Delta Turbidity ANN Model (DASM-T) Development Using DSM-2: Phase 2 Results

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ACRONYMS

ANN	Artificial Neural Network
CCF	Clifton Court Forebay
CCWD	Contra Costa Water District
CVP	Central Valley Project
DICU	Delta Island Consumptive Use
DSM2	Delta Simulation Model II
DWR	Department of Water Resources
FFW	Feed Forward Network
FWS	Fish and Wildlife Service
IEP	Interagency Ecological Program
MWD	Municipal Water District
MLP	Multi-layer Perceptron
NARX	Nonlinear Autoregressive Network with Exogenous Inputs
NTU	Nephelometric Turbidity Units
OMR	Old and Middle River
RMA	Resources Management Associates

SE Standard Error

SWP State Water Project

WARMF Watershed Analysis and Risk Management Framework

1 INTRODUCTION

The Delta smelt (*Hypomesus transpacificus*) is an endangered species endemic to the Sacramento-San Joaquin estuary of California, with low recorded abundance in the last decade by the Interagency Ecological Program (IEP). A 2008 Biological Opinion by the U.S. Fish and Wildlife Service (FWS) recommended changes in the manner in which flows and freshwater exports through the Delta are managed to address the decline in population of this species (http://www.fws.gov/sfbaydelta/ocap/). Delta smelt abundance is related to various water quality parameters, including temperature, conductivity, and turbidity, possibly due to linkages between Delta smelt migration and turbidity levels (Armor and Sommer, 2006). California Department of Water Resources (DWR) scientists have observed that there is an increase in Delta smelt salvage at the water export facilities when the turbidity exceeds a level of approximately 12 Nephelometric Turbidity Units (NTU).

To support implementation of the 2008 Biological Opinion, there is a need to understand and predict fate and movement of turbidity in the Delta. Besides greater collection of turbidity data that has been initiated since 2009, turbidity modeling is also needed. Two such approaches include mechanistic modeling using the Delta Simulation Model (DSM-2) (Liu and Sandhu, 2011) and using the Resource Management Associates RMA-2 model (RMA, 2008). These models compute turbidity within the Delta channels given inputs of flow and turbidity at all relevant boundaries. However, both modeling approaches require considerable user expertise and computational time to run, hence limiting their accessibility. There is an additional need for a tool that can be used to provide rapid predictions of turbidity in two situations: for near-term operations planning, where there is a need to estimate turbidity expected over subsequent days under a variety of operating scenarios, and, for long-term water supply planning, where there is a need to estimate turbidity-related export constraints in water operations models (e.g., CALSIM) run over multi-year periods. Under these conditions, running a fully mechanistic model of the system is generally not computationally feasible.

To fit this need for generating rapid predictions, Artificial Neural Networks (ANNs) were proposed as an alternative mathematical approach to conventional statistical methods and mechanistic models. ANNs use simple elements (neurons) and connections between elements using a range of functional forms to represent complex real-world data. The ANN methodology was inspired by biological nervous systems (Demuth and Beale, 2002) and has found broad application in the prediction and control of complex systems. An ANN can be trained, in a manner similar to calibrating a model, to perform a particular function through adjusting values that form the connections between elements (weights).

The ANN approach has been used broadly in the Sacramento–San Joaquin Delta in predicting salinity at various interior locations by the California Department of Water Resources (Finch and Sandhu, 1995; Sandhu et al., 1999) and for predicting salinity and impacts of sea level rise (Seneviratne et al., 2008). The salinity ANN developed by DWR was trained on DSM2 results that may represent historical or future conditions, through taking into account individual flow components and operational parameters as model inputs.

This work, i.e., the application of ANNs for turbidity modeling, was accomplished in two phases. Phase 1 of the Delta turbidity ANN model study explored the potential of developing an ANN turbidity model at a few locations within Delta, and to determine whether the methodology was suitable for broader-scale application. The study used model-calculated turbidity values from DSM2 for the period of 1990-2010 for training the ANN. Results from the Phase 1 work provided an important proof-of-concept of the use of ANNs for modeling turbidity in the Delta, and provided support for the use of the approach for planning and operational purposes (Chen and Roy, 2012). The ANN model was termed DASM-T, for Delta ANN Simulation Model-Turbidity.

Phase 2 of the work, presented in this report, extends the Phase 1 analysis to additional stations for a total of 16 stations within the Delta. Similar to the Phase 1 study, the DSM2 model was used to create datasets for the ANN training, based on combinations of different turbidity levels at boundary locations. The Phase I study used a DSM2 model calibrated using turbidity data for the wet season of 2010 at various locations within the Delta (Liu and Sandhu, 2011). An updated version of the DSM2 model, calibrated using extended record periods of flow and turbidity (2010-2012) by Resource Management Associates (RMA) was used in Phase 2 of the study (RMA 2013). The RMA-calibrated version of the DSM2 model used extended periods of flow records and combinations of turbidity values from USGS (Freeport and Vernalis) and watershed model simulations at boundary locations (Calaveras, Mokelumne, Cosmunes and Yolo) to simulate turbidity for the 1975-2011 period. Watershed model simulations that are embedded in the boundary turbidity values were developed using the Watershed Analysis and Risk Management Framework (WARMF) model. A total of 12 scenarios with different combinations of turbidity levels at boundary locations were used to generate datasets for training, following the approach used in the Phase 1 work.

2 APPROACH

2.1 OVERALL APPROACH

The overall approach of the Phase 2 study, similar to the Phase 1 approach, was to train the ANN model based on a set of boundary scenarios formulated to represent historical or potential future conditions in the Delta, generated by the DSM2 model. The DSM2 model was selected to simulate turbidity within the Delta, rather than using the observed data directly. This is because DSM2 is able to mechanistically simulate the response in turbidity at different Delta locations, due to changes in individual flow components and operating conditions that could potentially occur in the future. This range of responses may not be captured by using observed turbidity data available at these locations, which span a relatively short time frame (from 2009 to the present). The DSM2 model outputs are considered the next best option for developing a long-term data set that is able to account for future changes in Delta flow and operation under a reasonably wide range of hydrologic conditions. It is important to understand the initial goal of the present work is the emulation of DSM2 performance, with the testing and evaluation and performed against model-generated turbidity. More broadly, however, the ultimate goal is to represent the natural system, and the performance of the ANN can also be evaluated against new turbidity data, that are independent of DSM2 and of the dataset used for calibrating DSM2.

2.2 DSM2 MODEL

2.2.1 DSM2 TURBIDITY MODEL

An updated version of the DSM2 turbidity model developed by RMA was used to simulate turbidity within the Delta (RMA, 2013). The model was calibrated for the wet season of 2010, 2011 and 2012, using turbidity data available at 15-minute intervals, and using variable first-order decay rates through the Delta (varying in space, but constant in time). The model used a combination of suspended sediment data from USGS at Freeport and Vernalis and WARMF model output at other boundary locations (Yolo Bypass, the Calaveras, Cosumnes, and Mokelumne Rivers). Model simulated turbidity at 15-minute intervals and daily average values were comparable to values observed at a number of locations including the Sacramento River at Rio Vista, Decker Island, Prisoner's Point, Holland Cut, San Joaquin River at Jersey Point, Garwood, Mossdale, Brandt Bridge, and Old River at Bacon Island, and Victoria Canal.

2.2.2 FORMULATION OF BOUNDARY CONDITION SCENARIOS

The updated DSM2 turbidity model was used for simulating flow and turbidity relationships within the Delta under a set of formulated boundary scenarios. The DSM2 model was run for a period of 36 years assuming observed hydrology and water project operations from 1975–2011. The formulated boundary scenarios take into account combinations of different turbidity levels (low, middle, and high levels) from three sources: North Delta (Sacramento River + Yolo), San Joaquin River, and east side tributaries (Mokelumne, Cosumnes, and Calaveras Rivers). Turbidity from Delta Islands and Martinez locations were set as constants. The boundary scenarios also considered the effect of removing water project diversions. A total of 12 scenarios were formulated (Table 2-1). Historical water project operations were modified assuming that: 1) the Delta Cross Channel (DCC) gate is closed all months; and 2) south Delta temporary barriers are not installed. The assumptions are reasonable given that the ANN model will be used for the period of December through February. Detailed flow-turbidity relationships used to determine boundary turbidity inputs under low, middle or high turbidity conditions at different boundary locations are listed in Appendix A. The derived boundary conditions for the low, middle and high turbidity levels are shown graphically in Figure 2-1.

2.3 ARTIFICIAL NEURAL NETWORK MODEL

2.3.1 MODEL INPUTS

For the ANN model training, a set of six input variables were used. These input variables are considered to be the main boundary conditions that influence turbidity dynamics within Delta. These inputs include:

- North delta inflow
- East side stream inflow
- Calculated Old and Middle River (OMR) flow
- North delta turbidity
- East side stream turbidity
- San Joaquin River (Vernalis) turbidity

Table 2-1
DSM2 Simulations and Associated Turbidity
Boundary Conditions Used for Generating ANN Training Data

Run	Hydrology	Sacramento	SJR	Yolo	Cosumnes	Mokelumne	Calaveras	Islands	Martinez
1	Historical	Low	Low	Low	Low	Low	Low	10 ntu	26.6 ntu
2	Historical	Mid	Low	Mid	Mid	Mid	Mid	10 ntu	26.6 ntu
3	Historical	High	Low	High	High	High	High	10 ntu	26.6 ntu
4	Historical	Low	High	Low	Low	Low	Low	10 ntu	26.6 ntu
5	Historical	Mid	High	Mid	Mid	Mid	Mid	10 ntu	26.6 ntu
6	Historical	High	High	High	High	High	High	10 ntu	26.6 ntu
7	Historical w/o Exports	Low	Low	Low	Low	Low	Low	10 ntu	26.6 ntu
8	Historical w/o Exports	Mid	Low	Mid	Mid	Mid	Mid	10 ntu	26.6 ntu
9	Historical w/o Exports	High	Low	High	High	High	High	10 ntu	26.6 ntu
10	Historical w/o Exports	Low	High	Low	Low	Low	Low	10 ntu	26.6 ntu
11	Historical w/o Exports	Mid	High	Mid	Mid	Mid	Mid	10 ntu	26.6 ntu
12	Historical w/o Exports	High	High	High	High	High	High	10 ntu	26.6 ntu

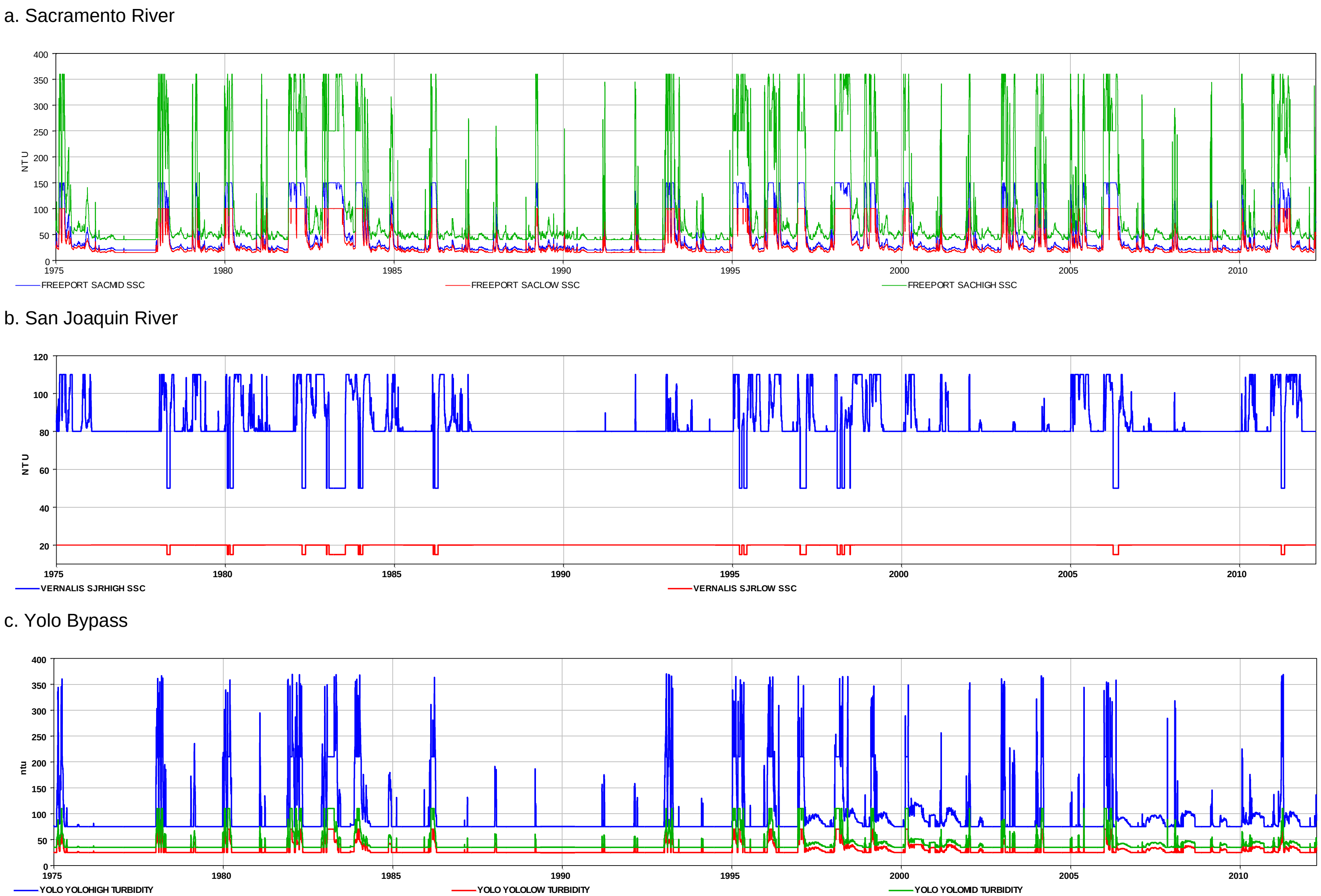
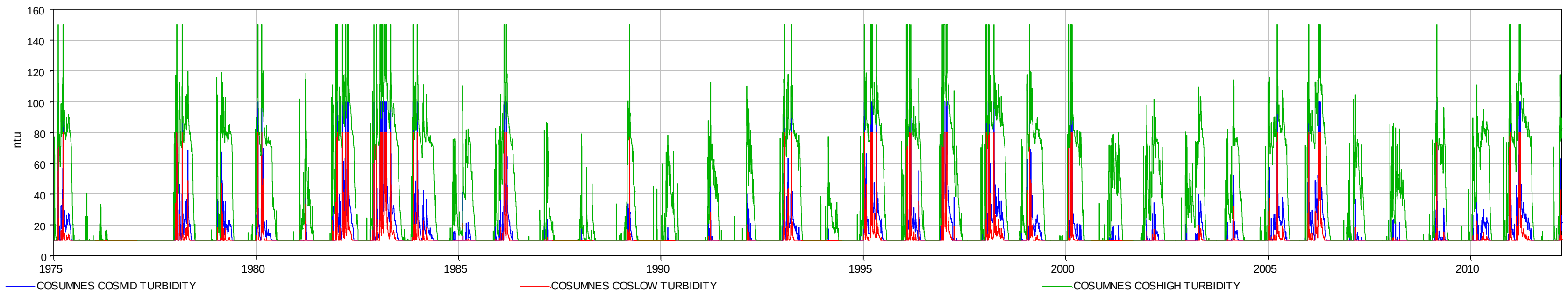
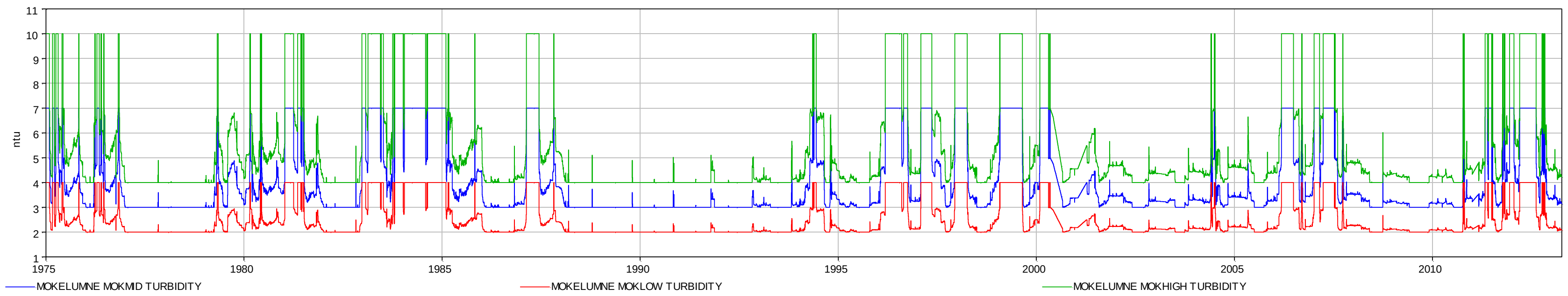


Figure 2-1 Boundary conditions of low, middle, and high turbidity levels at: a) Sacramento River; b) San Joaquin River; c) Yolo Bypass; d) Cosumnes; e) Mokelumne, and f) Calaveras Rivers.

d. Cosumnes River



e. Mokelumne River



f. Calaveras River

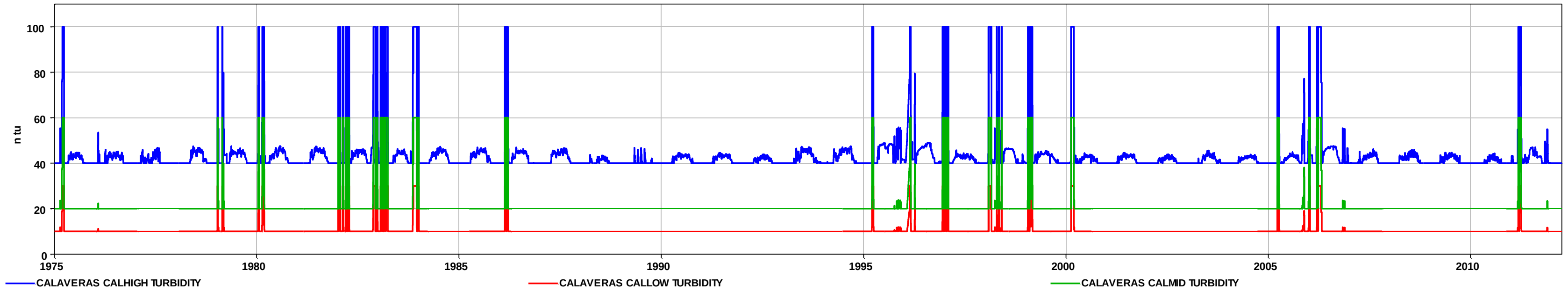


Figure 2-1 (continued) Boundary conditions of low, middle, and high turbidity levels at: a) Sacramento River; b) San Joaquin River; c) Yolo Bypass; d) Cosumnes; e) Mokelumne, and f) Calaveras Rivers.

The north delta inflow was calculated as the total of the Sacramento River and Yolo Bypass inflow. The east side stream flow was calculated as total of inflow from the Mokelumne River, the Cosumnes River and the Calaveras River. The current configuration of the Delta relies on the Old and Middle Rivers to convey water to the CVP-SWP export pumps. This pathway can result in reverse flows and have significant impacts on water project operations (Hutton, 2008). A south Delta water balance was used in determining OMR flows:

OMR flow = San Joaquin River flow at Vernalis

+ Indian Slough flow at Old River

– San Joaquin River flow downstream of HOR

– Clifton Court Forebay diversions

– Jones pumping plant diversions

– CCWD Old River intake diversions

– South Delta net channel depletion

When calculating the OMR flow, DSM2 boundary conditions were used for San Joaquin River flows at Vernalis, diversions at Jones Pumping Plant and CCWD Old River intake (Hutton, 2008). Computed data from DWR's Delta Island Consumptive Use (DICU) model were used in the water balance for south Delta net channel depletions. DSM2 simulated data were used in water balance calculation for flows at Indian Slough at Old River, San Joaquin River downstream of HOR (Head of Old River) and diversions at Clifton Court Forebay (CCF). A detailed approach for calculating the OMR flow was outlined by Hutton (2008) and described in the Phase 1 report (Chen and Roy, 2012).

A calculated OMR flow is used as it will allow for a more explicit relationship between exports and hydrodynamic conditions. This relationship is needed as forecast scenarios will be based on different operation scenarios. Phase I work of this study showed that DSM2 generated OMR values did not provide improvements over calculated OMR values.

The north Delta turbidity was calculated as flow-weighted averages of turbidities at the Sacramento River at Freeport and Yolo Bypass. The east side stream turbidity was calculated as flow weighted averages of turbidities at the Mokelumne, Cosumnes, and Calaveras Rivers. Turbidity from these tributaries and San Joaquin River at Vernalis was computed based on flow - turbidity relationship derived from an analysis (outlined in Appendix A) for low, middle and high turbidity input levels (RMA, 2013).

2.3.2 ANN OUTPUT LOCATIONS

Phase 2 of the work expanded the turbidity ANN locations in the Delta to a total of 16 stations (Figure 2-2). These stations include:

- West Delta
  - Sacramento River @ Rio Vista
  - Sacramento River @ Decker Island
  - SJR @ Jersey Point
- Central Delta
  - SJR @ Prisoner's Point
  - Old River @ Holland
  - Old River @ Quimby
  - Old River @ Bacon
  - Middle River @ Holt
  - Middle River @ Bacon Island
  - Turner Cut @ Holt
- South-Southeast Delta
  - Old River @ Hwy 4
  - Old River @ Clifton Court Intake
  - Victoria Canal
  - Middle River @ Union Point
  - Grant Line Canal @ Tracy
  - San Joaquin River @ Garwood

The DSM2 model simulates turbidity at locations throughout the Delta, a subset of which were used for this work. DSM2 output at 15-minute intervals was used to compute daily averages for the ANN training. DSM2 simulations of turbidity at the selected locations were used in training and for developing the Delta turbidity ANN model.

The training data set consisted of values over a 36-year hydrologic period for 12 boundary conditions, representing ~365x36x12 (=157,764) data points for each output location.

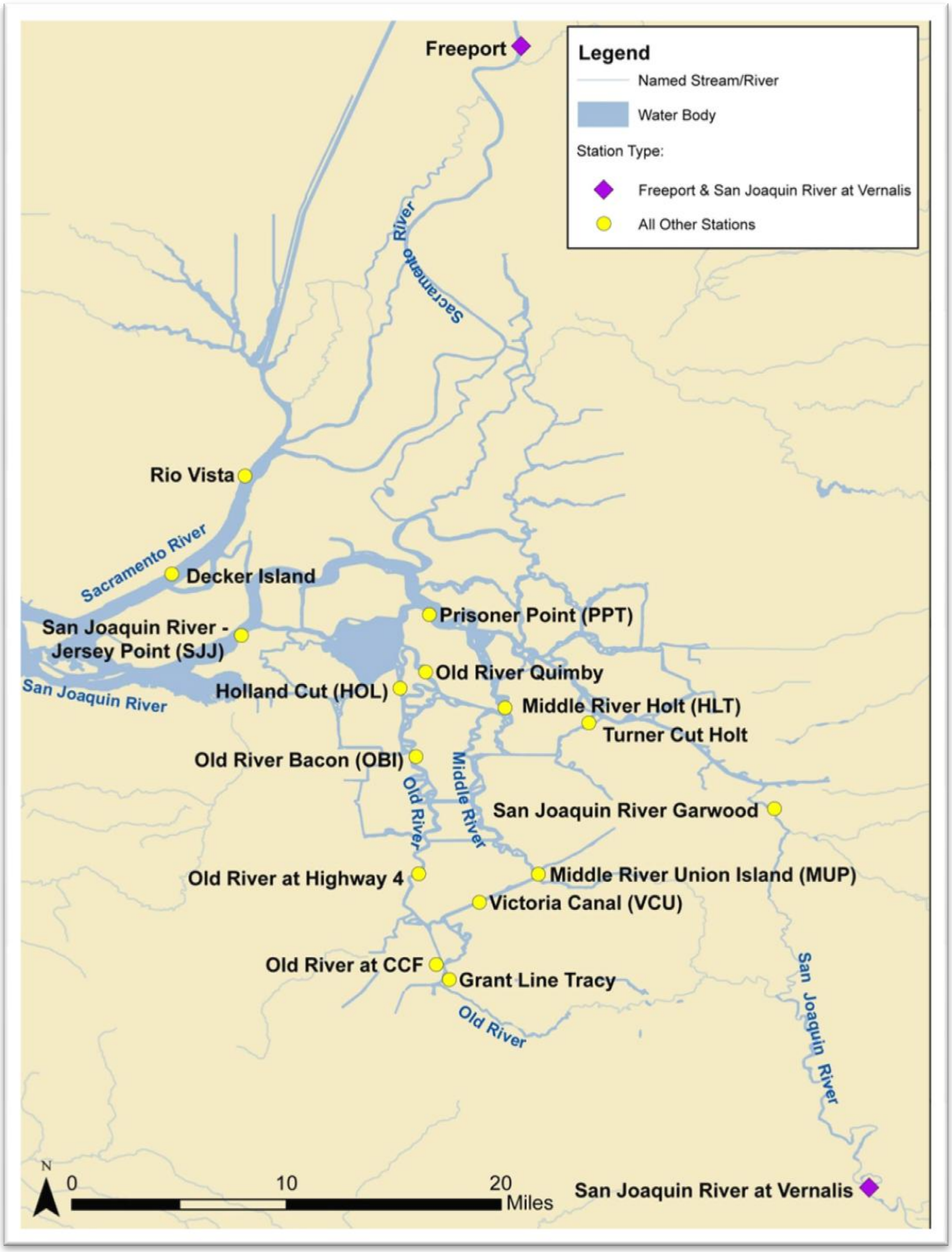


Figure 2-2 Locations of output stations for ANN training. Three letter codes, where shown, refer to CDEC station codes.

2.3.3 ANN Model Structure

The dynamic nature of flow and turbidity in the Delta requires a network structure that takes into account the time-series effect. Although other network structures have received attention in the recent literature, the multi-layer perceptrons (MLPs) are by far the most popular network structure used in water resources applications to date, representing more than 90% of peer-reviewed applications in the water resources field (Maier et al. 2010). For this reason, the feedforward MLP network was selected in this study, and is shown schematically in Figure 2-3.

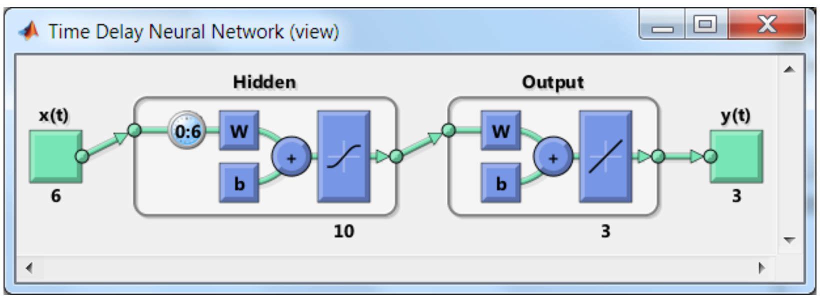


Figure 2-3 Feed-forward ANN model structure (inputs = 6 boundaries (3 flow + 3 turbidity), hidden neurons = 10; time delay = 7 days; outputs: turbidity at 3 locations). x(t) represents the input, y(t) the output, and W and b represents the weights and biases.

In this network, the input layer, termed *x(t)* contains time series of six input variables (3 flow inputs, and 3 turbidity inputs as described earlier). The hidden layer uses 10 neurons, which is formulated based on input variables using a set of weights (W) and biases (b). For 10 neurons and 6 input variables, this will yield a total of 60 weights and 60 bias parameters that need to be adjusted during training. An input time delay of 1–4 days can be used, each with its own set of weights and bias parameters. For a time delay of 4 days, the network will yield 240 weights and 240 bias parameters. The output layer, *y(t)*, contains the number of output variables defined for each ANN. The hidden layer is converted to the output layer through another set of weights and biases.

In addition to the feedforward network, the turbidity data were also fitted to a nonlinear autoregressive network with exogenous inputs (NARX) network, where the output of the model at the previous time steps is also used as an input as shown on the left side of Figure 2-4. The NARX network training can be implemented in what is termed the "open loop" mode, where the output data are used for training. Once the model is trained, it can be converted to a "closed loop," where the values of *y(t)* on the left side are obtained from ANN for the previous time step.

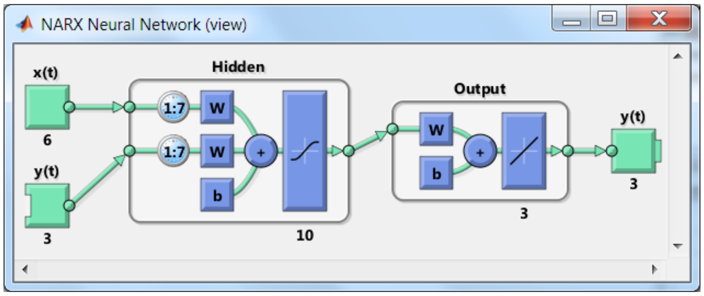


Figure 2-4 Matlab NARX ANN model structure (y(t) = f(x(t-1), …., x(t-d)); inputs = 6 boundaries (3 flow + 3 turbidity), hidden neurons = 10; time delay = 1-7 days; outputs: turbidity at 3 locations). During training, y(t) on the left side can be approximated by the training data (termed "open loop"), and during testing, y(t) can be replaced by the ANN predicted value (termed "closed loop").

2.3.4 Training Dataset Division

DSM2-simulated turbidity at sixteen locations of interest in the Delta from the twelve scenarios was used as training targets. During the training process, the model development dataset is usually divided into training, validation and testing purposes. The training dataset is used to compute the gradient and determine the model parameters (weights and bias). The validation dataset is used during training to find the minimum error point and prevent over-training. An error is monitored on the validation dataset during training. The validation error normally decreases during the initial phase of training, as does the training set error. However, when the network begins to over-fit the data, the error on the validation set typically begins to rise. When the validation error increases for a number of iterations, the training is stopped, and the parameters at the minimum validation error are returned. The test dataset is not used in the training or validation (e.g., for stopping the network) and provides an independent evaluation on network performance.

In this work, the data were divided in the following manner: 60%, 20%, and 20% was used for training, validation and testing, respectively. The data points for training, validation and testing were randomly selected from the entire dataset for each training cycle.

3 RESULTS

3.1 DSM2 SIMULATED TURBIDITY AT TARGET LOCATIONS

The updated DSM2 model from RMA was run using the formulated 12 scenarios of boundaries described in Chapter 2, for a time period of 36 years from 1975-2011. The simulated turbidity time series at sixteen target locations for each of the twelve scenarios are presented in Appendix B. These simulated turbidity values were used as targets in the ANN training. The goal of the training is to minimize errors between the ANN simulated and target turbidity simulated by DSM2 at each location.

3.2 ANN TRAINING RESULTS

The ANN training was conducted using the feed forward time series network with time delay. Because it can take several days for particles to travel from one location to the other location within the Delta as shown in the monitoring data, a time lag of at least 7 days in the inputs of the ANN model is desired. Therefore, for all the subsequent training, a time delay of 7 days was used. The number of neurons used was 10. The results for performance of all data, training, validation and test for one example training are shown in Figure 3-1.

Time-series comparison and daily/monthly scatter plots of ANN trained and DSM2 simulated turbidity are shown for each station in Appendix C. The model performance (measured in terms of R^2 and standard error, SE) of the feed forward network is shown in Table 3-1. The model fit for the West Delta stations is generally good, with R2 between 0.93-0.99 for daily time step. The fit for Central Delta is slightly lower, with R2 ranging from 0.88 – 0.95 for the daily time step. The South Delta stations show relatively good fit with R2 between 0.88-0.95 for the daily time step. The fit at Old River at Clifton Court Intake station is lower among the south Delta stations. This is likely due to flow management at this location that is more difficult to capture both by the DSM2 and ANN model.

The results suggested that an ANN model structure of feed forward network with 10 neurons and 7 days of delay resulted in relatively good model fit at various Delta locations. The fit for most of the stations are good (R^2 > 0.90), with some stations showing slightly poorer fits (R^2= 0.88-0.90).

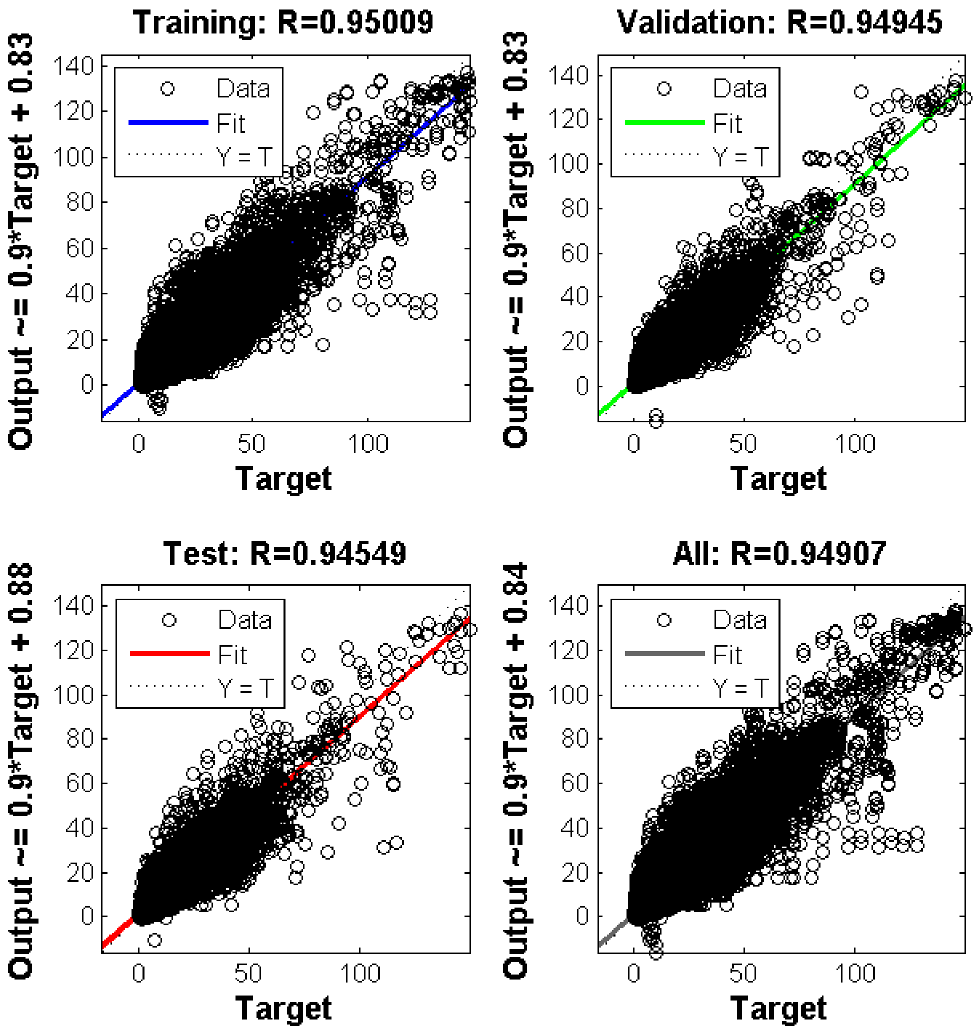


Figure 3-1 *Correlation between trained and DSM2 simulated turbidity for the training, validation and test dataset for feed-forward network training.*

Table 3-1
Comparison of ANN and DSM2 Simulated Turbidity at Delta Locations (FFW)
ANN Turbidity (ntu) = Φ1 + Φ2*DSM2 turbidity (ntu)

Location	Daily				Monthly			
	Φ2	Φ1	R^2	SE	Φ2	Φ1	R^2	SE
West Delta								
Sacramento River @ Rio Vista	0.9906	0.777	0.9924	5.258	1.005	-0.556	0.994	3.545
Sacramento River @ Decker Island	0.9903	0.844	0.9935	4.581	1.011	-0.899	0.997	2.300
SJR @ Jersey Point	0.9665	0.795	0.9660	4.121	1.020	-0.575	0.992	1.572
Central Delta								
SJR @ Prisoner's Point	0.8796	1.216	0.8788	3.860	1.046	-0.467	0.943	1.836
Old River @ Holland	0.9331	0.447	0.9330	2.239	1.019	-0.124	0.983	0.768
Old River @ Quimby	0.8951	1.028	0.8976	3.563	1.045	-0.445	0.944	1.731
Old River @ Bacon	0.9508	0.342	0.9514	2.220	1.016	-0.108	0.990	0.685
Middle River @ Holt	0.8844	0.701	0.8822	2.732	1.055	-0.336	0.965	1.129
Middle River @ Bacon Island	0.9490	0.373	0.9488	2.530	1.037	-0.267	0.986	0.984
Turner Cut @ Holt	0.9160	0.927	0.9160	4.249	1.050	-0.553	0.966	2.030
South-Southeast Delta								
Old River @ HWY4	0.9565	0.423	0.9549	2.976	1.018	-0.175	0.990	0.939
Old River @ Clifton Court Intake	0.8847	1.801	0.8840	6.155	1.047	-0.744	0.968	2.195
Victoria Canal	0.9517	0.448	0.9504	3.005	1.021	-0.195	0.983	1.255
Middle River @ Union Point	0.919	0.699	0.9212	3.717	1.049	-0.415	0.971	1.698
Grant Line Canal @ Tracy	0.9534	1.492	0.9529	5.387	1.054	-1.735	0.925	3.376
SJR @ Garwood	0.9361	1.652	0.9347	6.452	1.088	-2.268	0.942	3.855

3.3 NONLINEAR AUTOREGRESSIVE NETWORK (NARX)

The alternative network structure, the autoregressive NARX network was also used in the ANN training. The NARX network used output values the Delta stations from previous time steps as inputs to the model, and therefore generally has higher model performance.

The detailed comparison of trained ANN model results using the NARX network and the DSM2 model at each station is shown in Appendix D. The NARX model performance (in terms of R^2 and SE) is summarized in Table 3-2. The NARX model generally showed an R^2 of greater than 0.99 for most stations.

3.4 RESIDUALS ANALYSIS

Residuals are defined as the difference between the daily ANN and DSM2 simulated turbidity values at each station. The residuals at each station for the feed forward network and the NARX network were evaluated against the input variables for possible structure in the errors between ANN predicted and DSM2 simulated values. A spearman correlation was used to evaluate the correlation between residuals and the input variables. When no correlation and structure were found, the residuals were considered as random and no additional training was needed.

The residuals analysis was conducted by plotting residuals with respect to six inputs for the ANN model: three flow and three turbidity values. The results for the feed forward network and the NARX network are presented in Appendix E and F, respectively. For the feed forward network, residuals for the stations generally showed no correlation with turbidity inputs from the North Delta, east side streams and Vernalis (spearman correlation coefficient $|r| < 0.2$), and appear random. Patterns of relationships between residuals and turbidity inputs are generally similar among stations. The residuals appear slightly higher at low turbidities from the east side streams, suggesting the fit for the ANN model was better for higher turbidity inputs from the east side streams. Correlation between residuals and flow inputs at each station is also low, and appears random. The patterns of correlation between residuals and flow are similar among stations. There is a tendency of somewhat higher residuals at very low flow inputs. This suggests that for the months of interest for the turbidity model, which are the relatively high flow months of December through March, the ANN model emulation of DSM2 is better than the dry months of year.

Table 3-2
Comparison of ANN and DSM2 Simulated Turbidity at Delta Locations (NARX)
ANN Turbidity (ntu) = Φ1 + Φ2*DSM2 turbidity (ntu)

Location	Daily				Monthly			
	Φ2	Φ1	R^2	SE	Φ2	Φ1	R^2	SE
West Delta								
Sacramento River @ Rio Vista	0.9963	0.507	0.9986	2.281	1.005	-0.580	0.9997	0.770
Sacramento River @ Decker Island	0.9946	0.681	0.9982	2.390	1.006	-0.724	0.9995	0.954
SJR @ Jersey Point	0.9891	0.376	0.9905	2.203	1.004	-0.258	0.9994	0.427
Central Delta								
SJR @ Prisoner's Point	0.9896	0.114	0.9910	1.112	1.006	-0.073	0.9997	0.137
Old River @ Holland	0.9928	0.027	0.9937	0.705	1.002	0.008	0.9998	0.077
Old River @ Quimby	0.9883	0.111	0.9868	1.345	1.004	-0.037	0.9992	0.208
Old River @ Bacon	0.9960	0.026	0.9955	0.692	1.001	-0.003	0.9998	0.096
Middle River @ Holt	0.9954	0.026	0.9954	0.573	1.001	-0.002	0.9999	0.063
Middle River @ Bacon Island	0.9972	0.018	0.9973	0.590	1.001	-0.002	0.9999	0.061
Turner Cut @ Holt	0.9945	0.068	0.9945	1.133	1.002	-0.034	0.9999	0.124
South-Southeast Delta								
Old River @ HWY4	0.9918	0.082	0.9917	1.300	0.999	0.004	0.9998	0.142
Old River @ Clifton Court Intake	0.9767	0.360	0.9767	2.900	1.007	-0.107	0.9991	0.367
Victoria Canal	0.9931	0.058	0.9935	1.108	1.002	-0.016	0.9997	0.155
Middle River @ Union Point	0.9951	0.035	0.997	0.990	1.001	0.001	0.9999	0.118
Grant Line Canal @ Tracy	0.9975	0.081	0.999	1.238	1.004	-0.136	0.9998	0.169
SJR @ Garwood	0.9976	0.066	0.999	1.259	1.003	-0.086	0.9999	0.194

The residuals for the NARX network were evaluated in the same manner. In absolute terms, residuals from the NARX network were generally lower than the feed forward network (Appendix F). Similar patterns of no correlation between residuals and inputs of turbidity were found for the NARX network. This suggests little structure in the residuals due to turbidity inputs. There is also a tendency of greater residuals under low flow inputs, similar to that noted for the feedforward networks. The results therefore suggest better emulation of the DSM2 model during high flow months of interest.

3.5 SENSITIVITY ANALYSIS

The trained ANN networks for feed forward network were tested for sensitivity with respect to OMR flows under different turbidity levels at the boundary locations. The sensitivity analyses were conducted for the following conditions:

- OMR flows of -8000 to 1,000 cfs, with 1,000 cfs increments
- North Delta turbidity at three levels of 50, 100 and 150 NTUs
- Vernalis turbidity of 30 and 100 NTUs
- North Delta inflow of 30,000 cfs
- East side stream inflow of 1,500 cfs
- East side turbidity of 30 NTUs

The sensitivity analysis results are shown for stations in the West Delta, Central Delta and South Delta (Figure 3-2 to Figure 3-4). The analysis showed a general pattern of increase in turbidities at stations with higher North Delta and San Joaquin turbidity inputs. The sensitivity of turbidity to OMR flow varies among stations.

The West Delta stations showed no sensitivity or decreases in turbidity with respect to increases in OMR flows (i.e. -8000 cfs to -1000 cfs; Figure 3-2). The Central Delta stations showed significant decreases in turbidity with increases in OMR flows (i.e. -8000 cfs to -1000 cfs) at several stations: Prisoner Point, Holland Cut, Old River at Quimby Island, Old River at Bacon Island, Middle River at Holt and Middle River at Bacon Island (Figure 3-3).

The South Delta stations and one station in the Central Delta (Turner Cut Holt) showed increase in turbidity at stations with increases in OMR flow (i.e. -8000 cfs to -1000 cfs) and reverse trends under positive OMR flows under high turbidity input from the San Joaquin River (Figure 3-4). Under low turbidity input from San Joaquin, the South Delta stations showed opposite trend of decreasing turbidity with OMR (i.e. -8000 cfs to -1000 cfs) and reverse trends under positive OMR flow.

A similar analysis was conducted for the NARX network. Similar patterns to the feed forward network were found (Figure 3-5 to Figure 3-7).

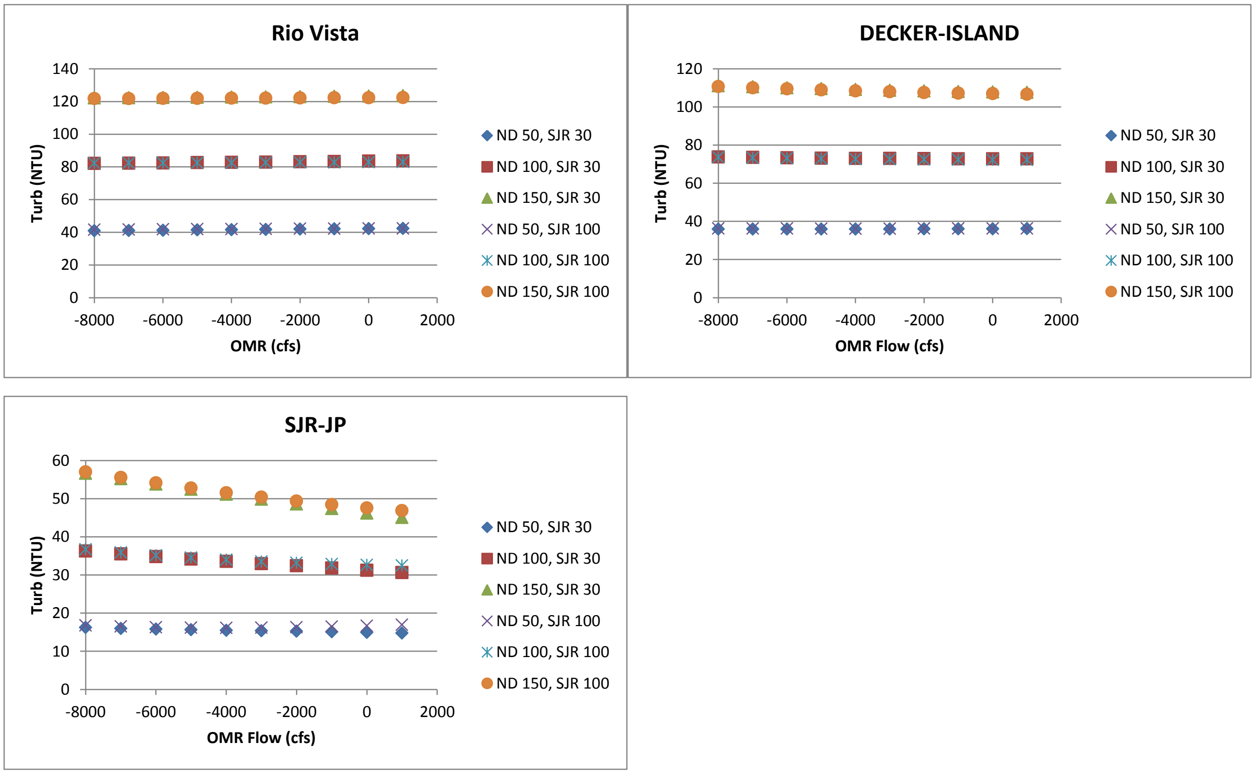


Figure 3-2 Sensitivity of FFW network turbidity at West Delta stations to OMR flow under different turbidity levels at North Delta and San Joaquin River at Vernalis

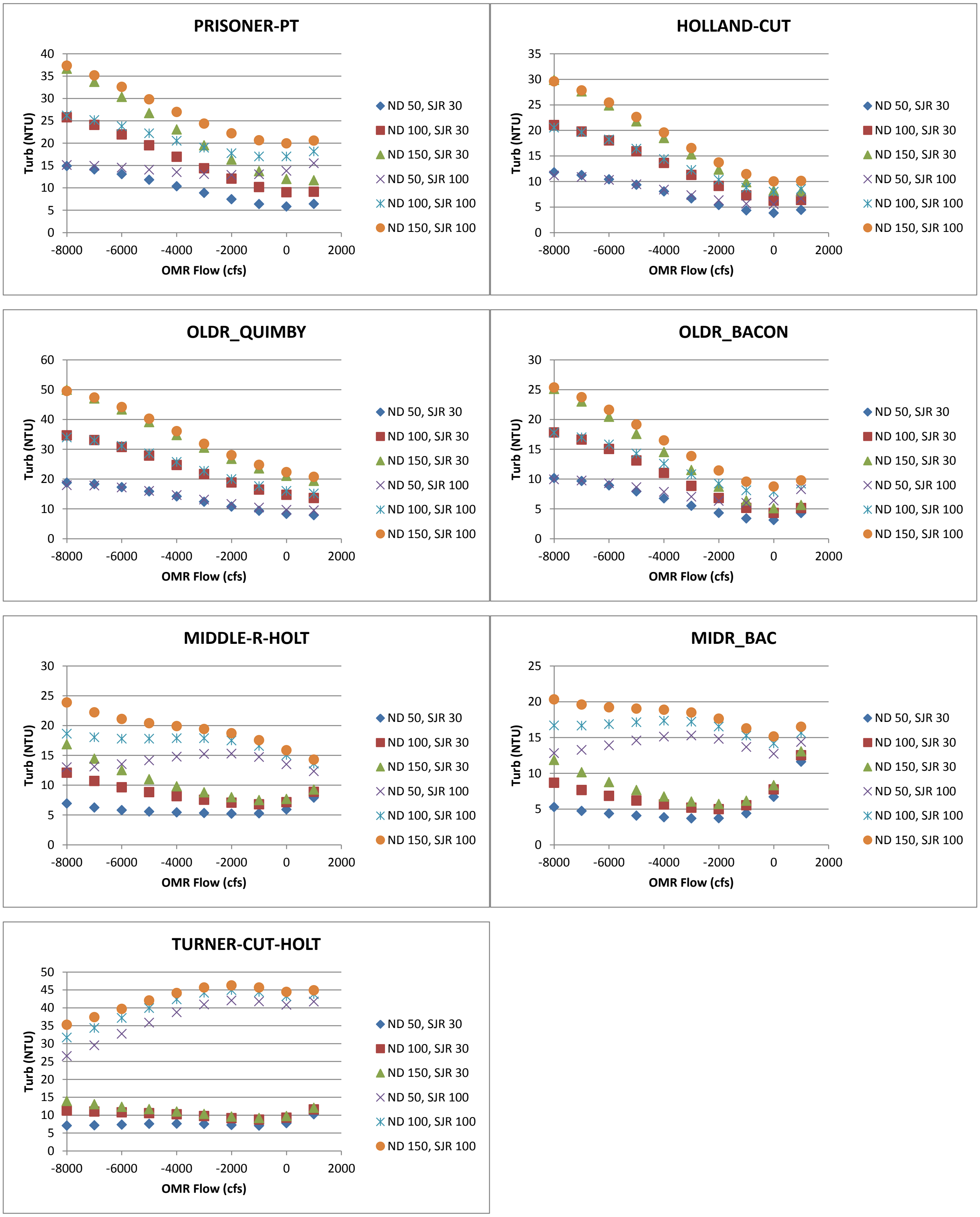


Figure 3-3 Sensitivity of FFW network turbidity at Central Delta stations to OMR flow under different turbidity levels at North Delta and San Joaquin River at Vernalis

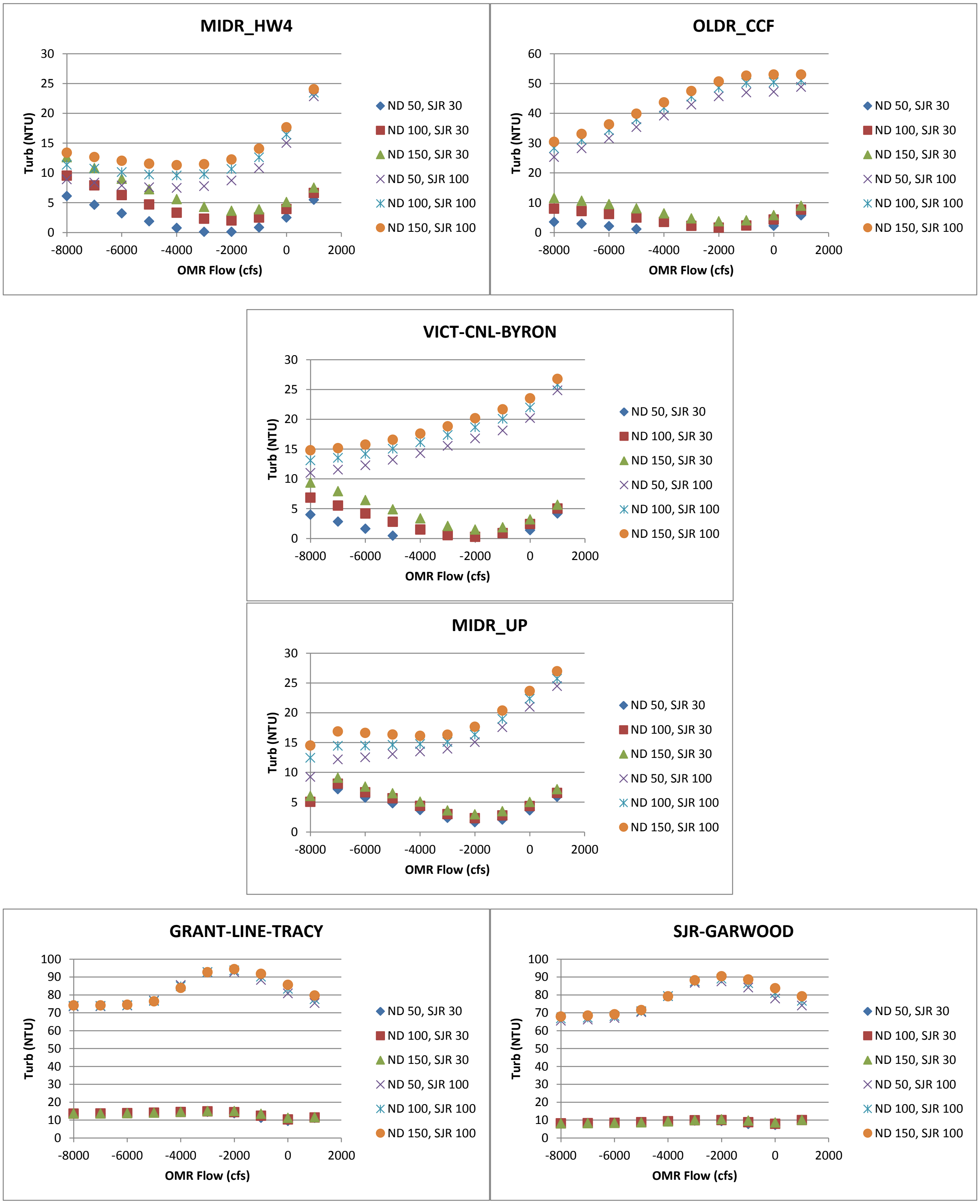


Figure 3-4 Sensitivity of FFW network turbidity at South Delta stations to OMR flow under different turbidity levels at North Delta and San Joaquin River at Vernalis

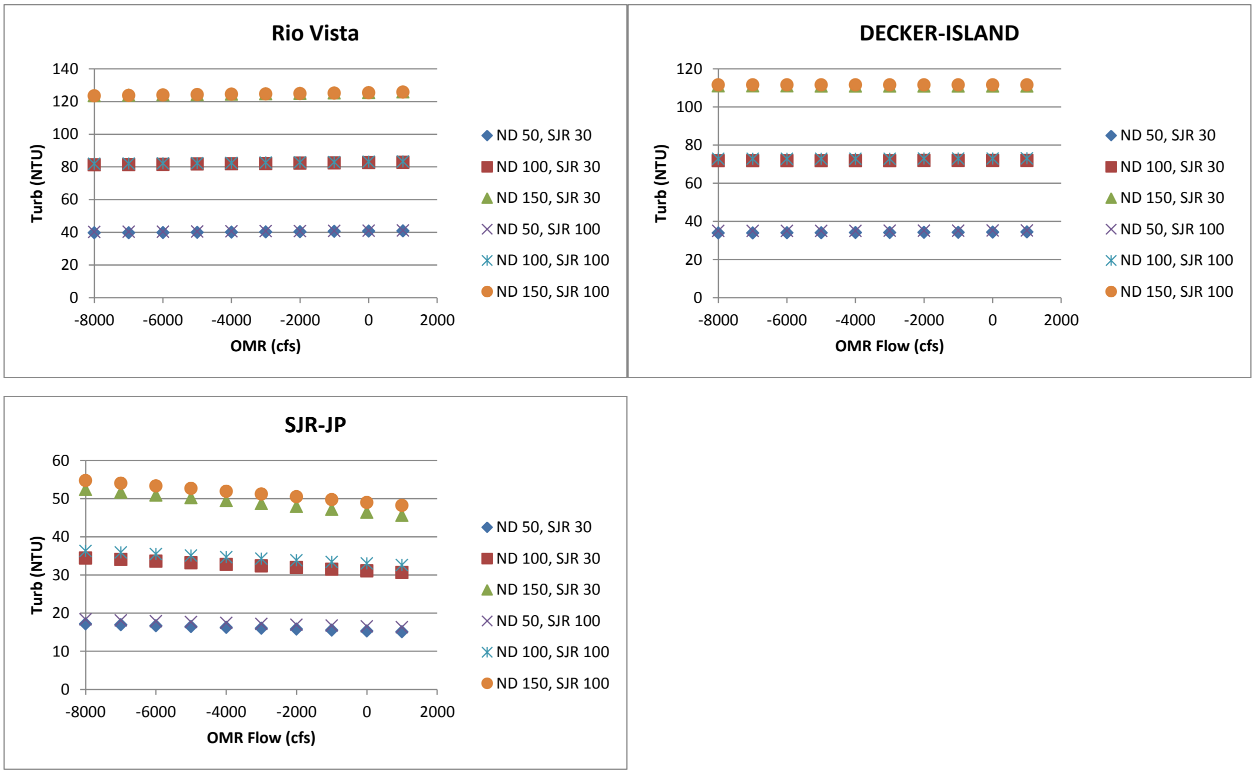


Figure 3-5 Sensitivity of NARX network turbidity at West Delta stations to OMR flow under different turbidity levels at North Delta and San Joaquin River at Vernalis

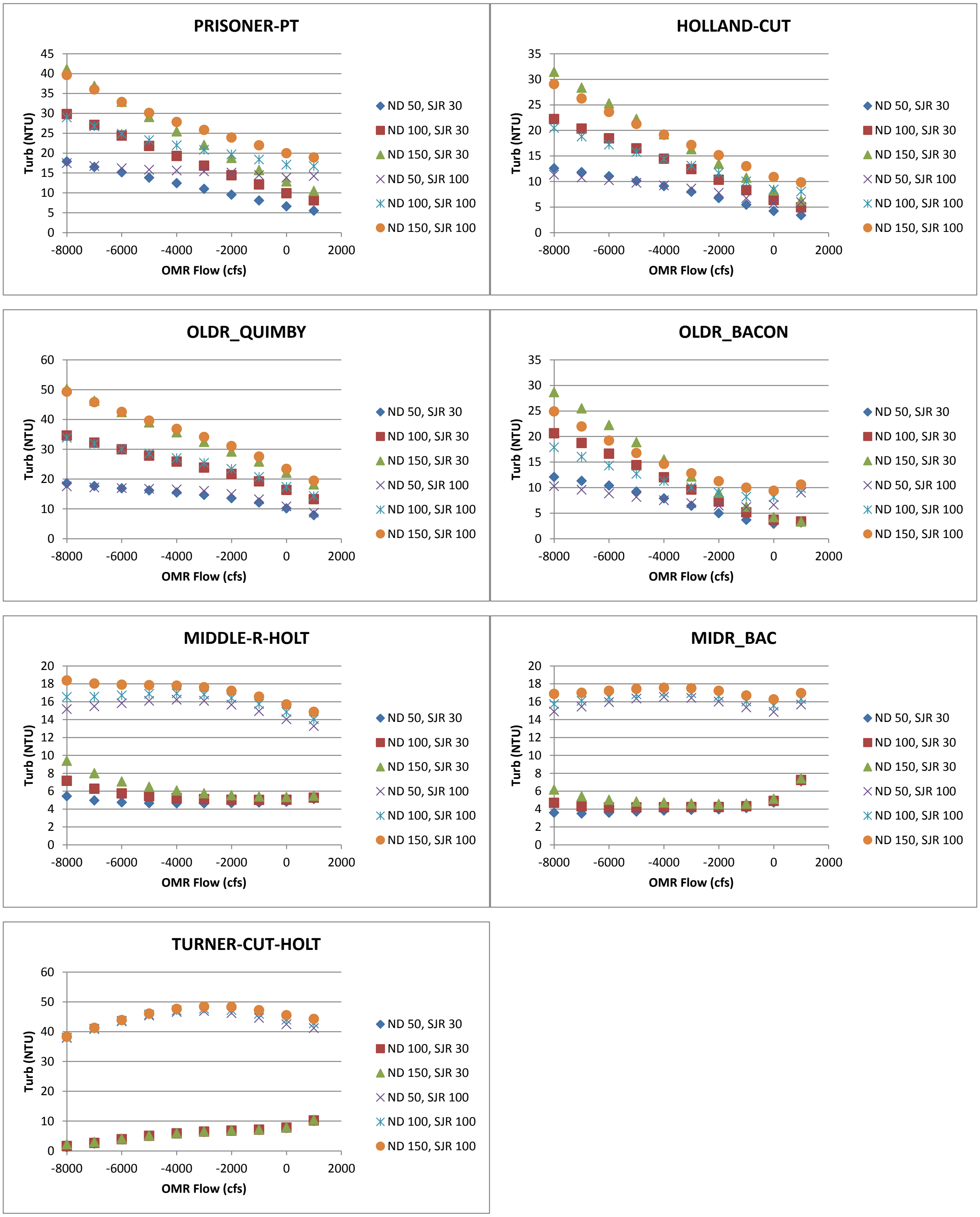


Figure 3-6 Sensitivity of NARX network turbidity at Central Delta stations to OMR flow under different turbidity levels at North Delta and San Joaquin River at Vernalis

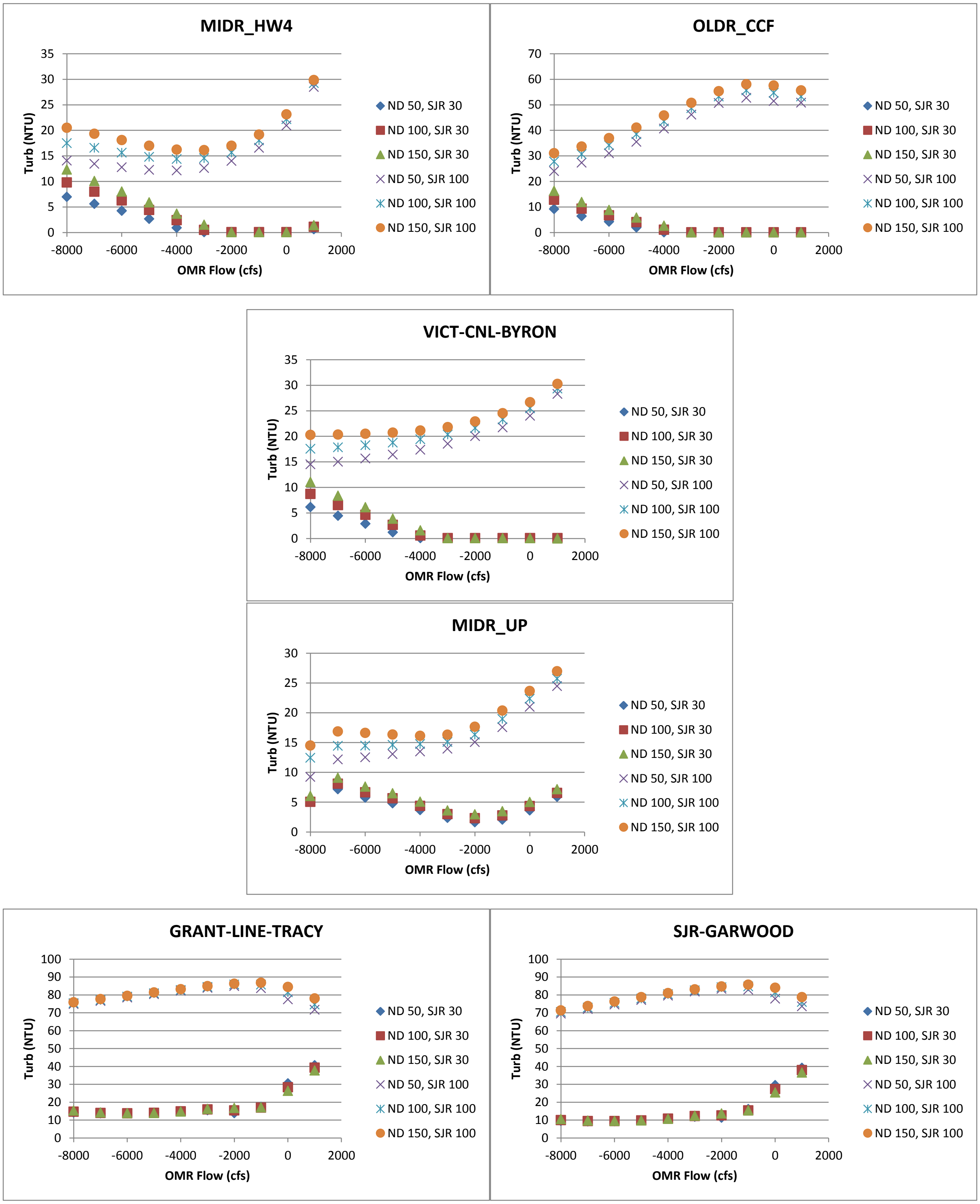


Figure 3-7 *Sensitivity of NARX network turbidity at South Delta stations to OMR flow under different turbidity levels at North Delta and San Joaquin River at Vernalis*

3.6 VALIDATION OF ANN NETWORKS WITH DSM2 SIMULATION

The trained NARX network was validated against the multi-year simulation from DSM2 during wet months for a long period of 1975-2011, based on estimated inputs of flow and turbidity (RMA 2013). These boundary conditions are different from those used in the training of the ANN and this test constitutes an independent validation of the trained ANN. The ANN results were compared to DSM2 simulated results on daily values and monthly averages for the months of December to February. The results for the NARX network (closed) suggested good agreement between ANN and DSM2 results for monthly values ($R^2 > 0.95$; Table 3-3). Fits with daily values were generally poorer than with the monthly values. The comparison of time-series predictions of the ANN and DSM2 models for the wet seasons of 1975-2011 at representative locations is shown in Figure 3-8. The comparison suggests that the ANN model is able to closely emulate DSM2 results during critical months from December to February for a set of boundary turbidity inputs that are different what was used for training. Scatter plots corresponding to these time series comparisons are shown in Appendix G.

Table 3-3
Comparison of Daily and Monthly Averages of ANN and DSM2 Simulated Turbidity at Delta Locations (NARX) for the Multi-year DSM2 Simulation

ANN Turbidity (ntu) = Φ1 + Φ2*DSM2 turbidity (ntu)

Location	Daily			Monthly		
	Φ2	Φ1	R^2	Φ2	Φ1	R^2
West Delta						
Sacramento River @ Rio Vista	1.0037	0.5227	0.943	1.018	-0.3901	0.9983
Sacramento River @ Decker Island	0.9222	3.4055	0.8937	0.947	2.0015	0.9863
SJR @ Jersey Point	0.9527	1.1407	0.9728	0.9703	0.5986	0.9977
Central Delta						
SJR @ Prisoner's Point	0.9538	0.6721	0.9523	0.9711	0.4202	0.995
Old River @ Holland	0.9827	0.2475	0.9696	0.9916	0154	0.9977
Old River @ Quimby	0.9606	0.6575	0.9629	0.9763	0.3886	0.9974
Old River @ Bacon	0.9943	0.0773	0.9659	1.0019	0.0053	0.9977
Middle River @ Holt	0.9299	0.2932	0.9336	0.9194	0.3528	0.9809
Middle River @ Bacon Island	0.9698	0.3182	0.9137	0.9899	0.1945	0.9835
Turner Cut @ Holt	0.9370	1.3250	0.7159	1.0251	0.6642	0.9397
South-Southeast Delta						
Old River @ HWY4	0.9326	0.5465	0.9012	0.9813	0.1748	0.9917
Old River @ Clifton Court Intake	0.8255	1.9823	0.7825	0.964	0.5875	0.9697
Victoria Canal	0.8933	0.7638	0.8552	0.9784	0.235	0.9827
Middle River @ Union Point	0.7839	1.5800	0.7216	0.8994	0.3377	0.9689
Grant Line Canal @ Tracy	0.8933	0.4085	0.7515	0.9659	-0.6719	0.9435
SJR @ Garwood	0.9087	1.7775	0.7674	0.9471	1.3216	0.9529

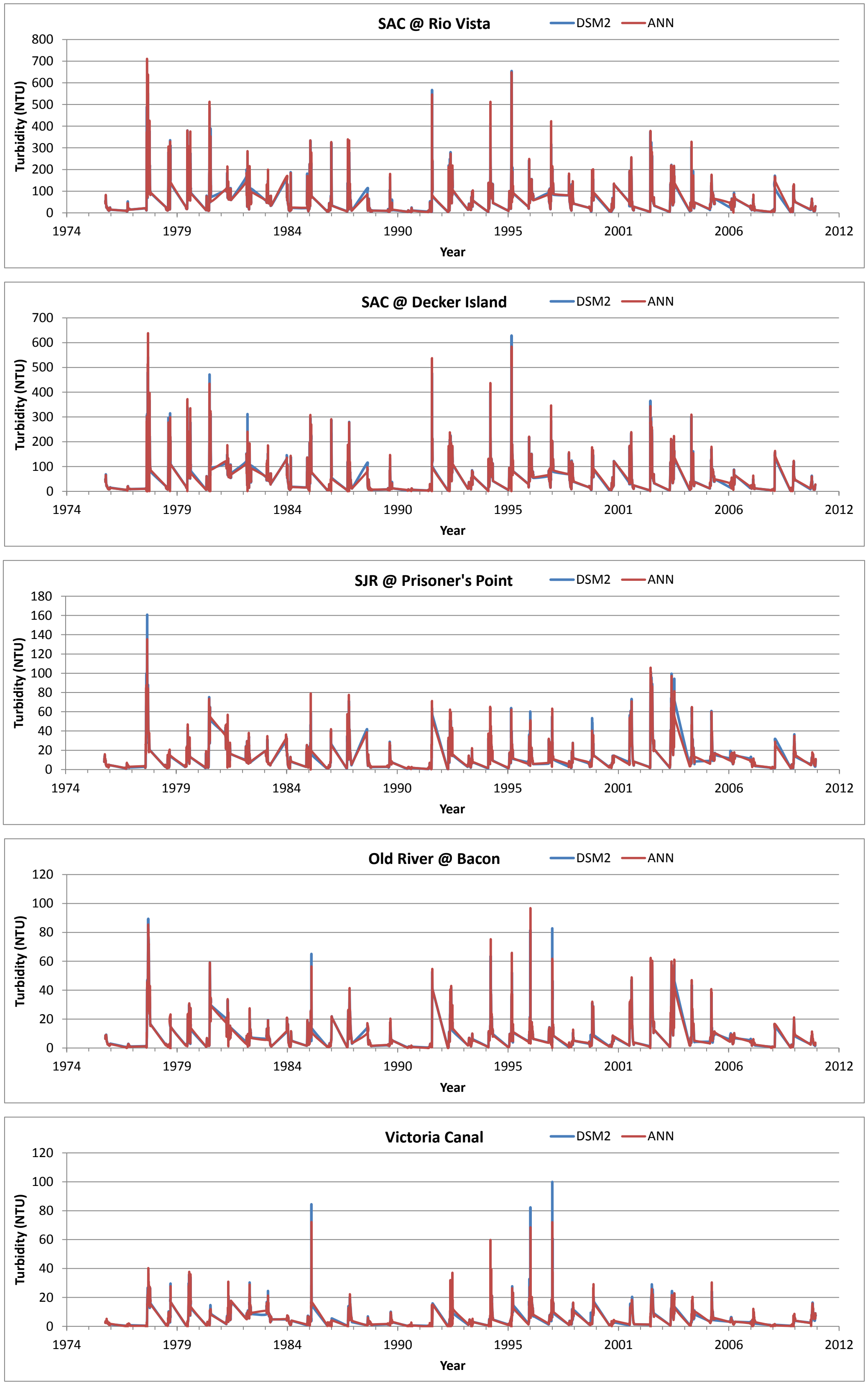


Figure 3-8 *Comparison of ANN and DSM2 simulation for the wet seasons of 1975- 2011 at representative locations. The Dec-Feb months are concatenated.*

3.7 ANN FORECAST FOR WET SEASON OF 2012/2013

The trained ANN network was used to forecast turbidity levels within the Delta for storm events during the wet season of 2012/2013, thus applying the ANN to conditions that had heretofore not been part of the training, directly or through DSM2 calibration. The observed Delta hydrology (flow at Freeport, east side streams and OMR flow) and turbidity at boundary locations (north Delta, east side streams and Vernalis) and WARMF predictions at these locations were used in the forecast. The forecast was performed using a range of OMR flow ranging from -6000 to 0 cfs, for several storm events. The ANN predictions for the full wet season up to date using the actual hydrology and turbidity data were compared to the observed data from CDEC and are presented here (Figure 3-9 to Figure 3-12). The observed data are shown as reported on the CDEC website; no effort was made to clean the data to remove outliers or unusual values. The NARX network was trained using the open network. In the forecast mode, the trained NARX networks were converted to closed networks and used for developing forecasts.

The results for the FFW networks (Figure 3-9 and Figure 3-10) showed good agreement with CDEC data at Rio Vista and Decker Island, however the ANN showed some over-predictions in peaks of turbidity and faster decreases in turbidity than the observed data at a number of locations in the central – south Delta. The ANN predictions also showed some under-predictions at a number of locations in the south Delta.

The results for the NARX networks (Figure 3-11 and Figure 3-12) generally showed a similar pattern to the FFW network predictions, with generally lower variation. The NARX predictions showed a similar trend of over-predicting peaks and faster decline in turbidity after storm at a number of locations in central – south Delta and under-predictions of turbidity at a number of south Delta locations.

The differences between the ANN forecasts and observed turbidity values were closely associated with DSM2 simulations of turbidity within the Delta. The discrepancies that appear in the ANN simulations are similar to those seen in the DSM2 calibration. A comparison of DSM2 calibration to the observed CDEC data for a previous time period (2008-2011) suggested similar issues, including: 1) some over-predictions in peak turbidity and faster decline after storms at a number of central-south Delta locations; and 2) under-predictions at south-Delta locations. To illustrate this, values are shown Figure 3-13 to Figure 3-17 at representative stations: Rio Vista (north Delta), Decker Island (north Delta), Prisoner's Point (central Delta), Old River Bacon (central Delta) and Victoria Canal (south Delta). As shown in Figure 3-13, DSM2 showed over-predictions in peak turbidity at Rio Vista for certain time periods, a pattern that is similar to the ANN predictions. The Decker island station showed reasonable matches with peak turbidity, but more rapid declines in the model compared to the data (Figure 3-14). The comparison at Prisoner's Point suggested over-predictions in peak turbidity and faster declines in turbidity after peaks than the observed data (Figure 3-15). This pattern is also evident in DSM2 simulations at other Delta locations. The comparison at Old River at Bacon and

Victoria Canal represent general under-predictions in turbidity at south Delta locations by DSM2 (Figure 3-16 and Figure 3-17).

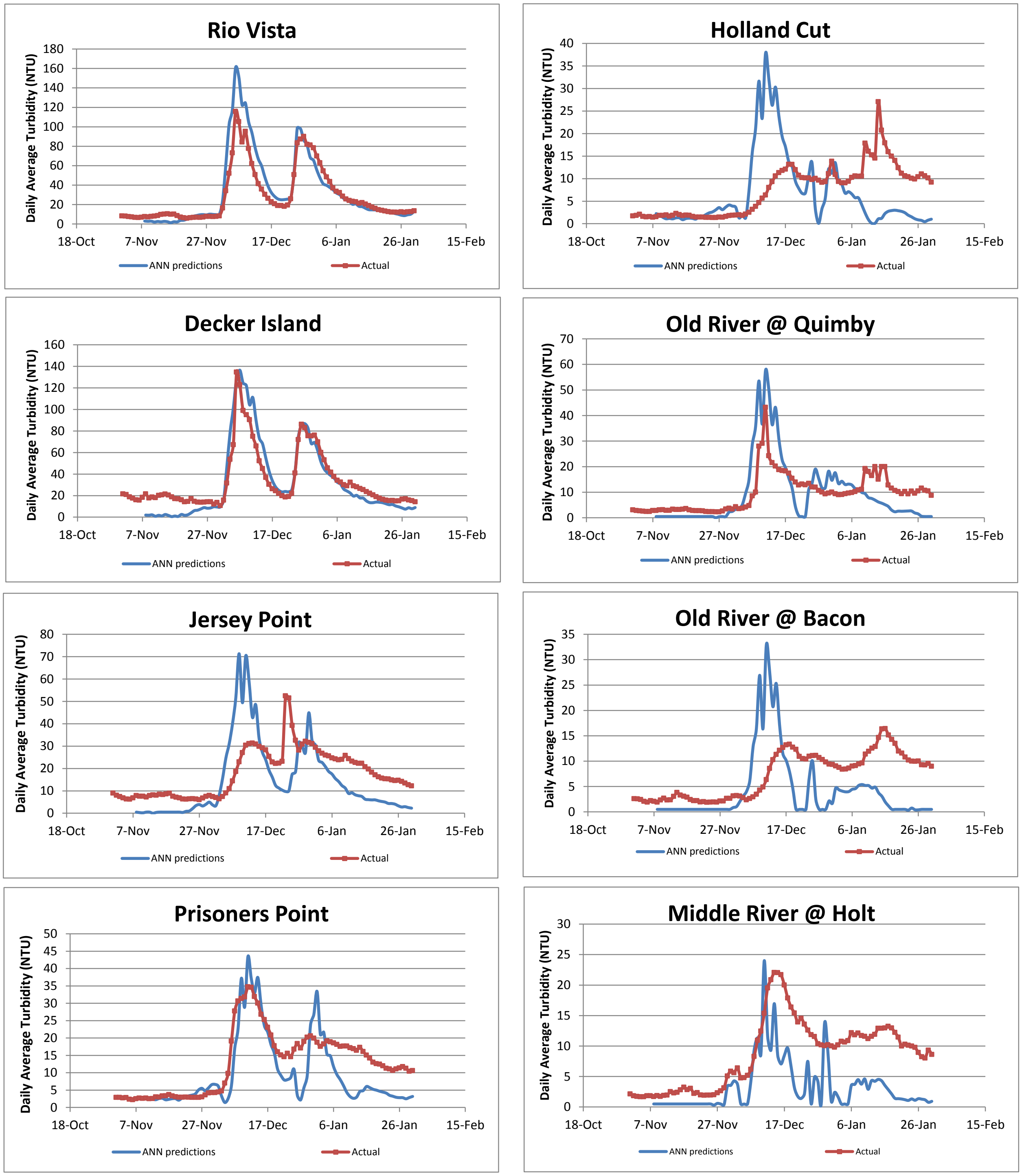


Figure 3-9 *Comparison of ANN FFW model forecast and actual turbidity data from CDEC at locations within Delta for wet season of 2013*

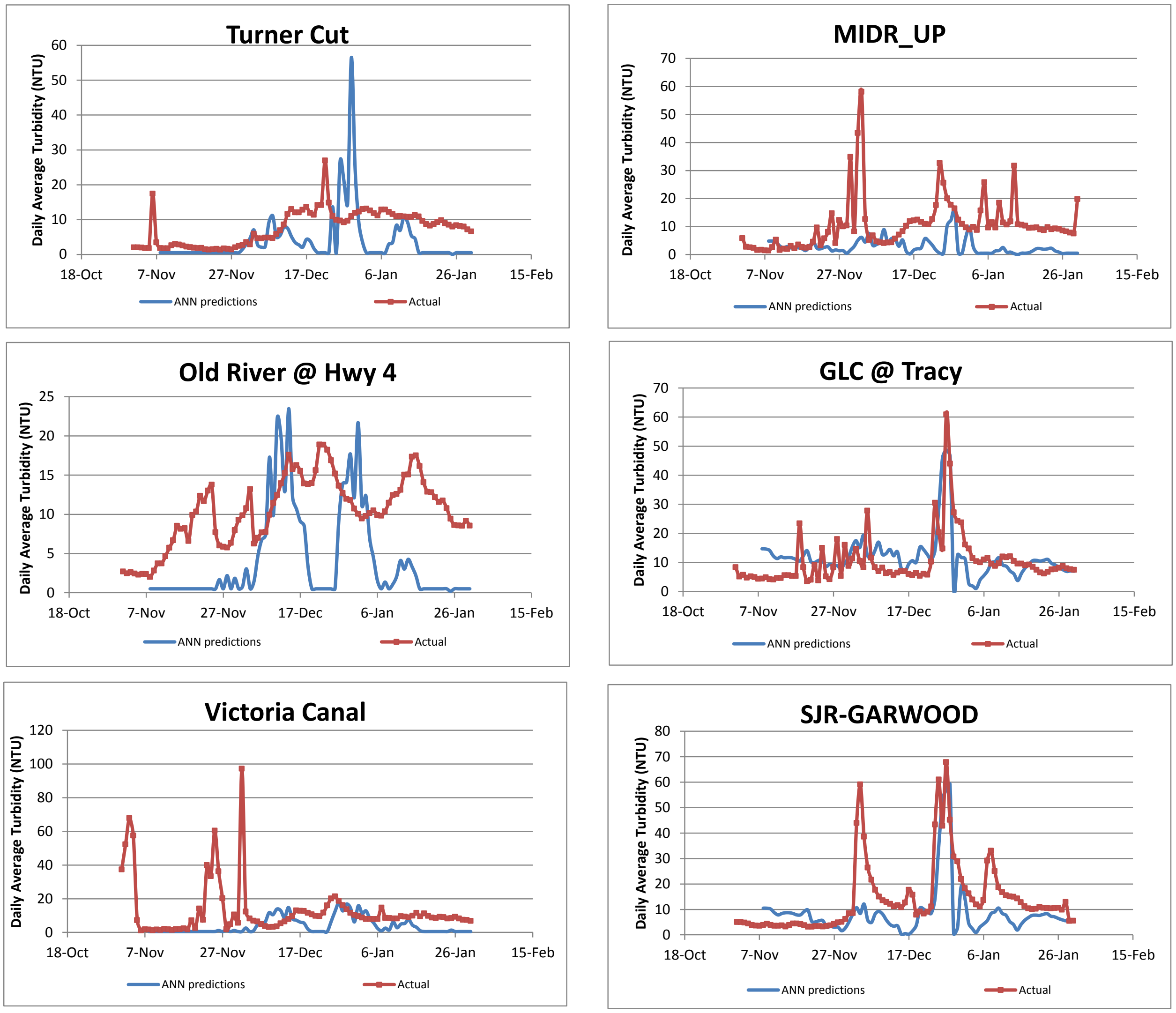


Figure 3-10 Comparison of ANN FFW model forecast and actual turbidity data from CDEC at locations within Delta for wet season of 2013

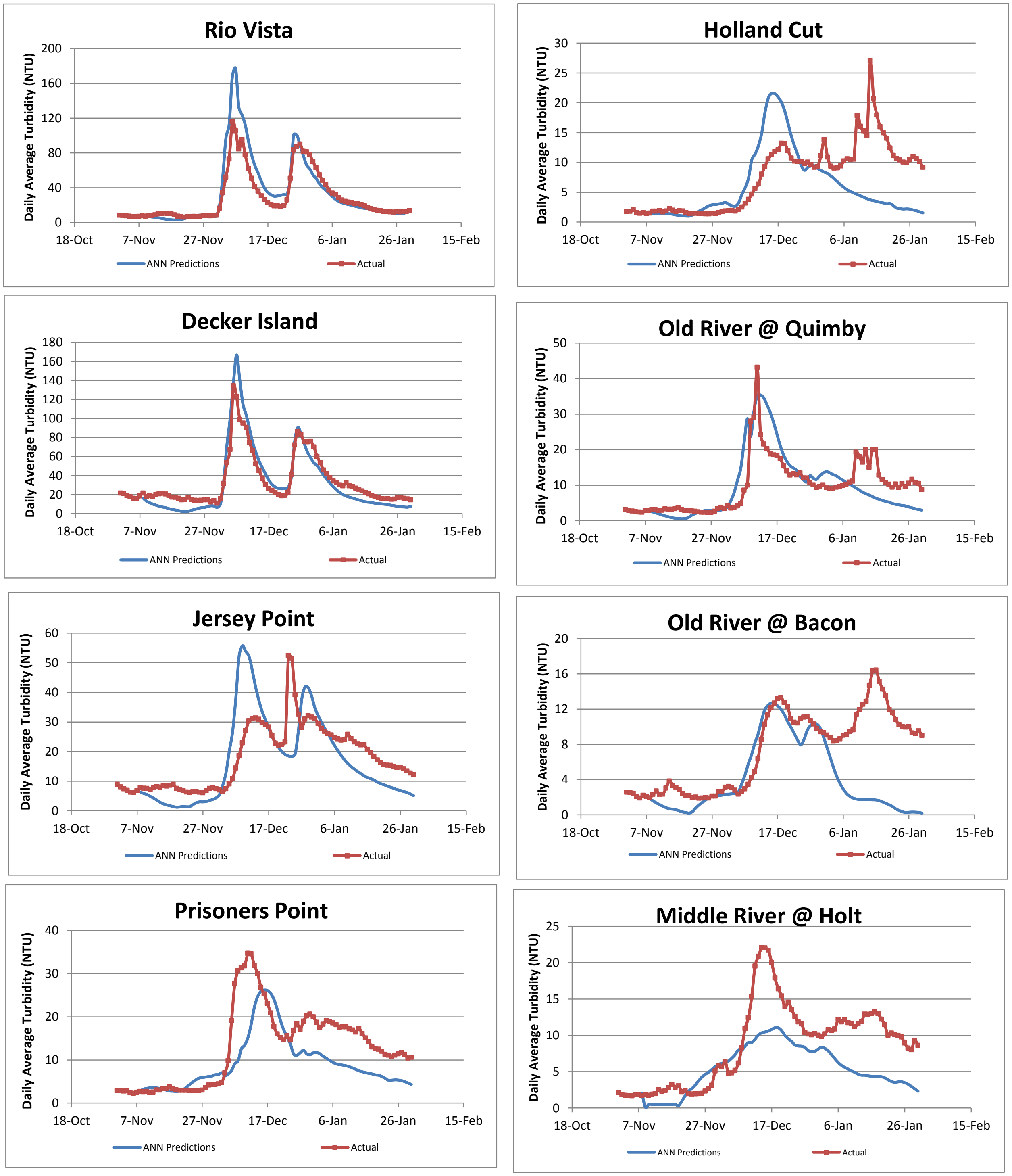


Figure 3-11 Comparison of ANN NARX model forecast and actual turbidity data from CDEC at locations within Delta for wet season of 2013

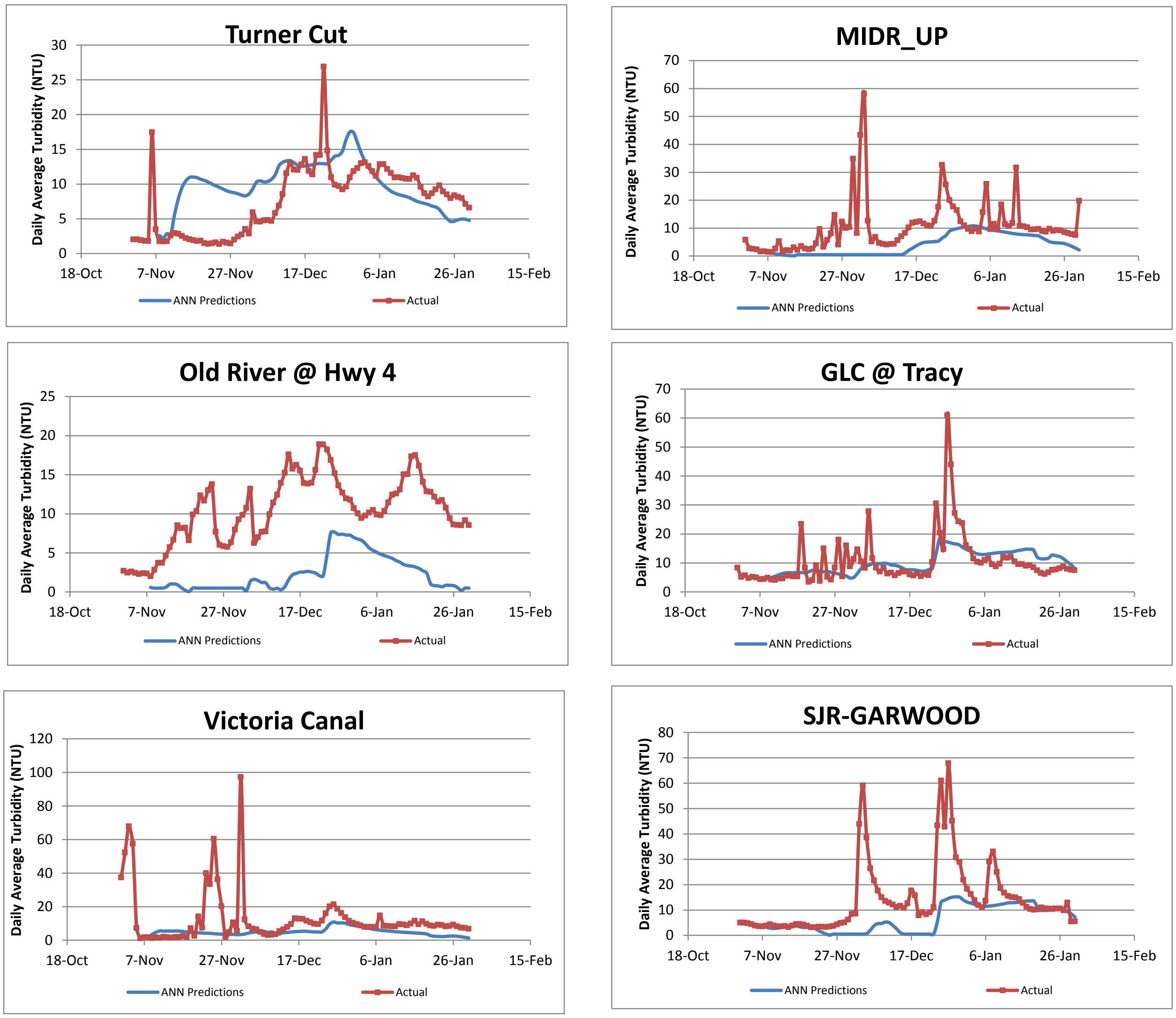


Figure 3-12 Comparison of ANN NARX model forecast and actual turbidity data from CDEC at locations within Delta for wet season of 2013

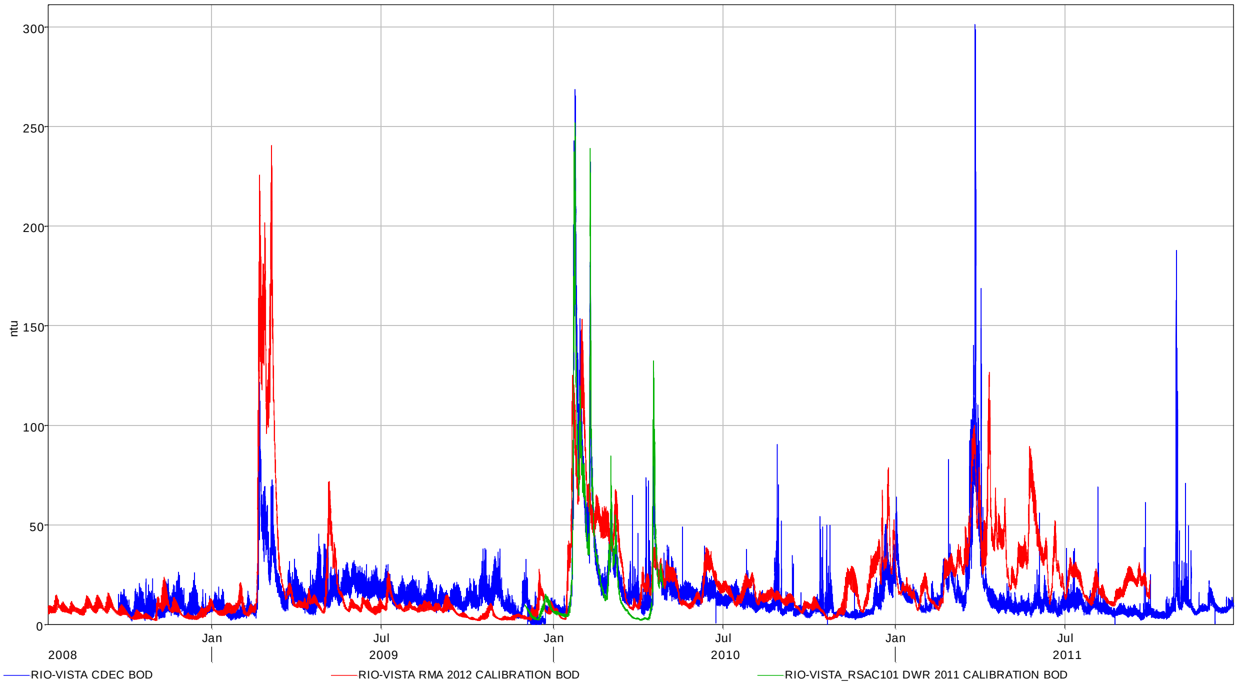


Figure 3-13 Comparison of DSM2 calibration to observed data from CDEC at Rio Vista. (Blue: CDEC data; red: RMA calibration; green: DWR 2011 calibration)

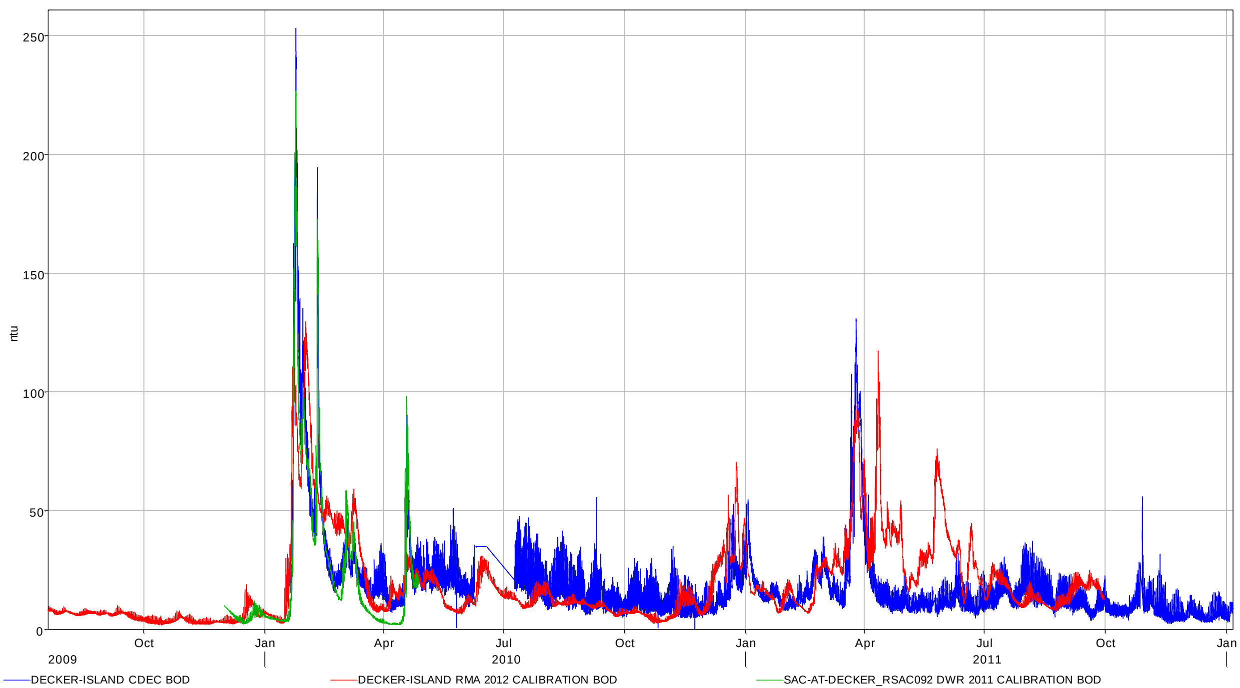


Figure 3-14 Comparison of DSM2 calibration to observed data from CDEC at Decker Island. (Blue: CDEC data; red: RMA calibration; green: DWR 2011 calibration)

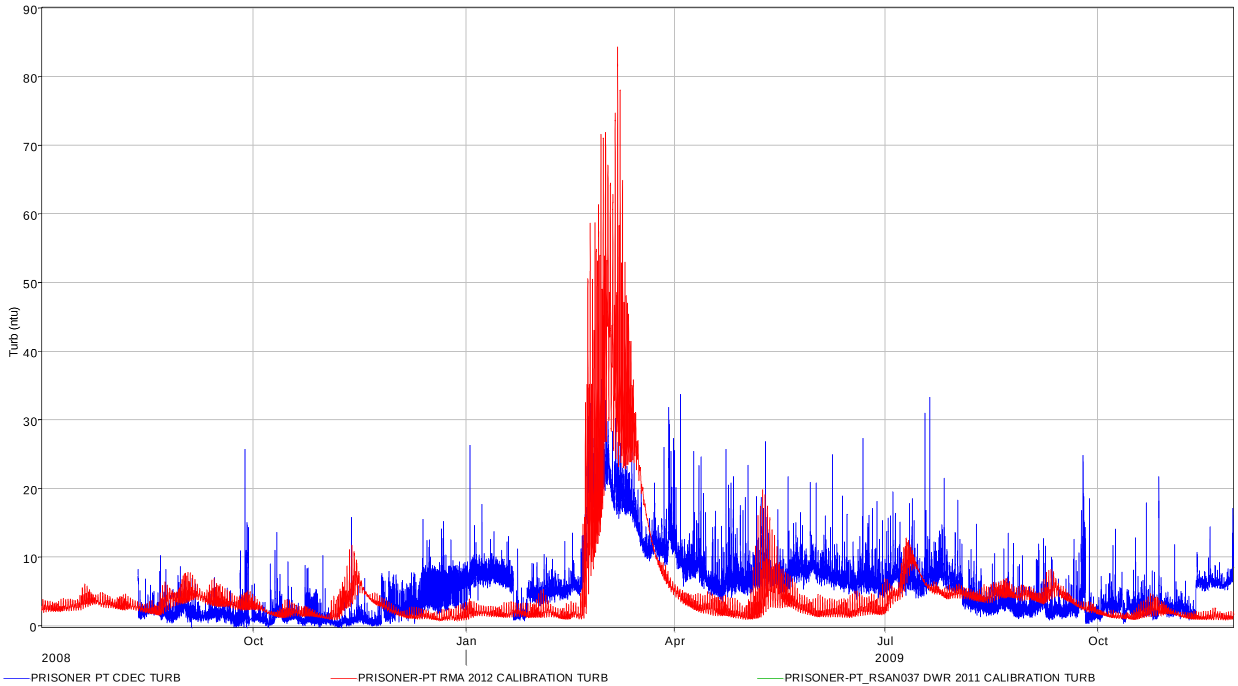


Figure 3-15 Comparison of DSM2 calibration to observed data from CDEC at Prisoner's Point. (Blue: CDEC data; red: RMA calibration)

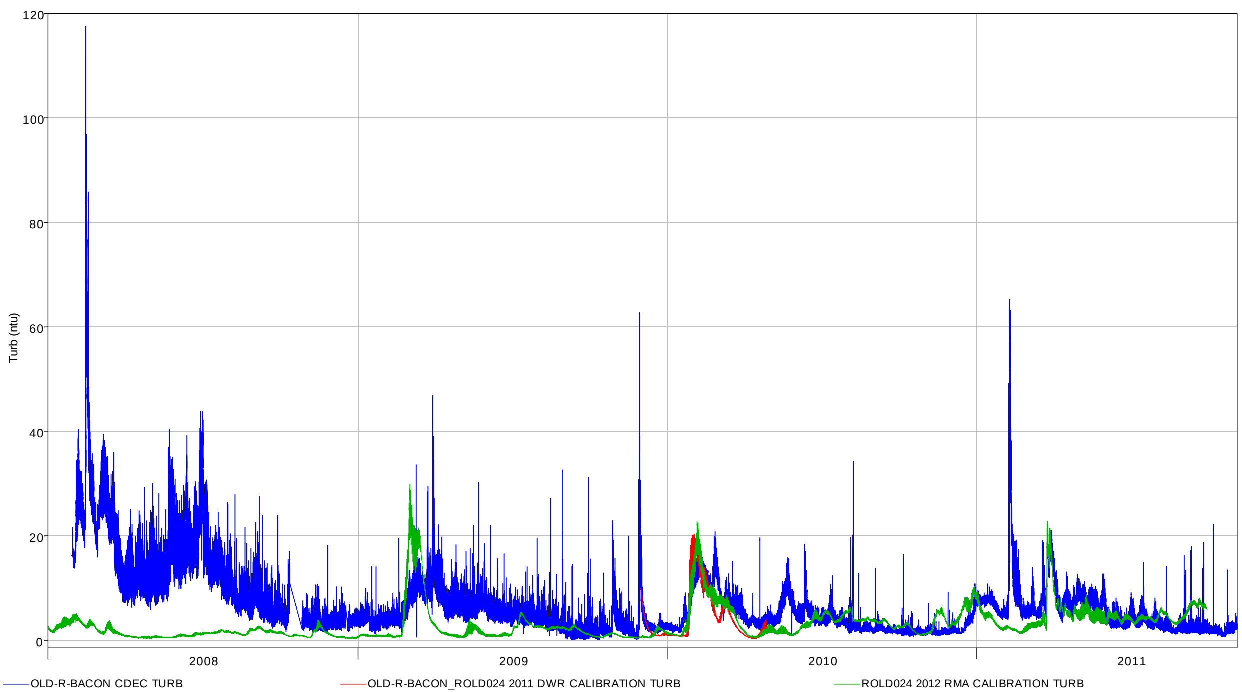


Figure 3-16 Comparison of DSM2 calibration to observed data from CDEC at Old River Bacon. (Blue: CDEC data; red: RMA calibration; green: DWR 2011 calibration)

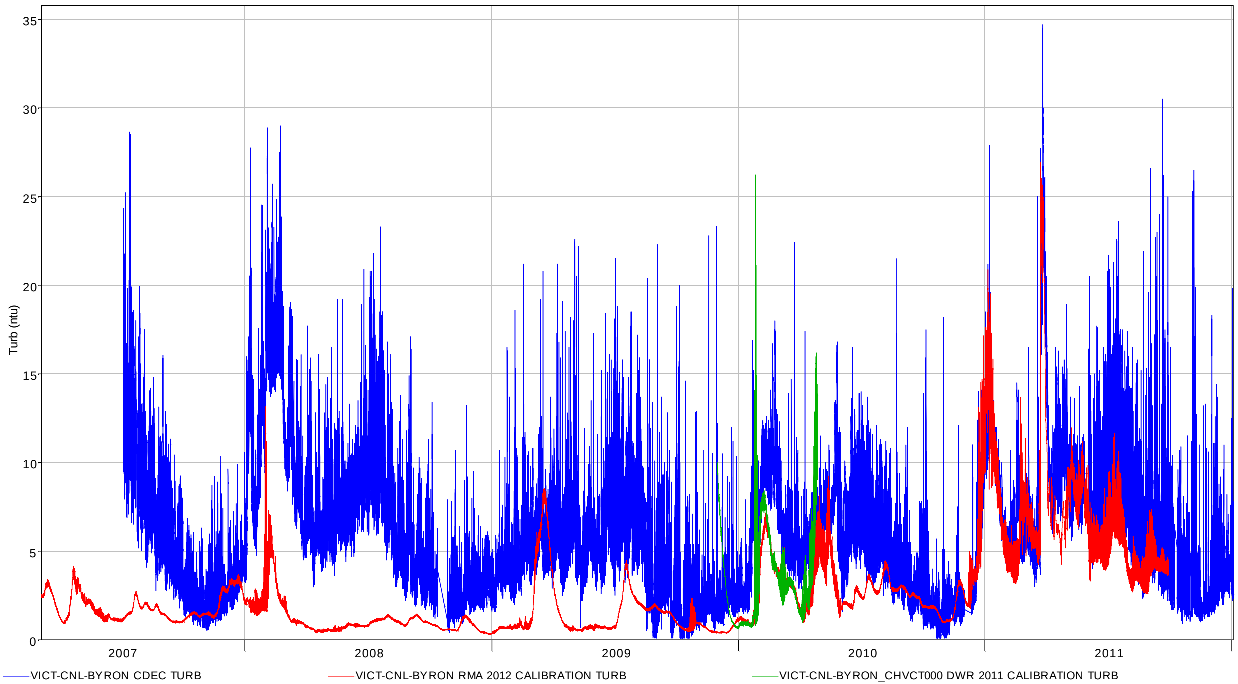


Figure 3-17 Comparison of DSM2 calibration to observed data from CDEC at Victoria Canal. (Blue: CDEC data; red: RMA calibration; green: DWR 2011 calibration)

These points can be further demonstrated through comparison of ANN NARX network results for the same time period and boundary conditions to DSM2 simulations (Figure 3-18 to Figure 3-22). The results suggest that ANN results closely follow DSM2 simulations which sometimes diverge from CDEC values at certain locations (as previously shown in Figure 3-13 to Figure 3-17). The discrepancy shown at these representative stations suggests that additional calibration of DSM2 on Delta turbidity will be beneficial to the overall goal of forecasting in the Delta.

Additional confirmation of this behavior was noted in independent DSM2 simulations performed by DWR (Bryant Giorgi, personal communication, February 11, 2013), where DSM2 output was compared to CDEC data for the wet season of 2012/2013. Plots at a representative set of stations from the DWR analysis are shown in Figure 3-23 through Figure 3-28. For the stations shown, the DSM2 results generally showed higher peaks and faster decline in turbidity after the storm, and under-predictions at South Delta locations (e.g. Victoria Canal, Old River at Highway 4). This pattern is very similar to what was noted in the ANN outputs that were trained to calibrated DSM2 data, thus supporting the need for additional calibration at some locations.

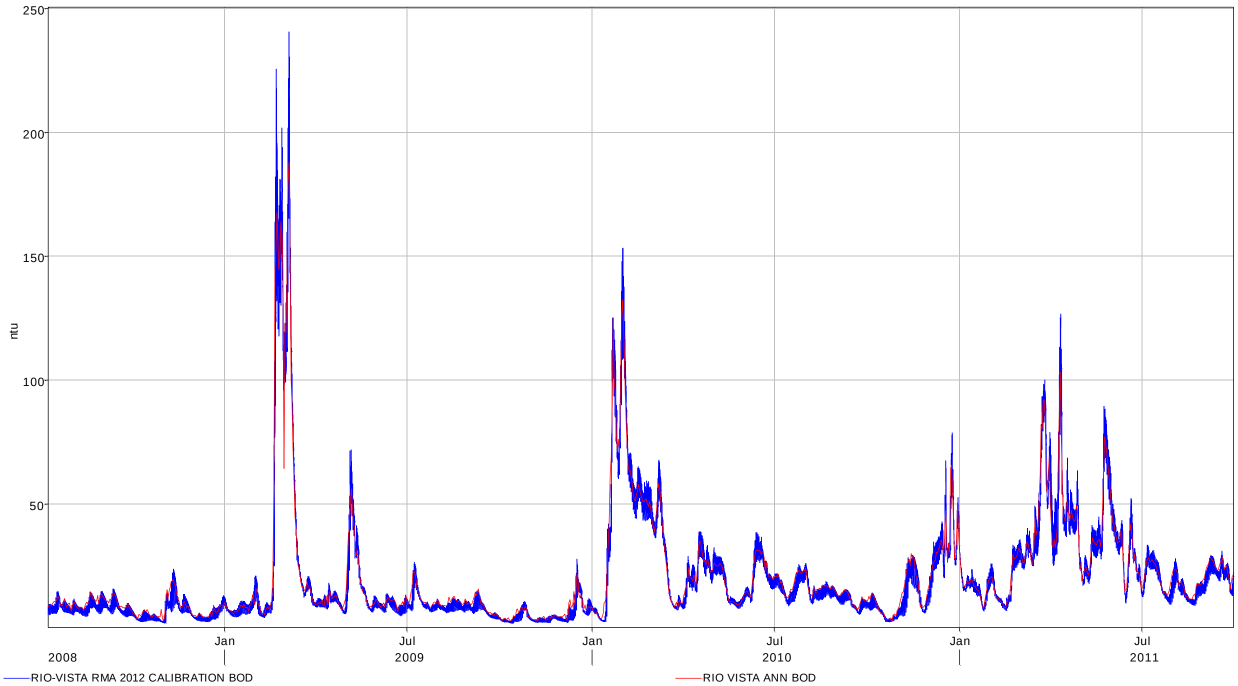


Figure 3-18 Comparison of ANN and DSM2 simulations at Rio Vista for 2008-2011.

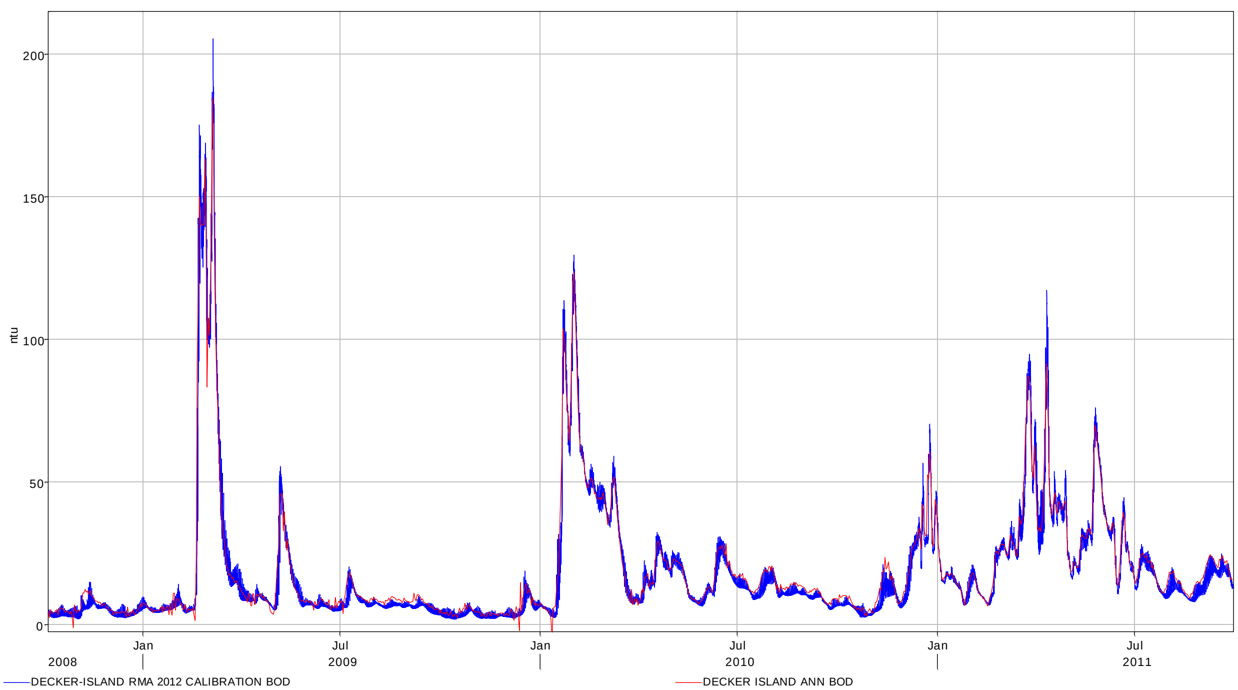


Figure 3-19 Comparison of ANN and DSM2 simulations at Decker Island for 2008-2011.

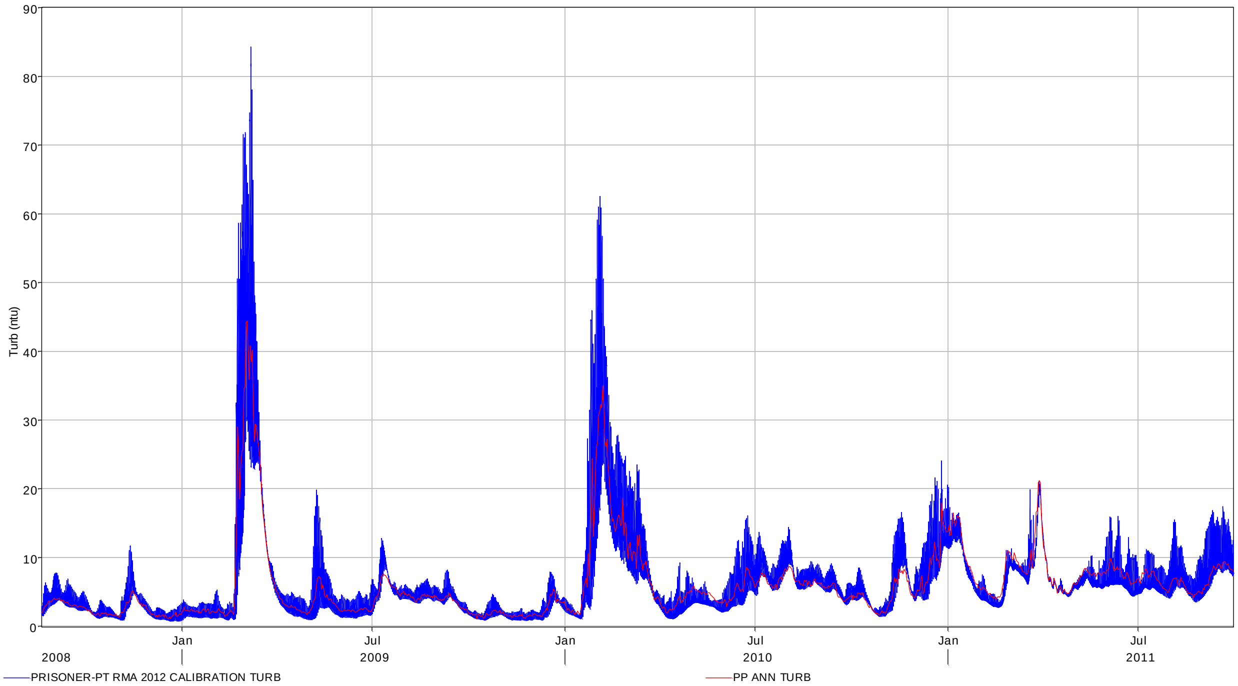


Figure 3-20 Comparison of ANN and DSM2 simulations at Prisoner's Point for 2008-2011.

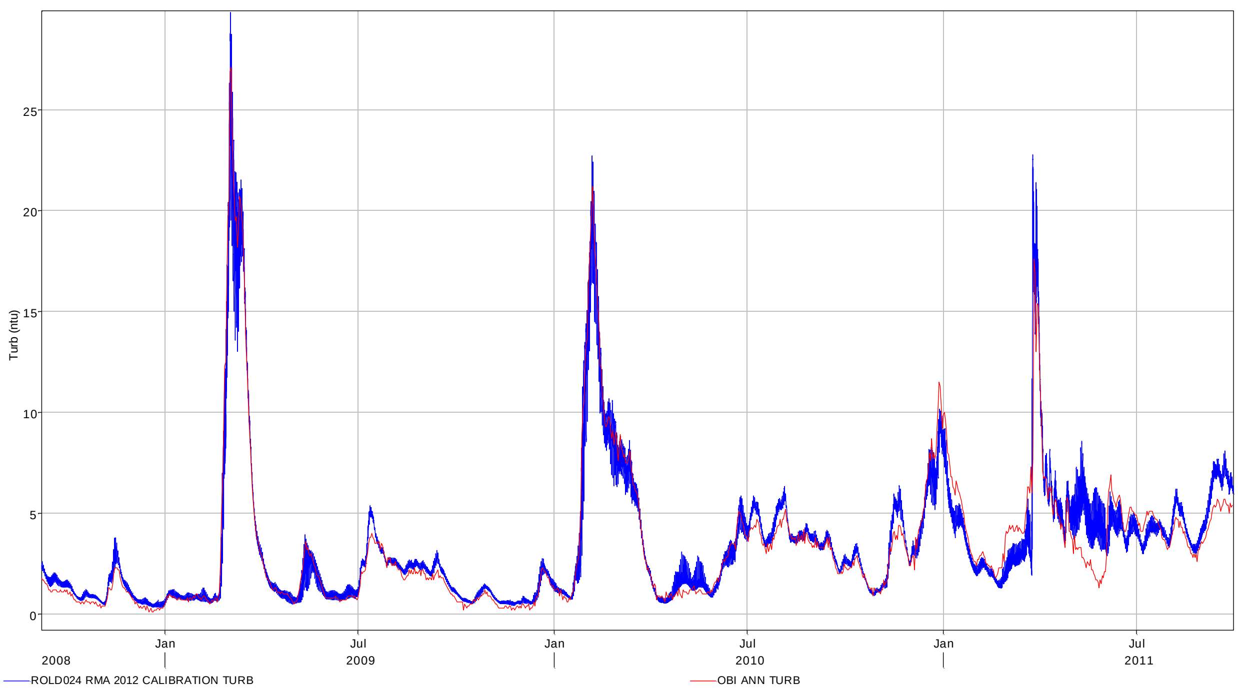


Figure 3-21 Comparison of ANN and DSM2 simulations at Old River Bacon for 2008-2011.

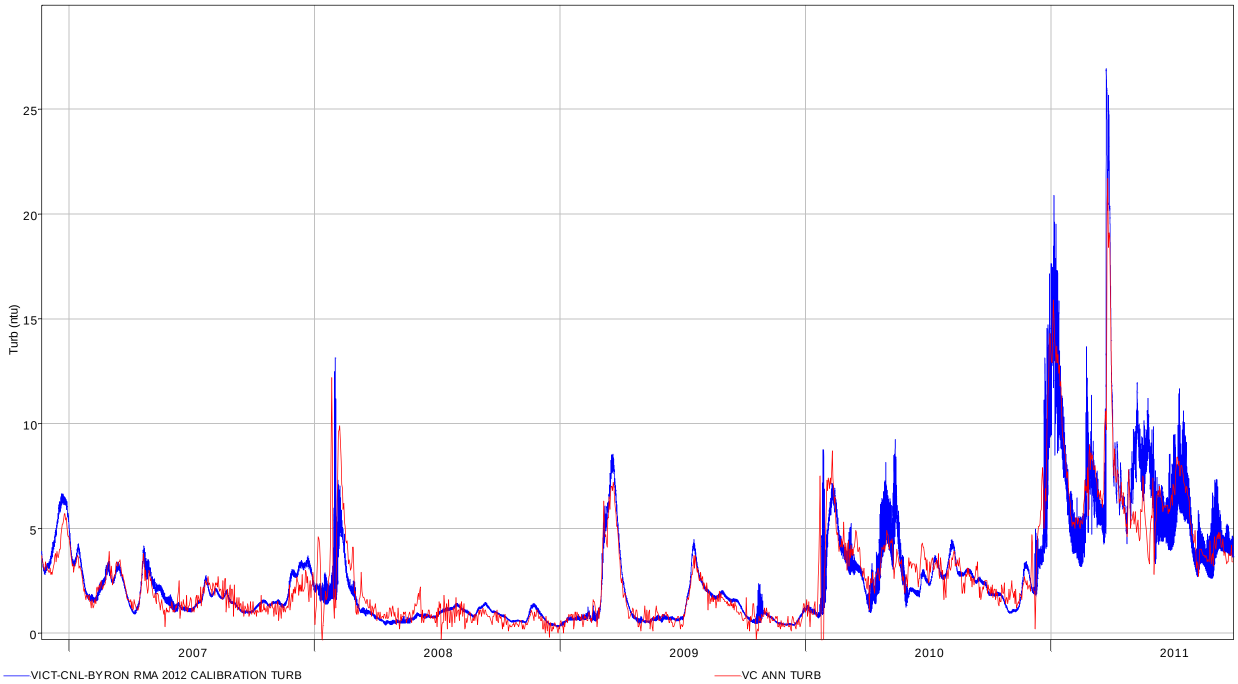


Figure 3-22 Comparison of ANN and DSM2 simulations at Victoria Canal for 2008-2011.

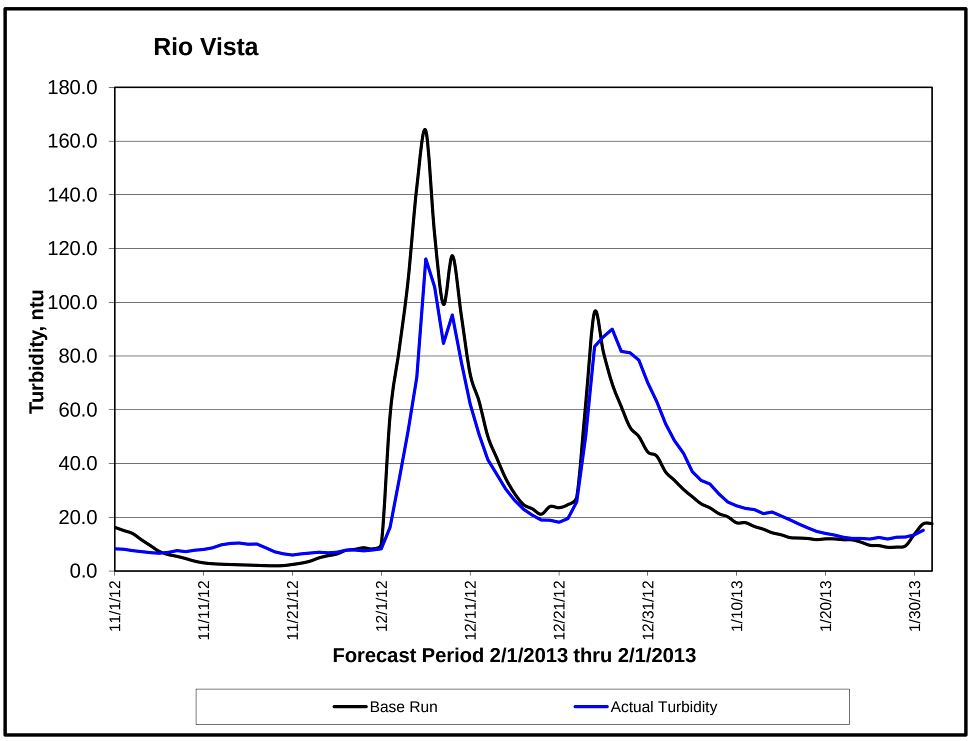


Figure 3-23 DSM2 simulations at Rio Vista (base run) compared to CDEC data for the wet season of 2012/2013 (actual turbidity). DSM2 runs performed by DWR.

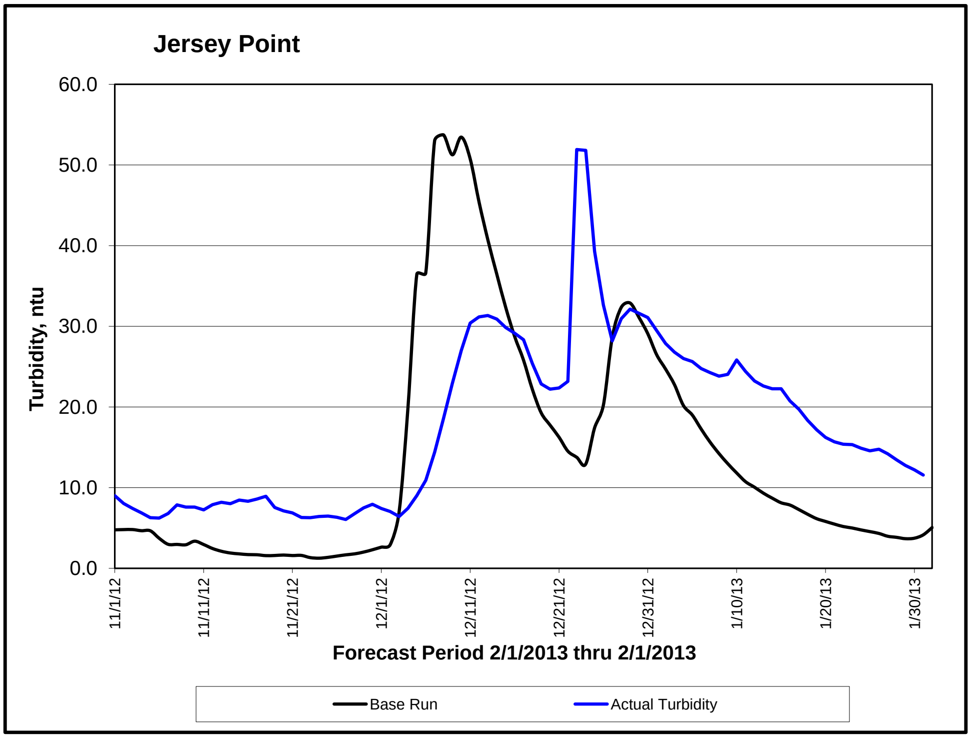


Figure 3-24 DSM2 simulations at Jersey Point (base run) compared to CDEC data for the wet season of 2012/2013 (actual turbidity). DSM2 runs performed by DWR.

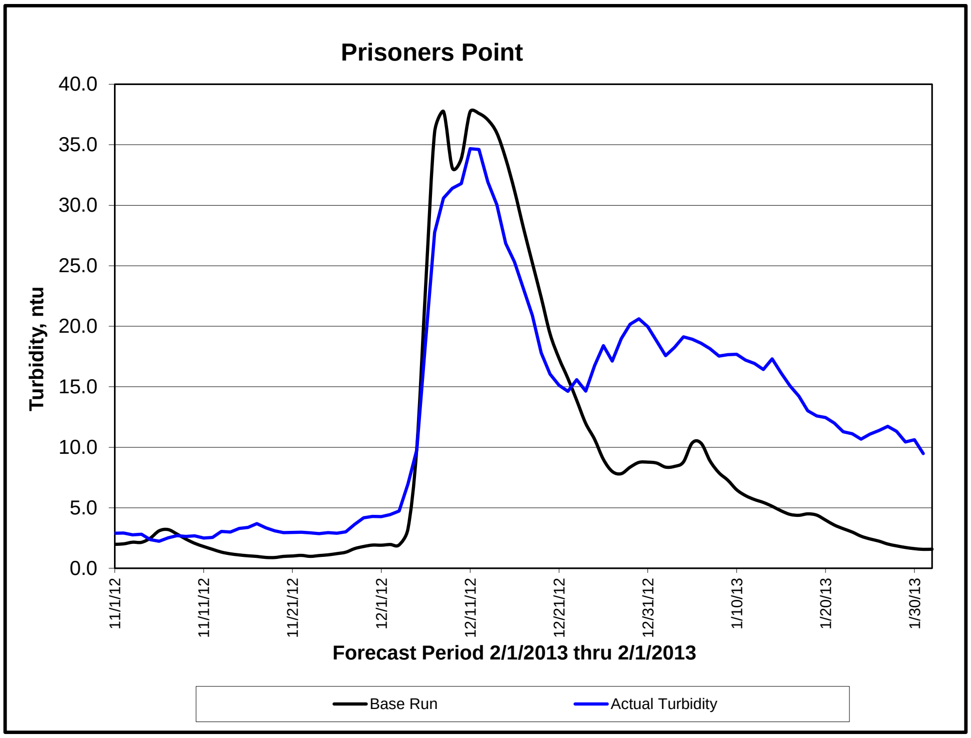


Figure 3-25 DSM2 simulations at Prisoner's Point (base run) compared to CDEC data for the wet season of 2012/2013 (actual turbidity). DSM2 runs performed by DWR.

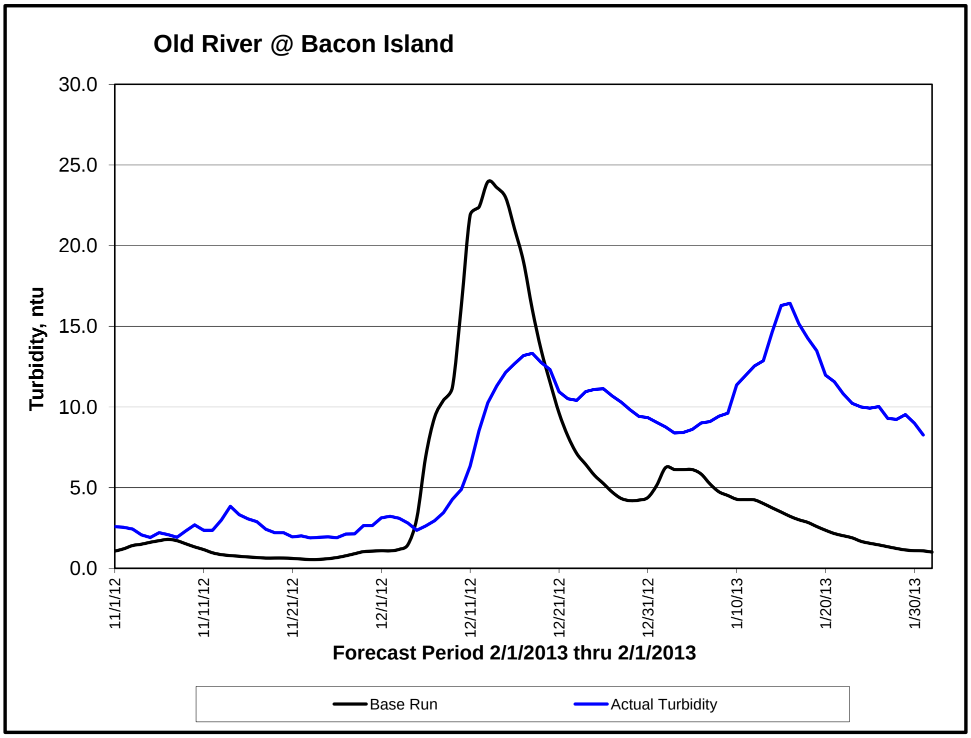


Figure 3-26 DSM2 simulations at Old River at Bacon Island (base run) compared to CDEC data for the wet season of 2012/2013 (actual turbidity). DSM2 runs performed by DWR.

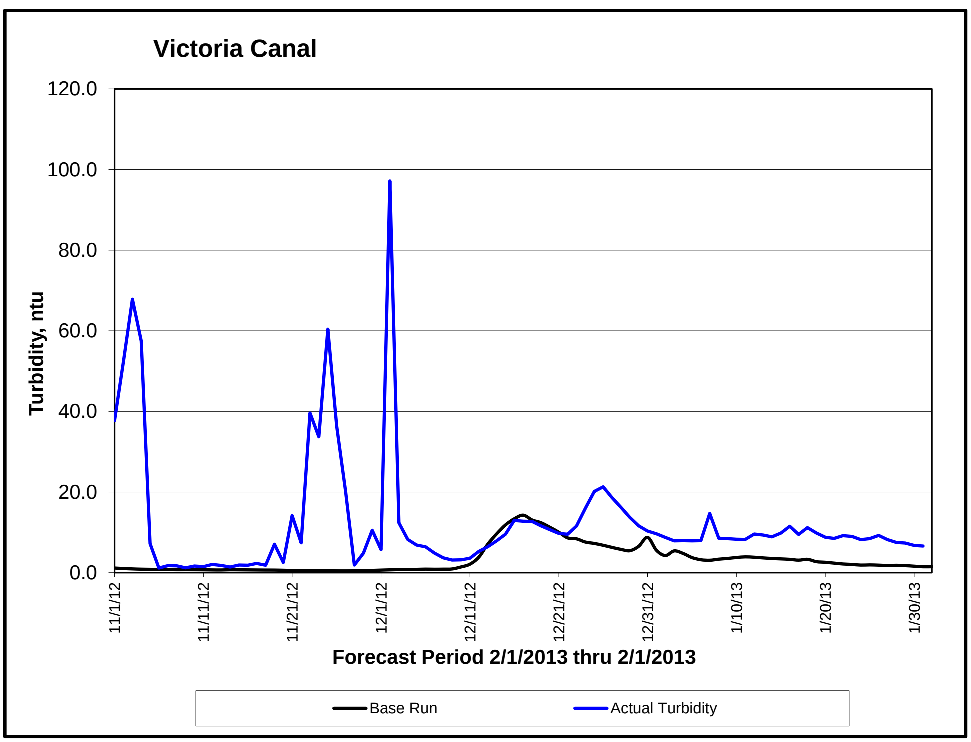


Figure 3-27 DSM2 simulations at Victoria Canal (base run) compared to CDEC data for the wet season of 2012/2013 (actual turbidity). DSM2 runs performed by DWR.

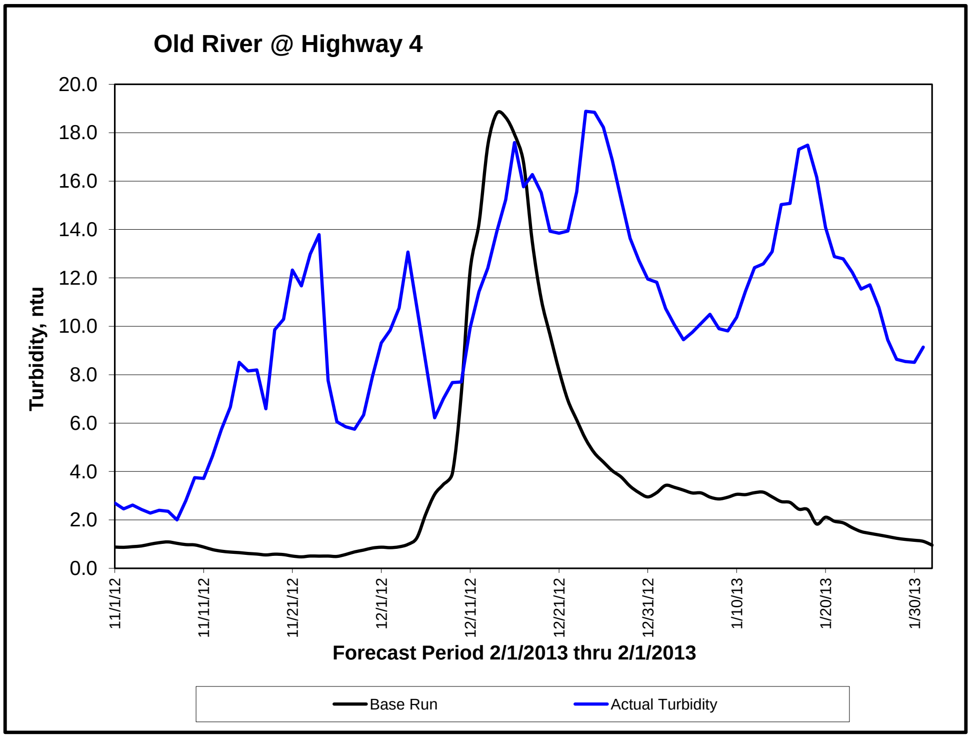


Figure 3-28 DSM2 simulations at Old River at Highway 4 (base run) compared to CDEC data for the wet season of 2012/2013 (actual turbidity). DSM2 runs performed by DWR.

4 SUMMARY AND DISCUSSION

The analysis presented here is the Phase 2 of a study to develop a turbidity ANN model for the Delta. Phase 2 of the study expands the first phase of the study to develop models at 16 locations within the Delta, and used an updated version of the DSM2 model to generate inputs and outputs for the ANN model. A total of 12 scenarios that take into account different levels of turbidity inputs at boundaries were used to generate the inputs to the ANN model.

The generated synthetic turbidity data were used to train feed forward network and the NARX network structures. The trained networks, when compared to DSM2 results, showed good emulation and were tested through correlations and evaluation of residuals against ANN inputs. The residuals analysis showed generally no correlation with flow or turbidity inputs, with higher residuals under lower flow. Validation for the NARX network for a multi-year DSM2 simulation for the period of 1975-2011 showed good agreement. This assessment generally demonstrates that the DSM2 behavior is adequately captured through the trained ANNs.

A sensitivity analysis of turbidities at various locations to OMR flow was conducted. The model showed different patterns of sensitivity to turbidity at different regions of the Delta. The West Delta stations showed no response or slight decrease in turbidity to the increase of OMR flow. The Central Delta stations showed decreases in turbidity to due to the increase of OMR flow, while the South Delta showed mixed results of increasing turbidity to OMR flow under high turbidity input from San Joaquin and the opposite trend under low turbidity input from San Joaquin. The sensitivity analysis provides insight on the ability of the water project operations (through management of OMR flows) to affect turbidity at specific locations. The sensitivity as presented here is essentially a summary of the DSM2-based responses of the system.

The use of the trained ANN networks in forecasting turbidity during wet season of 2012/2013 demonstrated that although the ANN networks closely followed DSM2 results, the forecasts strongly depend on quality of the underlying DSM2 simulation within the Delta. Thus, there were some locations for which the turbidity was underpredicted, or for which there was more rapid decline forecast than observed. This behavior was similar to that obtained from DSM2 for similar stations. In effect, the ANN performed well at representing DSM2 behavior under similar conditions. However, this behavior may not be matched by field observations. There are some mechanistic reasons for the underlying discrepancy. In particular, the first order decay for turbidity that is embodied in the DSM2 calibration may not be an adequate representation at all locations or under all conditions, where the observed data show turbidity levels remaining at elevated values for many days at a time. In contrast, other locations in the North Delta show rapid declines after a peak in turbidity that is well represented by both DSM2 and the ANN. An additional contributing factor may be processes such as wind and re-suspension that are not directly considered in the modeling.

Taken together, the ANN analysis as well as the review of the underlying DSM2 simulations, suggest two pathways for improving the quality of the turbidity forecasting in the Delta. A first step may consider additional calibration for DSM2, particularly focused on the stations that are required for turbidity compliance, to be followed by updated training. A second alternative may consider the exploration of ANNs using observed turbidity data as an alternative, and perhaps complementary, strategy to forecast near-term turbidity.

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