Identification of Paleotsunami Deposits Using XRF and Artificial Intelligence Methods on the Southern Coast of Lebak, Banten

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Abstract. The southern coastal area of Lebak, Banten is the southern region of Java which is prone to tsunami disasters. There is evidence of past tsunami events in the southern region of Java. However, not all tsunami deposits have identifiable sedimentological and micropaleontological traces. Geochemical proxies and artificial intelligence with machine learning methods can be used to identify paleotsunami deposits. Machine learning methods that can be used to cluster paleotsunami deposits are Agglomerative Hierarchical Clustering (AHC) and Support Vector Machine (SVM) with validation of model accuracy using the Receiver Operating Characteristic (ROC) and Area Under Curve (AUC) methods. Input data are XRF analysis data and macroscopic core sample description data. The output from data processing is in the form of prediction of tsunami and non-tsunami deposits at each depth of core data sample. The data is correlated and interpreted to identify tsunami events that occurred in the past. The identification results show that the tsunami deposition in the research area, namely the area around the Bagedur coastal coast and Bolang village had tsunami deposit characteristics based on macroscopic description, XRF analysis, and artificial intelligence clusterization. It is also thought to be correlative with the tsunami deposition of previous research in the area around the Binuangeun coastal coast.

1. Introduction

One of the areas in southern Java that is prone to tsunami disasters is the area around southern coast of Lebak, Banten. Previous research found a correlation between paleotsunami deposits in the Lebak and Pangandaran areas with the interpretation that these deposits were deposited from the same tsunami event because they are estimated to have an extension of 300 km [1]. The proxies most often used in paleotsunami sediment research are the proxies for sedimentology and micropaleontology. However, one disadvantage of these proxies is that not all tsunami deposits have observable sedimentological and micropaleontological traces, so other proxies are proposed, such as geochemical proxies. The use of geochemical proxies to help identify paleotsunami deposits was first made about 30 years ago, namely in the 1990s [2].

Technological developments greatly helped in discovering methods for clustering paleotsunami deposits by studying their patterns. One method that can be used to predict paleotsunami deposition patterns is the use of artificial intelligence with machine learning methods. One of the applications of geochemical proxies using machine learning in determining paleotsunami deposits has been carried out [3]. This method was applied to the 2011 Tohoku tsunami deposit in Japan. Based on the research results, machine learning can display prediction of tsunami and non-tsunami deposits after going through several
series of experiments to obtain the maximum predictive accuracy model by recognizing the pattern of the chemical content of the studied sediment like increases compounds in TiO$_2$, Fe$_2$O$_3$, K$_2$O, CaO, and MnO. Data processing from geochemical proxies using machine learning can be a method that is expected to predict tsunami event patterns and identify the process so that it is useful in mitigating future tsunami disasters.

2. The Potential of Tsunami Disaster in Lebak Area, Banten
The southern coastal area of Lebak is located in Lebak Regency, Banten Province. The area around the southern coast of Lebak, Banten is one of the areas on the South Coast of Java Island which is close to the southern subduction zone of Java trench which has the potential to create earthquakes that can cause tsunamis (figure 1) [4]. This tsunami determined to generate earthquake based on the scenario of historical large earthquakes that have occurred in the subduction zone of the southern region of Java. The value of fault parameters such as magnitude, length, width and slip are determined based on the tectonic arrangement and the scaling law of earthquakes (table 1). Lebak Regency has a coastline directly facing the Indian Ocean, which is geologically an active continental margin because it is a meeting point between the Indo-Australian oceanic plate and the Eurasian continental plate which is characterized by high seismic activity (the red round show on the map in the right side of figure 1) [4].

![Subduction zone and seismicity map](image)

**Figure 1.** Subduction zone which has the potential to create earthquakes that can cause tsunamis on the south of Java Island (left) & seismicity map of south coast Lebak, Banten (right) [4].

**Table 1.** The scenario of historical large earthquakes that have occurred in the subduction zone of the southern region of Java based on the tectonic arrangement and the scaling law of earthquakes [4].

| Fault  | Length (km) | Width (km) | Loc (°S) | Loc (°E) | Mag (Mw) | Strike (°) | Dip (°) | Rake (°) | Slip (m) | Depth (km) |
|--------|-------------|------------|----------|----------|----------|------------|---------|----------|----------|------------|
| Fault 1 | 128         | 100        | 8,73     | 105,83   | 8,7      | 315        | 10      | 89       | 20       | 10         |
| Fault 2 | 115         | 100        | 8,05     | 104,87   | 8,7      | 281        | 10      | 100      | 20       | 10         |
| Fault 3 | 215         | 100        | 7,83     | 103,82   | 8,7      | 300        | 10      | 114      | 20       | 10         |
3. Geochemical Proxies for Paleotsunami Deposits

Geochemical proxies of the geology of the study area, and a good understanding of depositional and chemical processes can help differentiate and understand chemical signatures in tsunami deposits. Geochemical proxies for current and past tsunami deposits are considered useful proxies and can be traced quantitatively, especially when other proxies cannot be used. Geochemical proxies describe sediment sources (based on mineralogy), co-components (biomaterials such as shells / organic matter from land or sea), and transport media [2]. Chemical analysis of Si, Al, Mg, Fe, K, Mn, Ti, P and Ca was performed by means of the X-ray fluorescence (XRF) spectrometer of analytical SiO\textsubscript{2} content slightly increases (4–5%) in the tsunami deposit while other elements occur in much lower concentrations [2]. Depletion in Fe and Ti, essentially found as rutile (TiO\textsubscript{2}) and titanomagnetite (Fe\textsubscript{2}xTi\textsubscript{x}O\textsubscript{3}), matches the low values of magnetic susceptibility observed in the tsunami deposit [5]. The main geochemical signatures of the tsunami deposit are originated from inherited phyllosilicates contained in the adjacent clayish units and diluted within a huge volume of non-magnetic minerals (i.e., calcite and silicon). Quantitative data normalized by Al\textsubscript{2}O\textsubscript{3} confirm the connection between the signature of the tsunami deposit and those of the mudflat. These results suggest an external source of SiO\textsubscript{2} and CaO (shell fragment and detrital calcite & silicates). The analysis displays an excellent positive correlation between Al\textsubscript{2}O\textsubscript{3} and major elements commonly associated with inherited minerals (TiO\textsubscript{2}, K\textsubscript{2}O, Na\textsubscript{2}O, Fe\textsubscript{2}O\textsubscript{3}). Conversely, SiO\textsubscript{2} and CaO display a negative correlation with Al\textsubscript{2}O\textsubscript{3} reaching a correlation coefficient of 0.95. In addition to inherited phyllosilicates from the clays and biogenic/detrital carbonates from the beach, a slight but notable increase in other elements (K\textsubscript{2}O, Na\textsubscript{2}O and MgO) is observed (Figure 2). MgO is mostly associated to dolomite while Na\textsubscript{2}O and K\textsubscript{2}O can be related to micaceous minerals and feldspars [5].

![Figure 2. Geochemical data of major elements on Lisbon tsunami deposit at Boca do Rio Estuary: quantitative data (wt.%) and trends in marine seawater (Ca, Na, Cl) and terrestrial/high-energy (Al, Fe, Ti, Zr) indicators (in cps). Elemental analysis (C, N, H, S) is also shown [5].](image-url)

4. The Concept of Artificial Intelligence in Paleotsunami Deposits Research

The application of artificial intelligence is very useful in identifying paleotsunami deposits and practical method with quantitative models. The use of artificial intelligence methods is of great interest to help identify paleotsunami deposits. This study utilizes XRF analysis data to identify the geochemical proxies in paleotsunami deposits and uses machine learning techniques to process the data. The machine learning technique used in this research is unsupervised clustering method of the XRF analysis processed using Agglomerative Hierarchical Clustering (AHC) method to cluster paleotsunami and non-paleotsunami deposits at each depth [6]. Machine learning techniques with the AHC method will classify according to the character of each element at each depth. It is necessary to try several suitable affinity and linkage methods to the prediction of the classification of paleotsunami and non-paleotsunami
deposits is in accordance with the manual prediction at the beginning by taking into account the peculiarities of the paleotsunami geochemical deposits. Then the results of the AHC clustering data are used as a reference for the descriptive data to classify paleotsunami deposits at each depth. Data result from AHC processed to Support Vector Machine (SVM) method. The application of the SVM method in this study is to provide prediction results in the form of prediction of paleotsunami and non-paleotsunami deposits on data whose patterns have been known from the processing of the AHC method. The classification results of the SVM method are checked for the accuracy of the prediction results by performing validation to test the accuracy or success of an AHC and SVM model in producing paleotsunami sediment predictions. The validation method used is the Receiver Operating Characteristic (ROC) Curve and Area Under Curve (AUC). Receiver Operating Characteristic (ROC) Curve and Area Under Curve (AUC) are validation techniques commonly used in comparing the results of artificial intelligence prediction models [7]. The ROC graph has a range of AUC values from 0 - 1. A good and ideal model has an AUC value close to 1 indicating that the model has very good accuracy, while an AUC value close to 0.5 indicates that the model is not accurate.

5. Research methods
The data in this study area were obtained from sampling in the form of coring data (wells) with a depth ranging from 1-2 m in a predetermined area which is thought to have paleotsunami deposits. Sampling was carried out at Bagedur Beach and Bolang Village, Malingping, Lebak Regency, Banten (figure 3). At Bagedur Beach one core data sample is taken and in Bolang Village three core data samples are taken, with the location coordinates as follows:

- Bagedur Beach (BGD-04): (6°42'55.6"S, 105°59'32.5"E)
- Bolang village 1 (BLG-01): (6°47'39.7"S, 105°58'18.0"E)
- Bolang village 2 (BLG-02): (6°47'41.0"S, 105°58'20.5"E)
- Bolang village 3 (BLG-03): (6°47'42.0"S, 105°58'21.6"E)

![Figure 3. Sampling location on the study area (modified from google maps).](image)

The results of the well data are then described macroscopically. After that the data is processed by doing XRF analysis and artificial intelligence with the following stages:

- XRF analysis is carried out for descriptive data that are suspected of having the characteristics of paleotsunami deposits to determine the content of the compounds contained at each depth.
- The content of compounds that are known from each depth in the XRF analysis, a prediction is made at the depth where tsunami deposits are suspected.
- Prediction is used as a reference in determining the most appropriate clustering method in the Agglomerative Hierarchical Clustering method whose prediction results will be used to classify paleotsunami and non-paleotsunami deposits in the description data.
Predicted data on the Agglomerative Hierarchical Clustering method are used as training and validating data which will be processed using the Support Vector Machine (SVM) method with a percentage of 80% training data and 20% validating data. Validation is done to test the accuracy or success of the model. The validation method used is the receiver operating characteristic (ROC) curve and area under curve (AUC). After obtaining a good accuracy value, testing is carried out on the new description data to predict both paleotsunami and non-paleotsunami deposits in the description data. The prediction results will be used as a reference in the depth correlation process at sample points where paleotsunami deposits are suspected.

6. Result & Discussion

6.1. Results of data processing

The process of clustering paleotsunami and non-paleotsunami deposits using artificial intelligence methods by processing input data in the form of XRF analysis data of 25 samples from data core of BGD-04 (0-100). Before being processed using machine learning, manual predictions of tsunami deposition predictions were carried out on sample data based on the results of research on the characteristics of paleotsunami geochemical deposits from several previous studies. The results of manual prediction resulted in the conclusion that at the predicted depth the tsunami deposit had a pattern in the form of high Fe₂O₃ and TiO₂ content and low SiO₂ and Al₂O₃ content. In general, based on previous research, the geochemical characteristics of tsunami deposits are an increase in TiO₂ compounds and elements of Fe, Ti, Ca and K and a decrease in phyllosilicate minerals that contain Si & Al, which are the most common soil mineral classes. The graph of each compound's content also shows a unique pattern in paleotsunami deposits. The following is a table of the results of manually predicting the estimated depth of tsunami deposits based on the chemical compound content and the graph of the compound content in the XRF analysis results. The graph shows the compound with the blue line graph has increased at several depths and the graph with the red line has decreased at several depths.

![Graph showing compound content in XRF analysis results](image)

Figure 4. The graph shows pattern in the suspected tsunami deposition layer on several depth (cm). Increases compounds were seen in TiO₂, Fe₂O₃, K₂O, CaO, and MnO at depths of 8, 18, 20, 47, and 92 cm. Meanwhile, the SiO₂, Al₂O₃, and P₂O₅ compounds also decreased at depths of 8, 18, 20, 47, and 92 cm.

The results of manual prediction are used as a reference in finding the best combination of methods in machine learning with the Agglomerative Hierarchical Clustering (AHC) method to predict XRF analysis data. The sample data used in this study were relatively small (25 samples). It is hoped that by obtaining the appropriate combination of methods, it can be helped to process data in the future with a larger amount of data because we know the best combination of methods in predicting the pattern of chemical compound content of paleotsunami deposits. After going through several experiments with the combination of the affinity and linkage methods used in the AHC method, the best method for predicting paleotsunami deposits based on geochemical characteristics is the affinity "cosine" and "average" linkage type methods. The experimental results of several method combinations are attached in the...
appendix. The prediction is exactly same as the manual prediction that has been done previously based on the geochemical characteristics of the tsunami deposit from previous studies. By finding an accurate model, it is hoped that more research data in the future will be more effective in processing and no need to use manual predictions.

Figure 5. The left side is AHC clustering result from sample BGD-04 (0-100). The right side shows the table of tsunami deposit prediction from XRF analysis and machine learning clustering (blue highlight show the tsunami deposits). The result shows the same prediction both XRF analysis & machine learning.

The prediction results of tsunami suspicion deposits in the XRF analysis data are transferred to the description data according to the predicted depths obtained because of the limitations of XRF analysis data that cannot be read at each depth of the data described. Descriptive data processing in sample BGD-04 (0-100) is used as training data and validating as core data for machine learning to recognize patterns from tsunami deposits based on the data provided. The results of the prediction data are then processed using the Support Vector Machine (SVM) method. As many as 80% (57 samples) of data were used as training data and 20% (15 data) of data were used as validating data. Before being processed using the SVM method, the data must be encoded first to change the information data so that machine learning can be understood. The following are the results of the encoding on the sample description data BGD-04 (0-100). The encoded data is processed using the SVM method. In the training data, the prediction results were obtained in the form of a tsunami deposition prediction of 7 points from 57 data points. Meanwhile, for the validating data, the prediction results obtained from the predicted tsunami deposits are 3 points from 13 data points. Following are the results of the prediction of training data and validating of tsunami suspected deposits from the SVM processing method.

The SVM model that has been created in python programming produces a ROC-AUC value of training data and validation of 100%. This result is very satisfying, considering that it is very rare to find 100% accuracy for both. However, it also needs to be evaluated that the input data on which machine learning is based is still small and not too complex, so the resulting accuracy is quite good because the input data is relatively simple. It is hoped that this model can be the basis for model development in future studies with more complex parameters. In addition, the results of this model need to be compared with other proxies that support evidence of suspected tsunami deposits or can be completed from previous research results so that it can be proven that there is a correlation between current research and previous research that has been carried out in relation to the existence of tsunami deposits in the past.

Following are the results of the machine learning accuracy assessment using the ROC-AUC method on training and validating data.

After obtaining good accuracy values in the training and validating data, then testing the other descriptive data on samples BLG-01, BLG-02, and BLG-03. Before testing, all core data are put together in one data file and encoding is carried out as in the previous data training and validating stages. The
output of this testing data is the prediction of the presence of tsunami suspicion deposits in each sample. Then the prediction data obtained from each core data is correlated to determine the temporal variation of the tsunami event, the characteristics of the sediment, and the depositional environment of each correlated data.

![Normalized Confusion Matrix](image1)

**Figure 6.** The confusion matrix of training data show prediction of tsunami deposits in 7 data and non-tsunami 50 data (left). The accuracy value of model based on ROC-AUC is 100% (right).

![Normalized Confusion Matrix](image2)

**Figure 7.** The confusion matrix of validating data show prediction of tsunami deposits in 3 data and non-tsunami 12 data (left). The accuracy value of model based on ROC-AUC is 100% (right).

6.2. Characteristics of paleotsunami deposits in the research area

The characteristics of paleotsunami deposits on the research area based on XRF analysis data, macroscopic descriptive data, and artificial intelligence methods have their own patterns in each of the analyzed data. The XRF analysis results show that the suspected tsunami deposits in the study area tend to increase in TiO$_2$ and Fe$_2$O$_3$ compounds and decrease in SiO$_2$ and Al$_2$O$_3$. This is possible because Fe and Ti are heavy minerals which are indicators of high energy deposition, while Si and Al are characteristics of minerals from land. The following table compares the content of compounds in paleotsunami deposits in the tsunami-suspected sediment layer.
Table 2. Summary of the characteristic description component on tsunami deposits.

| Depth | Sediment | white flakes | Root fibers | Pieces of logs | Quartz mineral | Shell fragments | Prediction |
|-------|----------|--------------|-------------|----------------|----------------|----------------|------------|
| 2     | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 3     | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 6     | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 5     | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 0     | Sand     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 10    | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 15    | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 20    | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 25    | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 30    | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 35    | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 40    | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 45    | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 50    | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 55    | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 60    | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 65    | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 70    | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 75    | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 80    | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 85    | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 90    | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 95    | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |
| 100   | Clay     | 1            | 0           | 0              | 1              | 1              | Tsunami deposit |

Based on descriptive data and artificial intelligence, it is known that there are distinctive characteristics of tsunami-suspected deposits in the descriptive data recognized by machine learning. The presence of shell chips is a key factor in determining whether sediment is tsunami deposition or not. The presence of shell fragments indicates a source of material originating from the sea which is thought to have originated from the tsunami phenomenon. In addition, the description data that has a shell fragment component is also correlative with the results of XRF analysis on the presumed paleotsunami deposit layer. White flakes in tsunami deposits usually indicate the presence of foraminifera microfauna on tsunami deposit. the presence of root fibers and pieces of wood indicates the depositional environment on land so that it is identified as not tsunami deposits.

6.3. Identification of past tsunami events

Based on the results of the comparison of the log correlation between the study area and the previous research around the Pesisir Selatan area of Lebak, Banten, it shows that there is a correlation between the thickness of the tsunami deposits at two layers of depth. The log data in figure 8a is the log from the research area located around Bagedur Beach, while the log in figure 8b is the log from the Binuangeun Coastal research area, Wanasalam Area, Banten by [10]. The correlation results show that a depth of 45-80 cm in the coastal logs of Binuangeun Beach contains tsunami deposits. It is estimated that the thickness of the tsunami deposit in the Binuangeun Coastal area is around 35 cm. These deposits are thought to be correlated with tsunami deposits on the Bagedur Coast which are found at a depth range of 18-49 cm which means that they have a thickness of about 31 cm so they are similar to tsunami deposits on the Binuangeun Coast. However, tsunami deposits on the Bagedur Coast are not continuous as in the Binuangeun Coastal sediments, but rather occur between layers of clay and sand. This shows the possibility of differences in the depositional environment in the study area with the previous research area located around the South Coast of Lebak Beach, Banten.
Figure 8. Correlation between research area in Bagedur Coast & Bolang Village (left) and previous research in Binuangeun Coastal Coast (right) [4]. Green colour is sedimentation layer of clay, yellow colour is sedimentation layer of sand, the blue square shows the prediction of tsunami deposits.

Based on description of data sample and compound’s content of XRF analysis we conclude that the research area sedimentation environment is lacustrine. The lacustrine environment is an intermediate area between land and sea. This is concluded from the depositional pattern which indicates an alternating sediment of clay and sand. Sand sediment is found among the dominant clay sediment and the presence of mollusk shells on the edge of the lake and their shells forming clusters several centimeters in thickness [8]. The chemical compound showed the similar pattern with geochemical data of major elements on Lisbon tsunami deposit at Boca do Rio Estuary [2].

Figure 9. Interpretation of tsunami sedimentation types (left) [9] and the presence of molusk shell fragment in research area show by yellow circle (right).

The tsunami depositional mechanism in the study area was identified from the features and sediment patterns recorded in the tsunami deposition candidate layer. Based on the features and depositional patterns, the authors classify the tsunami deposits into the coastal lacustrine basin deposit mechanism (coastal lacustrine basin). The existence of a barrier topography prevents the invasion of tsunami wave deposits, so that tsunami deposits in the lacustrine environment are generally found as a layer of sand interspersed with mud sediments. The tsunami deposition mechanism of this type indicates a tsunami
inundation carrying coastal sediments with a fast deposition process [9]. The following is the sedimentological profile and the mechanism of deposition in the lacustrine environment.

7. Conclusion
Based on the results and analysis of research conducted by the author. Then it can be concluded as follows:

- The graph of XRF analysis show uninc pattern with increasing/decreasing of some compound on several depth of paleotsunami deposit.
- The machine learning prediction show the same prediction with XRF analysis of paleotsunami deposit.
- The result of prediction data using XRF analysis & machine learning can be used to predict other sample data without XRF analysis.
- The macroscopic description data sample of paleotsunami show that the presence of shell fragment and white flakes are the key to determine tsunami deposit that indicates a source of material originating from the sea which is thought to have originated from the tsunami phenomenon.
- Based on description of data sample and compound’s content of XRF analysis, also based on study literature of sedimentation environment of tsunami deposit from any previous research we conclude that the research area sedimentation environment is lacustrine

Acknowledgments
The Authors would like to thank Program Study Geology and Geophysics Universitas Indonesia for Supporting this research. This Research was funded by Basic Research for Higher Education Grant, Ministry of Research and Technology.

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