A data-driven model for the prediction of stimulated reservoir volume (SRV) evolution during hydraulic fracturing

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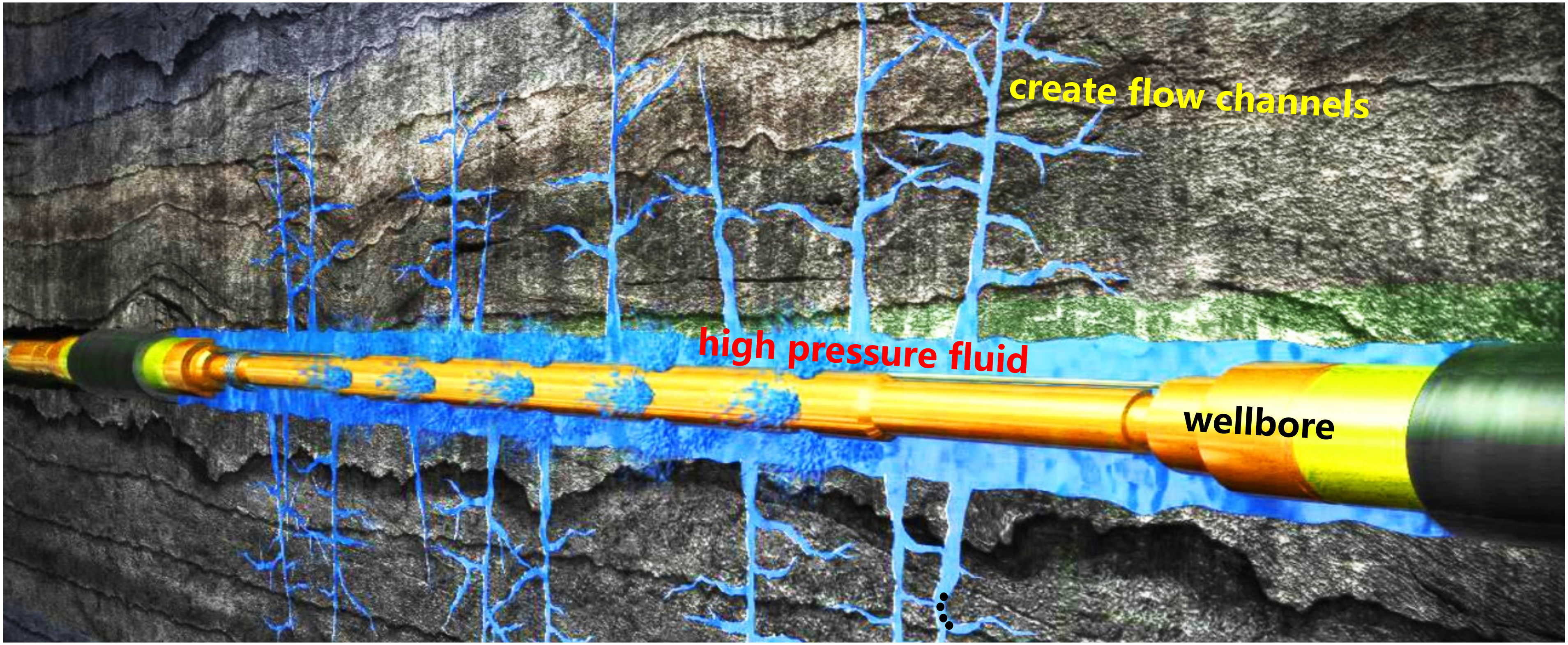
1. Introduction

1. Introduction

a) About Hydraulic Fracturing (HF)
b) The Mechanism of Microseismicity
c) What can microseismicity tell us? --Stimulated Reservoir Volume (SRV)
d) How can we predict SRV during HF?

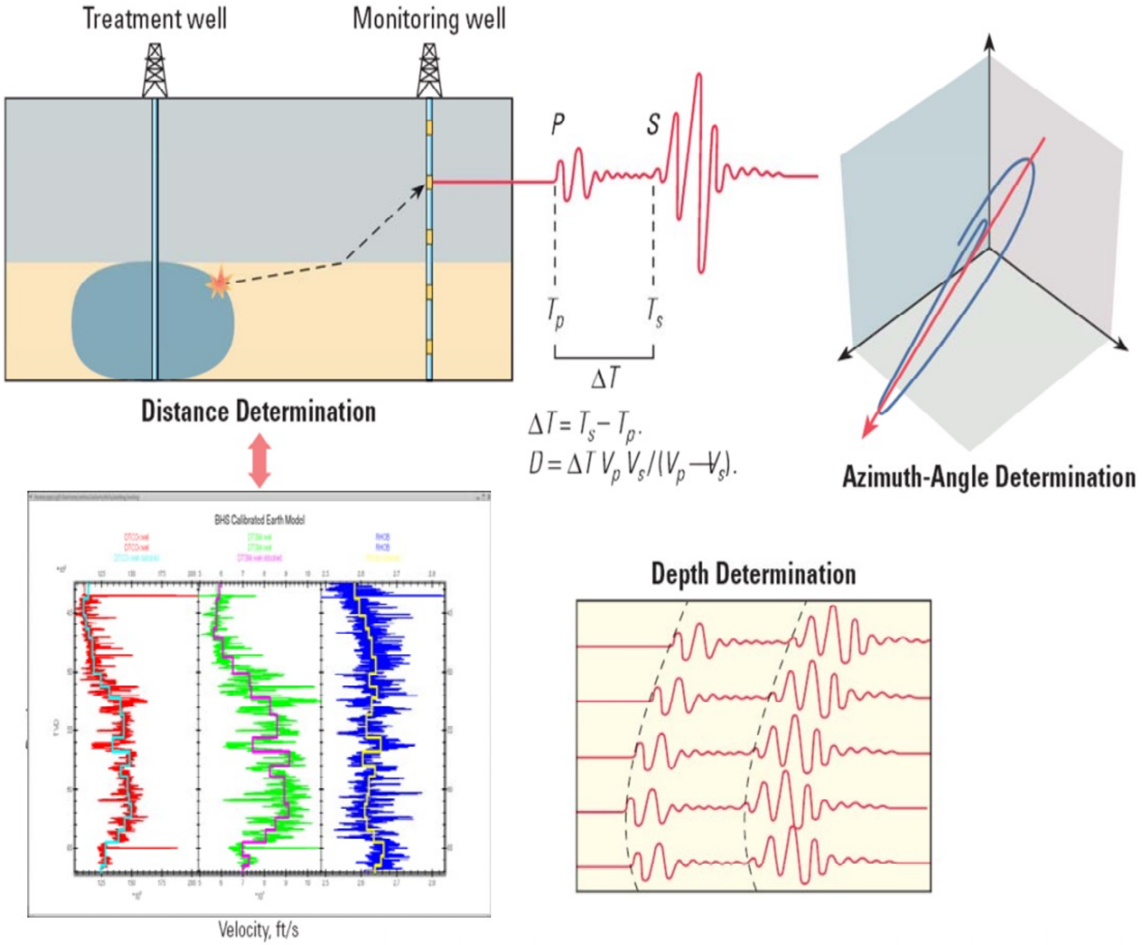
1. Introduction

a) About Hydraulic Fracturing (HF)



1. Introduction

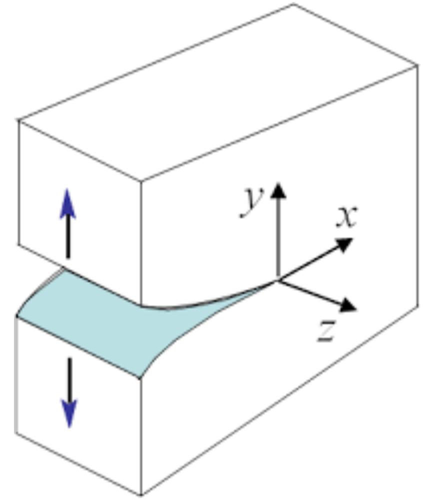
b) Mechanism of Microseismicity

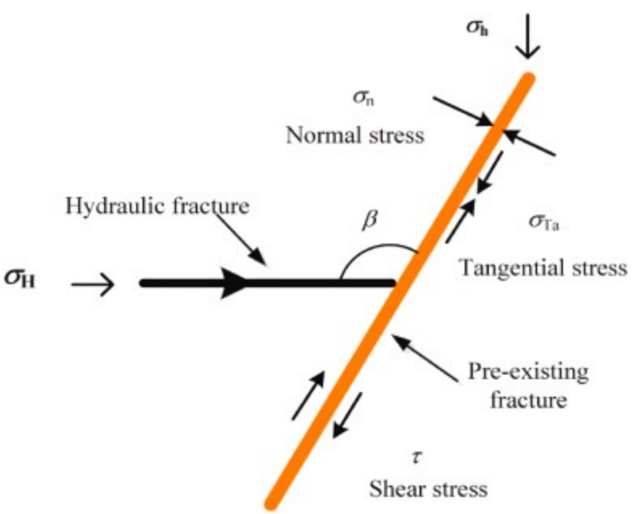


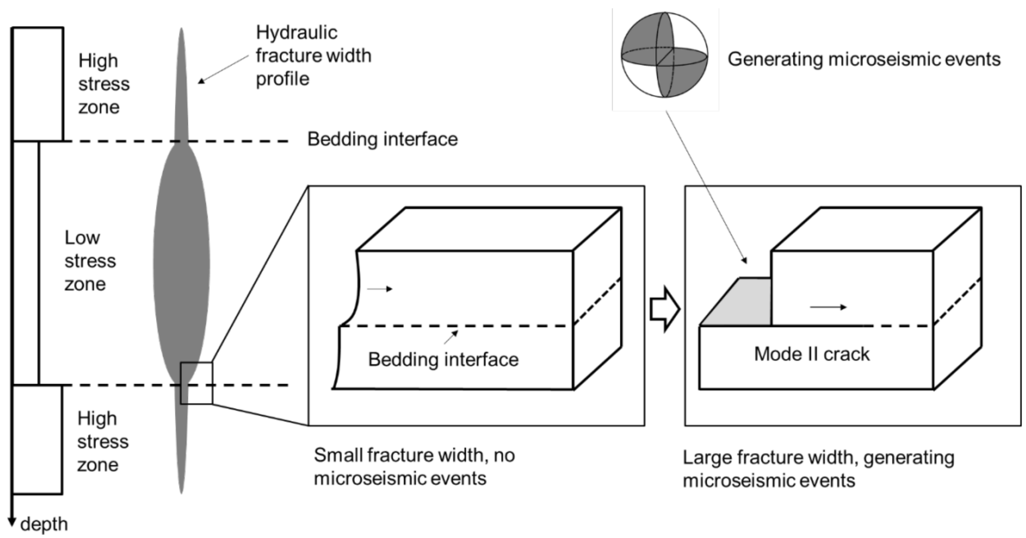
1. Introduction

b) Mechanism of Microseismicity

- Tensile opening
- Natural fracture slip
- Bedding plane slip







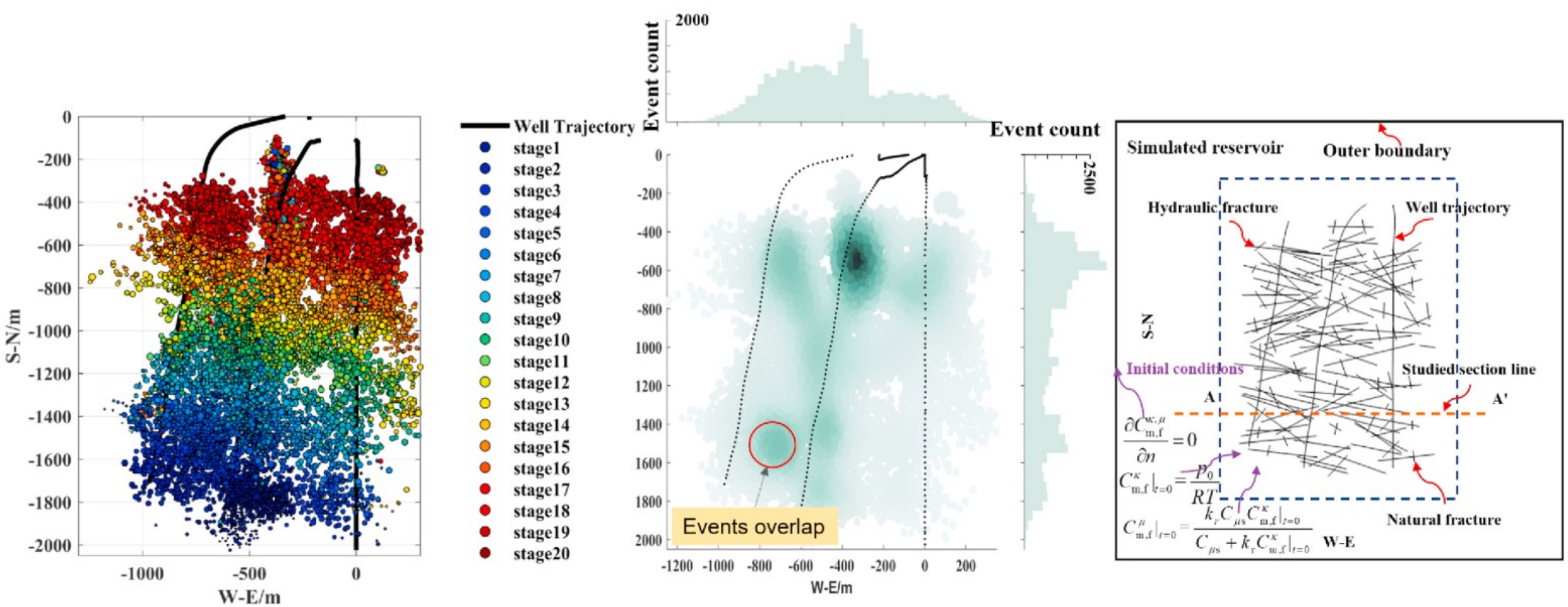
Tan et al., 2021

1. Introduction

c) What can microseismicity tell us?

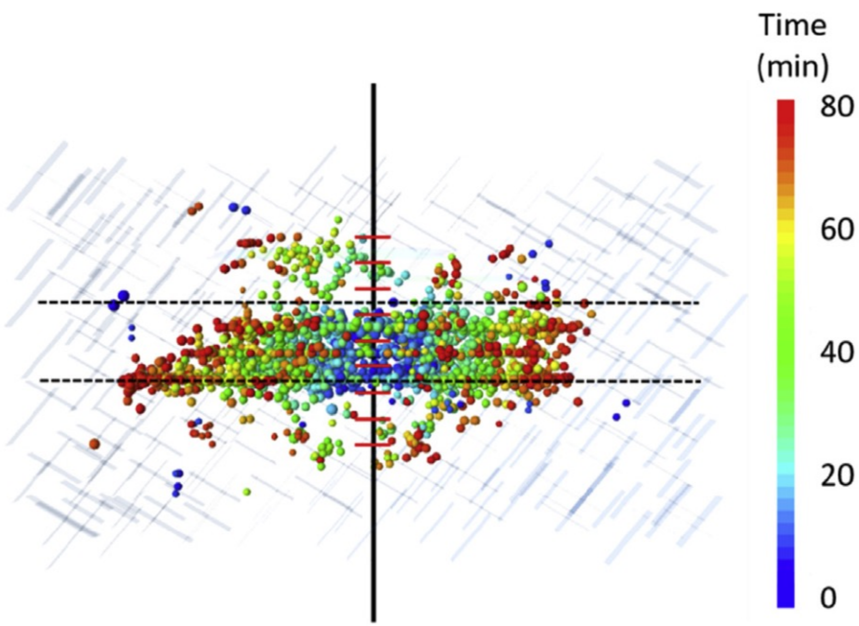
- determine the discrete fracture network (DFN)
- identify the state of stress in the vicinity of the treatment
- evaluate the geometry and complexity of hydraulic fractures
- … …

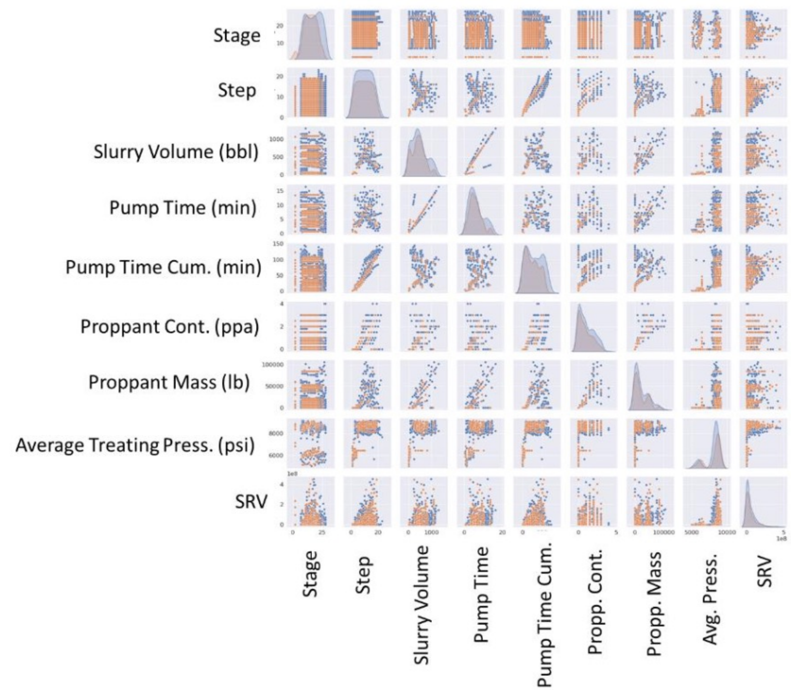
➡ *Stimulated Reservoir Volume (SRV)*



1. Introduction

d) How can we predict SRV during HF?



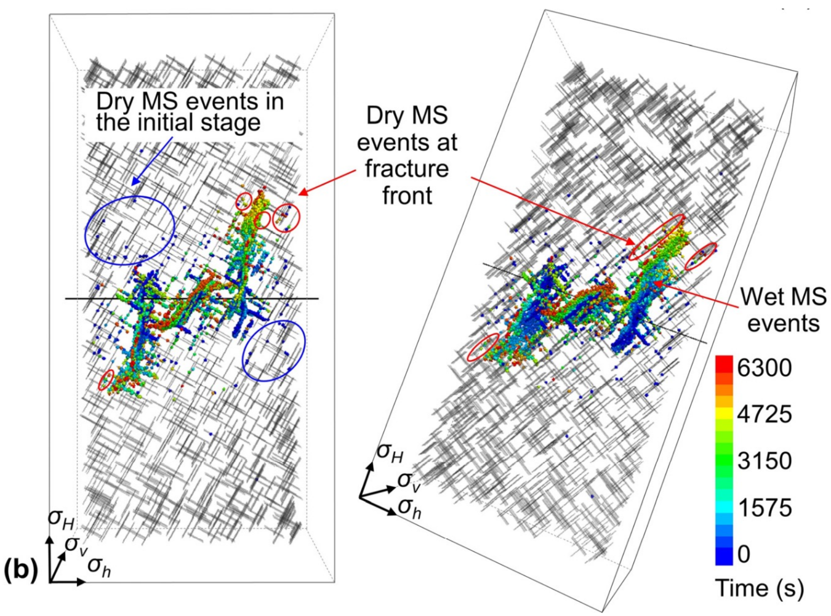


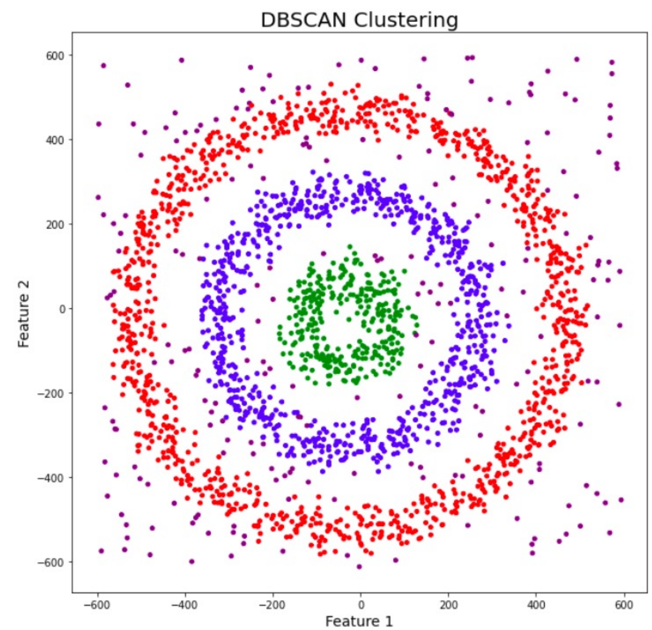
Physics-based models or Data-driven models

2. Method

2. Method

SRV calculation:

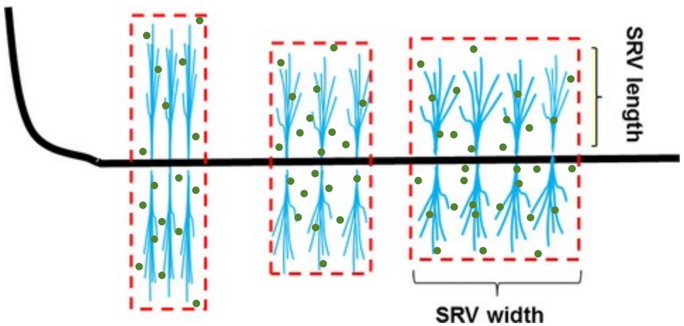




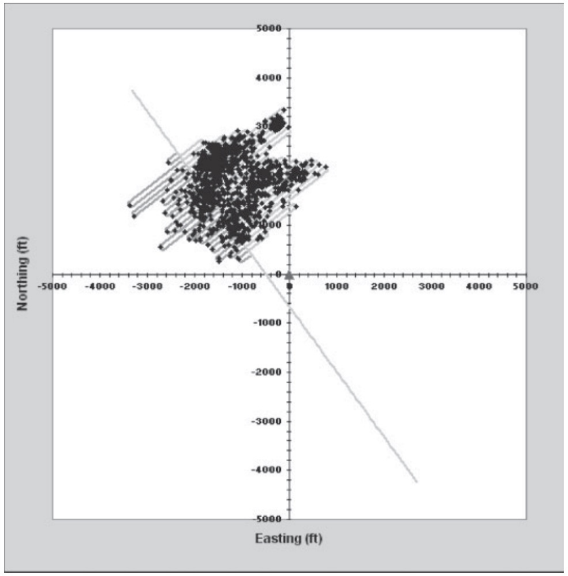
A spatiotemporal density-based clustering algorithm called ST-DBSCAN (*Birant & Kut 2007*) is firstly employed to exclude some 'dry' Micro-Seismic Events (MSEs). These dry events are defined as the events isolated from most MSEs near the hydraulic fractures (which are referred to as 'wet' events). Accounting for the dry events in the SRV calculation will overestimate SRV (*Maxwell et al. 2015*).

2. Method

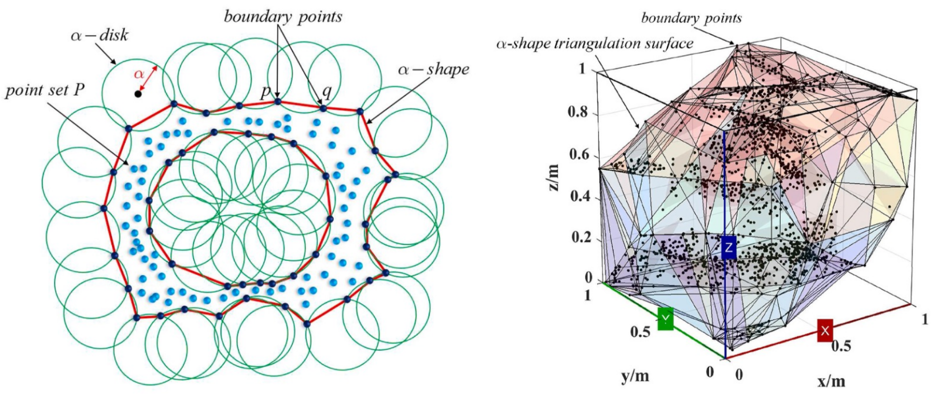
SRV calculation:



treat as simple cubics



bin method



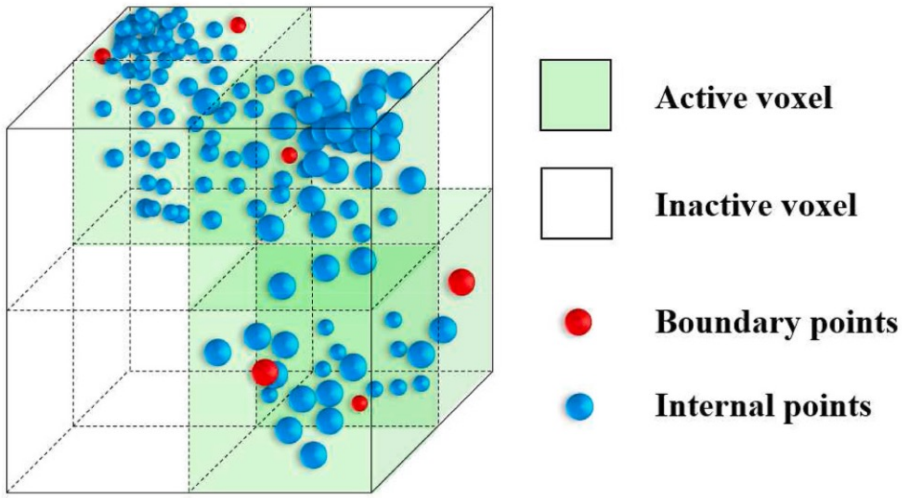
(a) 2D example of alpha shape

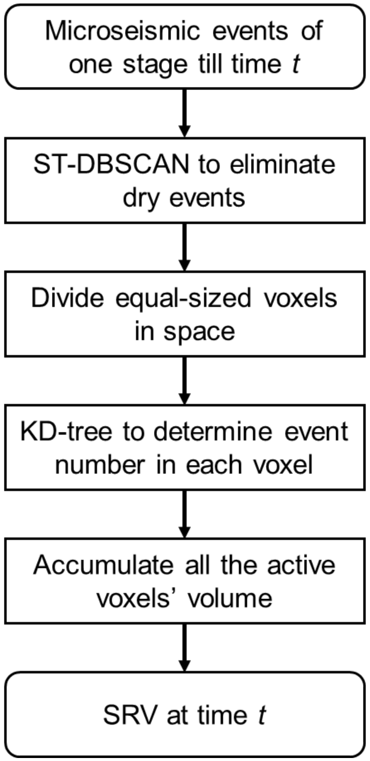
(b) 3D example of alpha shape

shape method

2. Method

SRV calculation:



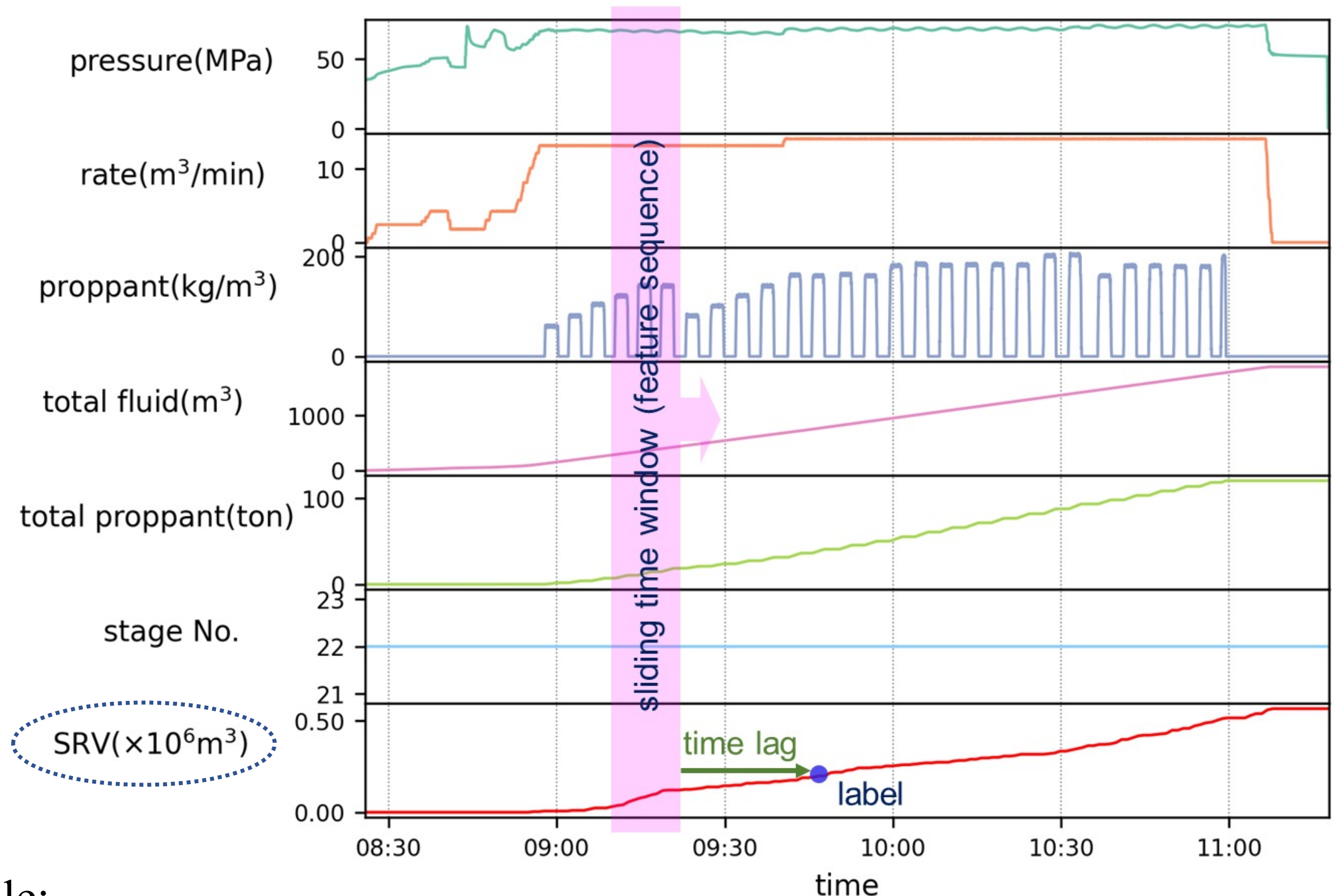


The voxelized method (*Liu et al. 2022*)

The three-dimensional space is discretized into homogeneous and non-overlapping voxels. The size of each voxel is 15m×15m×15m. The discretized voxels are indexed by an index matrix. The binary tree algorithm named K-Dimensional Tree is then used to efficiently search the number of MSEs in each voxel. A voxel is regarded as active and stimulated if the number of MSEs exceeds a threshold. SRV is acquired by accumulating all the active voxels in space.

2. Method

Data-driven model (sample):



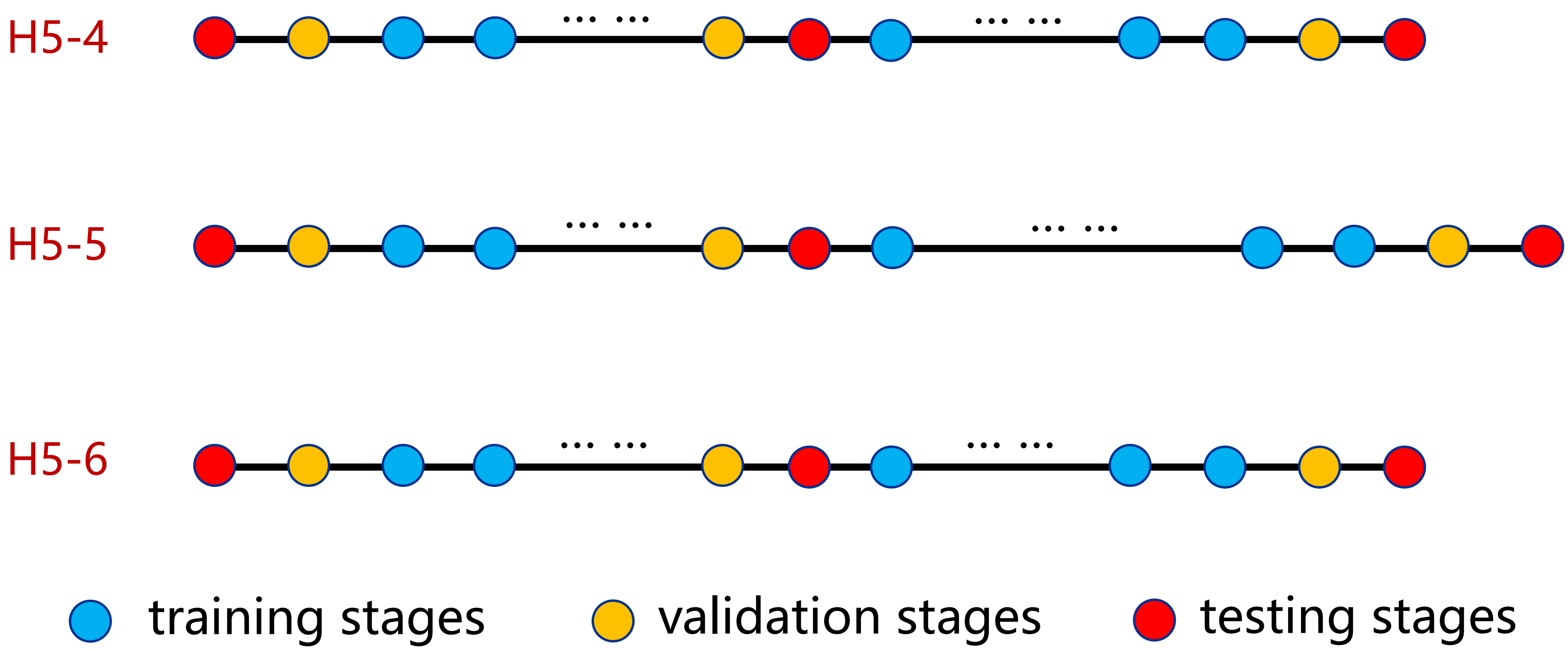
For example:

The features recorded from the 1st to the 10th min are used to predict the label at the 25th min.

2. Method

Data-driven model (dataset):

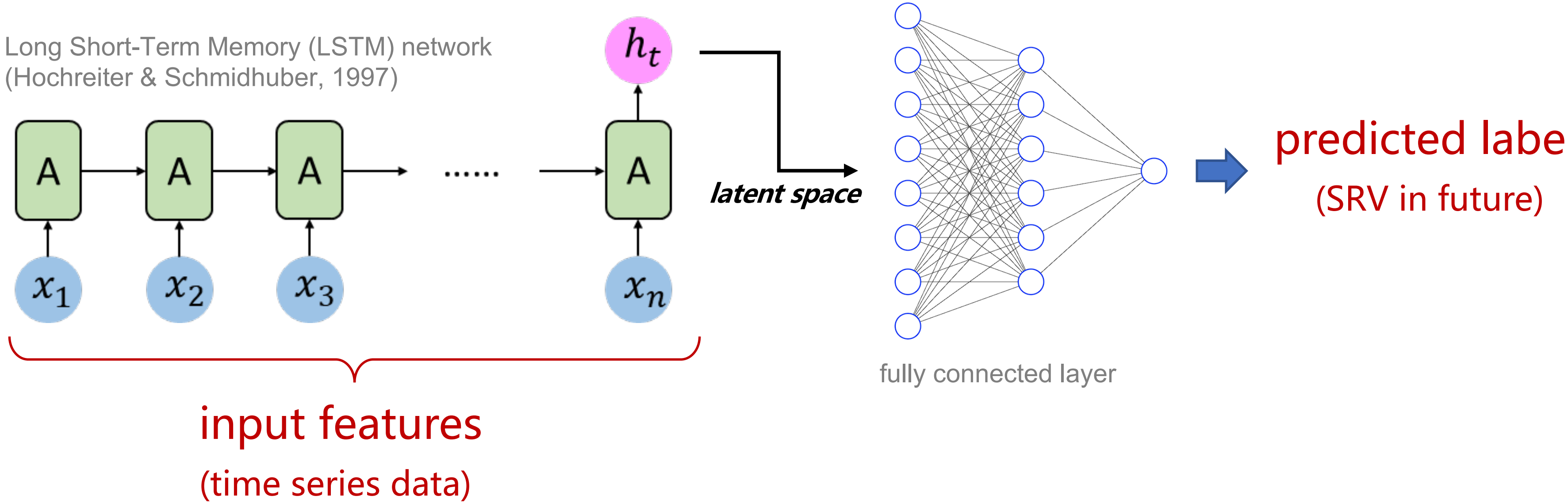
Treatment parameters & microseismicity records collected from Changning block, Sichuan Basin

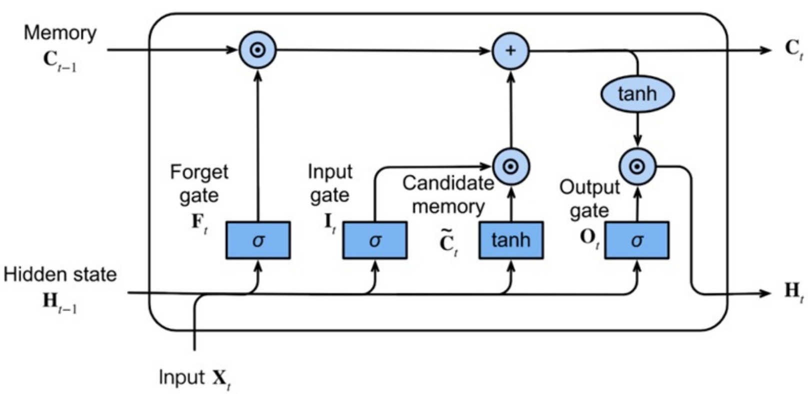


total: 71 stages, 11994 samples

2. Method

Data-driven model (neural network):





$$I_t = \sigma(X_t W_{xi} + H_{t-1} W_{hi} + b_i)$$
$$F_t = \sigma(X_t W_{xf} + H_{t-1} W_{hf} + b_f)$$
$$O_t = \sigma(X_t W_{xo} + H_{t-1} W_{ho} + b_o)$$
$$\tilde{C}_t = \tanh(X_t W_{xc} + H_{t-1} W_{hc} + b_c)$$
$$C_t = F_t \odot C_{t-1} + I_t \odot \tilde{C}_t$$
$$H_t = O_t \odot \tanh(C_t)$$

3. Results

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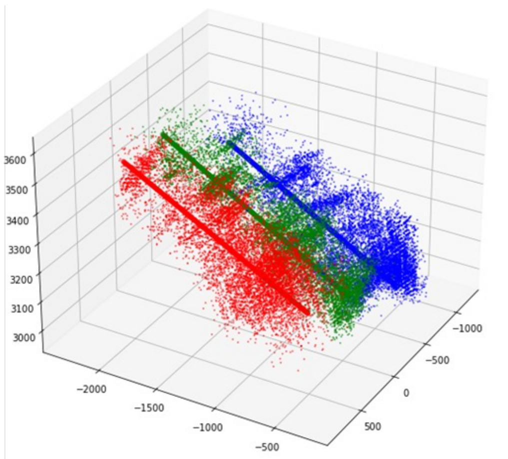
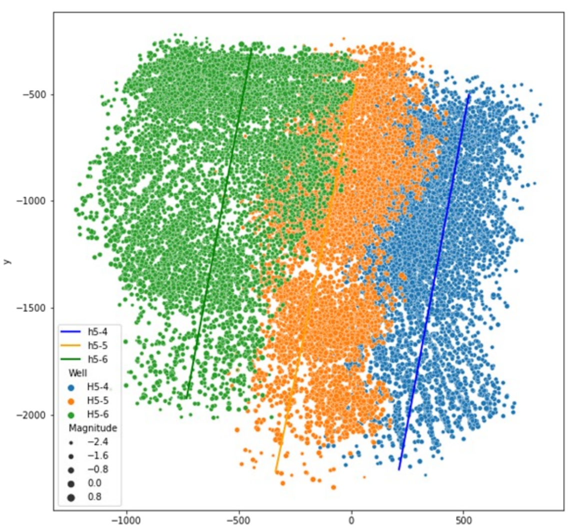
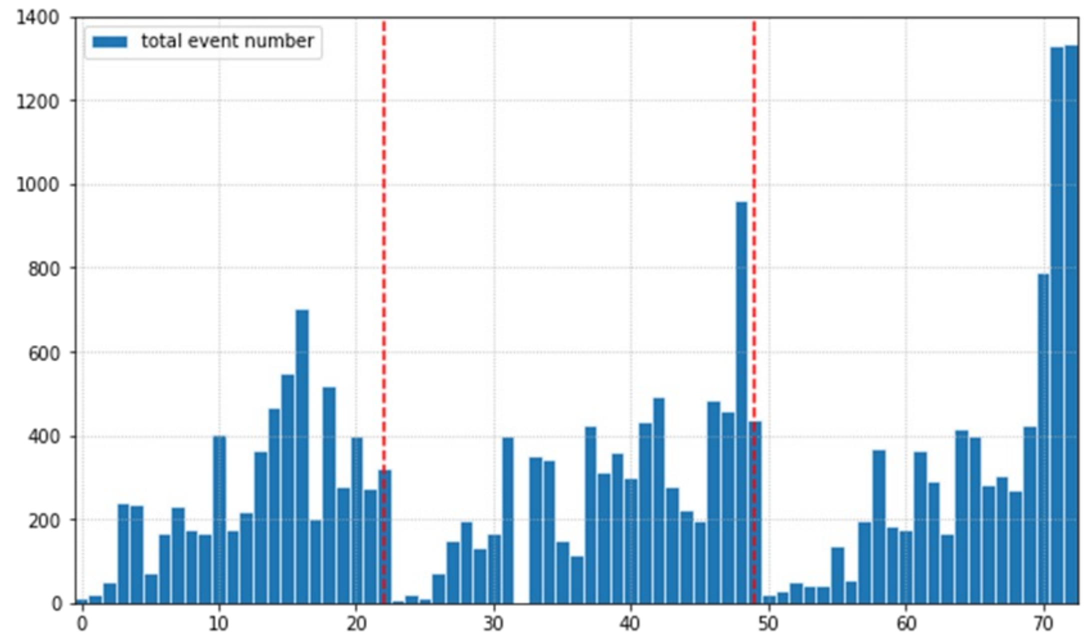
Microseismicity distribution



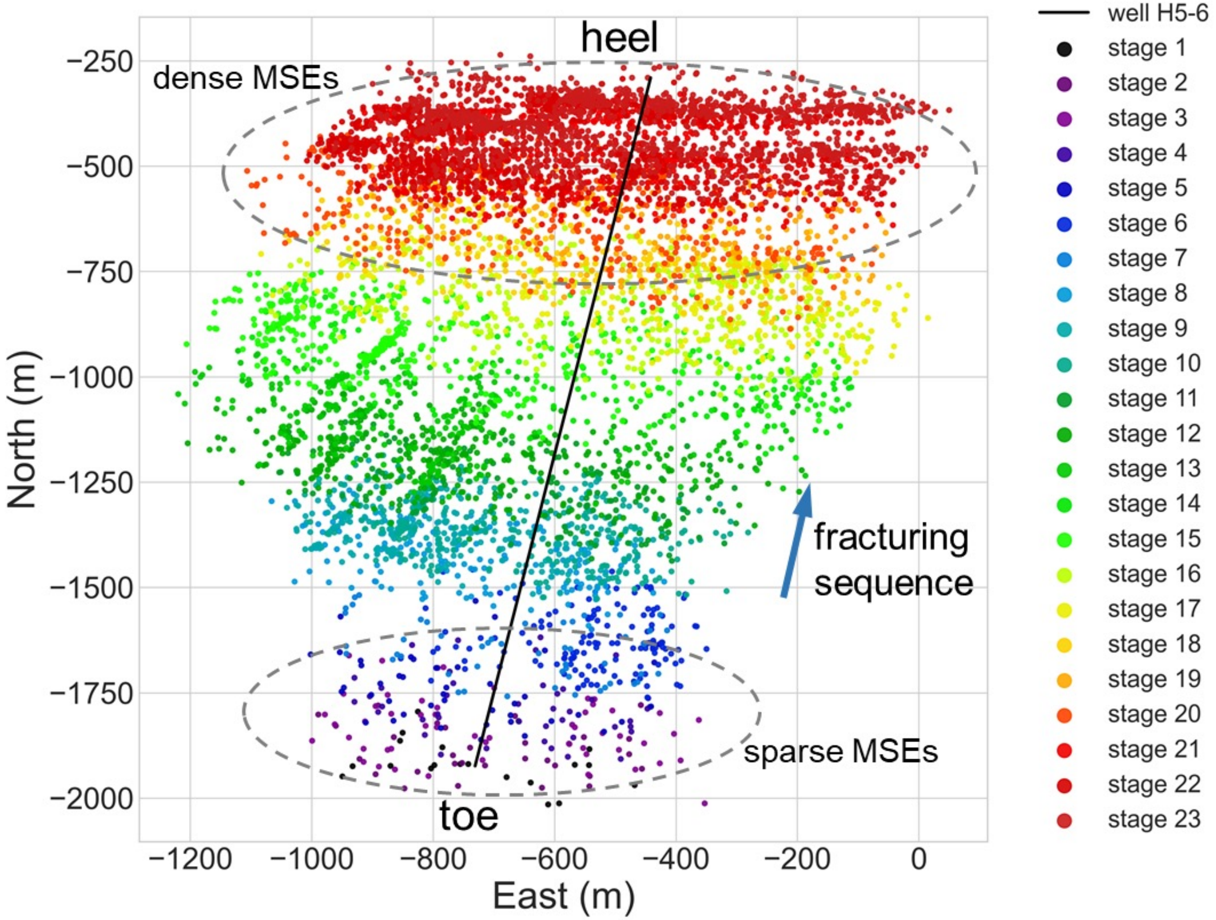




H5 platform

3. Results

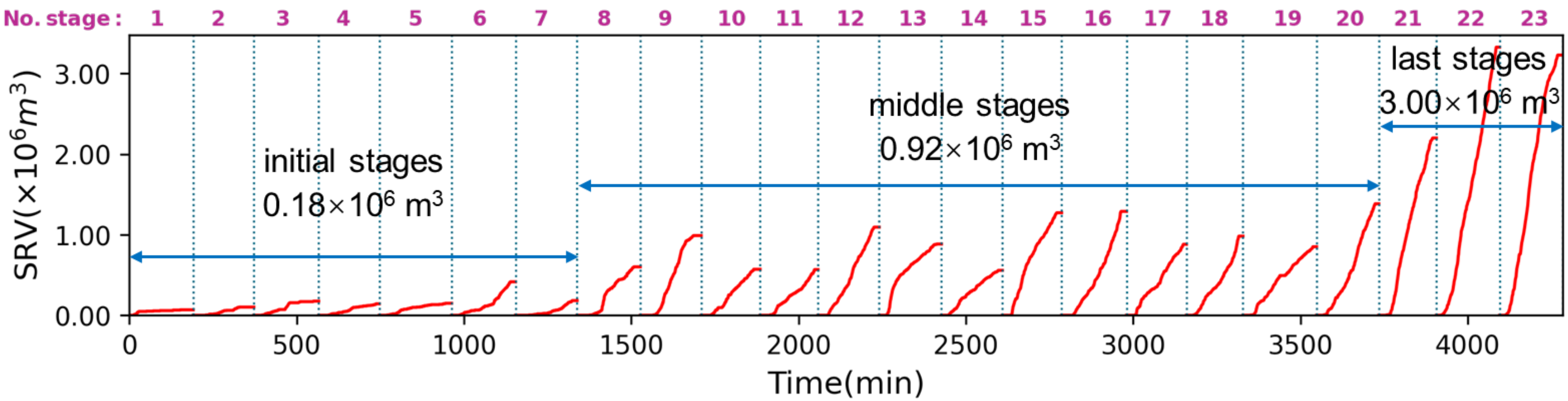
Microseismicity distribution



H5-6

3. Results

Microseismicity distribution



flat curves → steep curves

18w m^3 → 300w m^3

why?

① First, in-situ rock of the initial stages tends to be undisturbed and less cracked before fracturing treatment, thus making it difficult to be stimulated compared with the following stages.

② Second, due to the decrease of stress anisotropy by the stress shadow effect, hydraulic fractures at subsequent stages tend to generate more complex and branching networks (*Feng et al. 2023*).

3. Results

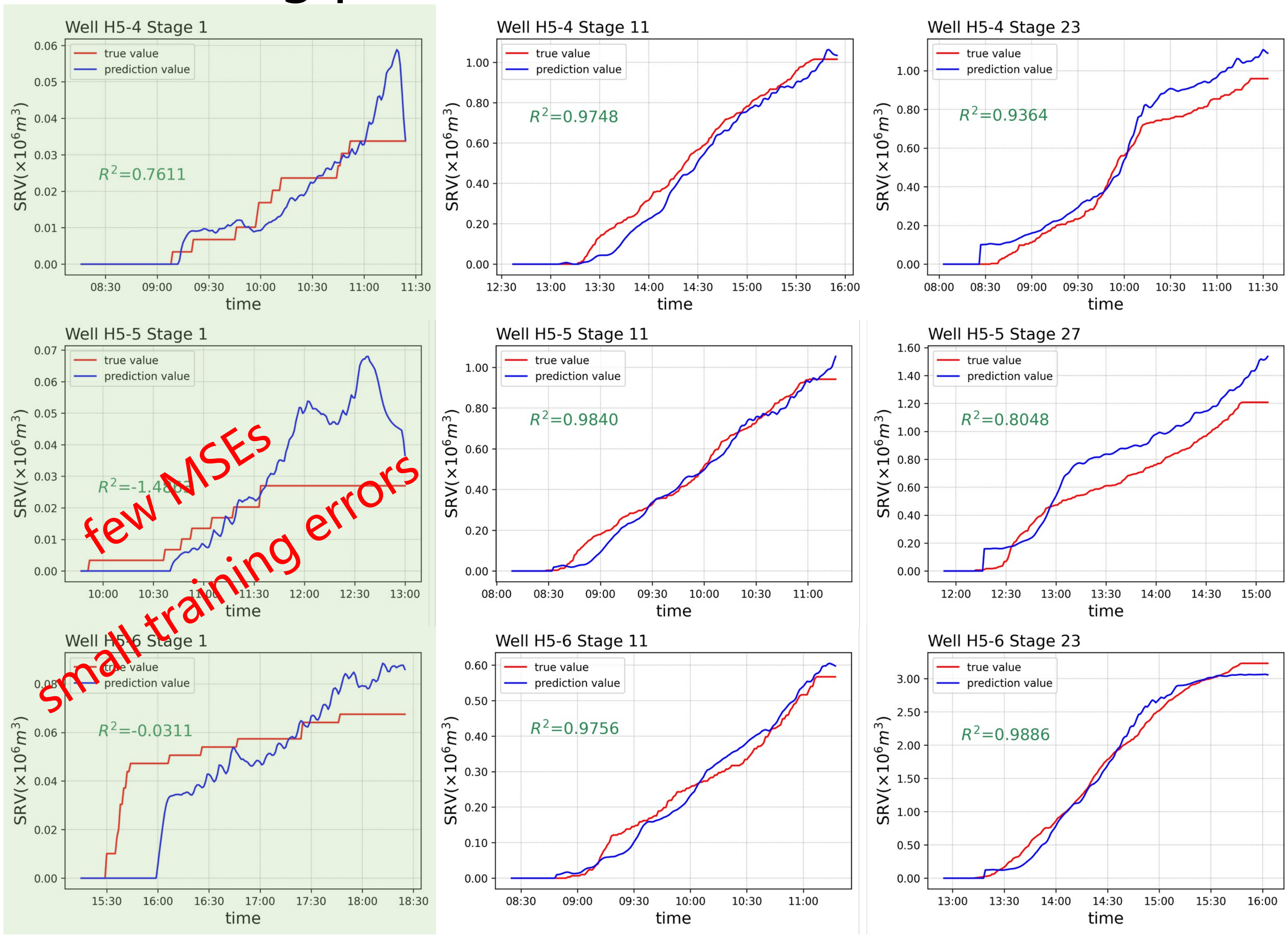
$$R^2 = 1 - \frac{\sum (y^i - \hat{y}^i)^2}{\sum (y^i - \bar{y})^2}$$

Machine learning predictions

H5-4

H5-5

H5-6



4. Discussion

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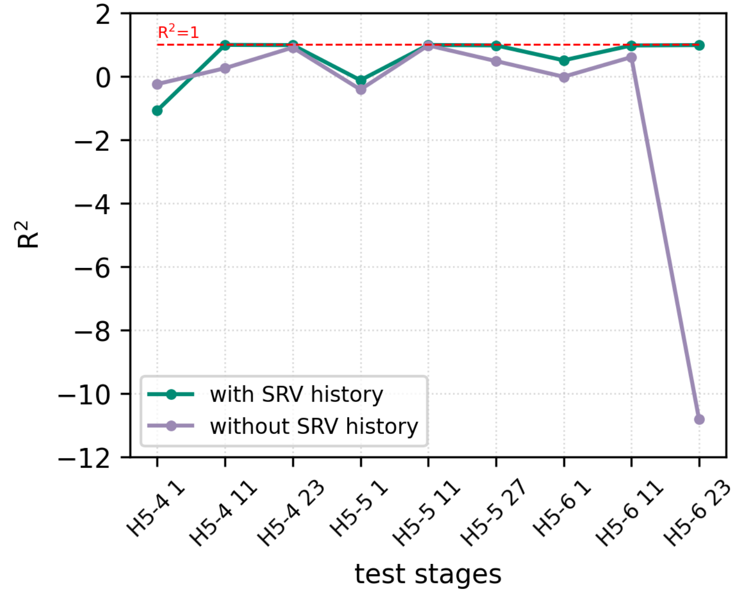
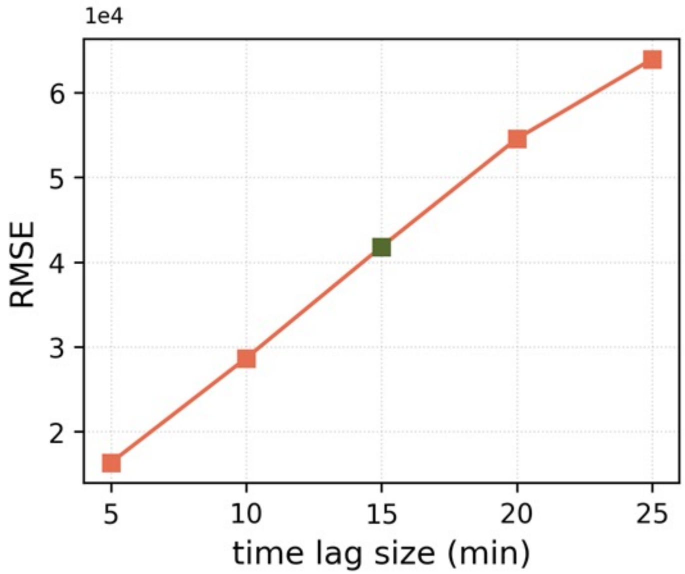
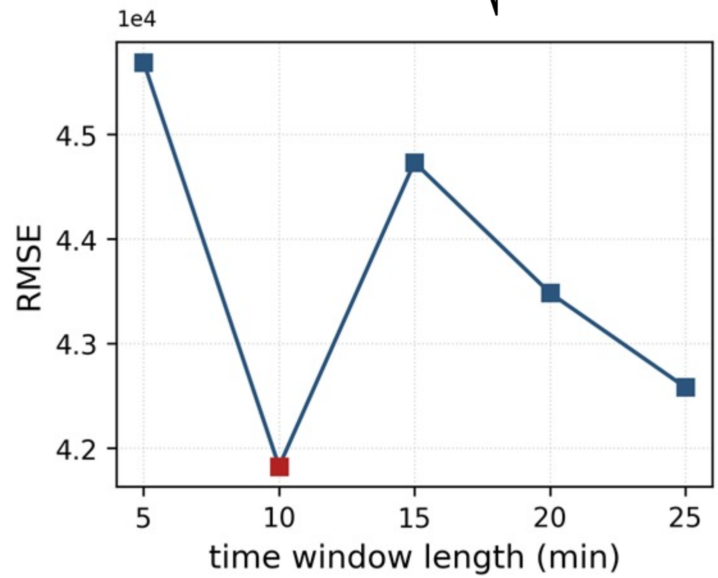


- Including SRV history as one feature will improve prediction accuracy, which means MSEs still need to be monitored and interpreted timely in field application.
- However, thanks to the fast development of machine learning technologies in geoscience, real-time source location of MSEs is currently feasible. A recent work by *Chen et al (2022)* reported an efficient (e.g., within 1 s) microseismic source localization method based on a random forest model.

4. Discussion

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y^i - \hat{y}^i)^2}$$





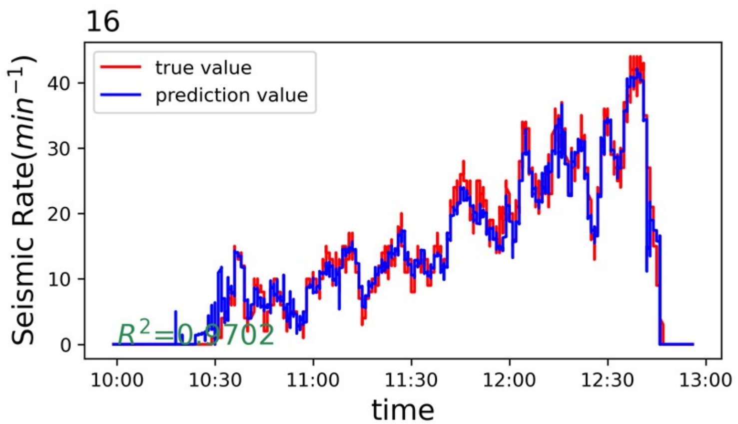
- There is a tradeoff relationship between time lag size and prediction accuracy. A larger time lag size degrades the performance of the model in that it is more difficult for the model to predict the SRV far away from now.
- The second figure confirms the rationality of choosing the past 10 minutes' information as inputs (i.e., the length of the time window is 10 minutes) since it produces the most accurate prediction

5. Conclusions

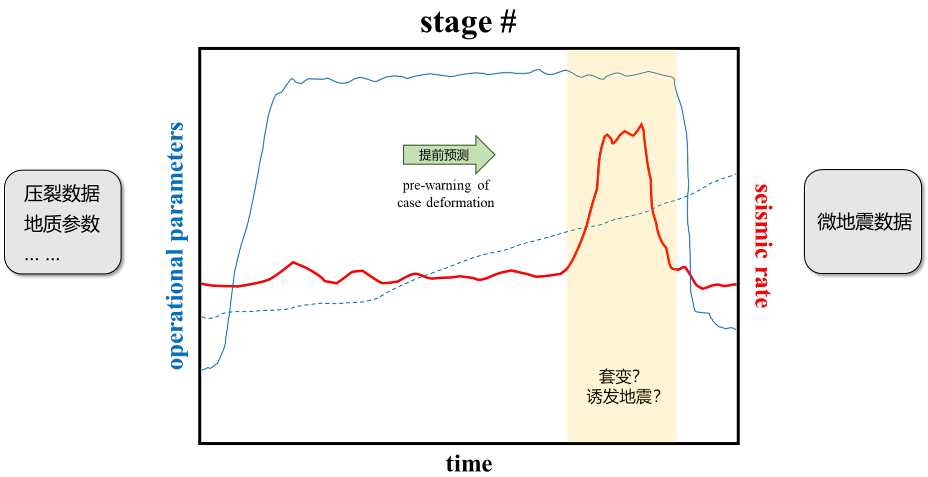
- This study presents a data-driven model for the prediction of SRV at a future moment during multi-stage hydraulic fracturing.
- A voxelize method is applied to calculate SRV values based on field monitored MSEs.
- The LSTM network is leveraged to extract information in sequence data including fracturing parameters and SRV history.
- The evolution of SRV varies in different stages but is well captured by the proposed model except the initial stages.
- The influence of the SRV history, the time lag size and the sliding time window length on model performance is investigated. The proposed model with a 10-minute sliding window and a 15-minute time lag produces the best performance.

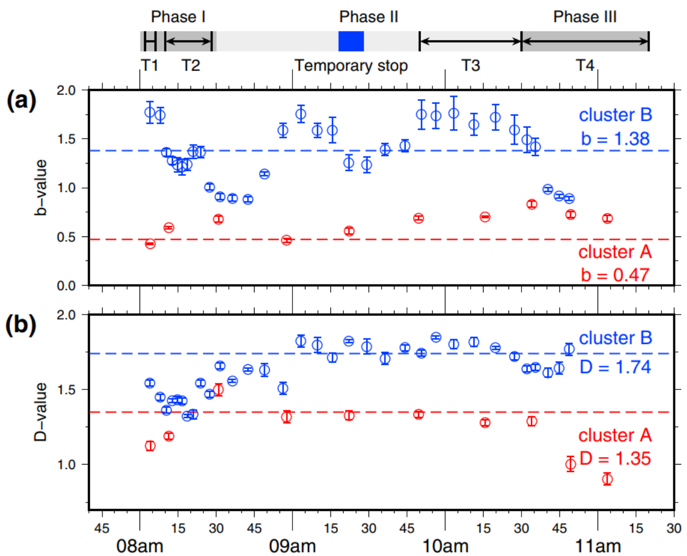
Next …

- collect more data from Sichuan Basin
- take advantage of geological data
- opt 1: determine label for reservoir assessment/optimization (SRV)
- opt 2: determine label for indicating induced seismicity/case deformation
- employ more machine learning models



Yu et al., JGR, 2023





Chen et al., JGR, 2018

Thank you !

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