Dynamic Data-driven Geophysical Systems Science

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Addressing geophysical challenges with relevance to planetary sustainability requires an effective integration of sensing, observation and inference with physical, chemical, biological and social models. The attendant questions of predictability, uncertainty and risk demand integration of *data* and *science* in multifaceted and symbiotic ways, ranging from "model-based" sensing to "data-driven" modeling. They are of great interest to both "GEO" and "IS" communities.

We think of geophysical applications in a systems science framework, often as feedbacks between data and models. For example, environmental data gathering (see Figure 1) can be made efficient when informed by environmental models whilst models are constrained by data to be effective. The observing system view and the numerical prediction view, thus, are merely two facets of a coupled system. Similarly, physical model errors can compensated by models learned from data and learning models from data can substantially benefit from physically-based priors. The physics and learning views are merely two facets of a common reality. The coupled "dynamics and data-driven" framework is in general cross-cutting. As a member trained and practicing in both GEO and IIS communities, the following, in my view are the key advances of interest in this framework.

Figure 1: coupling dynamics and data for information gathering and prediction. Shown here operations at Popocatepetl, UAS pictured top right.

(a) **Sensing is informed by the environmental context.** The classical approach to sensing is based on a "seeing is believing." There is a strong case to be made, however, for beliefs in sensing, i.e. what could we do if we had a little context. New approaches coupling light-field imaging with priors on features, for example, has led to advances in fluid imaging.

(b) **Scale-Space Information in inference.** Many inference problems such as downscaling, model reduction, data assimilation, uncertainty quantification, planning and control, are plagued by nonlinearity, dimensionality and uncertainty. New directions have emerged for automatically organizing the inference topology in scale-space, and using tractable information theoretic formulations to deal with these issues.

(c) **Learning to compensate for model error, learning model reduction.** Model error is an important topic in Geophysics. New Ensemble Learning approaches for compensating for model error hold considerable promise. Similarly, manifold learning approaches, particularly when they are dynamically deformable offer new directions for learning reduced models.

(d) **Pattern theory in Geophysical fluids:** Geophysical fluids are populated with features, thus bringing a pattern perspective to dynamics. Incorporating this in data assimilation, uncertainty quantification, and model reduction shows new robustness, with excellent results for Natural Hazard applications. Perceptual organization for fluids would be ground breaking.

(e) **Robust Stochastic Programming in Mitigation Planning:** The extension of stochastic programming to include uncertain probabilities enables new robustness and effectiveness in planning mitigation (and observational) strategies for climate induced coastal risk.