A statistical model for earthquake and/or rainfall triggered landslides

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November 23, 2022

Abstract

Coseismic and rainfall-triggered landslides are a common hazard in many terrains, and the risk associated with them can be quantified, usually by probabilistic modelling. These events are well-documented as a special case of a cascading hazard chain, and the assessment is commonly done via spatial modelling of susceptibility (suppressing temporal dependence) or tailoring models to specific areas and events. The interaction between Earthquakes and rainfall is not usually implemented in a model, as it is considered coincidental. However, because landslides have multiple triggering factors, there is a need for a statistical model that incorporates both features, in a manner such that the separate and joint effects can be estimated. This helps with understanding the interactions between primary events in the triggering of a single secondary hazard type that is crucial for generally applicable multi-hazard methodologies. The presented work aims at the apportioning of the relative and combined effect on landslide triggering by earthquakes and rainfall using a discrete approximation to a multivariate hierarchical point process. Doing so provides a building block in a general framework with the potential to be extended to other chains of events. A case study on the Italian region of Emilia-Romagna is included, using one of the longest and most complete landslide data sets known. Multiple models for the rainfall-earthquake interaction in landslide triggering are trialed, with the best explanation being additive effects from rainfall intensity, rainfall duration and coseismic triggering.

A statistical model for earthquake and rainfall triggering landslides

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AGU 100 ADVANCING EARTH AND SPACE SCIENCE
FALL MEETING
Washington, D.C. | 10–14 Dec 2018

Abstract

The risk associated with coseismic and rainfall-triggered landslides can be apportioned including the spatio-temporal overlapping of both triggering events to estimate separate and joint effects. This helps understanding the interactions between primary events triggering a single secondary hazard type, crucial for generally applicable multi-hazard methods. The proposed is a discrete approximation to a multi-hierarchical point process, providing a building block in a general framework with the potential to be extended to other chains of events.

1. Region and Data sets

Figure 1: Emilia-Romagna

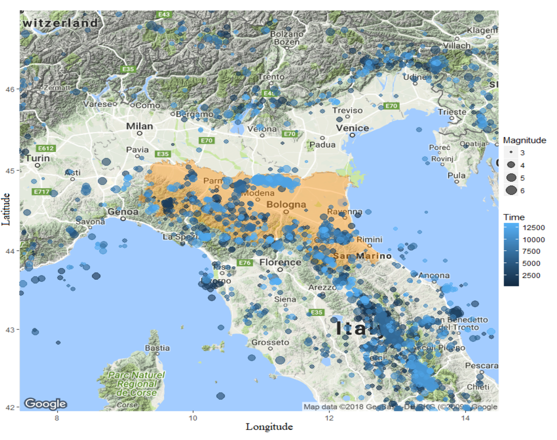

Figure 3: Earthquakes 1981-2015

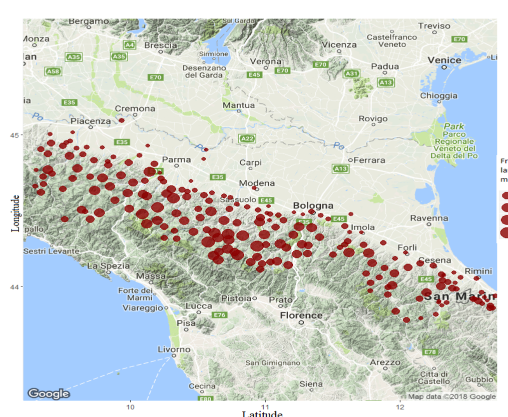

Figure 2: Landslides 1981-2015

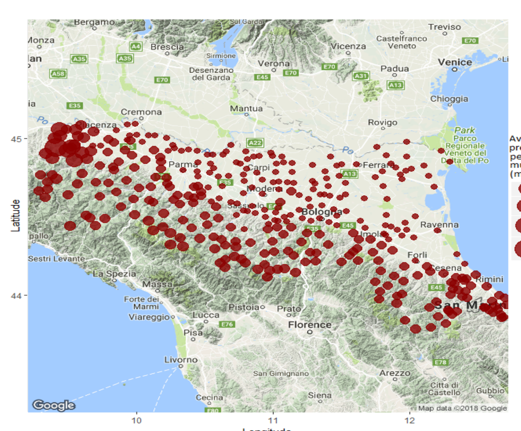

Figure 4: Rainfall 1981-2015

	Earthquakes	Rainfall	Landslides
Time precision	Seconds	Days	Day/Month
Location Precision	Epicentre	Town	Town
Magnitude	M_W	mm/day	number/day
Number of data	4330	1764054	7087

Table 1: Meta Data

2. "First day" problem

Landslide occurrence times are given to daily precision but there appears to be a problem...

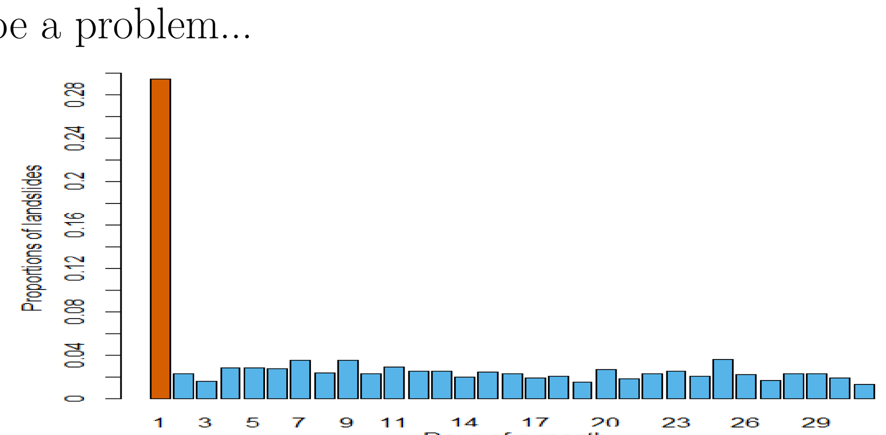

Figure 5: Proportion of landslides per day of a month

The problem is not season-related, as it is spread throughout all months:

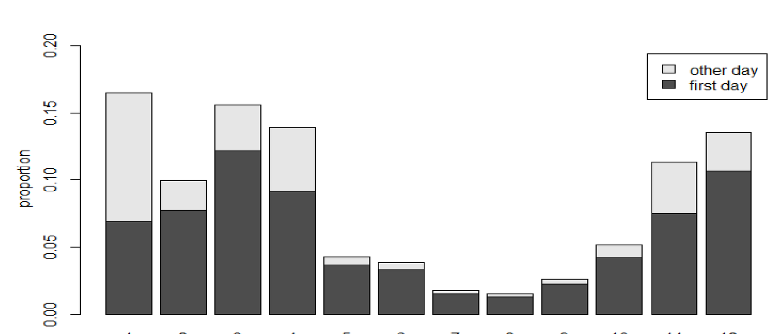

Figure 6: Proportion of 'first day' landslides per month

Solution: suppose that for days other than day 1 the true number of landslides is the recorded number plus some mis-recorded on day 1. We use the Bayes Theorem and the EM algorithm to reallocate first-day events across the entire month.

3. The Model

Daily landslides are modelled as a non-homogeneous point process at each location. The expected number of landslides is expressed as a location susceptibility multiplied by a function combining rainfall and seismic components in various ways.

Shaking: The moment magnitude (m) directly affect the landslide triggering; the distance from the epicentre (r) has an inverse effect.

$$C_E(x,t) = \sum_{t \le t_k < t+1} \frac{10^{1.5(m_k-3)}}{r_{x,k}^{\beta}} \tag{1}$$

Rainfall Intensity: The last two days rainfall average is the best estimate for intensity.

$$C_{R1}(x,t) = \frac{1}{2} \sum_{k=t-1}^{t} P(x,t) \tag{2}$$

Rainfall Duration: An exponentially weighted average of the last Δ days.

$$C_{R2}(x,t) = \frac{1}{\Delta} \sum_{\delta=1}^{\Delta} \omega^{\delta-1} P(x, t-\delta-1), \tag{3}$$

The values $\Delta = 150, \omega = 0.98$ produced the best fit to the data.

Three models for interaction

Multiplicative model: Duration * Intensity * Shaking
Additive model: Duration + Intensity + Shaking
Mixture model: (Duration*Intensity) + (Duration*Shaking)
The equations of the three models can be found in block 9.

4. ZIP model

7087 landslides in 12783 days and 138 towns: more than 98% of zero counts at day-location. A standard Poisson model can't cope, so we add an atom of probability at 0 to get a Zero-Inflated Poisson model. The probability of n landslides at location x and day t is:

$$\boxed{\Pr(N_{x,t} = n) = \begin{cases} q_{x,t} + (1-q_{x,t}) \exp(-\mu(x,t)), & n = 0 \\ (1-q_{x,t}) \frac{\exp(-\sum_x \mu(x,t))(\sum_x \mu(x,t))^n}{n!}, & n > 0. \end{cases}} \tag{4}$$

For the Zero Inflated model, the best explanation of excess zeros is the following, which includes the duration component:

$$\nu(x,t) = \nu_0 + \nu_2 C_{R2}(x,t) \tag{5}$$

physically, ν_2 should be negative, so that long dry periods increase the probability of no landslides.

5. Results

	Multiplicative	Additive	Mixture
μ_1 **(Short-term rain)**	7.417	5.341	6.139
μ_2 **(Long-term rain)**	6.147	9.462	9.769
μ_3 **(Earthquake)**	4×10^{-6}	6×10^{-4}	5×10^{-6}
ν_0 **(ZIP)**	109.12	11.798	11.464
ν_2 **(ZIP)**	39.02	-22.095	-22.567
Log-likelihood	-41045	-39889	-40101

Table 2: Parameter estimates and loglikelihoods.

All models have the same number of parameters, so the best model is the additive model, which has a negative ν_2 term.

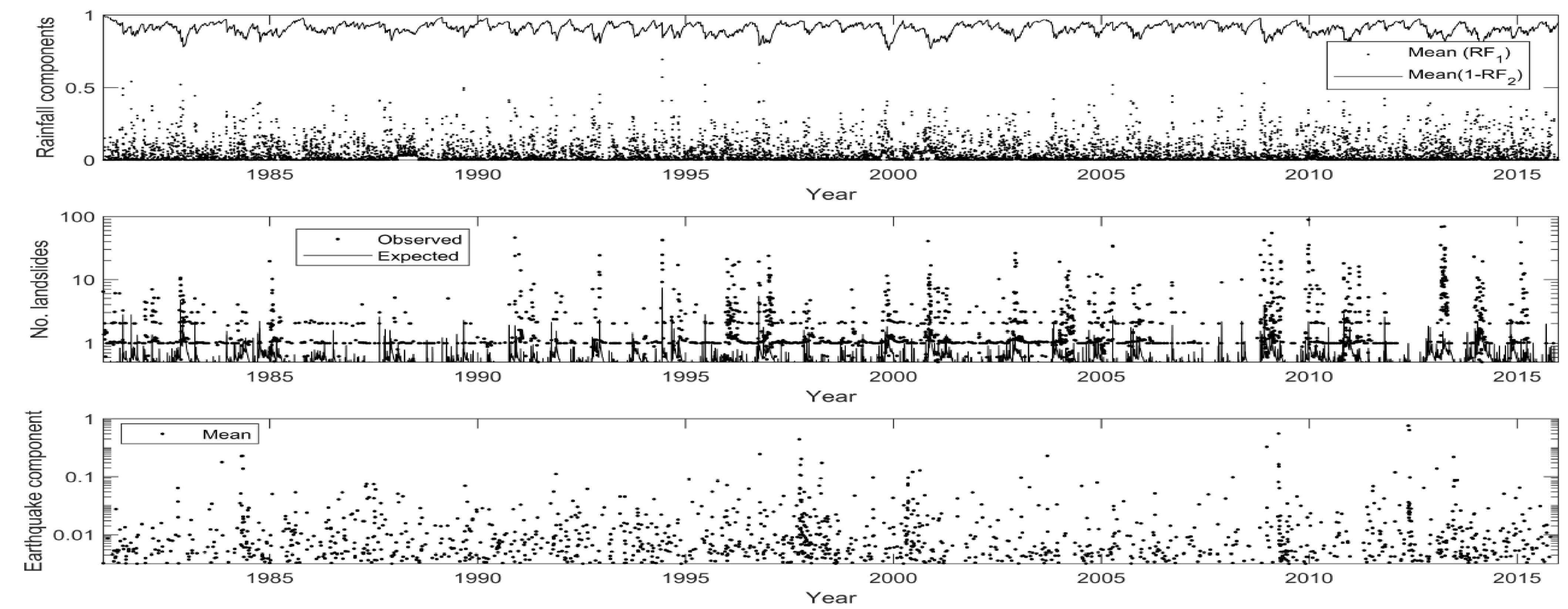

Figure 7: Expected vs. Observed landslides, against rainfall and earthquake events over time.

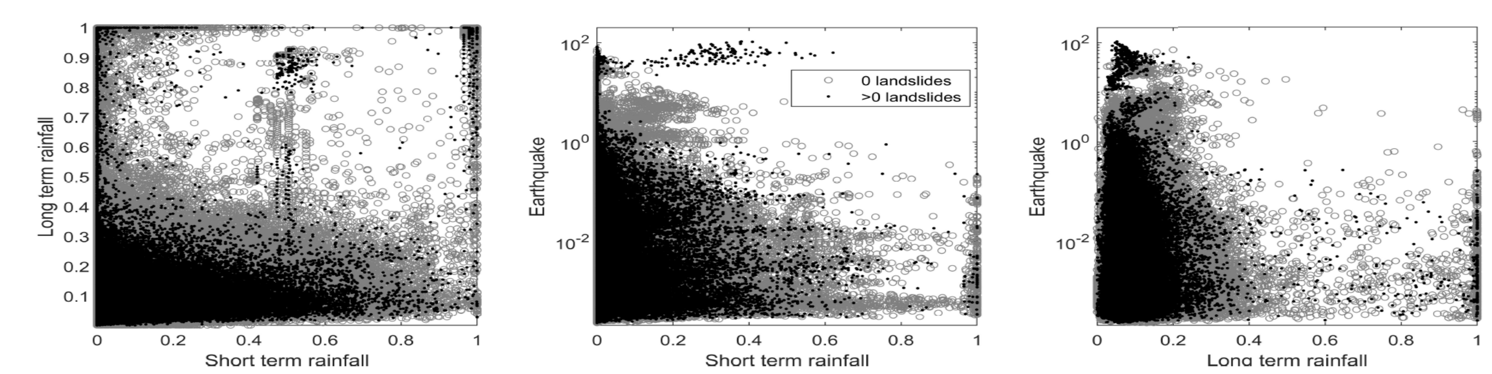

Figure 8: Plots of components vs. components

6. Information gained

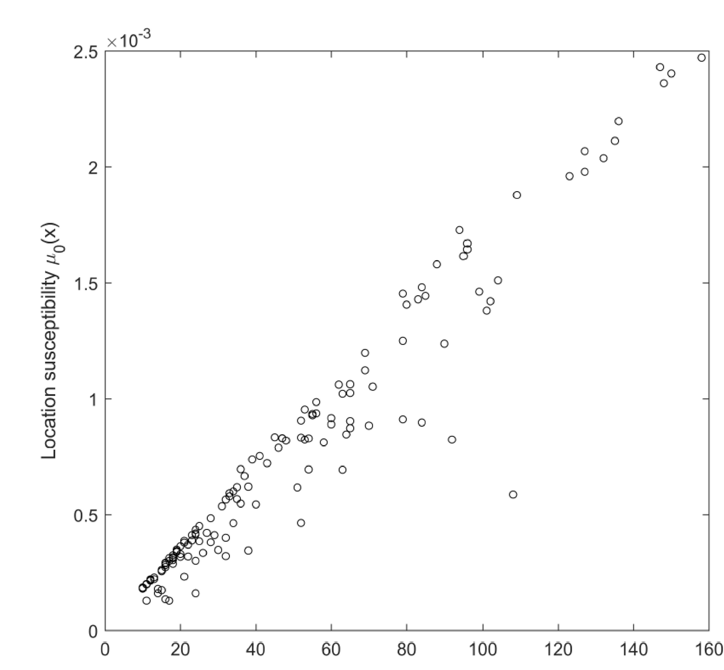

Figure 9: Estimated location susceptibilities against number of observed landslides

Figures 7 and 8 show the effect of rainfall on landslides, but also some possible seismic overlapping. In figure 9 each dot is a location. A model without explanatory power would show a straight line, as each μ_0 would be proportional to the number of landslides per location.

References

Gill, J. and Malamud, B. (2014). Reviewing and visualizing the interactions of natural hazards. *Reviews of Geophysics*, 52(4):680–722.

Peruccacci, S., Brunetti, M. T., Gariano, S. L., Melillo, M., Rossi, M., and Guzzetti, F. (2017). Rainfall thresholds for possible landslide occurrence in italy. *Geomorphology*, 290(Supplement C):39 – 57.

Rossi, M., Witt, A., Guzzetti, F., Malamud, B., and Peruccacci, S. (2010). Analysis of historical landslide time series in the Emilia-Romagna region, northern Italy. *Earth Surface Processes and Landforms*, 35:1123–1137.

7.Conclusions

- Point processes were used to model the triggering influence of multiple factors in different configurations.
- The methodology allows for a spectrum of behavior from "increased probability" [Gill and Malamud, 2014] (an event occurrence increases the chances for a secondary one), to direct triggering.
- The additive model was preferred, and the lack of long-term rainfall exerted a strong effect on the likelihood of no landslides (Rossi et al. [2010] and Peruccacci et al. [2017]).
- Next step: examine the possiblity of slow decay in earthquake effects.

9.Equations

Additive Model:

$$\mu(x,t) = \mu_0(x) \exp\left(\mu_1 C_{R1}(x,t) + \mu_2 C_{R2}(x,t) + \mu_3 C_E(x,t)\right) \tag{6}$$

Multiplicative Model:

$$\mu(x,t) = \mu_0(x) \left(\exp\left(\mu_1 C_{R1}(x,t)\right) + \exp\left(\mu_2 C_{R2}(x,t)\right).\right) + \exp\left(\mu_3 C_E(x,t)\right) \tag{7}$$

Mixture Model:

$$\mu(x,t) = \mu_0(x) \left(\exp\left(\mu_1 C_{R1}(x,t) + \mu_2 C_{R2}(x,t)\right) + \exp\left(\mu_2 C_{R2}(x,t) + \mu_3 C_E(x,t)\right)\right) \tag{8}$$