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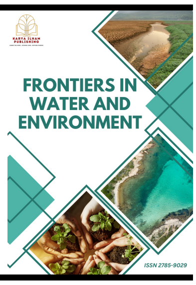

Assessing the Impact of an Earthquake on Water Quality Parameters: A Hybrid Satellite-Based and Ground Evaluation of Environmental Quality and Stability

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ABSTRACT

The immediate changes in water quality can have various causes and origins, depending on the sources of pollution, water quality can change. Monitoring surface water pollution is crucial for maintaining the natural environment and human health. Malaysia is not prone to earthquakes, but it is highly susceptible to various geological and geomorphological factors associated with hydrometeorological hazards. The most recent significant earthquake in Malaysia occurred in 2015 in Ranau, Sabah, with a magnitude of 6.0 on June 5th, lasting for 30 seconds and impacting the quality of surface water. Environmental hazards, such as earthquakes, can contribute to changes in water quality. This study aims to identify the key water quality parameters affected by the earthquake in Sabah, Malaysia. Data was collected before and after the earthquake, using both ground-based and satellite-based methods. Satellite data from Landsat 8, including Soil Adjusted Vegetation Index (SAVI), Normalized Difference Vegetation Index (NDVI), and Normalized Difference Water Index (NDWI), were analyzed before and after the earthquake. The Kruskal-Wallis test was used to determine significant water quality parameters impacted by the earthquake, focusing on physical and chemical parameters such as turbidity, color, pH, electrical conductivity (EC), total dissolved solids (TDS), dissolved oxygen (DO), nitrates (NO_3), iron (Fe), manganese (Mn), aluminum (Al), alkalinity, hardness, chloride (Cl), and sulfate (SO_4^{2-}) for the years 2014 and 2015. This nonparametric method enables the comparison of multiple independent samples without the need to assume normality. Ground data did not provide a clear understanding of how changes in the surface of the river and its surroundings affect the surface ground. The integration of satellite and ground data showed that alterations in river surface features, such as vegetation, soil,

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and water availability, had a significant impact on water quality parameters.

1. Introduction

Human activities have a significant impact on water quality in oceans, ponds, lagoons, lakes, and rivers. It is crucial to understand and address the challenges posed by this influence [13,19,52]. Currently, 2.2 billion people lack access to safe drinking water, with many unable to manage their own water sources. In some developing countries, the situation is even more dire, with a lack of sanitation facilities and basic hygiene practices. Additionally, approximately 3 billion people worldwide do not have access to basic handwashing facilities with soap and water at home. This lack of safe water, sanitation, and hygiene presents major public health challenges globally [55]. Monitoring water quality in countries facing water stress is crucial for identifying sources of pollution and assessing the human, technical, and financial resources required to meet present and future demands [7,90,92]. Hence, water quality remains a significant global challenge for the future, as even countries with rich freshwater resources are vulnerable to water-related issues. Water monitoring research indicates that the effects of global warming and world population growth over the next 50 years will lead to a 40% to 50% increase in water demand [87,91].This significant rise, along with urbanization and industrialization, is projected to greatly alleviate the need for water. These factors combined point to a threatening global water crisis [33,35].

Water quality is influenced by a variety of pollution sources, including human activities, social structures, and natural hazards. Geological events like earthquakes, landslides, heavy rainfall, as well as human actions such as mining, urbanization, agriculture, and industrialization can all impact water quality [5,20,51]. Monitoring water quality is crucial as it can be affected by natural occurrences and have repercussions on both humans and the environment [1]. Therefore, the emphasis of water quality monitoring should be on understanding the causes of water pollution and identifying spatial and temporal trends, rather than simply ranking water quality [65,105]. By addressing these challenges, water quality monitoring can help mitigate the impacts on social, political, and economic development [71,99]. It has been highlighted in numerous studies the importance of sustainable practices to combat pollution and improve the overall health of river ecosystems in the midst of rapid urban and industrial growth [21,95]. Human-induced water pollution arises from the clash between socio-economic progress and ecological conservation, posing a significant obstacle to achieving regional and urban sustainability. Thus, water quality fluctuates in relation to water resources, market, and spatial temporal land use patterns change [47,50].

It is crucial to develop a solution that can effectively address natural and human activities and interactions based on relevant data before and after significant changes in water quality, especially geological hazards like earthquakes and landslides [11,17,24,27,48]. Changes in surface water quality, such as rivers that support natural ecosystems, can be influenced by geological, morphological, and hydrological alterations in the river [6,66,75,97].These changes may appear in different physical, chemical, biological, microbiological parameters, and levels of turbidity. By gathering samples and studying the causes of water quality fluctuations, researchers can understand the effects of these changes and regulate water supply levels at a local or regional scale [12,28,32]. In developed countries, advanced technology is required to effectively monitor water quality changes, while developing countries face challenges due to limited resources and time-consuming monitoring methods [2,34,49,94]. Utilizing satellite data time series with various methods can help overcome these challenges and provide valuable information on water quality changes. Traditional methods often face constraints in assessing spatial and temporal trends in water quality, especially in the aftermath of natural disasters like earthquakes [29,58,76]. Remote sensing satellites can capture changes in rivers, riverbanks, vegetation, and soil before and after such events, offering a comprehensive view of water quality changes at local and global scales [37,63,89]. Remote sensing technology is a valuable tool for extracting water quality information from ungauged river areas that are difficult for humans to access or where there are technological obstacles. This data can be obtained using historical data and remote sensing technology and support the sample data [4,54,78].

Many studies use advanced space-based data collection methods to investigate earthquake causes and indicators [10,46,62,80,83]. Monitoring the Earth's surface with various sensors and historical data has improved environmental quality assessment, including vegetation, water, soil, and pollutants changes [9,16,70]. Despite stakeholder involvement, there is still much to learn about the facts and realities of earthquakes in Ranau, Sabah. Universities have successfully integrated various methods and approaches, including satellite data products, to visualize the spatial and temporal expansion of earthquakes by Richter scale and depth [14,15,31,39,45,61,68]. Numerous studies have investigated water quality monitoring, focusing on water sources and the relationship between water quality assessment and quantity. However, no single method comprehensively addresses all aspects of water quality monitoring procedures. Current approaches seek to enhance water quality monitoring tools and techniques, yet local knowledge on water quality monitoring and earthquakes remains limited. This study aims to bridge the gap in data collection methods for effective water quality monitoring by identifying and assessing various anomalies that have occurred in close proximity to earthquakes, shortly before or during the earthquake, and only in years with earthquake activity. Therefore, the research is positioned on detecting pre-earthquake and post-earthquake deformations using data from space-based sensors and ground-based stations and their impact on water quality. Understanding the underlying factors contributing to earthquakes and past seismic events is essential for accurate water quality monitoring evaluations.

2. Methodology

2.1 Study Area

The Liwagu River is a vital water source in Malaysia, especially in the Sabah state, where it provides water for a significant number of villages and cities. The domestic water supply in Ranau is heavily dependent on the Liwagu River, and any changes in its quality can have an impact on food security and human well-being by affecting water, food, and health conditions. In Ranau, the Liwagu River and Mansahaban River are the main sources of water for agricultural, household, and commercial use. Besides being a source of water for human consumption, the Liwagu River is also ecologically important for natural resource management. This has led the government and various universities to focus on monitoring the quality of water in the Liwagu River. Figure 1 illustrates the main earthquakes that have occurred around the Liwagu River [42,77,79].

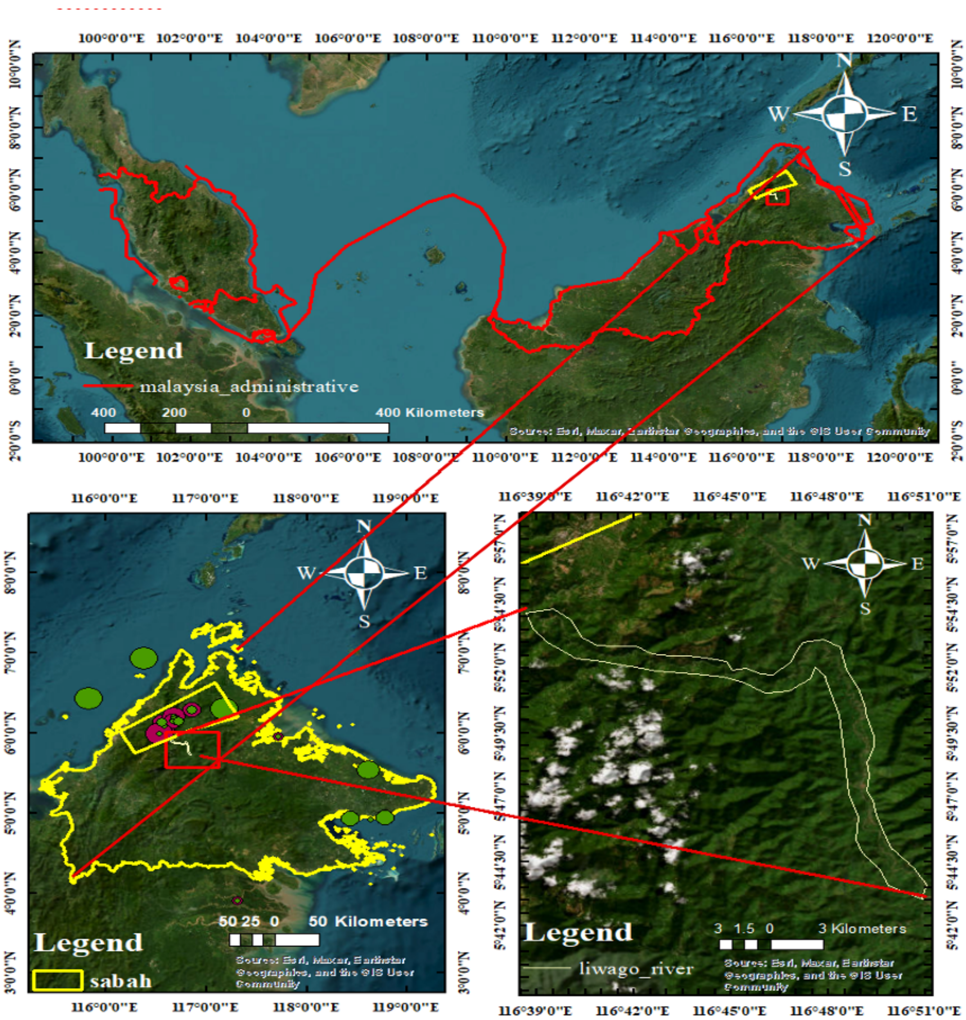


Fig. 1. Study area

2.2 Analysis

Turbidity levels can be affected by sediment disturbance, soil erosion from riverbanks collapsing, resulting in increased turbidity, which can have a significant impact on aquatic ecosystems and water quality. Ground shaking and fractures can alter water chemistry, pH, EC, TDS, DO affecting pH levels, electrical conductivity (EC), and dissolved oxygen (DO), potentially impacting water safety for consumption and aquatic life. During earthquakes, heavy metals and nutrients (such as NO_3, Fe, Mn, Al) can be released into water systems through soil disturbances and fractured rock layers. Changes in alkalinity, hardness, chloride (Cl), and sulfate (SO_4^{2-}) levels may occur due to shifts in groundwater flow or surface water mixing, indicating earthquake-induced changes in water composition. Monitoring water bodies using NDWI can help detect alterations in water extent and assess changes in water availability and quality post-earthquake. SAVI and NDVI indices can track vegetation health, which may be impacted by changes in water quality. Changes in vegetation post-earthquake could indicate issues like reduced water availability, contamination, or altered flow patterns.

2.3 Satellite Data Collection

NDVI (Normalized Difference Vegetation Index): Earthquakes are recognized as environmental hazards that can alter the vegetation cover on the Earth's surface. Historical satellite data can be used to analyze the extent and intensity of these changes over various spatial and temporal scales. The spatial characteristics of vegetation loss near rivers and the patterns of change should be considered when monitoring water quality [100,102,104]. NDVI is a useful tool for evaluating the health of vegetation before and after earthquakes. Healthy plants reflect more near-infrared (NIR) light and absorb more red light, resulting in higher NDVI values. NDVI values typically range from -1 to +1, with positive values indicating healthy, green vegetation [81,103].

Bands Required:
NIR: Band 5 (Near-Infrared, 0.85–0.88 µm)
Red: Band 4 (Red, 0.64–0.67 µm)

SAVI (Soil Adjusted Vegetation Index): SAVI is similar to NDVI but includes a soil brightness correction factor (L). It's particularly useful in areas where the vegetation is sparse or after some circumstances the vegetation density has reduced. Different changes of soil influence the NDVI reading. The value of L can be adjusted, with a common choice being 0.5.

Bands Required:
NIR: Band 5 (Near-Infrared, 0.85–0.88 µm)
Red: Band 4 (Red, 0.64–0.67 µm)
L: Soil adjustment factor (commonly set to 0.5)

NDWI (Normalized Difference Water Index): NDWI helps detect the water content in vegetation. It highlights areas with higher water content by comparing green and near-infrared light reflectance. A higher NDWI value usually indicates better or healthier vegetation.

Bands Required:
Green: Band 3 (Green, 0.53–0.59 µm)
NIR: Band 5 (Near-Infrared, 0.85–0.88 µm)

2.4 Ground Data Methods

This study applied the Kruskal-Wallis test to identify significant water quality parameters affected by the earthquake, focusing on both physical and chemical parameters. The parameters assessed included turbidity, color, pH, electrical conductivity (EC), total dissolved solids (TDS), dissolved oxygen (DO), nitrates (NO_3), iron (Fe), manganese (Mn), aluminum (Al), alkalinity, hardness, chloride (Cl), and sulfate (SO_4^{2-}) for the years 2014 and 2015. This nonparametric method is suitable for comparing multiple independent samples without the assumption of normality [23,44,82].The Kruskal-Wallis test, highlighting its application in comparing multiple groups when assumptions of parametric tests like ANOVA are not met. It explains the methodology, including the use of ranks, the significance of the test statistic, and the possibility of further nonparametric multiple comparison tests [30]. The Kruskal-Wallis test was specifically used in the study to analyze the effect of coating types on the conductivity of cathode ray tubes, showing significant differences between treatment groups [56]. In this study the null hypothesis (H) posited that water quality parameters are different before and after the earthquake, with a significance level (α) set at 0.05. If the p-value is greater than 0.05, it would reject the null hypothesis, indicating no significant difference; conversely, if the p-value is less than 0.05, this study would accept the null hypothesis, suggesting significant differences in water quality parameters. This approach aligns with standard hypothesis testing practices.

Figure 2 depicts the Liwagu River post-earthquake, highlighting the lush green vegetation surrounding the river. The photo also illustrates the deformation of the river basin and levees caused by the earthquake. Monitoring changes in river flood plains requires remotely sensed data, such as satellite imagery, which enables the detection of pre- and post-earthquake changes on green land cover, potential water around river, and soil expansions. The availability of historical satellite data allows for the observation of these changes over time.

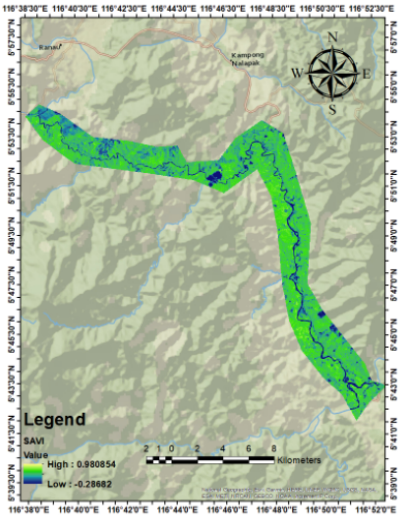
Fig. 2. Earthquake incident in Sabah on 5th June 2015

3. Results

3.1 Satellite Data Analysis

3.1.1. SAVI changes

By analyzing changes in land surface, we were able to observe how earthquakes altered the soil texture along the Liwagu River. The SAVI assessment results showed a decrease in values after the earthquake compared to pre-earthquake 0.980854 (High) and -0.28682 (Low), and 0.957053 (High) and -0.241909 (Low) post-earthquake. The higher SAVI values pre-earthquake indicated healthier and denser vegetation and greenery. This period likely reflected the stable pre-earthquake state of the ecosystem in the tropical riparian forest buffer zone. The decrease in SAVI values post-earthquake suggested a reduction in vegetation density or changes in soil moisture, possibly due to soil disruption or altered water flow patterns caused by the earthquake. The slight decrease in vegetation health after the earthquake, particularly in areas near the river, indicated the immediate impact of the earthquake on the surface, with some trees uprooted and stones displaced in unstable soil areas. It is important to note that vegetation in tropical regions tends to recover quickly. Therefore, these declines in the quality of vegetation health around rivers can affect different aspects of water quality, which can be seen in turbidity and color (Figure 3 and 4).



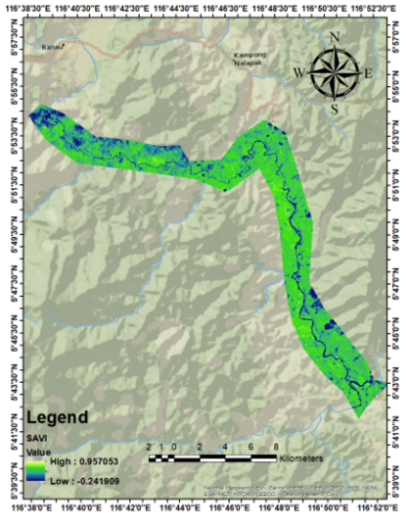
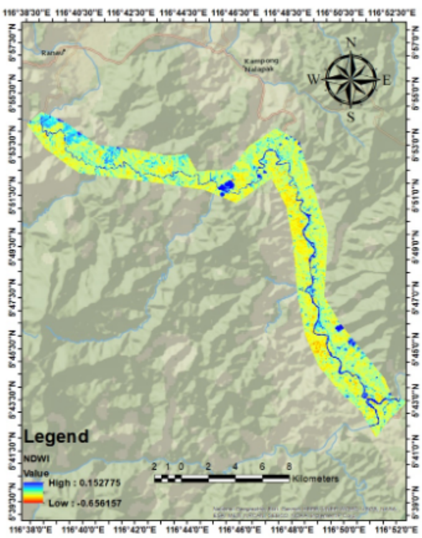


Fig. 3 SAVI value pre-earthquake **Fig. 4** SAVI value post-earthquake

3.1.2 NDWI changes

The rise in minimum NDWI values after the earthquake indicates a decrease in water content in certain areas, with pre-earthquake values at 0.152775 (High), -0.656157 (Low), and post-earthquake at 0.154362 (High), -0.541339 (Low). This change could be attributed to alterations in river flow, sediment deposition, or new formations like landslides obstructing water pathways. The slight uptick in maximum NDWI values suggests that some areas maintained their water content. The local risk of debris flow triggered by the earthquake, along with modifications in river morphology, slope changes, and slope failure, can impact water quality by dissolving soil minerals and altering water turbidity and color significantly. Pre-earthquake NDWI values indicated drier conditions in areas near the river, although some moisture was still present without water expansion and distribution. Tropical regions experience fluctuating water content due to rainfall patterns, with Sabah state being one of the highest recorded rainfall areas during the monsoon season, reflecting a slightly drier period. The post-earthquake increase in NDWI implies a slight rise in water availability or moisture retention, likely influenced by changes in water flow or soil displacement caused by the earthquake (Figures 5 and 6).



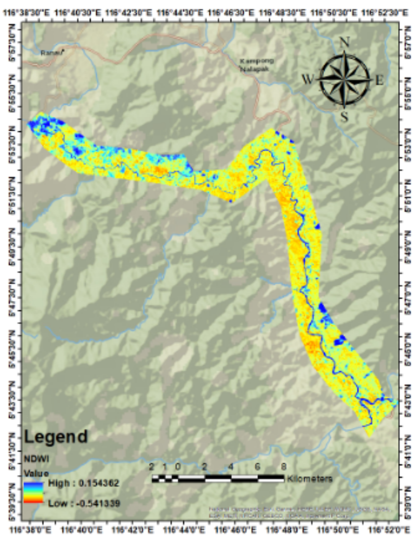
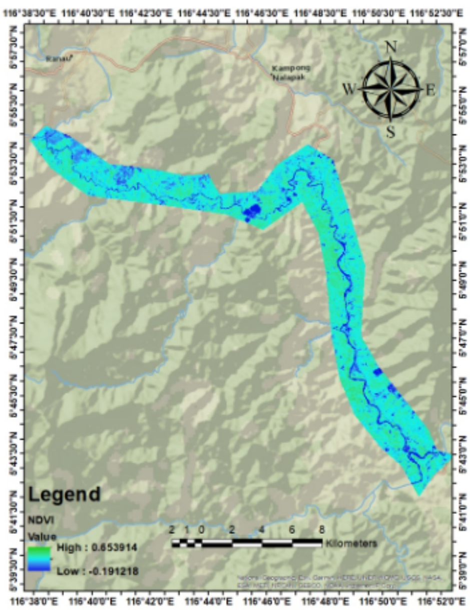


Fig. 5. NDWI value pre-earthquake **Fig. 6.** NDWI value post-earthquake

3.1.3 NDVI changes

The pre-earthquake NDVI values show healthy vegetation, which is typical for tropical areas during this time of year. pre-earthquake the NDVI values were 0.653914 (High) and -0.191218 (Low), while post-earthquake, they were 0.638046 (High) and -0.161277 (Low). The decrease in NDVI aligns with the SAVI results, indicating some stress on vegetation post-earthquake. Changes in NDVI values are crucial for understanding the significant impacts of earthquakes on river surface coverage. The high NDVI values pre-earthquake and post-earthquake (0.653914 to 0.638046) indicate that the study area has a rich vegetation cover. Both values are in the positive range, suggesting that the vegetation was relatively healthy and dense in parts of Sabah both pre-earthquake and post-earthquake. However, there is a slight decrease in the maximum NDVI value after the quake, indicating that vegetation has been slightly affected and the area around the river has lost some green coverage. The low NDVI values pre-earthquake and post-earthquake (-0.191218 to -0.161277) are negative but less so pre-earthquake and post-earthquake, suggesting that areas with sparse vegetation or barren land might have been less impacted. The slight decrease in NDVI after the earthquake indicates a mild reduction in vegetation health or density, possibly due to factors like soil disruption, landslides, or direct damage to vegetation caused by the earthquake. This comparison helps researchers and planners understand the environmental impact of earthquakes and guide recovery efforts in affected regions (Figures 7 and 8).



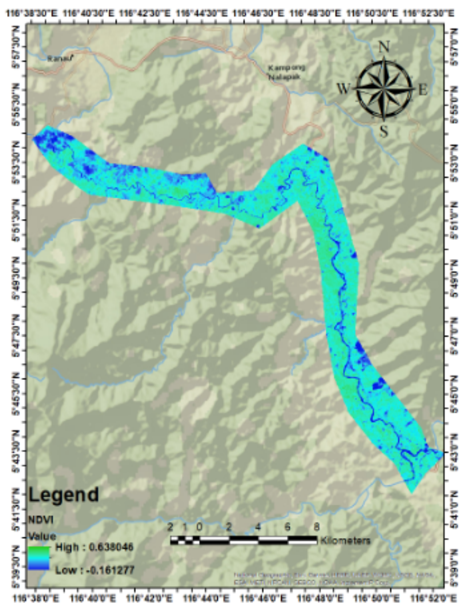


Fig. 7. NDVI value pre-earthquake **Fig. 8** NDVI value post-earthquake

This analysis investigates the variations in vegetation, soil, and water content in a river area before and after an earthquake. By comparing NDVI, SAVI, and NDWI values before and after the earthquake, we can observe changes that may be associated with differences in mineral, mud, and chemical composition. These changes could potentially impact water quality post-earthquake. Understanding post-earthquake water quality requires monitoring changes in water content and sediment movement. The increase in water index values in the lower NDWI range indicates potential sediment and chemical runoff into the water, which could degrade water quality. Monitoring contaminants, such as heavy metals or chemicals released from soil disruption, may be necessary to fully assess the impact. The slight decrease in vegetation indices (SAVI, NDVI) and the increase in the water index (NDWI) suggest that the earthquake disrupted both the soil-vegetation system and water distribution. These findings may indicate changes in vegetation health and water content post-earthquake, likely due to shifts in soil composition, flooding, and sediment redistribution. The earthquake likely disturbed the soil structure in the river area, potentially increasing the mineral and mud content in the water. This could be reflected in the NDWI changes, as increased water content in previously dry areas may also lead to increased sedimentation. Similarly, chemical changes such as altered pH or contamination from disturbed soil layers could impact vegetation, as evidenced by the slight decreases in SAVI, NDWI and NDVI values (Table 1).

Table 1
The total surface area change detection

Index	Height	Low
SAVI pre-earthquake	0.980854	-0.28682
SAVI post-earthquake	0.957053	-0.241909
NDWI pre-earthquake	0.152775	-0.656157
NDWI post-earthquake	0.154362	-0.541339
NDVI pre-earthquake	0.653914	-0.191218
NDVI post-earthquake	0.638046	-0.161277

3.2 Ground Data Collection
3.2.1 Water quality variation before and after the earthquake

This section analyzes and compares each parameter with corresponding graphs to assess the changes in water quality. The study observed fourteen parameters in 2015, divided into before the earthquake (1st January to 4th June) and after the earthquake (6th June). Descriptive statistics, including mean and standard deviation, were calculated to provide a comprehensive overview of each parameter.

Table 2
Summary of statistic descriptive before and after the earthquake in Bambangan and Kimolohing

Parameter	Bambangan				Kimolohing			
	Before earthquake		After earthquake		Before earthquake		After earthquake	
	Mean	St d.	Mean	St d.	Mean	St d.	Mean	St d.
Turbidity	**36.1**	37.92	**436.25**	1416.86	**17.28**	19.23	**309.6**	954.49
Colour	**91.54**	79.72	**760**	2283.69	**58.93**	67.77	**673**	1896.9
pH	7.55	0.4	7.53	0.12	7.53	0.23	7.55	0.1
EC	130.72	33.33	122.98	21.86	124.89	34.99	118.6	22.11
TDS	62.23	16.05	58.68	10.49	59.42	16.86	55.87	11.08
DO	8.28	0.58	7.84	1.48	8.25	0.58	8.11	1.55
NO_3^-	0.04	0.02	0.05	0.04	0.05	0.02	0.05	0.04
Fe	**0.25**	0.23	**1.13**	1.11	**0.16**	0.11	**1.07**	0.54
Mn	0.03	0.02	0.14	0.15	0.03	0.02	0.15	0.2
Al	0.03	0.01	0.06	0.05	0.05	0.07	0.04	0.04
Alkalinity	60.97	17.82	57.93	23.24	59.51	18.2	54.79	23.02
Hardness	62.14	19.37	64	15.53	55.59	18.52	59.83	12.5
Cl	8.15	7.85	7.93	5.27	7	3.57	7.07	3.59
SO_4^{2-}	4.92	2.72	5.33	3.5	5	2.77	4.73	4.2

Table 2 a summary profile of each parameter in 2015, highlighting the differences before and after the earthquake. The mean concentrations of parameters in Bambangan and Kimolohing were generally higher after the earthquake compared to before. For instance, the mean turbidity levels at Bambangan and Kimolohing were 36.1 NTU and 436.25 NTU before the earthquake, and 17.28 NTU and 309.6 NTU after the earthquake. Similarly, the mean color levels before the earthquake were 91.54 and 58.93 at Bambangan and Kimolohing, while after the earthquake, they increased to 760 and 673, respectively. These significant changes indicate the impact of the earthquake on turbidity and color levels.

Furthermore, the average concentration of Fe was higher before (0.25 mg/L; 0.16 mg/L) and after the earthquake (1.13 mg/L; 1.07 mg/L) at Bambangan and Kimolohing, respectively. The average concentration of Mn also increased (0.3 mg/L; 0.14 mg/L) at Bambangan and (0.03 mg/L; 0.15 mg/L) at Kimolohing. The elevated levels of Fe and Mn after the earthquake may be attributed to the soil mineralogy containing these elements, which were released into the water bodies due to soil erosion and landslides induced by the seismic activity. The average hardness concentration also showed an increase. However, the average concentrations of parameters such as dissolved oxygen (DO), electrical conductivity (EC), total dissolved solids (TDS), and alkalinity decreased in both locations. There were discrepancies in the average concentrations of certain parameters between Bambangan and Kimolohing, such as pH, aluminum (Al), sulfate SO42- and chloride (Cl). For example, the pH decreased from 7.55 to 7.53 at Bambangan but increased from 7.53 to 7.55 at Kimolohing. Nitrate (NO3-) levels increased from 0.4 mg/L to 0.05 mg/L in Bambangan but remained stable at 0.05 mg/L in Kimolohing.

Turbidity and Colour

Figure 9 shows the turbidity variation pattern before and after the earthquake in 2015, as detailed in Appendices C and D. The turbidity levels peaked at 5550 NTU and 3750 NTU, with color levels at 9000 and 7500, on June 17 th, about two weeks post-earthquake, before returning to normal by September 25th. Water color indicates clarity and was high on the same day as turbidity at both stations compared to pre-earthquake levels in Figure. 10 The increased turbidity and color disruption are attributed to sediment and suspended solids discharge, likely due to heavy rain causing debris and mudflow in the stream. Elevated levels of suspended substances above 40 mg/L and turbidity exceeding 55 NTU can cloud water colour, impacting river organisms by reducing light penetration and slowing photosynthesis. Prolonged high levels can lead to eutrophication, releasing toxic substances like carbon dioxide (CO2) harmful to humans and organisms, causing suffocation, fish mortality, and reduced reproduction.

Electric Conductivity and Total Dissolved Solids

Following the earthquake, EC and TDS concentrations decreased as obtained in Figure 10. Particularly, obtaining the earthquake as only an indicator. It might be significant to identify the earthquake's impact. However, it might be impacted by another factor such as dilution of rainwater in the river. The highest concentration of TDS and EC were on 2nd April at Kimolohing and 30th April at Bambangan. However, the mean concentration was equivalent to that of 2014. Moreover, the mean concentration of TDS was lower than before the earthquake. The previous study showed that these two parameters are reported as significant changes related to seismic activity in the groundwater system [40,43]. The presence of EC in the stream is related to groundwater discharge during the earthquake [41]. In addition, the debris flow triggered by the landslide upstream affects the flow of the river [85], associated with the volume of a tremendous amount of rainwater in the stream, causing dilution, which is the reason for the decrease of EC and TDS concentration in Liwagu River. However, it is difficult to assume if the earthquake influenced the change of water quality parameter in the Liwagu river.

Dissolved Oxygen and pH

Based on Figure 11, the DO concentration reached its lowest point on June 17th, measuring approximately 3.8 mg/L to 4 mg/L, despite the average value indicated in Table 2. Subsequently, it returned to its normal pattern by August 14th, reaching around 8 mg/L. These decreases coincided with the highest turbidity and color disturbance observed on the same day. Elevated turbidity levels can hinder the absorption of oxygen from the atmosphere into the water. The pH levels remained relatively stable between 7.2 and 7.8 following the earthquake, with an average value of 7.55. In contrast, the pH levels fluctuated before the earthquake, unlike the post-earthquake period.

Alkalinity and Hardness

Figure 12 illustrates the changes in alkalinity concentration at the Bambangan station, showing a decrease from April 30th to August 14th, followed by an increase on September 25th. The Kimolohing station exhibited a similar decreasing trend, with a slight increase on June 17th, while maintaining a comparable level to the Bambangan station. The average alkalinity levels decreased to 60.97 mg/L and 57.93 mg/L before and after the earthquake, respectively. Hardness levels at both sites decreased from May 14th to June 4th and then increased until June 17th, resulting in an overall increase in average hardness levels. The sources of alkalinity and hardness are attributed to the reaction of limestone in the rock type [57]. Additionally, previous research indicated that rocks dislodged from Mount Kinabalu during the earthquake, potentially introducing limestone-containing gravels and stones into the river, leading to a reduction in flow from upstream and subsequent decreases in alkalinity and hardness levels. A study by Qian *et al.*, [64] also observed a decrease in hardness following the Wenchuan earthquake in China.

Light Metal Element and Cloride

Based on Figure 13, at Kimolohing, there were three peaks of Al concentration observed: on 15th January (0.23 mg/L) and 26th February (0.2 mg/L) before the earthquake, and a third peak on 17th June (0.18 mg/L), approximately two weeks after the earthquake. In Bambangan, a peak in Al concentration was recorded on 17th June (0.18 mg/L) and another peak on 19th November (0.19 mg/L). The levels of Fe were notably high on 17th June, reaching 4.82 mg/L at Bambangan and 2.54 mg/L at Kimolohing. Post-earthquake, the average concentration of Fe increased. The literature suggests that ultramafic soil in Ranau contains high levels of iron, which can be washed into water sources through soil erosion and runoff. The discrepancy in iron concentration between the two treatment plants is intriguing, with upstream (Bambangan) showing lower levels compared to downstream (Kimolohing). This could be due to iron settling along the stream before reaching downstream areas. Additionally, Mn concentration peaked on 17th June, with levels of 0.57 mg/L at Bambangan and 0.42 mg/L at Kimolohing, and another peak was observed on 16th October (0.7 mg/L) at Kimolohing.

A previous study by Zuo *et al.*, [106] found that the overall trends in primary metal contents following the earthquake indicated a potential imbalance due to the mixing of diverse soil compositions brought about by landslides triggered by the earthquake. Environmental conditions and metal solubility are influenced by factors such as pH, temperature, and salinity, with metal solubilities generally lower at near-neutral pH compared to acidic or highly alkaline conditions. Following the earthquake, the pH likely remained around the neutral level of 7.5, leading to elevated levels of Fe, Al, and Mn post-earthquake. Metals can enter water bodies through various processes, including soil and rock weathering, atmospheric deposition, volcanic eruptions, and human activities such as mining and industrial use [18,22,74]. A recent review by Rosly *et al*., [67] suggested that the landslides and rockfalls during the earthquake in Ranau in June were linked to intense rainfall, potentially contributing to the presence of metals in the Liwagu River. Additionally, minimal changes in Cl levels indicate that the earthquake may not have had a significant impact (Figure 14).

Nitrate and Sulfate

Figure 15 showed that the highest concentration of NO3- was recorded on 17th June, with levels reaching 0.18 mg/L at Bambangan and 0.15 mg/L at Kimolohing. Following this peak, the NO3- levels exhibited a decreasing trend compared to the initial spike. In contrast, the concentration of SO42- remained relatively stable, showing minor fluctuations with no significant overall increase or decrease. A study conducted by Sato *et al*., [73] indicated that the rise in NO3- levels was attributed to rainfall post-earthquake, which led to the transportation of NO3-from upstream and nearby catchment areas into the river through sediment and material displacement. The earthquake-induced ground shaking caused cracks in the soil, damaging plant roots and reducing nutrient uptake. Ranau's main agricultural activities, including highland crops like fruits, rice, and tropical forests, could also contribute to the elevated NO3-levels in the Liwagu river.

Additionally, the river in Ranau typically contains nutrient concentrations such as NO3-from agricultural fertilizers and household products like soap and detergent. The shaking caused by the Ranau earthquake could potentially harm the root systems of plants in forests and agricultural areas, leading to reduced nutrient absorption. Subsequent heavy rainfall following the earthquake may have contributed to the elevated levels of NO3- in the river. It is difficult to definitively differentiate between non-point and point sources of pollution, but the earthquake may have exacerbated the introduction of pollutants into the river or created new sources of pollution.

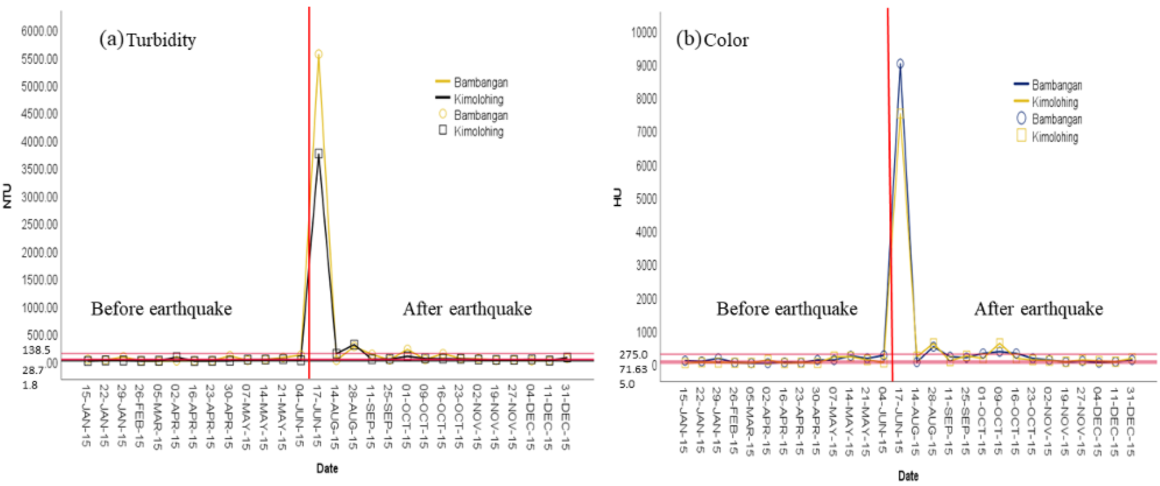


Fig. 9. Observation of parameter (a) turbidity, (b) color, the red vertical line is the earthquake on 5th June, and the horizontal red line is the minimum, average, and maximum in 2014

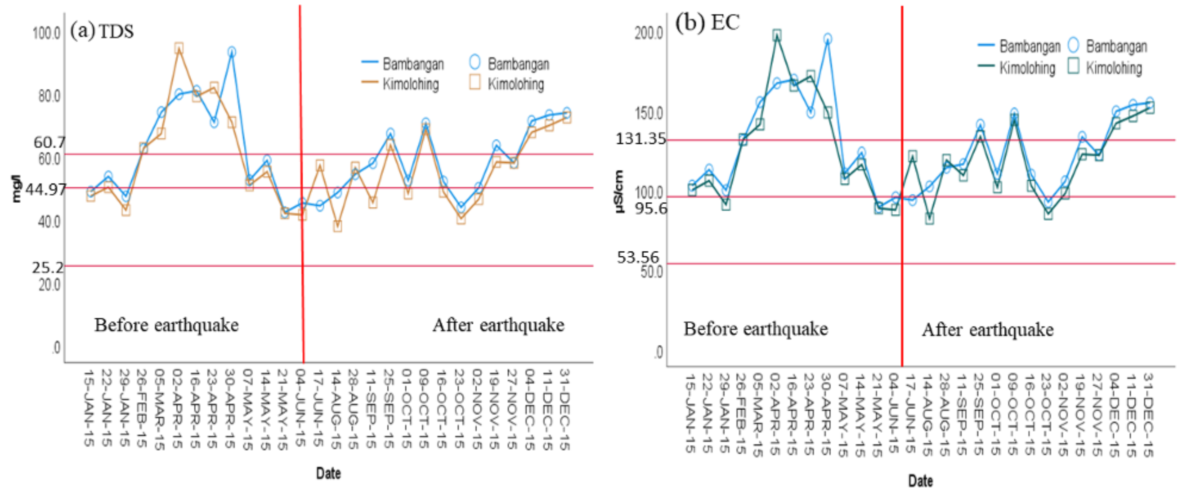


Fig. 10. Observation of parameter (a) TDS, (b) EC. The red vertical line is the earthquake on 5thJune, and the horizontal red line is the minimum, average, and maximum in 2014.

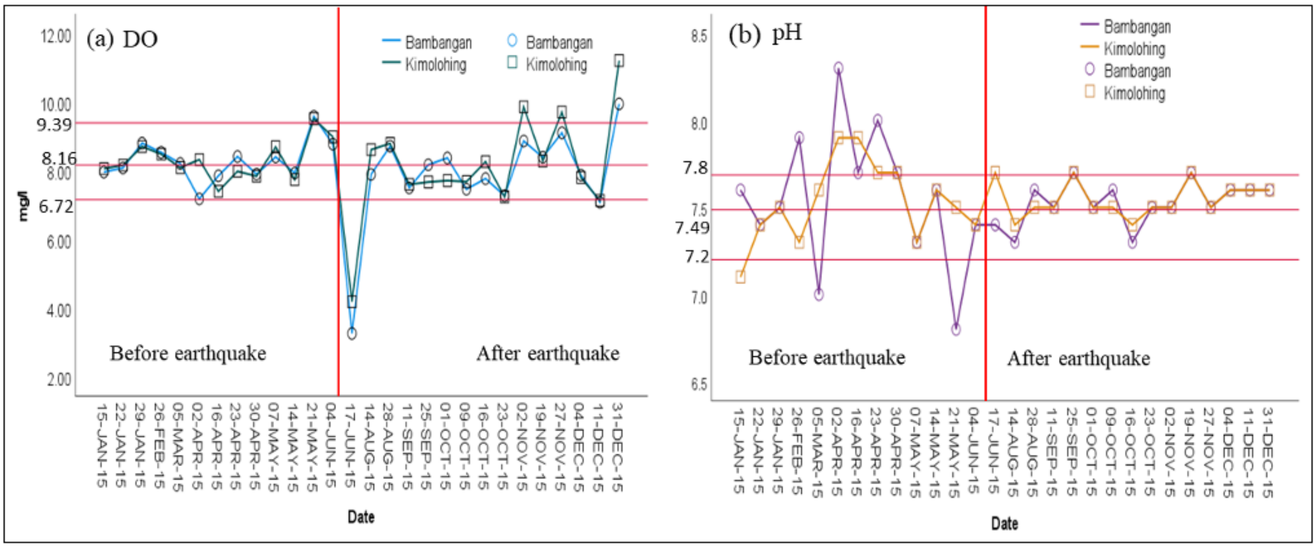


Fig. 11. Observation of parameter (a) DO, (b) pH. The red vertical line is the earthquake on 5thJune, and the horizontal red line is the minimum, average, and maximum in 2014.

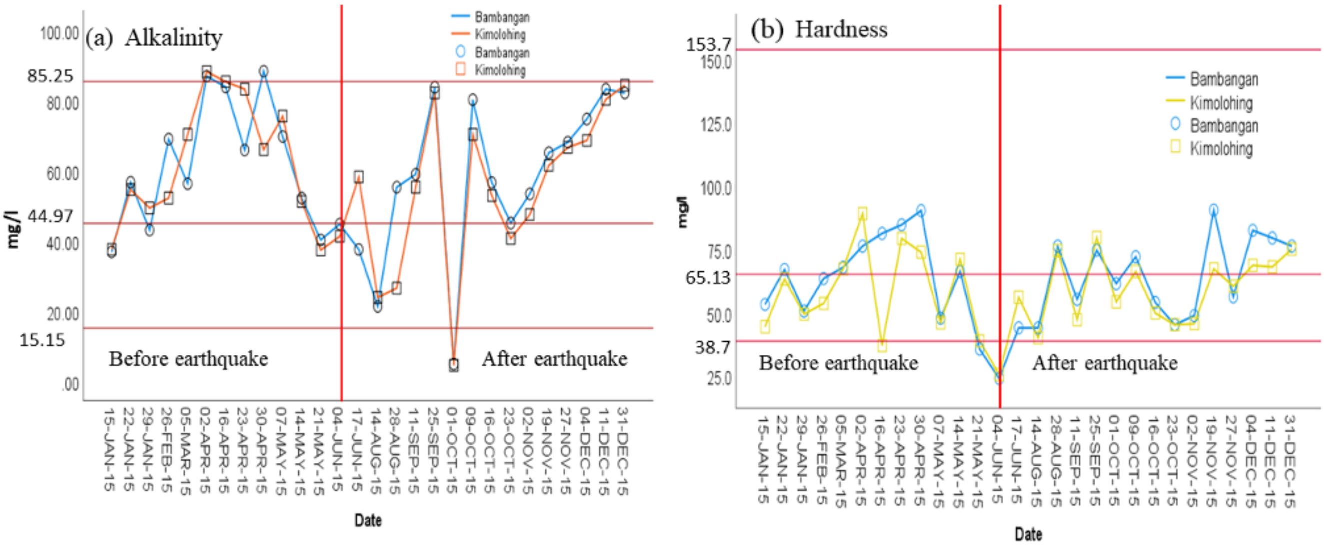


Fig. 12. Observation of parameter (a) alkalinity, (b) hardness. The red vertical line is the earthquake on 5thJune, and the horizontal red line is the minimum, average, and maximum in 2014.

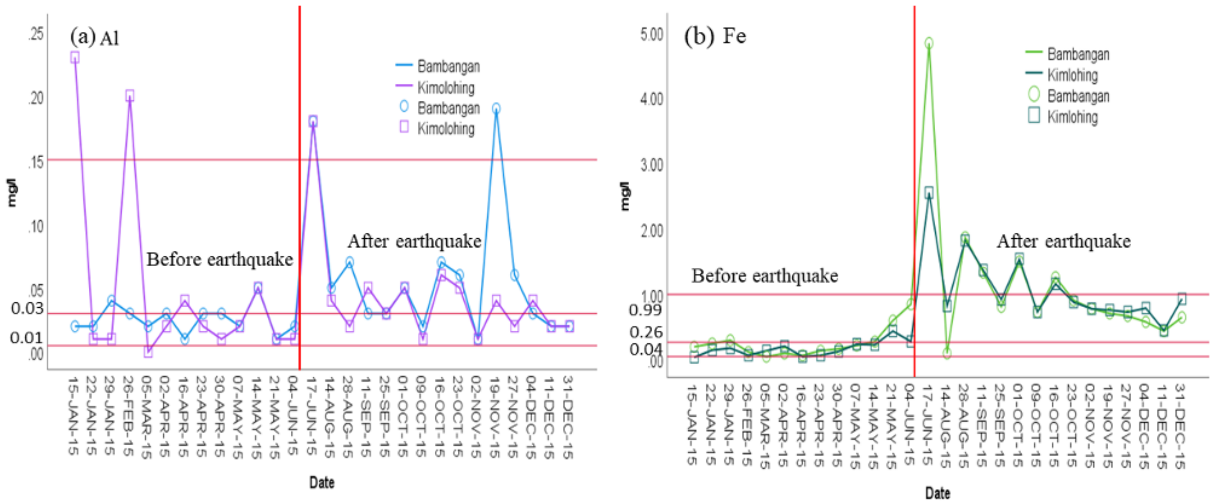


Fig. 13. Observation of parameter (a) Al, (b) Fe. The red vertical line is the earthquake on 5thJune, and the horizontal red line is the minimum, average, and maximum in 2014.

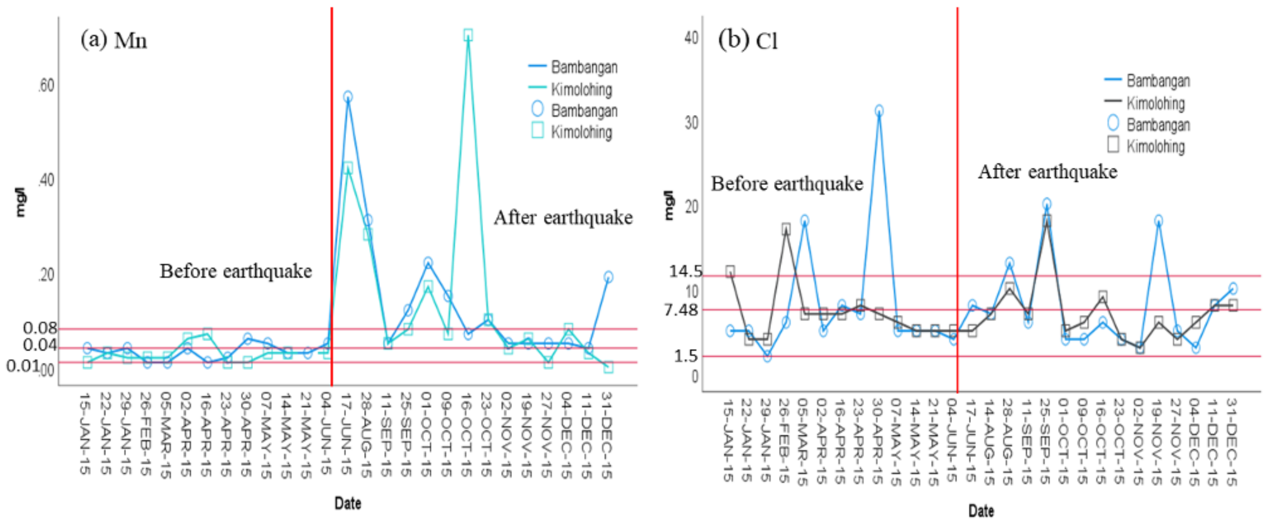


Fig. 14. Observation of parameter (a) Mn, (b) Cl. The red vertical line is the earthquake on 5th June, and the horizontal red line is the minimum, average, and maximum in 2014.

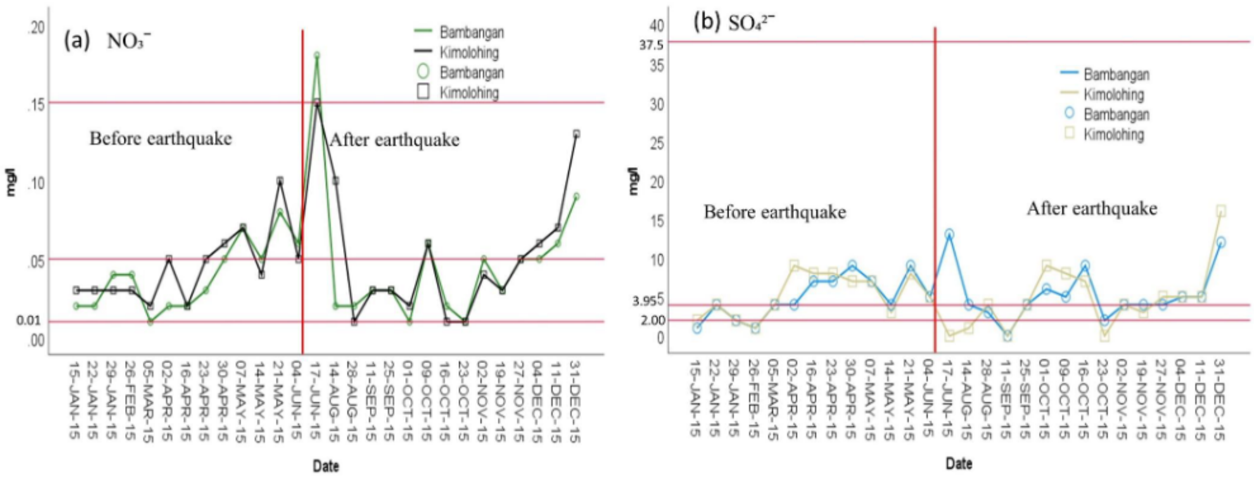


Fig. 15. Observation of parameters (a) NO3, and (b) SO42-. The red vertical line is the earthquake on 5th June; the horizontal red line is minimum, average, and maximum in 2014

3.2.2 Comparing water quality to baseline

As shown in Table 3, the baseline for the average water quality in 2014 was selected based on data from Appendix A and Appendix B, as there were no recorded landslides during that period [67]. Additionally, there was minimal change in land-use development and land-cover areas such as industrial, urban, or vegetation areas within a one-year timeframe. This allowed for the differentiation between pollution and earthquake impacts on the Liwagu River. Parameters such as pH, DO, and NO_3 exhibited insignificant differences. In contrast, turbidity, color, EC, TDS, alkalinity, Fe, Mn, Al, Cl, and SO_3^- levels were low in 2014 at the Bambangan station, except for hardness. Local authorities noted that the water quality in the river was not consistent, particularly in terms of turbidity, which increased rapidly after rainfall following the 2015 earthquake. Furthermore, the soil condition in the Ranau area has yet to fully recover.

Table 3
Average concentration of parameters in 2014 and 2015

Parameter	Unit	Bambangan		Kimolohing	
		2014	2015	2014	2015
Turbidity	NTU	30.77	**276.77**	24.00	**199.30**
Colour	HU	73.33	**495.38**	49.30	**424.55**
pH	-	7.53	7.50	7.44	7.52
EC	µs/cm	99.25	**123.80**	93.60	**120.19**
TDS	mg/L	45.43	59.00	44.90	56.76
DO	mg/L	8.05	7.84	8.07	8.04
NO_3^-	mg/L	0.04	0.05	0.05	0.05
Fe	mg/L	0.26	**0.88**	0.21	**0.73**
Mn	mg/L	0.03	0.14	0.03	0.12
Al	mg/L	0.02	0.05	0.05	0.06
Alkalinity	mg/L	43.85	56.19	52.15	55.59
Hardness	mg/L	61.80	60.56	62.06	57.19
Cl	mg/L	5.51	**8.53**	10.29	**7.74**
SO_4^{2-}	mg/L	4.03	5.22	3.67	4.57

3.2.3 Water quality change during early earthquake

Before the main shock, the early impending of the earthquake and the seismic movement happened underground, making the abnormal interaction between underground and surface water. This phenomenon might somehow influence the water quality in the river. The statistics descriptive of water quality before and during the early earthquake and the correlation explain the relationship within a variable.

Comparing Before and Pre-earthquake

Table 4 presents the statistical descriptive parameters before and during the pre-earthquake period. These tables aim to illustrate the impact of the early earthquake on water quality in the Liwagu River. The mean values for turbidity, color, EC, NO_3^-, alkalinity, hardness, Cl, and SO_4^{2-} increased at both sites before and during the pre-earthquake period. However, parameters such as pH, Mn, and Al showed no significant difference in mean values before and after the pre-earthquake period. Outliers were identified in the analysis, possibly due to the peak of parameters that could indicate the earthquake's impact. The data may not fully explain the increase in these parameters, which could be influenced by the earthquake's vibrations. Furthermore, the available information is limited in supporting the idea of using water quality indicators for predicting pre-earthquake events.

Table 4
Comparison of parameters (mean ± standard deviation) before and early stage of earthquake

Parameters	January - March	April - 4June	January - March	April - 4June
	Bambangan		Kimolohing	
Turbidity	26.9± 30.82	41.86±42.71	6.72±3.94	23.14±22.01
Colour	64±56.28	108.75±90.58	18±9.75	81.67±76.08
pH	7.48 ±0.33	7.6±0.45	7.38±0.19	7.61±0.21
EC	120.3±23.01	137.24±38.41	113.82±21.52	131.03±40.48
TDS	57.22±11.08	65.36±18.51	54.06±10.36	62.4±19.5
DO	8.32±0.34	8.25±0.72	8.3±0.28	8.23±0.7
NO_3^-	0.03±0.01	0.05±0.02	0.03±0	0.06±0.02
Fe	0.17±0.1	0.29±0.28	0.11±0.02	0.18±0.12
Mn	0.03±0.02	0.04±0.02	0.02±0.01	0.03±0.02
Al	0.03±0.01	0.03±0.01	0.09±0.11	0.02±0.01
Alkalinity	52.3±12.61	66.39±19.14	52.72±11.75	63.29±20.6
Hardness	60.4±7.99	63.23±24.57	55.56±9.49	55.61±22.64
Cl	7.2±6.22	8.75±9.08	8.8±5.63	6±1.32
SO_4^{2-}	2.4±1.52	6.5±2.0	2.6±1.34	6.33±2.45

Spearman Correlation between Parameters

A correlation matrix was constructed before the earthquake for fourteen parameters: turbidity, colour, pH, EC, TDS, DO, NO_3^-, Fe, Mn, Al, alkalinity, hardness, Cl, and SO_4^{2-}, as shown in Table 5 and Table 6 The Spearman correlation analysis was used to identify potential influencing factors on these parameters and the sources of pollution that could impact other water variables by determining the strength of the relationships between them. A positive coefficient indicates that one parameter increases or decreases as another parameter increases or decreases, while a negative coefficient indicates that one parameter decreases as another parameter increases. Significant correlations were identified based on p-values of 0.01 and 0.05, with coefficients close to 1.00. A p-value of 0.05 corresponds to a 5% error rate, while a p-value of 0.01 corresponds to a 1% error rate. A smaller error rate indicates a more reliable result. The study identified all parameters with significant correlations using both p-values of 0.05 and 0.01.

At Kimolohing in Table 5 with a p-value of 0.01, the pair of parameters show a strong association, such as turbidity with color and Fe (r=0.844; r=678), pH with EC (r = 0.852), TDS (r = 0.852), EC with TDS (r=1.00), alkalinity (r=0.917), and Cl (r=0.828), as their correlation coefficients are close to 1. Interestingly, TDS has the same correlation coefficient as EC. Additionally, DO is positively correlated with Fe (r = 0.833). At a p-value of 0.05, Fe shows a positive correlation (r = 0.678), pH has a positive correlation with alkalinity (r = 0.7), EC and TDS have a positive correlation with Fe (r = -0.667) and hardness (r = 0.750). DO has a negative correlation with Al (r = -0.759). Alkalinity has a positive correlation with Cl (r = 0.794). Finally, Cl has a positive correlation with SO_4^{2-} (r = 0.723). According to Peinado-Guevara *et al.*, [60], chlorides widely distributed in nature include sodium (NaCl), potassium (KCl), and calcium (CaCl2) salts. Cl shows a significant correlation with EC, and also a high correlation with EC that is not significant. This may explain the correlation between Cl and SO_4^{2-}.

Table 6 outlines the correlations among the parameters at the Bambangan site. With a p-value of less than 0.01, turbidity showed a strong positive correlation with Fe (r = 0.857), while colour was positively correlated with Fe (r = 0.898). This suggests that sediment might be the source of pollution leading to the presence of both parameters in the water. On the other hand, pH had a negative correlation with NO_3^- (r = -0.921). EC had a perfect positive relationship (r = 1.00) with TDS, and both parameters were positively correlated with alkalinity and hardness (r = 0.905). DO had a negative correlation with alkalinity (r = -0.857), while NO_3^- had a positive relationship with Fe (r = 0.855). Additionally, hardness was positively correlated with Cl (r = 0.913).

At a p-value less than 0.05, turbidity had a positive correlation with colour (r = 0.802), while colour had a negative correlation with pH (r = -765) and NO_3^- (r = 0.709). pH showed positive correlations with EC and TDS (r = 0.778) and hardness (r = 0.743), while it had a negative correlation with Fe (r = -0.778). Interestingly, EC and TDS had the same coefficient in every significant or insignificant correlation. Furthermore, DO had a positive correlation with NO_3^- (r = 0.795) and Fe (r = 0.786). Fe had a negative correlation with alkalinity and hardness (r = 0.762). Lastly, alkalinity was positively correlated with hardness (r = 0.762).

At the Bambangan water intake point, most parameters show a significant correlation with a p-value of 0.05 compared to Kimolohing. The most notable finding is that certain parameters, such as alkalinity, hardness, EC, and TDS, have the same coefficient. In water quality analysis, EC and TDS are known to have a significant impact on each other due to the K factor [69,93].Therefore, the coefficient should only show the same result for pairs like alkalinity with EC and TDS or hardness with EC and TDS. EC and TDS exhibit a strong relationship (r=1.00) at both water intake points, confirming the consistency with the graph pattern of the pair.

Wilson [98] mentioned that alkalinity and hardness are linked to common ions found in aquatic systems, with the principal cations responsible for hardness typically being Ca^{2+} and Mg^{2+} associated with the bicarbonate and carbonate fractions of alkalinity. In contrast, Fe and NO_3^- show significant relationships with all parameters, unlike in Kimolohing. Therefore, this discussion may not fully support the earlier result. The increase in EC in river water indicates groundwater discharge during the lead-up to an earthquake, suggesting that TDS and EC could be potential variables to monitor as earthquake precursors in the future. Additionally, alkalinity and hardness serve as indicators of groundwater presence. Furthermore, parameters showing significant correlations with both variables should be taken into consideration. Pre-earthquake signals typically do not manifest beyond underground seismic activity, with elements from the earth's crust entering underground water. Mild shaking may not significantly impact river water quality due to its distance from the mainshock.

Table 5
Spearman correlation matrix of the parameter during pre-earthquake in Kimolohing water intake point

Parameter	Turbidity	Colour	pH	EC	TDS	DO	NO_3^-	Fe	Mn	Al	Alkalinity	Hardness	Cl	SO_4^{2-}
Turbidity	1													
Colour	.844**	1												
pH	-0.254	-0.502	1											
EC	-0.159	-0.252	.852**	1										
TDS	-0.159	-0.252	.852**	1.000**	1									
DO	0.519	0.395	-0.515	-0.417	-0.417	1								
NO_3^-	0.417	0.291	-0.567	-0.509	-0.509	0.475	1							
Fe	.678*	0.647	-.675*	-.667*	-.667*	.833**	0.441	1						
Mn	0.235	0.136	0.273	0.147	0.147	-0.061	-0.553	0.098	1					
Al	-0.104	0.165	0.288	0.345	0.345	-.759*	-0.526	-0.518	0.399	1				
Alkalinity	-0.184	-0.218	.700*	.917**	.917**	-0.383	-0.542	-0.633	0.393	0.380	1			
Hardness	0.243	0.176	0.464	.750*	.750*	-0.083	-0.051	-0.267	-0.282	0.086	0.567	1		
Cl	-0.398	-0.470	0.664	.828**	.828**	-0.104	-0.421	-0.518	-0.076	-0.071	.794*	0.552	1	
SO_4^{2-}	0.098	-0.202	0.591	0.613	0.613	0.264	-0.147	-0.128	0.323	-0.220	0.587	0.341	.723*	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table 6
Spearman correlation matrix during pre-earthquake in Bambangan water intake point

Parameter	Turbidity	Colour	pH	EC	TDS	DO	NO_3^-	Fe	Mn	Al	Alkalinity	Hardness	Cl	SO_4^{2-}
Turbidity	1													
Colour	.802*	1												
pH	-0.551	-.765*	1											
EC	-0.429	-0.611	.778*	1										
TDS	-0.429	-0.611	.778*	1.000**	1									
DO	0.595	0.599	-0.707	-.833*	-.833*	1								
NO_3^-	.711*	.709*	-.921**	-.783*	-.783*	.795*	1							
Fe	.857**	.898**	-.778*	-.810*	-.810*	.786*	.855**	1						

Table 6 *(Continued)*

Mn	0.663	0.309	-0.206	-0.024	-0.024	0.024	0.421	0.410	1					
Al	0.062	-0.093	0.503	0.334	0.334	-0.321	-0.306	-0.062	0.206	1				
Alkalinity	-0.405	-0.659	0.671	$\mathbf{.905}^{**}$	$\mathbf{.905}^{**}$	$\mathbf{-.857}^{**}$	-0.627	$\mathbf{-.762}^{*}$	0.253	0.272	1			
Hardness	-0.405	-0.659	$\mathbf{.743}^{*}$	$\mathbf{.905}^{**}$	$\mathbf{.905}^{**}$	-0.595	-0.663	$\mathbf{-.762}^{*}$	-0.145	0.395	$\mathbf{.762}^{*}$	1		
Cl	-0.342	-0.517	0.459	$\mathbf{.812}^{*}$	$\mathbf{.812}^{*}$	-0.457	-0.462	-0.685	-0.199	0.066	0.660	$\mathbf{.913}^{**}$	1	
SO_4^{2-}	0.247	0.006	-0.342	0.037	0.037	0.346	0.406	0.037	0.100	-0.494	0.037	0.235	0.533	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

3.3 Significant Parameter
3.3.1 Output of Shapiro Wilk Test

Table 7 demonstrates *p*-value of each parameter by testing the hypothesis *distribution's variable is normality distributed* by using the Shapiro-Wilk test. The result shows that most of the *p*-value is less than 0.05, whereby the dataset is non-normal distributed. Some parameters' *p*-value appear to be greater than 0.05 however, this did not affect the result of the test.

Table 7
Output of Sharpiro Wilk test (*p*-value<0.05)

No	Parameter	Bambangan			Kimolohing		
		Statistic	df	*p*-value	Statistic	df	*p*-value
1	Turbidity	0.37	12	0.000*	0.322	13	0.000*
2	Colour	0.364	12	0.000*	0.331	13	0.000*
3	pH	0.817	12	0.015*	0.870	13	0.053
4	EC	0.914	12	0.238	0.959	13	0.741
5	TDS	0.923	12	0.312	0.944	13	0.509
6	DO	0.74	12	0.002*	0.777	13	0.004*
7	NO_3^-	0.786	12	0.006*	0.670	13	0.000*
8	Fe	0.705	12	0.001*	0.774	13	0.003*
9	Mn	0.742	12	0.002*	0.534	13	0.000*
10	Al	0.741	12	0.002*	0.727	13	0.001*
11	Alkalinity	0.942	12	0.525	0.962	13	0.789
12	Hardness	0.961	12	0.796	0.907	13	0.168
13	Cl	0.67	12	0*	0.796	13	0.006*
14	SO_4^{2-}	0.968	12	0.891	0.926	13	0.300

*Significant value <0.05

3.3.2 Result of Kruskal Wallis Test

Table 8 demonstrated the output of the Kruskal-Wallis test that the hypothesis is water quality parameters is significantly different. The parameters with the *p*-value less than 0.05 were Fe (0.001) and Mn (0.001) at both stations, turbidity (0.001), colour (0.003) at the Kimolohing, and Al (0.027) at Bambangan. Then, the null hypothesis is accepted, and it is assumed that there was significant difference in the water quality parameter in term of earthquake's impact (before and after the earthquake). The parameters with the *p*-value greater than 0.05 were turbidity (0.093), colour (0.072) at Bambangan, Al (0.162) at Kimolohing and pH (0.708; 0.703), EC (0.596; 0.896), TDS (0.596; 0.76), NO_3^- (0.889; 0.895), alkalinity (0.836, 0.777), hardness (0.908, 0.371), Cl (0.744; 0.808) and SO_4^{2-} (0.944; 0.613) at both stations. Then, the null hypothesis is rejected and there was no difference between before and after the earthquake.

Table 8
Summary output of Kruskal-Wallis test (*p*-value<0.05)

Parameter	Bambangan		Kimolohing	
	Kruskal-Wallis H	*p*-value	Kruskal-Wallis H	*p*-value
Turbidity	2.828	0.093	10.433	**0.001***
Colour	3.244	0.072	9.129	**0.003***
pH	0.14	0.708	0.145	0.703
EC	0.281	0.596	0.017	0.896
TDS	0.281	0.596	0.093	0.76
DO	1.074	0.3	0.373	0.541
NO_3^-	0.02	0.889	0.017	0.895
Fe	12.585	**0.001***	21.01	**0.001***
Mn	14.099	**0.001***	7.617	**0.001***
Al	4.888	**0.027***	1.954	0.162
Alkalinity	0.043	0.836	0.08	0.777
Hardness	0.013	0.908	0.801	0.371
Cl	0.106	0.744	0.059	0.808
SO_4^{2-}	0.005	0.944	0.255	0.613

The pollution source is highly exposed to the earthquake, which might be landslides and erosion sweeping away the vegetation cover from upstream. These might cause the level of turbidity and colour. On the other hand, metal elements such as Mn, Fe, and Al were introduced into the river by erosion from urban areas and sediment. According to previous studies [84], the soil in Ranau contained most light and heavy metal elements since the water was monitored in the urban area. Urban land use is the leading source of water pollution, while agricultural land use, forest land use, and other land use accounted for the remaining percentages. However, agricultural and forest-related activities have significant positive correlation with physical and chemical indicators of water quality. While urban development activities have greater impact on water quality by altering hydrological processes such as runoff and erosion [8]. Therefore, the earthquake alone did not dominate the impact on water quality in Liwagu River, even if the river is located at the epicenter.

4. Discussion

To analyze the relationship between site data (water quality parameters) and satellite data (indices like SAVI, NDWI, and NDVI), we can investigate how variations in water quality pre and post-earthquake correspond with changes in vegetation and water content. Notable water quality shifts between 2014 and 2015 include a significant increase in turbidity at both the Bambangan and Kimolohing sites, indicating a rise in suspended particles, possibly due to soil erosion or sediment displacement caused by the earthquake. Similarly, a marked uptick in color values suggests elevated levels of dissolved organic and inorganic materials, potentially originating from disturbed soils or increased runoff. Electrical conductivity (EC) and total dissolved solids (TDS) experienced slight upticks, indicating higher dissolved ion content in the water, likely from mineral runoff. Despite these alterations, pH levels remained relatively constant, indicating minimal changes in water acidity, and while dissolved oxygen (DO) levels slightly decreased, they remained stable overall. However, there were noticeable increases in metals like iron (Fe), manganese (Mn), and aluminum (Al), likely stemming from soil erosion or weathering, while nitrate (NO_3^-) levels remained consistent.

When examining the satellite data, both the soil-adjusted vegetation index (SAVI) and the normalized difference vegetation index (NDVI) showed a slight reduction after the earthquake, pointing to a decline in vegetation health. This decline may be related to the increased turbidity and color in the water, as sediment and pollutants from disturbed soils could have negatively impacted plant life, especially near the river. The increased metal content and suspended particles in the water likely contributed to the reduced SAVI and NDVI values. On the other hand, the normalized difference water index (NDWI) remained relatively stable, with only a slight increase, suggesting that while the earthquake may have increased water content through runoff or groundwater inflow, it did not significantly alter the water surface area. This stability in NDWI aligns with the minor changes observed in dissolved oxygen, TDS, and pH, which imply that while more suspended material was present, the overall moisture content and chemical balance of the water remained largely unchanged.

The significance of the satellite data for water quality monitoring has been neglected the previous studies focus on water quality monitoring based on the surface water changes detection [3,26,36,38,53,59,72,86,88,96,101,105].Moreover, according to the knowledge of scholar the application of NDVI, NDWI, and SAVI for water quality change detection assessment have been neglected and how the integration of these satellite data can shed light on the ground data collection and show the spatial and temporal changes of surface land cover and associated with the water quality. This study highlighted the correlation between satellite and water quality data indicates that the earthquake led to increased sediment and metal content in the water, which in turn negatively affected vegetation health along the river, as reflected in the lower SAVI and NDVI values. However, the water body's extent and chemical stability, as suggested by NDWI, remained largely unaffected. Additionally, the Shapiro-Wilk test highlighted those parameters such as turbidity, color, and metal concentrations (Fe, Mn, Al) showed significant deviations from normal distribution, pointing to the earthquake's uneven and pronounced impact on these factors. Conversely, parameters like EC, TDS, and hardness did not show significant deviations, suggesting they were less impacted by the seismic event.

5. Conclusion

The integration of water quality data and satellite indices provides a comprehensive understanding of the earthquake's impact on the physical environment and ecosystems. Ground data from 2014 to 2015 showed notable increases in turbidity, color, and metal content (Fe, Mn, Al), likely resulting from soil erosion and sediment displacement caused by seismic activity. This rise in suspended particles and dissolved materials in the water corresponded with decreased vegetation health, as evidenced by slight declines in satellite-based SAVI and NDVI indices, indicating that higher sediment and pollutants may have negatively affected plant life along the river.

Remarkably, the NDWI, which measures water content, remained consistent, suggesting minor changes in dissolved oxygen (DO), TDS, and pH. This stability implies that while the water body's chemistry was altered by increased sediment and metals, its overall moisture content and surface area were not significantly impacted. The Shapiro-Wilk test further supported these results, revealing non-normal distributions in parameters such as turbidity, color, and metal concentrations, indicating substantial variability and notable deviations from normal water quality post-earthquake. By combining satellite and water quality data, a comprehensive view of the earthquake's effects emerges. Although, water quality experienced significant disruptions in terms of turbidity and metal content, vegetation health was moderately affected, and overall water content remained stable. This integrated approach enables a more detailed assessment of both immediate and long-term environmental impacts, aiding in identifying the areas most impacted by seismic events.

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