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Ground Motion Prediction of High-Energy Mining Seismic Events: A Bootstrap Approach

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Abstract: Induced seismicity has been a serious problem for many coal mines in the Upper Silesian Coal Basin in Poland for many decades. The occurring mining tremors of the rock mass generate seismic vibrations that cause concern to the local population and in some rare cases lead to partial damage to buildings on the surface. The estimation of peak ground acceleration values caused by high energy mining seismic tremors is an important part of seismic hazard assessment in mining areas. A specially designed bootstrapping procedure has been applied to estimate the ground motion prediction model and makes it possible to calculate the confidence intervals of these peak ground acceleration values with no assumptions about the statistical distribution of the recorded seismic data. Monte Carlo sampling with the replacement for 132 seismic records measured for mining seismic tremors exceeding 150 mm/s^2 have been performed to estimate the mean peak ground acceleration values and the corresponding upper limits of 95% confidence intervals. The specially designed bootstrap procedure and obtained ground motion prediction model reflect much better the observed PGA values and therefore provide more accurate PGA estimators compared to the GMPE model from multiple regression analysis. The bootstrap analysis of recorded peak ground acceleration values of high-energy mining tremors provides significant information on the level of seismic hazard on the surface infrastructure. A new tool has been proposed that allows for more reliable determination of PGA estimators and identification in the areas in coal mines that are prone to high-energy seismic activity.

Keywords: underground coal mine; mining-induced seismicity; mining seismology; ground motion prediction equations; seismic hazard; peak ground acceleration; Monte Carlo method

Citation: Bańka, P.; Lurka, A.; Szuła, Ł. Ground Motion Prediction of High-Energy Mining Seismic Events: A Bootstrap Approach. *Energies* **2023**, *16*, 4075. https://doi.org/10.3390/en16104075

Academic Editor: Krzysztof Skrzypkowski

Received: 19 April 2023
Revised: 7 May 2023
Accepted: 10 May 2023
Published: 13 May 2023

1. Introduction

Induced seismicity has posed a serious problem for many coal mines in the Upper Silesian Coal Basin in Poland for more than a hundred years. The occurring mining tremors of the rock mass generate seismic vibrations that cause concern to the local population and in some cases lead to damage to underground galleries and buildings on the surface [1–5]. Recently, in this context, promising machine learning and deep learning techniques have been employed to determine the seismic source location and to prevent rockburst occurrence [6]. The Ground Motion Prediction Equations (GMPEs) are commonly used to calculate seismic peak ground acceleration (PGA) parameters to assess seismic hazards and usually include the characteristics of the source, path, and site effects of mining seismic events. The other frequently used parameter in seismic hazard assessment in mines is the peak ground velocity (PGV) parameter [7]. Peak ground acceleration (PGA) and peak particle velocity (PPV) are both measures of the intensity of ground motion during an earthquake or seismic event. The relationship between PGA and PPV depends on several factors, including the characteristics of the seismic source, the distance from the source, and the nature of the soil or rock through which the seismic waves travel. In general, there is a correlation between PGA and PPV, with higher PGA values typically corresponding to higher PPV values. However, this relationship is not straightforward, and the correlation between PGA and PPV can vary depending on the specific conditions of the seismic event. In this study, we have analyzed PGA values.

Ground motion prediction equations (GMPEs) are important because they provide a mathematical relationship between mining tremor characteristics, such as seismic energy and distance, and the resulting ground motion at a particular site. GMPEs are critical tools for assessing the seismic hazard of coal mines, designing mining earthquake-resistant structures, and managing seismic risk. Without these equations, it would be challenging to estimate the potential ground motion during a mine earthquake and design structures that can withstand it.

It is a known problem that the accuracy of ground motion prediction equations (GMPE) can be low, especially for high-energy mining tremors at distances close to the source. Therefore, it is very desirable to utilize methods leading to better predictions of seismic vibration parameters such as peak ground acceleration (PGA). The regression GMPE models usually assume the dependence of seismic peak ground acceleration (PGA) on hypocentral distance and magnitude or seismic energy. This approach was primarily presented by the Joyner–Boore model [8] and the parameters describing this model and its uncertainties are estimated using multiple linear regression methods. Due to the fact that recorded seismic data come from seismic surface stations installed in the area of local coal mines in the Upper Silesian Coal Basin, Poland, this model is local in nature.

According to the statistics reported by the Polish Mining Authority, in the years 2016–2020, 7114 high-energy mining tremors occurred in hard coal mines in Poland with seismic energies greater than 10^5 J (magnitudes M > 1.8) [9]. Despite the fact that a small fraction of these tremors were felt by people, and an even smaller fraction caused damage to buildings, the problem of induced seismicity in terms of surface infrastructure protection in Polish coal mining is considered very serious.

The estimation of peak ground acceleration parameters caused by high-energy mining seismic tremors with the use of the local GMPE model can be often biased by a large error component, mainly because the maximum likelihood estimate obtained for the GMPE model includes seismic observations both for strong and small seismic events. The solution to this problem would be to determine the GMPE model limiting the recorded seismic data set to strong seismic tremors, but such a procedure usually leads to unstable solutions of multiple regression model parameters of GMPE due to the fact that the limited seismic data consists of a small number of seismic records. Therefore, the estimation of the GMPE model parameters with a limited data set may be disqualified by the t and F statistical tests used to verify the statistical significance of the model parameters, especially in the case where the normality of the residual assumption is violated.

As a remedy to this problem, we propose a specially designed bootstrapping procedure that leads to much more stable estimation of GMPE model parameters. In our approach, bootstrapping is applied to estimate the GMPE model parameters with the use of the probabilistic density functions of these parameters, which makes it possible to calculate the confidence intervals of these parameters with no assumptions about the statistical distribution of the seismic data [10].

Statistical bootstrapping has been successfully utilized by researchers in many areas of seismology. For example, bootstrapping was used to determine the standard deviation of the parameters of the GMPE model and the estimation of confidence intervals [11–17]. Another application of bootstrapping in seismology is for determining the uncertainty of estimated seismic deformations [18], determining the confidence intervals of the location of historical earthquakes [19], calculating the horizontal component of the seismic slowness vector [20], calculating the b parameter of the Gutenberg–Richter law [21], as well as estimating the uncertainty of the values describing seismic magnitude attenuation function [22]. There are fewer research studies on the use of bootstrapping to calculate the confidence intervals of GMPE parameters for seismic ground vibrations caused by induced seismicity [23], or blasting works [24].

The purpose of this study is to evaluate one of the most important seismic hazard parameters, i.e., the peak ground acceleration (PGA) estimator, which is based on the bootstrapping statistical procedure on the basis of high-energy mining seismicity. In the context of seismic engineering, we propose a bootstrapping algorithm that has been used to estimate the uncertainty of the PGA calculated from a limited number of high-energy mining earthquake records from one of the seismically active coal mines in the Upper Silesian Coal Basin, Poland. Such a limited number of high-energy mining earthquake records is a typical situation while conducting seismic monitoring in mines. We have observed that the accuracy of recorded peak ground accelerations is higher based on the bootstrap ground motion prediction model compared to the ground motion prediction model based on the multiple regression procedure.

2. Materials and Methods

2.1. Experimental Setup

The data set for our bootstrap analysis consisted of mining-induced seismicity recorded between 2008 and 2018 in one of the seismically active coal mines in the Upper Silesian Coal Basin, Poland, Figure 1. Five surface seismic stations were installed in the analyzed area consisting of triaxial accelerometers with a frequency range between 1 and 200 Hz and a sampling rate of 500 samples per second. Each of the surface seismic stations was synchronized with the GPS unit, yielding very precise recording time accuracy in the order of microseconds. Additionally, we have utilized information on seismic event location and seismic energy collected by the underground seismic network installed in the coal mine.

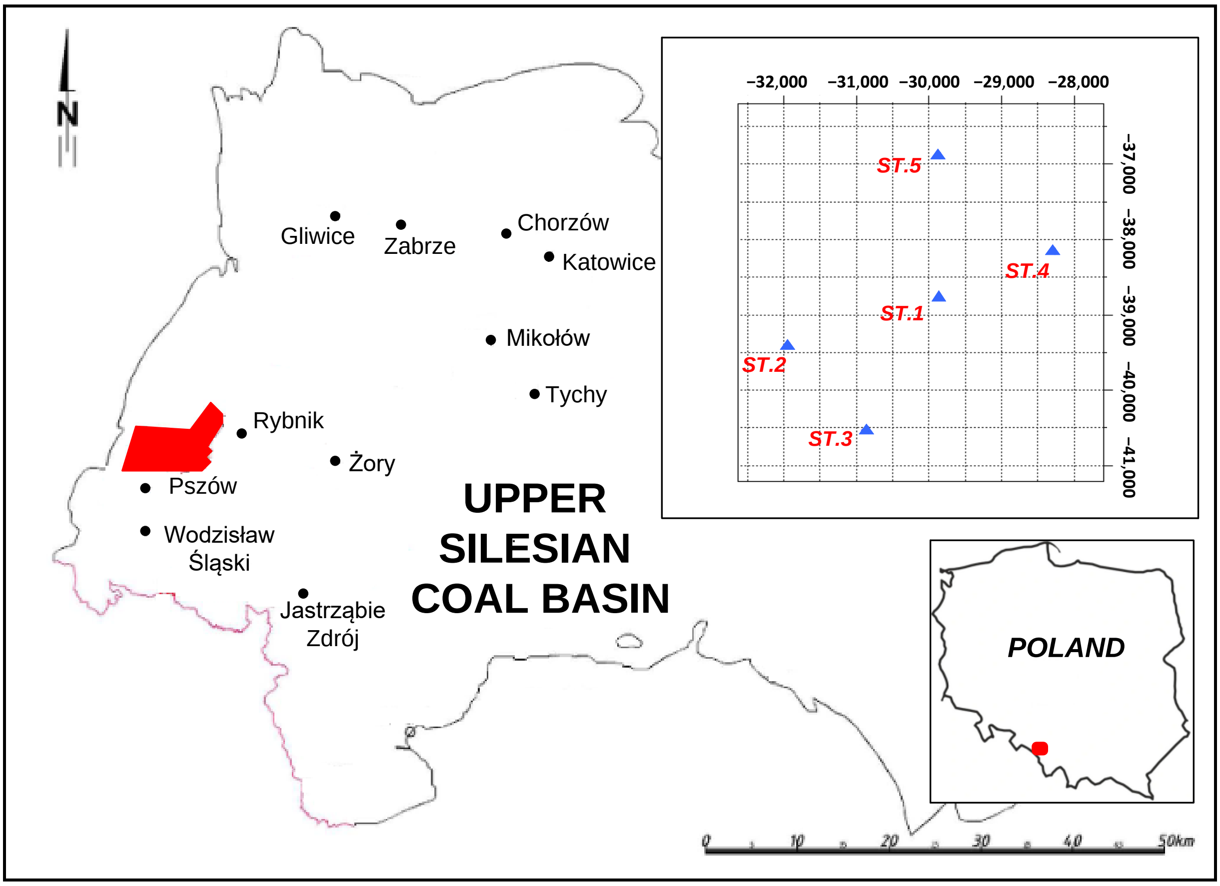
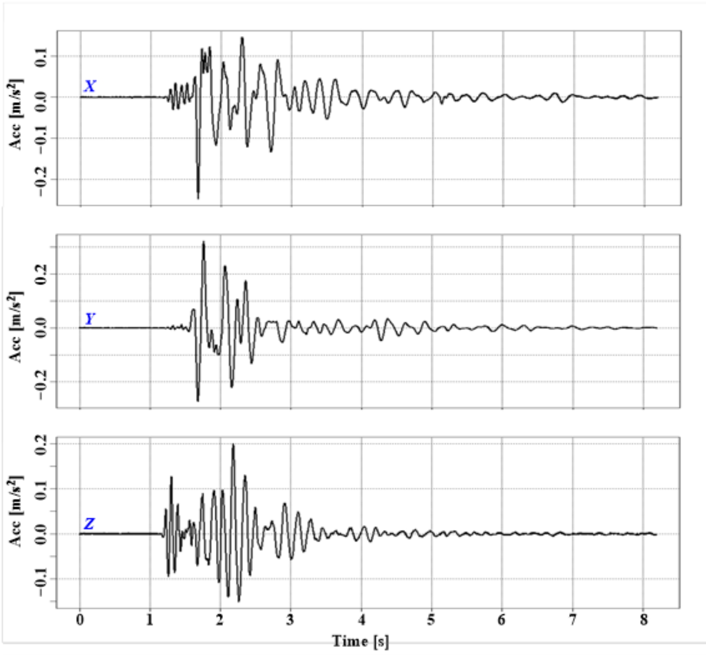


Figure 1. Location of the Upper Silesian Coal Basin, Poland. The analyzed research area is marked in red color and the distribution of seismic stations is shown in the upper right corner.

Our data consisted of 2625 seismic records of ground vibration accelerograms generated by mining seismicity in one of the coal mines in the Upper Silesian Coal Basin, Poland, which is characterized by a very high seismic hazard (Figure 2). Table 1 presents the basic statistics of the analyzed parameters, i.e., seismic energy, hypocentral distance, and peak ground acceleration (PGA). Figures 3–5 present histograms of the explanatory variables, i.e., log E—logarithm of seismic energy; log R—logarithm of hypocentral distance; and log PGA—logarithm of peak ground acceleration, used in our regression and bootstrap analysis.

(**a**)



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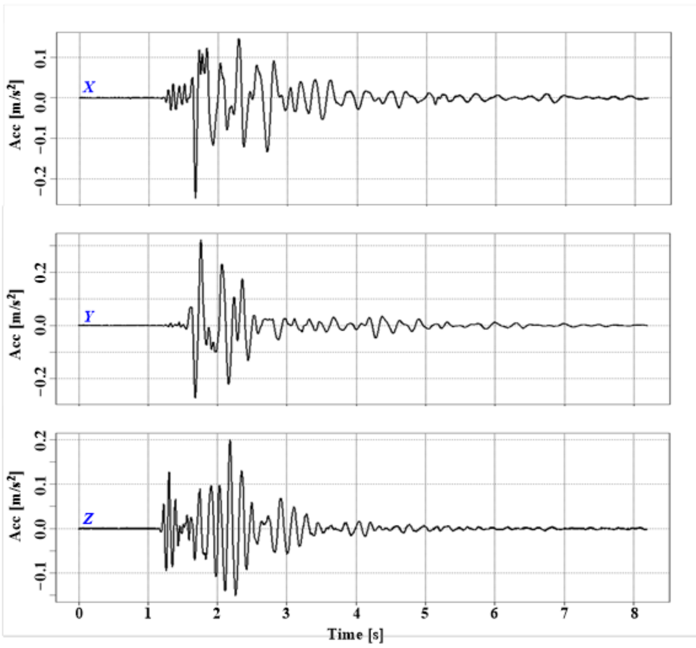

Figure 2. Examples of the three component (EW, NS, and Z) acceleration seismograms of 2 mining seismic events: (**a**) with seismic energy $E = 8.6 \times 10^6$ that occurred on 17 September 2017 and (**b**) with seismic energy $E = 5.5 \times 10^7$ [J] that occurred on 14 March 2019, both recorded at the station no. 1., horizontal axis units [s], vertical axis units [m/s^2].

Table 1. Basic statistics of the analyzed seismic data, Q1—first quartile, Q3—third quartile, Me—median.

	Min	**Q1**	**Me**	**Q3**	**Max**
E [J]	1.06×10^5	4.03×10^5	7.61×10^5	2.02×10^6	1.00×10^8
R [m]	66.408	770.154	1229.176	1863.36	4587.284
PGA [m/s^2]	0.004	0.017	0.031	0.056	1.204

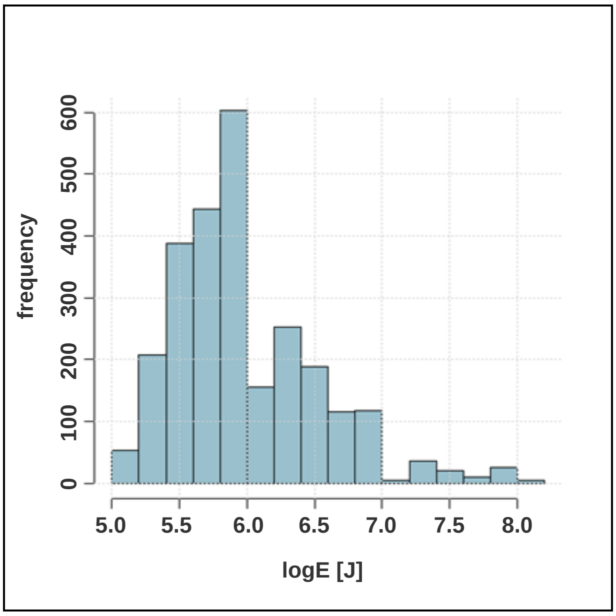

Figure 3. Frequency histogram of the logarithm of seismic energies of the analyzed mining seismic events.

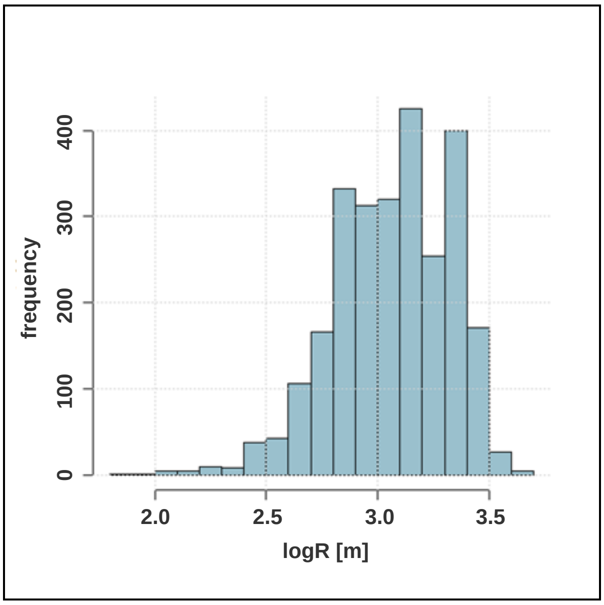

Figure 4. Frequency histogram of the logarithm of hypocentral distances of the analyzed mining seismic events.

We have analyzed seismic records of high-energy tremors with seismic energies in the range between 10^5 [J] and 10^8 [J]. The mining tremor with the highest energy caused seismic vibrations with the recorded peak ground acceleration value of 1086 mm/s^2. The epicenter of this tremor was located 589 m from the nearest surface seismic station. The maximum peak ground acceleration of 1204 mm/s^2 was generated by mining seismic events with an energy of 7×10^7 [J]. The epicenter of this tremor was 311 m from the nearest seismic station. In total, 75% of all analyzed seismic events have had energies not exceeding 2×10^6 [J] represented as the third quartile (Q3) of seismic energies, and 75% of all peak ground acceleration values did not exceed 56 mm/s^2 represented by the third quartile (Q3) of PGA in Table 1.

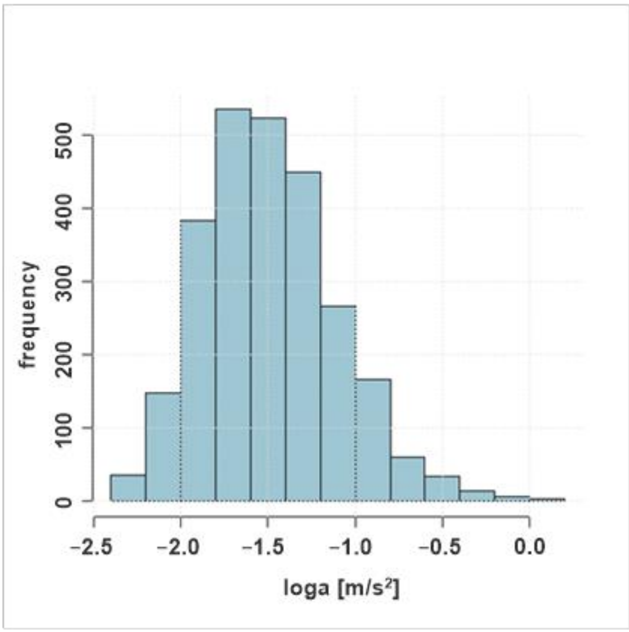

Figure 5. Frequency histogram of the logarithm of peak ground acceleration (PGA) values of the analyzed mining seismic events.

All peak ground acceleration values (PGA) were obtained from 2625 seismic records of mining-induced seismicity and corrected for local site response before performing further analysis [25].

2.2. Model Setup

2.2.1. Multiple Regression Model

We have selected the functional model for GMPE regression accounting for the first-order effects of seismic energy scaling, near source saturation, and geometrical spreading [8]:

$$logPGA = \beta_0 + \beta_1 logE + \beta_2 log\sqrt{R^2 + h^2} + u \tag{1}$$

Equation (1) can also be expressed in the equivalent vector form [26]:

$$\hat{Y} = X\hat{\beta} + \hat{\varepsilon} \tag{2}$$

Additionally, the general solution of (2) that we utilize is of the form [26]:

$$\hat{\beta} = \left(X^T X\right)^{-1} X^T \hat{Y} \tag{3}$$

where: PGA—peak ground acceleration [m/s^2]; E—seismic energy of mining tremors; R—hypocentral distance [m]; h—near source saturation term that minimizes the sum of squares of residuals and equal to 560 m; $\beta_0, \beta_1, \beta_2$—coefficients determined by multiple linear regression; u—normal variate with zero mean; $\hat{Y}$—vector with n elements of observations of $logPGA$; $\hat{\varepsilon}$—vector of errors; $\hat{\beta}$—vector of parameters, in our case: $\beta_0, \beta_1, \beta_2$; X—design matrix of n by three elements of observations on independent variables in (1); and n—number of observations.

We have omitted the term proportional to the hypocentral distance, R, in Equation (1) of the Joyner–Boore formula [8] because we found it statistically insignificant. Unfortunately, the estimation of the PGA values for high-energy values at small hypocentral distances of seismic tremors based on the GMPE model (1) is subject to a large error. This is mainly because the PGA estimates are obtained for observations that oscillate around the mean values that do not correspond to high-energy tremors. Moreover, additional errors in the prediction of PGA values based on formula (1) may also result from the fact that the distribution of the GMPE model does not follow the normal distribution. Additional errors may also arise due to the fact that the distribution of hypocentral distances, R, is determined mainly by the geometry of the local seismological network, whereas the distribution of the seismic energy tremors belongs to the asymmetric distribution determined by the Gutenberg–Richter law, Figure 3. The possible solution to the problem of these large errors is to estimate the GMPE model parameters in Equation (1) solely on the basis of the high-energy tremor records with PGA values exceeding some predetermined threshold. Such a procedure should make it possible to limit the sample to seismic recordings which caused the most significant effects on the surface infrastructure. Unfortunately, such regression parameter estimation is based on a limited sample size and usually leads to large errors in parameter estimates, often violating the basic assumptions regarding the normality and homoscedasticity of the random component u in (1). Therefore, we propose in our analysis to utilize an appropriately designed bootstrapping procedure.

2.2.2. Bootstrapping Estimation Model

Statistical inference based on a sample drawn from the general statistical population is conditioned by the knowledge of the probabilistic distribution of the analyzed regression parameter, and in most cases, the normal distribution is assumed. In the case of bootstrapping methods, the inference is not made on the basis of a sample but on the basis of a general population created by the resampling concept. The central idea of bootstrapping is to conduct a Monte Carlo simulation on an input data set with random sampling with replacement [27]. According to this idea, it is not necessary to test the assumptions about the statistical distribution of the analyzed parameters. Bootstrap linear regression parameter estimation can be conducted in two ways. The first is to resample the observations if the model parameters are assumed to be of a random nature. In the second approach, the parameters of the regression model are assumed as deterministic and determined on the basis of random sampling with replacement [27].

In the analysis of our seismic data we have utilized the second approach, and our bootstrap procedure has been performed in the following steps:

(a) the vector $\hat{\varepsilon}$ with the random components ε_i in Equation (2) is determined;
(b) the sampling with replacement is performed on $\hat{\varepsilon}$ giving bootstrap vector $\hat{\varepsilon}^{boot} = \left(\varepsilon_1^{boot}, \ldots, \varepsilon_n^{boot}\right)$;
(c) bootstrap vector $\hat{\varepsilon}^{boot}$ is added to the theoretical values in Equation (2) giving the vector $\hat{Y}^{boot} = X\hat{\beta} + \hat{\varepsilon}^{boot}$;
(d) the bootstrap regression parameters are calculated according to the Equation (3): $\hat{\beta}^{boot} = \left(X^T X\right)^{-1} X^T \hat{Y}^{boot}$;
(e) steps (b)–(d) are repeated r times giving r vectors $\hat{\beta}_r^{boot}$ estimating model parameters, which allows us to determine their bootstrap statistical distributions $\mathrm{F}(\hat{\beta}_r^{boot})$;
(f) the mean values of the r vectors of the bootstrap regression parameters are calculated as the estimators of the model parameters of Equations (1) and (2): $\mathrm{E}\left(\hat{\beta}^{boot}\right) = \frac{1}{r}\sum_{r=1}^{r} \hat{\beta}_r^{boot}$ and the corresponding lower and upper limits of 95% confidence intervals.

The above-presented bootstrap algorithm additionally allows us to determine the bootstrap confidence intervals of the estimated regression parameters (1). Additional assumptions have to be made for the confidence intervals calculated with the use of the ordinary least squares method (3). For small sample sizes, t-Student distribution is assumed, and for large sample sizes, the normal distribution is assumed. Such assumptions do not need to be made in determining bootstrap confidence intervals, and this is one of the advantages of the presented bootstrap method.

The significance of using a bootstrap approach to estimate peak ground acceleration (PGA) values caused by high-energy mining seismic tremors is that it allows for more accurate and reliable estimates of these values. In the case of estimating PGA values caused by high energy mining seismic tremors, the bootstrap approach has been used to estimate the distribution of peak ground acceleration values that are likely to be observed based on the available data. By using the bootstrap approach, it is possible to account for the variability and uncertainty in the data and obtain more robust estimates of the peak ground acceleration values. This is particularly important in the case of mining seismic tremors, where the data can be highly variable and noisy due to factors such as the complex geology of mining sites and the varying energy levels of the tremors. The bootstrap approach can help to improve the accuracy and reliability of peak ground acceleration estimates, which is essential for ensuring the safety of mining operations and protecting workers and equipment from potential damage caused by high-energy seismic events. The bootstrap ground motion prediction model we have utilized in our study provides more accurate peak ground acceleration estimators compared to traditional linear regression models by eliminating the normality and heteroscedasticity assumption of the analyzed samples which is violated for our mining seismic data.

3. Results and Discussion

Multiple Regression Results of Ground Motion Prediction Equations, GMPE

The calculated regression parameters of Equations (1) and (2) for the logarithm of the peak ground acceleration, PGA, are presented in Table 2. Figure 6 shows the recorded values of the logarithm of the peak ground acceleration at the surface stations and the theoretical values determined by the GMPE model (1). This regression procedure includes all the gathered seismic data records.

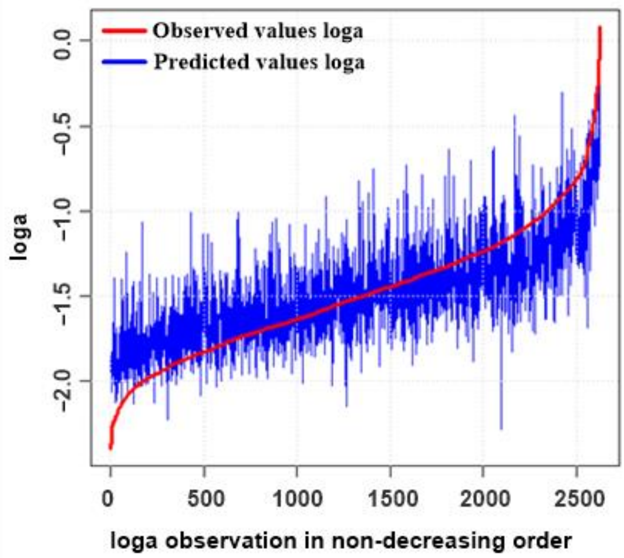

Figure 6. Comparison between empirical and theoretical peak ground accelerations; sorted values of the logarithm of the PGA are shown. Regression performed for all seismic data records.

A large discrepancy between theoretical and observed peak ground acceleration values can be readily noticed for extreme, i.e., low and high, PGA values in Figure 6. For low peak ground acceleration values, a significant overestimation of the GMPE model is visible, whereas for high peak ground acceleration values, the empirical values are significantly higher than the theoretical values determined by the GMPE model. As mentioned earlier, the solution to this problem can be to estimate the GMPE model parameters of peak ground acceleration models (1) and (2) only on the basis of seismic PGA records exceeding a certain predetermined threshold. Therefore, in further analysis, it was assumed that seismic records with PGA values not lower than 150 mm/s^2 would be included in calculations. This 150 mm/s^2 threshold value corresponds to the lower limit of the first degree of the mining seismic intensity scale, GSIS-2017 [3], and makes it possible to include seismic PGA records felt by local communities on the surface. This threshold value resulted in limiting the sample to 132 observations and also shows that only about 5% of all seismic PGA records caused noticeable effects on the surface infrastructure according to the GSIS-2017 mining seismic intensity scale.

Table 2. Estimated parameters of the GMPE model (1) with coefficient of determination R^2 and standard error of estimate S_{err}. Regression performed for all seismic data records. Symbol *** determines the value smaller than 10^{-16}.

Parameter	β_0	β_1	β_2	R^2	S_{err}
estimated value	−1.411	0.433	−0.869	0.595	0.242
p-value	***	***	***	-	-

Figure 7a shows the recorded values of the logarithm of peak ground acceleration at the surface stations and the theoretical values determined by the GMPE model (1) for all seismic records. Figure 7b shows the recorded values of the logarithm of peak ground acceleration at the surface stations and the theoretical values determined by the GMPE model (1) for the seismic records with PGA values not lower than 150 mm/s^2. It can be easily noticed that the discrepancy between the theoretical and observed peak ground acceleration values is much smaller for the GMPE model (1) which includes only seismic records with PGA values not lower than 150 mm/s^2 (Figure 7b). This partially validates the concept of using PGA values not lower than 150 mm/s^2 in the regression procedure. The calculated regression parameters of Equation (1) for the logarithm of peak ground acceleration with PGA values not lower than 150 mm/s^2 are presented in Table 3.

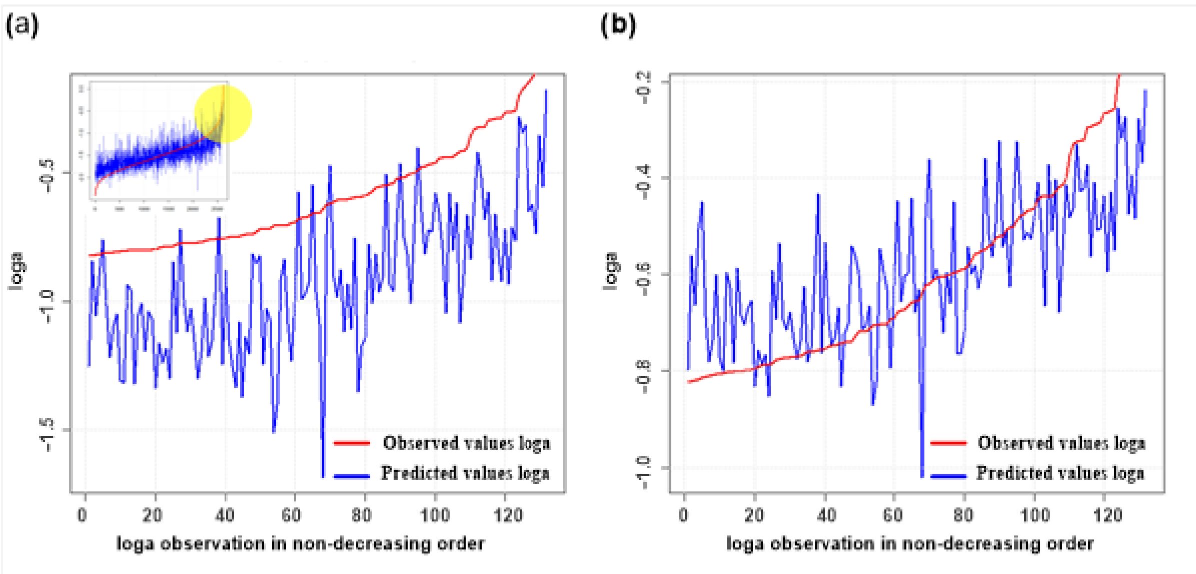

Figure 7. Comparison between empirical and theoretical peak ground accelerations; sorted values of the logarithm of PGA shown. (**a**) Regression performed for all seismic data records, (**b**) regression performed for seismic data records with PGA values not lower than 150 mm/s^2.

Table 3. Estimated parameters of the GMPE model (1) with coefficient of determination R^2 and standard error of estimate S_{err}. Regression performed for seismic data records with PGA values not lower than 150 mm/s^2. Symbol *** determines the value smaller than 10^{-16}.

Parameter	β_0	β_1	β_2	R^2	S_{err}
estimated value	−1.306	0.249	−0.349	0.488	0.154
p-value	***	***	***	-	-

The regression GMPE model parameters in Table 3 are statistically significant. Nevertheless, it is not enough to use this model for the prediction of peak ground acceleration values (PGA). The prediction accuracy and the correct construction of the confidence intervals require us to conduct the verification of the estimated GMPE model in terms of the normality and homoscedasticity of the random component. For the analyzed GMPE model shown in Table 3, the p-values were calculated for the Kolmogorov–Smirnov and Anderson–Darling statistical tests verifying the normality of the residual component. The obtained p-values are 0.0175 and 0.0197, respectively, indicating that the distribution of the residual component of this model does not form the normal distribution at the significance α = 0.05. Additionally, the Breusch–Pagan statistical test indicates the presence of heteroscedasticity in the analyzed model. Therefore, there are no grounds at the level of α = 0.05 to reject the hypothesis of the homoscedasticity of the random component.

Therefore, a bootstrap approach was used to estimate the model parameters and to determine the confidence intervals of the forecasts. This approach does not require the normality and homoscedasticity of the random component.

Bootstrap model of ground motion prediction equations (GMPE) obtained from seismic data records with PGA values exceeding 150 mm/s^2.

In order to determine the bootstrap model of ground motion prediction equations (GMPE), we have also constrained our seismic records to PGA values exceeding 150 mm/s^2. We have utilized the bootstrap procedure described in Section 2.2.2 and assumed that the number of replications r is equal to 1000. The number of bootstrap replications needed depends on the precision required for the estimation and the complexity of the model being analyzed. In general, the more bootstrap samples are used, the more accurate the estimation of the parameter of interest or the sampling distribution of a statistic will be. However, as the number of bootstrap samples increases, so does the computational cost of the analysis. There is no fixed number of bootstrap replications that can be universally recommended, as the appropriate number depends on the specific analysis and research question. A common rule of thumb is to use at least 1000 bootstrap samples to obtain stable and reliable estimates [27].

Based on these 1000 resamplings with replacement replications, we have estimated the mean values of the parameters of the GMPE model (1) and the corresponding lower and upper limits of 95% confidence intervals. These values are presented in Table 4.

Table 4. Estimates of the parameters of the bootstrap GMPE model with 95% confidence intervals.

	Mean Value	Lower Limit of 95% Confidence Interval	Upper Limit of 95% Confidence Interval
β_0	−1.373	−1.782	−0.960
β_1	0.303	0.225	0.378
β_2	−0.456	−0.649	−0.262

Figure 8 shows the GMPE model parameter distributions for our bootstrap procedure. The dashed red line shows the estimated mean values of the GMPE parameters, whereas the dashed blue lines show the lower and upper 95% confidence intervals.

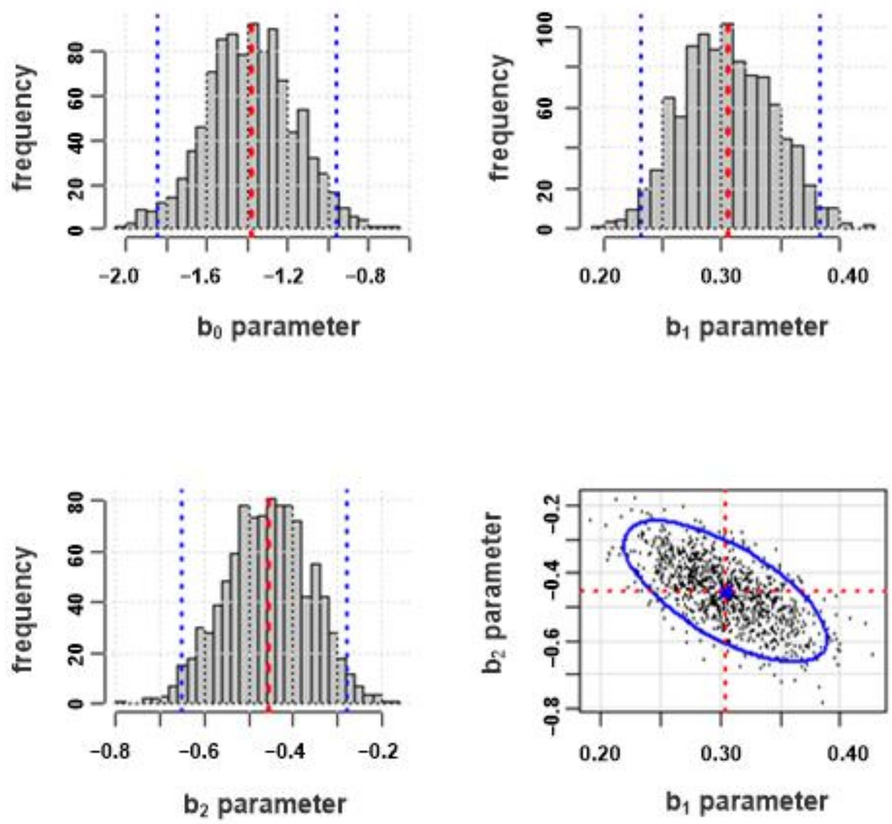

Figure 8. Empirical distributions of estimated bootstrap parameters with mean values and 95% confidence intervals. Blue full and dashed lines represents 95% confidence intervals. Red dashed lines represents mean values.

A comparison of the GMPE bootstrap model with the GMPE linear regression model from Table 3 is shown in Figure 9. It is clearly seen that theoretical values determined from the bootstrap GMPE model better correspond to the observed PGA values, i.e., the differences between theoretical and recorded PGA values are smaller for most of the observations for the second level of mining seismic intensity scale GSIS-2017 and in all observations of the third and fourth levels of the mining seismic intensity scale GSIS-2017. Table 5 summarizes these findings for the PGA values exceeding 600 mm/s^2. The differences between the theoretical values of the GMPE bootstrap model and the GMPE linear regression model from Table 3 reach 136 mm/s^2. Therefore, the bootstrap analysis of recorded peak ground acceleration values of high-energy mining tremors can provide important information regarding the level of seismic hazard on the surface infrastructure by estimating the level of the mining seismic intensity scale, Figure 9. By estimating bootstrap PGA values caused by high-energy mining tremors, it is possible to assess the seismic hazard on the surface infrastructure related to the level of the mining seismic intensity scale. For example, if the probability of the level of the mining seismic intensity scale is high, then the surface infrastructure may be at a higher risk of damage or failure due to the ground motions caused by the tremors. Thus, the proposed tool may be directly applicable for preventing damage to buildings and protecting local populations by identifying areas in coal mines that are prone to high-energy seismic activity and strong ground motions.

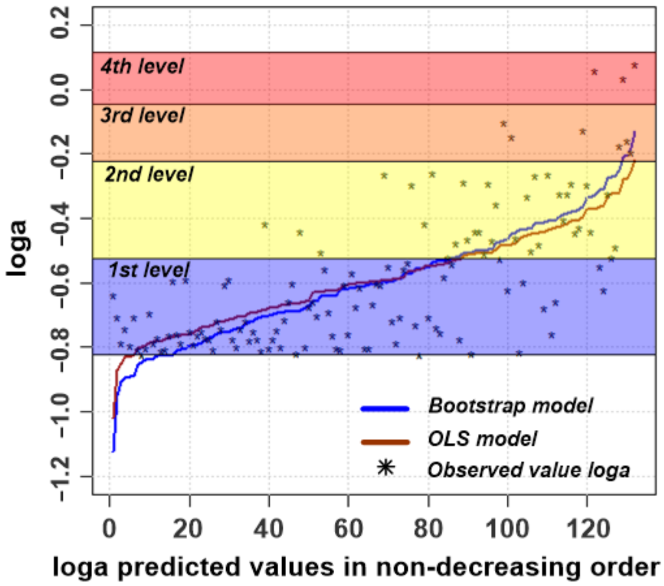

Figure 9. Comparison of the estimates of the bootstrap GMPE model and the linear regression GMPE model from Table 3. Levels of mining seismic intensity scale GSIS-2017 and observed logarithm of PGA values shown [3].

Table 5. Comparison of observed and estimated PGA values; units: 10^{-3} m/s^2.

Observed PGA Value	PGA Linear Regression GMPE Model	PGA Bootstrap GMPE Model	Difference: PGA Bootstrap and PGA Regression
636.60	554.03	657.94	103.91
671.70	481.73	561.00	79.27
693.60	532.65	626.89	94.24
715.80	334.26	356.37	22.11
747.00	402.93	434.26	31.33
789.80	328.14	341.78	13.64
1086.40	527.87	614.80	86.93
1143.90	426.90	469.14	42.24
1204.30	606.75	742.95	136.21

Based on the 1000 resamplings with replacement replications for 132 seismic records exceeding 150 mm/s^2, we have estimated the mean PGA values. The results of our analysis are presented in Figure 10a, which displays the estimated mean PGA values, and Figure 10b, which shows the upper limits of the 95% confidence intervals. In addition to estimating the mean PGA values, our analysis also involved performing a comparison test. This test involved plotting the mean and upper 95% confidence intervals for a linear regression model from Table 3, as shown in Figure 10. This allowed for a comparison between the estimated mean PGA values and the predictions from the regression model, which was previously fitted to the data. One can clearly observe that both the mean PGA values and the upper limits of the 95% confidence intervals of our bootstrapping method yield higher estimated values compared to the ordinary least square linear model (OLS) in the right part of Figure 10a,b and correspondingly smaller values for the left part of Figure 10a,b. This means we have obtained larger predicted values for samples 100–132, i.e., samples with the highest recorded PGA values, and smaller predicted values for samples 1–50, i.e., samples with the lowest recorded PGA. Overall, our analysis provides more valuable insights into the characteristics of the seismic records under consideration and helps to inform decisions related to seismic hazard assessment and risk management.

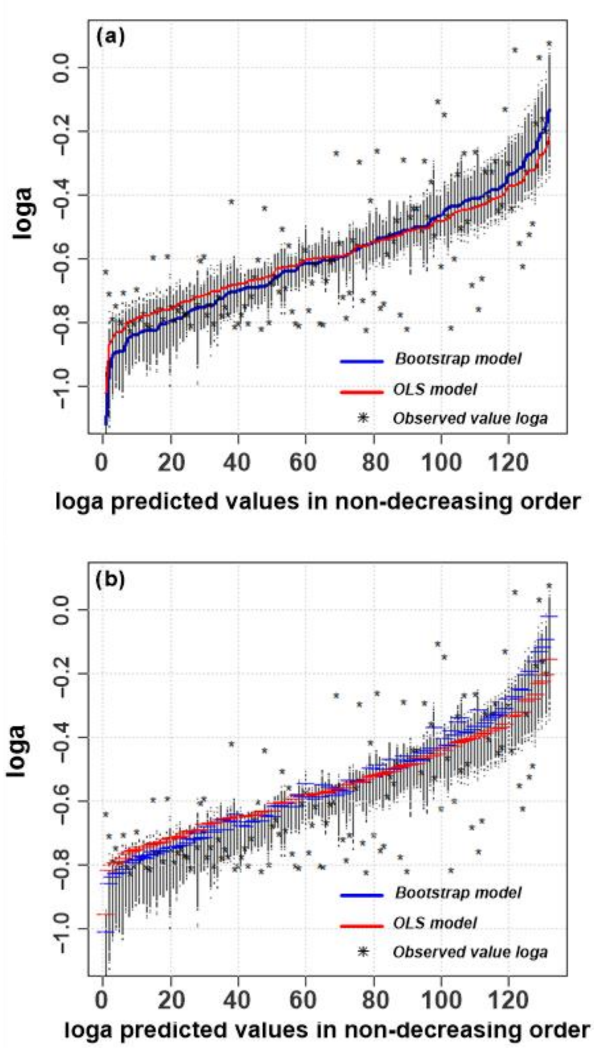

Figure 10. Estimated mean values (**a**) and the upper 95% confidence intervals (**b**) for the bootstrap GMPE model (blue line) and the GMPE model from Table 3 (red line).

Table 6 shows the upper limits of 95% confidence for both considered models for recordings exceeding the value of vibration acceleration equal to 0.6 m/s^2. It is clearly seen that the bootstrap GMPE model reflects the observed PGA values much better and therefore provides more accurate estimators compared to the GMPE model from Table 3. This finding has particular importance for the largest PGA values related directly to high seismic hazards and the highest impact on the surface infrastructure. The accuracy of the analyzed bootstrap model depends on the quality and representativeness of the observed seismic data. When these factors are properly accounted for, our bootstrap ground motion prediction model can provide a reliable and accurate estimate of the distribution of PGA values.

The proposed bootstrap tool for determining peak ground acceleration estimators and identifying areas in coal mines that are prone to high-energy seismic activity has several significant implications. First, it can improve safety in coal mines by identifying areas in coal mines that are prone to high seismic ground motion vibrations, and second, by providing more accurate estimations of peak ground acceleration values, the tool can help companies assess the risk of seismic events more effectively and implement appropriate risk management strategies.

Table 6. Comparison of the upper 95% confidence intervals of the estimated PGA values; units 10^{-3} m/s^2.

PGA Linear Regression GMPE Model	PGA Bootstrap GMPE Model	Difference: PGA Bootstrap and PGA Regression
630.28	866.52	236.25
546.44	715.26	168.83
602.83	814.17	211.34
363.22	408.71	45.48
442.38	515.06	72.68
349.39	377.87	28.49
594.40	778.79	184.39
468.82	561.58	92.75
705.14	1022.61	317.47

4. Conclusions

The specially designed bootstrapping algorithm has been developed and used to estimate the PGA values and their uncertainty calculated from a limited number of high-energy mining earthquake records for one of the seismically active coal mines in the Upper Silesian Coal Basin, Poland. This algorithm enables a new method for estimation, the peak ground acceleration parameter, PGA, which is one of the critical parameters for assessing seismic hazards in coal mines.

Seismic recordings of peak ground accelerations show that only high-energy mining tremors at close hypocentral distances can induce ground motions that pose a threat to underground and surface infrastructure. Therefore, the prediction of strong peak ground accelerations is one of the most important tasks in the analysis of seismic hazards in mines. Very often, the prediction of peak ground accelerations for strong mining tremors is often severely underestimated. Therefore, a specially designed bootstrapping procedure was introduced to determine ground motion prediction equations. It was found that the PGA prediction based on the bootstrapped ground motion prediction model reflects the recorded PGA accelerations more accurately than the ground motion prediction model based on the multiple regression procedure.

The proposed bootstrap tool for determining peak ground acceleration estimators and identifying areas in coal mines that are prone to high levels of seismic ground motions has significant implications for improving safety, enhancing risk assessment, and improving the design of mining infrastructure. By providing more accurate information on seismic hazards, the tool can help mining companies reduce the risk of accidents and damage to infrastructure and improve productivity and profitability.

Author Contributions: Conceptualization, P.B. and A.L.; methodology, A.L. and Ł.S.; software, Ł.S.; validation, P.B. and A.L.; formal analysis, A.L.; investigation, P.B. and A.L.; resources, P.B. and Ł.S.; data curation, Ł.S.; writing—review & editing, A.L.; visualization, Ł.S.; project administration, A.L. All authors have read and agreed to the published version of the manuscript.

Funding: The presented investigation is partially supported by the project EPOS-PL PLUS, European Plate Observing System POIR.04.02.00-00-C005/19, funded by the Operational Programme Smart Growth 2014–2020, Priority IV: Increasing the research potential, Action 4.2: Development of modern research infrastructure of the science sector, and co-financed from European Regional Development Fund. The presented investigation is also partially supported by the statutory activity of the Faculty of Mining, Safety Engineering and Industrial Automation, Silesian University of Technology, Poland.

Data Availability Statement: Seismograms and the peak ground acceleration data used in this study were collected and preprocessed under the research work conducted at the Silesian University of Technology and Central Mining Institute, Katowice, Poland between 2020–2022. Source data on the research and its results are in the possession of the authors of this article.

Conflicts of Interest: The authors declare no conflict of interest.

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