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Supporting Information for

[An automated, deep-learning-based method for investigating spatial-temporal evolution of seismicity]

[Enze Zhang[1,2†] and Hongfeng Yang[1,3]]

[1Earth System Science Programme, The Chinese University of Hong Kong, Sha Tin, NT, Hong Kong, China.

2Institute for Geophysics, The University of Texas at Austin, Austin, TX, USA.

3Shenzhen Research Institute, The Chinese University of Hong Kong, Shenzhen, China.

†Current address: Institute for Geophysics, The University of Texas at Austin, Austin, TX, USA.]

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Introduction

The supporting information provides additional information about the method development, model details, model validation, and further investigation on derived results.

Text S1. Choosing a proper learning rate and L2 regularization factor

We use the final validation loss to choose the learning rate and L2 regularization factor. If the learning rate is too large, the training loss will decrease greatly at the beginning but show little change later on, and the final validation loss is high. If the learning rate is too small, the training loss curve will show a nearly linear trend. The final validation loss will be high since it needs more training epochs to decrease than the patience threshold we set. L2 regularization factor penalizes large weights, and therefore it could suppress any irrelevant components of the weight vector by choosing the smallest vector that decreases the training loss. A too small weight decay can hardly have enough regularization effect while a too large weight decay could hurt the network training progress. From Table S1 to Table S6 shows the final validation loss by using different values of weight decay and learning rate for the three networks. For each network, we choose the learning rate and weight decay with the smallest final validation loss.

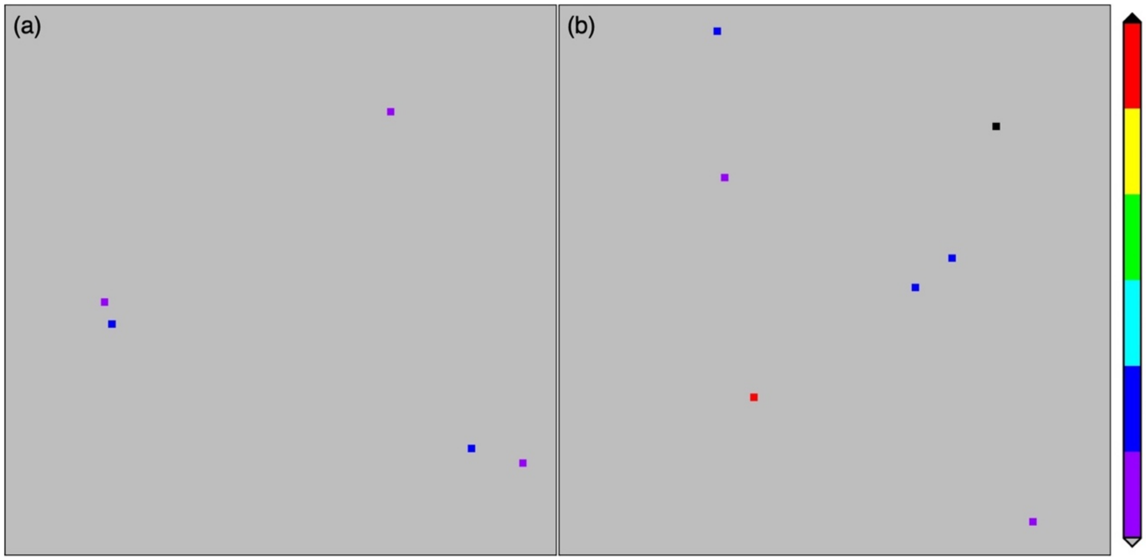

Figure S1. Example of earthquake artificial distributions maps. (a) shows the scatter distribution and (b) show the concentrated distribution with pixels having more than five earthquakes.

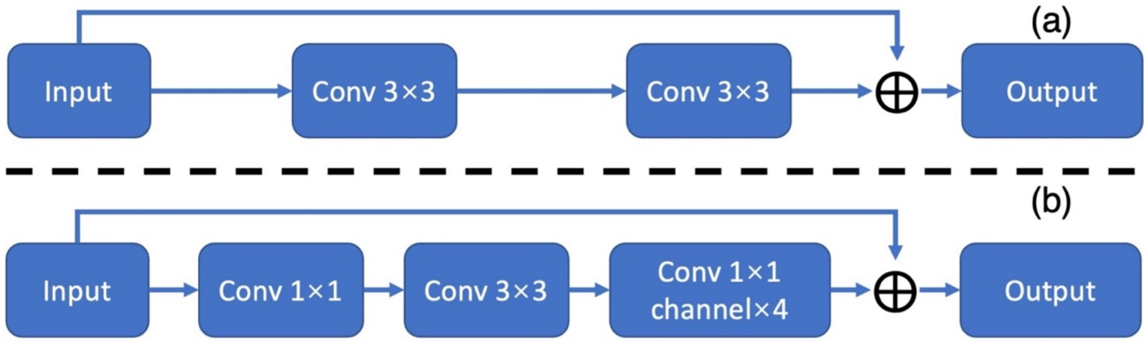

Figure S2. (a) The building block of residual learning used in ResNet-18 and ResNet-34. (b) The building block of residual learning used in ResNet-101. For both types of building blocks, the block adds its input with the feature map after going through convolutional layers to obtain the output.

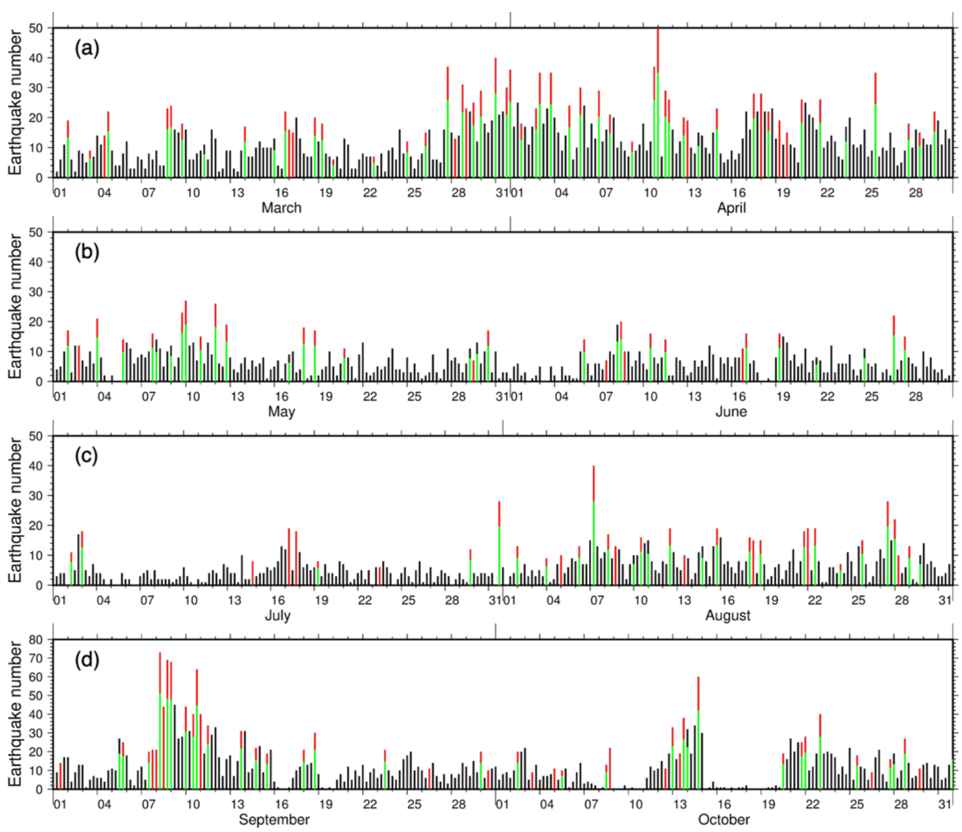

Figure S3. Comparison between manually-picked anomalous timings and network identifications in Weiyuan, 2019. The red bars represent the manually-identified anomalous timings. The green ones are identified by the well-trained network.

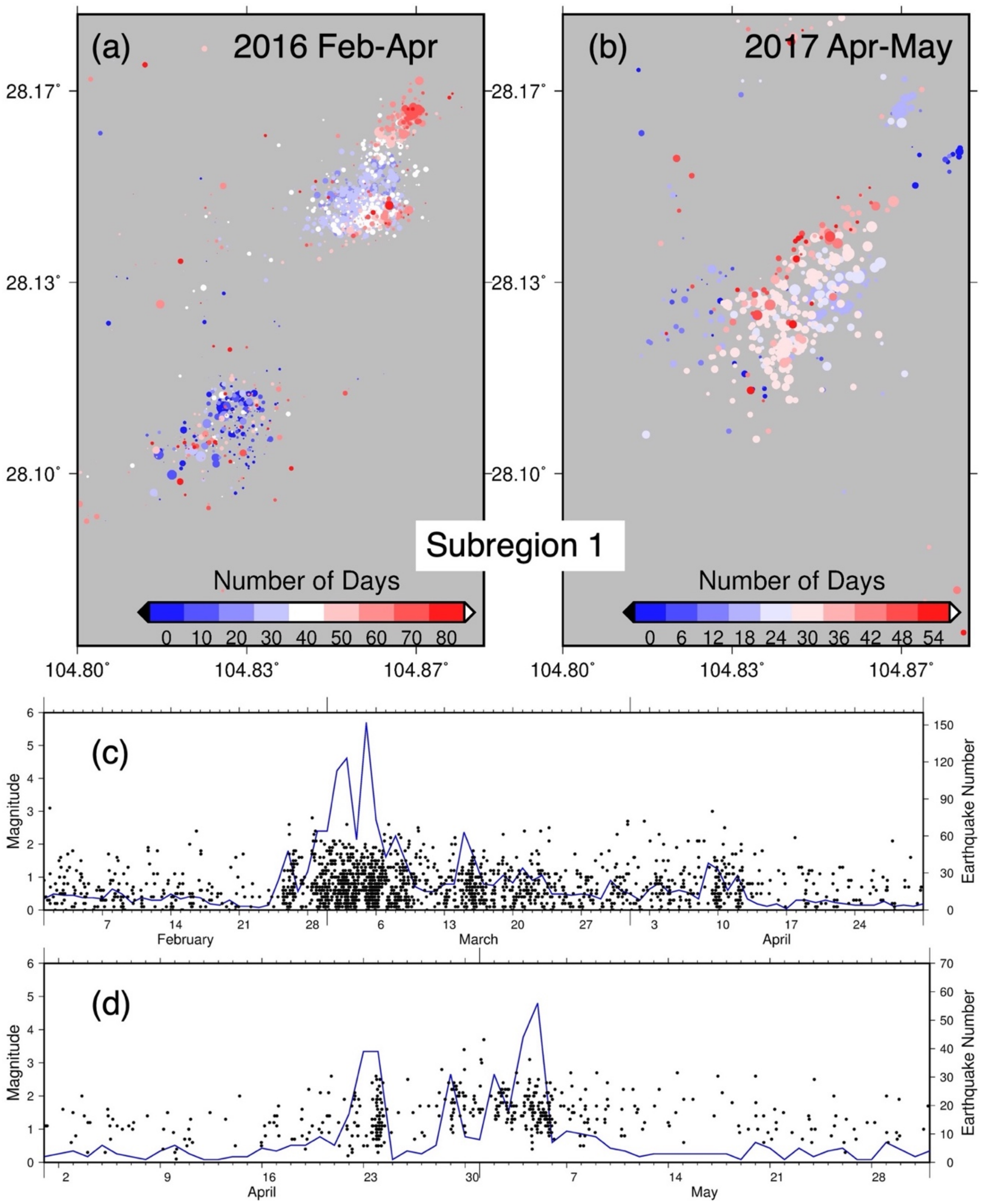

Figure S4. Seismicity in subregion 1 of Changning region during abnormal periods. (a) and (b) show the seismicity in subregion 1 from Feb to Apr 2016 and from Apr to May

2017, respectively. (c) and (d) are the corresponding time series of (a) and (b), showing the earthquake magnitudes and daily earthquake numbers in subregion 1.

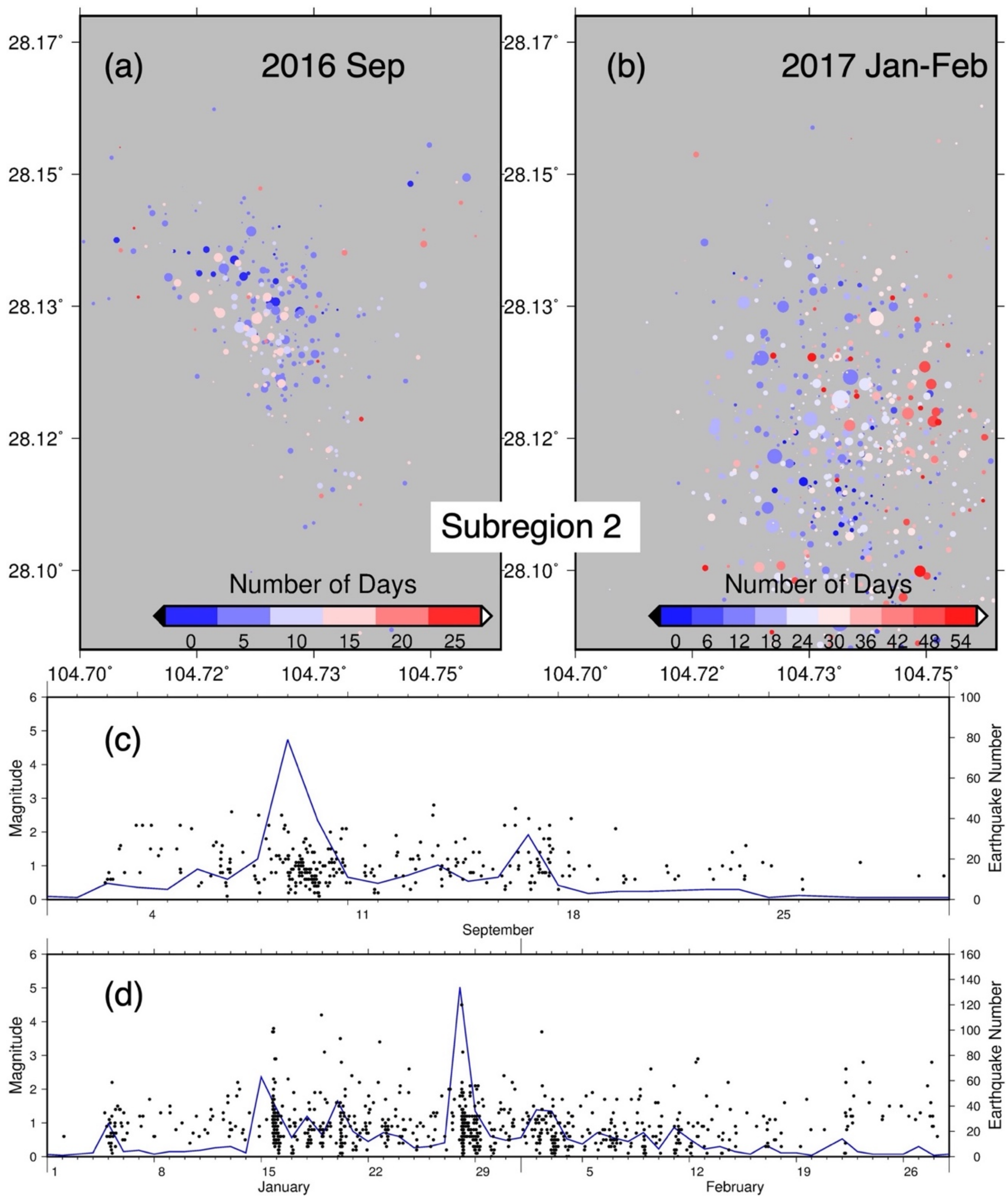

Figure S5. Seismicity in subregion 2 of Changning region during abnormal periods. (a) and (b) show the seismicity in subregion 1 in Sep 2016 and from Jan to Feb 2017, respectively. (c) and (d) are the corresponding time series of (a) and (b), showing the earthquake magnitudes and daily earthquake numbers in subregion 2.

Weight decay	0	0.001	0.003	***0.005***	0.01	0.03	0.05
Final validation loss	0.22	0.215	0.212	***0.161***	0.166	0.199	0.26

Table S1. Final validation losses using different L2 regularization factors (weight decay) for ResNet-18.

Learning rate	0.001	0.003	***0.005***	0.007	0.01
Final validation loss	0.161	0.152	***0.128***	0.167	0.228

Table S2. Final validation losses using different learning rates for ResNet-18.

Weight decay	0	0.001	0.003	***0.005***	0.01	0.03	0.05
Final validation loss	0.195	0.187	0.137	***0.133***	0.174	0.272	0.327

Table S3. Final validation losses using different L2 regularization factors (weight decay) for ResNet-34.

Learning rate	0.001	***0.003***	0.005	0.007	0.01
Final validation loss	0.175	***0.133***	0.162	0.139	0.161

Table S4. Final validation losses using different learning rates for ResNet-34.

Weight decay	0	0.001	0.003	***0.005***	0.01	0.03	0.05
Final validation loss	0.232	0.201	0.204	***0.145***	0.154	0.277	0.372

Table S5. Final validation losses using different L2 regularization factors (weight decay) for ResNet-101.

Learning rate	0.0005	***0.0007***	0.001	0.003	0.005	0.007
Final validation loss	0.426	***0.145***	0.149	0.153	0.182	0.193

Table S6. Final validation losses using different learning rates for ResNet-101.

Movie S1. A movie shows the artificial distribution maps where earthquake number increase gradually.

https://www.youtube.com/watch?v=DZDhHBKZdtY

Movie S2. Similar to Movie S1 but in Weiyuan, from Sep 2018 to Aug 2020.

https://www.youtube.com/watch?v=-MjzMq9Om_Y

Movie S3. A movie shows the spatial-temporal migration of anomalous seismicity in Changning, from 2016 to 2019.

https://www.youtube.com/watch?v=0JcnT08F-2g&t=1s