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EVENT GRAPH CONSTRUCTION METHOD ON NATURAL DISASTER RESEARCH

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KEY WORDS: Event Graph, Event Generalization, Soil Erosion, Event Extraction, Natural Disaster Analysis, Event Storage.

ABSTRACT:

The analysis of natural hazards is still lacking in real-time and comprehensiveness. To enhance the intelligent analysis of disasters, reduce natural disasters, and provide more timely and accurate disaster warnings. The method of constructing a natural disaster research event graph using the abstracts of research literature related to natural disaster analysis as the data source is proposed. First, a rule-based matching algorithm combined with syntactic analysis is used to extract the events of the disaster analysis process and spatio-temporal information from the abstract; Then build an event storage model based on Neo4j to store the event chain and related information; Then use Word2vec to convert events into word vectors, and define the event similarity as a linear sum of the object similarity and predicate similarity of the two events, combine event similarity setting equation to calculate core nodes and perform event generalization and fusion of graphs. Based on the above method, soil erosion is used as an example to construct an event graph and provide the basis for decision making services for intelligent analysis of natural disasters.

1. INTRODUCTION

China's current frequency of natural disasters. The Ministry of Emergency Management released the national natural disaster situation in the first half of 2022, revealing that natural disasters in China mainly include floods, hail and geological disasters, while droughts, earthquakes, snow hazard and forest fires also occur to varying degrees, affecting a total of 39,143,000 people. There are numerous causes of a natural disaster, such as climate change, soil erosion, and increased urban construction land, which cause soil erosion and the urban heat island effect, which leads to flooding (Lu,2022). Although many types of research literature analyze the time, location, causes, and consequences of various natural hazards, the areas analyzed are mostly concentrated in disaster-prone areas and the types of natural hazards are limited. As a result, if disaster analysis is conducted solely using the research methodology of one literature, a comprehensive analysis of multiple hazards across the country cannot be achieved. We can investigate the event development process for analyzing various natural disaster impact factors and provide a foundation for comprehensive intelligent analysis of natural disasters by extracting data from a large amount of scientific literature and building a natural disaster research event graph.

Zhang et al (2021) selected epidemic-related media reports as the data source, constructed an event graph of major emergencies through ontology construction, event extraction and event relationship extraction, and analyzed the knowledge of the reasoning of events. The results showed that the event graph could provide a scientific basis for the response and governance of major emergencies; Feng Jun et al (2020) selected academic journal articles, news texts and work reports related to urban flooding as data sources, constructed an event graph of urban flooding by extracting causal events and conducted a causal analysis. The results showed that the event graph could provide a basis for accurately finding the causes of flooding points; Du et al (2020) selected disaster databases as well as related literature as databases, first extracted the relationships between entities and entities, and then fused the data to construct a natural disaster emergency knowledge graph, which describes the attributes of disaster data, emergency tasks, and model methods, thus providing a knowledge base for disaster prevention and mitigation. In summary, using research literature as a data source to construct an event graph can provide a service basis for natural disaster analysis. The research themes of the above research literature are all names of the methods used to analyze the causes of natural disasters or by constructing event graphs or knowledge graphs, and not the process of analyzing a particular natural disaster. There is a certain pattern in the series of operations performed by the research literature in the analysis of a certain disaster, by defining these operations as events, it can be considered that the research literature is composed of many small events that form a large chain of events that complete the analysis of a disaster. By extracting the research method information of the natural disaster analysis research literature and constructing a natural disaster research event graph, we can provide basic services for the decision of the method route of analyzing natural disasters.

Therefore, this paper defines research methods, research themes and research results in research literature as different categories of events, extracts and generalizes these events, constitutes a natural disaster analysis event chain, builds a natural disaster research event graph, and provides a service basis for intelligent modeling of natural disaster analysis.

2. RELATED WORK

The concept of "event graph" was proposed by Ting Liu of Harbin Institute of Technology in 2017, which is still a relatively new concept. In recent years, several domestic companies and research institutions have explored the research related to " event graph ", and they have done some experimental (Liao et al.2020)

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and fundamental work (Che and Liu,2022); Zhong et al (2019) of the Chinese Academy of Sciences Institute of Automation and Zhu et al (2018) of Shanghai University have achieved fruitful results in event extraction and event ontology representation, respectively.

Event extraction, event relationship extraction and event generalization are the three core techniques for creating the event graph. In order to build a medical network opinion event graph, Shan et al (2019) used rule template matching to extract events as well as identify event relationships. They then used Word2vec to turn text into word vectors, generalized events with a high degree of similarity into one class and used the K-means clustering algorithm. Lin et al (2021) used template matching to extract events, trained word vectors using Word2vec, and then generalized events by calculating the similarity; Liu et al (2022) extracted events based on sequence labeling methods combined with deep learning models, designed causal concatenation lexicon, result lexicon and causal pattern rule base combined with Language Technology Platform(LTP)(Che et al. 2010) to extract event relationships, used node2vec algorithm to vectorize events and then calculated the similarity for event generalization, and finally constructed a financial emergent event graph; Wang et al (2022) extracted events based on event ontology, and used matching rules and deep learning methods to extract event elements and event relationships to construct an air pollution enforcement event graph. The core technology of constructing event graphs in different fields is similar, but the characteristics of information in each field are different, and the methods adopted in the core technology are also different.

Regarding event extraction, there are three main methods: rule matching method, machine learning method and deep learning method. Rule matching algorithm (Yang and Zhang, 2010), which first uses some natural language processing tools such as Jieba, HanLP and LTP. to pre-process the sentences such as word division, lexical annotation, semantic annotation and syntactic analysis, then sets the event type, the event trigger word, the template corresponding to the event type for matching, and finally, the events are extracted in a structured way; Machine learning algorithm (Han et al. 2018), which first expresses the text as a word vector and then combines word embedding and machine learning algorithms to construct a trigger word recognizer using machine learning algorithms such as random forests to improve the accuracy of trigger word recognition. Deep learning algorithms (Dai et al. 2022), introduce more neural networks for predicting the labels of word embeddings. Both machine learning and deep learning algorithms need to manually label a large amount of data for model training, while the rule matching method does not need to manually label a large amount of data, but it needs to manually set the matching template. If the text description structure is fragmented and the wording is not standardized, machine learning and deep learning algorithms will work better. Research literature usually use more standardized words, and the text structure is more obvious and easier to summarize the template, which is more suitable for the algorithm of rule matching.

Event relationship extraction is still basically at the stage based on connecting words, and most of them cannot be separated from connecting words, such as "because" and "so" corresponding to causal relationships; "then" and "next" correspond to the sequential relationships. Miao et al (2022) proposed an implicit causality extraction algorithm aiming to extract causal relationships without connectives; Ning et al (2019) proposed to use a bidirectional LSTM network structure to encode event packet extraction sequential relations; Han et al (2020) proposed to use a joint task model type to encode event sentence extraction sequential relationships. Although these two methods have achieved greater success in the event sequential relation extraction task, their proposed methods only focus on extracting semantic information before and after the event trigger word, for which Li et al (2022) proposed an event sequential relation recognition method that incorporates syntactic information, which makes the recognition results much better.

Event generalization refers to the abstraction of events with very different narratives but the same type into a cluster of events, which can reduce the scale of events in the event graph and improve the knowledge description ability and application universality of matter logic. Shan et al (2019) proposed an event generalization method based on K-means clustering by first converting event statements into summation averages of sentence vectors and word vectors, then clustering them using the K-means clustering method, and finally computing and adding the new events to the existing clusters; Cao et al (2020) proposed a framework for qualifying domain event generalization based on deep semantic matching, which consists of two modules: deep semantic computation and seed event matching. Multiple methods are effective in generalizing events, and their core idea is to express events in a computable way and determine whether they can be generalized by computing the similarity.

In summary, this paper takes soil erosion analysis research literature as an example, uses rule matching method to extract events and event relationships based on the characteristics of this type of research literature, and establishes a storage structure based on the association characteristics between information, then calculates the similarity of events, and organizes and generalizes the event chain by combining Gephi software and Neo4j databases to build a natural disaster research event graph.

3. METHODS

The construction of a natural disaster research event graph mainly includes four stages: data collection, information extraction, establishing event storage structure, event generalization and graph fusion, as shown in Figure 1.

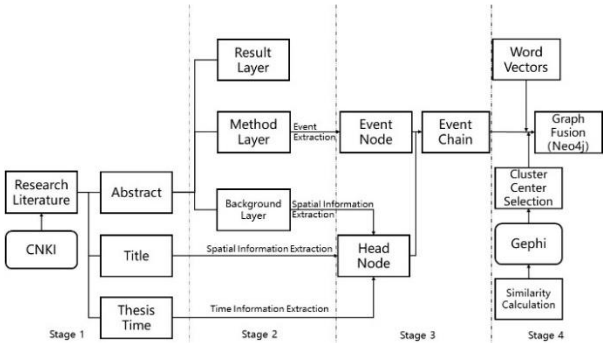

Figure 1. Overall process.

Data collection. Using the export literature function provided by CNKI to obtain information on papers such as publication date, title, abstract, etc.

Information extraction. The algorithm is designed to firstly divide the summary information, the background layer information, the method layer information and the result layer information by keyword matching combined with manual extraction. Then the method layer information is pre-processed by the Jieba tool combined with LTP for sentence separation, lexical annotation and syntactic analysis, and then the text is divided by text punctuation and words that indicate the structure of sentence taking over, and finally, the event is extracted based on the syntactic analysis results.

Establishing event storage structure. Natural disaster research literature is unstructured data, single research literature contains multiple research events, and multiple research events form a chain of events. After extracting information from the method layer to obtain the structured information, the data structure is designed to store the extracted information in the Neo4j graph database.

Event generalization and graph fusion. The similarity of events is calculated based on Wordvec2 trained event word vectors, and the generalization of events is performed in Gephi based on the similarity calculation core nodes, and the generalized event clusters are stored in the Neo4j graph database. Finally, existing generalized graphs are fused with the event graphs to get the natural disaster research event graph.

3.1 Information extraction

3.1.1 Event extraction

Since the essence of intelligent modeling is to make machines imitate human operations for disaster analysis, the relevant operation information generally exists in the method layer, which needs to be structured to extract the method layer information and constitute the method event chain. If the structured extraction of the whole text is carried out directly without processing, it will result in redundant data types. Therefore, the method of event extraction in this paper is to first divide the text into the background layer, method layer and result layer by using keyword recognition, and then perform structured information extraction on the method layer. Because the background layer and the result layer have more obvious template features, the matching templates of the background layer and the result layer are set to give priority to matching extraction, and after the extraction is completed, the remaining text belongs to the method layer by default. In the background layer, the research area template and the research theme template are set as shown in Table 1, and the identification is divided according to the template categories. In the result layer, the keywords are divided into 3 levels according to the keyword length as shown in Table 2, and the identification is divided according to the order of the levels.

Template Category	Keyword	Example
Research area	Take as an example	Take Yueyang County as an example
Research area	As a pilot area	Zhongyang County, Shanxi Province as a pilot area
Research area	As the research ...	Taking the Nantong mining area in Chongqing as the research object
Research theme	To understand...	To understand the ecological problems in the Xingjiang River Basin
Research theme	To explore...	To investigate the soil erosion and nutrient loss characteristics of forest land in Dianchi watershed since the implementation of reforestation project
Research theme	Having conducted...	Having conducted Dynamic Change Characteristics of Forest Land in Sichuan Province in the Late 1990s

Table 1. Background layer template.

Level	Keyword	Example
1	“The following conclusions were drawn”, “The results of the study showed that”, “The results of the study showed that”, “The analysis results are”, “The main performance is”	[... Analysis of the spatial and temporal variation of ecological security in the study area.] [The following conclusions were drawn] [(1) Overall 2000~....]
2	" Main Conclusions "," The following conclusions "," The results show that "," Research shows that "， " The study found that "," Research results "	[...and analyze the changes in soil erosion dynamics in comparison with the 2013 census results.] [The results show that] [(1) Luhe County...]
3	" Conclusion "," Results "	[...analyzed its spatial and temporal variation pattern with the help of spatial superposition function and linear regression equation.] [Results] [(1) The study area as a whole showed a shift from north .]

Table 2. Result layer template.

The main parts of the sentence are subject, predicate and object, and extracting these three elements can preserve the semantic information of the discourse while extracting the structured information. In the abstract of research literature, the subject is more abstract, and from a realistic point of view, it can be considered that the operator is the subject and the operator performs some analysis of the research area; from the perspective of the article, it can also be considered that the research area is the subject and the research area performs some analysis. Defining the research area as the subject facilitates subsequent intelligent modeling, but generally, the research area is mentioned in the background layer and not mentioned again at the method layer. Therefore, there is basically no subject in the method layer, and extracting the method layer events means extracting the predicate and object of the method layer.

LTP can perform word division, lexical annotation and syntactic analysis of sentences. Based on the results of LTP syntactic analysis, predicates and objects can be extracted. In the word separation stage, since there are many specialized terms in the geographic information field, such as the " dimidiate pixel model", the terminology will not be recognized if a custom dictionary is not added, but the LTP does not completely follow the dictionary after adding the dictionary, and the Jieba tool has better results than the LTP in word separation based on the dictionary. Therefore, after stratifying the text to divide the method layer, we first use the word division module of the Jieba tool to add a dictionary of specialized terms in the field of geographic information to divide the words. Then use LTP for lexical annotation as well as syntactic analysis, and finally extract the VOB phrase and identify A1 (object) based on semantic role annotation, set the predicate “v” as “O” label, set “A1” as “A”, store the information through the label, and complete the extraction of the event, as shown in Figure 2.

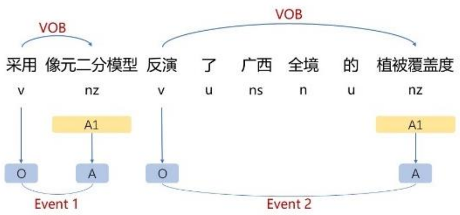

Figure 2. Event extraction.

3.1.2 Spatio-temporal information extraction

The publication time of research literature is an indicator of the novelty of current research methods, and usually, the research methods used in literature published more recently are more novel and the analysis results are relatively more detailed and accurate. At the same time, the title of the research literature contains information on the research area and research theme. Extracting information on the research area and research theme in the title can be used as a supplement to extract such information in the background layer, because some literature lacks descriptions of the research area and research theme in the background layer.

In summary, this paper sets the “Time” attribute of the title node is set as the time of the paper, and the time of the paper publication is defined as the time of the paper while obtaining the information of the paper; “Locate” attribute is the information of the research area, and the words with the lexical nature of the location name in the title are extracted as the research area by using the LTP. “Topic” attribute is the research theme, and because the title has a high generality, the research theme exists in the form of consecutive combinations of names and verbs in the title, so after lexical annotation and syntactic analysis of the title, the consecutive combinations of nouns and verbs are extracted as the research theme, as shown in Figure 3.

Figure 3. Spatio-temporal information extraction.

3.2 Establishing event storage structure

The natural disaster research literature is unstructured text, and the information in the text is extracted structurally by 3.1, but the extracted information is fragmented, and still cannot be applied without correlating the information. Therefore, a storage structure is needed to correlate the information. Since keywords indicating sequential in the abstracts of research literature occur less frequently, the use of keyword matching may miss mentioning a lot of information. Because most of the authors write in the order of operation, the events at the method level themselves have sequential relationships, and connecting the sequential events constitutes an event chain to obtain the event chain of single research, which is denoted as E= $\{H, e_1, e_2, \ldots, e_n\}$, consisting of n event nodes e and 1 head node H. The head node H is used to store generic information about the event chain, and the event node e is used to store information about individual events, as shown in Figure 4. The event chain is divided by the head node H. The relationship between the head node H and the event nodes is set as the pointing relationship of HeadID, and the relationship of ID values sets the sequential relationship between the event nodes. Event chain E is stored in the Neo4j database in order.

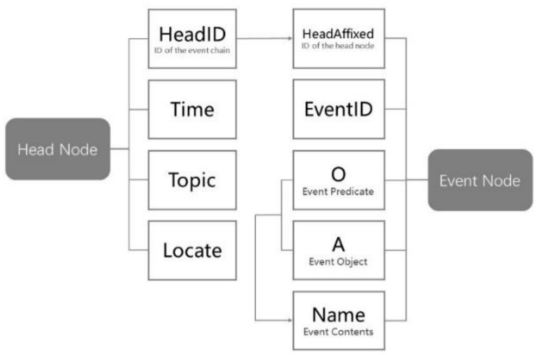

Figure 4. Event storage structure.

As shown in the figure, the head node is mainly used for event chain selection, and the event chain of the relevant studies of the target study can be effectively extracted based on the spatio-temporal information. The event nodes are used to store the relevant information of events, where O and A are the core information.

3.3 Event generalization and graph fusion

The generalization of events is a key step to explore the logical relationship between events. Generalizing the chain of events of a certain category of natural disaster research can explore the logical relationship between the process of analysis conducted by that category of natural disaster; generalizing the chain of events of different categories of natural disaster research can explore the common and different points of the analysis process of different categories. Word2vec is used to convert events into word vectors that can be computed, and two events with a similarity greater than a certain threshold can be considered as a category.

3.3.1 Event similarity algorithm

Shan et al (2010) defined the event as a six-tuple, and for the calculation of the similarity of two events, the formula was set to find out the similarity of each event element, and the weight factor was assigned to the similarity of each element to finally sum up the similarity of the events. In this paper, in the information extraction stage, the method layer events are extracted in the form of "predicate + object ", so the content of event nodes is represented as O+A (where O is the event predicate and A is the event object), and the similarity between O and A of event nodes is calculated based on the trained event word vector.

The event predicate O is calculated as shown in equation (1):

$$\mathrm{sim(O)} = \begin{pmatrix} \mathrm{sim(O_{11}, O_{11})} & \cdots & \mathrm{sim(O_{11}, O_{nm})} \\ \vdots & \ddots & \vdots \\ \mathrm{sim(O_{nm}, O_{11})} & \cdots & \mathrm{sim(O_{nm}, O_{nm})} \end{pmatrix} \tag{1}$$

The event object A is calculated as shown in equation (2):

$$\mathrm{sim(A)} = \begin{pmatrix} \mathrm{sim(A_{11}, A_{11})} & \cdots & \mathrm{sim(A_{11}, A_{nm})} \\ \vdots & \ddots & \vdots \\ \mathrm{sim(A_{nm}, A_{11})} & \cdots & \mathrm{sim(A_{nm}, A_{nm})} \end{pmatrix} \tag{2}$$

The similarity of the event as a whole is defined as a linear combination of the similarity of O and the similarity of A, as shown in equation (3):

$$\mathrm{sim(e)} = \mu_1 \mathrm{sim(O)} + \mu_2 \mathrm{sim(A)}, \quad \mu_1 + \mu_2 = 1 \tag{3}$$

where sim(e) = event similarity matrix
sim(O) = similarity matrix of event predicates
sim(A) = similarity matrix of event objects
n = HeadID
m = EventID
μ_1 = self-selected parameters
μ_2 = self-selected parameters

3.3.2 Obtaining core nodes

After calculating the event similarity, the two events judged to be similar need to be fused into one event, i.e., the event nodes are fused into one core node. In this paper, Gephi software is used to determine the core nodes in combination with the calculated event similarity. Event nodes and similarity data are imported into Gephi, and the event nodes are clustered by setting the number of clustering clusters n, combined with the clustering algorithm that comes with Gephi. For the clusters as well as the similarity between nodes, the article takes equation (4) and equation (5) to calculate and determine the core node N_{main}.

$$deg_i = \sum_1^n sim(N_i, N_n) \tag{4}$$

$$N_{main} = Node_{max\{deg_1, \ldots, deg_i \ldots, deg_n\}} \tag{5}$$

3.3.3 Graph fusion

The core nodes obtained by 3.3.2 are combined with the similar nodes and the generalized core nodes to form the directed graph atlas, and the edge attributes are set to the similarity between the points obtained in 3.3.1. The node generalization map is formed. Then, by reading the point information in the generalized graph atlas, the linear node structure in the event chain is formed into a mesh structure by deleting and linking the linear chain structure, as shown in Figure 5.

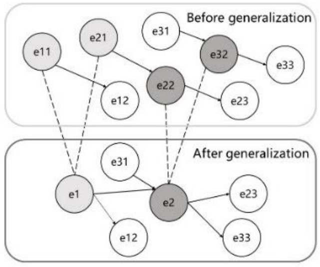

Figure 5. Event chain generalization.

4. EXPERIMENT

4.1 Data acquisition and pre-processing

The 300 pieces of research literature on the field of soil erosion GIS obtained and screened on CNKI were used as research objects, and the texts were matched based on the templates in Table I and Table II, and the texts were divided into background layer texts, method layer texts, and result layer texts, as shown in Figure 6.

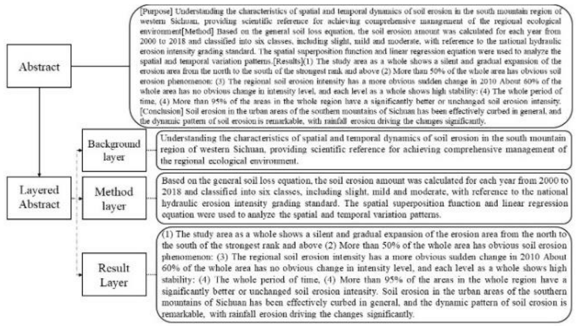

Figure 6. Abstract layering.

4.2 Soil erosion event chain storage

Based on the delineated method layer text, the predicate and object in the delineated sentences are extracted using the syntactic analysis function of the LTP module to construct event nodes. Set keywords for template matching on the literature title as well as the background layer text to obtain the research area as well as the research theme. Thus, the head node is constructed. Head nodes and event nodes are added to the Neo4j graph database respectively to complete the storage of the soil erosion event chain. The resulting Figure 7 shows that the header node includes Locate, Name (ID of the event chain), Time and Topic, and an event chain is connected with the header node. The storage structure of this paper stores the knowledge information in the header node, and combines the knowledge information and the event chain by ID to associate the knowledge with the event for an easy query.

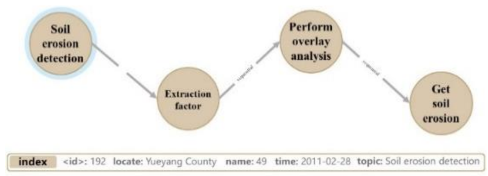

Figure 7. Event chain storage.

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4.3 Soil erosion event generalization and graph fusion

The event predicate O and event object A in the event node are extracted respectively, sim(O) and sim(A) are obtained by equation (1) and equation (2), and the experimental results are analyzed by taking multiple sets of values for $\mu 1$ and $\mu 2$. Finally, set $\mu_1=0.3$, $\mu_2=0.7$ to obtain sim(e), define the nodes with sim(e) > 0.7 as generalizable nodes, import the node combination {e1,e2,sim(e)} into Gephi, perform clustering in Gephi, set the number of clusters n = 30, obtain the clustering results as shown in Figure 8, obtain the center of generalized event clusters.

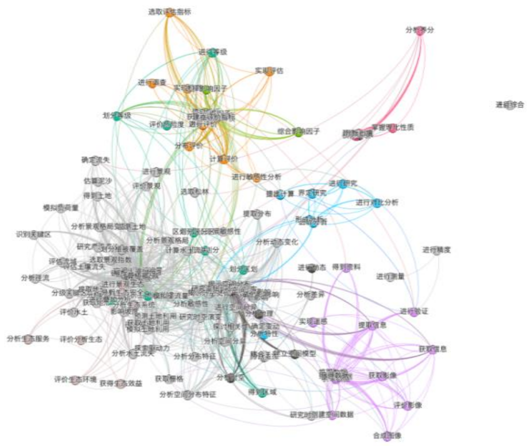


Figure 8. Selecting event cluster centers.

Fuse the generalizable events. The similarity of the events "Get factor", "Select factor" and "Extract factor" is calculated and clustering is performed in Gephi as shown in Figure 9. The core nodes are identified as "Extraction factor", and then the nodes with similarity greater than 0.7 to the core nodes are generalized as "extract factor".

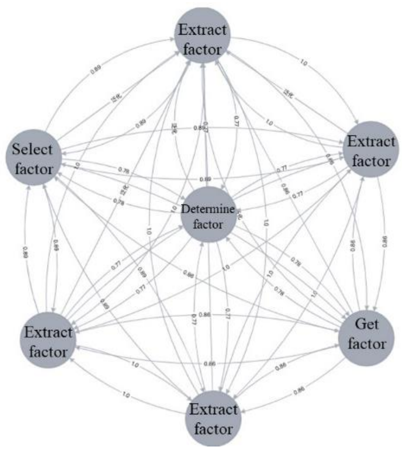
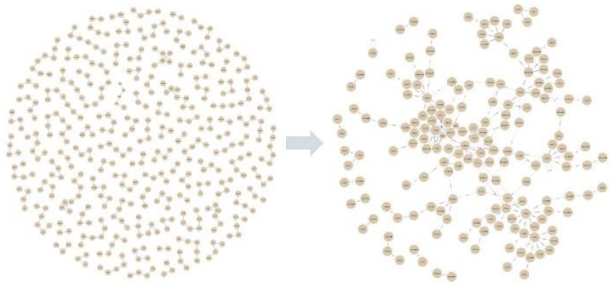


Figure 9. Event node generalization.

The Neo4j database was used to construct the soil erosion fusion matter map, and the generalized event nodes were fused with the non-generalized event nodes to obtain the final matter map for soil erosion analysis. The ungeneralized event graph is shown in Figure 10-a, showing a linear chain structure with each event chain independently; after generalization and fusion, the event graph is shown in Figure 10-b, where the related event chains are connected, showing a mesh structure.



a. Ungeneralized event graph. b. Generalized event graph.

Figure 10. Comparison before and after generalization.

The generalized event graph(partial) is shown in Figure 11 (some nodes are removed for clear presentation and different nodes are shown in different colors), with yellow as the head node; blue as the ungeneralized event node; brown as the generalized event node; and green as the tail node (the node with obvious tail characteristics after generalization). The yellow node in the figure can reach the green node through the event chain of the brown node and the blue node, i.e., the similar research methods in the event chain corresponding to different or similar research themes are connected after generalization. For example, two different research themes "Soil erosion hazard" and " Returning farmland to forest and grass space decision" have four identical generalization nodes and the same tail node. This means that after a specific pre-processing, both themes can be studied using one set of methods.

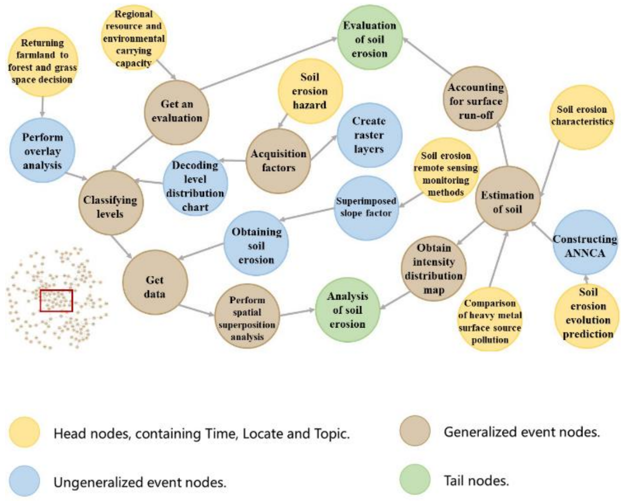


Figure 11. Generalized event graph(partial).

5. CONCLUSION

With the data of research literature related to natural disaster analysis, spatio-temporal information is extracted from the background layer and title, and the method event chain is extracted from the method layer; then structured events are transformed into word vectors, and an algorithm is set to calculate event similarity; finally, the event chain is generalized by combining the core nodes of similarity calculation, and the event chain and spatio-temporal information are stored jointly with the set storage structure, thus constructing a natural disaster research event graph. By deducing the analysis process of various types of natural disasters through the natural disaster research event graph, we can provide a service basis for the decision of analysis methods in areas lacking natural disaster. In the future, the intelligent modeling of natural disaster analysis can be realized by connecting the relevant operation modules of various analysis software to automatically conduct comprehensive analysis of the real-time dynamic changes of natural disasters, strengthen the intelligent analysis of natural disasters, and make the early warning of natural disasters timelier and more comprehensive.

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