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Conference and School on Predictability of Natural Disasters for our Planet in Danger. A System View; Theory, Models, Data Analysis

25 June - 6 July, 2007

Forecasting Natural Hazards

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Conference on Predictability of Natural Hazards
The Abdus Salam International Centre for Theoretical Physics
Trieste, Italy June 25-26, 2007

Forecasting *Natural Hazards*

- Earthquakes
- Wildfires
- Landslides
- Floods

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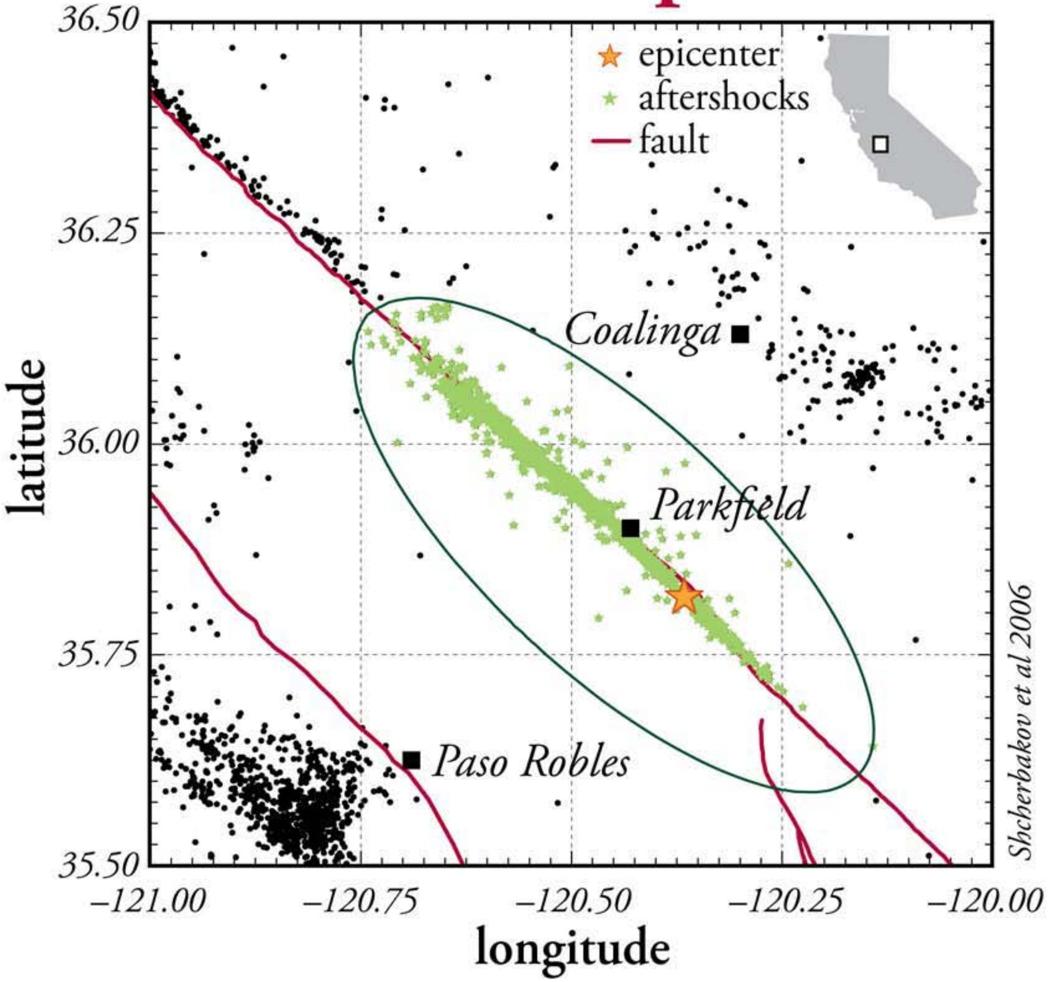
Earthquake Prediction

Precursors:

- Seismicity
- Fault creep
- Strain-tilt
- Electromagnetic
- Radon gas
- Seismic velocity change (v_p/v_s)
- Animal behavior (acoustic emissions)

Site of the Parkfeld Earthquake Prediction Experiment



Parkfield Earthquake
m=6.0
September 28, 2004
San Andreas Fault

Broad range of instrumentation

No precursory activity of any kind

Bakun et al.
Nature 437, 969 (2005)

Previous earthquakes
m≈6
1857, 1881, 1901,
1922, 1934, 1966

Probabilistic Earthquake Forecasting

Fault based models

- ***Generation I***

  Specify faults

  Specify recurrence statistics

  mean recurrence time

  coefficient of variation of return times

  Extrapolate forward from past earthquakes

- ***Generation II***

  Simulation based models

  “Virtual California (John Rundle)

  “SPEM” (Steve Ward)

  Specify faults

  Specify slip rates on faults

  Specify failure stress on faults

  Use backslip inputs (geometry does not evolve)

  Introduce elastic interactions between faults

Simulation based methods:
Virtual California

Faults in RED are shown superposed on a LandSat image of California.

Geologic data are used to set the model parameters.

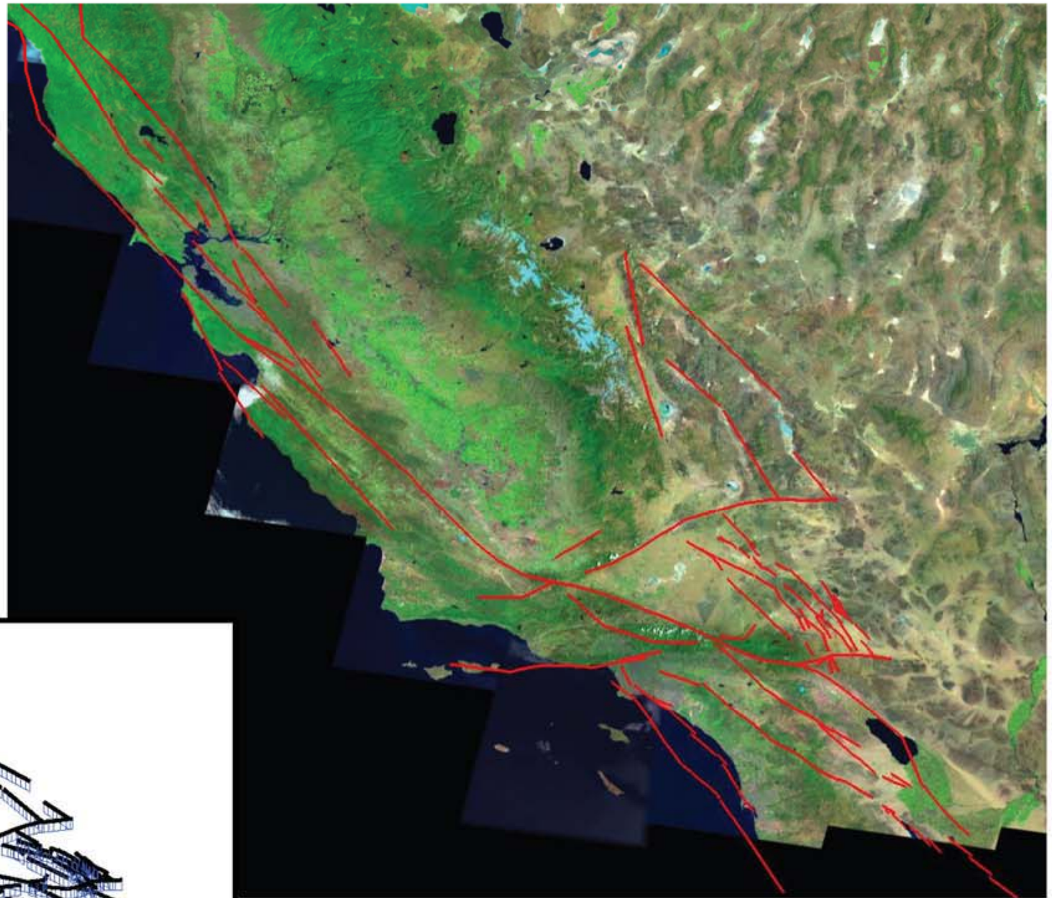
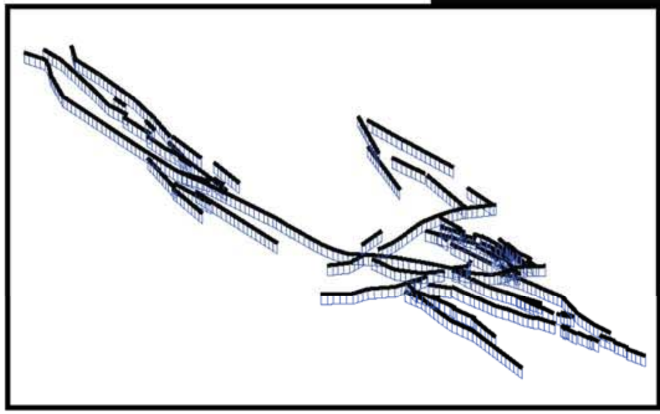


Image courtesy of Peggy Li, JPL



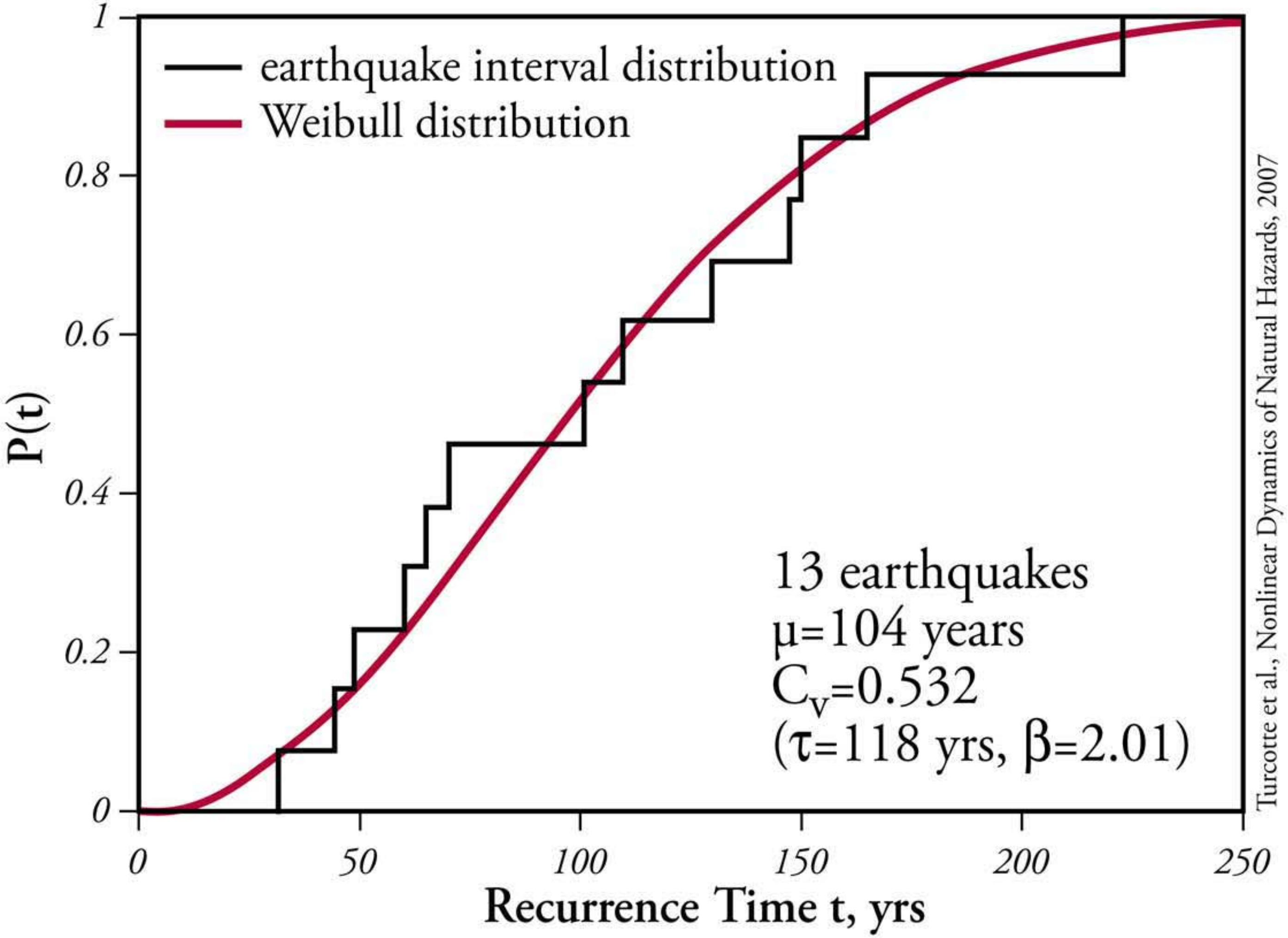
Fault model has 650 segments, 10 km x 15 km

Forecasting Natural Hazards

Great earthquakes m≈8

San Andreas Fault (Wrightwood site)

Biasi et al., 2002

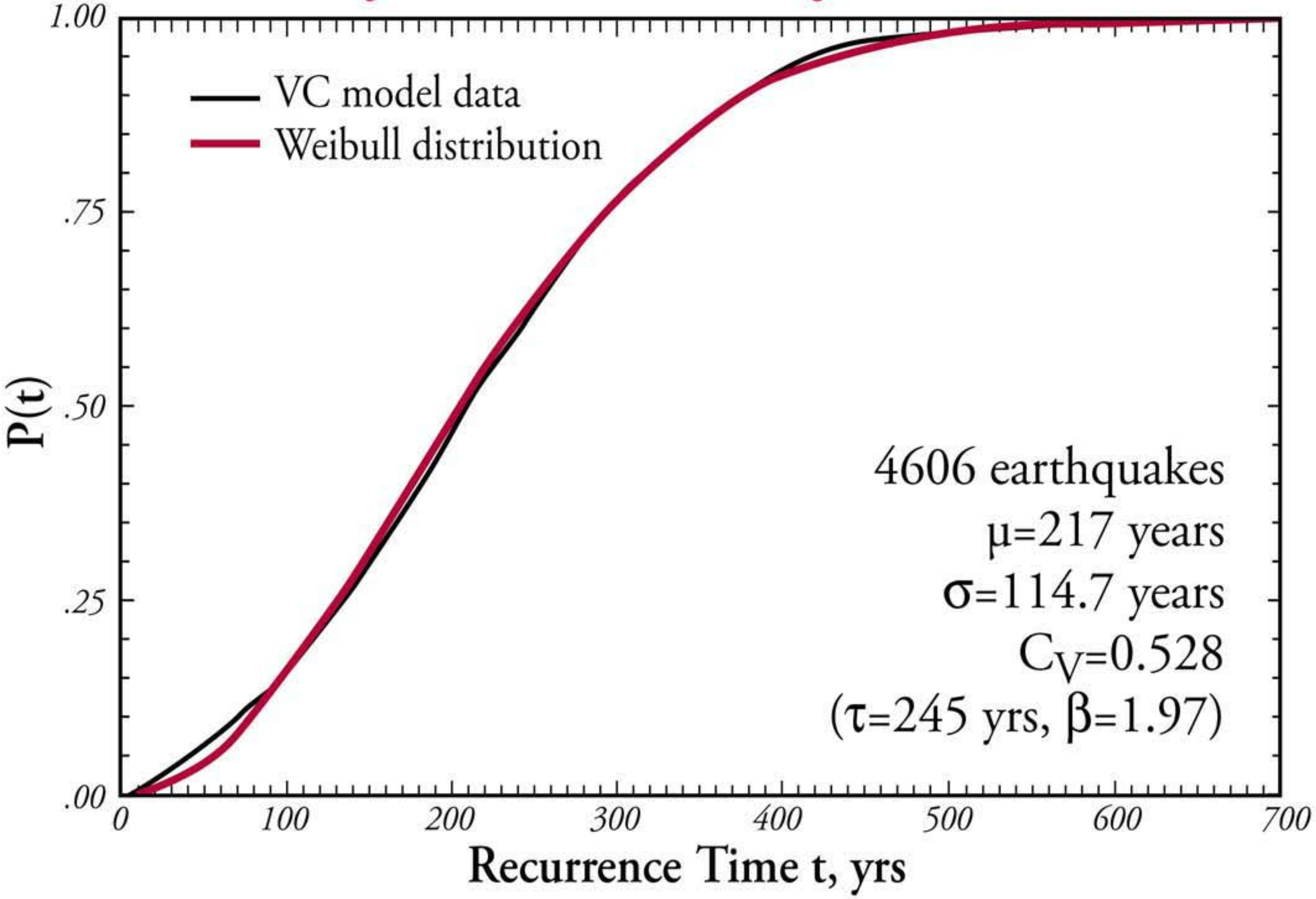


Turcotte et al., Nonlinear Dynamics of Natural Hazards, 2007

Recurrence statistics

for simulated m>7.5 earthquakes on the northern San Andreas fault

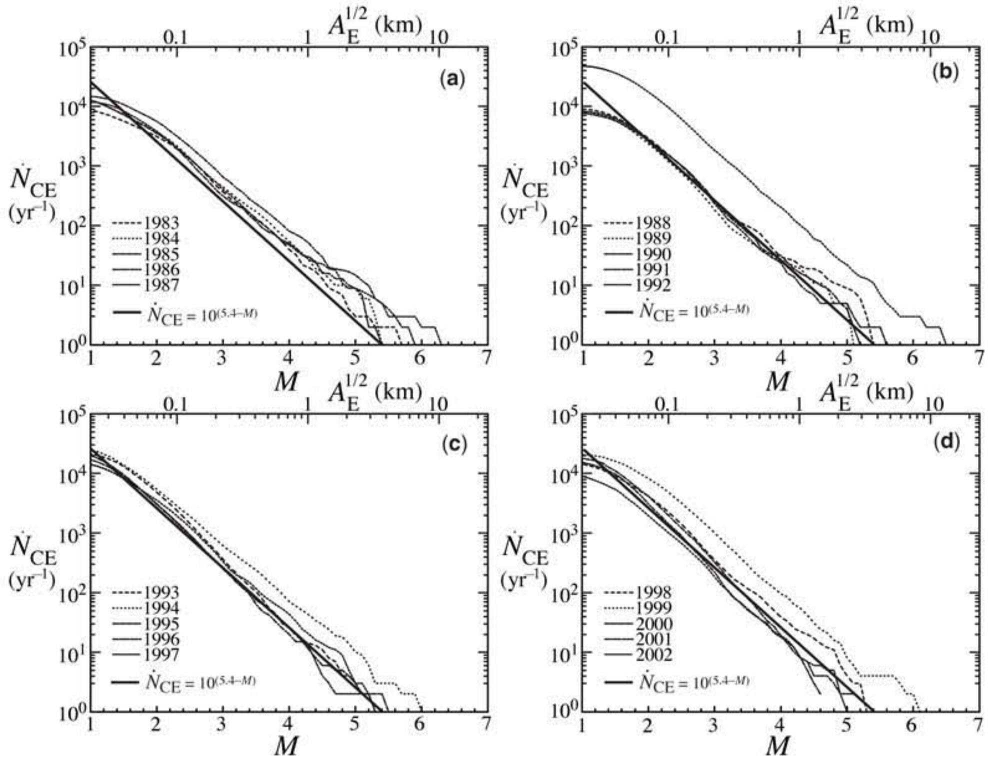
1 million year "Virtual California" simulation



	Cutoff M_c	No. N	Mean μ, yrs	S.D. σ, yrs	C. of V. C_v	Weibull	
						τ, yrs	β
Virtual California simulation (10^6 *yrs*)							
Northern San Andreas	7.5	4606	217	115	0.530	245	1.976
Southern San Andreas	7.5	5093	196	109	0.556	221	1.875
Hayward	7.0	2612	383	229	0.60	429	1.719
Calaveras	6.8	8174	122	87	0.715	135	1.42
San Gabriel	6.7	1913	522	398	0.762	568	1.325
San Jacinto	7.2	1075	929	562	0.605	1042	1.702
Observations (San Andreas)							
Parkfield	6.0	7	24.5	9.25	0.38	23.6	2.9
Wrightwood (*Biasi et al. 2002*)	7.+	13	104	55	0.532	118	2.01

Seismicity based models

Predict the occurrence of large earthquakes based on the number of small earthquakes that have occurred relative intensity (RI)



Relative intensity (RI) map

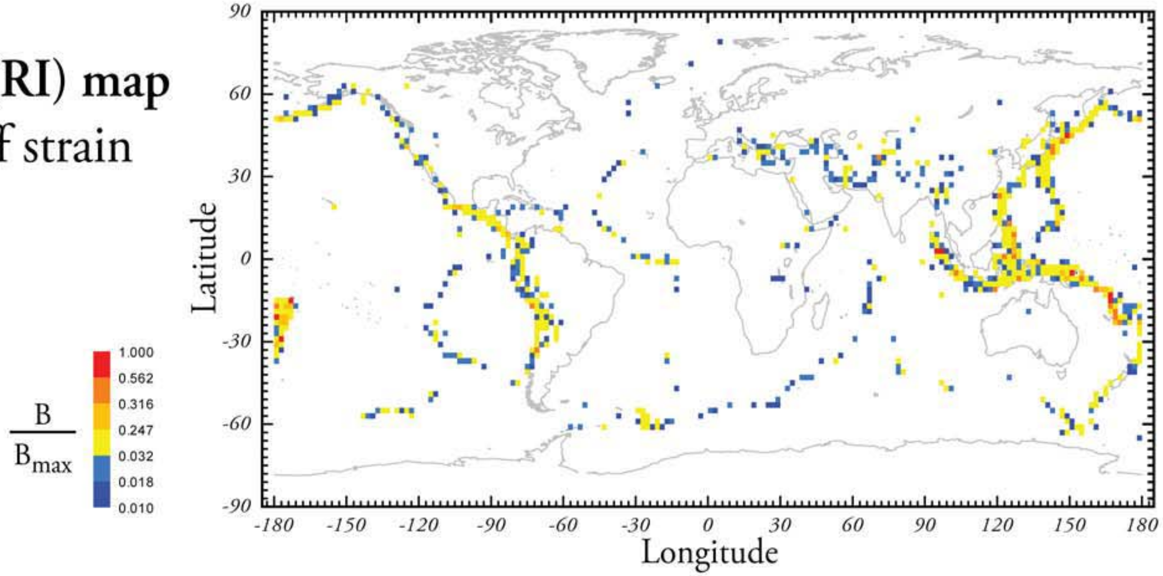
Cumulative Benioff strain

$B=\sum E_i^{1/2}$

m≥5.5 1976-2006

2°x2° cells

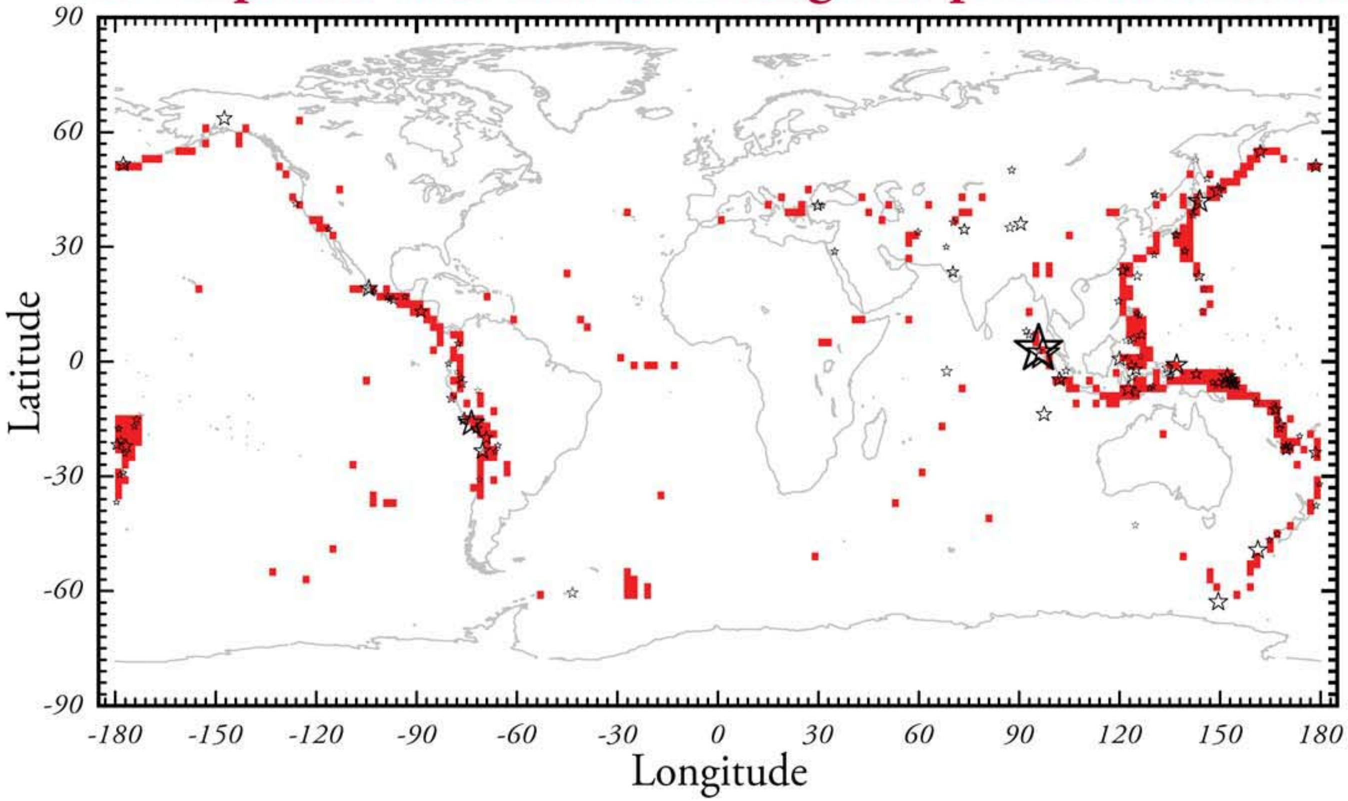
CMT catalog



Binary forecast

for the period 1996-2006

Earthquakes with m≥7.0 during this period are shown



Training period 1976-1996

Threshold $B/B_{max} \geq 0.03$

Fraction of area covered (alarm rate) F=0.23

Contingency table $m \geq 7.0$, $B/B_{max} = 0.03$

Forecast	Observed Yes	Observed No	Observed Total
Yes	$a = 75$	$b = 311$	$a+b = 386$
No	$c = 40$	$d = 1040$	$c+d = 1080$
Total	$a+c = 115$	$b+d = 1351$	$a+b+c+d = 1466$

Hit rate $H = \dfrac{a}{a+c} = 0.65$

(fraction of earthquakes successfully forecast)

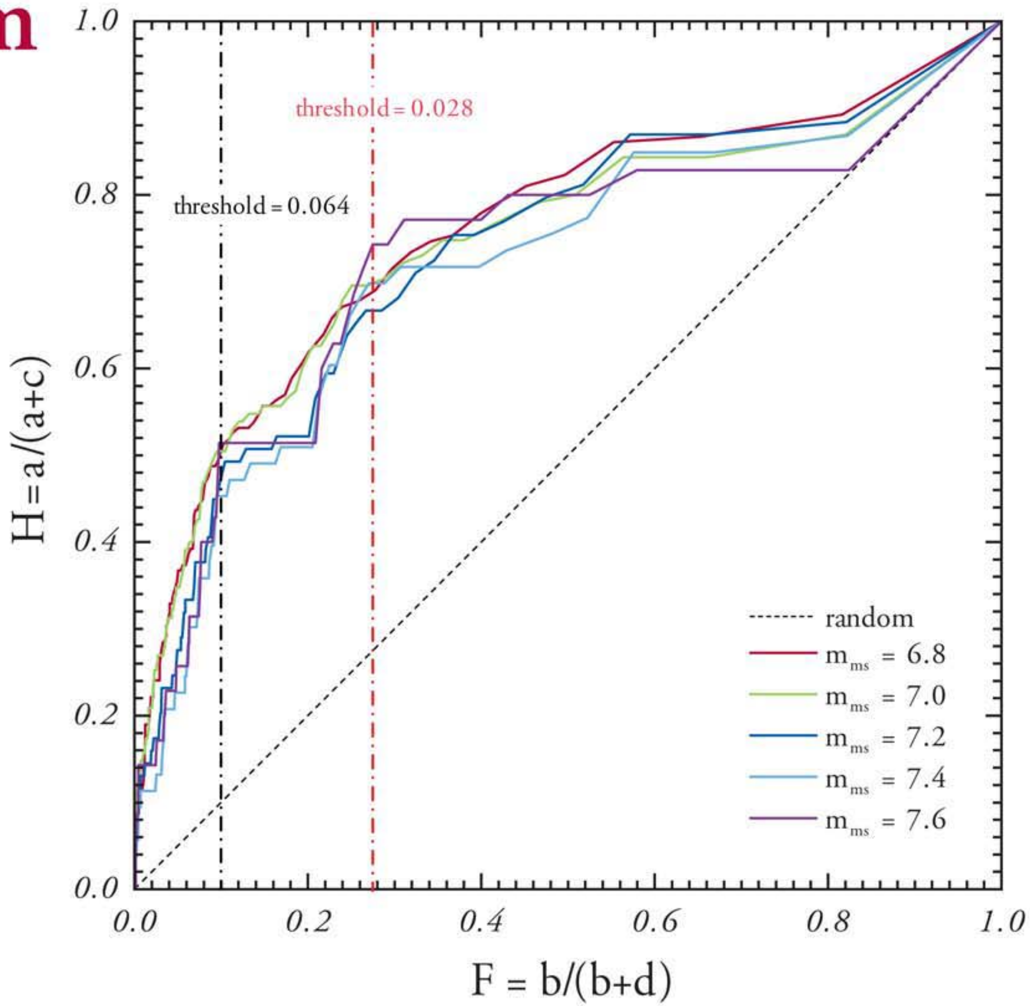
Alarm rate $F = \dfrac{b}{b+d} = 0.23$

(fraction of area covered by alarms)

Relative operating characteristic (ROC) diagram

(Molchan diagram)

Hit rate H
(fraction of earthquakes successfully forecast)



Alarm rate F
(fraction of area covered)

Temperal distribution of earthquakes

- ***Pattern recognition algorithms***

  Keílis-Borok et al

  M8

  Chains of premonitory earthquakes

  John Rundle et al

  Pattern informatics (PI)

- ***Accelerated moment release (AMR)***

  Bufe and Varnes

  Bowman and Sammis

Foward extrapolation of past seismicity using aftershock statistics

- *ETAS - Epidemic Type Aftershock Sequence*
  Ogata, Helmstetter, Sornette et al
- *BASS - Branching Aftershock Sequence Model*
  Turcotte et al., GRL, in press

BASS satisfies the *three scaling laws* generally associated with aftershocks:

Guttenberg-Richter frequency-magnitude scaling
Bath's law for a constant magnitude difference between a main shock and its family of aftershocks
Omori's law for the temporal decay of aftershock occurrence

BASS provides a *fully scale invariant* distribution of aftershocks.

Probabilistic BASS Model

1. The magnitude of the parent earthquake, m_p, is specified (the parent earthquake is the main shock unless one or more of the aftershocks is larger; in this case the parent earthquake is a foreshock).

2. The minimum magnitude of earthquakes to be considered, m_{min}, is specified.

3. The total number of daughter earthquakes (primary aftershocks) is determined from the relation

$$N_{dT} = 10^{b_d\left(m_p - \Delta m - m_{min}\right)}$$

Probabilistic BASS Model *(cont)*

4. Cumulative distributions for the magnitudes, P_{cm}, times, P_{ct}, and radial positions, P_{cr}, of daughter earthquakes (primary aftershocks) are given by

a) $P_{cm} = 10^{-b_d(m_d - m_{min})}$

b) $P_{ct} = 1/(1 + t_d/c)^{p-1}$

c) $P_{cr} = 1/\left(1 + r_d/\left(d \cdot 10^{0.5 m_p}\right)\right)^{q-1}$

Probabilistic BASS Model *(cont)*

5. Three random numbers are generated in the range $0<P_c<1$ and the m_d, t_d, and r_d of each daughter earthquake is calculated.

6. Each primary aftershock is taken to be a parent earthquake and families of secondary aftershocks are generated using the above procedure.

7. The process is repeated for third-order and higher-order aftershocks.

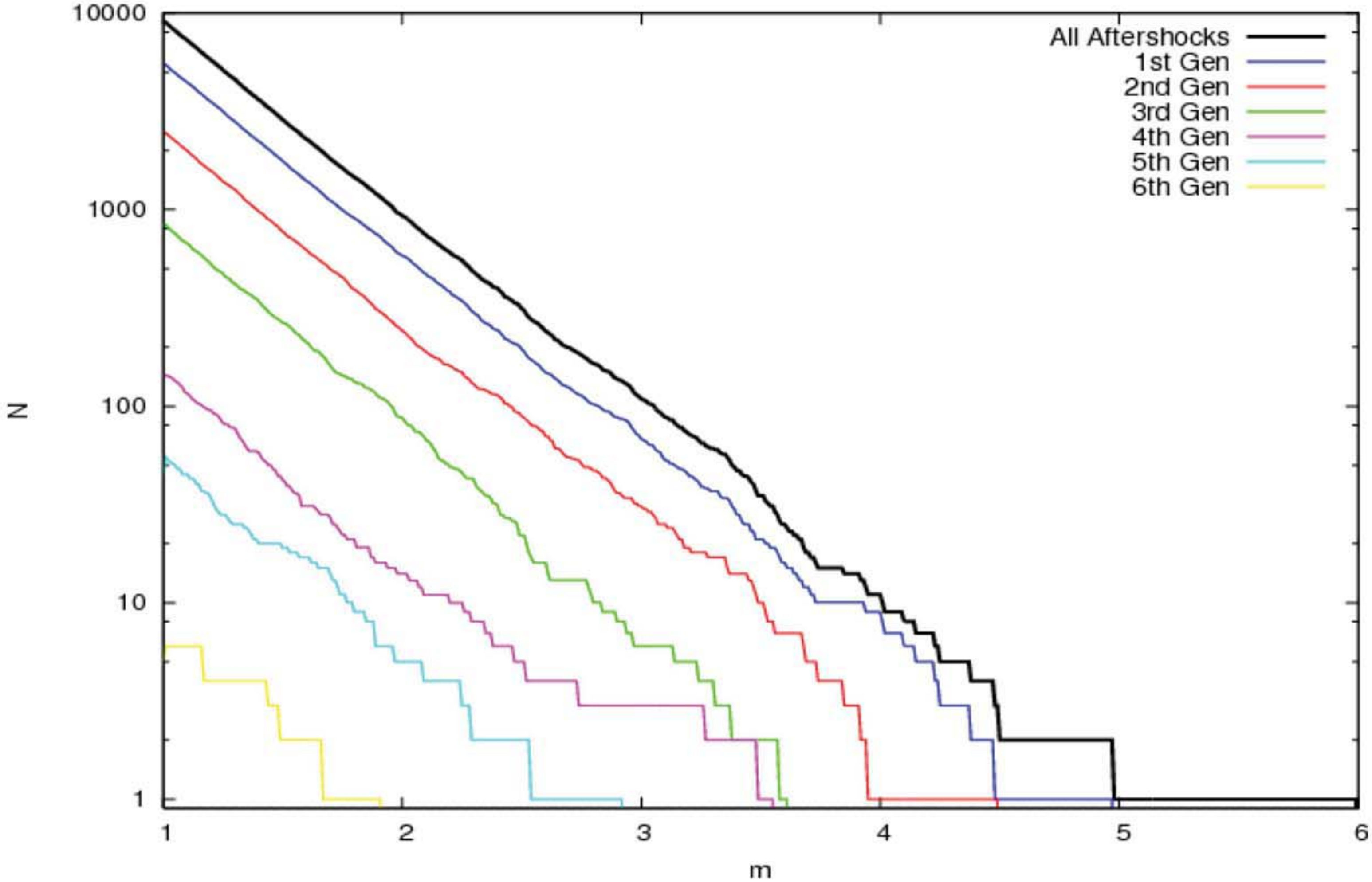
Example Calculation

- $m_p = 6$
- $m_{min} = 1$
- $\Delta m = 1.25$
- $b = 1$
- $c = 0.1$ day
- $p = 1.25$
- $d = 4m$
- $q = 1.35$

We find:

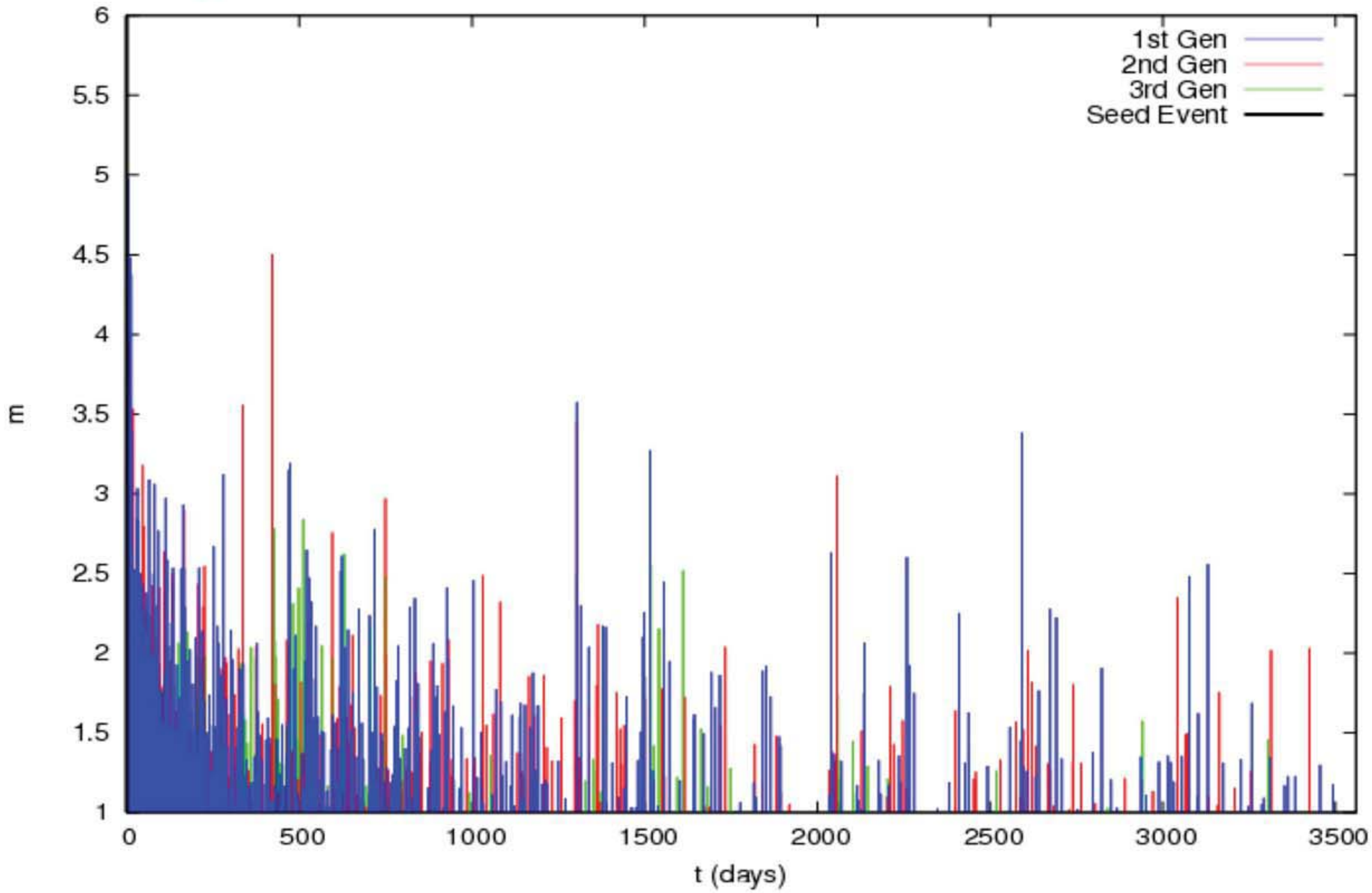
- 9,221 aftershocks
- 5,623 primary aftershocks
- 3,598 secondary and higher-order aftershocks
- $m = 4.94$ for the largest aftershock

Example Calculation *(cont)*



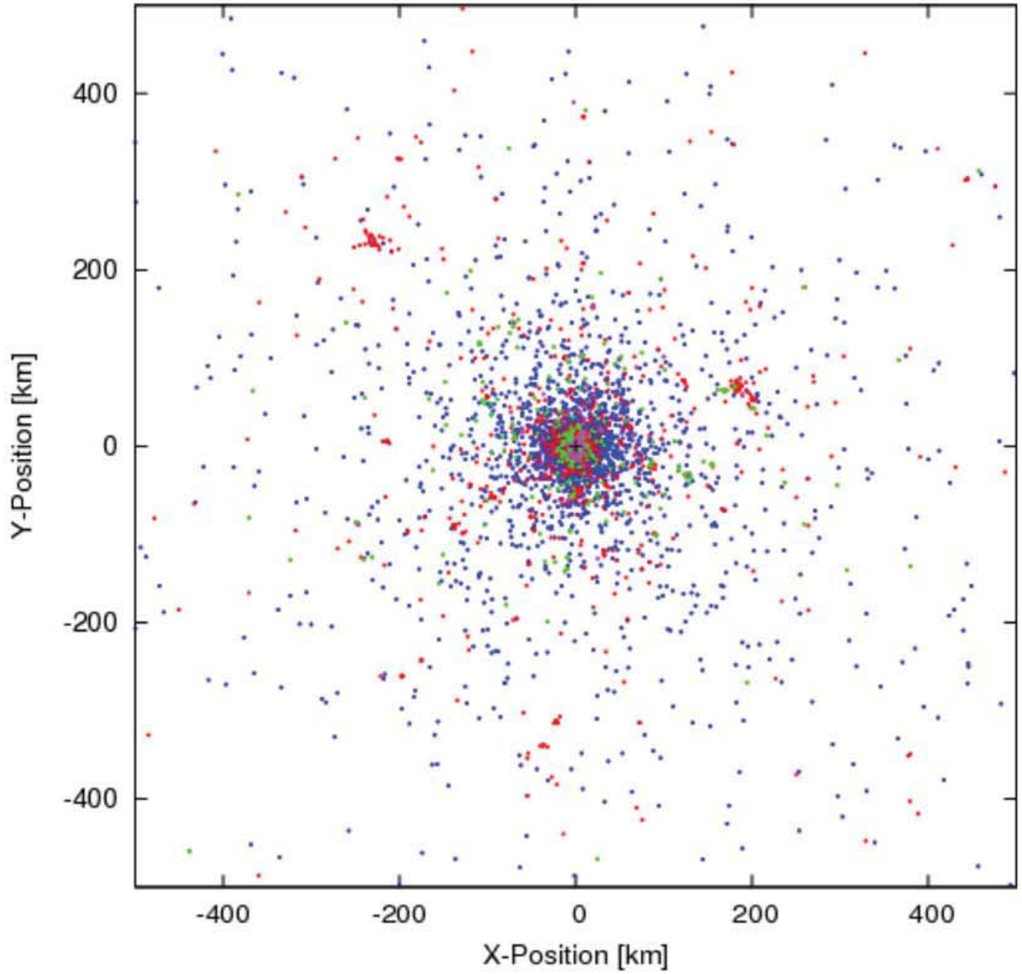
Cumulative number *N* of aftershocks with magnitudes greater than *m*. All aftershocks as well as various generations of aftershocks are shown.

Example Calculation *(cont)*



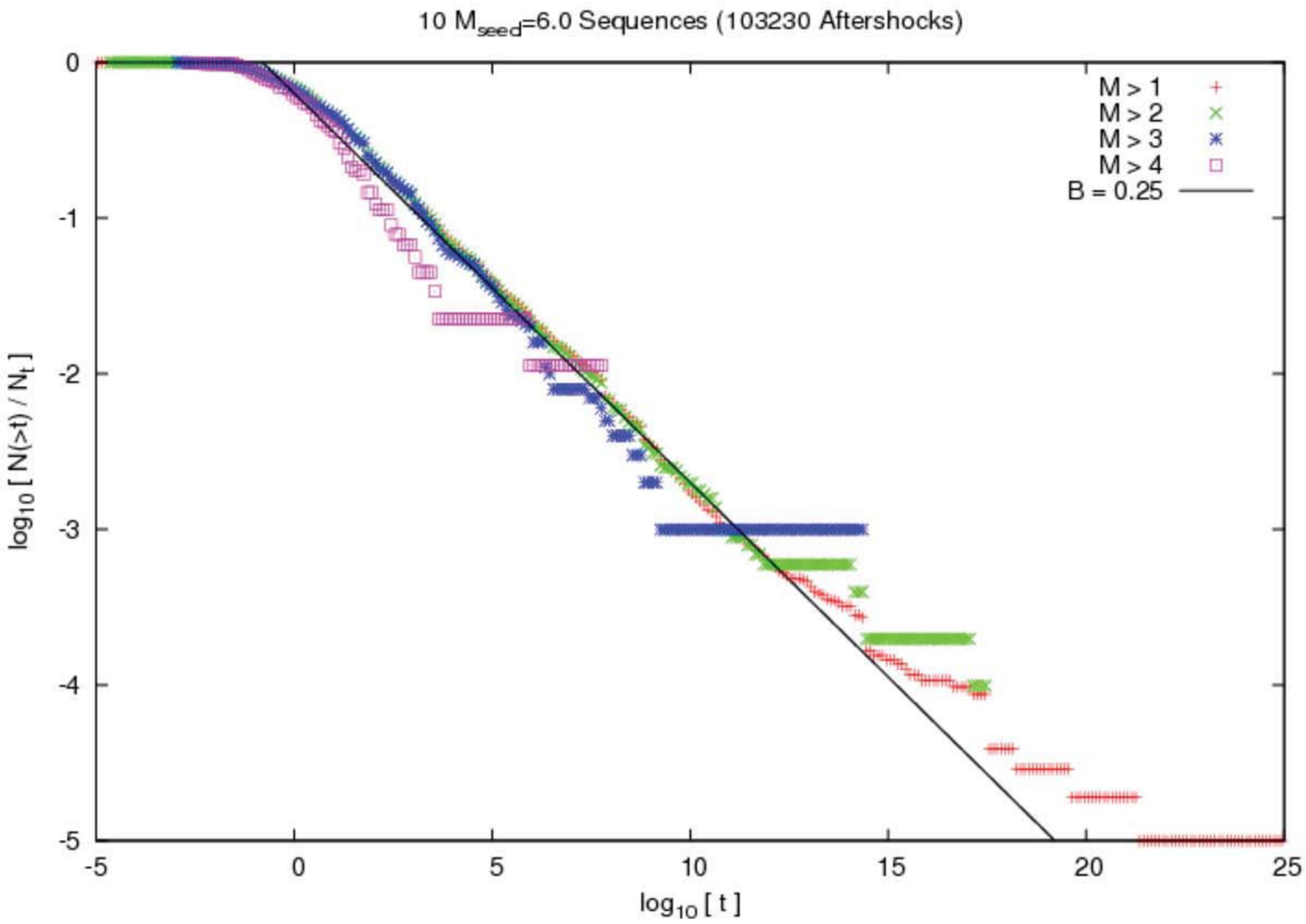
Magnitudes *m* of aftershocks as a function of the time at which they occur.

Example Calculation *(cont)*



Positions of aftershocks relative to the position $X = Y = 0$ of the initial mainshock.

Example Calculation *(cont)*



Landslide Events

- *Triggers*

  Earthquakes

  Heavy rainfall

  Rapid snowmelt

- ***Landslides in a Triggered Event:***

  Time: Minutes to weeks

  Number: Individual up to tens of thousands

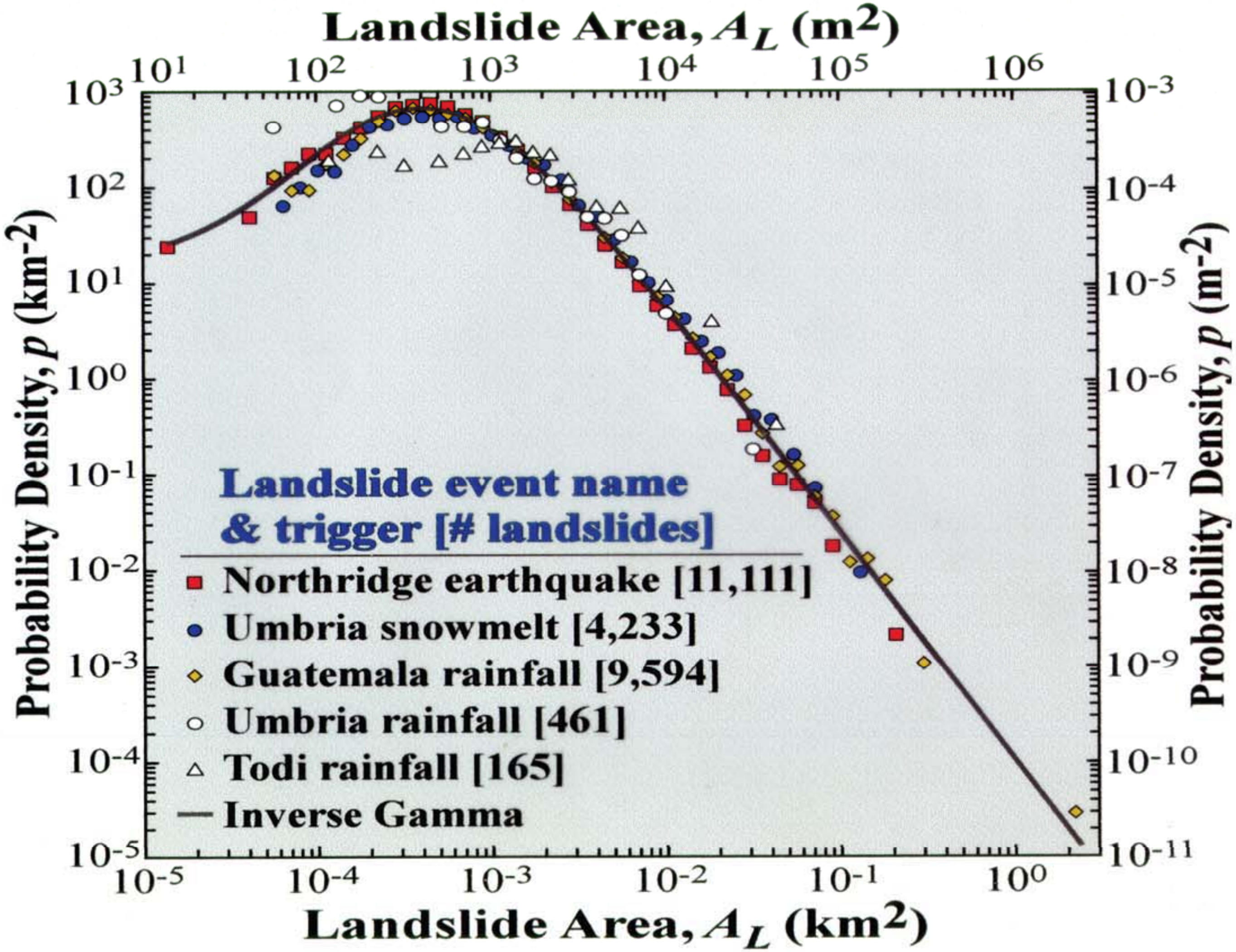
  Areas: Eight orders of magnitude

Five Triggered Landslide-Event Inventories

Location (Trigger)	Study area (km^2)	N_{LT}	A_{LT} (km^2)	$\bar{A}_L$ (km^2)
Northridge, California[a] (earthquake, 1/17/1994)	10,000	11,111	23.8	0.00214
Umbria, Central Italy[b] (rapid snowmelt, 1/1/1997)	2,000	4,233	12.7	0.00301
Guatemala[c] (heavy rainfall, 10-11/1998, Hurricane Mitch)	10,000	9,594[d]	29.5	0.00307
Umbria, Central Italy (heavy rainfall, 2004)	200	461	0.88	0.00191
Todi, Central Italy (heavy rainfall, 2004)	80	165	0.67	0.00405

[a] Harp and Jibson (1995) *USGS Open File Rep.*
[b] Guzzetti *et al.* (2002) *Earth Plan. Sci. Lett.*
[c] Bucknam *et al.* (2001) *USGS Open File Rep.*
[d] Our analyses: 277 landslides omitted w. aspect ratios >50; long narrow debris flows along valley floor.

- Small areas ($A_L < 0.0004$ km²): 'roll-over
- Medium and large areas: power-law ('fat' or fractal tail)



Probability Distribution

- Inverse gamma distribution (3 parameters)

$$p(A_L) = \frac{1}{a\Gamma(\rho)}\left[\frac{a}{A_L - s}\right]^{\rho+1}\exp\left[-\frac{a}{A_L - s}\right]$$

- Best-fit to three data sets (r^2=0.97)

  $\rho = 1.40$ *(power-law decay)*

  $a = 1.28 \times 10^{-3}$ km^2 *(location of max probability)*

  $s = -1.32 \times 10^{-4}$ km^2 *(exponential decay)*

Malamud *et al.*, Earth. Surf. Proc. Landforms 29, 687 (2004)

Power-Law Distribution for Flood Frequency

$$Q(T) = CT^{\alpha}$$

$Q(T)$ = Maximum discharge associated with recurrence interval of T yrs.

C, α = Constants

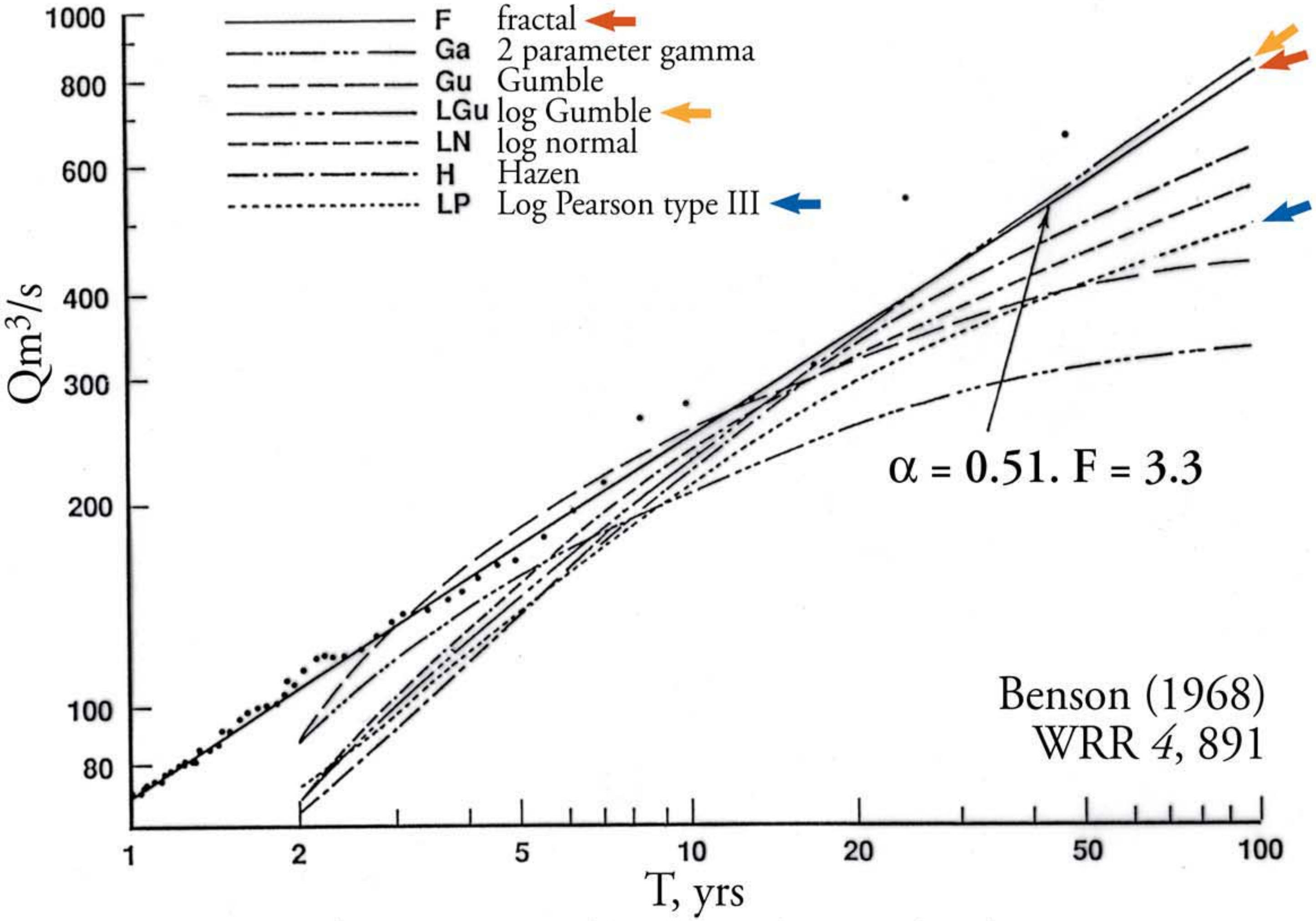
$$F = \frac{Q(10)}{Q(1)} = \frac{Q(100)}{Q(10)} = \text{Constant}$$

$$F = 10^{\alpha}$$

F = Flood Frequency Factor

Benchmark station

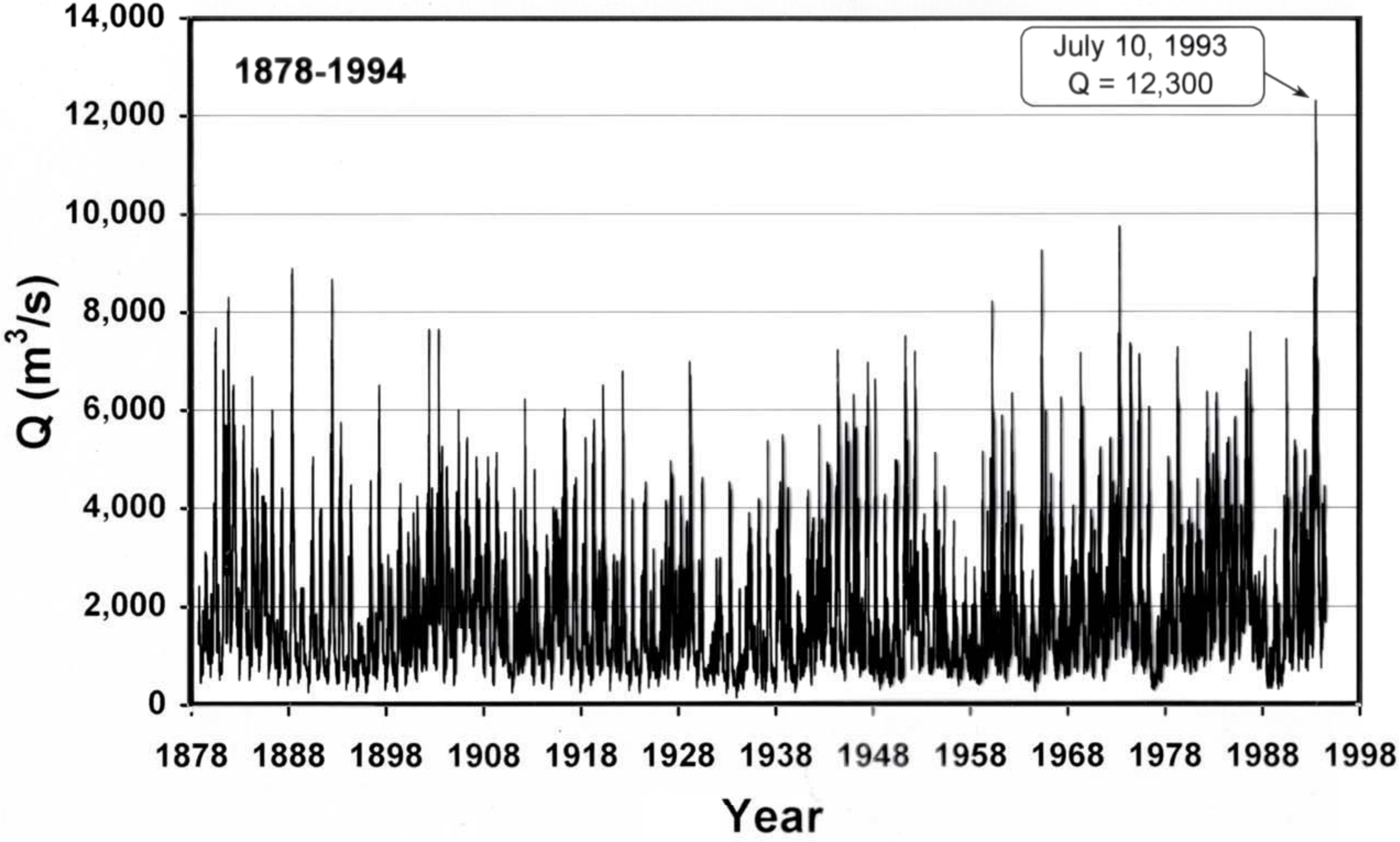
Middle Branch, Westfield River Goss Heights, MA 1911-1960

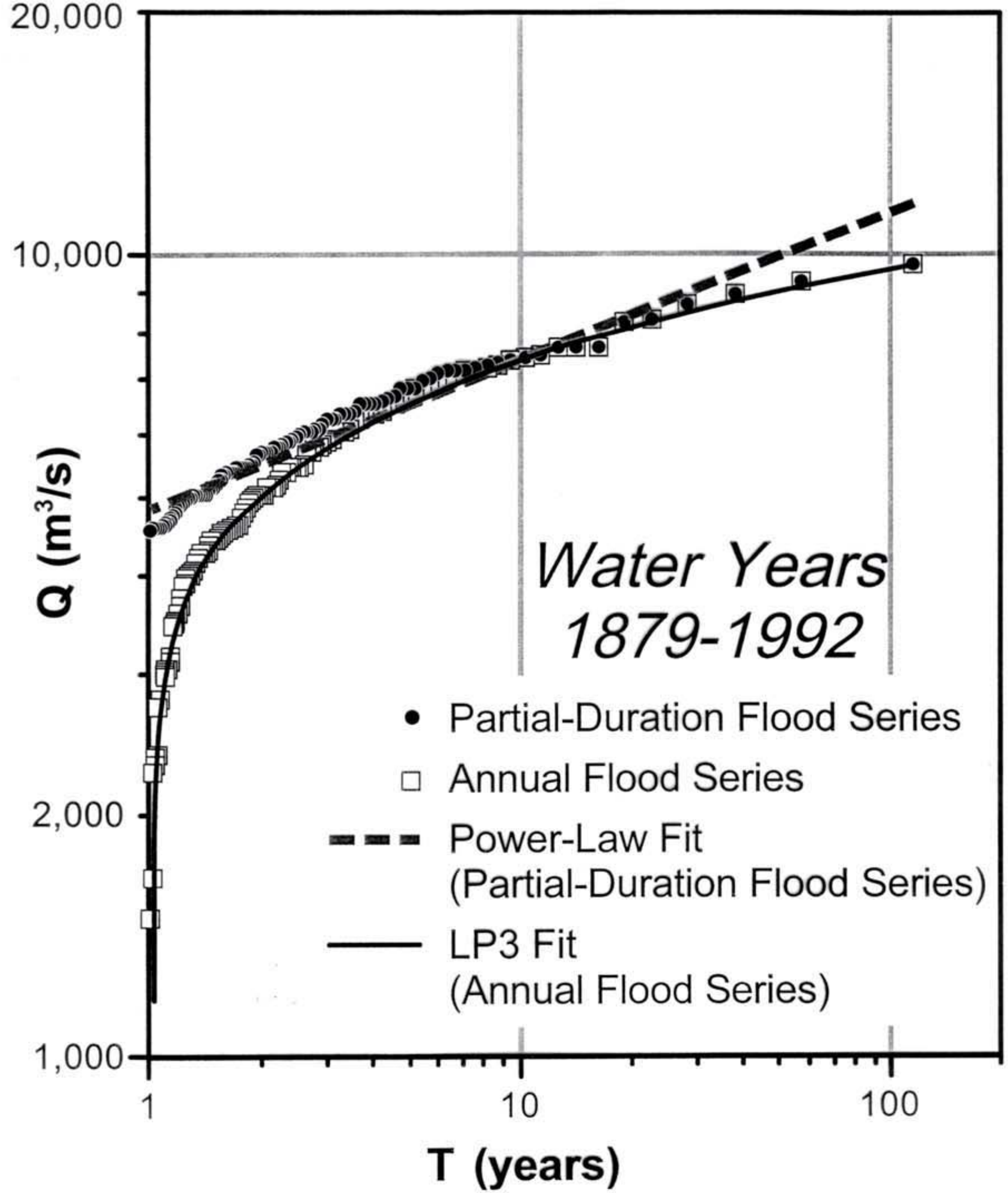


Turcotte and Greene, Stochastic Hydro. Hydraulics *7*, 33 (1993)

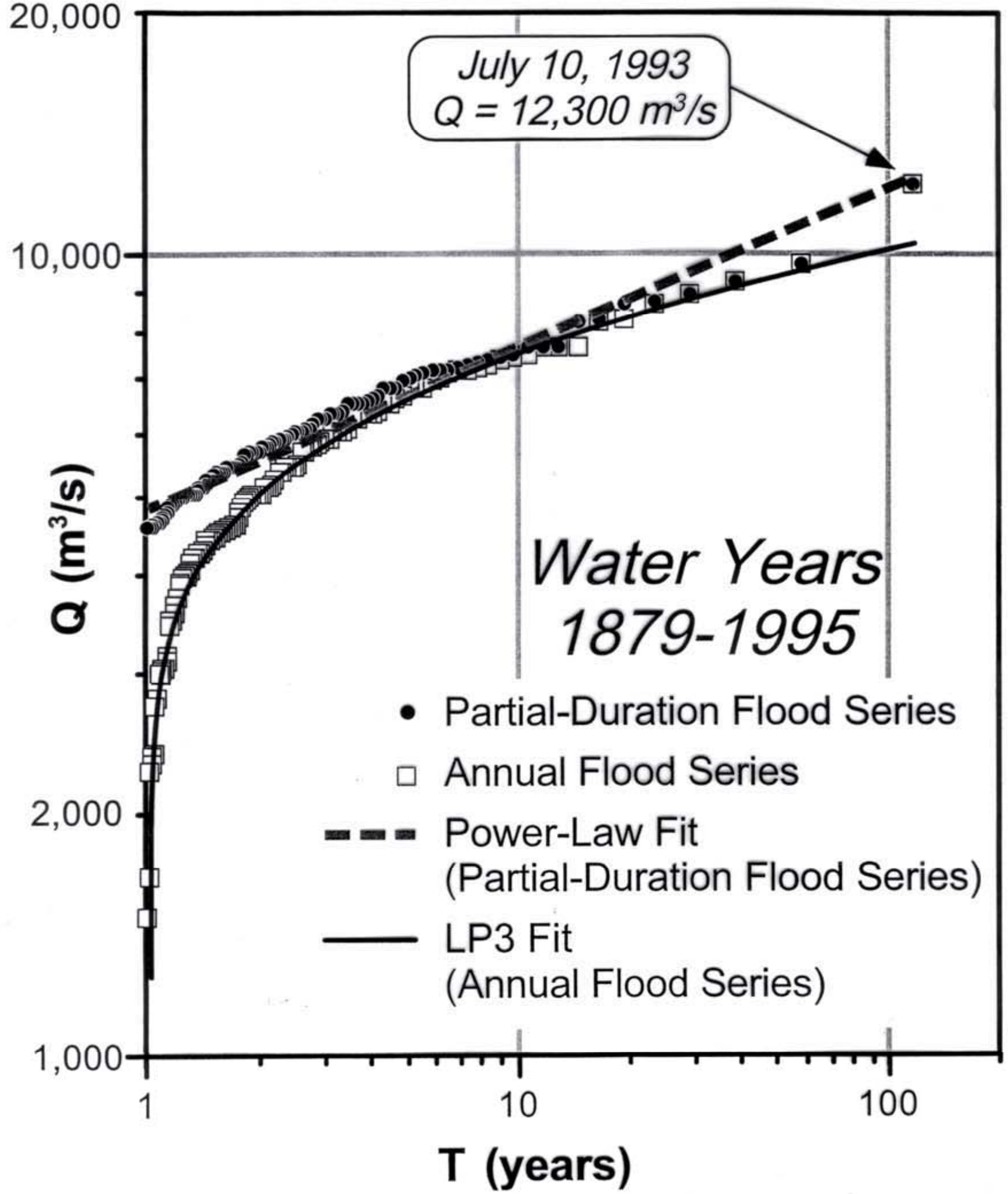
Average Daily Discharges

on the Mississippi River at Keokuk, Iowa





20,000
10,000
2,000
1,000
Q (m3/s)
1
10
100
T (years)
Water Years
1879-1992
Partial-Duration Flood Series
Annual Flood Series
Power-Law Fit
(Partial-Duration Flood Series)
LP3 Fit
(Annual Flood Series)



Malamud et al., Env. Eng. Geosci. *11*, 479 (1996)

Frequency-area statistics

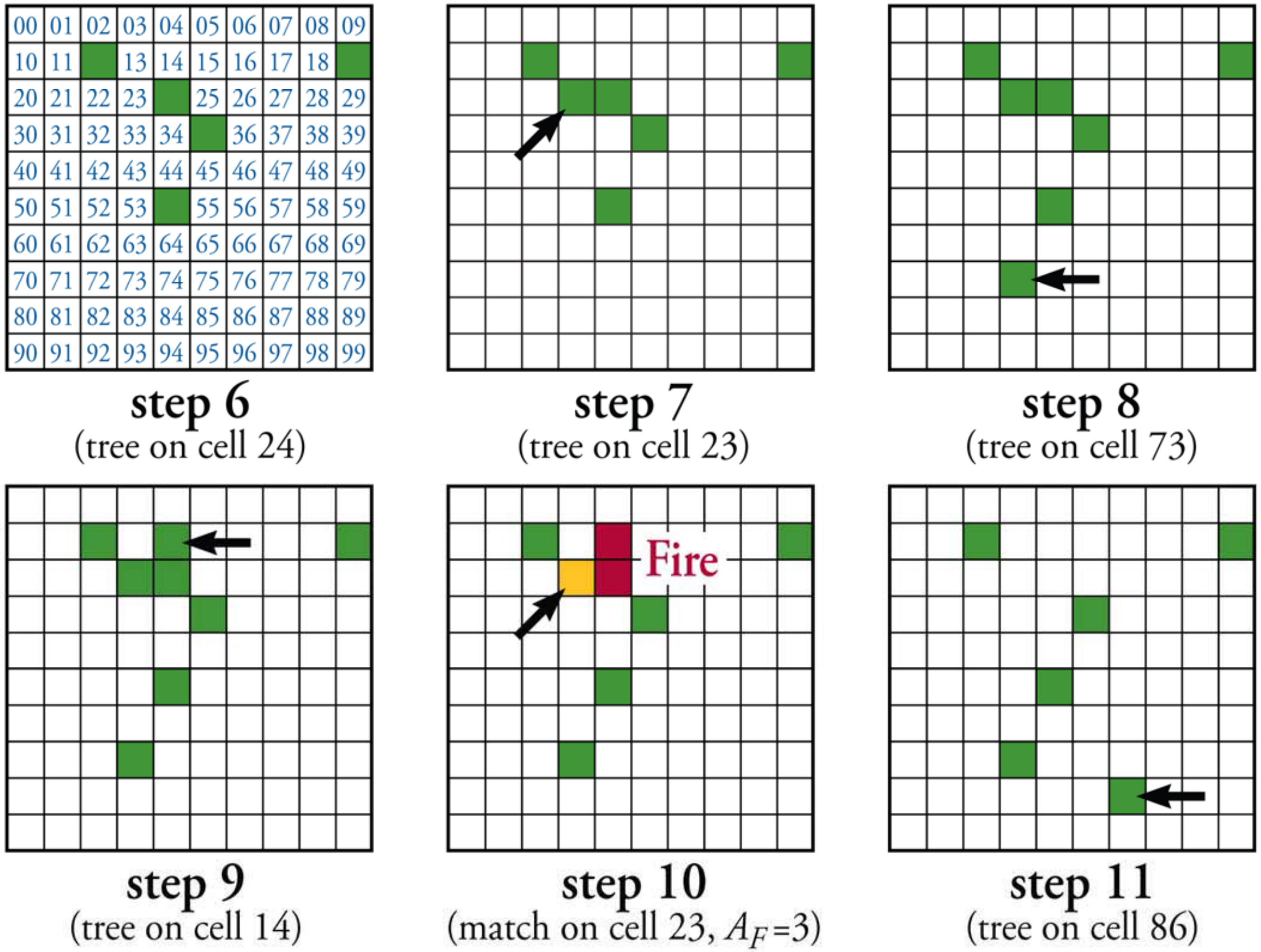
Forest-fire model

- Square grid of *n* x *n* sites.
- **TREE**: At each time step plant tree on random cell (1 per cell).
- **MATCH**: At every $1/f_s$ time steps drop a match on random cell.
- **FIRE**: If match dropped on tree it ignites and the fire consumes all adjacent (nondiagonal) trees.

Drossel and Schwabl, PRL 69, 1629 (1992)

Forest-fire model

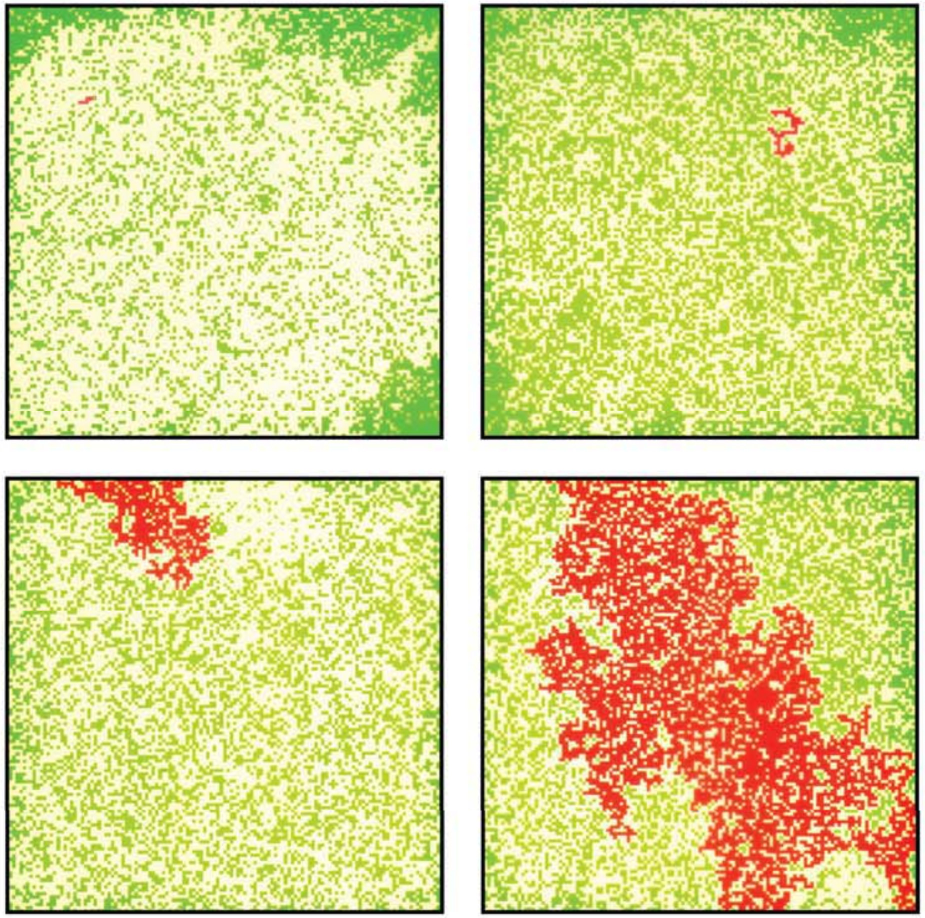
Sparking frequency $f_s = 0.2$ $(1/f_s = 5)$



Typical forest-fire model fires

Grid = 128 x 128 cells. **A_F = area of fire.**

Match dropped every $1/f_S$ = 2000 time steps



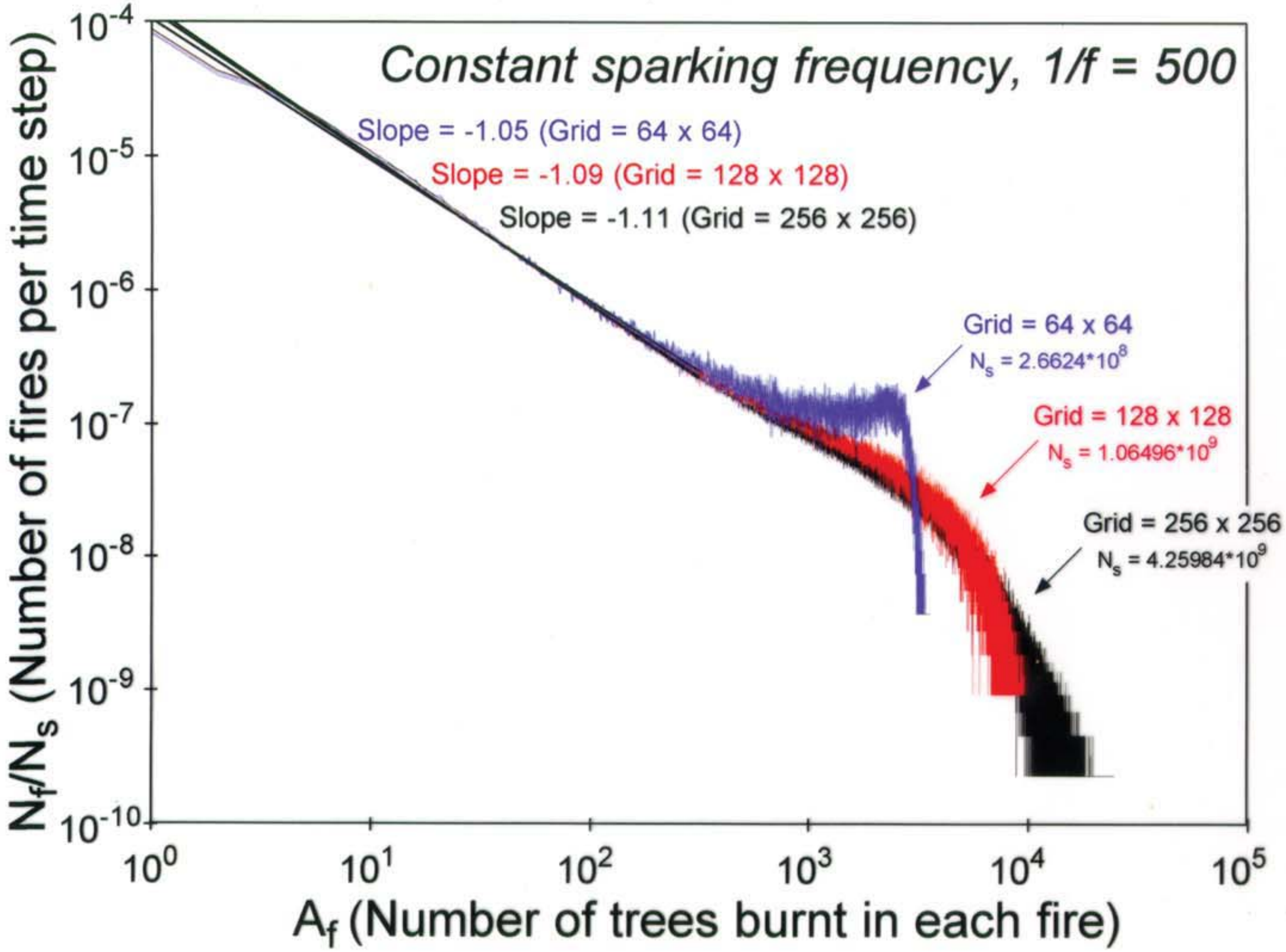
(a) A_F = **5 trees**

(b) A_F = **51 trees**

(c) A_F = **505 trees**

(d) A_F = **5327 trees**

Forecasting Natural Hazards

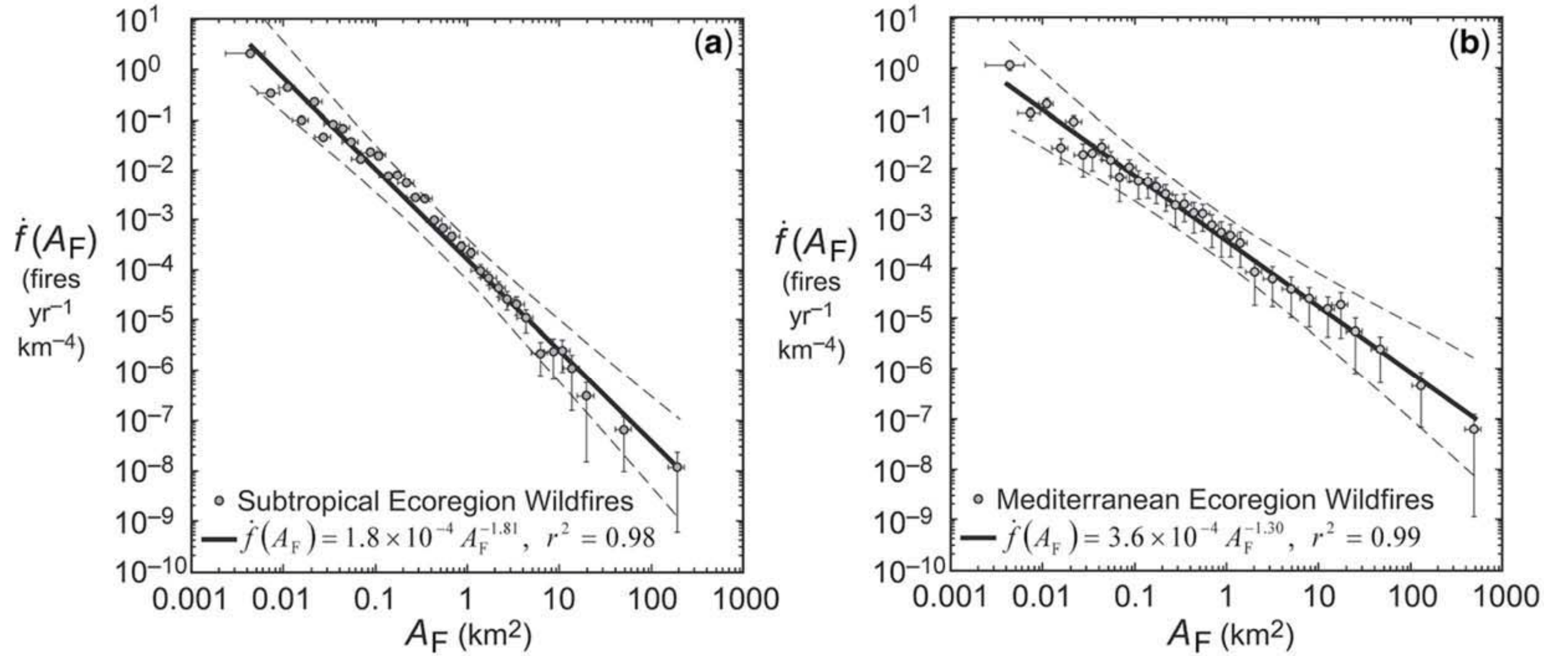


Explanation for forest-fire model (self-organized critical) behavior:

1. Trees are planted one at a time.
2. Tree clusters coalesce to form larger clusters.
3. Individual trees are primarily planted in small clusters, as they age they find themselves in larger and larger clusters.
4. Trees are lost burn dominantly in the very largest clusters.
5. This inverse cascade of trees from small to large clusters is self similar (fractal).

Turcotte, Rep. Prog., Phys., 62, 1377 (1999)

Frequency-area statistics for U.S. wildfires in two ecoregions 1970-2000



Malamud et al., Science *281*, 1840 (1998); Proc. Nat. Acad. Sci. USA *102*, 5494 (2006)

Conclusions

- Probabilistic Hazard Assessments play a valuable role in allocating resources
- Rates of occurrence of small events can be extrapolated to estimate rates of occurrence of large events