PREDICTING THE IMPACT OF CLIMATE CHANGE ON SALINITY INTRUSIONS IN COASTAL SOUTH CAROLINA AND GEORGIA

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INTRODUCTION

This paper summarizes findings from Water Research Foundation Project 4285, which was sponsored the Foundation and Beaufort-Jasper Water and Sewer Authority (Roehl et al. 2012). The project's thesis is as follows. Coastal fresh water intakes are at risk due to sea-level rise (SLR) and climate change. Because of past storms and droughts, long-term historical data already contains information about how a hydrologic system will respond. A predictive model that is accurate across a site's full range of historical forcing can be used to assess risk.

The project's goal was to develop and test a practical method for coastal utilities to assess their vulnerability to climate change and sea-level rise (SLR). It was executed by a team composed of Advanced Data Mining International, the South Carolina Sea Grant Consortium, the U.S. Geological Survey, and the University of South Carolina.

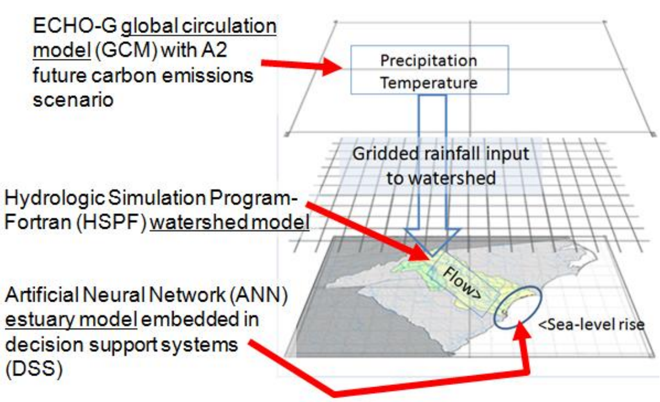

Figure 1. The method integrates three types of models – a global circulation model, a watershed model, and an estuary model packaged as a DSS.

APPROACH

The technical approach used to develop the method involved the following steps.

1. A global circulation model (GCM) predicts future rainfall (Figure 1).
2. The rainfall predictions are "downscaled" to a basin, and then input to a watershed model that predicts stream flows.
3. The predicted stream flows and parametrically incremented SLR are input to an estuary model that predicts the frequency, magnitude, and duration of salinity intrusion events.
4. The models are embedded in a Decision Support System (DSS) (Figure 2), which integrates data and models with point-and-click controls and supporting graphics to give users with varying degrees of technical skills equal access to the scientific knowledge needed to make informed decisions (Roehl et al. 2006). A DSS would allow utility personnel to run their own risk assessment scenarios

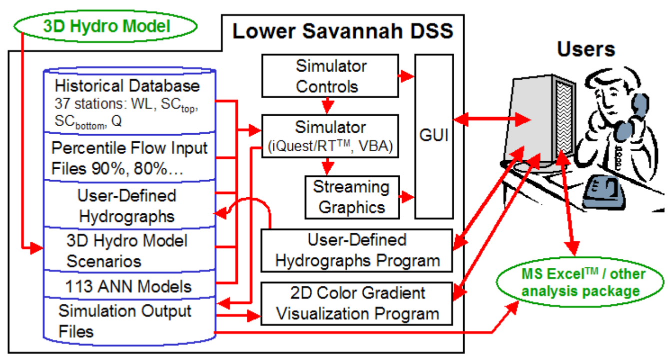

Figure 2. The M2M Decision Support System (DSS).

The method was demonstrated for intakes on two estuaries.

Pee Dee Basin (Figure 3) – was chosen for a full application of the method involving all three types of models. The estuary model used was the pre-existing "Pee Dee River and Atlantic Intracoastal Waterway Salinity Intrusion Model" (PRISM) that was originally developed for relicensing several hydroelectric dams by the Federal Energy Regulatory Commission (Conrads and Roehl 2007). PRISM was modified and recalibrated using 14 years of data (1995-2009)

Lower Savannah River (Figure 4) – was studied using only an estuary model, which was ranged to determine the affects of reduced stream flows and SLR. The model used was the pre-existing "Model to Marsh" DSS (M2M), which had originally been developed to predict the environmental impacts of a proposed deepening of Savannah Harbor (Conrads et al. 2006). The M2M was calibrated using 11 years of data (1994-2005)

Both PRISM and the M2M can be run with either percentages of historical flows or user-defined flows, such as those from GCM-forecasts. Sea level can be incremented by itself or in conjunction with flow changes to determine its impact on salinity intrusion.

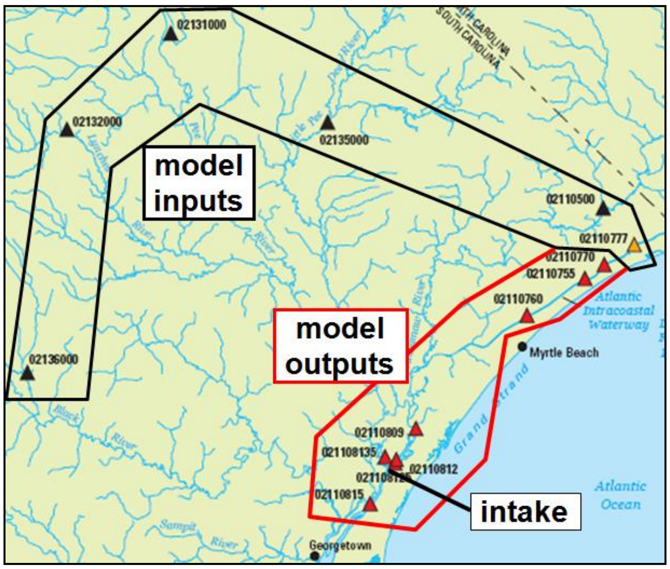

Figure 3. Map of the Pee Dee Basin showing USGS gaging stations, the intake location, and the PRISM estuary model inputs.

MODEL CALIBRATION

The three types of models were calibrated as follows.

GCM – as shown in Figure 5a, the predictions of four GCMs were evaluated for a historical calibration period. Figure 5b shows that the ECHO-G GCM (Legutke and Voss 1999) was the most accurate during the low flow conditions of interest.

Watershed Model – an HSPF model was developed to predict the five stream flows input into PRISM (Figure 3). Figure 6 shows the prediction of the largest flow.

Estuary Models – both the PRISM and M2M DSS'S predict salinity intrusion events using a multivariate, nonlinear curve fitting technique called an artificial neural network (ANN). ANNs are commonly used for industrial process control (Jensen 1994). The shape of an ANN's fit is learned rather than prescribed like statistical and physics-based models. Figures 7 and 8 show the DSS'S predictions near the intakes indicated in Figures 3 and 4.

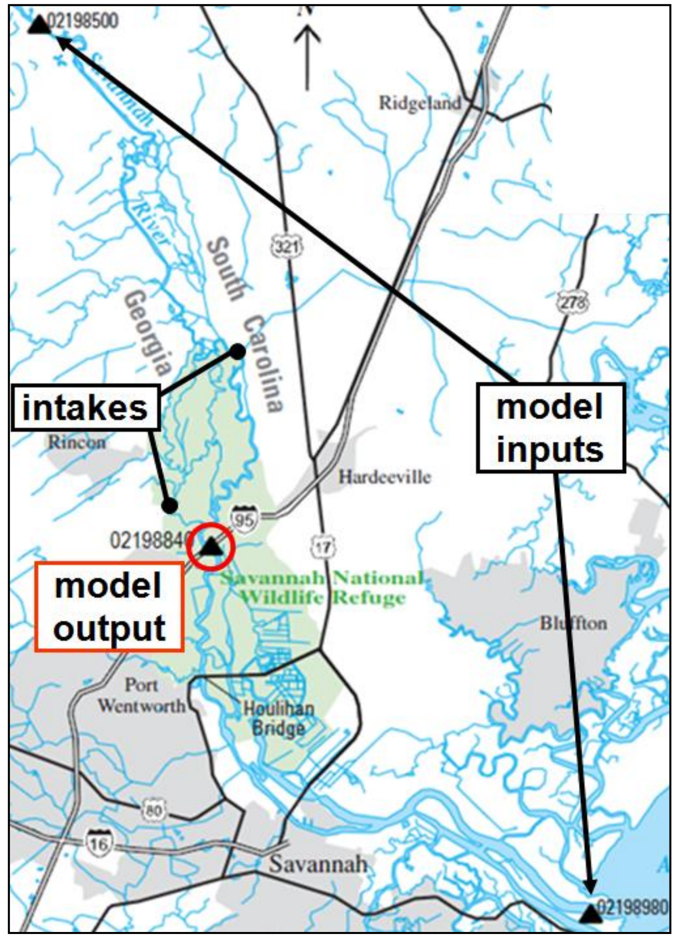

Figure 4. Map of Lower Savannah River showing USGS gaging stations, intake locations, and M2M estuary model inputs.

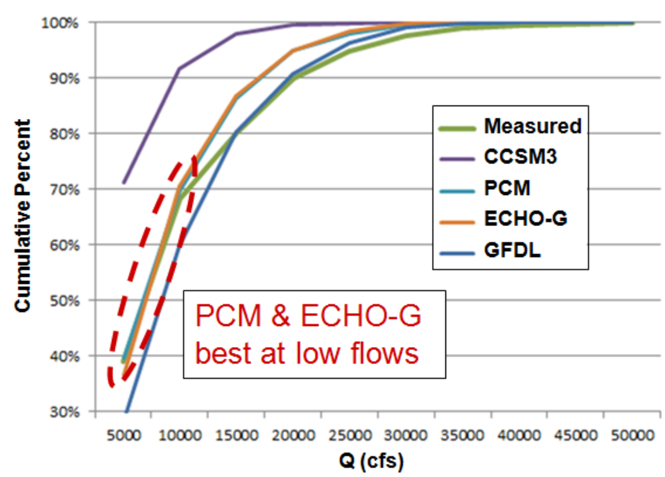

Figure 5a. Measured and GCM-predicted cumulative percentages of Pee Dee River flow (Q).

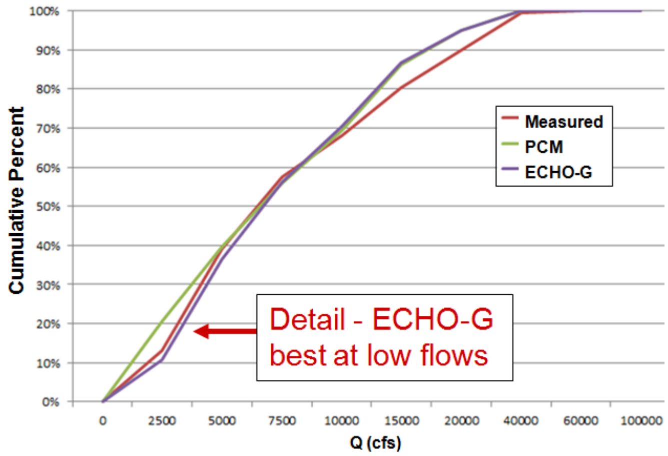

Figure 5b. Detail of Figure 5a. Note the non-linear horizontal scale.

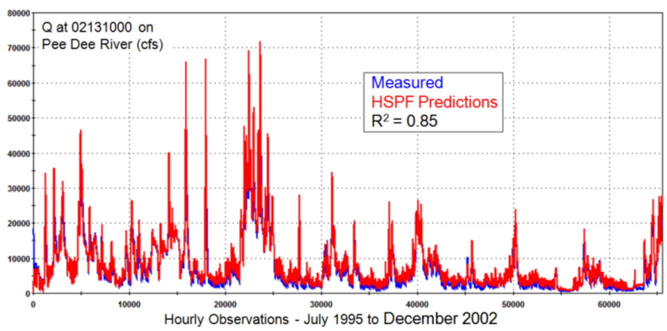

Figure 6. Pee Dee Basin measured and HSPF-predicted flows at the input gaging site with the highest flow.

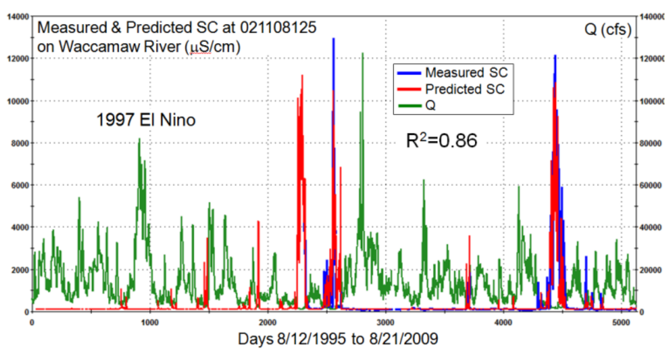

Figure 7. Pee Dee Basin measured and PRISM-predicted specific conductance (SC) with stream flow (Q).

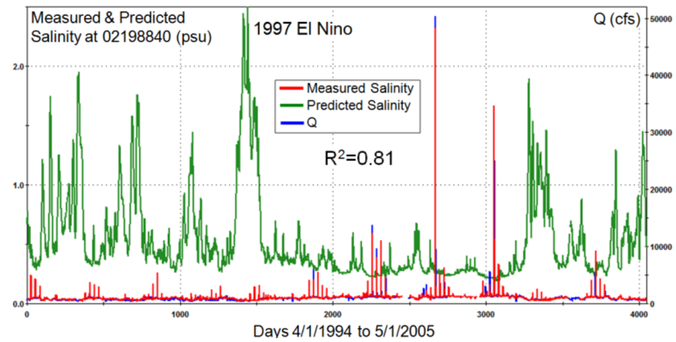

Figure 8. Lower Savannah River measured and M2M-predicted salinity with stream flow (Q).

RESULTS

Pee Dee Basin – the table in Figure 9 represents 42 different PRISM runs in which the 14-year historical flow was decremented (ΔQ) and SLR was incremented. The table lists the percent of days (%days) when the predicted SC exceeds 1,000 µS/cm ≈ 0.5 psu ≈ limit for drinking water. The information in the table is made more understandable when plotted in 3D (right of table). The higher slope along the SLR axis indicates that salinity is more sensitive to SLR than to ΔQ. Similarly, Figure 10 shows that the predicted number of events when the limit is exceeded for seven or more days is also more sensitive to SLR. Figure 11 shows that the %days above the limit is higher for the historical flows (top) than for the wetter conditions predicted by ECHO-G (bottom) 50 years later (2055-2069) .

Lower Savannah River – Figure 12 shows that the predicted %days above the limit varies with ΔQ more than in the Pee Dee Basin (Figure 9). This is due to the estuaries' differing geometries. Note the very different salinity responses in Figures 6 and 7, even though the estuaries are in the same region and experience similar meteorological and sea-level forcing.

Increase SLR

Decrease Q

ΔQ/SLR (ft)	%days > 1,000 µS/cm 0.0	0.5	1.0	1.5	2.0	2.5	3.0
0%	5	8	11	14	18	20	23
-5%	6	9	12	16	19	22	25
-10%	7	10	13	17	20	23	26
-15%	8	11	15	19	22	25	28
-20%	9	15	17	20	23	27	30
-25%	10	14	18	22	25	29	33

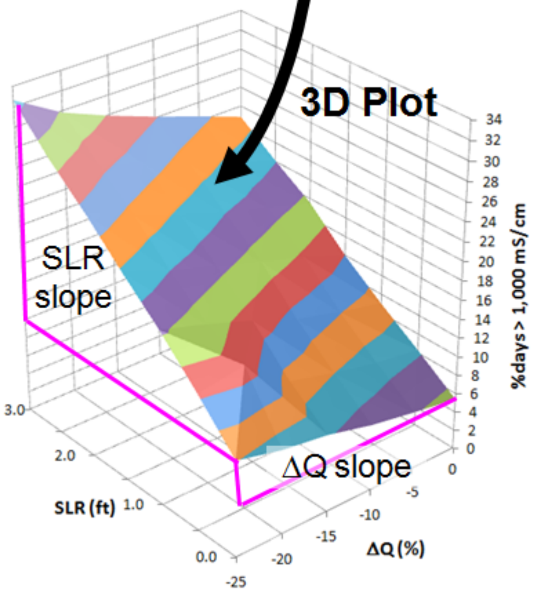

Figure 9. Pee Dee Basin %days when the predicted SC exceeds 1,000 µS/cm.

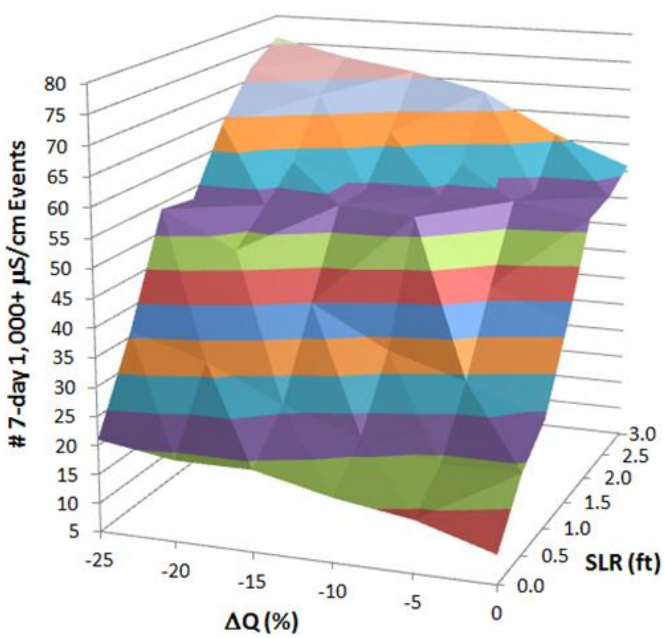

Figure 10. Pee Dee Basin number of events when the predicted SC exceeds 1,000 µS/cm for seven or more days.

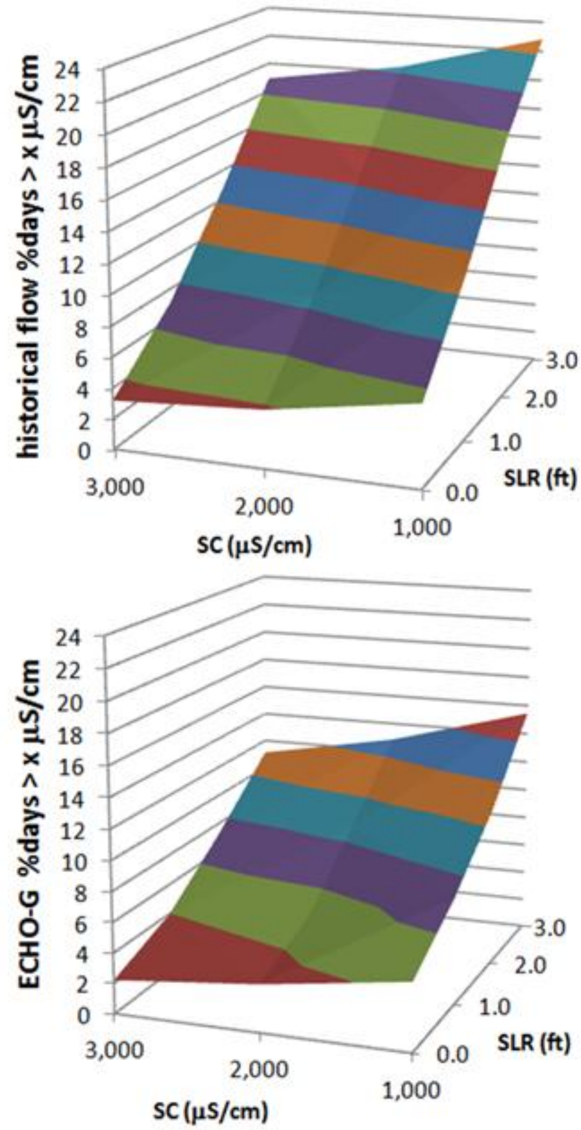

Figure 11. Pee Dee Basin %days when the predicted SC exceeds 1,000 µS/cm for the historical flows (top) and the ECHO-G 2055-2069 scenario (bottom) .

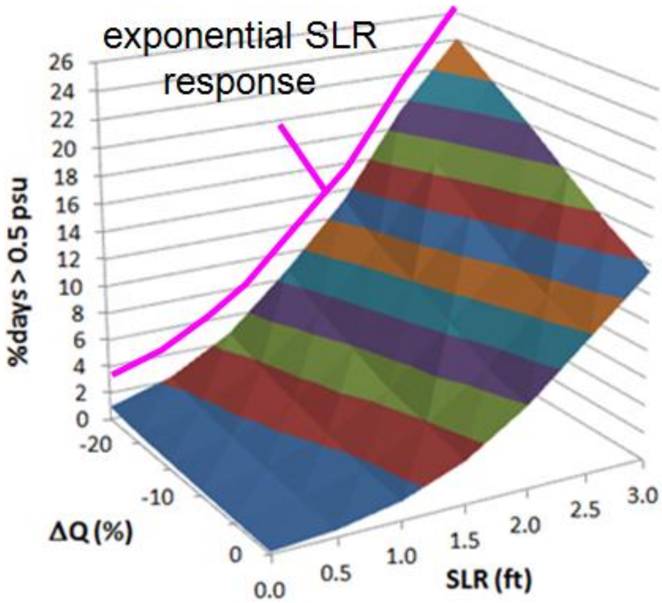

Figure 12. Predicted Lower Savannah River %days when the predicted salinity exceeds 0.5 psu.

CONCLUSIONS

- An accurate, site-specific model is required to credibly assess vulnerability.
- Empirical models can be more accurate, faster to develop, and easier to update with new data.
- Long-term data spans much of the anticiapted future ranges, and is needed to calibrate the model. If you already have data, you are ready to model. If not, start collecting.
- Easy-to-use DSS's deliver the needed science directly to utility personnel to run scenarios, assess risk, and make decisions.
- This method can be applied to other resources, such as groundwater.

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