Attachment 4: Water Quality Data Assimilation Modeling Work Plan

To the Monitoring Special Study Plan

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Abbreviations/Acronyms

TERM	DESCRIPTION
1D	one-dimensional
3D	three-dimensional
cfs	cubic square feet
CVP	Central Valley Project
DCD	Delta Channel Depletion
DMS2	Delta Simulation Model II
DWR	Department of Water Resources
EC	specific conductance
EnKF	ensemble Kalman filter
ETKF	ensemble transform Kalman filter
GTM	General Transport Model
HYDRO	hydrodynamic model component
LESTKF	Local error subspace transform Kalman filter
mS/cm	milliSiemens per centimeter
MSS	Monitoring Special Study
OLD	Old River at Tracy Road Bridge Monitoring Station
ORM	Old River near Mountain House Creek Monitoring Station
ORX	Old River above Doughty Cut Monitoring Station
PDAF	Parallel Data Assimilation Framework
SCHISM	Semi-implicit Cross-scale Hydroscience Integrated System Model
SEIK	singular “evolutive” interpolated Kalman
SWP	State Water Project
TDS	total dissolved solids
µS/cm	microSiemens per centimeter

1 Introduction

In the interior southern Delta, elevated levels of salinity (specific conductance [EC] level exceeding 1,000 milliSiemens per centimeter [mS/cm])[1] have been measured by a monitoring station located on Old River at Tracy Road Bridge (OLD) and intermittently have exceeded objectives set forth in the *2006 Water Quality Control Plan for the San Francisco Bay/Sacramento–San Joaquin Delta Estuary* (Bay–Delta Plan)[2]. The high ambient salinity compromises the ability of the interior southern Delta system to supply water for drinking, crop irrigation, recharging ground water, and diluting high-salinity plumes. High levels of salinity have been attributed to many causes, including mass loadings from the San Joaquin River (State Water Board 1980), as well as local salinity sources along the Old River and its tributaries of Tom Paine Slough, Paradise Cut, and Sugar Cut (ICF 2016; Montoya 2007, 2012). Redistribution of this salt is the result of tides, net circulation patterns induced by temporary barriers, and the seasonal and operational influences of San Joaquin River inflow.

Roughly 50 discharges were identified during transect studies that occurred in 2007 (see Table 2-1 in Montoya 2007) and 2012 (see Table 1, 2 in Montoya 2012) downstream of Old River Head on Old River and its tributaries, including point source discharges from three major municipal/industrial wastewater treatment plants (Manteca, City of Tracy, and Deuel Vocational Institute), agricultural drainages, and effluent groundwater. Although the plumes from the agricultural drains and effluent groundwater are known to be saline (350–4,500 mS/cm) due to the leaching of eroded, heavily mineralized, marine sedimentary rock from the Diablo Range (Montoya 2007), direct observations of salinity loads are generally lacking or rare in the interior southern Delta. Non-inclusion of such sources in a transport model of salinity can under-predict the salinity level in the system, which poses a challenge when using these modeling tools for characterizing the spatial and temporal distribution of salinity conditions, water quality management, and long-term planning studies for the system.

The purpose of this study is to apply a data-assimilation approach that integrates the extensive continuous monitoring network already implemented by the California Department of Water Resources' (DWR) North Central Regional Office's Water Quality Evaluation Section with a mechanistic transport model to infer the unknown salinity loads on a reach-based level in the system. This approach can address the underlying causes of the high level of salinity observed in the interior southern Delta and, together with hydrodynamic and salinity transport models, can provide more realistic modeling of the spatial and temporal distribution of water level, flow, and salinity conditions in the interior southern Delta.

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[1] The State Water Project (SWP) and Central Valley Project (CVP) will continue to be operated in accordance with Water Right Decision 1641 (D-1641) until a new water rights decision is adopted by the California State Water Resources Control Board (State Water Board).

[2] D-1641 and related State Water Resources Control Board communications clarify that enforcement action against DWR and the U.S. Bureau of Reclamation to implement the water quality objectives for agricultural beneficial uses in the south Delta is not appropriate where any noncompliance is the result of actions beyond the reasonable control of the SWP and CVP. (D-1641, p.159, para. 6; Letter from Celeste Cantú, Executive Director, State Water Resources Control Board, to Lester Snow, Director, DWR, re Delta Salinity Cease and Desist Order in State Water Board Order WR 2006-0006 (Oct. 13, 2006).

This technical study is complementary to other technical studies identified in Chapter 3, *MSS Study Area and Technical Studies*, of the Monitoring Special Study (MSS). The High-Speed Salinity Transect Mapping study has been providing frequent observational data of EC that will be used to validate the modeling results under various flow and gate-operation conditions.

Data obtained from the separate Point Source and Ion Sampling Study, detailed in Attachment 2, *MSS Salinity Point Source and Ion Sampling*, of the MSS, will provide additional insight on flow and salinity conditions in several ways. A planned rhodamine dye experiment for Paradise Cut and Old River will provide insight on the net-flow directions and null zones in these reaches, which can be used to better constrain the hydrodynamic model and improve water quality modeling. Additional water quality samples taken in and around Pescadero Tract could provide information about salinity loads due to agricultural return flows from Pescadero Tract. This data will be integrated into the model to refine water quality prediction for salinity.

In turn, the water quality data assimilation modeling, described in this workplan, will be used to inform regions with data gaps, types of data needed, and the observational effort required to reduce the uncertainties in the model. The inferred salinity loads as a data product will support the Bay–Delta Semi-implicit Cross-scale Hydroscience Integrated System Model (SCHISM) three-dimensional (3D) modeling study and can also be used to support other hydrodynamic modeling efforts in the Delta modeling community. A more detailed description on how this workplan can support and benefit from existing observations and other technical studies under the MSS (particularly SCHISM) is illustrated on Figure 3 of Attachment 3, *SCHISM 3D Hydrodynamic and Water Quality Modeling Work Plan*.

The products of this study will include regular progress reports, including validation results (as disseminated time series of estimated mass loadings), along with interpretive documentation.

2 Background

This study focuses on the section of Old River in the interior southern Delta that extends east–west from the head of Old River to the channel right above the Clifton Court intake. Old River branches into three streams at Doughty Cut: 1) Lower Old River in the South; 2) Middle River in the North; and 3) Grant Line Canal in the middle (Figure 1). The freshwater flow in the Old River mainly originates from San Joaquin River, where the inflow ranges from 100 cubic square feet per second (cfs) to above 10,000 cfs. Depending on the configuration of hydraulic structures, roughly 35 percent of San Joaquin River (measured at Vernalis) enters the head of Old River, and roughly 6 percent further continues down to Lower Old River. The hydrodynamics of the system is strongly affected by semidiurnal tides, with its amplitude of up to 3,000 cfs on Lower Old River, much greater than that of the tidally averaged flow (generally 10 cfs or 100 cfs), except during the storm events.

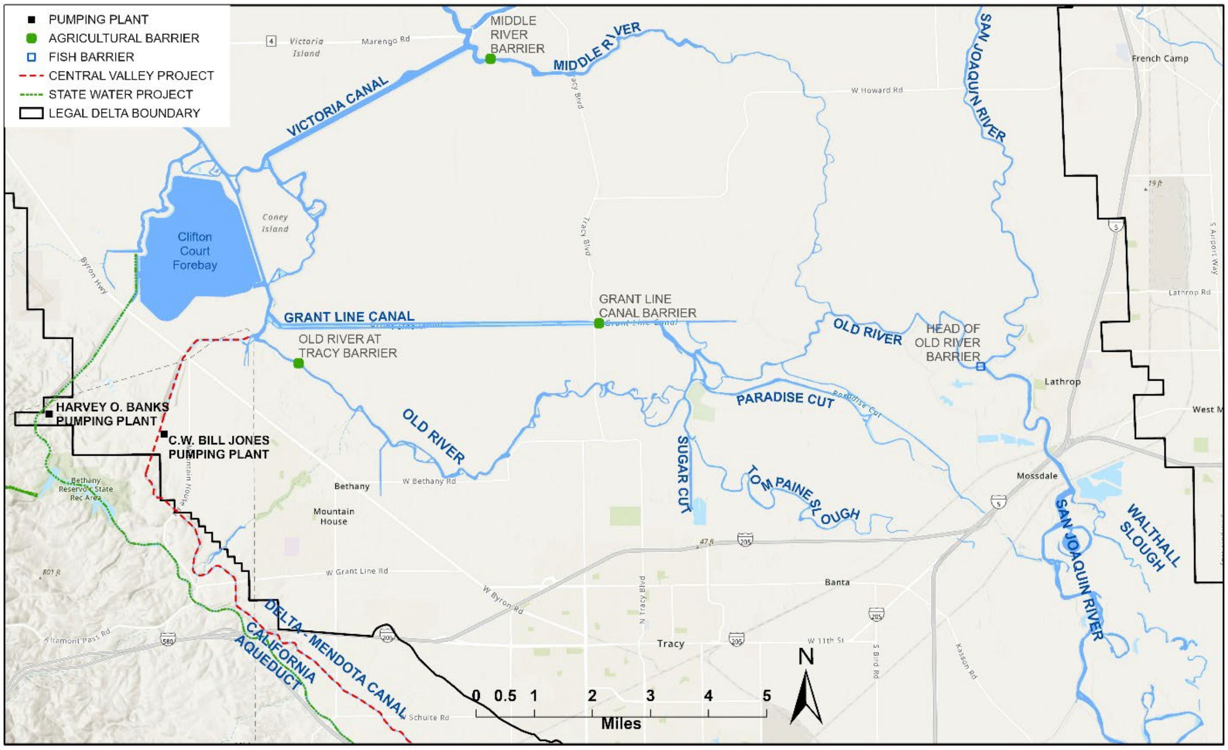

Figure 1. Map of the Study Area Showing Old River, its Upstream Sloughs, and Three Downstream Branches (Middle River, Grant Line Canal, and the Lower Section of the Old River

In addition to the freshwater inflow, the flow rates in the system are greatly altered by extensive water conveyance projects and hydraulic structures (Kimmerer 2004). The two major water projects, the federal Central Valley Project (CVP) and the State Water Project (SWP), divert a rough average of 3,000 cfs and 3,500 cfs, respectively, from the Delta system (shown on Figure 1 as C.W. Bill Jones Pumping Plant and Harvey O. Banks Pumping Plant, respectively). Due to the gate operation and flow export, these facilities lower the water level in the vicinity of adjacent channels. To maintain water level for irrigation purposes during the low-flow periods, three temporary agricultural barriers have been implemented on each of the main streams (Middle River near Victoria Canal, Old River near Tracy, and Grant Line Canal at Tracy Blvd) during the peak irrigation season of each year since 1990. Multiple culverts (ranging from six to nine) with flap gates are installed on each of the temporary barriers; these are tidally operated when there is a need for upstream water level protection, but may also be tied open to favor flushing and circulation. The presence and operation of these barriers raise the upstream water level and reduce the mean downstream flow on Lower Old River. During low—and even during medium—flow periods, the barriers can cause tidally averaged flow to reverse direction in channels immediately adjacent and upstream (an example of this can be observed on Old River near Mountain House Creek [ORM]), so that net flow is mainly in the upstream direction.

Three upstream tributaries are connected and tidally exchange with the Lower Old River (Sugar Cut, Tom Paine Slough, and Paradise Cut), along which water is removed for crop irrigation, and agricultural returns are drained back into the system. The salinity in these tributaries is often greater than that on the Old River due to agriculture drainage, groundwater seepage, and the lack of flushing. Paradise Cut is also hydraulically connected to the upstream San Joaquin River, but separated by a weir that can only be overtopped when the flow rate in San Joaquin River exceeds roughly 17,500 cfs. The connection between Tom Paine Slough and the Lower Old River is also regulated by a weir with six culverts; the gates on the culverts are mostly tidally operated to only allow unidirectional flow into Tom Paine Slough during flood tides, but can occasionally fully open to allow stormwater drainage or two-way tidal flushing during non-irrigation seasons.

Throughout the interior southern Delta, diked islands are located adjacent to the main streams and tributaries, which are known to exchange mass and flow with the channels through drainage, seepage, and diversion (referred to as *Delta Channel Depletion* [DCD]). Typically, the total drainage or pumping rate ranges from a few cfs to a few hundred cfs on Lower Old River and tributaries. Given that the tidally averaged flow during the low flow period is of similar order of magnitude (i.e., hundreds of cfs), DCD can have a strong impact on the flow and salinity in the system.

The salinity in the system varies spatially and temporally throughout tidal cycles and seasons. Along the tributaries, salinity is generally higher upstream than downstream, which results in a net positive flux of salt entering Lower Old River during the ebb tide. During the low flow period, the ambient salinity level on Lower Old River and effective flushing of the system can be affected by the tidally averaged flow through the reach. Many temporal patterns can result, depending on the relative contributions of mass and flow from Vernalis and of mass loadings from in-Delta sources. The spatial and temporal variations of salinity are what make the sources and mass loadings of the interior southern Delta possible to infer.

Correctly modeling the flow circulation patterns in the southern Delta system is key to the success of the modeling study, and modeling in turn represents an opportunity to synthesize information that is gathered as part of the project. Two such circulation patterns in the system have been identified: the null zones/convergency zones on the three branches down Doughty Cut; and the Pescadero circulation pattern. DWR will need to improve knowledge of these flow patterns before we can accurately assimilate EC sources in the system, and gaining insight into the flow patterns requires corroboration of observational data from various sources and hydrodynamic-modeling efforts.

Null zones/convergency zones on Old River, Grant Line Canal, and Middle River can be observed by comparing measured continuous flow rates from paired observational sites, one located at the entrance and the other at the exit of the branch. On Old River, additional depletion of ~100–200 cfs is required to explain the discrepancy between the upstream (OLD) and downstream (ORM) continuous flow rates. Similar null zones/convergency zones also exist on Grant Line Canal and Middle River, but with lower net depletion rates (100 cfs for Grant Line Canal, and 30 cfs for Middle River). Due to this change, the impact of adding such a null zone has been tested in a preliminary hydrodynamic run with the Delta Simulation Model II (DMS2). The tidally averaged flow and the tidal flow–range modeled have been improved compared to observations.

Tom Paine Slough has been known to be a major diversion channel for crop irrigation in the Pescadero district. Because the land elevation is higher in the south than the north of the Pescadero islands, the excess of applied water diverted from Tom Paine Slough is drained into

Paradise Cut. The backwater on Paradise Cut has extremely high EC (ranging from 2,500 to over 4,000 microSiemens per centimeter [µS/cm]), and an estimate of the channel depletion rate on this dead-end slough is important to answer questions about the water exchange rate between Paradise Cut and Old River and the impact of the high observed EC in this slough on the rest of the system. Test General Transport Model (GTM) runs show that a negative depletion rate of 10-cfs flow versus a positive 10-cfs depletion rate on Paradise Cut can result in drastically different modeled EC pattern. Therefore, correctly representing the Pescadero circulation pathway in this model is key to the success of DWR's data-assimilation approach.

3 Methods

A data-assimilation approach that couples a mechanistic water quality model (DSM2-GTM) and a statistical filter (Parallel Data Assimilation Framework) to infer local salinity sources is described below.

DSM2-GTM

DSM2 and its suite of models have been the primary models in studying the hydrodynamic model and ecosystem in the Delta for water resources planning and management over the last few decades (e.g., Kimmerer 2008; Sridharan et al. 2018), and it has been proven to be effective in modeling flow, water level, and tidal excursions in the system. DSM2 represents the Delta system by a network of connected open channels and reservoirs (DeLong et al. 1997) and models the mass and flow exchanges between the computational nodes. A recent publication documenting the tidal characteristics of DSM2 can be found in Sridharan et al. (2018); however, their modeling results can be further improved if DCD (Liang and Suits 2018) and gate operations are properly represented in the model.

The salinity field of the interior southern Delta is resolved by a one-dimensional (1D) GTM, which resolves advection using an explicit finite-volume approach and dispersion using an implicit, time-centered Crank–Nicolson scheme (Ateljevich et al. 2011). GTM is offline coupled to the DSM2 hydrodynamic model component (HYDRO), which provides the flow field.

Although more complex 3D hydrodynamic and water quality models have been applied in the system, the high computational cost required by these models makes the application of data assimilation cumbersome and thus less desirable compared to a simpler 1D model.

The work described in this study plan will be undertaken using historical or hindcast (a calculation used to determine probable conditions) data as it becomes available. This includes major tributary flows (i.e., Sacramento, San Joaquin, Mokelumne, Cosumnes, and Calaveras rivers and Yolo Bypass) and diversions (i.e., SWP and CVP, Contra Costa Water District, and North Bay Aqueduct). Outside of the interior southern Delta, sources and sinks are estimated using the DCD model (Liang and Suits 2017) and accompanying EC concentrations from Liang and Suits (2017, 2018). The assignments of consumptive use (sinks) and agricultural return flow (sources) from the DCD model is described in DWR 2015a and 2015b. As described in these reports, prior simulations with DCD suggests that modeling EC loads from the agricultural return flow helped to improve the local modeled EC, as well as X2, in the entire Delta system. Within the interior southern Delta, data assimilation is used to either supplement or replace these estimates.

PDAF

As part of the preliminary work for this project, the authors developed a statistical filter for DSM2-GTM using a Parallel Data Assimilation Framework (PDAF: http://pdaf.awi.de /trac/wiki), which has already been coupled to various surface-water hydrodynamic and water quality models worldwide (Nerger et al. 2005; Tödter and Bobo 2016; Saynisch and Thomas 2012; Irrgang et al. 2017). PDAF can be applied to high-dimensional models at relatively low computational cost due to its ability to run model ensembles in parallel. This framework encapsules a suite of state-of-the-art linear and nonlinear stochastic filters (Vetra-Carvalho et al. 2018; Nerger 2021; Nerger et al. 2012b). The possibility of quickly switching between different options of linear and nonlinear filters will enable the study team to further advance this approach for potentially assimilating other non-Gaussian water quality processes and parameters in the system.

The particular filter chosen to use is LESTKF (Local error subspace transform Kalman filter), which is an ensemble-based Kalman filter, a variant of SEIK (singular "evolutive" interpolated Kalman) developed by Nerger et al. (2012a) and presented in a form resembling ETKF (ensemble transform Kalman filter; Bishop et al. 2001). An ensemble-based smoother was further developed for LESTKF by Nerger et al. (2014) to reduce previous model error based on future observations and has been shown to be effective when the error covariance of a previous step correlates with error covariance of the current step.

Coupling Between the Two Models

The specific technique DWR is applying is called the *ensemble Kalman filter* (EnKF), and the conceptual demonstration of this approach is shown on Figure 2. In Figure 2, X^a represents a model state, for example, the combined model state of salinity field and salinity sources. The forecast/ dynamic model in this study is DMS2 for hydrodynamic processes, GTM for EC transport, and a structural time series model for model EC sources. The forecast models make prediction of the model states. Its time evolution of modeled states X^f is shown by the blue line. The observations are represented by the red dots. The idea of the EnKF is that rather than assuming that the predicted model state is unique, it is assumed that there is an ensemble of possibilities for model predictions. DWR also assumes that the observations are not perfect, but rather have a known observational error.

The gray bubble is called the *analysis state*, which is the assimilated model state. It lies somewhere in between the model (blue bubble) and observations (red bubble), and it is determined intuitively by the respective errors of the model versus the observations. The greater the model error, compared with observational error, the closer the analysis state will be to the observations. The model prediction with data assimilation is represented by the black line. Compared with the model prediction without assimilation (the blue line), this new prediction gives model results much closer to the observations.

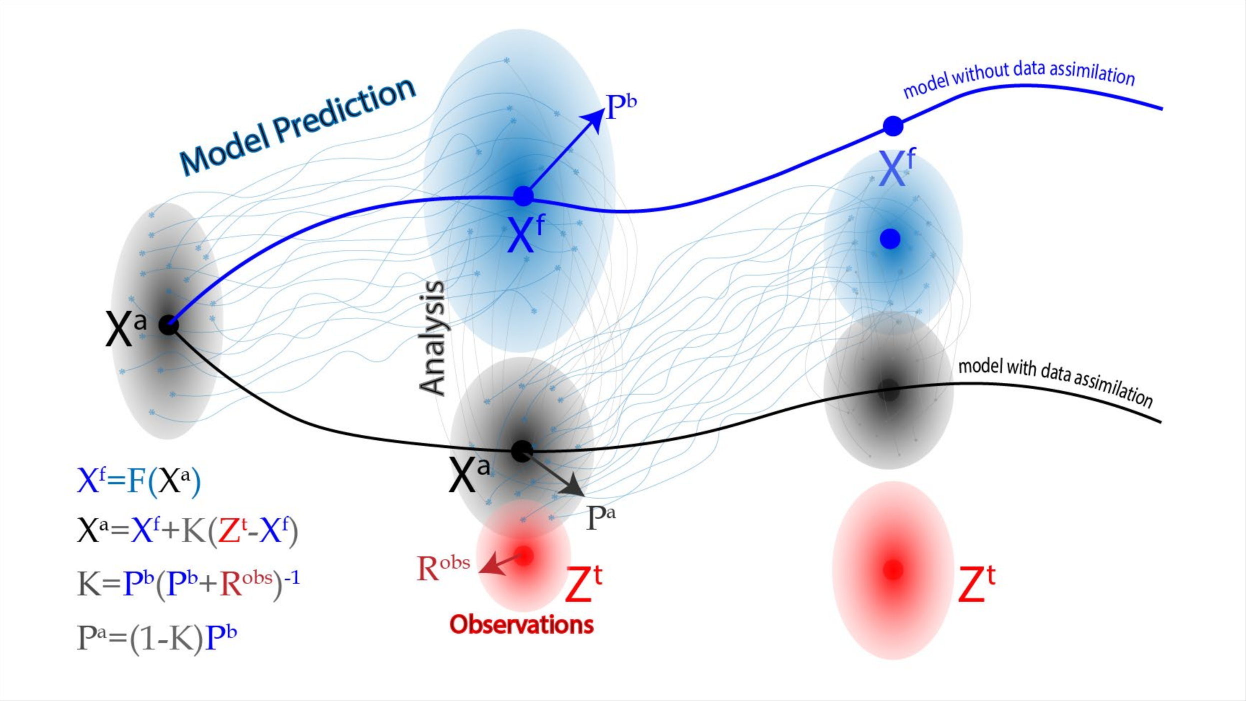

Figure 2. Conceptual Demonstration of the EnKF Approach

GTM is coupled with PDAF, and the detailed coupling process is shown on Figure 3. The DSM2–HYDRO is run first to generate output flow and diffusion, which will be used as input to drive GTM. The initial EC field and EC sources, used as a model input for GTM, are based on statistical priors generated from an ensemble of simulations. GTM will run for a predefined time interval (i.e., 1 hour in this study) and output a new EC field. The output EC field and EC sources form the model state for PDAF. Using the observed EC, PDAF will generate the filtered sources and filtered EC field. The filtered EC field will be used as the initial EC field for the next time step in GTM. The filtered sources will be used in a structural time series model to make a new prediction of EC sources, which will be used as the EC sources for the new time step. There are two ways to apply data assimilation. If only the right half of this diagram is applied, then data assimilation is only applied to the EC field. The run is referred to as Assimilation (no source). Alternatively, the entire diagram can be applied, and then data assimilation is applied to both the EC field and EC sources. The run is referred to as Assimilation (source). It is this second approach that provides the greatest accuracy, as well as insight concerning local contributions of salinity.

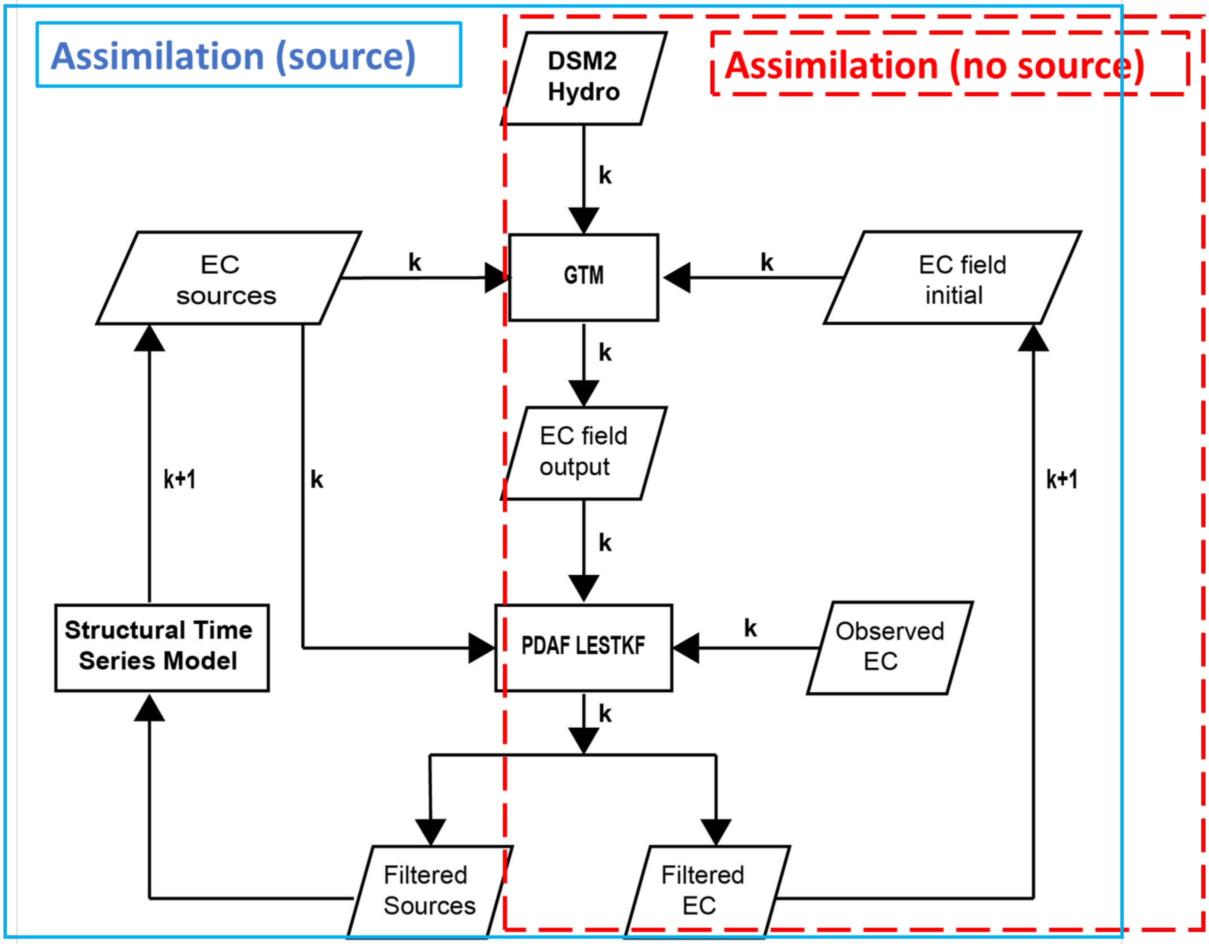

Figure 3. Diagram Illustrating the Online Coupling Process Between GTM and PDAF

4 Initial Findings from Proof-Of-Concept Simulations

The data-assimilation approach has been tested to infer EC loads for the study site on a preliminary basis. Six potential source locations (represented by the red circles on Figure 3) were chosen to assimilate the EC sources. Data assimilation was applied from March 2016 to December 2016, and the initial results for this test run are presented below. Note that these six locations used in the proof-of-concept simulations comprise only a small subset of the full set of candidate locations (see south Delta dischargers on Figure 4), which include the discharge locations identified in Table 1 and Figure 2 of Montoya (2012) and Delta Atlas, and in particular omits locations in Grant Line Canal and downstream of the Old River at Tracy Wildlife Association station.

The source locations were chosen based on the knowledge of significant dischargers previous identified in Montoya (2007, 2012). At these chosen locations, either an obvious and repeated pattern of increased EC was recorded by the EC transects, or at least one known significant EC drainage was identified nearby.

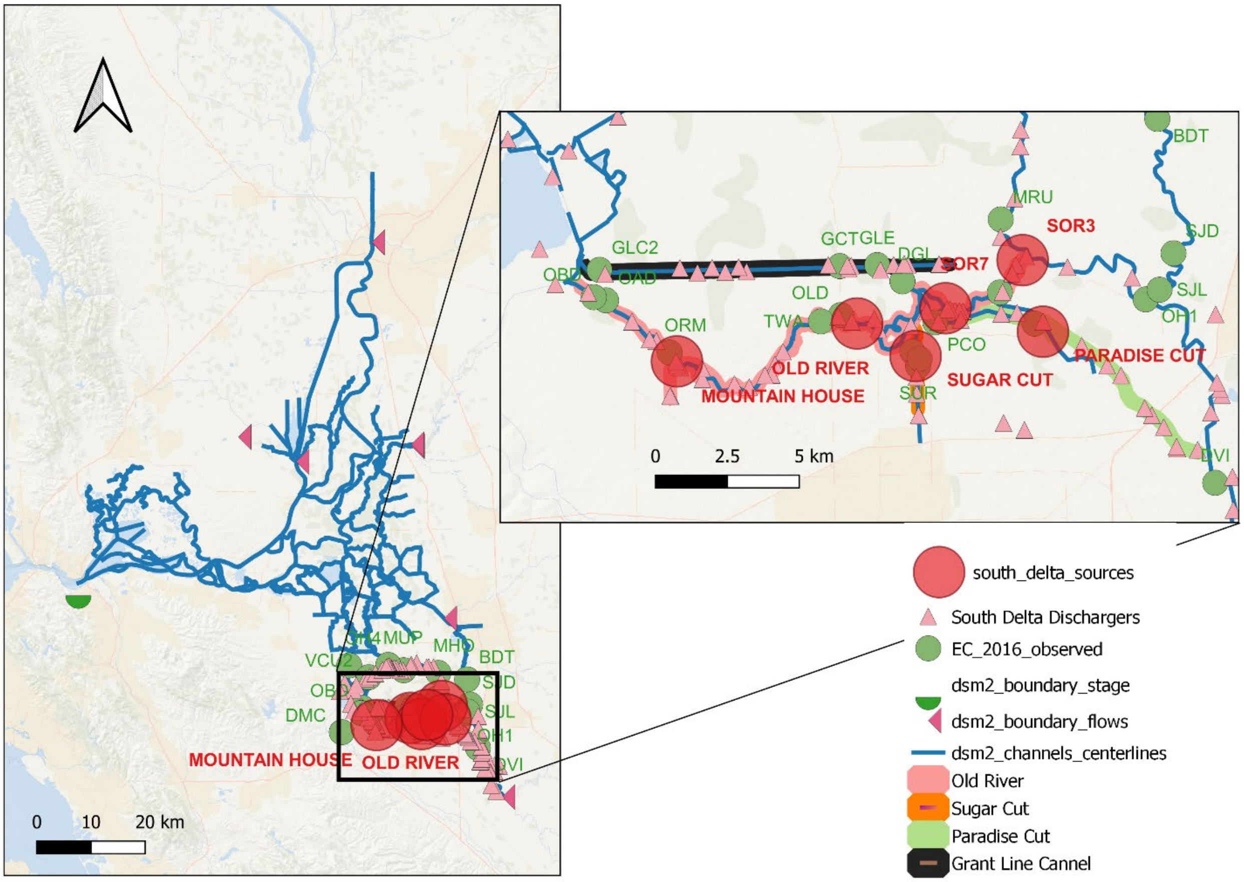

Figure 4. Maps of the Delta System (Left) and the Study Site (Inset)

Figure 5 shows the inferred EC sources using the data-assimilation approach. Salt flux from the six source locations was calculated from the EC load following the unit conversion by DWR (2018). EC (in units of µS/cm) is converted to total dissolved solids (TDS) concentration (in units of milligrams per liter) using a TDS constant (i.e., EC/TDS ratio) of 0.58, and then salt flux (with a unit kt/day) is calculated by TDS times the flow rate. There are no long-term. Continuous monitoring data of sources in the system, so there can be no direct validation of EC sources. However, Montoya et. all did have some observations of flow rate and EC levels from a few grab samples at these source locations in 2007 and 2012 (Montoya 2007, 2012); multiplying the maximum observed flow rate times the maximum observed EC yields a bracketing value for the maximum EC loads ever observed. Note that the Old River above Doughty Cut Monitoring Station (ORX) lumped all EC sources between Vernalis and Old River Head. In Montoya (2007), significant EC sources along this section of the stream were identified; however, not all EC sources have observational data. Therefore, the EC threshold given on Figure 5 for ORX did not include these EC loads and may thus be underestimated.

The red lines on Figure 5 highlight the observed upper limit of EC loads over the years of grab samples. The envelope of what was inferred matches well with the envelope of the grab samples as shown on Figure 5.

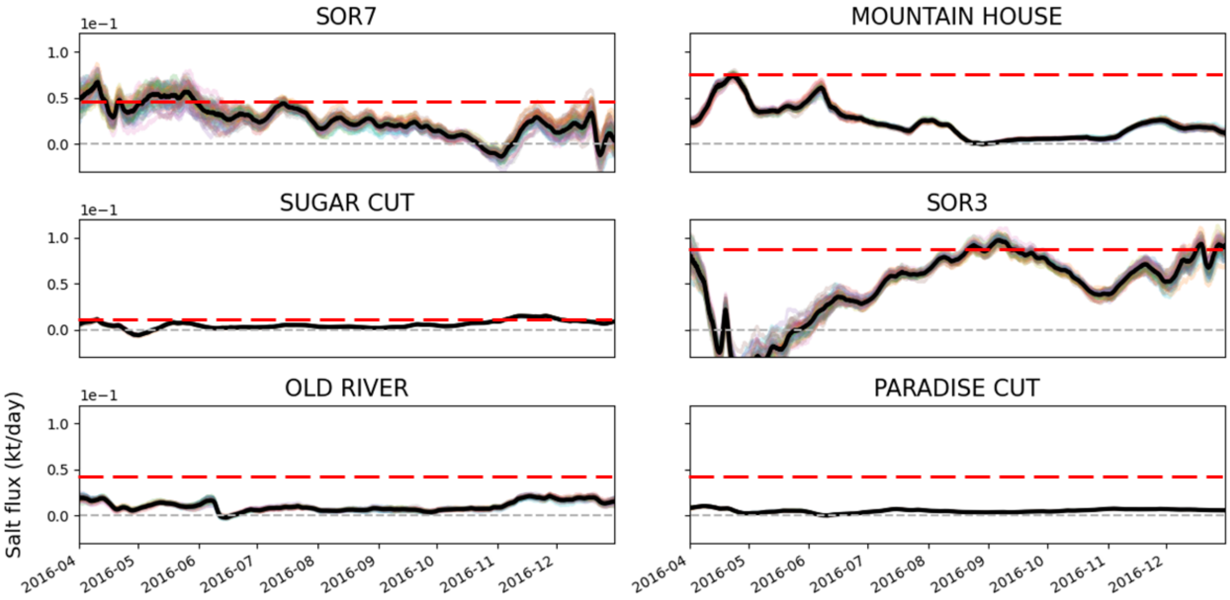

Figure 5. The inferred EC sources by the data-assimilation approach for 2016. The dark lines represent the ensemble mean of the inferred sources, the clouds of colored lines represent the ensembles, and the red lines represent the upper limit of EC sources ever observed at the corresponding source locations. The locations for the sources can be found on Figure 4.

The comparisons of modeled versus observed EC are shown on Figure 6. It is clear that inferring EC sources greatly helped to improve the modeled EC fields at all observational sites (dark blue lines) compared to EC sources modeled by DCD model (light blue lines) or without EC sources (median blue lines).

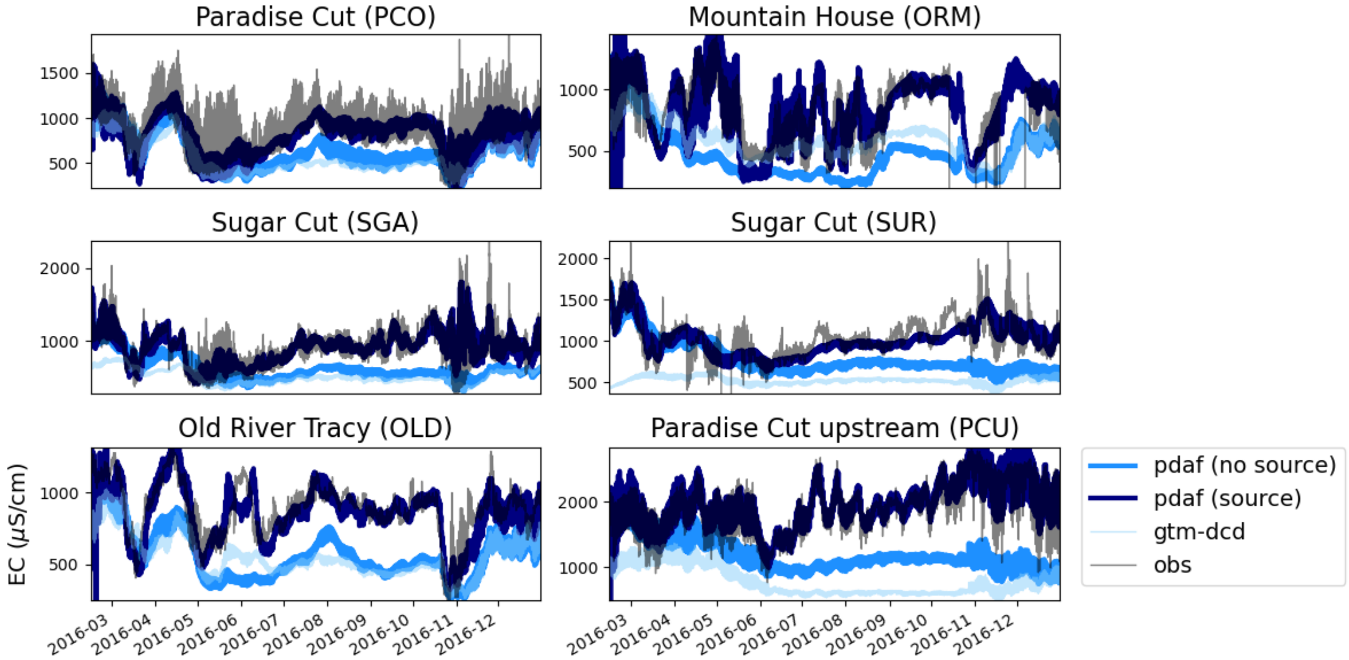

Figure 6. Comparisons between observed and modeled EC. The gray lines at the back represent real observations; the very light blue lines (normally at the very bottom) indicate modeling results without data assimilation, but instead it included Delta Channel Depletion, a separate offline model that estimates EC loads into the system. This serves as the best current EC model without data assimilation. The medium blue lines represent data assimilation on EC filed only (without inferring the EC sources). The dark blue lines represent data assimilation on both EC field and EC sources (with EC sources inferred from the model) and without using the Delta Channel Depletion model. The locations for the observational sites can be found on Figure 4.

Validation

Standard validation metrics are not sufficient for data-assimilation methods because the model results are nudged toward observations. As such, validation relies more than ever on reserved data and prediction. The following metrics will be reported.

1) Comparisons with observations at continuous monitoring stations with and without source terms, analogous to Figure 6 from the proof-of-concept run.
2) Prediction/extrapolation results showing the benefits of the inferred source terms when extrapolated in time or between years (which is expected to vary).
3) Spatial comparisons to high speed monitoring data, in order to confirm that between-station spatial patterns are correctly inferred from continuous stations.
4) Comparison with any grab samples or discharge measurements made available over the course of the project.
5) Characterization of sources that are not uniquely determined based on the model and monitoring network; the characterization will be carried out using response function (Green's function) methods and decompositions such as that of Pous (1985) that have

produced derivative works in various disciplines; this analysis will be carried out on a subset of 2022 data.

6) Analysis of skill improvements using the inferred salinity sources within SCHISM offline of data assimilation.

Uncertainties and Caveats

The prototype work described in the previous sections reveals a few uncertainties that may affect data assimilation work, such as regions that are poorly covered by monitoring or subject to uncertainty concerning mean flow direction. Some of these uncertainties will be addressed by targeted field observations or improved data analysis, and the resulting measured data will be incorporated into the method. Other uncertainties may remain unknown, in which case sensitivity studies will be used to quantify the impact of misspecification. Examples include the following.

- *Uncertainty in the amplitude and direction of mean flow during low-flow period near the null zone on Old River.* During the period when the Old River at Tracy Barrier is installed, the measured flow direction on Old River at Tracy is westward, whereas the measured flow rate at Mountain House (west of Tracy Blvd) is eastward. This indicates a convergence of flow between the two observation sites when the temporary agricultural barriers are installed. It is estimated that 100 to 200 cfs of water is diverted between the two sites, assuming that the flow measurements are accurate. However, the exact locations and the flow rate of the flow diversion are uncertain. Additional flow observational sites will be implemented between the two sites to gain insight on flow direction in the region. Until the data become available, assumptions will have to be made about the flow diversion to match the field observations of flow rates at both sites.

- *Uncertainty in the flow diversion from Tom Paine Slough and drainage into Paradise Cut.* Estimated diversions are on the order of tens of cfs. Previous modeling results show that the assimilated EC sources are sensitive to the net flow direction on Paradise Cut and the flow direction (i.e., sink) that occurs under current channel depletion models is thought to be in error. Currently, the Paradise Cut flow gauge is under recalibration for conditions when the temporary barriers are in place; also planned is a dye study that can corroborate the net-flow direction. Corroboration of analyzing observed data from multiple sources and modeling efforts will also help reduce this uncertainty.

- *Uncertainty concerning the locations of the most significant EC loads/sources and lack of uniqueness in the source inference method.* It is challenging to assimilate EC sources from all potential source locations (50+), so the work thus far has incorporated expert judgement and mapping data from Montoya (2007, 2012). The study will aggregate the sources across locations on a reach level (about 4–8 kilometers), which is the most specificity allowed by the DSM2 interface. The report will describe, via sensitivity tests, the consequences of misspecification. DWR will also use a modified method similar to that of Pous (1985), which computes combinations of sources that would not be well identified by the data.

5 Long-Term Monitoring and Reporting

Model scenario runs will help identify a range of natural conditions, under which EC loads at current levels will likely cause EC levels to exceed the reach-based compliance standard, and potential management actions that can be taken to address this issue. The model study will also be used to optimize the current continuous observational network and identify data gaps that can reduce model uncertainties. Lastly, this study will potentially contribute to the development of an operational EC model that can simulate the spatial and temporal variations of EC fields in almost real time.

6 Study Plan and Deliverables

DSM2 and PDAF will be applied from January 2016 to December 2023, applying updates as field data becomes available. Historical/hindcast data will be used to supply boundary-flow and water-quality data for Vernalis, as well as for remote boundaries and mass/volume sources that are outside the study area.

Key outcomes expected from the effort are as follows:

- Analysis of multiple sources of observational data (including flow rates, water levels, and Electronic Water Rights Information Management System flow-diversion rates) to obtain improved representation for and understanding of the local-flow null/convergence zones and Pescadero Tract circulation patterns. The knowledge gained from this analysis will be used to revise the existing DCD model and DSM2 baseline run. A presentation based on the findings from the integrated modeling and data analysis effort will be presented annually, or as needed, in an participating organization[3] meeting under the title "Revision of Assumptions and Inputs."
- Mass loadings for the interior southern Delta sources in .csv files on California Natural Resources Agency Open Data portal, along with interpretive information, versioned in accordance with technical progress, interested-party input, and availability of data. The key hypothesis of the data-assimilation component is that sources can be inferred sufficiently to explain mass loadings not explainable by Vernalis inflow with reach-level (4–8 kilometers) spatial accuracy.
- A Study Report to include the following.
    - Description of the methodology and data sources
    - Interannual comparisons of mass loadings
    - Quantification of errors with respect to high-speed measurements
    - Assessment of sensitivity to misspecification of source flows and candidate source locations
    - Quantification of the role/value of MSS-augmented measurements in reducing uncertainty

A list of anticipated tasks, milestones and deliverables are presented below.

- Task 1: Apply the data-assimilation approach from January 2016 to December 2021 to infer EC sources and refine the hydrodynamic-calibration and volumetric-conceptual/quantitative models.

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[3] This document uses the term *participating organization* instead of *stakeholder.*

    - Initial mass loadings for use in SCHISM in 2021 (from January to December 2021), anticipated for April 2022
    - Completion of full period and presentation to interested parties by December 2022

- Task 2: Update report based on January 2021–December 2022 field data.
    - Update report, anticipated for June 2023
    - Mass loadings revised for January 2016–December 2021 and updated through 2022, anticipated for June 2023

- Task 3: Complete a report on data integration/data assimilation, summarizing all findings for MSS (draft anticipated by June 2024 and final report anticipated by December 2024).

In addition, an annual presentation and summary of modeling assumptions will be delivered to interested parties to summarize data analysis and new modeling assumptions. This deliverable is listed under the SCHISM section, but it includes synthesis that is applicable to both models, as well as the field work of the MSS.

7 References

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