**Response to Reviewer:**

I am very grateful to your comments for the manuscript. Thank you for your advice. All your suggestions are very important. They have important guiding significance for our paper and our research work. We have revised the manuscript according to your comments. The response to each revision is listed as following:

**General Comment**

The manuscript entitled "*Analysis of Borehole Strain Anomalies Before the 2017 Jiuzhaigou Ms7.0 Earthquake Based on Graph Neural Network*" presents the results of analyzing strain meter data from four sites prior to a large magnitude earthquake aiming to identify pre-seismic signal using Neural network technique.

My general feeling reading the manuscript is that is well organized, interesting work providing some new useful information of exploiting graph neural network approach to estimate/define pre-seismic signal on strain time series. I think that the manuscript require some small modifications and some of its parts to be improved in order to be more explanatory and understandable but in any case, it is considered, in my opinion, as a nice work. However, not being very familiar with the neural networks I would like to see some more detail information concerning the analysis in some of the manuscript paragraphs.

As a first remark I would like to mention that although I am not a native English person, in several cases the text has to be reformatted, to be "easier" for the reader.

Another general comment that I have is that the text and the processing focus on the pre-seismic period and ignores completely the post seismic period. Of course, it is well explained by the authors, that the manuscript examines the possible anomalies on the preparatory stage of a strong earthquake, but since the earthquake occurred in 2017, and a long time passed since this event, it would be interesting to see if the area, and the strain data from the same stations, shows any similar behavior as during the pre-seismic period. In other words, as a validation of this processing it could be interesting to examine the years after the earthquake if there was another period that these 4 stations show anomalous days (as in Figure 9) without the occurrence of an earthquake. The authors used data only 1 year before the earthquake … using longer period is it possible that there is and another "anomalous" "S" shape period? Of course I can understand that the authors focus on the technique as a tool for extracting pre-seismic signals of an earthquake, but I would like to see some comment on this issue.

**Response**:

Thanks for your suggestion.

(1) Thank you for pointing out that the text may need reformatting in certain areas. We understand the importance of clear and accessible language for the reader. We will carefully review and revise the manuscript to ensure that the content is more fluid and easier to understand. Additionally, we will seek the assistance of a native English

speaker to help polish the language and improve the overall readability and accuracy of the text.

(2) First of all, I apologize for the limitation that our data only extends up to August 2017, making it impossible to verify whether similar anomalies occurred in the years following the earthquake. However, reviewers can refer to our previously published article, *Pre-earthquake Anomaly Extraction from Borehole Strain Data Based on Machine Learning* (Chi et al., 2023). In that study, we analyzed data from the Guza station (one of the stations studied in this manuscript) in relation to the 2008 Wenchuan Ms 8.0 earthquake and the 2013 Lushan Ms 7.0 earthquake. We found that a distinct "anomalous" S-shaped period appeared before and after both of these large earthquakes, as shown in Figure 1A. To further investigate whether similar "anomalous" S-shaped periods occurred during other timeframes, we conducted a cumulative analysis of anomalies from 2009 to 2011. The results, shown in Figure 1B, indicate that no "anomalous" S-shaped period was observed during this time.

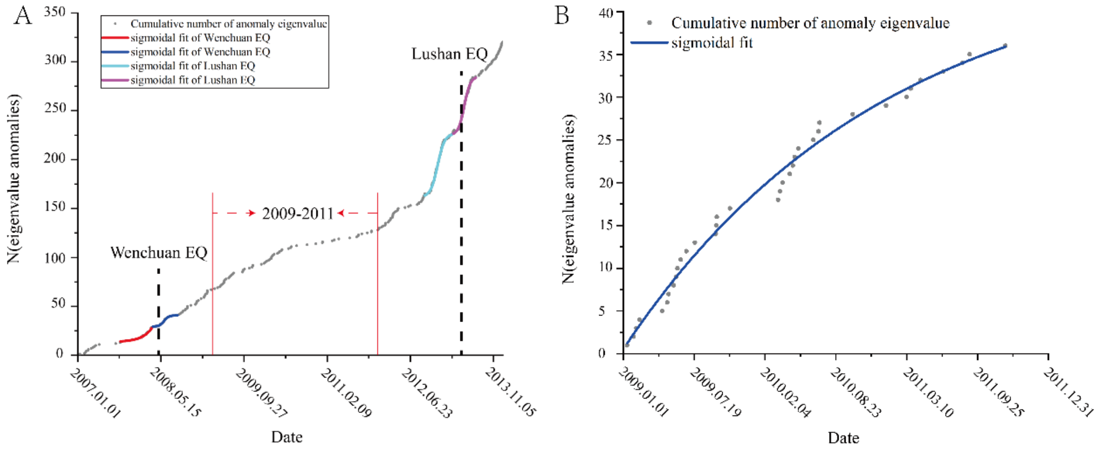


**Figure 1: Accumulated results of the abnormal days of borehole strain data at Guza station from 2007 to 2013 (Chi et al., 2019).**

Based on the above analysis, we believe that the "anomalous" S-shaped period identified in the manuscript before the earthquake is reasonable. Furthermore, the method we employed demonstrates its effectiveness as a tool for extracting pre-seismic anomaly signals.

**Some more detail comments:**

**Comment 1**

Line 16 "pro-seismic", I think that is more common the use of the term "pre-seismic".

**Response**:

Thanks for your suggestion.

Modified "pro-seismic". It is modified to "pre-seismic".

**Comment 2**

Line 19 "…such as volcanic eruptions…" I am not so sure that earthquakes trigger volcanic eruptions, if so please add a reference.

**Response**:

Thanks for your suggestion.

Modified "…such as volcanic eruptions…". It is modified to "…such as volcanic eruptions (Nishimura, 2017)…".

Nishimura used the data of large earthquakes and volcanic eruptions with a global magnitude of 7.5 or above as the research object, and analyzed the cumulative quantitative changes of volcanic eruptions at different distances within 5 years before and after these large earthquakes. Their results show that within 5 years after a major earthquake, the probability of volcanic eruptions within 200 km from the epicenter increases by about 50 % (Nishimura, 2017).

**Comment 3**

Line 41 "…the use of a GNN can mine additional hidden information between nodes…" this is a very general statement, please provide some examples.

**Response**:

Thanks for your suggestion.

In order to better understand "using GNN to mine additional hidden information between nodes", we give an example of a traffic flow prediction task.

Add this example to line 43 of the original manuscript: For example, in the traffic flow prediction task, nodes usually represent traffic monitoring points, and node features can be divided into explicit and implicit features. Explicit features are data that can be directly observed, e.g., the speed of vehicles passing through a node, while implicit features are information indirectly obtained through model learning or data mining methods, e.g., the congestion pattern of a specific node at different times of the day is found by analysing historical and real-time data (Chen et al., 2023).

**Comment 4**

Lines 49-51. Please describe a bit more analytical the meaning of a "node" how a node is defined? What is its characteristics and/or its physical meaning.

**Response**:

Thanks for your suggestion.

A definition of "node" has been added to line 49 of the original manuscript: For the graphical data structure consisting of a network of seismic stations, we take the monitoring stations at different locations as nodes, and the data directly observed by each station as explicit features. By analysing the historical observation data of the stations and the distances between the stations, we can mine the implicit features such as the response patterns of different stations in different seismic events, the correlation between stations, etc.

**Comment 5**

Figure 1. It would be nice to be added a map of the broad area (as inset) indicating the position of your area so to be easier for readers not familiar with the area to orientate themselves.

**Response**:

Thanks for your suggestion.

We have modified Figure 1 in the original manuscript by adding a map of the broad area (as inset) and labelling the location of the study area.

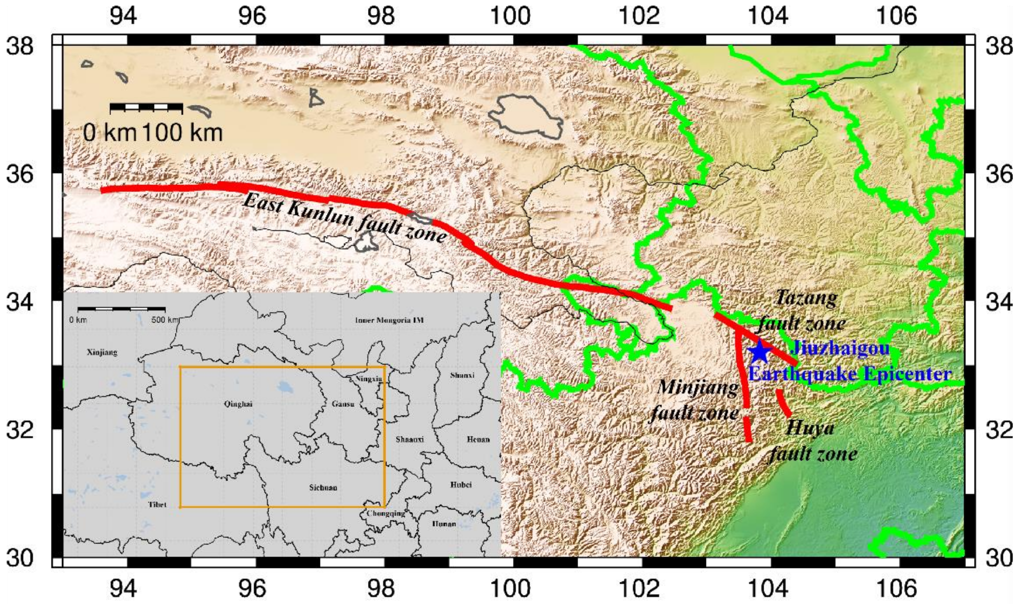


**Figure 2: Topographic map of epicentre of Jiuzhaigou earthquake. Blue star indicates epicentre; red line indicates fault zone. This map was generated by GMT software, v. 6.0.0rc5 (https://gmt-china.org/).**

## Comment 6

Line 146 ".. preprocessing of the surface strain $S_a$" Why the authors choose only the $S_a$ and not $S_{13}$ or $S_{24}$? Please explain. A comment on this issue (selection) could be added maybe in the end of Section 3.1 line 88.

**Response**:

Thanks for your suggestion.

In order to verify that our results are also applicable to $S_{13}$ or $S_{24}$, we selected the shear strain $S_{24}$ data from four stations, namely, Guza, Xiaomiao, Luzhou and Zhaotong, and analysed them using the same method. The anomalous day accumulation results of shear strain $S_{24}$ data from the four stations are shown in Fig. 3.

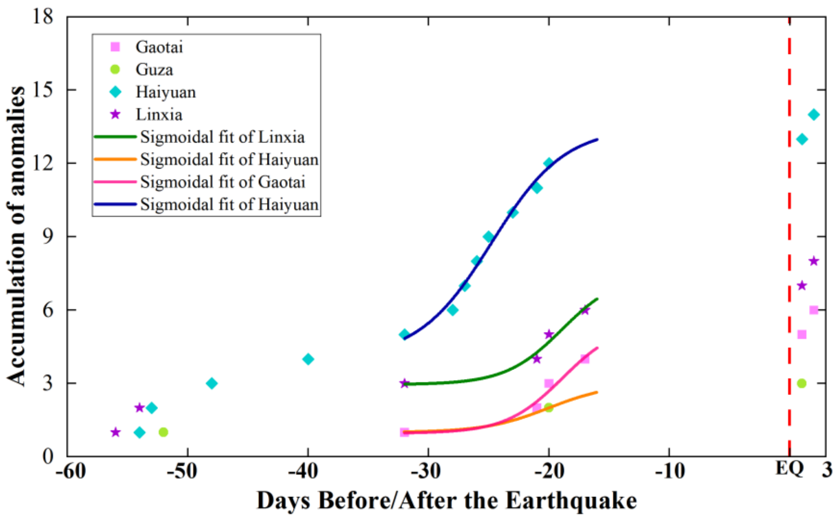

**Figure 3: Fitting results for the accumulation of anomalous days of $S_{24}$ component at four stations. Red dotted line represents time of earthquake; different types of dots indicate anomalous days at stations; curves of different colours represent results of S-shaped fit of anomalous accumulation of stations.**

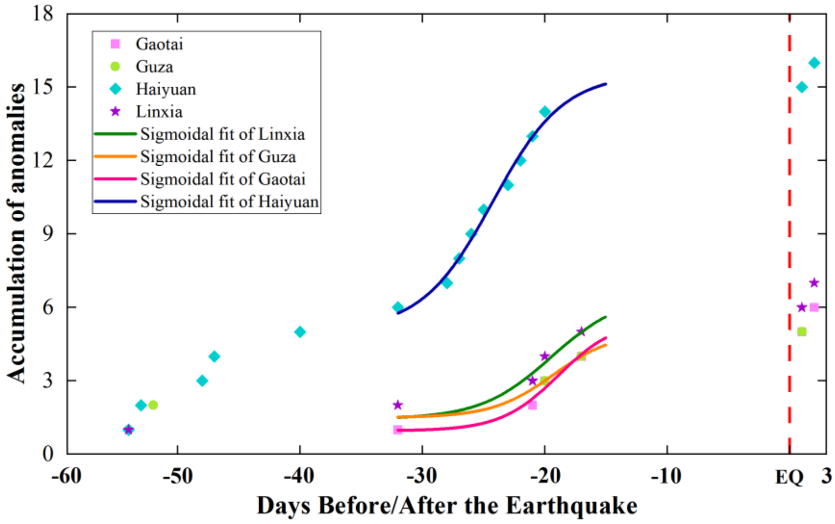


**Figure 4: Fitting results for the accumulation of anomalous days of $S_a$ component at four stations. Red dotted line represents time of earthquake; different types of dots indicate anomalous days at stations; curves of different colours represent results of S-shaped fit of anomalous accumulation of stations.**

We have processed the data of shear strain $S_{24}$ by using the same method and the results are shown in Fig. 3. The processing results of the surface strain $S_a$ are given in Fig. 4. We compared Fig. 3 with Fig. 4 and found that the processing results of shear strain $S_{24}$ and surface strain $S_a$ were very similar, and both showed similar acceleration scenarios at the same time period before the earthquake.

Qiu et al analyzed the borehole strain data of Guza station before Lushan Ms7.0 earthquake. It was found that due to the large fluctuation of the Dadu River flow, the borehole strain observation curve also showed reverse large fluctuation synchronously. However, for the observation components in different directions, the fluctuation amplitude of the borehole strain observation curve is quite different, so the shear strain converted by strain may not be able to fully receive the abnormal signal of all components (Qiu et al., 2015). According to Eq. (2) in the manuscript, compared with the shear strain $S_{24}$, the surface strain $S_a$ is more representative of the four components measured by the YRY-4 borehole strain gauge, and we believe that the surface strain $S_a$ represents the sum of the anomalous results of the four components, so we use the characteristics of the data of the surface strain $S_a$ as the object of study in this paper.

An explanation was added at the end of Section 3.1, line 88, of the original manuscript: Compared with shear strain $S_{13}$, the surface strain $S_a$ is more representative of the four components measured by the YRY-4 borehole strain gauge, so the data characteristics of surface strain $S_a$ are used in this paper as the object of study.

**Comment 7**

Figure 4. It would be helpful the figure caption to be more analytic. Especially as what it is presented in the final diagram.

**Response**:

Thanks for your suggestion.

We have revised Figure 4 in the original manuscript to provide a more detailed description of the information in Figure 4.

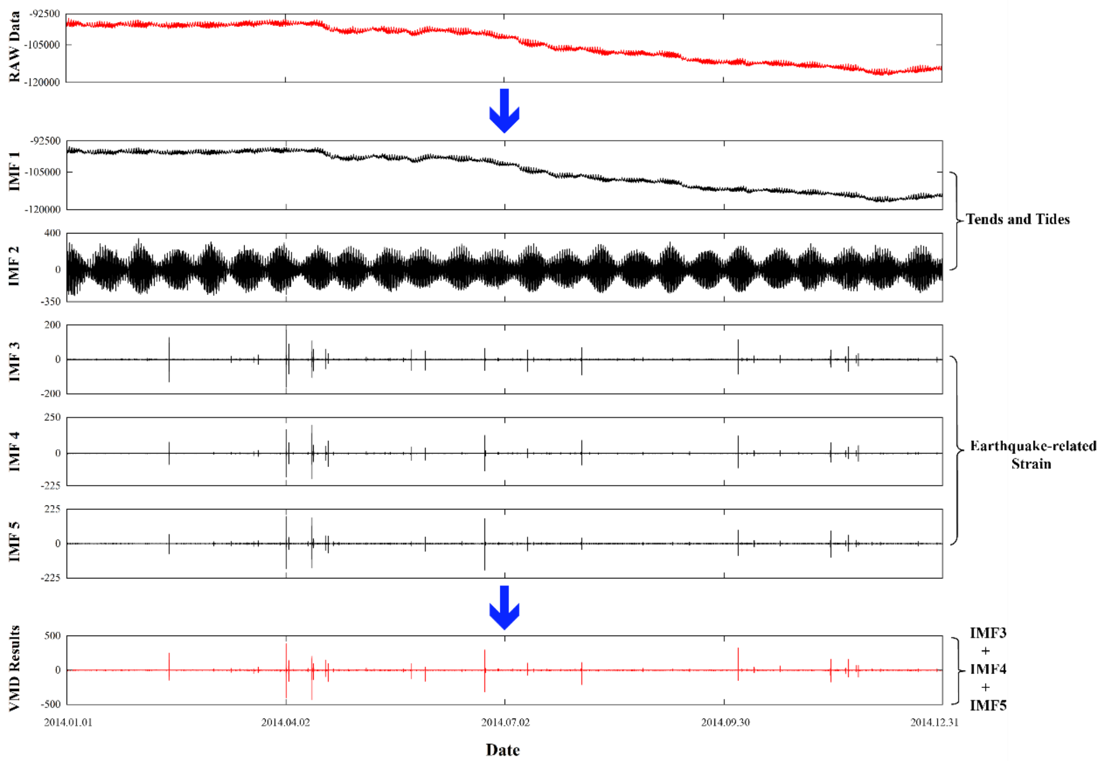


**Figure 5: Plot of decomposition results of $S_a$ data using VMD method at Linxia station.**

## Comment 8

Sections 4.2.1 and 4.25.2 I would like (personally) to see some more detail description of this part. Actually, I would like to be more explicable and defines (maybe with examples) some of the terms used on it … "layers", "gating mechanisms" etc.

**Response**:

Thanks for your suggestion.

Added a more detailed explanation and definition of "layer" in line 163 of the original manuscript: In a neural network, a "layer" is a basic building block, and each layer contains a set of neurons, which accepts input data, performs specific computational operations, and then passes the results to the next layer. Different types of layers have specific functions and characteristics, and by combining and configuring different layers, powerful and flexible neural network models can be constructed to achieve a variety of complex tasks.

Added a more detailed explanation and definition of "gating mechanism" in line 180 of the original manuscript: Gating mechanism is an important technique in neural networks, and the core idea is to control the flow of information dynamically, so as to efficiently capture and utilise long-dependent information. The gating mechanism controls the flow of information through the design of a "gate", which is usually a neural network layer with an activation function, whose output value is located between 0 and

1, and decides what information should be "remembered" and what information should be " forgotten " by the output value.

**Comment 9**

Equation 9. Define the parameter "T"

**Response**:

Thanks for your suggestion.

The parameter "T" is the output of the gated TCN module, and we have added the definition of the parameter "T" to line 187 of the original manuscript.

**Comment 10**

Line 237 "…75% of the samples and labels." Please define what are the samples and what are the labels.

**Response**:

Thanks for your suggestion.

A more detailed explanation and definition of "samples and labels" has been added to line 236 of the original manuscript: the model learns patterns and relationships in the data through samples and labels in the training set; the validation set is used to evaluate the performance of the model in order to adjust and optimise the model to get the best configuration and hyperparameters of the model. Our samples are the pre-processed and sliced data segments, which have a length of 60 and represent one hour of observations, and each sample contains strain data from four different stations within one hour. Our labels refer to the target values corresponding to each sample, which represent the strain data segments after one time step of the sample, and each label also contains strain data from 4 different stations within 1 hour.

**Comment 11**

Section 5.2 and Figure 9. Concerning the results presented in this section, could the authors comment on why the Haiyuan station shows this strong S shape anomalies, with many points, while the other stations (Linxia and Guza), although it appear that there are closer to the epicenter do not reveal a similar "strong" anomaly.

**Response**:

Thanks for your suggestion.

We have also noticed this phenomenon you mentioned. In earthquake precursor studies, the reasons for the phenomenon that stations closer to the epicentre receive fewer anomalous signals than stations farther away may be:

(1) Differences in geological structures: The propagation characteristics of seismic waves in different geological structures are different. (Yu et al., 2021) calculated the daily ApNe value of the corrected strain from January 1,2011 to January 1,2014, constructed the threshold interval according to the ApNe mean and 2 times the standard deviation, and accumulated the results exceeding the threshold. Their experiments selected six stations : GZ, XM, ZT, YS, RH and TC. Among them, GZ station is the closest to the epicenter, XM station is the second from the epicenter, and ZT station is the third from the epicenter. The anomalous accumulation results of ApNe values of

surface strains at stations GZ, XM and ZT are given in the figure below, from which it can be seen that the number of accumulations at the more distant station ZT is more than that at station XM, and the number of accumulations at station XM is more than that at station GZ, and the fitting results of the anomalous accumulations of the three stations all show a strong S-shape anomaly. We believe that it may be due to the fact that the geology near the epicenter may be relatively hard or uniform, making it difficult for seismic precursor signals to be significantly transmitted or captured by stations. The geological conditions of stations far away may be more conducive to the propagation or amplification of signals, which makes it easier to receive abnormal signals.

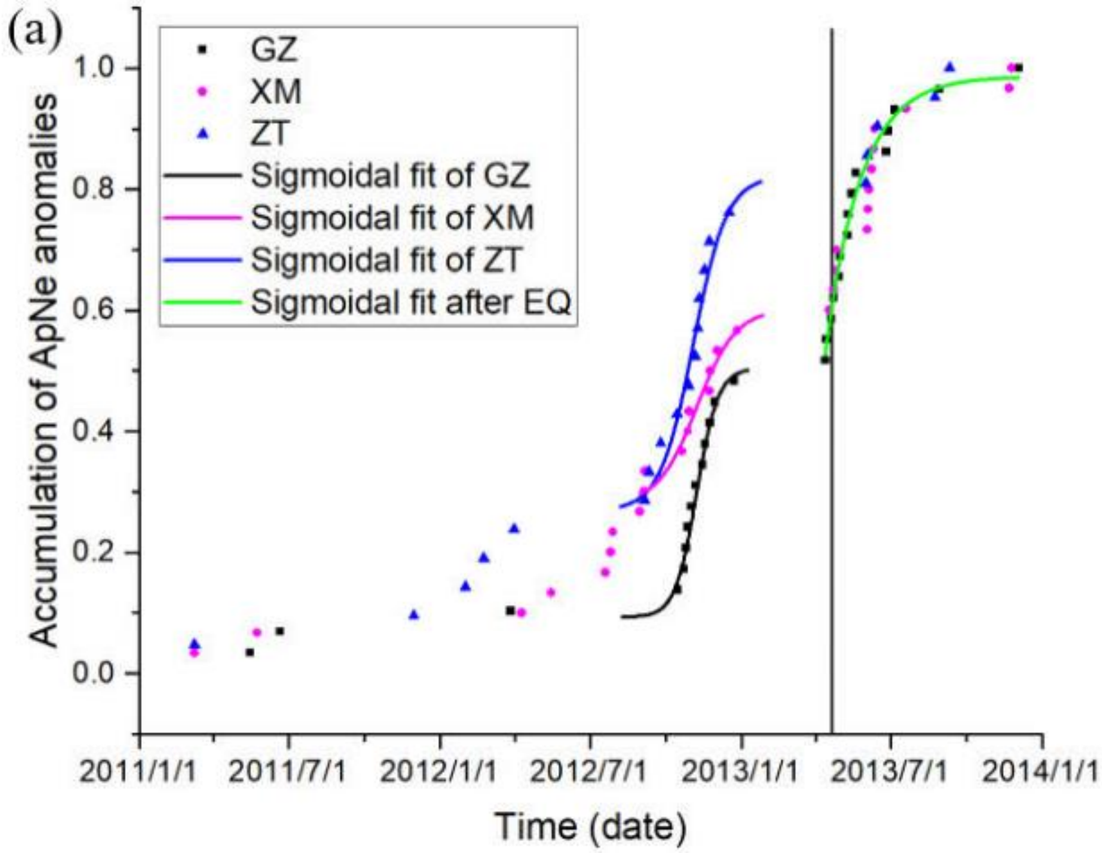


**Figure 6: Accumulation of ApNe anomalies at the GZ, XM, and ZT stations. The solid dots are the cumulative ApNe anomaly counts from 2011-2014. The black, pink, and blue lines are the sigmoidal fits at the GZ, XM, and ZT stations. The green line is the sigmoidal fit after the earthquake at the GZ station. The vertical red line is the day of the 2013 Lushan earthquake.**

(2) Locality of earthquake precursors : Some earthquake precursors (such as gas release, electromagnetic anomalies, etc.) have strong locality, which may not be significant near the epicenter, but more obvious at specific locations in the periphery of the epicenter. Kumar et al., (2021) analyzed ionospheric anomalies associated with the 2019 Indonesia earthquake (Mw=7.4) using GPS and VLF measurements from multiple stations. They found that the disturbance observed at the place closest to the epicenter is the smallest, and they believe that the ionospheric disturbance induced by the earthquake depends not only on the distance between the observation and the epicenter, but also on the direction of the observation point relative to the epicenter. This may be due to local crustal fissures, stress concentration areas or other geological features.

(3) Non-linear propagation of signals: Seismic precursor signals may be affected by a variety of factors during propagation, such as wave scattering, attenuation, and reflections and refractions between different strata. These non-linear propagation phenomena may lead to a weakening or complication of the signal near the epicentre, thus making it difficult for close stations to receive it effectively.

(4) Effect of depth of source and type of earthquake: The depth of the source and the type of earthquake also affect the distribution of precursor signals. Precursor signals from deep earthquakes may be more difficult to capture at shallow stations near the epicentre, and different types of earthquakes (e.g., strike-slip, backlash, etc.) may also result in different propagation characteristics of the precursor signals.

So it is reasonable that this phenomenon occurs. In this paper, we pay more attention to the similarity of the anomalies received by each station for the same earthquake before the earthquake, and we will further explore the reasons for this phenomenon in the next study.

**References**


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