LANDSLIDE FORECASTING AND EARLY WARNING – A PRELIMINARY REPORT

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LANDSLIDE EARLY WARNING SYSTEM (LEWS)

A Landslide Early Warning System transmits the information about the hazard before it occurs, providing an opportunity for people to act, to save lives and livelihoods, thus reducing the risk of the disaster (*Landslide SHEAR program*).

According to UNISDR, EWS is the set of instrumentation, which gives an information of Soil/Rock movement to people and makes them aware to prepare for hazardous situation and can hence minimize the loss.

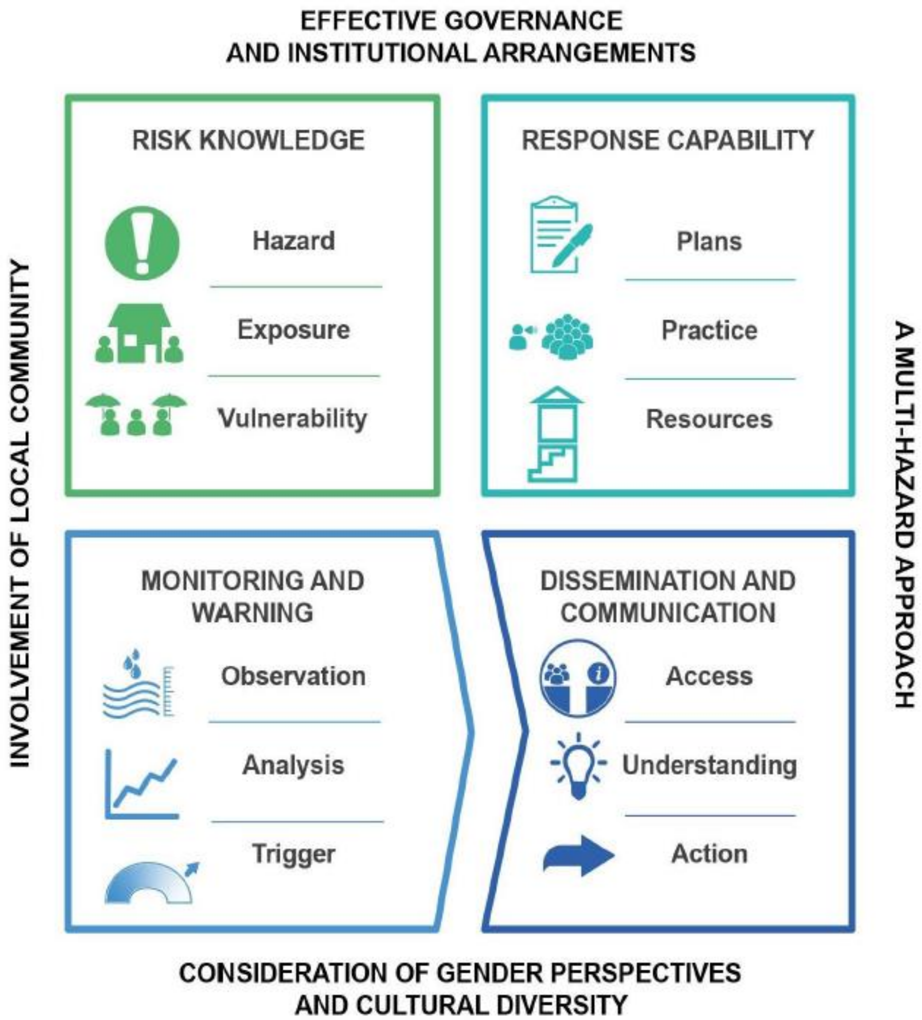


Figure 1*. Components of an effective early warning system (Practical Action, 2021; based on WMO, 2017)*

LANDSLIDE FORECASTING

A component of LEWS, forecasting is the prediction of spatial and temporal likelihood/probability of occurrence of slope failure.

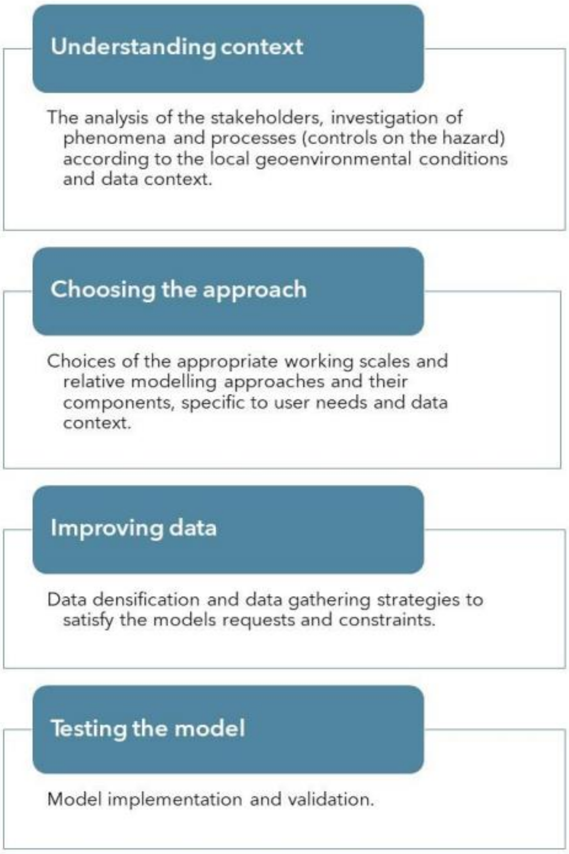
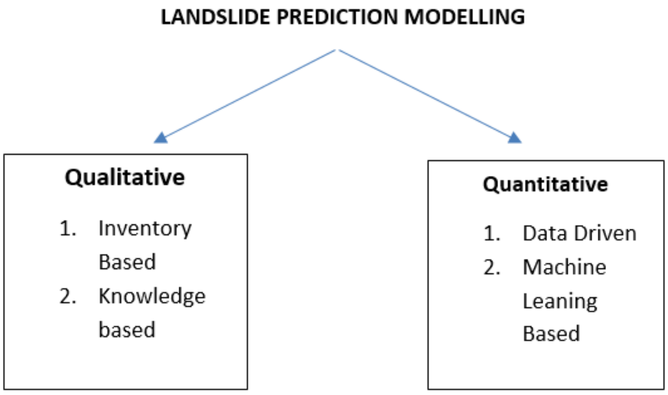


***Figure 2**. Approach for Landslide Forecasting -By SHEAR programme under which was the Landslip Project (Budimir et al. 2022)*

Brief review of the state-of-art in the field (National & International)

National

Kainthura and Sharma., 2022 compared Landslide prediction models based on different ML algorithms such as Bayesian Network (HBNRS), Backpropagation Neural Network (HBPNNRS), Bagging (HBRS), XGBoost (HXGBRS), and Random Forest (HRFRS). The study was conducted in Uttrakashi, using 373 landslide and 181 non landslide points for training-testing, The features



related to points used consist of 15 conditioning factors (Erosion, Bank failure, Hydrology, Rainfall etc.) which were filtered and used in training. It was found that rough set theory coupled with hybrid XGBoost algorithm has best performance in predicting landslides in the region with limited data. The accuracy was found to be 89.2%.

Abraham and Satyam., 2022 compared different rainfall threshold parameters for Landslide occurrence in Western Ghats, these were Empirical- ED, Probabilistic ED, ID, EI, and RS. CTRL-T and SIGMA model was used for calculating some of these parameters. RS (Rainfall severity - Soil wetness) and ED derived from CTRL-T were found best in the considered study area for prediction of landslide.

Harilal et al., 2019 developed regional and local ID thresholds for entire Sikkim, India and Gangtok respectively. The regional and local threshold were calculated as rainfall of 43.6 mm and 100 mm per day. They also concluded that Antecedent rainfall is the factor that mostly dominates Landslide events in Sikkim region.

Wanare et al., 2022 discussed various EWS methods- Wireless data transfer, Simplified measuring method, Acoustic emission, MEMS (Micro electromechanical systems) based approach, IOT based approach and Use of Tilt and Displacement sensors. This approaches are used to monitor and deformation, soil moisture, deformation (or tilt), soil suction, fracturing and associated emissions communicated using radio signals, or powered by solar power, low cost instrument. He discussed about indicators of slope failure and suggested optimal depth of displacement sensors for effective slope failure to be 1000 mm.

Abraham and Satyam., 2020 modified SIGMA model for Kalimpong town near Darjeeling for estimating rainfall thresholds used in forecasting of landslides. The thresholds in this model are defined from the function of standard deviation of a transformed statistical distribution derived from cumulative rainfall in n (any no. between 1 and 365) no. of days. The generated probability distribution plot tells the criticality of rainfall for landslides. The model was found to be 92% efficient.

Dikshit and Satyam., 2019 worked in Kalimpong for comparing different thresholds types- empirical (ID, Antecedent), Probabilistic (Bayes), Hydrological (FLaIR). He also monitored Chibo area of Kalimpong using MEMS Tech. for 5 months to measure water content, displacement etc. His results indicate that rainfall intensity of 0.95 mm hr^{-1}, Antecedent rainfall of 133.5 mm over 20 days, (from FlaIR model) rainfall of 152.5 mm, and at tilting rate of 0.1 per hour, all these conditions can generate landslides in the region. He suggested that combination of two-dimensional Bayesian probability and antecedent rainfall would provide a better estimate of landslide forecasting and stated the need of hourly rainfall data, and increased spatial-temporal accuracy of landslide points for better results.

International

Brunetti et al., 2021 showed how satellite rainfall products outperform ground observations in India for landslide forecasting by comparing rainfall data from different sources- IMD (ground-based), SM2R- soil moisture data (EUMETSAT'S ASCAT satellite-based data) converted to rainfall, IMERG-GPM (satellite-based), and PMERGE-H i.e. fusion of SM2R and GPM DATA (for improving resolutions). 197 Landslides event collected from entire India occurring in span of 13 years between 2007 to 2019 were used in the study. Duration and intensity for each LS event was reconstructed and CTRL-T tool was used for creating ED rainfall threshold from each type of rainfall dataset. It was found that AUC was in sequence PMERGE-H > IMERG-GPM > SM2R > IMD.

Chen et al., 2023 developed a model named iHydroSlide3D v1.0 that combines a Hydrological model CREST (Coupled Routing and Excess Storage) and a 3D slope stability model to predict the volume and area of future landslides. To match the spatial resolution of both the models a soil moisture downscaling method was used (90 m to 12.5 m).

Sequi and Veveakis, 2022 studied different deep seated landslides using combination of different material properties such as velocity, shear stress pore pressure, basal temperature and other properties of landslide's shear band, incorporated it in a mathematical heat-energy equation of the shear band located at the base of the landslide. This way properties of shear band were used to predict the instability of the landslide based on location around a steady state curve.

Casagli et al., 2023 reviewed various Remote sensing (RS) techniques for predicting the time of failure (ToF) of landslides. Certain precursors such as Tertiary creep, rainfall amount (using rainfall thresholds), acoustic or seismic emissions related to progressive fracturing and ground displacement (using Displacement velocity thresholds) are monitored using RS techniques such as MTInSAR, GBInSAR, Doppler radars and high resolution multispectral data to predict the landslide event.

Patton et al., 2023 showed that Landslide prediction can be done using rainfall data of scanty no. of Landslide events especially in data sparse remote regions. For the handling data scarcity they incorporated rainfall data of 6000 non landslide days. Predictor variables such as triggering and antecedent precipitation, groundwater etc. were used in Bayesian and frequentist methods to differentiate between landslide and non-landslide rainfall days by using logistic and poisson regression. It was found 3 hours precipitation data, Bayesian method and logistic regression produced good prediction results.

Guzzeti et al., 2020 reviewed all the LEWS developed and operational between 1977 to 2019 with regional (Hong kong, California, West Oregon, Seattle, Vancouver, Colombia, Rio de Janeiro, Java, Chittagong, South Taiwan, Italy), national (Taiwan, Italy, Norway, Central America and Caribbean, Indonesia, Scotland) and global coverage . Hong Kong has oldest working LEWS and Maximum working LEWS are based on rainfall thresholds (76.9%).

Nocentini et al. 2023 used machine learning algorithm Random Forest to aid in spatiotemporal prediction of landslides. The parameters of 410 Landslide events were used for training. These dynamic parameters were Cumulative Rainfall, Rainfall Intensity and, Month of Landslide, Landslide susceptibility Index etc. The Trained ML model was capable of predicting occurrence of landslide based on real-time input of these parameters. The parameters were also tested for their independence and significance. The final results were found better than the SIGMA model.

Teza et al., 2022 developed a MATLAB toolbox named Wadenow for Rainfall triggered Landslide velocity forecasting. Two methods named CWT (Continous Wavelet Transform) and CNN with two types of time-series data; Velocity and Rainfall related to Landslide events were used. CWT was used to create velocity and Rainfall scalograms, which were further classified by CNN to provide prediction of landslide velocities

LANDSLIDE FORECASTING METHODS SUMMARIZED

S.NO.	METHOD	DESCRIPTION				Source
		Summary	Location	Scale	Accuracy	
1.	Use of Hydrological models.	iHydroSlide 3D model; Mix of Hydrological (with soil moisture downscaling method) + 3D Slope stability model. SHALSTAB SHETRAN TRIGRS (Transient Rainfall Infiltration and Grid-based Regional Slope Stability)	China Kerala, India Kalimpong, India Kerala, India	Regional	AUC = 0.77	*Chen et al., 2023* *Abraham et al., 2023* *Abraham et al., 2021* *Abraham et al., 2023*
2.	Using Basal-failure plane's temperature and Groundwater pressure.	Uses basal temp of shear band and groundwater pressure to predict slide velocity using a formula related to Strain rate.		Local		*Sequi and Veveakis, 2022*
3.	Rainfall Thresholds Types; Are usually based on ID (Intensity-Duration), ED (Event cumulative-Duration), EI (Event cumulative-Intensity), RS (Rainfall Severity-Soil wetness) AR (Antecedent Rainfall)	SIGMA model – Thresholds are based on function of standard deviation of Precipitation data of each day. CTRL-T- (Calculation of threshold for rainfall induced Landslides-Tool) - Two statistical methods Frequentist statistical method and 'Bootstrap' non-parametric methods are used to generate the Threshold curve between the cumulative rainfall(mm) and rainfall days. The past events of landslides are plotted in a graph and threshold value of R.F. is known, which is used to predict new events PRAISE-MET + FLAIR model	Kalimpong India (Various locations)	Regional	92% AUC = 0.92	*Abraham et al., 2020, 2022* *Dikshit at al., 2019* *Gariano and Melillo et al., 2023* *Brunetti and Melillo., 2021*

		PRAISE (Prediction of Rainfall Amount Inside Storm Events) is used for R.F. Forecasting using NWP, MET is the historical meteorological data, FLAIR helps for identification of R.F. thresholds (such thresholds are very local).	Italy			*Luca and Capparelli., 2022*
4.	Displacement-Velocity thresholds Displacement forecasting	Predicts time of failure • By monitoring tertiary creep. • Sensing acoustic or seismic emissions related to progressive fracturing. • Uses doppler radar, GBInSAR, MTInSAR or A-DInSAR • Uses GNSS or other sensor data with ML/DL algorithms.	China	Local		*Segui et al., 2022* *Casagli et al., 2023* *Moretto et al. 2021* *Yang et al., 2022* *Duan at al., 2023*
5.	ML or DL methods such as (Eg. LHASA); Logistic Regression Random Forest, Bayesian Network, Backpropagation Neural Network, Bagging, XGBoost, And there hybrids., etc	• Takes sample of LS and non LS events. • For those points, find influencing factors. Conditioning factors can be parameters from bhukosh data such as rock state/hydrology/Erosion etc. or the cumulative rainfall (diff. meteorological datas), intensity and landslide susceptibility index . Also Suitable for data sparse regions, where; • It takes hourly precipitation data of few LS and large no. of Non LS events. • Or uses hybrid ML algorithms.	Alaska Uttarkashi Global Italy	Regional and Local	0.74 89.9% AUC = 0.91	*Nocentini et al., 2023* *Kainthura and Sharma et al., 2022* *Khan and Kirschbaum., 2022* *Patton et al., 2023*

	LSTM and DBN, etc.	• Also used in Displacement forecasting.	China			*Yang et al., 2022* *Duan at al., 2023*
6.	Real time monitoring of soil and ground movement, slope inclination, water content. etc.	Using wireless instruments or solar panel based sensors-MEMS, IOT sensors, tilt and displacement sensors.	India	Local		*Wanare et al., 2022* *Esposito et al., 2022*
7.	WADENOW-A MATLAB toolbox for forecasting LS velocities.	Uses CWT (Continous wavelet transform) and DL (Deep Learning methods such as CNN) CWT is used for creating scalograms of velocity and rainfall timeseries data CNN identifies trends and helps in forecasting.	Italy	Local	98%	*Teza et al., 2022*

PARAMETERS USED IN ABOVE METHODS

All essential parameters were compiled and following list was made. The regular monitoring of these parameters is essential for Landslide forecasting.

Sno.	PARAMETER	SOURCE
1.	Land Use	Satellite
2.	Aspect	Satellite
3.	Slope	Satellite
4.	RQD	Geotechnical/Field based
5.	Lithology	Field based/Geoportals
6.	Soil composition/Mineralogy	Field based/Geo-portals
7.	Fault/Fracture no.	Ground based
8.	Fault/Fracture spacing	Ground based
9.	Seismicity	Geo-portals
10.	Rainfall	Satellite/IMD geoportal/Field sensor data
11.	Soil wetness/moisture	Ground based/ Satellite
12.	Groundwater Pressure	Ground based
13.	Pore pressure	Ground based
14.	Soil/Overburden Thickness	Geophysical
15.	Shear Strength	Geotechnical
16.	Ground Displacement	Satellite/Field sensor based

Disclaimer- There may be more concerned parameters.

PHASE I- Rainfall Threshold Method

A triggering threshold is represented by a mathematical equation describing the critical rainfall condition above which landslides are triggered.

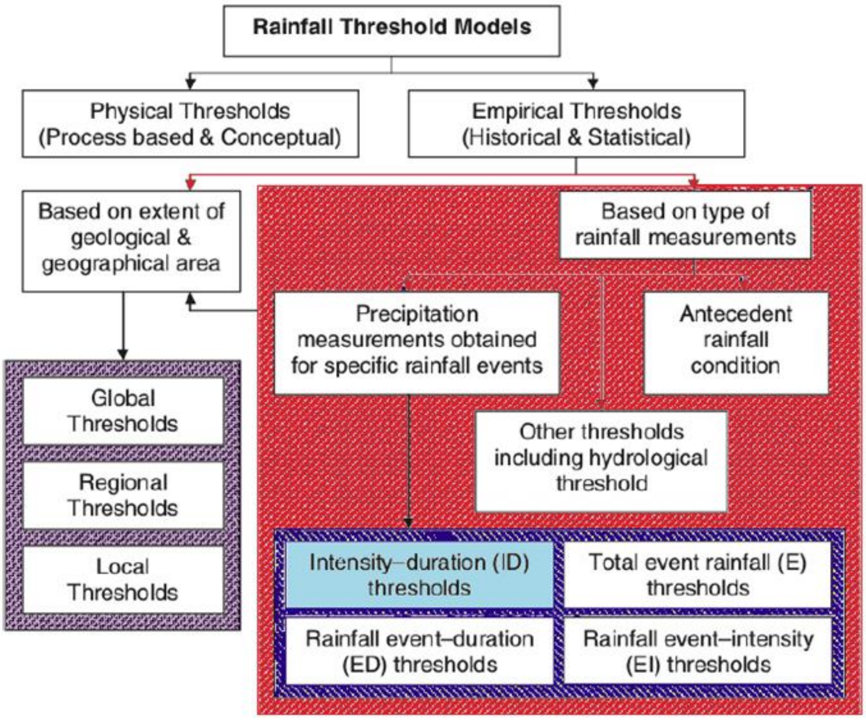


***Figure 3**. Flow diagram of rainfall threshold models for landslide occurrences recognized by Guzzetti et al. (2007).*

Some of the common threshold types include meteorological thresholds, probabilistic and hydro-meteorological (see figure 3.)

In this work we our using meteorological thresholds, these are derived considering the historical relationship between the occurrence of rainfall and landslides only. There types are; ID (Intensity-Duration), ED (Event cumulative and Duration), AR (Antecedent Rainfall).

1. ID (Intensity-Duration) Threshold

These thresholds are computed utilizing using the power law equation

$$I = \alpha D^{-\beta}$$

Where, I is rainfall intensity (mm/h), D is rainfall duration (h) , α is a scaling parameter (the intercept) and β is shape parameter which controls the slope of threshold curve.

Daily/Hourly intensities of rainfall events associated with the occurrence of landslides were calculated and plotted against the duration of events in hours in logarithmic scale

$$log\ (I) = log\ (\alpha) + \beta log(D)$$

The Eq. is in the form of a straight line $y = mx + c$. Approach is based on linear regression and the data is fitted using a power law.

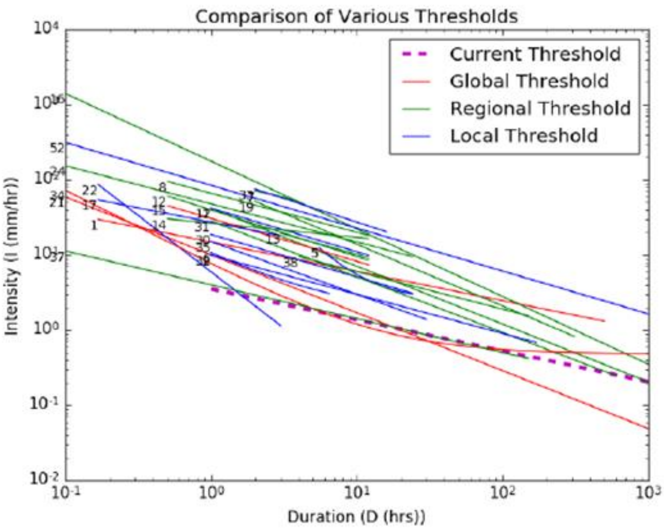


Figure 4. *Example of Rainfall intensity duration (ID) thresholds from literature (Dikshit and Satyam, 2018).*

2. ED (Event cumulative and Duration) Threshold

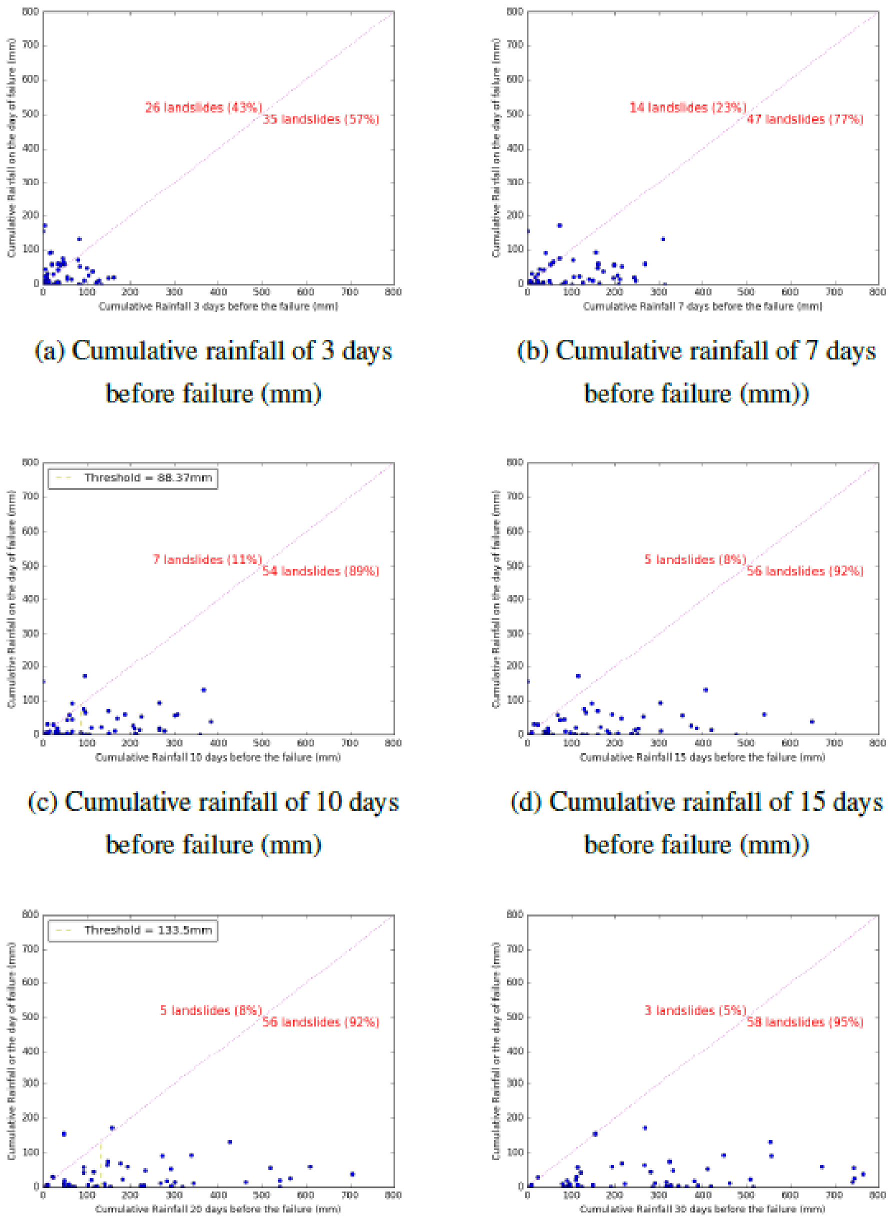
The cumulative rainfall event, E, is determined as the accumulated rain from the beginning of rainfall to the precipitation that induces the slope failure. The power law equation used to calculate this threshold is expressed as;

$$E = \alpha D^{-\gamma}$$

Whereby, cumulative rainfall event, E is measured in (mm), rainfall duration, D is expressed either in (hour) or (day), while α and γ are the coefficient of rainfall depth and the threshold

3. Antecedent Rainfall Threshold

Antecedent Rainfall is sum of rainfall, days before landslide event. Research suggest that an antecedent rainfall of 3 days to 4 months is significant in explaining landslide occurrences. Antecedent rainfall influences soil moisture and groundwater level thus causing slopes to failure.The no. of days used for this threshold type are 3, 7, 10, 15, 20, and 30. The plot is made for rainfall on day of failure and cumulative rainfall for specific days before failure. These plots are used to find the no. days are actually significant for landslide occurrence.



(a) Cumulative rainfall of 3 days before failure (mm)

(b) Cumulative rainfall of 7 days before failure (mm))

(c) Cumulative rainfall of 10 days before (mm)

(d) Cumulative rainfall of 15 days before failure (mm))

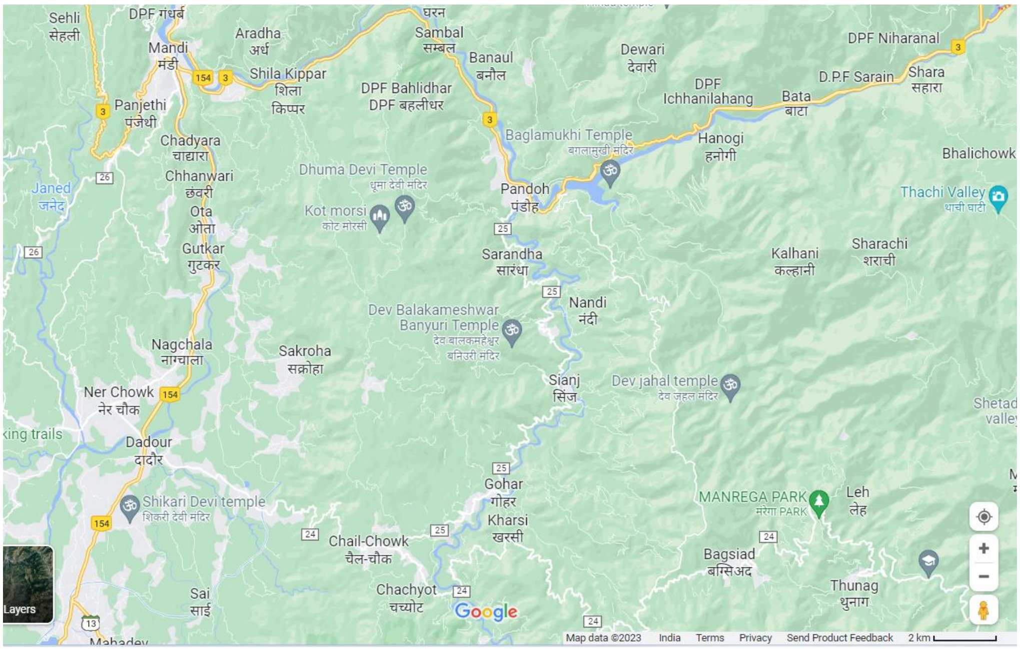
(e) Cumulative rainfall of 20 days before failure (mm)

(f) Cumulative rainfall of 30 days before failure (mm))

Figure 5*. An Example showing relationship between antecedent rainfall prior to failure (3, 7, 10, 20, 30 days) and daily rainfall for landslide occurrences (Dikshit and Satyam, 2018)*

STUDY AREA

The region selected for the study is a stretch of 41 km along the National Highway – 3 and 154 in



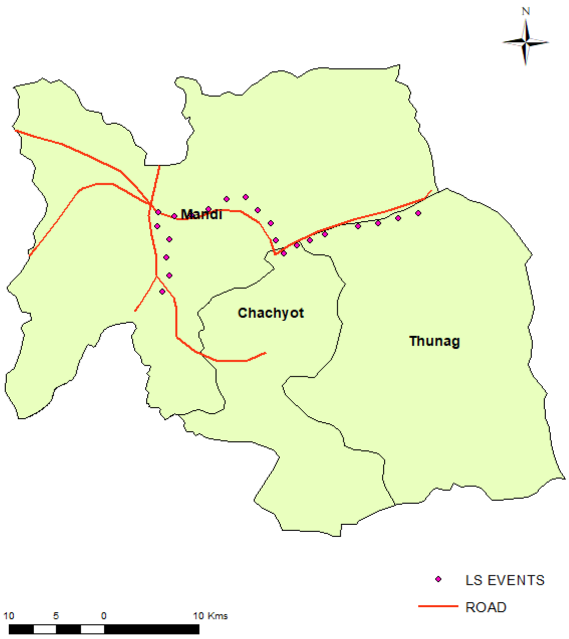


__Figure 6__. 1)Roads of Interest. 2) Map depicting slide events on NH 154 and 3 stretch in Mandi, Himachal Pradesh . 3) Recent Image of slide on Road.(Source-Google maps, IIT mandi data, Abp news imagery)

Pandoh region of Mandi district, Himachal Pradesh. The stretch extends between coordinates 31.55152, 76.89702 to 31.71653, 77.20919. The road is along Suketi and Beas river. The area has average elevation of 760 m and average yearly precipitation is 832 millimetres.

DATA USED

The data used was acquired and compiled by IIT Mandi. For 90 Landslide events occurring in year 2014, rainfall data for the day of landslide events and its 30 days before was utilised for this analysis.

Date and Location of Landslide event on the NH3 and 154 road.

Rainfall on and before the day of Landslide.

Sr. No.	Blocked on	latitude	longitude	Rainfall	Rainfall(one day ago)	Rainfall(two day ago)	Rainfall(three day ago)	Rainfall(four day ago)	Rainfall(five day ago)
1	7	11	12	15	16	17	18	19	20
1	20140812	31.701816	76.968287	0	3.9	2.9	2.4	6.4	7.7
2	20140812	31.701816	76.968287	0	3.9	2.9	2.4	6.4	7.7
3	20140812	31.694463	77.042545	0	3.9	2.9	2.4	6.4	7.7
4	20140812	31.68369	77.094219	0	3.9	2.9	2.4	6.4	7.7
5	20140812	31.691779	77.125837	0	1.9	1.2	1	1.8	3.7
6	20140716	31.691238	76.935228	35.2	0.5	4.9	1.5	0	0
7	20140716	31.705375	76.93618	35.2	0.5	4.9	1.5	0	0
8	20140716	31.708053	76.984254	35.2	0.5	4.9	1.5	0	0
9	20140716	31.717459	77.001487	35.2	0.5	4.9	1.5	0	0
10	20140716	31.717459	77.001487	35.2	0.5	4.9	1.5	0	0
11	20140729	31.677938	77.079819	12.9	12.7	19.7	4.3	0.5	8.5
12	20140729	31.68369	77.094219	12.9	12.7	19.7	4.3	0.5	8.5
13	20140729	31.68369	77.094219	12.9	12.7	19.7	4.3	0.5	8.5
14	20140729	31.68369	77.094219	12.9	12.7	19.7	4.3	0.5	8.5
15	20140729	31.691779	77.125837	8.2	6.6	18.1	1.8	0	9.7
16	20140729	31.691779	77.125837	8.2	6.6	18.1	1.8	0	9.7
17	20140729	31.691779	77.125837	8.2	6.6	18.1	1.8	0	9.7
18	20140729	31.699112	77.164132	8.2	6.6	18.1	1.8	0	9.7
19	20140729	31.704178	77.183315	8.2	6.6	18.1	1.8	0	9.7
20	20140730	31.699112	77.164132	11.5	8.2	6.6	18.1	1.8	0
21	20140730	31.677938	77.079819	5	12.9	12.7	19.7	4.3	0.5
22	20140730	31.677938	77.079819	5	12.9	12.7	19.7	4.3	0.5
23	20140730	31.677938	77.079819	5	12.9	12.7	19.7	4.3	0.5
24	20140730	31.677938	77.079819	5	12.9	12.7	19.7	4.3	0.5
25	20140730	31.691238	76.935228	5	12.9	12.7	19.7	4.3	0.5
26	20140730	31.691238	76.935228	5	12.9	12.7	19.7	4.3	0.5
27	20140730	31.705375	76.93618	5	12.9	12.7	19.7	4.3	0.5
28	20140730	31.705375	76.93618	5	12.9	12.7	19.7	4.3	0.5
29	20140730	31.717459	77.001487	5	12.9	12.7	19.7	4.3	0.5
30	20140730	31.717459	77.001487	5	12.9	12.7	19.7	4.3	0.5
31	20140730	31.717459	77.001487	5	12.9	12.7	19.7	4.3	0.5
32	20140730	31.694463	77.042545	5	12.9	12.7	19.7	4.3	0.5
33	20140730	31.705375	76.93618	5	12.9	12.7	19.7	4.3	0.5
34	20140730	31.717459	77.001487	5	12.9	12.7	19.7	4.3	0.5
35	20140730	31.717459	77.001487	5	12.9	12.7	19.7	4.3	0.5
36	20140815	31.673462	77.067939	28	27.6	10.9	0	3.9	2.9
37	20140815	31.673462	77.067939	28	27.6	10.9	0	3.9	2.9
38	20140815	31.677938	77.079819	28	27.6	10.9	0	3.9	2.9
39	20140815	31.677938	77.079819	28	27.6	10.9	0	3.9	2.9
40	20140815	31.677938	77.079819	28	27.6	10.9	0	3.9	2.9
41	20140815	31.677938	77.079819	28	27.6	10.9	0	3.9	2.9
42	20140815	31.68369	77.094219	28	27.6	10.9	0	3.9	2.9
43	20140815	31.691779	77.125837	37.5	42.4	4	0	1.9	1.2
44	20140815	31.691779	77.125837	37.5	42.4	4	0	1.9	1.2
45	20140815	31.694853	77.14504	37.5	42.4	4	0	1.9	1.2
46	20140815	31.699112	77.164132	37.5	42.4	4	0	1.9	1.2
47	20140815	31.68369	77.094219	28	27.6	10.9	0	3.9	2.9

Working;

The above table is the required format which shall be the input for this analysis.

As the above data is for a stretch of NH 3 and 154, Mandi, the forecast generated is applicable to same stretch, Mandi only. This tool can take inputs of any area (but most suited for smaller regions to give more accurate local forecasts as compared to regional forecasts) and give forecast based on the Three type of Thresholds- ID, ED, AR_x. x in AR is the no. of significant days for which antecedent rainfall is taken, this differs for each area of interest.

Different thresholds are more suitable for different areas. In this tool, users need to upload Landslide event and associated Rainfall data for any area in the above format, for generating a basic forecast, the tool will ask user values of E, D and Antecedent Rainfall 20 and 30 days before as antecedent rainfall of 20 and 30 days was found significant for area of interest of this study. With very few and easy changes in this code antecedent rainfall for any days suitable for user's interest region can be taken as input.

Finally, by using historical and latest Rainfall parameters entered by user, a basic forecast could be generated utilising all three types of thresholds, using all threshold makes this system more applicable to different areas as for different regions a different threshold is suited more.

NOTE: Landslide forecasting is complex as occurrence of landslides is affected by large no. of variables that differs in space and time. In this technique, only single but most important variable for landslide forecasting- Rainfall is used. As already mentioned above, large no. of other parameters (in phase 2 and 3 of experimental methodology for EWS) could be extracted and utilised for generating forecasts of more accuracy and reliability.

The accuracy assessment of this tool was not done due to lack of more and good quality data. If the quality of input to this tool i.e. Landslide event-Rainfall data of good accuracy could be utilised the output or forecast accuracy will surely increase.

METHODOLOGY USED

Two ways were used for the implementation of this method. Initially method was executed in excel and then using Python programming.

MODE 1

SOFTWARE /TOOL Used- Microsoft Excel

INPUT – Landslide event and associated rainfall data by IIT Mandi.

The parameters are generated from input data. These were Cumulative Rainfall (E), Duration (D), Intensity (I), and Antecedent Rainfall (AR) -3, 7, 10, 15, 20, 30 Days.

E	LOG(E)	D	LOG(D)	I	LOG(I)
113.7	2.05576	21	1.322219	5.414286	0.733541
113.7	2.05576	21	1.322219	5.414286	0.733541
113.7	2.05576	21	1.322219	5.414286	0.733541
113.7	2.05576	21	1.322219	5.414286	0.733541
69.6	1.842609	17	1.230449	4.094118	0.61216
42.1	1.624282	4	0.60206	10.525	1.022222
42.1	1.624282	4	0.60206	10.525	1.022222
42.1	1.624282	4	0.60206	10.525	1.022222
42.1	1.624282	4	0.60206	10.525	1.022222
42.1	1.624282	4	0.60206	10.525	1.022222
59.9	1.777427	8	0.90309	7.4875	0.874337
59.9	1.777427	8	0.90309	7.4875	0.874337
59.9	1.777427	8	0.90309	7.4875	0.874337
59.9	1.777427	8	0.90309	7.4875	0.874337
34.7	1.540329	4	0.60206	8.675	0.938269
34.7	1.540329	4	0.60206	8.675	0.938269
34.7	1.540329	4	0.60206	8.675	0.938269
34.7	1.540329	4	0.60206	8.675	0.938269
34.7	1.540329	4	0.60206	8.675	0.938269
46.2	1.664642	5	0.69897	9.24	0.965672
64.9	1.812245	9	0.954243	7.211111	0.858002
64.9	1.812245	9	0.954243	7.211111	0.858002
64.9	1.812245	9	0.954243	7.211111	0.858002
64.9	1.812245	9	0.954243	7.211111	0.858002
64.9	1.812245	9	0.954243	7.211111	0.858002
64.9	1.812245	9	0.954243	7.211111	0.858002
64.9	1.812245	9	0.954243	7.211111	0.858002

1. AR threshold

The Antecedent Rainfall Threshold is generated using cumulative rainfall for 3, 7, 10, 15, 20, 30 no. of days before failure. The plot is made for rainfall on day of failure and cumulative rainfall for specific days before failure.

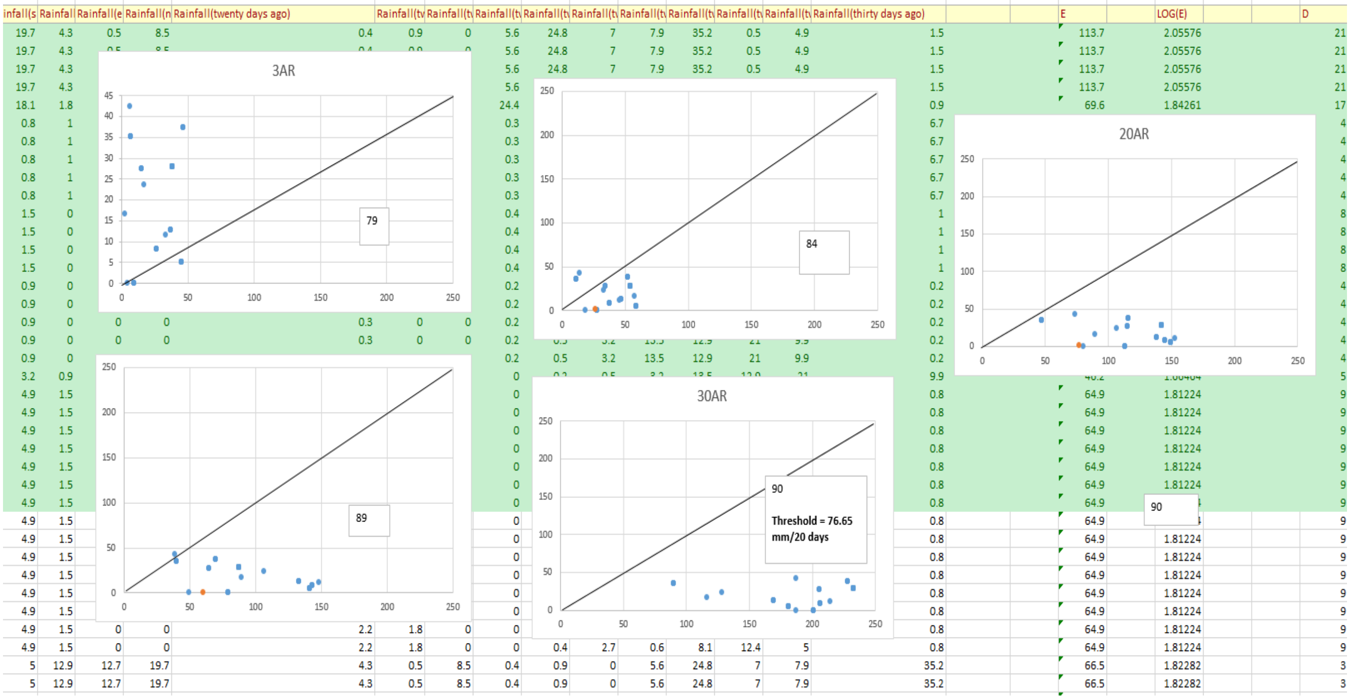


Figure 7. *Plots showing Antecedent Rainfall Threshold (for 3, 7, 15, 20, 30 days) for study area of NH 3 and 154. Orange dot signifies the threshold point. Threshold is significant for AR_{30} and AR_{20} and is calculated using probability distribution function for the data under the bisecting line. Plots were made in excel.*

2. ID and ED Threshold

The cumulative rainfall event, E, is determined as the accumulated rain from the beginning of rainfall to the precipitation that induces the slope failure. The power law equation used to calculate ED threshold. Daily intensities (I) of rainfall events and E associated with the occurrence of landslides were calculated and plotted against the duration (D) of events in hours in logarithmic scale to create ED and ID plots.

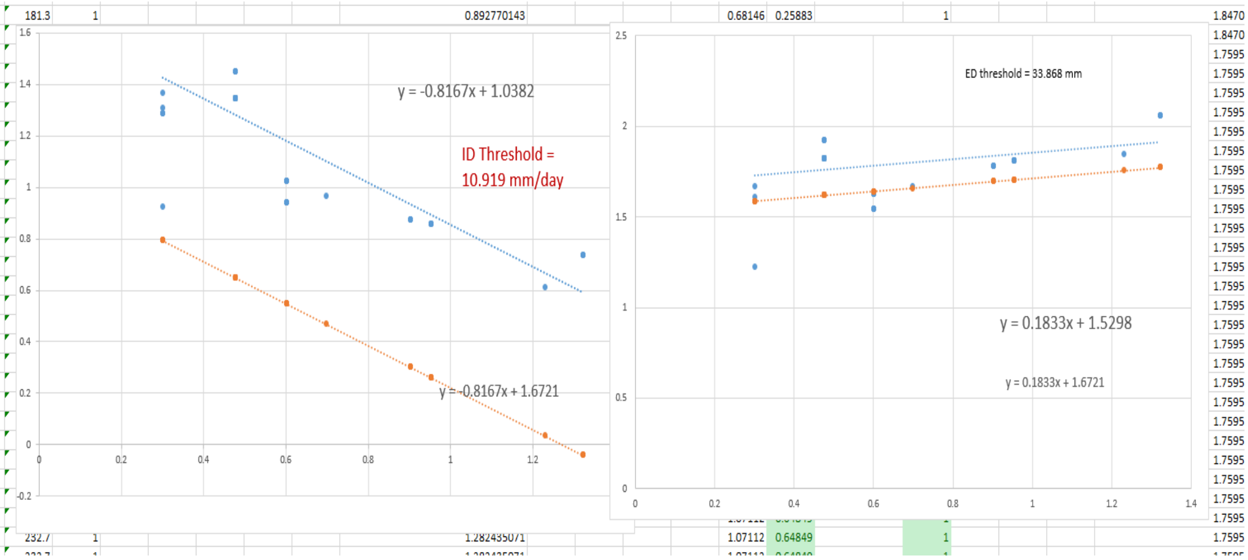


Figure 8. *Plots showing ID (Intensity-Duration) and ED (Event Cumulative Rainfall- Duration) Thresholds. The blue line is the best fit line and Orange line represents the Threshold line generated by equations of Power law and Gaussian distribution.*

MODE-2

Software/Tool – Python Programming in Jupyter Lab

INPUT – Landslide event and associated rainfall data by IIT Mandi.

The execution of the tool with code, outputs is mentioned below.

```
import pandas as pd
import numpy as np
import scipy
from scipy.stats import powerlaw
import matplotlib.pyplot as plt
from scipy.optimize import curve_fit
```

```
#######
data2 = pd.read_csv("G:\work_done\Paavithra\mandi_ls_data.csv")


####
y = data2.iloc[:,1:]


######


y = np.array(y)

######
LS = []


for v in y:
    pp = []
    uu = 0
    for a in v:
        uu = uu + 1
        if a == 0:
            if uu == 1:
                continue
            else:
                break
        elif a != 0:
            pp.append(a)
    E2 = sum(pp)
    D2 = uu
    I2 = E2/D2


    LS.append([E2,D2,I2])


LS = np.array(LS)







######
user = input('Enter event cumulative rainfall till today in mm (E): ')
dayy = input('Enter No. of Rainfall event Days (D): ')
user2 = fl
```

```
1232123232
AR_20 = input('Enter cumulative Rainfall of previous 20 Days (AR20): ')
AR_30 = input('Enter cumulative Rainfall of previous 30 Days (AR30): ')
```

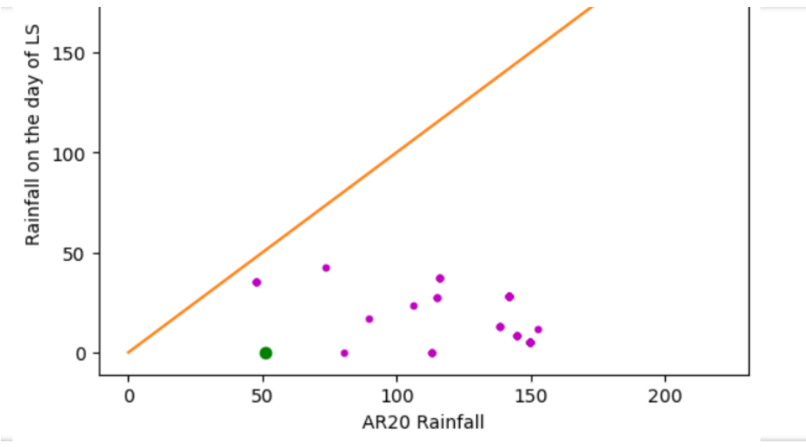
```
Enter event cumulative rainfall till today in mm (E):
```

```
Enter event cumulative rainfall till today in mm (E): 70
Enter No. of Rainfall event Days (D): 5

Enter cumulative Rainfall of previous 20 Days (AR20):
```

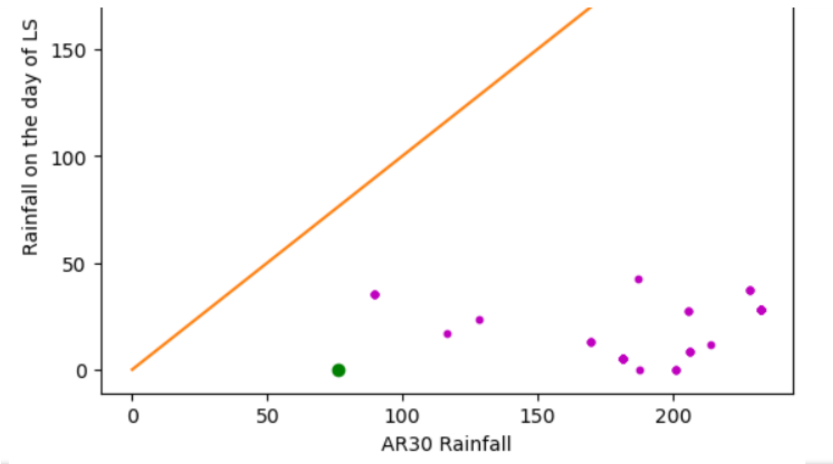
```
Enter event cumulative rainfall till today in mm (E): 70
Enter No. of Rainfall event Days (D): 5
Enter cumulative Rainfall of previous 20 Days (AR20): 95

Enter cumulative Rainfall of previous 30 Days (AR30): 150
```

```
#FOR AR

ar_list = []

AR20 = []
AR30 = []


for K in y[:,1:21]:
    AR = sum(K)
    AR20.append(AR)

for S in y[:,1:31]:
    AR = sum(S)
    AR30.append(AR)


AR20 = np.array(AR20)


AR30 = np.array(AR30)

Y_AR = y[:,0]
```

```
standTWENTY = np.std(AR20)
twentyar = 3*standTWENTY - standTWENTY

plt.scatter(AR20, Y_AR, color = "m", marker = "o", s = 10)

plt.plot(220,220)

plt.plot(twentyar, 0, "go")

plt.plot([0,50,100,150,200,220],[0,50,100,150,200,220])

plt.xlabel('AR20 Rainfall')
plt.ylabel('Rainfall on the day of LS')
#plt.title('')
#plt.plot(AR_20, 0, "go")
plt.show()
c = 0
n = 0
while c < 89:
    if AR20[c] > Y_AR[c]:
        n = n + 1
    c = c + 1
print('Landslides towards AR:',n, ', Landslides towards LS day:', (89-n), ', THRESH', twentyar)

##################################################
standTHIRTY = np.std(AR30)
thirtyar = 3 * standTHIRTY - standTHIRTY
plt.scatter(AR30, Y_AR, color = "m", marker = "o", s = 10)
#plt.plot(AR_30, 0, "go")
plt.plot(220,220)
plt.plot(thirtyar, 0, "go")
plt.plot([0,50,100,150,200,220],[0,50,100,150,200,220])
plt.xlabel('AR30 Rainfall')
plt.ylabel('Rainfall on the day of LS')
#plt.title('')
plt.show()
c = 0
n = 0
while c < 89:
    if AR30[c] > Y_AR[c]:
        n = n + 1
    c = c + 1
print('Landslides towards AR:',n, ', Landslides towards LS day:', (89-n), ', THRESH', thirtyar)
```




```
Landslides towards AR: 89 , Landslides towards LS day: 0 , THRESH 50.8201000868702
```

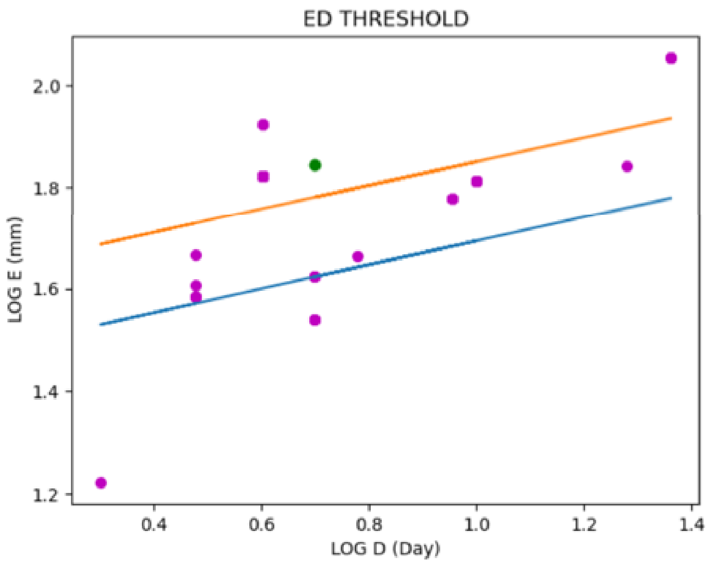



```
Landslides towards AR: 89 , Landslides towards LS day: 0 , THRESH 76.342750866579
```

The Threshold value for the study area is provided with the graph. The user's input of ED is depicted as green point.

```
#FOR ED

x_data = LS[:,1]
y_data = LS[:,0]
yy_data = LS[:,2]

x = np.log10(x_data)
y = np.log10(y_data)
yy = np.log10(yy_data)
```

```
dayy = float(dayy)
user = float(user)
#FOR BEST FIT
beta, alpha = np.polyfit(x, y, deg = 1)
y_line = alpha + beta * x
stdd = np.std(y_line)
thresh_line = y_line - 3*(stdd)
elog = np.log10(user)
logday = np.log10(dayy)
betaaa, alphaaa = np.polyfit(x, thresh_line, deg = 1)
Threshold = alphaaa + betaaa * logday
THRESH1 = np.power(10,Threshold)

plt.scatter(x, y, color = "m", marker = "o", s = 30)
plt.plot(x, thresh_line)
plt.plot(x, y_line)
plt.plot(logday, elog, "go")
plt.xlabel('LOG D (Day)')
plt.ylabel('LOG E (mm)')
plt.title('ED THRESHOLD')
plt.show()

print('For this area cumulative event rainfall more than',THRESH1,'mm can cause LS')
```

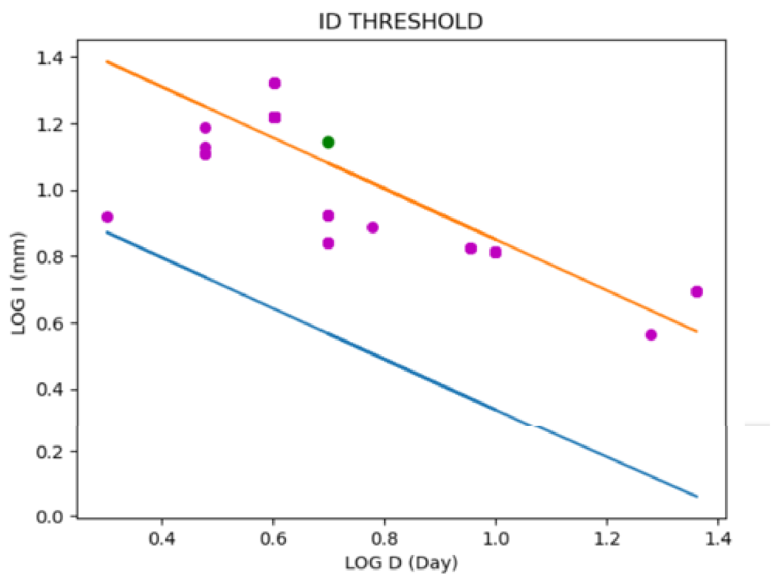



```
For this area cumulative event rainfall more than 41.969637440858236 mm can cause LS
```

Blue line is the ED threshold, Green point is the above input of E and D

```
#FOR ID
```

```
plt.scatter(x, yy, color = "m", marker = "o", s = 30)
user2 = float(user2)
b, a = np.polyfit(x, yy, deg = 1)
y_linee = a + b * x
elog2 = np.log10(user2)
stddd = np.std(y_linee)
thresh_linee = y_linee - 3*(stddd)
ba, aa = np.polyfit(x, thresh_linee, deg = 1)
Threshold2 = aa + ba * logday
THRESH2 = np.power(10,Threshold2)

plt.plot(x, thresh_linee)
plt.plot(x, y_linee)
plt.plot(logday, elog2, "go")
plt.xlabel('LOG D (Day)')
plt.ylabel('LOG I (mm)')
plt.title('ID THRESHOLD')
plt.show()

print('For this area rainfall intensity more than',THRESH2,'mm/day can cause 
LS')
####################################
```




```
For this area rainfall intensity more than 3.688833845984894 mm/day can cause LS
```

Blue line is the ID threshold, Green point is the above input of I and D.

Now based on the user's input being above or below the threshold value, votes are provided to each threshold type, if input value exceeds threshold type, there is a chance of landslide occurrence according to the threshold type, thus vote (Yes/No- for landslide occurrence) is calculated and summed for all threshold type to give a better final forecast of occurrence of landslide event.

Generation of Forecast

Based on the inputs, if input variables are exceeding the thresholds, VOTE is 1 and if not the VOTE is 0 for the method.

If sum of votes = 1, then there is Low probability of LS occurrence.

If sum of votes = 2, then there is Medium probability of LS occurrence.

If sum of votes = 3, then there is High probability of LS occurrence.

If sum of votes = 4, then there is Very High probability of LS occurrence.

```
#VOTING

VOTE = 0

if user > THRESH1:
    VOTE = VOTE + 1
    print('ED VOTE = 1')

else:
    VOTE = 0
    print('ED VOTE = 0')



if user2 > THRESH2:
    VOTE = VOTE + 1
    print('ID VOTE = 1')

else:
    print('ED VOTE = 0')




AR_20 = float(AR_20)
twentyar = float(twentyar)

if AR_20 > twentyar:
    VOTE = VOTE + 1
```

```python
    print('AR20 VOTE = 1')
else:
    print('AR20 VOTE = 0')



thirtyar = float(thirtyar)

AR_30 = float(AR_30)

if AR_30 > thirtyar:
    VOTE = VOTE + 1
    print('AR30 VOTE = 1')
else:
    print('AR30 VOTE = 0')


if VOTE == 0:
    print('\n\n"There is 0 % probability of Landslide occurence":)')
elif VOTE == 1:
    print('\n\n"There is a LOW probability of Landslide occurence":)')
elif VOTE == 2:
    print('\n\n"There is a MEDIUM probability of Landslide occurence"!')
elif VOTE == 3:
    print('\n\n"There is a HIGH probability of Landslide occurence"!!')
elif VOTE == 4:
    print('\n\n"There is a VERY HIGH probability of Landslide occurence"!!!!
:0')
```

```
For this area rainfall intensity more than 3.688833845984894 mm/day can cause LS
ED VOTE = 1
ID VOTE = 1
AR20 VOTE = 1
AR30 VOTE = 1


"There is a VERY HIGH probability of Landslide occurence"!!!! :0
```

NOTE: The use of python over excel improved the results of the tool

---

ACKNOWLEDGEMENT

I would like to express my sincere and heartfelt thanks to all those in prestigious DGRE, DRDO for providing me the opportunity, environment and support to work on a topic of my interest. I wish to express my sincere gratitude to my guide Dr. Snehmani Sir for helping me at each step and guiding me with best of his knowledge. A special thanks to Saurabh sir for solving technical issues and supporting the working of the tool. I would also like to thanks Dr. Prateek Chaturvedi for providing me his guidance and data from IIT mandi. I also thank MD Mehraj for his support.

3 Nov 2023 *Kamini Sharma, JRF,CSD*