elements, constructed the ontology layer from top to bottom, defined the concept hierarchy system, and established entity connections through data acquisition, data processing, knowledge extraction, and knowledge storage to complete the data layer filling, forming a construction method for the marine map visualization knowledge graph. Niu [33] introduced the knowledge graph as auxiliary information into the recommendation system and combined it with user weight bias factors and micro-map weight factors for collaborative filtering of the influence of different users and micro-maps, effectively solving the data sparsity problem and improving the accuracy of recommendations. Koteich [34] proposed a knowledge-based recommendation method to guide cartographers through the map-making process. Zhou [35] argued that it is possible to autonomously complete the judgment and allocation of various cartographic resources, including data, models, templates, methods, etc., promoting the automation and intelligence of map compilation under the constraints of the basic rules and regulations of map cartography and with the basic driving force of geological and map knowledge for cartographic work.

By linking data, features, and expression methods through a knowledge graph, the knowledge association of “map entities”, “entity relationships”, and “attribute characteristics” can be achieved, enhancing the intellectualization and intelligence level of map expression. Therefore, in aiming at intelligent recommendations for land use thematic mapping, we integrate a knowledge graph to associate the expression needs of land use, pan-map visualization dimensions, and map content with knowledge, proposing a map recommendation method tailored to the expression requirements of land use themes. With this method, we can recommend appropriate thematic map formats and visualization content to cartographers, satisfying a variety of needs for land use thematic expression.

## 2. Study Area and Data

### 2.1. Study Area

This study selects Zhangjiakou City as the research area to conduct a recommended experiment for land use thematic maps. Zhangjiakou City, a prefecture-level city of Hebei Province, is located in the northwest of Hebei Province, adjacent to Beijing City, and holds significant strategic importance. In 2023, the total area of the city was 36,357 square kilometers, with a permanent population of 4.05 million people. The land use types in Zhangjiakou City are diverse and complex, primarily comprising urban construction land (residential, commercial, industrial, and infrastructure construction), ecological land (nature reserves, parks, and green spaces), and water areas (rivers, lakes, reservoirs, and tidal flats).

### 2.2. Data Source

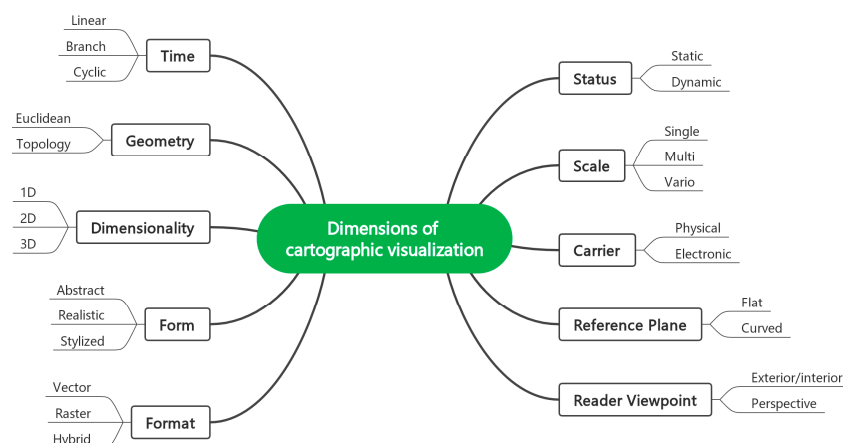
We selected land use change data of Zhangjiakou City from 2000 to 2015 from the “Atlas of Urban Land Use/Cover Change in China” as case data to further analyze the guiding role of the knowledge graph in the mapping of land use thematic maps. The data cover 14 areas—Chicheng County, Congli County, Huaian County, Huailai County, Jieyuan County, Kangbao County, Shangyi County, Wanquan County, Wei County, Xuanhua County,

Yangyuan County, Zhangbei County, Zhulu County and municipal district—with the aim of achieving an intuitive visualization of the land use change in each district and county of Zhangjiakou City from 2000 to 2015.

### 3. Theory and Method

#### 3.1. Pan-Map Visualization Dimension Theory

In the era of ICT, map visualization techniques have evolved beyond traditional methodologies that solely depend on visual variables such as shape, size, and color. The Pan-Map Visualization Dimension Theory (PVDT) is a crucial conduit linking expressive requirements to visualization forms [36]. As shown in Figure 1, the Pan-Map visualization system includes 10 dimensions: time, status, format, dimensionality, reference plane, carrier, geometry, form, scale, and reader viewpoint [13].



**Figure 1.** Visualization dimension system of Pan-map [1].

- Time captures the temporal evolution of spatial phenomena, manifesting in linear, branching, and cyclic structures.
- Status conveys the condition of each object or element on the map, including static and dynamic states.
- Geometry details the geometric shapes and topological relationships between graphic elements in map visualizations.
- Format involves arranging spatial objects, including vector, raster, and hybrid forms.
- Dimensionality refers to the spatial dimensions represented in maps, including one, two, three, or even more dimensions.
- Reference plane includes various planes and curves, enhancing the user's spatial understanding through the conversion of different reference surfaces.
- Carrier denotes the medium of map expression, such as physical and electronic media.
- Form encompasses three styles of expression: abstract, realistic, and stylized.
- Scale indicates the spatial extent and level of detail the map portrays, which can vary from single scale to multi-scale and vario-scale.
- Reader viewpoint offers multiple perspectives on spatial objects, including internal and external viewpoints and personal perspectives.

As shown in Figure 1, these dimensions are inter-related, and their integration, coordination, and constraints can produce a visually rich and diverse expression, thereby constructing various land use thematic maps [15]. This provides a theoretical foundation for creating scientific, aesthetic, and diverse thematic map products tailored to specific land use demands.

Dimensions are the fundamental components for expressing pan-map objects, and the pan-map visualization dimension system is the core of pan-map theoretical research. The study of the pan-map visualization dimensions should integrate various disciplines, including computer graphics, cartography, art, psychology, and computer science. Com-

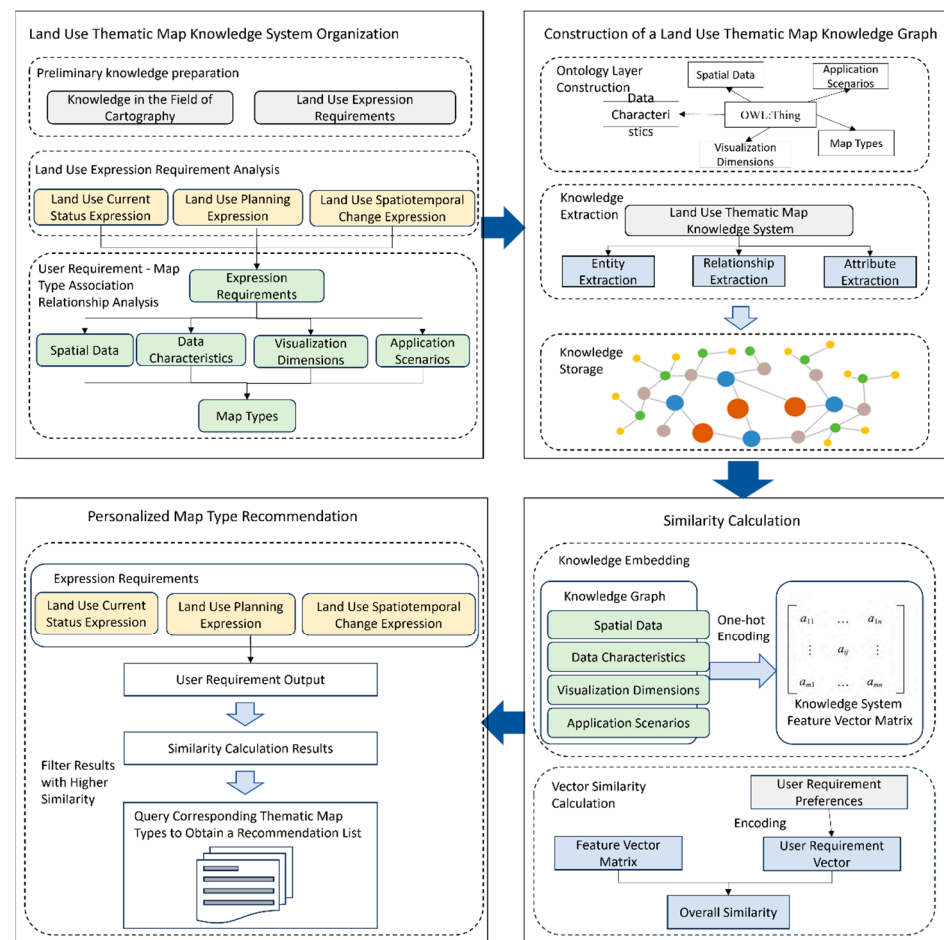
pared to pan-maps, traditional maps are primarily based on the theory of visual variables, using variables such as shape, size, color, orientation, brightness, and texture to express the qualitative or quantitative characteristics of geographical objects. This representation mainly revolves around the form of map symbols. However, the pan-map visualization dimension theory further expands the expression dimensions of maps beyond visual variables to include time, status, format, dimensionality, reference plane, carrier, geometry, form, scale, and reader viewpoint. The expression of spatial characteristics, dynamic characteristics, attribute characteristics of objects, as well as user interaction, has become important content to consider in the construction of maps. This greatly expands the modes of map representation in the ICT era.

### 3.2. Land Use Thematic Map Recommendation Method

A knowledge graph represents the confluence of applied mathematics, graphics, information visualization technology, and information science. It essentially constructs a semantic network among entities, illustrating knowledge through relationships in the format of “entity–relationship–entity” or “entity–attribute–attribute value” triplets [37,38]. Entities, the fundamental units of knowledge representation, are linked by various associations, and their attributes express specific information. Knowledge graphs have become instrumental in recommendation systems noted for their precise recommendations, diverse content, and high interpretability [39–41]. Therefore, integrating the knowledge graph approach with the PVDT can scientifically, efficiently, and logically support the customized and varied applications of pan-maps. This paper aims to fuse knowledge graphs with the PVDT to develop a semantic network that maps the relationships among spatial data, attribute features, and visualization dimensions and forms, thus creating a knowledge graph for land use thematic expression that meets the diverse knowledge acquisition needs of users regarding land use thematic maps.

Knowledge graph-based recommendation technology can establish connections between different entities in the process of land use thematic mapping [27,28]. It effectively links the expression needs of map users with appropriate thematic map forms [30–32]. The implementation process of the land use thematic map recommendation method in this paper is shown in Figure 2 and comprises four main processes:

- **Land use thematic map knowledge system organization:** This involves integrating the actual needs for land use thematic expression with the existing land use data. The analysis is conducted from four perspectives: spatial data, data characteristics, visualization dimensions, and application scenarios. The aim of this step is to determine the required map type, establish correlations between land use thematic expression needs and map types, and formulate a comprehensive knowledge system tailored for land use thematic expression.
- **Construction of land use thematic map knowledge graph:** Leveraging the previously organized knowledge system of land use requirements and map type correlation, this process defines the ontology layer of the knowledge graph. It employs knowledge extraction technology to derive the corresponding knowledge triplets from this layer, constructing a land use thematic map knowledge graph and forming a robust knowledge network to recommend suitable land use thematic maps.
- **Similarity calculation:** This step utilizes one-hot encoding to embed the user entity, expression needs, data characteristics, and visualization dimensions within the land use thematic map knowledge graph, thereby transforming this knowledge into feature vectors. The cosine similarity calculation model is then applied to analyze the overall similarity between the data characteristics and visualization dimensions of user needs and those represented in the knowledge base.
- **Personalized map type recommendation:** Based on the results of the similarity calculations, this phase involves selecting the thematic map types that most closely align with the user’s land use thematic expression needs. The method then recommends the most suitable map visualization forms accordingly.



**Figure 2.** Flowchart of land use thematic map knowledge recommendation.

### 3.2.1. Constructing the Knowledge System of Land Use Thematic Maps

To effectively implement land use thematic map recommendations, it is essential to first establish a knowledge system that identifies and analyzes the correlation between various user needs and map types. This system forms the foundational structure for constructing the land use thematic map knowledge graph. The system's development is designed to address the diverse needs for thematic expression, such as depicting the current status of land use, land use planning, and the spatiotemporal changes in land use, as illustrated in Figure 3. The construction process involves the following key steps:

- (1) **Analyzing thematic expression needs:** Leverage cartographic knowledge to categorize and understand different types of requirements for land use thematic expression.
- (2) **Dissecting data and scenarios:** Examine and segment the spatial data, data characteristics, and application scenarios pertinent to thematic expression. This includes dividing spatial data into categories such as land use data, land planning data, statistical data, image data, etc. Data characteristics are classified into temporal, spatial, and attribute features while application scenarios are divided into quantitative distribution, static element distribution, spatiotemporal change trend expression, etc.
- (3) **Visualization dimensions analysis:** Based on the identified thematic expression needs, assess the relevant visualization dimensions and their inter-relationships to formulate a combination that aligns with user preferences.
- (4) **Establishing correlations:** Utilize the preferred combination of visualization dimensions to establish comprehensive correlations among user needs, spatial data, data characteristics, visualization dimensions, thematic map forms, and application scenarios.

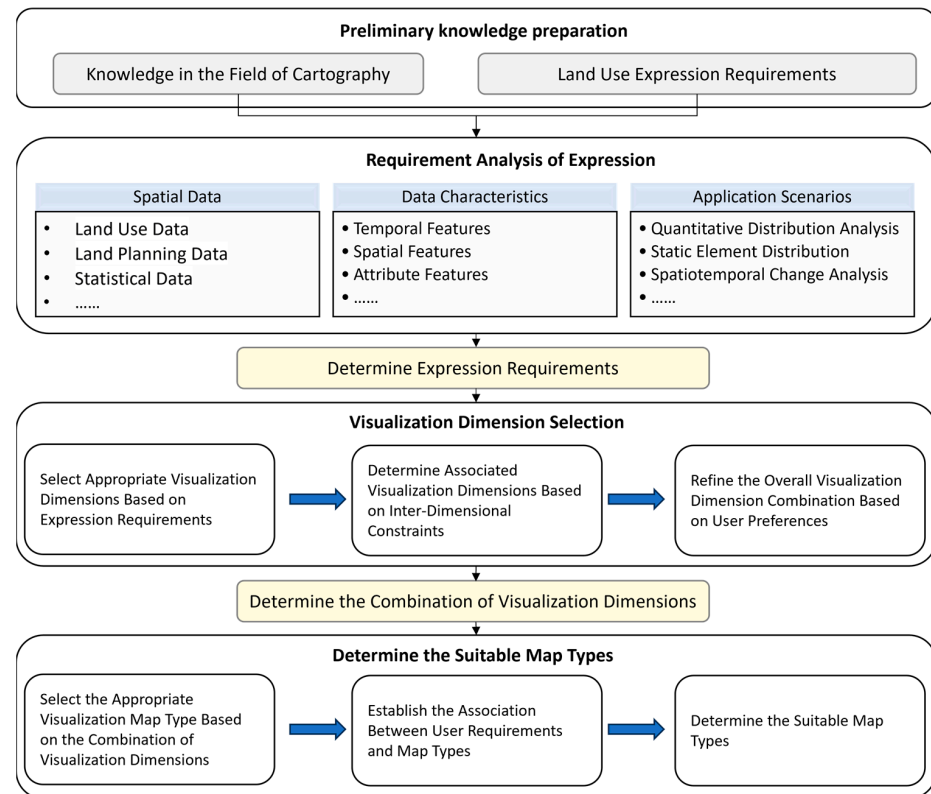


Figure 3. Mechanism for constructing the knowledge system of land use thematic maps.

### 3.2.2. Construction of the Land Use Thematic Map Knowledge Graph

In a knowledge graph, nodes represent concepts or entities, while edges symbolize relationships or attributes. Knowledge is typically encapsulated in the form of triplets, represented either as <head entity–relationship–tail entity> or <entity–attribute–attribute value>. The construction of a knowledge graph can be top-down or bottom-up; this paper employs a top-down approach to construct the knowledge graph, initially defining ontological elements and their inter-relationships and subsequently populating the graph based on this ontological framework.

An ontology comprises a collection of concepts, with the ontological layer of a knowledge graph representing various concepts and their connections. In mapping land use themes, a specific correlation exists among the data features of spatial data, visualization dimensions, application scenarios, and visualization methods [21]. Data features, the “essence” of map expression, determine what is connotatively expressed, encompassing temporal, spatial, and attribute features. Within attribute features, a further distinction is made between quantitative, sequential, and category counts. Sequential features articulate the logical relationships within spatial data elements, while category counts enumerate the thematic indicators present in spatial data. Visualization dimensions define the form of map expression, shaping the external characteristics and allowing for the creation of diverse map forms. The application field targets the transmission of information across various land use thematic scenarios, such as urban construction, ecological environments, land utilization, and industrial structures. For constructing the land use thematic map recommendation ontology, this paper identifies five principal categories of concepts—spatial data, data features, visualization dimensions, application scenarios, and visualization forms—to construct the ontology model for the land use thematic map recommendation. The definitions of the concept set and relationship set of the knowledge graph ontological layer are shown in Formulas (1) and (2), and the model result is shown in Figure 4.

$$Con = (C_1, C_2, C_3, C_4, C_5) \tag{1}$$

$$R = (C_1, r, C_i) (2 \leq i \leq 5) \tag{2}$$

where  $Con$  represents the concept set of the land use thematic map knowledge graph;  $C_1$  is the concept of spatial data;  $C_2$  is the concept of data features,  $C_3$  is the concept of visualization dimensions;  $C_4$  is the concept of application scenarios;  $C_5$  is the concept of visualization forms;  $R$  represents the relationship set of the land use thematic map knowledge graph,  $R(C_1, C_2)$  is the possession relationship,  $R(C_1, C_3)$  is the usage relationship,  $R(C_1, C_4)$  is the application relationship, and  $R(C_1, C_5)$  is the applicability relationship.

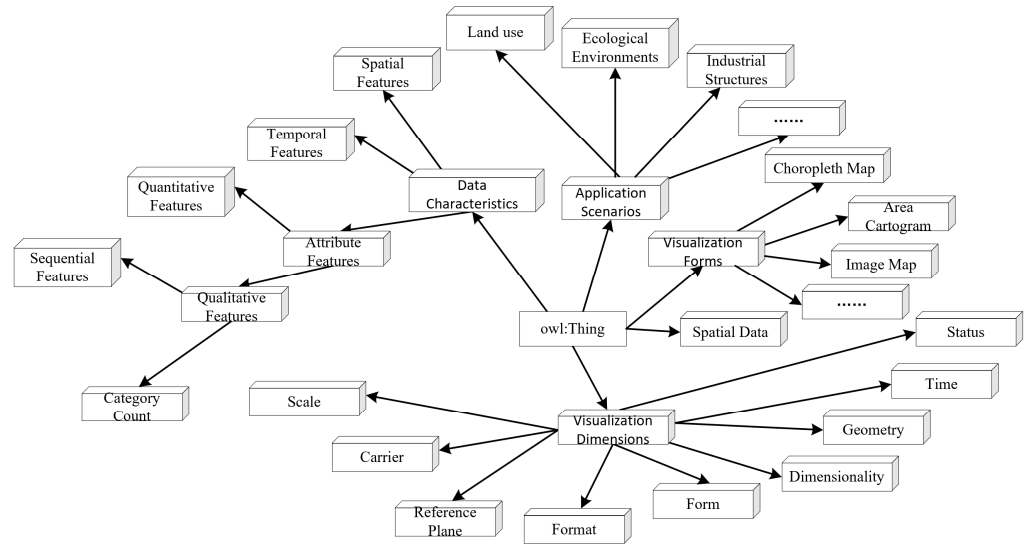


Figure 4. Ontogeny model of land use thematic map knowledge graph.

### 3.2.3. Land Use Thematic Map Knowledge Embedding

Knowledge graph embedding is a common method for knowledge representation that involves mapping entities and their relationships from a knowledge graph into a continuous vector space. This approach simplifies operations while maintaining the intrinsic structure of the knowledge graph [20]. In this paper, one-hot encoding is used for knowledge embedding, utilizing  $N$  state registers to encode  $N$  distinct states, where each register operates independently. This method is straightforward and highly reliable. The process of embedding spatial data information from the knowledge graph using one-hot encoding—thereby transforming knowledge into feature vectors—is depicted in Figure 5.

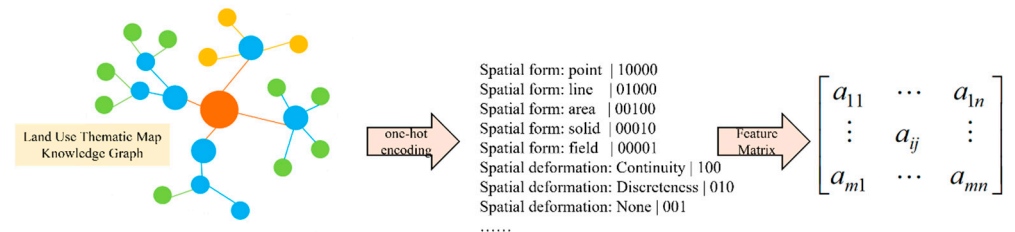


Figure 5. Knowledge embedding of one-hot encoding. (Note:  $\begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix}$  represents the

feature vector matrix obtained after one-hot encoding of the knowledge graph,  $m$  represents the number of spatial data entries,  $n$  represents the number of feature states,  $a_{ij}$  represents the encoding of the  $j$ -th state of the  $i$ -th spatial data in the feature vector matrix. In the left-hand figure, nodes of different colors represent different categories of entities in the knowledge graph, and lines of different colors represent different entity relationships).



### 3.2.4. Land Use Thematic Map Similarity Calculation

Based on the knowledge graph of land use thematic maps, this paper employs a similarity calculation model to analyze the data characteristics, visualization preferences, and application purposes of the map users and compares these with the overall similarity of entity data characteristics, visualization dimensions, and application scenarios in the knowledge base. According to the ranking of overall similarity values, the optimal map visualization form is recommended to the map users. The similarity calculation is shown in Formulas (3)–(6).

Data feature similarity:

$$sim(D_1, D_2) = \begin{cases} \frac{card(d_1 \cap d_2)}{card(d_1)}, & \text{Spatial morphology consistency} \\ 0, & \text{Spatial morphology difference} \end{cases} \quad (3)$$

Visualization dimension similarity:

$$sim(V_1, V_2) = \frac{A \cdot B}{\|A\| \|B\|} = \frac{\sum_{i=1}^n a_i \times b_i}{\sqrt{\sum_{i=1}^n (a_i)^2} \times \sqrt{\sum_{i=1}^n (b_i)^2}} \quad (4)$$

Application scenarios similarity:

$$sim(F_1, F_2) = \begin{cases} 1, F_1 = F_2, & \text{Application scenarios consistency} \\ k, F_1 \approx F_2, & \text{Application scenarios similarity} \\ 0, F_1 \neq F_2, & \text{Application scenarios difference} \end{cases} \quad (5)$$

Overall similarity:

$$similarity = \begin{cases} \omega_1 sim(D_1, D_2) + \omega_2 sim(V_1, V_2) + \omega_3 sim(F_1, F_2), \forall sim \neq 0 \\ 0, \exists sim = 0 \end{cases} \quad (6)$$

In the formula,  $sim(D_1, D_2)$  represents the data feature similarity,  $D_1, D_2$  represents the data features of spatial data,  $d_1, d_2$  represents the set of data features,  $card$  represents the cardinality or size of the data feature set,  $sim(V_1, V_2)$  represents the visualization dimension similarity,  $V_1, V_2$  represents the visualization dimensions of spatial data,  $A, B$  represents the visualization dimension feature vector,  $a_i, b_i$  represents the  $i$ -th element of the visualization dimension vector,  $sim(F_1, F_2)$  represents the application scenarios similarity,  $F_1, F_2$  represents the application scenarios of spatial data,  $k$  represents the degree of proximity of the application domain,  $k \in (0, 1)$ ;  $\omega$  represents the weights of the elements of similarity,  $\omega \in (0, 1)$ ,  $\omega_1 + \omega_2 + \omega_3 = 1$ ,  $sim$  represents the weight, and  $similarity$  represents the overall similarity. Since thematic map knowledge recommendation emphasizes the accurate expression of thematic content through the form of maps, the similarity of the visualization dimension has a higher impact weight on the map recommendation results compared to data features and application domains. Guo [13] pointed out that “the visualization dimension is the basic quantity of map visualization, and the association and combination of different dimensions constitute the visual unity of the map”. Therefore, based on a literature analysis and repeated experiments [13,14,36], this paper proposes setting the weights of the visualization dimension, data features, and application scenarios to 0.6, 0.2, and 0.2, respectively, for the analysis of thematic map knowledge recommendations for land use. The experimental results show that this weight ratio can produce better recommendation results.



were linear time structure, static, Euclidean geometry, two-dimensional, vector-based, flat, and single scale. These data were input into the knowledge graph, and the following recommendations were obtained:

- First to third places: zoning statistical map, dynamic map, Dorling cartogram.
- Fourth to sixth places: area cartogram, whisper map, kriskograms.

The original atlas used the zoning statistical map, which ranked first in the recommendations. We selected the dynamic map and Dorling cartogram from the recommended results and compared them with the original atlas visualization. Figure 7 shows the recommended graph, while Figure 8 presents the comparison results. Figure 7 has been simplified to highlight the superiority of the knowledge recommendation method. It shows the data feature nodes corresponding to the spatial data and the visualization dimension nodes, with different dimensions listed separately. Based on user needs for expressing quantitative attributes, the land use change data can utilize dynamic maps with “map + timeline” or alternative visualization forms like the Dorling cartogram and area cartogram to simplify administrative boundaries and emphasize thematic data.



Figure 7. Visualized recommendation result graph.

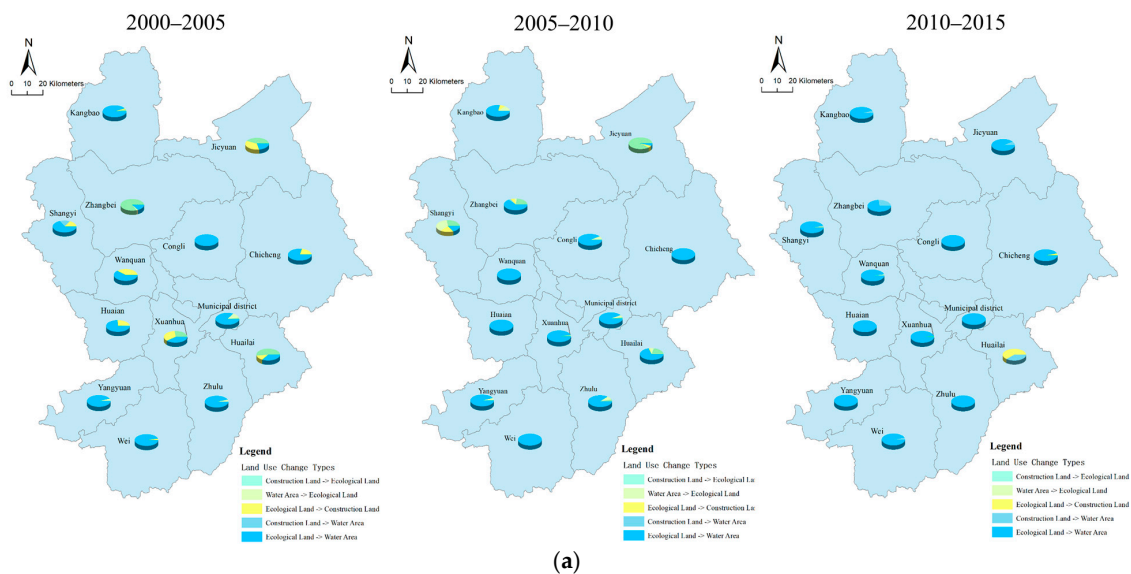
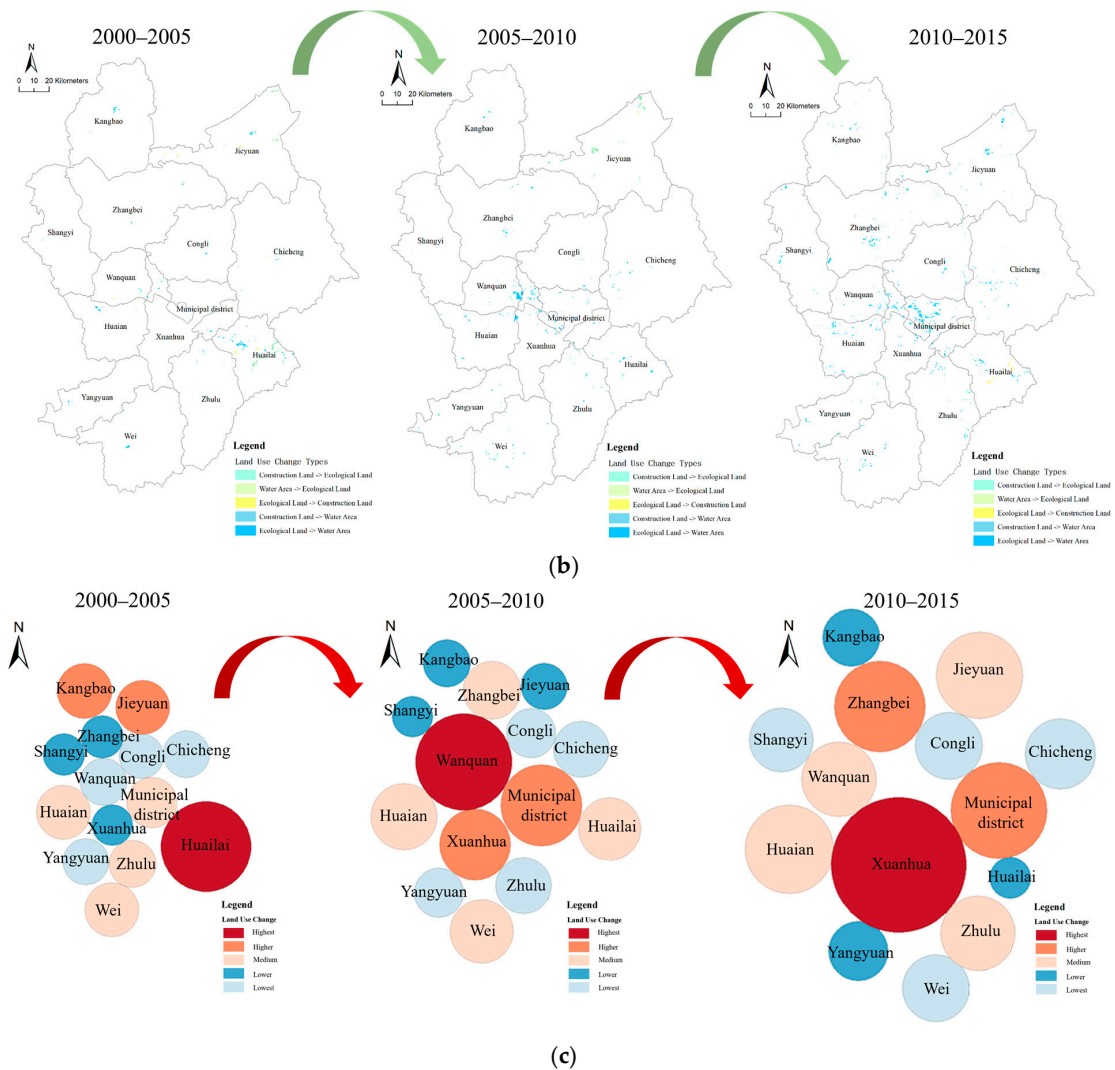


Figure 8. Cont.



**Figure 8.** Visualization results of land use change in Zhangjiakou city. (a) Statistical zoning map. (b) Dynamic map. (c) Dorling cartogram.

#### 4.2. Accuracy Analysis of Visual Recommendation for Different Types of Land Use Spatial Data

The recommendation process for four types of spatial data with different characteristics was conducted following the visualization recommendation procedure. This involved recording the overlap rate between the recommendation results and the original visualization forms of the experimental data and analyzing the proportion of the original visualization forms in the recommended list. The experimental results are presented in Table 1. For point data and volume data, the probabilities of the original visualization forms appearing in the top positions (1 to 5) are 100 percent and 90 percent, respectively. Point data have fewer kinds of visualization forms, with the visualization effect primarily reflected in the design of point symbols. Volume data typically adopt three-dimensional, multi-scale visualization dimensions, characterized by distinct visualization dimensions. The recommended visualization forms for line data and area data include traditional map forms such as line symbol maps and graduated statistical maps, as well as map forms like Dorling cartograms and area cartograms. These two types of data have a relatively large number of visualization dimension combinations. Consequently, the probability of the original visualization forms appearing in the top positions of the recommended list is the lowest, at 70 percent. Overall, the visualization forms recommended by the knowledge recommendation method cover the original visualization forms of the experimental data with a probability of at least 90 percent for line data and 100 percent for the other three

groups of data. The recommended results exhibit a high degree of overlap with the original visualization forms of the experimental data, indicating a high accuracy rate in the recommendations.

**Table 1.** The results of overall experiments.

Experimental Group	Data Type	Original Visualization Form in Top 5 of Recommendation List Ratio/(%)	Original Visualization Form in Positions 6–10 of Recommendation List Ratio/(%)	Overlap Rate of Recommendation Results with Original Visualization Form/(%)
1	Point	100	0	100
2	Line	70	20	90
3	Area	80	20	100
4	Volume	90	10	100

Creating a specialized and well-structured knowledge graph that encompasses extensive cartographic knowledge is a critical factor in influencing recommendation outcomes. In cartography, it is essential to describe temporal, spatial, quantitative, and qualitative characteristics, as well as the relationships between various visualization methods. In this case, five categories of spatial data, data characteristics, visualization dimensions, application fields, and visualization forms are selected to build a knowledge graph that integrates seemingly scattered features into a pan-map knowledge recommendation model. Compared to traditional cartographic methods, using a knowledge graph for pan-map recommendations reduces the randomness and arbitrariness that often occur when methods are selected independently. Since personal factors can influence the choice of different visualization methods, the final selection results may vary. The proposed method mitigates these influences, achieving a theoretically optimal outcome.

## 5. Discussion

This article addresses the problem of insufficient information association in traditional land use thematic maps by using a knowledge graph that integrates and associates spatial data, characteristics, visualization dimensions, forms, and application scenarios, thus enhancing the production and expression of these maps [41,42]. The land use thematic map knowledge graph associates cartographic concepts such as spatial data, data characteristics, visualization dimensions, visualization forms, and application scenarios through a knowledge network. This network stores knowledge of standard maps and various innovative forms of map-like knowledge into the knowledge base. Using this knowledge database, information association and integration of pan-map knowledge can be performed. By associating and integrating the differences and connections between different data characteristics, dimensions, forms, and applications, the land use thematic map knowledge graph serves as an internal driving force for the production of land use thematic maps, providing guidance and constraints for the expression of land use themes.

The land use thematic map knowledge graph allows cartographers to obtain and apply suitable visualization forms based on their preferences and evolving map types, enhancing knowledge organization and query capabilities and providing unified recommendations to ensure compliance with cartographic regulations and prevent the use of outdated information. As new map types emerge, the content of the land use thematic map knowledge graph can be further expanded through knowledge extraction and integration to meet a wider range of application scenarios. The land use thematic map knowledge graph, stored using a graph structure, offers strong correlation, knowledge organization, and aggregate query capabilities [35–37]. Under a unified knowledge recommendation framework, it is possible to combine and nest perspectives such as spatial data characteristics, dimensional preferences, and application requirements to recommend suitable map visualization forms. This not only facilitates compliance with cartographic regulations for land use cartographers, eliminating the need for constant reference checks, but also prevents issues such as using outdated information without awareness of updates, which could lead to biases and other similar problems.

The knowledge graph-based approach to land use thematic map recommendations helps managers (even those without prior knowledge) choose appropriate map visualization forms, addressing both conventional and intuitive public needs by encompassing various map types and integrating PVDT for better representation and innovation of maps. In terms of information transmission, the land use thematic map knowledge graph encompasses a variety of map forms, including standard maps and map-like forms [12,13]. This capability not only meets the land use thematic representation needs for accurately representing the shape characteristics, geographical location, and spatial relationships of spatial objects and recommending corresponding conventional map types, such as image maps, layered color maps, functional zoning maps, and graded statistical maps, but it also caters to the public's interest in focusing less on geographical characteristics and more on the intuitive display of spatial object attribute characteristics, topological characteristics, and virtual characteristics by recommending map-like forms such as cartogram maps and kriskogram maps [17]. Compared with existing research on map ontology construction and map knowledge recommendation, we started from the perspective of pan-map visualization dimension theory and proposed a knowledge expression model that integrates this theory. Unlike traditional map ontology models, this approach more prominently highlights the generalized characteristics of map data, map forms, and map applications, providing significant support for the further promotion and innovation of maps in the future.

## 6. Conclusions

Advancements in information technology have significantly lowered the barriers to map production. However, this progress has also led to a surge in “map accidents,” where maps fail to adhere to proper cartographic principles. The emergence of pan-map theory has not only broadened the scope of cartographic research but also created valuable opportunities for the effective creation of thematic maps, particularly in land use. Integrating knowledge graphs with pan-map theory provides a structured approach to enhancing the representation and understanding of land use through maps. Pan-maps transcend the constraints of precise spatial positions and shapes characteristic of traditional topographic maps, focusing instead on highlighting key points and conveying critical information to enhance map comprehension. The representation of geometric objects in pan-maps has expanded from two-dimensional to three-dimensional and even higher dimensions. Map expressions have evolved from static to dynamic, from surface structures to internal content, and from physical paper to electronic formats. Additionally, the language of maps has shifted from a single graphical symbol language to an organic combination of cognitive processes, natural language, geographic semantics, and graphical symbols. The content, products, and foundational theories of maps have undergone significant expansion.

By integrating pan-map visualization dimension theory with knowledge graphs, cartographic knowledge is no longer confined to professional cartographers. This integration facilitates innovative forms of map expression that cater to a diverse range of land use scenarios, fostering further development in the creation, expression, and application of land use thematic maps. The land use thematic map knowledge recommendation method proposed in this paper represents a novel exploration into the practical applications of pan-map theory. This would further advance the field of land use thematic expression. Future research could concentrate on incorporating emerging technologies and methods, such as automatic map knowledge extraction, automated construction of knowledge graphs, and AI-driven intelligent reasoning, into the study of land use thematic map knowledge recommendation.

**Author Contributions:** Y.C. conceived the study and edited the manuscript; Z.S. carried out ontology design; Y.L. and M.L. reviewed and improved the manuscript; D.H. and Z.Z. performed the statistical analyses. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by “Guangdong Province Marine Economic Development (Six Major Marine Industries) Special Fund Project”, grant number GDNRC [2023]25.

**Data Availability Statement:** Data and materials are available upon request. The data are not publicly available due to privacy.

**Acknowledgments:** All the authors wish to thank all who assisted in conducting this work.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## References

1. Wang, J.; Chen, Y.Q.; Shao, X.M.; Zhang, Y.Y.; Cao, Y.G. Land-use changes and policy dimension driving forces in China: Present, trend and future. *Land Use Policy* **2012**, *29*, 737–749. [\[CrossRef\]](#)
2. Long, H. Land use policy in China: Introduction. *Land Use Policy* **2014**, *40*, 1–5. [\[CrossRef\]](#)
3. Nkwasa, A.; Chawanda, C.J.; Jägermeyr, J.; Griensven, A.V. Improved representation of agricultural land use and crop management for large-scale hydrological impact simulation in Africa using SWAT+. *Hydrol. Earth Syst. Sc.* **2022**, *26*, 71–89. [\[CrossRef\]](#)
4. Zhu, J.; Zhu, M.Y.; Na, J.M.; Liang, Z.Q.; Lu, Y.; Yang, J. Incorporation of Spatially Heterogeneous Area Partitioning into Vector-Based Cellular Automata for Simulating Urban Land-Use Changes. *Land* **2023**, *12*, 1893. [\[CrossRef\]](#)
5. Van der Werf, H.M.G.; Knudsen, M.T.; Cederberg, C. Towards better representation of organic agriculture in life cycle assessment. *Nat. Sustain.* **2020**, *3*, 419–425. [\[CrossRef\]](#)
6. Foody, G.M. Status of land cover classification accuracy assessment. *Remote Sens. Environ.* **2002**, *80*, 185–201. [\[CrossRef\]](#)
7. Kong, X.; Liu, Y.; Liu, X.; Chen, Y.; Liu, D. Thematic maps for land consolidation planning in Hubei Province, China. *J. Maps* **2014**, *10*, 26–34. [\[CrossRef\]](#)
8. Huang, Q.H.; Liu, Y.X.; Li, M.C.; Mao, K.; Li, F.X.; Chen, Z.J.; Chen, L. Thematic maps for county-level land use planning in Contemporary China. *J. Maps* **2012**, *8*, 185–188. [\[CrossRef\]](#)
9. Polous, N. Smart Cartography: Representing complex geographical reality of 21st century. *Int. J. Cartogr.* **2023**, *9*, 619–637. [\[CrossRef\]](#)
10. Kraak, M.; Fabrikant, S.I. Of maps, cartography and the geography of the International Cartographic Association. *Int. J. Cartogr.* **2017**, *3* (Suppl. 1), 9–31. [\[CrossRef\]](#)
11. Roth, R.E. Cartographic Design as Visual Storytelling: Synthesis and Review of Map-Based Narratives, Genres, and Tropes. *Cartogr. J.* **2020**, *58*, 83–114. [\[CrossRef\]](#)
12. Liqiu, M. The constancy and volatility in cartography. *Acta Geod. Et Cartogr. Sin.* **2017**, *46*, 1637.
13. Guo, R.Z.; Ying, S. The rejuvenation of cartography in ICT era. *Acta Geod. Et Cartogr. Sin.* **2017**, *46*, 1274.
14. Guo, R.Z.; Chen, Y.B.; Ying, S.; Lu, G.N.; Li, Z.L. Geographic visualization of pan-map with the context of ternary spaces. *Geomat. Inf. Sci. Wuhan Univ.* **2018**, *43*, 1603–1610.
15. Guo, R.Z.; Chen, Y.B.; Zhao, Z.G.; He, B.; Lu, G.N.; Li, Z.L.; Ying, S.; Ma, D. A theoretical framework for the study of pan-maps. *J. Geomat.* **2021**, *46*, 9–15.
16. Guo, R.Z.; Chen, Y.B.; Zhao, Z.G.; Han, D.Z.; Ma, D.; Ying, S.; Ti, P.; Ke, W.Q.; Fang, Y. Scientific Concept and Representation Framework of Maps in the ICT era. *Geomat. Inf. Sci. Wuhan Univ.* **2022**, *47*, 1978–1987.
17. Shimizu, E.; Inoue, R. A new algorithm for distance cartogram construction. *Int. J. Geogr. Inf. Sci.* **2009**, *23*, 1453–1470. [\[CrossRef\]](#)
18. Xiao, N.; Chun, Y. Visualizing migration flows using kriskograms. *Cartogr. Geogr. Inf. Sc.* **2009**, *36*, 183–191. [\[CrossRef\]](#)
19. Reimer, A.W. Understanding chorematic diagrams: Towards a taxonomy. *Cartogr. J.* **2010**, *47*, 330–350. [\[CrossRef\]](#)
20. Zhu, Y.; Gu, J.; Lin, Y.; Chen, M.; Guo, Q.; Du, X.X.; Xue, C.Q. Field Cognitive Styles on Visual Cognition in the Event Structure Design of Bivariate Interactive Dorling Cartogram—The Similarities and Differences of Field-Independent and Field-Dependent Users. *ISPRS Int. J. Geo Inf.* **2022**, *11*, 574. [\[CrossRef\]](#)
21. Wang, J.Y.; Sun, Q.; Wang, G.X. *Principles and Methods of Cartography*; Science Press: Beijing, China, 2014.
22. Tian, J.; Huang, R.; Guo, Q. Study on intelligent choice of representation methods in thematic map. *Sci. Surv. Mapp.* **2007**, *32*, 170–172.
23. Nan, J.; Jian, M.A.; Wu, L.; Sun, Q. The Formalization Expression of Representation Method Rules Oriented to Automatic Recommendation. *Bull. Surv. Mapp.* **2015**, *9*, 36.
24. Wu, M.; Sun, Y.; Li, Y. Adaptive transfer of color from images to maps and visualizations. *Cartogr. Geogr. Inf. Sc.* **2022**, *49*, 289–312. [\[CrossRef\]](#)
25. Tennekes, M. Tmap: Thematic Maps in R. *J. Stat. Softw.* **2018**, *84*, 1–39. [\[CrossRef\]](#)
26. Du, J.; Wang, S.H.; Ye, X.Y.; Diana, S.S.; Karen, K. GIS-KG: Building a large-scale hierarchical knowledge graph for geographic information science. *Int. J. Geogr. Inf. Sci.* **2022**, *36*, 873–897. [\[CrossRef\]](#)
27. Zhang, Y.J.; Cheng, X.; Li, Y.S.; Wang, F.; Liu, X.J.; Wu, W.P. Research on land and resources management and retrieval using knowledge graph. *Geomat. Inf. Sci. Wuhan Univ.* **2022**, *47*, 1165–1175.
28. Meng, L.; Wang, G. Framework for Knowledge Graph-driven Construction of Natural Resources Big Data Mining Model in Guangdong Province. *Geomat. Spat. Inf. Technol.* **2020**, *43*, 91–94.

29. Ding, Y.; Xu, Z.; Zhu, Q.; Li, H.; Luo, Y.; Bao, Y.; Tang, L.; Zeng, S. Integrated data-model-knowledge representation for natural resource entities. *Int. J. Digit. Earth* **2022**, *15*, 653–678. [[CrossRef](#)]
30. Han, F.; Deng, Y.R.; Liu, Q.Y.; Zhou, Y.Z.; Wang, J.; Huang, Y.J.; Zhang, Q.L.; Bian, J. Construction and application of the knowledge graph method in management of soil pollution in contaminated sites: A case study in South China. *J. Environ. Manag.* **2022**, *319*, 115685. [[CrossRef](#)]
31. Li, H.T.; Wang, Y.; Zhang, S.H.; Song, Y.Q.; Qu, H.M. KG4Vis: A knowledge graph-based approach for visualization recommendation. *IEEE Trans. Vis. Comput. Graph.* **2021**, *28*, 195–205. [[CrossRef](#)]
32. Li, L.Y.; Peng, C.J.; Guo, B.Q.; Nie, C.Y. Construction of Knowledge Map of Marine Map Visualization Method. *J. Geomat.* **2022**, *47*, 77–80.
33. Niu, X.; Yang, J.; Yan, H. WeMap Recommendation by Fusion of Knowledge Graph and Collaborative Filtering. *J. Ge Inf. Sci.* **2024**, *26*, 967–977.
34. Koteich, B.; Saux, É.; Laddada, W. Knowledge-Based Recommendation for On-Demand Mapping: Application to Nautical Charts. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 786. [[CrossRef](#)]
35. Zhou, C.H.; Wang, H.; Wang, C.S.; Hou, Z.Q.; Zheng, Z.M.; Shen, S.Z.; Cheng, Q.M.; Feng, Z.Q.; Wang, X.B.; Lv, H.R.; et al. Geoscience knowledge graph in the big data era. *Sci. China Earth Sc.* **2021**, *64*, 1105–1114. [[CrossRef](#)]
36. Ti, P.; Hou, X.; Li, Z.L.; Chen, Y.B.; Guo, R.Z. Construction of Pan-Map Representation Mechanism Based on Visualization Dimension System. *Geomat. Inf. Sci. Wuhan Univ.* **2022**, *47*, 2015–2025.
37. Sun, Z.; Vashishth, S.; Sanyal, S.; Talukdar, P.; Yang, Y. A Re-evaluation of Knowledge Graph Completion Methods. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, Online, 5–10 July 2020; pp. 5516–5522.
38. Zheng, K.; Xie, M.H.; Zhang, J.B.; Xie, J.; Xia, S.H. A knowledge representation model based on the geographic spatiotemporal process. *Int. J. Geogr. Inf. Sci.* **2022**, *36*, 674–691. [[CrossRef](#)]
39. Xiong, W.; Hoang, T.; Wang, W.Y. DeepPath: A reinforcement learning method for knowledge graph reasoning. *arXiv* **2017**, arXiv:1707.06690.
40. Wang, S.; Zhang, X.; Ye, P.; Du, M.; Lu, Y.; Xue, H. Geographic knowledge graph (GeoKG): A formalized geographic knowledge representation. *ISPRS Int. J. Geo inf.* **2019**, *8*, 184. [[CrossRef](#)]
41. Tian, L.; Zhou, X.; Wu, Y.P.; Zhou, W.T.; Zhang, J.H.; Zhang, T.S. Knowledge graph and knowledge reasoning: A systematic review. *J. Elect. Sci. Tech.* **2022**, *20*, 100159. [[CrossRef](#)]
42. Xu, J.; Kim, S.; Song, M.; Jeong, M.B.; Kim, D.H.; Kang, J.; Rousseau, J.F.; Li, X.; Xu, W.J.; Torvik, V.; et al. Building a PubMed knowledge graph. *Sci. Data* **2020**, *7*, 205. [[CrossRef](#)]

**Disclaimer/Publisher’s Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.