Integreating geological and seismological data in point process models for seismical analysis

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Contents

Earthquakes

What is it?

- it is a sudden movement of the earth lithosphere
- unpredictable natural disaster

Main causes (excluding human activities):

- volcanic activity

Earthquakes

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- it is a sudden movement of the earth lithosphere
- unpredictable natural disaster

Main causes (excluding human activities):

- volcanic activity
- tectonic activity
  (events occur along the boundary plates and active faults)

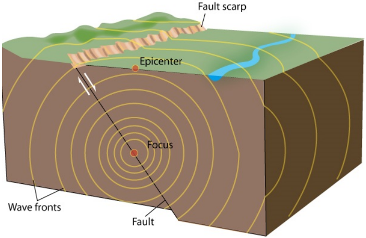

Figure: Seismic waves from a focus of an earthquake

Earthquakes

DATA + **STATISTICAL ANALYSIS** $\rightarrow$ give supports to policy decisions with

HAZARD MAPS

characterise the seismicity

PREDICTIVE MAPS

show the probability of occurrence considering the time

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Statistical models based on **Point process theory** (Illian et al.; 2008)

The most used is the **ETAS model** (Ogata, et all.; 2006):

- it explains induced activity of the phenomena
- input information: spatio-temporal coordinates
- DOES NOT include the effect of COVARIATES (external environmental variables, such as geological information in the study area)

Research goal

Integreation in point process models earthquake data and external geological information

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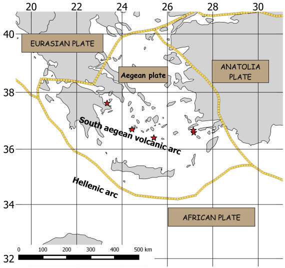
Application
Study area: Greece (the most seismic European-Mediterranean region)

Siino, M., et al (2016). Spatial pattern analysis using hybrid models: an application to the hellenic seismicity, Stochastic Environmental Research and Risk Assessment



Data

Seismic catalog

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It contains:

- time
- focal parameters: latitude, longitude and depth
- magnitude

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DATE (yyyy-month-dd)			TIME (GMT)	LAT. (N)	LONG. (E)	DEPTH (km)	MAGNITUDE (Local)
2017	MAY	6	14 57 42.4	39.08	23.24	9	3.4
2017	MAY	6	15 09 13.7	39.54	26.08	11	2.5
2017	MAY	6	16 55 53.5	39.54	23.25	11	1.6
2017	MAY	6	17 55 23.1	39.08	23.26	11	1.4
2017	MAY	6	18 09 04.8	38.46	23.49	9	1.7
2017	MAY	6	18 58 11.7	38.45	23.48	18	1.2
2017	MAY	6	20 47 40.9	41.29	23.52	11	1.4
2017	MAY	6	20 48 40.3	38.38	20.46	12	0.9
2017	MAY	6	21 32 24.8	40.19	20.57	10	1.9
...	...	...	...	...	...	...	...

Seismic catalog

Quality aspects:

- Accuracy of focal parameters
  - a volume is represented by a point
  - depends on the magnitude and number of seismic stations

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- Accuracy of focal parameters
  - a volume is represented by a point
  - depends on the magnitude and number of seismic stations
- Catalog completeness
  - M_c, the minimum magnitude above which all earthquakes within a certain region are reliably recorded (Mignan and Woessner; 2012)

Seismic catalog

- **Source:** Hellenic Unified Seismological Network, (HUSN) - Institute of Geodynamics *(http://www.gein.noa.gr/en/seismicity/earthquake-catalogs)*
- **Period:** 1964 - 2017
- **Number of stations:** 150

Seismic catalog

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- **Period:** 1964 - 2017
- **Number of stations:** 150
- M_c**:** 2.4 (data from 2005 to 2014)
- HUSN part of the European Integrated Data Archive *(http://www.orfeus-eu.org/data/eida/)*

Seismic catalog

- **Selected subset:** 1105 events with magnitude $\geqslant 4$ between 2005 and 2014

Seismic catalog

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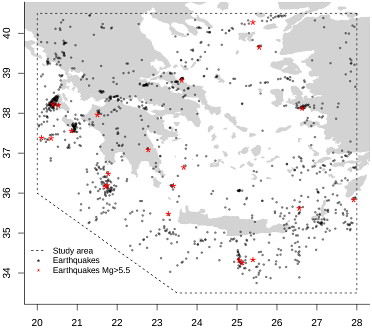
- **Main features:**
  - Spatial inhomogeneity
  - Cluster behaviour
  - Multi-scale interactions (clustering changes with the distances)
  - Random shifting of coincident points (Baddeley et al.2015)

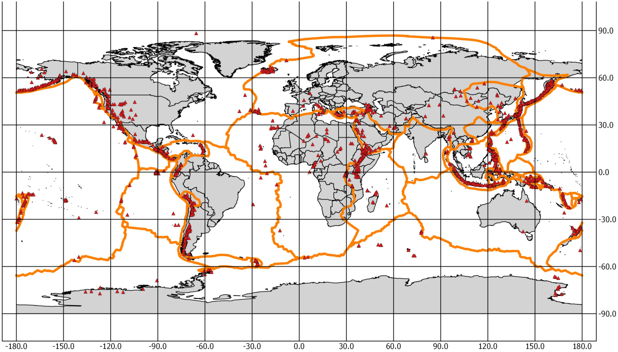


Data

Seismic catalog	Geological information

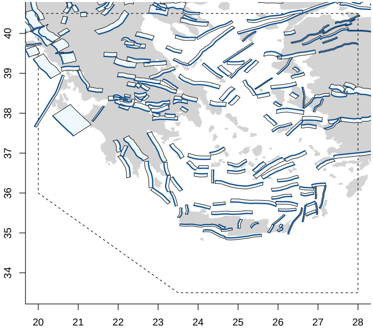
Plate boundaries and volcanoes

- Updated digital model of plate boundaries (https://github.com/fraxen/tectonicplates) (Bird; 2003)
- Global Volcanism Program database (http://volcano.si.edu) (Siebert and Simkin; 2014)

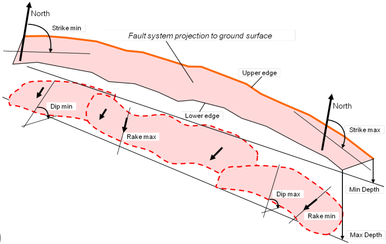


Faults

Greek Database of Seismogenic Sources, GreDaSS (Caputo et al.; 2013)



(a)

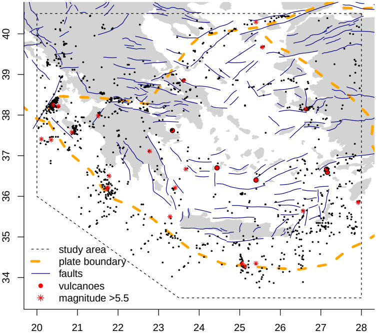


(b)

Figure: (a) Composite seismogenetic sources (b) Main geometric (strike, dip, width, depth) and kinematic (rake) parameters that charcaterised a composite source.

Composite source → complex fault system with several aligned individual seismogenic sources that cannot be separated

Research questions



With a model, we aim:

- to investigate and quantify dependencies on the covariates (faults, plate boundaries and volcanoes)
- to describe the multiscale interaction structure
- to estimate an intensity map

Methodology

Spatial point process

- $W \subset \mathbb{R}^2$ is the study window
- $\mathcal{X}$ is a process, a random countable subset of W
- $\boldsymbol{\upsilon} = \{\mathbf{u}_i\}_{i=1}^{n}$ spatial coordinates of catalogue data where $i = \{1, \ldots, 1105\}$
- $\boldsymbol{\upsilon}$ is a realisation of $\mathcal{X}$

First- and second-order properties

1. **First-order property**

$$\rho(\mathbf{u}) = \lim_{|d_{\mathbf{u}}| \to 0} \frac{E(N(d\mathbf{u}))}{d\mathbf{u}}$$

is the expected number of events in an infinitesimal region $d\mathbf{u}$ that contains the point $\mathbf{u}$

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- Also called intensity function
- For a homogeneous process $\rho(\mathbf{u}) = k$
- For an inhomogeneous process, $\rho(\mathbf{u})$ can be estimated as a function of underlying environmental variables $(Z(\mathbf{u}))$

First- and second-order properties

2. **Second-order property**

$$\rho^{(2)}(\mathbf{u}_i, \mathbf{u}_j) = \lim_{|d\mathbf{u}_i| \to 0, |d\mathbf{u}_j| \to 0,} \frac{E(N(d\mathbf{u}_i)N(d\mathbf{u}_j))}{|d\mathbf{u}_i||d\mathbf{u}_j|}$$

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- Different types of interactions:

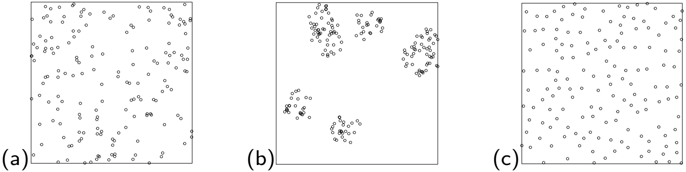

Figure: (a)complete spatial randomness (**CSR**), (b) cluster or (c) inhibitive interaction

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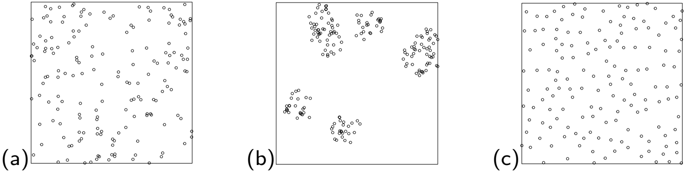

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- **Multiscale interaction**: the second-order property changes with distance

Hybrid of Gibbs models

- $\mathcal{X}$ is defined by a probability density $f(\boldsymbol{\upsilon})$ where $\boldsymbol{\upsilon} = \{\mathbf{u}_i\}_{i=1}^{n}$
- There are several types of Gibbs processes:
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- For example, the density of m Geyer components (with interaction ranges $r_1, \ldots r_m$ and saturation parameters $s_1, \ldots, s_m$) is

$$f(\boldsymbol{\upsilon}) = \prod_{j=1}^{m} \prod_{i=1}^{n} \underbrace{\beta(\mathbf{u}_i)}_{\text{Trend part}} \underbrace{\gamma_j^{min(s_j, t(\mathbf{u}_i, \boldsymbol{\upsilon} \backslash \mathbf{u}_i; r_j))}}_{\text{Several interaction parameters } \gamma_j}$$

Different interaction structure for different interaction distances r_i.

Analysis

Steps

R packages: **spatstat (Baddeley et al.; 2005), maptools, rworldmap**

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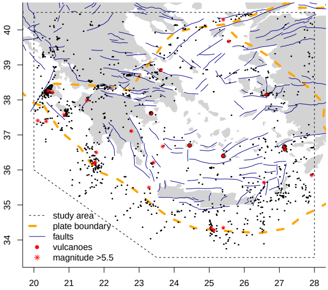
2. Define the study window and the spatial point pattern (`owin, ppp`)



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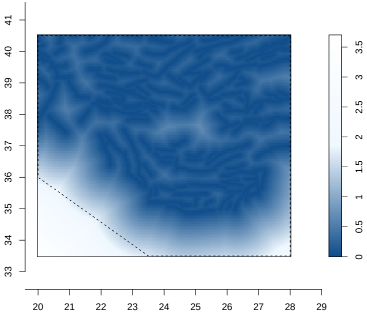

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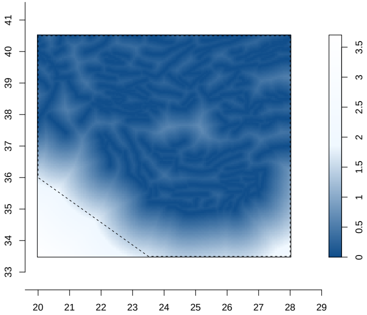

Figure: $D_f(\mathbf{u})$ distance to the nearest fault

4. Descriptive analysis (`Kest, rhohat, berman.test, ...`)

Steps

5. Estimation and model selection of inhomogeneous: (`ppm`)

Poisson models   Hybrid of Gibbs models

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Poisson models Hybrid of Gibbs models

$$\rho(\mathbf{u}) = exp\{\beta_0 + g(\mathbf{u};\boldsymbol{\beta}) + h(D_v, D_{pb}, D_f; \boldsymbol{\alpha}) + HybridComponent(\gamma_j)\}$$

	Description
$g(\mathbf{u};\boldsymbol{\beta})$	Function of the spatial coordinates
$h(D_v, D_{pb}, D_f; \boldsymbol{\alpha})$	Function of the spatial covariates (D_v, D_{pb}, D_f)
HybridComponent	if it is null, **inhomogeneous Poisson model** otherwise **Hybrids of Geyer processes** that depends on γ_1, γ_2, ...
$\{\boldsymbol{\beta}, \boldsymbol{\alpha}, \gamma_1, \gamma_2, ...\}$	Parameters to estimate

Steps

6. Model diagnostic based on: AIC, deviance, analysis of the spatial residuals, residual K and G-functions
   (`AIC`, `anova`, `diagnose.ppm`, `Kres`, `Gres`)

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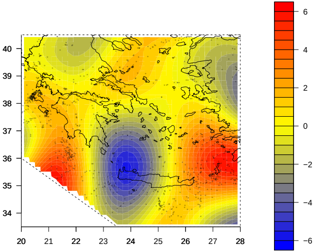
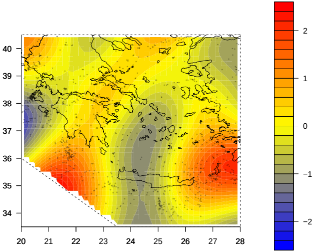


(a) Raw residuals for the selected inhomogenous Poisson model

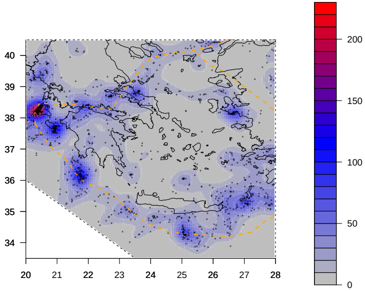


(b) Raw residuals for the selected hybrid model

- For the hybrid model, smaller range and reduction of the spatial trend of the smoothed raw residuals

Steps

7. Estimation of the spatial intensity: (`predict`)



- **Final selected model:**
  - Hybrid model of 4 Geyer processes describes adequately the cluster mutiscale structure
  - Increasing the distance to the nearest fault and to the plate boundary the intensity decreases.
  - The distance to the nearest volcano (D_v) is not significant $\rightarrow$ volcanic Hellenic arc area mostly characterised by microseismic activity.

Remarks and future works

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- Integrate in point process models earthquake data and external geological information is a **new field of research**
- For Greek data, using Hybrid of Gibbs models, we describe both:
  - spatial inhomogeneity depending of geological covariates
  - multi-scale interaction between points
- Limits of the analysis:
  - spatial analysis, no prediction
  - we could consider other available information: magnitude, meta data related to the geological information,...

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- **METHODOLOGY**
  - We are considering spatio-temporal point process models, such as **log-Gaussian Cox process** (Diggle et al.,2013; Siino et al., 2016) and **ETAS model**, adding geological covariates
  - Using a spatio-temporal models, it is possible to set up a surveillance setting and produce **predictive maps**

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- **ANALYSIS**
  - It would be interesting make the results available to a wider audience
  - Integrate the results into a statistical environmental risk maps for natural disasters
  - For example, Nicolis; 2015 visualises on web and mobile devices the outputs of the ETAS model of Chile seismicity (Environmental Smart Cities)

Thanks for you attention.

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