

Introduction to decision trees and random forests

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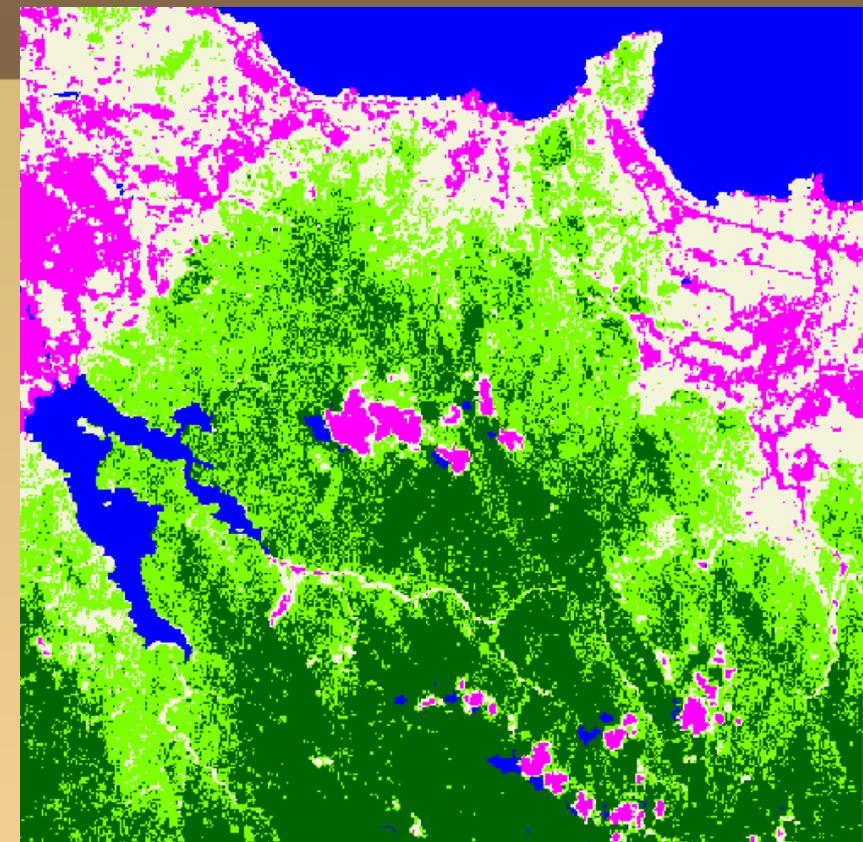
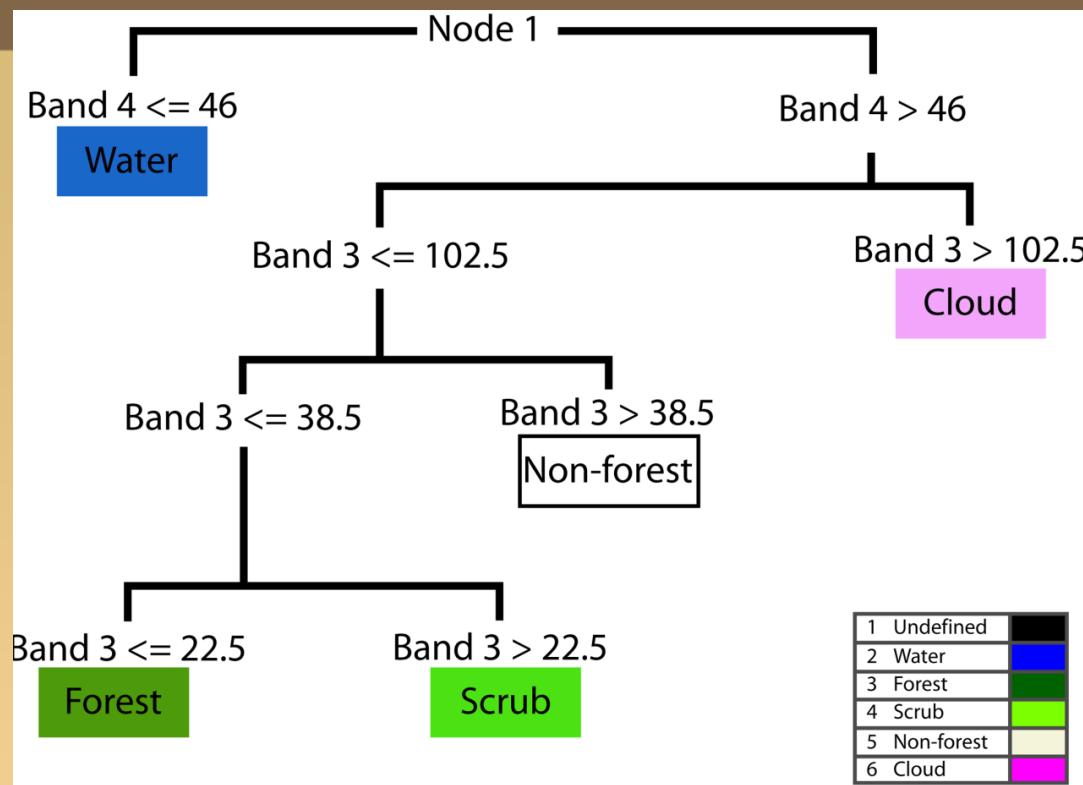
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What are decision trees?

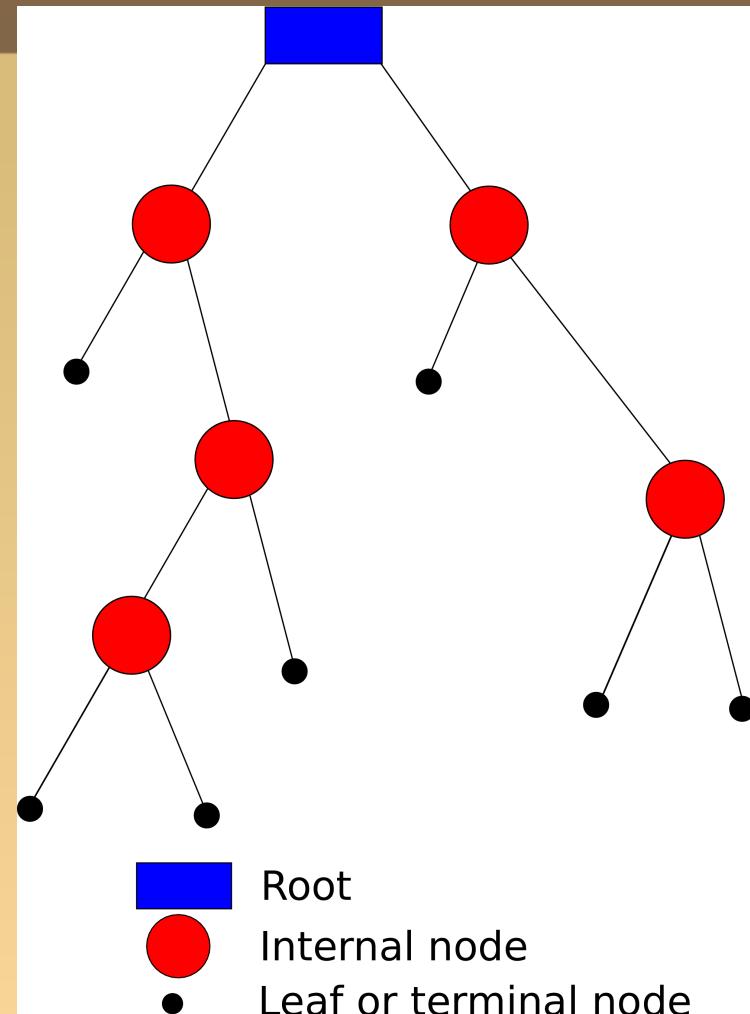
- A predictive model that uses a set of binary rules applied to calculate a target value
- Can be used for classification (categorical variables) or regression (continuous variables) applications
- Rules are developed using software available in many statistics packages
- Different algorithms are used to determine the “best” split at a node

Example classification tree

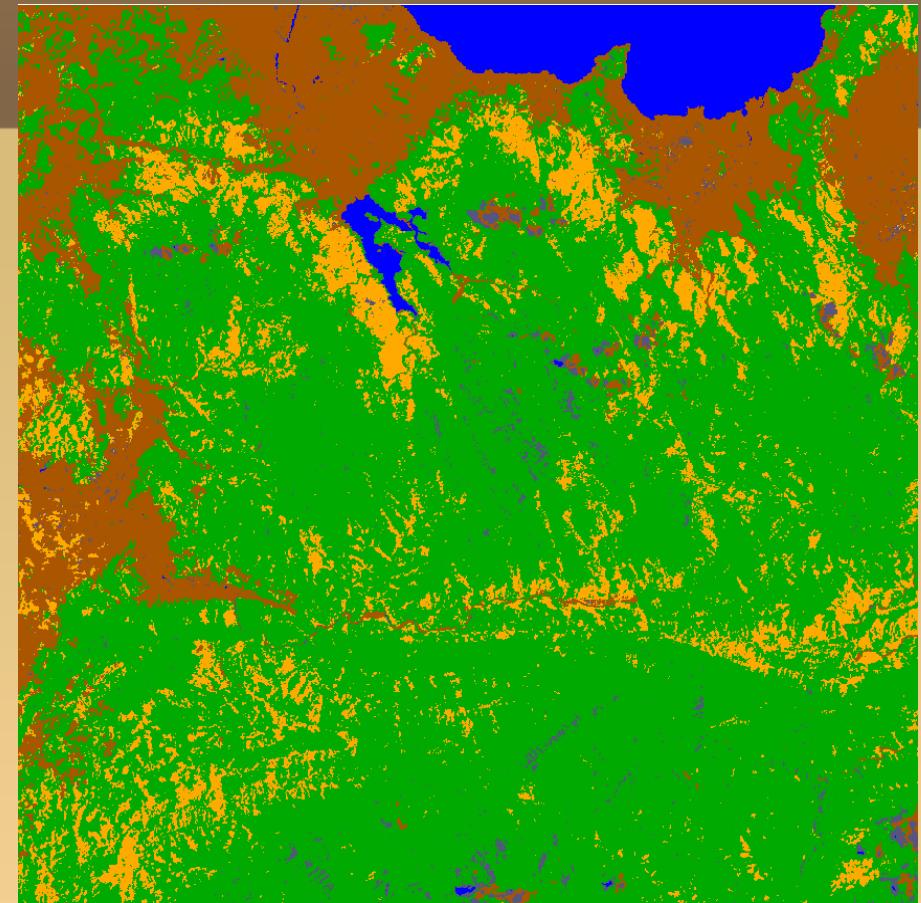


How do classification trees work?

- Uses training data to build model
- Tree generator determines:
 - Which variable to split at a node and the value of the split
 - Decision to stop (make a terminal note) or split again
 - Assign terminal nodes to a class

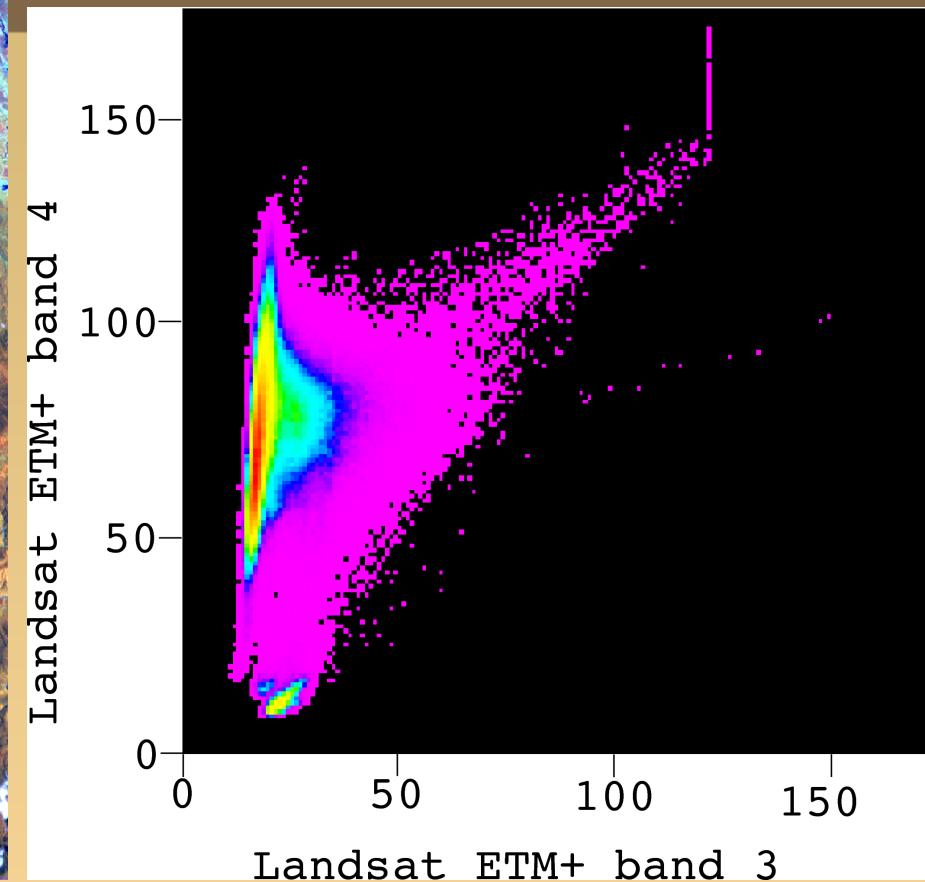


Dividing feature space – recursive partitioning



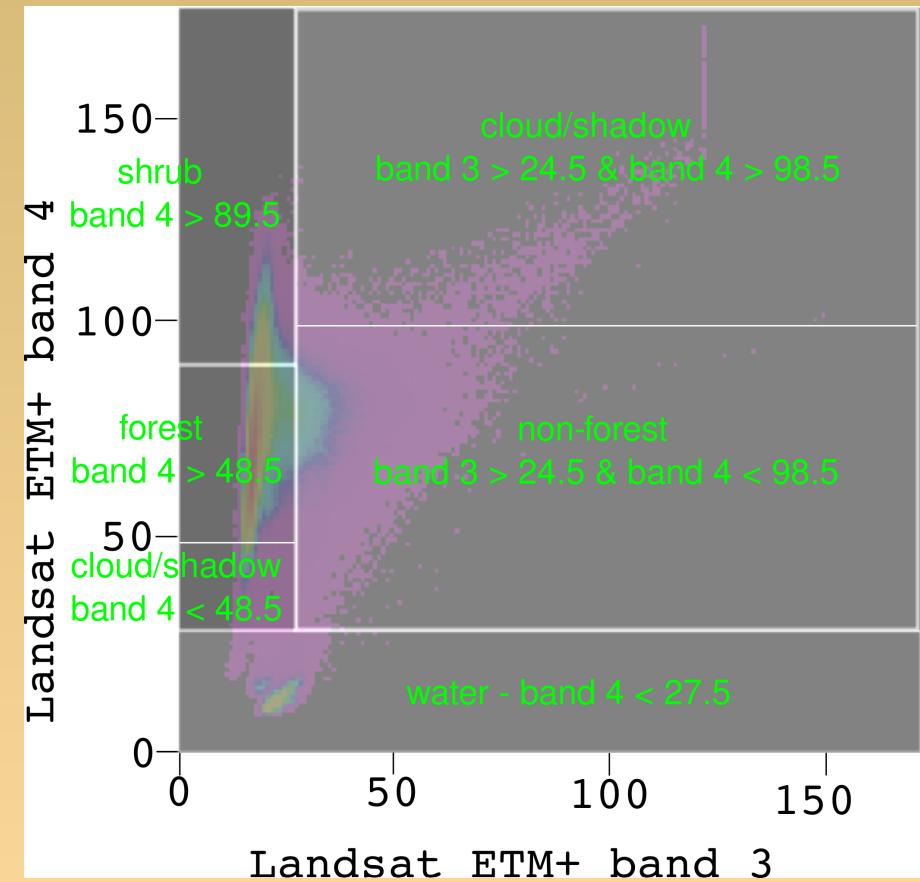
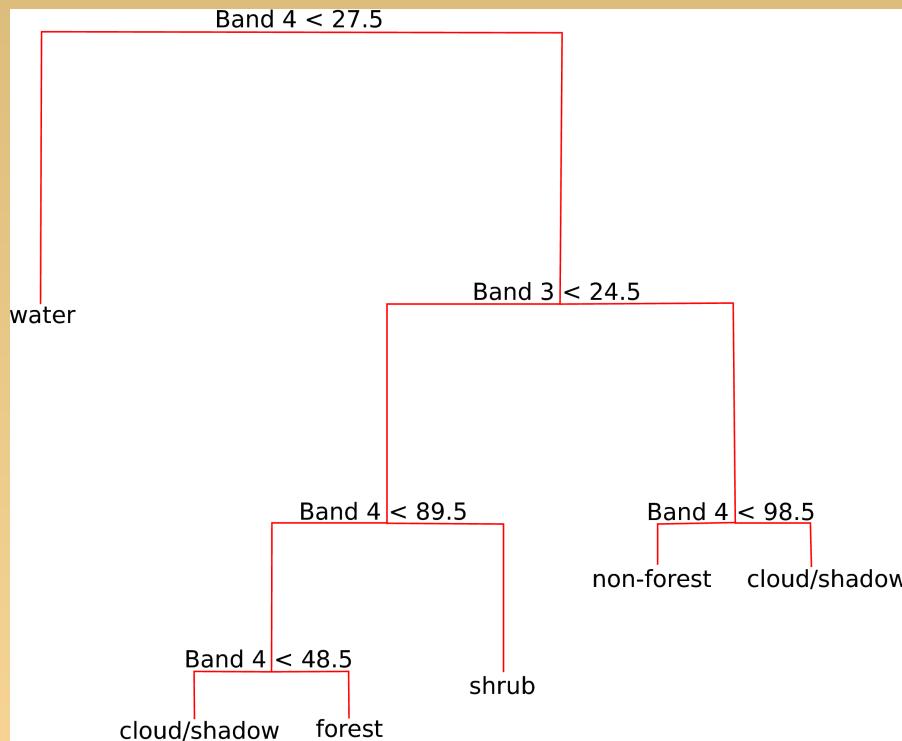
Blue = water
Green = forest
Yellow = shrub
Brown = non-forest
Gray = cloud/shadow

Dividing feature space – recursive partitioning

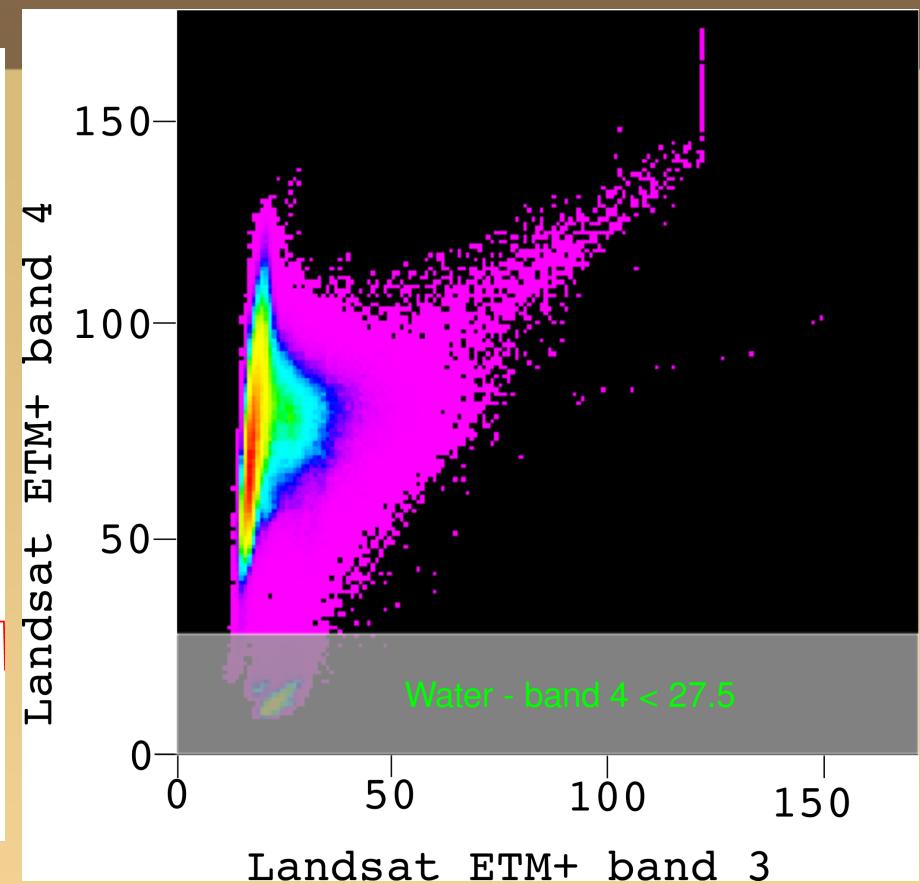
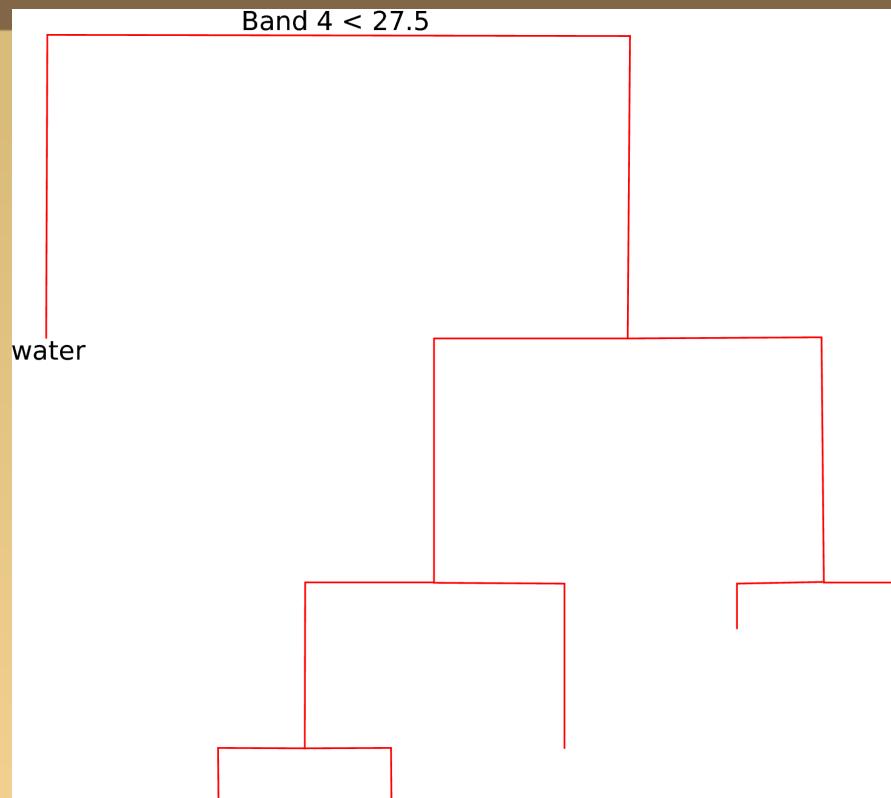


Dividing feature space – recursive partitioning

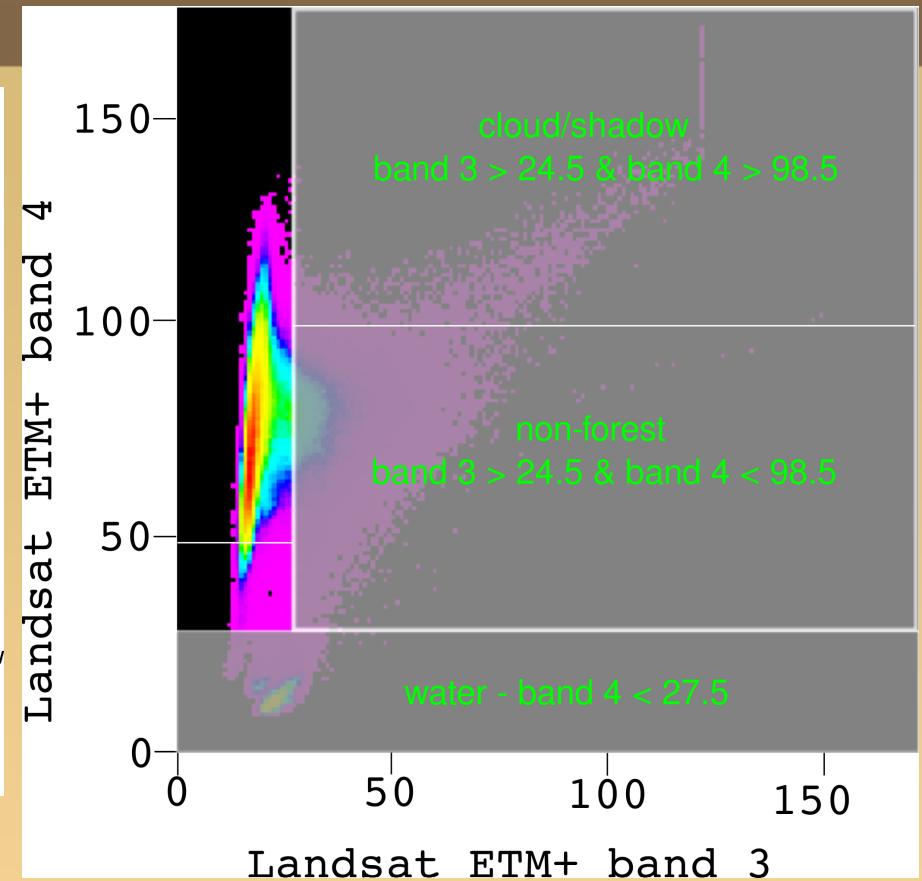
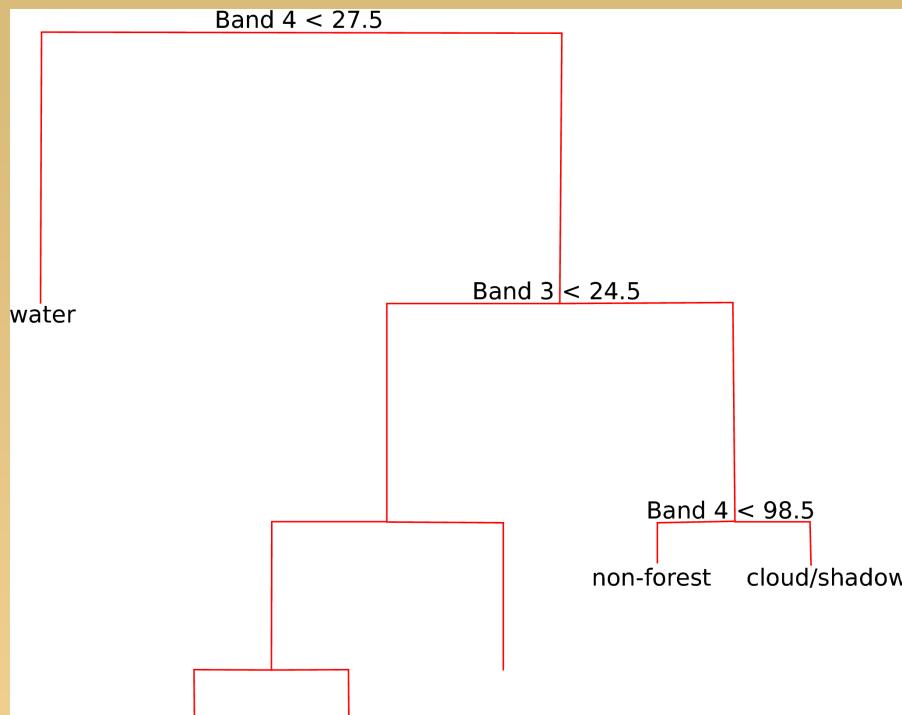
A constant (class or predicted function value) is assigned to each rectangle



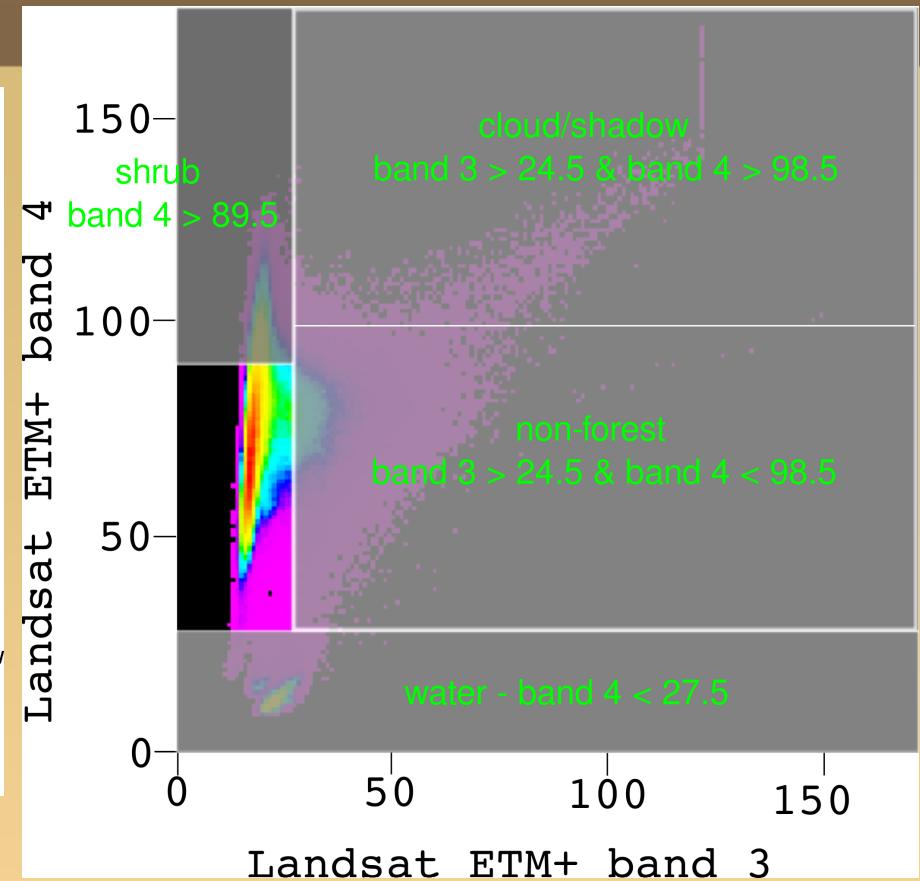
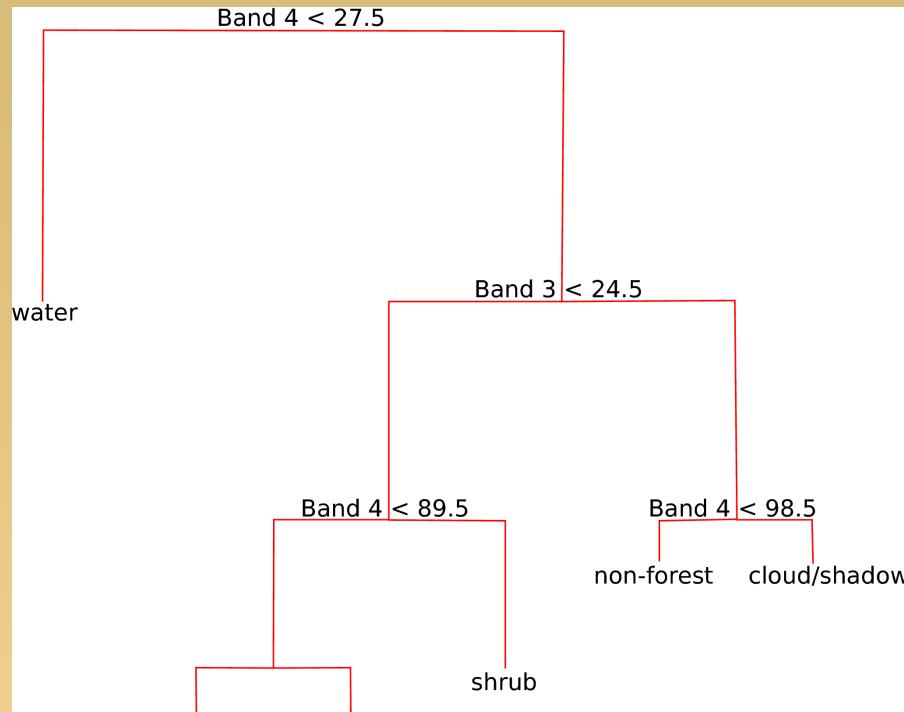
Dividing feature space – recursive partitioning



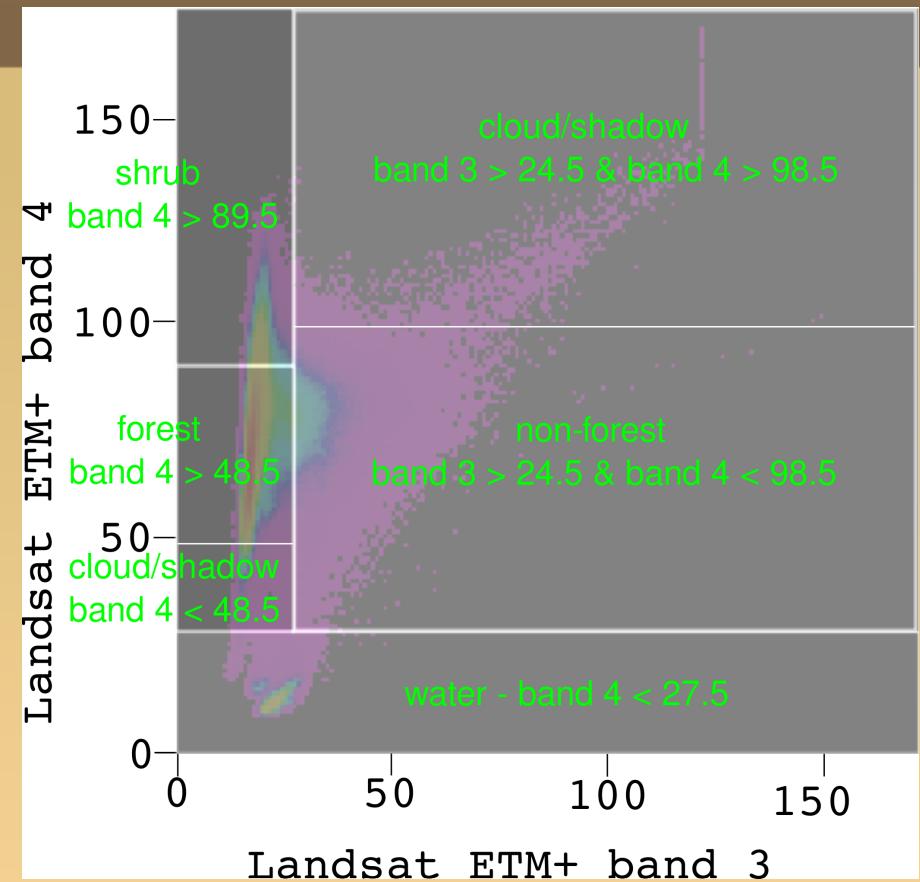
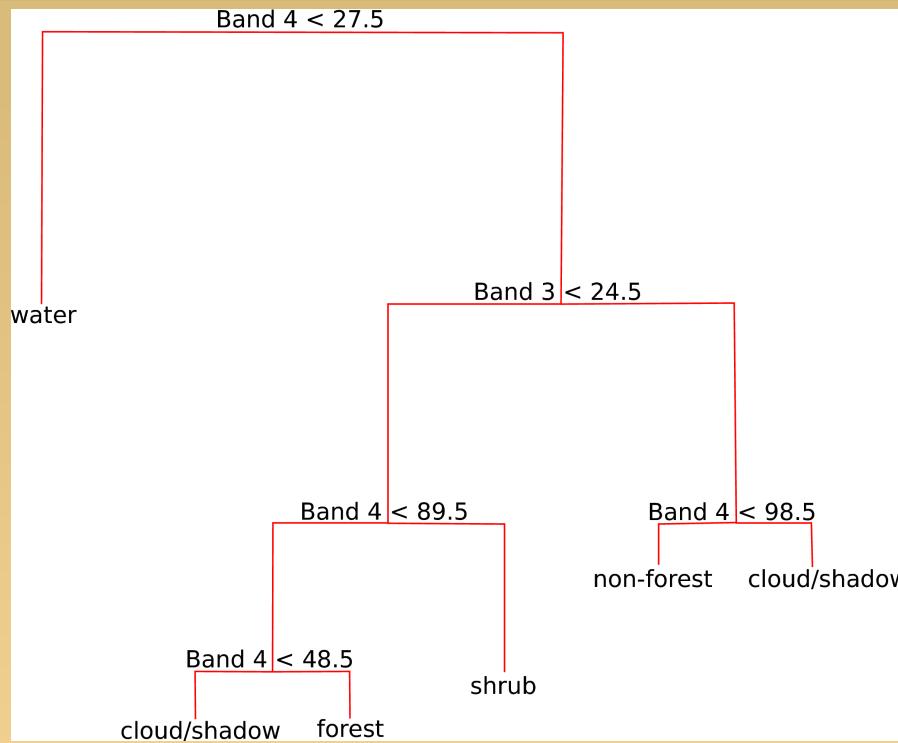
Dividing feature space – recursive partitioning



Dividing feature space – recursive partitioning



Dividing feature space – recursive partitioning

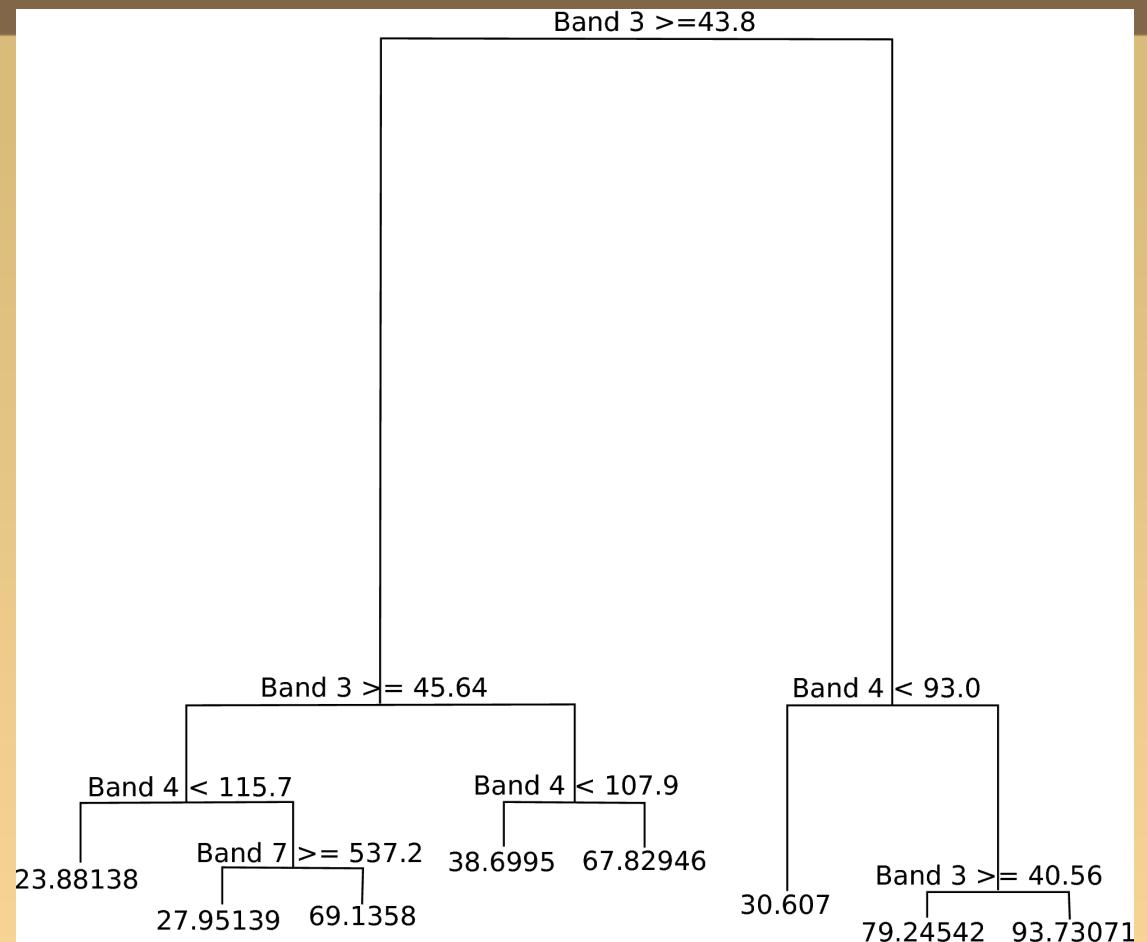


Editing (pruning) the tree

- Overfitting is common since individual pixels can be a terminal node
- Classification trees can have hundreds or thousands of nodes and these need to be reduced by pruning to simplify the tree
- Pruning involves removing nodes to simplify the tree
- Parameters such as minimum node size, and maximum standard deviation of samples at a node can restrict tree size

Regression trees

- Regression calculates relationship between predictor and response variables
- Structure is similar to classification tree
- Terminal nodes are predicted function (model) values
- Predicted values are limited to the values in the terminal nodes



Decision tree advantages

- Easy to interpret the decision rules
- Nonparametric so it is easy to incorporate a range of numeric or categorical data layers and there is no need to select unimodal training data
- Robust with regard to outliers in training data
- Classification is fast once rules are developed

Drawbacks of decision trees

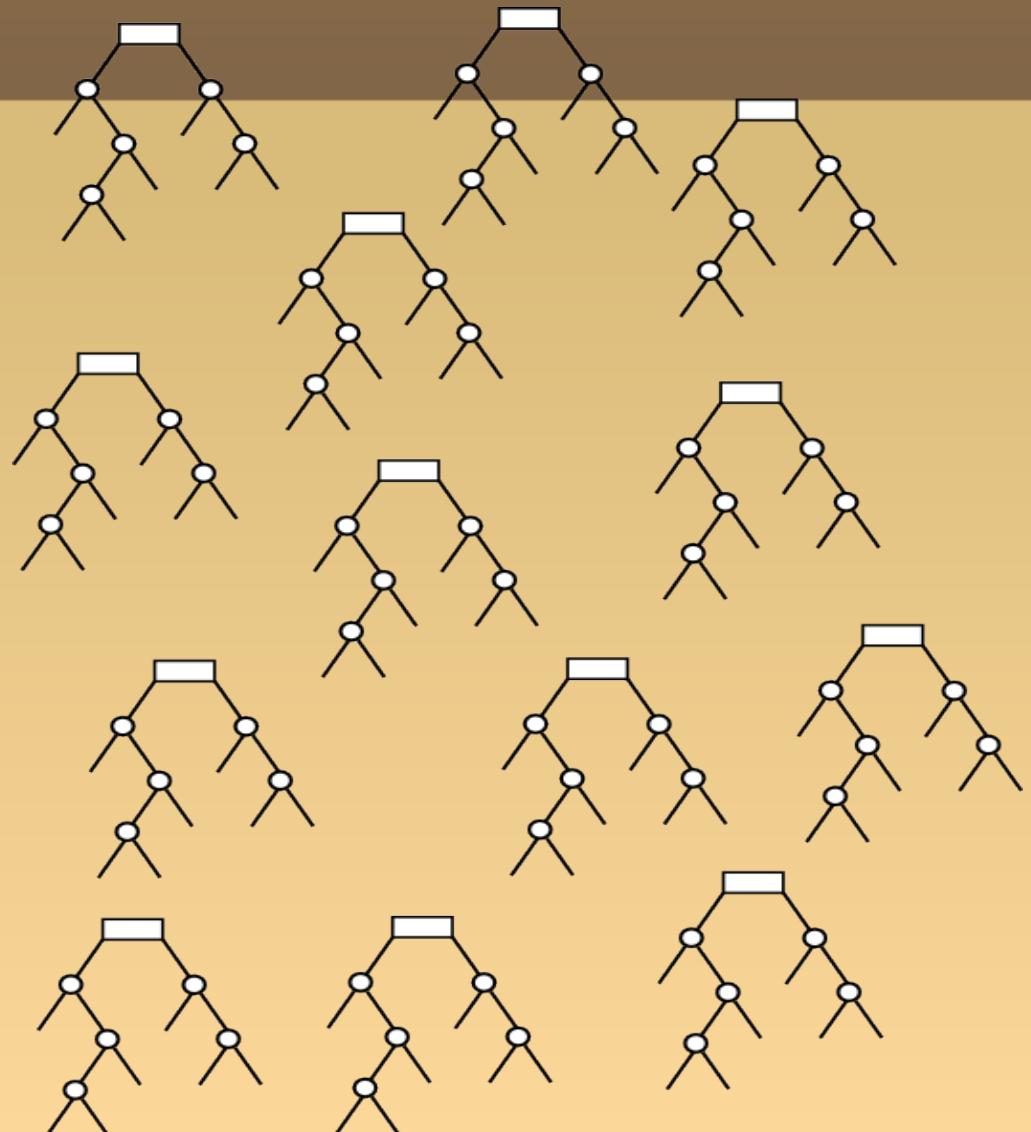
- Decision trees tend to overfit training data which can give poor results when applied to the full data set
- Splitting perpendicular to feature space axes is not always efficient
- Not possible to predict beyond the minimum and maximum limits of the response variable in the training data

Packages in R

- tree – The original decision tree package
- rpart – A slightly newer and more aggressively maintained package

What are ensemble models?

- Combines the results from different models
- Models can be a similar type or different
- The result from an ensemble model is usually better than the result from one of the individual models



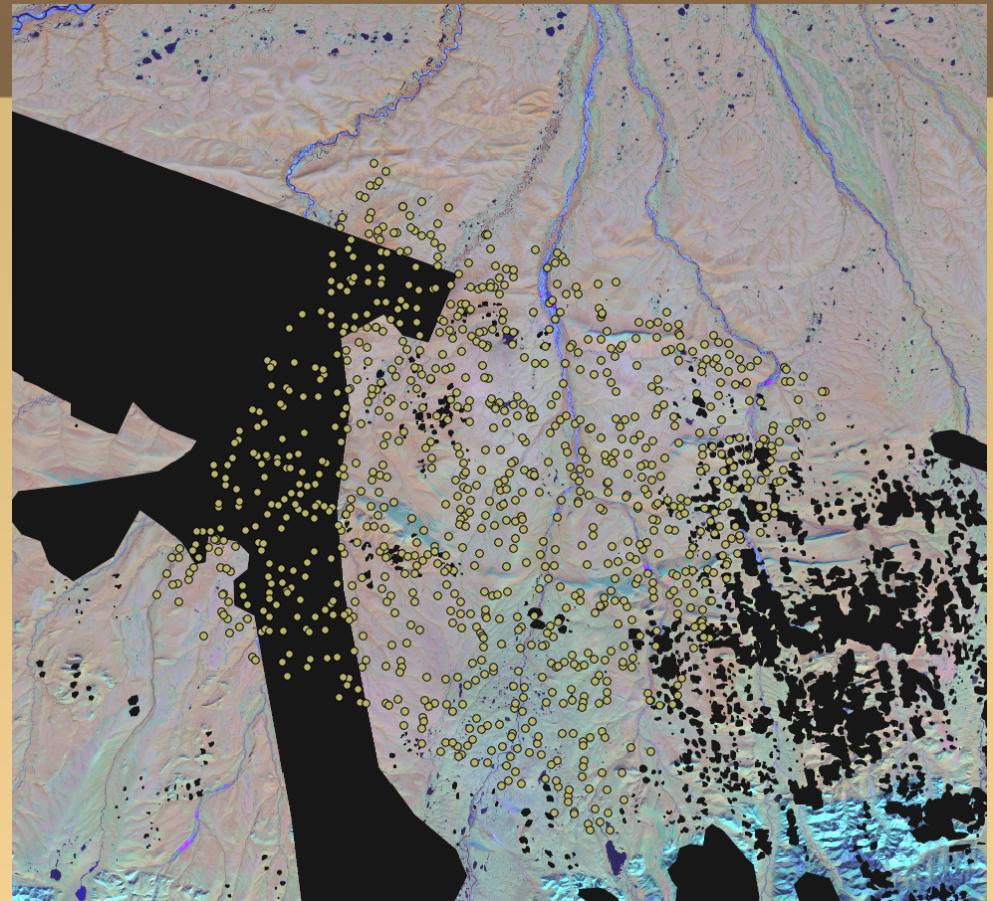
What is random forests

- An ensemble classifier using many decision tree models
- Can be used for classification or regression
- Accuracy and variable importance information is provided with the results



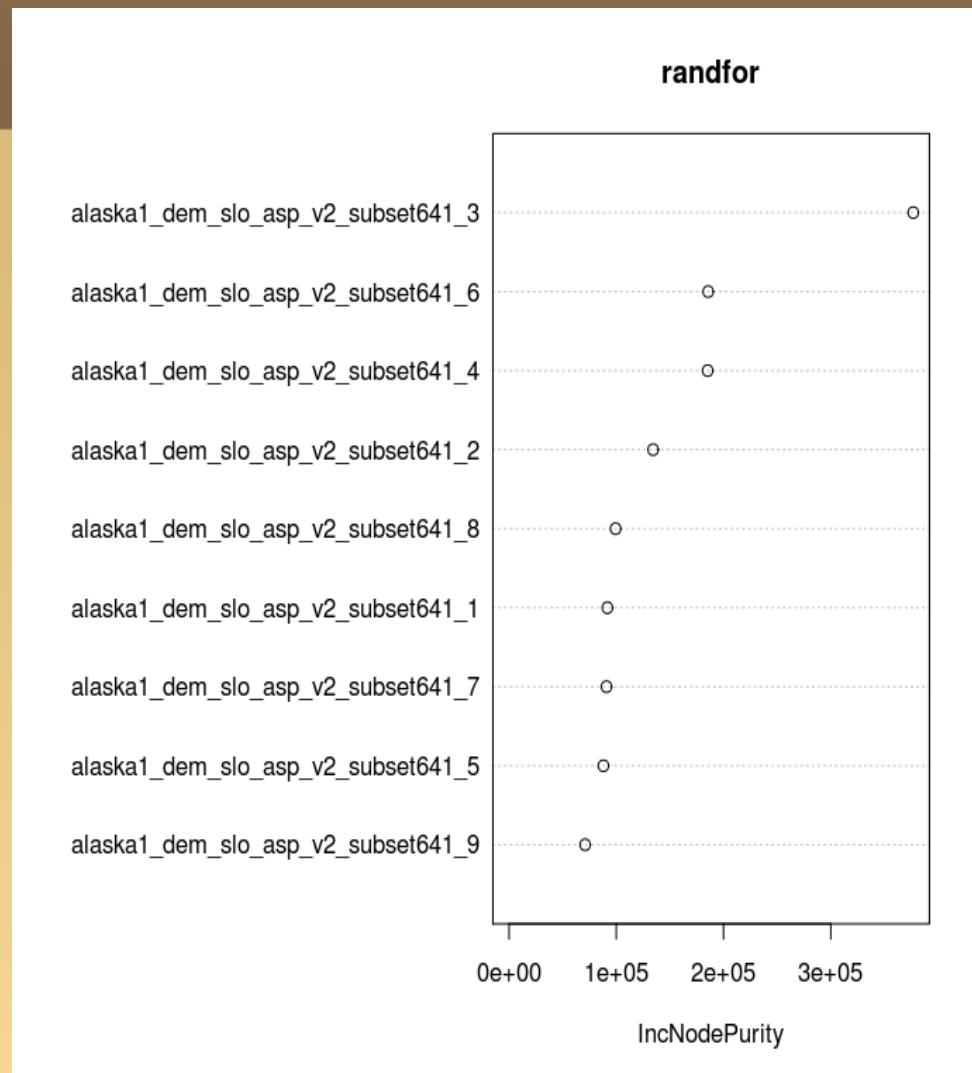
How random forests work

- A different subset of the training data are selected (~2/3), with replacement, to train each tree
- Remaining training data (OOB) are used to estimate error and variable importance
- Class assignment is made by the number of votes from all of the trees and for regression the average of the results is used



Use a subset of variables

- A randomly selected subset of variables is used to split each node
- The number of variables used is decided by the user (mtry parameter in R)
- Smaller subset produces less correlation (lower error rate) but lower predictive power (high error rate)
- Optimum range of values is often quite wide



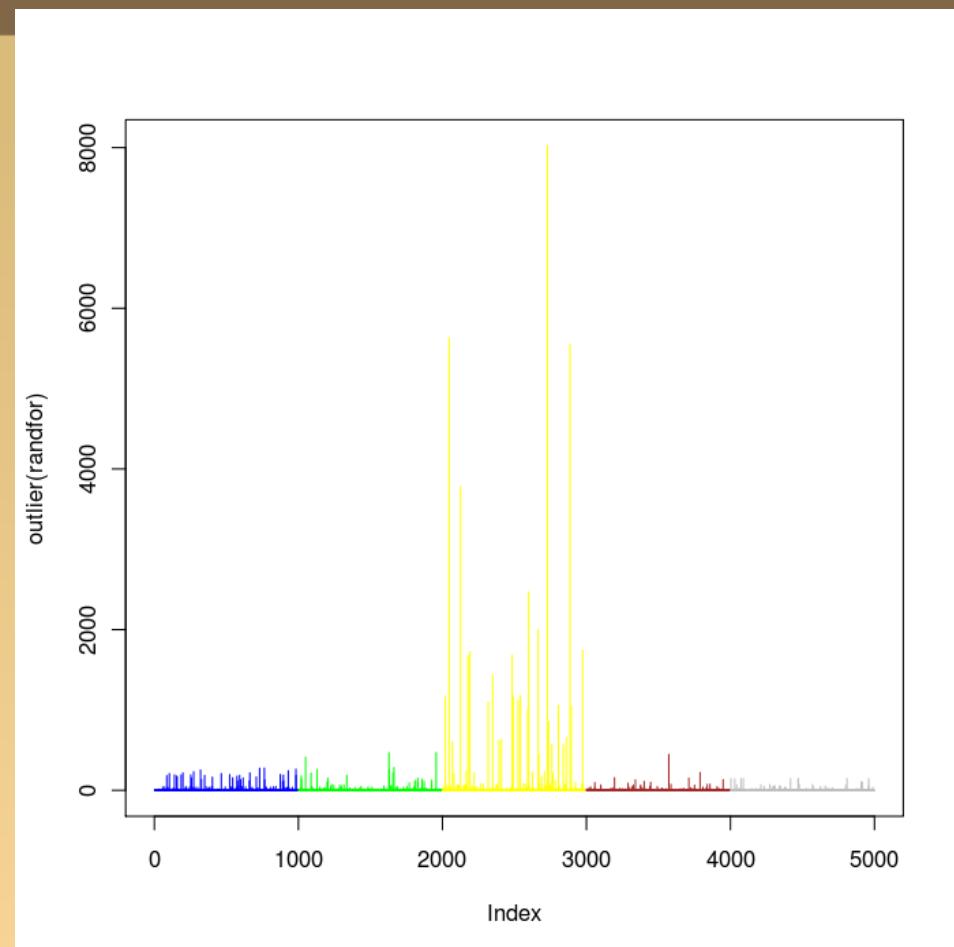
Common variables for random forests

- Input data (predictor and response)
- Number of trees
- Number of variables to use at each split
- Options to calculate error and variable significance information
- Sampling with or without replacement

```
randomForest(x, y=NULL, xtest=NULL,  
ytest=NULL, ntree=500,  
            mtry=if (!is.null(y) && !is.factor(y))  
                  max(floor(ncol(x)/3), 1) else  
                  floor(sqrt(ncol(x))),  
            replace=TRUE, classwt=NULL, cutoff,  
            strata,  
            sampsize = if (replace) nrow(x) else  
                        ceiling(.632*nrow(x)),  
            nodesize = if (!is.null(y) && !is.factor(y))  
                        5 else 1,  
            importance=FALSE, localImp=FALSE,  
            nPerm=1,  
            proximity, oob.prox=proximity,  
            norm.votes=TRUE, do.trace=FALSE,  
            keep.forest=!is.null(y) && is.null(xtest),  
            corr.bias=FALSE,  
            keep.inbag=FALSE, ...)
```

Proximity measure

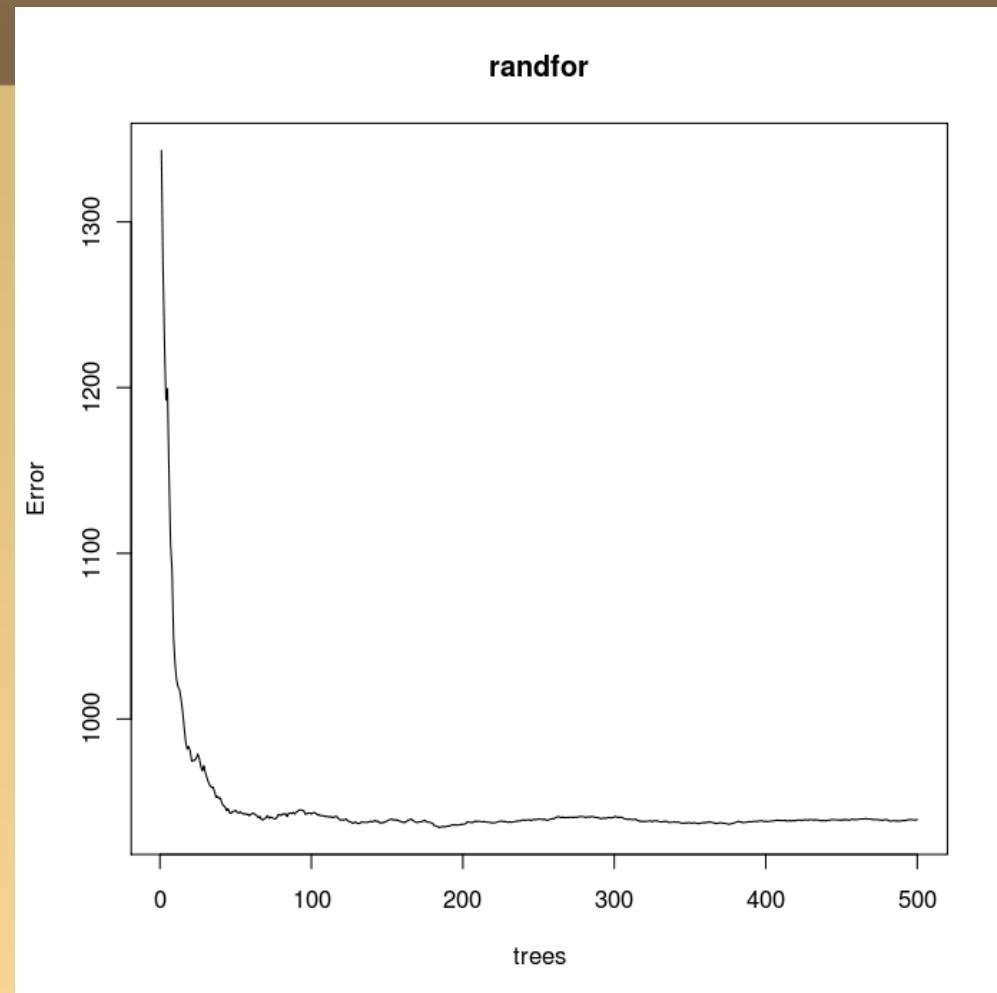
- Proximity measures how frequent unique pairs of training samples (in and out of bag) end up in the same terminal node
- Used to fill in missing data and calculating outliers



Outliers for classification

Information from Random Forests

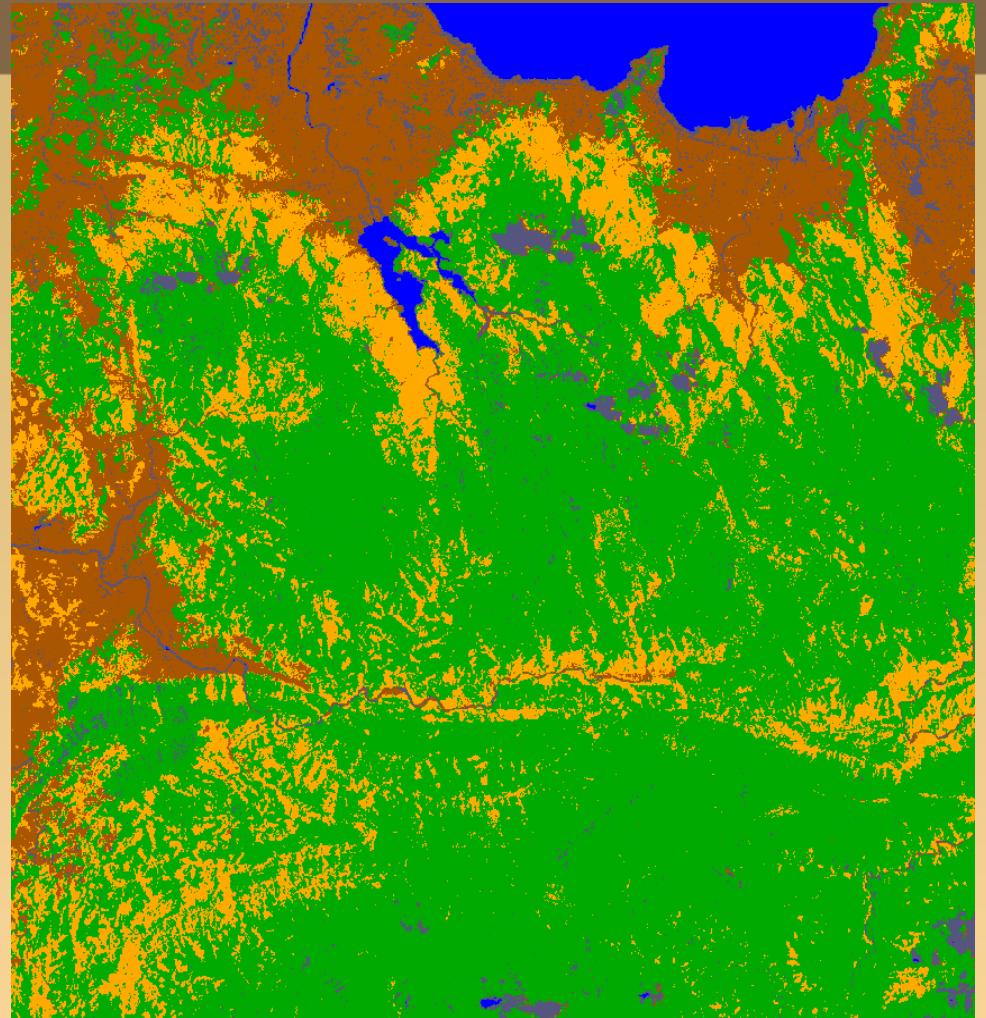
- Classification accuracy
- Variable importance
- Outliers (classification)
- Missing data estimation
- Error rates for random forest objects



Error rate vs. number of trees

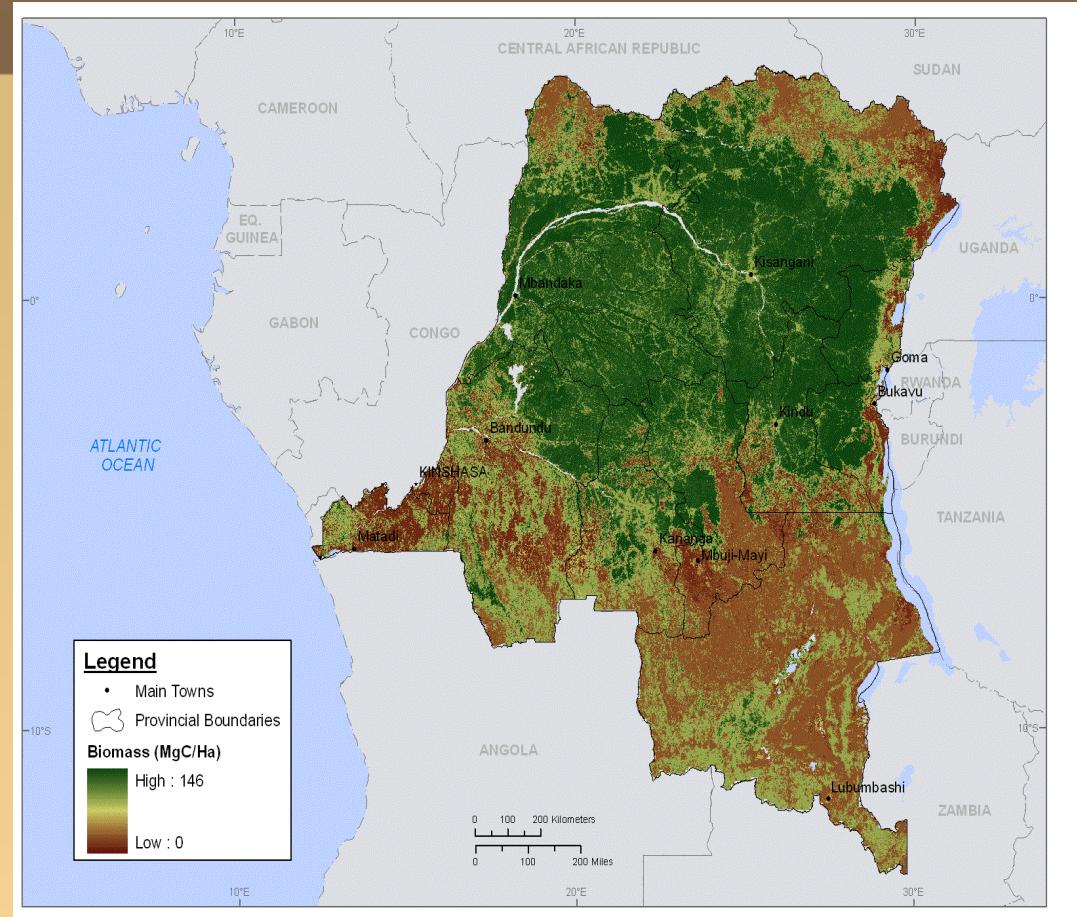
Advantages of random forests

- No need for pruning trees
- Accuracy and variable importance generated automatically
- Overfitting is not a problem
- Not very sensitive to outliers in training data
- Easy to set parameters



Limitations of random forests

- Regression can't predict beyond range in the training data
- In regression extreme values are often not predicted accurately – underestimate highs and overestimate lows



Common remote sensing applications of random forests

- Classification
 - Land cover classification
 - Cloud/shadow screening
- Regression
 - Continuous fields (percent cover) mapping
 - Biomass mapping



Resources to learn more about random forests

- [http://www.stat.berkeley.edu/~breiman/
RandomForests/cc_home.htm#prox](http://www.stat.berkeley.edu/~breiman/RandomForests/cc_home.htm#prox)
- http://en.wikipedia.org/wiki/Random_forest
- The randomForest Package (for R) description