

Estimating seawater intrusion impacts on coastal intakes as a result of climate change

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Many coastal utilities will find it challenging to adapt to future climate conditions in which sea-level rise and extreme weather cycles could increase the frequency and duration of seawater intrusion into estuaries. This article describes a method of assessing risk to utility water supplies and details its use in two coastal systems supplying freshwater to municipalities in Georgia and South Carolina. The method uses long-term weather and hydrologic data to develop empirical models that represent the seawater intrusion process in the vicinity of an intake. Data available from past droughts and storms provided sufficient variability to model the range of anticipated future weather and hydrologic conditions. The model can be varied using permutations of historical conditions and climate change forecasts to estimate future impacts at the intake. The models and data are deployed in a spreadsheet program that features a graphical user interface and supporting graphics, making it readily usable by utility personnel.

Keywords: *climate change, intake, model, risk analysis, salinity intrusion, sea-level rise*

There are many theories about the causes of climate change but little disagreement that it is happening. Climate change and sea-level rise (SLR) will alter hydrologic patterns, resulting in changes in the salinity intrusion dynamics of coastal rivers where many water utility intakes are located. The increase in the degree of saltwater intrusion along the Georgia and South Carolina coasts during the record-breaking drought in the southeastern United States from 1998 to 2002 showed how climate change and SLR increase the threat to freshwater estuarine intakes. This development also underscored utilities' need for reasonable estimates of future changes in the frequency, duration, and magnitude of salinity intrusion near their water intakes.

PROJECT DESCRIPTION

Project objectives. The objectives of this project were twofold:

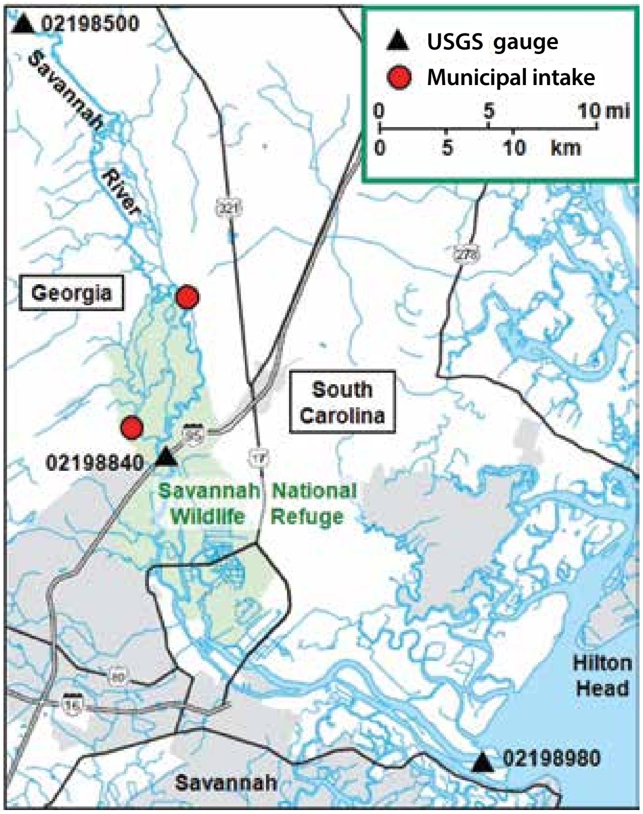
- Develop an approach, or template, that coastal utilities could use to evaluate the threat posed by climate change and SLR to their intakes.
- Demonstrate the effectiveness of the approach by applying it to two separate estuarine systems in Georgia and South Carolina.

The authors, working with the US Geological Survey (USGS), had previously developed specific-conductance models of the Lower Savannah River and Grand Strand region estuarine systems, which feature two and three municipal freshwater intakes, respectively (Conrads et al, 2007, 2006). The models convert inputs that primarily represent freshwater stream flow and sea level into predictions of specific conductance at several locations. In both systems it was found that the relationships among sea level, freshwater stream flow, and salinity intrusion are complex and nonlinear and that weather extremes such as droughts and increased sea levels brought by hurricanes can produce large intrusion episodes. It is possible that the negative effects of climate change experienced by utilities could be exacerbated by increasing interannual climate variability (specifically, more droughts) and escalating freshwater demands from upstream farms, industries, and water utilities.

Project study areas. The Savannah River estuary is a deltaic system that branches into a series of interconnected distributary channels (Figure 1). Among the area's most important resources are the Savannah National Wildlife Refuge and the nearby port terminals of the Savannah Harbor. Two municipal water intakes are in the freshwater portion of the upper estuary. The city of Savannah maintains an intake on the Abercorn Creek tributary, approximately 1 mi upstream of USGS gauge 02198840, which provides specific conductance and water level measurements. The intake for the Beaufort–Jasper Water and Sewer Authority is located at a canal that withdraws from the Savannah River approximately 15.5 river mi upstream of USGS gauge 02198840. The salinity model used in the current project, the Savannah River Model-to-Marsh (M2M), was originally developed to evaluate the effect of a proposed deepening of the Savannah Harbor on the refuge and other areas. The USGS gauging stations on the Savannah River near Clyo (02198500) and at Fort Pulaski

A full report of this project, *Estimating Salinity Effects Due to Climate Change on the Georgia and South Carolina Coasts* (4285), is available for free to Water Research Foundation subscribers by logging on to www.waterrf.org.

FIGURE 1 Lower Savannah River estuarine system



Adapted from Conrads et al, 2013

USGS—US Geological Survey

(02198980) provided the data representing the model's input boundary conditions.

Figure 2 shows the second study area, which is the estuarine system composed of the Lower Pee Dee River, the Waccamaw River tributary, and the Atlantic Intracoastal Waterway (AIW). The Pee Dee River (named the Yadkin River in North Carolina) flows through several hydroelectric facilities, the last one approximately 15 mi upstream from the state border. The reach of the AIW from just south of Little River Inlet to just north of Hagley Landing provides freshwater for the coastal communities of the Grand Strand.

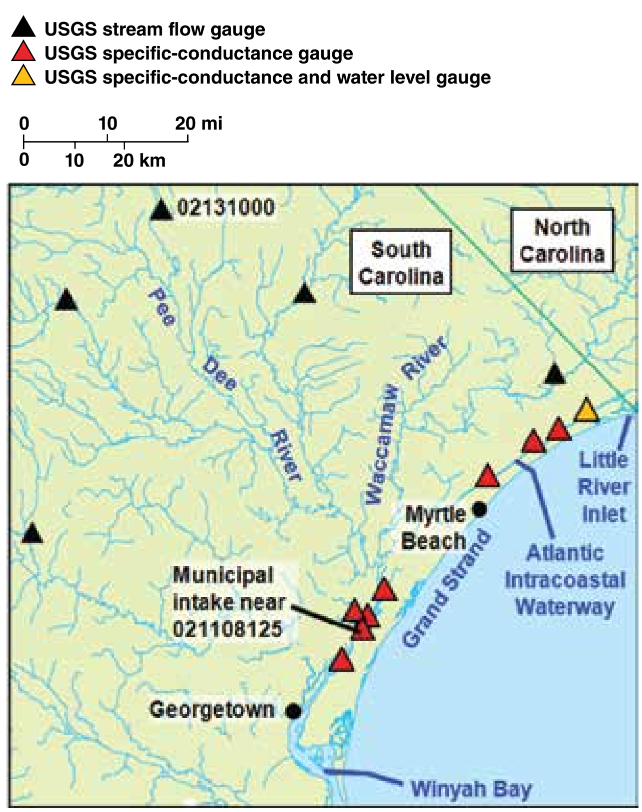
Three municipal surface water intakes are in the tidal freshwater portions of the system. During a drought from 1998 to 2002, salinity intrusion forced the intake near USGS gauge 021108125 to close until increased stream flow moved the freshwater–saltwater interface downstream. Figure 2 also shows the USGS monitoring sites on the Waccamaw River and AIW that provided some of the data used to develop the specific-conductance model, referred to as the Pee Dee River and Atlantic Intracoastal Waterway Salinity Intrusion Model (PRISM). The model was developed to support the process of the relicensing of the hydroelectric facilities by the Federal Energy Regulatory Commission, which occurs at 50-year intervals. Additional information about the research effort is available elsewhere (Conrads et al, 2013; Roehl et al, 2012).

APPROACH

Model descriptions. M2M and PRISM are actually decision support systems (DSS) that integrate several empirical specific-conductance submodels, the real-time databases needed for running simulations, graphical user interfaces, and streaming graphics. The DSSs are spreadsheet applications[1] that are easily distributed and immediately usable by water resource managers and other stakeholders. Deploying the models in this transparent form gives resource managers and stakeholders with varying levels of computer skills equal access to the scientific knowledge they need to make the best possible decisions (Roehl et al, 2006).

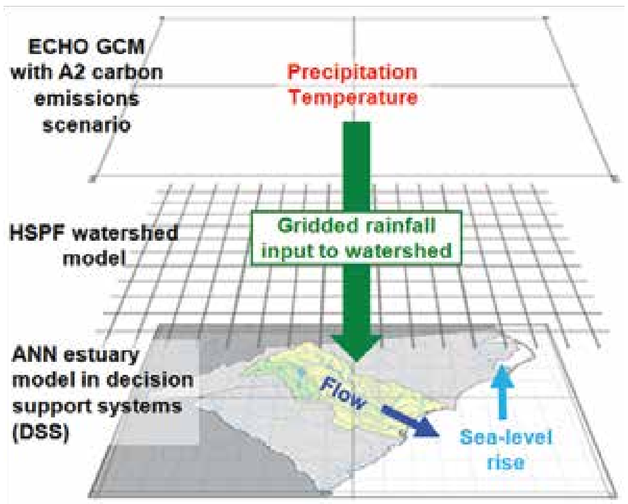
The original DSSs were modified to allow users to modulate the sea-level input and unregulated stream flows, and the PRISM submodels were redeveloped using an additional 6.5 years of field data. These modified DSSs were renamed M2M-2 and PRISM-2. The data used to develop the M2M submodels and run simulations span 11 years from 1994 through 2005, and the PRISM-2 data span 14 years from 1995 to 2009. Both data sets incorporate a broad range of climate and sea-level conditions, including record droughts, high rainfall El Niño climate periods, and hurricanes. Developing the empirical submodels from this range of data makes them applicable to studies involving climate change and SLR scenarios.

FIGURE 2 Lower Pee Dee River and Waccamaw River estuarine system



USGS—US Geological Survey

FIGURE 3 Conceptual approach to modeling the effects of climate change on salinity intrusion



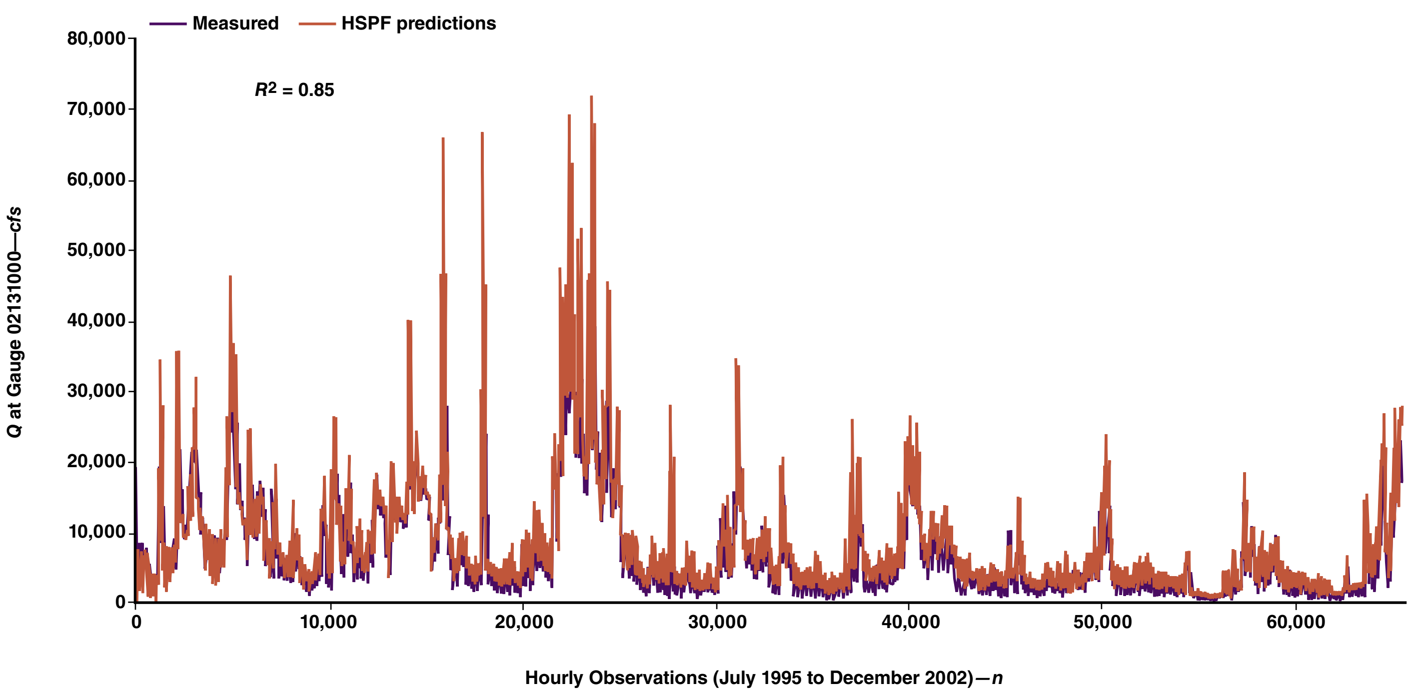
Adapted from Conrads et al, 2013

ANN—artificial neural network, GCM—global circulation model, HSPF—Hydrologic Simulation Program–Fortran

The submodels were developed using multilayer perceptron artificial neural network models, commonly used for process engineering applications (Jensen, 1994). They synthesize nonlinear functions to fit multivariate data and offer significant advantages over traditional mechanistic modeling codes for modeling estuary hydrology, including prediction accuracy, speed of development, execution speed, and breadth of deployment options (Conrads & Greenfield, 2008; Conrads & Roehl, 1999).

Forecasting the effect of climate change at an intake. Estuary salinity variability is largely driven by stream flow and tidal water levels, both of which are affected by climate change. Forecasting of future stream flows requires integration of global circulation, regional circulation, watershed runoff, and salinity intrusion models (Figure 3). Global circulation models (GCMs) make large-scale (> 250-km^2 grid) estimations of precipitation and temperature conditions for various carbon emission scenarios. These scenarios are typically 100-year projections. To generate precipitation and temperature predictions for a watershed (approximate 12-km^2 grid), the GCMs are coupled to regional circulation models that generate regional precipitation and temperature predictions, which are input to a watershed model. The watershed model then predicts the stream flow inputs to an estuary model such as PRISM-2. The Pee Dee Basin stream flow forecast was generated by the University of South Carolina at Columbia and the South Carolina Sea Grant Consortium for the years 2055–2069, 60 years from the start of the PRISM-2 study period. The

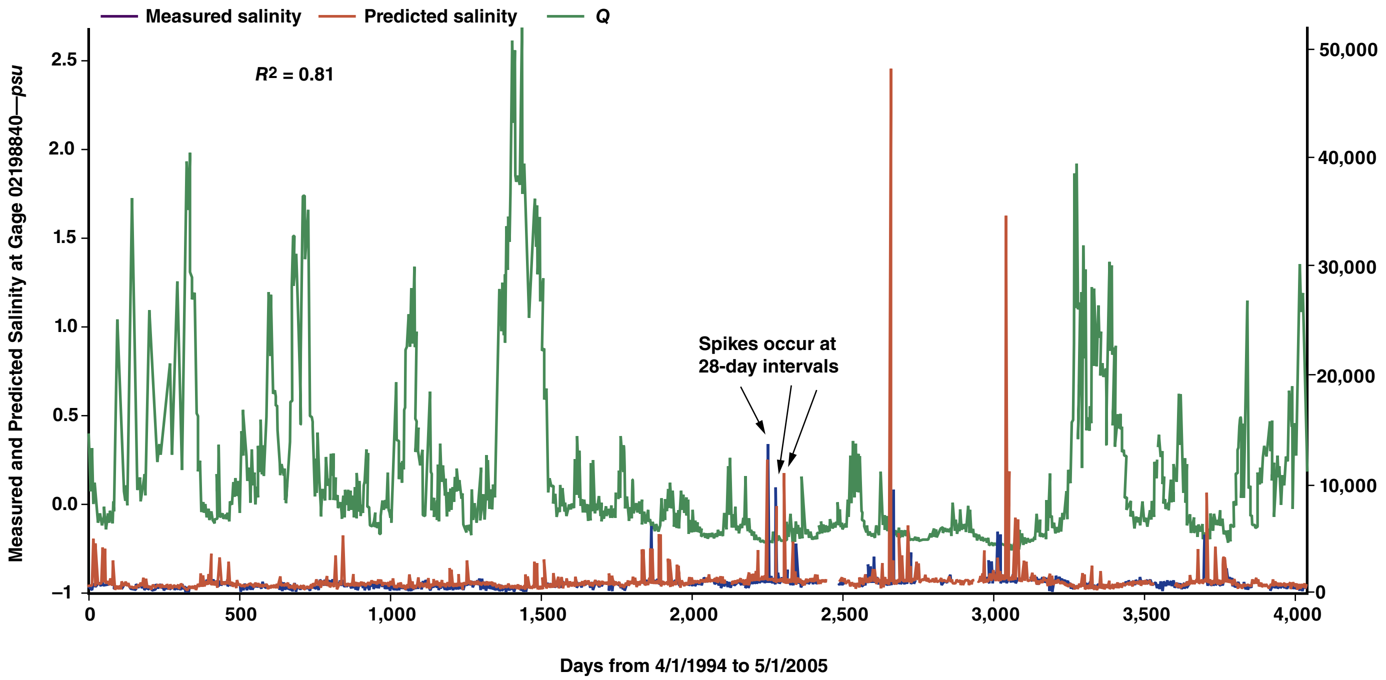
FIGURE 4 Measured and HSPF model-predicted flow *Q* at USGS gauge 02131000



Source: Roehl et al, 2012

HSPF—Hydrologic Simulation Program–Fortran, *n*—number, USGS—US Geological Survey

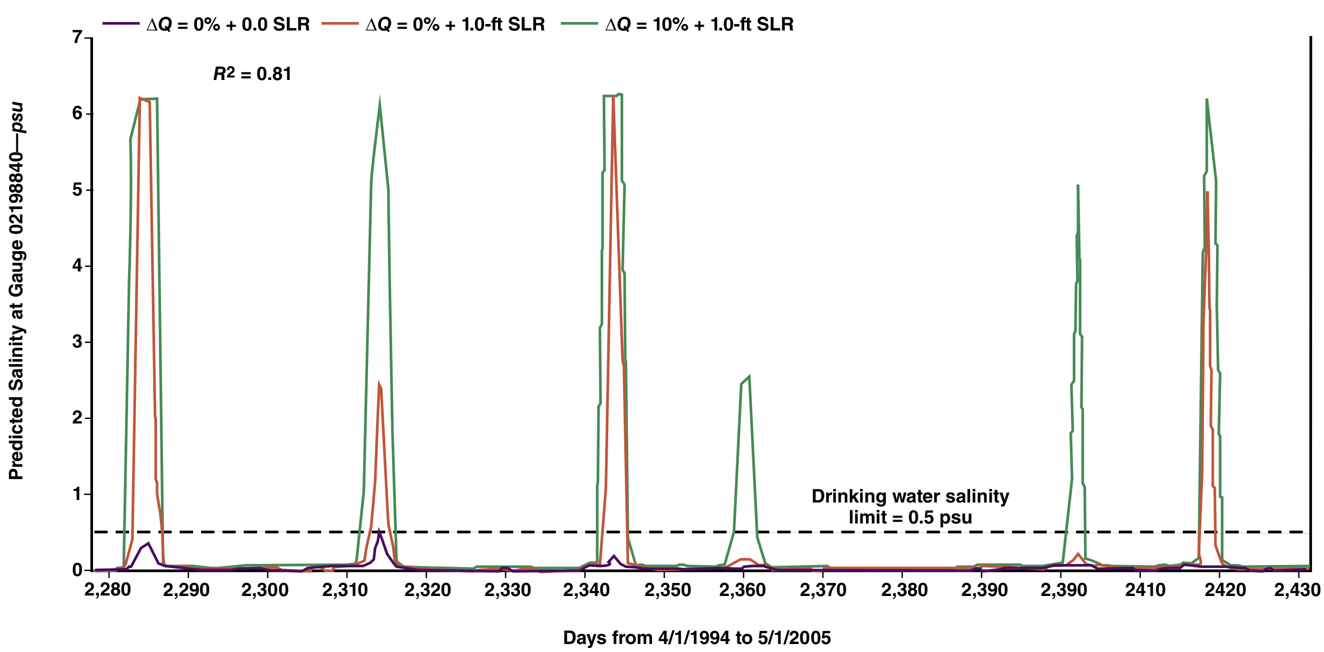
FIGURE 5 Measured and predicted salinity at USGS gauge 02198840 with flow Q at USGS gauge 02198500



Source: Roehl et al, 2012

psu—practical salinity unit, USGS—US Geological Survey

FIGURE 6 Detail of salinity simulation results for three flow Q scenarios at USGS gauge 02198840



Source: Roehl et al, 2012

ΔQ—the percentage change in historical stream flow, psu—practical salinity unit, SLR—sea-level rise, USGS—US Geological Survey forecast was made using the Hydrologic Simulation Program–Fortran (HSPF) watershed model from the US Environmental Protection Agency and the ECHO GCM (Legutke & Ross, 1999). It was used to predict future Pee Dee Basin stream flow (*Q*) from a climate forecast by ECHO for input to PRISM-2. The HSPF application was calibrated using approximately 30 years of historical climate and stream flow data. PRISM-2 used stream flow inputs corresponding to five gauging stations. Figure 4 compares predictions made by the HSPF application with the measured *Q* at the station with the historically highest stream flows, USGS gauge 02131000 on the Pee Dee River.

Of the many existing GCMs, four were evaluated. ECHO was selected because it predicted historical low stream flow conditions most accurately when coupled with the HSPF application. To predict future stream flows, ECHO was run with the A2 future carbon emissions scenario, which assumes that nations will continue to pursue their interests individually rather than cooperatively in dealing with climate change (IPCC, 2000). Alternative emissions scenarios produce different climate forecasts.

RESULTS

The results in this section help demonstrate how large amounts of seemingly complex data can be reduced to forms that are readily understood by resource managers. M2M-2 output is given in practical salinity units (psu), and PRISM-2 output is in specific-conductance units of microsiemens per centimetre. The upper salinity limit for drinking water is 0.5 psu, or approximately 1,000 µS/cm.

For the Lower Savannah River, Figure 5 shows the measured salinity at USGS gauge 02198840 with the freshwater *Q* at USGS gauge 02198500 for the 11-year study period. Figure 5 also shows the predicted salinity at gauge 02198840 when historical input data were used; as shown in the figure, predicted salinity is sufficiently accurate to largely obscure the measured values. At low *Q*, salinity spikes appear at 28-day intervals, coincident with the new moon and indicating the role of tidally driven sea levels in intrusion episodes. Figure 6 shows a detail of simulation results for three scenarios: historical *Q* (ΔQ = 0%) with zero SLR (identical to the predictions in Figure 5), ΔQ = 0% with a 1.0-ft SLR, and ΔQ = –10% with a 1.0-ft SLR. The detail shows that a 1.0-ft SLR causes spikes to appear and that their magnitude and duration increase with a *Q* decrease.

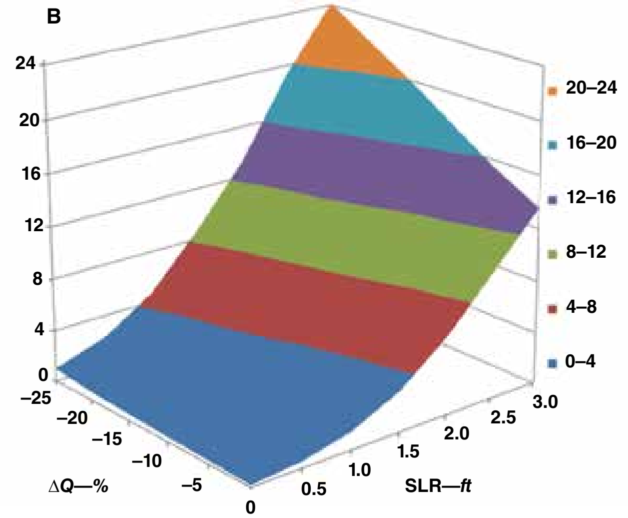
Forty-two scenarios were run in which SLR and *Q* were modulated parametrically, and statistics were calculated for each scenario that described the frequency and duration of episodes when the water supply intake would likely have to be shut down. For example, Figure 7 shows the percentage of study period days (% days) when the salinity exceeded 0.5 psu in tabular form (part A) and as a three-dimensional response surface (part B). The table indicates that SLR increases the percentage more than *Q* reduction. For example, at ΔQ = 0% and SLR = 3.0 ft, % days = 13.6. At ΔQ = –25% and SLR = 0 ft, % days is only 1.0. The surface shows that % days increases linearly as ΔQ becomes more negative and exponentially with increasing SLR. The combined effect is that % days increases much more per decrement in ΔQ at high SLR than at low SLR. For example, at SLR = 0 ft, % days increases only slightly as ΔQ decreases from 0 to –25%. At SLR = 3.0 ft, the percentage increases much more as ΔQ decreases to –25%. Similarly, at ΔQ = 0 ft, % days increases less as SLR increases from 0 to 3.0 ft than at ΔQ = –25%. Given that the details of how climate change and SLR will evolve are uncertain, results like those shown in Figure 7, which were derived from a predictive model developed from a

FIGURE 7 Percentage of days predicting salinity > 0.5 psu at USGS gauge 02198840

A

ΔQ	% Days > 0.5 psu						
	0.0-ft SLR	0.5-ft SLR	1.0-ft SLR	1.5-ft SLR	2.0-ft SLR	2.5-ft SLR	3.0-ft SLR
0%	0.2	0.5	1.4	3.1	5.9	9.7	13.6
–5%	0.3	0.7	1.8	3.9	7.0	11.2	15.4
–10%	0.4	0.9	2.3	4.6	8.6	12.5	17.7
–15%	0.5	1.4	3.0	5.8	10.0	14.5	20.0
–20%	0.6	1.7	3.8	7.1	11.4	16.8	22.0
–25%	1.0	2.2	4.7	8.7	13.3	19.3	24.1

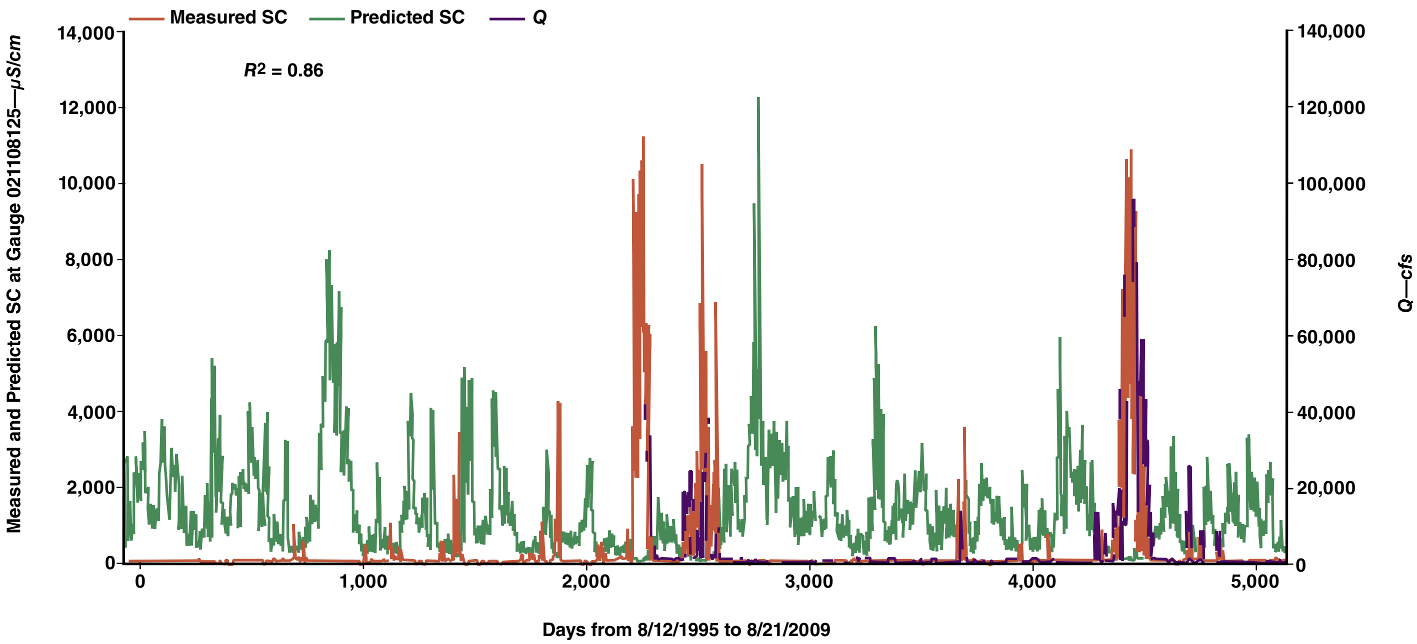
B



Source: Roehl et al, 2012

ΔQ—the percentage change in historical stream flow, psu—practical salinity unit, SLR—sea-level rise, USGS—US Geological Survey

FIGURE 8 Measured and predicted specific conductance with flow *Q* at USGS gauge 021108125

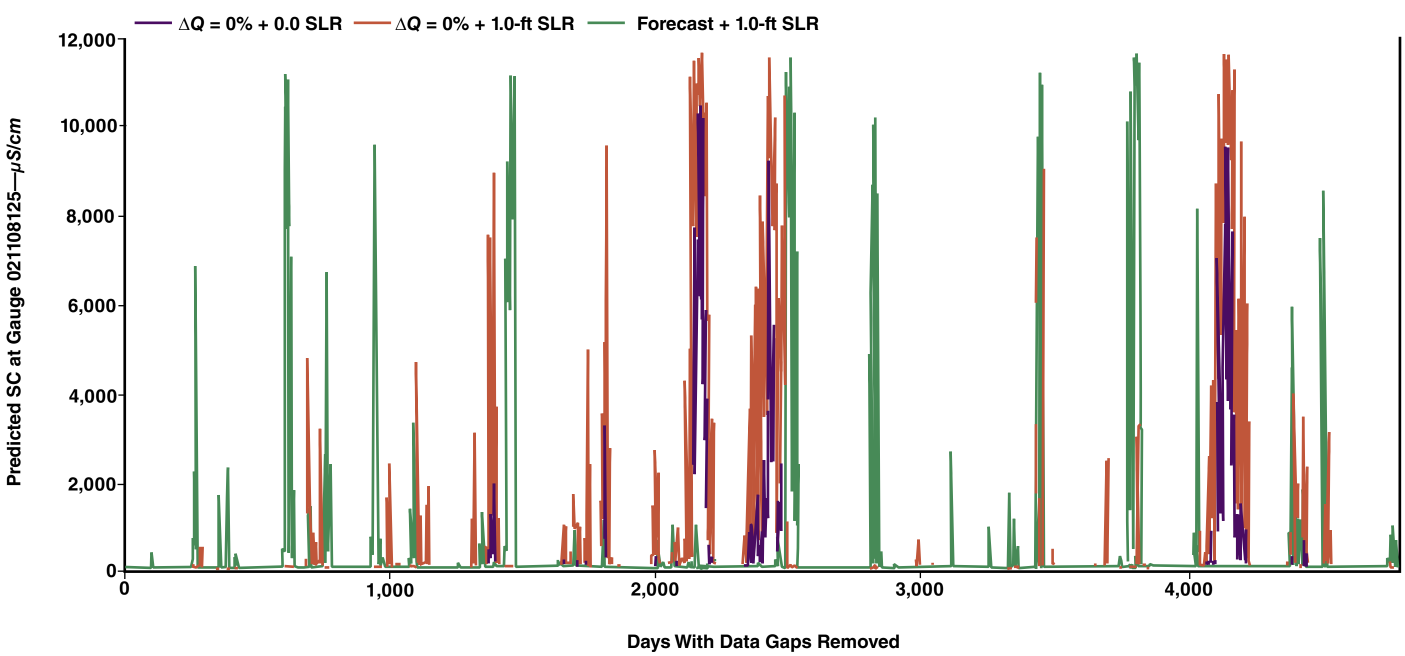


Adapted from Roehl et al, 2012

SC—specific conductance, SLR—sea-level rise, USGS—US Geological Survey

The measured specific conductance starts at day 2,305

FIGURE 9 SC simulation results for three flow *Q* scenarios at USGS gauge 021108125



Source: Roehl et al, 2012

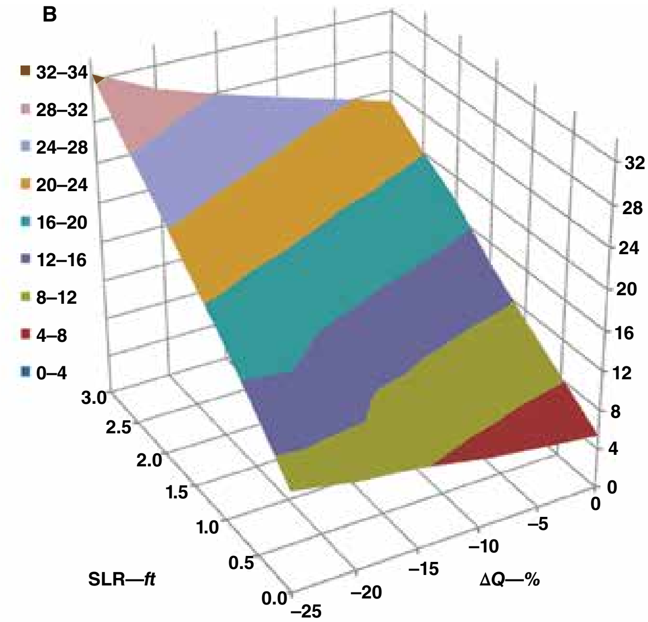
Δ*Q*—the percentage change in historical stream flow, SC—specific conductance, SLR—sea-level rise, USGS—US Geological Survey

FIGURE 10 Percentage of days that predicted SC > 1,000 µS/cm at USGS gauge 021108125

A

ΔQ	% Days > 0.5 µS/cm						
	0.0-ft SLR	0.5-ft SLR	1.0-ft SLR	1.5-ft SLR	2.0-ft SLR	2.5-ft SLR	3.0-ft SLR
0%	5.4	8.3	11.0	14.0	17.6	20.1	22.8
–5%	6.1	9.0	12.1	15.7	18.8	21.5	24.5
–10%	7.0	10.0	13.3	17.2	20.0	23.1	26.1
–15%	8.2	11.3	15.2	18.6	21.7	24.9	27.9
–20%	8.9	15.1	16.8	20.0	23.5	26.6	29.8
–25%	10.1	14.4	18.3	21.8	25.5	28.8	32.6

B



ΔQ—the percentage change in historical stream flow, SC—specific conductance, SLR—sea-level rise, USGS—US Geological Survey

large and widely ranging data set, provide perhaps the most credible information available to utilities concerned about the long-term viability of their current intake.

For the Waccamaw River, Figure 8 shows the measured specific conductance at USGS gauge 021108125 with stream flow *Q* for the 14-year study period. Here *Q* was aggregated from stream flows measured at five upland gauges. The measured specific conductance starts at day 2,305. Also shown is the specific conductance predicted by the artificial neural network submodel when historical input data were used. Three prolonged periods of high specific conductance appear in the vicinities of days 2,300, 2,600, and 4,400, which coincide with periods of low *Q*. It is clear that the nature of salinity intrusion here is different from that at gauge 02198840 on the Savannah River (Figure 5), suggesting that details of the process physics that cause behaviors of interest can vary greatly from location to location and that it is essential that predictive models used as planning tools be customized for each location.

Salinity intrusion occurs when two of the following three conditions—low stream flow, high tidal range, and/or high mean sea levels—are met. In the Savannah River example, the salinity spikes in Figure 5 are of short duration and occur at 28-day intervals when *Q* is low and the gravitational force of the moon causes the tidal range to be high. High mean sea levels just increase the magnitude of the spikes. In the Waccamaw River example, the intrusions shown in Figure 8 are less periodic and of longer duration because the tidal range is less influential than stream flow and sea level.

Figure 9 shows simulation results for three scenarios: historical *Q* (Δ*Q* = 0%) and sea level (identical to the predictions in Figure 8); Δ*Q* = 0% and sea level + 1.0-ft SLR; and the ECHO–HSPF forecast *Q* with historical sea level + 1.0-ft SLR. The simulation period is 1995–2009 for the first and second scenarios and 2055–2069 for scenario 3. Scenario 2 indicates that increased SLR increases the magnitude, duration, and frequency of specific-conductance spikes. Scenario 3 generally shows spikes occurring at times that vary from the first two scenarios and are of shorter duration. Conrads and colleagues (2013) found that the % days when the specific conductance exceeded 1,000 µS/cm were forecast to increase in the spring and fall and decrease in the winter and summer.

As in the previous Savannah River analysis, 42 *Q*–SLR scenarios were run to predict specific conductance at USGS gauge 021108125, and the % days when the predicted specific conductance exceeded 1,000 µS/cm was calculated (Figure 10). Similar to the results for gauge 02198840 (Figure 7), % days was affected more by SLR than by Δ*Q*. However, the three-dimensional response surface shown in Figure 10, part B, is more planar than that shown in Figure 7, part B, such that the effect of Δ*Q* is relatively constant with increasing SLR. Similarly, the numbers of predicted salinity intrusion episodes lasting at least seven, 14, and 21 days were counted for the study period. Figure 11 shows the number of 7-day intrusions. This type of information indicates how frequently an intake might be inundated for extended periods, a major concern for utilities with limited source or storage options.

TABLE 1 Percentage of days with SC > 1,000, 2,000, and 3,000 µS/cm at USGS gauge 021108125

SLR ft	SC—% Days > 1,000, 2,000, and 3,000 µS/cm								
	Historical SC			Historical *Q*			ECHO–HSPF *Q*		
	1,000	2,000	3,000	1,000	2,000	3,000	1,000	2,000	3,000
0.0	7	4	4	5	4	3	4	3	2
1.0				11	9	7	7	5	4
2.0				18	15	13	11	9	7
3.0				23	20	19	15	13	11

Source: Roehl et al, 2012

HSPF—Hydrologic Simulation Program–Fortran, *Q*—flow, SC—specific conductance, SLR—sea-level rise, USGS—US Geological Survey

Blank cells indicate no historical data for these parameters.

Table 1 compares % days when the specific conductance exceeded 1,000, 2,000, and 3,000 µS/cm for the historical specific conductance, the specific conductance predicted from the historical *Q* with SLR, and the specific conductance predicted from the ECHO–HSPF *Q* with SLR. The % days of the single historical specific-conductance scenario were comparable to the two prediction scenarios with zero SLR. The higher % days of the historical *Q* scenarios originated from historical, extended droughts, which were not a factor in the ECHO–HSPF *Q* scenarios. The droughts caused the long-duration intrusions in the first two scenarios in Figure 9.

APPLICATIONS AND RECOMMENDATIONS

The general problem for utilities that want to plan for climate change and SLR is assessing how their specific resources will be affected. Initially, the problem might seem intractable because the details about how climate will evolve are unknowable with any certainty. However, the current project has demonstrated an approach that produces tools that are straightforward to use and should be reliable if utilities can be flexible about the degree and timing of anticipated changes in climate and sea level. The tools are tables and graphics that predict how often and for how long intakes will be inundated by salinity intrusion for any reasonable combination of freshwater stream flow change or SLR. Similar analogs are available for inland water resources such as lakes, streams, and groundwater, and the anthropogenic forcing includes human demand. The two essential elements that were extensively leveraged for both the Savannah and Waccamaw River intakes were

- long-term time series data that captured a broad range of complex natural system behaviors and inherently span much of the change that experts predict will come with climate change, as manifest in the ECHO A2 scenario and
- predictive models that accurately represent the process physics captured by the long-term time series data.

The first element, long-term time series data, is of fundamental importance and obviously time-consuming to obtain if not

FIGURE 11 Predicted number of long-term episodes of SC > 1,000 µS/cm at USGS gauge 021108125

A

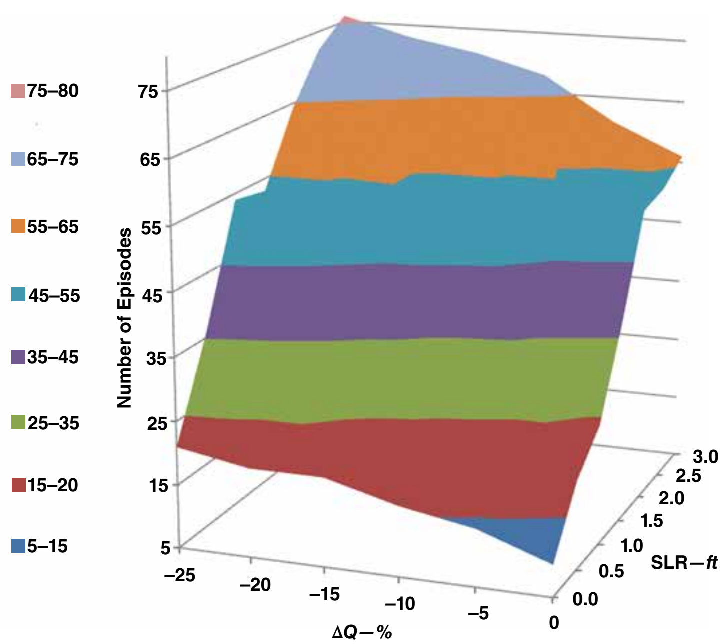
ΔQ	Number of Long-Term Episodes						
	0.0-ft SLR	0.5-ft SLR	1.0-ft SLR	1.5-ft SLR	2.0-ft SLR	2.5-ft SLR	3.0-ft SLR
0%	10	19	24	37	52	53	56
–5%	14	19	29	42	54	53	61
–10%	16	22	33	53	54	57	68
–15%	19	26	40	54	54	62	71
–20%	19	32	48	53	58	68	73
–25%	21	36	54	53	64	72	76

Source: Roehl et al, 2012

Δ*Q*—the percentage change in historical stream flow, SC—specific conductance, SLR—sea-level rise, USGS—US Geological Survey

Results show predicted number of episodes of SC > 1,000 µS/cm for at least seven consecutive days.

B



already in hand. The second element, predictive models, can be developed at any time so long as a reasonable amount of data is available. The models are readily updated as new data become available. For some systems, such as estuaries, empirical models like those used here can be developed more quickly and be more accurate than conventional mechanistic modeling codes. Ideally data and models are already available and merely need to be exercised to produce the tables and graphics needed by resource managers to begin assessing risk and planning for climate change.

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FOOTNOTES

[1]Microsoft Excel®, Redmond, Wash.

PEER REVIEW

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