remote sensing

Supplement to Rainfall Induced Shallow Landslide Temporal Probability Modelling and Early Warning Research in Mountains Areas: A Case Study of Qin-Ba Mountains, Western China

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1. Identification of triggering and non-triggering rainfall events

Identifying triggering and non-triggering rainfall events is a critical step in the process of defining rainfall threshold and temporal probability models. To identify triggering rainfall events, researchers generally use the cumulative rainfall (E_T) over a period of time (D_T) as a threshold to truncate the rainfall sequence into multiple independent rainfall events. We used Python language to compile a complete processing flow, which includes the following steps:

(1) To determine the beginning time of a rainfall event, we used Python Pandas' "rolling" function to calculate the cumulative rainfall over D_T from front to back (red line in Figure S1a), and the odd intersection point with the threshold (E_T, blue line in Figure S1b) was marked as the start time.

(2) A similar method was used to identify the end time of rainfall events, and the rolling function is executed from back to front (Figure S1b).

(3) The detected start and end times were combined to truncate the rainfall sequence. There may be invalid values, such as zero and light rainfall, on both sides of the truncated rainfall event (TRE) (Figure S1c); therefore, we removed the values less than E_T / D_T on both sides. After that, all the TRE end times were extended by three days because landslides may occur at the end or a few days after a rainfall event; here, we called that corrected TRE (CTRE).

(4) Considering that landslides may occur every day in the CTRE, the CTRE needs to be decomposed daily to obtain the triggering and non-triggering rainfall events. A detailed example is shown in Figure S1c. Using the program shown in Figure S1, we could automatically identify triggering and non-triggering rainfall events with the same criteria considering different combinations of D_T and E_T.

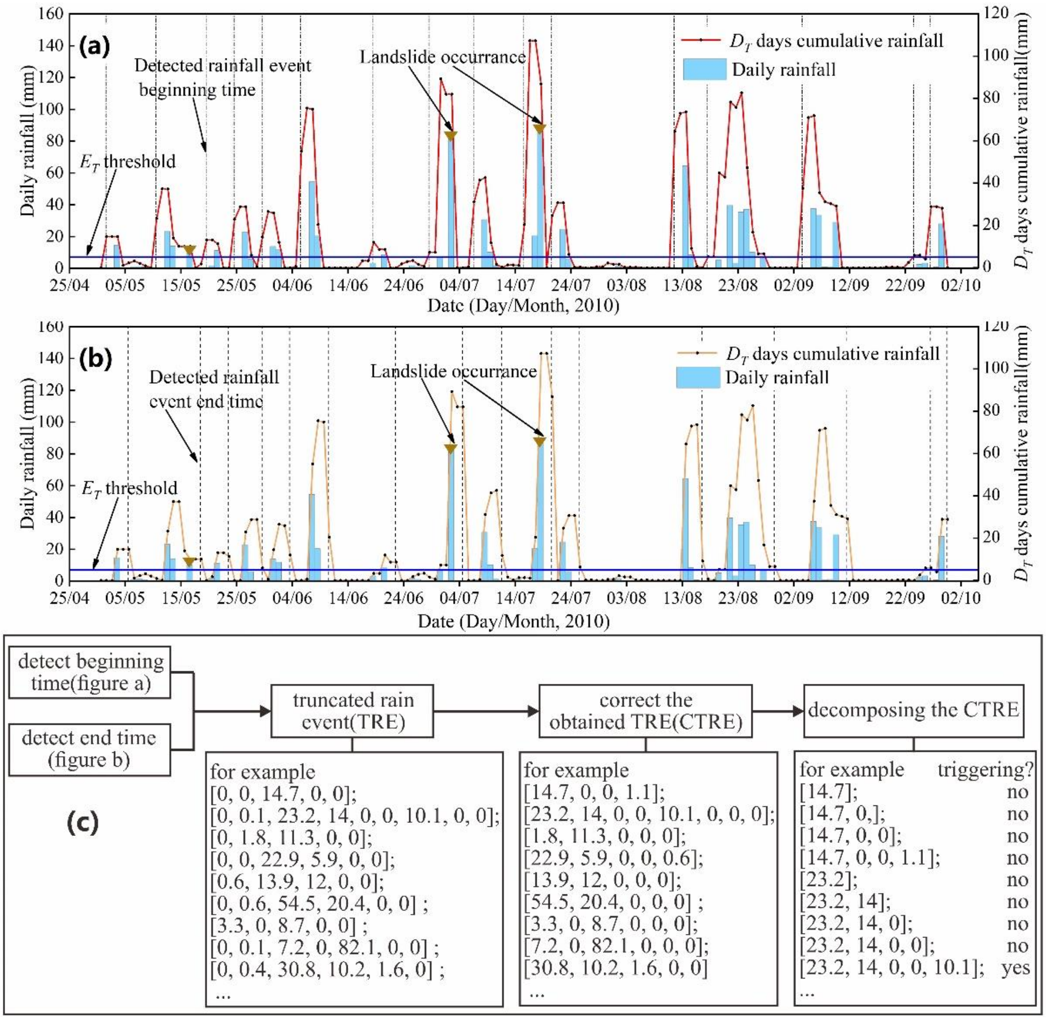

Figure S1. Flowchart for identifying rainfall events.

2. ROC curve

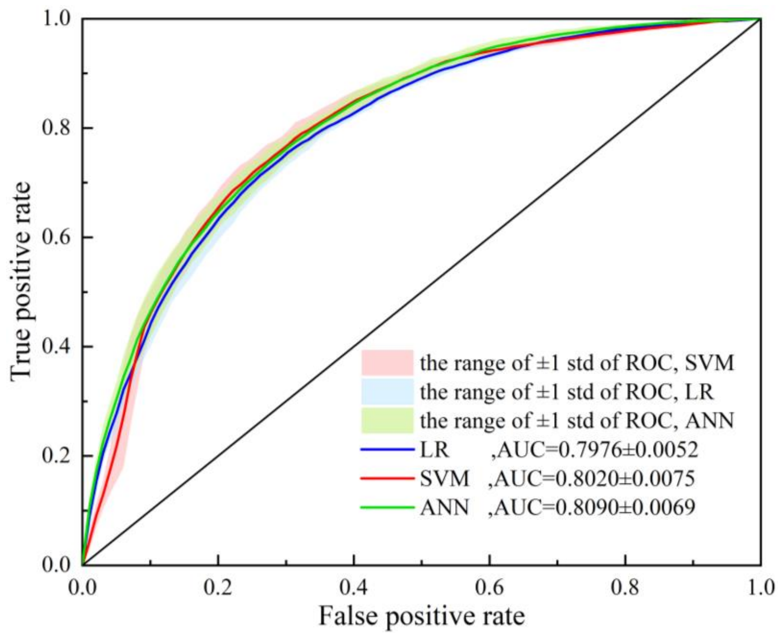

Figure S2. ROC curves for the LR, SVM and ANN models

3. Independence test for the spatial and temporal probability

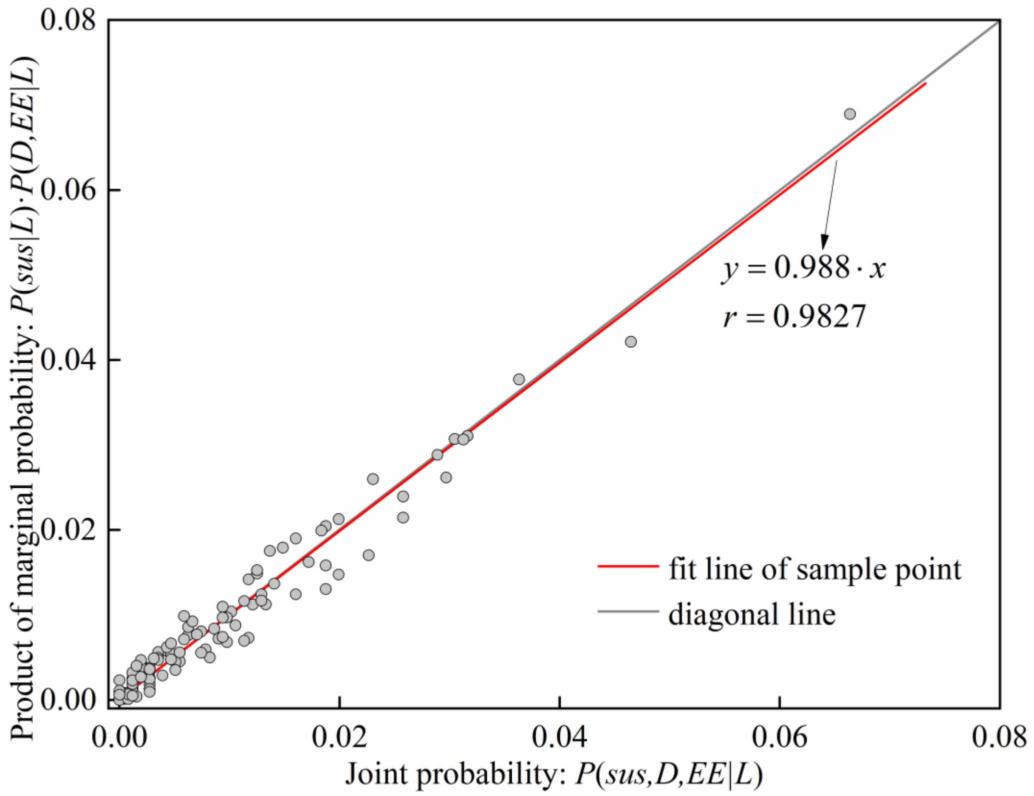

Figure S3. Landslide data from 2001 to 2020 were used to test the independence of the joint probability (*P (sus, D, EE*∣*L)*) and product of marginal probability (*P(sus*∣*L)·P(D,EE*∣*L)*). The fit line has a slope of 0.988 and is close to 1, confirming this independence.

4. Simulation warning result

We use the PLEWM and DLEWM to simulate warnings in the rainy season (July to September) each day from 2016 to 2020. The results are summarized monthly and shown in Table S1. The estimated losses and investments were calculated according to the criterion established in Table 1.

Table S1. Statistical information for the DLEWM and PLEWM for daily warning from July to September 2016-2020. A refers to the study area, and for interpretation, we use a bold font for the smaller part of the warning zone, investment and loss in the two LEWMs.

Early warning model	date	Area of warning zone at each level (A)				Landslide number occurred in warning zone at each level				Investment (10,000CNY)	Loss (10,000CNY)
		1st-level	2nd-level-	3rd-level	4th-level	1st-level	2nd-level-	3rd-level	4th-level		
PLEWM	2016-07	29.333	**1.411**	**0.228**	**0.028**	3	0	0	1	**3.958**	24.1
	2016-08	30.359	**0.578**	**0.061**	**0.002**	0	0	0	0	**1.416**	0
	2016-09	29.444	**0.459**	**0.091**	**0.006**	0	1	0	0	**1.33**	**4**
	2017-07	30.182	**0.752**	**0.061**	**0.005**	0	0	0	0	**1.788**	0
	2017-08	30.136	**0.752**	**0.102**	**0.010**	0	0	0	0	**1.992**	0
	2017-09	26.945	**2.116**	**0.816**	**0.123**	4	12	10	6	**8.48**	**100.6**
	2018-07	29.115	**1.526**	**0.341**	**0.018**	13	42	64	116	**4.56**	**411.6**
	2018-08	30.746	**0.239**	**0.013**	**0.002**	0	0	1	0	**0.546**	2
	2018-09	29.094	**0.803**	**0.103**	**0.000**	0	0	0	0	**2.018**	0
	2019-07	30.203	**0.684**	**0.095**	**0.018**	13	2	1	0	**1.892**	**114**

	2019-08	29.716	**1.072**	**0.193**	**0.019**	15	0	6	2	**3.068**	132.2
	2019-09	27.013	**2.359**	**0.593**	**0.035**	3	7	5	1	**7.37**	62.1
	2020-07	30.018	**0.841**	**0.125**	**0.016**	3	4	1	0	**2.31**	**42**
	2020-08	29.241	**1.509**	**0.221**	**0.029**	16	16	11	5	**4.134**	**214.5**
	2020-09	29.559	**0.367**	**0.071**	**0.003**	0	2	0	0	**1.042**	8
grand total		441.104	**15.468**	**3.114**	**0.314**	70	86	99	131	**45.904**	**1115.1**
DLEWM	2016-07	**27.979**	2.364	0.582	0.075	3	0	0	1	7.653	24.1
	2016-08	**29.414**	1.358	0.216	0.012	0	0	0	0	3.678	0
	2016-09	**28.658**	1.156	0.178	0.008	1	0	0	0	3.088	8
	2017-07	**28.856**	1.697	0.412	0.034	0	0	0	0	5.318	0
	2017-08	**28.857**	1.687	0.414	0.042	0	0	0	0	5.365	0
	2017-09	**26.438**	2.341	1.039	0.183	8	3	13	8	10.300	102.8
	2018-07	**28.304**	2.188	0.483	0.026	88	57	84	6	6.513	1100.6
	2018-08	**29.756**	1.115	0.121	0.008	0	0	1	0	2.780	2
	2018-09	**28.251**	1.323	0.408	0.017	0	0	0	0	4.418	0
	2019-07	**29.324**	1.344	0.297	0.034	14	0	2	0	4.152	116
	2019-08	**29.218**	1.448	0.325	0.008	20	2	1	0	4.264	170
	2019-09	**25.846**	2.926	1.099	0.128	4	3	7	2	11.276	**58.2**
	2020-07	**29.332**	1.277	0.369	0.022	5	1	2	0	4.208	48
	2020-08	**27.964**	2.355	0.597	0.085	21	18	7	2	7.774	254.2
	2020-09	**28.633**	1.103	0.231	0.032	0	0	2	0	3.391	**4**
grand total		**426.83**	25.682	6.771	0.714	164	84	119	19	84.16	**1887.9**

Table S2. Statistics on the warning results of different warning models for two extreme rainfall events in Lveyang county

date	Number of landslides							
	PLEWM				DLEWM			
	1st-level	2nd-level-	3rd-level	4th-level	1st-level	2nd-level-	3rd-level	4th-level
20180711	0	8	25	50	0	45	32	6
20180714	0	8	29	62	64	0	35	0
Loss (10,000CNY)	183.2				826.6			

5. The criteria of correct warning, false warning and missed warning in multi-level early warning model

we refer to the research of Calvello and Piciullo [1], to define the concept of correct warning, missed warning and false warning for multi-level early warning model. they classify landslide events into 4 levels based on the number or density of landslides occurring within the warning zone (Table S3), and defined correct warning (CW), false warning (FW) and missed warning (MW) based on the level of the landslide event and the warning level (Table S4), where TN means true negative.

Table S3. Criteria for classification of landslide event levels [1]

Landslide event level	Landslide event level classification criteria	
	No. of landslide	Density (No. of landslide/km^2)
1st-level	0	0
2nd-level	1	0.001-0.02
3rd-level	2-10	0.021-0.1

4th-level	>10	>0.1

Table S4. Criteria for defining correct warning, false warning, and missed warning for multilevel warning models [1]

		Landslide event levels			
		1st	2nd	3rd	4th
Warning levels	1st	TN	CW	MW	MW
	2nd	CW	CW	MW	MW
	3rd	FW	CW	CW	CW
	4th	FW	FW	CW	CW

Reference

1. Calvello, M.; Piciullo, L. Assessing the performance of regional landslide early warning models: the EDuMaP method. *Natural Hazards and Earth System Sciences* **2016**, *16*, 103-122, doi:10.5194/nhess-16-103-2016.