International Journal of *Geo-Information*

Article

A Study on a Spatiotemporal Entity-Based Event Data Model

Mingming Wang [1], Jiangshui Zhang [1,2,*], Yibing Cao [1], Shenghui Li [3] and Minjie Chen [1]

1 Institute of Geographic Space Information, Information Engineering University, Zhengzhou 450052, China; wmm2016324@outlook.com (M.W.)
2 Key Laboratory of Smart Earth, Xi'an 710054, China
3 Department of Surveying and Mapping Engineering, Henan College of Surveying and Mapping, Zhengzhou 451464, China
* Correspondence: wat_ter@163.com

Abstract: An event is an important medium for recording, expressing, and understanding the real world. Additionally, a data model can provide a digital and structured description method for the real world. Therefore, studying event data models is highly important for describing the real world. By analyzing the representational categories of the existing event data models, the representation of existing event models was found to have different emphases and not be sufficiently balanced, and the universality and comprehensiveness need to be improved. Therefore, based on the advantages of the ontological event model in expressing semantic information and the advantages of the object-event-based spatiotemporal data model in expressing entity multidimensional characteristics and dynamic processes, a spatiotemporal entity-based event data model and the modeling method were designed to provide model support for event organization and processing. Additionally, the Long March and its important battles were selected as case studies to validate the proposed model. The validation shows that the proposed model performs well in terms of event dynamics, hierarchical structure, and complex interrelationships.

Keywords: spatiotemporal entity; event data model; change processes; event dynamics; hierarchical structure; the Long March

Citation: Wang, M.; Zhang, J.; Cao, Y.; Li, S.; Chen, M. A Study on a Spatiotemporal Entity-Based Event Data Model. *ISPRS Int. J. Geo-Inf.* **2024**, *13*, 360. https://doi.org/10.3390/ijgi13100360

Academic Editors: Wolfgang Kainz, Mara Nikolaidou, Christos Chalkias, Marinos Kavouras and Margarita Kokla

Received: 4 August 2024
Revised: 9 October 2024
Accepted: 11 October 2024
Published: 14 October 2024

1. Introduction

Events originate in cognitive science and are considered the storage unit of human memory and understanding of the real world [1]. Events, an important concept for understanding the real world, are the core of modeling, representation, and analysis in many fields, such as history, cultural heritage, multimedia, and geography [2]. Events are a basic part of daily life and an indispensable unit that represents the real world [3]. On this basis, many scholars have conducted in-depth studies on events, including their definition and classification [4–7], information extraction [8,9], modeling expression [2,6,10,11], logical reasoning [12,13], and evolutionary pattern analysis [14–16], providing theoretical and technical support for digital representation and analysis of the real world. In the study of events, constructing event models is critical as the embodiment of theories, including the basic concepts of events, the standard for the organization of information extraction results, and the technical support for logical reasoning and evolution analysis.

An event is the basic semantic unit for understanding the real world [17]. To digitally represent the real world, it is necessary to conduct modeling research based on event characteristics and representation requirements. Based on the grammatical and semantic characteristics of the record text of events, scholars construct event models from the data processing perspective [18–20]. Some scholars start from the content of event representations and models and express event data based on object and ontology theory [2,21].

With the promotion of basic surveying and mapping in the new era and the construction of Real 3D China, upgrading traditional 4D data to entity information products is an important task in the current surveying and mapping field, and entity modeling, as a key technical issue, cannot be ignored [22–24]. Moreover, since representing the object by events is a complex and changeable dynamic process, both entities and events are necessary for comprehensive dynamic systems modeling [25]. Therefore, by reviewing previous event data models, the advantages and deficiencies of existing event models were summarized in terms of the completeness, versatility and expansion ability of event representation elements. On this basis, with the entity as the core, a spatiotemporal entity-based event data model and its construction method were proposed.

The rest of this paper is organized as follows. Section 2 provides a general overview of the current event data models. In Section 3, a spatiotemporal entity-based event data model and the construction method are proposed to address the problems in the existing data models, and the proposed model is compared with previous data models. In Section 4, Long March and its important battles are selected as the research objects to validate the proposed model and modeling method.

2. Related Work

2.1. Analysis of the Event Data Model Research Status

The event data model is the abstraction, organization, and expression of events in the real world. It is highly important for event data organization, storage, expression, and analysis. The models may have different emphases when describing event elements because the business scenario requirements of event modeling are different; thus, the event data model has advantages and disadvantages in expressing events. In this paper, the existing event models were sorted from the aspects of modeling methods and representation content, and the existing event models were divided into event semantic element models, ontology-based event models, and event-oriented spatiotemporal data models. The following text is a brief analysis of these three types of event data models.

2.1.1. Event Semantic Element Model

The event semantic element model refers to an event model formed by the disassembly, analysis, and combination of event data sources and the syntax and semantics of event representations from a linguistic point of view. For this model type, some scholars have focused on syntactic structures such as subject–predicate–object–definite verb complements in the event description text [26] and model and express the keywords for event description and their combinations. Some scholars are oriented to the needs of specific task scenarios, such as buzzwords in news reports [14], multilingual postinformation integration [27], and Weibo [28] and Twitter event extraction [29], and organize and process the information of concern from specific event sources. In addition to focusing on the syntax and semantics of event data sources, some scholars have built event models based on the semantic elements required for event representation, such as the subject and object, spatiotemporal characteristics, generation methods, and results. Some models of this type focus on the 5W1H semantic elements (who, what, when, where, and how) [18,19], and some scholars or institutions represent events by constructing templates or frameworks for specific types of events, such as ACE and FrameNET [30]. The structure of the event semantic element model is simple; the event semantic element model is oriented to specific requirements and constructed from event syntactic features and semantic structures. It is used for the extraction and simple analysis of the basic elements of an event. However, the expression of the deep semantic-logical relations and dynamic processes of events are missing.

2.1.2. Ontology-Based Event Model

The ontology-based event model based on ontology theory abstracts the concepts and relationships of various events and expresses them in standardized semantic structures. The models can be divided into general event ontology models, semantic link-oriented event ontology models and domain event ontology models according to the construction goal and application scope of the models. The general event ontology model has a high level of abstraction, does not rely on domain features, and focuses on the basic elements, semantic relationships, and hierarchical structure required for event representation, such as the simple event model (SEM) [2], the International Committee for Documentation of the International Council of Museums-Conceptual Reference Model (CIDOC-CRM) [31], F [32], ABC [33] and the event ontology model proposed by Liu et al. [10]. The semantic link-oriented event ontology model is an intermediate model with a simple design and fewer constraints that relies on linking external vocabularies or other event ontologies to improve the expression content, such as event ontology (EO) [34] and linking open descriptions of events (LODE) [35]. In addition, many scholars design ontologies based on domain event characteristics and business needs [4,36,37]. By extending the general event ontology model, a domain ontology-event model can be constructed [38–40]. The ontology-based event model has a higher level of abstraction, focuses on the representation of concepts and relationships in events, summarizes and extracts the characteristics of semantic elements of events better, supports the representation of the main content and some interrelationships and hierarchical structure of events, and conducts rule-based reasoning on characteristic patterns of events and the correlations between different events based on semantic logic; however, research on the dynamic processes involved, the complex relationships and hierarchical structures within and between events is still lacking and not easy to achieve. In addition, the design of this type of model emphasizes the qualitative expression of semantic patterns and rarely mentions quantitative data representation.

2.1.3. Event-Oriented Spatiotemporal Data Model

Event-oriented spatiotemporal data models are spatiotemporal data models in the GIS field with events as the core of expression. The spatiotemporal data model introduces the concept of an event to represent dynamic geographic phenomena. Event-oriented spatiotemporal data models can be divided into the spatiotemporal data model that represents state changes, the process-oriented spatiotemporal data model, and the object-event-based spatiotemporal data model according to the core content of representation and the technical methods of modeling. The spatiotemporal data model representing state change considers state change as an event, and events are described as states at different times [6]. The process-oriented spatiotemporal data model is based on state expression, takes process as the core, and combines isolated states with structure and association relationships [25,41,42]. The above two types focus on processing vector and raster data and can represent the spatiotemporal dynamic characteristics of events; however, they lack the representation of the participating entities of events, their multidimensional features, and the associations between entities and events. Many scholars have adopted object-oriented thinking and proposed object-event-based spatiotemporal data models [21,43–45]. This type of model has better support for the spatiotemporal characteristics, attribute characteristics, and process expression of the entity; however, it is still not perfect in expressing the semantic relationship of events and the event structure and lacks formal semantic description and reasoning ability [4].

2.2. Problem Analysis

In summary, some problems remain in the existing event models. ① The generality and representation of the models need to be improved. The event ontology model and the event semantic element model emphasize the representational characteristics and semantic-logical structure of events and do not address the dynamic characteristics and interrelationships of the event entities. The event-oriented spatiotemporal data model perfectly expresses the changes in event characteristics and entities but insufficiently expresses the semantic characteristics of events. ② Expressing event structure is not sufficiently thorough. The existing event data models have structured the event elements; however, for event details, they lack the support of a deeper expression model, have more macroscopic semantic expressions, and have fewer microscopic expressions. ③ Models focus on the external causes, chronological relationships and causal relationships of events, only qualitatively assign roles to the entities in the event, and ignore the relationship between events and entities and their multidimensional characteristics, so the search for internal causes of events from the perspective of entities cannot be achieved. Therefore, for the same entity that may participate in multiple and multitype events, the following problems may exist when the existing event models are used: if the event semantics element model or the ontology model is used, it can express the macroscopic element characteristics of the event; however, the level of detail of the event expression is ignored, and generating multiple sets of data is prone to cause problems such as data redundancy and difficulty in association management between different data. In contrast, if the existing object-event-based spatiotemporal data model is used for modeling, the representation of the semantic information and hierarchical structure of events is not sufficiently comprehensive. Therefore, in this study, the spatiotemporal entity, the core element of events, is used as the modeling basis to construct an event data model based on spatiotemporal entities.

3. Methodology

Event description is the result of people's cognition and abstraction of the change process and, thus, has strong subjectivity. In real life, there may be multiple recorded versions of the same event; therefore, multi-source event information must be fused and complemented to form a "most authentic" description of an event and thus explore and discover unknown and potential events. In addition, analyzing the event characteristics can reveal various interrelationships, such as time series, space, and cause and effect, as well as a significant hierarchical structure among the events, between the events and the entities, and between the entities. Therefore, event representation requires a multilevel and dynamically correlated composite model. After combining the advantages of the ontology-event model in the semantic representation of events and the advantages of the object-event-based spatiotemporal data model in the multidimensional representation of entity dynamic changes and associative relationships, spatiotemporal entities were taken as the core to address the problems in the existing event description models and the demand for event representation for multi-source data fusion and multilevel and dynamic association expression. Additionally, an event-oriented, spatiotemporal entity-based event data model to support multi-source event data fusion and the digital description and representation of dynamic associations between events, between events and entities, and between entities was proposed.

3.1. Modeling Idea

A multilevel event data model consisting of an entity layer, a change layer, and an event layer was constructed by analyzing the representation structures of events, spatiotemporal entities, and their change processes, as shown in Figure 1. The entity layer was the basis for event-entity-level analysis and the main carrier for expressing the event process. The data at the model change layer were obtained through the extraction and aggregation analysis of the entity feature changes, thus providing data support for the subsequent quantitative analysis based on the entity characteristics and offering the possibility to discover potential events (by analyzing the aggregation mode between events and feature changes). The event layer was formed by aggregating the change layer and combining entities. This layer records the basic elements of the event, the composition structure, and the correlation between events, serving as the macro expression of the event and the analysis of the event structure.

Specifically, entities in the real world contain multidimensional features such as attributes, spatial locations, spatial forms, interrelationships, and compositional structures, which can be comprehensively expressed at the entity layer based on the multi-granular spatiotemporal object data model. Entities at different times have different states and relationships. The change layer was formed by extracting discrete or continuous changes in their attributes, locations, forms, relationships, and compositional structures. Additionally, a mapping relationship exists between the event and the contained entities, the event is composed of sub-events, and an interrelationship exists between the events, as shown in Figure 2.

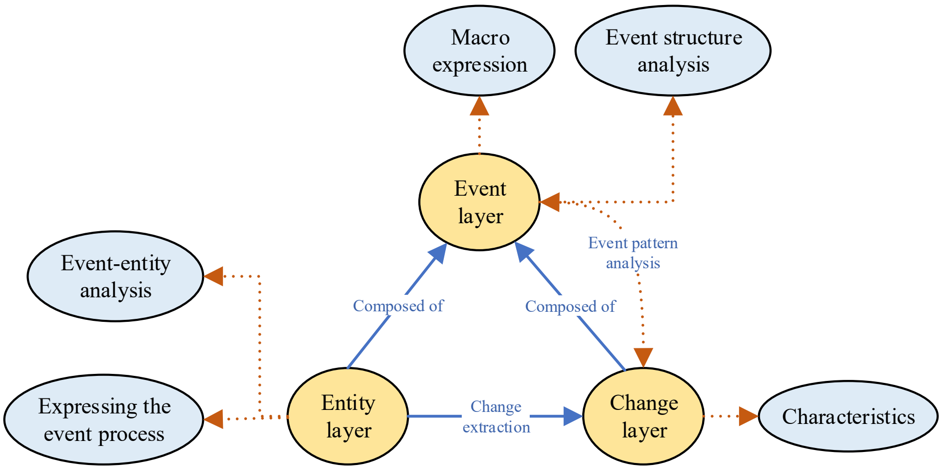

Figure 1. Ideas for modeling events.

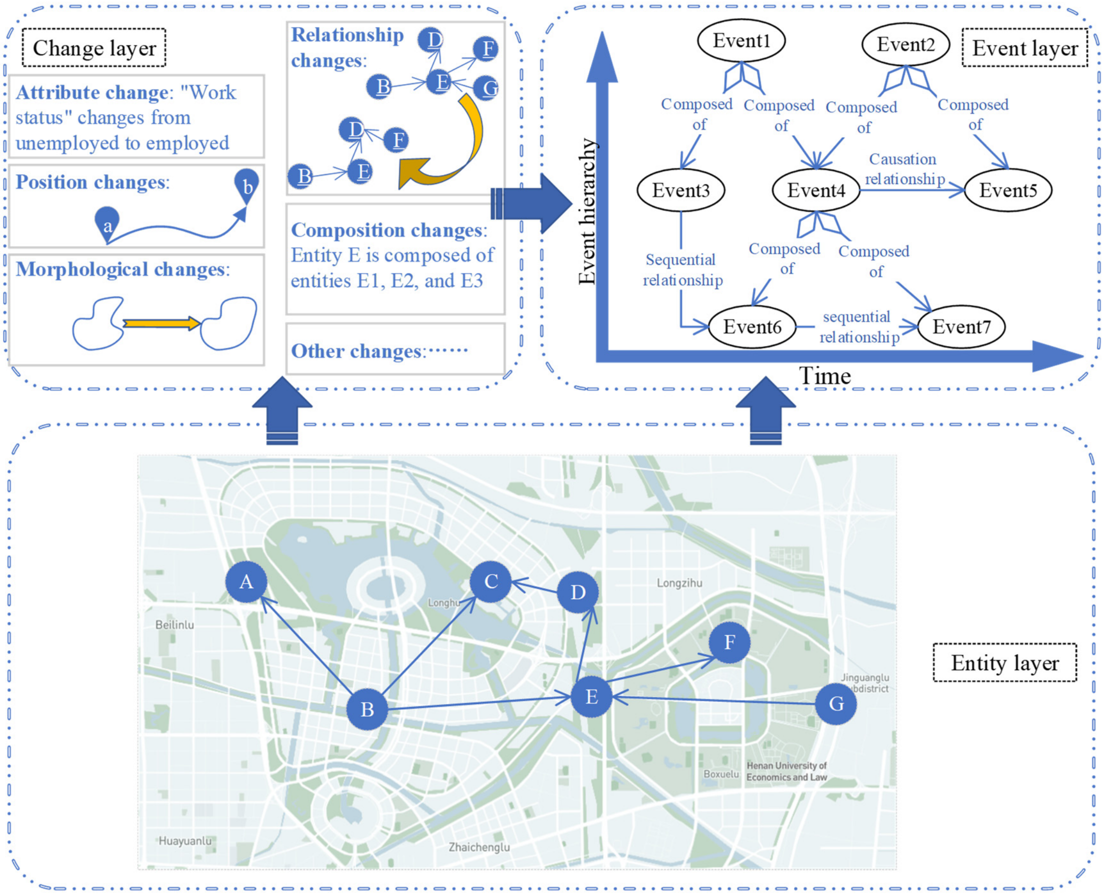

Figure 2. An example of event modeling based on spatiotemporal entities. (In the figure, blue circular symbols represent entities, while ellipses represent events. Uppercase letters (A–G) denote the sequence of entities, while lowercase letters (a, b) represent different location names. denotes the compositional relationships between events, and indicates the associative relationships between events or entities.).

An event model based on spatiotemporal entities is a dynamic and extensible data model. In this model, when the same entity participates in multiple events, it only needs to be created once. All events in which the same entity participates are bound to the entity. The entity participation in each event is distinguished by the event identifier and the role played by the entity. This mapping relationship between events and entities can enable different events to extract event elements from entities according to their description requirements. This improves the reusability of the model and solves the problem that the existing event data model needs to redefine the event elements and construct the model when new events (types) are generated, thus providing the ability to compose event data from multiple sources and types and the data support for the association analysis of the participation of the same entity in multiple events.

3.2. Spatiotemporal Entity-Based Event Data Model

3.2.1. Model Structural Characteristics

Various previous event data models [2,21,25] and multi-granular spatiotemporal object data models are referenced in this paper, and a spatiotemporal entity-based event data model with the entity as the core was proposed, as shown in Figure 3. The model first improves and expands the core classes in SEM, i.e., extending the four original core classes—event (what happened), actor (people or things involved), place (position), and time (time)—into the event (what happened), entity (which spatiotemporal entities are involved), change (what changes have taken place in these spatiotemporal entities), spatial position, and time.

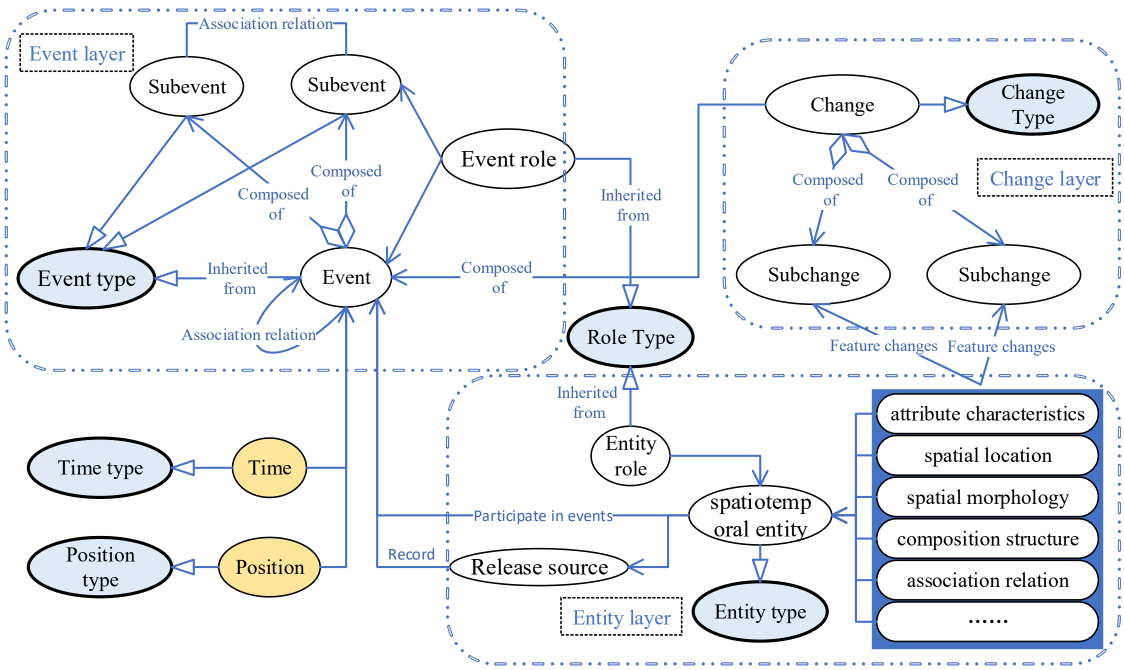

Figure 3. Spatiotemporal entity-based event data model. (In the figure, the light blue ellipses represent core classes such as event, entity, change, spatial position, time, and role Type. The yellow and white ellipses depict the instantiation of these core classes. Rounded rectangles, which are based on the multidimensional characteristics of the entities, illustrate various aspects of the instances, denotes the core class to which each instance belongs, indicates the sources of the instance's features, as well as the relationships among instances, and represents the compositional structure between the instances.).

The entity class expressed by the multi-granular spatiotemporal object data model contains eight dimensions/feature items of the entity: the spatiotemporal reference, spatial position, spatial form, attribute characteristics, composition structure, interrelationship, behavior characteristics, and cognitive characteristics. It can more comprehensively represent the entity. Since behavior and cognition are the active abilities of an entity and are relatively complicated, they may be involved in event simulation and complex analysis. The model in this paper serves the structured organization and representation of existing event data and does not consider the modeling of entity behavior and cognition. Moreover, to better and more accurately express events and more conveniently extract events, a change intermediate layer is added between the entities and events. The change process can be the long- or short-term change in an entity's characteristics, or it can be the changes in various characteristics of multiple entities. An event is a special case of a change process, a combination of change processes, and refers to the change process that an observer believes is significant and is formed through a person's cognition and abstraction of the entity change process. Adding the change process can better express the event components and make it easier to abstract events. In addition, the SEM is designed based on the minimum constraint on features to achieve the versatility of the model. Thus, describing the relationships between events is relatively simple. This paper increases and expands the expression of event relationships; for details, please see the section on the relationship expression strategy in the model.

In the model, each core class (event, entity, change, spatial position, and time) has different types. For example, time can be divided into discrete and continuous time in different formats. For example, time systems with different time references, such as UTC, GPS time, and atomic time (AT), can be used. Similarly, the change type includes discrete and continuous changes. The position type can be a spatial position point, a line path, an area, etc. The types of events can be distinguished according to the event characteristics, such as events expressing the movement trajectory of an entity and events expressing the change in the attribute and spatial characteristics of the entity. The event type corresponds to events in the specific field, such as terrorism, war, and popular events.

At the event layer of the model, events and their sub-events are used to represent the composition structure among events. Events have interrelationships, and the event role records the roles that events play in other events. The change layer of the model is the change process data of the spatiotemporal entity, and the data are from the entity layer and have a combination and mapping relationship with the specific events in the event layer. The entity layer of the model includes two types of spatiotemporal entities: those that participate in events and those that record events. The spatiotemporal entities have roles, and the roles played by the entities in the events are recorded. The characteristic changes of the spatiotemporal entities participating in the event form the data at the event change layer. The spatiotemporal entities that record the events are the event release sources; for example, the publisher and the releasing organization are all release sources. The recorder is a special spatiotemporal entity that is the source of events with a record relationship.

3.2.2. Model Representation Strategy

(1) Aggregation and Processing Mechanisms for Multi-source Event Data

Due to the subjectivity of event descriptions, different data sources may have different emphases and different contents when describing the same event. Therefore, the event data source (including the release time and release organization, publisher, and authority, which can be extended) was added to the basic event attributes of the event model. Additionally, for the uniqueness and authenticity of the subsequent visualization and analysis, a screening and aggregation processing mechanism for different data sources was added in the data processing stage, as shown in Figure 4, that is, to select an event description that is closer to "real" as the data source for the final visualization or analysis. Of course, event data can be changed or aggregated from different sources at any time as needed to facilitate the fusion of multi-source data, improve the flexibility of data application, and increase the dimension of event interpretation.

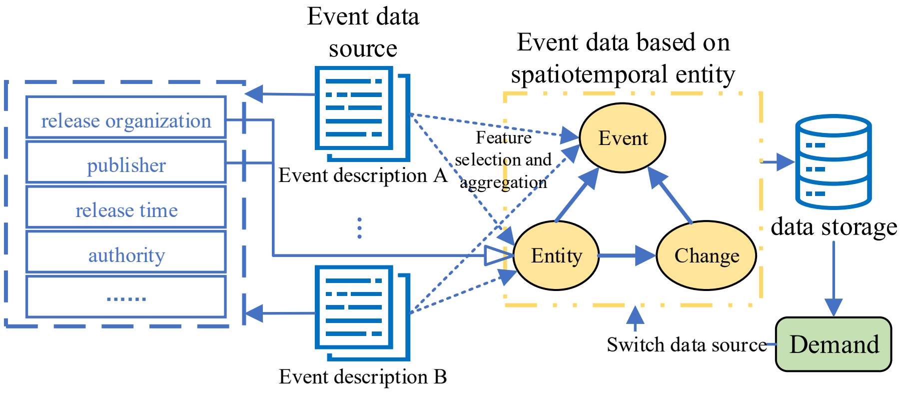

Figure 4. Aggregation and processing mechanisms for multi-source event data.

When selecting and aggregating different data sources, selecting or determining the authority and accuracy of different sources and expressions of events is necessary. Determining the authority and accuracy is difficult, and the result may not be accepted by everyone. Therefore, the most suitable method is to perform selection and aggregation based on the multidimensional features in the data source. Possible situations include the following: (1) this feature is described in only one data source; (2) this feature has multiple descriptions, and the number of mentions in each description is the same; and (3) this feature has multiple descriptions, and the number of mentions in each description is different. In the first case, the unique description can be directly selected; however, in the latter two cases, the authority of the source needs to be determined. Therefore, in this study, authoritative descriptions of sources were added to the model to select and aggregate event features.

Of course, the aggregation and processing of multi-source data involve many technologies. Our strategy at the onset of model design was to reserve characteristic items and mechanisms for such event information while not imposing constraints on the specific implementation technologies required for data aggregation and processing. This allows users to develop and design customized solutions based on the specifics of their data. Such an approach enhances the model's generality and expandability. As depicted in Figure 3, we designed a 'Release Source' within the entity layer. This is a special type of spatiotemporal entity that is associated with specific event sources, capable of describing the issuing institution, personnel involved, time of release, and its authority. Based on the processing mechanism shown in Figure 4, we can develop specific technologies for feature selection and fusion, embedding the characteristics of events and entities into the model to construct structured event data. This enables the selection of appropriate data sources based on application needs, such as choosing information issued by a designated or more authoritative 'Release Source' as the source of event descriptions or aggregating information from several 'Release Sources' as the basis for event descriptions.

(2) Representation of roles in the model

The role is indispensable to the event description and can reflect the semantic structure of events. In the event model based on a spatiotemporal entity, two kinds of roles exist: the role of the entity in the event and the role of the event itself.

- The role of the entity in the event

The role of the entity in the event and the expression of the role in the previous event models are similar in connotation, and both refer to the specific function or role played by the participants in the event. For example, in an attack, the roles are attacker and victim.

Since the same participating entity in different events is created only once when describing events using the entity as the carrier, two main situations exist in the actual scenario: 1. the same entity plays different roles in the same event at different times, and 2. the same entity plays different roles at the same time but in different events. For the first case, this paper adds a time version to the role in the event data model to update the role change in the entity in the same event; for the second case, by establishing a mapping relationship between the event and entity layers, the events are associated with the roles played by the entities.

- Role of the event

In a series of events, some events trigger other events, and some events cause results. The role of the event reflects the semantic and logical relationship between the events, which is the basis for a qualitative understanding of the evolution pattern of the event, and its expression content is similar to or greater than that of the interrelationship. In the model, the role of the event is expressed in the same way as the role of the entity in the event, except that the former needs to be described only at the event level.

Here, the different roles of the associations among events and their roles in the model need to be distinguished. The interrelationship between events refers to the interaction between events, which is a dynamic interaction. The role of the event is the role played by the event in other events. This is the core element in the definition of an event and is an identity definition, and there are similarities between the two. In some scenarios, the two express similar connotations, such as causal relationships in association relationships and "causes" and "consequences" in events. Additionally, the two are different. Relationships are dynamic and directional, and some can even be measurable. Roles are qualitative expressions and do not have directionality, but roles can be described more concisely, freely, and broadly than interrelationships. For example, as shown in Figure 5, new product release events may include multiple sub-events, such as "event opening", "product introduction", and "media interviews", and the roles of these sub-events can be defined as "event preparation", "core display", and "information dissemination" but cannot be expressed using the interrelationship.

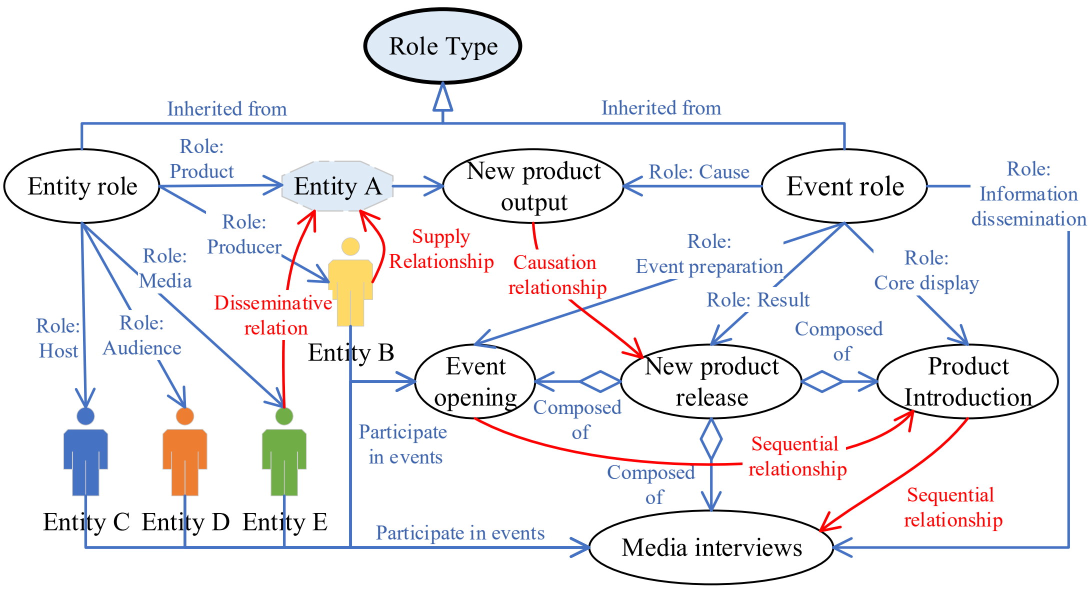

Figure 5. Distinction between roles and relationships: A case study of new product release events. (In the figure, denotes the core class to which each instance belongs, indicates the sources of the instance's features as well as the relationships among instances, where those in red represent relationships, and those labeled with 'role' indicate assigned roles, while represents the compositional structure between the instances.).

(3) Relational expressions in events

Many scholars have conducted studies on the relationships among events according to the order of advancement of events and from the integrated point of view of the chronological and semantic logic of event developments. Worboys et al. divided the relationship between events into initiation, continuation/promotion, obstruction/blockage, and termination. They believed that the relationship between geospatial objects and events is a participation and involvement relationship (the object participates in the event, and the event involves the object) [25]. In contrast, some scholars summarize relationships with time as the center. For example, Allen analyzed the relationship between two-time intervals and summarized 13 basic temporal relationships [46]. In addition, in geographic information science, various associations exist between entities, such as temporal relationships (such as temporal distance relationships and temporal topological relationships), spatial relationships (such as topological relationships and orientation relationships), and semantic relationships (such as synergistic relationships, host hostile relationships, command relationships) [47].

This paper refers to the above viewpoints and proposes that relationships among events include not only the semantic and logical relationships between events but also the temporal and spatial relationships between events, and expresses the interrelationships existing in the events from three perspectives of interevent, event-entity, and inter-entity considering spatiotemporal entity factors.

- Relationships between events

The interrelationship between events is the key to understanding the intrinsic event characteristics. It expresses the interaction mechanism between events. With time as the center, the association between events involves the sequential relationship, distance relationship, and topological relationship of the time and range of event occurrence. The association relationships between events include coreference and causation relationships according to the semantic and logical relationships between events. Using space as the investigation point, the relationships between events include the spatial topological relationships and azimuth relationships between the event positions or areas. In this model, the interrelationship between events is described at the event level. Moreover, to consider the directionality of the event interrelationship and the convenience of subsequent analysis, the interrelationship between the same pair of events is expressed for each event; however, the direction of the relationship is different.

- Relationships between events and entities

The relationships between events and entities include the basic relationships of the entities involved in the events or the participation of the entities in the events, and the deep relationships between the events and the entities, such as ripple, dominance, and diffusion relationships. This type of relationship is the basis for analyzing events from the entity's point of view. In the model in this paper, to reduce data redundancy, this type of relationship is only recorded at the event layer and is not described at the entity layer.

- Association relationships between entities

The interrelationship between entities is the key cause of the generation of association relationships between events. It refers to the interaction and mutual influence relationships between entities. In the model, the interrelationship between entities is described at the entity layer and is bound to the specific entity. The interrelationship has attributes such as the start entity, end entity, association strength, and time version.

(4) Event granularity and expression mode of composition

This paper proposes that event granularity is controlled by factors such as time scale, spatial scale, and degree of abstraction and cognition; these three factors are strongly correlated. For example, on a time scale, a change in dynasties throughout history is an event with a long time span, a specific battle is an event with a relatively short time span, and the formation of troops in a specific battle is an event with an even shorter time span. These events correspond to events of different granularity, including large, medium, and small. Similar to the temporal scale, the spatial scale may also be correlated with the event granularity, e.g., large-scale national development planning events, medium-scale urban change events, and small-scale residential relocation events. Events are the result of people's abstraction and cognition of the change process. Events with different granularities are generated according to different observation angles and cognitive methods. However, the location determines the field of view; large-granularity events cover a large spatiotemporal category and express the main macroscopic events with a higher level of abstraction, and small-granularity events represent more detailed microscopic events within the smaller spatiotemporal category and a lower level of abstraction. Event granularity and event composition have a strong correlation, and events with large and small granularity mostly have a parent-child composition relationship, so event composition is used to express event granularity in the model.

In addition to the model representation contents and expression strategies, the model constructed in this paper, which serves data integration, is an objective description. It can also support the expression of some special needs, such as event viewpoints and emotions, which are highly subjective and domain-specific. Therefore, they are not expressed in the model and can be added to the basic attributes of the event in the form of extension items.

3.2.3. Formal Description of the Model

This paper provides a formal description of the model as follows. The structural relationships between the elements of the equation are illustrated in Figure 6. First, the description of the event set *Ev*, as shown in Equation (1), includes six parts: *evBasic* represents the basic attributes of an event; *evRSet* represents the set of roles the event plays in other events; *EntSet* is the set describing the entities involved in the event; *ChgSet* is the set representing the changes contained in the event; *subEvSet* is the set representing the sub-events; and *evRelSet* is the representing relationship between events.

$$Ev = \{\boxed{evBasic}, \boxed{evRSet}, \boxed{EntSet}, \boxed{ChgSet}, \boxed{subEvSet}, \boxed{evRelSet}\}$$

$$\boxed{evBasic} = \{evNm, evTp, sTm, eTm, plc, exAttr\}$$

$$\boxed{evRSet} = \{evRo_i \mid evR_i = (roTp, tV, rEID)\}$$

$$\boxed{ChgSet} = \{Chg_i | Chg_i = (ChgTp, EntID, sVal, eVal, SubChg)\}$$

$$\boxed{subEvSet} = \{Ev_i | Ev_i = (evBasic, evRSet, EntSet, ChgSet, subEvSet, evRelSet)\}$$

$$\boxed{evRelSet} = \{evRe_i | evRe_i = (reTp, rS, sEv, eEv, tV)\}$$

$$\boxed{EntSet} = \{Ent_i | Ent_i = (\overset{①}{\boxed{entRSet}}, \overset{②}{\boxed{AttrSet}}, \overset{③}{\boxed{PosSet}}, \overset{④}{\boxed{MorphSet}}, \overset{⑤}{\boxed{CompSet}}, \overset{⑥}{\boxed{RelSet}})\}$$

$$① \boxed{entRSet} = \{enRo_i | enRo_i = (roTp, tV, rEID)\}$$

$$② \boxed{AttrSet} = \{Attr_i | Attr_i = (aTp, aVal, tV)\}$$

$$③ \boxed{PosSet} = \{Pos_i | Pos_i = (posNm, Coord, tV)\}$$

$$④ \boxed{MorphSet} = \{M_i | M_i = (mTp, mPath, tV)\}$$

$$⑤ \boxed{CompSet} = \{C_i \mid C_i = (cTp, pEnt, cEnt, tV)\}$$

$$⑥ \boxed{RelSet} = \{enRe_i | enRe_i = (reTp, rS, sEnt, eEnt, tV)\}$$

Figure 6. Hierarchical Structure of Equation Elements.

The basic attributes of an event *evBasic* include the event name *evNm*, event type *evTp*, *sTm* and *eTm*, which represent the start time and end time of the event, respectively, *plc*, which records the event position, and the reserved extension item *exAttr*, which represents other extended attributes of the event, such as the event level and event situation of the emergency event, as shown in Equation (2).

$$Ev = \{evBasic, evRSet, EntSet, ChgSet, subEvSet, evRelSet\} \quad (1)$$

$$evBasic = \{evNm, evTp, sTm, eTm, plc, exAttr\} \quad (2)$$

The roles played by an event in other events are a set, represented by *evRSet*, where *roTp* represents the role the current event plays in other events, *tV* is the time version, and *rEID* is the ID of the affected event, as shown in Equation (3).

$$evRSet = \{evRo_i | evR_i = (roTp, tV, rEID)\} \quad (3)$$

The purpose of adding the changes is to facilitate subsequent analysis and visualization, achieve macroscopic event characteristic analysis, and achieve microscopic, directional (specified characteristics), as well as quantitative expression and analysis of the events. The *ChgSet* that represents the change contained in an event is a set, as shown in Equation (4), where *ChgTp* represents the feature type of the change, *EntID* represents the identity of the entity involved in the change, and *sVal* and *eVal* are the initial and end values of the change, respectively. In addition, *SubChg* in the formula is also a set of changes, just as ChgSet; if there is no subchange, *SubChg* is empty.

$$ChgSet = \{Chg_i | Chg_i = (ChgTp, EntID, sVal, eVal, SubChg)\} \quad (4)$$

Using *subEvSet* to represent the composition structure between an event and its subevents can more clearly express the hierarchical relationship of events, and *subEvSet* is a set consisting of *Ev*, as shown in Equation (5). When the event composition is independently expressed, it is a special event relationship.

$$subEvSet = \{Ev_i | Ev_i = (evBasic, evRSet, EntSet, ChgSet, subEvSet, evRelSet)\} \quad (5)$$

Due to the generation logic, chronological order, spatial position, etc., various associated relationships exist, such as semantics and timing between events, which are uniformly expressed by event relationships. The set *evRelSet* is used to represent the relationship between this event and other events, as shown in Equation (6), where *rTp* represents the relationship type, *rS* represents the relationship strength, *sEv* and *eEv* are the first and end events of the relationship, respectively, and *tV* is the time version.

$$evRelSet = \{evRe_i | evRe_i = (reTp, rS, sEv, eEv, tV)\} \quad (6)$$

In the entity set *EntSet* involved in the event, *entRSet* represents the set of roles played by the entity in the event, and *AttrSet*, *PosSet*, *MorphSet*, *CompSet*, and *RelSet* correspond to the sets of attribute characteristics, spatial position, spatial form, compositional structure, and interrelationship of the entity, respectively, as shown in Equation (7).

$$EntSet = \{Ent_i | Ent_i = (entRSet, AttrSet, PosSet, MorphSet, CompSet, RelSet)\} \quad (7)$$

To consider that the same entity may play different roles at different times, a time version is added to the roles. Similar to *evRSet*, *roTp* represents the role the current entity plays in the event, *tV* is the time version, and *rEID* is the affected event ID, as shown in Equation (8).

$$entRSet = \{enRo_i | enRo_i = (roTp, tV, rEID)\} \quad (8)$$

AttrSet is the set of attribute feature types and attribute values of each time version, as shown in Equation (9), where *aTp* is the attribute feature type, *aVal* is the attribute value, and *tV* is the time version.

$$AttrSet = \{Attr_i | Attr_i = (aTp, aVal, tV)\} \quad (9)$$

PosSet represents the set of spatial positions at each time version and comprises the place name *posNm* and coordinates of different time versions (tV). The coordinates are in the rectangular coordinate system (x, y, z) or the geodetic coordinate system (*lon, lat, elev*), as shown in Equation (10).

$$PosSet = \{Pos_i | Pos_i = (posNm, Coord, tV)\}, \tag{10}$$

where *MorphSet* represents morphological features and is a set composed of the morphologies of entities at different time versions (tV). The *mTp* records the morphological type, such as point, line, surface, or 3D model, and *mPath* is the path address of the file for this morphology stored in standard format, as shown in Equation (11).

$$MorphSet = \{M_i | M_i = (mTp, mPath, tV)\}, \tag{11}$$

where *CompSet* is the set of *comi* structures of the entity at different time versions (tV), *cTp* represents the type of the composition structure, and *pEnt* and *cEnt* are the parent entity and child entity of the entity, respectively, as shown in Equation (12).

$$CompSet = \{C_i | C_i = (cTp, pEnt, cEnt, tV)\} \tag{12}$$

RelSet represents the interrelationship between entities at different time versions (tV). Each interrelationship $enRe_i$ is expressed by *rTp*, *rS*, *sEnt*, and eEnt, where *rTp* represents the relationship type, *rS* represents the relationship strength, and *sEnt* and *eEnt* are the first entity and end entity of the relationship, respectively, as shown in Equation (13).

$$RelSet = \{enRe_i | enRe_i = (reTp, rS, sEnt, eEnt, tV)\} \tag{13}$$

3.3. Spatiotemporal Entity-Based Event Modeling Process

Event data acquisition and modeling based on spatiotemporal entities involve a bottom-up sequence. First, the entity characteristics and basic event elements are extracted, and then the event, spatiotemporal entity, and change process data are obtained. The entity characteristics are the basis for the microscopic analysis of events, the structure and relationship among events are necessary components for the macroscopic expression and analysis of events, and the extraction of the change process is an important data source for the subsequent quantitative analysis.

In this paper, event modeling based on spatiotemporal entities uses a combination of machine extraction, rule matching, and human correction, as shown in Figure 7. Specifically, first, for the event text description information, based on the detail level of the text description, the data were cleaned to remove records with errors and incomplete descriptions, and the effective text that can extract the event elements or entity characteristics was screened. In describing the same object with different names in the text, the descriptions were normalized. Additionally, the time and position description texts were converted to standard formats. Next, the extraction schemas were designed, and the sample data were annotated for directional training on the universal information extraction (UIE) model in PaddleNLP to achieve the preliminary extraction of entity features and basic event elements. Finally, based on rule matching, the features and event elements of the entity are completed (the associations, roles, and structures between the entity and the event are added) and organized to form complete spatiotemporal entity data and spatiotemporal entity-based event data on which basis the feature change process of the entity in the event was aggregated and extracted.

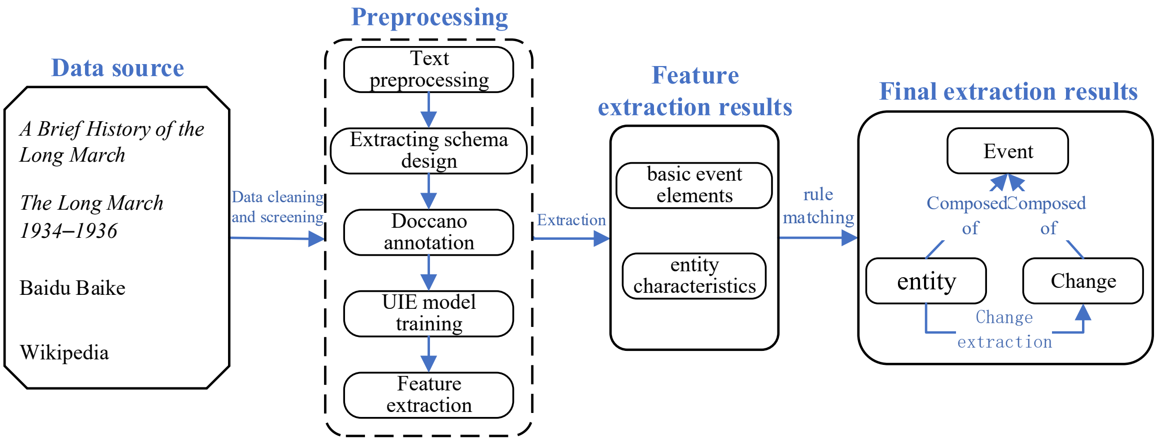

Figure 7. Spatiotemporal entity-based event modeling process.

4. Results

4.1. Comparison to Other Event Models

This paper refers to previous studies from the perspective of investigating the description ability of the event model [48]. From the comprehensiveness and depth of representation of the event elements, i.e., "time, space, participants, relationships and hierarchies in the event", and the representation of the dynamic process and the ability of multi-scenario adaptation, the proposed model was investigated and compared with previous event models, as shown in Table 1.

The entity-centered event model proposed in this paper can represent the spatiotemporal characteristics of events, the participating entities, and the relationships and structures of events well; moreover, the model is naturally scalable in handling cross-domain data and allows to easily integrate multi-source and multidomain data. For the semantic information expression of events, this paper refers to the description of the ontology-event model and designs the roles of events and entities, the release source of events and the interrelationships between events, between entities, and between events and entities to represent semantic information. In addition, the model proposed in this paper adds a change layer between the event and entity layers to provide more support for event queries and quantitative analysis. For example, (1) What events are related to event A? (2) What role does event A play in other events? (3) Which entities are involved in the occurrence of event A? (4) Which characteristic changes of entity B caused event A? (5) What events are entity B involved in? (6) What is the role of entity B in event A? (7) What is the evolutionary pattern or pattern of event category T?

4.2. Modelingand Visualization of the Long March Event

4.2.1. Data Processing and Modeling

The Long March and its important battles were selected as the research objects. The data were sourced from *A Brief History of the Long March*, *The Long March 1934–1936* and descriptions of the Long March from Baidu Baike and Wikipedia. Through text screening, key descriptive texts of the overall process of the Long March and Four Crossings of the Chishui River were collated.

Table 1. Comparison and analysis of the expression of different event models.

Category	Model		Completeness of Elements Expressing the Event					Dynamic Process Expression	Versatility	Scalability
			Time	Space	Object	Relationship	Structure			
Event semantic element model	A model based on syntactic features of text describing the event		Y	Y	Y	L	N	N	L	L
	A data integration model oriented to the needs of task scenarios		Y	Y	Y	L	N	N	L	L
	Event representation semantic structure model		Y	Y	Y	L	L	N	M	L
Ontology-based event model	The universal event ontology model	SEM	Y	Y	Y	L	Y	N	M	M
		CIDOC-CRM	Y	Y	Y	L	Y	N	M	L
		ABCs	Y	Y	Y	L	Y	L	M	M
		F	Y	Y	Y	L	Y	N	M	M
		Event ontology model	Y	Y	Y	L	L	L	M	M
	Semantic link-oriented event ontology model	EO	Y	Y	Y	L	Y	N	M	L
		LODE	Y	Y	Y	N	Y	N	M	L
	Domain event ontology model		Y	Y	Y	U	U	N	L	L
Event-oriented spatiotemporal data model	The spatiotemporal data model for representing state change		Y	Y	N	L	N	Y	L	L
	Process-oriented spatiotemporal data model		Y	Y	N	L	L	Y	L	L
	Object-event-based spatiotemporal data model		Y	Y	Y	L	L	Y	M	M
Spatiotemporal entity-based event data model			Y	Y	Y	M	M	M	M	M

Note: "Y" indicates that the event elements or dynamic processes are represented; "N" indicates that the event elements or dynamic processes are not represented; "U" indicates that it is uncertain whether the event elements or dynamic processes can be represented; "L" indicates that the content of event elements is insufficiently represented or that the model's generalizability, scalability, or dynamic process representation is poor; and "M" indicates that the content of event elements is richly represented or that the model has good generalizability and scalability or that the dynamic process representation is complete.

According to the modeling method in Section 3.3, the data of the Long March and important campaigns were processed, including ① data cleaning (removing erroneous and incomplete records, screening and organizing effective texts, and unifying the names of entities with different names, i.e., unifying the naming of multiple names for the same entity; for example, the Central Committee of the Communist Party of China (CPC) and CPC; the 31st Red Army and 31st Army; the Central Red Army and the First Front Army of the Chinese Workers' and Peasants' Red Army; and the National Revolutionary Army and National Government Army), ② data conversion (converting time and position text into usable date and coordinate formats, etc.), ③ designing and extracting schema, labeling sample data, training the UIE model, and extracting event elements and entity features, and ④ based on rule matching, determining the entity characteristics and event elements (by adding the interrelationships, roles, and structures between the entity and events). On this basis, the feature change process of the entity in the events was aggregated and extracted.

To add an interrelationship, based on the description content of the event text, the organization structure, the persons, and the interrelationship between them were added. The data were added to the person or organization structure. The association relationships include the interrelationship type, start object, and end object. The interrelationships mainly refer to the following relationships: affiliation relationships (unit A belongs to unit B), command relationships (the commanding personnel or the organization commands the units), cooperative operation relationships (cooperative operations between the two units), and adversarial relationships (the battle between the two hostile units). Specific rules are as follows. The organizational structure was judged by comparing different time versions of organizational institution sequence data (sourced from *A Brief History of the Long March*), and the affiliation relationship was assigned to the organization structure; the hierarchical relationships in the Kuomintang Army and the Communist Army were screened and constructed, and the synergistic, adversarial relationships were added to spatiotemporal entities in events; if an organization structure exists in the character's position, the command relationship (the commander commands the troops) and the affiliation relationship (the person belonging to the army) between the character and the organization structure were established. The addition of roles was divided into two parts. First, the role attributes in the event were added to the person and organization entities, and the role types of the people and organizations in the event were determined and assigned values. The roles of the characters include the roles of commanding and combat personnel, and the roles of organizations include combat units (attackers and defenders) and command organizations. Next, the roles of sub-events in the event were divided. Here, the stage of each campaign in the Long March was used as the role, including the loss stage, turning stage, northwards and southwards division stage, and development and consolidation stage. The additions of organizational institutions and affiliation relations were performed by rule matching on the serial data of organization institutions at different time points, which are not described in detail here. The final extracted data structure is shown in Figure 8.

From Figure 6, we can observe that *Ev* and *subEvSet* both represent an event set, and there is a nested structure between them. In the formalized model expression, the main contents of event descriptions are represented by *evBasic*, *evRSet*, *EntSet*, *ChgSet*, and *evRelSet*. Furthermore, the entity set *EntSet* is composed of *entRSet*, *AttrSet*, *PosSet*, *MorphSet*, *CompSet*, and *RelSet*. Therefore, the processed data results were demonstrated according to these 10 main components, as shown in Table 2.

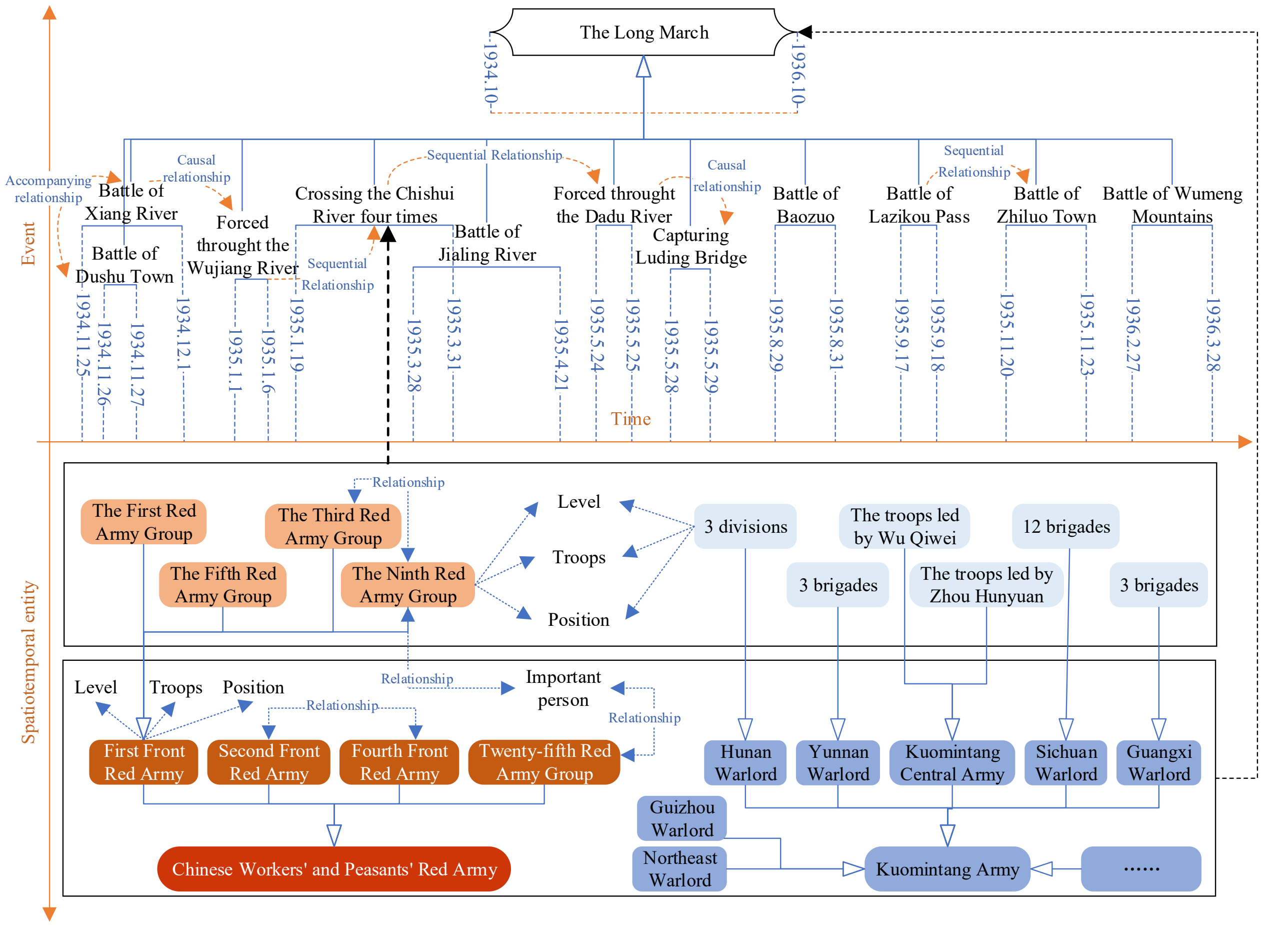

Figure 8. Long March event data structure. (In the figure, rounded rectangles represent entities, with different colors indicating different categories of entities. For example, red tones represent the Red Army, while blue tones represent the Nationalist Army. Additionally, ⟶▷ denotes the subordination relationships between entities or events, - - -▶ represents the correspondence between the entity layer and the event layer, ······▶ indicates the attributes or relationships of the entities, and ↷ symbolizes the relationships between events.).

Table 2. Example of data processing results for the Long March event.

Name	Type	Detail
evBasic	Formal Description of the Model	$\boxed{evBasic} = \{evNm, evTp, sTm, eTm, plc, exAttr\}$
	Sample of Processed Results	{"evID": "30001", "evName": "Long March", "evType": "War Event", "sTime": "1934-10", "eTime": "1936-10", "place": [{"posName": "Central Soviet Area", "coor": [116.027114, 25.88623]}, {"posName": "Western Hunan", "coor": [116.413383697123, 39.9109245472995]}, . . .]}
evRSet	Formal Description of the Model	$\boxed{evRSet} = \{evRo_i \mid evR_i = (roTp, tV, rEID)\}$
	Sample of Processed Results	{"subEventID": "30002", "subEventName": "Battle of Xiang River", "subEventRole": "Defeat Phase—First Red Army", "rTimeVersion": "25 November 1934"}
ChgSet	Formal Description of the Model	$\boxed{ChgSet} = \{Chg_i \mid Chg_i = (ChgTp, EntID, sVal, eVal, SubChg)\}$
	Sample of Processed Results	{"chgType": "Troops", "enID": "100045", "enName": "Second Red Army", "sVal": {"sValue": "approximately 9700 people", "sTimeVersion": "7 August 1934"}, "eVal": {"eValue": "approximately 3300 people", "eTimeVersion": "7 October to 24 October 1934"}}

Table 2. *Cont.*

Name	Type	Detail
evRelSet	Formal Description of the Model	$evRelSet = \{evRe_i \mid evRe_i = (reTp, rS, sEv, eEv, tV)\}$
	Sample of Processed Results	{“rType”: “Sequential Relationship”, “rStrength”: 1, “startEventID”: “30002”, “startEventName”: “Battle of Xiang River”, “endEventID”: “30003”, “endEventName”: “Battle of Dushu Town”, “evTimeVersion”: “1 December 1934”}
entRSet	Formal Description of the Model	① $entRSet = \{enRo_i \mid enRo_i = (roTp, tV, rEID)\}$
	Sample of Processed Results	{“role”: “Combat Unit”, “rEvent”: “Meeting with the Red Fourth Front Army”, “rType”: “Combat Role”, “rTimeVersion”: “19 November 1935”}
AttrSet	Formal Description of the Model	② $AttrSet = \{Attr_i \mid Attr_i = (aTp, aVal, tV)\}$
	Sample of Processed Results	[{“aType”: “Military Branch”, “Value”: [{“aValue”: “Workers’ and Peasants’ Red Army”, “aTimeVersion”: “7 August 1934”}]}, {“aType”: “Troops”, “Value”: [{“aValue”: “approximately 9700 people”, “aTimeVersion”: “7 August 1934”}, {“aValue”: “approximately 3300 people”, “aTimeVersion”: “October 7 to October 24 1934”}]}]
PosSet	Formal Description of the Model	③ $PosSet = \{Pos_i \mid Pos_i = (posNm, Coord, tV)\}$
	Sample of Processed Results	{“pTimeVersion”: “7 August 1934”, “pos”: [{“name”: “Hunan-Jiangxi Soviet Area “, “longitude”: 113.959219, “latitude”: 26.071451}, {“name”: “Guidong County, Zhaiqian Area”, “longitude”: 113.91820901900007, “latitude”: 25.987843785000052}]}
MorphSet	Formal Description of the Model	④ $MorphSet = \{M_i \mid M_i = (mTp, mPath, tV)\}$
	Sample of Processed Results	[{“mType”: “point”, “mTimeVersion”: “7 August 1934”, “pos”: [{“name”: “Hunan-Jiangxi Soviet Area”, “longitude”: 113.959219, “latitude”: 26.071451}, {“name”: “Guidong County, Zhaiqian Area”, “longitude”: 113.91820901900007, “latitude”: 25.987843785000052}]}, {“mType”: “model”, “mTimeVersion”: “7 August 1934”, “path”: “/data/Red_Front_Army.jpg”}]
CompSet	Formal Description of the Model	⑤ $CompSet = \{C_i \mid C_i = (cTp, pEnt, cEnt, tV)\}$
	Sample of Processed Results	{“comType”: “Administrative Composition”, “cTimeVersion”: “7 August 1934”, “parentEntity”: [“Chinese Workers’ and Peasants’ Red Army”], “childEntity”: [“Second Red Army Corps”, “Sixth Red Army Corps”, “Red Army School”]}
RelSet	Formal Description of the Model	⑥ $RelSet = \{enRe_i \mid enRe_i = (reTp, rS, sEnt, eEnt, tV)\}$
	Sample of Processed Results	{“rType”: “Hostile Relationship”, “rTimeVersion”: “7 October 1934 to 24 October 1934”, “rStrength”: 1, “sEntity”: “Second Red Army”, “eEntity”: “19th Division of the Guangxi Army”, “sEntityID”: “100045”, “eEntityID”: “100049”}

4.2.2. Event Visualization of the Long March and Its Important Battles

(1) Event structure visualization of the Long March and its important battles

Through data processing, the event structure of the Long March and the important battles were visualized, which includes two parts: the visualization of the Long March event structure and the dynamic visualization of the event structure of the Long March and each battle at different times. The expression strategies for both visualization modules were centered around events, represented by red and blue rounded rectangles for parent and child events, respectively. The basic characteristics of these events, such as occurrence time, location, type, and participating entities, were outlined using green and yellow circles. Diverging rays were used to depict the connections between an event and its sub-events, as well as between an event and its characteristic features. Additionally, the relationships between sub-events are dynamically and interactively rendered using curves. Ultimately, this approach employs a firework-like dispersal as a metaphor to vividly represent the intrinsic elements and structural relationships characteristic of the events. The event structure visualization of the Long March is shown in Figure 9, with the basic elements of the Long March event, such as event ID, start time, end time, event type, and position information (only the first two positions are shown due to the limitation of the visualization effect), and the entities involved in the Long March event, such as the First, Second and Fourth Front Armies and the Red 25th Army. The included sub-events and the interrelationships between them are also visualized.

Figure 9. Spatiotemporal entity-based Long March event structure (Figure (**a**) depicts the overall event structure of the Long March. In this diagram, rounded rectangles represent events, including the Long March and its sub-events. Green circles indicate attribute information of these events, while orange circles denote entities included within the 'contain entities' attribute of an event. Additionally, through interactive operations such as clicking, double-clicking, and dragging, users can explore the relationships between sub-events and other events, as illustrated in Figure (**b**,**c**)).

On the event-entity real-time feature interface, the force-directed layout was used to dynamically visualize the event structure of the Long March and each campaign at different times, as shown in Figure 10. In the figure, the Long March or each battle, the composition of events and the changes of the multidimensional characteristics of the entities involved in different time versions can be selected. Given the extensive content visualized, to enhance the visualization effects, we designed interactive operations for this module. By clicking on a node, its sub-nodes can be collapsed, and a red outline was added to the collapsed node to distinguish it. Furthermore, to facilitate focused observation of specific content, the system allowed users to drag and drop nodes to adjust their layout, enabling targeted observation of key information.

(2) Visualization of the spatiotemporal evolution of the Long March and its important battles

In this section, the spatiotemporal processes of the Long March events and specific battles (e.g., Four Crossings of the Chishui River) were visualized, as shown in Figure 11. The figure includes the drawing of different combat unit trajectories, the drawing of important areas (revolutionary base areas), and the visual content control function based on the level of combat units and the level of events to improve the visualization effect.

(3) Visualization of the overall context of the Long March and its important battles

As an extension and supplement to the visualization of the spatiotemporal evolution of events, the visualization of event context is based on the supplementary display of the event description text at each time version. Additionally, it can implement the visualization of the sequence of events and the associations of important positions mentioned in the text with the spatiotemporal evolution process. In the context of events, when clicking on the event description text at a time version, the position of the current combat unit and the important locations mentioned in the description text can be displayed on the map, as shown in Figure 12.

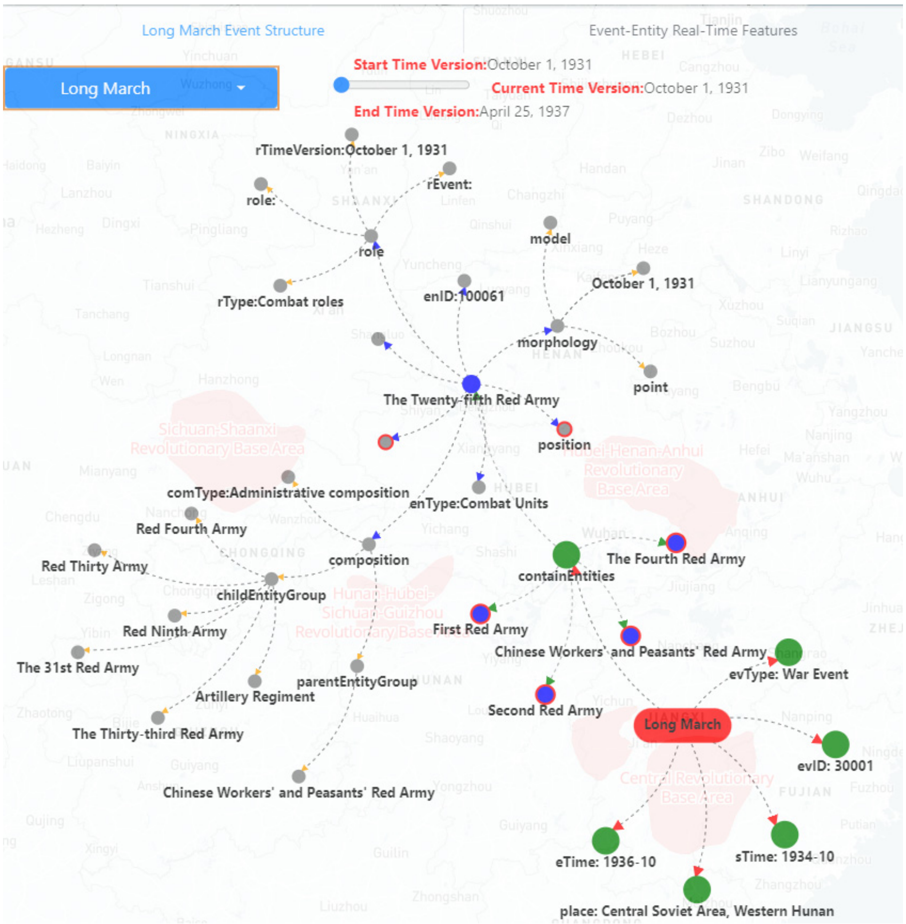

Figure 10. Dynamic visualization of the event structure of the Long March and the campaigns at different time versions.

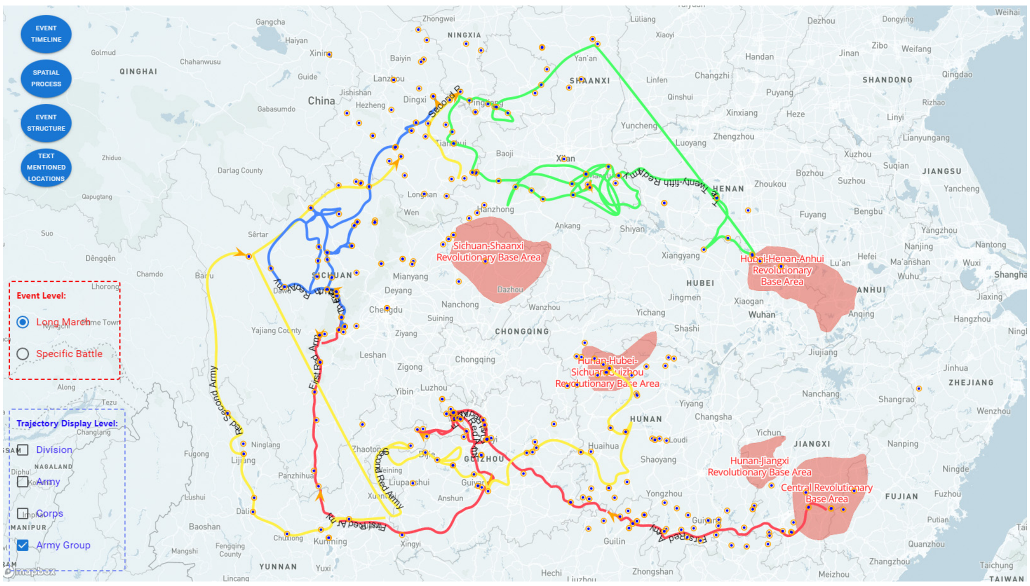

Figure 11. Visualization of the spatiotemporal evolution of the Long March and important battles. (In the figure, the red color scheme represents the First Red Front Army and its affiliated units, the yellow color scheme represents the Second Red Front Army and its affiliated units, the blue color scheme represents the Fourth Red Front Army and its affiliated units, and the green color scheme represents the 25th Red Army and its affiliated units.).

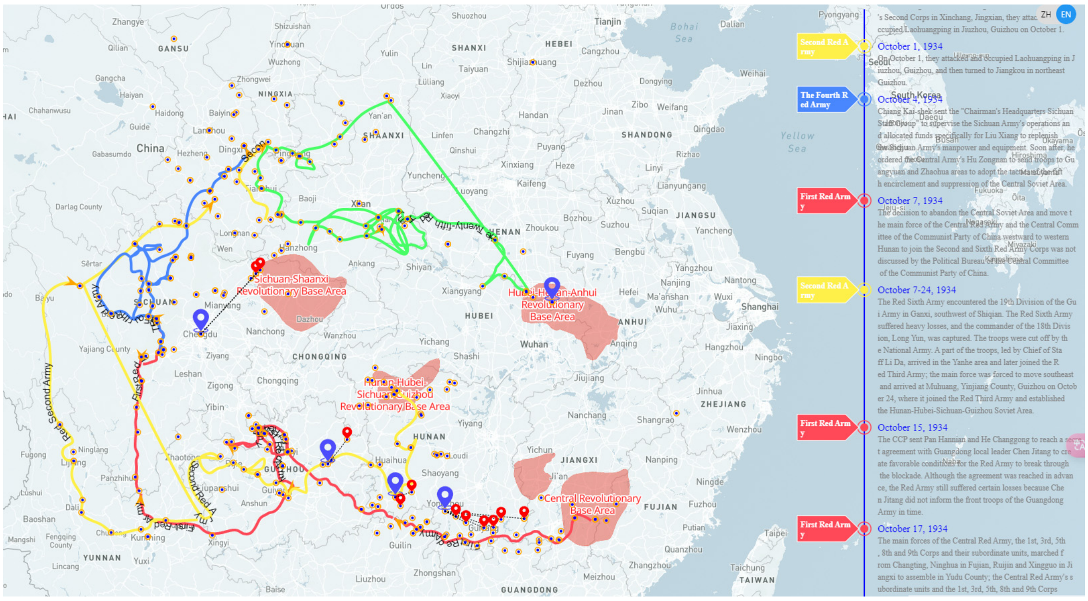

Figure 12. Context of events and locations mentioned in the text.

5. Discussion and Conclusions

The research purpose of event data modeling was to solve the problems of diversification and unstructured event data and to provide model support for the digitization, informatization, visualization, and scientific analysis of event information. However, for the existing event data models, due to the limitations inherent in the modeling methods used, the advantages are inherent and independent of each other in terms of the representational category, with an emphasis on the refinement and synthesis of data, the semantic expression of events, or the expression of dynamic processes. Additionally, a data model with comprehensive representation and balanced advantages is lacking. Moreover, because the existing models do not perform an in-depth analysis of the relationships between events and their participating entities and describe the multidimensional entity characteristics as not sufficiently comprehensive, the hierarchical structure and interrelationship representation of events are not perfect. This study fully studied the important role of entities and their characteristic changes in events and proposed a spatiotemporal entity-based event model to address the problems in the existing event data models and the need for multi-source data fusion and multilevel, dynamically linked representations in the event-oriented characterization with spatiotemporal entities as the core. The proposed model supports the multiperspective, multilevel, comprehensive three-dimensional expression and analysis of events from the perspective of the individual participating entities, the group perspective, and the macro perspective of the event. Downwardly, the proposed model can explore the characteristic changes of the participants in the event and support the microscopic analysis of events; upwardly, the proposed model can support the event semantic logic mining to serve macro decision-making.

This paper achieves only the modeling and basic visualization of spatiotemporal entity-based event data. However, much work still urgently needs to be undertaken: ① From the perspective of model data processing, assessing the quality and detail of the source data is crucial, as is selecting more precise event data sources for data fusion. ② From the standpoint of data application, we have currently only implemented the structuring of event data based on spatiotemporal entities. However, evaluating the accuracy and objectivity of event descriptions based on structured event data has significant practical implications for data application. ③ The current experiments were limited to simple visual analyses; the multilevel structure visualization supported by the model and event query analysis remain areas for further exploration.

Author Contributions: Methodology, Mingming Wang; Software, Mingming Wang; Validation, Mingming Wang; Resources, Mingming Wang; Data curation, Mingming Wang and Shenghui Li; Writing—original draft, Mingming Wang; Writing—review & editing, Mingming Wang, Jiangshui Zhang, Yibing Cao, Shenghui Li and Minjie Chen; Project administration, Jiangshui Zhang and Yibing Cao; Funding acquisition, Jiangshui Zhang and Yibing Cao. All authors have read and agreed to the published version of the manuscript.

Funding: The Project was supported by the National Key Research and Development Program of China, grant numbers 2021YFB3900900 and 2016YFB0502300.

Data Availability Statement: The data are not publicly available due to further research.

Acknowledgments: This research was funded by the National Key Research and Development Program of China, grant numbers 2021YFB3900900 and 2016YFB0502300. The authors would like to thank Yixin Hua and Nan Jiang for providing the experimental environment, topic selection and other support.

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

References

1. Chen, X. Why did John Herschel fail to understand polarization? The differences between object and event concepts. *Stud. Hist. Philos. Sci. Part A* **2003**, *34*, 491–513. [CrossRef]
2. Van Hage, W.R.; Malaisé, V.; Segers, R.; Hollink, L.; Schreiber, G. Design and use of the Simple Event Model (SEM). *J. Web Semant.* **2011**, *9*, 128–136. [CrossRef]
3. Richmond, L.L.; Gold, D.A.; Zacks, J.M. Event perception: Translations and applications. *J. Appl. Res. Mem. Cogn.* **2017**, *6*, 111–120. [CrossRef] [PubMed]
4. Wang, W.; Zhao, D. Chinese News Event Ontology Construction and Auto-population. *Comput. Eng. Sci.* **2012**, *34*, 171–176.
5. Chinchor, N.; Marsch, E. MUC-7 Information Extraction Task Definition. In Proceedings of the a Seventh Message Understanding Conference (MUC-7), Fairfax, VA, USA, 29 April–1 May 1998.
6. Peuquet, D.J.; Duan, N. An event-based spatiotemporal data model (ESTDM) for temporal analysis of geographical data. *Int. J. Geogr. Inf. Syst.* **1995**, *9*, 7–24. [CrossRef]
7. Claramunt, C.; Thériault, M. Managing time in GIS an event-oriented approach. In *Recent Advances in Temporal Databases*; Springer: Berlin/Heidelberg, Germany, 1995; pp. 23–42.
8. Lu, Y.; Liu, Q.; Dai, D.; Xiao, X.; Lin, H.; Han, X.; Sun, L.; Wu, H. Unified Structure Generation for Universal Information Extraction. *arXiv* **2022**, arXiv:2203.12277.
9. Yu, M.; Bambacus, M.; Cervone, G.; Clarke, K.; Duffy, D.; Huang, Q.; Li, J.; Li, W.; Li, Z.; Liu, Q.; et al. Spatiotemporal event detection: A review. *Int. J. Digit. Earth* **2020**, *13*, 1339–1365. [CrossRef]
10. Liu, Z.; Huang, M.; Zhou, W.; Zhong, Z.; Fu, J.; Shan, J.; Zhi, H. Research on Event-oriented Ontology Model. *Comput. Sci.* **2009**, *36*, 189–192, 199.
11. Liu, Y.; Li, R.; Wang, S.; Wu, H.; Gui, Z. Deducing Flood Development Process Using Social Media: An Event-Based and Multi-Level Modeling Approach. *ISPRS Int. J. Geo-Inf.* **2022**, *11*, 306. [CrossRef]
12. Zhang, X.; Liu, Z.; Liu, N.-z. Concept Algebra-based Representation Model and Conceptual Calculation Rules for Event. *Comput. Sci.* **2015**, *42*, 83–88+101.
13. Liu, W.; Xu, W.; Tang, Y.; Fu, J.; Zhang, X.; Liu, Z. Formalized Representation and Reasoning of Event Action Based on Extended Description Logic and Logic Program. *Comput. Sci.* **2014**, *41*, 116–125+145.
14. Liu, D.; Lin, C.; Ren, L.; Ruizhang, H. Hierarchical storyline generation method for hot news events. *J. Comput. Appl.* **2023**, *43*, 2376–2381.
15. Yang, Z.; Hua, Y.; Cao, Y.; Zhao, X.; Chen, M. Network Patterns of Zhongyuan Urban Agglomeration in China Based on Baidu Migration Data. *ISPRS Int. J. Geo-Inf.* **2022**, *11*, 62. [CrossRef]
16. Wei, Y.; Jiang, N.; Li, Z.; Zheng, D.; Chen, M.; Zhang, M. An Improved Ant Colony Algorithm for Urban Bus Network Optimization Based on Existing Bus Routes. *ISPRS Int. J. Geo-Inf.* **2022**, *11*, 317. [CrossRef]
17. Liu, X.; Fu, J.; Zeng, Z.; Wu, J. A Comparative Study of Event-centric Ontology Models. *J. Libr. Inf. Sci.* **2021**, *6*, 52–60.
18. Li, Q.; Ma, Y.; Yang, Z.G. Event Cube—A Conceptual Framework for Event Modeling and Analysis. In Proceedings of the 18th International Conference on Web Information Systems Engineering (WISE), Moscow, Russia, 7–11 October 2017; pp. 499–515.
19. Horie, S.; Kiritoshi, K.; Ma, Q. Abstract-Concrete Relationship Analysis of News Events Based on a 5W Representation Model. In Proceedings of the 1st International Workshop on Consistency and Inconsistency (COIN) at 27th International Conference on Database and Expert Systems Applications (DEXA), Porto, Portugal, 5–8 September 2016; pp. 102–117.

20. Chung, S.; Timberlake, A. Tense, aspect, and mood. In *Language Typology and Syntactic Description*; Shopen, T., Ed.; Cambridge University Press: Cambridge, UK, 1985; Volume 3, pp. 202–258.
21. Wang, Z.; Zhuang, D.; Wang, Y. Research on Spatio-temporal Processes Description of Historical Events and Its Visualization. *Comput. Eng.* **2014**, *40*, 50–55.
22. Chen, J.; Liu, J.; TIAN, H. Basic directions and technological path for building 3D realistic geospatial scene in China. *Geomat. Inf. Sci. Wuhan Univ.* **2022**, *47*, 1568–1575.
23. Zhao, X.; Zhang, J.; Cao, Y.; Yang, F.; Yang, Z.; Fan, X. Spatio-temporal knowledge embedding method considering the lifecycle of geographical entities. *Int. J. Appl. Earth Obs. Geoinf.* **2024**, *131*, 103967. [CrossRef]
24. Zhao, X.; Cao, Y.; Wang, J.; Fan, X.; Chen, M. A hierarchical spatio-temporal object knowledge graph model for dynamic scene representation. *Trans. GIS* **2023**, *27*, 1992–2016. [CrossRef]
25. Worboys, M.; Hornsby, K. From objects to events: GEM, the geospatial event model. In Proceedings of the International Conference on Geographic Information Science, Adelphi, MD, USA, 20–23 October 2004; pp. 327–343.
26. Pustejovsky, J. Events and the semantics of opposition. In *Events as Grammatical Objects*; Pustejovsky, J., Tenny, C., Eds.; CSLI Publications: Stanford, CA, USA, 2000; pp. 445–482.
27. Liu, Y.P.; Peng, H.; Li, J.X.; Song, Y.Q.; Li, X. Event detection and evolution in multi-lingual social streams. *Front. Comput. Sci.* **2020**, *14*, 15. [CrossRef]
28. Lu, Z.Y.; Yu, W.R.; Zhang, R.C.; Li, J.X.; Wei, H. Discovering Event Evolution Chain in Microblog. In Proceedings of the 2015 IEEE 17th International Conference on High Performance Computing and Communications (HPCC), Int Symposium Cyberspace Safety & Secur, New York, NY, USA, 24–26 August 2016; pp. 635–640.
29. Ritter, A.; Mausam; Etzioni, O.; Clark, S. Open domain event extraction from twitter. In Proceedings of the the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Beijing China, 12–16 August 2012; pp. 1104–1112.
30. Wang, X.Z.; Wang, Z.Q.; Han, X.; Jiang, W.Y.; Han, R.; Liu, Z.Y.; Li, J.Z.; Li, P.; Lin, Y.K.; Zhou, J.; et al. MAVEN: A Massive General Domain Event Detection Dataset. In Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP), Online, 16–20 November 2020; pp. 1652–1671.
31. Doerr, M. The CIDOC Conceptual Reference Module—An ontological approach to semantic interoperability of metadata. *AI Mag.* **2003**, *24*, 75–92.
32. Scherp, A.; Franz, T.; Saathoff, C.; Staab, S. F--a model of events based on the foundational ontology dolce+ DnS ultralight. In Proceedings of the the Fifth International Conference on Knowledge Capture, Redondo Beach, CA, USA, 1–4 September 2009; pp. 137–144.
33. Lagoze, C.; Hunter, J. The ABC ontology and model. In Proceedings of the International Conference on Dublin Core and Metadata Applications, Tokyo, Japan, 24–26 October 2001; pp. 160–176.
34. Raimond, Y.; Abdallah, S. The Event Ontology. Available online: https://motools.sourceforge.net/event/event.html (accessed on 13 October 2024).
35. Shaw, R.; Troncy, R.; Hardman, L. Lode: Linking open descriptions of events. In Proceedings of the The Semantic Web: Fourth Asian Conference, ASWC 2009, Shanghai, China, 6–9 December 2009; Proceedings 4. pp. 153–167.
36. Ma, L.; Li, H.; Lian, S.; Liang, R.; Gong, J. A Method of Modeling Natural Disaster Event Domain Ontology. *Geogr. Geo-Inf. Sci.* **2016**, *32*, 12–17.
37. Wang, W.; Zhao, D.Y. Ontology-Based Event Modeling for Semantic Understanding of Chinese News Story. In Proceedings of the 1st CCF Conference on Natural Language Processing and Chinese Computing, Peking Univ, Beijing, China, 31 October–5 November 2012; pp. 58–68.
38. Liu, J.; Liu, H.; Chen, X.; Guo, X.; Guo, W.; Zhu, X.; Zhao, Q.; Li, J. Terrorism Event Model by Knowledge Graph. *Geomat. Inf. Sci. Wuhan Univ.* **2022**, *47*, 313–322. [CrossRef]
39. Gottschalk, S.; Demidova, E. EventKG: A multilingual event-centric temporal knowledge graph. In Proceedings of the European Semantic Web Conference, Heraklion, Greece, 3–7 June 2018; pp. 272–287.
40. Tan, G.; Hou, X.; Zhuang, W. Research on Semantic Organization of Multimedia Resources of Intangible Cultural Heritage. *Res. Libr. Sci.* **2017**, *24*, 42–52. [CrossRef]
41. Yuan, M. Representing Complex Geographic Phenomena in GIS. *Cartogr. Geogr. Inf. Sci.* **2001**, *28*, 83–96. [CrossRef]
42. Claramunt, C.; Parent, C.; Thériault, M. Design patterns for spatio-temporal processes. In Proceedings of the Data Mining and Reverse Engineering: Searching for semantics. IFIP TC2 WG2. 6 IFIP Seventh Conference on Database Semantics (DS-7), Leysin, Switzerland, 7–10 October 1997; pp. 455–475.
43. Chen, M.; Jiang, N.; Chen, D. Study on Spatio-temporal Events of Multi-granularity Modeling and Visualization Methods. *Geomat. World* **2018**, *25*, 30–35.
44. Lin, G.; Feng, X.; Wang, L.; Du, J. An Event-centric Object Oriented Spatio-temporal Data Model. *Acta Geod. Cartogr. Sin.* **2002**, *31*, 71–76.
45. Chen, D.; Wang, P.; Cui, H.; Su, Y. Research on Event Modeling Framework Based on Multi-granular Spatiotemporal Object. *Geospat. Inf.* **2020**, *18*, 21–25+33+26.
46. Allen, J.F. Maintaining knowledge about temporal intervals. *Commun. ACM* **1983**, *26*, 832–843. [CrossRef]

47. Zheng, Z. Research on Key Technology of Spatio-Temporal Object Associative Relationship Generation, Management, and Visualization. Doctoral Dissertation, PLA Information Engineering University, Zhengzhou, China, 2020.
48. Scherp, A.; Mezaris, V. Survey on modeling and indexing events in multimedia. *Multimed. Tools Appl.* **2014**, *70*, 7–23. [CrossRef]