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Earthquake Forecasting Model and Hazard Analysis in Bengkulu Province of Indonesia

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Abstract: We have made intensity and magnitude of earthquake forecasting models based on Autoregressive Integrated Moving Average (ARIMA) approachment and residual model using ARCH, GARCH and TGARCH of them in Bengkulu Province. In addition, we have mapped distribution of peak ground acceleration on bedrock. Peak ground acceleration value was obtained by mathematic calculating of Fukusima dan Tanaka equation. It was used earthquake history data in Bengkulu Province for 1970 to June 2016. The result of this interpretation showed that Muko-muko regency has the highest peak ground acceleration value (361-402 gal). It also allowed on western of North Bengkulu Regency.

Key words: Earthquake forecasting model, peak ground acceleration, ARIMA, Fukusima, earthquake

INTRODUCTION

Tectonically, Bengkulu Province is located in the coastal island formed in the subduction zone, Indo-Australia plate towards Eurasia plate (Hartono and Soepri, 2004; Natawidjaja *et al*., 2007). Western parts of Bengkulu Province was one area in Sumatera Island who might experience a large earthquake and tsunami. History showed that Bengkulu have been experienced tectonic earthquake reached 7-8 Ms which resulted in a lot of infrastructure damage and casualties. Peak Ground Acceleration (PGA) could be a measure for estimating the effects of earthquake that have occurred in the past and also could predict the effects of earthquake that might occur in the future.

Rizal have published the result of earthquake analysis in Bengkulu Provinsi area using time series model approachment of ARFIMA and distribution map of epicentre every years. Form one of the resulting model (earthquake magnitude), there was autocorrelation of a residual. It was because the incidence of earthquake have high volatility. It is reinforced by the results of testing a variant that is not constant.

Liang and Qiwei has published the results estimation model of Autoregressive Conditional Heteroscedasticity (ARCH), Generalized Autoregressive Conditional Heteroscedasticity (GARCH) which produced least absolute deviations estimation. This models was able to produce the forecast which good enough for the data that as a high volatility such as financial data. Podobnik *et al*. (2004) used ARCH dan GARCH to modelling a high-frequency financial data (Podobnik *et al*., 2004). Yun have done similar topic but they modelling it using VaR. Sabiruzzaman *et al*. (2010) compared both of model: GARCH and Threshold Generalized Autoregressive Conditional Heteroscedasticity (TGARCH) to forecasting trading index volume.

ARCH, GARCH and TGARCH Models: Suppose that $\{X_t: t \in R^+\}$ as line of time series which associated to process {(t}, model GARCH (p, q) with $p \geq 1$ dan $q \geq 0$ given by:

$$X_t = \sigma_t \varepsilon_t$$
$$\sigma_t^2 = \sigma_t(\theta)^2 = c + \sum_{t=1}^{p} b_i X_{t-i}^2 + \sum_{j=1}^{q} a_j \sigma_{t-j}^2 \tag{1}$$

where, $c>0$, $b_j \geq 0$, dan $a_j \geq 0$ are unknown parameters, {(t} is a sequence of independent and identically distributed random variables wtih mean 0 and variance 1 and {(t} is independent of $\{X_{t-k}, k \geq 1\}$ for all t. When q = 0 Eq. 1 become an Auto Regressive Conditional Heteroscedastic (ARCH). The maximum quasi likelihood estimation method can be motivated by temporarily assumsing that ε_t~iid N (0, 1). Given $\{(X_k, \sigma_k^2), 1 \leq k \leq v\}$ with $v \geq$ max (p, q), the conditional density function of $X_{v+1}, ..., X_n$ is:

$$\left(\prod_{t=v+1}^{n} \sigma_t^2\right)^{-\frac{1}{2}} \exp\left(-\frac{1}{2}\sum_{t=v+1}^{n}\frac{X_t^2}{\sigma_t^2}\right) \tag{2}$$

Maximising Eq. 2 with σ_t^2 replaced by $\hat{\sigma}_t^2$, we obtain the quasi maximum likelihood estimator (Hall and Yao, 2003):

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$$\hat{\theta}_{ML} = \text{argmin} \sum_{t=v+1}^{n} \left(\frac{Xt_t^2}{\hat{\sigma}_t(\hat{\theta})^2} + \log(\hat{\sigma}_t(\theta)^2) \right)$$

A TGARCH (p, q) model assumes the form like this:

$$X_t = \sigma_t \varepsilon_t$$
$$\sigma_t^2 = \sigma_t(\theta)^2 = c + \sum_{t=1}^{p} b_i X_{t-i}^2 + \sum_{j=1}^{q} (a_j + c_j d_{t-j}) \sigma_{t-j}^2 \quad (3)$$

Where:

$$d_{t-j} = \begin{cases} 1 & \sigma_{t-j} < 0 \\ 0 & \sigma_{t-j} \geq 0 \end{cases}$$

and a_j, b_i and c_j and are nonnegative parameters satisfaying conditions similar to those of GARCH (Wu, 2010).

Peak Ground Acceleration (PGA) is equal the maximum ground acceleration that occurred during earthquake shaking at a location. Peak ground acceleration is equal to amplitude of the largest absolute acceleration recorded on an accelerogram at a site during particular earthquake (Douglas, 2003). In an earthquake, damage to buildings and infrastructure is related more closely to ground motion of which peak ground acceleration is a measure, rather than the magnitude of the earthquake itself.

Peak ground acceleration on bedrock values vary in different earthquake and in differing site within one earthquake event, depending on a number of factors (Lorant, 2010). These include the length of the fault, magnitude, the depth of hypocentre and the distance from the epicentre. The ground type can significantly influence ground acceleration, so peak ground acceleration values can display extreme variability over distances of a few kilometres particularly with moderate to large earthquake (Fukushima and Tanaka, 1990). Peak ground acceleration value on bedrock could be obtained by Eq. 4:

$$\log \alpha = 0.41M - \log(R + 0.032 \times 10^{0.41M}) - 0.0034R + 1.30$$

Where:

M = Magnitude of earthquake
R = Distance of epicenter and
α = Peak ground acceleration on bedrock

Peak ground acceleration could be expressed in g as either a decimal or percentage in m/sec^2 (1g = 9.81 m/sec^2) or in gal where 1 gal is = 0.01 m/sec^2. Peak ground acceleration could be correlated to macroseismic intensities on the Mercalli scale (MMI) but these correlation are associated with large uncertainty. Peak ground acceleration was measured by instruments and the Mercalli intensity was a scale uses personal reports and observations to measure earthquake intensity (Cua *et al*., 2010). It rather, how to hard the earth shakes at a given geographic point (Lorant, 2010).

MATERIALS AND METHODS

We used earthquake historical data for 1970 to June 2016 (which magnitude ≤4 Ms). For simplify the writing, we supposed that a was earthquake intensity variable and mean of magnitude variable as B.

The first modelling stage was begun by identification of ARIMA model for each variable based on characteristics of Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) plotting (Sugianto *et al*., 2006). The second, we made residual variant model of ARCH, GARCH and TGARCH included: residual heteroskedasticity testing using Lagrange Multiplier (LM), autocorrelation test used Portmanteau examiner, test for normality used Jarque Bera examiner, tested the effects asymmetri and volatility threshold used cross correlation test.

In addition, we also analyzed peak ground acceleration on bedrock, it was begun by mapping the distribution of earthquake epicenter in Bengkulu Province on each magnitude. It have done to seen about distribution of epicentre and depth of hypocentre at near Bengkulu Province on similar magnitude. The next we calculated peak ground acceleration value as in Eq. 4. Before that firstly, we calculated epicentre distance to observed site. Distance of each site about 200 m. The results of them then interpreted to maps and it correlated to table of Japan meteorological agency seismic intensity scale. It used to see earthquake effects in past and to estimate probability of earthquake effects in the future (Box and Jenkins, 1994).

RESULTS AND DISCUSSION

Rizal have calculate ACF and PACF value on each variable of A and B. Description graph of ACF for Variable A is decreased exponentially and PACF cut-off graph on the first lag till 5. Whereas, ACF Cutoff graph of variable B on the first lag till to 2 and PACF cutoff till to 5. We allowed criteria of Box and Jenkins (1994), to choosing a model and order of them. There are two tentative models of time series for variable of A and B, included Akaike Information Criterion (AIC) value and Adj R^2 has shown on Table 1.

On Table 1, we have chosen the best model to analysis for the next step (text highlight color). Criteria of choosing based on AIC minimum value whereas for nilai Adj. R^2 value used if it has same value to AIC value where selected criteria of them was Adj. R^2 maximum value.

Table 1: Tentative model of variable A and B based on characteristic of ACF and PACF

Variables	Models	AIC	Adj. R^2
A	ARIMA (1,0,0)	8.348	0.486
	ARIMA (2,0,0)	8.317	0.505
	ARIMA (3,0,0)	8.306	0.513
	ARIMA (4,0,0)	8.304	0.517
	ARIMA (5,0,0)	8.285	0.529
B	ARIMA (2,1,2)	2.001	0.368
	ARIMA (3,1,1)	1.974	0.376
	ARIMA (3,1,2)	1.985	0.372
	ARIMA (4,1,1)	1.968	0.386
	ARIMA (4,1,2)	2.073	0.322
	ARIMA (5,1,1)	1.965	0.375
	ARIMA (5,1,2)	1.976	0.372

Table 2: Significant estimation and examination of: model (ARIMA (5, 0, 0) of variabel A)

Parameters	Coeffient	p-values	Results
C	23.016	0.002	Significant
AR (1)	0.466	0.000	Significant
AR (2)	0.084	0.302	Not significant
AR (3)	0.072	0.375	Not significant
AR (4)	0.040	0.624	Not significant
AR (5)	0.187	0.011	Significant

Table 3: Significant estimation and examination of model (ARIMA (5, 1, 1) of varible B)

Parameters	Coeffient	p-values	Results
C	-0.013	0.000	Significant
AR (1)	0.196	0.009	Significant
AR (2)	0.053	0.480	Not significant
AR (3)	0.024	0.740	Not significant
AR (4)	0.008	0.904	Not significant
AR (5)	0.097	0.177	Not significant
MA (1)	-0.990	0.000	Significant

Selected model of variable a was ARIMA (5, 0, 0) or writable as AR (5) whereas ARIMA (5, 1, 1) for variable B.

Models parameter selecting of variable A dan B estimated by maximum likelihood approach. For simple calculation we used programme od eviews package and we have got them as given on Table 2.

With used 5% of real degree, constant model value, parameter of AR (1) and (5) significant models, so that we found forecasting model for variable a as given by:

$$A_t = 23.016+0.466A_{t-1}+0.187\,A_{t-5}$$

Whereas for variable B, parameter value of AR (1) and MA (1) would significant on 5% of real degree (Table 3), so we found forecasting model for variable B as given by:

$$B_t = -0.013+0.196B_{t-1}-0.990_{\varepsilon t-1}$$

After this step, we examined for residual autocorrelation where initial hypothesis (H_0) have no one autocorrelation on the first lag to h with examination criteria that H_0 would be rejected if $p<0.05$. The result of residual autocorrelation examination for variable A and B have seen in Table 4 p-value on the higher lag of testing standard 5% for each variable were lag 12th and 10th, respectively. It means that in variable A no one correlation between residual if lag >12. In other hand, no one correlation on variable B if lag is >10. Whereas in previous of lag was autocorrelation. So, we have to make some models from model residual using ARCH, GARCH, or TGARCH approachment.

Table 4: Portmanteau test autocorelation for models variabel A and B

Variables	Models	Portmanteau test: Lag	p-values	H_0
A	ARIMA	11	0.04650	Rejected
	(5,0,0)	12	0.07230	Accepted
B	ARIMA	9	0.00229	Rejected
	(1,1,1)	10	0.00563	Accepted

Table 5: ARCH-LM test for models variable A and B

Lag (h)	Variable A: LM	p-values	Variable B: LM	p-values
1	2.017	0.045	-0.567	0.571
2	-0.800	0.424	1.209	0.228
3	1.153	0.250	-0.227	0.820
4	-1.055	0.292	1.065	0.288
5	-1.066	0.287	2.077	0.039
6	1.748	0.082	1.289	0.199
7	-0.458	0.647	-0.771	0.441
8	1.429	0.154	-1.464	0.145
9	-1.103	0.271	0.694	0.488
10	-2.155	0.032	0.246	0.805
11	0.734	0.463	0.078	0.937
12	-0.057	0.954	0.226	0.820

The influence ARCH Model for variable A and B have obtained by examination of ARCH-LM. This examination would produce rejecting of zero hypothesis if statistic of LM (h) higher than χ^2 (h) or p-value is lower than testing of actual level value. According to Table 5, there are magnitude of p-value more lower for some lag on each variable, so it have to done residual modelling of ARCH, dan GARCH.

To see the whether or not to used approach of TGARCH, we have done Cross Correlation (CC) examination procedure toward residual. Criteria of examination is if cross correlation value lower than actual level (5%) there is asymmetric effect on it's lag. Have done cross correlation calculating until 36th lags on each variable A and B. In variable A, cross correlation value of <0.05 there were 26 lags and 30 lags of variabel B. Calculating result of them and their comparing results with actual level (5%) have shown on Table 6.

According to Hantoro and Soepri (2004), Hall and Yao (2003), Lorant (2010), Sabiruzzaman *et al.* (2010), we could arranged tentative models of ARCH, GARCH and

Table 6: Value of ARCH-LM for tentative models which elected of variable A

	Values of cross correlation			
Lags	Variable A	Results	Variable B	Results
0	0.0042	Yes	-0.0082	Yes
1	0.9946	No	0.9963	No
2	-0.0069	Yes	-0.0092	Yes
-	-	-	-	-
15	0.0760	No	0.0974	No
16	-0.0680	Yes	0.0890	No
17	-0.0090	Yes	0.0463	Yes
-	-	-	-	-
27	0.0332	Yes	0.0251	Yes
28	-0.0612	Yes	0.0278	Yes
-	-	-	-	-
35	-0.0450	Yes	-0.0341	Yes
36	-0.0876	Yes	-0.0550	Yes

Table 7: Value of AIC and Adj. R^2 for residual tentative models of variable A

Models	AIC	Adj. R^2
ARCH (1)	8.276	0.524
ARCH (2)	8.281	0.521
ARCH (3)	8.412	0.517
ARCH (4)	8.335	0.521
ARCH (5)	8.359	0.525
GARCH (1,1)	8.268	0.527
GARCH (1,2)	8.264	0.522
GARCH (2,1)	8.279	0.526
GARCH (2,2)	8.282	0.523
Threshold GARCH (1, 1)	8.270	0.521
Threshold GARCH (1, 2)	8.287	0.511
Threshold GARCH (2, 1)	8.269	0.496
Threshold GARCH (2, 2)	8.283	0.517

Table 8: Value of AIC and Adj. R^2 for residual tentative models of variable B

Models	AIC	Adj. R^2
ARCH (1)	1.783	0.320
ARCH (2)	1.803	0.314
ARCH (3)	1.764	0.365
GARCH (1,1)	1.674	0.358
GARCH (1,2)	1.792	0.321
GARCH (2,1)	1.716	0.315
GARCH (2,2)	1.709	0.300
Threshold GARCH (1, 1)	1.684	0.358
Threshold GARCH (1, 2)	1.686	0.362
Threshold GARCH (2, 1)	1.787	0.319
Threshold GARCH (2, 2)	1.697	0.363

TGARCH. In Table 7, variable of A has thirteen models that suitable as the best model and variabel of B has twelve models (Table 8).

Criteria to choosing of models based on minimum AIC value and the highest of Adj. R^2 value. Based on those criteria, models which suitable with variable A including: ARCH (1), GARCH (1, 2) and threshold GARCH (2, 1). Whereas variable B including: ARCH (3), GARCH (1, 1) and threshold GARCH (1, 1).

According to Table 9 and 10, three model that have tested no one auto-correlated to their residual. Based on the lowest RMSE and MAE value, selected model of variable A as ARCH (1) which time series eqution as given by:

$$h_t = 195.672 + 0.093\varepsilon_{t-1}^2$$

Table 9: Value of ARCH-LM for tentative models which elected of variable A

	ARCH (1)		GARCH (1, 2)		Threshold GARCH (2, 1)	
Lags	LM	p-values	LM	p-values	LM	p-values
1	0.085	0.931	0.048	0.961	-0.113	0.910
2	0.064	0.948	0.002	0.997	-0.011	0.990
3	-0.179	0.858	-0.063	0.949	-0.139	0.889
4	-0.073	0.941	0.014	0.988	-0.006	0.994
5	-0.036	0.970	-0.039	0.968	0.057	0.954
6	1.710	0.089	1.347	0.179	1.013	0.312
7	0.041	0.967	-0.017	0.985	-0.026	0.979
8	0.382	0.702	0.354	0.723	0.473	0.636
9	0.395	0.693	0.361	0.718	0.236	0.813
10	-0.227	0.820	-0.211	0.833	-0.230	0.818

Table 10: Value of RMSE and MAE of residual model variable A

Models	RMSE	MAE
ARCH (1)	21.308	17.763
GARCH (1, 2)	21.502	18.103
Threshold GARCH (2, 1)	22.088	18.676

Table 11: Value of ARCH-LM for tentative models which elected of variable A

	ARCH (1)		GARCH (1, 2)		Threshold GARCH (1, 1)	
Lags	LM	p-values	LM	p-values	LM	p-values
1	-0.500	0.617	0.043	0.965	0.068	0.945
2	-0.412	0.680	-0.645	0.519	-0.649	0.517
3	-1.290	0.198	1.633	0.104	1.840	0.067
4	-0.138	0.890	0.113	0.909	0.149	0.881
5	0.186	0.852	0.226	0.821	0.130	0.896
6	0.047	0.962	0.804	0.422	0.546	0.585
7	0.058	0.953	-0.594	0.553	-0.617	0.537
8	0.576	0.565	0.038	0.969	0.076	0.938
9	1.844	0.066	0.208	0.835	0.216	0.829
10	-0.683	0.495	-0.564	0.573	-0.230	0.818

Table 12: Value of RMSE and MAE of residual model Variable B

Models	RMSE	MAE
ARCH (3)	0.652	0.503
GARCH (1, 1)	0.668	0.513
Threshold GARCH (1, 1)	0.668	0.513

Figure 1 showed that the pattern of predicted residual data identic to the pattern of actual residual data. According to Table 11 and 12, model for variable B was: ARCH (3) which time series equation as given below:

$$g_t = 0.102 + 0.201\,\varepsilon_{t-1}^2 - 0.034\,\varepsilon_{t-2}^2 - 0.781\,\varepsilon_{t-3}^2$$

The next was plotting actual residual data versus predicted (fitted) residual data from selected model (Fig. 2). The pattern of predicted residual data also identic with actual residual data.

After we obtained time series model of variable A and B we also have made peak ground acceleration on bedrock of Bengkulu Province map using Fukushima and Tanaka (1990) equation. It used to estimate as characteristics of kinematic wave or vibration response on bedrock. Before that, epicentre distribution of Bengkulu Province showed in Fig. 3. This map used to describe distribution of epicentre based on magnitude and depth of hypocentre.

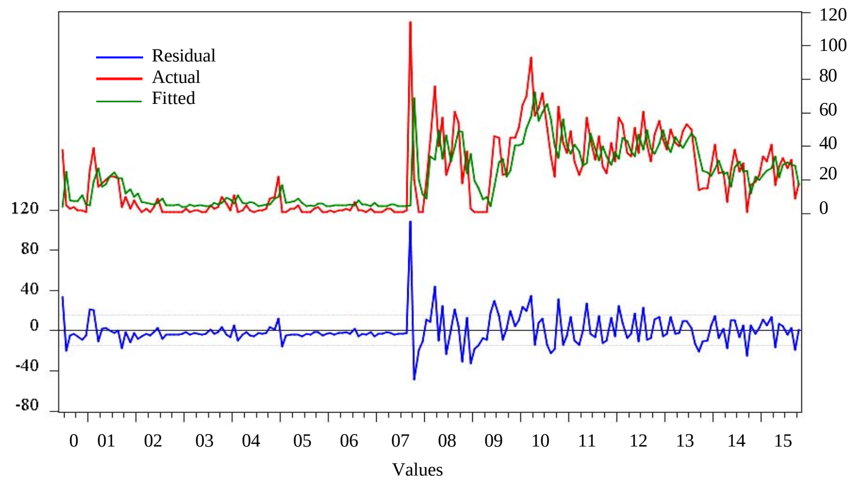

Fig. 1: Actual versus predicted (fitted) residual data plotting from selected model of variable A

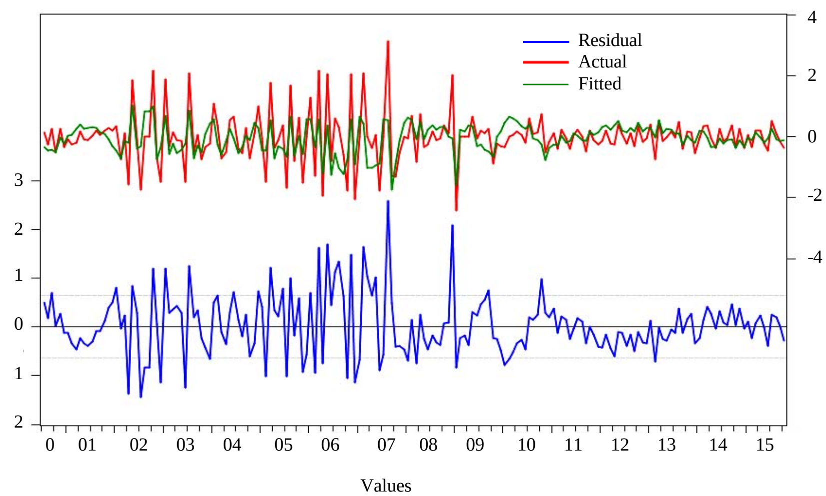

Fig. 2: Actual versus predicted (fitted) residual data plotting from selected model of variable B

Star symbol shown as shallow earthquake, circle symbol for intermediate depth of earthquake and the colour of symbol was magnitude.

Figure 4 showed that earthquake epicentre in near of Bengkulu Province relatively shallow depth which magnitude more dominant at 4 and 5 Ms whereas the number in other magnitude (6-8 Ms) than least. This interpretation showed that earthquake energy accumulation on subduction zone always collapse and it has low value. Major earthquake in Bengkulu Province has potential to repetition in the future, so we should to study the effects of earthquake that occurred in the past. In addition, we predict the effects that may occur in the future based on peak ground acceleration on bedrock analysis.

Figure 4 was spatial distribution of peak ground acceleration value that have been happened in Bengkulu Province at 1970 until June 2016. In general, high peak ground acceleration value in Bengkulu Province was identified to shallow depth earthquake, intermediate to large magnitude and closed to observation sites. The epicentre of which led to large peak ground acceleration value not only going around in Mentawai Ridge but also going around active faults that runs along the eastern part of Bengkulu Province (Bukit Barisan) which shown by the red line.

The highest peak ground acceleration value has identified in Eastern and Northern of Mukomuko Regency (316-402 gal) that shown red contour. Yellow contour (141-150 gal) distributed in around Western of North

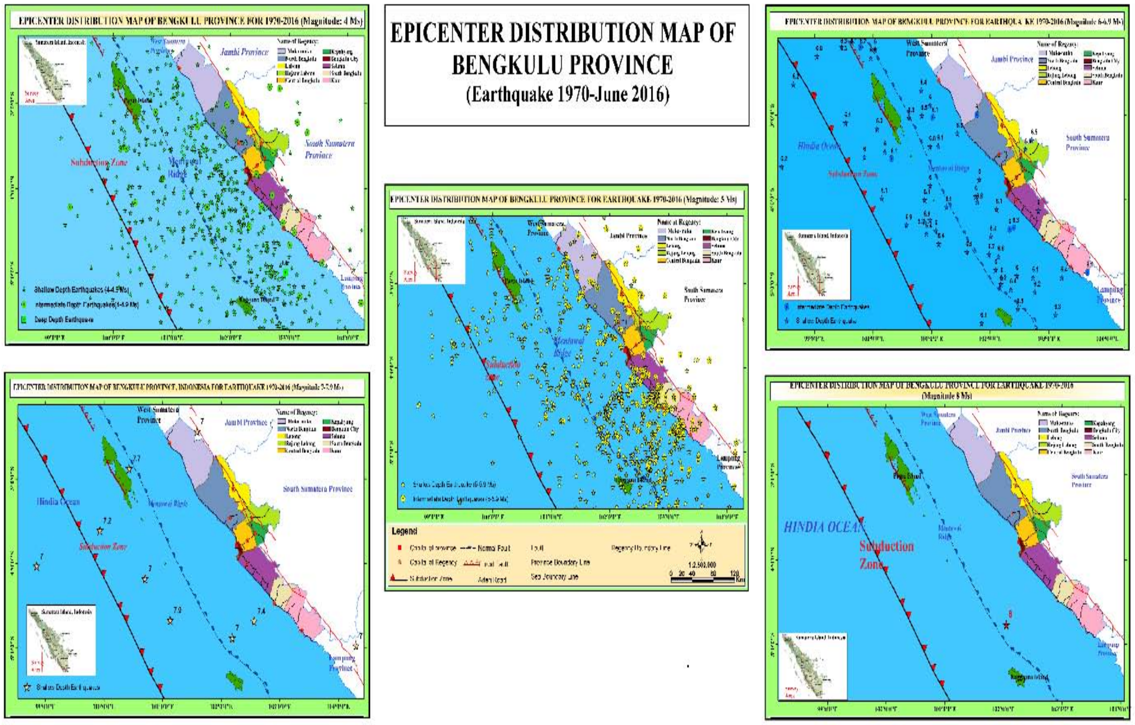

Fig. 3: Earthquake distribution map of Bengkulu Province from 1970 until June 2016 which magnitude about 4-8 Ms

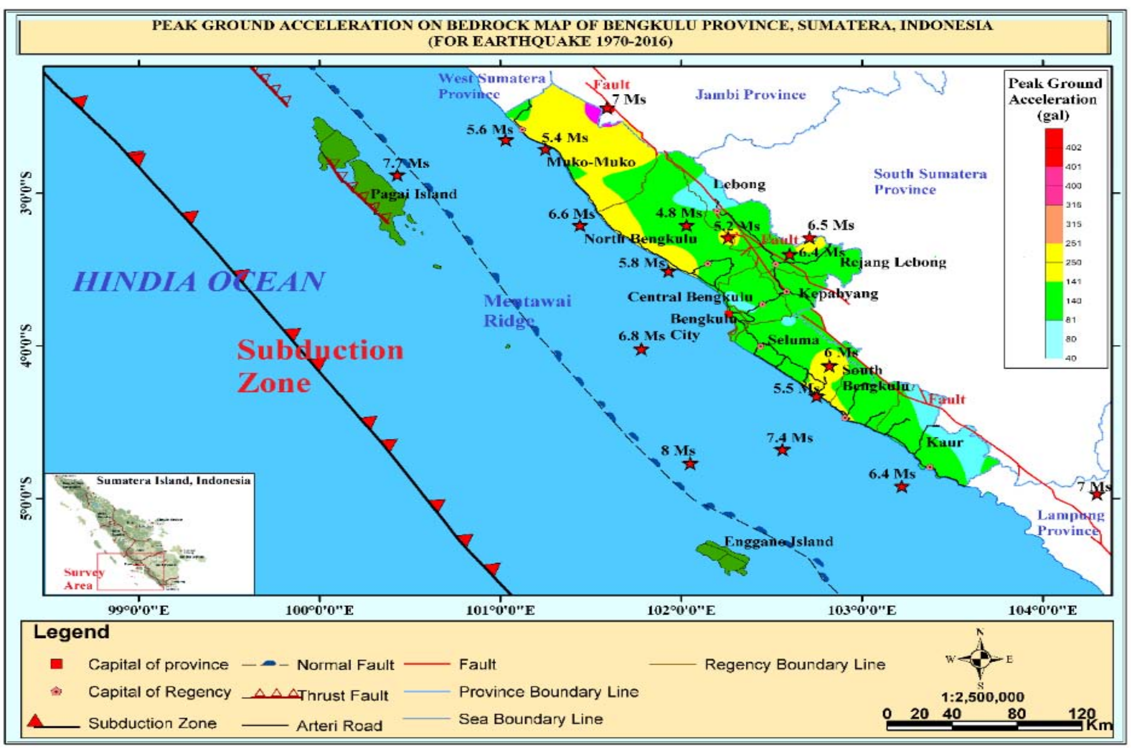

Fig. 4: Peak ground acceleration on bedrock in Bengkulu Province. Star symbols shown shallow depth of earthquake and the colour of contour shown the value of peak ground acceleration value

Table 13: Representation of peak ground acceleration, MMI, effects on people, ground and slopes of Bengkulu Province that might effected on earthquake in past and predicted in the future

Magnitudes	PGA (gal)	MMI	Area (regency)	Effects on people	Grounds and slopes
3.5-4.4	25-80	V-VII	Eastern of Rejang Lebong, Kaur and Bengkulu Tengah	Many people are frightened. Some people try to escape from danger Most sleeping people awake	No landslides or cracks occur
4.5-4.9	80-140	V-VIII	All of area except Muko-muko	Most people try to escape from danger by running outside Some people find it difficult to move	Cracks may appear in soft ground and rock falls and small slope failures take place
5.0-5.4	140-250	VI-IX	Muko-muko, Western of Nort Bengkulu and a part of Seluma and Rejang Lebong	Many people are considerably frightened and find it difficult to move	Cracks may appear in soft ground. Rock falls and small slope failures would take place
5.5-5.9	250-315	VIII-X	Western Muko-muko	Difficult to keep standing	Small to medium cracks appear in the ground and larger landslides take place
6.0-6.4	315-400	IX-X	Western Muko-muko	Impossible to keep standing and to move without crawling	Cracks can appear in the ground and landslides take place
6.5 and up	>400	X-XII	Eastern Muko-muko	Thrown by the shaking and impossible to move at will	The ground is considerably distorted by large cracks and fissures and slope failures and landslides take place which can change topographic features

Bengkulu, Eastern part of Rejang Lebong and part of Seluma. Green contour (81-140 gal) identified all of Bengkulu area and the others were blue contour (40-80 gal)

Based on Table 13 about seismic scale of Japan Meteorology Agency Seismic Intensity scale, the effects may be felt by people for 316-402 gal were impossible to keep standing, thrown by the shaking and impossible to move without crawling or to move at will. Ground would appeared cracks and landslides take place which could change topography features. MMI Scale estimation was IX-XII. For more complete, it shown on Table 13.

Based on Fig. 3 and Table 4, we could estimate prone and secure area of Bengkulu Province toward earthquake effects. Although, peak ground acceleration on bedrock was significant influence on possible effect, earthquake hazard analysis would be more complete if associated with peak ground acceleration on surface rock (sediment). It called as wave responses on local geology condition of sediment (Sugianto *et al*., 2006). Through in this correlation we can determine the magnitude of wave amplification of the bedrock to reach the sediment.

CONCLUSION

Time series model that suitable for Bengkulu Province earthquake was: variabel A (earthquake intensity): AR (5) ARCH (1) for variable B (magnitude) was ARIMA (5, 11) ARCH (3). When compared to the forecast results using ARFIMA approach, the a models produce an estimate of relatively equal value. Different things happen in the variable B where the value of the estimate has a significant difference. This is consistent with the results on the model ARFIMA that by ARCH LM test, residual variable forecast model B contains autocorrelation. Hence the model of the quake, suggested using ARIMA (5, 11) ARCH (3).

Earthquake epicentre of Bengkulu Province has location on Mentawai Ridge zone and active fault which around Eastern of Bengkulu Province area (near Bukit Barisan). From 1970 until June 2016, Eastern-Northern of Muko-muko has the highest peak ground acceleration valeu (314-402 gal) compared with other regency. It estimated come through cracks and landslides take place which would change topography features. This effects was went to experience a repetition in the future, so it's need for continuous dissemination in in order to improve public education role in the face of earthquake.

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