Complexity and Extreme Events in Geosciences: An Overview

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Complexity and Extreme Events in Geosciences: An Overview

A. Surjalal Sharma,[1] Daniel N. Baker,[2] Archana Bhattacharyya,[3] Armin Bunde,[4] Vijay P. Dimri,[5] Harsh K. Gupta,[5] Vijay K. Gupta,[6] Shaun Lovejoy,[7] Ian G. Main,[8] Daniel Schertzer,[9] Hans von Storch,[10,11] and Nicholas W. Watkins[12,13,14]

Extreme events are an emergent property of many complex, nonlinear systems in which various interdependent components and their interaction lead to a competition between organized (interaction dominated) and irregular (fluctuation dominated) behavior. Recent advances in nonlinear dynamics and complexity science provide a new approach to the understanding and modeling of extreme events and natural hazards. The main connection of extreme events to nonlinear dynamics arises from the recognition that they are not isolable phenomena but must be understood in terms of interactions among different components, within and outside the specific system. A wide range of techniques and approaches of complexity science are directly relevant to geosciences, e.g., nonlinear modeling and prediction, state space reconstruction, statistical self-similarity and its dynamical origins, stochastic cascade models, fractals and multifractals, network theory, self-organized criticality, etc. The scaling of processes in geosciences has been one of the most active areas of studies and has the potential to provide better tools for risk assessment and analysis. Many studies of extreme events in geosciences are also contributing to the basic understanding of their inherent properties, e.g., maximum entropy production and criticality, space-time cascades, and fractional Lévy processes. The need for better data for extreme events is evident in the necessity for detailed statistical analysis, e.g., in marine storms, nonlinear correlations, etc. The Chapman Conference on Complexity and Extreme Events held (2010) in Hyderabad,

[1]Department of Astronomy, University of Maryland, College Park, Maryland, USA.

[2]Laboratory for Atmospheric and Space Physics, University of Colorado, Boulder, Colorado, USA.

[3]Indian Institute of Geomagnetism, Navi Mumbai, India.

[4]Institut für Theoretische Physik III, Justus-Liebig-Universität Giessen, Giessen, Germany.

[5]National Geophysical Research Institute, Hyderabad, India.

[6]Department of Civil, Environmental and Architectural Engineering and Cooperative Institute for Research in Environmental Science, Boulder, Colorado, USA.

[7]Department of Physics, McGill University, Montreal, Quebec, Canada.

[8]School of GeoScience, University of Edinburgh, Edinburgh, UK.

[9]LEESU, Ecole des Ponts ParisTech, Universite Paris-Est, Paris, France.

[10]Institute of Coastal Research, Helmholtz-Zentrum Geesthacht, Geesthacht, Germany.

[11]Meteorological Institute, University of Hamburg, Hamburg, Germany.

[12]British Antarctic Survey, Cambridge, UK.

[13]Centre for the Analysis of Time Series, London School of Economics and Political Science, London, UK.

[14]Centre for Fusion, Space and Astrophysics, University of Warwick, Coventry, UK.

India, was focused on the understanding of natural hazards mainly from the perspective of complexity science. The emerging theme from the conference was the recognition of complexity science as the interdisciplinary framework for the understanding of extreme events and natural hazards.

1. INTRODUCTION

Complexity refers to the behavior of systems with many interdependent components that lead to organized as well as irregular (irreducibly stochastic) features. In such systems the knowledge of the parts does not necessarily lead to the predictable behavior of the entire system. The coupling among the components is essentially nonlinear, and this leads to a rich variety of dynamical behavior, geometrical patterns, and statistical distributions that are seen in virtually all disciplines. In geosciences the studies of nonlinear dynamical process and complexity have been an active field of research for many decades [*Lovejoy et al.*, 2009]. The basic ideas underlying complexity science have now matured to the point that they are generating new approaches to addressing problems in many different disciplines, including geosciences. One such area is the nature of extreme events, in particular the natural hazards, whose connection to complexity arises from the recognition that they are not isolable phenomena but must be understood in terms of interactions among different components, inside and outside the specific system.

Extreme events are of both natural and anthropogenic origin and are of widespread concern mainly because of their damaging consequences [*Lubchenco and Karl*, 2012]. Although there is no single definition, at least in the physical sciences, of extreme events [*Bunde et al.*, 2002; *Jentsch et al.*, 2006; *Moffat and Shuckburgh*, 2011], there *is* a significant, widely accepted body of work [*Coles*, 2001], since that of *Fisher and Tippett* [1928], which informs much statistical practice and goes by the name of extreme value theory. In science and applications, however, the practical interpretation of the degree of "extremeness" often mixes the statistical attributes of infrequent occurrence and low probability, the physics- or prediction-related property of being unexpected, and the societal or economic aspect of strong impact, etc. In general, it is not so clear that extreme events can be characterized or "marked" by only one or even a few measures. However, it is, nonetheless, clear that extreme events are typically rare, and in the distribution of events of all magnitudes they are identified as those outside the bulk; that is, they occur in the tail of the distribution. A main objective in the analysis of extreme events thus relates directly to the understanding of the distribution functions of the events, in particular the values in the tail. Even when a single probability distribution suffices to capture a system's amplitude

variation, however, we may still distinguish at least two scenarios. One is the case where the distribution is relatively "short tailed" in its fluctuations, the model for this being the Gaussian. In this framework, extreme events really are rare and, in the Gaussian example, will only very rarely exceed three standard deviations from the mean. Conversely, if the underlying distribution is actually heavy tailed, with examples being the power law, lognormal, and stretched exponential families, the mean will be a much less adequate characterization of the expected behavior, and we will see effects like the 80–20 rule of thumb from actuarial science, where 80% of losses come from only 20% of claims [e.g., *Embrechts et al.*, 1997].

Another feature of extreme events is that they occur suddenly, often without clear warning, and on large spatial scales compared to the system size. Such long-range order, i.e., the value of a physical variable at an arbitrary point is correlated with its value at a point located far away, is also a property of thermodynamic phase transitions. In the case of second-order phase transitions the correlation length reaches the system size, giving rise to arbitrarily large extreme events at the critical point because of the competition between random fluctuations and cooperative dynamical interactions. This leads to the recognition that long-range correlations are important indicators of the emergence of extreme events. In view of these features the dynamical and statistical approaches of complexity science provide a natural framework for the study of extreme events [*Sharma et al.*, 2010]. An aspect of correlation of particular importance to extremes, and not always recognized, is that while a low probability of occurrence must indeed imply that such an event will be, on average, rare, the correlations in time between extreme events can mean that several such "black swan" tail events may still follow each other in close succession (dubbed "bunched black swans" by *Watkins et al.* [2011]). The recurrence time distribution is not simply prescribed by the frequency distribution, a point which becomes progressively more significant as temporal correlations become longer ranged.

A widely known property of many natural phenomena is the dynamical instability of nonlinear systems, which leads to limits of predictability because of sensitivity to the initial conditions, even for systems with few degrees of freedom. This behavior in deterministic systems such as the Lorenz equations [*Lorenz*, 1963] is a key dynamical origin for irregularity in nature and is now known as *chaos*. The Lorenz

attractor, perhaps the best known case, has contributed immensely to the understanding of dynamical systems studies but has weaker ties to atmospheric circulation, of which it is a model. Such dynamical systems, known as strange attractors, also have the interesting geometrical property of being a fractal with self-similar characteristics. This property introduced by *Mandelbrot* [1967] arose from its preponderance in nature.

For systems with many degrees of freedom, thermodynamics or information theory can often be used to provide significant constraints on the dynamics of a population. In a thermodynamic system at equilibrium a formal entropy can be defined as a conjugate variable to temperature, and the scaling properties can be determined by maximizing the Boltzmann-Gibbs entropy subject to known constraints. Near-equilibrium states can also be modeled using this approach, if the rate of entropy production (by an irreversible process) is constrained to be a minimum, and provides an explanation for spontaneous self-organization in space and time for many open chemical and physical systems (an idea dating back to *Prigogine* [1945]). For such irreversible systems it is actually difficult to define or interpret the meaning of a macroscopic entropy in a rigorous way. As a consequence such systems are often analyzed using the more general concept of information theory [*Shannon*, 1948]. Here we also maximize an entropy-like function (with no Boltzmann pre-factor), also subject to constraints, and determine the maximum expectation value of the log (probability) of states [*Jaynes*, 1957]. In this formulation a power law distribution of event sizes may result physically from the geometric degeneracy of the system's energy states, with an exponent constrained by a geometric mean of the energy (see, e.g., *Main and Burton* [1984] for the case of earthquake populations).

For some systems, under certain constraints, the maximum entropy solution is also one of maximum entropy production [*Dewar*, 2003; *Martyushev and Seleznev*, 2006]. For example, the longitudinal temperature profile of the Earth is close to that predicted by a state of maximum entropy production [*Paltridge*, 2005]. Physically this state provides a mechanism for maintaining the atmosphere in a permanent state of balance between stable laminar flow and turbulence at intermediate Rayleigh number over long time scales.

Tsallis [1995] has proposed an alternate explanation for the common observation of power law statistics in complex systems, based on a nonextensive generalization of the Boltzmann-Gibbs entropy. The main disadvantages of this approach are that simple constraints such as system energy per se cannot be applied and there is no direct connection to information theory because the Tsallis entropy is not additive for independent sources of uncertainty.

The interplay of dynamics, geometry, and information and their effects on the scaling properties of the population and the predictability of individual events is an important feature of complexity science in general and in the studies of extreme events in particular. This chapter is an overview of recent advances in the understanding of extreme events in the natural world, in particular those made through the use of nonlinear dynamics, statistical physics, and related approaches. The topics covered include the recent studies of earthquakes, river flows, and climate variations, which have demonstrated long-range dependences (clustering) in the appearance of extreme events. These have important practical implications for climate change, natural hazard forecasting, and risk management. Frequency-magnitude statistics of many natural hazards follow power laws, exhibiting features of complex behavior, but robust power law statistics for a population often occur hand in hand with restricted predictability of individual events. This poses significant challenges in developing and communicating operationally useful forecasts of such events. The interdisciplinary nature of the research leads naturally to strong connections with a wide range of applications. Here we focus on the relationship between the science underlying the behavior of a complex system and the emergence of intermittent, perhaps clustered, extreme events, and identify approaches that may lead to significant advances in understanding in future.

2. NONLINEAR DYNAMICS, COMPLEXITY, AND EXTREME EVENTS

The complex behavior in deterministic systems with a few degrees of freedom, such as the Lorenz attractor, led to models of low-dimensional chaos for dynamical systems. In mathematical terms such systems are represented by a small number of first-order ordinary differential equations. These were complemented by approaches that include more complex spatiotemporal dynamics, namely, in the form of partial differential equations such as Ginzburg-Landau and Kuramoto-Sivashinsky equations. While these models were successful in representing many laboratory systems, they faced many difficulties in describing large-scale open natural systems. The next advance came from the recognition of the nonlinear coupling and the dissipative nature of many dynamical systems, responsible for the contraction of phase space. These two properties underlie the elucidation of strange attractors as the hallmark of chaotic dynamics, leading to many new developments in the dynamical systems theory. One application of dynamical systems with a few degrees of freedom to understanding of the Hurst effect is given by *Mesa et al.* [this volume]. Another set of applications require the assumption of an effectively low-dimensional nature of large-scale systems and of the applicability

of the "embedding theorem," thus enabling the reconstruction of dynamical models from time series data. The converse assumption, of high dimensionality, has been termed "stochastic chaos" and is the assumption used in multifractal and other stochastic approaches [see, e.g., *Lovejoy and Schertzer*, this volume]. The use of low dimensionality as a paradigm has stimulated many new approaches to the study of seemingly complicated behavior in many natural systems, including in geosciences. In the studies of the dynamics of the geospace environment this approach provided the first predictive models of geomagnetic activity, enabled by the extensive data from ground-based and spaceborne instruments reviewed by *Sharma* [1995].

Various studies reveal that many of the Earth's processes show fractal statistics, where the relevant distributions follow power laws with noninteger ("fractal") exponents. Fractal structures that show self-similarity and are governed by a noninteger dimension are ubiquitous in geosciences. For example, they occur in the frequency size statistics of events and in the behavior of various physical properties such as density, susceptibility, electrical resistivity, and thermal conductivity. Nonlinearity and nonuniqueness are nearly always encountered in the inverse problem in geophysical exploration, including the components of data acquisition, processing, and not least interpretation (often by expert elicitation). Fractal dimension plays a vital role in the design of survey networks with proper sampling and gridding [*Dimri*, 1998; *Srivastava et al.*, 2007]. The interpretation of geophysical data such as gravity and magnetic data has shown good results assuming a fractal distribution of sources. Theoretical relation between fractal sources and their geophysical response has been used to derive source parameters [*Maus and Dimri*, 1994]. The fractal theory has led to the development of a wide variety of physical models of seismogenesis including nonlinear dynamics that can be used to characterize the seismicity pattern of a region [*Kagan and Knopoff*, 1980; *Sunmonu and Dimri*, 2000]. Similarly, the "coda" or tail of a seismogram can be modeled well with a fractal distribution of scatterers that emerge in a growing fracture population [*Vlastos et al.*, 2007].

The late Per Bak and colleagues sought to explain the widespread appearance of spatial fractals and temporal "$1/f$" noise by proposing a new class of avalanche-like models [*Bak et al.*, 1987] that exhibited fractally structured growing instabilities ("avalanches"), obeying heavy-tailed (algebraic) and thus extreme probability distributions. In fact, Bak most tersely expressed his intent a little later (with K. Chen [*Bak and Chen*, 1989, p. 5]) in the memorably short abstract: "Fractals in nature originate from self-organized critical dynamical processes." These self-organized critical (SOC) processes not only have extremes but also entire structures determined by them. There are now many models of self-organized criticality and significant developments toward an analytical theory. The applications of the SOC paradigm range from geosciences (including earthquakes, forest fires, solar activity, and rainfall) to the financial markets, while the renewed emphasis on the heavy tails generated by SOC processes has had a direct influence on modern network science and its applications. Although generally the SOC approach does not provide dynamical predictions, it describes the statistical features and thus yields the probabilities of events. For example, SOC provides a single unifying theory for much of what had previously been separate empirical observations of earthquake phenomena [*Main*, 1996]. While this provides a useful basis for seismic hazard calculation based on the population [*Main*, 1995], the proximity to criticality and the inherent stochastic element inevitably degrades any predictive power for *individual* events (see http://www.nature.com/nature/debates/earthquake/equake_frameset.html) [*Kagan*, 2006]. Similarly, in those (common) cases where the dynamics act over large ranges of scale, multifractal processes provide an interesting paradigm for extremes. In these cascade type processes the variability at any given resolution (i.e., the process averaged at the given scale) is precisely the consequence of the wide scale range of the dynamics. This includes not only the range from the largest scale to the resolution scale, but somewhat surprisingly, it also depends on the smaller scales whose variability is not completely "smoothed out" and which leads to extreme variability in the form of "fat-tailed" (power law) probability distributions. Since they involve both fractal structures and power law distributions, multifractal processes thus provide a "nonclassical" route to SOC.

More generally, the advances in the studies of complexity in many areas of geosciences have led to new predictive and diagnostic approaches that exploit how patterns, processes, and probabilities are mutually coupled. For example, nonlinear dynamics and complexity can be exploited to reduce forecast error, to understand atmospheric flow transitions, to test climate models by analyzing their atmospheric variability [*Govindan et al.*, 2002; *Vyushin et al.*, 2004; *Rybski et al.*, 2008], and to explain atmospheric and oceanic teleconnections [*Tsonis*, this volume]. The nonlinear aspects of the climate can regulate El Niño's background state, while the related approaches to data analysis, which are becoming increasingly popular, can be used to check the consistency of general circulation models in the representation of fundamental statistical properties of the atmosphere. In other areas of geosciences the role of nonlinear dynamics and complexity in complex landscape patterns of Earth's surface and hydrologic processes are well recognized, as presented in this volume.

Recent advances in the studies of extreme events from the viewpoint of nonlinear dynamics and complexity have demonstrated the existence and role of long-term memory in many complex systems [*Bunde et al.*, 2005; *Sharma and Veeramani*, 2011; *Mesa et al.*, this volume]. For example, when the memory can be described by a linear autocorrelation function that decays algebraically with an exponent γ, then the probability density function of the return intervals between events above some threshold no longer show the exponential decay typical for uncorrelated data but a stretched exponential decay characterized by the same exponent γ as the autocorrelation function [*Bunde et al.*, 2005]. Also, the return intervals themselves are long-term correlated, again characterized by the same exponent. This approach provides a new way to understand the clustering of extreme events. When the linear correlations vanish, and long-term memory exists only in the form of nonlinear correlations, such as the volatility bunching seen in finance [e.g., *Mantegna and Stanley*, 2000], the effect becomes even stronger, and both the probability distribution functions of the return intervals and their autocorrelation function decay as a power law [*Bogachev et al.*, 2007].

When considering complexity in the atmosphere and ocean, and to some extent space plasmas (especially when modeled using magnetohydrodynamics), we must recall the strong historical and theoretical links with the field of fully developed turbulence, in particular the classical turbulence laws associated with the pioneers L. F. Richardson, A. N. Kolmogorov, A. Obukhov, S. Corrsin, and R. Bolgiano. These classical laws were proposed as emergent laws in the field of sufficiently strong hydrodynamic turbulence where "developed turbulence as a new macroscopic state of matter" [*Manneville*, 2010] appears at high Reynolds number (*Re*). This new state has been considered as a form of matter with properties that cannot simply be reduced to, or simply deduced from, the governing Navier-Stokes equations. Although fluid (and plasma) geosystems certainly differ from incompressible hydrodynamics in several important respects, we may, nevertheless, expect higher-level laws to emerge and that they will share at least some of the features of fully developed turbulence.

In the atmosphere, key obstacles to applying classical turbulence are the strong anisotropy (especially stratification) and intermittency. However, over the years, new types of models and new symmetry principles have been developed in order to generalize the classical laws so as to handle these issues. For weather the key generalizations are from isotropic to anisotropic notions of scale and from smooth, quasi-Gaussian variability to strong, cascade-generated multifractal intermittency. *Lovejoy and Schertzer* [this volume, and references therein] argue that this leads to a model of atmospheric and oceanic dynamics as a system of coupled aniso-tropic cascade processes. They go on to indicate how the same approach can be extended to much longer (climate) time scales.

Extreme events in the Earth's near-space environment are driven by the solar wind, which brings the energetic plasma and fields from the solar eruptive events such as coronal mass ejections (CME) to geospace. Forecasting of space weather is an active field of research, and recently many new techniques and approaches have been developed. The nonlinear dynamical approach to space weather forecasting played a pioneering role by showing the predictability of space weather. Research in this area is now quite advanced and has provided techniques for dynamical and statistical forecasting [*Ukhorskiy et al.*, 2004]. Many extreme space weather events in the recent past have caused serious damage to technological systems such as satellites, power transmission, etc. [*National Research Council (NRC)*, 2008]. Although these events may not seem devastating by themselves, a confluence of natural hazards in the different regions of the Earth's environment can make our society and its technological systems highly vulnerable because of the interconnectedness [*Baker and Allen*, 2000]. In this aspect the nonlinear dynamical framework for the study of the clustering of events, described above, becomes directly relevant to the extended Earth and space system. The studies of these extreme events in nature are summarized in the following sections.

3. EARTH SCIENCES: EARTHQUAKES AND LANDSCAPE DYNAMICS

One aspect of near-critical dynamics anticipated by *Bak et al.* [1987] and others is that earthquakes can also occur or be induced in the interior of the plates not just at the boundaries. For example, the Bhuj earthquake (M_w 7.7) of 26 January 2001 is recognized to be the deadliest among the recorded intraplate earthquakes [*Gupta et al.*, 2001], and many aspects, including its recurrence time, have been studied extensively. This earthquake has attracted further interest as an analog for the New Madrid earthquakes (M_w 7.5–8.0) that struck the central United states almost two centuries ago [*Ellis et al.*, 2001]. From the standpoint of extreme event studies the recurrence time of such earthquakes is of key interest. In this case the recurrence time is estimated to be ~1500 years. The bounds on recurrence times are naturally limited by the available data, and this estimate suffers from the lack of sufficient data. However, this also highlights the need for integrating the different types of available data with the models to develop better estimates for key features such as the recurrence times, aftershock distributions, etc. The studies of more than 500 aftershocks ($M > 2.0$) of the Bhuj earthquake using the data of 3-D velocity, gravity, magnetic,

GPS, and satellite observations have shown its features such as rupture propagation along two trends in India [*Kayal and Mukhopadhyay*, 2006]. The studies of the postseismic deformation of this earthquake [*Rastogi et al.*, this volume], focused on the changes in the seismicity of the Gujarat region in space and time, have identified the Kachchh and the Saurastra regions as more vulnerable, consistent with the observed increase in seismicity. They modeled the postseismic stress changes due to the earthquake and interpreted the deformation in these regions due to the migration of the stress pulse via viscoelastic process in lower crust and upper mantle resulting from the 20 MPa stress drop of the 2001 Bhuj earthquake.

The Koyna Dam located in western India is the most outstanding example of reservoir-triggered seismicity (RTS) where triggered earthquakes have been occurring since the impoundment in 1962 in a restricted area of 20×30 km^2. These include the largest RTS earthquake of M 6.3 on 10 December 1967, 22 earthquakes of $M > 5$, and about 200 $M \sim$ 4 earthquakes [*Narain and Gupta*, 1968; *Gupta*, 2002]. The maximum credible earthquake estimated for the Koyna region is M 6.8, and it is reasonable to infer that the Koyna region was stressed close to critical before the relatively small perturbation to the stress field on impoundment of the reservoir. The impoundment could serve only as a trigger, leading to many small events as well as the extreme, as well as fluctuations in the subsurface pore fluid pressure. So far about 60% of the energy of an M 6.8 earthquake has been released, and the rest of the energy could be released over the next 3 to 4 decades [*Gupta et al.*, 2002]. The occurrence of $M > 5$ earthquakes is governed by factors like the rate of loading, highest water levels reached, duration of retention of the high water levels, and whether the previous water maxima has been exceeded or not (Kaiser effect). In a very exciting development a borehole to probe the physical state and mechanical behavior of the Koyna fault parameters at the hypocentral depths of 7 km is under advanced stages of planning [*Gupta et al.*, 2011]. Downhole measurements complemented by observations on cores and cuttings, analyses of fluids and gas samples, and geological and geophysical characterization studies would help answer questions related to the genesis of stable continental region earthquakes in general with a special emphasis on RTS.

If Earth's brittle lithosphere is in a state of self-organized criticality, as implied by these and other observations, that, in turn, begs the question of how the system evolved to such a marginally stable, far-from-equilibrium, stationary state in the first place. Using the information theoretic approach outlined above, *Dewar* [2003] showed that the most likely (maximum entropy) state for such systems was one where the entropy production rate was also a maximum. This is not a general conclusion (maximum entropy production is not a principle as such, though it is often referred to as one) and depends on key assumptions being met for specific systems, for example, that there exists a single, stable, attractor steady state solution. *Main and Naylor* [2008, 2010] tested the hypothesis of maximum entropy production (MEP) on synthetic earthquake populations generated by a dissipative cellular automaton model. By tuning the dissipation (entropy production), MEP occurs when the global elastic strain is near critical, with small relative fluctuations in macroscopic strain energy expressed by a low seismic efficiency and broad-bandwidth power law scaling of frequency and rupture area. These phenomena, all as observed in natural earthquake populations, are hallmarks of the broad conceptual definition of SOC, though the MEP state is near but strictly subcritical. In the MEP state the strain field retains some memory of past events, expressed as coherent "domains," implying a degree of predictability, albeit strongly limited in practice by the proximity to criticality and our inability to map the natural stress field at an equivalent resolution to the numerical model. The resulting theoretical and practical limitations have led to the debate on earthquake predictability moving on to what can be done (or not) with the data in real time, in a low-probability, high-impact forecasting environment, and what the consequences might be for operational forecasting, including quantifying the consistency, quality, and utility of any forecast and issues of communication between scientists, the relevant authorities, and the general public in an uncertain, complex, and nonlinear world [*Jordan et al.*, 2011].

4. ATMOSPHERIC AND OCEAN SCIENCES

Obviously, it is difficult to accurately define what an extreme event in atmospheric, oceanic, hydrologic, cryospheric, or others disciplinary contexts of the Earth system are. When "climate" is defined as the statistics of atmospheric, oceanic, cryospheric, and hydrologic states and "climate change" is defined as the change of these statistics, this helps, but when enlarging the time scales, other components add to this system [cf. *van Andel*, 1994]. However, the difficulty of defining extreme events is largely a consequence of the subjective nature of this usual yet vague definition of climate. When the weather and the climate are objectively defined in terms of their type of scaling variability [e.g., *Lovejoy and Schertzer*, this volume], then precise definitions of extremes are indeed possible. *Lovejoy and Schertzer* [this volume] argue that an objective scaling approach is needed to clarify the key distinction, occulted in the usual approaches, between low-frequency weather and the climate and that this is a prerequisite for objective definitions of climate states and climate change.

For the time being, we refer to extremes in the present context mostly to short-term events, which extend over a few hours, maybe a few days, but hardly more than a few months. Some of them are caused by mechanisms, which are considered mostly external to the climate system, namely, earthquakes or landslides, which may accompany tsunamis and other catastrophic events. Others are due to the internal dynamics of mainly the oceanic and atmospheric systems, such as extreme rainfall events associated with river flooding, but not all flooding is associated with extreme rainfall because of the role of river networks in aggregating flows as explained in section 5. Marine storms, such as tropical or midlatitude cyclones cause havoc not only because they are associated with rainfall but because of related storm surges and coastal inundations [*von Storch and Woth*, 2008]. Such events go along with massive societal losses, in particular with loss of life sometimes of the order of 100,000 lives and more, the last time in 2006 when tropical storm Nargis struck the coast of Myanmar [*Fritz et al.*, 2009]. Other important examples are the Sumatra-Andaman M_w 9.2 earthquake of 26 December 2004 and the resultant tsunami that claimed over 250,000 human lives in south and southeast Asian countries and caused immense financial losses [*Dimri and Srivastava*, 2007; *Gupta*, 2008; *Swaroopa Rani et al.*, 2011] and the Tohoku, Japan, M_w 9.0 earthquake of 11 March 2011 and the resultant tsunami that caused nuclear accidents [*Lay and Kanamori*, 2011]. The Japan earthquake has given rise to a global debate on the anticipated maximum size of an earthquake in a given region and the safety of nuclear power plants in the coastal region. As a matter of fact, in the first 11 years of the 21st century the number of human lives lost because of earthquakes has exceeded the total number of human lives lost in the entire 20th century because of earthquakes.

To what extent such extreme events really go along with catastrophes with societal losses depends very much on the vulnerability of the society and of the degree of adaptation. Thus, a tropical cyclone may cause much more damage when hitting the coast of the United States than when the same storm hits the coast of Cuba.

Since climate is presently changing, and will likely continue to do so as a response to ever increasing greenhouse gas concentrations in the atmosphere (also the characteristics of some extreme events are changing and will change in future), the state of knowledge has been assessed recently in the 2011 report of the *Intergovernmental Panel on Climate Change* (*IPCC*) [2011]. For the present change the *IPCC* [2011, p. 7] asserts

> There is evidence that some extremes have changed as a result of anthropogenic influences, including increases in atmospheric concentrations of greenhouse gases. It is likely that anthropogenic influences have led to warming of extreme daily minimum and maximum temperatures on the global scale. There is medium confidence that anthropogenic influences have contributed to intensification of extreme precipitation on the global scale. It is likely that there has been an anthropogenic influence on increasing extreme coastal high water due to increase in mean sea level. The uncertainties in the historical tropical cyclone records, the incomplete understanding of the physical mechanisms linking tropical cyclone metrics to climate change and the degree of tropical cyclone variability provide only low confidence for the attribution of any detectable changes in tropical cyclone activity to anthropogenic influences.

For the future, the *IPCC* [2011, pp. 10, 11, 12] finds the following changes "likely": ". . . frequency of heavy precipitation or the proportion of total rainfall from heavy falls will increase in the 21st century over many areas of the globe"; "Average tropical cyclone maximum wind speed is . . . to increase, although increases may not occur in all ocean basins. . . . the global frequency of tropical cyclones will either decrease or remain essentially unchanged"; and "It is very likely that mean sea level rise will contribute to upward trends in extreme coastal high water levels in the future."

Although the usual approach to assessing possible anthropogenic climate change is to use numerical models, this can also be done by first understanding the natural variability and then developing statistical tests to assess the probability of any observed changes occurring naturally. This approach is discussed in detail by *Lennartz and Bunde* [this volume]. By providing probability information as a function of space-time scales, scaling approaches to atmospheric variability thus provide a different, complementary path to studying anthropogenic effects. *Pielke et al.* [2009, p. 413] give evidence in support of the hypothesis that

> Although the natural causes of climate variations and changes are undoubtedly important, the human influences are significant and involve a diverse range of first-order climate forcings, including, but not limited to, the human input of carbon dioxide. Most, if not all, of these human influences on regional and global climate will continue to be of concern during the coming decades.

When dealing with the issue of real-time warning and prediction as well as the issue of determining present statistics and possible future changes of these statistics, mostly dynamical models are applied: models of the form $\Delta Y/\Delta t = \Sigma$ processes, where some processes are explicitly described by first principles such as mass conservation and others (such as boundary layer turbulence) are parameterized; that is, their net effect on the resolved scales and parameters is semiempirically closed [cf. *Müller and von Storch*, 2004]. Such models usually exhibit chaotic behavior, so that the predictability is limited often to only a few days (e.g., in case of the extratropical atmosphere) or even hours (convective rainfall). However, this chaotic feature does not inhibit the model from skillfully representing the statistics of the system

properly, as well as their dependence on certain external factors; the best example represents the annual cycle, as a response to solar radiation. Thus, contemporary climate models can simulate thousands of years, exhibiting a realistic chaotic behavior and realistic long-term memory [cf. *Rybski et al.*, 2008]. (For a broader discussion about models, their specifics and their role in a societal context, refer to *von Storch et al.* [2011].) At present, there is a discussion if the low-frequency variability of global circulation models is too low or not compared with paleodata [*Lovejoy and Schertzer*, this volume, Figures 1a and 1b].

The model simulations include the formation of extreme events, for instance, mesoscale marine storms, such as polar lows in the Atlantic [*Zahn and von Storch*, 2010] or medicanes (rare hurricane-like small storms in Mediterranean Sea) [*Cavicchia and von Storch*, 2012]. Their formation is realistic in terms of numbers, across-scales link to large-scale conditions, and dynamical features; they allow the derivation of scenarios of future conditions associated with elevated greenhouse gas concentrations in the atmosphere.

On the longer time scales, there is an emerging realization that abrupt and prevalent temperature variability with significant impacts has recurred in the past when the Earth system was forced beyond threshold, although scaling approaches suggest that they could be the result of internal variability mechanisms repeating scale after scale over wide ranges (e.g., cascades and multifractals). The emerging evidence supports the recognition that Earth's climate has characteristics of a critical phenomenon and also is sensitive to small changes in solar output on the centennial time scale. Quasi-cyclic manifestations of "critical forcing parameter" like solar cycles appear in the spectra because of their imprint at the time of major changes.

The reconstructed proxy record of temperature variability decoded from tree rings provides suitable data for the study of abrupt changes in temperature. The study by *Tiwari et al.* [this volume] is based on the spectra of empirical orthogonal functions of a newly reconstructed tree ring temperature variability record decoded from the western Himalaya for the period spanning 1227–2000 A.D., addressing the frequency resolution of interdecadal and interannual oscillatory modes. The spectral analysis of first principal component (PC1) with about 61.46% variance reveals the dominance of some significant solar cycles notably peaking around 81, 32, 22, and 8–14 years. This analysis in the light of the recent ocean-atmospheric model results suggests that even small variation in solar output in conjunction with atmospheric-ocean system and other related feedback processes could have caused abrupt temperature variability at the time of "criticality" through the triggering mechanism. Identification of different natural frequency modes from a complex noisy temperature record is essential for a better understanding of the climate response to internal/external forcing.

5. HYDROLOGIC SCIENCE: FLOODS AND DROUGHTS

The *NRC* [1991] classified hydrologic science as a distinct geoscience. The importance of the global water cycle and its nonlinear interactions with the natural Earth system and the engineered Earth system was instrumental in devoting an entire chapter to nonlinearity in the *NRC* [1991] volume titled "Hydrology and Applied Mathematics." The *NRC* [2012] has revisited the challenges and opportunities. Our focus here is on hydrologic extremes that include high-frequency flood events and low-frequency drought events. Analyses of paleo-hydrologic and paleoclimate time series for understanding droughts have a long history in hydrology that dates back to the classic work of *Hurst* [1951]. Indeed, the "Hurst effect" has become quite well known in the nonlinear science literature [*Feder*, 1988], and Hurst's scaling approach has since been greatly generalized by *Mandelbrot* [1999] and others into a multifractal approach with the implications for the extremes mentioned above, including power law tails on the rain rate and river flow distributions [e.g., *Bunde et al.*, this volume]. *Mesa et al.* [this volume] give a brief overview of the pertinent literature from hydrologic science, climate science, and dynamical systems theory. Simulations from the Daisyworld model with and without the hydrologic cycle as a simple climate model reveal complex nonstationary behavior that inhibits consistent interpretation of the Hurst exponent using three well-known estimation methods. Challenging problems for future investigations are suggested that offer a broad context for nonlinear geophysics in understanding droughts.

Accurate estimates of the magnitude and frequency of floods are needed for the design of water-use and water-control projects, for floodplain definition and management, and for the design of transportation infrastructure such as bridges and roads. These practical engineering needs have led to the development of regional flood frequency analysis that *Dawdy et al.* [2012] have summarized. For example, *Fuller* [1914] analyzed peak flows from around the world, but particularly from the United States, and observed that the mean of the maximum annual flood can be related to the drainage area as a power law with an exponent of 0.8. Similar empirical relationships have since been employed to relate discharge to drainage basin characteristics.

Unfortunately, the accuracy of flood quantile estimates is constrained by the data available at a stream gauging site: record lengths are often limited to 100 years and are typically less than 30 years. To overcome these limitations, numerous

statistical methods to estimate flood quantiles have been developed through the years. Furthermore, quantile estimates are often needed for ungauged sites at which no historical stream flow data are available. The challenging problem of prediction in ungauged basins (PUB) led to an international decadal initiative [*Sivapalan et al.*, 2003].

Global warming, and other human influences like large-scale deforestation in the Amazon River basin, is changing the global and regional water cycle and the climate system. Owing to strong nonlinear coupling between climate and the water cycle, future floods are not expected to be statistically similar to the past [*Milly et al.*, 2002; *Dawdy*, 2007]. As a result, estimates of flood quantiles using historic data would be biased. Can the results in the regional flood frequency analyses be understood in terms of physical mechanisms producing floods? This is a key question. A geophysical understanding of regional flood frequencies is anchored in spatial power law statistics or scaling as summarized below.

How the scaling behavior in the quantiles of annual peak discharge arises and how the slopes and intercepts can be predicted from physical processes require understanding of scaling relations in individual rainfall-runoff events. Experimental research along this line was initiated in the small 21 km^2 Goodwin Creek experimental watershed in Mississippi [*Ogden and Dawdy*, 2003]. Event scaling was a major shift in focus from the study of regional annual flood statistics that is well established in the literature. *Ogden and Dawdy* [2003] first observed scaling relations in peak discharges for 226 individual rainfall-runoff events that spanned hourly to daily time scales and found that the scaling slopes and intercepts vary from one event to another. The mean of 226 event slopes (0.82) was close to the common slope of mean annual and 20 year return peak discharges (0.77), which suggested that it should be possible to predict scaling in annual flood frequencies from event scaling.

Key results in the last 20 years have established the theoretical and observational foundations for developing a nonlinear geophysical theory or the scaling theory of floods in river basins. It has the explicit goal of linking the statistics of space-time rainfall input and the physics of flood-generating processes and self-similar branching patterns of drainage networks with spatial power law statistical relations between floods and drainage areas across multiple scales of space and time. A substantial literature in the last 30 years has developed around stochastic point process models and multifractal approaches to space-time rainfall intensities. *Gupta et al.* [2007] reviewed the developments in the scaling flood theory. Published results have shown that the spatial power law statistical relations emerge asymptotically from conservation equations of mass and momentum in self-similar (self-affine) channel networks as drainage area goes to infinity. These

results have led to a key hypothesis that the physical basis of power laws in floods has its origin in the self-similarity (self-affinity) of channel networks. Self-similarity is also the basis for the widely observed fractal structure and Horton relations in river networks [*Rodriguez-Iturbe and Rinaldo*, 1997; *Gupta et al.*, 2007; *McConnell and Gupta*, 2008]. Observed power laws in floods range from hours and days of individual flood events to an annual time scale of flood frequencies. They serve as the foundation for developing a new diagnostic framework to test different assumptions governing multiscale spatiotemporal variability in physical processes that arise in predicting power law statistical relations between floods and drainage areas [*Gupta et al.*, 2010].

Important new developments are taking place toward generalizing the scaling theory of floods to medium and large basins involving annual flood frequencies. For example, *Poveda et al.* [2007] discovered a link between mean annual runoff that is estimated from annual water balance and annual flood scaling statistics. Their study included many large river basins in Colombia that have varying hydrology and climates ranging from arid to humid. *Lima and Lall* [2010] found scaling in annual flood quantiles in large basins of Brazil (~800,000 km^2). They developed a Bayesian approach to estimate scaling parameters on interannual time scales. Generalizations to large basins have important relevance to flood prediction under climate change [*Milly et al.*, 2002]. Future work requires an understanding of how scaling slopes and intercepts in annual flood quantiles are modified in a changing climate, which can serve as a basis for making future flood predictions. All these developments and many others not given here have made a substantial contribution to solving the PUB problem [*Sivapalan et al.*, 2003].

6. SPACE WEATHER: SOLAR ACTIVITY, MAGNETOSPHERE, IONOSPHERE, AND SOCIETAL IMPACTS

Extreme events in space weather occur during periods when the magnetosphere is strongly driven by the solar wind, bringing energetic plasma and fields from the solar eruptive events such as coronal mass ejections to geospace. Many extreme space weather events have caused serious damage to technological systems such as satellites, power transmission systems, etc. Some well-known examples are the collapse of the Hydro Quebec power grid during the great geomagnetic storm of March 1989, the Canadian telecommunication satellite outage during a period of enhanced energetic electron fluxes at geosynchronous orbit in January 1994, the electrical breakdowns and satellite malfunctions during the magnetic cloud event of July 2000 (Bastille Day event), the disabling of

GPS-based aviation system during the severe space weather events of October–November 2003 (Halloween storms), the disturbances in commercial airline traffic during several days of enhanced geomagnetic activity in January 2005, etc. [*NRC*, 2008]. Although these events may not seem devastating by themselves, a confluence of natural hazards in the different regions of the environment of the Earth can make our society and its technological systems highly vulnerable because of their interconnectedness [*Baker and Allen*, 2000; *NRC*, 2008]. In this aspect the nonlinear dynamical approach, with its ability to integrate many interacting components, becomes a natural framework for the study of the extreme events in the extended Earth and space system.

The modeling of space weather events relies strongly on the availability of good geospace data, and among the most widely used data are the geomagnetic indices. Geomagnetic field data from ground magnetometer stations around the globe have been recorded for more than one and half centuries, and these data have been used to compute the geomagnetic indices. Among the many indices the auroral electrojet indices (*AE*, *AL*, and *AU*) characterize the substorms, and the ring current index *Dst* represents the geomagnetic or space storms. The substorms, with a characteristic time of ~1 hour, are episodic in nature and are the essential elements of magnetospheric dynamics. The auroral electrojet indices provide the detailed dynamical features of the global aspects of substorms. On the other hand, the geomagnetic storms, with a typical time scale of ~10 hours, are the more global space weather disturbances during which intense substorms occur. The auroral electrojet indices computed from the horizontal component of the magnetic field disturbances reflect the strengths of the large-scale ionospheric currents driven by the reconfiguration of the magnetosphere during substorms. They are highly variable during strongly disturbed periods, with peak values of 1000–2000 nT during extreme events cited earlier.

The substorms with *AL* index values less than −1000 nT are considered strong disturbances and can be characterized as extreme events. The geomagnetic storms with *Dst* values less than −100 nT are referred to as intense storms. The substorms occur during the storms, and their episodic nature and high variability are evident in the sharp peaks of the electrojet indices. As is the case with extreme events in general, there is no single measure of the extreme events in space weather. For example, the *Dst* index for the well-known "Carrington" storm of 1–2 September 1859 is estimated to have reached a value of −1760 nT [*Tsurutani et al.*, 2003], and its effects were felt across the globe. The more recent Bastille Day event of 14–16 July 2000 with a *Dst* minimum of −300 nT was an extreme space weather event that led to significant damage to satellites and other techno-

logical infrastructure. It should be emphasized here that the main objective in the studies of extreme events is the nature of their distribution.

From observed solar-terrestrial dynamics and detailed studies of the complexity of the magnetospheric system, many studies (see reviews of *Sharma* [1995], *Klimas et al.* [1996], *Vassiliadis* [2006], and *Baker* [2012, this volume]) have shown evidence that the solar wind–magnetosphere-ionosphere realm clearly is characterized by nonlinear dynamics. It is argued that methods borrowed from other branches of physics, chemistry, and engineering can offer useful, if imperfect, analogies on how to deal with nonlinearity in the Sun-Earth system. Ultimately, space weather prediction probably must depart from idealized local "stability" analyses of various plasma domains to consider true global system responses and must incorporate realistic, nonlinear aspects. Forecasting of space weather using data-based nonlinear dynamical models of solar wind–magnetosphere coupling [*Vassiliadis et al.*, 1995; *Valdivia et al.*, 1996; *Ukhorskiy et al.*, 2004; *Chen and Sharma*, 2006] would be useful not only at high latitudes where geomagnetically induced currents pose a risk to power transmission grids but also at equatorial and low latitudes where the development of irregular structure in the ionosphere can cause degradation and even disruption in the operation of satellite-based communication and navigation systems such as the GPS. A disturbance dynamo set up by enhanced currents in the auroral ionosphere during magnetic substorms can after a few hours give rise to conditions in the equatorial ionosphere that are conducive for the development of such irregular structure [*Bhattacharyya*, this volume].

In the light of such understandings, there is strong motivation to go away from the usual plasma physics techniques to consider more aggressive and comprehensive approaches. It may be that the magnetotail has a distributed set of interacting control agents, some of which are local plasma conditions and some of which are remote in the ionosphere or solar wind. Thus, it may appear that instabilities are spontaneous or seemingly random. We need to use new analysis tools to address such issues. Incorporating both traditional forecasting methods for solar storms and also using the array of methods embodied in the most modern tools of nonlinear dynamics offers the best hope for dealing with extreme space weather events [*Sharma and Veeramani*, 2011; *Baker*, this volume].

The vision of a space weather forecasting plan begins with understanding what is, in effect, space "climate." It is known that the Sun undergoes an approximately 11 year cycle of increasing and then decreasing sunspot activity. Some solar cycles have been relatively weak, while others in the historical record have been very strong [*Baker*, this volume]. The

stronger maxima tend to have more episodes of strong solar flares, intense outbursts of ultraviolet light, and (perhaps) greater chances of solar particle "superstorms." Conversely, weaker maxima may exhibit fewer of these extreme characteristics. However, even these general patterns of behavior are not absolute. Some of the largest historical events, for example, occurred during a relatively weak sunspot maximum period [see *Baker*, this volume]. On even shorter temporal scales it is known that forecasting space weather events will require continuous and effective observations of the Sun and its corona. Being able to observe the initiation of a powerful solar flare and detecting an earthward bound CME at its early stages gives society the best chance of predicting a powerful geomagnetic storm. Such CME observations can provide perhaps 18 hour (or longer) alerts that a solar-induced geomagnetic storm is imminent.

By using models developed in the research community and driving such models with space-based and ground-based solar observations, the natural hazard community has moved an important step closer to providing tens of hours warning of impending geomagnetic storms. Both ground-based and space-based observations of the Sun can be fed into highly capable models to forecast solar wind conditions near Earth. In the magnetosphere-ionosphere system, models of the complete, coupled geospace system can be used to provide forecasts ranging from tens of minutes to several days. The present hazard response plan still has a long way to go to achieve the levels of accuracy and reliability that are desired by the U.S. industrial, military, and commercial sectors. Moreover, knowing with accuracy the near-Earth solar and solar wind drivers of space weather still demands further understanding of the nonlinear responses of the geospace system that are described here [*Baker*, this volume]. The complex feedbacks within the solar wind–magnetosphere-ionosphere system may ultimately limit our ability to predict the size, duration, and precise location of magnetospheric current systems that can wreak havoc on human technologies, but we must understand these better to avert severe consequences for humans.

7. OVERARCHING ISSUES: INTERDISCIPLINARY APPROACH, DATA, AND LARGE-SCALE SIMULATIONS

As we have seen above, at least three research threads have all made significant contributions to fundamental complexity science and to the geosciences over the last 40 or more years. One thread has been the use of low-dimensional deterministic models, particularly chaotic ones, based on ordinary differential equations or maps [*Lorenz*, 1963; *May*, 1976]. This has been accompanied by data analysis methods such as

the recovery of attractors by embedding and has led to many applications [*Abarbanel et al.*, 1993; *Kantz and Schrieber*, 1999]. In space weather this approach has provided the earliest predictive models and is now the basis for near-real-time forecasting. The irregular behavior of geomagnetic activity, however, cannot be described entirely by complexity in low-dimensional dynamics, and there are strong multi-scale features that exhibit long-range behavior.

A second thread, described as stochastic chaos above, has involved the use of additive stochastic models that can exhibit heavy tails and/or long-range dependence. Described as H self-similar by applied mathematicians, these models include Mandelbrot's Lévy (alpha stable) motion for heavy tails, his fractional Brownian motion for long-range dependence, and his subsequent fractional hyperbolic model of 1969 that combined both effects. Here H is a single self-similarity exponent, which is the same as the more familiar Hurst exponent in the absence of heavy tails [e.g., *Mercik et al.*, 2003]. Related models like autoregressive fractionally integrated moving average, which are not completely self-similar but do show long-range dependence, have been extensively studied in applied statistics [e.g., *Beran*, 1994]. A third thread has developed from the recognition that the "wild" variability seen in some natural systems, particularly features such as nonlinear correlation in amplitudes that gives rise to observed "volatility bunching," can be modeled by multiplicative cascade multifractal models rather than additive monofractal ones. These generalize the single scaling exponent to a continuous spectrum of exponents.

Clearly, exactly what sort of extremes a given natural system exhibits may reflect the extent to which the above descriptions apply to it, as, for example, discussed in the contribution by *Watkins et al.* [this volume], where the implications of monofractal and multifractal models of integrated extreme "bursts" above a threshold are compared. Focusing on the burst problem, we note that several interdisciplinary stochastic approaches exist that provide quantitative information about extreme bursts. Some are more focused on the probability of single large events, while others are more concerned with extended dwell times above a given spatio-temporal threshold. As mentioned above, a statistical extreme value theory is available. In addition, there is a mathematical theory of record breaking [*Nevzorov*, 2001]; while image processing and fluid dynamics contribute the idea of level sets, stochastic processes offer sojourn times [*Berman*, 1992]; and as noted above, complexity science has contributed models of "avalanches" in the space-time activity of nonequilibrium systems, where the term "avalanche" refers here to a cascading, spatiotemporal, coherent energy release event. It can be seen that even without historical and disciplinary factors, it would be completely natural for

knowledge relevant to a given burst problem to be siloed and so not yet be "joined up." In practice, the choice of approach has also differed between and within application domains, sometimes reflecting the data's own limitations and also reflecting the differing cultures and assumptions of theoretical physics, complexity science, the geosciences, applied stochastic modeling, and statistical inference. Although such knowledge is not yet integrated, particularly for Earth and sciences applications, nonetheless, significant efforts have started along this direction.

The rise of complexity science in geophysics has given currency to the expression "emergent" for higher-level laws, i.e., properties that cannot be predicted easily from the elementary interactions. For example, processes which appear complicated at one scale often produce emergent laws in a suitable limit at a higher scale that are relatively simple. A great deal of complexity science has so far been precisely the elaboration of various nonlinear models or, even paradigms, which allow one to reduce "complexity" to "simplicity" in this way. In many, even most, geophysical cases, these nonlinear models capture a good deal of the phenomenology and physics of processes that had hitherto been impervious to realistic modeling. It is particularly true for cases where ubiquitous assumptions of homogeneity and linearity had reigned. For example, the prototypical example of self-organized criticality, the classical sandpile model, has been widely applied across the geosciences including studies of the atmosphere where cascades can generate a "nonclassical" SOC. By generically describing some phenomena that are so extreme that even their mean behaviors are determined by avalanche-like events, it is frequently the only type of model that is even remotely realistic, e.g., earthquakes and forest fires.

The space-time variability of physical processes on multiple scales is common to many disciplines of geosciences. But this feature presents a huge scientific challenge in developing physically based models. Let us briefly explain this cross-cutting and overarching issue. The first challenge is suitable parameterizations of processes at "appropriate scales" that are required in specifying the coupled conservation equations of mass, momentum, energy, etc. Typically, observations are not available at the scales of interest, which require statistical parameterizations. For example, the coupled conservation equations underlying the scaling theory of floods [*Gupta et al.*, 2010] need how much rainfall becomes runoff involving surface and subsurface processes in each hillslope (~0.05 km^2) of a river basin. But each basin has a large number of hillslopes. For example, a basin of area A has 20A hillslopes, so a 100 km^2 "small basin" has about 2000 hillslopes. There is no known measurement technology that can be used to measure runoff in each hillslope even for a single experimental basin in the world, because runoff varies both in space and time among hillslopes. Furthermore, no known theory is available that can be used to parameterize runoff from hillslopes, so new theories are needed to solve this problem. As new and diverse approaches are developed from different fields of geosciences, a major issue for future conferences and workshops would be to identify if parameterization models have some features in common that can apply across disciplines.

In taking stock, it is clear that complexity science has been most effective in quantifying the dynamical features and scaling laws of spatiotemporal data of various types and in providing an explanation for such data in a unified framework, sometimes when there is no competing theory. It has helped us solve the puzzle of why such scaling laws in a population of events can be robust, while at the same time leading in many cases to pessimism (some would say realism) on the potential for the predictability of the timing of individual extreme events. Principles of self-organization have been shown to have a thermodynamic explanation in terms of entropy production (minimum for a near-equilibrium, linear system, leading to Euclidean geometry, or maximum for a far-from-equilibrium nonlinear one, leading to fractal geometry), though this may not be universal for all systems and is a subject of much debate. Scaling laws are extremely useful in quantifying hazard and risk in an operational sense, but much needs to be done to quantify the uncertainties in forecasting future risk based on a limited sample of past extreme events [*Main et al.*, 2008].

8. CONCLUSION

The long-term dependencies in geophysical systems and their implications for catastrophic extreme events have direct applications to other areas such as life sciences. The elucidation of long-range (scaling) dependencies can be used in forecasting extreme events [*Bunde et al.*, this volume]. Indeed, over the last 30 years, work on general scaling processes has shown that the extremes are precisely the consequence of variability that builds up scale after scale over huge ranges.

An important aspect of extreme events research is the extensive demands for computational resources. Enhanced computational resources have led to investigations of complexity in a wide range of Earth and space systems, and this cyber-enabled discovery will lead to more complex but reliable forward models. The ensemble of model results can then yield statistical properties that reflect the uncertainties and their propagation, providing the scaling behaviors with respect to the external forcing parameters. These statistical approaches are essential for characterizing extreme events accurately or their uncertainties realistically if this is not possible.

The different geoscience disciplines have many important problems that need to be studied using approaches beyond those commonly used within the specific discipline. The underlying features of many of these problems arise from the nonlinear nature, and complexity science provides a framework for studying the seemingly unconnected phenomena. This has been evident from the progress made in the Earth and space sciences based on the understanding of nonlinear dynamics, chaos, fractals, multifractals, scaling, etc.

Currently, the first principle or theoretical models are limited in providing predictable models of extreme events. Among the many reasons for this is the disparate space and time scales associated with extreme events. A promising approach is the data-driven modeling in which the inherent features of the many phenomena contributing to an extreme event can be used together, independent of a priori assumptions, to build an integrative model. We are also entering a new age of data-intensive research, where key information can be extracted and new objects and patterns identified from very large, continuously recorded data sets, a process known as "data assimilation" [*Hey et al.*, 2009]. It remains to be seen whether predictive power can be improved by such models or such improved short-term databases and methods of assimilation, but this can only be done by applying rigorous tests that reflect the epistemic (model dependent) and aleatoric (statistical) uncertainties involved.

REFERENCES

Abarbanel, H. D. I., R. Brown, J. J. Sidorowich, and L. S. Tsimiring (1993), The analysis of observed chaotic data in physical systems, *Rev. Mod. Phys.*, *65*, 1331–1392.

Bak, P., and K. Chen (1989), The physics of fractals, *Physica D*, *38*, 5–12.

Bak, P., C. Tang, and K. Wiesenfeld (1987), Self-organized criticality: An explanation of 1/*f* noise, *Phys. Rev. Lett.*, *59*, 381–384.

Baker, D. N. (2012), Extreme space weather: Forecasting behavior of a nonlinear dynamical system, in *Complexity and Extreme Events in Geoscience*, *Geophys. Monogr. Ser.*, doi:10.1029/2011GM001075, this volume.

Baker, D. N., and J. H. Allen (2000), Confluence of natural hazards: A possible scenario, *Eos Trans. AGU*, *81*(23), 254.

Beran, J. (1994), *Statistics for Long-Memory Processes*, Chapman and Hall, New York.

Berman, S. (1992), *Sojourns and Extremes of Stochastic Processes*, Chapman and Hall, New York.

Bhattacharyya, A. (2012), Development of intermediate-scale structure in the nighttime equatorial ionosphere, in *Complexity and Extreme Events in Geoscience*, *Geophys. Monogr. Ser.*, doi:10.1029/2011GM001078, this volume.

Bogachev, M. I., J. F. Eichner, and A. Bunde (2007), Effect of nonlinear correlations on the statistics of return intervals in multifractal data sets, *Phys. Rev. Lett.*, *99*, 240601, doi:10.1103/PhysRevLett.99.240601.

Bunde, A., J. Kropp, and H. J. Schellnhuber (2002), *The Science of Disasters*, Springer, Berlin.

Bunde, A., J. F. Eichner, J. W. Kantelhardt, and S. Havlin (2005), Long-term memory: A natural mechanism for the clustering of extreme events and anomalous residual times in climate records, *Phys. Rev. Lett.*, *94*, 048701, doi:10.1103/PhysRevLett.94.048701.

Bunde, A., M. I. Bogachev, and S. Lennartz (2012), Precipitation and river flow: Long-term memory and predictability of extreme events, in *Complexity and Extreme Events in Geoscience*, *Geophys. Monogr. Ser.*, doi:10.1029/2011GM001112, this volume.

Cavicchia, L., and H. von Storch (2012), The simulation of medicanes in a high-resolution regional climate model, *Clim. Dyn.*, doi:10.1007/s00382-011-1220-0, in press.

Chen, J., and A. S. Sharma (2006), Modeling and prediction of the magnetospheric dynamics during intense geospace storms, *J. Geophys. Res.*, *111*, A04209, doi:10.1029/2005JA011359.

Coles, S. (2001), *An Introduction to Statistical Modeling of Extreme Values*, Springer, New York.

Dawdy, D. (2007), Prediction versus understanding, *J. Hydrol. Eng.*, *12*(1), 1–3.

Dawdy, D. R., V. W. Griffis, and V. K. Gupta (2012), Regional flood frequency analysis: How we got here and where we are going, *J. Hydrol. Eng.*, in press.

Dewar, R. (2003), Information theory explanation of the fluctuation theorem, maximum entropy production and self-organized criticality in non-equilibrium stationary states, *J. Phys. A Math. Gen.*, *36*, 631–641, doi:10.1088/0305-4470/36/3/303.

Dimri, V. P. (1998), Fractal behavior and detectibility limits of geophysical surveys, *Geophysics*, *63*, 1943–1947.

Dimri, V. P., and K. Srivastava (2007), Tsunami propagation of the 2004 Sumatra earthquake and the fractal analysis of the aftershock activity, *Indian J. Mar. Sci.*, *36*(2), 128–135.

Ellis, M., J. Gomberg, and E. Schweig (2001), Indian earthquake may serve as analog for New Madrid earthquakes, *Eos Trans. AGU*, *82*(32), 345.

Embrechts, P. M., C. Kluppelberg, and T. Mikosch (1997), *Modelling Extremal Events for Insurance and Finance*, Springer, Berlin.

Feder, J. (1988), *Fractals*, Plenum, New York.

Fisher, R. A., and L. H. C. Tippett (1928), Limiting forms of the frequency distribution of the largest or smallest member of a sample, *Proc. Cambridge Philos. Soc.*, *24*, 180–190.

Fritz, H. M., C. D. Blount, S. Thwin, M. K. Thu, and N. Chan (2009), Cyclone Nargis storm surge in Myanmar, *Nat. Geosci.*, *2*, 448–449, doi:10.1038/ngeo558.

Fuller, W. E. (1914), Flood flows, *Trans. Am. Soc. Civ. Eng.*, *77*, 567–617.

Govindan, R. B., D. Vjushin, A. Bunde, S. Brenner, S. Havlin, and H.-J. Schellnhuber (2002), Global climate models violate scaling

of the observed atmospheric variability, *Phys. Rev. Lett.*, *89*, 028501, doi:10.1103/PhysRevLett.89.028501.

Gupta, H. K. (2002), A review of recent studies of triggered earthquakes by artificial water reservoirs with special emphasis on earthquakes in Koyna, India, *Earth Sci. Rev.*, *58*, 279–310.

Gupta, H. K. (2008), India's initiative in mitigating tsunami and storm surge hazard, *J. Earthquake Tsunami*, *2*(4), 287–295.

Gupta, H. K., N. P. Rao, B. K. Rastogi, and D. Sarkar (2001), The deadliest intraplate earthquake, *Science*, *291*, 2101–2102.

Gupta, H. K., P. Mandal, and B. K. Rastogi (2002), How long will triggered earthquakes at Koyna, India, continue?, *Curr. Sci.*, *82*, 202–210.

Gupta, H. K., S. Nayak, and Y. J. Bhaskar Rao (2011), Planning a deep drilling project in the Koyna region of India, *Eos Trans. AGU*, *92*(34), 283.

Gupta, V. K., B. Troutman, and D. R. Dawdy (2007), Towards a nonlinear geophysical theory of floods in river networks: An overview of 20 years of progress, in *Nonlinear Dynamics in Geosciences*, edited by A. A. Tsonis and J. B. Elsner, chap. 8, pp.121–151, Springer, New York.

Gupta, V. K., R. Mantilla, B. M. Troutman, D. Dawdy, and W. F. Krajewski (2010), Generalizing a nonlinear geophysical flood theory to medium-sized river networks, *Geophys. Res. Lett.*, *37*, L11402, doi:10.1029/2009GL041540.

Hey, A. J. G., S. Tansley, and K. Tolle (Eds.) (2009), *The Fourth Paradigm: Data-Intensive Scientific Discovery*, 286 pp., Microsoft Res., Redmond, Wash.

Hurst, H. (1951), Long term storage capacity of reservoirs, *Trans. Am. Soc. Civ. Eng.*, *116*, 776–808.

Intergovernmental Panel on Climate Change (IPCC) (2011), Summary for policymakers, in *Intergovernmental Panel on Climate Change Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*, edited by C. B. Field et al., pp. 1–19, Cambridge Univ. Press, New York.

Jaynes, E. T. (1957), Information theory and statistical mechanics, *Phys. Rev.*, *106*, 620–630.

Jentsch, V., H. Kantz, and S. Albeverio (2006), Extreme events: Magic, mysteries, and challenges, in *Extreme Events in Nature and Society*, edited by S. Albeverio, V. Jentsch, and H. Kantz, pp. 1–18, Springer, Berlin.

Jordan, T., Y. Chen, P. Gasparini, R. Madariaga, I. Main, W. Marzocchi, G. Papadopoulos, G. Sobolev, K. Yamaoka, and J. Zschau (2011), Operational earthquake forecasting: State of knowledge and guidelines for utilization, *Ann. Geophys.*, *54*(4), 361–391, doi:10.4401/ag-5350.

Kagan, Y. Y. (2006), Why does theoretical physics fail to explain and predict earthquake occurrence?, in *Modeling Critical and Catastrophic Phenomena in Geoscience: A Statistical Approach*, edited by P. Bhattacharyya and B. K. Chakrabarti, *Lect. Notes Phys.*, *705*, 303–359.

Kagan, Y. Y., and L. Knopoff (1980) Spatial distribution of earthquakes: The two-point correlation function, *Geophys. J. R. Astron. Soc.*, *62*(2), 303–320, doi:10.1111/j.1365-246X.1980.tb04857.x.

Kantz, H., and T. Schrieber (1999), *Nonlinear Time Series Analysis*, Cambridge Univ. Press, Cambridge, U. K.

Kayal, J. R., and S. Mukhopadhyay (2006), Seismotectonics of the 2001 Bhuj earthquake (*Mw* 7.7) in western India: Constraints from aftershocks, *J. Ind. Geophys. Union*, *10*, 45–57.

Klimas, A. J., D. Vassiliadis, D. N. Baker, and D. A. Roberts (1996), The organized nonlinear dynamics of the magnetosphere, *J. Geophys. Res.*, *101*(A6), 13,089–13,113.

Lay, T., and H. Kanamori (2011), Insights from the great 2011 Japan earthquake, *Phys. Today*, *64*, 33–39, http://dx.doi.org/10.1063/PT.3.1361.

Lennartz, S., and A. Bunde (2012), On the estimation of natural and anthropogenic trends in climate records, in *Complexity and Extreme Events in Geoscience*, *Geophys. Monogr. Ser.*, doi:10.1029/2011GM001079, this volume.

Lima, C. H. R., and U. Lall (2010), Spatial scaling in a changing climate: A hierarchical Bayesian model for nonstationary multisite annual maximum and monthly streamflow, *J. Hydrol.*, *383* (3–4), 307–318, doi:10.1016/j.jhydrol.

Lorenz, E. N. (1963), Deterministic nonperiodic flow, *J. Atmos. Sci.*, *20*, 130–141.

Lovejoy, S., and D. Schertzer (2012), Low-frequency weather and the emergence of the climate, in *Complexity and Extreme Events in Geoscience*, *Geophys. Monogr. Ser.*, doi:10.1029/2011GM001087, this volume.

Lovejoy, S., et al. (2009), Nonlinear geophysics: Why we need it, *Eos Trans. AGU*, *90*(48), 455.

Lubchenco, J., and T. R. Karl (2012), Predicting and managing extreme weather events, *Phys. Today*, *65*, 31–36, http://dx.doi.org/10.1063/PT.3.1475.

Main, I. G. (1995), Earthquakes as critical phenomena: Implications for probabilistic seismic hazard analysis, *Bull. Seismol. Soc. Am.*, *85*, 1299–1308.

Main, I. (1996), Statistical physics, seismogenesis, and seismic hazard, *Rev. Geophys.*, *34*, 433–462.

Main, I. G., and P. W. Burton (1984), Information theory and the earthquake frequency-magnitude distribution, *Bull. Seismol. Soc. Am.*, *74*, 1409–1426.

Main, I. G., and M. Naylor (2008), Maximum entropy production and earthquake dynamics, *Geophys. Res. Lett.*, *35*, L19311, doi:10.1029/2008GL035590.

Main, I. G., and M. Naylor (2010), Entropy production and self-organized (sub) criticality in earthquake dynamics, *Philos. Trans. R. Soc. A*, *368*, 131–144, doi:10.1098/rsta.2009.0206.

Main, I. G., L. Li, J. McCloskey, and M. Naylor (2008), Effect of the Sumatran mega-earthquake on the global magnitude cut-off and event rate, *Nat. Geosci.*, *1*, 142, doi:10.1038/ngeo141.

Mandelbrot, B. B. (1967), How long is the coast of Britain? Statistical self-similarity and fractional dimension, *Science*, *155*, 636–638.

Mandelbrot, B. B. (1999), *Multifractals and 1/f Noise: Wild Self-Affinity in Physics (1963-1976): Selecta Volume N*, Springer, New York.

Manneville, P. (2010), *Instabilities, Chaos and Turbulence*, 2nd ed., Imperial College Press, London.

Mantegna, R. N., and H. E. Stanley (2000), *Econophysics*, Cambridge Univ. Press, Cambridge, U. K.

Martyushev, L. M., and V. D. Seleznev (2006), Maximum entropy production principle in physics, chemistry and biology, *Phys. Rep.*, *426*, 1–45.

Maus, S., and V. P. Dimri (1994), Scaling properties of potential fields due to scaling sources, *Geophys. Res. Lett.*, *21*, 891–894.

May, R. M. (1976), Simple mathematical models with very complicated dynamics, *Nature*, *261*, 459–467.

McConnell, M., and V. Gupta (2008), A proof of the Horton law of stream numbers for the Tokunaga model of river networks, *Fractals*, *16*(3), 227–233.

Mercik, S., K. Weron, K. Burnecki, and A. Weron (2003), Enigma of self-similarity of fractional Levy stable motions, *Acta Phys. Pol. B.*, *34*(7), 3773–3791.

Mesa, O. J., V. K. Gupta, and P. E. O'Connell (2012), Dynamical system exploration of the Hurst phenomenon in simple climate models, in *Complexity and Extreme Events in Geoscience*, *Geophys. Monogr. Ser.*, doi:10.1029/2011GM001081, this volume.

Milly, P. C. D., R. T. Wetherald, K. A. Dunne, and T. L. Delworth (2002), Increasing risk of great floods in a changing climate, *Nature*, *415*, 514–517.

Moffat, H. K., and E. Shuckburgh (Eds.) (2011), *Environmental Hazards: The Fluid Dynamics and Geophysics of Extreme Events*, World Sci., Singapore.

Müller, P., and H. von Storch (2004), *Computer Modelling in Atmospheric and OceanicSciences: Building Knowledge*, 304 pp., Springer, New York.

Narain, H., and H. Gupta (1968), Koyna earthquake, *Nature*, *217*, 1138–1139.

National Research Council (NRC) (1991), *Opportunities in the Hydrologic Sciences*, Natl. Acad. Press, Washington, D. C.

National Research Council (NRC) (2008), *Severe Space Weather Events: Understanding Societal and Economic Impacts: A Workshop Report*, Natl. Acad. Press, Washington, D. C.

National Research Council (NRC (2012), *Challenges and Opportunities in the Hydrologic Sciences*, Natl. Acad. Press, Washington, D. C.

Nevzorov, V. B. (2001), *Records: Mathematical Theory*, Am. Math. Soc., Providence, R. I.

Ogden, F. L., and D. R. Dawdy (2003), Peak discharge scaling in a small Hortonian watershed, *J. Hydrol. Eng.*, *8*(2), 64–73.

Paltridge, G. W. (2005), Stumbling into the MEP racket: An historical perspective, in *Non-equilibrium Thermodynamics and the Production of Entropy: Life, Earth, and Beyond*, edited by A. Kleidon and R. D. Lorenz, chap. 3, pp. 33–40, Springer, New York.

Pielke, R., et al. (2009), Climate change: The need to consider human forcings besides greenhouse gases, *Eos Trans. AGU*, *90*(45), 413, doi:10.1029/2009EO450008.

Poveda, G., et al. (2007), Linking long-term water balances and statistical scaling to estimate river flows along the drainage network of Colombia, *J. Hydrol. Eng.*, *12*, 4–13.

Prigogine, I. (1945), Modération et transformations irreversibles des systemes ouverts, *Bull. Cl. Sci. Acad. R. Belg.*, *31*, 600–606.

Rastogi, B. K., P. Choudhury, R. Dumka, K. M. Sreejith, and T. J. Majumdar (2012), Stress pulse migration by viscoelastic process for long-distance delayed triggering of shocks in Gujarat, India, after the 2001 M_w 7.7 Bhuj earthquake, in *Complexity and Extreme Events in Geoscience*, *Geophys. Monogr. Ser.*, doi:10.1029/2011GM001061, this volume.

Rodriguez-Iturbe, I., and A. Rinaldo (1997), *Fractal River Basins*, Cambridge Univ. Press, Cambridge, U. K.

Rybski, D., A. Bunde, and H. von Storch (2008), Long-term memory in 1000-year simulated temperature records, *J. Geophys. Res.*, *113*, D02106, doi:10.1029/2007JD008568.

Shannon, C. E. (1948), A mathematical theory of communication, *Bell Syst. Tech. J.*, *27*, 379–423, 623–656.

Sharma, A. S. (1995), Assessing the magnetosphere's nonlinear behavior: Its dimension is low, its predictability high, *U.S. Natl. Rep. Int. Union Geod. Geophys. 1991–1994, Rev. Geophys.*, *33*, 645–650.

Sharma, A. S., and T. Veeramani (2011), Extreme events and long-range correlations in space weather, *Nonlinear Processes Geophys.*, *18*, 719–725, doi:10.5194/npg-18-719-2011.

Sharma, A. S., D. N. Baker, V. P. Dimri, and A. Bunde (2010), Complexity and extreme events: Interdisciplinary science of natural hazards, *Eos Trans. AGU*, *91*(30), 265.

Sivapalan, M., et al. (2003), IAHS decade on predictions in ungauged basins (PUB), 2003-2012: Shaping an exciting future for the hydrologic sciences, *Hydrol. Sci. J.*, *48*, 857–880.

Srivastava, R. P., N. Vedanti, and V. P. Dimri (2007), Optimum design of a gravity survey network and its application to delineate the Jabera-Damoh structure in the Vindhyan Basin, central India, *Pure Appl. Geophys.*, *164*, 1–14.

Sunmonu, L. A., and V. P. Dimri (2000), Fractal geometry of faults and seismicity of Koyna-Warna region west India using Landsat images, *Pure Appl. Geophys.*, *157*, 1393–1405.

Swaroopa Rani, V., K. Srivastava, and V. P. Dimri (2011), Tsunami propagation and inundation due to tsunamigenic earthquakes in the Sumatra-Andaman subduction zone: Impact at Vishakhapatnam, *Mar. Geod.*, *34*, 48–58, doi:10.1080/01490411.2011.547802.

Tiwari, R. K., R. R. Yadav, and K. P. C. Kaladhar Rao (2012), Empirical orthogonal function spectra of extreme temperature variability decoded from tree rings of the western Himalayas, in *Complexity and Extreme Events in Geoscience*, *Geophys. Monogr. Ser.*, doi:10.1029/2011GM001133, this volume.

Tsallis, C. (1995) Some comments on Boltzmann-Gibbs statistical mechanics, *Chaos Solitons Fractals*, *6*, 539–559.

Tsonis, A. A. (2012), Climate subsystems: Pacemakers of decadal climate variability, in *Complexity and Extreme Events in Geoscience*, *Geophys. Monogr. Ser.*, doi:10.1029/2011GM001053, this volume.

Tsurutani, B. T., W. D. Gonzalez, G. S. Lakhina, and S. Alex (2003), The extreme magnetic storm of 1–2 September 1859, *J. Geophys. Res.*, *108*(A7), 1268, doi:10.1029/2002JA009504.

Ukhorskiy, A. Y., M. I. Sitnov, A. S. Sharma, and K. Papadopoulos (2004), Global and multi-scale features of solar wind-magnetosphere coupling: From modeling to forecasting, *Geophys. Res. Lett.*, *31*, L08802, doi:10.1029/2003GL018932.

Valdivia, J. A., A. S. Sharma, and K. Papadopoulos (1996), Prediction of magnetic storms by nonlinear models, *Geophys. Res. Lett.*, *23*, 2899–2902.

van Andel, T. H. (1994), *New Views on an Old Planet: A History of Global Change*, 2nd ed., 439 pp., Cambridge Univ. Press, Cambridge, U. K.

Vassiliadis, D. (2006), Systems theory for geospace plasma dynamics, *Rev. Geophys.*, *44*, RG2002, doi:10.1029/2004RG000161.

Vassiliadis, D., A. J. Klimas, D. N. Baker, and D. A. Roberts (1995), A description of solar wind-magnetosphere coupling based on nonlinear filters, *J. Geophys. Res.*, *100*(A3), 3495–3512.

Vlastos, S., E. Liu, I. G. Main, and C. Narteau (2007), Numerical simulation of wave propagation in 2-D fractured media: Scattering attenuation at different stages of the growth of a fracture population, *Geophys. J. Int.*, *171*, 865–880.

von Storch, H., and K. Woth (2008), Storm surges, perspectives and options, *Sustainability Sci.*, *3*, 33–44, doi:10.1007/s11625-008-0044-2.

von Storch, H., A. Bunde, and N. Stehr (2011), The physical sciences and climate politics, in *The Oxford Handbook of Climate Change and Society*, edited by J. S. Dyzek, D. Schlosberg, and R. B. Norgaard, pp. 113–128, Oxford Univ. Press, Oxford, U. K.

Vyushin, D., I. Zhidkov, S. Havlin, A. Bunde, and S. Brenner (2004), Volcanic forcing improves Atmosphere-Ocean Coupled General Circulation Model scaling performance, *Geophys. Res. Lett.*, *31*, L10206, doi:10.1029/2004GL019499.

Watkins, N., S. Rosenberg, S. Chapman, M. Naylor, and M. Freeman (2011), When black swans come in bunches: Modelling the impact of temporal correlations on the return periods of heavy tailed risk, *Geophys. Res. Abstr.*, *13*, EGU2011-12404.

Watkins, N. W., B. Hnat, and S. C. Chapman (2012), On self-similar and multifractal models for the scaling of extreme bursty fluctuations in space plasmas, in *Complexity and Extreme Events in Geoscience*, *Geophys. Monogr. Ser.*, doi:10.1029/2011GM001084, this volume.

Zahn, M., and H. von Storch (2010), Decreased frequency of North Atlantic polar lows associated with future climate warming, *Nature*, *467*, 309–312.

D. N. Baker, Laboratory for Atmospheric and Space Physics, University of Colorado, Boulder, CO 80309, USA.

A. Bhattacharyya, Indian Institute of Geomagnetism, Navi Mumbai 410 218, India.

A. Bunde, Institut für Theoretische Physik III, Justus-Liebig-Universität Giessen, Giessen D-35390, Germany.

V. P. Dimri and H. K. Gupta, National Geophysical Research Institute, Hyderabad 500606, India.

V. K. Gupta, Department of Civil, Environmental and Architectural Engineering, Boulder, CO 80309, USA.

S. Lovejoy, Department of Physics, McGill University, Montreal, QC H3A 2T8, Canada.

I. G. Main, School of GeoScience, University of Edinburgh, Edinburgh EH9 3JN, UK

D. Schertzer, LEESU, Ecole des Ponts ParisTech, Universite Paris-Est, F-77455 Paris, France.

A. S. Sharma, Department of Astronomy, University of Maryland, College Park, MD 20742, USA. (ssh@astro.umd.edu)

H. von Storch, Institute of Coastal Research, Helmholtz-Zentrum Geesthacht, D-21502 Geesthacht, Germany.

N. W. Watkins, British Antarctic Survey, Cambridge CB3 0ET, UK.