Random Forest Documentation for 'Conservation Priority Species Richness'

1. Modeling Procedure

We used classification Random Forests (RF) analysis to explore associations among SC Stream Assessment response variables and NFHAP spatial predictor variables (Breiman 2001, Cutler et al. 2007). Machine learning techniques such as RF provide an alternative modeling paradigm to traditional statistics, where no a priori model is defined, and complex data structures (non-normal distributions, interactions) are accommodated. Machine learning techniques use an algorithm to learn the relationship between the response and its predictors by identifying dominant patterns in the dataset (Breiman 2001, Elith et al. 2008). Random Forests represent an advance in machine learning techniques that have increased the accuracy and prediction power of single classification and regression trees by the creation of an ensemble of trees (Breiman 2001). Random forests are non-parametric, can handle both categorical and continuous data as either predictor and/or response variables, can handle high-order interactions, are insensitive to outliers, and can accommodate missing data by using surrogates (Breiman 2001, De'ath and Fabricius 2000, Urban 2002). Categorical Random Forests fit an ensemble of trees to a dataset, where each individual tree in the forest is built using a randomly selected bootstrap sample of the training dataset. In addition, only a random subset of predictor variables is considered for node and splitpoint selection (Amit and German 1997). In this way, two elements of randomness are injected into the procedure. Observations not included in the bootstrap samples are passed down their respective trees, and each tree's terminal nodes contain a predicted categorical response to different combinations of observed values among predictor variable pathways. Each tree has a 'vote' in the most important predictive variables to split on, and on the categorical responses of different values of input combinations; and the majority of votes among the ensemble of trees 'wins'. Therefore, we can a) predict and rank variables that most strongly influence an outcome (variable importance plot), and b) isolate and examine the behavior of individual predictors on the outcome, while holding the effect of all other predictive variables constant (partial dependence plots).

RF modeling was conducted by building 5000 trees using default values for other parameters in the randomForest package in the R programming environment (R Core Team 2012). RF models have known biases in variable importance selection for highly correlated predictor variables; therefore we conducted a preliminary screening of our abiotic variables to eliminate highly correlated variables. Correlations remaining in models are listed in documentation item 6.

Literature Cited

Amit, Y., and D. German. 1997. Shape quantization and recognition with randomized trees. Neural Computation **9**:1545-1588.

Breiman, L. 2001. Random Forests. Machine Learning **45**:5-32.

Cutler, D., T. Edwards, K. Beard, A. Cutler, K. Hess, J. Gibson, and J. Lawler. 2007. Random forests for classification in ecology. Ecology 88: 2783 – 2792.

De'ath, G., and K.E. Fabricus. 2000. Classification and regression trees: a powerful yet simple technique for ecological data analysis. . Ecology **81**:3178-3192.

Elith, J., Leathwick, J. R., Hastie, T. 2008. A working guide to boosted regression trees. Journal of Animal Ecology **77**:802-813.

R Core Team. 2012. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org/.

Urban, D. L. 2002. Classification and regression trees.*in* B. a. J. B. G. McCune, editor. Analysis of Ecological Communities. MjM Software Design, Oregon

2. Error Estimates Procedure

The RF algorithm builds trees based on repeated randomized samples of the dataset, hence it is not essential to hold back data for testing after model creation to obtain an unbiased estimate of error. Model performance was evaluated with three accuracy measures calculated using the resubstitution method (Theodoridis and Kourtroumbas 2006). The three measures were the Proportion Correctly Classified (PCC), Cohen's weighted Kappa statistic (weighted $_{\kappa}$), and the area under the receiver operating curve (AUC). Both PCC and weighted $_{\kappa}$ are derived from the model confusion matrix, which gives the number of actual versus predicted classifications of group membership. PCC performance measures are given in two forms: 1) an overall PCC percentage (accuracy) representing the number of correctly classified cases divided by the total number of cases across all outcome classes, and 2) a measure of accuracy for a specific outcome class (precision). Weighted $_{\kappa}$ corrects the overall PCC for agreement caused by chance, and gives a value ranging from -1 to 1 (Cohen 1968). A positive value indicates greater agreement between modeled and measured classifications than expected by chance alone, and a negative value indicates less agreement than expected by chance alone (Table 2). Cohen's weighted $_{\kappa}$ was calculated using the vcd package in R (R Core Team 2012). The AUC is derived from plotting the true positive rate (sensitivity) against the false positive rate (specificity), with each point plotted representing a sensitivity/specificity pair. The area under the resulting plot is a measure of how well the model correctly classifies groups. AUC values range from 0 to 1, with values > 0.5 indicating better model performance than expected by chance alone (Swets 1988). We used the ordROC function in the nonbinROC R package in R to calculate AUC values (http://cran.rproject.org/web/packages/nonbinROC/index.html).

Literature Cited

Cohen, J. 1968. Weighted kappa: nominal scale agreement with provision for scaled disagreement or partial credit. Psychological Bulletin. 70:213

R Core Team. 2012. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org/.

Swets, J. A. 1988. Measuring the accuracy of diagnostic systems. Science **240**:1285-1293.

Theodoridis, S., and K. Kourtroumbas. 2009. Pattern Recognition. 4th edition. Elsevier, New York.

3. Response Variable Definition

Researchers developed a quantitative and objective index to assess and rank conservation priority among South Carolina stream fish species using South Carolina Stream Assessment data (SCDNR 2014). The quantitative index used to assign conservation priority is based on multiple attributes related to risk of imperilment including: abundance, frequency of occurrence, range size, and existing range-wide conservation status. This index resulted in a list of 54 South Carolina Stream Fish species representing highest conservation priority among all species found in the state. Sites with low conservation priority richness may reflect degraded stream quality.

Fish data used to calculate this metric were collected as part of the South Carolina Stream Assessment. This metric was calculated using data from 167 wadeable freshwater stream sample locations in South Carolina's upstate, a region which includes four major drainage basins (Catawba/Wateree Rivers, Broad River, Saluda River, Savannah River), and four Level IV ecoregions (Blue Ridge, Inner Piedmont, Outer Piedmont, Slate Belt; Omernik 1987). Conservation Priority Richness is initially calculated as a count (richness) of priority species at a given sample location. Several subsequent steps were taken to transform conservation priority richness into a three-category metric, with designations for 1) low conservation priority species richness, 2) intermediate conservation priority species richness, and 3) high conservation priority species richness. We first had to account for the fact that streams with larger drainage areas have naturally greater species richness than streams with smaller drainage areas. To incorporate this trend in metric scoring, we developed Maximum Species Richness (MSR) graphs. MSR graphs were created by plotting Conservation Priority Richness against the log (base 10) transformed values of the corresponding drainage basin area. Lines delineating the 95th and 5th percentiles (where allowed) were drawn. The area between the two lines was trisected based on a method developed by Lyons (1992). Data points falling above the middle trisection scored 'high', those falling within the middle trisection scored 'intermediate', and those falling below the middle trisection scored 'low' (Figure 1).

Literature Cited

Lyons, J. 1992. Using the index of biotic integrity (IBI) to measure environmental quality in warmwater streams of Wisconsin. U.S. Department of Agriculture, Forest Service, General Technical Report NC-149. St. Paul, Minnesota: U.S. Department of Agriculture, Forest Service, North Central Forest Experiment Station. 51p.

Omernik, J. M. 1987. Ecoregions of the conterminous United States. Annals of the Association of American Geographers 77(1): 118-125.

SCDNR. 2014. South Carolina's State Wildlife Action Plan (SWAP). South Carolina Department of Natural Resources, Columbia, SC.

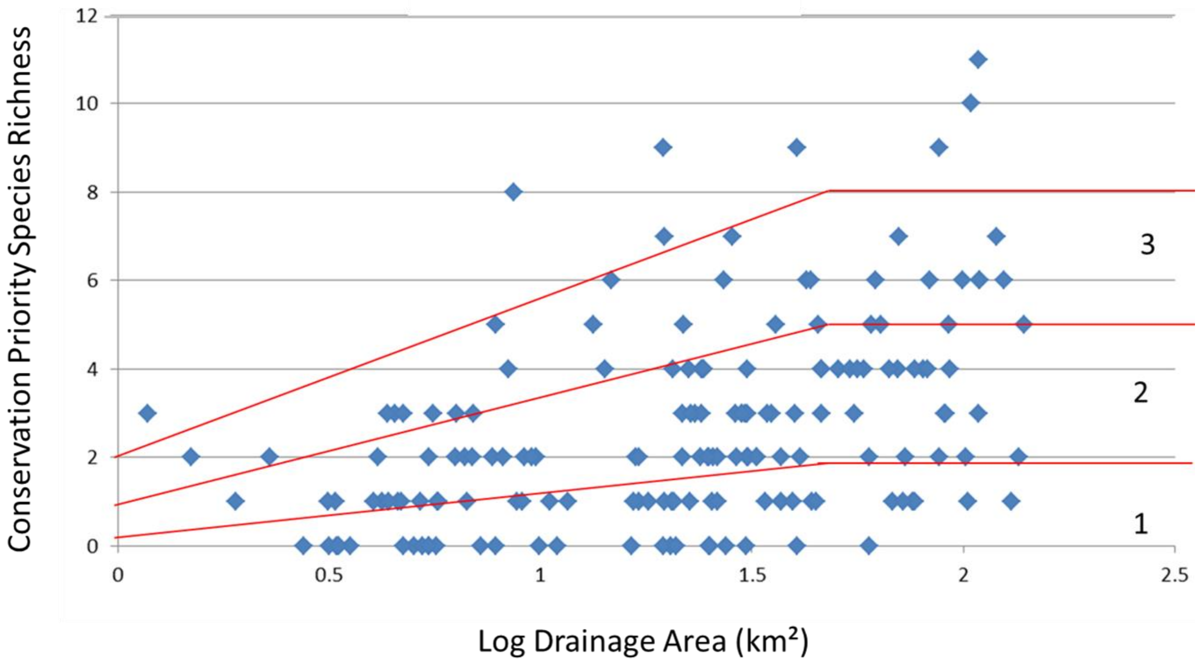


Table 1. MSR graph for Conservation Priority Species Richness. Number of conservation priority species plotted against the log (base10) transformed value of the drainage basin area (km2). N=167. Numbers along right side of figure denote scoring values (classification values) for different regions of the plot.

4. Variables Retained in Model

```
[1] "Dam_coC"              "C_H20_01"         "C_URBAN_01"           "C_FOREST_01"
 [5] "C_WETLAND_01"        "LengthkmC"        "SLOPE"                "SOILHYGRP"
 [9] "SOILPERM"            "Ele_meanC"        "U_Score_PriorityRich"
```

5. Model Call

```
*  randomForest(formula = U_Score_PriorityRich ~ ., data = PRS[,-1], keep.forest = TRUE, importance =
   TRUE, ntree = 5000,      do.trace = TRUE, type = 2)
             Type of random forest: classification
             Number of trees: 5000
             No. of variables tried at each split: 3
```

* The original call to randomForest (R package 'randomForest'; v4.5-36)

6. Correlations Remaining in Model

```
"i= 1 variables C_URBAN_01 and C_FOREST_01 correlation= -0.702056051893182"
"i= 2 variables Dam_coC and LengthkmC correlation= 0.673193517268735"
"i= 3 variables SLOPE and Ele_meanC correlation= 0.62549820453505"
"i= 4 variables C_FOREST_01 and SLOPE correlation= 0.500785079845662"
"i= 5 variables C_WETLAND_01 and SLOPE correlation= -0.370434112992506"
"i= 6 variables SOILHYGRP and SOILPERM correlation= -0.306473274941338"
"i= 7 variables SOILHYGRP and Ele_meanC correlation= -0.296283159965248"
"i= 8 variables C_WETLAND_01 and Ele_meanC correlation= -0.293212487579473"
"i= 9 variables C_FOREST_01 and SOILHYGRP correlation= 0.244443648761545"
"i= 10 variables C_FOREST_01 and C_WETLAND_01 correlation= -0.243466649477764"
```

7. List of Important Variables (Mean Decrease Accuracy)

Table 1. List of important variables in descending order of importance. Table denotes mean decrease in accuracy, and a weighting factor based on the percentage of importance explained relative to the most important predictor variable (SLOPE).

Predictor Variable	MeanDecreaseAccuracy	Weighting Factor
SLOPE	20.332	1.000
C_WETLAND_01	19.917	0.980
C_FOREST_01	17.370	0.854
SOILPERM	14.626	0.719
LengthkmC	11.120	0.547
Dam_coC	8.833	0.434
SOILHYGRP	3.318	0.163
C_H20_01	2.752	0.135
Ele_meanC	2.616	0.129
C_URBAN_01	2.425	0.119

8. Variable Importance Plot

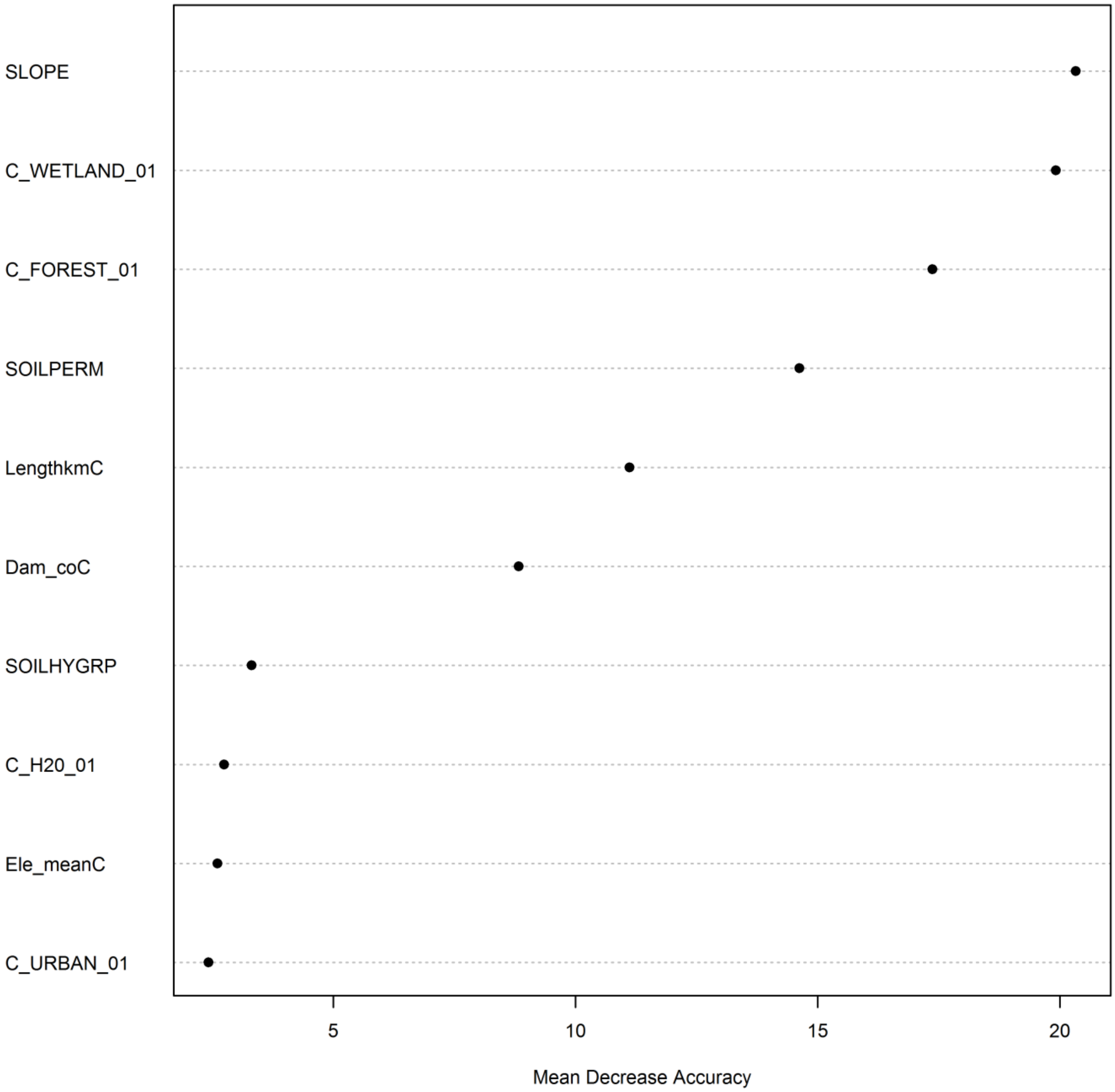
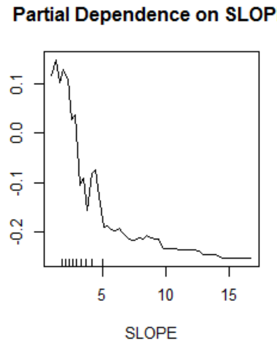


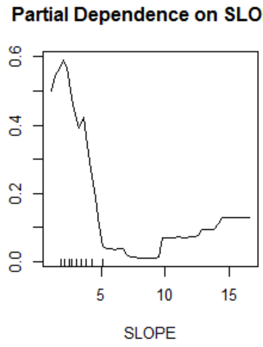
Figure 2. Top ranked variables from random forests classification for predicting Conservation Priority Species Richness in Upstate South Carolina**.**

9. Partial Dependence Plots

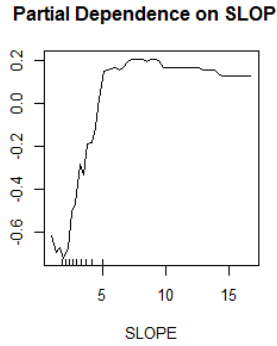
Partial dependence plots isolate and examine the relationships between top ranked predictors and Conservation Priority Species Richness (1=low conservation priority species richness, 2=intermediate conservation priority species richness, 3=high conservation priority species richness) while holding the effect of all other predictive variables constant.



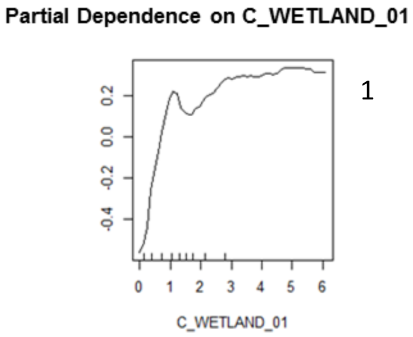
1



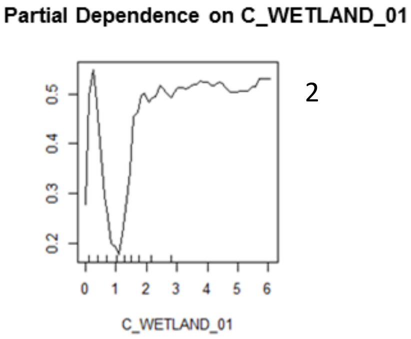
2



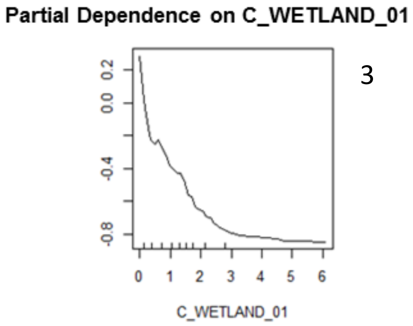
3



1

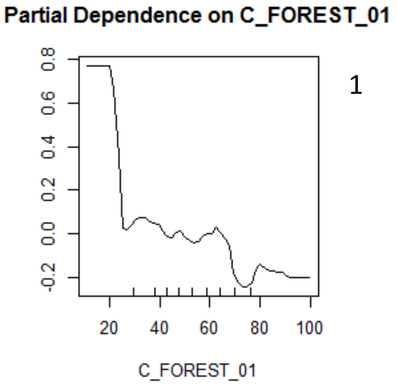


2

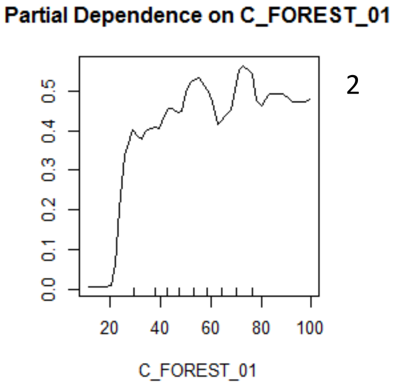


3

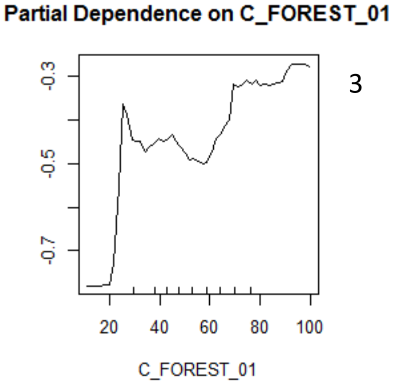
Partial Dependence on C_WETLAND_01


Partial Dependence on C_FOREST_01
-0.2
0.0
0.2
0.4
0.6
0.8
20
40
60
80
100
C_FOREST_01

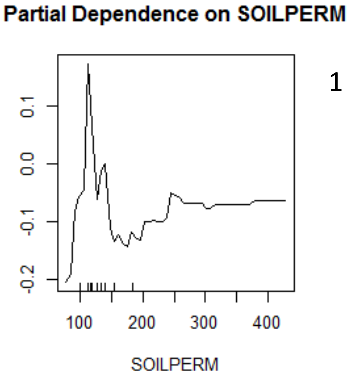
1


Partial Dependence on C_FOREST_01
0.0
0.1
0.2
0.3
0.4
0.5
20
40
60
80
100
C_FOREST_01

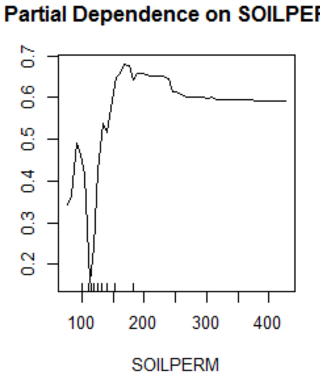
2


Partial Dependence on C_FOREST_01
-0.7
-0.5
-0.3
20
40
60
80
100
C_FOREST_01

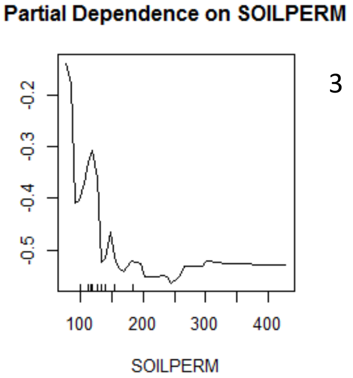
3


Partial Dependence on SOILPERM
-0.2
-0.1
0.0
0.1
100
200
300
400
SOILPERM

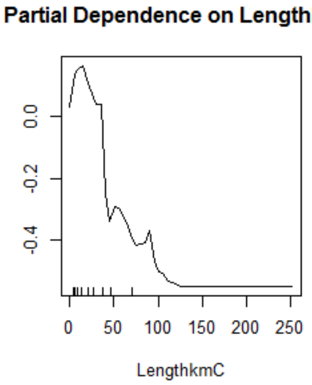
1


Partial Dependence on SOILPERM
0.2
0.3
0.4
0.5
0.6
0.7
100
200
300
400
SOILPERM

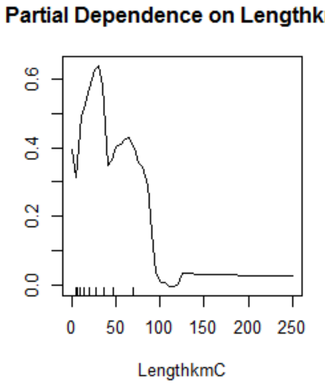
2


Partial Dependence on SOILPERM
-0.5
-0.4
-0.3
-0.2
100
200
300
400
SOILPERM

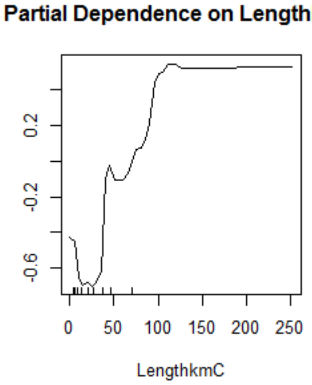
3


Partial Dependence on LengthkmC
0.0
-0.2
-0.4
0
50
100
150
200
250
LengthkmC

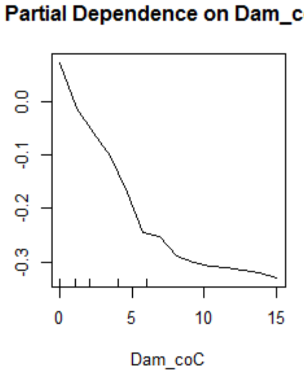
1


Partial Dependence on LengthkmC
0.6
0.4
0.2
0.0
0
50
100
150
200
250
LengthkmC

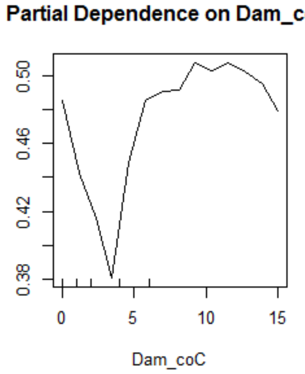
2


Partial Dependence on LengthkmC
0.2
-0.2
-0.6
0
50
100
150
200
250
LengthkmC

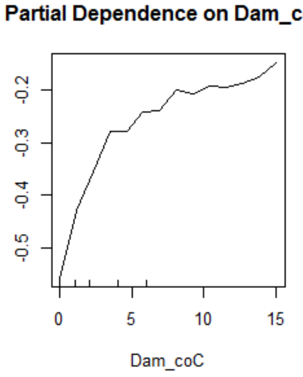
3


Partial Dependence on Dam_coC
0.0
-0.1
-0.2
-0.3
0
5
10
15
Dam_coC

1

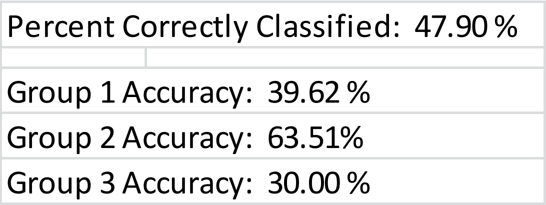

Partial Dependence on Dam_coC
0.50
0.46
0.42
0.38
0
5
10
15
Dam_coC

2

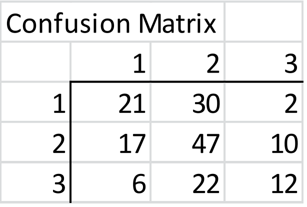

Partial Dependence on Dam_coC
-0.2
-0.3
-0.4
-0.5
0
5
10
15
Dam_coC

3

10. Error Estimate: PCC Result and Confusion Matrix



Percent Correctly Classified: 47.90 %	
Group 1 Accuracy: 39.62 %	
Group 2 Accuracy: 63.51%	
Group 3 Accuracy: 30.00 %	



Confusion Matrix			
	1	2	3
1	21	30	2
2	17	47	10
3	6	22	12

11. Error Estimate: Weighted K Result

*w*K = 0.22 (Fair Strength of Agreement)

12. Error Estimate: AUC Result

AUC = 0.62 (Model performance better than expected by chance alone)