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Received: 2 October 2019 | Revised: 13 December 2019 | Accepted: 18 December 2019

DOI: 10.1002/ett.3899

SPECIAL ISSUE ARTICLE

WILEY

An ontology-based system for discovering landslide-induced emergencies in electrical grid

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Funding information
FloodPrep, Grant/Award Number: (NE/P017134/1); LandSlip, Grant/Award Number: (NE/P000681/1)

Summary

Early warning systems (EWS) for electrical grid infrastructure have played a significant role in the efficient management of electricity supply in natural hazard prone areas. Modern EWS rely on scientific methods to analyze a variety of Earth Observation and ancillary data provided by multiple and heterogeneous data sources for the monitoring of electrical grid infrastructure. Furthermore, through cooperation, EWS for natural hazards contribute to monitoring by reporting hazard events that are associated with a particular electrical grid network. Additionally, sophisticated domain knowledge of natural hazards and electrical grid is also required to enable dynamic and timely decision-making about the management of electrical grid infrastructure in serious hazards. In this paper, we propose a data integration and analytics system that enables an interaction between natural hazard EWS and electrical grid EWS to contribute to electrical grid network monitoring and support decision-making for electrical grid infrastructure management. We prototype the system using landslides as an example natural hazard for the grid infrastructure monitoring. Essentially, the system consists of background knowledge about landslides as well as information about data sources to facilitate the process of data integration and analysis. Using the knowledge modeled, the prototype system can report the occurrence of landslides and suggest potential data sources for the electrical grid network monitoring.

KEYWORDS

data sources discovery, early warning system, electrical grid system, energy management, high variety data, IoT data, landslide hazard, ontology

1 | INTRODUCTION

People around the globe rely heavily on electrical energy, provided by the electrical grid system, often more than other sources of energy. The electrical grid is a complex network of electrical power system which includes electricity generation, transmission and distribution (T&D), and consumption. It provides a variety of operation to deliver electrical power from the place where it is generated to the consumers.[1] The infrastructure of the electrical grid system comprises

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of several key components to support the delivery of electricity to consumers: (a) *Generating Plants* – where electricity is produced; (b) *Transmission Networks* — an infrastructure which allows high voltage electricity to be transported over long distances; (c) *Substations* — where the electricity voltage is changed by utilizing a transformer mechanism; and (d) *Distribution Networks* — an infrastructure, similar to the transmission lines, to transmit lower voltage electricity. High voltage electricity from the generating plants is transmitted along the transmission lines from where it reaches the substations in the grid network. Following a reduction in the voltage of the electricity by the transformer at the substation, it travels along the distribution line to various types of consumers (including industrial consumers, commercial consumers, and resident consumers). Specifically, transmission and distribution networks are set up to cover the whole geographic area in the country. The transmission network carries overhead electricity lines on pylons, a steel lattice tower, while the distribution network transmits electricity either through an overhead line or underground. The overhead line in the distribution network is carried on small steel towers, concrete poles, or wooden poles.[2]

Reliability is the most crucial element in the operation of electrical grid systems. A failure of the grid system infrastructure can lead to disruption of electricity supply, leading to major economic chaos in the country as well as impacting upon the safety and well being of people in the affected area. In particular, the transmission and distribution network within the grid system infrastructure is frequently affected by climate change and natural hazards such as landslides, earthquakes, and flooding. Grid systems are often the most frequently affected by landslides as can be noted from reports in several countries. In 2018, a landslide occurred near Invergarry in Scotland and damaged overhead power lines.[3] As a consequence, 23 000 people in Skye and the Western Isles had their electricity supply cut off for several hours after the event. The same year, in Thailand,[4] a landslide in a waste dump zone at the Electricity Generating Authority of Thailand Mae Moh mine in Lampang province, damaged some electricity poles and led to road closures in the area. The disruption was so serious that an evacuation plan for the people had to be put in place. The Wenchuan Earthquake in 2008[5] caused serious damage to the Sichuan electrical grid system. A number of electrical equipment, transmission, and distribution networks were broken and buried due to landslides that occurred during the earthquake. Due to minimal protection of transmission and distribution networks, they are very vulnerable to such natural hazards. EWS can therefore play a vital role in monitoring the grid network to predict such failures and minimize the consequent disruptions.

Nowadays, early warning system (EWS) for natural hazards utilize strong technical underpinning and sophisticated knowledge of natural hazards such as the hazard context and risk factors to enable dynamic and timely decision-making. Landslides, the natural hazard this paper focuses on, have global significance given their frequency of occurrence as well as potential to cause disruption. Where electrical grid systems are commonly affected by landslides, it is because of parts of the grid infrastructure being located in landslide-prone areas. Moreover, landslides are also closely linked with a variety of other natural hazards such as storms, earthquakes, floods, and volcanic eruptions. These hazards can also affect electrical grid systems. Therefore, the prediction of individual landslide occurrence is beneficial to the monitoring of electrical grid infrastructure. However, such prediction is complex as it depends on many local factors, variables, and anthropogenic activities (caused or produced by human beings). Current EWS for landslides rely on scientific methods such as hyperlocal rainfall monitoring, slope stability models, and analysis of remotely sensed images. With the emergence of Internet of Things (IoT), decision-makers are also analyzing observation and measurement data produced by sensors (eg, soil moisture, soil movement, rainfall, humidity, wind speed) which are deployed in landslide prone areas.[6,7] Furthermore, other observation and measurement data such as wind speed, wind direction, soil temperature, tilt, and vibration are also being used for the monitoring of electrical grid system.[2,8]

Before EWS for landslide can optimally utilize information from multiple, heterogeneous time series of data sources (IoT sensors), it is essential to realize a common knowledge base for capturing the core conceptual information and the cross co-relationship between events (that could be potentially discovered by analyzing those data sources). Moreover, cross co-analysis of time series data sources is not only useful for the discovery of event correlation but also allows for the interaction of electrical grid system with EWS. For example, a landslide detected by processing of time series data from IoT sensors (eg, using accumulative rainfall threshold) provides information about location and time of the landslide occurrence. This information can be used to identify parts of the electrical grid infrastructure that are potentially vulnerable to the detected landslide and need to be monitored intensively. However, discovering such cross correlation of events from heterogeneous time series data sources has many challenges including a lack of common terminology that make analysis particularly difficult.

The main *contributions* of this paper are as follows.

1 A formal knowledge base of landslide domain concepts to enable the integration of time series data from multiple and heterogeneous data sources for the early prediction of landslide events.
2 A process for the harmonization of the knowledge base and electrical grid information services for monitoring of electricity grid network.

The results of landslide prediction are utilized to suggest the monitoring of electrical grid infrastructure in order to minimize the loss of electric energy during natural hazard events. Underpinning this knowledge base is the Landslip Ontology that captures the concepts of and relationships between landslide, landslide-related hazards, warning signs, sensor data, and other time series data sources. The purpose of the ontology is to facilitate data discovery, which will be used to find potential data sources for landslide prediction and electrical grid infrastructure monitoring. The proposed Landslip Ontology is evaluated using competency questions for electrical grid systems in landslide prone areas. The experimental results show the accuracy of the data discovery mechanism and indicate the benefits of using Landslip Ontology in electrical grid management applications.

The rest of the paper is organized as follows: related work is discussed next followed by a discussion on the landslip scenario in Section 3. Landslip Ontology is described in Section 4 and the design of data sources discovery system in Section 5. Evaluation of the Landslip Ontology is discussed in Section 6. Finally, conclusion and future work are presented in Section 7.

2 | RELATED WORKS

2.1 | Data Utilization in Multihazard EWS

The term, multihazard, refers to a collection of multiple major hazards that a country faces.[9] There is a possibility that several hazardous events occur simultaneously and are interrelated. Tropical storms, for example, are one of the most common environmental hazards (in the tropics), which can trigger multiple hazards such as heavy rainfall that in turn can induce flash flooding. Furthermore, heavy rain and flooding can increase the moisture content of soil in mountainous areas inducing landslides. To minimize the loss of life and property damage from these interrelated hazards, a comprehensive strategy for hazard management is required. In general, a strategy for hazard management comprises of four phases:[10] (a) *mitigation* — actions to minimize the cause and impact of hazards and prevent them from developing into full-blown disasters; (b) *preparedness* — action plans and educational activities for communities to confront unpreventable hazard events; (c) *response* — actions for emergency situations to protect peoples' lives and properties during hazard or disaster events; and (d) *recovery* — the actions to restore damaged properties and community's infrastructures and to provide medical care to the affected population. These four phases require supporting tools and technologies to improve the effectiveness of hazard management.

Several modern multihazard EWSs take advantage of the data explosion on social media. The authors in Reference 11 propose using a Twitter data analysis framework for identifying Tweets that are relevant to a particular type of disaster (eg, earthquake, flood, and wildfire). Several classification techniques, including keywords and hashtags matching and classification machine learning, are also evaluated to identify tweets which are relevant to a particular hazard. The work in Reference 12 studies the potential of using social media data to identify peatland fires and haze events in Sumatra Island, Indonesia. A data classification algorithm is used to analyze the Tweets and the results are verified by using hotspot and air quality data from NASA satellite imagery. A data classification algorithm is also used in Reference 13 to automatically classify Tweets and text messages (from the Ushahidi crowdsourcing application) generated during the Haiti earthquake in 2010. The goal of their work is to provide an information infrastructure for timely delivery of appropriately classified messages to the appropriate responsible departments. Work in Reference 14 proposed a decision support system that integrates crowd sourcing information with Wireless Sensor Networks (WSN) to improve the coverage of monitoring area in flood risk management in Brazil. The research introduces the Open Geospatial Consortium (OGC) standards to facilitate the data integration among crowd sourcing information and WSN.

2.2 | IoT Resource Management

The emergence of IoTs allows decision-makers to analyze observation and measurement data produced by IoT devices. These IoT devices have the ability to sense, process, communicate, and store the data observed or measured from the physical world.[15] Moreover, the number of IoT devices has increased dramatically and they are heterogeneous in nature. Based on this, efficient techniques for IoT resources management have been investigated to address the challenging problems of IoT (eg, IoT management framework, data processing, and security).[16-20] Here, several frameworks for IoT resource management have been proposed. Authors in Reference 16 proposed a paradigm of Everything-as-a-Resource to enable efficient resource allocation of collaborative applications on the web. The framework has been applied to IoT applications in the health care domain. Reference 17 proposes a resource preservation net (RPN) framework for IoT resource management in edge computing. The framework has been applied to smart health care applications where real-time systems with complex and dynamic behavior are essential parts of the systems but suffer from resource shortage and resource management efficiency challenges. In the RPN framework, a smart health care workflow and nonconsumable resource pools are defined to enable process execution and resource assignment in the cloud and solve the problem of resource management efficiency. Besides, a number of approaches on IoT data analysis have been proposed to address issues in multihazard and electrical grid applications. The work in Reference 18 presents a novel technique of machine learning and neural network to predict the severity of floods. Essentially, a machine learning technique is utilized to analyze new datasets of flood events to predict the severity of flood events and classify outcomes into normal, abnormal, and high-risk flood. The prediction of the flood severity aims to address issues of flood mitigation. Security and privacy are crucial issues in IoT resource management due to the sensitivity of IoT data in many application domains. The research in Reference 19 focuses on securing IoT-enabled applications at the Fog layer to secure a massive amount of sensitive data produced by IoT devices and enable efficient resource consumption (ie, memory, storage and processing) of the IoT devices. The work in Reference 20 proposes a secure fog-based platform for Supervisory Control and Data Acquisition (SCADA)-based IoT critical infrastructure. The platform is designed to address the performance and security issue of SCADA systems and enhance security of data generated from IoT devices and deploy edge data centers in fog architecture.

2.3 | Semantic Web Technologies and High Variety Data Management for Multi-hazards

Earth Observation (EO) and ancillary data provided by multiple data sources are accessible by different methods ranging from direct download to various standard Web Services APIs (eg, Web Map Services, Web Feature Services, Sensor Observation Services, RESTful API, SOAP-based API, etc.). In addition, there is heterogeneity among EO and ancillary data provided by different data sources[21] including: (a) syntactic heterogeneity—the difference in data format or data model for presenting datasets (eg, plain text, CSV, Excel, XML, JSON, O&M, SensorML, etc.); (b) structural heterogeneity—the difference in data schema for describing the same types of datasets (eg, describing soil moisture using different XML Schemas); and (iii) semantic heterogeneity — difference in meaning or context of the content in datasets. This heterogeneity reveals the challenging problems brought forth by the high variety of data in multi-hazard applications. Semantic Web Technologies play a significant role by providing languages and tools for modelling domains including consistent and formal descriptions of concepts and relationships among the data and hazardous events. According to the W3C definition,[22,23] the Semantic Web is a web of data that provides a common framework for data sharing and reuse across applications, enterprises, and communities.

Ontology, a key element of the Semantic Web, is a specification of a conceptual model for describing knowledge about a domain of interest. A basic concept in a form of ontology can be described by an resource description framework (RDF) triple[24] which is comprised of a subject, a predicate and an object. Concepts described by RDF can be extended by Web Ontology Language[25] to construct an ontology for representing rich and complex knowledge about things. In the case of multihazard applications, an ontology can be used to: (a) represent domain knowledge through concepts, their attributes and relationships between data sources, data and hazards and (b) facilitate data integration across multiple data sources that represent variety, velocity, and volume characteristics of Big Data.

Ontologies are widely used in hazard management to model knowledge about hazards and to manage actual data derived from EO and ancillary sources. Ontologies also promote the associative retrieval in spatial big data.[26] Hazard assessment and risk analysis are two of the common application areas where ontologies are used. The Semantic Sensor Network (SSN)[27] and the Semantic Web for Earth and Environmental Terminology (SWEET)[28] are two of the commonly applied ontologies in hazard management applications. The SWEET ontology is reused to conceptualize the knowledge from several areas, such as buried assets (eg, pipes and cables), soil, roads, the natural environment and human activities. Additionally, the Ontology of Soil Properties and Process (OSP) is proposed in their work to describe the concept of soil properties (eg, soil strength) and processes (eg, soil compaction). The ontology is used to express how asset maintenance activities affect each other. Furthermore, References 27 and 29 present the application of SSN for wind monitoring. The former uses SSN with Ontology for Quantity Kinds and Units[30] to conceptualize wind properties (eg, wind speed and direction) while the latter uses SSN and SWEET to model the concepts of wind sensors and data streams of wind observations. The Landslides ontology[31] extends SSN to organize knowledge for the landslides domain such as the concepts of landslides, earthquake, geographical units, soil, precipitation, and wind. Even though these ontologies provide comprehensive concepts for sensor data and hazard event, and provide a reusable, widely used semantic underpinning, they do not cover conceptual aspects of human sensors (eg, social media data). Hence, currently additional processes are required when applying these ontologies to EWS for multihazard applications.

The related literature in the context of multihazard management can be classified based on the following three perspectives: *data sources*, *hazardous event analytics*, and *EO and ancillary time series data management*. It can be seen that effective multihazard management demands high quality and rich data from a vast amount of data sources that are related to the hazard of interest. Data sources utilized by multihazard management applications can be sensors and/or data services that provide EO and ancillary data. Such data sources include *physical sensors* (eg, remote sensors, in situ sensors, WSN) and *human sensors* (eg, social media, blogs, and crowd sourcing). Recent data analytics research for multihazard management is focused on hazardous event analysis, which has three main directions: *event identification*, *event verification*, and *event prediction*. The research in this area reveals the challenging problems in EO and ancillary time series data management, especially the discovery of potential time series data sources given the complexity and high variety of such data sources in multihazard management applications.Several ontologies[32-34] have been proposed for not only modeling knowledge about hazards but also managing EO and ancillary data. They have shown that current standard ontologies for data sources discovery do not exist. In addition, existing applications of ontology in this domain mostly investigate specific problems, in other words these approaches are not generalized. They fail to model the relationship between data sources and the domain knowledge, which is an important factor for efficient data integration and data sources discovery.

3 | LANDSLIDE SCENARIO FOR ELECTRICAL GRID EWS

Efficient EWS for landslide multihazards is essential for the prevention and mitigation of electrical grid failure in hazard-prone areas. Generally, the development of EWS for natural hazards can be accomplished through several approaches,[35] depending on: (a) the rules stakeholders engage in hazard risk reduction, (b) geographical conditions of the hazard-prone area, and (c) EO and ancillary data provided by responsible parties. The approaches have shown the significance of the synchronization of EWS for landslide multihazards and EWS for electrical grid systems. Based on this, a scenario-based approach[36] is applied in this work to specify the scope of the EWS for an electrical grid system and its synchronization. The scenario-based approach describes a story that represents the ordinary uses of a system in the domain of interest from both, domain experts' and ontology developers' viewpoints. The scenario thus helps to identify the scope of the domain ontology.

3.1 | Scenario

The Landslip scenario for electrical grid EWS focuses on the *preparedness phase* of disaster management where the prediction of individual landslides' occurrence using time-series data sources is used to predict possible failure of electrical grid infrastructure. Several techniques for landslide prediction rely on the analysis of time-series data from rain-gauge sensors.[37,38] An example of the technique is to calculate local rainfall thresholds for the occurrence of landslides.[39] In the local areas of interest, the rainfall threshold is determined by the extraction of local rainfall events from daily accumulative rainfall to reconstruct triggering rainfall conditions for landslide occurrences in particular areas. Here, the calculated thresholds are used for analyzing real-time accumulative rainfall for predicting the occurrence of landslides and their location. Parts of transmission networks or distribution networks that are vulnerable to landslides in the predicted areas are identified and monitored.

The interaction between landslide and electrical grid system is considered when designing the scenario. Figure 1 illustrates a situation before the occurrence of a landslide event in a remote location. This area is a high slope and encompasses both natural environment (eg, rivers and mountains) and built environment (eg, schools, hospitals, road, water supply, and electricity). The area is prone to landslides and is monitored by the National Disaster Management Authority (NDMA). An expert from NDMA explores potential data sources from the *Data Sources Discovery Service (DS)* and gathers EO and ancillary data from the discovered data sources. The expert then utilizes the *EWS for landslide* to detect warning signs by analyzing daily rainfall, soil moisture, and water level and informs decision-makers of the potential landslide

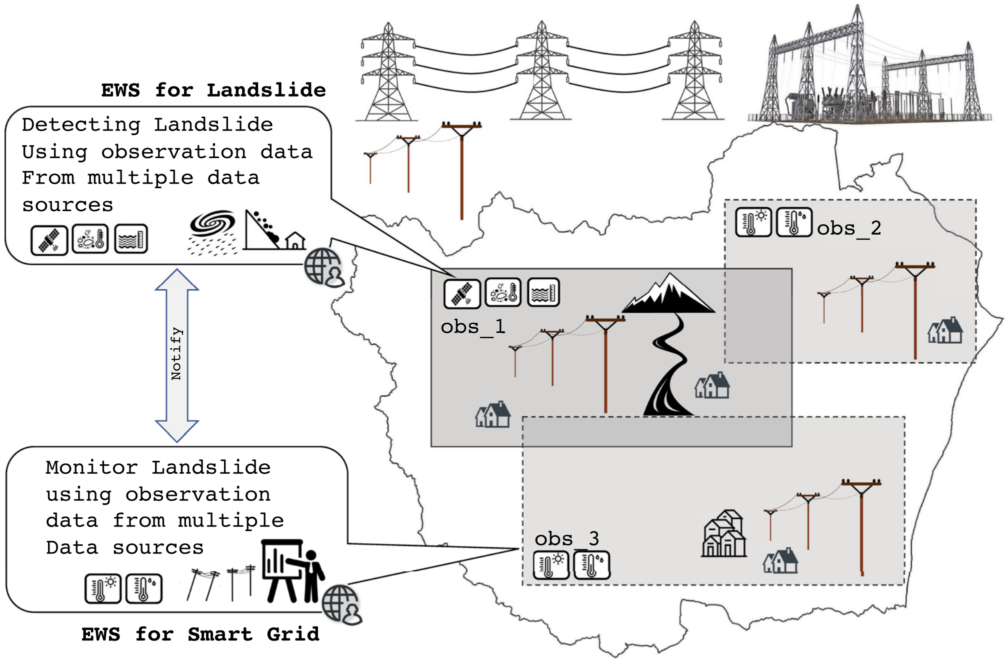

FIGURE 1 Landslip scenario for electrical grid early warning system

hazard. The EWS also sends event notifications to other systems to inform of the potential landslide hazard. The event notification is accompanied with additional information including prediction time, geo-location of landslide occurrence, and geographical boundary of the place where the landslide is likely to occur. Meanwhile, the *EWS for electrical grid system* monitors the overall operation for the delivery of electricity to consumers. On receiving an event notification from the landslide EWS, the electrical grid EWS uses the geographical boundary to identify distribution networks and list of distribution poles that are located there is a potential landslide hazard that needs to be monitored. This process is achieved by invoking third party services provided by electrical grid system providers. Here, the geo-locations of the distribution poles are identified. These geo-locations are used to discover data sources that provide observed properties for distribution pole monitoring (eg, wind speed, wind direction, soil temperature, tilt, and vibration). Gathered from data sources, the observed properties are analyzed in real time to monitor the failure of each individual distribution pole. To summarize, the distribution poles that are highly vulnerable to landslides are identified and the EWS informs the decision-maker about the possibility of a potential failure of the distribution poles.

3.2 | Concepts

The scenario reveals the essential role of data-driven EWS for landslide risk prediction and electrical grid system monitoring, which comprises of five main components.

- *Exposure* — refers to people and the environment in landslide hazard-prone areas. The environment comprises natural and built environments. The natural environment encompasses of living and nonliving things (eg, animals, river, forest, mountain, etc.). The built environment[40] is a core foundation of the community, which is constructed by people. It is comprised of infrastructure and facilities (eg, house, school, road, bridge, electricity, water supply, etc).
- *Stakeholder* — refers to people or organizations who have a stake in the landslide or the electricity grid failure event.The stakeolders could include: (a) *data collectors and providers* who deploy sensor devices in a landslide hazard-prone area or electricity grid components and provide EO and ancillary data collected from the sensor devices to EWS for analysis. The third parties who provide EO and ancillary data collected from others are also considered as data providers and (b) *Decision-makers* who have the responsibility for conducting landslide hazard risk assessment using EO and ancillary data. They make a decision based on the result from the Decision Support System and hazard risk management plan in order to inform people in a risk area and other organizations before the occurrence of landslides.

- *Event* — refers to an occurrence which is related to a hazard and electrical grid system. The hazard itself is also considered as an event based on the context. Hazard-related events can be classified as prehazard events, posthazard events, and events during a hazard. Since the aim here is to monitor the failure of the electrical grid system, landslide events are the majority of events in this scenario. Landslide events can indicate the distribution networks and list of distribution poles to be monitored by the EWS for an electrical grid system.
- *Data Sources* — refers to any sensor devices and data services that provide EO and ancillary data to data consumers. These data sources have different capacities to provide data. Sensor devices are components that observe and measure physical phenomena and transform the observation and measurement into a human-readable form. A data service is an application software that stores and provides data collected from multiple sensor devices. Nowadays, EO and ancillary data for multihazard and electrical grid management applications are available from several types of data sources.
- *Decision Support Applications* — refers to an integrated system that provides functionalities for stakeholders to monitor, forecast and predict, validate and assess hazardous events. In this scenario, EO and ancillary data collection systems, DS, and EWS for landslide and electrical grid are significant components of Decision Support Applications. These applications enable stakeholders to take timely actions to reduce the impact of landslide hazard and electric power shortage in advance. For example, once is it established that the failure of distribution poles is likely to happen, a decision-maker can co-operate with an electrical grid provider to prepare for the maintenance of the poles or prepare for mobile power generation in the landslide occurrence area.

The data-driven EWS realizes dynamic and timely decision-making for landslide prediction and monitoring of the electrical grid system by analyzing EO and ancillary data. Such data includes historical landslide events, electrical grid components, and historical and real-time data produced by sensor devices. Additionally, several sensor devices have been deployed in the landslide hazard-prone area by organizations who are responsible for landslide hazard management. Also, electrical grid components are equipped with sensors devices to observe the status of the components. These sensor devices produce EO and ancillary data and send to EWS to monitor the landslide hazard and electrical grid system in real time.

Furthermore, the organizations store the data in their local repositories and provide the data repositories as data sources for further analysis. Here, metadata of these data sources are published to a *DS*, which is a part of Decision Support Systems. The DS allows data publishers to advertise their data sources by registering data sources metadata via a data sources registry service. Furthermore, it allows data source consumers to explore potential data sources from the service to be used in their applications.

4 | LANDSLIP ONTOLOGY FOR ELECTRICAL GRID NETWORK MONITORING

The monitoring of electrical grid network failure, the focus of this paper, relies on the prediction of landslides. This prediction requires rich information from multiple data sources to provide more accurate predictions. For this purpose, the Landslip Ontology[41] is reused and utilized to provide an efficient data sources discovery mechanism in landslide prediction and electrical grid network monitoring. Basically, the landslip Ontology was designed and developed to conceptualize the knowledge of landslide hazard and its warning signs. Moreover, knowledge of data sources is also provided to facilitate data sources discovery and landslide precursor verification. The ontology has been used to support data integration and analysis in landslide early warning application using social media. The Landslip Ontology comprises of two main modules, Landslip Common and Landslip Data Sources. According to the scenario mentioned in Section 3, the Landslip Data Sources is reused for efficient data integration in the EWS for landslide and electrical grid systems. To account for the lack of electrical grid knowledge representation, the Landslip Ontology is reused by tying together with external services provided by the electrical grid providers in order to indicate failure of the electrical grid network.

4.1 | Scope and Purpose

The goal of the Landslip Ontology application for electrical grid system monitoring is to indicate the distribution poles in the electrical grid system that are vulnerable to landslide hazard and are likely to fail. Thus, the application of the Landslip

Ontology focuses on the preparedness phase of disaster management where landslide events play an important role to enhance the efficiency of the monitoring. The Landslip Ontology conceptual knowledge of landslide hazard, multihazard interaction, and landslide-related incidents is utilized to support data integration and analysis in landslide hazard and electrical grid systems. The concepts of landslide hazards are linked to EO and ancillary data, which constitute a set of properties for landslide observation. Although the ontology focuses on the landslide multihazard domain, the concept of data source in the ontology can also be applied for the electrical grid system application. The level of granularity is determined based on the competency questions and the terms identified thereof. However, external services from the electrical grid system are also required in order to answer the competency questions.

4.2 | Knowledge Sources

Built for landslide EWS, the ontology is designed based on knowledge and experiences from scientists and experts who have the domain knowledge of landslide hazard management. Research[42,43] and standard specifications[27,28,44-46] involving multihazards and geo-spatial data models are also used as additional knowledge sources to design the ontology. Further, related research works[1,2,47,48] were reviewed as knowledge sources of electrical grid systems and the assessment of electrical grid networks for the design the harmonization of the ontology and the electrical grid information services. Moreover, this knowledge is also used to conceptualize data sources for an electrical grid network assessment.

Figure 2 is a snapshot of the Landslip Ontology, which is comprised of two modules, *Landslip Common Ontology* and *Landslip Data Sources Ontology*. The Landslip Common Ontology defines concepts about landslide hazard and its interaction with other hazards and anthropogenic processes. The Landslip Data Sources Ontology defines concepts about observation and data sources for landslide hazard and electrical grid systems. The Landslip Ontology reuses SSN ontology and terminology defined in OGC standards (eg, Observation and Measurement,[44] SensorML,[45] and SOS[46]).

4.3 | Landslip Common Ontology

The Landslip Common Ontology conceptualizes the knowledge of landslides hazard. The ontology model combines theoretical knowledge and human experiences to identify warning signs before the occurrence of landslides. Landslides are one of the most significant multihazards found in many places around the globe.[49] Landslides not only interact with but

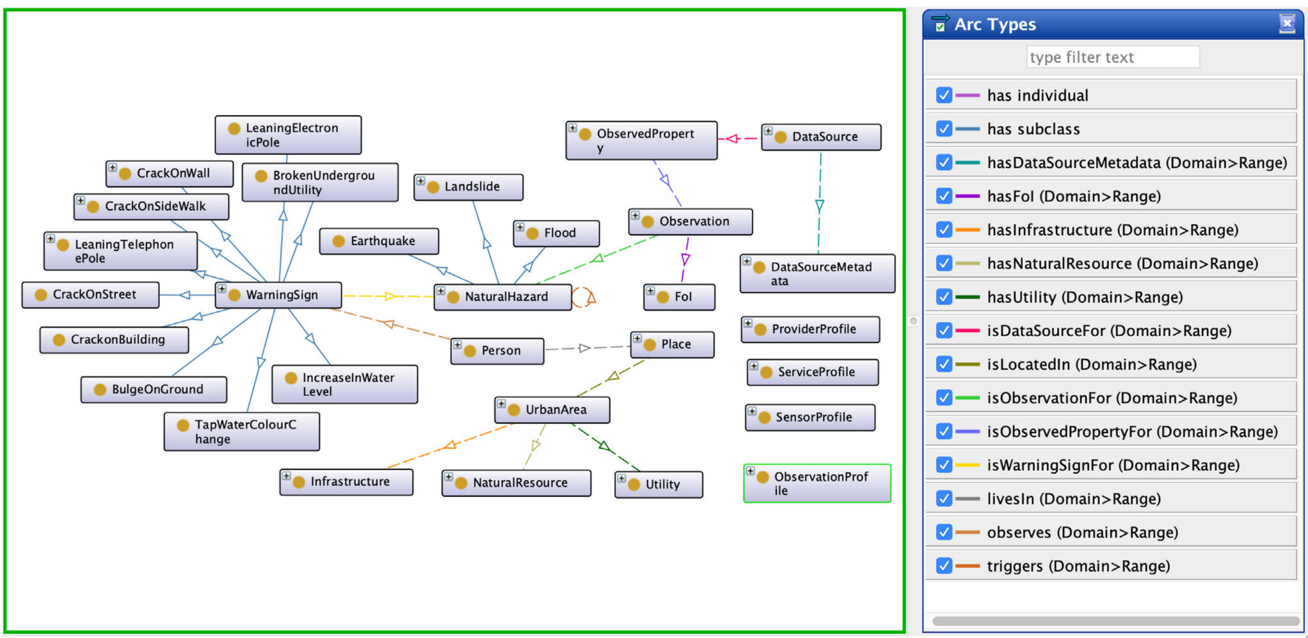

FIGURE 2 Snapshot of Landslip Ontology

are also triggered by other hazards.[42] Therefore, the Landslip Common Ontology conceptualizes knowledge of landslides and the interaction with other multihazards.[42,43] It also conceptualizes knowledge of warning signs, observed by humans, which are used to indicate possible landslide events before the occurrence of a landslide. Thus, the ontology represents warning signs of a landslide, observed and reported by people in a social network, that can be used to facilitate social media-based early warnings.

The Landslip Common Ontology comprises of four main concepts:

- *RemoteArea* — defines concepts about a remote area that is prone to landslide. The remote area encompasses both natural environment (eg, river and mountain) and built environment which includes infrastructure (eg, road and railway), utility (eg, electricity and tap water) and place (eg, school, health care unit, and house). Located in a landslide-prone area, these elements can be affected by landslides and other multi-hazards.
- *NaturalHazard* — defines a set of multihazards that can trigger landslides. This concept mainly captures knowledge about the interactions between landslide hazard and other multihazards (eg, flood, earthquake, tsunami, and drought). In addition, it also captures the interactions between other multi-hazards that can, in turn, indicate the (potential) occurrence of landslides.
- *AnthropogenicProcess* — defines a set of human activities that are contributing factors in causing landslides.[42]The knowledge of interactions within the processes is also captured to conceptualize direct and indirect indication of landslide hazards. Direct indications refer to the processes that trigger landslides while indirect indications refer to the processes that trigger other processes, which in turn, trigger landslides.
- *WarningSign* — defines a set of incidents for landslide hazard indication, other multihazards and anthropogenic processes. The concept of warning signs is mainly focused on incidents that are observed by a person or EWS.

4.4 | Landslip Data Sources Ontology

EO and ancillary data observed by sensor devices indicate events or changed pattern of landslide phenomena.[50] Such data (eg, rain, soil moisture, electrical grid components) from a variety of sensor devices is collected by data providers and provided as data sources for stakeholders to be used in their landslide hazard applications.[51] Due to the wide variety and geographically distributed nature of EO and ancillary data sources, it is essential to investigate efficient data source discovery[52] to provide sufficient amount and quality of data sources for landslide hazard risk assessment and electrical grid system monitoring. the Landslip Data Sources Ontology is thus designed to enable discovery of data sources semantically. This ontology represents concepts and relationships of EO and ancillary data, data sources, sensor devices, and data providers. When combined with the Landslip Common Ontology, the knowledge of landslide hazards can enhance data source discovery mechanisms to efficiently discover data sources that are related to the hazard of interest. Specifically, the knowledge of landslide warning sign can identify appropriate observed properties and data sources for the verification of a landslide precursor. This capability enables EWS to provide dynamic and timely decision-making for landslide hazards.

The Landslip Data Sources Ontology is comprised of three main concepts. The concepts of observation and sensors reuse existing ontologies, SSN Ontology[27] and OGC standard.[44-46]

- *DataSource* — is the central concept of the Landslip Data Sources Ontology. A data source is any sensor (eg, physical sensor, human sensor) or data service that provides EO and ancillary data. DataSource defines a set of comprehensive information about observation and data sources metadata.
- *Observation* — defines a set of observed properties (EO and ancillary data) that are used to observe features of interest related to landslide hazard. Examples of observed properties include rain, earthquake magnitude, soil moisture, soil movement, temperature, humidity, and wind speed. These observed properties are accessible to EWS via data sources.
- *DataSourceMetadata* — defines a set of information, which is essential for the data acquisition mechanism. This concept is comprised of four groups of profiles namely, ObservationProfile, SensorProfile, ServiceProfile, and ProviderProfile. The ObservationProfile represents a set of observed properties provided by a data source. SensorProfile provides information about sensor type, a feature of interest, and a list of events to be observed. ServiceProfile provides information which can be used to access a service (eg, service type, endpoint, provider). Finally, ProviderProfile provides information about a data provider (eg, provider name, contact address).

TABLE 1 Landslip Ontology features

Feature	Value
Number of classes	98
Number of properties	26
Number of individuals	30
Description logic expressivity	$\mathcal{ALCH}(\mathcal{D})$

4.5 | Ontology Metrics

An ontology comprises of a finite list of concepts and the relationships among them to represent the domain of interest.[53] The ontology metrics illustrate the number of classes, properties, individuals, and Description Logic (DL) expressivity of the ontology. *Classes* describe concepts of the domain of interest at an abstract level. *Properties* describe features and attributes of the classes and relationship among classes. *Individuals* are instances that represent concrete objects of the classes. For example, the classes `Landslide, Earthquake` represent landslide and earthquake events, respectively. A property `triggers` represents the relationship between `Landslide` and `Earthquake` concepts where a specific `Earthquake` event triggers a specific `Landslide` event. A specific landslide event (eg, landslides triggered by the Hokkaido earthquake in Japan, 2018) is an individual or instance of `Landslide`. Table 1 shows a summary of the ontological features of Landslip Ontology in terms of size (number of classes, properties, and individuals), expressivity, and complexity of the core knowledge of the Landslip Ontology.

The DL expressivity represents the complexity of the logic underlying a particular ontology.[54] For Landslip Ontology, $\mathcal{AL}$ (Attributive Language)[55] is used to represent its complexity. Here the DL expressivity of Landslip Ontology is represented by $\mathcal{ALCH}(\mathcal{D})$ which comprises of (a) $\mathcal{AL}$ — a DL used to describe the ontology, (b) $\mathcal{C}$ — an extension for representing Concept Negation; (c) $\mathcal{H}$ — an extension for representing role hierarchy; and (d) $\mathcal{D}$ — an extension for representing data type.

5 | ELECTRICITY GRID NETWORK MONITORING USING LANDSLIP ONTOLOGY

To enable efficient electrical grid network monitoring under the condition of landslide hazard, EWS for electrical grid systems need to harmonize the Landslip Ontology with information services provided by electrical grid providers. For example, the EWS utilizes knowledge base provided by the ontology to indicate the potential occurrence of landslide and its location. Such information, particularly the landslide location, can then be utilized by invoking the information services to retrieve a list of distribution poles that it is necessary to monitor due to the landslide. To realize this, interaction between the electrical grid system and the landslide hazard needs to be investigated and processes for the harmonization between the Landslip Ontology and the electrical grid information services need to be defined.

In this research, we focus on the monitoring of electrical grid network where the transmission network and the distribution network are deployed across large regions in the country including remote areas that are prone to hazards. A significant correlation between the electrical grid network and landslide occurrence is *geographical information* (eg, geo-location and geographical coverage). With a prediction of landslide, geographical coverage of the landslide affected area is identified. In addition, the geographical coverage is represented as a boundary or bounding box coordination. Meanwhile, geo-locations of electric pylons and poles within an electrical grid network are identified by their individual geographical coordination (eg, latitude, longitude). Based on this, potential vulnerable electric pylons and poles are indicated by searching for pylons and poles where their geo-locations are inside the geographical coverage of the predicted landslide.

The process of harmonizing the Landslip Ontology and electrical grid information services in electrical grid EWS is divided into two subprocesses: landslide EWS process and electrical grid EWS process. These subprocesses interact with each other and require EO and ancillary data for their analysis. EWS for landslide collects EO and ancillary data from multiple sensors deployed in the landslide prone area to analyze and predict the occurrence of landslide.

The EO and ancillary data produced by data sources (eg, IoT sensors) is a representation of observations. The *observation* is a collection of measurement of phenomena for observing the changing pattern of the area of interest. The measurement of phenomena is represented as an *observed property*, which is observed or measured by sensors deployed in the area of interest. Landslide observation comprises of sensors that observe or measure properties of landslides. Examples of the observed properties for landslide are precipitation, soil movement, soil potential, temperature, and humidity.

The sequence diagram in Figure 3 illustrates the interaction among the components of landslide EWS in order to monitor and predict the occurrence of landslides. Initially, multiple data sources provided by different providers are registered to the data sources registry. In addition, the actual knowledge of landslides is constructed based on the Landslip Ontology. Both data sources, metadata, and landslide knowledge, are stored in a triplestore, which is a semantic database. A hazard application utilizes the system by querying the knowledge base to retrieve processing rules that can be used for the monitoring of landslides in the area of interest. Next, the system submits a query to the knowledge base again to perform data source discovery to search for potential data sources that correspond to the processing rules. Thereafter, the EWS collects data sources based on suggested information from the knowledge base and starts processing based on the suggested rules. Subsequently, decision-makers are notified of landslide events detected by the EWS. Such information includes event types, time, geo-location, affected area, and other processing results. This information is also used by other systems including the electricity grid monitoring system.

Figure 4 illustrates the utilization of knowledge base in an electricity grid monitoring systems (EGMS). Once a landslide is predicted, the landslide EWS sends a notification with the landslide information to the EGMS. The information includes geo-locations and the areas likely to be affected by the predicted landslide. The areas are are represented by the bounding box from the observation. This extracted information is used to identify electricity poles, which are at risk of failure caused by landslide. Next, the EGMS calls external services provided by electricity grid providers to retrieve a list of electricity poles located in the affected areas including their metadata. Thereafter, the EGMS submits a query to the knowledge base to get potential processing rules and observed properties, which are used to monitor the failure of the potential electricity poles. Next, data sources are discovered by invoking the DS to facilitate the monitoring of electricity pole failure. Collecting data from potential data sources, EGMS is able to process the EO and ancillary data to monitor the failure of the electricity grid network in the landslide prone area.

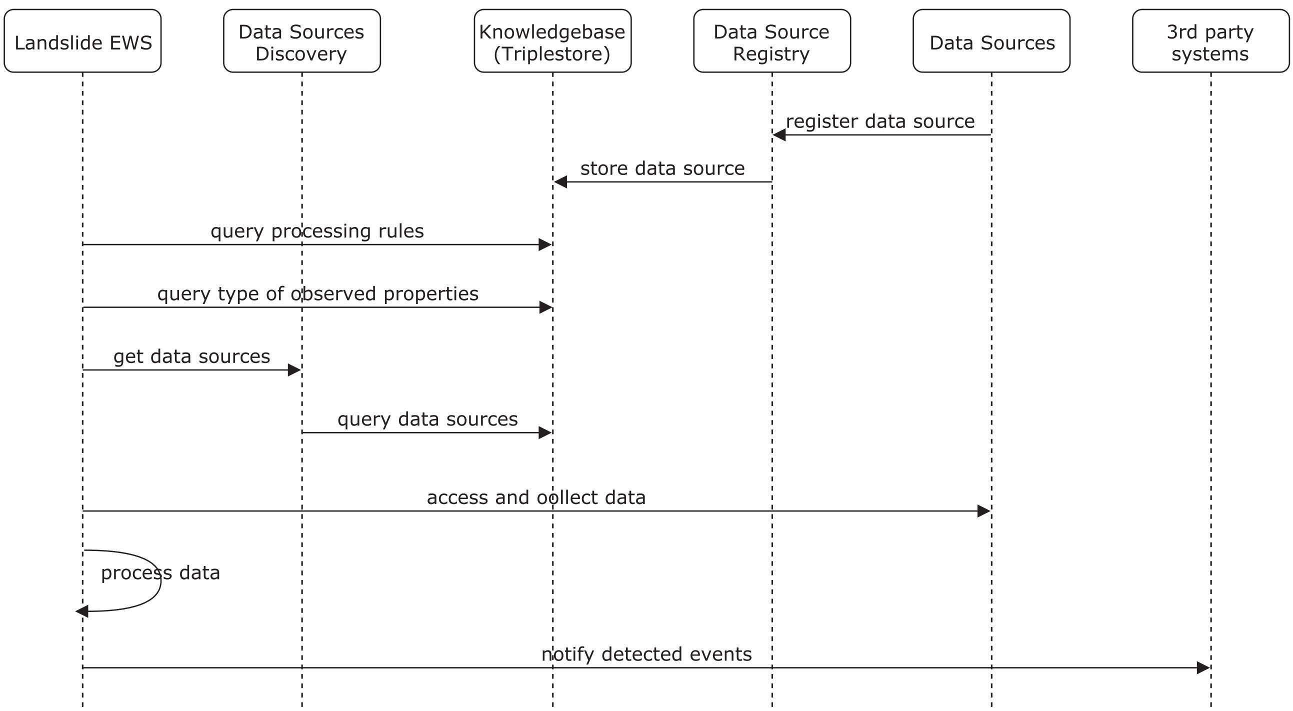

FIGURE 3 An interaction among the components of early warning systems for landslide

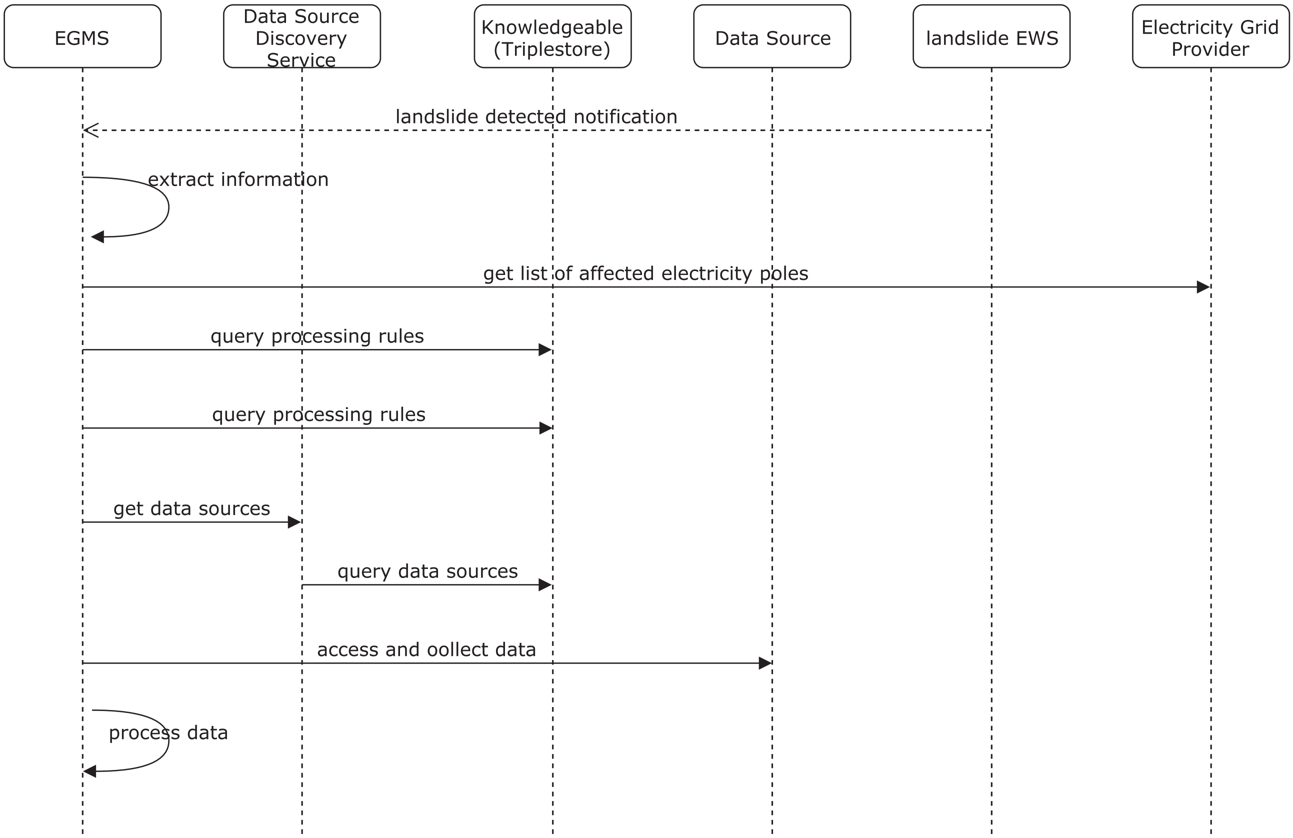

FIGURE 4 A utilization of knowledge base in electricity grid monitoring system

6 | EVALUATION

An evaluation was conducted to verify the coverage of the Landslip Ontology and its application in electrical grid network monitoring. This includes the harmonization between the Landslip Ontology and electrical grid information services. While various approaches for evaluating an ontology exist, competency questions remain the most common approach.[56,57] This approach stipulates that an ontology must be able to represent the competency questions using its terminology and answer these questions using the axioms.[58] According to the use case mentioned in Section 3, competency questions were developed as shown in Table 2. As the Landslip Ontology provides only knowledge of landslide and data sources, the evaluation requires the the harmonization between the Landslip ontology and electrical grid information services. Here, the result from the Landslip Ontology query will be used as an input to invoke the electrical grid information services.

The evaluation was conducted using a set of synthesized data that represents the use case of landslide hazard mentioned in Section 3. We manually added information of natural hazards and EO and ancillary data to our knowledge base. The information includes landslide hazard, hazard triggers, warning signs, EO and ancillary data, and data sources.

TABLE 2 An example of competency questions

	Competency questions
Q1	Which distribution networks are affected by landslide *L*?
Q2	Which distribution poles are affected by landslide *L*?
Q3	Which distribution networks are located in a landslide prone area?
Q4	Which distribution networks or substations need to be monitored because of the potential of the occurrence of a landslide hazard?
Q5	What observed properties *O* can be used to monitor a distribution network *D*?
Q6	What data sources are providing observed property *O* to monitor a distribution network *D*?

The data sources include both data sources for landslide hazard and electrical grid system. We performed validation over the dataset using Pellet to check for ontology consistency, concept satisfiability, classification, and realization. Based on the competency questions, we performed preliminary experiments by querying over the knowledge base.

In order to write competency questions and to demonstrate that the Landslip Ontology can be applied for electrical grid network monitoring and answer these questions, we used the SPARQL Protocol and RDF Query Language (SPARQL). Using SPARQL, we defined a formal query for each natural language competency question to get answers from the knowledge base. Figures 5 and 6 show snapshots of the SPARQL queries for *Q2* and *Q6* and the output for the competency question *Q6* on running the query in Protégé.[59] By executing the query based on the competency questions *Q1* to *Q6*, we could verify the coverage of the Landslip Ontology. From the results, it can be seen that the ontology is able to identify a

Q1, Q2

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX :
<http://www.semanticweb.org/ncl/ontologies/2018/6/landslip#>

SELECT  ?geo ?p ?value
      WHERE { :landslide_1 :hasGeoLocation ?geo .
                   ?geo ?p ?value
                   FILTER (?p = :bbox)}
```

Q3

```
SELECT  ?hazard ?geo ?p ?value
      WHERE { ?hazard rdf:type :Landslide .
                   ?hazard :hasGeoLocation ?geo .
                   ?geo ?p ?value
                   FILTER (?p = :bbox) }
```

Q4

```
SELECT ?hazard ?geo ?p ?value
      WHERE { :flood_1 :triggers ?hazard .
              ?hazard rdf:type :Landslide .
                   ?hazard :hasGeoLocation ?geo .
                   ?geo ?p ?value
                   FILTER (?p = :bbox)}
```

Q5

```
SELECT    ?observedProperty
WHERE {
      ?observation :isObservationFor :gridnetwork_1 .
      ?observedProperty :isObservedPropertyFor ?observation .}
```

Q6

```
SELECT  ?gridnetwork ?observation ?observedProperty
?dataSource ?metadata ?profile ?p ?value
WHERE {
      ?observation :isObservationFor ?gridnetwork .
      ?observedProperty :isObservedPropertyFor ?observation .
      ?dataSource :isDataSourceFor ?observedProperty .
      ?dataSource :hasDataSourceMetadata ?metadata .
      ?metadata :hasProfile ?profile .
      ?profile ?p ?value .
      VALUES (?gridnetwork) { (:gridnetwork_1) } .
      FILTER (?p != rdf:type)
}
```

FIGURE 5 SPARQL queries for competency questions Q1 to Q6

gridnetwork	observation	observedProperty	dataSource	metadata	profile	p	value
gridnetwork_1	obs_3	soil_moisture_1	dataSource_1	ds_metadata_1	service_profile_11	where	""@
gridnetwork_1	obs_3	soil_moisture_1	dataSource_1	ds_metadata_1	service_profile_11	dbname	"mysql"@
gridnetwork_1	obs_3	soil_moisture_1	dataSource_1	ds_metadata_1	service_profile_11	table	"NorthSlopHigherRawData"@
gridnetwork_1	obs_3	soil_moisture_1	dataSource_1	ds_metadata_1	service_profile_11	serviceURL	"http://127.0.0.1/rest/moisture"@
gridnetwork_1	obs_3	soil_moisture_1	dataSource_1	ds_metadata_1	service_profile_11	serviceProvider	"Amrita"@
gridnetwork_1	obs_3	soil_moisture_1	dataSource_1	ds_metadata_1	service_profile_11	serviceAdapter	"Rest_adaptor_11"@
gridnetwork_1	obs_3	soil_moisture_1	dataSource_1	ds_metadata_1	service_profile_11	serviceType	"REST"@
gridnetwork_1	obs_3	soil_moisture_1	dataSource_1	ds_metadata_1	service_profile_11	column	"*"@
gridnetwork_1	obs_3	soil_moisture_1	dataSource_1	ds_metadata_1	sensor_profile_1	featureList	"foi_karela_bbox_1"@
gridnetwork_1	obs_3	soil_moisture_1	dataSource_1	ds_metadata_1	sensor_profile_1	eventList	"Landslide"@
gridnetwork_1	obs_3	soil_moisture_1	dataSource_1	ds_metadata_1	sensor_profile_1	sensorType	"in-situ"@
gridnetwork_1	obs_3	soil_moisture_1	dataSource_1	ds_metadata_1	provider_profile_1	providerName	"Amrita"@
gridnetwork_1	obs_3	soil_moisture_1	dataSource_1	ds_metadata_1	obs_profile_11	phenomenonBeginTime	"2004-01-01T00:00:00"^^<http://www.w3
gridnetwork_1	obs_3	soil_moisture_1	dataSource_1	ds_metadata_1	obs_profile_11	phenomenonEndTime	"2018-07-21T00:00:00"^^<http://www.w3
gridnetwork_1	obs_3	soil_moisture_1	dataSource_1	ds_metadata_1	obs_profile_11	featureOfInterest	"foi_karela_bbox_1"@

FIGURE 6 SPARQL query output for competency question Q6

list of pylons and poles in an electrical grid network. Furthermore, the ontology can suggest potential data sources and their metadata, which can be used by domain experts to perform timely decision making against the failure of electrical grid network.

7 | CONCLUSIONS AND FUTURE WORK

An effective EWS for electrical grid network monitoring relies on a comprehensive set of EO and ancillary data provided by geographically distributed data sources. In this paper, we have demonstrated the application of the Landslip Ontology, an ontology for the landslide domain, for the electricity grid domain. Specifically, we utilized the ontology with external services for electrical grid information to monitor a failure of the electrical grid network due to the occurrence of landslide. We proposed a process for harmonizing the Landslip Ontology and electrical grid information services for efficient EWS in the electrical grid domain. The Landslip Ontology supports the EWS for electrical grid system by enhancing the efficiency of electrical grid network monitoring under the condition of landslide hazard. Moreover, the ontology enables decision makers to find potential data sources for monitoring. We have performed evaluation by verifying the coverage of the ontology based on competency questions. Designed for the landslide domain, the Landslip Ontology needs to harmonize with electrical grid information services to answer the questions. The preliminary experiment over a set of synthesized data has shown seamless harmonization of the ontology and the information services. Moreover, it has shown the consistency, concept satisfiability, classification, and realization of the ontology. We have also designed the architecture of an ontology-based data sources discovery system to realize our proposed ontology. This system is an essential component that allows EWS to discover the relevant data sources and access rich information from the data sources. Our immediate future work on this research is to evaluate the application of Landslip Ontology in a real-world application of electrical grid EWS.

ACKNOWLEDGEMENTS

This research is partially supported by two Natural Environment Research Council projects including LandSlip (NE/P000681/1) and FloodPrep (NE/P017134/1).

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How to cite this article: Phengsuwan J, Shah T, Sun R, James P, Thakker D, Ranjan R. An ontology-based system for discovering landslide-induced emergencies in electrical grid. *Trans Emerging Tel Tech*. 2020;e3899. https://doi.org/10.1002/ett.3899