One example of a "data assimilative system" is depicted in Figure 13 (the lower portion follows Robinson and Lermusiaux, 2001). The system is composed of three fundamental elements: 1) an observational network with data telemetry, 2) an interdisciplinary model, and 3) a data assimilation scheme. Interdisciplinary data are collected and transmitted in real-time or near real-time from various platforms of the sampling network or array. Each platform has its own intrinsic capabilities and limitations in terms of types of sensors and systems that can be utilized and a defined spatial and temporal range of measurements. Data and error estimates are transferred for incorporation into the interdisciplinary model. The interdisciplinary dynamical model is composed of multiple modules (e.g., for physics, biology, and chemistry) and each module is represented with a set of equations with variables appropriate for describing the relevant processes. Importantly, these modules are coupled. The data-melding step produces state variable and parameter estimates of observed physical variables (OSVi), observed biological variables (OSVj), observed chemical variables (OSV_k), and unobserved variables (USVs) along with associated errors. This information feeds back to the data assimilative model for inclusion in the next model iteration and for model improvement and back to the sampling network enabling adaptive sampling (e.g., based on error simulation as discussed earlier). Adaptive sampling is accomplished using several possible modes: changing sensor sampling rates, changing gains of sensors and systems, and redirection of mobile sampling assets to locations of special informational value (e.g., fronts, upwelling sites, eddies, blooms, and regions where processes are leading to large model error estimates). Important goals of the data assimilation procedure are: 1) to develop and improve model formulations and functional dependencies, 2) to estimate parameters and variables as well as rates that cannot be measured, 3) to estimate or predict state variables and parameters on time and space scales inaccessible to some or all of the observational sampling assets (e.g., a smart interpolating function), 4) to provide model initializations, 5) to identify and elucidate ocean processes, 6) to design experimental or operational sampling networks using Observational System Simulation Experiments (OSSEs), 7) to optimize use of sampling assets through adaptive sampling, and 8) to make predictions for research and operational environmental management including uncertainty and error estimates. A general goal is to accurately predict the distributions of selected state variables given their values at some initial time.

It is worth noting the challenges of data assimilation and specifically inherent limitations in predictability in the form of nonlinear error propagation and error-scale transfers (Robinson and Lermusiaux, 2001). Other, observational and modeling problems remain for future work. For