Supplementary Information for

A PANN-Based Grid Downscaling Technology and Its Application in Landslide and Flood Modeling

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1. Figure S1 illustrates the performance comparison between the Linear interpolation and PANN methods in Section 3.1 of the main text. (a) corresponds to the cross-section shown in Figure 3 of the main text, while (b) and (c) compare the performance of the two methods. It is evident that the average deposit error of the PANN method is 95.13% lower than that of Linear interpolation, demonstrating a significant reduction in error.

2. Table S1 presents an analysis of the numerical distribution of elevations in Figure S1 (a). It is evident that when compared to the fine grid, both the Linear interpolation and PANN method exhibit minimal, median, mean, and median sampling errors in the terrain height that do not exceed 2%. In terms of standard deviation, the relative error for Linear interpolation is 11.77%, while for PANN, it is 1.93%. These findings indicate that the terrain distribution achieved by PANN is closer to the fine grid, resulting in smaller terrain changes caused by sampling.

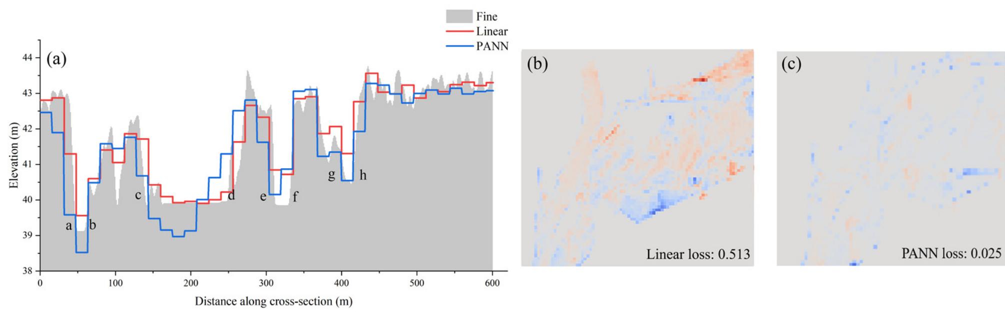

Figure S1. (a) is a topographic profile cut from Figure (3) in the main text. (b) and (c) are the comparison of Linear interpolation and PANN methods, respectively.

Table S1. Elevation analysis of cross-section using Linear and PANN methods. Unit: meters (m).

	Minimum	Maxima	Mean	Median	Standard Deviation
Fine	39.110	43.751	41.763	42.245	1.402
Linear	39.562	43.563	41.842	41.867	1.237
PANN	38.523	43.275	41.559	41.626	1.429

3. Figure S2 illustrates the performance comparison between the Cubic interpolation and PANN methods in Section 3.1 of the main text. (a) corresponds to the cross-section shown in Figure 3 of the main text, while (b) and (c) compare the performance of the two methods. It is evident that the average deposit error of the PANN method is 94.96% lower than that of Cubic interpolation, demonstrating a significant reduction in error.

4. Table S2 presents an analysis of the numerical distribution of elevations in Figure S2 (a). It is evident that when compared to the fine grid, both the Cubic interpolation and PANN method exhibit minimal, median, mean, and median sampling errors in the terrain height that do not exceed 2%. In terms of standard deviation, the relative error for Cubic interpolation is 9.77%, while for PANN, it is 1.93%. These findings indicate that the terrain distribution achieved by PANN is closer to the fine grid, resulting in smaller terrain changes caused by sampling.

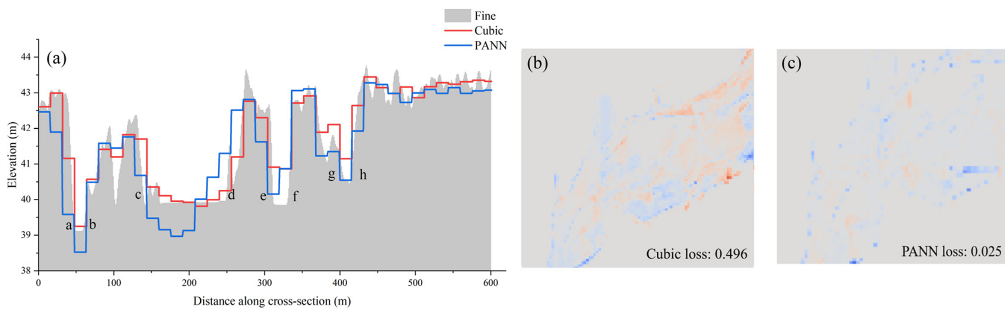

Figure S2. (a) is a topographic profile cut from Figure (3) in the main text. (b) and (c) are the comparison of Cubic interpolation and PANN methods, respectively.

Table S2 Elevation analysis of cross-section using Cubic and PANN methods. Unit: meters (m).

	Minimum	Maxima	Mean	Median	Standard Deviation
Fine	39.110	43.751	41.763	42.245	1.402
Cubic	39.245	43.445	41.822	41.889	1.265
PANN	38.523	43.275	41.559	41.626	1.429

5. Three different loss functions tested in the experiment are L1, L2, and Huber Loss. Among them, y_i represents the label value, and y_i^p represents the predicted value.

$$L1 = \sum_{i=1}^{n} \left| y_i - y_i^p \right| \tag{S1}$$

$$L2 = \sum_{i=1}^{n} \left(y_i - y_i^p \right)^2 \tag{S2}$$

$$L_{Huber}(y, y_i^p) = \begin{cases} \frac{1}{2}(y - y_i^p)^2 & \text{for } |y - y_i^p| \le \delta \\ \delta |y - y_i^p| - \frac{1}{2}\delta^2 & \text{otherwise} \end{cases}, \quad \delta = 0.5 \tag{S3}$$

6. The parameter sensitivity experiment analyzed the changes in accuracy and efficiency under different sampling rates and loss function configurations, as shown in Table S3. It can be seen that when adopting the L2 loss function, PANN has the highest accuracy at all sampling rates. When the down-sampling rate is 16 times, the average deposit error of PANN is only 0.21m, with an acceleration ratio of 4096 times. By comparison, when the down-sampling rate of base method is 2 times, the average deposit error is 0.19 m, while the acceleration ratio is only 8 times. Therefore, it is recommended to use a 16 times down-sampling rate PANN model with L2 loss function in practical applications, which fully preserves accuracy and significantly improves efficiency.

Table S3. Sensitivity analysis results of different parameters.

	Average Deposit error (m)					Time Speed Up				
	2x	4x	8x	16x	32x	2x	4x	8x	16x	32x
Base	0.19	0.52	0.71	0.89	2.73	8	64	512	4096	32768
Linear	0.20	0.49	0.75	0.92	2.85					
Cubic	0.19	0.53	0.74	0.88	2.78					
PANN L1	**0.05**	0.14	0.20	0.27	1.61					
PANN L2	**0.05**	**0.13**	**0.17**	**0.21**	**1.54**					
PANN Huber	0.07	0.17	0.21	0.25	1.60					

7. Figure S3 shows the changes in loss of the model mentioned in section 2.4 of the main text, providing evidence that PANN continuously optimizes the sampling scheme during the learning process. To mitigate the impact of experimental uncertainty, a paired samples t-test was conducted to compare the performance of the baseline method and the PANN method. The calculated P-value was 2.339e-36. Therefore, the null hypothesis that there is no significant difference between the two models can be rejected, demonstrating the significant performance improvement of PANN. The experiment utilized 4 Tesla V100 GPUs with 32GB memory and PyTorch (version 1.7.1) for implementation. The optimization strategy was refined through experimentation, which involved using Group-norm instead of Batch-norm and employing the L2 loss function rather than smooth L1 or Huber loss. The use of the SGD optimizer was found to exaggerate terrain details and potentially lead to numerical instability. To address this, the Adam optimizer was adopted with an initial learning rate of 10e-2. Additionally, a cosine annealing optimization scheme was employed, spanning 50 epochs, with a batch size of 4. The NCCL-distributed data-parallel method, coupled with checkpoint technology, was utilized to accelerate the training process.

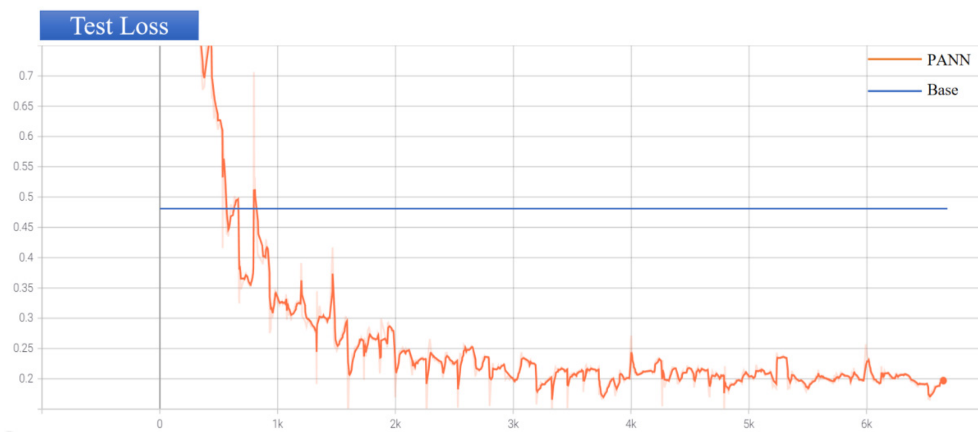

Figure S3. The training process of PANN compared with the most widely used nearest neighbor interpolation method as Baseline. The horizontal axis represents the number of iterations, and the vertical axis represents the relative L2 loss. After about 4500 iterations, the model tends to converge.