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IMPROVING FRESHWATER INFLOWS TO THE NOS CHESAPEAKE BAY OPERATIONAL FORECAST SYSTEM (CBOFS) AND ASSESSING THE IMPACTS ON SALINITY SIMULATIONS

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Abstract

The Chesapeake Bay Operational Forecast System (CBOFS) is a 3D hydrodynamic model which generates 48-hour forecasts of water level, currents, temperatures and salinity throughout the Chesapeake Bay. A limitation of the current CBOFS is that it does not use forecast information available from modern river forecast models. Currently, river inflows are derived by persisting the flow observations from U.S. geological survey stream gages, and the gages used measure runoff from only 79% of the Bay watershed area. In this study, we investigate the potential benefits of using hydrologic modeling to provide CBOFS with more accurate estimates of river inflows. Specifically, we study the impact of using more detailed and accurate streamflow inputs on the model's ability to predict salinity. In our simulation experiments, we increased the number of river inflow nodes from 13 to 60. Salinity is studied because of its sensitivity to freshwater inflows and its importance to marine life in the Bay. As expected, adding more freshwater to the model does reduce high salinity bias from CBOFS that has been noted in earlier studies; however, some bias still remains. The spatial pattern of salinity simulation improvements are also consistent with expectations. That is, more improvement is seen in shallow waters closer to the added river inputs. To expedite this study, we used the Research Distributed Hydrologic Model (RDHM) to simulate flows on small rivers. Moving forward, the more feasible path for operational implementation on small rivers is to use flows from NOAAs National Water Model.

Introduction

NOAAs National Ocean Service runs Operational Forecast Systems (OFSs) for critical ports and estuaries in the United States. Operational Forecast Systems provide useful information about water conditions for many users such as ship navigators, recreational boaters, fishermen, fisheries managers, public health officials, hazardous material response teams, search and rescue personnel, and others. The Chesapeake Bay OFS (CBOFS) generates 48-hour forecasts for water level, currents, temperatures and salinity throughout the Chesapeake Bay (NOAA National Ocean Service, 2011). Here we study how the hydrodynamic model underlying CBOFS can be improved by improving the accuracy of hydrologic inflows from the surrounding rivers and streams. Specifically, we analyze the impacts of freshwater inflow improvements on salinity simulations.

Why is this important?

There are known limitations with respect to river inflows in the current CBOFS implementation. First, CBOFS only explicitly accounts for 13 river inflows into the Bay using data from U.S. Geological Survey (USGS) stream gages (Figure 1). These 13 river inflows represent only about 79% of the Chesapeake Bay drainage area. Second, river inflows to CBOFS for the 48-hour forecast period are estimated by simply persisting observed flow data. This does not accurately reflect the impacts of rising flows during storm events. At this time, several available hydrologic models are capable of simulating flows from all rivers draining to the Bay. These models can produce more accurate inflows by explicitly accounting for more of the watershed drainage area. In addition, use of forecast information from hydrologic models will improve upon persistence estimates at inflow locations.

We focus on salinity because our hypothesis is that improving the river inflow accuracy will have a relatively large impact on the CBOFS salinity forecasts compared to other variables such as currents. Also, positive salinity bias is a known issue in the operational CBOFS model (Lanerolle et al., 2016). We investigate whether adding inflow nodes to the operational CBOFS model might have dramatic local impacts on salinity forecasts in smaller river estuaries within the Bay.

Salinity has important impacts on the Bay ecosystem. Salinity affects the health and spatial distribution of numerous Chesapeake Bay species such as fish, oysters, and blue crabs. Salinity also influences biological process rates which can affect processes important to humans such as harmful algal blooms and oyster growth.

NOAA already uses salinity and temperature forecasts from CBOFS to make real-time predictions about the prevalence and location of stinging sea nettles and harmful Vibrio bacteria (NOAA OPC, 2019; NCCOS 2020). Li et al. (2001) describe the scientific foundation for the sea nettle forecasting system while Lanerolle et al. (2016) do the same for the Vibrio forecasting. In both cases, an empirical relationship translates temperature and salinity outputs from CBOFS into forecast variables of interest: sea nettle encounter probabilities and Vibrio concentrations. Improved river inflows to CBOFS should improve these sea nettle and Vibrio forecasts.

What is unique about this study?

Like the operational CBOFS implementation, academic and regulatory hydrodynamic model implementations in the Chesapeake Bay most often do not explicitly account for inflows from smaller watersheds (Xu et al., 2012; Feng et al., 2015; Cerco et al., 2010). In some cases, this is because the main study foci were on the deeper parts of the bay. An exception is the work of Ye et al. (2018) which accounts for more of the smaller tributaries. They noted that adding the smaller tributaries into their modeling did improve the accuracy of their results; however, they did not elaborate on details. Our study more explicitly addresses the impacts of accounting for the smaller tributaries. In addition, we use hydrodynamic and hydrologic models which are already used in NOS and NWS operations. Therefore, the transition from research-to-operations should be relatively easy.

This study was completed through a unique inter-office collaboration within NOAA. NOAA's North Atlantic Regional Team (NART) funded three summer internships for undergraduates while the NOAA Chesapeake Bay Office and Chesapeake Research Consortium facilitated these internships. NOAAs National Weather Service (NWS) Middle Atlantic River Forecast Center (MARFC) hosted the three students and guided the research with assistance from modelers at the NOS Center for Operational Products and Services (COOPS) and the Coast Survey Development Laboratory (CSDL).

How does this study contribute to the NOAA goals?

The goals of this study are in line with the NOAA Water Initiative Vision and Five-Year Plan (NOAA, 2016), which includes goals to advance water quality forecasting in riverine and estuarine environments and to create new capabilities to leverage water quality predictions for ecological applications. This research tackles only a small piece of this bigger picture, but did so using minimal resources. The hydrologic model used in this study is a regional model selected so that it could be run at the MARFC to complete the project; however, the same methods could be used to pass outputs from NOAAs National Water Model (NWM, 2020) to CBOFS. The NWM is a major component of the NOAA Water Initiative.

Our outcomes do the following: (1) demonstrate that there is value in substantially increasing the number of river inflow nodes to CBOFS, (2) demonstrate that CBOFS remains computationally stable with this increase in river nodes, and (3) provide configuration details that could be used to modify the current operational CBOFS model.

Methods

Hydrodynamic Model

Lanerolle et al. (2011) describe the development and skill assessment of the model that underlies the current Chesapeake Bay Operational Forecast System, CBOFS2. While the first CBOFS was based on a 2-dimensional model and only provided information on water levels and depth-averaged currents, CBOFS2 is a 3-dimensional model and provides information on water levels, currents, temperature, and salinity. CBOFS2 is an implementation of Rutgers University's Regional Ocean Model System.

For our baseline simulation, we ran CBOFS2 using a model configuration and forcing files provided by Lyon Lanerolle (personal communication, 2016). The baseline simulation input files are identical to those Lanerolle et al. (2011) used for their 'synoptic simulation.' For meteorological fluxes, Lanerolle et al. (2011) combined gridded data from the North American Regional Reanalysis (Mesinger et al., 2006) with local gage information. For the open ocean boundary conditions they used monthly climatology data from the World Ocean Atlas 2001 (Conkright et al., 2002). The only difference in our calculations for this baseline run is that we recompiled the executable on a different High Performance Computing development platform. The original simulations were run on NOAAs 'Jet' machine while our simulations were run on NOAAs 'Theia' platform.

Figure 1 shows the CBOFS2 model mesh along with the locations of the river input nodes used by Lanerolle et al. (2011). The flows estimated at a given node are sometimes estimated from more than one upstream US Geological Survey gage as specified in Table 1. These are also the gages used for operational CBOFS2 runs as of October 2020.

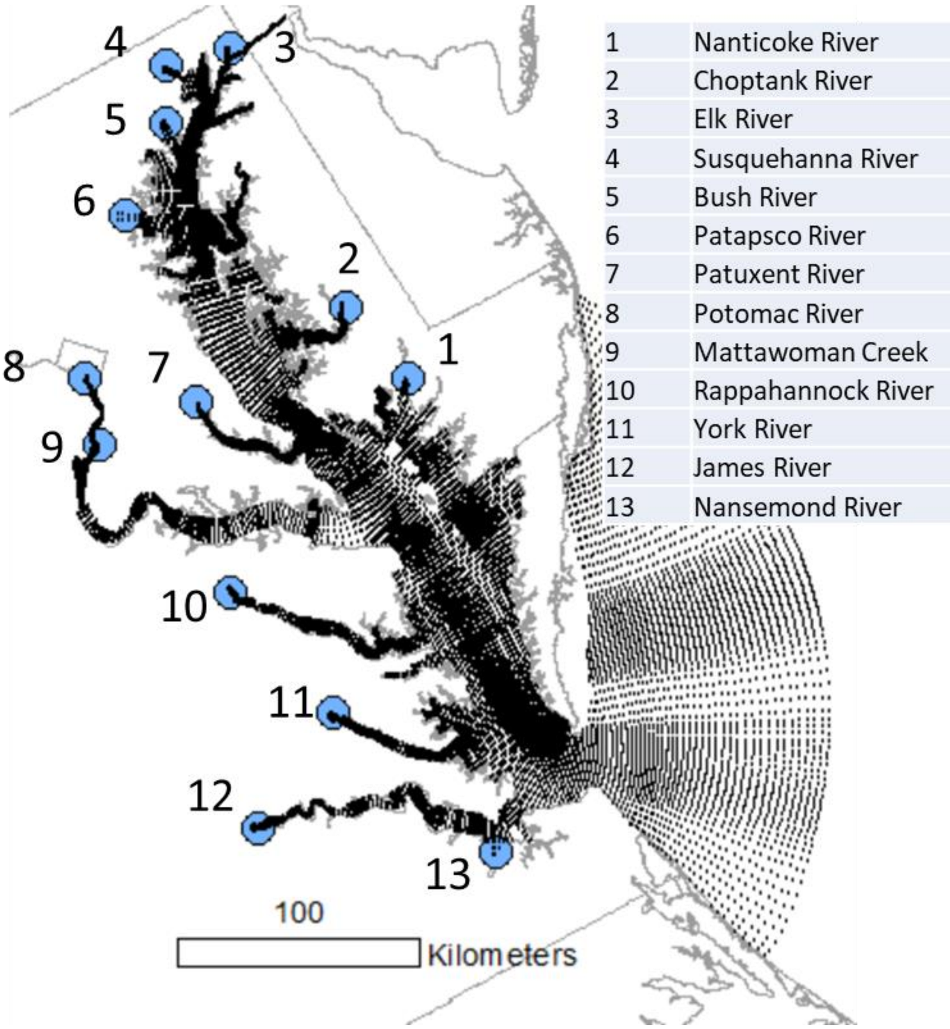

Figure 1. CBOFS2 model mesh and river inflow node locations for operational runs.

Table 1. USGS Flow Observation Stations used to Derive CBOFS2 inflows.

	CBOFS Input Node	USGS ID	Name	Drainage Area (mi2)
1	Nanticoke River	Unknown		
2	Choptank River			
		1491000	Choptank R near Greensboro MD	113
		1491500	Tuckahoe Cr near Ruthsburg MD	85.2
3	Elk Creek			
		1495000	Big Elk Cr at Elk Mills MD	51.6
4	Susquehanna River			
		1578310	Susquehanna R at Conowingo MD	27100
		1580520	Deer Cr near Darlington MD	164
5	Bush River			
		1581757	Otter Point Creek near Edgewood MD	55.6
6	Patapsco River			
		1589352	Gwynns Falls at Wash Blvd at Balt	65.9
7	Patuxent River			
		1594440	Patuxent R near Bowie MD	348
		1594526	W Branch at Upper Marlboro MD	89.7
8	Potomac River			
		1646500	Potomac R near Little Falls	11560
9	Mattawoman Creek	1658000	Mattawoman Cr nr Pomonkey MD	54.8
10	Rappahannock			
		1668000	Rappahannock R near Fredericksburg	1595
11	York River			
		1673000	Pamunkey R near Hanover VA	1078
		1674500	Mattaponi R near Beulahville VA	603
12	James River			
		2037500	James R near Richmond VA	6753
		2041650	Appomatox River at Matoaca VA	1342
13	Nansemond River			
		2049500	Blackwater R near Franklin VA	613

An important consideration when passing flows from a river outside of the model to CBOFS2 nodes is to ensure that there is no numerical instability due to rapidly changing conditions at the boundary nodes. To maintain stability, we followed the methods used by Lanerolle et al. (2011). Large river flows are distributed laterally across several CBOFS2 boundary nodes in proportion to the normal water depth. In addition, a pre-defined vertical velocity distribution is prescribed as a function of depth at the boundary nodes to approximately account for the effects of bottom friction. Figure 2 conceptually illustrates this lateral and vertical distribution of flows at the upstream end of the James River, VA.

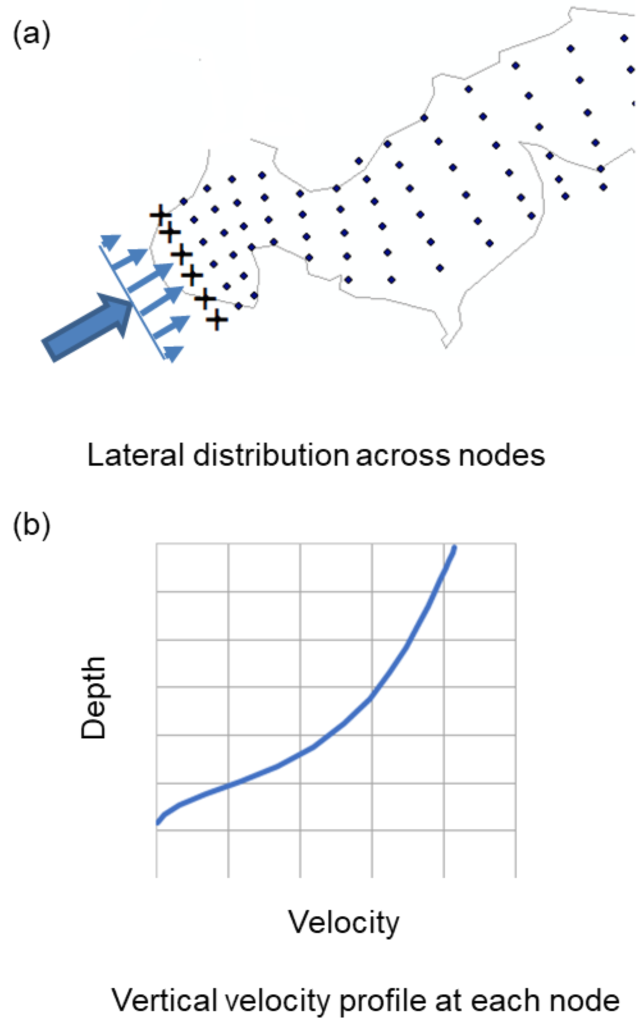

Figure 2. (a) Example of lateral flow distribution across nodes for the James River CBOFS2 inflow, (b) default vertical velocity profile at inflow nodes.

Watershed Model

Using a watershed model with more complete coverage of the Chesapeake Bay Drainage area is a primary component of this study. The dark green shaded area in Figure 3a shows the watershed drainage areas captured by the USGS gages listed in Table 1. CBOFS2 does not explicitly account for the light green and yellow shaded areas in Figure 3a within the Chesapeake portion of the map. For the rivers included in the operational CBOFS2, USGS flows are adjusted to account for the intervening drainage areas between the gage locations and the 13 Bay input nodes shown in Figure 1 (also as black dots in Figure 3b). In this study, we experimented with adding additional rivers and connections to CBOFS2. Initially we took a cautious approach and only increased the number of rivers represented from 13 to 22. Because this increase caused no model stability problems, we then proceeded to increase the number of rivers to 60 and these are the results reported here. The 60 rivers includes all rivers within the Chesapeake Watershed with a drainage area of at least 50 mi^2. Figure 3b highlights basins added.

We refer to model runs with the 13 original input nodes as Scenario 1 (S1) and the model runs with 60 river inputs as Scenario 2 (S2). Table 2 summarizes percentage of the Chesapeake Watershed area observed and accounted for in each scenario. In the simulation mode used here, both scenarios use observed flows where available. In Scenario 1, drainage area coefficients are computed to account for the locations of the stream gages as described by Xu et al. (2012), and flows are scaled by these amounts to represent the water contributions downstream of these gages (hence the increase from 79% observed to 85% observed and modeled). In Scenario 2, 10% additional area is accounted for by the 47 additional input nodes for small rivers, making the total area observed and modeled 95%.

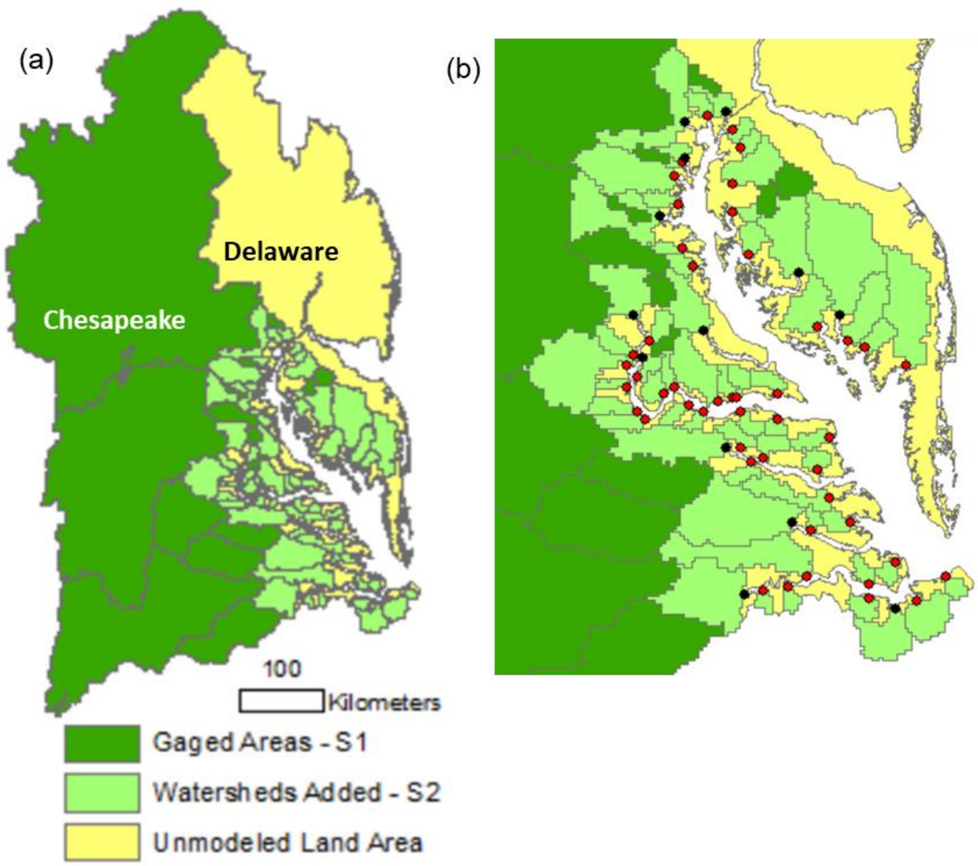

Figure 3. Modeled areas for Scenarios 1 and 2: (a) middle Atlantic domain, and (b) zoomed to watersheds added for Scenario 2; black dots are the original input nodes and red dots are added input nodes.

Table 2. Percent of drainage area observed and modeled in simulation studies.

Scenario	% area observed	% area observed + modeled
S1	79	85
S2	79	95

To simulate outflows for the ungaged sub-watersheds in Scenario 2, we used the Hydrology Laboratory's Research Distributed Hydrologic Modeling System (HL-RDHM) (Koren et al., 2004). In our implementation, HL-RDHM is applied at a 2-km grid cell resolution to the entire Chesapeake drainage basin. Figure 4 shows the river network formed by inter-connected 2-km grid cells in the model. Our HL-RDHM implementation uses the gridded Snow-17, the gridded Sacramento Soil Moisture Accounting Model with Heat Transfer (SAC-HT), and kinematic wave routing as described by Koren et al. (2007). The forcings used for snow melt and rainfall-runoff modeling include gridded hourly precipitation, gridded hourly temperature, and gridded monthly evapotranspiration demand estimates. The precipitation grids were from MARFCs multi-sensor precipitation analyses which blend radar estimates with quality controlled rain-gage estimates to yield 'best estimate' grids. The hourly temperature grids were created by blending hourly and daily point temperature observation data to generate hourly grids. The gridded evapotranspiration demand fields provided as default inputs to HL-RDHM were developed based on remotely sensed vegetation fields, select calibrated watersheds, and monthly climatological data.

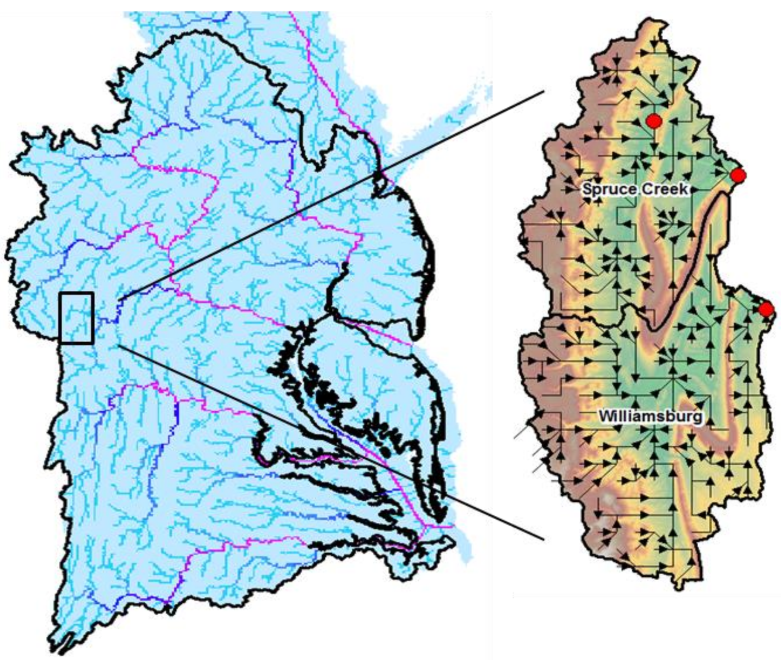

Figure 4. HL-RDHM modeled rivers based on 2-km grid cells with a magnified area showing the cell-to-cell network in two headwater basins.

No comprehensive calibration was done for these HL-RDHM hydrologic model simulations. Parameters for the snow, rainfall-runoff, and routing calculations are *a priori* parameters derived from physical data sets (Koren et al., 2007; Mizukami and Koren, 2008) or default values for a region. Approximate adjustments to the monthly evapotranspiration demand grids were applied to match experience with calibrating a few small basins in the region.

Some of the 60 river simulation points shown in Figure 3 are downstream of the USGS gages used in the operational CBOFS2 runs. For any of the rivers containing a gage in Table 1, the observed data is used for the gaged portion of the basin and the HL-RDHM modeled flow is added for the ungaged portion of the basin. This limits hydrologic simulation errors to only the ungaged areas, shaded light green in Figure 3.

We selected the HL-RDHM software for use in this study because it has performed well in model inter-comparisons (Reed et al., 2004; Smith et al., 2012), it is relatively easy to re-run simulations for long periods of time, and the software is already running in real-time at the Middle Atlantic River Forecast Center. While we leveraged HL-RDHM to facilitate this study, no more development work is being done on HL-RDHM and much more effort at the National level goes into building the National Water Model (NWM) for real-time forecasts (OWP, 2020). While it was infeasible to use the NWM in this study, we expect that the NWM will be a more practical platform to simulate river flows from ungaged basins in future applications. The simple methods to pass river flows to CBOFS2 used here are applicable to either HL-RDHM or NWM output. The same CBOFS2 configuration files could be used in either case.

Study Design

In our results, we show outputs from two model scenarios:

- Scenario 1 (S1): The baseline case with 13 rivers represented.
- Scenario 2 (S2): The enhanced scenario with 60 rivers represented.

Each scenario was analyzed for two different time periods. The first time period was the same as that used by Lanerolle et al. (2011), spanning June 2003 to September 2005; however, we discarded the first six months of output from our analysis to avoid model spin-up errors. For additional validation, we selected a more recent period from January 1, 2016 to December 31, 2016. For this period, archived forcings were provided by NOS COOPs from their operational database. No model spin-up was required for the 2016 period because initial conditions were taken from saved operational model states.

Validation

We validated salinity simulations from CBOFS2 against salinity observations from the Chesapeake Bay Programs Tidal Water Quality Monitoring program (CBP, 2020). For the time periods in this study, we downloaded data for 64 sampling locations that correspond to CBOFS2 output locations and have valid data. The salinity observations are discrete observations taken by boat, once or twice per month at each site. At each site, observations are available at multiple depths, 1-m intervals from the water surface to the Bay floor. Figure 5 shows the identifiers and locations for the observations.

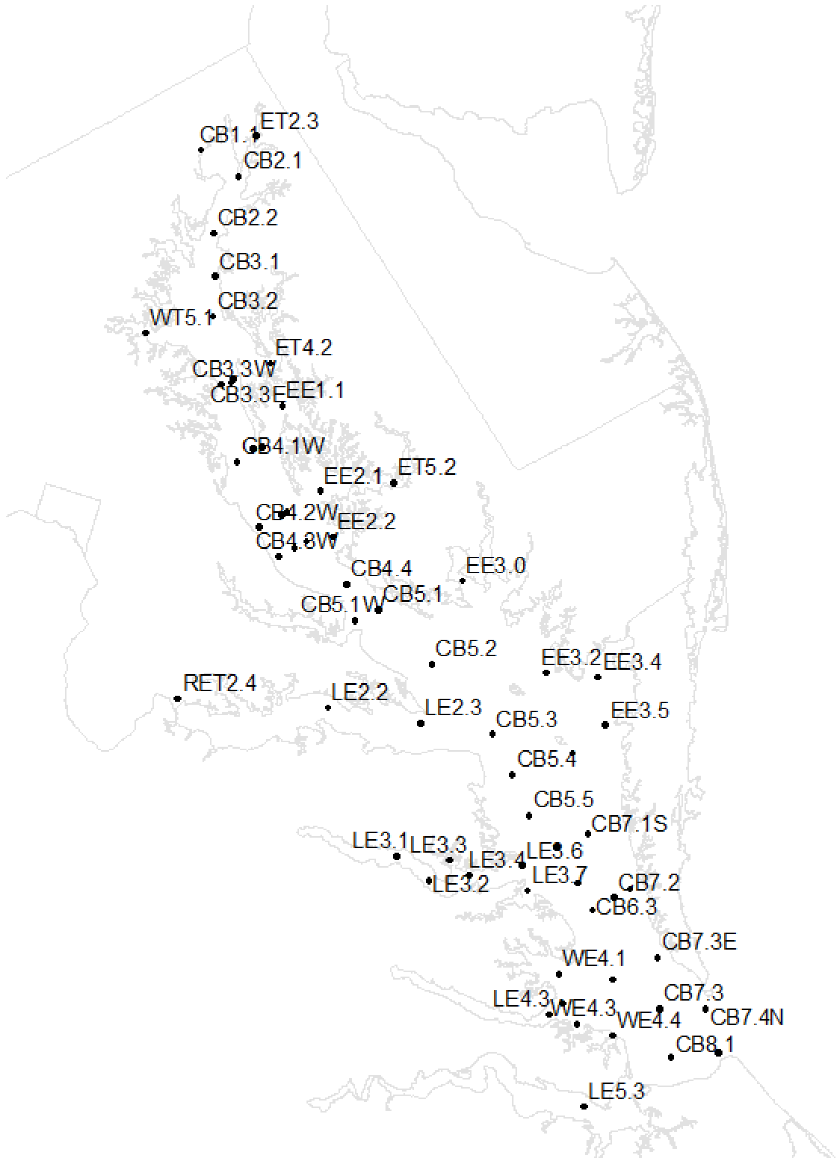

Figure 5. Chesapeake Bay Program monitoring stations used for validation.

We evaluate the salinity simulations from Scenarios 1 and 2 using three main methods for each location: (1) we compute and map summary statistics comparing simulated and observed salinities (at the 1-m depth and for the profile average), (2) plot and compare simulated and observed salinity profiles for individual locations, and (3) plot time series of 1-m simulated and observed salinity to observe temporal trends. To facilitate these comparisons, simulated salinity estimates output from CBOFS2 are interpolated vertically to the standard 1-m interval observation depths.

Many of the statistic and graphics presented here were generated using Python scripts developed for this project. These scripts leverage the Matplotlib and GeoPandas libraries.

Results and Discussion

Figures 6a and 6b show the Scenario 1 profile mean error in the salinity forecasts for all sampling locations and the 2004 and 2016 study periods respectively. To compute 'Profile Mean Error', the error is averaged over all observed depths and all the sampling times during the study period. During both study periods, the Scenario 1 salinity is too high over most of the Bay, which is consistent with the observations of Lanerolle et al. (2011). This positive error is more pronounced and consistent across all locations during the 2016 period compared to 2004. Figures 6c and 6d show the profile mean salinity error predicted by Scenario 2. Not surprisingly Scenario 2 mean errors are lower during both periods due to the additional freshwater inflows to the model. For Scenario 1 the average mean error over all locations is 0.96 psu for 2004 and 3.8 psu for 2016 (where psu is practical salinity unit). For Scenario 2, these values drop to 0.47 psu for 2004 and 2.9 psu for 2016. Figures 6e and 6f show the change in salinity between the two scenarios (Scenario 2 – Scenario 1). In Figures 6e and 6f, all plotted values are negative, indicating that salinities were reduced in Scenario 2 across the board.

Still looking at average statistics for the whole profile, Figures 7a and 7b show the Root Mean Squared Error (RMSE) for Scenario 1 and Scenario 2 in 2016. Figure 7c shows the Scenario 1 RMSE minus Scenario 2 RMSE. Values in Figure 7c are all positive except for one location, indicating that the errors are higher in Scenario 1 compared to Scenario 2. This shows that adding more accurate freshwater inflows increases salinity simulation accuracy across the Bay. Figure 7d highlights the stations where the five largest improvements in RMSE are observed: EE3.0, ET5.2, LE3.3, WE4.4, and LE5.3. These locations are more strongly influenced by the freshwater inflows from the relatively smaller tributaries which are not accounted for in Scenario 1. Figure 7d also includes the one location, CB1.1, where S1-S2 salinity was slightly negative, indicating a worse simulation. This will be explained in the analysis below.

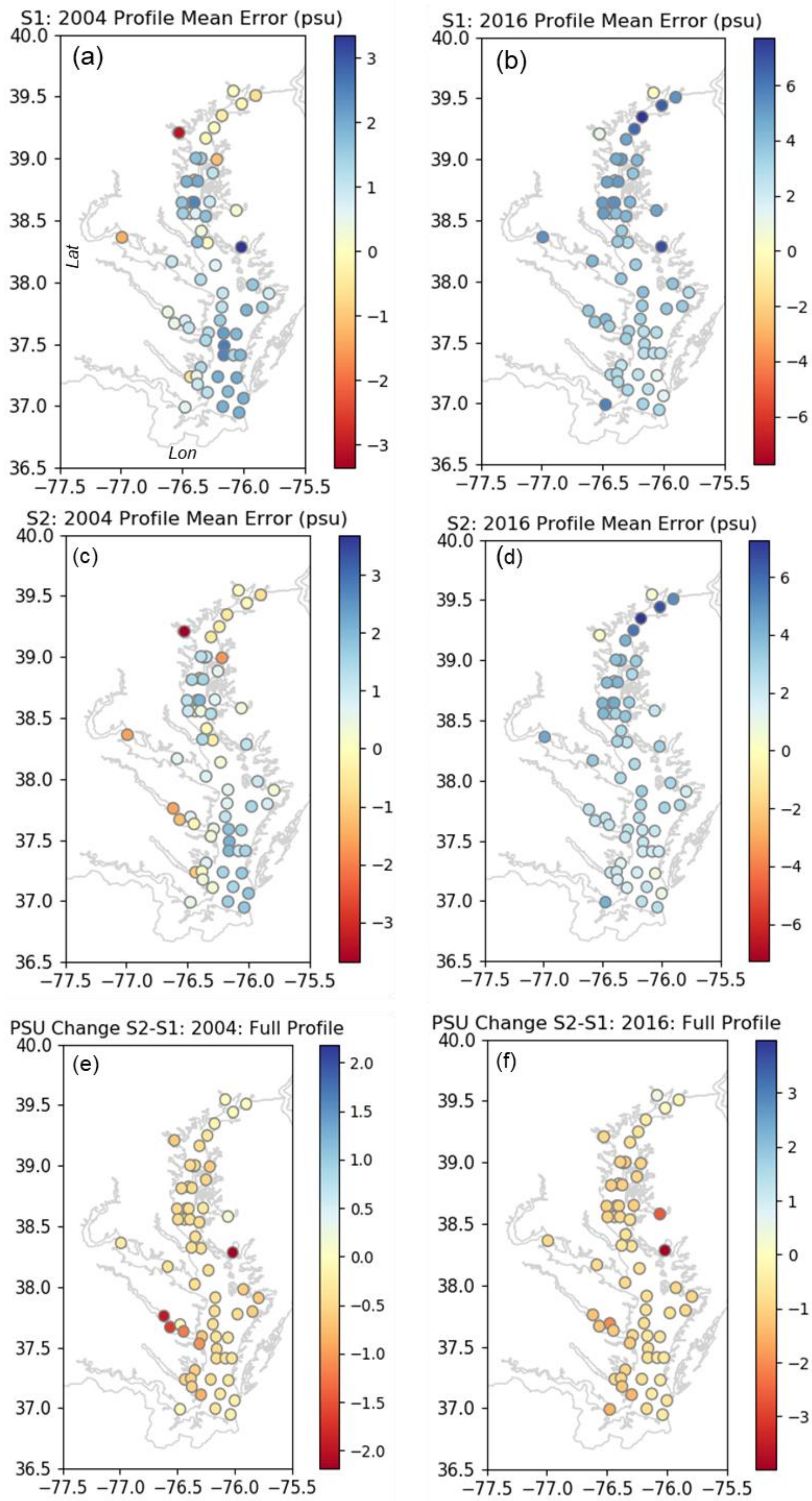

Figure 6. Mean profile error computed over all sampling depths and observation times for each location: (a) Scenario 1 2004, (b) Scenario 1 2016, (c) Scenario 2 2004, (d) Scenario 2 2016, (e) Scenario 2 – Scenario 1 2004 (negative values show decreases in predicted salinity), and (f) Scenario 2 – Scenario 1 2016.

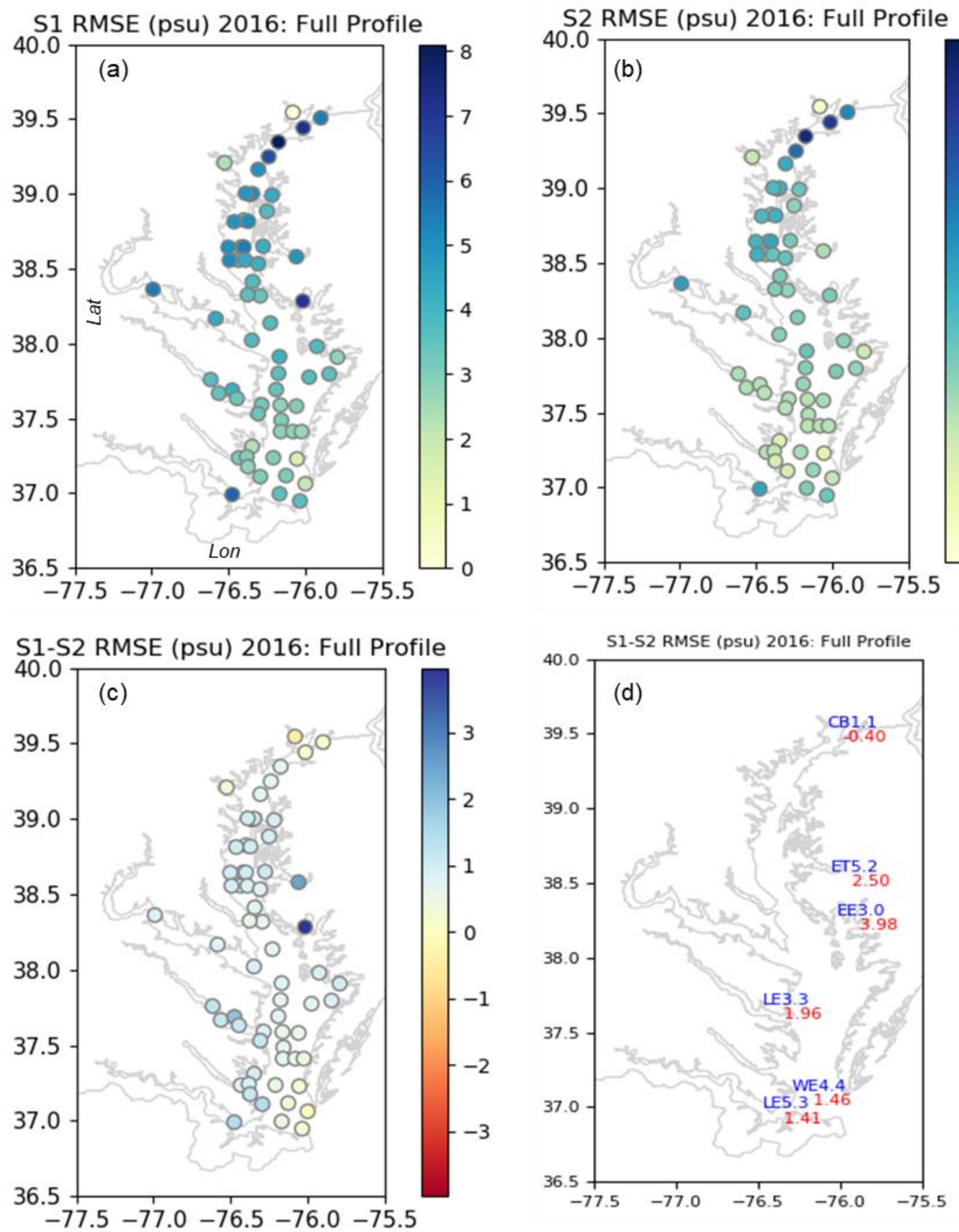

Figure 7. Profile Root Mean Squared Error (RMSE) computed over all sampling depths and all observation times at each location: (a) Scenario 1 2016, (b) Scenario 2 2016, (c) Scenario 1 – Scenario 2 : positive numbers mean improvement in Scenario 2, and (d) 5 locations with the largest RMSE improvement and one location with negative improvement.

Table 3. Summary statistics for the 2016 period averaged across the whole profile and all observation times. ME=mean error (a.k.a. bias); MAE=mean absolute error; RMSE=root mean squared error.

	ID	S1 MAE	S1 ME	S1 RMSE	S2 MAE	S2 ME	S2 RMSE	S2-S1 ME	S1-S2 RMSE
1	CB1.1	0.03	-0.02	0.03	0.39	0.39	0.44	0.41	-0.40
2	CB2.1	6.70	6.65	7.22	6.62	6.62	6.95	-0.03	0.27
3	CB2.2	7.76	7.74	8.11	7.28	7.28	7.51	-0.46	0.60
4	CB3.1	6.36	6.36	6.44	5.69	5.69	5.74	-0.67	0.70
5	CB3.2	4.90	4.90	5.03	4.16	4.15	4.28	-0.74	0.74
6	CB3.3C	3.84	3.83	4.11	3.08	3.05	3.38	-0.78	0.74
7	CB3.3E	5.08	5.08	5.16	4.03	4.01	4.12	-1.07	1.04
8	CB3.3W	4.71	4.70	4.87	3.73	3.67	3.89	-1.03	0.98
9	CB4.1C	3.22	3.16	3.53	2.58	2.43	2.88	-0.73	0.66
10	CB4.1E	5.12	5.12	5.15	4.07	4.07	4.10	-1.05	1.04
11	CB4.1W	4.87	4.87	4.92	3.82	3.82	3.90	-1.05	1.03
12	CB4.2C	4.04	4.04	4.21	3.29	3.29	3.48	-0.75	0.74
13	CB4.2E	5.44	5.44	5.48	4.43	4.43	4.48	-1.01	1.00
14	CB4.2W	5.02	5.02	5.06	4.00	4.00	4.05	-1.03	1.01
15	CB4.3C	3.56	3.56	3.80	2.85	2.84	3.10	-0.72	0.70
16	CB4.3E	3.99	3.98	4.36	3.13	3.06	3.48	-0.93	0.87
17	CB4.3W	5.03	5.03	5.13	4.02	4.02	4.14	-1.01	0.99
18	CB4.4	3.54	3.54	3.81	2.85	2.83	3.13	-0.71	0.68
19	CB5.1	3.13	3.03	3.45	2.49	2.32	2.80	-0.71	0.65
20	CB5.1W	3.52	3.52	3.57	2.93	2.93	2.98	-0.60	0.59
21	CB5.2	3.51	3.48	3.75	2.81	2.76	3.05	-0.73	0.70
22	CB5.3	4.04	4.04	4.17	3.28	3.28	3.42	-0.76	0.75
23	CB5.4	3.53	3.53	3.64	2.84	2.84	2.96	-0.69	0.68
24	CB5.5	3.34	3.33	3.47	2.60	2.55	2.72	-0.78	0.75
25	CB6.1	2.64	2.62	2.84	2.07	2.01	2.28	-0.61	0.56
26	CB6.2	2.86	2.84	3.00	2.17	2.11	2.34	-0.73	0.66
27	CB6.3	2.67	2.61	2.87	1.99	1.86	2.24	-0.75	0.63
28	CB6.4	2.76	2.53	3.00	2.15	1.73	2.44	-0.80	0.56
29	CB7.1N	3.73	3.73	3.77	3.04	3.04	3.08	-0.70	0.69
30	CB7.1S	2.82	2.75	3.00	2.27	2.11	2.46	-0.64	0.53
31	CB7.2	2.52	2.30	2.77	1.98	1.73	2.24	-0.57	0.53
32	CB7.2E	2.51	2.45	2.67	2.09	1.86	2.25	-0.59	0.41
33	CB7.3	2.69	2.60	3.08	2.38	2.12	2.72	-0.48	0.36
34	CB7.3E	1.42	1.22	1.52	1.21	0.74	1.30	-0.49	0.22
35	CB7.4N	1.92	1.49	2.02	1.89	0.89	2.05	-0.61	-0.02
36	CB8.1	3.28	3.26	3.58	2.61	2.45	3.05	-0.81	0.53
37	CB8.1E	3.19	3.00	3.64	2.90	2.52	3.37	-0.48	0.28
38	EE1.1	3.77	3.77	3.77	2.82	2.82	2.82	-0.95	0.95
39	EE2.1	4.26	4.26	4.27	3.19	3.19	3.20	-1.08	1.06
40	EE2.2	4.24	4.24	4.24	3.50	3.50	3.50	-0.74	0.74
41	EE3.0	7.07	7.07	7.07	3.08	3.08	3.10	-3.99	3.98
42	EE3.2	3.83	3.83	3.83	2.93	2.93	2.93	-0.90	0.90
43	EE3.4	2.72	2.72	2.81	1.77	1.77	1.85	-0.95	0.96
44	EE3.5	3.58	3.58	3.60	2.72	2.72	2.75	-0.86	0.86
45	ET2.3	5.33	5.33	5.40	5.16	5.16	5.22	-0.16	0.18

ID		S1 MAE	S1 ME	S1 RMSE	S2 MAE	S2 ME	S2 RMSE	S2-S1 ME	S1-S2 RMSE
46	ET4.2	4.26	4.26	4.34	3.28	3.28	3.38	-0.98	0.96
47	ET5.2	4.87	4.87	4.88	2.30	2.23	2.38	-2.64	2.50
48	LE2.2	4.25	4.25	4.38	3.42	3.42	3.58	-0.83	0.80
49	LE2.3	3.70	3.70	3.79	2.81	2.80	2.92	-0.90	0.87
50	LE3.1	3.59	3.59	3.66	2.33	2.28	2.40	-1.30	1.25
51	LE3.2	3.45	3.45	3.50	2.26	2.26	2.33	-1.19	1.17
52	LE3.3	4.22	4.22	4.23	2.25	2.25	2.27	-1.97	1.96
53	LE3.4	3.32	3.32	3.34	2.19	2.19	2.22	-1.13	1.12
54	LE3.6	3.22	3.22	3.25	2.35	2.35	2.39	-0.87	0.86
55	LE3.7	3.39	3.39	3.41	2.26	2.26	2.28	-1.13	1.13
56	LE4.3	2.93	2.90	3.08	2.11	2.02	2.25	-0.87	0.83
57	LE5.3	5.75	5.75	5.93	4.28	4.28	4.51	-1.47	1.41
58	LE5.5W	4.11	4.08	4.17	3.19	3.07	3.30	-1.01	0.88
59	RET2.4	5.32	5.32	5.50	4.48	4.47	4.67	-0.85	0.84
60	WE4.1	2.30	2.30	2.32	1.32	1.32	1.35	-0.98	0.97
61	WE4.2	2.96	2.92	2.98	2.06	2.00	2.10	-0.92	0.88
62	WE4.3	2.81	2.81	2.82	1.63	1.62	1.65	-1.19	1.17
63	WE4.4	3.01	3.01	3.02	1.55	1.55	1.56	-1.46	1.46
64	WT5.1	2.15	1.12	2.34	1.75	0.22	2.04	-0.91	0.30
	Avg	3.81	3.76	3.94	2.95	2.85	3.09	-0.91	0.85
	Stdev	1.32	1.38	1.33	1.20	1.29	1.21	0.56	0.57

Figure 8 shows 2016 salinity profile plots for station EE3.0 at 11 times throughout the year. The Scenario 2 outputs at EE3.0 are closer to observations than Scenario 1 outputs. This station is located in Fishing Bay and relatively near the outflows of the Nanticoke and Wicomico Rivers (see reference map in the lower right of Figure 8). Very little salinity stratification is observed or simulated at this location. Further illustrated by numerous observed salinity profiles in Appendix B, low stratification is not uncommon for locations in shallower portions of the Bay where the water is well mixed. At EE3.0 observed values are available to 6-m while simulated values are only available to 4-m. These differences could be due to inaccurate CBOFS2 bathymetry. It is well known that bathymetry is a key input to achieve accurate shallow water hydrodynamic modeling and Ye et al. (2018) illustrate the importance of accurate bathymetry in Chesapeake Bay modeling. Bathymetry errors, particularly in shallow portions of the Bay, could have a substantial impact on the results we are presenting here. However, it is beyond the scope of this work to explicitly assess multiple sources of error beyond freshwater changes on the modeling.

Figure 9 shows observed and simulated profile plots at the CB5.2 observation station, which is located in deeper water near the center of the Bay. Here, away from the influence of local tributaries, the differences between Scenario 1 and Scenario 2 are much smaller. More stratification with depth is also observed at this location compared to EE3.0 because freshwater is not fully mixing in deeper portions of the Bay.

In Figure 10, salinity profiles for station LE3.1 show moderate effects of the freshwater inflow changes from Scenario 1 to Scenario 2. The impacts are somewhere in between the small estuary station (EE3.0) and the mid-Bay station (CB5.2).

For the same stations assessed in Figures 8-10, Figures 11a-c show time series of simulated and observed salinity at a 1-m depth (left axis) along with time series of river inflows (right axis). Out of all 64 stations in this study, EE3.0 saw the biggest average RMSE improvement of about 4 psu from Scenario 1 to 2 (Figure 7 and Table 3). The salinity time series in Figure 11a reflect this average improvement. The local inflow time series in Figure 11a, which are the sum of the Nanticoke and Wicomico simulations, indicate why the salinity simulations are so much different. Although the CBOFS2 baseline (Scenario 1) includes an inflow node near the Nanticoke outlet, it does not use any gauges from the Nanticoke or Wicomico Rivers to derive inflow estimates, yielding inflow estimates that are far too low at the Nanticoke node. Scenario 2 corrects this problem.

Figure 11b plots salinity and flow time series for CB5.2, which is located in the middle of the Bay. The flow traces in 11b include the totals from all tributaries. As at EE3.0, sudden drops in salinity are associated with large freshwater events, affirming the importance of river inflows on salinity distribution throughout the Bay. Not surprisingly, the difference between Scenarios 1 and 2 is not as large at CB5.2, closer to the center of the Bay. At the 1-m depth shown here, the improvement in salinity mean absolute error (MAE) from Scenario 1 to 2 (S1-S2) is 4.0 psu for EE3.0 but only 0.7 psu for CB5.2.

Figure 11c is for LE3.1 located near the outlet of the Rappahannock River. The inflows in Figure 11c are for the Rappahannock. Scenario 2 includes more inflow and produces lower salinity simulations as expected. The Scenario 2 salinity at 1-m drops closer to the observations, not as dramatically as at location EE3.0, but more so than at CB5.2. The MAE improvement from S1 to S2 is 1.3 psu for station LE3.1.

Although Scenario 2 consistently improves the salinity predictions over Scenario 1, it does not completely eliminate the high bias from the simulations at most locations (see Figures 6c and d as well as Figures 11a-c). Despite the remaining bias, the CBOFS2 model does show a consistent temporal correlation with observations in Figures 11a-c as well as at other locations (see Appendix C for other locations).

Figure 7c shows one location, CB1.1, where the Scenario 2 salinity error was slightly higher than the Scenario 1 error in terms of RMSE. CB1.1 is located at the mouth of the Susquehanna River. Figure 12 shows that observed and simulated salinities for this site during much of 2016 are close to zero. However, in the low flow period from September through November 2016, Scenario 2 simulates some non-zero salinity values at the 1-m depth in the range of 0 to 3 psu. During this time period, Scenario 1 simulates lower salinities close to 0. Scenario 1 simulations are closer to observations, which include only one non-zero observation during this period, 0.09 psu on 10/19/2016. Flow data for the Susquehanna River at Conowingo Dam from the USGS are plotted along with the Scenario 1 and 2 Susquehanna inflows in Figure 12. These data indicate that the Susquehanna flows fed to the CBOFS2 operational model (Scenario 1) were too high during September and October of 2016. The reason for this erroneous inflow is unknown. Because the erroneous, higher flows in Scenario 1 actually yield a better salinity simulation at CB1.1, this suggests that sources of model error other than streamflow are causing the salinity over-estimates in Scenario 2.

We selected the sites in Figures 8-12 to highlight different types of locations within the Bay. This included a relatively shallow location near the edge of the Bay where the local river flows have a relatively large influence (EE3.0), a station near the main channel of the Bay (CB5.2), a station near the outlet of a medium size river (LE3.1), and a station near the outlet of a major river (CB1.1). Graphics and tabular results for all 64 observation stations and both the 2005 and 2016 simulation periods are also available to further support our conclusions. These details are provided in Appendices A, B, and C due to their considerable length.

Out of the 64 stations analyzed in the 2016 period, the average profile mean error (ME) improved by 0-1 psu in 44 stations, 1-2 psu at 17 stations, 2-3 psu at 1 station, and 4 psu at 1 station (Table 3, Figure 6f). The average profile ME increased by 0.4 psu for one station (CB1.1) for reasons explained above. As expected, we see greater improvements in shallower waters near tributary inflows.

While we see strong evidence of salinity simulation improvements from more accurate river inflows, there is still an overall salinity bias in Scenario 2. From Table 3, the ME over all observing stations dropped from 3.76 to 2.85 psu for the 2016 period, a modest improvement. Lanerolle et al. (2016) note that this improved level of salinity accuracy would not be adequate for applications such as Vibrio forecasting, citing accuracy requirements for CBOFS as +/-1 psu and +/-1 degree C. To achieve results closer to these values for Vibrio forecasting, Lanerolle et al. (2016) statistically post-process the CBOFS2 output. This would still be recommended with the improved freshwater inflows we demonstrate here.

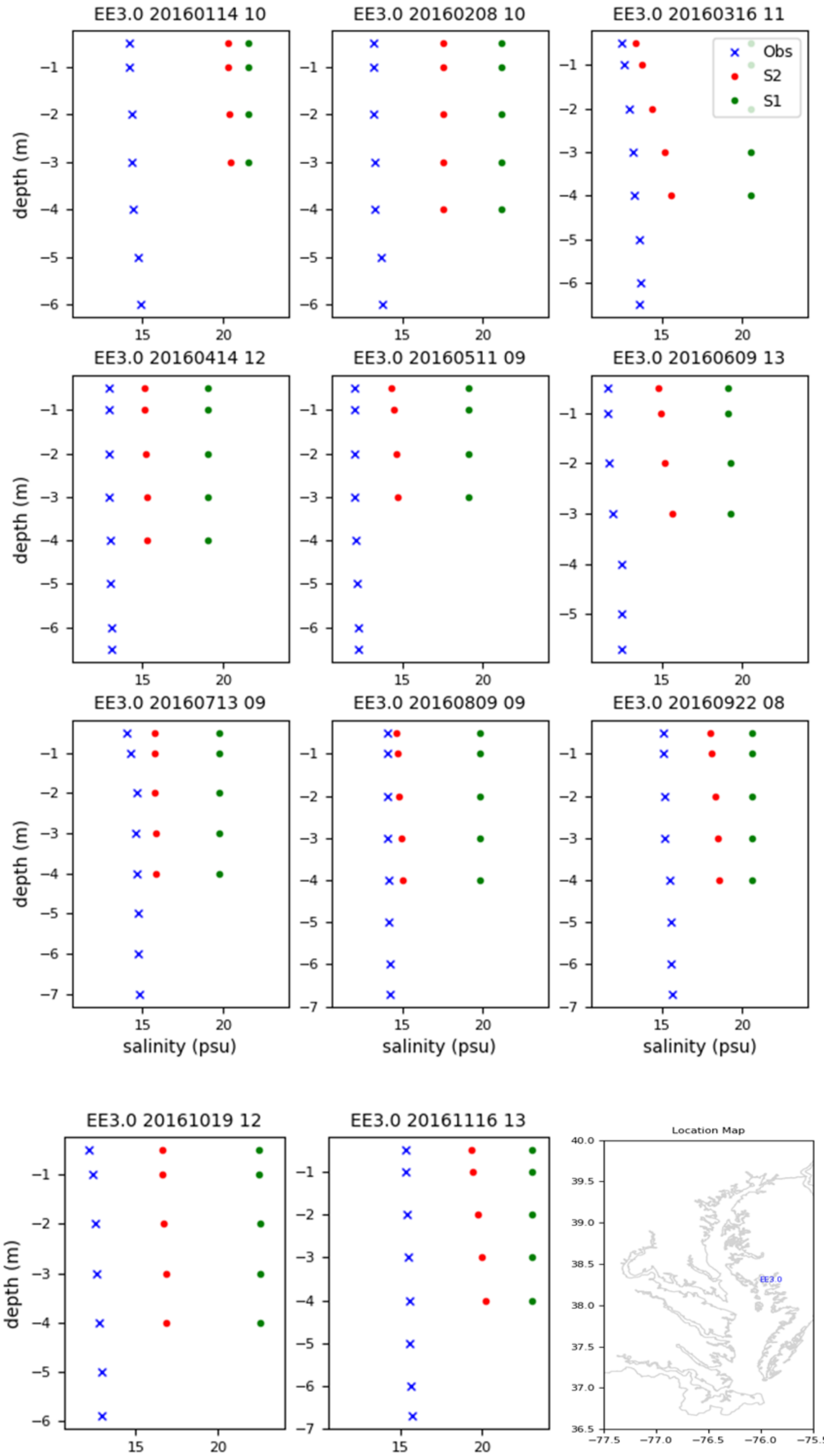

Figure 8. Salinity profile plots for all observation dates in the 2016 simulation period at location EE3.0.

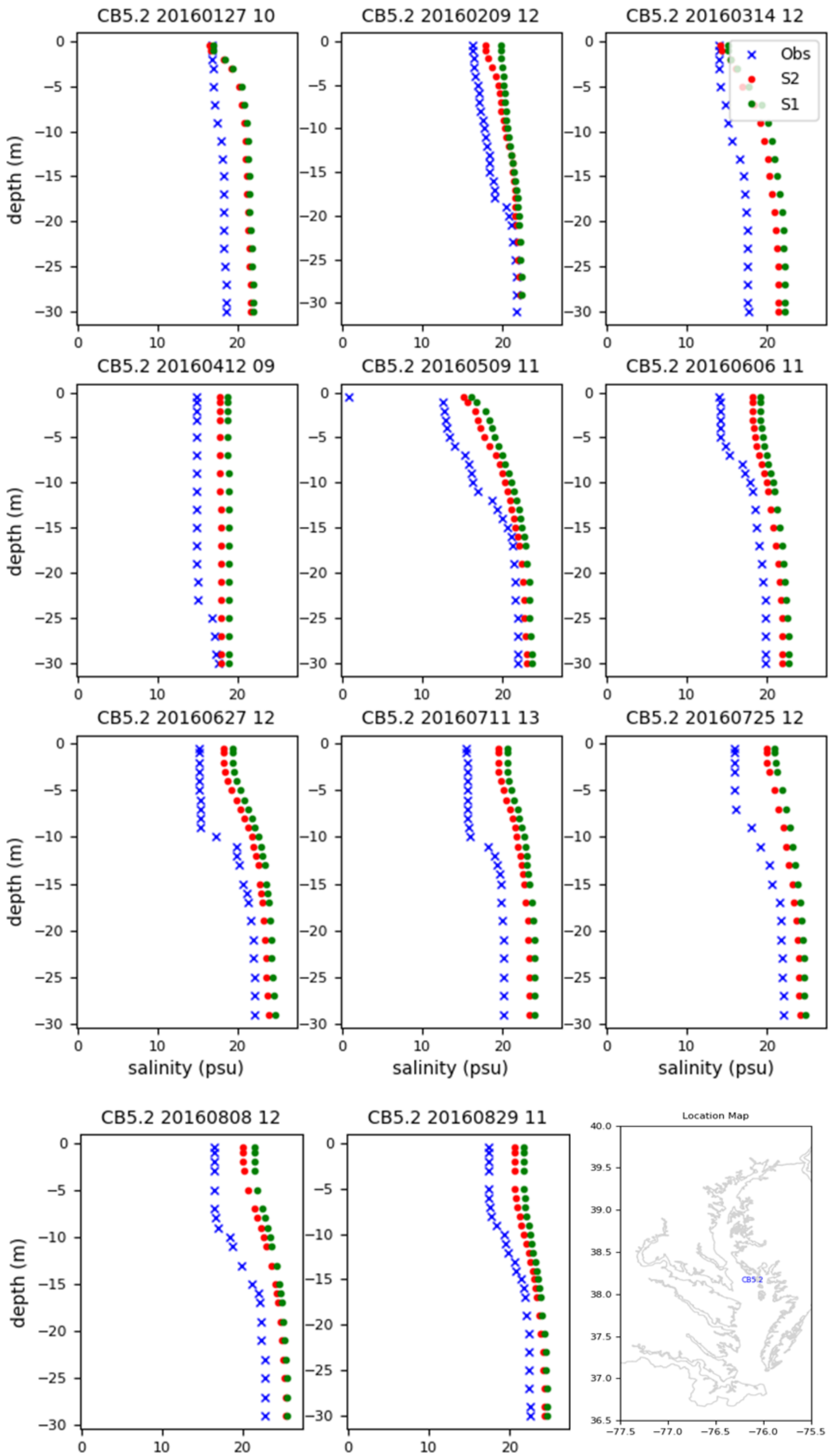

Figure 9. Salinity profile plots for all observation dates in the 2016 simulation period at location CB5.2.

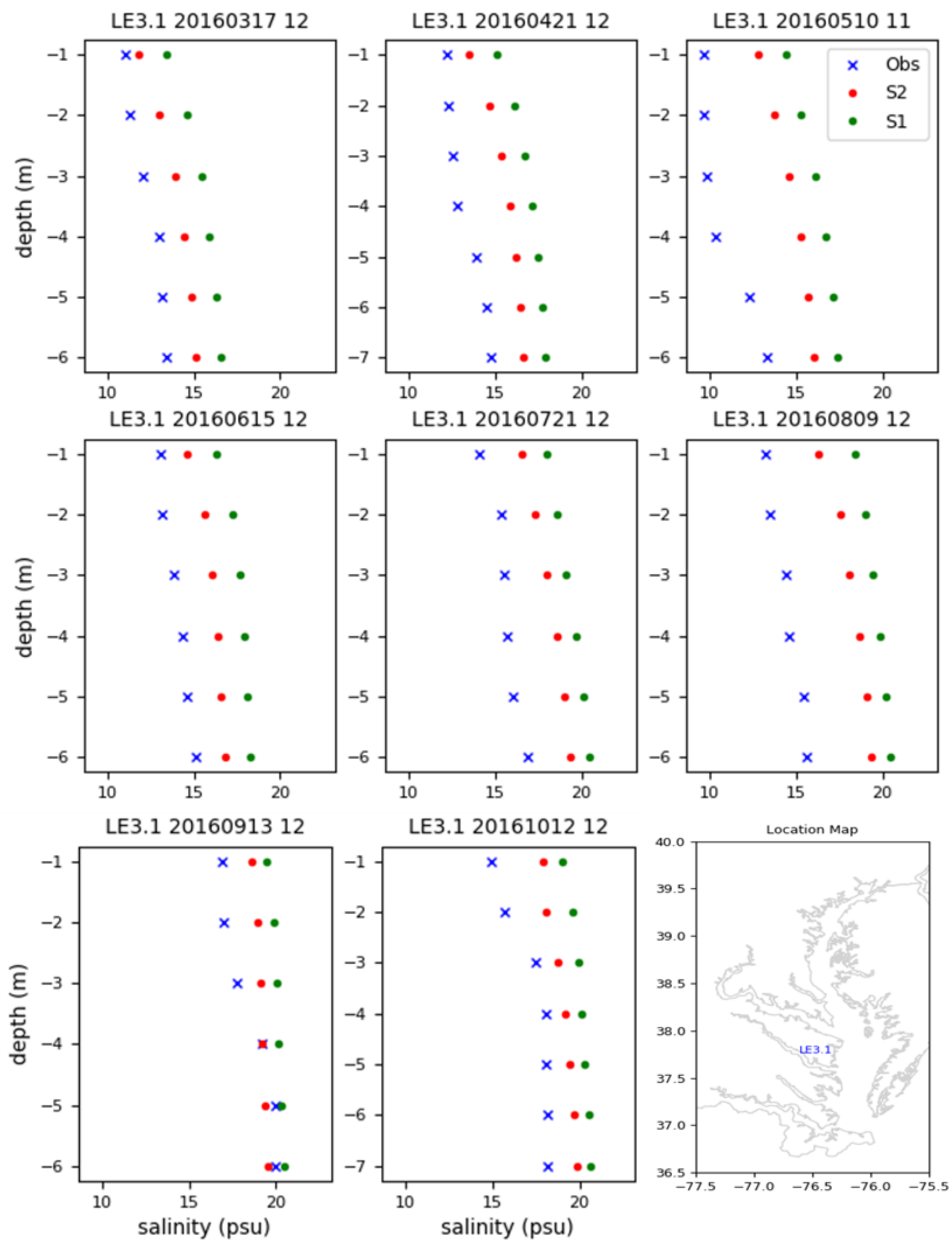

Figure 10. Salinity profile plots for all observation dates in the 2016 simulation period at location LE 3.1.

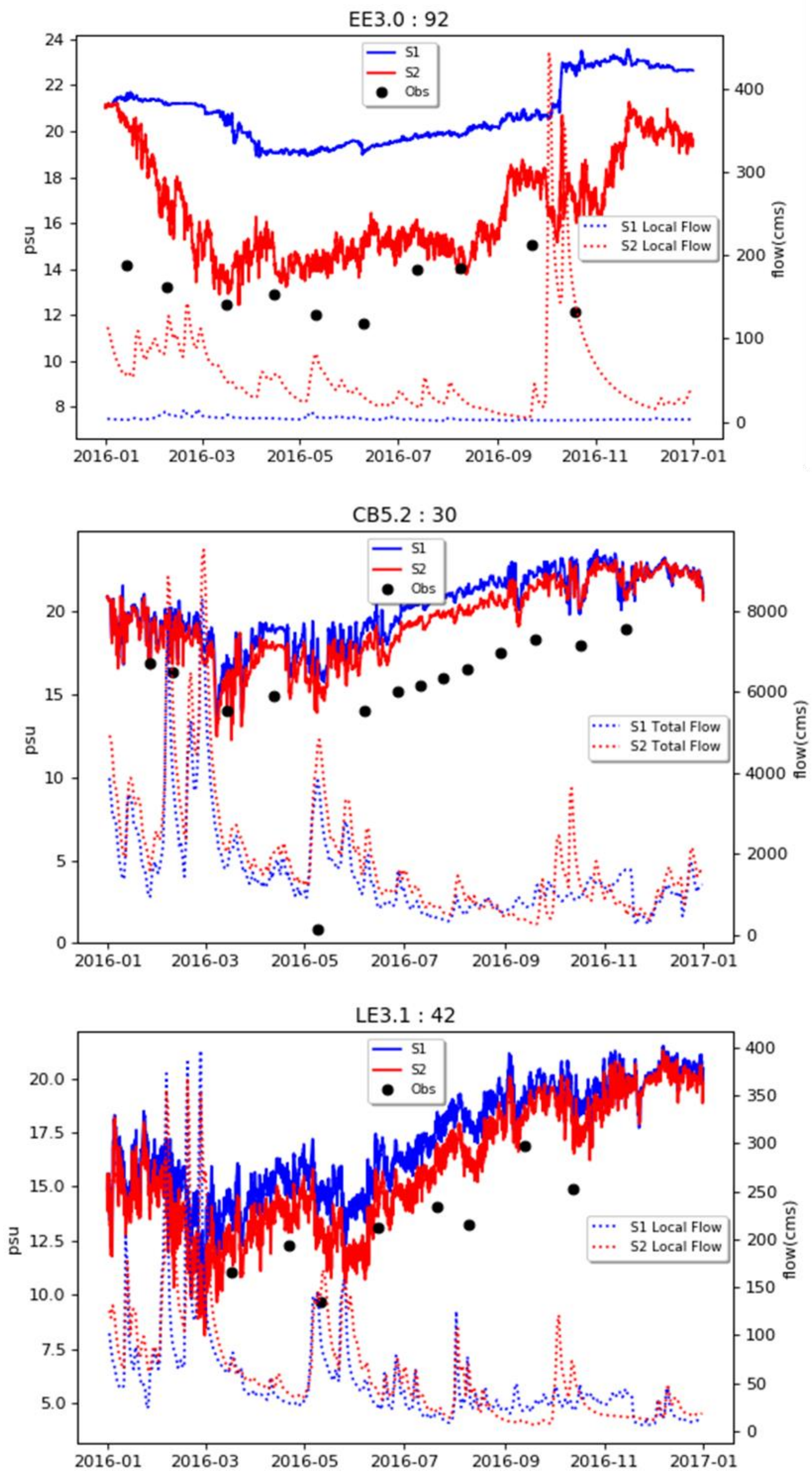

Figure 11. Simulated salinity from Scenarios 1 and 2 along with discrete observations at 1-m depth and relevant inflows. (a) EE3.0 with inflows from the nearby Nanticoke and Wicomico Rivers, (b) CB5.2 with inflows from all tributaries, (c) LE3.1 with inflows from the Rappahannock River.

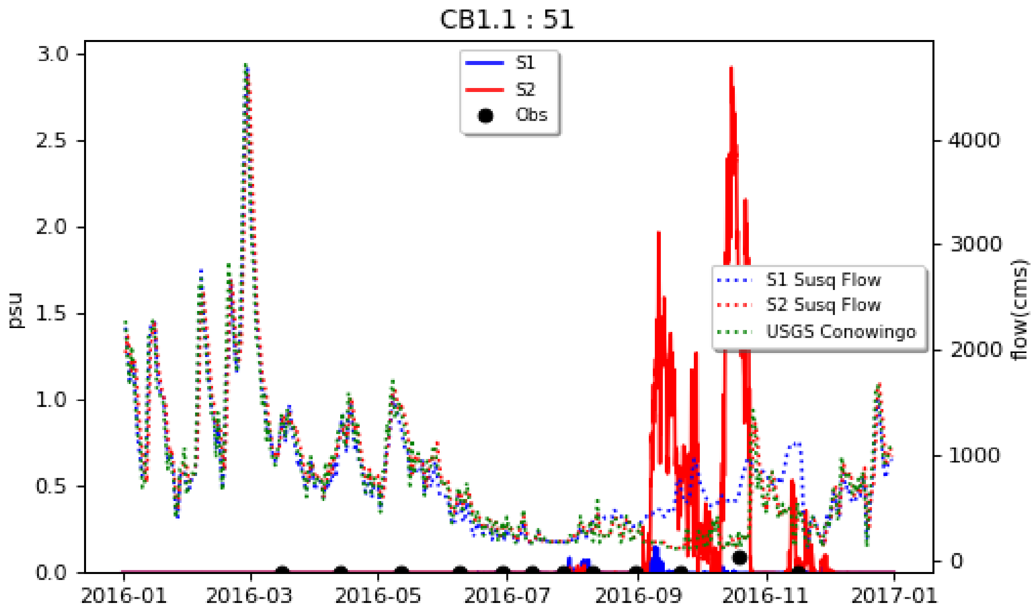

Figure 12. Simulated salinity from Scenarios 1 and 2 along with discrete observations at 1-m depth. Station CB1.1 is at the mouth of the Susquehanna R. Simulated and observed salinity are zero except during low flow periods. S1, S2, and USGS observed flows below Conowingo Dam are shown.

Conclusions and Recommendations for Future Work

Increasing the number of inflow nodes in CBOFS2 from 13 to 60 and explicit hydrologic modeling of an additional 16% percent of the land area improve salinity simulations. Lower mean errors (a.k.a. bias) and lower root mean squared error (RMSE) confirm this when comparing simulations to observations at 64 sampling sites. Spatial trends in the results are consistent with expectations. That is, greater improvements are seen from Scenario 1 to 2 at sampling sites in shallower water and near river inflows that are not modeled in Scenario 1.

In our Scenario 2 simulations, we used observed inflows for 79% of the Chesapeake drainage and model simulations for an additional 16% of the area. The accuracy of the watershed modeling in added areas is limited in part because the gridded hydrologic model is uncalibrated. In addition, this study was limited to simulations, without considering the additional errors that would be introduced in a forecast period driven by precipitation forecasts rather than observed precipitation. Nonetheless, our results show that additional work to implement more detailed hydrologic modeling in the NOAA operational forecast environment is likely to produce benefits. Our CBOFS2 simulations with 60 nodes ran smoothly without numerical stability problems.

A reasonable next step towards operational implementation and to assess results in forecast mode would be to run a CBOFS2 60 inflow configuration with live data in parallel to the current operational model. Our configuration has been provided to NOS COOPs for possible use in this manner.

The most practical source of inflows for ungaged rivers in a real-time configuration would be the National Water Model (NWM). For reasons explained above, we used the HL-RDHM model in this study. For small, ungaged basins, we would expect NWM and HL-RDHM forecasts to be relatively comparable, although more analysis of this would be prudent. Long period simulations for NWM at all 60 locations of interest were not available for this study.

For forecasts at inflow nodes associated with larger rivers, such as the Susquehanna, Potomac, James, we would recommend using the official RFC model forecasts where available, rather than NWM, because they are known to be substantially more accurate. As evidence of this, Figure 13 shows a comparison of the 3-day average RMSE calculated from all 12 UTC medium-range NWM v2.0 forecasts and 12 UTC RFC operational forecasts from July 1, 2019 to April 30, 2020. Figure 13a includes data for 62 gaged headwater basins (approximately 300 mi^2 in size) where MARFC has been tracking NWM performance, as well forecasts for the largest rivers flowing to the Bay. NWM forecasts for the three largest Chesapeake Rivers have a substantially higher RMSE than the RFC forecasts (Figure 13a). For smaller basins, while NWM forecast errors still tend to be higher, the differences represent considerably less volume than differences for the three largest rivers. Regardless, outside of the major rivers, the RFC model forecasts are not available for the 60 local watersheds we modeled in Scenario 2, so NWM is the best available option for these locations. With this approach, initial application of NWM would only be in about 16% of the modeled area, capturing the dynamics in these smaller tributaries while avoiding the larger volume errors seen on larger rivers. With the resolution of NWM and some additional testing, future implementations could also increase the number of connecting nodes beyond 60.

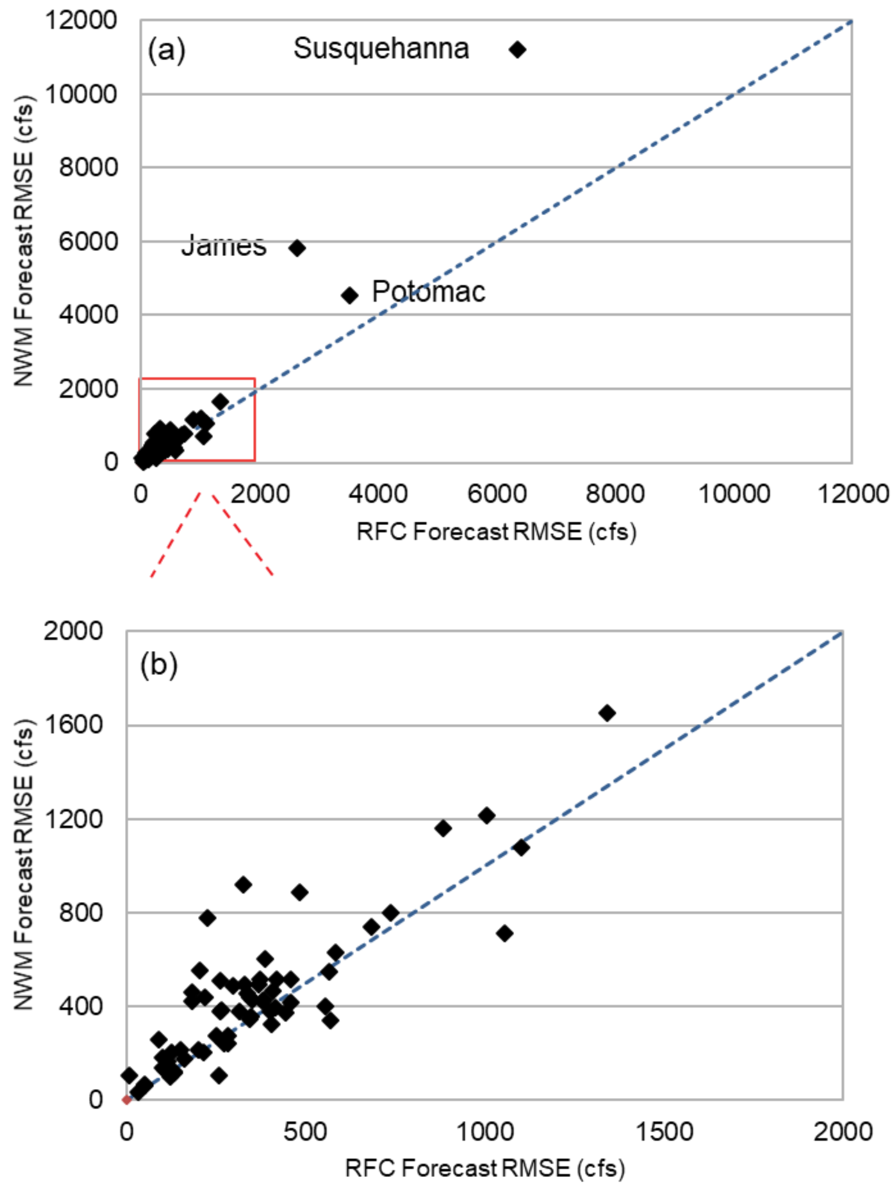

Figure 13. 3-day average RMSE calculated for NWM and RFC operational forecasts at 62 headwater basins plus the outlets of four major tributaries (Susquehanna, Potomac, Rappahannock, and James): (a) all locations, and (b) all but the three largest basins.

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Appendices

Appendix A. Tabular results for 2004 period.

Appendix B. Simulated and observed profile plots for all times and locations.

1. 2004 (212 pages)
2. 2016 (114 pages)

Appendix C. Simulated and observed time-series plots for all locations.

1. 2004 (8 pages)
2. 2016 (8 pages)

(CONTINUED FROM FRONT COVER)

NWS	ER 46	An Objective Method of Forecasting Summertime Thunderstorms. John F. Townsend and Russell J. Younkin. May 1972. (COM-72-10765).
NWS	ER 47	An Objective Method of Preparing Cloud Cover Forecasts. James R. Sims. August 1972. (COM-72-11382).
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