A Formal Framework for Disaster Risk Properties*

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Abstract
Disaster risk properties (or disaster variables) such as intensity, exposure, severity, vulnerability, resilience, and capacity are significant because they provide essential information for understanding and managing disaster risk and cascading effects. While there are an increasing number of datasets that record these properties based on different criteria, such as regional levels (e.g., community resilience at counties vs. census tracts), thematic levels (e.g., social vulnerability based on race vs. socioeconomic status), or even for different hazard types (e.g., disaster risk for earthquakes vs. hurricanes), we lack a formal model that captures the semantics of these properties, i.e., their interactions with one another, and their context. Context is described through relations that constrain each property specific to an entity or as a property of an entity with respect to another entity. For example, intensity is exclusively the property of a disaster event, whereas vulnerability is a property of an element-at-risk concerning a specific hazard type. Here, we propose the Disaster Properties Ontology (DPO) that formalizes seven core properties in the disaster domain. It is built by re-using existing standard ontologies such as OWL-Time, GeoSPARQL, SOSA, and PROV-O. Additionally, DPO is developed as a sub-module of a more comprehensive Disaster Management reference Domain Ontology (DMDO).

Keywords
ontology engineering, disaster management, disaster properties, semantic web, knowledge graphs

1. Introduction

Existing ontologies in the disaster management domain [1, 2, 3, 4, 5] focus on modeling disaster events and their impacts, because they are the most visible and tangible aspect of disasters, and are often the primary concern of disaster management efforts. However, this does not mean that disaster properties such as intensity, exposure, vulnerability, capacity, and resilience are insignificant. In fact, these properties are crucial in the development of disaster risk prediction models [6, 7] and risk maps [8]. They are important to understanding and assessing the potential severity and impacts of a disaster, as well as informing the development of disaster management plans, including emergency response plans, evacuation plans, and recovery plans that are tailored to the specific needs and risks of those areas. Integrated information on these properties

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can be used by disaster managers to focus on areas with high levels of exposure and vulnerability, and low levels of resilience to prioritize the allocation of resources and interventions to those areas and communities that are most at risk.

Disaster properties have also been integrated as key concepts in central documents of global efforts and action plans to reduce disaster risk in UN-led efforts such as the Hyogo Framework for Action [9] and Sendai Framework for Disaster Risk Reduction [6]. Many national and international agencies provide a range of datasets (some of which are discussed in Sec. 2.1) that record these properties, which, when used within a disaster Knowledge Graph (KG) framework, can intelligently inform disaster management and response efforts. Since the situation where disasters occur is complex and dynamic, characterized by interactions between environmental, human, infrastructural, and technological elements, a holistic approach to risk assessment that considers both the physical and social aspects of disasters is important. And oftentimes, properties such as vulnerability, resilience, and capacity are more "societal factors" than anything else. KGs provide exactly this advantage of creating connections between diverse data—through rapidly integrating heterogeneous data; clarifying and harmonizing the terms/attributes in the data; facilitating rapid exploration; and revealing potentially subtle connections through inferences. We can therefore leverage KGs and attendant ontologies to integrate data about the risk variables associated with interconnected elements in a complex situation to obtain a deeper knowledge of the situation (capacity, weaknesses, etc.), but also understand its risk mechanisms (how a disaster can generate a sequence of events, or where the effects of physical, social or economic disruption are high), and therefore assess the disaster risk of the situation as a whole, including cascading impacts and cascading risks. However, there is no ontology pattern or FAIR ontology resource [10] that formalizes these disaster properties, the entities they reference or define, or their context within the disaster domain.

In this paper, we describe a shared ontology that contextualizes and relates the following six properties that quantitatively determine the spatiotemporal aspects of DisasterRisk: Intensity, Severity, Exposure, Vulnerability, Resilience, and Capacity. The Disaster Properties Ontology (DPO) is expressed in the Resource Description Framework (RDF) here. It is one of the first steps towards developing a more comprehensive Disaster Management reference Domain Ontology (DMDO) for use within the KnowWhereGraph project [11]. DMDO is developed following a modular approach and consists of three core modules. The event module conceptualizes disaster-related events, their observations, and spatiotemporal aspects. The operational module focuses on modeling disaster management plans, processes, tasks, resources, and activities. The third module is DPO, which describes the essential properties of disaster risk. The goal of DPO is to provide a formal semantic framework for describing how the risks of disaster are influenced by the characteristics of some hazardous events, as well as the regions and populations that might be impacted.

The rest of this paper is organized as follows. In Section 2, we first present a use case that demonstrates the usefulness of DPO, and then present a set of competency questions that we use to scope the semantics of the terminology. In Section 3 we provide background on the concepts reused across the different modules of DMDO that are central for representing disaster properties. In Section 4, we describe DPO and its ontological structure. Section 7 presents the conclusion and future work.

2. Use Case

The development of DPO was motivated by the data integration needs within the KnowWhere-Graph (KWG) project[1] and for question-answering and geo-visualization of the graph by its partner agencies. KWG [11, 12] aims at providing a densely interlinked knowledge graph for environmental-intelligence applications. By semantically enriching and pre-integrating data for decision-makers and data scientists, custom tailored to their spatial area of interest, the time needed to address an emerging crisis or to gain situational awareness can be significantly reduced. We highlight data integration within KWG as a specific use case to demonstrate the usefulness of DPO. We have also included a selection of competency questions that were used to guide the development of this ontology.

2.1. Specific Data Integration Needs

A primary objective of Direct Relief[2], a humanitarian aid organization that uses KWG, is to understand the social vulnerability of a region, specific health needs of a population, capacity of local health centers and pharmacies, and impacts caused by a disaster. They use this information to effectively assess the needs of the affected populations, mobilize resources, and provide appropriate assistance. To address their specific analytic and decision-making needs, KWG integrates data from several datasets that record disaster properties. Examples include 1) magnitude and impact of meteorological and hydrological disasters such as hurricanes, tornadoes, and floods from NOAA[3], 2) wildfire magnitude in terms of acres burned, and exposure in terms of the number of burn days from MTBS[4] and NIFC[5], 3) social vulnerability index values from the CDC [13], 4) drought intensity from NDMC[6], 5) capacity of Federally Qualified Health Centers for a range of medical specialities from the UDS[7], 6) county-specific population health statistics for diabetes and mental health from the CDC[8], etc. While these are just a few of the currently integrated datasets in KWG, in the future, we also hope to create cross-walks with other graphs that contain datasets such as 1) the National Risk Index dataset from FEMA [8], 2) flood risks based on flood forecasts[9], 3) regional PFAS exposure levels in water and soil from the EPA[10] etc. All these datasets can be used to inform disaster management and response efforts, as well as to conduct research on disaster risk reduction and resilience, and DPO will provide a framework to effectively integrate them in the knowledge graph.

2.2. Competency Questions

We have included competency questions that are primarily meant to define the scope and level of detail of semantics to be formalized. These questions were developed in collaboration with

[1] https://knowwheregraph.org/
[2] https://www.directrelief.org/
[3] https://www.ncdc.noaa.gov/stormevents/
[4] https://mtbs.gov/direct-download
[5] https://data-nifc.opendata.arcgis.com/datasets/nifc::wildland-fire-incident-locations/about
[6] https://droughtmonitor.unl.edu/DmData/DataDownload.aspx
[7] https://data.hrsa.gov/data/download?data=HSCD#HSCD
[8] https://nccd.cdc.gov/DHDSPAtlas/?state=County
[9] https://ufokn.com/
[10] https://echo.epa.gov/trends/pfas-tools

partner agencies that use KWG.

- Which communities in Florida are more vulnerable to the impacts of a hurricane?
- How has the vulnerability of roads/bridges in New Orleans changed since the floods that were triggered by Hurricane Katrina?
- How does the resilience of Phoenix compare to other metropolitan cities with respect to water shortage?
- What is the historical frequency and intensity of earthquakes in California?
- What are some of the bridges and tunnels in California that need to be retrofitted to minimize seismic-related damage?
- What is the capacity of the local government of Santa Barbara to respond to wildfires in the Santa Ynez mountains?
- How does the level of disaster risk in California vary across different counties for different hazards and vulnerabilities?
- How do the vulnerability and resilience of bridges contribute to earthquake disaster risk in San Francisco?

3. Background: Hazard Meets Disaster

As mentioned, DPO is one module of the reference domain ontology DMDO, that also includes the event-, observation-, and operational-specific aspects of the disaster domain in separate modules. Four core classes in DMDO that are re-used across the modules as well as in DPO are Hazard, Disaster, Impact, and ElementAtRisk, which we will describe here.

Hazard and disaster are two related but distinct concepts in the context of disaster management. According to the United Nations Office for Disaster Risk Reduction (UNDRR) [14], a hazard is a potential threat, natural or human-made, that *can cause* harm to people, property, or the environment, while a disaster is a situation that results when a hazard actually *causes* significant damage or disruption to human, economic, or environmental systems. UNDRR also defines a disaster as *a serious disruption of the functioning of a community or a society at any scale due to hazardous events interacting with conditions of exposure, vulnerability, and capacity* [14]. For example, an earthquake on its own may be a hazard, but if it occurs in an area with poor building construction standards and a lack of emergency preparedness, it can lead to a disaster, causing significant damage and loss of life. Similarly, a chemical spill may be a hazard, but if it occurs near a populated area with inadequate response capabilities, it can escalate into a disaster, causing widespread health and environmental impacts. The taxonomy of hazards (e.g., earthquake-, or flood-related hazards from UNDRR [15]) is implemented using HazardType class. Disaster impacts are the negative effects of a disaster. These include human impacts, such as death, injuries, diseases, and mental disorders, as well as economic and environmental impacts [14]. Element-at-risk refers to the people, buildings, infrastructure, and other assets that are impacted during any disaster event [16]. Fig. 1 shows the relationships between these four concepts in DMDO.

That being said, most FAIR[11] ontologies in disaster management focus on representations of hazard and disaster *events*, and their impacts, and ignore modeling the *risk variables* or *properties*

[11]We emphasize FAIR principles because they are critical in supporting data integration, discovery, and reuse [10]

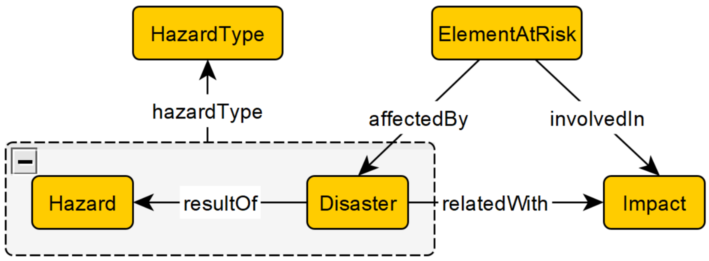

Figure 1: Schema showing the interrelationships between Hazard, Disaster, Impact, and ElementAtRisk in the Disaster Management Domain Ontology. Yellow boxes are classes. Edges are object properties. The edge extending from the grey box with a dashed border is common to the two grouped classes.

that are critical in predicting and reacting to each phase of the disaster life cycle. Specifically, from the text definitions it is clear that exposure, resilience, vulnerability, capacity, and intensity play crucial roles in the evolution of a hazard into a disaster, influencing the severity of a disaster, and its scale of impact. Indeed, disasters result from complex and interconnected relationships among all of these properties. For example, a highly vulnerable and exposed community with low resilience and limited capacity may be at high disaster risk if faced with a hazard of moderate magnitude. In contrast, a highly resilient and well-prepared community with ample capacity may face a hazard of greater magnitude with lower disaster risk.

Understanding and managing these factors is critical for effective disaster management and reduction of the impacts on communities and individuals. Through the DPO ontology, we aim to capture this complexity by formalizing these interrelationships, in a structured and systematic way. This will enable the representation of data about specific disasters, such as the location, magnitude, and impact of a particular earthquake, along with data about the vulnerability and resilience of the affected population and infrastructure, materialized in an integrated KG. The resulting KG will allow disaster managers to better understand and analyze the factors that contribute to disasters, and to develop effective strategies for mitigating their impacts.

4. The Disaster Properties Ontology

4.1. Overview

DPO focuses on modeling critical disaster properties that collectively help predict and assess the likely occurrence and impact of some disasters. These include: Vulnerability, Intensity, Severity, LevelOfExposure, Capacity, Resilience, and DisasterRisk. Each disaster property is modeled either as an intrinsic property or referential property of one of four core concepts from DMDO: HazardType, Disaster, DisasterImpact, and ElementAtRisk (described in Sec. 3). That is, each disaster property is represented as a property of an entity (e.g., intensity of an earthquake), or property of an entity with reference to another entity (e.g., vulnerability of a bridge relative to earthquakes). For each concept, we provide the semantic modeling choices using schema diagrams (Fig. 2-Fig. 6), including a discussion regarding these choices.

The concept of *place* is important for grounding these properties in space (and time) in a way that allows geometry representation and spatial computation within a KG. To model time and place, we reuse OWL-Time [17] and GeoSPARQL [18], respectively. We use the extended SOSA/SSN ontology [19] to model relationships between properties and the entities or features of interest that they represent. Specifically, we denote every property as a subclass of sosa:ObservableProperty. Finally, we want to denote who recorded the property or how the property was quantitatively derived. Detailed provenance is not modeled in our treatments here, but we suggest using the general EntityWithProvenance pattern as a placeholder, which can then be extended as needed using the PROV-O Ontology [20].

The OWL file for DPO can be found online here.

4.2. Vulnerability

Definition. *The conditions determined by physical, social, economic, and environmental factors or processes that increase the susceptibility of an individual, a community, assets, or systems to the impacts of hazards.* (Source: UNDRR [14])

In the context of disaster management, vulnerability refers to the characteristics and conditions that make elements-at-risk, such as individuals, communities, and infrastructure, more or less susceptible to the negative impacts of disasters. Vulnerability is thus represented as a property of ElementAtRisk using the relation vulnerabilityOfElementAtRisk (subproperty of ssn:isPropertyOf) in Fig. 2. Elements with less vulnerability will tend to experience lower impacts and this connection is denoted using the determineImpact relation.

Vulnerability is both dynamic and context-specific [21], influenced by a range of factors, including socioeconomic status, physical location, resources, ethnicity, gender, health status, and disaster preparedness, among others. Since all these specific factors also impact exposure, resilience, and capacity, within DPO, we generically denote this connection using the influences and its inverse influencedBy relations. More detailed descriptions, from scientific text that establishes this semantic connection, are detailed here.

- **Exposure:** Vulnerability is influenced by the degree to which an element is exposed to hazards. For e.g., a coastal community is more exposed to floods, and, therefore, more vulnerable to their impacts.
- **Resilience:** Vulnerability is influenced by the degree to which an element is sensitive to the negative impacts of hazards, such as due to their age, health status, or level of infrastructure.
- **Capacity:** Vulnerability is influenced by the degree to which an element is able to adapt and cope with the negative impacts of hazards, such as through access to resources, information, and social networks.

Note: Exposure, Resilience and Capacity are discussed broadly in later sections.

Vulnerability can be determined both before and after a disaster. Before a disaster, vulnerability can be assessed specifically to an abstract hazard type (denoted by associatedWithHazardType). For example, CDC's Social Vulnerability Index dataset [13] records the potential negative effects on communities that may be caused by natural or human-caused disasters, or disease outbreaks. After a disaster, vulnerability can be assessed by examining the impact of the disaster on various communities and populations, and this relation is denoted by associatedWithDisaster. Vulnerability is thus defined with reference to HazardType and Disaster.

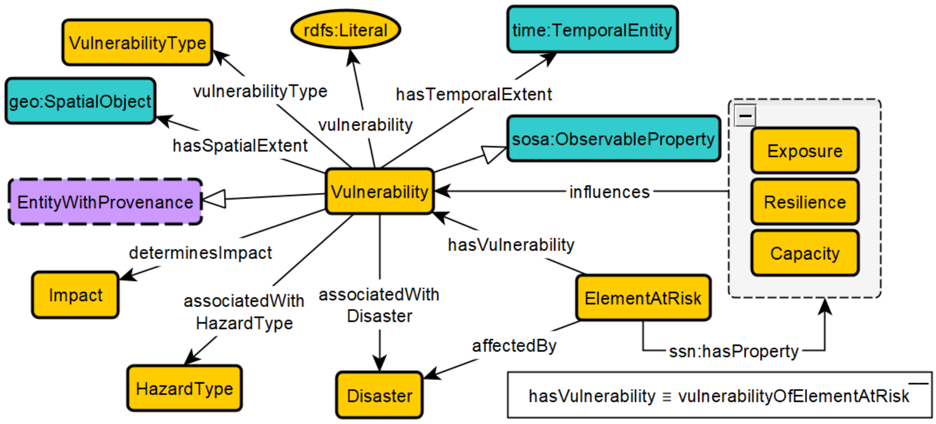

Figure 2: Schema diagram for the Vulnerability class and its semantic connections. Yellow boxes are classes; blue boxes are classes from external standard ontologies; purple boxes are also external classes but acknowledge external dependency (i.e., they are left unmodeled in DPO); and edges with filled arrows are object properties.

The spatial and temporal dimensions of vulnerability can have a significant impact on the likelihood and severity of disasters, as well as the ability of individuals and communities to prepare for, respond to, and recover from disasters [21, 22]. The spatial and temporal extents are denoted by the two relations hasSpatialExtent and hasTemporalExtent, respectively. Vulnerabilities can be classified into different types based on their origin, nature, and impact relative to the affected region. Some of the common types of vulnerabilities include: physical, social, economic, institutional, and environmental [22, 23, 24]. These are denoted using the VulnerabilityType class and vulnerabilityType relation. Lastly, the measure of vulnerability (as a quantitative or qualitative value) is denoted using the vulnerability data property.

4.3. Intensity and Severity

Definitions. 1. *Intensity is the strength of a hazard.* (Source: FEMA [25]) 2. *Severity is a measure of the adverse effects of a disaster on a community or an environment.* (Source: [26])

The terms intensity and magnitude are typically used near synonymously in disaster management to denote the size, strength, amount of energy released, or extent of a disaster event, often on some rating scale, depending on the type of disaster and the context. Severity, on the other hand, refers to the amount, or degree of damage caused, the number of people affected, or the economic losses incurred [14]. Intensity is thus a property of Disaster (denoted using hasIntensity relation), while Severity is a property of Impact (denoted using hasSeverity relation) as shown in Fig 3. Both intensity and severity can be measured in terms of a specific property denoted using the sosa:ObservableProperty. For example, the intensity of a hurricane may be measured in terms of its wind speed or its diameter, while the number of resulting deaths is a severity measure in the severity index proposed by [26]. Intensity may also correspond to a scale denoted using the basedOnScale relation. For example, earthquake magnitude is typically measured on the Richter scale, while the intensity of a hurricane or typhoon may be measured on the Saffir-Simpson scale.

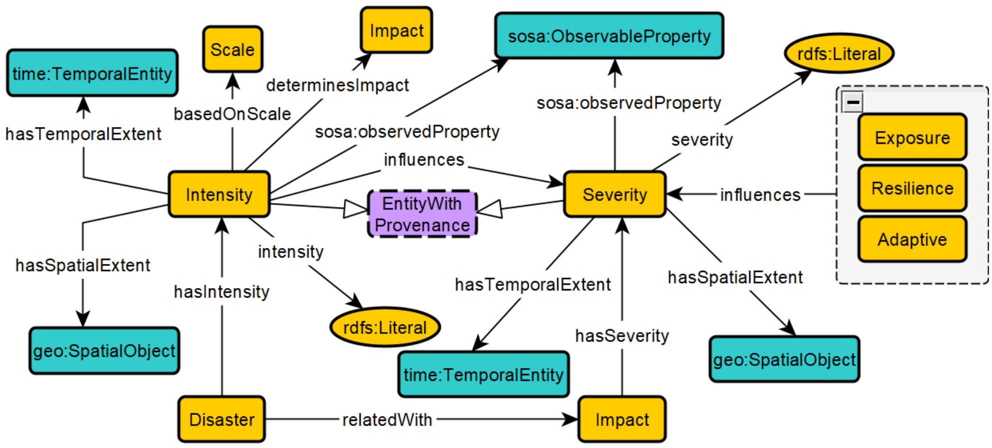

Figure 3: Schema diagram for the Intensity and Severity classes and their semantic connections.

Besides Vulnerability, Exposure, Capacity, and Resilience, Severity is influenced by Intensity (denoted using the influences relation). In general, the higher the intensity of a disaster, the greater the severity is likely to be. For example, a strong earthquake (i.e., having high intensity) can cause significant damage (i.e., high severity) to infrastructure, and can result in many casualties, while a weaker earthquake (with lower magnitude or intensity) may have less impact (i.e., lower severity). Finally, both Intensity and Severity can vary spatially and temporally, and both will have provenance in terms of the data sources that are reporting on them. Measures of intensity and severity are denoted using the data properties intensity and severity, respectively.

4.4. Exposure

Definition. *The situation of people, infrastructure, housing, production capacities, and other tangible human assets located in hazard-prone areas.* (Source: UNDRR [14])

In disaster management, exposure refers to the degree to which people, infrastructure, and assets are located in areas that are susceptible to hazard events, such as floods, earthquakes, or hurricanes [27]. Thus, Exposure is represented as a property of ElementAtRisk with respect to a disaster, denoted through the hasExposure and associatedWithDisaster relations, respectively, as shown in Fig. 4. Exposure influences the potential impact of a disaster event on a particular area or population, denoted using the determinesImpact relation.

Like vulnerability, exposure can be influenced by a range of social, economic, and environmental factors, such as population growth, urbanization, land use, and climate change. The interrelationships between exposure and other disaster properties are complex and multifaceted and should be considered in order to effectively manage and reduce disaster risk. Both vulnerability and resilience affect exposure (denoted through the influences relation) and this semantic connection is described below.

Exposure evolves both on spatial and temporal scales [28] represented using the hasSpatialExtent and hasTemporalExtent relations. For example, the geographic location of a population or community, such as their proximity to or their position within a floodplain, affects their exposure to a coastal flood. Simultaneously, any possible evacuation success is significantly

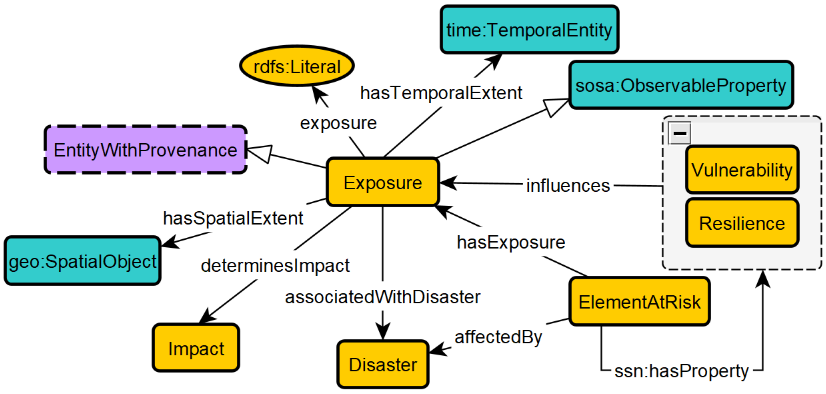

Figure 4: Schema diagram for the Exposure class and its semantic connections.

time-dependent, and thus, population exposure to a flood hazard is highly dynamic.

- **Vulnerability**: Exposure is influenced by vulnerability, as vulnerable populations may be more likely to live in areas that are at risk of hazard events. Conversely, Exposure also influences vulnerability as pointed out in Sec. 4.2 and Fig. 4.2.
- **Resilience**: Exposure is influenced by the resilience of an element-at-risk. Poorly constructed or maintained infrastructure can increase exposure.

4.5. Capacity and Resilience

Definitions.: 1. *Capacity is the combination of all the strengths, attributes, and resources available within an organization, community, or society to manage and reduce disaster risks and strengthen resilience.* (Source: UNDRR [14]). 2. *Resilience is the ability of a system, community, or society exposed to hazards to resist, absorb, accommodate, adapt to, transform, and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions through risk management.* (Source: UNDRR [14])

Capacity and resilience are two important concepts in disaster management that are closely related but distinct. Capacity is inherently a property of the individuals and groups (denoted using hasCapacity) directed towards responding to and coping with disasters. In contrast, resilience is a referential property of built and natural entities (denoted using hasResilience) and refers to the degree of impact that they can tolerate in response to a specific disaster event or type of hazard (denoted using associatedWithDisaster and associatedWithHazardType relations). Capacity is thus the collective ability of the human or social agents in a situation to manage resilience, and this connection is denoted using the influences relation. Resilience is also clearly related to the vulnerability of an entity (denoted using the influences relation), although considering its capacity. Put another way, there can be a situation where even when the resilience of an entity is overcome if capacity is high enough, the structure or functioning of the entity can still be maintained in the face of disturbances or impacts. Finally, the measures of capacity and resilience are denoted using the capacity and resilience data properties. Types of these measures, for example corresponding to social or economic activities, are denoted through the CapacityType and ResilienceType classes and associated relations as shown in Fig. 5.

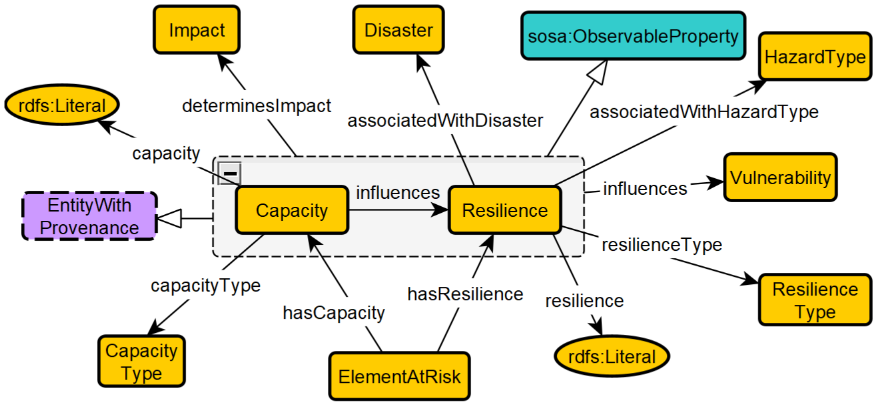

Figure 5: Schema diagram for the Capacity and Resilience classes and their semantic connections.

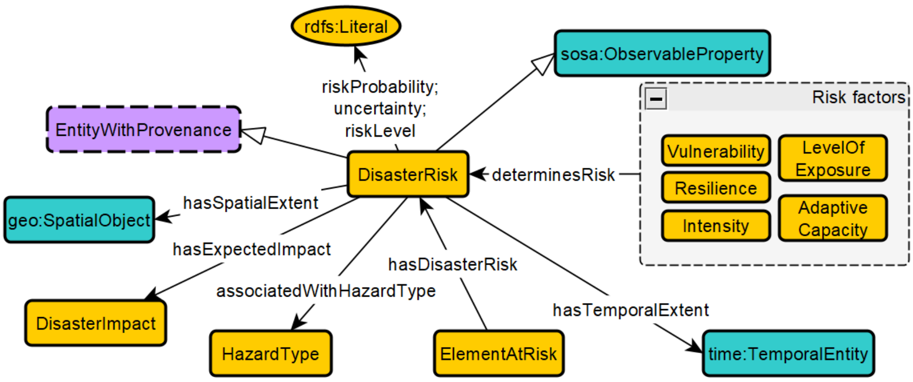

Figure 6: Schema diagram for the DisasterRisk class and its semantic connections.

4.6. Disaster Risk

Definition.: *The potential loss of life, injury, or destroyed or damaged assets that could be experienced by a system, society, or a community in a specific period, determined probabilistically as a function of hazard, exposure, vulnerability, and capacity.* (Source: UNDRR [14]).

Many equations for disaster risk have been proposed in literature [29, 30, 6] and used in practice [8], but foundationally, as the definition suggests, risk is quantified as a function of: 1) the likelihood of occurrence and probable intensity of a hazardous event; 2) the specific context in which the disaster may materialize and result in exposure; and 3) the potential extent of resulting impacts, which, in turn, is a result of vulnerability, resilience, and capacity. Even though risk is a quantitative forward-looking concept, the vulnerability, exposure, and intensity of a disaster that has already occurred can be used to measure cascading risk for other cascading disasters [31]. The relationship between these factors and DisasterRisk is denoted using the determinesRisk relation in Fig. 6. Most risk-forecast datasets, such as FEMA's National Risk Index Map[8] attribute risk to specific places, such as counties or census tracts. We, therefore, associate DisasterRisk as a property of ElementAtRisk using the hasDisasterRisk relation.

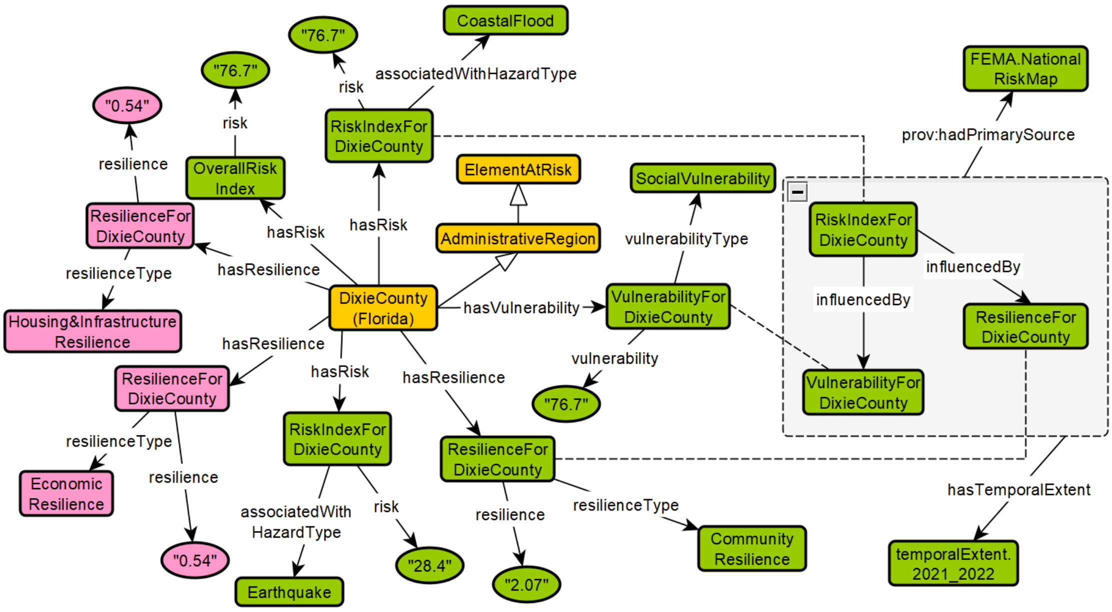

Figure 7: This diagram shows instance data that populates a portion of DPO. Concepts in green boxes correspond to data from FEMA's National Risk Index Map [8]. Concepts in pink correspond to data from Baseline Resilience Indicators for Communities dataset from [32].

The relationship between DisasterRisk and the specific type of hazardous event that is likely to occur is represented using the associatedWithHazardType relation. Likewise, the expected impact or potential consequence of that event is denoted using the hasExpectedImpact relation. Understanding the level of risk can help inform efforts to reduce vulnerability and increase preparedness, which in turn can mitigate the potential impacts of a disaster. The probability and level of risk can be denoted through the riskProbability and riskLevel data properties. Although risk estimates the potential for something adverse to occur, there is uncertainty associated with this estimate. This is denoted using the uncertainty data property.

5. Ontology Evaluation and Usage

DPO was reviewed by domain experts in humanitarian relief (specifically experts from Direct Relief), to evaluate the ontology's coverage, structure, and overall quality. The Hermit reasoner within Protege was used to evaluate its logic-based consistency. We then used several relevant datasets previously mentioned in Section 2.1, to evaluate if DPO sufficiently covers their semantics. Fig. 7 shows an example of how some parts of these datasets are represented using DPO. Finally, we evaluated the usefulness and effectiveness of DPO by testing its ability to support query answering using the set of competency questions mentioned in Sec. 2.2.

6. Related Work

Risk and vulnerability are central concepts to many scientific and socio-behavioral disciplines as well as practical services. Consequently, a broad range of conceptualizations of these terms exist in contexts ranging from computer software to information systems and business [33, 34, 35]. However, since these terms are quite referential and context-dependent (e.g., vulnerability of a system to malware vs. vulnerability of a geographic region to earthquakes), these ontologies should be reused with caution in the broader scope of data integration needs for knowledge graphs that aid in disaster management.

Within the context of disaster management, vulnerability, and risk are the most common concepts included in ontologies. Beyond mentioning them as a class, or their types in a class hierarchy, however, there is no contextual information available through property dependencies. For example, [36] models a set of classes related to vulnerable systems and vulnerable drivers, and vulnerability assessments. Likewise, the MONITOR ontology [5] mentions vulnerability, risk, and types of risk. The Referential quality pattern [37] uses the foundational ontology DOLCE to model Affordance, Resilience, and Vulnerability as qualities. As such, given the very broad scope of this pattern, they do not mention any dependencies of these terms with disaster-related features or event concepts. Moreover, none of these ontologies have a FAIR resource available, in the sense of a formalized, Web-accessible, machine-interpretable version.

Currently, available FAIR resources within scope, but each including only one concept from DPO are as follows: 1) the Hazardous Situation pattern [4] models exposure of a hazardous event; 2) RiskOnto [38] models several concepts relevant to general risk assessment; and 3) the INGENIOUS ontology [39] models risk; 3) COVER [40] models Vulnerability as a Risk Enabler and inherent to an Object At Risk, enabling the manifestation of a Risk Event.

7. Conclusion

KGs assisting with disaster management must provide a comprehensive and semantically cohesive view of disaster events and their associated impacts and information on resources such as emergency shelters, medical facilities, transportation routes and other critical infrastructure for improved disaster preparedness and recovery efforts. However, in addition to these entities, it is critical to consider the underlying properties of vulnerability, severity, resilience, exposure, and capacity, that affect a situation and the entities involved to withstand or recover from disasters. To this end, we have developed the Disaster Properties Ontology that formally models the disaster properties that influence disaster risk mechanisms. By carefully reviewing standard definitions for these terms, we have defined them as intrinsic or referential properties—this is also observable through the schema.org domain and range restrictions.

Future Work: The next step is extending DPO to build the disaster management operational framework that conceptualizes the management of risk, including risk analysis and assessment, and the implementation of strategies and specific actions to control, reduce and transfer risks. The operational module will also focus on modeling plans (e.g., emergency response plans, disaster resilience plans); connecting resources with responders and capacity; and organizing tasks and activities for disaster impact mitigation, response, and recovery efforts.

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