A statistical model for earthquake and rainfall triggering landslides

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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

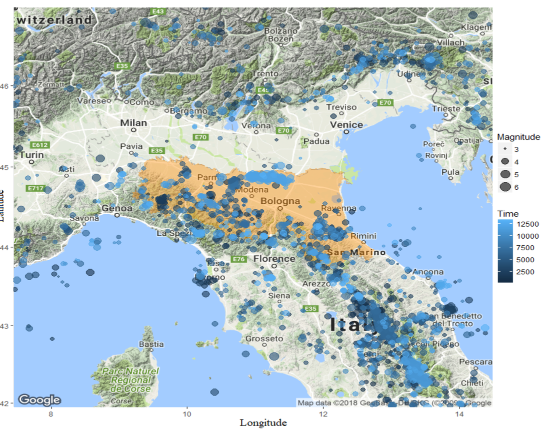

Figure 3: Earthquakes 1981-2015

Figure 2: Landslides 1981-2015

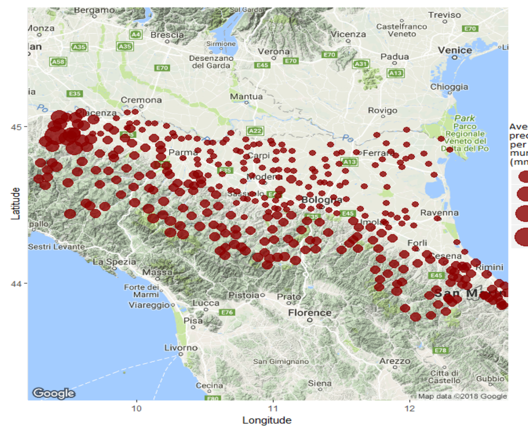

Figure 4: Rainfall 1981-2015

	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...

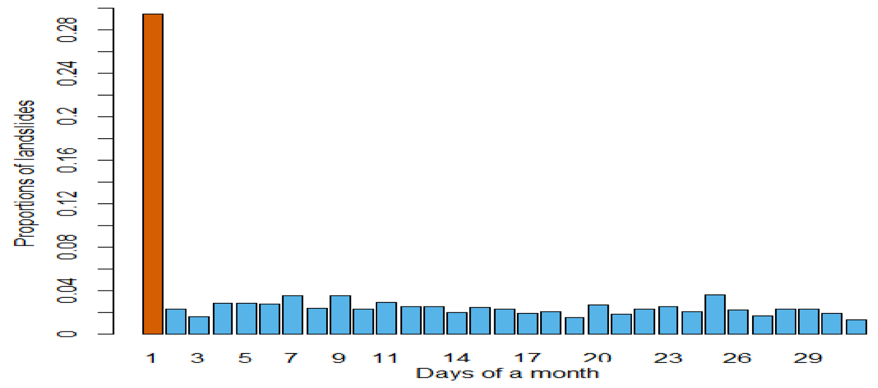

Figure 5: Proportion of landslides per day of a month

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

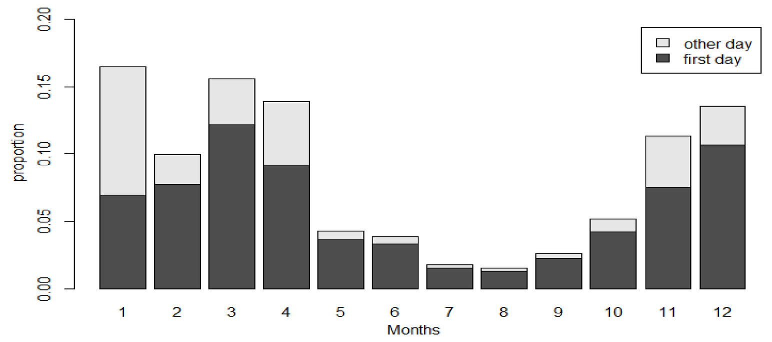

Figure 6: Proportion of 'first day' landslides per month

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:

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

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.

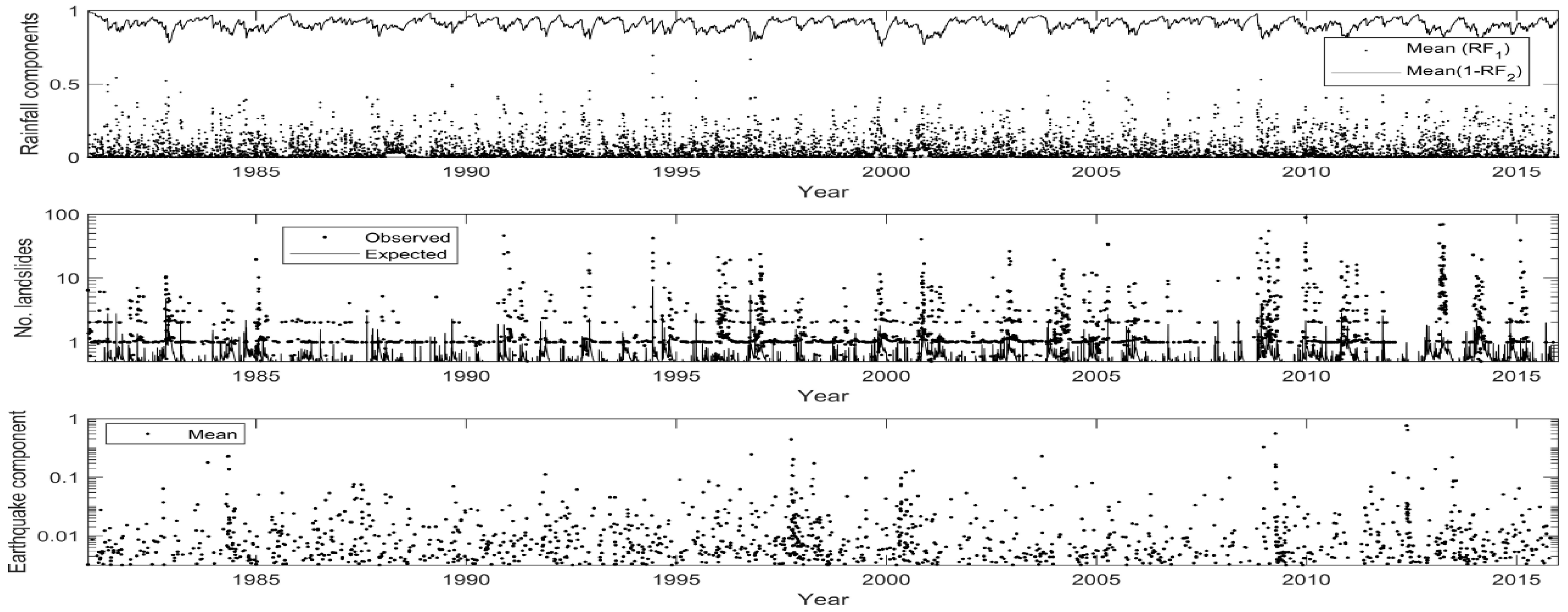

Figure 7: Expected vs. Observed landslides, against rainfall and earthquake events over time.

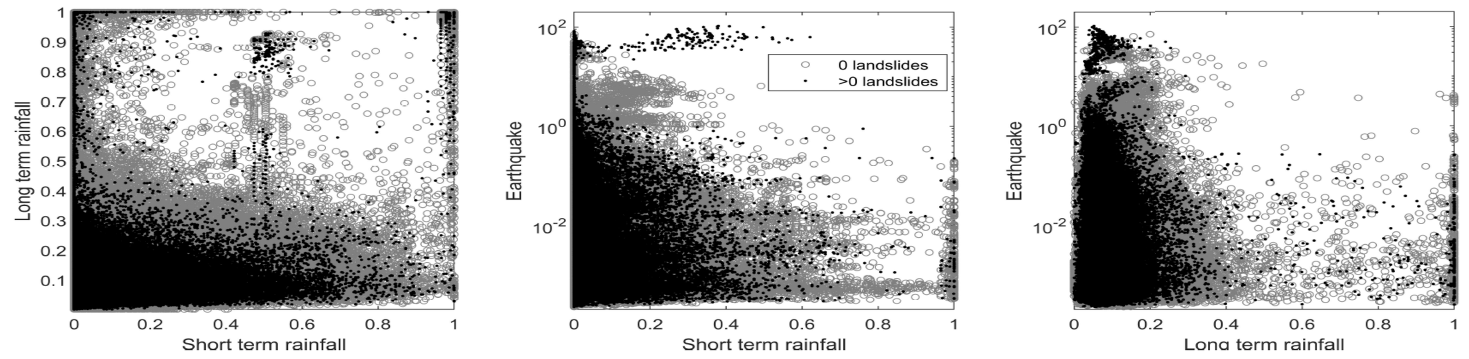

Figure 8: Plots of components vs. components

6. Information gained

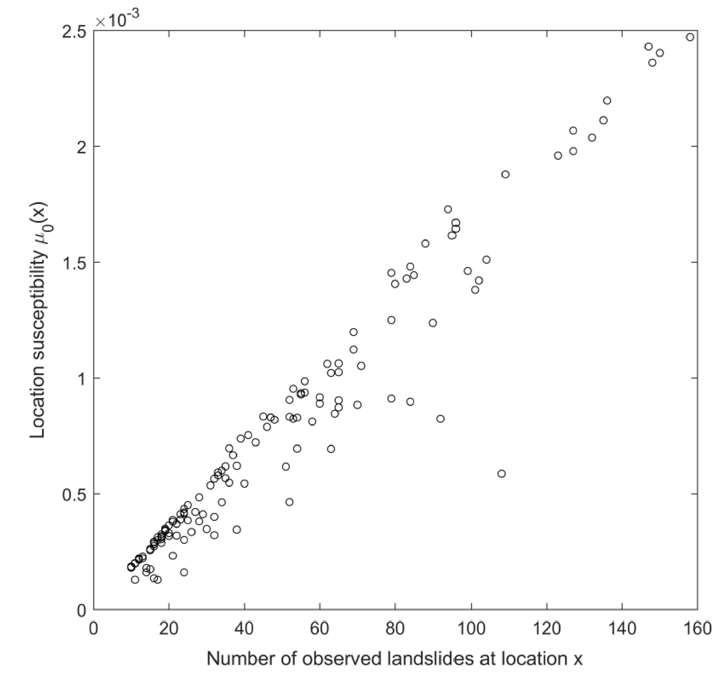

Figure 9: Estimated location susceptibilities against number of observed landslides

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:

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

Mixture Model:

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