validation strategies exist in benchmarking the techniques, although a 3-D spherical so-called European benchmark was suggested by Uli Christensen more than a decade ago. Here we present a simple analytic benchmark for Stokes flow that can be implemented straightforwardly across different numerical solution strategies in order to verify pressure and velocity solutions. Solving the forward problem $A * u = f$ (where A is the Laplacian) analytically for a given velocity field u that is divergence free, we compute a right-hand side f. Subsequently we use our numerical code for the inverse problem $u = A^{-1} * f$ to retrieve u from f. Our numerical modeling code is a modified version of the mantle dynamics code TERRA introduced by Baumgardner 1985, with pressure and velocity defined on a staggered mesh, where an Uzawa algorithm is applied to take the pressure solution step. We observe a divergence reduction from an initial first-guess velocity field by more than six orders of magnitude, confirming the incompressibility constraint is enforced to high numerical accuracy. We also verify 2nd order accuracy for the velocity field with velocity and pressure solutions in agreement of better than one per mil in our high resolution cases. These benchmark results indicate high numerical accuracy for the momentum solution of the TERRA mantle dynamics code.

NG72B-0937 1330h POSTER

Testing A New Model for Quantifying Anisotropic Scale Invariance and Unmixing Geophysical and Geochemical Patterns

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A new power-law model has been proposed to represent the relationship between area of the set consisting of wave numbers with spectral energy density above S (A(>S)) on the 2-D frequency plane and S. Comparing the new model with the commonly used spectral energy density and wave number model, the new model can be used to quantify the anisotropic scaling property whereas the latter may wash out the anisotropy of the field. The power-law relation is exact if the field concerned possessing isotropic scale invariance or generalized scaling invariance involves only rotational and ratio-scale changing transforms. The relation, however, approximates to power-law type for a field with linear generalized scale invariance. The equation is valid for dealing with common exploration geophysical and geochemical fields encountered in mineral exploration and environmental assessment. The S-A filtering technique developed on the basis of the new power-law relation can decompose a mixing field into components on the basis of distinct scaling properties in the frequency domain. It is demonstrated that the method has potential to become a general technique for image processing and pattern recognition. This paper will introduce the principal of the model and several case studies will be used to demonstrate the validation of the model and the application of the S-A method in separation of geophysical and geochemical anomalies from background values in assist in mineral exploration. The testing datasets include Landsat TM images from the Mitchell-Sulphurests Mineral district, northwestern BC; Airborne radiometric data and airborne Magnetic data from Abitibi Greenstone Belt; and Trace element concentration images interpolated from point lake sediment samples from the Nova Scotia, Canada. It has been demonstrated that the model generally holds true for all the testing datasets. More interestedly, the separated anomalous and background components by means of the S-A method on the basis of distinct scaling properties of have shown clear spatial patterns related to mineralization and background geological processes, respectively. The S-A can be suggested as an effective method for separation of anomalies from background for mineral exploration.

URL: http://www.gisworld.org/geodas

NG72B-0938 1330h POSTER

Modeling and Synchronizing Chaotic Systems From Geomagnetic Time Sequences at Etna Volcano

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Natural geomagnetic variations are due to secondary fields induced in the Earth by ionospheric and magnetospheric current systems. These variations point out a strongly dissipative and nonlinear system, which is a necessary condition for the existence of chaotic dynamics. The magnetospheric data analysis revealed an organized evolution, which is a manifestation of low-dimensional magnetospheric dynamics. Moreover, it appears that a relatively small number of magnetospheric state variables dominate the evolution. The entities of these variables are not known at present, and very little of the dynamic system that governs their evolution is understood. The magnetospheric system could be considered as an input-output system perturbed externally by a deterministic solar wind signal. External disturbances of the magnetosphere by the solar wind system make the system non-autonomous.

In this work, data collected from the magnetic monitoring network of Etna volcano are analyzed in a very short sampling interval. We firstly apply a nonlinear time series analysis to examine the behaviour of geomagnetic signal to obtain useful information about the internal deterministic component of a magnetospheric time series. These results reveal the low-dimensional character of the dynamics and give us information about relevant properties of a suitable model for the description of geomagnetic dynamic behaviour. Using a nonlinear forecasting approach, the limited predictive ability has been tested, revealing a strong sensibility to initial conditions, which is a necessary condition for a time series to be chaotic. The dependence of initial conditions represents a difficulty when an analogue model describing the geomagnetic variations should be derived. To overcome this problem, we propose a innovative method for chaotic dynamic system identification using a procedure based on a master-slave synchronization approach. Once a possible internal dynamic of the system has been estimated, a fundamental point is to understand what the major external factors of influence are. In such a way, we make an estimate of a possible external deterministic forces of the system. Certainly, the strong coupling between solar wind parameters, magnetosphere and ionosphere constitute the most significant state variables, which determine the dynamic behaviour.

NG11A MCC: 121 Monday 0830h

Recent Advances in Nonlinear Geophysics I: Model Testing and Validation *(joint with OS, P, S, T)*

Presiding: **K F Tiampo,** University of Colorado**; A Braverman,** Jet Propulsion Laboratory**; D Nychka,** National Center for Atmospheric Research

NG11A-01 0830h

Does Geophysics Need "A new kind of Science"?

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Stephen Wolfram's book "A New Kind of Science" has received a great deal of attention in the last six months, both positive and negative. The theme of the book is that "cellular automata", which arise from spatial and temporal coarse-graining of equations of motion, provide the foundations for a new nonlinear science of "complexity". The old science is the science of partial differential equations. Some of the major contributions of this old science have been in geophysics, i.e. gravity, magnetics, seismic waves, heat flow. The basis of the new science is the use of massive computing and numerical simulations. The new science is motivated by the observations that many physical systems display a vast multiplicity of space and time scales, and have hidden dynamics that in many cases are impossible to directly observe. An example would be molecular dynamics. Statistical physics derives continuum equations from the discrete interactions between atoms and molecules, in the modern world the continuum equations are then discretized using finite differences, finite elements, etc. in order to obtain numerical solutions. Examples of widely used cellular automata models include diffusion limited aggregation and site percolation. Also the class of models that are said to exhibit self-organized criticality, the sand-pile model, the slider-block model, the forest-fire model. Applications of these models include drainage networks, seismicity, distributions of minerals,and the evolution of landforms and coastlines. Simple cellular automata models generate deterministic chaos, i.e. the logistic map.

NG11A-02 0845h INVITED

Assessing uncertainty in mesoscale numerical weather prediction models

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Current methods of meteorological forecasting are largely deterministic and produce predictions with unknown levels of uncertainty. Specifically, forecast errors and uncertainties arise from an incomplete knowledge of initial conditions and from shortcomings in model physics. We report on the early stages of a project aimed at developing calibrated probabilistic forecasts based on operational ensembles of mesoscale numerical weather predictions. Our approach builds on the general ideas of Bayesian model averaging, conditionally heteroscedastic regression, and simulation-enhanced ensembles. Joint work with Fadoua Balabdoui, Yulia Gel and Anton Westveld.

NG11A-03 0900h INVITED

Discriminating Cloud Over ice Using MISR Data

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The uncertainties in the radiative feedback to climate by clouds pose the most formidable obstacle to climate prediction by General Circulation Models (GCMs). Particularly, in polar regions where the ice and snow cover the ground, the net radiative impact of clouds is uncertain (Charlock and Ramanathan 1985; Li and Leighton 1991). One of the reasons for this uncertainty is that scene identification and cloud detection remain difficult over snow- and ice-covered surface.

MISR (Multi-angle Imaging SpectroRadiometer) is a sensor in EOS, and contains nine cameras looking at the earth from different angles simultaneously. Its multi-angle information allows a relatively new approach for discriminating cloud from snow/ice. In this talk, we propose a novel method to discriminate cloud over ice based on MISR observations. Demonstrations and validations of the proposed method will also be given based on MISR data from the polar regions.

NG11A-04 0915h

The Risk of Spurious Model Validation, An Illustration with Cloud Remote Sensing Data

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Dynamical models with many degrees of freedom (i.e., spatial grid-points) that claim to be realistic should reproduce the structure and evolution of the geophysical fields they represent over a large range of spatial- and temporal scales, not just large domain averages and their slow tends in time. Atmospheric-, oceanic- and coupled general circulation models (GCMs) as well as meso-scale and micro-scale models

are all good candidates for detailed validation across many scales.

Because of their inherently wide-area coverage and reasonable spatial and temporal sampling, remote sensing observations from space are seen as an attractive source of validation data for Earth system models. Upward-looking ground-based devices can also be used for atmospheric process modeling. However, remotely-detected radiances are not natural model output. Either a "forward" radiative transfer stage should follow the dynamical computation, or geophysical parameters need to be retrieved or "reconstructed" from the radiances. Generally speaking, neither task is simple enough to be considered error-free.

There is a wide variety of techniques for characterizing space-time variability to choose from in a multi-scale validation exercise: Fourier- and wavelet-spectra, auto-correlation analysis, structure-functions (a.k.a. semi-variograms), fractal dimensions, multifractal statistics, etc. At the larger scales we may require a one-to-one deterministic correspondence between models and observations; at smaller scales, a weaker statistical correspondence is likely to be sufficient.

With this general validation framework in mind, we consider the remote-sensing data needs for cloud-model validation. Even before the systematic model-data comparisons are performed, we need to examine the integrity of the remote-sensing data as a validation benchmark. In other words, the remote-sensing products need to be themselves validated, again scale-by-scale, in the sense used by NASA's Earth Observation System (EOS) program: error-bars with respect to ground-truth or otherwise reliable in-situ measurements are assigned, and hopefully their magnitude explained. To be useful for cloud-model validation, we require the remote sensing data, at a minimum, to be free of bias in their 1-point statistics at the observation (pixel) scale and in their 2-point correlations at all observable scales.

Fourier-, wavelet- and multifractal singularity spectra are used, in combination with 3D and 1D (pixel-by-pixel) radiative transfer, to uncover systematic differences between *inherent* (in-situ) and *apparent* (remotely observed) cloud structure according to visible/near-IR satellite imagery as well as time-height transects from ground-based milli-meter radar. All of these biases are such that if not thoroughly investigated –hence removed, or at least identified– they can lead to a spurious validation of dynamical cloud models in one respect or another.

URL: http://nis-www.lanl.gov/~adavis

NG11A-05 0930h INVITED

A statistical approach to merge output from dynamic models with ground observations

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In this research we consider a purely stochastic model to represent rainfall variability in time and space. The model is based on truncating and transforming a multivariate Gaussian variable.

We use the truncated normal model to combine the information given by ground observations with predictions produced by a purely deterministic regional climate model (RCM). RCM models use initial and boundary conditions from different sources and models to produce their predictions, but they do not use ground observations, so they can be seen as prior information on the rainfall of a given area. Furthermore, the output of RCM models relates to averages over fairly large grid cells. So we have observations from two sources at different spatial scales.

Our model allows for the updating of samples of the RCM model output conditioning on the observed point observations. The posterior distribution of the model parameters is explored using a Markov Chain Monte Carlo method that consists on a series of Metropolis Hastings steps for a chosen arrangement of the parameters in blocks. We considered a set of data from an area in Nebraska where monthly rainfall is available at 39 stations as well as predictions from an RCM over 28 50km by 50km grid cells.

NG11A-06 0945h INVITED

Evaluation of Point Process Models for Earthquakes

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A point process consists of events (e.g. earthquakes) occurring at random points in time. It is specified by a conditional intensity $\lambda(t \mid H_t)$ such that

$$\Pr(\text{event } \in (t, t+dt) \mid H_t) \approx \lambda(t \mid H_t)dt.$$

The history H_t incorporates times, usually magnitudes, and possibly locations, of previous events. In general, λ is parameterized, for example the stress release process has

$$\lambda(t \mid H_t) = \alpha + \nu\left(\rho t - \sum_{t_i<t} 10^{0.75 m_i}\right),$$

where earthquakes of magnitude m_i occur at times $t_1, t_2, \ldots \in T$, where T is the observed time interval. Model parameters can be estimated by maximizing the log-likelihood

$$\log L = \sum_i \lambda(t_i) - \int_T \lambda(t)dt.$$

Probability forecasts of hazard can then be produced by repeated simulation. The history can also include non-catalog information, provided an auxiliary model is available to predict such information forward.

Due to the complexity of the seismogenesis process, most mathematical models can only be, at best, a rather crude approximation. By considering a number of simple models, each constructed from a few characteristics, it is possible to decide whether these particular characteristics are present in the observed data. The accumulation of observed characteristics are then suggestive of a more comprehensive model.

The question then arises as to how adequately a given model describes the data, particularly relative to competing models. The Akaike Information Criterion (AIC), by penalizing overfitting, can be used to eliminate parameters unless the resulting model provides a significant improvement in fit. Examination of the residual point process(es), which basically transform the data using the fitted model, can identify systematic deficiencies in the model. Repeated simulation and refitting can be used to assess goodness of fit, and hence verify the fitted model. Standard errors and thus, in principle, prediction intervals can also be derived. The performance of the model in probabilistic forecasting is bounded above by the point process entropy, which can be estimated by simulation if it cannot be calculated directly.

NG11B MCC: 121 Monday 1015h

Recent Advances in Nonlinear Geophysics II: Natural Hazards/Nonlinear Physical Processes *(joint with S, MR)*

Presiding: **S Tebbens,** University of South Florida**; S Burroughs,** University of Tampa**; K McCall,** University of Nevada, Reno**; R Guyer,** Los Alamos National Laboratory

NG11B-01 1015h INVITED

Model Verification and Other Oxymorons of Real-World Forecasting

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Models of physical systems can never be verified; at best our models can be shown to be consistent with observations. For dynamic systems this implies that the model can shadow the the phenomena of interest (ideally the data) to within the observational uncertainty for some (initially unknown) initial condition. When shadowing trajectories exist, operational questions of model tuning, adaptive observations and the selection of initial conditions can be approached by looking for indistinguishable states of the model given the observations (see Judd and Smith, Physica D, 151, 125–141, 2001 and references thereof).

All models are imperfect; for nonlinear systems this implies a time scale on which they cannot shadow for any empirically reasonable definition of observational uncertainty. At these time scales, there is no "uncertainty in the initial condition" as there is no "initial condition" of the model which is consistent with the physical system. With a focus on weather forecasting and climate modelling, this talk considers how to best proceed given that all models are wrong. How should we interpret the output of models which have not yet been falsified? And more relevantly, how can we best use forecasts models which have?

URL: http://www.maths.ox.ac.uk/~lenny

NG11B-02 1030h INVITED

Dynamics of Shoreline Position

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Change in the position of a shoreline over time results from the interaction of a large number of processes, which appear to produce a random pattern of change. Complexity analysis has been applied to a twenty-year record of mean high water shoreline positions surveyed approximately biweekly along four transects at Duck, NC. A Lomb Periodogram permits spectral analysis of the unevenly spaced data. The spectral analysis reveals that the signal is a 1/f noise with b, the scaling exponent, equal to one. Properties of 1/f noises are power-scaling, long-range persistence, and slight non-stationarity. Power-scaling signals exhibit spectral density that increase with wavelength, and contain no characteristic wavelength. Long-range persistence of a signal measures the temporal correlation among values of like magnitude relative to the mean. Non-stationarity of a signal measures the drift of the mean over time. Runs (successive movement in the same direction) for both erosion and accretion range from 1 to 7 consecutive surveys lasting from weeks to months and conform to a Gaussian distribution. The magnitudes of lateral excursions of shoreline position conforms to a Gaussian distribution with a mean of zero and a standard deviation of 3 meters. The size distribution of both runs and lateral excursions show a balance between erosion and accretion.

The distributions derived from the field data were used to create a synthetic signal that is statistically identical to the shoreline position time series. In contrast to the field time series, the synthetic signal is uniformly spaced (daily) and is run for 100 years. The synthetic signal exhibits erosional and accretionary runs and excursions at all scales and drifts within a narrow envelope of plus or minus 30 meters.

The size distributions of both runs and excursions in shoreline position indicate that they result from a Poissonian process, i.e. random, with no memory, analogous to a fair coin toss. But, the persistence measure, b=1, indicates that the position of the runs and excursions is not random in time. Thus, similar shoreline positions tend to cluster in time, so that a particular shoreline position is more likely to be followed by a similar position, rather than randomly distributed in time. The analysis indicates that the physical processes operating at this beach are self-organizing over a broad range of time scales, resulting in a stable shoreline position in the face of a high rate of sea level rise (calculated to be 5 cm/decade at this site).

NG11B-03 1045h INVITED

Self-Organized Evolution of Sandy Coastline Shapes: Connections with Shoreline Erosion Problems

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Landward movement of the shoreline severely impacts property owners and communities where structures and infrastructure are built near the coast. While sea level rise will increase the average rate of coastal erosion, even a slight gradient in wave-driven alongshore sediment flux will locally overwhelm that effect, causing either shoreline accretion or enhanced erosion.

Recent analysis shows that because of the nonlinear relationship between alongshore sediment flux and the angle between deep water wave crests and local shoreline orientation, in some wave climates a straight coastline is unstable (Ashton et al., Nature, 2001). When deep-water waves approach from angles greater than

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