Utilization of google maps for depicting landslide pattern in Indonesia

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Abstract. The historical landslide data in GIS (Geographic Information System) environment is valuable to estimate pattern in landslides distribution and frequency, which are useful for landslide hazard analysis and mitigation. By using the landslide reports released officially by The National Agency for Disaster Management (BNPB), those non-spatial data need to be converted into the spatial ones. The reports primarily contain location, date of event, impact and triggering factor. This study is exploring Google Maps which is a web mapping service to process the historical landslide data of Indonesia. By preparing historical landslide data in the form of spreadsheet, Google Maps directly can change the whole data into a custom map ‘landslide distribution map’. The attribute can be edited, the map can change interactively, and vice versa. The appearance of the custom map can be styled by a certain column so its statistical information comes up. A landslide distribution map produced in Google Maps can be shared to others and can be exported as a GIS layer for further analysis. This article shows the utilization of facilities provided by Google Maps to prepare and analyse the landslide inventory map.

1. Introduction

Historical landslide data is a key factor to prepare a landslide susceptibility mapping. Along with some causative landslide factors, an assessment of landslide susceptibility can be done [1–7]. The historical landslide or inventory landslide data is derived by combining some data or acquisition processes. The commonly efforts for obtain landslide inventory data are performed by collecting some landslide event information from news, local governments, interpretation from remote sensing data, and field survey.

Complete landslide data are very recommended for quantitative landslide susceptibility assessment, although there will never be [8]. Before providing a such data, an initial landslide historical data should be prepared. Some studies concerned to global landslide catalogue compiled from local government reports and news reports [9–11]. Similar to the global landslide catalogue, Indonesian landslide inventory collected from landslide reports have an uncertainty related to the location of each landslide occurrence [12]. This uncertainty is caused by a lack or an absence of geographical coordinates on the landslide reports. The such inventory landslide data were used to gain a general landslide trend, not to provide data for quantitative risk assessment [9]. A direct map overlay by using the such landslide data, is not appropriate [13]. It is basically for understanding the landslide characteristic leading to mitigate the disaster. By the knowledge, some causative factors to assess the landslide susceptibility mapping in a certain area, can be identified properly.
The landslide data sourced from local government have to be organized in the GIS (Geographic Information System) environment as well as a spatial visualization of landslide inventory data. In this study, a landslide dataset owned by The National Agency for Disaster Management (BNPB) is used, namely Indonesian Disaster Data and Information (DIBI). It can be accessed at http://bnpb.cloud/dibi/. DIBI landslide catalogue provides the landslide historical data which is sequential according to the date of the incident. Besides using DIBI as the main data, news reports are also used as a support. The news reports are useful for adding information and also for confirming the landslide data.

Indonesian landslide occurrence distribution and its trends have already discussed in some previous studies, either for small or larger area, in various way to obtain the data [12,14–17]. However, the such studies for the entirely Indonesian territory have not been found and the using of Google Map for this field has never been discussed. This article tried to convey the distribution of landslide events throughout Indonesian region as a custom map on Google Maps.

Google Maps is widely available, free of charge, and powerful tool for spatial visualization with simple, that requires little training or experience to use it [18]. It succeeded in making customizable multi-purpose maps, familiar and accessible to millions of ordinary web users around the globe from outside the fields of geosciences [19]. Some studies used Google Maps as a tool to describe the spatial distribution for health fields [18,19].

This study is curious to explore the utilization of Google Maps for plotting every landslide location in the midst of the lack of updated administrative maps. This article shows the utilization of facilities provided by Google Maps to prepare and analyse the landslide inventory map.

2. Landslide occurrence reports
DIBI landslide data are used as a main data source and news reports are used as supporting data. Not all landslide event data in DIBI landslides catalogue were found on the news reports. It is probably, the landslide event is only local disaster which does not have a significant impact. If there is fatality in a landslide occurrence, the news reports about the disaster can be found easily. Furthermore, the news is assisting to gain the additional information for completing the existing one. For instance, the coordinate information of a landslide event in Tegalmanik Sub-village, Situbondo District on March 31, 2009; could be found on the news. The news is also important to crosscheck the error in reporting of landslide data. As an example, the location of a reported landslide occurred in Tegasasri, but the correct one is Tegalsari. Based on the observations, the compilation of inventory data sourced from DIBI would be better if cross-checked with news reports.

3. Exploring Google Maps for landslide data representation and analysis

3.1. Converting non-spatial data into spatial ones (in GIS environment)
In this step, we have to prepare a spreadsheet (tabular data). Tabular data are consisting of columns and rows. Each column represents a particular variable and each row corresponds to a given member of the data [20]. Google Maps has a restriction for amount of records that can be saved in a spreadsheet i.e. 2000 rows (records). It means if the data have more than 2000 records, the data analysis on Google Maps becomes not optimal due to the data separation into some files. In this study, a spreadsheet was made to collect landslide occurrence data for two months (February and March 2019) which has 193 records.

To build a landslide database, the conceptualization for the database should be made. Referring to [10], landslide catalogue should contain several primary elements like information location, time and trigger; and secondary elements like type and relative size of the event, latitude and longitude, and impact information. Advantageous to use Google Maps is the attribute can be edited easily followed by
interactive map changes. Therefore, in the presented worksheet of this study (Figure 1), not every element is included, due to the element can be modified, added, or edited in the process in Google Maps. In this study, the spreadsheet has 11 fields, i.e. (1) no., (2) date, (3) sub-village, (4) village, (5) sub-district, (6) district, and (7) province, (8) coordinate, (9) impacts, (10) URL source and (11) trigger. All of them were acquired from DIBI landslide catalogue except URL source. No information about the type and relative size of the landslide event in DIBI catalogue, so that the information is not included in this data compilation.

![Figure 1. Screenshot of a spreadsheet of historical landslide data.](image)

By preparing historical landslide data in the form of spreadsheet (Figure 1), Google Maps directly can change the whole data into a custom map ‘landslide distribution map’. The data have to contain a column with one of the following: (1) latitude-longitude information, (2) addresses and (3) place names. They were imported in Google Maps and then map features were added automatically, by assigning certain column that tells the Google Maps where to put placemarks on the map. The location information can be contained in one column or more. In this study, some columns are used to mention the location information. Besides, we also have to assign a column to be a title of each placemarks. The column of date was chosen as a title to describe the temporal information of landslide distribution.

### 3.2. Editing, manipulating and analyzing the spatial data

When a spreadsheet has already imported into Google Maps, many data are already shown on the map, but sometimes some data does not appear on the map due to errors in defining the location. There are mismatches between the location in the spreadsheet and in Google Maps. It can be fixed easily by correcting the wrong locations in their records. By correcting the wrong location, the error is already disappeared, and the placemark is added on the map. Many cases happened in the name of sub-district because some of them could not be found in Google Maps. The result is a landslide distribution in Indonesia for two months (February – March 2019) as shown in Figure 2.
Figure 2. Landslide distribution in Indonesia for February – March 2019.

The appearance of layer features on the map (Figure 2) is in the default view, a uniform style. It can be customized by changing the style into other styles like sequence of numbers, individual styles and styles by data column. The last one is the main facility in analysing landslide data, correcting the data, as far as understanding their trends.

The landslide map has 11 fields as well as the spreadsheet used as input. Some of them were used in analysing. By assigning province as the data column (styled by province), it can be seen that every province has its own symbol colour. The symbols for each province can be changed to increase the contrast among them. It can be used to ease in checking the correctness of the provincial names, whether every location is located in the right province or not. We found some incorrect province names in the data, especially in Java which has many landslide event data.

A feature which has incorrect province names can be fixed by selecting the feature first, and then editing the records. Once being revised, users can obtain simple statistical information about the number of landslides occurring per province which can be used in the landslide analysis. Even more, the number of events is already sorted largest to smallest. The top five of landslide frequency during February-March 2019 sequentially occurred in Central Java (79), West Java (72), East Java (19), South Sulawesi (4), and Special Region of Yogyakarta, DIY (3).

By using “styled by trigger”, we get so many classes, due to the trigger has not been classified clearly. In the historical data, the trigger is stated in numerous statements, e.g. heavy rain, heavy rain and long rain (3 hours), rain, extreme rain, heavy and long rain (2 hours) and much more. In order to make an analysis on trigger, we have to classify the records. As an example, some records containing heavy and long rain with some various explanation about its duration were classified into “heavy and long rain”. Before being edited, the number of landslides caused by heavy and long rain was 44. But after being edited, the number was changed into 50. To edit the records, we only need to open the table and searching the records that we want to edit. It is very simple, and the number of “heavy and long rain” class automatically has changed. By using the facility in manipulating data, a user can edit the data in a column of trigger so as all of the records have been classified.

The column of impact is need to analysed. The column of impact has very diverse records which explains some information e.g. the number of impacted houses, the level of damage, affected people, injuries and fatalities. To analyse certain information of impact, some new columns can be created to split many information included in the impact column. For example, we can make a new column of number of fatalities, number of damaged houses, etc. Data manipulation can be done as much as possible in accordance with the purpose of data exploration to be carried out.

4. Discussion

The column of “no.” contains the landslide report sequences. By using “styled by no.”, the data can be presented based on the range or based on the category due to the column has a number data type. Meanwhile the data type of province, trigger and impacts columns are text; then can be presented based
on category only. Yet in this study, the information from column of impacts can be split into some new columns e.g. number of fatalities, number of damaged houses, etc., which have number data type. If based on the range, Google Maps provides a maximum of 12 classes. If using category, the data are presented for maximum in 20 categories. Therefore, to obtain the optimum analysis of data, we have to classify the records in such category-based columns in no more than 20 classes.

It has to be careful in using Google Maps because it is only a search engine. As well as a search engine, frequently the result of searching is not only one yield, there are many options. If the plotting is manually i.e. one by one in plotting landslide event data, the user can determine which one the most appropriate from some options. However, by importing a spreadsheet into Google Maps, Google Maps will choose one location randomly and make it as a placemark. A landslide event in Kali Bebeng Sub-village, Magelang District on March 30, 2019 was incorrectly plotted, shifting to the area next to it in its neighbouring district i.e. Sleman.

Based on the observed landslide data, we can derive the spatial and temporal distribution of landslide in Indonesia. During two months only, 193 landslides occurred in Indonesia. Locations of landslide events have already plotted in map of Indonesia in form of point feature. They are spread throughout Indonesia region, but not evenly. The landslide events mostly were occurred in Java Island. The number of landslides in Java is very dominant which reached 89.64% from the all landslide events at the time. The number is not totally valid. For example, based on the news on the internet, other four landslide events were reported in Papua during this period. According to this case, it can be related to the presence or absence of news about certain landslides. Not every landslide recorded in DIBI landslide catalogue could be found on the news report. Usually it happens to small-scale landslides with not much impact. Based on the observed landslide data, more landslides events (61.66%) could not be traced on news reports, dominated by landslide events in Java (94.12%). It represents that there is a possibility that many small-scale landslides have occurred in outside Java region but not being recorded. This is a depiction of how landslide data in Indonesia does not show balanced information between Java and other regions. As well as the global landslide database [9], DIBI landslide catalogue is suitable for obtaining the general trend of landslide, not for providing the landslide data to assess susceptibility, hazard, or risk quantitatively.

By using “styled by date”, we can obtain the order of the day that most landslides occur. The most landslides happened in a day of 6 March, 2019 as many as 11 events. But based on the top ten days with the most landslides, the data mentioned that eight of them were in February, 2019. It can be related to monthly rainfall. The analysis could be extended to the more data covering longer period.

A custom map “historical landslide map” can be made on Google Maps in two ways whether by importing a spreadsheet into Google Maps or by plotting each landslide location one by one on Google Maps. The first way is more efficient, since the plotting of large number of landslide locations can be done at once. The second way, it needs more time, if the number of landslide location is very large. But, the second way has some advantages e.g. location selection is determined by user and the exported file in Keyhole Markup Language (.kml) can be open and further processed in GIS software.

The observed landslide data covered a short time period only due to the major aim of this study is to highlight the use of Google Maps in processing the landslide event catalogue. By using the facility in Google Maps, the next study can be conducted to process the long time period of landslide data, so as the obtained landslide trend can be more representative.

5. Conclusions
A custom map “historical landslide map” can be prepared on Google Maps in two ways whether by importing a spreadsheet into Google Maps or by plotting each landslide location one by one on Google Maps. If analysis does not need to be processed further, the first way is recommended. Two data types of column in Google Map are numbers and text. To obtain the optimum analysis of data in text data
type, a user has to classify the records in such category-based columns in no more than 20 classes. Google Maps can be advantageous for communicate an information of spatio-temporal landslide data to the scientific and common societies. It will be valuable to increase public awareness of landslides or as inputs for disaster management.

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