The HIP Ontology: a formal framework to support disaster risk reduction and management*

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Abstract

Open data initiatives and knowledge graphs, in synergy, have contributed to an increasing volume of disaster-related data in the Semantic Web. Synthesizing and enriching these data is critical to support all aspects of data-driven disaster risk reduction and management. A standard template that coherently defines, maps, and classifies the wide range of hazards to which communities are exposed is a key input for this task. The UNDRR-ISC Hazard Information Profiles (HIPs) provide evidence-informed standardization of hazard nomenclature and definitions and a "science-backed" classification. Unfortunately, they are not in a machine-readable format. This paper develops the HIP Ontology as its FAIR counterpart in RDF format that allows its utilization for the greater alignment and consistency of disaster data and systems within and across sectors. Moreover, since HIPs are developed through extensive and rigorous scientific consultation, the HIP Ontology will provide an important layer of data standardization, strengthening the data ecosystem for policy-making and risk management at the global, regional, and national levels. In addition, we also present the Disaster Event Ontology, which provides a schema of key concepts and relationships to link observations and spatiotemporal representations of disaster data with specific hazard types in the HIP Ontology. The two ontologies together will enhance interoperability, integration, and comprehension of disaster datasets within knowledge graphs.

Keywords

ontology, disaster management, disaster classification, hazard information profiles, knowledge graphs

1. Introduction

The integration of multi-faceted disaster-related data into knowledge graphs (KGs) is a rapidly evolving area of research and practice [1, 2] with several initiatives developing disaster-domain ontologies and vocabularies [3, 4]. Despite progress, challenges persist in modeling and integrating these data within an interconnected Open Knowledge Network (OKN). We draw attention to two key issues. First, the lack of a reference disaster-domain ontology prevents existing disaster-related ontologies, vocabularies, data schema, and code lists from being integrated or aligned. Second, no formal and FAIR-based [3], standardized disaster classification scheme exists

Ontology Showcase and Demonstrations Track, 9th Joint Ontology Workshops (JOWO 2024), co-located with FOIS 2024, 15-19 July, 2024, Enschede, Netherlands.

*This research has been supported by the National Science Foundation under Grant No. 2033521: "KnowWhereGraph: Enriching and Linking Cross-Domain Knowledge Graphs using Spatially-Explicit AI Technologies".

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that is suitable for linked data adoption. This paper addresses the latter challenge and proposes an ontological framework to connect this classification scheme with other disaster-themed data, enhancing their interoperability and accessibility within the Semantic Web.

Disaster data from authoritative portals like the Humanitarian Data Exchange[1], DesInventar[2], and EM-DAT[3] are not readily semantically interoperable due to terminology discrepancies. Even linking related datasets from the same US federal agency is problematic due to ambiguity, e.g., NOAA uses the term "storm" to refer to "storm events", "storm tracks", and "storm impacts". Another example is how cyclonic phenomena are referred to by different terms across ocean basins: "hurricane" in the North Atlantic, "typhoon" in the western North Pacific, and "tropical cyclone" in the Indian Ocean and South Pacific Ocean [5]. A standardized vocabulary with mappings between synonymous hazard terms and other contextual relationships can improve the consistency and accuracy of exchanged disaster information [6].

Before 2021, disaster vocabularies like the CRED disaster classification and the IRDR Peril classification had limited scope and inconsistent naming conventions, hindering their ability to harmonize diverse data. These vocabularies lacked context on drivers, outcomes, and risks, limiting their effectiveness in linking disaster data for response and mitigation strategies. In 2021, the United Nations Office for Disaster Risk Reduction (UNDRR) and the International Science Council (ISC) launched the Hazard Information Profiles (HIPs), as a standardized hazard vocabulary to monitor and implement the Sendai Framework for Disaster Risk Reduction 2015-2030 [6]. HIPs provides standardized hazard terms and definitions to inform government strategies and actions on risk reduction and operational risk management policies. Covering over 300 hazard types, from natural phenomena to human-induced events, HIPs offers detailed descriptions, conceptual clarity, and systematic classification. Developed through a comprehensive scientific consultation, HIPs compiles rich metadata for each hazard type, offering conceptual clarity, systematic classification, clear documentation, and supporting materials. The framework is also regularly updated to include new disasters and revised hazard definitions based on the latest scientific evidence. Despite their authoritative nature, it is informally documented and lacks machine-readable formats. Adapting them to linked data is crucial for enhancing their integration into global frameworks and improving their effectiveness in disaster risk reduction and sustainable development.

This paper presents two key contributions.

1. The HIP Ontology, the formalized counterpart of HIPs[4], represented in OWL syntax. We utilized the Scientific Taxonomy Pattern [7] and extended SKOS [8] to hierarchically organize concepts. Additionally, we developed a metadata schema to include specific semantic annotations for various details of each hazard type, facilitating their expansion into meaningful semantic relations and rules.
2. The Disaster Event Ontology (DEO), which conceptualizes disaster-related events, related observations, spatiotemporal aspects, and causal relations. This ontology is meant to link the HIP Ontology to other disaster-themed data.

[1] https://data.humdata.org/
[2] https://www.desinventar.net/
[3] https://www.emdat.be/
[4] Throughout the rest of the paper we will use HIPs to refer to the informal classification scheme.

We envision the HIP Ontology as a catalyst for advancing disaster management services towards FAIR, collaborative, and unbiased Disaster Management Systems. The formal framework will bolster the long-term development and sustainability of the HIPs classification by establishing a structured workflow for revisions. The HIP Ontology will extend its value beyond disaster management, for instance, in healthcare, as already explored in [9] to study the effects of climate change on populations, clinicians, and healthcare systems.

The remainder of this paper is organized as follows. In Sec. 2, we introduce HIPs, followed by a background on hazard events and their context in Sec. 3. In Sec. 5, we briefly overview state-of-art and limitations. We present a use case demonstrating the motivation for developing the HIP Ontology in Sec. 4. Sec. 6 describes the HIP Ontology and DEO, followed by a demonstration of their implementation in the KnowWhereGraph [1] in Sec. 7. Finally, Sec. 8 concludes the paper and outlines future work.

2. The Hazard Information Profiles for Hazard Types

The HIPs [6] provide a standardized classification of hazard types, curated through rigorous scientific consultation and peer review by experts. Designed to inform policy-making, practice, and reporting in disaster risk reduction and management, this authoritative resource includes hazard types that meet specific criteria: have the potential to impact communities, have measurable spatial and temporal components, and are associated with proactive operational measures.

The HIPs categorize hazards into eight main types, each further subdivided by cluster type, encompassing a range of specific hazards:

- Meteorological and Hydrological hazards: 9 hazard clusters and 60 specific hazards
- Extraterrestrial hazards: 1 hazard cluster and 9 specific hazards
- Geo-hazards: 3 hazard clusters and 35 specific hazards
- Environmental hazards: 2 hazard clusters and 24 specific hazards
- Chemical hazards: 9 hazard clusters and 25 specific hazards
- Biological hazards: 10 hazard clusters and 88 specific hazards
- Technological hazards: 9 hazard clusters and 53 specific hazards
- Societal hazards: 4 hazard clusters and 8 specific hazards

The structure of HIPs, with examples, is detailed in Sec. 6.1.1. The HIPs technical review document [6] describes this organization and provides comprehensive metadata to improve definition clarity and precision. Each HIP includes details such as hazard type name, reference number, authoritative definitions, the UN organization providing guidance, and additional annotations like synonyms, scientific descriptions, metrics, and numerical limits. Contextual metadata, including links between hazards, risks, and impacts, are also included to facilitate stakeholder engagement in loss and damage accounting and multi-hazard analysis. The hazard type list in HIPs is open-ended and regularly updated through international consensus to maintain its relevance and accuracy.

3. Hazards, Disasters, and Impacts

Conceptually, a hazard event and its type (i.e., which is what HIPs references), are distinct yet semantically interconnected entities. The context of hazards as events is crucial for accurately interpreting and utilizing HIPs.

This section offers a high-level overview of hazards, disasters, and impacts as spatiotemporal, measurable events. Hazards are distinct from disasters, where disasters occur when hazards adversely affect the human population. UNDRR defines[5] a disaster as a hazardous event interacting with conditions of exposure, vulnerability, and capacity, ultimately resulting in impact. Disasters can also be perceived as future risks determined probabilistically based on hazard, exposure, vulnerability, and capacity. Therefore, understanding, studying, quantifying, and reducing risk is essential for disaster prevention. Conceptually, they are distinct: disasters as events versus disasters as a risk. Nevertheless, a robust framework of hazard types and definitions that HIPs provides serves as a critical tool to manage events, investigate risks, and implement mitigation strategies.

Hazards are spatiotemporal and meteorological events that often trigger cascading effects, where one event can lead to additional events that may coincide, be connected, or disperse spatiotemporally [10]. Each event episode within a disaster cascade can vary in nature, frequency, duration, intensity, and other hazard property measurements, making it challenging to compare spatial and temporal scales of the resulting impacts. Many datasets intertwine impacts with larger disaster events, treating disaster and impact as identical phenomena. Moreover, datasets such as NOAA's Storm Events Database[6] attribute deaths and damages to entire disaster events like Category 5 hurricanes rather than distinct storm-related episodes (e.g., strong wind, coastal flood, debris flow, lightning). Such modeling makes it difficult to estimate the hazard potential or risk from any one particular physical phenomenon (e.g., damage from a lightning strike vs. a coastal flood), or even delineate the full impact area of one particular historical event (e.g., the epicenter of an earthquake vs. the vast expanse of resulting infrastructure damage). Despite these challenges, hazards and disasters are interconnected with their impacts, yet existing ontologies poorly model these connections. A comprehensive examination of interactions between hazard categories and impact types is essential for accurate risk estimation, mitigation, and recovery efforts based on empirical evidence and predictive models. Such analyses benefit greatly from standardized and harmonized hazard types and definitions.

4. The KnowWhereGraph Use Case

The HIP and DEO ontologies are developed and evaluated within the framework of the KnowWhereGraph (KWG) [1], a densely linked geospatial knowledge graph. KWG integrates over 35 datasets from the environmental, social, and public health domains, to facilitate humanitarian relief efforts by providing up-to-date disaster situation-aware data [11]. Drawing from diverse hazard- and disaster-related sources, including federal agencies like NOAA and FEMA, KWG encompasses a wide array of disaster themes. These encompass hurricane trajectories, storm impacts, disaster declarations, as well as fire-related phenomena such as burn scars, smoke plumes, and fire forecasts.

From a data integration and querying standpoint within KWG, the imperative was to establish connections across diverse datasets covering various facets such as hazard occurrences, resultant impacts, affected regions, and demographic information. For instance, modeling linkages between wildfire incidents, resultant smoke plumes, and populations with underlying health

[5]https://www.undrr.org/terminology/disaster
[6]https://www.ncdc.noaa.gov/stormevents/

conditions facilitated the identification of areas necessitating N95 mask distribution to mitigate smoke-related health risks. From the perspective of applications that interface KWG, the need was to resolve disparate datasets referring to identical hazard types (e.g., wildfires sourced from MTBS and NIFC agencies [12]) and summarize attributes about the same hazard event recorded across multiple data repositories.

In developing the KWG Ontology [12], which extends the HIP and DEO ontologies, our objectives were to: 1) incorporate a consistent ontology pattern for uniform querying across all hazard observational data (e.g., droughts, hurricanes, wildfires); 2) align named events (e.g., Hurricane Katrina) across disparate datasets (e.g., NOAA Storm Events, FEMA Disaster Declarations Summaries, NOAA Historical Hurricane Tracks); 3) employ methods to integrate data with authoritative classification schemes and vocabularies.

Below are examples of informal competency questions that were used to set basic requirements for designing the HIP Ontology and DEO:

- (CQ1) List all the fires that impacted Santa Barbara between 2005 and 2010.
- (CQ2) What were the human mortality impacts caused by hurricanes in the U.S. in 2005?
- (CQ3) What was the total dollar damage in California from floods that happened in 2021?
- (CQ4) List all Category 5 hurricanes that have impacted the U.S. since 2010.

The observational, spatial, and temporal context of hazards and spatial concepts in KWG is modeled by reusing external standard ontologies, including SOSA/SSN [13], GeoSPARQL [14], and OWL-Time [15]. In Fig. 1, the core classes from KWG are denoted using orange boxes, illustrating how these classes extend the standard ontologies to integrate data effectively. This figure also depicts the kernel pattern used for uniform querying across hazards and places within KWG. Furthermore, this template highlights the reusability of three standard ontologies for modeling hazard, disaster, and impact events in the subsequent sections.

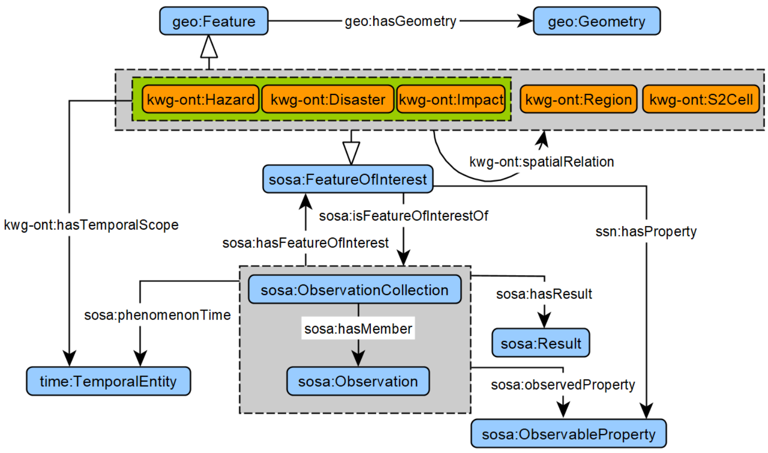

Figure 1: The five core classes of KWG (kwg-ont), in orange, extending the SOSA (sosa), SSN (ssn), GeoSPARQL (geo), and OWL-Time (time) ontologies.

5. Existing Work and Limitations

The disaster domain witnesses the ongoing development of numerous ontologies each year, primarily centered around terms related to the components of the disaster management cycle [16]. A recent comprehensive review identified 69 ontologies focusing on keywords such as Disaster, Vulnerability, Risk, Crisis, Humanitarian, Early Warning, and Emergency [3]. Although there are comprehensive frameworks, such as the EDXL Ontologies [17], designed to facilitate information exchange during emergencies, none of these ontologies serves as a dedicated controlled vocabulary specifically for hazards, providing standardized identifiers, representative relationships, and annotated metadata for various hazard types. Existing ontologies proposing disaster classification lack publicly accessible formal representations [4]. Although standardized and reference vocabularies exist for the domain, they remain informal (e.g., EM-DAT, DesInventar, IRDR Perils). In contrast, other domains, particularly biomedicine, have embraced formalized controlled vocabularies as standard practice, exemplified by renowned ontologies like the Gene Ontology and the Disease Ontology. The divide between knowledge modelers and disaster domain experts presents a significant challenge, contributing to the absence of a formalized controlled vocabulary for hazards [3]. We anticipate that the development of the HIP Ontology will bridge this gap, facilitating the refinement of HIPs and enhancing their suitability for intelligent disaster management capabilities.

6. Description of the Modeling

Scope and Overview: The HIP Ontology is developed as a part of the broader framework of the Disaster Management Domain Ontology (DMDO) [18], which is currently undergoing comprehensive development to address the broader data representation, integration, and analytic needs in the disaster domain. We applied the Modular Ontology Methodology (MOMo) [19], which treats ontology design patterns as fundamental components, enabling flexible schema development. DMDO is intended to be a reference ontology, providing a generic but data-aware conceptualization of the disaster management life cycle [16], which distinguishes the *operational phase* (denoting actions undertaken to reduce the impact of the disaster), from the *phenomenon phase* (denoting the occurrence of the actual disaster and its impacts). This classification is adopted for the modularization of the DMDO ontology into two core independent but coherent ontologies: the *Disaster Event Ontology*, and the *Disaster Operational Ontology*. The Disaster Event Ontology (DEO), detailed in Sec. 6.2, conceptualizes and organizes observational data about different types of phenomena in the domain by largely reusing SOSA. Previously, in Fig. 1 we demonstrated the KWG pattern that adopts SOSA, GeoSPARQL, and OWL-Time for this specific purpose. The Disaster Operational Ontology (DOO), which is being developed as future work, is meant to model the concepts of

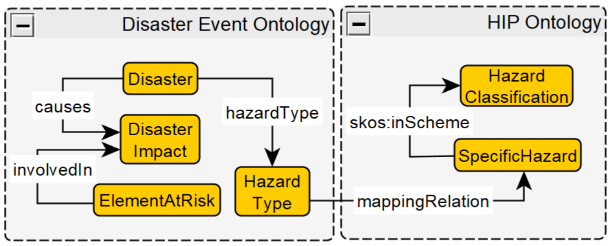

Figure 2: High-level overview of the Disaster Event Ontology (DEO) and the HIP Ontology.

operational effectiveness before, during, and after an emergency. Describing the DOO pattern is outside the scope of this paper. Aside from this, DMDO offers integration adaptability to include ancillary modules, such as the Disaster Properties Ontology [18] to model hazard properties.

In the rest of this section, we describe the HIP Ontology, the DEO, and their alignment. The ontology modeling presented here was developed through an iterative and collaborative process with a team comprising of knowledge modelers from the KWG project and domain experts in the disaster relief community. The conceptualization is discussed in this paper using generic schema diagrams, and the detailed ontology and documentation are available in a public repository: https://github.com/KnowWhereGraph/dmdo/tree/main/modules/disaster-event-module.

General notation of schema diagrams: Edges with filled arrows are object properties and edges with broad heads indicate subclass relationships.

6.1. The HIP Ontology

The HIP Ontology modeling is presented in two parts. First, we introduce the conceptual model aimed at formalizing the hierarchical classification structure of HIPs. Next, we present a metadata framework meticulously designed to encapsulate the metadata extracted from their PDF technical review document [6].

6.1.1. Modeling the Classification Structure

As discussed earlier in Sec. 2, each HIP is structured into three hierarchical facets, representing distinct categories of hazard terminology: *Hazard Type*, *Hazard Cluster*, and *Specific Hazard*. Terms within each facet are interconnected with one or multiple terms in the parent facet. For example, in Fig. 3, we observe a subset of HIPs where three specific hazards (Nuclear Agents, Biological Agents, Chemical Warfare Agents) are linked to the same hazard cluster (CBRNE), which is, in turn, associated with multiple hazard types in the topmost facet. Initially, we constructed the HIP Ontology as a poly-hierarchical ontology using only subclass relations. This choice stemmed from the lack of explicit relation types such as partonomy, membership, or hypernymy defined over the links in HIPs. However, we soon recognized that this approach led to incorrect inferencing. For instance, adopting a strict class-subclass poly-hierarchical classification over the example in Fig. 3 would mean inferring any instance of Chemical Hazard (e.g., Hydrogen Cyanide) as an instance of Biological Hazard, which is undesirable. Consequently, we opted to relate facets and their instances in the HIP Ontology using other semantic relations that are not necessarily transitive, such as hypernymy and membership relations.

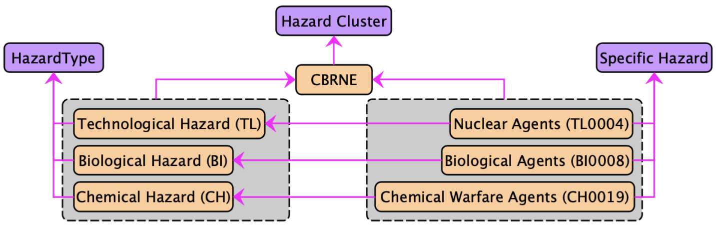

Figure 3: Poly-hierarchical classification of HIPs denoted using a subset of terms. Top-level facets are denoted with purple boxes. Arrows denote links between terms across facets, as described in HIPs.

Fig. 4 (a) illustrates the schema diagram detailing the hierarchical organization of HIP Ontology concepts. The diagram showcases the three distinct facets of HIPs, which are represented as disjoint subclasses within the `hip:HazardClassification` scheme. This scheme is identified as a subclass of the `skos:ConceptScheme` class [8]. At the lowest level of the hierarchy is the `hip:SpecificHazard` class, which encapsulates all named hazards. The `hip:HazardType` class at the top level of the hierarchy represents generic hazard types categorized by their nature of origin. Situated between these levels, the `hip:HazardCluster` class serves to group specific hazards based on their corresponding generic hazard types. This class is denoted as a subclass of `skos:Collection`, as it specifically intends to group related hazards into clusters. Concepts within each facet are designated as subclasses of the respective facet type. Cross-facet relations among concepts are established through two taxonomic relations: hypernym-hyponym and membership, facilitating a comprehensive hierarchical structure within the HIP Ontology.

The non-transitive relation `hip:broader`, denoted as a sub-property of `skos:broader`, signifies that a specific hazard or hazard cluster concept has a narrower scope than a hazard type concept. Similarly, the `hip:isMemberOf` relation, a sub-property of `skos:isMemberOf`, denotes the membership of a specific hazard within a hazard cluster. Extending SKOS relations within the HIP namespace is specifically done to axiomatically constrain their domain and range. Fig. 3 (b) illustrates the subset of HIPs from Fig. 3 structurally formalized in the HIP Ontology.

6.1.2. Modeling the Metadata Framework

In addition to structural information, each HIP includes a comprehensive set of metadata detailed in columns 1 and 2 of Tab. 1. Column 3 of the table specifies the properties utilized to model each metadata item. This metadata framework is designed to capture temporal trends within the taxonomy and enhance the functionality of HIPs as reference specifications by attributing provenance to concept names, definitions, and descriptions.

6.2. The Disaster Event Ontology

The conceptual scope of DEO encompasses aspects related to disaster events and their impacts, connections to their classification schemes, associated properties of interest, risk elements,

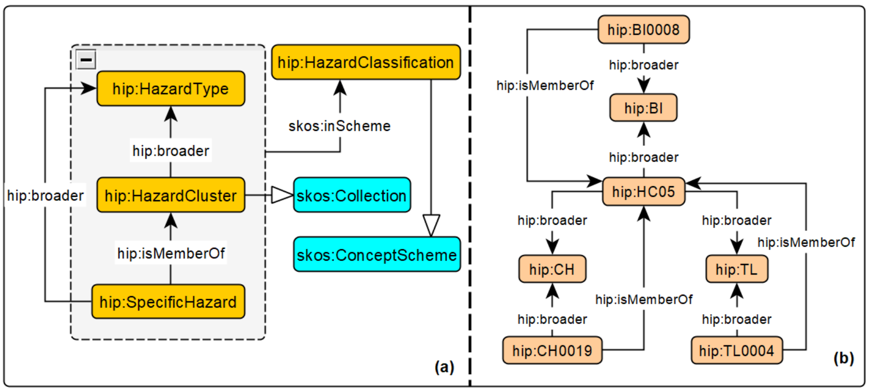

Figure 4: (a) Schema diagram denoting the structural organization of concepts in the HIP ontology. (b) Example of the HIPs classification (from Fig. 3) as modeled in the HIP Ontology.

HIP annotation details extracted from the natural-language documentation		HIP Ontology mapping/metadata term
Element	**Description**	
Name and Reference	Name of the specific hazard.	`rdfs:label`, `hip:vernacularName`
	Reference number.	`hip:identifier`
	Hazard type, and cluster type.	`hip:broader`, `hip:narrower`, `hip:hasMember`
Definition	A hazard definition, sourced from an authoritative source (such as a UN agency) or up-to-date academic and scientific sources, that reflect scientific consensus, and are of broad international relevance. Reference(s) for the definition is cited.	`hip:definedAs` o `hip:Definition` (`hip:Definition` is an entity with provenance)
Annotations	Possible synonyms, equivalents in non-English languages	`hip:synonym`
	Additional description elements that expand on the primary definition.	`hip:describedAs` o `hip:Description`
	Relevant and available, globally used metrics and numeric limits.	`hip:measurementUnit` o `qudt:Unit`
	References to key relevant UN conventions or multilateral treaties.	`hip:relatedInstrument` o `hip:Instrument`
	Examples of drivers, outcomes, and risk management practices or processes providing concrete information on the contexts and possible impacts of hazard.	hip:hasDriver o hip:Driver, hip:hasOutcome o hip:Outcome
	Key references from publicly available scientific and institutional sources to support facts and statements made in the HIPs.	`hip:definitionSource o prov:Entity` `hip:descriptionSource o prov:Entity`
Coordinating Organization	The UN or international organizations that provide technical guidance on the hazard.	`hip:coordinatingEntity o prov:Agent`

Table 1
Metadata elements and properties used in the HIP Ontology.

and spatiotemporal characteristics. Fig. 5 and Fig. 6 illustrates the schema diagrams for DEO, demonstrating its extension of external ontologies. The three primary classes in this ontology are `Event`, `ElementAtRisk`, and `PossiblyCausesRelation`, which are described below.

`Event`: The definitions of hazard, disaster, and impact as events or phenomena vary among authoritative sources. Although upper ontologies like UFO and BFO provide valuable conceptual distinctions for high-level concepts such as events and risks, we choose not to use them to minimize complexity and overhead. Our goal is to develop a practical and functional domain ontology efficiently, without the theoretical rigor required by foundational ontologies. We focus on a broader definition of event (“*event is anything that occurs*” – cf.Wikipedia) to categorize oc-

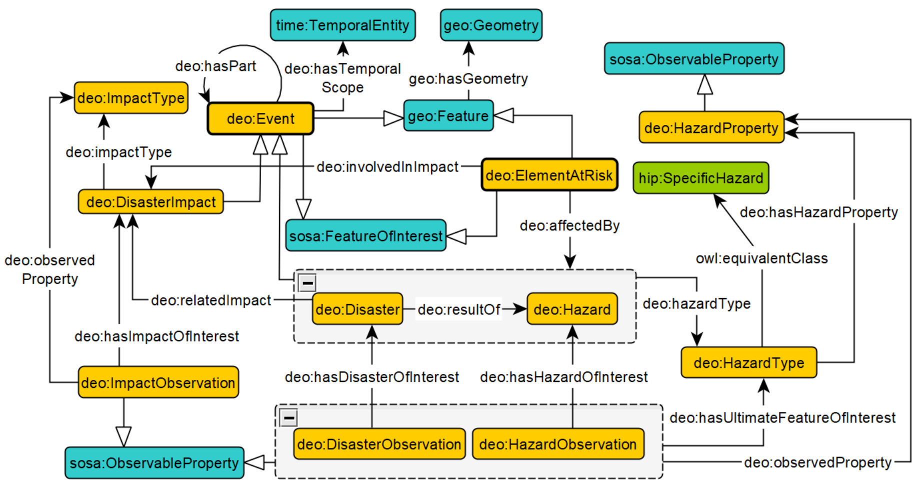

Figure 5: Schema diagram illustrating key concepts and properties in the Disaster Event Ontology. The core classes `Event` and `ElementAtRisk` are outlined in bold.

currences with measurable properties as `deo:Event`. Both hazard and disaster occurrences have distinct attributes that characterize their intensity, magnitude, and extent. For instance, hurricanes are characterized by sustainable wind speeds, heavy precipitation, and storm surges, while earthquakes are typically recorded by magnitude at the epicenter. Impacts also have measurable properties such as the number of deaths, homes damaged, roads affected, and economic loss, as captured in disaster damage databases like EM-DAT and DesInventar. We model `deo:Hazard`, `deo:Disaster`, and `deo:DisasterImpact` as subclasses of `Event`, and as subclasses of the SOSA class `sosa:FeatureOfInterest`, which represents any entity whose property is measured during an observation. Specifying `deo:Event` as a subclass of `geo:Feature` enables standardized representation and querying of geometric attributes and spatial relationships of events with other geospatial data. The `deo:hasTemporalScope` property captures temporal details of when an event occurred, while `deo:hasPart` represents mereological relationships between event segments or episodes. This `deo:hasPart` relation can be specialized to denote spatiotemporal parts of events (e.g., tracks segments of a hurricane), or impact parts (e.g., impacts of individual episodes of a hurricane).

Each instance of `deo:Hazard` and `deo:Disaster` represents a specific type of hazard, identified by the `deo:HazardType` class and related using the `deo:hazardType` property. The `deo:HazardType` class refers to the hazard theme and is the ultimate feature of interest in SOSA terminology. It acts as the connector between the DEO and the HIP ontology. In Fig. 5, the class-equivalence mapping between the `hip:SpecificHazard` and `deo:HazardType` illustrates how observations and other hazard-themed data represented using DEO can utilize the HIP ontology for classification and enrichment. The relation between a hazard type and its specific properties (e.g., a hurricane's size, intensity, speed, and direction) is represented using the `deo:hasHazardProperty` relation. Similarly, the impact type of a disaster is denoted using the `deo:ImpactType` class and `deo:impactType` property.

`PossiblyCausesRelation`: Hazards can serve as the origins of disasters or as a series of cascading events that lead to disasters [10]. We denote the relationship between `deo:Disaster` and `deo:Hazard` using `deo:resultOf`. For example, in the case of Hurricane Katrina, the event remained a hazard until making landfall, after which it transformed into a disaster event causing damage, deaths, and injuries along its path. The `deo:relatedImpact` relation denotes the relationship between `deo:Disaster` and `deo:Impact`.

The `deo:possiblyCauses` relation generalizes any explicit or inferred causal or correlation relation between events, including the `deo:relatedImpact` and `deo:resultOf` relations as shown in Fig. 6. However, causal links between hazards or disasters are often not explicit within a dataset or across different datasets integrated into KWG. Given the complex and cascading nature of disasters and their underlying risk drivers, causal relationships in disaster contexts are non-linear and cannot be simplistically captured by, or inferred into a causal predicate. To address this complexity, we adopt reification to attach provenance and additional information, such as interacting factors and conditions, quantitative models, or participatory methods used to determine causal relations. The reified class `deo:PossiblyCausesRelation` is employed from the causal ontology design pattern [20] to facilitate this need.

`ElementAtRisk`: Disasters occur when valuable assets interact with hazards. The class `deo:ElementAtRisk` encompasses entities of value that may be adversely affected by hazards, including living beings, buildings, facilities, economic activities, and social structures. Specific

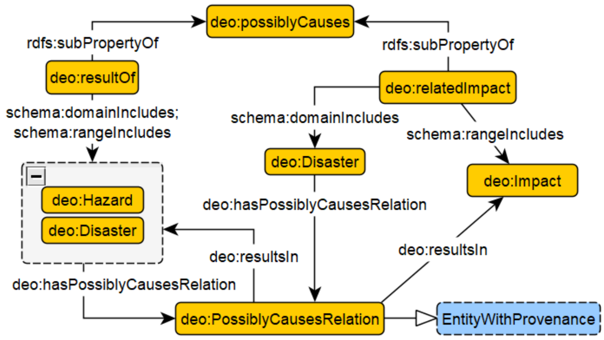

Figure 6: The schema diagram shows the general `possiblyCauses` relation between two events, its subproperties, and the reified `PossiblyCausesRelation` class.

hazard properties determine the *severity* of impact on these assets, including the *exposure* of the asset to the hazard and the *intensity* of the hazard. The degree of impact is influenced by the intrinsic properties of each element-at-risk, and these are 1) the propensity of an element to suffer a loss due to a specific hazard–*vulnerability*, and 2) the capacity of an element to cope with the hazard–*resilience*). The Disaster Properties Ontology [18] elaborately models these properties within the context of DMDO.

The `deo:affectedBy` relation is used to denote when an element-at-risk is impacted by a hazard or disaster, while the `deo:involvedInImpact` relation relates the element-at-risk with the actual impact phenomenon. Assets can be affected directly by a hazard (e.g., a house is flooded; a person is injured by a landslide) or indirectly (e.g., services are interrupted, roads are blocked). The concept of *element-at-risk* can be categorized (e.g., population, buildings) and characterized (e.g., population income distribution, building age) in various ways. However, formally incorporating any specific classification scheme into DEO is outside its current scope.

7. Evaluating the HIP Ontology in KnowWhereGraph

Here, we present the integration of the HIP ontology and DEO within KWG. Fig. 7 depicts a subset of KWG's hazard classes mapped to the HIP Ontology. This ontology now serves as the framework for integrating various hazard datasets in KWG. Purple boxes represent top-level hazard classes from each dataset, while yellow boxes indicate their subclasses. Mapping is done at both core and subclass levels. During implementation, we found gaps in HIPs, such as incomplete coverage of specialized NIFC (National Interagency Fire Center) fire classes, including prescribed fire, wildland fire, and complex fire.

Upon further review, we found that some hazards in the *Specific Hazard* facet of HIPs may need additional categorization. For example, NOAA classifies tropical cyclones by maximum sustained winds into tropical depression (33 knots), tropical storm (34 to 63 knots), and hurricane (64 knots). While HIPs cover tropical cyclone, tropical depression, and tropical storm, "hurricane" is only listed as a synonym for tropical cyclone. This creates a modeling issue with NOAA's dataset, where "hurricane" denotes a specific type of tropical cyclone. Therefore, as shown in Fig. 7, we avoid mapping the `kwg-ont:NOAA_TropicalCyclone` class to any HIP class to

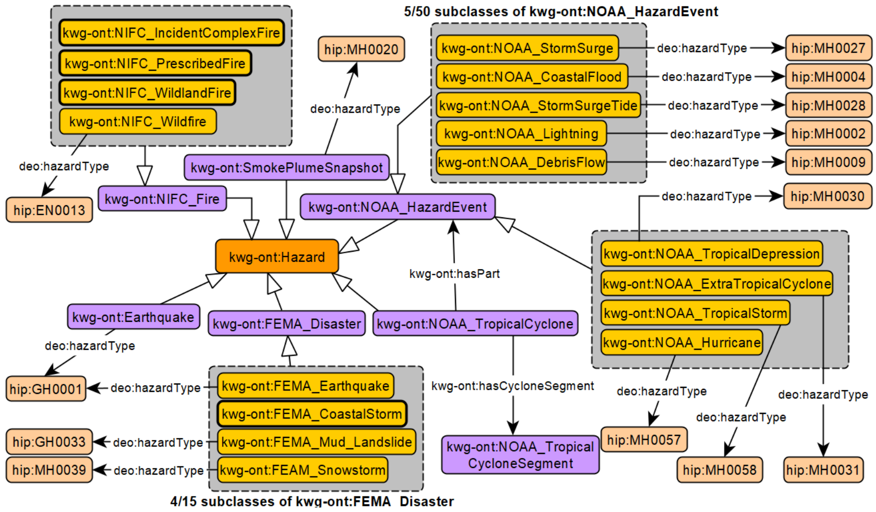

Figure 7: Illustration of the mapping between KWG (purple and yellow boxes) with concepts in the HIP Ontology (pink boxes). Concepts outlined in bold boxes do not have a corresponding mapping in HIPs.

prevent incorrectly classifying all NOAA hazard events as hurricanes.

We revisit competency question CQ1 from Sec.4 to illustrate querying and inferencing. Fig.8 shows the SPARQL query for CQ1, while Fig. 9 demonstrates KWG data instantiation using DEO and HIP. In this figure, green and purple boxes represent instances and classes from the NOAA storm events dataset, respectively. Solid-line arrows indicate asserted statements and dotted-line arrows show inferred statements using a reasoner for CQ1.

```
PREFIX time: <http://www.w3.org/2006/time#>
PREFIX deo: <http://knowwheregraph/ontology/deo#>
PREFIX sosa: <http://www.w3.org/ns/sosa/>
PREFIX hip: <https://undrr-hip.org/>
select ?impact where { ?impact a deo:ImpactObservation ;
                                sosa:hasUltimateFeatureOfInterest hip:MH0058 ;
                                sosa:phenomenonTime | time:inXSDgYear "2005"^^xsd:gYear.  }
```

Figure 8: SPARQL query to implement CQ1 from Sec. 4.

Besides evaluating DEO and HIP in the KWG through data integration and querying, the ontologies were reviewed by experts from Direct Relief to assess their coverage, structure, and quality. The Hermit reasoner in Protégé was used to check their logical consistency.

8. Conclusion

Integrating diverse types of hazard data in a KG enhances our understanding of hazards to build more resilient communities and reduce disaster risk. Achieving this requires a machine-readable hazard vocabulary to resolve ambiguity and create interlinked descriptions of entities that provide context to hazard data. The HIPs classification scheme offers a detailed and standardized hazard vocabulary developed through significant human effort. However, while they serve as a

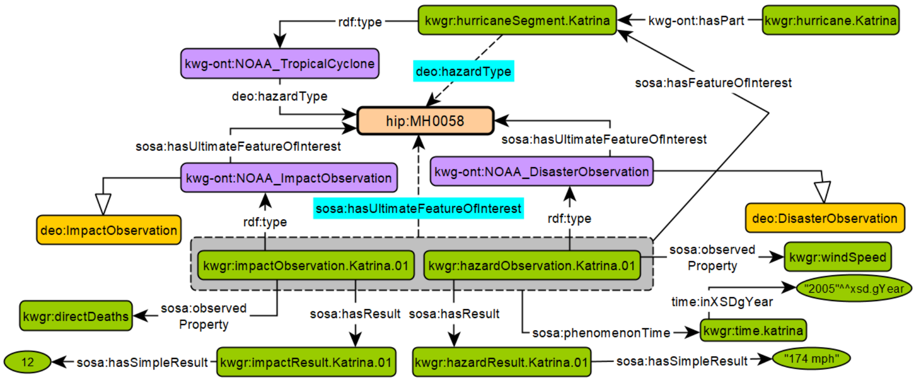

Figure 9: Example of KWG instance data that uses the HIP Ontology and populates a portion of DEO.

formal reference for disaster management practitioners, they lack *formalization* for implementation in information systems, particularly knowledge graphs. In this paper, we translate HIPs into a FAIR vocabulary to fulfill the data integration needs and querying capabilities within KWG. The resulting HIP Ontology hierarchically organizes terms and metadata elements from HIPs using a consistent ontology pattern. Additionally, we present the Disaster Event Ontology, which conceptualizes and organizes observational data related to different types of events in the hazard-disaster domain, largely re-using existing standardized ontologies. Together, the HIP ontology and DEO can be extended and specialized 1) for more fine-grained modeling of specific disaster needs (e.g., to model wildfire-specific disaster response actions), 2) to model specific synergies among (e.g., post-disaster and prevention actions). The long-term stewardship of the ontology will be facilitated through KWG's self-sustaining open-source ecosystem.

Future Work: The development of the HIP Ontology has identified certain gaps in the current HIPs classification, which present opportunities for future work. As a first step, we want to engage with the developers of the HIPs to revise the schema for better alignment and consistency with data. This includes identifying and mapping identical concepts within the same facet. An example is "Tsunami" represented as four distinct specific hazards in HIPs, with distinct identifiers (`MH0029`, `GH0006`, `GH0017`, `GH0035`), based on their origin (i.e, marine, seismogenic, volcanogenic, submarine landslide trigger). Additionally, we aim to identify and address hazards that require further classification for improved representation of data.

Other aspects of future work involve applying machine learning and graph embeddings to KGs utilizing the HIP Ontology to 1) identify and model multi-hazard relationships, such as heavy rainfall resulting in a landslide or a volcanic eruption triggering a landslide; 2) annotate hazard types with the spatial regions where they are prevalent.

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