UMoncton CCNB-Innov Project *Technical Report*

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Contents

Abstract

List of Acronyms

ML Machine Learning

WESP-AC Wetland Ecosystem Services Protocol for Atlantic Canada

PCA Principal Component Analysis

CNN Convolutional Neural Network

CI Causal Inference

EF **EF!** (**EF!**)

NB New-Brunswick

NRNB Natural ressources NB

WS Water Storage & Delay

PR Phosphorus Retention

SR Sediment Retention & Stabilization

NR Nitratre Remove & Retention

SFST Stream Flow Support

VT Variance Threshold

1 Introduction

This document should be served as supplementary file for the report. It contains various results not included in the main document.

2 Classification

First, in section **??**, we train our algorithms using our D1 dataset. Section **??**, **??** and **??** use the respective D2, D3 and D4 datasets.

2.1 All Features (D1)

This section trains our algorithms using all features provided by the WESP-AC 3.4, with the exception of the unnecessary features. We compare our results using multiple data filling methods, however we only present the best performing methods. First, we present the training results and the ensemble learning approach using all features in section **??**. Our ensemble learning algorithm consists of combining the top five best performing algorithms and average out the predictions. Section **??** presents a feature reduction approach using the results from section **??**.

2.1.1 Training Results

Table **??** provides an overview of some of the best performing algorithms with specific filling methods.

Function	**Model**	**Data**	**Accuracy**
PR	GradientBoosting	BFill, FFill, Interpolated, Mean, Mode	95.0%
	RandomForest	BFill, FFill, Interpolated, Mean, Median	95.0%
NR	LogisticReg.	BFill, Custom, FFill, Interpolated, KNN, Mean	81.0%
SR	GradientBoosting	Iterative, Median, Mode	90.0%
WS	GradientBoosting	BFill, Interpolated, Mode, KNN, Mean, Median	95.0%
SFST	DecisionTree	Iterative, Mode	100.0%
PR Ben.	LinearDiscriminant	BFill, Custom, Iterative	95.0%
	GradientBoosting	BFill, FFill, Interpolated, Mean, Mode	95.0%
NR Ben.	GradientBoosting	BFill, Custom, FFill	95.0%
SR Ben.	Ridge	All Data	100.0%
WS Ben.	GradientBoosting	BFill, Interpolated, Mode	95.0%
SFST Ben.	DecisionTree	Mode	95.0%
	GradientBoosting	BFill	81.0%

Table 1: Best Model Accuracies

In this table, each **EF!** is shown with the accuracy of the best performing model and data filling method.

To increase the validity of using **ML!** (**ML!**) for this task, we propose ensemble learning. The results from ensemble learning are shown in section **??**. We also propose feature selection which consists of using a limited amount of features to achieved similar. Feature selection would enable us to use less features (E.g 10) to achieve similar results. Feature selection is presented in section **??**.

2.1.1.1 Ensemble Learning

To increase the performance of our algorithms, we propose using ensemble learning to combine multiple models. Overall, the ensemble learning did not increase the performance of our algorithms, as shown in table **??**.

Function	Accuracy	Ensemble Accuracy
PR	95.24%	95.24%
NR	80.59%	80.59%
SR	90.48%	85.71%
WS	95.24%	95.24%
SFST	100.0%	95.24%
PR Ben.	95.24%	90.48%
NR Ben.	95.24%	95.24%
SR Ben.	100.0%	100.0%
WS Ben.	95.24%	95.24%
SFST Ben.	95.24%	95.24%

Table 2: Ensemble Model Accuracies

Figures **??**, **??**, **??**, **??**, **??**, **??**, **??**, **??**, **??** and **??** show the confusion matrices for each EFs using ensemble learning.

2.1.2 Feature Selection

Feature selection consists of using techniques to reduce the number of features required to train the algorithms while achieving similar results. In this section we explore the three feature reduction techniques, presented in section **??**.

Using the accuracy as metric, we compare the algorithms for each ecosystem function trained with reduced features. The best performing algorithm for each function was selected based on accuracy from table **??**. Each algorithm was trained with the three reduction techniques with features ranging from all features to only tow features. Figures **??** to **??** show the results for each **EF!** with the three reduction techniques.

Interesting behavior can be observed when analyzing the results from these figures. Tables **??** and **??** respectively show the best overall accuracies and the best using two features. The overall accuracy consists of the method that achieved the best accuracy regardless of the number of features. The best two features takes the best accuracy from the three method which only used two feature to predict the class.

2.1.2.1 Ensemble Learning To increase the performance of our feature reduction approach, we propose using ensemble learning. This is proposed to average out errors to increase the performance without retraining or the need for complex algorithms. Our ensemble model, for each **EF!**, is based on the top five models achieved from the feature reduction with no more than 10 features per model. Table **??** show the performance for each function before and after the ensemble learning.

Function	Best Acc.	2nd Best Acc.	Ensemble Learning Acc.	Features Used
PR	95.24%	95.24%	95.24%	F1, F14, F21, F23, F24, F28, F29, F30, F41, F43, F44, F45, F46
NR	76.19%	76.19%	76.19%	F43, F44, F45, F46
SR	90.48%	80.95%	85.71%	F1, F14, F24, F25, F28, F29, F30, F31, F3e, F43, F44, F45, F46, OF22
WS	90.48%	90.48%	90.48%	F1, F29, F31, F43, F44, F45, F46, F65
SFST	95.24%	95.24%	95.24%	F43, F44, F45, F46
PR Benefit	85.71%	85.71%	85.71%	F14, F41, F43, F44, F46, F47, F55
NR Benefit	90.48%	90.48%	90.48%	F1, F14, F31, F3d, F41, F43, F46, OF10, OF19, OF9
SR Benefit	100.00%	100.00%	100.00%	F1, F14, F23, F25, F28, F29, F3e, F41, F43, F44, F45, F46, OF19, OF21
WS Benefit	95.24%	95.24%	95.24%	F3c, F3e, F49, F50, F51, F52, F54, OF17, OF23, OF38, OF5, OF7, OF9
SFST Benefit	90.48%	85.71%	90.48%	F1, F14, F23, F30, F3e, F43, F44, F45, F46

Table 3: Ensemble Learning Accuracy

In this table, the first column represents the **EF!**, while the second and third represent the best and second best accuracy from section **??** with a maximum of 10 features. The fourth column represent the accuracy of the ensemble learning model while the last column consists of the features of all five models used for ensemble learning.

2.2 Specific Features (D2)

In this section we train the same algorithms as the previous section. However, the algorithms are trained only and their respective specific features using the D2 dataset. Our goal for this section is to reduce possible noise that can be caused by using all features. Similarly to the previous section, we compare using all features versus using feature reduction techniques and ensemble learning.

2.2.1 Training Results

In terms of training results, we present an overview of the best performing algorithms and filling method. Our training results are more exploratory and are used to pinpoint specific algorithms and data filling methods for each **EF!**. Table **??** provides an overview of some of the best performing algorithms and data.

Function	**Model**	**Data**	**Accuracy**
PR	RidgeClassifier	All Data	95.2%
NR	RidgeClassifier	All Data	85.7%
SR	SGDClassifier	BFill, Mean	95.2%
WS	GradientBoostingClassifier	All Data	100.0%
SFST	DecisionTreeClassifier	All Data	95.2%
PR Ben.	DecisionTreeClassifier	BFill	100.0%
NR Ben.	SVC	All Data	100.0%
SR Ben.	RidgeClassifier	All Data	100.0%
WS Ben.	RandomForestClassifier	Custom, FFill, Interpolated, Iterative	95.24%
SFST Ben.	MLPClassifier	Interpolated	71.43%

Table 4: Best Model Accuracies

In this table, we present which model and data filling method achieved the best accuracy for each **EF!**.

2.2.2 Ensemble Learning

We also combine the best performing algorithms using ensemble learning. Overall, the ensemble learning did not increase the performance of our algorithms, as shown in table **??**.

Function	**Accuracy**	**Ensemble Accuracy**
PR	95.24%	95.24%
NR	85.71%	85.71%
SR	95.24%	95.24%
WS	100.0%	100.0%
SFST	95.24%	95.24%
PR Ben.	100.0%	100.0%
NR Ben.	100.0%	100.0%
SR Ben.	100.0%	100.0%
WS Ben.	95.24%	95.24%
SFST Ben.	71.43%	71.43%

Table 5: Ensemble Model Accuracies

Figures **??**, **??**, **??**, **??**, **??**, **??**, **??**, **??**, **??** and **??** show the confusion matrices for each EFs using ensemble learning.

2.2.3 Feature Selection

We also use the three feature reduction techniques to reduce the features used while trying to achieve similar results. We compare both the overall accuracy and the best accuracy using only two features. Tables **??** and **??** respectively show the best overall accuracies and the best using two features.

2.2.3.1 Ensemble Learning Table **??** show the performance for each **EF!** before and after ensemble learning.

Function	**Best Acc.**	**2nd Best Acc.**	**Ensemble Learning Acc.**	**Features Used**
PR	90.48%	90.48%	90.48%	F17, F20, F21, F23, F24, F28, F29, F31, F33, F34, F35, F36, F43, F44, F45, F49, OF22, OF26, OF27
NR	76.19%	76.19%	76.19%	F1, F24, F28, F31, F3c, F43, F44, F45
SR	80.95%	80.95%	80.95%	F17, F28, F29, F31, F33, F34, F35, F36, F43, F44, F45, F49, F9, OF22
WS	100.00%	100.00%	95.24%	F20, F28, F31, F3c, F3d, F3e, F43, F44, F45, F49, OF22, OF26
SFST	95.24%	95.24%	95.24%	F1, F14, F24, F31, F43
PR Benefit	95.24%	95.24%	90.48%	F41, F48, F50, F52, OF19, OF20, OF21, OF22, OF23, OF24
NR Benefit	90.48%	90.48%	85.71%	F13, F41, F50, F51, F52, OF10, OF19, OF20, OF21, OF22, OF24, OF9
SR Benefit	100.00%	100.00%	100.00%	F24, F28, F41, OF19, OF20, OF21, OF24
WS Benefit	95.24%	95.24%	95.24%	F51, OF17, OF18, OF23, OF24, OF8
SFST Benefit	57.14%	57.14%	57.14%	F50, OF18, OF22, OF25, OF28

Table 6: Ensemble Learning Accuracy

2.3 Extra(D3)

This section is used to train our various classification algorithms on D3, which consists of extra features collected outside the WESP-AC.

2.3.1 Training Results

In this section, we present an overview of the best performing algorithms and filling method. Table **??** provides an overview of some of the best performing algorithms and data.

Function	Model	Data	Accuracy
PR	SVC	Iterative	95.24%
NR	SVC	FFil	71.43%
SR	DecisionTreeClassifier	Mean	61.90%
WS	GradientBoostingClassifier	FFill	71.43%
SFST	DecisionTreeClassifier	Mode, KNN	71.43%
PR Ben.	SGDClassifier	Interpolated	85.71%
NR Ben.	KNeighborsClassifier	KNN	66.67%
SR Ben.	SVC	Mean	76.19%
WS Ben.	DecisionTreeClassifier	Custom, BFill	71.43%
SFST Ben.	MLPClassifier, GaussinNB	FFil	71.43%

Table 7: Best Model Accuracies

2.3.2 Ensemble Learning

We also use the best performing five algorithms with their respective filling method and combined them. Overall, the ensemble learning did not increase the performance of our algorithms, as shown in table **??**.

Function	Accuracy	Ensemble Accuracy
PR	95.23%	90.48%
NR	71.42%	61.90%
SR	61.90%	61.90%
WS	71.42%	66.66%
SFST	71.42%	66.66%
PR Ben.	85.71%	76.19%
NR Ben.	66.66%	66.66%
SR Ben.	76.19%	76.19%
WS Ben.	71.42%	66.66%
SFST Ben.	71.42%	66.66%

Table 8: Ensemble Model Accuracies

2.3.3 Feature Selection

Similar to previous section, we perform feature reduction using our three techniques on this data. We present both the best overall accuracies using any number of features and the best accuracy fr each **EF!** using only two features. Tables **??** and **??** respectively show the best overall accuracies and the best using two features.

2.3.3.1 Ensemble Learning Using a maximum of 10 features per model, we combine the top five for ensemble learning to increase the performance. Table **??**, in the annexe, show the performance for each function before and after ensemble learning.

2.4 Specific Features and Extra (D5)

In this section, we train our algorithms and compare them using our D4 dataset which consists of the specific and extra **features**.

2.4.1 Training Results

In terms of training results ,table **??** provides the overview of some of the best performing models.

Function	**Model**	**Data**	**Accuracy**
PR	RidgeClassifier	All Data	95.4%
NR	MLPClassifier	Interpolated, Itterative	85.71%
SR	SVCClassifier	BFill, Mean	90.48%
WS	GradientBoostingClassifier	BFill	100.0%
SFST	GradientBoostingClassifier	All Data	95.24%
PR Ben.	RidgeClassifier	All Data	100.0%
NR Ben.	AdaBoostClassifier	All Data	95.24%
SR Ben.	RidgeClassifier,	All Data	100.0%
WS Ben.	AdaBoostClassifier	Median, Mean, Interpolated, Iterative	95.24%
SFST Ben.	DecisionTreeClassifier	Median	80.95%

Table 9: Best Model Accuracies

In this table, each **EF!** is shown with their best accuracy achieved with a specific model and data filling methods.

2.4.2 Ensemble Learning

The ensemble learning approach using the top five algorithms is shown in table **??**.

Function	Accuracy	Ensemble Accuracy
PR	95.24%	95.24%
NR	85.71%	80.95%
SR	90.47%	95.24%
WS	100.0%	95.24%
SFST	95.24%	95.24%
PR Ben.	100.0%	95.24%
NR Ben.	95.24%	95.24%
SR Ben.	100.0%	100.0%
WS Ben.	95.24%	95.24%
SFST Ben.	80.95%	76.19%

Table 10: Ensemble Model Accuracies

In this table, each **EF!** is shown with the best training accuracy and the ensemble learning results.

Figures **??**, **??**, **??**, **??**, **??**, **??**, **??**, **??**, **??** and **??** show the confusion matrices for each **EF!** using ensemble learning.

2.4.3 Feature Selection

We also perform our three feature reduction techniques on this dataset. Tables **??** and **??** respectively show the best overall accuracies and the best using two features.

2.4.3.1 Ensemble Learning Table **??** show the performance for each function before and after the ensemble learning and the features used.

Function	Best Acc.	2nd Best Acc.	Ensemble Learning Acc.	Features Used
PR	90.48%	85.71%	85.71%	F28, F29, F31, F43, F44, F45
NR	80.95%	76.19%	76.19%	F24, F43, F44, F45
SR	80.95%	80.95%	85.71%	F28, F31, F34, F35, F43, F44, F45, Federal Class, OF22, Provincial Class
WS	95.24%	90.48%	90.48%	F28, F31, F3e, F43, F44, F45, Federal Class, Hydrogeomorphic, Moss Cover, OF22, Provincial Class, Regime
SFST	95.24%	95.24%	95.24%	F1, F14, F24, F31, F43, Federal Class

PR Benefit	90.48%	90.48%	90.48%	F41, F48, F50, Hydrogeomorphic Class, Living Moss Depth, Moss Cover, OF20, OF21, OF22, OF24, Phragmites, Provincial Class, Regime
NR Benefit	80.95%	80.95%	80.95%	F41, Federal Class, Living Moss Depth, Moss Cover, OF10, OF19, OF21, OF9, Organic Depth, Provincial Class
SR Benefit	100.00%	100.00%	100.00%	F24, F28, F41, Hydrogeomorphic, Moss Cover, OF19, OF20, OF21, Provincial Class, Regime, Surface Water Present
WS Benefit	95.24%	95.24%	95.24%	F51, Living Moss Depth, OF17, OF18, OF23, OF24, OF8, Organic Depth, Soil Type, Vegetation Cover, Woody Canopy Cover
SFST Benefit	66.67%	61.90%	71.43%	Federal Class, Hydrogeomorphic, Living Moss Depth, Moss Cover, OF18, OF22, OF25, OF28, Provincial Class, Regime, Soil Type, Surface Water

Table 11: Ensemble Learning Accuracy

3 Regression

Regression is a common type of algorithm often used in **ML!** with a key difference to classification. Classification predicts a class, such as 0 or 1, while regression predicts a continuous value. In our case, the continuous value would be the score for the function or benefit of an **EF!**. The classification results from **??** have shown great promise and is interesting for the project. However, the algorithms trained for classification used the normalized scores both for the function and benefit. In turn, the algorithms are specific to regions, such as for NB, and depend on the calibration wetlands. If different calibration wetlands are used or the region modified, the algorithms could underperform significantly. For this reason, we propose using regression to predict the non-normalized scores of the various **EF!**. We use the non-normalize score such that it does our approach does not depend on calibration sites or region. The data was collected, modified and generated using simple pre-processing techniques as seen from section **??**. We present our results using all features, specific features, extra features and a combination of both. We use the Mean Squared Error (MSE) which averages the squares of the errors and is defined in equation **??**.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{1}$$

3.1 All Features(D1)

Similar to our classification code, we perform a grid search of various regression algorithms. We trained our algorithms and techniques for the**NR!** (**NR!**),**PR!** (**PR!**),**SR!** (**SR!**),**WS!** (**WS!**) and **SFST!** (**SFST!**) for both the function and the benefit. More information about the training procedure can be found within the github under the regression folder. The algorithms used for regression are explained in table **??**. Similar to classification, we propose comparing the regression algorithms using all features for the **EF!**. We first train our algorithms using all features, implement dimension reduction, features selection and ensemble learning.

Function	Model	Data	RMSE
PR	AdaBoostRegressor	mean	0.12
NR	AdaBoostRegressor	median	0.15
SR	AdaBoostRegressor	median	0.34
WS	AdaBoostRegressor	bfill	0.25
SFST	AdaBoostRegressor	ffill	0.21
PR Benefit	MLPRegressor	mean	1.30
NR Benefit	MLPRegressor	iterative	0.38
SR Benefit	RANSACRegressor	ffill	0.91
WS Benefit	AdaBoostRegressor	BFill	1.25
SFST Benefit	AdaBoostRegressor	Iterative	0.49

Table 12: Model MSE

3.1.1 Training Results

Table ?? presents the training results using the best algorithm and filling method for each EF. Figures ?? to ?? show the best algorithm using various fill methods.

3.1.1.1 Ensemble Learning Ensemble learning consists of combining multiple models to increase the results by averaging out the predictions. Figures ?? to ?? show the graphical results of the ensemble learning approach while table ?? show the MSE.

Function	best	Ensemble
PR	0.12	0.4621
NR	0.15	0.4978
SR	0.34	0.4796
WS	0.25	0.4280
SFST	0.21	0.5130
PR Benefit	1.30	1.2220
NR Benefit	0.38	0.8190
SR Benefit	0.91	0.9797
WS Benefit	0.98	0.9945
SFST Benefit	0.57	0.6444

Table 13: Ensemble Learning Results

In this table, each **EF!** has the overall best accuracy and the ensemble learning which combines the top five models.

3.1.1.2 Class Grouping Similar to classification, our goal for this section is to predict the ratings for a specific site. We use the regression predictions to classify if a site is lower, moderate or higher. We first normalized the prediction results using the NB minimum and maximum of each function which are presented in table ??. We also collected the boundaries for each **EF!** in NB, which are presented in table ??

Function	Minimum	Maximum
WS	1.58	8.61

Table 14: Minimum and Maximum

Function	Lower Boundary	Higher Boundary
WS	3.07	6.17
PR	3.66	6.11
NR	2.06	4.42
SR	3.02	6.67
SFST	1.05	6.51
WS Benefit	2.65	6.50
PR Benefit	3.29	6.68
NR Benefit	4.10	7.76
SR Benefit	2.94	6.19
SFST Benefit	1.86	5.30

Table 15: Ecosystemic Boundaries

First, we provide the grouping using the best performing model for each **EF!**. We also provide an ensemble learning approach that combines the top five model. Table **??** and **??** respectively represent these results while **??** is a voting method.

Function	Lower Acc.	Moderate Acc.	Higher Acc.	Total Acc.
WS	100.00%	83.33%	100.00%	95.24%
PR	75.00%	88.89%	87.50%	85.71%
NR	85.71%	85.71%	100.00%	90.48%
SR	100.00%	100.00%	100.00%	100.00%
SFST	100.00%	57.14%	100.00%	85.71%
WS Benefit	100.00%	100.00%	100.00%	100.00%
PR Benefit	100.00%	85.71%	100.00%	95.24%
NR Benefit	90.00%	100.00%	100.00%	95.24%
SR Benefit	100.00%	88.89%	100.00%	95.24%
SFST Benefit	87.50%	83.33%	100.00%	90.48%

Table 16: Best Models Accuracies

Function	Lower Acc.	Moderate Acc.	Higher Acc.	Overall Acc.
WS	100.00%	83.33%	100.00%	95.24%
PR	75.00%	88.89%	87.50%	85.71%
NR	85.71%	85.71%	100.00%	90.48%
SR	100.00%	100.00%	100.00%	100.00%
SFST	100.00%	57.14%	100.00%	85.71%

Function	Lower Acc.	Moderate Acc.	Higher Acc.	Overall Acc.
WS Benefit	100.00%	100.00%	100.00%	100.00%
PR Benefit	100.00%	85.71%	75.00%	90.48%
NR Benefit	90.00%	100.00%	100.00%	95.24%
SR Benefit	100.00%	88.89%	100.00%	95.24%
SFST Benefit	87.50%	83.33%	100.00%	90.48%

Table 17: Accuracies of Ensemble Models

Function	Lower Acc.	Moderate Acc.	Higher Acc.	Overall Acc.
WS	100.00%	16.67%	75.00%	71.43%
PR	100.00%	0.00%	62.50%	42.86%
NR	100.00%	0.00%	28.57%	42.86%
SR	100.00%	80.00%	0.00%	66.67%
SFST	100.00%	85.71%	0.00%	57.14%
WS Benefit	100.00%	0.00%	0.00%	52.38%
PR Benefit	90.00%	0.00%	100.00%	61.90%
NR Benefit	10.00%	0.00%	100.00%	23.81%
SR Benefit	10.00%	0.00%	100.00%	14.29%
SFST Benefit	0.00%	0.00%	100.00%	33.33%

Table 18: Accuracies of Voting Systems

3.1.2 Dimension Reduction

Due to the large quantity of features, the models could struggle to learn valuable information. We decided to implement dimension reduction techniques to reduce the input vector during training. We compare various methods such as Primary Component Analysis (PCA) against non-reduced results. The various techniques and their descriptions are shown below:

Dimension reduction does not aim to remove features, rather it uses all features and produces a smaller input vector. The model still requires all features, the dimension reduction algorithm compresses the features in a vector. Graphical results for the best algorithm and fill method can be found in figures **??** to **??**.

3.1.3 Feature Reduction

Similar to classification, we propose using feature reduction as our main contribution to this project. It consists of reducing the number of features used to train our algorithms while achieving similar results. Compared to dimension reduction, this technique does not create a new input vector. Rather, it finds the features which are most important to achieve similar results and trains the algorithms on those features. Feature reduction is interesting to our project since it would enable research to obtain the scores and ratings of **EF!**s with fewer features. By using less feature, on-site technicians would have less information to capture. This in turn would enable more sites to be analyzed to provide more sites to the WESP-AC.

Similar to our classification section, we explore two SelectKBest algorithms and a variance threshold. Since most fill methods achieved similar results, we only present the results using the median fill method. Tables **??** and **??** respectively present the lowest MSE using any amount of features and with a limit of two features.

Function	**RMSE**	**# Feat.**	**Selected Features**
WS	0.4287	52	OF17, OF22, OF24, OF25, OF26, OF28, OF33, F1, F3_c, F3_d, F3_e, F3_f, F3_g, F4, F5, F7, F8, F9, F10, F12, F13, F14, F17, F19, F22, F23, F24, F25, F28, F29, F30, F32, F33, F34, F35, F36, F37, F39, F40, F41, F43, F44, F45, F46, F47, F48, F49, F56, F59, F64, F65, S1
NR	0.3461	79	OF27, OF18, F5, OF34, F65, S4, S5, OF5, F31, F35, F45, F25, F33, F54, OF13, F24, F34, F3_g, F43, F2, OF15, F3_d, OF16, F14, OF9, OF14, F3_a, F62, F68, OF2, OF11, F7, F3_f, OF6, F13, F3_c, F8, OF26, F6, OF38, OF4, F9, OF17, F23, F58, F22, F1, F17, S2, F3_e, F52, F36, F29, OF28, F40, F4, F30, F28, F47, F44, F15, OF7, F20, OF3, OF25, F51, F21, F3_b, OF22, F53, F64, F10, OF8, OF10, F56, F50, OF23, F19, F48
PR	0.2392	71	OF2, OF6, OF10, OF11, OF16, OF17, OF20, OF21, OF22, OF24, OF25, OF26, OF28, OF30, F1, F3_a, F3_b, F3_c, F3_d, F3_e, F3_f, F3_g, F4, F5, F6, F7, F8, F9, F10, F12, F13, F14, F15, F16, F17, F18, F19, F20, F22, F23, F24, F25, F28, F29, F30, F32, F33, F34, F35, F36, F37, F38, F39, F40, F41, F43, F44, F45, F46, F47, F49, F50, F51, F52, F53, F56, F63, F64, F65, F67, S1
SR	0.5871	40	OF22, OF26, F1, F3_d, F3_e, F3_g, F4, F5, F7, F9, F13, F14, F15, F17, F22, F23, F24, F25, F28, F29, F30, F31, F32, F33, F34, F35, F36, F37, F39, F40, F41, F43, F44, F45, F46, F47, F49, F64, F65, S1

Function	RMSE	# Feat.	Selected Features
SFST	0.4257	29	OF25, OF28, F1, F3_c, F3_e, F5, F9, F13, F14, F16, F21, F23, F24, F25, F28, F29, F30, F31, F32, F35, F36, F40, F41, F43, F44, F45, F46, F47, F68
WS Benefit	0.9116	70	OF2, OF4, OF5, OF6, OF7, OF14, OF15, OF16, OF17, OF18, OF19, OF21, OF22, OF23, OF24, OF25, OF28, OF31, OF33, OF34, OF37, OF38, F1, F2, F3_a, F3_c, F3_d, F3_e, F4, F5, F8, F9, F12, F13, F17, F18, F20, F21, F22, F23, F24, F28, F29, F30, F31, F32, F36, F38, F40, F43, F44, F45, F46, F47, F49, F50, F51, F52, F54, F55, F56, F58, F62, F64, F65, F67, F68, S1, S4, S5
NR Benefit	1.3035	15	OF5, OF9, OF10, OF15, OF19, OF21, OF23, F1, F3_c, F14, F31, F41, F43, F46, F47
PR Benefit	1.1653	7	OF19, F14, F24, F41, F43, F46, F47
SR Benefit	0.7250	82	OF2, OF3, OF4, OF6, OF7, OF8, OF9, OF10, OF11, OF13, OF14, OF16, OF17, OF18, OF19, OF21, OF23, OF24, OF25, OF27, OF28, OF30, OF33, OF34, OF38, F2, F3_a, F3_b, F3_c, F3_d, F3_e, F4, F5, F6, F7, F8, F12, F13, F14, F15, F16, F18, F19, F21, F22, F23, F24, F25, F28, F29, F30, F31, F32, F33, F34, F35, F36, F37, F39, F40, F41, F43, F44, F45, F46, F47, F48, F49, F50, F51, F52, F53, F54, F56, F57, F58, F64, F65, F67, F68, S1, S4
SFST Benefit	0.6321	28	OF5, OF9, OF18, OF22, OF25, OF28, F1, F2, F3_e, F3_g, F5, F9, F13, F14, F20, F23, F24, F25, F28, F29, F30, F31, F41, F43, F44, F45, F46, F47

Table 19: Method with the Lowest RMSE and Number of Features

Function	RMSE	# Feat.	Selected Features
WS	0.8058	2	F31, F43
NR	2.4040	2	OF18, S4
PR	0.6298	2	F43, F44
SR	1.4341	2	F43, F44
SFST	0.5892	2	F43, F44
WS Benefit	1.5053	2	OF17, OF18
NR Benefit	2.2781	2	OF10, OF22

Function	RMSE	# Feat.	Selected Features
PR Benefit	1.3365	2	F41, F44
SR Benefit	2.0066	2	OF18, F41
SFST Benefit	1.9459	2	OF18, F12

Table 20: Models With Two Features

Using the best model for each **EF!**, we also present graphical results in the annexe using figures **??** to **??**.

These figure show the results for the three reduction techniques ranging from using two features to all features. It enables us to better understand how the number of features affect the overall performance.

3.1.3.1 Ensemble Learning We also performed ensemble learning on the feature reduction results. In the annexe, figures **??** to **??** show results for the top five models for each **EF!** regardeless of the number of features.

Smilarly, figures **??** to **??** show graphs but with a limit of 10 features and results proportionate to the MSE.

Table **??** show the results of the former while table **??** show the ladder.

3.1.3.2 Class Grouping We also propose class grouping with a limit of 10 features for each ecosystem function. We also present the class grouping results of ensemble learning and a voting system for the top five models. These results are presented respectively in table **??**, **??** and **??**.

3.2 Specific Features(D2)

In this section, we perform regression on the **EF!**s using only their specific features. We use our D2 dataset using various algorithms and filling methods.

3.2.1 Results

Table **??** presents the training results using the best algorithm and filling method for each **EF!**.

In the annexe, figures **??** to **??** show the best algorithm using various fill methods.

3.2.1.1 Ensemble Learning Figures **??** to **??** show the graphical results of the ensemble learning approach while table **??** show the MSE.

Function	best	Ensemble
PR	0.10	0.4872
NR	0.14	0.3103
SR	0.09	0.3293
WS	0.06	0.2399
SFST	0.17	0.3002
PR Benefit	0.21	1.011
NR Benefit	0.07	0.3548
SR Benefit	0.10	0.7878
WS Benefit	0.36	0.7338
SFST Benefit	1.59	1.2543

Table 22: Ensemble Learning Results

3.2.1.2 Class Grouping Table **??** and **??** respectively represent these results while **??** is a voting method.

Function	Lower Acc.	Moderate Acc.	Higher Acc.	Total Acc.
WS	100.00%	100.00%	100.00%	100.00%
PR	75.00%	88.89%	100.00%	90.48%
NR	85.71%	71.43%	100.00%	85.71%
SR	90.00%	100.00%	100.00%	95.24%
SFST	83.33%	71.43%	100.00%	85.71%
WS Benefit	100.00%	85.71%	100.00%	95.24%
PR Benefit	100.00%	85.71%	100.00%	95.24%
NR Benefit	90.00%	100.00%	100.00%	95.24%
SR Benefit	100.00%	88.89%	100.00%	95.24%
SFST Benefit	50.00%	66.67%	71.43%	61.90%

Table 23: Best Models Accuracies

Function	Lower Acc.	Moderate Acc.	Higher Acc.	Overall Acc.
WS	100.00%	100.00%	100.00%	100.00%
PR	50.00%	88.89%	100.00%	85.71%
NR	71.43%	85.71%	100.00%	85.71%
SR	90.00%	100.00%	100.00%	95.24%
SFST	83.33%	71.43%	100.00%	85.71%
WS Benefit	100.00%	85.71%	100.00%	95.24%
PR Benefit	100.00%	85.71%	100.00%	95.24%
NR Benefit	80.00%	100.00%	100.00%	90.48%
SR Benefit	100.00%	88.89%	100.00%	95.24%

Function	**Lower Acc.**	**Moderate Acc.**	**Higher Acc.**	**Overall Acc.**
SFST Benefit	50.00%	66.67%	71.43%	61.90%

Table 24: Accuracies of Ensemble Models

Function	**Lower Acc.**	**Moderate Acc.**	**Higher Acc.**	**Overall Acc.**
WS	100.00%	0.00%	0.00%	52.38%
PR	100.00%	0.00%	75.00%	47.62%
NR	14.29%	28.57%	100.00%	47.62%
SR	100.00%	60.00%	0.00%	61.90%
SFST	0.00%	0.00%	100.00%	38.10%
WS Benefit	9.09%	28.57%	100.00%	28.57%
PR Benefit	0.00%	0.00%	100.00%	19.05%
NR Benefit	0.00%	0.00%	100.00%	19.05%
SR Benefit	0.00%	0.00%	100.00%	9.52%
SFST Benefit	0.00%	0.00%	100.00%	33.33%

Table 25: Accuracies of Voting Systems

3.2.2 Feature Reduction

Similar to classification, we propose using feature reduction as our main contribution to this project. It consists of removing or reducing the number of features used to train our algorithms while achieving similar results. Compared to dimension reduction, this technique does not create a new input vector. Rather, it finds the features which are most important to achieve similar results and trains the algorithms on those features. Feature reduction is interesting to our project since it would enable research to obtain the scores of functions with fewer features. By using less feature, on-site technicians would have less information to capture. This in turn would enable more sites to be analyzed to provide more sites to the WESP-AC.

Similar to our classification section, we explore the two SelectKBest methods and a variance threshold. Since most fill methods achieved similar results, we only present the results using the median fill method. Tables **??** and **??** present the lowest MSE using any amount of features and with a limit of two features. Table **??** show a comparaison of our training MSE and our reduced feature MSE.

3.2.2.1 Ensemble Learning We also performed ensemble learning on the feature reduction results. In the annexe, figures **??** to **??** show ensemble learning for the top five models for each **EF!** regardeless of the number of features.

Function	Model	Data	MSE
PR	AdaBoostRegressor	Iterative	0.10
NR	AdaBoostRegressor	Median	0.14
SR	MLPRegressor	Custom	0.09
WS	MLPRegressor	Iterative	0.06
SFST	AdaBoostRegressor	Median	0.17
PR Benefit	RandomForestRegressor	KNN	0.21
NR Benefit	MLPRegressor	Custom	0.07
SR Benefit	TensorFlow	BFill	0.10
WS Benefit	DecisionTreeRegressor	Mode	0.36
SFST Benefit	TheilSemRegressor	BFill	1.59

Table 21: Model MSE

Similarly, figures **??** to **??** show graphs but with a limit of 10 features and proportionate to the RMSE.

Table **??** show the results of the former while table **??** show the ladder.

3.2.2.2 Class Grouping

We also propose class grouping with a limit of 10 features for each ecosystem function. We present the results of ensemble learning and a voting system for the top five models. These results are presented respectively in table **??**, **??** and **??**.

3.3 Extra Features(D3)

In this section, we perform regression on the EFs using extra features, known as our D3 dataset.

3.3.1 Results

Table **??** presents the training results using the best algorithm and filling method for each EF. This approach achieve poor performance throughout our experiment, for this reason it was not further explored.

3.4 Specific and Extra Features(D5)

In this section, we perform regression on the **EF!**s using specific and extras features using our D4 dataset.

3.4.1 Results

Table **??** presents the training results using the best algorithm and filling method for each **EF!**.

Figures **??** to **??** show the best algorithm using various fill methods.

3.4.1.1 Ensemble Learning Figures **??** to **??** show the graphical results of the ensemble learning approach while table **??** show the MSE.

Function	**best**	**Ensemble**
PR	0.12	0.5722
NR	0.18	0.3344
SR	0.21	0.3497
2692SFST	0.18	0.3827
PR Benefit	0.63	1.003
NR Benefit	0.4377	0.3548
SR Benefit	0.52	0.8806
WS Benefit	1.08	2.5478
SFST Benefit	2.29	1.5508

Table 26: Ensemble Learning Results

3.4.2 Feature Reduction

We also propose using feature reduction on this dataset in the aim to find information about features.

Tables **??** and **??** respectively present the lowest MSE using any amount of features and with a limit of two features. Table **??** show a comparaison of our training MSE and our reduced feature MSE.

3.4.2.1 Ensemble Learning We also performed ensemble learning on the feature reduction results. Figures **??** to **??** show ensemble learning for the top five models for each **EF!** regardeless of the number of features.

Figures **??** to **??** show the same but with a limit of 10 features and proportionate to the RMSE.

Table **??** show the results of the former while table **??** show the ladder.

3.4.2.2 Class Grouping We also propose class grouping with a limit of 10 features for each ecosystem function. We also present the class grouping results of ensemble learning and a voting system for the top five models. These results are presented respectively in table **??**, **??** and **??**.

4 Best Results ML

Function	Classification		Regression	
	Accuracy	Features	Accuracy	Features
PR	**85.71%**	**F43, F45**	76.19%	F43, F44, F45, F5, OF18, OF27, OF34, S4
NR	**80.95%**	**F24, F43, F44, F45**	80.95%	F43, F44, F45, F5, OF18, OF27, OF34, S4
SR	80.95%	OF22, F35, F43, F44, F45, F49	**90.48%**	**F24, F28, F31, F43, F44, F45, F5,OF18, OF28**
WS	**90.48%**	**F43, F46**	85.71%	f22, F31, F43, F44, F46, F5, OF18, OF27
SFST	**95.24%**	**F43, F44**	80.95%	F43, F44, F45, F46, OF18, OF27
PR Benefit	**90.48%**	**OF24, F41**	80.95%	F14, F3c, F41, F44, OF18, OF19, OF27
NR Benefit	**100.00%**	**OF9, OF10, OF19, OF21, 'F41**	85.71%	F41, F5, OF10, OF18, OF22, OF27, OF30
SR Benefit	**100.00%**	**OF19, OF21, F41**	85.71%	F12, F41, OF18, OF22, OF27, OF30
WS Benefit	**95.24%**	**OF17, OF23**	90.48%	F5, OF17, OF18, OF23, OF27, OF34, S4
SFST Benefit	**80.95%**	**F43, F44**	80.95%	F12, F43, F44, F45, F5, OF18, OF27, OF30

Table 27: Function Features Comparison

4.1 Feature Pertubation

The models are trained using real datasets, and the best model for each configuration is selected based on its performance on a validation dataset. The configurations include different features and model hyperparameters. After identifying the best models, we perform a detailed analysis to evaluate how perturbations in individual features impact the model's predictions. The perturbations involve changing each feature to its possible values and observing the results.

For each feature, we measure the change in model accuracy when the feature is perturbed. First, we calculate the original accuracy of the model on the test dataset. Then, we perturb the feature to each of its possible values, one at a time, and measure the accuracy of the model on the perturbed dataset. The difference between the perturbed accuracy and the original accuracy is computed to understand how sensitive the model's accuracy is to changes in each feature.

We also measure the impact on the predicted class labels for each feature. We obtain the original predictions of the model on the test dataset and perturb the feature to each of its possible values. For each perturbation, we measure the percentage of samples where the perturbed predictions are lower or higher than the original predictions. The net class change impact is calculated as the difference between the higher and lower percentages. This analysis reveals how changes in each feature influence the predicted class labels, indicating whether perturbations tend to make the predictions higher or lower.

The results of the feature perturbation analysis are visualized in plots showing the change in accuracy for each feature perturbation and the net impact on class predictions. Positive values in the net class change impact plots indicate more samples with higher predicted classes, while negative values indicate more samples with lower predicted classes. These visualizations provide a comprehensive understanding of how feature perturbations affect model performance and predictions.

The possible class options for each feature are as follows:

1. OF17: 4
2. OF19: 2
3. OF21: 4
4. OF22: 4
5. OF23: 3
6. F24: 6
7. F31: 5
8. F35: 5
9. F41: 2
10. F43: 3
11. F44: 3
12. F45: 5
13. F49: 4

For classification, figures **??** to **??** show the change in accuracy. Figures **??** to **??** show the net change in class.

For regression, figures **??** to **??** show the net change in MSE while **??** to **??** show the average change in class.

4.2 Feature Values

We also compare the results by analyzing the values of the features for our predictions. Tables **??** to **??** show the prediction results using our classification models. Each table represents their unique **EF!** with the features used to generate predictions. We also show the actual values and the occurrence of this permutation. These results enables us to better understand how the algorithms react to change in features.

5 Annexes

5.1 Datasets

Feature Name	Type	Description
Provincial Class	Class (6)	This classification divides wetlands into six distinct types based on their ecological characteristics. It aids in the management and conservation of wetland resources.
Provincial Class	Class (10)	This extended classification categorizes wetlands into ten types, providing a more detailed understanding of wetland diversity for conservation strategies.
Water Regime	Class (4)	This indicator classifies water regimes into four types, describing the hydrological conditions of a wetland. It is essential for wetland management.
Vegetation Type	Class (7)	This classification identifies seven types of specific vegetation present in wetlands. It helps in assessing the ecological status of wetland areas.
Veg. Cover	Class (5)	This classification indicates the percentage cover of specific vegetation types, divided into five classes. It provides insights into vegetation distribution.
Woody Canopy	Class (4)	This classification describes the percentage cover of high woody canopy (over 5 meters), divided into four classes. It is useful for understanding forest structure in wetlands.
% Moss Cover	Class (5)	This classification specifies the percentage cover of moss in wetlands, divided into five classes. It is important for ecological assessments.
Phragmites	Class (3)	This feature indicates the presence of Phragmites (an invasive plant species) in a wetland, classified as yes or no. It is crucial for invasive species management.
Soil Type	Class (3)	This classification identifies the soil types in wetlands, divided into three classes. It helps in understanding soil characteristics and their impact on wetland ecology.
Surface Water	Class (7)	This classification indicates the percentage of surface water present in a wetland, divided into seven classes. It is important for hydrological studies.
Depth Sat.	Class (4)	This feature measures the depth of water saturation in soil, divided into four classes. It helps in understanding soil moisture conditions.
Depth Moss	Float	This feature measures the average depth of living moss in centimeters. It provides insights into the health and growth of moss in wetlands.
Organic Depth	Float	This feature measures the average depth of organic material in soil in centimeters. It is crucial for understanding soil composition and fertility.
Hydrogeomorphic	Class (11)	This classification divides wetlands into eleven hydrogeomorphic classes, based on their geomorphology and hydrology. It is essential for wetland characterization and management.

Table 28: Feature Descriptions for Various Wetland Attributes

5.2 Features

Name	Title	Description
OF1	Province	Always New Brunswick in the case of the project.
OF2	Accumulated water area within 1 km	Recent orthoimagery (ESRI Hybrid), mosaic of very high spatial resolution aerial photographs, 1 km buffer layer, and area measurement tool.
OF3	Accumulated water and wetlands within 1 km	Recent orthoimagery (ESRI Hybrid), mosaic of very high spatial resolution aerial photographs, regulated wetlands layers – 2010 and 2020, 1 km buffer layer, and area measurement tool.
OF4	Size of the largest area or corridor of vegetation	Recent orthoimagery (ESRI Hybrid), mosaic of very high spatial resolution aerial photographs, Forest layer (location of plantations), and area measurement tool. Always ¿ 1000 hectares for this project.
OF5	Distance from a large expanse of vegetation	Recent orthoimagery (ESRI Hybrid), mosaic of very high spatial resolution aerial photographs, Forest layer (location of plantations), and area and distance measurement tool. 1 – Is there a massif of more than 375 ha of unmanaged vegetation nearby? Yes. 2 – What is the minimum distance between the edge of the evaluation area and the edge of the nearest massif of more than 375 ha of unmanaged vegetation? 3 – Is there a physical separation between the edge of the evaluation area and the edge of the massif of more than 375 ha of unmanaged vegetation?
OF6	Uniqueness of herbaceous plants	Recent orthoimagery (ESRI Hybrid), mosaic of very high spatial resolution aerial photographs, and circular buffer layers of 100 m, 1 km, and 5 km radius centered on a point chosen in the evaluation area based on its proximity to a road or main forest path and its accessibility. In our context, the vegetation cover of the evaluation area is usually composed of less than 10% herbaceous plants (including mosses). In this case, put 0 (P. Adamus, personal communication, 30/06/2020).

Continued on next page

Table 29 – continued from previous page

Name	Title	Description
OF7	Uniqueness of woody cover	Recent orthoimagery (ESRI Hybrid), mosaic of very high spatial resolution aerial photographs, circular buffer layers of 100 m, 1 km, and 5 km radius centered on a point chosen in the evaluation area based on its proximity to a road or main forest path and its accessibility, and Forest layer (location of plantations). In our context, the terrestrial environment within a radius of 5 km, 1 km, and 100 m from the edge of the wetland is composed of more than 10% woody cover. In this case, put 0 (P. Adamus, personal communication, 04/08/2021).
OF8	Percentage of local vegetation cover	Recent orthoimagery (ESRI Hybrid), mosaic of very high spatial resolution aerial photographs, circular buffer layer of 5 km radius centered on a point chosen in the evaluation area based on its proximity to a road or main forest path and its accessibility, and Forest layer (location of plantations).
OF9	Type of soil degradation	Recent orthoimagery (ESRI Hybrid), mosaic of very high spatial resolution aerial photographs, circular buffer layer of 5 km radius centered on a point chosen in the evaluation area based on its proximity to a road or main forest path and its accessibility, and Forest layer (location of plantations).
OF10	Road distance to the nearest population center	Recent orthoimagery (ESRI Hybrid), mosaic of very high spatial resolution aerial photographs, road network and forest path layers, and linear measurement tool.
OF11	Distance to the nearest maintained road	Recent orthoimagery (ESRI Hybrid), mosaic of very high spatial resolution aerial photographs, road network and forest path layers, and linear measurement tool.
OF12	Wildlife access	Recent orthoimagery (ESRI Hybrid), mosaic of very high spatial resolution aerial photographs, and circular buffer layer of 5 km radius centered on a point chosen in the evaluation area based on its proximity to a road or main forest path and its accessibility.
OF13	Distance from an accumulated water body	Recent orthoimagery (ESRI Hybrid), mosaic of very high spatial resolution aerial photographs, and linear measurement tool.
OF14	Distance from a large accumulated water body	Recent orthoimagery (ESRI Hybrid), mosaic of very high spatial resolution aerial photographs, and linear and area measurement tool. Always more than 10 km in the context of the project.

Continued on next page

Table 29 – continued from previous page

Name	Title	Description
OF15	Proximity to tides	Always more than 40 km in the context of the project.
OF16	Contact with the terrestrial environment	Recent orthoimagery (ESRI Hybrid), mosaic of very high spatial resolution aerial photographs, and very high spatial resolution digital elevation model. Visual estimation.
OF17	Damage caused by non-tidal waters	Use of the layer from the atlas of 2 countries one forest (2C1Forest) called Active river area for the Northern Appalachian-Acadian Region. Add a 5 km buffer around the layer.
OF18	Relative elevation in the watershed	Very high spatial resolution digital elevation model.
OF19	Watershed sensitive to water quality	Always 1 in the context of this project (designated watersheds).
OF20	Degraded water quality upstream	Visual observations, recent orthoimagery (ESRI Hybrid), and mosaic of very high spatial resolution aerial photographs (0.1 m; GéoNB 2018).
OF21	Degraded water quality downstream	Visual observations, recent orthoimagery (ESRI Hybrid), and mosaic of very high spatial resolution aerial photographs.
OF22	Wetland percentage of the contribution area	New Brunswick wetland layers (2010 and 2020), contribution area layer, and area measurement tool. Reference wetland: local wetland/not the wetland complex. Excel file created for calculations.
OF23	Non-vegetated surface in the contribution area	Contribution area layer and area measurement tool. Negligible; significant; important or very important.
OF24	Surface from an ascending slope	Recent orthoimagery (ESRI Hybrid), mosaic of very high spatial resolution aerial photographs, hydrographic network layer, very high spatial resolution digital elevation model, and very high spatial resolution slope layer. Soil depth: see Madawaska County soil study (1980).
OF25	Orientation	Orientation of the current direction.
OF26	Internal flow distance (Flow path length)	Hydrographic network layer + Linear measurement tool to measure the distance between the inlet and outlet of water flowing in the wetland.
OF27	Growing degree days	Growing degree days layer.

Continued on next page

Table 29 – continued from previous page

Name	Title	Description
OF28	Fish access or use	No data.
OF29	Species conservation concern	See with ACCDC data, eBirds, Ornitho Club, available rare plant data. No data.
OF30	Important Bird Area (IBA)	Always 0 in the context of this project (important bird areas layer).
OF31	Black duck nesting area	No data.
OF32	Concentration areas for wintering deer or moose	On public lands, deer wintering area layer, only for W16 and W17.
OF33	Other conservation designation	Natural protected areas layers, provincially significant wetlands, and Nature Conservancy Canada.
OF34	Conservation effort	Always 0 in the context of the project.
OF35	Mitigation measure	Always 0 in the context of the project.
OF36	Sustained scientific use	Always 0 in the context of the project.
OF37	Limestone region	Bedrock geology and forest soils layers of NB.
OF38	Property type	Crown land layer. Public lands: Activities permitted according to status; 2nd condition = general case. Private lands: 4th condition.
F1	Wetland Type	Focus on vegetation type.
F2	Adjacent or secondary wetland type	
F3	Diversity - Height (vertical stratification of the canopy) and nature of the cover	
F4	Dominance of the most abundant shrub species	
F5	Diameter classes of woody species	

Continued on next page

Table 29 – continued from previous page

Name	Title	Description
F6	Intermingling of height classes	
F7	Large snags (Standing dead trees)	
F8	Downed wood	
F9	Nitrogen fixer	
F10	Extent of Sphagnum Moss	
F11	% of bare soil and thatch/litter	
F12	Soil irregularity	Use of the DEM + Shading layer to see topographic variation.
F13	Terrestrial inclusion	Area of terrestrial inclusions in the evaluation area. The high-resolution spatial DEM could be used.
F14	Soil texture	Use the document "Soils of New Brunswick: The second approximation" (Fahmy et al. 2010) + Soil layer + Excel table to draw a conclusion on soil types and their granulometry.
F15	Shorebird feeding habitats	
F16	% Herbaceous part of the wetland vegetation	The mosaic of very high-resolution spatial aerial photographs could be used.
F17	Forb cover	
F18	Carex cover	
F19	Dominance of the most abundant herbaceous species	
F20	Cover of invasive plants	
F21	Invasive cover in the terrestrial environment	
F22	Fringing wetlands	
F23	Lacustrine wetlands	

Continued on next page

Table 29 – continued from previous page

Name	Title	Description
F24	% of the EA without surface water	
F25	% of the EA with persistent surface water	
F26	% of shaded water in summer	
F27	% of the EA that is seasonally flooded only	
F28	Annual water fluctuation	
F29	Predominant depth class	
F30	Depth class – Uniformity of proportions	
F31	% of stagnant water (non-flowing)	
F32	Minimum size – Stagnant open water	
F33	% of accumulated water that is open	
F34	Width of the vegetation zone in the wetland	The mosaic of very high-resolution spatial aerial photographs could be used.
F35	Extent of flat shoreline	Mosaic of very high-resolution spatial aerial photographs and high-resolution slope layer. Classification of slope percentage (0-5%; ¿ 5%).
F36	Robust emergent vegetation	
F37	Intersection of emergent vegetation with open waters	
F38	Extent of persistent deep water	

Continued on next page

Table 29 – continued from previous page

Name	Title	Description
F39	Non-vegetated aquatic cover	
F40	Isolated island	
F41	Floating algae and duckweed	
F42	Connection to the canal and duration of outgoing flow	The “Wet Areas Mapping” layer could be used. Since we were able to conduct tests with the multiprobe during the driest period in most wetlands, the conclusion to this question was that the water was persistent for the majority of the wetlands, except for W18, where the stream was dry.
F43	Outflow confinement	The very high spatial resolution DEM could be used.
F44	Tributary channels	The “Wet Areas Mapping” layer could be used.
F45	Inflow water temperature	Use of the multiprobe.
F46	Flow resistance	
F47	pH measurement	Use of the multiprobe (use a comma instead of a dot to record the response).
F48	TDS and/or conductivity	Use of the multiprobe (use a comma instead of a dot to record the response).
F49	Beaver probability	
F50	Evidence of groundwater	High-resolution slope layers and “Wet Areas Mapping” layers could be used.
F51	Internal gradient	Use of precise contour lines, level of the inlet minus the level of the outlet divided by the distance traveled by the stream, expressed as a percentage (all in an Excel file).
F52	% of the perimeter’s vegetative buffer	The mosaic of very high-resolution spatial aerial photographs and the Forest layer (location of plantations) could be used, with a 30m buffer for precision.
F53	Buffer zone cover type	The mosaic of very high-resolution spatial aerial photographs could be used.
F54	Buffer zone slope	The mosaic of very high-resolution spatial aerial photographs and the high-resolution slope layer is used. The slope layer is divided into three classes, based on the type of slope.

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Table 29 – continued from previous page

Name	Title	Description
F55	Steep cliffs or banks	1 – Mosaic of very high-resolution spatial aerial photographs: Absence of vegetation? 2 – Very high spatial resolution DEM: classification with 2 m elevation classes (max. elevation = 515 m - min. elevation = 151 m). 3 – Validation with the topographic profile: 2 m elevation change?
F56	New or extended wetland	Road and forest path layers and the chronosequence of aerial photograph mosaics could be used.
F57	Fire history	National Burned Area Composite.
F58	Visibility	
F59	Non-consumptive uses - actual or potential	
F60	Central zone not visited	
F61	Frequently visited area	
F62	BMP - Soils	Always 0 in the context of this project.
F63	BMP - Wildlife protection	Always 0 in the context of this project.
F64	Consumptive uses (provisioning services)	
F65	Drinking water	Since the designated watershed provides drinking water, all wetlands have drinking water within 100 m of the EA.
F66	Calcareous minerotrophic peatland	Always 0 in the context of this project. The characteristics of this ecosystem should be better studied. Forest soil layers, bedrock geology, and "Wet Areas Mapping" layers should be considered.
S1	Abnormal inflow patterns	The mosaic of very high-resolution spatial aerial photographs could be used, and the chronosequence of aerial photograph mosaics could be used.
S2	Accelerated input of contaminants and/or salts into the wetland or its contribution area	

Continued on next page

Table 29 – continued from previous page

Name	Title	Description
S3	Accelerated nutrient input into the wetland or its contribution area	
S4	Excessive sediment load from the contribution area	The mosaic of very high-resolution spatial aerial photographs could be used, and the chronosequence of aerial photograph mosaics could be used.
S5	Soil or sediment degradation within the evaluation area	The mosaic of very high-resolution spatial aerial photographs could be used, and the chronosequence of aerial photograph mosaics could be used.

5.3 Machine Learning Algorithms

Algorithm	Type	Parameters
Ridge	Class./Reg.	• `alpha`: [0.1, 0.5, 1.0] • `solver`: ['auto', 'svd', 'cholesky', 'lsqr', 'sparse_cg', 'sag', 'saga', 'lbfgs']
Decision Tree	Class./Reg.	• `criterion`: ['gini', 'entropy', 'log_loss'] (Class.), ['squared_error', 'friedman_mse', 'absolute_error', 'poisson'] (Reg.) • `splitter`: ['best', 'random'] • `min_samples_split`: [2, 3, 4, 5] • `max_features`: [None, 'sqrt', 'log2']
Random Forest	Class./Reg.	• `n_estimators`: [50, 100, 200] • `criterion`: ['gini', 'entropy', 'log_loss'] (Class.), ['squared_error', 'friedman_mse', 'absolute_error', 'poisson'] (Reg.) • `min_samples_split`: [2, 5] • `max_features`: ['sqrt', 'log2']
Gradient Boosting	Class./Reg.	• `loss`: ['log_loss', 'deviance', 'exponential'] (Class.), ['squared_error', 'absolute_error', 'huber', 'quantile'] (Reg.) • `learning_rate`: [0.001, 0.01, 0.1] • `n_estimators`: [50, 100, 200] • `warm_start`: [True, False]
AdaBoost	Class./Reg.	• `n_estimators`: [50, 100, 200] • `learning_rate`: [0.001, 0.01, 0.1, 1.0] • `algorithm`: ['SAMME', 'SAMME.R'] (Class.), `loss`: ['linear', 'square', 'exponential'] (Reg.)

K-Neighbors	Class./Reg.	• `n_neighbors`: [5, 10, 15, 20] • `weights`: ['uniform', 'distance'] • `algorithm`: ['auto', 'ball_tree', 'kd_tree', 'brute'] • `leaf_size`: [30, 50, 70] • `metric`: ['euclidean', 'manhattan', 'minkowski']
MLP (Neural Network)	Class./Reg.	• `hidden_layer_sizes`: [(50, 50, 50), (100, 100, 100), (100, 100, 100, 100)] • `activation`: ['identity', 'logistic', 'tanh', 'relu'] • `solver`: ['lbfgs', 'sgd', 'adam'] • `learning_rate`: ['constant', 'invscaling', 'adaptive']
Logistic Regression	Classifier	• `penalty`: ['l1', 'l2', 'elasticnet', 'none'] • `C`: [0.1, 0.5, 1.0, 5.0, 10.0] • `solver`: ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'] • `max_iter`: [100, 200, 300]
SGD	Class./Reg.	• `loss`: ['hinge', 'log', 'modified_huber', 'squared_hinge', 'perceptron'] (Class.), ['squared_error', 'huber', 'epsilon_insensitive', 'squared_epsilon_insensitive'] (Reg.) • `penalty`: ['l2', 'l1', 'elasticnet'] • `learning_rate`: ['constant', 'optimal', 'invscaling', 'adaptive'] • `warm_start`: [True, False]
Support Vector Machines (SVM)	Class./Reg.	• `C`: [0.1, 1.0, 10.0] • `kernel`: ['linear', 'poly', 'rbf', 'sigmoid'] • `degree`: [1, 3, 5] • `gamma`: ['scale', 'auto']

Gaussian Naive Bayes	Classifier	• `var_smoothing`: [1e-9, 1e-8, 1e-7]
Linear Discriminant Analysis	Classifier	• `solver`: ['svd', 'lsqr', 'eigen'] • `shrinkage`: [None, 'auto', 0.1, 0.5, 1.0]
ElasticNet	Regressor	• `l1_ratio`: [0.25, 0.5, 0.75] • `fit_intercept`: [True, False] • `precompute`: [True, False] • `copy_X`: [True, False] • `warm_start`: [True, False] • `positive`: [True, False] • `selection`: ['cyclic', 'random']
Bayesian Ridge	Regressor	• `alpha_1`: [1e-7, 1e-6, 1e-5] • `alpha_2`: [1e-7, 1e-6, 1e-5] • `lambda_1`: [1e-7, 1e-6, 1e-5] • `lambda_2`: [1e-7, 1e-6, 1e-5]
Kernel Ridge	Regressor	• `alpha`: [0.00001, 0.0001, 0.001, 0.01] • `kernel`: ['linear', 'poly', 'rbf', 'sigmoid', 'precomputed'] • `degree`: [1, 2, 3, 5, 10] • `coef0`: [0.0, 0.5, 1.0]
Linear Regression	Regressor	• `fit_intercept`: [True, False] • `copy_X`: [True, False] • `positive`: [True, False]
RANSAC Regressor	Regressor	• `min_samples`: [None, 1, 2, 5, 10] • `max_trials`: [1, 10, 50, 100, 150] • `loss`: ['absolute_error', 'squared_error']

Theil-Sen Regressor	Regressor	• `max_subpopulation`: [1, 10, 100, 500] • `n_subsamples`: [None, 1, 5, 10, 25]

Table 30: Machine Learning Algorithms

5.4 Classification

5.4.1 All Features

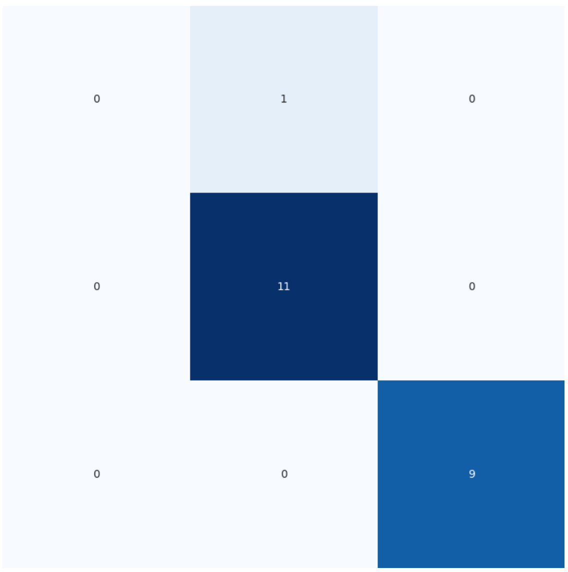

Figure 1: Ensemble for PR

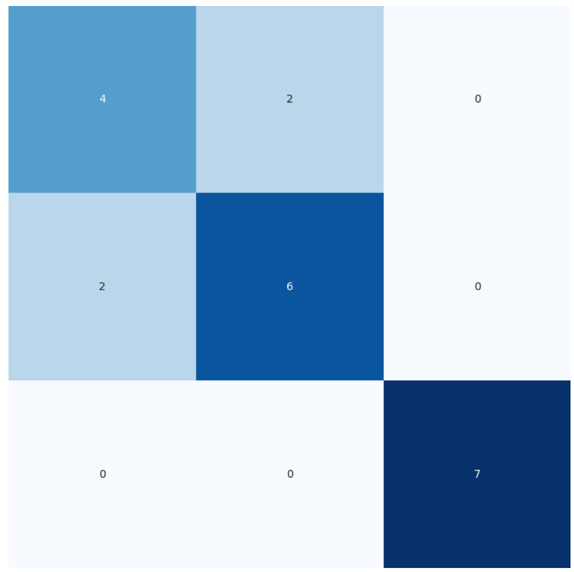

Figure 2: Ensemble for NR

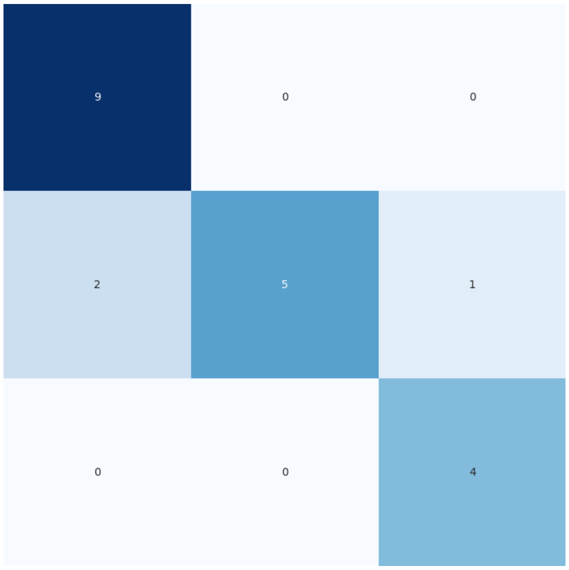

Figure 3: Ensemble for SR

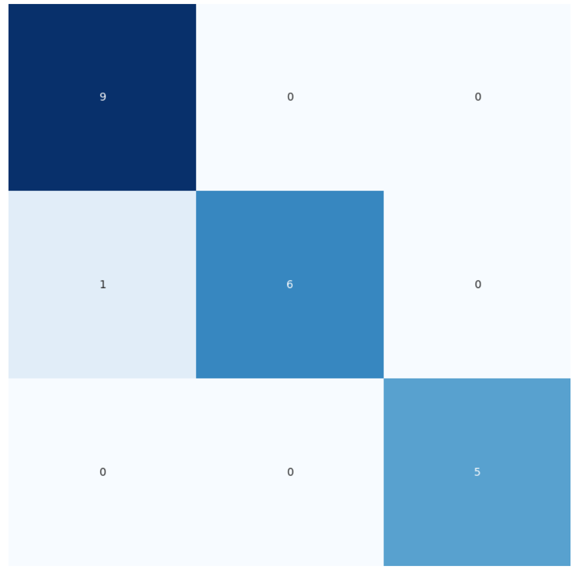

Figure 4: Ensemble for WS

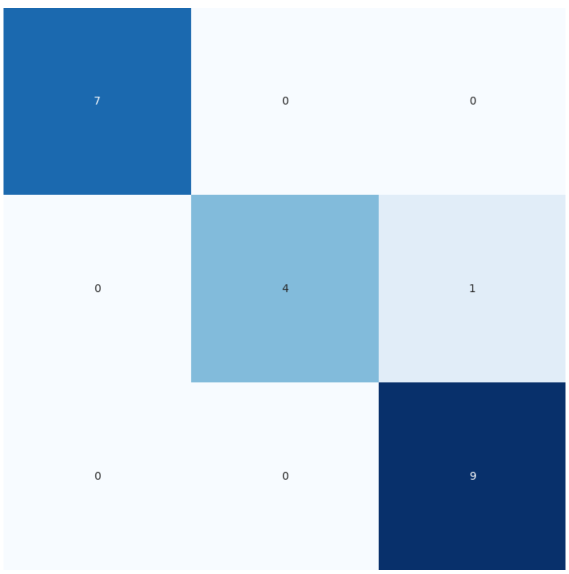

Figure 5: Ensemble for SFST

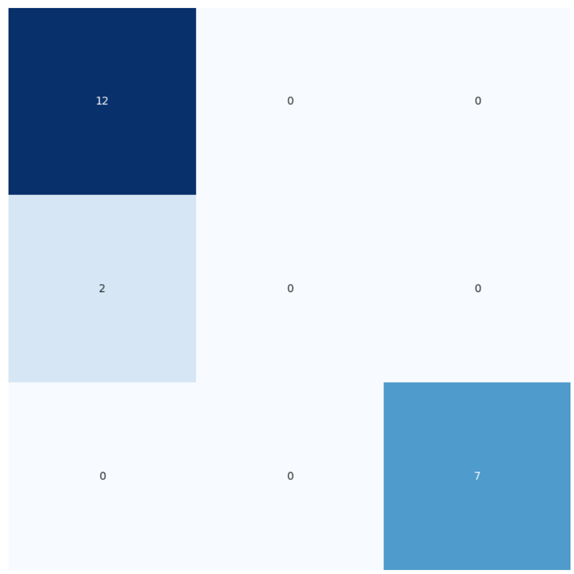

Figure 6: Ensemble for PR Benefit

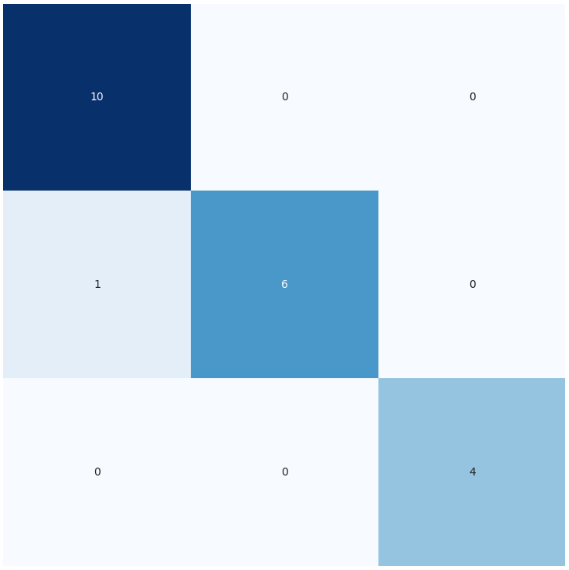

Figure 7: Ensemble for NR Benefit

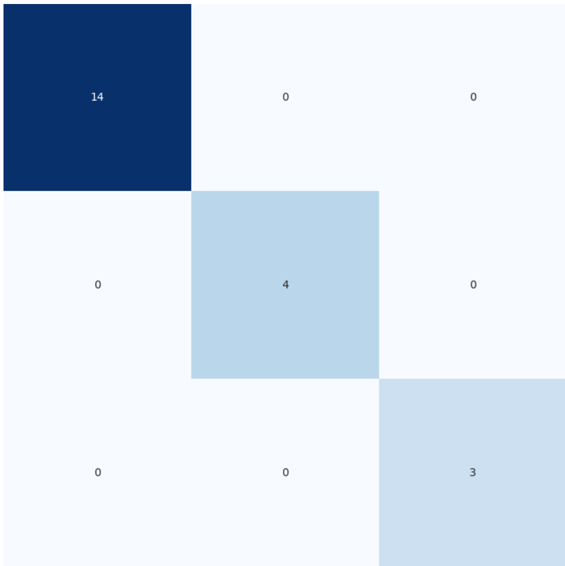

Figure 8: Ensemble for SR Benefit

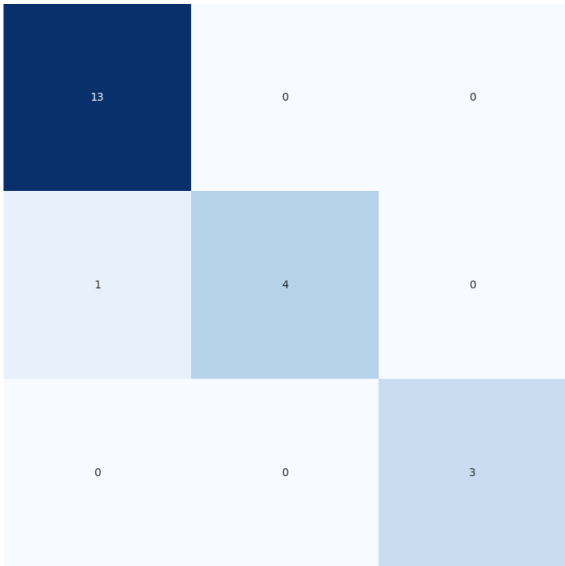

Figure 9: Ensemble for WS Benefit

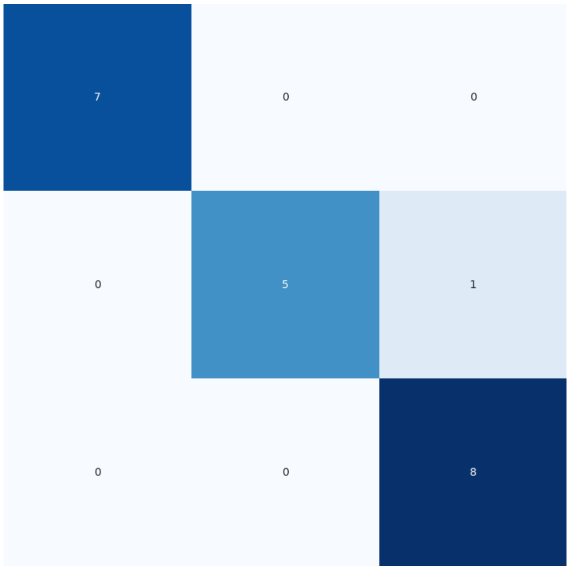

Figure 10: Ensemble for SFST Benefit

Function	Accuracy	# Feat.	Selected Features
PR	95.24%	8	F1, F14, F24, F28, F41, F43, F44, F45
NR	80.95%	13	F1, F14, F22, F23, F24, F28, F29, F30, F43, F44, F45, F46, F47
SR	95.24%	14	OF22, F1, F3_e, F13, F14, F25, F35, F36, F41, F43, F44, F45, F46, F49
WS	100.00%	41	OF22, OF24, OF25, OF26, OF28, F1, F3_c, F3_d, F3_e, F4, F5, F7, F9, F13, F14, F17, F22, F23, F24, F25, F28, F29, F30, F31, F32, F33, F34, F35, F36, F37, F40, F41, F43, F44, F45, F46, F47, F49, F56, F65, S1
SFST	100.00%	56	OF3, OF5, OF6, OF10, OF18, OF23, OF24, OF25, OF26, OF27, OF28, OF31, OF33, F1, F3_b, F3_c, F3_d, F3_e, F3_f, F4, F5, F9, F13, F14, F15, F17, F22, F23, F24, F25, F28, F29, F30, F31, F32, F33, F34, F35, F36, F37, F38, F39, F40, F41, F43, F44, F45, F46, F47, F49, F56, F58, F64, F65, F67, S2
PR Benefit	100.00%	88	OF2, OF4, OF5, OF8, OF11, OF13, OF14, OF15, OF16, OF17, OF18, OF19, OF20, OF21, OF22, OF24, OF25, OF26, OF27, OF28, OF31, OF34, OF38, F1, F2, F3_a, F3_c, F3_e, F3_f, F3_g, F5, F6, F7, F8, F9, F10, F13, F14, F15, F16, F17, F19, F20, F21, F22, F23, F24, F25, F28, F29, F30, F31, F32, F33, F34, F35, F36, F37, F38, F39, F40, F41, F43, F44, F45, F46, F47, F48, F49, F50, F51, F52, F53, F54, F55, F56, F57, F58, F59, F62, F63, F64, F65, F67, F68, S1, S2, S4
NR Benefit	95.24%	28	OF9, OF10, OF19, OF20, OF21, OF22, OF38, F1, F3_c, F3_d, F3_e, F9, F13, F14, F22, F23, F24, F30, F31, F41, F43, F44, F45, F46, F47, F52, F65, S1
SR Benefit	100.00%	4	OF19, OF21, F41, F43
WS Benefit	100.00%	20	OF7, OF9, OF15, OF17, OF20, OF23, OF27, OF33, F3_b, F3_c, F3_e, F4, F5, F20, F31, F32, F49, F50, F51, S5
SFST Benefit	95.24%	47	OF9, OF10, OF17, OF22, OF24, OF25, OF26, OF28, F1, F3_c, F3_d, F3_e, F3_f, F4, F5, F7, F9, F10, F13, F14, F17, F19, F22, F23, F24, F25, F28, F29, F30, F32, F33, F34, F35, F36, F37, F40, F41, F43, F44, F45, F46, F47, F49, F50, F56, F65, S1

Table 31: Maximum Accuracy

Function	**Accuracy**	**# Feat.**	**Selected Features**
PR	85.71%	2	F43, F45
NR	76.19%	2	F43, F44
SR	61.90%	2	F43, F44
WS	90.48%	2	F43, F46
SFST	95.24%	2	F43, F44
PR Benefit	85.71%	2	F41, F43
NR Benefit	76.19%	2	OF10, F41
SR Benefit	95.24%	2	OF19, F41
WS Benefit	90.48%	2	OF17, OF23
SFST Benefit	80.95%	2	F43, F44

Table 32: Maximum Proportionate Accuracy

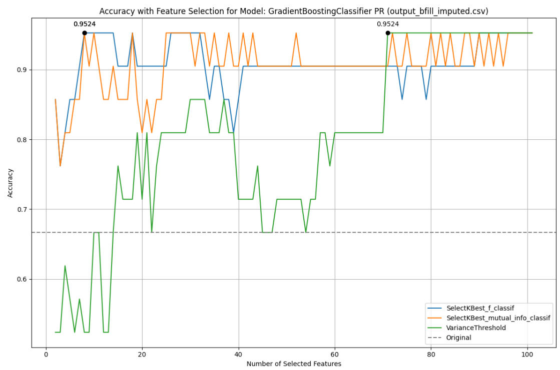

Figure 11: PR

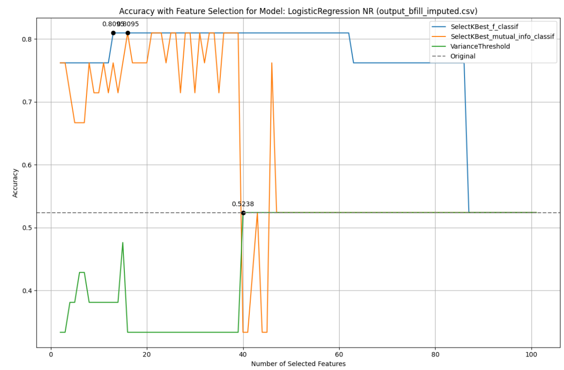

Figure 12: NR

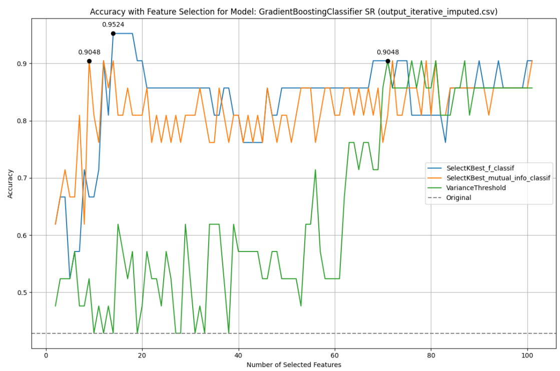

Figure 13: SR

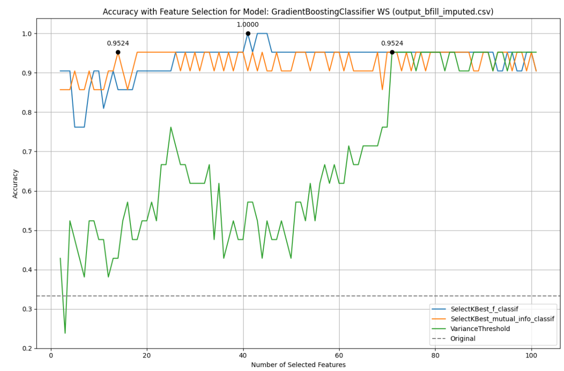

Figure 14: WS

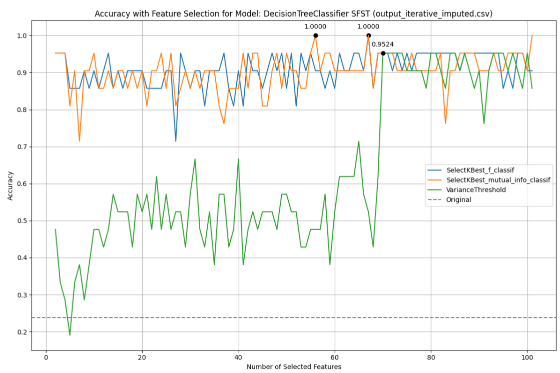

Figure 15: SFST

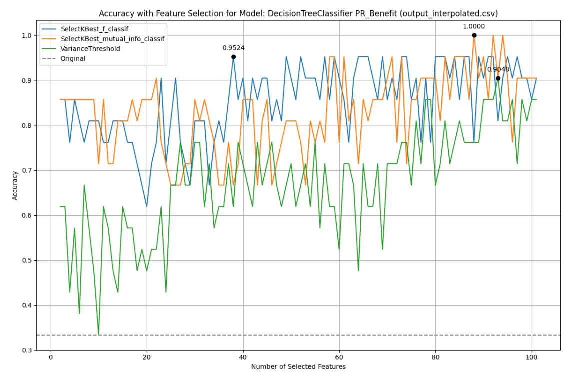

Figure 16: PR Benefit

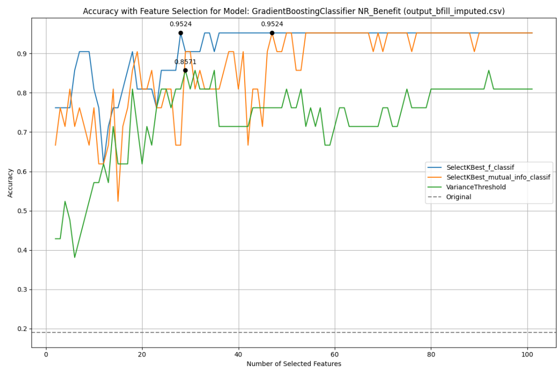

Figure 17: NR Benefit

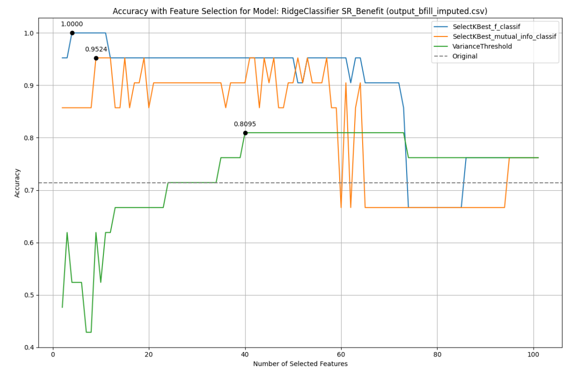

Figure 18: SR Benefit

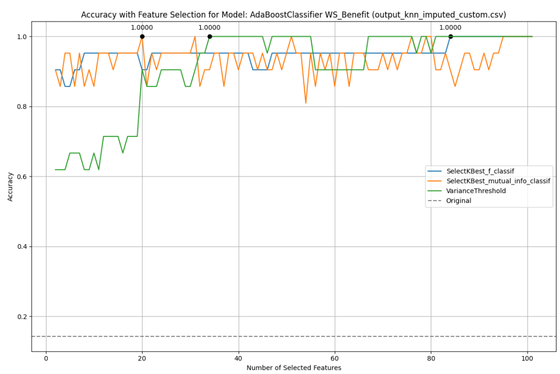

Figure 19: WS Benefit

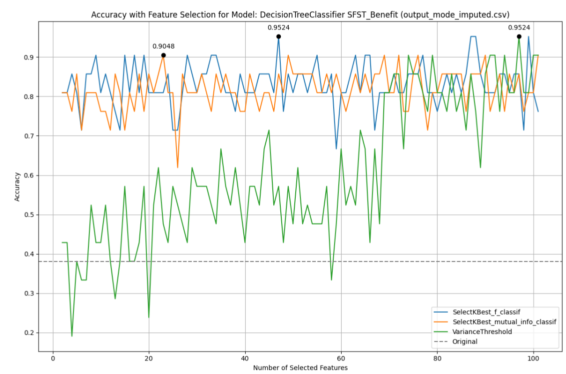

Figure 20: SFST Benefit

5.4.2 Specific Features

Function	Accuracy	# Feat.	Selected Features
PR	0.9524	14	OF26, F17, F21, F23, F24, F28, F29, F31, F34, F35, F43, F44, F45, F63
NR	0.8571	23	OF16, OF22, OF25, OF27, F1, F3b, F3c, F3d, F3e, F3g, F17, F22, F23, F24, F28, F31, F33, F34, F36, F43, F44, F45, F49
SR	0.8095	6	OF22, F35, F43, F44, F45, F49
WS	1.0000	9	OF22, F3c, F3d, F3e, F28, F43, F44, F45, F49
SFST	0.9524	2	F1, F43
PR Benefit	0.9524	7	OF19, OF22, OF24, F41, F48, F50, F52
NR Benefit	0.9524	12	OF9, OF10, OF19, OF20, OF21, OF22, OF23, OF24, F41, F50, F51, F52
SR Benefit	1.0000	3	OF19, OF21, F41
WS Benefit	0.9524	2	OF17, OF23
SFST Benefit	0.5714	2	OF22, OF28

Table 33: Maximum Accuracy

Function	Accuracy	# Feat.	Selected Features
PR	0.8571	2	F43, F45
NR	0.7619	2	F43, F44
SR	0.6190	2	F43, F44
WS	0.8571	2	F43, F44
SFST	0.9524	2	F1, F43
PR Benefit	0.9048	2	OF24, F41
NR Benefit	0.7619	2	OF10, F41
SR Benefit	0.9524	2	OF19, F41
WS Benefit	0.9524	2	OF17, OF23
SFST Benefit	0.5714	2	OF22, OF28

Table 34: Maximum Proportionate Accuracy

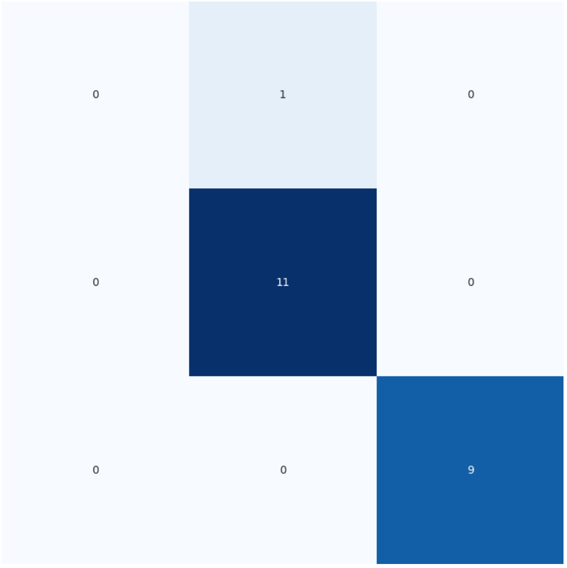

Figure 21: Ensemble for PR

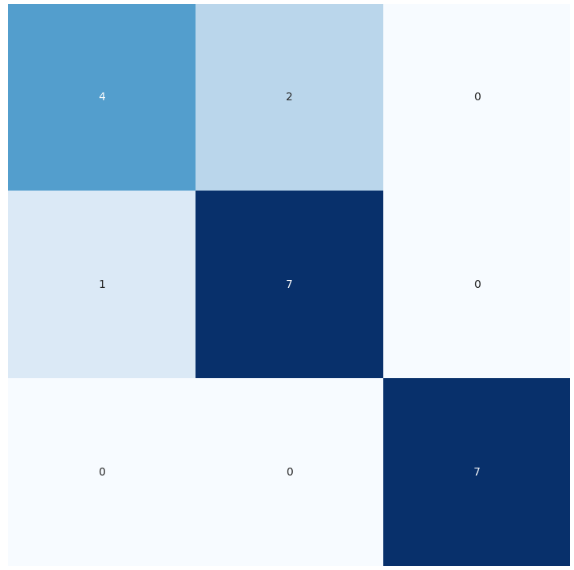

Figure 22: Ensemble for NR

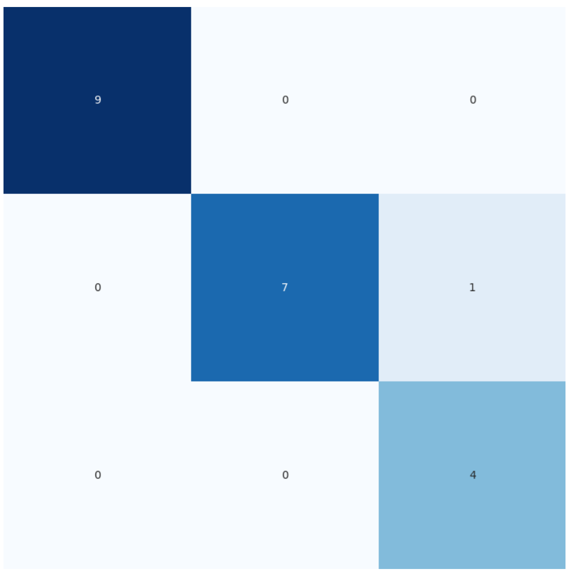

Figure 23: Ensemble for SR

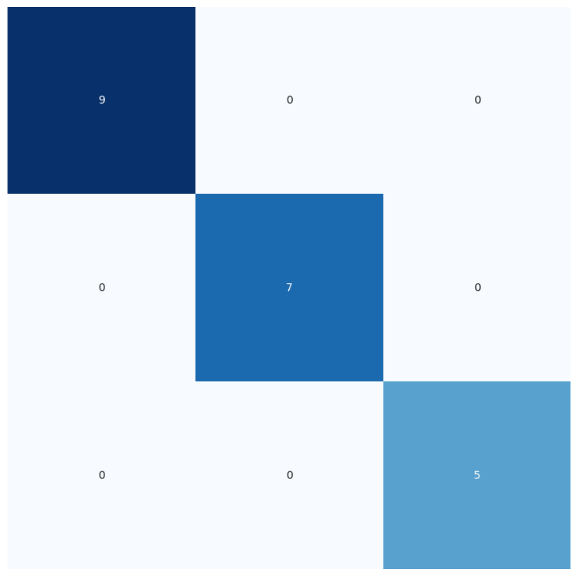

Figure 24: Ensemble for WS

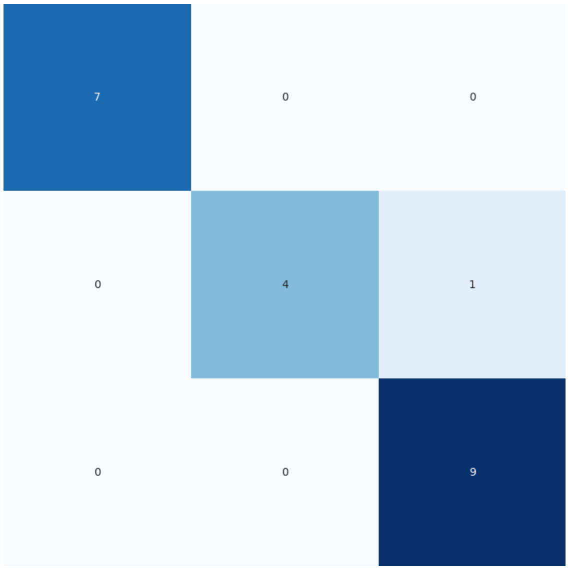

Figure 25: Ensemble for SFST

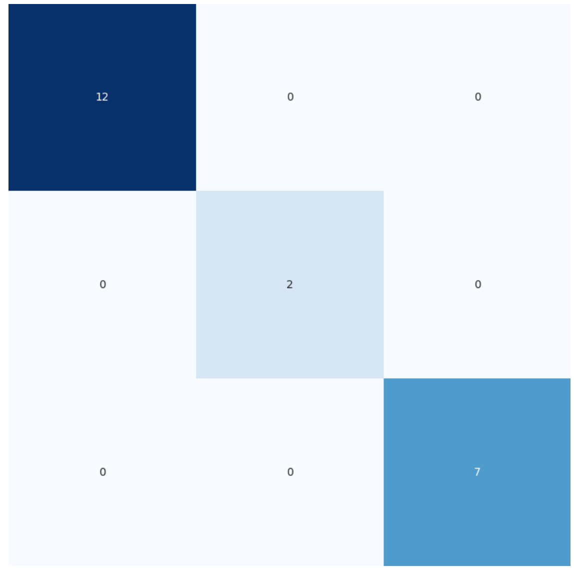

Figure 26: Ensemble for PR Benefit

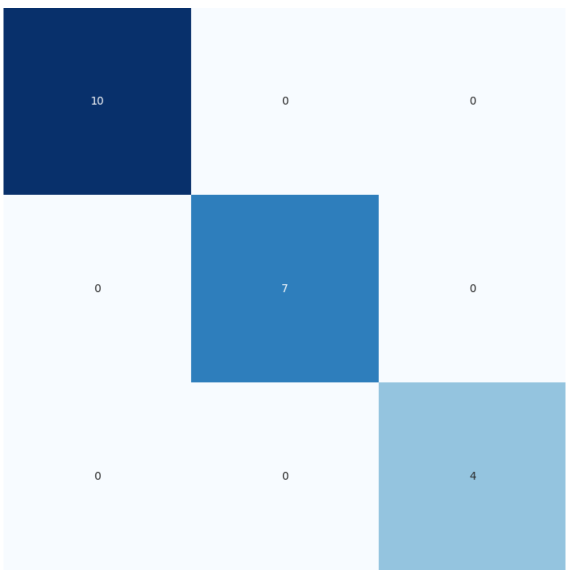

Figure 27: Ensemble for NR Benefit

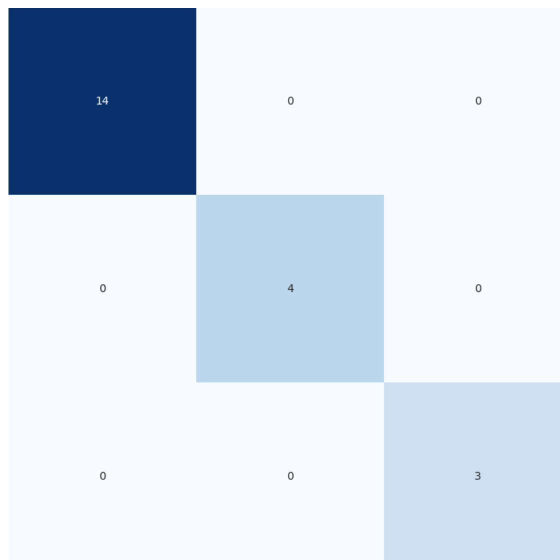

Figure 28: Ensemble for SR Benefit

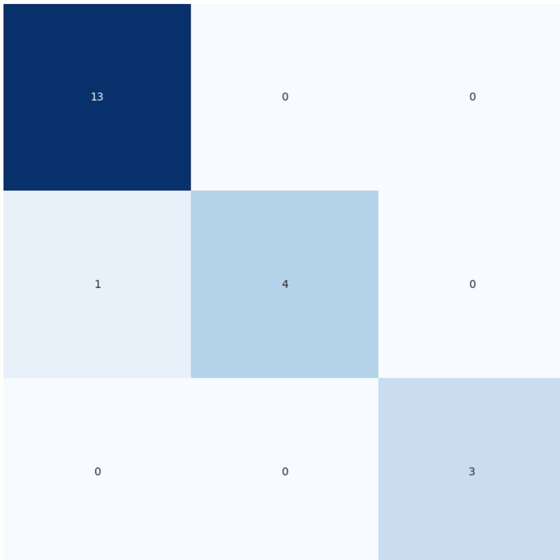

Figure 29: Ensemble for WS Benefit

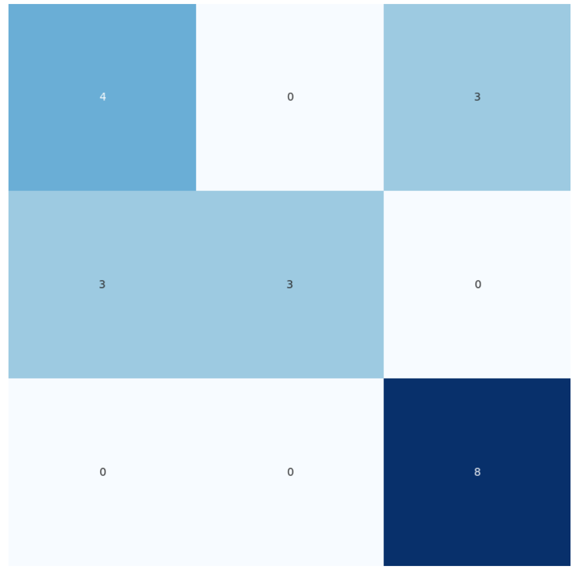

Figure 30: Ensemble for SFST Benefit

5.4.3 Extra Features

Function	Accuracy	# Feat.	Selected Features
PR	0.8571	9	Provincial_Class, Federal_Class, Regime, Vegetation_Type, Vegetation_Cover, Woody_Canopy_Cover, Moss_Cover, Soil_Type, Surface_Water_Present, Saturation_Depth, Living_Moss_Depth, Organic_Depth, Hydrogeomorphic_Class
NR	0.6667	9	Provincial_Class, Federal_Class, Regime, Vegetation_Type, Vegetation_Cover, Woody_Canopy_Cover, Moss_Cover, Soil_Type, Surface_Water_Present, Saturation_Depth, Living_Moss_Depth, Organic_Depth, Hydrogeomorphic_Class
SR	0.6190	11	Provincial_Class, Federal_Class, Regime, Vegetation_Type, Vegetation_Cover, Moss_Cover, Phragmites, Soil_Type, Surface_Water_Present, Living_Moss_Depth, Organic_Depth
WS	0.8095	5	Provincial_Class, Federal_Class, Regime, Vegetation_Type, Hydrogeomorphic_Class
SFST	0.7143	2	Provincial_Class, Federal_Class

Function	Accuracy	# Feat.	Selected Features
PR Benefit	0.7619	6	Provincial_Class, Federal_Class, Regime, Vegetation_Type, Vegetation_Cover, Woody_Canopy_Cover, Moss_Cover, Soil_Type, Surface_Water_Present, Saturation_Depth, Living_Moss_Depth, Organic_Depth, Hydrogeomorphic_Class
NR Benefit	0.6667	5	Provincial_Class, Federal_Class, Regime, Moss_Cover, Living_Moss_Depth
SR Benefit	0.8095	6	Provincial_Class, Federal_Class, Regime, Vegetation_Type, Vegetation_Cover, Woody_Canopy_Cover, Moss_Cover, Soil_Type, Surface_Water_Present, Saturation_Depth, Living_Moss_Depth, Organic_Depth, Hydrogeomorphic_Class
WS Benefit	0.7619	9	Provincial_Class, Federal_Class, Regime, Woody_Canopy_Cover, Phragmites, Surface_Water_Present, Living_Moss_Depth, Organic_Depth, Hydrogeomorphic_Class
SFST Benefit	0.6667	5	Provincial_Class, Federal_Class, Moss_Cover, Surface_Water_Present, Hydrogeomorphic_Class

Table 35: Maximum Accuracy

Function	Accuracy	# Feat.	Selected Features
PR	0.7619	2	Provincial_Class, Moss_Cover
NR	0.5714	2	Provincial_Class, Federal_Class
SR	0.4286	2	Provincial_Class, Hydrogeomorphic_Class
WS	0.5238	2	Provincial_Class, Federal_Class
SFST	0.7143	2	Provincial_Class, Federal_Class
PR Benefit	0.7143	2	Provincial_Class, Federal_Class
NR Benefit	0.5714	2	Provincial_Class, Federal_Class
SR Benefit	0.7143	2	Provincial_Class, Moss_Cover
WS Benefit	0.6190	2	Moss_Cover, Living_Moss_Depth
SFST Benefit	0.5714	2	Provincial_Class, Federal_Class

Table 36: Maximum Proportionate Accuracy

Function	Best Acc.	2nd Best Acc.	Ensemble Learning Acc.	Features Used

PR	85.71%	85.71%	80.95%	Federal Class, Hydrogeomorphic Class, Living Moss Depth, Moss Cover, Organic Depth, Provincial Class, Regime, Saturation Depth, Soil Type, Surface Water Present, Vegetation Cover, Vegetation Type, Woody Canopy Cover
NR	66.67%	66.67%	61.90%	Federal Class, Hydrogeomorphic Class, Living Moss Depth, Moss Cover, Organic Depth, Provincial Class, Regime, Saturation Depth, Soil Type, Surface Water Present, Vegetation Cover, Vegetation Type, Woody Canopy Cover
SR	57.14%	52.38%	66.67%	Federal Class, Hydrogeomorphic Class, Living Moss Depth, Moss Cover, Organic Depth, Provincial Class, Regime, Saturation Depth, Soil Type, Surface Water Present, Vegetation Cover, Vegetation Type, Woody Canopy Cover
WS	80.95%	80.95%	80.95%	Federal Class, Hydrogeomorphic Class, Living Moss Depth, Moss Cover, Organic Depth, Provincial Class, Regime, Saturation Depth, Soil Type, Surface Water Present, Vegetation Cover, Vegetation Type, Woody Canopy Cover
SFST	71.43%	71.43%	76.19%	Federal Class, Hydrogeomorphic Class, Living Moss Depth, Moss Cover, Organic Depth, Provincial Class, Regime, Saturation Depth, Soil Type, Surface Water Present, Vegetation Cover, Vegetation Type, Woody Canopy Cover

PR Benefit	76.19%	76.19%	71.43%	Federal Class, Hydrogeomorphic Class, Living Moss Depth, Moss Cover, Organic Depth, Phragmites, Provincial Class, Regime, Saturation Depth, Soil Type, Surface Water Present, Vegetation Cover, Vegetation Type, Woody Canopy Cover
NR Benefit	66.67%	66.67%	66.67%	Federal Class, Hydrogeomorphic Class, Living Moss Depth, Moss Cover, Organic Depth, Provincial Class, Regime, Saturation Depth, Soil Type, Surface Water Present, Vegetation Cover, Vegetation Type, Woody Canopy Cover
SR Benefit	80.95%	76.19%	76.19%	Federal Class, Hydrogeomorphic Class, Living Moss Depth, Moss Cover, Organic Depth, Provincial Class, Regime, Saturation Depth, Soil Type, Surface Water Present, Vegetation Cover, Vegetation Type, Woody Canopy Cover
WS Benefit	76.19%	71.43%	66.67%	Federal Class, Hydrogeomorphic Class, Living Moss Depth, Moss Cover, Organic Depth, Phragmites, Provincial Class, Regime, Saturation Depth, Soil Type, Surface Water Present, Vegetation Cover, Vegetation Type, Woody Canopy Cover
SFST Benefit	66.67%	61.90%	61.90%	Federal Class, Hydrogeomorphic Class, Living Moss Depth, Moss Cover, Organic Depth, Provincial Class, Regime, Saturation Depth, Soil Type, Surface Water Present, Vegetation Cover, Vegetation Type, Woody Canopy Cover

Table 37: Ensemble Learning Accuracy

5.4.4 Specific + Extra Features

Function	Accuracy	# Feat.	Selected Features
PR	0.9524	22	Provincial Class, Federal Class, Regime, Moss Cover, Phragmites, Soil Type, Surface Water Present, Living Moss Depth, Organic Depth, Hydrogeomorphic Class, OF26, F17, F21, F23, F24, F28, F29, F31, F33, F43, F44, F45
NR	0.8095	4	F24, F43, F44, F45
SR	0.8571	13	Provincial Class, Federal Class, Moss Cover, Hydrogeomorphic Class, F22, F28, F29, F31, F33, F36, F43, F44, F45
WS	1.0000	20	Provincial Class, Federal Class, Regime, Vegetation Type, Moss Cover, Surface Water Present, Living Moss Depth, Organic Depth, OF22, OF26, F3c, F3d, F3e, F22, F28, F31, F43, F44, F45, F49
SFST	0.9524	2	F1, F43
PR Benefit	0.9524	13	Provincial Class, Regime, Moss Cover, Phragmites, Living Moss Depth, Organic Depth, OF19, OF22, OF24, F41, F48, F50, F52
NR Benefit	0.9524	13	Provincial Class, Federal Class, Moss Cover, Living Moss Depth, Organic Depth, OF9, OF10, OF19, OF21, OF22, F13, F41, F52
SR Benefit	1.0000	3	OF19, OF21, F41
WS Benefit	0.9524	2	OF17, OF23
SFST Benefit	0.6667	9	Provincial Class, Federal Class, Moss Cover, Soil Type, Surface Water Present, Hydrogeomorphic Class, OF18, OF25, OF28

Table 38: Maximum Accuracy

Function	Accuracy	# Feat.	Selected Features
PR	0.8571	2	F43, F45
NR	0.7619	2	F43, F44
SR	0.6190	2	F43, F44
WS	0.8571	2	F43, F44
SFST	0.9524	2	F1, F43
PR Benefit	0.8571	2	Moss Cover, F41
NR Benefit	0.7619	2	OF10, F41
SR Benefit	0.9524	2	OF19, F41

Function	Accuracy	# Feat.	Selected Features
WS Benefit	0.9524	2	OF17, OF23
SFST Benefit	0.4762	2	Provincial Class, Moss Cover

Table 39: Maximum Proportionate Accuracy

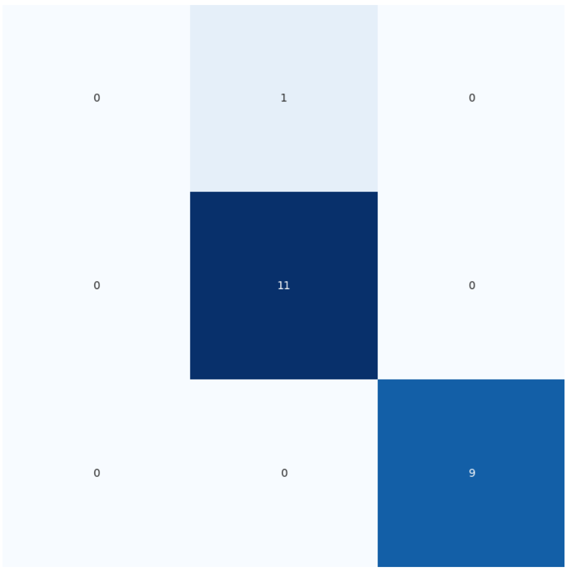

Figure 31: Ensemble for PR

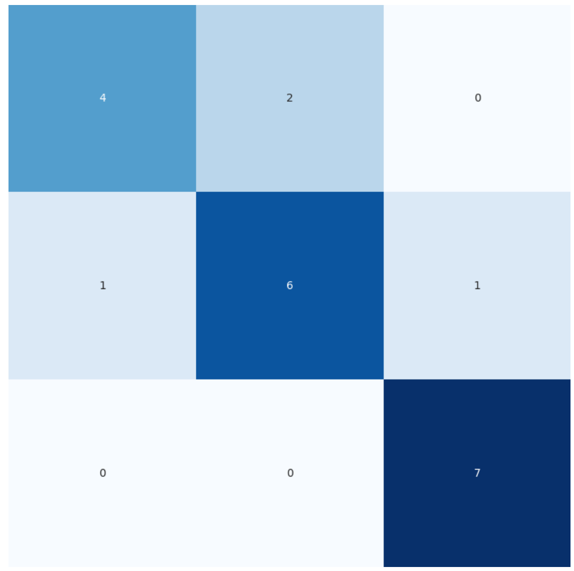

Figure 32: Ensemble for NR

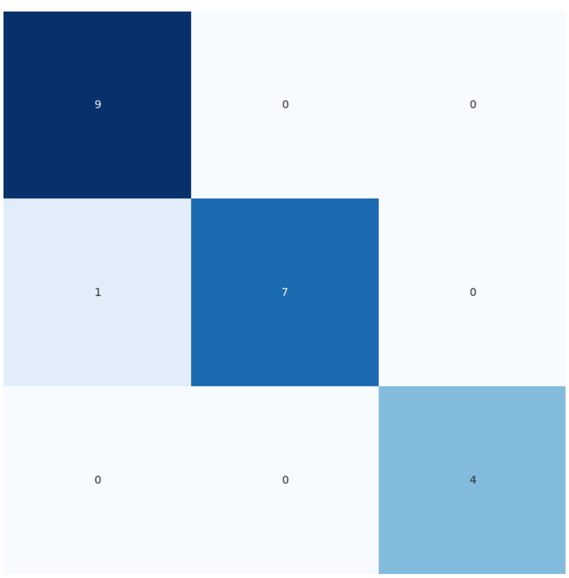

Figure 33: Ensemble for SR

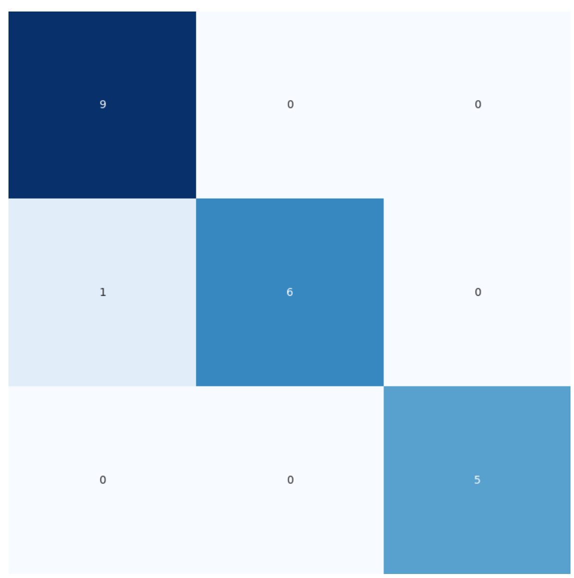

Figure 34: Ensemble for WS

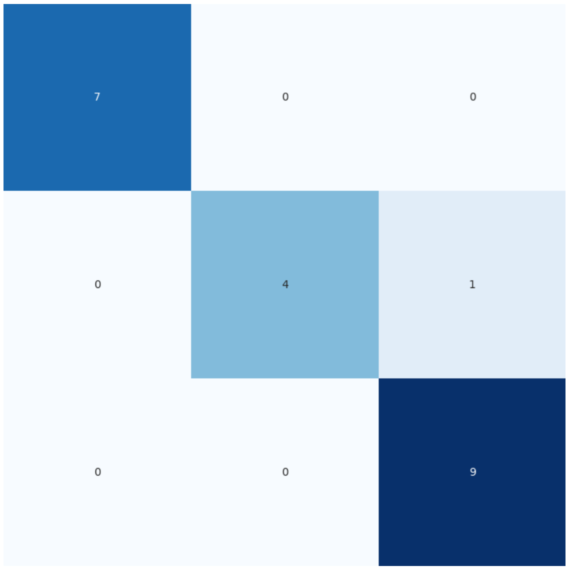

Figure 35: Ensemble for SFST

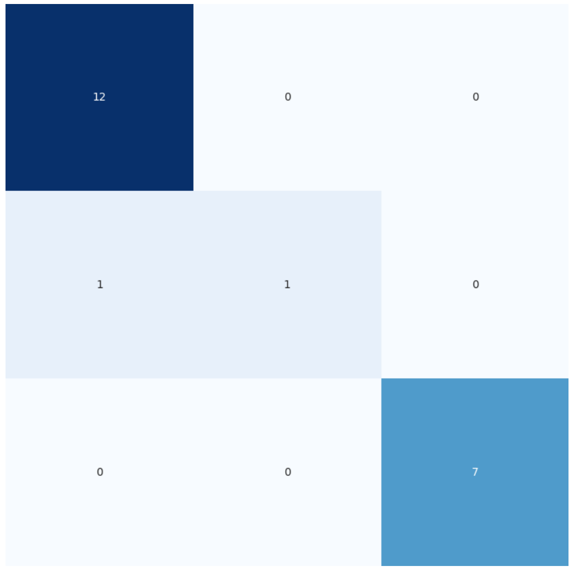

Figure 36: Ensemble for PR Benefit

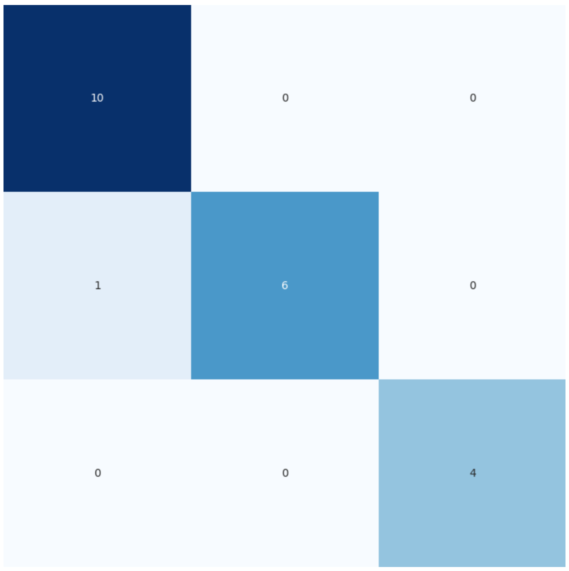

Figure 37: Ensemble for NR Benefit

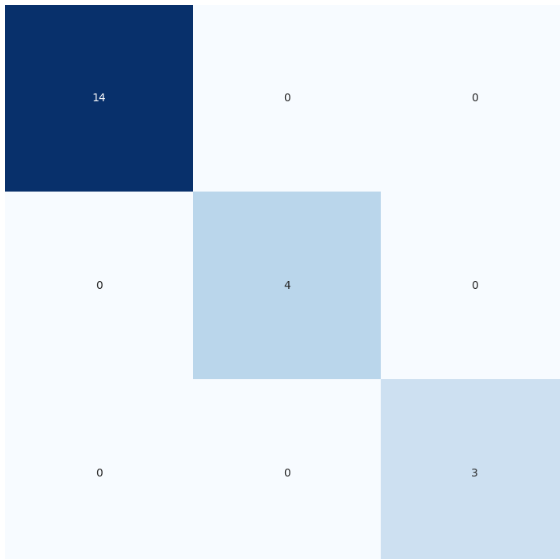

Figure 38: Ensemble for SR Benefit

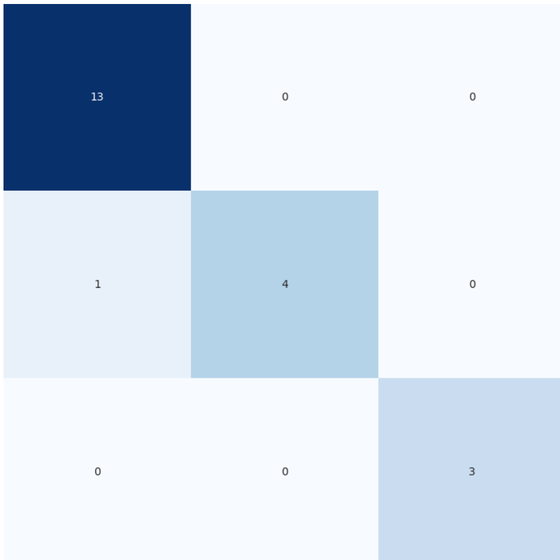

Figure 39: Ensemble for WS Benefit

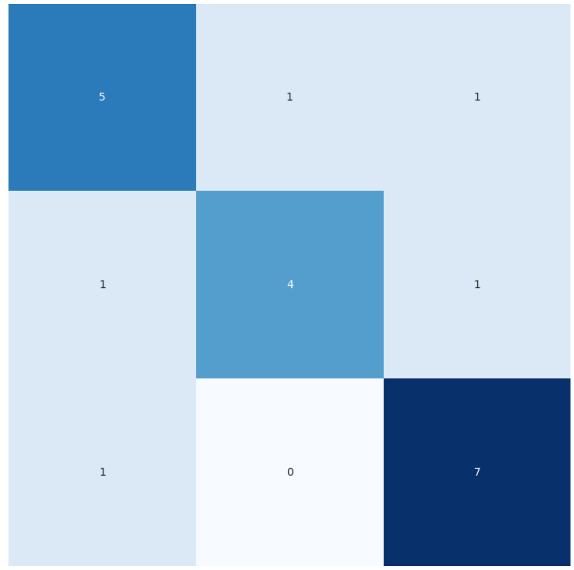

Figure 40: Ensemble for SFST Benefit

5.5 Regression Models

5.5.1 All Features

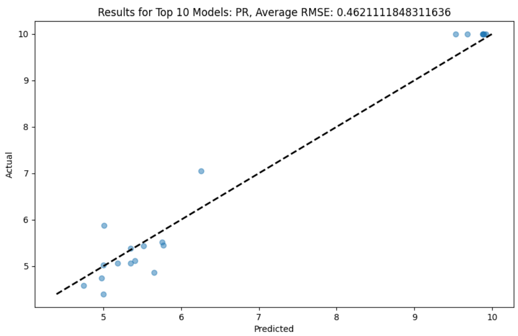

Figure 41: PR

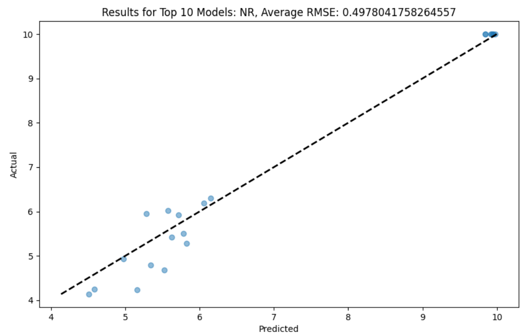

Figure 42: NR

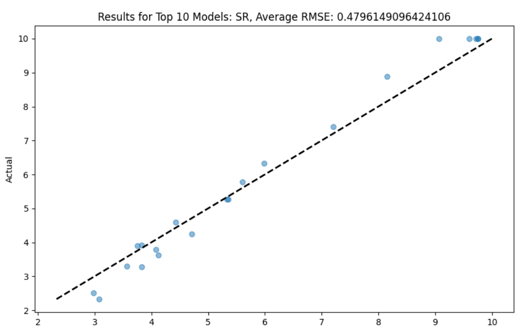

Figure 43: SR

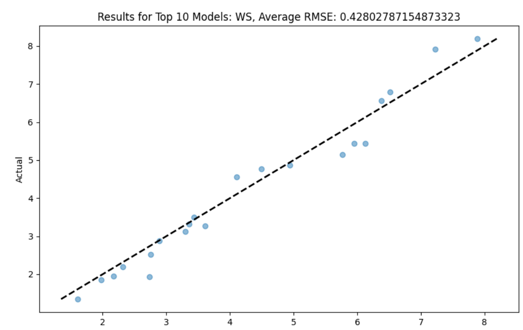

Figure 44: WS

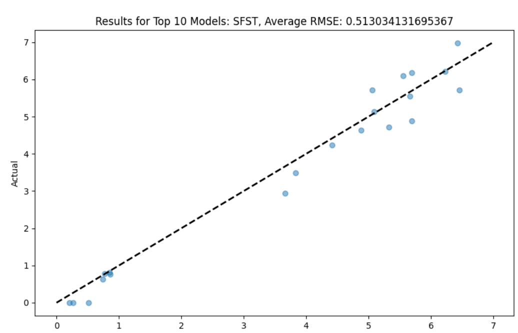

Figure 45: SFST

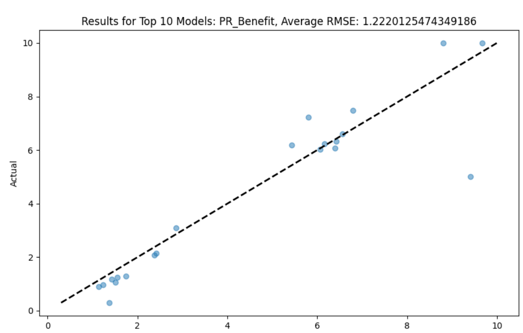

Figure 46: PR Benefit

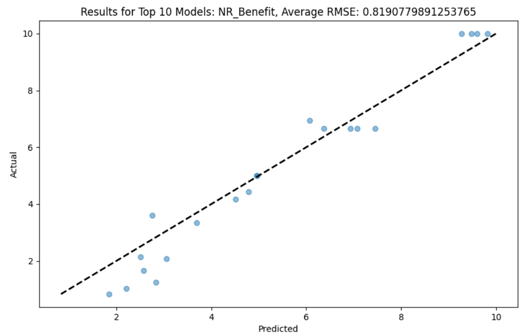

Figure 47: NR Benefit

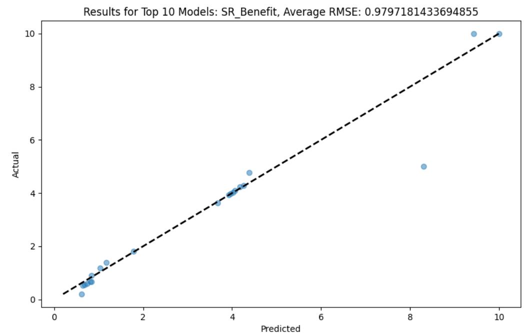

Figure 48: SR Benefit

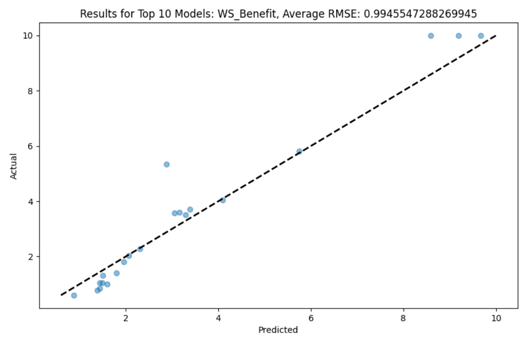

Figure 49: WS Benefit

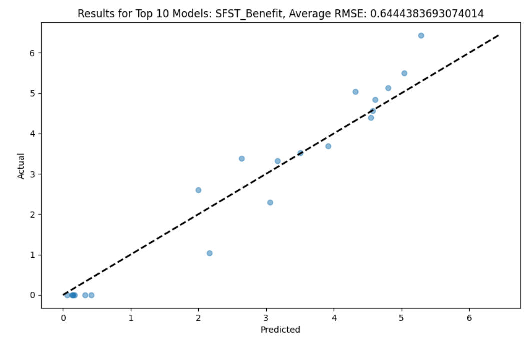

Figure 50: SFST Benefit

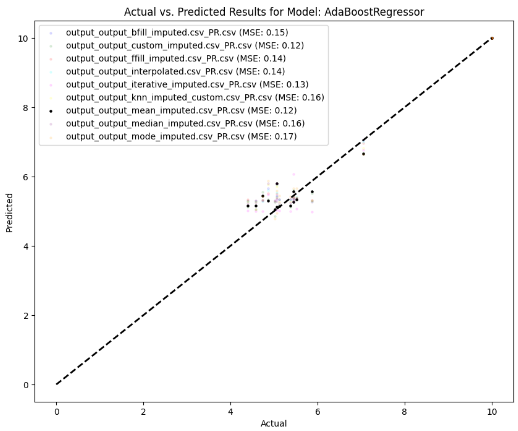

Figure 51: PR

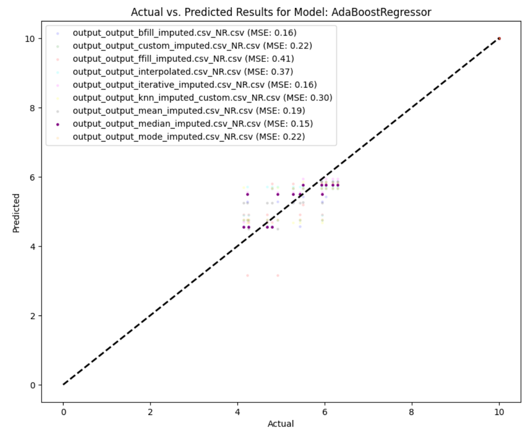

Figure 52: NR

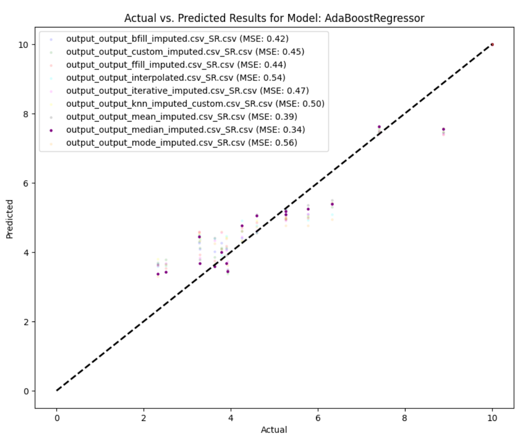

Figure 53: SR

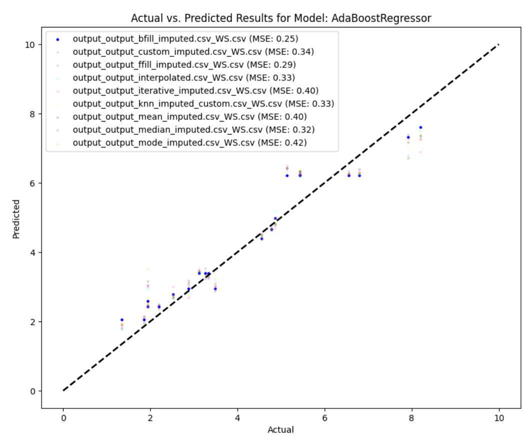

Figure 54: WS

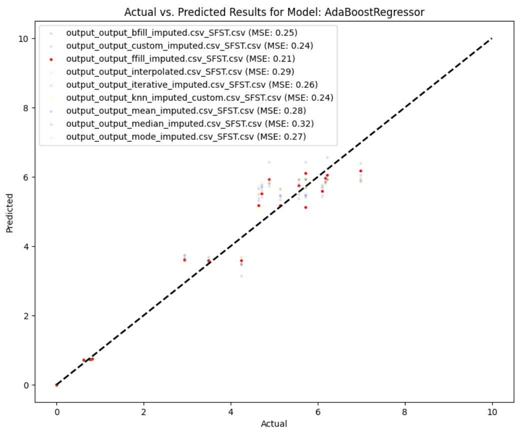

Figure 55: SFST

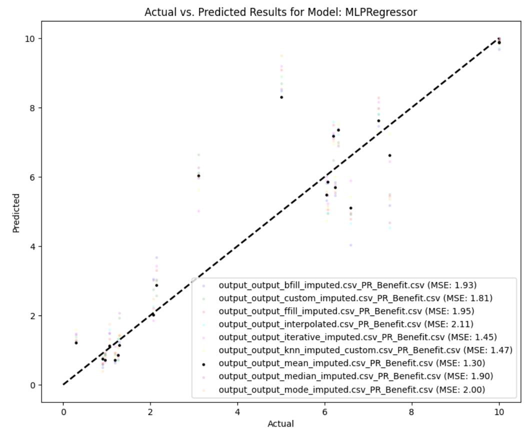

Figure 56: PR Benefit

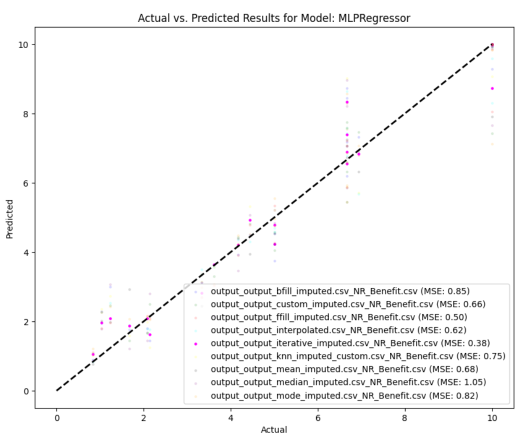

Figure 57: NR Benefit

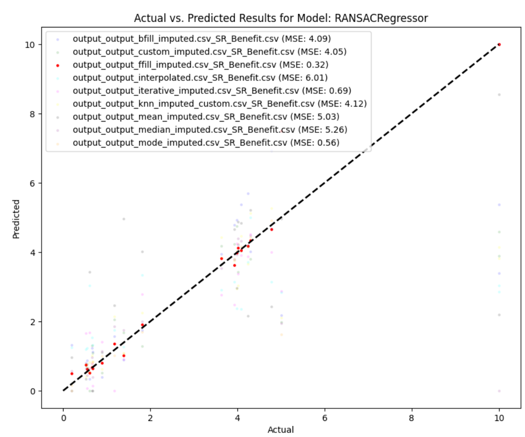

Figure 58: SR Benefit

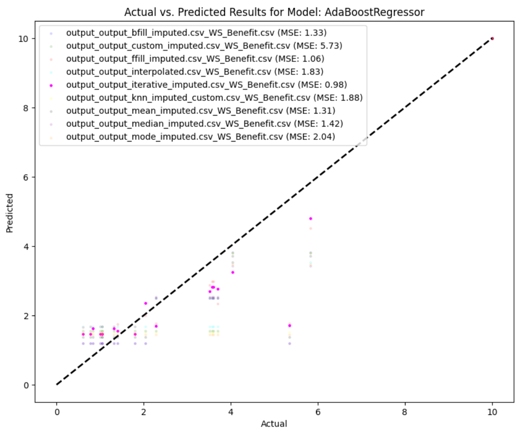

Figure 59: WS Benefit

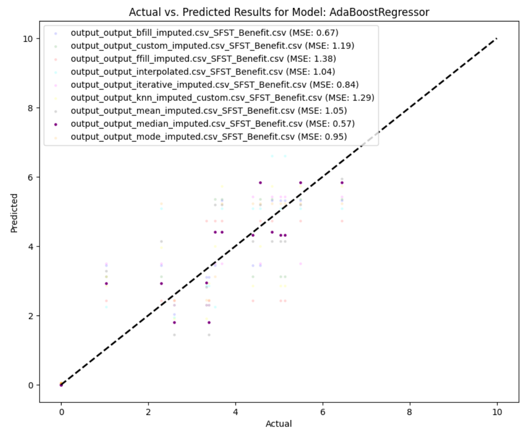

Figure 60: SFST Benefit

1. **PCA (Principal Component Analysis)**: A statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components.
2. **t-SNE (t-Distributed Stochastic Neighbor Embedding)**: A machine learning algorithm for visualization developed by Laurens van der Maaten and Geoffrey Hinton. It is a nonlinear dimensionality reduction technique well-suited for embedding high-dimensional data for visualization in a low-dimensional space of two or three dimensions.
3. **UMAP (Uniform Manifold Approximation and Projection)**: A dimension reduction technique that can be used for visualization similarly to t-SNE, but also for general non-linear dimension reduction. It is based on manifold learning techniques and ideas from topological data analysis.
4. **Isomap (Isometric Mapping)**: A non-linear dimensionality reduction method based on the geometric distances in the data, which is effective for datasets where nonlinear manifold structures are present.
5. **LLE (Locally Linear Embedding)**: Another nonlinear dimension reduction technique that computes low-dimensional, neighborhood-preserving embeddings of high-dimensional inputs.
6. **Truncated SVD (Singular Value Decomposition)**: An algorithmic approach for dimensionality reduction that uses truncated singular value decomposition. It is similar to PCA but suitable for sparse datasets.
7. **ICA (Independent Component Analysis)**: A computational method for separating a multivariate signal into additive subcomponents that are maximally independent.
8. **Kernel PCA**: An extension of PCA using techniques of kernel methods, which uses a kernel function to project dataset into a higher-dimensional space where linear separation is possible.
9. **Gaussian Random Projection**: A simple and computationally efficient way to reduce dimensionality by projecting the original data into a randomly generated subspace of lower dimensionality using a Gaussian random matrix.

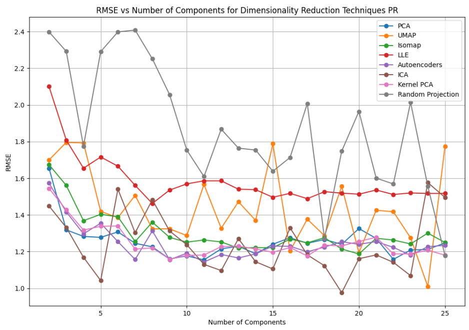

Figure 61: PR

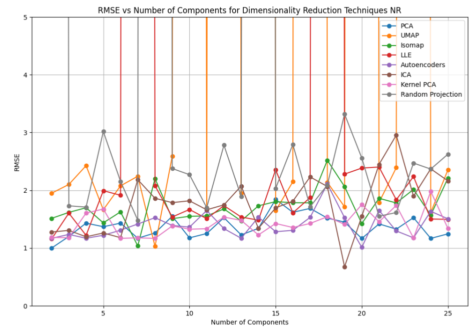

Figure 62: NR

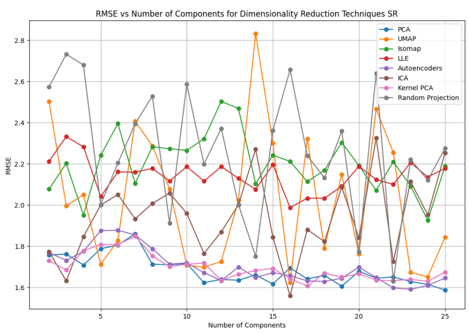

Figure 63: SR

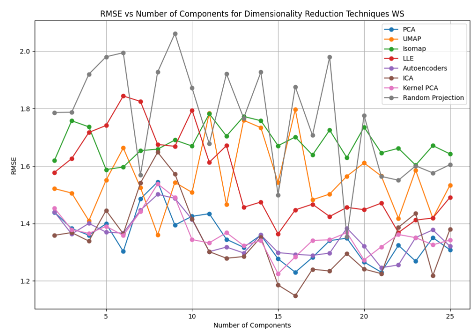

Figure 64: WS

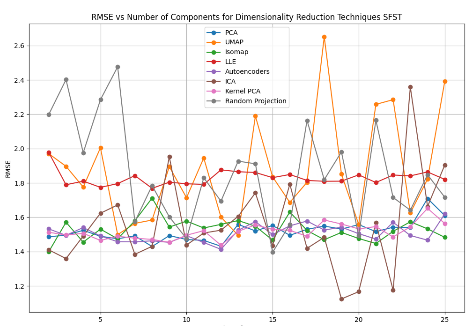

Figure 65: SFST

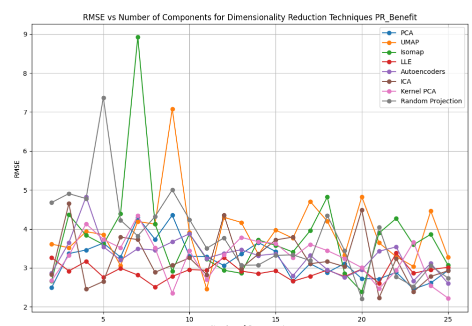

Figure 66: PR Benefit

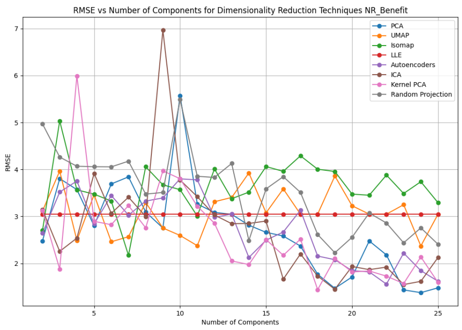

Figure 67: NR Benefit

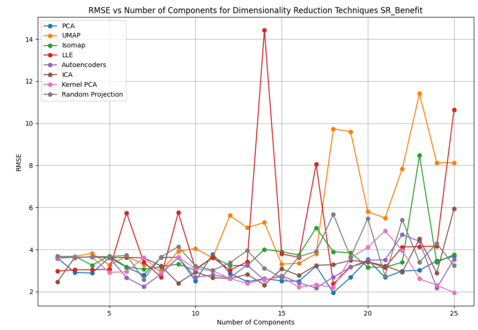

Figure 68: SR Benefit

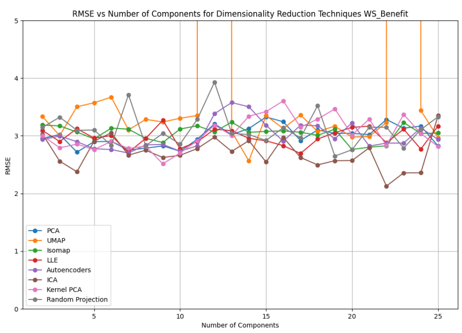

Figure 69: WS Benefit

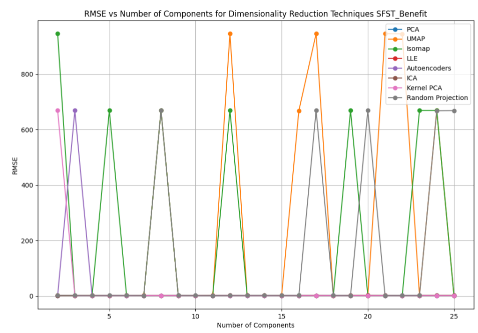

Figure 70: SFST Benefit

Function	RMSE	# Feat.	Selected Features
WS	0.4287	52	OF17, OF22, OF24, OF25, OF26, OF28, OF33, F1, F3_c, F3_d, F3_e, F3_f, F3_g, F4, F5, F7, F8, F9, F10, F12, F13, F14, F17, F19, F22, F23, F24, F25, F28, F29, F30, F32, F33, F34, F35, F36, F37, F39, F40, F41, F43, F44, F45, F46, F47, F48, F49, F56, F59, F64, F65, S1
NR	0.3461	79	OF27, OF18, F5, OF34, F65, S4, S5, OF5, F31, F35, F45, F25, F33, F54, OF13, F24, F34, F3_g, F43, F2, OF15, F3_d, OF16, F14, OF9, OF14, F3_a, F62, F68, OF2, OF11, F7, F3_f, OF6, F13, F3_c, F8, OF26, F6, OF38, OF4, F9, OF17, F23, F58, F22, F1, F17, S2, F3_e, F52, F36, F29, OF28, F40, F4, F30, F28, F47, F44, F15, OF7, F20, OF3, OF25, F51, F21, F3_b, OF22, F53, F64, F10, OF8, OF10, F56, F50, OF23, F19, F48
PR	0.2392	71	OF2, OF6, OF10, OF11, OF16, OF17, OF20, OF21, OF22, OF24, OF25, OF26, OF28, OF30, F1, F3_a, F3_b, F3_c, F3_d, F3_e, F3_f, F3_g, F4, F5, F6, F7, F8, F9, F10, F12, F13, F14, F15, F16, F17, F18, F19, F20, F22, F23, F24, F25, F28, F29, F30, F32, F33, F34, F35, F36, F37, F38, F39, F40, F41, F43, F44, F45, F46, F47, F49, F50, F51, F52, F53, F56, F63, F64, F65, F67, S1
SR	0.5871	40	OF22, OF26, F1, F3_d, F3_e, F3_g, F4, F5, F7, F9, F13, F14, F15, F17, F22, F23, F24, F25, F28, F29, F30, F31, F32, F33, F34, F35, F36, F37, F39, F40, F41, F43, F44, F45, F46, F47, F49, F64, F65, S1
SFST	0.4257	29	OF25, OF28, F1, F3_c, F3_e, F5, F9, F13, F14, F16, F21, F23, F24, F25, F28, F29, F30, F31, F32, F35, F36, F40, F41, F43, F44, F45, F46, F47, F68

Function	RMSE	# Feat.	Selected Features
WS Benefit	0.9116	70	OF2, OF4, OF5, OF6, OF7, OF14, OF15, OF16, OF17, OF18, OF19, OF21, OF22, OF23, OF24, OF25, OF28, OF31, OF33, OF34, OF37, OF38, F1, F2, F3_a, F3_c, F3_d, F3_e, F4, F5, F8, F9, F12, F13, F17, F18, F20, F21, F22, F23, F24, F28, F29, F30, F31, F32, F36, F38, F40, F43, F44, F45, F46, F47, F49, F50, F51, F52, F54, F55, F56, F58, F62, F64, F65, F67, F68, S1, S4, S5
NR Benefit	1.3035	15	OF5, OF9, OF10, OF15, OF19, OF21, OF23, F1, F3_c, F14, F31, F41, F43, F46, F47
PR Benefit	1.1653	7	OF19, F14, F24, F41, F43, F46, F47
SR Benefit	0.7250	82	OF2, OF3, OF4, OF6, OF7, OF8, OF9, OF10, OF11, OF13, OF14, OF16, OF17, OF18, OF19, OF21, OF23, OF24, OF25, OF27, OF28, OF30, OF33, OF34, OF38, F2, F3_a, F3_b, F3_c, F3_d, F3_e, F4, F5, F6, F7, F8, F12, F13, F14, F15, F16, F18, F19, F21, F22, F23, F24, F25, F28, F29, F30, F31, F32, F33, F34, F35, F36, F37, F39, F40, F41, F43, F44, F45, F46, F47, F48, F49, F50, F51, F52, F53, F54, F56, F57, F58, F64, F65, F67, F68, S1, S4
SFST Benefit	0.6321	28	OF5, OF9, OF18, OF22, OF25, OF28, F1, F2, F3_e, F3_g, F5, F9, F13, F14, F20, F23, F24, F25, F28, F29, F30, F31, F41, F43, F44, F45, F46, F47

Table 40: Method with the Lowest RMSE and Number of Features

Function	RMSE	# Feat.	Selected Features
WS	0.8058	2	F31, F43
NR	2.4040	2	OF18, S4
PR	0.6298	2	F43, F44
SR	1.4341	2	F43, F44
SFST	0.5892	2	F43, F44
WS Benefit	1.5053	2	OF17, OF18
NR Benefit	2.2781	2	OF10, OF22
PR Benefit	1.3365	2	F41, F44
SR Benefit	2.0066	2	OF18, F41
SFST Benefit	1.9459	2	OF18, F12

Table 41: Models With Two Features

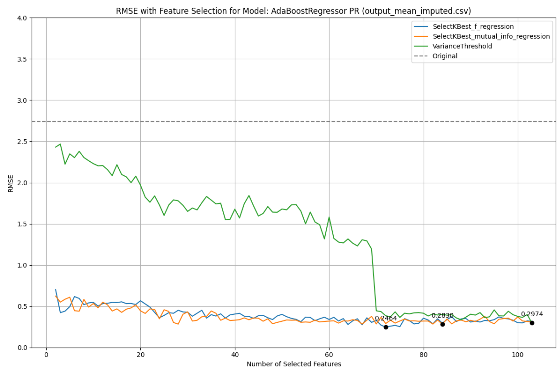

Figure 71: PR

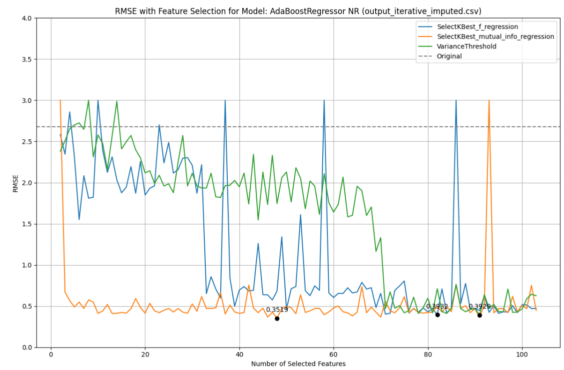

Figure 72: NR

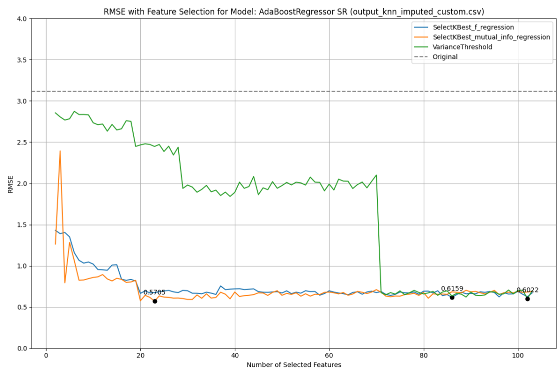

Figure 73: SR

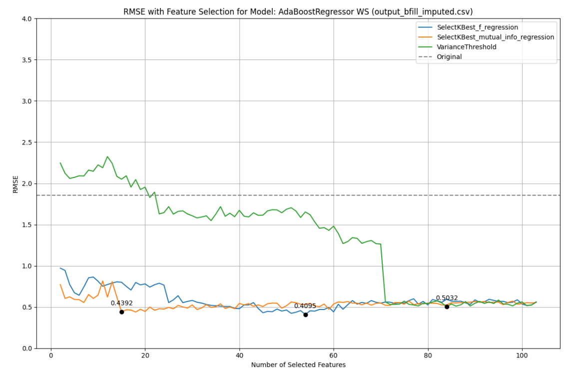

Figure 74: WS

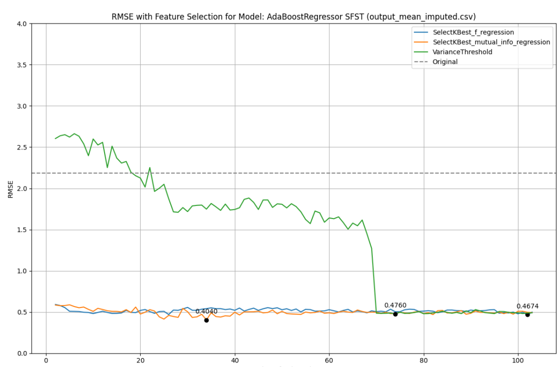

Figure 75: SFST

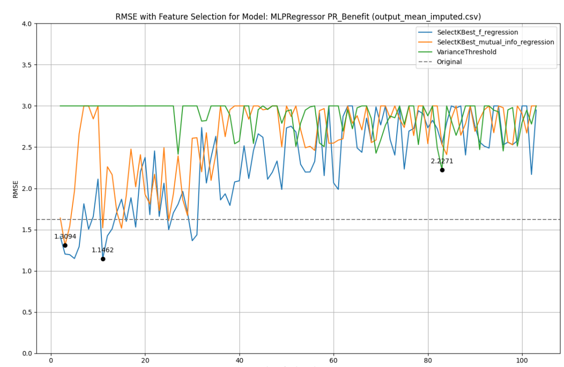

Figure 76: PR Benefit

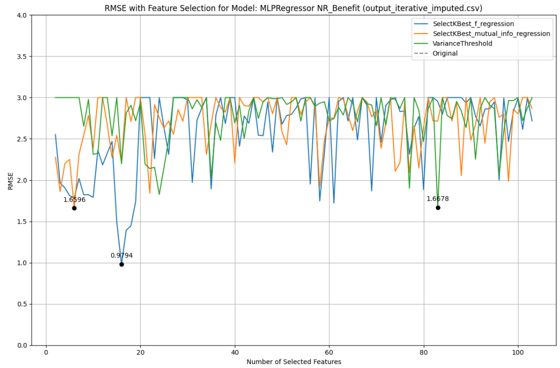

Figure 77: NR Benefit

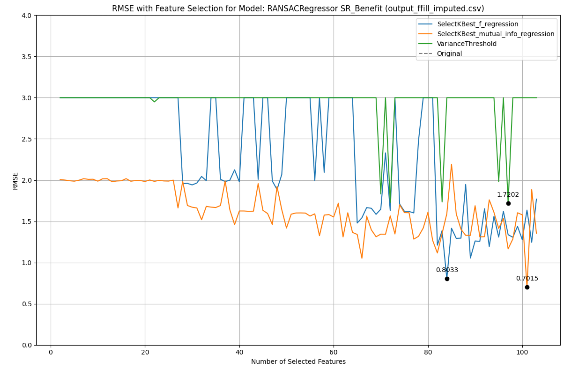

Figure 78: SR Benefit

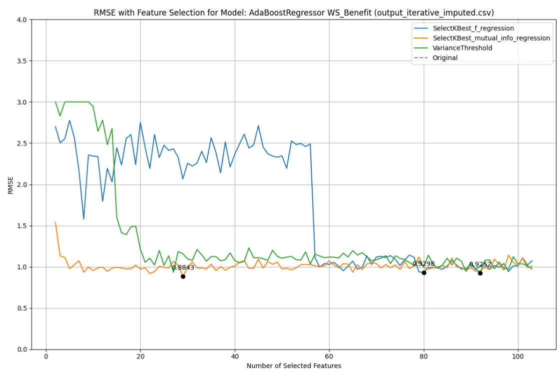

Figure 79: WS Benefit

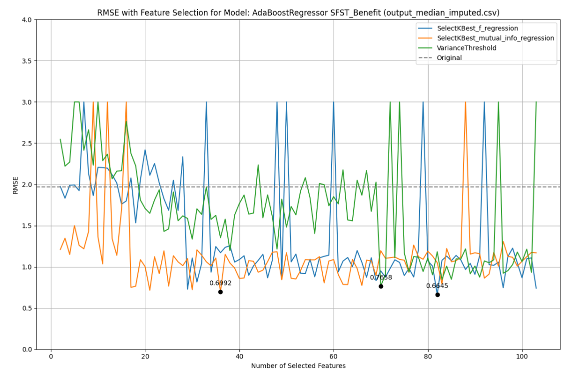

Figure 80: SFST Benefit

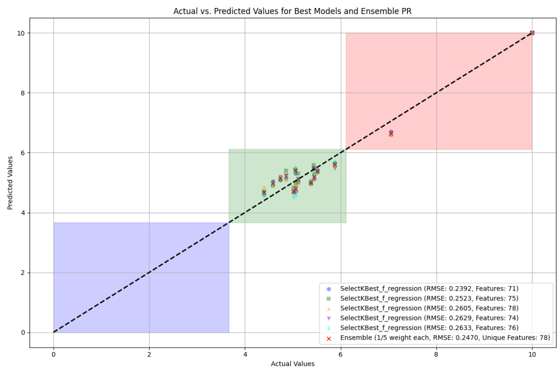

Figure 81: PR

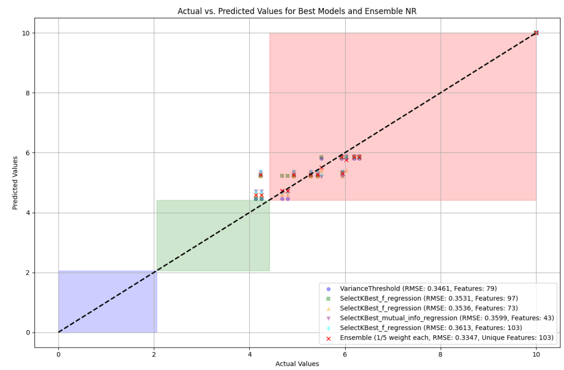

Figure 82: NR

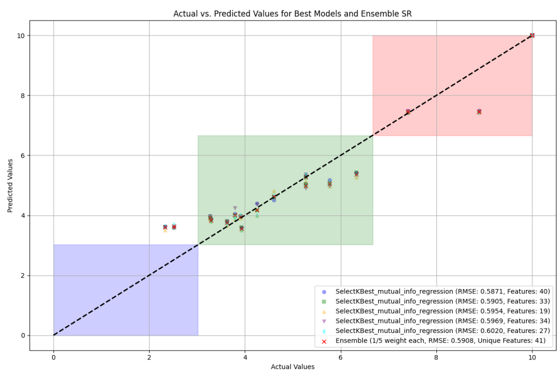

Figure 83: SR

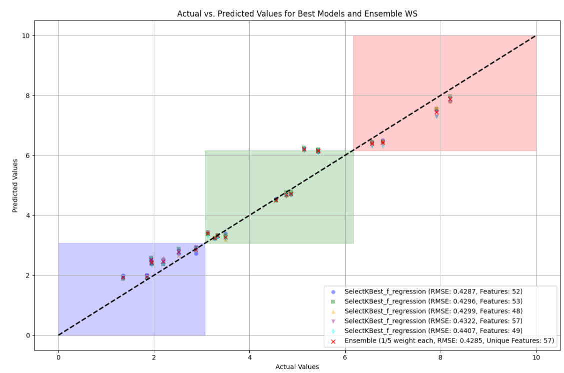

Figure 84: WS

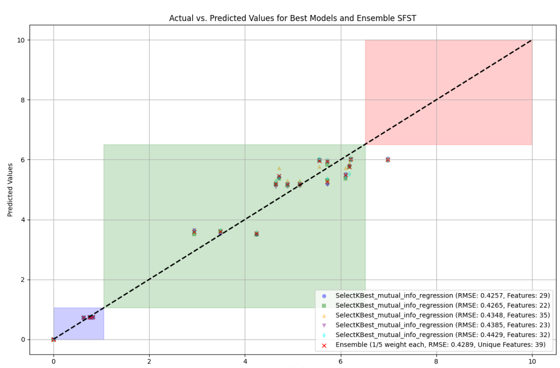

Figure 85: SFST

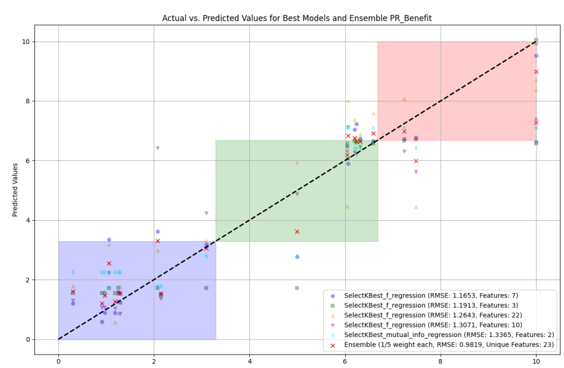

Figure 86: PR Benefit

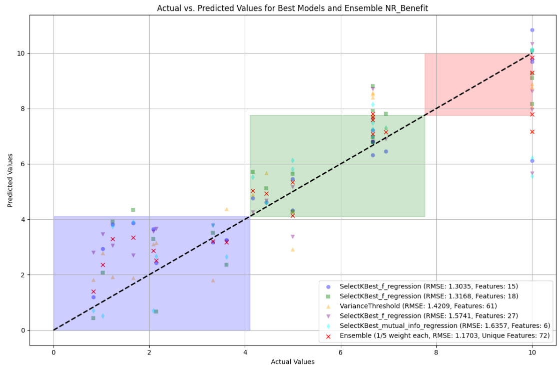

Figure 87: NR Benefit

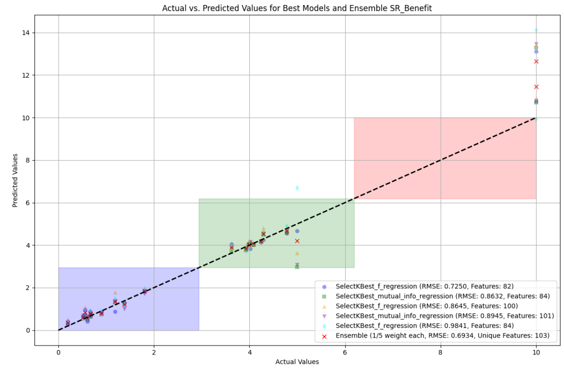

Figure 88: SR Benefit

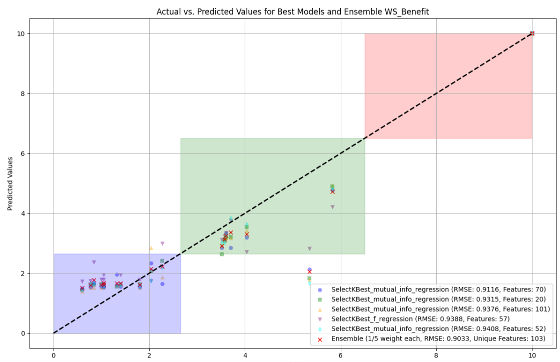

Figure 89: WS Benefit

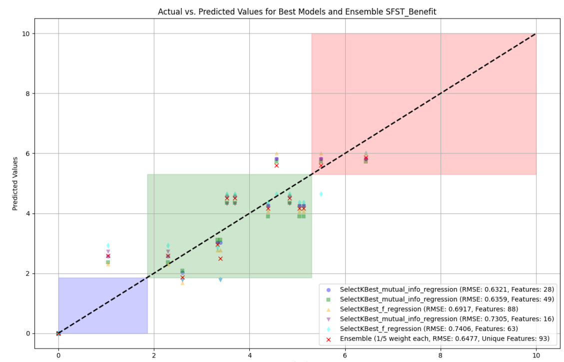

Figure 90: SFST Benefit

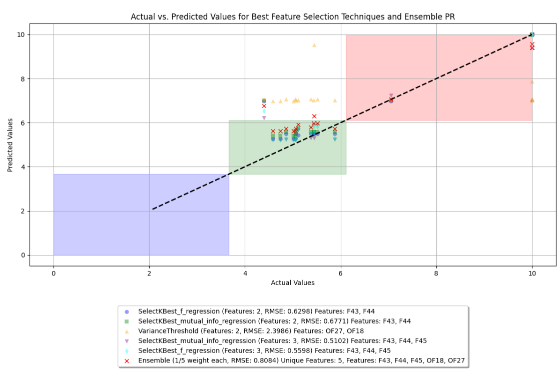

Figure 91: PR

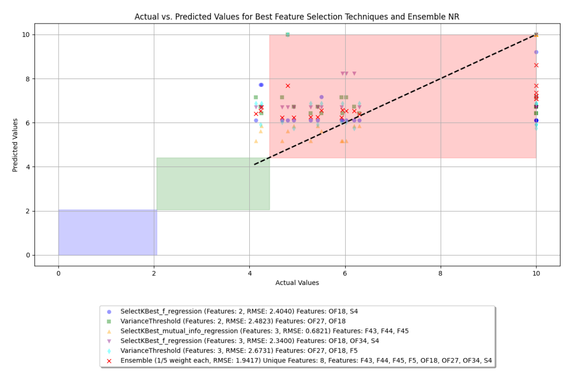

Figure 92: NR

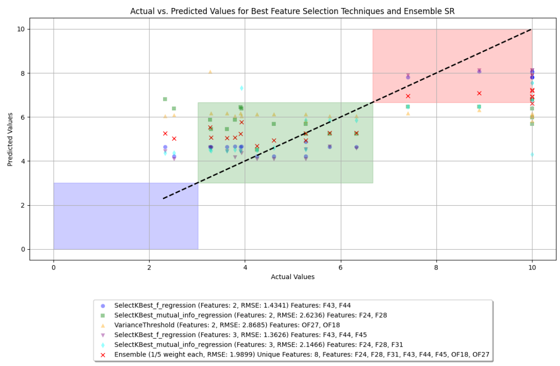

Figure 93: SR

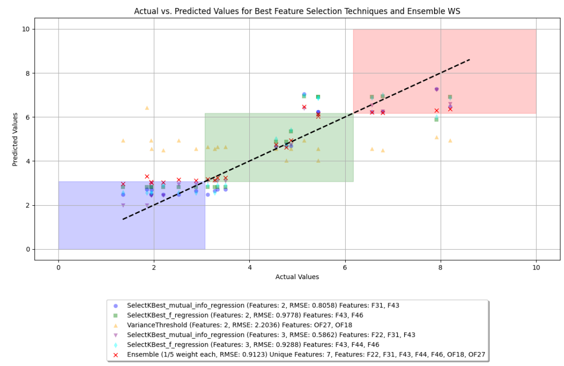

Figure 94: WS

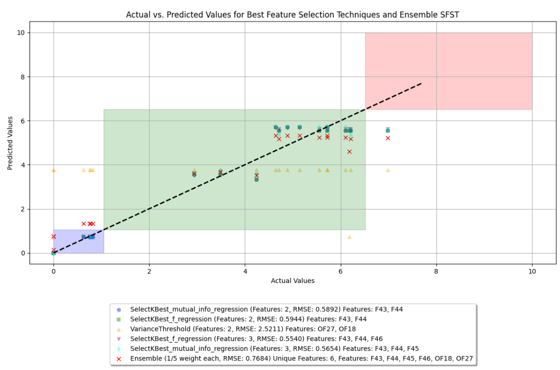

Figure 95: SFST

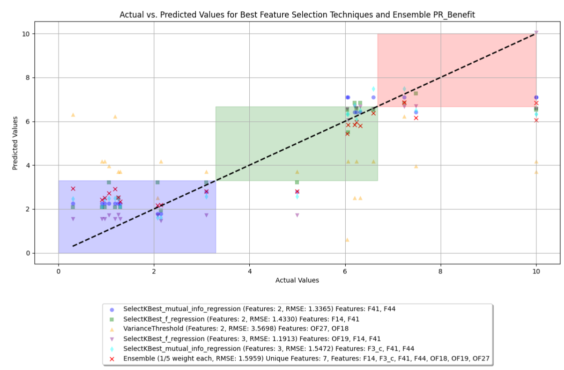

Figure 96: PR Benefit

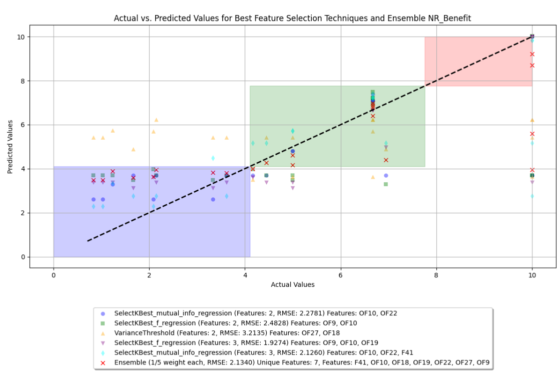

Figure 97: NR Benefit

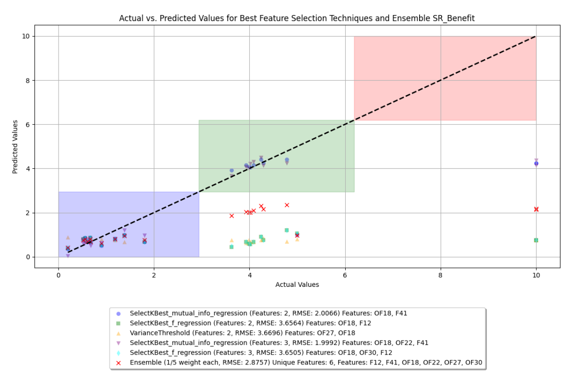

Figure 98: SR Benefit

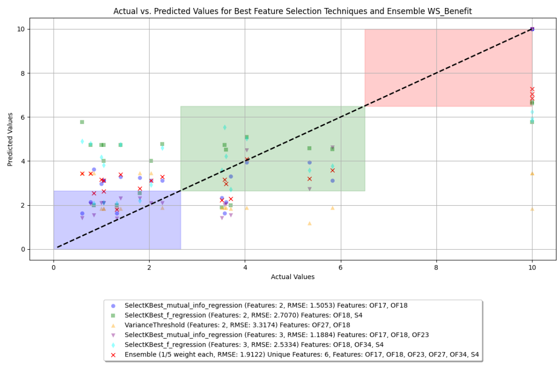

Figure 99: WS Benefit

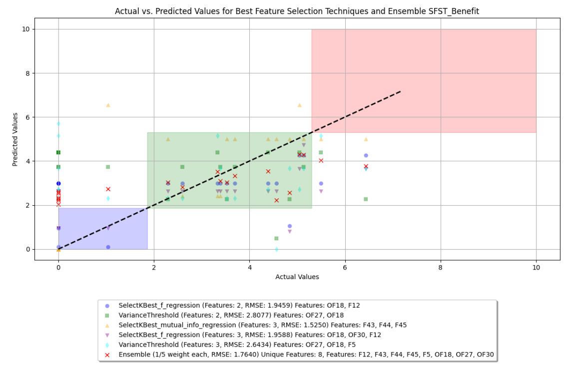

Figure 100: SFST Benefit

Function	**RMSE**	**# Feat.**
PR	0.3145	21
NR	0.33437547	34
SR	0.6469	18
WS	0.2169	19
SFST	0.3910	20
PR Benefit	0.5895	11
NR Benefit	0.6958	14
SR Benefit	1.9307	14
WS Benefit	0.8317	6
SFST Benefit	1.4418	6

Table 42: Ensemble Learning using All Features

Function	**RMSE**	**# Feat.**	**Selected Features**
PR	0.6683	5	F31,F43,F44,F45,OF27
NR	0.6181	5	F24,F31,F43,F44,F45
SR	1.0530	7	F28, F29, F31, F43, F44, F45, OF27
WS	0.6909	5	F22, F31, F43, F44, F45
SFST	0.5319	5	F4,F14,F24, F31, F43
PR Benefit	0.8605	6	F51,OF15,OF17,OF18,OF23,OF2441, OF19, OF20, OF21, OF22, OF24
NR Benefit	1.3996	12	F13, F41, F51, F52, OF10, OF11, OF19, OF21, OF22, OF23, OF24, OF9
SR Benefit	2.7040	5	F24, F41, OF18, OF22, OF24
WS Benefit	1.2814	5	F51, OF8, OF17, OF18, OF23,
SFST Benefit	1.6216	4	OF18, OF25, OF27, OF28

Table 43: Ensemble Learning using limited features

Model	Lower Acc.	Moderate Acc.	Higher Acc.	Overall Acc.	Top Features
PR	1.85%	64.20%	90.74%	62.43%	F43, F44, F45, F46
NR	25.93%	56.08%	68.78%	50.26%	F1, F24, F28, F29, F31, F43, F44, F45
SR	55.93%	77.04%	53.09%	60.14%	F24, F28, F29, F31, F43, F44, F45
WS	67.34%	64.20%	62.96%	65.61%	F22, F24, F28, F29, F31, F43, F44
SFST	67.28%	61.90%	66.67%	65.26%	F1, F14, F23, F24, F30, F41, F43, F44, F45, F46
PR Benefit	76.67%	53.44%	39.81%	61.90%	OF19, F14, F24, F41, F43, F46, F47
NR Benefit	68.15%	68.78%	47.22%	64.37%	OF9, OF10, OF22, F41, F43, F65
SR Benefit	85.93%	35.39%	3.70%	56.44%	OF18, F3c, F29, F31, F41, F43
WS Benefit	69.02%	55.03%	49.38%	61.55%	OF17, OF18, OF23, OF24, F51
SFST Benefit	42.59%	70.99%	45.50%	51.68%	F1, F14, F24, F29, F31, F43, F44, F45, F46

Table 44: Classification Accuracies and Top Features for Various Models

Model	Lower Acc.	Moderate Acc.	Higher Acc.	Overall Acc.	Top Features
PR	0.00%	100.00%	100.00%	76.19%	F43, F44, F45, F5, OF18, OF27
NR	0.00%	71.43%	42.86%	80.95%	F43, F44, F45, F5, OF18, OF27, OF34, S4
SR	30.00%	80.00%	50.00%	90.48%	F24, F28, F31, F43, F44, F45, F5, OF18, OF27
WS	100.00%	50.00%	100.00%	85.71%	F22, F31, F43, F44, F46, F5, OF18, OF27
SFST	100.00%	42.86%	100.00%	80.95%	F43, F44, F45, F46, OF18, OF27
PR Benefit	100.00%	85.71%	25.00%	80.95%	F14, F3_c, F41, F44, OF18, OF19, OF27

Model	Lower Acc.	Moderate Acc.	Higher Acc.	Overall Acc.	Top Features
NR Benefit	100.00%	85.71%	50.00%	85.71%	F41, F5, OF10, OF18, OF19, OF22, OF27, OF9
SR Benefit	100.00%	0.00%	0.00%	85.71%	F12, F41, OF18, OF22, OF27, OF30
WS Benefit	54.55%	71.43%	66.67%	90.48%	F5, OF17, OF18, OF23, OF27, OF34, S4
SFST Benefit	37.50%	100.00%	42.86%	80.95%	F12, F43, F44, F45, F5, OF18, OF27, OF30

Table 45: Ensemble Model Accuracies

Model	Lower Acc.	Moderate Acc.	Higher Acc.	Overall Acc.	Top Features
PR	0.00%	100.00%	100.00%	76.19%	F43, F44, F45, F5, OF18, OF27
NR	0.00%	85.71%	42.86%	61.90%	F43, F44, F45, F5, OF18, OF27, OF34, S4
SR	30.00%	80.00%	33.33%	85.71%	F24, F28, F31, F43, F44, F45, F5, OF18, OF27
WS	100.00%	50.00%	75.00%	85.71%	F22, F31, F43, F44, F46, F5, OF18, OF27
SFST	100.00%	42.86%	100.00%	80.95%	F43, F44, F45, F46, OF18, OF27
PR Benefit	100.00%	85.71%	25.00%	80.95%	F14, F3_c, F41, F44, OF18, OF19, OF27
NR Benefit	100.00%	85.71%	50.00%	76.19%	F41, F5, OF10, OF18, OF19, OF22, OF27, OF9
SR Benefit	100.00%	0.00%	0.00%	47.62%	F12, F41, OF18, OF22, OF27, OF30
WS Benefit	36.36%	71.43%	66.67%	80.95%	F5, OF17, OF18, OF23, OF27, OF34, S4
SFST Benefit	37.50%	100.00%	42.86%	57.14%	F12, F43, F44, F45, F5, OF18, OF27, OF30

Table 46: Voting System Accuracies

5.5.2 Specific Features

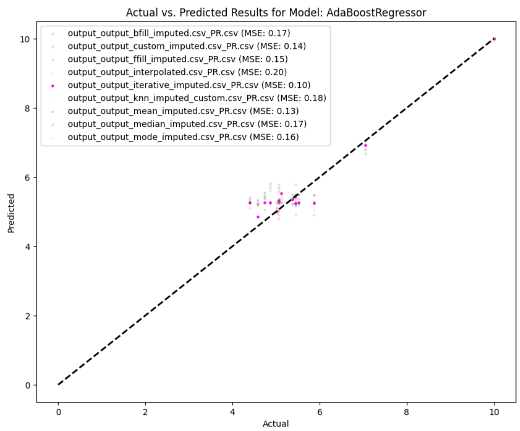

Figure 101: PR

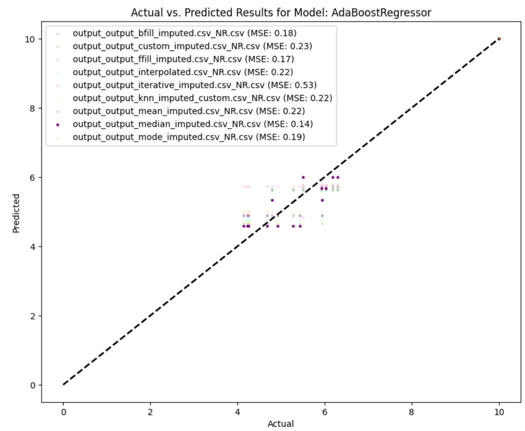

Figure 102: NR

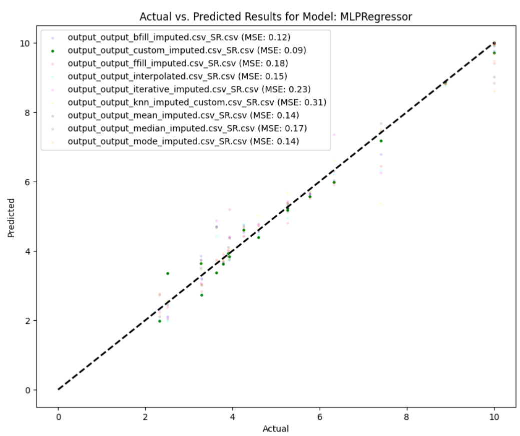

Figure 103: SR

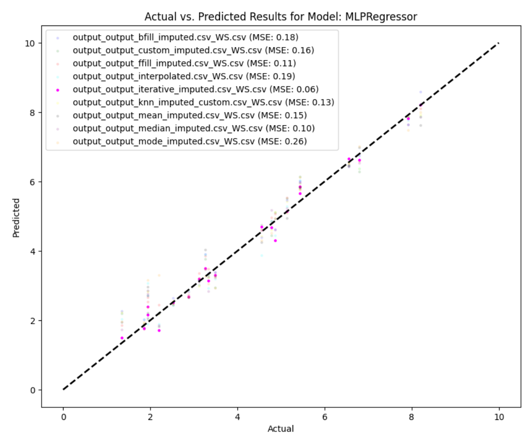

Figure 104: WS

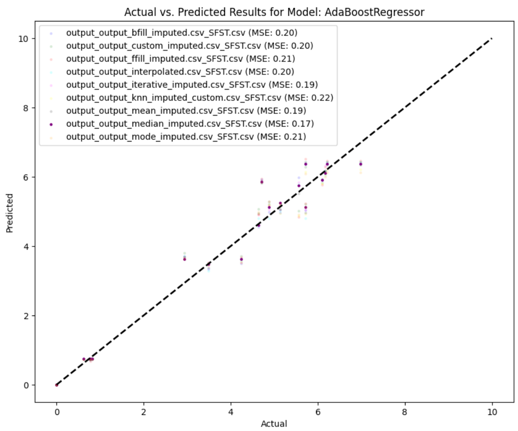

Figure 105: SFST

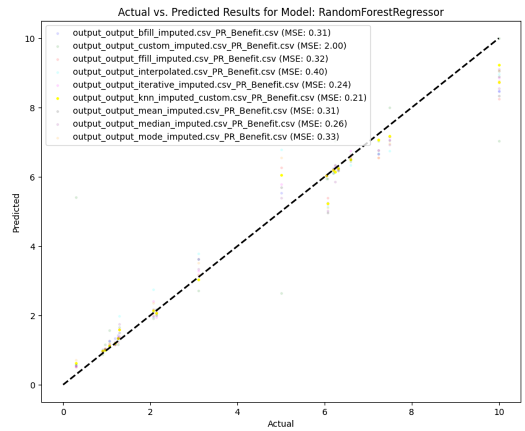

Figure 106: PR Benefit

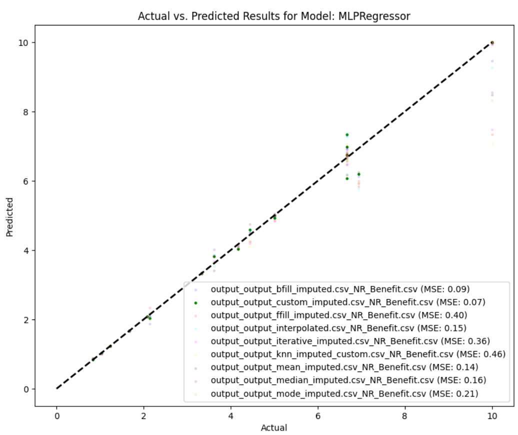

Figure 107: NR Benefit

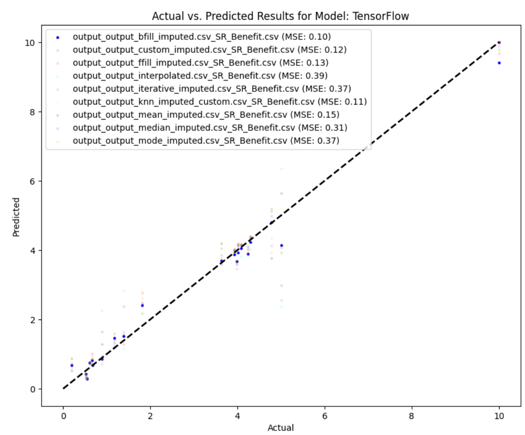

Figure 108: SR Benefit

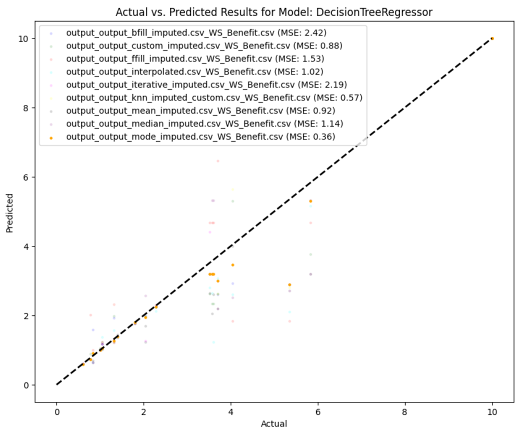

Figure 109: WS Benefit

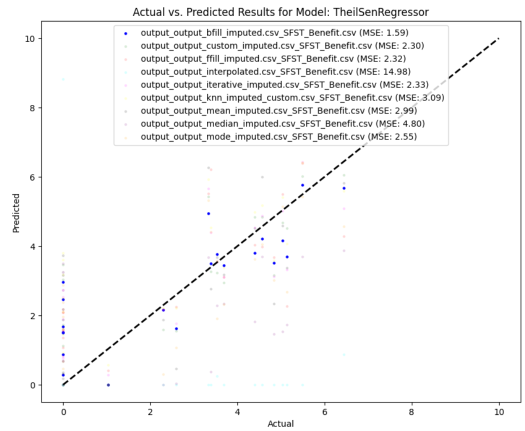

Figure 110: SFST Benefit

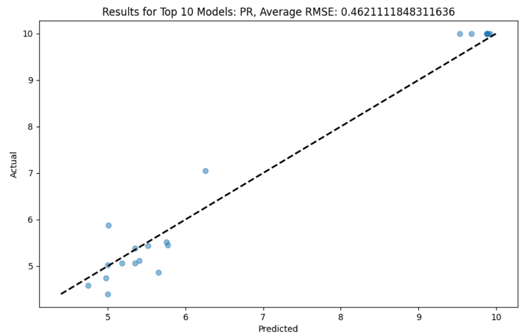

Figure 111: PR

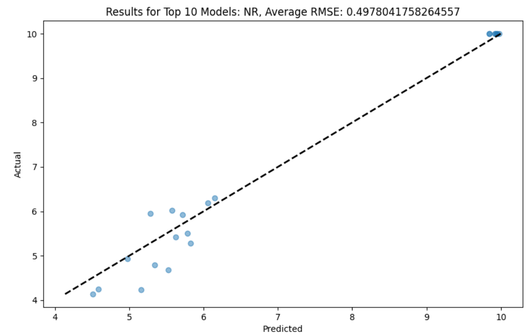

Figure 112: NR

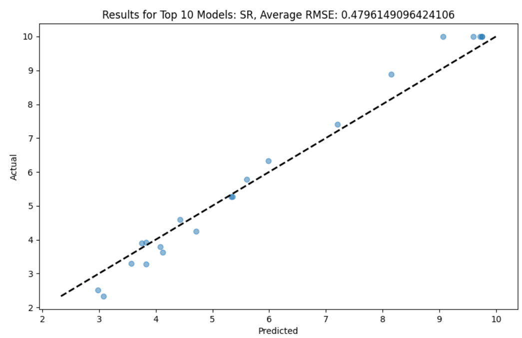

Figure 113: SR

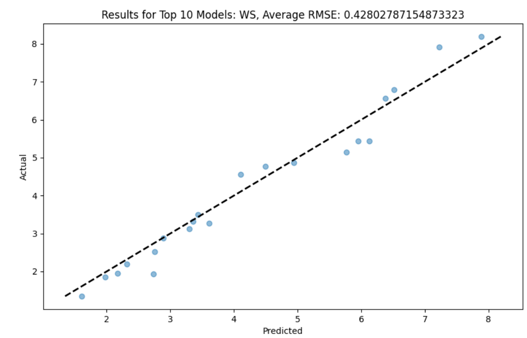

Figure 114: WS

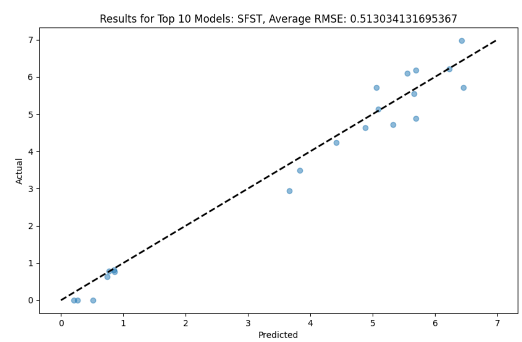

Figure 115: SFST

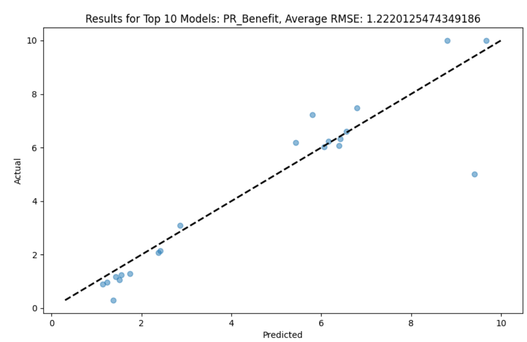

Figure 116: PR Benefit

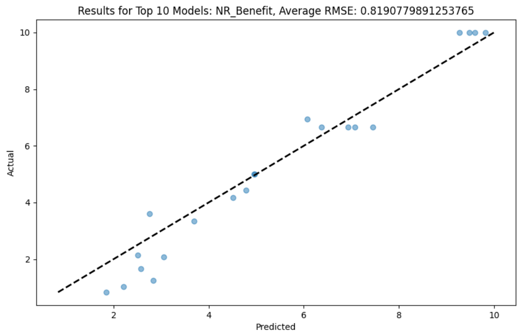

Figure 117: NR Benefit

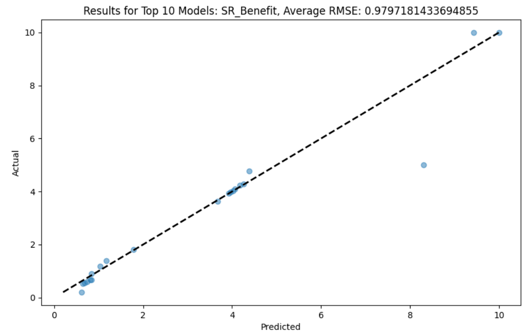

Figure 118: SR Benefit

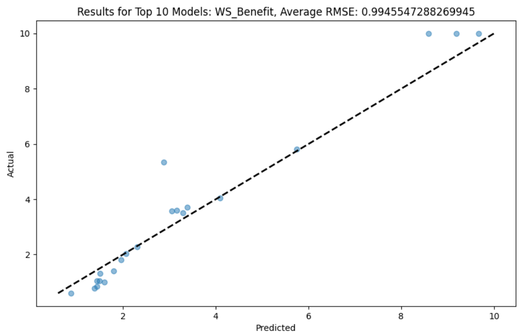

Figure 119: WS Benefit

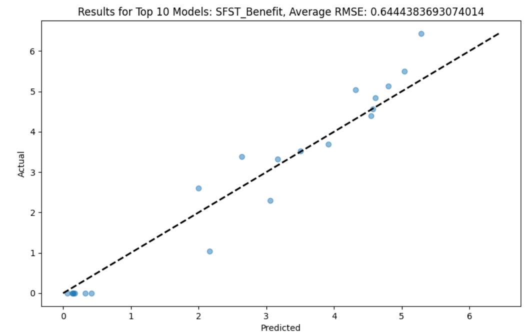

Figure 120: SFST Benefit

Function	MSE	# Feat.	Selected Features
WS	0.1624	15	OF22, OF26, F3_c, F3_d, F3_e, F3_g, F20, F22, F28, F31, F43, F44, F45, F48, F49
NR	0.3267	24	OF16, OF18, OF25, OF26, F1, F3_b, F3_c, F3_d, F3_e, F3_g, F17, F21, F22, F23, F24, F28, F31, F33, F34, F36, F43, F44, F45, F49
PR	0.2943	15	OF22, OF26, F21, F23, F24, F28, F29, F31, F33, F34, F35, F43, F44, F45, F63
SR	0.2876	16	OF22, OF26, F9, F17, F22, F28, F29, F31, F33, F34, F35, F36, F43, F44, F45, F49
SFST	0.3808	12	F1, F3_e, F14, F21, F24, F25, F29, F31, F33, F34, F43, F47
WS Benefit	0.6431	5	OF17, OF18, OF23, OF24, F51
NR Benefit	0.3692	13	OF9, OF10, OF11, OF19, OF20, OF21, OF22, OF23, OF24, F41, F50, F51, F52
PR Benefit	0.4724	11	OF18, OF19, OF20, OF21, OF22, OF23, OF24, F41, F48, F50, F52
SR Benefit	1.2175	13	OF18, OF19, OF20, OF21, OF23, OF24, F24, F28, F41, F50, F52, F55, S4
SFST Benefit	1.3430	6	OF18, OF22, OF25, OF27, OF28, F50

Table 47: Method with the Lowest RMSE and Number of Features

Function	RMSE	# Feat.	Selected Features
WS	0.6797	2	F31, F43
NR	2.0502	2	OF18, F6
PR	0.5445	2	F43, F44
SR	1.2642	2	F43, F44
SFST	0.5447	2	F1, F43
WS Benefit	1.2985	2	OF17, OF18
NR Benefit	2.2721	2	OF10, OF22
PR Benefit	1.2150	2	OF19, F41
SR Benefit	2.9551	2	OF18, F41
SFST Benefit	1.5528	2	OF27, OF18

Table 48: Models With Two Features

Function	Lowest RMSE	Lowest RMSE 2 Features	MSE
PR	0.2943	0.5445	0.10
NR	0.3267	2.0502	0.14
SR	0.2876	1.2642	0.09
WS	0.1624	0.6797	0.06
SFST	0.3808	0.5447	0.17

Function	Lowest RMSE	Lowest RMSE Proportionate	MSE
PR Benefit	0.4724	1.2150	0.21
NR Benefit	0.3692	2.2721	0.07
SR Benefit	1.2175	2.9551	0.10
WS Benefit	0.6431	1.2985	0.36
SFST Benefit	1.3430	1.5528	1.59

Table 49: Combined Accuracy Table

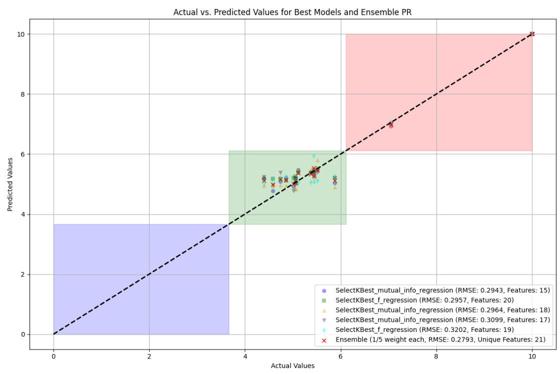

Figure 121: PR

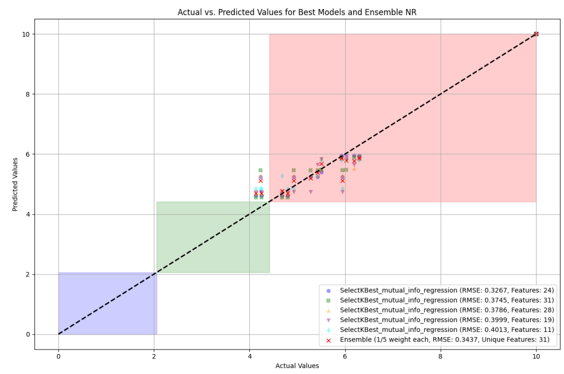

Figure 122: NR

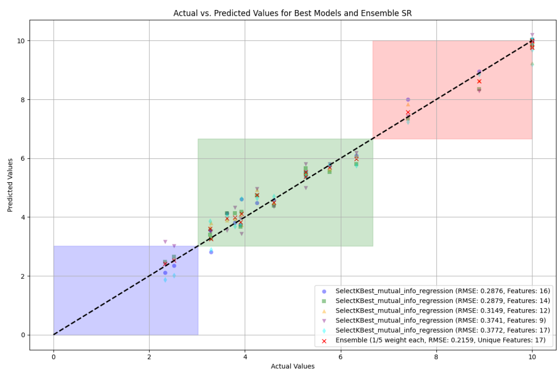

Figure 123: SR

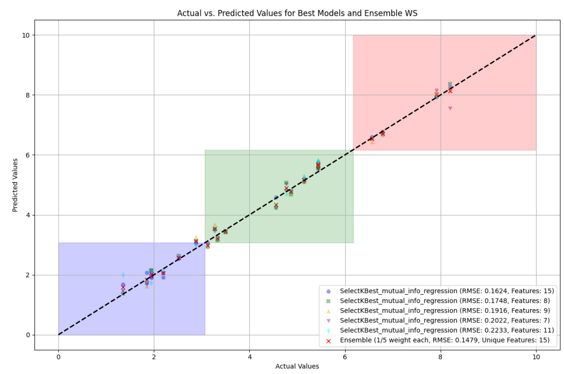

Figure 124: WS

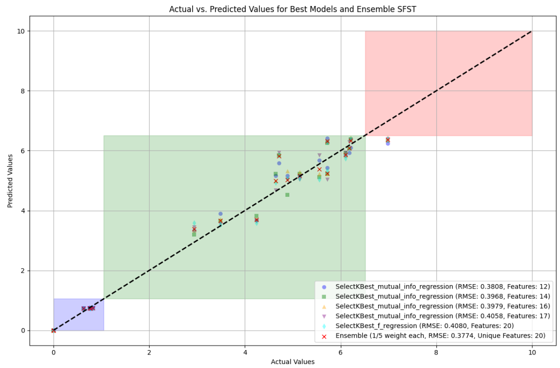

Figure 125: SFST

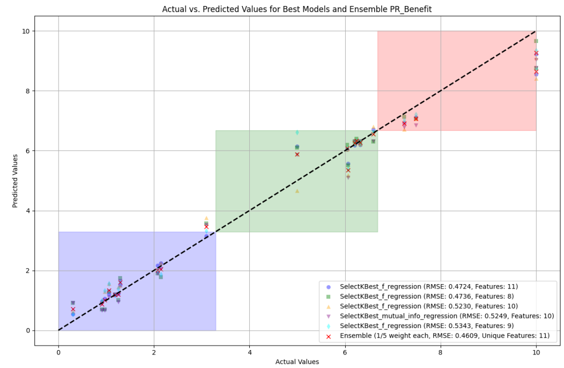

Figure 126: PR Benefit

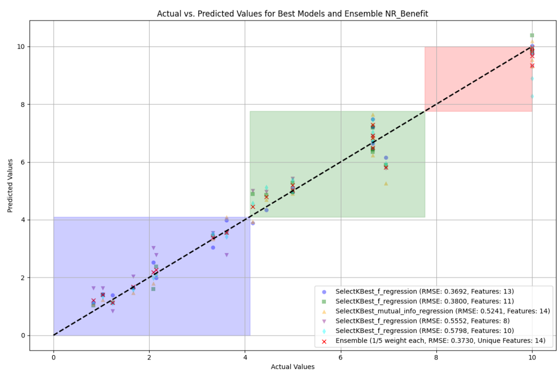

Figure 127: NR Benefit

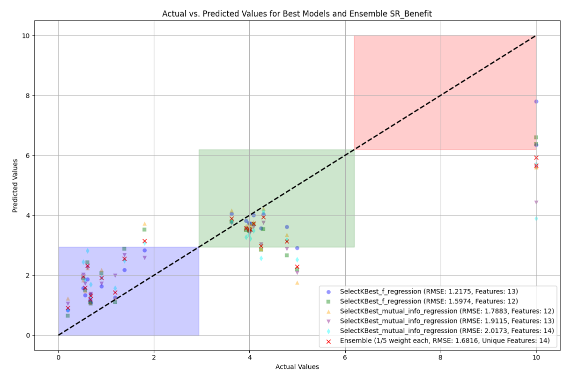

Figure 128: SR Benefit

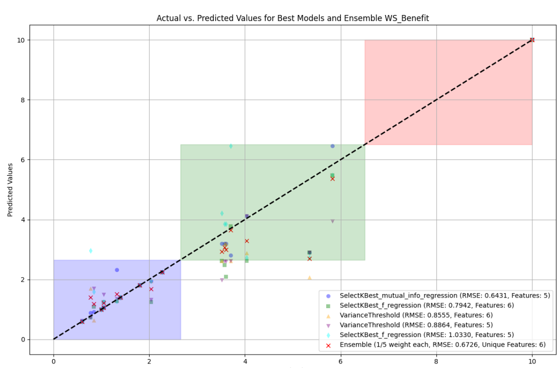

Figure 129: WS Benefit

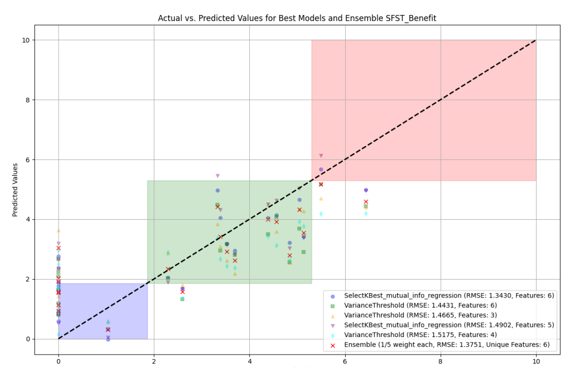

Figure 130: SFST Benefit

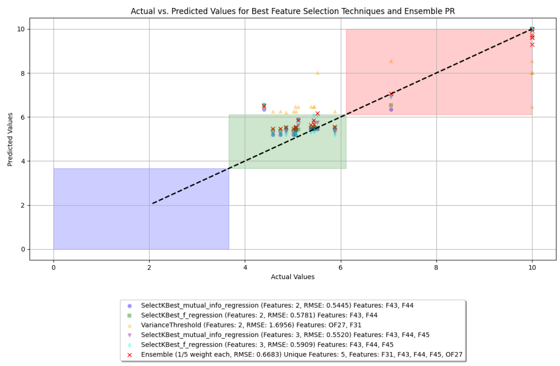

Figure 131: PR

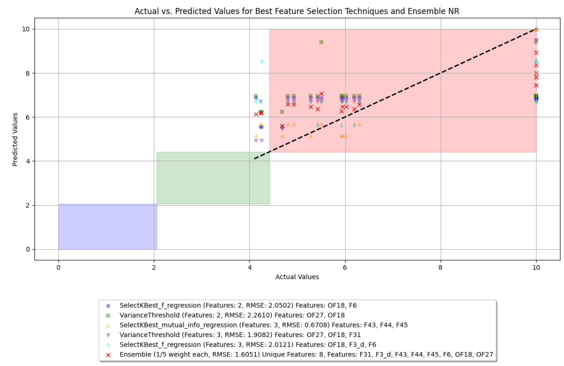

Figure 132: NR

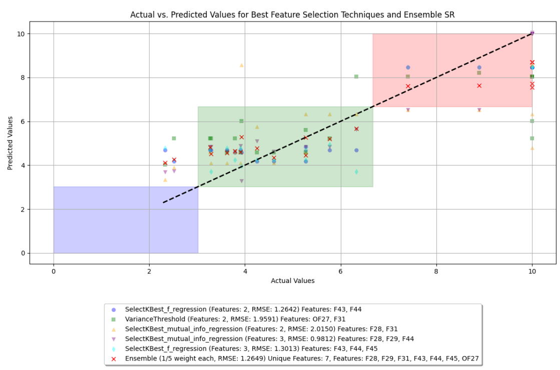

Figure 133: SR

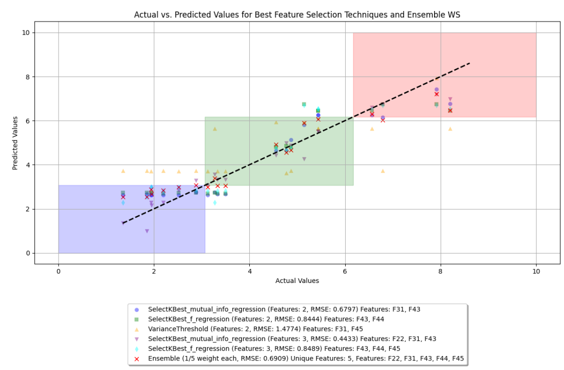

Figure 134: WS

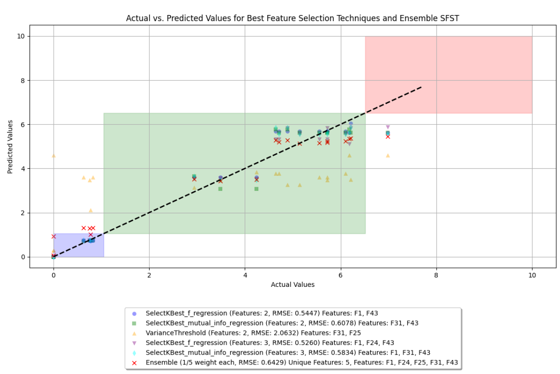

Figure 135: SFST

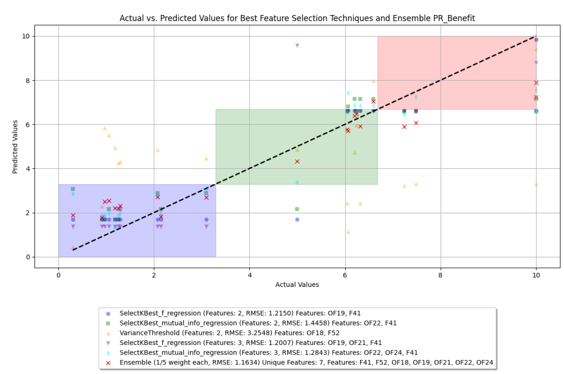

Figure 136: PR Benefit

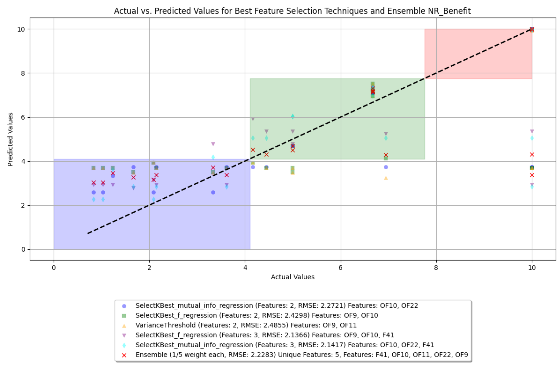

Figure 137: NR Benefit

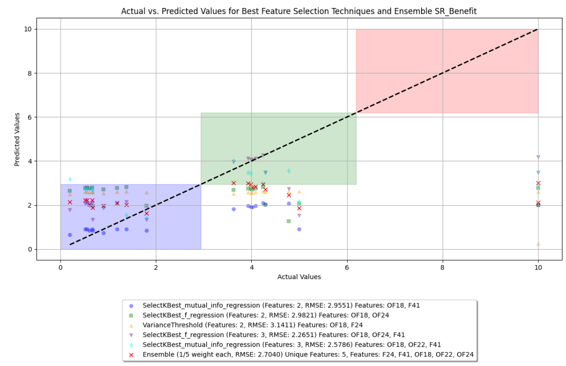

Figure 138: SR Benefit

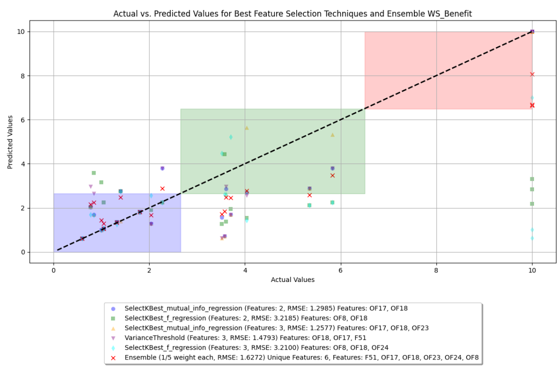

Figure 139: WS Benefit

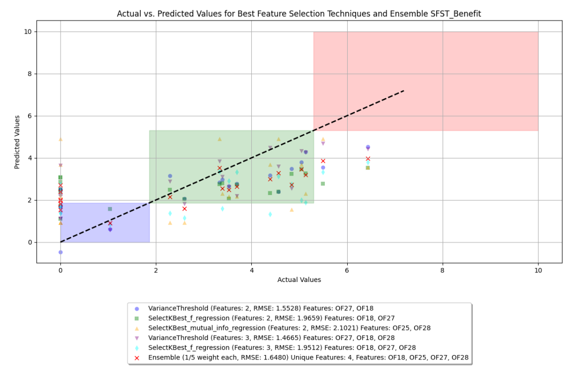

Figure 140: SFST Benefit

Function	RMSE	# Feat.
WS	0.4285	57
NR	0.3347	103
PR	0.2470	78
SR	0.5908	41
SFST	0.4289	39
WS Benefit	0.9033	103
NR Benefit	1.1703	72
PR Benefit	0.9819	23
SR Benefit	0.6934	103
SFST Benefit	0.6477	93

Table 50: Ensemble Learning using All Features

Function	RMSE	# Feat.	Selected Features
WS	0.7547	6	F22,F24,F31,F43,F44,F46
NR	0.6878	20	F1,F12,F23,F24,F25,F28,F29,F31,F43,F44, F45,D46,D65,F68,OF18,OF34,OF37,S2,S4,S5
PR	0.7463	4	F43,F44,F45,F46
SR	1.1949	8	F1,F24,F28,F31,F43,F44,F45,F46
SFST	0.5659	4	F43,F44,F45,F46
WS Benefit	1.0354	6	F51,OF15,OF17,OF18,OF23,OF24
NR Benefit	1.9944	7	F20,F31,F3c,F41,F43,OF18,0F22
PR Benefit	1.2953	6	F14,F3c,F41,F43,F44.OF19
SR Benefit	1.2354	8	F12,F43,F44,F45,F46,F53,OF18,OF30
SFST Benefit	1.1440	20	F1, F12, F14, F23, F25, F29, F31, F39, F3d, F43, F44, F45, F46, F53, F57, F6, OF14, OF18, OF28, OF30

Table 51: Ensemble Learning using limited features

Model	Lower Acc.	Moderate Acc.	Higher Acc.	Overall Acc.	Top Features
WS	89.56%	58.64%	78.70%	78.66%	OF22, F3_e, F22, F28, F31, F43, F44, F45
PR	4.63%	83.54%	90.74%	71.25%	OF26, F17, F23, F24, F28, F29, F36, F43, F44, F45
NR	28.04%	61.38%	83.07%	57.50%	F1, F23, F24, F31, F43, F44, F45
SR	54.44%	76.30%	67.90%	63.49%	OF22, F22, F28, F29, F31, F36, F43, F44, F45
SFST	71.60%	63.49%	67.13%	67.20%	F1, F3_e, F14, F24, F29, F43, F47
WS Benefit	90.30%	44.76%	86.67%	74.60%	OF17, OF18, OF23, OF24, F51
PR Benefit	87.04%	77.25%	54.63%	77.60%	OF19, OF20, OF21, OF22, OF23, OF24, F41, F52
NR Benefit	84.07%	78.84%	64.81%	78.66%	OF9, OF10, OF19, OF20, OF21, OF22, OF23, F41
SR Benefit	88.15%	53.09%	3.70%	65.08%	OF18, OF19, OF23, OF24, F24, F28, F41, F50, F52
SFST Benefit	36.67%	72.22%	40.95%	48.25%	OF18, OF22, OF25, OF27, OF28, F50

Table 52: Classification Accuracies and Top Features for Various Models

Model	Lower Acc.	Moderate Acc.	Higher Acc.	Overall Acc.	Top Features
WS	100.00%	50.00%	100.00%	85.71%	F22, F31, F43, F44, F46, F5, OF18, OF27
PR	0.00%	100.00%	100.00%	76.19%	F43, F44, F45, F5, OF18, OF27
NR	0.00%	71.43%	42.86%	80.95%	F43, F44, F45, F5, OF18, OF27, OF34, S4
SR	30.00%	80.00%	50.00%	90.48%	F24, F28, F31, F43, F44, F45, F5, OF18, OF27
SFST	100.00%	42.86%	100.00%	80.95%	F43, F44, F45, F46, OF18, OF27

Model	Lower Acc.	Moderate Acc.	Higher Acc.	Overall Acc.	Top Features
WS Benefit	54.55%	71.43%	66.67%	90.48%	F5, OF17, OF18, OF23, OF27, OF34, S4
PR Benefit	100.00%	85.71%	25.00%	80.95%	F14, F3_c, F41, F44, OF18, OF19, OF27
NR Benefit	100.00%	85.71%	50.00%	85.71%	F41, F5, OF10, OF18, OF19, OF22, OF27, OF9
SR Benefit	100.00%	0.00%	0.00%	85.71%	F12, F41, OF18, OF22, OF27, OF30
SFST Benefit	37.50%	100.00%	42.86%	80.95%	F12, F43, F44, F45, F5, OF18, OF27, OF30

Table 53: Ensemble Model Accuracies

Model	Lower Acc.	Moderate Acc.	Higher Acc.	Overall Acc.	Top Features
WS	100.00%	50.00%	75.00%	85.71%	F22, F31, F43, F44, F46, F5, OF18, OF27
PR	0.00%	100.00%	100.00%	76.19%	F43, F44, F45, F5, OF18, OF27
NR	0.00%	85.71%	42.86%	61.90%	F43, F44, F45, F5, OF18, OF27, OF34, S4
SR	30.00%	80.00%	33.33%	85.71%	F24, F28, F31, F43, F44, F45, F5, OF18, OF27
SFST	100.00%	42.86%	100.00%	80.95%	F43, F44, F45, F46, OF18, OF27
WS Benefit	36.36%	71.43%	66.67%	80.95%	F5, OF17, OF18, OF23, OF27, OF34, S4
PR Benefit	100.00%	85.71%	25.00%	80.95%	F14, F3_c, F41, F44, OF18, OF19, OF27
NR Benefit	100.00%	85.71%	50.00%	76.19%	F41, F5, OF10, OF18, OF19, OF22, OF27, OF9
SR Benefit	100.00%	0.00%	0.00%	47.62%	F12, F41, OF18, OF22, OF27, OF30

Model	**Lower Acc.**	**Moderate Acc.**	**Higher Acc.**	**Overall Acc.**	**Top Features**
SFST Benefit	37.50%	100.00%	42.86%	57.14%	F12, F43, F44, F45, F5, OF18, OF27, OF30

Table 54: Voting System Accuracies

Function	**Model**	**Data**	**MSE**
PR	SGDRegressor	ffill	3.44
NR	RandomForestRegressor	mean	3.35
SR	ElasticNet	iterative	6.41
WS	RandomForestRegressor	iterative	2.87
SFST	RandomForestRegressor	iterative	3.51
PR Benefit	AdaBoostRegressor	interpolated.csv	6.16
NR Benefit	RANSACRegressor	mean	5.63
SR Benefit	AdaBoostRegressor	knn	5.39
WS Benefit	AdaBoostRegressor	knn	9.13
SFST Benefit	KNeighborsRegressor	iterative	3.33

Table 55: Model MSE

5.5.3 Extra Features

Function	Model	Data	MSE
PR	AdaBoostRegressor	iterative	0.12
NR	AdaBoostRegressor	ffill	0.18
SR	MLPRegressor	ffill	0.21
WS	MLPRegressor	iterative	0.20
SFST	MLPRegressor	custom	0.18
PR Benefit	RANSACRegressor	mean	0.63
NR Benefit	MLPRegressor	interpolated.csv	0.10
SR Benefit	TheilSenRegressor	interpolated.csv	0.52
WS Benefit	AdaBoostRegressor	median	1.08
SFST Benefit	DecisionTreeRegressor	median	2.29

Table 56: Model MSE

5.5.4 Specific + Extra Features

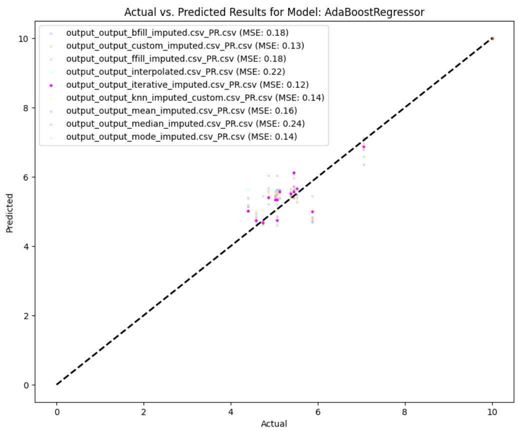

Figure 141: PR

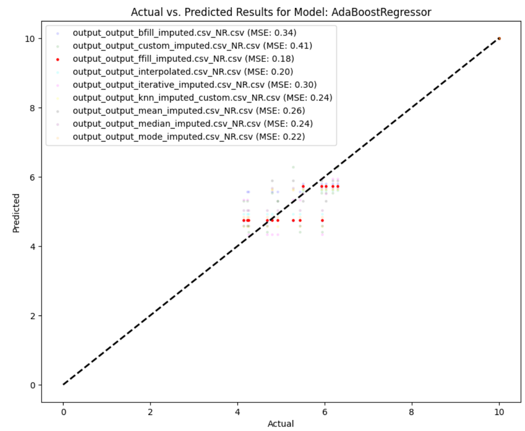

Figure 142: NR

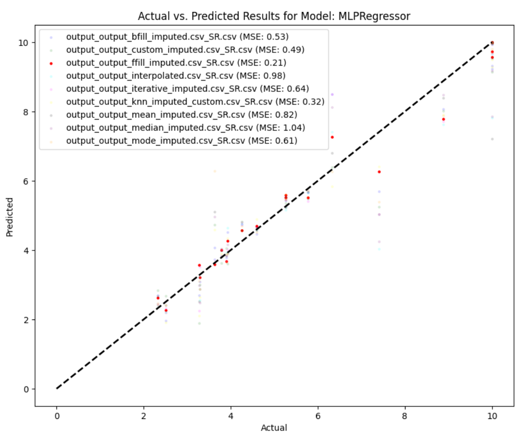

Figure 143: SR

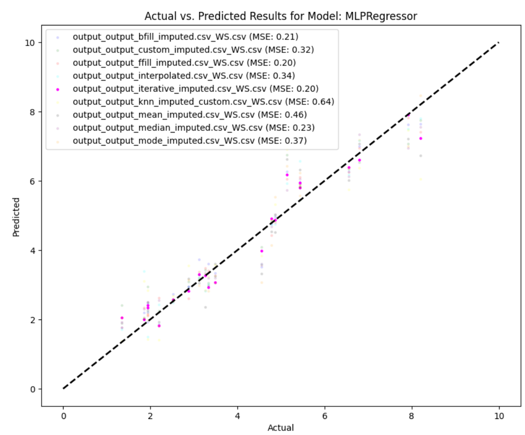

Figure 144: WS

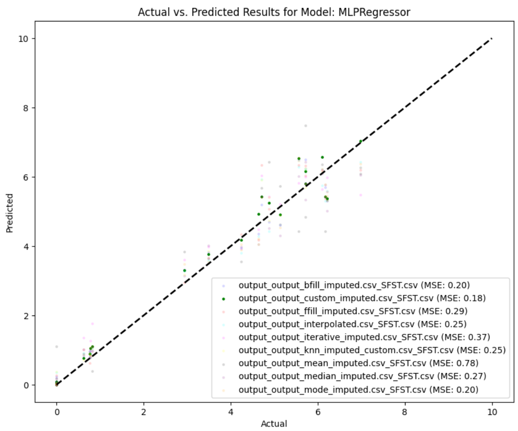

Figure 145: SFST

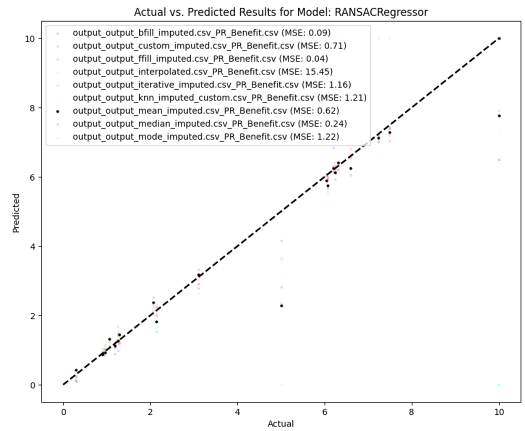

Figure 146: PR Benefit

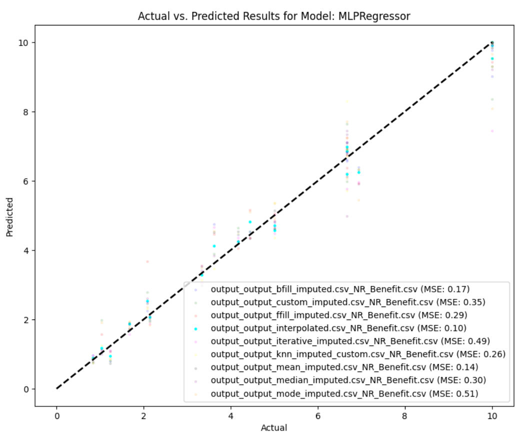

Figure 147: NR Benefit

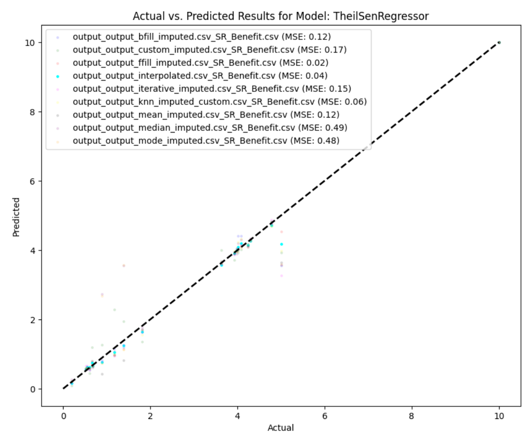

Figure 148: SR Benefit

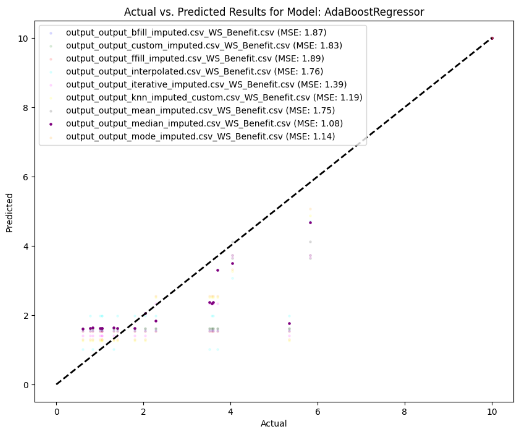

Figure 149: WS Benefit

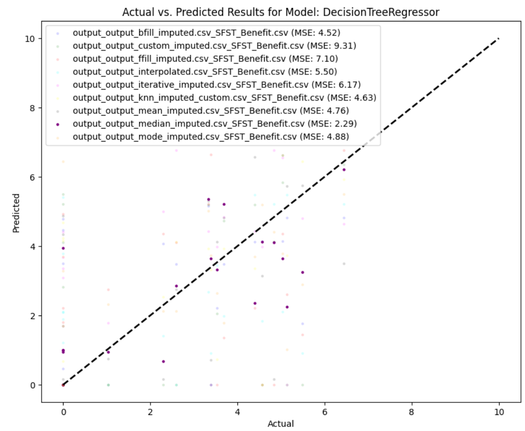

Figure 150: SFST Benefit

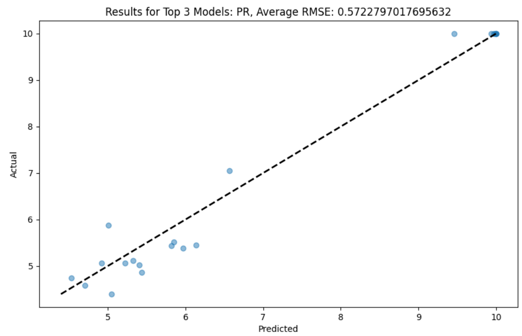

Figure 151: PR

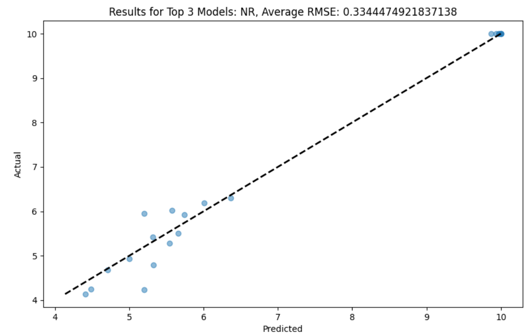

Figure 152: NR

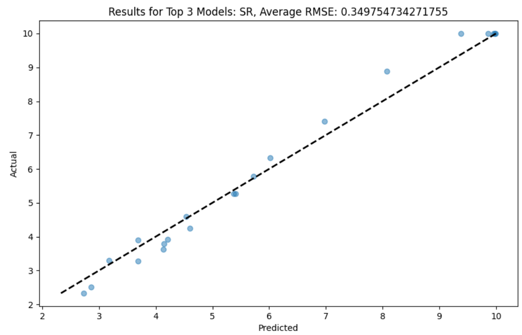

Figure 153: SR

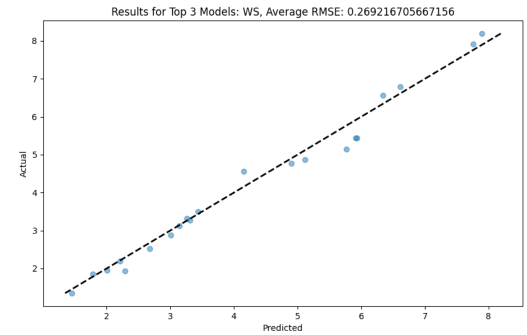

Figure 154: WS

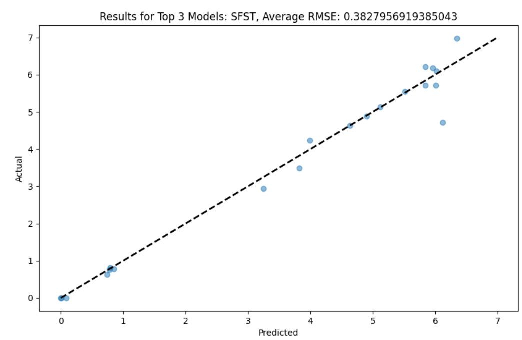

Figure 155: SFST

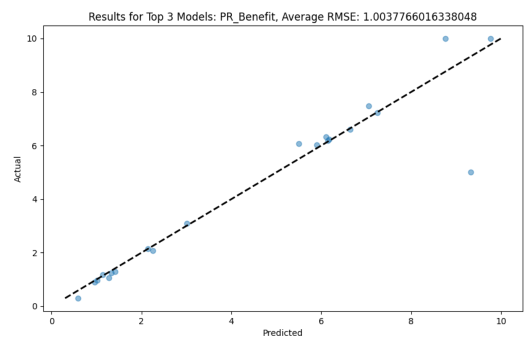

Figure 156: PR Benefit

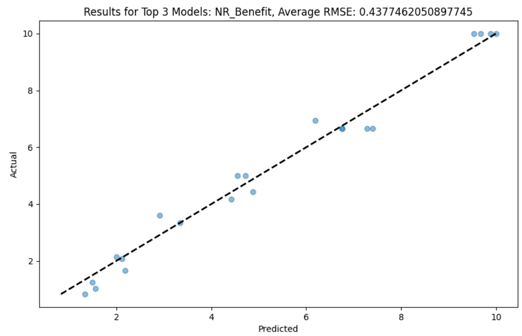

Figure 157: NR Benefit

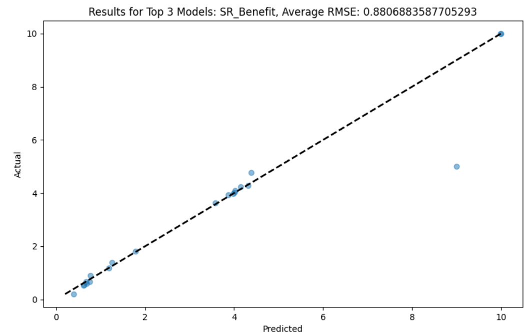

Figure 158: SR Benefit

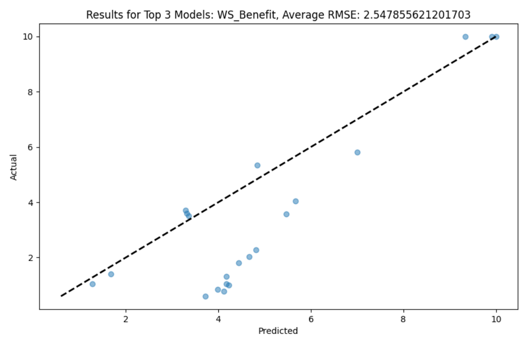

Figure 159: WS Benefit

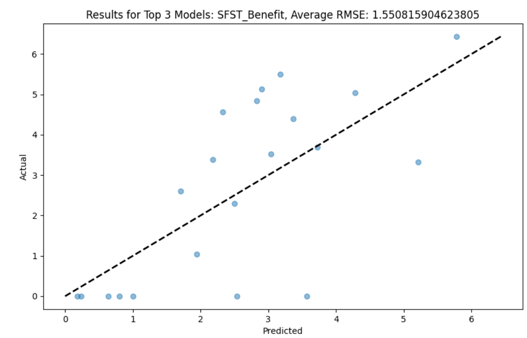

Figure 160: SFST Benefit

Function	RMSE	# Feat.	Selected Features
WS	0.2578	9	Provincial_Class, Hydrogeomorphic_Class, OF22, F22, F28, F31, F43, F44, F45
NR	0.3627	47	Provincial_Class, Federal_Class, Regime, Vegetation_Type, Vegetation_Cover, Woody_Canopy_Cover, Moss_Cover, Phragmites, Soil_Type, Surface_Water_Present, Saturation_Depth, Living_Moss_Depth, Organic_Depth, Hydrogeomorphic_Class, OF16, OF18, OF25, OF26, OF27, F1, F3_a, F3_b, F3_c, F3_d, F3_e, F3_f, F3_g, F6, F17, F18, F20, F21, F22, F23, F24, F28, F31, F33, F34, F36, F43, F44, F45, F48, F49, F54, S5
PR	0.3238	35	Provincial_Class, Federal_Class, Regime, Vegetation_Type, Vegetation_Cover, Woody_Canopy_Cover, Moss_Cover, Phragmites, Soil_Type, Surface_Water_Present, Saturation_Depth, Living_Moss_Depth, Organic_Depth, Hydrogeomorphic_Class, OF22, OF26, OF27, F17, F20, F21, F23, F24, F28, F29, F31, F33, F34, F35, F36, F38, F43, F44, F45, F49, F63
SR	0.6086	21	Provincial_Class, Federal_Class, Regime, Moss_Cover, Soil_Type, Surface_Water_Present, Hydrogeomorphic_Class, OF22, OF26, F17, F22, F28, F29, F31, F33, F34, F35, F36, F43, F44, F45
SFST	0.4772	22	Provincial_Class, Federal_Class, Regime, Vegetation_Type, Moss_Cover, Surface_Water_Present, Living_Moss_Depth, Organic_Depth, Hydrogeomorphic_Class, F1, F3_c, F3_e, F3_f, F14, F21, F24, F25, F29, F31, F34, F43, F47
WS Benefit	0.8803	12	Provincial_Class, Federal_Class, Vegetation_Type, Moss_Cover, Soil_Type, Living_Moss_Depth, Hydrogeomorphic_Class, OF17, OF18, OF23, OF24, F51
NR Benefit	0.3845	15	Moss_Cover, Saturation_Depth, Living_Moss_Depth, OF9, OF10, OF11, OF19, OF20, OF21, OF22, OF23, OF24, F41, F51, F52

Function	RMSE	# Feat.	Selected Features
PR Benefit	0.7840	21	Provincial_Class, Federal_Class, Regime, Vegetation_Type, Woody_Canopy_Cover, Moss_Cover, Soil_Type, Surface_Water_Present, Saturation_Depth, Living_Moss_Depth, Organic_Depth, OF18, OF19, OF20, OF21, OF22, OF23, OF24, F41, F50, F52
SR Benefit	0.8515	27	Provincial_Class, Federal_Class, Regime, Vegetation_Type, Vegetation_Cover, Woody_Canopy_Cover, Moss_Cover, Phragmites, Soil_Type, Surface_Water_Present, Saturation_Depth, Living_Moss_Depth, Organic_Depth, Hydrogeomorphic_Class, OF18, OF19, OF20, OF21, OF23, OF24, F24, F28, F41, F50, F52, F55, S4
SFST Benefit	1.6496	9	Provincial_Class, Federal_Class, Moss_Cover, Surface_Water_Present, Hydrogeomorphic_Class, OF18, OF22, OF25, OF28

Table 57: Method with the Lowest RMSE and Number of Features

Function	RMSE	# Feat.	Selected Features
WS	0.7074	2	F31, F43
NR	2.2793	2	OF18, F6
PR	0.6000	2	F43, F44
SR	1.1035	2	F28, F45
SFST	0.5405	2	F1, F43
WS Benefit	1.3563	2	OF17, OF18
NR Benefit	2.2742	2	OF10, OF22
PR Benefit	1.4014	2	Hydrogeomorphic_Class, F41
SR Benefit	2.0913	2	OF18, F41
SFST Benefit	1.9371	2	Provincial_Class, Moss_Cover

Table 58: Models With Two Features

Function	Lowest RMSE	Lowest RMSE 2 Features	MSE
PR	0.3238	0.6000	0.12
NR	0.3627	2.2793	0.18
SR	0.6086	1.1035	0.21
WS	0.2578	0.7074	0.20
SFST	0.4772	0.5405	0.18
PR Benefit	0.7840	1.4014	0.63

Function	**Lowest RMSE**	**Lowest RMSE 2 Features**	**MSE**
NR Benefit	0.3845	2.2742	0.10
SR Benefit	0.8515	2.0913	0.52
WS Benefit	0.8803	1.3563	1.08
SFST Benefit	1.6496	1.9371	2.29

Table 59: Combined Accuracy Table

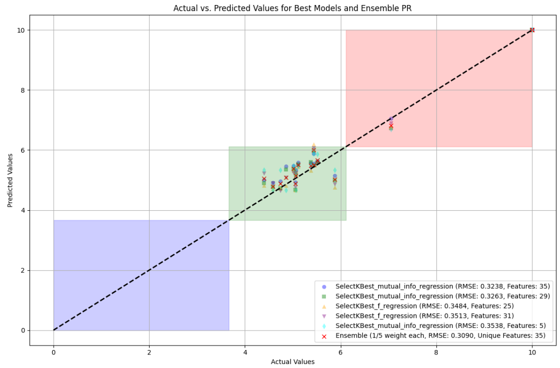

Figure 161: PR

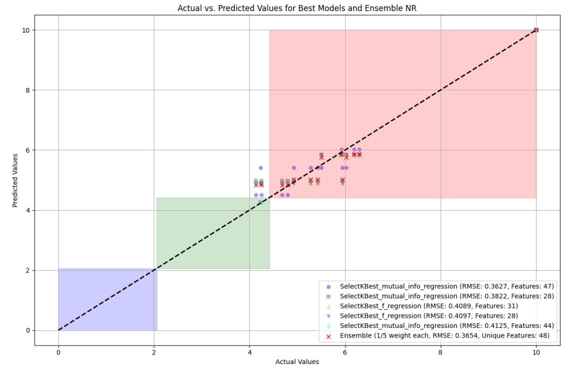

Figure 162: NR

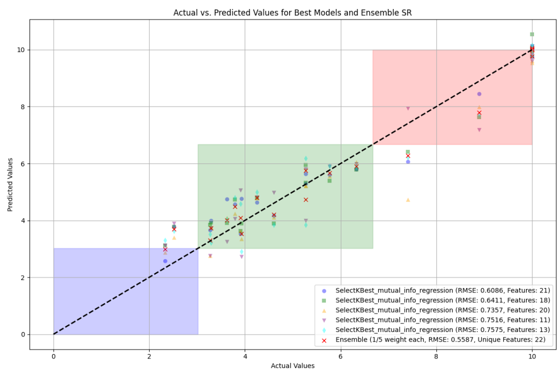

Figure 163: SR

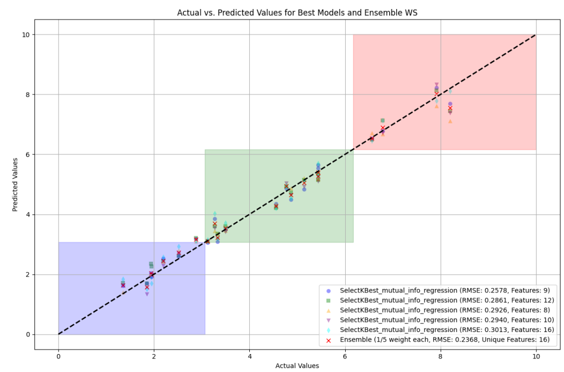

Figure 164: WS

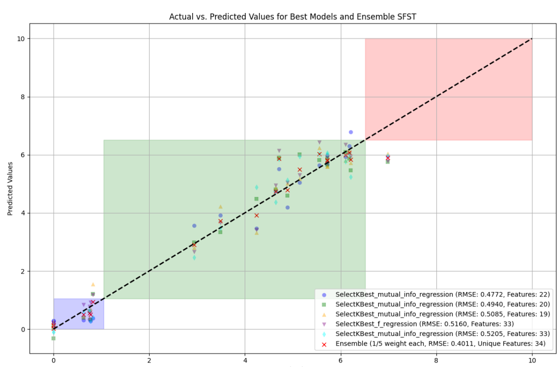

Figure 165: SFST

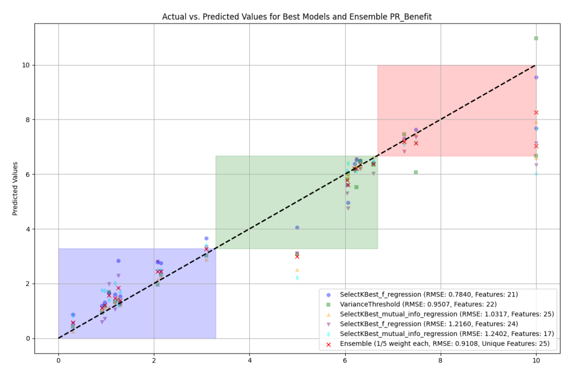

Figure 166: PR Benefit

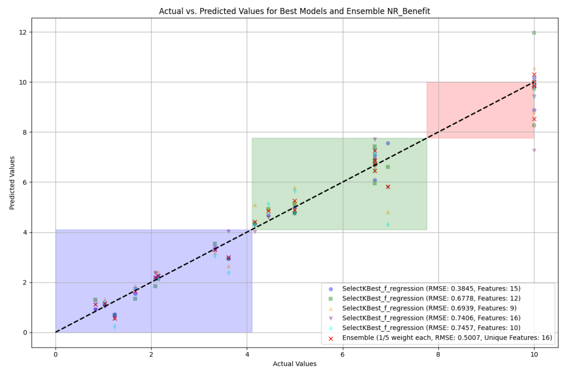

Figure 167: NR Benefit

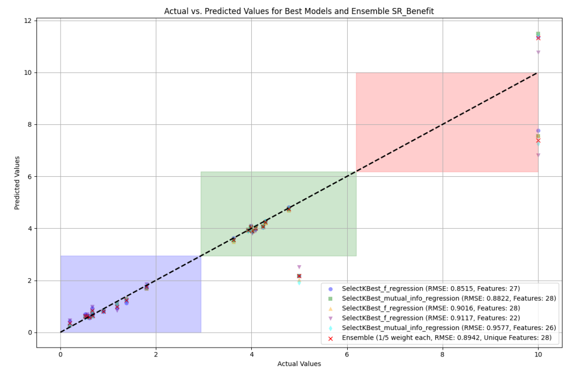

Figure 168: SR Benefit

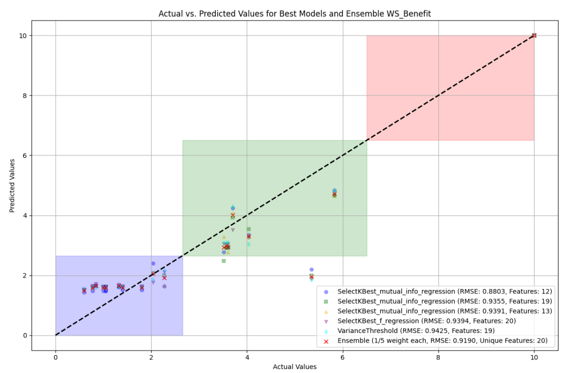

Figure 169: WS Benefit

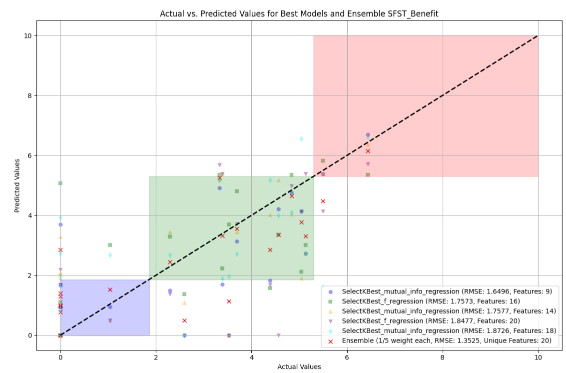

Figure 170: SFST Benefit

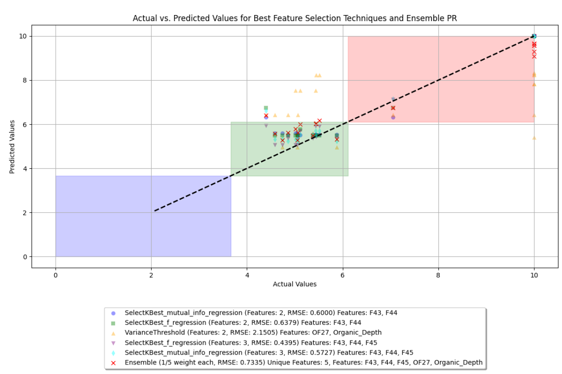

Figure 171: PR

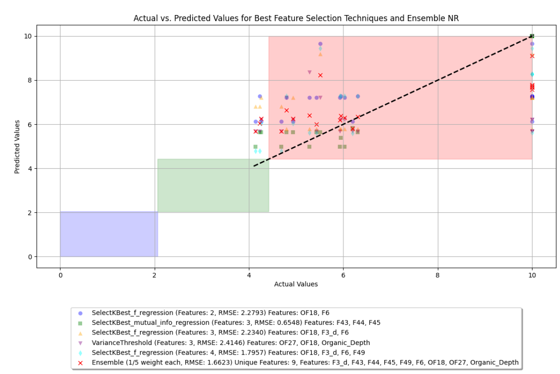

Figure 172: NR

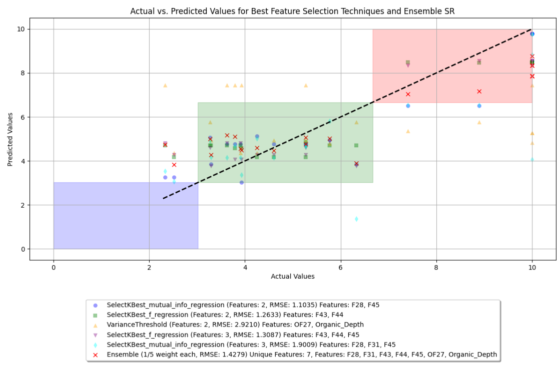

Figure 173: SR

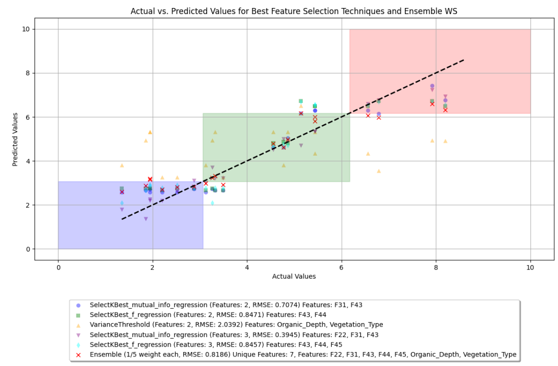

Figure 174: WS

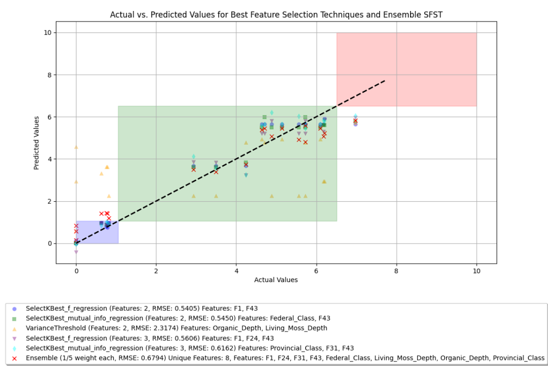

Figure 175: SFST

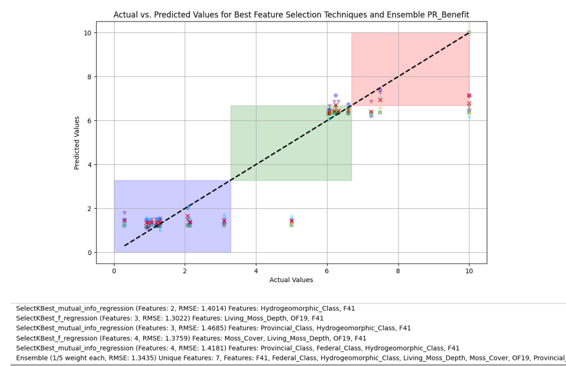

Figure 176: PR Benefit

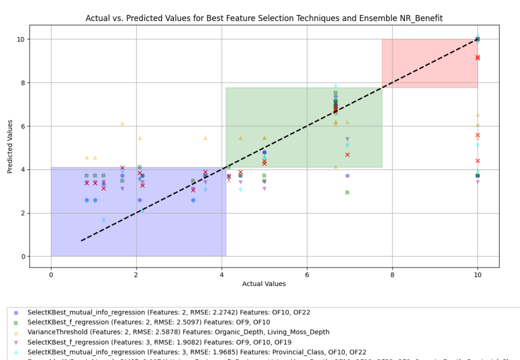

Figure 177: NR Benefit

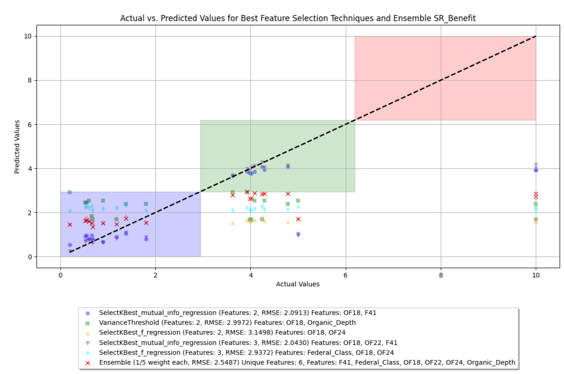

Figure 178: SR Benefit

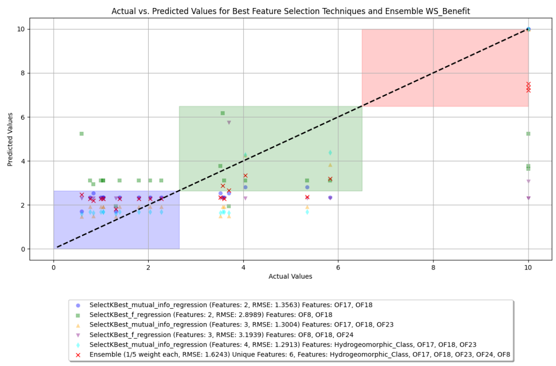

Figure 179: WS Benefit

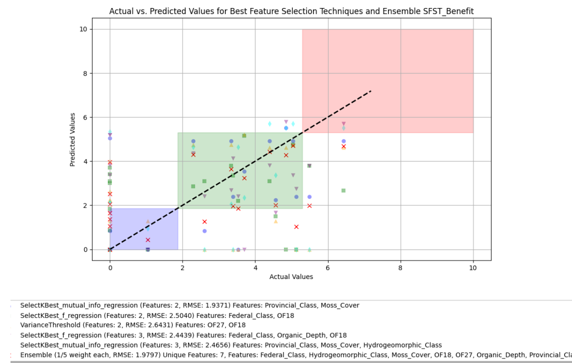

Figure 180: SFST Benefit

Function	RMSE	# Feat.
WS	0.2368	16
NR	0.3654	48
PR	0.3090	35
SR	0.5587	22
SFST	0.4011	34
WS Benefit	0.9190	20
NR Benefit	0.5007	16
PR Benefit	0.9108	25
SR Benefit	0.8942	28
SFST Benefit	1.3525	20

Table 60: Ensemble Learning using All Features

Function	RMSE	# Feat.	Selected Features
WS	0.8186	8	F22,F31,F43,F44,F45, Organic Depth, Vegetation Type
NR	1.6623	9	F3d, F43, F44, F45, F49, F6, OF18, OF27, Organic Depth
PR	0.7335	5	F43, F44, F45, OF27, Organic Depth
SR	1.4279	7	F28, F31, F43, F44, F45, OF27, Organic Depth
SFST	0.6794	8	F1, F24, F31, F43, Federal Class, Living Moss, Organic Depth, Provincial Class
WS Benefit	1.0354	6	F51,OF15,OF17,OF18,OF23,OF24
PR Benefit	1.3435	7	F41, Federal Class, Hydrogeomorphic, Living Moss, Moss Cover, OF19, Provincial Class
NR Benefit	1.0074	7	Living Moss, OF10, OF19, OF22, OF9, Organic Depth, Provincial Class
SR Benefit	2.5487	6	F41, Federal Class, OF18, OF22, OF24, Organic Depth
WS Benefit	1.6243	6	Hydrogeomorphic, OF17, OF18, OF23, OF24, OF8
SFST Benefit	1.9797	7	Federal Class, Hydrogeomorphic, Moss Cover, OF18, OF27 Organic Depth, Provincial Class

Table 61: Ensemble Learning using limited features

Model	Lower Acc.	Moderate Acc.	Higher Acc.	Overall Acc.	Top Features
WS	80.81%	64.20%	70.37%	74.07%	Provincial_Class, Hydrogeomorphic_Class, OF22, F22, F28, F31, F43, F44, F45
PR	13.89%	77.78%	87.50%	69.31%	Provincial_Class, Federal_Class, F43, F44, F45
NR	32.80%	65.08%	76.19%	58.02%	Provincial_Class, F24, F43, F44, F45
SR	62.22%	60.00%	62.35%	61.73%	F28, F29, F31, F44, F45
SFST	56.17%	60.85%	76.39%	65.43%	F1, F43
WS Benefit	68.35%	46.56%	44.44%	57.67%	Hydrogeomorphic_Class, OF17, OF18, OF23, OF24, F51
PR Benefit	80.00%	44.97%	29.63%	58.73%	Regime, Moss_Cover, Living_Moss_Depth, OF19, OF20, OF21, OF22, OF24, F41
NR Benefit	70.74%	80.42%	49.07%	69.84%	Living_Moss_Depth, OF9, OF10, OF19, OF20, OF21, OF22, OF23, F41
SR Benefit	93.70%	53.91%	0.00%	67.72%	Provincial_Class, Federal_Class, Regime, Vegetation_Type, Living_Moss_Depth, Organic_Depth, Hydrogeomorphic_Class, OF18, OF24, F41
SFST Benefit	59.72%	32.10%	48.15%	47.97%	Provincial_Class, Federal_Class, Moss_Cover, Surface_Water_Present, Hydrogeomorphic_Class, OF18, OF22, OF25, OF28

Table 62: Classification Accuracies and Top Features for Various Models

Model	Lower Acc.	Moderate Acc.	Higher Acc.	Overall Acc.	Top Features
WS	100.00%	50.00%	100.00%	85.71%	F22, F31, F43, F44, F46, F5, OF18, OF27
PR	0.00%	100.00%	100.00%	76.19%	F43, F44, F45, F5, OF18, OF27
NR	0.00%	71.43%	42.86%	80.95%	F43, F44, F45, F5, OF18, OF27, OF34, S4
SR	30.00%	80.00%	50.00%	90.48%	F24, F28, F31, F43, F44, F45, F5, OF18, OF27
SFST	100.00%	42.86%	100.00%	80.95%	F43, F44, F45, F46, OF18, OF27
WS Benefit	54.55%	71.43%	66.67%	90.48%	F5, OF17, OF18, OF23, OF27, OF34, S4
PR Benefit	100.00%	85.71%	25.00%	80.95%	F14, F3_c, F41, F44, OF18, OF19, OF27
NR Benefit	100.00%	85.71%	50.00%	85.71%	F41, F5, OF10, OF18, OF19, OF22, OF27, OF9
SR Benefit	100.00%	0.00%	0.00%	85.71%	F12, F41, OF18, OF22, OF27, OF30
SFST Benefit	37.50%	100.00%	42.86%	80.95%	F12, F43, F44, F45, F5, OF18, OF27, OF30

Table 63: Ensemble Model Accuracies

Model	Lower Acc.	Moderate Acc.	Higher Acc.	Overall Acc.	Top Features
WS	100.00%	50.00%	75.00%	85.71%	F22, F31, F43, F44, F46, F5, OF18, OF27
PR	0.00%	100.00%	100.00%	76.19%	F43, F44, F45, F5, OF18, OF27
NR	0.00%	85.71%	42.86%	61.90%	F43, F44, F45, F5, OF18, OF27, OF34, S4
SR	30.00%	80.00%	33.33%	85.71%	F24, F28, F31, F43, F44, F45, F5, OF18, OF27
SFST	100.00%	42.86%	100.00%	80.95%	F43, F44, F45, F46, OF18, OF27

Model	**Lower Acc.**	**Moderate Acc.**	**Higher Acc.**	**Overall Acc.**	**Top Features**
WS Benefit	36.36%	71.43%	66.67%	80.95%	F5, OF17, OF18, OF23, OF27, OF34, S4
PR Benefit	100.00%	85.71%	25.00%	80.95%	F14, F3_c, F41, F44, OF18, OF19, OF27
NR Benefit	100.00%	85.71%	50.00%	76.19%	F41, F5, OF10, OF18, OF19, OF22, OF27, OF9
SR Benefit	100.00%	0.00%	0.00%	47.62%	F12, F41, OF18, OF22, OF27, OF30
SFST Benefit	37.50%	100.00%	42.86%	57.14%	F12, F43, F44, F45, F5, OF18, OF27, OF30

Table 64: Voting System Accuracies

5.6 Results Analysis

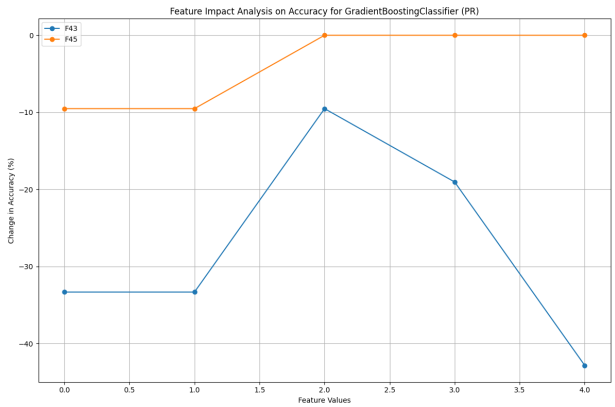

Figure 181: PR

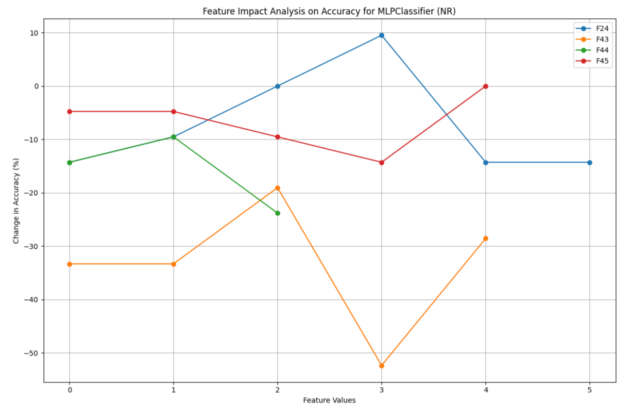

Figure 182: NR

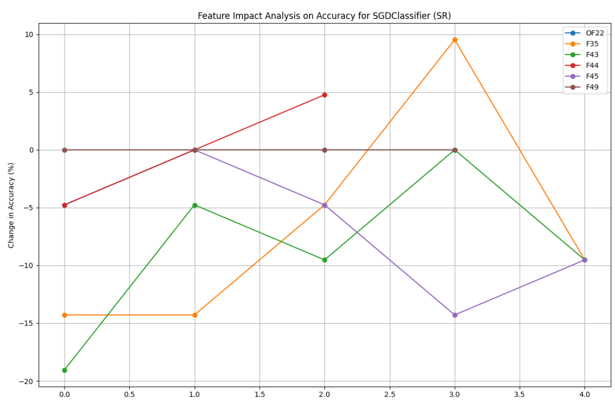

Figure 183: SR

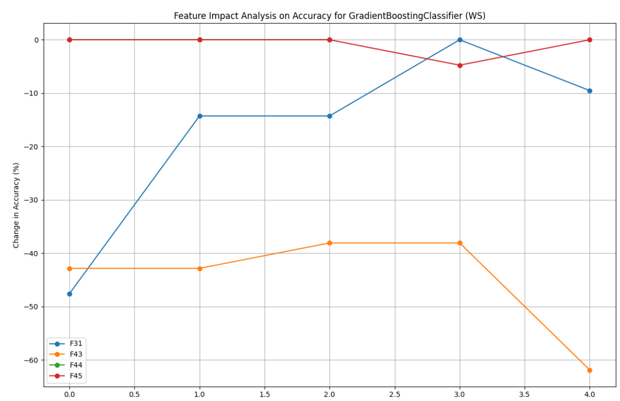

Figure 184: WS

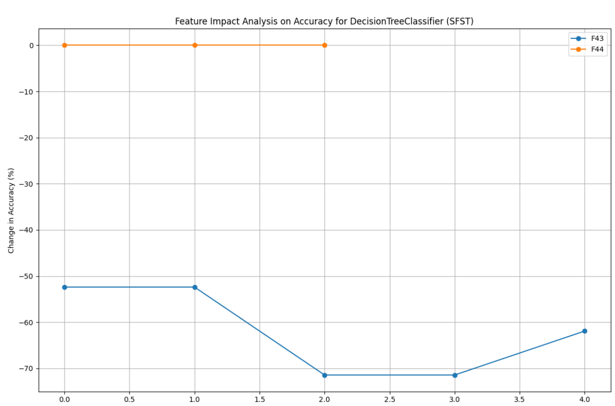

Figure 185: SFST

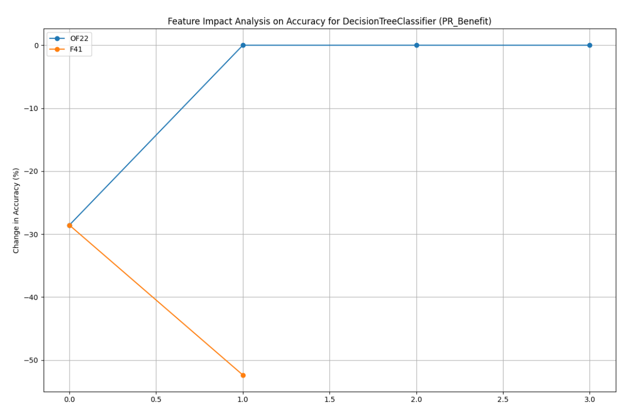

Figure 186: PR Benefit

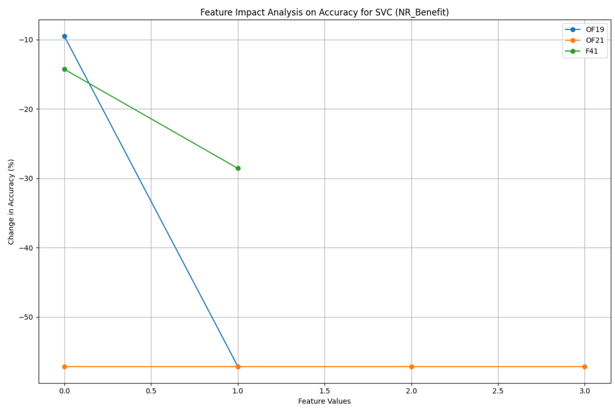

Figure 187: NR Benefit

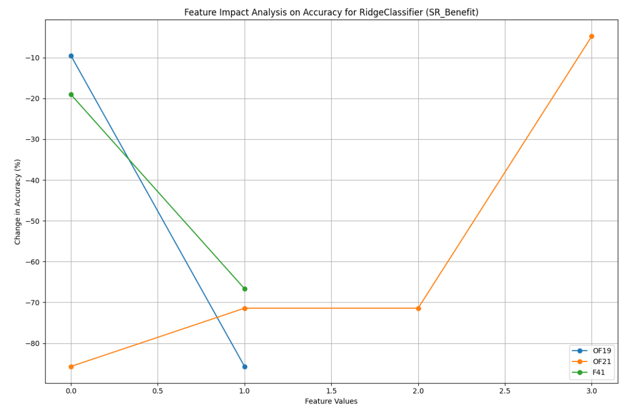

Figure 188: SR Benefit

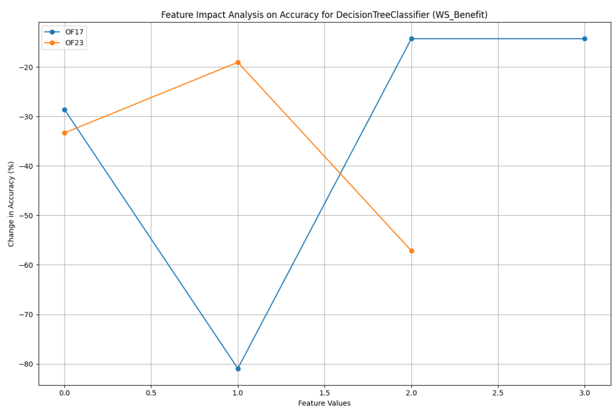

Figure 189: WS Benefit

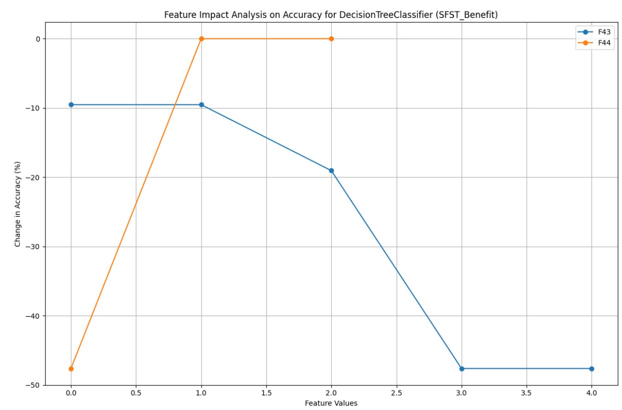

Figure 190: SFST Benefit

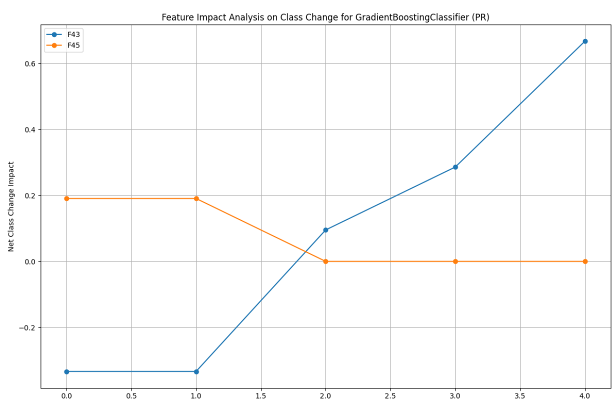

Figure 191: PR

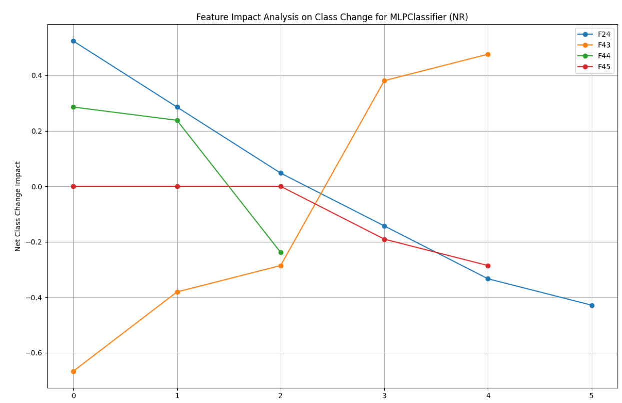

Figure 192: NR

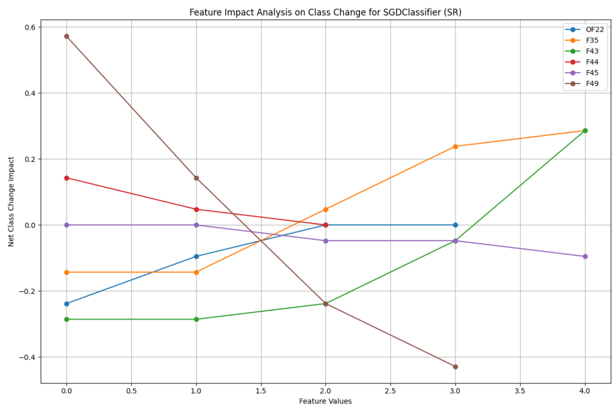

Figure 193: SR

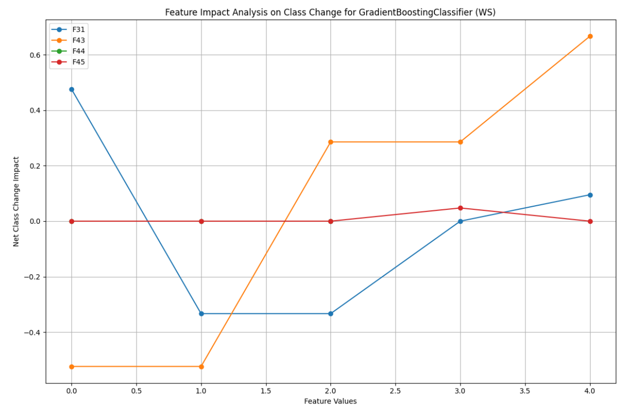

Figure 194: WS

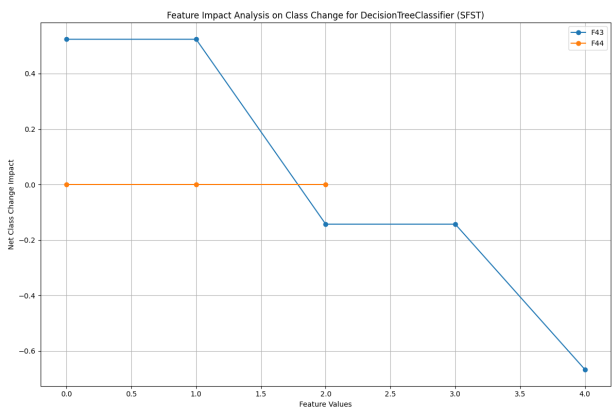

Figure 195: SFST

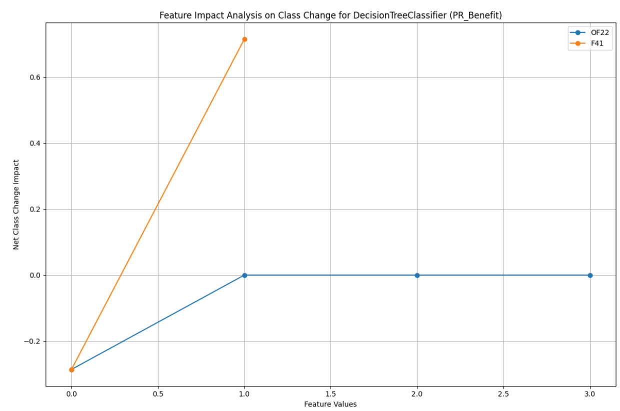

Figure 196: PR Benefit

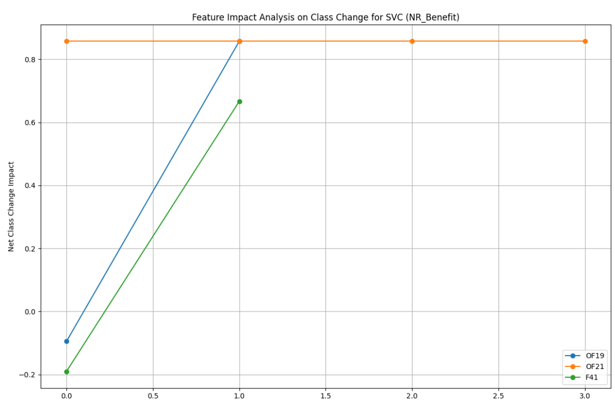

Figure 197: NR Benefit

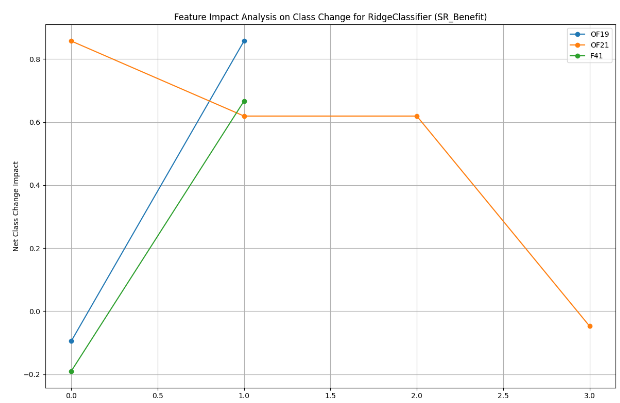

Figure 198: SR Benefit

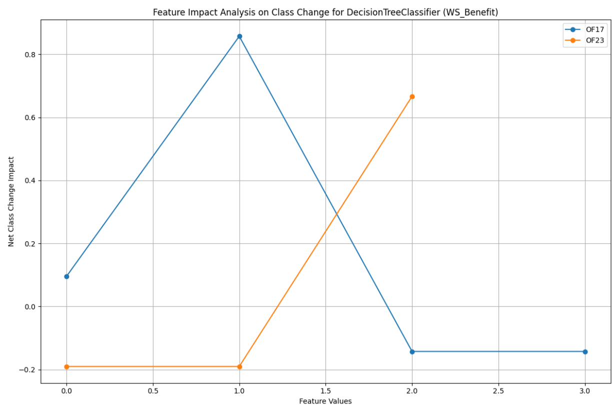

Figure 199: WS Benefit

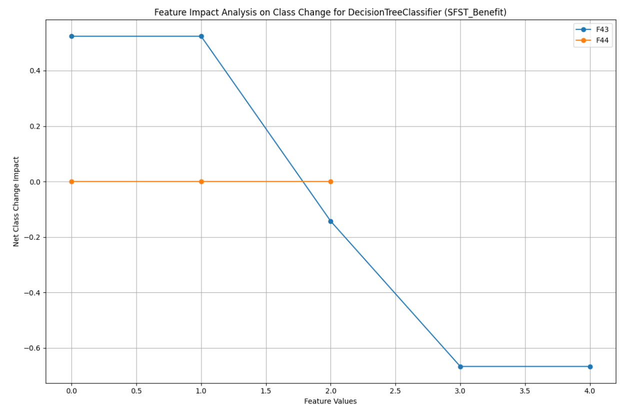

Figure 200: SFST Benefit

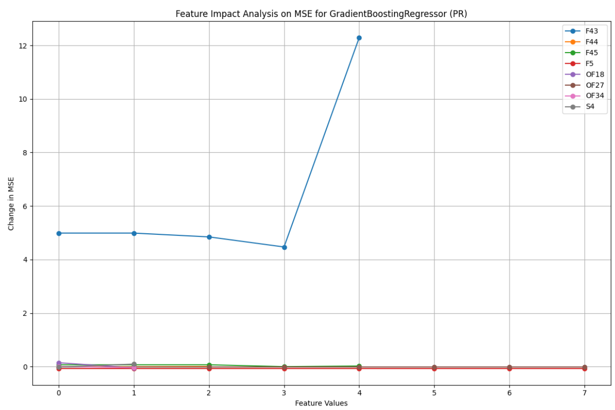

Figure 201: PR

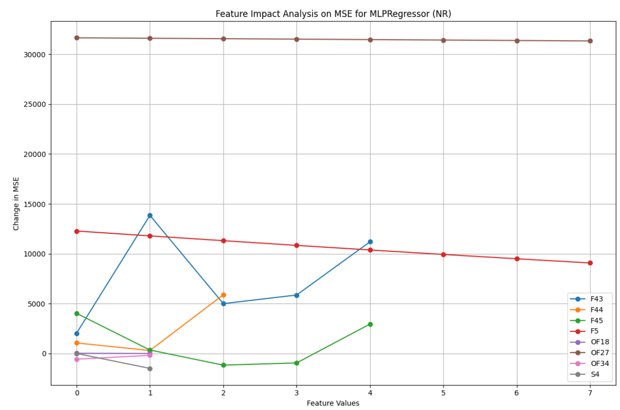

Figure 202: NR

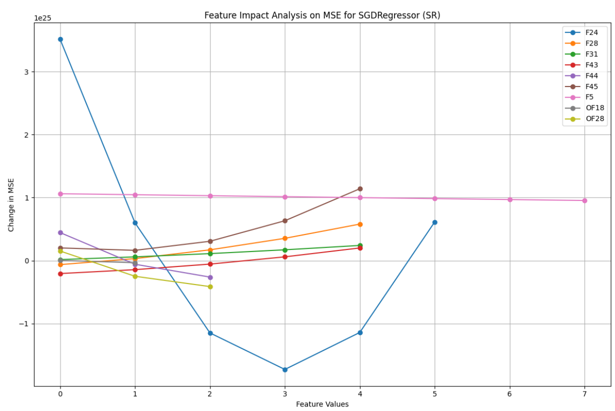

Figure 203: SR

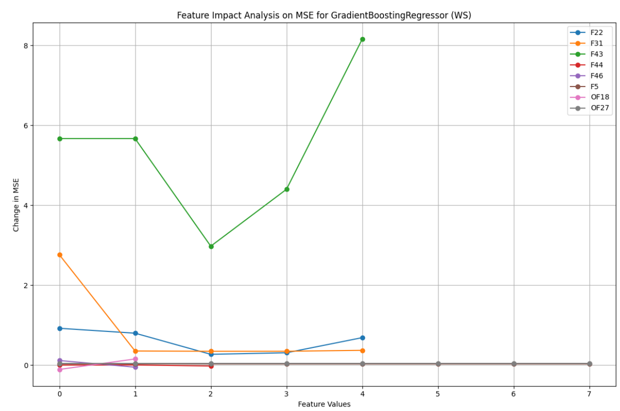

Figure 204: WS

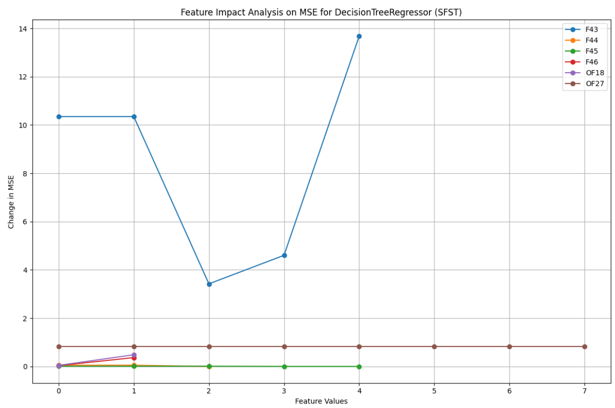

Figure 205: SFST

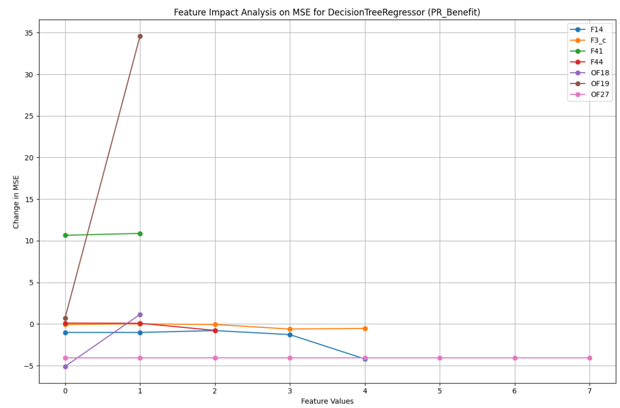

Figure 206: PR Benefit

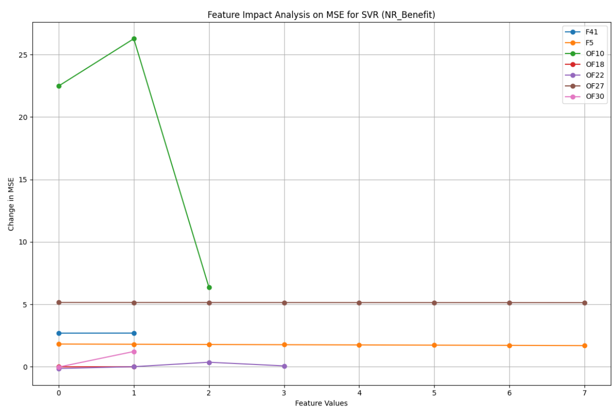

Figure 207: NR Benefit

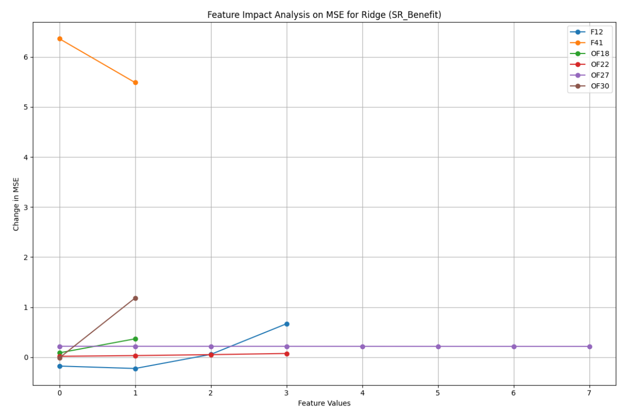

Figure 208: SR Benefit

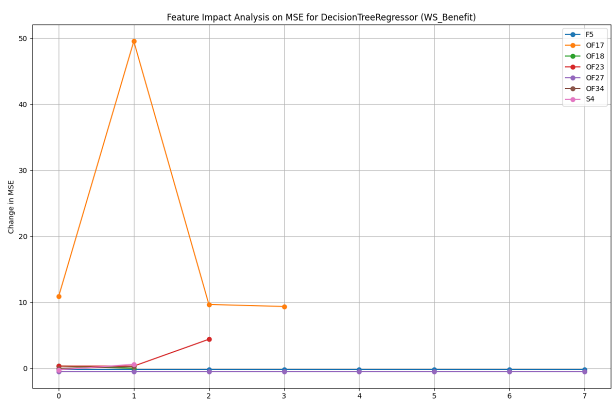

Figure 209: WS Benefit

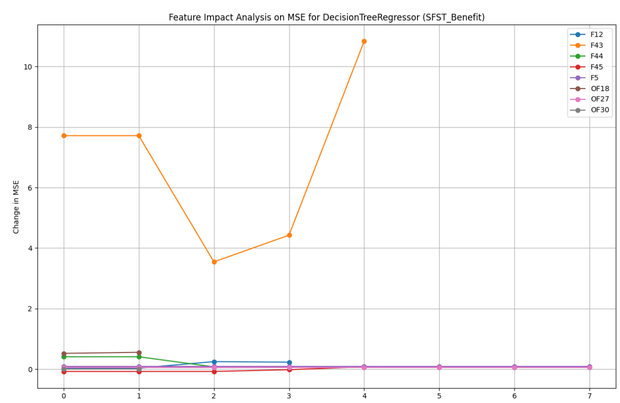

Figure 210: SFST Benefit

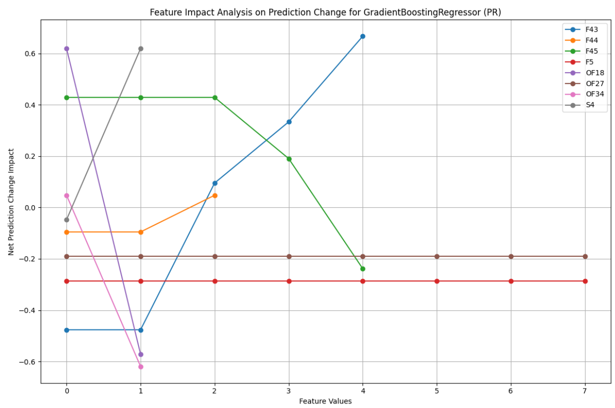

Figure 211: PR

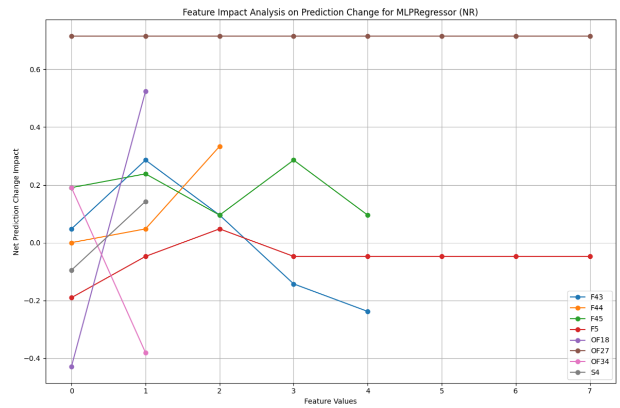

Figure 212: NR

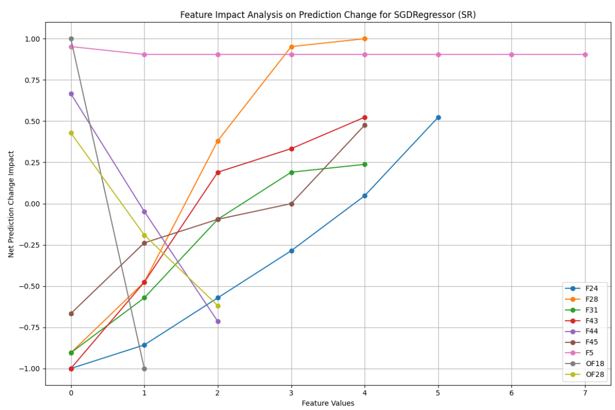

Figure 213: SR

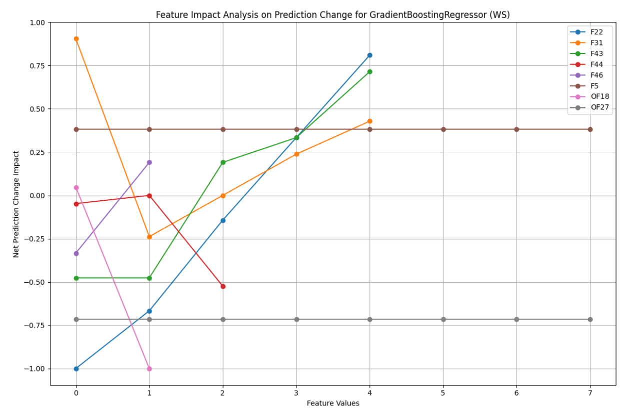

Figure 214: WS

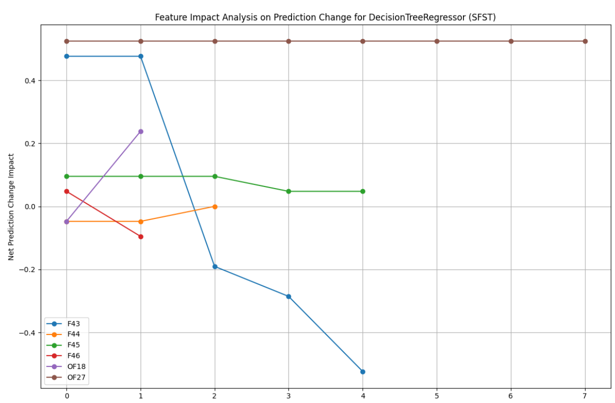

Figure 215: SFST

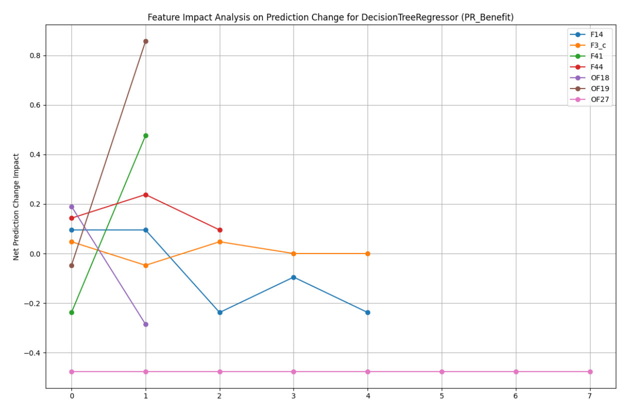

Figure 216: PR Benefit

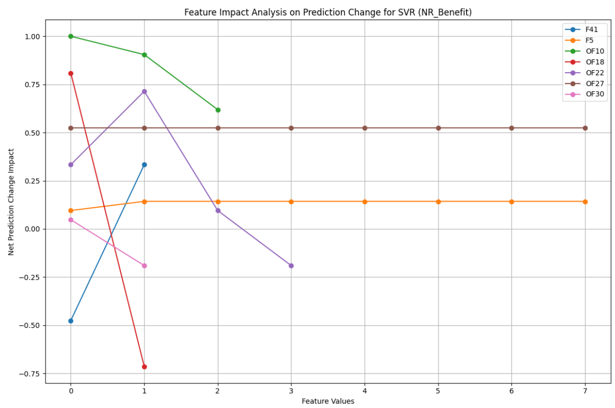

Figure 217: NR Benefit

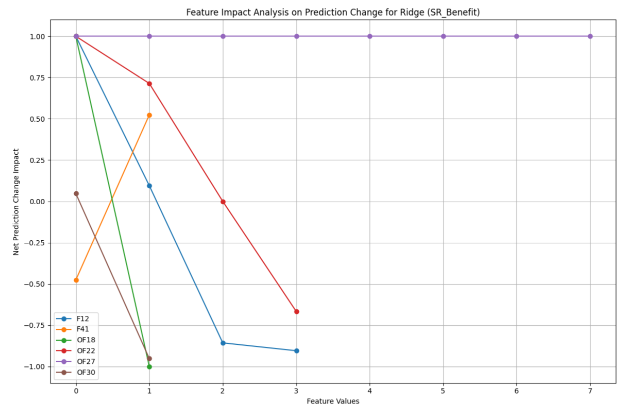

Figure 218: SR Benefit

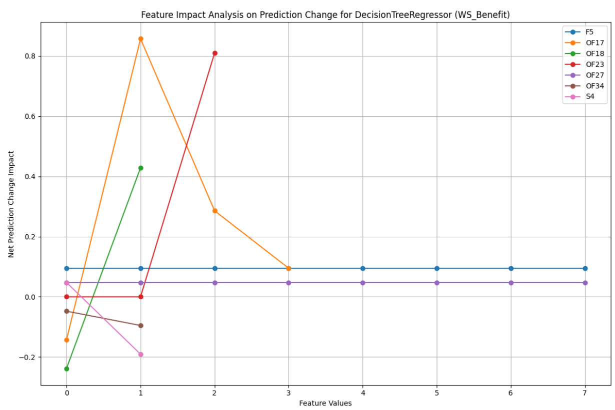

Figure 219: WS Benefit

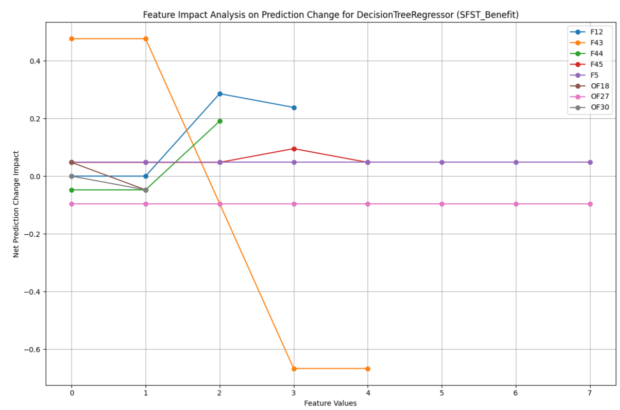

Figure 220: SFST Benefit

5.7 CausalML

F43	F45	Actual	Predicted	Occurrences
1	0	1	1	1
1	1	1	1	1
1	2	1	1	1
1	3	1	1	1
1	**3**	**2**	**1**	**1**
1	4	1	1	1
1	**5**	**0**	**1**	**1**
1	5	1	1	3
2	2	1	1	1
2	3	1	1	1
2	**4**	**2**	**1**	**1**
2	5	1	1	1
4	0	2	2	3
5	0	2	2	4

Table 65: Results for PR

F24	F43	F44	F45	Actual	Predicted	Occurrences
1	**1**	**2**	**4**	**0**	**1**	1
1	**1**	**2**	**5**	**0**	**1**	**1**
1	2	1	3	1	1	1
2	1	1	2	1	1	1
2	1	1	3	1	1	1
2	1	1	5	1	1	1
2	**1**	**2**	**5**	**1**	**0**	**1**
2	2	1	2	1	1	1
2	4	0	0	2	2	1
2	5	0	0	2	2	1
3	**1**	**1**	**5**	**0**	**1**	**1**
3	1	2	0	0	0	1
3	**2**	**2**	**4**	**1**	**0**	**1**
4	**1**	**2**	**1**	**1**	**2**	**1**
4	2	1	5	0	0	1
5	1	2	3	0	0	1
5	4	0	0	2	2	1
5	5	0	0	2	2	1
6	4	0	0	2	2	1
6	5	0	0	2	2	2

Table 66: Results for NR

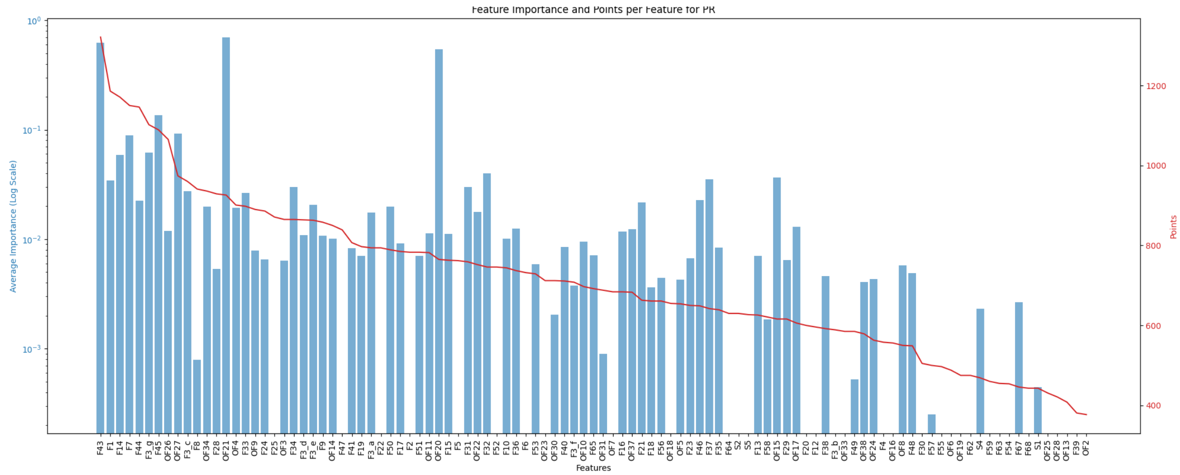

Figure 221: PR

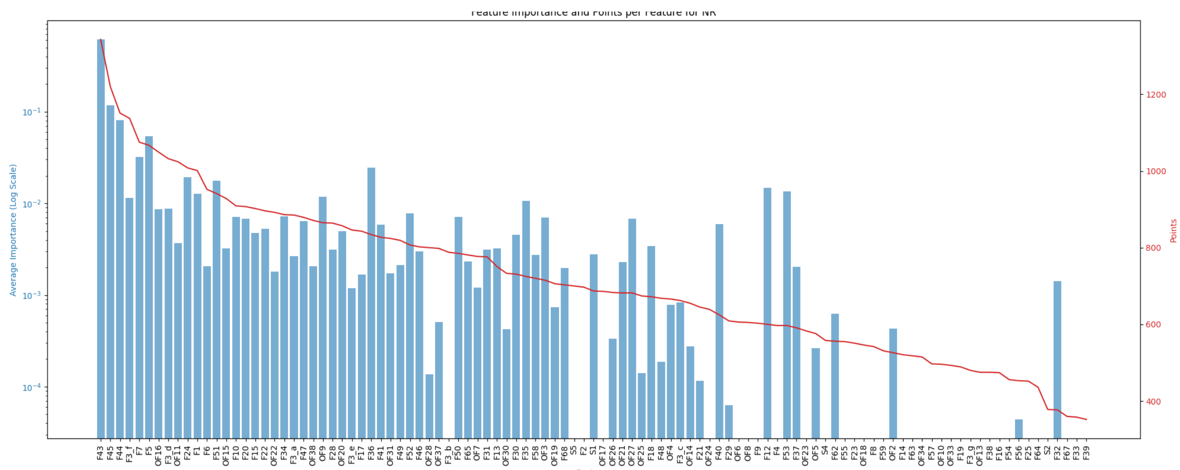

Figure 222: NR

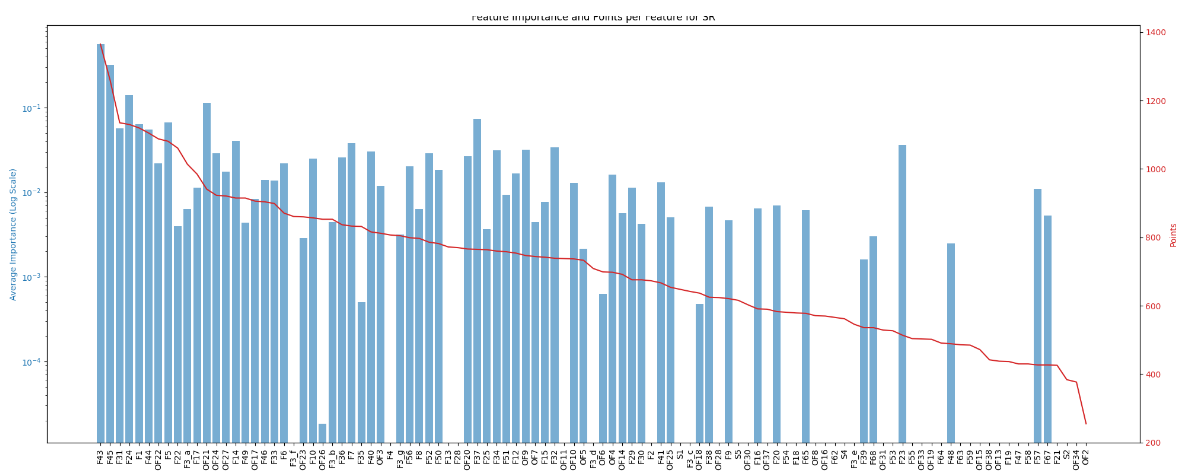

Figure 223: SR

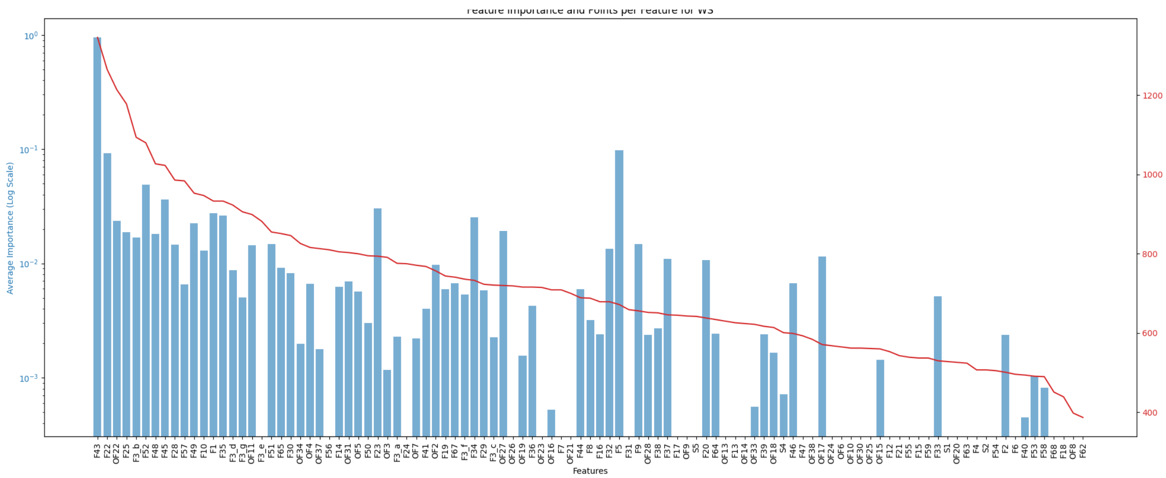

Figure 224: WS

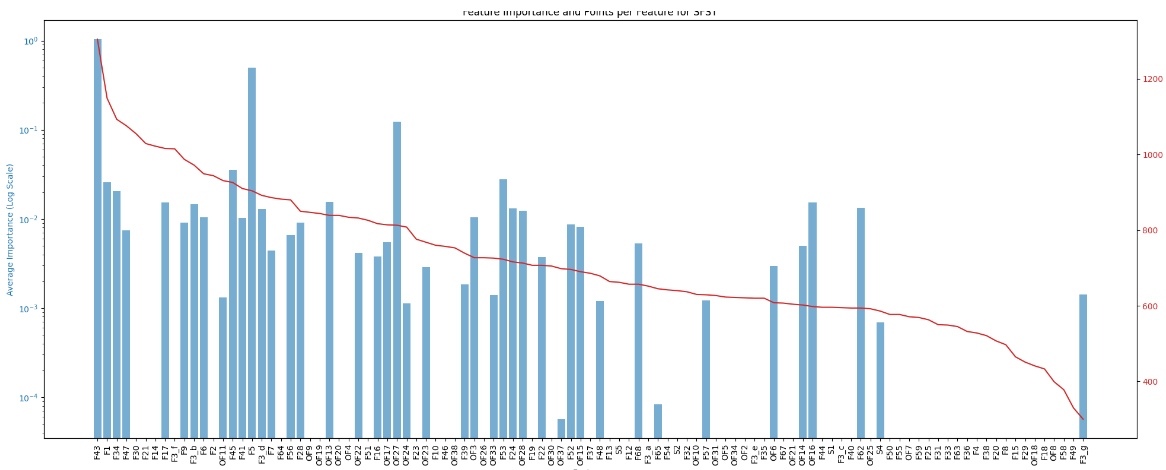

Figure 225: SFST

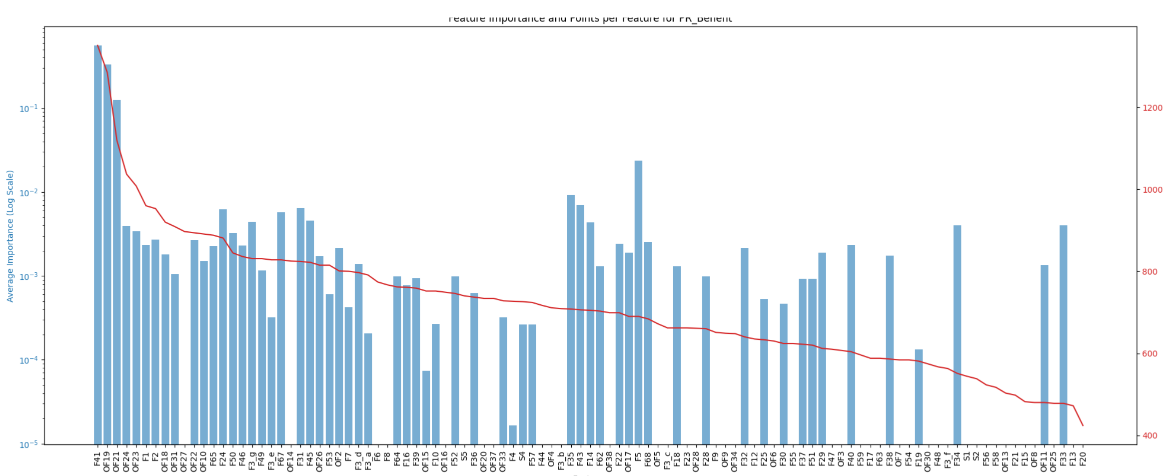

Figure 226: PR Benefit

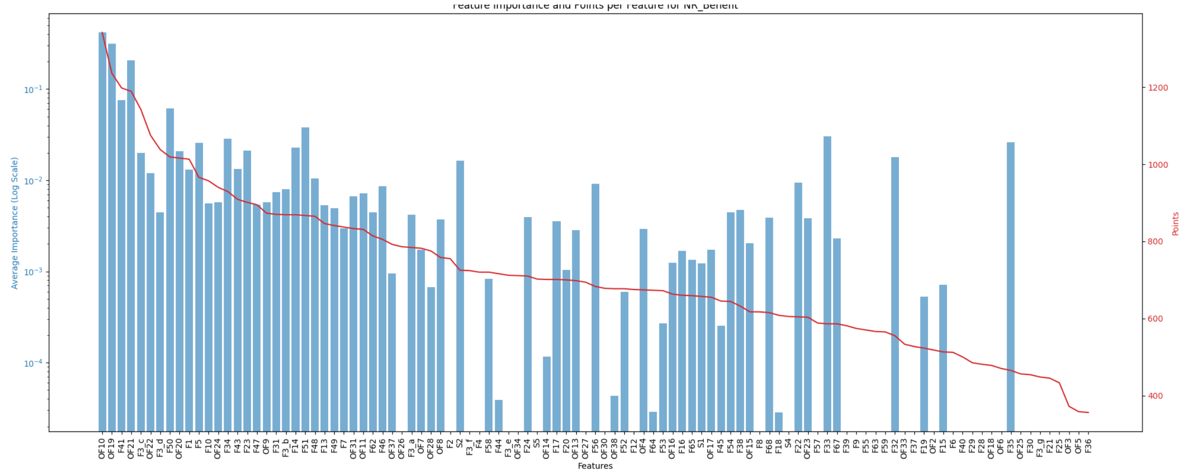

Figure 227: NR Benefit

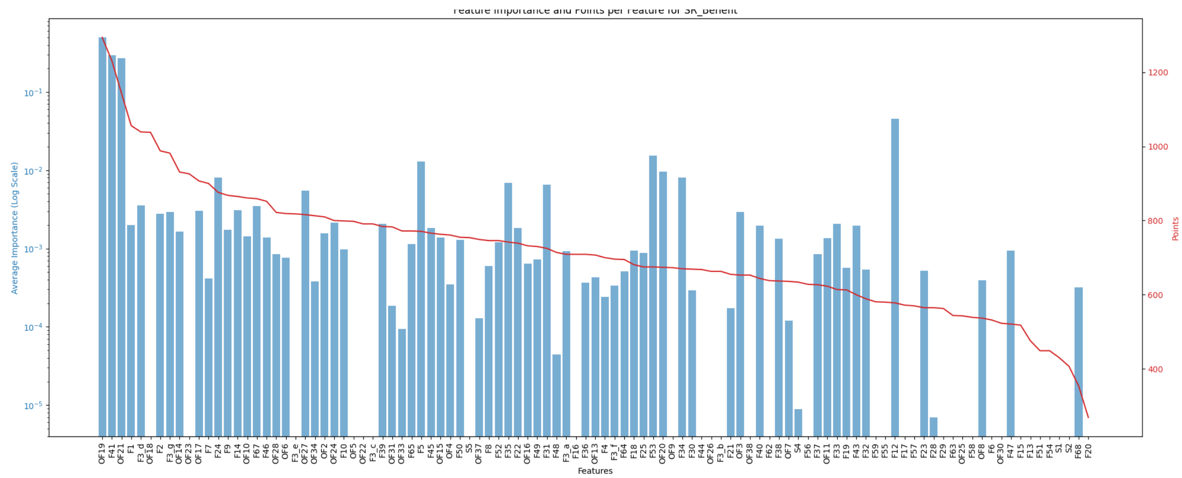

Figure 228: SR Benefit

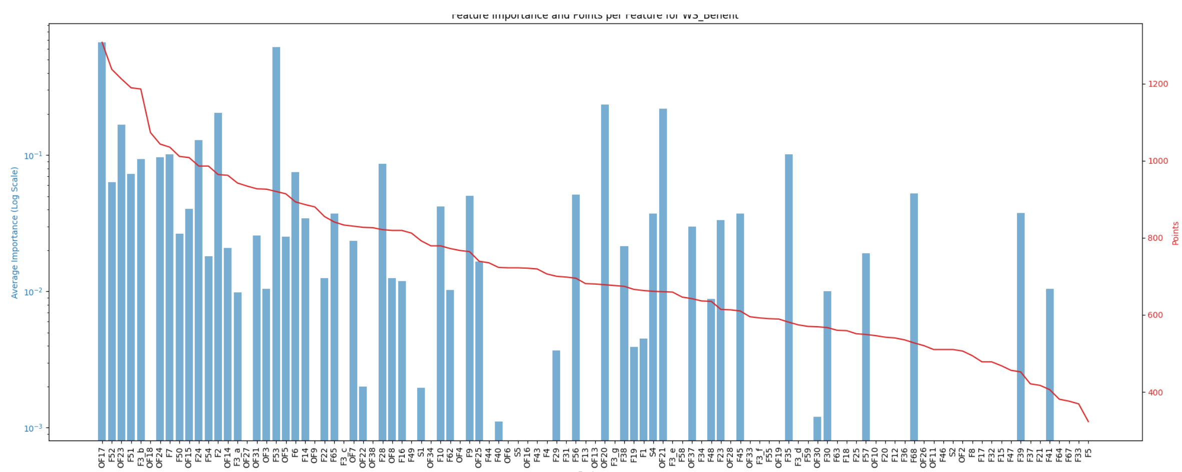

Figure 229: WS Benefit

OF22	F35	F43	F44	F45	F49	Actual	Predicted	Occurrences
1	0	1	2	4	1	0	0	1
1	0	1	2	5	2	0	0	2
1	0	2	1	5	2	0	0	1
1	0	2	2	4	1	0	0	1
1	2	1	2	3	1	0	0	1
1	**5**	**1**	**1**	**5**	**3**	**0**	**1**	**1**
2	0	1	2	1	1	0	0	1
2	0	4	0	0	1	2	2	1
2	**0**	**4**	**0**	**0**	**2**	**2**	**0**	**1**
2	**0**	**5**	**0**	**0**	**1**	**1**	**2**	**1**
2	1	1	2	0	2	0	0	1
2	5	1	1	2	2	1	1	1
2	5	1	1	3	1	1	1	1
2	5	2	1	2	1	1	1	1
3	0	2	1	3	1	1	1	1
3	**0**	**4**	**0**	**0**	**1**	**1**	**2**	**1**
3	**0**	**5**	**0**	**0**	**1**	**1**	**2**	**1**
3	0	5	0	0	1	2	2	1
3	4	5	0	0	1	2	2	1
3	5	1	1	5	1	1	1	1

Table 67: Results for SR

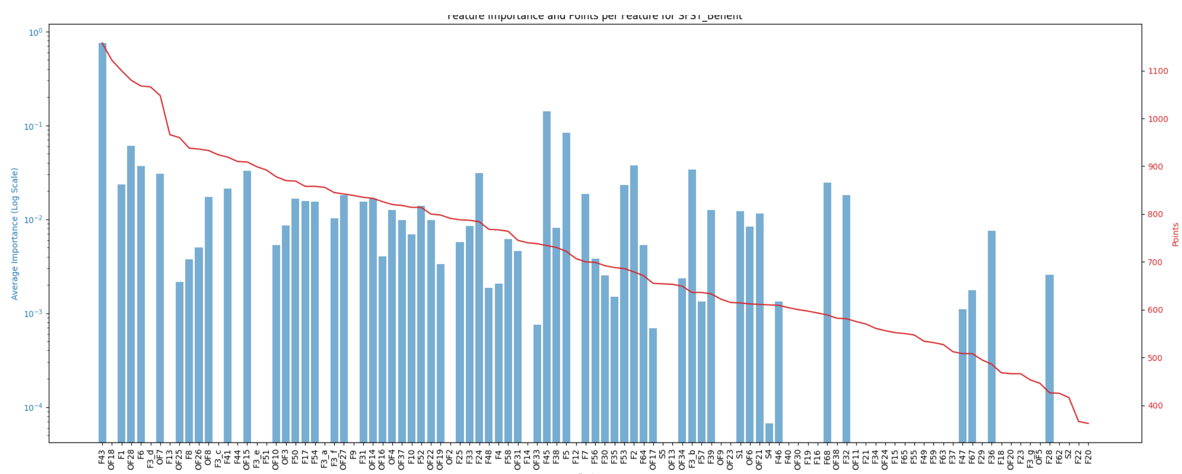

Figure 230: SFST Benefit

F31	F43	F44	F45	Actual	Predicted	Occurrences
0	4	0	0	2	2	1
0	5	0	0	2	2	2
1	1	1	5	0	0	1
1	1	2	3	0	0	1
1	1	2	4	0	0	1
1	1	2	5	0	0	2
2	1	2	1	0	0	1
3	1	1	3	0	0	1
3	**1**	**1**	**5**	**1**	**0**	**1**
4	1	1	2	0	0	1
4	2	1	3	1	1	1
5	1	2	0	0	0	1
5	2	1	2	1	1	1
5	2	1	5	1	1	1
5	2	2	4	1	1	1
5	**4**	**0**	**0**	**1**	**2**	**1**
5	4	0	0	2	2	1
5	**5**	**0**	**0**	**1**	**2**	**1**
5	5	0	0	2	2	1

Table 68: Results for WS

F43	F44	Actual	Predicted	Occurrences
1	1	2	2	4
1	**2**	**1**	**2**	**1**
1	2	2	2	5
2	1	1	1	3
2	2	1	1	1
4	0	0	0	3
5	0	0	0	4

Table 69: Results for SFST

OF22	F41	Actual	Predicted	Occurrences
1	0	0	0	3
1	0	**1**	**0**	**1**
1	1	2	2	3
2	0	0	0	5
2	**0**	**1**	**0**	**1**
2	1	2	2	2
3	0	0	0	4
3	**0**	**2**	**0**	**1**
3	1	2	2	1

Table 70: Results for PR Benefit

OF19	OF21	F41	Actual	Predicted	Occurrences
0	0	1	2	2	1
0	4	0	0	0	10
0	**4**	**0**	**1**	**0**	**4**
0	4	1	1	1	3
0	**4**	**1**	**2**	**1**	**1**
1	4	0	2	2	1
1	4	1	2	2	1

Table 71: Results for NR Benefit

OF19	OF21	F41	Actual	Predicted	Occurrences
0	0	1	2	2	1
0	4	0	0	0	14
0	4	1	1	1	4
1	4	0	2	2	1
1	4	1	2	2	1

Table 72: Results for SR Benefit

OF17	OF23	Actual	Predicted	Occurrences
1	1	2	2	2
1	3	2	2	1
2	1	0	0	2
2	3	1	1	1
4	1	0	0	11
4	**1**	**1**	**0**	**1**
4	2	1	1	2
4	3	1	1	1

Table 73: Results for WS Benefit

F43	F44	Actual	Predicted	Occurrences
1	**1**	**1**	**2**	**2**
1	1	2	2	2
1	**2**	**1**	**2**	**1**
1	2	2	2	5
2	1	1	1	3
2	**2**	**2**	**1**	**1**
4	0	0	0	3
5	0	0	0	4

Table 74: Results for SFST Benefit

Model	**Top 2 Important Features**	**Bottom 2 Important Features**
Ridge	'F43': 0.536779 'F45': 0.192897	'OF8': -0.012789 'OF13': -0.009090
DecisionTreeRegressor	'F43': 1.515596 'F29': 0.037213	'F65': -0.022642 'F24': -0.017126
GradientBoostingRegressor	'F43': 1.346256 'OF26': 0.021221	'F3d': -0.003275 'F13': -0.000601
RandomForestRegressor	'F43': 1.182576 'OF26': 0.042053	'F13': -0.001210 'F3f': -0.000922
AdaBoostRegressor	'F43': 1.431664 'OF26': 0.020958	'F15': -0.001777 'F49': -0.001246
KNeighborsRegressor	'F5': 0.708910 'F3d': 0.003255	'OF27': -0.055648 'F41': 0.000000
MLPRegressor	'OF27': 1.309096 'F14': 0.515494	'F5': -2.923432 'F25': -0.309051
ElasticNet	'F43': 0.441983 'F45': 0.245119	'OF2': 0.000000 'F39': 0.000000
SVR	'F5': 0.048764 'OF27': 0.010900	'OF18': -0.000016 'F3g': -0.000009
BayesianRidge	'F43': 0.383303 'F45': 0.171036	'OF8': -0.004480 'OF38': -0.003056
KernelRidge	'F43': 0.542174 'F45': 0.191382	'OF8': -0.013750 'OF13': -0.008700
LinearRegression	'F43': 0.590500 'F7': 0.202867	'OF8': -0.012748 'OF6': -0.011382
RANSACRegressor	'OF21': 9.560983 'OF20': 7.545941	'F52': -0.194904 'OF16': -0.166460
TheilSenRegressor	'F43': 0.393848 'F45': 0.244852	'OF28': -0.006563 'OF8': -0.006284
Average Importance	'Feature OF21': 0.702052 'Feature F43': 0.625989 'Feature OF20': 0.544127 'Feature F45': 0.135707	'Feature F25': -0.009865 'Feature OF16': -0.011711 'Feature OF6': -0.011840 'Feature F5': -0.138349
Voting System	'Feature F43': 1321 points 'Feature F1': 1186 points 'Feature F14': 1171 points 'Feature F7': 1150 points	'Feature OF28': 421 points 'Feature OF13': 408 points 'Feature F39': 381 points 'Feature OF2': 377 points

Table 75: Features for PR Models

Model	Top 2 Important Features	Bottom 2 Important Features
Ridge	'F43': 0.390725 'F44': 0.165844	'OF6': -0.020725 'OF33': -0.013250
DecisionTreeRegressor	'F43': 1.774561 'F24': 0.057620	'F3e': -0.008175 'F49': -0.005408
GradientBoostingRegressor	'F43': 1.620630 'F24': 0.022750	'F3c': -0.000362 'F12': -0.000226
RandomForestRegressor	'F43': 0.817959 'F12': 0.218402	'F47': -0.011895 'F21': -0.009079
AdaBoostRegressor	'F43': 1.720332 'F24': 0.038324	'F50': -0.000827 'F12': -0.000806
KNeighborsRegressor	'F5': 0.533441 'OF27': 0.061891	'OF13': -0.000245 'OF9': -0.000204
MLPRegressor	'F5': 0.153295 'F45': 0.111910	'F2': -0.017481 'F14': -0.014245
ElasticNet	'F43': 0.506674 'F45': 0.266837	'OF2': 0.000000 'F38': 0.000000
SVR	'F5': 0.025143 'OF27': 0.006574	'OF5': -0.000005 'F3g': -0.000004
BayesianRidge	'F43': 0.428843 'F45': 0.148416	'OF6': -0.007226 'OF34': -0.006675
KernelRidge	'F43': 0.406266 'F44': 0.176189	'OF6': -0.021310 'OF8': -0.014864
LinearRegression	'F43': 0.346340 'F44': 0.199381	'OF6': -0.027631 'OF33': -0.018511
RANSACRegressor	'F45': 0.448435 'F44': 0.221599	'F33': -0.038320 'F8': -0.023706
TheilSenRegressor	'F43': 0.316211 'F44': 0.201227	'OF6': -0.027462 'OF33': -0.015219
Average Importance	'Feature F43': 0.612435 'Feature F45': 0.117268 'Feature F44': 0.081121 'Feature F5': 0.053705	'Feature F8': -0.004219 'Feature F33': -0.004765 'Feature OF6': -0.005082 'Feature OF33': -0.006181
Voting System	'Feature F43': 1343 points 'Feature F45': 1220 points 'Feature F44': 1151 points 'Feature F3f': 1137 points	'Feature F32': 377 points 'Feature F67': 360 points 'Feature F33': 358 points 'Feature F39': 352 points

Table 76: Features for NR Models

Model	**Top 2 Important Features**	**Bottom 2 Important Features**
Ridge	'F43': 1.147478 'F45': 0.091115	'OF24': -0.025517 'F24': -0.016204
DecisionTreeRegressor	'F43': 1.754513 'F22': 0.147253	'F20': -0.014787 'F29': -0.009592
GradientBoostingRegressor	'F43': 1.511286 'F22': 0.110634	'F20': -0.003293 'F46': -0.001353
RandomForestRegressor	'F43': 1.575029 'F22': 0.124296	'F20': -0.006019 'F2': -0.002894
AdaBoostRegressor	'F43': 1.391152 'F22': 0.044818	'OF6': -0.003275 'F51': -0.002221
KNeighborsRegressor	'F5': 0.559163 'OF27': 0.011390	'OF13': -0.001688 'OF9': -0.001394
MLPRegressor	'F5': 0.805548 'OF27': 0.188689	'F45': -0.084892 'F3e': -0.080038
ElasticNet	'F43': 0.898375 'F25': 0.020736	'OF27': -0.003515 'OF18': -0.000012
SVR	'F5': 0.036869 'F43': 0.000169	'OF27': -0.001506 'OF18': -0.000024
BayesianRidge	'F43': 0.726329 'F3b': 0.036111	'F68': -0.006553 'F6': -0.005987
KernelRidge	'F43': 1.163232 'F52': 0.098785	'OF24': -0.025737 'F24': -0.017471
LinearRegression	'F43': 1.185014 'F52': 0.186445	'OF24': -0.041529 'F24': -0.022150
RANSACRegressor	'F43': 0.787310 'F22': 0.434157	'F12': -0.331444 'F18': -0.283120
TheilSenRegressor	'F43': 1.195570 'F52': 0.204452	'OF24': -0.036281 'OF21': -0.026817
Average Importance	'Feature F43': 0.951765 'Feature F5': 0.097695 'Feature F22': 0.091916 'Feature F52': 0.048698	'Feature OF20': -0.008094 'Feature F62': -0.009468 'Feature F18': -0.020177 'Feature F12': -0.026529
Voting System	'Feature F43': 1346 points 'Feature F22': 1265 points 'Feature OF22': 1214 points 'Feature F25': 1178 points	'Feature F68': 451 points 'Feature F18': 439 points 'Feature OF8': 398 points 'Feature F62': 387 points

Table 77: Features for WS Models

Model	**Top 2 Important Features**	**Bottom 2 Important Features**
Ridge	’F43’: 1.145591 ’F1’: 0.032092	’F49’: -0.007396 ’F15’: -0.004882
DecisionTreeRegressor	’F43’: 1.956398 ’F48’: 0.016230	’OF3’: -0.012433 ’F47’: -0.006130
GradientBoostingRegressor	’F43’: 1.658540 ’F21’: 0.016892	’OF18’: -0.003418 ’F2’: -0.001442
RandomForestRegressor	’F43’: 1.507879 ’F44’: 0.017893	’F65’: -0.002316 ’OF15’: -0.001130
AdaBoostRegressor	’F43’: 1.680548 ’F21’: 0.008374	’OF18’: -0.005203 ’F8’: -0.003271
KNeighborsRegressor	’F5’: 0.650557 ’OF27’: 0.009803	’OF13’: -0.001657 ’OF9’: -0.001100
MLPRegressor	’F5’: 6.260377 ’OF27’: 1.699317	’F35’: -0.410244 ’F36’: -0.313736
ElasticNet	’F43’: 0.809538 ’F45’: 0.102403	’OF18’: -0.000019 ’OF2’: 0.000000
SVR	’F5’: 0.026701 ’F43’: 0.000142	’OF18’: -0.000016 ’OF5’: -0.000004
BayesianRidge	’F43’: 0.811364 ’F34’: 0.018542	’F15’: -0.002554 ’OF8’: -0.002456
KernelRidge	’F43’: 1.142568 ’F1’: 0.031358	’F49’: -0.007572 ’F15’: -0.004914
LinearRegression	’F43’: 1.219160 ’F1’: 0.046488	’F49’: -0.009860 ’F31’: -0.005465
RANSACRegressor	’F43’: 1.518405 ’F34’: 0.129466	’F36’: -0.016735 ’F48’: -0.012570
TheilSenRegressor	’F43’: 1.308138 ’F1’: 0.044073	’F49’: -0.008300 ’F20’: -0.005366
Average Importance	’Feature F43’: 1.039090 ’Feature F5’: 0.497852 ’Feature OF27’: 0.122599 ’Feature F45’: 0.035529	’Feature F4’: -0.014221 ’Feature OF9’: -0.019349 ’Feature F36’: -0.023610 ’Feature F35’: -0.027724
Voting System	’Feature F43’: 1305 points ’Feature F1’: 1149 points ’Feature F34’: 1093 points ’Feature F47’: 1076 points	’Feature OF8’: 399 points ’Feature F58’: 378 points ’Feature F49’: 330 points ’Feature F3g’: 300 points

Table 78: Features for SFST Models

Model	Top 2 Important Features	Bottom 2 Important Features
Ridge	'F41': 0.703613 'OF19': 0.405519	'OF20': -0.055471 'F48': -0.012283
DecisionTreeRegressor	'F41': 0.933778 'OF19': 0.555612	'OF30': -0.028011 'OF11': -0.001123
GradientBoostingRegressor	'F41': 0.877237 'OF19': 0.507981	'OF5': -0.004187 'F65': -0.001427
RandomForestRegressor	'F41': 0.949723 'OF19': 0.528025	'F3c': -0.001661 'OF11': -0.000769
AdaBoostRegressor	'F41': 1.009670 'OF19': 0.518803	'F17': -0.000691 'OF30': -0.000016
KNeighborsRegressor	'F5': 0.288869 'OF14': 0.000170	'OF27': -0.042150 'OF26': -0.000768
MLPRegressor	'F41': 0.069968 'F45': 0.054308	'OF27': -0.066358 'OF16': -0.048331
ElasticNet	'F43': 0.073112 'F41': 0.045888	'OF5': -0.010997 'OF13': -0.001769
SVR	'OF27': 0.010856 'F5': 0.009396	'OF5': -0.000006 'F3a': -0.000004
BayesianRidge	'F41': 0.154028 'OF21': 0.064929	'OF25': -0.018223 'F15': -0.013258
KernelRidge	'F41': 0.691473 'OF19': 0.396402	'OF20': -0.043222 'F48': -0.011175
LinearRegression	'F41': 0.751667 'OF19': 0.556543	'OF20': -0.031105 'S2': -0.012739
RANSACRegressor	'F41': 0.850172 'OF19': 0.528539	'OF21': -0.031337 'F48': -0.030173
TheilSenRegressor	'F41': 0.777552 'OF19': 0.557333	'OF20': -0.040786 'F48': -0.007471
Average Importance	'Feature F41': 0.558198 'Feature OF19': 0.331069 'Feature OF21': 0.124913 'Feature F5': 0.023782	'Feature OF7': -0.003062 'Feature OF16': -0.003171 'Feature F48': -0.004729 'Feature OF20': -0.008562
Voting System	'Feature F41': 1351 points 'Feature OF19': 1285 points 'Feature OF21': 1119 points 'Feature OF24': 1037 points	'Feature OF25': 478 points 'Feature F33': 478 points 'Feature F13': 472 points 'Feature F20': 424 points

Table 79: Features for PR Benefit Models

Model	**Top 2 Important Features**	**Bottom 2 Important Features**
Ridge	'OF19': 0.671544 'OF21': 0.468303	'OF20': -0.035512 'F62': -0.005597
DecisionTreeRegressor	'OF19': 0.844500 'OF21': 0.403633	'OF7': -0.000485 'OF24': -0.000437
GradientBoostingRegressor	'OF19': 0.821696 'OF21': 0.666593	'OF3': -0.001737 'F52': -0.001574
RandomForestRegressor	'F41': 0.813527 'F12': 0.655125	'OF18': -0.076716 'OF23': -0.049900
AdaBoostRegressor	'OF19': 0.806301 'OF21': 0.631670	'F12': -0.000092 'OF30': -0.000044
KNeighborsRegressor	'F5': 0.184602 'OF13': 0.000152	'OF27': -0.019385 'F35': -0.000665
MLPRegressor	'F24': 0.038007 'OF19': 0.036784	'OF5': -0.044193 'OF20': -0.043179
ElasticNet	'OF27': 0.043120 'F34': 0.041926	'OF13': -0.000296 'OF2': 0.000000
SVR	'OF27': 0.027782 'F5': 0.006478	'OF5': -0.000007 'F3a': -0.000003
BayesianRidge	'OF21': 0.129610 'OF20': 0.092130	'F15': -0.013227 'OF16': -0.012066
KernelRidge	'OF19': 0.660613 'OF21': 0.500996	'OF20': -0.022330 'OF38': -0.003980
LinearRegression	'OF19': 0.898653 'OF21': 0.714826	'OF20': -0.023416 'S2': -0.008183
RANSACRegressor	'OF19': 0.906854 'F41': 0.409029	'F32': -0.004250 'OF22': -0.002480
TheilSenRegressor	'OF19': 0.891270 'F41': 0.396657	'F33': -0.004966 'F34': -0.003339
Average Importance	'Feature OF19': 0.497638 'Feature F41': 0.294398 'Feature OF21': 0.268613 'Feature F12': 0.045374	'Feature OF22': -0.001403 'Feature OF5': -0.001777 'Feature F20': -0.001792 'Feature OF18': -0.002347
Voting System	'Feature OF19': 1294 points 'Feature F41': 1231 points 'Feature OF21': 1143 points 'Feature F1': 1056 points	'Feature S1': 430 points 'Feature S2': 407 points 'Feature F68': 354 points 'Feature F20': 269 points

Table 80: Features for SR Benefit Models

Model	**Top 2 Important Features**	**Bottom 2 Important Features**
Ridge	'F45': 0.354192 'F43': 0.223956	'OF38': -0.029008 'OF33': -0.021786
DecisionTreeRegressor	'F43': 1.823320 'F25': 0.050814	'OF22': -0.006792 'OF28': -0.006266
GradientBoostingRegressor	'F43': 1.535820 'OF22': 0.023043	'F23': -0.000647 'F65': -0.000644
RandomForestRegressor	'F43': 1.094504 'F44': 0.097645	'F31': -0.001984 'F25': -0.001022
AdaBoostRegressor	'F43': 1.700848 'F22': 0.019314	'OF2': -0.002059 'S4': -0.001717
KNeighborsRegressor	'F5': 0.430873 'OF27': 0.118516	'OF13': -0.000089 'F41': 0.000000
MLPRegressor	'F43': 0.150892 'F45': 0.147232	'F3d': -0.018913 'F17': -0.014442
ElasticNet	'F43': 0.426430 'F45': 0.233256	'OF18': -0.000013 'OF2': 0.000000
SVR	'OF27': 0.023293 'F5': 0.008348	'OF18': -0.000016 'F54': -0.000006
BayesianRidge	'F43': 0.310904 'F45': 0.239989	'OF38': -0.012652 'F54': -0.009201
KernelRidge	'F45': 0.349817 'F43': 0.231780	'OF38': -0.025551 'OF33': -0.022170
LinearRegression	'F45': 0.380422 'F44': 0.171212	'F3c': -0.042531 'OF38': -0.036337
RANSACRegressor	'F45': 2.335171 'F24': 1.789909	'OF31': -0.330208 'F3c': -0.245296
TheilSenRegressor	'F45': 0.448860 'F52': 0.173472	'F3c': -0.036481 'OF38': -0.032400
Average Importance	'Feature F43': 0.563853 'Feature F45': 0.320945 'Feature F24': 0.140763 'Feature OF21': 0.114374	'Feature F58': -0.013924 'Feature OF38': -0.021798 'Feature F3c': -0.026023 'Feature OF31': -0.028798
Voting System	'Feature F43': 1365 points 'Feature F45': 1260 points 'Feature F31': 1135 points 'Feature F24': 1130 points	'Feature F21': 426 points 'Feature S2': 384 points 'Feature OF34': 377 points 'Feature OF2': 255 points

Table 81: Features for SR Models

Model	Top 2 Important Features	Bottom 2 Important Features
Ridge	'OF10': 0.434765 'OF19': 0.414841	'F29': -0.029499 'OF33': -0.025170
DecisionTreeRegressor	'OF10': 0.796662 'OF19': 0.563827	'F51': -0.001892 'OF23': -0.000782
GradientBoostingRegressor	'OF10': 0.671728 'OF19': 0.464892	'F65': -0.004832 'OF3': -0.003717
RandomForestRegressor	'OF10': 0.836535 'OF19': 0.444950	'OF3': -0.003660 'OF5': -0.003092
AdaBoostRegressor	'OF10': 0.708734 'OF19': 0.393413	'OF3': -0.009379 'OF5': -0.007220
KNeighborsRegressor	'F5': 0.327369 'OF27': 0.003880	'OF26': -0.002144 'F24': -0.001972
MLPRegressor	'F35': 0.309029 'F34': 0.088340	'OF27': -0.878888 'F3g': -0.151826
ElasticNet	'OF9': 0.106174 'OF10': 0.081926	'OF5': -0.039847 'OF27': -0.021988
SVR	'F5': 0.012487 'OF9': 0.000024	'OF27': -0.005404 'OF5': -0.000020
BayesianRidge	'OF10': 0.142219 'OF9': 0.092250	'OF3': -0.025231 'OF5': -0.021868
KernelRidge	'OF10': 0.424293 'OF21': 0.421672	'F29': -0.034079 'OF33': -0.024907
LinearRegression	'OF21': 0.607966 'OF19': 0.595742	'OF33': -0.018405 'F3g': -0.016241
RANSACRegressor	'OF10': 0.845077 'F50': 0.680531	'OF20': -0.141968 'OF21': -0.098952
TheilSenRegressor	'OF19': 0.630024 'OF21': 0.585880	'OF33': -0.017230 'F7': -0.015492
Average Importance	'Feature OF10': 0.417809 'Feature OF19': 0.312239 'Feature OF21': 0.205786 'Feature F41': 0.075133	'Feature OF6': -0.007846 'Feature OF25': -0.008854 'Feature F3g': -0.014606 'Feature OF27': -0.065078
Voting System	'Feature OF10': 1342 points 'Feature OF19': 1236 points 'Feature F41': 1198 points 'Feature OF21': 1189 points	'Feature F25': 433 points 'Feature OF3': 372 points 'Feature OF5': 358 points 'Feature F36': 356 points

Table 82: Features for NR Benefit Models

Model	**Top 2 Important Features**	**Bottom 2 Important Features**
Ridge	'OF17': 0.901439 'OF23': 0.333440	'OF37': -0.087702 'F20': -0.063504
DecisionTreeRegressor	'OF17': 1.460172 'OF23': 0.207532	'F23': -0.006009 'OF5': -0.003486
GradientBoostingRegressor	'OF17': 1.489140 'OF23': 0.131793	'F41': -0.003486 'F65': -0.002410
RandomForestRegressor	'F53': 7.896065 'OF24': 0.623784	'OF18': -2.847741 'OF22': -0.226609
AdaBoostRegressor	'OF17': 1.300579 'OF23': 0.082517	'F21': -0.001078 'OF34': -0.000603
KNeighborsRegressor	'OF27': 0.359802 'F5': 0.237931	'F35': -0.000053 'F45': -0.000035
MLPRegressor	'F2': 2.912182 'F6': 0.921916	'F5': -9.126598 'F3c': -2.098251
ElasticNet	'OF17': 0.411531 'F54': 0.084062	'F5': -0.020583 'F31': -0.001072
SVR	'OF27': 0.028316 'OF5': 0.000032	'F5': -0.001905 'OF18': -0.000007
BayesianRidge	'OF17': 0.851256 'OF23': 0.199564	'F20': -0.033465 'OF11': -0.023769
KernelRidge	'OF17': 0.835658 'F24': 0.376621	'OF37': -0.072615 'F20': -0.055666
LinearRegression	'OF17': 0.888735 'OF23': 0.385073	'OF37': -0.178323 'OF21': -0.095820
RANSACRegressor	'OF20': 3.351361 'OF21': 3.174862	'S2': -0.562348 'OF6': -0.521871
TheilSenRegressor	'OF17': 0.850844 'OF23': 0.332914	'OF37': -0.128644 'F20': -0.045430
Average Importance	'Feature OF17': 0.671066 'Feature F53': 0.620027 'Feature OF20': 0.235132 'Feature OF21': 0.218170	'Feature F33': -0.103096 'Feature F3c': -0.145086 'Feature F3d': -0.161077 'Feature F5': -0.651739
Voting System	'Feature OF17': 1307 points 'Feature F52': 1237 points 'Feature OF23': 1212 points 'Feature F51': 1189 points	'Feature F64': 381 points 'Feature F67': 376 points 'Feature F33': 369 points 'Feature F5': 323 points

Table 83: Features for WS Benefit Models

Model	Top 2 Important Features	Bottom 2 Important Features
Ridge	'F43': 1.068454 'F50': 0.068869	'OF20': -0.020697 'OF11': -0.012037
DecisionTreeRegressor	'F43': 1.323816 'OF28': 0.159743	'F65': -0.007496 'OF16': -0.006533
GradientBoostingRegressor	'F43': 1.196512 'OF28': 0.082922	'F47': -0.001079 'F18': -0.000807
RandomForestRegressor	'OF28': 0.538508 'OF22': 0.071115	'F43': -1.649695 'OF18': -0.549475
AdaBoostRegressor	'F43': 0.969779 'OF28': 0.094944	'OF5': -0.004574 'F3f': -0.002689
KNeighborsRegressor	'F5': 0.763124 'OF27': 0.157415	'OF13': -0.000378 'OF9': -0.000315
MLPRegressor	'F45': 1.611972 'F3b': 0.504369	'F3a': -0.517319 'OF2': -0.487867
ElasticNet	'F43': 0.821764 'OF18': 0.086786	'OF2': 0.000000 'F39': 0.000000
SVR	'F5': 0.059692 'OF27': 0.027247	'F3g': -0.000010 'OF2': -0.000007
BayesianRidge	'F43': 0.769779 'OF18': 0.039686	'OF20': -0.017260 'OF11': -0.013994
KernelRidge	'F43': 1.045855 'F50': 0.051678	'OF20': -0.029024 'OF11': -0.014729
LinearRegression	'F43': 1.074091 'F50': 0.103631	'S2': -0.015593 'OF20': -0.012721
RANSACRegressor	'F43': 2.910780 'F45': 0.534127	'F9': -0.129027 'F23': -0.081989
TheilSenRegressor	'F43': 1.144618 'F6': 0.082759	'OF21': -0.062422 'OF20': -0.053491
Average Importance	'Feature F43': 0.755861 'Feature F45': 0.141279 'Feature F5': 0.083083 'Feature OF28': 0.061002	'Feature F3e': -0.012449 'Feature F3d': -0.015819 'Feature OF13': -0.020652 'Feature F3a': -0.025738
Voting System	'Feature F43': 1158 points 'Feature OF18': 1122 points 'Feature F1': 1100 points 'Feature OF28': 1080 points	'Feature F62': 425 points 'Feature S2': 416 points 'Feature F22': 366 points 'Feature F20': 362 points

Table 84: Features for SFST Benefit Models

6 Bibliography