Received November 20, 2021, accepted December 6, 2021, date of publication December 23, 2021,
date of current version January 20, 2022.

Digital Object Identifier 10.1109/ACCESS.2021.3137841

Low-Cost Sensor-Based and LoRaWAN Opportunities for Landslide Monitoring Systems on IoT Platform: A Review

SWAPNIL BAGWARI[1], ANITA GEHLOT[2], RAJESH SINGH[2], NEERAJ PRIYADARSHI[3], (Senior Member, IEEE), AND BASEEM KHAN[4], (Senior Member, IEEE)

[1]School of Electronics and Electrical Engineering, Lovely Professional University, Phagwara, Punjab 144411, India
[2]Division of Research and Innovation, Uttaranchal University, Dehradun, Uttrakhand 248007, India
[3]CTiF Global Capsule, Department of Business Development and Technology, Aarhus University, 7400 Herning, Denmark
[4]Department of Electrical and Computer Engineering, Hawassa University, Hawassa 05, Ethiopia

Corresponding author: Baseem Khan (baseem.khan04@ieee.org)

ABSTRACT Landslides are a frequent natural hazard during the rainy season, causing infrastructural and economic damage globally. Several studies on landslide monitoring techniques have been conducted in order to reduce various types of losses. There is an extensive review in this article of the ground monitoring method that uses a variety of sensors and some of the primary advances that help to enhance architecture and fulfill user needs. Study of cost-effective ground monitoring technique analysis in different landslide warning systems and some known cases in research article based on coverage area and energy harvesting methods also discussed. Moreover, WSN architecture identified and creates classes according to their benefits and drawbacks as well as performance is evaluated such as efficiency, reliability, quality of service, and network lifetime.

INDEX TERMS IoT, landslide monitoring, slop stability, LoRaWAN, ground vibration, wireless sensor network.

I. INTRODUCTION

In most recent decades, in mountainous regions around the globe landslides pose an unprecedented threat to life, property, infrastructure, and natural ecosystems. Various extreme events are associated with severe weather events that persistently expand through climatic change and global warming in many areas of the world. Landslide monitoring is a central factor of all of the risk evaluations for landing threats, often intending to provide early warning of an imminent loss in the sense of life, populations, or facilities at risk [1]. Landslides are mainly triggered by a natural event or human-made construction event often connected to significant financial and social consequences. Different studies have been conducted on landslide forecasting and landslide hazard mitigation. The identification and risk assessment of landslide hazards have in recent years become an important topic for landslide studies, therefore so much significant work has been done in these fields. Landslide risk evaluation tasks involve recognizing possible landslide hazards as well as quantitatively estimating their probability of a landslide within a particular time frame. We must consider and forecast landslide behavior since we cannot eliminate and must live with landslide hazards. To mitigate or reduce the effects of landslide occurrence, robust surveillance and warning system's role is to gather useful information is very important. Landslide detection and, in particular, early warning systems have gained tremendous attention in recent years. It tracks slop movements in potential landslide areas and monitors variations in landslide data points, which reduce the impact of the landslide. The vision of with us years ahead is a globally connected society where everyone and everything has unrestricted access to data that can be shared at any time and from any location. Existing landslide monitoring and wireless-based techniques will have to be examined for their potential evolution to bring this vision to realization. Currently available wireless technologies, such as a global system for mobile communication (GSM), a general packet radio service (GPRS), broadband, wireless fidelity (Wi-Fi), and satellite will incorporate new components to meet the demands of today and the future,

The associate editor coordinating the review of this manuscript and approving it for publication was Byung-Seo Kim.

respectively. In some cases, however, the current state of the art may not be able to deal with certain situations. For the long-term realization of landslide monitoring, the introduction of entirely new connectivity techniques with smart sensors and a high computing processor will be essential. With this research, we intend to explore and provide a low-cost solution for landslide surveillance. A robotic total station or a satellite imaginary technique may not be appropriate in all circumstances. Due to its high cost, and for a small infrastructure for example in hilly areas may be unable to implement it. IoT (Internet of Things) architecture incorporated with smart sensors, low-power modules, and long-range communication work together to produce better results at lower implementation expenses. However, sensors deployment strategy is another concern which needs to be address efficiently. Moreover the security of data in the personal area network and long-range server oriented performance are not much encountered in available articles. In comparison to traditional human-based prevention and the IoT based landslide prevention, the technology is reliable, responsive, covered a large area, and provides accurate data and looks more promising for future work. In IoT technology, cloud-based architecture should ensure strong internet connectivity for the whole duration of accessing services. Moreover, bandwidth requirements increase according to geo-data, and trained manpower is required to extract useful information from big data unless any artificial intelligence is not incorporated. The IoT has improved the efficiency of such types of applications, but power consumption and the ability to communicate over long distances remain challenges. Moreover, Photovoltaic performance in these remote and wild conditions begins to decline very early overtime. Solar cells can be an appropriate solution only in emergency warning situations, in which an initial response monitoring infrastructure is to be established. The study shall help to focus on long-range coverage edge-sensitive IoT-based architecture to maximize the output of the landslide monitoring system.

The main contributions and innovations of this paper are organized as follows: Section II describes, we present the types of instrumentation and methods available for landslide monitoring. A discussion of cost-effectiveness is carried out in the context of landslide-specific areas, where high-cost solutions are not possible. Section III outlines WSN networks with a comparative analysis of architecture, routing protocol, and quality assessment. This section also describes IoT architecture and the importance of the edge-fog layer to screen and recognize time-sensitive data for landslide events. Section IV describes emerging technologies in the (Long Range Wide Area Network) LoRaWAN network in detail. We provide discussion and conclusion in Sections V and VI.

II. BACKGROUND METHODS OF LANDSLIDE MONITORING

Ample of monitoring techniques are available for geoscientists in recent years. The monitoring of hydrological, kinematic, and climatic parameters plays an important role in promoting slope stability models. Landslide monitoring broadly categorized in two ways i.e. remote-based sensing and ground-based sensing as shown in figure 1. Remote sensing technique consists of terrestrial surveying, space-borne and aerial not in physical contact and ground-based sensing technique with the contact of the slop or monitored area. Remote sensing technique without contact technique has the advantage to monitor large areas. In this are many systems that are developed like satellite radar interferometry or laser scanning. Although it is having the disadvantage of higher cost, precise ground resolution, and data acquisition discontinuity. Sensor networks include sensor nodes and sink nodes, used mainly to acquire field information in real-time. Mainly the rain gauge and displacement gauge are part of the sensor nodes. Their aim is to identify rainfall information, water supplies, mountain displacement, and other information to monitor geo-risks in real-time. Wired or wireless technology networks connect sensor nodes and monitoring node data to sink nodes automatically via wired or wireless networks and then connect to remote geo-hazard data transmission networks via sink nodes, thereby enabling the remote transmission of data monitoring in real-time.

A. ROLE OF REMOTE SENSING WITHOUT PHYSICAL CONTACT

The remote sensing approach involved collecting information on an object or phenomena without interaction with the object and therefore in comparison to observation on the premises, in particular on the earth. More recently, the convergence of rapid low-cost and compact unmanned aerial vehicle (UAV) development and advances in cost and size of sensor nodes resulted in new, promising environmental remote sensing, surface modeling, and surveillance scenarios [4], [5]. This includes not only observing specific movements, but also atmospheric and geotechnical parameters [3]. However, landslide forecasting is not accurate without considering patterns of movements and reactions to climate events [2]. Optical very high resolution (VHR) data are mostly used for landslide monitoring using analytical methods or visual inspection [5], [6]. VHR images discriminate lithology's or different terrains like water content, wreathing, and vegetation cover [7], [8]. Through optical images, vegetation cover rate for landslide mapping can be achieved using NDVI i.e. Normalized difference vegetation index [9], [10]. Whereas, integration of monitoring technique ground-based Interferometric synthetic aperture radar (GBInSAR) and numerical modeling are used to detect rock fall in central Italy. GBInSAR installed system has capabilities of sense millimetric changes in displacement in any weather condition [13]. The infrared thermography part of remote sensing measures the radiant temperature of a surface from a long-distance. It gives a temperature map of the object examined in a pixel matrix for different important parameters like object emissivity, humidity, path length, and air temperature [14]. For efficient modeling of landslide inventory uses images from Planet Scope, provides global 3m every day Earth observations.

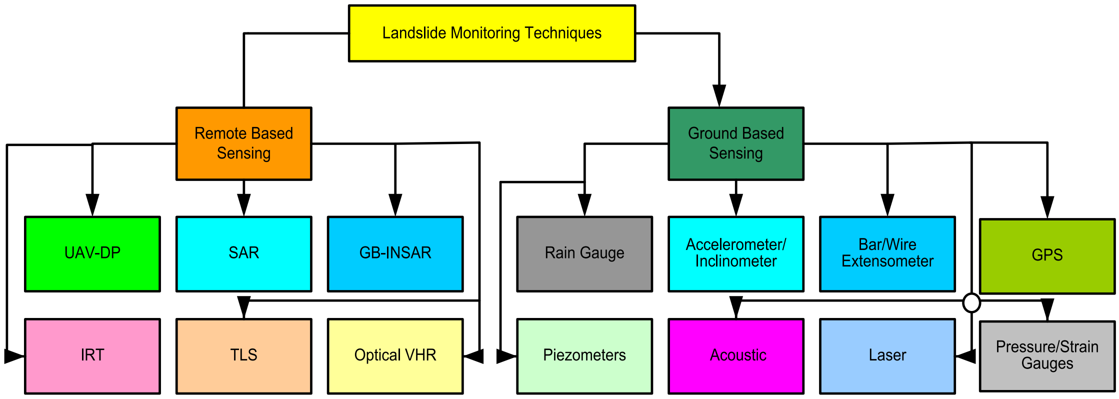


FIGURE 1. Landslide Monitoring Techniques.

To increase landslide mapping efficiency, researchers present a semi-automated framework that integrates variation observation and region-based level set evolution (RLSE) [15].

Terrestrial Laser Scanning with high resolution produced minor details like a crack pattern or opening in any structural object [16], [17]. This technique capable of monitoring 3D temporal displacement [18], soil moisture content, and type of material [19], [20]. Unmanned aerial vehicles digital photogrammetry acquired 3D geometric slopes information from photo sequence, stereoscopic overlaps captured through digital camera [21], [28]. Digital photogrammetry is useful for an activity for the far range to landslide characterization [22] and short-range precision monitoring of deformation and metrological applications [23]. Terrestrial Laser Scanning emits an in-phase electromagnetic beam [24], measure centimeter to millimeter accuracy coordinates, and provides a 3D image of an object in a short time [25], [26]. The analysis of landslide hazards requires monitoring continuous surface displacement and geomorphological locations. Methods based on Ground-based like GNSS, tachometry allow very accurate observations whereas remote sensing-based like, interferometric synthetic aperture radar (InSAR), light detection and ranging (LiDAR), satellite photogrammetry, and terrestrial allows distributed observations at high spatial resolution.

B. ROLE OF SENSORS NETWORKS WITH PHYSICAL CONTACT

The most common method for evaluating and analyzing landslide hazards is the remote sensor (RS) method [105]. Figure 2 shows the different sensors and parameters evaluated while implementation of landslide monitoring. There are different types of landslides such as debris flow, rock fall, rotational flow, and so on. In a type of debris flows carry solid materials that cause damage to properties and human life. Most of the studies focused on the monitoring of debris flow calibration using test bed but not focused on the real-time nature of debris flow. One the study shows good results by using multifunctional sensor nodes which drift with debris flow and receive information simultaneously and transmit data wirelessly to the station. The issue with this approach is to design sensor nodes column which should not break when a debris flow, deployment of nodes, cost, long term running time, and fast reaction from nodes. The authors proposed a system that comprises of two separate modules i.e. named insider a WSN (Wireless Sensor Network) fixed on the river band and another device which is coordinator node received data from the insider node. Insider device made of MSP430 microprocessor, 3-axis accelerometer ADL330 with the range of +-3g and 802.15.4 radio protocol based transceiver module i.e. CC2420. With system D cell battery is attached which provides power for forty-seven days in standby mode. Moreover, the solar panel with a rating of 4V/75mAh is also attached to the system. Mostly when the device is an inactive node there is a chance of getting the buffer register overwritten in the receiver end. To resolve that issue length of clock cycles of data transmission held high for larger cycles in comparison to data generation [28].

A complete system proposed with fifty geological sensors and twenty WSN's in Idukki, Kerala state, India. For three years rainfall, pore pressure, moisture, movement, as well as geological and hydrological data gathered to enable a better knowledge of landslides. Deep earth probe used and design according to hydrological and geological conditions, location accessibility, and terrain structure. DEPs (Deep earth probe) were tested first in pilot deployment and then in the main deployment. In pilot deployment total of ten sensors with six wireless sensors are used which is increased to twenty DEPs and twenty wireless sensor nodes in the main deployment. These DEPs installed in different six positions go from two for toe region of the hill in a different location, one in the middle region, one near to the crown of the hill, and last in the stable zone of the hill mostly in the upper part. The WSN consists of a global system for mobile communication (GSM), a general packet radio service (GPRS), broadband, wireless fidelity (Wi-Fi), and satellite network. However, this makes the WSN network costly and not possible to use in every use case of deployment. Their data shows a sudden increment in pore water pressure and soil movements between 18th July to 20th July 2009, which gives warning to peoples from Kerala state through television channels. Their

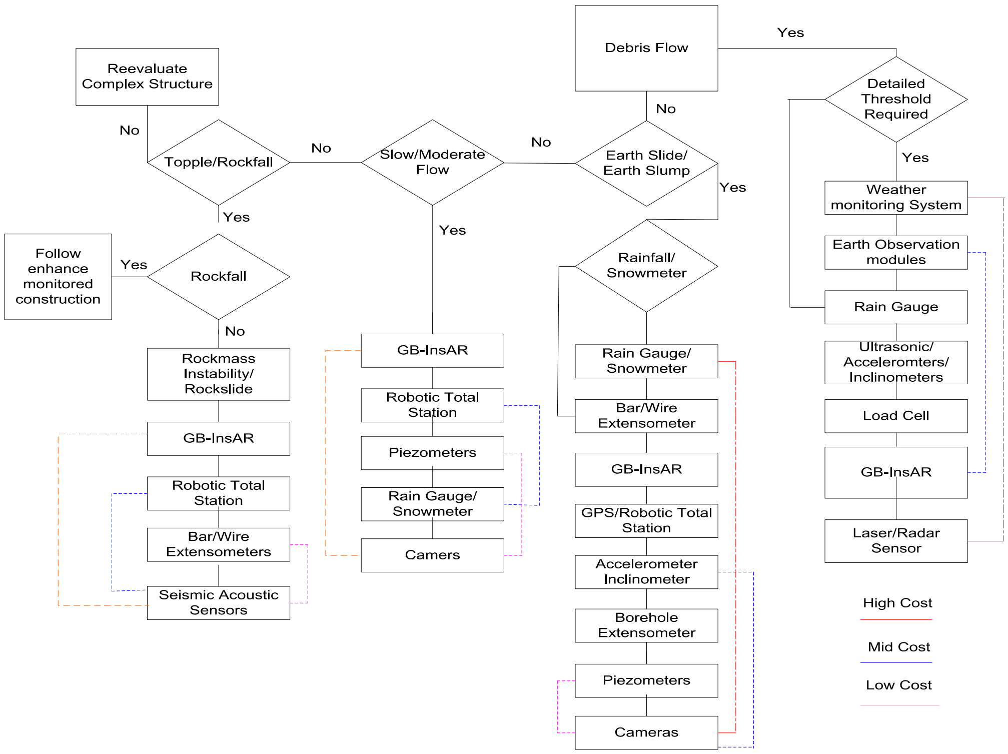


FIGURE 2. **Instrumentation Choice for Early Warning System [159].**

next step is to minimize the cost and power consumption to cover a larger area [29]. Long-term monitoring of slops and early warning facilitate road users on Simpong Pulai-Kuala Berang highway. The sensors installed in slop are not a type of electrical because they may damage by lightning. Instead in the proposed system robotic arm with a laser beam is used. It is controlled by in-house software with a data acquisition system and satellite communication system.

In another location, warnings are set to correlate with rainfall in 24 hours and slop failure. If the rain gauge records more than 100mm in 24 hours concerned authorities consultation is required [30]. Internet-enabled multiple sensor systems are used for the monitoring of landslides presented. Soil moisture sensor used to detect anomalies in pour water pressure therefore same way anomalies detected in tilt and acceleration data. Multi-sensor fusion is applied to increase the precision in analysis data. Oracle Sunspot battery-powered sensor node has an inbuilt MMA7455L 3-axis accelerometer, ARM902T processor with Texas instruments CC2420 radio transceiver written in JAVA script. VH400 soil moisture is used which takes less than 7mA of current while any operation. It is also not sensitive to water salinity and overtime does not corrode [31]. A laboratory-based test bed designed to develop and warning system through rainfall-induced landslide and found significant results to develop the study of slope failure using volumetric soil moisture sensors. Sensors respond to major changes in instability in the toe region, the creation of seepage area, and found noncircular sliding. Results show due to unknown properties, hydrologic properties, soil fabric, and soil morphology may connect with soil failures To test slope failure sandy soils named the river and residual granite soil was used which have 7.14mm and 01.75mm uniform coefficient and particle size respectively [32]. A test bed experimental setup tested using ADXL355 sensor with respect to water level filtration. Results shows 3-axis values on the cloud server with respect to weight position and water filtration in the subsequent area [49]. Measurements from MEMS tilt sensors have been incorporated with the SIGMA (Sistema Integrato Gestione Monitoraggion Allerta) model using a decisional algorithm at a test site in Darjeeling Himalayas, India, to overcome the limits of statistical rainfall threshold. As a result of integrating the tilt meter measurements into the SIGMA model, the amount of false alerts issued decreased from 70 to 38, with an improvement in the reliability index from 18.10 to 20:23 [50]. The power consumption of WSN networks in the landslide-prone area is the main concern for designers and researchers. Activities must be accurately detected, the information transferred to the server in and saving important energy of sensors nodes are the key challenges. Termed SMARTCONE is proposed to minimize energy in standby conditions to put central processing unit (CPU) and sensor in sleep mode with consumption of 0.05mA at 3.6V. Smartcone collects data about vibration, temperature, humidity, acceleration, and GPS trajectories. The Geocube is proposed with the coupling of low-cost wireless GPS and sensors to detect landslide properties

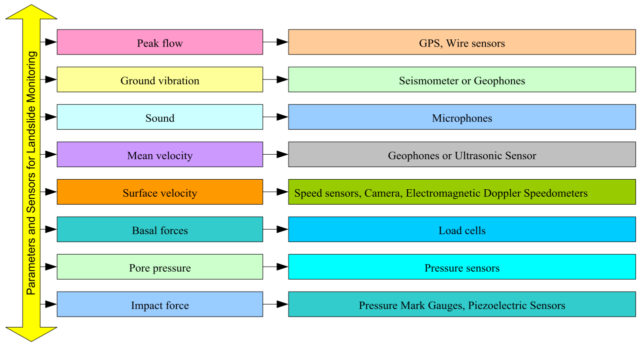


FIGURE 3. Parameter and sensors used for Landslide Monitoring [36].

like seismic waves, micro-seismicity, and slope hydrology. A small computer-based coordinator equipped with a radio node (Xbee) to communicate with Geocubes and both either wired or internet using a satellite link to communicate with long-distance computers. A total of 19 Geocube nodes were tested for 82 days. Nodes are placed on PVC tubes in the top-soil over the length of 30cm with a distance of 20m between Geocude nodes. The sensor nodes consist of wind velocity, air pressure, air humidity, air/soil temperature, wind direction, soil water content, and soil water tension setup around 60 cm underground [33]. WSN network overall cost must be less to set up for a wide area in the landslide-prone area. A low-cost solution is provided by an accelerometer to provide the displacement, inclination, and vibration data. Data transmitted to the gateway node using Zigbee and further in the server for monitoring [34]. Table 1 shows the different types of sensors used in their study to monitor landslides. As our one intention is to propose a low-cost solution for a regional location hence sensors study are covered in this section in detail. Figure 3 presented the parameters and sensors used for the landslide monitoring.

To detect ground movement ADXL202 biaxial accelerometer is used and sends to the gateway through Bluetooth. Due to Bluetooth, it covers only a 30m range (line of sight) with 40mA of current consumption during communication. This approach will be costly because of the communication link as more and more Bluetooth modules are required to cover a large area. In this scope testbed designed with silty-sand and the cohesion is 0.11Kg/cm^2 with an angle of internal friction is 39.7 degrees. Rainfall intensity is set to 30mm/hr with five sensor nodes [12]. Rockfall is another frequent hazard due to variations in temperature and perception. It destabilizing rocky slopes and civil engineers are trying to get the best result through different simulation tools. Stone node an effective low-power designed to acquire inertial measurement during falling rocks. The MEMS sensors sampled up to 1 kHz and have only battery life of up to 56h with testing more than 100 induced tests more than a heavy impact of 400g. Sensors like accelerometers, gyroscopes, and barometers are used to monitor rockfall. Rockfall simulation tools used for the trajectory probability of 3D shapes of rocks, avalanches, and debris flow [35]. Measurement of surface velocity for debris flow can be performed by using Doppler speedometers to work on measure the reflected wave frequency of moving objects. Objects can be the front side of the flow, coarse particles, surface waves, or a part of different mixtures. If the transmitter is fixed in one position then the emitted wave makes an angle concerning the moving surface. The surface velocity can be measure by [36]

$$\mathrm{V} = \mathrm{C} \times \frac{\mathrm{F_d}}{2 \times \mathrm{Cos}\theta \times \mathrm{F_0}} \tag{1}$$

$$\mathrm{F_d} = \mathrm{F_r} - \mathrm{F_0} \tag{2}$$

where C, is the radio propagation speed, F_d is the Doppler Frequency, F_0 is transmission frequency and F_r is received frequency.

In [37] early warning landslide warning system was proposed by taking into consideration of geological knowledge, kinematic characterization, risk scenario, choice of an installation monitoring system, and setting off alarms. The system consists of thirteen wire extensometer, one thermometer, one rain gauge, and three cameras at the rockslide zone of Torgiovannett, central Italy. Geological data such as an average thickness of clay layers, dip direction, tension crack, and stratigraphic layer. Extensometer is used to monitor cracks in different locations. Sensor networks set of radio processors, MICA2MPR400CB, current transducers Celesco PT8101-0020, 16 bit ADC resolution with 0.007mm, data logger, and gateway (R232-MIB 510 by Crossbow) via GPRS to server. The velocity is manually checked every day and if the value of two or more sensors exceeds more than the threshold an automatic notification is sent to the concerned. Measurement of flow rate in glaciers using accurate satellite positioning is proposed. Due to extreme weather data collection through glaciers is not easy. In the proposed system 2.4GHz Zigbee WSN created using cellular/mess architecture. The network consists of 20 on-ice GPS receiver nodes and four loggers on a rock at the side of the glacier. Moreover, systems work in the night, cloudy environment or low sunlight using solar-powered batteries [38]. A geophone is a transducer that detects and translates vibrations into an electrical signal. Since geophone reacts vertically to the axis, Geophone 3-axis should use in the system. Geophone tends to be very sensitive and self-excited sensors so proper signal conditioning like amplification and noise removal external circuitry is required. Recently MEMS technologies offers low-cost, noise-calibrated circuitry and small seize sensors. An accelerometer can be used to measure tilt in 3-axis which can replace geophones. Moreover, it is difficult to compare the results of ground measurement from geophone or accelerometer in similar coupling conditions [2]. Sensors like Accelerometer ADXL335 can detect soil movement, tilt, and vibration. ADXL335 is low power, small and conditioned output voltage sensor in the three-axis. Moreover, the performance of low-cost water proof accelerometer and methodology also available for geodynamics calibration [3].

The formula of one axis acceleration is

$$A_i = \frac{\left[\frac{X_i}{1024} \times V_{ADC} - V_i\right]}{S_i} \quad i = x, y, z \tag{3}$$

where A_i is acceleration value in X, Y and Z axis, X_i is sampling value, V_{ADC} is voltage reference value, V_i is voltage value without acceleration, S_i is sensitivity of accelerometer in i axis. The dielectric permittivity of the soil depends on the content of the water. The sensor of soil moisture can use changing resistance to measure the soil water content.

Volumetric content of the soil can be achieved by placing the sensor into the soil [70]. Soil moisture is calculated as follows

$$S_M = \frac{(V_{ADC} - T_{offset}) \times 200}{(1023 - T_{offset})} \tag{4}$$

where, S_M is soil moisture, V_{ADC} is ADC value and T_{offset} is ADC value at 0 Kpa, respectively. Physical properties of soil and water change with respect to temperature and humidity. Thus the environmental changes are the important parameters for landslide early warning systems.

Table 1 shows the researcher's choice to monitor landslide dynamics using different sensors approach or methods. Different researchers have their choice according to cost-effectiveness, coverage area, and types of wireless architecture, ground sensing elements, and low consumption modules. Figure 4 shows the deployment strategies mostly used by researchers to place the sensor in the ground and attached computing modules to PVC tubes. However, there are lots of sensors available from different manufacturers but researchers must read the whole datasheet of sensors before using it. The LM35 IC is a high-precision temperature sensor whose change in temperature linearly proportional to the output voltage. To get the temperature and humidity value DHT22 sensor is more reliable and compact. Moreover, no external calibrated circuit is required. As we can see ADXL345 MEMS sensor consumes low power in comparison to the BN0055 sensor with the same functionality as shown in Table 2.

C. ROLE OF FUZZY LOGIC AND ARTIFICIAL INTELLIGENCE

Artificial intelligence and machine learning are emerging art of analytics tools that are broadly incorporated in landslide monitoring and prevention. Authors [120] proposed fuzzy logic and the A-star algorithm to improve the routing of the WSN network and reduce the power consumption. Proposed A-star algorithms improvised by artificial intelligence to search the optimal path of the network node and maintained unbalanced energy.

The proposed work shows the improvement in WSN lifetime by 20-25%. Most of the work going to prevent landslide prevention using image analysis, susceptibility assessment, and generation of warning systems.

Related datasets to prevent landslides are mostly obtained by three sources.

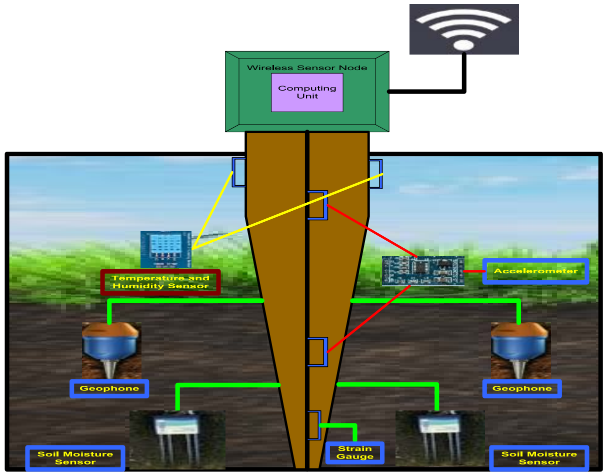


FIGURE 4. Sensor Unit Column.

1) Remote sensing data through ground-observing satellites.
2) The collection of data through on-site sensors.
3) The collection of data through fieldwork.

In the current scenario, an accurate warning system is a reasonable approach to reduce the risk and significantly minimize casualties and economic losses [105]. To prevent landslide rainfall is the most trigger value for landslides around the whole world [106]. Rainfall threshold divided into two categories: precipitation which caused landslides and precipitation which did not cause landslides and can therefore be predicted by the incidence of past landslides [107], [108]. Machine learning can help decision-making to better recognize and track risks posed by landslides.

D. RAINFALL THRESHOLD METHODS

The approximate position of Landslides cannot be predicted by a single value threshold. However, there are lots of studies are going on using mathematics models and statistics. Support vector machine widely used linear classifier for shallow landslides [109]–[111]. However, to enhance the spatiotemporal forecasting for a regional area integrated approach is required to set rainfall threshold with an assessment of landslide susceptibility. Authors in [112] proposed a hazard matrix using landslides and rainfall triggering thresholds. Hazard matrix composed of three elements (i) historical landslide data and preparation of threshold value of rainfall from rainfall intensity and duration of rainfall. (ii) for assessment of landslides, a back propagation artificial neural network (ANN) is used (iii) combination of shallow slide and rainfall threshold levels. In [108] statistical rainfall thresholds were applied after a complete assessment of landslide susceptibility using the RF model. This study enhanced the forecasting after coupling of both methodologies. Authors [106] developed combines the satellite rainfall data and surface susceptibility to provide landslide prediction using the landslide hazard assessment model (LHASA). According to the

TABLE 1. Low-cost sensors proposed in landslide early warning system.

Ref No	Temperature Sensor	Humidity Sensor	Wind Speed	Rainfall Sensor	Accelerometer	Piezometers	Rain Gauge	Extensometer	Camera	Gyroscope	Barometric Sensor	Soil humidity Sensor	Ground Vibration sensor
Phengsuwan [39]	✓	-	-	✓	-	-	-	-	-	-	-	✓	-
Dikshit [40]	-	-	-	-	✓	-	-	-	-	-	-	✓	-
Giorgetti [41]	✓		-	-	✓	-	✓	✓	-	-	-	✓	-
Ju[42]	-	-	-	-	✓	-	✓		-	-	-	✓	-
Intrieri [37]	✓	-	-	-	-	-	✓	✓	✓		-	-	-
El Moulat [43]	✓	✓	-	✓	✓	-	-	-	-	✓	-	✓	-
Honghui [44]	-	-	-	✓	-	-	-	-	-	✓	-	-	-
Ooi [45]	✓	-	-	-	✓	-	-	-	-	✓	-	-	-
Kanungo [46]	✓	✓	✓	✓	✓	✓	-	✓	-	-	-	-	-
Kebaili [47]	-	-	-	-	✓	-	-	-	-	-	-	✓	-
Hong [48]	-	-	-	✓	-	-	-	-	-	-	-	-	-
G. Chen [95]	-	-	-	-	✓	-	-	-	-	-	✓	-	-
T. Issariyakul [96]	-	-	-	-	-	-	-	-	-	-	-	-	✓
A. Varga [97]	-	✓	-	-	✓	-	-	-	-	-	✓	-	✓
A. Bounceur [98]	-	-	-	-	✓	-	-	-	-	-	-	-	✓
A. Bounceur [99]	✓	✓	✓	✓	-	-	-	-	-	-	✓	✓	-
M. Lounis [100]	-	-	-	-	✓	-	-	-	✓	-	-	-	-

TABLE 2. Power consumption details of sensors.

Type of Sensors	Functions	Working Mode	Low Power Mode	Standby	Voltage (V)		Temperature (°C)		Applications
					Min	Max	Min	Max	
BN0055	1.Gravity & Linear Acceleration 2. Gyroscope	12.3mA	0.4mA	0.04mA	2.4	3.6	-40	+85	To measure tilt and angular velocities of slop.
ADXL345	Acceleration	140µA	23µA	0.1µA	2.0	3.6	-40	+85	To measure slop changes
SHT-21	Temperature & Humidity	1.5mA	NA	50µA	3.3	6.0	-40	+80	To measure atmospheric changes
SM-24	Geophone	NA	NA	NA	NA		-40	+100	To translate ground movement to voltage

value of the model, low, moderate, and high alarms are generated. However, in most cases large amount of raw data are available or captured through sensors, it required deep learning methods to extract meaningful full features from the raw rainfall data to predict a landslide. Researchers [113] designed an unsupervised deep belief network (DBN) model to train a large amount of unlabeled data. The data set is the combination of precipitation, daily rainfall, and average yearly rainfall. The SoftMax classier was included on the top layer of DBN and stacked by RBM. There are also four layers of landslides divides according to the intensity i.e. minor, medium, large-scale, and big landslides.

E. PIXEL BASED METHODS

An image is a combination of an analytical unit of pixels, have an assigned bit value of electromagnetic energy which can be explored to detect the change without consideration of spatial context [114]. Pixels could be categorized into two types for instance as ''no landslide'' or ''landslide'' by defining pixels values in green or red bands [115]. Most of the studies compared the classification of pre and post-data sets of landslide imaginary pixels and very useful analysis to measured changes to prevent a landslide in the future. Authors [116] found better results by the ANN approach when the classification is not distributed. Support vector machine (SVM) algorithms found a better threshold value of multi-temporal images stacked spectral features [117]. Images with fine resolution i.e. one or two-meter FFNN algorithm with sigmoid transfer and one hidden layer can find better classification [118]. However, pixel-based data required parametric tuning and precise correction on geometrical data. Outliers and noise have promising effects on the accuracy of these methods [119]. However, there is a limitation of pixel-based methods as they required high imaginary resolution data set. To overcome this issue object-based image analysis has more advantages.

F. OBJECT-BASED METHODS

Object-based image analysis is another method to group structure pixels in regions for conducting the classification. OBIA (object based image analysis) allows several diagnostic of landslide features and divided into mainly following types as follows [120], [122]:

- Spectral features (Colors, Texture, Tones, Pixels values, etc.)
- Spatial features (Shape topography, Patterns, Object sizes, etc.)
- Contextual features
- Morphological parameters

Moreover, to acquired more appropriate features machine learning methods may use with OBIA in VHR imagery. The widely used machine learning algorithms include K nearest neighbor [123], Random forest [124], and support vector machine [125]. Authors applied appropriate features like slop, surface roughness [126], curvature and slop [128], and alone curvature [126], [127]. Authors [129] separated the features of the landslide from vegetated surfaces by using the K-means algorithm to find out the threshold value of NDVI (normalized difference vegetation index).

G. ROLE OF OPTICAL FIBER TECHNOLOGY

To monitor internal changes in rock and soil masses optical fiber sensing technology can be used. An optical sensing monitoring network can be created by placing optical fibers in the surface and interior of the landslide-prone area. Deformation characteristics of the internal layer of the landslide area can be perceived and captured. A fiber optic inclinometer device was established, consisting of FBG (Fiber Bragg Grating) arrays mounted along a flexible tube that could be inserted into traditional boreholes to measure the movement of subterranean layers [76]. FBG known for quasi-distributed optical fiber sensing is the most advanced optical fiber monitoring technique [89]. Bending loss, interference in light intensity, and a lifetime of optical measuring instruments issues overcome by BOTDA and BOTDR fiber sensing technology [90], [91].

III. LANDSLIDE INFORMATION TRANSMISSIONS METHODS

Landslide monitoring and particularly early warning have rapidly gained interest since catastrophic landslides around the world have repeatedly appeared. There are also several important aspects to consider in the development of a WSN for monitoring landslides.

- The ability to function for long periods in harsh environments is needed.
- Landslide monitoring is a rare occurrence that takes a very prolonged time of active monitoring. This is challenging for energy consumption.
- The WSN works in extreme conditions where there are unexpected node failures. To ensure network robustness, synchronization and routing algorithms must be error-tolerant.
- Network parameters must be managed and established remotely and independently to handle network life and event-driven mechanisms: acquisition intervals retransmit numbers allowed, sensors to be enabled, etc.

WSN's include clients, gateway, and sensor nodes. The wireless sensor node translates and converts the analog data that is gathered from the sensor into digital data to make it accessible by computer. Furthermore, it plays the purpose of forwarding this information to the gateway. The Gateway, where the measurement information collected from the sensor node transmits and processed to the final server, which links the wireless Communication Module to the server [72]. As shown in figure 2 [131] WSN networks for the Internet of Things (IoT) span in a variety of geographic ranges. RFID, NFC based on wireless personal area networks are close proximity type of communication networks. It used to communicate in short distance with low or without infrastructure. Researchers used different wireless communication technology to prevent landslides according to the infrastructure availability. In the current section different wireless communication technology and routing protocols are discussed which are used by different researchers or may help to choose in the future with this study.

In any type of disaster management system robust, deployable and secure communication network is required for pre and post-analysis of disaster. Several disaster management surveys carried out and have been discovered to be completely dependent on WSN, which is regarded as a critical component of IoT in which remotely located nodes perceive and act accordingly [92]. The label network ensures a collection of devices consists of hardware and software linked to a certain geographic area, or which enable the worldwide sharing of information and communication. A transmission network is interrupted and blocked in the event of a catastrophe strikes, and that is one of the main problems that lead to suffering for evaluation and rescue by the local communities and it has a negative effect on operations. An appropriate wireless network is indeed important for disaster avoidance, including ongoing monitoring and early disaster detection,

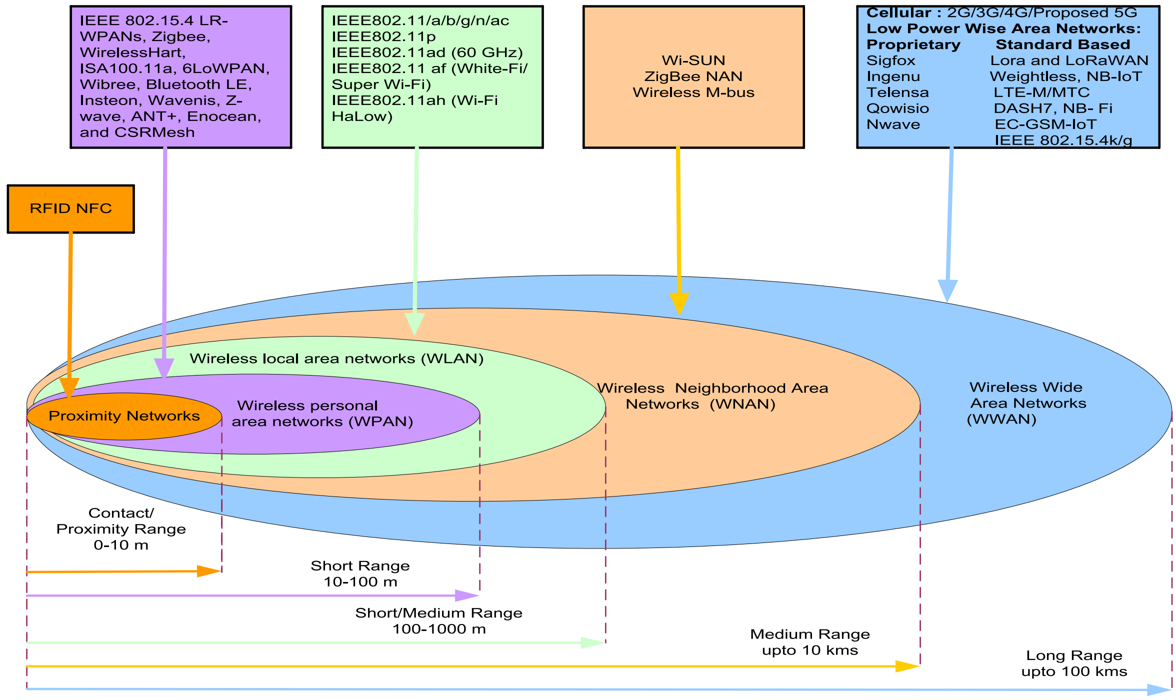


FIGURE 5. Wireless Information Transmission Coverage [140].

which will allow citizens to receive timely warning alarms. WSN network connectivity and coverage are the two most frequently available essential factors to ensure efficient management of resources. It is indeed a challenge to identify an optimal method for deploying nodes that would reduce costs, computer reduction, and overhead communication, be node failure resistant while maintaining high network connectivity coverage. Coverage and wireless connectivity networks may be viewed together in a sensor network as a quality metric representing the accuracy of the data obtained by nodes and the area. There is therefore an unprevail problem in optimizing coverage area and retention using resource-dependent nodes. A network of sensors is responsible for data collection, aggregation, and analysis of distributed data. Distributed data enable the study of landslide geographical dynamics and detect the patterns which are required for the particular landslide-prone area. For example in the one case of landslide particular pattern of pore water pressure and slope displacement could indicate the critical condition of the slope. In sensor networks, multiple hop communications can cover a wide area at a limited wiring cost. Moreover by using the IoT data can be easily provided to the researcher by implementing a server or smart application. WSN avoids physical contact between sensors and data loggers through electrical wires. This is more relevant as in steep areas human intervention is not possible. Moreover, an electrical wire can be damaged by animals or by falling some objects. Energy-efficient algorithms for sensor networks have been developed to run the system for months. In any application of disaster monitoring, a long period of monitoring is required with less cost and less intervention of humans [27]. Figure 5 shows different wireless technology can be adopted to improvise the application according to the requirement. In most of the application distributed and hierarchal WSN is used. However, in some applications, human intervention is not possible. Energy harvesting, smallest route path, larger coverage area with less power usage should be the key features of WSN's in landslide-prone areas. In this regard, the key points of different architecture study and summarize points are provided in the following Table 3. WSN installed in the slope of mount Subasto Targiovanetto, Italy for several months to test metrics like path statistics, radio link, link quality node issues, and battery level. The network coordinator works as a channel towards the internet by using GPRS. CSMA/CA at the MAC layer and TDMA at the network layer ensure low collision and synchronization between nodes increased sleep duration around 96.6% [7]. Ad-hoc Multi-hop sensor network technique is used to transfer data from one node to another node in a long distance. Sensor fusion allows verifying data between sensor signals which reduces the chances of false alarms. Moreover, sensor nodes will find signal strength independently among all nodes [69]. Rainfall-induced landslide monitoring using flexible switching between star to tree topologies in different weather conditions to make efficient transmission is proposed. The system provides a measurement of earth vibration; soil pours water pressure, moisture, and temperature, and soil movement. The data will be sent to the gateway from each node using XBee and finally, send to the server using GSM/GPRS. Switching from one topology to another topology will depend on the rain threshold level. If there is no rain or light rain start topology will be preferred otherwise tree topology. Each sensor column is made of a Waspstone board, Xbee module, temperature sensor, soil moisture sensor, and accelerometer with a lithium battery capacity of 6600mAh, and voltage of 3.7V. After test working hours of only 243.6 hours (10.15 days) from the next recharge of the battery. With the proper switching of topologies, the result shows a total working duration increased to 1.8 years. One of the sub-components of nodes i.e. data logger is fed by an electric wire which maybe not feasible to use in all cases of landslide-prone areas [70]. A WSN is defined as a self-organizing multi-hop network that monitors and controls physical phenomena [71].

A. QUALITY ASSESSMENT CRITERIA FOR NETWORKS

Quality of network can be measured by many matrices like overhead routing, packet loss ratio, packet delivery ratio, end to end delay, average throughput, and current consumption.

1) PDR

The proportion of data packets received from the destination node to the total number of packets transmitted from the source node [93].

$$PDR\,(\%) = \frac{\sum(\text{Number of Packets Recieved})}{\sum(\text{Number of Packets Sent})} \tag{5}$$

2) ROUTING OVERHEAD

The overhead routing is the maximum number of routing packets created by the routing algorithm during simulation [93].

$$\text{Routing Overhead} = \frac{\text{No. of Routing Packets}}{\text{No. of routing packets} + \text{No. of data packets}} \tag{6}$$

3) E2E DELAY

The average amount of time needed to transmit data packets successfully from origin to destination throughout the network. The E2E can be obtained by the following equation [94].

$$\text{E2E}\,(\%) = \frac{\sum \text{Arival time}}{\sum \text{Number of Packets}} \tag{7}$$

4) PLR

The proportion of the number of packets transmitted to the received data packets among the packets transmitted. PLR can be calculated by the given equation [93].

$$PLR\,(\%) = \frac{\text{Number of Packets Sent} - \text{Number of Packets Received}}{\text{Number of Packets Sent}} \times 100 \tag{8}$$

5) AVERAGE ENERGY CONSUMPTION

It is the proportion of total energy consumed by the end node within the network by the present energy. It can be obtained by the following equation [93].

$$\text{AEC} = \frac{\sum \text{Energy consumption by each node}}{\text{Network Energy}} \tag{9}$$

6) AVERAGE THROUGHPUT

The average ratio of the data packets obtained successfully for the amount of time it takes during the simulation. From the given following equation the value of Average throughput can be achieved [93].

$$\text{Average Throughput} = 8 \times \text{Simulation Time} \times \text{Number of Bytes Received} \times 1000\text{Kbps} \tag{10}$$

The majority of the research papers include a conceptual solution for landslide prevention and management based on ground monitoring sensors. Ground monitoring parameters like slope angle, soil humidity, vibration, 3-axis acceleration, and slop movement are key monitoring areas for researchers. Few researchers include a study to increase the lifetime of the network. A landslide is a long process of monitoring ground movement and environment changes so a long lifetime network is the main challenge. As a result, in order to extend the network's life expectancy, it should use efficient routing protocols. Table 3 provides the different WSN protocols used in different applications to enhance the lifetime of the network. Table 4 also provides the comparison of WSN models, methods, analysis, proposed work plan, and future directions for the landslide monitoring system.

B. IoT BASED METHODS FOR LANDSLIDES PREVENTION

In the current scenario IoT opened promising solutions to the issues related to precision agriculture, surveillance, the health sector, and industry due to light-weight, easy-to-program, flexibility, interoperability, and heterogeneity. IoT is a new technology used to link the continuum of devices and things widely and allows a host of heterogeneous objects to interact with the physical environment to be envisaged. The key IoT technologies used in landslide prevention are examined in this section. By use of IoT-based interactive monitoring warning for the prevention of Landslide produced preliminary results and had good prospects for application. There are several key elements that are included in these IoT-enabled applications. These techniques involve network sensor development, optical fiber detection technology, geospatial data transfer technology, the use of big data assessment and cloud computing, early warning models for geospatial hazards, and geo-hazard alert systems for the release of information. Authors [129] proposed data-driven IoT based framework to contribute the following advantages in the landslide monitoring systems.

- It will fill the gap of a landslide monitoring system that is provided near to real-time data and independent of the accessibility of the landslide-prone area,

extreme weather condition, workforce restrictions, and limitations.
- It improves the feasibility of available monitoring systems in terms of deployment, less cost, scalability, higher range, and precise data.
- Its supports researchers, geologists, government, and stakeholders to visualize near real-time data using IoT based state-of-the-art framework.

In [103] WSN and GPRS two-tier IoT network proposed for early warning system for landslide monitoring. The system is the compromise of a multi-node to detect corresponding physical changes from the landslide-prone area and send data of humidity, tilt angle, and temperature using low power WSN SX1212 module. Moreover, the system significantly improves the prevention, effectiveness, and management of landslide monitoring. The landslide surveillance system [104] was designed and tested through a camera sensor and IoT on near to real-time image analysis. It uses a low-cost Raspberry Pi computing unit to interface the camera using a camera serial port to perform vision-based algorithms to a monitored landslide. The android application shows the alarm notifications to stakeholders. However, there a requirement of filling of research gap using the element of machine learning or artificial intelligence in the proposed system to detect landslides.

Authors in [105] customized sensor units with independent sensing modules incorporated IoT technologies to monitor landslides. The modules collect periodically sensory data using a low duty cycle and retrieve data by Sigfox network to the server handled by the ELK stack. The device enhances the result of monitoring strategies i.e. deployment, scalability, cost, accuracy, and collection of remote raw data in long-range and near to real-time. KIGAM-LAMOS monitoring stations have been set up on 12 natural slopes in eight Korean national parks. Each station contained a variety of sensors for measuring rainfall and unsaturated soil parameters in real time, as well as data collection and transmission systems. The safety slope factor was determined using real-time rainfall data, highlighting the monitoring system's ability to detect landslide threats over time [101]. The voice response IoT (VRITHI), first IoT system to use voice and data channels for cooperative communication. In a memory-constrained context, evaluation results show that VRITHI is able to minimize external DoS attacks from 82–65 percent to less than 28 percent, and increase real-time communications as well. The green IoT energy savings are greater than 50% compared to other IoT protocols [102]. However, the efficiency of the system can be increased with the incorporation of Fog layer. Another difficulty in analyzing data gathered across IoT is too big that they are geo-related and are sparsely distributed. To deal with such a challenge, an Internet-based GIS system is required which remove the noisy data from the cloud for better prevention from landslides [73]. The sensing unit transferred data to cloud servers through the gateway node. Data reached to the cloud is further manipulated and send to the user's end or researcher's end. In this type of architecture,

FIGURE 6. Challenges of IoT based geo hazards prevention [130].

it will take more time to generate an emergency alarm as data need to travel from sensing units to the cloud and then come back to take action [74]. Fog-based IoT architecture followed two different types of implementation, the first is device-fog-cloud, and the second is fog-device. In device-fog-cloud architecture, feasible computing is achieved by fog nodes whereas complex tasks are performed by the cloud node. Whereas in fog-device, fog nodes resolved the issues thus bandwidth of the infrastructure saved and overall efficiency will be increased. As data analysis in fog performs near to IoT devices the system will be more responsive to time-sensitive data [75]. In the Landslide application, it is required to save data in the closed network so the probability of false alarm can be reduced and computed data is saved till it does not reach the cloud server. As we know, the surrounding atmosphere area of landslide monitoring is harsh and complex moreover some deployed sensor nodes might be blocked or fail to communicate due to physical damage or atmospheric interference. Higher fault tolerance is required in the case of sensor node failure [84]. Due to unattended long monitoring in harsh conditions sensor nodes work efficiently and a lifetime of the system works in limited power sources [77], [85]–[88].

In [86] proposed an efficient disaster prediction system that ensures the working of sensor nodes in working and irrespective of various possible destructive factors. Figure 6 [130] shows the reliability challenges [131]–[133] to meet the IoT solution in near to real form for complex and harsh environments. Moreover, LPWAN technologies need to be explored for this application due to less human intervention for any type of service as well as a limited power source. The study also shows the future use case challenge in landslide prevention. Table 4 shows the comparison of WSN and IoT networks used in different regions of the world in the field of landslide monitoring. As landslide monitoring is required long days of monitoring the reliability of IoT-based systems should continuously provide better service.

C. 3S & IoT

3S technology includes RS (Remote sensing), GPS (Global positing system), and geographical information systems (GIS) [135]. The combination of three technologies presents

TABLE 3. Comparison of efficient WSN architecture networks for LEWS.

Type	Key points	Architecture/Protocols
Data-Centric [51-56]	• Randomly Deployed Sensors • Power insufficient network • Not Required global clock synchronization • Not suitable for covering a large-scale area • Latency increases proportionally to the size of the network	1. **Flooding:** a) Each sensor node sends data to its neighbors. b) Implosion, overlap, and short network lifetime are the disadvantages. 2. **Gossiping:** a) Avoid implosion due to randomly send data from source to sink. b) Overlap and long propagation delay are still issue due to the random generation of the path. 3. **SPIN:** a) Relative Localization advantage b) Lack of QoS, does not guarantee data delivery from source to sink 4. **Directed Diffusion**: a) Node to node communication without any addressing mechanism. b) Less network power consumption using cache and aggregate data mechanisms. c) Not suitable for immediate reporting where generate trigger acknowledgment is a priority. 5. **Gradient Based Routing**: a) Improved version of direct diffusion and extend the lifetime of the network by 90%. b) Advantages of data diffusion and compression. 6. **Rumor Routing:** a) More energy efficient comparison to flooding. b) It establishes only one network between the source and sink and does not guarantee a successful path. 7. **Energy Aware Routing for Low Energy Ad Hoc Sensor Networks:** a) Incorporation of sub-optimal routes extends network lifetime. b) Less network lifetime due to using the same optimal path every time which creates high traffic in some nodes in comparison to less utilized nodes. 8. **Information Dissemination by negotiation:** a) Fully distributed network, high rate of data retrieval, and capability to deal with static and mobile sensors.
Hierarchical Architecture [57-62]	• Network scalability was addressed. • Power consumption is maintained with respect to a large network.	1. **LEACH**: a) It ensures even distribution of energy load among sensors using the randomized rotation of cluster heads. b) Switching overhead waste power of the network. 2. **PACT:** a) Efficient switching algorithm among cluster head. b) Lower power consumption among cluster head switching. Moreover, cluster switching is probabilistic and does not always lead to an optimal path. c) Not use power harvesting methods to increase the network lifetime. 3. **HEED**: a) Extend network lifetime comparison to PACT through residual energy of each node and intra-communication cost of cluster. b) Selection of cluster head is probabilistic. 4. **PEGASIS:** a) Creates chains of sensor node and sends transmit data to the base by only one node. b) It is power efficient and energy conserve because of the minimal cluster setup and node sleep process. c) Delay from distant nodes is the disadvantage. 5. **Hierarchical PEGASIS:** a) Improved PEGASIS architecture by decreasing the propagation delay from sensor nodes. b) Coding of CDMA in the TDMA slot can decrease the bandwidth of the channel which creates a power inefficient network. 6. **TEEN:** a) Use a hard and soft threshold to transmit data to the base station. It is complicated to say whether the sensor node is alive or not due to threshold values. b) Not useful when successive data is required in the application. This architecture sends data after reaching the point when the hard threshold (set value) and soft threshold (deviation set value) will collapse. c) APTEEN is an extension of TEEN which takes queries like historical, persistent, and network snapshots. 7. **Secure Cell Relay:** a) It is more secure than SecRout and provides security against sinkhole, hello flood, selective forwarding, and Sybil.
Location-Based Architecture [63-65]	• Enable the knowledge of sensor nodes position using routing algorithms	1. **GAF:** a) This architecture conserves energy after identifying the routing protocols which disable nodes that are not in use. b) It extends the network lifetime. c) Nodes cannot filter compressed aggregate data. 2. **SPAN:** a) Efficient algorithm to select coordinators nodes to send data from the source node to the sink node. All the nodes which are not used as coordinators are set in sleep to save energy. b) This architecture supports the sleep of as many as nodes to save energy and maintain throughout as well as seamless coordination. 3. **ALS:** a) It is a power-efficient, location-based architecture that supports routing between multiple moving and destination sources. b) It provides better results in covered space and high network density.
Quality of Service Architectures [66-68]	• Real-time data delivery approach • QoS architecture is complex to design due to high overhead maintenance.	1. **SAR:** a) one-hop neighbor creates many trees and avoids low QoS node and energy resources. b) Deals with better reliability, robustness, and latency but suffer from overhead. 2. **SPEED:** a) It is capable of sending packets from optimal paths and managing network congestions using a backpressure routing scheme. b) It provides real-time data with services like point-to-point communication, communication to all nodes, and one node representing the whole area of nodes. c) It is incorporated with Neighborhood Feedback Loop. 3. **Energy-Aware QoS Routing:** a) It provides better routing for imaging and video transmission. b) Low cost, delay constrained, and complex routing problem priority over real-time vs non-real-time data at nodes.

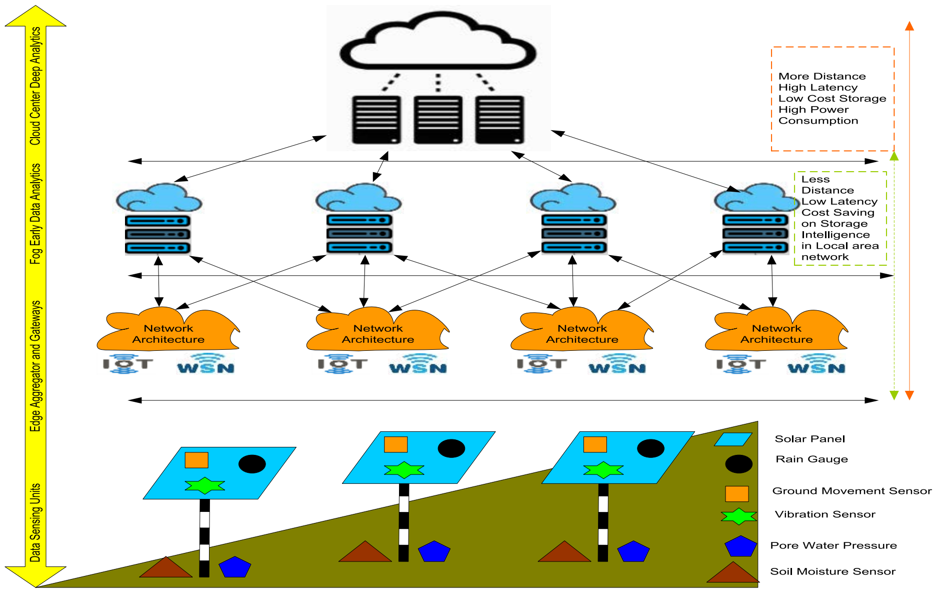


FIGURE 7. Edge-Fog-Cloud Architecture.

the future direction and challenges associated with it. RS technology collects disaster information either ground monitoring or through satellite images [136]; and precise spatial location through GPS [137] and the analysis management, and storage using GIS [138] open a new era to monitor any type of possible disaster. Moreover with the integration of IoT technology make the overall system intelligent to prevent geohazards [139], [140].

IV. IMPORTANCE OF LoRaWAN TECHNOLOGIES

Low-Power Wide Area Network (LPWAN) class offers long-range communication at low energy consumption. Due to emerging technologies, battery-powered IoT devices using LoRaWAN to communicate can run for many years even without replacement [79]. LoRaWAN is likely the most widely adopted LPWAN standards. It features simple network architecture, strategic planning, and all-embracing connectivity, which is effective for outdoor IoT applications. Lora's operation depends on bandwidth, spreading factor, and coding rate. Bandwidth is a range of frequency spectrum for data transmission. SF factor is related to chirp rate and reliability. The higher the spreading factor result indicates a low bit error rate and a lower bit rate. The coding rate shows redundant information to get a correction parameter for forwarding error [80]. Company owns the network itself, much of which has migrated to open standards such as LoRaWAN domain.

Figure 7 presented the Edge-Fog-Cloud architecture. With the random multiple access phase (RRPMA), Ingenu developed a proprietary LPWAN technology in 2.4 GHz to offer M2M industrial solutions and private networks. Ingenu has an uplink data rate, up to 624 kb/s, and downlink data rate, up to 156 kb/s, as compared to alternative solutions. On the contrary, because of the high spectrum band used, the energy consumption has increased and the range is smaller. The third generation partnership project is an enhanced narrowband IoT platform that reduced complexity and cost but extends the coverage based on GSM IoT. Figure 8 proposed physical contact ground sensing, long-range wireless communication, and vision node to monitor landslide activity. Sensor node consists of smart MEMS sensors to sense physical changes such as temperature, humidity, rainfall intensity, slope angle, ground vibration, wind speed, acoustic, etc of the monitoring area and inbuilt of low range wireless unit such as Xbee, Bluetooth, etc as per requirement. The sensor node transmits data to the coordinator node by using better protocols or architecture as surveyed in Table 2. Data transmission from the sensor node to the coordinator node must ensure better topology. Once the data received from the coordinator node data further sent to the gateway node. The gateway node is a combination of sensing different wireless logics. Gateway node made of LoRa module will cover large area and data can be sent to the base station which may far from 5 to 10 Km depending on the surrounding area. Moreover, the gateway node with a computing unit and Wi-Fi module can act as Fog layer which filtered the data further send it to the cloud server. However, a vision node is also placed on the monitoring area which records the real-time changes and will be useful to perform post analysis if somehow alarm is not triggered through the proposed system. Moreover, data captured by vision sensor is useful to apply machine learning or deep learning with the consideration of geological information which received from sensors networks. Table 5 shown different types of available LPWAN services in terms of coverage, power, battery life, operating frequency, sleep mode, etc. to incorporate in such type application i.e. landslide, flood, avalanche, or any type of disaster monitoring where human intervention is not possible frequently.

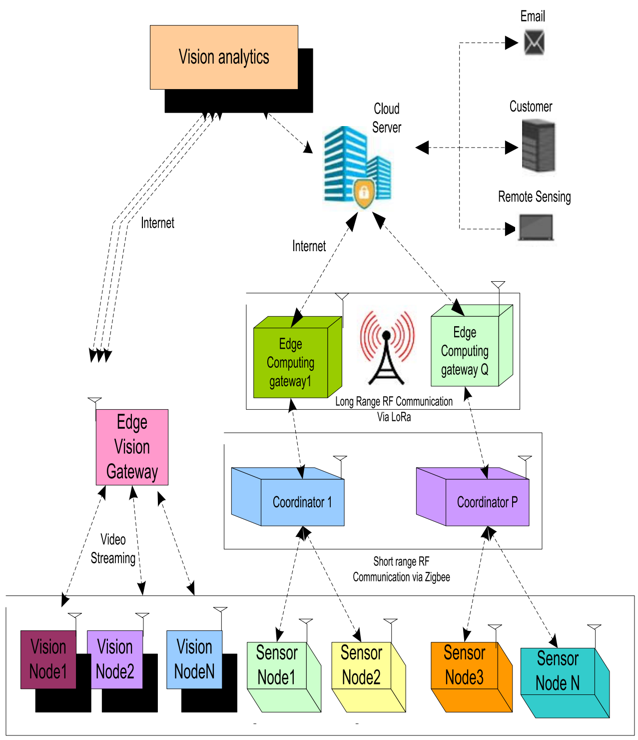


FIGURE 8. Proposed Architecture for Landslide Monitoring System.

A. WEIGHTLESS-IoT

Weightless special interest group provides open LPWAN standard technologies i.e. Weightless-N, Weightless-W, and Weightless-P. Weightless-W has been designed to operate in white TV areas (470–790 MHz), as a two-directional (uplink/downlink) solution. Although the work related to Weightless-IoT related to landslide application is not explored but potential growth acknowledges by different studies discussed in this section. Weightless-N is intended to extend the Weightless-W profile and reduce energy consumption at the cost of a decrease of data rate (from 1 Mb/s in Weightless-W to 100 kb/s in Weightless-N) (up to 10 years of life in the battery). Weightless-N is focused on the extremely narrow band, unlike Weightless-W (UNB) the technology operates and works in the UHF 800–900 MHz band. Weightless-P can operate over 169, 433, 470, 780, 868, 915, and 923 MHz provides an effective performance two-way communications solution. However, battery life for 3-8 years is more costly for power consumption and terminals than for Weightless N [82].

B. SIGFOX

SigFox follows the model subscriber-driven and defined network in two layers as shown in such as SigFox support system and network equipment. Sigfox support system is responsible to receive the message from the network and provide it to the public internet whereas network equipment is made of base stations and antennae. To cover a large area SigFox has big potential to use as different researches tested the range of 63 km [141], while [142]–[144] claims the range of 50 km and [145] claims the range of 40 km. SigFox's cloud limits the four downlink messages and six uplink messages per day [146]. These policies are used to limit the load scalability of networks. Moreover in terms of security SigFox system utilizes a Virtual private network for backhauling. This ensures its support system is more secure in comparison to air interference.

C. NB-Fi

NB-Fi is not a standalone protocol but it is comprised of OSI (Open system interconnect) layers developed by the NB-Fi alliance and with the help of an organization called WAVIoT. WAVIoT amid similar or other parties to manu-facture custom protocol devices while the NB-Fi alliance will issue annual licenses for the production of devices. NB-Fi devices are easy to use and connect with a base station using GPRS, Ethernet, and satellite to server [147]. Moreover, NB-Fi base access points use edge computations and perform a considerable quantity of internally processed data. This helps NB-Fi to run during interruptions also which is very useful in such type of application [147]. WAVIoT provides three types of deployment methods especially for NB-Fi LPWANs [148].

- Large telecom companies are given access to public networks, which can span an entire state or country. Numerous cellular base stations can be found here.
- Private networks are manufactured for small organizations and have coverage of the limited area, using multi-cell.
- Corporation networks are being marketed into the simplest cases, covering a smaller area with a one "mini gateway."

NB-Fi devices have adjusted transmission power to 27,16 or 14dBm but according to NB -Fi alliance site claims link budget can be extended to 174dB. As we know to increase the transmission power with increase the link budget and hence the power consumption will also increase. In [149] researcher claim to communicate NB-Fi devices to the base station in an urban environment with a range of 16.6 km. It has also shown the latency of thirty seconds in uplink whereas latency of sixty seconds found in the downlink.

V. DISCUSSION AND RECOMMENDATIONS

We found that the environment, geological behavior, land use structure, rainfall intensity, and type of landslide characteristics are different in regional to the regional level. Therefore, low cost and long coverage areas are demanding solutions in the current scenario to implement a landslide monitoring system for a particular regional level. However, the implementation of the overall system is challenging in the following cases:

A. DEPLOYMENT OF SENSOR NODES

System design should be robust as trees, natural obstructions, or placement of system may be inclined in such type of

TABLE 4. Comparison of WSN and IoT for landslide monitoring.

Ref No.	Region	Methods	Network	Analysis	Proposed Work	Future Directions
33	Super Sauze (France)	Sensor-based network monitoring	Ad-hoc	Accelerometer, barometric pressure, and tilting	Prototype for data collection, analysis, and investigation	Lack of structured warning management
34	Nusa Tenggara (Indonesia)	Vibration sensors	Ad-hoc	Ground vibration measurement	Prototype to measure vibration caused by ground movements	No warning system to the public
29	Kerala (India)	Energy optimization algorithms	Heteroge neous network	Moisture, Pore pressure, acceleration, and rainfall	Detailed analysis of energy-saving and data reduction for effective landslide detection	Worst Environmental changes reduce network efficiency
101	Korea	Low coverage communication (Bluetooth)	WSN	Acceleration, ground vibration, slop angle	Prototype for landslide detection using the test bed	Low battery life and lack of alarm management.
37	Torgiovannett o (Italy)	Even driven mechanism	WSN	Stain, wind speed, tensile, rainfall, temperature, moisture, humidity	Proposed efficient network for fault-tolerant, self-organizing, low link quality, and low battery consumption.	Real-time deployment challenges are missing.
102	Test Bed Experiment	Low area coverage using Zigbee and low power camera sensor.	Heteroge neous network	Image compression, object detection, slop movement, sleep schedule	Two-layer heterogeneous network to test anomaly changes and inter-layer validation.	The prototype supports laboratory experiments. Lacks scalability in harsh environments.
103	Test Bed Experiment	Multiple network assistance designed with GPRS and WSN	WSN	Humidity, displacement, and slope angle.	Long area coverage and less power consumption.	Lacks in the incorporation of energy-efficient routing protocols.
104	Test Bed Experiment	Camera sensor	IoT	Camera sensor, raspberry pi, Android App	Capturing video transmission and detect landslides using vision-based algorithms.	A large amount of data storage is required and may improve efficiency using AI.

application. In the case of landslide monitoring application mobility of sensors is not required but placement in the right position plays an important role in inaccuracy. Calibration of sensors may require periodically for cases like soil probe moisture sensor. Moreover, battery replacement should be minimized as sensors are placed in landslide-prone areas or very remotely. However, the location may have no grid electricity so energy harvesting is required in terms of using low power module, solar energy, and using efficient wireless communication protocol to save energy in edge node. Some significant variations are also measured in warning systems using tilting sensors due to animal or human intervention. The installation of the system should also be monitored by the officials to minimize the incidence of false alarms [58].

B. REQUIREMENT OF IoT ARCHITECTURE

In Landslide prone areas connectivity between IoT nodes and the cloud is more vulnerable to loss due to no network area or high latency. This dependency can make delays in real-time decisions. Edge and fog computing plays an important role in generating an alarm in real-time to enhance the reliability of early warning systems. Data forwarded to the cloud is filtered by the fog layer. However, the security of data is still a major challenge. Moreover, the edge node will be sensitive to a critical threshold value and should able to give a response if cloud infrastructure is disconnected for a long duration.

C. LONG-RANGE CONNECTIVITY

Wi-Fi consumes a significant amount of energy but has reduced ownership costs overall. It provides Internet access using minimum resources of hardware or software. Mesh protocol BLE devices offer better alternatives not suitable for areas where human intervention is not easily possible, and therefore especially for landslide-prone areas. Furthermore, applications associated with the system installed in disaster areas are in off-grid areas with limited access to the internet network. From Table 5 LPWAN technology such as LoRa, SigFox, Weightless-IoT, etc. promises wide-area connectivity with low consumption, but a rational solution is still challenging in this area.

D. ON FIELD IMPLEMENTATION

Pre-alerting duration required real-time data collection, manipulation, and communication. Real results analysis cannot be dependent on only simulation platforms but rather tests are required in the field area for accurate monitoring. Any methodology should not suffer from approximations modeling like numerical or empirical. For better understating,

TABLE 5. Different LPWAN's technologies comparative analysis [83].

Technology	Range in KM (Urban, Rural)	Packet Size	Modulation	Downlink Communication	Duplexing	Operating Frequencies	Encryption	Sleep mode	Transmission (), Tx, Rx Power()	Battery Life
LoRaWAN	5,18	19-250 Bytes	LoRa C-SS	Yes	HD C-SS	433/868/780/ 915 MHz ISM	AES-128	1µA	14-27 dBm 28 10.5	10Years (3.6V lithium AA-cell)
SigFox	10, 50	12 Bytes UL, 8 Bytes DL	DBFSK(Uplink) GFSK(Downlink)	Very Limited	Limited HD	Between 865-924 MHz	Optional AES-128	6nA	14-12 dBm 10-50 mA 10 mA	10 Years (9V Battery)
LTE-M	<11, 11	up <1 Mbps, down < 1 Mbps	BPSK,QPSK,16QAM, 64QAM	Yes	FD,HD FDD,TDD	LTE Licensed	3GPP 128-256 bit	8 µA	20dBm 300mA 53.33mA	10 Year (5Wh Battery)
NB-IoT	<100,100	200 kbps	QPSK	Yes	HD FDD	LTE Licensed	3GPP 128-256 bit	3 µA	20-23 dBm 74-220mA 46mA	10 Year (5Wh Battery)
Wightless-P	2 to 5, 25	5-260 Bytes (GMSK) 131-514 Bytes (OQPSK)	GMSK, offset-QPSK	Yes	HD	Sub -GHz ISM	AES-128 AES - 256	<4 µA	15 dBm 49mA 13mA	3-8 (Coin Cell)
NB-Fi	10, 30	Unknown	DBPSK	Yes	Full Duplex	433/868.8/915 MHz ISM	XTEA-256	1.5 µA	14-27dBm 44mA 12mA	20 Years (AA-cell)
DASH7	2 KM	0-256 Bytes	2-GFSK	Yes	Half Duplex	433/868/915 MHz ISM	AES-128	1-2 µA	10 dBm 29.2mA 15mA	10 Years (Coin Cell or thin-film)
EC-GSM	<15,15	Unknown	GMSK, 8PSK	Yes	HD FDD	GSM Licensed	3GPP 128-256 bit	10 µA	23 or 33 dBm 123,1228 mA 66 mA	10-14 years (5Wh battery)

for landslide dynamics, model-based simulation, as well as long-term field monitoring, is required.

E. VISION NODE

Nowadays with the implementation of low-cost vision-enabled computing nodes such as Raspberry Pi can be useful to capture real-time video. The camera sensor is important and can be useful to detect two instances such as to detect the changes in real-time or to do past analysis if the deployed system not works as per expectation and to record if any untouched feature which is ignored while designing the system. Moreover, machine learning on the image data sets also can be applied as discussed in this paper earlier. Authors [116] found better results by the ANN approach when the classification is not distributed. SVM algorithms found a better threshold value of multi-temporal images stacked spectral features [117].

F. ARTIFICIAL INTELLIGENCE

On the cloud server, acquisition technology provides a large amount of sensor data. The perspectives can however be compiled and analyzed by using algorithms like deep learning and machine learning. Moreover, researchers and government entities should collaborative the data sets of the testes regional area with all geological information so other entities can use those data sets and train their machine learning models. Authors [120] proposed fuzzy logic and the A-star algorithm to improve the routing of the WSN network and reduce the power consumption.

VI. CONCLUSION AND FUTURE WORKS

The confluence of a rapidly increasing global population and rising extreme climate as a result of recent climate change indicates a significant increase in the risk of landslides in the near future. Deformation of the landslide can be very slow (few mm per year) and sometimes even suddenly very fast. This study reveals the types of techniques available to monitor landslides and shows the ways to implement the landslide monitoring systems according to cost-effectiveness. The precise result can be achieved by the incorporation of both techniques i.e. remote sensing and ground-based monitoring but in such way cost of the system will be increased significantly. This paper shows the approach of different landslide monitoring systems implemented through sensors and a robust wireless network. We found that for small area landslide monitoring can be implemented through smart sensors and wireless networks and make a low cost-effective device for mankind. One of the challenges facing sensor network deployment is to minimize energy consumption in sensor nodes via the use of appropriate energy-saving architecture or algorithms. Furthermore, using embedded-based machine learning edge processing, major probability can investigate ways to extend the network or battery lifetime. Another key challenge of the landslide monitoring system is to make it more collaborative and flexible. The use of enabling technologies standalone makes a lower impact comparison to working together makes a high impact. Moreover, some abrupt changes are also recorded in early warning systems using tilt sensors due to animal or human interference. Thus the deployment of the system should be monitored by authorities to reduce the chances of false alarm. In this paper, a general probable architecture also proposed shows the low latency result using edge, fog, and IoT layer. Eventually, appropriate connectivity, a prolonged deployment of real-time sensor networks, a computer vision node, the integration of deep learning and machine learning, and power conversion are among the key recommendations included and discussed in this study to ensure proper implementation.

REFERENCES

[1] G. J. Dick, E. Eberhardt, A. G. Cabrejo-Liévano, D. Stead, and N. D. Rose, ''Development of an early-warning time-of-failure analysis methodology for open-pit mine slopes utilizing ground-based slope stability radar monitoring data,'' *Can. Geotechnical J.*, vol. 52, no. 4, pp. 515–529, Apr. 2015, doi: 10.1139/cgj-2014-0028.

[2] M. Angeli, A. Pasuto, and S. Silvano, ''A critical review of landslide monitoring experiences,'' *Eng. Geology*, vol. 55, no. 3, pp. 133–147, 2000, doi: 10.1016/S0013-7952(99)00122-2.

[3] S. Uhlemann, ''Assessment of ground-based monitoring techniques applied to landslide investigations,'' *Geomorphology*, vol. 253, pp. 438–451, Jan. 2016, doi: 10.1016/j.geomorph.2015.10.027.

[4] I. Colomina and P. Molina, ''Unmanned aerial systems for photogrammetry and remote sensing: A review,'' *ISPRS J. Photogram. Remote Sens.*, vol. 92, pp. 79–97, Jun. 2014, doi: 10.1016/j.isprsjprs.2014.02.013.

[5] M. R. James and S. Robson, ''Straightforward reconstruction of 3D surfaces and topography with a camera: Accuracy and geoscience application,'' *J. Geophys. Res., Earth Surf.*, vol. 117, p. F3, Sep. 2012, doi: 10.1029/2011JF002289.

[6] G. Metternicht, L. Hurni, and R. Gogu, ''Remote sensing of landslides: An analysis of the potential contribution to geo-spatial systems for hazard assessment in mountainous environments,'' *Remote Sens. Environ.*, vol. 98, nos. 2–3, pp. 284–303, Oct. 2005, doi: 10.1016/j.rse.2005.08.004.

[7] A. L. Parker, J. Biggs, and Z. Lu, ''Investigating long-term subsidence at medicine lake volcano, CA, using multitemporal InSAR,'' *Geophys. J. Int.*, vol. 199, no. 2, pp. 844–859, Nov. 2014, doi: 10.1093/gji/ggu304.

[8] F. Bardi, ''Integration between ground based and satellite SAR data in landslide mapping: The San Fratello case study,'' *Geomorphology*, vol. 223, pp. 45–60, Oct. 2014, doi: 10.1016/j.geomorph.2014.06.025.

[9] T. Lamri, S. Djemaï, M. Hamoudi, B. Zoheir, A. Bendaoud, K. Ouzegane, and M. Amara, ''Satellite imagery and airborne geophysics for geologic mapping of the Edembo area, Eastern Hoggar (Algerian Sahara),'' *J. Afr. Earth Sci.*, vol. 115, pp. 143–158, Mar. 2016, doi: 10.1016/j.jafrearsci.2015.12.008.

[10] C.-Y. Lin, H.-M. Lo, W.-C. Chou, and W.-T. Lin, ''Vegetation recovery assessment at the Jou-Jou Mountain landslide area caused by the 921 Earthquake in Central Taiwan,'' *Ecol. Model.*, vol. 176, nos. 1–2, pp. 75–81, Aug. 2004, doi: 10.1016/j.ecolmodel.2003.12.037.

[11] R. Bürgmann, P. A. Rosen, and E. J. Fielding, ''Synthetic aperture radar interferometry to measure Earth's surface topography and its deformation,'' *Annu. Rev. Earth Planetary Sci.*, vol. 28, no. 1, pp. 169–209, 2000, doi: 10.1146/annurev.earth.28.1.169.

[12] X. Liu, C. Zhao, Q. Zhang, Y. Yin, Z. Lu, S. Samsonov, C. Yang, M. Wang, and R. Tomás, ''Three-dimensional and long-term landslide displacement estimation by fusing C- and L-band SAR observations: A case study in Gongjue County, Tibet, China,'' *Remote Sens. Environ.*, vol. 267, Dec. 2021, Art. no. 112745.

[13] M. Barla and F. Antolini, ''An integrated methodology for landslides' early warning systems,'' *Landslides*, vol. 13, no. 2, pp. 215–228, 2016, doi: 10.1007/s10346-015-0563-8.

[14] L. Spampinato, S. Calvari, C. Oppenheimer, and E. Boschi, ''Volcano surveillance using infrared cameras,'' *Earth-Sci. Rev.*, vol. 106, nos. 1–2, pp. 63–91, May 2011, doi: 10.1016/j.earscirev.2011.01.003.

[15] P. Lu, W. Shi, Z. Li, and Y. Qin, ''Landslide mapping from PlanetScope images using improved region-based level set evolution,'' *IEEE Geosci. Remote Sens. Lett.*, early access, Oct. 26, 2021, doi: 10.1109/LGRS.2021.3122964.

[16] F. Ardizzone, G. Basile, M. Cardinali, N. Casagli, S. Del Conte, C. Del Ventisette, F. Fiorucci, F. Garfagnoli, G. Gigli, F. Guzzetti, G. Iovine, A. C. Mondini, S. Moretti, M. Panebianco, F. Raspini, P. Reichenbach, M. Rossi, L. Tanteri, and O. Terranova, ''Landslide inventory map for the Briga and the Giampilieri catchments, NE Sicily, Italy,'' *J. Maps*, vol. 8, no. 2, pp. 176–180, Jun. 2012, doi: 10.1080/17445647.2012.694271.

[17] G. Gigli, ''Brief communication 'Analysis of deformations in historic urban areas using terrestrial laser scanning,''' *Natural Hazards Earth Syst. Sci.* vol. 9, no. 6, p. 1759, 2009, doi: 10.5194/nhess-9-1759-2009.

[18] A. Abellán, J. M. Vilaplana, J. Calvet, D. García-Sellés, and E. Asensio, ''Rockfall monitoring by terrestrial laser scanning–case study of the basaltic rock face at Castellfollit de la Roca (Catalonia, Spain),'' *Natural Hazards Earth Syst. Sci.*, vol. 11, no. 3, pp. 829–841, Mar. 2011, doi: 10.5194/nhess-11-829-2011.

[19] M. Franceschi, G. Teza, N. Preto, A. Pesci, A. Galgaro, and S. Girardi, ''Discrimination between marls and limestones using intensity data from terrestrial laser scanner,'' *ISPRS J. Photogramm. Remote Sens.*, vol. 64, no. 6, pp. 522–528, Nov. 2009, doi: 10.1016/j.isprsjprs.2009.03.003.

[20] M. Sturzenegger and D. Stead, ''Quantifying discontinuity orientation and persistence on high mountain rock slopes and large landslides using terrestrial remote sensing techniques,'' *Natural Hazards Earth Syst. Sci.*, vol. 9, no. 2, pp. 267–287, Mar. 2009, doi: 10.5194/nhess-9-267-2009.

[21] Z. Zhang, S. Zheng, and Z. Zhan, ''Digital terrestrial photogrammetry with photo total station,'' in *Proc. Int. Arch. Photogramm. Remote Sens.*, Istanbul, Turkey, 2004, pp. 232–236.

[22] A. Wolter, D. Stead, and J. J. Clague, ''A morphologic characterisation of the 1963 vajont slide, italy, using long-range terrestrial photogrammetry,'' *Geomorphology*, vol. 206, pp. 147–164, Feb. 2014, doi: 10.1016/j.geomorph.2013.10.006.

[23] M. Scaioni, ''Close-range photogrammetric techniques for deformation measurement: Applications to landslides,'' in *Modern Technologies for Landslide Monitoring and Prediction*. Berlin, Germany: Springer, 2015, pp. 13–41, doi: 10.1007/978-3-662-45931-7_2.

[24] M. Jaboyedoff, T. Oppikofer, A. Abellán, M.-H. Derron, A. Loye, R. Metzger, and A. Pedrazzini, ''Use of LIDAR in landslide investigations: A review,'' *Natural Hazards*, vol. 61, no. 1, pp. 5–28, Mar. 2012, doi: 10.1007/s11069-010-9634-2.

[25] D. Tapete, S. Morelli, R. Fanti, and N. Casagli, ''Localising deformation along the elevation of linear structures: An experiment with space-borne InSAR and RTK GPS on the Roman aqueducts in Rome, Italy,'' *Appl. Geography*, vol. 58, pp. 65–83, Mar. 2015, doi: 10.1016/j.apgeog.2015.01.009.

[26] V. Pazzi, ''Testing cost-effective methodologies for flood and seismic vulnerability assessment in communities of developing countries (Dajç, northern Albania),'' *Geomatics, Natural Hazards Risk*, vol. 7, no. 3, pp. 971–999, 2016.

[27] A. Rosi, M. Berti, N. Bicocchi, G. Castelli, A. Corsini, M. Mamei, and F. Zambonelli, ''Landslide monitoring with sensor networks: Experiences and lessons learnt from a real-world deployment,'' *Int. J. Sensor Netw.*, vol. 10, no. 3, pp. 111–122, 2011.

[28] H. Lee, A. Banerjee, Y. Fang, B. Lee, and C. King, ''Design of a multifunctional wireless sensor for *in-situ* monitoring of debris flows,'' *IEEE Trans. Instrum. Meas.*, vol. 59, no. 11, pp. 2958–2967, May 2010, doi: 10.1109/TIM.2010.2046361.

[29] M. Ramesh, ''Design, development, and deployment of a wireless sensor network for detection of landslides,'' *Ad Hoc Netw.*, vol. 13, pp. 2–18, May 2014,Ä doi: 10.1016/j.adhoc.2012.09.002.

[30] W. H. Fung, R. J. Kinsil, S. Jamaludin, and S. Krishnan, ''Early warning and real-time slope monitoring systems in West and East Malaysia,'' in *Landslide Science for a Safer Geoenvironment*. Cham, Switzerland: Springer, 2014, pp. 569–575, doi: 10.1007/978-3-319-05050-8_88.

[31] K. Smarsly, K. Georgieva, and M. König, "An internet-enabled wireless multi-sensor system for continuous monitoring of landslide processes," *Int. J. Eng. Technol.*, vol. 6, no. 6, pp. 520–529, Dec. 2014, doi: 10.7763/IJET.2014.V6.752.
[32] A. Tohari, M. Nishigaki, and M. Komatsu, "Laboratory rainfall-induced slope failure with moisture content measurement," *J. Geotech. Geoenviron. Eng.*, vol. 133, no. 5, pp. 575–587, May 2007.
[33] L. Benoit, P. Briole, O. Martin, C. Thom, J. P. Malet, and P. Ulrich, "Monitoring landslide displacements with the Geocube wireless network of low-cost GPS," *Eng. Geol.*, vol. 195, pp. 111–121, Oct. 2015, doi: 10.1016/j.enggeo.2015.05.020.
[34] D. Tran, D. Nguyen, and S. Tran, "Development of a rainfall-triggered landslide system using wireless accelerometer network," *Int. J. Adv. Comput. Technol.*, vol. 7, no. 5, p. 14, 2015.
[35] G. Caviezel, A. Schaffner, M. Cavigelli, and L. Niklaus, "Design and evaluation of a low-power sensor device for induced rockfall experiments," *IEEE Trans. Instrum. Meas.*, vol. 67, no. 4, pp. 767–779, Nov. 2017, doi: 10.1109/TIM.2017.2770799.
[36] M. Arattano and L. Marchi, "Systems and sensors for debris-flow monitoring and warning," *Sensors*, vol. 8, no. 4, pp. 2436–2452, Apr. 2008, doi: 10.3390/s8042436.
[37] E. Intrieri, G. Gigli, F. Mugnai, R. Fanti, and N. Casagli, "Design and implementation of a landslide early warning system," *Eng. Geol.*, vol. 147, pp. 124–136, May 2012, doi: 10.1016/j.enggeo.2012.07.017.
[38] I. Martin, T. O'Farrell, R. Aspey, S. Edwards, T. James, P. Loskot, T. Murray, I. Rutt, N. Selmes, and T. Bauge, "A high-resolution sensor network for monitoring glacier dynamics," *IEEE Sensors J.*, vol. 14, no. 11, pp. 3926–3931, Nov. 2014, doi: 10.1109/JSEN.2014.2348534.
[39] J. Phengsuwan, T. Shah, P. James, D. Thakker, S. Barr, and R. Ranjan, "Ontology-based discovery of time-series data sources for landslide early warning system," *Computing*, vol. 102, no. 3, pp. 745–763, Mar. 2020, doi: 10.1007/s00607-019-00730-7.
[40] A. Dikshit, D. N. Satyam, and I. Towhata, "Early warning system using tilt sensors in Chibo, Kalimpong, Darjeeling Himalayas, India," *Natural Hazards* vol. 94, no. 2, pp. 727–741, 2018, doi: 10.1007/s11069-018-3417-6.
[41] A. Giorgetti, "A robust wireless sensor network for landslide risk analysis: System design, deployment, and field testing," *IEEE Sensors J.*, vol. 16, no. 16, pp. 6374–6386, Aug. 2016, doi: 10.1109/JSEN.2016.2579263.
[42] N.-P. Ju, J. Huang, R.-Q. Huang, C.-Y. He, and Y.-R. Li, "A real-time monitoring and early warning system for landslides in southwest China," *J. Mountain Sci.*, vol. 12, no. 5, pp. 1219–1228, Sep. 2015, doi: 10.1007/s11629-014-3307-7.
[43] M. El Moulat, O. Debauche, S. Mahmoudi, L. A. Brahim, P. Manneback, and F. Lebeau, "Monitoring system using Internet of Things for potential landslides," *Proc. Comput. Sci.*, vol. 134, pp. 26–34, Aug. 2018, doi: 10.1016/j.procs.2018.07.140.
[44] H. Wang, T. Xianguo, L. Yan, L. Qi, and N. Donglin, "Research of the hardware architecture of the geohazards monitoring and early warning system based on the IoT," in *Proc. Comput. Sci.*, vol. 107, pp. 111–116, Jan. 2017, doi: 10.1016/j.procs.2017.03.065.
[45] G. L. Ooi, P. S. Tan, M.-L. Lin, K.-L. Wang, Q. Zhang, and Y.-H. Wang, "Near real-time landslide monitoring with the smart soil particles," *Jpn. Geotech. Soc.*, vol. 2, no. 28, pp. 1031–1034, Jan. 2016, doi: 10.3208/jgssp.HKG-05.
[46] D. Kanungo, "Ground based real time monitoring system using wireless instrumentation for landslide prediction," in *Landslides: Theory, Practice and Modelling*. Cham, Switzerland: Springer, 2019, pp. 105–120, doi: 10.1007/978-3-319-77377-3_6.
[47] M. O. Kebaili, K. Foughali, K. FathAllah, A. Frihida, T. Ezzeddine, and C. Claramunt, "Landsliding early warning prototype using MongoDB and web of things technologies," *Proc. Comput. Sci.*, vol. 98, pp. 578–583, Oct. 2016, doi: 10.1016/j.procs.2016.09.090.
[48] Y. A. N. G. Hong and R. F. Adler, "Towards an early warning system for global landslides triggered by rainfall and earthquake," *Int. J. Remote Sens.* vol. 28, no. 16, pp. 3713–3719, 2007, doi: 10.1080/01431160701311242.
[49] S. Bagwari, A. Gehlot, R. Singh, and A. Thakur, "Rainfall induced landslide monitoring system," *Int. J. Eng. Appl.*, vol. 9, no. 1, pp. 19–30, 2021, doi: 10.15866/irea.v9i1.19543.
[50] M. T. Abraham, N. Satyam, B. Pradhan, S. Segoni, and A. Alamri, "Developing a prototype landslide early warning system for Darjeeling Himalayas using SIGMA model and real-time field monitoring," *Geosci. J.*, vol. 4, pp. 1–13, Oct. 2021, doi: 10.1007/s12303-021-0026-2.
[51] C. Schurgers and M. B. Srivastava, "Energy efficient routing in wireless sensor networks," *Proc. Commun. Netw.-Centric Oper., Creating Inf. Force*. vol. 1, Apr. 2001, pp. 1–5, doi: 10.1109/MILCOM.2001.985819.
[52] D. Braginsky and D. Estrin, "Rumor routing algorithm for sensor networks," in *Proc. 1st ACM Int. workshop Wireless sensor Netw. Appl.*, Atlanta, GA, USA, 2002, pp. 22–31, doi: 10.1145/570738.570742.
[53] R. C. Shah and J. M. Rabaey, "Energy aware routing for low energy ad hoc sensor networks," in *Proc. IEEE Wireless Commun. Netw. Conf. Rec.*, Mar. 2002, pp. 350–355, doi: 10.1109/WCNC.2002.993520.
[54] Y. Yao and J. Gehrke, "The cougar approach to in-network query processing in sensor networks," *ACM SIGMOD Rec.*, vol. 31, no. 3, pp. 9–18, 2002, doi: 10.1145/601858.601861.
[55] N. Sadagopan, B. Krishnamachari, and A. Helmy, "The ACQUIRE mechanism for efficient querying in sensor networks," in *Proc. 1st IEEE Int. Workshop Sensor Netw. Protocols Appl.*, May 2003, pp. 149–155, doi: 10.1109/SNPA.2003.1203365.
[56] D. Liu, X. Hu, and X. Jia, "Energy efficient information dissemination protocols by negotiation for wireless sensor networks," *Comput. Commun.*, vol. 29, no. 11, pp. 2136–2149, Jul. 2006, doi: 10.1016/j.comcom.2006.01.008.
[57] W. B. Heinzelman, A. P. Chandrakasan, and H. Balakrishnan, "An application-specific protocol architecture for wireless microsensor networks," *IEEE Trans. Wireless Commun.*, vol. 1, no. 4, pp. 660–670, Oct. 2002, doi: 10.1109/TWC.2002.804190.
[58] Pei, Guangyu, and Charles Chien, "Low power TDMA in large wireless sensor networks," in *Proc. Commun. Netw.-Centric Oper., Creating Inf. Force*. vol. 1, Oct. 2001, pp. 347–351, doi: 10.1109/MILCOM.2001.985817.
[59] O. Younis and S. Fahmy, "HEED: A hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks," *IEEE Trans. Mobile Comput.*, vol. 3, no. 4, pp. 366–379, Oct./Dec. 2004, doi: 10.1109/TMC.2004.41.
[60] Lindsey, Stephanie, and Cauligi S. Raghavendra, "PEGASIS: Power-efficient gathering in sensor information systems," in *Proc. IEEE Aerosp. Conf.*, vol. 3, Mar. 2002, pp. 1–3, doi: 10.1109/AERO.2002.1035242.
[61] Manjeshwar, Arati, and Dharma P. Agrawal, "TEEN: Arouting protocol for enhanced efficiency in wireless sensor networks," in *Proc. IPDPS*, vol. 1, 2001, pp. 1–5, doi: 10.1109/IPDPS.2001.925197.
[62] X. Du, Y. Xiao, H. H. Chen, and Q. Wu, "Secure cell relay routing protocol for sensor networks," *Wireless Commun. Mobile Comput.*, vol. 6, no. 3, pp. 375–391, May 2006.
[63] Y. Xu, J. Heidemann, and D. Estrin, "Geography-informed energy conservation for ad hoc routing," in *Proc. 7th Annu. Int. Conf. Mobile Comput. Netw.*, 2001, pp. 70–84, doi: 10.1145/381677.381685.
[64] B. Chen, K. Jamieson, and H. Balakrishnan, "Span: An energy-efficient coordination algorithm for topology maintenance in ad hoc wireless networks," *Wireless Netw.*, vol. 8, no. 5, pp. 481–494, 2002, doi: 10.1023/A:1016542229220.
[65] R. Zhang, H. Zhao, and M. A. Labrador, "The anchor location service (ALS) protocol for large-scale wireless sensor networks," in *Proc. 1st Int. Conf. Integr. Internet Sensor Netw.*, 2006, pp. 1–18, doi: 10.1145/1142680.1142704.
[66] K. Sohrabi, J. Gao, V. Ailawadhi, and G. J. Pottie, "Protocols for self-organization of a wireless sensor network," *IEEE Pers. Commun.*, vol. 7, no. 5, pp. 16–27, Oct. 2000, doi: 10.1109/98.878532.
[67] T. He, J. A. Stankovic, C. Lu, and T. Abdelzaher, "SPEED: A stateless protocol for real-time communication in sensor networks," in *Proc. 23rd Int. Conf. Distrib. Comput. Syst.*, 2003, pp. 1–8, doi: 10.1109/ICDCS.2003.1203451.
[68] K. Akkaya and M. Younis, "An energy-aware QoS routing protocol for wireless sensor networks," in *Proc. 23rd Int. Conf. Distrib. Comput. Syst. Workshops*, 2003, pp. 1–5, doi: 10.1109/ICDCSW.2003.1203636.
[69] R. Azzam, C. Arnhardt, and T. M. Fernandez-Steeger, "Monitoring and early warning of slope instabilities and deformations by sensor fusion in self-organized wireless ad-hoc sensor networks," in *Proc. Int. Symp. Regional Conf. Geo-Disaster Mitigation ASEAN-Protecting Life Geo-Disaster Environ. Hazards*, Yogyakarta, IN, USA, Feb. 2010, pp. 25–26.
[70] C. D. Nguyen, T. D. Tran, N. D. Tran, T. H. Huynh, and D. T. Nguyen, "Flexible and efficient wireless sensor networks for detecting rainfall-induced landslides," *Int. J. Distrib. Sensor Netw.*, vol. 11, no. 11, Nov. 2015, Art. no. 235954, doi: 10.1155/2015/235954.
[71] *Internet of Things: Wireless Sensor Networks*, International Electrotechnical Commission, Geneva, Switzerland, 2014.
[72] S. Jeong, J. Ko, and J. Kim, "The effectiveness of a wireless sensor network system for landslide monitoring," *IEEE Access*, vol. 8, pp. 8073–8086, 2020, doi: 10.1109/ACCESS.2019.2960570.

[73] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of Things (IoT): A vision, architectural elements, and future directions," *Future Gener. Comput. Syst.*, vol. 29, no. 7, pp. 1645–1660, Sep. 2013, doi: 10.1016/j.future.2013.01.010.
[74] S. Pundir, M. Wazid, and D. P. Singh, "Intrusion detection protocols in wireless sensor networks integrated to Internet of Things deployment: Survey and future challenges," *IEEE Access*, vol. 8, pp. 3343–3363, 2020.
[75] M. Wazid, A. K. Das, N. Kumar, and A. V. Vasilakos, "Design of secure key management and user authentication scheme for fog computing services," *Future Gener. Comput. Syst.*, vol. 91, pp. 475–492, Feb. 2019.
[76] P. Lu, W. Shi, Z. Li, and Y. Qin, "Landslide mapping from planetscope images using improved region-based level set evolution," *IEEE Geosci. Remote Sens. Lett.*, early access, Oct. 26, 2021, doi: 10.1109/LGRS.2021.3122964.
[77] H. C. Lee, K. H. Ke, Y. M. Fang, B. J. Le, and T. C. Chan, "Open-source wireless sensor system for long-term monitoring of slope movement," *IEEE Trans. Instrum. Meas.*, vol. 66, no. 4, pp. 767–776, Apr. 2017.
[78] M. T. Abraham, N. Satyam, B. Pradhan, and A. M. Alamri, "IoT-based geotechnical monitoring of unstable slopes for landslide early warning in the Darjeeling Himalayas," *Sensors*, vol. 20, no. 9, p. 2611, May 2020.
[79] É. Morin, M. Maman, R. Guizzetti, and A. Duda, "Comparison of the device lifetime in wireless networks for the Internet of Things," *IEEE Access*, vol. 5, pp. 7097–7114, 2017.
[80] T. Eirich T. Kramp O. Hersent N. Sornin, and M. Luis. *LoRaWAN Specication*. Accessed: Nov. 5, 2018. [Online]. Available: https://lora-alliance.org/resource-hub/lorawantm-specification-v102
[81] T.-H. To and A. Duda, "Simulation of Lora in NS-3: Improving Lora performance with CSMA," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2018, pp. 1–7.
[82] F. Adelantado, X. Vilajosana, P. Tuset-Peiro, B. Martinez, J. Melia-Segui, and T. Watteyne, "Understanding the limits of LoRaWAN," *IEEE Commun. Mag.*, vol. 55, no. 9, pp. 34–40, Sep. 2017.
[83] B. Buurman, J. Kamruzzaman, G. Karmakar, and S. Islam, "Low-power wide-area networks: Design goals, architecture, suitability to use cases and research challenges," *IEEE Access*, vol. 8, pp. 17179–17220, 2020.
[84] C.-C. Shen, C. Srisathapornphat, and C. Jaikaeo, "Sensor information networking architecture and applications," *IEEE Pers. Commun.*, vol. 8, no. 4, pp. 52–59, Aug. 2001.
[85] J. Ma, Y. Yang, A. He, C. Li, and L. Li, "A load balancing multi-relay selection scheme of debris flow monitoring," in *Proc. IEEE Inf. Technol., Netw., Electron. Autom. Control Conf.*, May 2016, pp. 990–995.
[86] J.-F. Tu, Y. Yang, C.-H. Li, A.-P. He, and L. Li, "A context-adaptive and energy-efficient wireless sensor network for debris flow monitoring," in *Proc. Int. Conf. Wireless Commun. Sensor Netw.*, Dec. 2014, pp. 1–5.
[87] E. T.-H. Chu, "Energy-balanced sampling workload allocation in wireless sensor networks," *Comput. Math. Appl.*, vol. 64, no. 5, pp. 1376–1389, Sep. 2012.
[88] S.-Y. Chiang, Y.-C. Huang, and Y.-C. Kan, "A power scheme of a wireless sensor network node for debris flow monitoring with move-triggered wake-up," *J. Chin. Inst. Eng.*, vol. 39, no. 7, pp. 841–849, Oct. 2016.
[89] K.-T. Lau, L. Yuan, L.-M. Zhou, J. Wu, and C.-H. Woo, "Strain monitoring in FRP laminates and concrete beams using FBG sensors," *Compos. Struct.*, vol. 51, no. 1, pp. 9–20, Jan. 2001.
[90] C. Y. Hong, Y. F. Zhang, M. X. Zhang, L. M. G. Leung, and L. Q. Liu, "Application of FBG sensors for geotechnical health monitoring, a review of sensor design, implementation methods and packaging techniques," *Sens. Actuators A, Phys.*, vol. 244, pp. 184–197, May 2016.
[91] H.-F. Pei, J.-H. Yin, H.-H. Zhu, C.-Y. Hong, W. Jin, and D.-S. Xu, "Monitoring of lateral displacements of a slope using a series of special fibre Bragg grating-based in-place inclinometers," *Meas. Sci. Technol.*, vol. 23, no. 2, Feb. 2012, Art. no. 025007.
[92] P. P. Ray, M. Mukherjee, and L. Shu, "Internet of Things for disaster management: State-of-the-art and prospects," *IEEE Access*, vol. 5, pp. 18818–18835, 2017.
[93] A. Khasawneh, M. S. B. A. Latiff, O. Kaiwartya, and H. Chizari, "A reliable energy-efficient pressure-based routing protocol for underwater wireless sensor network," *Wireless Netw.*, vol. 24, no. 6, pp. 2061–2075, Aug. 2018, doi: 10.1007/s11276-017-1461-x.
[94] B. Nazir and H. Hasbullah, "Energy efficient and QoS aware routing protocol for clustered wireless sensor network," *Comput. Electr. Eng.*, vol. 39, no. 8, pp. 2425–2441, Nov. 2013.
[95] G. Chen, J. Branch, M. Pflug, L. Zhu, and B. Szymanski, "SENSE: A wireless sensor network simulator," in *Advances in Pervasive Computing and Networking*. Boston, MA, USA: Springer, 2005, pp. 249–267, doi: 10.1007/0-387-23466-7_13.
[96] T. Issariyakul and E. Hossain, "Introduction to network simulator 2 (NS2)," *Introduction To Networking Simulator NS2*. Boston, MA, USA: Springer, 2009, pp. 1–18, doi: 10.1007/978-0-387-71760-9_2.
[97] A. Varga, "Using the OMNeT++ discrete event simulation system in education," *IEEE Trans. Educ.*, vol. 42, no. 4, p. 11, Nov. 1999, doi: 10.1109/13.804564.
[98] A. Bounceur, M. Bezoui, and R. Euler, *Boundaries and Hulls of Euclidean Graphs: From Theory to Practice*. Boca Raton, FL, USA: CRC Press, 2018, doi: 10.1201/9781315169897.
[99] A. Bounceur, "Finding the boundary nodes of a WSN using the D-LPCN algorithm and its simulation under cupcarbon," in *Proc. 1st EAI Int. Conf. Future Internet Technol. Trends*, Aug. 2017, pp. 1–5.
[100] M. Lounis, K. Mehdi, and A. Bounceur, "A cupcarbon tool for simulating destructive insect movements," in *Proc. 1st IEEE Int. Conf. Inf. Commun. Technol. Disaster Manage.*, Algiers, GA, USA, Mar. 2014, pp. 1–5.
[101] Y.-S. Song, B.-G. Chae, K.-S. Kim, J.-Y. Park, H.-J. Oh, and S.-W. Jeong, "A landslide monitoring system for natural terrain in Korea: Development and application in hazard evaluations," *Sensors*, vol. 21, no. 9, p. 3040, Apr. 2021.
[102] S. Kumar, S. Duttagupta, and V. P. Rangan, "Resilient green cellular IoT for landslide monitoring using voice channels," *J. Sensor Actuator Netw.*, vol. 10, no. 3, p. 59, Sep. 2021.
[103] J. Li, C. K. Li, K. Li, and Y. Liu, "Design of landslide monitoring and early warning system based on Internet of Things," *Appl. Mech. Mater.*, vols. 511–512, pp. 197–201, Feb. 2014, doi: 10.4028/www.scientific.net/AMM.511-512.197.
[104] S. Aggarwal, P. K. Mishra, K. V. S. Sumakar, and P. Chaturvedi, "Landslide monitoring system implementing IoT using video camera," in *Proc. 3rd Int. Conf. Converg. Technol. (I2CT)*, Pune, India, Apr. 2018, pp. 1–4.
[105] S. Bernat and S. M. Arbanas, "Method for prediction of landslide movements based on random forests," *Landslides*, vol. 14, no. 3, pp. 947–960, Jun. 2017, doi: 10.1007/s10346-016-0761-z.
[106] D. Kirschbaum, "Satellite-based assessment of rainfall-triggered landslide hazard for situational awareness," *Earth's Future*, vol. 6, pp. 505–523, Dec. 2018, doi: 10.1002/2017EF000715.
[107] Z.-L. Wei, Q. Lü, H.-Y. Sun, and Y.-Q. Shang, "Estimating the rainfall threshold of a deep-seated landslide by integrating models for predicting the groundwater level and stability analysis of the slope," *Eng. Geol.*, vol. 253, pp. 14–26, Apr. 2019, doi: 10.1016/j.enggeo.2019.02.026.
[108] S. Segoni, D. Lagomarsino, R. Fanti, S. Moretti, and N. Casagli, "Integration of rainfall thresholds and susceptibility maps in the Emilia Romagna (Italy) regional-scale landslide warning system," *Landslides*, vol. 12, no. 4, pp. 773–785, Aug. 2015, doi: 10.1007/s10346-014-0502-0.
[109] Z. R. D. Omadlao, N. M. A. Tuguinay, and R. M. Saturay, Jr., "Machine learning-based prediction system for rainfall-induced landslides in benguet first engineering district," OSF Preprints, Aug. 2019, doi: 10.31219/osf.io/csx6r.
[110] N. Rachel, "Landslide prediction with rainfall analysis using support vector machine," *Indian J. Sci. Technol.*, vol. 9, no. 21, pp. 11–15, 2016, doi: 10.17485/ijst/2016/v9i21/95275.
[111] A. Vallet, D. Varron, and C. Bertrand, "Hydrogeological threshold using effective rainfall and support vector machine (SVM) applied to a deep seated unstable slope (Sèchilienne, French Alps)," in *Proc. Conf. Gravitaire*, 2013, pp. 1–6.
[112] A. Pradhan, "A shallow slide prediction model combining rainfall threshold warnings and shallow slide susceptibility in Busan, Korea," *Landslides*, vol. 16, no. 3, pp. 647–659, 2019, doi: 10.1007/s10346-018-1112-z.
[113] L. Huang and L.-Y. Xiang, "Method for meteorological early warning of precipitation-induced landslides based on deep neural network," *Neural Process. Lett.*, vol. 48, no. 2, pp. 1243–1260, Oct. 2018, doi: 10.1007/s11063-017-9778-0.
[114] M. Hussain, D. Chen, A. Cheng, H. Wei, and D. Stanley, "Change detection from remotely sensed images: From pixel-based to object-based approaches," *ISPRS J. Photogram. Remote Sens.*, vol. 80, pp. 91–106, Jun. 1998.
[115] M. Isever, *Two-Dimensional Change Detection Methods: Remote Sensing Applications*. London, U.K.: Springer, 2012, doi: 10.1007/978-1-4471-4255-3.
[116] D. Lu, P. Mausel, and E. Brondézio, "Change detection techniques," *Int. J. Remote Sens.*, vol. 25, pp. 2365–2401, May 2004.
[117] F. Bovolo, L. Bruzzone, and M. Marconcini, "A novel approach to unsupervised change detection based on a semisupervised SVM and a similarity measure," *IEEE Trans. Geosci. Remote Sens.*, vol. 46, no. 7, pp. 2070–2082, Jul. 2008, doi: 10.1109/TGRS.2008.916643.

[118] K. Pawluszek, A. Borkowski, and P. Tarolli, "Sensitivity analysis of automatic landslide mapping: Numerical experiments towards the best solution," *Landslides*, vol. 15, no. 9, pp. 1851–1865, Sep. 2018, doi: 10.1007/s10346-018-0986-0.

[119] M. I. Sameen and B. Pradhan, "Landslide detection using residual networks and the fusion of spectral and topographic information," *IEEE Access*, vol. 7, pp. 114363–114373, 2019.

[120] T. Martha, N. Kerle, V. Jetten, and C. van Weste, "Characterising spectral, spatial and morphometric properties of landslides for semi-automatic detection using object-oriented methods," *Geomorphology*, vol. 116, nos. 1–2, pp. 24–36, 2010.

[121] T. R. Martha, N. Kerle, C. J. van Westen, V. Jetten, and K. V. Kumar, "Object-oriented analysis of multi-temporal panchromatic images for creation of historical landslide inventories," *ISPRS J. Photogramm. Remote Sens.*, vol. 67, pp. 105–119, Jan. 2012, doi: 10.1016/j.isprsjprs.2011.11.004.

[122] A. Stumpf and N. Kerle, "Object-oriented mapping of landslides using random forests," *Remote Sens. Environ.*, vol. 115, no. 10, pp. 2564–2577, Oct. 2011, doi: 10.1016/j.rse.2011.05.013.

[123] B. Feizizadeh, T. Blaschke, D. Tiede, and M. H. R. Moghaddam, "Evaluating fuzzy operators of an object-based image analysis for detecting landslides and their changes," *Geomorphology*, vol. 293, pp. 240–254, Sep. 2017, doi: 10.1016/j.geomorph.2017.06.002.

[124] B. Pradhan and M. Al-Zuhairi, "Integration of LiDAR and QuickBird data for automatic landslide detection using object-based analysis and random forests," in *Proc. Laser Scanning Appl. Landslide Assessment*, 2017, pp. 69–81.

[125] D. C. Duro, S. E. Franklin, and M. G. Dubé, "A comparison of pixel-based and object-based image analysis with selected machine learning algorithms for the classification of agricultural landscapes using SPOT-5 HRG imagery," *Remote Sens. Environ.*, vol. 118, pp. 259–272, Mar. 2012.

[126] M. Van Den Eeckhaut, N. Kerle, J. Poesen, and J. Hervás, "Object-oriented identification of forested landslides with derivatives of single pulse LiDAR data," *Geomorphology*, vols. 173–174, pp. 30–42, Nov. 2012, doi: 10.1016/j.geomorph.2012.05.024.

[127] G. Sofia, "Geomorphic features extraction from high-resolution topography: Landslide crowns and bank erosion," *Nature Hazards* vol. 61, pp. 65–83, May 2012, doi: 10.1007/s11069-010-9695-2.

[128] P. Giri, K. Ng, and W. Phillips, "Wireless sensor network system for landslide monitoring and warning," *IEEE Trans. Instrum. Meas.*, vol. 68, no. 4, pp. 1210–1220, Apr. 2019.

[129] R. Dhanagopal and B. Muthukumar, "A model for low power, high speed and energy efficient early landslide detection system using IoT," *Wireless Pers. Commun.*, vol. 117, pp. 2713–2728, Nov. 2021.

[130] F. Huang, J. Zhang, C. Zhou, Y. Wang, J. Huang, and L. Zhu, "A deep learning algorithm using a fully connected sparse autoencoder neural network for landslide susceptibility prediction," *Landslides*, vol. 17, no. 1, pp. 217–229, Jan. 2020.

[131] Y. Wang, Z. Liu, D. Wang, Y. Li, and J. Yan, "Anomaly detection and visual perception for landslide monitoring based on a heterogeneous sensor network," *IEEE Sensors J.*, vol. 17, no. 13, pp. 4248–4257, May 2017.

[132] Y. Chen, M. Irfan, T. Uchimura, G. Cheng, and W. Nie, "Elastic wave velocity monitoring as an emerging technique for rainfall-induced landslide prediction," *Landslides*, vol. 15, no. 6, pp. 1155–1172, Jun. 2018.

[133] A. Dikshit, R. Sarkar, B. Pradhan, S. Acharya, and A. Alamri, "Spatial landslide risk assessment at Phuentsholing, Bhutan," *Geosciences*, vol. 10, no. 4, p. 131, 2020.

[134] T. Ameloot, P. Van Torre, and H. Rogier, "A compact low-power LoRa IoT sensor node with extended dynamic range for channel measurements," *Sensors*, vol. 18, no. 7, p. 2137, 2018.

[135] M. Gamperl, J. Singer, and K. Thuro, "Internet of Things geosensor network for cost-effective landslide early warning systems," *Sensors*, vol. 21, no. 8, p. 2609, Jun. 2021.

[136] A. Botta, W. De Donato, V. Persico, and A. Pescapè, "Integration of cloud computing and Internet of Things: A survey," *Future Gener. Comput. Syst.*, vol. 56, pp. 684–700, Mar. 2016.

[137] C. Kurtz, A. Stumpf, J.-P. Malet, P. Gançarski, A. Puissant, and N. Passat, "Hierarchical extraction of landslides from multiresolution remotely sensed optical images," *ISPRS J. Photogram. Remote Sens.*, vol. 87, pp. 122–136, Jan. 2014, doi: 10.1016/j.isprsjprs.2013.11.003.

[138] S. M. Karunarathne, M. Dray, L. Popov, M. Butler, C. Pennington, and C. M. Angelopoulos, "A technological framework for data-driven IoT systems: Application on landslide monitoring," *Comput. Commun.*, vol. 154, pp. 298–312, Mar. 2020.

[139] G. Mei, "A survey of Internet of Things (IoT) for geohazard prevention: Applications, technologies, and challenges," *IEEE Internet Things J.*, vol. 7, no. 5, pp. 4371–4386, Apr. 2019.

[140] B. S. Chaudhari, M. Zennaro, and S. Borkar, "LPWAN technologies: Emerging application characteristics, requirements, and design considerations," *Future Internet*, vol. 12, no. 3, p. 46, Mar. 2020.

[141] M. Chernyshev, Z. Baig, O. Bello, and S. Zeadally, "Internet of Things (IoT): Research simulators and testbeds," *IEEE Internet Things J.*, vol. 5, no. 3, pp. 1637–1647, Jun. 2018.

[142] Z. Ali, H. Ali, and M. Badawy, "Internet of Things (IoT): Definitions, challenges and recent research directions," *Int. J. Comput. Appl.*, vol. 128, no. 1, pp. 37–47, Oct. 2015.

[143] T. Xu, J. B. Wendt, and M. Potkonjak, "Security of IoT systems: Design challenges and opportunities," in *Proc. IEEE/ACM Int. Conf. Comput.-Aided Design*, 2014, pp. 417–423.

[144] H. Ding, L. S. Sun, J. L. Wang, and X. Wang, "Design and realization of 3S technology-based geological disaster database system in Liaoning province," *Appl. Mech. Mater.*, vols. 580–583, pp. 2708–2712, Jul. 2014.

[145] C. Pohl and J. L. Van Genderen, "Review article multisensor image fusion in remote sensing: Concepts, methods and applications," *Int. J. Remote Sens.*, vol. 19, no. 5, pp. 823–854, 1998.

[146] H. Wang, M. Liu, S. Hong, and Y. Zhuang, "A historical review and bibliometric analysis of GPS research from 1991–2010," *Scientometrics*, vol. 95, no. 1, pp. 35–44, Apr. 2013.

[147] M. S. Hossain, S. R. Chowdhury, N. G. Das, S. M. Sharifuzzaman, and A. Sultana, "Integration of GIS and multicriteria decision analysis for urban aquaculture development in Bangladesh," *Landscape Urban Planning*, vol. 90, nos. 3–4, pp. 119–133, Apr. 2009.

[148] S. J. Liu and G. Q. Zhu, "The application of GIS and IoT technology on building fire evacuation," *Proc. Eng.*, vol. 71, pp. 577–582, Dec. 2014.

[149] M. T. Arafin, D. Anand, and G. Qu, "A low-cost GPS spoofing detector design for Internet of Things (IoT) applications," in *Proc. Great Lakes Symp. VLSI*, May 2017, pp. 161–166.

[150] H. Mroue, A. Nasser, S. Hamrioui, B. Parrein, E. Motta-Cruz, and G. Rouyer, "MAC layer-based evaluation of IoT technologies: LoRa, SigFox and NB-IoT," in *Proc. IEEE Middle East North Afr. Commun. Conf. (MENACOMM)*, Apr. 2018, pp. 1–5.

[151] U. Raza, P. Kulkarni, and M. Sooriyabandara, "Low power wide area networks: An overview," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 2, pp. 855–873, 2nd Quart., 2017.

[152] N. Poursafar, M. E. E. Alahi, and S. Mukhopadhyay, "Long-range wireless technologies for IoT applications: A review," in *Proc. 11th Int. Conf. Sens. Technol. (ICST)*, Dec. 2017, pp. 1–6.

[153] Q. M. Qadir, T. A. Rashid, N. K. Al-Salihi, B. Ismael, A. A. Kist, and Z. Zhang, "Low power wide area networks: A survey of enabling technologies, applications and interoperability needs," *IEEE Access*, vol. 6, pp. 77454–77473, 2018.

[154] K. Mekki, E. Bajic, F. Chaxel, and F. Meyer, "A comparative study of LPWAN technologies for large-scale IoT deployment," *ICT Exp.*, vol. 5, no. 1, pp. 1–7, Mar. 2019.

[155] SigFox. (2019). *Uplink/Downlink Messages*. Accessed: Aug. 25, 2019. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6387435/

[156] WAVIoT. (2018). *What is NB-Fi Protocol*. Accessed: Jul. 18, 2018. [Online]. Available: https://waviot.com/technology/nb-fi-specification/

[157] WAVIoT. (2018). *NB-Fi LPWA Network*. Accessed: Jul. 18, 2018. [Online]. Available: https://waviot.com/technology/waviot-lpwa-network

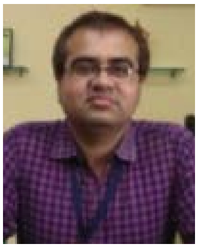
[158] J. Finnegan and S. Brown, *A Comparative Survey of LPWA Networking*. Maynooth, Ireland: Maynooth Univ., 2018. [Online]. Available: https://www.semanticscholar.org/paper/A-Comparative-Survey-of-LPWA-Networking-Finnegan-Brown/386bbe71d9682f8c2ded5b12240089ae00953c5f

[159] E. Intrieri, "Brief communication 'Landslide early warning system: Toolbox and general concepts,'" *Natural Hazards Earth Syst. Sci.*, vol. 13, no. 1, pp. 85–90, 2013.

SWAPNIL BAGWARI is currently pursuing the Ph.D. degree in electronics and communication engineering with Lovely Professional University. He is also associated as an Assistant Professor with Lovely Professional University with more than 11 years of experience in academics. He has one patent granted and 35 patents published in his account. He has published more then ten research papers in refereed journals and conferences. He has organized several summer internships and expert lectures for students.

ANITA GEHLOT is currently associated as an Associate Professor with Uttaranchal University with more than ten years of experience in academics. She has four patents granted and 2000 published in her account. She has published more than 50 research papers in refereed journals and conferences. She has organized several workshops, summer internships, and expert lectures for students. She has been awarded a ''Certificate of Appreciation'' from the University of Petroleum and Energy Studies for exemplary work. She has published ten books in the area of embedded systems and the Internet of Things with reputed publishers, such as CRC/Taylor & Francis, Narosa, GBS, IRP, NIPA, and RI publication. She is an Editor of a special issue published by the AISC book series, Springer with the title *Intelligent Communication, Control, and Devices* 2018.

RAJESH SINGH is currently associated as a Professor with Uttaranchal University with more than 15 years of experience in academics. He has been awarded as the Gold Medalist in M.Tech. and honors in his B.E. He has organized and conducted several workshops, summer internships, and expert lectures for students as well as faculty. He has four patents published and more than 100 patents published in his account. He has published around 100 research papers in refereed journals/conferences. His research interests include embedded systems, robotics, wireless sensor networks, and the Internet of Things. Under his mentorship students have participated in national/international competitions, including the Texas competition in Delhi and the Laureate Award of Excellence in robotics engineering in Spain. Twice in the last four years, he has been awarded a ''Certificate of Appreciation'' and ''Best Researcher Award 2017'' from the University of Petroleum and Energy Studies for exemplary work. He got a ''Certificate of Appreciation'' for mentoring the projects submitted to the Texas Instruments Innovation Challenge India Design Contest, from Texas Instruments, in 2015. He has published ten books in the area of embedded systems and the Internet of Things with reputed publishers, such as CRC/Taylor & Francis, Narosa, GBS, IRP, NIPA, and RI publication. He is an Editor of a special issue published by the AISC book series, Springer with the title *Intelligent Communication, Control, and Devices* 2017 and 2018.



NEERAJ PRIYADARSHI (Senior Member, IEEE) received the M.Tech. degree in power electronics & drives from the Vellore Institute of Technology (VIT), Vellore, India, in 2010, and the Ph.D. degree from the Government College of Technology and Engineering, Udaipur, Rajasthan, India. He was a Postdoctoral Researcher in bioenergy and green engineering with the Department of Energy Technology, Aalborg University, Esbjerg, Denmark. He is currently associated with the CTiF Global Capsule, Department of Business Development and Technology, Aarhus University. In previous postings, he was with BITT Ranchi, MIT Purnea, JK University, Geetanjali Institute, Global Institute, and SS Group, Rajasthan, India. He is also associated with the Bioenergy and Green Engineering, Department of Energy Technology, Aalborg University. He has published over 60 papers in journals and conferences of high repute, such as IEEE Systems Journal, *IET Electric Power Applications*, *IET Power Electronics*, IEEE Access, *Electric Power Components and Systems*, *International Transactions of Electrical Energy System* (Wiley), *Energies* (MDPI), and *International Journal of Renewable Energy Research*, and granted ten international patents. He successfully organized two international workshops and one National workshop in different organization. Under his guidance 25 DST, Government of Rajasthan projects have been sanctioned for financial support. His current research interests include power electronics, control systems, power quality, and solar power generation. He is also invited as a guest speaker in many international/national conferences. He is a Reviewer of the IEEE Transactions on Industrial Informatics, IEEE Transactions on Industry Applications, IEEE Systems Journal, *Journal of Cleaner Production* (Elsevier), *International Journal of Electrical Power and Energy Systems*, *IET Power Electronics*, *Energy for Sustainable Development* (Elsevier), *Energy Reports* journal (Elsevier), *Sustainable Energy Technologies and Assessments* (Elsevier), *International Journal of Energy Research* (Wiley), *Electronics Letters* (IET), *Electric Power Components and Systems* (Taylor & Francis), IEEE Access, *IET Renewable Power Generation*, *International Journal of Modeling and Simulation*, *International Journal of Renewable Energy Research*, *International Journal of Power Electronics and Drives*, and reputed Elsevier SCI indexed journals. He is working as the Chief Editor of four edited books of renowned publisher (*Intelligent Renewable Energy Systems: Integrating Artificial Intelligence Techniques and Optimization Algorithms* (Wiley), *Advances in Power Systems and Energy Management* (Springer), and De Gruyter Publisher, Germany).

BASEEM KHAN (Senior Member, IEEE) received the B.Eng. degree in electrical engineering from Rajiv Gandhi Technological University, Bhopal, India, in 2008, and the M.Tech. and D.Phil. degrees in electrical engineering from the Maulana Azad National Institute of Technology, Bhopal, in 2010 and 2014, respectively. He is currently working as a Faculty Member at Hawassa University, Ethiopia. His research interests include power system restructuring, power system planning, smart grid technologies, meta-heuristic optimization techniques, reliability analysis of renewable energy systems, power quality analysis, and renewable energy integration.