Uncertainty Analysis Plan for Hydrodynamic Modeling Support of the Water Supply Impact Study, St. Johns River, Florida

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Introduction

A hydrodynamic model has been developed for the lower 300 km of the St. Johns River (SJR) from the mouth, near Mayport, up to and including Lake Harney. The model area also includes three large side-channel lakes, Crescent Lake, Lake Woodruff and Lake Jesup. The model application will be used to quantify temporal and spatial changes to hydrodynamic variables resulting from diversion of river discharge to meet future consumptive use. These calculated changes will, in turn, be used by other working groups to assess potential environmental harm.

Flow reduction reduces the ability of a river to provide natural flushing and repel salinity intrusion (Fischer et al., 1979). These issues require analysis of mixing processes that are dominated by lateral and vertical velocity shear and thus require simulation of three-dimensional velocity fields. In addition, the estuarine portion of the SJR is a partially-stratified estuary where the nonlinear interactions between mixing and stratification are important factors controlling flow. The need to simulate mixing and stratification for the ultimate purpose of predicting pollutant transport and salinity intrusion dictated the use of a 3D hydrodynamic model. EFDC (Environmental Fluids Dynamic Code), a public-domain model (U.S. EPA, 2010), was selected for this study.

Application of the hydrodynamic model to the study area is divided into three broad tasks: calibration, confirmation, and uncertainty analysis. Calibration is the determination of model parameters and methods for setting initial and boundary conditions such that the model demonstrates the skill deemed acceptable for the larger environmental analysis. Demonstration of skill is by careful comparison of simulated with observed variables. Confirmation assesses model robustness by comparison of the results from the calibrated model with observations taken from one or more different time periods that, ideally, are distinct in character from the calibration period (Chapra, 1997). Uncertainty analysis seeks to identify, and when possible quantify, all factors that can cause variation of the model results. The sections below outline the goals and proposed methodologies for assessing uncertainty inherent in the hydrodynamic model study of the SJR in support of the Surface Water Impact Study.

Goal of Uncertainty Analysis

The term *uncertainty analysis* refers both to a general procedure to document, usually in a qualitative way, the confidence placed by scientists and engineers in their results and conclusions (IPCC, 2005) and specific, quantitative analyses designed to determine confidence in the output of a numerical model. The primary goal of both these types of uncertainty analysis is the same: to provide resource managers with the information necessary to allow an informed decision. The fact that uncertainty exists does not mean that policy decisions cannot be made or management strategies adopted, but rather that responsible decisions and sound strategies account for uncertainty. Although this document will hereafter narrow the discussion of overall uncertainty to model uncertainty, the implicit goal of the analyses remains to inform the decision process so that the model can be a useful tool for decision-makers.

The utility of uncertainty analysis is, first, as described above, for assessing the numerical model's ability to predict future conditions for "what-if" scenarios. Uncertainty analysis additionally illustrates how the model, and by inference the real-world system, responds to various perturbations to the system, such as winds, tide, rainfall, and discharge. Uncertainty analysis, then, helps us develop an understanding of the *cause* of variability of river stage, flow, salinity, and flushing at different locations and times. Finally, uncertainty analysis can direct future data collection efforts by determining what improvement could be expected to model output given an expected improvement to model input developed through a proposed data collection plan, for example, as part of an adaptive management strategy.

Methodology

Assessment of model uncertainty is in practice present throughout the modeling process of calibration, confirmation, sensitivity testing, model uncertainty analysis, and scenario testing for future conditions. How each of these tasks addresses uncertainty is described below. A point of note is that neither model identification, assessing the adequacy of the constituent hypotheses of the model structure (Beck, 1987; Shirmohammadi et al., 2006), nor model verification, demonstrating the correctness of the numerical solution of the underlying model equations (Roache, 1998), are considered here as part of uncertainty analysis. Certainly selection of a model with the appropriate internal structure for the spatial and temporal demands of the problem at hand is essential to model skill. A model based on the vertically-averaged Navier-Stokes equations, for example, would not be useful for predicting the location of a salt wedge in a stratified estuary no matter how well the model simulated tidal amplitude. For this study, we accept that EFDC (Environmental Fluids Dynamic Code) through its documented history of use (Martin and McCutcheon, 1999) is both an appropriate model selection for our modeling application and a verified model. This assertion is, of course, open to review. The non-modeler should note, however, that neither appropriate internal model structure nor model verification implies that the model application to a particular system is necessarily good, correct, accurate, or useful. That determination is the motivation for this uncertainty analysis plan.

Model Calibration

The model calibration process entails not only adjustment of model parameters to produce a best-fit with observed data, but decisions by the modeler regarding spatial grid scale, location of system boundaries, temporal and spatial scales of boundary conditions, and importance of initial conditions. Perhaps most importantly, the modeler must decide how external observations of the system are used to identify important internal processes in the model. Finally, the calibration process demonstrates model sensitivity of model output to model parameters and inputs over wider ranges of values than would typically be used for post-calibration sensitivity. These aspects of the calibration process have utility for demonstrating model robustness and will be documented in the calibration reports along with conventional graphical and statistical analyses of computed deviations.

Model Confirmation

Model confirmation will test model predictions against observations over as wide a range of meteorological conditions as possible within the available 10-year period of 1996 – 2005. The confirmation tests provide a quantifiable assessment of the overall uncertainty of model predictions, since the computed deviations of observed and simulated values encompass all uncertainties associated with the basic model parameters and assumptions. Reckhow (1994) considers that “model predictions compared to observations in a predictive scenario is a reasonable alternative to Monte Carlo analysis.”

Model confirmation will be made using graphical comparisons with data and various statistics generated from comparison and differencing of observed and simulated time-series. These comparative statistics will include linear coefficient of regression, slope and intercept of linear regression line, average absolute error, average relative error, root-mean-square error, index of agreement, and bias. [Shahrokh ?] Analyses will be made for water level, discharge, and salinity over a range of temporal scales (hourly, daily, monthly, and seasonal).

Model Uncertainty Analysis

Model uncertainty analysis (UA) is a model evaluation methodology that can provide additional information about the sources of model uncertainty. Aspects of UA include sensitivity analysis, assignment of variance to individual model variables and parameters, and propagation of the defined uncertainty through the model (Mattot et al., 2009). UA generally focuses on reducible uncertainty of input data stemming from imperfectly measured or sampled data. The techniques can also be applied to irreducible uncertainty, for example, arising from natural variability.

Beck (1987) and Matott et al. (2009) provide reviews of the wide range of model evaluation categories and analysis techniques that fall into the discipline of UA. For the purpose of this report, we consider only the three broad and commonly used categories of sensitivity analysis, first-order error analysis (FOEA), and Monte Carlo simulation (MCS) (Zhang and Yu, 2004).

Sensitivity analysis is a simple assessment to determine the relative effect each model input variable or parameter has on the simulated model results. Although simple, sensitivity analysis has utility to calibration and for insight into how the real-world system responds to individual forcing functions that may be difficult to separate by observation alone.

FOEA includes sensitivity analysis but also accounts for variance of individual model inputs and propagates, through linear combination, uncertainty through the model (Zhang and Yu, 2004; Brown, 1987). FOEA thus provides (a) the relative sensitivity of each variable, (b) the relative contribution of each variable to model uncertainty, and (c) error bounds on model output. In addition, FOEA can estimate the expected increase in model performance from an expected improvement to an input variable (Blumberg and Georgas, 2008), for example by additional monitoring, thus helping to determine the efficacy of proposed data collection plans.

Zhang and Yu (2004) consider the main limitation of FOEA to be the dependence on the results to the linearization of the system performance function at the central values of the input variables (where the central values are at the calibrated state.) This assumption is inappropriate for nonlinear models when values deviate far from the central state. Blumberg and Georgas (2008) note the weakness of the assumption of zero correlation between input variables.

MCS is a category of UA that seeks to describe model input variables and parameters as probability density functions (PDFs) and then propagate uncertainty through the model using multivariate combinations of model inputs. The result of MCS is quite powerful in that the aggregation of model uncertainty is expressed as complete PDFs of the model output.

There are two disadvantages to MCS: (a) computational burden and (b) the difficulty of assigning PDFs to uncertain input variables and parameters. The class of three-dimensional hydrodynamic models used for this study is computationally intensive and, as expressed by Martin and McCutcheon (1999), "the computational burden of making thousands of simulations practically limits the application [of Monte Carlo analysis] to simpler water quality models." Uncertainty in model inputs and parameters often includes lack of knowledge regarding their probability distributions. This important aspect of MCS then requires subjective estimation. When such lack of knowledge exists, the advantage of MCS over simpler methods, such as FOEA, is reduced.

FOEA (Brown, 1987; Zhang and Yu, 2004; Blumberg and Georgas, 2008) will be used in this study to quantify the contribution to model uncertainty of the model forcing functions and parameters. The goal of FOEA is to demonstrate the degree to which uncertainty inherent in model input variables affects uncertainty in the spatial and temporal model predictions of water level, velocity, water age, and salinity throughout the estuary. FOEA will consider bathymetry, bottom roughness, ocean tide, surface water discharge, spring and diffuse groundwater discharge, wind, direct rainfall-evaporation, and ocean salinity. Uncertainty will be quantified for both a dry year and a wet year.

Surface water discharges from ungauged watersheds were estimated using a hydrologic model, HSPF (Hydrological Simulation Program FORTRAN). HSPF simulates the amount and temporal variability of surface water runoff using meterological inputs and watershed characteristics (e.g. rainfall, evaporation, land-use, soils, slopes), and a set of input parameters that largely define the rates with which water moves between various storage compartments. The work of Zhang and Yu (2004) and Shirmohammadi et al. (2006) discuss the explicit application of FOEA to HSPF. For this study the parameter space for HSPF was exhaustively analyzed using PEST, model independent parameter estimation software (Matott, 2009). This work will be described in a separate report on the HSPF calibration. Uncertainty analysis related to HSPF is implicitly included here through variance of the surface water discharges to the EFDC main-stem model and through testing of predicted alterations to discharge by future land-use.

The application of FOEA to the SJR hydrodynamic model will generally follow the methodologies outlined by Blumberg and Georgas (2008) with inclusion of separate assessments of variance for input variables following Zhang and Yu (2004). These methods require calculation of dimensionless sensitivity coefficients. These calculations could be made at representative locations, but the method used here will be to calculate dimensionless sensitivity coefficients within each model cell for each hour. This four-dimensional field will then be sampled by taking median values over pre-defined river segments and over each month for both a dry and wet year. Results for dimensionless sensitivity coefficients will show the relative sensitivity of each model output variable to each input variable in space and time.

Estimates of the percent contribution of each input variable to output variance will be made by combining the dimensionless sensitivity coefficients with estimates of input variance. These estimates will, again, be shown over aggregated river segments by month. Finally, the combined dimensionless sensitivity coefficients and input variances will be used to estimate error bars for time-series of model output, primarily arising from uncertainty in model forcing functions.

The result of this UA will

(a) provide insight into the model response, and by inference the real-world response, to input variables,
(b) demonstrate where to focus future data collection efforts, if necessary,
(c) define a reasonable error range for model output variables,
(d) assess the utility of the predictive model as a decision tool for policy-makers.

Future Model Variations

Uncertainty of model predictions for future conditions also includes variables that can change randomly in the future. This study considers the following four variables as having both the potential to affect the hydrodynamics of the river and a reasonable likelihood to change over the planning horizon:

(a) sea level rise due to global climate change,

(b) hydrologic alteration of watersheds due to urbanization and other land-use changes,

(c) channel deepening of Jacksonville Harbor, and

(d) diversion of water from wastewater treatment discharges for re-use.

These variables will be assessed for a twenty-year planning horizon, the year 2030.

A fifth variable under consideration for the project is altered precipitation due to global climate change. The potential for this future change is being assessed through a contract with David Yates, National Center for Atmospheric Research. Results of this study will be considered as part of the qualitative uncertainty analysis for the larger study. Presently, however, insufficient information is available for developing a specific model scenario and this item will not be addressed using the model.

Sea Level Rise

Sea level rise (SLR) refers to the gradual rise of mean ocean level at the SJR mouth. The observed mean rate of local SLR for an 80-year period of record near the river mouth at Mayport is 2.4 mm yr^{-1} (USACE, 2009). Local SLR is partly caused by an increased volume of the global oceans, and partly by subsidence of the Florida peninsula. Global SLR for the same period is 1.7 mm yr^{-1}, thus subsidence accounts for about 0.7 mm yr^{-1}. The present rate of global SLR is estimated as 3 – 3.5 mm yr^{-1} (Rahmstorf, 2007) and will likely continue to increase due to global warming (Bates et al., 2008; Rahmstorf, 2007).

Land-use Changes

The SJR watershed contains regions that have experienced relatively high population growth over the last several decades. Population growth has caused an increase in urban land-use and impervious surface. Urban land-use has generally displaced rural and agricultural areas. Population growth is likely to continue over the next two decades so that land-use changes will also likely continue to occur. The

SJRWMD Water Supply Assessment 2003 (2006) estimated a District-wide population increase of 67% between 1995 and 2025.

Urbanization of watersheds generally increases annual runoff volume, increases the intensity of peak storm discharges, and reduces tributary base flows. These hydrologic alterations could, in turn, affect the main-stem of the river and estuary through alteration of water level, velocity, salinity patterns, and flushing.

Drainage patterns and natural storage areas in the USJR basin were altered in the first half of the previous century by construction of a complex system of levees and canals, initially to drain land for agriculture and more recently for flood control. This development generally led to diversion of water from the SJR basin to the Indian River Lagoon. The St. Johns River Water Management District (SJRWMD) is currently developing water resources projects to re-divert water back to the SJR basin to both increase water supply to the SJR and prevent harmful discharge of freshwater to the estuarine Indian River Lagoon. These structural alterations will offset downstream water withdrawals particularly in the USJR near Taylor Creek Reservoir.

Channel Deepening

Jacksonville Harbor extends from the river mouth near Mayport about 20 miles to the Talleyrand Terminal in Jacksonville. The structure of the harbor has been highly modified for navigation. The principle navigational channel is a 20-mile long, dredged channel with a project depth of 40 ft (MLLW). The U.S. Army Corps of Engineers is presently engaged in a general re-evaluation of the harbor design to address both current and future navigational problems (USACE, 2007). The re-evaluation will consider a maximum deepening of the navigational channel to 50 ft depth.

Diversion of Wastewater for Re-use

Domestic wastewater is a product of the collection and treatment of domestic sewage. In many urban areas throughout the study area, sewage is collected and piped from residences to a central treatment facility where the sewage is treated and discharged, either directly or through wetland systems, to the St. Johns River. As most domestic water sources are from groundwater, this practice results in a transference of Floridan Aquifer water to the SJR.

Re-use of treated wastewater has two important benefits. First, the re-use water is used for non-potable uses, such as lawn irrigation, thus reducing demand for threatened groundwater sources. Second, some wastewater streams contain excessive levels of nutrients that can harm water quality of the receiving waters. Re-use, then, can both conserve water supply and improve water quality of the SJR.

The two main areas of wastewater discharge to the SJR are near the large urban centers of Jacksonville and Orlando. Wastewater streams in the Jacksonville area average about 80 MGD. The principle discharge in the Orlando area is through a treatment wetland associated with the Iron Bridge Water Reclamation Facility and averages about 20 MGD.

As water demands increase in the future, it is likely that greater fractions of wastewater streams will be diverted for re-use. On the other hand, increases in domestic water consumption will also increase total flows to wastewater treatment facilities. These competing factors will be assessed on a facility-by-facility basis to estimate 2030 wastewater discharge volumes and the fractions used for re-use.

Future model variations will be assessed in two ways, first, by sensitivity analysis of the expected change for each variable, and second, by testing multivariate combinations. The former provides a simple method of assessing future changes as additive alterations to the model base scenarios. The latter provides a means to assess possible non-linear interactions between variables. The scenario combinations will also be combined with a zero and full water withdrawal scenario to test for nonlinear interactions of future conditions with water withdrawals.

For the sensitivity tests, we will separate the individual effects of each variable by comparison with a 2030 Base Case. (The 2030 Base Case includes 2030 land-use, structural alterations to the USJR, and an "intermediate" sea level rise scenario defined as a continuation of the present rate of sea level rise to the year 2030.) Sensitivity tests are made by comparison of the 2030 Base Case with the following five scenarios :

(a) 2030 Land-use with no SLR
(b) 2030 Land-use with a "high" SLR
(c) 1995 Land-use with an "intermediate" SLR
(d) 2030 Land-use with channel deepening

(e) 2030 Land-use with re-use

The five scenarios (a-e) test, respectively, the isolated effect of (a) SLR, (b) increasing rates of SLR, (c) land-use change, (d) channel deepening, and (e) re-use. The “high” SLR case will follow the USACE (2009) methodology and results in a 2030 mean sea level at Mayport comparable to, but somewhat greater than, Rahmstorf (2007).

For testing non-linear interactions, multivariate combinations of the above variables will be made for the 2030 Base Case (which includes “intermediate” SLR) in combination with two channel deepening scenarios, two re-use scenarios, and two water withdrawal scenarios. The channel deepening and reuse scenarios are simple “with/without” conditions. The water withdrawal scenarios use zero and 155 MGD withdrawals. The permutation results in eight scenarios for testing. For completeness, each of these scenarios will also be combined with a 2030 land-use scenario with a “high” SLR scenario. The additional eight scenarios are designed to capture possible interactions of future changes for a more severe SLR condition. SLR is singled out for testing of a more severe condition because it is the sole variable under consideration for future variation that is truly uncontrollable.

Unknown Future Variations

The possibility exists that future changes to the system could arise from unknown factors not considered here, or factors, such as climate change for which patterns of alteration are highly speculative. Such possible alterations require allowance for adaptive management that includes monitoring for future trends and periodic reassessment of policy decisions.

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