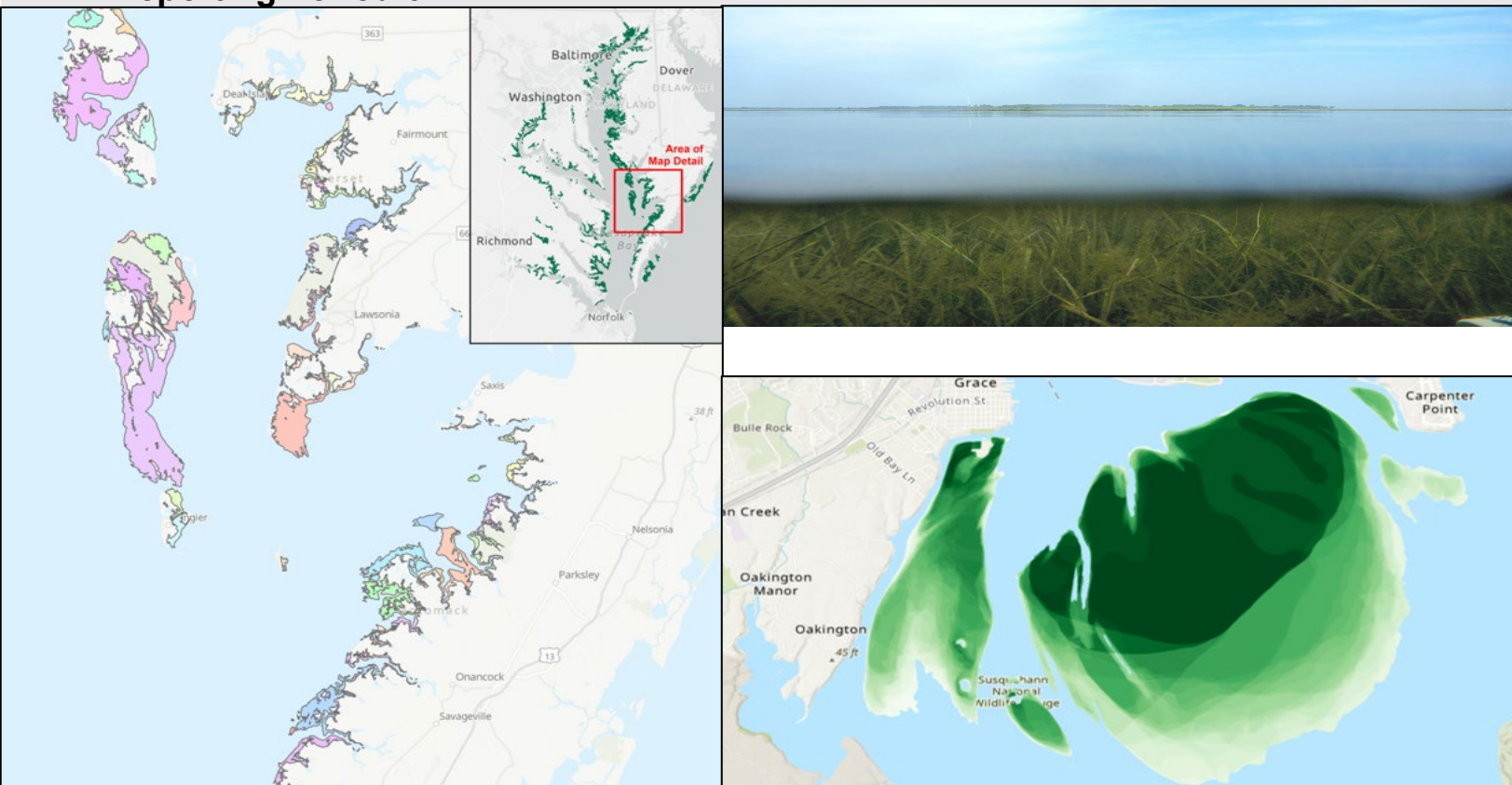


Protecting Chesapeake Bay Submerged Aquatic Vegetation (SAV) Given Changing Hydrologic Conditions: Priority SAV Area Identification and Solutions Development

Reporting Period 6



February 14, 2025

Scope of Work 2: Protecting Chesapeake Bay Submerged Aquatic Vegetation (SAV) Given Changing Hydrologic Conditions: Priority SAV Area Identification and Solutions Development

February 14, 2025

PRESENTED TO

Chesapeake Bay Trust

108 Severn Avenue
Annapolis, MD 21403

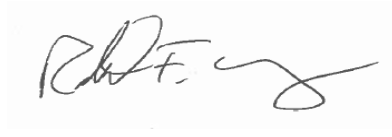
PRESENTED BY

Tetra Tech, Inc.

10711 Red Run Blvd.
Suite 105
Owings Mills, MD 21117

P (410) 356-8993

Prepared by:



Robert F. Murphy
Marine Ecologist/Project Manager

7/15/2024

Reviewed by:



Cole Blasko
Environmental Scientist

7/15/2024



EXECUTIVE SUMMARY

The Chesapeake Bay is the largest estuary in North America, providing immense ecologic and economic benefits such as shipping ports, seafood, and recreational opportunities. The estuary is fed by major river systems, each creating smaller sub-estuaries that reflect the conditions of watershed features. In turn, land use patterns have a large effect on the diverse ecosystems of the Chesapeake Bay and its living resources. Submerged aquatic vegetation (SAV) is a critical habitat found in nearshore waters of the Chesapeake Bay where it provides a wide range of ecosystem services including, but not limited to, oxygenation of the water column, sediment stabilization, wave attenuation, and provision of critical habitat for a large variety of organisms. Approximately 16 species of SAV have been documented in the Chesapeake Bay, ranging from obligate freshwater species to full salinity true seagrasses. SAV populations throughout the Chesapeake Bay have declined over the past century due primarily to decreasing water quality as a result of eutrophication, sedimentation, and direct anthropogenic disturbance (e.g. dredging). As a consequence, land managers have increasingly implemented the installation of a variety of best management practices (BMPs) that intend to curb and reduce the flow of nutrients and sediments into the Chesapeake Bay and its tributaries with the intent to improve water quality in support of living resources. However, to date, there has been no systematic study that evaluates the effectiveness of BMPs on habitat, including SAV. Here we present an approach that identifies priority SAV beds and a geospatial analysis of BMPs that likely have the largest effect on SAV persistence.

Prioritization of SAV beds necessitated a discussion for the Chesapeake Bay Program SAV Workgroup to reach a consensus on those attributes that ought to be considered important parameters for beds. Tetra Tech developed and implemented a framework for a weighted decision tree that included eight (8) weighted metrics that defined priority SAV beds. The first seven criteria (bed size, bed maturity, bed density, species richness/diversity, rare/sensitive species, habitat value, and species representativeness) are combined using a weighting system and composite index score. These preliminary beds were then manually assessed under the final criteria of distribution. This approach yielded 12 priority beds, and their catchments, that were used to identify BMPs most likely to influence SAV bed health.

The methodology for identifying BMPs that are mostly likely to lead directly to SAV protection, conservation, and restoration revolves around the integration and analysis of ecological data using machine learning modeling techniques. Four machine learning models were developed in Python and trained and tested using BMP data as well as other ancillary environmental data from 2008 through 2022. More specifically, each machine learning model was trained and tested to predict one of four SAV health indicators: (1) species richness, (2) sensitivity/rare species, (3) bed size, and (4) bed density. Streamflow, also referred to as stream discharge, is an important transport mechanism for nutrients and other constituents (e.g., sediment) across the landscape, and is an example of an ancillary environmental dataset included in the machine learning model analysis. The results from the four models can be summarized by two primary categories: (1) the predictive accuracy across different SAV health indicators and (2) insights into which environmental factors most significantly impact those SAV health indicators. Many of the BMPs assessed in this study are used to manage and control the volume of flows and flux of sediments and nutrients into tributaries that eventually drain to Chesapeake Bay. Interestingly, annual minimum daily discharge was among the most important variables for predicting all four SAV health indicators. As such, county-level reported BMPs that attenuate peak flows via reductions in surface runoff is a management strategy that should be considered as a priority to maintaining healthy SAV habitats in the Chesapeake Bay.

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APPENDICES

Appendix A: Additional Priority Beds – Tangier Sound

Appendix B1: Partial Dependence Plots for Species Richness (provided as separate PDF file)

Appendix B2: Partial Dependence Plots for Rare/Sensitive Species (provided as separate PDF file)

Appendix B3: Partial Dependence Plots for Bed Size (provided as separate PDF file)

Appendix B4: Partial Dependence Plots for Bed Density (provided as separate PDF file)

ACRONYMS/ABBREVIATIONS

Acronyms/Abbreviations	Definition
BMP	Best Management Practice
CART	Classification and Regression Tree
CAST	Chesapeake Assessment Scenario Tool
CBP	Chesapeake Bay Program
GIS	Geographic Information System
HUC	Hydrologic Unit Code
IEI	Index of Ecological Integrity
MRLC	Multi-Resolution Land Characteristics
MSE	Mean Squared Error
NAD	North American Datum
NHD	National Hydrography Dataset
NLCD	National Land Cover Database
PB	Priority Bed
PB ID	Priority Bed Identification Number
PDP	Partial Dependence Plot
R ²	R-squared
RCOA	Regional Conservation Opportunity Areas
SAV	Submerged Aquatic Vegetation
TN	Total Nitrogen
TP	Total Phosphorus
USGS	United States Geological Survey
UTM	Universal Transverse Mercator
VIMS	Virginia Institute of Marine Science
VIP	Variable Importance Plots

1.0 PRIORITY SAV BEDS

The first objective was to identify ten priority SAV beds based on criteria developed with the Steering Committee. The methodology and results of the bed prioritization is presented below.

1.1 METHODOLOGY AND DECISION TREE

SAV extent is transient nature due to various environmental, climatological, and seasonal factors. As such, preprocessing of SAV bed spatial data was required before applying prioritization criteria. The spatial extent of the past six years of SAV bed data were used to establish the initial bed footprints upon which the criteria were applied. These six years include the most recent spatial data available (2022) and extend back to when SAV extent and density was at its greatest (2017). These years therefore include the conditions under which future SAV beds will be subject to and are appropriate for establishing bed footprints to be prioritized under this analysis.

Other spatial considerations were made to aggregate beds to a scale that is appropriate for conservation. Over 240,000 bed polygons resulted from the union of the 2017 – 2022 data discussed above. These beds were dissolved so that overlapping or adjacent bed boundaries were combined into 5,067 larger contiguous beds. Furthermore, a threshold of 5 acres was set as it is the minimum area that would be considered for conservation. Beds smaller than this threshold were grouped with the nearest bed larger than the threshold. It is important these small beds less than 5-acres are not discarded because conservation practices may be applied to and/or impact groupings of SAV beds. The 5-acre threshold resulted in 1,555 grouped/aggregated beds. This is a reasonable number upon which the prioritization criteria can be applied. Final aggregated beds are presented in Figure 1.

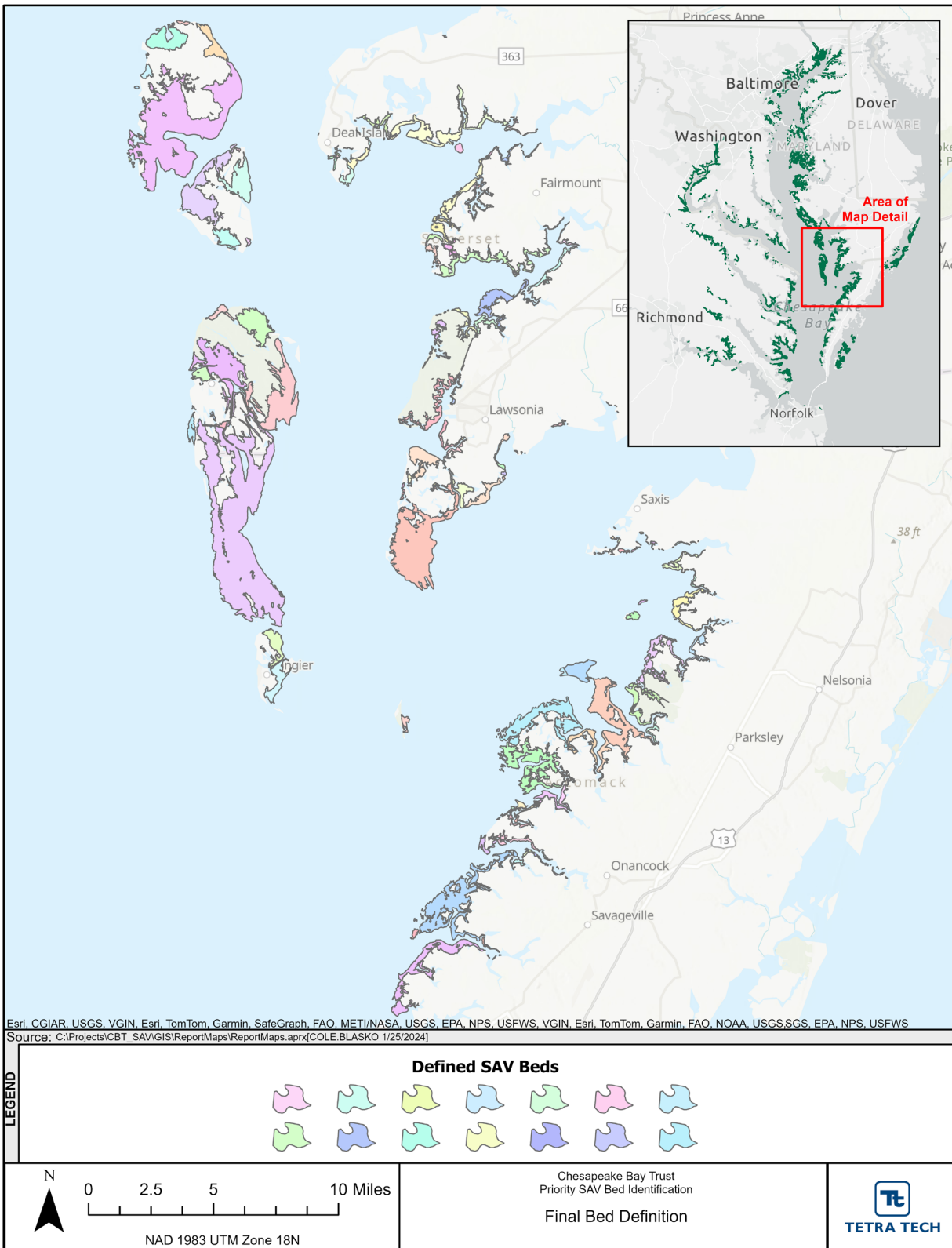


Figure 1. Example of bed aggregation to define final SAV beds

1.2 DECISION TREE CRITERIA AND INDICES

A decision tree approach was utilized to account for eight different prioritization criteria (Figure 2). The first seven criteria (*Bed Size*, *Bed Maturity*, *Bed Density*, *Species Richness/Diversity*, *Rare/Sensitive Species*, *Habitat Value*, and *Representativeness*) are combined using a weighting system and composite index score. A threshold of 0.9 determines which beds are preliminarily prioritized. This threshold was chosen based on the distribution of the composite index and yielded 114 preliminary beds. These preliminary beds were then manually assessed under the final criteria of *Distribution*. Each criterion is discussed in detail in Sections 1.2.1 through 1.2.8 below and criteria results are presented in Section 1.3. Preliminary bed results and priority bed selection are discussed in Section 1.4.

Overall, weighting of each criterion relied on best professional judgement of the project team and input from the Steering Committee. *Habitat value* was given the highest weight since ultimately, SAV beds are desirable as habitat for other living resources. *Bed density* was given a lower rating, but higher than some other criterion as density also implies excellent growth conditions and the ability to slow water flow and reduce suspended sedimentation. Each criterion was weighted corresponding to its relative importance in contributing to SAV bed protection. *Bed Size* was weighted rather low at 10% because size heavily influences the other criteria and will therefore be accounted for indirectly under those weighted scores. For example, species richness/diversity is likely to be greater in larger beds. *Species Richness* and *Sensitive/Rare Species* were each scored the same at 10%, given the relative importance of both. These criteria reflect SAV biodiversity and are inter-related. *Bed Maturity* was also scored at 10% as this attribute reflects longevity of a particular bed, demonstrating a favorable location in the Bay.

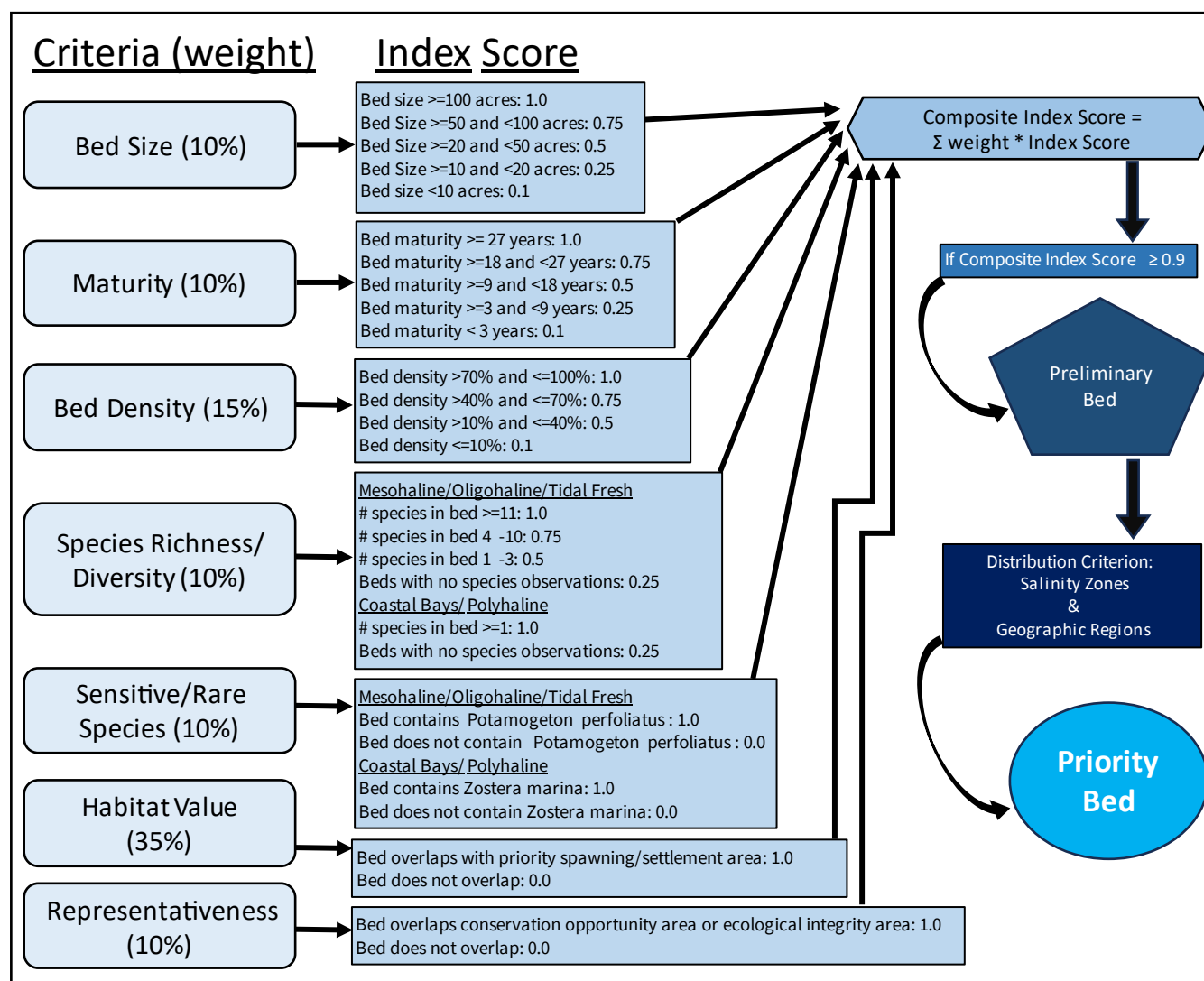


Figure 2. Decision tree schematic

1.2.1 Bed Size

SAV bed size is important in an ecological context as larger acreage equals greater habitat provision. Furthermore, since SAV provides ecosystem benefits including wave dampening, sediment retention and stabilization, larger beds are considered more valuable (De Boer 2007; Ward et al. 1984) .

Total area of each aggregated bed was calculated using the NAD 1983 UTM zone 18N projection for this *Bed Size* criterion. The data source of this criterion is the Virginia Institute of Marine Science (VIMS) geographic information system (GIS) data archive (<https://www.vims.edu/research/units/programs/sav/reports/>).

1.2.2 Bed Maturity

Bed maturity reflects the continuity of a bed over time, persistence through variable environmental conditions. Beds that persist over time indicate good to excellent conditions for SAV survival and are therefore desirable beds to protect and conserve.

The Steering Committee advised that all years of available data be used for this criterion. Although VIMS has spatial SAV data dating back to 1971, there was not bay-wide coverage until 1984. As such, data from 1984 through 2022 was used. Additionally, there were no data available for 1988 and therefore 38 years of data are included in the calculation of this criterion rather than 39 years.

The *Maturity* criterion was calculated by first overlapping all 38 years of SAV bed footprint spatial data. Each overlapping area was assigned a number equal to how many years SAV has been present in that unique polygons' boundary (Figure 3). Next, the area weighted average number of years for each aggregated bed was calculated upon which the index score was assigned. The data source of this criterion is the VIMS GIS data archive.

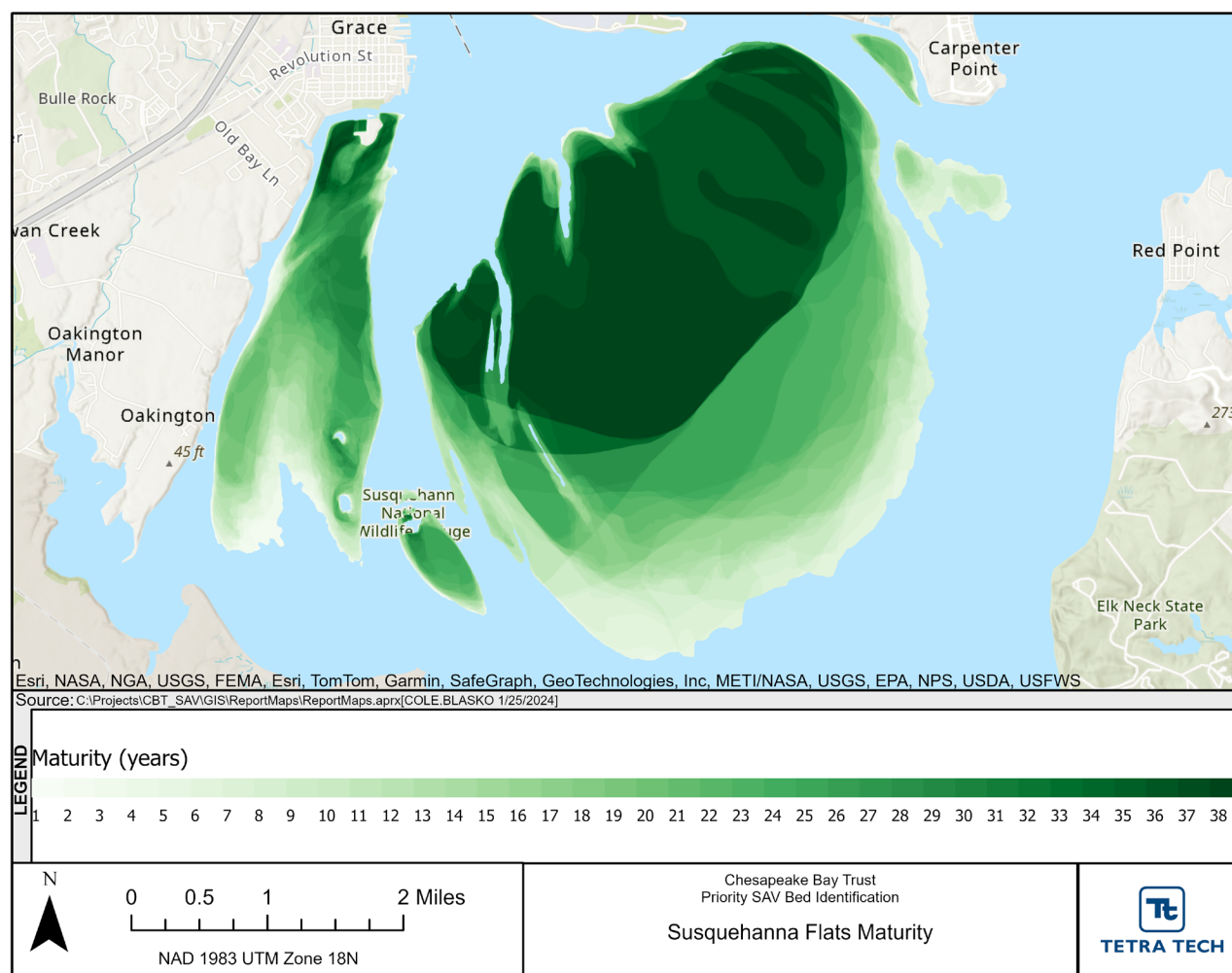


Figure 3. Example of the Maturity criterion for the Susquehanna Flats SAV bed

1.2.3 Bed Density

The density of shoots in an SAV bed may be indicative of good water quality conditions, appropriate sediment type, and favorable energy exposure. Denser beds also contribute to a positive feedback loop of improving environmental conditions such as reducing resuspension of sediments and reduced erosion (Gruber et al. 2011; Gurbisz et al. 2017).

The 2017-2022 data that was used to define the aggregated beds was also used to calculate the *Bed Density* criterion. First, the union of these six years of data were used to obtain the maximum density present in any one area of each bed over the past six years (Figure 4). Next, the area weighted average density for each aggregated bed was calculated upon which the index score was assigned. The data source of this criterion is the “DENSITY” field in the attribute table of shapefiles from the VIMS GIS data archive where beds are given a score from one to four based on percent coverage.

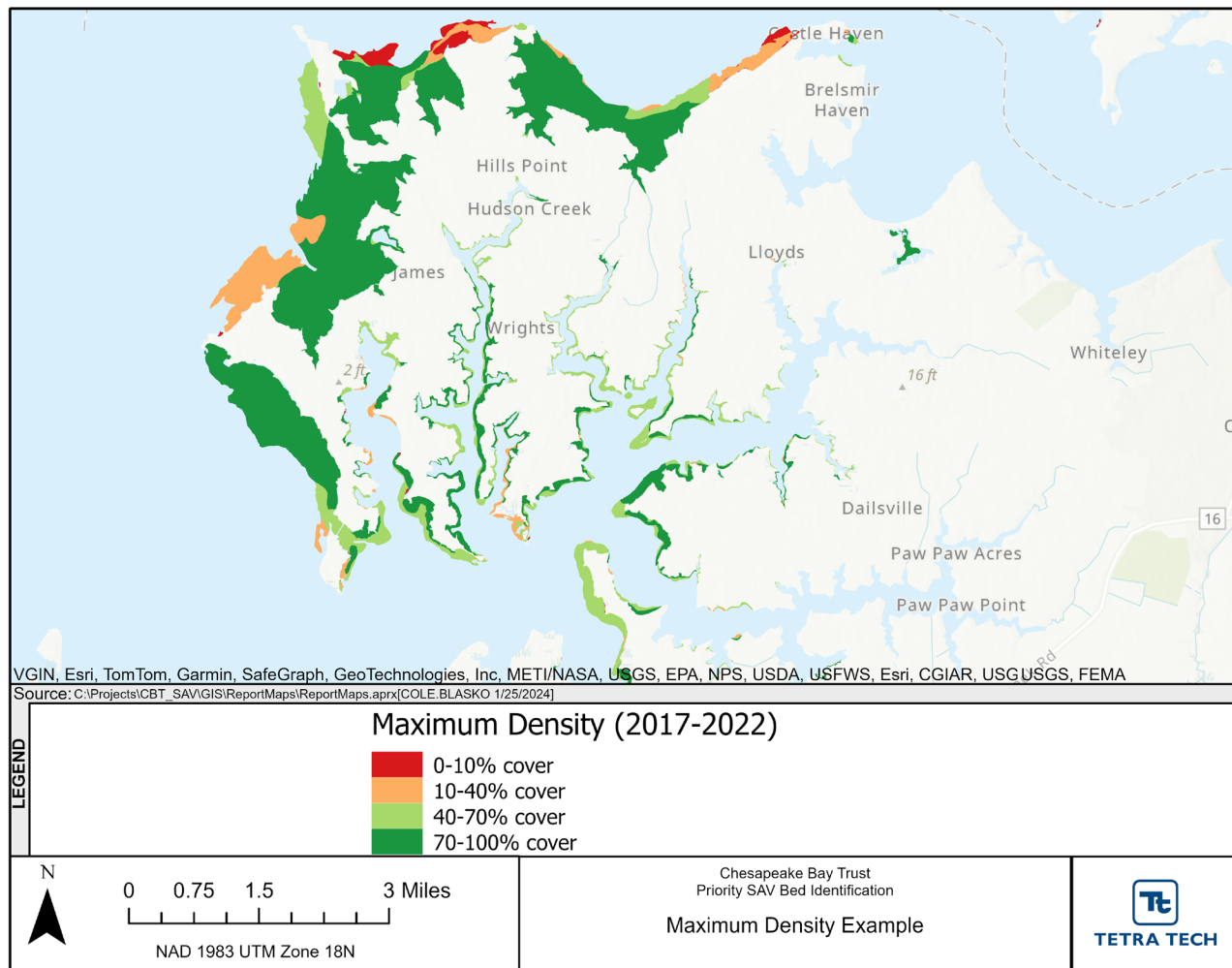


Figure 4. Example of six-year maximum bed density distribution

1.2.4 Species Richness/Diversity

Biodiversity in SAV bed structure serves many purposes. The presence of multiple species, and associated variability in plant morphology, provides a diverse structured habitat exploited by a variety of organisms. Additionally, beds comprised of multiple species are typically more resilient to bed collapse due to varying responses to environmental stressors.

The Steering Committee advised that the last ten years of data be used for establishing the *Species Richness/Diversity* criterion. The data source of this criterion is the VIMS species by segment data archive (https://www.vims.edu/research/units/programs/sav/access/tables/species_segment/) where species observations are recorded at the segment scale. Over the past ten years, 24 unique species have been recorded in 48 of the 103 total segments in the bay. The remaining 55 segments have not had any observations over the past ten years. These species data were compiled and pre-processed in spreadsheet format then joined to the spatial data for calculation of the *Species Richness/Diversity* criterion.

1.2.5 Sensitive/Rare Species

Approximately seventeen species of SAV are commonly found in the Chesapeake Bay. Species diversity increases with decreasing salinity, with up to a dozen species of SAV observed in some of the bays oligohaline and tidal fresh areas (Bergstrom et al. 2006). We identified two species that were included in this metric, based on salinity.

The *Sensitive/Rare Species* criterion varies depending on the salinity zone that each SAV bed falls under. The same data and pre-processing used for the *Species Richness/Diversity* criterion was applied here. The data source of this criterion is the VIMS species by segment data archive. The coastal bays and polyhaline salinity zones only contain two species altogether (*Ruppia maritima*, and *Zostera marina*). Of these species, *Zostera marina* is considered sensitive/rare in these salinity zones. The tidal fresh, oligohaline, and mesohaline salinity zones contain 24 unique species. *Potamogeton perfoliatus* is considered the sensitive/rare species in these salinity zones.

1.2.6 Habitat Value

Perhaps the most valuable function of healthy, persistent, and large SAV beds is the habitat provision available to a variety of invertebrate and fish species, both ecologically and economically important. While it is well understood that SAV beds provide both refugia and feeding opportunities for a variety of organisms (Beck et al. 2001; Bell et al. 1988; Brown-Peterson et al. 1993; Orth and Heck Jr. 1980), spatial data on the distribution of these organisms in the Chesapeake Bay is inconsistent and could include over 300 finfish species alone. In consultation with the steering committee and discussions with the SAV Workgroup, the species list was narrowed down to taxa where good spatial data existed, were economically and/or ecologically important, and had a fairly wide distribution within the Chesapeake Bay and its tributaries. Species identified as highly dependent on SAV at some point of their life history include Striped Bass (*Morone saxatilis*), American Shad (*Alosa sapidissima*), Hickory Shad (*A. mediocris*), Blueback Herring (*A. aestivalis*), Alewife (*A. pseudoharengus*), Summer Flounder (*Paralichthys dentatus*), and Blue Crab (*Callinectes sapidus*). Of these species, there is little spatial data on distribution of post-larval and juvenile Summer Flounder, the life stages dependent on SAV beds. However, these life stages are known to preferentially exploit eelgrass beds (Able et al. 1990; Packer and Hoff 1999; Sackett et al. 2008), so the inclusion of eelgrass noted in the Sensitive/Rare criterion also covers Summer Flounder habitat.

The *Habitat Value* criterion was developed using spatial datasets from the Chesapeake Bay Program (CBP; provided by CBP 1/10/2024). These data include the spawning and nursery areas for Alewife, American Shad, Blueback Herring, and Hickory Shad. Spawning areas for Striped Bass and high-density areas of male and female blue crab were also used. These spatial data layers were merged together (Figure 5) and the *Habitat Value* criterion was calculated based on whether an SAV bed intersects any of these selected habitat areas.

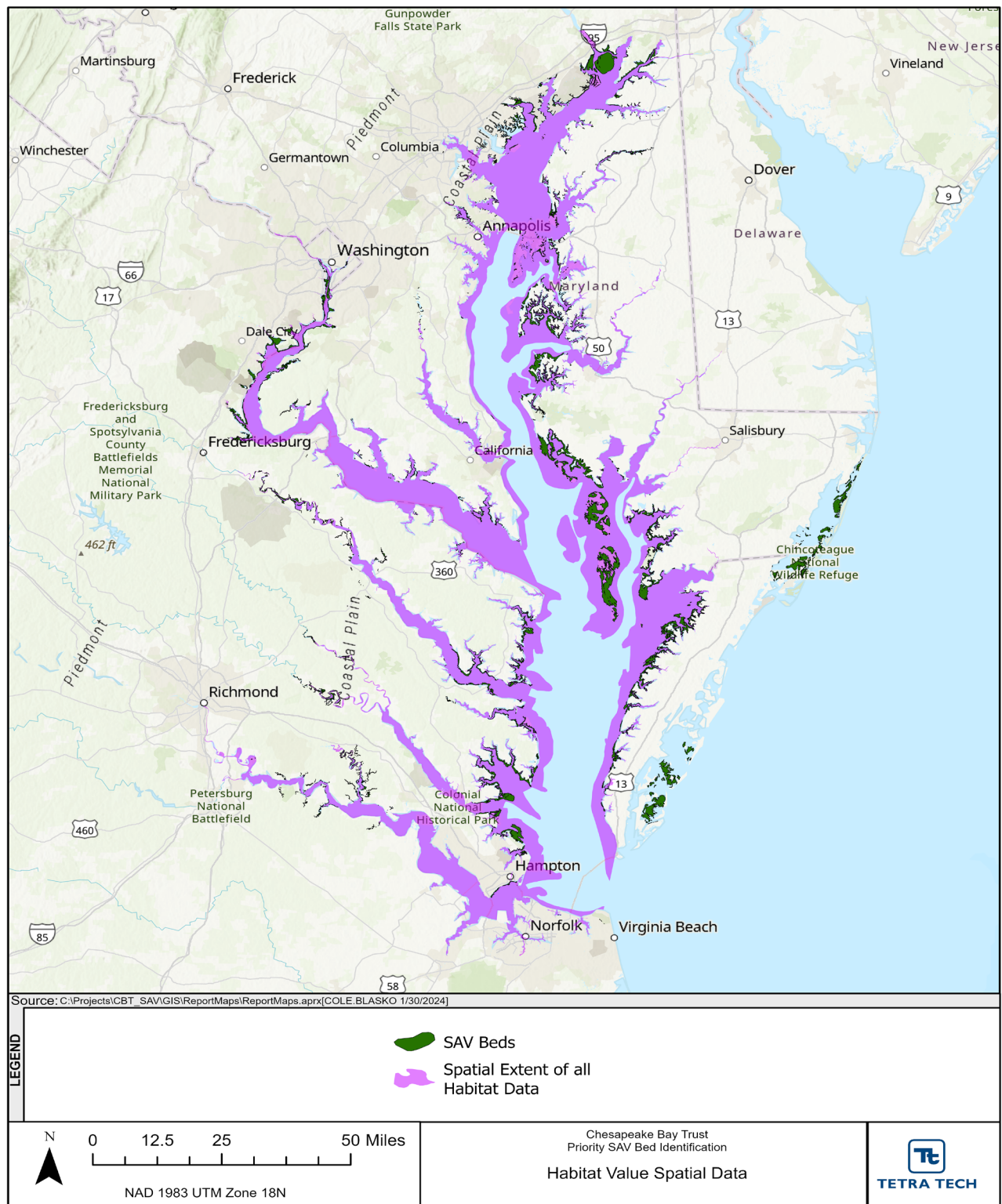


Figure 5. Spatial footprint of all habitat spatial data merged together

1.2.7 Representativeness

The Representativeness criterion captures regions of the Bay deemed special due to their location and structure. The *Representativeness* criterion was developed using spatial datasets from the Chesapeake Bay Program (<https://gis.chesapeakebay.net/mpa/scenarioviewer/>). These data include the Regional Conservation Opportunity Areas (RCOA), and Index of Ecological Integrity (IEI) areas. These spatial data layers were merged together and the *Representativeness* criterion was calculated based on whether an SAV bed intersects any of these priority areas (Figure 6).

The Chesapeake Bay Program describes the RCOA as:

“The RCOA vision is to identify and map a connected network of resilient and ecologically intact habitats that will support biodiversity under changing conditions to prioritize restoration and inform land protection. RCOAs will supplement State Wildlife Action Plans in identifying core habitats and restoration/connectivity opportunities. Similar to the IEI, the RCOAs follow a complete wildlife approach. It shows areas where conservation and restoration will have the largest impact on threatened species and habitats.”

The Chesapeake Bay Program describes the IEI as:

“The index of ecological integrity (IEI) is a measure of relative intactness (i.e., freedom from adverse human modifications and disturbance) and resiliency to environmental change (i.e., capacity to recover from or adapt to changing environmental conditions driven by human land use and climate change) on a 0-1 scale. It is a composite index derived from up to 21 different landscape metrics, each measuring a different aspect of intactness (e.g., road traffic intensity, percent impervious) and/or resiliency (e.g., ecological similarity, connectedness) and applied to each 30 m cell. The IEI acts as an all-encompassing measure of habitat quality, and provides inclusion of both habitat types addressed by the Watershed Agreement (with Management Strategies and Outcomes) and those omitted.”

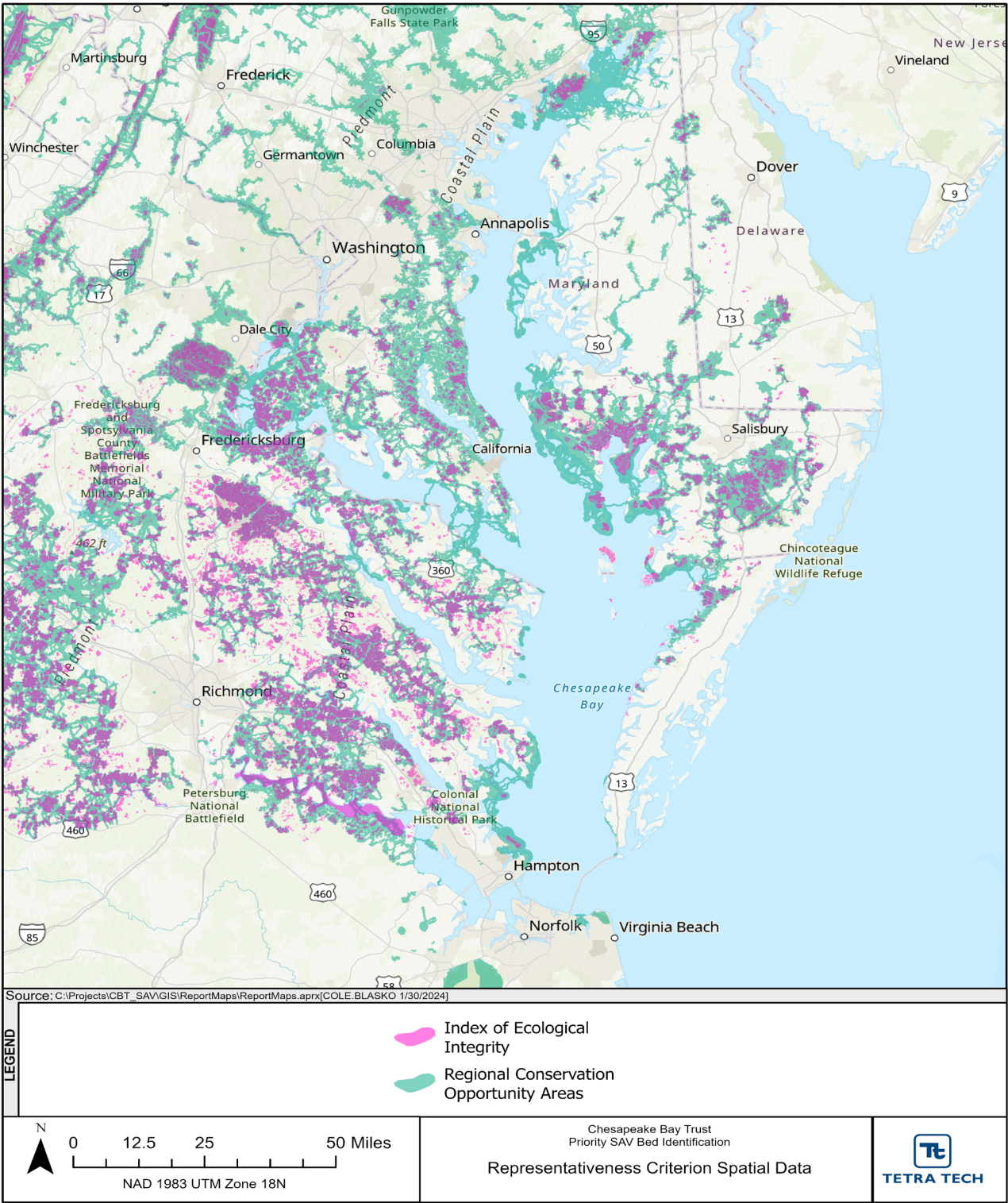


Figure 6. Spatial footprint of data used for the Representativeness criterion

1.2.8 Distribution

Geographical distribution of species and species complexes is considered an important factor prior to the BMP analysis. Beds scored highly throughout the Chesapeake Bay system, but having a practical distribution among salinity regimes and geographical representation was considered an important criterion.

The *Distribution* criterion uses the preliminary bed results from the composite index score calculated from the seven prior criteria (Figure 2). Salinity zones and geographic regions are considered when choosing the final ten priority beds. This criterion is further discussed in section 1.4.

1.3 CRITERIA RESULTS

The distribution of SAV beds for each of the seven initial criteria is shown in Figure 7 through Figure 13 and Table 1 below.

Bed sizes ranged from 5-acres to 8,303-acres. The size distribution is right/positive-skewed with an average size of 108-acres and a median size of 22-acres. Index score thresholds were placed at natural breaks in the size distribution and yielded five index classes (Figure 7). All beds greater than 100-acres in size were assigned a perfect index score of 1.0. This threshold of 100-acres leaves 254 SAV beds in top consideration under this criterion for protection and conservation. This threshold is lenient in that it includes 16% of all beds under this top consideration. However, 100-acres is large for SAV beds in general and setting this threshold higher would unfairly exclude very large beds from top consideration.

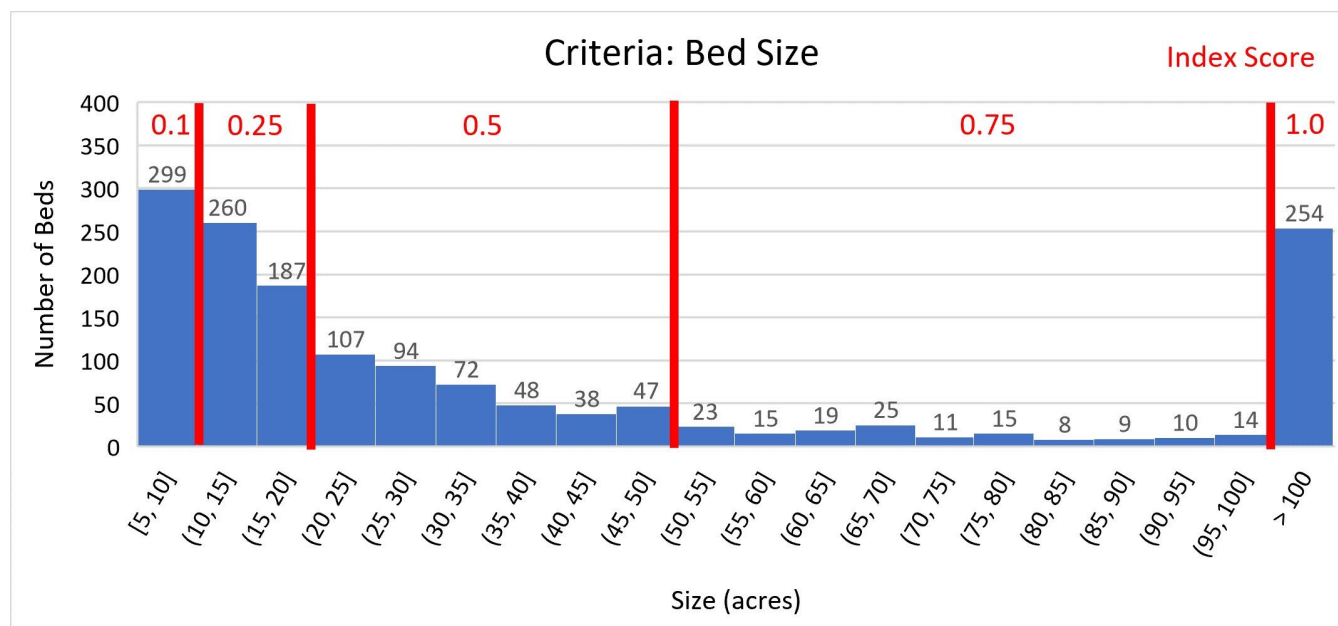


Figure 7. Distribution of aggregated SAV bed results for the Bed Size criterion

Bed maturity ranged from 1-year to 31-years old. The distribution is right/positive-skewed with an average age of 9.3-years and a median age of 7.8-years. Index score thresholds were placed at natural breaks in the maturity distribution and yielded five index classes (Figure 8). All beds with a maturity of greater than 27-years were assigned a perfect index score of 1.0. This criterion is more selective in that only 13 beds were classified under the top index score for highest consideration of protection and conservation practices.

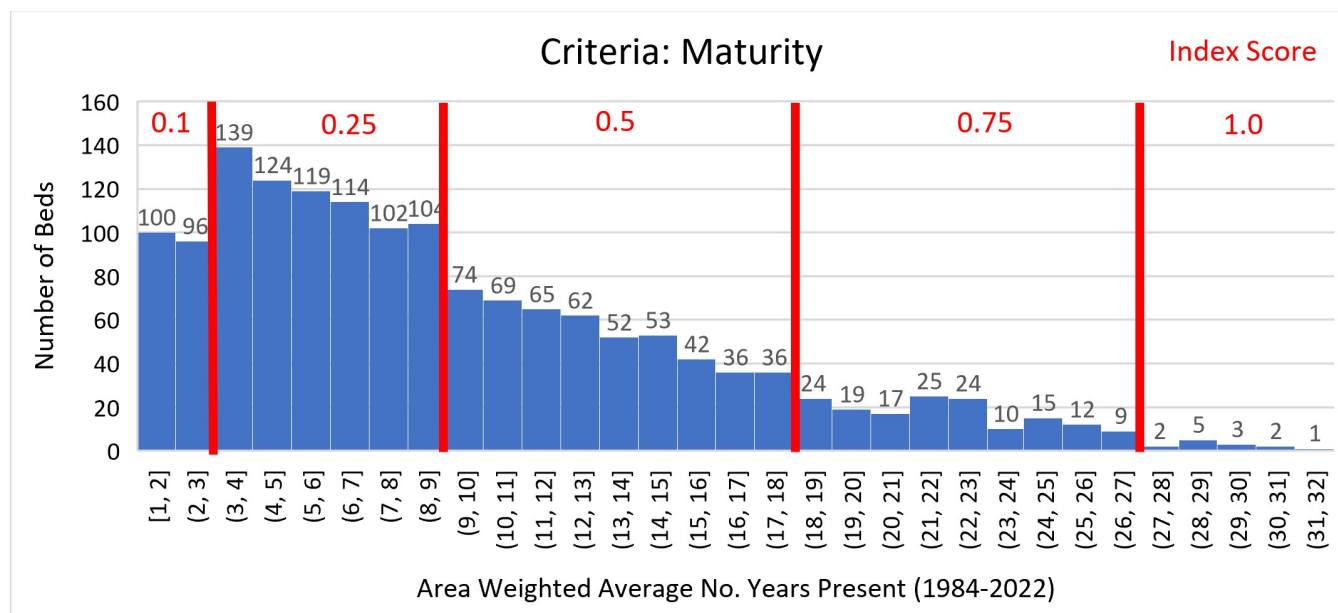


Figure 8. Distribution of aggregated SAV bed results for the Maturity criterion

Bed density, as assigned in the VIMS data, ranges from 0-10% cover to 70-100% cover. The four classifications established by VIMS were used directly as the index score thresholds (Figure 9). The distribution of the data is left/negative-skewed where the average, median, and mode all fall in the highest classification of over 70% cover for area weighted maximum bed density between 2017 and 2022.

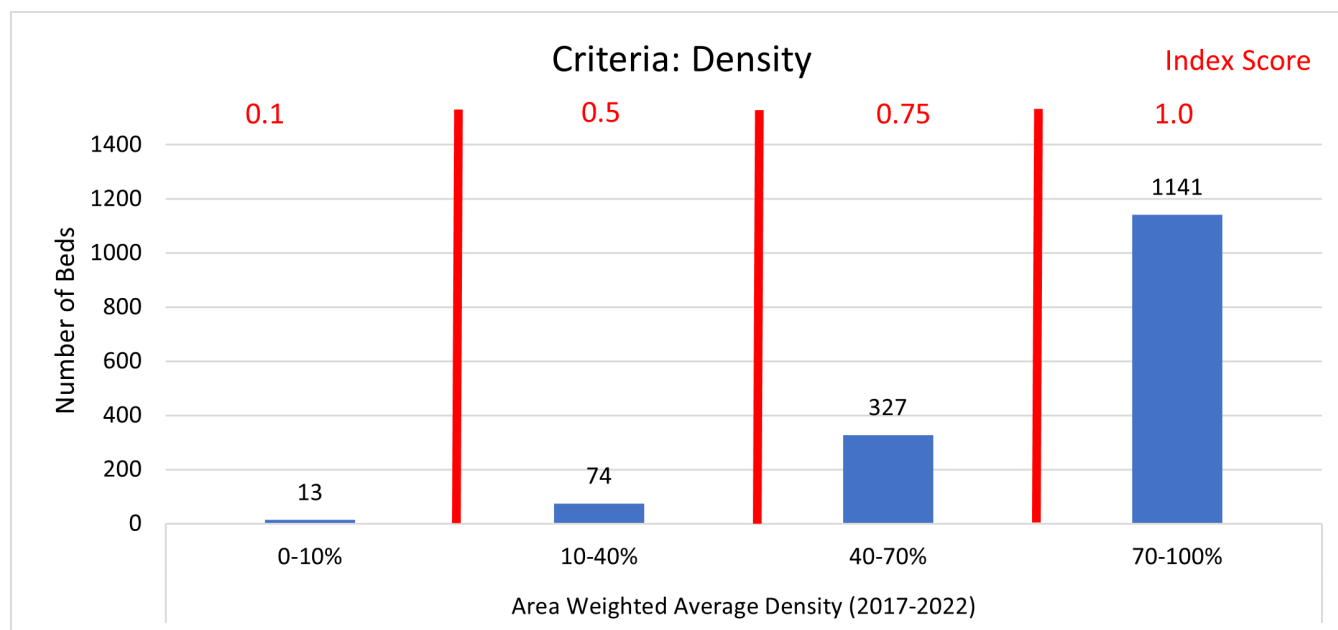


Figure 9. Distribution of aggregated SAV bed results for the Bed Density criterion

The *Species Richness/Diversity* criterion was assigned index scores based on the salinity zone in which the SAV bed falls within (Figure 10). Additionally, there were 368 (25% of all beds) that did not have any observations recorded in the past ten years but does not mean that SAV species do not exist here. These beds were assigned an index score of 0.25 rather than zero so that they are not unfairly excluded from consideration altogether due to

this one criterion. For coastal bay and polyhaline salinity zones that do not have rich/diverse SAV species due to inherent conditions there is only one other index score assigned as all beds in these salinity zones had exactly two species observed. As such, an index score of 1.0 was given for these beds. For tidal fresh, oligohaline, and mesohaline salinity zones, three additional index scores were assigned. First, a natural break in the distribution exists for beds with species counts between one and three. These beds were assigned an index score of 0.5. Next, beds with less than ten species were assigned a score of 0.75 and beds with more than ten species were assigned an index score of 1.0.

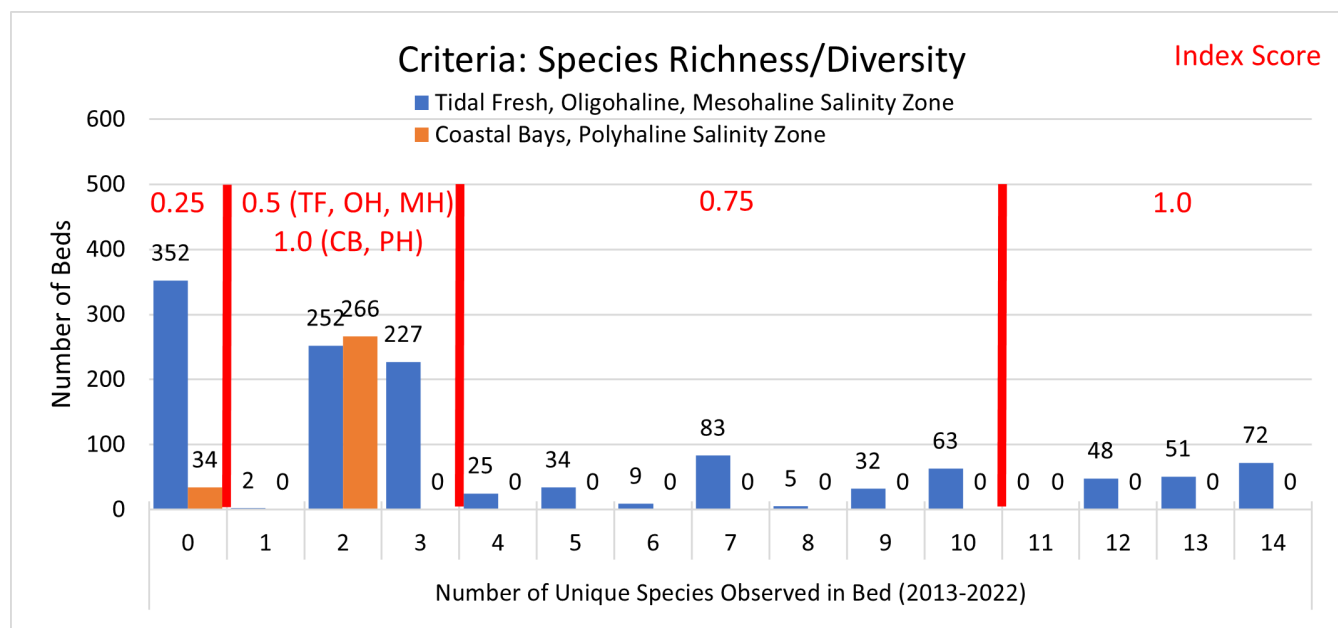


Figure 10. Distribution of aggregated SAV bed results for the Species Richness/Diversity criterion

The *Sensitive/Rare Species* criterion also varies based on salinity zone in which the bed resides. For coastal bays and polyhaline salinity zones *Zostera marina* is the species of interest and for tidal fresh, oligohaline, and mesohaline salinity zones *Potamogeton perfoliatus* is the species of interest. All salinity zones were given the same binary index scoring classification where if an SAV bed contained the species of interest it was assigned a score of 1.0 and was otherwise assigned a score of zero (Figure 11). Of the 1,555 total beds, 584 (37.5%) contained the species of interest.

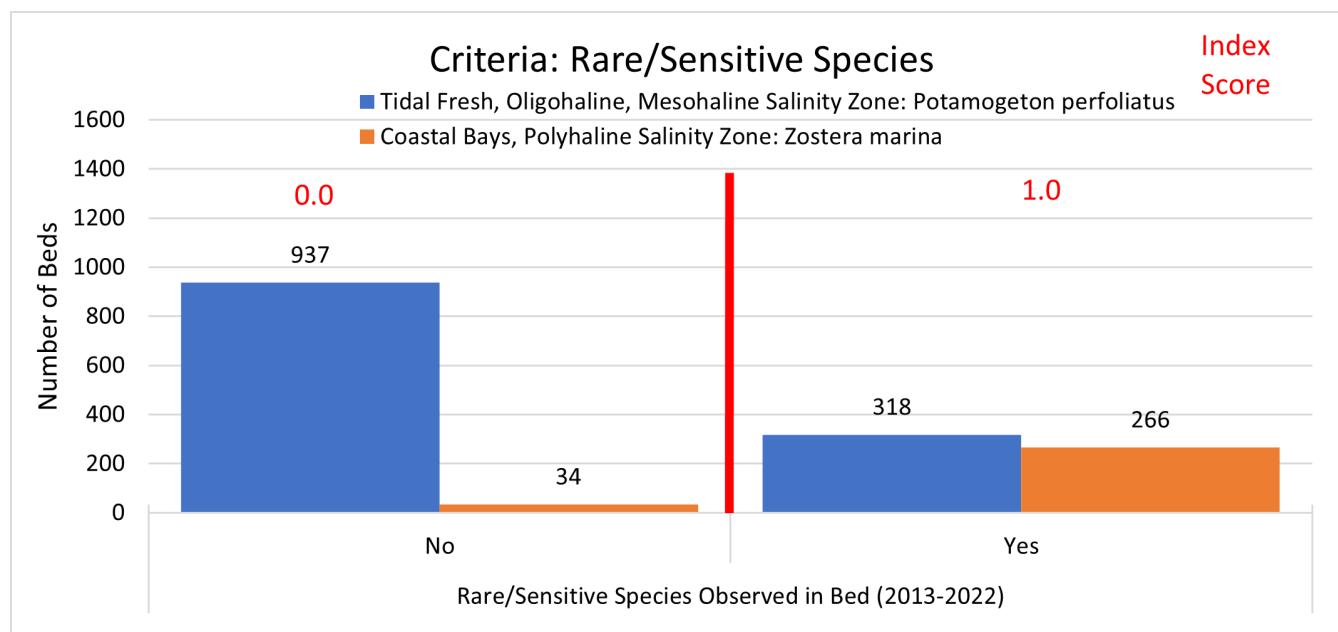


Figure 11. Distribution of aggregated SAV bed results for the Rare/Sensitive Species criterion

The *Habitat* and *Representativeness* criteria were also assigned index scores in a binary fashion because SAV beds either do or do not intersect the spatial region of interest as described in sections 1.2.6 and 1.2.7 above. 1241 (79.8%) of SAV beds overlap a select habitat and were assigned a perfect index score of 1.0 (Figure 12). 807 (51.9%) of SAV beds overlap ecological integrity or conservation opportunity areas and were assigned a perfect index score of 1.0 (Figure 13).

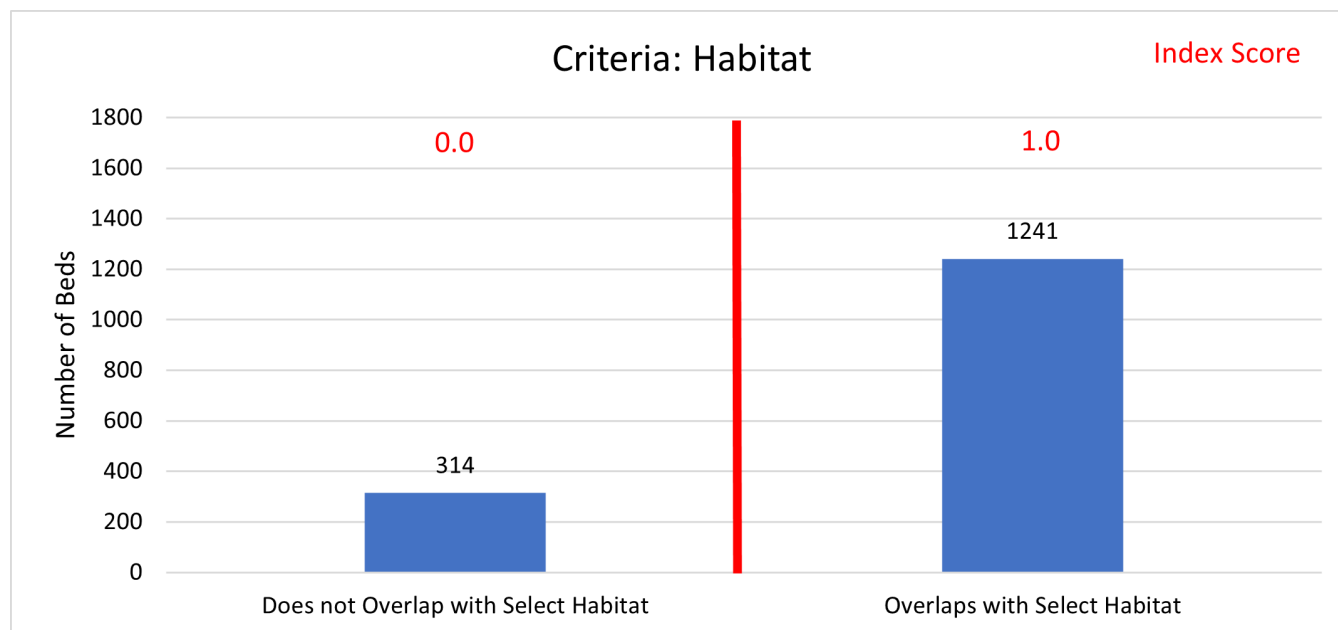


Figure 12. Distribution of aggregated SAV bed results for the Habitat criterion

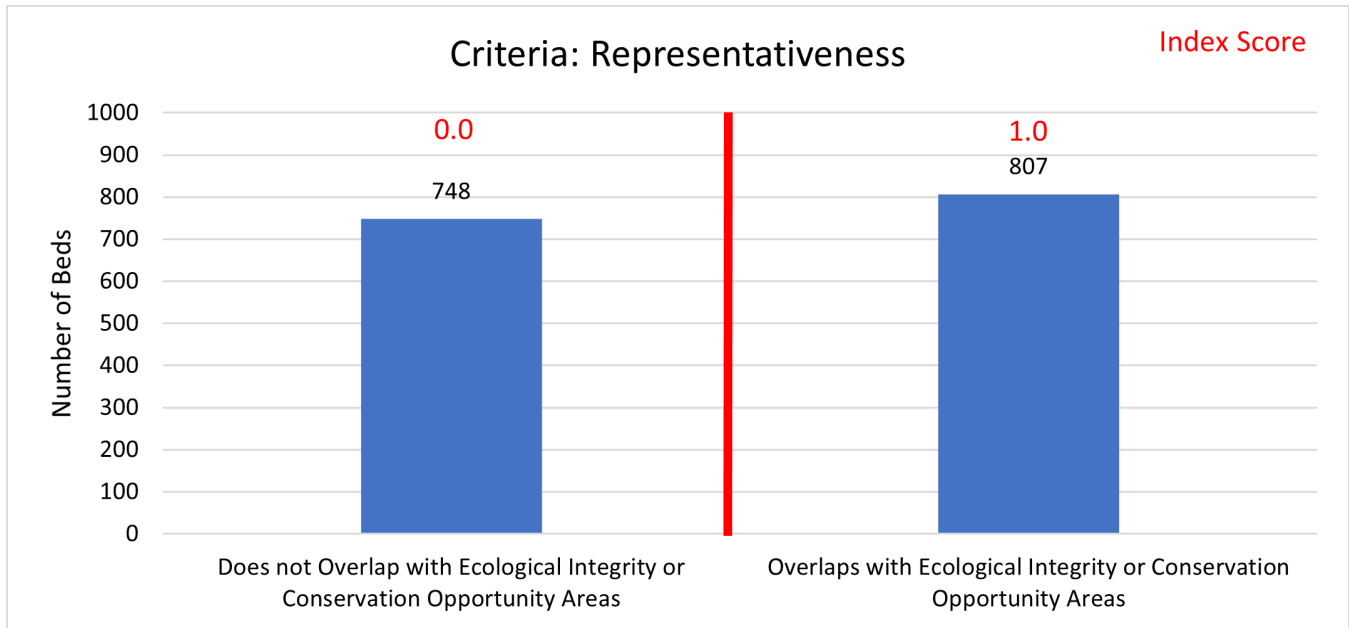


Figure 13. Distribution of aggregated SAV bed results for the Representativeness criterion

Table 1. Index score thresholds and number of SAV beds that fall under each category for all criteria

Criteria (weight)	Index Score	Number of Beds ^a
Bed Size (10%)	Bed size ≥ 100 acres: 1.0 Bed Size ≥ 50 and < 100 acres: 0.75 Bed Size ≥ 20 and < 50 acres: 0.5 Bed Size ≥ 10 and < 20 acres: 0.25 Bed size < 10 acres: 0.1	254 (16%) 149 (10%) 406 (26%) 447 (29%) 299 (19%)
Maturity (10%)	Bed maturity ≥ 27 years: 1.0 Bed maturity ≥ 18 and < 27 years: 0.75 Bed maturity ≥ 9 and < 18 years: 0.5 Bed maturity ≥ 3 and < 9 years: 0.25 Bed maturity < 3 years: 0.1	13 (1%) 155 (10%) 489 (31%) 702 (45%) 196 (13%)
Bed Density (15%)	Bed density VIMS score > 3 and ≤ 4 ($> 70\%$ and $\leq 100\%$ cover): 1.0 Bed density VIMS score > 2 and ≤ 3 ($> 40\%$ and $\leq 70\%$ cover): 0.75 Bed density VIMS score > 1 and ≤ 2 ($> 10\%$ and $\leq 40\%$ cover): 0.5 Bed density VIMS score ≤ 1 ($\leq 10\%$ cover): 0.1	1,152 (74%) 326 (21%) 66 (4%) 11 (1%)
Species Richness/ Diversity (10%)	<u>Mesohaline/Oligohaline/Tidal Fresh</u> # species in bed ≥ 11 : 1.0 # species in bed 4-10: 0.75 # species in bed 1-3: 0.5 Beds with no species observations: 0.25 <u>Coastal Bays/Polyhaline</u> # species in bed ≥ 1 : 1.0 Beds with no species observations: 0.25	171 (11%) 251 (16%) 481 (31%) 352 (23%) 266 (17%) 34 (2%)
Sensitive/Rare Species (10%)	<u>Mesohaline/Oligohaline/Tidal Fresh</u> Bed contains <i>Potamogeton perfoliatus</i> : 1.0 Bed does not contain <i>Potamogeton perfoliatus</i> : 0.0 <u>Coastal Bays/Polyhaline</u> Bed contains <i>Zostera marina</i> : 1.0 Bed does not contain <i>Zostera marina</i> : 0.0	318 (20%) 937 (60%) 266 (17%) 34 (2%)
Habitat Value (35%)	Bed overlaps with priority spawning/settlement area: 1.0 Bed does not overlap: 0.0	1,241 (80%) 314 (20%)
Representativeness (10%)	Bed overlaps conservation opportunity area or ecological integrity area: 1.0 Bed does not overlap: 0.0	807 (52%) 748 (48%)

a. The number of beds that were assigned each index score are presented here. Percentages may not sum to 100% due to rounding.

1.4 PRIORITY SAV BED RESULTS

There are 114 SAV beds that received a composite index score greater than 0.9 (Figure 14). The final *Distribution* criterion was applied to only these 114 Preliminary Beds (Figure 15).

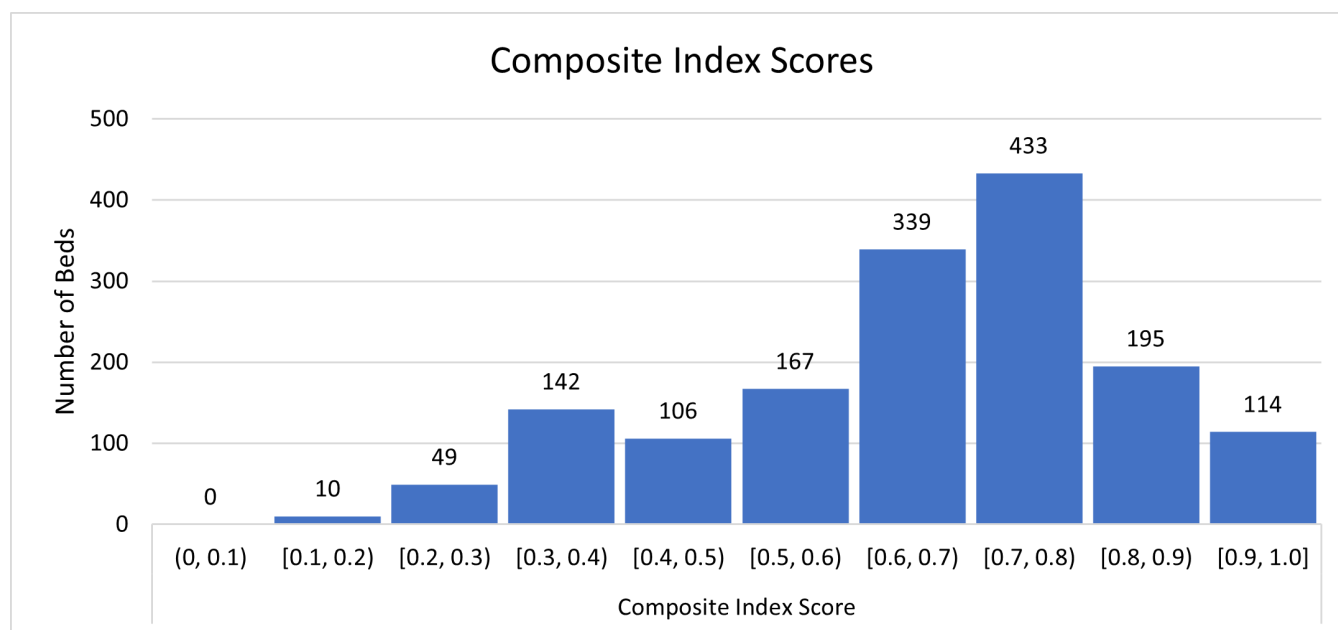


Figure 14. Distribution of composite index scores for all SAV beds

In general, the rationale behind choosing the first 5 Priority Beds (referred to as PB#) is as follows:

- Four beds received a perfect composite index score of 1.0 and were all selected as Priority Beds. All four of these beds fall in the polyhaline salinity zone on the western shore of the southern end of Chesapeake Bay in Virginia. One of these beds is adjacent to the Plum Tree Island National Wildlife Refuge (PB1); one bed is on the north shore of the mouth of the York River (PB2); and two beds are in Mobjack Bay (PB3 and PB4) (Figure 15 and Table 2).
- Next the Susquehanna Flats SAV bed was chosen as a Priority Bed due to its high composite index score of 0.975, being the largest SAV bed in the Chesapeake Bay, and being a high-profile/prominent SAV bed in terms of ecological importance. The Susquehanna Flats bed is in the tidal fresh salinity zone at the mouth of the Susquehanna River in the northern-most tip of Chesapeake Bay in Maryland (PB5 in Figure 15 and Table 2).

The geographic and salinity zone distribution of these first 5 Priority Beds are at the two extremes. As such, the geographic and salinity zone distribution of the remaining 5 Priority Beds were determined by selecting beds from Preliminary Bed clusters with the following rationale:

- In Virginia, the east shore of the southern end of Chesapeake Bay is in the polyhaline salinity zone and contains a cluster of 19 Preliminary Beds. Of these 19 beds, eight of them were tied for the highest composite index score of 0.975. The largest of these eight is 1,880 acres in size and, as such, was chosen as PB6 (Figure 15 and Table 2).
- The Potomac River contains 13 Preliminary Beds on both banks in Maryland and Virginia. All these beds are in the oligohaline salinity zone. Of these 13 beds, five of them were tied for the highest composite index score of 0.95. The largest of these five is 743 acres in size and, as such, was chosen as PB7 (Figure 15 and Table 2).
- Another cluster of 13 Preliminary Beds exists east of Washington DC and southeast of Baltimore. These 13 Preliminary Beds are in the mesohaline salinity zone of Maryland. Two beds were chosen from this cluster to ensure even distribution across salinity zones. Additionally, one bed was chosen on the east

shoreline and one on the west shoreline to ensure even geographic distribution. The bed on the east shoreline was chosen because it was the largest (477 acres) of eight beds with the highest composite index score of 0.925 (PB8 in Figure 15 and Table 2). The bed on the west shoreline was chosen due to having the highest composite index score of 0.95 (PB9 in Figure 15 and Table 2).

- The final cluster of 20 Preliminary Beds is that which contains the Susquehanna Flats bed which was already chosen as a Priority Bed in the tidal fresh salinity zone. However, this cluster also includes beds in the polyhaline salinity zone which to this point has been under-represented in distribution. Seven beds in the polyhaline salinity zone of this cluster are tied for the highest composite index score of 0.95. The largest bed with a size of 988 acres was chosen as PB10 (Figure 15 and Table 2). This bed's drainage area is also separate from that of the Susquehanna Flats beds which further improves the geographic distribution of the Priority Bed selection.

Two additional Priority Beds were added in the Tangier Sound. These beds (PB11 and PB12) are shown in Figure 15 and their criteria results and index scores are summarized in Table A - 1. These Priority Beds in the Tangier Sound are not included in the decision tree or indices calculations/graphs above because they were not chosen through that methodology. See Appendix A for a detailed description of selection rationale.

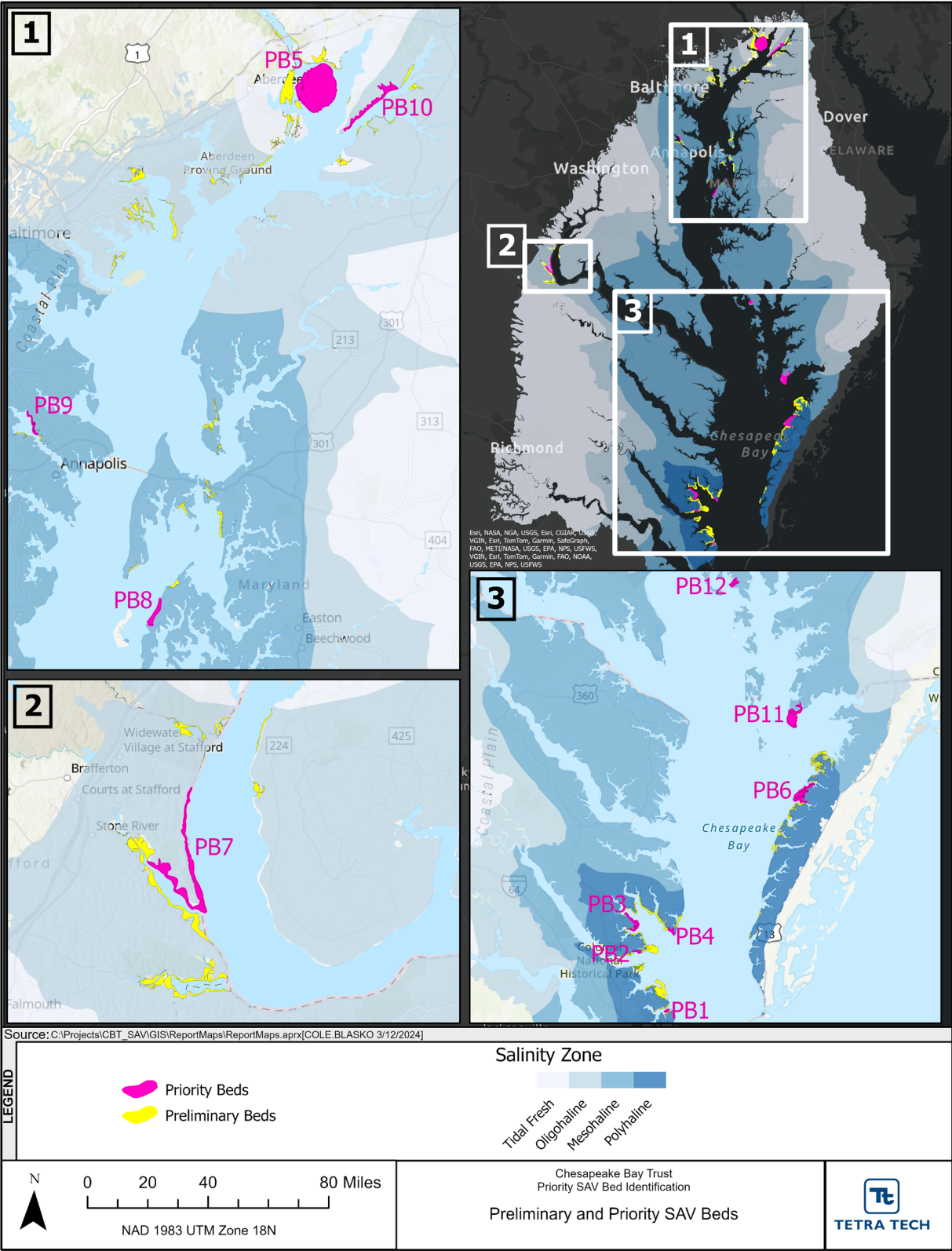


Figure 15. Preliminary and Priority Bed locations

Table 2. Summary of criteria and index scores for Priority Beds

Bed ID	PB1	PB2	PB3	PB4	PB5	PB6	PB7	PB8	PB9	PB10
Bed Size - acres	118 (1.0)	206 (1.0)	741 (1.0)	313 (1.0)	7,566 (1.0)	1,880 (1.0)	743 (1.0)	477 (1.0)	133 (1.0)	988 (1.0)
Maturity – area weighted avg. years	29.1 (1.0)	29.8 (1.0)	28.2 (1.0)	28.1 (1.0)	26.6 (0.75)	26.0 (0.75)	20.3 (0.75)	12.9 (0.5)	21.9 (0.75)	15.2 (0.5)
Bed Density – area weighted avg. VIMS score	4.0 (1.0)	3.8 (1.0)	3.9 (1.0)	3.5 (1.0)	3.9 (1.0)	3.3 (1.0)	4.0 (1.0)	3.1 (1.0)	4.0 (1.0)	4.0 (1.0)
Species Richness/ Diversity – No. Species	2 (1.0)	2 (1.0)	2 (1.0)	2 (1.0)	13 (1.0)	2 (1.0)	10 (0.75)	7 (0.75)	7 (0.75)	12 (1.0)
Sensitive/ Rare Species	All Priority Beds contain the sensitive/rare species for its respective salinity zone. (1.0)									
Habitat Value	All Priority Beds intersect valuable habitat areas. (1.0)									
Representativeness	All Priority Beds intersect Regional Conservation Opportunity Areas (RCOA) or Index of Ecological Integrity (IEI) areas. (1.0)									
Composite Index Score	1.0	1.0	1.0	1.0	0.975	0.975	0.95	0.925	0.95	0.95

Values in parenthetical notation denote the index score for each criterion.

2.0 PRIORITY SAV BED DRAINAGE AREA CHARACTERISTICS

Drainage areas to each priority bed were determined in a multi-step process. First, National Hydrography Dataset (NHD) catchments that intersect Priority Beds were identified and labeled with the Priority Bed ID in which they intersect. Next, the stream network was routed upstream to the headwaters and all associated catchments were identified as draining to each Priority SAV bed. Finally, catchments draining to the same Priority SAV bed were merged to obtain one contiguous drainage area (Figure 16). This mostly automated process was not perfect for all Priority Beds and manual adjustments of drainage areas were performed where necessary. For example, some catchments were large and spanned to the opposite shoreline of where the Priority Bed resides. These drainage areas in the uplands of the opposite shoreline were manually edited out of the Priority Bed drainage area in some cases. Additionally, the Susquehanna Flats SAV bed does not touch a shoreline directly. Therefore, NHD catchments on the shoreline were selected for upstream routing even though they did not intersect the Priority SAV bed itself.

Drainage area delineation methods described above define only the direct drainage area to each SAV bed rather than everything upstream in the Chesapeake Bay. Due to the size of the Chesapeake Bay itself, its large watershed area, and the inherent mixing that occurs within the bay, the direct drainage areas that are defined in Figure 16 account for a more direct connection between SAV health and all potential influences from their associated upland areas. For example, the drainage area for PB4 in Mobjack Bay is defined as only the uplands on the adjacent coastline and is relatively small (981 acres). If, on the other hand, the entire upstream portion of the Chesapeake Bay and its drainage area were characterized as influencing SAV health in Mobjack Bay, the relationship between SAV health and all influencing variables would not be clear and any direct relationships between the two would be difficult to confirm or correlate.

2.1 LAND USE

Land use data presented herein is from the Multi-Resolution Land Characteristics Consortium (MRLC) National Land Cover Database (NLCD). These data encompass 16 land use classes at a 30-meter spatial resolution; both of which are at a fine enough scale for later BMP analyses to be conducted as discussed in Section 4.3. Additionally, these data are updated every few years (2008, 2011, 2013, 2016, 2019, and 2021) and offer a temporal resolution fine enough to conduct a dasymetric disaggregation of spatiotemporal BMP data as discussed in Section 4.3.

The most recent NLCD data (2021) is presented below as an overview of what land uses drain to each Priority SAV bed 1 - 10 (Figure 16). Drainage areas to each Priority Bed range in size from 981-acres to 17,681,518-acres while ratios of drainage area size to Priority Bed size range from 2.3 to 11,390 (Figure 17). These ratios are relevant because, a single BMP implemented in a drainage area that is only 2.3 times the size of the SAV bed, for example, will have greater impact on the health of that SAV bed compared to BMPs implemented in drainage area that is 11,390 times the size of the SAV bed.

Furthermore, BMPs of varying types are only implemented on their applicable land cover. As such, the distribution of land cover within each drainage area is also important to consider. Forest is the dominant land cover in the five largest drainage areas (PB2, PB3, PB5, PB7, PB10). Land cover in PB1 and PB9 is dominated by developed land cover while wetlands are the dominant land cover in PB4 and PB6. Not displayed in Figure 16 or Figure 17, open water is the dominant land cover in PB11 and PB12 (see Appendix A for more details) Finally, PB8 is the only drainage area with cultivated crops as its dominant land cover.

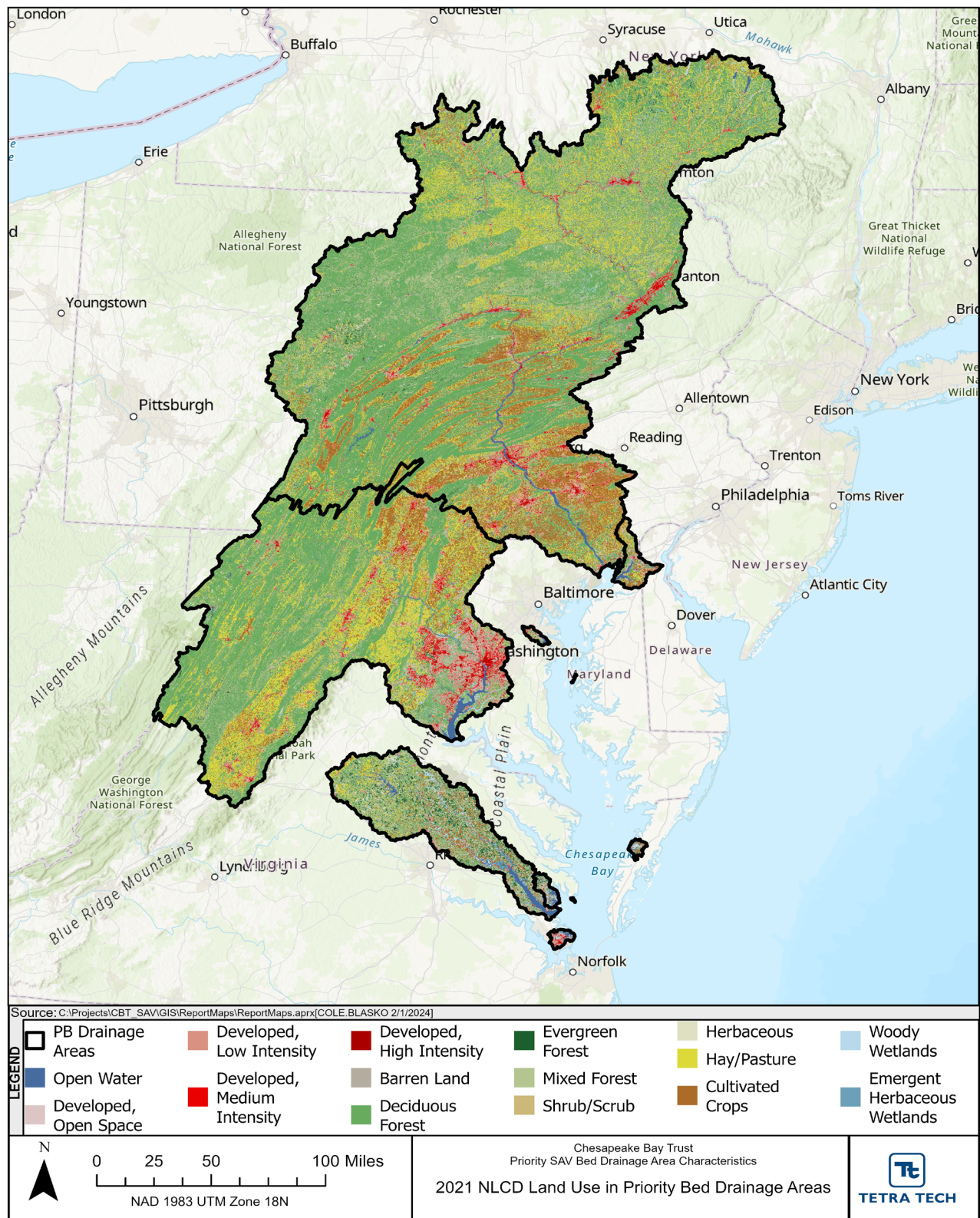


Figure 16. Land use (2021 NLCD) and catchments to each Priority Bed 1 - 10

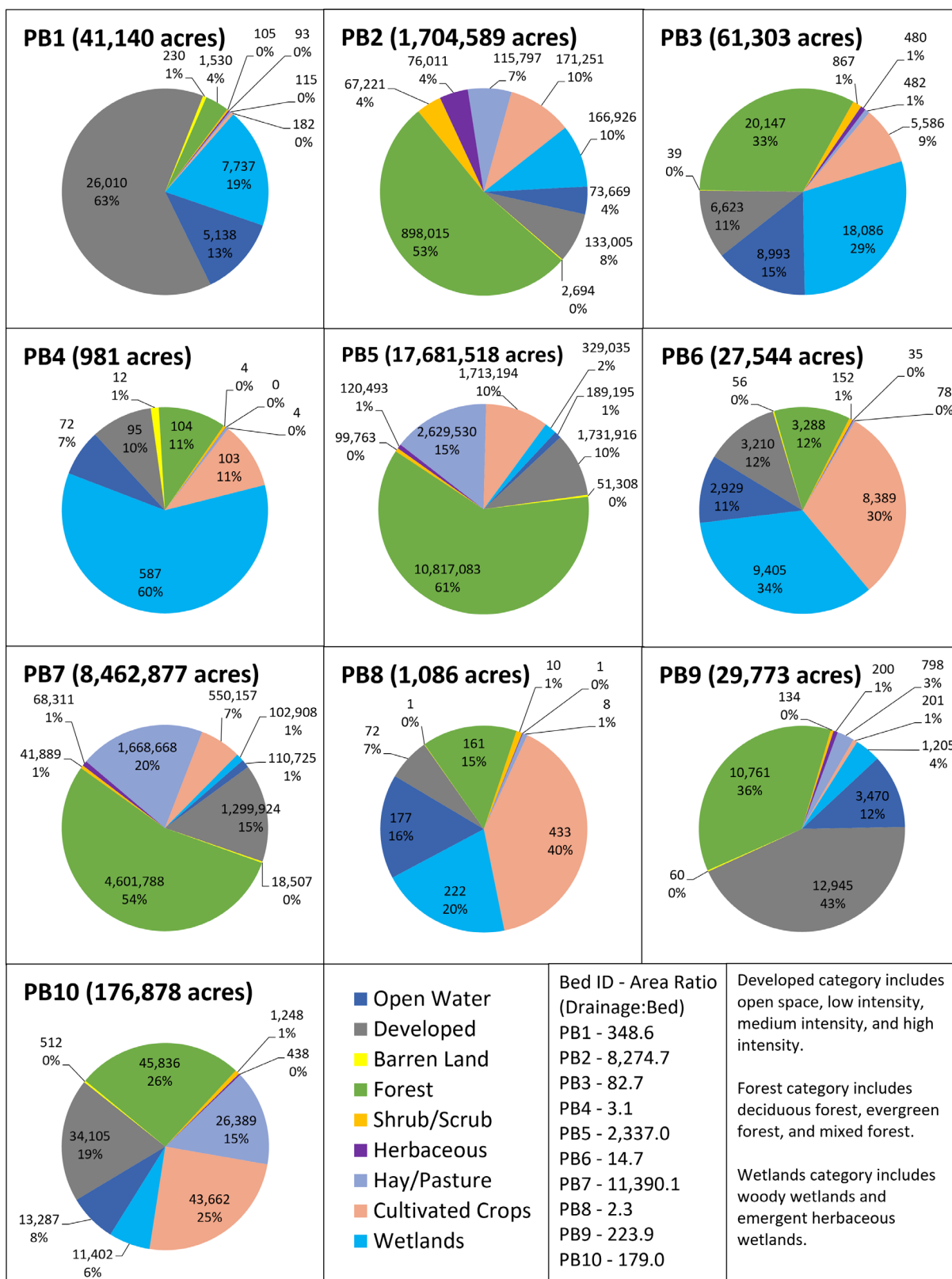


Figure 17. Land use (2021 NLCD) in Priority Bed 1 - 10 drainage areas and ratio of drainage area size to SAV bed size

2.2 BMP IMPLEMENTATION

The number of unique BMPs available from the Chesapeake Assessment Scenario Tool (CAST) is extensive (289 unique BMPs). BMPs within each Priority Bed drainage area are provided in supplementary excel file [CBT SAV Supplemental Data ML Model.xlsx](#). BMP data are available from CAST at various spatial scales including point (i.e., latitude and longitude), HUC12 scale, HUC10 scale, county-wide, and state-wide. Point data were plotted using the latitude and longitude provided and was directly overlaid with drainage areas to Priority Beds. BMP data reported at larger scales (i.e., HUC12, HUC10, county, and state) were dasymetrically disaggregated to their associated land use as described in Section 4.3.

3.0 MACHINE LEARNING APPROACH

The methodology for identifying BMPs that are mostly likely to lead directly to SAV protection, conservation, and restoration revolves around the integration and analysis of ecological data using the Python programming language, with a particular focus on advanced machine learning techniques to assess various ecological indicators. The initial steps include preparation of input data. This preprocessed dataset then serves as the basis for further analysis, specifically focusing on ecological variables such as species richness and bed density among others.

Employing a machine learning model to aid in determining the drivers of SAV health is a viable approach for the following reasons:

- Machine learning models are statistically based and reproducible.
- Machine learning models can account for many input variables/predictors.
- Machine learning models can elucidate temporal patterns and complex interactions between the many variables/predictors.
- Machine learning model output includes relative importance plots of what variables/predictors are most closely correlated to SAV health, among others.

The approach for the machine learning model is to use known BMP and stream discharge data within drainage areas to priority SAV beds to train and test a model that predicts SAV health as measured through proxies. Figure 18 provides an overview of the machine learning approach.

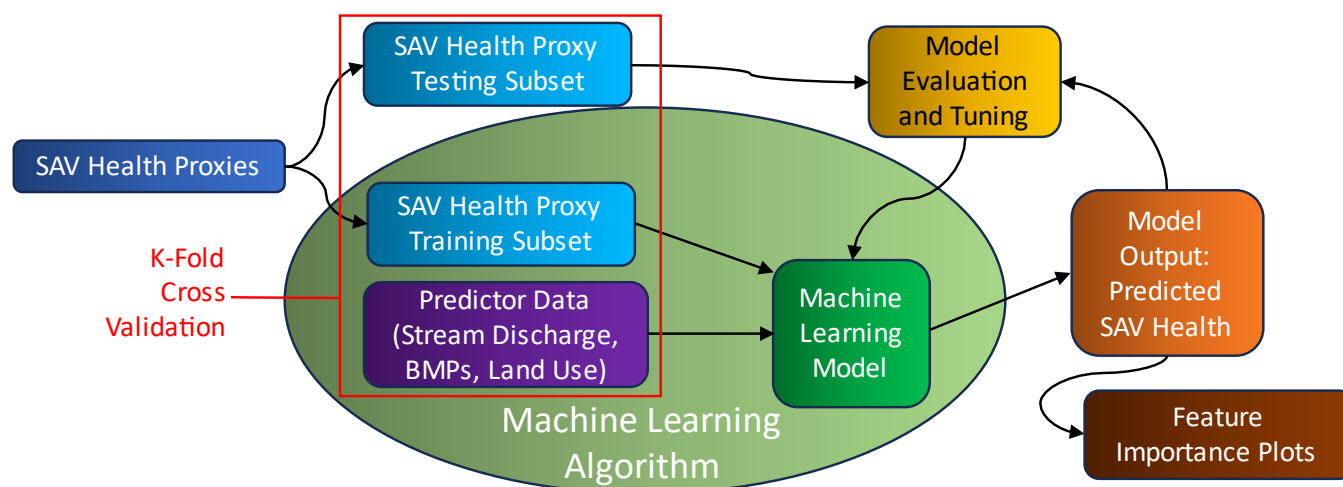


Figure 18. Diagram of the machine learning approach

3.1 MODEL SELECTION

Many predictive models such as random forests and generalized linear models require complete records (a row of data) without any missing data. When incomplete records are encountered, they must be deleted, or a separate imputation model must be run first to fill in the missing values. To leverage all available data, we selected to use Extreme Gradient Boosting (XGBoost; Chen and Guestrin 2016) which is a tree-based, gradient boosting model (Friedman 2001) that can predict ecological outcomes based on a range of environmental predictors and handle missing values. “Boosting” is a generic modeling term that means a given model is re-run hundreds of times, each time improving on the previous instance. XGBoost is an extension of Classification and Regression Trees (CART; Breiman et al. 1984) models. In CART, a single “tree” (i.e., model) is generated by identifying splitting values for

each predictor. XGBoost uses an ensemble tree method (similar to random forest) but places more importance to misclassified observations thereby attempting to concentrate model improvements on areas where the existing trees are performing poorly. Random forest differs from XGBoost in that it generates multiple trees in a parallel manner and cannot handle missing data. XGBoost is nonparametric, is nonlinear, and has been shown to produce output with a high level of accuracy across multiple types. While relatively new, XGBoost has begun to dominate the machine learning space for its speed and predictive capabilities, relative to other algorithms. Thus, the core of this analysis employs XGBoost.

3.2 MODEL SETUP AND TUNING

There are 180 data points in the model (12 priority beds across 15 years). To achieve a conservative estimate of model performance, it is important that the test dataset is independent from the training dataset. As such, a K-Fold cross-validation method was employed that systematically splits the dataset into a specified number (in this case, five) of smaller subsets or "folds". Here, each fold had 36 data points. The model is trained on four of these folds while the remaining fold is used for testing. This process is repeated such that each fold serves as the test set once, ensuring that all data points are used for both training and testing across the iterations. This methodology helps mitigate overfitting and provides a more generalized indication of model performance across different data samples. Four different models were developed using the K-Fold cross validation methodology to address each of the four SAV health proxies described in Section 4.1.

3.3 MODEL EVALUATION AND INFERENCE

As discussed above, the modeling process is robustly validated through K-Fold cross-validation (with five splits) to ensure the model's performance is reliable and replicable across different subsets of data. Each iteration of the model outputs predictive accuracy metrics such as Mean Squared Error (MSE) and R-squared (R^2), which are systematically recorded and later averaged to evaluate overall model performance.

While predictive power is important, inference as to how predictors relate to SAV health is also of interest. Many machine learning methods are referred to as "black box" models, as inference into how they came to their predictions can be opaque. One way to gain inference is through variable importance plots (VIPs; Breiman 2001), which provide insights into which environmental factors most significantly impact ecological variables. This multifaceted approach not only enhances the accuracy of ecological predictions but also aids in understanding the complex relationships within ecological data.

4.0 MODEL INPUT DATA

Model input data were aggregated annually by the Priority Bed drainage area determined in Section 2.0. The model was run using data from 2008 through 2022 as this timeframe is when BMP data were available. SAV health is the response variable by which the impacts of the remaining input data will be assessed. In other words, SAV health responds to, or changes as a result of all other related inputs. Not all variables that influence SAV health are able to be included in the model due to data availability and their relative negligible impact they may have on SAV health. However, inputs with the largest degree of influence on SAV health included in the model are (1) land use of the contributing direct drainage area, (2) discharge of the streams in the aforementioned drainage area, and (3) BMPs present in the aforementioned drainage area.

The various types of input data are summarized in the subsections below.

4.1 SAV HEALTH PROXIES

There is no single defining factor of overall SAV health. Rather, it can be described by multiple factors, or proxies, that when combined can serve as determinants of overall SAV health. SAV bed size, SAV density (percent vegetative cover), number of SAV species present in each bed, and whether rare/sensitive SAV species are present in each bed served as the proxies in this study. These four variables were summarized annually and all data were obtained from the VIMS GIS data archive¹.

As with the decision tree criteria for selecting Priority Beds, the rare/sensitive species health proxy is also dependent upon salinity zone in which the SAV bed exists. For the coastal bays and polyhaline salinity zones the rare/sensitive species is *Zostera marina* and for the tidal fresh, oligohaline, and mesohaline salinity zones the rare/sensitive species is *Potamogeton perfoliatus*. Therefore, while salinity zone was not explicitly used on its own as a predictor variable in the model, the salinity zone is still accounted for indirectly in the rare/sensitive species health proxy modeled response data.

The extent and location of SAV beds vary temporally and spatially. As such, SAV beds are defined as the aggregate footprint of the past six years of available data (2017-2022), as described in Section 1.1. Due to the transient nature of SAV beds, the health proxies described above apply to the Priority Beds if and only if an SAV bed from any one year intersects any part of the Priority Bed. For example, an SAV bed in 2009 may have a different spatial extent than what the aggregate 2017-2022 Priority Bed has but can intersect a corner of that Priority Bed. In this case, the health proxies defined in that 2009 bed would apply due to the intersection. A visual analysis indicated this SAV health proxy assignment is appropriate because drainage area to the 2009 SAV bed (by which the other model inputs are summarized) will be the same, or very similar, to those defined by the aggregate 2017-2022 defined Priority Bed.

In most cases, multiple beds from any one year intersected a Priority Bed. Therefore, health proxy data had to be statistically summarized to a single value for model input. SAV bed size was calculated as the sum of the area of all intersecting SAV beds within the same year. SAV density was calculated as the average density of all intersecting SAV beds within the same year. The number of SAV species was calculated as the maximum number of species in any given intersecting SAV bed within the same year. The rare/sensitive SAV species variable is binary in nature and if any one of the intersecting SAV beds within a given year contained the rare/sensitive species, the corresponding value was assigned.

Results of the four SAV health proxies are shown in Figure 19 through Figure 22 below.

¹ VIMS GIS data archive: <https://www.vims.edu/research/units/programs/sav/reports/>

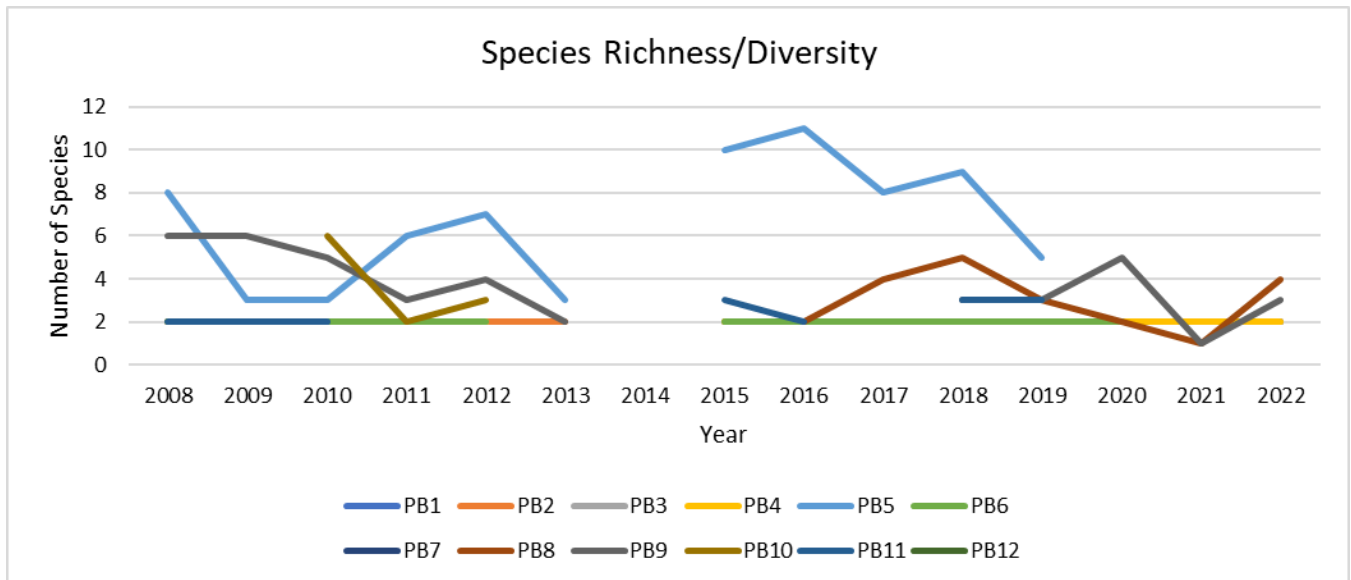


Figure 19. Species richness/diversity SAV health proxy: maximum number of species in each intersecting bed from 2008-2022.

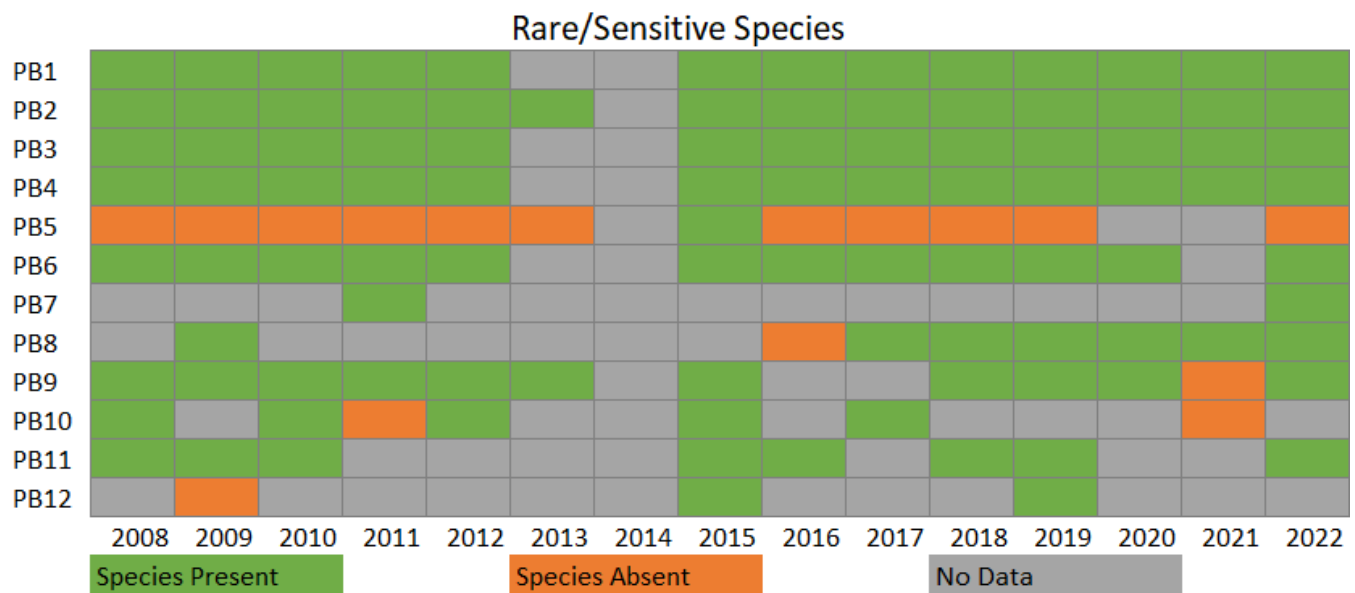


Figure 20. Rare/sensitive species SAV health proxy: presence (value of 1) or absence (value of 0) in each intersecting bed from 2008-2022.

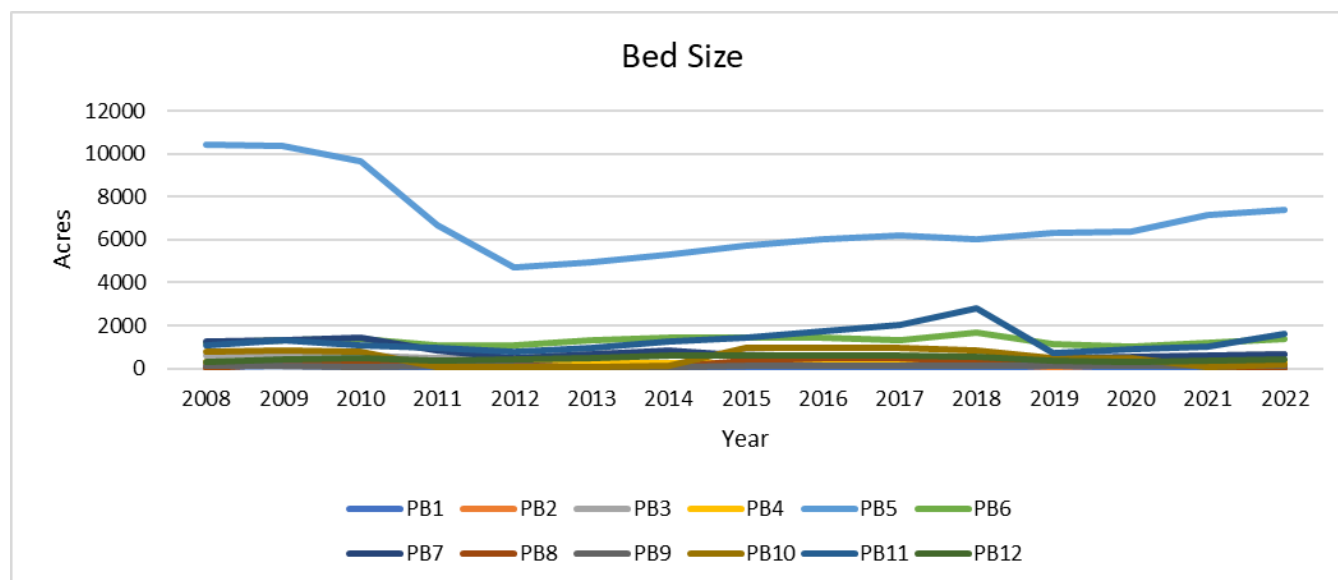


Figure 21. Bed size SAV health proxy: sum of the area of each intersecting bed from 2008-2022.

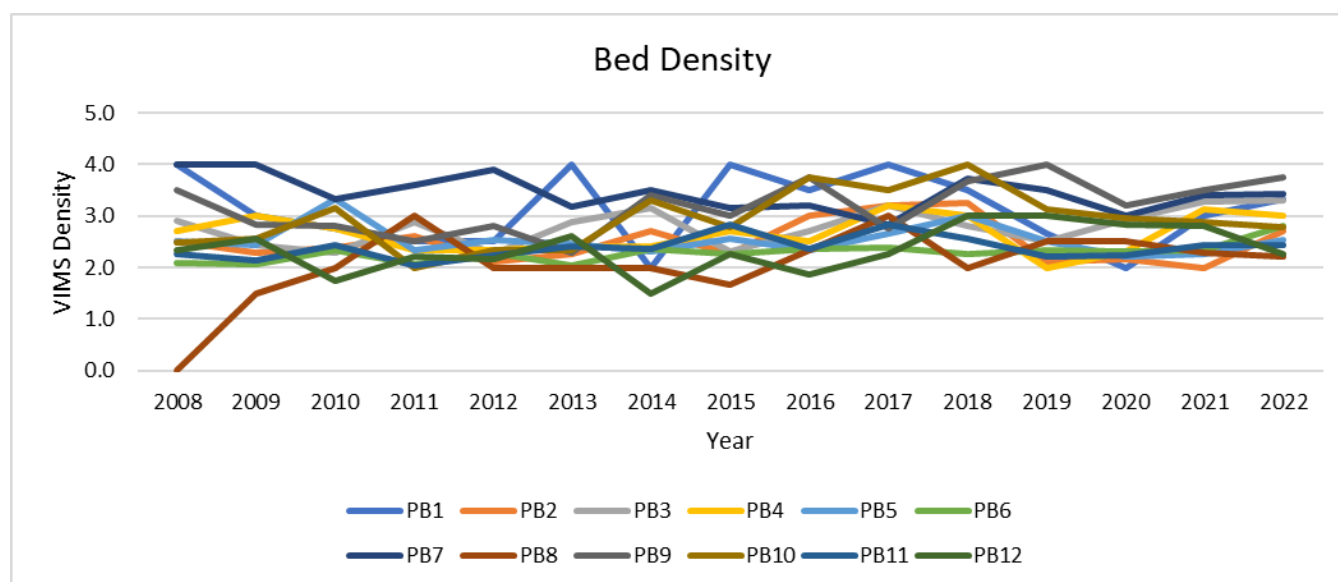


Figure 22. Bed density SAV health proxy: average of the density of each intersecting bed from 2008-2022. Note that VIMS density values correspond to percent vegetative cover where: 0 = No SAV; 1 = 0-10%; 2 = 10-40%; 3 = 40-70%; and 4 = 70-100%.

4.2 PREDICTOR DATA: STREAM DISCHARGE

Streamflow, also referred to as stream discharge, is an important transport mechanism for nutrients and other constituents (e.g., sediment) across the landscape and into estuarine waters such as the Chesapeake Bay. The velocity of streamflow impact streambed scouring and the magnitude of streamflow (i.e., the amount of freshwater

water transported downstream) impacts the salinity of estuarine waters; and ultimately, the aquatic environment supporting SAV and associated aquatic organisms.

Mean daily streamflow data were obtained from the U.S. Geological Survey (USGS) for all stations within the priority bed catchments for the 2008-2022 study period using the `dataRetrieval` R package (R Core Team, 2024) and R version 4.3.2 (DeCicco et al., 2024). A total of 221 unique streamgages were identified with data records that were 95% or more complete. These streamgages were each assigned to a priority bed based on their spatial location in the upstream catchment draining to the priority bed (Figure 23). There were five priority beds that had available USGS streamgage data; however, several priority beds did not have data available (Table 3). Statistical summaries of the mean daily streamflow data were calculated by aggregating streamgage mean daily flow for a particular priority basin by (1) an annual time step and (2) the entire study period (2008 – 2022). Statistical aggregation methods included: minimum, mean, and maximum as well as several determining streamflow percentiles (10, 25, 50, 75, and 90). The USGS considers normal streamflows to lie between the 25th and 75th percentiles for a long-term period (i.e., 20-30 years; Helsel et al., 2020; USGS, 2024). Here, the long-term period is assumed to be the study period (2008-2022). Furthermore, the 10th and 90th percentiles for the study period represent low and high streamflow conditions, respectively.

Table 3. Number of USGS streamgages for each priority basin

Priority Bed Number	Number of USGS Streamgages
1	0
2	9
3	0
4	0
5	105
6	0
7	104
8	0
9	1
10	2
11	0
12	0

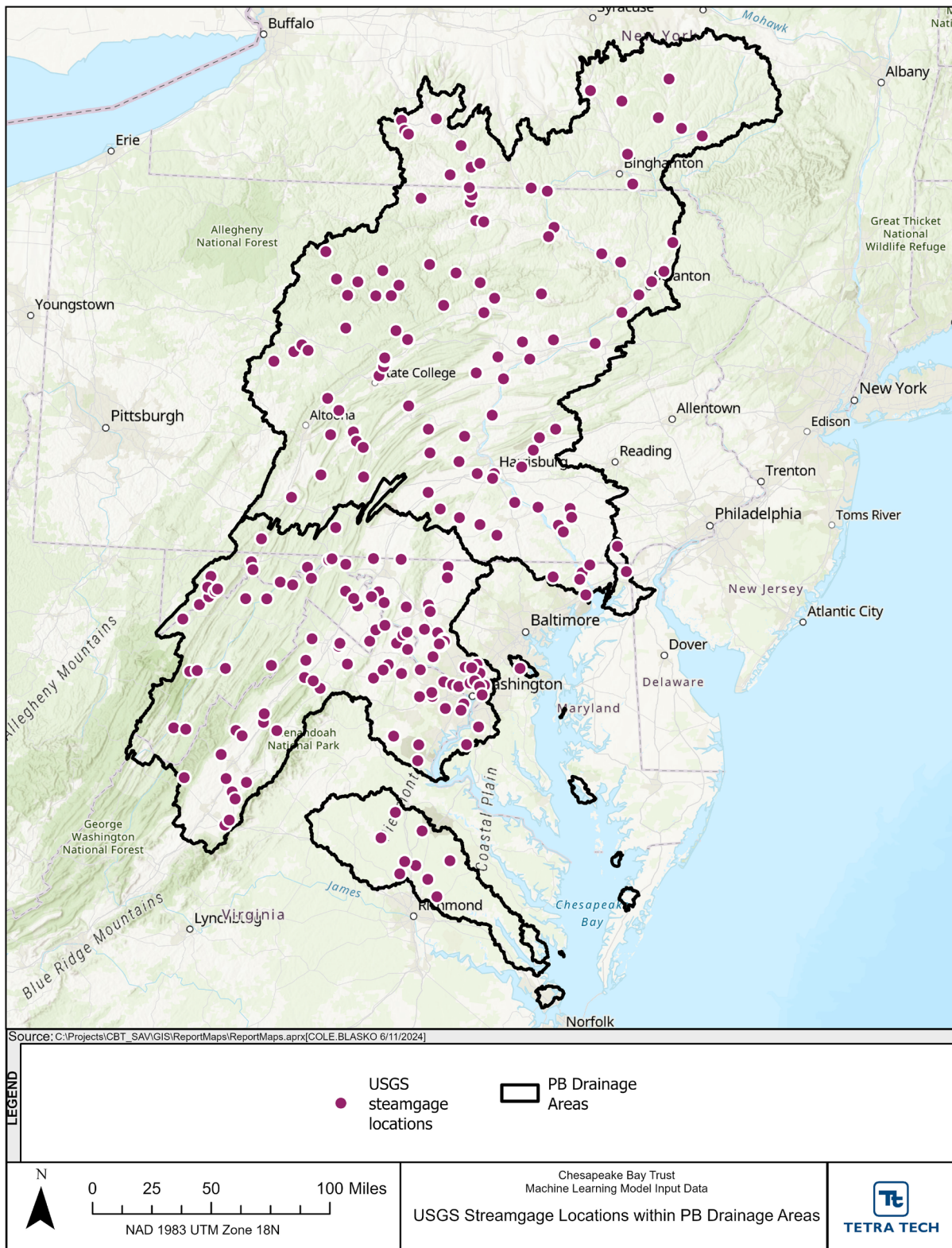


Figure 23. USGS streamgage locations (n = 221) in the study region

4.3 PREDICTOR DATA: LAND USE AND BMPS

Watershed land use can affect SAV by influencing nutrient and sediment loading to estuaries which in turn affects water clarity and the survival of photosynthetic vegetation (Estes et al. 2009; Li et al. 2007). As discussed in Section 2.1 the Multi-Resolution Land Characteristics Consortium (MRLC) National Land Cover Database (NLCD)² was used in this project. These data encompass 16 land use classes at a 30-meter spatial resolution and are updated every few years (2008, 2011, 2013, 2016, 2019, and 2021); all of which are at a fine enough resolution for BMPs to be assigned to their corresponding land use according to Table 4. BMP data processing is discussed in detail below.

Table 4. Land use year used for dasymetric allocation of BMPs

BMP Year	NLCD Year Used
2008-2009	2008
2010-2011	2011
2012-2013	2013
2014-2016	2016
2017-2019	2019
2020-2022	2021

Agricultural BMPs strive to manage and control the flow of sediment and nutrients into tributaries. For example, agricultural BMPs are designed to retain applied fertilizer on farmland or to reduce soil erosion resulting in decreases in tributary nutrient loading and sedimentation. Similarly, stormwater BMPs in more urbanized areas (wet/dry ponds, holding facilities, etc) are designed to slow transport of sediment and reduce erosional impacts from heavy flows, thereby reducing suspended solids. As such, BMPs are an important predictor variable in the model that is expected to influence SAV health.

As discussed in Section 2.2, the number of unique BMPs available from CAST is extensive (289 unique BMPs) but can be summarized into 64 unique BMP groups. BMP data are available from the Chesapeake Assessment Scenario Tool (CAST)³ at various spatial scales including point (i.e., latitude and longitude), HUC12 scale, HUC10 scale, county-wide, and state-wide. Point data were plotted using the latitude and longitude provided and was directly overlaid with drainage areas to Priority Beds. BMP data reported at larger scales (i.e., HUC12, HUC10, county, and state) require a dasymetric approach. All BMP data is provided in the supplementary excel file [CBT SAV Supplemental Data ML Model.xlsx](#).

Dasymetric mapping is an advanced technique used to spatially refine any tabular data by redistributing values based on ancillary information that indicates the spatial distribution within a region. This approach begins by gathering essential data sets, in this case State, County, HUC12, HUC10 and point source BMP data from CAST and NLCD land use data, which provides detailed classifications of land cover types such as urban, agricultural, and water bodies. Both datasets need to be geographically aligned and cleaned for any discrepancies, ensuring they are projected into the same coordinate system for accurate analysis.

The next step in dasymetric mapping involves defining homogeneous units within the NLCD by identifying which land cover types are likely to contain BMP data. For example, cover crops do not occur in urban areas or bodies of water. Dasymetric allocation specifically apportions the tabular data for a given area to only those NLCD pixels

² Multi-Resolution Land Characteristics Consortium (MRLC) National Land Cover Database (NLCD). <https://www.mrlc.gov/>

³ The Chesapeake Assessment Scenario Tool. <https://cast.chesapeakebay.net/>

where it makes sense. Land uses associated with each BMP are provided in the supplementary excel file [CBT SAV Supplemental Data ML Model.xlsx](#). In the case of the cover crop BMP, these values were apportioned to only the cultivated crops class of the NLCD. This method fine-tunes the distribution by employing areal interpolation techniques, which break down large spatial scale data to finer spatial units within each land cover type. The refined data is converted to geotiff format for use in visualization and further analysis. This process helps in producing maps that depict spatially heterogeneous BMP estimates that allows for allocation of BMPs to priority SAV bed drainage areas.

5.0 RESULTS

The results from the XGBoost regression models, analyzed through the K-Fold cross-validation methodology, can be summarized in two primary categories: (1) the predictive accuracy across different ecological indicators and (2) insights into which environmental factors most significantly impact ecological variables. These results are discussed in the sections below.

5.1 PERFORMANCE METRICS

Performance metrics reported in Table 5 reveal varying degrees of predictive accuracy across different ecological indicators. For instance, the model predicting 'bed_size' demonstrated a high Average R^2 Score of 0.94, indicating that approximately 94% of the variance in 'bed_size' can be explained by the predictors used in the model. This is coupled with a relatively high Mean Squared Error (MSE) of 280,069.14 acres, which suggests relatively high variability in error magnitude across predictions, potentially influenced by the scale of 'bed_size' measurements. It should be noted that the average error, or $\sqrt{MSE}$, is 529 acres which is within reason and relatively small compared to the range of priority bed sizes of 117 acres to 7,565 acres.

On the other hand, the 'species_richness' model had a moderate R^2 Score of 0.45 reflecting a decent fit where 45% of the variance is explained. However, an MSE of 2.62 indicates predictive accuracy may be incorrect by up to three species when rounded to the nearest integer. The “rare/sensitive species” model could not explain the variance very well using the predictor variables as indicated by an R^2 value of 0.20. However, the relatively low MSE of 0.08 shows very little difference between observed and predicted values.

Finally, the “bed density” model performed the worst in terms of R^2 with a value of 0.10 and moderately well in terms of MSE with an average value of 0.21.

Accuracy of the model is determined, in part, by the accuracy of the response variables measured. All four ecological indicators were obtained from the VIMS data as described in Section 1.2. Species Richness and Sensitive/Rare Species are discrete variables and are accurate in terms of their magnitude. However, Species observations were performed at the segment scale within the bay. Because segments are spatially larger than individual beds, and because observations may have only occurred in a specific location within the segment, the species assigned to individual beds may not be representative in reality but are based on the best available data present. Bed size is a continuous variable and is only as accurate as the aerial imagery interpretation and bed delineation conducted by VIMS but is likely the most accurate among all ecological indicators. However, bed density is likely the least accurate variable among the ecological indicators for multiple reasons. First, is that density is categorized into four classes, each of which have a large range of vegetative cover. As such, a small change in vegetative cover (e.g., 39% to 41%) would result in a relatively large change in density categorization from 2 to 3 respectively considering that there are only 4 density classes. Second, is that density categorizations have a degree of subjectivity to them because they are assigned using a crown density scale that is based on visual comparisons of aerial imagery to reference images⁴. This may partially describe why Bed Density had the lowest R^2 value among the four ecological indicators.

Interpreting these results within the framework of K-Fold cross-validation offers further insights. The variations in MSE and R^2 across the ecological indicators suggest that while some models like 'bed_size' may have robust predictive capabilities due to strong relationships between features and outcomes, others like 'bed_density', which

⁴ VIMS Monitoring Methods for SAV. <https://www.vims.edu/research/units/programs/sav/methods/>

has an R^2 of just 0.098, might be influenced by weaker or more complex feature interactions that are not as readily modeled.

Table 5. XGBoost regression with cross-validation predictive accuracy

Ecological Indicator (response variable)	Average Mean Squared Error ^a	Average R^2 Score
Species Richness	2.62	0.45
Sensitive/Rare Species	0.08	0.20
Bed Size	280,069.14	0.94
Bed Density	0.21	0.10

a. MSE is in units of the response variable. (Species Richness and Sensitive/Rare Species have units of species; Bed Size has units of acres; Bed Density is a unitless index assigned by VIMS that scores from 1-4 based on percent vegetative cover of a bed)

5.2 FEATURE IMPORTANCE PLOTS

Each predictor had a different impact on the resulting predictive accuracy of the XGBoost model. Across all four SAV health proxies there were 223 unique predictor variables, most of which were not calculated as important. Thus, only the top 23 to 24 predictors are displayed in Figure 24 through Figure 27. These figures show the amount by which each variable contributes to the model's predictions. *However, this method does not indicate whether the variable has a positive or negative effect on the predictions.* Most BMPs that ranked in the top 23 to 24 predictors in terms of importance were reported at the county-scale. This shows that tracking of BMPs at this scale is effective in terms of spatial accuracy and reporting participation from the public. Also, predictors among all three categories of data (i.e., streamflow, land use, BMP) ranked relatively high among the four SAV health proxies. This indicates that SAV health is not dependent on one source, but rather the complex relationships between many environmental, anthropogenic, and climatological influences.

For both species-related SAV health proxies, there are three predictors that are separated from the rest in terms of importance: (1) cover crops of traditional wheat; (2) woody wetlands land cover; and (3) annual minimum daily discharge. In fact, annual minimum daily discharge is the most important predictor variable for three of the four SAV health proxies of rare/sensitive species, bed size, and bed density and second most important for species richness. This is an important finding because it indicates that low annual flows improve SAV health through multiple mechanisms. First, lower flows impart less bed shear stress and thus, less scour which allows SAV to remain rooted in place. Second, lower flows deliver less nutrients to the bay and keep salinity at a more constant concentration compared to higher flows or storm pulses that deliver large amounts of nutrients and cause salinity in the bay to change rapidly. Both of these mechanisms are critical for long term SAV health among all four ecological indicators.

Finally, bed size and bed density have the exact same top three predictor variables in terms of importance. It can therefore be inferred that bed size and bed density are influenced by similar environmental factors while SAV species are influenced by a slightly different set of environmental factors.

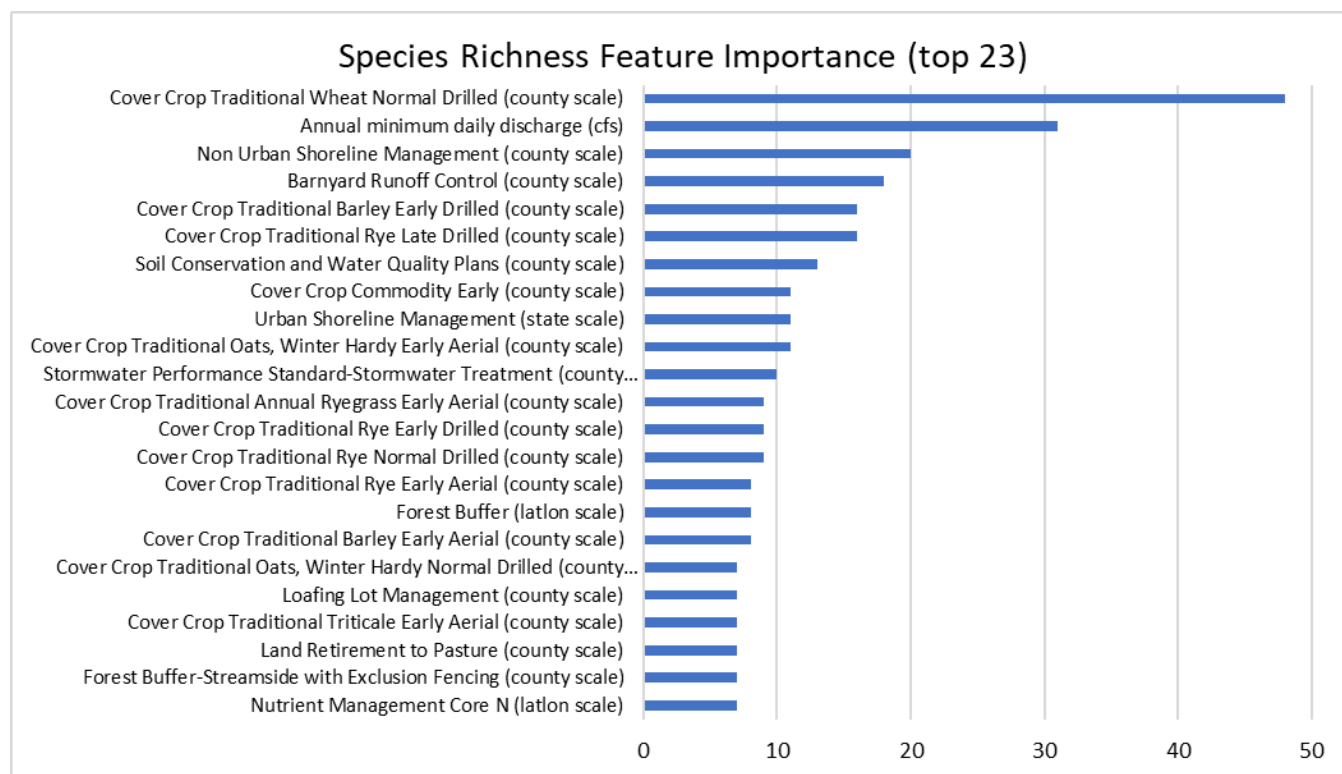


Figure 24. Relative importance of each predictor for species richness

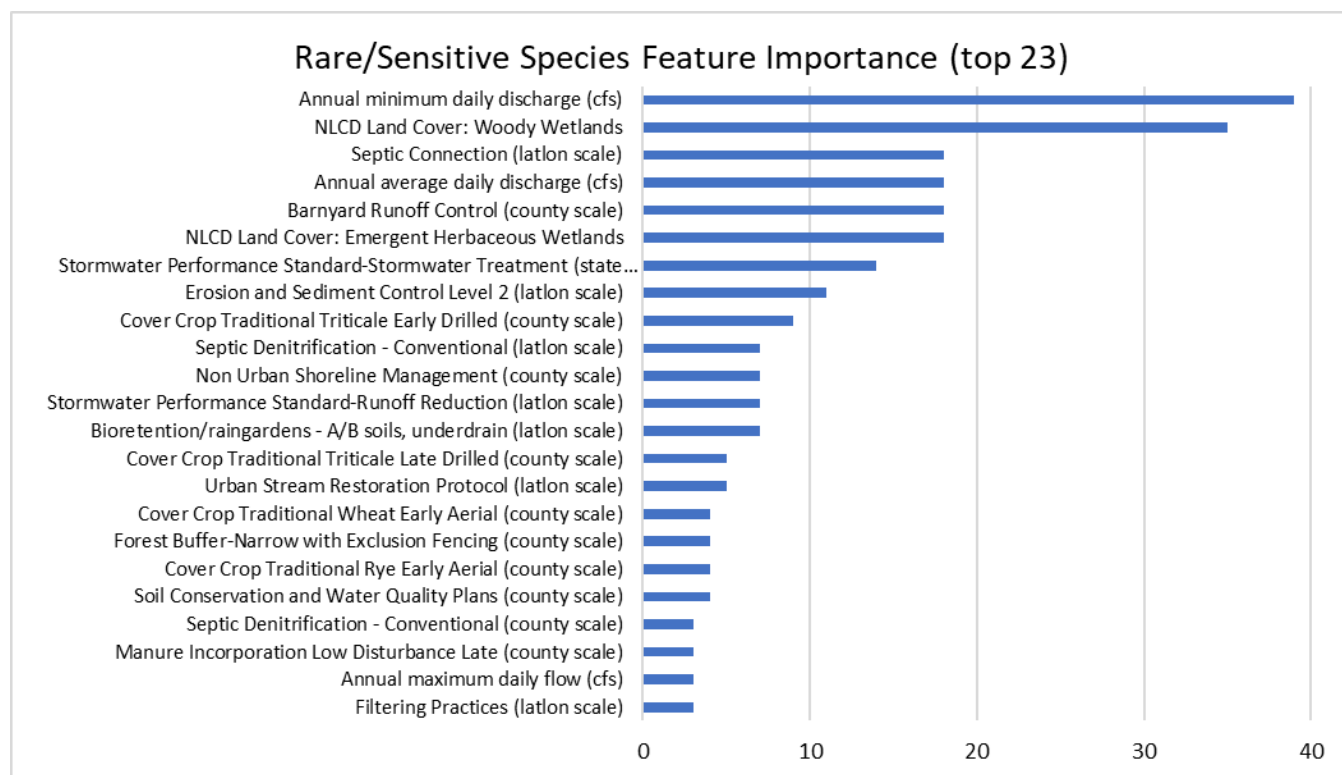


Figure 25. Relative importance of each predictor for rare/sensitive species

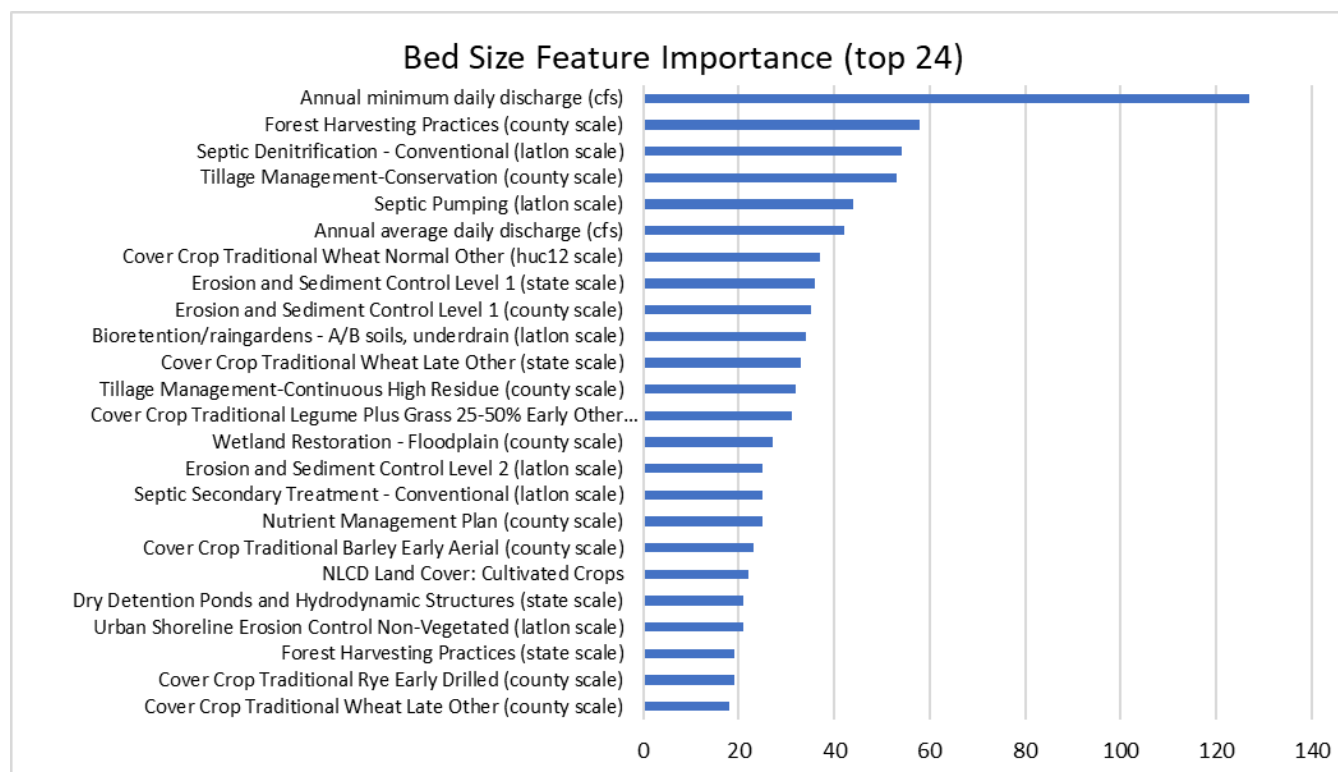


Figure 26. Relative importance of each predictor for bed size

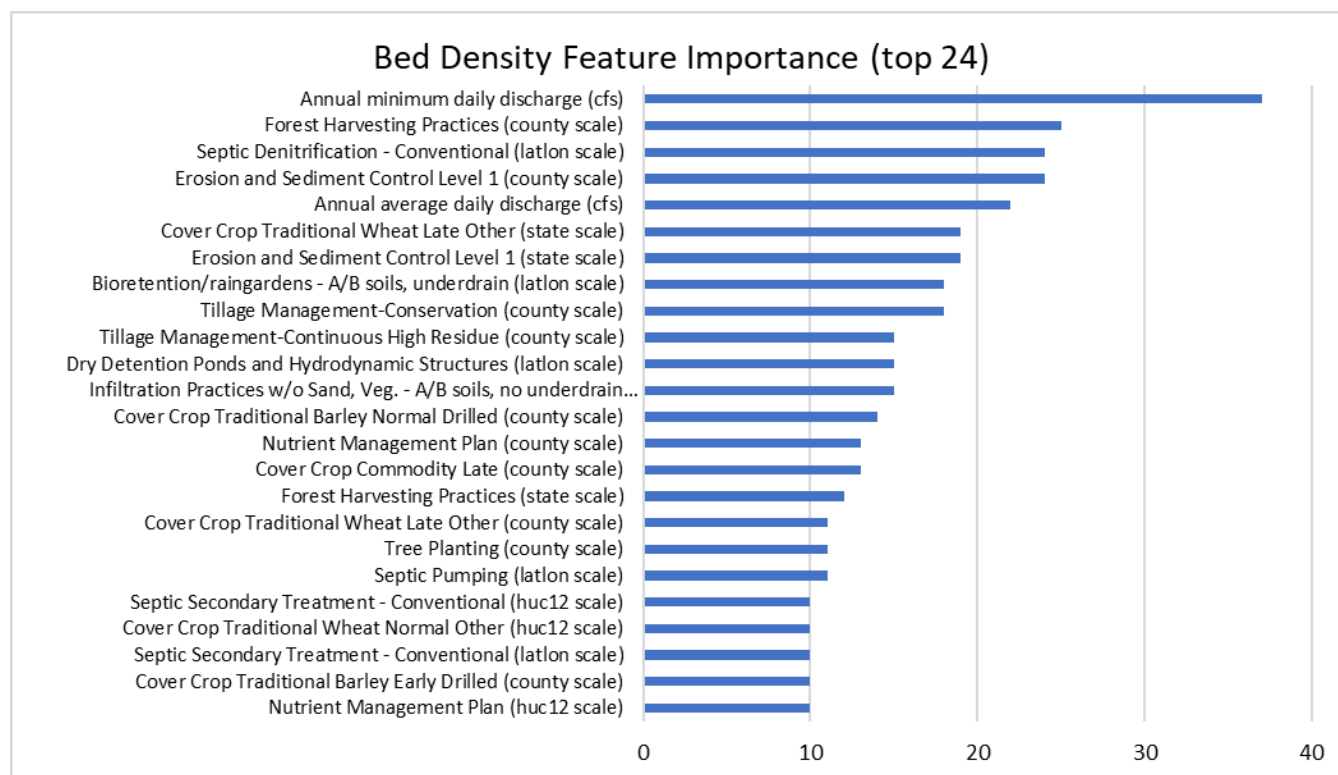


Figure 27. Relative importance of each predictor for bed density

5.3 PARTIAL DEPENDENCE PLOTS

Partial dependence plots (PDPs) help visualize how predictor variables are related to the response, which in this case are the SAV health proxies (Friedman, 2001). After modeling each predictor, PDPs are generated and show a range of values for a single predictor (x-axis) for the average predicted response (y-axis). Predictors in the model take their values from the input dataset, so that the observed variation among the other predictors is accounted for in the PDP.

PDPs for all predictor variables used across all four SAV health proxies are provided in supplemental PDF documents:

- Appendix B1: Partial Dependence Plots for Species Richness.pdf
- Appendix B2: Partial Dependence Plots for Rare/Sensitive Species.pdf
- Appendix B3: Partial Dependence Plots for Bed Size.pdf
- Appendix B4: Partial Dependence Plots for Bed Density.pdf

A variable with very little predictive power would be represented by a flat line on a PDP. Most of the predictor variables have little influence in predicting SAV health as indicated by the high frequency of flat, horizontal lines in the PDPs in Appendix B1 through Appendix B4.

However, variables that ranked high in the variable importance plots were further assessed using their PDPs. For instance, PDPs of the annual minimum daily discharge, which ranked high among all four SAV health proxies in the variable importance plots, is shown in Figure 28. Annual minimum daily discharges (x-axis) that were low, resulted in higher SAV health proxies, as represented by the partial dependence values (y-axis). This downward-trending line shows that the annual minimum daily discharge has a negative correlation to SAV health.

Positive correlations between predictor and response variables frequently exist among the BMPs. Namely, one example from each SAV health proxy is discussed below.

- Species Richness: Figure 29 shows that commodity cover crops planted early have a positive correlation with species richness such that ~100-acres planted within a drainage area to an SAV bed increases the number of species within that bed from an average of 2.8 species to 3.6 species. At the county scale, commodity cover crops planted early were shown to be the eighth most important predictor of species richness (Figure 24).
- Rare/Sensitive Species: Figure 30 shows that bioretention/raingarden BMPs with an underdrain have a positive correlation with rare/sensitive species such that treating ~1750-acres of land with this BMP increases the number of rare/sensitive species of SAV within a given bed from 0.871 species to 0.878 species. At the latitude/longitude scale, bioretention/raingardens with an underdrain were shown to be the thirteenth most important predictor of rare/sensitive species (Figure 25).
- Bed Size: Figure 31 shows that cover crops of traditional barley planted early via aerial seeding have a positive correlation with SAV bed size such that implementation of ~100 acres planted with a drainage area to an SAV bed increases the area of the bed by approximately one acre from 1176.2-acres to 1177.2-acres. At the county scale, cover crops of traditional barley planted early via aerial seeding were shown to be the eighteenth most important predictor of bed size (Figure 26).
- Bed Density: Figure 32 shows that bioretention/raingarden BMPs without an underdrain have positive correlation with bed density such that treating ~14-acres of land with this BMP increases the density of the SAV bed within the same drainage area from 2.686 to 2.696. This unitless increase of 0.01 in bed density correlates to a relatively small increase in percent vegetative cover as specified by the VIMS

density values that range from one to four. At the county scale, bioretention/raingardens without an underdrain were not shown to be the top 25 most important predictors of bed density (Figure 27).

These examples highlight the insights provided via PDPs and provide the directionality of the influence each predictor variable has on the response variables, which is not given in the variable importance plots. It should be noted that the units on each axis of the PDP is important. For example, a positive correlation may be very slight, as in the case of the rare/sensitive species partial dependence on bioretention/raingardens increasing only from 0.871 species to 0.878 species (Figure 30). On the other hand, a positive correlation may be more significant, as in the case of the species richness partial dependence on commodity cover crops increasing from 2.8 species to 3.6 species over the full range of cover crop area implementation (Figure 29).

These PDPs also underscore the advantage of not combining BMPs of similar types in this analysis. Nuanced differences like bioretention/rain gardens having or not having underdrains can be assessed independently. In this case, presence of underdrains did not influence the positive correlation this BMP had on rare/sensitive species (Figure 30) or bed density (Figure 32). However, this may not always be the case and is an important type of assessment to conduct when there are many predictor variables of similar effect, such as BMPs.

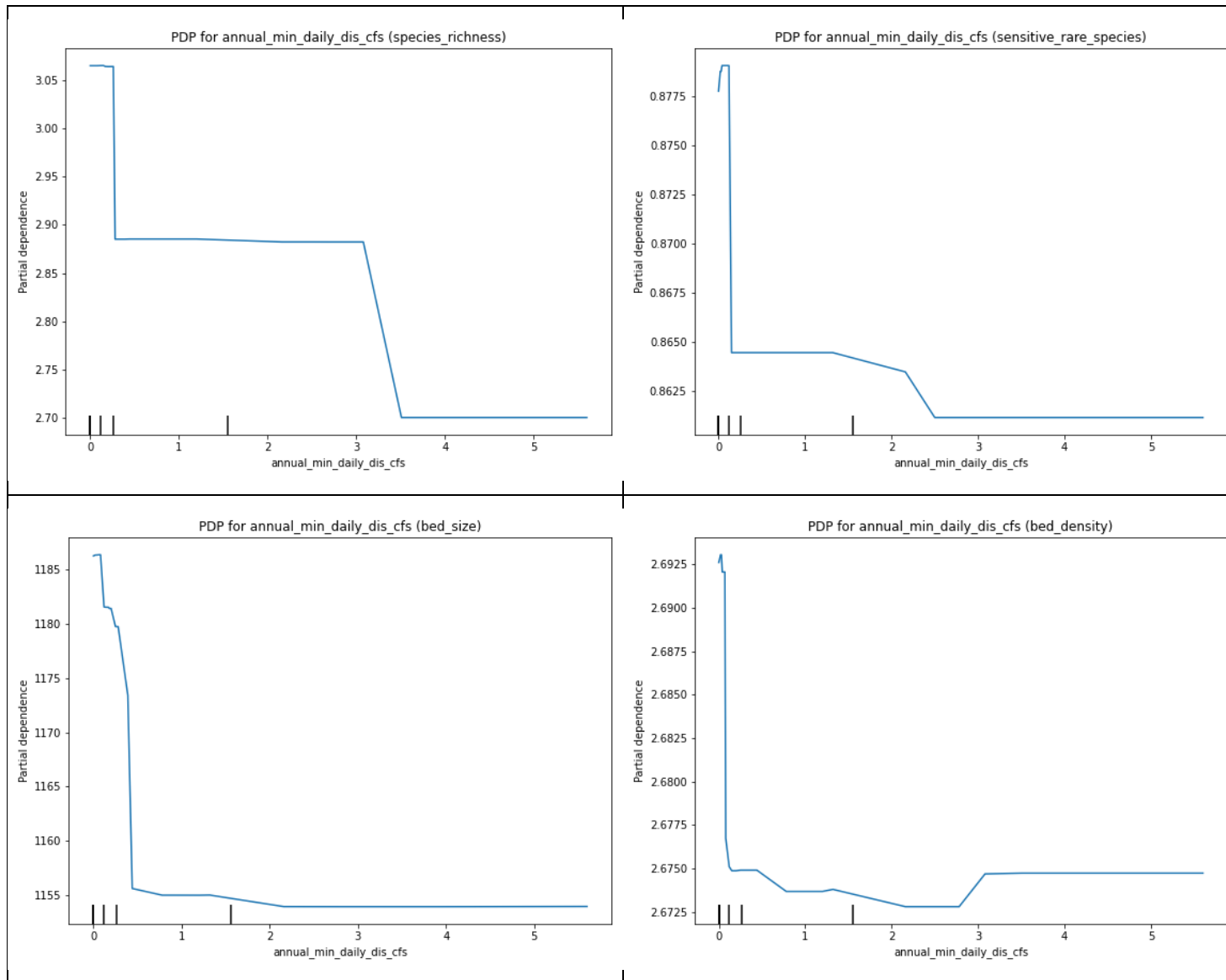


Figure 28. PDPs of Annual minimum daily discharge (cfs). Top left: Species Richness. Top right: Rare/Sensitive Species. Bottom left: Bed Size. Bottom right: Bed Density.

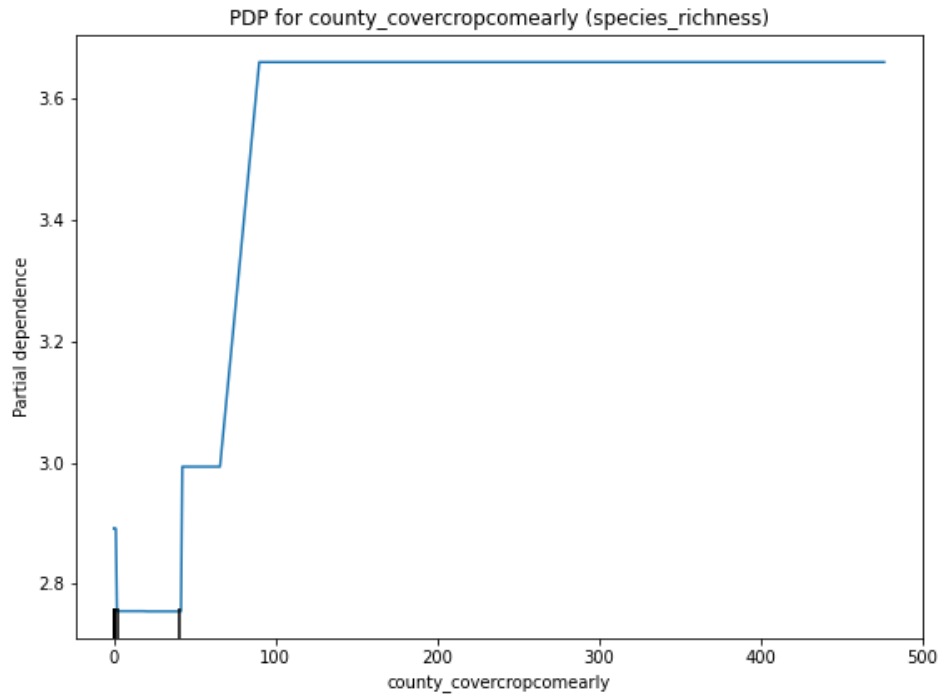


Figure 29. PDP of the "cover crop commodity early" BMP predictor variable (x-axis) for the species richness response variable (y-axis)

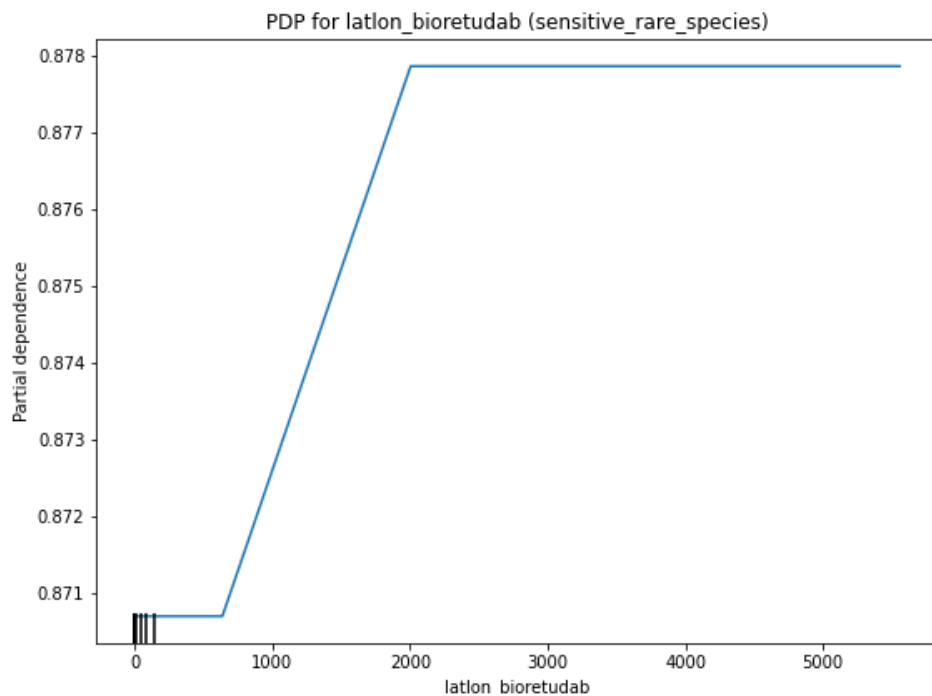


Figure 30. PDP of the "bioretention/raingardens – A/B soils, underdrain" BMP predictor variable (x-axis) for the rare/sensitive species response variable (y-axis)

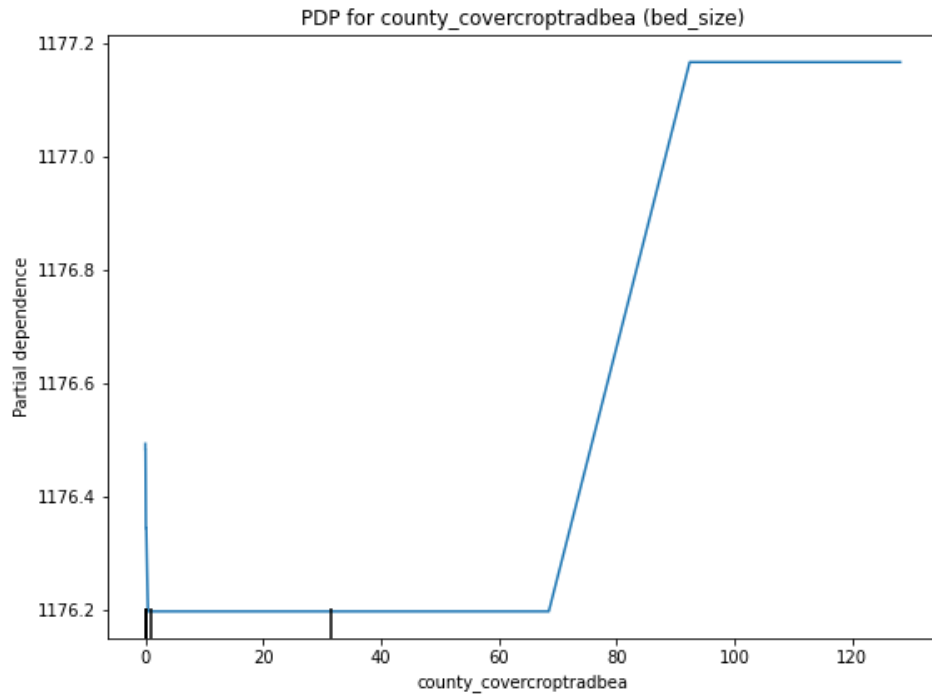


Figure 31. PDP of the "cover crop traditional barley early aerial" BMP predictor variable (x-axis) for the bed size response variable (y-axis)

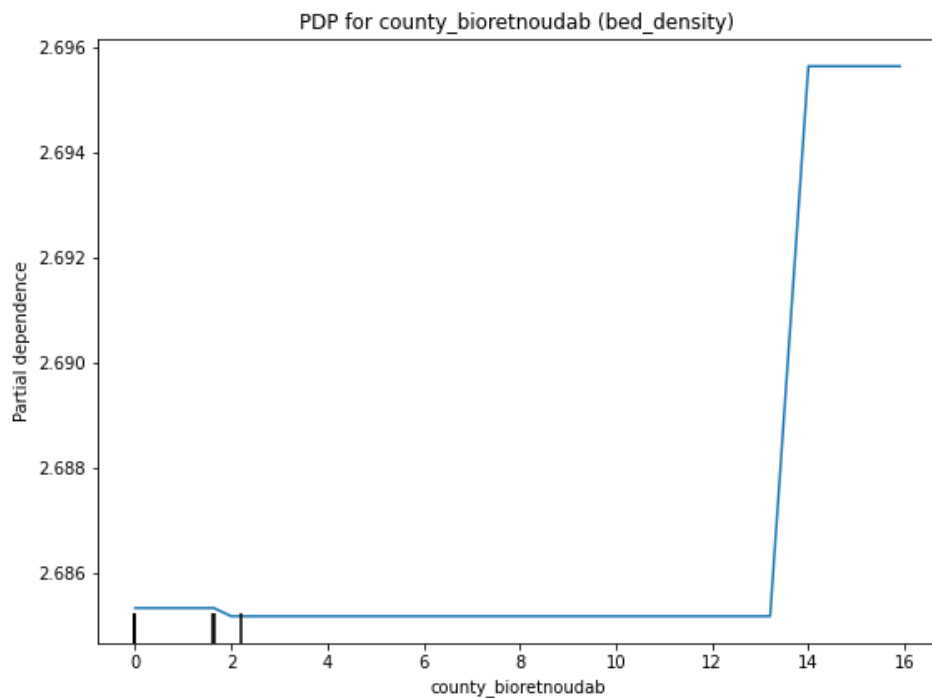


Figure 32. PDP of the "bioretention/raingardens – A/B soils, no underdrain" BMP predictor variable (x-axis) for the bed density response variable (y-axis)

6.0 DISCUSSION

SAV beds are often considered the “canary in the coalmine” in terms of coastal water quality since they are immobile and susceptible to multiple perturbations including eutrophication, sedimentation, wave exposure, and toxic runoff (Batiuk et al. 2000; Boesch et al. 2001; Kemp et al. 2005; Orth et al. 2010; Ward et al. 1984).

6.1 FACTORS INFLUENCING SAV HEALTH

This study assessed the health of SAV beds in the Chesapeake Bay as a response to changes over time among three primary variables: stream discharge, land use, and BMPs. Stream discharge can affect SAV through multiple mechanisms. High or flashy flows that occur during and after a precipitation event may impart greater shear stress on the bed, increase nutrient and sediment delivery potential, and alter salinity concentration in the bay. Steady baseflow or low flow conditions for extended periods of time provides stable bed conditions with lower erosion and sedimentation rates, lower nutrient delivery potential, and steady salinity concentrations in the bay. Watershed land use can affect SAV by influencing nutrient and sediment loading to estuaries which in turn affects water clarity and the survival of photosynthetic vegetation (Estes et al. 2009; Li et al. 2007). Changes in flow and land use are relatively easy to monitor but pose challenges to land and watershed managers in terms of protecting, conserving, and restoring SAV. Implementation of BMPs offers a mechanism to mitigate these anthropogenic negative influences of changing flow and land use.

The BMPs assessed in this study strive to manage and control the volume of flows and flux of sediments and nutrients into tributaries that eventually drain to Chesapeake Bay. BMPs of various types are typically associated with a particular land use. For example, certain agricultural BMPs are designed to reduce nutrient loading to tributaries, while other BMPs on agricultural lands are designed to reduce soil erosion, a major source of tributary sedimentation. Similarly, stormwater BMPs, typically implemented on more urban areas, are designed to attenuate peak flow volumes which slows the transport of sediments and reduces erosional effects, thereby reducing suspended solids.

6.2 RECOMMENDATIONS

Recommendations for which BMPs will be most effective in protecting, conserving, and restoring SAV are provided below. These recommendations serve as broad guidelines for which BMPs will be most effective. In reality, BMP effectiveness may vary greatly and are a function of many variables whose relationships among each other are typically stochastic in nature. For example, incorrect installation, lack of maintenance, nutrient saturation, overall age, or changing local conditions may cause a BMP to not perform at its most optimal effectiveness. As such, BMP selection, location, and maintenance requires local knowledge of primary environmental stressors. Also, opportunities where BMP implementation can improve both upland and receiving water conditions should be considered and prioritized as well.

The size of drainage area varies greatly among the twelve priority SAV beds from less than 1,000 acres for PB4 to 17.68 million acres for PB5. When BMPs are implemented at great distances from the bay, their net effectiveness can be attenuated by the many other influencing factors that are occurring between the source and receiving waters (i.e., other tributaries, point source nutrient contributions, etc.). As such, the proximity of BMPs to the Chesapeake Bay, and the size of the drainage area should be considered when evaluating BMP effectiveness in improving SAV health.

As shown in Figure 24 through Figure 27, annual minimum daily discharge is among the most important variables for predicting all four SAV health proxies. As discussed in Section 5.2, lower flow volumes improve SAV health through multiple mechanisms compared to higher, more flashy flow volumes. Therefore, BMPs that attenuate peak flows via reductions in surface runoff is a management strategy that should be prioritized. Reduction of flow volumes will be of particular importance when considering the influences of climate change and the continued

urbanization observed in land use change; both of which increase flow volumes through more frequent and intense storm events and increased impervious surfaces, respectively.

The following outline provides management recommendations, and specific BMPs related to each recommendation, for decreasing flow volumes in drainage areas to SAV beds, which was shown by the predictive model to be most effective in improving all four SAV health metrics.

Increase rainfall abstractions through additional vegetative interception.

- Cover crops intercept rainfall and uptake soil moisture during the non-cash crop season.
- Conservation tillage provides additional vegetative/residue coverage for rainfall interception.

Promote greater soil infiltration rates on agricultural lands through increased hydraulic conductivities.

- Practices that improve agricultural soil health to increase infiltration rates and capacity.

Decrease runoff from agricultural lands through other management strategies.

- Crop irrigation management maximizes irrigation efficiency so that no water is lost to surface runoff.
- Water control structures raise and lower the water table within the agricultural soil profile to prevent saturation excess overland flow during a precipitation event.

Decrease runoff from urbanized land uses.

- Permeable pavement allows water to infiltrate into the soil in urbanized areas rather than being sent to the stormwater drainage system.

Attenuate peak flows by modifying the timing of channel routing.

- Bioretention practices, raingardens, and detention/retention basins all decrease peak flow volumes by temporarily storing excess runoff.

The following outline provides management recommendations that are not aimed directly at decreasing flow volumes but provide ancillary benefits that are typically associated with lower flow volumes (e.g., decreased nutrient and sediment loads).

Reduce nutrient loading to tributaries on agricultural lands.

- Nutrient management practices adjust the rate, placement, and timing of nutrient applications such that nutrient loads in runoff is minimized.
- Denitrifying bioreactors reduce the amount of dissolved nitrate in tile drainage and groundwater sources.

Reduce soil erosion on agricultural lands.

- Conservation tillage leaves residue cover on the soil, which decreases the erosive potential of rainfall. Cover crops intercept rainfall and roots help to stabilize the soil profile.

The above recommendations should be implemented where the most opportune situations exist. For example, if a drainage area to an SAV bed is relatively small and is dominated by urban land uses, the attenuation of peak flows from this highly impervious drainage area may prove to be most effective. This may be achieved through a single detention/retention basin near the downstream end of the contributing area. On the other hand, if a drainage area to an SAV bed is large and is dominated by forested land use, attenuation of peak flows may not be readily achieved through BMP implementation, even if it is widespread. Rather, focusing on reduction of nutrient loading through BMPs such as nutrient management or denitrifying bioreactors may provide the greatest benefits to SAV health.

6.3 MODEL LIMITATIONS

The following limitations exist among the input datasets used in the model and may have impacted the prediction accuracy:

- SAV bed density was used as a metric in the decision tree when selecting priority SAV beds and was also used as a response variable in the machine learning model as a proxy for SAV health. There is a degree of uncertainty associated with SAV bed density because it is reported in the VIMS data as four numeric classes with values ranging from one to four. Each of these density classes represents a range of vegetative cover. For example, a small change in vegetative cover (e.g., 39% to 41%) can result in a change in density categorization (e.g., from category 2 to category 3). Additionally, density categorizations have a degree of subjectivity to them when assigned using a crown density scale based on visual comparisons of aerial imagery to reference images.
- SAV species present in SAV beds were used as metrics in the decision tree when selecting priority SAV beds and were also used as a response variable in the machine learning model as a proxy for SAV health. Species observations are reported at the segment scale, which is spatially larger than individual SAV beds. As such, species may be observed in a segment but may not be present in the SAV bed in question. The opposite may also be true where a species is present in a particular SAV bed but is not observed in the segment. Species observations are also opportunistic in that they typically do not occur in a spatiotemporally representative manner. In other words, samples are recorded in random locations at random times rather than following a spatial or temporal sampling design.
- Stream discharge data were used as a predictor variable in the machine learning model. The USGS gages available during the study period were not present in drainage areas for all 12 priority SAV beds (Table 3). Seven of the twelve SAV drainage areas had no USGS gages present, and therefore, no stream discharge data. Two of the twelve SAV drainage areas had ~10 times more USGS gages present in them compared to other drainage areas. This distribution of stream discharge data availability may have influenced the model weights associated with stream discharge-related predictor variables.
- BMP data were used as a predictor variable in the machine learning model. The dasymetric allocation of BMPs discussed in Section 4.3 helps to minimize the spatial uncertainty associated with BMPs reported at coarse spatial scales. However, there remains a degree of uncertainty inherent in these data because dasymetric allocation assumes the BMP data is distributed homogeneously across its associated land use and within its reported spatial scale. Additionally, while likely rare, it is possible that human-induced BMP reporting errors (e.g., acres of cover crops) may have been introduced into CAST.

6.4 FUTURE IMPROVEMENTS AND NEXT STEPS

Results of the machine learning model gave insight as to how accurately the data used in this analysis can predict SAV health. Additionally, and perhaps more importantly, the results of the machine learning model give insight as to the relative importance of which predictor variables have the greatest influence on SAV health.

This analysis established the approach of how environmental, anthropogenic, and climatological predictors can provide insights into which most significantly impacts ecological variables (SAV health). Additionally, it laid the groundwork for the data collection, cleaning, and processing required for such an analysis. While useful information for making watershed management and implementation decisions has been provided, this work can be expanded upon for improved model results and further insights:

- **Run the XGBoost model for all SAV beds within Chesapeake Bay** - The current set of 180 data points (12 beds for 15 years) used in this analysis is a relatively small number for developing and training a machine learning model. Running the model for all SAV beds would require intensive data processing of very large datasets but would likely improve R^2 and MSE accuracy metrics significantly.
- **Predictor variable addition and consolidation** - Other improvements could also be made to the predictor variables.

- First, more predictor variables can be added to the analysis. Discussions with the steering committee have identified possible data and data sources including:
 - locations of shoreline hardening
 - tidal data
 - water quality data (i.e., temperature, total phosphorus [TP], total nitrogen [TN], turbidity)
 - ratios of SAV bed size to drainage area size
- Second, the BMP predictor variables could be combined so that a single BMP reported at various spatial scales can be represented as one line item in the feature importance plots. Similarly, BMPs of the same type (e.g., cover crops of different crop species) could be combined. Aggregation of these BMPs may indicate that certain predictor variables are more or less important than others when combined in this way. However, a trade-off to this approach is that the analysis would no longer show which spatial scales are most important for tracking BMPs.
- **Deeper exploration of variable importance directionality** – This study provides an overview of variable importance via variable importance plots and partial dependence plots. Additional machine learning explanation tools could be applied to further explore variable dependences that are of strategic significance to CBP. Example techniques that may support this work include principal components analysis (PCA) and the analysis of SHapley Additive exPlanations (SHAP) values (Strumbelj and Kononko, 2014; SHAP, 2025a; SHAP, 2025b).
- **Climate change scenarios** – Additional scenario could be run to investigate how SAV health would be impacted under future conditions and would give insights as to what management practices would be effective in mitigating these impacts. These scenarios could be informed by existing Chesapeake Bay models, and other projects and resources provided by the Submerged Aquatic Vegetation Workgroup⁵; specifically the Shiny App developed and the Modeling Climate Impacts on SAV in Chesapeake Bay report (Hensel et al., 2003).
- **Expand approach beyond SAV health** - This quantitative approach can be applied to other resources of importance in the bay such as fish communities, oyster beds, etc.

⁵ Submerged Aquatic Vegetation Workgroup. [Submerged Aquatic Vegetation Workgroup \(chesapeakebay.net\)](https://chesapeakebay.net/submerged-aquatic-vegetation-workgroup)

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APPENDIX A: ADDITIONAL PRIORITY BEDS – TANGIER SOUND

Through discussions with the Steering Committee, it was suggested that Priority Beds be located in the Tangier Sound due to this being an area of ecological importance. Most criteria score relatively high and were not a driver of the low composite index scores. More specifically, the *Size*, *Density*, *Habitat*, and *Representativeness* criteria all score high in the Tangier Sound with most beds receiving a perfect score of 1.0. The *Maturity* criterion scores somewhat lower but there remain 9 beds in the Tangier Sound that receive a score of 0.75 or 1.0. These 9 beds would receive a high composite index score if all other criteria also score highly. However, Priority Beds were not initially chosen in the Tangier Sound through the established criteria and decision tree methodology because the *Species Richness* and *Rare/Sensitive Species* criteria both score low in this area of the bay with scores of 0.5 or less. This resulted in composite index scores to be less than the threshold of 0.9 and thus, no beds in the Tangier Sound were chosen as Priority Beds. Index scores for all criteria are presented in Figure A - 1 through Figure A - 7.

The Tangier Sound is part of the mesohaline salinity zone (Figure 15). As such, the *Species Richness* and *Rare/Sensitive Species* criteria are more stringent compared to the coastal bays and polyhaline salinity zones (Figure 2). The steering committee expressed interest in revising both these species criteria scoring indices where the mesohaline salinity zone is split into multiple regions so that SAV beds score higher in the Tangier Sound. Initial exploration of this idea indicated that if the Tangier Sound had its *Species Richness* and *Rare/Sensitive Species* criteria scored the same as the polyhaline salinity zone, both criteria would receive perfect scores of 1.0 for most, but not all of the Sound. These higher scores would then make the *Maturity* criterion the controlling factor of the composite index score and would result in nine SAV beds becoming preliminary beds in the Tangier Sound as noted above.

This approach however revealed a second issue in that most beds with high *Maturity* scores exist only on the islands within the Tangier Sound (Figure A - 2) and therefore the drainage areas to these beds would be relatively small in size and likely not include many BMPs to be assessed by the machine learning model. Because the impetus of this study is to assess BMPs relationship to SAV health, this approach and these beds were dropped from further consideration and thus, the Steering Committees' suggestion to revise the criteria index scoring methodology was not incorporated. Further reasoning for not revising the criteria index scoring methodology is that it was initially developed in an unbiased manner. Changing the criteria for the mesohaline salinity zone only for the Tangier Sound would be forcing the results to be what is wanted/expected and would not be statistically defensible.

Following the considerations previously discussed, the final Tangier Beds were selected as beds with relatively high criteria scores, and relatively large drainage areas (so that BMPs can be assessed in the machine learning model) within the mainland of Maryland on the east coast of the Chesapeake Bay. Locations of the Tangier Sound Priority Beds are shown in Figure 15 as PB11 and PB12 and the criteria scores are presented below in Table A - 1. It was also decided that these two Tangier Sound beds would be Priority Beds in addition to the ten beds selected through the decision tree methodology rather than replacing two beds previously selected. Therefore, 12 total beds were assessed in the machine learning model.

Land use in PB11 and PB12 are dominated by open water (48% and 82% respectively) and wetlands (45% and 18% respectively). PB11 includes small areas of developed (3%), cultivated crops (2%), and forest (1%) land uses.

Table A - 1. Summary of criteria and index scores for the Tangier Sound Priority Beds

Bed ID	PB11	PB12
Bed Size - acres	2,866 (1.0)	635 (1.0)
Maturity – area weighted avg. years	18.5 (0.75)	22.0 (0.75)
Bed Density – area weighted avg. VIMS score	3.6 (1.0)	3.9 (1.0)
Species Richness/ Diversity – No. Species	3 (0.5)	3 (0.5)
Sensitive/ Rare Species	0 (0.0)	0 (0.0)
Habitat Value	Priority Bed intersects valuable habitat area (1.0)	
Representativeness	Priority Bed intersects Regional Conservation Opportunity Areas (RCOA) or Index of Ecological Integrity (IEI) areas. (1.0)	
Composite Index Score	0.825	0.825

Values in parenthetical notation denote the index score for each criterion.

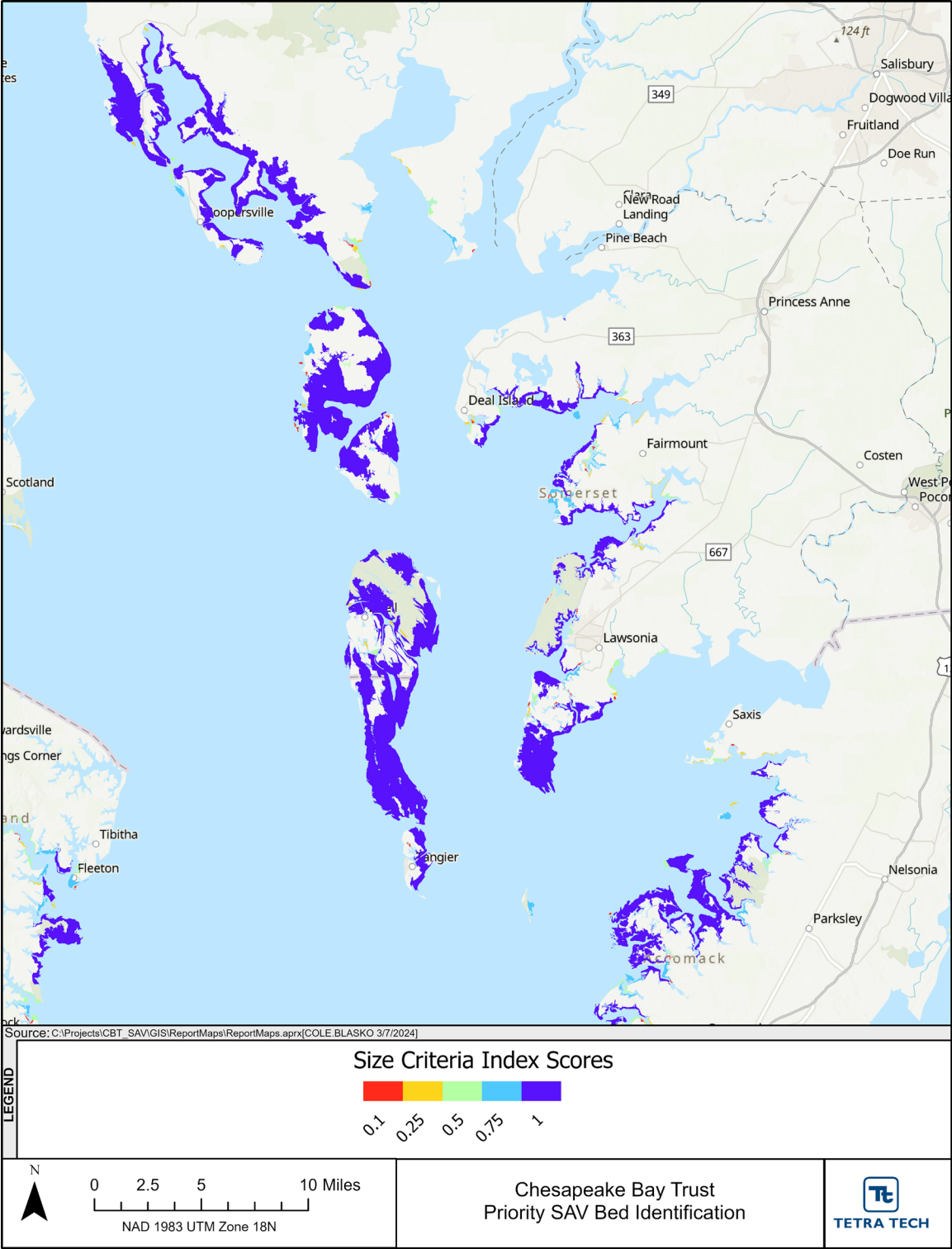


Figure A - 1. Size criteria index scores in the Tangier Sound

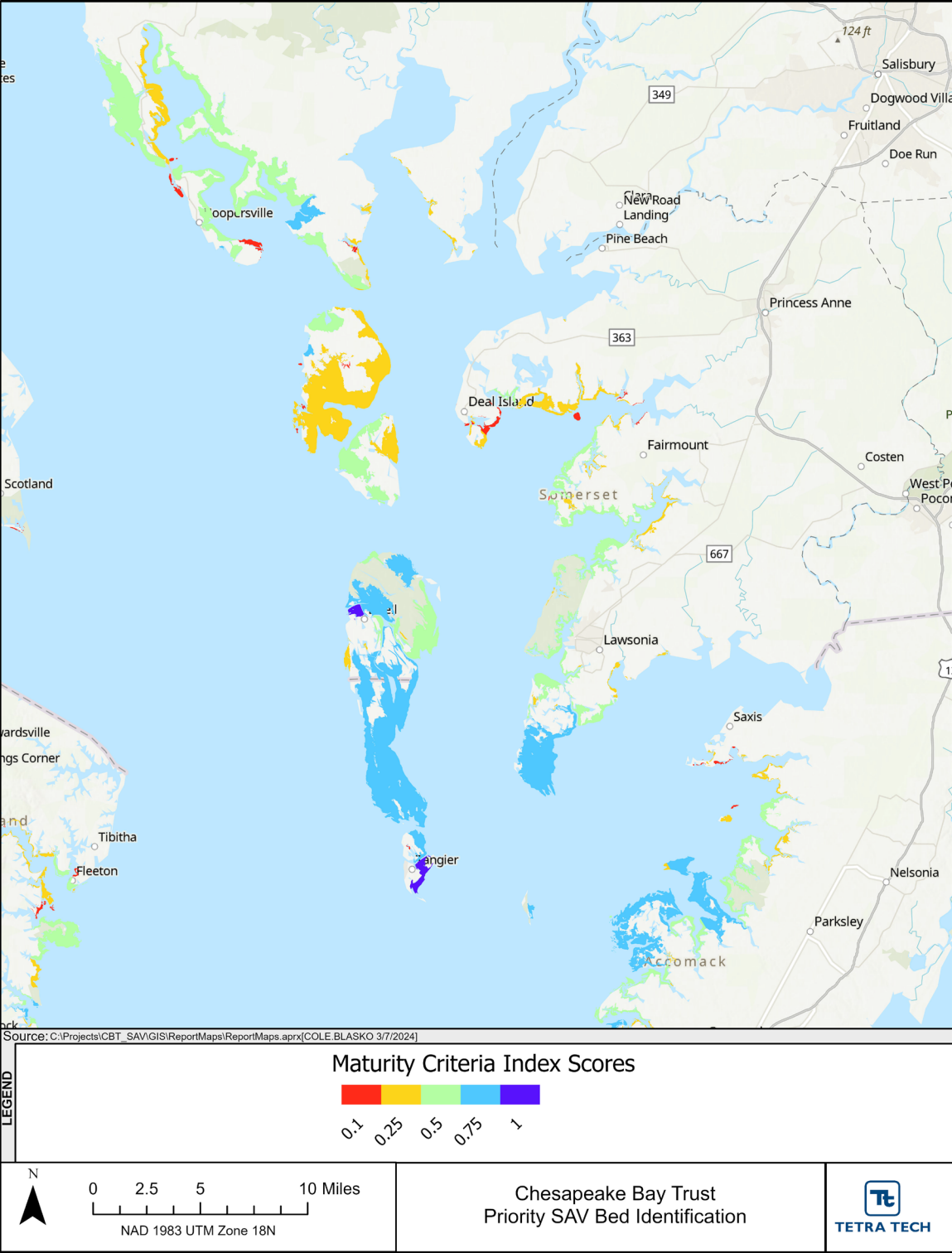


Figure A - 2. Maturity criteria index scores in the Tangier Sound

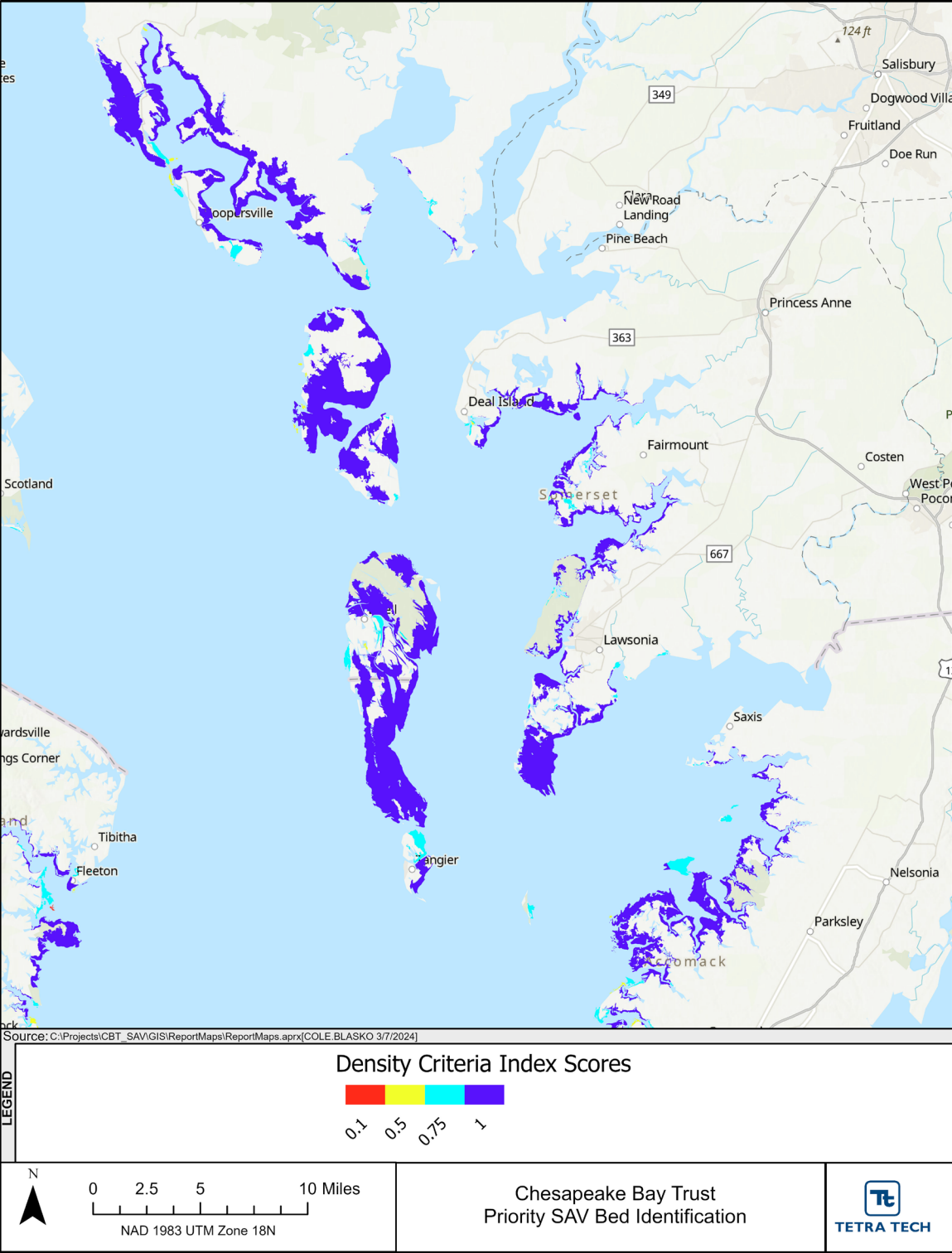


Figure A - 3. Density criteria index scores in the Tangier Sound

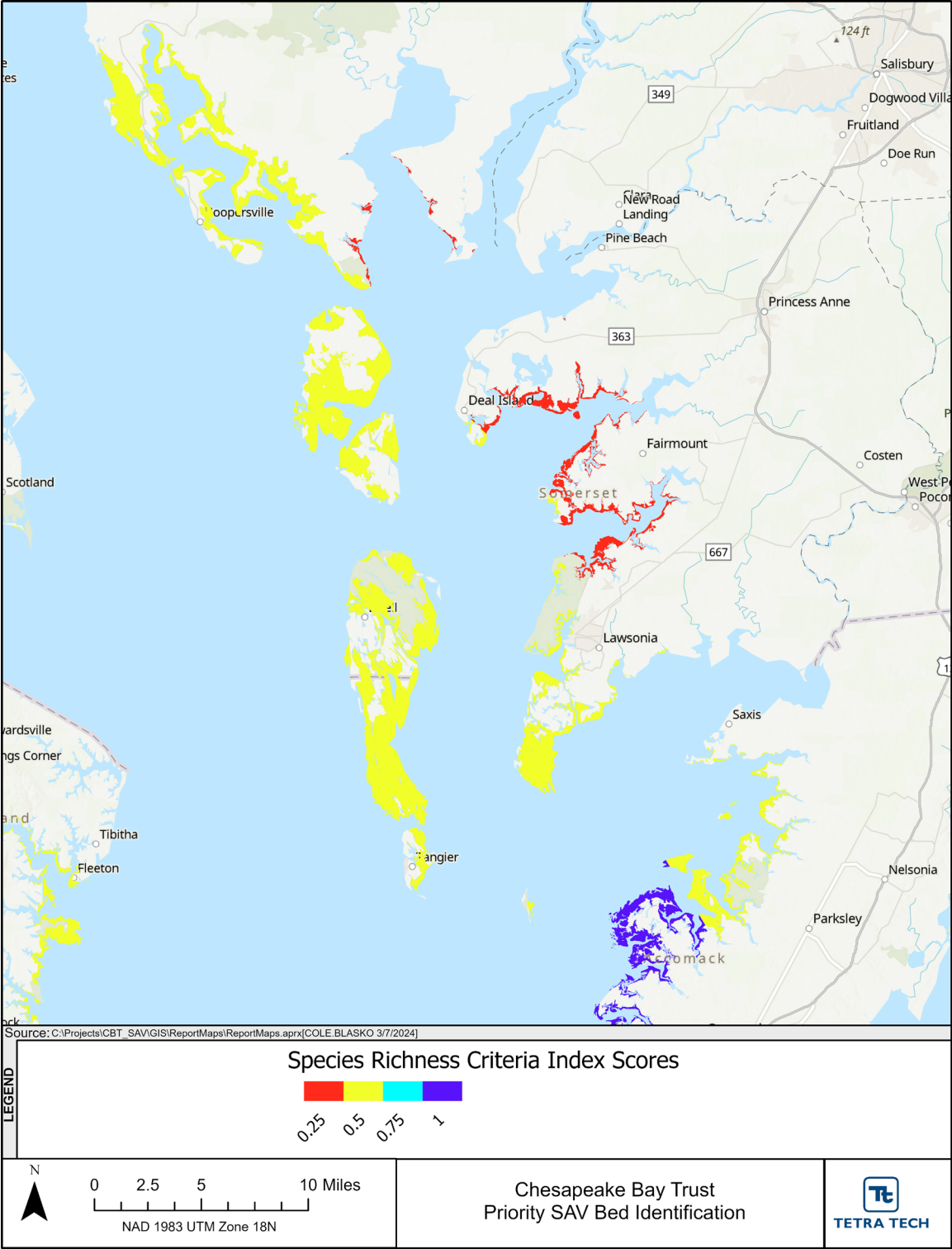


Figure A - 4. Species Richness criteria index scores in the Tangier Sound

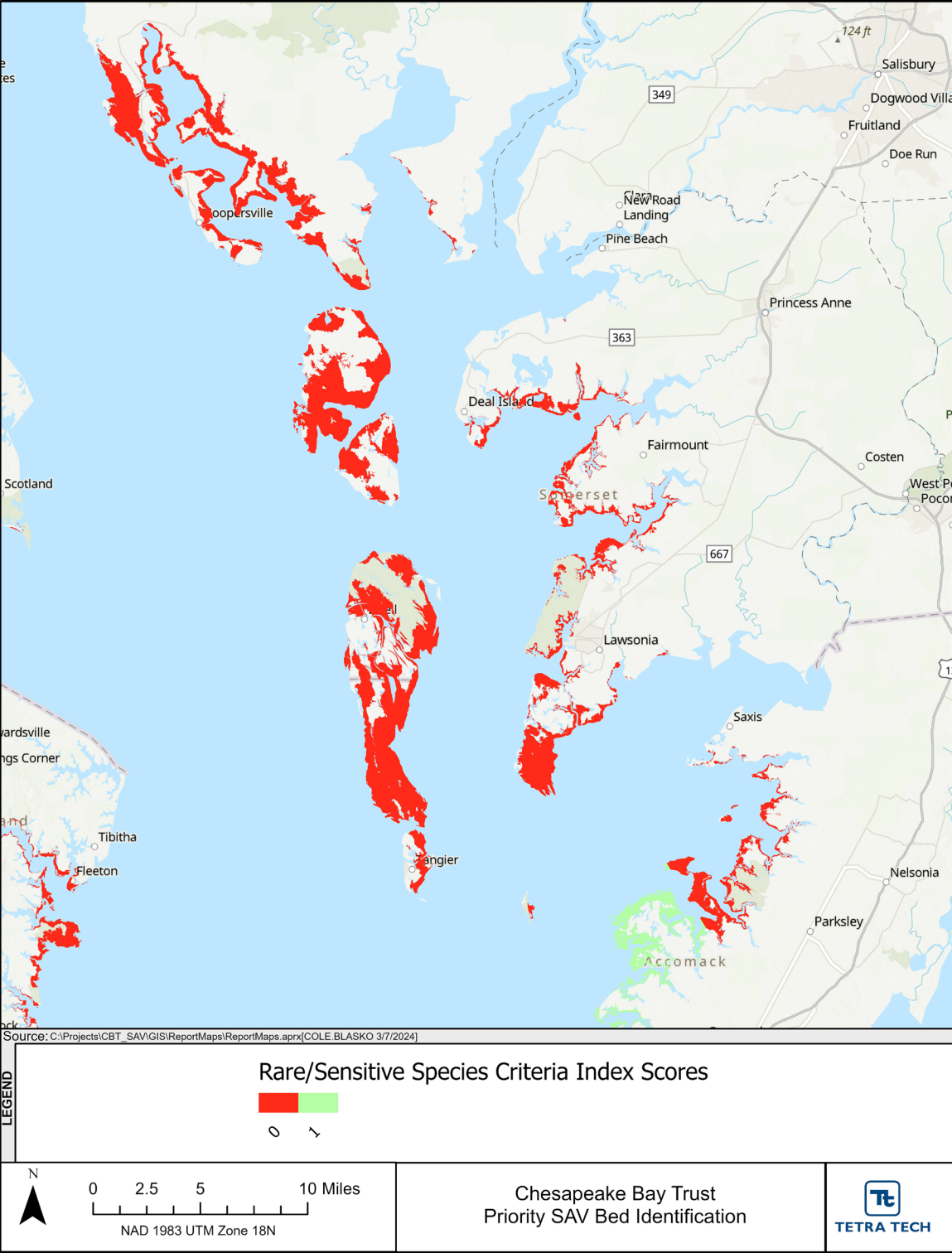


Figure A - 5. Rare/Sensitive Species criteria index scores in the Tangier Sound

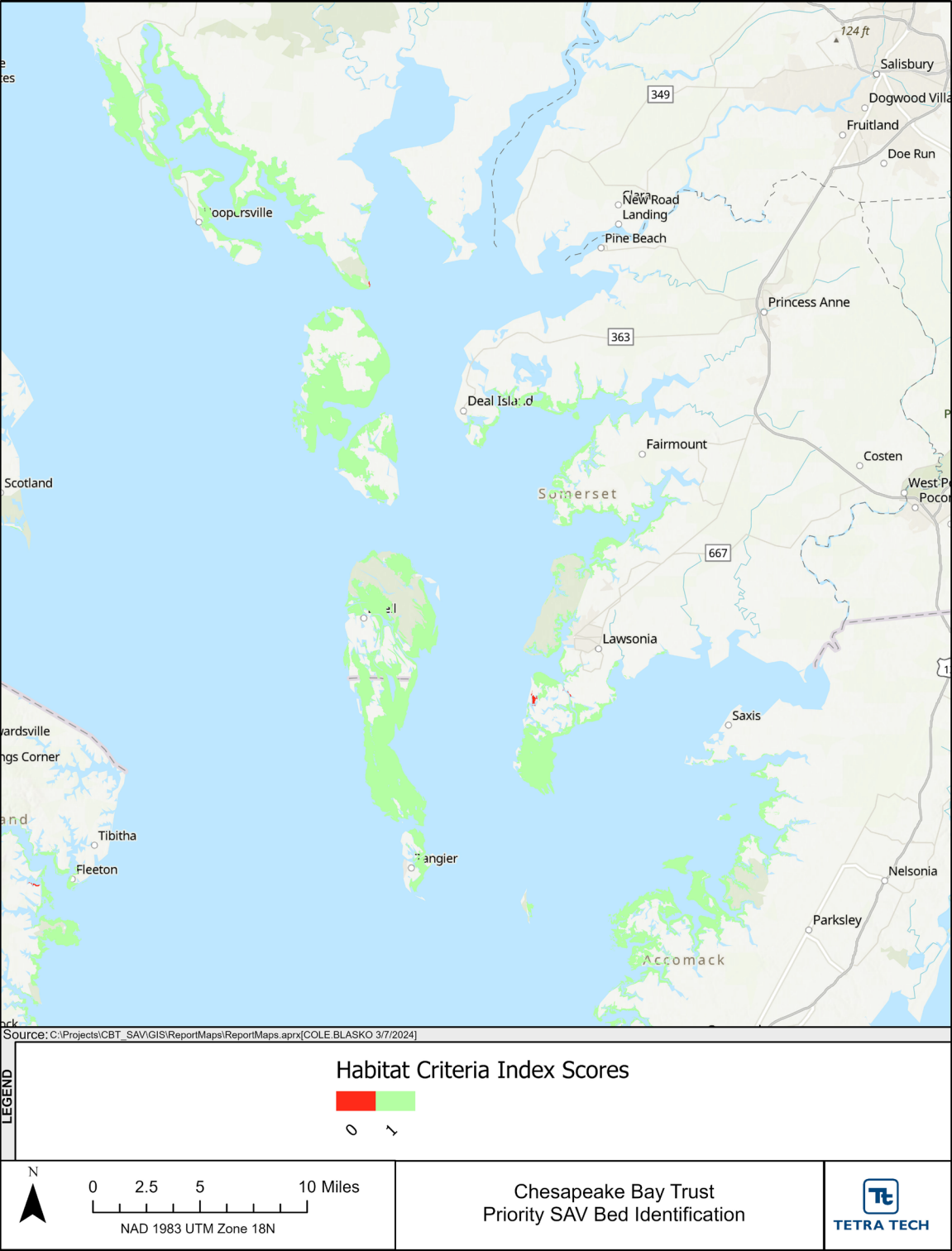


Figure A - 6. Habitat criteria index scores in the Tangier Sound

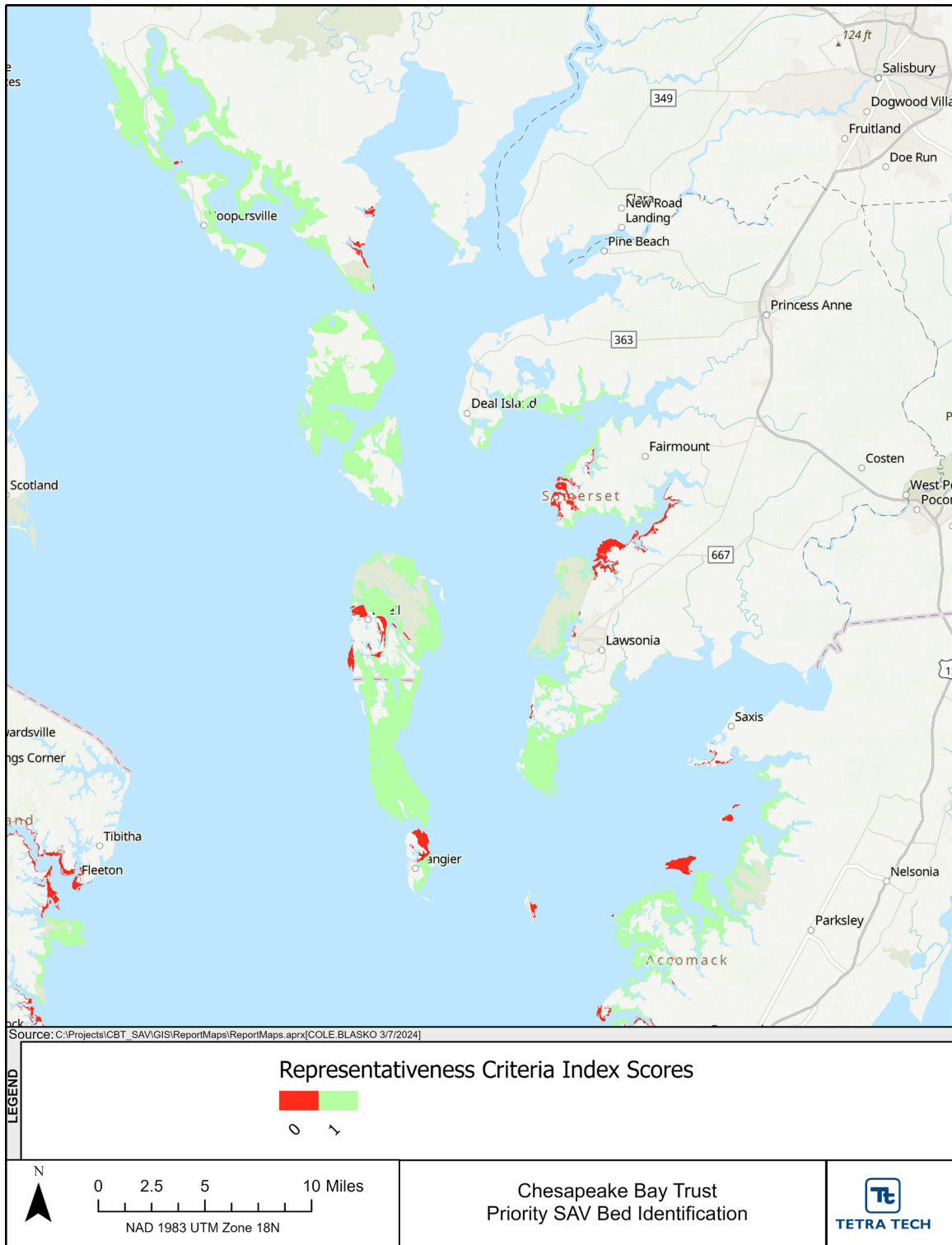


Figure A - 7. Representativeness criteria index scores in the Tangier Sound