Projection of Submerged Aquatic Vegetation in Maryland under Sea-Level Rise

EESLR 2019 Quantifying the benefits of natural and nature-based features in Maryland's Chesapeake and Atlantic Coastal Bays to inform conservation and management under future sea level rise scenarios.

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Table of Contents

1 Methods

This project is a test of, and refinement of, the submerged aquatic vegetation (SAV) component of the Sea Level Affecting Marshes (SLAMM) model. The SAV component of SLAMM was developed in 2014 under contract to, and with the considerable assistance of, USGS and US EPA (Lee II et al. 2014). SAV prediction functionality has been incorporated in the model since SLAMM version 6.3 (Clough et al. 2016). That model was developed for Pacific Northwest estuaries and was specific to *Zostera marina* and the sometimes-unique geometry of the Pacific Northwest estuaries. For this project our team explored what data might be required to assist the empirical-model formulation to the degree that it will effectively predict and project SAV abundance in Maryland's portion of the Chesapeake Bay.

The SLAMM SAV model uses a generalized linear model (GLM) as a general modeling approach. Specifically, a logistic regression model was chosen, that had been used successfully to model the distribution of *Zostera* in Europe (Bekkby et al. 2008; Van der Heide et al. 2009). The model predicts a percent likelihood of SAV presence in each raster cell within a model's domain.

The Maryland model was developed within a calibration domain and then tested on an alternative spatial model domain for validation. Additional input data sets were added to the model to improve model accuracy.

1.1 Study Area

Calibration and validation study areas were chosen based on feedback from the Ecological Effects of Sea Level Rise (EESLR) Project Team and SAV Workgroup. In addition, these areas were expanded to some degree so that a gradient of SAV presence and absence could be used to train the model.

1.1.1 Calibration Model Domain

Tangier Sound was selected as the calibration study area (Figure 1). Figure 2 shows the rectangular extent of the study area with SAV displayed in red over satellite imagery. Approximately 2.3% of the calibration study area is covered with SAV or 15,579 acres.

1.1.2 Validation Model Domain

Areas in and around the Choptank River were selected as the validation study area. Figure 3 illustrates the validation site which is roughly northwest of the calibration location. Approximately 1.1% of the validation domain is covered with SAV or 7,353 acres.

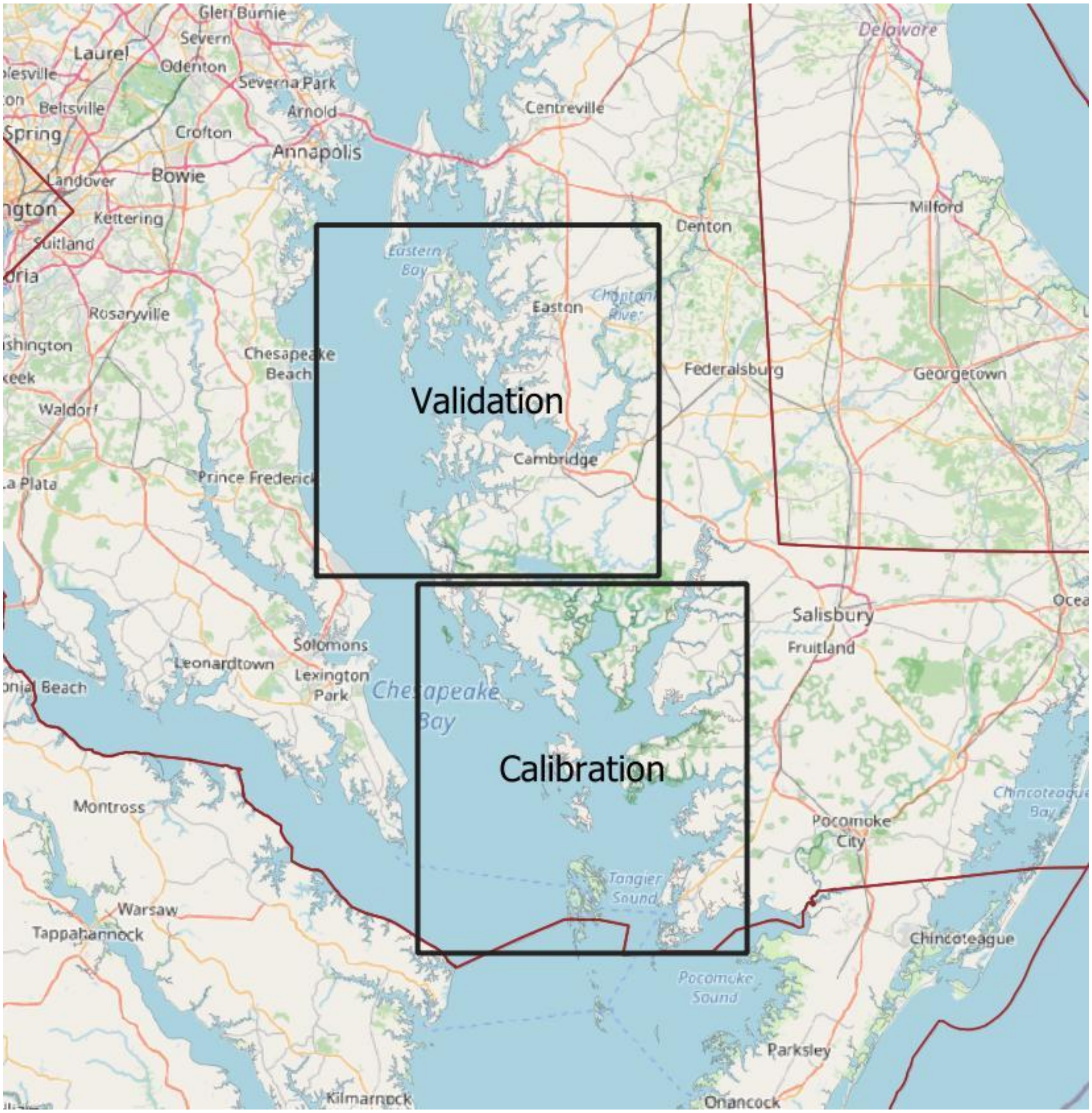

Figure 1. Calibration and Validation Domain Chosen for SAV Model Development

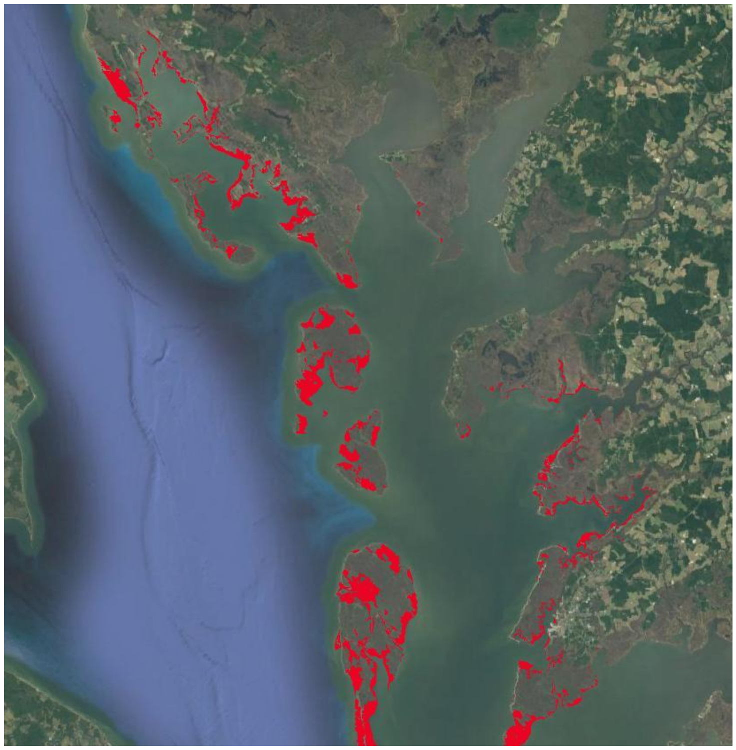

Figure 2. Calibration area shown over satellite imagery (top) with SAV presence shown in red

Figure 3. Validation region shown over satellite imagery (top) with SAV presence shown in red

1.2 Spatial Input Data

Raster input data were gathered to parameterize the model in terms of elevation, water quality, and water velocity. The cell size used in this project was 10 m by 10 m. This section describes spatial data sources and the steps used to process the data for use in SLAMM.

1.2.1 SAV Distribution

SAV presence or absence was derived using VIMS Survey Data (Virginia Institute of Marine Science 2010-2019). Cells designated as having SAV if SAV was present in at least 7 out of 10 years (2010-2019) or if it was present in the most recent year (2019).

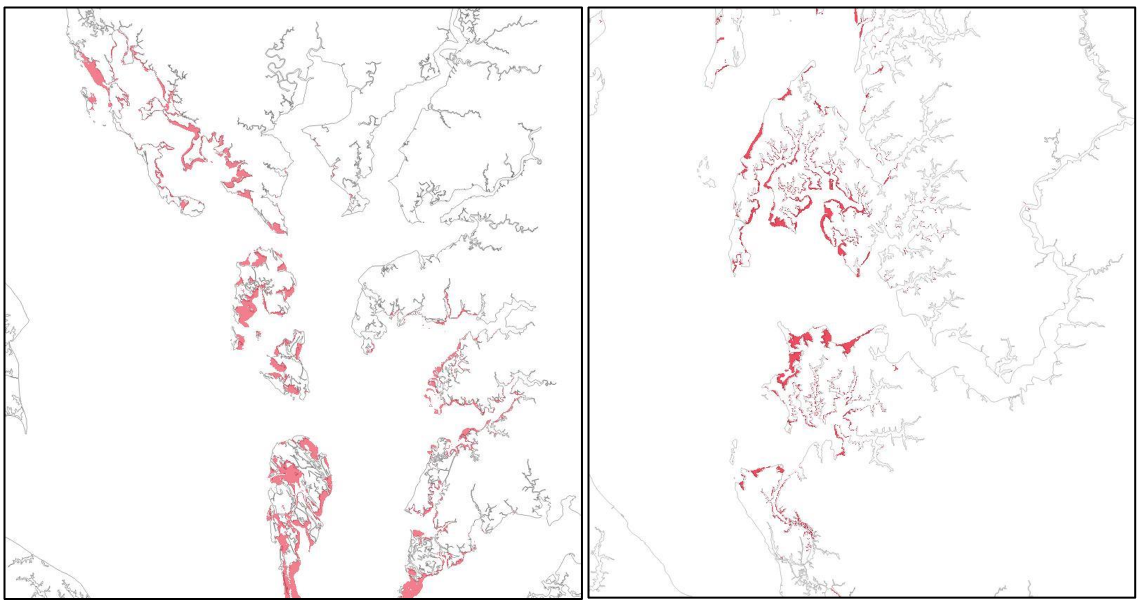

Figure 4. SAV distribution inputs for the Calibration area (left) and Validation area (right)

1.2.2 Elevation, Distance to Shoreline, and Open Water

Cell elevation and distance to shoreline were taken from the SLAMM model simulation of Maryland that is also part of the EESLR project (for more information, see Warren Pinnacle Consulting, Inc. 2021). The base dataset for this model application was the 2016 USGS CoNED Topobathymetric Model for Chesapeake Bay Region. Digital elevation models (DEMs) from MD iMAP were used instead of CoNED for those Maryland counties that had more recent LiDAR. See the SLAMM project documentation for more information on this dataset (Warren Pinnacle Consulting, Inc. 2021).

The SLAMM model outputs elevations relative to mean tide level (MTL) for use in current-condition SAV modeling and future projections under sea-level rise (SLR). Slopes were calculated from these outputs as well.

Distance to MLLW (mean lower low water) and MHHW (mean higher high water) were also output in units of meters.

Another output from the SLAMM model pertained to the open-water boundary. SAV were assumed to not inhabit areas that the SLAMM model predicts as having vegetated tidal wetlands. For these purposes, an open-water layer was also derived from SLAMM model outputs, including tidal flats, but excluding regularly-flooded emergent marsh habitats.

1.2.3 Water Quality Data

SAV are known to have water-quality requirements in terms of water clarity, temperature, salinity, and bottom substrate. To test whether the prediction of SAV presence could be improved based on water quality data, layers from the Chesapeake Bay Habitat Tool were brought into the model (The Nature Conservancy 2015). These data took observations from Chesapeake Bay Program monitoring data 2009-2012 and interpolated them over three dimensions using the Chesapeake Bay and Tidal Tributary River Interpolator Tool.

From this data source, 15 data layers were derived and tested for statistical importance:

- Water Clarity – Total Suspended Solids (TSS) (2 layers -- summer averages, bottom and surface)
- Water Clarity – Chlorophyll *a* (4 layers-- summer and spring averages, bottom and surface)
- Water Temperature (4 layers-- summer and spring averages, bottom and surface)
- Salinity (4 layers-- summer and spring averages, bottom and surface)
- Bottom Sediment Substrate (percent mud)

Figure 5 shows some examples of spatial-data layers extracted from the Chesapeake Bay Habitat Tool.

Unlike the data derived from SLAMM discussed above (elevations, distance to shoreline) and the data regarding water velocity discussed below, water-quality estimates under sea-level-rise (SLR) projections were not available. However, water quality data did make a significant difference in improving model predictions. Therefore, as a simplification, water quality data were held constant under SLR projections, and water quality over dry lands was interpolated from their nearest open-water cell.

Areas in and around Blackwater National Wildlife Refuge (NWR) were not spatially covered by data from the Chesapeake Bay Habitat Tool. As the NWR has unique water-quality conditions due to being partially impounded, interpolation from surrounding waterways was not deemed appropriate. Therefore, this region was omitted from the model calibration and validation.

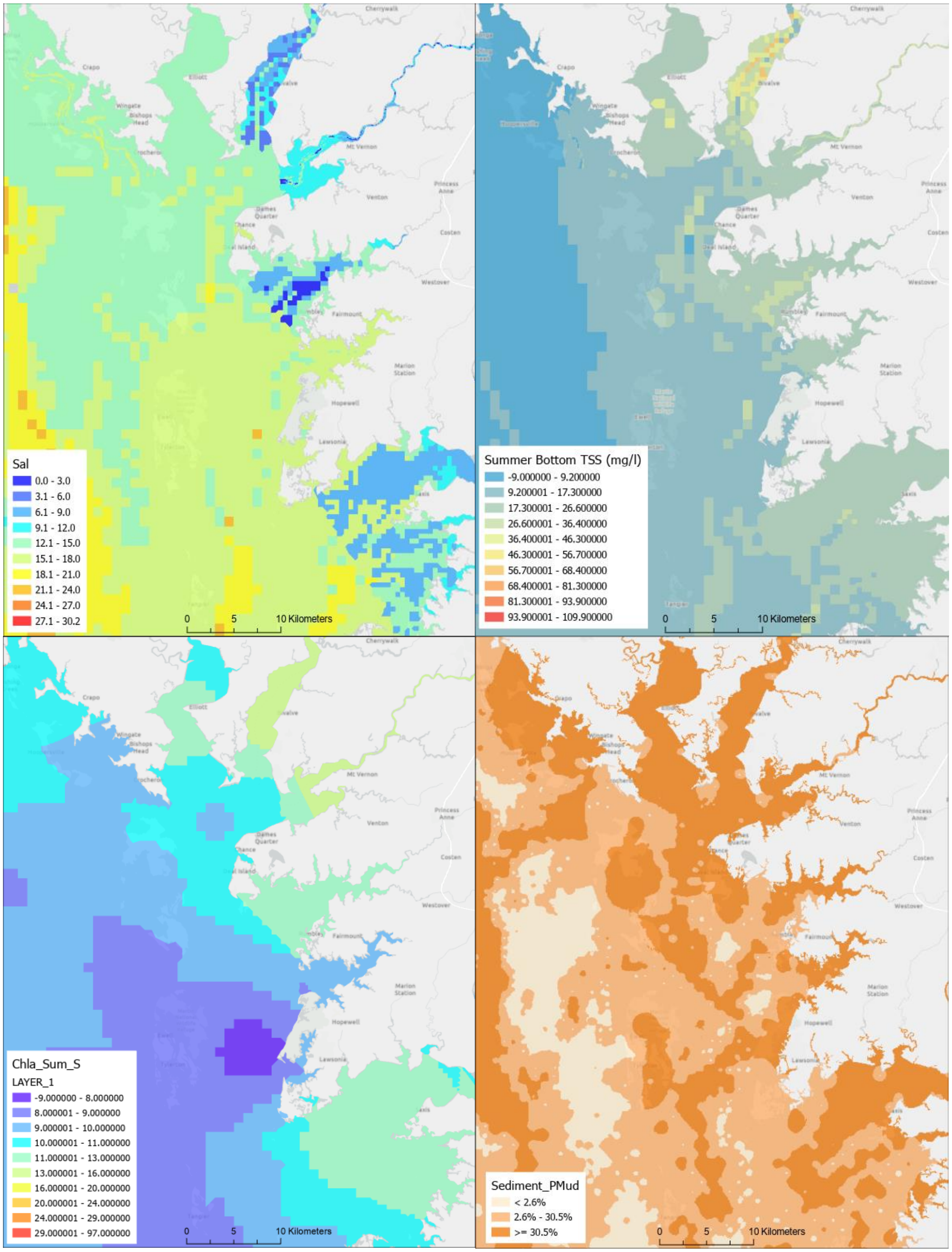

Figure 5. Example data from the Chesapeake Bay Habitat Tool

Clockwise from Upper left, Salinity, Bottom TSS, Percent Mud and Chlorophyll a in the summer

1.2.4 Water Velocity

SAV are also known to be sensitive to high water velocity. To examine the potential impact of water velocity on SAV presence, data were extracted from the GMU hydrodynamic model that was also produced for this EESLR project (Advanced Circulation Model or ADCIRC)[1]. Based on an initial data examination, storm-surge velocity was not closely correlated with SAV absence or presence. Therefore, a six-day data period was extracted from a storm simulation, but prior to the storm's arrival. In this case, the days that were averaged were Aug 20-25, 2011 (pre-Hurricane Irene).

The spatially variable ADCIRC model grid was spatially interpolated to produce the regularly-spaced raster inputs required for this project (using Triangulated Irregular Network TIN interpolation from QGIS version 3.10.11). The maximum and average velocity data from the six-day data period were extracted from the model.

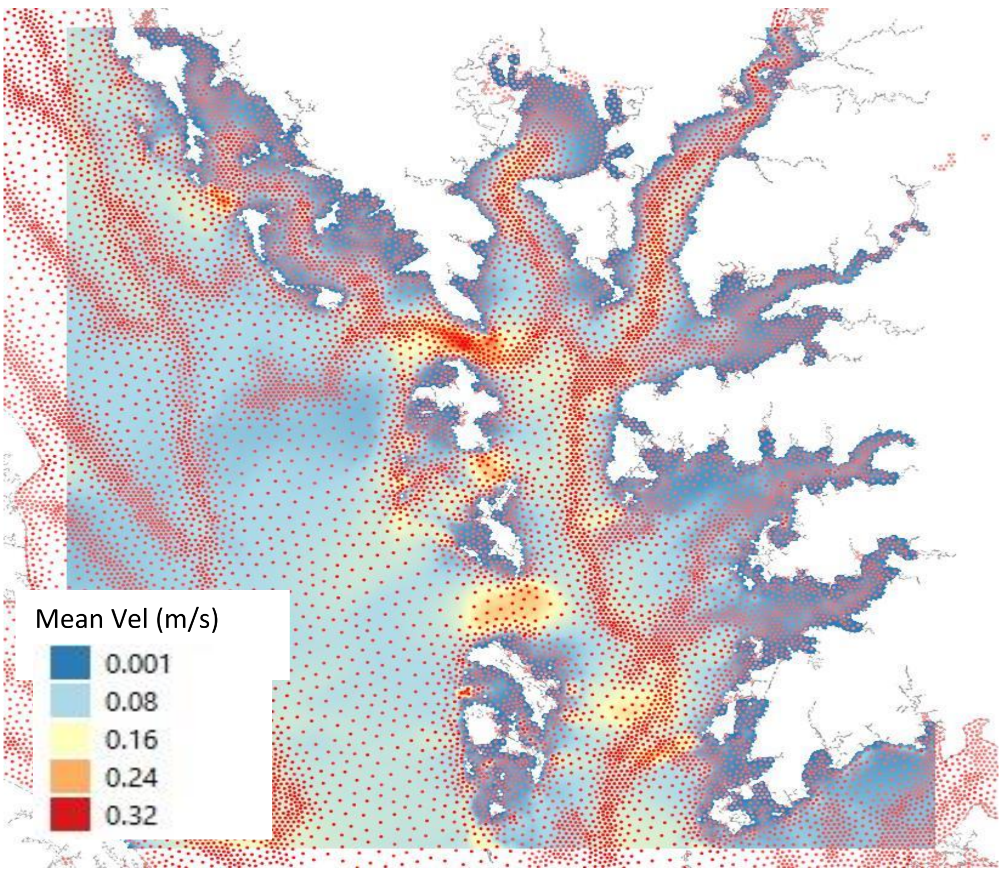

Figure 6. Mean Velocity export from ADCIRC, interpolated into model grid cells for the calibration area

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[1] Model results were prepared by George Mason University, Flood Hazards Research Lab: https://fhrl.vse.gmu.edu/

ADCIRC water-velocity results were also available under SLR projections, so this additional feedback was added to the SLAMM SAV model projections. ADCIRC models showed increasing velocity over existing SAV habitat under conditions of rising ocean levels.

1.3 Model Calibration

An empirical model was produced using RStudio[2]. First, model data were limited to those cells that have an elevation range consistent with observed SAV elevations. The 1st percentile to 99th percentile of observed SAV elevations were used or -1.71 meters to 0.45 meters of elevation relative to MTL. The average elevation of SAV was also calculated as -0.52 meters relative to MTL and that was defined as the "optimal SAV elevation."

After data were selected based on their elevations, box plots were derived for all data layers to examine the relevance of each variable. Each of these figures includes two box plots, one on the left side that illustrates the range of values for cells without SAV and one on the right for cells with SAV (Figure 7). Box plots were also used to verify a logical consistency with the conceptual model. For example, Figure 7 shows that SAV cells are more likely when they have a lower "[vertical] distance to optimal elevation," and also prefer cells that have lower mean-water velocity. The full set of box plots derived for the calibration and validation area are available in Appendix B of this document.

A generalized linear model was then derived using all of the spatial layers available, totaling 20 parameters. From this model, the importance of each variable input could be estimated (using the "t-statistic" as shown in Figure 8). Using these variable-importance results, models with smaller numbers of variables were tested by deriving a "pseudo R^2 statistic" (Figure 9) and also by examining maps of spatial predictions (Figure 9 to Figure 15). The pseudo R^2 statistic is larger when the model has more predictive capability. Figure 8 shows that this metric only improves slightly when the model has 20 parameters vs. 9 parameters. In general, the spatial maps with higher numbers of variables match the pattern of SAV distribution well, with the highest density of SAV found in the southwest of the calibration domain and the lowest density found in the northeast.

Based on these lines of evidence, a model with eight or nine parameters seemed best to carry forward for validation and model projections.

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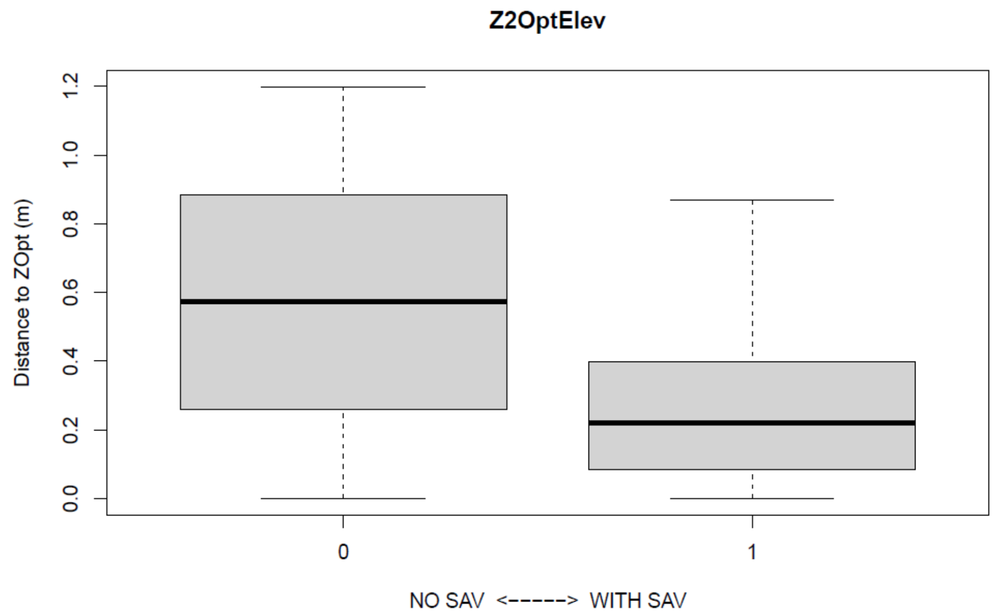
[2] (RStudio version 2021.09.1 Build 372 running R version R-4.1.1.) All R scripts used for this project are available upon request.



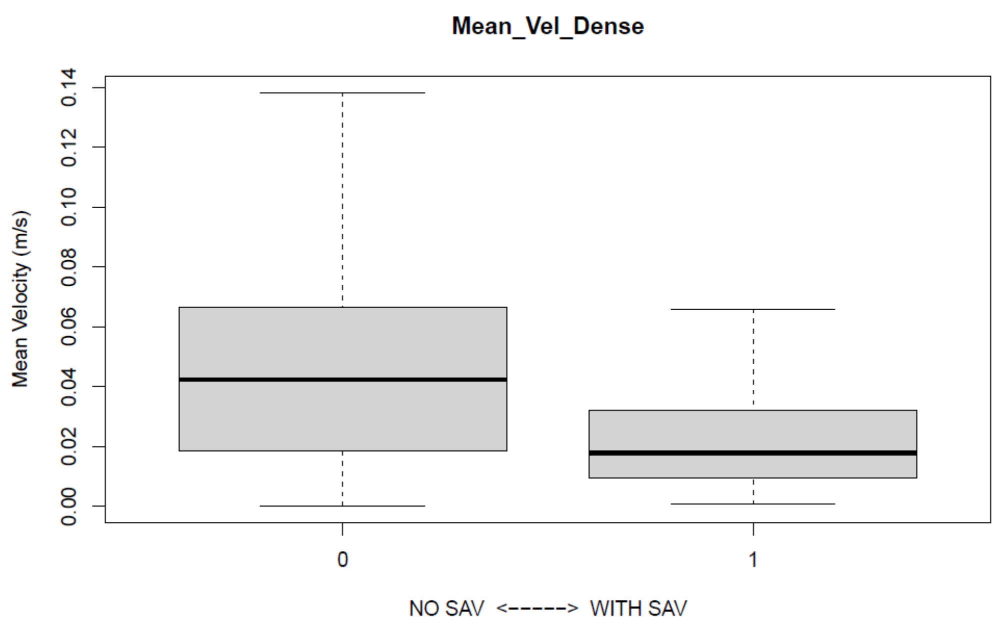


Figure 7. Comparative box plots for “distance to optimal elevation” (top) and “mean velocity” (bottom)

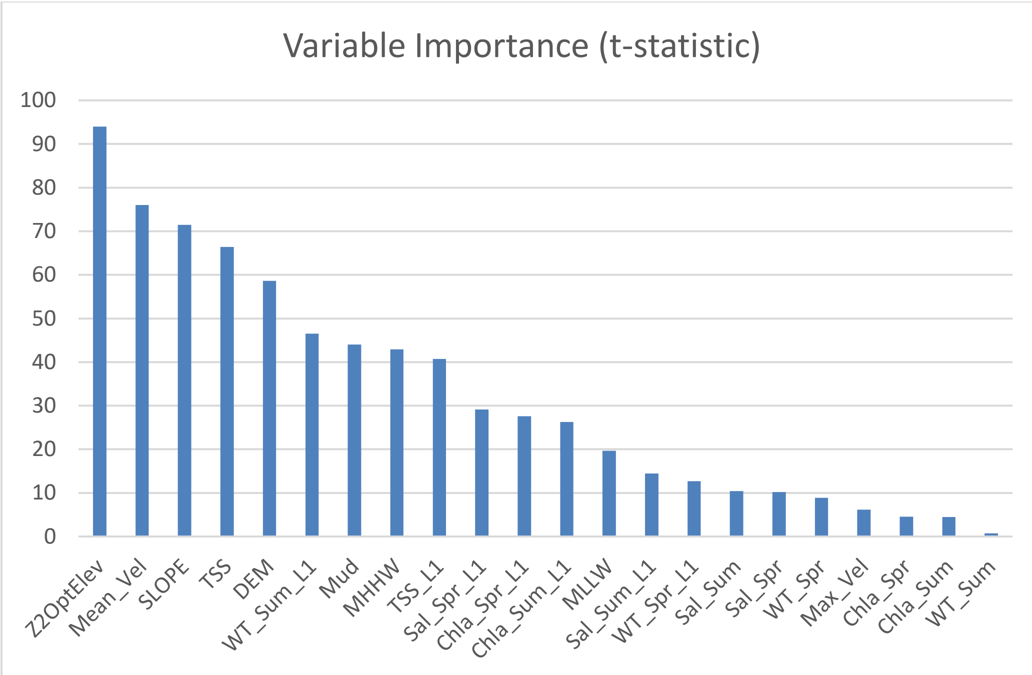


Figure 8. Relative variable importance for all spatial layers when all available inputs are included in the model

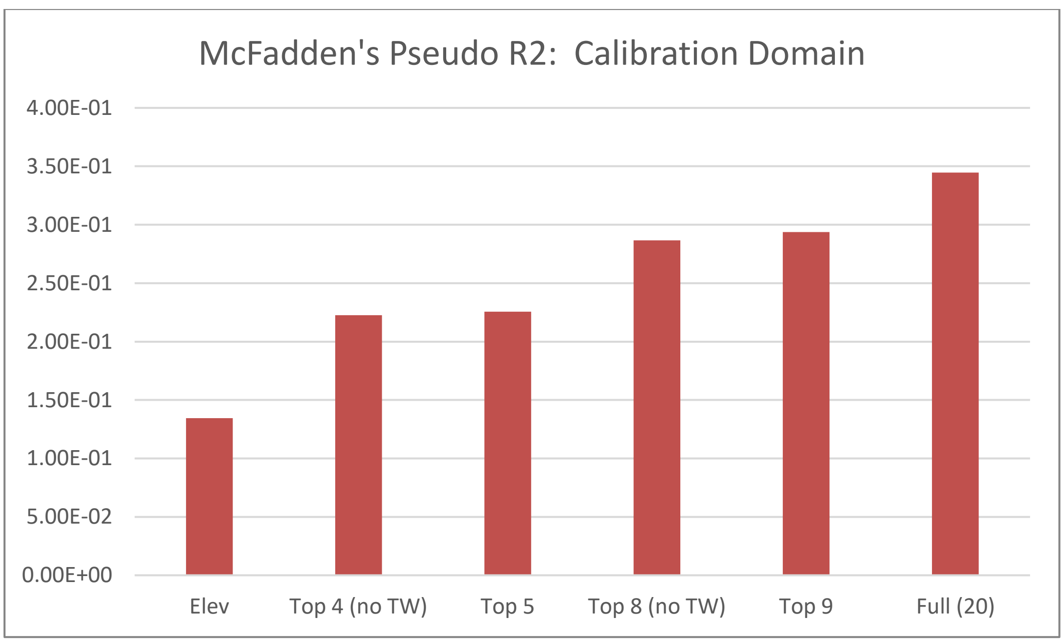


Figure 9. McFadden’s Pseudo R-Squared for Six Different Model Calibrations (TW = water temperature)

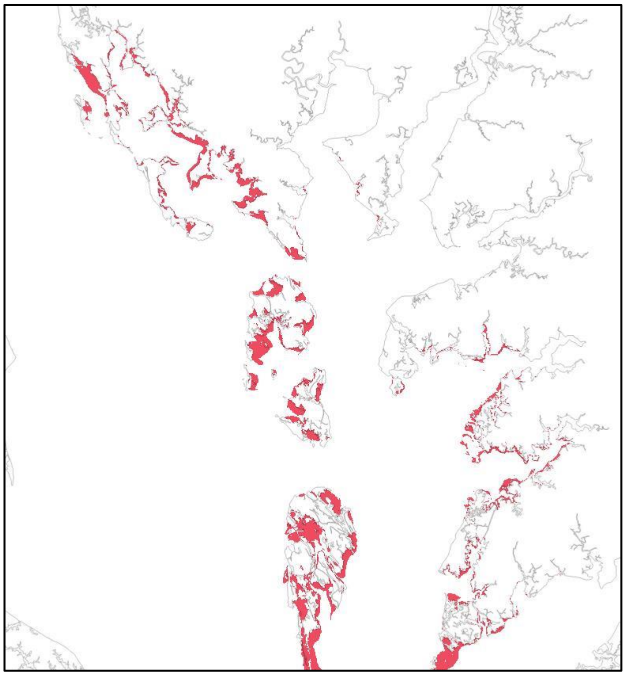


Figure 10. Observed SAV Footprint

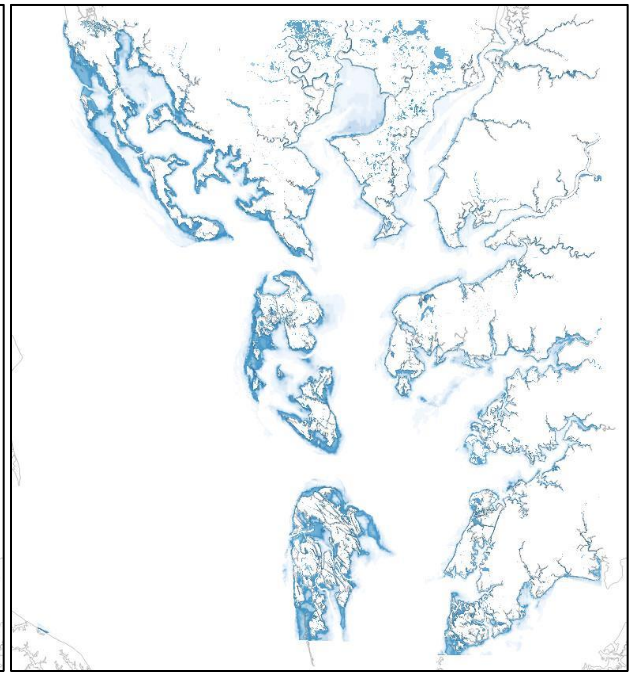


Figure 11. Calibration, Time Zero, Elevation Only

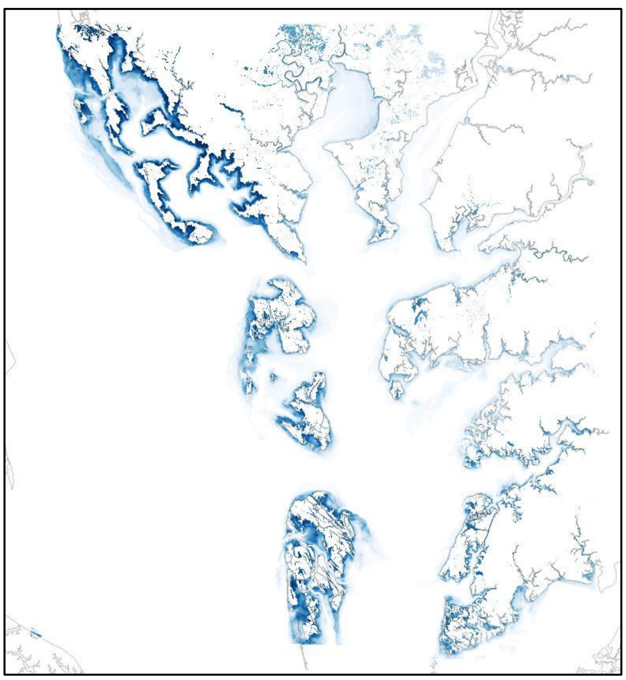


Figure 12. Calibration, Time Zero, Top 4 Parameters

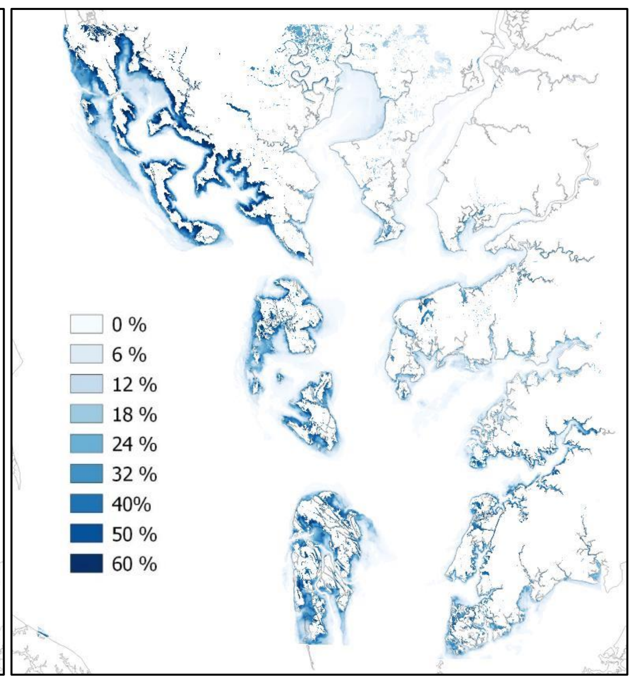


Figure 13. Calibration, Time Zero, Top 5 Parameters

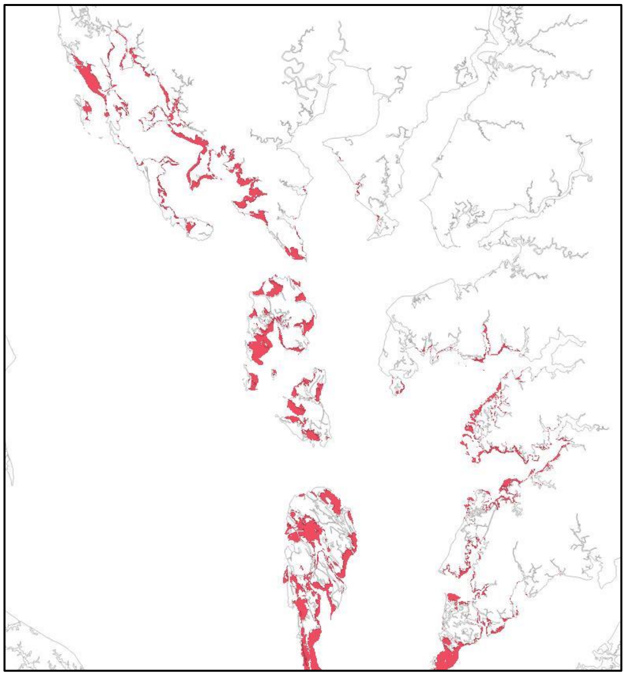


Figure 14. Observed SAV Footprint

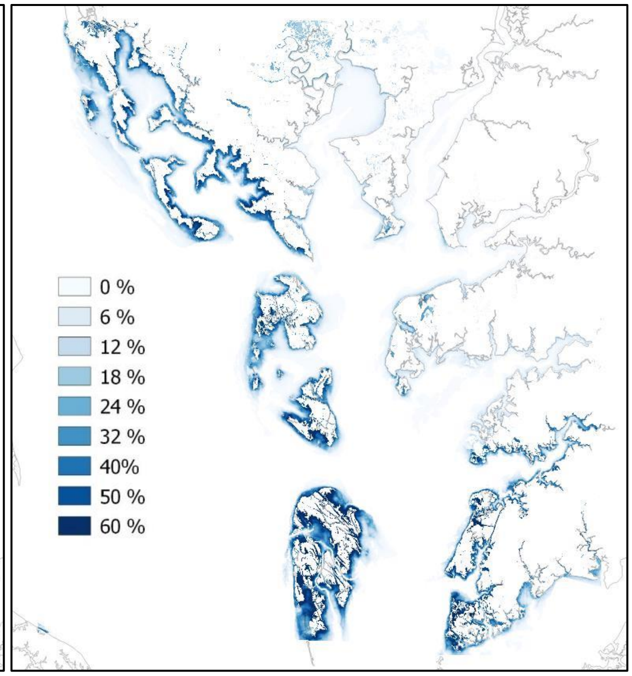


Figure 15. Calibration, Time Zero, Top 8 Parameters

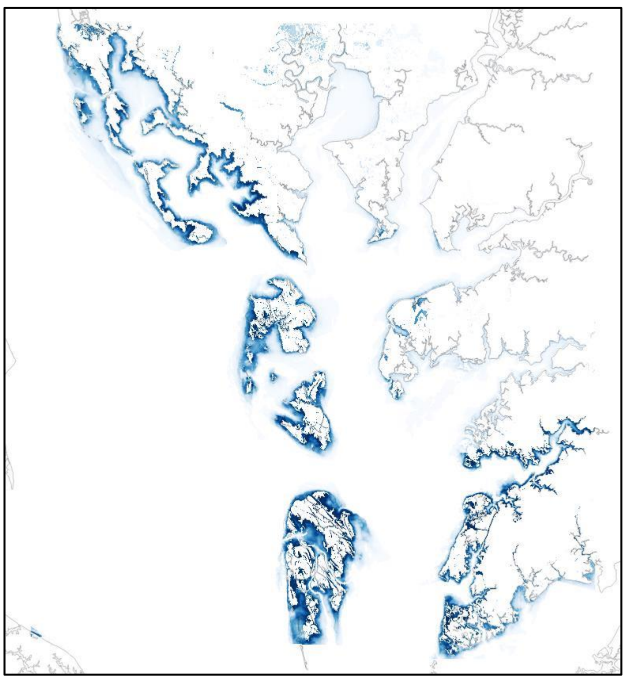


Figure 16. Calibration, Time Zero, Top 9 Parameters (Selected)

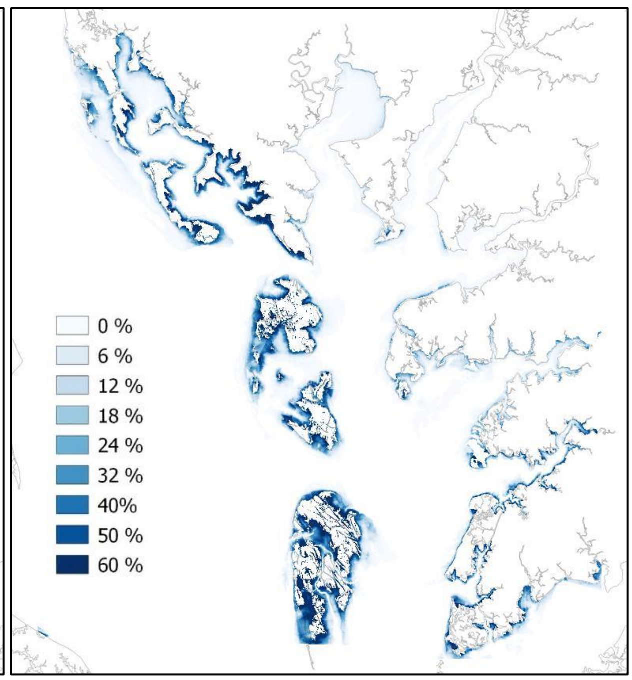


Figure 17. Calibration, Time Zero, All 20 Parameters

1.4 Model Validation

The elevation-only, and top 4-, 5-, 8-, and 9-parameter models were then applied to the validation area. The elevation-only model included the elevation input (DEM) and the vertical distance to optimal elevation, which was derived from the DEM. Elevation and vertical distance to the optimal elevation are considered one parameter because they are derived from a single elevation map. The top-4 model included the elevation inputs plus mean velocity, slope, and total suspended solids. The top 5 model included those inputs plus water temperature. The top 8 model included those inputs plus percent mud, distance to mean higher high water (MHHW), distance to mean lower low water (MLLW) and salinity. The two distance-to-shoreline variables (MHHW and MLLW) are both exported from SLAMM and are considered one parameter because they are very closely related. The top 9 model included those inputs plus chlorophyll *a*.

As it was not straightforward to calculate the pseudo R^2 for the validation error, a different model metric was examined: the mean prediction error across the study area. The prediction error for each cell was calculated by subtracting the predicted percent likelihood of SAV from 1.0 in cells with SAV presence. For cells without SAV presence, the percent likelihood of SAV represents the prediction error (as a “perfect” prediction would be zero percent likelihood).

For the calibration region, mean prediction error showed a similar pattern as the pseudo R^2 with decreasing marginal benefits of adding each parameter, especially after the eighth or ninth parameter was added (blue bars in Figure 18). For validation, however, the results were different. The elevation-only model actually outperformed the “top 4” and “top 5” models in terms of prediction error, but as parameters were added, the model predictions improved. Interestingly, the “top 9” model performed almost equally well in the calibration and validation sites. Therefore, that model was chosen for use in model projections.

Figures 18-21 show spatial results for each of these tested models, and the “top 9” model performs well in predicting the locations and magnitude of SAV presence within the validation zone.

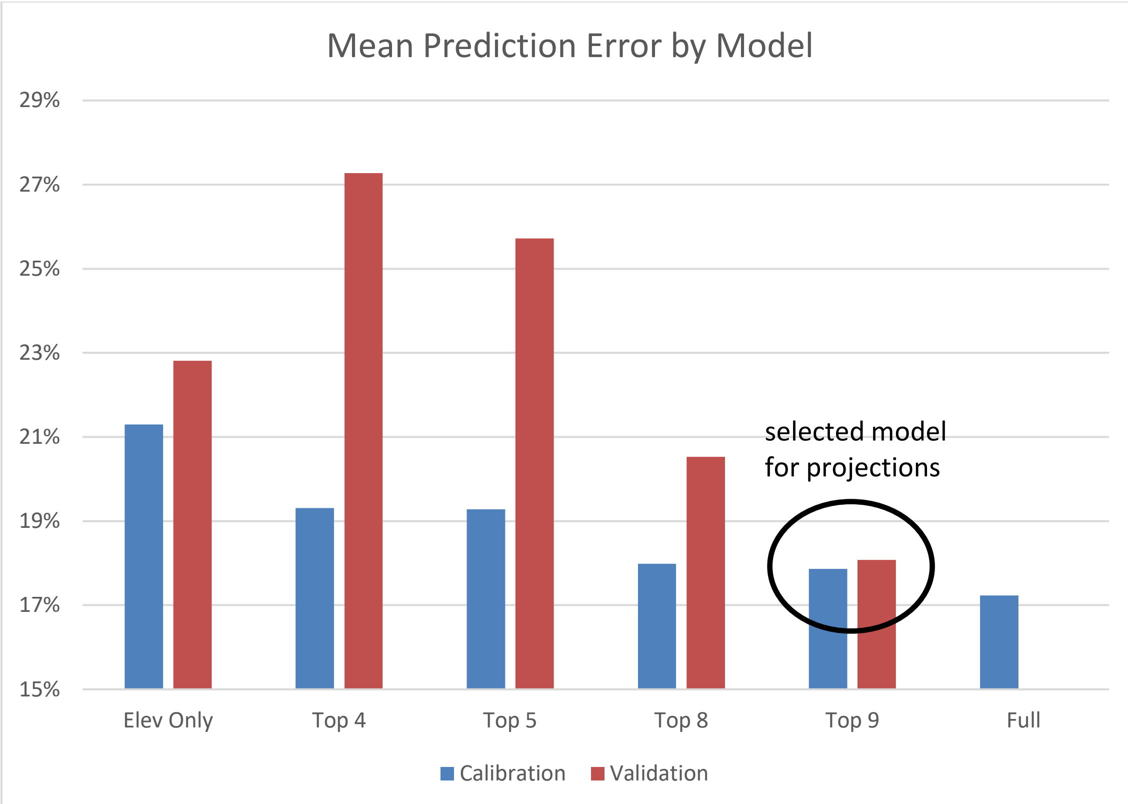


Figure 18. Mean Prediction Errors across models in the calibration and validation study areas

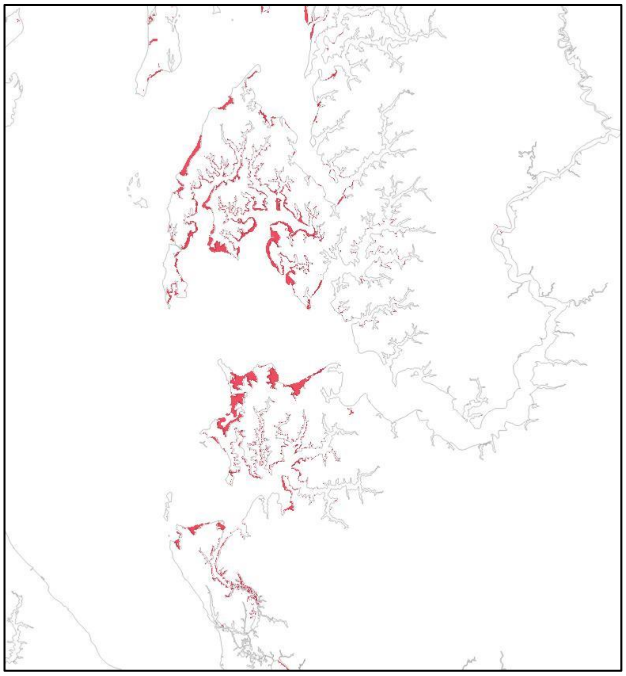


Figure 19. Validation Observed SAV Footprint

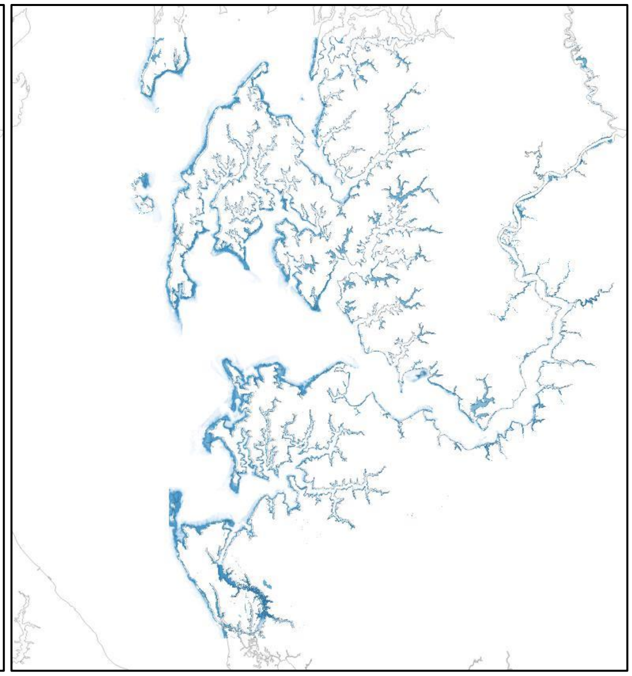


Figure 20. Validation, Time Zero, Elevation Only

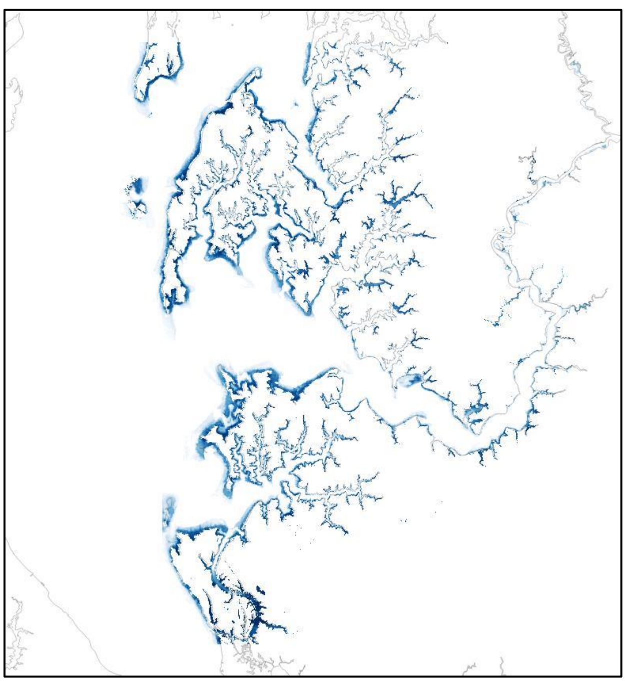


Figure 21. Validation, Time Zero, Top 5 Parameters

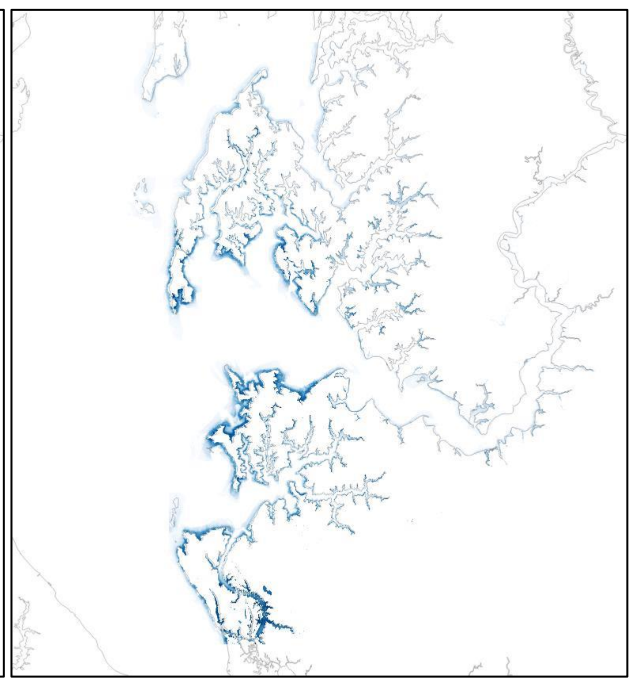


Figure 22. Validation, Time Zero, Top 9 Parameters (Selected)

1.5 Selected Model

As discussed above, the selected model was the "top 9" parameter model.

While the SLAMM SAV model is not a mechanistic model, it was reassuring that model coefficients matched the expected relationship to each model input. For example, the model suggested that SAV presence is reduced by high velocity, high slopes, and high TSS (negative coefficients). On the other hand, spring water temperature is positively correlated with SAV presence (positive coefficient). The model's coefficients are listed here and summarized in Figure 23. Surface vs. bottom layers were chosen based on variable importance (Figure 8).

(Intercept)	-12.00
DEM	0.61
Vertical Dist. to Optimal Elev.	-1.56
Mean Velocity	-27.54
Slope	-0.68
TSS, Bottom Layer	-0.23
Water Temp. Spring, Surface	1.28
Percent Mud, Substrate	-8.9E-03
Distance to MHHW	-9.9E-04
Spring Salinity, Surface	0.24
Summer Chl. *a*, Surface	-0.35
Distance to MLLW	-6.3E-04

Note that this is called a "nine parameter model" even though there are 11 coefficients, because the two distance to shoreline variables (MLLW and MHHW) are both exported from SLAMM and are very closely related and the two elevation parameters (DEM and "Z2OptElev" or the vertical distance to the optimal SAV elevation) are derived from a single elevation map.

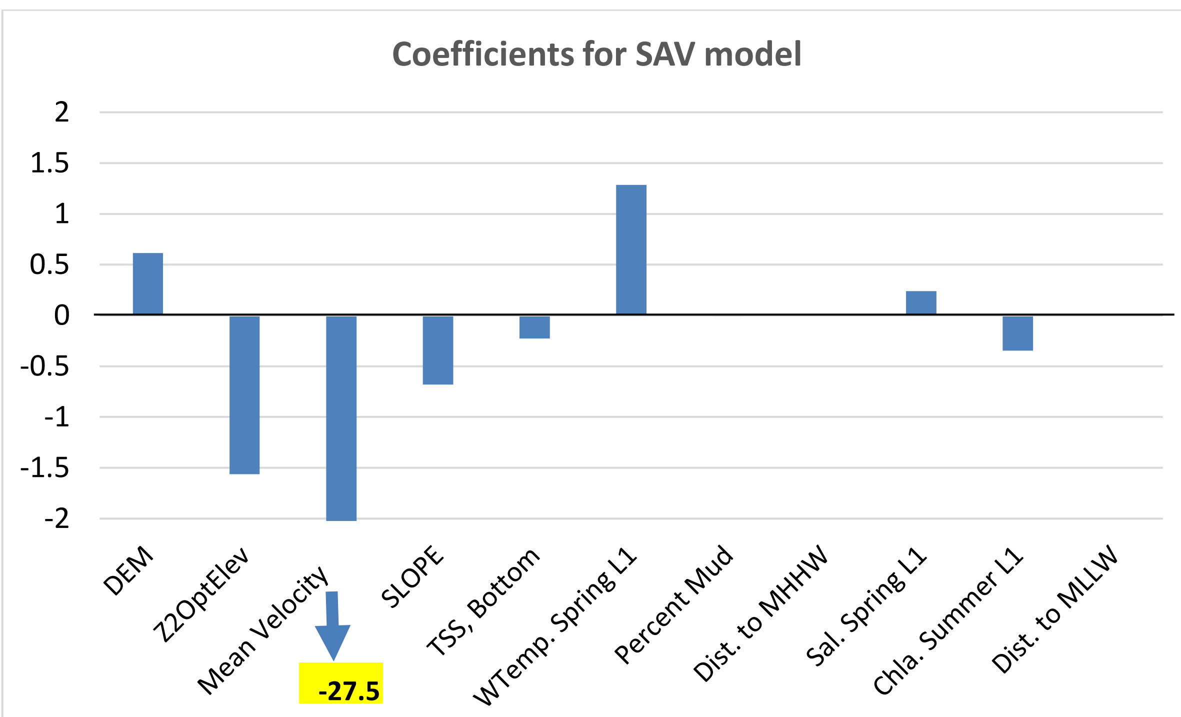


Figure 23. Model Coefficients for the selected SAV model

1.6 Model Projections

Model projections under conditions of SLR were run in the calibration and validation study areas. Projections were run with sea-level rise starting in the year 2010, which was assumed to represent the "current condition." Modeled scenarios and years included sea-level rise projections of approximately 0.4 meters by 2040-2050, 1 meter by 2070, and 2 meters by 2100 (Table 1). Projections were taken from *Sea-level rise: Projections for Maryland 2018* (Boesch et al. 2018), using SLR estimates relative to the Cambridge tide-gauge station produced by Robert Kopp. Shorthand names were produced for each SLR scenarios, e.g., "1% probability, stabilized emissions." The first part corresponds to the likelihood of the scenario (1% probability SLR meets or exceeds estimated value) and the second part refers to the emissions pathways after 2050. The projections for relative sea-level rise in Maryland through 2050 are based on the Stabilized Emissions pathway. Beyond 2050, Boesch et al. 2018 provides projections for Growing (RCP8.5), Stabilized (RCP4.5), and Paris Agreement (RCP2.6) emission pathways. The Upper Limit of Likely Range scenario is based on the high-end or maximum of a range, rather than a single percent likelihood. See Figure 24 for further explanation of the Upper Limit of Likely Range scenario.

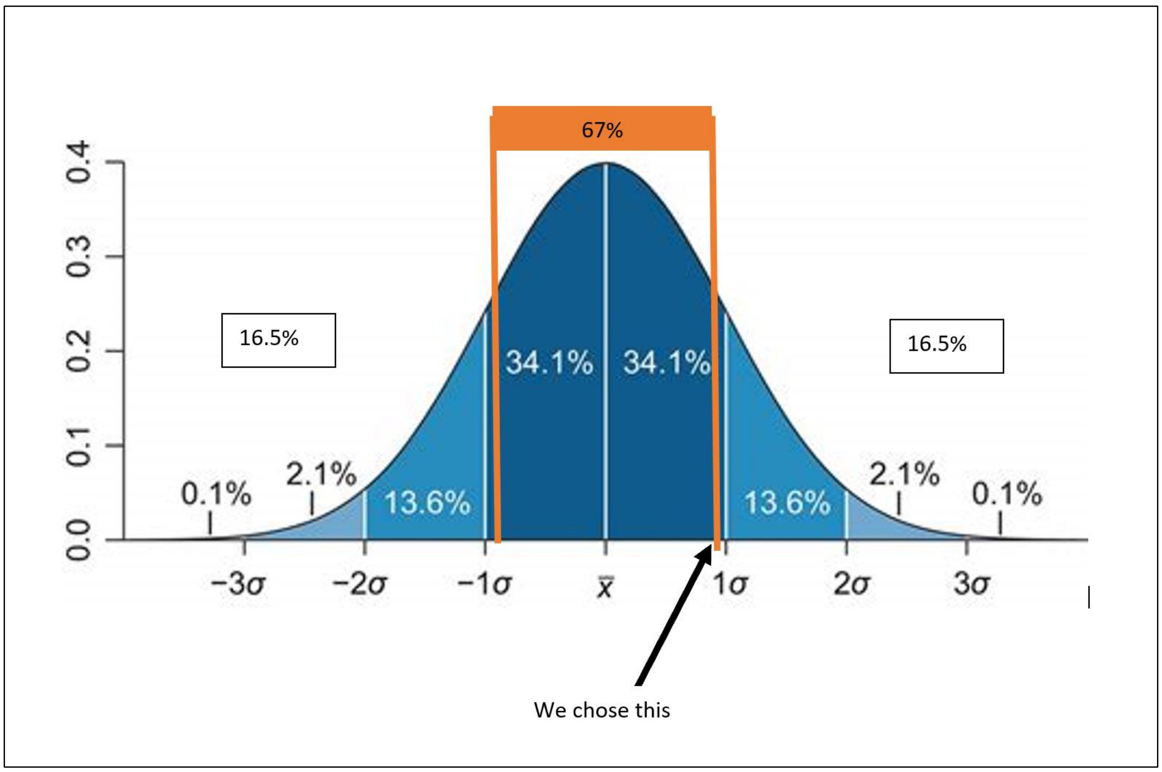


Figure 24. Upper Limit of Likely Range scenario.

The "likely range" is defined as the range which contains the central two thirds, or 67%, of the estimates of sea level rise, for a given emissions pathway. This range is centered on the mean and similar to the mean +/- one standard deviation (which would equate to 68% of estimates). We chose the high-end member of this 67% likelihood range, which corresponds to a 16.5% chance that SLR will meet or exceed that value

Table 1. SLR scenarios modeled

Year	SLR since 2010	Projection scenario
2010	0 m	Current conditions
2040	0.42 m	1% probability, stabilized emissions
2050	0.42 m	upper limit of likely range, growing emissions
2070	1.05 m	1% probability, growing emissions
2100	1.98 m	1% probability, growing emissions

To help understand the relative role of elevations, water quality, and water velocity, model projections were run in three different ways:

- A model incorporating "elevation only" was run to see where potential SAV habitat would be located on the basis of bed elevation alone;
- A model keeping "velocity constant" was run that included water quality and elevation datasets. This model helps show where potential SAV elevation habitat is not predicted to be colonized on the basis of water-quality data.
- A model projection was run incorporating elevation, water quality, and future predicted changes in water velocity. This is generally considered the model's projection.

For the calibration domain (Tangier Sound and vicinity), under 0.42 meters of SLR, Figure 25 suggests that about 50% of SAV habitat will be lost (yellow bars at 2040 and 2050). This is due to the combination of a reduction in elevation-appropriate habitat and water-velocity impacts. Figure 25 also shows that, based on elevation alone, SAV habitat could increase under 1 m of SLR (orange bar at 2070), but water quality in this potential new habitat does not suggest an expansion of SAV (grey bar at 2070). Furthermore, because of the addition of water velocity, loss rates of 60% are actually predicted to occur.

For the validation domain (Choptank River and vicinity), a similar story is told for 0.42 meters of SLR, with 54% of habitat predicted to be lost due to elevation and water velocity (Figure 26). Less elevation habitat is predicted to open up in 2070, but total predicted loss rates are also lower at 46%. Projection differences in the two sites seem to be driven by different water-quality and elevation gradients in the study areas.

Figure 25-32 show spatial maps of SAV predictions for model projections in both model domains. The full set of all spatial model outputs for the calibration and validation areas can be found in Appendix A of this document, including projection maps for all three tested models (elevation-only, velocity-constant, and model projections). GIS raster files (GeoTiff) of model inputs and outputs are also available upon request.

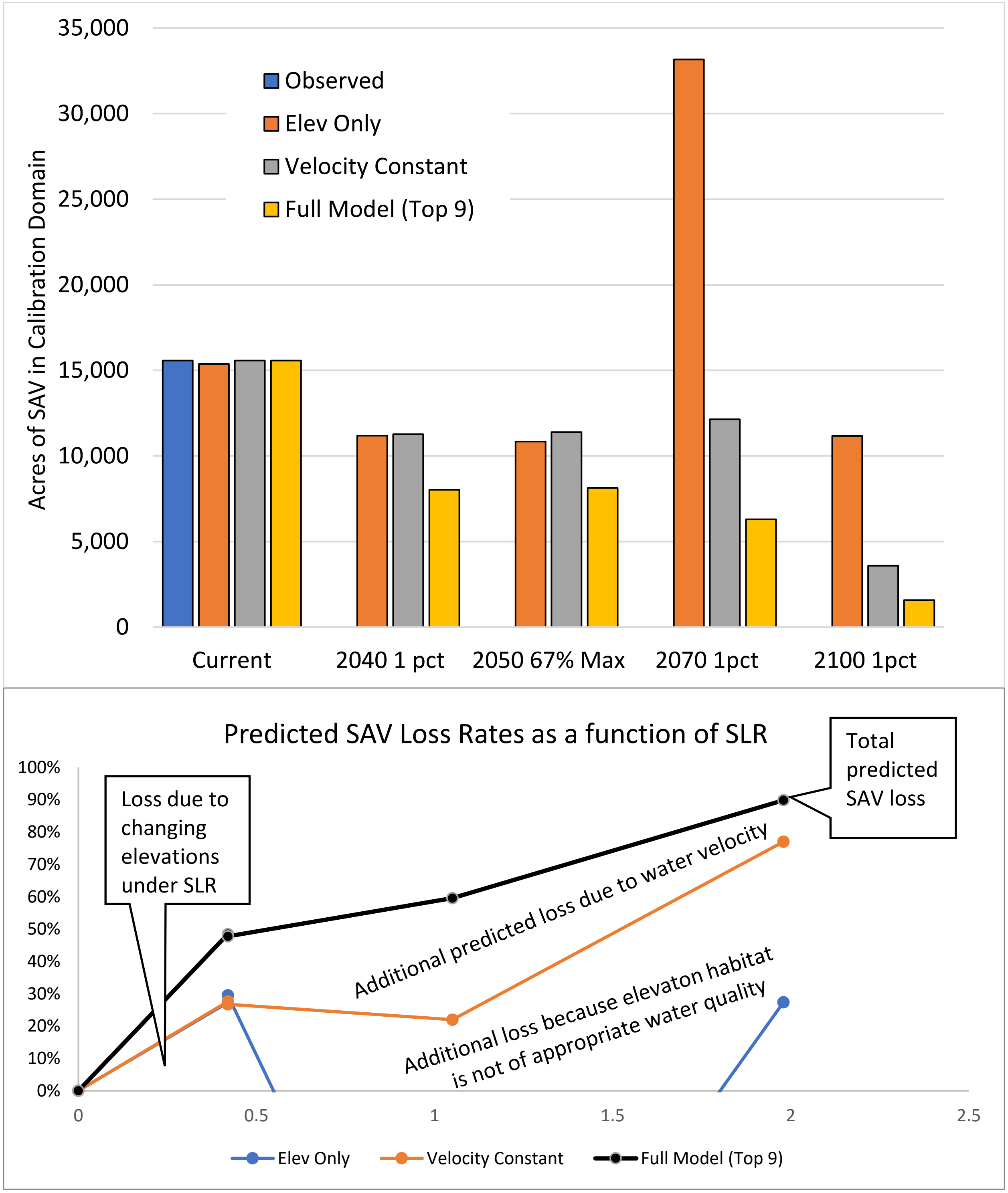
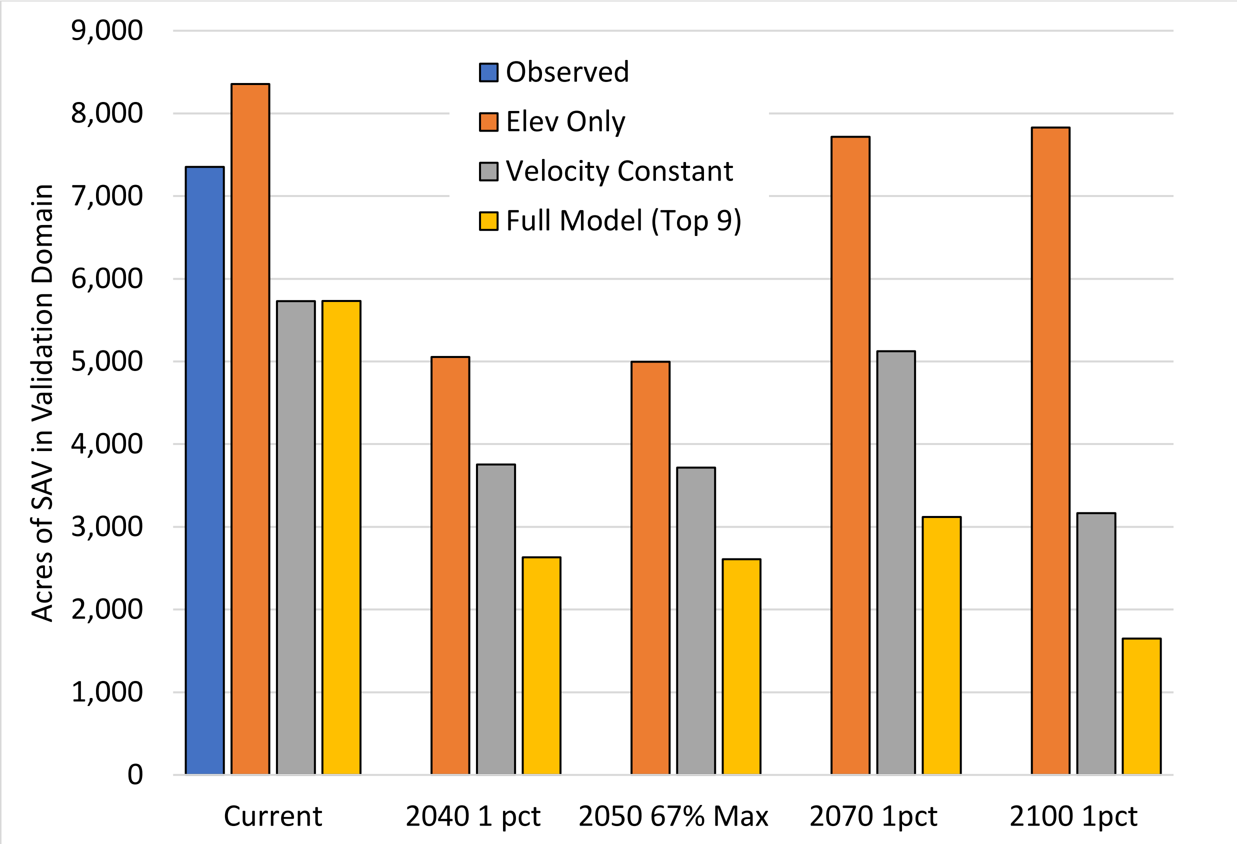


Figure 25. Summary of model projection results for the calibration region. Acre predictions (top) and predicted loss rates (bottom).



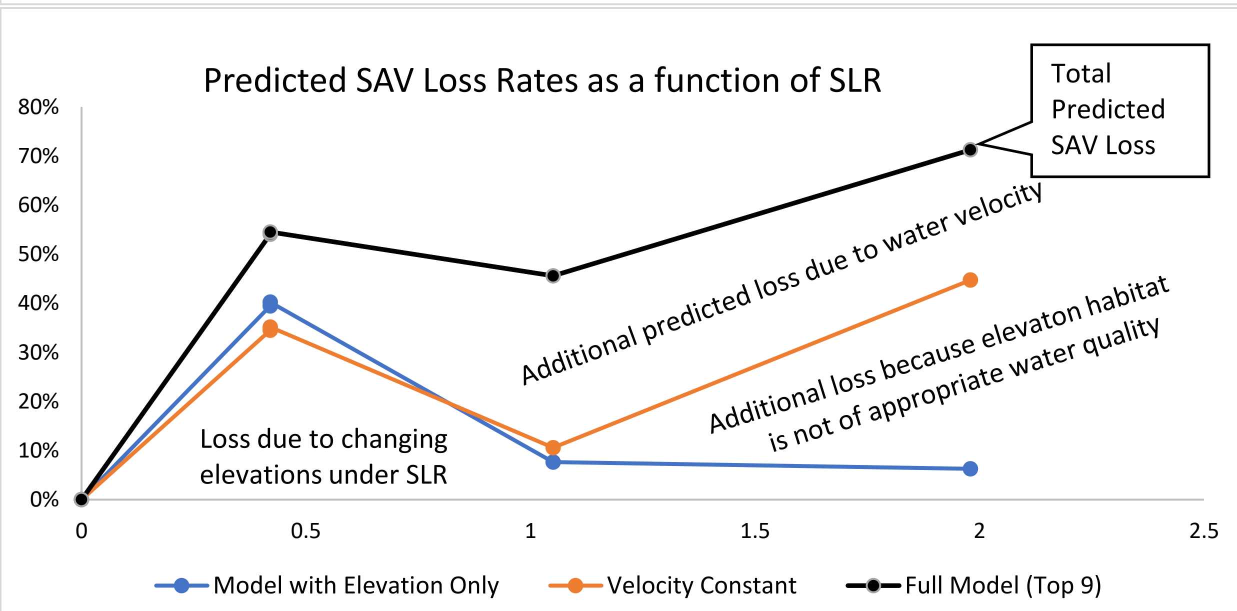


Figure 26. Summary of model projection results for the validation region. Acre predictions (top) and predicted loss rates (bottom).

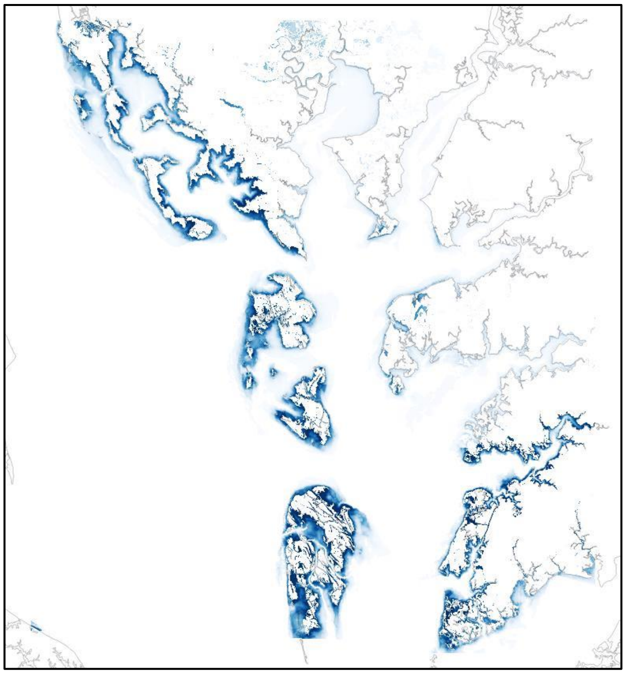


Figure 27. Calibration, Time Zero, Top 9 Variables (Selected Model)

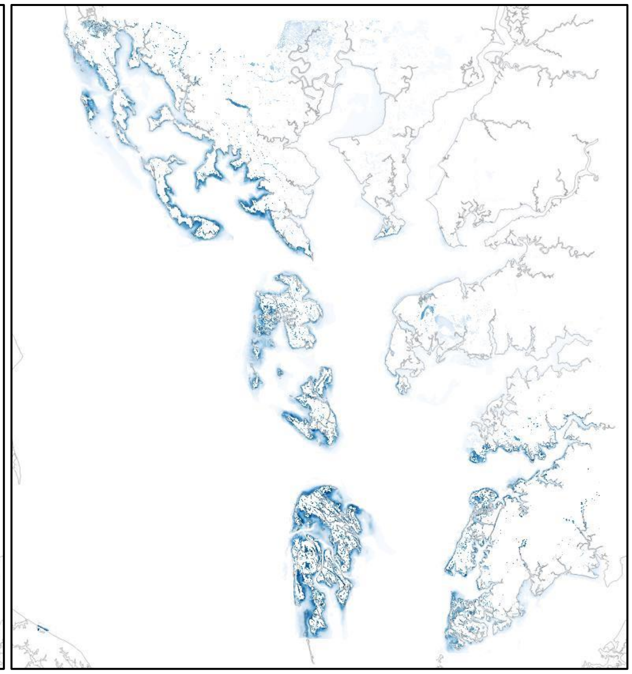


Figure 28. Calibration Site Projection, 2050, 0.42 m SLR

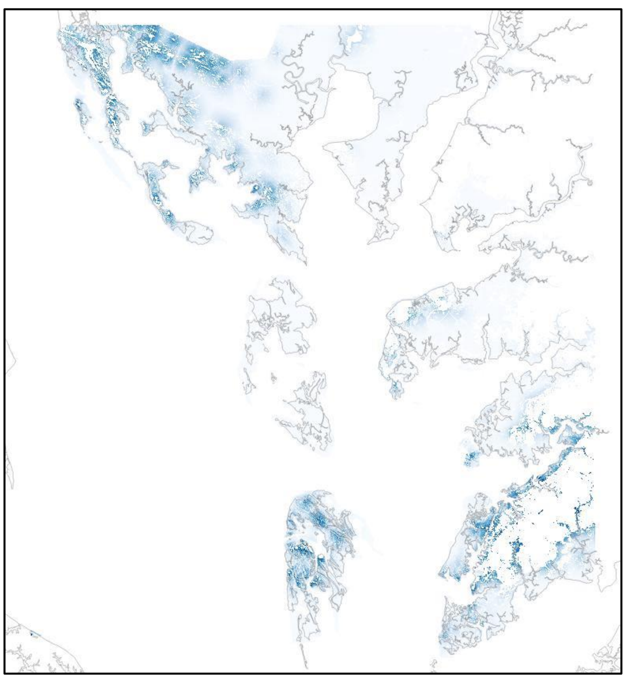


Figure 29. Calibration Site Projection, 2070, 1.05 m SLR

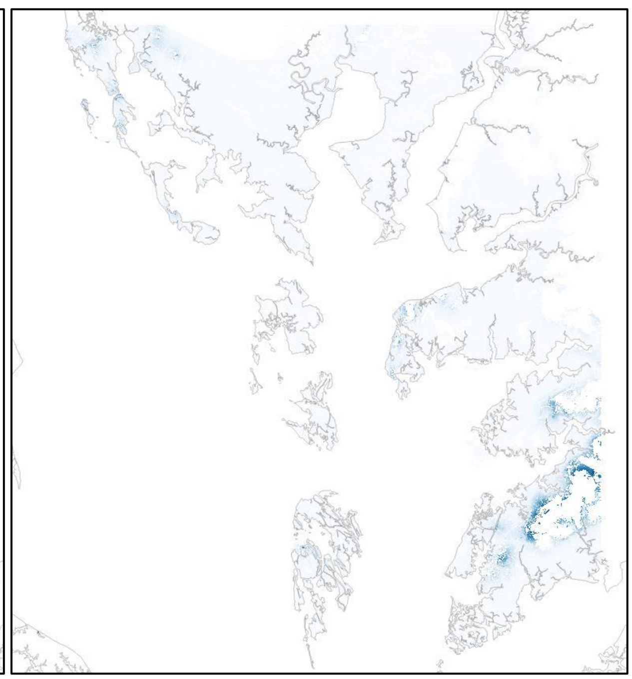


Figure 30. Calibration Site Projection, 2100, 1.98 m SLR

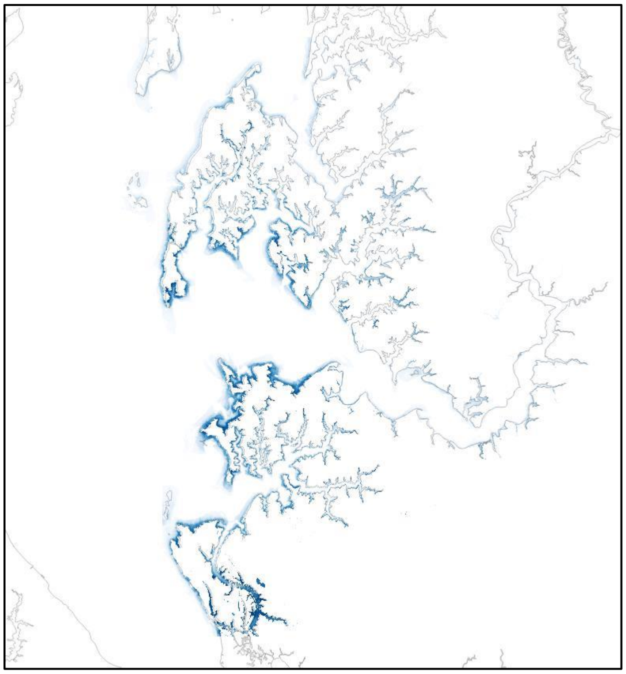


Figure 31. Validation, Time Zero, Top 9 Variables (Selected Model)

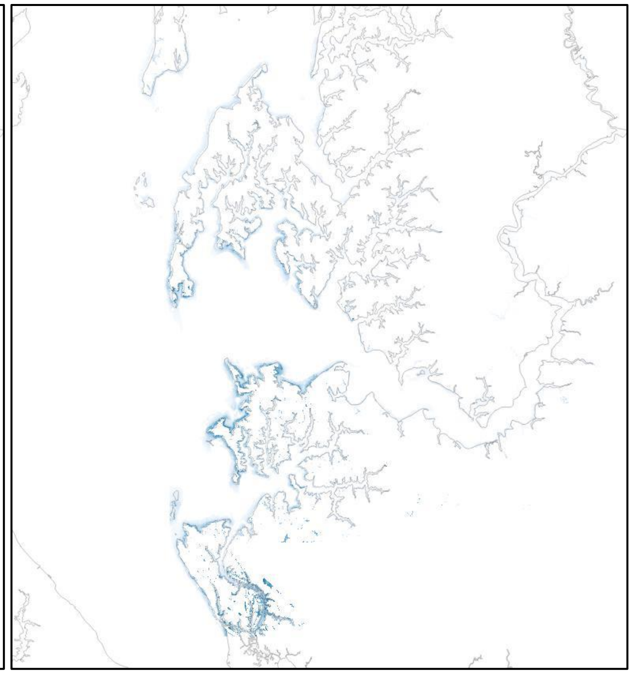


Figure 32. Validation Site Projection, 2050, 0.42 m SLR

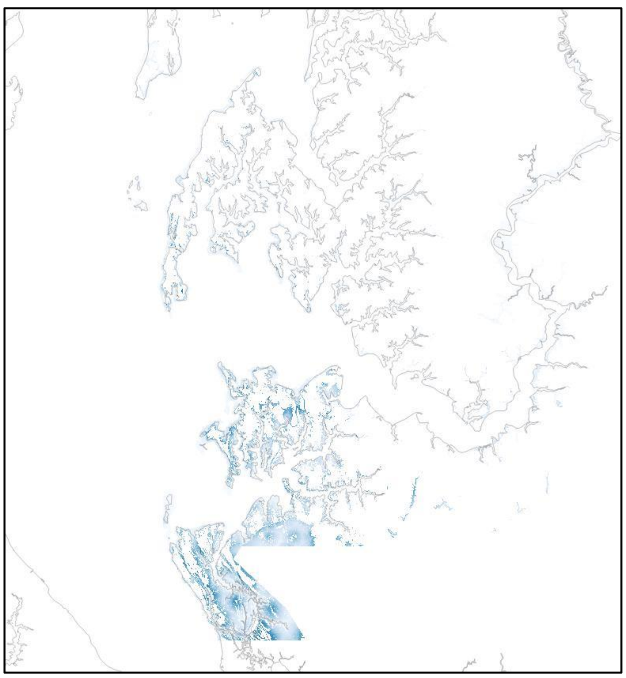


Figure 33. Validation Site Projection, 2070, 1.05 m SLR

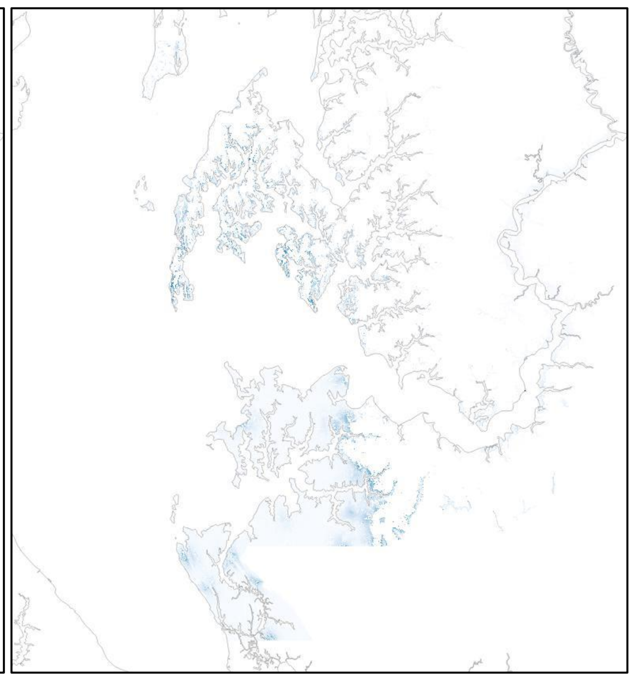


Figure 34. Validation Site Projection, 2100, 1.98 m SLR

2 Results Summary

With the addition of site-specific water quality and water velocity data, the SLAMM SAV model was able to successfully predict SAV absence or presence within two locations in the Chesapeake Bay.

There were three primary inputs to the empirical model that was used to predict SAV presence:

1. Physical properties such as depth, slope, and distance to shoreline
2. Water velocity
3. Measured water quality data such as clarity (TSS and Chl a), salinity, water temperature, and bottom substrate.

As there was an abundance of water-quality data the model was tested with different data sets from different seasons (summer vs. spring) and water depths (top vs. bottom). The variables with the strongest relationship to SAV were selected.

Derived box plots and model coefficients suggest that abundance of SAV varies as expected with each of the model's input variables.

For example:

- SAV has an optimum depth as expected relative to mean tide level (about half a meter of depth)
- SAV prefers low-velocity
- SAV prefers clear water over turbid water
- SAV prefers near-shoreline locations
- SAV is more abundant in locations with a lower mud component of bottom substrate
- SAV is more abundant in higher-saline locations

A model was selected with 11 inputs representing nine parameters as a top performer in both model calibration and model validation. Modeling with all available model inputs was potentially problematic, both in terms of the effort required to find and prepare data for the model, and also because highly correlated model inputs can potentially be problematic within model projections.

In rough order of their importance to model projections, the nine model parameters were:

- Elevation (including distance to optimal elevation)
- Water Velocity (mean during non-storm event)
- Slope
- Total Suspended Solids (summer, bottom)
- Water Temperature (summer, surface)
- Percent Mud in Substrate
- Distance to Shoreline
- Salinity (spring, surface)
- Chl. *a* (spring, surface)

The SAV model was calibrated using Tangier Sound data and then the same model performed well in a validation site at the mouth of the Choptank river. This model calibration was then used for model projections in both Choptank and Tangier Sound.

For model projections

1. Physical properties such as water depth, slope, and distance to shoreline were calculated from SLAMM simulations
2. Water velocity was estimated from project hydrodynamic modeling
3. Measured water quality data were extrapolated over dry land and were then kept constant under SLR.

Model projections were run in three different ways:

- A model incorporating "elevation only" was run to see where potential SAV habitat could open up on the basis of bed elevation
- A model keeping "velocity constant" was run to see where potential SAV elevation habitat were not predicted to be colonized on the basis of water-quality data.
- A model projection was run incorporating elevation, water quality, and future predicted changes in water velocity.

Model projections were run under SLR of approximately 0.4 meters by 2040-2050, and also some worst-case scenarios (1 meter by 2070 and 2 meters by 2100). Looking at 2050 results, with a 0.42-meter SLR, projections at both locations indicate that SAV abundance will be reduced by about a factor of two (48% in the calibration domain and 54% in the validation domain.) Looking further into the future with higher SLR (2070 with 1 meter of SLR), elevation-only models suggest that more habitat for SAV will become available as marshes are lost and low-lying dry lands become permanently inundated. However, due to a combination of water-velocity and water quality considerations, the models project losses in 2070 as well (60% losses in the calibration domain and a 46% loss in the validation domain). Under 2 meters of SLR in 2100, the calibration domain suggests a 90% loss of SAV in Tangier Sound and the validation domain suggests a 71% loss in the Choptank River. Obviously, the assumptions about water quality are most uncertain and subject to error under this type of a projection. Additionally, when considering higher SLR scenarios, there is uncertainty about whether the substrate of current marsh beds would provide a suitable habitat for SAV; marsh soils are high in peat and SAV prefers sandy soils.

Further testing would be required to extend this model to all of the Chesapeake Bay and Atlantic Coastal Bays of Maryland. Interpolated water quality data from the Chesapeake Bay Habitat Tool are not available for Maryland's Coastal Bays, so this region would need to be excluded or an alternative data source developed. The calibrated model can first be applied to new spatial domains and model performance statistics can verify the generality and usability of the model. If the model does not perform well, adjustments may need to be made in terms of optimal depth as a function of tide range, for example. Further testing would be required to see if a single set of model parameters can be successfully applied across the entirety of the Chesapeake Bay.

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Appendix A: Full Set of Spatial Model Results

Provided in a separate file

Appendix B: Full set of Model-Input Box Plots

Provided in a separate file