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Progress toward autonomous ocean sampling networks

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ABSTRACT

The goals of the Autonomous Ocean Sampling Network (AOSN) are reviewed and progress toward those goals is assessed based on results of recent, major field experiments. Major milestones include the automated control of multiple, mobile sensors for weeks using spatial coverage metrics and the transition from engineering a reliable data stream to managing the complexities of decision-making based on the data and the possibilities of timely feedback.

1. Introduction

The Autonomous Ocean Sampling Network (AOSN) concept (Curtin et al., 1993) leverages autonomous mobile platforms and assimilative dynamic models to observe and predict dynamic ocean fields. While advances in autonomous underwater vehicles have enabled distributed observation of dynamic processes by fleets of robotic vehicles, continuous fields must still be realized from a limited number of discrete observations. Dynamical models can interpolate and extrapolate observations deterministically, and thus can generate continuous realizations of ocean fields from discrete measurements. Realizations based on statistical models can provide continuity for random variables. The temporal evolution of three-dimensional ocean fields results from both deterministic and stochastic processes, and thus even with perfect observations, prediction skill will deteriorate in time. The great challenges of AOSN revolve around learning how to better sample the ocean field, and improving the skill of assimilative models for synthesis and prediction of the evolution of those same fields.

Historically, maps of ocean fields have been based on arrays of fixed-point (moorings, stations) and Lagrangian (floats) data, and, more recently, on quasi-synoptic cross-sections (tow-yos). The time scale of experiment design, deployment, data acquisition, and analysis was years. Such experiments yielded time series that revealed a broadband cascade in the ocean energy spectrum. High-resolution, local maps associated with specific expeditions onboard research vessels yielded initial insights into processes governed by spatial gradients. Observations from spacecraft and with surface radar provided powerful new mapping capability for near-surface ocean fields. The current Argo array provides for the first time persistent, comprehensive subsurface observations on a global scale. The sampling resolution of this Lagrangian array, however, is controllable only by initial seeding. Plans to expand and stabilize an ocean observing system have been formulated and are slowly being implemented.

Pragmatic calculations using true ocean time and space scales and the real cost and complexity of in-situ observations show that a systemic challenge of reducing error in ocean field estimation is sparse sampling. The AOSN initiative (Curtin et al., 1993; Curtin and Bellingham, 2001) was launched to develop new tools and methodologies to address the sparse sampling problem and reduce errors in ocean field estimation to enable definitive hypothesis testing. The premise is that there is a significant advantage to adapting the distribution of observations on time and space scales comparable to the processes driving the variability, and to persisting long enough to accumulate robust statistics on coherence scales. This premise is supported by the growing literature on targeted observations spanning a wide range of disciplines including meteorology.

For this introduction, we draw on experience from the AOSN-II field program in August 2003 in Monterey Bay. We also consider follow-through from that field program, as manifested in the Adaptive Sampling and Prediction (ASAP) program and the Monterey Bay 2006 field program (MB06). AOSN efforts have been directed toward three principal contributions:

(1) *Multiple, mobile sensors that can resolve synoptic fields and spatial gradients to a desired level of precision*: Mapping of transient spatial fields with minimum error requires network-class autonomous vehicles that are in a practical cost-size envelope (Curtin et al., 2005). Staying within this envelope enables enough in-water testing within a realistic budget to

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achieve acceptable reliability and ultimate use of such vehicles. Since mobile, platforms with persistence are slow due to energy constraints, their trajectories can be greatly influenced by ambient currents. If positioned poorly, they can be placed disadvantageously; for example, clustered in a region far from an evolving area of interest. Thus the performance of an AOSN is intimately connected with feedback control and decision-making processes.

(2) *Control of mobile sensor arrays in a feedback loop with response time sufficient to stabilize and reduce error in evolving mapped fields*: This loop not only provides a means to constrain errors in mapping gradients with multiple vehicles using local linearization, but also provides the flexibility to respond quickly to unexpected anomalies. Underlying this need is a fundamental design question: where should control authority reside in the system? Communications are not always readily available, and consequently mobile platforms must have some level of control authority. Balancing this is the reality that an individual vehicle will not be privy to information generated by other AOSN components, and thus may make non-optimal decisions if not controlled centrally. Finding the right balance of autonomy for individual assets and investing in the right level of communications to support collective planning remain challenging problems.

(3) *Decision making that provides a range of options for the experimenter faced with uncertainty*: Such options are easy to understand when directly connected to testing hypotheses or assessing the skill of predictive tools such as numerical models. Recalling that AOSN activities involve collaboration of teams of PIs, the availability of well-framed options helps building consensus on the best course of action when intuition is weak, there is disagreement among experts with similar objectives, or there are a variety of competing objectives. Practical experience from the AOSN-II and MB06 field programs taught that different goals can often be accommodated within sampling plans. Thus the premature down-select of objectives can be counterproductive. Once the various sampling needs are understood, it is often possible to take advantage of the multiplatform nature of the observation system to satisfy multiple investigative needs.

The sensitivity of AOSN performance to real-time decision making creates many demands, not all of which are technical. AOSN, as a system of systems, depends on individual elements operating as components of an integrated system (Fig. 1). Many of the components deployed to date have been developed by and are operated by individual research groups, each with their own agendas. In a traditional field program, investigators depend

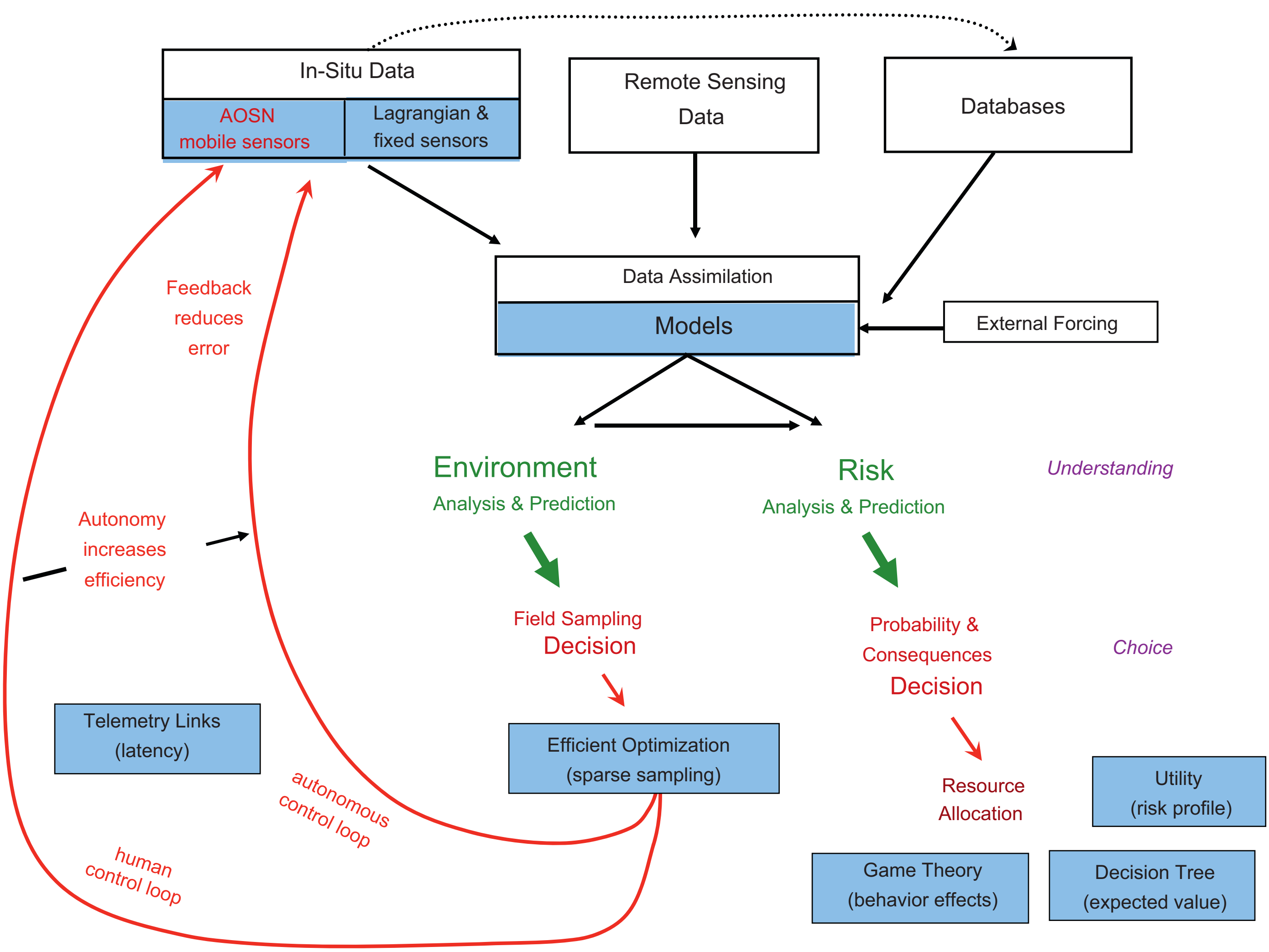

Fig. 1. Autonomous Ocean Sampling Network (AOSN) as a critical element of an ocean mapping and prediction system (AOSN system). Blue boxes are essential tools. AOSN technology enables the operation of timely feedback loops that converge on minimum error states. Feedback evolves from human to autonomous control with the development of intelligent algorithms based on experience.