# LLM-based Progressive Triple Extraction from Infographics for Climate Change Ontology Construction

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**Abstract**

Discussions on environmental issues involve diverse stakeholders, and differences in their background knowledge are one of the factors that hinder consensus building. To address this challenge, previous work manually constructed a climate change ontology and demonstrated the usefulness of a system that visualizes its causal structure as a knowledge graph through a workshop-based evaluation. However, manual ontology construction requires substantial effort. In this study, we propose a method for extracting knowledge required for ontology construction from infographic materials in the form of triples (subject–predicate–object) using a large language model (LLM). The proposed method takes infographic materials as image inputs to an LLM and employs a four-stage extraction prompt based on the methodology used for manual ontology construction. Specifically, it (1) organizes and summarizes sentences related to four types of relations—Cause, Effect, Predicted Effect, and Countermeasure—into a summary document, (2) extracts triples using these four predicates based on the summary document, (3) generates additional triples by using the object of each extracted triple as the subject of a new triple, and (4) performs one additional expansion using the objects obtained in Step (3) as new starting points. To evaluate whether the extracted triples appropriately represent the contents of the source materials, three evaluators assessed 100 triples selected from the 2,565 triples extracted from 48 infographic topics. On average, 83.0% of the triples were consistent with the contents of the source materials. These results suggest that, although human verification remains necessary, the proposed method can complement the knowledge required for ontology construction and contribute to improving its efficiency.

**Keywords**

Climate Change Ontology, Large Language Model, Triple Extraction, Infographic, Knowledge Graph

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## 1. Introduction

In online discussions, it can be difficult to exchange opinions smoothly through real-time interactions, such as asking questions as in face-to-face discussions. In particular, online discussions in specialized domains involve diverse stakeholders with different levels of background knowledge. Consequently, even the same technical term may be interpreted differently by different participants. These differences can make it difficult for participants to correctly understand one another's statements and may hinder consensus building. Therefore, it is important to understand not only the meanings of technical terms but also the relationships among them and the grounds for arguments based on domain knowledge. To address these challenges, developing a system that helps stakeholders with different levels of background knowledge understand relationships among pieces of domain knowledge and facilitates their understanding of opinions may be effective. Against this background, a project focusing on climate change and other environmental issues has been undertaken to develop an online discussion support system[1]. Based on domain knowledge organized as an ontology, this system visualizes causal structures related to the entered information as knowledge graphs, thereby linking posted opinions with relevant domain knowledge.

In previous work, a climate change ontology for this system was manually constructed from two climate change documents comprising approximately 500 pages in total, and the construction process required approximately one month. Developing a method for reducing the time required for ontology construction is therefore an important challenge for facilitating the broader use of ontologies.

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In this study, we propose a method for supporting ontology construction that uses an LLM to extract, in the form of triples, the knowledge required for ontology construction from domain-specific documents, with the aim of reducing the cost of ontology construction. The proposed method employs a staged LLM-based extraction process based on the manual ontology construction procedure described in our previous study[2]. In this process, newly extracted concepts are used as starting points for further triple extraction in a step-by-step manner. Climate change infographics are used as the source materials. This paper describes the proposed method in detail and evaluates whether the extracted triples appropriately represent the content of the source materials.

## 2. Related Work

Studies have investigated the use of ontologies to structure knowledge for the systematic organization and sharing of knowledge related to climate change and environmental issues. Shimizu et al.[3]constructed and published the KnowWhereGraph Ontology, which integrates climate change-related knowledge concerning natural disasters, agriculture, health, and other domains. KnowUREnvironment[4] provides a knowledge graph generated by extracting concepts and their relations from literature on environmental topics such as climate change and biodiversity. These resources serve as knowledge bases for organizing, sharing, and utilizing a broad range of environmental knowledge. In contrast, this study focuses on a climate change ontology designed to visualize relations among concepts as a knowledge graph, thereby supporting the understanding of background knowledge in online discussions.

In recent years, studies on supporting ontology and knowledge graph construction using large language models (LLMs) have been conducted. Kommineni et al.[5] proposed a framework that supports the ontology construction process in a stepwise manner, from the generation of Competency Questions to the construction of ontologies and knowledge graphs. Schmidt et al.[6] performed document-level relation extraction using Ontology-guided Retrieval-Augmented Generation (Ontology-guided RAG), which retrieves and references existing ontologies during the extraction process, with the aim of improving extraction accuracy. In contrast, this study focuses on extracting triples that represent causal structures for the visualization of knowledge to support online discussions. A distinctive feature of our approach is that the LLM-based extraction process reflects a domain-specific manual ontology construction procedure and progressively expands the extracted knowledge using previously extracted concepts. Furthermore, we use infographic materials that concisely summarize environmental knowledge by major topic, facilitating the selection of information to be extracted.

## 3. Online Discussion Support System

### 3.1. Bulletin Board System

Fig. 1 shows the demonstration screen of the bulletin board system used to support online discussions. In the proposed system, when a user enters a text and clicks "Run Annotation," climate change–related terms appearing in the text (e.g., Drought) are automatically annotated (Fig. 1, left). When the user selects one of the annotated terms or searches for a keyword, a knowledge graph centered on the selected term is generated and displayed (Fig. 1, right).

In this system, annotation is performed when a term in the input text partially matches a concept in the climate change ontology. To display the generated knowledge graph, a SPARQL query is executed against the climate change ontology represented in RDF, and the graph is displayed based on the query results. For example, when “IncreaseInJapaneseDeerPopulation” is selected in the system, a three-layer breadth-first search is performed starting from this concept. Fig. 2 illustrates the correspondence between the ontology and the knowledge graph using “IncreaseInJapaneseDeerPopulation” as the starting point. In this figure, knowledge is extracted from the ontology described in Turtle format through a three-layer breadth-first search starting from “IncreaseInJapaneseDeerPopulation”, and the

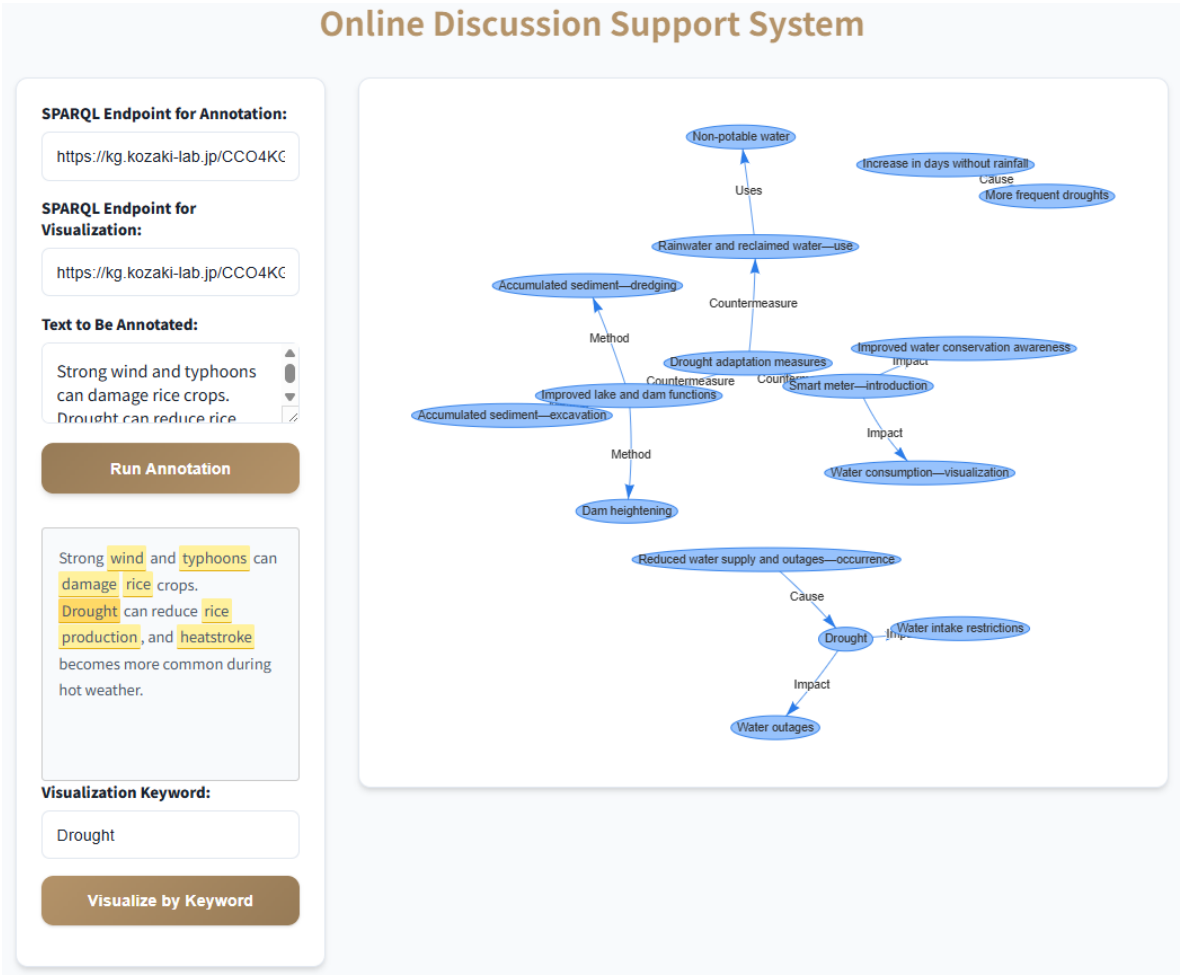



**Figure 1:** Example of the Online Discussion Support System Interface.

knowledge graph is generated based on the extracted triples.

In this search, "IncreaseInJapaneseDeerPopulation" is first used as the starting concept. At Level 1, concepts directly connected to it, such as "JapaneseDeer" and "JapaneseDeer-ExpansionOfWinteringAreasAtHigherElevations", are obtained. These concepts are then used as the starting points for the Level 2 search. At Level 2, concepts such as "ReducedSnowfall" are obtained from "JapaneseDeer-ExpansionOfWinteringAreasAtHigherElevations". The resulting concepts are subsequently used as the starting points for the Level 3 search, in which concepts such as "MildWinter" are obtained from "ReducedSnowfall". By visualizing these triple relationships as nodes and edges, users can trace multistep causal relationships and related knowledge.

When the system was tested in an environmental workshop, experts evaluated it as being able to visualize the relationships appropriately to a certain extent. This result suggests that even users without specialized knowledge can visually understand the meanings of terms appearing in discussions and their related knowledge, thereby supporting their understanding of the discussion.

## 3.2. Manual Construction of the Climate Change Ontology

Because the bulletin board system generates knowledge graphs based on the climate change ontology, the underlying ontology plays an essential role. Therefore, in our previous work, we constructed the ontology from domain-specific documents according to the developed methodology. The materials used and the steps of the methodology are described below.

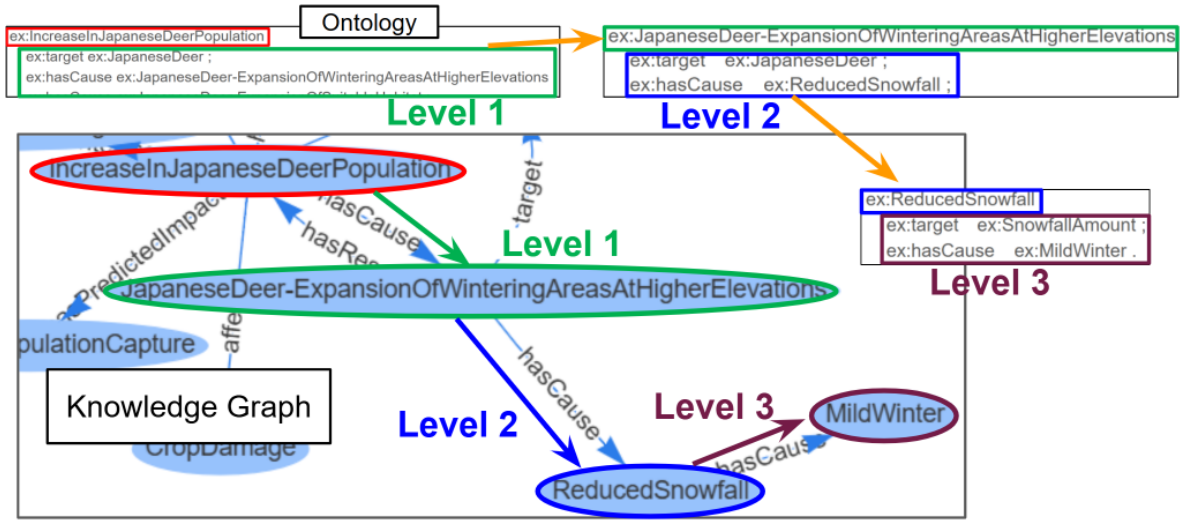



**Figure 2:** Correspondence Between the Ontology and the Knowledge Graph.

### 3.2.1. Materials Used

In previous work, two documents on the 1994 Lake Biwa drought[7][8], provided by experts participating in the project, and one climate change infographic document[9] were used as knowledge sources for constructing the climate change ontology. The documents on the Lake Biwa drought contain investigation reports on environmental changes before and after the drought and their impacts. In contrast, the infographic document summarizes the impacts of climate change and adaptation measures for 48 topics, including organisms and disasters, using figures and text arranged over two pages for each topic. The source materials used for ontology construction and the content produced through the procedures described below were originally written in Japanese. In this paper, they are presented in English translation.

### 3.2.2. Manual Construction Method

Fig. 3 shows the procedure for manually constructing the climate change ontology. In our previous work, we developed a methodology for constructing the climate change ontology from domain-specific documents used as knowledge sources. The individual steps are described below in correspondence with the steps shown in Fig. 3.

*Step 1:* Organization of Materials for Ontology Construction. To clarify the scope of ontology construction from the domain-specific documents, four relation types—Cause, Effect, Predicted Effect, and Countermeasure—were selected, and a summary document was prepared focusing mainly on sentences related to these relation types. These four relation types were selected because climate change knowledge is often developed around causal relationships, and knowledge concerning causes, effects, future effects, and countermeasures is considered important in online discussions.

*Step 2:* Construction of Concepts and Relations. The main subject of the summary document (e.g., Increase in the Japanese Deer Population) was identified and defined as the central concept. Concepts corresponding to the Cause, Effect, Predicted Effect, and Countermeasure relations of the central concept were then extracted from the summary document. Triples were constructed using the central concept as the subject, the relation type as the predicate, and the corresponding concept as the object (e.g., S = Increase in Japanese Deer Population, P = hasCause, and O = Japanese Deer - Expansion of Wintering Areas at Higher Elevations). Defining a central concept enabled knowledge to be organized around the main topic of the document and the relations to be organized systematically.

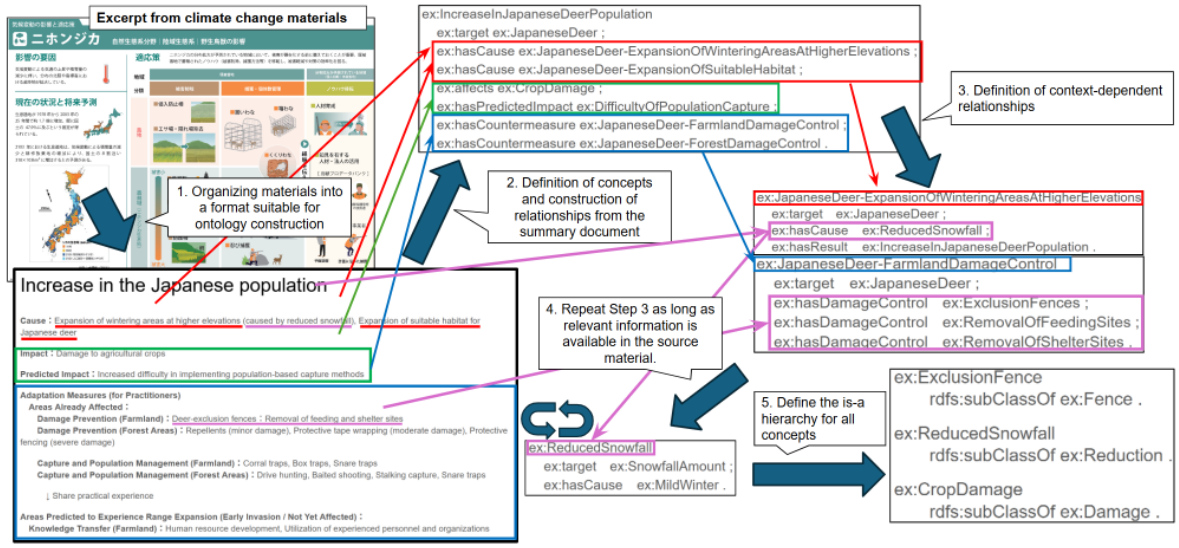



**Figure 3:** Methodology for Manual Ontology Construction.

*Step 3:* Construction of Relations for Newly Defined Concepts. Each concept defined in the preceding step was used as the subject to construct further triples based on the content of the material (e.g., S = Japanese Deer - Expansion of Wintering Areas at Higher Elevations, P = hasCause, and O = Reduced Snowfall). At this stage, the predicates were not restricted to the four relation types; relations described in the material were considered.

*Step 4:* Iterative Relation Construction. The same procedure was recursively applied to the concepts defined in the preceding step, and triples were constructed progressively until no new concepts could be obtained (e.g., S = Reduced Snowfall, P = hasCause, and O = Mild Winter). By constructing further triples using newly defined concepts again as subjects, a knowledge structure was constructed in which all concepts were connected to the main subject of the document.

*Step 5:* Construction of the Class Hierarchy. An is-a hierarchy was defined for all concepts constructed through the preceding steps, thereby organizing them into an ontology.

### 3.2.3. Challenges of Manual Construction

Using the procedure described above, a climate change ontology consisting of 1,717 concepts and 2,101 relations was constructed. However, manual ontology construction requires the domain-specific documents to be read and understood and the concepts and relations to be manually defined, making the process both time-consuming and labor-intensive. In particular, constructing the ontology for a single infographic topic requires approximately seven hours. As the number of source materials increases, the workload becomes even greater, making efficient ontology construction difficult. To address this issue, this study proposes a method that uses a large language model (LLM) to extract the knowledge required for ontology construction from infographic materials in the form of triples.

## 4. LLM-Based Triple Extraction Method

### 4.1. Proposed Method

To reduce the workload required to construct the climate change ontology, this study proposes a method that uses an LLM to extract the knowledge required for ontology construction from infographic materials in the form of triples. Based on the manual ontology construction methodology described in Sect. 3.2, the prompt was designed so that the LLM performs material organization, relation construction starting

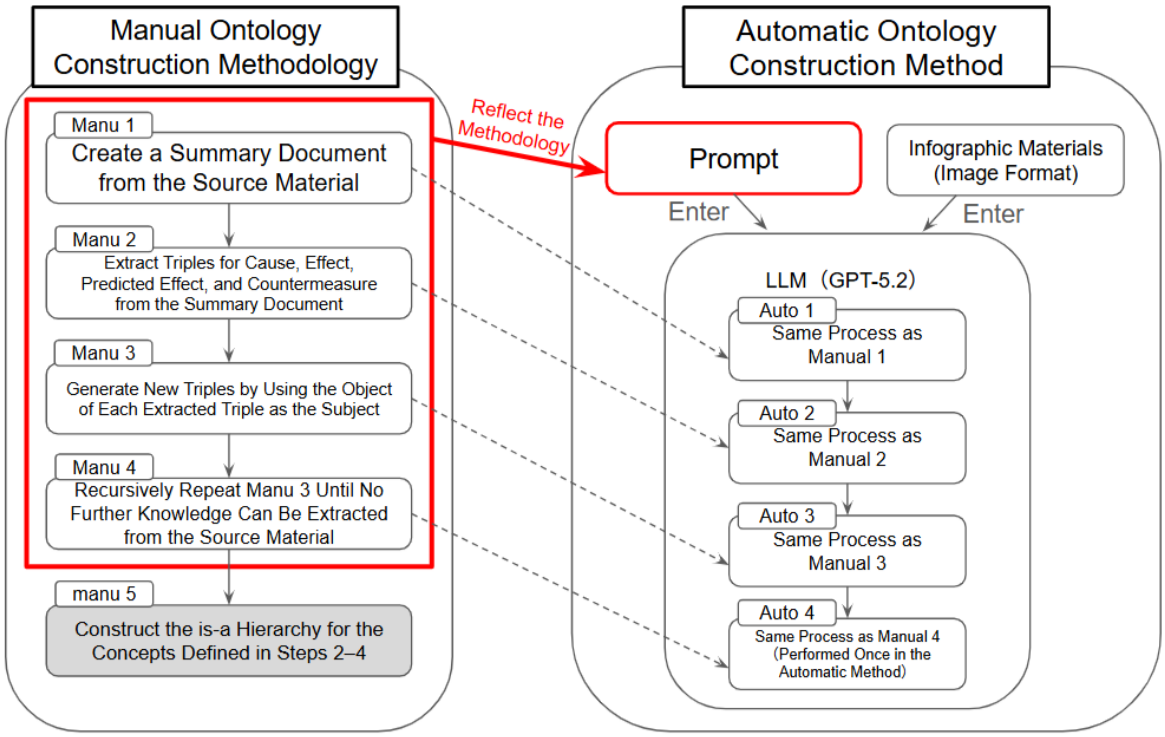



**Figure 4:** LLM-Based Triple Extraction Method Reflecting the Manual Ontology Construction Methodology.

from a central concept, and relation construction for newly defined concepts in a stepwise manner. In addition, the infographic materials were selected because their compact organization of figures and text makes them suitable for an initial evaluation using image inputs to an LLM. Two images corresponding to one infographic topic are provided as input for each triple extraction task.

Fig. 4 presents the overall workflow of the proposed method. In Fig. 4, the manual construction steps are denoted by "Manu," whereas the automatic extraction steps are denoted by "Auto." Manu1–Manu5 correspond to Steps 1–5 in Sect. 3.2. For LLM-based triple extraction, images of the infographic material and a prompt designed on the basis of the methodology represented by Manu1–Manu4 are simultaneously provided to GPT-5.2. The LLM then sequentially executes Auto1–Auto4 according to the prompt. Although the procedure in Manu4 is repeated during manual construction, the corresponding procedure was repeated only once in this study as an initial evaluation. Furthermore, the construction of the is-a hierarchy represented by Manu5 is outside the scope of the proposed method; this study focuses solely on the extraction of relational triples.

## 4.2. Prompt Design

In the proposed method, a prompt was designed to enable the LLM to reproduce the manual ontology construction methodology represented by Manu1–Manu4 in Fig. 4 by performing the Auto1–Auto4 processes based on that methodology. A single prompt was used in this study, consisting primarily of extraction conditions, extraction procedures, and an output format. The full prompts and implementation code actually used in this study are available in the GitHub repository.

### 4.2.1. Extraction Conditions

Seven constraints were defined to enable the LLM to reproduce the methodology used in manual construction.

1. **Language Constraint.** Triple outputs were restricted to Japanese.

2. **Conditions for SPO Extraction.** The LLM was instructed to extract subjects and objects at the concept level and not to use an entire sentence directly as a subject or object. For example, from the sentence "When seawater temperature rises, the distribution range of Pacific saury changes," concepts such as "increase in seawater temperature" and "Pacific saury" are extracted separately, rather than treating the entire sentence as a single concept. When a single description contains multiple events, the LLM was also instructed to divide it into multiple triples. In this study, to extract diverse types of knowledge contained in the infographics, the examples of triples provided in the prompt were not limited to a specific category but included concepts with different meanings, such as organisms, phenomena, changes in state, and actions.

3. **Meanings of the Predicates.** Four predicate types were defined: Cause, Effect, Predicted Effect, and Countermeasure. A triple using Cause as its predicate was constrained so that it could be interpreted as "The cause of S is O," whereas a triple using Effect could be interpreted as "O occurs as an effect of S." Similarly, Predicted Effect was defined so that it could be interpreted as "The predicted effect of S is O," and Countermeasure as "The countermeasure for S is O." To ensure that the meaning of each predicate was interpreted unambiguously, the corresponding English property names—hasCause, affects, hasPredictedImpact, and hasCountermeasure—were also provided in parentheses.

4. **Semantic and Syntactic Conditions.** All extracted triples were required to have a structure that could be naturally interpreted as "The P of S is O." The LLM was also instructed not to use predicate names such as Cause or Effect as subjects or objects.

5. **Conditions for Ontology Construction.** Because this study focuses on triples other than hierarchical relations, class hierarchies (subClassOf) were excluded from the construction scope. In addition, concepts for which the target would be unclear if represented only by an event, such as "increase" or "dieback," were required to follow the "target–event" format. For example, "increase in catch" is represented as "Pacific saury–increase in catch," and "dieback" as "rice plant–dieback."

6. **Conditions for Causal Direction.** The direction of each relation was standardized according to the meaning defined for its predicate. When a description in the source material did not express a direct relation, the LLM was instructed to supplement an intermediate concept and represent the relation in stages. For example, the indirect relation "Climate change causes an increase in the Japanese deer population" is represented as "Climate change–Effect–reduced snowfall" and "Reduced snowfall–Effect–increase in the Japanese deer population," through an intermediate concept.

7. **SPO Constraints.** Cause, Effect, Predicted Effect, and Countermeasure were required to be used as predicates. When other predicates were used, the LLM was instructed to express them in nominalized form. In addition, all predicates were required to be output as Japanese property names.

#### 4.2.2. Extraction Procedure

In addition to the extraction conditions, a four-stage extraction procedure corresponding to Manu1–Manu4 was defined to enable the LLM to execute the manual construction methodology step by step.

*Step 1:* Generation of a Summary Document. Sentences related to Cause, Effect, Predicted Effect, and Countermeasure are extracted and organized from the input materials to generate a summary document.

*Step 2:* Triple Extraction. Based on the summary document generated in Step 1, triples are extracted using

the subject of the material as the subject and one of Cause, Effect, Predicted Effect, or Countermeasure as the predicate.

*Step 3:* Triple Extraction Starting from the Objects. The object of each triple extracted in Step 2 is used as the subject to extract new triples.

*Step 4:* Iterative Processing. Triples are extracted progressively by repeatedly executing the procedure in Step 3. However, as an initial evaluation, the Step 3 procedure was repeated only once in Step 4, and no further iterations were conducted.

Among these steps, the progressive triple extraction in Steps 2–4 corresponds to the three-layer breadth-first search of the knowledge graph described in Sect. 3.1.

#### 4.2.3. Output Format

The output was formatted as JSON and contained the OCR results for the two input images, the summary document generated in Step 1, and the triples extracted in Steps 2–4. Each triple was also accompanied by an evidence sentence supporting its extraction and the number of the step in which it was extracted (Steps 2–4).

## 5. Evaluation

To evaluate the usefulness of the triples extracted by the proposed method, two experiments were conducted. In these experiments, (1) an evaluation based on a comparison between the manually constructed triples and the extracted triples and (2) a human evaluation of the extracted triples were conducted. In the first experiment, triples that did not match the manually constructed triples were also evaluated by humans to determine whether they could be used to expand the ontology. The first experiment examines whether the proposed method can reproduce or complement manually constructed ontology knowledge, whereas the second examines whether the extracted triples are supported by the source infographics.

GPT-5.2 was used via the OpenAI API for the experiments. The default API settings were used for the generation parameters.

### 5.1. Comparison Method Between Manually Constructed and Automatically Extracted Triples

#### 5.1.1. Triple Extraction Conditions

This evaluation used the prompt described in Sect. 4.2.

#### 5.1.2. Evaluation Target

To compare the manually constructed ontology with the automatically extracted triples, the evaluation was conducted using nine infographic topics for which manual ontology construction had already been completed.

#### 5.1.3. Evaluator

The comparison was manually performed by the first author of this study.

#### 5.1.4. Evaluation Method

An evaluation was conducted to examine (1) the extent to which the triples extracted by the proposed method matched the manually constructed triples and (2) whether the proposed method could extract triples that, although not matching the manually constructed triples, were still usable for ontology

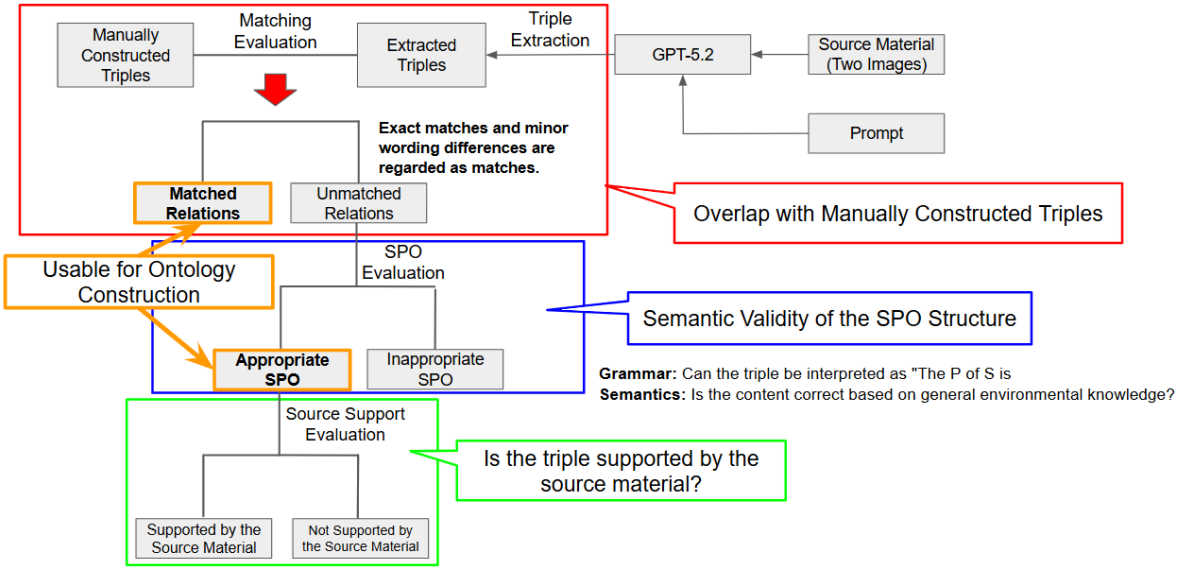



**Figure 5:** Workflow for Comparing the Manually Constructed Ontology with the Extracted Triples and Evaluating Their Validity.

construction. The evaluation was performed according to the procedure shown in Fig. 5 and consisted of the following three steps.

First, the automatically extracted triples were compared with the manually constructed triples for each topic to evaluate their matching rate. A triple was regarded as matching if its subject, predicate, and object were identical or if they differed only in wording while conveying the same meaning (red box in Fig. 5).

Next, triples that did not match were evaluated to determine whether the relations among the subject, predicate, and object were semantically appropriate. Specifically, we examined whether the meaning of the relation could be interpreted solely from S, P, and O when the triple was interpreted as “The P of S is O,” and assessed the validity of its content based on general knowledge in the environmental domain. For example, the triple “Increase in Seawater Temperature–Effect–Pacific Saury” was judged to be inappropriate because the object did not specify what kind of effect would occur to Pacific saury (blue box in Fig. 5). Based on these evaluation criteria, triples evaluated as either “Matched Relations” or “Appropriate SPO” were regarded as usable for ontology construction (orange box in Fig. 5).

Finally, for triples judged to be semantically appropriate, we evaluated whether they had been extracted based on the source material. If the corresponding information was explicitly described in the source material, the triple was classified as Supported by the Source Material; otherwise, it was classified as Not Supported by the Source Material (green box in Fig. 5).

## 5.2. Evaluation Method for Consistency with the Source Materials

### 5.2.1. Triple Extraction Conditions

This evaluation used the prompt described in Sect. 4.2.

### 5.2.2. Evaluation Target

The evaluation targeted the triples automatically extracted from all 48 infographic topics. Ten topics were selected from the 48, and 10 triples were randomly sampled from each topic, resulting in a total of 100 triples. To avoid bias in the number of extracted triples among topics, the topics were ranked in both ascending and descending order according to the number of extracted triples, and five topics were selected from each ranking at intervals of four. Furthermore, because the average ratio of the numbers

of triples extracted in Steps 2–4 described in Sect. 4.2 was 5:3:2, five triples extracted in Step 2, three in Step 3, and two in Step 4 were randomly selected from each topic.

#### 5.2.3. Evaluators

To assess whether the extracted triples appropriately represented the contents of the source materials, three graduate students majoring in information engineering (two second-year master's students and one first-year master's student) independently conducted the manual evaluation.

#### 5.2.4. Evaluation Method

The evaluation was conducted in two stages. First, we determined whether the interpretation of each triple was consistent with its evidence sentence. Second, for triples judged to be inconsistent, we determined whether the interpreted content was supported by the original source material. In addition, Fleiss' kappa coefficient was calculated to assess the agreement among the three evaluators. The triple (Drought, hasCause, Low Rainfall) is used as an example.

(1) The triple (Drought, hasCause, Low Rainfall) is interpreted according to the predefined sentence pattern as "The cause of drought is low rainfall." If the evidence sentence is "Drought occurred due to low rainfall," the triple is judged to be consistent because both convey the same meaning. In contrast, if the evidence sentence is "The cause is low rainfall," it is judged to be inconsistent because the subject of the cause is not explicitly specified.

(2) For triples judged to be inconsistent, the infographic material from which each triple was extracted was examined. Although the evidence sentence alone did not explicitly specify that the cause referred to drought, the triple was judged to be supported by the source material if the infographic clearly indicated that the sentence referred to drought. Otherwise, it was judged not to be supported by the source material.

## 6. Results and Discussion

This section first presents the results of a comparison between the manually constructed ontology and the triples extracted from nine infographic topics using the prompt described in Sect. 4.2. It then presents the number of triples extracted from 48 infographic topics using the same prompt and the results of the evaluation of their consistency with the source materials.

### 6.1. Results and Discussion of the Comparison Between Manually Constructed and Automatically Extracted Triples

#### 6.1.1. Triple Extraction Results

Table 1 presents the number of triples extracted from nine infographic topics using the prompt described in Sect. 4.2 and the results of the comparison with the manually constructed triples. Whereas 540 triples were manually constructed, 504 triples were extracted using the prompt.

#### 6.1.2. Evaluation Results

Of the 504 triples extracted using the prompt described in Sect. 4.2, a total of 100 triples were randomly selected, with 11 or 12 triples sampled from each topic. These triples were compared with the manually constructed ontology according to the evaluation method described in Sect. 5.1.

As shown in Table 1, 19 of the 100 triples matched the manually constructed triples, corresponding to a matching rate of 19%. Among the remaining 81 nonmatching triples, 59 were judged to be semantically appropriate as SPO triples. Together with the 19 matching triples, 78 triples, or 78%, were judged to be usable for ontology construction. Furthermore, among the 59 triples judged to be semantically

appropriate, 56, or approximately 95%, were confirmed to have corresponding descriptions in the source materials.

#### 6.1.3. Discussion

As shown in Table 1, the matching rate with the manually constructed triples was low at 19%. On the other hand, approximately 73% (59/81) of the nonmatching triples were judged to be usable for ontology construction, and approximately 95% of the triples judged to be semantically appropriate as SPO triples were confirmed to have corresponding descriptions in the source materials. An examination of the triples that did not match the manually constructed triples revealed several factors contributing to the mismatches. For example, some of the nonmatching triples were appropriate as SPO triples and were confirmed to correspond to the source materials. Differences in concept granularity were also observed. For example, the manual construction represented a more specific concept that included the target of damage prevention, such as "sika deer–farmland damage prevention," whereas the automatic extraction represented a more abstract concept, such as "damage prevention." Furthermore, differences in the direction of the subject-object and in the predicates used to represent the same content were observed. For example, the manual construction represented the relationship as "certified wildlife capture operator–certifying authority–prefectural governor," whereas the automatic extraction represented it as "prefectural governor–certification target–certified wildlife capture operator." Some nonmatching triples were also found to inadequately represent the content of the source materials.

It should be noted that, even in the manual construction used in this study, the concepts selected may vary depending on the ontology developer, and the reproducibility of concept selection across ontology developers was not evaluated. Therefore, the manually constructed results were used not as the sole ground truth but as a reference for comparison with the automatically extracted results. In addition, whereas the manual construction process iteratively constructs relationships until no new concepts are obtained, the number of iterations in the automatic extraction was limited in this study as part of an initial evaluation. Consequently, the manual construction and automatic extraction differ in the extent to which knowledge is expanded, and this difference may affect the number of extracted triples and the match rate. In future work, it will be necessary to compare the number of extracted triples and the match rate with the manual construction without limiting the number of iterations, and to investigate the effect of the number of iterations on the extraction results.

These results indicate that, although the triples selected through manual construction and automatic extraction differed, the proposed method could extract triples from perspectives different from those adopted in manual construction, suggesting its potential to complement manual construction. On the other hand, when relationships were not explicitly described in the source materials, inappropriate predicates or semantic relationships were sometimes generated. Therefore, the proposed method is considered appropriate for use as an ontology construction support method that incorporates manual verification of the extracted triples.

In addition, this study did not quantitatively evaluate the time required for the overall process, including manual verification and correction after automatic extraction. Therefore, the extent to which the proposed method can reduce the time required for ontology construction needs to be investigated in future work.

### 6.2. Results and Discussion of the Evaluation of Consistency with the Source Materials

#### 6.2.1. Triple Extraction Results

Table 2 summarizes the results of triple extraction from all 48 infographic topics. In total, 2,565 triples were extracted. Of these, 1,395 triples (approximately 54.4%) were extracted in Step 2, 787 (approximately 30.7%) in Step 3, and 383 (approximately 14.9%) in Step 4.

**Table 1**
Results of Triple Extraction and Comparison with Manually Constructed Triples.

| Manual triples | Automatic triples |
|---|---|
| 540 | 504 |

| Evaluation | Result |
|---|---|
| **Matched triples (n = 100)** | 19 / 100 (19%) |
| **Total Usable triples (n = 100)** | 78 / 100 (78%) |
| **Supported by source (n = 59)** | 56 / 59 (95%) |

#### 6.2.2. Evaluation Results

Among the 2,565 triples extracted based on the prompt described in Sect. 4.2, 100 triples were evaluated for consistency with the source materials according to the evaluation method described in Sect. 5.2. The evaluation results are shown in Table 3.

As shown by the consistency rates in Table 3, Evaluator A judged 68 of the 100 triples to be consistent with the source materials, Evaluator B judged 89 triples to be consistent, and Evaluator C judged 92 triples to be consistent.

In addition, Fleiss' kappa coefficient was calculated to assess the agreement among the three evaluators, resulting in $\kappa = 0.463$. The evaluation results for each extraction step are shown on the right side of Table 3. Evaluator A judged 33 (66.0%), 21 (70.0%), and 14 (70.0%) triples in Steps 2, 3, and 4, respectively, to be consistent with the source materials. Evaluator B judged 48 (96.0%), 23 (76.7%), and 18 (90.0%) triples, respectively, to be consistent with the source materials, while Evaluator C judged 49 (98.0%), 24 (80.0%), and 19 (95.0%) triples, respectively, to be consistent with the source materials.

#### 6.2.3. Discussion

As shown in Table 3, differences in the evaluation results were observed between Evaluator A and Evaluators B and C. Fleiss' kappa coefficient was 0.463, indicating moderate agreement among the three evaluators. In addition, for all evaluators, no substantial decrease in consistency with the source materials was observed from Step 2 to Step 4. These results suggest that, within the scope of this study, a certain level of quality may be maintained even when knowledge is extracted stepwise using previously extracted triples as starting points. However, this study did not compare the proposed method with a simpler method without stepwise extraction or conduct an ablation study in which specific steps were omitted. Therefore, the effect of stepwise knowledge extraction on the extraction results has not yet been clarified. In future work, it will be necessary to evaluate the effect of stepwise extraction by comparing with a simpler extraction method and by conducting evaluations in which specific steps are omitted. In addition, the present evaluation was conducted by three graduate students majoring in information engineering, and no evaluation was conducted by experts in the climate change domain or by ontology users. Future work should include evaluations by such experts and users to examine the usefulness of the extracted results from different perspectives.

This study evaluated the proposed method using specific infographics in the climate change domain. Therefore, its applicability to infographics with different structures and layouts has not been investigated. In addition, because this study focused only on the climate change domain, its applicability to other domains remains to be examined. Furthermore, because this study used source materials written in Japanese and limited the output of triples to Japanese, its applicability to other languages has not been investigated. On the other hand, since the relations to be extracted are explicitly specified in the prompt, the proposed method may be applicable to other domains by redefining the relations according to the target domain. In future work, it will be necessary to investigate the applicability of the proposed method to infographics with different structures and layouts, as well as to other domains and languages.

**Table 2**
Results of Triple Extraction from 48 Infographic Topics.

| | Step2 | Step3 | Step4 | Total |
|---|---|---|---|---|
| **Total** | 1395 | 787 | 383 | 2565 |
| **Percentage of the total** | 54.4% | 30.7% | 14.9% | 100% |
| **Average / infographic** | 29.06 | 16.40 | 7.98 | 53.44 |

※ Average / Infographic: Average number of triples extracted at each step per infographic.

**Table 3**
Consistency Rates in the Overall Evaluation (Left) and by Extraction Step (Right).

| Evaluator | ✓ | ✗ | Total | Consistency rate |
|---|---|---|---|---|
| **A** | 68 | 32 | 100 | 68% |
| **B** | 89 | 11 | 100 | 89% |
| **C** | 92 | 8 | 100 | 92% |

| Step | Evaluator A | Evaluator B | Evaluator C |
|---|---|---|---|
| **Step2(n=50)** | 33(66.0%) | 48(96.0%) | 49(98.0%) |
| **Step3(n=30)** | 21(70.0%) | 23(76.7%) | 24(80.0%) |
| **Step4(n=20)** | 14(70.0%) | 18(90.0%) | 19(95.0%) |

## 7. Conclusion

In this study, we proposed a method for extracting triples from infographic materials using a large language model (LLM) to reduce the cost of constructing a climate change ontology for an online deliberation support system. The proposed method employs a prompt designed based on the manual ontology construction methodology, enabling the LLM to perform a sequence of processes from organizing the source materials to progressively extracting triples.

In the evaluation experiment, the comparison with the manually constructed triples showed that the proposed method was able to extract triples usable for ontology construction from perspectives different from those adopted during manual construction. Furthermore, in the consistency evaluation of the triples, it was confirmed that, even when knowledge was progressively extracted from previously extracted triples, the triples remained consistent with the source materials.

These results indicate that, although the proposed method cannot completely replace manual construction, it has the potential to support the construction of a climate change ontology and contribute to the efficient construction and expansion of the ontology used in the online deliberation support system.

In addition, because this study focused only on specific climate change infographics, the applicability of the proposed method to infographics with different layouts and to other domains needs to be investigated in future work.

In future work, we will investigate the automatic construction of is-a hierarchies. Furthermore, to integrate the concepts extracted in this study into an existing ontology, we aim to extend the proposed method into a comprehensive ontology construction support framework that covers both relation triple extraction and hierarchical structure construction, drawing on LLM-based concept placement[10] and ontology expansion methods[11].

Note that the full prompts, implementation code, and extraction results used in this study are available in the CCO4KG GitHub repository: https://github.com/oecu-kozaki-lab/CCO4KG .

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## Disclosure of Interests

The authors have no competing interests to declare that are relevant to the content of this article.

## Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT for language editing, grammar correction, and translation. The authors reviewed and revised the resulting content and took full responsibility for the final content of the paper.

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