

## Article

# Spatial–Temporal Energy Data Analysis and Elemental Fractal Interpretation of Microseismic Monitoring for Rock Mass Area Failure

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## Abstract

The early warning of rock mass failure in deep hard-rock mines presents a significant challenge for mine safety management. Microseismic monitoring data offer a novel analytical approach to address this issue. This study investigates the evolutionary patterns of rock mass failure in mining areas through the analysis of spatiotemporal energy data from microseismic events. Initially, key spatiotemporal energy parameters are extracted to identify microseismic events associated with localized damage and their periodic characteristics. Subsequently, a spatiotemporal fractal dimension analysis method is established to achieve fractal interpretation of the data by integrating field cloud maps. Finally, an early warning model centered on temporal energy is constructed, which delineates warning zones through a comprehensive evaluation of fractal dimensions, thereby providing decision-making support for mine safety.

**Keywords:** deep hard rock mines; microseismic monitoring; spatial–temporal energy data; fractal; numerical simulation; data interpretation

## 1. Introduction

The early warning of rock mass instability in deep hard rock mines is the core challenge for disaster prevention and control in mining engineering. Microseismic monitoring technology can capture the real-time evolution process of microfractures inside rock masses, providing key data support for identifying disaster precursors [1]. The spatiotemporal energy information contained in microseismic events directly reflects the accumulation, expansion, and catastrophic process of rock damage and is an important entry point for understanding the mechanism of rock failure and achieving accurate early warning. Thoroughly exploring the evolution laws of microseismic spatiotemporal energy data has important theoretical and practical significance for enhancing the early warning capability of dynamic disasters in deep mines.

Domestic and foreign scholars have conducted extensive research on microseismic data interpretation and engineering applications, with a focus on event localization, source parameter inversion, and activity statistical analysis [2–7]. However, existing warning methods often rely on single-parameter thresholds or empirical feature analysis, and there is insufficient exploration of the coupled evolution laws and inherent nonlinear characteristics of the multiple factors of spatiotemporal energy. As a powerful tool for



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characterizing the self-organization and evolution of complex systems, fractal theory has been preliminarily introduced into microseismic activity analysis [8–11], but its combination with microseismic warning research is still in the exploratory stage. Especially, there is still a relative lack of research on coupled fractal characterization methods for microseismic spatiotemporal energy information and the construction of quantitative warning models based on this, which limits the deepening of warning from “phenomenon description” to “mechanism deduction” [12–14].

To fill the research gap mentioned above, this article aims to establish a rock mass failure warning method based on spatiotemporal energy fractal analysis. Based on microseismic monitoring data from a typical deep hard rock copper mine in Xinjiang, the key parameters of time, space, and energy are systematically extracted to identify microseismic event sequences related to local damage. Furthermore, a spatiotemporal fractal dimension analysis method is constructed, combined with on-site cloud images, to reveal the evolution patterns of microseismic activity’s spatiotemporal aggregation and energy dissipation. Ultimately, an integrated warning model with a time-domain energy evolution trend as the core is constructed, and the quantitative identification and graded warning of potential hazardous areas are achieved through comprehensive evaluation of fractal dimension values.

The structure of this article is as follows: The second part systematically elaborates on the research methods and theoretical foundations, including the principles of fractal dimension calculation and data analysis processes. The third part is a case study that showcases and analyzes the fractal characteristics of microseismic spatiotemporal energy parameters and the results of early warning applications. The fourth part discusses the effectiveness and limitations of the method. Finally, we summarize the research findings of the entire article.

## 2. Research Methods

Fractal theory was proposed by Mandelbrot to describe the widely existing irregular and self-similar structures in nature. During the process of rock fracture, microseismic events often exhibit statistical self-similarity in terms of time, space, and energy distribution; that is, they have similar clustering patterns at different observation scales. This characteristic makes fractal dimension an effective tool for characterizing the spatiotemporal complexity and energy release orderliness of microseismic activity.

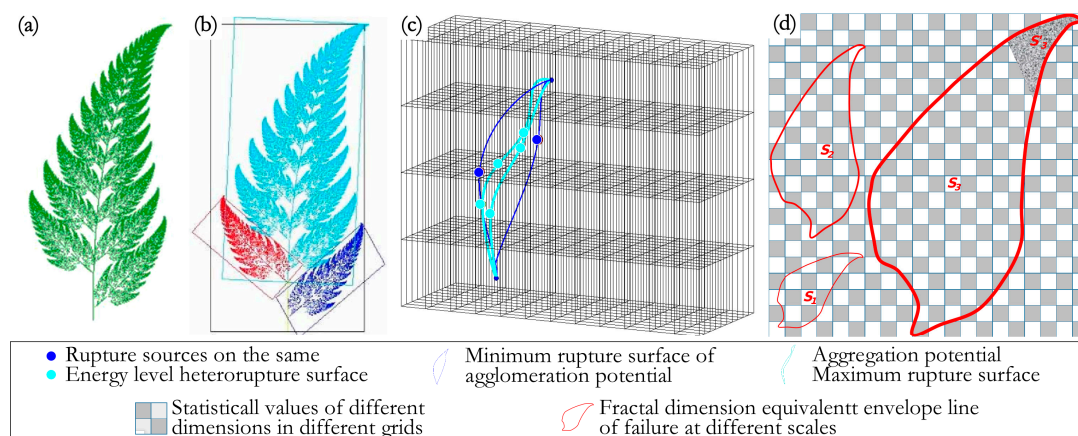
The core basis for introducing fractal analysis in this study is that although there is uncertainty in the localization and energy estimation of individual microseismic events, a large number of events still follow certain organizational rules as a whole. By calculating the time fractal dimension ( $D_t$ ), spatial fractal dimension ( $D_s$ ), and energy fractal dimension ( $D_e$ ), we can quantify the clustering of microseismic activity in time, the clustering pattern in space, and the non-uniform distribution characteristics in the energy field, respectively. These dimensions not only reflect the self-organizing behavior during rock fracture but also reveal the cross-scale correlation mechanism from local damage to macroscopic instability.

Specifically, the sudden change in fractal dimension often corresponds to a transition in the system state and can serve as a precursor signal for rock instability. Therefore, combining fractal theory with microseismic data can not only surpass the limitations of traditional single-parameter thresholds but also extract more stable and physical warning indicators from the overall perspective of the system.

This study is based on data from a mine microseismic monitoring system, using the three key elements of microseismic events—time, space, and energy—as the entry point to investigate the relationship between ground pressure disasters and spatiotemporal energy data. By integrating the history of mine ground pressure and production activities, this research establishes a foundational data archive for subsequent fractal-based

warning analysis. The methodological workflow is structured as follows. First, there is data preprocessing, where microseismic monitoring events are preprocessed and subjected to basic time-series analysis to lay the groundwork for fractal warning research. Next is evolution pattern analysis, where the spatiotemporal energy evolution characteristics and distribution patterns of microseismic activity—induced by fault layer damage and surrounding rock instability during deep mining in hard rock mines—are explored. Next is precursor information extraction, where multidimensional quantitative precursor information for rockburst occurrence is extracted from the perspectives of time series, spatial series, energy field, and frequency field. Last is warning implementation, where based on the above analysis, potential warning locations are identified and corresponding warnings are implemented.

The overall concept and logical diagram are shown in Figure 1. Figure 1a illustrates the core features of fractal theory, namely its inherent self-similar structure and scale invariance, reflecting the essential properties of fractal geometry. Figure 1b further elucidates the similarity relationship between local and global fractals at different spatial scales, intuitively reflecting the fractal relationship of “parts containing the whole”. Figure 1c focuses on the tip effect during the process of rock mass fracture, presenting the stress concentration phenomenon and spatial distribution characteristics of a single fracture surface during its formation. Figure 1d reveals the similarity relationship between the morphology and structure of different fracture surfaces in the study area from a system perspective, indicating that rock fractures also have significant fractal organization patterns in spatial distribution. Overall, the four figures systematically illustrate the multi-level connotation and application logic of fractal theory in the analysis of the spatiotemporal energy of microseismic rock fractures, from theoretical attributes to scale relationships, fracture mechanisms and spatial patterns.



**Figure 1.** Hypothesis on the comparative relationship between fractal similarity and microseismic spatiotemporal energy data similarity; (a) Schematic diagram of individual self-similarity; (b) A similar schematic diagram of the complex; (c) Schematic diagram of rock fracture and crack; (d) Schematic diagram of similar fracture scales of different rocks ( $S_1$ ,  $S_2$ ,  $S_3$  are different fracture sources).

This article introduces fractal theory into the interpretation of microseismic monitoring data, primarily based on the following considerations: Microseismic activity exhibits chaotic and disordered characteristics on the surface, and due to limitations in monitoring technology, there is often uncertainty in the localization and energy determination of individual events. The core advantage of fractal theory lies in its ability to identify hidden “ordered” structures from such seemingly disordered data—that is, the self-similarity and scale invariance exhibited by data in space–time and energy distribution. By calculating the space–time fractal dimension and time–energy fractal dimension, nested analysis

can be conducted on the clustering behavior of microseismic events, quantifying their evolutionary patterns, thereby transcending the reliance on the accuracy of individual events and extracting more stable and reliable monitoring and early warning precursor information from the overall system. This provides a solid mathematical and physical foundation for fundamentally understanding the spatiotemporal energy organization laws of rock mass failure and achieving accurate early warning.

### 2.1. Data Sources and Preprocessing

The data for this study comes from a microseismic monitoring system installed in a deep copper mine in Xinjiang. The system consists of a Phase I, Phase II, and Phase III website monitoring system and its network, consisting of single-component and three-component sensors, data acquisition instruments, data processing centers, and surface monitoring and early warning platforms. The underground monitoring network covers an area of +850 m to −250 m. We selected raw waveform data recorded between 1 July 2019 and 31 July 2020 and used system software and self-developed algorithms, such as the Geiger positioning method based on P-wave and S-wave arrival time difference, to locate events and calculate source parameters (earthquake time, spatial coordinates, and radiation energy). To ensure data quality, preprocessing was carried out to remove noise, blasting and other interference events, ultimately obtaining microseismic events for subsequent analysis.

### 2.2. Theoretical Basis: Box Dimension Calculation Method

The fractal dimension serves as a key metric for quantifying the complexity and spatial occupancy characteristics of a dataset. In this study, the box-counting dimension method is employed for computation, with its core formula presented as follows:

$$D = \lim_{\varepsilon \rightarrow 0} \frac{\lg N(\varepsilon)}{\lg(1/\varepsilon)} \quad (1)$$

where  $\varepsilon$  represents the unit scale of the covering element,  $N(\varepsilon)$  denotes the number of such elements required to cover the dataset within a closed interval, and  $D$  is the box-counting dimension.

For a given statistical unit, the values of  $\ln N(\varepsilon)$  and  $\ln \varepsilon$  are computed and then subjected to data fitting, yielding the fractal dimension  $D$  along with the associated fitting coefficient.

Specifically, in the analysis of temporal factors, the following partitioning approach is adopted:

$$\varepsilon_t = \frac{T}{m}, (m = 1, 2, 3 \dots M) \quad (2)$$

where  $\varepsilon_t$  represents the unit time scale used for partitioning,  $T$  denotes the total duration of the monitoring period covering the entire failure process of the sample,  $m$  indicates the number of partitions, and  $M$  is the number of partitions applied to the smallest time interval that contains the maximum number of events.

The logarithmic values of  $\varepsilon$  and  $N(\varepsilon)$  are then linearly fitted using the principle of the least squares method.

$$Q = \sum_{i=1}^n [Y_i - (b_0 + b_1 X_i)]^2 \quad (3)$$

When  $Q$  attains its minimum value, the parameters  $b_0$  and  $b_1$  correspond to the least squares estimators of the regression coefficients.

This condition is derived by applying the necessary conditions for extremum in calculus, namely setting the partial derivatives of  $Q$  with respect to  $b_0$  and  $b_1$  equal to zero.

$$\frac{\partial Q}{\partial b_0} = -2 \sum_{i=1}^n [Y_i - (b_0 + b_1 X_i)] \quad (4)$$

$$\frac{\partial Q}{\partial b_1} = 2 \sum_{i=1}^n [Y_i - (b_0 + b_1 X_i)] X_i \quad (5)$$

Thus,

$$b_1 = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sum_{i=1}^n (X_i - \bar{X})^2} = \frac{\sum_{i=1}^n (X_i - \bar{X})Y_i}{\sum_{i=1}^n (X_i - \bar{X})^2} \quad (6)$$

$$b_0 = \bar{Y} - b_1 \bar{X} \quad (7)$$

The residual  $e_i$  is defined as

$$e_i = Y_i - \hat{Y}_i = Y_i - b_0 - b_1 X_i \quad (8)$$

Here,  $e_i$  represents the error between the observed value and the fitted value at the  $i$ -th data point. Subsequently,

$$\sum_{i=1}^n (Y_i - \bar{Y})^2 = \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 + \sum_{i=1}^n (\hat{Y}_i - \bar{Y})^2 \quad (9)$$

The optimal partition parameter  $m$  is determined by maximizing the goodness of fit, which subsequently yields the corresponding time division unit scale.

### 2.3. Framework for Spatiotemporal Energy Fractal Analysis

The analytical framework proposed in this article revolves around three core elements: time, space, and energy. The specific steps are as follows.

**Time series fractal analysis:** Divide the total monitoring duration  $T$  into different time scales  $et = T/m$  ( $m = 1, 2, 3, \dots, M$ ), count the number of time units  $N(et)$  containing microseismic events at each scale, and calculate the time fractal dimension  $D_t$  using the method in Section 2.2 to characterize the clustering and periodicity of microseismic activity over time.

**Spatial distribution fractal analysis:** In the three-dimensional spatial domain, cubic grids with different edge lengths are used to cover the point cloud of microseismic events. The number of grids containing events at each scale,  $N(es)$ , is counted, and the spatial fractal dimension,  $D_s$ , is calculated to reveal the spatial aggregation pattern and dominant direction of microseismic events.

**Energy field fractal analysis:** The radiation energy values of microseismic events are mapped to their occurrence locations to form a spatial energy field. Using a similar method, the fractal characteristics of energy values in spatial distribution are analyzed, and the energy fractal dimension  $D_e$  is calculated to characterize the concentration and dissipation patterns of energy release.

**Construction of comprehensive warning model:** The fractal indicators ( $D_t$ ,  $D_s$ , and  $D_e$ ) mentioned above are integrated with the temporal energy evolution trend (such as energy release rate) to construct a multi-parameter warning model. By setting fractal dimension thresholds or identifying their abrupt features, combined with on-site geological and mining conditions, comprehensive discrimination and warning level classification of potential rock mass failure areas can be achieved.

The above three fractal dimensions ( $D_t$ ,  $D_s$ , and  $D_e$ ) do not exist in isolation but together characterize the multidimensional characteristics of microseismic activity during rock mass failure. The time fractal dimension reflects the temporal clustering pattern of

events, the spatial fractal dimension reveals the geometric structure and dominant direction of the damaged area, and the energy fractal dimension characterizes the concentration and dissipation path of energy release. The combination of the three can construct a multidimensional warning feature space, where the synergistic changes in fractal dimension (such as a decrease in  $D_s$  accompanied by an increase in  $D_e$ ) often indicate local stress concentration and energy accumulation, thereby indicating potential damage risks.

This framework achieves a transition from “qualitative description” to “quantitative discrimination” by combining fractal indicators with energy release trends (such as unit time energy release rate). In practical applications, we calibrate the threshold intervals of each fractal dimension through historical data and dynamically adjust them based on on-site geological and mining conditions to improve the adaptability and reliability of the warning model.

#### 2.4. Visualization and Verification

In the calculation of fractal dimension, the choice of scale range (the range of values of  $\epsilon$ ) has a significant impact on the results. This study ensures the robustness of calculations through the following methods:

**Time scale:** Based on the total monitoring duration  $T$ , time units are divided into proportional sequences to ensure coverage of multiple typical time scales from hours to months;

**Spatial Scale:** Based on the spatial distribution range of microseismic event point clouds, a cubic grid is used for coverage, with grid edge lengths gradually increasing from 10 m to 200 m, to capture spatial structural features at different scales;

**Energy scale:** Energy values to spatial grids are mapped and the fractal dimension of energy is calculated by counting the number of grids covered by the energy field at each scale, with a focus on the continuity of distribution in high-energy areas.

Using Thiessen polygons and the Kriging interpolation algorithm, interpolated cloud maps of microseismic event spatial distribution, energy field, and fractal dimension space are generated to visualize the analysis results. The preliminary validation of the warning model will be based on a retrospective comparative analysis of historical microseismic data and known rock mass failure areas.

### 3. Basic Data Analysis of Microseismic Monitoring

The microseismic index of mines is a series of indicators used to study the small seismic activity within the mining area. They are usually used to describe the small mining seismic activity before major damage occurs. In the analysis of microseismic indicators in mines, some common features are used to study and predict disaster occurrence [15–19], including the following aspects. First is the trigger sequence, where the analysis of microseismic indicators can reveal the triggering relationship and sequence between microseismic events. Especially, by observing the temporal relationship and spatial distribution of microseismic activity, it is possible to infer the possible mainshock and precursor events in microseismic sequences. Next, by studying duration and energy release characteristics of microseismic events, preliminary estimates of the evolution and possible scale of microseismic activity can be made. A microseismic event with a longer duration and greater energy release indicates the potential for larger-scale microseismicity. Last, the study of microseismic indicators also includes analyzing the spatial distribution of microseismic events. By observing the distribution characteristics of microseismic events within microseismic fault zones or specific regions, the spatial pattern of microseismic activity and potential fault structural features can be understood. Meanwhile, analyzing the magnitude distribution of microseismic events can help obtain information about the nature of microseismic activity and potential fault locations.

### 3.1. Overview of the Mine

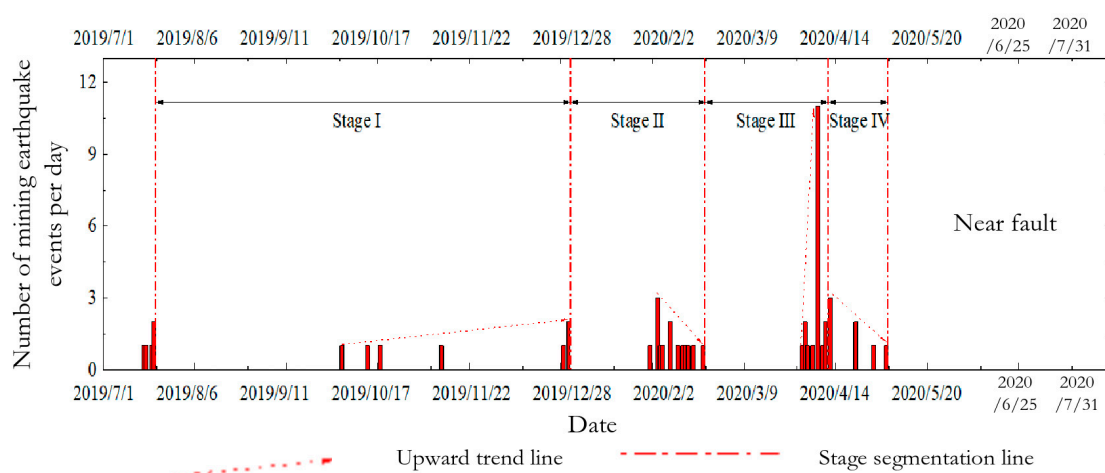
The Ashele copper mine is located on the south side of the Kazakhstan major fault zone and on the north side of the Qinghai Tibet Plateau fold zone, adjacent to the Markakuri deep fault to the west and the Altai orogenic belt to the east. The exposed strata in the region are mainly Early Paleozoic metamorphic rock series and ancient continental dome basement, with clastic sedimentary rocks as the cover layer, formed in the Early Paleozoic era. The regional strata are volcanic rocks. The ore-bearing strata in the mining area are the Meiziya Formation, which was formed by years of sedimentation of detrital mudstone. It has the characteristics of multi-stage mineralization and contains various resources such as silver, copper, and tin.

The Ashele copper mine features an ore body with a dip angle ranging from  $55^{\circ}$  to  $75^{\circ}$ . Its overall orientation trends approximately north–south, with an easterly lean. The distribution range is from the horizontal exploration line 3 # to the exploration line 11 #, with a spatial range of +800~–250 m. Currently, the deep production middle section of the Ashele copper mine mainly consists of nine middle sections ranging from +400 to ~0 m, with a height of 50 m. The large-diameter deep-hole open stoping with subsequent backfilling mining method is used. The mining site is arranged vertically to the direction of the ore body, with a length of the thickness of the ore body and a width of 20 m. The mining sequence is from north to south, with one mining interval. As the mining depth gradually increases, stress and the disasters it brings become more frequent.

The Ashele copper mine has established a microseismic monitoring network covering the entire mining area. The system has deployed sensors at approximately 12 levels where the ore bodies are located, forming a dense monitoring array with 80 to 100 channels. This network fully serves the production areas of the mine's Phase I, Phase II, and Phase III, achieving full coverage of the monitoring area. Currently, the system operates stably, capable of receiving underground microseismic data in a complete and real-time manner, and relies on a professional platform for efficient data processing and analysis. Based on the reliable data from this system, the mine has been able to effectively study, judge, and predict the activity trends of microseismic events, providing good technical support for ground pressure management and safe production.

### 3.2. Analysis of Time Series Indicators

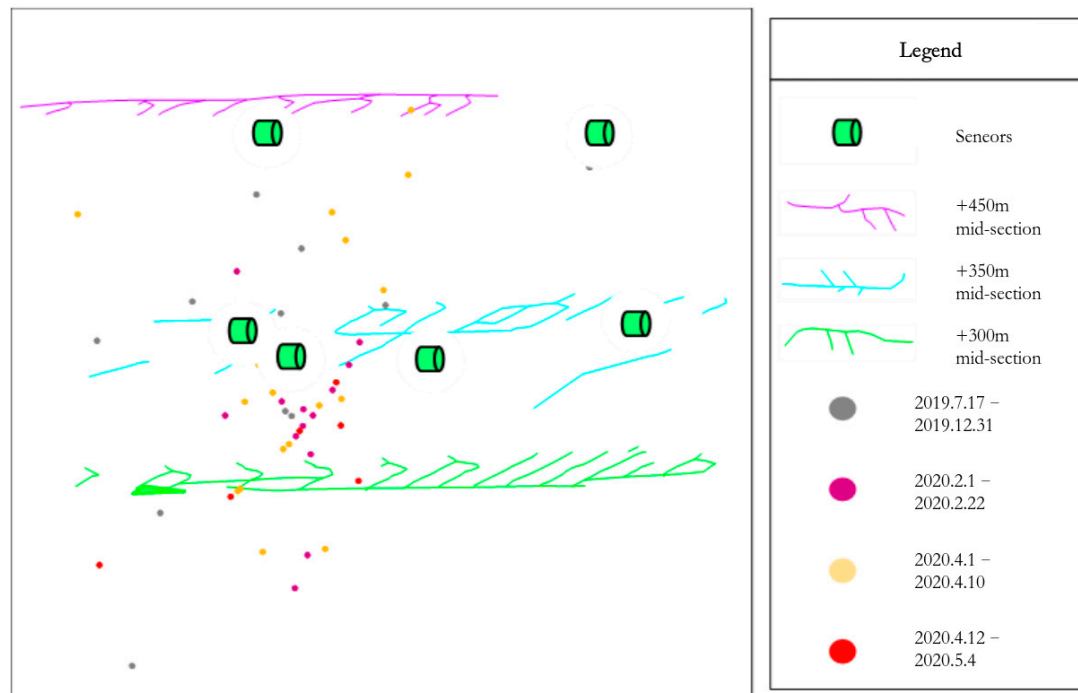
This study takes local damage and microseismic monitoring data in the research area as the research object and analyzes the dataset and the time variation and trend of specific seismic source parameters, as shown in Figure 2. In addition, event warning research is conducted by combining feature analysis with fractal interpretation models.



**Figure 2.** Sequential analysis of microseismic precursor indicators: event count.

### 3.3. Analysis of Spatial Sequence Indicators

This article takes the rock mass failure and microseismic monitoring data of a deep copper mine in Xinjiang as the research object. Mining seismic events that occurred from 17 July 2019, to 4 May 2020, were selected from the first and second microseismic monitoring system databases for analysis. The monitoring was conducted through sensor arrays deployed across approximately 12 levels within the mine, forming an 80–100-channel network that covered the entire mining area of Phases I, II, and III. This system enabled complete data acquisition and analysis, providing a reliable basis for event forecasting. The main event distribution and time evolution are shown in Figure 3.



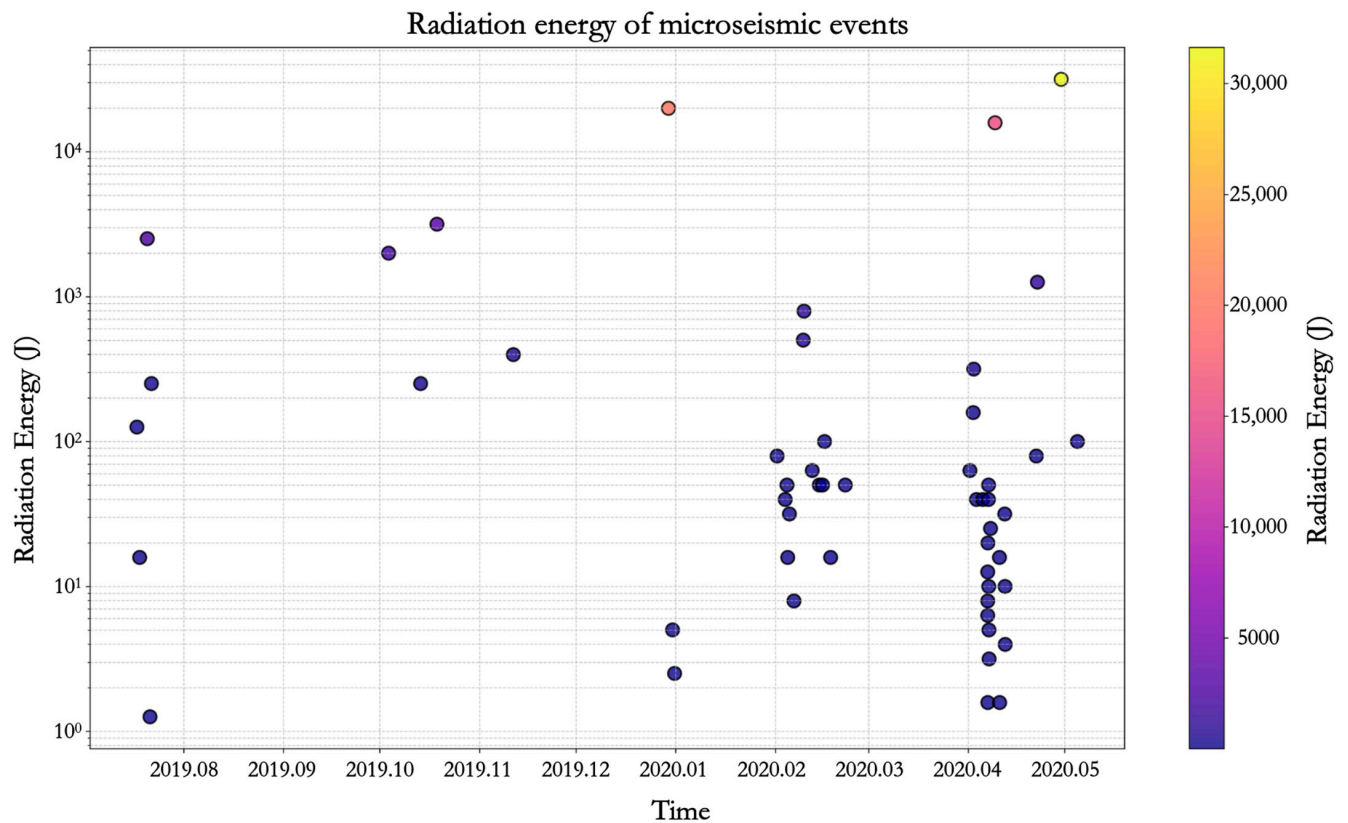
**Figure 3.** Relationship between the location and period of microseismic events.

### 3.4. Analysis of Energy Sequence Indicators

Based on the characterization and analysis of destructive events, this study aims to explore the precursor response characteristics of disaster warning through the spatiotemporal fractal dimension and demonstrate the possibility and applicability of achieving regional disaster warning. The temporal characteristics of energy release are one of the key precursor indicators. To quantitatively describe the overall trend of energy release during the monitoring period, we conducted linear regression analysis on the radiation energy sequences of all microseismic events (Table 1). It indicates that during the observation period from July 2019 to May 2020, the energy release sequence showed a weak positive trend, but this trend was not statistically significant. This indicates that although there may be a tendency for a slow accumulation of energy release from a long-term perspective, the process is not simply a “monotonic linear growth” but is accompanied by significant fluctuations and clustering characteristics (Figure 4). This non-stationary, clustered energy release pattern is more consistent with the physical mechanism of accumulation, convergence, and intermittent instability of microcracks during the gradual failure process of rock masses and also highlights the limitations of relying solely on linear trends for early warning.

**Table 1.** Source parameters of microseismic events in the target area, including coordinates and radiant energy.

| Engineering ID | Event Name          | Source Coordinates (m) |     |     | Radiant Energy (J) |
|----------------|---------------------|------------------------|-----|-----|--------------------|
|                |                     | X                      | Y   | Z   |                    |
| 1              | 2019.7.17.11.23.42  | 217                    | 536 | 432 | 125.89             |
| 2              | 2019.7.18.7.59.04   | 303                    | 427 | 430 | 15.85              |
| 3              | 2019.7.20.16.31.26  | 419                    | 391 | 384 | 2511.89            |
| 4              | 2019.7.21.13.09.23  | 325                    | 449 | 411 | 1.26               |
| 5              | 2019.7.21.23.48.24  | 308                    | 431 | 373 | 251.19             |
| 6              | 2019.10.3.18.06.39  | 454                    | 412 | 251 | 1995.26            |
| 7              | 2019.10.13.16.46.13 | 269                    | 429 | 374 | 251.19             |
| 8              | 2019.10.18.18.35.30 | 264                    | 468 | 378 | 3162.28            |
| 9              | 2019.11.11.12.51.03 | 361                    | 453 | 345 | 398.11             |
| 10             | 2019.12.29.18.39.33 | 418                    | 415 | 311 | 19,952.62          |
| 11             | 2019.12.31.0.58.16  | 338                    | 410 | 389 | 5.01               |
| 12             | 2019.12.31.16.23.40 | 386                    | 456 | 351 | 2.51               |
| 13             | 2020.2.1.13.12.40   | 318                    | 448 | 334 | 79.43              |
| 14             | 2020.2.4.1.47.26    | 296                    | 465 | 367 | 39.81              |
| 15             | 2020.2.4.14.55.12   | 333                    | 421 | 371 | 50.12              |
| 16             | 2020.2.4.20.28.22   | 323                    | 441 | 345 | 15.85              |
| 17             | 2020.2.5.9.21.39    | 321                    | 446 | 330 | 31.62              |
| 18             | 2020.2.6.19.21.01   | 317                    | 448 | 341 | 7.94               |
| 19             | 2020.2.9.16.32.30   | 346                    | 451 | 269 | 501.19             |
| 20             | 2020.2.9.22.05.15   | 319                    | 450 | 279 | 794.33             |
| 21             | 2020.2.12.11.28.33  | 340                    | 423 | 341 | 63.1               |
| 22             | 2020.2.14.16.24.19  | 318                    | 451 | 322 | 50.12              |
| 23             | 2020.2.15.16.24.02  | 307                    | 457 | 348 | 50.12              |
| 24             | 2020.2.16.7.23.35   | 314                    | 451 | 338 | 100                |
| 25             | 2020.2.18.4.40.51   | 310                    | 421 | 398 | 15.85              |
| 26             | 2020.2.22.18.07.55  | 301                    | 462 | 358 | 50.12              |
| 27             | 2020.4.1.12.24.22   | 333                    | 425 | 365 | 63.1               |
| 28             | 2020.4.2.13.04.01   | 320                    | 457 | 282 | 158.49             |
| 29             | 2020.4.2.16.51.10   | 257                    | 446 | 416 | 316.23             |
| 30             | 2020.4.3.13.27.26   | 341                    | 429 | 310 | 39.81              |
| 31             | 2020.4.5.12.09.55   | 305                    | 460 | 344 | 39.81              |
| 32             | 2020.4.7.1.04.55    | 325                    | 442 | 325 | 6.31               |
| 33             | 2020.4.7.1.05.55    | 312                    | 453 | 342 | 12.59              |
| 34             | 2020.4.7.1.25.28    | 286                    | 472 | 388 | 7.94               |
| 35             | 2020.4.7.1.51.46    | 265                    | 478 | 462 | 1.58               |
| 36             | 2020.4.7.2.34.49    | 323                    | 438 | 354 | 19.95              |
| 37             | 2020.4.7.6.32.57    | 341                    | 428 | 309 | 39.81              |
| 38             | 2020.4.7.7.35.34    | 333                    | 429 | 346 | 50.12              |
| 39             | 2020.4.7.8.58.43    | 325                    | 438 | 349 | 10                 |
| 40             | 2020.4.7.10.16.33   | 293                    | 459 | 410 | 5.01               |
| 41             | 2020.4.7.11.25.51   | 270                    | 478 | 435 | 3.16               |
| 42             | 2020.4.7.22.11.55   | 324                    | 444 | 327 | 25.12              |
| 43             | 2020.4.9.8.15.29    | 389                    | 448 | 291 | 15,848.93          |
| 44             | 2020.4.10.16.54.13  | 327                    | 433 | 361 | 15.85              |
| 45             | 2020.4.10.18.19.58  | 370                    | 373 | 430 | 1.58               |
| 46             | 2020.4.12.8.13.36   | 319                    | 440 | 368 | 31.62              |
| 47             | 2020.4.12.10.36.36  | 319                    | 447 | 332 | 10                 |
| 48             | 2020.4.12.11.38.42  | 387                    | 385 | 283 | 3.98               |
| 49             | 2020.4.22.3.55.10   | 344                    | 426 | 307 | 79.43              |
| 50             | 2020.4.22.12.14.21  | 320                    | 463 | 335 | 1258.93            |
| 51             | 2020.4.29.21.27.44  | 298                    | 465 | 308 | 31,622.78          |
| 52             | 2020.5.4.22.50.23   | 305                    | 458 | 351 | 100                |

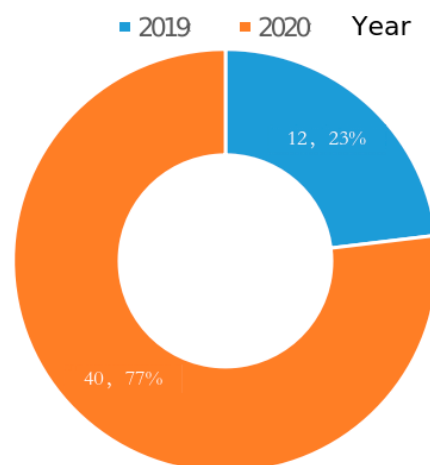


**Figure 4.** Distribution of microseismic event energy.

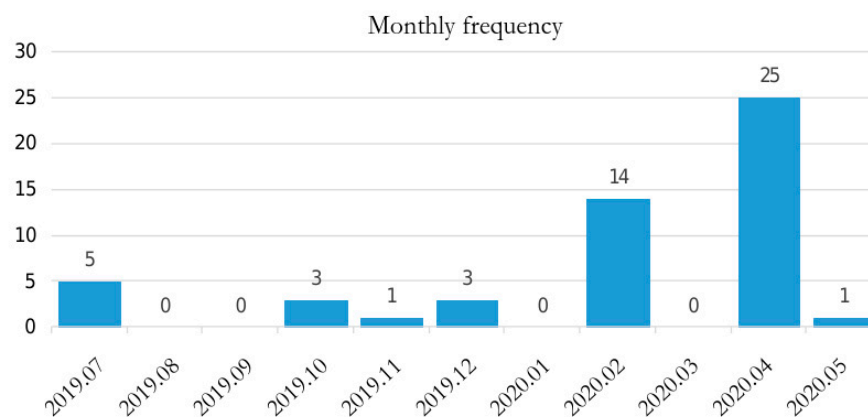
#### 4. Spatiotemporal Energy Information Fractal Interpretation of Microseismic Events

##### 4.1. Distribution Relationship of Various Frequencies

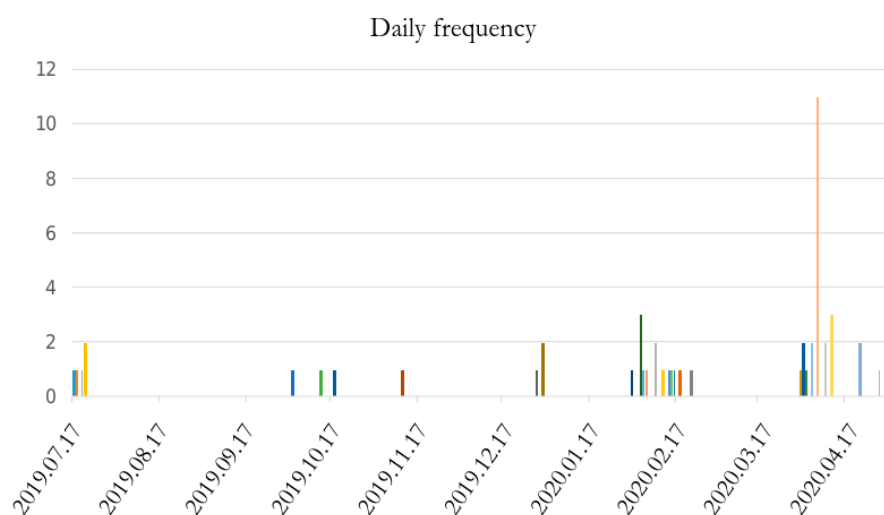
To analyze and study the precursor response of microseismic indicators before the occurrence of damage in the research area, redundant information is removed, and various frequency data during this period are statistically calculated. The specific annual, monthly, daily, and period frequency indicators are shown in Figures 5–8.



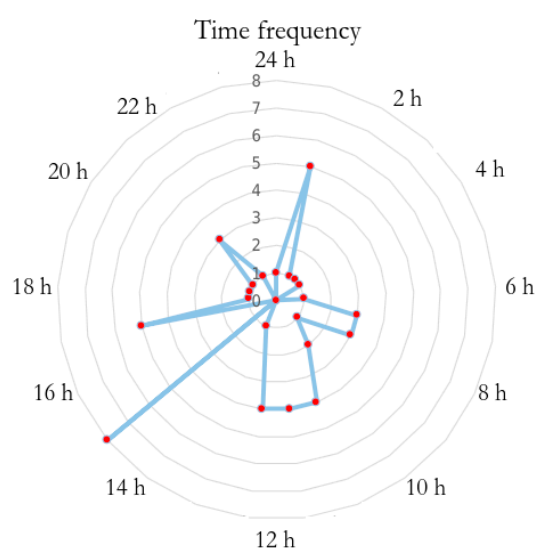
**Figure 5.** Annual frequency statistics based on time indicators.



**Figure 6.** Monthly frequency statistics based on time indicators.



**Figure 7.** Daily frequency statistics based on time indicators.



**Figure 8.** Time period frequency statistics based on time indicators.

As shown in Figure 5, the frequency of events increased from 12 in 2019 to 40 in 2020. This significant year-on-year increase may indicate intensified seismic activity, changes in monitoring sensitivity or coverage, or the beginning of a more active phase. To determine whether this represents a macro-trend of increased instability, it is necessary to correlate this frequency variation with other parameters.

Furthermore, from the perspective of risk management, this increase deserves closer attention and further analysis to assess whether it implies an upgrading trend or potential damage to geological activities.

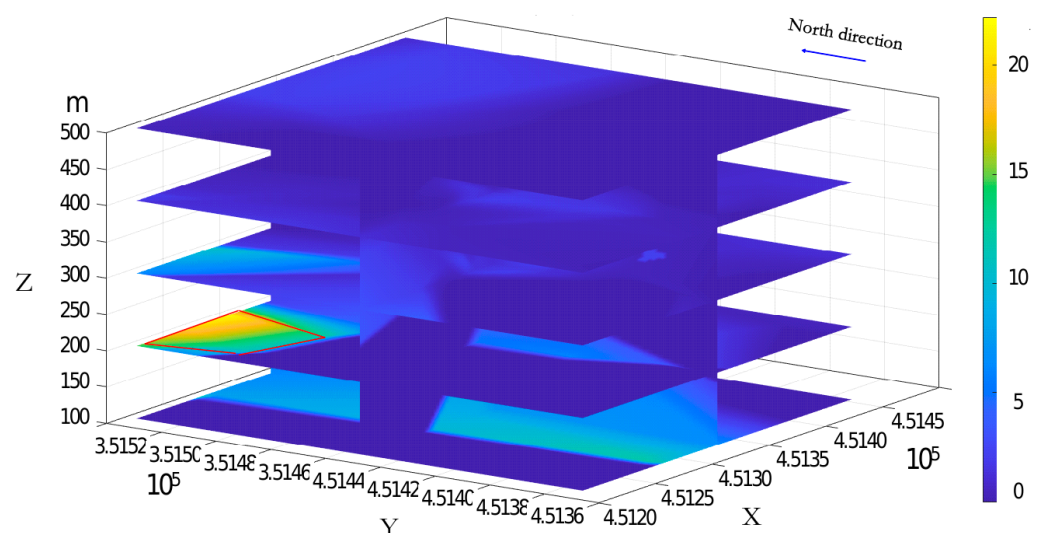
Figure 6 shows that the monthly frequency exhibits a certain degree of volatility. There was a significant increase in April 2020, reaching 25 occurrences, while the frequency in August and September 2019 was 0, indicating that relatively large-scale events did not occur or had extremely low energy. In addition, the frequency in February 2020 was significantly higher than in other months, reaching 14 times.

In Figure 7, It can be seen that during the entire event spanning from July 2019 to May 2020, there were relatively high frequencies on fewer dates, while the frequencies on most dates were between 1 and 3; The frequency of February and April 2020 was significantly higher than other months, and the frequency on 7 April 2020 was 11, which is a significant outlier. The data shows that certain specific dates correspond to special mining seismic activity, microseismic events, or abnormal situations.

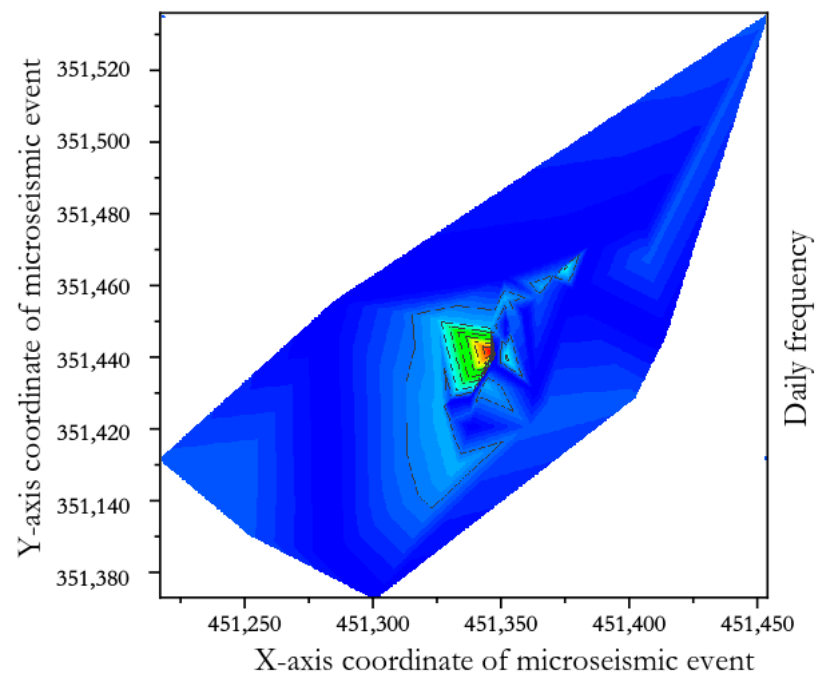
According to Figure 8, the frequency of microseismic events reaches its peak at 16:00, during which a total of eight events were recorded, indicating that microseismic activity is most active during this period. The second peak occurs during the noon period (11:00 to 13:00), with a frequency of four times. The frequency distribution in the morning (8:00 to 10:00) and afternoon (14:00) is relatively uniform, with one to three occurrences recorded in each time period. In contrast, there are fewer event records in the early morning (0:00 to 4:00) and nighttime (18:00 to 23:00), with a frequency of only one to five times in each time period.

#### 4.2. Spatial Agglomeration Dimensionality Index and Interpretation

Based on the spatial distribution and energy information of microseismic events occurring at depths of +251 m to +462 m between 11:23:42 on 17 July 2019 and 22:50:23 on 4 May 2020, preprocessing was conducted. Combined with numerical simulation, the Thiessen polygon and Kriging interpolation algorithm were used to calculate the spatial fractal index, energy fractal index, event frequency, and cloud map of microseismic events in the region (as shown in Figures 9 and 10).



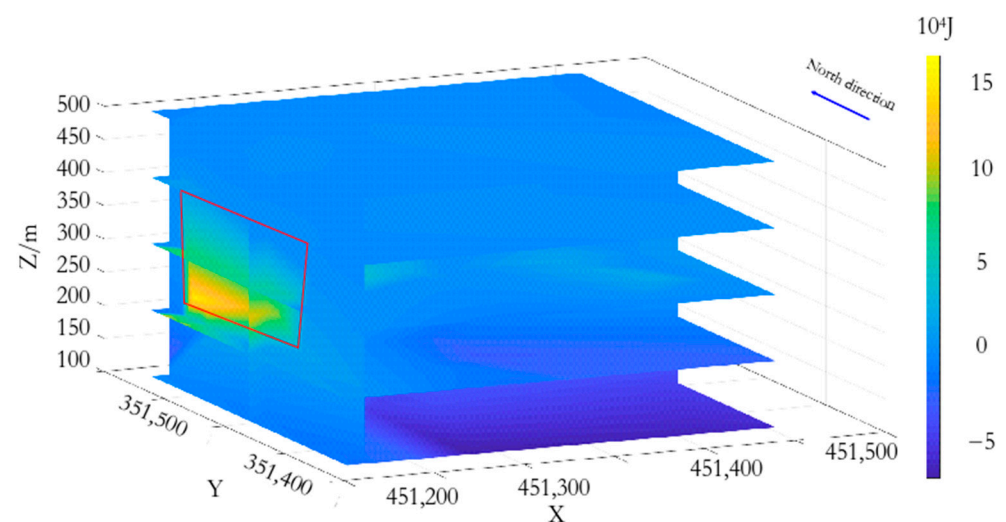
**Figure 9.** Fractal interpolation cloud map of spatial clustering of microseismic events in the study area (The red line is the warning area).



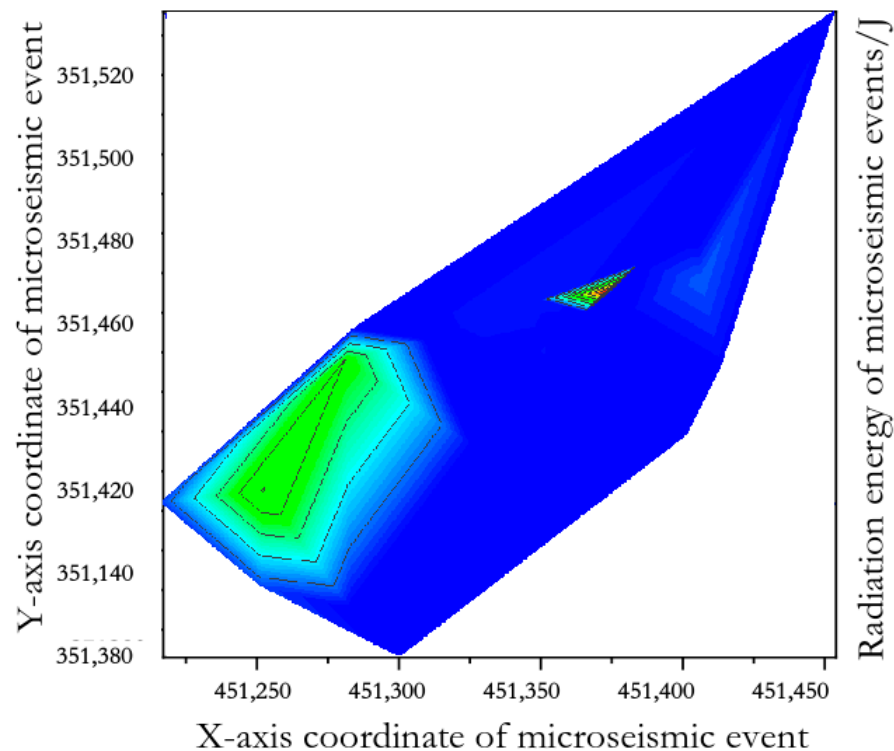
**Figure 10.** Spatial agglomeration of microseismic events in the study area using dimensionality interpolation cloud map (top view).

#### 4.3. Energy Dissipation Fractal Dimension Index and Interpretation

As shown in Figures 11 and 12, the distribution of microseismic energy is relatively concentrated in two adjacent high-value distribution areas, mainly located in the middle range of 200 m to 300 m in elevation. The fault trace, identified within the marked area of the map/image and oriented relative to due north, strikes approximately northeast–southwest. Its geometry is characterized by a strike of about  $N66^{\circ} E$  and a dip of approximately  $25^{\circ}$ . It can be seen that larger microseismic events occur in high-energy regions, especially in areas with larger energy potential differences.



**Figure 11.** Fractal interpolation cloud map of energy dissipation of microseismic events in the study area (The red line is the warning area).



**Figure 12.** Fractal interpolation cloud map of energy dissipation of microseismic events in the study area (top view) (The red line is the warning area).

## 5. Discussion

This study is based on the time series fractal interpolation cloud map of microseismic spatiotemporal aggregation frequency and energy dissipation and achieves the prediction of rock mass failure and dangerous areas from a spatial perspective. Despite the short monitoring period, the spatiotemporal evolution of microseismic activity within a complete production activity cycle was successfully captured, providing a key basis for understanding the immediate response characteristics of the rock mass at this specific stage and laying an important foundation for establishing long-term evolution models.

The spatial distribution analysis (Figure 9) shows that the high-frequency zone of microseismic events is mainly concentrated in the 200 m middle section and its surrounding areas, with a destructive ellipsoidal distribution along the NNE 45° direction, revealing that this direction is the dominant failure surface. Further observation revealed (Figure 10) that the event exhibits a centripetal clustering trend in space and presents a potential trend of connectivity and breakthrough. The energy dissipation fractal cloud map identifies two main high-energy regions, reflecting the overall coordinated development of faults in space. It is worth noting that the high-frequency region and high-energy region are highly consistent in space, indicating that microseismic activity has inherent consistency in space and energy distribution.

However, the positioning accuracy and coverage range of existing monitoring networks are not sufficient to fully distinguish whether the spatial clustering patterns mentioned above originate from mining-induced evolution or are influenced by the composite effects of neighboring tectonic activities. Therefore, in order to more accurately clarify the source mechanism and improve the reliability of early warning, it is recommended to integrate regional seismic network data for joint analysis in the future to effectively identify the contributions of different sources.

This study achieved a shift in warning perspective from “phenomenon description” to “mechanism correlation” by introducing fractal theory. The synergy of time, space, and energy fractal dimensions ( $D_t$ ,  $D_s$ , and  $D_e$ ) reveals the temporal clustering, spatial aggregation, and non-uniform energy release characteristics of microseismic events during rock mass fracture. The synergistic evolution (such as  $D_s$  decreasing accompanied by  $D_e$  increasing) marks the critical transition of the rock mass from diffuse damage to local energy concentration, providing a quantitative basis for inferring the damage state. The research results have clear engineering application value: microseismic clustering along the NNE  $45^\circ$  direction provides spatial targeting for precise support and monitoring deployment. The multi-parameter comprehensive early warning model constructed can achieve risk classification and hazardous area positioning through real-time calculation of fractal indicators and energy trends and form a decision support loop in linkage with the production system, promoting the intelligent and accurate development of mine dynamic disaster early warning. Subsequent research needs to verify the universality of threshold values in multiple mining scenarios and integrate geological and mining dynamic information to build a more resilient intelligent warning platform.

## 6. Conclusions

This study is based on fractal theory and constructs and validates a comprehensive framework for microseismic spatiotemporal energy analysis. The following core conclusions were obtained in this case study of deep hard-rock mines:

- (1) A comprehensive analysis framework for microseismic spatiotemporal energy based on fractal theory was proposed and validated. This framework integrates the three elements of time, space, and energy, and case studies show that it can effectively reveal the self-organizing and scale invariant characteristics of microseismic activity in terms of spatiotemporal aggregation and energy dissipation. Compared to traditional methods that rely on a single parameter such as event frequency or total energy, this framework can more systematically depict the evolution process of rock mass failure precursors from “disorder” to “order”, providing a new approach for extracting stable warning signals from complex data.
- (2) This study revealed the precursor patterns of microseismic activity with clear directionality in the study area. Through fractal dimension calculation and cloud visualization, two key facts have been discovered: firstly, microseismic events aggregate in an elliptical shape along the NNE  $45^\circ$  direction in space, indicating that this direction is a potential dominant failure surface, providing a direct basis for on-site support design and key monitoring area delineation. This discovery warns that relying solely on general indicators may underestimate the risk of high-energy release, highlighting the necessity of independent fractal analysis of energy fields.
- (3) We achieved quantitative identification and graded warning of potential hazardous areas and preliminarily verified their engineering applicability. By integrating spatiotemporal fractal dimension, energy fractal dimension, and energy release trend, this study constructed a multi-parameter comprehensive early warning model. This model successfully transforms abstract “fractal features” into quantifiable risk discrimination thresholds, achieving the localization and hazard-level classification of potential rock mass failure areas. The consistency between on-site investigation feedback and numerical simulation results has preliminarily verified the applicability and warning potential of the model in practical engineering.

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