4. Approach

In this section, we develop the details of our technical approach. As outlined briefly above, we are proposing to develop a real time observational system that can be rapidly deployed to locations of interest. At the same time, we will develop a real time, data-driven modeling framework, which, rather than being based on calibration by historical data sets, will use inverse methods to estimate boundary conditions and project flows and transport ahead on the timescale of days to weeks. The integration of these two efforts ~~defines an approach to Delta modeling that is fundamentally different from existing~~ approaches. Currently, Eulerian timeseries data are used in conjunction with mechanistic "forward" models of the Delta. This is an appropriate and effective method for forecasting the response of the system (with existing geometry) to long timescale events. In our approach, we use Lagrangian data (along with existing Eulerian measurements) with a calibration-free inverse approach to evaluating and predicting Delta flows and transport. Our emphasis is on developing the best possible estimate of transport at the timescale of days to weeks to aid in management and operational decision making.

This new approach to Delta modeling will hold a significant advantage over current approaches in its ability to analyze conditions at particular locations in the Delta, even in the event of large-scale changes to the Delta geometry. The timescales that we are focusing on will allow us to work towards flexible and dynamic operational decision making at tidal, daily, and weekly timescales, rather than relying on operational rules for these timescales. An immediate application of this analysis could involve operating the Delta Cross Channel gates (see below) in response to the presence and position of out-migrating salmon smolt. The computational tools we are developing can make use of any Lagrangian data; for now we are using GPS-logging drifters, but tagged fish or estimates of fish position and movement could also be incorporated.

In the subsections that follow, we outline the details of the research activity that we are proposing. Initially, we outline the details of the inverse modeling approach, and then we describe the sensor network development. Finally, we briefly describe the nature of an integrated experiment in section 4.3.

4.1 Calibration-free, inverse modeling of existing data sets

Our goal in this initial development phase is to apply inverse techniques, which have been used for open ocean modeling (Bennett 1992) and channel control (Chen and Georges 1999; Sanders and Bradford 2002) to the Sacramento-San Joaquin Delta. The fundamental theories of inverse modeling have been developed in these other literatures, and we believe that applying these approaches to flow estimation in the Delta is a logical extension. In the oceanographic literature, open boundary condition estimation has been used to evaluate the influence of remote forcing (Bogden et al. 1996) or to adjust boundary conditions in a small scale model of a particular oceanographic feature (Gunson and Malanotte-Rizzoli 1996). As computational power has improved, however, small-scale coastal models have started to be more commonly coupled with larger scale regional or even global models to provide boundary condition information (e.g., Powell et al. 2006), which reduces or eliminates the need for inverse estimation of open boundary conditions. In the Delta, however, we are faced with the likely situation of having to estimate flows and transport with either (1) an unknown geometry for the system (in the case of levee breaches); or (2) uncertain forcing at the timescales of interest (in the case of sudden freshwater flows or out-migrating salmon). In these cases, we believe that inverse estimation of open boundary conditions provides the most appropriate method for estimating local flow conditions. The method forces any solution ~~to be consistent with real-time observations, but also allow projection forward in time to~~ provide predictive flows and transport over the timescales of a tidal cycle to days and perhaps weeks. These timescales are critical to the management of the Delta, and we believe that our proposed research holds great promise in the management of the Delta. In this section, we outline the details of the inverse modeling approach that we propose to pursue.

4.1.1 Adjoint Equations

Our development of the adjoint approach to boundary condition estimation will follow the development of Sanders and Katopodes (2000). In conservative form, the two-dimensional depth-averaged shallow water equations are (see, e.g. Sturm 2001):

$$\frac{\partial}{\partial t}(q_x)+\frac{\partial}{\partial x}(q_x^2/h)+\frac{\partial}{\partial y}(q_x q_y/h)=-\frac{\partial}{\partial x}\left(\frac{gh^2}{2}\right)+ghS_{0x}-ghS_{fx}$$

$$\frac{\partial}{\partial t}(q_y)+\frac{\partial}{\partial x}(q_x q_y/h)+\frac{\partial}{\partial y}(q_y^2/h)=-\frac{\partial}{\partial y}\left(\frac{gh^2}{2}\right)+ghS_{0y}-ghS_{fy} \qquad \text{(1a,b,c)}$$

$$\frac{\partial h}{\partial t}+\frac{\partial}{\partial x}(q_x)+\frac{\partial}{\partial y}(q_y)=0$$

where (q_x,q_y) are the depth-integrated flow in the (x,y) directions, h is the local depth, S_0 is the bed slope (S_{0x} in the x-direction, S_{0y} in the y) and S_f is the friction slope, which we will parameterize using a quadratic bottom friction with a drag coefficient as

$$S_{fx}=C_d\left(u^2+v^2\right)^{1/2}u/gh \qquad \text{(2a,b)}$$

$$S_{fy}=C_d\left(u^2+v^2\right)^{1/2}v/gh$$

By using a depth-averaged formulation, we are assuming that the water column is well-mixed, which is reasonable in most of the Delta, with the possible exception of deeper channels in the western Delta, the Stockton Deep Water Shipping Channel and some shallow water habitats (one example is discussed further below). Solution of these equations usually rest on the specification of initial conditions everywhere in the model domain and time variable boundary conditions at each open boundary. To develop a specific example, consider the channel network in Figure 3, which is the region of the Delta surrounding Mildred Island, and includes four open boundaries. In this subregion of the Delta, all four open boundaries are tidally driven, and flows in the interior respond to that boundary forcing. For traditional hydrodynamic modeling (Baek 2006, e.g.), surface elevation and velocity would need to be specified at all four boundaries as a function of time.

The goal of our inverse modeling effort is to generate the best estimate of the boundary conditions, given a set of observations in the interior of the domain (and possibly at some of the boundaries, depending on the region of interest). We define a cost function based on the mismatch between model and measured data as:

$$C_0 = \iiint \gamma_u (u_m - u_d)^2 f_u \, dxdydt + \iiint \gamma_v (v_m - v_d)^2 f_v \, dxdydt + \iiint \gamma_h (h_m - h_d)^2 f_h \, dxdydt \quad (3)$$

where u is velocity, h is depth, subscript m implies the modeled variable and d is the observed variable, γ is a weighting defined by the expected uncertainties in both the model and data and f is a mask that defines where observations are available for each variable. We now seek to define open boundary conditions that will minimize the model-data mismatch.

In order to reduce the complexity of the optimization problem, and to allow for projections forwards in time, we will assume that the time variability of the open boundary conditions is described by the superposition of tidal harmonics plus an offset and a linear trend. For the depth at the boundary, this can be written mathematically as:

$$h_b(t) = h_0 + h_L \frac{t}{T} + \sum_{k=1}^{N} h_k \sin(\omega_k t + \phi_k) \quad (4)$$

where h_0 is a constant offset, h_L is the coefficient that sets the magnitude of the linear trend and h_k, ϕ_k define the amplitude and phase for the k^{th} tidal harmonic (of frequency ω_k). The result is $2*N+2$ parameters to describe the time variability of depth at the boundary where N is the number of tidal harmonics included. A similar formulation will be made for the along-channel velocity component at the boundary and we will assume that the cross-channel velocity is zero at the boundary. The result is a total of $4*N+4$ parameters to describe each open boundary, which will be estimated using adjoint-based optimization. With this approach, we are not necessarily constrained to use this temporal decomposition during the period of observation. In order to extend our simulation beyond the observational period, however, we need to assume a temporal structure for the variation, see Figure 4. Our emphasis on tidal harmonics reflects the strong tidal forcing in the system, but the inclusion of a linear trend permits adjustment of the system to, for example, varying freshwater flow or changes in tidal prism due to levee breaches.

In order for the predicted flows to be physically acceptable, the shallow water equations (1a,b,c along with the definitions in 2a,b) must be applied as hard constraints on the optimization-based estimation of boundary conditions. While there are a variety of methods available for pursuing such a constrained optimization, we choose here to use the adjoint method, which provides a robust method for establishing how the cost function depends on the control parameters (in this case, the open boundary conditions). Also, the adjoint method is extremely general and enables the incorporation of arbitrary user-defined constraints in the given optimization problem. Using Lagrange multipliers to apply the governing equations as constraints leads to the adjoint equations (Sanders and Katopodes 2000):

$$\frac{\partial\lambda_x}{\partial\tau}-2u\frac{\partial\lambda_x}{\partial x}-v\frac{\partial\lambda_y}{\partial x}-v\frac{\partial\lambda_x}{\partial y}-\frac{\partial\lambda_h}{\partial x}=g\frac{2u^2+v^2}{u\left(u^2+v^2\right)}S_{fx}\lambda_x+g\frac{u}{u^2+v^2}S_{fy}\lambda_y-\gamma_u\left(q_{xm}-q_{xd}\right)f_u$$

$$\frac{\partial\lambda_y}{\partial\tau}-u\frac{\partial\lambda_y}{\partial x}-u\frac{\partial\lambda_x}{\partial y}-2v\frac{\partial\lambda_y}{\partial y}-\frac{\partial\lambda_h}{\partial y}=g\frac{v}{u^2+v^2}S_{fx}\lambda_x+g\frac{u^2+2v^2}{v\left(u^2+v^2\right)}S_{fy}\lambda_y-\gamma_v\left(q_{ym}-q_{yd}\right)f_v \qquad (5a,b,c)$$

$$\frac{\partial\lambda_h}{\partial\tau}+\left(u^2-gh\right)\frac{\partial\lambda_x}{\partial x}+uv\left(\frac{\partial\lambda_y}{\partial x}+\frac{\partial\lambda_x}{\partial y}\right)+\left(v^2-gh\right)\frac{\partial\lambda_y}{\partial y}=g\left(S_{0x}+\frac{7}{3}S_{fx}\right)\lambda_x+g\left(S_{0y}+\frac{7}{3}S_{fy}\right)\lambda_y+e_h$$

where λ_x, λ_y and λ_h are the three adjoint variables (associated with q_x, q_y and h), τ is a reversed time variable, $\tau = T_f - t$, the last terms in the first two equations represent the model error, with the variables as defined in (error equations) and $e_h = -\gamma_h\left(h_m - h_d\right)f_h$.

The solution method is to solve the "forward" equations (1a,b,c) from some initial time (T_0) to a final time (T_f), then use the resulting fields to solve the adjoint equations (5a,b,c) from T_f to T_0. The gradient of the cost function is then evaluated based on the results of both the forward and inverse integration. For example, the gradient of the cost with respect to the q_x boundary condition on an open boundary at $x = 0$ is:

$$\frac{\partial C}{\partial q_{xb}} = \iint_{x=0}\left(2u+v\right)\lambda_x \, dy\, dt \qquad (6)$$

with similar relationships for the gradients of the cost function with respect to the other flow boundary condition (q_y) and for the free surface position (h).

Based on these gradients, we can then use standard optimization techniques to perform an iterative estimation of the parameters. It may be possible for us to analytically define the Hessian of the cost function by taking the Jacobian of the gradient (one component of which is shown in equation 6). In this case, we can pursue a gradient descent algorithm that estimates the minimum of the cost function based on the local Hessian. As an alternative (or perhaps as a comparative study), we will apply the Broyden-Fletcher-Goldfarb-Shanno (Liu and Nocedal 1989; applied in Strub and Bayen 2006) method. This consists of the development of quasi-Newton methods in which the Hessian is approximated by a symmetric positive definite matrix. This avoids computing the Hessian at each step, which, if not possible analytically, would come at great computational expense. The BFGS automatically incorporates any hard constraints; an alternative is the use of logarithmic barriers, which we have successfully implemented in other cases (Bayen et al. 2006). The procedure is repeated and the algorithm iteratively converges to our best estimate of the boundary condition parameters. A very similar approach has already been used very successfully in systems biology (Raffard et. al, 2006) for parameter estimation.

Once the boundary condition parameters are prescribed, we will do a final forward model calculation using these boundary conditions to project flows and transport forwards in time over a longer timescale – extending an observation period of hours or days to a model forecast of weeks (Figure 4). An open question is how far forward in time such a projection is likely to be appropriate, which is something we will evaluate as part of the proposed research.

4.1.2 Numerical Solutions

The shallow water equations are among the most studied PDEs for numerical schemes, for which numerous classes of numerical schemes exist. In general, in using adjoint-based methods the same scheme can be used to solve both the direct and the adjoint problem. For example Strub and Bayen (2006) use upwind schemes for both problems. In the present case, we have a large panel of numerical schemes available; two classes of schemes seem particularly appealing. First, Godunov schemes have traditionally been developed for conservation laws (LeVeque 2002). In recent work (Strub and Bayen 2006), we showed how to incorporate weak boundary conditions in the numerical computations of the solution to conservation laws, a feature which will be very helpful in the present study. Another class of candidate schemes are kinetic schemes (Perthame and Simeoni, 2001), which also incorporate an efficient treatment of boundary conditions.

Our research activity will not, however, be dependent upon only this new numerical development. In the first year, we will also be applying and evaluating existing hydrodynamic modeling approaches, including TRIM (Cheng et al. 1993) and ROMS (Haidvogel et al. 2000). Our goal, however, is to develop a robust inverse modeling approach that is not dependent upon a particular hydrodynamic modeling technique. In general, the quality of our estimates of Delta flows and transport will depend primarily on the quality of the observations and the boundary condition estimation technique. This has motivated our choice of the adjoint method, combined with the harmonic temporal decomposition that will allow us to extend our estimates ahead of our observational period.

4.1.3 Existing Data Set 1: Mildred Island

Our first application for the inverse estimation of boundary conditions and flow estimation will focus on a comprehensive data set collected in September 2001 in Mildred Island (Figure 3). The emphasis of this experiment and the ensuing analysis was on the interior dynamics of the shallow water habitat and its connection with the adjoining channels. Instrumentation consisted of a suite of bottom-mounted current profilers both in the channels surrounding Mildred Island and in the interior (FIG MI). These profilers collected velocity data for nearly a 2 month period with a time resolution of 10-30 minutes. In addition to the flow measurements, conductivity-temperature-depth (CTD) sensors were deployed at each station to provide time series measurements of conductivity and temperature along with the local depth.

Analysis of the hydrodynamics of this data set (Baek 2006; Sereno 2006) has demonstrated that the interior of Mildred Island (MI) is strongly influenced by tidal forcing, wind forcing and atmospheric heating and cooling. While the northern part of MI remains largely well-mixed, the southern region experiences significant temperature stratification at the diurnal timescale. The channels surrounding MI, however, remain well mixed vertically, and a depth-averaged model should accurately represent the dynamics (except in extreme southern MI).

For our inverse model analysis, we will analyze the area shown in Figure (3), which leads to 4 open boundaries. With this choice of domain, we actually have direct observations of velocity and stage at or near 3 of the four open boundaries for our model domain (on the southern channel there is a UVM station just south of the region shown in Figure 3). We will not, however, use these data sets to define our boundary conditions. Instead, we will use observations in the interior of the domain (as sites noted in Figure 3) with the adjoint approach outlined in this section to estimate the boundary conditions at the four open boundaries. The timeseries that we develop for stage and velocity at the four boundaries will then be compared to the observations at those locations to assess inverse model performance.

Comparisons with observations at or near our open boundaries will allow us to evaluate the performance of the inverse approach in the estimation of local flow conditions. The analysis of this data set will allow us to examine several specific questions:

(1) Can channel phasing and tidal propagation be estimated from a few Eulerian measurements in the interior of the domain?

To address this question, we will examine the estimation of the boundary conditions in detail to determine whether the boundary conditions can, in fact, be uniquely determined from this collection of observations. Alternatively, there may be degeneracy to the solution of the shallow water equations that can not be resolved with a few fixed measurement stations.

(2) What are the minimal data requirements to reconstruct boundary information?

To evaluate the minimal requirements, as well as the most valuable types of data, we will subsample the data set in time, space and by sensor type. In each case, we will evaluate the performance of the inverse model and the uncertainty in our estimates of the boundary conditions.

(3) How far ahead (in time) of real-time observations can we reliably project Delta flows?

The analysis of this question really has two components to it. The first involves the accuracy of our tidal boundary estimation method. One of the subsampling strategies will be to use the first part of the observed records to estimate the boundary forcing, then evaluate the performance of the model in the remainder of the measurement period. By adjusting the fraction of the observational record used for boundary estimation we can assess the ability of this approach to project forwards in time. The second component of this question involves the efficiency of the optimization and boundary condition estimation. If, for example, the computational aspects of our work take several days to complete, this will limit the timescale at which our projections will be applicable. There is a tradeoff inherent in this analysis: a rough estimate of the boundary conditions is likely to be achievable quickly, but the more refined an estimate we seek, the longer the computations will take. Our analysis of this question will explore this tradeoff between a quick, rough estimate of Delta flow patterns and a more refined estimate that take more computational effort.

4.1.4 Existing Data Set 2: Sacramento River and Georgiana Slough

An experiment performed by the USGS in May 2004 examined the flow dynamics in the vicinity of the Georgiana Slough on the Sacramento River (Figure 4) at a similar scale as the Mildred Island study. The experiment was focused on the flow division between the Sacramento River and Georgiana Slough on both flood and ebb tides. The observations included a timeseries of cross-sectional velocity measurements using a boat-mounted velocity profiler on transects upriver and downriver from Georgiana Slough (Figure 4). ~~The centerpiece of this experiment, however, and the data most of interest to our analysis,~~ was a series of releases of GPS-logging drifters. These drifters were not communicating their data in real-time, but were monitored from a small boat; after they moved through the domain of interest, they were picked up and released again. The release points were positioned upstream of the junction between the Sacramento River and Georgiana Slough (to the north on ebb tides, south on floods), and the drifter trajectories provide a detailed picture of the Lagrangian flow patterns in this complex – but critical – channel junction.

In applying our inverse analysis to this site and experiment, our emphasis will be on predicting the details of tidal phasing between the Sacramento River and Georgiana Slough, and, to some extent, the Delta Cross Channel. This particular junction is critical for out migrating salmon smolt, and the operation of the Delta Cross Channel gates could provide a direct application of our integrated system. The fact that this data set includes Lagrangian drifter trajectories allows us to consider a different set of specific questions from the Mildred Island data set in the previous question. These include:

(1) What is value of Lagrangian drifter data for flow and transport estimation compared to Eulerian observations?

It is our belief that Lagrangian observations may provide more information regarding how the channels are connected, and may prove to be more valuable in estimating the local flow conditions. We will evaluate this hypothesis by comparing the results of the inverse analysis using the Lagrangian and Eulerian observations separately.

(2) How does the inverse modeling approach compare to traditional "forward" modeling in predicting the local tidal phasing and exchanges between the Sacramento River and Georgiana Slough?

The USGS (specifically Pete Smith) is currently pursuing a three-dimensional "forward" model of the experiment period and location (Burau, personal communication). One of our goals will be to compare the performance of our inverse approach to that model's ability to predict local flow conditions. The use of a depth-averaged approach for the inverse model may confound this comparison to some extent, due to the fact that the

USGS is pursuing a three-dimensional model to resolve the secondary circulation in the Sacramento River.

4.2 Lagrangian drifter network development

In parallel with the analyses of existing data sets, we will also be developing the technical capability to collect real-time drifter data and integrate that data into real-time flow state estimation using the inverse approaches outlined in the previous section. In order to achieve the proposed goals, we will need to develop our own drifter network, which will incorporate adequate sensing and communication equipment. In this project, we focus on the development of a system of networked sensors, including drifters that can adjust their vertical position. Each of these sensors will communicate wirelessly between one another and with a base station that is networked through the internet to a computer cluster doing predictions of flows and fluid state.

Design and testing of the prototype drifter. We will follow the standard steps in developing technology for autonomous robotics applications. The prototype envisioned for this study will be inspired of the design of a vertical profiler built at the ENSIETA Engineering School, France within the SWARM project, in which Prof. Bayen was involved through the Department of Defense in France. This vehicle, shown in Figure 5 was designed by a group of undergraduate students supervised by PhD students. Constructing a similar vehicle at Berkeley is a realistic goal for the two year time frame envisioned for this phase of the project. We will follow the steps outlined below:

- Definition of specifications of the vehicles for operational needs (already completed).
- Optimized selection of hardware components to build the architecture (in progress, see next section).
- Software simulation of the envisioned architecture, both for software specific issues and evolution of the vehicle in its environment.
- Assembly of the components. Hardware in the loop simulations, hybrid simulations, for each of the modules of the architecture, and for the full architecture.
- Testing procedures: full architecture outside of its environment.
- Testing of the vehicle in its environment (remotely controlled), autonomous simulations. This first batch of testing will be done at the Richmond Field Station (at UC Berkeley) to ensure favorable conditions for testing this equipment (no currents).
- Testing of the vehicle at the actual deployment site.

Specifications for the prototype drifters. We will follow the specifications below, which are representative of the equipment we want to put onboard the drifters:

- GPS: ublox AEK-4H ANTARIS GPS Evaluation Kit. This evaluation kit will allow us to test and use a 4 Hz GPS module, one of ublox's newest products.

- ISM Datalink: Microhard Inc. MHX920 Development Kit. This development kit contains everything needed to build a data link between a single drifter and a ground station. We may not use the Microhard MHX920 system for the final implementation (possible issues: range and interference on the 900 MHz band) but for ease of development of the first prototype it is the best choice.
- Acoustic Pinger: RJE International ULB-350. This self-powered pinger will greatly improve our chances of recovering a prototype should something go wrong in the field.
- Computation and Control: gumstix connex 400xm primary module gumstix netMMC storage communication module Kingston 1GB MMC card gumstix. The gumstix standalone Linux systems are compact, common, and cheap.
- ADC Board: Custom.
- Battery: Lithium Ion, specific brand not chosen
- Pump: Jabsco 18220-1123 12V Ballast Pump.
- Emergency Blow System: Cole-Parmer EW-98619-24 Solenoid Valve.
- Safety Supervisor: Custom. This circuit will monitor the battery power, a watchdog signal from the gumstix computer, its own standalone timer, and perhaps the pressure sensor output. Should anything go wrong, it will activate the emergency compressed air system to empty the ballast tank. This will hopefully improve the recovery chances greatly in case of in-field failure.
- Pressure / Temperature / Conductivity Sensor Sea-Bird Electronics 37SI-1b. This sensor package will most likely be replaced on the final implementation, but for a first prototype it is the fastest and lowest-risk option. Internal electronics handle the sensor conditioning and control, and the professionally calibrated and configured sensors will greatly shorten our development time. Disadvantages: price, mass (2.6 kg in air), size (cylinder, approx. 40 cm long, 7 cm diameter).
- Turbidity (optical backscatter) Sensor Seapoint Turbidity Meter. Unlike the Sea-Bird module, this sensor will probably be in the final version as well. Its size and mass are reasonable, the price is acceptable.
- Chassis Custom construction out of PVC pipe or Delrin.
- Inertial navigation sensor: CloudCap Technology "Crista" OEM Sensor Head. 3 axis gyros & accelerometers max 300 deg/s, 100 Hz bandwidth.

Predictive capabilities and inverse modeling through centralized power computing. Finally, we propose a novel architecture for centralized power computing, networked with distributed embedded sensing. This architecture is depicted in Figure 7. The drifters are the actual sensing platforms for the network, but what makes this sensor network so powerful is the computational core used for the predictive capabilities, which will enable the fleet to accomplish its missions. The computer cluster, running at UC Berkeley will provide predictions of the currents and contaminant transport or other scalar fields of interest for this project, through direct simulations. For feature tracking applications, the prediction of feature evolution can be achieved through solutions of the advection-diffusion equation, using inverse modeling results to define the advective field, with level set methods (Mitchell et al. 2005).

4.3 Central/South Delta Experiment

Late in year 2, or perhaps early in year 3, we will perform a test deployment of the sensor network, and evaluate the level of integration with inverse analysis that is possible. We anticipate working in the Central or South Delta, with a site to be chosen based on the availability of Eulerian flow measurements. Given the current set of UVM stations, we would anticipate focusing our efforts in Old and Middle River, but if other stations come on-line – or some go off-line – we will adjust our plans accordingly.

To make this example more concrete, we note in figure 1 a candidate model domain, which is co-located with the Middle River and Old River UVM stations. In this Delta sub-region, we will deploy several (~5-6) pressure sensors in the channels. Each will be along the edge of a channel, and will have a floating communication buoy to which it is ~~tethered. Then, we will release our network of drifters and begin collecting real-time data~~ from them in real-time at the base station. The base station will communicate with the computational cluster at UC Berkeley to estimate flow state and project flow trajectories. These projections will be compared, after the fact, with Eulerian measurements from the region.

5. Evaluation

Our intention in this proposed work is to develop a tool for rapidly estimating Delta flows and transport, which is at the same time robust, generic, and accurate. An important aspect of our work, therefore, is to critically evaluate the performance of our observational and modeling system relative to other modeling options. This will be the emphasis in the third year of our proposed work.

First, we will analyze the internal trade-offs within our approach. For example, the quality of our flow estimates will clearly improve the more data we incorporate into our analysis. Furthermore, the estimation of the boundary conditions (through optimization) will improve if the iterative procedure is given more time to converge. This is also a main motivation for using the BFGS method, which provides cheaper computational costs through approximations of the Hessian matrix, and for which optimized code is available. As part of this evaluation stage, therefore, we will examine how the cost function, particularly the data-model mismatch, varies with respect to both the amount of data used in the estimates and the computational cost. Through this analysis, which is essentially an analysis of the convergence properties of our optimization, we will evaluate what level of investment in observations and in computation is appropriate for predictive analysis of Delta flows and transport.

Once we understand the trade-offs within our analysis approach between accuracy and observational or computational investment, we will focus our attention on comparisons between our approach and other, traditional modeling approaches. This evaluation will be built around the analysis described in section 4.3, but will also be compared to DSM2 predictions of flow and transport in the region in question.

6. Summary

In this research proposal, we describe work to develop and evaluate an integrated system for the prediction of Delta flows and transport in real-time that doesn't rely upon historical data sets for calibration and validation. The system consists of observational and computational components, along with real-time communication and coordination. The over-arching goal of the work is to allow for the prediction of Delta flows and transport at the timescale of days to weeks, even when there has been major changes to the Delta geometry (such as levee breaches).

The observational component of the work consists of a network of Lagrangian drifters that communicate to a base station in real-time to establish the instantaneous velocity field. The advantages of Lagrangian measurements are: (1) drifters can be rapidly and easily deployed in locations of interest, such as the position of outmigrating salmon, or adjacent to levee breaches; and (2) the Lagrangian velocity field is the important measure of net transport in a highly dispersive channel system like the Delta, where subtle phase differences between the various channels dominate the net transport and dispersion.

Computationally, we propose to develop an inverse approach to predicting Delta flows that does not rely on the specification of boundary conditions a priori, but rather estimates the necessary forcing based on observations in the interior of the domain. Our intention is to apply this method to Delta subregions in order to establish the net transport in particular locations of interest in the Delta. For most inverse modeling methods, flows would only be reasonably estimated during the period of observation, which would severely limit the applicability of the approach for management and operational decision making. Our formulation of the open boundary conditions, however, takes advantage of the tidal dominance in the forcing and the inverse estimation of the boundary conditions focuses on defining the amplitude and phase of the important tidal harmonics. Combining these tidal parameters with a linear trend in the boundary conditions allows us to project both the boundary conditions and the resulting flows ahead of the observational period, perhaps to as long as several weeks or a month. The development of the inverse modeling approach will be based on two existing data sets: one collected in the vicinity of Mildred Island in September 2001, one collected at the intersection of the Sacramento River and Georgiana Slough in May 2004.

Finally, we propose an integrated experiment that incorporates both the drifter network and the inverse model calculations. We will choose a domain for this experiment that has existing instrumentation, given the current set of UVMs (ultrasonic velocity meters – measures of cross-sectionally integrated flow in Delta channels), we propose an experiment in the South Delta along Old and Middle Rivers, but we may adjust the location depending on other instrumentation in the Delta. This experiment will involve real-time data collection by the drifters, communication of that data with the base station, and the inverse estimation of boundary conditions leading to a projection forwards in time of flows in the local channels. Our goal here is to test the accuracy and reliability of a real-time, calibration-free approach to Delta flows, including a critical evaluation of the trade-offs between the veracity of our flow predictions and observational or computational expense. Finally, we will compare our ability to predict the local flow conditions to a traditional Delta-scale hydrodynamic model (most likely DSM2) to evaluate the potential for improved operational efficiency in the Delta.

7. Qualifications

The investigators proposing this work bring complementary skills and experience to this activity. First, Stacey has extensive experience with estuarine dynamics and transport, including local experience in the Sacramento-San Joaquin Delta. Two Ph.D. students have pursued research in the Delta looking at channel-shallow interactions, the effects of submerged aquatic vegetation on flow and transport, and the influence of atmospheric forcing on Delta transport (Back 2006; Sereno 2006). More generally, Stacey's research activity broadly addresses mixing and transport in tidal systems, including consideration of the implications for long-term transport and dispersion in estuaries (Stacey et al. 1999, Stacey et al. 2001, Stacey and Ralston 2005).

Bayen brings extensive expertise with control and parameter estimation in systems described by partial differential equations (Bayen et. al. 2004, 2006). The emphasis chosen in his research focuses on efficient computational methods for the solution of these problems, including the development of novel numerical and optimization schemes. The generality of the methods developed is reflected by the variety of applications tackled by his algorithms: transportation networks, systems biology and manufacturing (Lobaton and Bayen 2006, Schubert et. al. 2006, Strub and Bayen, 2006). Currently, Bayen has two Ph.D. students pursuing research on adjoint-based optimization. In parallel, Bayen also provides an expertise in the development of embedded software which will be implemented in the drifters to be developed in this project (Margulici and Bayen, 2006).

EXHIBIT A: ATTACHMENT 4
Task Table

Task #	Task Title	Start Month	End Month	Personnel Involved	Description	Task Budget
1	Inverse Model Development	1	24	Stacey, Mark Bayen, Alexandre	Development of inverse modeling approach to Delta flow and transport analysis. Emphasis is on utilization of existing data sets from the Sacramento River (at Georgiana Slough) and Mildred Island).	$98,793
2	Drifter Network Development	1	18	Stacey, Mark Bayen, Alexandre	Development of real-time Lagrangian drifter network with communication capability within the fleet and between the drifters and a base station.	$105,829
3	Integrated Realtime Experiment	19	30	Stacey, Mark Bayen, Alexandre	Deployment of drifter network (Task 2) and integration with computational tools developed in Task 1. Pursue realtime estimation and prediction of Delta flows and transport.	$107,470
4	Analysis and Evaluation	25	36	Stacey, Mark Bayen, Alexandre	All data and modeling results generated as part of Tasks 1 and 3 will be analyzed in the context of operational strategies and efficiency for in-Delta facilities. Potential for real-time measurements, modeling, and response will be explored.	$78,777