Lessons Learned From Soil Liquefaction during the 2018 Palu Earthquake
(*GIST 58 Final Project*)

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Introduction

Figure 1: Aerial Photograph of devastation caused by soil liquefaction at Petobo District in Palu, Indonesia (Photo Credit: The Jakarta Post)

On September 28th, 2018 at 5:02pm (UTC +7), a magnitude 7.5 earthquake hit Central Sulawesi province. It hit approximately 50 miles north of the provincial capital city: Palu, Indonesia. What followed was a tsunami that reached at least 7.22 feet (2.1 meters) high and inundated 0.31 miles (0.5 kilometers) inland, 770 aftershocks triggered by landslides in the hilly areas, and, most importantly, soil liquefaction upended thousands of each built manmade infrastructure (buildings, roads, pipes, electric lines, etc.). The soil liquefaction, alone, was responsible for damaging more than 60,000 buildings/houses (90-95% of the total homes damaged by the earthquake). As a result of the three occurrences, Palu's overall economy was disrupted. The numerous sectors that were hardest hit were: Construction, Social, Agriculture, Manufacturing, Financial Services, Public, Non-Profit, Tourism, etc.

The overall aim of this case study is to attempt utilize methods that can be used to understand the impact of the impacts of liquefaction can have on Palu, and the lessons that disaster management personnel and the Indonesia public can learn to become better prepared not just for the next inevitable earthquake and liquefaction not just in the local scale, but, at most, advocate other countries that may have a similar problem with liquefaction globally. The case study will first give a concise **background** of the city we are studying. Then the paper will go through the methods used to conduct the analysis, particularly unsupervised classification. The

Results section will then primarily be about the analysis and statistics because of utilizing what has been described in the **Methods** section. Finally, the **Conclusion** section will go into improvements and problems of this case study will be discussed.

Background

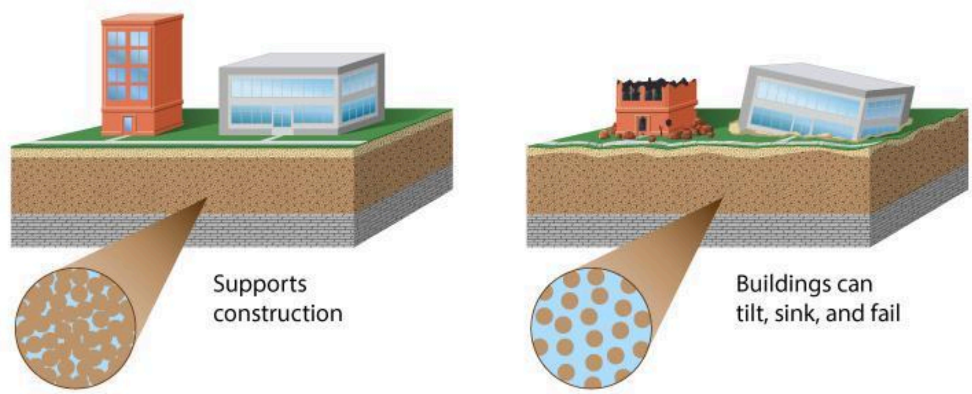

Figure 2: Image of Soil Liquefaction Example (Credit: Southwest Research Institute (SWRI))

A powerful earthquake can cause water-logged sediment minerals in the soil to lose some of their strength. This phenomenon is known as soil liquefaction. The saturated (water-logged) sediment compresses (becomes small) during an earthquake, weakening the ground's tight relationship. The water pressure in the soil then accumulates to the point where it begins to rise to the surface. As a result, the soil starts to behave like a liquid when the force of the water pressure is too great over the bond water-logged sediment minerals. As a result, it disturbs the surface sufficiently to force things that were initially on it to either move in either 2D direction or submerge like quicksand **(Figure 2 is a visual representation of liquefaction)**.

The city of Palu is situated right next to the Palu-Koro Fault: The fault is part of the Palu-Koro Fault System, which is responsible for causing strike-slip earthquakes in Central Sulawesi. As a result, the area around Palu is subject to powerful earthquakes and tsunamis (as a result of powerful earthquakes) over the past millennia. What made the 2018 earthquake stand out from the others was that the soil liquefaction was one of the worst in history. The two notable districts that were hard-hit by liquefaction were Petobo district (located on the Southeastern side of the city), Balaroa district (located on the Western side of the city), and Jono Oge (located south of Petobo District). The three districts, to this day, have remained uninhabited ever since.

Unfortunately, there is “relatively little research… focused on liquefaction in Indonesia” (Syfia et. Al 2) compared to several other regions in the world at risk of liquefaction (Ex: Japan, San Francisco Bay Area, Pacific Northwest, etc.). Without this necessary information, the recovery process will be much more costly and time-consuming than is currently happening in 2018. For example, Disaster management agencies on a national, provincial, and local level will have a significantly harder time helping those effected by the soil liquefaction in a timely, efficient manner because the roads and houses were severely damaged which would hinder its ability to rescue victims.

With unsupervised classification, the classified images will give people an idea of where the affected areas may be, and which areas that Palu should focus on reinforcing the next time soil liquefaction ever strikes again.

Methods

The satellite imagery used for this study comes from Landsat 8. The image was then clipped where the city is the focus of it all and includes the body of water and mountain slopes,and to exclude as much cloud cover as possible to ensure that the computer is able to cluster and classify fairly. Coordinates were provided through USGS Earth Explorer. The image before the earthquake was taken on September 23rd, 2018 while the image after the earthquake was taken on October 2nd, 2018.

Each image has their own file and follows the same process via the Javascript code. The project defined 4 classes for the classification process: Vegetation, Bare Land, Urban & Affected Areas, and Water. The K-Means Unsupervised Classification process was done in Google Earth Engine (shown in **Figure 3** below). It's trained to identify up to 8 different classes in both images to ensure that it can sufficiently differentiate between the 4 classes. Once that is done, the final classified image will be merged into either one of 4 possible colors in the set based on those 8 different possibilities.

The classification process in Google Earth Engine turned out to require more time than initially expected. Assigning colors to each cluster will be different from one another every time one uses K-Means clustering. In other words, the palette used to label a color for one image won't be the same palette one will use for the other image. It takes time to figure out which class abstractly represents the Landsat 8 image. The same goes for merging several clusters together from the original to the final classified image.

Overall, the classification process wasn't perfect, for example, the clustering process identified a cloud on the upper right of **Figure 3B** as a body of water, when it really isn't. However, the pictures in **Figure 3** gives me at least something to work with.

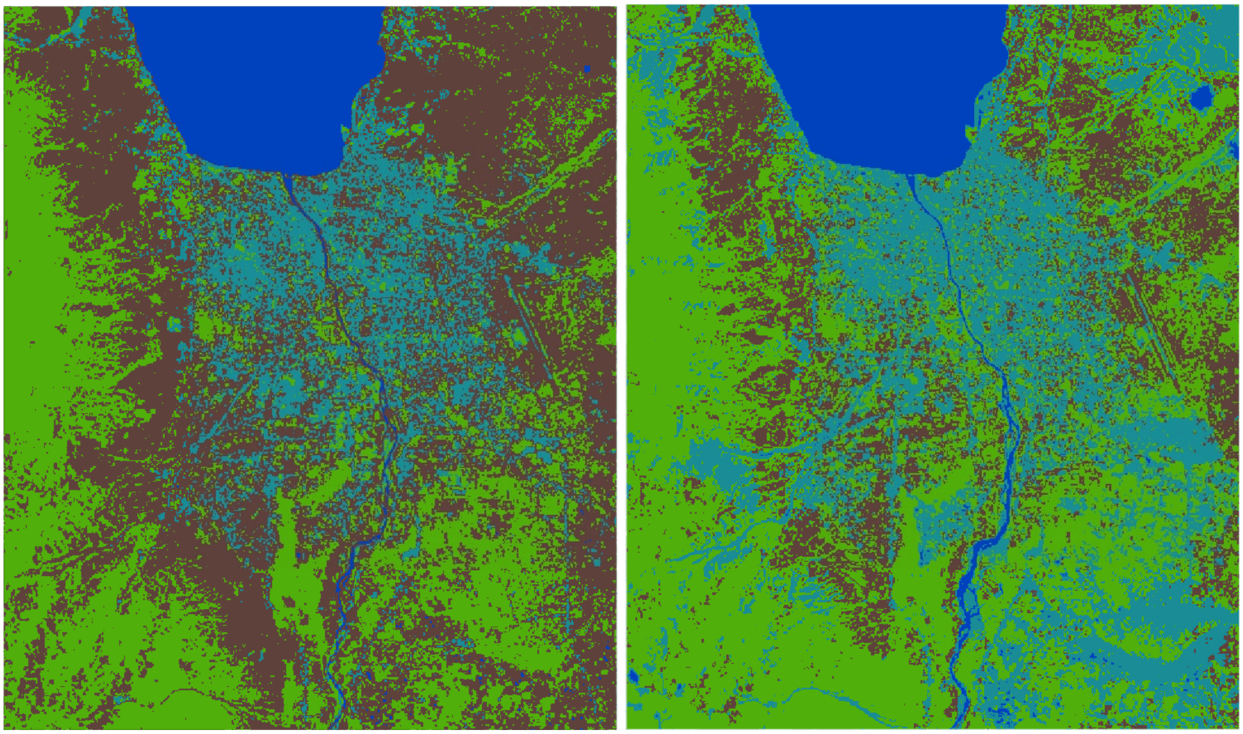

Figure 3: Clustering of Palu; Left Image **(Figure 3a)** is the image before the earthquake; Right image **(Figure 3b)** is the image after the earthquake.

Once both images were exported as TIF files, both classified images were then reprojected to a Universal Transverse Mercator Projection (UTM) 50N because Palu's extent from North-to-South is longer than its East-to-West extent and it also falls into the 50N zone on the UTM map. Its symbologies were then modified, and then the total amount per classified field was calculated. The areas of interest (Balaroa, Jono Oge, and Petobo Districts) were then digitized as polygon features. Each process described in this paragraph was done in ArcGIS Pro. The final result is displayed in **Figure 4** on the next page.

Results

Unsupervised Classification

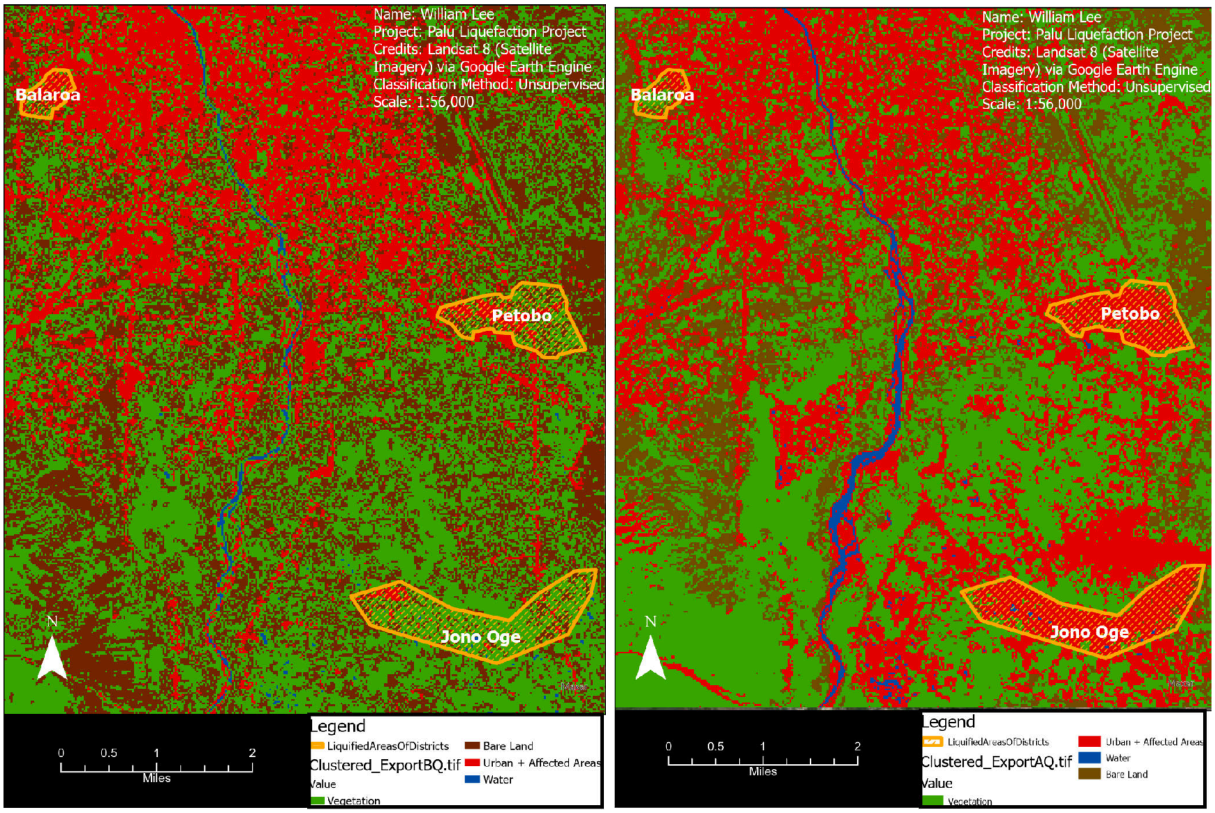

Figure 4: Unsupervised Classification of Palu's Balaroa, Jono Oge, and Petobo Districts. The Orange Hatched Fill Polygon Represents Notable Areas of Interest where liquefaction occurred; Left Image **(Figure 4a)** Is the classified image before the earthquake; Right Image **(Figure 4b)** is the classified image after the earthquake.

The effects of the earthquake, according to the unsupervised classification, has caused a noticeable increase within the city's boundaries. In both the liquified areas of Petobo and Jono Oge districts, Red (Urban + Affected Areas) is the dominant color after the earthquake while the bare land and vegetation areas make up a small percentage within the area. For Balaroa, on the other hand, the vegetation and bare land experienced an increase while the urban areas experienced a decrease. For the count of pixels in each classified category.

For the pixel count in each classified category, **Table 1** surprisingly shows a decrease in both the Bare Land and Urban & Affected Areas Category. However, Urban & Affected Areas still has the second highest number of classified pixels in the second image.

Table 1: The Entire Raster

Classified Category	Number of Classified Pixels Before Earthquake	Number of Classified Pixels After Earthquake	Percentage Increase/Decrease (±%)
Vegetation	41,888	49,778	+18.84%
Bare Land	82,953	72,133	-13.04%
Urban & Affected Areas	77,279	72,001	-6.83%
Water	60,950	69,158	+13.47%

Conclusion

Overall, I've been able to replicate the study that Mutiara Syifa, Prima Riza Kadavi, and Chang-Wook Lee have replicated in their article titled: "An Artificial Intelligence Application for Post-Earthquake Damage Mapping in Palu, Central Sulawesi, Indonesia". The authors use a classification technique called artificial neural network (ANN) which involves artificial intelligence to classify their 5 classes. The damage areas are highlighted in the Petobo and Jono Oge districts in **Figure 5**, and their results below:

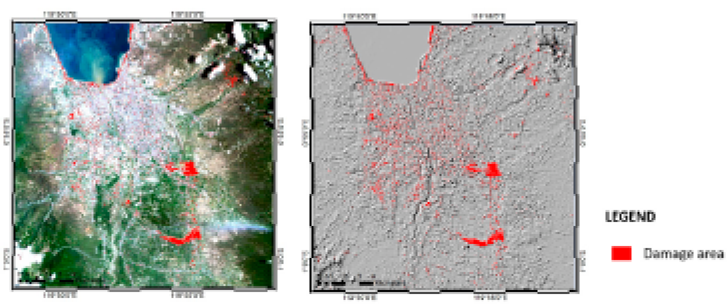

Figure 5: ANN classification technique to identify the damage areas in Red.

In conclusion, soil liquefaction has inundated the three districts mentioned in the city of Palu. In order to prevent a catastrophe like this from happening again, the local, provincial, and national authorities must invest more into understanding how Palu can help. While there is no way to avoid the dangers of soil liquefactions, Palu residents must come together to figure out how best to prepare in case it strikes again.

Potential Use Cases

There are plenty of possibilities that may involve using an unsupervised map comparison. But there a couple that are in most need. Disaster Management agencies can use this information to identify which communities are more at risk for soil liquefaction. While it may occur at anywhere, some areas like in Petobo district and Jono Oge distrcts were the most hard hit. It's unknown why they're the hardest hit given the fact that they're miles apart, however, it gives these agencies an opportunity to figure out what other major factor contributed to burying land parcels into mud. It could be the elevation, soil makeup, geology, etc. This map may also be useful for telecommunications. When the earthquake hits, residents would now resort to cellphones and radios for any news and information regarding their status during this time. However, when a disaster may happen at a hard hit area, the choice for residents to call for help may be limited because of the downgraded status Palu's telecommunication systems.

Problems & Improvements:

Notable limitations were identified while conducting the analysis. For example, on the top-right half of the raster after the earthquake erroneously classified the mountainous region as an urban/affected area.

Due to time constraints, I wasn't able to include other analyses such as Normalized Difference Built-Up Index (NDBI), it may be a useful tool to analyze the difference between vegetation and the urban & affected areas. It subtracts Band 5 from Band 6 (as a numerator) for Landsat 8 and then the denominator will add both Bands 5 and 6. The negative value, would've represented a negative value.

Bibliography

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