Brazilian natural disasters integrated into cyber-physical systems: computational challenges for landslides and floods in urban ecosystems

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***Abstract*—Natural disasters cause a high impact in society, resulting in human and economic losses, so much so that increasing the efficiency in monitoring these phenomena becomes a necessity. The integration of cyber-physical systems and their IoT devices, connectivity, machine learning, and Big Data can help to achieve this efficiency. This paper presents key points of the phenomenology of these processes, with challenges and opportunities for applied computing in urban environmental studies in Brazil, as well as investigates studies and techniques that have been used to monitor landslides and floods.**

***Index Terms*—Environmental monitoring, IoT, Machine Learning, Smart Environment**

I. Introduction

Risk management has gone through substantial changes with technological advances promoted by digital transformation, using new ways to analyze large volumes of data and Artificial Intelligence in an Internet of Things context. New perspectives for the landslides and floods monitoring are related to the use of cyber-physical systems approach, which seeks to integrate the physical environment into the computational world, using the computational tools available to overcome the challenges in the context of urban natural disasters.

Natural disasters are events resulting from natural processes that cause serious damage and loss to a community, whose impacts exceed the local capacity to restore normality. Examples of natural disasters are earthquakes, hurricanes, tsunamis, floods, droughts, fires, and mass movements. In Brazil, among these events, floods and landslides are the most recurrent in urban environments and those that cause the most catastrophic events to society.

Cyber-physical systems provide an intuitive interface, a human-to-human, man-to-machine, and machine-to-machine interaction mechanism, by facilitating continuous network connectivity and refined application control by users, which can improve resilience to natural disasters and also facilitate prediction and mitigation of these events [1].

This paper aims to present the contextualization of the challenges for real-time monitoring and prediction of landslide and flood events in Brazil, providing support to decision makers. It also presents phenomenology key points of these types of disasters and discusses the application of machine learning and *Big Data* computational techniques in this context.

II. Phenomenology and urban environmental monitoring

Monitoring is one of the most popular topics today due to the studies and development of high performance computational applications. This work explores the urban phenomenological study, regarding to landslides and floods caused by human and nature action. Space-time issues are prerequisites in any of the environmental assessments presented.

A. Landslides

The generic term *mass movements* includes a variety of movements of instability of soil masses, rocks or debris, generated by the action of gravity on sloping terrains, having water infiltration as the main triggering factor, mainly from rains. There are several national and international classifications related to mass movements (creep, slides, falls, flows). This work adopts the classification proposed by Augusto Filho [2] and focus on landslide processes.

Landslides are important processes in the slope evolution, characterized by rapid movements (m/h to m/s), with well-defined lateral limits and depth (surface of rupture). Stabilized volumes can be easily identified or at least inferred. They may involve soil, saprolite, rock, and deposits. They are subdivided according to the rupture mechanism, geometry, and mobilized material.

There are several types of landslides, e.g. translational, rotational, and wedge. The geometry of these movements varies according to the existence, or not, of structures or weaknesses in the moved materials that condition the formation of the surface ruptures.

Effective agents are elements directly responsible for triggering landslides, which are differentiated in preparatory (rainfall, erosion by water and wind, freezing and melting,

Fig. 1. Planar landslides in the mountainous region of the State of Rio de Janeiro. Source: Sirden-CTGeo-IPT.

variation in temperature and humidity, chemical dissolution, action of sources and springs, fluctuation in the level of lakes, tides, and groundwater, animal and human action, including deforestation) and immediate (intense rain, vibrations, ice and snow melting, erosion, earthquakes, waves, wind, human action, etc.).

Other natural conditions of great importance are the intrinsic characteristics of the natural massif (rocky and earth), the vegetation cover, and the action of rainwater (saturation and/or elevation of the water table, generation of neutral pressures and percolation forces, distribution of rain over time), in addition to the processes of rock alteration and erosion of the altered material.

Landslide outbreaks can also be induced by anthropic action, e.g. the execution of inadequate cuts and landfills, the concentration of rainwater and wastewater, and the removal of vegetation. Often, induced landslides mobilize materials produced by the occupation itself, involving soil masses of varying dimensions, garbage, and debris.

1) Computational challenges and opportunities on landslides: The immediate detection of landslide activity provided by real-time systems can be crucial to save human lives and protect property. Traditional field observations, even when carried out regularly, are not able to detect changes at the moment when slides occur. Moreover, active landslides can be dangerous for field work and often occur during rain, when visibility can be poor.

The continuous provision of data by remote real-time monitoring leads to a better understanding of the dynamic behavior of landslides, which allows professionals to create more effective models to prevent or stop this kind of event. Landslide monitoring is often expensive and most surveillance systems require installation by specialists. The advantage is that the systems that detect these movements can be coordinated with warning systems [3].

Nowadays, for urban environments, monitoring for landslides focuses on rain data. In Brazil, the National Center for Monitoring and Alerting of Natural Disasters (or Centro Nacional de Monitoramento e Alerta de Desastres Naturais – CEMADEN) develops a pilot project in nine risk areas, located in the municipalities of Nova Friburgo-RJ, Teresópolis-RJ, Petrópolis-RJ, Angra dos Reis-RJ, Mauá-SP, Santos-SP, Blumenau-SC, Recife-PE, and Salvador-BA, with the installation of humidity, pluviometry, and displacement sensors through Robotic Total Station (RTSs).

Traditional monitoring systems are very expensive, which in Brazil represents an impediment to massive installation in risk areas, since most municipalities cannot afford to maintain these systems. In addition to the financial issue, it is usual for equipment installed in risky areas, especially those in precarious settlements, to suffer from depredation. Thus, the challenge is related to the selection of low-cost sensors, installation, transmission, and data analysis in order to monitor the slopes in real time with the same quality as complex systems.

B. Floods

Flooding processes represent one of the main types of natural disasters, with floods in Brazil representing approximately 60% of all disaster records, of which 40% are only in the Southeast region [4]. The absence or inefficiency of drainage systems tends to increase the occurrence frequency, the magnitude, and the range of the floods.

The natural climatic and geomorphological conditions of a given location (e.g. pluviometry, relief, size and shape of the basin, and hydraulic gradient of the river) are determinants in the frequency of occurrence, typology, and dynamics of surface runoff, and the term *flooding* covers several types of hydrometeorological processes that are part of the natural dynamics.

Floods can be triggered by fast and heavy rains, intense long-term rains, melting in the mountains, and other climatic events such as hurricanes and tornadoes, being intensified by environmental changes and/or anthropic interventions, such as soil waterproofing, river engineering, and the reduction in the flow of channels due to constructions or siltation.

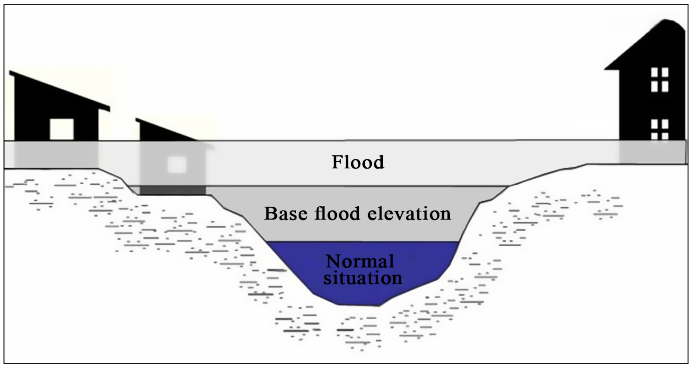

Fig. 2. Schematic profile of the flood and based flooding elevation. Source: [6].

The waterproofing of large areas generates, as consequence, reduction in the absorption of rainwater by the soil, thus altering the availability of water resources and increasing the surface runoff that interferes with the city's supply and contributes to the elevation of the water level in the urban drainages. Furthermore, the urban occupation occurs after the removal of the vegetation cover, which potentializes the effect of soil loss and ends up causing the silting up of the water courses, which may cause a reduction of up to 80% of the original flow capacity of the urban drainages [5].

Rainwater, when reaching a watercourse, causes the increase of the flow for a certain period. Sometimes, during the flood period, the flow rates reach such magnitude that they can overcome the discharge capacity of the drainage channel and overflow into marginal areas not normally occupied by the waters. This overflow characterizes a flood and the marginal area, which periodically receives these excess water, is called the river's floodplain. Figure 2 presents a schematic sketch of the flood dynamics in a watercourse.

Another factor that induces the process is the undersizing of the drainage crossing structures (galleries, bridges, pipes, etc.) combined with the drainage silting up. These structures generally impede the flow, delaying the flow of water. When associated with solid waste discharged into drains, the process tends to be more intense, with floods frequently occurring due to urban growth. In this context, flooding also occur, which are "momentary accumulations of water in a given area due to deficiency in the micro-drainage system, which may or may not be related to processes of a fluvial nature" [6].

1) Challenges and computational opportunities on floods: Investing in solutions for monitoring watercourses and rainfall often involves substantial financial investments, precluding municipalities from implementing these technological solutions. For appropriate monitoring, it is necessary to measure rainfall, water flow and, mainly, water level of rivers and urban streams. The greater the number of installed sensors, the better the analysis and, thereby, the quality of the alert system for the population.

In Brazil, some cities, Civil Defense agencies, the National Water Agency, and CEMADEN have been using platforms to collect the level and flow of rivers, rain gauges, meteorological radars, and mathematical models. The city of São Carlos-SP has a system of submerged sensors installed in the main water courses that are connected to each other by wireless network. However, most level and flow measurement systems rely on manual data collection.

Thus, there are challenges associated with the implementation of these systems, since depending on the size of the hydrographic basin, the portions of the headwaters may face communication problems. Other difficulties are the power supply in these systems, the validation of data from low-cost sensors, as well as the prediction of events in real time for issuing alerts.

C. Phenomenology and challenges

Based on the presented phenomena and the computational challenges that need to be faced to carry out the digital transformation in urban events monitoring, Table I summarizes the main triggering and predisposing agents, while Table II presents the main parameters to be monitored in each type of phenomenon.

III. Cyber-physical approach and computational technologies applied to natural disasters

Cyber-Physical Systems – CPSs, integrate computing, communication and storage resources with monitoring and control of entities in the physical world that need to be executed safely, efficiently and in real time. CPSs consist of interconnected objects, incorporated with sensors, which collect information from the physical world, and actuators, which act on the environment. These objects are integrated into an intelligent decision system, which represents the cyber world [7].

Due to their characteristics and properties, CPSs are used in a wide range of fields, such as smart factories, emergency response, environmental monitoring, building automation, critical infrastructure, healthcare and medicine, intelligent transport, and service robots.

A cyber-physical system can simplify modeling and mitigate natural disasters because its architecture has networks of sensors and actuators that allow to reduce and/or remedy the impacts caused by these events. In this context, the physical world comprises the environmental events to be supervised or controlled. CPSs work with distributed information and communicate with the target environment through sensors and actuators that interact with each other and convert other forms of energy into electrical signals and vice versa [1].

The approach of using the cyber-physical concept for environmental monitoring goes through several phases, incorporating in each phase the use of IoT devices and their connectivity, as well as more appropriate computational technologies for complex data analysis, such as machine learning and Big Data. The next sections explore each of these technologies, associating them with studies and research on the problem of landslides and floods.

TABLE I
MAIN TRIGGERING AND PREDISPOSING AGENTS OF THE PHENOMENA

		Triggering or predisposing agent			
		Anthropic intervention	Rain	Hydrographic basin	Geological and geotechnical conditionings
Phenomenon	Landslides	✓	✓		✓
	Floods	✓	✓	✓	

TABLE II
MAIN PARAMETERS FOR MONITORING

		Parameters				
		Movement	Pluviometry	River flow and level	Soil moisture	Temperature, Air humidity, Atm. pressure
Phenomenon	Landslides	✓	✓		✓	
	Floods		✓	✓		✓

A. *Internet of Things – IoT*

The Internet of Things is a network of objects that communicate and interact autonomously over the Internet, allowing the monitoring and management of these devices via software to increase the efficiency of systems and processes, enable new services and improve people's quality of life. In the context of this paper, IoT devices are those that can be used to monitor parameters relevant to the phenomenology of natural disasters, both for landslides and floods.

1) IoT on landslides: Brazil has a national network for monitoring natural disasters, the National Center for Monitoring and Alerting of Natural Disasters (Centro Nacional de Monitoramento e Alerta de Desastres Naturais - CEMADEN), whose mission is to carry out the monitoring of natural threats in areas at risk in Brazilian municipalities susceptible to the occurrence of natural disasters. CEMADEN uses a network of calibrated sensors, with well structured maintenance and operation. However, the center still faces challenges such as increasing monitored areas, increasing monitoring resolution, and reducing process costs through the use of low-cost sensors.

Mendrot and Stringhini [8] made a systematic review that maps the main types of sensors used in the monitoring of landslides (Figure 3), as well as the types of connectivity, energy sources, and hardware used in the same application domain.

2) IoT on floods: The study presented in [9] provides an application of wireless sensor networks and geospatial services to monitor the level of the rivers that run through the city of São Carlos-SP and to use the data provided by the sensors to detect floods. This type of approach has become important due to the constant occurrence of floods in Brazil, as well as technological advances in the detection of floods in urban rivers, helping to save lives and avoid material losses. The proposed model uses modules *Xbee* that communicate in the IEEE 802.15.4 *ZigBee* standard, providing less energy consumption, smaller physical size and greater communication range in each node.

B. *Connectivity*

There is a lot of interest in developing effective natural disaster management systems and for that, the information must come from heterogeneous and interconnected sources. In this context, IoT technologies using wireless communication have been widely used to monitor natural disasters in remote and inaccessible areas. In this sense, we can categorize communication according to the way information flows from the sensor node to the integration with the edge and the digital infrastructure.

Two categories of communication are more frequent: cooperative and non-cooperative. In the cooperative communication model (device to device – D2D), a sensor node communicates with other nodes to obtain the information of interest, in a multi-hop retransmission scheme. In the non-cooperative model, the data flows without the need to use other nodes. The two models are illustrated in Figure 4.

D2D communication has also been used in natural disaster scenarios to manage the radio spectrum and energy consumption, providing high quality of experience (QoE), and better quality of service (QoS). In disasters, the effective use of radio resources is extremely important, since it aims to serve a large number of affected people, collecting information from different nodes in the areas of the disaster. In this context, D2D communication is an effective solution, allowing an efficient allocation of the spectrum without adding any further delay in the upload of information for the users' devices [10].

Non-cooperative communication is the most frequent model for implementations, since its devices are more easily offered by the market and also because it benefits from existing infrastructure in an urban environment. In this scenario, cellular and LPWAN technologies stand out.

1) Cellular communication: In an urban environment, cellular communication is present almost throughout the Brazilian territory, allowing the transfer of data in cellular technologies, such as 2G (GSM, DAMPS, PDC), 2.5G (GPRS), 2.75G (EDGE), 3G (UMTS)/WCDMA, HSPA, HSUPA, EvDO), 4G (LTE, LTEA), and 5G. M2M (Machine-to-Machine) connectivity is referenced in the cellular context or MTC (Machine-

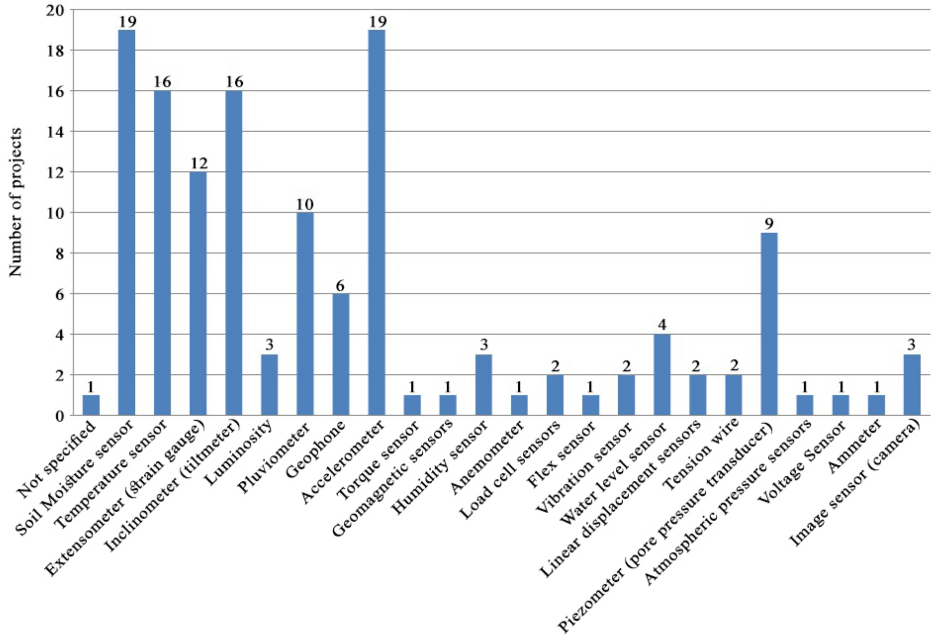

Fig. 3. Types of IoT sensors used to monitor landslides in the projects analysed by Mendrot and Stringhini [8].

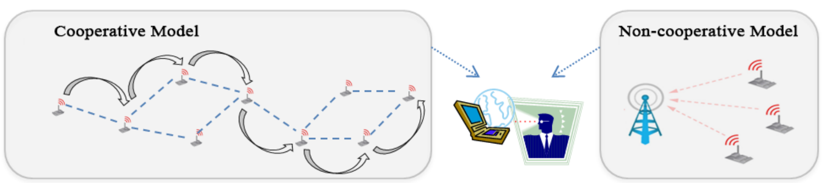

Fig. 4. IoT device connectivity models.

type Communication) within 3GPP (3rd Generation Partnership Project) [11].

It is worth highlighting the perspectives of 5G systems that will bring crucial resources such as flexibility, (re)configuration and network resilience and, therefore, will play a fundamental role in improving communication in disaster situations. Furthermore, in 5G, the network will support the IEEE 802.21 standard (Media Independent Handover – MIH), allowing seamless transfer between multiple available networks without interruption. 5G networks are expected to not only achieve much faster transmission throughput, but also to support emerging use cases related to IoT, M2M communication, transmission services, and rescue communication during natural disasters. 5G will meet these demands by adopting new technologies, such as proximity services, where devices communicate directly with each other, instead of relying on carrier base stations that may have been destroyed or damaged [10].

2) Low Power Wide Area Network – LPWAN: In the case of natural disaster scenarios, usually remote and inaccessible, there are IoT applications that require a wide coverage area, long battery life, low bandwidth and low cost devices. To these contexts, it can be well applied the technologies known as Low Power Wide Area Network – LPWAN, which include the Narrow-Band IoT – NB-IoT [12], the Low Power Wide Area Network – LoRa WAN [13], Sigfox, the Random Phase Multiple Access – RPMA, and Wi-Fi HaLow [14].

C. Machine Learning

The machine learning field studies the construction of computer programs that learn (i.e., automatically improve their performance) from data analysis. Machine learning techniques have shown good results in recognizing patterns in the most varied application domains, including those related to natural disasters [15].

1) Machine learning applied to landslides: In order to conduct a survey of applications of machine learning techniques in the analysis of landslides and floods, searches for scientific publications were carried out on the indexed bases Web of Science^{TM} Core Collection, from Clarivate Analytics, and Scopus$^{®}$, by Elsevier. These searches were limited to articles in English published between 2015 and 2020. For each the phenomenon, a specific search string was used in order to obtain the most relevant publications in each area. For

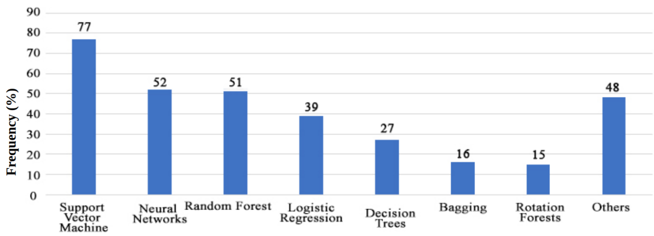

Fig. 5. Main machine learning techniques applied to landslides prediction.

landslides, the following search terms were used: *landslide*, *machine learning*, *prediction*.

It was observed that, in the analyzed publications, machine learning was used to identify landslide susceptibility maps, as well as to make predictions. The algorithms used for these purposes and their respective relative frequencies in the selected publications were: Support Vector Machines (24%), Random Forests (16%) [16], Neural Networks (16%), Logistic Regression (12%) and Decision Trees (8%) [17], Bagging (5%), Rotation Forests (4%), and others (AdaBoost, Naïve Bayes, MultiBoost, Radial Base Functions, Deep Learning, Linear Regression – making 15%). Figure 5 shows the absolute frequency of the algorithms in the analyzed works. Hybrid learning models were also used, as in the work of [18] to predict landslides time intervals.

For the application of machine learning techniques, both in susceptibility mapping and prediction, environmental conditions data from the regions of interest are necessary. In the review carried out, there were identified 62 articles that mention these data, being the most used: slope, lithology, elevation, plan curvature, land use and occupation, distance to roads, distance to rivers, profile curvature, topographic wetness index, distance to faults and rainfall.

In Brazil, few studies have been found; the work of Bragagnolo et al. [19], on the use of neural networks for mapping the susceptibility of landslides, stands out. China is the main reference about the subject, with 53 publications, followed by Vietnam (25) and India (14).

2) Machine learning applied to floods: Mosavi, Ozturk and Chau [20] carried out a systematic literature review to map the state of the art of using machine learning to predict floods. The review initially considered more than 6000 articles and then selected among them the works in which the accuracy and performance of at least two learning models were compared. The selection resulted in 180 articles. The algorithms most used in the selected works were Artificial Neural Networks (ANNs), Multilayer Perceptron Networks, Adaptive Neuro-Fuzzy Inference System (ANFIS), Wavelet Neural Network, Support Vector Machines, Decision Trees, and Ensemble Prediction Systems. Among these, the most used between 2008 and 2017, the period covered by the review, were the ANNs.

Only one of the publications selected in the review ([21]) comes from Brazil. The work used ANNs, weather radars and telemetric data to simulate and predict flash floods in the hydrographic basin of the Tamanduateí River, a densely urbanized area in the metropolitan region of the state of São Paulo.

In the studies analyzed in the review, there are forecasting models for flooding for different periods, from short to long term. Short-term forecasts, generally used in warning systems, are made in real time or hourly, daily or weekly. Long-term forecasts, on the other hand, are used more in public policy management and have monthly, seasonal or annual intervals. In the studies analysed, real-time forecasts are between 1h and a few minutes in advance, while hourly forecasts precede floods by 1h to 3h and, in some cases, by 18h to 24h. Daily forecasts occur 1 to 6 days before the event. Monthly forecasts can precede events by up to three months, for example.

The review carried by Mosavi, Ozturk and Chau (2018) also identified four trends in the area's literature that have significantly contributed to improve the quality of flood predictions: (1) hybridization through the integration of different learning algorithms and/or soft computing techniques, statistical methods and physical models (in contrast to pure learning approaches); (2) the use of data decomposition techniques to improve the quality of datasets and, consequently, the accuracy of forecasts; (3) the use of sets of methods (ensemble systems), to improve the generalizability of models and reduce uncertainty in forecasts; (4) the use of optimization algorithms to better adjust the parameters of the learning algorithms.

D. Big Data

Big Data technologies have become a key component in research and development in the area of natural disaster management and have been changing the way this type of disaster is studied and treated. Big Data in this context mainly refers to large volumes of data from different sources and types, stored and processed efficiently to support the different phases of disaster management (i.e., monitoring, detection, post-disaster assessment, operational assistance in rescuing, recovery and reconstruction of the affected areas) [22].

Among the types of data commonly used are: sensor data, satellite images, unmanned aerial vehicle images, space-time data collected in real time (such as GPS and telephone call detail records), crowdsourcing, and government databases (such as census and maps). Modern systems support reactive or preventive decision-making to disasters through the integration and multimodal analysis of data from heterogeneous sources. To provide fast and accurate responses, based on updated data, they rely on tools for processing data both in batches (such as Hadoop and Spark, both from Apache) and in real time (such as Apache Storm), generally executed on distributed and scalable platforms, such as computational clouds [23]. Real-time processing is necessary, for example, in detecting changes in the situation of the monitored locations, while batch processing is useful, for example, in the extraction of predictive models from historical and statistical data series.

Many recent studies also show that Volunteered Geographic Information (VGI) contributes to improving disaster and risk management, as it increases the density and coverage of data collection. VGI are spatio-temporal data produced by ordinary citizens, on social media platforms (such as Facebook and Twitter), collaborative mapping (such as OpenStreet Map) and crowdsourcing, or collective collaboration (such as Ushahidi) [24]. From VGI, it is possible to extract information, for example, on the location, severity, and extent of the events that occurred and also to identify the resulting population agglomerations and displacements. The systematic review by Albuquerque et al. [25] maps works that employ VGI in disaster management. An application example in Brazil was presented by Horita et al. [24], who proposed a method to combine data from precipitation radars and VGI in the identification of flood areas in the city of São Paulo-SP.

As occurs with other types of systems that use Big Data, a cyber-physical system for natural disaster management needs to deal with data collection, transmission, storage, integration, analysis, and visualization. The integration of data from different sources improve the quality and completeness of the data, but before it can be made, the collected data needs to be filtered (to remove anomalies) and standardized. Machine learning techniques can be applied to automate error detection and data integration [22].

To detect changes in the situation of the monitored locations and enable the appropriate response actions, the cyber-physical system needs to process the data in (almost) real time. Remote sensing devices can collect data at high rates, but have low energy autonomy, and storage and processing capacity very limited in general. For this reason, the processing and persistence of the large volume of generated data needs to be done on a more robust and scalable computing platform, such as the clouds, but with the non-negligible cost of transferring the data to the platform. In this scenario, making efficient use of the platform in order to guarantee low latency in detecting events in real time is not a trivial problem.

Recent research [26], [27] indicates that using fog computing – that is, bringing data processing (or part of it) to devices at the edge of the network – can be more advantageous than focusing it all on devices in the cloud. The nodes in the fog can, for example, handle data processing in real time and send pre-processed data to nodes in the cloud [28]. The nodes in the cloud, in turn, can take care of persistent storage of data and processing (in batches) of historical data. With this approach, data can be processed closer to where it is collected whenever possible, thereby reducing network traffic and latency, among other benefits.

IV. Conclusion

Cyber-physical systems can assist in predicting and mitigating landslide and flood events. The implementation of a network of low-cost sensors connected in real time with the intelligent prediction system, applying the appropriate technique associated with the knowledge of the phenomena, will allow the population to have information in advance, safeguarding lives. As discussed in this paper, the development of such systems involves several computational challenges entangled with complexities of natural disasters. We can list some lessons learned from the study of projects developed in Brazil and related works, that must be adapted to local conditions.

The low-cost sensors increases the possibilities of distributed monitoring. However, sensor networks usually need to be installed in risk areas, with precarious settlement locations, where they can be exposed to vandalism, also representing a challenge for the energy supply and connectivity for these sensors. Thus, their implantation can have high operational costs and demands intensive planning. Moreover, community engagement may be required to ensure their long-term maintenance. The machine learning techniques used today assist in the identification and understanding of events, as well as in their prediction. However, data with a high spatial and temporal resolution of natural disasters are scarce, mainly from low-cost sensors deployed in a distributed manner. Generating data in these scenarios requires considerable effort, and learning models can lengthen the process with an intense step of training the algorithms with simulations of the phenomena.

The cyber-physical system integrate the sensors in physical environment into cybernetic environment, while IoT components show data about the phenomena. Volunteered Geographic Information tools can be used to complement the data under different perspectives and engage community to collaborate, for providing efficient and rapid response during and after the disasters. On the one hand, combining data from different sources (e.g. sensors, social media, and government) in a Big Data approach can improve the response of the cyber-physical system. On the other hand, handling the large volume and the heterogeneity of data in a timely manner is not trivial.

In a Nutshell, there are several challenges in the implementation of the cyber-physical system, from the selection of sensors to the alert. To deal with these challenges, it is necessary a multidisciplinary effort including professionals from areas such as Geology, Hydrology, Engineering, Computing, among others.

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References

[1] J. Estrela, Vania V.and Hemanth, O. Saotome, E. G. H. Grata, and D. R. F. Izario, "Emergency response cyber-physical system for flood prevention with sustainable electronics," in *Proceedings of the 3rd Brazilian Technology Symposium*, Y. Iano, R. Arthur, O. Saotome, V. Vieira Estrela, and H. J. Loschi, Eds. Cham: Springer International Publishing, 2019, pp. 319–328.

[2] O. Augusto Filho, "Mass movements identification, modeling, analysis and mapping: some experiences in the southern of Brazil, Sao Paulo state," *Landslides: evaluation and stabilization. Balkema, Taylor & Francis Group, London*, pp. 57–68, 2004.

[3] L. Highland, P. T. Bobrowsky *et al.*, *The landslide handbook: a guide to understanding landslides*. US Geological Survey Reston, 2008.

[4] E. Marcelino, *Desastres naturais e geotecnologias: conceitos básicos*. Santa Maria, RS, Brazil: Instituto Nacional de Pesquisas Espaciais – INPE, 2008. [Online]. Available: http://mtc-m18.sid.inpe.br/col/sid.inpe.br/mtc-m18

[5] A. dos Santos, *Enchentes e deslizamentos: causas e soluções – Áreas de risco no Brasil*. São Paulo, SP, Brazil: Pini, 2012.

[6] C. Carvalho, E. Macedo, and A. Ogura, *Mapeamento de Riscos em Encostas e Margens de Rios*. Brasília, DF, Brazil: Instituto de Pesquisas Tecnológicas do Estado de São Paulo – IPT.

[7] T. Sanislav, G. D. Mois, S. Folea, and L. Miclea, "Integrating wireless sensor networks and cyber-physical systems: challenges and opportunities," in *Cyber-Physical system design with sensor networking technologies*, ser. Control, Robotics & Sensors, S. Zeadally and N. Jabeur, Eds. Institution of Engineering and Technology, 2016, pp. 47–76.

[8] A. Mendrot and D. Stringhini, "Redes de sensores sem fio para monitoramento e detecção de deslizamentos de terra: uma revisão sistemática," in *Proc. of the 2019 Conferencia Ibero Americana Computação Aplicada (IADIS)*, 12 2019, pp. 309–313.

[9] L. Degrossi *et al.*, "Using wireless sensor networks in the sensor web for flood monitoring in Brazil: Lessons learned," in *Proc. of the 10th International Conference on Information Systems for Crisis Response and Management (ISCRAM)*, 2013, pp. 1–5.

[10] A. Adeel, M. Gogate, S. Farooq, C. Ieracitano, K. Dashtipour, H. Larijani, and A. Hussain, "A survey on the role of wireless sensor networks and IoT in disaster management," in *Geological Disaster Monitoring Based on Sensor Networks*. Springer, 2019, pp. 57–66.

[11] A. Čolaković and M. Hadžialić, "Internet of things (IoT): A review of enabling technologies, challenges, and open research issues," *Computer Networks*, vol. 144, pp. 17–39, 2018.

[12] R. S. Sinha, Y. Wei, and S.-H. Hwang, "A survey on LPWA technology: LoRa and NB-IoT," *ICT Express*, vol. 3, no. 1, pp. 14–21, 2017.

[13] N. Sornin, M. Luis, T. Eirich, T. Kramp, and O. Hersent, "LoRaWAN specification," LoRa alliance, Tech. Rep., 2015.

[14] Wi-Fi Alliance, "Wi-Fi HaLow." [Online]. Available: https://www.wi-fi. org/discover-wi-fi/wi-fi-halow

[15] L. Bai, J. Wang, X. Ma, and H. Lu, "Air pollution forecasts: An overview," *International journal of environmental research and public health*, vol. 15, no. 4, p. 780, 2018.

[16] T. Xiao, K. Yin, T. Yao, and S. Liu, "Spatial prediction of landslide susceptibility using GIS-based statistical and machine learning models in wanzhou county, three gorges reservoir, china," *Acta Geochimica*, pp. 1–16, 2019.

[17] D. T. Bui, T. A. Tuan, H. Klempe, B. Pradhan, and I. Revhaug, "Spatial prediction models for shallow landslide hazards: a comparative assessment of the efficacy of support vector machines, artificial neural networks, kernel logistic regression, and logistic model tree," *Landslides*, vol. 13, pp. 361–378, 2015.

[18] Y. Wang, H. Tang, T. Wen, and J. Ma, "A hybrid intelligent approach for constructing landslide displacement prediction intervals," *Applied Soft Computing*, vol. 81, p. 105506, 2019.

[19] L. Bragagnolo, R. da Silva, and J. Grzybowski, "Artificial neural network ensembles applied to the mapping of landslide susceptibility," *CATENA*, vol. 184, p. 104240, 2020.

[20] A. Mosavi, P. Ozturk, and K.-w. Chau, "Flood prediction using machine learning models: Literature review," *Water*, vol. 10, no. 11, p. 1536, 2018.

[21] A. J. Pereira Filho and C. C. dos Santos, "Modeling a densely urbanized watershed with an artificial neural network, weather radar and telemetric data," *Journal of Hydrology*, vol. 317, no. 1-2, pp. 31–48, 2006.

[22] M. Yu, C. Yang, and Y. Li, "Big data in natural disaster management: a review," *Geosciences*, vol. 8, no. 5, p. 165, 2018.

[23] S. A. Shah, D. Z. Seker, S. Hameed, and D. Draheim, "The rising role of big data analytics and IoT in disaster management: Recent advances, taxonomy and prospects," *IEEE Access*, vol. 7, pp. 54 595–54 614, 2019.

[24] F. E. Horita, R. Vilela, R. Martins, D. Bressiani, G. Palma, and J. P. de Albuquerque, "Determining flooded areas using crowd sensing data and weather radar precipitation: a case study in Brazil." in *Proc. of the 15th International Conference on Information Systems for Crisis Response and Management (ISCRAM)*, 2018.

[25] J. P. de Albuquerque, M. Eckle, B. Herfort, and A. Zipf, "Crowdsourcing geographic information for disaster management and improving urban resilience: an overview of recent developments and lessons learned," *European handbook of crowdsourced geographic information*, pp. 309–321, 2016.

[26] X. Wei and L. Wu, "A new proposed sensor cloud architecture based on fog computing for internet of things," in *2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)*. IEEE, 2019, pp. 615–620.

[27] J. Dizdarević, F. Carpio, A. Jukan, and X. Masip-Bruin, "A survey of communication protocols for internet of things and related challenges of fog and cloud computing integration," *ACM Computing Surveys (CSUR)*, vol. 51, no. 6, pp. 1–29, 2019.

[28] R. Brzoza-Woch, M. Konieczny, P. Nawrocki, T. Szydlo, and K. Zielinski, "Embedded systems in the application of fog computing—Levee monitoring use case," in *2016 11th IEEE Symposium on Industrial Embedded Systems (SIES)*. IEEE, 2016, pp. 1–6.