Natural hazards, risk and uncertainty — some hot topics

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“[D]isaster loss is as much a critical global challenge to economic development and social progress as disease is”

“The global expected average annual loss . . . in the built environment associated with tropical cyclones . . ., earthquakes, tsunamis and floods is now estimated at US$314 billion.”

“[Underlying risk drivers include] globalized economic development, poverty and inequality, badly planned and managed urban development, environmental degradation and climate change.”

[Although [risk reduction measures] have enabled a reduction of extensive risks, the value of assets in hazard-prone areas has grown, generating an increase in intensive risks . . . risk reduction measures to protect a floodplain against a 1-in-20-year flood may encourage additional development on the floodplain in a way that actually increases the risks associated with a 1-in-200-year flood.

What is risk?

UNISDR definitions (http://www.unisdr.org/we/inform/terminology)

**Risk:** The combination of the probability of an event and its negative consequences

**Hazard:** A dangerous phenomenon, substance, human activity or condition that may cause loss of life, injury or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, or environmental damage

**Exposure:** People, property, systems, or other elements present in hazard zones that are thereby subject to potential losses

**Vulnerability:** The characteristics and circumstances of a community, system or asset that make it susceptible to the damaging effects of a hazard.
What is risk? A hypothetical example

The hazard

The exposure

The vulnerability

Mathematical / statistical formalisation

Risk \equiv f(\text{Hazard, Exposure, Vulnerability}) \sim \text{Expected Loss}
Disasters and risk

Around the world last week . . .

**Bangladesh:** Cyclone Mora kills at least 6; half a million people displaced

**India:** hailstorm kills at least 27, dozens injured

**Russia:** thunderstorm kills 16 with at least 125 injured

**South Africa:** worst drought in 100 years leads to restrictions on use of showers and toilets in Cape Town

**Sri Lanka:** mudslides kill more than 200 people, 2 000 homes destroyed and more than half a million people displaced

**USA:** Volcanic ash cloud leads to red alert for aviation in Alaska

Notes on last week’s round-up

- Most don’t hit international headlines — but associated ‘extensive risks’ responsible for > 45% of total economic losses & ~ 14% of disaster mortality across 85 countries (GAR2015, §4.1)
- The ones we hear about are ...
Disasters and risk

The ones we hear about
Disasters and risk

The ones we hear about
The ones we hear about
Disasters, risk and uncertainty

Raising awareness: design

Evidence synthesis

Model limitations

Decision support

Summary

Disasters and risk

The ones we hear about
Disasters and risk

The ones we hear about

- Geologists Warned of Haiti Earthquake
- Why earthquakes risked all
- The storm
- The Telegraph
- 12 ways to avoid the next catastrophe

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Natural hazards, risk and uncertainty
Brunel workshop, 9th June 2017
The ones we hear about
The ones we hear about
The ones we hear about
The need to confront uncertainty

- High-profile ‘failures’ often associated with overconfidence ⇔ failure to acknowledge uncertainty in risk assessment
- Scientists often lack training in treatment / communication of uncertainty
- Users uncomfortable making decisions under uncertainty
Uncertainty

The need to confront uncertainty

- High-profile ‘failures’ often associated with overconfidence ⇔ failure to acknowledge uncertainty in risk assessment
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- Users uncomfortable making decisions under uncertainty

- Comprehensive risk assessments require that all uncertainties are acknowledged and accounted for, in hazard, exposure, vulnerability and risk
- Few attempts have been made to do this in any hazard area
Sources of uncertainty

- Stochastic / aleatory uncertainty
- Chaotic system behaviour
Sources of uncertainty

- Process
- Data
  - Sparse observations, short / incomplete records for model calibration
  - Measurement error
  - Indirect measurement of quantities of interest
  - Incompletely observed boundary / initial conditions & forcing functions
Sources of uncertainty

**Process**
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**Data**
- Sparse observations, short/incomplete records for model calibration
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**Models**
- Models are at best approximations of reality
- Numerical solution of system equations introduces more approximation
- Parameter values estimated by calibrating imperfect models to imperfect data
- Model outputs known only at tested parameter/input combinations
Some opportunities for statistical thinking

- Raising awareness of **fundamental principles**:
  - Experimental design / data requirements
  - Model-based approach to data interpretation
  - Decision-making under uncertainty

- Evidence synthesis: combining information from multiple sources (data and models)

- Accounting for **model limitations**
Raising statistical awareness: background and context

- Disaster risk reduction involves many sectors / disciplines / groups:
  - Natural hazards science (avalanche, climate, earthquake, flood, landslide, tsunami, volcano, …)
  - Engineering
  - Social science
  - Decision- and policymakers (international, national, regional, local)
  - Official agencies and NGOs
  - Communities
Raising statistical awareness: background and context

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- **Historical ‘responsive’ approach** to disasters: responsibility for different aspects lay with specific sectors / disciplines / groups

- **Current move towards more holistic approach**, but inevitably starts with sector-specific thinking:
  - Statistical content of training curricula varies between sectors
  - Emerging recognition in (some parts of) some sectors that better awareness could bring considerable benefits
Example: seismic engineering

- **Seismic risk assessment**: vulnerability of buildings represented using **fragility curves**
- Curves give probability of specified damage level (ordinal scale) as function of intensity of ground shaking
- Derived either from post-event survey data or from computer simulations of buildings
- Curves often essentially probit regression: defined by **two parameters** \((\alpha, \beta)\) say
Fragility modelling: current directions

- Risk assessments tend to use generic fragility curves for broad classes of buildings.
- Interest in improving understanding of how fragility depends on construction characteristics e.g. in EU FP7 INFRARISK project.
- INFRARISK case study requires seismic risk assessment for highways and secondary roads around Bologna, Italy.
- 340 bridges identified — engineers want credible fragility curves.
Example: seismic engineering

Case study: meta-analysis of published bridge fragilities

- Literature search found **373 existing curves** (i.e. pairs \((\alpha, \beta)\)) for all or some bridges
- Some authors considered **multiple bridges**, some bridges studied by multiple authors
- Information on **construction characteristics** available e.g. bridge width, pier height etc.
  - Aggregated to **categorical variables** (mostly binary e.g. width < 20m or ≥ 20m)
- **REC** consulted for advice about deriving relationship between fragility parameters and construction characteristics
And the conversation went (roughly) like this . . .

Engineer:  *So, how can I relate the published fragility curves to the construction characteristics of the bridges?*
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**Engineer:** So, how can I relate the published fragility curves to the construction characteristics of the bridges?

**Statistician:** Well, probably the simplest thing would be to fit an ANOVA model for the $\alpha$s and $\beta$s, with fixed effects for the construction characteristics. You’ll probably need random ‘bridge’ and ‘author’ effects as well.
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Engineer: Yes, I thought of that, but I can’t find any software to fit random-effects models when the construction characteristics are unknown.
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Statistician:  *What do you mean, “the construction characteristics are unknown”?*

Engineer:  *I don’t have the information for all characteristics for all bridges.*

[dialogue ensues, during which it becomes apparent that there are substantial amounts of missing covariate information]
The conversation continued . . .

**Statistician** (speculatively): *Well, the only way I know to fit that kind of model with substantial amounts of missing data is either via an EM algorithm or in a Bayesian framework. How do you feel about that?*
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**Engineer**: *Um.*

**Statistician**: *Tell you what: send me a subset of the data with a small number of the most important covariates, and I’ll write a script in OpenBUGS to fit the model for you. Then you can play around and adapt it for the full dataset in your own time.*
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**Engineer:** *[grateful noises]*
Modelling the bridge fragility coefficients

- Data subset derived from 25 peer-reviewed papers, covering 37 bridges in total
  - Some studies provide multiple \((\alpha, \beta)\) values for the same bridges (different models / simulators) — 1125 records in database
  - Five construction characteristics considered: four binary, one with three categories
  - Individual construction characteristics unknown for between 6 and 19 of the 37 bridges
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- Subsequent **Bayesian analysis** with informative priors also failed to converge — start to suspect **identifiability problems due to missing covariate configuration**?

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Example: seismic engineering

Simplifying the fragility coefficient models

- Dropped characteristics with most missing information: still no convergence
Example: seismic engineering

Simplifying the fragility coefficient models

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- Dropped all characteristics to retain just bridge- and author-specific random effects, and reverted to REML fitting in \texttt{lme4}
  - Inter-bridge variability estimated as zero
Example: seismic engineering

Simplifying the fragility coefficient models

- Dropped characteristics with most missing information: still no convergence
- Dropped all characteristics to retain just bridge- and author-specific random effects, and reverted to REML fitting in \texttt{lme4}
  - Inter-bridge variability estimated as zero
- Time to look carefully at the data?
Visualising the published fragility coefficients

Estimates of log $\alpha$

Estimates of log $\beta$

'Topographic' colour scales run from dark blue (low values) to pale blue, green, yellow and tan (high values)
Lessons from this example

- Data in this area will not necessarily support desired analyses
- Data limitations not always understood
- This is not an isolated incident! Similar experiences in several sectors
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**Take-home message**

Urgent need to promote appreciation of **what data are required to answer questions of interest**

*Before and after the Amatrice earthquake, August 2016*
Evidence synthesis

- Comprehensive risk assessment inevitably involves synthesis of information from **multiple data sources** and **multiple models**.
- Evidence from different sources may be **apparently contradictory**
- **Challenge**: how to **combine and integrate information** — and provide defensible assessments of uncertainty?
Evidence synthesis

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**Contention**

- Requires careful thought about **structure of problem**
- **Graphical methods** help to clarify structure
Case study: evidence synthesis for climate projections

- Climate change is major driver of disaster risk (see earlier quotes from GAR2015) — need to prepare for climate of the future
- Planning requires information on climate of next few decades (or more)
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Planning requires information on climate of next few decades (or more)

Most climate change projections based on deterministic climate simulators — either general circulation models (GCMs, global) or regional climate models (RCMs):

- Represent main physical / chemical processes in atmosphere & oceans.
- Future projections conditioned on different scenarios of global development / greenhouse gas emissions.
- Numerical solution of dynamical equations on 3-D grid — resolution coming down to $\sim 50 \times 50 \text{km}^2$ (GCMs), $\sim 10 \times 10 \text{km}^2$ (RCMs), takes $\sim 1$ month to run one 100-year simulation.
Case study: climate projections

Example: global temperature projections, 2016–2035

- Information available:
  - ‘Observed’ temperatures, 1986–2005 (HadCRUT3)
  - Outputs from 32 GCMs, 1986–2005 (CMIP5)
  - 2016–2035 GCM outputs (RCP8.5)
Case study: climate projections

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  - Outputs from 32 GCMs, 1986–2005 (CMIP5)
  - 2016–2035 GCM outputs (RCP8.5)

Question:

What will global temperatures be in the future?
Features of climate projection problem

- Some simulators seem better than others at reproducing past observations
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- Projections vary between simulators $\Rightarrow$ choice of simulator (particularly GCM) often represents significant source of uncertainty
  - Users advised to consider information from several simulators — multimodel ensemble (MME)
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  - Users advised to consider information from several simulators — multimodel ensemble (MME)
- Simulators too computationally expensive for most users to run — usually use existing ensembles e.g. CMIP5
  - No statistical design — unsystematic sampling of simulators, choice of runs etc., “ensemble of opportunity”
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Questions:
- How to use / combine information from multiple simulators?
- How to provide decision-relevant uncertainty assessment?
Climate projections: issues to consider

- **Individual simulators have strengths and weaknesses** according to developers’ priorities
  - **Implication:** common approach of assigning (scalar) weights to simulators is wrong
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- Simulators share code & have evolved from small number of ‘ancestors’
  - **Implication:** simulators share discrepancies with real climate system
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Simulators are expensive to develop ⇒ full range of modelling decisions not sampled (∼40 GCMs currently available worldwide)

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Projections are not predictions: aim is to reproduce statistical properties of actual climate

- **Implication**: combining information must focus on statistical descriptors of system behaviour
Climate projections: a formal framework

- Any statistical descriptor is parameter vector $\theta$ in a statistical model.
- Fit statistical models with common structure (‘mimics’) separately to climate observations and to outputs from each simulator.
  - Obtain estimates $\hat{\theta}_0$ (for real climate system), $\hat{\theta}_1, \ldots, \hat{\theta}_m$ (for $m$ simulators).
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E.g. global temperatures show linear trend in each 20-year period.

Linear trend suggests mimic:

$$Y_t = \mu_0 + \mu_1 (t - \bar{t}) + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma^2).$$

Descriptor vector is

$$\theta = (\mu_0^{(\text{historical})}, \mu_1^{(\text{historical})}, \sigma^{(\text{historical})}, \mu_0^{(\text{future})}, \mu_1^{(\text{future})}, \sigma^{(\text{future})}).$$
A graphical model for the climate projection problem

- Want to use estimates $\hat{\theta}_0, \hat{\theta}_1, \ldots, \hat{\theta}_m$ to learn about descriptor $\theta_0$ for real climate system
- NB explicit representation of shared simulator discrepancy 🐦
Climate projections: a formal framework

Climate projections: an analytical solution

- Posterior $\pi \left( \theta_0 | \theta_0, \hat{\theta}_1, \ldots, \hat{\theta}_m \right)$ available in closed form when
  
  (a) Simulator outputs are exchangeable given simulator consensus $\theta + \mathcal{N}$
  (b) All conditional distributions in graph are Gaussian
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- Closed-form solution allows empirical Bayes approach to analysis (plug in required covariance matrix estimates) — easy to implement
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- Posterior mean is matrix-weighted average of simulator outputs and observations
  
  - Matrix-valued weights mean each simulator contributes only where informative (‘exploit strength, discount weakness’)
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  - Implications for design of climate simulator experiments
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  - Implications for design of climate simulator experiments

Non-exchangeable simulators

- Unrealistic to assume simulators exchangeable given consensus: GCMs have evolved in ‘families’ & some have different ‘variants’ (e.g. Knutti et al., 2013, *Geophys. Res. Lett.*)

- Suggests extending framework to account for ensemble genealogy

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- Graphical structure conceptually straightforward.

*The CMIP5 ‘family tree’*

Non-exchangeable simulators

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- Suggests extending framework to account for ensemble genealogy
- Graphical structure conceptually straightforward
- Empirical Bayes complicated by sparse grouping structure for covariance estimation e.g. some families with single members — use random-effects on both mean and covariance structure

*From Knutti et al., 2013, Geophys. Res. Lett.*
Non-exchangeability: does it matter?

**Captain Hindsight** says:

- Non-exchangeability only matters when (a) simulator grouping structure is clear (b) ⚠️ is small relative to total variation
Non-exchangeability: does it matter?

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Posterior predictive distributions for mean global surface air temperature, 2016–2035

Global temperatures...

Dropping exchangeability assumption makes no obvious difference to empirical Bayes (‘poor man’) predictive distributions for future global temperatures
Evidence synthesis: take-home messages

- **Graphical models** provide powerful tool for thinking about & communicating evidence synthesis problems
  - Graph structure often dictated by problem context in physical systems (cf many biological / medical / economic applications)

- **Simplified representation of data structure may be adequate** if some sources of variation are relatively unimportant
  - **Thorough exploratory analysis** can save effort in the long run …
Model limitations

- Climate projection example involved outputs from multiple simulators treated as ‘black boxes’
- Alternative class of problems: risk / hazard assessments using single simulators because, e.g.:
  - Simulator developers want to understand how to improve simulators
  - Computational constraints make it infeasible to run multiple simulators in ‘one-off’ situations
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- But uncertainty arises because all simulators have limitations:
  - Models are at best approximations of reality
  - etc. [from earlier slide]
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**Emulators can help!!!**
Case study: volcanic ash dispersal modelling

- 2010 Eyafjallajökull eruption closed European airspace completely for six days: total cost to aviation industry estimated at £1.1 billion

- Closures due to concerns that ash concentrations were too high for safe operation of jet engines

- UK Met Office responsible to international aviation industry for ash concentration forecasts in North Atlantic

- NB considerable (but poorly-quantified) uncertainty led to conservative operational decisions ⇒ improved uncertainty assessment could yield substantial benefits
Ash dispersion: features of problem

- Met Office ash concentration forecasts produced using NAME (Numerical Atmospheric-dispersion Modelling Environment)
- Combines eruption characteristics with weather forecasts and models of dispersion processes (wet / dry deposition, sedimentation etc.)
- Many uncertainties e.g. eruption characteristics not known, meteorological clouds may obscure satellite observation of ash cloud, uncertain weather forecasts etc.
- NAME runs too slowly to explore uncertainties in real-time event management situations ⇒ emulation seems attractive
Expert elicitation used to set uncertainty ranges on key inputs:

- Three half-day sessions
- Two experts from Met Office (plus other members of dispersion group)
- Modellers from Reading University Meteorology
- Facilitator: Andy Hart, FERA
Emulation of NAME for Eyjafjallajökull eruption

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- Standard emulation techniques and **history matching** used to design ‘small’ ensemble of NAME runs
  - Provides **defensible uncertainty assessments** for simple summary measures (e.g. total ash over specified region)
  - Allows modellers to **identify key uncertainties** in NAME inputs
Emulation of NAME

NAME emulation: quantities considered in expert elicitation

**Source**
- Plume height
- Vertical distribution of ash
- Mass eruption rate
- Size distribution of ash / tephra
- Duration of eruption
  - Particle shape
- Size / area of eruption
  - Particle density

**Advection and dispersion**
- Standard deviation of horizontal velocity for free tropospheric turbulence
- Standard deviation of vertical velocity for free tropospheric turbulence
- Horizontal Lagrangian timescale for free tropospheric turbulence
- Vertical Lagrangian timescale for free tropospheric turbulence
- Standard deviation of horizontal velocity for meander
- Horizontal Lagrangian timescale for meander
  - Vertical mixing by convection
    - Boundary-layer height

**Loss processes**
- Deposition velocity
- Maximum deposition velocity for dry deposition
- Aerodynamic resistance
- Laminar resistance
- Surface resistance
- Sedimentation velocity
- Precipitation threshold for wet deposition
- Scavenging coefficients for rain and snow in cloud and below cloud
NAME emulation: current state of play

- **Modellers were challenged by elicitation exercise**
  - But appreciated what was learned
  - Experienced facilitator essential
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Opens possibility for probabilistic ash forecasts

Next question: what should one do with such a forecast?
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- **Next question**: what should one do with such a forecast?

- Which leads to...
Usage and communication of uncertainty assessments

- Users require **clear, concise, relevant information** from science community
- **How to provide this** in presence of uncertainty?

Contentions:

- **Awareness of probabilistic decision theory** resolves many issues
- **Ideas have received little exposure** within *any* community involved with natural hazards and disaster risk
- **Ideas can also inform research into uncertainty communication**
Support for contentions . . .

Unanimous(!) view from 60 scientists, statisticians and users at workshop *Uncertainty in Climate Prediction: Models, Methods and Decision Support*, Newton Institute for Mathematical Sciences, Cambridge, December 2010:

- Scientists need to provide **decision-relevant probabilistic uncertainty assessments**
- Users (and scientists) need **training in rational decision-making under uncertainty**
Decision theory: implication for uncertainty assessment

Key question for providers of uncertainty assessments:

Are your probabilities suitable for calculating expected losses / utilities?

or, in plain English

Would you use them to make bets using your own money?
Decision theory: implication for uncertainty assessment

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or, in plain English

Would you use them to make bets using your own money?

- Formal probabilistic approaches provide credibility by forcing transparent, defensible judgements ...

- But challenge remains to communicate judgements and resulting uncertainties effectively to non-specialists
Uncertainty communication

- Widely acknowledged that interpretation of probability statements can vary widely
  - Leads to use of verbal scales ‘very likely’, ‘likely’ etc. by (e.g.) Intergovernmental Panel on Climate Change
  - Many alternative suggestions ...
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- Recent developments in statistical community use animation to show ‘what might happen’
  - Exploit move to web-based information delivery
Uncertainty communication

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- Particularly relevant to natural hazards & risk assessment: visualisation of uncertainty in spatial surfaces

- Idea (Adrian Bowman, Glasgow): animate smooth ‘walk-through’ of posterior / uncertainty distribution of surface
  - Interpolate between independent draws from posterior, such that every frame in animation has correct first- and second-order structure
Example: earthquakes again

- Before 20th century, evidence for earthquake magnitudes & locations comes from anecdotal / damage reports
- Standard approach (still used):
  1. Convert each report to **ordinal macroseismic intensity scale** based on severity of reported phenomena
  2. Plot macroseismic intensities on map
  3. Draw **isoseismals** (‘lines of equal intensity’) — often by hand
  4. Derive index related to event size e.g. ‘area of region with intensity > 3’
  5. Develop index-magnitude calibration relationship from events where magnitudes are known.
### Specimen reports: earthquake of 9th November 1852

<table>
<thead>
<tr>
<th>LOCALITY</th>
<th>APPARENT DIRECTION</th>
<th>SHOCKS, NUMBER.</th>
<th>DURATION AND TIME.</th>
<th>OBSERVED PHENOMENA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dublin City,</td>
<td>S. to N. or S. E.</td>
<td>One, and probably one at a previous part of the night.</td>
<td>4 to 4 15 A.M. Most probably at 4 5 Dublin time. Whole time of tremor about 8 or 10 seconds.</td>
<td>The shock perceived by multitudes both awake and suddenly aroused by it from sleep; those who were awake and standing, or in motion, felt little; those who leaned against walls or other objects were fully alive to the reality and extent of the motion. Observers who were awake differ as to accompanying noise, but evidence for its occurrence preponderates. The sound is variously described as of “a rushing wind,” a “rumbling sound like a fire-engine on pavement,” &amp;c. Almost all sleepers suddenly aroused by the shock were conscious of a heavy, hollow sound, like the fall of a heavy soft body on a large hollow floor. The motion is generally described as vibratory, ending in one or two sudden heaves. It is uncertain whether the sound accompanied or closely succeeded the shock; most probably the latter. Houses were heavily shaken; a shattered chimney thrown down at Phibsborough; water thrown out of full vessels. A few minutes after the shock, the street gas-lights were observed to be agitated as in a storm, arising obviously from the agitation of the water in the gasometer tanks at the works. (Letter from Mr. Wilson, Christ-Church-place.) The balance-weights of window-sashes swung against the sash-casings, north side of Dublin. Sparrows were thrown from their roosting-places, Great Southern and Western Railway goods shed, and Mountjoy-square, and many picked up dead on the ground in the morning.</td>
</tr>
<tr>
<td>S. by S. and N. W. by N. A telescope standing on end fell towards the north in Nassau-st.—G. Yeates. A picture was shaken down from its fastenings on a wall running S. by W., and N. by E., and so circumstanced as to prove that the direction of emergence of shock was upwards at a considerable angle from S. to N.—R. Mallet. Some observers were conscious of three distinct heaves during the continuance of the tremor. (Letter, I. Farrell,</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*From Mallet, R. (1854) “Notice of the British Earthquake of November 9, 1852”, Trans. Royal Irish Academy*
Example: felt areas for UK earthquakes

Maps of the 1852 earthquake

**Mallet’s map, 1854**

**British Geological Survey map, 1980s(?)**
Example: felt areas for UK earthquakes

**Isoseismals: a formal framework**

- Consider **probability** $p(x, y)$ of reported intensity at location $(x, y)$ exceeding some threshold
- Define **isoseismal** as contour $p(x, y) = \tau$ (say)
Isoseismals: a formal framework

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- Define isoseismal as contour \( p(x, y) = \tau \) (say)

- Assume isoseismals are elliptical (reasonable on physical grounds) and work on (e.g) logit scale

- Then

\[
\text{logit } p(x, y) = \beta_0 + \beta_1 x + \beta_2 y + \beta_3 x^2 + \beta_4 y^2 + \beta_5 xy
\]

with constraints \( \beta_3 \leq 0 \) and \( 4\beta_3\beta_4 \geq \beta_5^2 \).
Isoseismals: a formal framework

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  with constraints $\beta_3 \leq 0$ and $4\beta_3\beta_4 \geq \beta_5^2$.
- Constraints enforced most naturally by reparameterising and working in Bayesian framework.
- **Result:** posterior for ellipse parameters (NB allows formal quantification of uncertainty that was not previously possible) …
Isoseismals, 9th November 1852: visualising the posterior

For algorithm, see [http://www.stats.gla.ac.uk/˜adrian/papers/graphics-for-uncertainty-paper.pdf](http://www.stats.gla.ac.uk/˜adrian/papers/graphics-for-uncertainty-paper.pdf)
Globally, natural disasters are as important as disease.

Opportunities for statistical input:
- Raising awareness about experimental design / data requirements
- Raising awareness of principles of decision-making under uncertainty — feeding into communication strategies
- Graphical model representations help to articulate problem structure
- Emulators allow uncertainty assessment for real-time event management

Web-based information delivery provides opportunity for creative methods of uncertainty communication.
Take-home messages

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- Web-based information delivery provides opportunity for creative methods of uncertainty communication

😊 Thank you for your attention 😊

More details of PURE:

- [http://connect.innovateuk.org/web/pure-research-programme](http://connect.innovateuk.org/web/pure-research-programme)
- [http://www.pure-network.org](http://www.pure-network.org)