IoT-Based Strategies for Risk Management of Rainfall-Induced Landslides: A Review

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Abstract: The Internet of Things (IoT) technology has the potential to revolutionize many areas of everyday life including the risk management of rainfall-induced landslides. The IoT technology can enhance risk management strategies with the deployment of advanced monitoring and early warning systems. The IoT advances such systems with the provision of cost-efficient, flexible, and scalable technology to collect, transfer and analyze data on the triggering variables of rainfall-induced landslides. Data collected on the triggering variables contribute to advancing landslide risk management (LRM) by enabling a more consistent and reliable hazard assessment. Conversely, monitoring can contribute to the reduction of consequences in an LRM framework with the implementation of an early warning system. Consequences are reduced by issuing timely warnings to evacuate the people and property under threat, thus reducing the landslide risk. This paper aims to review IoT-based strategies for risk management by mainly focusing on the IoT technology. A brief overview of the different IoT technologies is provided to evaluate their capacity in addressing the needs of monitoring systems for rainfall-induced landslides. Characteristic IoT system architecture is examined by decomposing an IoT-based monitoring system into its main components. The functionality of each of the components is investigated and an overview of sensors, instruments, services and equipment characteristic for monitoring rainfall-induced landslides is examined.

Keywords: IoT; internet; things; risk; rainfall; landslide.

1 Introduction

The adverse effects of climate change on society are becoming evident in every aspect of life. The recent study by IPCC (2014) states that the climate is changing continuously as a result of global warming. Changes in the climate will cause a notable increase in the frequency of triggering events of landslides such as extreme rainfalls, snowmelts, and temperature changes. For example, in the report of the Ministry of Climate and Environment of Norway (2013), it is stated that the temperature and precipitation in Norway will increase by 4.6 degrees and 30 percent by the end of the century. Both the increase in the frequency of triggering events and the expanding population towards hazard-prone areas will increase the risk associated with landslides. In order to deal with the increasing landslide risks, there is a need to develop and implement efficient landslide risk management (LRM) strategies.

In the traditional risk assessment framework, there exists only a limited consideration of soil behavior based on some crude approximations and empirical approaches (e.g., Bhosale et al. 2017), with Geographical Information System (GIS) programs, aerial photographs, and landslide inventory data often employed to determine the landslide risk in a specified area. In the last decade, studies on sensor-based solutions and real-time monitoring of slopes (Millis et al. 2008; Shukla et al. 2014; Hou 2018) have enabled the development of LRM strategies based on Monitoring and Early Warning (MEW) systems. MEW systems support the management of landslide risks with a more consistent and reliable hazard assessment based on collected data on the triggering variables and reduction of consequences with timely warnings to protect the elements under risk. However, widespread deployments of MEW-based strategies have been inhibited by the high cost of sensors, the requirement of frequent maintenance and the inflexibility of cable-based systems. Some of these challenges can be successfully resolved by adopting recent development within the domain of environmental Internet of Things (IoT). The IoT is a powerful concept of interacting with the physical world through a network of natural or manmade objects that are connected to the internet and process the collected information automatically, with or without human intervention, to gain crucial insights that support more efficient management of limited resources (KlimaDigital 2019). The adoption of the environmental IoT has the potential to revolutionize LRM with the provision of cost-efficient, flexible, scalable MEW systems. The flexibility and scalability of IoT based MEW systems support significant automatization of LRM through the implementation of advanced data analysis, statistical learning algorithms, and efficient integration of data with advanced landslide prediction models and early warning systems.

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LRM is a complex process including scientific analysis, engineering experience, and human values. Basically, the LRM framework should include the evaluation of the risk, comparison with the threshold value, and implementation of precautions to control the risk if necessary. Accurate and efficient landslide risk evaluation requires using proper LRM framework. The potential of IoT technologies in improving risk assessment of landslide will be examined in this study with a focus on rainfall-induced landslides (RIL).

2 IoT Solutions for Monitoring Rainfall-Induced Landslides

An IoT deployment can be commonly decomposed in four dependent layers: perception, network, middle-ware and application layer (e.g., Cvitic et al. 2016), as presented in Figure 1. The main function of the perception layer is data collection. The technology enabling the perception layer consists of a series of IoT devices connected in a network. The perception layer interacts with the network layer, which collects data from the perception layer and transfers the data to the middle-ware layer. The middle-ware layer supports a wide range of functionality including data collection, storage, filtering, transformation, and advanced data analytics commonly associated with cloud computing. Following the processing in the middle-ware layer, the data are passed to the application layer. An end-user accesses an IoT deployment through the application layer, where the collected data are integrated within the MEW system. The main functionality of the application layer is to provide support to the implementation of the landslide prediction models and early warning systems to support LRM.

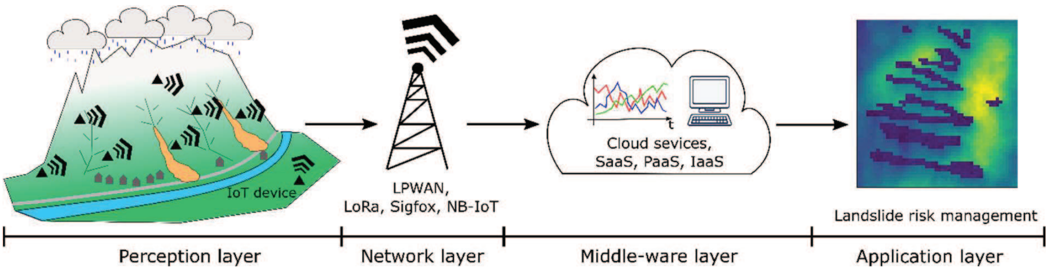

Figure 1. IoT architecture for a shallow landslide monitoring system.

2.1 Perception layer

The perception layer consists of a network of connected IoT devices providing sensing, actuating, controlling, and monitoring activities (Ray 2018). The IoT devices collect data from sensors or other instruments, exchange the data with connected devices, and process the data locally or send to a server or cloud for further processing. The hardware of the IoT devices is often optimized for specific applications and usually features reduced processing and memory capabilities for cost and power efficiency. An overview of common IoT hardware platforms can be found in Ray (2018). The following paragraphs will review common types of parameters monitored in RIL and monitoring sensors/tools utilized in conventional MEW systems.

Hardware solutions for monitoring RIL feature a variety of technologies and types. Their main role in the perception layer is to collect and transfer information on the current site conditions such as surface and sub-surface deformations, and hydrogeological, atmospheric and soil conditions. Depending on the failure mechanism and specific field conditions, different parameters and conditions may have priority to be monitored.

Pecoraro et al. (2019) summarized and compared 29 local MEW systems operational all around the world, with an overview of the parameters monitored and instruments employed. The majority of systems reported in the study monitor the slope deformation parameters such as displacement, velocity, acoustic emission, cracking, acceleration and strain. Among the triggering variables, rainfall is monitored in the majority of the local MEW systems with some systems monitoring snowmelt and volcanic activities. Groundwater conditions are monitored in 16 out of 29 MEW systems, with the focus on pore-water pressures and groundwater levels. Pecoraro et al. (2019) reported that the studies on RIL monitored only geotechnical and meteorological conditions to evaluate the stability of the slope and detect failure initiation. Geotechnical conditions are monitored with a range of instruments including inclinometers, piezometers, perforated standpipes, extensometers, differential monitoring of stability (DMS) columns, tiltmeters, crackmeter, and optic fibers. Meteorological conditions were monitored with rain gauges and weather stations. In the following paragraphs, the sensors utilized for monitoring slope conditions in several specific MEW deployments will be examined.

In a MEW system reported in Smith et al. (2014), hydrological monitoring was performed by the United States Geological Survey (USGS) in an un-channeled headwater basin in the Elliott State Forest, Oregon, USA. The approximate area of the monitored basin was 4.3 km^2 with steep slopes generally greater than 30°. The MEW system was based on volumetric water content sensors, tensiometers, and piezometers with the power provided by solar panels, deep-cycle batteries, and a solar charge controller. Additionally, tipping bucket rain gauges and in-place inclinometers were employed to measure the rainfall intensity and sub-surface deformations.

Baum et al. (2005) monitored two slopes, located in Everett and in Edmonds, north of Seattle, Washington, USA as a part of an earlier USGS study. The instrumentation at the two slopes included tipping bucket rain gauges, soil-water reflectometers, soil temperature probes, piezometers, tensiometers, and borehole water-content profilers.

A MEW system was deployed to monitor four slopes in Hong Kong (Millis et al. 2008). Instrumentation was installed to monitor surface and sub-surface movement, groundwater level, soil suction, moisture content, and other environmental factors. Monitoring the surface movements was achieved with vibrating wire crackmeters, multi-point translation, rotation and settlement sensors (TRS), automatic differential GPS receivers (DGPS), and manual surveys of monitoring points. In-place inclinometers and time domain reflectometry (TDR) coaxial cables were employed to monitor the sub-surface deformations. Hydrogeological conditions were monitored by tipping bucket rain gauges, Casagrande piezometers, and multilevel piezometers in addition to the rain gauge network throughout Hong Kong. Soil suction and water content were monitored by using Jet-fill tensiometers and TDR for volumetric water content.

A MEW system was developed in Wushan Town, Three Gorges Reservoir, China (Yin et al. 2010) to monitor a slope where the failure mechanism is related to the fluctuations of the water level in the reservoir. Although the failure mechanism is not directly related to rainfall, the instrumentation of the slope and the monitored parameters are quite similar. The utilized tools for monitoring the slope are GPS for surface deformations, TDR coaxial cable, and inclinometers for sub-surface deformations, pore water pressure monitoring instruments, ultrasonic open channel automatic flow meters, and tipping bucket type automatic rain gauges to record precipitation, and lastly Brillouin optical time domain reflecting sensing system(BOTDR) to monitor strain.

Uhlemann et al. (2016) investigated the MEW system for monitoring rainfall-induced Hollin Hill landslide in North Yorkshire, UK. The surface deformations were monitored by GPS tracking points and tilt meters. Conventional inclinometers, Shape Acceleration Array (SAA) inclinometers and waveguide acoustic emissions monitoring sensors were employed to monitor sub-surface deformations. Piezometers were placed at approximately the shear surface depth as determined by the inclinometers to monitor the pore water pressure. The atmospheric conditions, such as barometric pressure, humidity, precipitation, temperature, and wind speed and direction were monitored via weather station.

IoT technology can advance existing monitoring solutions with the deployment of cost-and power-efficient, scalable and flexible IoT devices. There are several ongoing projects investigating the advantages of IoT technologies in collecting and transferring data from sensors commonly employed in MEW systems for landslides (KlimaDigital 2019; Chaturvedi 2018). Chaturvedi (2018) investigated the use of low-cost IoT solutions for monitoring and predicting RIL in India. The KlimaDigital project investigates the applications of environmental IoT for monitoring rainfall, soil moisture, pore water pressure, and displacements with cost-effective, low-power Narrowband-IoT (NB-IoT) technology, which will be discussed in the following chapter.

2.2 Network layer

The network layer has the central role of transferring the data from IoT devices to the middle-ware layer. The implementation of IoT solutions for RIL monitoring can be significantly advanced by adopting networking solutions supporting low-power-wide-area networks (LPWANs). In comparison to more conventional solutions, LPWANs support data transfer on longer distances then wireless networks (e.g., WiFi, Bluetooth) and are more cost- and power-efficient with lower costs of hardware and services then cellular networks (e.g., 2G/GSM, 4G) (Mekki et al. 2018). LPWANs are well suited for the implementation of RIL monitoring due to the requirements for data transfer on long distances (i.e., tens of kilometers), low data rates (e.g., tens of bytes or lower) and low maintenance and long battery life (e.g., five to ten years) (Mekki et al. 2018). The efficiency of LPWANs and IoT devices enables cost reductions when compared to conventional monitoring systems based on cellular networks or cables.

During the last few years, several technologies enabling LPWAN deployments have been developed (Mekki et al. 2018). Among them, Sigfox, LoRa, and NB-IoT are leading technologies supporting the deployment of LPWANs. A brief comparison of the three leading technologies is presented in Table 1. It is important to note that the LPWAN technologies are continuously being developed with the values in Table 1 likely to change and depend on the local implementations of the technologies. Sigfox and LoRa operate in the unlicensed spectrum, while NB-IoT operates in the licensed spectrum, which may be important in location saturated with IoT devices in the unlicensed spectrum. NB-IoT supports the highest data transfer rates, with a significantly lower rate provided by Sigfox, which may be important in determining the number of sensors per device and data transfer rates. The data transfer range is on the magnitude of tens of kilometers, with Sigfox supporting the largest range. LoRa and NB-IoT support bidirectional communication which allows for remote access and updates, thus potentially reducing maintenance cost. The deployment costs will also depend on the available infrastructure at the deployment location. For example, NB-IoT can use existing cell towers which eliminates the cost of a base station. Based on the information in Mekki et al. (2018), Sigfox and LoRa are likely to be applied in deployments with low data rates and low costs. Implementations focusing on the quality of service with higher data rates are likely to be implemented with the NB-IoT technology.

Table 1. Overview of LPWAN technologies based on (Mekki et al. 2018).

	Sigfox	LoRa	NB-IoT
Frequency	Unlicensed	Unlicensed	Licensed
Maximum data rate	100 bytes per second (bps)	50 kilobytes per second (kbps)	200 kbps
Bidirectional	Limited	Yes	Yes
Maximum payload length	12 bytes	243 bytes	1600 bytes
Range	10 km urban, 40 km rural	5 km urban, 20 km rural	1 km urban, 10 km rural

2.3 Middle-ware layer

Depending on the implementation, the middle-ware layer can support varying levels of functionality commonly associated with cloud services. These usually include functionalities such as Software as a Service (SaaS), Platform as a Service (PaaS), and Infrastructure as a Service (IaaS). SaaS relates to cloud services providing software accessed over the web to a range of actions including data processing and analytics. These services can include advanced machine learning algorithms that support advanced analysis of large amounts of data collected with the IoT network. PaaS provides a platform for users to develop, test and deploy their own applications. When compared to SaaS and PaaS, IaaS provides only cloud infrastructure services.

2.4 Application layer

An end-user accesses an IoT deployment through the application layer. In this layer, landslide prediction models and early warning systems can be implemented to support the LRM systems.

3 Discussion

Geotechnical Instrumentation and Monitoring Market is estimated to be valued at 4.64 billion USD by 2022, and is projected to grow at a compound annual growth rate of 11.37% between 2017 and 2022 (MarketsandMarkets 2018). Despite these promising numbers, monitoring of landslides is rarely done because conventional systems are resource intensive. According to the World Bank report (2005), 3.7×10^6 km^2 of land surface is prone to landslides worldwide, and nearly 300 million people live in areas of potential landslide risk (Dilley et al. 2005). From 2004 to 2010, 2,620 deadly landslides were documented worldwide, causing 32,322 fatalities—the highest reported value so far (Petley 2012). Landslides cause damage to infrastructures such as roads, railways, pipelines, structures, embankments, buildings, and other built environment. Munich RE (2014) and Haque et al. (2016) reported that the global total annual losses caused by landslides are about 18 billion € or about 17% of the annual average global natural disaster losses that total about 110 billion €. As discussed in this paper, the need for more automated and efficient MEW systems for landslides can not only contribute to landslide risk reduction but also opens up new multi-disciplinary research fronts.

With the recent development of sensory technology, the MEW-based LRM strategy is becoming more commonly used on marginally stable slopes. In the MEW strategy, the slope is instrumented with sensors to monitor important information on triggering variables, which include several geotechnical, hydrological and meteorological parameters. Common types of sensors for monitoring RIL were presented in several case studies in Section 2.1. Information on the triggering variables is then used to reduce uncertainties commonly associated with these parameters due to lack of knowledge and inherent variability resulting from remote assessment areas, variability in geotechnical, hydrological and climate conditions, costly data collection techniques, and modelling errors. Reducing uncertainties in the triggering variables provides a basis for more reliable predictions of landslide probability with more accurate estimates of landslide initiation and runout distance. Improving landslide probability estimates enhances the landslide risk assessment by enabling a more consistent and reliable hazard assessment. Conversely, monitoring can contribute to the reduction of consequences in the risk management framework with the implementation of an early warning system. An early warning system can be based on certain threshold values relating to the measurements of the triggering variables (e.g., rainfall intensity, displacements) or risk estimates (e.g., expected economic losses). Exceedance of the threshold values would result in varying degrees of early warnings depending on the severity of the threshold exceedance. With the warning activated, the people under risk can be evacuated, and the high-value mobile elements can be also removed thus reducing the landslide risk.

IoT solutions have the potential to facilitate wider use of MEW strategies for managing landslide risks with the provision of low-cost IoT devices, cost-efficient data transfer rates, longer battery life, and reduced maintenance. In addition to cost-efficient monitoring, the core element of the IoT technology is the capacity to support communication, with or without human intervention, between IoT devices in a monitoring network and with devices and humans external to the network. Such features enable implementation of advanced functionality within MEW systems and external services that may access its data. These could include, for example, intelligent transport systems, which may automatically access information from the IoT-based landslide monitoring systems and enable further actions to prevent adverse consequences on road users.

Considerable automatization of landslide MEW systems can also introduce additional vulnerabilities in LRM strategies that originate from the interactions between the cyber and physical threats characteristic for cyber-physical MEW systems. The accuracy, lifetime, efficient transmission and self-maintainability of sensors and IoT devices remain the focus, as the cyber system forms the backbone of the wireless sensors and IoT devices used for MEW systems. Manipulation of an MEW system, through cyber or physical threats, could significantly impact the reliability and safe operation of the physical systems that rely on the MEW system—and thus the society that depends on it. An intended cyber threat on IoT-enabled MEW systems will lead to either FALSE alarms at normal operation conditions or NO alarm at the onset of a landslide event. Accurate and efficient detection, mitigation and response to landslide threats require that deployed IoT-based MEW systems are resilient to any possible cybersecurity risk. Cybersecurity of MEW systems is an emerging yet unsolved challenge, and this aspect needs to addressed and examined. Examples of such events already exist. Cyber threats are becoming an emerging issue in the field of landslide monitoring, as reported by Arbanas (2018) evidenced by a recently executed cyber-attack on a landslide monitoring system in Croatia.

Efficient analysis of the data collected by the IoT based systems is an important key to understand the conditions controlling the spatiotemporal occurrence of the landslides. The value of collected information is crucial in justifying the costs of deploying a monitoring system and ensuring timely warnings to reduce adverse effects of a landslide on life and property. Analyses of large amounts of data can be supported by the developments in statistical and machine learning methods. However, such algorithms are often data-driven with the validity of their predictions being often characterized by the data quality in the calibration datasets. Ensuring the validity of such models on rare and unobserved events (e.g., extreme rainfall) is central in validating their applicability. Consequently, there is a need for transparency in the implemented data analysis algorithms to ensure the interpretability of the model and the effects of each of the model variables on landslide and warning predictions.

Due to the sensitivity of the analyzed data, there can be considerable consequences related to false landslide predictions at normal conditions, and lack of landslide predictions at the onset of a landslide. To avoid losses that may be associated with both situations, human-centered MEW systems should be considered to support critical decision making and avoid excessive reliance on automated MEW systems subjected to cyber and physical threats.

4 Conclusion

The paper provided an insight into the potential of the recent innovations in the domain of the environmental IoT in providing solutions for managing landslide risks. The environmental IoT is showing a strong potential to transform LRM with the provision of cost-efficient, flexible, and scalable MEW systems. Achieving the full potential of IoT within LRM will require additional research activities on several topics including the deployment of IoT solutions based on LPWANs for monitoring landslides, development of methods and algorithms for data analysis and landslide predictions, and combined cyber-physical risk management of IoT-based monitoring systems.

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