Training for seismic and tsunami warning operators on strengthening standard operating procedures for seismic data and tsunami warning in the South China Sea region

Advances of automatic earthquake processing of China Seismic Networks

Lihua Fang

Institute of Geophysics, China Earthquake Administration

Chine Earthquake Networks Center

2021-12-09

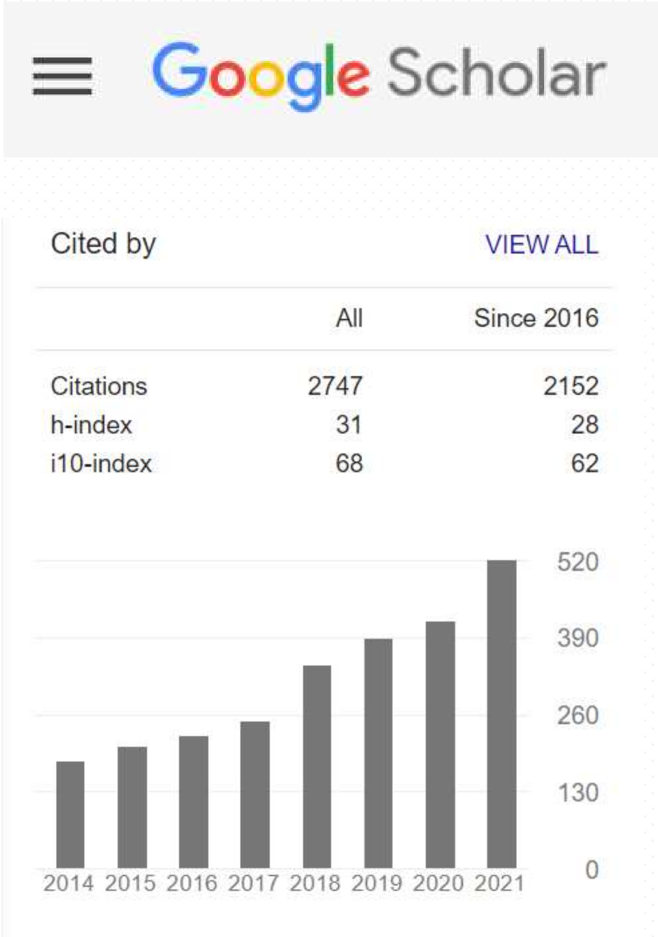
Lihua Fang

https://www.researchgate.net/profile/Lihua-Fang-3

https://scholar.google.com/citations?user=ENeCjMYAAAAJ&hl=en

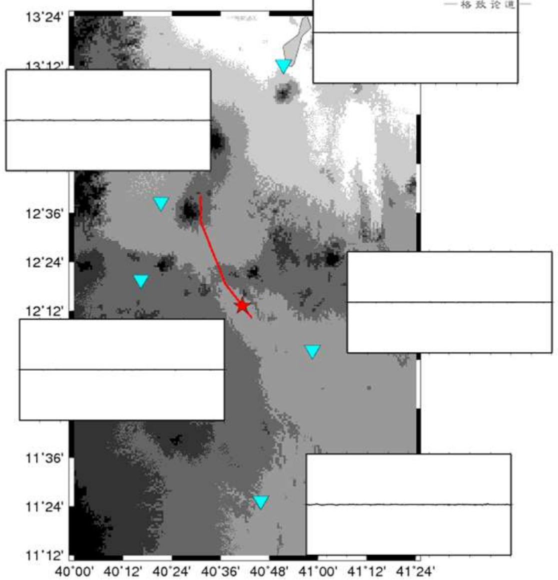
He currently works at the Institute of Geophysics, China Earthquake Administration. He is the director of the Seismology division. He is the vice director of the Key Laboratory of the Earthquake source Physics of the CEA.

His research interests include ***artificial intelligence in seismology, fine-scale earthquake relocation, ambient noise tomography***, and so on. He is the editorial committee of *Earthquake Science, Acta Seismologica Sinica, Earthquake Research Advances*, and so on. He hosted many special issues about AI Seismology for SRL, ERA, Chinese Journal of Geophysics.

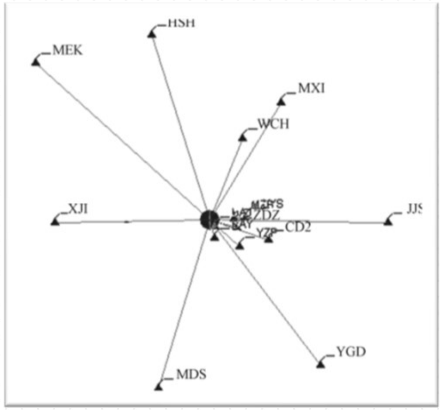


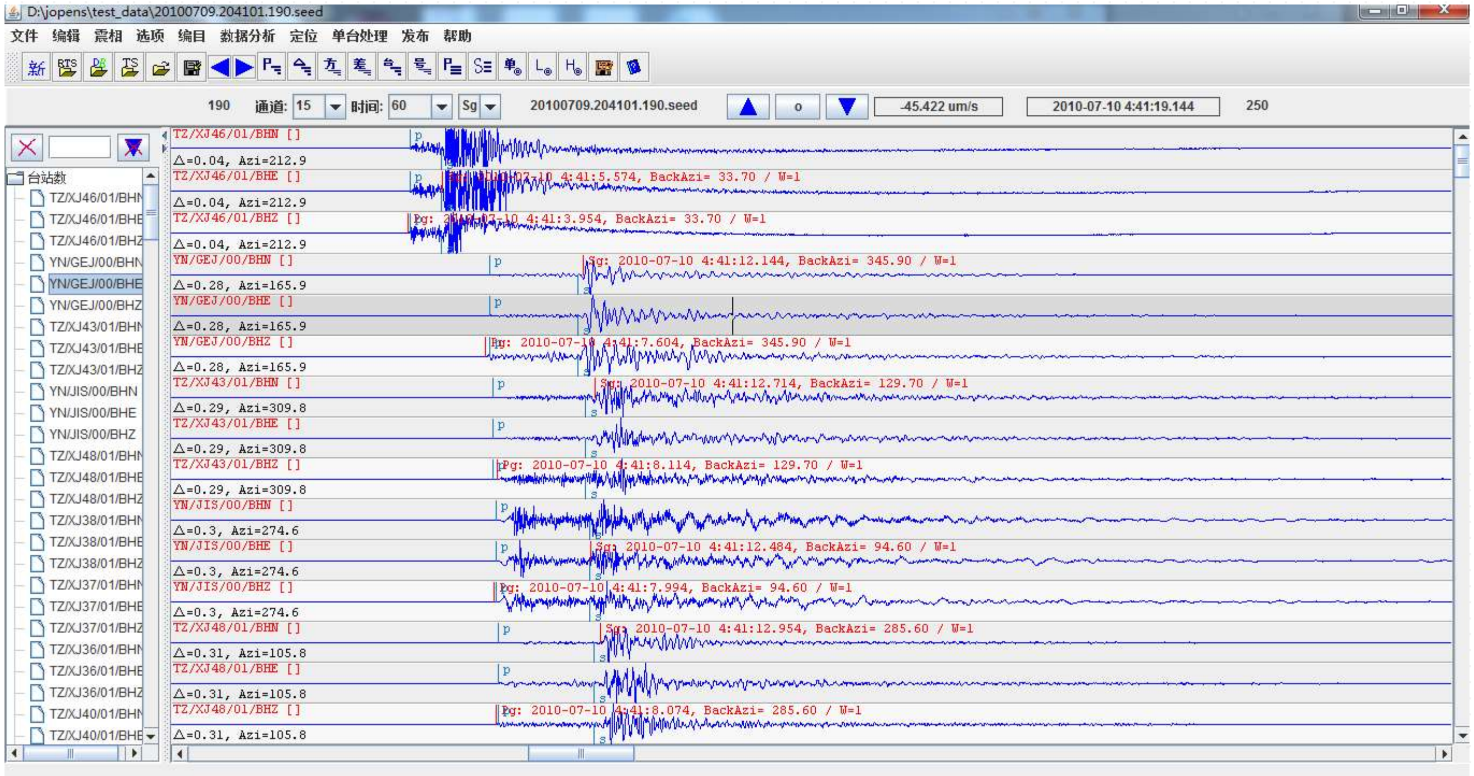
Outline

1. Research Backgrounds
2. Progress of earthquake automatic processing
3. Development and application of RISP in China

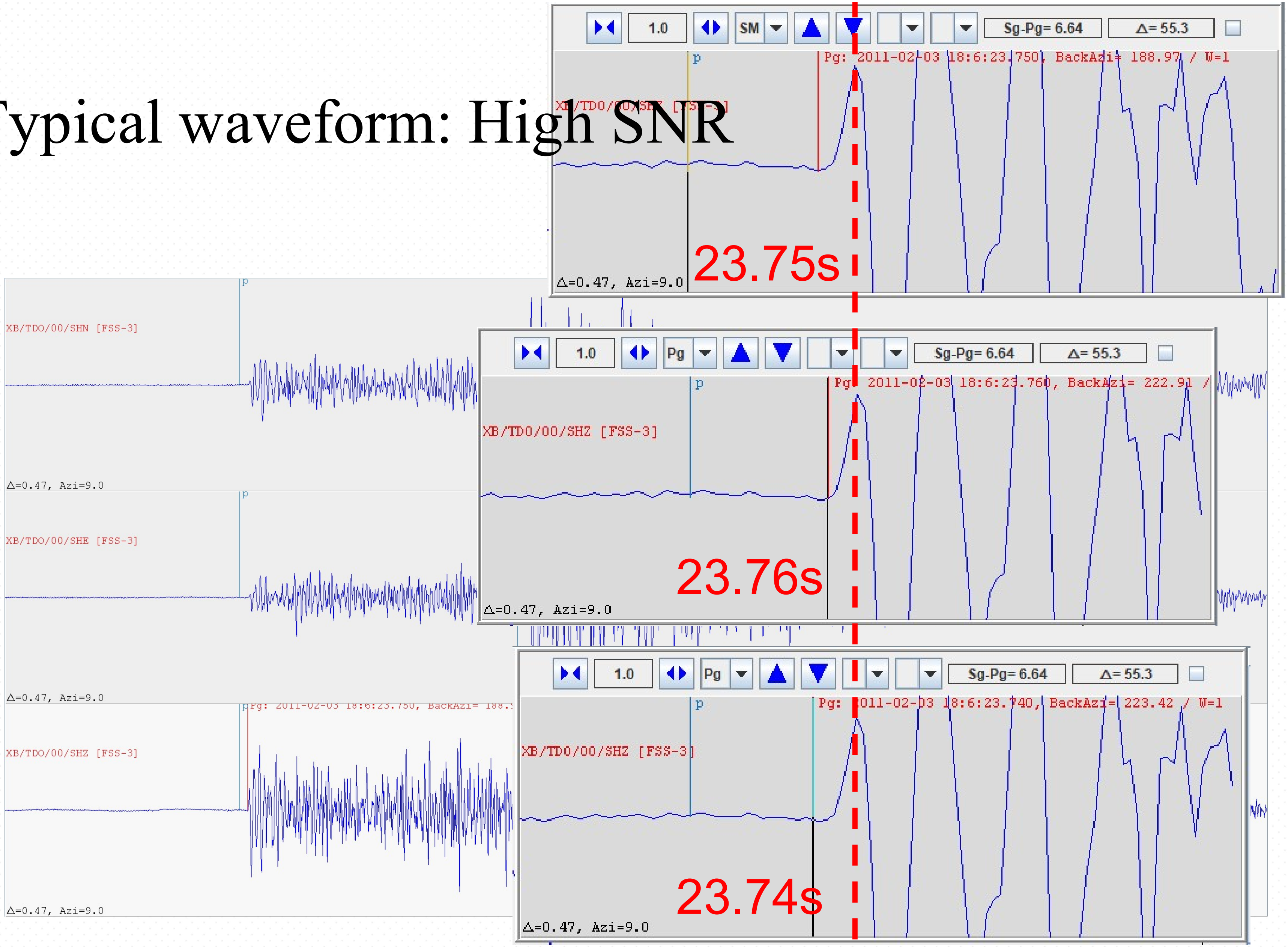


Earthquake processing by analyst

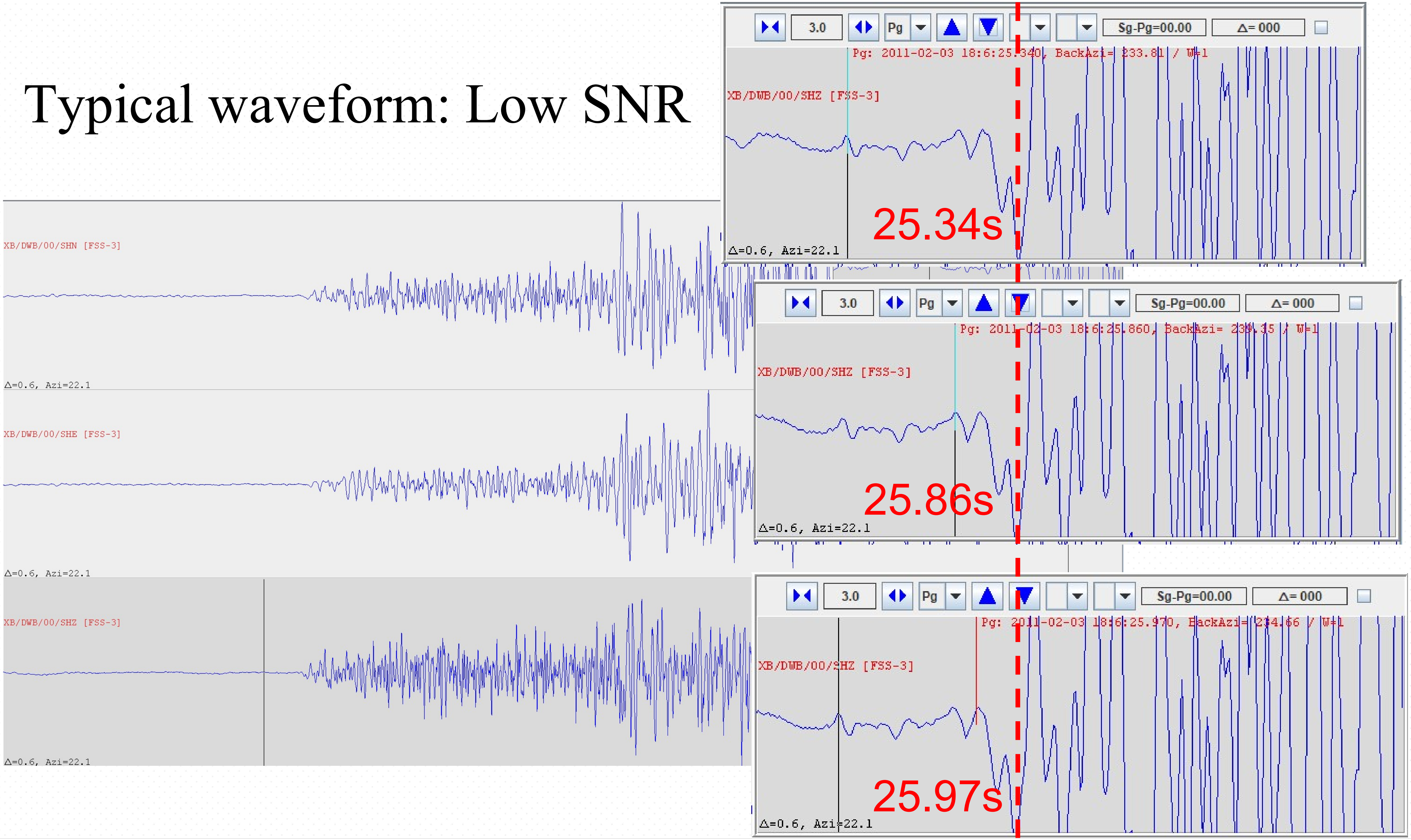




Typical waveform: High SNR



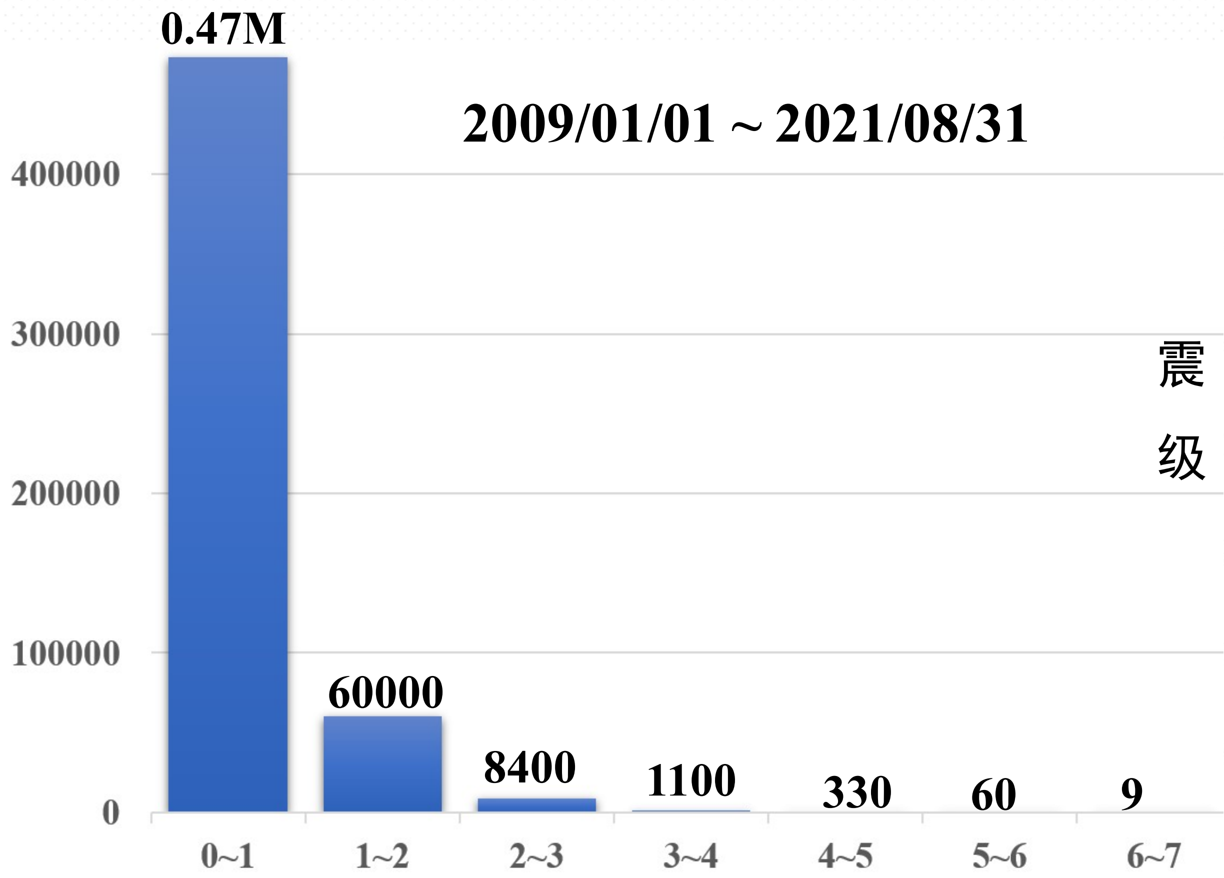
Typical waveform: Low SNR

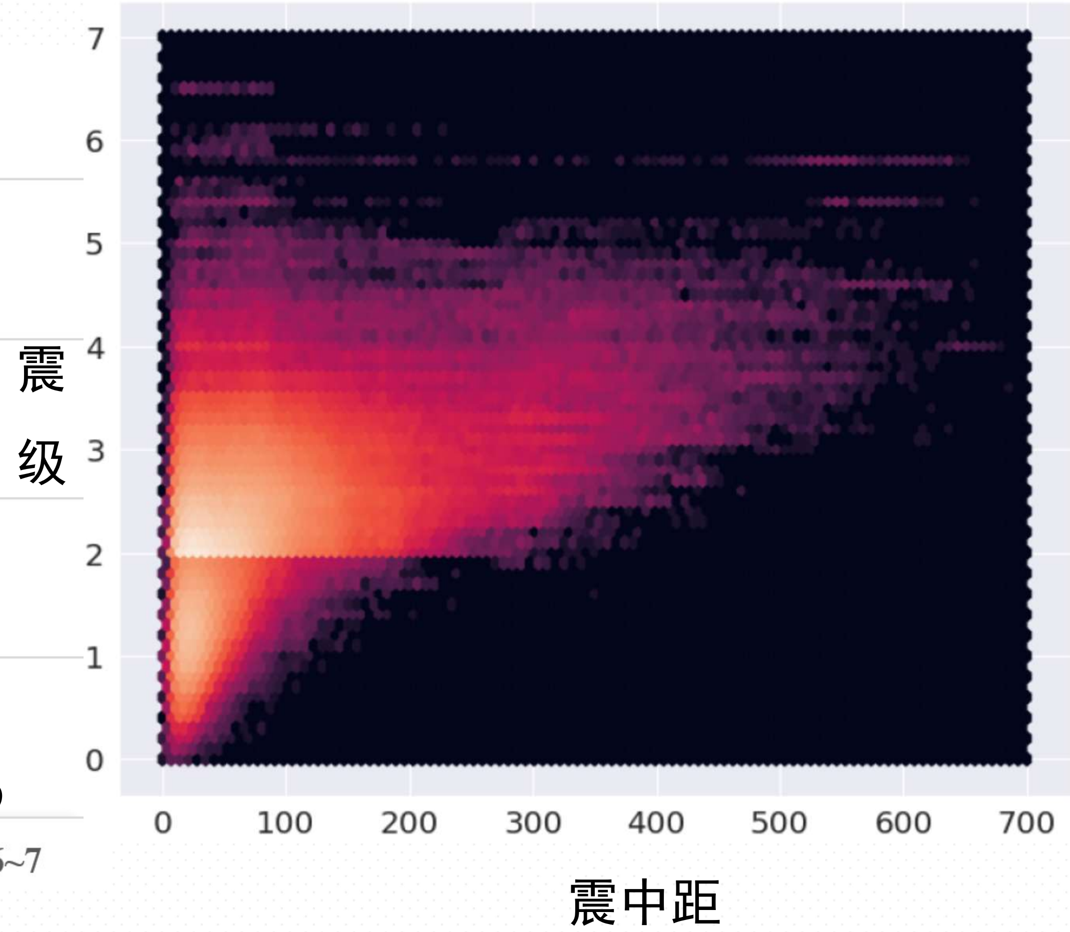


Most of the earthquakes are microseismics

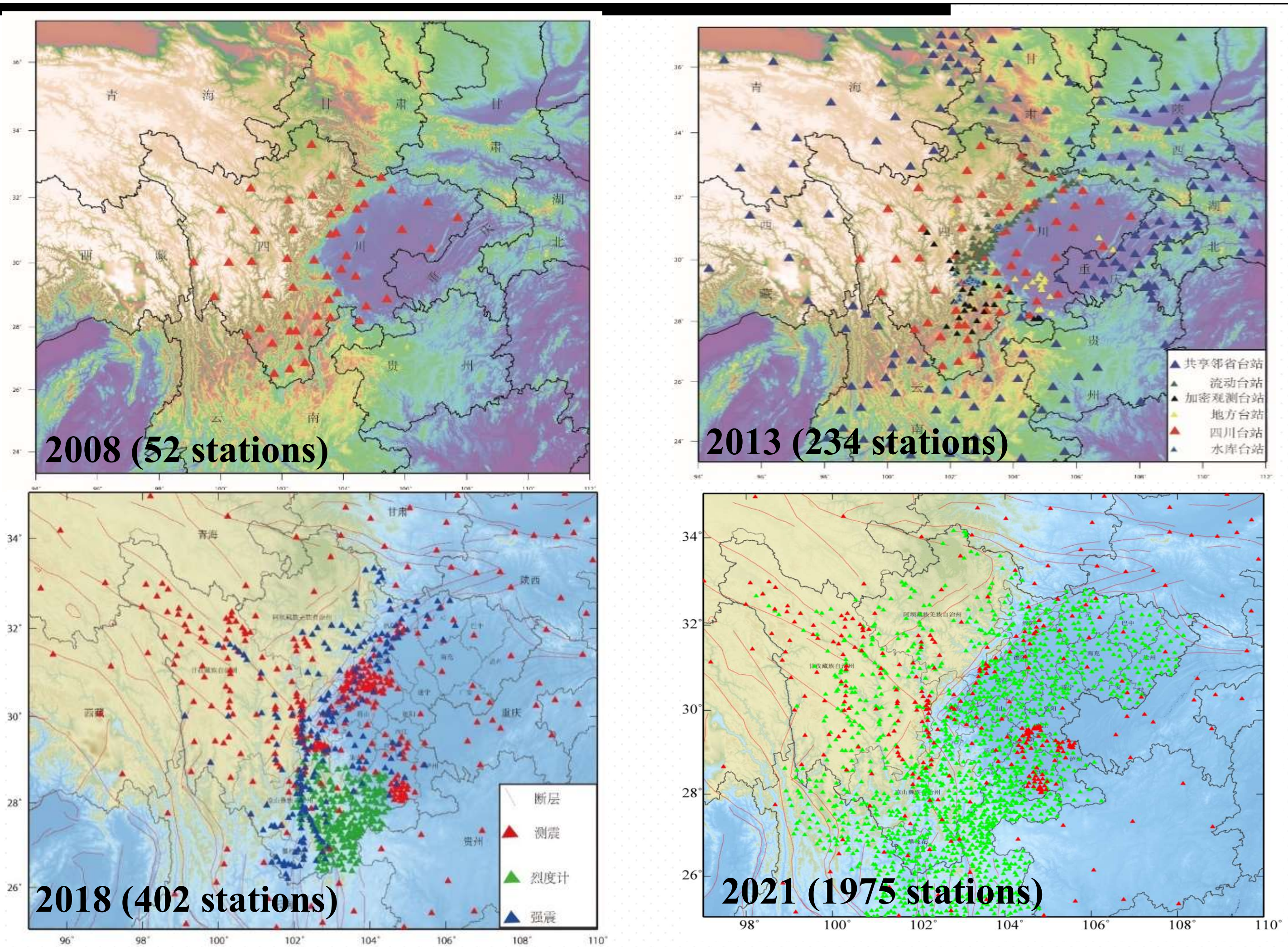
M<1.0, 87%， M<2.0, 98%

87% earthquakes are smaller than ML1.0





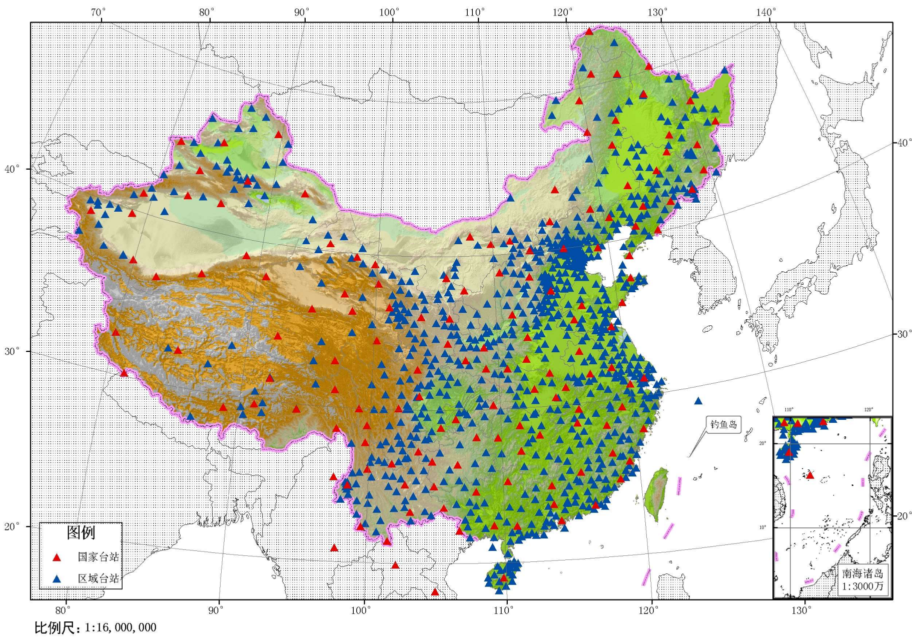
Increasing of seismic stations



China has constructed the largest seismic network in the world.

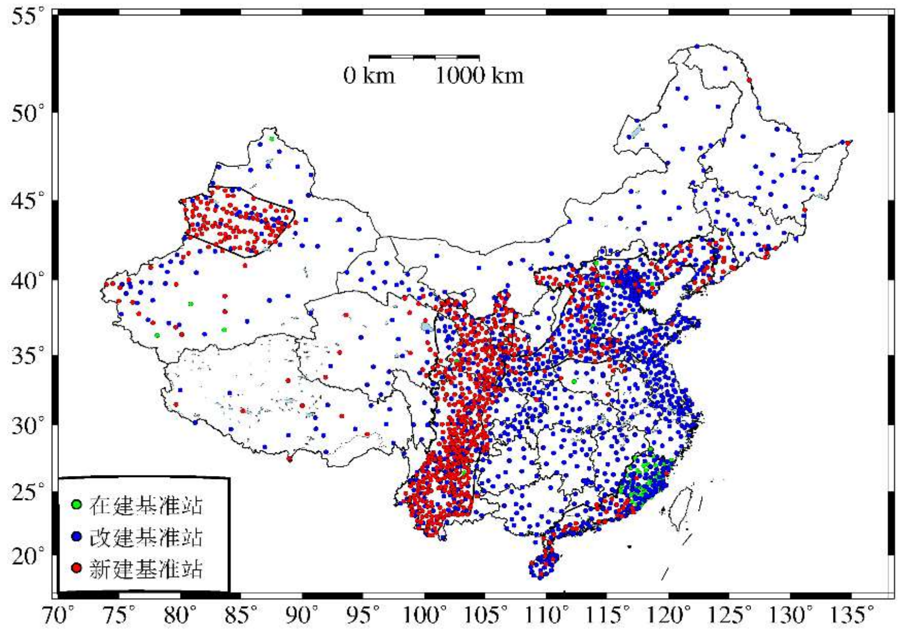
Seismic stations before 2021

~1200

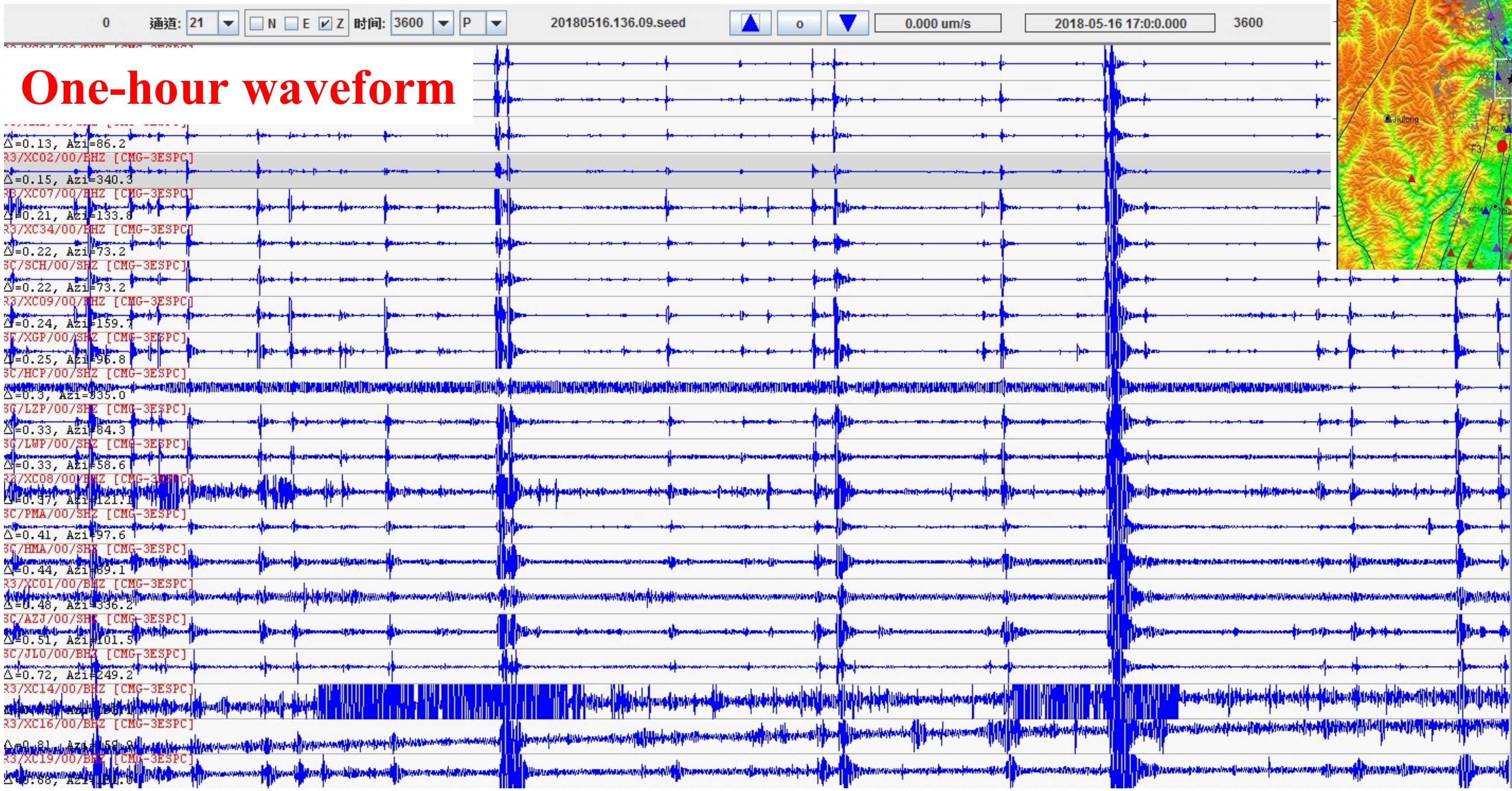


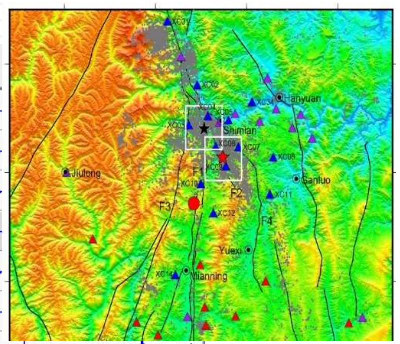
Seismic stations at present

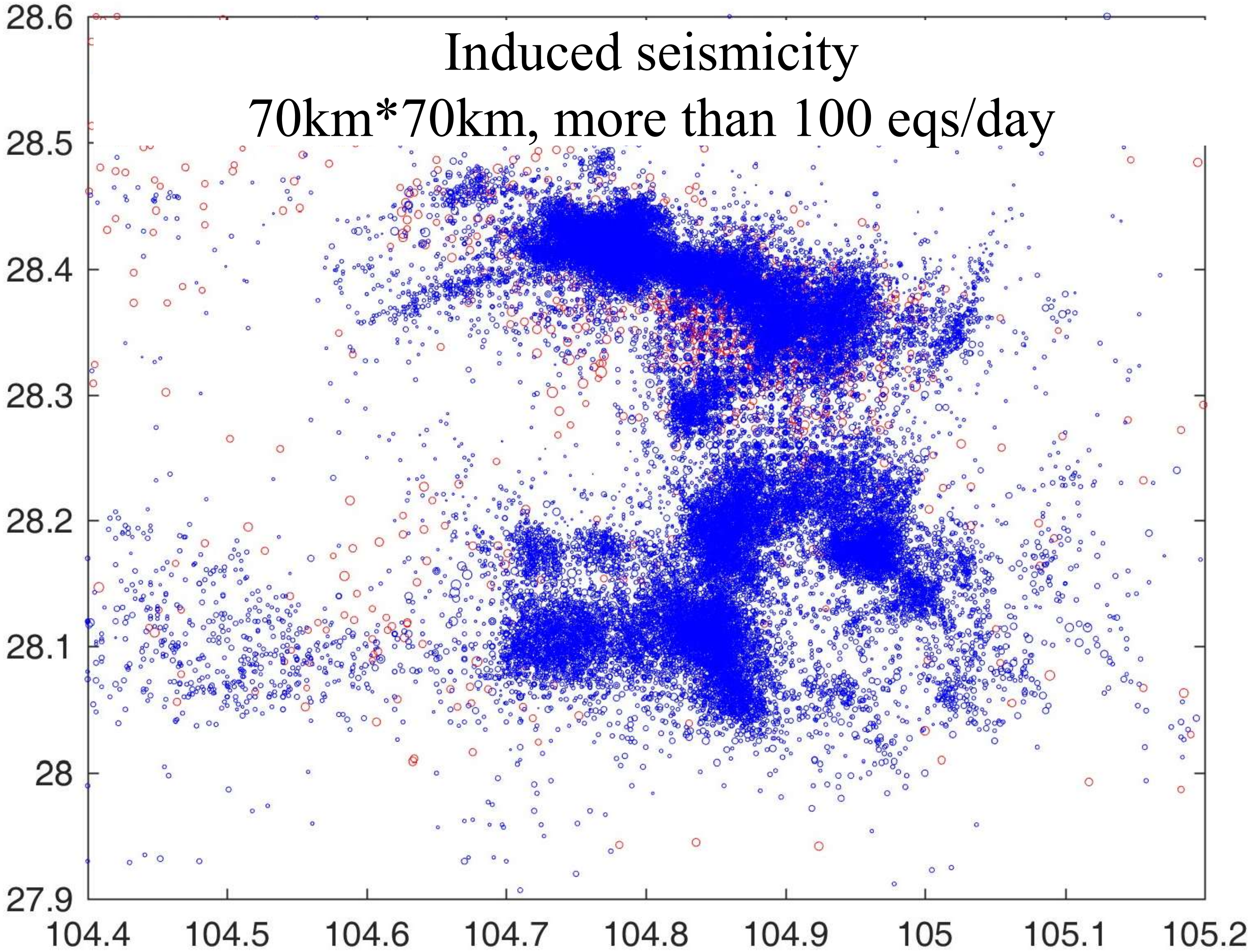
~15000



Sichuan Shimian M4.1 earthquake sequence
more than 1500 aftershocks were recorder by a dense seismic network



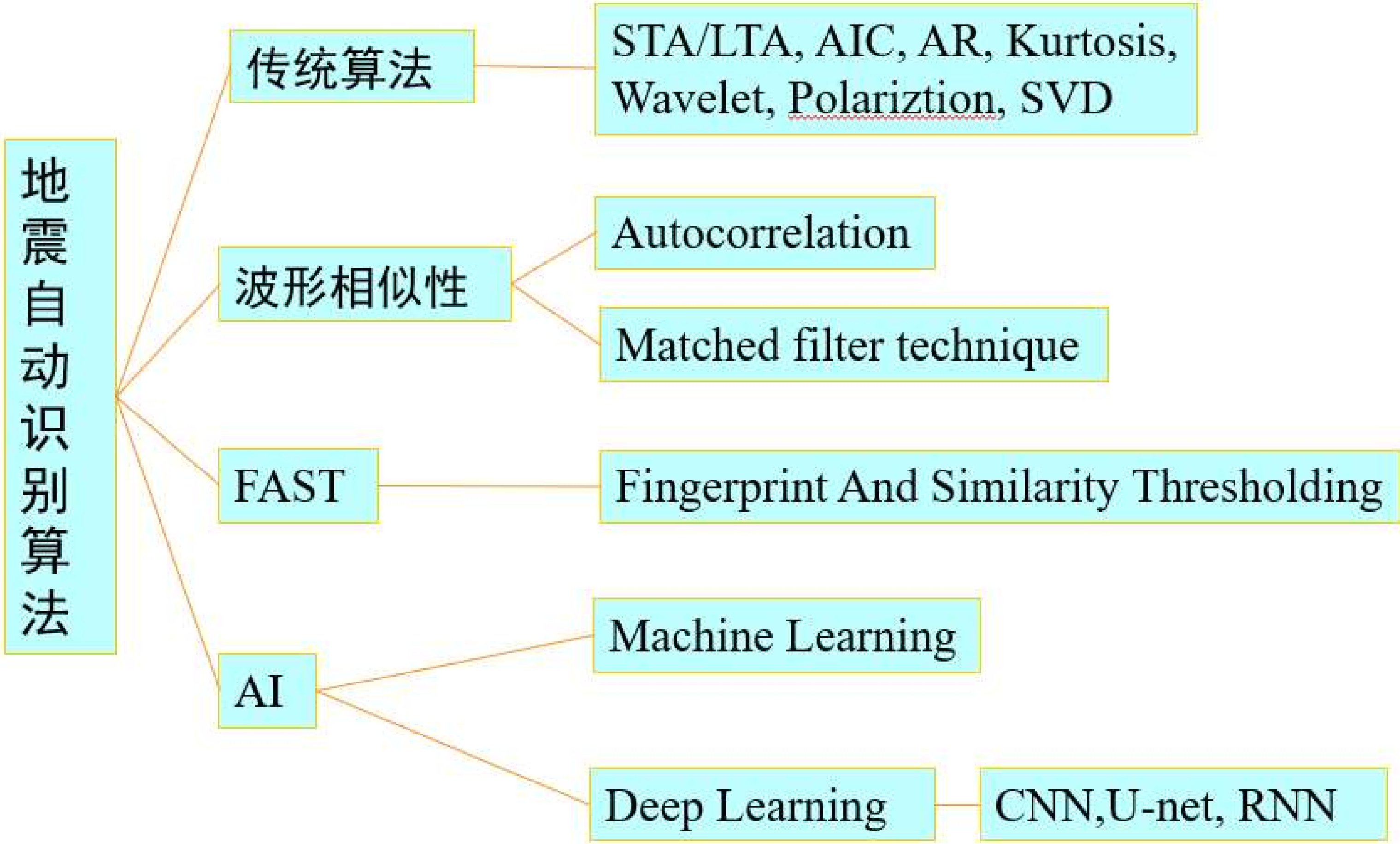



Induced seismicity
70km*70km, more than 100 eqs/day
28.6
28.5
28.4
28.3
28.2
28.1
28
27.9
104.4
104.5
104.6
104.7
104.8
104.9
105
105.1
105.2

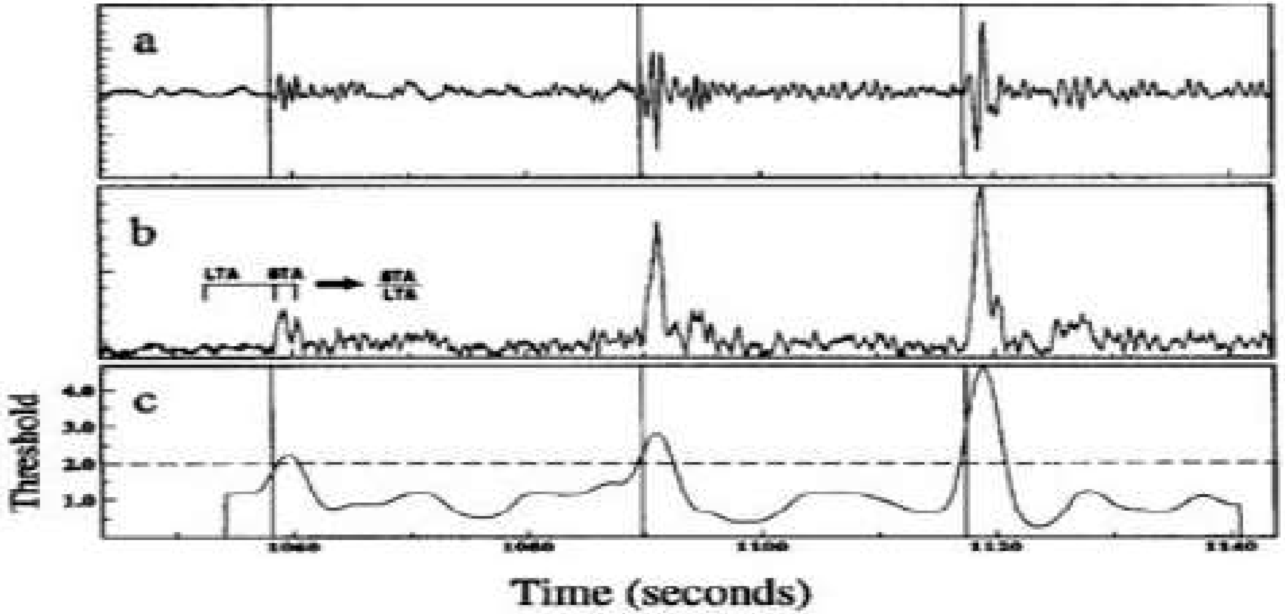
Outline

1. **Research Backgrounds**
2. **Progress of earthquake automatic processing**
3. **Development and application of RISP in China**

Earthquake automatic detection method
Since 1978



Standard Approach to Detection/Location



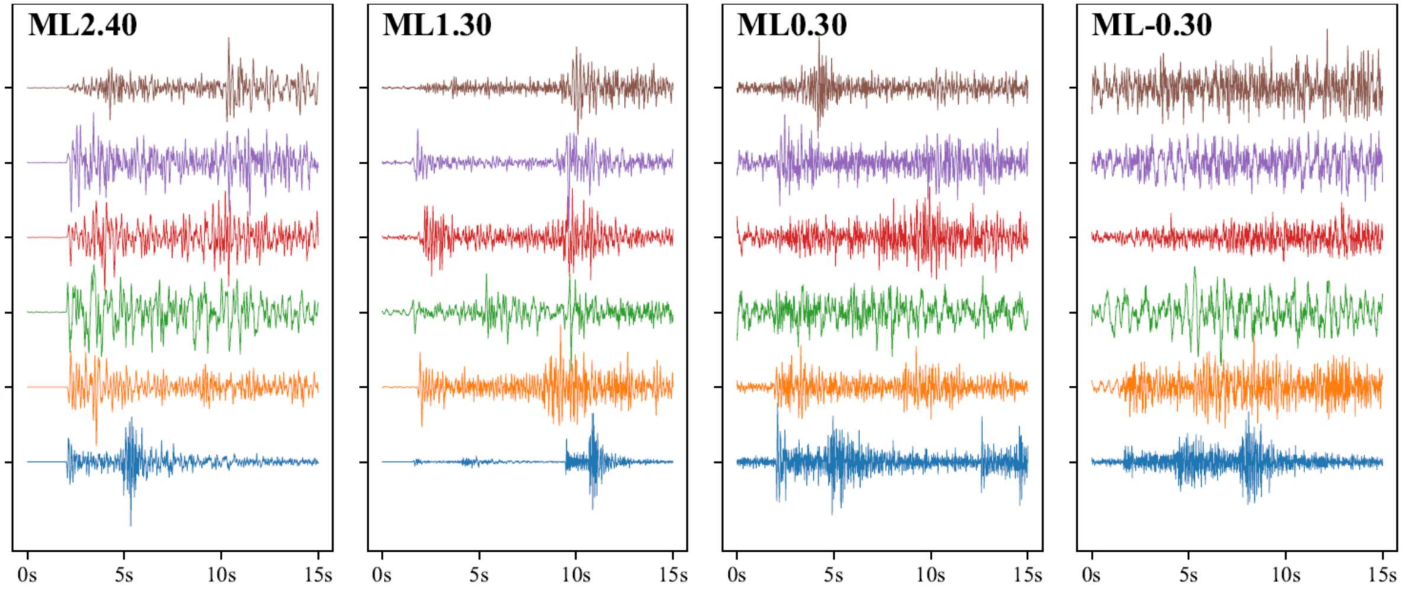
Earle and Shearer [1994]

STA: Short Term Average

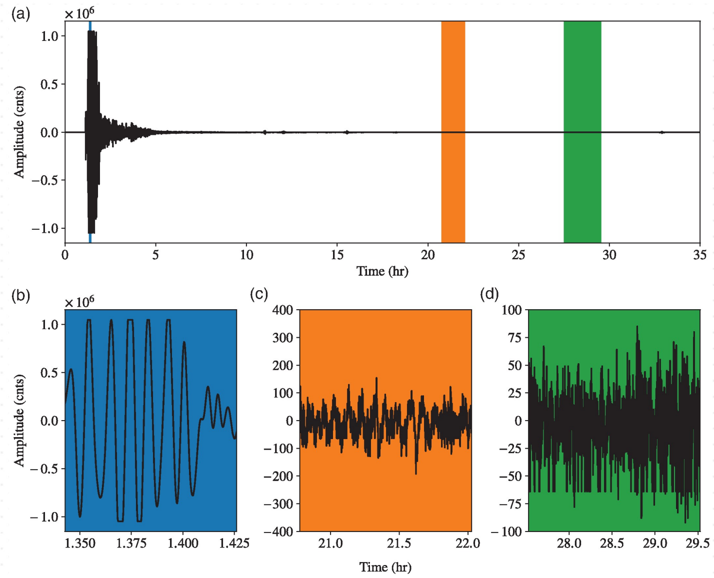
LTA: Long Term Average

Difficulties in microseismic detection

➢ Large amount, weak signal, noise interfere, few record station

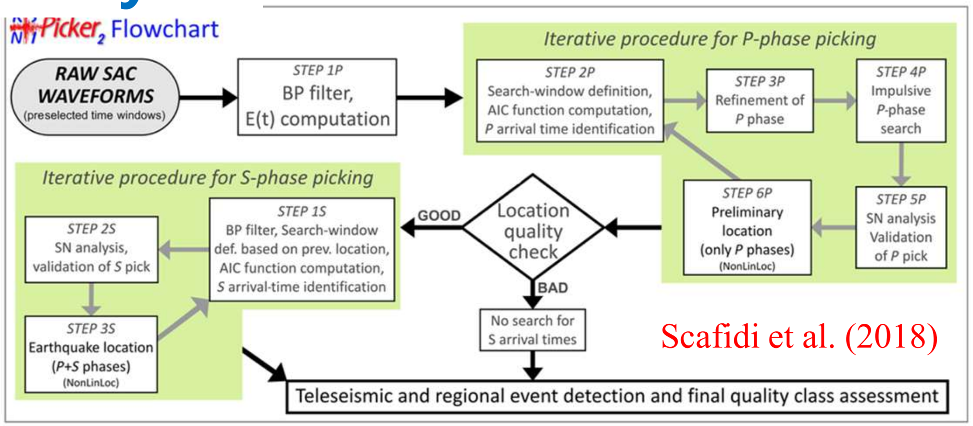


Aftershocks of the Yangbi earthquake



Earthquake + Noise

Italy

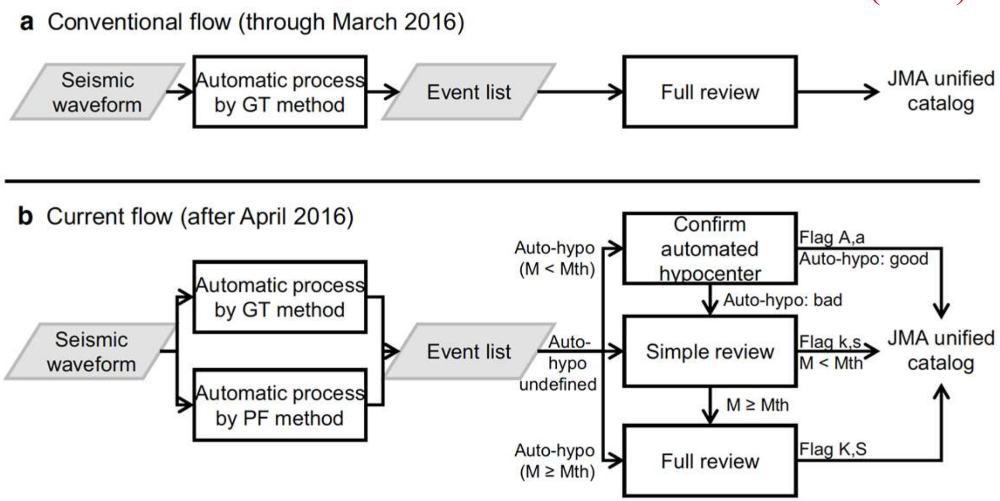


Scafidi et al. (2018)

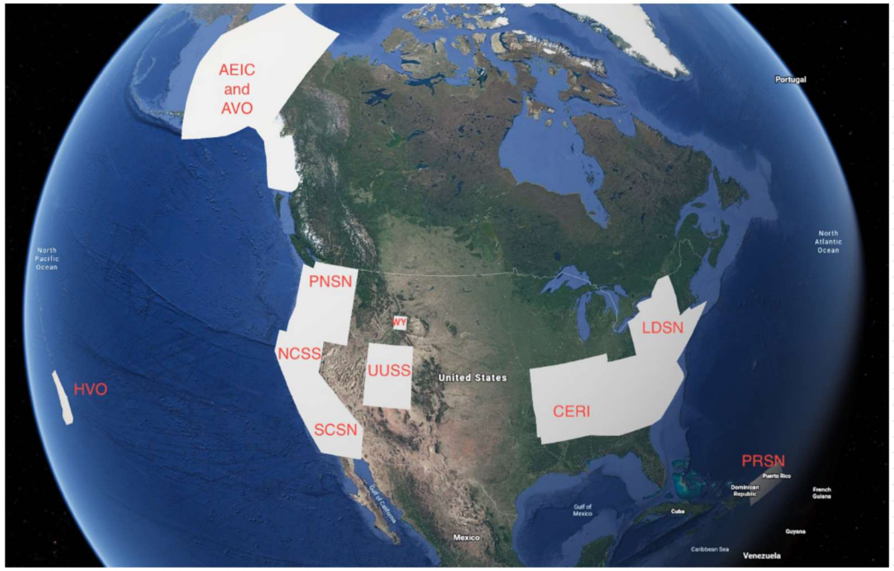
▲ **Figure 1.** Flowchart of the Regional Seismic network of Northwestern Italy-Picker Version 2 (RSNI-Picker$_2$) iterative working procedure (modified from Spallarossa *et al.*, 2014). AIC, Akaike information criterion; BP, band-pass; SAC, Seismic Analysis Code; SN, signal-to-noise. The color version of this figure is available only in the electronic edition.

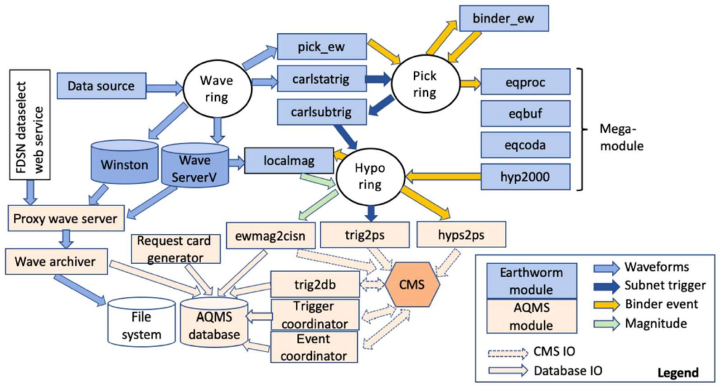
Japan

Tamaribuchi et al. (2018)



USA

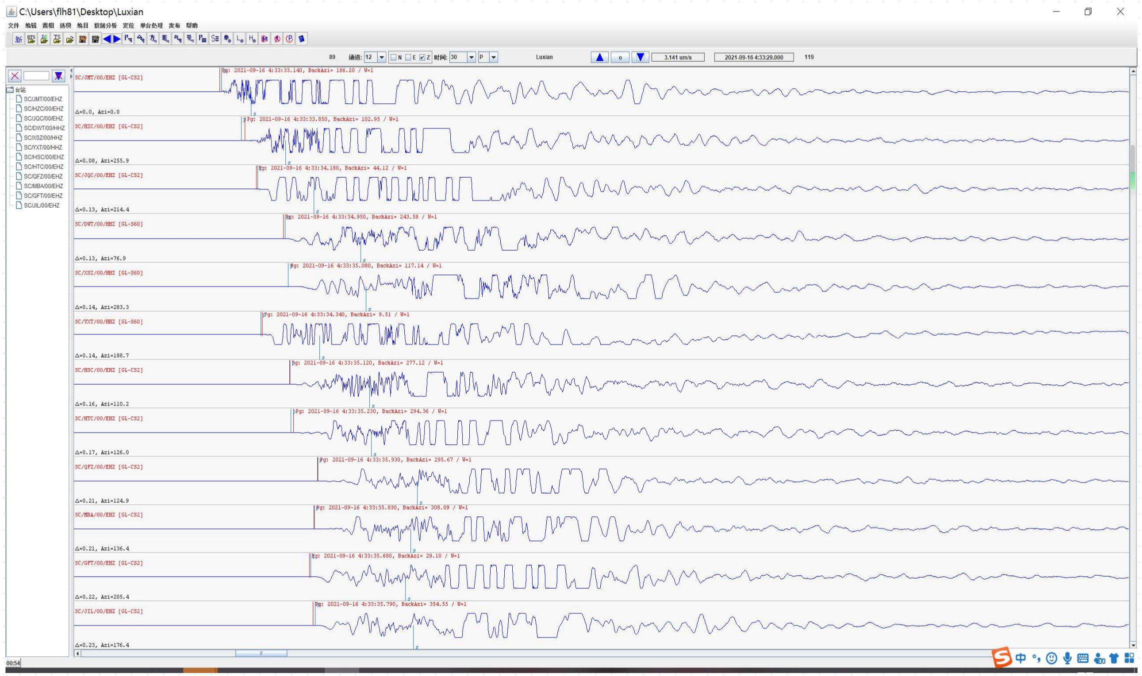




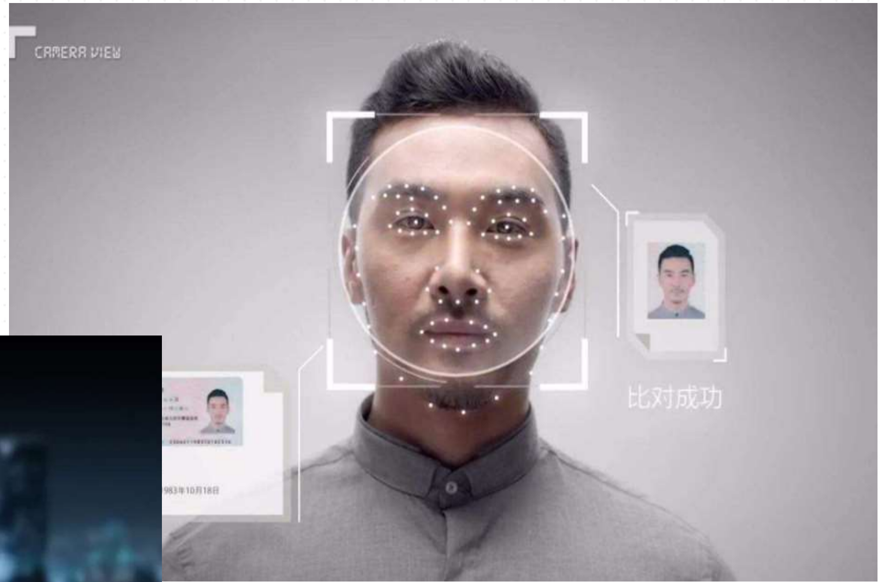
Hartog et al., 2019

SeisComp/GFZ

MSDP/CEA

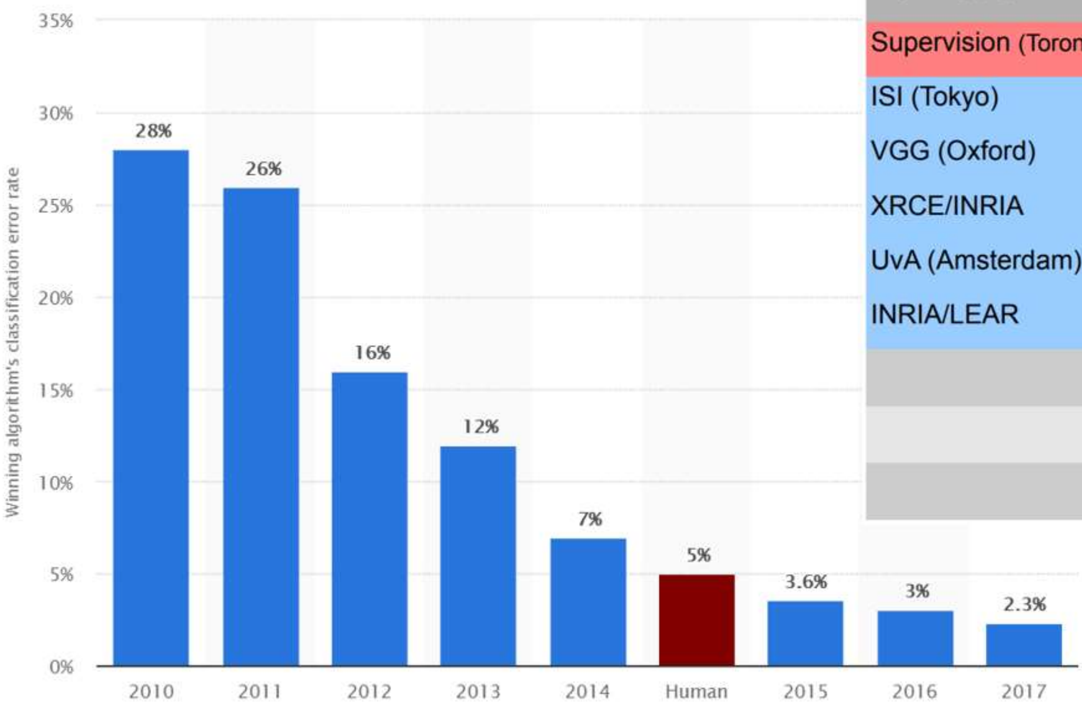



BJHAD


CAMERA VIEW
比对成功


AI

Computer vision large-scale visual recognition challenge (ILSVRC) winning error rates (2010-2017)



© Statista 2019

2012 Teams	%error
Supervision (Toronto)	15.3
ISI (Tokyo)	26.1
VGG (Oxford)	26.9
XRCE/INRIA	27.0
UvA (Amsterdam)	29.6
INRIA/LEAR	33.4

2013 Teams	%error
Clarifai (NYU spinoff)	11.7
NUS (singapore)	12.9
Zeiler-Fergus (NYU)	13.5
A. Howard	13.5
OverFeat (NYU)	14.1
UvA (Amsterdam)	14.2
Adobe	15.2
VGG (Oxford)	15.2
VGG (Oxford)	23.0

2014 Teams	%error
GoogLeNet	6.6
VGG (Oxford)	7.3
MSRA	8.0
A. Howard	8.1
DeeperVision	9.5
NUS-BST	9.7
TTIC-ECP	10.2
XYZ	11.2
UvA	12.1

2017, Institute of Geophysics of China Earthquake Administration (IGPCEA) hosted an international contest titled “Aftershock Detection AI Contest”

第四赛季 | 第三赛季 | **第二赛季**

排名	参赛者	所在组织
1 ↑6	REAPS	福建省地震局
2 ↓1	PS_Picker	福建省地震局
3	塘苗路7号a汪	浙江省地震局
4 ↓2	daswerden	cea-igp

第四赛季 | **第三赛季** | 第二赛季

排名	参赛者	所在组织
1	塘苗路7号a汪	浙江省地震局
2	daswerden	cea-igp
3	Earth Brain	中国科学技术大学
4	PS_Picker	福建省地震局

第四赛季 | 第三赛季 | 第二赛季

排名	参赛者	所在组织
1	塘苗路7号a汪	浙江省地震局
2	Earth Brain	中国科学技术大学
3	PS_Picker	福建省地震局
4	daswerden	cea-igp

SRL Opinion Paper: **SeismOlympics**

GeoScienceWorld Journals Books GeoRef Publishers OpenGeoSci Citation Manager Help

Seismological Research Letters

Archive Content About The Journal About the Society SSA Member Sign In

EDITORIAL | SEPTEMBER 06, 2017

SeismOlympics

Lihua Fang; Zhongliang Wu; Kuan Song

Seismological Research Letters (2017) 88 (6): 1429–1430.

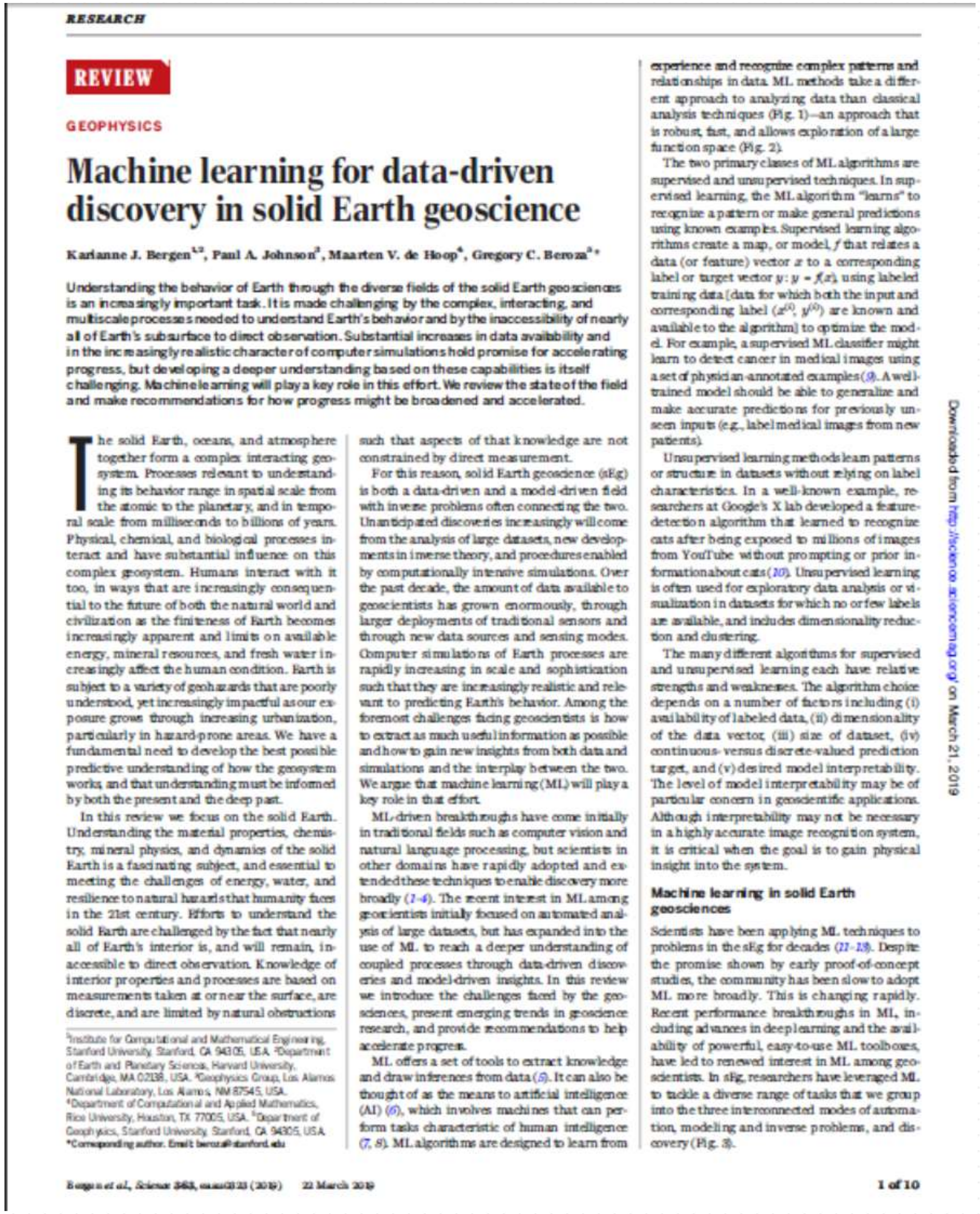
https://doi.org/10.1785/0220170134 Article history

OPINION

SeismOlympics

On 23 May 2017, a clear day in Chengdu, the capital city of Sichuan Province in China, located ~80 km away from the epicenter of the 2008 M_s 8.0 Wenchuan earthquake, Alibaba Cloud (the largest cloud computing company in China, a subsidiary of Alibaba Group; see Data and Resources) and the Institute of Geophysics of the China Earthquake Administration (IGPCEA), jointly launched a seismological programming contest titled "Aftershock Detection Artificial-Intelligence Contest." The initial target of this contest was to identify as many aftershocks as possible from the continuous seismic waveforms of the 2008 Wenchuan earthquake, which is the first in a series of seismological programming contests. According to the public relations manager of Alibaba Cloud and the scientists at IGPCEA, this activity has the dual mission of exploring the limits of computational capability for seismological research, as well as enlisting seismologists and data scientists to contest, a metric was designed similar to the rules of the game in gymnastics. The contest has two kinds of scores; the automatic picking of the aftershocks is a set exercise, whereas the association and location are optional and can gain extra bonus points.

The Data Management Centre of the China National Seismic Network at IGPCEA provides three-component broadband seismic-waveform data recorded by 16 permanent seismic stations surrounding an aftershock area of the Wenchuan mainshock. The data format is a standard binary Seismic Analysis Code with 100 Hz sampling frequency. The total volume of the waveform data reaches 240 GB. The waveform dataset begins one month before the mainshock and ends four months after the mainshock. The continuous waveforms can be downloaded freely after registering on Tianchi, a data-mining platform by Alibaba Cloud.



REVIEW

GEOPHYSICS

Machine learning for data-driven discovery in solid Earth geoscience

Karianne J. Bergen[1,2], Paul A. Johnson[3], Maarten V. de Hoop[4], Gregory C. Beroza[5]*

Understanding the behavior of Earth through the diverse fields of the solid Earth geosciences is an increasingly important task. It is made challenging by the complex, interacting, and multiscale processes needed to understand Earth's behavior and by the inaccessibility of nearly all of Earth's subsurface to direct observation. Substantial increases in data availability and in the increasingly realistic character of computer simulations hold promise for accelerating progress, but developing a deeper understanding based on these capabilities is itself challenging. Machine learning will play a key role in this effort. We review the state of the field and make recommendations for how progress might be broadened and accelerated.

The solid Earth, oceans, and atmosphere together form a complex interacting geosystem. Processes relevant to understanding its behavior range in spatial scale from the atomic to the planetary, and in temporal scale from milliseconds to billions of years. Physical, chemical, and biological processes interact and have substantial influence on this complex geosystem. Humans interact with it too, in ways that are increasingly consequential to the future of both the natural world and civilization as the finiteness of Earth becomes increasingly apparent and limits on available energy, mineral resources, and fresh water increasingly affect the human condition. Earth is subject to a variety of geohazards that are poorly understood, yet increasingly impactful as our exposure grows through increasing urbanization, particularly in hazard-prone areas. We have a fundamental need to develop the best possible predictive understanding of how the geosystem works, and that understanding must be informed by both the present and the deep past.

In this review we focus on the solid Earth. Understanding the material properties, chemistry, mineral physics, and dynamics of the solid Earth is a fascinating subject, and essential to meeting the challenges of energy, water, and resilience to natural hazards that humanity faces in the 21st century. Efforts to understand the solid Earth are challenged by the fact that nearly all of Earth's interior is, and will remain, inaccessible to direct observation. Knowledge of interior properties and processes are based on measurements taken at or near the surface, are discrete, and are limited by natural obstructions such that aspects of that knowledge are not constrained by direct measurement.

For this reason, solid Earth geoscience (sEg) is both a data-driven and a model-driven field with inverse problems often connecting the two. Unanticipated discoveries increasingly will come from the analysis of large datasets, new developments in inverse theory, and procedures enabled by computationally intensive simulations. Over the past decade, the amount of data available to geoscientists has grown enormously, through larger deployments of traditional sensors and through new data sources and sensing modes. Computer simulations of Earth processes are rapidly increasing in scale and sophistication such that they are increasingly realistic and relevant to predicting Earth's behavior. Among the foremost challenges facing geoscientists is how to extract as much useful information as possible and how to gain new insights from both data and simulations and the interplay between the two. We argue that machine learning (ML) will play a key role in that effort.

ML-driven breakthroughs have come initially in traditional fields such as computer vision and natural language processing, but scientists in other domains have rapidly adopted and extended these techniques to enable discovery more broadly (1–4). The recent interest in ML among geoscientists initially focused on automated analysis of large datasets, but has expanded into the use of ML to reach a deeper understanding of coupled processes through data-driven discoveries and model-driven insights. In this review we introduce the challenges faced by the geosciences, present emerging trends in geoscience research, and provide recommendations to help accelerate progress.

ML offers a set of tools to extract knowledge and draw inferences from data (5). It can also be thought of as the means to artificial intelligence (AI) (6), which involves machines that can perform tasks characteristic of human intelligence (7, 8). ML algorithms are designed to learn from experience and recognize complex patterns and relationships in data. ML methods take a different approach to analyzing data than classical analysis techniques (Fig. 1)—an approach that is robust, fast, and allows exploration of a large function space (Fig. 2).

The two primary classes of ML algorithms are supervised and unsupervised techniques. In supervised learning, the ML algorithm "learns" to recognize a pattern or make general predictions using known examples. Supervised learning algorithms create a map, or model, f that relates a data (or feature) vector x to a corresponding label or target vector y: $y = f(x)$, using labeled training data [data for which both the input and corresponding label $(x^{(i)}, y^{(i)})$ are known and available to the algorithm] to optimize the model. For example, a supervised ML classifier might learn to detect cancer in medical images using a set of physician-annotated examples (9). A well-trained model should be able to generalize and make accurate predictions for previously unseen inputs (e.g., label medical images from new patients).

Unsupervised learning methods learn patterns or structure in datasets without relying on label characteristics. In a well-known example, researchers at Google's X lab developed a feature-detection algorithm that learned to recognize cats after being exposed to millions of images from YouTube without prompting or prior information about cats (10). Unsupervised learning is often used for exploratory data analysis or visualization in datasets for which no or few labels are available, and includes dimensionality reduction and clustering.

The many different algorithms for supervised and unsupervised learning each have relative strengths and weaknesses. The algorithm choice depends on a number of factors including (i) availability of labeled data, (ii) dimensionality of the data vector, (iii) size of dataset, (iv) continuous- versus discrete-valued prediction target, and (v) desired model interpretability. The level of model interpretability may be of particular concern in geoscientific applications. Although interpretability may not be necessary in a highly accurate image recognition system, it is critical when the goal is to gain physical insight into the system.

Machine learning in solid Earth geosciences

Scientists have been applying ML techniques to problems in the sEg for decades (11–18). Despite the promise shown by early proof-of-concept studies, the community has been slow to adopt ML more broadly. This is changing rapidly. Recent performance breakthroughs in ML, including advances in deep learning and the availability of powerful, easy-to-use ML toolboxes, have led to renewed interest in ML among geoscientists. In sEg, researchers have leveraged ML to tackle a diverse range of tasks that we group into the three interconnected modes of automation, modeling and inverse problems, and discovery (Fig. 3).

[1]Institute for Computational and Mathematical Engineering, Stanford University, Stanford, CA 94305, USA. [2]Department of Earth and Planetary Sciences, Harvard University, Cambridge, MA 02138, USA. [3]Geophysics Group, Los Alamos National Laboratory, Los Alamos, NM 87545, USA. [4]Department of Computational and Applied Mathematics, Rice University, Houston, TX 77005, USA. [5]Department of Geophysics, Stanford University, Stanford, CA 94305, USA.
*Corresponding author. Email: beroza@stanford.edu

"Aftershock Detection AI Contest" is cited in ***Science*** by Stanford University and Harvard University.

Recently, the Institute of Geophysics at the Chinese Earthquake Administration (CEA) and Alibaba Cloud hosted a data science competition with more than 1000 teams centered around automatic detection and phase picking of aftershocks following the 2008 M_s 8.0 Wenchuan earthquake (119, 120). The ground-truth phase-arrival data, against which entries were assessed, were determined by CEA analysts. Such challenges are useful for researchers seeking to test and improve their detection algorithms. Future competitions should have greater impact if they are accompanied with some form of broader follow-up, such as publications associated with top-performing entries or a summary of effective methods and lessons learned from competition organizers.

Progress in China

余震捕捉AI大赛

Fang et al., 2017, SRL

Perol et al., SA

Li et al., GRL

Meier et al., JGR

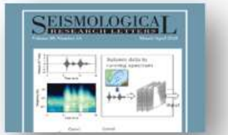
Ross et al., JGR, BSSA

DeVries et al., Nature

SRL、PEPI、地球物理学报专辑

Zhu et al., GJI

Zhu et al., PEPI



开始进入实际应用

Liu et al., GRL

Park et al, GRL

Wang et al., GRL

Zhang et al., SR

PhaseNet

EQTransformer

…

实用化软件出现

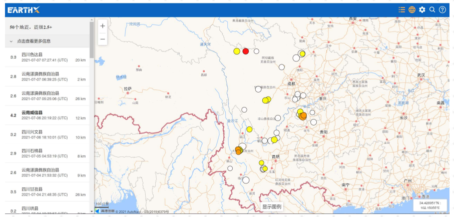
RISP

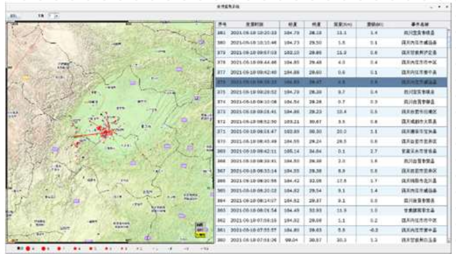
Earth X

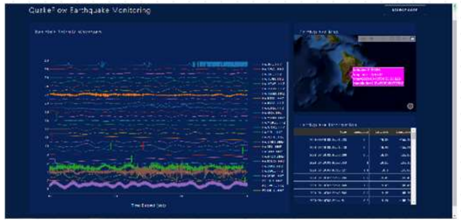
PAL, PALM….

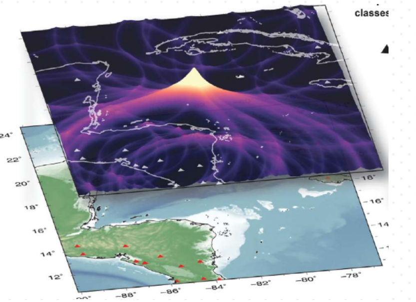
第二届人工智能地震学研讨

漾濞地震、玛多地震…

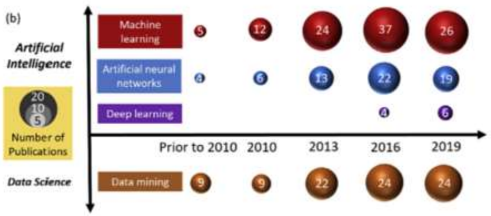








2017



2018

- 2018-Automatic microseismic event picking via unsupervised.pdf
- 2018-Convolutional neural network for earthquake detection.pdf
- 2018-Convolutional neural network for earthquake detection_SM.pdf
- 2018-Deep learning of aftershock patterns following large.pdf
- 2018-Generalized Seismic Phase Detection with Deep Learning.pdf
- 2018-Locality-Sensitive Hashing for Earthquake Detection.pdf
- 2018-Locating earthquakes with a network of seismic stations via a deep.pdf
- 2018-Machine Learning Seismic Wave Discrimination-EEW.pdf
- 2018-P Wave Arrival Picking and First-Motion Polarity.pdf
- 2018-Real-Time Classification of Earthquake using Deep Learning .pdf
- ic Signal Noise Discrimination.pdf
- fication and First-Break Picking Using Convoluti
- 进展.pdf
- 习及实现进志.pdf

2019

- 2019-综述Machine Learning in Seismology-Turning Data into Insi
- 2019-综述Machine learning for data-driven discovery in solid Ear
- 2019-通过无监督机器学习自动拾取微震事件.pdf
- 2019-基于支持向量机的地震体波震相自动识别及到时自动拾取.pdf
- 2019-基于深度学习卷积神经网络的地震波形自动分类与识别.pdf
- 2019-机器学习在地震检测与震相识别的应用综述.pdf
- 2019-Unsupervised_Clustering_of_Seismic_Signals_Using_Deep_C
- 2019-Systematic identification of external influences in.pdf
- 2019-PhaseNet-a deep-neural-network-based seismic arrival-tim
- 2019-PhaseLink A Deep Learning Approach to Seismic.pdf
- 2019-Machine Learning-enhanced Realistic Framework for Real-t
- 2019-Improving Regional and Teleseismic Detection for.pdf
- 2019-IEEE-First Arrival Time Identification Using Transfer.pdf
- 2019-Hybrid Event Detection and Phase Picking Algorithm using
- 2019-High-resolution seismic tomography of Long Beach, CA usi
- 2019-FAST-Unsupervised Large-Scale Search for Similar Earthqua
- 2019-EPS-P-wave first-motion polarity determination of wavefor
- 2019-Deep learning for seismic phase detection and picking in th
- 2019-Deep Learning for Picking Seismic Arrival Times.pdf
- 2019-Deep learning and process understanding for data-driven E
- 2019-Deep learning and its application in geochemical mapping.
- 2019-CRED-A Deep Residual Network of Convolutional and Recu
- 2019-Continuous chatter of the Cascadia subduction zone reveal
- 2019-Classification of Local Seismic Events in the Utah Region.pc
- 2019-Automated_detection_of_basal_icequakes_and_discriminati
- 2019-Artificial Neural Networks as Emerging Tools for Earthquak
- 2019-Artificial intelligence in seismology Advent, performance ar

2020

- 2020-结合台阵策略的震相拾取深度学习方法.pdf
- 2020-基于样本增强的卷积神经网络震相拾取方法.pdf
- 2020-基于深度卷积神经网络的地震震相拾取方法研究.pdf
- 2020-机器学习算法及其在地震学中的应用-2-F.docx
- 2020-Seismic+phase+picking+in+China+Seismic+Array+using+a+deep+convolu
- 2020-Ross_SM_3D fault architecture controls the dynamism of earthquake swarm
- 2020-Real-time Earthquake Early Warning with Deep Learning Application to.pdf
- 2020-Rapid prediction of earthquake ground shaking intensity using raw.pdf
- 2020-Mousavi_et_al-2020-Nature_Communications.pdf
- 2020-M-Array-based convolutional neural networks for.pdf
- 2020-Machine-Learning-Based Analysis of the Guy-Greenbrier.pdf
- 2020-Locating induced earthquakes- Zhang xiong et al 2020.pdf
- 2020-Leveraging Deep Learning in Global 24-7 Real-Time Earthquake Monitoring
- 2020-Injection-Induced Earthquakes on Complex Fault Zones.pdf
- 2020-High-Accuracy Discrimination of Blasts and Earthquakes.pdf
- 2020-EL-Picker 基于集成学习的余震P 波初动实时拾取方法.pdf
- 2020-easyQuake-Walter_etal_SRL_2020.pdf
- 2020-Earthquake Detection using Deep Learning Based—Thesis.pdf
- 2020-Earthquake detection in the Jiangsu region, China using GPU-based.pdf
- 2020-Deep Neural Networks for Earthquake Detection.pdf
- 2020-Deep neural networks design and analysis for automatic phase.pdf
- 2020-CRPN_+A+cascaded+classification+and+regression+DNN+framework+for
- 2020-Comparison of Single-Trace and Multiple.pdf
- 2020-Clustering earthquake signals and background.pdf
- 2020-Clustering earthquake signals and background noises in continuous seismi
- 2020-Chaichengping_transfer_learning.pdf
- 2020-BayesianDeepLearning_Estimation_of_Local_Earthquake_Location_from_Sin
- 2020-Automatic Seismic Phase Picking Using Deep Learning for the EGS Collab p

2021

- 2021-基于深度学习的地震检测模型在区域台网的泛化性研究.pdf
- 2021-基于深度学习到时拾取自动构建长宁地震前震目录.pdf
- 2021-基于深度学习UNet 网络的初至波拾取方法.pdf
- 2021-基于机器学习算法的银川台阵资料自动化震相分析和定位.pc
- 2021-机器学习在地震预测中的应用进展.pdf
- 2021-机器学习在地震学中的应用进展.pdf
- 2021-Transfer_learning_Improving_neural_network_based_p.
- 2021-Monitoring the 2020 Magna, Utah, Earthquake Sequer
- 2021-Machine_learning_applied_to_anthropogenic_seismic_
- 2021-Machine learning and fault rupture a review-Advances
- 2021-Laboratory earthquake forecasting A machine-PNAS.p
- 2021-Inversion for Shear-Tensile Focal-srl-2020420.1.pdf
- 2021-Insights of the September 2007 Cerralvo with AI.pdf
- 2021-essoar.10506483.1-Deep Learning for Geophysics Curr
- 2021-essoar.10504921.1_Automatic seismic waveform identi
- 2021-essoar.10502882.2.Focal mechanisms of small earthqu
- 2021-EL-Picker 基于集成学习的余震 P 波初动实时.pdf
- 2021-DeepPhasePick-A method for Detecting and Picking S
- 2021-ARRU Phase Picker Attention Recurrent-srl-2020382.1.
- 2021-Array-Based Convolutional Neural.pdf
- 2021-Application of a convolutional neural network for seisr

The pros and cons of different methods

- **Traditional method**

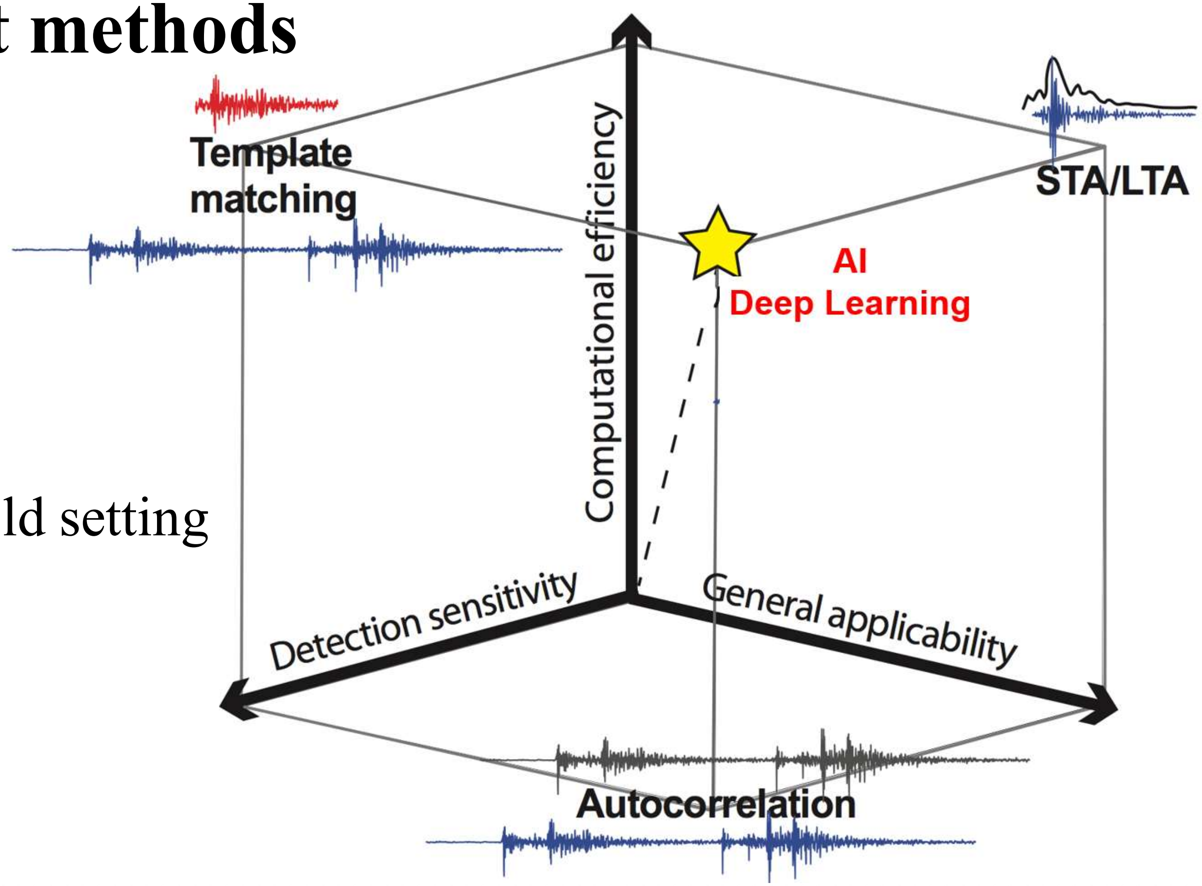
pros: high efficiency

cons: SNR, false pick-up, S-wave, threshold setting

- **Template matching method**

pros: relatively complete catalog

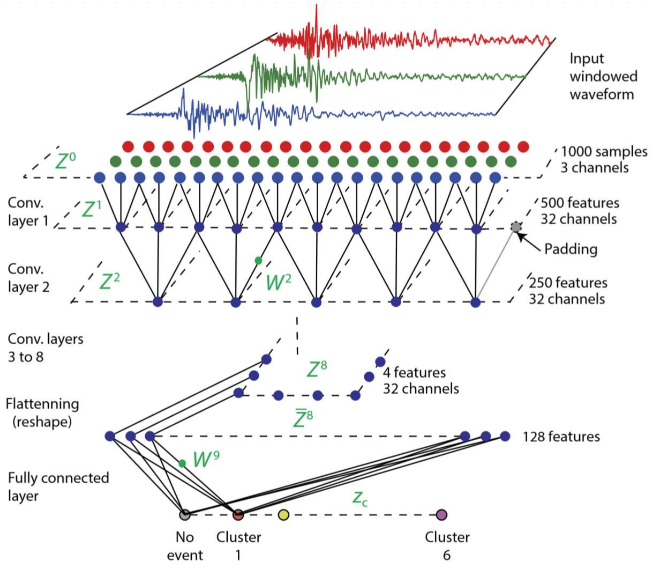
cons: need template, template completeness, efficiency, lack of seismic phase information



Modified from Yoon (2015)

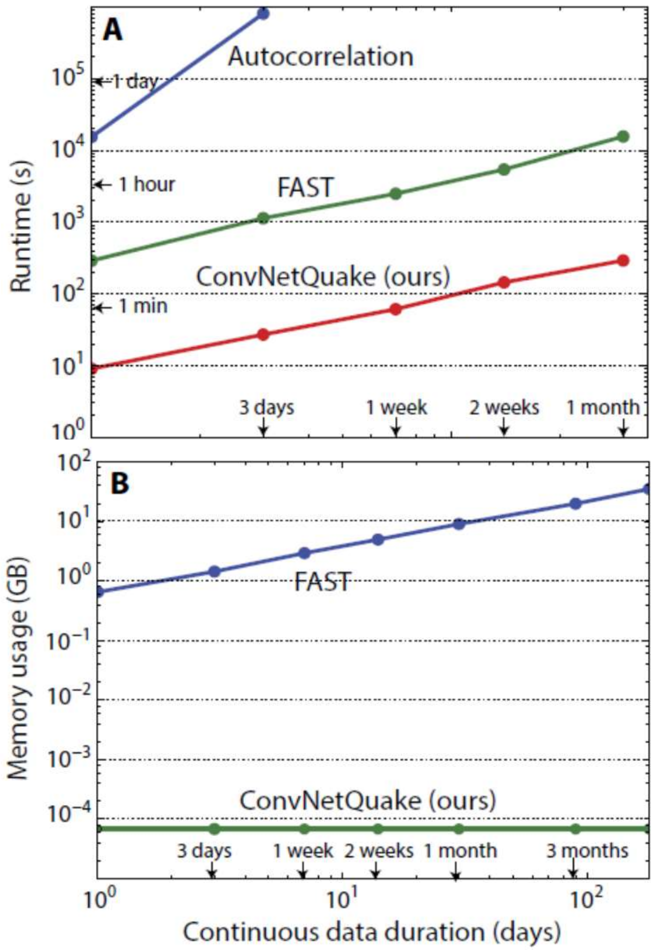
Earthquake detection with deep learning

High efficiency, high precision, low computation cost, open source codes



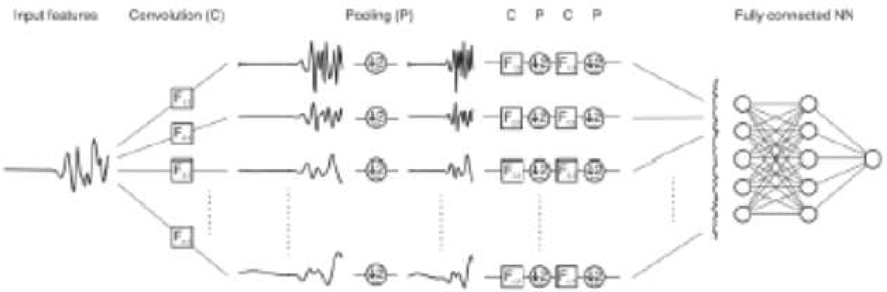
	Autocorr	FAST	CNN
Precision	100%	88.1%	**94.8%**
Recall	77.5%	80.1%	**100%**
Runtime	9.5d	48m	**1m**

Perol et al., 2018, Sci. Adv.



Deep Learning earthquake detection methods

ConvQuakeNet – Perol et al., 2018
DetNet – Zhou et al., 2019
Yews – Zhu L. et al., 2019
ConvNet – Dokht et al., 2019
CapsNet – Chen et al., 2020



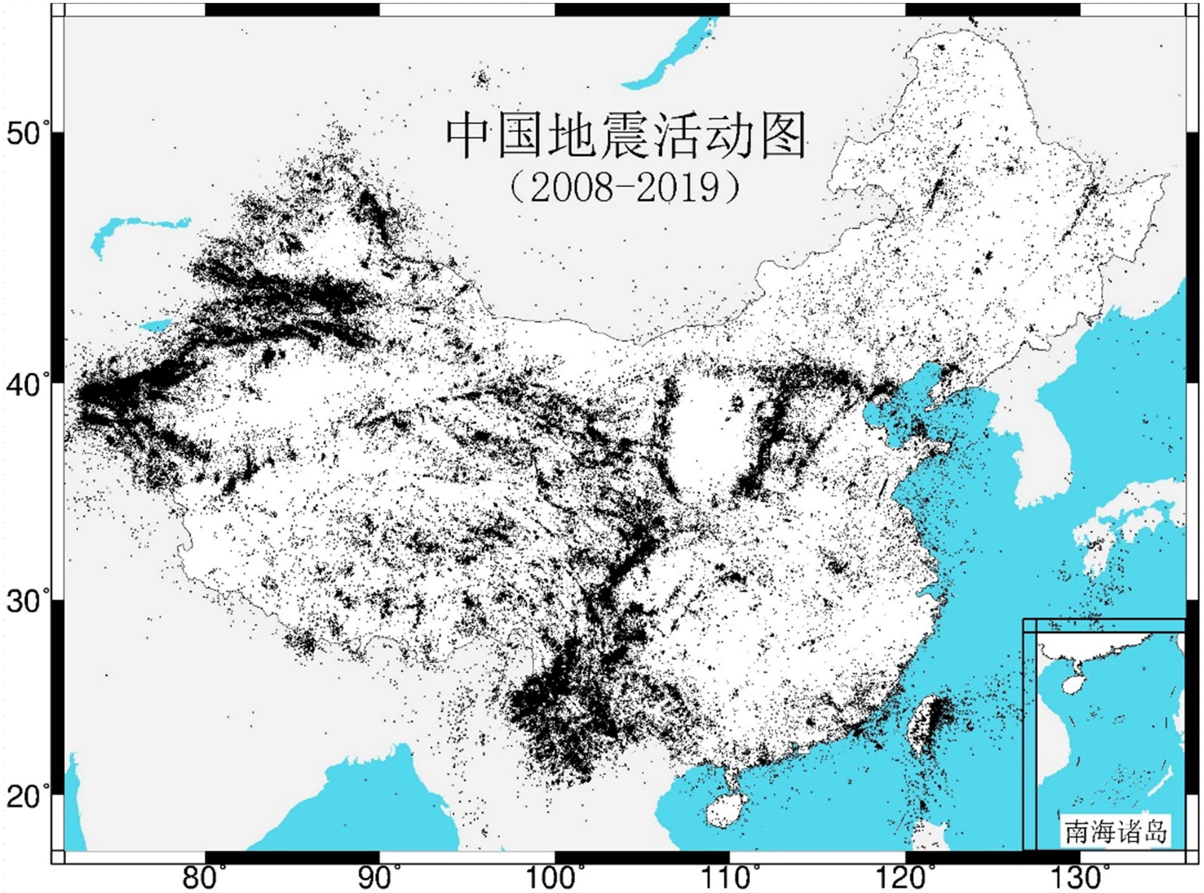
Ross et al. 2018a

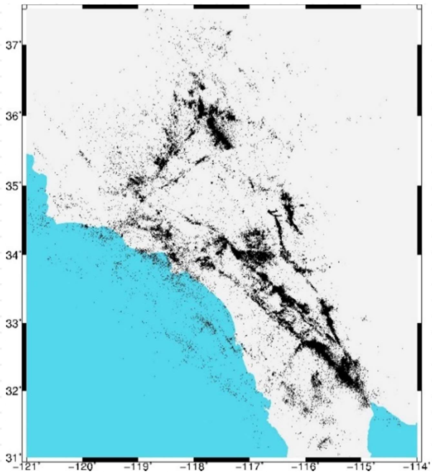
GPD – Ross et al., 2018b
CRED – Mousavi et al., 2018
PhaseNet – Zhu and Beroza, 2019
PickNet – Wang et al., 2019
Cospy – Pardo et al., 2019
EqT – Mousavi et al., 2021
S-EqT – Xiao et al., 2021

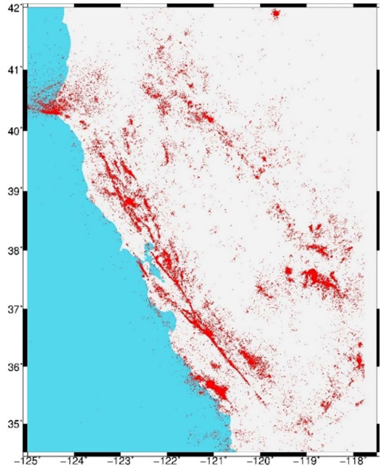
Outline

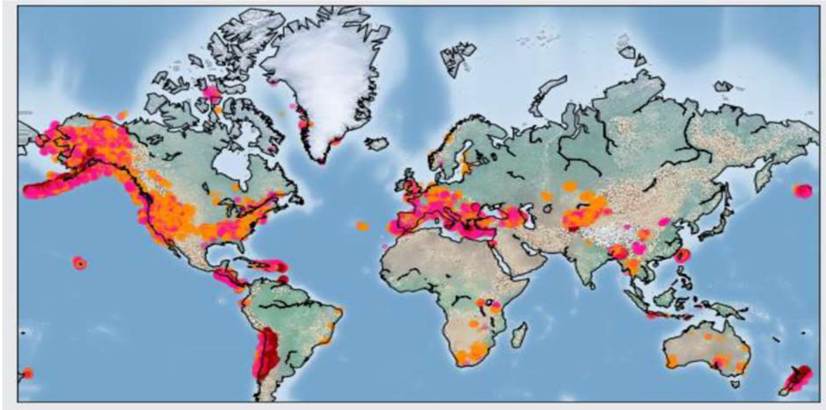
1. Research Backgrounds
2. Progress of earthquake automatic processing
3. Development and application of RISP in China

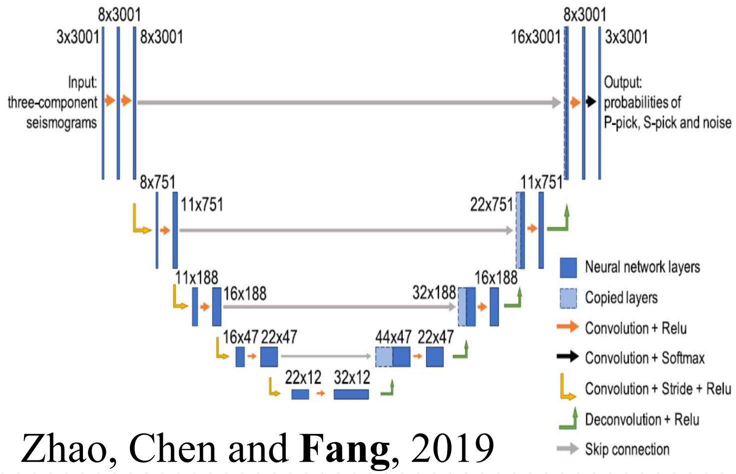
AI training dataset: 5M 3C earthquake waveforms



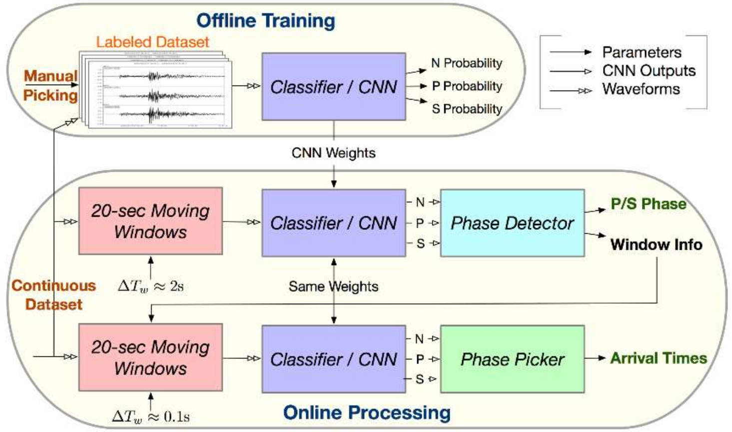




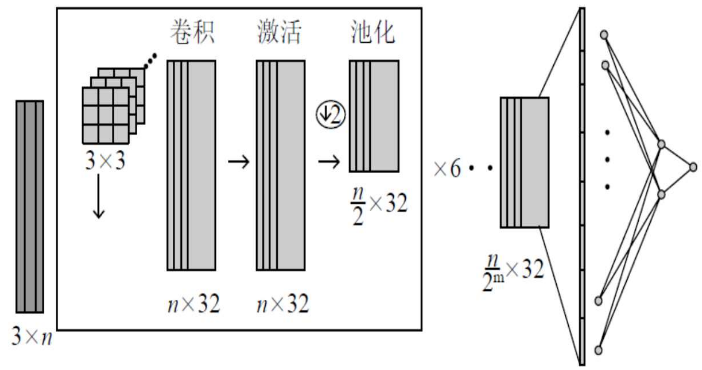




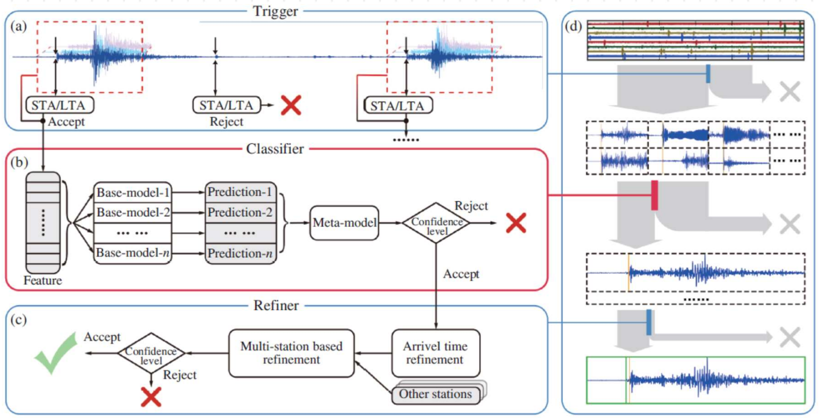
Zhao, Chen and **Fang**, 2019



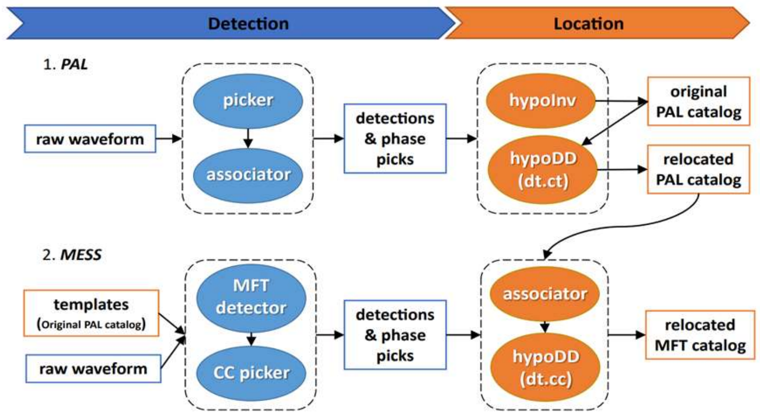
Zhu, Peng, **Fang** et al, 2019



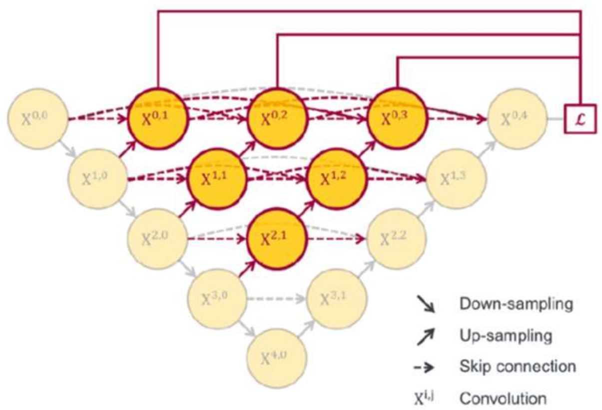
Zhou, **Fang** et al, 2020



Shen, Zhang, **Fang** et al, 2021

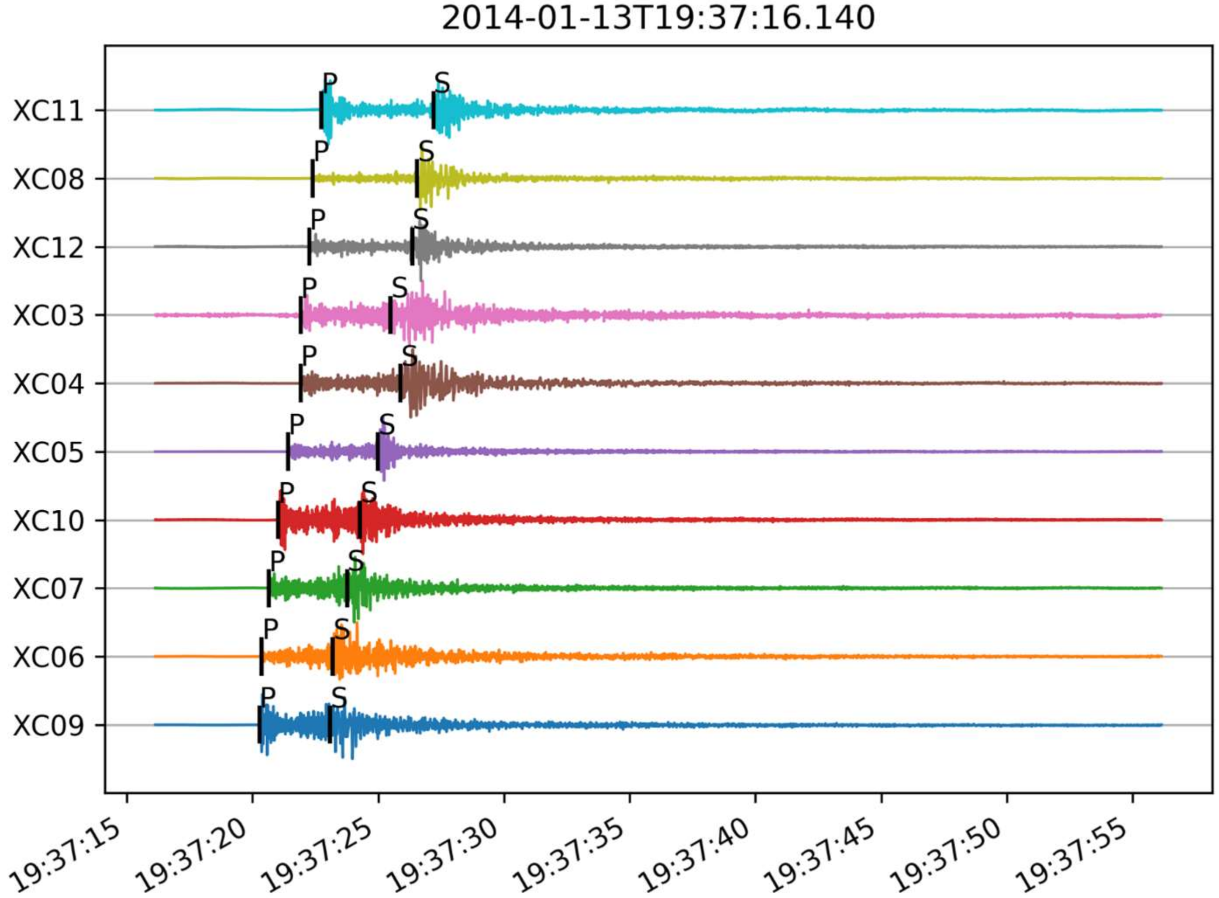


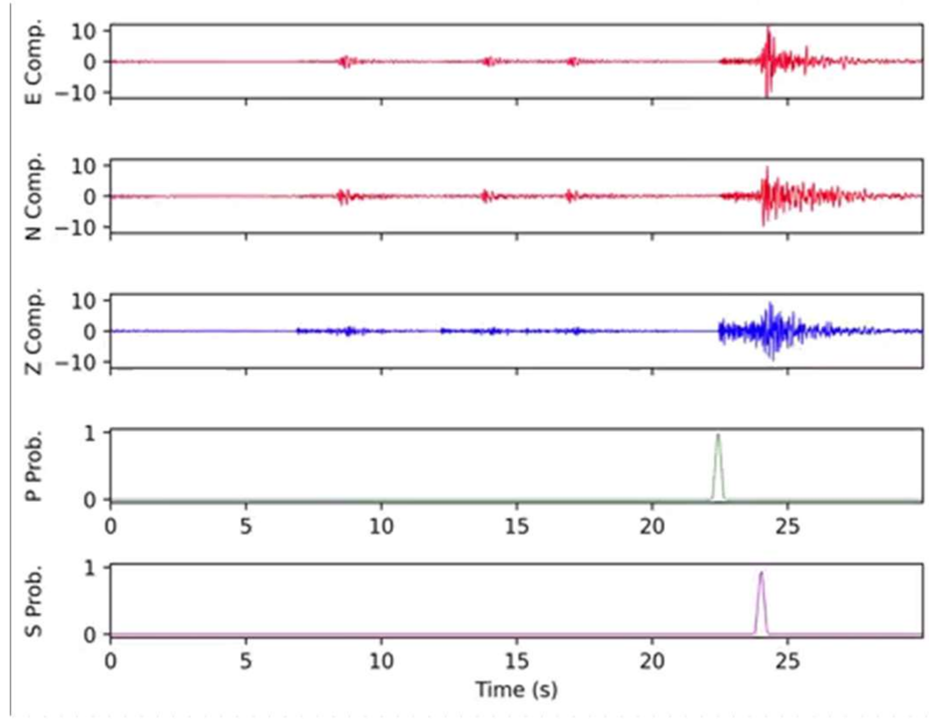
Zhou, Zhou, **Fang** et al, 2021



Li and **Fang**, 2021, in prep

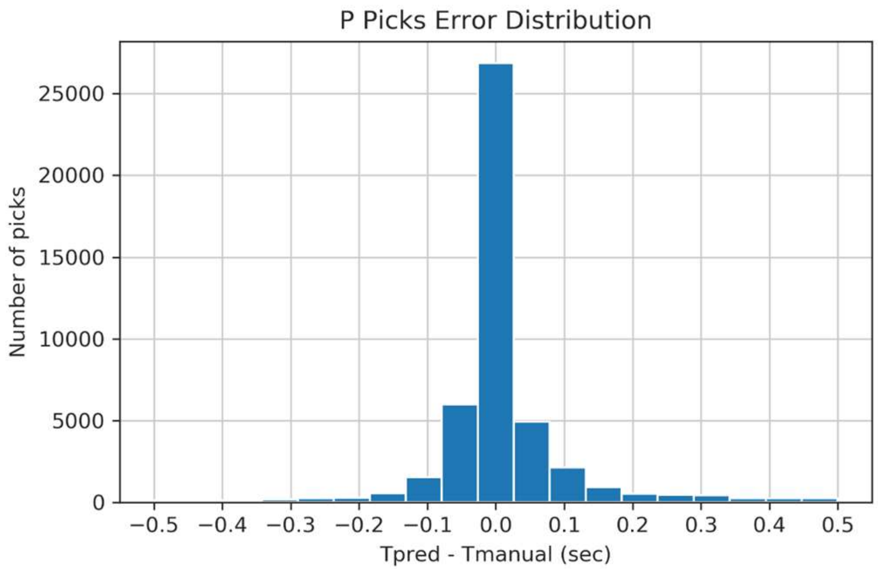
Earthquake detection example





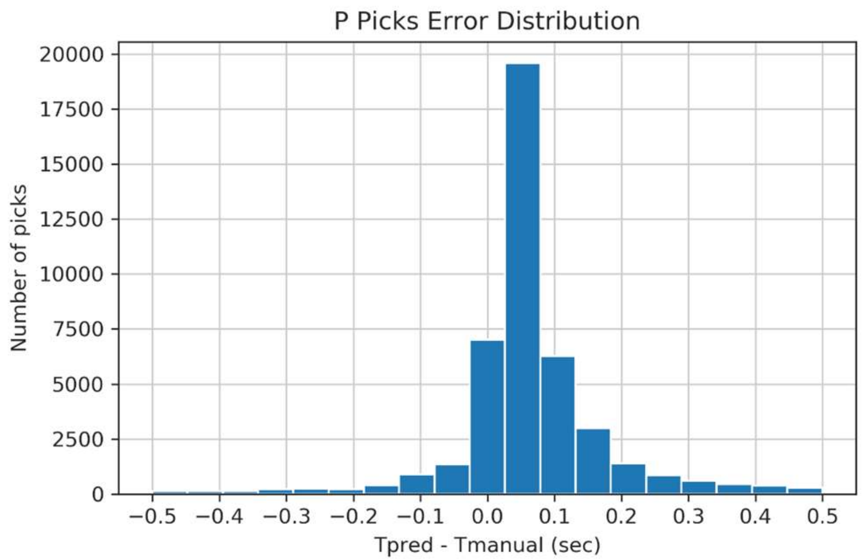
Performance of AI-based detection method

New Unet/Unet++ model outperms PhaseNet



CSESnet

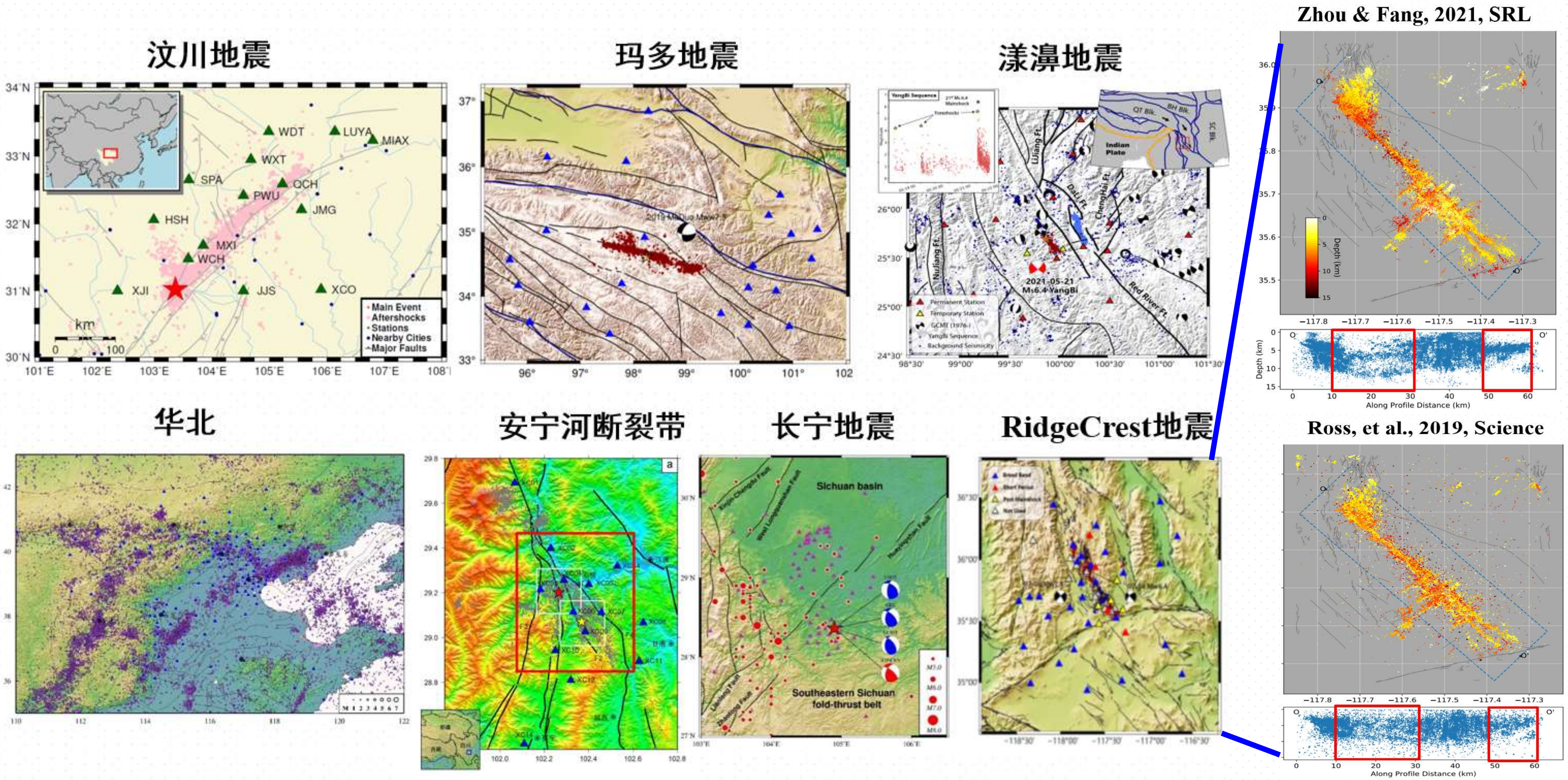
Recall = 0.933
F1 = 0.900
Mean = 0.049



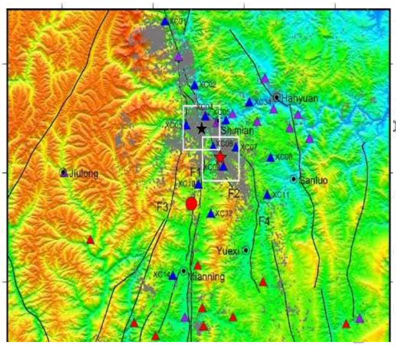
PhaseNet

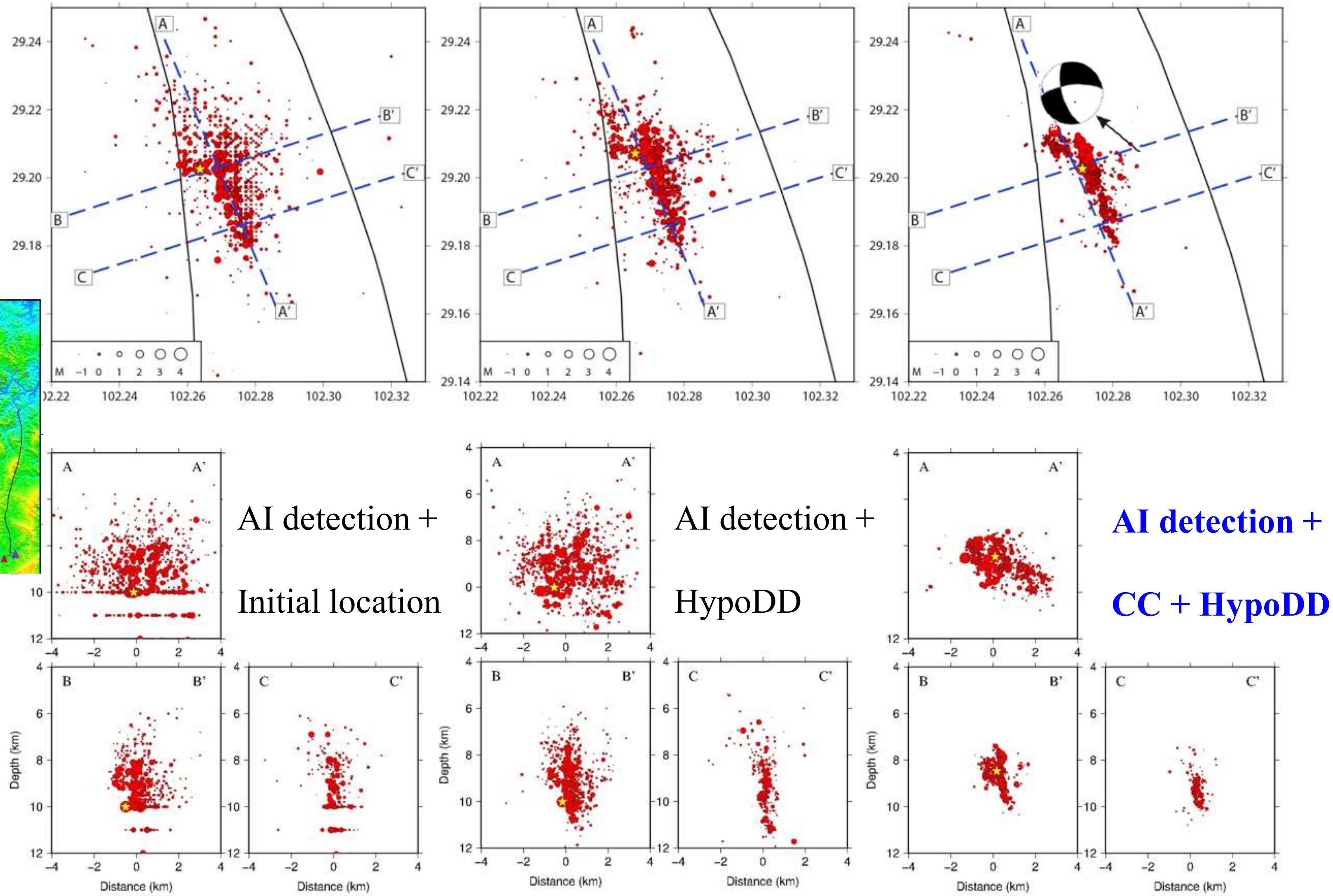
Recall = 0.881
F1 = 0.887
Mean = 0.088

Extensive test in China and USA

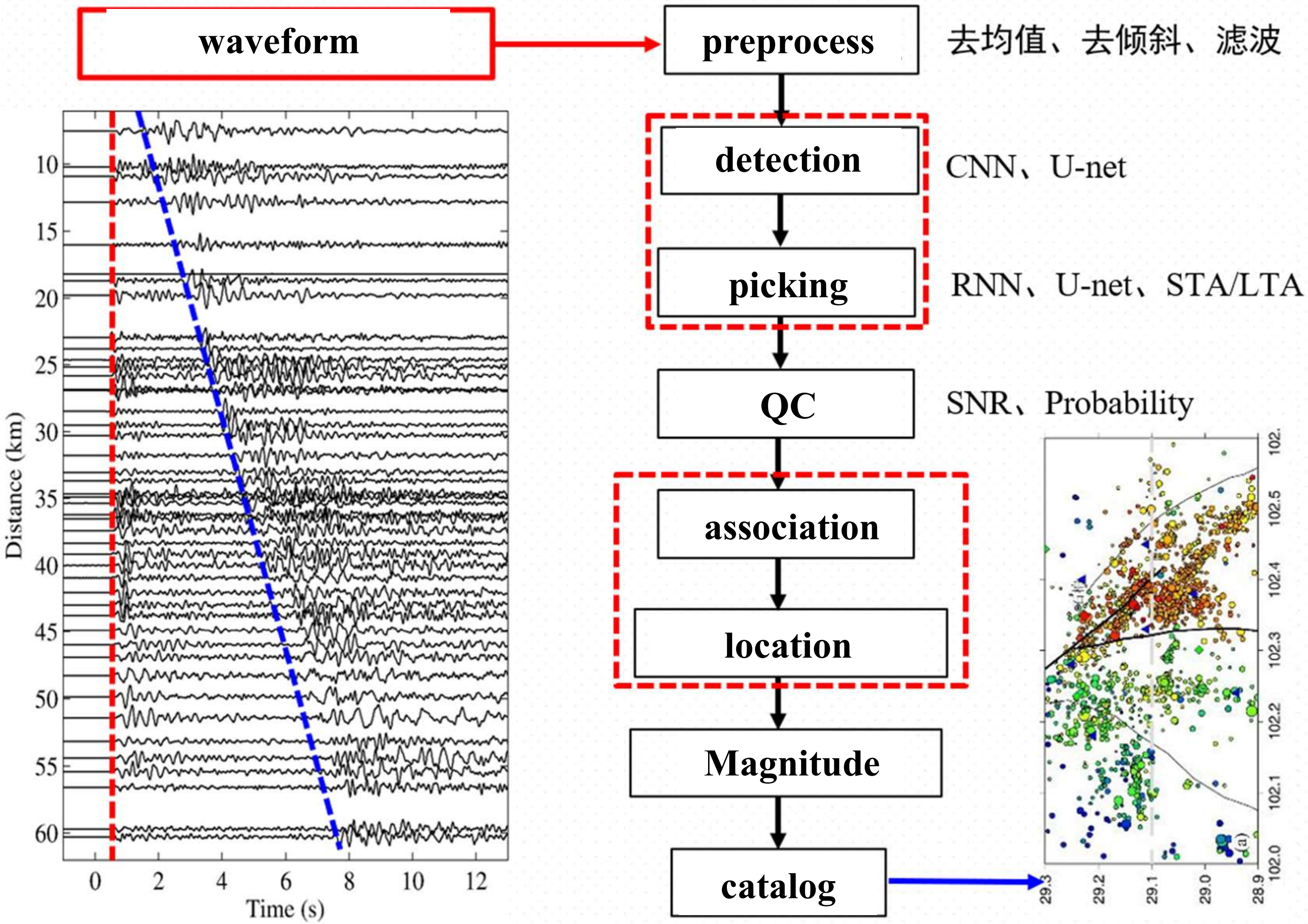


Sichuan Shimian M4.1 earthquake sequence



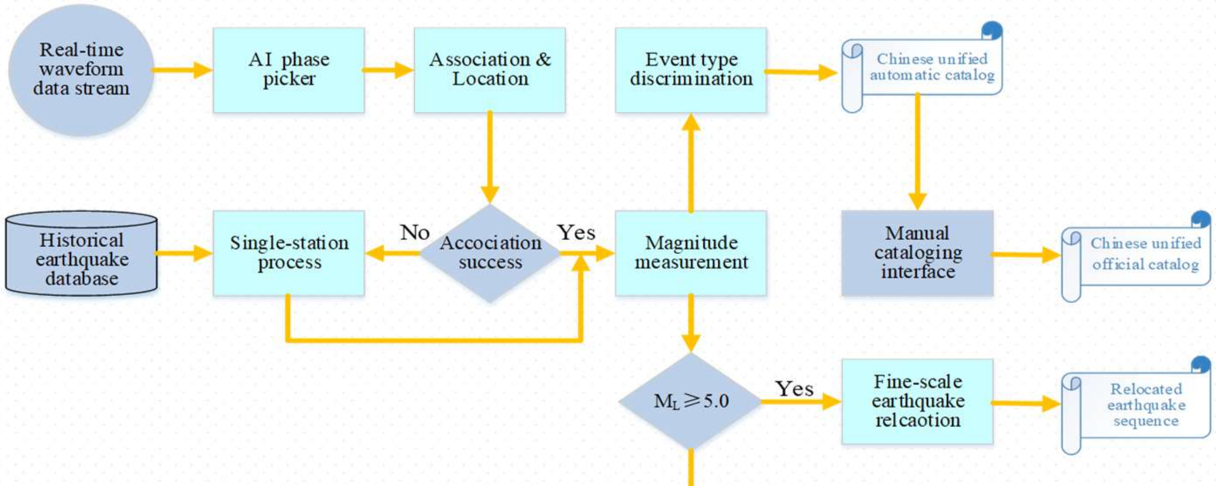


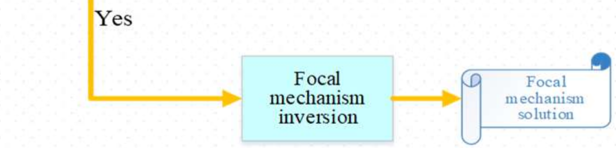
Flowchart of continuous waveform processing



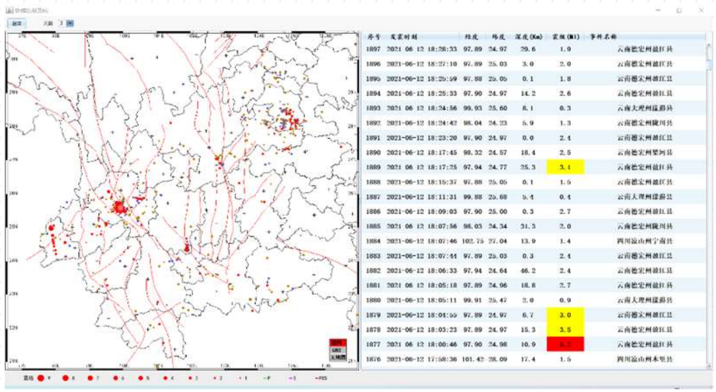
Realtime Intelligent Seismic Processing system (*RISP*)

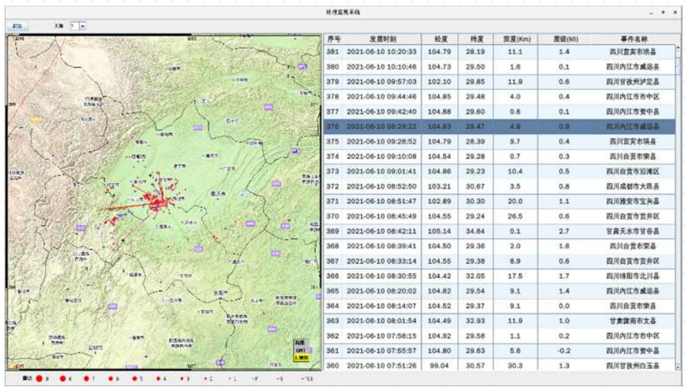
- Simulate manual processing flow
- Combination of AI and automation
- Efficient phase association algorithm
- Suitable for multi-scale seismic network
- Seamless connection with current system

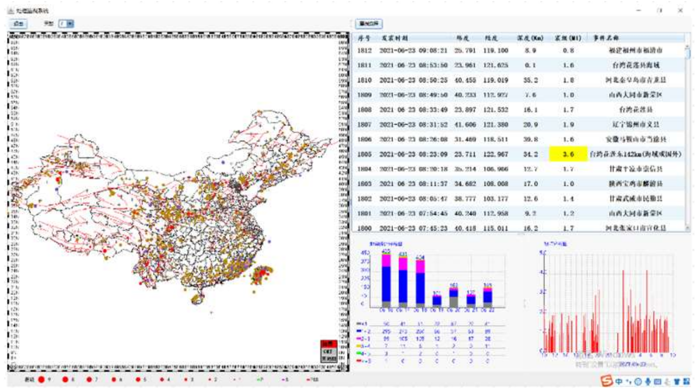




LIAO ShiRong, ZHANG HongCai, FAN LiPing et al. 2021. Development of a real-time intelligent seismic processing system and its application in the 2021 Yunnan Yangbi M_S6.4 earthquake *Chinese Journal of Geophysics* (in Chinese),64(10): 3632-3645,doi: 10.6038/cjg2021O0532.

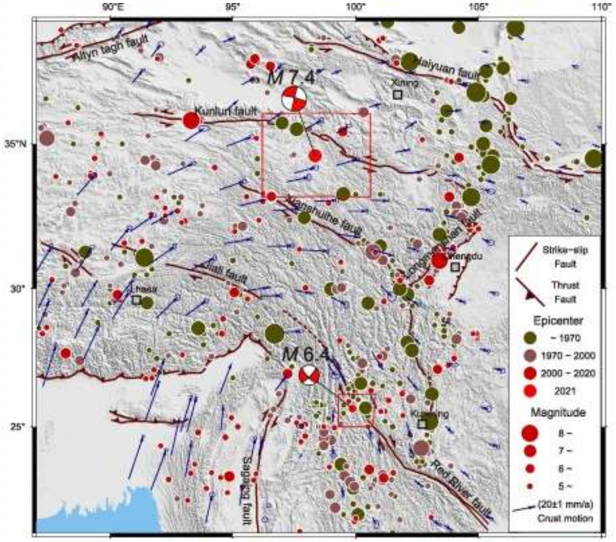


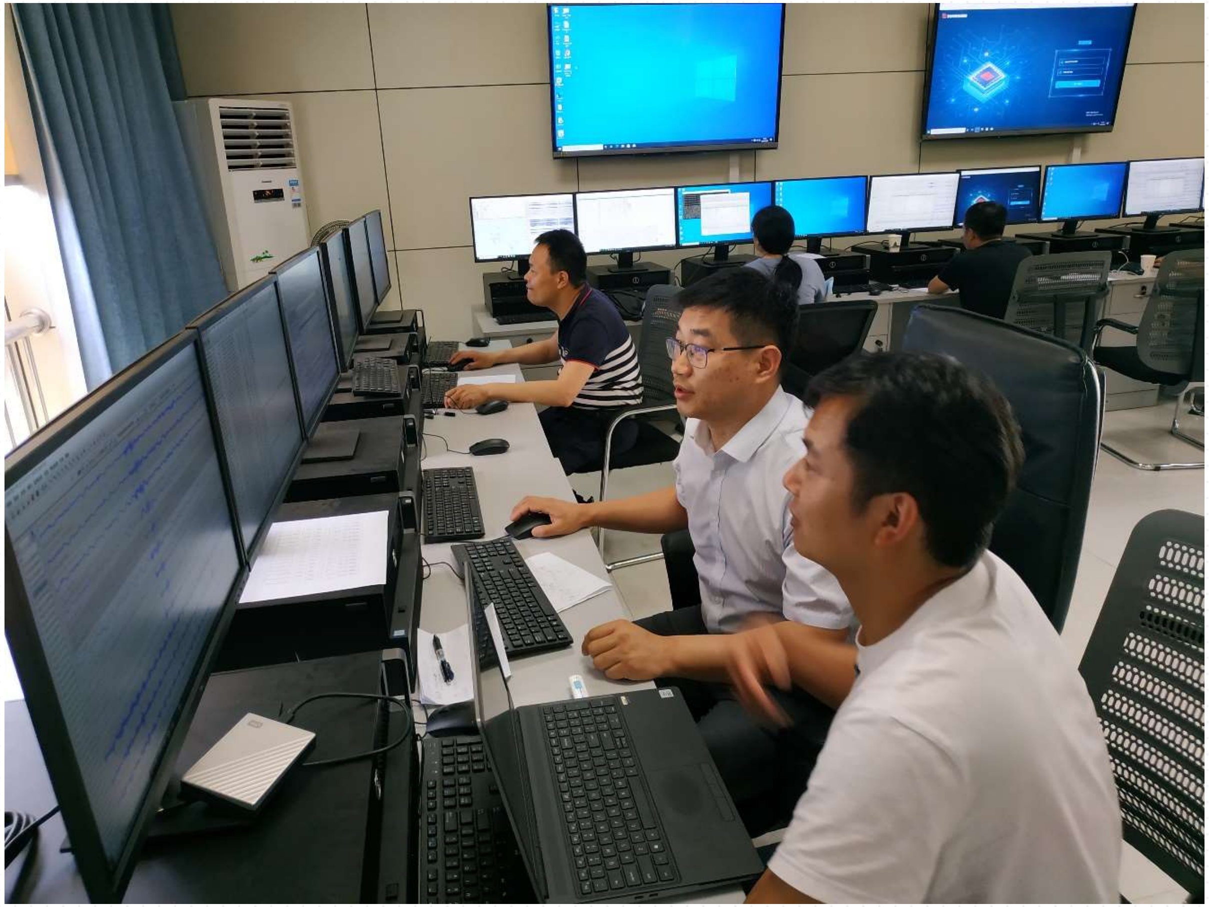




2021/05/21 Yunnan **Yangbi** M6.4 Earthquake
2021/05/22 Qinghai **Maduo** M7.4 Earthquake

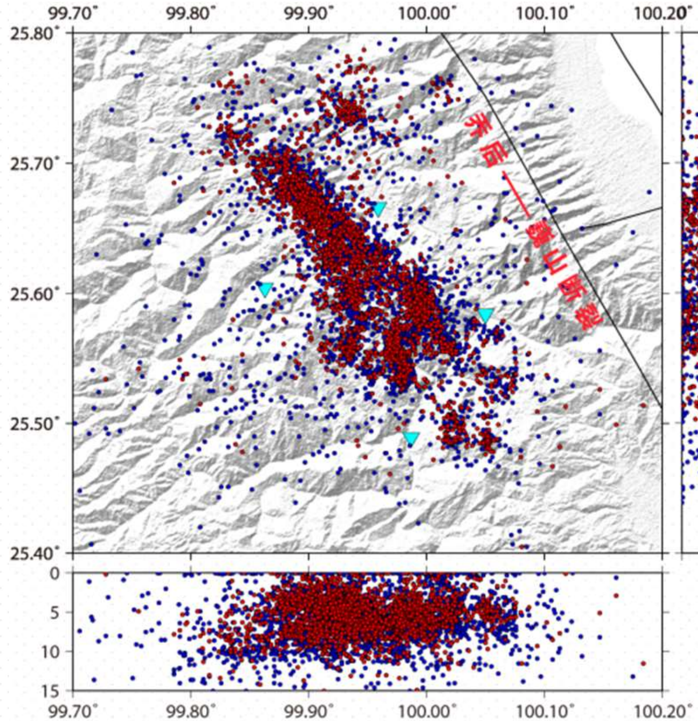
The research group installed *RISP* system in Qinghai and Yunnan



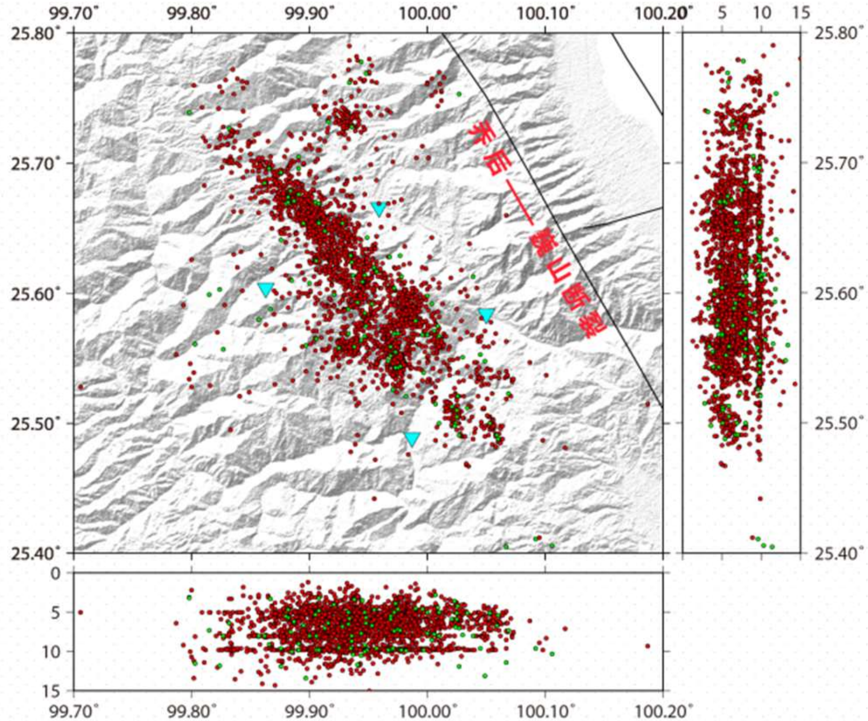


Yangbi M6.4 aftershock sequence processed by *RISP*

- **5/28-6/27： RISP 6667 aftershocks/Analyst 2752 aftershocks, 2.42**
- **Matching rate 95.75%; missed 117 (4.25%); detected more than 4032 eqs**



RISP



Analyst

Comparison of *RISP* and manual catalogs for the Yangbi EQ

- ✓ **OT difference: 0.10 ± 0.50 s; <1 s, 90%**
- ✓ **Epi difference: 1.50 ± 1.30 km; <3 km, 90.2%**
- ✓ **Dep difference: - 1.30 ± 2.80 km; <5 km, 96.7%**
- ✓ **Mag deviation: 0.15 ± 0.23; <0.4, 90.7%**

第 64 卷 第 10 期 地球物理学报 Vol. 64, No. 10
2021 年 10 月 CHINESE JOURNAL OF GEOPHYSICS Oct., 2021

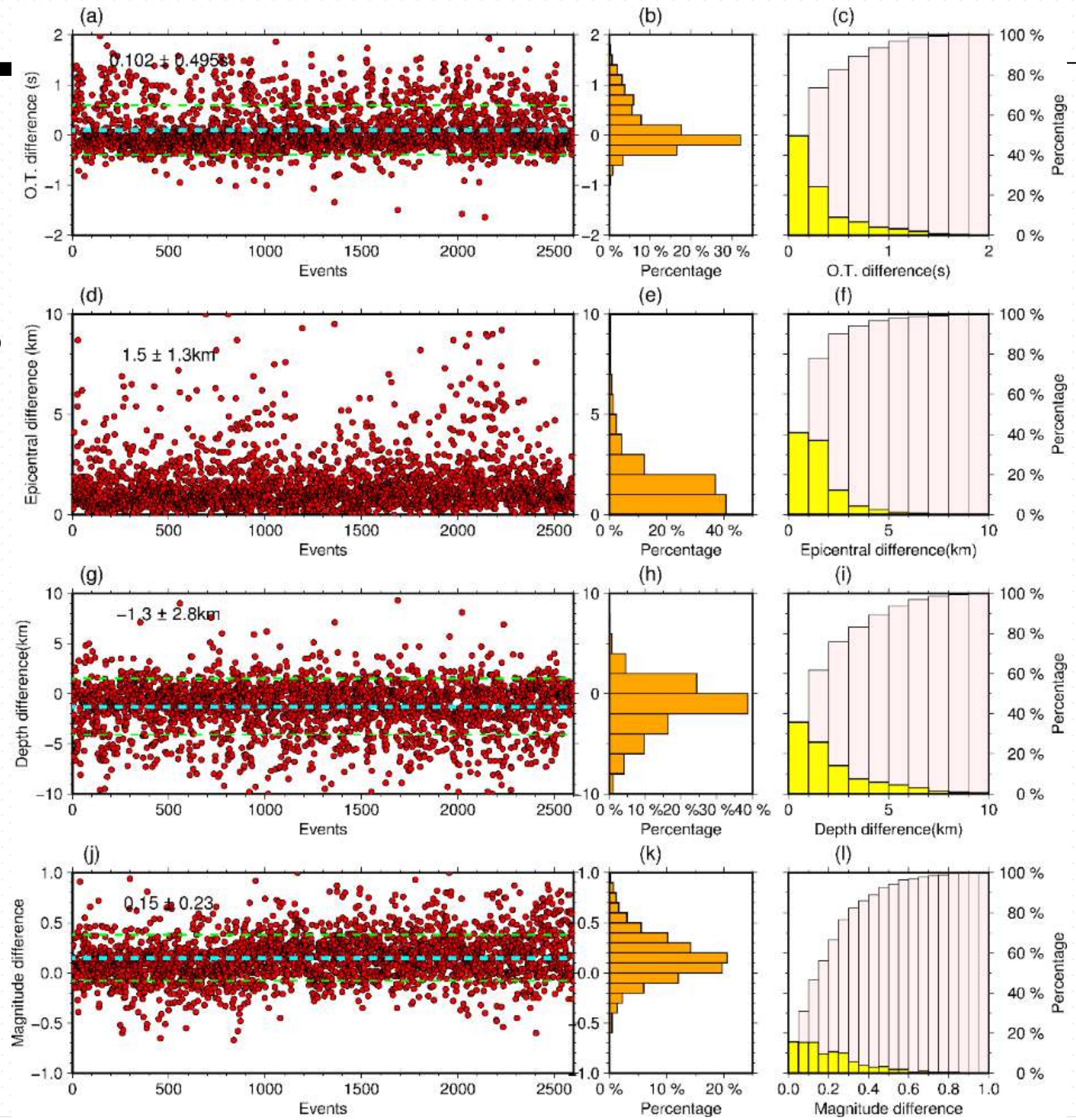
廖诗荣，张红才，范莉苹等. 2021. 实时智能地震处理系统研发及其在 2021 年云南漾濞 M_S6.4 地震中的应用. 地球物理学报，64(10): - ，doi:10.6038/cjg2021O0532.

Liao S R, Zhang H C, Fan L P, et al. 2021. Development of a real-time intelligent seismic processing system and its application in the 2021 Yunnan Yangbi M_S6.4 earthquake. *Chinese J. Geophys.* (in Chinese), 64(10): - , doi:10.6038/cjg2021O0532.

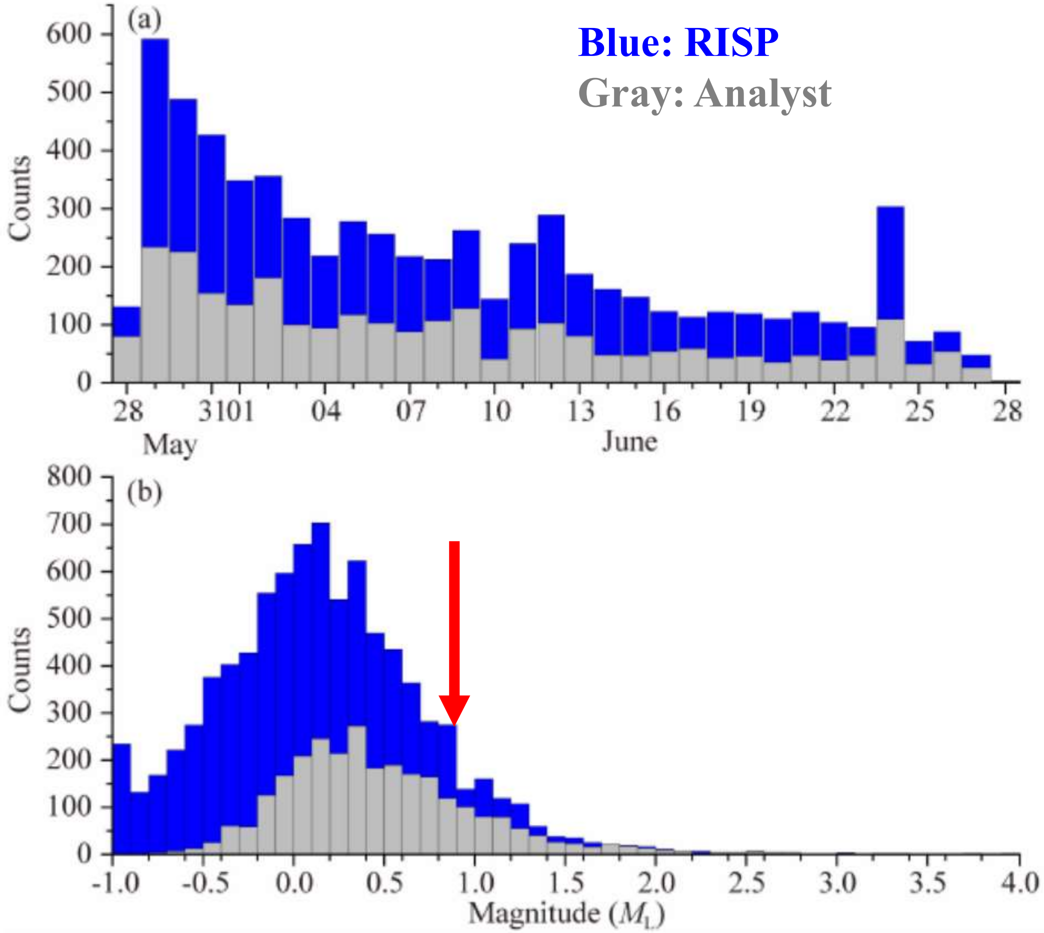
实时智能地震处理系统研发及其在 2021 年云南漾濞 M_S6.4 地震中的应用

廖诗荣[1]，张红才[1,2]，范莉苹[3,4]，李珀任[3]，黄玲珠[1]，房立华[3,4,5*]，秦敏[6]

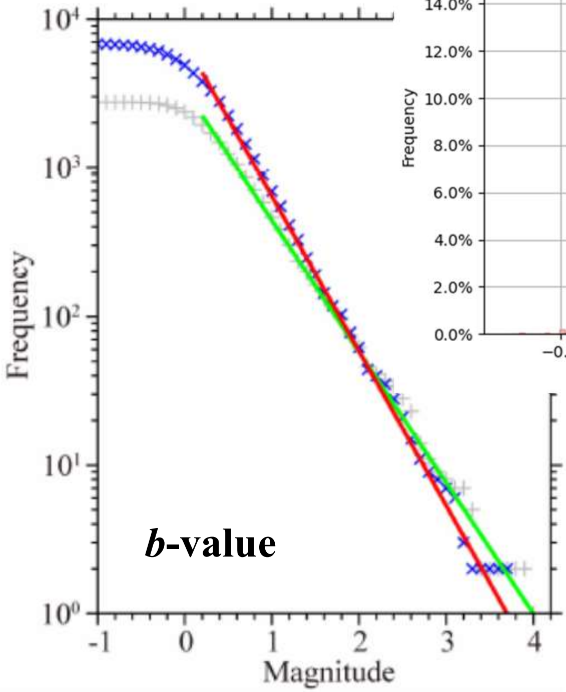
1 福建省地震局，福州 350003
2 中国地震局厦门海洋地震研究所，厦门 381000
3 中国地震局地球物理研究所，北京 100081
4 中国地震局震源物理重点实验室，北京 100081
5 防灾科技学院，河北三河 065201
6 云南省地震局，昆明 650224

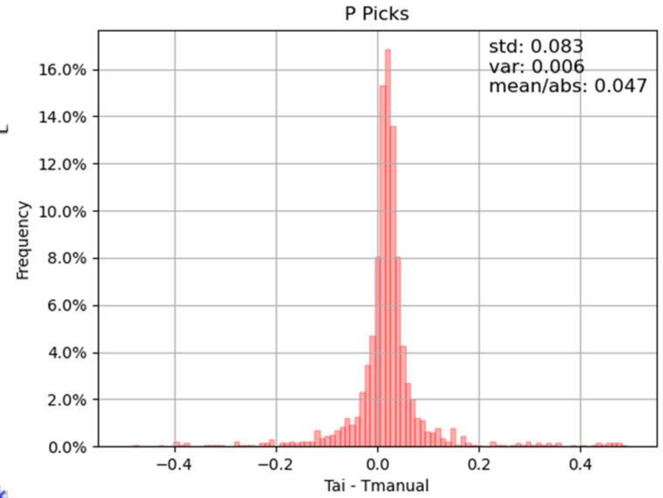


Comparison of numbers of aftershocks detected by RISP and analysts



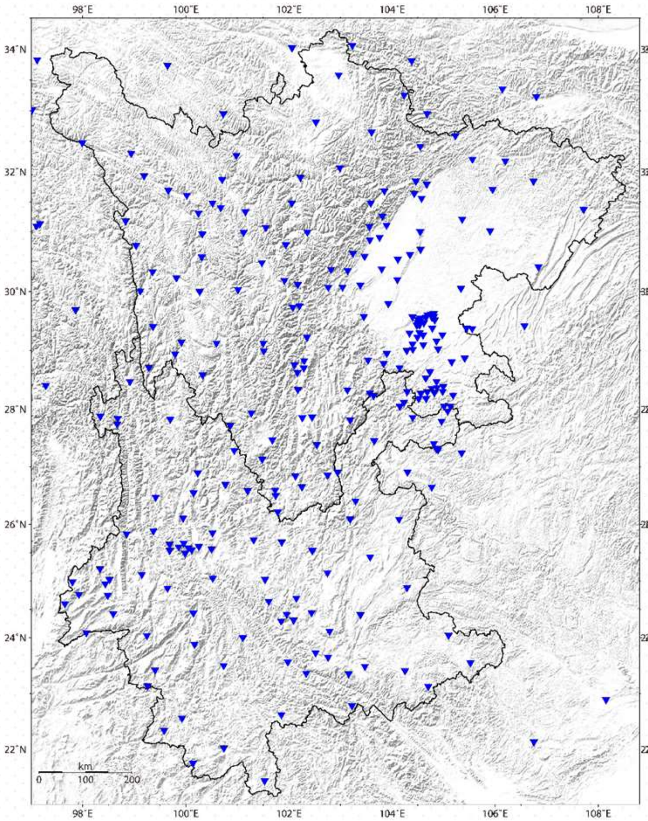
The arrival time of P wave picked by AI is less than 0.1s, and about 95% is less than 0.2s



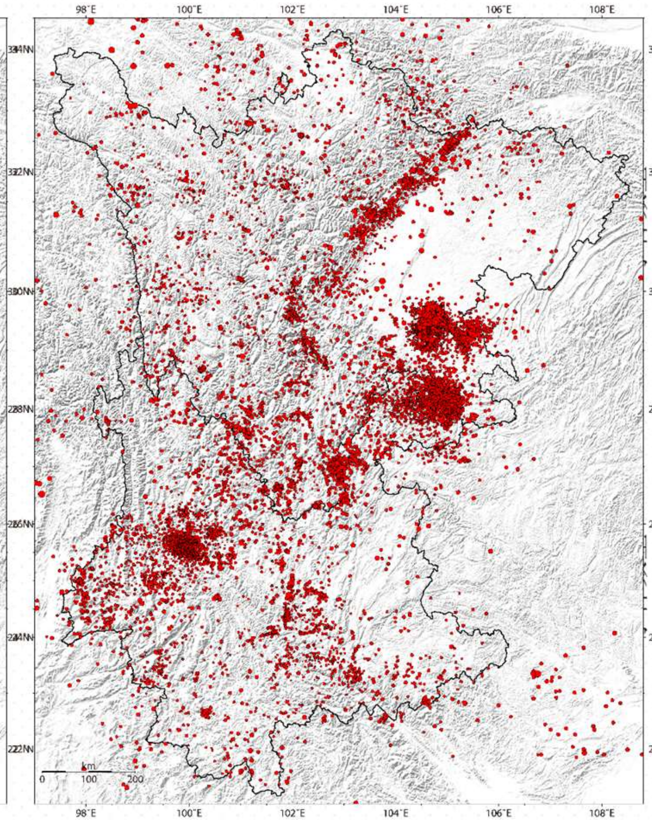


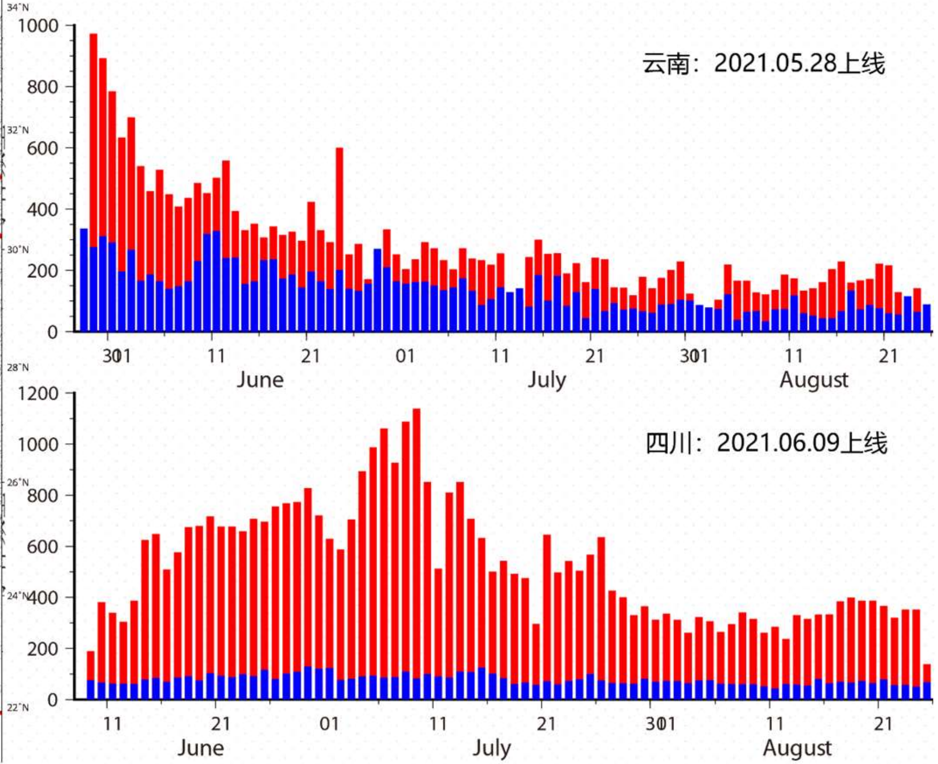
Application of ***RISP*** in Sichuan and Yunan seismic network

298 stations



RISP processed 50000+ eqs in two months

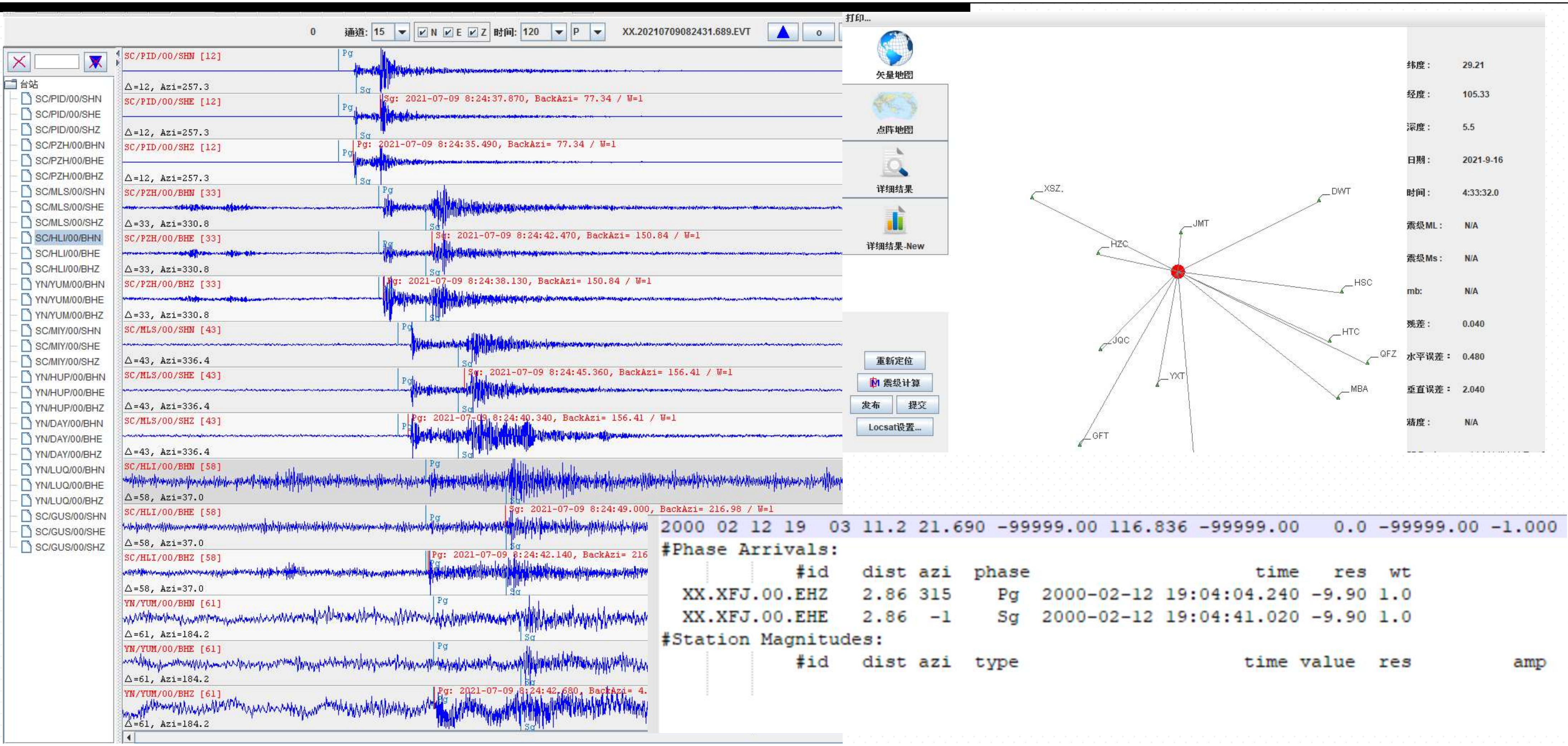




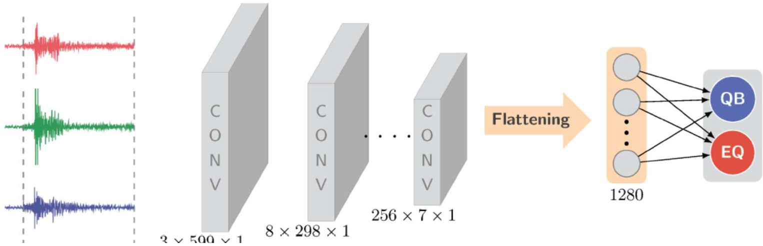
Human-computer interaction processing

Check/verify 100 earthquakes only needs 9 mins

Processing efficiency is improved at least 30 times!



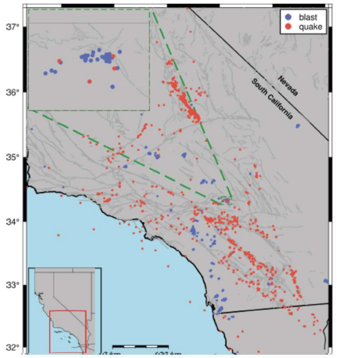
Earthquake classification

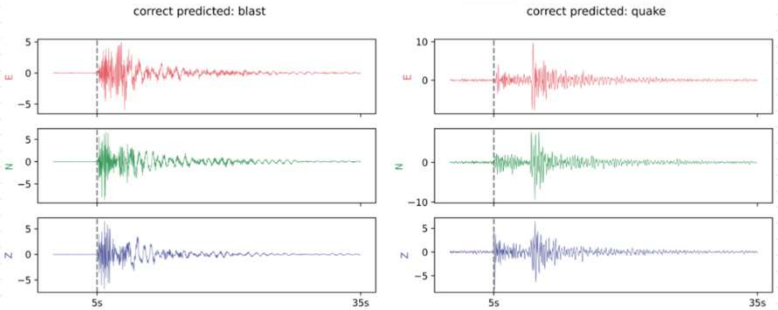


Accuracy: 94.95%

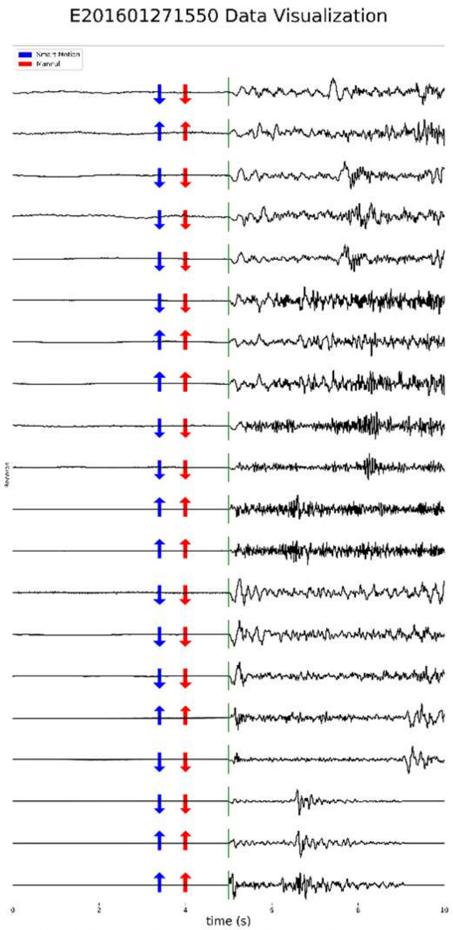
	precision	recall	F1-score
quake	0.97	0.94	0.95
blast	0.93	0.96	0.94

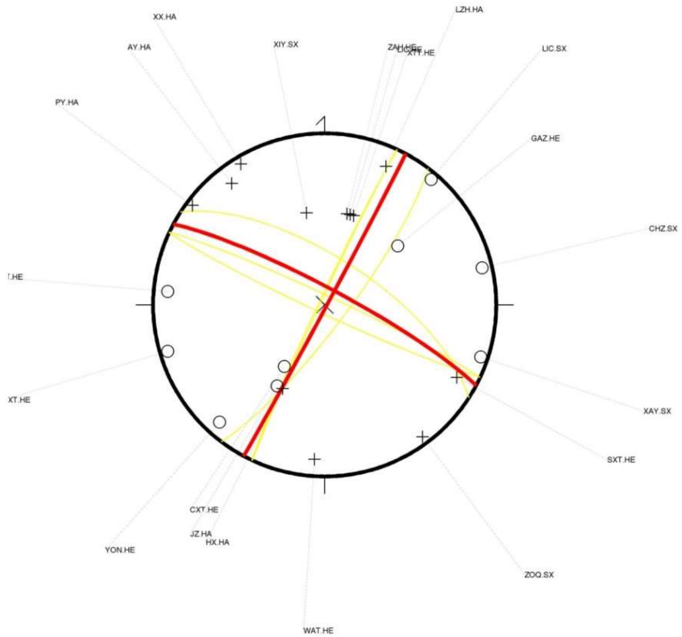
recordings	blast	quake
raw	64255	55157
snr>8	19376	24843





First motion → Focal mechanism





Very promising, quick developing stage

1. The generalization problem
2. Difficult to detect second P and S waves at large distance
3. The tradeoff between miss picks and false detection
4. More on detection and phase picking, few on polarity and classification

Special issue of AI seismology in EQS and SRL

Call for papers in a special issue of Artificial Intelligence in Seismology

Share:

In recent years, artificial intelligence has developed rapidly in the field of seismology. To further promote the integration of artificial intelligence and seismology, we'd like to invite contributions to a special issue of Artificial Intelligence in Seismology. The topics include, but not limited to, the following: microseismic detection, earthquake early warning, seismic phase arrival pickup, seismic signal denoising, focal mechanism inversion, tomographic inversion, and so on.

Earthquake Science (EQS) is an English international journal sponsored by the Seismological Society of China and the Institute of Geophysics, China Earthquake Administration. It is a core journal of seismology and geophysics in China and has over 30 years of publication history. The journal is being re-organized (with Prof. Xiaodong Song serving as the Editor-in-Chief). With a renewed effort and your support, we strike to become a flagship journal of earthquake science research in the region and beyond.

You can submit your manuscripts at the following website:

https://mc03.manuscriptcentral.com/eqs

The deadline for submission is June 30, 2022. If you have any questions, please contact one of the editorial staff below. If you are planning to submit a paper, please email your tentative title to the email address as soon as possible.

Currently, guest editors of the special issue include: Lihua Fang, Jianwei Ma, Xinming Wu, Zefeng Li, Han Yue, Weitao Wang, Jian Wang, and Weiqiang Zhu.

Deadline 06/30/2022

We look forward to your contributions and an exciting and timely special issue.

SRL Call for Papers

Big Data Problems in Seismology

Seismological Research Letters (*SRL*) is soliciting papers for a Focus Section on Big Data Problems in Seismology.

Seismology has undoubtedly entered an era of big data, with major seismic data centers like IRIS now storing hundreds of terabytes of waveform data. Recently, the emerging use of large-N arrays and Distributed Acoustic Sensing (DAS) have been rapidly accelerating the accumulation of large seismic data sets. At the same time, machine learning (especially deep learning) and other more general tools from data science are providing brand-new perspectives to examine these large data sets. Since the Focus Section on Machine Learning for Seismology in *SRL* in early 2019, the application of machine learning in seismology has grown sharply. It has become increasingly standard to use machine learning in seismic data analysis, including relatively mature applications in automation of earthquake detection, phase picking and phase association. Seismologists are becoming adept to big seismic data problems and witnessing a gradual paradigm shift of seismological research. This focus section invites papers covering a wide spectrum of big data problems in seismology, with applications to earthquake source or earth structure analyses using machine learning, DAS and large-N arrays, or any of these new techniques in combination. We also welcome contributions on technical challenges and solutions to storage, processing and visualization of big seismic data.

Guest Editors for the special section are:

Zefeng Li, University of Science and Technology of China; zefengli@ustc.edu.cn

Daniel Trugman, The University of Texas at Austin; dtrugman@jsg.utexas.edu

Lihua Fang, Institute of Geophysics, China Earthquake Administration; flh@cea-igp.ac.cn

Jonathan Ajo-Franklin, Rice University; ja62@rice.edu

Avinash Nayak, Lawrence Berkeley National Laboratory; anayak7@lbl.gov

Deadline for submission of manuscripts: 1 March 2022

Deadline 3/1/2022

References

1. Yijian ZHOU, Abhijit GHOSH, Lihua FANG*, Han YUE, Shiyong ZHOU, Youjin SU. 2021. A High-Resolution Seismic Catalog for the 2021 Ms6.4/Mw6.1 YangBi Earthquake Sequence, Yunnan, China: Application of AI picker and Matched Filter. Earthquake Science, in press.
2. Jiang Ce, Fang Lihua*, Fan Liping, Li Boren, Comparison of seismic detection performance between Phasenet and EQTransformer: Taking YangBi earthquake and Maduo earthquake as examples. Earthquake Science, in press.
3. 廖诗荣，张红才，范莉苹，李珀任，黄玲珠，房立华*，秦敏．2021．实时智能地震处理系统研发及其在2021年云南漾濞Ms6.4地震中的应用．地球物理学报，64(10)，doi:10.6038/cjg2021O0532．
4. 周本伟, 范莉苹, 张龙, 李珀任, 房立华*. 2020. 利用卷积神经网络检测地震的方法与优化. 地震学报，42(6):669-683. Doi:10.11939/jass.20200045.
5. 赵明, 陈石, 房立华*, David A Yuen. 2019. 基于U形卷积神经网络的震相识别与到时拾取方法研究. 地球物理学报, 62(8):3034-3042.
6. Fang Lihua, Wu Zhongliang*, Song Kuan, SeismOlympics, Seismological Research Letters, 2017, 88(6):1429-1430, doi: 10.1785/0220170134.
7. Long Zhang, Lihua Fang*, Weilai Wang, Zuoyong Lv, 2020. Seismic phase picking in China Seismic Array using a deep convolutional neuron network, Earthquake Science, 33, 72-81. doi: 10.29382/eqs-2020-0072-03.
8. Zhu, L., Z. Peng, J. McCllean, C. Li, D. Yao, Z. Li, and L. Fang. 2019. Deep learning for seismic phase detection and picking in the aftershock zone of 2008 Mw 7.9 Wenchuan earthquake, Phys. Earth Planet. In. 293(2019), 106261. https://doi.org/10.1016/j.pepi.2019.05.004.
9. Zhou, Y., H. Yue, L. Fang, S. Zhou, L. Zhao, and A. Ghosh. 2021. An Earthquake Detection and Location Architecture for Continuous Seismograms: Phase Picking, Association, Location, and Matched Filter (PALM), Seismol. Res. Lett. XX, 1–13, doi: 10.1785/0220210111.
10. 申大忠, 张琦, 徐童, 房立华 等. EL-Picker: 基于集成学习的余震P 波初动实时拾取方法. 中国科学: 信息科学, 2021, 51:912-926, doi: 10.1360/SSI-2020-0214.

If you are interested in RISP and want to install the processing system, please contact me: flh@cea-igp.ac.cn

Thank you!

Lihua Fang

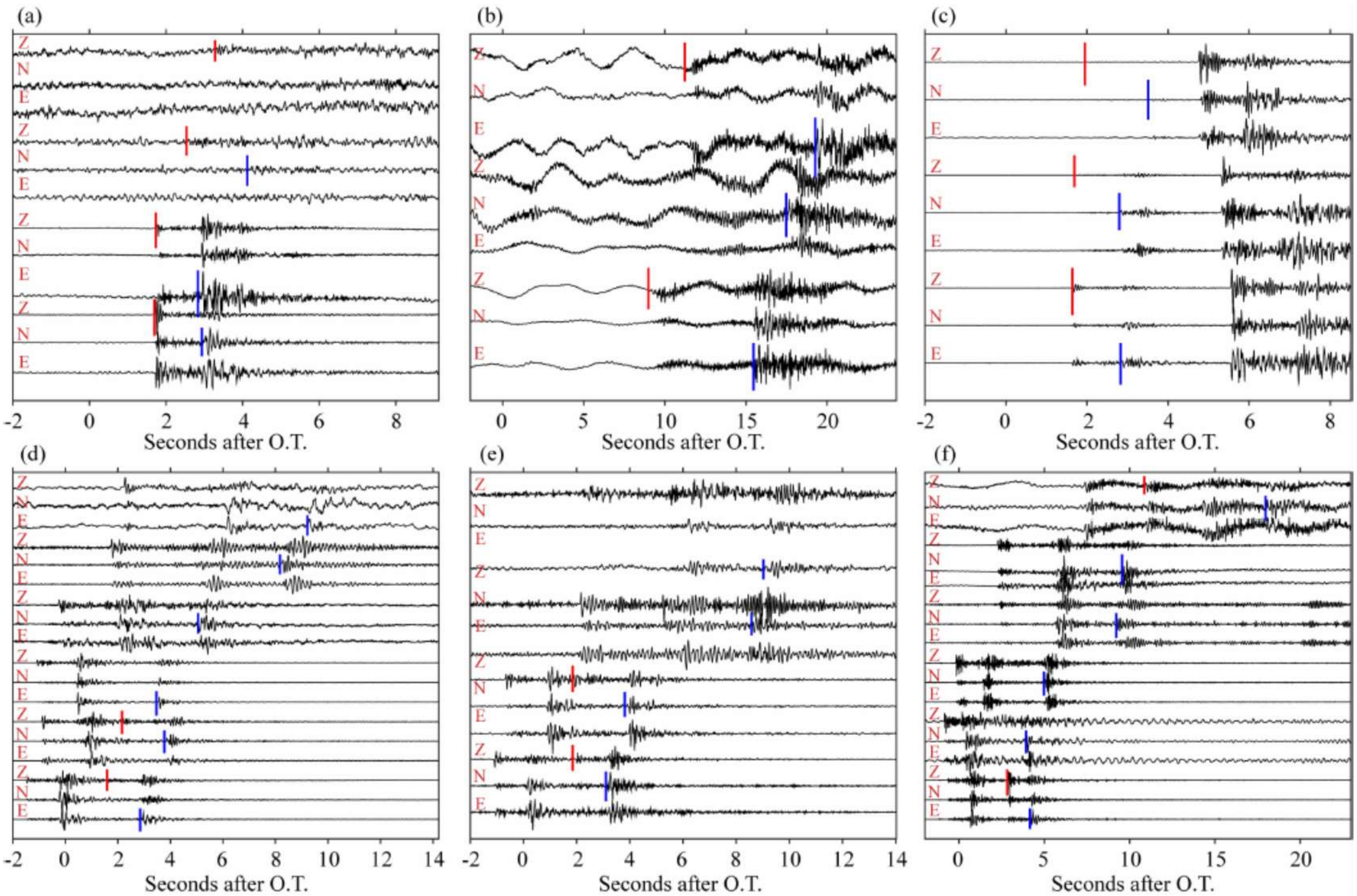
Tele： 010-68729203

Email： flh@cea-igp.ac.cn

https://www.researchgate.net/profile/Lihua-Fang-3

https://scholar.google.com/citations?user=ENeCjMYAAAAJ&hl=en

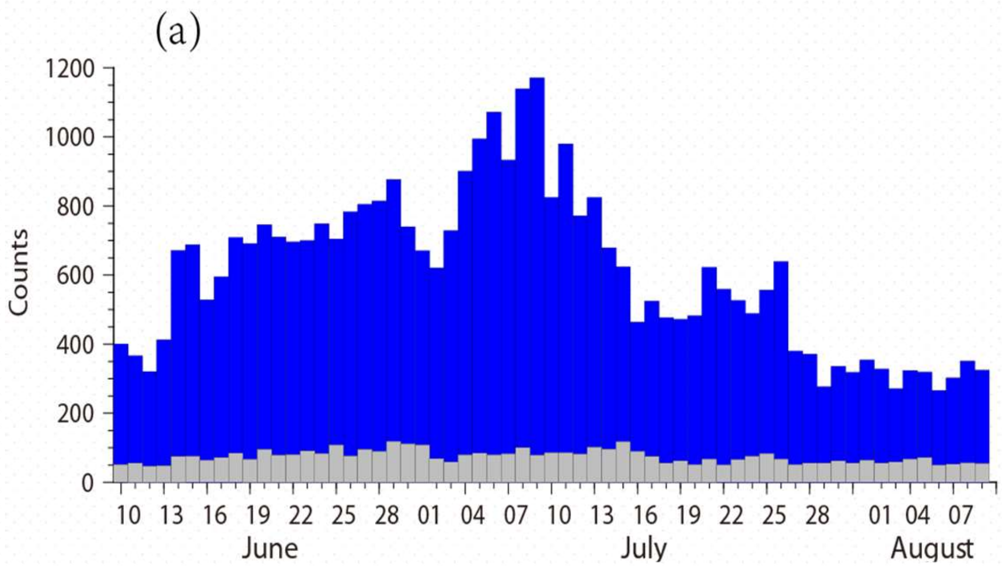
AI missed EQS

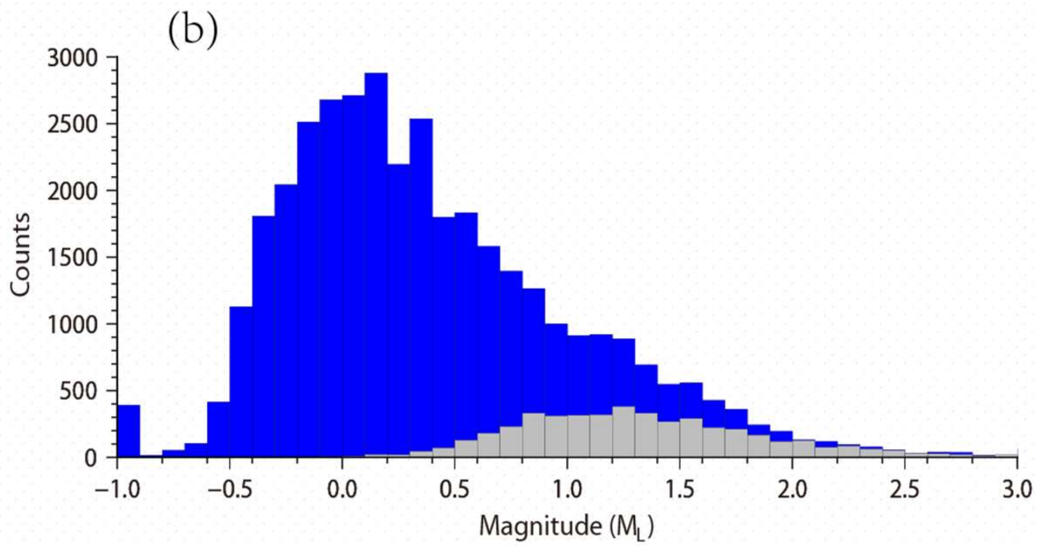


Application of ***RISP*** in Sichuan seismic network

多检测事件：7月9日自动1133个，人工79个，多检测1054个事件。1033个(98.0%)为地震或爆破事件，21个(2.0%)为误检测。

漏检原因：漏检339个。其中有233个可以离线检测到，多数由于数据流中断、台站延时较大及系统维护等原因造成。另106个是由于多震叠加、清晰震相少等导致未能检测到。



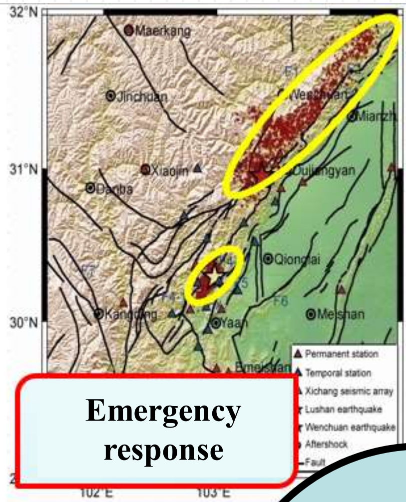


确定震源区大小

受灾区域估计

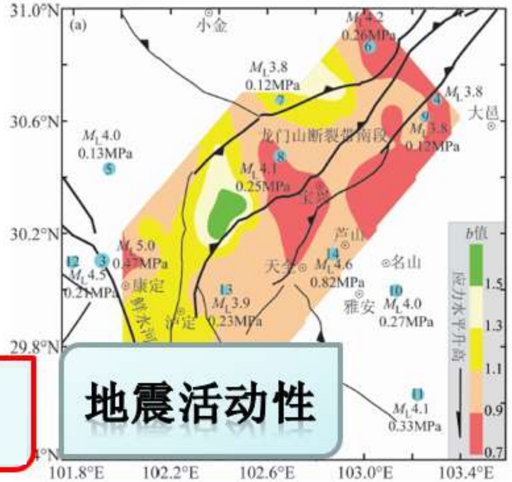
震源破裂过程快速反演

辅助确定断层面



Emergency response

Earthquake prediction



地震活动性

Earthquake catalog

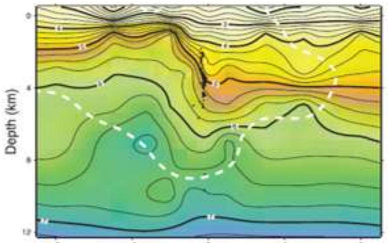
隐伏活动断层

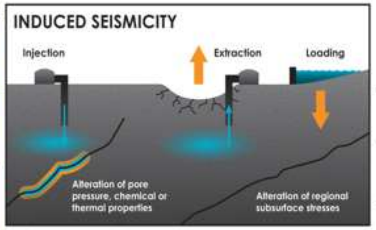
地震安评与风险评估

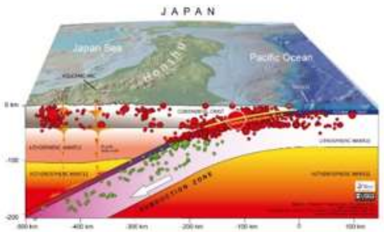
走时层析成像

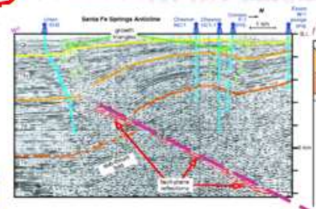
Seismic Tomography

Active fault

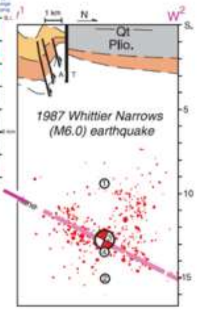




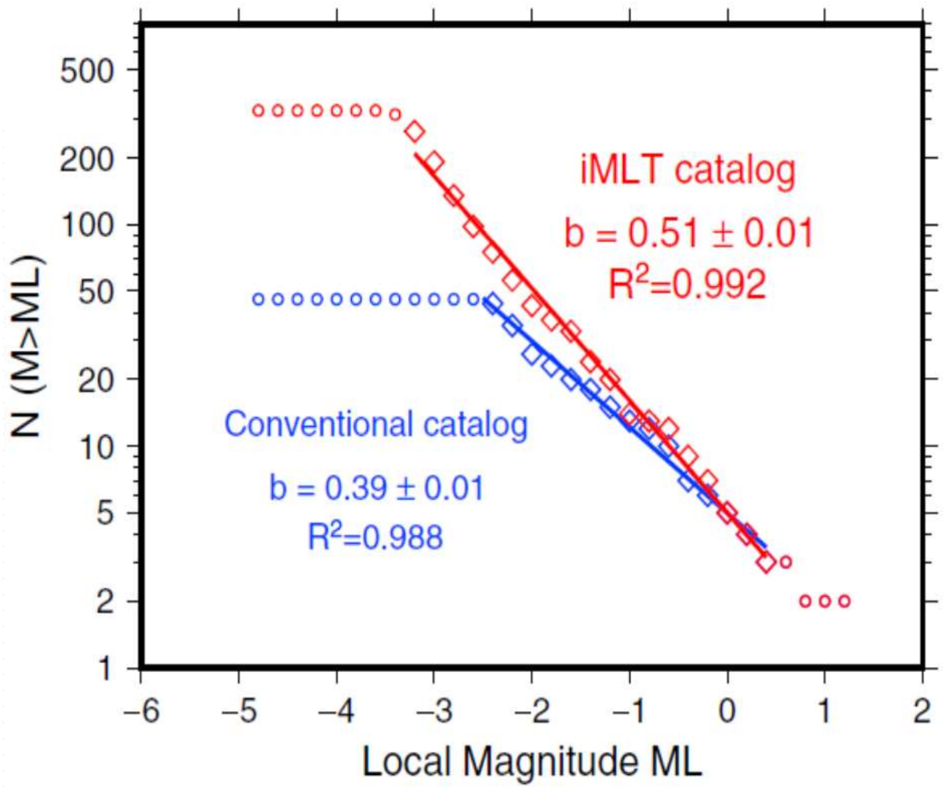




Shaw and Shearer,1999, Science



G-R Law and ETAS model estimation



Meng et al., 2017

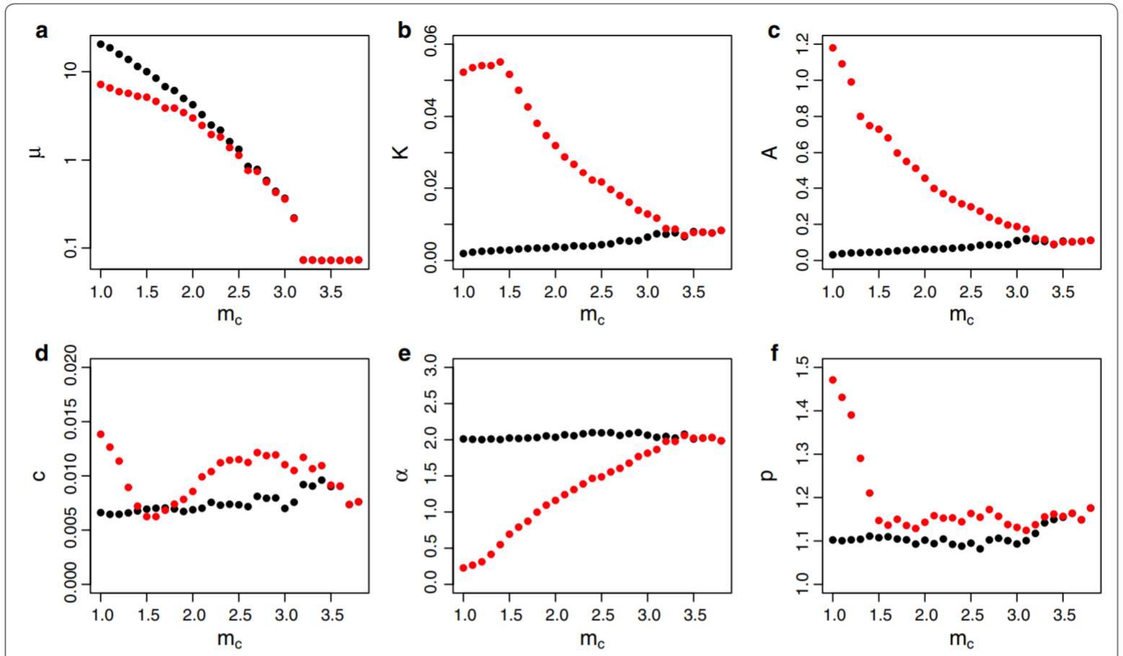
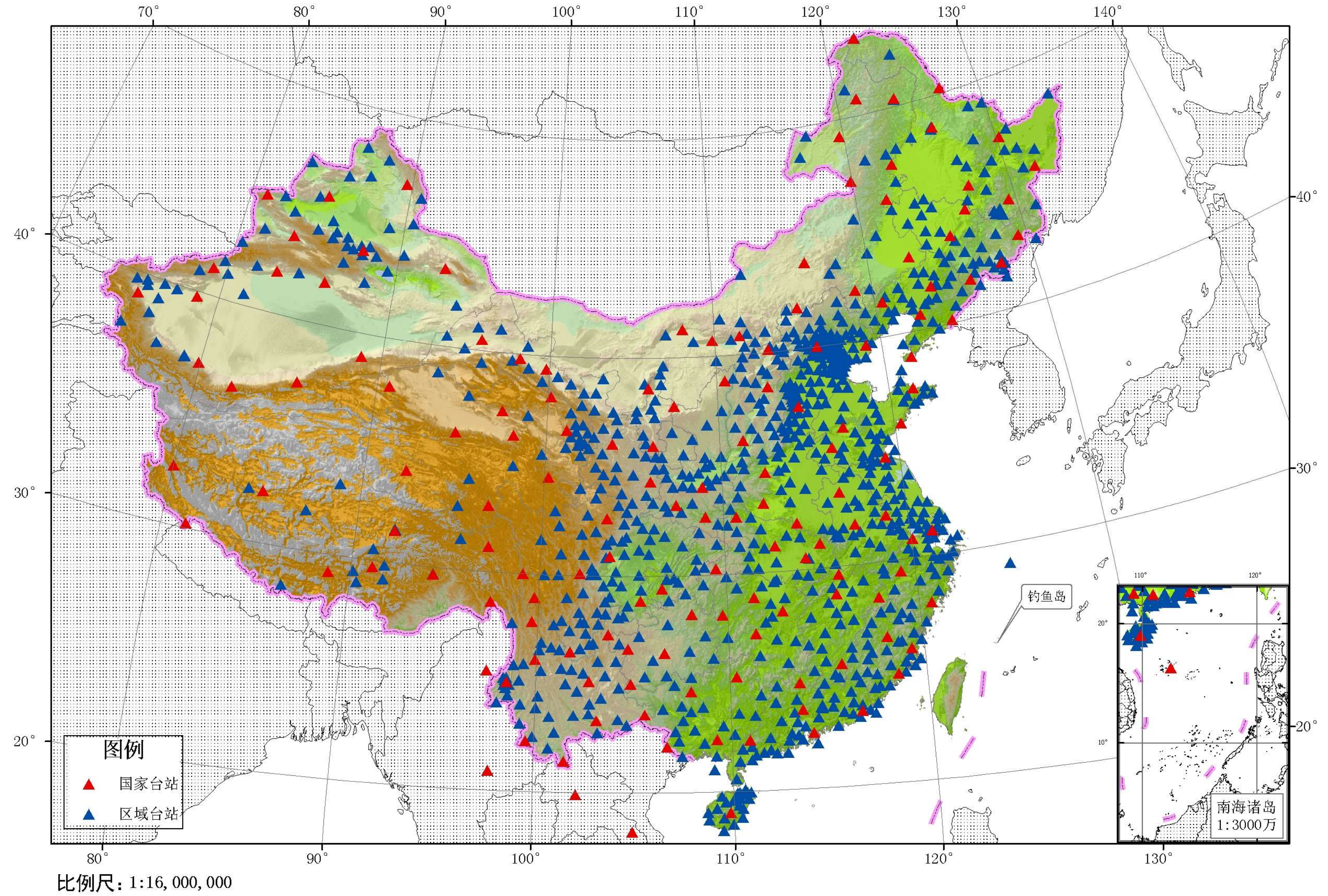


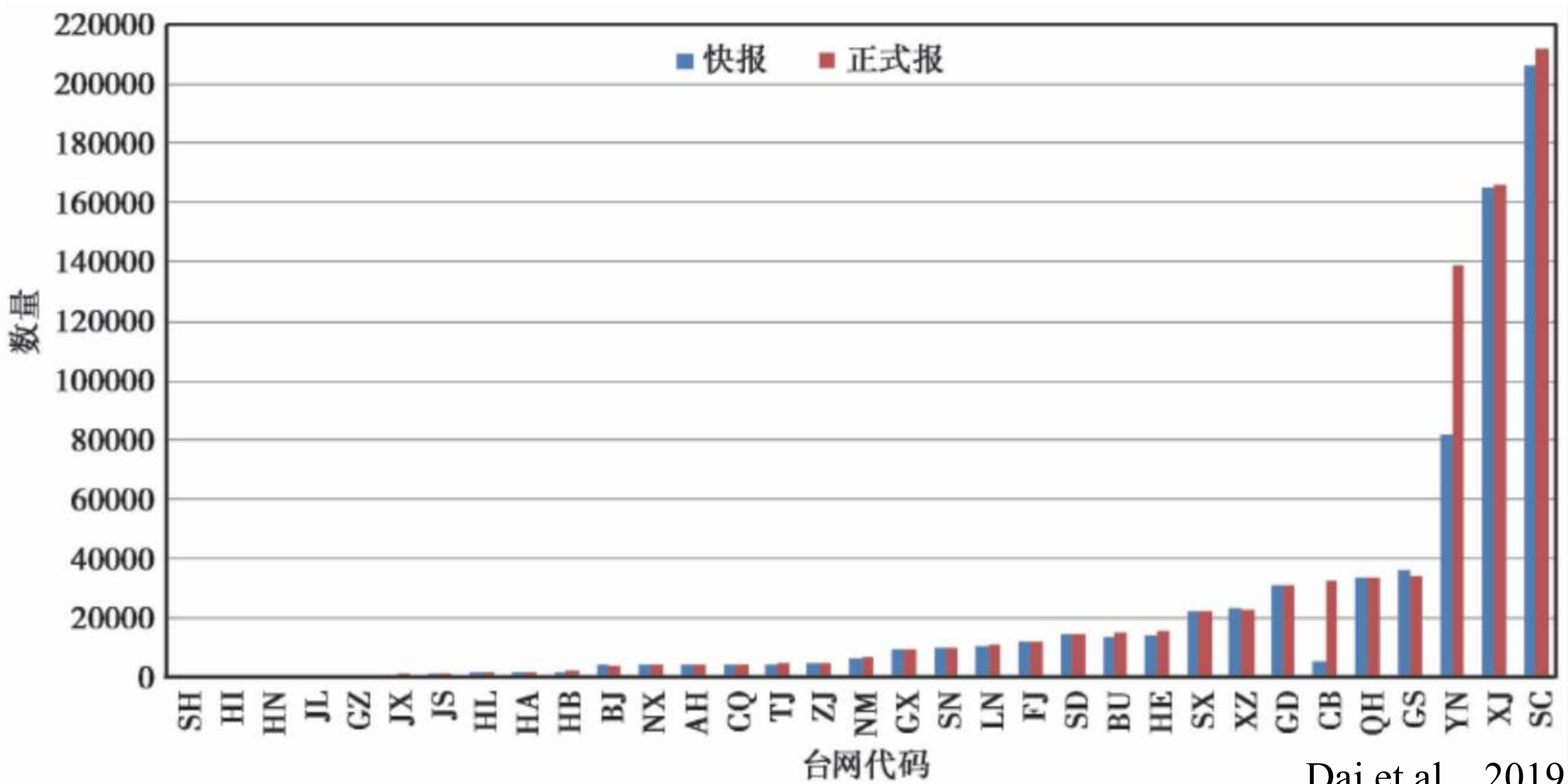
Fig. 4 ETAS parameters estimated from the Kumamoto aftershock sequence with different magnitude thresholds: **a** μ, **b** K, **c** A, **d** c, **e** α, and **f** p. The *red* and *black dots* are the estimates based on the original and the replenished datasets, respectively

Zhuang et al. 2017

Seismic stations in China（ ~1200, before 2021）



Earthquakes in different regional seismic networks

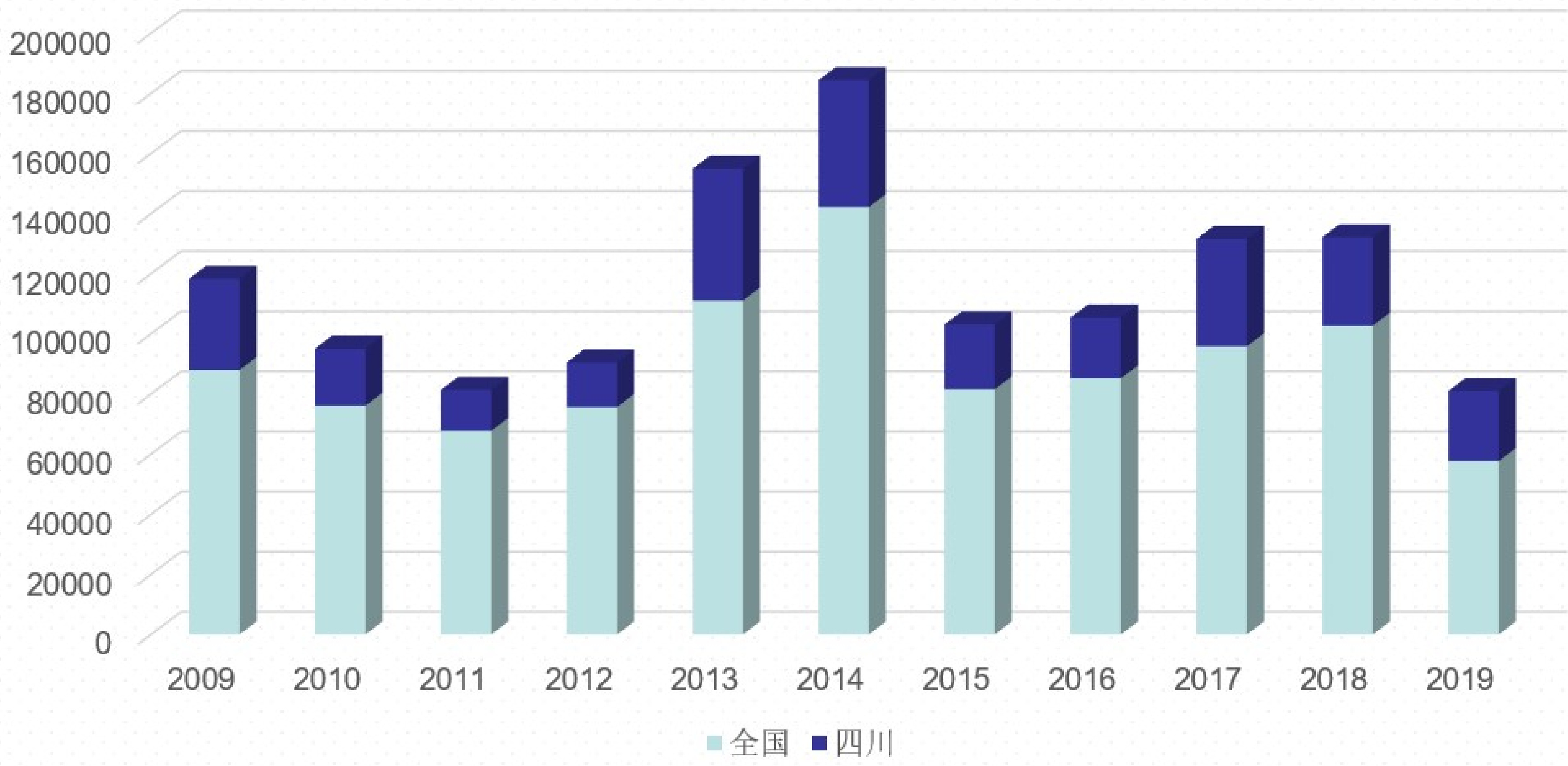


Dai et al，2019

Sichuan、Xinjiang and Yunnan account for ~63% seismicity in China

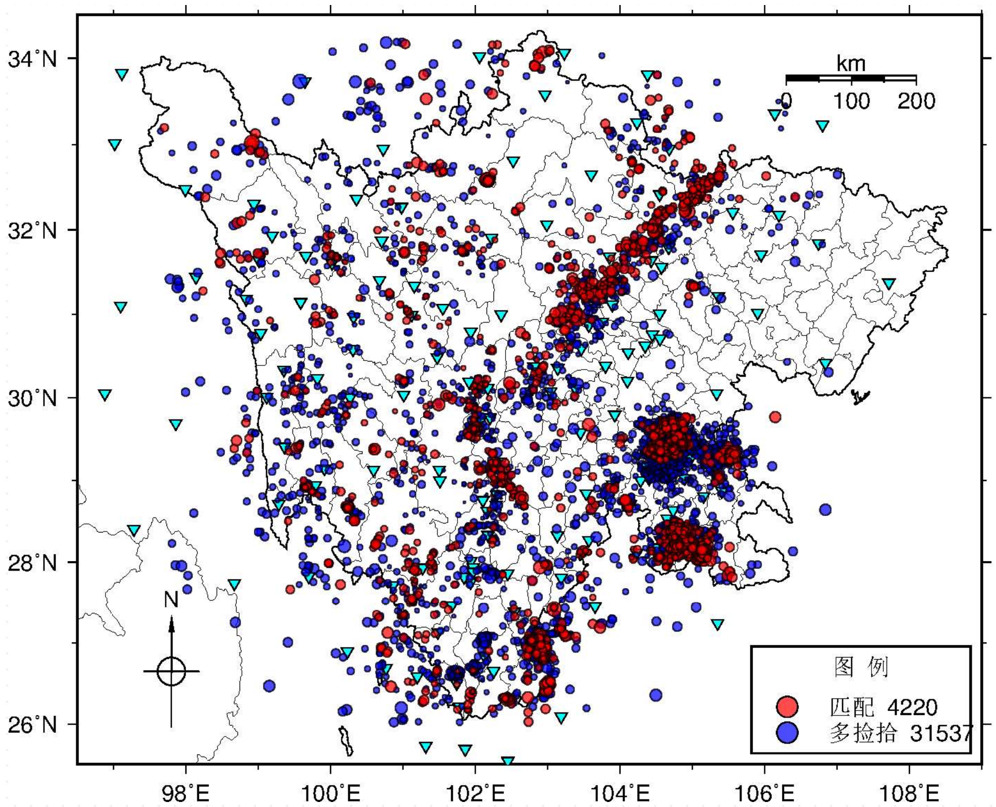
Earthquakes in Sichuan and China

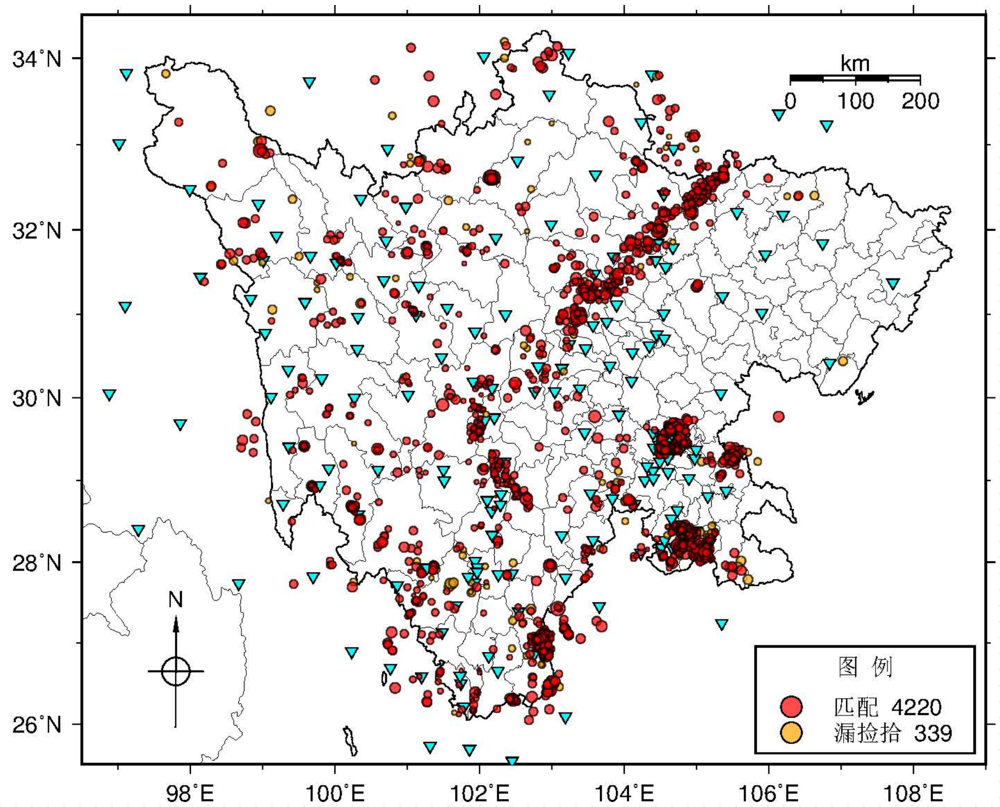
100,000 eqs per year



Application of ***RISP*** in Sichuan seismic network

- 6/10-8/10:AI 35757，Mannual 4559，7.84 times
- Matched 4220，matching rate 92.6%； missed 339 (7.4%);detected 31537 more





Application of ***RISP*** in Sichuan seismic network

Comparison of RISP and manual catalogs

- ✓ **OT difference:**

  0.27±0.69 s; <1.0 s, 86.2%

- ✓ **Epi difference:**

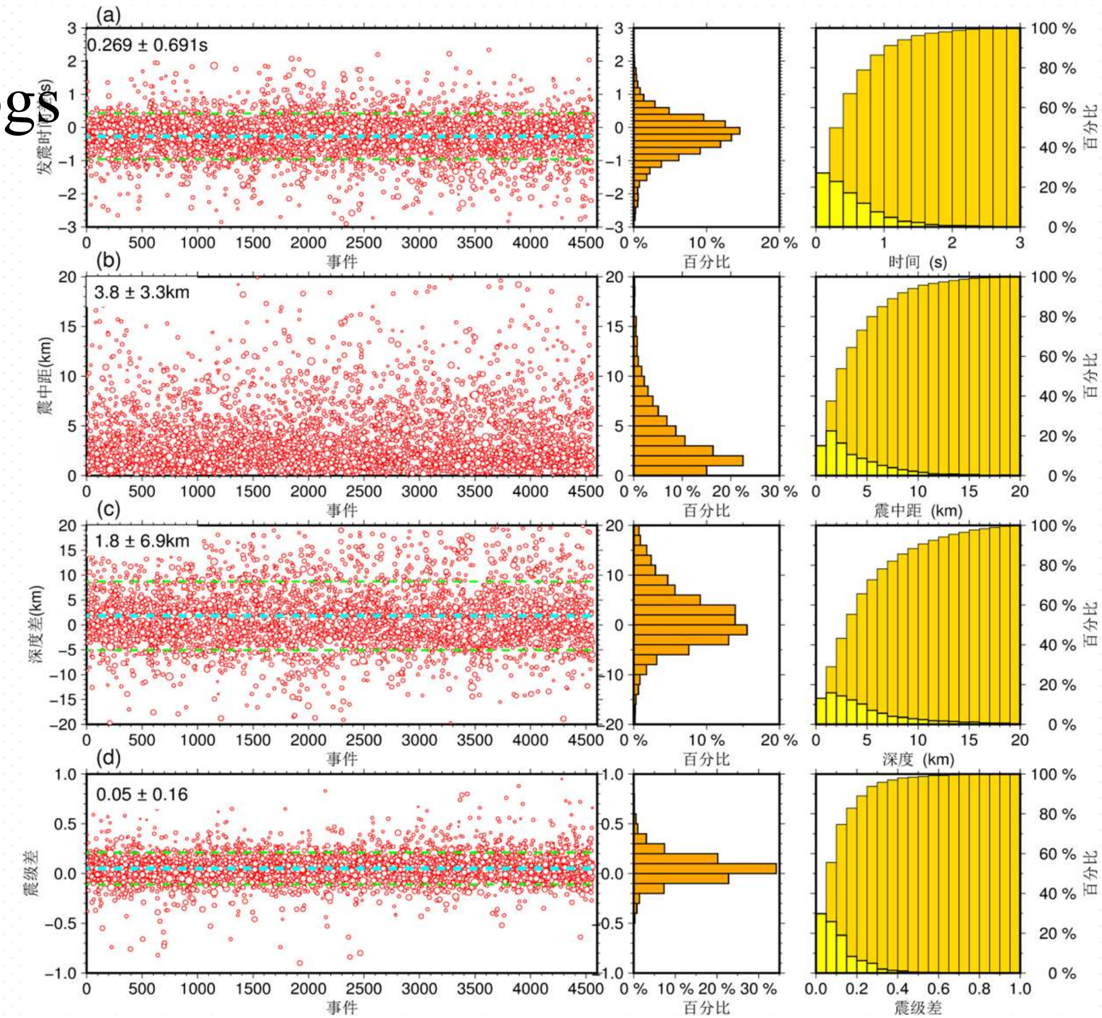
  3.8±3.3 km; <10km, 94.2%

- ✓ **Dep difference:**

  1.8±6.9 km; <10km, 89.5%

- ✓ **Mag deviation:**

  0.05±0.16; <0.3, 93.6%



Lihua Fang

Institute of Geophysics, China Earthquake Administration
Verified email at cea-igp.ac.cn - Homepage

Seismology

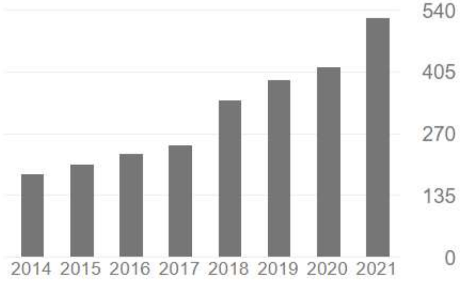
FOLLOW

TITLE	CITED BY	YEAR
Relocation of the mainshock and aftershock sequences of Ms7.0 Sichuan Lushan earthquake LH Fang, JP Wu, WL Wang, ZY Lü, CZ Wang, T Yang, Y Cai Chinese Science Bulletin 58 (28-29), 3451-3459	176	2013
Aftershock distribution of the Ms 8.0 Wenchuan earthquake and 3-D P-wave velocity structure in and around source region JP Wu, Y Huang, TZ Zhang, YH Ming, LH Fang Chin. J. Geophys. 52 (2), 320-328	130	2009
四川芦山Ms7.0级地震及其余震序列重定位 房立华， 吴建平， 王未来， 吕作勇， 王长在， 杨婷， 蔡妍 科学通报 58 (20), 1901-1909	98	2013
华北地区基于噪声的瑞利面波群速度层析成像 房立华， 吴建平， 吕作勇 地球物理学报 52 (3), 663-671	91	2009
High resolution Rayleigh wave group velocity tomography in North China from ambient seismic noise L Fang, J Wu, Z Ding, GF Panza Geophysical Journal International 181 (2), 1171-1182	84	2010
Sedimentary and crustal thicknesses and Poisson's ratios for the NE Tibetan Plateau and its adjacent regions based on dense seismic arrays W Wang, J Wu, L Fang, G Lai, Y Cai Earth and Planetary Science Letters 462, 76-85	82	2017
Double difference location of the Ludian Ms6. 5 earthquake sequences in Yunnan province in 2014 WL WANG, JP WU, LH FANG, GJ LAI Chinese Journal of Geophysics 57 (9), 3042-3051	81	2014

Cited by

VIEW ALL

	All	Since 2016
Citations	2730	2140
h-index	31	27
i10-index	68	61



Public access

VIEW ALL

5 articles — 26 articles

not available — available

Based on funding mandates

Co-authors

EDIT


Yao Huajian
USTC (Univ of Science and Tech…


Xiwei Xu （徐锡伟）
Director，Research Professor, N…


Giuliano Panza
Olim Università di Trieste - Dipart…