A Systematic Review: Big Data Analytics and Landslides

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Abstract

Landslides are among the natural disasters that most affect the population in Brazil and in the world, as they are responsible for numerous human, economic, social and environmental losses. High-resolution aerial and satellite imagery, that contribute to identify this type of event are valuable sources of information, even if they are not the only ones. Machine learning (ML) techniques are often adopted to identify relevant patterns, as high performance computing and data visualization are widely and successfully applied to natural disaster-related data, particularly for landslides. The greater the volume of data processed during machine learning, the better the accuracy of the results obtained. Among other reasons, Big Data (BD) has stood out for its ability to integrate and generate a large volume of data from different sources and in different formats. The use of BD concepts and techniques has become common in several areas of knowledge, in particular for the storage and analysis of data related to natural accidents and, thus, helping to improve decision making as well as prevention of disasters. With the emergence of the BD, it came the challenge of aligning decision-making processes, so that there is no shortage of information or useless data for decision makers. In the case of Brazil and considering, especially, applications to landslide data, there is a lack of articles dealing with the subject. The aim of this study is to investigate the main features used on machine learning techniques, to map the literature, thus pointing out new routes and opportunities in the field. In the systematic review, the eligibility criteria adopted are studies published in the last 4 years (from January 2015 to December 2019), in English, at national and international levels, including publications in scientific events and relevant journals, through databases such as Scopus and Web of Science. The search was performed in a structured form with the terms "Big Data", "machine learn*","landslid*", "forecast*" and "predict*" and the like through the boolean operator "AND" or "OR" in order to restrict the theme to the aspects to be discussed. The researches were included when they contained a description of the BD and ML techniques, and could be applied to landslide studies.*

1 INTRODUCTION

Landslides are one of the most catastrophic events that have a huge impact on humans and have received attention for centuries in several countries around the world. On one hand, the driving factors of landslides are complex.

Landslides can be predicted as it is possible to monitor their conditioning or potentiating agents and the mechanisms related to the movement of materials in the different types of landslide. In other words, it is possible to identify the areas that are most susceptible to landslide, in addition to their typology and magnitude. In this way, it is possible to define and implement distinct mechanisms and actions to avoid and/or minimize the negative consequences caused by this phenomenon in a certain area. To this end, land management should consider three factors: avoiding the emergence of risk areas and situations, identifying and characterizing these already existing regions, and resolving or reducing the risks that exist (Vedovello and De Macedo, 2007).

Big Data is no longer a buzzword nowadays. Big Data carries with it the opportunity to change business models design and everyday decision making that requires emerging data analysis. Its most diffused definition is: “Big Data is high-volume, high-velocity and high-variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight, decision making and process automation” (Gartner Glossary, 2020).

Big Data and predictive analytics have the potential to revolutionize natural disasters such as landslides prevention, presenting a doozy of an opportunity and a challenge to our field (Wang and Sun, 2013).

Landslides prediction methods can be grouped into two types, qualitative and quantitative. The qualitative techniques (landslide inventory and weighted methods) rely on judgment of experts. On the other hand, quantitative techniques (statistical, probabilistic and deterministic methods) are based on mathematical approach. Recently, machine learning algorithms have been used for developing quantitative models (Shirzadi et al., 2018).

Existing literature reviews of Big Data, machine learning and landslide can be divided into two categories: traditional literature reviews and systematic literature reviews (SLR).

In order to understand trends in Big Data, machine learning and landslide could provide a potential guide for future research. In addition, governments could integrate the current knowledge of landslides into their sustainable development policy, planning and programming.

Despite the increasing interest in the use of machine learning techniques to forecast landslides, there is still a lack of research examining the landscape and the spatial data in the Big Data environment in relation to natural disasters such as floods and landslides, particularly in Brazil (Correia et al., 2020). The aim of this study is to investigate the main features used on machine learning techniques, to map the literature and point out new routes and opportunities in the field.

2 METHODS

The basic objective of a Systematic Literature Review (SLR) is to gather and assess the available research related to the subject of interest (the research question), thus achieving impartial results that can be audited and repeated. An SLR is a rigorous methodological review of research results, whose objective is not just to group existing works on this subject; it is also meant to help developing evidence-based guidance for professionals involved in the area of study (Kitchenham, 2004).

Moreover, to demonstrate that the work is new to the existing body of knowledge, the results of an SLR should identify the state of the art regardless to the research question (Levy and Ellis, 2006). The authors of this study planned and conducted the systematic review.

A review protocol at the planning phase was proposed. This review protocol includes: questions definition, search strings, study selection, data extraction, and data analysis. This study used the Parsifal (2018). Parsifal is an online tool designed to support researchers to perform systematic literature reviews within the context of Software Engineering. Geographically distributed researchers can work together within a shared workspace, designing the protocol and conducting the research.

In the first stage, we raised a set of research questions based on the objective of this paper. Then, in the second stage, aiming at the research questions, we designed search strings to find out the studies relevant to answer our questions. In this moment, the stage involves the determination of search terms. After this, the next step is the selection of literature resources. In the third stage, we defined study selection criteria to identify the relevant studies that can really contribute to our study. As part of this stage, pilot study selection was employed to accepted or rejected the literature select in the past step of our process. The remaining two stages involve data extraction and data synthesis, respectively. In the data extraction stage, we initially devised data extraction form and subsequently refined it through pilot data extraction. Finally, in the data synthesis stage, we determined the proper methodologies for synthesizing the extracted data.

2.1 Research Questions

This section describes the process followed to accomplish this systematic literature review, which is based on a known and validated methodology (Kitchenham et al., 2008). The Parsifal – through Systematic Review was used. This is an online tool designed to support researchers to perform systematic literature which lends support for planning, executing, and summarizing an SLR, as proposed by Kitchenham (2004). Moreover, to identify the scenario for scientific literature on landslides, bibliometric analysis techniques (Ikpaahindi, 1985) and content analysis (Duriau et al., 2007) were used.

For the study to achieve its objectives, some research questions are proposed:

(1) RQ1. How has the literature on the use of Big Data analytics on landslides evolved over time?

Seeking answers of a more quantitative nature, this question has been broken down into the following:

RQ1.1. How has the number of publications about this subject evolved over time?

RQ1.2. What are the main periodicals for this subject and how has the number of publications evolved over the last four years?

(2) RQ2. Which and where are the main references about the use of Big Data techniques for landslides prediction?

RQ2.1. Which countries contributed most in terms of publications over the last four years (considering the number of publications)?

RQ2.2. Which have been the most influential studies over the last four years (considering the number of citations)?

RQ2.3. Who are the main authors (considering the number of publications)?

(3) RQ3. Which machine learning techniques have been used for landslides prediction (by the number of keywords)?

RQ3 aims at identifying the ML techniques that have been used to predict landslides. Practitioners can take the identified ML techniques as candidate solutions in their practice. For ML techniques that have not yet been employed in landslides prediction, researchers can explore the possibility of using them as potential feasible solutions.

(4) RQ4. What is the overall estimation accuracy of ML models?

RQ4 is concerned with the estimation accuracy of ML models. Estimation accuracy is the primary performance metric for ML models. This question focuses on the following four aspects of estimation accuracy: accuracy metric, accuracy value, data set for model construction, and model validation method.

(5) RQ5: Are there any ML models that distinctly outperform other ML models?

The evidence of comparisons between different ML models can be synthesized to determine which ML models consistently outperform other ML models. Thus, RQ5 aims to identify the ML models with relatively excellent performance.

(6) RQ6 What are the main features used by ML techniques?

The ML feasibility use is related with data acquisition. In case of landslides areas, the conditioning factors may be different according to the region. In addition, data gathering rely on devices such as satellites and accelerometers.

2.2 Research Questions the sampling processes

The initial sample was taken from the indexed databases Web of Science Core™ Collection through the ISI Web of Knowledge™ portal (Thomson Reuters) and Scopus® by Elsevier B.V. These databases were selected since they provide interfaces that make it possible to perform simultaneous searches on different sources using the common set of search strings. In a broad way, i.e., without restriction on periodicals, periods or areas of knowledge, studies from January 2015 until December 2019 were identified.

Works that did not meet the requirements above were rejected under the quality criterion (Kitchenham and Charters, 2007; Kitchenham et al., 2008).

Figure 1 represents the initial schematic presentation of the process for identifying and selecting the sample for the study. The following steps were used to construct the search terms:

(a) Derive major terms from the research questions.

(b) Identify alternative spellings and synonyms for major terms.

(c) Check the keywords in relevant papers or books.

(d) Use the Boolean OR to incorporate alternative spellings and synonyms.

(e) Use the Boolean AND to link the major terms

With the use of previous definitions for the search strings, the searches were carried out on the databases indexed in Web of Science and Scopus. Based on the results obtained, the strings were refined eliminating publications in which the expressions contained in the search string were not connected with Big Data technologies and landslides prediction.

Previous Search 1 and Search 2 are introduced individually to highlight the relevance of these subjects. Afterward they were combined by AND operator which resulted in 387 candidate papers.

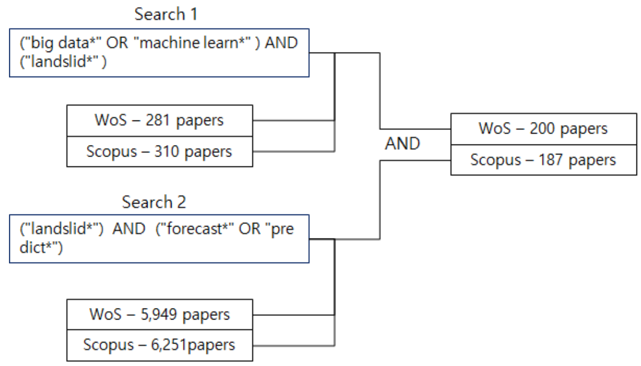

Figure 1. Search and selection process – search phase. Source: the authors, 2020.

Figure 2 represents selection phase divided in three steps. Where a step restricted the publications written in English and from 2015 to 2019, resulting in 337 relevant papers. The result of the search and first selection were inserted into the database of the Parsifal tool where additional steps were performed.

Parsifal tool automatically removed duplicated articles, i.e. step b, resulting in 226 relevant papers.

Finally, inclusion and exclusion criteria (defined below) were applied to the candidate papers to identify the relevant papers, which provide potential data for answering the research questions. Thus 155 publications were accepted.

Inclusion criteria:

- Clearly mention machine learning to predict landslides

Exclusion criteria:

- Deal with the topic superficially
- Not related to Big Data, ML or AI
- Not related to landslides prediction

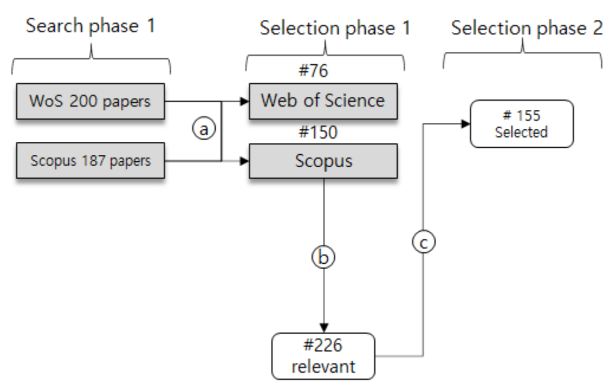

Figure 2. Search and selection process – selection phase. Source: the authors, 2020.

2.3 DATA ANALYSIS

By data extraction, we exploited the selected studies to aggregate evidence for answering the research questions. A single piece of evidence might have small evidence force, but the aggregation of many of them can make a point stronger. The quantitative data in this review were achieved by using varying experimental designs.

We employed different strategies to synthesize the extracted data pertaining to different kinds of research questions. The synthesis strategies are explained in detail as follows.

For the data pertaining to RQ1, RQ1.1, RQ1.2, RQ2, RQ2.1, RQ2.2 and RQ2.3, we used narrative synthesis method. That is, the data were tabulated in a manner consistent with the questions. Some visualization tools, including bar chart, and pie chart. The citations and publications were analyzed to identify the most influential studies. This analysis is based on the premise that authors cite publications they consider important to the development of their studies; therefore, the documents cited with greatest frequency probably exercise a greater influence that the least often cited (Ramos-Rodríguez and Ruíz-Navarro, 2004).

For the data pertaining to RQ3, that concerns the main ML techniques, we used counting method. That is the same method used to RQ6 but here we count how often a landslide factor was used as input to ML techniques.

On the other hand, data pertaining to RQ4 and RQ5, which focus on the comparison of estimation accuracy between different estimation models, we used vote counting method. We just need to count the number of experiments in which model A is reported to outperform model B and the number of experiments in which model B is reported to outperform model A. The two numbers are then used as the basis to analyze the overall comparison between model A and model B. By this way, we can obtain a general idea about whether an estimation technique outperforms another technique or not.

The use of content analysis techniques is intended to respond to questions RQ3 and RQ6. This technique was adopted because it offers flexibility in defining a coding scheme for the techniques of the landslides and machine learning and for the research question in the landslide's features contained in the sample. This is then used in the frequency statistics for these codes and their relationships.

3 RESULTS

This section contains the results of the process of surveying quantitative data related to the periods, publications, authors, citations and other information involving the periodicals that are part of the sample.

First, we present an overview of the selected studies. Second, we report and discuss the review findings according to the research questions, one by one in the separate subsections. During the discussion, we interpret the review results not only within the context of the research questions, but also in a broader context closely related to the research questions.

3.1 BIBLIOMETRIC ANALYSIS

This subsection contains the results of the process of surveying quantitative data related to the periods, publications, authors, citations and other information involving the periodicals that are part of the sample.

3.1.1 Publications/year/period

It was identified 155 studies in the field of landslides prediction using machine learning techniques. They were published during time period 2015-2019 and we focus on papers written in English. 7 papers (4%) were found up to 2015, 12 (8%) are from 2016, 23 (15%) from 2017, 33 are from 2018 (21%), 80 from 2019 (52%), totaling the 155 publications selected. It is emphasized that 52% of the publications are from 2019, clearly showing the intensity, currency and increased interest by researchers in the subject (Figure 3).

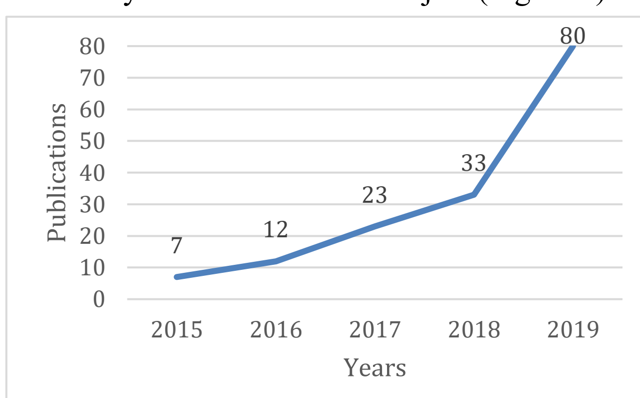

Figure 3. Number of publications in recent years. Source: the authors, 2020.

3.1.2. Frequency of the citations in the periods

Table 1 presents the frequency of citations in the period starting in 2015, showing the most influential studies over the last five years. The precursor work of Bui Dieu Tien et al. (2015) fulfils the criteria of the sample and uses a case study to deal with the landslides' prediction by the use of five machine learning models, having MLP Neural Nets model the highest prediction capability (90.2 %).

Table 1. The 10 most influential articles about this study's theme.

Publication	Citations	Source
Bui, Dieu Tien et al. (2015)	305	Scopus
Goetz, J. N. et al. (2015)	138	Scopus
Pham, Binh Thai et al.[1] (2016)	120	WoS
Pham, Binh Thai et al. (2017)	116	Scopus
Pourghasemi, Hamid Reza; Kerle, Norman (2016)	90	Scopus
Bui, Dieu Tien et al. (2016)	84	Scopus
Chen, Wei et al. (2017)	80	Scopus
Shirzadi, Ataollah et al. (2017)	75	Scopus
Chen, Wei et al. (2018)	74	Scopus
Pham, Binh Thai et al.[2] (2016)	68	WoS

Sources: (**1**) "Scopus®" (Elsevier B.V.) and (**2**) ISI Web of Knowledge™ (Thomson Reuters).

3.1.3. Publications /periodicals/periods

The 155 works in the sample were published in 78 different periodicals. Table 2 shows only the top 10 journals that present the most of publications about this study topic between 2015 and December 2019. In first place is the Environmental Earth Sciences journal, with 11 publications.

Table 2. The selected journals with the most publications. Source: the authors, 2020.

Periodicals	No. of Publications
Environmental Earth Sciences	11
Landslides	9
Catena	8
Remote Sensing	8
Bulletin of Engineering Geology and the Environment	6
Geocarto International	6
Science of the Total Environment	6
Engineering Geology	5
Sensors (Switzerland)	5
Applied Sciences (Switzerland)	4

3.1.4 Countries/publications

It was also verified where the main references about the use of Big Data techniques for the landslides' prediction were located (Figure 4). Of the 155 articles considered, China has more publications (51) followed by Vietnam (22); Iran (15); India (13); South Korea (7); Turkey (6); Japan and Austria (4); Malaysia and Croatina (3), Taiwan, Norway, Italy, Indonesia, Australia and Algeria (2 each one), Tunisia, Sri Lanka, Slovakia, Serbia, New Zealand, Netherlands, Korea, Jordan, Greece, Germany and Brazil (1).

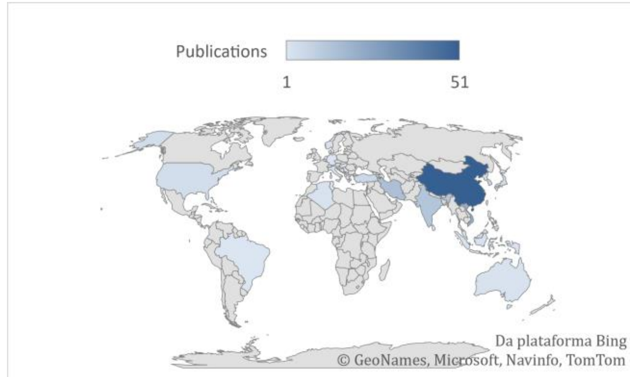

Figure 4. Countries that have more publications about BD and landslides prediction. Source: the authors, 2020.

3.1.5 Types of ML techniques

From the selected studies, it was identified the most used types of ML techniques that had been applied to predict landslides (Figure 5). The identified machine learning techniques were support vector machine (77, the most used), neural network (52), random forest (51), logistic regression (39), decision tree (27), bagging (16), rotation forest (15) and others (adaboost - 10, naive bayes - 9, multiboost - 8, rbf - 8, deep learning - 8, linear regression - 2, xgboost - 2, knn - 1, radial base - 0).

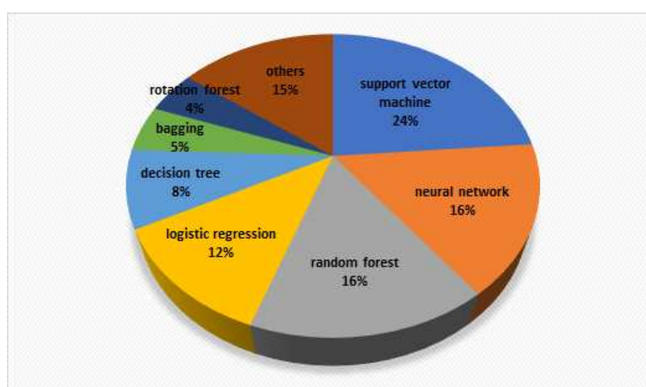

Figure 5. ML techniques identified. Source: the authors, 2020.

3.1.6 Overall estimation accuracy and the most outperformed ML models

In order to provide a panoramic overview regarding most used ML techniques performance, we considered accuracy metric. In classification problems, accuracy is the number of correct predictions, positive or negative, divided by the total number of predictions made (Sokolova et al. 2006).

From selected sample of 46 papers, those about the use of ML techniques that informed overall accuracy metric for testing, we estimated average accuracy in 86.74%, having a peak of 96% as reported by Emrehan Kutlug Sahin, Ismail Colkesen & Taskin Kavzoglu in the article "A comparative assessment of canonical correlation forest, random forest, rotation forest and logistic regression methods for landslide susceptibility mapping" (2018), when they combined ensemble learning methods and the conventional statistical method decision tree method to landslide displacement prediction for Yenice district of Karabuk in Turkey.

Furthermore, we can find that random forest and support vector machine overall outperform the other ML models. Nonetheless, we should avoid drawing such a misleading conclusion that RF and SVM are always preferable without any restriction.

3.1.7. Most usual features

The 62 works in the sample that mentioned factor used to predict landslides through ML technique we highlight: slope, lithology, elevation, plan curvature, land use, aspect, distance to roads, distance to river, profile curvature, topographic wetness index, distance to faults and rainfall as the most used.

4 CONCLUSIONS

This article shows that of the 155 selected studies, 2019 was the year with the largest number of studies about BD, ML techniques and landslides prediction, and there is an increasing trend of publications about this subject. Regarding the periodicals that published the most about this theme, Catena and Environmental Earth Sciences journals stand out.

The country with the most publications is China, few publications from Brazil about this topic were noted; in the case of Brazil and considering, especially, applications to landslide data, there is a lack of articles dealing with the subject. The most used machine learning technique, identified in the selected studies, was the support vector machine.

It was estimated an average accuracy in 86.74% and it could find that random forest and support vector machine overall outperform the other ML models. According to the systematic review, there is still a shortage of studies about Big Data, machine learning techniques and landslide's prediction, mainly in Brazil; however, it was noted there has been a growing interest about the topic in recent years.

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