TETRA TECH

Best Management Practices (BMPs) and Solutions Development for Protecting SAV Locally Given Changing Hydrologic Conditions

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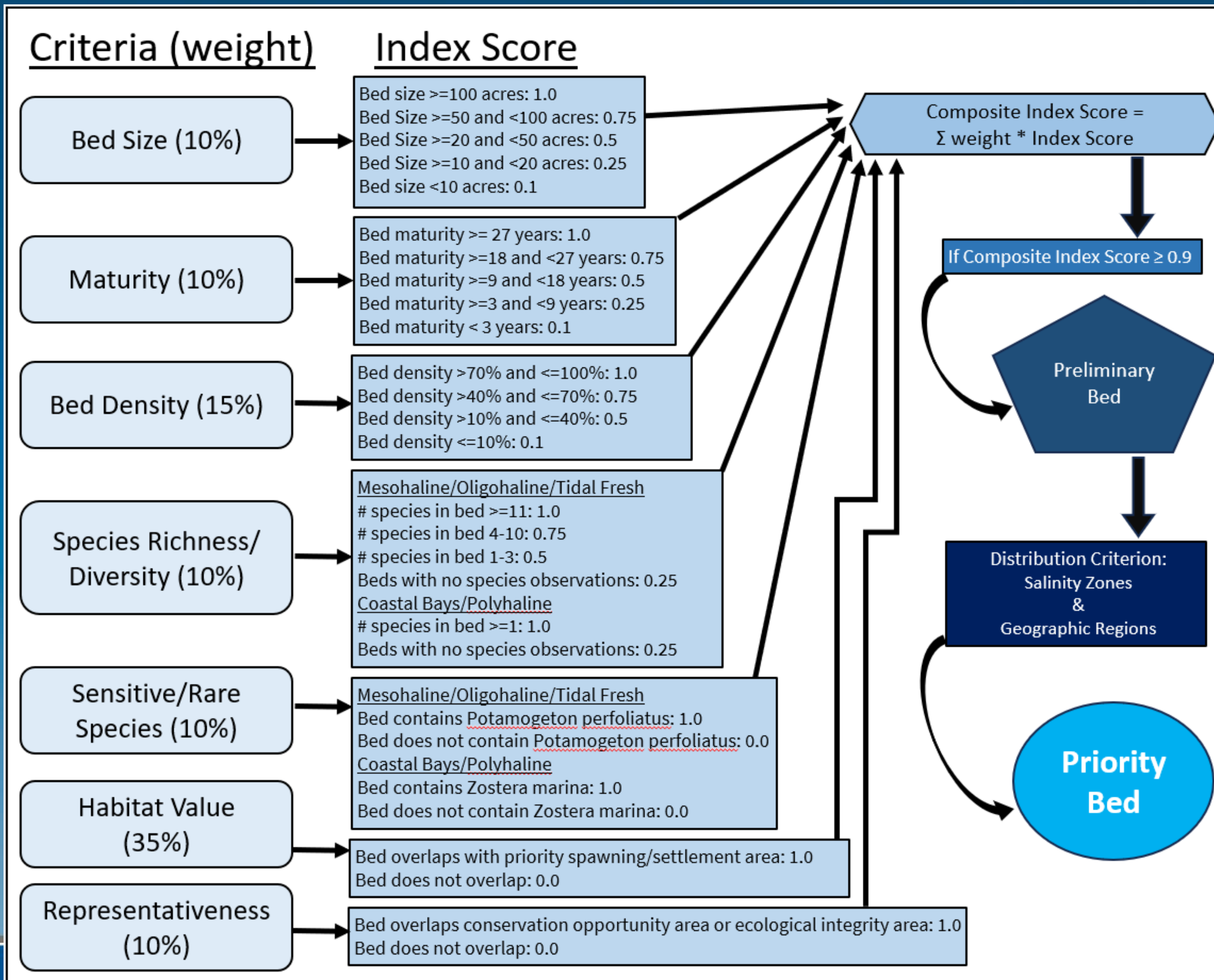
Project Goals

- **Identify priority (i.e. healthiest/most valuable) SAV beds baywide**
- **Machine learning model development**
  - Statistical approach to understanding what drives SAV health
  - Can input many variables/predictors
  - Accounts for timing and complex interactions between the many variables/predictors
  - Output is relative importance plot of what variables/predictors are most closely correlated to SAV health
- **Summary of BMPs that are most likely to lead directly to SAV protection, conservation, and restoration.**

Outline

- **Project overview and timeline**
- **Quick review:**
  - Priority Bed Criteria and Selection
  - Machine Learning approach
  - Model selection, setup, and tuning
- **Model input data**
- **Model results**
- **BMP Implications**
- **Future Improvements**

SAV Bed Prioritization- Decision Tree



SAV Bed Prioritization - Criteria Scoring

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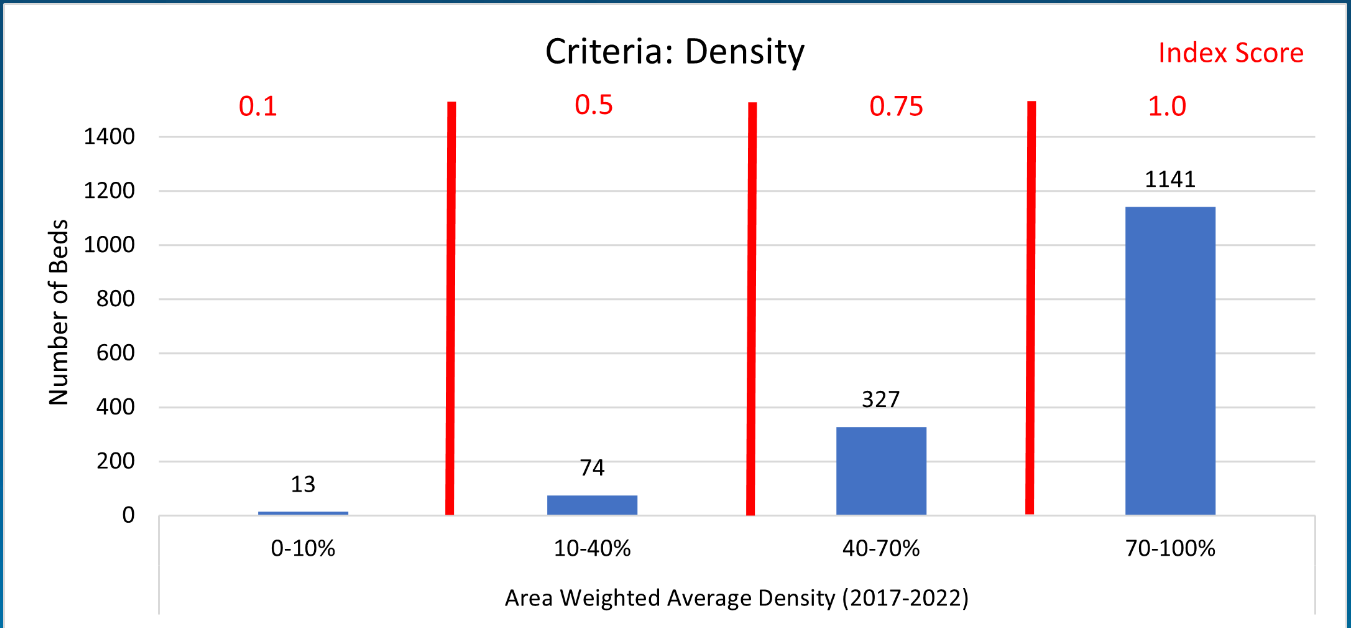
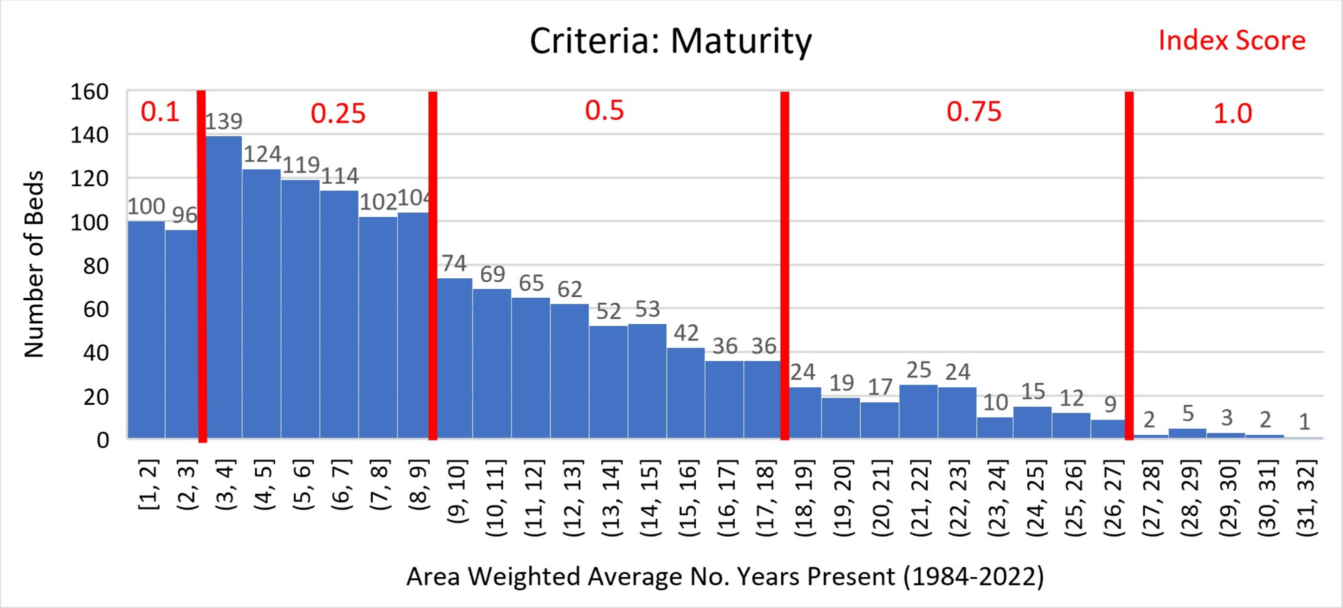
Criteria (weight)	Index Score	No. Beds [a]
Bed Size (10%)	Bed size >=100 acres: 1.0 Bed Size >=50 and <100 acres: 0.75 Bed Size >=20 and <50 acres: 0.5 Bed Size >=10 and <20 acres: 0.25 Bed size <10 acres: 0.1	254 (16%) 149 (10%) 406 (26%) 447 (29%) 299 (19%)
Maturity (10%)	Bed maturity >= 27 years: 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 <=100% cover): 1.0 Bed density VIMS score >2 and <=3 (>40% and <=70% cover): 0.75 Bed density VIMS score >1 and <=2 (>10% and <=40% cover): 0.5 Bed density VIMS score <= 1 (<=10% cover): 0.1	1,152 (74%) 326 (21%) 66 (4%) 11 (1%)
Species Richness/ Diversity (10%)	Mesohaline/Oligohaline/Tidal Fresh # 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 Coastal Bays/Polyhaline # 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%)	Mesohaline/Oligohaline/Tidal Fresh Bed contains Potamogeton perfoliatus: 1.0 Bed does not contain Potamogeton perfoliatus: 0.0 Coastal Bays/Polyhaline Bed contains Zostera marina: 1.0 Bed does not contain Zostera marina: 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%)

PB Criteria Results





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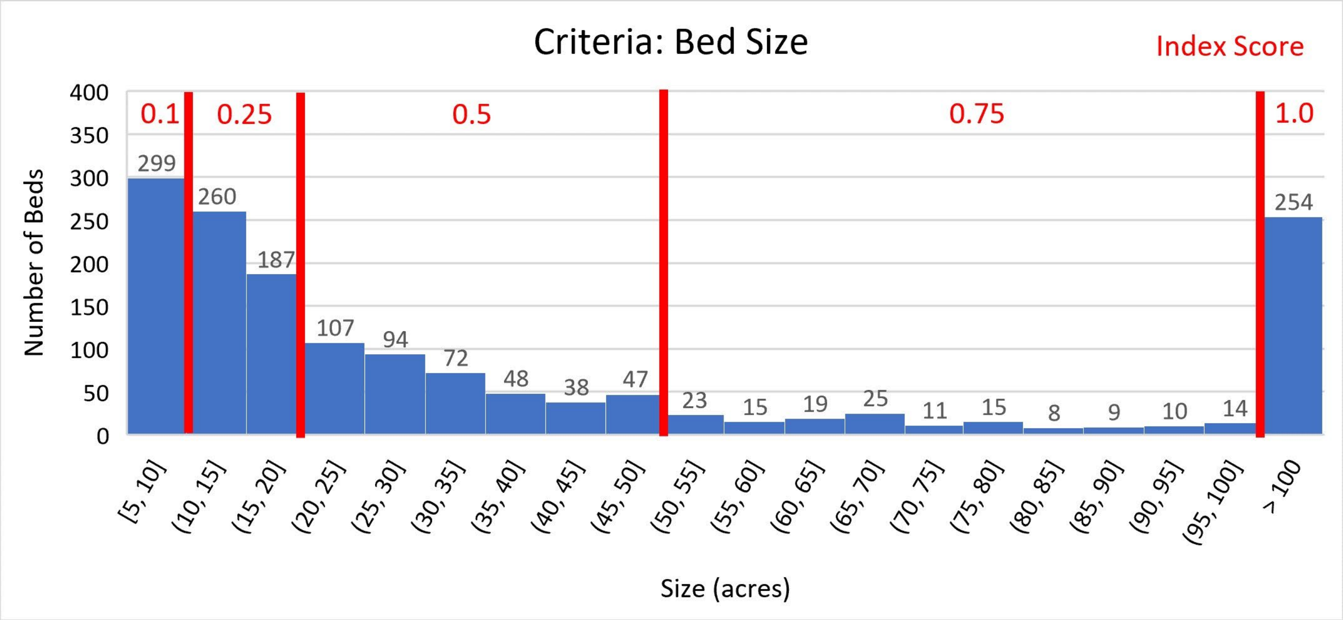

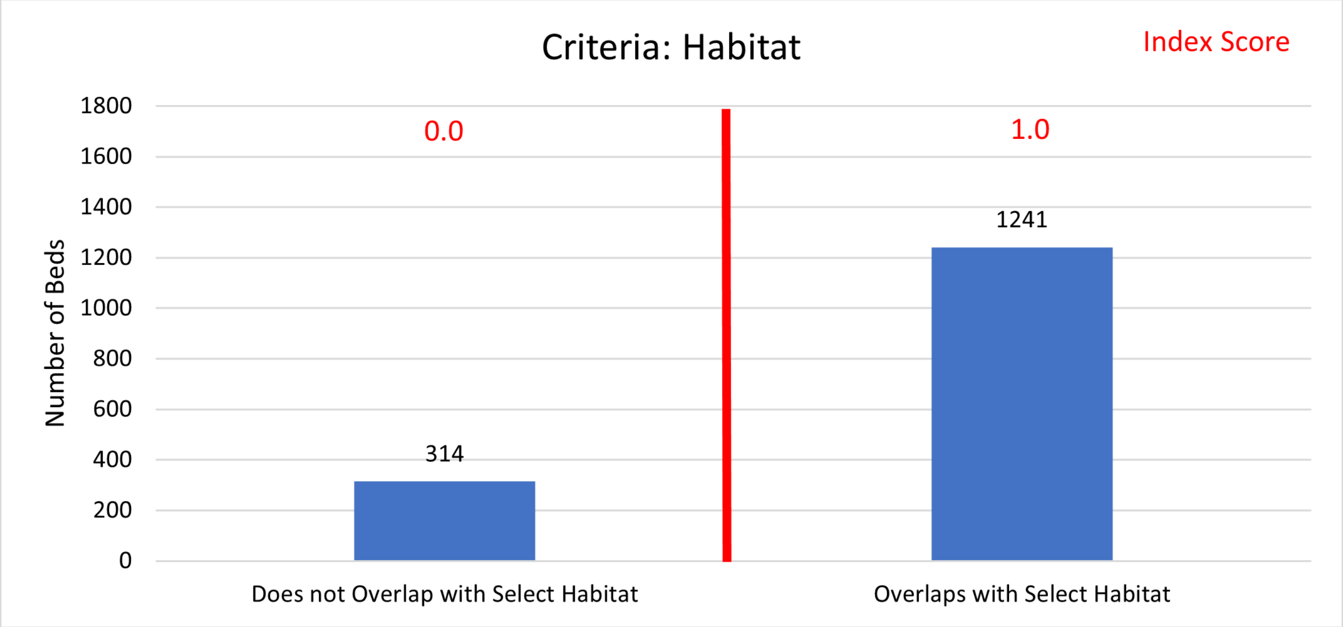

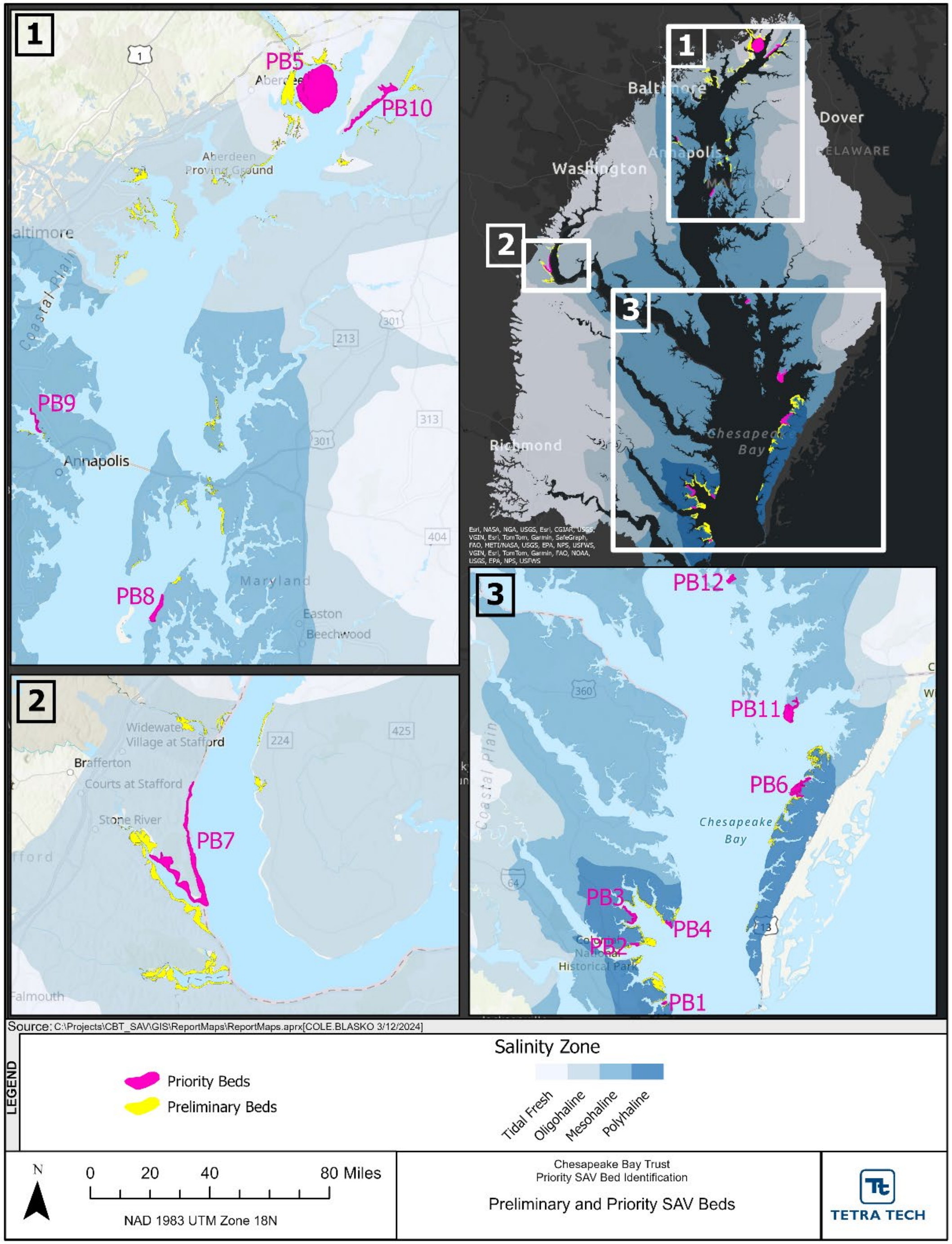

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- 12 beds
- Broad geographic/salinity representation

Machine Learning Approach

- **"Summary of BMPs that are most likely to lead directly to SAV protection, conservation, and restoration."**
- **Machine learning model development**
  - Statistical approach to understanding what drives SAV health
  - Can input many variables/predictors
  - Accounts for timing and complex interactions between the many variables/predictors
  - Output is feature importance plot of what variables/predictors are most closely correlated to SAV health

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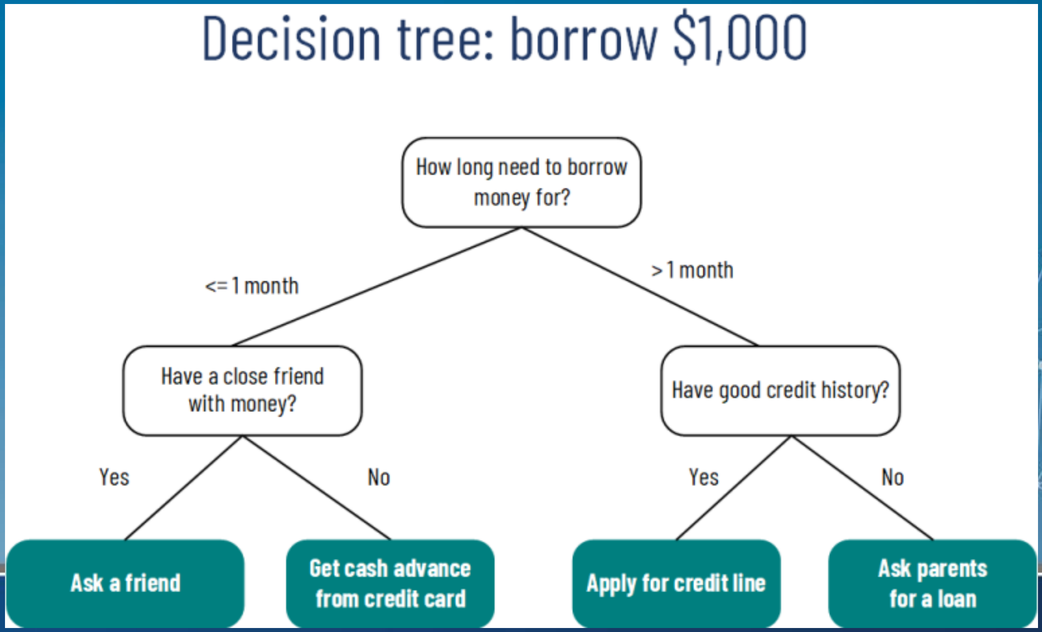
Model Selection

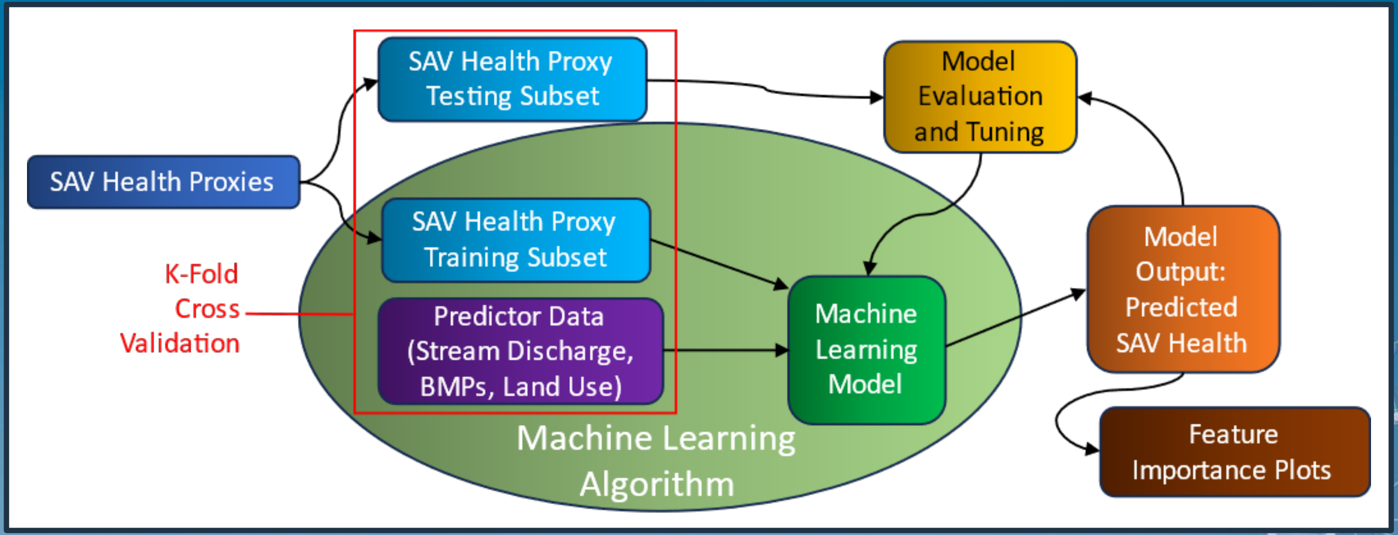
- **XG Boost**
  - Tree-based: represents all paths to possible outcomes
  - Can handle missing values
  - "Boosting" is a generic modeling term that means a given model is re-run hundreds of times, each time improving on the previous instance
  - Places more importance to misclassified observations thereby attempting to concentrate model improvements on areas where the existing trees are performing poorly



Source: https://why-change.com/2021/11/13/how-to-create-decision-trees-for-business-rules-analysis/

Model Setup and Tuning

- **K-Fold Cross Validation**
  - Test dataset independent of training dataset
  - 180 data points (12 Priority Beds across 15 years)
  - 5 folds of 36 data points each
    - 4 folds are for training
    - 1 fold is for testing
  - Repeat process such that all folds serve as test set once



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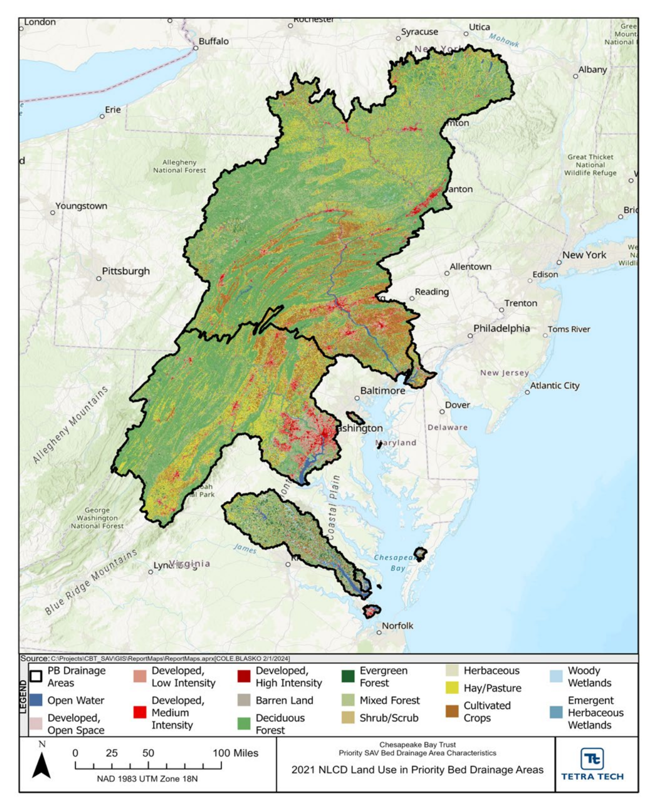
Machine Learning Model

Input Data
(aggregated by Priority Bed Drainage Area) → Model → Results: Priority Bed Health Drivers
(feature importance plots)

Predictor dataset: Land Use

- Calculated percent cover and acres for each priority basin and year

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



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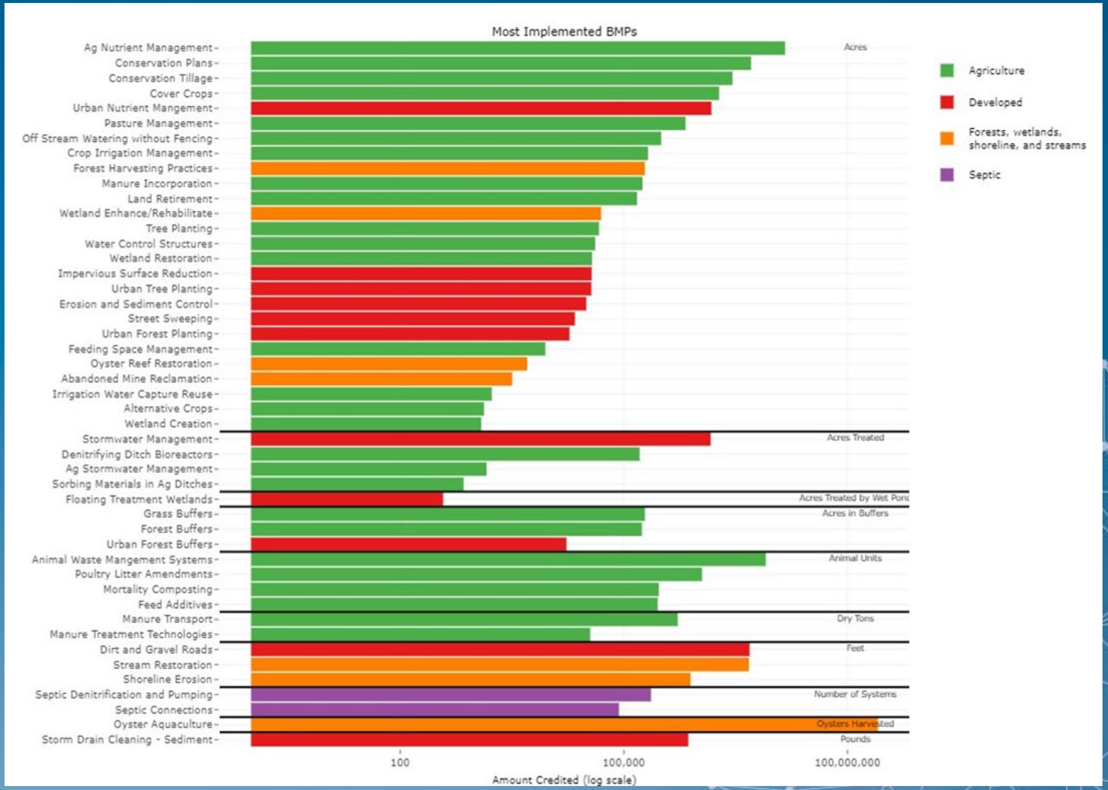
Predictor dataset: BMPs

289 BMPs implemented in the Chesapeake Bay Watershed
(https://cast.chesapeakebay.net/Documentation/wipbmpcharts)

Dasymetrically allocated to corresponding land use



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Machine Learning Model

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→

Model

→

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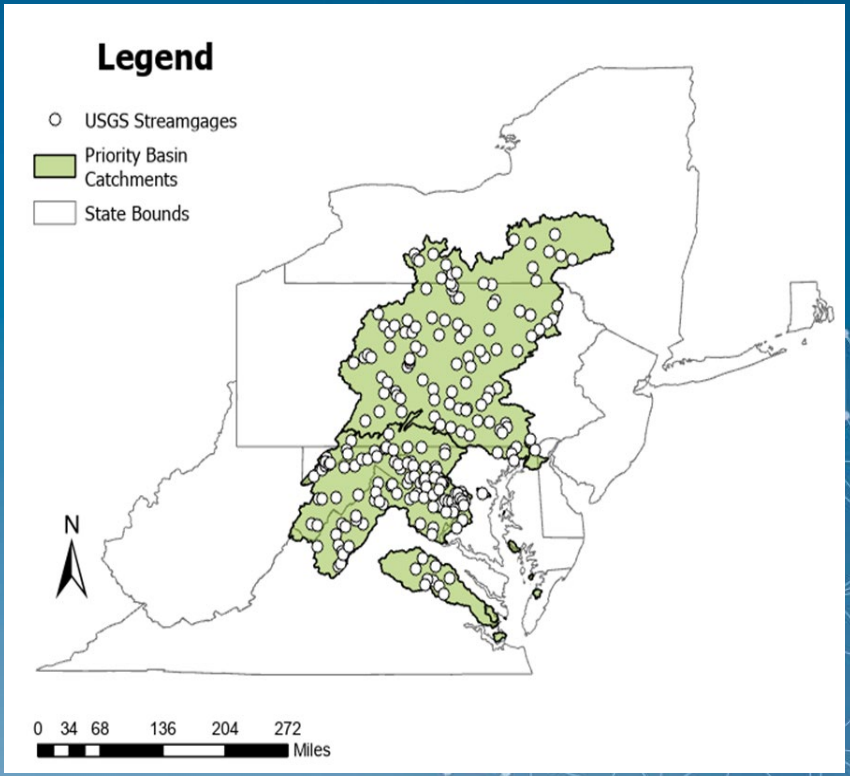
Predictor dataset: Discharge

- Statistics calculated at annual timestep and for entire study period (2008 – 2022).
  - Minimum, mean, maximum
  - Flow percentiles (e.g., 25^{th}, 50^{th}, 75^{th})
  - Low flow conditions (e.g., 10^{th} percentile)
  - High flow conditions (e.g., 90^{th} percentile)



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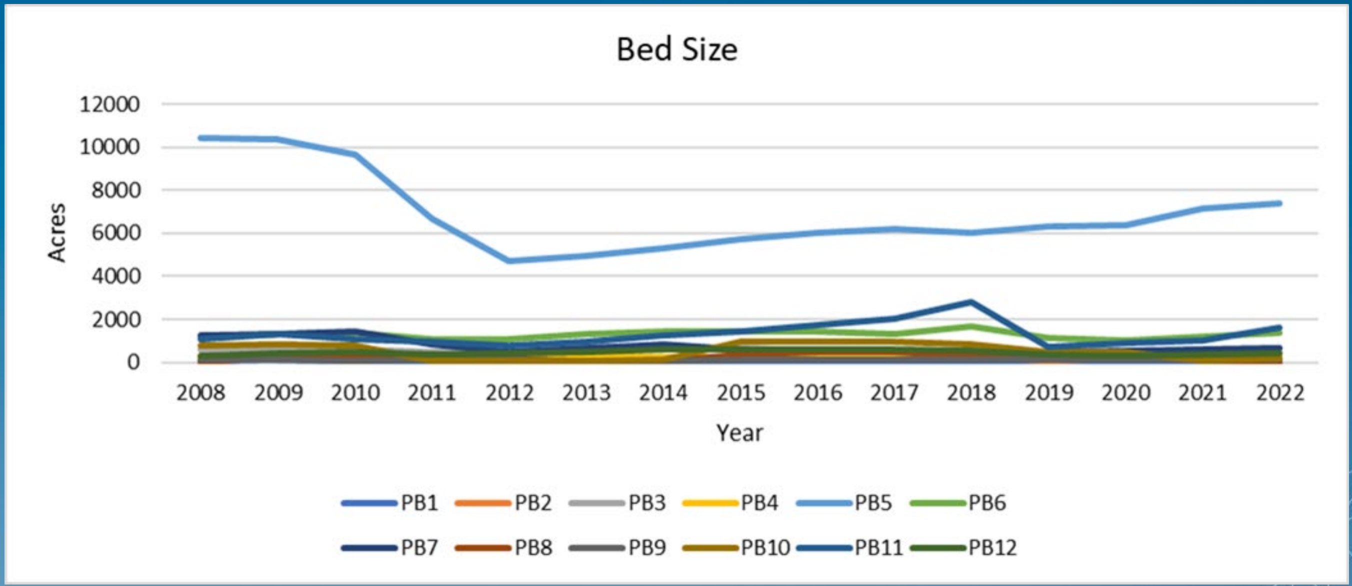
Modeled Response dataset: SAV Health Proxies



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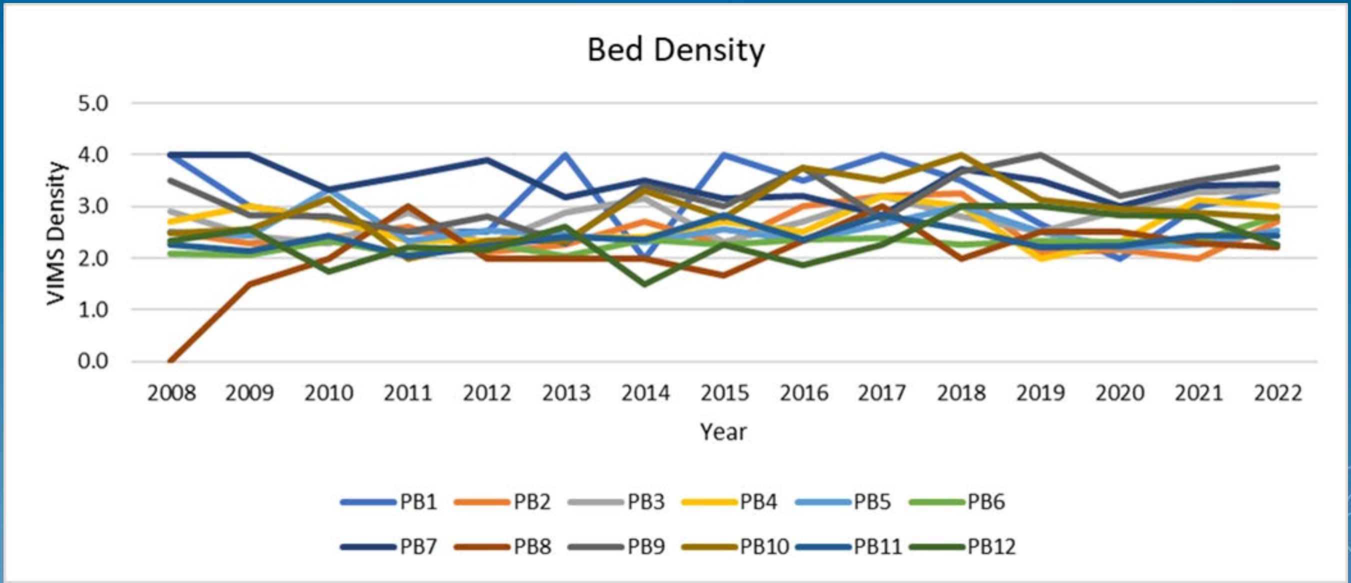

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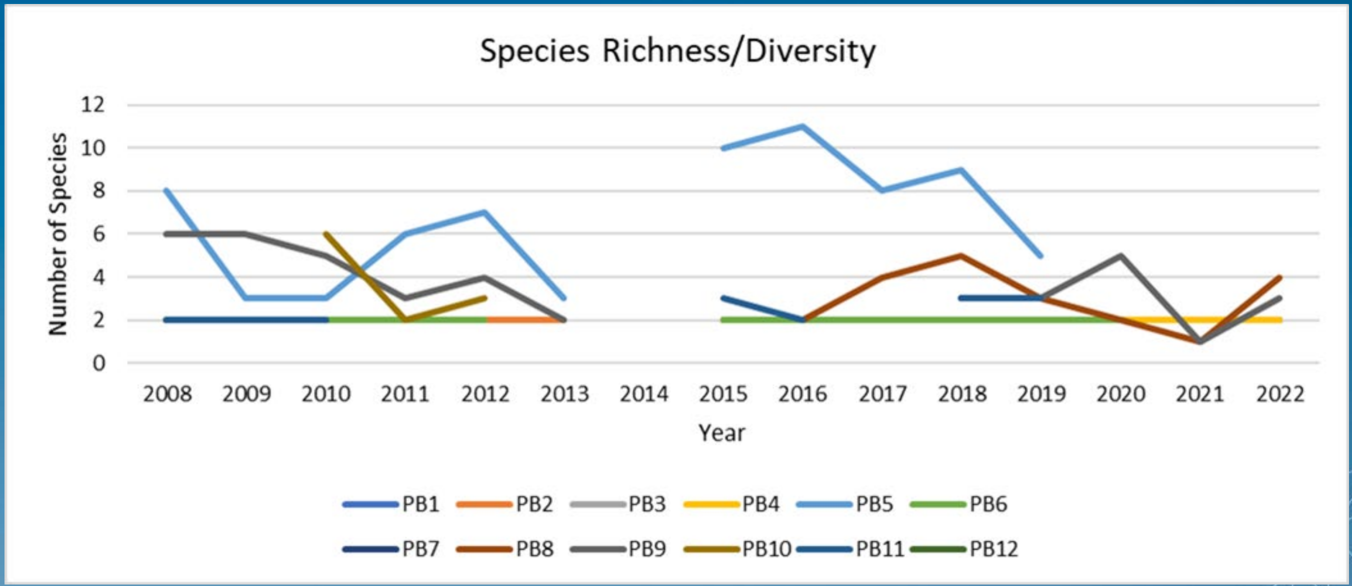

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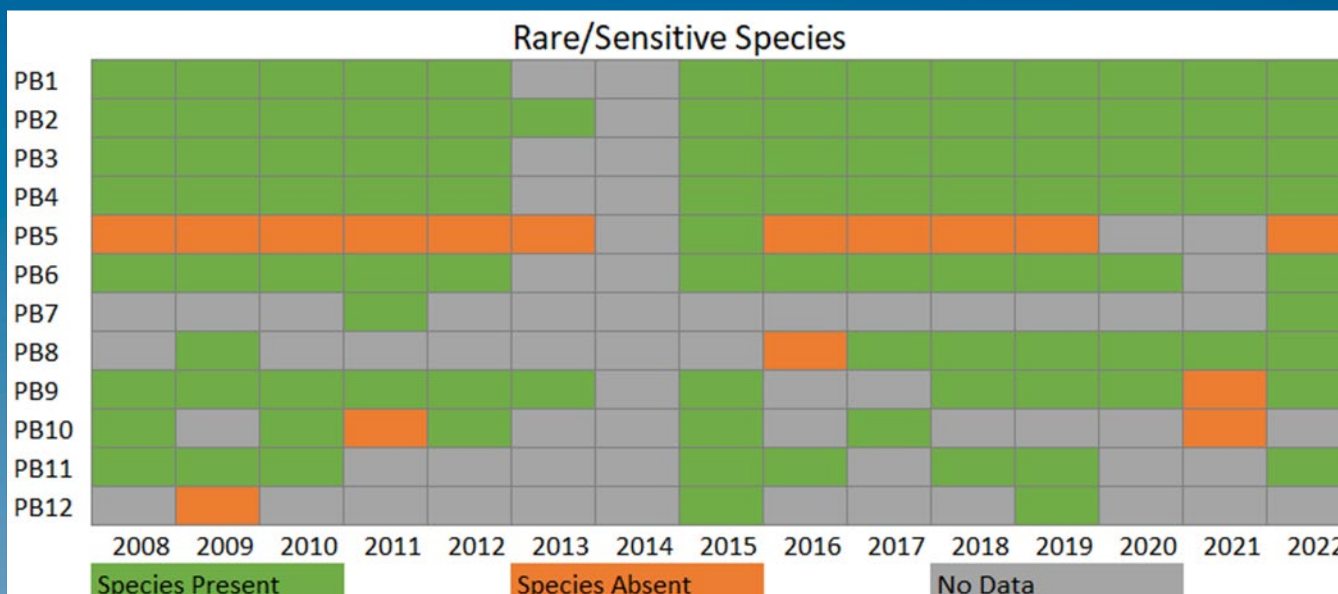

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Model Performance Metrics for Bed Size

Ecological Indicator (response variable)	Average Mean Squared Error [a]	Average R^2 Score
Bed Size	280,069.14 [b]	0.94

a. MSE is in units of the response variable. (Bed Size has units of acres)

b. The average error ($\sqrt{MSE}$) is 529 acres (0.82 mi^2). Priority beds range in size from 117 acres to 7,565 acres.

- MSE indicates high variability in error magnitude across predictions, potentially influenced by the magnitude of size measurements.
- 94% of the variance can be explained by the predictors used in the model.
- Bed size 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.

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Machine Learning Model

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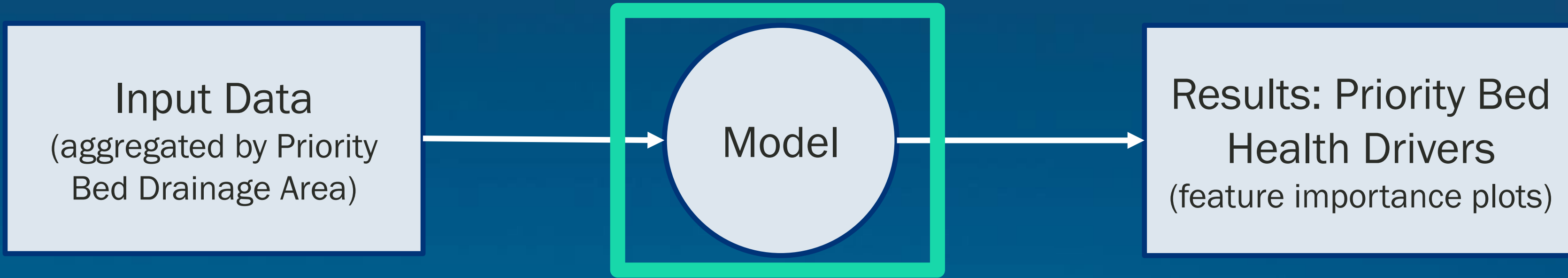
Model Performance Metrics for Bed Density

Ecological Indicator (response variable)	Average Mean Squared Error [a]	Average R^2 Score
Bed Density	0.21	0.10

a. MSE is in units of the response variable. (Bed Density is a unitless index assigned by VIMS that scores from 1-4 based on percent vegetative cover of a bed)

- Model performed moderately well in terms of MSE with an average value of 0.21.
- Worst model performance in terms of R^2 with a value of 0.10.
- Density has four class ranges of vegetative cover. A small change in vegetative cover (e.g., 39% to 41%) can result in a large change in density categorization (e.g., 2 to 3)
- 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.

Machine Learning Model



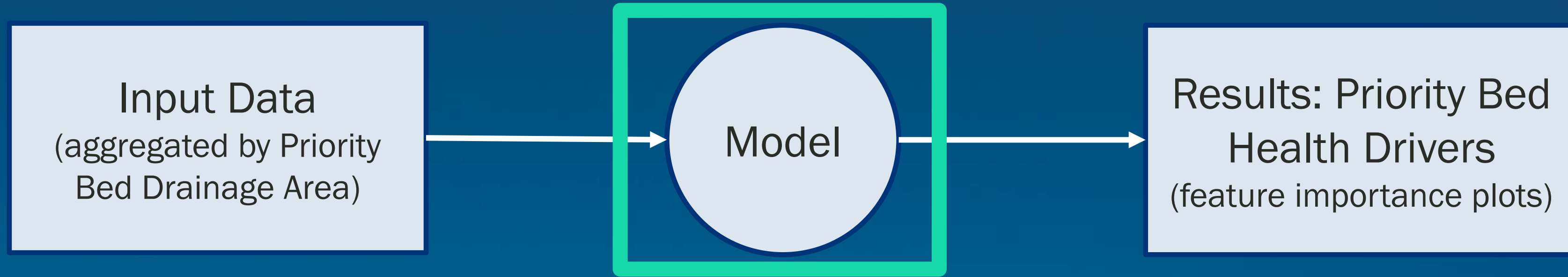
Model Performance Metrics for Species Richness

Ecological Indicator (response variable)	Average Mean Squared Error [a]	Average R^2 Score
Species Richness	2.62	0.45

a. MSE is in units of the response variable. (Species Richness has units of species)

- Predictive accuracy may be incorrect by up to three species when rounded to the nearest integer.
- Moderate R^2 where 45% of the variance is explained by the model.
- Species observation is at the segment scale which is spatially larger than individual beds. Species may occur in the segment but not in the bed. The opposite may also be true where a species in the bed was not observed in the segment.

Machine Learning Model



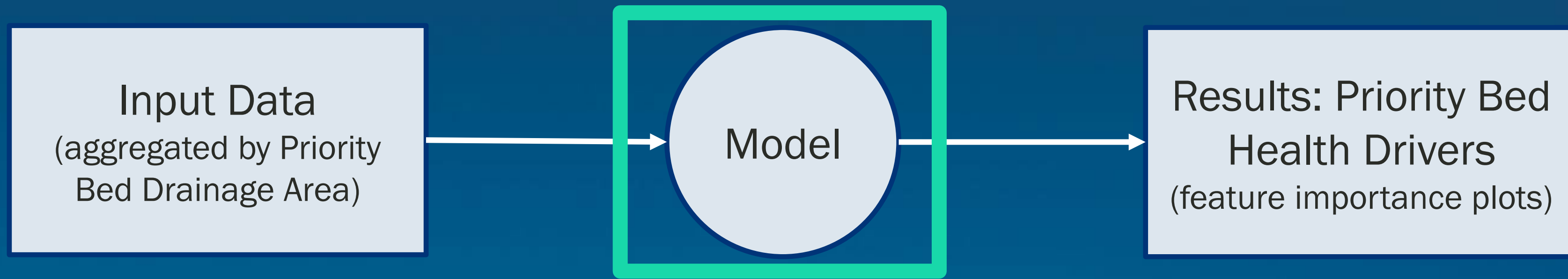
Model Performance Metrics for Rare/Sensitive Species

Ecological Indicator (response variable)	Average Mean Squared Error [a]	Average R^2 Score
Sensitive/Rare Species	0.08	0.20

a. MSE is in units of the response variable. (Sensitive/Rare Species has units of species)

- Relatively low MSE of 0.08 shows very little difference between observed and predicted values likely due to the small range of values (i.e., 0 - 1).
- Model could not explain the variance very well using the predictor variables as indicated by an R^2 value of 0.20.
- Species observation is at the segment scale which is spatially larger than individual beds. Species may occur in the segment but not in the bed. The opposite may also be true where a species in the bed was not observed in the segment.

Machine Learning Model



Model Performance Metrics

- What does this all mean?
  - Strong relationships between features and outcomes results in robust predictive capabilities (e.g., Bed Size)
  - Weaker or more complex feature interactions are not as readily modeled. (e.g., Bed Density)

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Machine Learning Model

Input Data
(aggregated by Priority Bed Drainage Area)
→ Model →
Results: Priority Bed Health Drivers
(feature importance plots)

- 223 predictor variables – most were not important
- BMPs reported at the county-scale generally ranked higher. Tracking of BMPs at this scale is effective in terms of spatial accuracy and reporting participation from the public.
- Predictors among all three categories of data (i.e., streamflow, land use, BMP) ranked relatively high among the four SAV health proxies. SAV health is not dependent on one source, but rather the complex relationships between many environmental, anthropogenic, and climatological influences.

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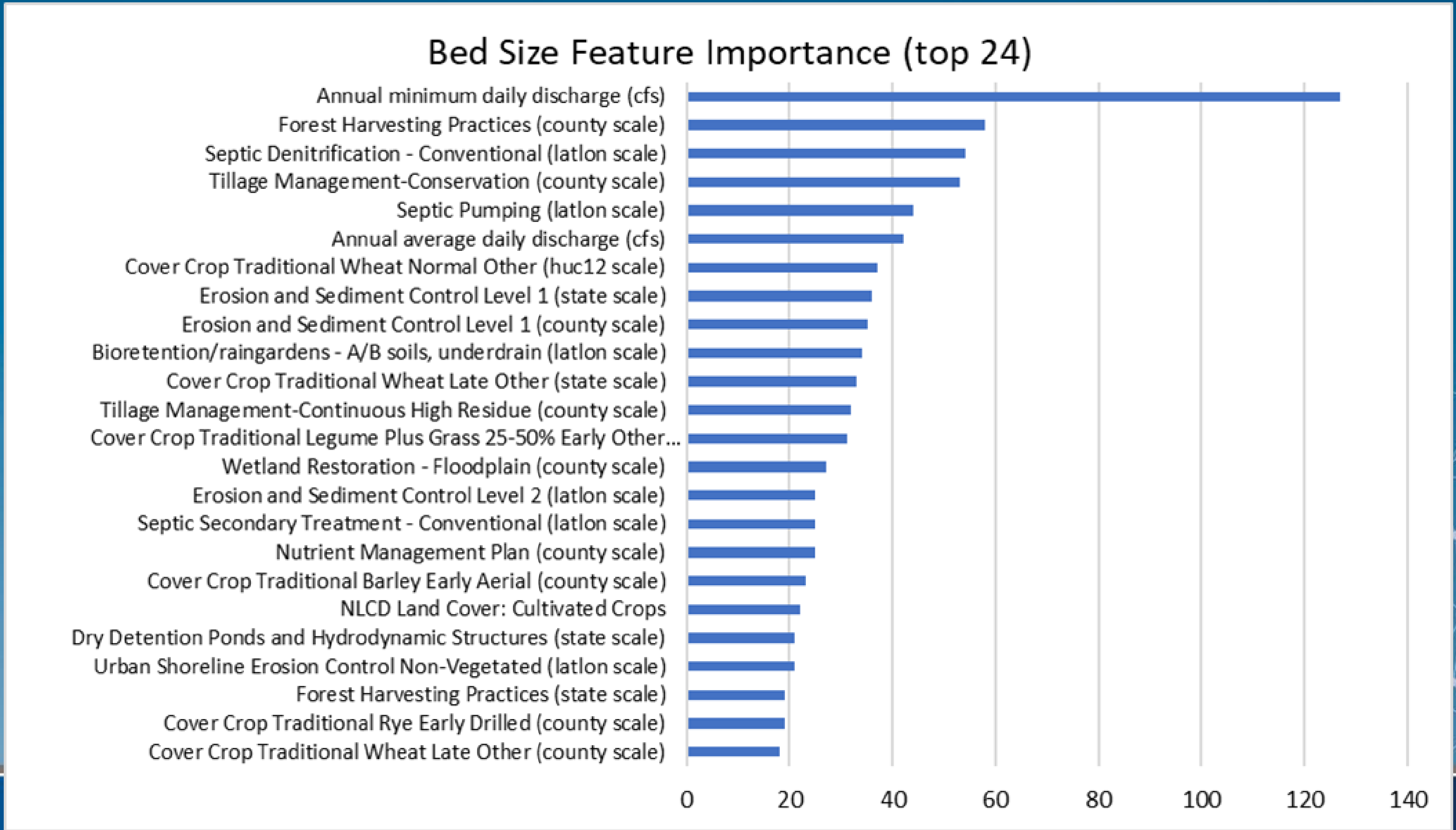

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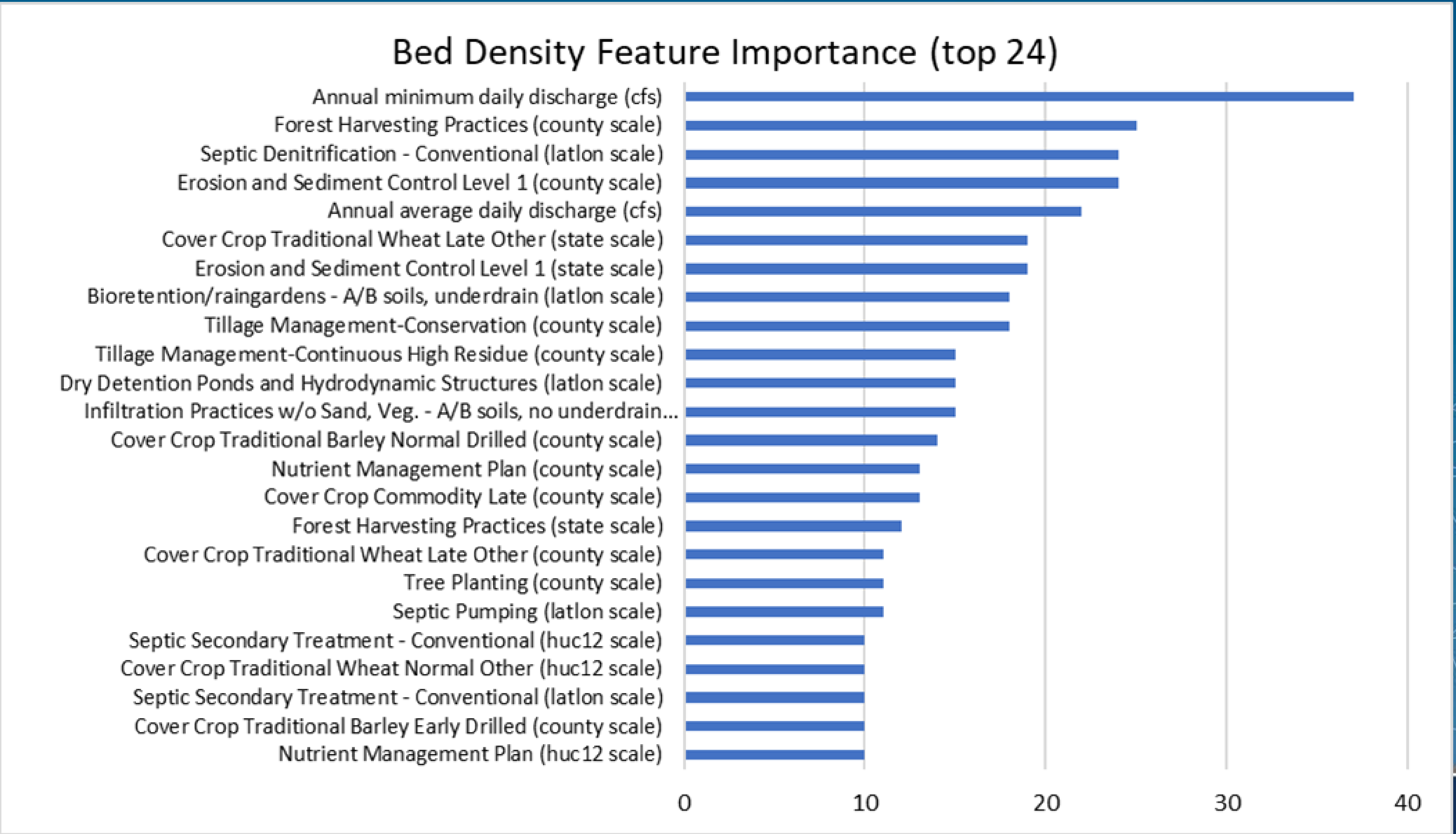

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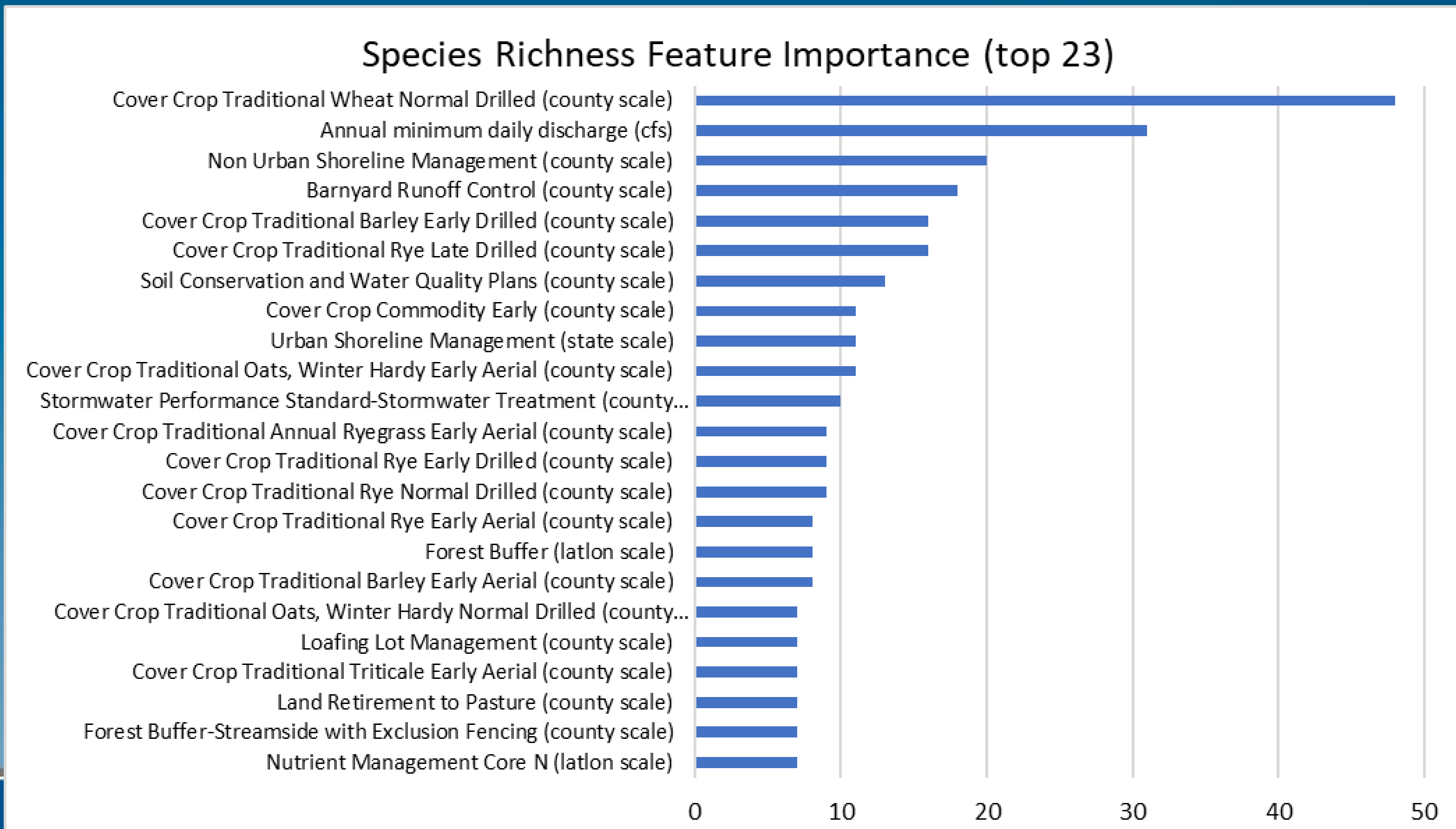

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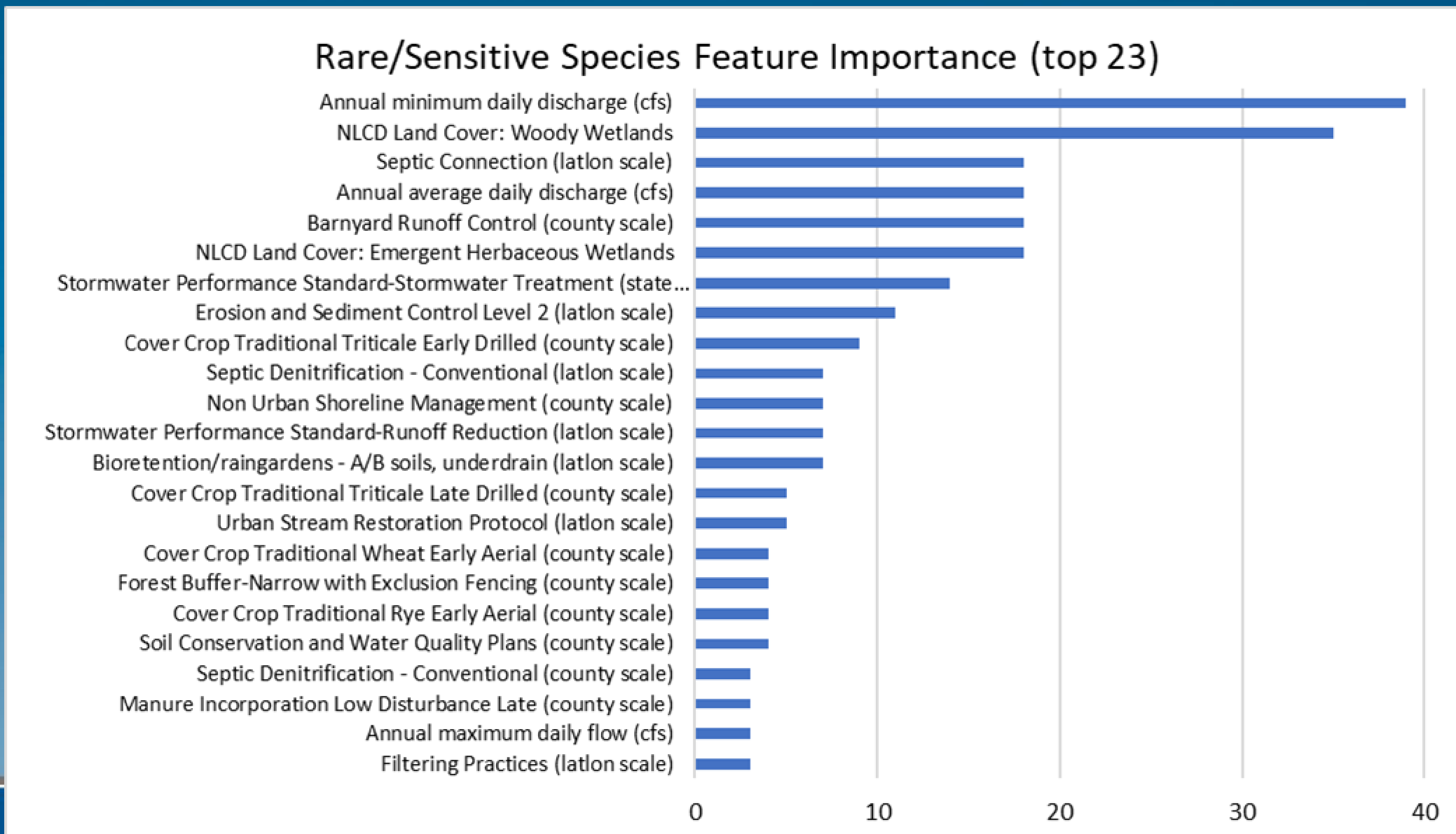
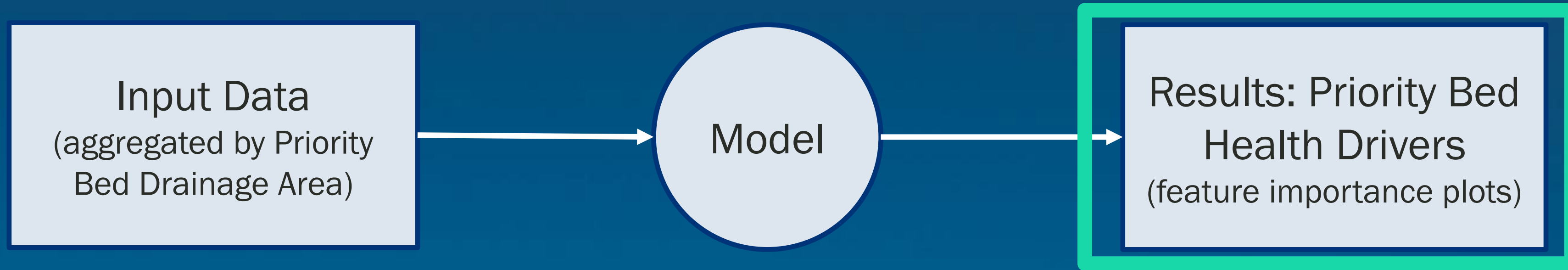
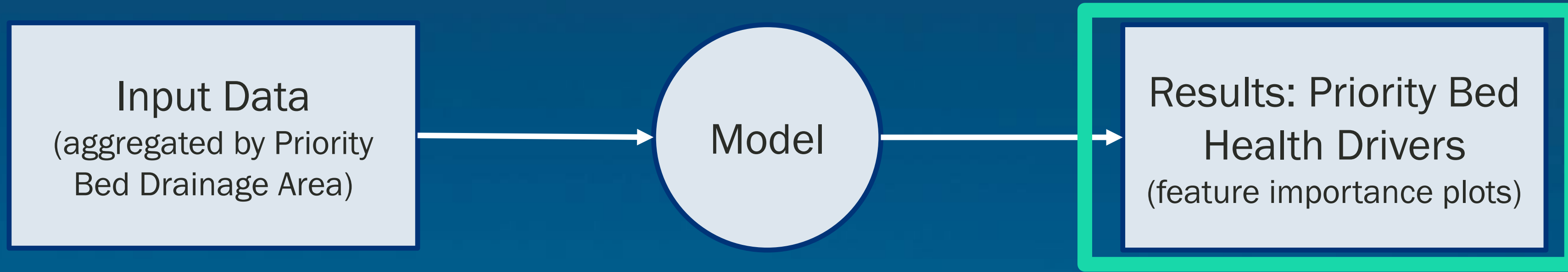


Machine Learning Model



- Bed size and bed density have the same top three predictor variables in terms of importance.
  - Bed size and bed density are influenced by similar environmental factors
  - SAV species are influenced by a slightly different set of environmental factors

Machine Learning Model



- For species-related SAV health proxies, three predictors are separated from the rest in terms of importance
  1. Cover crops of traditional wheat
  2. Woody wetlands land cover
  3. Annual minimum daily discharge

Machine Learning Model

Input Data (aggregated by Priority Bed Drainage Area) → Model → Results: Priority Bed Health Drivers (feature importance plots)

- Annual minimum daily discharge is the most important predictor variable for three of the four SAV health proxies and second most important for the fourth
- Important finding because this may indicate two different things:
  - Likely positive relationship = lower sedimentation and eutrophication rates which improves long term SAV health across all ecological indicators

BMP Impacts on SAV

Agricultural BMPs

- Reduce nutrient loading
  - nutrient management
  - denitrifying bioreactors
- Reduce soil erosion
  - conservation tillage
  - cover crops
- Reduce runoff
  - cover crops
  - soil health – infiltration practices

Stormwater BMPs

- Reduce runoff
  - bioretention
  - rain gardens
  - detention / retention basins
  - permeable pavement

Future Improvements

Run model for all SAV beds within Chesapeake Bay.

- The current set of 180 data points (12 beds for 15 years) is relatively small number for developing and training a machine learning model.
- Would likely improve R^2 and MSE accuracy metrics significantly.

Add more predictor variables the analysis.

- Locations of shoreline hardening
- Tidal data
- Water quality data (i.e., temperature, TP, TN, turbidity)
- Ratios of SAV bed size to drainage area size

Combine BMP predictor variables to decrease line items in feature importance plots

- Spatially (e.g., county, state, HUC)
- By type (e.g., cover crops of different crop species)

Future Work

Run climate change scenarios

- Informed by existing Chesapeake Bay models and other projects and resources provided by the Submerged Aquatic Vegetation Workgroup/CBP

Machine Learning approach could be applied to other resources of importance in the Chesapeake Bay

- Fish communities
- Oyster beds

Acknowledgements

- Brooke Landry – MD DNR

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- Dave Wilcox – VIMS
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- Meghan Fitzpatrick – US EPA
- Christina Thomas – US EPA

- Funding: Chesapeake Bay Trust

Questions?

Discussion

Annual minimum daily discharge was most important for predicting SAV health.

- Positive relationship or negative relationship?
- What does this mean for BMP implementation?

Are top BMPs from feature importance plots more prevalent in some drainage areas but not others?

Is implementation of top BMPs from feature importance plots increasing or decreasing over time?