# Volcanic Activity: Frontiers and Challenges in Forecasting, Prediction and Risk Assessment

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When a volcano shows signs of unrest scientists are asked to forecast whether an eruption will happen, when it will happen and what kind of eruption it will be. They are also expected to provide information on hazardous volcanic phenomena and their effects, and how long the eruption will last. Eruptions are complex phenomena, however, involving magma ascent to the Earth's surface and interactions with surrounding crust and surface environments during eruption. Magma may change its properties profoundly during ascent and eruption, and many of the governing processes of heat and mass transfer can be highly non-linear. There are both epistemic and aleatory uncertainties involved, which can be large, making precise prediction of a certain event in time and space a formidable or impossible objective; that is, volcanoes can be intrinsically unpredictable. As with other natural phenomena, forecasting is a more achievable goal and needs to be expressed in probabilistic terms that take account of the uncertainties. Ensemble modeling in which uncertainties are sampled with Monte Carlo techniques is likely to become the basis for such forecasting. Despite the limitations, there is significant progress in anticipating volcanic activity and, in favorable circumstances, in making predictions. Data from enhanced monitoring techniques are being combined with advanced numerical models of volcanic flows and their interactions with the environment. Statistical analysis of volcanological data and improvements in methods to treat subjective information are also beginning to provide viable, complementary approaches to basic numerical modeling.

## INTRODUCTION

Earth scientists are required to look into the future to advise governments and inform the public about threats from natural hazards. The challenges of prediction become immediate when a volcano is about to erupt. About 500 million people live close enough to volcanoes to be affected by eruptions [*Newhall*, 2000]. Volcanic phenomena can affect climate and are an important contributing factor in forecasting global environmental change. The challenges of forecasting volcanic activity are considerable and come at a time when the demands and expectations of society are increasingly onerous. Some societies are

The State of the Planet: Frontiers and Challenges in Geophysics
Geophysical Monograph 150, IUGG Volume 19

10.1029/150GM28

becoming ever more litigious, and prospects of scientists having to justify their judgements in court are emerging.

Volcanic activity has many features in common with other natural hazards, such as extreme weather, earthquakes and landslides. Natural hazards are characteristically complex and involve numerous parameters and processes. Some of the controlling processes are highly non-linear, so that in certain circumstances abrupt changes of behaviour can happen, such as the sudden transition from effusive to explosive eruption. Of particular significance is the need to understand and quantify uncertainty. There is both epistemic and aleatory uncertainty in natural phenomena [*Woo*, 1999], the former being defined as deficiencies in knowledge about natural processes and the latter as natural variability within those processes. Many volcanic processes are stochastic, and need to be characterised by statistical models. Complex nonlinear systems can be very unstable close to critical thresholds between stable states, becoming inherently unpredictable. Such attributes and the importance of quantifying uncertainty are now central in forecasting volcanic phenomena. As a consequence, volcanologists will inevitably shift from deterministic to probabilistic perspectives. This change in focus will require alterations in the conceptual framework within which observations on volcanoes are interpreted. There will be many challenges, because uncertainties in many aspects of volcanic systems are large, and may prove hard to quantify.

Here we consider emerging new approaches to prediction, forecasting, the assessment of volcanic risk, and provision of scientific advice. We also discuss the roles of statistical analysis and computer modelling. This paper complements those of *Sparks* [2003], who reviewed the methods of forecasting volcanic eruptions based around interpretation of monitored data, and of *Newhall and Hoblitt* [2002], who developed parallel themes.

## VOLCANIC PROCESSES AND HAZARDS

Volcanism is caused by the buoyant ascent of magmas to the Earth's surface. Magmas change their properties as they ascend, principally due to changes in pressure and temperature. The properties of a magma and its interactions with its surroundings determine whether a given magma erupts or not, and dictate the nature of the activity, if it does erupt. These properties and interactions give rise to a range of physical effects that can be monitored. Important interactions include: fracturing of rocks due to propagation of dykes (*Rubin*, 1995), generating seismicity; escape of pressurised gases and heating of ground waters, leading to 'long-period' volcano-seismic events [e.g. *Chouet,* 1996; *Neuberg,* 2000]; and variations of magma pressure in chambers and conduits leading to ground deformation [e.g. *Voight et al.,* 1999; *Dzurisin,* 2000]. Ascending or erupting magma can cause perturbations of electric, gravity and magnetic fields. Additionally, fluxes of magma and gas, geochemical and petrological variations in erupted products, and observations of surface activity provide important information. Observations from space of heat, strain, topography, gravity, electromagnetic transients and atmospheric emissions are also emerging as a major source of information [*Wadge,* 2003]. Systematic monitoring and observations provide the basis for forecasting, but require understanding of the processes to interpret.

Major types of volcanic hazards, their effects and extents are listed in Table 1. The scale and occurrence of volcanic hazards are inversely related, with small events occurring worldwide at a rate of 10–20 per month, whereas catastrophic eruptions (>10 km$^3$), that might affect the economy of an entire country, occur every hundred years or so [*Pyle,* 1998]. The very largest volcanic eruptions (>1000 km$^3$) could threaten civilization [*Rampino,* 2002] and occur about every 50,000 years on average [*Mason et al.,* 2004].

**Table 1**. Summary of the effects and extents of major volcanic hazards.
L = local; R = regional; N = national; I = international

| Hazard | Threat to life | Threat to property | Areas affected |
|---|---|---|---|
| ash and pumice fall | low except near vent<br>high for aviation | depends on thickness:<br>roof collapse, bomb damage, fire | L,R,N,I |
| pyroclastic flows | very high | very high | L,R |
| lava flows | low | very high | L |
| lahars/flooding | high to moderate | high | L,R |
| gases/dusts/acid rain | low to moderate | moderate | L,R |

Volcanic hazards can be entirely caused by the volcanic activity itself, but external factors can be important. Lavas and pyroclastic flows, for example, are strongly influenced by topography. Tephra fall hazards depend on wind strength and direction [e.g. *Bonadonna et al.,* 2002]. Collapse of a lava dome to form pyroclastic flows can be triggered by intense rainfall [*Matthews et al.,* 2002]. Flank collapses can be triggered by earthquakes, as happened on 18th May 1980 at Mount St Helens [*Endo et al.,* 1981]. Separate earthquake–volcano interactions can apparently take place over surprisingly long distances and time-scales [*Linde and Sacks,* 1998; *Hill et al.,* 2002]. Other, subtle complex-systems dynamics [e.g. stochastic resonance; *Weisenfeld and Moss,* 1995] may link volcanic responses to low-level external forcings, such as tides or atmospheric pressure or hydrological cycles [*Jupp et al.,* 2004]. Thus forecasting of hazards in both space and time requires not only understanding of the eruptive processes themselves, but also understanding of the surface and subsurface environment and external processes that interact with volcanic phenomena.

## PREDICTION AND FORECASTING

Prediction and forecasting are sometimes used interchangeably, but can be usefully distinguished. A prediction involves a statement about a specific event that is regarded as inevitable within certain defined time limits and, in its most developed form, is found in established laws of physics (e.g. Newton's Laws of motion of bodies). Scientists may judge, for example, that a volcano that is showing unrest will definitely erupt and that lava will reach a village. The prediction will have limited value unless some constraints on time, place and scale are specified, even if these assessments are themselves uncertain to some degree. Forecasting, on the other hand, is a probabilistic statement that a specific event might occur with a certain likelihood in a given time-frame, commonly with associated scales and effects being defined as well.

The requirements for prediction, as defined above, are stringent, because the event must be inevitable. It might be thought that a volcano like Vesuvius, with an historical record of frequent eruptions, would meet the requirements of inevitability of another eruption. However, all volcanoes become extinct and the criteria for recognising that a volcano has had its last ever eruption are very problematic, if not unknowable (and conditional on definitions of 'eruption' and 'extinct'). One cannot be certain that the 1944 eruption of Vesuvius was not its last ever eruption, even though the probability that this is so would be widely judged as diminishingly small. In most eruptions the case for inevitability cannot be easily made.

Many volcanoes erupt in such a way that patterns of behaviour can be established and an eruption can be forecast, and even predicted if these patterns are repeated sufficiently often. In 2000, the eruption of Mount Hekla in Iceland was accurately predicted. Several years earlier borehole strain meters had been deployed in central Iceland and, in the 1991 eruption, large and systematic strain variations (Figure 1), together with seismic data, traced the propagation to the surface of a dyke from a magma chamber about 6 km below Hekla [*Linde et al.,* 1993]. The agreement between the observations and conceptual model gave a high degree of confidence that an eruption was inevitable when the same pattern was repeated in March 2000. Scientists from the Icelandic Meteorological Office informed Icelandic radio that an eruption was imminent in 20 minutes. The prediction was announced at the beginning of a news broadcast and the eruption occurred within 2 minutes of the expected time. In the 1981–1983 activity of Mount St. Helens, patterns of periodic dome growth with precursory ground deformation allowed accurate forecasts to be made of the timing of dome extrusion events [*Swanson et al.,* 1983]. These forecasts became increasingly focussed on narrow time windows to the extent that they, too, might be viewed as predictions.

The above examples show that forecasting and prediction are easier at persistently active volcanoes or in long-lived eruptions with established and repeatable patterns of activity; forecasting and prediction become more difficult for dormant volcanoes with a limited or no historical record. The

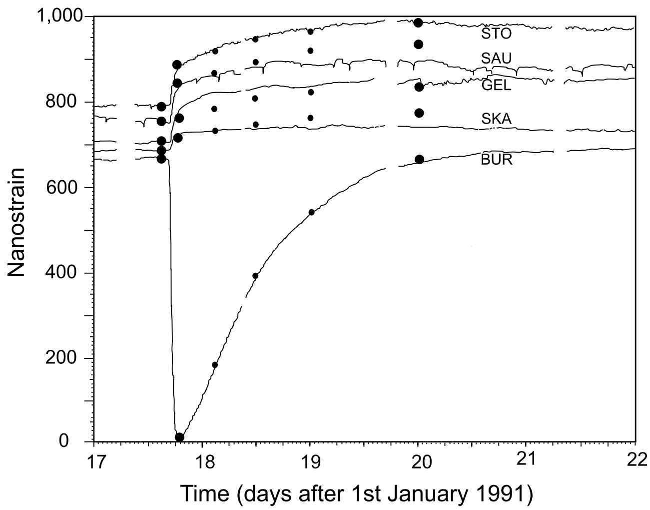


**Figure 1**. Strain measured in five borehole strainmeters in Iceland in 1991 associated with the eruption of Hekla Volcano [after *Linde et al.*, 1993]. The eruption took place within 20 minutes of the start of the changes in strain at the time when the strain at BUR reached a minimum. Four of the stations show an expansion (positive changes) and the closest station to the volcano (BUR) shows an initial contraction. The data are interpreted as the ascent of a dyke from the magma chamber to the surface.

issue of whether a restless volcano is going to erupt has been a source of angst, controversy and, in some cases, the undermining of scientific credibility. The cause célèbre is the 1976 volcanic crisis at La Soufrière, Guadeloupe, which led to major public disagreements between scientists [*Fiske,* 1984]. One group, led by Haroun Tazieff, judged that the seismic swarm and phreatic activity was not the prelude to a major eruption. Others regarded these disturbances as potential signs of a major eruption, which would endanger over 70,000 people, and so advised an evacuation. The authorities, concerned to incur no public risk in the light of events in Martinique in 1902, accepted the precautionary advice and the consequent three-month evacuation caused hardship and considerable economic cost, running into several hundreds of millions of dollars. A magmatic eruption did not happen and, in some sense, Tazieff's assessment might be construed as "right". A considered appraisal of the Guadeloupe case suggests, however, that the more cautious scientists had better appreciation of scientific uncertainties and the inadequacy of knowledge about how volcanoes work, a view supported by subsequent analysis [*Feuillard et al.,* 1983]. In contrast, the climatic eruption of Mount Pinatubo in June 1991 is a good example of a successful forecast based on a spread of evidence, including precursory seismicity, and variations in $SO_2$ emissions [*Punongbayan et al.,* 1996]. The prospect of a very substantial explosive eruption was deduced from geological evidence of past eruptions and dating of pyroclastic deposits. The decision to evacuate 250,000 people based on the various strands of evidence was a judgement call and the advice of the Philippine Institute of Volcanology and US Geological Survey to the authorities avoided huge loss of life.

In view of the inherent difficulties in prediction of volcanic phenomena it is often better to address future volcanic activity in terms of probabilistic forecasting. For many eruptions, forecasts are qualitative and expressed in terms such as 'very likely' or more cautious statements that a volcano is showing the signs of unrest and might erupt. Every volcanologist is, however, acutely aware of the problems provoked by calling an evacuation and then nothing happens. The scientists are perceived to have been "wrong", and to have raised a false alarm. For this reason it is better to present forecasts rather than predictions, and to find ways of expressing these in probabilistic terms based on quantitative scientific evidence and analysis.

In the USA public and political decision-makers are used to weather forecasts. In general, weather forecasters have gained public credibility both by a record of improving the accuracy of forecasts and by getting the public accustomed to basic concepts of probability. The statement that there is an 80% chance of rain in a particular town is familiar, and most people will accept that if it doesn't rain then it was not necessarily a wrong forecast. Even in this arena, however, forecasters still have difficulties with extreme conditions and can lose credibility when the weather is much more severe than anticipated. Likewise volcanologists have considerable problems with forecasting the onset and effects of extreme volcanic events.

We now illustrate some of these matters and present practices with the example of the Soufrière Hills volcano, Montserrat, since that ongoing eruption (which started in July 1995) is very familiar to us.

## MONTSERRAT: CASE STUDY IN FORECASTING, PREDICTION AND RISK ASSESSMENT

The focus on the Soufrière Hills volcano, Montserrat is selective, but the eruption has displayed a wide range of volcanic phenomena and has proved to be a very good testing ground for development of new approaches to prediction, forecasting and risk assessment. Here we illustrate the principles of probabilistic forecasting with the example of tephra fall hazards. We also consider pyroclastic flow hazards on Montserrat to illustrate methods of risk assessment.

### *Tephra Fall Hazards*

Tephra fall is one of the better understood of volcanic processes (Plate 1). Understanding the dynamics of volcanic plumes is reasonably advanced, as summarised in *Sparks et al.* [1997], with quantitative models for plume ascent, for the interaction of plumes with the wind, and for tephra transport. These models have been calibrated against observed events and consequently there is confidence that the models are simulating natural processes appropriately. There is also information on hazardous effects; for example, mass accu-

**Plate 1.** An ash-laden volcanic plume at the Soufrière Hills Volcano is blown across Montserrat. Note that the source of the plume is from a pyroclastic flow about 1 km to the east of the crater of the volcano.

mulations of tephra that can lead to roof collapse are well documented [*Blong,* 1984].

The study of *Bonadonna et al.* [2002] on assessment of tephra fall hazards on Montserrat illustrates the main features of probabilistic modelling. The model treated the tephra dispersal as an advection–diffusion problem with a source function that reflected the observed origin of the ash plumes from above the pyroclastic flows along the valleys, and the observed approximately exponential decrease of plume height with distance along the valley. The model also considered Vulcanian explosions sourced at the crater. Model simulations were first run for individual volcanic events and for the effects of activity in the sequence from June 1996 to June 1997, under the atmospheric conditions prevailing at the time (wind speeds and directions). Parameters in the model were then adjusted to give best-fits to the observed thickness variations. The volcanic activity of 1996–1998 was then used to build a characteristic scenario for the volcano of combinations of dome collapses, pyroclastic flows and explosions. This scenario was then run several hundred times using re-sampling of the statistical data on daily wind speeds and directions at 1 km intervals up to a height of 20 km for 1992–1996, to generate a statistical distribution of resulting tephra accumulations across the island.

Figure 2 plots the model output in contours of probability (as a percentage) that tephra accumulation will exceed 12 kg/m$^2$ (Figure 2a) and 120 kg/m$^2$ (Figure 2b). The first value represents the threshold above which crops commonly fail, and the latter value is the threshold at which roof collapse becomes a problem. This particular model assumes that either erosion or human intervention (e.g. sweeping roofs) removes the ash between each tephra fall event. Such probabilistic models were used on Montserrat to assess vulnerability to roof collapse and to make a risk assessment of the health hazards due to respirable volcanic dust. The forecasts have also been used to guide the UK government in planning the sustainable development of the island.

Tephra fall also poses health hazards. In the case of Montserrat the volcanic dust (<10 µm) contains 10–25 wt% cristobalite, which is a carcinogen and causes silicosis, a chronic lung disease [*Baxter et al*., 1999]. The model of *Bonadonna et al.* [2002] was an input into a risk assessment commissioned by the UK Department of Health. In this assessment, simulations of tephra dispersal were combined in a synthesis with other information and processes, including models of ash suspension, epidemiological data and biological data such as in vivo and in vitro experimental results. Multiple model runs were made to assess the exposure of the population to suspended ash. The results of this study have identified outdoor workers (eg gardeners) and children as having relatively high exposure. This study illustrates the way in which relatively ‘soft’ qualitative data can be incorporated into a multi-factor simulation. To produce a probabilistic assessment of human exposure to suspended dusts it is, for example, necessary to parameterise the erosion process, since once ash is eroded it is no longer available for suspension. At the moment, it is beyond present understanding to replicate in a model all the complex processes of tephra erosion and redistribution on a tropical island, but a simple time-dependent removal scheme could be parameterised from empirical information. This was combined with statistical information on rainfall to provide a significant advance on the end member probabilistic maps in Figure 2.

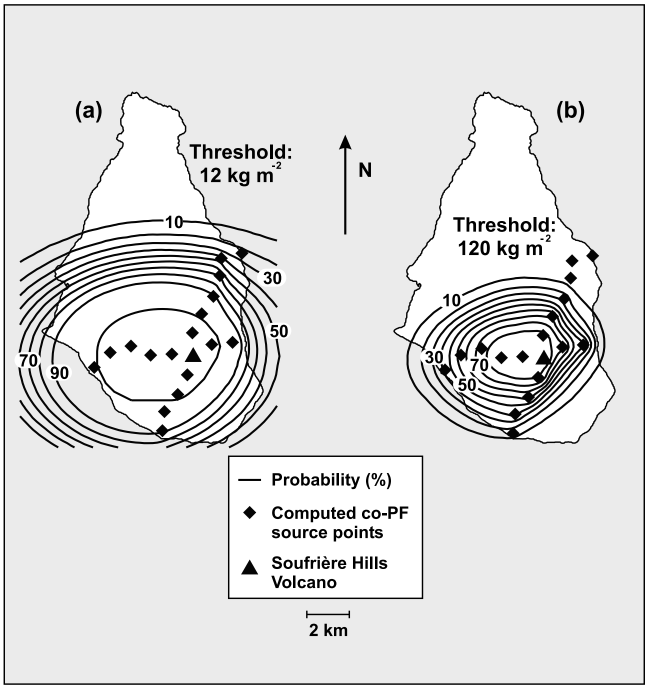


**Figure 2**. Maps showing contours of probability (as a percentage) across the island of Montserrat of accumulation of 12 and 120 kg/m$^2$ or more of volcanic ash over a 3-year period [after *Bonadonna et al.,* 2002]. The maps are based on a scenario of activity similar to that experienced on the island. Pyroclastic flows extend in the scenario down the valleys and plumes (co-PF) are source at the points indicated by the solid diamonds. The mass accumulations are equivalent to ash thicknesses of about 1 cm (for 12 kg/m$^2$) and 10 cm (for 120 kg/m$^2$).

Such modelling can always be improved. An ambitious target might be to produce a probabilistic model of dome growth, collapse and explosion rather than simply adopt a specific, albeit plausible, single scenario as a class example. Monte Carlo sampling of all uncertainties in key parameters that control the underlying volcanic processes could then be incorporated to represent a wide range of potential scenarios. However, the processes of dome growth are not yet well enough understood to do more than develop ‘soft’ parameterisations, as in the case of erosion. Such models are in the future and will require significant computing power and code development, although adroit use of newly-emerging model inference techniques [*O'Hagan et al.,* 1999] offer the prospect of reduced computing costs. Eventually one can imagine volcano forecasting centres that assist observatory teams with synoptic outputs, just as weather centres have sprung up to underpin local and regional forecasts.

### *Pyroclastic Flow Hazards*

The principal hazard on Montserrat during the eruption is the formation of pyroclastic flows from collapse of the lava dome [*Cole et al*., 2002]. The assessment of hazards and attendant risks from pyroclastic flows and their accompanying hot turbulent clouds of ash (surges) is described here to illustrate generic issues in relation to prediction and methods of probabilistic forecasting.

The andesite dome has grown in pulses [*Watts et al.,* 2002]. In each pulse a lobe of lava extrudes in a particular direction (Plate 2a). Rockfalls and collapse-induced pyroclastic flows are generated preferentially at the leading edge of a lobe (Plate 2b) and tend to flow away in the same direction as the extrusion direction [*Calder et al.,* 2002]. This behaviour is very useful for forecasting, since the probability of flows going down a particular valley is greatly increased when the dome is extruded in that direction. Pulses in extrusion rate can be marked by the onset of shallow seismicity or by changes in cyclic patterns of ground deformation, as recorded by tiltmeters [*Voight et al.,* 1999], and both symptoms are commonly associated with formation of a new lobe in a new growth direction.

Most major dome collapses on Montserrat (defined here as 3 million cubic metres or greater since only flows of this size or above are large enough to threaten populated areas) occurred within a few hours or days of a pulse in extrusion rate. There have been many such pulses and switches in the extrusion direction, which tend to occur at intervals of a few weeks to a few months. From May to December 1997 the surges and accompanying major dome collapses occurred quite regularly at 6–7 week intervals [*Voight et al.,* 1999; *Sparks and Young,* 2002]. For a while, the regularity of the pattern was sufficiently clear to provide a basis for forecasting. On the other hand, some of the largest dome collapses appear to have been triggered by intense rainfall [*Voight and Elsworth,* 2000; *Matthews et al.,* 2002]. One of these occurred on 3 July 1998 in a period when there was no dome growth. Two large dome collapses occurred on 20 March 2000 and 29 July 2001 (volumes of 20 and 45 million m$^3$, respectively) and were associated with intense rainfall of over 80 mm/hour.



**Plate 2.** Activity of the Soufrière Hills volcano, Montserrat illustrating factors determining the directions of pyroclastic flows. In (a) a lobe of lava is extruded towards the north between August 5 and 9, 2002 (view from the east), and in (b) small collapses from the leading edge of a lava lobe generates rock-falls and pyroclastic flows towards the north of the island (view from the north). Images reproduced by permission of the Montserrat Volcano Observatory.

The critical issues in hazard forecasting of pyroclastic flows are the areas that a flow (or series of flows) will inundate and the occurrence of the associated overlying clouds of hot turbulent suspended ash (known as surges) that can spill out of the valleys that confine the main flows. Data on run-out distances and areas affected on Montserrat have led to empirical relationships between flow volume and run-out distance [*Calder et al.,* 1999]. The observed distributions of particular flow deposits can be used to construct a semi-empirical model of run-out [*Wadge et al.,* 1998]. The model incorporates gravitational flow across the observed topography, which is described by a digital elevation model (DEM). The model contains three friction parameters, which can be adjusted by trial and error, or by Monte Carlo techniques, to give a best-fit to the observations. The model can then be run for events that have not yet happened to assess volcanic hazards. Such models have many uncertainties and hidden assumptions. For example, at Soufrière Hills dome collapses typically last for tens of minutes to several hours and may involve numerous individual avalanches. On 25 June 1997, there were three main collapses in 20 minutes [*Loughlin et al.,* 2002]. Using the final total volume of the deposits in a particular collapse episode as a basis for defining mobility by run-out distance, or inundation area, or to estimate friction coefficients might lead to misleading or inappropriate results. There is rarely sufficient information to discriminate the volumes of individual pulses. The fact that dome collapse episodes are almost always pulsed multi-collapse events [*Calder et al.,* 2002] means that there are intrinsic uncertainties and pitfalls in analysing the resulting field data. Another element of semi-empirical models is that the frictional parameters not only reflect the true frictional properties of the flow but implicitly incorporate topographic effects on flow which, as yet, are not explicitly modelled.

The behaviour of the surge clouds is even more problematic because quantitative models of surge generation and dynamics are not yet available. On Montserrat, the development of surge clouds seems to be linked not only with flow volume, but also with the internal pressurisation of the dome, which itself is thought to be related to the extrusion rate [*Cole et al.,* 2002; *Calder et al.,* 2002]. Surge cloud generation and behaviour can also be sensitive to topographic features and can be influenced by wind. Finally, surge clouds can generate dense "secondary" pyroclastic flows, which can move obliquely down valleys away from the main originating flow [*Druitt et al.,* 2002b]. Thus the dispersal of surge clouds is not yet amenable to rigorous modelling and so the assessment of hazards must depend more on qualitative judgements based on observations in circumstances of considerable uncertainty.

*Risk Assessment of Dome-Collapse Pyroclastic Flows*

We illustrate the development of a quantitative risk assessment of pyroclastic flow hazards, the main hazards issue in the management of the Montserrat crisis, using the recent example of one particular residential area, the Belham Valley. The problem emerged in 2002 when relentless dome growth raised concerns that a large collapse could inundate the lower parts of the Belham Valley, northwest of the volcano (Plate 3). This section describes the modelling procedures that were used to estimate risks and thus inform decisions by the civil authorities. The accompanying map (Figure 3) shows the area evacuated after 8 October 2002 on the basis of scientific advice. This area was re-occupied in August 2003 after a huge dome collapse to the east, on 12 July 2003, removed the threat. For Montserrat, a Risk Assessment Panel has conducted such assessments and involves the scientific staff of MVO and external experts. The authors acted as Chair of the Panel (RSJS) and expert in risk assessment methods (WPA).

**Plate 3.** The andesite lava dome of the Soufrière Hills volcano, Montserrat in May 2003, showing the main features pertinent to hazard assessment. If the dome were to collapse down Tyres Ghaut then pyroclastic flows would enter into the lower Belham Valley (see Figure 6), an area that was evacuated after 8$^{th}$ October 2002 because of this threat. (note: 'ghaut' is used locally to denote a valley with a stream or river).

The risk to the lower Belham Valley area is a function of the probability that a pyroclastic flow will inundate part or all of the area and the vulnerability of people there. Historical data indicate that 90% of people in areas directly affected by pyroclastic flows and surges are killed [*Baxter*, 1990]. Only those on the fringes of the devastated area might survive and so vulnerability is very high. To estimate risk quantitatively the Montserrat Panel was required to estimate the probability that a flow would happen over a fixed period of time. The time window used was 6 months as this was a useful timescale for decision-makers and was commensurate with the temporal variations in dome-building eruptions.

The procedure for estimating the hazards involved a systematic series of steps in a structured discussion and use of procedures to combine relatively hard and soft information. The risk assessments used, wherever possible, quantitative models of volcanic processes. Thus to assess the run-out distances empirical correlations [*Calder et al.,* 1999] and models (e.g. *Wadge et al.,* 1998) were used. For Belham Valley, the Panel concluded that collapses of 3 million cubic metres or more would have a high likelihood of reaching the lower valley and that collapses of 10 million cubic metres or more would reach the sea and affect most, if not all of the area.

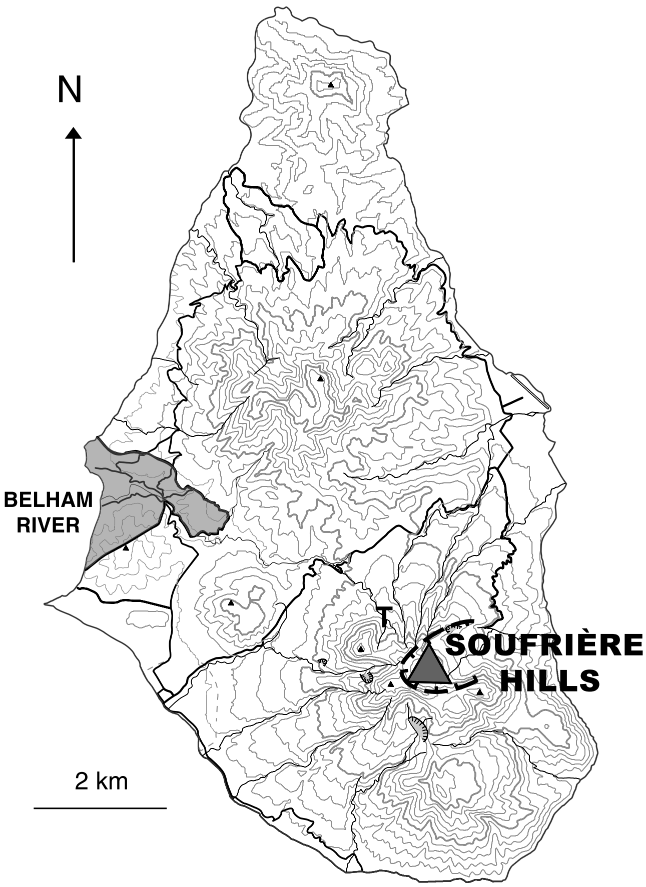


**Figure 3**. A map showing the location of the Belham Valley, Tyres Ghaut (marked T) and the area (shaded) which was evacuated after 8th October 2002 due to the assessed high level of potential risk from collapse of the lava dome to the northwest. Contour intervals are 200 feet.

The assessment also used a structured method of expert elicitation in which the judgements of the Risk Assessment Panel were pooled. The method, described in *Cooke* [1991], has become a common approach in many scientific and engineering situations that involve significant uncertainty, and it has been applied for the first time in a volcanic crisis on Montserrat. Each expert assesses their judgement of some parameter and his or her confidence limits on that assessment, based on shared, available scientific information. Experts are calibrated by a facilitator, so that the pooled results of the group are weighted according to the individual experts' ability to be informative and knowledgeable. This procedure is designed to give greater weight to those individuals with good judgement in urgent circumstances; that is, a ranking relevant to decision-making capabilities in crisis conditions, and not merely a metric of considered scholarship. The procedure has the advantage of reducing the influence of overconfident, vocal or highly opinionated individuals, while providing a neutral medium for the inclusive incorporation of a spectrum of views, and the outcome can be viewed as a mathematically rational consensus of the opinions of all participants.

A formalised expert elicitation provides a mechanism for structured scientific discussions in an evidence-based approach in which all sources of information (e.g. observations, empirical relationships and theoretical models) are utilised. In the case of the Belham Valley assessment the directionality of dome growth and surge cloud behaviour are examples of components in the estimation of overall probabilities of pyroclastic flow hazards where expert judgement elicitations have proved helpful. For endogenous collapses, directionality of the lava lobe was judged on empirical evidence to be the main determinant of the collapse direction. However, the group discussion concluded that the evidence did not support a random process, since certain directions had not been common during the eruption (possibly related to buttressing effects of older, pre-existing domes) and that switches which might trigger collapses tended to occur away from the direction of previous stagnated lobes, which acted as a barrier [*Watts et al.,* 2002]. The Panel also considered the chances of a collapse triggered by rainfall unrelated to dome growth direction. In this case the previous episodes had all been down the eastern flanks of the volcano. Additionally, the chances of such an event would be greater in the rainy season than in the dry season. An important factor also was the frequency of collapses of 3 million cubic metres or above; not all switches caused a significant collapse. Other factors included the chances of the eruption stopping, and large collapses in directions other than to the northwest over the 6-month period, which would either reduce or entirely remove the threat to the Belham Valley. Thus relatively soft information was integrated into the procedure to produce probabilities of a range of collapse events that might affect the Belham Valley.

The final stage of the risk assessment involved Monte Carlo re-sampling of the probability density functions (pdf) of all controlling factors that contribute to the hazards in different areas, in repeated simulations. The final output evaluates the integrated probability of occurrence of life-threatening events, expressed as the risk of a person being killed in a particular area, or as the associated probability of exceeding a number of casualties in the population at large (Figure 4). The individual risk exposure can be compared with a suitable risk scale: for Montserrat, the comparison was with the UK Chief Medical Officer's Risk Scale. Societal risk diagrams like Figure 4 help illustrate to public officials the consequences of decisions. Volcanic risks can also be compared with other kinds of risk: for instance, casualty exceedance curves in Figure 4 compare the case of the lower Belham Valley being occupied by residents with the case the area is evacuated.

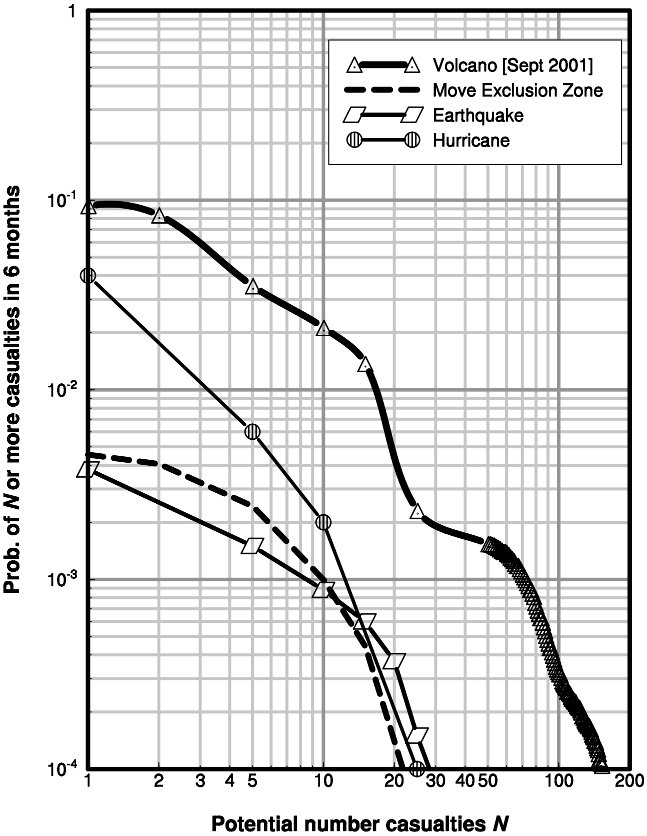


**Figure 4.** Example of probability curves for societal risk in Montserrat. Each curve shows the probability plotted against number of casualties over a 6-month period, and is the mean of thousands of simulations using Monte Carlo re-sampling from uncertainty distributions on the parameters that influence risk. The upper curve (solid line) is the exposure with the Belham Valley area (Figure 3) populated before the evacuation, and the lower curve (dashed line) shows the reduction in risk with evacuation. Regional risk curves for hurricanes and tectonic earthquakes are shown for comparison. Note that for each curve uncertainties at the 5% and 95% levels were calculated but are not shown for clarity.

Evacuation reduces societal risk by a factor of 10, to levels below those associated with hurricanes in the Caribbean and close to the long-term exposure to earthquakes.

## STATISTICS IN VOLCANOLOGY

We now consider the statistical analysis of data, particularly time series data, to extract information on volcanic processes in the context of forecasting and assessment of hazards and risks. With burgeoning amounts of instrumental and other data being acquired statistical analysis is emerging as a major area of research that goes well beyond simply providing measures of uncertainty. Here we give two examples.

### *Longevity of the Soufrière Hills Volcanic Eruption*

The Soufrière Hills eruption has continued for over eight years. The civil authorities have asked the scientists at MVO how long the eruption will last, as an accurate assessment has implications for the sustainable development of the island. To address this issue, duration data on 137 dome-forming eruptions taken from the Smithsonian Institution database [*Simkin and Siebert,* 1994] were gathered, re-interpreted, and fitted to a Generalised Pareto Distribution model (Figure 5). The Generalised Pareto family of distributions have special properties that make them particularly appropriate for analysing extreme-value information in a peaks-over-threshold approach, the mathematical utility of which for 'heavy-tailed' distributions has been recently elucidated (Woo, 1999). An unanticipated outcome was the identification of two distinct groupings in the size distribution of the selected dataset: most dome eruptions (85%) last less than 5 years and fall on a frequency-duration trend (Figure 5) different to those that last more than 5 years. In the latter cases, the eruptions can be very long-lived. Based on this analysis (and no other information) there was, for instance, only a 3% chance of the eruption lasting less than a further 6 months, having already lasted 94 months. There is a 50% chance that the eruption duration will last 20 years or longer, and a 5% chance of lasting more than 180 years.

Such analyses are limited by the quality and nature of the data. There are problems in defining durations because the beginning of an eruption is usually accurately recorded but the ending is often poorly or vaguely recorded. Further, there are

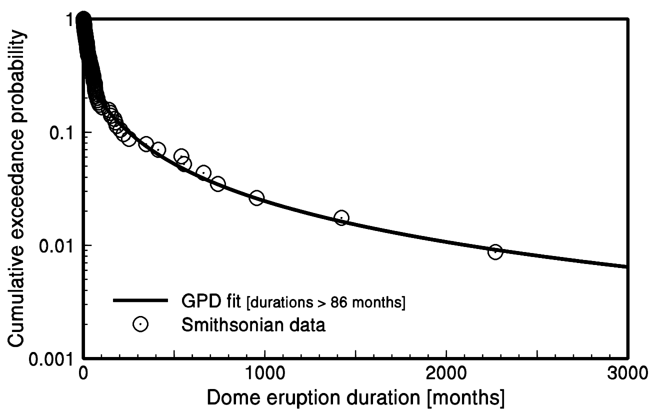


**Figure 5.** The exceedence probability distribution for the durations of 137 dome-building eruptions, drawn from the Smithsonian database. The data for eruptions lasting longer than 86 months are fitted to a Generalised Pareto Distribution law, which can be used to estimate the likelihood of the duration of an eruption exceeding a given number of months. In the text we have used the distribution for long-lived eruptions (>86 months) to assess the probability of the eruption stopping, given that the eruption had lasted 94 months.

only 15 cases of eruptions lasting more than 5 years so the database is very limited and, in some of these cases, conservative decisions had to be made about what constituted a coherent long-term episode of dome-building when punctuated activity is reported. Nevertheless, the two different distributions are quite distinctive and alternative assumptions on the reliability and uncertainties in the Smithsonian database fail to remove the feature.

This example shows that process information can be extracted by a data-analytic approach, which invites the question of why dome eruptions that last much more than 5 years tend to become very long-lived. A possible answer is that this is sufficiently long for conduits to become mature and stabilise so that heat loss to the walls is balanced or even exceeded by heat advection by magma flow with the longevity of the eruption being controlled by the dynamics of the chamber rather than by gradual freezing of the magma at shallower level. This is certainly not the only possibility; the point is that the data and its analysis provoke scientific enquiry.

*Explosion Sequence Time Series*

Seventy-five Vulcanian explosions occurred at the Soufrière Hills volcano between 22 September and 22 October 1997. The timings of this sequence were investigated by *Connor et al.* [2003]: on average, there was an explosion every 9.5 hours, but individual intervals varied from as short as 4 hours to as long as 33 hours. *Voight and Cornelius* [1991] had found that, in the run-up to an eruption, time series of volcanic data, such as Real Time Seismic Amplitude Measurement (RSAM) or deformation rate, could fit a Weibull distribution which, in the context of engineering reliability, is widely used to represent times-to-failure in materials. However, the Soufrière Hills explosion data did not fit this form of relationship (Figure 6a), suggesting that the physical controls on intervals between the events were not just an analogue of material mechanics in which strain rate increased with time until failure (explosion) was inevitable. A memory-less (Poisson) process also failed to reflect the data, indicating that the timing to the next explosion had some independence on previous explosions. Instead, *Connor et al.* [2003] found that the explosion interval data fitted a log-logistic statistical distribution extremely well.

They proposed the following dynamic equation as representing the causative processes:

$$t\frac{d\Omega}{dt} = k\Omega - \frac{k}{\Omega_{eq}}\Omega^2 \tag{1}$$

where t is the time since the last explosion, $\Omega$ is some state variable, k is a power-law exponent and $\Omega_{eq}$ is a characteristic value of $\Omega$ when the two right hand terms are equal. A log logistic survivor function that describes the statistical distribution of repose periods can then be defined [*Connor et al.,* 2003] which fits the observations within 99% confidence limits (Figure 6b). This kind of analysis illustrates that constraints or process information with relevance to hazards can be extracted from such an analysis; in other

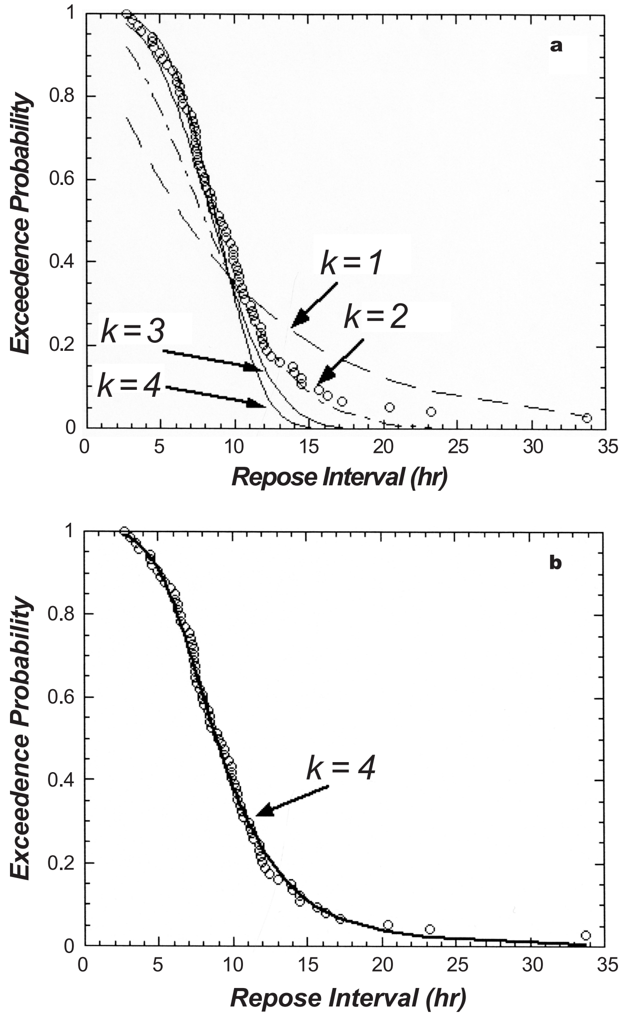


**Figure 6**. Statistics of intervals between Vulcanian explosions at the Soufrière Hills volcano, Montserrat in September and October 1997. (a) Comparison of the observed interval distribution (open circles) and calculated distributions using the Weibull model with a time constant of $\hat{\mu} = 9.6$ hours and various values of the power exponent k [after *Connor et al.,* 2003]. Using k = 4, estimated from experimental data, gives a good fit to the observed distribution at $t < \hat{\mu}$, but a poor fit at $t > \hat{\mu}$. The exponential (Poisson) model corresponds to k = 1, and does not fit the observed distribution. (b) The observed distribution of repose intervals are fit with > 99% confidence using a log-logistic survivor function with a time constant of $\hat{\mu} = 9.0$ hours (observed distribution median) and an exponent of k = 4 [after *Connor et al.,* 2003].

words, it throws light on the context of what is, otherwise, an abstract statistical model.

For the Montserrat case, the best-fit statistical model suggests that the stochastic dynamics of the system must have certain properties: equation (1) represents two competing processes acting on different time scales which, respectively, increase and decrease internal gas pressure. *Connor et al.* [2003] postulated that after an explosion, gas pressure increases by exsolution from magma, but gas escape by permeable flow through the magma reduces the gas pressure. At early stages, gas exsolution is dominant and gas pressure increases. Later, gas escape plays an increasingly important role and counteracts the exsolution-driven increase in gas pressure. This competing-processes model is consistent with current understanding of the mechanisms of repetitive explosive eruptions at Montserrat [*Voight et al.,* 1999; *Druitt et al.,* 2002a; *Melnik and Sparks,* 2002]. However, a full fluid dynamic model of magma ascent that incorporates all the complex interacting processes involved has not yet been developed. Indeed, a test for the viability of numerical models should be that their outputs mimic closely both the statistical and temporal properties of the natural data.

Such an approach has forecasting relevance, as proposed by *Voight and Cornelius* [1991]. Almost all statistical models can lead to some form of distributional ‘hazard function’ which, in this case, can be interpreted as the relative probability of an explosion at some definite time after a previous explosion. This probability is constant for a Poisson arrival process, asymptotic after some definite time for a Weibull distribution, but reaches a maximum before declining for a log-logistic model.

This type of analysis of a complex stochastic dynamic system, the analysis of large sample data, and the assessment of uncertainty in wider areas of public concern are somewhat outside the traditional realms of statistical inference [see, e.g., *Chatfield,* 2002], but constitute important propositions for advancing volcanology. As such, they need to be integrated into an overall strategy for modelling volcanic activity, hazards and risks.

## MODELLING STRATEGIES IN VOLCANOLOGY

Forecasting of complex volcanic phenomena involves a combination of empiricism, understanding (often at an intuitive level) of the underlying physical processes, and modelling. Monitoring data and observations provide the ingredients for the empirical approach in that patterns may be recognised and interpreted within a framework of physical theory or conceptual models. Monitoring data can also validate quantitative models to increase confidence in their output (although schemes that generate self-fulfilling prophecies must be avoided). However, models should be used with awareness of their limitations as well as their strengths.

The issue of quantifying uncertainty is becoming more prominent. Simplified (scenario-based) deterministic models are exceedingly useful for gaining a good first-order understanding of volcanic processes, but are likely to prove inadequate when it comes to providing models with utility for forecasting and prediction. Given the stochastic and nonlinear nature of many volcanic processes and the uncertainties (which can be large) in the controlling parameters, practical models are likely to follow the approaches now routinely adopted in other natural hazards forecasting, such as floods and extreme weather events. In meteorology, for instance, the integration of results from an array of prediction models, with explicit perturbations to model formulations, initial conditions and parameter probability distributions, generate an ensemble of outcomes that can be treated in a statistical manner and presented as a full probabilistic forecast [see, e.g., *Palmer,* 2000]. This is only just beginning to happen in volcanology. A major challenge is to ensure that such ensemble forecasting encompasses all the key factors involved in the natural processes. In particular, the existence of epistemic uncertainty has to be recognised and assimilated into the procedure, which will entail a suitable suite of alternative models being interrogated jointly. While, in practical terms, this would be a non-trivial undertaking, it would provide a proper rational basis for evaluating the value of such forecasts [*Palmer,* 2000].

In volcanology numerical modelling is becoming an important aspect of forecasting and risk assessment, and evolving approaches have largely focused on numerical simulations. Aided by increasing computer power as well as improving understanding of the physics involved, such models are becoming increasingly sophisticated [e.g. *Neri and Macedonio,* 1996; *Papale,* 1999; *Melnik and Sparks*, 1999]. A presumption is that such models will eventually simulate nature so well that they can be used for forecasting. These expectations may prove to be optimistic, not least because experience has demonstrated with climate modelling that, when uncertainties in such models are disaggregated and appraised individually, the spread of overall uncertainty increases [*Morgan and Keith,* 1995]. Here we discuss the limitations of modelling and consider complementary strategies, while recognizing that numerical models give important insights into volcanic processes.

Most computer modelling of natural phenomena has adopted a strategy of simplification to make matters tractable: those details that are thought to matter most are represented as accurately as possible, and other details, not considered important, are abridged or omitted. Knowing, however, which details matter most can be tricky: models are prone to be incomplete, sometimes leaving out details that could matter under certain conditions. Parametric or even structural uncertainties remain implicit, so that no matter how detailed the model that is created, complete confidence cannot be invested in its predictions about the behaviour of the real system.

Typically, numerical models for volcano dynamics involve several partial differential equations and equations of state that describe the system behaviour. The number of degrees of freedom in the system, and hence number of parameters needed to characterize it adequately, is typically large (commonly a few tens). To make the models computationally manageable and help interpret outputs, simplifications have to be made. For example, published models of pyroclastic flows only involve two particle sizes [*Neri and Macedonio,* 1996]. Certain features of volcanic flow systems are exceedingly computationally demanding: vesiculation processes in explosive eruptions may involve formation of $10^{15}$ bubbles per cubic metre. Keeping track of what every bubble and melt region does cannot be achieved without making major simplifications that may introduce artificial or unphysical features into the model. As computer codes become more complicated the chances of errors and numerical artifacts increase, and complex codes need substantiating. There may be a limit, however: *Oreskes et al.* [1994] assert that absolute validation is impossible for numerical models in the Earth Sciences.

When numerical models are compared to natural data the issue of uniqueness emerges. It is relatively easy for a skilled modeller to make a model with large numbers of parameters fit the data: the process is one of hindcasting, rather than forecasting. For example, *Barmin et al.* [2002] investigated a model of periodic behaviour of lava dome eruptions and were able to generate simulations similar to the activity of Mount St Helens and Santiaguito lava domes. Such models are very good for gaining insight into how Nature has behaved, but are not unique. There is also inevitably much empiricism in all such models; for example, in high-speed multiphase flows assumptions are made about turbulence based on empirical closure models that have yet to be confirmed in particle-gas mixtures.

It is thus difficult to envisage how deterministic models can be used successfully in forecasting. Interestingly, most of the models that have been developed so far as forecasting tools in volcanology are less physics-based and more overtly empirical, as exemplified by the tephra fall and pyroclastic flow run-out models used on Montserrat. One new direction for numerical models will be to incorporate the quantification of uncertainty. An obvious approach will be to assign uncertainties to every parameter and run ensemble models in which sample the uncertainties using Monte Carlo techniques and repeat calculations a large number of times.

On the topic of uncertainty, an emerging issue for numerical models is the difficult but critical difference between aleatory and epistemic uncertainty, and how to recognize it. Any system has aleatory uncertainty that is real and reflects truly random features like noise and time evolution of magma system properties. Unfortunately model parameters always involve a mixture of both kinds of uncertainty. A good example is conduit dimensions, which are critically important to conduit flow models because of the high powers of flow rate dependence on conduit shape (e.g the fourth power of diameter for a cylindrical conduit). Conduits are non-uniform in Nature and cannot be measured directly, so their shape and dimensions are inevitably poorly constrained with large epistemic uncertainty. Notwithstanding this, conduits are commonly assumed to have a fixed simple geometry (e.g. cylinders of constant diameter). In reality, conduit dimensions might have small aleatory uncertainty (*sensu stricto*), if they could be accessed, but they can evolve with time and be hard to define spatially if there are property gradients between the magma and the wall-rock. So it is unlikely that conduit models can ever be very accurate.

On top of that, many volcanic processes are also highly non-linear. Modelling research in simplified volcanic systems has identified multiple solutions, such that a system can jump suddenly from one state to another [*Jaupart and Allegré,* 1991; *Melnik and Sparks,* 1999; *Slezin,* 2002]. Where systems are close to thresholds for instability, technically known as cusps in catastrophe theory, they can become inherently unpredictable. Worryingly, complex numerical models are unlikely to capture this kind of behaviour easily because of the large epistemic uncertainties in some critical parameters.

Greater use of statistical models and methods should provide an alternative and complementary approach to multivariate, multiparameter forward numerical models. Here we have illustrated how statistical analyses can lead to insights into processes. Statistical models should be given considerable weight in hazards assessments as they are data-based, reflecting how the system actually behaves rather than how it might behave. Such models are effectively free of epistemic uncertainty, except with respect to the measurements themselves. This point has been made strongly by *Young et al.* [2002] in the context of modelling stochastic systems, in particular the climate.

We suggest that the future direction of modelling research for volcanology will involve combining statistical and numerical modeling techniques in a common strategy, with interplay between both. For example, a good test of the validity of a numerical model is that is can reproduce the statistical features of natural data.

## THE STATE OF A VOLCANIC PLANET

Over the coming century there are likely to be several major volcanic eruptions (defined as those exceeding 1 $km^3$), which will affect large numbers of people. With the increasing global population, the dramatic growth of megacities close to active volcanoes, and stresses related to rapid environmental change and globalisation, there is the potential for much larger and more serious volcanic crises and disasters than in the twentieth century. It is certainly plausible that the casualties in a large eruption near an area of dense population could greatly exceed the largest death toll of the last century (30,000 people at Mont Pelée), and might create sufficient destruction to imperil the economies of individual countries and perhaps even continental regions. Human beings are, without doubt, much more vulnerable to volcanic hazards as a consequence of rapid environmental change and globalisation. On the other hand, the advances in understanding of volcanic processes combined with the huge advances in science and technology mean that the scientific community is in a much better position to anticipate volcanic eruptions and, in some circumstances, predict their occurrence, estimate their impact and take steps to protect populations and mitigate the effects.

Many of the scientific tools for dealing with volcanic crises are already available and will continue to improve. The next few decades are bound to produce an increasing number of volcanoes that are adequately monitored. As computer power increases and cheap data storage moves from gigabytes to terabytes there will be huge improvements in the analysis of data from monitoring networks and in the modeling of volcanic processes. There are also likely to be major advances in technology (e.g. satellites, nanotechnology instruments and detectors), which will have significant impact on the ability to analyse signals and monitor volcanoes: remote measurements from space, in particular, offer great promise for enhancing operational forecast models [*Wadge,* 2003].

The approaches to hazards analysis and prediction are likely to move towards probabilistic assessments and, inevitably, to increased use of statistical models. In the latter case, numerical simulations of volcanic processes will be developed in ensemble style, incorporating elements of epistemic and aleatory uncertainty, with comparison of statistical properties of model outputs with real data. A transformation is taking place in the scientific expertise that will be needed to develop these vital quantitative forecasting and prediction tools, and much needs to be done to provide volcanologists with the appropriate knowledge and skills to meet the challenges.

Despite reasons for optimism only a small number of active volcanoes are adequately monitored, and many of these are volcanoes within the Developed World. Most of the world's active volcanoes and a large proportion of the 500 million people living close to volcanic threats are in less developed regions where such volcanoes are either not monitored at all or, at best, have only rudimentary observational or instrumental networks. The challenge is therefore to provide these regions with working access to the technological and scientific advances that can mitigate disaster and assist sustainable development.

*Acknowledgements.* RSJS acknowledges a Royal Society-Wolfson Award and support from research grants including the EC (MULTIMO EVG1-2000-00574) and NERC. WPA acknowledges a Benjamin Meaker Visiting Fellowship at IAS, Bristol, and support from EC projects MULTIMO EVG1-2000-00574 and EXPLORIS EVR1-CT-2002-40026. The authors acknowledge the tremendous help of staff of the Montserrat Volcano Observatory and many colleagues involved in the hazards and risk assessments on Montserrat. The authors thank Gordon Woo for stimulating discussions, and Colin Wilson, Chris Newhall and Chris Hawkesworth for careful and helpful reviews. Table 1 follows a suggestion from Colin Wilson.

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