RESPONSES TO REVIEWER ONE'S COMMENTS

We would like to express our sincere appreciation for your valuable comments and suggestions on our manuscript. We have carefully considered the comments and have revised the manuscript accordingly. The comments are laid out below in italicized font. Our response is given in normal font and changes/additions to the manuscript are given in the blue text.

 # *General comments:*

1. *#Abstract: It would be worth rephrasing to make the message clear and better reflect the key findings and the value of this study.*

Response: Thank you for this constructive suggestion. We agree entirely that enhancing the clarity and impact of our findings will strengthen the paper. We have revised the Abstract to better underscore our key findings and the value of this study as follows:

The intersection of the Xiaojiang Fault and the Red River Fault at the southeastern margin of the Tibetan Plateau experiences intense tectonic activity. At this intersection, frequent earthquakes have induced hydrochemical variations in thermal springs. In this study, bayesian change point analysis is applied, and a multicomponent synergy anomaly detection model is developed using five years of monitoring data (2019–2024) from two thermal springs in the region to achieve real-time forecasting of occurrence timing for $M \geq 4$ earthquakes. A 45-day response time threshold is established as the optimal period for capturing key hydrochemical precursors to $M \geq 4$ earthquakes. Parameters are optimized for individual components based on their distinct geochemical responses to seismic stress, thereby significantly enhancing the model's performance and adaptability. The model shows reliable real-time detection capabilities, with probability of detection (POD) ranging from 0.83 to 0.95 and threat score (TS) between 0.59 and 0.70. It identified pre-earthquake high-value anomalies in Na^{+}, Ca^{2+}, Cl^{-}, SO_4^{2-}, δD, and $\delta^{18}O$, with TS ≥ 0.50, which can serve as sensitive indicators for strong earthquake forecasting. The multicomponent synergy alarm mechanism for hydrochemistry overcomes the limitations of single-parameter methods and improves overall forecasting performance. The number of hydrochemical components with synchronous anomalies serves as a reliable criterion for determining alarm intensity, with higher intensity typically correlating with larger earthquake magnitudes or shorter epicentral distances. The model can be universally applied to hot spring monitoring across diverse tectonic regions through targeted parameter optimization, offering an attempt at a method to advancing earthquake forecasting.

2. *#Introduction: The Introduction is mostly well written. However, some minor issues should be state clearer and some relevant references are missing. Please see minor comments below.*

Response: We appreciate your careful reading and valuable suggestions for improvement. We have carefully addressed all minor comments provided below to enhance clarity where needed and have added the relevant references as requested. The revised Introduction now incorporates these improvements.

3. *#Method and data:*

a) Some results are presented and discussed in Section 3.3 and 3.4, which makes the structure unclear. The authors are suggested to reorganize some contents in 3.3 and 3.4, and move them into results and discuss them accordingly.

b) Also, some contents in this section are too lengthy. The authors are suggested to simplify some of the method (for example, the introduction of limitations of BCP *method could go to later section or Supplementary information).*

Response: Thank you for your thoughtful suggestions regarding the organization and conciseness of the manuscript. We agree that the structure could be improved for better clarity and flow. In response to point (a), we will reorganize the content in Sections 3.3 and 3.4 by moving appropriate parts to the Results and discussion sections, respectively, to more clearly distinguish between experimental findings and their interpretation. For point (b), we will simplify the Methods section by relocating the detailed limitations of the BCP method to the Discussion section, as suggested, to maintain focus on the core methodology. We will incorporate these changes in the revised manuscript.

4. *#Results and discussion: The results presented here are convincing; however, some lack in-depth discussion, causing some implications of the study to be obscured. It is recommended that the authors further discuss how some of these findings could be applied to other tectonically active regions around the world.*

Response: We thank the reviewer for their positive assessment of our results and their valuable suggestion regarding the discussion. We agree that further elaboration on the broader implications would strengthen the manuscript. In response, we have significantly expanded the Results and discussion section to explicitly discuss how these findings could be applied to other tectonically active regions globally.

We added the following content to the last part of the 4.4. Limitations and prospects section:

Owing to significant differences in hydrogeological settings, tectonic activity, and the current limitations in quantitatively modeling geothermal water circulation under specific geological conditions, a universal set of model parameters applicable across all hot springs within even the same tectonic region cannot be established. This highlights the necessity of anomaly detection model, which involves optimizing parameters specifically for individual hot springs based on their unique pre-seismic responses in different hydrochemical components. The model aims to leverage the inherent differences among these hydrochemical components, integrating them to enhance forecasting efficacy. Crucially, this methodological framework is transferable. For application in other tectonic regions, the model can be adapted by similarly optimizing the parameter combinations for the target hot spring(s) based on their specific hydrochemical components. This addresses the challenge posed by varying tectonic and hydrogeological conditions leading to divergent hydrochemical behaviors. By enabling the application of the model to hot spring monitoring in specific regions through this targeted parameter optimization, the model provides an attempt at a method to advancing earthquake forecasting.

 # *Specific comments:*

1. *#Lines 26-27 Please specify how these isotopes changes before earthquake.*

Response: We appreciate your comment. Indeed, directly observable significant changes in hydrochemical components before earthquakes are not commonly recorded across most seismic events and have been reported primarily in certain representative cases, often marked by high abnormal values (i.e., increased concentrations) (Skelton et al., 2014; Zhang et al., 2021; Gori and Barberio, 2022; Yan et al., 2022; Yakupoğlu et al., 2025). More frequently, precursory signals are subtle, which highlights the need for sensitive detection methods.

In this study, we employed a model designed to capture both conspicuous and subtle anomalies, with the aim of identifying more short-term precursory signals. As continuous hydrochemical monitoring continues to develop, there is a growing need to identify reliable hydrochemical indicators for practical earthquake forecasting applications, this is a key motivation of our work.

Based on existing understanding of pre-earthquake anomalies, our model was configured under the assumption that ion and isotope concentrations typically exhibit sustained high values prior to earthquakes. Specifically, the model triggers an alarm when the following conditions are met: If the daily value on day i−p2 exceeds p1 times the 15-day moving average on day i−p2−1, and simultaneously, the 15-day moving average on day i surpasses p3 times that on day i−p2, the system triggers an alarm on day i.

This logic effectively targets sustained increases in concentration, ensuring that both abrupt rises and gradual accumulations of ions/isotopes are captured. Therefore, the pre-earthquake changes in these hydrochemical components identified by the model are all sustained high-value anomalies.

Based on the above statement, we have added more details in Lines 26-27:

The model identified pre-earthquake high-value anomalies in Na^+, Ca^{2+}, Cl^-, SO_4^{2-}, δD, and $\delta^{18}O$, with a threat score (TS) value exceeding 0.50, which can serve as sensitive indicators for strong earthquake forecasting.

References:

Gori, F., Barberio, M. D.: Hydrogeochemical changes before and during the 2019 Benevento seismic swarm in central-southern Italy, Journal of Hydrology, 604, https://doi.org/10.1016/j.jhydrol.2021.127250, 2022.

Skelton, A., Andrén, M., Kristmannsdóttir, H., Stockmann, G., Mörth, C. M., Sveinbjörnsdóttir, Á., Jónsson, S., Sturkell, E., Guðrúnardóttir, H. R., Hjartarson, H., Siegmund, H., and Kockum, I.: Changes in groundwater chemistry before two consecutive earthquakes in Iceland, Nature Geoscience, 7(10), 752-756, https://doi.org/10.1038/ngeo2250, 2014.

Yakupoğlu, N., Sabuncu, A., Erbil, C., Kırkan E., Çetin H., and İnan S.: Pre-earthquake hydrogeochemical anomalies in spring waters: two distinctive cases from western Türkiye, Journal of Hydrology, 662, https://doi.org/10.1016/j.jhydrol.2025.133920, 2025.

Yan, Y., Zhou, X., Liao, L., Tian, J., Li, Y., Shi, Z., Liu, F., and Ouyang, S.: Hydrogeochemical Characteristic of Geothermal Water and Precursory Anomalies along the Xianshuihe Fault Zone, Southwestern China, water, 14(4),

https://doi.org/10.3390/w14040550, 2022.

Zhang, L., Guo, L., Zhou, X., Yang, Y., Shi, D., and Liu, Y.: Temporal variations in stable isotopes and synchronous earthquake-related changes in hot springs, Journal of Hydrology, 599, https://doi.org/10.1016/j.jhydrol.2021.126316, 2021.

2. *#Line 79 Please add relevant references for this statement.*

Response: We added two references to support this statement on line 79:

The hydrochemical components (e.g., Na^+, Cl^-, SO_4^{2-}) of thermal springs tend to exhibit high stability, rapid upward migration, and limited susceptibility to environmental interference (Luo et al., 2023; Yakupoğlu et al., 2025).

References:

Luo, Z., Zhou, X., He, M., Liang, J., Li, J., Dong, J., Tian, J., Yan, Y., Li, Y., Liu, F., Ouyang, S., Liu, K., Yao, B., Wang, Y., and Zeng, Z.: Earthquakes evoked by lower crustal flow: Evidence from hot spring geochemistry in Lijiang-Xiaojinhe fault, Journal of Hydrology, 619, https://doi.org/10.1016/j.jhydrol.2023.129334, 2023.

Yakupoğlu, N., Sabuncu, A., Erbil, C., Kırkan E., Çetin H., and İnan S.: Pre-earthquake hydrogeochemical anomalies in spring waters: two distinctive cases from western Türkiye, Journal of Hydrology, 662, https://doi.org/10.1016/j.jhydrol.2025.133920, 2025.

3. *#Line 89 what are the common machine learning algorithms.*

Response: We sincerely thank the reviewer for identifying the lack of clarity in this statement. Given the limited sample size inherent to earthquake precursor studies—owing to short monitoring histories and low seismic occurrence rates—data availability often precludes data-intensive deep learning architectures. Therefore, 'common machine learning algorithms' herein refer to widely adopted methods in hydrochemical anomaly detection, including Isolation Forest, Local Outlier Factor, Autoencoder, among others. We have revised the text to explicitly specify the algorithms referenced for clarity. The updated sentence on line 89 now reads:

Existing studies have demonstrated the effectiveness of widely adopted machine learning algorithms (e.g., Isolation Forest, Local Outlier Factor, and Autoencoder) in identifying abnormal periods in hydrochemical data while also emphasising the need for scenario-specific optimisation of key indicators (Zhu et al., 2024).

4. *#Line 172 Please provide the references for this equation and explain the meaning of each parameter.*

Response: Thank you for your feedback. We confirm the validity of this equation, with reference and parameter clarifications are provided in lines 171-174:

To ensure data accuracy, cation–anion balance error tests were performed for each sample, with all ionic deviations kept within ± 5%. The ion balance error (Appelo and Postma, 2004) is calculated as below:

$$ib(\%) = \frac{\sum cations - \sum anions}{\sum cations + \sum anions} \times 100 \quad (1)$$

where $\sum cations$ represents the sum of cation concentrations (in milliequivalents per liter, meq/L), and $\sum anions$ represents the sum of anion concentrations.

References:

Appelo, C.A.J., and Postma, D.: Geochemistry, Groundwater and Pollution (2nd ed.), A.A. Balkema Publishers, Leiden, 17pp, ISBN04 1536 428 0, 2004.

5. *#Line 186-187 Ambiguous. Consider rephrasing it to: '22 earthquakes with $M \geq 4$'.*

Response: We agree with the reviewer's point and will revise the sentence accordingly for clarity. The revised part is:

The QJ site was within the preparation zones of 22 earthquakes with $M \geq 4$ during its monitoring period (2019/06/01–2024/05/21), while the WN site was within the preparation zones of 12 earthquakes with $M \geq 4$ during its observation period (2021/10/03–2024/05/21) (Table S1).

6. *#Line 203 Please explain why you chose ω=1. Have you conducted a sensitivity analysis?*

Response: Thank you for raising this important point. In this study, ω serves as a coefficient in the seismic moment distance attenuation correction, which was introduced to optimize and quantify the potential correlation between seismic moment and hydrochemical component. Based on previous research focused on radon (Rn), values of ω = 1.3 and ω = 3 have been commonly adopted (Piersanti et al., 2016). We conducted a sensitivity analysis by testing multiple ω values (including 0, 0.5, 1, 1.5, 2, 2.5, and 3) and observed that the correlation peak consistently emerged within the same lag range across all ω settings. Among these, ω = 1 produced the pronounced correlation result (Figure S5).

We apologize for not providing a more detailed explanation in the original manuscript. Since ω is not a critical parameter in the model and does not affect the prediction target of M ≥ 4 earthquakes, we did not include an extensive sensitivity analysis. However, in response to your comment, we will be happy to add these details in the Supplementary Materials to improve the clarity of our approach.

The supplementary information is as follows:

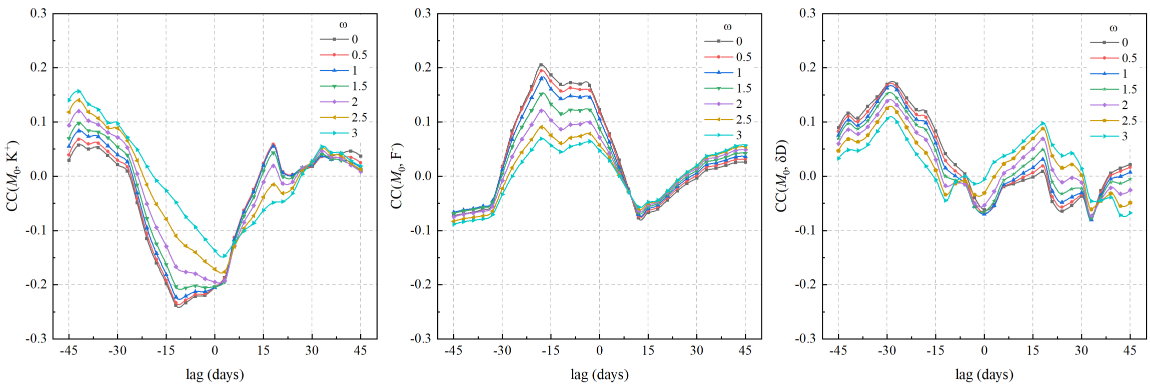

Figure S5. Cross-correlation function analysis of the 15-day moving average time series of hydrochemical components and distance-corrected seismic moment for multiple ω values (including 0, 0.5, 1, 1.5, 2, 2.5, and 3).

Figure S5 presents the cross-correlation analysis results between M_0 with different ω values and K^+, F^-, and δD, which represent the cations, anions, and water isotopes with prominent correlations, respectively. The ω values range from 0 to 3 with a step increment of 0.5. As ω varies, the peak of the lag time remains stable, indicating that relationships exist between M_0 and hydrochemical components at specific lag times. When ω takes values of 0, 0.5, and 1, the cross-correlations are relatively significant and exhibit minimal difference. Therefore, considering the practical physical significance, this study selects a ω value of 1.

References:

Piersanti, A., Cannelli, V., and Galli, G.: The Pollino 2012 seismic sequence: clues from continuous radon monitoring, Solid Earth, 7(5), 1303-1316, https://doi.org/10.5194/se-7-1303-2016, 2016.

7. #Line 238 Please explain why a 15-day backward moving average is applied.

Response: We thank the reviewer for their comment regarding the use of the 15-day backward moving average. This data processing step is fundamental in earthquake-related fluid geochemistry for the following reasons:

Noise filtration and signal preservation: The primary purpose is to effectively filter out short-term, high-frequency noise, predominantly caused by rainfall infiltration and dilution effects, which create sharp spikes in the data. Ambient temperature and atmospheric pressure at the spring outlet are ignored because they have a negligible effect on the hydrochemistry. Simultaneously, this window size is optimal for preserving medium-to-long-term trends that are more likely to be associated with tectonic processes, such as crustal strain and deep fluid migration.

Objective of short-term forecasting: The model is applied to enhance our capability for short-term and imminent earthquake forecasting (within a 45-day window). So, the moving average window time is set to be shorter than the earthquake response time threshold (45 days).

Common practice in the field: The use of a moving average over this timescale (e.g., 14-day) is a well-established methodology in precursory fluid geochemical analysis, as evidenced by its application in numerous previous studies (Piersanti et al., 2016; Fu et al., 2017; Zhao et al., 2021). We use a 15-day window, which is more applicable to 3-day resolution data.

Operational utility for real-time monitoring: We specifically employed a backward-looking moving average because it is practically viable for real-time data monitoring and analysis. This approach allows for the continuous updating of the baseline trend as each new data point arrives, which is essential for timely earthquake forecasting.

References:

Fu, C., Yang, T., Tsai, M., Lee, L., Liu, T., Walia, V., Chen, C., Chang, W., Kumar, A., and Lai, T.: Exploring the relationship between soil degassing and seismic activity by continuous radon monitoring in the Longitudinal Valley of eastern Taiwan, Chemical Geology, 469, 163-175, https://doi.org/10.1016/j.chemgeo.2016.12.042, 2017.

Piersanti, A., Cannelli, V., and Galli, G.: The Pollino 2012 seismic sequence: clues from continuous radon monitoring, Solid Earth, 7(5), 1303-1316, https://doi.org/10.5194/se-7-1303-2016, 2016.

Zhao, Y., Liu, Z., Li, Y., Hu, L., Chen, Z., Sun, F., and Lu, C.: A case study of 10 years groundwater radon monitoring along the eastern margin of the Tibetan Plateau and in its adjacent regions: Implications for earthquake surveillance, Applied Geochemistry, 131, https://doi.org/10.1016/j.apgeochem.2021.105014, 2021.

8. *#Line 250 Please cite references here about this definition.*

Response: We included two new citations in the sentence on Line 250:

The cross-correlation function (Chatfield, 1975; Brockwell and Davis, 1991) is defined as:

References:

Brockwell, P. J., and Davis, R. A.: Time Series: Theory and Methods (Second Edition), Springer-Verlag, New York, 407pp, ISBN978-1-4419-0319-8, 1991.

Chatfield, C.: The Analysis of Time Series: Theory and Practice, Chapman and Hall, New York, 173pp, ISBN978-0-412-14180-5, 1975.

9. *#Line 315 This paragraph is more like results and discussion (limitation). It is not appropriate to present here.*

Response: We sincerely thank you for this insightful comment. We agree entirely that the paragraph in question, which discusses the limitations of our findings, is more appropriately placed in the Results and discussion section rather than where it was previously located. Our intention was not to present a full limitations section prematurely, but rather to use the inherent limitations of Bayesian analysis as a direct motivator and contrasting backdrop for introducing our detection model. However, we appreciate that deviating from standard structure can be disruptive. We have followed this suggestion and have moved this paragraph to the Results and discussion section of the manuscript.

10. *#Line 577 Please describe this conclusion in more detail.*

Response: We are grateful for your thoughtful comment. We agree completely that providing more detail will significantly strengthen the clarity and impact of our conclusion. In response, we have revised the conclusion in Line 577 to provide a more comprehensive and clearer summary:

The anomaly detection model demonstrates reliable real-time anomaly detection capabilities, with POD ranging from 0.83 to 0.95 and TS between 0.59 and 0.70, and it shows similar anomaly detection results across different springs to the same earthquake. The model identifies Na^{+}, Ca^{2+}, Cl^{-}, SO_4^{2-}, δD, and $\delta^{18}O$ can serve as effective indicators for strong earthquakes forecasting, all showing pre-earthquake high values and TS above 0.50. Among these, δD and $\delta^{18}O$ exhibit higher sensitivity to seismic activity, characterized by multiple consecutive anomalies pre-earthquake.